Situated Spatio-temporal Visual Analytics

by

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ABSTRACT

We propose the concept of situated spatial temporal data (spatio-temporal) analytic as a tool that support user's ability to access data that of situational nature at location and time of the captured data (in-situ). The tool allows user to perform in-situ, trajectory data analytic tasks. Spatio-temporal visual analytic research to date has primarily focused on analytics in traditional computing paradigms and separated analytical processes of data representation and its context. With the advancement in Augmented Reality (AR), Head-Mounted Display (HMD), and sensor technologies, an emerging computing paradigm, i.e. situated analytics, enables access to spatio-temporal data nearly any time and place. Situated analytics involves inspecting the data in the context of the environment where it has been collected in. Although, situated spatio-temporal analytics has the potential to transform the way we engage with data comparing to traditional computing paradigms, it is necessary to explore the key design aspects of situated spatio-temporal analytics that enable in-situ analytic tasks and improve users' analytic skills and experience.

We empirically validated the potential of situated spatio-temporal analytics by comparing situated and non-situated analytics and found the situated group was more accurate compared to the non-situated group. We explored different user-generated spatio-temporal data visualization designs and interactions for an in-situ setting and proposed design recommendations to support in-situ data exploration and analytical activities. Based on design recommendations, we developed Situated Space-time Cube Analytics (SSCA) that utilizes two-dimensional (2D) and three-dimensional (3D) visualization, interactive data filtering, and embodied interaction. We conducted the SSCA prototype evaluation study to establish an understanding of in-situ data exploration activities, Visual Information Seeking Mantra (VISM) interaction taxonomy, and challenges in view visualization. From the SSCA evaluation study, we propose further

design recommendations that reduces challenges found in the SSCA prototype and would improve the users' exploration and interaction with the data. We used these design recommendations to develop Situated Spatio-temporal Multiple-Views Analytics (SSMA).

Obstacles are those frightful things you see
when you take your eyes off your goal.
— Henry Ford

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ACRONYMS

2D two-dimensional

3D three-dimensional

AR Augmented Reality

CCTV Closed-circuit Television

CO Carbon Monoxide

CSV Comma Separated Value

DC data occlusion

FOV field of view

fps frame per second

GPS Global Positioning System

GUI Graphical User Interface

HCI Human-Computer Interaction

HMD Head-Mounted Display

IoT Internet of Things

in-situ ability to access data that of situational nature at location and time of the captured data

LFOV limited field of view

OpenCV Open Source Computer Vision

POI Period of Interest

RFID Radio-Frequency Identification

ROI Region of Interest

STC Space-Time Cube

SSCA Situated Space-time Cube Analytics

SSMA Situated Spatio-temporal Multiple-Views Analytics

spatio-temporal spatial temporal data

TLX NASA Task Load Index

UI User Interface

VISM Visual Information Seeking Mantra

VR Virtual Reality

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Sections of this thesis have been published in conference proceedings and journal publications, either previously or forthcoming at the time of publication. Permissions for these works to appear in this dissertation have been granted by their respective publishers. Following is a list of prior publications in which portions of this work appeared, organized by chapter.

Portions of Chapter 3, and 4

Fouad Alallah, Yumiko Sakamoto, Pourang Irani. 2020. Exploring the Need and Design for Situated Video Analytics. In *Symposium on Spatial User Interaction*, SUI '20. Association for Computing Machinery, New York, NY, USA, Article 15. 1-11. DOI: https://doi.org/10.1145/3385959.3418458.

Portions of Chapter 5

Fouad Alallah, Ahmed Faleel, Yumiko Sakamoto, Bradley Rey, and Pourang Irani. SSCA: Embodied Interactions for Situated Analytics. In Agus, Marco and Aigner, Wolfgang and Höllt, Thomas (eds.) *EuroVis 2022 - Short Papers.* DOI: https://doi.org/10.2312/evs.20221088.

Portions of Chapter 6

Fouad Alallah, Ahmed Faleel, Yumiko Sakamoto, Bradley Rey, and Pourang Irani. Evaluation of Situated Space-time Cube Analytics for In-situ Data Exploration. *Information Visualization 2022*; 0 (0): 00-00. **Submitted October 05, 2022.**

PUBLICATIONS

Other publications that resulted from course works and collaborations with researchers are as follows:

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[2] **Fouad Alallah**, Ali Neshati, Yumiko Sakamoto, Khalad Hasan, Edward Lank, Andrea Bunt, and Pourang Irani. 2018. Performer vs. Observer: Whose Comfort Level Should We Consider When Examining the Social Acceptability of Input Modalities for Head-Worn Display? In *Proceedings of the 24th ACM Symposium on Virtual Reality Software and Technology (VRST '18)*.Association for Computing Machinery. New York, NY, USA, Page 10, pages 9.

[3] Yumiko Sakamoto, Hosne Al Walid Shaiket, **Fouad Alallah**, Kenny Hong, Pourang Irani. (2020). Self-Reporting Individual Movement Data During a Pandemic: Survey Study (Preprint). 10.2196/preprints.18704.

[4] Ali Neshati, **Fouad Alallah**, Bradley Rey, Yumiko Sakamoto, Marcos Serrano, and Pourang Irani. 2021. SF-LG: Space-Filling Line Graphs for Visualizing Interrelated Time-series Data on Smartwatches. In *Proceedings of the 23rd International Conference on Mobile Human-Computer Interaction (MobileHCI '21)*. Association for Computing Machinery, New York, NY, USA, Article 5, 1–13.

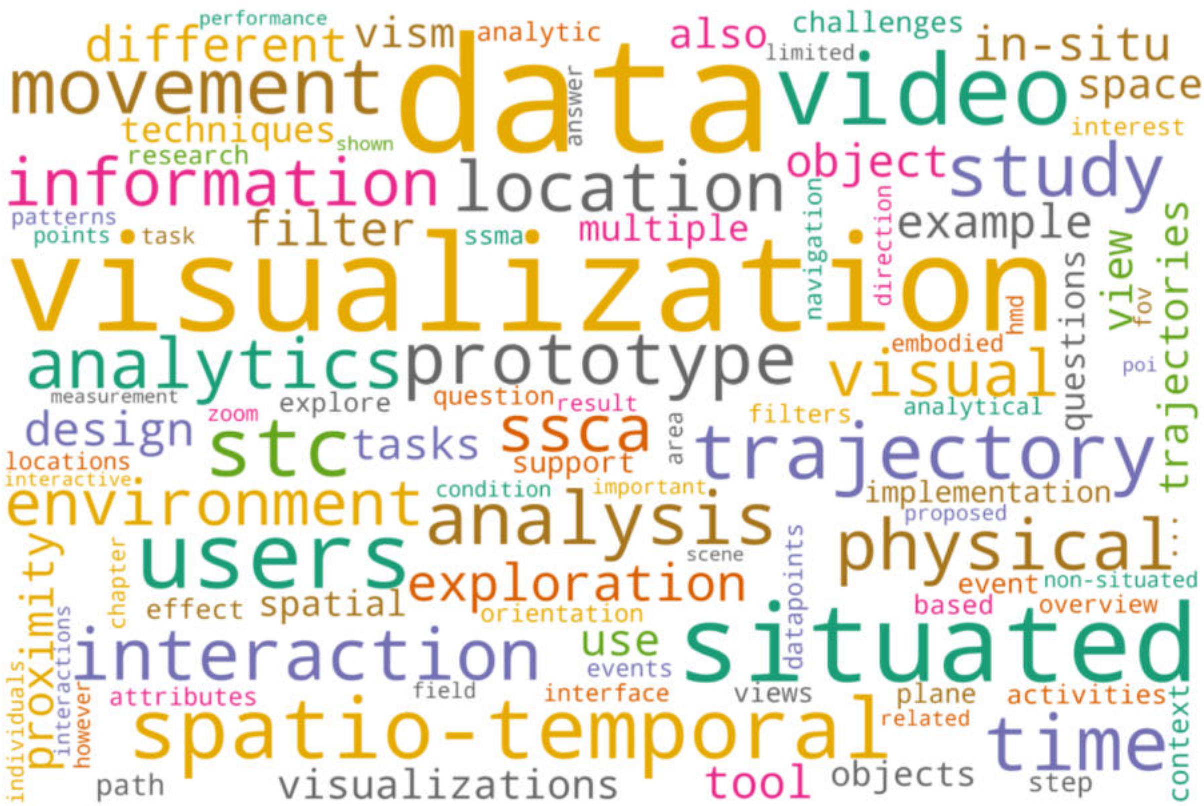


Figure 1: A generated words cloud for the dissertation.

1 INTRODUCTION

Spatial temporal data (spatio-temporal) is high-dimensional multivariate data that includes both time- and space-related attributes to describe phenomena or events in a certain location and time. Spatio-temporal data can be collected from various sources such as sensors, Internet of Things (IoT), Global Positioning System (GPS) devices, and video surveillance technologies [68]. Object trajectory data is one of the common examples of spatio-temporal data where an object occupies a single location at a given time. Object trajectory movement provides critical insights into a variety of phenomena and supports in making informed decisions. For example, in public safety, such data include the discrete event(s) [103, 119] (e.g., public property vandalism, or a car accident), stationary event(s) (e.g., a group of individuals meeting at a location), and/or continuous movement [103, 119] (e.g., an individual walking from point A to B, vehicles driving on a highway, or animal movement in the wild) [120, 161]. Scientists and laypeople make use of trajectory data to extract important patterns within the natural or physical environment and build knowledge of various events. Table 1 shows a simple example of a spatio-temporal dataset of an individual movement within a geographic region and time span. For convenience, from this point forward, the terms "spatio-temporal data", "trajectory data", and "movement data" will be used interchangeably to refer to objects' trajectory data.

Table 1: A simple example of a movement dataset of individuals walking inside a building.

ObjId	Date	Time	xLoc	yLoc
⋮	⋮	⋮	⋮	⋮
25	2019-05-10	13:08:29	114.9898587	30.522544
26	2019-05-10	13:08:29	114.9890013	30.522301
26	2019-05-10	13:08:30	114.9890015	30.522302
⋮	⋮	⋮	⋮	⋮

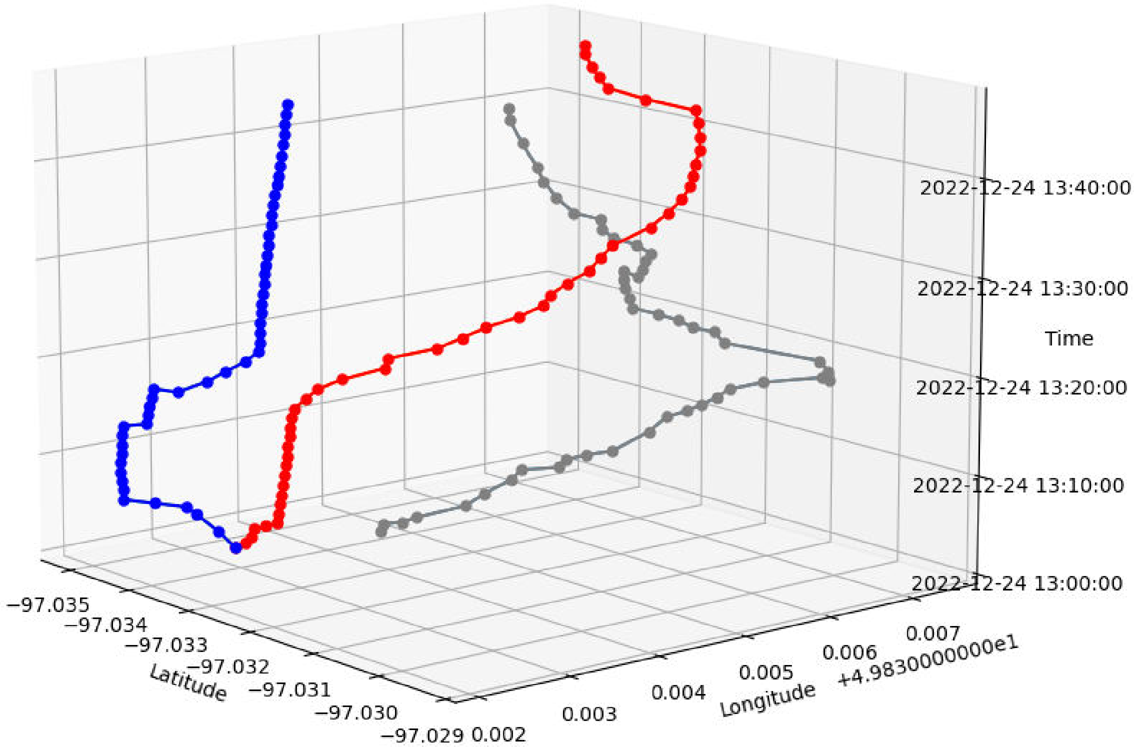


Figure 2: An illustration of STC visualization of spatio-temporal data from Table 1

Data visualization is a powerful tool for transforming raw movement data into a meaningful visual representation. Map, two-dimensional (2D), and three-dimensional (3D) visualization are examples of various visualization methods that give the data visual context and allow users to comprehend more easily than text alone. Data visualization allows users to explore movement data, identify relevant events, and gain interesting insights from the data. For several decades, data visualization research has mainly focused on using traditional computing paradigms (i.e., analysis on a computer while using classical desktop interfaces) to explore movement data [60, 70, 87, 100, 110, 114, 142, 165]. These visualizations are displayed on different display devices that range from small hand-held to desktop displays. Traditionally, an analyst would physically sit in front of small monitors, explore the event of interest in the data, interact with spatio-temporal data using input modalities (e.g., mouse, keyboard, and traditional screen), and filter data using a graphical user interface (Graphical User Interface (GUI)) controls (e.g., buttons and sliders). In the last few decades, the computing paradigm has shifted from large computing equipment that took up whole rooms to compact portable computers , and this shift continues toward immersive realities and wearable computing devices that support a new form of interaction.

The vast majority of spatio-temporal data visualizations were designed for traditional computing paradigm without considering the physical environment and spatial context in which data is collected, structured, and displayed. This is primarily due to technological constraints, visualization design requirements, or the absence of a need to combine analytical activities for both data representation and its spatial context. In certain situations, the separation of analytical processes for data representation and physical environment will not only impose an additional cognitive load on the user to mentally link data with the physical space, recall the physical environment when looking at a visualization out of its context, but also limit users' understanding and sense-making [144, 156, 160]. The notion is that the distance between the data visualization and their references is essential. In fact, Tobler's first law of geography, as cited in [153], stated that "everything is related to everything else, but near things are more related than distant things." This statement promotes the notion that could be applied to the relationship between users, data, and the physical context. By minimizing this distance and enabling individuals to more immediately connect with representations and their references (i.e., being in-situ), it becomes possible to make it simpler for users to make sense of data and act on it in the real world.

Situated analytics is an emerging field of research that aims at removing the gap between users, data, and analytical tools, and considers the physical environment and spatial context in which data is collected, organized, and displayed. It helps researchers and analysts to better understand relationships between data visualization and the physical environment while being in-situ. Situated analytics leverages multiple technologies such as Human-Computer Interaction (HCI), 3D Immersive realities, data visualization, and visual analytics. Immersive realities technologies, e.g., AR and Virtual Reality (VR), support spatio-temporal data visualization [54, 83, 156]. AR enables users to see digital information overlaid on the physical world around them and interact with data visualization and physical world at the same time [38, 144], while VR enables users to enter a completely virtual environment with no or little possibility of direct interaction with the physical world [54, 144]. Although VR and AR enable users to immerse with visualization, they are quite different in terms of how users interact with and navigate their respective environments. In VR, users are limited to a small navigation space, and their analytical activities mainly are focused on understanding the data. In contrast, AR users are not limited by navigation space and their analytical activities can also include understanding the data and context in which the data is related to the physical world. This difference is due to the fact that VR creates a fully artificial environment that isolate users from the real world, while AR builds upon the existing physical world. As a result, AR has the potential to support situated movement data visualization and provide a more immersive and realistic experience for users.

Situated analytics facilitates greater comprehension of spatio-temporal data representation than traditional visualization tools. Urban planning is one of the fields that clearly demonstrates the advantages of situated visualization and in-situ data analysis. Urban planners use maps to visualize air quality data collected throughout the city. Although maps are effective in providing an overview of the air quality around the city, they are separated from the physical sites and do not provide sufficient information for making decisions on future city plans. Therefore, planners visit sites throughout the city to collect additional data such as population density, traffic patterns, and vegetation, to make decisions regarding future plans. SiteLens has been proposed to map the carbon monoxide concentration data in physical space at the location where they were collected, enabling city's planners to perform in-situ analysis of data related to sensors and physical sites [156].

In the remaining of this chapter, we begin with a set of simple scenarios that shows the potential benefits of situated spatio-temporal visual analytics. Next, we outline the dissertation's research objective, research path route, and contributions.

1.1 SCENARIOS

1.1.1 *Technical analytics task scenario*

First, we meet Mahmood on one of his daily routine, see Figure 3. Mahmood works in the information technology department as a computer and network technician. Two days ago, he has received emails regarding interference with Wi-Fi connections in a building's atrium. To determine the cause of the issue, Mahmood needs to analyze the wireless network. Mahmood puts on an HMD and walks around the building testing the Wi-Fi signal, in term of strength and speed, at various points of interest. Mahmood visualizes wireless signal data on October 26. As he moves around the space, virtual coloured labels begin to appear on the floor to indicate the signal strength at various locations. Green, yellow, and red colours represent a strong, average, and weak signal, respectively. Mahmood notices the wireless single was strong on October 26. Then, Mahmood filters and visualizes more data between October 26 and 28. Mahmood finds the wireless signal quality significantly dropped between October 27 and 28. As Mahmood follows the visualization data point and makes his way near the space's router, he notices a large display has been mounted close to the router, potentially interfering with Wi-Fi connections. With the help of the visualization and being in-sit, Mahmood can decide to increase the number of routers or relocate the router.

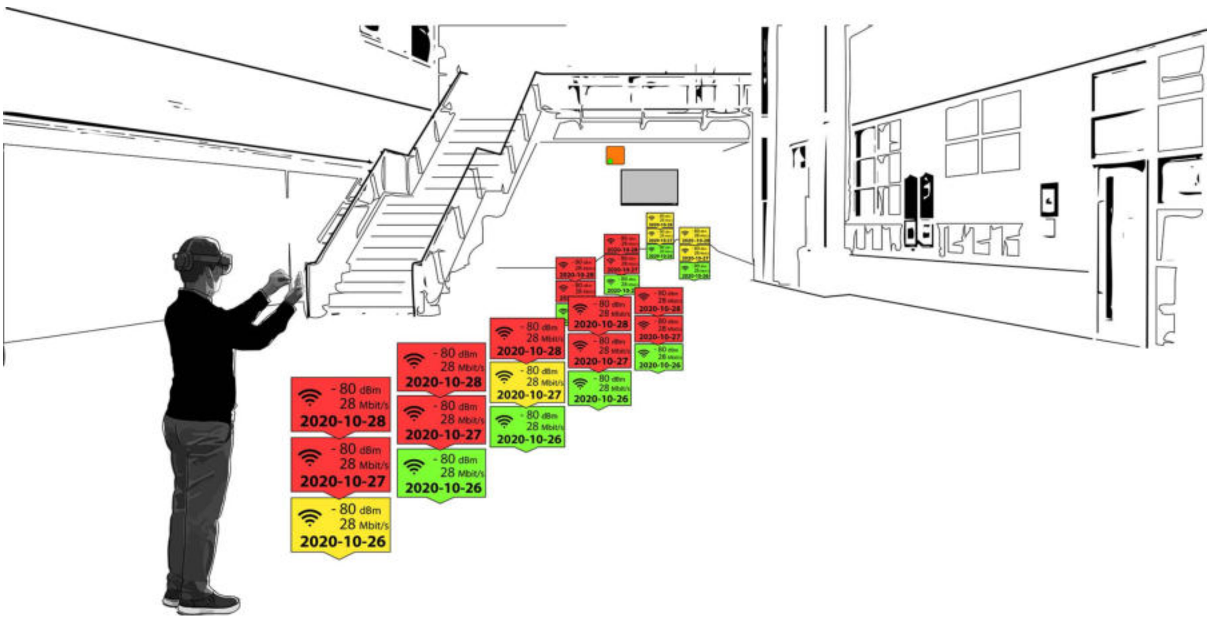
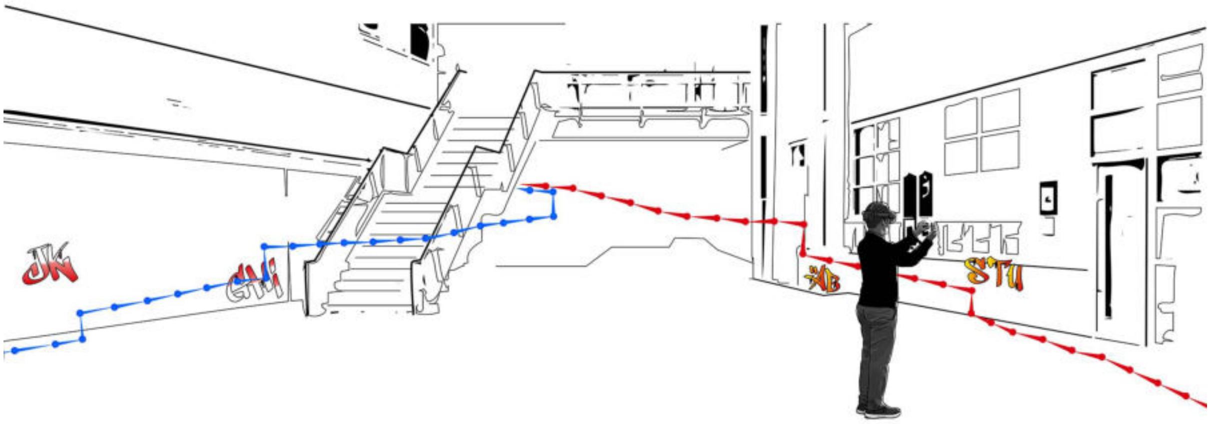


Figure 3: An example of situated visual analytics to troubleshoot a wireless router (orange box). The network signal quality is visualized and mapped into the space (Red: Weak signal, Yellow: Average signal, Green: Strong signal). The visualization enables the technician to examine the wireless router's signal strength over the last several days in order to determine the cause of the network interference.

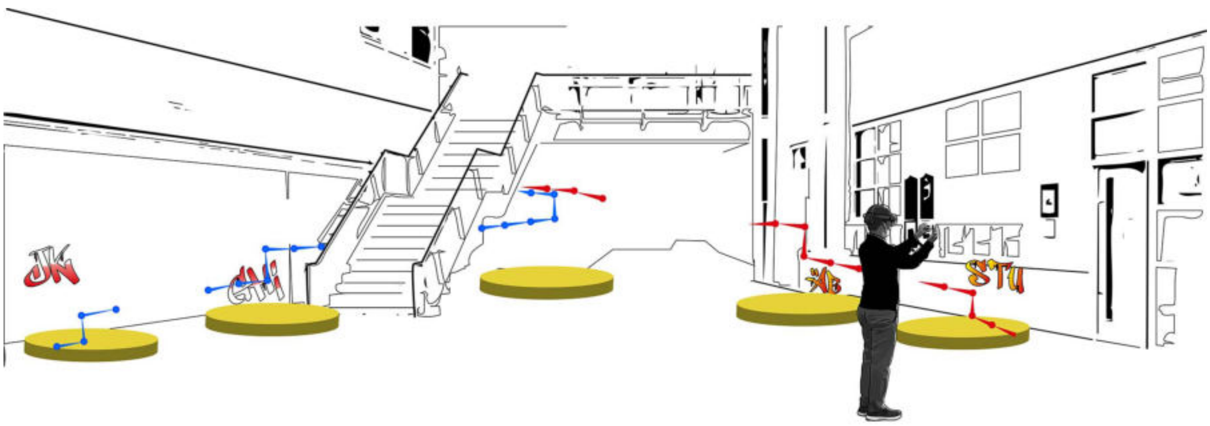
This instance exemplifies the potential of SA. Primarily, it covers a common problem that many technicians regularly face, such as network interference. The task is performed in-situ during the technician's regular checking. Also, the task has an analytic component, involving the exploration of data and filtering datapoints based on router signal quality for different dates. In addition, being in-situ helps the technician to identify the change in the environment that causes issues.

1.1.2 *Movement Trajectories of Individuals Scenario*

In a safety and security context, Ahmed is a security personnel working at a university campus. One day, Ahmed receives a call from the security department to investigate and report a spray paint vandalism incident on a building atrium. Ahmed is required to report the course of the incident, location of graffiti, individuals involved in the incident, etc. Ahmed quickly responds to the call and moves to the incident location. As he moves to the atrium and wears the HMD, movement trajectories data of individuals - from ubiquitous sensors, GPS devices, cellphones, or video footage - are virtually appeared and mapped to the space, see Figure 4. Each coloured movement path represents an individual movement in the space. With a movement path, each sphere represents the locations of individuals at a specific time. Ahmed walks toward the locations of graffiti and the individuals meeting point, then, he applies filters on data at locations of interest. The tool helps Ahmed to locate and describe in details the graffiti, identify the number of individuals involved in the vandalism act, and a location where they met before leaving the atrium.



(a) The security personnel has quickly noticed two individuals' movement trajectories (blue and red). By tracking the individual movement trajectories, he spotted the location of graffiti (two on the left wall and two on the right wall).



(b) The security personnel filtered the movement data by selecting regions of interest (i.e., yellow cylinders) to show the location where two individuals met, and locations of the painting, individuals' movement direction.

Figure 4: An example of situated visualization of vandalism incident.

These two scenarios illustrate the type of tasks involved in spatio-temporal data analysis. They cover common analytical tasks related to spatio-temporal data, in this case, analysis of spatio-temporal data. For example, the task is carried out in-situ, with movement data being mapped onto the space and changes to the physical environment being observed (e.g., viewing graffiti and estimating damages). Additionally, the task has an analytical component, which includes filtering movement data based on specified locations and times. Also, being in-situ enables the user to establish the connection between individuals' actions and the effects of the actions in the environment.

Individuals in the previous examples were interested in finding, understanding, and conveying important patterns in data directly related to, embedded into, physical environment, artifacts, and people around them. Situated analytics involves the inspection and filtration of data within the actual context it was collected [144]. Situated visualization and user interfaces support a novel paradigm that gives users access to data in the location and context of a primary, non-digital task (e.g., associating data sources with real world physical objects). Thus, situated interfaces and visualizations are akin to an "information companion". Situated visualization supports data access when needed, and integrates the data into the user's surrounding environment, under varied physical body movements and mobility contexts, whether the user is standing, turning, or walking.

We envision the shift of spatio-temporal data analysis methods/techniques from non-situated paradigms to situated which integrates spatio-temporal analytics tools and activities into the physical environment. We are interested in exploring the potential of this suggested approach and whether it enhances the reliability of the analytical tasks and expand the understanding of data and its context. We are interested in designing and implementing a situated spatio-temporal visual analytic tool that supports spatio-temporal analytical tasks and enables a suitable form of user interaction.

1.2 RESEARCH OBJECTIVE AND OVERVIEW

The following is the primary research objective of this thesis:

Explore the key design aspects of situated spatio-temporal analytics that enable in-situ analytic tasks and improve users' analytic skills and experience.

The route from this aim to the goal starts with exploring the literature of current spatio-temporal data visualization analytics. The following are the stages along this route (described in Figure 5):

A. We undertake a comprehensive analysis of the literature surrounding situated analytics. This review reveals a gap in the literature. Only little is known about how to benefit from in-situ exploration of spatio-temporal data since situated analytics is still an emerging area [49, 144]. This raises the question of whether situated analytics facilitates task performance compared to non-situated settings. Also, the literature review helps with the most updated and appropriate design for spatio-temporal data visualization (Chapter 2).

B. We conduct an empirical study to investigate spatio-temporal data analysis activities in both non-situated and situated analytic activities. We compare participants' performance in both conditions in term of accuracy, completion time, and confidence (Chapter 3).

C. An elicitation workshop is carried out which includes sketching and ideation activities for situated analytics. This workshop aims to capture visualization designs to support situated spatio-temporal data visualization, and potentially enhance the analytical process in an AR environment (Chapter 4).

D. We implement a SSCA tool. SSCA, with the help of interactive data filters and proxemics and embodied interaction, visualizes data using Space-Time Cube

(STC) and supports users' data analytic tasks to allow them to make informed decisions regarding spatio-temporal data (Chapter 5).

e. An evaluation, through an initial exploratory study, for our SSCA tool to allow for situated data exploration. Through set questions for users to answer regarding the dataset, we quantitatively and qualitatively record user interactions and metrics along with subjective experience data to allow us to evaluate our system (Chapter 6).

f. We implement an alternative SSMA that addresses concerns and challenges associated with the situated STC visualization and integrates visual information seeking mantra processes based on user location around the visualization physical space (Chapter 7).

1.3 CONTRIBUTIONS

This thesis provides many contributions to the research community, some of which are as follows:

1. Examine and evaluate spatio-temporal analysis activities between non-situated and situated analytic activities. We conduct an empirical study comparing Situated and Non-situated spatio-temporal Analytics. We were the first to empirically show the effectiveness of situated compared to non-situated analytics (in terms of accuracy).

2. Explore design aspects of situated analytics and how participants would visualize data that is spatio-temporal in nature, such as events and movement data. We report user-generated visualization designs and interfaces to support in-situ video analytic tasks.

3. Analyze user-generated visualization using our generated knowledge on how to exploit the user's immediate environment to place and represent visualizations.

4. Design and develop SSCA prototype that allows situated spatio-temporal analytics, i.e., movement trajectories in STC visualization. STC visualization embeds movement trajectories into the actual environment where the data was captured.

5. Explore embodied interaction (proxemics, orientation, and mid-air gestures) as means to perform analytic tasks such as visual inspection of spatio-temporal filtering of the trajectories.

6. Address various approaches for evaluating the SSCA prototype, such as observing video recordings of users during their interaction with the tool, logging prototype events to understand users' analytic tactics and strategies, and interviewing users regarding their subjective experience of the system.

7. Develop SSMA using multiple-view visualizations. SSMA is an alternative interactive situated visualization that is aware of users' locations within physical space to enable suitable visual information seeking mantra steps and address challenges users faced during SSCA evaluation study.

Each step on this route leads to the next, with the complete route including all the prerequisites for a comprehensive exploration of Situated spatio-temporal data analytics.

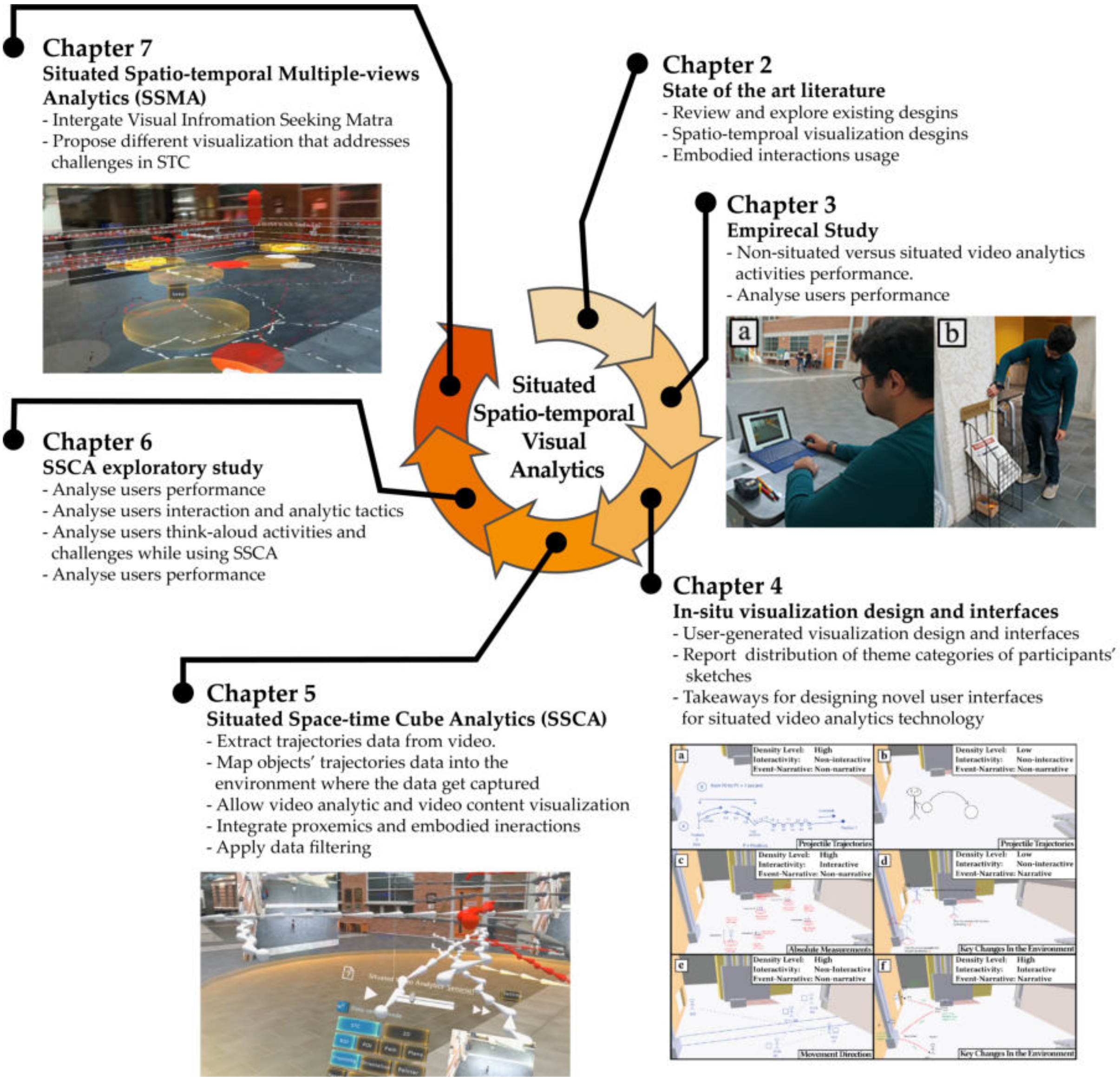


Figure 5: An overview of the research route taken in this dissertation, from the initial exploration of in-situ analytics to the final goal of proposing alternative visualization to support situated spatio-temporal data visual analytics. Each step along this path leads to the next, with the complete path encompassing all the initial requirements in a holistic exploration of Situated spatio-temporal data analytics.

2 STATE OF THE ART LITERATURE

This chapter introduces comprehensive literature of important areas that inspire this dissertation, including spatio-temporal data, exploratory spatio-temporal data analysis, spatio-temporal data visualization techniques, situated analytics and embodied interaction. We start with explaining what is spatio-temporal data, frameworks of questions that can be asked about spatio-temporal data, and STC technique to visualize spatio-temporal data in traditional and VR computing paradigms. Next, we discuss current progress on spatio-temporal data visualization tools and techniques in traditional and immersive computing (i.e., AR) platforms. Then, we present concepts, characteristics, and definitions of situated analytics. After that, we briefly cover related work in embodied interaction, where the user's body is used as a means to interact with devices and data. Finally, we outline the gap in the literature regarding situated spatio-temporal visual analytics.

2.1 WHAT IS SPATIO-TEMPORAL DATA?

Any phenomenon or event in life has spatial and temporal attributes. Spatial is a term that refers to the physical location of the event. Temporal is a term that refers to a certain point in time of the event. When data of the phenomenon is recorded in both spatial and temporal aspects, the collected data is called spatial-temporal data (or spatio-temporal data for short). The complexity of spatio-temporal data varies depending on the data sources and recording precision (i.e., the precision of location and time of the collected data). For example, spatio-temporal data extracted from video footage contains basic attributes such as object identifier, date, recording time, and location coordinates (e.g., $x - y$ coordinates of a video footage space) whereas spatio-temporal data recorded from an airplane with a high-precision tracking system and high-rate data capture contains more attributes such as altitude, speed, etc. Spatio-temporal data analysis is a developing field of research. Application domains that benefit from spatio-temporal data analysis include, but are not limited to, security, criminology, transportation, zoology, biology, meteorology, and urban planning. In this dissertation, the spatio-temporal data used in this research will be taken from video footage for the sake of simplicity.

2.2 INFORMATION VISUALIZATION INTERACTION TAXONOMIES

Several information visualization interaction taxonomies have been proposed [4, 23, 133, 138, 149, 152]. As part of visual analytics research and agenda, these taxonomies aim at characterizing the design space of interaction approaches to facilitate analytic reasoning and sense-making [55]. Although many of the proposed taxonomies have similarities in some aspects, they have differed in terms of their granularity [163]. For example, researchers have proposed taxonomies classification such as low-level interaction taxonomies [23, 32, 43, 86, 133], dimensional taxonomies [138, 149] (e.g., to describe interaction types, directness, and modes), space and parameters of interaction [152], and user tasks [4, 169].

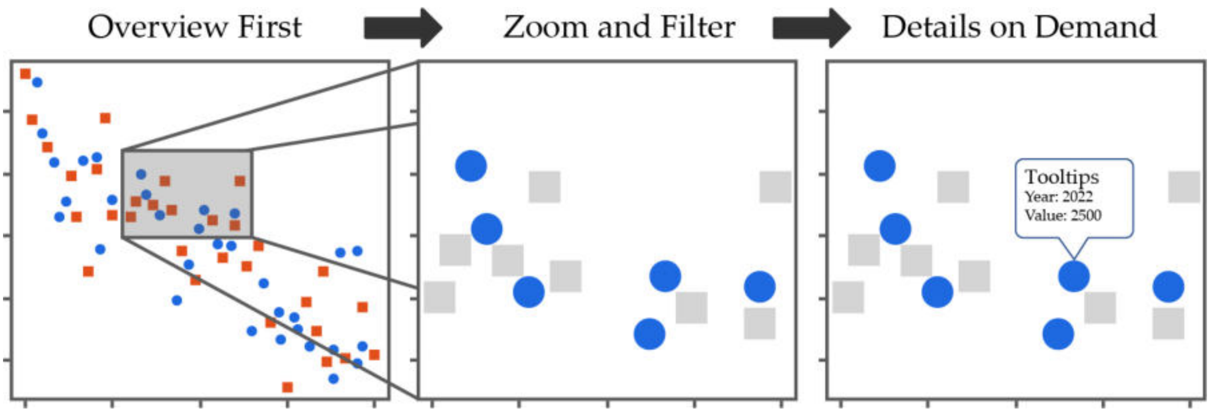


Figure 6: An example of visual information seeking mantra by Shneiderman [133]. In the first step, a user views the all data points to make sense of the data as a whole (two categories). In the second step, he zooms into the centre of the graph and filters out the orange dataset. Finally, the user shows details information about one data point.

VISM is a well-known and general navigation and exploration taxonomy [133]. The mantra is *Overview first*, *Zoom and filter*, then *Details-on-demand*. In overview step, an analyst views a visualization with all data plotted. This step provides a general sense of data as a whole. In the second step, i.e., zoom and filter, the analyst focuses on particular areas of interest in the visualization (zoom) and selects a subset of the data (filter) to only see relevant information. Finally, details-on-demand step allows the analyst to request additional information about a particular data point, see Figure 6.

VISM is a low-level interaction taxonomy and it highlights the fundamental aspects of dealing with data visualization [133]. In high-density visualizations, exploration techniques often sequentially move from obtaining an overview of the data, zooming and filtering the data, to finally viewing specific details of the remaining data [134]. VISM can be a repetitive process, depending on the task complexity and the exploratory activity, until the user finds the answer to the query. VISM is widely used in visualization tools on desktop environments to support information visualization interaction [133, 134].

2.3 EXPLORATORY SPATIO-TEMPORAL DATA ANALYSIS

In general, data analysis often starts out with an exploratory search to formulate tentative and broad queries. These queries often narrow down the data to be examined. These primary explorations then lead to further questions and newly revealed information, hypotheses generation, and ultimately answers to the questions [5, 8, 15, 41, 119].

Several frameworks for visualization exploratory search have been proposed, for example, by Bertin [15], Peuquet [119], Andrienko, Andrienko, and Gatalsky [8], and Amini et al. [5]. Bertin [15] introduced a theoretical framework for developing and assessing information graphics based on two notions *question type* and *reading level*. *Question type* relates to variables that are presented in a dataset: "There are as many types of questions as components in the information" [15]. For instance, a dataset with individual locations by hours contains two main components, hour and location. Therefore, two possible questions can be asked:

Q 1. At a given hour what is the location of individual x?

Q 2. For a given location, at what time was the individual at that location?

In Bertin's framework, each question type has three stages of reading: 'elementary', 'intermediate', and 'overall'. The reading level reflects whether the question references a single data element, a set of elements, or all elements forming a phenomenon as a whole [15].

Although Bertin presents the framework for general data, other researchers specifically proposed conceptual models for spatio-temporal data [5, 8, 119]. For example, Peuquet [119] introduced three types of questions in spatio-temporal data. Analysis task queries could be about the event '*what*', the moment in time it occurred '*when*', or location where it happened '*where*'. With the knowledge of two of the questions, Three questions can be formulated as:

- *when* + *where* → *what*: A description of a single object or group of objects presented at a given location or set of locations at a given time or multiple times.
- *where* + *what* → *when*: A description of the single or multiple point(s) in time of a single or multiple objects that are located at one or more points in space.
- *when* + *what* → *where*: A description of an object or set of objects located at one or more points in space at a single or multiple point(s) in time.

