The influence of camera placement on the situation awareness of the remote supervisor of an autonomous agricultural machine

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ABSTRACT

Work is ongoing to develop fully autonomous agricultural machines where a remotely-located supervisor will replace an onboard operator. A high-quality automation interface will be required to achieve this significant development in agricultural machinery. Previous researchers have determined that real-time visual information is needed in an automation interface to instill the necessary high degree of trust. This thesis reports on our investigation on the impact of camera placement on the ability of the supervisor to obtain information from real-time video. We pre-recorded video clips for nine combinations of camera tilt angle (20° 30° and 40°) and height (1.5m, 1.75m, and 2.0m) to study the camera's location impact yielding nine distinct image velocities. Participants, recruited from the student population, completed two tasks. First to watch two side-by-side videos and indicate their preferred camera view. Second, watch a video of a sprayer moving across a field plot and assess the difficulty of identifying and interpreting randomly placed cues visible in the video clips. This study aims to determine whether camera placement influences the situation awareness of the supervisor and, if there is an influence, to identify the camera placement that maximizes the supervisor's situation awareness. Based on the experimental results from part one's protocol, we conclude that a look-ahead associated with a camera angle of 30º and a camera height of 1.5m was the preferred placement combination. No significant difference was present between the various camera angles for the degree of difficulty in detecting and interpreting frisbees. The test subjects equally rated the 2.0m camera height as preferred in seeing field information. By comparison, 1.5m camera height was the preferred camera height for interpreting field information.

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DEDICATION

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1.0 Introduction

1.1 Overview

Researchers have made several efforts to develop an autonomous agricultural machine (AAMs) for past decades, and producing such a driverless agricultural machine is almost a reality. Several works have described that the technology best designed to ensure the safety and efficiency of farm operations is the one that maximizes the exchange of available information between the machines and the human operator, who are likely supervising these fleet of devices from a remote station (Sanchez and Duncan, 2009). Stentz et al. (2002); Berenstein et al. (2012); Adamides et al. (2012) have all suggested the AAMs will require the inputs of the human operators playing a supervisory role to optimizes the machine functions, improve safety and reliability; and reduces mechanical breakdown. Furthermore, researchers expect the supervisor to observe one machine or fleets of machinery from the field through the automation interface (Blackmore et al. 2002; Stentz et al. 2002; Moorehead et al. 2012). Therefore, to facilitate the exchange of critical information between the human-machine systems and maximise the interactions, the autonomous interface must be carefully designed to provide the supervisor with the ability to obtain prompt field information through the automation interface.

Understanding the concept of situation awareness is essential for the operator to gain the correct information from the field. Panfilov and Mann (2018); Stentz et al. (2002); Berenstein et al. (2012) all advised that live video recording of the environment (i.e. real-time visual information) provides the supervisor with a better understanding of the field and better insight into any challenge with the operated vehicle. Therefore, real-time visual information is a crucial element of the design of an autonomous interface. A recent study also suggests the importance of latency in designing agricultural machinery and operating a system that is beneficial to the supervisor. Green et al. (2021) concluded that systems require high-quality live video recordings and stable transmission architectures to obtain real-time visual information. Edet and Mann (2020); Panfilov and Mann (2018) worked on the significance of real-time sensory information in the design of remotely supervised AAMs and provided significant findings from their studies. They both concluded that real-time visual information is helpful when it provides appropriate information about the field and the tractor and is also available in live video recordings rather than in graphical display forms.

Having demonstrated the importance of real-time visual information in the development of AAMs, it is also good to show how the placement of a camera (i.e. camera height and camera angle) controls the effectiveness of real-time visual information. Tang and Mann (2003) studied the effect of camera placement real-time sensory information during a guidance task where the evaluation was based primarily on the performance of the driver's guidance. The current research involves using nine different combinations of camera height (1.5m,1.75m, and 2.0m) and camera tilt angle (20,30 and 40 degrees) to produce nine image velocity conditions. In the study by Tang and Mann (2003), the operator obtained the visual information from the look-ahead camera mounted displayed on the screen within the operator's seat in the tractor. They derived a term known as "image velocity" (i.e., the rate at which visual information rolls vertically across the computer screen while the tractor moves forward). The image velocity is a function of the tractor's speed, the camera's optical characteristics, and the camera's placement (i.e., camera height and camera angle). The ability to obtain the appropriate real-time visual information from the monitor is dependent upon the image velocity. As the image velocity increases, it becomes challenging for the human operator to obtain and interpret the data from the screen, as indicated by a decline in the driver's performance (Tang and Mann 2003).

2.0 Literature Review

2.1 The use of automation in the field of agriculture

The primary outcome of agricultural mechanization is the improved efficiency of agricultural production at a reduced cost. Improved efficiency and reduced cost could occur by deploying information technologies that support intelligent machines to produce the level of efficiency desired (Shaw 2005; Johnson et al. 2009). Mechanization generally involves using improved agricultural machines in different stages in agriculture, which will improve overall productivity. Such level of development is achievable by the use of automation and robots in agriculture, especially for tasks that are generally slow and repetitive, which will enable farmers to focus on improving overall agricultural productivity (Shaw 2005; Johnson et al. 2009; Yin and Noguchi 2013).

Early developments in the use of robots for agricultural purposes began in 1920, with further advancements occurring in the early 1960s in autonomous machines. Agricultural robots became prominent in later years, following research in broader aspects of machine vision guidance using computers and electronics, enabling smaller and more intelligent robotic machines (Yaghoubi et al. 2013). With a machine vision system, cameras are used in obtaining visual information from the field and then analyzed by the computer. The computer then sends the image data to the robot. The use of sensors and digital imaging in robots also better enables farmers to picture the field during operation. Robots generally use this advancement in machine learning technology to avoid hazards on the field and ensure proper crop selection during harvesting (Yaghoubi et al. 2013; Bechar and Vigneault 2016).

Many application areas of robots and automation exist within different aspects of agriculture. Robots or drones used for agricultural purposes are called agricultural robots, and these robots are helpful in weed control, seed planting, soil analyses, combating plant diseases, and harvesting (Johnson et al. 2009; Yaghoubi et al. 2013). Deployment of agricultural robots for the harvesting operation is still the most popular among them, although automating these tasks could generally be challenging (Johnson et al. 2009; Yaghoubi et al. 2013). Robots and automation in agricultural practices also decrease generated air pollution and energy consumption on the farm (Gonzalez-de-Soto et al.

2016). They also help eliminate situations dangerous to humans and are generally quicker, and do not require breaks or holidays like human operators (Yaghoubi et al. 2013; Bechar and Vigneault 2016). Many farming activities are repetitive and can be both tedious and demanding for human operators. Farm managers could easily use robots to produce a high level of accuracy, reliability, consistency, and efficiency that is often lacking from average human operators due to the demanding nature of farming activities (Yaghoubi et al. 2013).

One major challenge to the design and development of agricultural robots is the ability of such machines to successfully operate in a non-uniform landscape and farming environment with in-field variability (Johnson et al. 2009). Another similar challenge involves running farm robots in unknown and unpredictable scenarios such as extreme heat, dust, and vibration during field operations. Despite these limitations, researchers agree that agricultural robots are safer, more reliable, and help achieve precision (Johnson et al. 2009; Bechar and Vigneault 2017). However, agricultural robots are also generally more expensive to procure, and they must be deployed and operated by specialists. This need for specialists is why the commercial availability of this technology is still limited and why only a few research efforts have had successful adoption by farmers worldwide (Bechar and Vigneault 2016). Despite these limitations, the global decline in human resources required to meet the demand in food production will surely compensate for using these technologies (Bechar and Vigneault 2016).

While engineers design agricultural robots to perform main tasks like pruning, weeding, and handling, the robots must simultaneously perform other supporting tasks like localization and navigation using communication and command between the primary and supporting task systems. These tasks are systems must be synchronized together effectively to obtain the required output from an intelligent robotic machine (Bechar and Vigneault 2016). Field robots can also be used in decision-making and to perform different tasks in real-time, such as autonomous navigation with the aid of the global positioning system (GPS) and sensors (Yin and Noguchi 2013). Other essential components and devices that agricultural robots require to perform their tasks include the steering and control mechanism, mobility, and end effectors (Oberti and Shapiro 2016).

Therefore, designing partially autonomous agricultural robots has provided a strong background in research in hardware and software components essential to achieving the dream of fully autonomous agricultural machines (Oberti and Shapiro 2016). Engineers could implement agricultural robots as a single-robot/autonomous agricultural system that utilizes at least one human operator per robot on the farm. However, engineers could also implement them as a multi-robot system, which involves one human operating several agricultural robots in the same field plot (Yin and Noguchi 2013). Multi-robot systems should improve efficiency.

Future developments of in-field and greenhouse machines must incorporate the ability to detect and identify the specific properties of crops and different field environments in which they operate. Such detection and identification will require manipulators, sensing systems, and end effectors specially designed for such adaptability (Bechar and Vigneault 2017). Researchers believe that these improved developments will enhance crop imaging and enable farmers to adequately access the data necessary to predict crop information. However, to maximize the potential benefits of using robots and automation in agricultural production, reliability and inherent safety of crops, environment, machine, and the operators must be guaranteed. Technological innovation is undoubtedly close to achieving the goal of making these complex machines intelligent and secure for use in a fully autonomous agricultural environment (Bechar and Vigneault 2016).

While most researchers' efforts currently focus on developing a remotely supervised autonomous agricultural machine, embracing innovative technology in robotics and automation will play a more prominent role in modernizing agriculture globally. This modernization will reshape all farming practices with improved crop efficiency and better yields.

2.2 Developments in autonomous agricultural machines that humans remotely supervise

2.2.1 Human-Automation System

Automation involves using machines to do tasks that humans can do. At the same time, a human-automation system is any system that integrates the functions of any human operator with those of a machine (Janssen et al. 2019). Therefore, a human-automation system has a more significant role in the ongoing developments of agricultural automation, especially in aspects of display design and the extent of trust that can be placed on this system by the operators (Sanchez and Duncan 2009). Salvendy (2012) described the human-machine interaction as a system that performs different tasks through the combination of human and machine. Furthermore, such interactions can produce optimal results when designers carefully consider how the device displays information to best enable the human's focus on the tasks they are to complete with the system.

Machinery displays have generally become more complex as technology advances. For example, a typical tractor in the 1950s had very little information to display, while digitization and sensors from the 1980s onward created more features and displays in general. Consequently, engineers design modern machines with many indicators and display systems that are increasingly complex (Sanchez and Duncan 2009). The issue of trust and reliability in human-machine systems has also drawn much attention. As machine designs progress through different stages of automation, it is always important to know the level of trust the human operator places in the system. One way to achieve a high level of reliability between human-machine systems is ensuring the level of confidence in any automated system is above the level of self-confidence for a similar manually operated system (Sanchez and Duncan 2009).

2.2.2 Partial Automation

Automation's goal is to ensure higher productivity where machines operate faster, with an improved overall speed and lower cost of production (Stentz et al. 2002). Given the repetition and difficulty of the farming tasks previously performed by human operators, they further stated that full automation is the ultimate goal. Bye et al. (1999) further stated the need to allocate some functions between the operator and machine to achieve the objectives of automation, which are crucial to ensure a safe, reliable, and efficient system.

Sandom and Harvey (2009) explained three primary principles for partially automating a system: the left-over principle, the compensatory principle, and the complementarity principle. Each principle has a distinct way of allocating tasks between the human and the machine to optimize performance. The left-over principle describes the most straightforward automation philosophy. It suggests the device should perform as many functions as can be automated with the remaining tasks allocated to the human operator (Grote et al. 2000; Sandom and Harvey 2009). The significant advantage of the left-over principle is in utilizing the capabilities of a machine, such as speed and accuracy during automation, while one of the disadvantages is that it ignores past experiences the human operators can offer. The compensatory principle addresses the disadvantages of the left-over principle while the complementarity principle allocates tasks based on limitations and capabilities of the human and machine as described by Fitts (1951). The complementarity principle explains the need to share functions between devices and operators in a complex, dynamic system (Bye et al. 1999).

Sandom and Harvey (2009) summarize the three function allocation principles based on purpose and function. The purpose of the left-over principle is to ensure the efficiency of the automating process as much as possible. In contrast, the compensatory principle maximizes the efficiency of human-machine interaction. The complementarity principle ensures the operation of the machinery system across different conditions. Regarding their functionality, the complementarity principle supports the human operator to operate efficiently while the compensatory principle reduces extra burdens on humans due to automation. The left-over principle then supports human operators taking over roles that cannot be automated. The complementarity principle is the best suited for most agricultural systems because it ensures flexibility of function and often allocates tasks to optimize system performance (Bye et al. 1999). In addition, the complementarity principle views the human as a dynamic system that can learn. In contrast, the left-over principle recognizes the human as a machine, and the compensatory principle has a reduced capacity for processing change from any information.

