Unsupervised Neural Computation for Event Identification in Structural Health Monitoring Systems

By

Loren Card

A Thesis submitted to
the Faculty of Graduate Studies
In Partial Fulfillment of the Requirements for the Degree of

Master Of Science

Department of Electrical and Computer Engineering
University of Manitoba
Winnipeg, Manitoba

THE UNIVERSITY OF MANITOBA

FACULTY OF GRADUATE STUDIES

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Of

MASTER OF SCIENCE

Abstract

This thesis report explores the use of unsupervised neural computation for event identification (EID) in structural health monitoring (SHM) systems. EID techniques are useful in SHM systems for minimizing the size of SHM data sets, and the costs associated with analysing, transmitting and storing SHM data. The approach to EID explored is adaptive, self-configuring and does not require detailed information about the structure being monitored.

A frequency sensitive competitive learning (FSCL) technique is used to model the output of an SHM system. SHM system output states which disagree with the model are deemed "novel" and identified as SHM events. The EID system is implemented in PERL and operates on SHM data stored by a database server running the MySQL DBMS software.

The EID system is evaluated with SHM data from three structures including the Taylor Bridge, the Portage Creek Bridge and the Golden Boy Statue. The EID system is able to identify strain gauge events of $0.75\mu\varepsilon$, $12.5\mu\varepsilon$, $1.25\mu\varepsilon$ or smaller in the SHM measurement data from the Taylor Bridge, the Portage Creek Bridge, and the Golden Boy respectively. The EID system is able to identify accelerometer events of $.0045g$, $0.0020g$ or smaller in the SHM measurement data from the Portage Creek Bridge, and the Golden Boy respectively.

The EID system is compared to a simplified event identification (S-EID) system, which does not use power spectral density estimation or unsupervised neural computation. The S-EID system is shown to be effective but less sensitive than the EID system to SHM events. The EID system is capable of adapting to noisy environments.

Some example SHM events, believed to be the result of seismic activity, from the Portage Creek Bridge are presented and discussed.

Acknowledgements

I would like to thank my wife and family for their love and support. I am blessed to have them, and would be lost without them. I would like to thank my advisor, Dr. Dean K. McNeill, for his friendship and guidance throughout my career as a graduate student. I would like to thank Dr. Douglas Thomson, for insightful comments and recommendations regarding the research in this thesis. Special thanks go to Dr. Aftab Mufti and ISIS Canada, for providing access to the structural health monitoring data and systems which made this work possible. I would also like to thank Liting Han for her help working with the ISIS SHM data aquisition systems. I gratefully acknowledge the financial support of the Natural Sciences and Engineering Research Council of Canada (NSERC).

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1 Introduction

The practice of Structural Health Monitoring[1] (SHM) is gaining popularity and interest in the engineering community. Stewards of civil infrastructure are increasingly recognizing a need to monitor structures, in order to better assess structural "health." Aging infrastructure and limited maintenance budgets require innovative approaches to ensure public safety while balancing costs. SHM technology has the potential to help increase safety, reduce life cycle costs, improve maintenance strategies, and provide important structural performance feedback to designers.

This thesis explores the use of unsupervised neural computation for event identification (EID) in SHM systems. EID mechanisms have several applications in SHM systems. They can be used to solve some key problems associated with current SHM practice.

1.1 Problems with SHM Addressed by Event Identification

Conceptually, the practice of SHM is straightforward. A structure is fitted with a number of sensors in key locations. Sensors monitor physical quantities such as strain, acceleration, displacement, or temperature. A data acquisition (DAQ) system continuously interrogates the sensors and records measurements to a database. Occasionally, "events" occur which excite a structure. The resulting SHM measurements reflect the structure's behaviour during the event. Using data analysis techniques, SHM measurements are used to make an assessment of the structure's "health." A general outline of a typical SHM system is shown in Figure 1.