Andrienko, Andrienko, and Gatalsky [8] developed a conceptual model based on Bertin framework. They noted that an analyst has certain requirements in terms of what task has been given and what is to be discovered. Their model introduced two search tasks: 1) an elementary question where the question is related to a single event, or 2) a general question where the question is related to multiple events (See Figure 7). In the first search task, the analyst focuses more on identifying the characteristics of

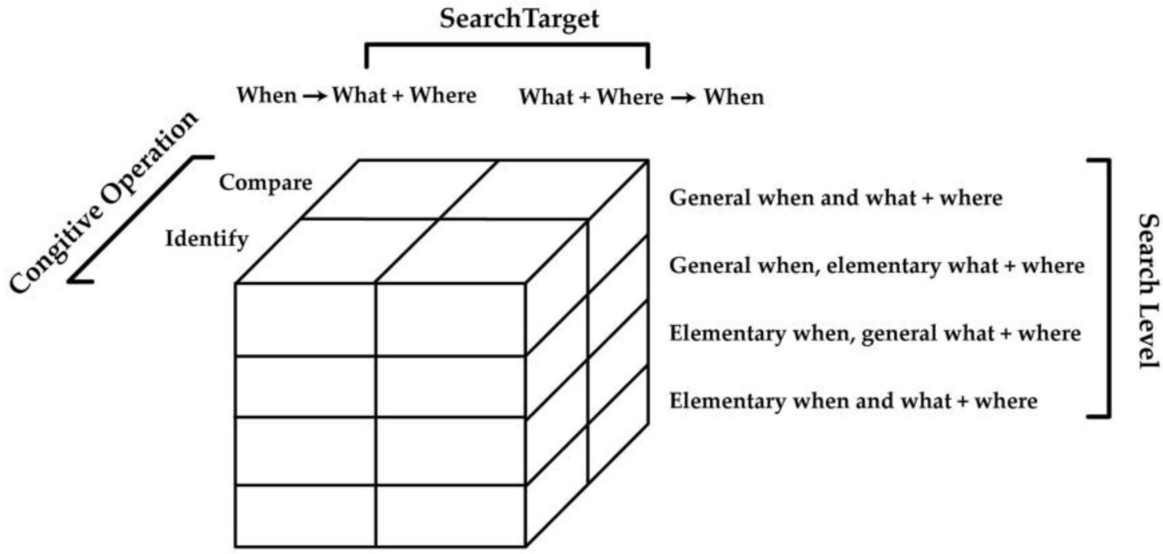


Figure 7: Andrienko, Andrienko, and Gatalsky typology focus on "search levels" which adds more exploration dimensions to spatio-temporal data [8]. Adopted from [8].

objects or locations, whereas in the second search task, the focus is more toward comparing or summarizing characteristics at different locations or times.

Amini et al. [5] built on previous frameworks in [15, 119] and proposed a taxonomy that classified questions related to spatio-temporal datasets. Amini et al. [5] considered numerous common question variables (i.e., object, time, space, or speed and other derived variables) related to movement datasets. Each question variable may have a value that the question is referring to (e.g., an object, a moment in time, or one point in time), or multiple values (e.g., number of objects, or number of events). Amini et al. used the terminology *singular* or *plural* to differentiate between the two cases. Also, they considered each question variables' values to be provided or need to be discovered (*known* or *unknown*), see Figure 8. This updated framework provides a better understanding of the task design space, and aids in estimating a task's total difficulty level.

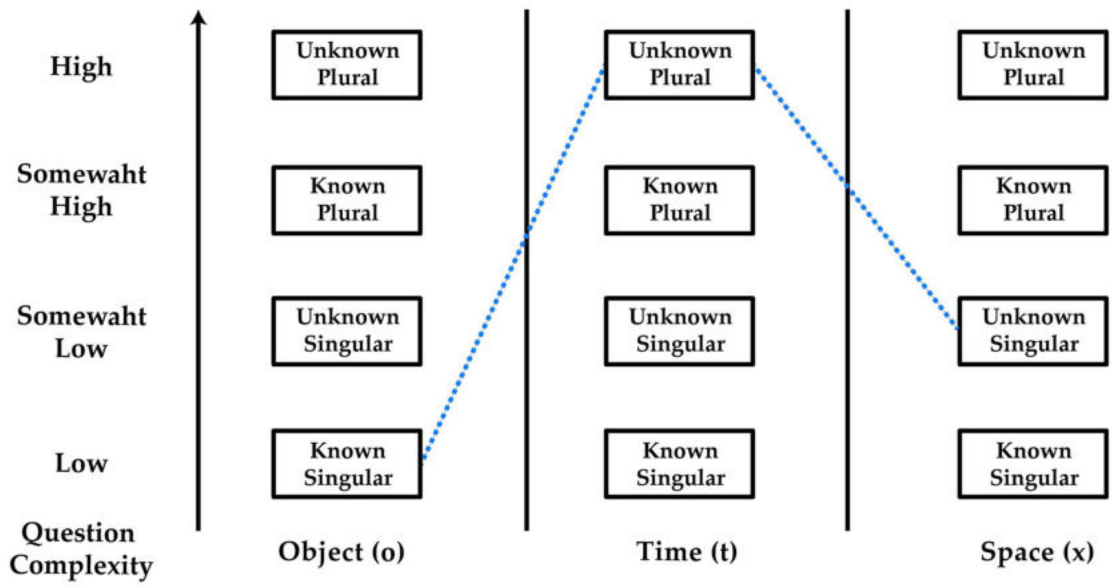


Figure 8: The taxonomy of questions for spatio-temporal data proposed by Amini et al. [5]. An example of a complex question, presented in the blue line, would be: How many times the individual x has been stationary for 3 hours? In this question, the location is unknown and singular, the time is unknown and plural, and the object is known and singular. Adopted from [5].

2.4 SPATIO-TEMPORAL DATA VISUALIZATION TECHNIQUES

Exploratory spatio-temporal data analysis leverages human visual-cognitive and analytical skills in conjunction with scientific visualization tools and techniques to effectively explore movement datasets [8, 15]. In the following sections, different spatio-temporal visualization techniques will be presented.

2.4.1 *Static Spatio-Temporal and STC Visualization*

Static paper photography and maps were the earliest visualization techniques used to visualize spatial, temporal, and spatio-temporal data [148]. For instance, the classic photograph Napoleon's march towards Moscow illustrates Napoleon's army status during the Russian campaign in 1812 [148]. The visualization represents multivariate data, such as the size of the army, the distance travelled, the temperature, latitude and longitude, army travel direction, and position in relation to various dates. The visualization uses a combination of a map (to show the spatial data of the army) and time series techniques (to show the changes in the army size over time). Also, a detailed map was used to represent spatio-temporal data of the cholera pandemic. In 1854, a famous historical cholera pandemic visualization was presented to spatially identify locations of cholera cases in London over a period of time. In the visualization, the black cluster bar represents the number of deaths at a specific location in the city.

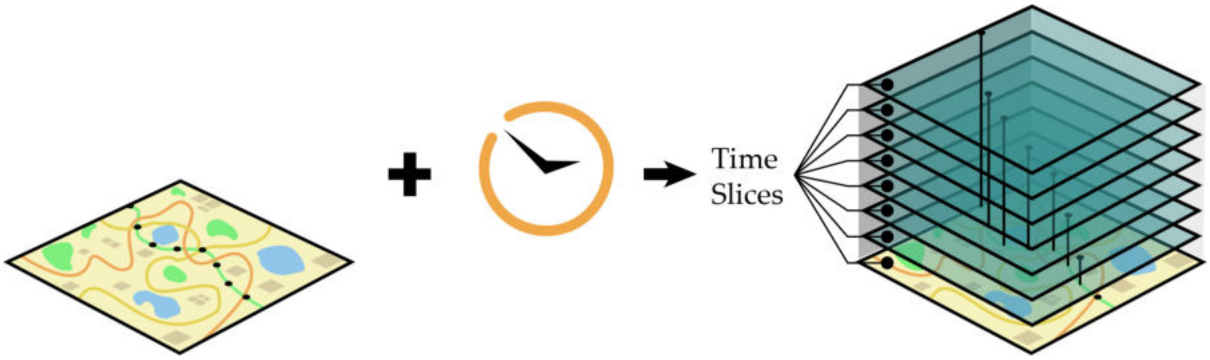


Figure 9: STC's core notion is to use 2D visualization of spatial data and add time as z-axis. Object's spatial data (the x- and y-axis) are plotted at its corresponded time slices (z-axis), the result will be a multivariate spatio-temporal visualization of objects in the dataset.

STC was first introduced in the regional science domain to study and visualize humans' space-time activities, as well as relations between various constraints affecting human movement [66]. Space and time are seen as inseparable components of time-geography research. The horizontal plane (x, y or latitude, longitude) indicates an object's position in space, while the vertical axis represents its position in time. To help users comprehend the information, the representation generates a 3D visual environment to convey spatio-temporal patterns and their relationships, see Figure 9. This visual representation facilitates the accurate viewing of spatio-temporal datasets such as individuals' trajectories features, including changing speed, meeting location, stationary duration, etc. [99]. The use of the initial STC representation was restricted for several decades, since it involved manual redrawing to inspect alternate points of view. Unlike static spatio-temporal visualization, computer-based visualization techniques offer two major properties: interaction and dynamics. These properties enable and support exploratory spatio-temporal data analysis. There have been several tools developed based on the STC in different computing paradigms, such as desktop, AR, and VR.

2.4.2 *Desktop-based STC Tools*

With the emergence of computer-based visualization, the STC concept has been implemented and integrated into visualization tools of various domains [25, 30, 61, 88, 89, 91, 113, 162, 170]. For instance, STC has been commonly used to visualize movement trajectories in air-traffic analysis [25], historical events [78, 91], human trajectories [61, 118], and animal migration [89]. A broader usage of STC is to explore other types of spatial-temporal data, such as event-based [88, 113, 170] and origin-destination-based [30, 162] datasets. STC may be used with small datasets of movement data to emphasize the perception of particular movement features. It may also be used with much larger movement datasets to discover cumulative similarities and differences in the behaviours of population subsets. With the increasing amount of movement data, the need for new visualization techniques is increasing. There is a need for new visualizations that aid in looking at movement data from different perspectives.

In recent years, STC has gained popularity as a visualization method in geovisualization and visual analytics [5, 7, 25, 52, 54, 76, 118]. Kristensson et al. [92] conducted a user study on the STC, in an attempt to identify tradeoffs associated with the use of STC to visually present spatio-temporal data to users. The study findings suggest that STC supports the comprehension of simple and complex spatio-temporal data.

Occlusion is a common issue with the STC visualization [5]. When data is occluded, it is overlapping or hiding other data points from view and the user cannot see it. This can affect the user's ability to understand the data and can also lead to decreased performance. Thus, STC has been enhanced using common interaction techniques that reduce the effect of the data occlusion through changing user viewpoint or filter data [57]. For example, visualization tools should give users the ability to pan, zoom, and change the view of the visualization space. This would allow them to see more of the data and would make it easier for users to understand data. Another approach, to reduce data occlusion issue is to include a timeline as the primary interaction method, temporal zooming or focusing, and map linkage with matching symbols [90]. Since then, several desktop STC visualizations have been developed using these common interaction techniques [5–8, 78, 118].

Andrienko, Andrienko, and Gatalsky [8] presented a web-based and desktop tool called 'CommonGIS'. It visually represents large-scale geographic data to highlight interesting patterns and important events. The tool is a web-based software designed to be publicly available and allows experts and laypeople to use the tool. The tool interface supports interaction via focusing, brushing, and providing multiple visualizations, including 2D and STC.

Huisman et al. [78] examined the STC's suitability for application in archaeology research. They extended STC via implementing graph-theoretical techniques to visualize basic archaeological events. For example, the tool visualizes the spatial-temporal relationships between artifacts discovered at various places during different time spans. The tool enables different visual representations (e.g., base map, STC, and scatterplot), and interaction (e.g., zooming, panning, filtering) to support users' analytical tasks. The modified version of STC allows for a better understanding of potential interactions or clashes between different cultures discovered through archaeological dig sites.

Orellana et al. [118] have used STC to visualize GPS spatio-temporal data collected from visitors in natural recreational areas. The tool helps in understanding visitors' movement patterns such as 1) movement suspension patterns (e.g., visitors walked and stopped at places of interest), 2) generalized sequential patterns (e.g., the sequence of common locations visitors went to irrespective of their movement trajectories). These two movement patterns were examined within the context of a geographical location to characterize the aggregated flow of visitors and to present visitors' preferences and interactions with the surrounding environment.

Andrienko et al. [6] have proposed a modification on STC to overcome the challenge of exploration of a large dataset of vehicle trajectories of a city spread over a long time period. The authors proposed a technique, called Trajectory Wall, that visualizes the set of spatially similar trajectories into a stack of bands. Each band is divided into units that is coloured based on the trajectory attributes such as speed, acceleration, and distance. Also, the bands can be sorted based on temporal order.

Amini et al. [5] have implemented a tool called Space-Time Visualizer (STV) that visualizes the trajectory data of individuals. The tool's interface allows users to switch between STC and 2D map. In the STC and 2D visualization, users can change the camera viewport by clicking the left mouse button and then dragging the mouse to pan the viewport. To zoom in or out of the trajectory data, users scroll the mouse wheel. To tilt and rotate the scene in the 3D view, users click and drag the right mouse button anywhere in the main viewport. In the STC visualization, users can make a right mouse click and drag anywhere in the main viewport, which results in tilting and rotating the view. To show detailed information such as date and time (i.e., tooltip) for a specific individual's movement data point, users hover the mouse cursor over that data point. Another desktop application was introduced by Andrienko and Andrienko [7] which demonstrated the use of STC to support the process of data analysis, reasoning, and sense-making of vessel movement data. The tool helps analysts to explore and analyze Automatic Identification System data as well as analytical tasks, such as finding when, where, and how long vessels have been stopped. These stop events could show the pattern of vessels entering or exiting a bay or port.

A commercial desktop software, called GeoTime, is another tool for spatio-temporal data analysis, [59]. The tool visualizes spatio-temporal in both STC and 2D. An event is presented in a sphere shape and connected with a tube. In addition, the tool allows users to view the data from different viewpoints via performing rotating the STC canvas. The tool supports data subset selection of space and time using dragging on a slider widget. Also, GeoTime interface allows users to combine two visualization techniques: time flattening, where the only spatial attribute is shown; and space flattening, where one spatial and one temporal attributes are shown.

Video surveillance technologies are another desktop application that uses spatio-temporal data to enhance video data analysis. Video analysis is a sequential and time-consuming process. Often, a video analyst is required to watch a long video segment of individual movements to understand the movement event as a whole. Therefore, most video analysis tools integrate spatio-temporal data visualization. These tools can extract spatio-temporal data of objects in the video, visualize objects' movement trajectories in STC, support sense-making, and understand events of interest. For instance, VATAS is a visualization system that allows for the automated analysis and annotation of movement trajectory events in videos [99]. VATAS processes a video through four phases. In the first phase, the input video is processed through registration and frame alignment. Next, moving objects in the video images are detected, and the shape and boundaries of each object are defined. In the third phase, all detected object movements are tracked across all video frames. Finally, the moving object trajectories are classified in a 2D graph. Another method for visualizing object movement is to use a 3D graph (e.g., space-time cube). Video Summagator prototype summarizes and navigates objects in video footage by showing keyframe images of a movement [114].

Another method used to visualize object movement data is to extract movement data from a video, and then lay the extraction results on top of the same video [139, 140]. In Stein et al. [140] and Stein et al. [139], for instance, proposed tools extract objects' movement from a live video stream (i.e., soccer game) and then combined it with the visualization of movement data with a live video stream again. This tool detects moving objects (i.e., players or a ball), simultaneously generates a panoramic view of the pitch, extracts the moving object's location, and visualizes the object's movement on top of the original video. This tool also visualizes the empty and dominant regions of the soccer field.

Action-Based Multi-field was leveraged to present snapshots of video keyframes, along with object movement trajectories, in another video visualization system [17] This system first processes and extracts objects from a given video, then allows for the hand-labelling of object features (e.g., object size, id, action type, relationship information, and plausibility), which are then plotted in a volumetric visualization.

Other video tools allow interactive exploration of spatio-temporal data and video content. To illustrate, a video visual analytic system was proposed that visualizes object movement trajectories from a given video [73]. This system displays different frames (i.e., from the beginning, middle, and end of the video) along with their temporal position, in addition to a coloured line that represents an object trajectory connecting the frames. Moving object trajectory compression and clustering algorithms have also been implemented in video interaction and navigation. For example, clustering and schematic techniques were used to visualize moving object trajectories in 2D [72, 74]. These techniques provide the ability to visually cluster moving object trajectories based on object location, orientation, and velocity. Furthermore, Fast-Forward Video Visualization tool presents two techniques: Object Trail Visualization and Predictive Trajectory Visualization [75]. The Object Trail Visualization technique visualizes an object's movement with a persistent transparent trail of detected objects, supporting object identification. Predictive Trajectory Visualization displays arrows on an object's movement path to support motion perception and prediction. An interactive visualization tool was proposed to visualize surveillance video data [110]. This tool extracts object movement data from video, then provides three unique interactive exploration visualizations of the movement data.

2.4.3 *Virtual Reality-Based Visualization*

In the field of information visualization, researchers have been wary about using 3D representations for abstract data and hence have seen a little benefit in using spatially immersive technology [106]. Early research has focused on interaction techniques for

2D data visualization on desktop computers [80]. When the first 3D visualization was introduced around 1980-1990, researchers were persuaded that 3D visualizations based on linear perspective, shading, and shadows provided advantages over typical 2D visualization [106]. Therefore, researchers have conducted user studies to confirm the advantages of 3D over 2D visualization on desktop paradigms. However, the results of studies did not show any advantages for 3D representations over standard 2D representations in abstract data visualization [34, 35]. Different factors could contribute to this finding, such as limited display devices (i.e., flat desktop display screens) and the lack of human spatial judgment on 2D displays. With the emergence of immersive displays, researchers started seeing the potential in 3D visualization compared to the previous one in the '80s as these visualizations were originally rendered on a flat (i.e., 2D) display screen [106]. With the advancement in technology, the new immersive HMDs are equipped with advanced sensors and binocular displays that enhance users' stereoscopic depth perception. Human depth perception is known as the visual capacity to see the environment in 3D as well as the ability to judge the distance between an object far from users. Several factors such as height in the visual field, occlusion, relative density, relative size, etc, affect human depth perception in stereoscopic displays [37]. We refer the reader to [37, 106] for more detailed information about depth perception cues. In the research community, 3D visualization has become associated more with a binocular presentation [47, 106].

Recently, researchers have studied the effect of depth cues and the choice of technology on 3D visualization effectiveness. Ragan et al. [124] conducted a study to investigate the effect of combining binocular presentation and head-tracked view on users' performance of a task that required accurate spatial inspections of visual geometries. The study result showed this combination improved participants' spatial judgment accuracy. McIntire, Havig, and Geiselman [108] have reviewed studies comparing binocular (3D) displays to monocular (2D) displays across research domains. They found that binocular displays have performance benefits in 60% of the studies with the suggestion that 3D is only inherently useful if the phenomenon of interest actually uses the third dimension. Authors in [108] concluded that binocular 3D is more effective for depth-related activities, such as spatial comprehension of complicated visualization and spatial manipulation.

In recent years, researchers have shown more interest in virtual environment systems in an attempt to overcome the barriers in the traditional computing paradigm such as limited screen sizes, resolutions, and data visualization FOV. Researchers have started exploring the potential of virtual reality display technologies that can be used to improve visual analytic systems [25, 52, 83, 144]. Several tools have been presented to visualize complex and large spatio-temporal data in VR. For example, Kjellin et al. [88] developed a tool that visualizes movement data in a virtual reality projector. The tool provides three visualizations, such as a static 2D map, 2D animation, and stereoscopic STC [88]. The author conducted user studies on movement datasets to compare the performance of the three visualizations. The authors concluded that STC outperform 2D map and animation in terms of accuracy and completion time for tasks related to identifying individuals' meeting locations, whereas 2D map was more precise in predicting future meeting locations.

Theuns [143] proposed different movement data visualization prototypes for VR headsets, including STC. In the STC prototype, the author used a different design where the spatial attributes are presented on vertical axes and temporal attribute is presented on a horizontal axis. The author's design decision for this unconventional design choice is to allow users to scale up the visualization while giving users the ability to navigate and view the movement data.

Okada et al. [116] presented a large-scaled STC prototype in VR to visualize spatio-temporal social media data (i.e., micro-blogs of tweets) at Disneyland Tokyo. The tool helps users to better understand the overall tendency of tweets by aggregating tweets of each coordinate at different time steps, calculating scores, and then visualizing them as piled cubes. Due to the height of the piled cubes, flying around the visualization is used as an exploration and navigation technique. In addition, the authors developed a user interface to allow users to interact with these cubes and view tweets' details. Nguyen et al. [115] proposed I-Flight, a VR-based visualization prototype, for bees' spatial movement data. The bees' movement data (i.e., flight paths) is collected from Radio-Frequency Identification (RFID) tags attached to bees' backs. The tool aims at mapping the insect flight data in a simulated 3D geo-spatial environment to help scientists study bee behaviour.

Buschmann et al. [25] presented a real-time visualization tool that visually represented large air-traffic spatio-temporal trajectory data. The authors investigated the use of 3D animation in the analysis of air-traffic. The tool provides interactive data filters, mapping trajectory characteristics to geometric representations and appearances. Also, the tool supports different visualization metaphors such as temporal focus + context, density maps, and overview + detail techniques.

Filho, Freitas, and Nedel [52] and Filho, Stuerzlinger, and Nedel [54] also presented an STC visualization, called VirtualDesk, that visualizes multidimensional and movement trajectory data in a VR platform. The visualization is virtually placed on top of an analyst's physical work desk while the analyst is seated in front of the desk. The visualization is scaled to fit the desk at the analyst's arm reach. The tool enables embodied interaction, such as mid-air gestures (i.e., virtual hands) to directly manipulate data and the visualization viewpoint. The Mid-air gestures corresponded to a common visualization interaction: one or two hands grabbing to pan, two hands stretching to scale, and two hands spinning to rotate the visualization.

Homps, Beugin, and Vuillemot [76] implemented a VR tool for trajectory datasets (e.g., players' performance, flow simulation, car traffic, and turbulent flows) exploration and manipulation. Also, the tool supports time-based trajectory animation, where a small sphere follows each trajectory path from a start point to an end point. In this research, the authors proposed the usage of configurable volumetric probes that virtually attached to a VR controller (i.e., spheres, cuboids, and cylinders) as a means of trajectory filtering and selection. Users can make an arm movement to select part of the dataset they are interested in via touching them with 3D probes. For example, the sphere is used to select trajectories that pass through a region of interest, or it is used to select specific trajectories (a detached pointer) that are some distance away from the user. A cuboid is used to specify a 3D region of space and then delimit all trajectories that go through this 3D region. The cylinder is used as a slicer to allow users to select similarly oriented trajectories. To filter data, users can use the controller buttons to create Boolean operations to show or hide the trajectories they selected.

Whitlock, Smart, and Szafir [158] have studied the perception of five visual elements (size, colour, height, orientation, and depth) and how to best visualize data across multiple computing paradigms (i.e., AR, VR, and Desktop). The authors investigated how users interpreted visualizations across various computing displays by measuring users' accuracy and completion time of three analytic tasks (extrema, quadrant means, and trend detection tasks) over the visual elements. The analysis of the data suggested that the visual elements of depth and size are more effective and easier to distinguish in AR and VR compared to a desktop. This indicates that stereo viewing resolves some of the challenges of desktop 3D visualizations.

2.4.4 *VR 3D Visualization Challenges*

Despite the fact that VR supports complex spatio-temporal visualization and an immersive experience than the traditional desktop [25, 52, 54, 76, 158], two main challenges would prevent users from leveraging both data representation and its context during the analytical processes such as physical-world isolation and limited navigation space.

First, although VR headset provides users with an immersive experience, it isolates them from the physical world. Thus, in AR users are restricted from incorporating the physical environment during the data analytical processes when it is needed. In some situations, it is possible to virtually replicate the physical environment in VR and then map the data representation on it. Nonetheless, this procedure will not only be complex and time-consuming, but it will also fail to capture the ongoing changes in the physical environment [144, 156, 160]. In addition, VR poses a safety concern that must be considered. For instance, users may be focused on the visualization and virtual world that they forget to pay attention to their surroundings, potentially leading to accidents due to tripping or running into physical objects placed in their surroundings.

In addition to the VR physical-world isolation, the ability to move within the virtual environment, referred to as locomotion, remains an active research challenge [42]. Typically, the size of space, in which VR is installed, often restricts users' navigation which can be time-consuming and frustrating. Locomotion is one of the most often performed activities since it enables the user to access spatially different regions within the virtual environment for data exploration and search tasks [109, 141]. Researchers have proposed different VR locomotion techniques that allow users to experience a similar level of freedom and naturalness as they would in the real world [42, 45].

Boletsis [16] conducted a comprehensive literature review of 36 prevalent VR locomotion techniques and identified four categories of locomotion: Motion-based, Room-scale-based, Controller-based, and Teleportation-based techniques. Similarly, Al Zayer, MacNeilage, and Folmer [1] reviewed over 200 VR locomotion techniques papers and classified them into the same four categories as in Boletsis. Zhang et al. [166] concluded that these strategies mostly relate to movement on the ground plane and proposed to add another category for locomotion techniques based on whether the user may move beyond the ground (i.e., fly) or not.

Despite advancements in VR technologies, 25 - 60 % of the population experience VR sickness symptoms [58]. VR sickness is caused by three main factors: VR hardware (e.g., refresh rate and resolution), content (e.g., navigation speed, scene, graphics changes), and human factor (i.e., individual differences, exposure duration) [28, 31, 95, 130]. Researchers have proposed different techniques in an attempt to reduce the effect of VR sickness during locomotion including, but not limited to adjusting frames rate [167], adding peripheral Visual Effects [51, 117], and reducing the user field of view [22]. However, these techniques do not show significant effects in reducing VR sickness.

A recent study investigated whether presenting data virtually or physically affects user comprehension and recollection [126]. In the study, the authors compare two identical representations of the same dataset, one in physical form and the other in VR. Participants completed comprehension questions while having access to the model, then they were asked data-related questions after the model was removed. The study concluded that while physicalization helps reduce the completion time, the virtual representation and technical VR configuration (i.e., VR lag) significantly reduce the participants' experience quality.

Data analysis in VR might be difficult with VR visualization. Inadequate implementation of the aforementioned VR factors, for instance, might negatively impact users' focus and experience during analytical activities.

2.5 SITUATED ANALYTICS

Since the primary goal of visual analytics is to support users' analytic reasoning and decision-making process via the use of visualization, situated analytics use situated visualization to achieve the same goal [144, 160]. In this section, important aspects and terms are introduced to describe and understand situated visualization, the definition of situated visualization, its conceptual framework, and examples of spatio-temporal situated visualization tools. In addition, we present interaction techniques that potentially support situated analytics.

2.5.1 *Situated Visualization Key Characteristics*

White [155] highlighted three common situated visualization characteristics. The first characteristic is that *data* in the visualization must be related to the physical context. In situated visualization, regardless of what data we are interested in visualizing, *data* often has embedded spatial, temporal, or spatio-temporal attributes. These attributes are necessary when *data* is being visualized. For example, data such as locations of objects, Wi-Fi signal strengths, or temperature readings are geo-referenced; it implies spatio-temporal relationships that should be considered when visualizing the data. Identifying the *context* is an important aspect of situated visualization because it influences the visualization and the relationship between the visualization and context. Depending on the application domain, the context could include a single or multiple objects [48, 157, 172] or entire physical scene [62, 131, 156, 172]. In the case of a physical object being considered as context, the visualization is registered and attached to the object in the view of the user. For example, ElSayed et al. [48] proposed a prototype that displays product's information (e.g., price, ingredient, and nutritional information) on one or more product packages. When the scene becomes the context, situated visualization is mapped into the entire space. For instance, Fraga-Lamas et al. [56] reviewed AR tools that are used in industry to support shipbuilding and maintenance; then proposed an AR tool, called Shipyard 4.0, that enables decision makers to analyze data on its context to aid in the decision-making process.

The second characteristic is that visualization must be based on the relevance of the data to the physical context. Once the context has been identified, the relationship between physical context and visualization will be established to what is referred as *relevance*. In this dissertation, we are interested in three relationships: semantic, spatial, and temporal. In semantic relationship, the relevance between the *context* and *data* comes more from the users' understanding of the context. For instance, an individual does shopping at a store and identifies product items, regardless of their location in the store, and displays related information in a simple and meaningful way. In the spatial relationship, the data has a specific position with respect to the context such as visualizing the trajectory movement of individuals or infrastructure in a geographical location. In the temporal relationship, the relationship would occur in conjunction with a semantic or spatial relationship. For example, data about an individual being stationary at a geographical location could be presented at the exact location and in a semantic representation (e.g., stacking data points at one location).

The third characteristic is the display where presentation of the visualization must take place in the physical context. After the relevance of data to the physical context has been recognized, it is essential to consider the means to *display*, *spatial presentation*, *representation*, and *interaction* to support in-situ user experiences [155]. There are many methods to display visualizations relative to the user and the context. In this dissertation, the focus will be on see-through immersive AR displays (i.e., HMDs).

We are interested in this type of display for a few reasons. First, AR displays support visualization that is associated with the users and the context provides users with immersive experiences. Second, it lacks some of the AR challenges such as sickness, restricted space, limited mobility, etc (see Section 2.4.4). Finally, AR displays enable complex presentation and a wide range of interactions, as discussed in Section 2.5.4. Spatial presentation specifies the coordinate system that can be used to place the data to an object or space [155]. Researchers have presented different coordinate systems to place GUI and virtual contents in 3D environments [94, 155]. Examples of coordinate systems, including but not limited to body-referenced, object-referenced, and world-referenced [50]. For other coordinate systems, we refer the reader to [50, 94]. A presentation that is body-referenced, is one that is attached to the user's body. A visualization or GUI, for example, can be anchored to the hand of the user via wearing a sensor or using computer vision to track the hand. The visualization or GUI will remain in the user's hand independently of the head or display movement. A presentation that is object-referenced presentation is attached to an object in the world. An example of this would be product visualization on a package that remains attached regardless of changes in position of the package relative to the world. Finally, world-referenced refers to a visualization that is mapped into the physical environment, such as a room, field, or geographical location. An example of this would be STC visualization of individuals' movement data that is mapped and fixed to the physical location regardless of the movement or orientation of the user or display, see Section 1.1.2.

In this dissertation, we are interested in world-referenced visualization as our focus will be on spatio-temporal movement data. Representation is concerned with alternative visualizations and interaction between the visualization and physical context. After determining world-referenced as a coordinate system, we need to consider how to present information in the physical context. This includes factors such as size, colour, and visualization type. Each of these can affect perception in different ways. For example, if two values are mapped to different colours, but those colours are very similar, it may be difficult for a user to tell them apart. Similar to presentation, interaction describes the coordinate system that the user uses to interact with the visualization. The interaction may consist of any mix of display-referenced, body-referenced, object-referenced, and world-referenced coordinate systems depending on user analytical activities (e.g., data exploration, and data filtering). Interaction and presentation are often associated and occurred in distinct reference frames. More details will be discussed in Section 2.5.4. These three characteristics are what make situated visualizations unique, and what allow them to effectively communicate information about the physical world.

2.5.2 *What is Situated Visualization?*

The term *situated visualization* refers to an emerging idea within the area of information visualization. The concept of situated visualization has received attention from several academic fields including AR, visualization, and HCI. Thus, a variety of research and implementations of this concept have been proposed which concentrate on the operational elements of the situatedness. However, there is inconsistency in the terminology and adoption of the concept of situatedness [19].

There have been two primary definitions of situated Visualization in the research community during the last two decades [157, 160]. The early definition of situated visualization was introduced by White, Feiner, and Kopylec [157]. White, Feiner, and Kopylec [157] presented a definition of situated visualization, referring to visualization that is “related to and displayed in its environment”. This definition is broad and does not provide more information about the environment. Furthermore, the definition does not go into depth on where the visualization should be placed in relation to the environment. Willett, Jansen, and Dragicevic [160] extended the definition of White, Feiner, and Kopylec by introducing the concept of physical referent where data is visualized. Willett, Jansen, and Dragicevic [160] differentiated between embedded and situated visualization and data representations. In the embedded visualization, visualization is mapped into the physical referent as closely as possible. On the other hand, the authors in [160] considered the situated visualization to “place the entire visualization in a relevant location, but do not necessarily physically align individual data presentations or visual marks with their corresponding referents”. Bressa et al. [19] reviewed 44 publications that explicitly use the phrase “situated visualization". All 44 publications used either one of the two definitions or both of them. In this dissertation, however, we adopt the definition presented by Willett, Jansen, and Dragicevic [160]. We are interested in trajectory data that physically align with the location where the data was captured.

2.5.3 *Situated Visualization Tools*

The primary benefit of using situated visualization techniques over traditional and AR visualization techniques is that they provide the spatial relationship between the data and the physical environment and enable in-situ user experiences [48, 62, 84, 121, 156, 157, 168, 171]. Situated visualization has been used to show a wide range of data types, including engineering, science, and environmental data [19]. In this section, we will present situated visualization techniques for data that have spatio-temporal attributes.

Situated visualization supports data collection and analysis in earth science. For example, Whitlock, Wu, and Szafir [159] highlighted challenges in data collection and analysis practice in environmental research and public safety. The fieldwork procedures require analysts to first pre-plan their activities based on data from earlier collecting attempts and archive data streams. The next step is for analysts to physically transport updated data to a central location so it can be synchronized with other sources and used to update future collecting efforts and operating procedures. This method decontextualizes data acquired from the environment, restricts analysts from responding to new data, and obscures any error in data gathering by creating spatial and temporal gaps between data collection and analysis. Authors in [159] introduced a visualization tool that integrates data collection (using mobile devices) and situated visualization that simulates the changing status of field sites.

Urban planning and maintenance is another domain that took advantage of situated visualization. For example, SiteLens is a tool that visualizes spatial data of Carbon Monoxide (CO) from different sensor datasets [156]. SiteLens represents CO measurement points in the context of the physical site where the CO measurement was recorded. Each measurement point is represented as a sphere, with the sphere location being based on the location of the measurement. Additionally, the altitude of each sphere represents the level of CO in each region of space. SiteLens's users use a handheld AR device to visualize CO data as they walk within a city. Another application domain that leverages situated visualization is in underground infrastructure maintenance. A mobile AR system was developed to assist field workers at underground infrastructure inspecting and scheduling maintenance via visualization of their physical locations [131].

In addition, situated visualization has been used to identify points of interest around a city. For example, Yelp Monocle is a commercial mobile application that allows users to locate businesses in the area around them [135]. The application uses a user's location to provide a list of businesses that are nearby. Virtual cards with business information (e.g., name, address, phone number, ranks, and hours of operation) are displayed through a mobile device camera. It should be noted, however, that the data displayed in this AR mobile application is not physically related to viewing real-world buildings which could lead to challenges such as limited visibility and information clutter [62, 172]. Other situated visualization tools take the aspect of layout and presentation of when to visualize buildings' names around a city. Several techniques have been proposed to address such challenges [62, 172]. For example, Grasset et al. [62] introduced an image-based method that combines a visual saliency algorithm with edge analysis to identify potentially important image regions and geometric constraints for annotation placement. Zollmann, Poglitsch, and Ventura [172] proposed situated visualization techniques for buildings' labels including dynamic annotation placement, dynamic label alignment and occlusion culling. The basic concept behind the algorithms is to utilize spatio-temporal data as an input source for modifying the visualization rather than just presenting it.

Beside Urban planning and points of interest identification, situated visualization has been used for indoor and outdoor navigation. For instance, Guarese et al. [64] proposed a prototype that helps event's attendants to navigate and access indoor spaces (e.g., auditorium). The prototype displays 2D trajectories to chairs in the space and information for each specific chair (e.g., temperature, hearing aid, power plugs, and wheelchair accessibility). The attendants can interact with the prototype via AR interface, and refine their search by toggling and combining the displayed attributes. One of the key uses of AR is outdoor navigation. Guarese and Maciel [65] introduced AR-based outdoor GPS navigation, called HoloNav. The prototype uses Microsoft HoloLens to display virtual trajectory lines and arrows on terrain to guide users to different locations around geographical space in the city. The Microsoft HoloLens communicates with a mobile device and receives GPS data via Google Maps API.

2.5.4 *Interaction for Situated Visualizations*

Interaction is another fundamental component of situated visualizations. Due to the unique challenges inherent in situated visualizations, suitable interaction modalities and interfaces are required for each visualization platform, to elicit the appropriate/desired user behaviour [24]. One of the main benefits of situated visualization is the ability to visualize information at multiple scales. Additional benefits include the visualization of information at large scales, and the navigation of information via physical and virtual means[24].

Two decades-old, Dourish [44] introduced hypotheses about embodiment that form the conceptual basis for HCI and defined embodied interaction in a more general way as "the existence and occurrence of a thing in the world", which incorporates physical objects, dialogues, and actions. A more recent and specific definition of embodied interaction, which we have adopted in this dissertation, has also denoted interactive systems controlled by the body's parts, e.g., mid-air and feet gestures [26, 77]. Since then, the HCI community has shown a growing interest in embodied interaction and explored its potential for the new emerging platforms [9, 39, 54, 137]. More research has been focusing on understanding and incorporating proxemics and embodied interaction due to the natural use of physical navigation in immersive and situated analytics. Greenberg et al. [63] applied *Proxemics Behaviour theory* by Hall [67] into ubiquitous computing. Proxemics is the study of applying interpersonal distance to better understand interactions between individuals. Greenberg et al. [63] considered "inter-entity" distance usage, in which an "entity" can be a variety of people, devices, or digital content. Jakobsen et al. [81] built on Greenberg et al.'s work and explored proxemics-based interactions with visualizations. These forms of navigation and interaction can be efficient for situated visualization and require/warrant further exploration.

In the context of situated visual analytics, the objective is to include multi-sensor and proxemics that allow users to communicate and immerse themselves in their data to help the actual analysis activities involved in the environment. Although proxemics was originally specified for user-to-user distances [105], it has since been extended to user-display proximity and movement perception for interaction [12, 97]. Several embodied interactions have been studied to interact with spatio-temporal data visualizations including through hands-touches [39], mid-air gestures [54, 112, 145], foot gestures [39], and various proxemic dimensions related to digital artifacts [12, 105, 145] (i.e., user distance, user body orientation, movement, location). Body movement has also been used to explore the visualization space [12, 158]. Prouzeau et al. [122] observed that some users have used their body movement to reach directly into 3D scatter plots to inspect points of interest. Similarly, Batch et al. [13] reported that participants used their body movements to navigate the virtual space, arrange different visualizations within the space, and revisit them to report their findings. Finally, Simpson, Zhao, and Klippel [136] conducted a study to compare body movement and orientation in place to explore 3D scatter plots; preliminary results showed that participants with poor spatial memory were more efficient in the body movement condition.

As the benefit and use case of proxemic interaction is clear, we look to enable these forms of interaction for situated spatio-temporal data analytics pertaining to spatio-temporal trajectory data. Furthermore, being in-situ, and allowing for many forms of interaction through AR HMD (i.e., proximity, orientation, mid-air gestures) we look to leverage these affordances to create a prototype to perform situated analytical tasks.

2.6 Lessons learned

Based on the above state-of-the-art review, several gaps were identified in the literature as follows:

First, to date, the majority of spatio-temporal trajectory data analytics and visualization research has mainly focused on using traditional computing paradigms (i.e., analysis on a regular desktop monitor, using classical desktop interfaces and input modalities) to explore data and detect patterns [5, 7, 25, 76, 118]. The visualization community explored the potential of AR for data visualization and proposed visualization prototypes for large and complex trajectory data that would be difficult to understand on a traditional desktop [52, 54].

Second, although VR headset has advantages over desktop-based visualizations in terms of immersive experience and complex data visualization, it still has several limitations, including limited navigation space [42, 45], VR sickness symptoms [28, 31, 95, 130], physical-world and context isolation [144, 156, 160].

Third, situated visualization has the potential to provide several benefits over desktop and VR platforms; however, little is known about how to take advantage of in-situ exploration of spatio-temporal. One of the primary benefits is that situated visualizations enable users to have in-situ experiences [144], a better understanding of the spatial relationships between data and the physical world [156]. This is especially important for data that is highly contextual, such as geographical data. Given the emerging area of situated analytics, new technologies are evolving with the ability to generate spatio-temporal data and different use cases. Consequently, it is necessary to empirically validate the potential of situated analytics by comparing Situated and Non-situated analytics.

Fourth, we have not come across situated visualization designs recommendation that supports situated spatio-temporal data visualization. There is a need to explore further design choices for situated visualization through elicitation studies and workshops [150]. This can be achieved through a process of participants' sketching situated visualization, and being in-situ which influence the participants' integration of their designs.

Fifth, although several design choices for STC have been proposed in the literature, we could not find any situated visualization that utilized STC to visualize trajectory data of individuals and map visualization into the environment where the data was collected for in-situ exploration. STC is a well-known visualization technique to visually represent spatio-temporal data and has been used in different computing paradigms, such as traditional desktop and VR. An elicitation study and updated STC design from the literature review will help in implementing a prototype for situated STC visualization.

Sixth, to understand how users leverage the proposed situated STC visualization prototype, a preliminary exploratory evaluation is needed. This evaluation will not only help us determine whether the prototype supports situated data exploration, but also explores interaction taxonomy, i.e. VISM by Shneiderman [133], and identifies challenges users might face while using the prototype. Additionally, the evaluation study can help to address concerns and challenges associated with the situated STC visualization and to propose alternative situated visualization that integrates VISM into the prototype and overcomes concerns and challenges.

3 SITUATED VS. NON-SITUATED DATA ANALYSIS

In this chapter, our focus is primarily on whether situated data analytics facilitates task performance. We restate the definition of situated visualization as to "place the entire visualization in a relevant location, but do not necessarily physically align individual data presentations or visual marks with their corresponding referents" [160]. For a better comprehension of the study, in situated condition, data is not visualized onto the physical environment (using AR), but the participants watch the video clips (i.e., spatio-temporal data) and check the video in the physical environment where data were collected. Thus, we conducted an empirical study comparing participants' spatio-temporal data analytics performance in in-situ analysis group and non-in-situ analysis group. To illustrate, we conducted a study that observed video-analysis activities in two settings, in-situ (i.e., situated) vs. as traditionally done, at the desk (i.e., non-situated). The dependent variables for each video scenario were based on the exploratory search tasks found in video analysis tools in the literature [11, 14, 27, 36, 72, 96, 99, 102, 114, 123, 139]. Additionally, for an exploratory purpose, we assessed participants' confidence levels for their own judgements.

3.1 PARTICIPANTS

The study was advertised using posters at a local university. Forty (40) participants (M = 18, F = 21, other = 1) volunteered. Their age ranged between 18 and 41 (M = 24.70, SD = 6.59). They were randomly assigned to either the Situated or Non-Situated condition. 20% of the participants reported English as their first language, and none of the participants had any language issues throughout the study. All participants reported normal or corrected-to-normal vision.