The central goal of the automation system includes relieving the drudgery in farming operations, which often requires the human operator to master the rapid complexity in using these automated machines. Analyzing the performance of machine systems performance is therefore crucial to understanding and enhancing the overall efficiency of the semi-autonomous agricultural machine. Once the designed device achieves the efficiency desired through the function allocation principles, the operator and the automated device share the roles.

2.2.3 Fully Autonomous Agricultural Machine

Researchers have completed several studies to develop Autonomous Agricultural Machines (AAMs). The world seems close to seeing the reality of the technology that would significantly improve agricultural productivity (Edet and Mann 2020). For AAMs to be functional and practical, an engineer must design an automation interface. The interface must be able to communicate the relevant information required by the remote supervisor of the machine (Edet et al. 2019). Researchers expect the remote supervisor to control a fleet of machines or a single machine operating from one or more fields through an automation interface (Blackmore et al. 2002; Stentz et al. 2002; Johnson et al. 2009; Moorehead et al. 2012).

This is likely to be two-way communication as the operator is expected to send instructions and obtain status information from the AAM while playing an active supervisory role (Stentz et al. 2002; Moorehead et al. 2012; Endsley 2016; Irwin et al. 2019). The exchange of information between the supervisor and the machine is critical because the human operator requires a clear understanding of the environment (referred to as situation awareness). This understanding enables appropriate responses to signals or prompts from the machine via the display interface, which will likely require an action from the human supervisor (Stentz et al. 2002; Irwin et al. 2019).

Situation awareness has been explained as a fundamental concept to obtain appropriate field information in the drive for automation (Endsley 2016; Sirkin et al. 2017; Irwin et al. 2019). It is, therefore, important for engineers and researchers to carefully design the automation interface to ensure effective communication between the human-machine system and achieve maximum efficiency (Stentz et al. 2002; Blackmore et al. 2013).

Essential factors to consider in the design of the automation interface include the graphical interface and the real-time visual information. Rakhra and Mann (2018) concluded that user-centred display elements significantly helped maximize the level of situation awareness of the operator of an agricultural machine. Panfilov and Mann (2018) investigated the role of visual information in remotely supervising an autonomous agricultural machine and recommended that real-time visual information (i.e., video) be included in the interface design because it helped users understand how the machine was functioning. They also stated that live video is important as this provided a better level of security to the human operator. They further concluded that the supervisor requires real-time video feedback that includes a general view of the machine within the field.

Green et al. (2021) researched the effect of video transmission latency in an autonomous system using cellular video transmission and video data on an Ethernet-enabled radio transmission network. Their study is essential to obtaining a good understanding of latencies while transmitting live video from the environment to the operator of an AAM. The results of their research indicated that transmission latency differs between video resolutions for data obtained across various field locations using both the Ethernet and cellular video transmission systems. Specifically, they observed that improved video quality had higher latency while lower video quality had lower latency. Therefore, they suggested that high-quality network infrastructure must be available on the farm for high-quality transmission of videos in any farm's autonomous system to enable the supervisor to obtain appropriate real-time visual information from the tractor.

Other essential features of an efficient automation interface are a remote supervisor and a computer system mounted on board. While each autonomous tractor can operate remotely, more extensive coordination should also involve the human operator. The human's roles will be to assign tasks to each tractor and track and observe the operation of the machines (Moorehead et al. 2012). Endsley (2016) also stated that automation is yet to become a reality because of the current safety levels provided by humans compared to machines. Therefore, fully autonomous systems will remain highly dependent on human operators to maximize operator safety and trust efficiency. A high level of situation awareness will undoubtedly be required to achieve this. The role of the computer will be to facilitate information sharing between the supervisor and the machine over wireless communication cables to send and receive status information (Stentz et al. 2002; Moorehead et al. 2012).

While the design of the automation interface could feature a supervisory control or have fully automatic control as a possibility, it is most likely to be built with supervisory control. For example, Blackmore et al. (2002) designed a system that would enable control of the machine that used a "coordinating process" to be controlled by the human supervisor within the farm office. This remote system has a mimic display that would include a "real-time video link to steerable onboard cameras" to ensure the supervisor has a "better understanding of the tractor's environment."

2.3 Non-agricultural applications of remote supervision

Remote supervision has a more extended history outside agriculture, including marine, medicine, military, nuclear, etc. This section provides an introductory study of the progress within these fields related to automation in agriculture. In addition, we present this section to understand possible developments in AAMs further.

2.3.1. Remote supervision in medicine

Telesupervision is one common application of remote supervision in the medical field to solve the limitations of distance, access, and time in clinical supervision, which is key to continuing skilled development in the health sector (Martin et al. 2017). This advanced innovative technology is deployed mainly for communication in local and remote areas where access to adequate supervision is lacking in medicine by using cameras and infrared sensors to track patient's status (Martin et al. 2017). It is also often used to provide care to patients and offers supervisory assistance to junior medical officers in remote locations (Cameron et al. 2015; Martin et al. 2017). In addition, this technology decreases the personnel shortage and access to quality health care by patients through supervised rehabilitation from a remote area (O'Neil et al. 2020; Cameron et al. 2015; Martin et al. 2017).

2.3.2 Remote supervision in marine environments

In periods of natural disasters like earthquakes and tsunamis, remotely operated vehicles (ROVs) have been used underwater for search and rescue operations (Murphy et al. 2011).

Although effective human-robot interaction is still a challenge in using rescue robot technology, it is a valuable innovation both economically and for human recovery (Murphy et al. 2011). Human intervention in this autonomy is required during most recovery teleoperations to interpret complex tasks and look out for quick information when the disaster has become highly unpredictable (Murphy et al. 2009; Murphy et al. 2011).

2.3.3 Remote supervision in military applications

The unmanned aerial vehicle (UAV) is a vital military weapon that uses autonomous technology to operate. Enemy territories are usually targeted using this remotely controlled device or autonomously done with an onboard computer with several sensors embedded together to an electronic transmitter that aims at targets (Ma'sum et al. 2013). The aircraft usually has interface design components and a remote supervisor overseeing fleets of vehicles from a central location and can be used for surveillance and forestry conservation (Cummings and Mitchell 2008; Lewis 2013; Ma'sum et al. 2013).

There are essential lessons observed in the previously mentioned systems critical to developing the automation interface for an AAM. An automation interface is essential in all the remote applications examined because it provides the necessary information sharing between the operator and the machine on the field or in water. The interface is also equipped with visual information of the surrounding area to understand the tasks underway. The role of the human supervisor is also essential in the coordinating process to ensure safety and instill a high degree of reliability and trust. The operator is also responsible for supervising multiple systems from a central location and helps to interpret complex tasks ahead of the machine. Finally, it is equally essential to maintain constant communication between the computer and the device through the interface.

2.4.0. The Automation interface

2.4.1. The need for an automation interface

Blackmore et al. (2002), Stentz et al. (2002), and Johnson et al. (2009) all affirm that full automation in agricultural machines could occur with a supervisor capable of supervising several AAMs as long as an automation interface is available. They also concluded that autonomous vehicles would not operate in isolation from experienced operators because of the need to share of information. There is, therefore, a need to identify the critical components that will allow such development to become a reality. Some of the crucial elements required for an automation interface are listed below:

1. The Mode Change
2. Geographic Information System (GIS) Database
3. Route Plan Generator (RPG)
4. Implement Database
5. Independent Real-time Video
6. Tractor Database
7. Communication Infrastructure
8. Perception System

2.5.0 Real-time visual requirements demonstrated as being essential for the automation interface

Stentz et al. (2002) stated that video footage is essential for operators to effectively supervise the machine remotely while Panfilov and Mann (2018) suggested that live video will provide additional support for the operator while making decisions would have more details of any change with the tractor. Therefore, the focus here is to consider in further detail some of this information.

2.5.1 Importance of real-time visual information

Research to determine the significance of real-time visual information in the design of the autonomous agricultural machine has been conducted (Panfilov and Mann 2018; Edet and Mann 2020). The conclusion of Edet and Mann (2020) states that “overall visual information of highly important or preferred parts of the sprayer and its environment (as determined by experienced operators) should be retained in the format of a live video rather than encoding information as part of the graphical display.” This conclusion is similar to the recommendation that an automation interface should have a provisional display of live video that captures the field and the tractor as given by Panfilov and Mann (2018).

2.5.2 Specific visual information that is essential to the design of autonomous agricultural sprayer

Generally, experienced sprayer operators preferred three key areas to view while the tractor is in operation: i) sight ahead of the sprayer, ii) view of the boom with the nozzle, and iii) the aerial sight of the sprayer (Edet and Mann 2020).

There are several essential features that operators are looking for in these views. Among them is the boom height, application rate, headlands, and spray pattern (Edet and Mann 2020). This information will help the experienced operator to check for any warning or prompt that could result in danger or tractor malfunctioning, like avoiding obstacles and ensuring the wheels are correctly on track during operation (Edet and Mann 2020). Lyon (2017) states that trust and reliability are important issues that should be considered by designers of AAMs. For this reason it is essential to incorporate real-time visual information as an integral component of this interface.

2.6.0 The concept of image velocity

Although there is limited literature to support the relationship between image velocity and camera placement, it is critical to consider the previous study of Tang and Mann (2003) regarding the importance of camera placement (camera height and camera tilt angle) when displaying real-time visual information for guidance purposes. They researched different combinations of camera height and tilt angle in a manual guidance task with evaluation based primarily on driver’s guidance performance. This understanding will provide good background information regarding the concept of image velocity, a discussion of some of the theoretical analyses used in the study, and the major findings from their work. This explanation will ultimately lead us to study the influence of image velocity on the situation awareness of the autonomous agricultural machine because placement of the camera on the AAMs must be considered carefully to ensure that visual information can be used effectively by the remote supervisor.

The objective of the previous study was to determine the relationship between the operator’s performance and image velocity and also to determine how camera placement and the optical parameters of the camera affect the driver’s performance during agricultural operations. The study was completed using a camera-based control aid in providing guidance information to the operator during a guidance task. The forward-looking camera captured an image of the farm environment to produce an “image velocity” when displayed on the cab-mounted monitor, which is a function of the velocity of the tractor, camera placement, and the optical characteristic of the camera.

To provide a mathematical expression for image velocity, the relationship between the image heights of the camera to the longitudinal distance is multiplied by the tractor velocity as shown from the expression below:

$$V = \frac{H}{d} \cdot v_t \qquad (1)$$

where

V= velocity of the image produced on the monitor (mm/s)

d = longitudinal ground distance from the leading camera (m)

H = height of the image produced on the screen (mm)

V_t = tractor velocity (m/s).

The linear ground distance produced by the camera is a function of the optical lens, camera height, and the tilt angle which can be expressed by the below equation:

$$d = h \cdot [\tan(90 - \alpha - \beta + \theta) - \tan(90 - \alpha - \beta)] \qquad (2)$$

where

α= camera tilt angle (°)

β= bottom portion of the linear view of the camera (°)

h = camera height (m)

θ =linear field of view of the camera (°)

From equation 1 and 2 above, the image velocity equation was derived as:

$$V = \frac{H . v\mathrm{t}}{h\ .[\tan(90 - \alpha - \beta + \theta) - \tan(90 - \alpha - \beta)]} \qquad (3)$$

A more accurate equation for the above was derived by selecting the portion of the linear view of the camera that produced a similar image position on the monitor during the guidance task because the forward-looking camera is not positioned straight to the ground as seen in figure 2.1 below. Therefore the mathematical expression for the image velocity of the camera is expressed by equation 4 below:

$$v_i = \frac{H.vt}{h.\{\tan(90-\alpha-\beta+(\frac{n-i+1}{n}).\theta)-\tan(90-\alpha-\beta+(\frac{n-i}{n}).\theta)\}} \qquad (4)$$

where

i= ith band from the screen top

n= possible number of bands from the monitor.