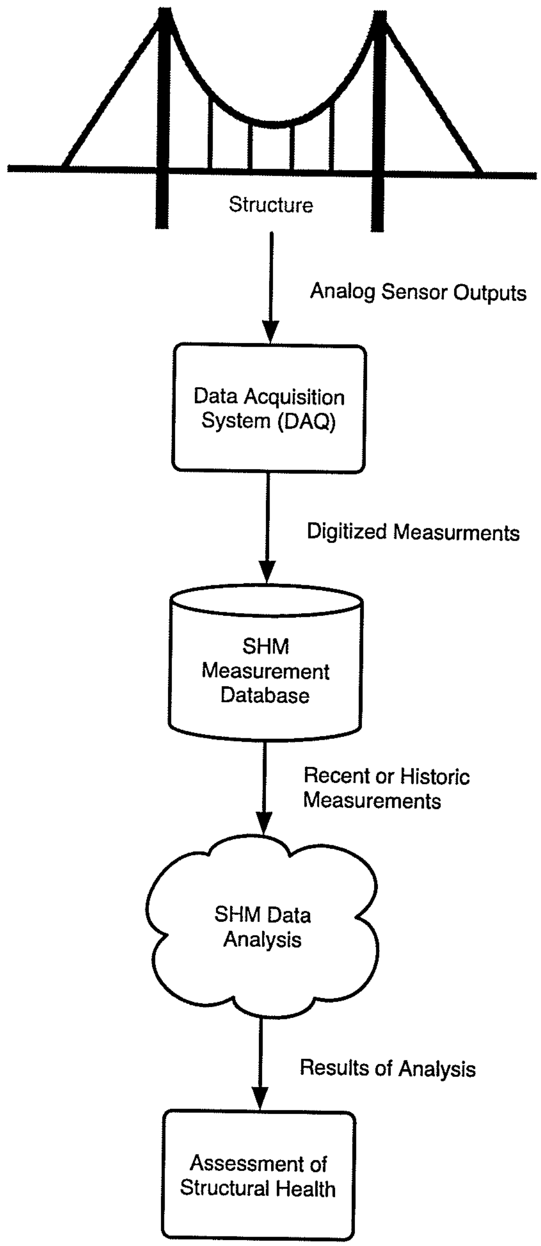

Figure 1: A Basic SHM System.

In practice, SHM systems present some challenges. One challenge currently facing many SHM system projects is the rate at which SHM data is collected. A single sensor channel, sampled with 16 bits, at 100Hz, will generate about 17 megabytes of data every day. A DAQ system with 100 such sensor channels will record about 630 gigabytes of data in a year. Consider that an owner may have thousands of structures in an inventory, and the amount of data involved can become overwhelming.

The transmission, storage, and analysis of every raw sensor measurement is expensive and impractical. Fortunately, effective SHM can be accomplished without retaining a complete sensor record. SHM data is by nature repetitive and consistent. By identifying events in SHM data, the costs associated with manipulating such large data sets can be mitigated.

SHM data analysis (by a human or a machine) can be focused on key events, rather than endless monotonous SHM measurements. A researcher, or bridge owner might be interested in the number of heavy trucks passing over a bridge. The reaction of the bridge to the heavy truck traffic may also be of interest. An EID system could help identify the times at which such events occurred.

SHM data storage costs can be addressed by using an EID system such as the one explored in this thesis. Since SHM data tends to be so monotonous, it is more efficient to discard a portion of the uneventful sensor readings. Lowering sampling rates to lessen the burden of data storage is not appropriate since the higher-frequency components of a structure's behavior are then lost. Simply discarding SHM data at regular intervals (for example keeping only the readings from the first few minutes of every hour) is problematic since the readings associated with any novel event may be lost. SHM measurements associated with events can be stored in preference to monotonous readings. Keeping a small subset of the monotonous readings at regular intervals, in addition to the events, can satisfy long-term structural analysis needs.

SHM data communication costs can be drastically reduced with the help of an EID system. An SHM system which blindly transmits every measurement it acquires, may be wasting vast communications resources. Such an SHM system may be transmitting measurements which amount to the structure saying "Nothing is happening." An SHM system which incorporates an EID process could remain silent most of the time, occasionally reporting "This event just happened."

1.2 EID System Design Considerations

There is currently a need for versatile SHM methods, which can be applied to a wide variety of structures. Civil infrastructure inventories may be diverse and may include many styles and types of structures. In academia, researchers have the luxury of designing an SHM system tailored specifically for a showcase structure. Most civil structures are not showcase pieces. Most do not merit custom-designed SHM systems. Owners do not have the resources to tailor SHM systems to a structure beyond identifying the number, types, and locations for sensors to be used. Utilitarian everyday structures are important however, and merit generic "install it, and forget it," styled SHM systems. Such generic SHM systems, deployed ubiquitously, will be the kind which prove most useful, and reduce ownership and maintenance costs.

The approach to EID explored in this thesis is agnostic of the structure it monitors, and should be useful in many SHM systems. Every attempt has been made to keep the system as versatile, automated, and robust as possible, without sacrificing system performance. In order to help maximize the utility of the EID system, it has been designed to configure itself, and operate without supervision. Given a source of SHM data, the system will autonomously identify those SHM measurements which represent events or structural activity.

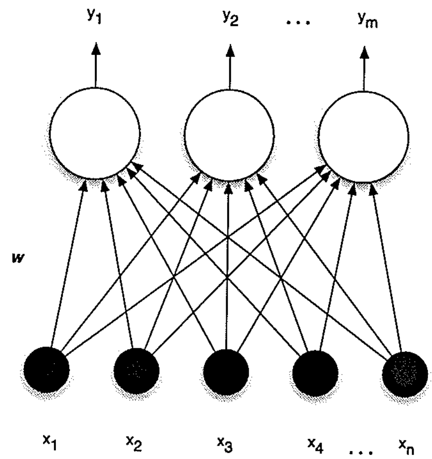

Figure 2: Basic Neural Network Architecture.

2 Unsupervised Neural Computation

Neural computing systems were originally inspired by the function of animal brains[2], where many simple interconnected learning units (neurons) operate in parallel to achieve their collective task. The strength of the interconnections between the individual neurons are adjusted so that the system can adapt and "learn." Figure 3 shows a graphical representation of a basic neural network structure. Neural computing systems are commonly applied where algorithmic solutions to a problem are difficult, but an abundance of example data is available with which to train the system. For example, recognition of hand written characters from image data is difficult to accomplish algorithmically, but a suitable neural computing system may learn the task when trained with enough examples.