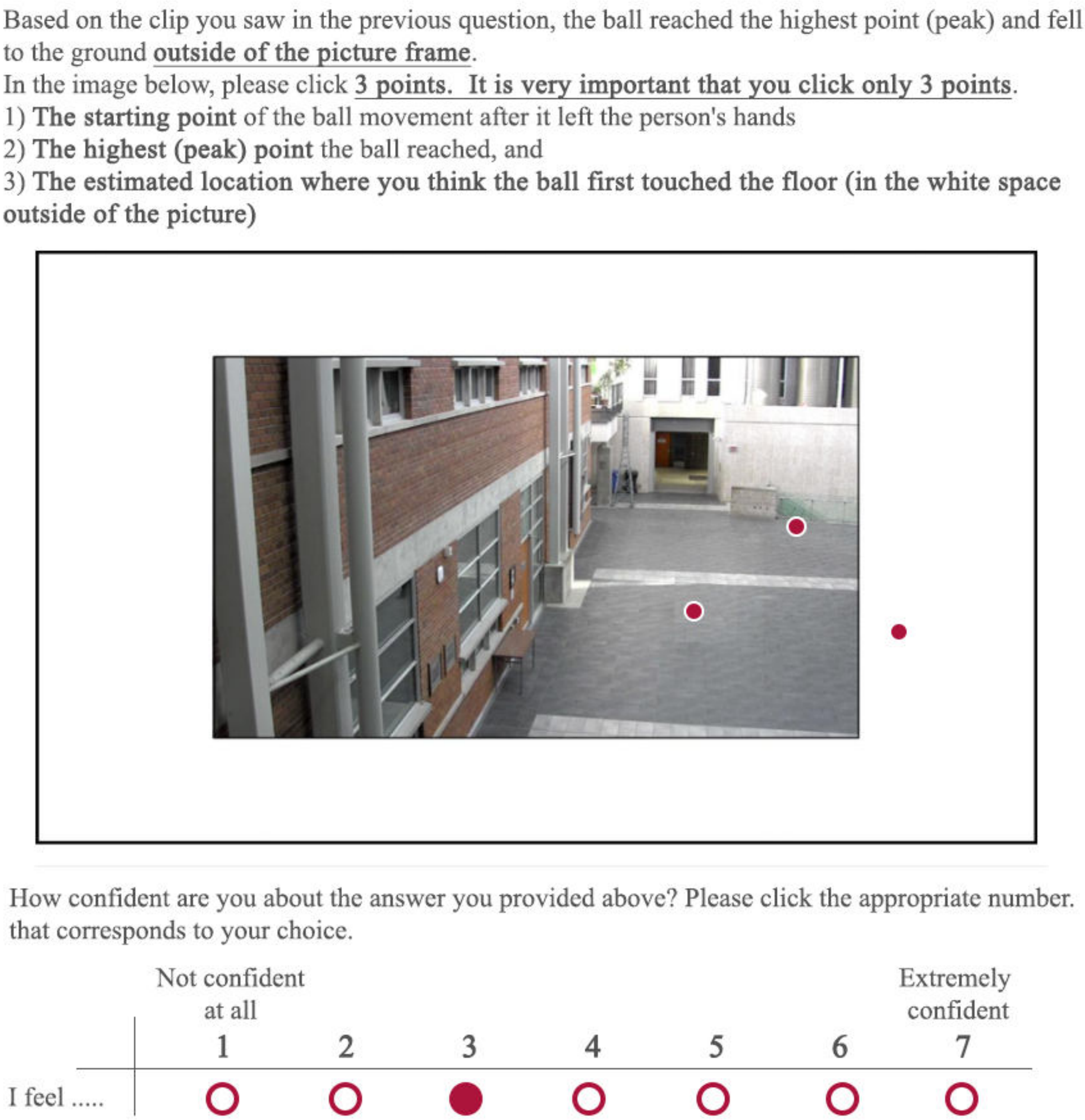
3.2 APPARATUS

For visual analysis, a Microsoft Surface Pro 2 was used in both the Situated and Non-Situated conditions. Its screen size was 10.8 inches (27 cm) by 12 inches (30 cm) and the resolution was 1920 x 1080. To support the participants' mobility during the study in the Situated condition, they were able to switch between laptop mode and tablet mode via a detachable keyboard. Participants were allowed to switch between the two modes as needed. For example, when a participant wanted to explore the scene physically, they would choose tablet mode for a better video viewing experience. Furthermore, they were provided with two measurement tools (a ruler and a measurement tape), pen, paper, and a stopwatch to help them answer the analytic tasks. To develop video stimuli (i.e., video clips), a video camera (the Canon HF-M52) was used, see Section 3.4 for detailed video scenarios.

3.3 METHOD

A two by two mixed between (1: Situated vs. 2: Non-Situated) within (1: On-Camera vs. 2: Off-Camera) design study was conducted. The scenario clips and questions were uploaded on an online survey system, Qualtrics. Upon arrival of the participants and their signing of the consent form, a research assistant explained to them the general procedure. Their main task was to perform visual analytics to answer questions. Thus, participants were asked to watch video clips on the Microsoft Surface Pro 2 first. Participants were instructed to be as fast and accurate as possible, but no time limit was set. The participants in the Situated condition were instructed to walk around and gather information that could help them to answer the questions, see Figure 11. The questionnaire (on Qualtrics) consisted of three main sections. The first section was a practice session. The next section gathered participants' demographic and vision data. The last section provided stimuli and questions: There were five blocks in this section. Each block had its own purpose (i.e., scenario types): 1) projectile trajectories

[21, 87], 2) key changes in the environment [110], 3) movement direction [73, 82, 87], 4) movement/action duration [110], and 5) absolute measurements [14, 21]). Further, each block contained four questions focusing on its scenario type. The selection of scenario types was made based on common video analysis activities found in [14, 21, 73, 82, 87, 110]. Participants were presented with one scenario block at a time, each containing video clips, questions related to an event in each video, and questions about participant confidence. To minimize the order effect, scenario order was counterbalanced for all the participants. Participants were allowed to analyze freely: replay, pause, rewind, and frame-step, as well as watch the video multiple times. We collect participants' completion time, clicks coordinates on images, answers to questions, and confidence level. Participants used the imperial or metric system when reporting their measurements, based on their preference. Figure 10, show an example of a question after watching a projectile trajectories scenario. Each study lasted roughly 75 minutes and each participant received a $15 gift card for their participation.


Based on the clip you saw in the previous question, the ball reached the highest point (peak) and fell to the ground **outside of the picture frame**.
In the image below, please click **3 points. It is very important that you click only 3 points**.
1) **The starting point** of the ball movement after it left the person's hands
2) **The highest (peak) point** the ball reached, and
3) **The estimated location where you think the ball first touched the floor (in the white space outside of the picture)**

How confident are you about the answer you provided above? Please click the appropriate number. that corresponds to your choice.

	Not confident at all 1	2	3	4	5	6	Extremely confident 7
I feel	○	○	●	○	○	○	○

Figure 10: An example question of projectile trajectories scenario where camera optical axis was perpendicular to ball trajectory and part of the event was off-scene.

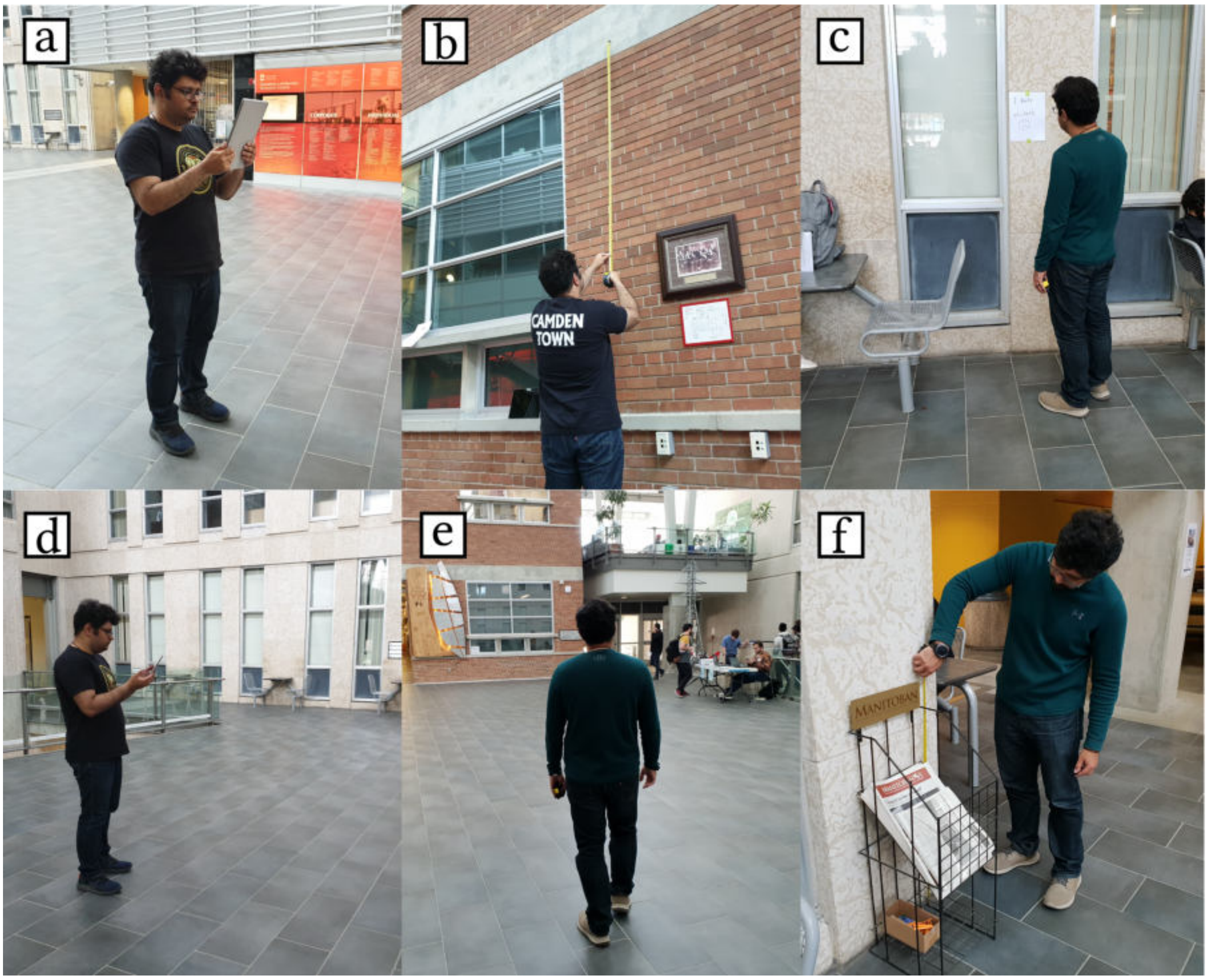


Figure 11: After a situated group participant watched video clips and read questions related to the scenario, the participant walks to the location of events in the video to find (a,b) the ball's location when it touched the ground and reached its apex, (c) the marker's colour used in the vandalism act, and (d) the ball's locations after it left actors' hands, (e) the time it took the actors to reach a predefined location, and (f) the newspaper stand height.

3.4 VIDEO CLIPS

Five scenarios were acted out by three actors (two males and one female). Two conditions for each scenario were produced: video clips in the on-camera condition captured all of the action within the camera field of view (FOV), whereas, in the off-camera condition, some parts of the action occurred outside of the camera FOV. The researcher showed a video clip of the actors in a local university building's atrium which was empty at the time. We positioned our camera at a height akin to that of the actual security cameras there. All videos were recorded in 1920 x 1080 resolution at 30 frame per second (fps). We used an open source software called "Tracker" [21] to identify the accurate/correct responses (i.e., answer keys) from the video to be shown to participants. Twenty-six unique video clips were recorded. There were 4 to 8 clips in each scenario block. 44.125 seconds was the mean duration of all videos with a minimum of 5 and maximum of 215 seconds as the range of duration for all videos. The experiment was comprised of original and unaltered footage (no added special effect or modification was present). The following scenario types were used in the study:

3.4.1 *Projectile Trajectories*

Participants viewed eight videos. Four variations of this scenario were created using two types of camera optical axes (perpendicular or parallel) and two types of FOV (on- or off-camera) (Figure 12). In the on-camera clip, an actor threw a soccer ball and the trajectory ends within the camera FOV, see Figure 12 (a) and (c). However, the trajectory ends on the outside of the FOV in off-camera clips, see Figure 12 (b) and (d). Questions asked were regarding the ball's trajectory; 1) after it left the actor's hands, 2) at its apex, 3) at contact with the ground.

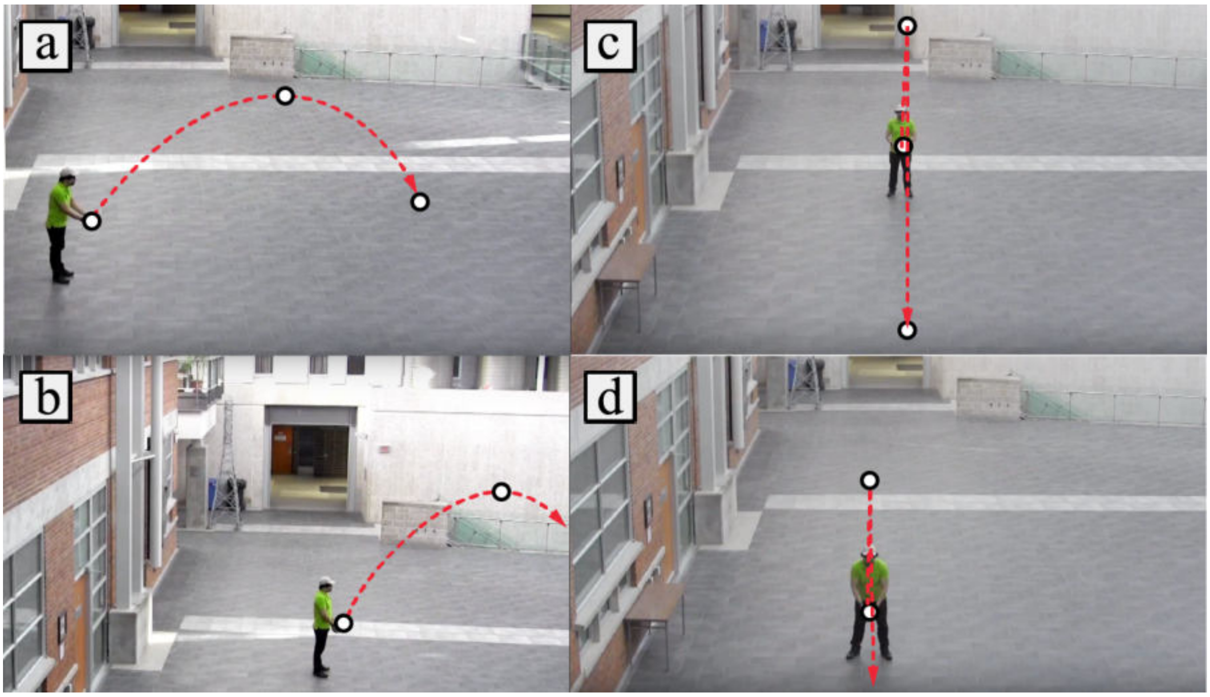


Figure 12: (a) and (b) show the ball being thrown perpendicular to the camera, with (a) in FOV and (b) not entirely in FOV. Image (c) and (d) show the ball being thrown parallel to the camera, with (c) in FOV and (d) not entirely in FOV. Note the red arrows and white dots were not shown to participants.

3.4.2 *Key Environment Changes*

Four videos explored questions related to physical changes that happen within a scene's environment (in this case, a vandalism event). Four white sheets of paper were posted in four different locations to simulate this event: two were placed on-camera while others were placed off-camera, see Figure 13. An actor walked into the camera FOV, sat down at a table next to the wall for a few seconds, walked toward one of the white papers, draw a shape with a colour marker, then left the scene. Each sheet was marked with a different colour (black, red, green, or blue). The participants were asked to report the colour.

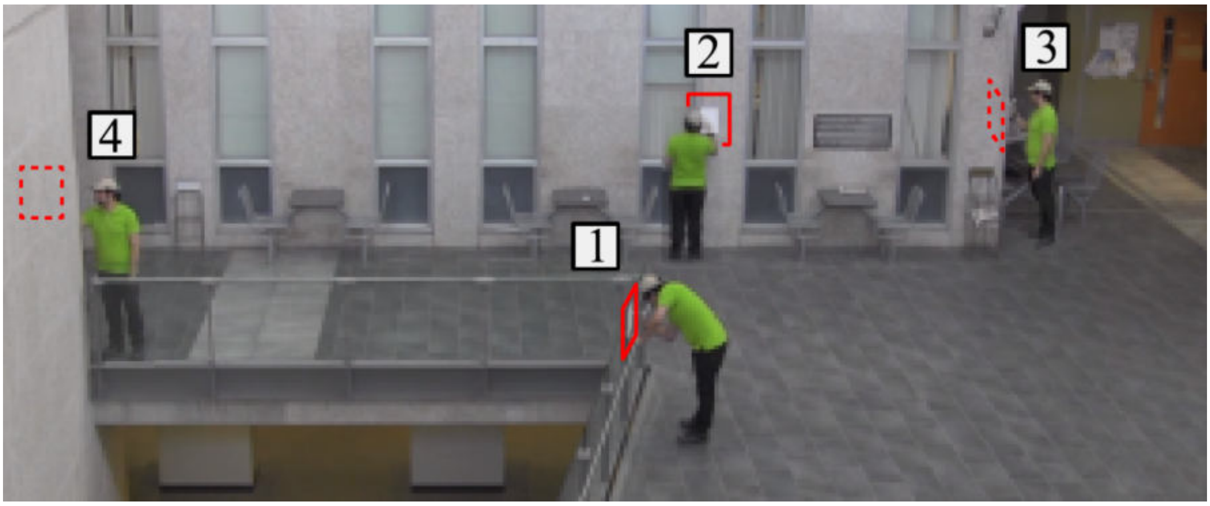


Figure 13: A stitched image of the actor acting in the four video clips. The figure shows different locations of posted white papers. The locations (1) and (2) in the camera FOV whereas (3) and (4) are outside of the camera FOV. Please note that the red boxes were not shown to the participants.

3.4.3 *Movement Directions*

Four videos explored participants' abilities in tracking object movements and directions. In on-camera clips, three actors stood in a circle facing each other and threw a soccer ball between themselves (five passes in). Participants' tasks were to; 1) click on the location of the ball after it left an actor's hand, and 2) draw the ball's movement and direction on a piece of paper. For off-camera clips, a red bag was placed on a table: the first actor picks up the bag, walks in a straight-line path and leaves the camera FOV for a few seconds. The actor then passes the bag to the second actor, who walks in straight-line into camera FOV for several seconds, then exits the camera FOV. Then the bag is passed to the third actor. The third actor then walks in a straight line into camera FOV for a few seconds and stops. Participants were asked to identify the location and direction of the bag exchanges, using mouse clicks.

3.4.4 *Duration of Movement/Action*

Four videos explored the participants' measurement perception and estimation of event duration. For the on-camera material, three meeting points were predefined. In the video clips, three actors meet at each location for a certain amount of time, then disperse. Participants' tasks were to 1) measure the duration of each meeting. For the off-camera material, two actors sit at a table and talk for several seconds, then stand up to walk out of the camera FOV. Participant's tasks were to 1) estimate the time the actors spent to arrive at a predefined location, outside of the camera FOV.

3.4.5 *Absolute Measurements*

Participants' perception regarding absolute measurements was explored with four videos. For the on-camera material, an actor places a piece of duct tape on the floor or on a newspaper stand next to the wall (two scenarios), then leaves the camera FOV, see Figure 14-b. Participants' tasks were to 1) report the length of the duct tape, and 2) height of the newspaper stand. For the off-camera material, one actor begins on a lower floor, then walks halfway up a flight of stairs, stands for a few seconds, then walks back down to the lower floor, see Figure 14 (a). The upper half of the actor's body was shown to the camera FOV and was visible within the clip. Participants' tasks were to 1) report the height of the actor. The same action was repeated in another video clip by an actor of a different height.

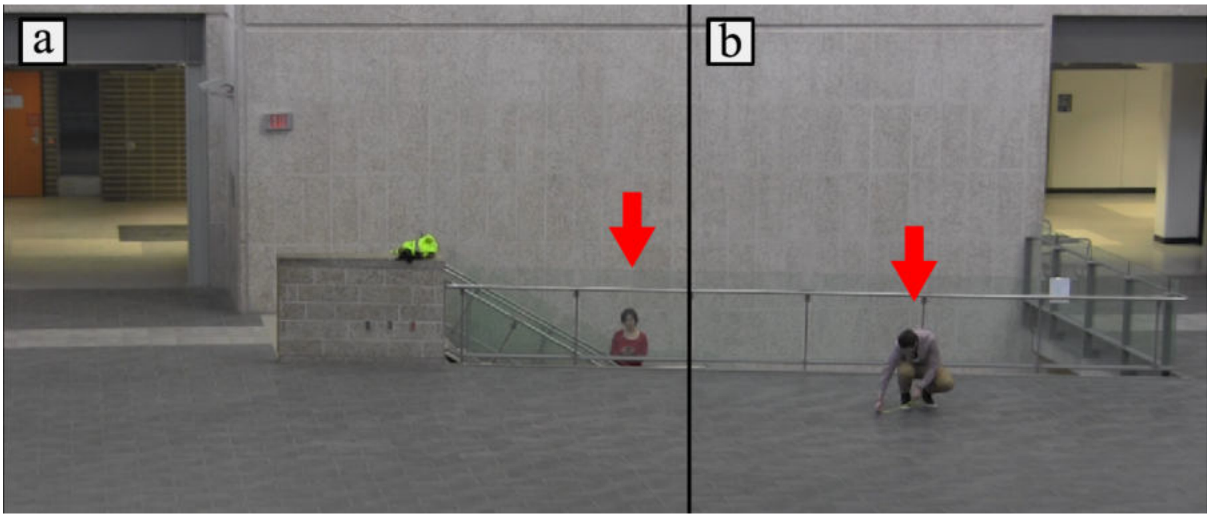


Figure 14: Image (a) shows a snapshot from the absolute measurement scenario off-camera material. The actor walked up the stair and stood where the red arrow is pointing. Image (b) shows the actor put duct tape on the ground where the red arrow is pointing. Participants were asked to report the actor's height and the length of the duct tape. Please note that the red arrows were not shown to participants.

3.5 RESULTS

After checking assumptions, mixed two by two ANOVAs were conducted throughout Study 1, to explore the effect of condition (Between: Situated vs. Non-Situated) and the analysis type (Within: On-camera vs. Off-camera) on each dependent variable. Participants' familiarity with the building did not differ across conditions, $F(1, 38) = .28$, $p = .60$. Participants' responses were compared against the answer keys we had generated. We report a significant value when $p <= .05$.

3.5.1 *Projectile Trajectories*

Response error: The distance between the participants' responses (i.e., where the participants clicked on the monitor) and the correct response (in pixels) were computed to indicate the magnitude of the participants' response error. A significant condition effect emerged, $F(1, 38) = 16.66$, $p = .0002$, $\eta p^2 = .31$. Scene type effect was also significant, Wilks' Lambda = .73, $F(1, 38) = 14.14$, $p = .0006$, $\eta p^2 = .27$. Further, a significant interaction effect emerged, Wilks' Lambda = .38, $F\ (1, 38) = 7.25$, $p = .011$, $\eta p^2 =$

.16. Simple main effect analyses confirmed that for both on- and off-camera scenes while participants in Situated condition made less error($ps < .05$, see Figure 15 for the means. Being in the scene allows participants to view the video clips from different view-points, and this reduced their levels of errors. Hence, interestingly, participants in Non-Situated analysis made greater errors, compared to Situated condition, even when the video clip captured the entire scene within the camera FOV, indicating that revisitation is essential when we need to make an accurate evaluation.

Completion time: There was a significant condition effect, $F(1, 38) = 21.79$, $p = .00004$, $\eta p^2 = .36$. Compared to the Situated condition, participants spent less time when they were in the Non-Situated condition to complete their tasks. Further, the scene type effect was also significant, Wilks' Lambda = .30, $F(1, 38) = 88.73$, $p < .000001$, $\eta p^2 = .70$. There was a significant interaction effect, Wilks' Lambda = .56, $F(1, 38) = 29.41$, $p = .000004$, $\eta p^2 = .44$, see Figure 16. Pairwise comparisons indicated that in both on-camera and off-camera materials, participants in the Situated condition spent longer time than their counterparts did.

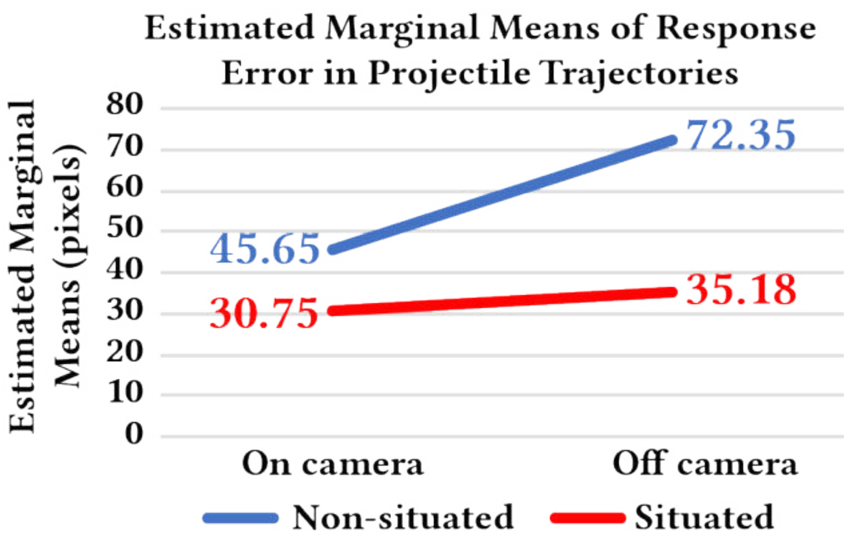


Figure 15: The interaction effect on the response error for projectile trajectories ($p = .01$).

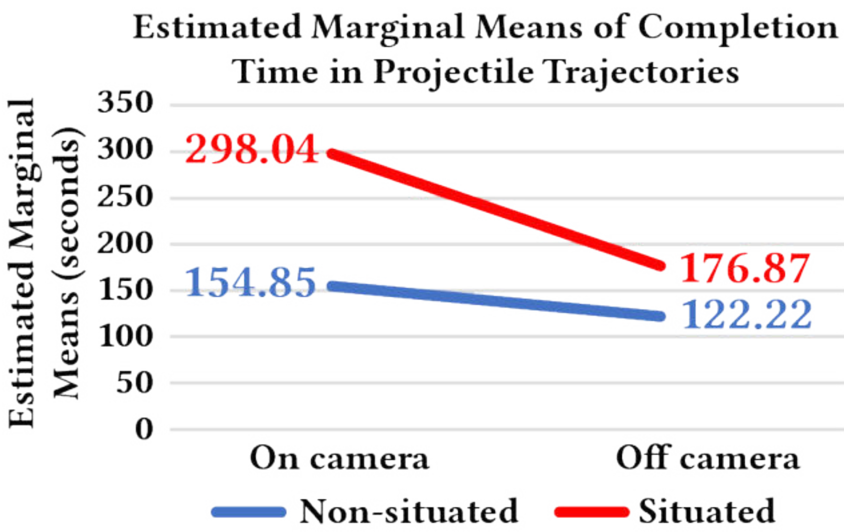


Figure 16: The interaction effect on the completion time in projectile trajectories (p = .000004).

3.5.2 *Key Changes In the Environment*

Response accuracy: For the dependent variable, the percentage of the participants' correct responses in a colour detection task was used. No interaction effect nor scene type effect emerged (*ps* > .14). A main effect of condition emerged, however; $F(1, 38) = 667.45$, $p < .000001$. As predicted, participants in the Situated condition responded perfectly ($M = 1.00$, $SD = .00$) on colour detection task while participants in the Non-Situated condition did poorly ($M = .18$, $SD = .14$). Once again, even when the scenes were captured completely within the Camera FOV, Non-Situated participants could not perform equally well as their situated counterparts.

Completion time: The effect of analysis type was found, Wilks' Lambda = .34, $F(1, 38) = 75.34$, $p < .001$, with a large effect, $\eta p^2 = .67$. Participants processed the on-camera materials faster ($M = 109.88$, $SD = 45.82$) than the off-camera materials ($M = 186.03$, $SD = 73.62$). There were no significant interaction nor condition effects (*ps* > .05).

3.5.3 *Duration of Movement/Action*

Response accuracy: No significant effects were found (*ps* > .15).

Completion time: A significant condition effect was found, $F(1,38) = 21.57$, $p < .00004$, $\eta p^2 = .36$. Further, there was a significant analysis type effect, Wilks' Lambda = .52, $F(1, 38) = 34.81$, $p < .000001$, $\eta p^2 = .48$. Finally, there was a significant interaction effect (Wilks' Lambda = .76, $F(1, 38) = 12.11$, $p = .001$, $\eta p^2 = .24$). Simple main effect analysis confirmed that the only off-camera, participants in Situated condition took significantly longer than those who were in Non-Situated condition, but not with on-camera($p < .00001$, see Figure 17. This was because participants in Situated condition often imitated actors in the video clips to obtain their answer. Whereas, participants in Non-Situated condition simply quickly guessed the time the actors took to get to their destinations.

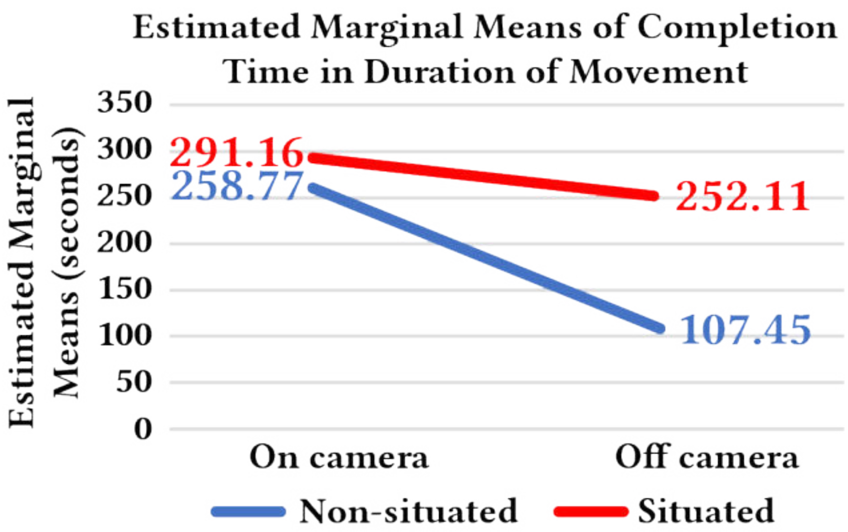


Figure 17: The interaction effect on the completion time in duration of movement/action ($p = .00001$).

3.5.4 *Movement Direction*

Response accuracy: No significant effects were found (*ps* > .19).

Completion time: No significant condition effect nor interaction effects were found (*ps* > .28). An analysis type effect emerged, however (Wilks' Lambda = .66, $F(1, 38) = 19.98$, $p = .00007$, $\eta p^2 = .35$. On average, processing on-camera material required longer time (M = 575.40, SD = 475.15) than processing off-camera materials (M = 366.23, SD = 231.20) regardless of the condition.

3.5.5 *Absolute Measurements*

Response accuracy: A main effect of condition emerged, $F(1, 38) = 28.61$, $p = .000004$, $\eta p^2 = .43$. The analysis type effect was not found ($p > .05$); however, an interaction effect emerged, Wilks' Lambda = .89, $F(1, 38) = 4.91$, $p = .03$, $\eta p^2 = .11$. Simple main effect analyses yielded that only with In-scene material, participants in Non-Situated condition made larger errors than the participants in the Situated condition did(p = .00001).

Completion time: A condition effect emerged; $F(1, 38) = 13.95$, $p = .001$, $\eta p^2 = .27$. Participants in the Situated condition spent longer time (M = 181.83; SD = 65.23) than their counterparts did (M = 107.75, SD = 60.06). An effect of analysis type was also found: Wilks' Lambda = .77, $F(1, 38) = 11.64$, $p = .002$, $\eta p^2 = .23$. Participants spent longer time when they were analyzing on-camera materials (M = 118.88, SD = 51.32) than off-camera materials (M = 170.69, SD = 113.16). There was no interaction effect (p =. 06).

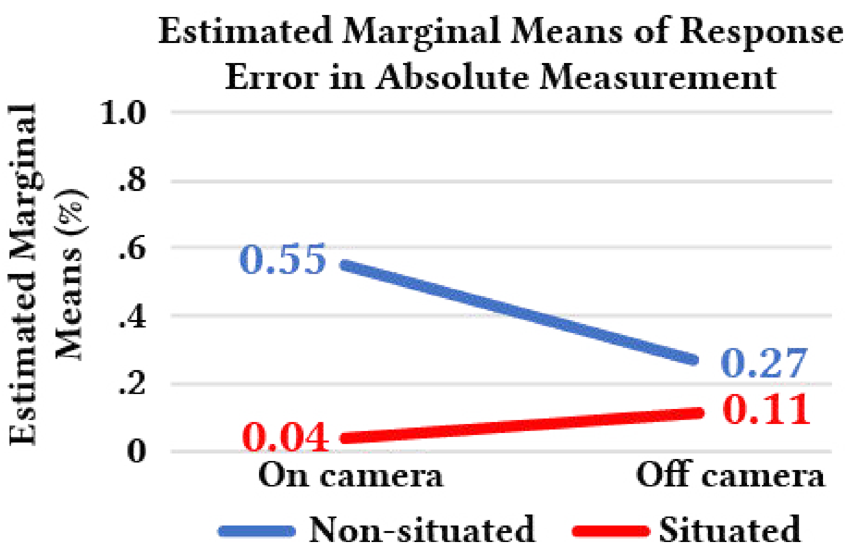


Figure 18: The interaction effect on the response error for absolute measurements: Estimated marginal means of response error magnitude (p = .03).

3.5.6 *Overall Confidence*

A question ("How confident are you about the answer you provided above?") assessed the participants' confidence level regarding their own analytical performance using a 7-point Likert scale. This question was provided immediately after each task. For the analysis, the mean of each task confidence was used. A main effect of condition and analysis type was found. When participants were in Situated condition, their confidence was significantly higher; $F(1, 38) = 8.74$, $p = .005$, $M = 5.52$, $SD = .41$, than their counterparts' ($M = 4.90$, $SD = .84$). Further, analyzing on-camera materials made the participants feel more confident about their analytic performance; $F(1, 38) = 21.38$, $p = .00004$, $\eta p^2 = .36$, $M = 5.36$, $SD = .75$, compared to the off-camera materials, $M = 5.09$, $SD = .75$. No interaction effect was found. This generally higher confidence level (note mid-point is 3.5) was surprising. Thus we further looked at the level of confidence when participants were *not* in the situation *nor able to see the entire scene*. Their mean confidence level was 4.76 with $SD = .84$.

3.6 DISCUSSION

Significant effects around the response error/accuracy confirmed potential benefits of situated analytics in comparison to the traditional Non-Situated analytic method. Participants' errors were generally larger when they analyzed the videos in an office as opposed to the actual location, as expected. Furthermore, participants' Non-Situated analysis performances were often affected by the type of analysis; the magnitude of errors the participants made varied depending on the type of analysis (on/off-camera) when they performed estimations on projectile trajectories and absolute measurement tasks. It is somewhat alarming that, when Non-Situated analyses were conducted, participants' errors were greater compared to the Situated analyses, even when the video clip contained the whole incident within the Camera FOV. This finding potentially implies the importance of situated analyses.

The accuracy came with a cost, however. Although the situated analytic method improved accuracy, users moving through the scene naturally increased the amount of time it takes to make estimate judgements. This trade-off is further justified when we observed that certain participants express frustration about the lack of information obtained from the physical environment. One can argue that in the non-situated settings, a better video quality or multiple camera angles could somehow mimic benefits similar to situated video analysis. However, going over multiple video clips could be impractical. Finally, situated video analysis boosted the participants' confidence in their judgements; such increased levels of confidence could be important when they are using visual analyses to make decisions, for example. Surprisingly, participants who were not in the location also showed rather high confidence level, even when they could not see the entire scene: such somewhat undeserving confidence level could be potentially costly. In summary, the results of Study 1 generally indicate sufficient potentials for us to explore SA further, with the caveat that it can take participants longer. In the next step, thus, we head towards an exploration of situated analytics platform, using AR.

4 SITUATED VIDEO DATA VISUALIZATION

In this chapter, we present an elicitation workshop that included sketching and ideation activities. The goal of this workshop is to capture visualization designs to support situated video data visualization, with the potential to improve the analytic process in AR environment. In addition, we examine user-generated visualization to gain a better understanding of how to exploit the user's immediate surroundings and the design recommendations that help manifest these needs in the design of situated visualizations.

4.1 PARTICIPANTS

The study was advertised on campus bulletin boards at a local university. Twelve participants (8 males and 4 females) were recruited, none of whom partook in the first study. Their ages ranged between 20 and 31 (M = 24.50, SD = 4.37). 25% of them reported that English was their first language and 16% preferred not to report their first language. No language issues were exhibited during the study. All participants reported normal or corrected-to-normal vision. Each session was conducted with two participants (i.e., pair). Two people were required so the participants could bounce back and forth their ideas with their partner. For the time constraint, we did not include more than 2 people in a session. Participants took turns throughout the session. They received a $20 gift card as compensation for their time.

4.2 APPARATUS

A Microsoft Surface Pro 2 and Microsoft HoloLens were used for the following reasons, 1) to familiarize participants with the experiences of video viewing while being mobile and in-situ, 2) to have platforms which incorporate participants' sketches using AR while making them aware that their drawings will *not* be in VR in the study, 3) to help participants understand the mapping of the events they see in the video clip in the actual location. Once again, for the ability to switch from laptop mode to tablet mode and vice-versa, a detachable keyboard was provided to the paired participants to support their mobility. A video camera, the Canon HF-M52, was used to record video scenarios in a manner similar to that of study in Chapter 3. All five scenarios were performed in FOV and on one clip (1:24 mins). The video clips' size and format were the same for both the Microsoft Surface Pro 2 and Microsoft HoloLens to counterbalance the large screen size difference between the two devices. A4 sheets of paper (21 cm X 29.7 cm) were provided to participants with a 2D and 3D representation of the space in the video that was captured in. Coloured pens for use in sketching activities were also provided to participants. This technique shows positive results in previous situated visualization studies [20].

4.3 METHOD

Six workshop sessions were coordinated with two participants each. Each session took between 1.5 and 2 hours (including 10 minutes of interview). At the beginning of each session, a research assistant was introduced as a moderator/note taker. After signing a consent form, participants filled out a short demographic questionnaire. The Microsoft Surface 2 and Microsoft HoloLens were introduced, and an instruction for watching video on both devices was provided. The two participants, were then taken to a university atrium where the video was captured, thus now situated. Participants sat at a table next to each other, and were informed that their help was needed to develop a situated visualization in 3D space of event data from a video scenario. Participants were provided with one scenario at a time, each containing a set of instructions. The order of scenarios was counterbalanced for all groups. First, participants were asked to watch the video using both the Microsoft Surface 2 and the Microsoft HoloLens, and to walk toward the location where the event(s) took place. Second, participants were asked to discuss how they would visually represent an event in the video. Third, participants were asked to sit at a table and sketch their visualization ideas on the provided paper, to represent the events from the video. Participants were asked to produce two 2D sketches to describe their ideas per scenario; they processed one scenario at a time.

A post-study interview with participants was conducted to explore participants' experiences further related to 1) potential benefits of the sketched visualization approaches when used for analysis, 2) how the drawings would enhance understanding of events, 3) challenges faced while transforming a 2D video event into a 3D drawing, 4) preference in using 2D or 3D to visualize extracted video data, and 5) preferences for future situated analysis platforms.

4.4 RESULT

We systematically coded the transcripts, sorted the photos based on ideas, analyzed the use of different form factors in participants' sketches, and created a summary of all findings with relevant quotes from the transcripts. Sixty sketches were generated in total (i.e., 6 pairs x 2 per scenario x 5 scenarios). These sketches were redrawn digitally, see Appendix Section A.1, copying the original drawings as closely as possible. Each digital sketch was summarized and analyzed in detail. For the analysis, a research assistant watched the video clip participants had watched, looked at the participants' drawings, then drafted a short explanation of what each drawing expressed. These processes yielded three major components from the participants' ideas: 1) Information Density Levels, 2) Interactivity, and 3) Event-Narrative. Examples of the emergent sketch themes are provided in Table 2.

Table 2: The distribution of theme categories of participants' sketches.

Scenario	Information Density Levels		Interactivity		Event-Narrative	
	Low-density	High-density	Interactive	Non-interactive	Narrative	Non-narrative
Projectile Trajectories	4	8	2	10	3	9
Key Changes in the Environment	7	5	3	9	1	11
Movement Direction	8	4	1	11	4	8
Duration of Movement/Action	7	5	2	10	3	9
Absolute Measurements	10	2	1	11	2	10
Total (%)	**36 (60.00%)**	**24 (40.00%)**	**9 (15.00%)**	**51 (85.00%)**	**13 (21.67%)**	**47 (78.33%)**

4.4.1 *Information Density Levels*

We split the data into two, low- and high-density levels, based on the level of information density. While low-density drawings did not include details of any event data, they provided an abstract view of the event and a quick sense of the event. Participants were generally inclined to produce sketches that revealed a minimum amount of event data. An example of a low-density drawing in which a character is shown throwing a ball is demonstrated in Figure 19 (b). Drawings falling into the category of high-density detail of visualization with more detailed information about the events such as time, location, duration, etc, can be seen in Figure 19 (a), Figure 19 (c), and Figure 19 (f). High-density drawings captured important and relevant event data (see Figure 19). Sixty percent (60.00%) of drawings fell into the low-density category. The level of analysis (i.e., Low vs. High) varied depending on the video event scenarios, see Section 3.4. For example, the absolute measurements scenario is a simple scenario where data, (e.g., the height of person) can be communicated with a simple visual representation, see Table 2; more overview drawings (10) than detailed drawings (2) were produced by participants. On the other hand, users were prompted to create more high-density detail drawings than low-density detail drawings for more complex scenarios such as in the projectile trajectories scenario.