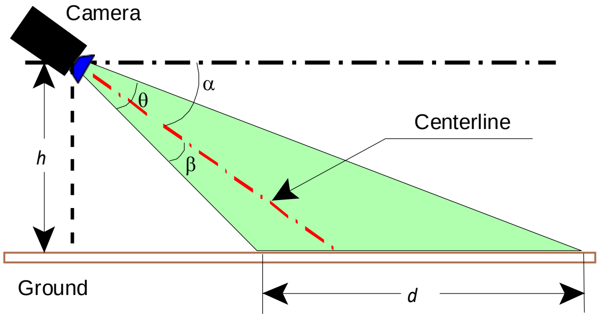


Fig 2. 1: Geometric expression of the longitudinal view produced by a forward-looking camera (from Tang and Mann 2003)

The experimental results of Tang and Mann (2003) indicated that at tractor velocities between 1.6 and 2.8 km/h, the operator's self-confidence produced an inverse relationship with image velocity. Driver's performance was thus recorded to be better at lower image velocity and decreased at higher image velocity during tractor operation. The camera tilt angle of 20° was determined to be subjectively preferred by the test participants' because it produced the greatest look-ahead view, although a 30° tilt angle was statistically desirable as a camera angle for the most general field of view. The look-ahead distance further influenced the camera height as driver performance improved at higher image velocity of the tractor; hence a camera height of 1.1 m was the preferred height compared to 1.5 m height above ground level.

2.7.0 Methods for evaluating camera placement in autonomous agricultural machines

Human factor specialists have conducted previous studies to determine an objective measurement of various human system performances. The most common among them are situation awareness, fatigue, and mental workload (Salvendy 2012). Situation awareness was selected as a measure to evaluate the placement of the camera because it is a well-developed idea that has found relevance in studies related to automation and interface design (Endsley 2012; Rakhra and Mann 2018; Nguyen et al. 2019; Edet and Mann 2020).

2.7.1 Situation awareness

The definition of situation awareness (SA) is "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" (Endsley 1995).

SA is important for reliable operations in many applications as it helps define critically what is happening in the environment and is highly effective for decision making and actions; performance measures depend on that action – for example, steering a tractor (Nguyen et al. 2019). According to Endsley (1998), there are three levels of SA: i) perception, ii) comprehension, and iii) projection. Level 1 SA is the perception of information from the surroundings. These could involve using various senses (e.g. touch, smell, visual, auditory etc.) to hear the engine's sound or feel other vibrations during a typical agricultural operation. Level 2 describes the understanding of the perceived information at level 1, while level 3 is the projection of a future scenario based on the earlier perception and comprehension of the information. Endsley (2016) stated that level 1 SA is achieved when the processor perceives the information requiring action to be taken. Users under this level are sometimes faced with the challenge of perceiving too much information or the likelihood of not detecting the most critical information for the task at hand. To achieve level 2 SA, operators must be able to comprehend information that was perceived previously. The ability to process and further integrate the information is key here in order to form appropriate understanding of the task (Endsley 2016). The operator's experience is also helpful to understand the system and the role to play in a given scenario, otherwise it becomes challenging if there is lack of experience or lack of understanding of the information obtained (Endsley 2016). Endsley (2012) required that to achieve level 3 SA, the operator must be able to perceive the right information, understand the meaning of such in line with the desired objective, and have the ability to project into the near future. Knowledge of the system is also required here while maintaining good mental alertness by avoiding information overload in order to move from level 1 through to level 3. Another expectation in level 3 SA is the ability to proactively respond to situations and predict what could go wrong.

2.7.2 Measurement of situation awareness

Salmon et al. (2009) conducted an experiment to measure SA in a complex system. These multiple approaches included a freeze probe recall method, observer rating method, real-time probe methods, and post-trial subjective rating procedures.

Freeze probe recall deals with direct measurement of situation awareness during freezes in a task simulation and the outcomes indicate this is the only procedure that has a statistically significant relationship in line with the task performance. During a simulation, a task is frozen randomly while SA queries are then administered in such scenario after which the responses are related to the actual state of the process, and SA calculated afterward (Salmon et al. 2009). Although this is a direct SA method, it could be challenging applying this method to real life processes (Salmon et al. 2009; Endsley 2012). Self-rating approaches are usually applied to obtain a subjective assessment of situation awareness of the participant. It is known to be a quick and easy method, although usually has a low recall level and poor correlation with performance (Salmon et al. 2006).

SA performance measurement focuses on a specific aspect of a task to rate the participant which is generally difficult and is often used as a secondary assessment tool. Participants could also produce a wrong decision, making the given task which could affect the level of SA (Endsley et al. 1998).

2.8 Research objectives

Challenges of obtaining real-time visual information are discussed in the literature review. Work has been done in the areas of autonomous agricultural machines by researchers in the past. However, little effort has been spent on the problem of designing an automation interface that focused on the presentation of real-time live video to maximize the situation awareness of the remote supervisor of the AAMs (Edet and Mann 2020).

This research aims to determine the influence of camera placement on the situation awareness of the remote supervisor of an autonomous agricultural machine. An experimental protocol was established that required volunteer subjects to interact with pre-recorded video to simulate elements of the task of remotely supervising an autonomous agricultural machine. The specific objectives of the research are:

1. Determine the camera placement preferred by the subject during the remote supervision task.
2. Determine the camera placement that least contributed to the difficulty of detecting and interpreting randomly-placed cues during the remote supervision task.
3. To determine if the subject’s level of experience concerning the operation of agricultural sprayers influences the experimental results.

3.0 Materials and Methods

3.1 Production of “look-ahead” videos

A two-part experimental protocol was designed for this study. Part one of the experimental protocol investigated the effect of camera placement on the preference of view of test participants. Their main task was to watch two side-by-side video clips of a sprayer in a field with different “look-ahead” characteristics and identify preference of view (in terms of obtaining real-time visual information from the field environment). Part two of the experimental protocol examined the effect of camera placement on the difficulty associated with detecting and interpreting visual information gleaned from the field surface, assessed using randomly placed marked frisbees while watching the recorded video clips of a sprayer in a field. The two-part experimental protocol was first completed using inexperienced agricultural machinery operators recruited from the university student population, and subsequently repeated using experienced sprayer operators.

The two-part experimental protocol required a set of “look-ahead” videos that would subsequently be used to determine the influence of camera placement (in terms of height and tilt angle) on the usability of the visual information for the task of remotely supervising an autonomous agricultural machine. This initial section of the Materials and Methods documents the process used to produce the “look-ahead” videos.

A GoPro camera was selected for this purpose because these cameras produce high-quality video, are durable, and are cost effective. Furthermore, GoPro cameras were readily available in the Agricultural Ergonomics Laboratory at the University of Manitoba. One GoPro camera was mounted in a forward-facing direction (Fig.3.1) on an all-terrain vehicle (ATV) that had been loaned to the University of Manitoba’s extra-curricular student agBOT team by JCA Electronics. Arrangements were made to use the ATV during the summer, when the student agBOT team did not need it. A sturdy plastic material was used to create the mounts for these cameras (Fig.3.1)

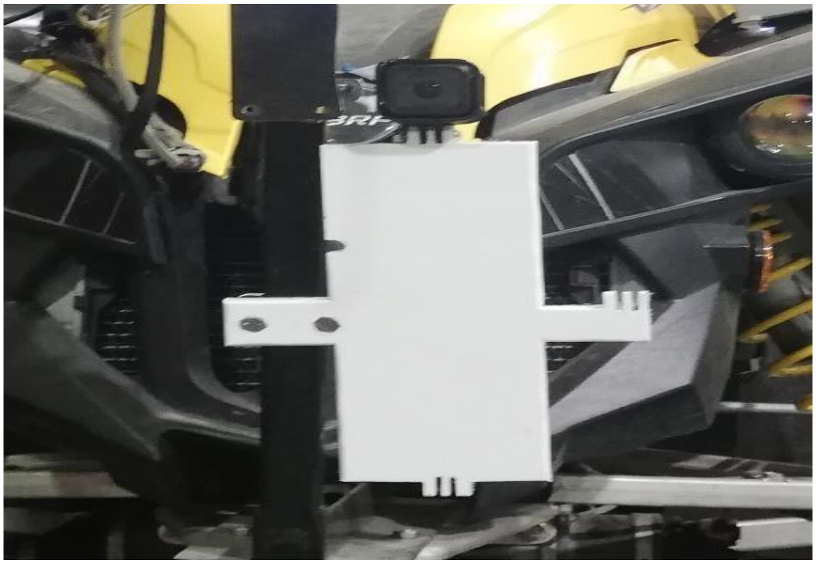


Fig 3. 1: Front facing mount

Fig 3. 2: An ATV with camera mounted on the field plot

The forward-facing camera was mounted to the existing overhead camera boom on the ATV (Fig.3.2); this overhead camera boom had been added to the ATV by the student agBOT team to mount a camera for a machine vison application. The mount is adjustable and the camera can be adjusted ranging from 0.5 to 2.0 m above ground.

Arrangements were made to use a summer fallow plot on the University of Manitoba's research fields at The Point on the eastern-most edge of the Fort Garry campus. Prior to the recording of each video footage, a total of 20 frisbees were placed along the path to be driven by the ATV. In total, there were 25 white frisbees that had been modified by painting red or green shapes (five distinct shapes) onto their tops (Fig.3.3).

Fig 3. 3: Symbols and colors on frisbees

A random generator was used to specify the placement of each frisbee for each unique trial. Table 1 shows the placement of the frisbees. For the 5th percentile & 20º tilt angle trial, for example, a frisbee with a red square was placed to the left of the path of travel at a distance 3m along the path of travel. A frisbee with a green circle was placed to the right of the path of travel at a distance 13m along the path of travel. There were a total of 10 frisbees placed along the path of travel to the right and left of the centerline of the path of travel, and an additional 10 frisbees placed along the return path of travel. There were an additional 5 frisbees placed immediately in front of the ATV along the centerline of the path of travel. The exact locations where these frisbees were located is provided in the final five rows in each section of Table 3.1, with "up" used to indicate frisbees that were placed along the initial path up the length of the field and "down" used to indicate frisbees that were placed along the path back down to the starting position. Video footage was generated by manually driving the ATV along pre-determined paths in the summer fallow plot.

Table 3. 1: Placement of frisbees for each trial

5th Percentile, 20°			5th Percentile, 30°			5th Percentile, 40°		
Shape/Color	Distance	Side	Shape/Color	Distance	Side	Shape/Color	Distance	Side
Square/Red	3	Left	Triangle/Green	2	Right	Circle/Red	3	Right
Circle/Green	13	Right	Octagon/Red	15	Right	Hexagram/Red	13	Right
Square/Green	26	Right	Circle/Green	25	Left	Square/Green	22	Left
Triangle/Red	37	Left	Triangle/Red	33	Left	Triangle/Green	32	Right
Triangle/Red	43	Left	Circle/Red	50	Left	Octagon/Red	47	Left
Hexagram/Red	60	Left	Hexagram/Green	51	Left	Hexagram/Green	53	Right
Hexagram/Green	69	Right	Hexagram/Red	62	Right	Octagon/Green	69	Right
Triangle/Green	79	Left	Octagon/Green	72	Right	Square/Red	79	Right
Square/Green	81	Right	Square/Green	82	Right	Circle/Green	90	Left
Octagon/Red	97	Left	Triangle/Red	92	Right	Square/Green	93	Left
Octagon/Red	3	Left	Octagon/Red	8	Right	Circle/Green	4	Right
Square/Red	17	Right	Circle/Green	20	Left	Triangle/Red	13	Left
Hexagram/Red	22	Right	Green/Square	29	Left	Circle/Green	26	Right
Circle/Green	40	Right	Triangle/Green	33	Right	Triangle/Green	37	Right
Square/Green	45	Left	Octagon/Green	46	Left	Octagon/Red	49	Left
Circle/Red	55	Left	Octagon/Red	55	Left	Hexagram/Green	58	Left
Triangle/Green	64	Right	Triangle/Red	65	Right	Square/Green	65	Right
Octagon/Green	77	Right	Circle/Red	76	Right	Hexagram/Red	76	Left
Circle/Green	83	Right	Square/Red	82	Left	Square/Red	83	Left
Octagon/Red	92	Right	Hexagram/Red	96	Right	Octagon/Green	95	Right
Circle/Red	10	Up	Square/Red	40	Up	Circle/Red	30	Up
Hexagram/Red	30	Up	Hexagram/Green	60	Up	Octagon/Red	50	Up
Triangle/Red	70	Up	Square/Green	60	Down	Hexagram/Red	60	Up
Hexagram/Green	20	Down	Hexagram/Red	70	Down	Triangle/Red	30	Down
Octagon/Green	60	Down	Circle/Green	90	Down	Triangle/Red	60	Down
95th Percentile, 20°			95th Percentile, 30°			95th Percentile, 40°		
Shape/color	Distance	Side	Shape/color	Distance	Side	Shape/color	Distance	Side
Triangle/Red	1	Left	Hexagram/Green	8	Left	Square/Green	2	Left
Square/Red	12	Left	Hexagram/Red	18	Right	Octagon/Red	18	Left
Hexagram/Red	24	Right	Circle/Green	22	Left	Circle/Green	25	Left
Square/Green	34	Right	Triangle/Green	34	Right	Hexagram/Red	32	Right
Hexagram/Green	43	Right	Octagon/Red	45	Right	Triangle/Red	46	Right
Square/Green	54	Left	Square/Green	60	Left	Triangle/Red	52	Left
Hexagram/Red	61	Right	Triangle/Red	67	Left	Triangle/Green	63	Right
Octagon/Green	80	Right	Octagon/Green	77	Left	Square/Green	71	Right
Octagon/Red	87	Left	Triangle/Red	86	Right	Hexagram/Red	89	Left
Circle/Red	95	Left	Circle/Red	96	Right	Square/Red	99	Left
Square/Red	1	Right	Circle/Green	1	Right	Octagon/Green	3	Left
Triangle/Red	20	Right	Hexagram/Red	17	Left	Triangle/Green	19	Right
Hexagram/Red	29	Left	Hexagram/Red	23	Left	Square/Red	30	Left
Triangle/Green	33	Right	Octagon/Green	33	Right	Hexagram/Red	33	Left
Octagon/Red	42	Right	Triangle/Green	50	Left	Circle/Red	46	Right
Square/Green	54	Left	Circle/Green	56	Right	Circle/Green	59	Right
Octagon/Green	68	Right	Octagon/Red	69	Right	Octagon/Red	63	Left
Circle/Green	79	Left	Triangle/Red	73	Right	Square/Green	74	Right
Octagon/Red	87	Right	Square/Green	89	Left	Hexagram/Green	81	Left
Circle/Red	97	Right	Hexagram/Green	95	Left	Triangle/Red	97	Left
Hexagram/Green	20	Up	Octagon/Red	0	Up	Circle/Green	10	Up

Circle/Green	80	Up	Square/Red	40	Up	Octagon/Red	70	Up
Circle/Green	100	Up	Square/Green	30	Down	Circle/Red	100	Up
Triangle/Red	10	Down	Circle/Red	60	Down	Hexagram/Green	50	Down
Triangle/Green	50	Down	Square/Red	80	Down	Octagon/Green	70	Down
Aerial shot, 20°			Aerial shot, 30°			Aerial shot, 40°		
Shape/color	Distance	Side	Shape/color	Distance	Side	Shape/color	Distance	Side
Circle/Green	5	Left	Hexagram/Red	9	Right	Octagon/Red	10	Right
Square/Green	19	Right	Octagon/Red	20	Left	Triangle/Red	18	Left
Circle/Red	22	Right	Square/Green	25	Left	Square/Red	27	Left
Square/Red	40	Right	Square/Red	39	Left	Triangle/Red	32	Right
Octagon/Red	44	Right	Circle/Green	41	Right	Triangle/Green	45	Left
Octagon/Green	56	Left	Octagon/Red	52	Right	Hexagram/Red	60	Left
Circle/Green	63	Right	Triangle/Red	91	Left	Square/Green	70	Right
Octagon/Red	79	Left	Hexagram/Green	72	Right	Circle/Green	77	Left
Triangle/Green	85	Left	Triangle/Green	84	Right	Octagon/Green	88	Right
Hexagram/Green	99	Left	Circle/Red	95	Right	Square/Green	92	Right
Octagon/Green	1	Left	Hexagram/Red	4	Right	Octagon/Red	5	Left
Square/Red	20	Left	Square/Red	17	Left	Square/Green	17	Left
Hexagram/Red	25	Right	Circle/Green	30	Left	Hexagram/Red	28	Right
Octagon/Red	33	Right	Circle/Red	33	Right	Triangle/Green	39	Right
Circle/Green	49	Left	Triangle/Red	48	Right	Octagon/Green	43	Left
Circle/Red	53	Left	Triangle/Green	60	Left	Hexagram/Red	60	Left
Hexagram/Green	61	Right	Square/Green	65	Right	Circle/Green	67	Left
Triangle/Red	71	Left	Hexagram/Green	76	Right	Circle/Green	79	Right
Square/Green	90	Right	Square/Green	81	Right	Square/Red	83	Right
Triangle/Green	96	Left	Triangle/Red	96	Right	Octagon/Red	93	Right
Square/Green	70	Up	Octagon/Red	30	Up	Hexagram/Green	40	Up
Hexagram/Red	90	Up	Octagon/Green	50	Up	Triangle/Red	50	Up
Triangle/Red	40	Down	Octagon/Green	50	Down	Circle/Red	80	Up
Triangle/Red	50	Down	Circle/Green	70	Down	Hexagram/Green	10	Down
Hexagram/Red	70	Down	Hexagram/Red	90	Down	Circle/Red	20	Down

Video footage was generated using nine different combinations of camera placement comprising of three camera tilt angles (20, 30 and 40º) and three camera heights (1.5, 1.75 and 2.0 m), yielding nine distinct image velocity conditions. The camera height of 1.5 m was selected to represent the sitting height of a 5th percentile male driver sitting on the ATV (Fig.3.4). The camera height of 1.75 m was selected to represent the sitting height of a 95th percentile male driver sitting on the ATV. Finally, the camera height of 2.0 m was selected to represent somewhat of an aerial (or overhead view). The ATV was manually driven at a velocity of 5 km/h from one end of the field to the other to obtain the video clips for the part one of the experimental protocol of the study; this produced videos approximately 60 s in duration.

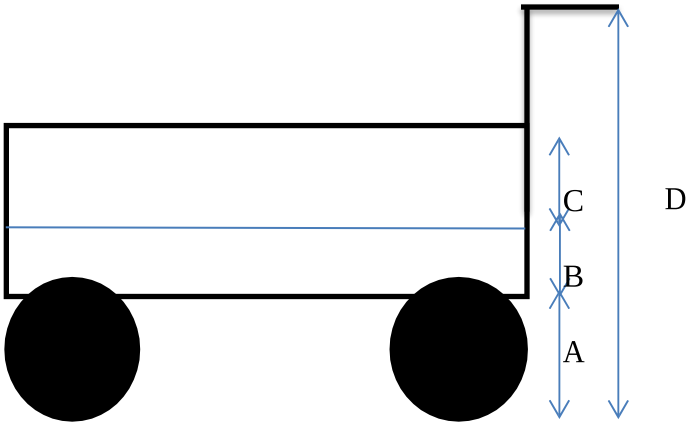


Fig 3. 4: Schematic showing how the camera heights were selected. A denotes the height from the ground surface to the foot-rest of the ATV (A = 30 cm), B is defined as "popliteal height", which is the distance from the base of the wheel to the underside of the thigh in the seated position (B_5 = 39.5 cm for a 5th percentile male and B_{95} = 49 cm for a 95th percentile male), C is sitting eye height (C_5 = 85 cm for a 5th percentile male and C_{95} = 96.5 cm for a 95th percentile male), and D denotes the highest possible placement of the camera using the mounting bracket that was designed; this has been described as the "aerial" view (D = 2.0 m above the ground). Thus the three camera heights were: $H_5 = A + B + C_5$; $H_{95} = A + B + C_{95}$; $H_{aerial} = D$.

For part two of the experimental protocol, the ATV was driven up the field, also at a velocity of 5 km/h, made a headland turn, and then returned to the starting edge of the field plot along a separate path. This produced videos of approximately 180 s in duration.

3.2 Experimental protocols

3.2.1 Effect of camera placement on "look-ahead" preference

This first part of the experimental protocol investigated the preferred look-ahead perspective using the live video recordings obtained from a field plot at the University of Manitoba (refer to previous section for details on production of the "look-ahead" videos). The video clips were to be watched by participants on a computer screen as a means of replicating the remote supervision task where the supervisor would rely on video to obtain real-time visual information from the environment during farming operations. There were two groups of participants recruited for this task (i.e., inexperienced agricultural machinery operators recruited from the university student population and experienced sprayer operators recruited from relevant producer groups) following protocols approved by the Human Ethics Board at the University of Manitoba. The participants had a task to watch two side-by-side videos having distinct "look-ahead" characteristics (created by varying camera height and tilt angle) and to indicate their preferred camera view. There were a total of 36 side-by-side videos to watch and they were asked to indicate preference as a means of providing real-time visual information during remote supervision of an autonomous agricultural machine.

Fig 3. 5: Screen shot of 2 video clips side by side on computer system

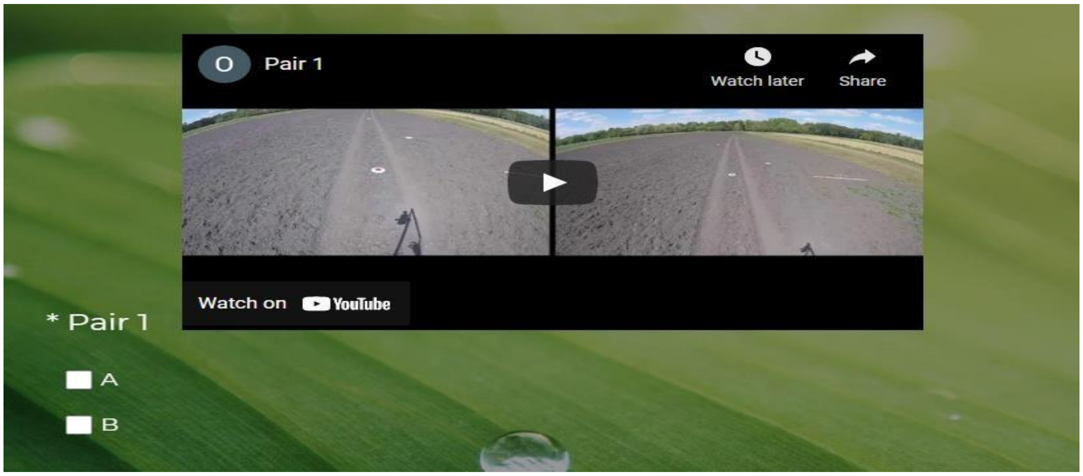
Twenty one test subjects with no requirement of previous experience of having operated an agricultural sprayer were recruited from the University of Manitoba student body as the first set of participants. The first nine test participants among these numbers were physically present in the lab at the University of Manitoba to complete their task and were able to interact with the principal investigator during completion of the experimental protocol. After watching the videos (which were 60s in duration), they were to indicate their preference (A or B) on the datasheet (Table 3.2) provided by the principal investigator in the lab.

Table 3. 2: Sample datasheet provided for the in-person participants in the lab for part one protocol

Pair 1	A	B	Pair 19	A	B
Pair 2	A	B	Pair 20	A	B
Pair 3	A	B	Pair 21	A	B
Pair 4	A	B	Pair 22	A	B
Pair 5	A	B	Pair 23	A	B

Pair 6	A	B	Pair 24	A	B
Pair 7	A	B	Pair 25	A	B
Pair 8	A	B	Pair 26	A	B
Pair 9	A	B	Pair 27	A	B
Pair	A	B	Pair 28	A	B
Pair	A	B	Pair 29	A	B
Pair	A	B	Pair 30	A	B
Pair	A	B	Pair 31	A	B
Pair	A	B	Pair 32	A	B
Pair	A	B	Pair 33	A	B
Pair	A	B	Pair 34	A	B
Pair	A	B	Pair 54	A	B
Pair	A	B	Pair 36	A	B

The remaining twelve participants completed an online evaluation of the recorded video clips through a survey link provided, as in-person data collection could not continue due to the Covid-19 pandemic. The online participants were unable to have any interaction with the principal investigator during this task, however, the experiment was designed using an online survey to reflect every scenario encountered during the in-person assessment. They were to equally indicate their preference (A or B) by a tick in the column provided in the online survey questionnaire (Fig 3.6&3.7).