4.4.2 *Interactivity*

Only 15% of the sketches contained an interactive component. Various interactive functions were introduced by participants. For example, functions such as clicking on a vandalized wall to reveal more information such as the time of occurrence, duration of the act, and height of the actor, see Figure 19 (f). The use of physical movement was also proposed in the sketches. In Figure 19 (c), a participant indicates that standing on the location of an individual or object could reveal more situational information.

4.4.3 *Event-Narrative*

Annotations were included by some participants to directly instruct a user to explore (e.g., asking users to click, and stand at the location of interest) for further information, Figure 19 (c). Another example of annotation usage leveraged chronological order of events in the video to inform users, Figure 19 (d). Twenty-one point sixty-seven percent (21.67%) of the sketches included event narratives.

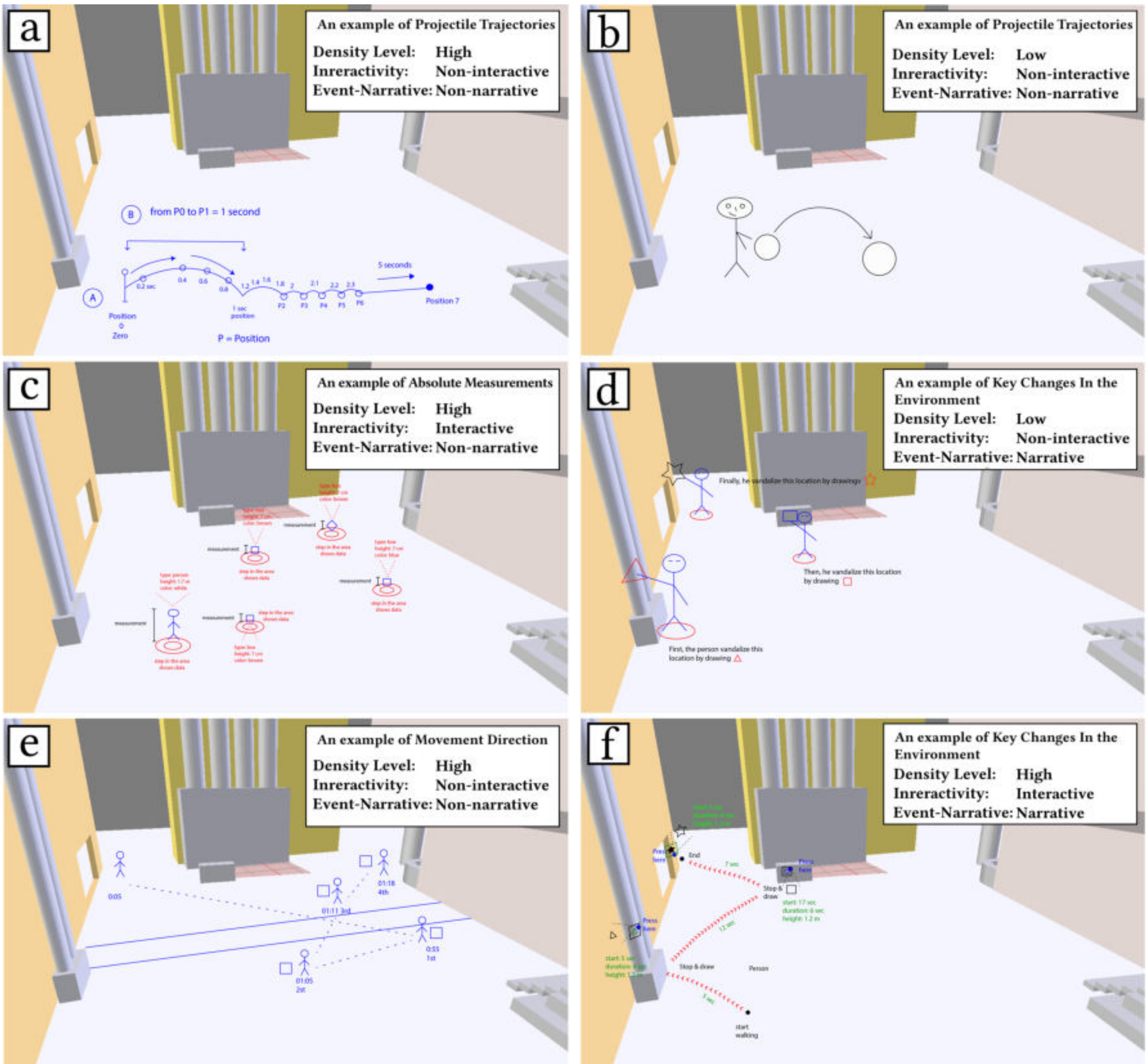


Figure 19: Sample of participants' sketches.

4.4.4 *Interview*

Participants were interviewed after the design session, to capture their thoughts about their experiences and drawings. Analysis of the participants' interviews revealed the following four themes.

2D and 3D Data Visualization: First, all the participants preferred 3D data representations over 2D representations supporting in-situ video analysis. Physical mobility between events, and different viewpoints of the data were among the rationales given by participants for preference of 3D. For example, P1 mentioned that a 3D visualization "... helps you to move around different event in the video and can look at them as you are part of the event" [sic]. P2 reported "... video events happened in 3D space and to make sense of the event data it should be visualized in the same 3D space" [sic]. Further, participant P10 stated that "... you can see the object from all viewpoint" [sic]. Other participants suggested that 3D visualization supports a multivariate representation of events where "you can add depth into it you can add more information" [sic] (P3). Thus, all the participants recognized the strength of 3D visualizations.

Benefits of Situated Video Visualization: Participants reported several anticipated benefits of the video visualization techniques; 1) *reduction of video browsing time* (P1, P2, P3), 2) providing a better understanding of events (P3, P4, P5, P8, P11), and 3) supporting interactivity which increases engagement with events (P4, P5, P9, P12). Participants felt that visualizing the information could reduce the time and effort of event exploration. For example, P1 mentioned that "in the video you have to watch 1 to 2 minutes where in the picture drawing (drawing of the video events) you can see the data and people can look at it in like 10 seconds ... video watching is sequential you have to watch all the video." In addition, participants felt that their drawings could *enhance user understanding* of video events. As reported by P3 and P4 "I think for people less trained, our drawing will help them understand the 3D aspect by adding depth into the scenario" [sic] (P3), and "data that we draw has all the necessary information that someone needs to examine events in the video" [sic] (P5).

Situated Video Analysis Platform: Participants reported their analysis platform preference (i.e., Microsoft Surface 2 vs. Microsoft HoloLens) if they were to conduct future analysis of a 3D drawing of a video. Forty one point sixty seven (41.67%) of them preferred tablet use, whereas 58.33% preferred the HMD; $X^2(1, N = 12) = .33, p = .56$. Despite a stated appreciation for a HMD, device weight, size, complex interactions, and social acceptability were the main reasons and limitations participants cited for preferring the tablet. Interestingly, however, none of these comments refer to the efficacy of an HMD. Freehand interactions, mobility, and a better sense of immersion between the virtual and physical environment were among the rationales provided by participants who felt positive about the HMD. For example, P1 felt that using an HMD will help her to focus on the task, stating "... (you) are not distracted and you can focus on the objects" [sic]. Participants P9, P11, and P12 mentioned that tablets do not support full immersion with a digital world. For example, P11 stated "... I was seeing the same video using the tablet, it was very hard for me to generate the sense of the location, time, and direction." [sic]. Participants P5, P7, and P8 expressed the ease of mobility in a 3D scene using an HMD. For example, P8 stated "... It gives the ability to move easily and have your hand free." (P8). Thus, they recognized the potential of an HMD.

Situated Video Visualization Challenges: One participant felt that the visualization of the extracted video data could capture important and relevant data, such that it could replace traditional videos, stating that "The drawing we come up with will make it easy for video analyzers to understand and make sense of what happened even if they did not see the video" [sic] (P6). On the other hand, several participants expressed their concerns about possible errors made in the process of transferring and encoding extracted data from a video to visualization. For example, P4 mentioned that "... the hindrances of transforming video events is that if designers made mistakes or wrongly transform the data." [sic].

4.5 DISCUSSION

Participants' responses revealed interesting visualization themes, insight, and challenges. The information density levels in visualization, which was found in our participants' sketches, is a common finding in information visualization [134]. The high-density visualization is considered as a first step in visual investigation and exploration techniques, "Overview first, zoom, filter, and then focus details-on demand" [134]. Participants expressed interaction in their drawings to support event exploration. For example, hand gestures (i.e., clicking) and physical body movement (i.e., standing at a certain location). Further investigation is required to explore different interaction techniques that are suitable for situated video visualization. Furthermore, narrative visualization incorporates information, communication, and exploration visualization to convey a story [79]. Some of the participants maintain a narrative of the events when they sketched video clips of the scenarios. Textual annotation is a design tactic used to leverage the information presented, to direct user attention, stress the chronological order of events, or show transitions in an event [79]. When extracting data from the video, it is important to use tools that ensure the validity and accuracy of the data. Based on the observation of the studies, a shortcoming of the situated video analysis technique would be the physical effort required by users when they're in the place of the event. However, situated video analysis techniques could be beneficial for different application domains. For example, during a sport training session (e.g., a soccer player visualizing kicked ball trajectories using situated video analysis, may obtain a better understanding during training regarding how to replicate such a kick).

5 SITUATED SPACE-TIME CUBE ANALYTICS

In Chapter 3, the analysis of the data indicates that situated analytics has many possible benefits, such as accuracy and deeper exploration, over traditional desktop platforms. Also, in Chapter 4, the analysis of user-generated visualization design informed us how to exploit the user's immediate environment to place and represent visualizations [20, 46]. In this chapter, we present our approach for SSCA prototype as well as the core principles and design choices of the tool. The emerging knowledge from Chapter 3 and 4 coupled with STC design choices from the literature, see Table 3, will be used to develop SSCA prototype. SSCA uses STC to visualize trajectory data of individuals and maps visualization into the environment where the data was collected to support in-situ exploration; see Figure 20. SSCA prototype should account for the situated nature of the visualizations and can consider new forms of interaction, such as proxemics and embodied interaction, and utilize flexible displays such as AR display.

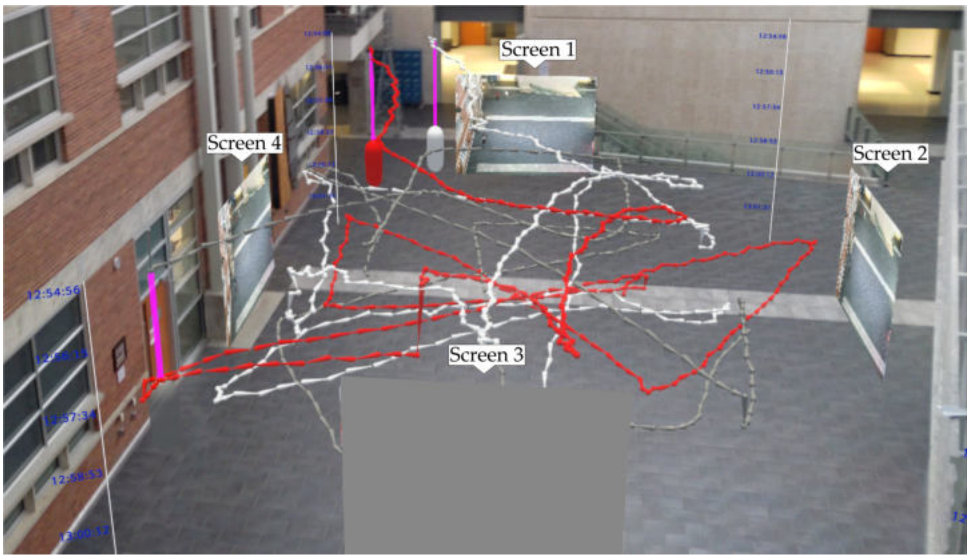


Figure 20: A top down view of the mapped objects' data in SSCA and four virtual video displays on the visualization's walls.

5.1 SSCA DESIGN CHOICES

Two studies investigated situated video analysis (in Chapter 3) and visualization sketches (in Chapter 4) in a rather holistic manner. The results of the first study repeatedly indicated the potential benefit of situated video analysis. Furthermore, results from the second study revealed meaningful themes and design considerations for future prototypes. The following take-aways are presented for future consideration by designers of situated video analytic interfaces:

- For situated video analysis, future analytic programs should incorporate a low- and a high-level detailed visualization of events, to provide the capability to interact with the event data and narrative.
- Visualizations for situated video analysis should include the original video footage as a tool for validation or reference.
- The use of annotations in situated video analysis visualization supports event narrative via grabbing users' attention, clarifying chronological order of events, and indicating event transitions. Also, textual annotation could be used as a way to capture and exchange user insight and conclusions.
- Situated video analysis visualization could incorporate multiple levels of contextual information to support multivariate types of analyses (e.g., including fine details relating to, but not limited to, the variables of time, duration, object classification, object location, object direction, object velocity, event summary, etc).
- Interaction with situated visualizations should consider not only the location but also the user's physical body movements as an input modality.

Table 3: Design principles from the literature that have been considered during the SSCA prototype implementation.

Design Aspect	Principle	Year	Authors/Citation	Title
Visual Encoding	Colour and Shape	2003	Andrienko et al. [8]	Exploratory Spatio-temporal Visualization ...
		2009	Huisman et al. [78]	Developing a Geovisual Analytics Environment ...
		2012	Orellana et al. [118]	Exploring visitor movement patterns in natural ...
		2020	Filho et al. [54]	Evaluating an Immersive Space-Time Cube ...
		2020	Homps et al. [76]	ReViVD: Exploration and Filtering of Trajectories ...
	Movement direction	2015	Amini et al. [5]	The Impact of Interactivity on Comprehending ...
		2016	Buschmann et al. [25]	Animated visualization of spatial–temporal ...
		2019	Filho, Freitas, and Nedel [52]	Comfortable Immersive Analytics With the ...
		2020	Filho et al. [54]	Evaluating an Immersive Space-Time Cube ...
		2021	Andrienko and Andrienko [7]	Visual Analytics of Vessel Movement
		2014	Andrienko et al. [6]	Visualization of Trajectory Attributes in Space-Time
		2015	Amini et al. [5]	The Impact of Interactivity on Comprehending ...

	Time axis downward	2016	Buschmann et al. [25]	Animated visualization of spatial–temporal ...
		2019	Filho et al. [52]	Comfortable Immersive Analytics With the ...
		2020	Filho et al. [54]	Evaluating an Immersive Space-Time Cube ...
		2021	Andrienko and Andrienko [7]	Visual Analytics of Vessel Movement
Visual Encoding	Support 2D/STC	2010	Kjellin et al. [88]	Evaluating 2D and 3D Visualizations of ...
		2012	Orellana et al. [118]	Exploring visitor movement patterns in natural ...
		2014	Geotime [59]	GeoTime
		2015	Amini et al. [5]	The Impact of Interactivity on Comprehending ...
		2016	Buschmann et al. [25]	Animated visualization of spatial–temporal ...
	Relative motion	2003	Andrienko et al. [8]	Exploratory Spatio-temporal Visualization ...
		2010	Kjellin et al. [88]	Evaluating 2D and 3D Visualizations of ...
		2014	Geotime [59]	GeoTime
		2015	Amini et al. [5]	The Impact of Interactivity on Comprehending ...
		2003	Andrienko et al. [8]	Exploratory Spatio-temporal Visualization ...

		2012	Orellana et al. [118]	Exploring visitor movement patterns in natural ...
	Text direction	2012	Grasset et al. [62]	Image-driven view management for augmented ...
		2015	Amini et al. [5]	The Impact of Interactivity on Comprehending ...
	Video player	2018	Lawrence, Dey, and Billinghurst [98]	The Effect of Video Placement in AR ...
		2014	Damen et al. [40]	You-Do, I-learn: Discovering Task Relevant ...
Interaction	Panning, zooming, rotating, and time slider	2014	Andrienko et al. [6]	Visualization of Trajectory Attributes in Space-Time
		2015	Amini et al. [5]	The Impact of Interactivity on Comprehending ...
		2016	Buschmann et al. [25]	Animated visualization of spatial–temporal ...
		2020	Homps et al. [76]	ReViVD: Exploration and Filtering of Trajectories ...
		2021	Andrienko and Andrienko [7]	Visual Analytics of Vessel Movement
	Play animation	2003	Andrienko et al. [8]	Exploratory Spatio-temporal Visualization ...
		2012	Nguyen et al. [114]	Video Summagator: An Interface for Video ...
		2015	Amini et al. [5]	The Impact of Interactivity on Comprehending ...
		2021	Andrienko and Andrienko [7]	Visual Analytics of Vessel Movement

Interaction	Mid-air	2012	Grasset et al. [62]	Image-driven view management for augmented ...
		2015	Müller et al. [112]	A Study on Proximity-Based Hand Input ...
		2020	Trajkova et al. [145]	Move Your Body: Engaging Museum ...
		2020	Filho et al. [54]	Evaluating an Immersive Space-Time Cube ...
	Proxemic	2019	Prouzeau et al. [122]	Scaptics and Highlight-Planes: Immersive ...
		2020	Batch et al. [13]	There Is No Spoon: Evaluating Performance ...
		2016	Badam et al. [12]	Supporting visual exploration for multiple ...
	Orientation	2015	Marquardt and Greenberg [105]	Proxemic interactions: From theory to practice
		2020	Trajkova et al. [145]	Move Your Body: Engaging Museum ...

5.2 PROTOTYPE IMPLEMENTATION

To enable in-situ exploration of an STC visualization, we designed and developed SSCA, an AR application that supports 2D/3D visualizations of trajectory data. SSCA can import a spatio-temporal dataset and map it onto the environment in which the event took place.

5.3 TRAJECTORY DATASET

In this dissertation, we decided to use video footage as a source of trajectory data for two reasons. First, video footage provides a rich source of important data such as trajectories corresponding to individual moving objects, activities and interactions between objects, and relevant events. These data not only support the in-situ spatio-temporal data analysis activities but also provide detailed information about the objects within the video. Second, we were interested in capturing objects' spatio-temporal data from a physical environment that we have access to and can revisit during the development and testing of the prototype, especially during the COVID-19 lockdown. Nevertheless, the proposed prototype should be capable of using trajectory data from different sources, such as sensors, GPS, and other tracking devices.

We video recorded actors performing in-situ tasks based on pre-defined scenarios in the University of Manitoba Engineering building atrium. Videos were recorded in 1920 x 1080 resolution and 30 fps. We implemented a computer vision tool for processing video frames and extracting movement data, see Figure 21. We used motion detection and tracking algorithms from Open Source Computer Vision (OpenCV) library version 3.0 to track and extract objects' movements and locations [18]. The process to extract the trajectory data using the software as follows: First, a user selects the source of the trajectory data from video footage or a live stream via camera. Second, the user chooses one of object tracking algorithms. Then, the user specifies perspective transformation points where the position of the image's pixels is calculated and transformed into a top-down, *birds-eye-view*. Next, key points are measured in the video and physical scene to perform perspective transformation from the image to the measurement. With these transformations, we could map the actor's trajectories to the physical space. Finally, when the user selects to log the trajectory data and run the analysis, the system exports the trajectory data as Comma Separated Value (CSV) files.

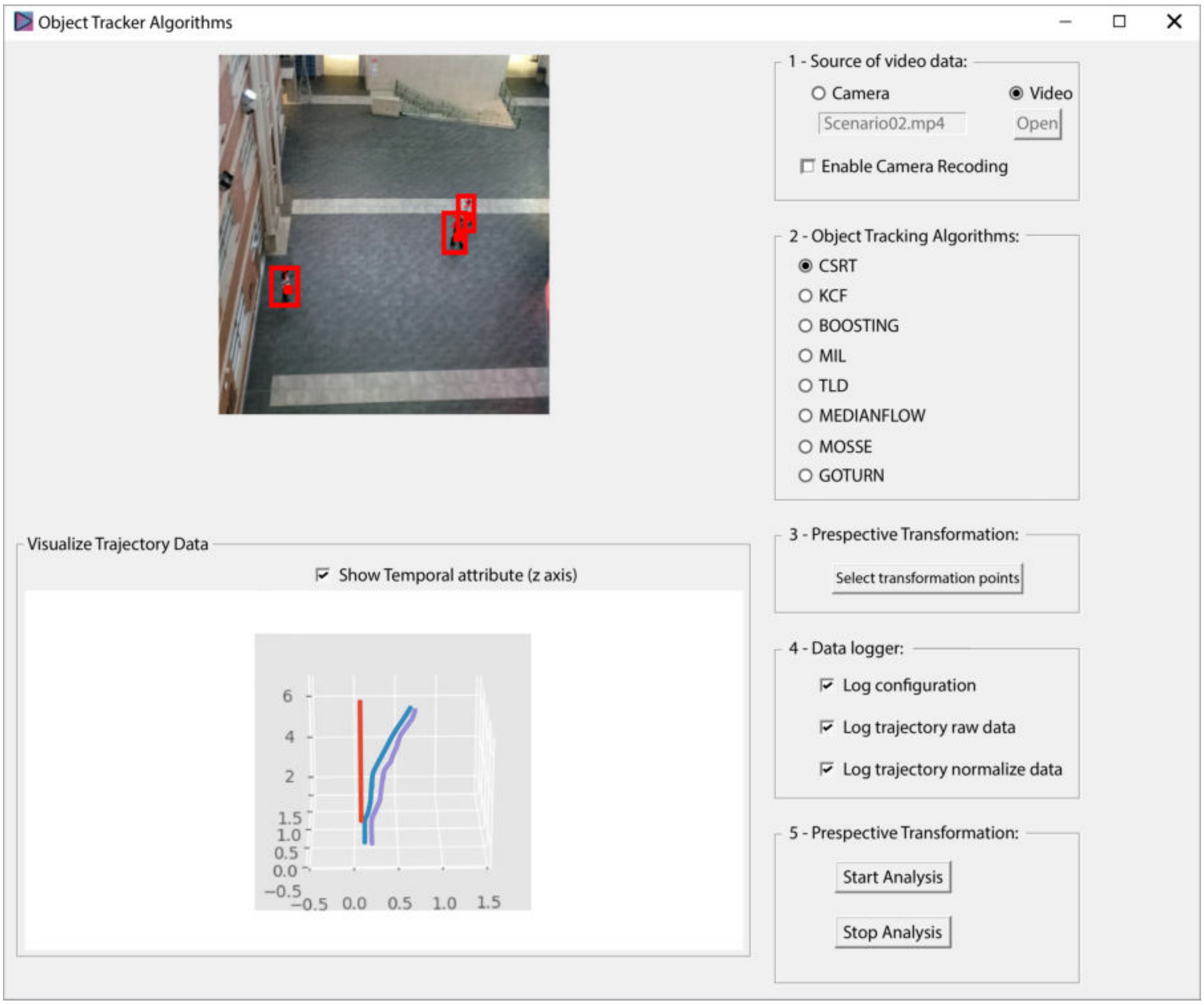


Figure 21: The implemented computer vision software used to extract trajectory data into CSV file.

Prior to data visualization of data on HoloLens 2, we preprocessed the raw data using filters to reduce data clutter, without reducing information content. These filters reduce data clutter when individuals are stationary, removing all datapoints between the first location where the individual became stationary and the last location before they become mobile. The trajectory data is then embedded into the physical scene to match the individuals' movement in the scene. Unity[1] 3D was used to process the trajectory data CSV files, to generate the STC visualization, and to build out the interactions and user interfaces. The Mixed Reality Tool Kit (V2.6) [154] was used in conjunction with the Microsoft HoloLens 2 [111]. The HoloLens 2 has a 2K resolution per eye, a 43° horizontal and 29° vertical field of view, and image rendering at 60 fps. To map the visualization on the physical space, the user is required to stand on a pre-defined reference point to calibrate and run the SSCA prototype.

Based on the literature (see Table 3) and our findings (i.e., in Chapter 3 and Chapter 4), we considered six critical components in the design of our prototype: 1) a situated STC visualization to map the extracted spatio-temporal data to the environment [144, 156], 2) an easy-to-access interface [10, 101, 154, 164], 3) a video player to view the video data content for data integrity and validation (Chapter 4, [40, 71, 98]), 4) two analytical modes to view video content and trajectory data [5, 59], 5) an interactive data filtering to filer and interact with video and spatio-temporal data [5, 133] , and 6) embodied interactions to support data filtering [62, 122, 145]. In the following sub-sections, we detail the design choices for each component, and how some design recommendations cannot be applied in the context of situated analytics.

5.4 2D/STC VISUALIZATION

We used similar 2D/STC design choices (e.g., use of a cone shape for visualized datapoints, a measurement plane, a time axis, and relative motion of visual elements) [5, 25, 54, 61, 91]. Thus, we implemented 2D and STC visualizations of individuals' trajectory data that can display data within the environment, see Figure 22. The main difference between these two visualizations can be seen in their mapping of data within the scene. While 2D visualization places all data on the ground, the STC visualization spreads out the data within the air around the user. The different coloured capsules within our visualization represent unique individuals and objects

1 A cross-platform game engine used to create three-dimensional (3D) and two-dimensional (2D) games.

in the scene. Spheres represent objects' locations at a point in time. Furthermore, the tapered line segments between two spheres indicate the direction of movement.

Figure 22: The implemented 2D (left image) and STC (right image) visualizations of individuals' trajectory data.

5.5 RELATIVE MOTION OF VISUAL ELEMENTS

Relative motion of visual elements is used to show how objects move with respect to each other. A red 2D measurement plane was implemented in STC visualization mode to show the selected time on the time axis, a green sphere along each trajectory shows the selected location of the actor or entity at specific time, and a vertical pink line from the datapoint to the ground shows the object's location similar to previous work [5]. Amini et al. [5] discussed two approaches to control relative motion of objects in desktop STC. The first method is to fix the ground map plane and trajectories to the camera view and then user drag the measurement plane, up or down, to show user location changes. The second method is to fix the measurement plane to the camera view and drag ground map plane and trajectories up and down to show the change in location. The second method causes the trajectory data to move along the time axis, thus it is not in the place where the object was. Through pilot testing, we found the first approach more suitable in situated visualization contexts, therefore, trajectory data has to be mapped into the environment.

5.6 TIME AXIS AND DIRECTION

One important design decision for our situated STC visualization is to decide on the direction in which time is displayed. We implemented the time passing in a downward direction, similar to the approach of previous works [5, 54]. This direction of time places the current inspection of time closer to where the user is standing. In most of STC visualizations, the time axis is fixed at one [5, 53, 85], two [128], or three [53] of the visualization's back walls. However, we found this to be not applicable for situated STC visualization. During our pilot testing, we asked our colleagues to use the prototype to explore data and provide feedback in terms of recommendation and suggestions. We noticed that they were constantly exploring data at locations far from or facing the opposite direction of the horizontal axis. Thus, to support this case, we placed a time axis in each of the four corners of the situated STC visualization walls.

(a) The initial around-hand interface design.

(b) The crossing-based target selection interface.

Figure 23: The redesign of the around-hand interface during the pilot study feedback.

5.7 AROUND-HAND INTERFACE

We built our User Interface (UI) on the Mixed Reality Tool Kit 2.6 around-hand UI and controllers [154]. The main UI allows the user to quickly access interface elements when needed, watch and scrub video data, switch between 2D and STC visualizations, and filter data using different embodied interactions. The main interface appears/disappears with the raising of a hand into one's field of view. To avoid false interface activation, the user is required to look at their hand. Once the main interface is no longer needed, the user drops their hand to cover the interface. The interface is divided into two areas: 1) a video player aligned to the left of the interface, and 2) controllers aligned to the right; see Figure 24. We ran an initial pilot study with colleagues to test the interface and the placement of the controllers, asking for their feedback. One of the three colleagues was left-handed. Users had reported difficulties interacting with controllers due to an initially small size, see Figure 23 (a). Furthermore, users reported the issue of hand-video occlusion and overlapping, especially when interacting with the UI. Through iterative upgrades to the UI, we got inspired by crossing-based target selection technique known for better performance [10, 101, 164], see Figure 23 (b). Crossing-based target selection is commonly used in AR and VR platforms to move virtual characters and select both stationary and moving objects [164]. To address hand-video occlusion and overlapping, video player and controllers were implemented so they automatically get positioned to the left or the right of each other based on the hand used to activate the interface. For instance, if the user activates the interface with the right-hand the video will be aligned to the right of the interface and the controllers aligned to the left and vice versa, see Figure 24.

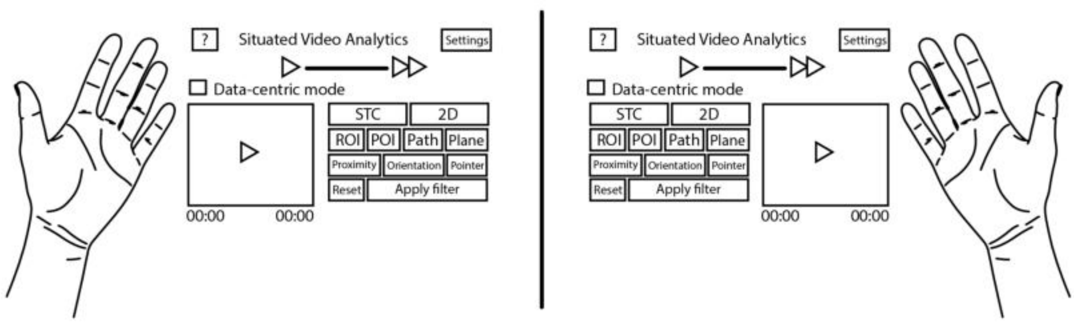


Figure 24: Around-hand interface is activated and anchored to the person's hand once one of their hands is raised. On the left, interface buttons are automatically placed to the right side. On the right, the opposite behaviour occurs when the right hand is raised.

5.8 VIDEO PLAYER

Video players have been added to the around-hand interface and the walls of the visualization. Within the UI, the user can play, pause, and scrub the video timeline using mid-air hand gestures (i.e., pinch and drag). Also, scrubbing through the video timeline will animate the virtual capsules along trajectories paths. When the user is playing and/or scrubbing the video, the visualization elements embedded into the actual environment will move with respect to the video. Based on the enabled visualization type, playing the video will result in different behaviour. For example, when playing video with the 2D visualization selected, the visualization elements move in x and y axes and trajectory data gradually appears in 2D over time. In this 2D animated mode, the focus is more on the spatial aspect of the data, see Figure 25. When playing video in STC visualization mode, the capsule objects move in x and y, and trajectory data gradually appear in 3D over time. Each capsule object projects a line to a datapoint that represents the spatial and temporal aspect in 3D, see Figure 25. Users can jump into a different part of the video using a timeline slider that updates the locations and movements of the virtual capsule objects. The user has to activate the around-hand interface to be able to watch the video. One downside of this approach is that if the video is long, user will need to hold his/her hand up for a long period which is prone to fatigue and lead to a feeling of heaviness in the upper limbs [71]. A possible solution would be adding extra video screen(s) in the user FOV. This raises another design question regarding the placement of the video. Researchers have looked at the placement of Video-based content in AR [40, 98]. Video windows can be either fixed to a specific physical environment or attached to the Head-Mounted display HMD FOV. Depending on the tasks and the data content, placing the video on top or very close to data causes occlusions [40]. To prevent this issue, the video should be located in a proper location that does not occlude the data. Therefore, we placed wide video screens, size 4 by 3 meters each, on four sides of the visualization walls. The user can play video from the around-hand interface, drop their hand, and continue watching it on the video screens.

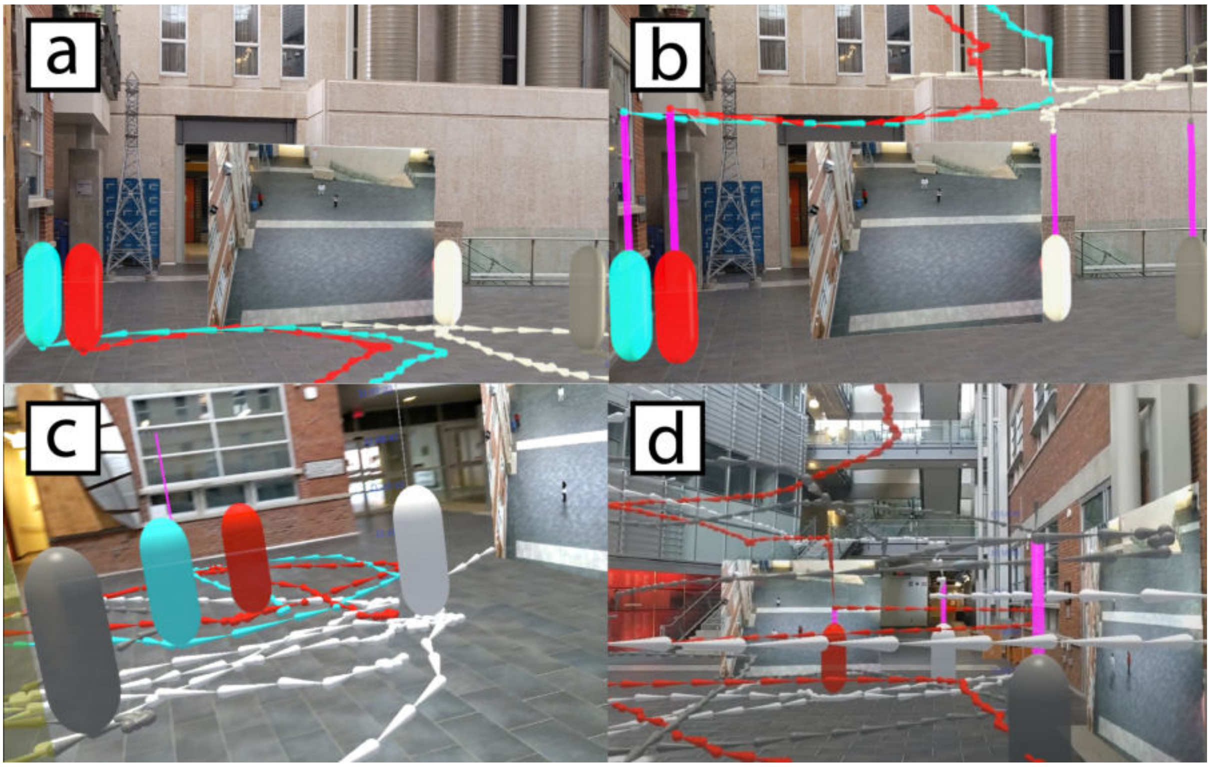


Figure 25: The result of playing the video in sequential analysis mode in (a) 2D and (b) STC. In data-centric mode, (c) shows video played in 2D whereas (d) shows video played in STC.

5.9 TWO ANALYTIC MODES

The tool provides two analytic modes: *Sequential Analysis*, and *Data-centric*. When sequential analysis mode is enabled, the trajectory data points are revealed as they would over time, see Figure 25 (a) and (b). In this mode, the user uses the video player to show the data points in a sequential manner. Within this mode, users can view data through both visualization methods. In data-centric mode, all movement data points are shown at once, see Figure 25 (c) and (d). When STC or 2D visualization is enabled and video is playing, the moving capsules behave similarly as in sequential analysis mode; however, all points within the data are shown at once.

5.10 INTERACTIVE DATA FILTERING

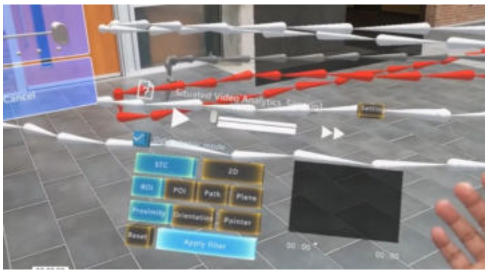
Data filtering is an important procedure by which a subset of a dataset is chosen to narrow down the exploration and investigation process. Our prototype allows interactive data filtering through ROI, POI, trajectory path selector, datatips, and a measurement plane that moves up or down the time axis with the current time of the plane displayed. These filters can be applied to either the 2D or STC visualization through the use of different embodied interactions.

5.10.1 *Region of Interest (ROI)*

When a Region of Interest (ROI) filter is created using one of the embodied interactions, a yellow cylinder with a height of 10 cm is placed at user's current location. Then, the user adjusts the cylinder's radius using a slider to select the desired area of interest. As the cylinder radius and user location change, only datapoints located within the cylinder area (πr^2) will be highlighted in green colour as a visual cue to the user, see Figure 26. Once the user enables a filter of the data, selected datapoints are shown, and video frames segments within the created ROI will only be shown when the user plays video.

5.10.2 *Period of Interest (POI)*

In Period of Interest (POI) filter, the user can select trajectory data based on a time span of interest. Based on the selected embodied interaction, the user moves the selected time window over the entire timeline to select the desired POI, and all datapoints within that POI will be highlighted, see Figure 27.



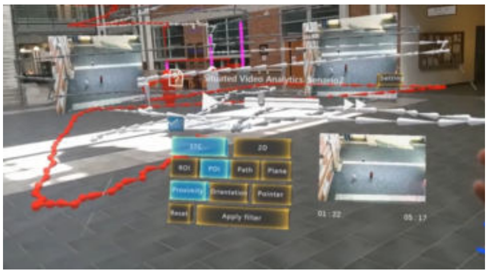
(a) First, the user selects ROI filter from the Around-hand menu.

(b) Then, the user adjusts the cylinder's radius using a slider to select the desired area of interest.

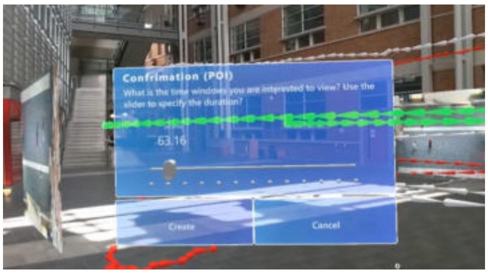
(c) As the cylinder's radius and user location change, only data points located within the area of the cylinder (π r^2) will be highlighted in green as a visual cue to the user. Then the user confirms the selection.

(d) After that, the user has created two ROI filters and viewed them from a distance.

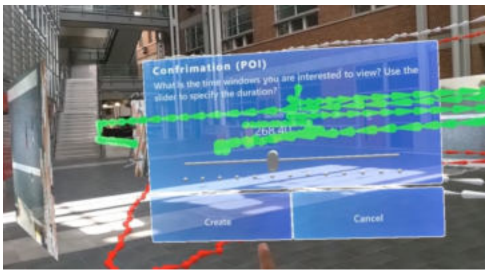
Figure 26: Steps on how to create ROI filter.



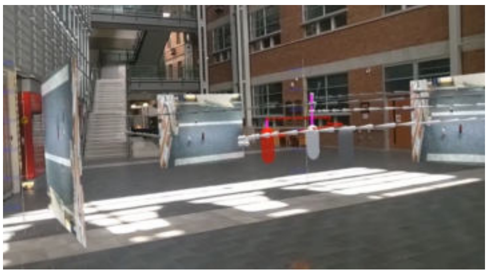
(a) The user enables the POI filter.



(b) A virtual popup window that allows the user to narrow the time range of interest widow.

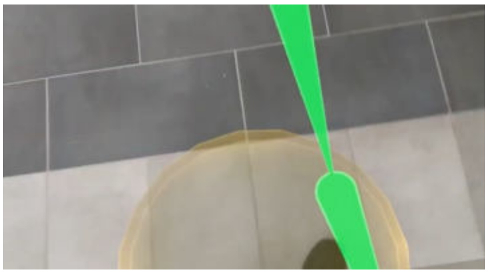


(c) The user selects time span of interest.

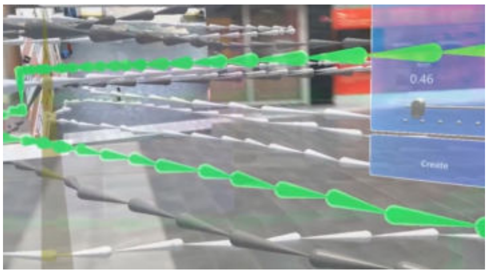


(d) The image shows the result of visualization after applying the POI filter.

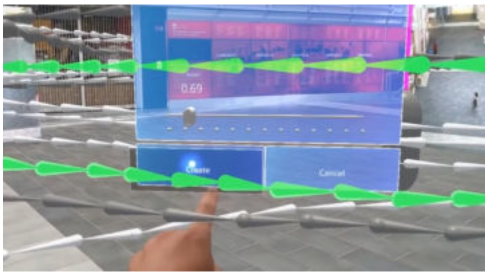
Figure 27: Steps on how to create a POI filter.



(a) When the user selects trajectory path selector and proximity interaction, a yellow cylinder will appear. Any trajectory's datapoint located above the cylinder, the trajectory will be highlighted.



(b) Only red trajectory path is highlighted in green.



(c) The user confirms the selection by creating the filter.

(d) All trajectories were filtered out except the red one.

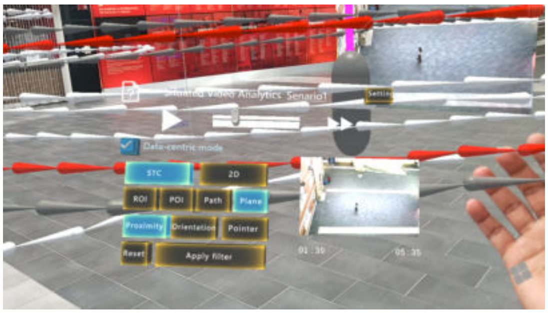
Figure 28: Steps on how to create Trajectory path filter.

5.10.3 *Trajectory Path Selector*

The trajectory path selector is a filter used for selecting single or multiple trajectories. In this filter, once the user selects the desired trajectory, all points that belong to the path trajectory will be highlighted. When users confirm the selection, only selected trajectories will appear to them, see Figure 28. The selection method depends on embodied interaction chosen by the user, discussed in details in the next section.