* Pair 1

☐ A

☐ B

Fig 3. 6: Sample screenshot of online tick box for participants (Pair 1)

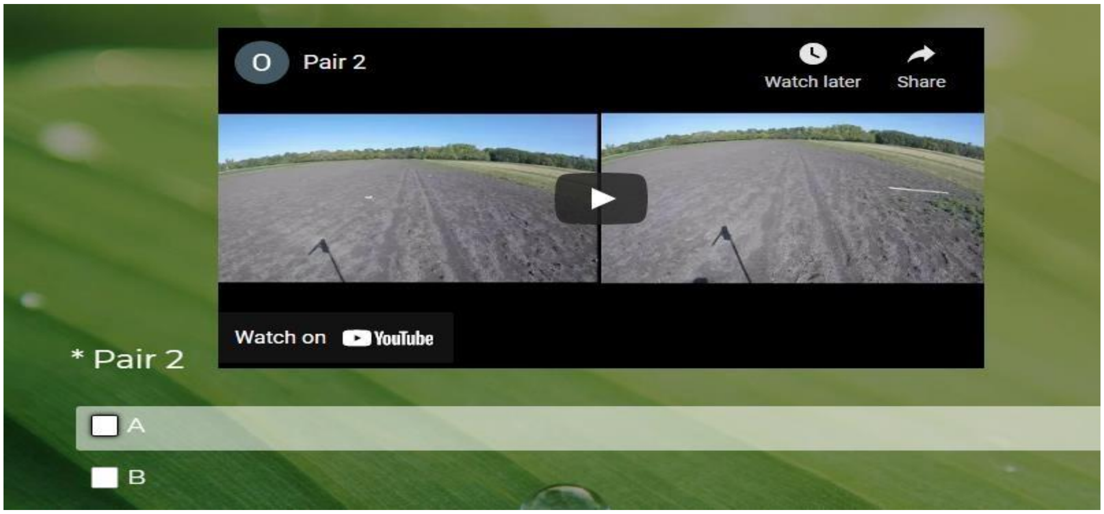


Fig 3. 7: Sample screenshot of online tick box for participants (Pair 2)

Every instruction required to complete the test was provided and described in the survey, which lasted approximately same duration as the in-person task. Figure 3.5 shows the screenshot of the two images side-by-side on the monitor for this protocol.

Subsequently, we intended to supplement the data from the first group of test subjects by recruiting experienced sprayer operators from the farming community. In total, five experienced sprayer operators participated in the first part of the experimental protocol, completing their tasks online through the survey link provided. The participants had previous experience of driving an agricultural sprayer, which ranged between 5 to 15 years and were recruited from the province of Manitoba. The only difference in the experimental protocol between the student participants and the participants who were experienced sprayer operators was that the survey link was modified so that the side-by-side video clips were displayed within the context of an automation interface (Fig.3.8).

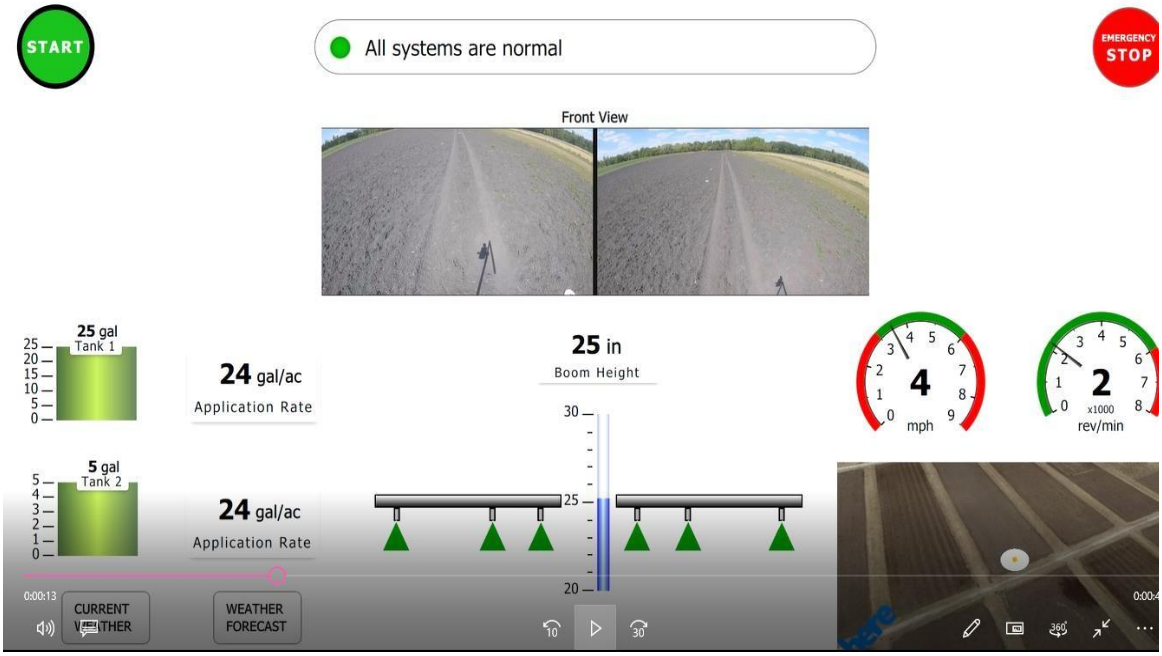


Fig 3. 8: Screen shot of 2 video clips side by side within the context of the automation interface

In analyzing the data from the protocol described above, I used a pairwise comparison technique to determine the camera placement that was preferred by the subject participants for both groups of participants (i.e., inexperienced machinery operators and experienced sprayer operators). This enabled me to determine which of the camera angles was preferred most often. Results from both the in-person and the online survey were pooled to yield a sample of 21 inexperienced machinery operators and 5 experienced sprayer operators.

3.2.2 Effect of camera placement on the difficulty of detecting and interpreting field information

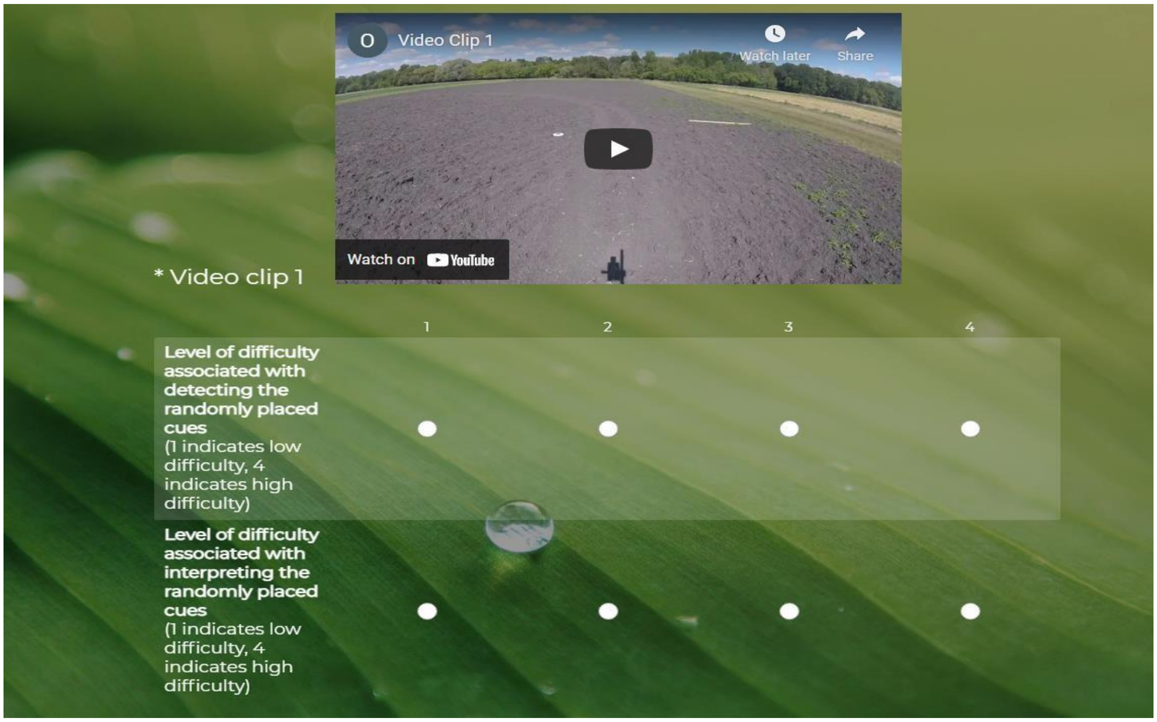
The second part of the experimental protocol investigated the effect of camera placement on the rate of detecting and interpreting the randomly placed frisbees from the video clips presented to the test subjects. The second part of the experimental protocol was completed immediately following the completion of the first part of the experimental protocol, therefore, the same group of participants completed both parts of the experimental protocol. The video clips were watched by the participant after which he or she was expected to rate the level of difficulty associated with detecting the randomly placed frisbees and the level of difficulty associated with interpreting the randomly placed frisbees. This will indicate the level of difficulty associated with detecting and interpreting detailed information from the field surface during an actual spraying operation. During the in-person tests, participants completed part one of the protocol and were asked to observe a break of approximately 5 min before proceeding to part two. This was to minimize the impact of fatigue on the second part of the experimental protocol. This scenario was also incorporated into the online survey as test subjects were advised to take a break of 5 min before continuing with the second part of the experimental protocol, although I have no means of determining whether participants observed this request during the online survey.

This part of the study included nine video clips (each 180s in duration) that were pre-recorded (each with 20 randomly placed frisbees laid on the field surface) and watched by participants. Participants are expected to watch a video of a sprayer moving across a field plot and were to rate the degree of difficulty associated with detecting and interpreting the symbols painted onto white frisbees. The two batches of participants required to perform the task here were approved by the Human Ethics Board of the University of Manitoba and were the same set of participants that carried out protocol one discussed above. The in-person participants recorded their choices on a data sheet provided by the principal investigator in the lab (Table 3.3), while the online set ticked the appropriate box within the online survey (Figs. 3.10&3.11).

Fig 3. 9: Screen shot of Part 2 video clips with frisbees appearing on the soil

Table 3. 3: Sample datasheet provided for the in-person participants in the lab for part two protocol

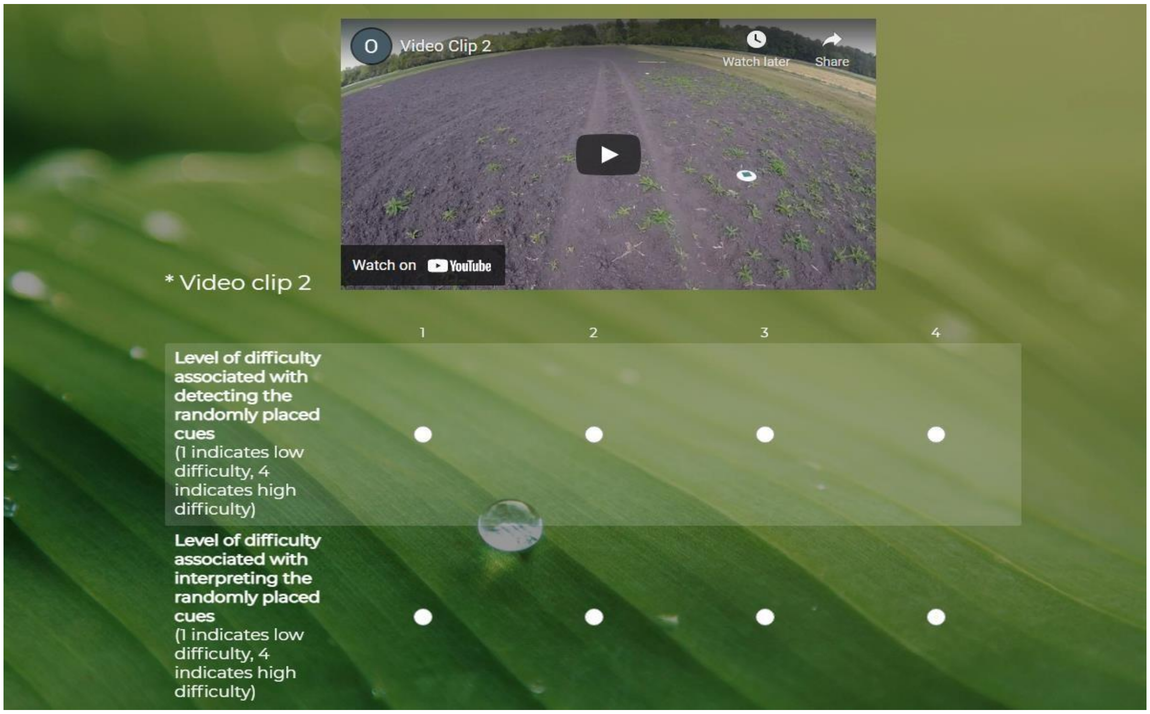
	(1 indicates low difficulty, 4 indicates high difficulty)				(1 indicates low difficulty, 4 indicates high difficulty)			
1.	1	2	3	4	1	2	3	4
2.	1	2	3	4	1	2	3	4
3.	1	2	3	4	1	2	3	4
4.	1	2	3	4	1	2	3	4
5.	1	2	3	4	1	2	3	4
6.	1	2	3	4	1	2	3	4
7.	1	2	3	4	1	2	3	4
8.	1	2	3	4	1	2	3	4
9.	1	2	3	4	1	2	3	4



* Video clip 1

	1	2	3	4
Level of difficulty associated with detecting the randomly placed cues (1 indicates low difficulty, 4 indicates high difficulty)	○	○	○	○
Level of difficulty associated with interpreting the randomly placed cues (1 indicates low difficulty, 4 indicates high difficulty)	○	○	○	○

Fig 3. 10: Sample screenshot of online tick box for participants (video clip 1)



* Video clip 2

	1	2	3	4
Level of difficulty associated with detecting the randomly placed cues (1 indicates low difficulty, 4 indicates high difficulty)	○	○	○	○
Level of difficulty associated with interpreting the randomly placed cues (1 indicates low difficulty, 4 indicates high difficulty)	○	○	○	○

Fig 3. 11: Sample screenshot of online tick box for participants (video clip 2)

After watching the videos presented, they were to indicate the level of difficulty in detecting and interpreting randomly-placed frisbees for each task using a four-point Likert scale with four indicating high difficulty. Within each journey across the field plot, there are 25 randomly placed white frisbees that were laid on the soil prior to collection of the video. Figure 3.9 shows a screenshot of one video clip containing the frisbees.

To also augment the data from the first group of test subjects, the five participants from the farming community who were experienced sprayer operators equally completed their task of watching the nine pre-recorded video clips through the online survey with the task of evaluating the autonomous interface showing a recording of a live video clips playing within the context of an automation interface. The screenshot in figure 3.12 shows the image of the automation interface with video playing for part two of the protocol.

Results from both the in-person and the online survey were also pooled together and the dataset were obtained for the 21 inexperienced machinery operators as well as the five experienced sprayer operators.

Fig 3. 12: Screen shot of part 2 video clips playing within the context of the automation interface

The average ratings from the responses collected (i.e., 1 to 4) from each participant (both students and experienced operators) were determined for each video clip and the video with the lowest value was taken as the one that would least contribute to the difficulty in detecting and interpreting the randomly placed frisbees.

3.3 Transitioning to online survey using Survey Monkey

Before the COVID-19 pandemic, the experimental protocol on the effect of image velocity on the situation awareness of a remote supervisor of an autonomous agricultural machine was designed to run with in-person participants coming to the lab to interact with the principal investigator while watching the video clips. As a result of the pandemic, we were no longer able to bring human participants into the lab to complete the experimental study. Therefore, an amendment was made to the experimental protocol to incorporate an online data collection process using an online tool, SurveyMonkey, to substitute for in-person data collection within the agricultural ergonomics laboratory. In this case, participants completed the experiment in strictly an online environment and had no chance of physical interaction with the principal investigator while completing their tasks. Data are presented separately for the 9 participants who completed the experimental protocol and the 12 participants who completed the experimental protocol using the online survey as a means of enabling me to determine whether the data could be pooled or whether they should be interpreted separately.

4.0 Experimental Results and Discussion

In the following sections, results of this study are presented. Two sets of data were gathered which corresponds to the two-part experimental protocols discussed in the previous chapter. Data for the effect of camera placement on the "look-ahead" perspective and effect of camera placement on the difficulty of detecting and interpreting field information were both gathered for analysis. For experimental protocol one, the alternative choice coefficient (discussed further in below section) values were calculated from the proportion of participants who selected each option (A or B) in the various side-by-side comparisons. For the second protocol, participants were to rate the degree of difficulty associated with detecting randomly placed frisbees and the degree of difficulty associated with interpreting the randomly placed frisbees based on a four-point Likert scale (where a score of one designates the lowest difficulty).

For each protocol mentioned above, the data were grouped into three experimental cohorts based on the different test location and the experience of the participants recruited (i.e., In-person Inexperienced, Online Inexperienced and Online Experienced). Of the initial 21 participants recruited from the student population at the University of Manitoba, the first nine participants were physically present in the lab while the subsequent twelve participants completed the experiment online (due to the start of the pandemic); the data have been presented separately to reflect potential differences arising from the difference in experimental environment. In a subsequent study, five experienced sprayer operators completed the experimental protocol online.

Alternative choice coefficients are presented for each of the three experimental cohorts in Table 4.1 (detailed calculations of the alternative choice coefficients are presented in Appendix 1). Tables 4.2 and 4.3 present the mean Likert scores for each of the three experimental cohorts.

Table 4. 1: Alternative choice coefficients calculated for nine combinations of camera height and tilt angle and for three experimental cohorts (i.e., In-person Inexperienced, Online Inexperienced and Online Experienced)

Camera Height (m)	Tilt Angle (º)	Alternative Choice Coefficient (ACC)		
		In-person Inexperienced (n=9)	Online Inexperienced (n=12)	Online Experienced (n=5)
1.5	20	0.09	0.09	0.12
1.5	30	0.16	0.14	0.14
1.5	40	0.10	0.10	0.11
1.75	20	0.08	0.09	0.08
1.75	30	0.18	0.16	0.15
1.75	40	0.06	0.09	0.08
2.0	20	0.07	0.07	0.08
2.0	30	0.20	0.17	0.16
2.0	40	0.06	0.09	0.08

Table 4. 2: Mean Likert scores calculated for the task of detecting cues for nine combinations of camera height and tilt angle and for three experimental cohorts (i.e., In-person Inexperienced, Online Inexperienced and Online Experienced)

Camera Height (m)	Tilt Angle (º)	Mean Likert Score (Detecting Cues)		
		In-person Inexperienced (n=9)	Online Inexperienced (n=12)	Online Experienced (n=5)
1.5	20	1.50	1.44	1.80
1.5	30	1.08	1.11	1.20
1.5	40	2.42	2.56	2.40
1.75	20	1.67	2.00	2.00
1.75	30	1.08	1.11	1.60
1.75	40	2.67	3.00	2.40
2.0	20	1.67	1.78	2.00
2.0	30	1.17	1.00	1.40
2.0	40	2.83	3.11	3.20

Table 4. 3: Mean Likert Scores calculated for the task of interpreting cues for nine combinations of camera height and tilt angle and for three experimental cohorts (i.e., In-person Inexperienced, Online Inexperienced and Online Experienced)

Camera Height (m)	Tilt Angle (º)	Mean Likert Score (Interpreting Cues)		
		In-person Inexperienced	Online Inexperienced	Online Experienced
1.5	20	1.50	1.56	1.80
1.5	30	1.08	1.11	1.20
1.5	40	2.50	2.56	2.40
1.75	20	2.00	2.00	2.00
1.75	30	1.42	1.33	1.40
1.75	40	2.58	3.00	2.60
2.0	20	1.67	2.11	2.20
2.0	30	1.42	1.00	1.60
2.0	40	2.75	3.11	2.80

Statistical analysis (Tables 4.4-4.6) using analysis of variance (ANOVA) indicated that the data from these different experimental cohorts could be grouped together (i.e., 26 datasets comprising 9 In-person Inexperienced, 12 Online Inexperienced and 5 Online Experienced) and treated as a single population. The p-values obtained (p = 0.432, p= 0.281, p= 0.291) suggest there are no significant differences between the experimental cohorts (i.e., In-person Inexperienced, Online Inexperienced and Online Experienced) in terms of the task of watching all the pre-recorded video clips presented before them. Therefore, the data have been pooled together for further analysis to increase the sample size.

Table 4. 4: A summary of the ANOVA analysis to determine if there are any significance difference in the data based on location and experience of the operator for protocol one

Tests of Between-Subjects Effects

Dependent Variable: Alternative choice coefficient (ACC)

Source	Type III Sum of	Df	Mean Square	F	Sig.	Partial Eta

	Squares					Squared
Corrected Model	.005[a]	3	0.002	0.951	0.432	0.11
Intercept	0.11	1	0.11	59.092	0	0.72
Location and experience	0.005	3	0.002	0.951	0.432	0.11
Error	0.043	23	0.002			
Total	0.381	27				
Corrected Total	0.048	26				

Table 4. 5: A summary of the ANOVA analysis to determine if there are any significance difference in the data based on location and experience of the operator for protocol two (degree of difficulty in detecting frisbees)

Tests of Between-Subjects Effects

Dependent Variable: Rated average difficulty in detecting frisbees

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	1.851[a]	3	0.617	1.357	0.281	0.150
Intercept	55.515	1	55.515	122.086	0.000	0.841
Location and experience	1.851	3	0.617	1.357	0.281	0.150
Error	10.458	23	0.455			
Total	109.379	27				

Corrected Total	12.310	26

Table 4. 6: A summary of the ANOVA analysis to determine if there are any significance difference in the data based on location and experience of the operator for protocol two (degree of difficulty in interpreting frisbees)

Tests of Between-Subjects Effects

Dependent Variable: Rated average difficulty in interpreting frisbees

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	1.524^a	3	0.508	1.322	0.291	0.147
Intercept	57.796	1	57.796	150.457	0.000	0.867
Location and experience	1.524	3	0.508	1.322	0.291	0.147
Error	8.835	23	0.384			
Total	113.200	27				
Corrected Total	10.359	26				

4.1 Camera placement based on preferred "look-ahead" position

The data from this section were analyzed using the unranked pairwise comparison technique used in making decisions by comparing data in pairs to obtain the best option. With this technique, each option is compared one-by-one with all other options, with a value of one assigned to the preferred option while a value of zero is assigned to the less-preferred option. Once all side-by-side comparisons are made, alternative choice coefficients (ACC) are calculated for each of the options considered (Niec et al. 2010; Mulder 2018); the option with the greatest alternative choice coefficient is deemed to be the most preferred option. This method has also been used in research where paired images were presented to participants to draw conclusions on the best outcome as the method represents an accurate assessment of the data analysis and is generally considered a suitable method for decision-making for studies involving preference (Phelps et. al 2015).

In this study, nine options were considered (i.e., the nine combinations of camera height and tilt angle). This yielded a total of 36 side-by-side comparisons. In each of the 36 side-by-side comparisons, participants were asked to make a choice of either A (left image) or B (right image) to indicate their preference after watching two distinct video footages placed side by side on the system. The pairs of video clips were randomized to ensure that participants could not anticipate the next pair of video clips during the experiment. For example, the video clips presented as pair one to the test subjects was a video with a combination of the third and eighth image velocity conditions (video clips 3 on the left screen and 8 on the right screen) and the participants would have to choose either A or B on the datasheet which corresponds to either video clip 3 or 8. For all the participants considered, a count of the choices were then obtained by replacing the 'A' or 'B' selected with each of the actual image velocity conditions. This was used to calculate the proportion of participants who preferred each view relative to each other and these proportions were then reported in decimal form.

The rationale for this decision was to determine the best choice of look-ahead views from each available look-ahead combination presented before each participant. The alternative choice coefficients (ACC) were then calculated and the option with the highest ACC indicated the most preferred "look-ahead" position. For this study, the ACC values (Table 4.7) for combined datasets were calculated from the proportions of the responses obtained for each option A or B indicating preference of view from each of the nine video combinations of camera placement (i.e., height and tilt angle). From the proportions obtained, we also assigned a value of one and zero to the responses of individual participants to create a dummy alternative. The equation for ACC can be expressed as below for each of the nine unique camera placement conditions:

$$\mathrm{ACC}_1 = \frac{A1}{\sum A1{:}A9}$$

where $A_1 = V_{1,2} + V_{1,3} + V_{1,4} + V_{1,5} + V_{1,6} + V_{1,7} + V_{1,8} + V_{1,9} + V_{1,D}$,

V is the proportion of the responses obtained from each option of paired video clips (A or B), and D is the dummy alternative created with a value of 1 and 0 added to each proportion.

$$ACC_2 = \frac{A2}{\sum A1{:}A9}$$

$A_2 = V_{2,3} + V_{2,4} + V_{2,5} + V_{2,6} + V_{2,7} + V_{2,8} + V_{2,9} + V_{2,D}$

$$ACC_3 = \frac{A3}{\sum A1{:}A9}$$

$A_3 = V_{3,4} + V_{3,5} + V_{3,6} + V_{3,7} + V_{3,8} + V_{3,9} + V_{3,D}$.