5.10.4 *Datatips*

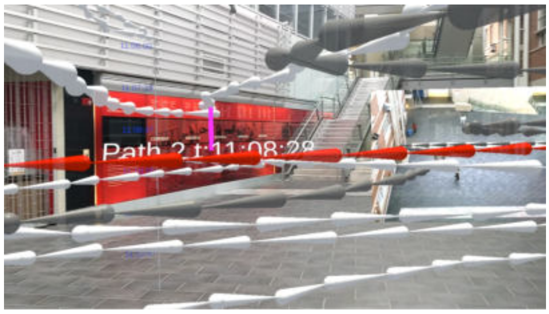
A datatip is a small text box that displays detailed information about individual datapoint (e.g., trajectory id, location value, and time). Also, datatips orient themselves to face the users regardless of their position with the immersive STC visualization. Users can show/hide datatips using Mid-air gesture and hide all shown datatips at once by resetting the filter from the around-hand menu. When datatip is enabled, a solid line is projected from the each datapoint location to the floor and the datatips will be placed in the floor. In addition, there is another effect of showing the detailed information of a data point on the video player: when playing and pausing the video, showing detailed information of a data point, the video player jumps to the frame of that data point in the video.



(a) The user selects the Measurement plane filter from the Around-hand menu.

(b) For example, here the plane is located beneath the user's head level and the datatips appear at the upper end of the pink lines.

(c) When the plane is above the user's head, the datatips appear at the bottom end of the lines.



(d) Once the user confirms the selection, the datatips for selected datapoints will appear.

Figure 29: Steps on how to show datapoints' datatips using Measurement plane.

5.10.5 *Measurement Plane*

The measurement plane was implemented, only in the 3D visualization, to allow users to select one or more datapoints that share the same location at the time axis.

Once the measurement plane is selected, a red 2D plane appears to the user. When the plane touches datapoints, datatips will be shown at once. Whenever the user moves the 2D plane along the time axis (upward or downward), all points that intersect with the plane will show pink lines and their datatips. As the plane touches trajectories' datapoints, datatips for these datapoints will be shown at once. Depending on the location of the plane (i.e., above or beneath the user's head), datatips (path id and time) of the datapoints will be shown at the end of the lines, see Figure 29.

When users apply the same filter multiple times on the data, the resulted data will be a union of the applied filters, see Figure 26 (d). On the other hand, when different filters are applied to the data, the resulted data will be an intersection of the applied filters.

5.11 EMBODIED INTERACTION

We implemented embodied interactions, more specifically body proximity, orientation, and mid-air gesturing for use in our situated visualization contexts. Users can use these embodied interactions to explore, navigate, and filter data. Users can make different combinations of visualization types, filters and embodied interactions, see Table 4 for the different crossing-base selection combination possibilities.

Table 4: Each visualization has three embodied interactions. The interface will show the applicable data filtering based on the user's selection of the visualization and embodied interaction.

Visualization	**Embodied Interaction**	**Applicable Data Filters**				
		ROIs	POIs	Path	Plane	Detailed information
STC	Proximity	✓	✓	✓	✓	
	Orientation		✓	✓	✓	
	Mid-air gesture				✓	✓
2D	Proximity	✓	✓	✓		
	Orientation		✓	✓		
	Mid-air gesture					✓

5.11.1 *Proximity*

Since the trajectory data to be explored is mapped into the environment, in-situ exploration is supported through body proximity to data and through simple body movement throughout the environment. This allows for closer exploration of certain areas of the visualization and even enables exploration of a scene's environment that is not captured in video data. In both 2D and 3D visualization views, users can move around, physically navigate, and explore the trajectory data in the main view-port. When no embodied interactions are enabled, the user's location and head movement (position and orientation) are used to change the user viewpoint to the situated visualization of trajectory data (e.g., translate viewpoint up, down, left, and right). Additionally, Proximity can be used as a brushing tool to allow the user to perform three-dimensional geometric queries on the dataset. For instance, when users enable Proximity and an ROI filter, a user's location and set interpersonal distance zones, via a dialogue box, are considered as input parameters to the filter. In the POI filter, Proximity, through a user's cardinal movements (moving forward, backward, left, or right), enables the selection of a time period, again with the length of the period chosen through a dialogue box. This combination of filter and interaction results in a highlighting of the selected filtered data. To emulate the choice of period, users walk forward or left to move the period forward and back or right to move the period back. For the measurement plane approach, users similarly use proximity interaction. The user uses their body proximity to move the measurement plane, up or down, over the time axes. As the measurement plane touches trajectories' datapoints, a solid line is projected from each datapoint selected to the floor, and the datatips appear placed on the floor.

To select a path, the user needs enable Proximity, Path filter, and specify the interpersonal zone radius. Once the visual interpersonal zone is created, users move and allow the visual interpersonal zone to intersect with the x, y location of any datapoint belonging to any trajectory. When the interpersonal zone intersects with any trajectory, the trajectory gets highlighted with a green shader.

5.11.2 *Orientation*

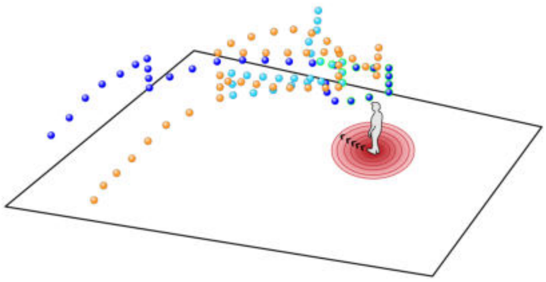
We define the body or head orientation as the direction the body or head is facing. In our prototype, we considered an absolute orientation of the head relative to Earth-vertical and Earth-horizontal axes. For vertical head rotation, we limit the head rotation to range between 20° above the Earth-vertical and 30° below the Earth-vertical in order to make head movement more natural and convenient. Similarly, the range of the horizontal head rotation was between 30° above the Earth-vertical and 30° below the Earth-vertical.

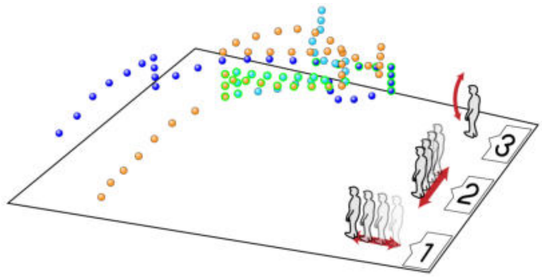
Orientation interactions are enabled for POI, measurement plane, and trajectory path selector. During the prototype design stage and initial pilot study, with colleagues, participants tried vertical and then horizontal head orientation (and vice versa) to create POI filters. Participants reported that vertical head rotation was more convenient and made them focus on data ahead of them comparing to horizontal head rotation. Therefore, we considered using the vertical orientation for user interaction with the POI filter. After users create the filter and specify the time span, a green shader highlights part of the dataset. Then, users rotate their head up or down which results in the movement of the green shader over the timeline forward or backward. Similar to POI, vertical head movement will make the measurement plane move up or down, over the time axis. The users can move around and freely make horizontal head movements before confirming their selection.

In trajectories paths selector filter, the concept of visible raycasting was used to enable users to select trajectories. When users enable orientation and trajectory path selector, a 2D customized raycast will be shot from the users' location and onward. Users are given the ability to adjust the width and length of the raycast for better trajectories selection. Users can make 360° horizontal head rotation which will cause the raycast to rotate as well. Trajectories that intersect with the raycast area (i.e. `width x length`) will be highlighted with the green shade.

5.11.3 *Mid-air Gesture*

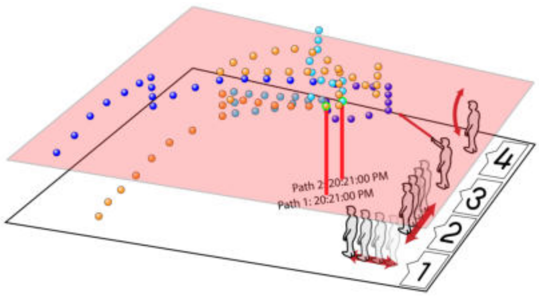
We refer to the mid-air gesture interaction as Pointer in our prototype. The user uses an index finger to point at the Plane, performs a pinch gesture, then moves their hand up and down to adjust the location of the Plane in the time axis. The Pointer interaction provides fast access to a data point's detailed information (i.e., datatip) when movement data is shown. For example, pointing at a data point highlights it with a green sphere. Then, performing a single pinch gesture shows a datatip to aid in determining actual temporal information and the trajectory it belongs to. Repeating the same gesture to that point will hide the detailed information. Furthermore, pointer interaction is used to interact with filter dialogue box controllers when the dialogue box is far from user reach.

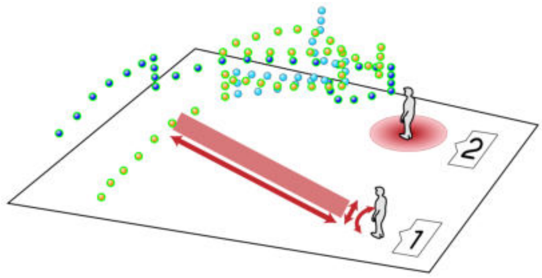




(a) In the ROI filter, users' proximity is used for environment navigation and data brushing. Users enable proximity to select the region of interest where users' location and interpersonal distance zones (circle area (πr^2)) are considered as input parameter to the ROI filter.

(b) In the POI, users can use 1) forward and backward movement, 2) left or right movement, or 3) vertical head-rotation to move the selected time window over the entire timeline to select the desire POI and all datapoints within POI will be highlighted in green colour.





(c) In measurement plane, users can use 1) forward and backward movement, 2) left or right movement, 3) mid-air gesture, or 4) vertical head-rotation to move the measurement plane, up or down, over the time axes.

(d) In trajectories paths selector, user can use 1) proximity or 2) length and width adjustable rotate-able virtual ray-cast (orientation) to select trajectories when the interpersonal zone or the ray-cast intersects with any trajectory.

Figure 30: Four interactive filters of the data implemented in the tool are (a) ROI, (b) POI, (c) measurement plane, and (d) trajectories paths selector.

6 EVALUATING SITUATED SPACE-TIME CUBE ANALYTICS

The purpose of the chapter is to: 1) establish an understanding of in-situ spatio-temporal data exploration activities using our SSCA prototype, 2) explore interaction taxonomy, i.e. VISM by Shneiderman [133], to determine whether the VISM taxonomy supports situated visualization and interaction techniques. As part of the evaluation, we deployed the SSCA prototype on an HMD device, through which the prototype logs and video records participants' interactions with the visualization (filters and embodied interactions used), as well as their body and head movement, orientation, and additional in-situ environment information.

6.1 IN-SITU USER STUDY

As part of the study, we deployed the SSCA prototype on the HMD device, through which the prototype logs and video records participants' interaction with visualization (filters and embodied interaction used), as well as their body and head movement, orientation, and additional in-situ environment information.

6.1.1 *Participants*

We recruited eight participants (P1-8; one female and seven males) from a local university by advertising through posters and messaging platforms. Participants' ages ranged from 18 to 44 years old (M = 28.75, SD = 9.19). All participants reported normal or corrected-to-normal vision and successfully passed the Ishihara colour blindness test [132]. Prior to the study, a 7-point Likert scale assessed participants familiarity with the location used for the study, VR and AR exposure, video analysis experience, and 3D visualization analysis. To assess participants' familiarity with the location, a 7-point Likert scale (1= Not familiar at all; 7 = Extremely familiar) used where participants' responses ranged between two and seven (*M* = 5.86, *SD* = .69), indicating that they were rather familiar with the building where the study took place (*M* = 5.86, *SD* = .69). Fifty percent (50%) of participants had exposure to AR, while 70% of participants had exposure to VR prior to the study. Their perceived expertise for AR was (*M* = 2.50, *SD* = 1.51) and VR was (*M* = 3.42, *SD* = 2.22). Also, participants were asked whether they had conducted any video analysis prior to the study, and 37.50% (n = 3) reported 'Yes', 50.00% (n = 4) reported 'Maybe', and 12.50 % (n = 1) reported 'No'. We further explored how frequently they conducted such analyses. Participants did not conduct video analyses very often (*M* = 2.86, *SD* = 1.07). Moreover, participants were asked whether they had conducted visual data analysis using 3D visualization. Sixty two point five (62.5%) of participants reported that they had analyzed data in 3D visualization. Only one participant (12.5%) reported that she/he had used AR or VR walkthroughs (like the one used in our study).

6.1.2 *Study Procedure*

SSCA has the capability to import a spatio-temporal dataset and then map that data into the environment in which the event took place. In the study, trajectory datasets were extracted from short video recordings of a group of individuals, one for practice session, and one for the actually study. Videos were recorded in 1920 x 1080 resolution and 30 fps. The video clips recorded actors performing in-situ tasks based on pre-defined scenarios in a building atrium. In total, 12 questions were asked of each participant for each video; these questions and their related categories can be seen in Table 5. The questions were created such that they followed the taxonomy for questions related to movement data by Amini et al. [5]. Using this taxonomy, our questions were constructed such that they ranged in complexity and the use of known/unknown and individual/multiple datapoints.

6.1.2.1 *Pre-study Preparation*

The day before the study, a research assistant share with participants a link to an online tutorial video regarding the SSCA prototype to watch (22 minutes long) before coming to the university to participate in the study. The video provided the participants with introductory information regarding what movement/trajectory data is, the type of visualizations used, the filters available, and how to use the SSCA UI and interaction. This step was implemented for three reasons; 1) so the participants can familiarize themselves with the system at their own speed, 2) to prevent potential cognitive fatigue/overload during the study, and 3) to minimize the study duration for COVID-19 related safety reasons.

6.1.2.2 *Tutorial and Practice*

As SSCA is a prototype, and many of the components were novel to participants, the tutorials and practice sessions were important in creating a positive experience for participants while allowing us to collect more robust data. The elements shown within the introductory video that participants watched on their own prior to arriving were discussed, with the participants given ample time to ask any questions they had. Furthermore, the filters, analytic modes, and visualizations available were described in more detail with a corresponding video that was played for each participant (17 minutes long). Throughout, videos were used for two main reasons: 1) to allow for increased social distancing, and 2) so that we could better guarantee that all participants received the same information (i.e., equal treatment).

Once the tutorials were finished, the participant had a chance to see how each filter, analytic mode, and visualization looked through the HMD itself. Here, a dataset created solely for this purpose was used. Finally, upon arriving in the atrium in which the remainder of the study would be conducted, participants completed a full practice session which involved participants answering data-driven and situated environmental questions. This session utilized a unique dataset created solely for practice, with a procedure identical to that of the recorded task completion. This allowed users to fully explore the SSCA prototype with no pressure of evaluation.

6.1.2.3 *Study Session*

Participants attended a 90-minute in-person study session, which included informed consent, a demographic survey, further tutorials, practice tasks, the recorded study tasks, and discussion. Finally, at the conclusion of the study, the research assistant answered questions that participants had about the study[1]. Participants were asked to verbalize what they were thinking and talk through their thought process to use the prototype to answer the task question. This helps us to explore whether: 1) participants used *Visual Information Seeking Mantra* and in which order during their in-situ interaction with situated STC visualization, and 2) participants faced challenges during the study.

Before participants start the actual study, the research assistant loads a new dataset, starts video recording in HMD, sanitizes the device, and hands back the HMD to the participants to start the study. Participants were encouraged to use their own analytic strategies to answer the study questions. Also, participants were asked to think-aloud during the study, wherein participants would speak their thoughts aloud throughout the experiment [29]. Then, participants start the actual study by viewing the question to answer. If participants were not in the center of the atrium, a message is shown to participants asking them to move to a white marker at the center of the atrium. Then, a question will appear to participants asking them to 1) use filter and embodied interaction to visually answer the question, 2) stand in front of their answer for 4 seconds to show entire filtered data, and 3) select "Done" in the question window to confirm their answer and move to the next task. Participants were asked to be as fast and accurate as possible to complete the study. After completing the

1 Since the study was conducted in 2021, COVID-19 precautions were taken throughout (i.e., sanitizing of the HMD, social distancing, continued mask use, electronic forms), with the study session and procedure approved by an internal committee designed to ensure safety during the pandemic.

study, participants were asked to remove the HMD and fill out, on a computer, post-exposure to SSCA and NASA Task Load Index (TLX) questionnaires [69].

6.1.3 *Quantitative and Qualitative Data*

The user study captured both quantitative and qualitative data. This included recorded video from the HMD on-device cameras as well as think-aloud audio recorded from the microphones. Furthermore, we recorded log data (i.e., participant's location, movement, orientation, filter/mode/interaction selection, etc.) from the prototype's interactions and usage. Finally, we additionally collected demographic, user experience, and TLX questionnaire data.

6.1.4 *Coding Procedure*

Participants' think-aloud audio files were extracted and transcribed. These, along with visualizations of participants' movement data were used for coded analysis. Three graduate students (2 Ph.D. and 1 master), close to the project, performed the coding.

We established our codebook based on the VISM [134], and common challenges that can be found in HMD. The codebook included the operational definitions for VISM activities and situated prototype challenges related to information visualization. Thus, the codebook presents two scoring indices: (1) VISM (i.e., Overview First (O-F), Zoom and Filter (Z&F), and Detail on Demand (DoD), and (2) Data Visualization Challenges (i.e., limited field of view (LFOV) and data occlusion (DC)). LFOV is a common problem with head-mounted displays HMDs. Most HMDs have a small FOV, typically between 30-40 degrees. This can cause issues for users, as they may have difficulty seeing objects that are outside of their field of view. DC is a common issue in 3D visualization where one or more datapoints overlap other datapoints. This results in users being unable to differentiate between datapoints in the visualization.

We provide raters with operational definitions for three VISM activities and situated prototype challenges. In VISM, the rater has to use the operational defintions and identify the VISM event that participants have used during each think-aloud task done. In situaed prorotype challenges, each rater has to use the operational definition to identify the challenge participants faced during each study task. A sample of the codebook can be found in Appendix A, see Section A.3.

The codebook and coding instructions were given to all 3 raters. Raters independently coded the transcribed text of think-aloud of each task for all participants. After coding independently, raters convened in triads to reach consensus on the participants' usage of VISM, sequence of VISM steps occurred, and the challenges participants faced. The sessions involved a two-step process. First, the group facilitator separately recorded each rater's codes assigned independently and combined them in one file. The facilitator then pointed out instances where there was total consensus among the group and instances where unanimity was lacking. If there was unanimous agreement among the three parties, the codes were then inserted into the database, ending the session. If agreement could not be obtained separately, raters debated each case to establish a consensus.

6.2 RESULTS

Our user study captured both quantitative and qualitative data. Using the SSCA prototype, the analysis of the data enables us to provide an early exploration and evaluation of the general experience and usage, including the exploration strategies for in-situ spatio-temporal trajectory data.

In the following section, we report on; 1) users' overall performance, 2) analytic tactics involving the SSCA prototype, 3) proxemics interaction, 4) measuring reliability of three raters for participants' think-aloud of interaction taxonomy, and challenges in STC situated information visualization, 5) general user experience and feedback.

6.2.1 *Users Performance*

We analyzed participants' performance in terms of completion time and accuracy. We measured participants' completion time for all tasks, see Figure 31. The participants' mean completion time was 35.36 minutes (SD = 12.78). Participants used different visualization types, filters, embodied interactions to answer the questions, see Figure 32 and Figure 33 for examples. The analysis of participants' answers to questions via visual representation shows high accuracy. Participants provided correct answers for all questions, except questions 2 and 4 (M = 0.88, SD = 0.35) where one participant verbally found the answer to questions 2 and 4 but did not filter the data out.

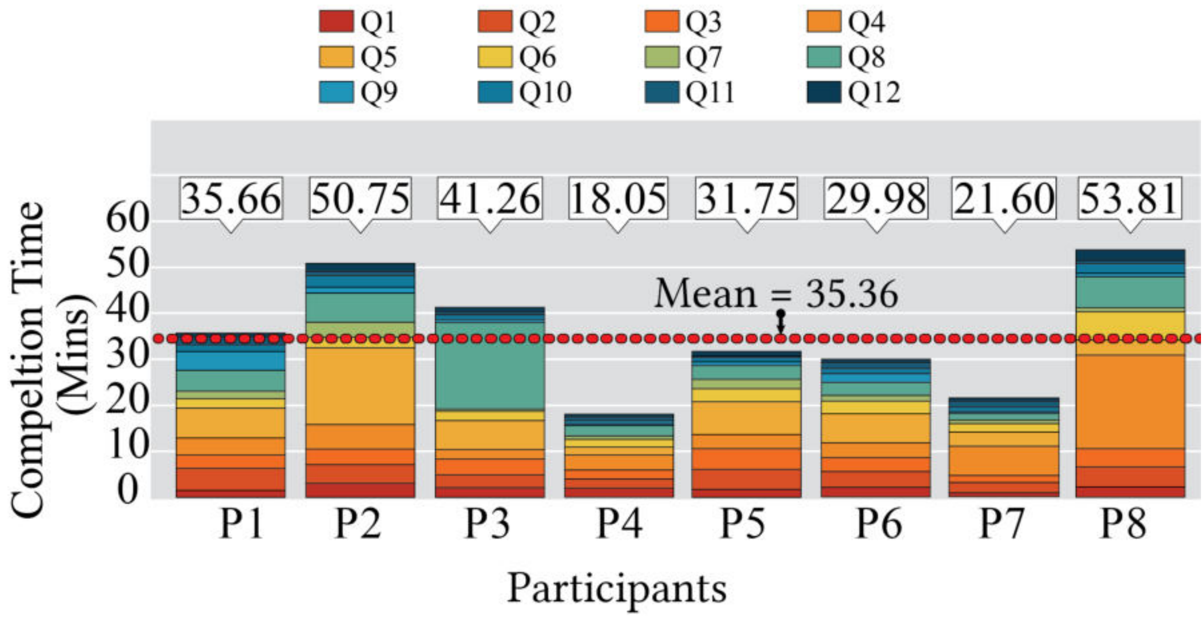


Figure 31: Stacked bar shows participants' completion time for all tasks. The dashed line represents mean completion.

6.2.2 *User Analytical Tactics Using SSCA*

As it one of our main goals, we were interested in analyzing how users explore the spatio-temporal data leveraging the SSCA prototype to perform their in-situ analytical tasks. This was done through exploration of the analytic tools used in the SSCA prototype and the use of proxemics and embodied interaction. The following sections describe how participants performed visual data analysis using SSCA.

6.2.2.1 *Analytic Modes*

All the participants used only the data-centric mode (i.e., all trajectory data was shown at once) to answer the questions given.

6.2.2.2 *Visualizations*

Over the course of the study, all participants combined, enabled the STC visualization for 238 mins and 57 seconds (M= 2.4891) as opposed to the 2D visualization which was only used for 43 minutes and 56 seconds (M= 0.457). STC was used as the sole visualization by all participants for 6 questions (Q1, Q7, Q9-Q12), while both 2D and STC visualizations were used for the other 6 questions. For example, questions Q2, Q3, Q4, Q5, Q6, and Q8 were used by 2, 5, 6, 5, 3, 1 participants respectively. During the data exploration of all questions, some participants (22.91%) tested both visualizations by switching between them frequently to find the right visualization that help them to find the answer. Subsequently, they selected one, and applied the final filters to answer the questions. Participants P1, P2, P3, P7, for example, preferred 2D over STC for path selection because they found it difficult to do so in STC. This is due to the fact that they were unaware of datapoints above their heads at the locations where they were standing. Participants were looking at the floor to select a path using proximity.

6.2.2.3 *Filters*

Participants utilized different analytical tools/filters to answer the questions. Yet, commonly, participants followed a similar approach. This included, to firstly set a visualization type, secondly, to filter or to take action on the data in some way, and finally to use interactions to discover the correct answer.

A range of filters were used by participants throughout the study; for a complete breakdown please see Table 5. As an example, in Q1, 5 participants (62.5%) used STC, Tooltip, and Pointer to show which object was stationary the longest, whereas the other 3 participants used different combinations to uncover the answers. Some participants used similar visualization, filter, and interaction but in different order (Q1, Q4, Q5, Q6, Q8). For example, in Q1, participant (P8) used STC, Path, Proximity first then STC, ROI, Proximity whereas participant (P3) used STC, Tooltip, and Pointer then STC, Path, Proximity. Also, all participants used STC, Plan, and Proximity when the question related to detailed information (trajectory id, location (x,y), and time) about objects (Q6). During the video analysis process and logged data, we noticed that for questions that have a period of time component (i.e., Q3 and Q8), participants (P7 and P8) created the POI filter after exploring the data points since the POI filter will select the time window directly without the need to move into data points location (i.e., physical zooming). In addition, most of the participants chose to highlight data points that were relevant to the answer while keeping data points of other objects within the scene (see Figure 32) whereas other participants highlighted data points that were relevant to the answer while also filtering out other objects' data points, (see Figure 33).

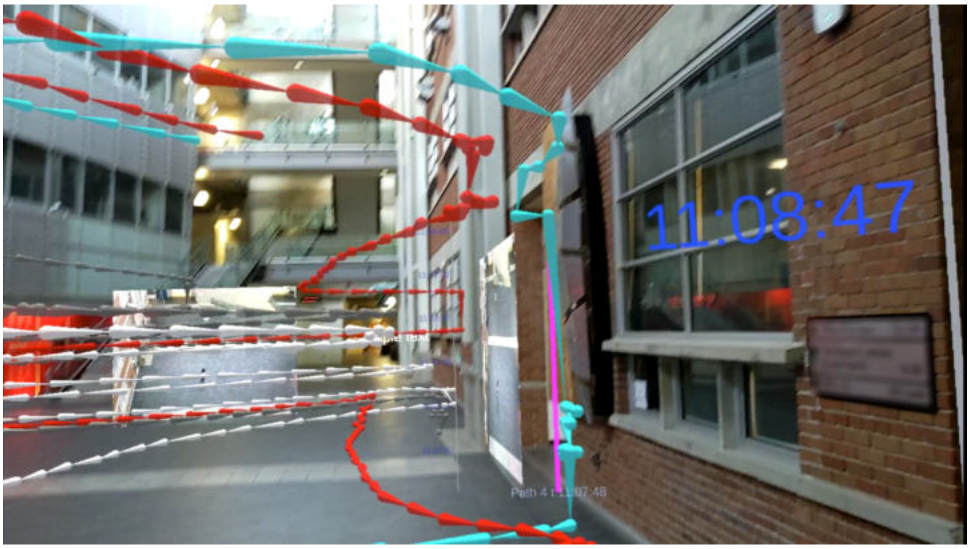


Figure 32: P2's visual representation of Question 1 answer. P2 used STC, Tooltip, and Pointer to select the starting point for the longest stationary object (the blue object).

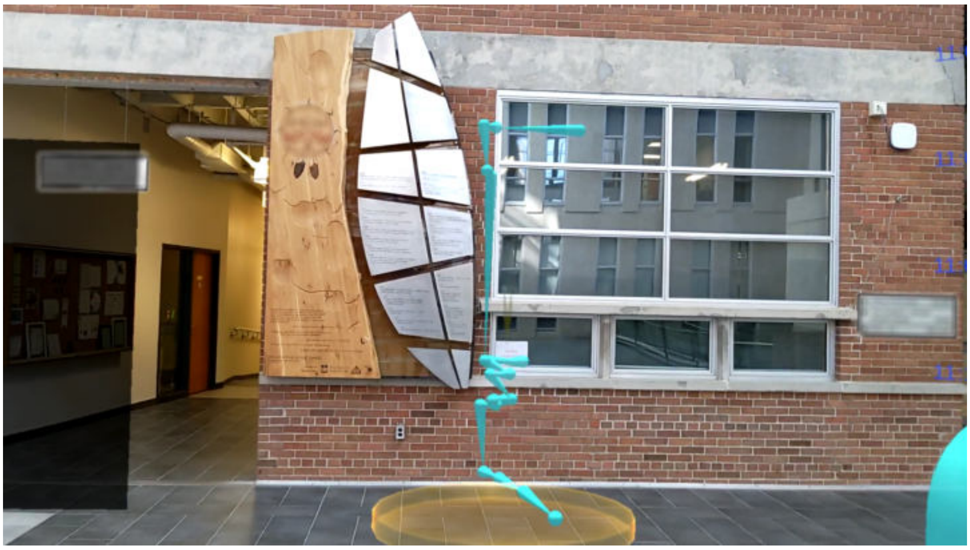


Figure 33: P8's visual representation of Question 1 answer. P8 first used STC, Path, and Proximity to filter out red, white, and grey objects; then they used STC, ROI, and Proximity to select the location of the object that was stationary the longest.

Table 5: List of questions, question complexity (using Amini et al. [5]), question category, analytical tactics used to answer the 12 questions by participants.

No.	Question	Question Complexity	Question Category	Visualization, Filter/Action, Embodied Interaction	Percentage
Q1	Which one of the object was stationary the longest?	Somewhat High	Movement Data	[STC, Tooltip, Pointer]	62.5%
				[STC, ROI, Proximity]	12.5%
				[STC, Toolip, Pointer],[STC, Path, Proximity]	12.5%
				[STC, Path, Proximity],[STC, ROI, Proximity]	12.5%
Q2	Where is the meeting location where four object first met?	Somewhat Low	Movement Data	[STC, Play Video, Pointer],[STC, ROI, Proximity]	71.4%
				[STC, Play Video, Pointer]	14.3%
				[STC, Toolip, Pointer]	14.3%
Q3	Select the walking path of white object between 11:08:14 and 11:09:20?	High	Movement Data	[STC, Path, Proximity],[STC, POI, Proximity]	62.5%
				[STC, Path, Proximity],[2D, POI, Proximity]	25.0%
				[2D, Path, Proximity],[2D, POI, Proximity]	12.5%
Q4	Select the location where the white object was the close to the blue object.	Somewhat High	Movement Data	[STC, Tooltip, Pointer]	25.0%
				[STC, Path, Proximity],[STC, ROI, Proximity]	25.0%
				[2D, Path, Proximity],[2D, ROI, Proximity]	12.5%
				[2D, Path, Proximity],[STC, Tooltip, Pointer]	12.5%
				[2D, Path, Proximity]	12.5%
				[2D, ROI, Proximity],[STC, Path, Proximity]	12.5%
Q5	Select the movement path of white, grey, and red object when they walking next to each other in the same direction?	High	Movement Data	[STC, POI, Proximity]	28.6%
				[STC, Path, Proximity],[2D, Play Video, Pointer],[STC, POI, Proximity]	14.3%
				[STC, Tooltip, Pointer]	14.3%
				[STC, Path, Proximity],[STC, Play Video, Pointer],[STC, POI, Proximity]	14.3%
				[STC, Play Video, Pointer],[STC, POI, Proximity]	14.3%
				[2D, Path, Proximity],[2D, Play Video, Pointer],[2D, ROI, Proximity]	14.3%

Q6	Show detail information of white, grey, and red locations at 11:10:31?	Somewhat Low	Movement Data	[STC, Plane, Pointer]	50.0%
				[STC, Plane, Proximity]	25.0%
				[STC, Path, Proximity],[STC, Plane, Proximity],[STC, ROI, Proximity]	12.5%
				[2D, Path, Proximity],[STC, Plane, Proximity]	12.5%
Q7	Was there any coffee shop in the scene?	Somewhat Low	Scene Data	[STC, NA, Physical Navigation]	100%
Q8	At what individuals were looking at between 11:10:41 and 11:10:45?	Somewhat Low	Scene Data	[STC, POI, Proximity]	37.5%
				[STC, POI, Proximity],[STC, Play Video, Pointer]	25.0%
				[STC, POI, Proximity],[STC, Plane, Pointer]	12.5%
				[STC, Plane, Proximity],[STC, Tooltip, Pointer]	12.5%
				[STC, Tooltip, Pointer],[STC, Play Video, Pointer]	12.5%
Q9	What was written inside the biggest logo on the wooden board next blue object?	Somewhat Low		[STC, NA, Physical Navigation]	100%
Q10	Show detailed information of white, grey, and red locations at 11:10:31?	Somewhat Low			
Q11	The white object was standing next to EITC wall. How many public televisions were placed on the wall?	Somewhat Low			
Q12	What was the name of the building board next to the wooden board?	Somewhat Low			

6.2.2.4 *Video Player*

We examined individual differences in the usage of the video player provided throughout the study. Except for one participant (P3), everyone interacted with the video player. Their total interaction frequency for all the 12 tasks ranged from 0 to 26 minutes (M = 9.13; SD = 8.15). As indicated by relatively large SD, the variability in participants' interaction frequency was high, reflecting individual differences.

Interestingly, no participants interacted with the video player in answering Q3 (Movement Data with high complexity), Q6 (Movement Data with somewhat low complexity), or Q12 (Scene Data with low complexity). However, Q1, 7, 9, and 10 also required rather short time despite the fact some participants used video player for these items, implying that the use of video player might not be a direct reason for longer task completion time; see Figure 61 in Appendix A. In contrast, for Q2 (Movement Data with somewhat low complexity) and Q5 (Movement Data with high complexity), approximately 63% of the participants interacted with the video player at least once. A closer look at the video player data revealed that participants used it 1.5 times on average when they were answering Q2 while their average was 3 times in answering Q5. Taken together, it appeared that the task type or the complexity level did not influence the participants' video player use. However, we would like to note that while having a range of complexities as in Amini et al. [5]'s study, we believe that being in-situ may have helped participants. For instance, being in-situ might have helped the participants' information seeking process. They had more advantages in our context as participants in our study had access to different filters, visualization and interaction. It is also possible that the motive for the use of video player could be more closely linked to the participants' desire for seeking more detailed/specific information.

6.2.2.5 *Proxemics and Embodied Interactions*

In most commercial and research settings for desktop STC visualizers, and in a broader set of visualization software, tools are implemented with several interaction features (i.e., zooming, rotating, panning, filtering, and selecting) that support users' ability to answer various queries [5]. Within our study, in both 2D and STC visualization, the analysis of video recordings showed that users performed panning, zooming, and rotating mainly through the use of body proximity, compared with the use of head orientation during their exploration. Furthermore, all participants preferred the Proximity interaction over Orientation interaction. Participants were asked to rate their perceived convenience regarding filters using proximity; Figure 34 illustrates the averages of participants' ratings. Importantly, proximity as a form of interaction, was seen as convenient or extremely convenient (a score of 6 or 7 on the Likert scale respectively) across all four filters by majorities of participants; this includes 62.5% of participants for the Plane filter, 87.5% of participants for the Path filter, 62.5% of participants for the POI filter, and 87.5% of participants for the ROI filter.

6.2.3 *Measuring Reliability*

Fleiss kappa [107] was computed to assess the agreement between three raters in identifying 1) the three VISM activities and its sequence in the 8 participants' think-aloud activities, i.e., (a) O—F, (b) Z&F, (c) DoD; 2) the challenges participants encountered during the study, i.e., (a) LFOV, (b) DC, or of both (a) and (b).

The three raters had an excellent agreement in recognizing the three VISM steps and its sequence ($Kappa = 1$, $z = 42.9$, and $p = 0.0000$). Raters identified 18 VISM sequence combinations in 96 tasks, please refer to the supplementary materials for a list of these 18 combinations. These VISM sequence combinations range from single activity, such as O—F or Z&F, to a multiple steps, such as O—F, O—F, Z&F, Z&F, DoD or O—F, O—F, Z&F, Z&F, Z&F.

Table 6: A summary of VISM patterns and their usage during the study.

VISM	Total number	Percentage
O-F, Z&F, DoD	42	43.75%
O-F+, Z&F+	27	28.13%
Z&F+	13	13.54%
Z&F+, DoD+	11	11.46%
Z&F+, O-F, Z&F, DoD	1	1.04%
O-F+	1	1.04%
O-F+, DoD+	1	1.04%

6.2.4 *VISM Structure Patterns*

A VISM structure pattern is a given sequence of VISM steps and the number of units composing them. Our analysis of 18 VISM sequence combinations revealed that the bulk of the step sequences exhibit recurring patterns. Two VISM sequences, for example, comprised a single Z&F and three consecutive Z&Fs. Another example is three VISM sequences were 1) one O—F followed by one Z&F, 2) one O—F followed by two Z&Fs, and 3) two O—Fs followed by three Z&Fs. We labelled these patterns using regular expressions, composed of VISM steps: [Step+] where Step is one of [O—F, Z&F, DoD] and the "+" sign indicates repetition of the preceding step. For example, Z&F+ patterns means that Z&F step has been used one or more times. Similarly, O—F+, Z&F+ pattern indicated that O—F was used one or more, followed by one or more Z&F times. Table 6 contains 7 unique VISM sequence patterns used and the usage percentages during the study.

6.2.5 *SSCA Challenges*

Similar to VISM steps, there was an excellent agreement between the three raters for identifying the challenges participants encountered during the study, *Kappa* =

1, z = 25.1, and p = 0.0000. Raters identified challenges (LFOV and DC) that were faced by the participants during the study. During participants' think-aloud activities, raters noted that participants mentioned LFOV in HMD headset to be a challenge in 31.25% of tasks. Furthermore, raters recorded that participants mentioned DC to be a challenge in 10.42% of the tasks. Also, raters mentioned that in 8.33% of the tasks, participants stated both LFOV and DC to be a challenge.

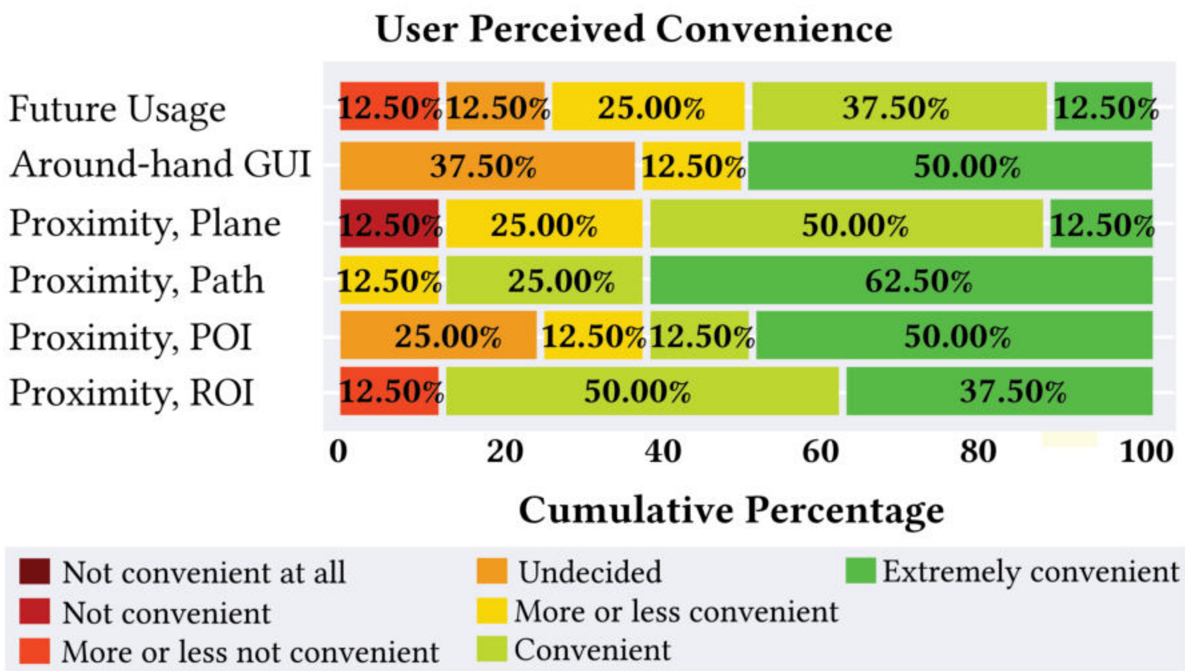


Figure 34: Participants' overall rating on how convenient they found Proximity interaction in conjunction with all filters. As well, how participants felt about the around-hand interface and the usage of the prototype for future video analysis are reported.

6.2.6 *User Experience and Feedback*

Upon completion of the tasks using SSCA, our final questionnaires gathered participants' perception and feedback of our prototype. We asked participants' general experience with SSCA; "How much did you enjoy using this technology?" on a 7-point Likert scale (1; Did not enjoy at all, 7; Enjoyed it a lot). All the participants enjoyed their experience of using SSCA, with responses ranging from 5 to 7 (M = 6.25, SD = .89).

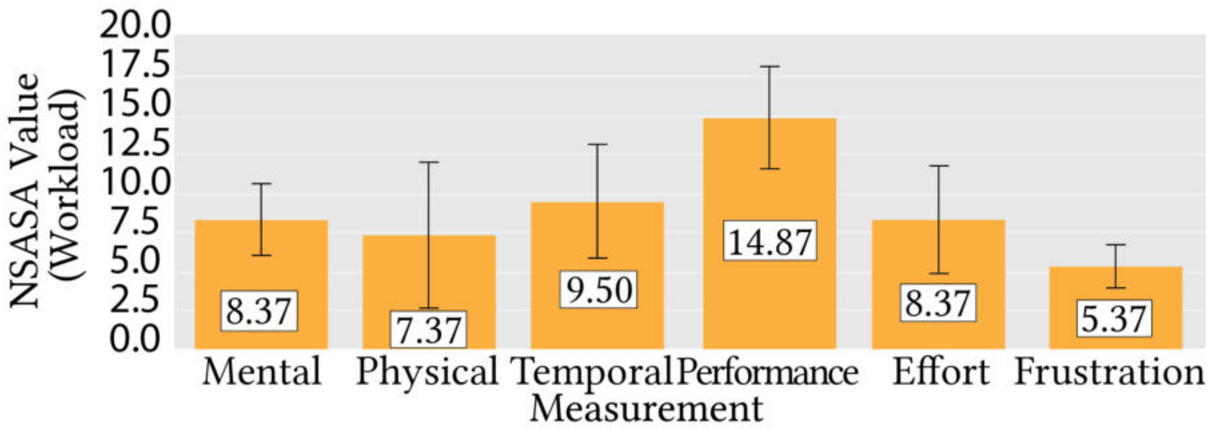


Figure 35: Average scores and standard deviations for the NASA TLX and its six sub-components (lower is better except for the performance sub-component where higher is better).

In terms of workload, as measured by the NASA-TLX questionnaire, see Figure 35, results were favourable for the SSCA tool[2]. First, SSCA required relatively low mental workload (M = 8.37, SD = 2.28). Second, since participants moved around in-situ to explore data and find answers to questions, we were expecting a higher physical workload rating. Yet, participants rated the physical workload lower than mental workload (M = 7.37, SD = 4.66). For temporal demand, participants rated tasks with a mean of 9.50 (SD = 3.64). In terms of perceived performance, participants felt they were quite successful in completing study tasks (M = 14.87, SD = 3.25). This could be because the prototype is new technology to participants. Finally, participants did not need to work hard to maintain their level of performance (M = 5.37, SD = 3.42) with frustration the lowest rated perceived workload variable (M = 5.37, SD = 1.40). Thus, on average, participants scored lower than midpoints when they were asked about their levels of mental/physical workloads, temporal demand, required effort, and experienced frustration associated with their experience of using SSCA. Their average perceived performance success was high, in contrast. Altogether, participants' responses to NASA-TLX questionnaire indicates they had favourable reactions towards using SSCA.