Table 4. 7: Calculated ACC value for combined participants

Pair	Alternative										Check Sum
	1	2	3	4	5	6	7	8	9	D	
1,2	0.12	0.88									1.0
1,3	0.85		0.15								1.0
1,4	0.65			0.35							1.0
1,5	0.08				0.92						1.0
1,6	0.42					0.58					1.0
1,7	0.62						0.38				1.0
1,8	0.12							0.88			1.0
1,9	0.50								0.50		1.0
1,D	1.0									0	1.0
2,3		0.88	0.12								1.0
2,4		0.88		0.12							1.0
2,5		0.15			0.85						1.0
2,6		0.88				0.12					1.0
2,7		0.92					0.08				1.0
2,8		0.12						0.88			1.0
2,9		0.88							0.12		1.0
2,D		1.0								0	1.0
3,4			0.88	0.12							1.0

3,5			0.12		0.88						1.0
3,6			0.77			0.23					1.0
3,7			0.85				0.15				1.0
3,8			0.23					0.77			1.0
3,9			0.54						0.46		1.0
3,D			1.0							0	1.0
4,5				0.12	0.88						1.0
4,6				0.81		0.19					1.0
4,7				0.77			0.23				1.0
4,8				0.15				0.85			1.0
4,9				0.50					0.50		1.0
4,D				1.0						0	1.0
5,6					0.92	0.08					1.0
5,7					0.92		0.08				1.0
5,8					0.15			0.85			1.0
5,9					0.88				0.12		1.0
5,D					1.0					0	1.0
6,7						0.50	0.50				1.0
6,8						0.12		0.88			1.0
6,9						0.65			0.35		1.0
6,D						1.0				0	1.0
7,8							0.12	0.88			1.0
7,9							0.58		0.42		1.0
7,D							1.0			0	1.0
8,9								0.92	0.08		1.0
8,D								1.0		0	1.0
9,D									1.0	0	1.0
Sum	4.36	6.59	4.66	3.94	7.40	3.47	3.12	7.91	3.55	0	45
ACC	0.10	0.15	0.10	0.09	0.16	0.08	0.07	0.18	0.08	0	1.0

Note: Alternative 1=1.5m,20º, Alternative 2=1.5m,30º, Alternative 3=1.5m,40º, Alternative 4=1.75m,20º, Alternative 5=1.75m,30º, Alternative 6=1.75m,40º, Alternative 7=2.0m,20º, Alternative 8=2.0m,30º, Alternative 9=2.0m,40º, Alternative D=Dummy.

Data collected from the twenty-six participants were further subjected to statistical analysis to obtain the optimum camera angle. I used Analysis of variance (ANOVA) to obtain the effects of camera height, camera tilt angle on the alternative choice coefficient (ACC) values (Table 4.8). The effects of both camera tilt angle and camera height were highly significant ($p < 0.05$ for both) on the ACC. There was also an interaction between these two factors with $p < 0.05$.

A multiple comparison of means was used to analyze the data further (Table 4.9). The analysis indicated the effect of camera height is significant (Tukey's HSD Test, α =0.05) while Table 4.10 showed that the camera height of 1.5 m is different from the other two heights assessed.

Table 4. 8: A summary of ANOVA analysis indicating the effects of camera height, camera tilt angle on Alternative choice coefficient

Tests of Between-Subjects Effects

Dependent Variable: ACC

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	.046[a]	8	0.006	4.33192E+01	3.3483E-10	0.951
Intercept	0.333	1	0.333	2.53226E+03	8.0881E-21	0.993
Camera height	0.001	2	0.001	4.96630E+00	1.9162E-02	0.356
Camera angle	0.039	2	0.020	1.48613E+02	6.4542E-12	0.943
Camera height * camera angle	0.005	4	0.001	9.84856E+00	2.1067E-04	0.686
Error	0.002	18	0.000			
Total	0.381	27				
Corrected Total	0.048	26				

a. R Squared = .951 (Adjusted R Squared = .929)

Table 4. 9: A summary of the statistical multiple comparison of mean of alternative choice coefficient (ACC) on camera height

Dependent Variable: ACC

Tukey HSD

(I) camera height		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence interval Lower band	95% Confidence interval Upper band
1.50	1.75	0.00848	0.005409	2.84192E-01	-0.00532	0.02229
	2.00	.01705*	0.005409	1.45164E-02	0.00324	0.03085
1.75	1.50	-0.00848	0.005409	2.84192E-01	-0.02229	0.00532
	2.00	0.00856	0.005409	2.78301E-01	-0.00524	0.02236
2.0	1.50	-.01705*	0.005409	1.45164E-02	-0.03085	-0.00324
	1.75	-0.00856	0.005409	2.78301E-01	-0.02236	0.00524

Based on observed means. The error term is Mean Square (Error) = .000. *. The mean difference is significant at the .05 level.

Similarly, Table 4.11 presented a multiple comparison of means to analyze the effect of camera tilt angle on the ACC which is significant (Tukey's HSD Test, α =0.05) while Table 4.12 showed that the camera angle of 30º is different from the other two camera angles assessed.

Table 4. 10: A summary of the statistical multiple comparison of mean with different camera height

Tukey HSD[a,b]

Camera height	N	Subset 1	Subset 2
2.00	9	0.10258	
1.75	9	0.11114	0.11114
1.50	9		0.11962
Sig.		0.278	0.284

Based on observed means. The error term is Mean Square (Error) = .000. Means for groups in homogeneous subsets are displayed. a. Uses Harmonic Mean Sample Size = 9.000; b. Alpha = .05.

Table 4. 11: A summary of the statistical multiple comparison of mean of alternative choice coefficient (ACC) on camera tilt angle

Multiple Comparisons

Dependent Variable: ACC

Tukey HSD

(I) camera angle		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence interval Lower band	95% Confidence interval Upper band
20	30	-.07742*	0.005409	5.38029E-09	-0.09123	-0.06362
	40	0.00629	0.005409	4.89703E-01	-0.00752	0.02009
30	20	.07742*	0.005409	5.38029E-09	0.06362	0.09123
	40	.08371*	0.005409	5.32239E-09	0.06991	0.09752
40	20	-0.00629	0.005409	4.89703E-	-0.02009	0.00752

				01		
	30	-.08371*	0.005409	5.32239E-09	-0.09752	-0.06991

Based on observed means. The error term is Mean Square (Error) = .000. *. The mean difference is significant at the .05 level.

Table 4. 12: A summary of the statistical multiple comparison of mean with different camera tilt angle

Tukey HSD[a,b]

Camera angle	N	Subset	
		1	2
40	9	0.08111	
20	9	0.08740	
30	9		0.16482
Sig.		0.490	1.000

Means for groups in homogeneous subsets are displayed. Based on observed means. The error term is Mean Square (Error) = .000.

a. Uses Harmonic Mean Sample Size = 9.000; b. Alpha = .05.

Based on the responses from the participants recruited for part one protocol in this study, videos with the look-ahead position of 30º were selected from the nine combination of camera placement as the ones with the highest ACC values and, therefore, 30º was considered as the preferred camera tilt angle.

4.2 Camera placement based on difficulty of detecting and interpreting field information

For the experimental protocol on degree of detecting and interpreting randomly placed frisbees, participants were required to provide ratings of each video footages watched based on i) the degree of difficulty in detecting the randomly placed objects on the field and ii) the degree of difficulty in interpreting the randomly placed objects on the field. Each task is based on the four-point Likert scale, where one signifies the lowest rating. The average ratings obtained for each participant were then calculated and this was plotted (figure 4.1) to determine the camera placements (i.e., height and tilt angle) with the lowest level of difficulty in detecting field information as the preferred camera tilt angle.

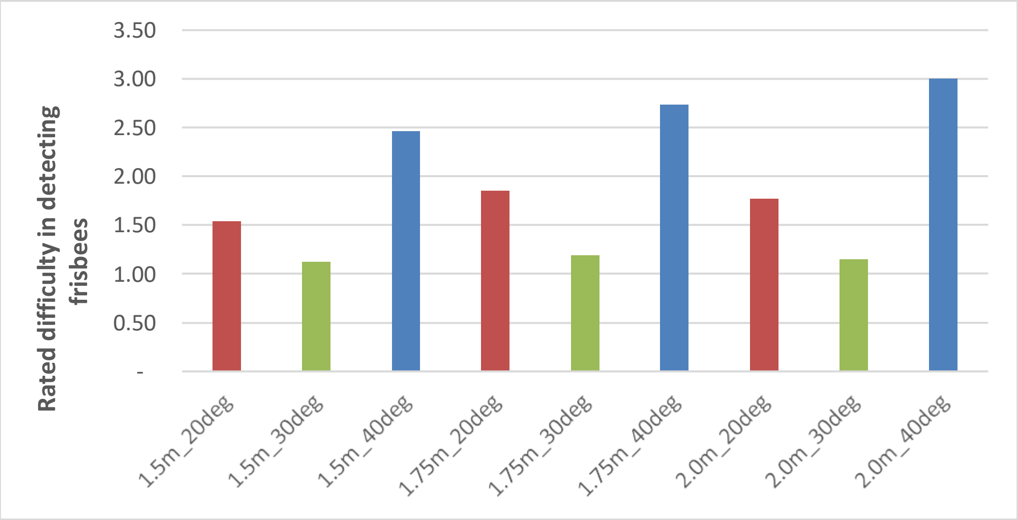


Fig 4. 1: Degree of difficulty in detecting frisbees between different subjects

Similarly, the plot of degree of difficulty in interpreting randomly placed frisbees on the field (figure 4.2) showed that the camera position associated with the 30º tilt angle produced the least difficulty and thus, the preferred camera angle.

Therefore, based on data plotted from the in-person, online and the experienced sprayer operators combined, the look-ahead conditions with the least difficulty in interpreting and detecting field information were those from the videos with 30º camera.

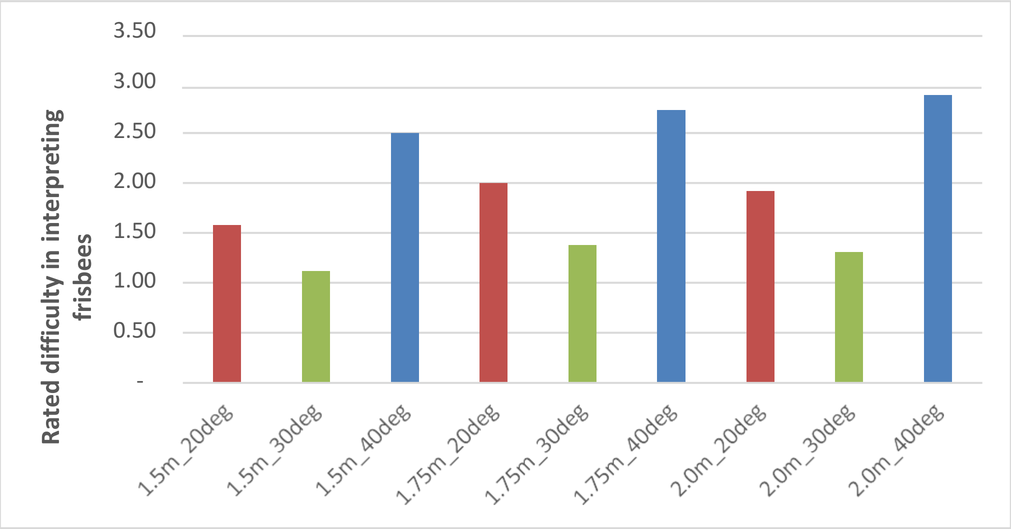


Fig 4. 2: Degree of difficulty in interpreting frisbees between different subjects

For part two protocol of this study, ANOVA was also used to determine the effects of camera height, camera tilt angle on the rated degree of difficulty in detecting (Table 4.13) and interpreting (Table 4.14) field information. The effects of both camera tilt angle and camera height were highly significant as well ($p < 0.05$ for both) on the rated difficulty. There was also an interaction between these two factors with ($p < 0.05$).

Table 4. 13: A summary of ANOVA analysis indicating the effects of camera height, camera tilt angle on rated average of detecting frisbees

Tests of Between-Subjects Effects

Dependent Variable: Rated average difficulty in detecting frisbees

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	11.579[a]	8	1.447	35.668	0.000	0.941
Intercept	97.069	1	97.069	2392.074	0.000	0.993
Camera height	0.424	2	0.212	5.227	0.016	0.367
Camera	10.866	2	5.433	133.889	0.000	0.937

angle						
Camera height * camera angle	0.289	4	0.072	1.778	0.177	0.283
Error	0.730	18	0.041			
Total	109.379	27				
Corrected Total	12.310	26				
a. R Squared = .941 (Adjusted R Squared = .914)						

Table 4. 14: A summary of ANOVA analysis indicating the effects of camera height, camera tilt angle on rated average of interpreting frisbees

Tests of Between-Subjects Effects

Dependent Variable: Rated average difficulty in interpreting frisbees

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	9.744[a]	8	1.218	35.655	1.70738E-09	0.941
Intercept	102.841	1	102.841	3010.381	1.72186E-21	0.994
Camera height	0.582	2	0.291	8.517	2.49501E-03	0.486
Camera angle	9.105	2	4.552	133.257	1.62373E-11	0.937
Camera height * camera angle	0.058	4	0.014	0.422	7.90386E-01	0.086
Error	0.615	18	0.034			
Total	113.200	27				
Corrected Total	10.359	26				

a. R Squared = .941 (Adjusted R Squared = .914)

A multiple comparison of means was also used to analyze the data from part two protocol further (Table 4.15). The analysis indicated the effect of camera height is significant on the average rated difficulty (Tukey's HSD Test, α =0.05) while Table 4.16 and Table 4.17 showed all the camera angles were different from others for both average difficulty in detecting and interpreting frisbees. The results and analysis from this section further provides more evidence to support the conclusion obtained from the section on look-ahead perspectives stating the 30º camera angle as the preferred tilt angle.