Finally, participants were asked what they disliked about the prototype. Seven participants reported that the limited HMD FOV was a common issue. For instance,

2 Note the midpoint for each question was 10.

during participants' attempts to answer question 5, P8 stated "... I need to stand at the visualization corners to have a complete view of all objects' movement." and P3 stated "... I will stand over there for a better view." The limited FOV impacts participants' data exploration and analysis process, forcing participants to move away from the area they were interested in to better view the data before creating filters (P1, P2, P4). Also, data occlusion in 3D visualization is another challenge participants faced. For example, during participants' exploration, in question 3, P3 stated "... It is hard to view all movement data at once as data points overlap." and P7 states "... I am looking for uncrowded space so I can select the white path." Another example for LFOV and DC challenges, while P1 was exploring data for question 2 (see Table 5), participant stated "The objects' movement paths are colliding with one another, which makes it a bit hard to find the answer... I forget data points that are above my head level."

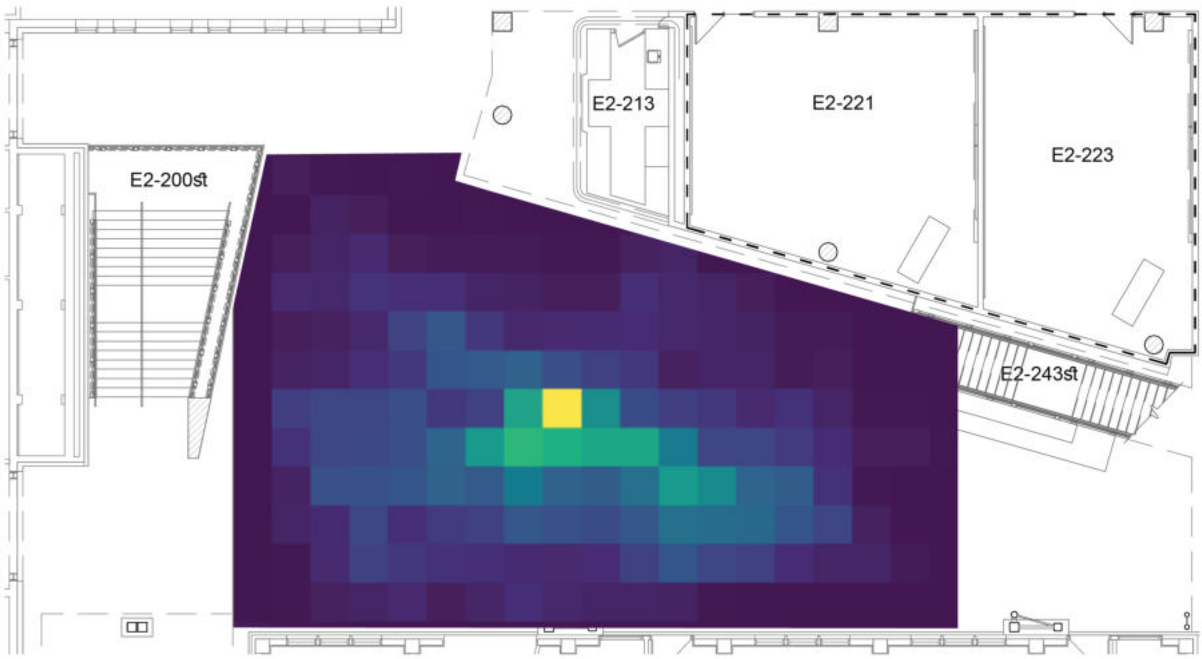


Figure 36: Participants' movement heat map during the study overlay the building's atrium. The bright yellow square is the location where participants start the task. Participants moved around to explore the data to answer the questions. Due to the HMD limited FOV, participants tended to move to the visualization canvas edges when they were asked to visually present their answers.

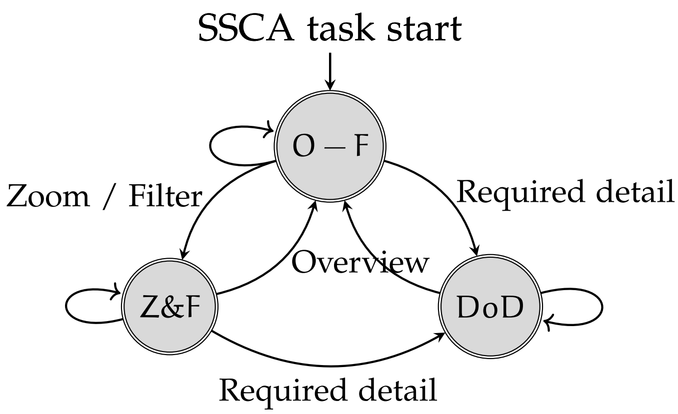


Figure 37: We generated a deterministic finite-state automaton for VISM in SSCA prototype. Initially, participants start with overview of the visualization first as the initial state.

6.3 DISCUSSION

In our study, participants' data exploration provided a better view of the data as a whole because the visualization could be viewed throughout the space they were occupying. Over the course of the study, STC visualization was used 84.70% comparing to 15.30% for 2D visualization. One possible explanation is that participants are interested in simultaneously examining spatial and temporal attributes for complicated tasks (e.g. *what* and *when*, or *when* and *where*). When participants have difficulty finding the answer, they break down complex queries (i.e., focusing on *where*), use 2D visualization, narrow down the exploration area, then use STC to complete the task. Another explanation would be that participants choose one visualization over another with consideration of the filter type. Participants P1, P2, P3, and P7, for instance, favoured 2D over STC for route selection because they found it challenging in STC. In addition, participants would change between 2D and STC to overcome challenges such as LFOV or DC, for instance, when participants were unaware of datapoints above their heads at the locations where they were standing.

All participants have used data-centric mode (i.e., all trajectory data was shown at once) to answer study questions. This might be due to not only that the sequential method takes substantially more time to analyze data compared to the data-centric approach but also that participants can see and follow trajectories paths all the time during their analysis activities.

Although participants used STC visualization over the course of the study compared to 2D visualization, STC suffers from the challenges such as limited field of view and data occlusion. Such challenges may restrict how information is displayed and explored, which could lead to more head orientation and body movement being required. In addition, large virtual interfaces result not only in data occlusion but also in physical environment object occlusion. For example, virtual video players placed in the physical space were occluded with some of the physical objects in the environment. P10 stated " I see it. It is behind the large display." P9 stated "... I think it is behind this big virtual screen." This will impact user performance in terms of completion time. Researchers in [146] have shown the effect of FOV and information density on search performance in stationary setting, yet in-situ this is less explored, however equally as important.

Navigation and exploration are one of the fundamental activities that exemplify the exploratory nature of information visualization and adhere to the information-seeking process (overview, zoom and filter, then details on demand) [133]. The analysis of participants' qualitative and quantitative data during the study provide us a better understanding of how participants utilized VISM via SSCA to complete study tasks. For example, the majority of the VISM sequences began or included an overview first (i.e. O—F with 75.00%). Raters' ratings, the analysis of logged data, and video recordings revealed that after participants read each question, they moved to the edges of the visualization to get a high-level overview and context of the space and data, see Figure 36. Participants often then moved, i.e. zoomed, to the area of interest then applying an appropriate filter resulting in 98.96% of the VISM sequences to include Z&F. In most commercial and research settings for desktop STC, tools are implemented with several interaction features (e.g., zooming, rotation, and panning) that support users' ability to answer various queries similar to our study [5]. In both 2D and STC visualization, the analysis of the study video recordings showed users performed panning, zooming, and rotating through the use of physical navigation of the space (i.e., body proximity and head orientation) especially when the data had a natural spatial embedding into the physical environment. Finally, participants concluded the exploration pattern, as needed, by obtaining more detailed information by inspecting elements with 57.29% including DoD.

In our study, we identified seven VISM patterns used by participants during in-situ data analysis to accomplish study tasks. However, further VISM patterns could be presented depending on the users analytical task, tasks' question, and size of the situated visualization. Therefore, we present a deterministic finite-state automation for VISM in the SSCA prototype that could generate a wide range of VISM patterns. Our future work would be to implement this determinate finite-state to support participants in-situ navigation and exploration activities.

Several factors could influence analysts' analytical strategies and tasks to explore and gain insights from data. For instance, in our user study, the environment where the data are mapped was indoor and uncrowded with people. Participants were preoccupied with the study tasks and did not notice when a few bystanders passed by. It is interesting to explore the implications of situated analytics in outdoor, crowded places, and/or under different weather conditions. It is worth mentioning that our system can extract and visualizing outdoor and/or crowded places; however, one limitation could be due to HoloLen's computational power and limited FOV. Another important aspect is the characteristics of dataset. For example, our tools visualize datasets that were previously stored on HMD. Our tool has the capability to visualize spatio-temporal data stream. Also, the level of dataset detail presented in the visualization is another important aspect. In our tool, data was preprocessed to reduce data clutter without reducing information content or disrupting data. However, limiting the amount of visualized data may result in the omission of pertinent and critical data in some application domains.

Interestingly, no participants used Orientation as a form of interaction to explore data. Although participants had first-hand experience with Proximity and Orientation interactions with all filters (via the video tutorial and practice session), all participants preferred to use Proximity over Orientation during the actual study. We believe this can be mainly attributed to the fact that as Orientation is used, loss of data occurs as data leaves the FOV. Another possible reason could be that Proximity is simply easier to learn, less physically demanding, and natural to use compared to Orientation. Further investigation is needed into the proper mechanics of using Proximity to allow for natural and efficient exploration.

Also, participants had high confidence (i.e., they felt they performed well, according to NASA-TLX) with little frustration, physical, and cognitive workload. Moreover, all the participants indicated that they enjoyed using SSCA, and for visual analytics, having both video and trajectories data would be effective. Altogether, considering how little effort, mental, and physical workload were required (all lower than midpoints in the scale) in performing visual data analytics with SSCA, we would like to conclude that SSCA has a great potential in situated data analytics.

7 SITUATED SPATIO-TEMPORAL MULTIPLE-VIEWS ANALYTICS (SSMA)

In this chapter, we propose design recommendations and alternative situated visualization implementation that reduces challenges found in the SSCA prototype and would improve the users' exploration and interaction with the data. First, we start with lessons learned from the SSCA evaluation, including the SSCA challenges participants experienced (i.e., *LFOV* and *DC*) and the in-situ data exploration activities conducted during the SSCA prototype evaluation study. Then, we introduce design recommendations based on lessons learned from the SSCA challenges and in-situ data exploration. Next, we present an implementation of SSMA, a visual encoding system we use to support design recommendations and represent trajectory data, and the notion of multiple views and placement of multiple views to help in reducing the limited field of view and data occlusion challenges in the SSCA. Finally, we present the integration of visual information seeking mantra and multiple views to support the data navigation and exploration.

7.1 SSCA EVALUATION: LESSONS LEARNED

In the following section, we summarize our lessons learned from SSCA evaluation study.

7.1.1 *SSCA Challenges Summary*

We present LFOV and DC challenges and discuss possible factors that contribute to these challenges. This will help us in proposing the design recommendation to address these challenges.

7.1.1.1 *Limited Field of View (LFOV)*

Based on the data analysis and our observation during the SSCA evaluation, we have identified several factors that contribute to LFOV. The first factor is the HMD's lenses and screens. The SSCA was implemented and deployed on Microsoft HoloLens 2. The display has 3:2 aspect ratio which provides a 43° horizontal and 29° vertical field of view[1], see Figure 38. Human FOV is around 210° horizontal and 29° vertical [125]. The HoloLens 2 narrow FOV makes it difficult for users to perceive the visualization and negatively impacts users' performance. The second key factor that influences how users view situated visualization is the size of the physical space in which situated visualization is mapped. As seen in previous chapters, one of the fundamental aspects of situated trajectory data visualization is to maintain the spatial relationship between the visualization and the physical space. When the spatio-temporal trajectory data is collected from a small space, the situated visualization can be displayed within the HMD's field of view and the user will view the entire visualization. However, when the situated trajectory data visualization is collected from a large space, the HMD's LFOV causes users to view different parts of the visualization and increase their physical exploration within the large space. In addition, the temporal aspect of the trajectory data is the third factor that impacts how users explored the situated visualization. For instance, the time axis scale (i.e., height of the time axis) in the SSCA was higher than the participants' heights, which makes the datapoints out of the HMD's FOV. As a result, participants were unaware of datapoints above their

1 For Microsoft HoloLens 2 technical specifications, Please visit the official website at this link.

heads' level at the locations where they were standing at during the SSCA evaluation study.

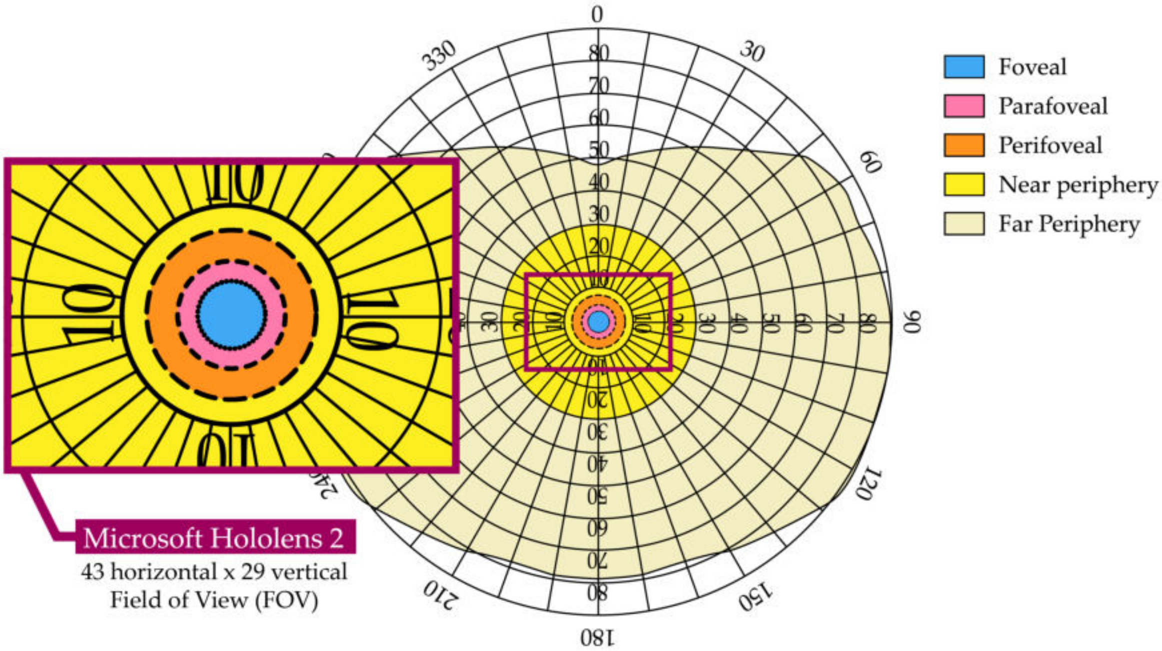


Figure 38: Microsoft HoloLens 2 field of view. The device has an aspect ratio of 3:2 which results in 43° horizontal and 29° vertical using the basic Pythagorean theorem. The figure was redrawn from [147].

7.1.1.2 *Data Occlusion (DC)*

Similar to 3D visualization, DC is a common issue in situated visualization, where data points are obscured by other datapoints. This happens when 1) datapoints are plotted on top of each other, 2) datapoints markers (i.e., spheres representing objects' locations) are significantly larger when near to the user's view than those that are further away, or 3) too many datatpoints are presented at once. DC may complicate the interpretation of the visualization and could lead to an inaccurate conclusion. To elaborate, datapoints near the users' viewpoints could divert users' attention away from other regions that are farther away from where they stand. During the SSCA evaluation, participants used several strategies to overcome DC, including changing their physical position around the datapoints and changing their viewpoint by reorienting their heads. Nevertheless, users will continually encounter DC issues, resulting in an increase in users' physical movements (changing locations and viewpoints) during data exploration activities with the physical space of situated visualization.

7.1.2 *In-situ Data Exploration*

In-situ data exploration is an initial step in situated spatio-temporal data visualization. Often, data exploration is conducted with and without previous preconceptions of what one is seeking. During the SSCA evaluation study, participants were given questions related to the trajectory data and instructed to explore the data and then determine the answers to the questions. In this case, participants' data exploration activities take on a narrower exploratory approach in which they visually inspect the data, move about the physical environment, and filter out data to answer questions posed by the tasks. VISM has been used as a design framework for designing non-situated information visualization tools to support users' data exploration activities [133]. Our SSCA design and evaluation study showed that VISM also applies to situated trajectory data visualization. For instance, participants have used VISM to perform in-situ data exploration and analytical tasks. In the overview's first step, participants viewed the trajectory data visualization to get a general sense of data and its context as a whole. To acquire the general sense of the data and its context, participants walked to the edges of the visualization and examined different areas using head orientation, as shown in Figure 36. During the zoom and filter step, participants often moved, i.e. zoomed, to the area of their interest. Participants performed panning, zooming, and rotating through the use of physical navigation of the space (i.e., body proximity and head orientation) particularly when the data had a natural spatial embedding into the physical environment. The current SSCA implementation enables users to zoom in to the area of interest to obtain a more detailed view of the data. However, while zooming in on a particular area, the datapoints for other areas remain visible, which can result in data occlusion and loss of focus. To address this issue, situated visualization should consider two methods of zooming. The first method is to allow users to zoom in on an area of interest while displaying all datapoints. This method helps users to perform comparisons between the area of interest and neighbouring areas to identify the relationships or patterns in the data. The second method is to allow users to zoom in on an area of interest while hiding all datapoints that are not currently of interest. This approach reduces data occlusion and directs users' focus on the most relevant data. It is important to allow users to easily switch between the two zooming modes, depending on their intended navigation and exploration objectives. After zooming in on an area of interest, users can use different interactive filters to further filter out irrelevant data. To reduce users' data exploration activities, the situated trajectory data analytics tool can identify and create filters for common trajectory data patterns, then place filters at the location of the detected patterns. For example, the situated trajectory data analytics tool can run a pattern analysis script to detect common patterns such as meeting locations, stationary locations and durations, and walking paths of individuals, then automatically create and map data filters for these patterns within the physical environments. In the final step, detailed on demand, participants concluded the exploration pattern, as needed, by obtaining more detailed information and inspecting datapoints.

One of the important findings from the SSCA evaluation study analysis is that VISM steps of overview first, zoom and filter, then detailed on demand were not always followed in that sequence due to participants' different exploration and analytical tactics, see Table 6. This finding is important since it contributes to the design requirements of situated trajectory data analytics tools. Thus, situated visualization should support VISM, enable a simple transition between each step, and communicate immediate visual feedback of the current step status, enabling users to perform data exploration activities effectively.

7.2 Situated Spatio-Temporal Analytics Design Recommendations

We outlined the design recommendations that are applicable for situated trajectory data visualization, reduce challenges in the SSCA, and support in-situ data exploration. These recommendations were based on the lessons learned from the SSCA evaluation, which can help inspire new designs for situated trajectory data. We explained each of the design recommendations and how it's implemented in the prototype in Section 7.3.

D1. Situated trajectory data analytics tool should reduce the limited field of view and data occlusion issues using multiple views and 2D/3D visualization.

D2. Situated trajectory data analytics tool should maintain the mapping of the trajectory data in physical space at the location where data were collected.

D3. Situated trajectory data analytics tool should facilitate the accurate viewing of trajectory data features including movement direction, meeting location, stationary duration, etc.

D4. Situated trajectory data analytics tool should enable in-situ data exploration via incorporating visual information seeking mantra (VISM).

D5. Users should be able to switch easily between visual information seeking mantra (VISM).

7.3 SSMA Prototype Implementation

We based our SSMA implementation on the SSCA prototype and design recommendations. We reused some of the SSCA components such as video player controls, four video screens, interactive data filtering, and proxemics and embodied interactions (Mid-air gesture). The around-hand menu is updated with new controllers that will be explained in the upcoming sections. We also added new trajectory data visualizations based on the design recommendations in Section 7.2. We illustrated each design recommendation and how we implement it. Also, the same trajectory dataset extracted from our computer vision tool will be used in the SSMA prototype. Microsoft HoloLens 2 [111], Mixed Reality Tool Kit (V2.6) [154], and Unity 3D tool was used as a development framework. The raw data were preprocessed to reduce data clutter without reducing information content. Unity 3D is used to process the trajectory data CSV files, generate the 2D/3D visualization, as well as build out the interactions and user interfaces. To map the visualization on the physical space, the user is required to stand on a pre-defined reference point to calibrate and run the SSMA prototype.

We began with the visual encoding systems used to represent situated trajectory data visualization. We then introduced the concept of multiple views, the transformation of STC into multiple views, and integrating the multiple views visualization and visual information seeking mantra interaction.

7.3.1 *Visual Encoding Systems*

Visual encoding is the process by which visual elements are used to visually represent data, and it is a key factor in determining how users interpret and understand visualizations. A few studies have looked at the basic visual encoding elements of information visualizations and provided recommendations on their effectiveness for designers Bertin [15], Cleveland and McGill [33], and Mackinlay [104]. Bertin [15] has defined a matrix for encoding mechanisms that are used to provide visual representation of data and their suitability for supporting common tasks such as association (or similarity), selection, order, and quantity. Bertin [15]'s matrix consists of *Size*, *Position*, *Texture*, *Colour*, *Orientation*, and *Shape*. Figure 39 shows the list of visual marks and their effectiveness.

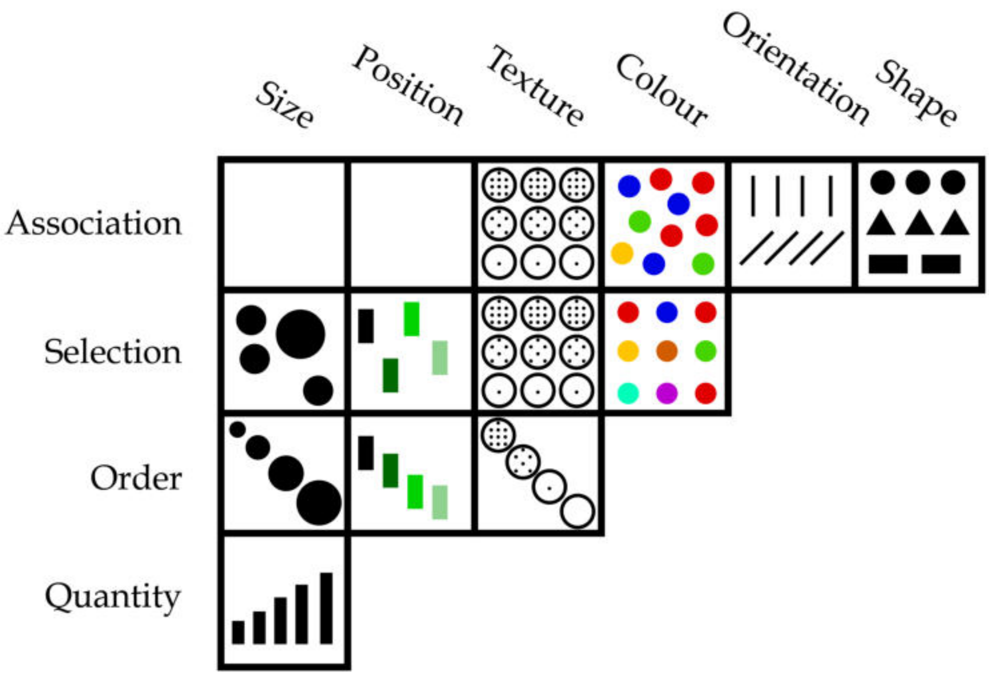


Figure 39: Bertin's ranking of the different visual variables for different tasks. Adapted from [15].

Cleveland and McGill [33] have introduced a wider range of visual variables, called elementary perceptual tasks, that deal with the representation of quantitative data on common graphs. Cleveland and McGill have ranked these visual perceptual tasks (from most to least accuracy) based on empirical examination into *Position*, *Length*, *Angle and slope*, *Area*, *Volume*, *Colour*, and *Density*. Figure 40 shows the ranks of Cleveland and McGill Visual encoding matrix.

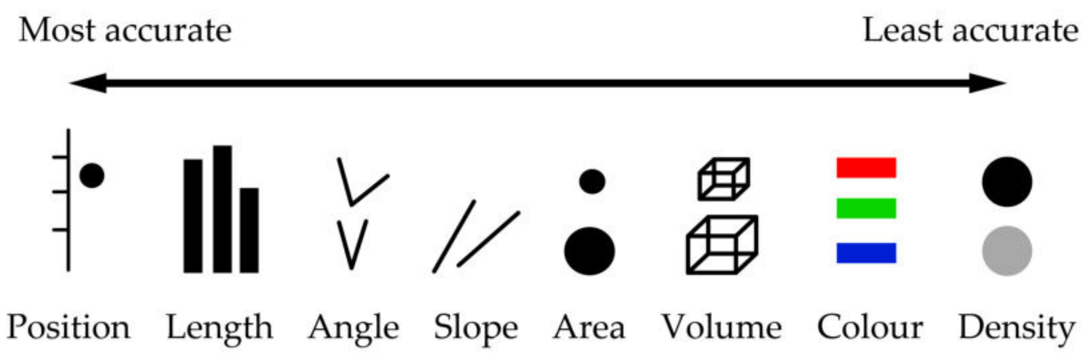


Figure 40: Cleveland and McGill's visual encoding system. This encoding system matrix is an extension of Bertin's visual matrix [33]. Adapted from Cleveland and McGill.

One of the drawbacks of Cleveland and McGill's approach is that it only considers the quantitative data; an extension to Cleveland and McGill has been introduced by Mackinlay [104]. Mackinlay looked at the visual encoding system not only for quantitative data but also for non-quantitative data [104]. Mackinlay considers examining the visual encoding system for a different data type. Mackinlay has categorized the efficacy of visual variables based on the characteristics of three data types: ordinal, nominal, and quantitative, see Figure 41.

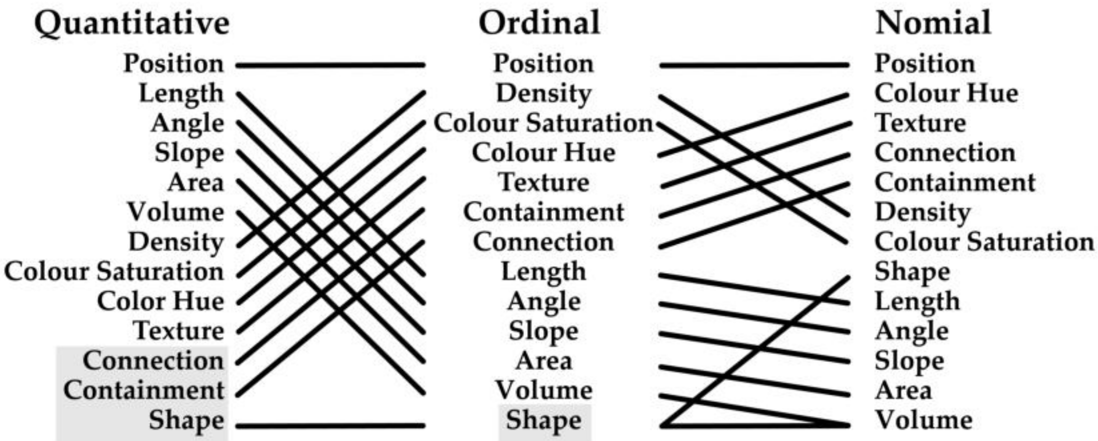


Figure 41: Mackinlay's ranking of the different visual variables for different tasks. Adapted from [104].

The vast majority of 2D and 3D visualizations are using one of the aforementioned visual encoding systems. These visual encoding systems can present trajectory data in a situated visualization context, while taking into account the challenges associated with situated visualizations, such as limited field of view and data occlusion. By using the appropriate visual encoding system, it is possible to create an effective situated visualization for trajectory data. Mainly, we find Mackinlay's visual encoding matrix more general and suitable for encoding trajectory data attributes [104]. In Section 7.3.3, we explained visual variables used during the design process to encode trajectory data attributes.

7.3.2 *Multiple Views*

In data visualization, a multiple views system is defined as two or more distinct views to support the exploration of a dataset's attributes [2, 129]. The need for multiple views arises when trying to make sense of a multivariate dataset (e.g., trajectory data), where a single visualization is complex to comprehend all the dataset attributes. Often, single visualization could be insufficient to fully understand the relationship between different attributes. There are several potential reasons for this, including the display's limited size, the user's cognitive limitations in processing a huge dataset, and the necessity to switch between various viewpoints on the same data to understand the attributes [129]. The multiple views concept has been used in different application domains, such as network topology, NFS file system, and geographic web server data visualization [129]. We saw a potential for using the multiple views concept in the context of situated trajectory data visualization, and the prototype is named after this notion. Participants who used the SSCA prototype often faced complex queries and LFOV when exploring data. Multiple views visualization can simplify the data exploration process by breaking down complex queries and decreasing the limited field of view challenges. When analysts have different visualization views of the same data, they can break down complex queries and focus on the attributes of interest. For example, analysts may be investigating a query that has spatial (location of an object) and temporal (between time span), they break down the query and inspect the visualization view that shows location of the object while inspecting another visualization that shows time.

7.3.3 *Multiple Views Design*

We outlined trajectory data attributes that will be used in the multiple views. Then, we demonstrated how these attributes get encoded for each view. After that, we illustrated how STC gets transformed into multiple views. In the SSCA prototype, STC visualization represents trajectory data attributes in one 3D visualization, including object id, objects' spatial locations (i.e. latitude and longitude), objects' spatio-temporal changes, movement direction, meeting and stationary location, and movement speed. We took advantage of multiple views to represent these attributes into different visualization views and make them available to users at the same time. We decided to have three visualization views: 1) Situated spatial 2D visualization, 2) Situated time-longitude 2D visualization, and 3) Situated time-latitude 2D visualization.

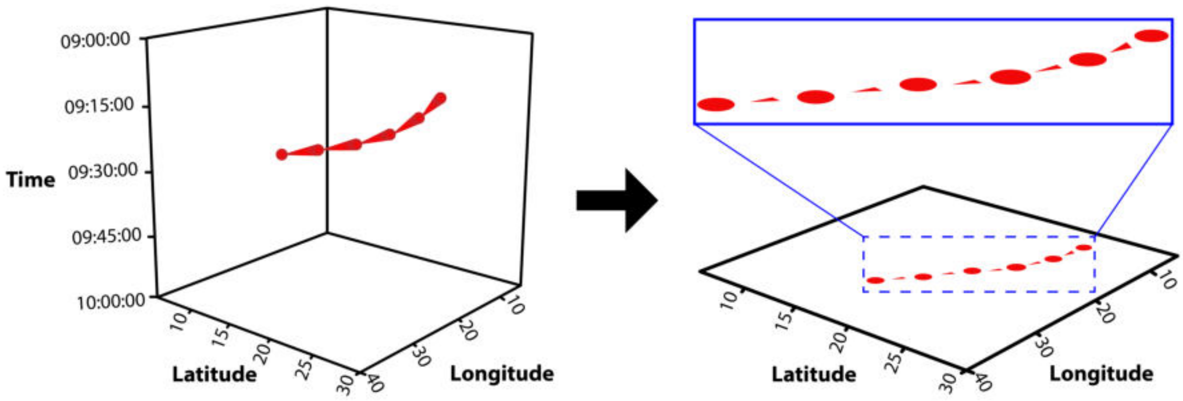


Figure 42: The STC visualization (left graph) and the corresponding 2D visualization of the same dataset (right 2D graph). The *Colour Hue* represents different object Id. The *Shape* (i.e., circle mark) was used to represent each datapoint of the object trajectory. The *Position* of the circle was used to represent latitude and longitude. The *Position*, *Shape*, and *Orientation*, i.e., arrow marks, were used between a consecutive pair of datapoints to represent the movement direction of the object. The position is used to map the latitude and longitude.

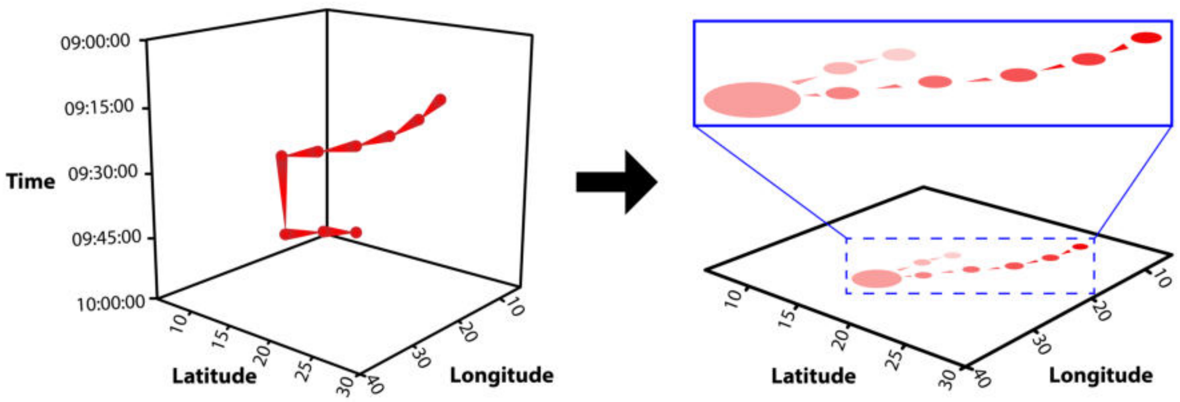


Figure 43: In the STC visualization, the vertical arrow indicates the stationary duration of the object. In 2D visualization, the *Size* of the circle encodes the meeting and stationary duration of the object. Also, the *Colour Saturation* (i.e., intensity of *Colour Hue*) encodes the time.

7.3.3.1 *View 1: Situated Spatial 2D Visualization*

Situated spatial 2D visualization allows users to mainly focus on spatial attributes (i.e., latitude and longitude) besides other attributes (e.g, object id, movement direction, etc.). We use Cleveland and McGill's visual encoding matrix to encode the trajectory data attributes, see Figure 41. Thus, we encoded object trajectory data using *Colour Hue* where each datapoint is encoded in *Shape* (i.e., circle). The object's location within the physical environment is encoded using *Position* (i.e., X-and Y-axis). We also used *Shape* (i.e., triangle shape) to encode the object's movement direction between two consecutive datapoints, see Figure 42. The triangle does not connect the datapoints which helps in reducing the overlapping between the datapoints. Although the situated spatial 2D visualization helps users to focus only on spatial attributes, we provided users with the ability to enable/disable further visual encodings, via a virtual popup configuration window from the around-hand interface, such as time and meeting and stationary location when needed. To illustrate, we used *Colour Saturation* (i.e., the intensity of colour hue) to encode the time. So, when the circle colour is solid, the time is at the beginning and vice versa, see Figure 43. In addition, we used *Area* of the datapoint (circle shape) to encode the meeting and stationary location and duration. For example, the diameter of the circle indicates the duration when the object is stationary. The larger the circle diameter the longer the object has been stationary, see Figure 43. The situated spatial 2D visualization design supports design recommendations (D1, D2, and D3), see Section 7.2. This visualization design reduces the limited field of view challenge by flattening the time axis in STC and then encoding it with *Colour Saturation*, and the data occlusion challenge by reducing the visual marks in visualization such as shape and size of datapoints and movement direction.

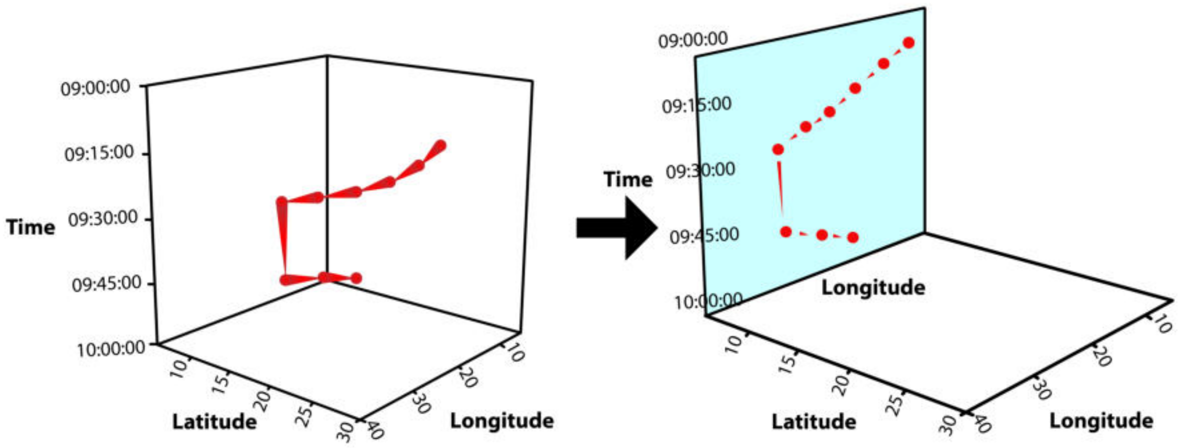


Figure 44: The time-longitude 2D visualization design. In this visualization, Mackinlay's visual encoding matrix is used to encode time and longitude attributes of the trajectory data. Then, the visualization was placed into the left wall of 3D visualization.

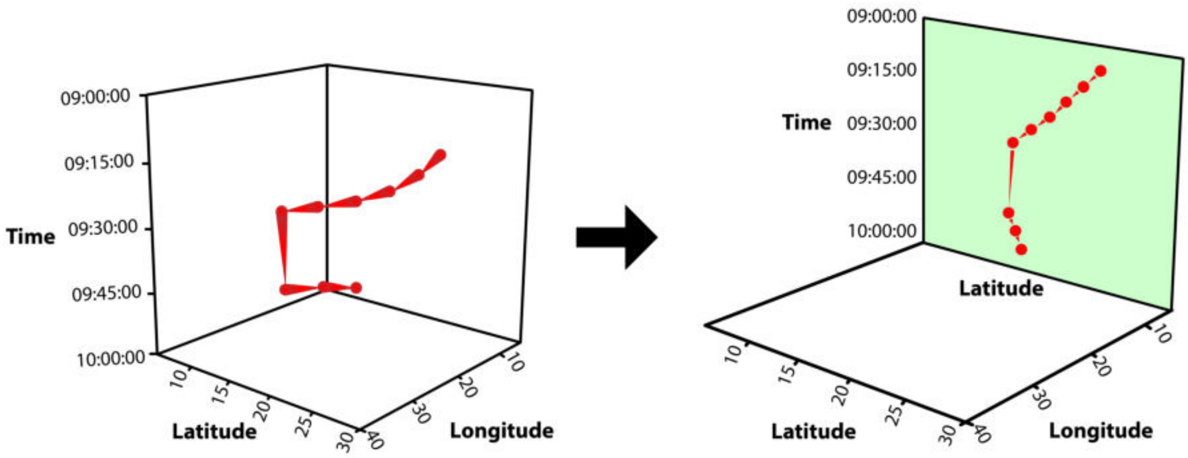


Figure 45: The time-latitude 2D visualization design. In this visualization, Mackinlay's visual encoding matrix is used to encode time and latitude attributes of the trajectory data. Then, the visualization was placed into the right wall of 3D visualization.

7.3.3.2 *View 2 and 3: Situated Time-longitude and Time-latitude 2D Visualization*

In situated time-longitude 2D visualization, the emphasis is on time, a spatial attribute (i.e., longitude). Also, it visualizes other attributes such as movement direction, movement speed, meeting, stationary location, and duration. We used vertical 2D plane to encode the trajectory data attributes, see Figure 44. The horizontal axis (i.e. X-axis) represents and maps object's longitude location with the physical space. The vertical axis (i.e., Y-axis) represents the time where the axis starts at from the top to graph plane, similar to the approach we used in the SSCA. Similar to Situated spatial 2D visualization, we used *Colour Hue* to encode different objects and *Shape* (i.e., circle) to encode each datapoint. The time and longitude attributes of each datapoint is encoded using *Position* (i.e., X-and Y-axis). Also, we used *Shape* (i.e., triangle shape) to encode the object's movement direction and *Orientation* (i.e., triangle slope) to encode the speed of object movement, see Figure 44. In the visualization view, the triangle mark does connect the datapoints to help users to observe and understand the changes in time, longitude, movement direction, and speed. The time-latitude 2D visualization, in Figure 45, is identical to time-longitude 2D visualization in terms of design and visual encoding; however, the only difference between them is instead of visualizing time and longitude, it visualizes the time and latitude. The situated time-longitude and time-latitude 2D visualization supports design recommendations (D1, D2, and D3), see Section 7.2. Also, these two 2D visualizations reduce the limited field of view challenge by resizing time axis so it is below the user's head level, thus it is easy for users to view the time axis and minimize the vertical head movement.

7.3.3.3 *Placement of Multiple Views*

The placement of data representation, in terms of position and orientation, is important in situated visualization, especially when data has embedded spatial attributes and multiple views. It is important to maintain the spatial relationship between data and the physical world, and the correct position and orientation of visualization to create an immersive experience for users. In addition, the placement of multiple views should enable and support users' analytical tasks. Based on the structure of the physical environment and trajectory data, we mapped the data into the physical environment within a cuboid shape, see Figure 46. The cuboid has six rectangular faces, which are the outside surface of the situated trajectory data visualization. This is beneficial, as it allows for more flexibility when managing the placement of multiple views into the physical environment. Therefore, we utilized these faces to place different aspects of the data visualization. We are interested in using five of the faces to place the multiple views.