Table 4. 15: A summary of the statistical multiple comparison of mean with different camera tilt angle

Multiple Comparisons

Dependent Variable: Rated average difficulty in detecting frisbees

Tukey HSD

(I) camera angle		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence interval Lower band	95% Confidence interval Upper band
20	30	.56667*	0.094961	3.43703E-05	0.32431	0.80902
	40	-.96975*	0.094961	2.40677E-08	-1.21211	-0.72740
30	20	-.56667*	0.094961	3.43703E-05	-0.80902	-0.32431
	40	-1.53642*	0.094961	5.31137E-09	-1.77878	-1.29406
40	20	.96975*	0.094961	2.40677E-08	0.72740	1.21211
	30	1.53642*	0.094961	5.31137E-	1.29406	1.77878

09

Based on observed means. The error term is Mean Square (Error) = .041. *. The mean difference is significant at the .05 level.

Table 4. 16: A summary of the statistical multiple comparison of average difficulty in detecting frisbees on camera tilt angle

Tukey HSD^{a,b}				
Camera angle	N	Subset		
		1	2	3
30	9	1.19506		
20	9		1.76173	
40	9			2.73148
Sig.		1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed. Based on observed means. The error term is Mean Square (Error) = .041. a. Uses Harmonic Mean Sample Size = 9.000; b. Alpha = .05.

In terms of the camera height, the analysis from Table 4.18 showed that camera height of 2.0 m was rated as one with least difficulty in detecting frisbees while Table 4.19 showed the camera height of 1.5 m was rated as one with least difficulty in interpreting frisbees.

Table 4. 17: A summary of the statistical multiple comparison of average difficulty in interpreting frisbees on camera tilt angle

Tukey HSD^{a,b}				
Camera angle	N	Subset		
		1	2	3
30	9	1.28457		
20	9		1.87037	
40	9			2.70000
Sig.		1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed. Based on observed means. The error term is Mean Square (Error) = .041. a. Uses Harmonic Mean Sample Size = 9.000; b. Alpha = .05.

Table 4. 18: A summary of the statistical multiple comparison of mean with different camera height for rated difficulty in detecting frisbees

Tukey HSD^{a,b}			
Camera height	N	Subset	
		1	2
1.50	9	1.72346	
1.75	9	1.94753	1.94753
2.00	9		2.01728
Sig.		0.073	0.747

Means for groups in homogeneous subsets are displayed. Based on observed means. The error term is Mean Square (Error) = .000. a. Uses Harmonic Mean Sample Size = 9.000; b. Alpha = .05.

Table 4. 19: A summary of the statistical multiple comparison of mean with different camera height for rated difficulty in interpreting frisbees

Tukey HSD^{a,b}			
Camera height	N	Subset	
		1	2
1.50	9	1.74506	
1.75	9		2.03704
2.00	9		2.07284
Sig.		1.000	0.912

Means for groups in homogeneous subsets are displayed. Based on observed means. The error term is Mean Square (Error) = .000. a. Uses Harmonic Mean Sample Size = 9.000; b. Alpha = .05.

6.0 Conclusions

As a reminder to the reader, the objective of this research was to determine the influence of camera placement on the situation awareness of the remote supervisor of an autonomous agricultural machine. More specifically, the research was conducted:

1. To determine the camera placement that was preferred by the subject during the remote supervision task.
2. To determine the camera placement that least contributed to the difficulty of detecting and interpreting randomly-placed cues during the remote supervision task.
3. To determine whether the level of experience of the subject with respect to operation of agricultural sprayers has any influence on the experimental results.

Measures of situation awareness were used to determine the camera placement that maximizes the situation awareness for participants remotely supervising an agricultural sprayer. Camera placement which was measured as a combination of camera height and camera tilt angle was observed to influences the look-ahead views observed by persons supervising the machines.

In terms of the camera position, the participants preferred a camera tilt angle of 30º because it gave the best look-ahead distance while the camera heights of 1.5m was the preferred camera height.

For the degree of difficulty in detecting and interpreting frisbees, the statistical results indicated no significance difference between the various camera angles considered. The test subjects however rated the 2.0m camera height as the camera height that provided the least difficulty in detecting frisbees while 1.5m camera height was rated as the camera height that provided the least difficulty in interpreting field information.

For all data collected and analyzed in this study, there was no significant difference between the levels of responses based on the experienced of the subjects with respect to operating agricultural sprayers.

Overall, the result of this experimental study indicated that the look-ahead cameras on an AAMs should be placed at a tilt angle of 30 º and height of 1.5 m above the ground to enable the remote supervisor glean the best real-time visual information of the environment.

7.0 Recommendations for future work

1. Small number of experienced operators should be employed to remotely supervise the spraying task on the field with the actual mounting of the GoPro camera to confirm the camera placement that maximizes the situation awareness of the operator.
2. A digital rotating camera at 360 degree views could be used to capture the images on the field to improve the quality of the video which will allow the participants to have a better view of the field. This is likely to also provide better supervision to operator in actual field operation.

3. More University students could be recruited in the future for similar study to increase the sample size since it is easier to get more numbers while the few experienced operators could perform the subsequent field testing based on the results obtained.

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Appendix A Calculation of the Alternative Choice Coefficients for In-person Inexperienced

Pair	Alternative										Check Sum
	1	2	3	4	5	6	7	8	9	D	
1,2	0.00	1.0									1.0
1,3	0.78		0.22								1.0
1,4	0.67			0.33							1.0
1,5	0.00				1.0						1.0
1,6	0.56					0.44					1.0
1,7	0.67						0.33				1.0
1,8	0.00							1.0			1.0
1,9	0.56								0.44		1.0
1,D	1.0									0.00	1.0
2,3		1.0	0.00								1.0
2,4		1.0		0.00							1.0
2,5		0.00			1.0						1.0
2,6		1.0				0.00					1.0
2,7		1.0					0.00				1.0
2,8		0.00						1.0			1.0
2,9		1.0							0.00		1.0
2,D		1.0								0.00	1.0
3,4			1.0	0.00							1.0
3,5			0.00		1.0						1.0
3,6			0.78			0.22					1.0
3,7			0.78				0.22				1.0
3,8			0.11					0.89			1.0
3,9			0.67						0.33		1.0
3,D			1.0							0.00	1.0
4,5				0.00	1.0						1.0
4,6				0.78		0.22					1.0
4,7				0.78			0.22				1.0
4,8				0.00				1.0			1.0
4,9				0.67					0.33		1.0
4,D				1.0						0.00	1.0
5,6					1.0	0.00					1.0
5,7					0.89		0.11				1.0

5,8					0.11			0.89			1.0
5,9					0.89				0.11		1.0
5,D					1.0					0.00	1.0
6,7						0.33	0.67				1.0
6,8						0.00		1.0			1.0
6,9						0.67			0.33		1.0
6,D						1.0				0.00	1.0
7,8							0.00	1.0			1.0
7,9							0.67		0.33		1.0
7,D							1.0			0.00	1.0
8,9								1.0	0.00		1.0
8,D								1.0		0.00	1.0
9,D									1.0	0.00	1.0
Sum	4.24	7.0	4.56	3.56	7.89	2.88	3.22	8.78	2.87	0.00	45
ACC	0.09	0.16	0.10	0.08	0.18	0.06	0.07	0.20	0.06	0.00	1.0

Appendix B Calculation of the Alternative Choice Coefficients for Online Inexperienced

Pair	Alternative										Check Sum
	1	2	3	4	5	6	7	8	9	D	
1,2	0.17	0.83									1.0
1,3	0.92		0.08								1.0
1,4	0.58			0.42							1.0
1,5	0.08				0.92						1.0
1,6	0.25					0.75					1.0
1,7	0.50						0.50				1.0
1,8	0.17							0.83			1.0
1,9	0.42								0.58		1.0
1,D	1.0									0.00	1.0
2,3		0.83	0.17								1.0
2,4		0.83		0.17							1.0
2,5		0.25			0.75						1.0
2,6		0.83				0.17					1.0
2,7		0.92					0.08				1.0
2,8		0.17						0.83			1.0
2,9		0.83							0.17		1.0
2,D		1.0								0.00	1.0
3,4			0.83	0.17							1.0
3,5			0.17		0.83						1.0
3,6			0.75			0.25					1.0
3,7			0.92				0.08				1.0
3,8			0.25					0.75			1.0
3,9			0.42						0.58		1.0
3,D			1.0							0.00	1.0
4,5				0.17	0.83						1.0
4,6				0.83		0.17					1.0
4,7				0.67			0.33				1.0
4,8				0.25				0.75			1.0
4,9				0.42					0.58		1.0
4,D				1.0						0.00	1.0
5,6					0.92	0.08					1.0
5,7					1.0		0.00				1.0
5,8					0.17			0.83			1.0

5,9					0.92				0.08		1.0
5,D					1.0					0.00	1.0
6,7						0.58	0.42				1.0
6,8						0.17		0.83			1.0
6,9						0.67			0.33		1.0
6,D						1.0				0.00	1.0
7,8							0.17	0.83			1.0
7,9							0.42		0.58		1.0
7,D							1.0			0.00	1.0
8,9								0.92	0.08		1.0
8,D								1.0		0.00	1.0
9,D									1.0	0.00	1.0
Sum	4.09	6.49	4.59	4.1	7.34	3.84	3.0	7.57	3.98	0.00	45
ACC	0.09	0.14	0.10	0.09	0.16	0.09	0.07	0.17	0.09	0.00	1.0

Appendix C Calculation of the Alternative Choice Coefficients for Online Experienced

Pair	Alternative										Check
	1	2	3	4	5	6	7	8	9	D	Sum
1,2	0.2	0.8									1.0
1,3	0.8		0.2								1.0
1,4	0.8			0.2							1.0
1,5	0.2				0.8						1.0
1,6	0.6					0.4					1.0
1,7	0.8						0.2				1.0
1,8	0.2							0.8			1.0
1,9	0.6								0.4		1.0
1,D	1.0									0.00	1.0
2,3		0.8	0.2								1.0
2,4		0.8		0.2							1.0
2,5		0.2			0.8						1.0
2,6		0.8				0.2					1.0
2,7		0.8					0.2				1.0
2,8		0.2						0.8			1.0
2,9		0.8							0.2		1.0
2,D		1.0								0.00	1.0
3,4			0.8	0.2							1.0
3,5			0.2		0.8						1.0
3,6			0.8			0.2					1.0
3,7			0.8				0.2				1.0
3,8			0.8					0.2			1.0
3,9			0.6						0.4		1.0
3,D			1.0							0.00	1.0
4,5				0.2	0.8						1.0
4,6				0.6		0.4					1.0
4,7				0.8			0.2				1.0
4,8				0.2				0.8			1.0
4,9				0.4					0.6		1.0
4,D				1.0						0	1.0
5,6					0.8	0.2					1.0
5,7					0.8		0.2				1.0
5,8					0.2			0.8			1.0

5,9					0.8				0.2		1.0
5,D					1.0					0.00	1.0
6,7						0.6	0.4				1.0
6,8						0.2		0.8			1.0
6,9						0.6			0.4		1.0
6,D						1.0				0.00	1.0
7,8							0.2	0.8			1.0
7,9							0.8		0.2		1.0
7,D							1.0			0.00	1.0
8,9								0.8	0.2		1.0
8,D								1.0		0.00	1.0
9,D									1.0	0.00	1.0
Sum	5.2	6.2	5.0	3.8	6.8	3.8	3.4	7.2	3.6	0.00	45
ACC	0.12	0.14	0.11	0.08	0.15	0.08	0.08	0.18	0.08	0.00	1.0