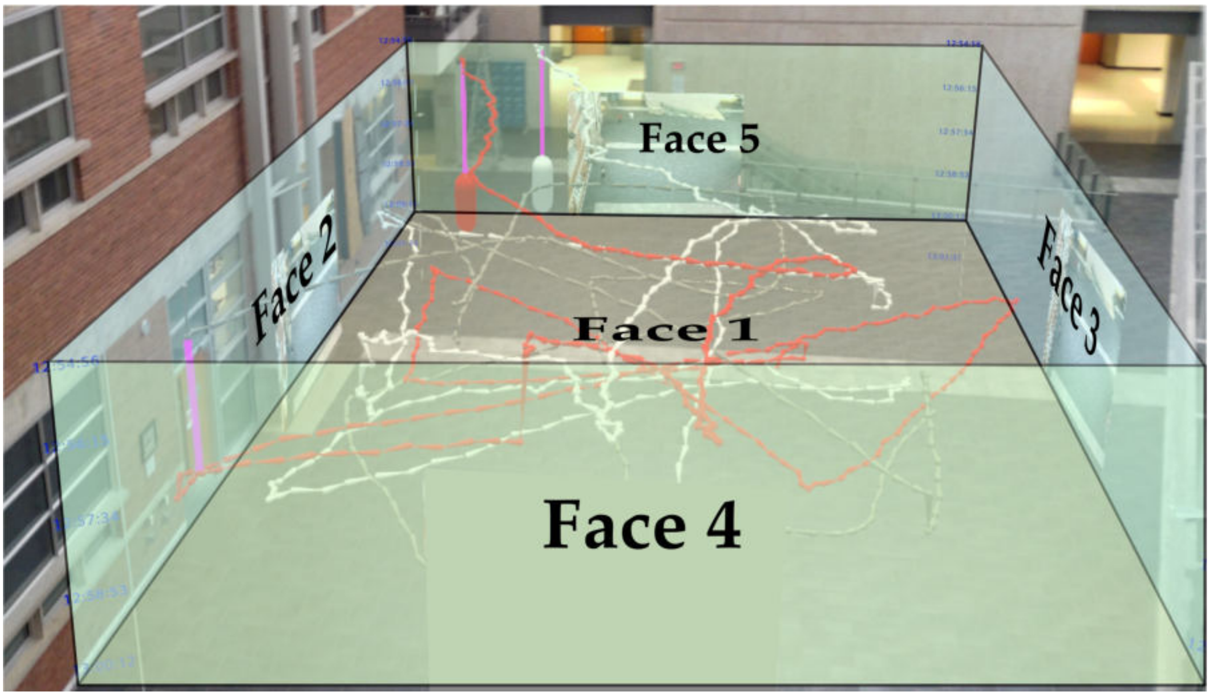


Figure 46: The mapping of the multiple views into the cuboid shape within the physical environment. In cuboid's first face, i.e., Face 1, will be used to place the Situated spatial 2D visualization. Face 2 and 3 will be used to place Situated time-longitude 2D visualization whereas Face 4 and 5 will be used to place Situated time-latitude 2D visualization.

The cuboid's first face will be used as a canvas for Situated spatial 2D visualization. This face maintains the mapping of objects' locations into the physical environment floor. The second and third faces will be used as canvases for time-longitude 2D visualization. Similarly, the fourth and fifth faces will be used as canvases for situated time-latitude 2D visualization. The reason for using two faces for the same time-longitude is to allow users to access trajectory data that is out of their field of view. In general, multiple views should be placed in such a way that they are easily accessible and visible to the users. For example, when users stand in the middle of the situated visualization while facing one of time-longitude or time-latitude 2D visualization, the users will have access to data that is located behind where they stand. This multiple views layout is effective because it allows users to see the data from different perspectives and understand the relationships between them. Therefore, placing time-longitude and time-latitude visualizations on cuboid's faces supports design recommendations (D1, D2, and D3). Figure 47 and Figure 48 show an example of STC visualization of trajectory data into multiple views.

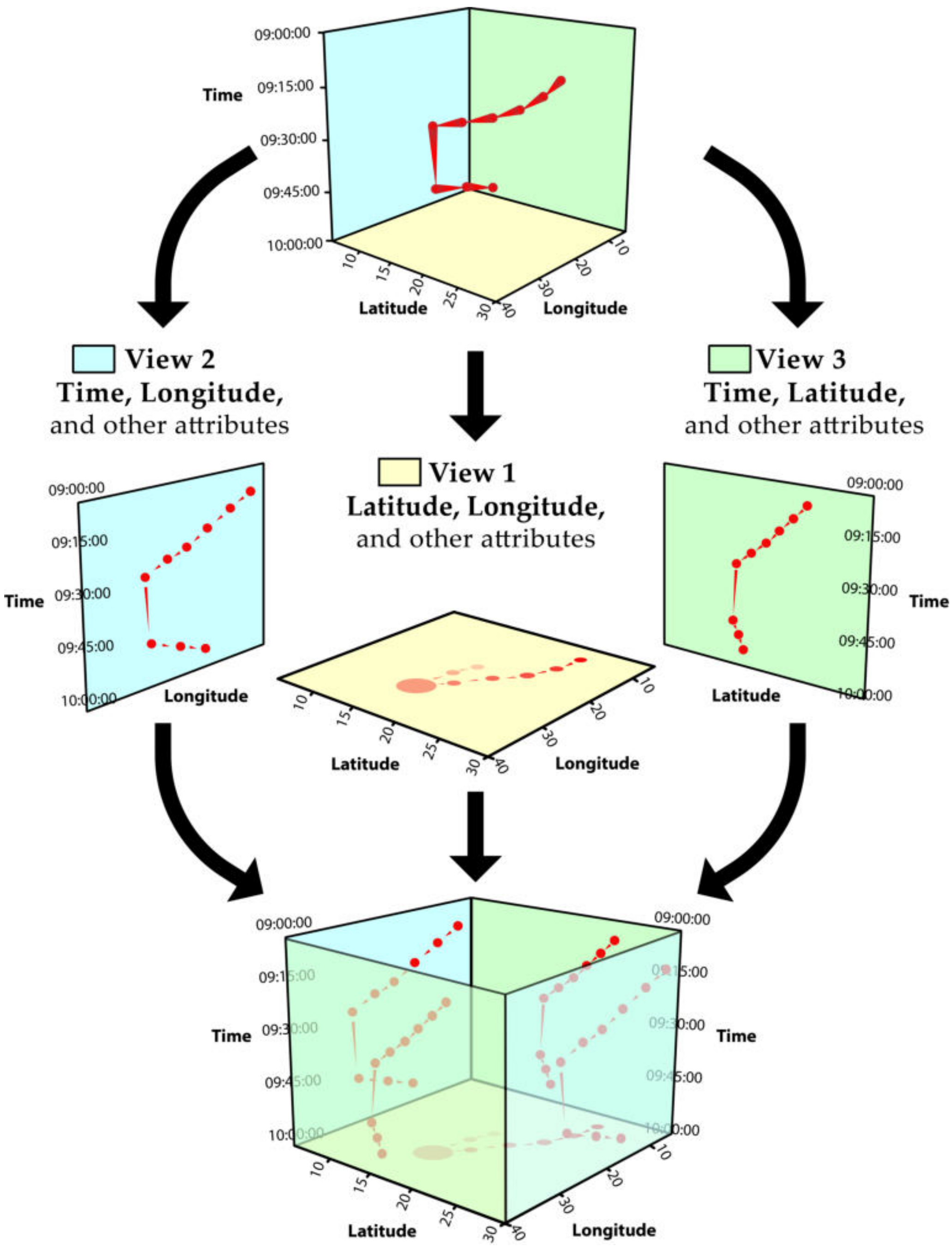


Figure 47: This figure shows a step-by-step transformation of STC visualization into multiple views that is applicable to situated visualization.

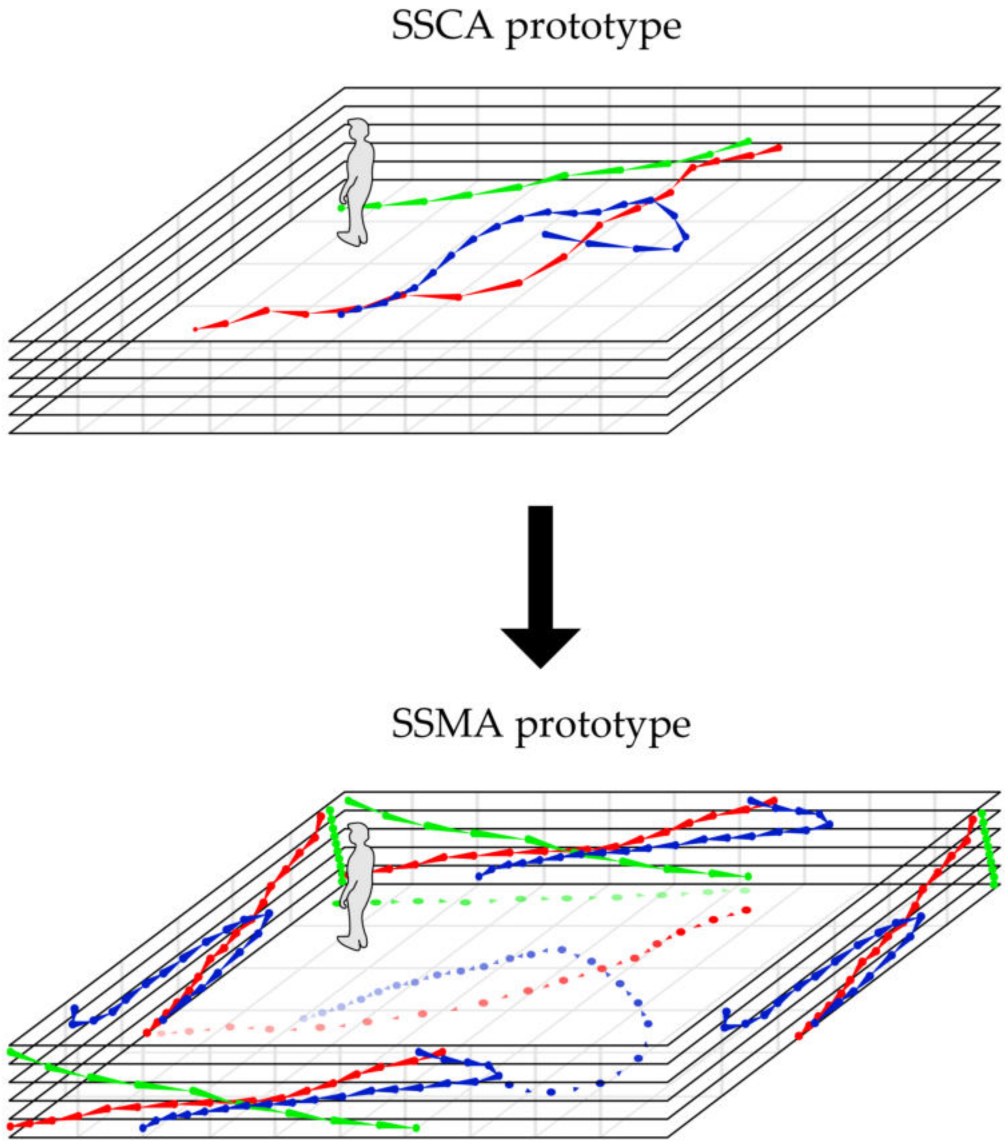


Figure 48: This illustration shows the difference between SSCA and SSMA prototypes and how multiple views are placed on the cuboid's faces.

7.3.4 *Visual Information Seeking Mantra (VISM) Interaction*

Navigation and data exploration is a fundamental activity that exemplifies the exploratory nature of situated and non-situated information visualization. VISM is a well-known and general navigation and exploration taxonomy [133] and it is used by users in situated visualization. Hence, we are interested in enabling interactive VISM to support users' in-situ data exploration and navigation. Therefore, we integrated the VISM: overview first, zoom and filter, and detail on demand. For the sake of implementation simplicity, we broke the zoom and filter step into two steps. We aim at 1) allowing a simple and dynamic transition between the first two VISM steps, 2) communicating immediate visual feedback of the current step status, and 3) enabling users to perform data exploration activities effectively. We considered taking advantage of the user's location within the physical environment, around-hand interface, and floating AR controllers as means to achieve such objectives and to support design recommendations (D4 and D5), see Section 7.2.

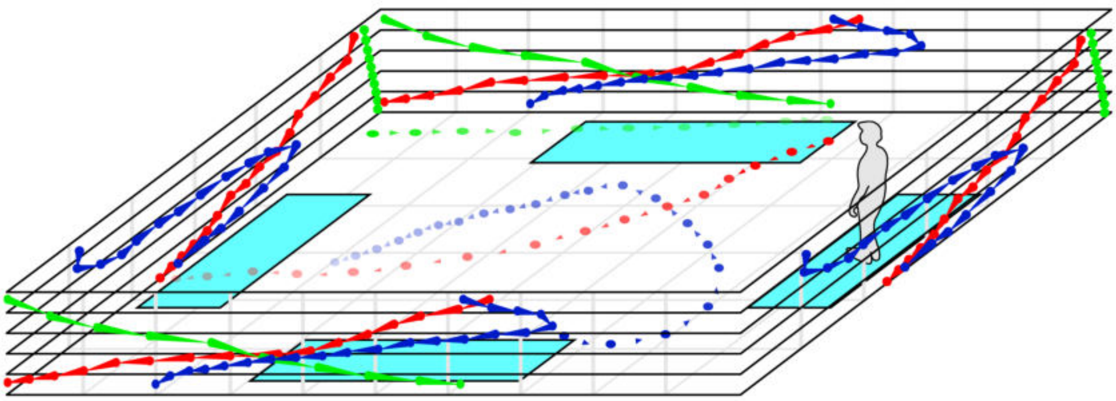


Figure 49: An integration of overview first step into SSMA visualization. The user stands in one of the blue areas to activate the overview first step, where the situated spatial, time-longitude, and time-latitude 2D visualizations are shown.

7.3.4.1 *Overview First*

In the overview first step users view all multiple views visualizations of trajectory data to get a general sense of data and their context as a whole. By understanding how users interacted and explored situated visualization, we considered the situated visualization edges and the users' location to activate the overview first step. Thus, we created four interactive zones at the four edges of the cuboid, as shown in Figure 49. As the user walks into and stands within one of the zones, this results in showing multiple views. We also allowed the user to keep the overview step regardless of the user's location. For example, the user can activate the overview by selecting the "Overview" button on the around-hand menu or pointing and pinching the floating AR "Overview" button, see Figure 50.

Figure 50: The implementation of the 'Overview first' step into SSMA visualization. At the top, the floating AR buttons Overview, Zoom, and Filter. The user can activate overview first step by pointing and pinching the Overview button.

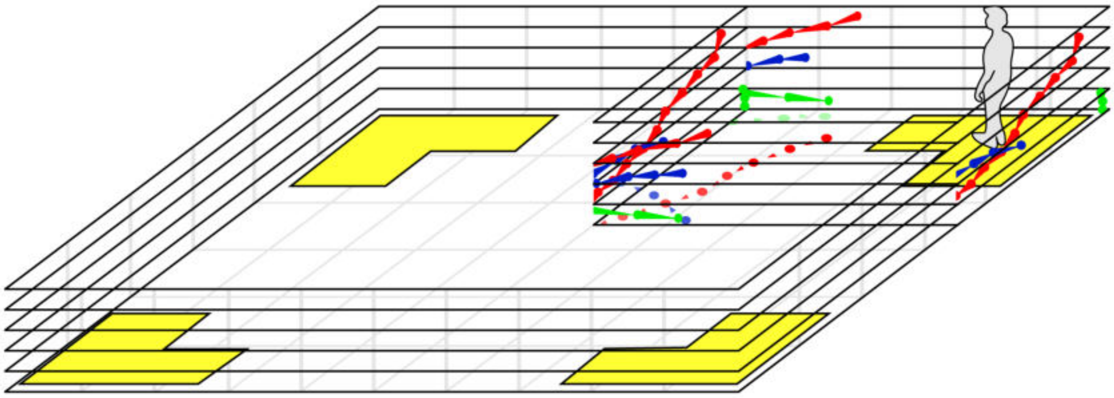


Figure 51: An integration of zoom step into SSMA visualization. The cuboid of situated trajectory data visualization is divided into four equal cuboids that represent distinct parts of the physical environment. Four yellow areas at the corners of the cuboid to activate the zoom step.

7.3.4.2 *Zoom*

Zoom step is effective in facilitating navigation in large datasets and large physical space. We considered two methods of zooming. The first method is to allow the user to perform physical zooming into the area of interest while showing multiple views of the trajectory data. This strategy assists users in identifying links or trends in the data by comparing the area of interest to neighbouring regions. The second method is to allow the user to zoom in on an area of interest and hide all datapoints that are not currently of interest, this method reduces data occlusion and directs users' focus on the most relevant data. This is especially useful when navigating datasets mapped into large space, as it can be difficult to find the specific datapoint one is looking for. We divided the cuboid of situated trajectory data visualization into four equal cuboids that cover different areas of the physical environment. Then, we used five of the faces to place the multiple views, see Section 7.3.3 for trajectory data for each area of the physical environment. Users can zoom into the cuboid of interest while the other cuboids are hidden. To create this effect, we created four interactive zones at the four corners of the cuboid, see Figure 51. The prototype tracks the user's movement and determines their location within the visualization. Once the user's location has been determined within one of the zones, the system then renders the appropriate cuboid of the scene and hides other cuboids, Figure 52. Additionally, we provided users with the option to maintain the zoom step even when they are not positioned in one of the interactive zones located at the cuboid's four corners. When the user activates the zoom step by selecting the "Zoom" button on the around-hand menu or the floating AR "Zoom" button, the prototype detects the cuboid where the user is standing and then activates the zoom step, see Figure 50.

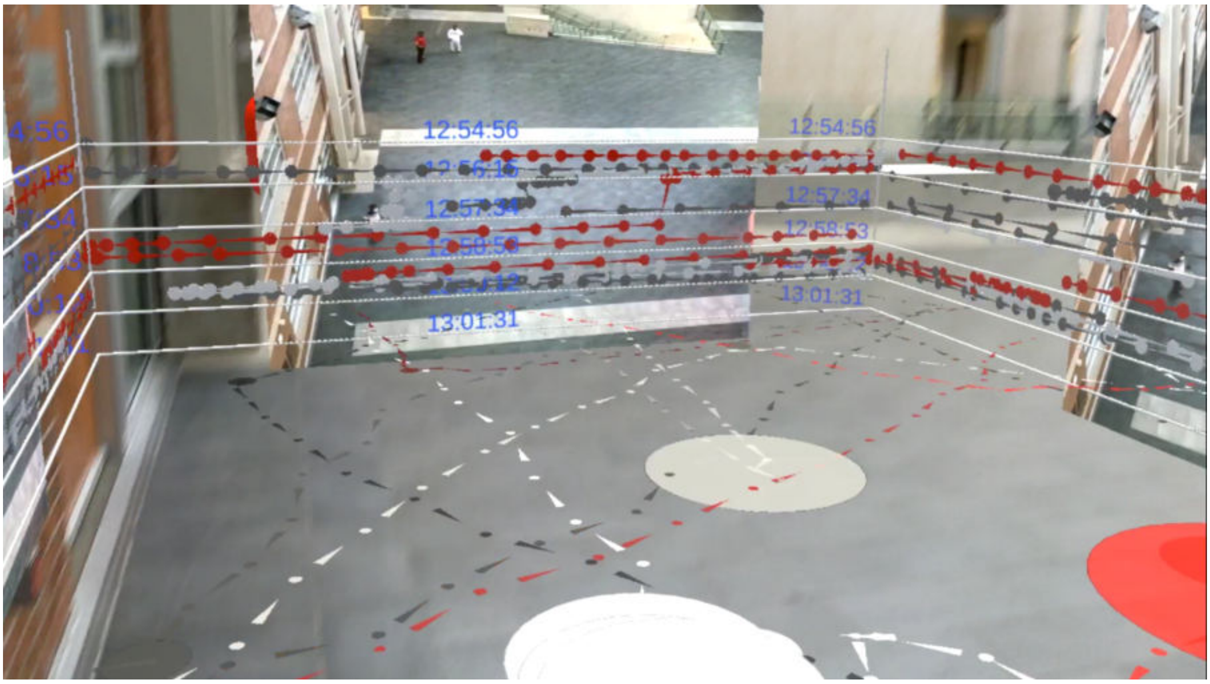


Figure 52: The implementation of the zoom step into SSMA visualization. As the user approaches a corner, they may zoom in on the cuboid of interest while the other cuboids are concealed. Other methods to activate the zoom step are to use a floating AR button or around-hand menu "Zoom". The user can activate overview first step by pointing and pinching the Overview button.

7.3.4.3 *Filter*

The use of the filter step is yet another essential stage in the process of navigating and exploring data. It enables the user to focus on the most relevant data. We created an interactive zone at the base face of the cuboid to enable the user to activate the filter step. When the user enters the filter step zone, interactive data filtering can be used to filter data such as ROI, POI, trajectories paths selector, and a measurement plane. Analysts often identified and posed common inquiries related to trajectory data, such as which object stayed stationary the longest, where a group of objects met, and which objects walked the same path. We created pre-defined filters (a yellow cylinder with a height of 10 cm) for such common inquiries and automatically place them in the physical environment, namely at the location where the events happened. Each pre-defined filter has a unique symbol placed at the top that distinguishes it from the others and assists the user in determining which queries or patterns they are interested in. When the user approaches a specified pre-defined filter, the filter's symbol disappears, and data within the filter area (i.e., cylinder area) transform into 2D or STC visualization. The user can configure the type of visualization, i.e., 2D or STC, shown from the virtual popup configuration window from the around-hand interface. We considered showing STC when viewing the filter data for the following reasons. First, the filter area is not a big area and the effect of data occlusion and limited field of view challenges are limited. Second, in the binocular display, 3D is more effective for depth-related activities such as spatial comprehension of complicated visualization and spatial manipulation [88]. If the user moves away from the filter, it turns to its original status. The user can keep the pre-defined filter in STC by enabling the interactive button "Keep". The user can repeat the same process for all pre-defined filters or create their own interactive data filtering. The pre-defined filters support the user's analytical tasks by reducing the user's cognitive load to access data and time to explore and navigate data. Figure 53 demonstrates an example of the pre-defined filter of two objects walking the same path whereas Figure 54 shows the implementation of the redefined filter concept.

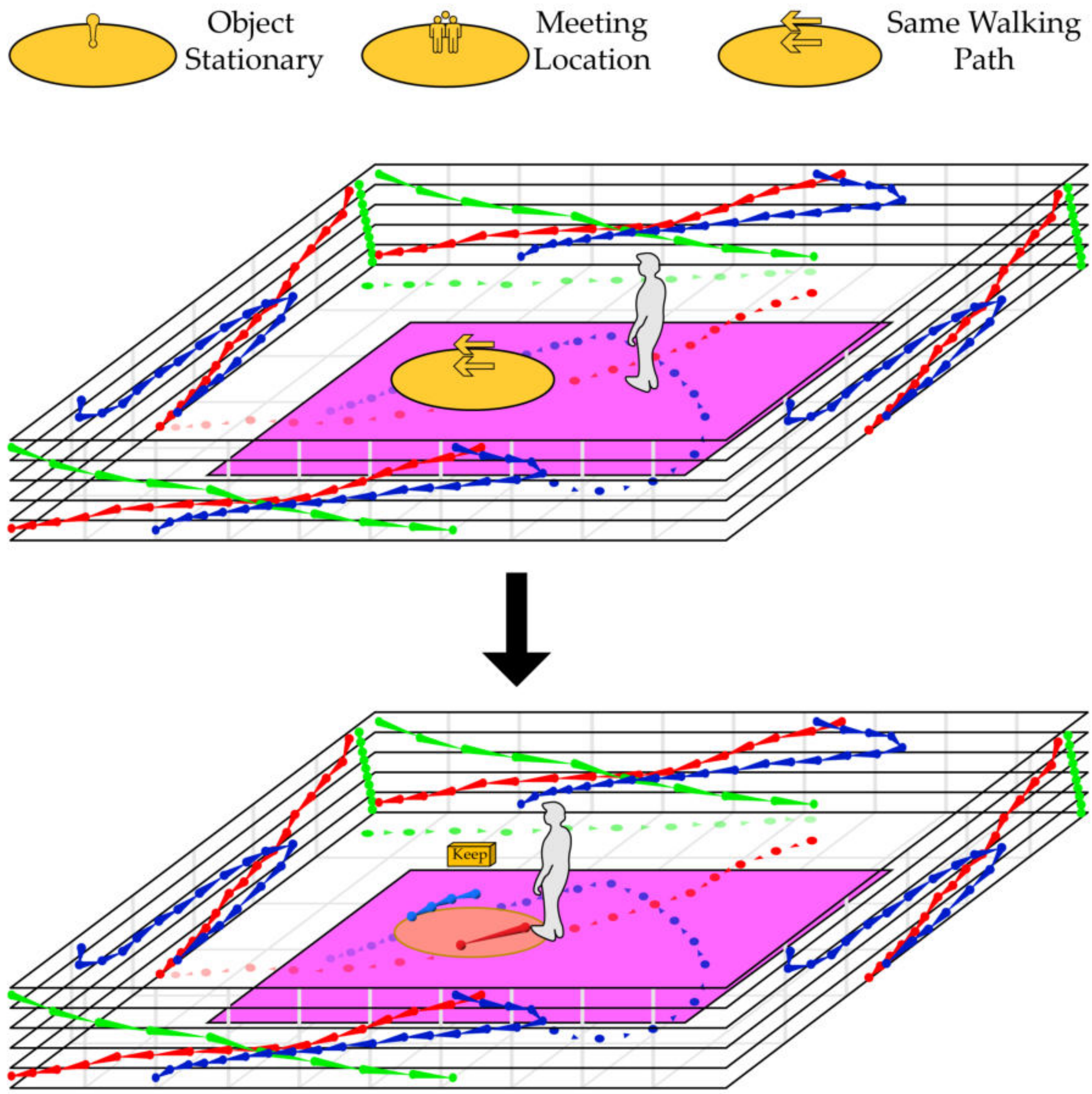


Figure 53: The integration of the filter step into SSMA visualization. At the top of the figure, three pre-defined filters are created for common inquiries such as object stationary, meeting location, and same walking path. In the multiple views visualization, the same walking path filter is located where the event occurred at the filter zone. As the user gets closer to the pre-defined filter, data within the filter area is shown in STC or 2D. The user can retain the STC or 2D visualization when enabling the interactive "Keep" button.

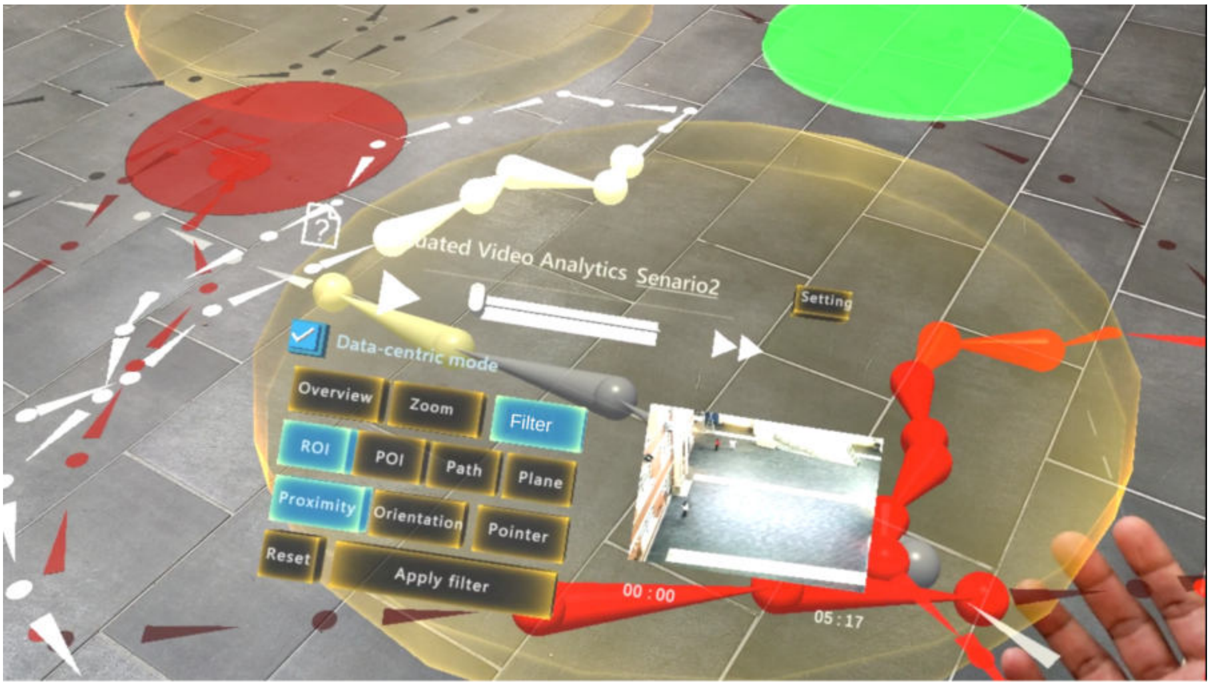


Figure 54: An example of a filter created by the user which shows the datapoints in 2D visualization.

7.3.4.4 *Detailed on Demand*

The last step of the VISM gives, on demand, more information about each datapoint. We used datatip, a small text box that displays detailed information similar to the one used in the SSCA, to display detailed information about individual datapoint (e.g., trajectory id, location value, and time). Users can show/hide datatip for any datapoint in any visualization view. Datatips orientate themselves to face the users regardless of their position with the immersive multiple views visualization. Users can toggle the visibility of datatips using the Mid-air gesture and hide all visible datatips at once by resetting the filter from the around-hand menu. The way datatip is displayed differs based on the visualization view. When datatip is enabled in the situated spatial 2D visualization view, for instance, a solid line is projected from a datapoint on the floor to 50 cm above the floor, where the datatip will be positioned. In situated time-longitude and time latitude 2D visualization, when datatips are enabled, a solid line is projected from a datapoint to 20 cm below the datapoint, and then the datatip is placed. In addition, we reused the effect of showing the datatip of a datapoint on the video player: when playing and pausing the video, showing detailed information about a datapoint, the video player jumps to the frame of that datapoint in the video.

8 CONCLUSION

This dissertation provides a detailed report on the exploration of interactive situated spatio-temporal data analytics to support in-situ data analytics for HMD devices. We investigated a range of topics including spatial-temporal data visualization, information visualization interaction, embodied interaction, AR technology, and situated analytics to meet our research objective as stated in the introduction chapter:

Explore the key design aspects of situated spatio-temporal analytics that enable in-situ analytic tasks and improve users' analytic skills and experience.

In the following sections, we provide summaries of this dissertation and our findings based on results presented in chapters 3-7 and discuss several assumptions and limitations of this work. In exposing these limitations, we aim to shed light on the many future opportunities that the dissertation opens up for researchers in the situated analytics field. We then state our final conclusions which will inspire future research.

8.1 SUMMARY

In this dissertation, we explored and implemented situated spatio-temporal data analytics that supports users' in-situ analytical tasks. In Chapter 3, We conducted a user study that empirically compared analytical activities for spatio-temporal data in Situated and Non-situated groups. The study results suggest that there is significant effect around the tasks' response error/accuracy which confirmed possible benefits of situated analytics in comparison to the traditional Non-Situated analytics. Participants' errors were generally larger when they analyzed the spatio-temporal data in an office as opposed to the actual location where data was collected. Participants largely benefited from environmental cues for many analytic tasks.

After validating the potential of situated analytics, we were interested in exploring possible visualization designs for situated spatio-temporal analytics and how being in-situ influenced the users' visualization designs and integration of their designs. In Chapter 4, we conducted elicitation workshops to explore end-users' views on how to design different situated visualization and interaction for spatio-temporal data. The detailed analysis of sketches resulted in emergent themes, interaction, and revealed design considerations for situated visualization prototypes.

In order to implement a novel situated spatio-temporal analytics, we took into account both design recommendations from the literature and design considerations from elicitation workshops. In Chapter 5, we implemented SSCA that enables users to explore the spatio-temporal data, in 2D and STC visualization, in the environment where the data was captured. SSCA prototype supports in-situ data exploration activities via a range of interactions (proxemics, orientation, and gestural interaction), and different interactive data filters (region of interest, period of interest, measurement plane, and trajectory path selector).

SSCA demonstrated the advantage of mapping spatio-temporal data into the physical space and enabling data filtering and interaction. However, there is a need to establish an understanding of in-situ spatio-temporal data exploration activities using our SSCA prototype, and to explore interaction taxonomy, to determine whether the VISM taxonomy supports situated visualization and interaction techniques. In Chapter 6, we evaluated SSCA tool through a usability study within the space where the data was originally captured. The analysis of collected data revealed that users' exploration and navigation activities adhere to VISM. In addition, LFOV and DC were challenges participants faced during the study. Also, SSCA obtained a good overall assessment for its proximity interaction with all filters, around-hand interface, and the usage of the prototype for future data analysis.

Based on our acquired knowledge regarding challenges inherent in SSCA as well as the in-situ data exploration activities, in chapter Chapter 7, we presented design considerations that includes proper visual encoding, multiple views visualization, and proper placement of each multiple views within the physical space. These design considerations help situated visualization designers to improve user experience, interact with data, and reduce the negative effects of LFOV and DC. We implemented SSMA using the design considerations to effectively visualize spatio-temporal data and integrate VISM interaction taxonomy to support the in-situ data exploration and navigation.

8.2 SITUATED SPATIO-TEMPORAL ANALYTICS DESIGN CONSIDERATIONS

Situated spatio-temporal data analytics, where data is extracted from video footage, is still in its early stages. There are various opportunities for researchers to contribute to the body of knowledge in this area. Elicitation and SSCA evaluation studies results revealed important design considerations for situated spatio-temporal data analytics designers and developers. Therefore, we suggest the following design recommendations to the visualization community:

D1. For situated video analysis, future analytic programs should incorporate a low- and a high-level detailed visualization of events, to provide the capability to interact with the event data and narrative.

D2. Visualizations for situated video analysis should include the original video footage as a tool for validation or reference.

D3. The use of annotations in situated video analysis visualization supports event narrative via grabbing users' attention, clarifying chronological order of events, and indicating event transitions. Also, textual annotation could be used as a way to capture and exchange user insight and conclusions.

D4. Situated video analysis visualization could incorporate multiple levels of contextual information to support multivariate types of analyses (e.g., including fine details relating to, but not limited to, the variables of time, duration, object classification, object location, object direction, object velocity, event summary, etc).

D5. Interaction with situated visualizations should consider not only the location but also the user's physical body movements as an input modality.

D6. Situated trajectory data analytics tool should reduce the limited field of view and data occlusion issues using multiple views and 2D/3D visualization.

D7. Situated trajectory data analytics tool should maintain the mapping of the trajectory data in physical space at the location where data were collected.

D8. Situated trajectory data analytics tool should facilitate the accurate viewing of trajectory data features including movement direction, meeting location, stationary duration, etc.

D9. Situated trajectory data analytics tool should enable in-situ data exploration via incorporating visual information seeking mantra (VISM).

D10. Users should be able to switch easily between visual information seeking mantra (VISM) based on users' location within the physical space.

8.3 SSCA APPLICATIONS AND USAGE SCENARIOS

As discussed earlier in Chapter 3, the ability to explore information in-situ has the potential to provide a benefit of situated spatio-temporal analytics over traditional desktop analysis. We envision several application domains to take advantage of situated spatio-temporal analytics. Here, we highlight two examples of potential usage scenarios for viewing and exploring spatio-temporal in-situ.

8.3.0.1 *Sport Coaching*

Typical coaching routines involve coaches and players watching back game footage to try and better understand both positive and negative actions taken during a game. The analysis of this footage helps to ascertain future decisions on how to best play and to create training routines necessary to make those changes. However, a current drawback of this routine is the separation of the video analysis, containing spatio-temporal player movement trajectories, to the practice area within the game's typical environment. By utilizing a tool similar to SSMA, coaches and players can, while situated, view the trajectory data taken from the game footage. This could potentially be beneficial, as players and coaches could then physically place themselves in the environment where change needs to occur, further being able to explore the data in-situ and in real-time.

8.3.0.2 *Factory Traffic Patterns*

Factories and other workplaces at times track the movement of employees in an attempt to ensure efficiency. Regularly, this is done through video surveillance footage captured around the work environment. However, a birds-eye-view may not at times be able to capture the nature or reason for things like aggregation of employees or slow movement. Thus, exploring the movement data itself while being in-situ can add potentially beneficial information (i.e., environmental factors, positioning of items, etc.) to managers looking to streamline processes. Again, by providing a means for combined data and environmental exploration, a prototype such as ours could prove helpful outside of traditional desktop exploration.

8.4 Assumptions and Limitations

Given that situated spatio-temporal data analytics is an emerging and broad research area, thus it requires few assumptions and entails a number of constraints. In this section, these assumptions and constraints for each chapter are discussed as follows:

Our user study empirically validated the potential of situated via comparing users' data analysis performance between Situated and None-situated groups. One potential limitation of our study is that almost all participants (97.5%) had no prior expertise with video analysis or physical scene investigation because we lacked access to a pool of professional participants with expertise in the areas of video analysis and scene investigation. While university students are typically skilled at critical thinking and abstract reasoning, they may not have the same level of expertise as professionals in these fields. As a result, the findings of our study may not be generalizable to the wider population. However, we believe that the insights gained from our study are valuable, as they provide a fresh perspective on the potential of situated analytics.

An in-situ elicitation study was conducted to explore how participants captured spatio-temporal in a video footage, and generated situated visualization designs to represent such data into the physical environment where video clips were captured. The step-by-step instructions and producers of the study aided participants in comprehending the task, and generating interesting visualization designs, themes, and insight. In order to expand upon the findings of this study, it will be essential to include participants with experience in both HCI and art. This will provide a more diverse range of perspectives and could lead to new visualization designs, themes, and insights. Additionally, this approach would allow for a more thorough understanding of important aspects of the two fields. Participants, with HCI and art background, could suggest interaction and visualization designs different than what has been proposed in this study. This could expand emerging themes and distribution of theme categories. Also, our study analysis and results are based on five video clips (five scenarios) from the literature [11, 14, 27, 36, 72, 96, 99, 102, 114, 123, 139] which includes

Projectile Trajectories, Key Environment Changes, Movement Directions, Duration of Movement/Action, and Absolute Measurements. Other scenarios such as crowd and traffic analysis, object's key postures, individual walking patterns, etc., could yield different themes and their categories.

We introduced our approach for SSCA prototype, core principles, and design choices of the prototype. Our SSCA prototype employs STC visualization to display common trajectory movement datasets (i.e., latitude, longitude, and time) in a small to medium physical space. However, the prototype is inapplicable to more complicated spatio-temporal data with multiple spatial attributes. For example, the trajectory movement of a projectile, as seen in Section 3.4.1, required the visualization of latitude, longitude, altitude, and time. STC can express latitude, longitude, and time with relative ease. To represent altitude in STC, there exist two possible solutions: 1) adding additional visual encoding (e.g., colour hue), or 2) utilizing the z-axis to indicate altitude rather than time. Consequently, while SSCA is used for displaying basic spatio-temporal information, it is not clear how it is suitable for datasets with a greater number of spatial attributes.

We conducted an evaluation study to comprehend in-situ spatio-temporal data exploration using our SSCA prototype and examined interaction taxonomy, i.e., VISM, to see if it supported situated visualization and interaction. As part of the assessment, we deployed the SSCA prototype on the HMD headset, and collected and analyzed qualitative and quantitative data of user interaction with the prototype. Several factors could influence analysts' analytical strategies and tasks to explore and acquire insights from data such as environment (indoor or outdoor), environment crowdedness, and/or environment light conditions. For instance, in our user study, the environment where the data are mapped was indoor and uncrowded with people. Participants were preoccupied with the study tasks and did not notice when a few bystanders passed by. This raised the questions of whether conducting the same study at outdoor and/or environment that is crowded with people will yield similar results or not. Also, in-situ data analysis in public and crowded places has a significant stigma attached to wearing HMD devices, especially the ones equipped with cameras, in public [3, 173]. This can lead to users' anxiety and self-consciousness, which can in turn negatively impact their performance. In some cases, users may avoid using HMD headsets altogether when around other people. This is an important future direction to consider, as the use of in-situ data analysis techniques is likely to become available. Another HMD's issue is that the environment must be lit in a certain way for the HMD to function properly. For example, if an environment is too bright, the cameras on the headset can become saturated and cause visualization to appear as a white blur. Conversely, if an environment is too dark, the cameras may not be able to pick up enough information, and visualization will not appear. The ideal lighting situation for HMD is therefore one in which the environment is evenly lit enough that a human can see without difficulty. If HMD is used in an environment that does not meet these criteria, it is likely that user performance will be negatively impacted.

In addition, our SSCA evaluation was conducted during COVID-19 pandemic restrictions with little access to participants. Our small ($N = 8$) sample may limit the generalizability of our findings. Studying with a larger participant pool would likely produce an increased set of diverse results and/or more clear standout combinations of tools used within our SSCA prototype. However, we note that in previous AR/VR prototype exploration works, this number of participants is often used [93, 127]. Due to the unavailability of experts, through our exploratory study, we recruited lay individuals. These two groups of users have the potential to produce different results. While this may be the case, we do note that our participants followed the typical information seeking mantra and were still successful in answering the questions given. Furthermore, as seen in our potential applications and usage scenarios, increasingly lay individuals, rather than data analysts, could benefit from a tool much like our SSCA prototype.

We provided design recommendations and implementation of SSMA prototype to reduce challenges found in the SSCA prototype (i.e., LFOV and DC) and would improve the user's exploration and interaction with the data via VISM integration.

SSMA leverages visual encoding and multiple-views visualization to overcome SSCA challenges. However, one important consideration for situated spatio-temporal analytics is the structural features of the physical environment including but not limited to shape and floor. Spaces can have different 3D shapes, such as cubes, cuboids, cylinders, spheres, etc. The shape of the space is an important factor in the way spatio-temporal data visualization is mapped into the space and integration of VISM. In our case, for instance, the physical environment in which the spatio-temporal data was collected is a cuboid shape. Cuboid shape faces are not only used to map the data visualization and place the multi-views but also to anchor the VISM interactive zones.

8.5 some areas deserving future work

In this section, we highlight a few aspects that are relevant to situated spatio-temporal analytics. These have received some attention, but are currently unexplored research areas in relation to the concepts presented in this dissertation.

8.5.1 *Evaluate SSMA user performance*

Finally, in order to validate our assumption that SSMA reduces LFOV and DC challenges and improves in-situ data analysis, it is important to assess SSMA's users' performance. Also, we are planning to conduct an empirical study to compare SSCA and SSMA users' performance, analytics tactics, and advantages or disadvantages in typical tasks.

8.5.2 *Multivariate Spatio-temporal Data Visualization*

In addition to the visualization of individuals' trajectories data demonstrated in Chapter 5 and 7, other important considerations for situated spatio-temporal visualization need to be explored further. For instance, future research is to visualize multivariate situated spatio-temporal visualization that includes individuals' estimated pose over time. Human pose estimate is often defined as the process of estimating the articulated joint positions of a human body from an image or video footage of that individual [151]. Wang et al. [151] conducted a survey of recent 3D human pose approaches that could extract individuals' poses. As a consequence, it is feasible to develop a more sophisticated computer vision tool that not only extracts individuals' spatio-temporal data from video footage but also extracts 3D individuals' human pose. To illustrate, it would be beneficial to visually represent individuals' poses with multiple 3D skeletons over time along with trajectory data into the physical environment. Such situated visualization will enrich analysts' understanding of events and individuals' actions compared to situated spatio-temporal data analytics. Therefore, an elicitation workshop is an important step in the design of a situated visualization to represent trajectory data and 3D human poses. This type of workshop allows for designing visualizations that are more effective in conveying the desired information.

Also, we implemented computer vision tool to extract spatio-temporal data from video footage, then loaded it to the SSCA to visualize and map the data. As we envision situated spatio-temporal analytics in Section 1.1.2, we believe that the full potential of our prototype can be realized when spatio-temporal data is available and accessible on demand - from ubiquitous sensors or video footage - in near real-time. Our SSCA visualizes datasets that were previously stored on HMD. Our tool has the capability to visualize spatio-temporal data stream. Also, the level of dataset details presented in the visualization is another important aspect. In our tool, data was preprocessed to reduce data clutter without reducing information content or disrupting data. However, limiting the amount of visualized data may result in the omission of pertinent and critical data in some application domains. A future research direction would be toward supporting Closed-circuit Television (CCTV) with built-in robust and advanced computer vision software that extracts and broadcasts spatio-temporal data, via wireless networks, to immersive displays (e.g., HMDs) in real-time rather than after the footage has been collected.

8.5.3 *Support In-situ Data Exploration*

In Chapter 2, Section 2.5.1, we presented situated visualization characteristics and how data mapping onto its physical context is an important aspect White [155]. However, when the data is mapped onto a large physical space, HMDs LFOV remains an open challenge where users cannot view the whole data (i.e., an overview) or a subset of the data (i.e., zoomed/filtered) unless they change their positions within the visualization canvas. The question is: How to maintain data mapping onto the physical environment while enabling an overview of the data or a subset of the data? One possible future direction is to add a mini-interactive STC visualization to the SSCA or SSMA tool. Basically, the mini visualization visually represents the same dataset used in SSCA or SSMA tool. Also, the mini visualization will be attached to the around-hand to support easy access when an overview of data or a subset of data is required. The interaction with the mini-STC visualization could lead to future research. For example, what would be a suitable interaction with mini-STC visualization to interact and manipulate data? Can we use the interaction with mini-STC and simultaneously reflected it on SSCA or SSMA? We are interested in further exploring how best to enable users to interact and view a large amount of data on the AR platform.

8.5.4 *Situated visualization on different space shape*

As a future direction, we are interested in exploring other physical space shapes and how the SSMA prototype can be used for different space shapes. Also, the floor's structure (e.g., flat, slopped, or stepped floor) could cause safety issues during users' in-situ data exploration and navigation. For instance, during in-situ data exploration and navigation, users could lose their balance and get injured. The space we used to develop SSCA has a flat floor. Based on our observation of the participants during the study, participants did not have any safety issues with the flat floor. This might not be the case for slopped or stepped floors. Ultimately, consideration of physical spaces' structure is essential during the designing of situated spatio-temporal analytics.

8.6 A FINAL WORD

In summary, we foresee the transition of spatio-temporal data analysis methods/techniques from non-situated paradigms to situated paradigms that incorporate situated analytics and embodied interaction to enable in-situ data exploration and navigation at the surrounding environment. We believe situated analytics is an emerging and exciting field of research that has the potential to transform how we interact with the world around us. We strongly believe that our contribution of this dissertation adds valuable knowledge to the research community.

A STUDY MATERIALS

A.1 PARTICIPANTS' SKETCHES

Sixty sketches were generated by six groups (in pair of two). All the groups were asked to draw two visual representations for each of the following video scenarios: 1) Projectile Trajectories, 2) Key Changes in the Environment, 3) Movement Direction, 4) Duration of Movement/Action, and 5) Absolute Measurements. We digitally redrew participants sketches as the following:

A.1.1 *Group one sketches*

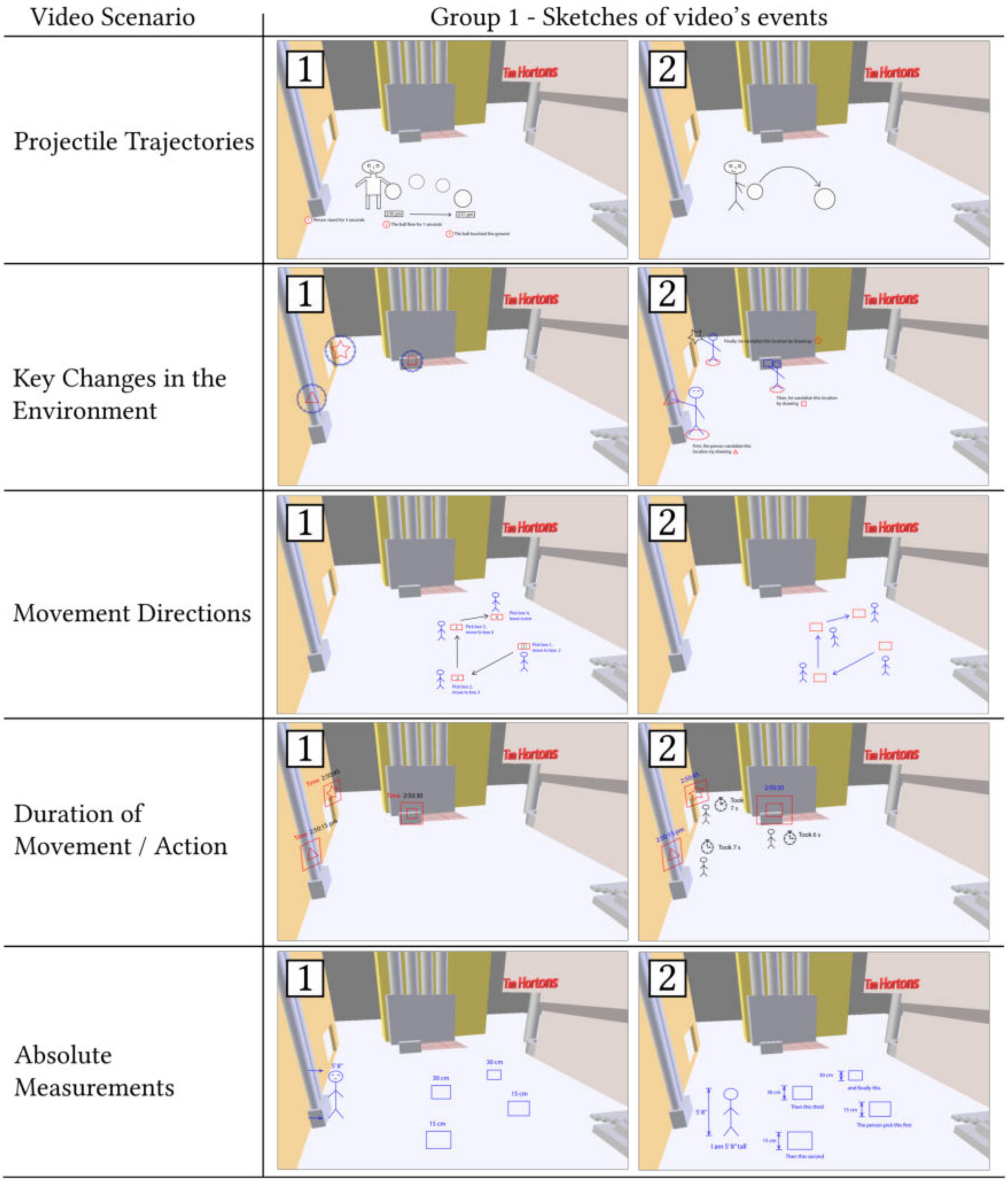


Figure 55: A redraw of group one sketches.

A.1.2 *Group two sketches*

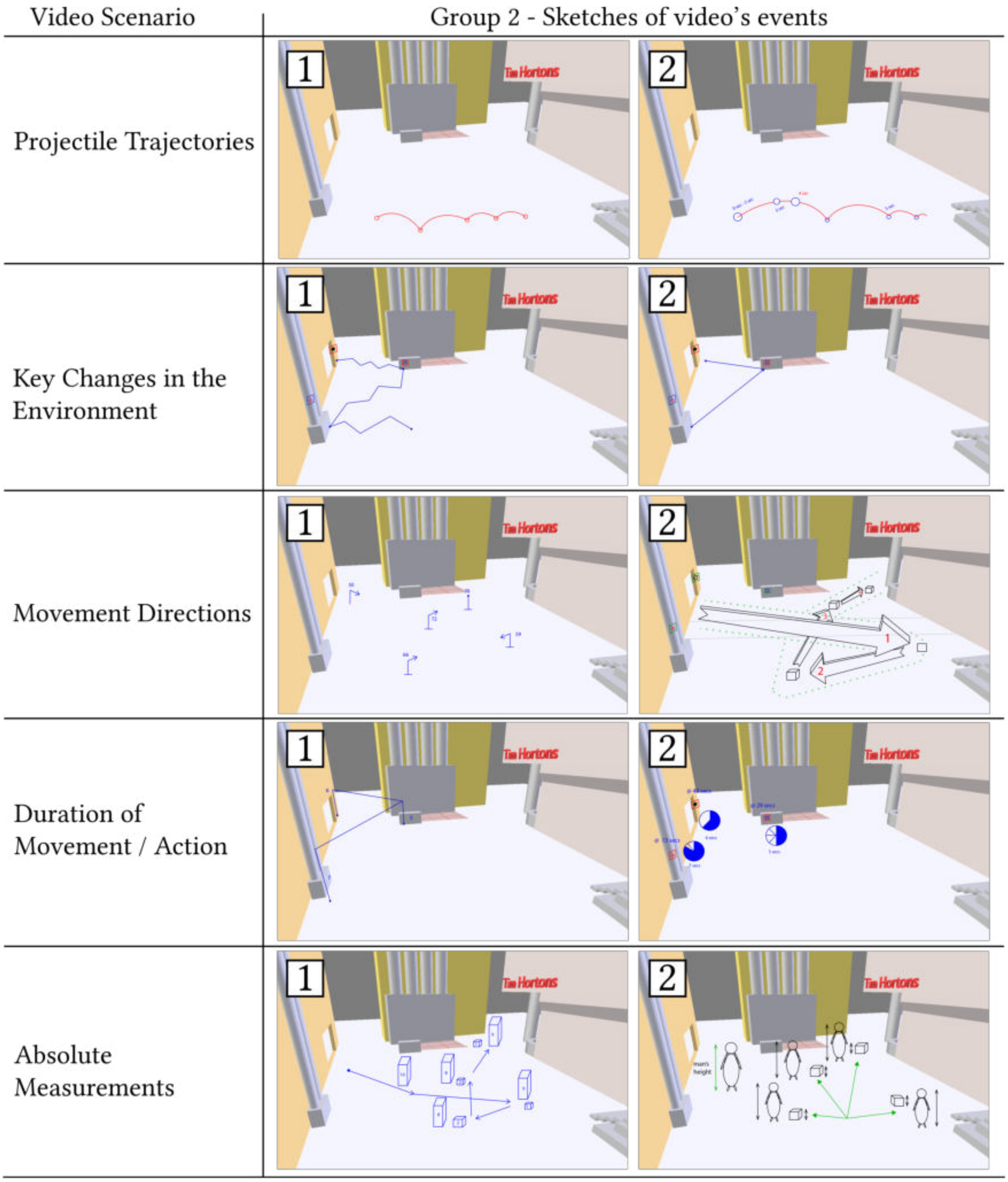


Figure 56: A redraw of group two sketches.

A.1.3 *Group three sketches*

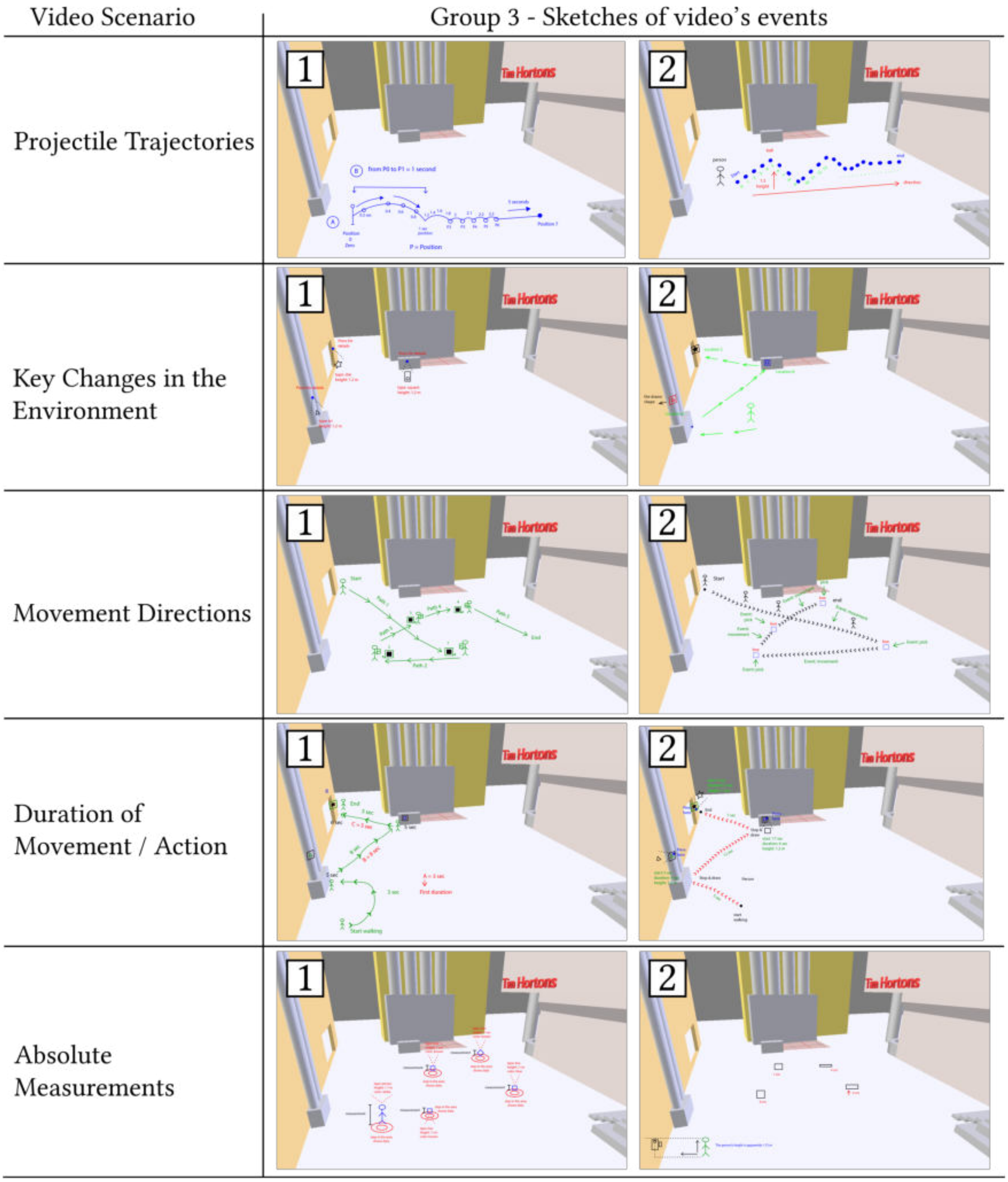


Figure 57: A redraw of group three sketches.

A.1.4 *Group four sketches*

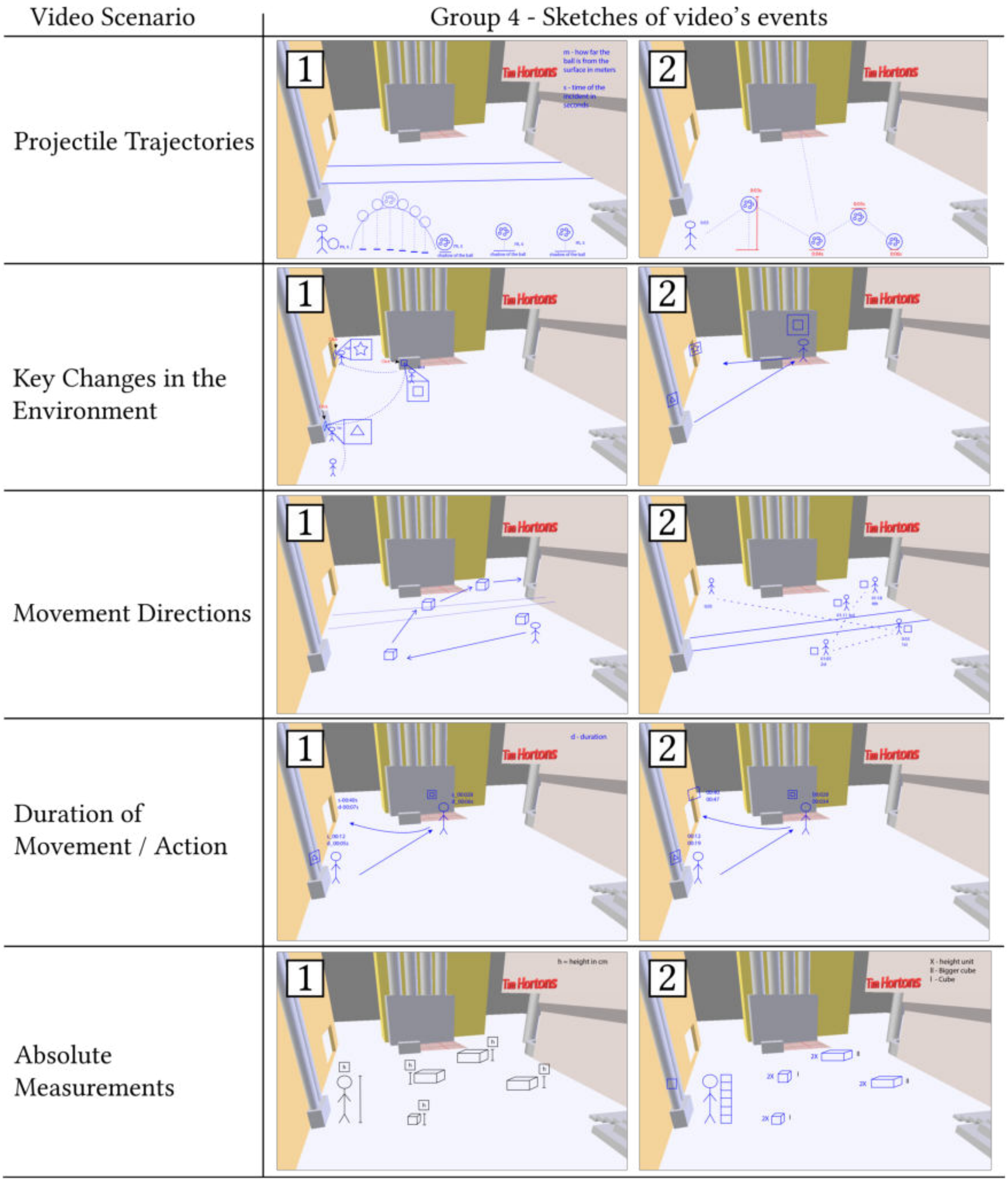


Figure 58: A redraw of group four sketches.

A.1.5 *Group five sketches*

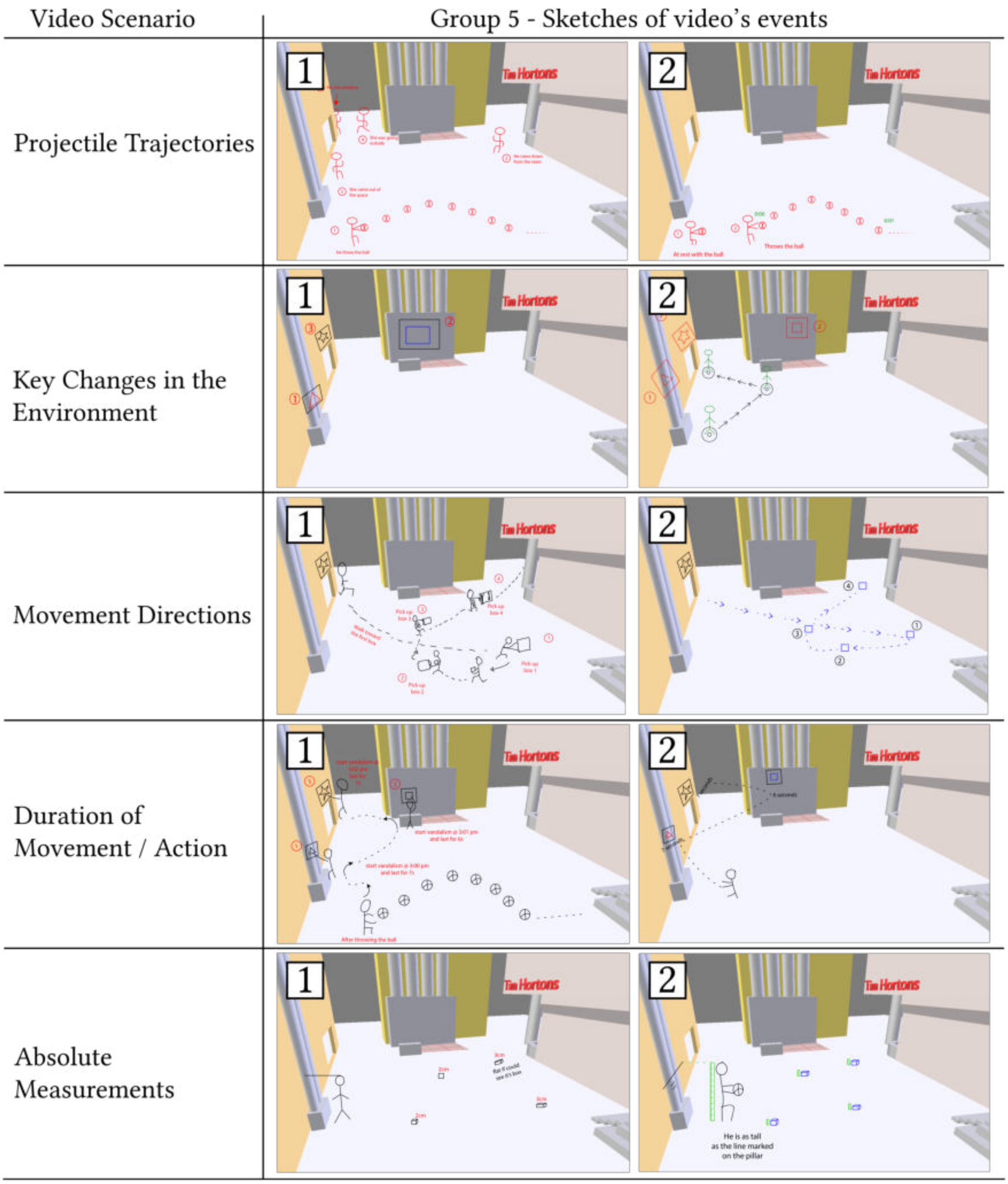


Figure 59: A redraw of group five sketches.

A.1.6 *Group six sketches*

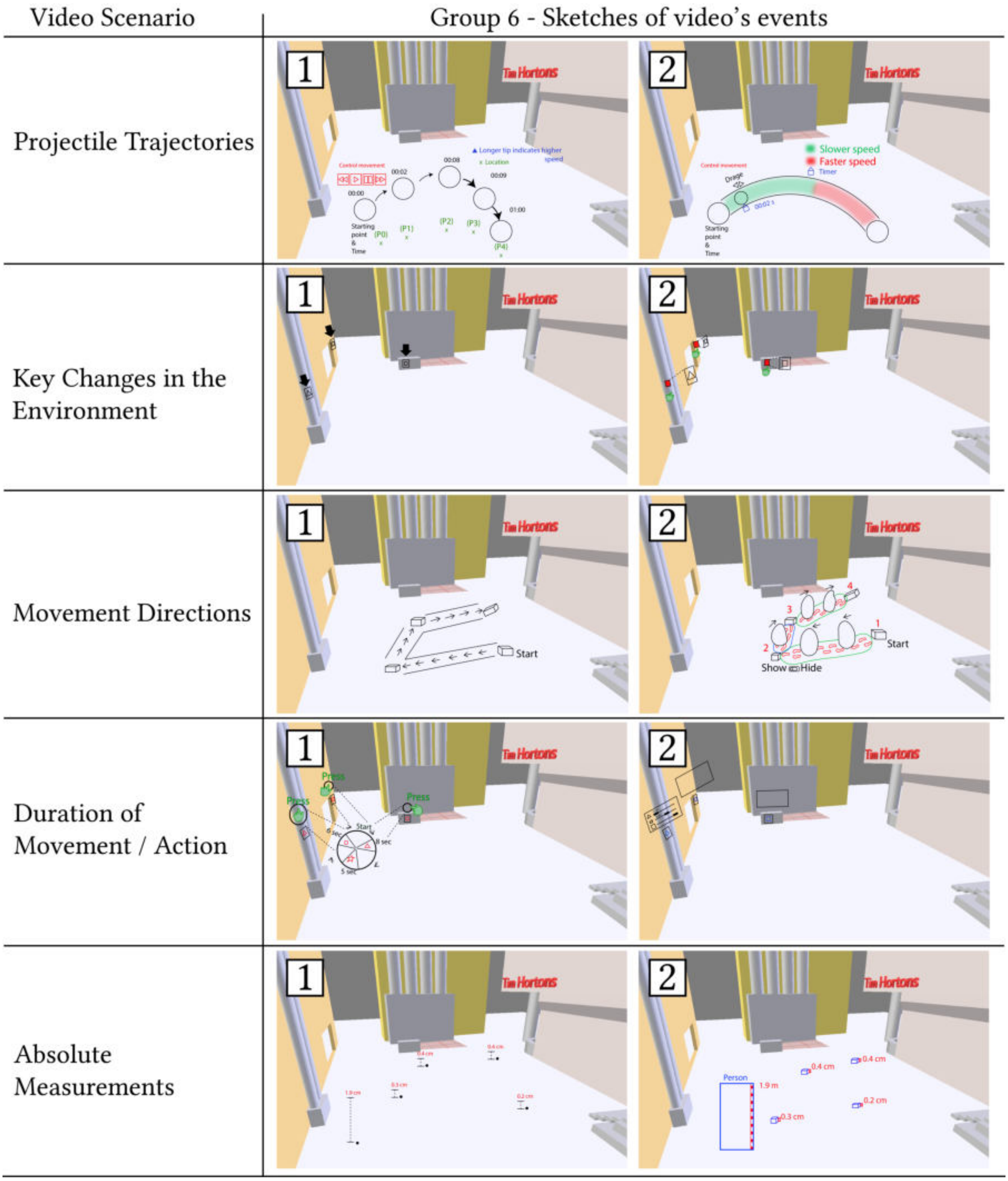


Figure 60: A redraw of group six sketches.

A.2 SSCA EVALUATION STUDY

A.2.1 *Participants' completion time*

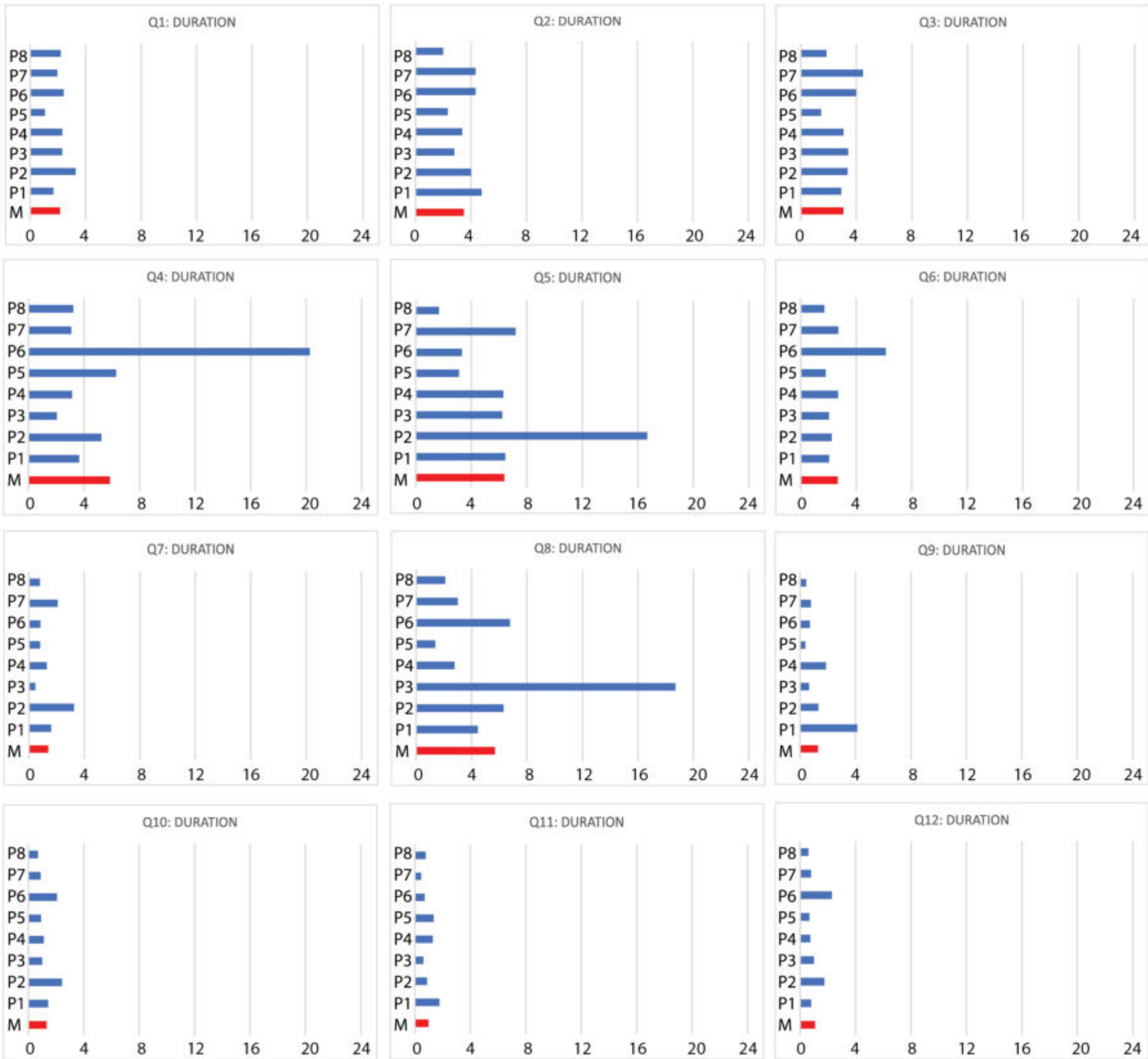


Figure 61: Each sub-graph represents the mean completion time (red bar) and the completion time for each participant (blue bar for P1 to P8).

A.3 SSCA EVALUATION STUDY

A.3.1 *Simple of codebook for Participant 8*

Participant 8 – Raw data

Important concepts to study

In this qualitative coding study, we are interested in two key concepts: 1) Navigation and exploration activities and 2) Situated prototype challenges.

Concept 1: Navigation and Exploration Activities

In order to measure this concept, we will use three activities: 1) Overview First (i.e., O-F for short), Zoom and Filter (i.e., Z&F for short), then Details-on-Demand (i.e., DoD for short). The following are operational definitions for these activities:

Operational Definitions

1. **Overview first (O-F):** In this activity, a user views a visualization with all data plotted to understand the data set as a whole.
2. **Zoom and filter (Z&F):** In this activity, a user focus on particular areas of the visualization (zoom) and selects a subset of the data (filter).
3. **Details-on-Demand (DoD):** In this activity, a user views details of a single data item when the user requests these details.

Concept 2: Situated prototype challenges

In order to measure this concept, we will use two challenges: 1) limited field of view (i.e., LFOV for short) and 2) Data occlusion (i.e., DC for short). The following are operational definitions for the two challenges:

Operational Definitions

1. **Limited field of view (LFOV):** Field of View is the terminology which explains how "big" an augmented reality visualization is when viewed through an AR headset. A limited field of view issue occurs when a user cannot view the complete virtual data visualization at once. User is required to move their view left-right or up-down to see virtual data visualization.
2. **Data occlusion (DC):** In data visualization, the idea of data occlusion refers to a visual element that blocks another one. Data occlusion occurs when a user cannot differentiate between specific data points because some data points overlap other data points.

Coding instructions:

This section will explain what you need to do as a coder. There are three main coding tasks. Please complete the three tasks in the order they appear to you.

Coding task 1:

The goal of this task is to code data navigation and exploration activities in the text. To successfully complete this task, please follow these steps:

1. Go to the first row in the table under the coding sheet
2. Read the participant's think-aloud text
3. Identify exploration activities in the text, then type in the short form of navigation and exploration activities (O-F, Z&F, or DoD)
4. Repeat steps 2 and 3 for all the rows in the table
5. If you complete coding task 1 for all rows, please move to Coding task 2

Coding task 2:

The goal of this task is to order data navigation and exploration activities in the text. To successfully complete this task, please follow these steps:

1. Go to the first row in the table under the coding sheet
2. Read the participant's think-aloud text
3. Identify the order of data navigation and exploration activities as the order they appear in the text, then type in the short form of activities
4. Repeat steps 2 and 3 for all the rows in the table
5. If you complete coding task 2 for all rows, please move to coding task 3

Coding task 3:

The goal of this task is to code the challenges (Limited field of view (LFOV) and Data occlusion (DC)) in the text. To successfully complete this task, please follow these steps:

1. Go to the first row in the table under the coding sheet
2. Read participant's think-aloud text
3. Identify the situated prototype challenges (LFOV and DC) in the text, then type in these challenges.
4. Repeat steps 2 and 3 for all rows in the table.
5. If you complete coding task 3 for rows, please save this file.
6. Open the next 'participant 9 – raw data.docx' data and follow the coding instruction

Coding sheet:

Participant's Audio Script	Coder Answer
Task / Question 1: I need to move to the centre. Okay, now the question says, " Which object was the stationary the longest? Use the filter and embodied interaction to answer the question. To Visually represent your answer, please stand for 4 seconds in front of it." Okay, I need to have a better view of the entire data. Let me quickly look around for which object is stationary the longest. There are some locations where other objects were stationary. Okay, it seems the light blue object. Let me take a closer look at it. So the blue is the longest stationary object. I will use the ROI and Proximity to show my answer. I like that I can move the filter with my location. Nice. Now. It is hard to view my answer when I am very close to it. I need to step back a bit to show the answer. 1,2,3,4. Okay. I am done with this question, so I will open the dialogue and press confirm button.	Coding task 1: Coding task 2: Coding task 3:
Task / Question 2: Okay, the next question, "Where is the meeting location where four objects first met? Use the filters and embodied interaction to answer the question. To visually represent your answer, please stand for 4 seconds in front of it." Let me start by looking around to see where the four objects were relatively close to one another. The objects' movement paths are colliding with one another, which makes a bit hard to find the answer. I need to change my view to a better one. I should find the location where four objects were stationary. Here, I can see only three objects, not four were stationary. I feel this is not the location. So let me trace the walking path of the red object. I see the blue was next to the red object. I should move to the edge to have a wider view of people's movements. What about the white and grey objects? Let me trace them as well. I will play the video to watch their movement. Aha, I guess this is the location of the first meeting. For a few seconds, I forget data points that are above my head level. Now, I can answer the question. I will use POI and Proximity to filter the answer. Now, let me adjust the filter's width. Move to the back to show my answer. I will wait for a bit, and then done.	Coding task 1: Coding task 2: Coding task 3:
Task / Question 3: Question 3, select the walking path of the white object between 11:08:14 and 11:09:20? Use the filters and embodied to answer the question. To visually represent your answer, please stand for 4 seconds in front of it. So, first, I need to select the white path. Oh no. I selected white and grey. I will rest the filter. I need to move to a location where the white object path does not intersect or occlude with other objects. Again, I will choose Path, Proximity and apply filter. It looks good, points for the white object are highlighted. Press Create. Let me check the question again. Now, I need to select the time mentioned in the question. So between 11:08:14 and 11:09:20. POI filter will be the right filter to select the duration of time. I will use Proximity. I can keep an eye on the time slider and the highlighted data points. Okay, STC, POI, Proximity, and Apply filter. Yes, I need to move to the right to 11:08:14. Good, I selected the movement of the white object during the time in the question. I need to move to the edge to view my answer better. Let me move to the other edge to another view of my answer. Okay, stand for 4 seconds. I am done with this question.	Coding task 1: Coding task 2: Coding task 3:
Task / Question 4: Question 4. Select the location where the white object was the closest to the blue object. Use filters and embodied interaction to answer the question. To visually represent your answer, please stand for 4 seconds in front of it. I will begin with getting closer to white and blue objects. I should remove red and grey paths. Let me move a bit to select the white and blue. Let me move back a bit to see what I have selected. I made a mistake; I will rest the filter. Let me select 2D visualization, so it is easy to choose the white and blue paths. Okay, the blue path is selected. Now, I will apply the filter to select the white and blue paths. Okay, now I can look where the two objects were the closest. I will check the question again. Here is the spot. I will use the ROI and Proximity to select the location. I need to view this data from a distance. Okay, done and confirm. Move to the centre.	Coding task 1: Coding task 2: Coding task 3:
Task / Question 5: Select the movement of the white, grey, and red objects when they were walking next to each other and in the same direction? Use the filters and embodied interactions to answer the question. To Visually represent your answer, please stand for 4 seconds in front of it. So the cone shape that connects the data point should point in the same direction and next to each other. So the focus should be on white, grey, and red. Okay, so I will use 2D, ROI, and Proximity. Oh no, this is not where they walk next to each other. I used the wrong filter. I should use Path, Proximity to select all objects except the blue one. I see the three paths where the three objects are walking on the same path. I need to focus on the cones' direction between data points. I have another option, I will watch the video. So, they walk in the same direction over here. I will use 2D, ROI, and Proximity. So here where they walk in the same direction. I should step back and look at this to subset of data. I am done with this question. Confirm.	Coding task 1: Coding task 2: Coding task 3:
Task / Question 6: Let's see question 6. It says show detailed information of white, grey, and red location at 11:10:31? Use the filter and embodied interactions to answer the question. To visually represent your answer, please stand for 4 seconds in front of it. At what location the three objects would be? Okay, I will begin with selecting these three objects using 2D, Path, and Proximity. Apply the filter. What was the question again? Okay, I will use the Plane filter and Proximity. What? Oh, there is a red background on the hand menu, I cannot apply the filter! Oh, I remember now. This filter does not work on 2d; change it to 3D, Plane, Proximity, and apply. I need to move slowly to get 11:10:31. Let me check the question to make sure. Yes. I got it 31 seconds and done. I will back up to see my answer. Done. Confirm.	Coding task 1: Coding task 2: Coding task 3:

Task / Question 7: Move to question 7, was there any coffee shop in the scene? Please navigate the space. If there is one, please stand in front of it for 4 seconds and speak your answer out. A coffee shop! Let me check the video. No coffee shop in the video. Excuse me, I have a question for question 7 about the coffee shop in the scene. Do I have to see it in the video, or should it be in the area where we are at right now? [*The research assistant responded "if you could not see it in the video, you can explore the environment where you are at to find the answer".*] Okay, thank you. Let me check the surrounding space. Oh, I just noticed one there. Let me go there. Yes, there is a coffee shop right here, "Tim Hortons" which is right close to me. Done, and confirm.	Coding task 1: Coding task 2: Coding task 3:
Task / Question 8: Question 8, at what individuals were looking at between 11:10:41 and 11:10:45? Please stand in front of it for 4 seconds and speak your answer out. Okay, I will choose STC, POI, and Proximity. Wait, let me check the time again. So it is from 11:10:41 and 11:10:45. Okay, let me apply the filter. I need to move a bit to the side. 11:10:41 and 11:10:45, 11:10:41 and 11:10:45, so I need to minimize the width of the time slot in the time slider. Okay, I will play the video and see where they looked at. I do not need to go there. The video showed me where individuals were standing, talking to each other, and looking at an image on the wall where the white object was pointing at the image. Okay, finish this question, Done and Confirm.	Coding task 1: Coding task 2: Coding task 3:
Task / Question 9: Now, question 9 says, what was written inside the biggest logo on the wooden board next to the blue object? Please stand in front of it for 4 seconds and speak your answer out. I need to look for the wooden board. Let me see the video again to find the board. I will get closer to the video screen to see if I can see this wooden board. Oh boy, it is hard to find the answer in the video screen, I play the video and see the blue object capsule move. I will move to the edge to have a better view. Oh, now I notice the wooden board next to the blue object. I will get closer to it to see what is written. I see now the biggest logo. Inside the logo, I see ENGAP. I believe this is written inside the biggest logo.	Coding task 1: Coding task 2: Coding task 3:
Task / Question 10: What was the sign on the door at the last meeting location for the grey, red, white objects? Please stand in front of it for 4 seconds and speak your answer out. So the last meeting. I should look at the video again to find the location of the last meeting. So the door near objects last meeting location is there. I should go there for more details. What I see on the door is ' E1-270, the Alan A. Borger Sr. Executive Conference Room' and a paper that says 'Do not Enter'. Done. Confirm.	Coding task 1: Coding task 2: Coding task 3:

Task / Question 11: The white object was standing next to the Engineering and Information Technology Complex wall. How many public televisions were placed on the wall? Please stand in front of it for 4 seconds and speak your answer out. Okay, where is the wall? Is it close to the building's main gate? Let's take a look. Maybe it is the red wall on the other side. Yeah, the number of TV on the wall is only one TV.	Coding task 1: Coding task 2: Coding task 3:
Task / Question 12: What was the name of the building board next to the wooden board? Please stand in front of it for 4 seconds and speak your answer out. So I need to find the building's name. The question says it is near the wooden board. Let's check this out. Okay, the name of the building is EITC – E2, 200 level.	Coding task 1: Coding task 2: Coding task 3:

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