Figure 3 is a graphical representation of an unsupervised neural computing system. Neural network input vectors (represented by white circles) are mapped to a multi-dimensional input space. (2-D in this simple example.) Learning units

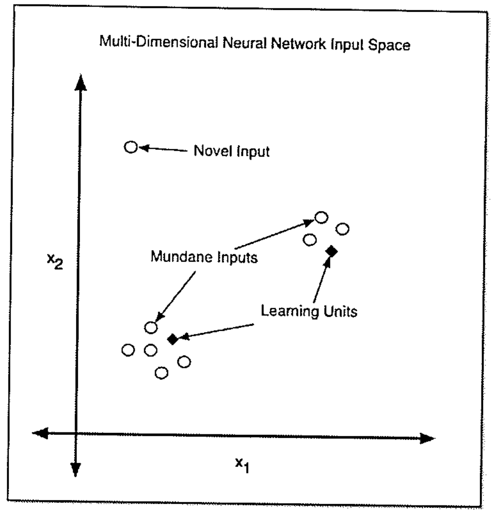

Figure 3: Unsupervised Neural Computation.

(represented by black diamonds) are also positioned in the space. A "novelty detector" can be built by associating a "Novelty Index" (NI) with the input vectors. The NI of an input vector is the distance to the closest learning unit. The unsupervised computing system uses a learning algorithm to train itself to identify "novelty" by adjusting the position of the learning units. The learning units are positioned in the multi-dimensional input space to reflect the most common"mundane" input states. Novelty is detected when an input disagrees with the model represented by the learning units. (Graphically, a novel input is one which is located far away from any learning unit.)

Many different types of learning algorithms exist[3]. The results reported in this thesis make use of an approach known as Frequency Sensitive Competitive Learning (FSCL). FSCL has been used in the past for vector quantization[4] and in robot vision systems[5].

In this thesis, the output y_i of a given learning unit i is simply the Euclidean distance between its input vector $\boldsymbol{x}$ and weight vector $\boldsymbol{w}_i$.

$$y_i = \|\boldsymbol{w}_i - \boldsymbol{x}\| \tag{1}$$

Each learning unit i is said to "compete" to have its weight vector $\boldsymbol{w}_i$ updated. For each input vector $\boldsymbol{x}$ presented to the network, a single winning unit is selected based upon its output y_i and its success in winning previous competitions. Each learning unit maintains a count c_i of the number of times it has won. The winner, denoted i^*, is the learning unit with the smallest $y_i c_i$ product.

$$i^* = i \mid (y_i = min(y_i c_i)) \tag{2}$$

Using the minimum $y_i c_i$ product as the criteria for choosing the winning learning unit makes the selection process sensitive to the frequency with which the learning units win. A frequency-sensitive competition ensures that all of the learning units participate in the system. The weights of the winning unit $\boldsymbol{w}_{i^*}$ are updated by adjusting them slightly towards $\boldsymbol{x}$ according to equation 3. Here ϵ is used as a learning rate parameter, typically set between 0.0001 and 0.001.

$$\boldsymbol{w}_{i^* new} = \boldsymbol{w}_{i^* old} + \epsilon(\boldsymbol{w}_{i^* old} - \boldsymbol{x}) \tag{3}$$

The overall effect of this system is that the learning units' weight vectors $\boldsymbol{w}_1 \ldots \boldsymbol{w}_n$ will move to represent a model of all the $\boldsymbol{x}$ input vectors the system has seen. As stated previously, a novelty detector (or event identification system) can be built by using the minimal y_i distance between $\boldsymbol{x}$ and $\boldsymbol{w}_i$ as a "Novelty Index," designated NI.

$$NI = min(y_i) \tag{4}$$

3 Unsupervised Neural Computation for Event Identification

3.1 The EID System

This section describes how an unsupervised neural computing system can be used to create an event identification (EID) system for the analysis of SHM data. Figure 4 shows a conceptual overview of the EID system. The following subsections describe the EID process in detail, and the apparatus used for the EID system implementation.

3.1.1 An SHM Data Source

The first component of the the EID system is a source of SHM data. The EID system can operate on data collected directly from a DAQ system. (For example, to limit the amount of data later stored or transmitted.) Alternatively, the EID system can operate on a stored database of SHM measurements. (For example, to focus an analysis process, or implement a data decimation scheme.)

3.1.2 Windows of SHM Data

The SHM data is separated into 2-second windows for analysis. 2-second windows were chosen since this interval seems to represent an approximate time-interval for many types of SHM events. Generally speaking, a bridge subjected to a heavy vehicle traffic event will react and return to its normal resting state within a couple of seconds. Windows with a 50% overlap were chosen so that no SHM event could occur between windows undetected. Events which last longer than 2-seconds are still detected, as long as they cause significant activity in the SHM system sensor outputs within a 2-second interval. Similarly, events which occur in smaller time intervals are also detected, so long as they also cause significant activity.

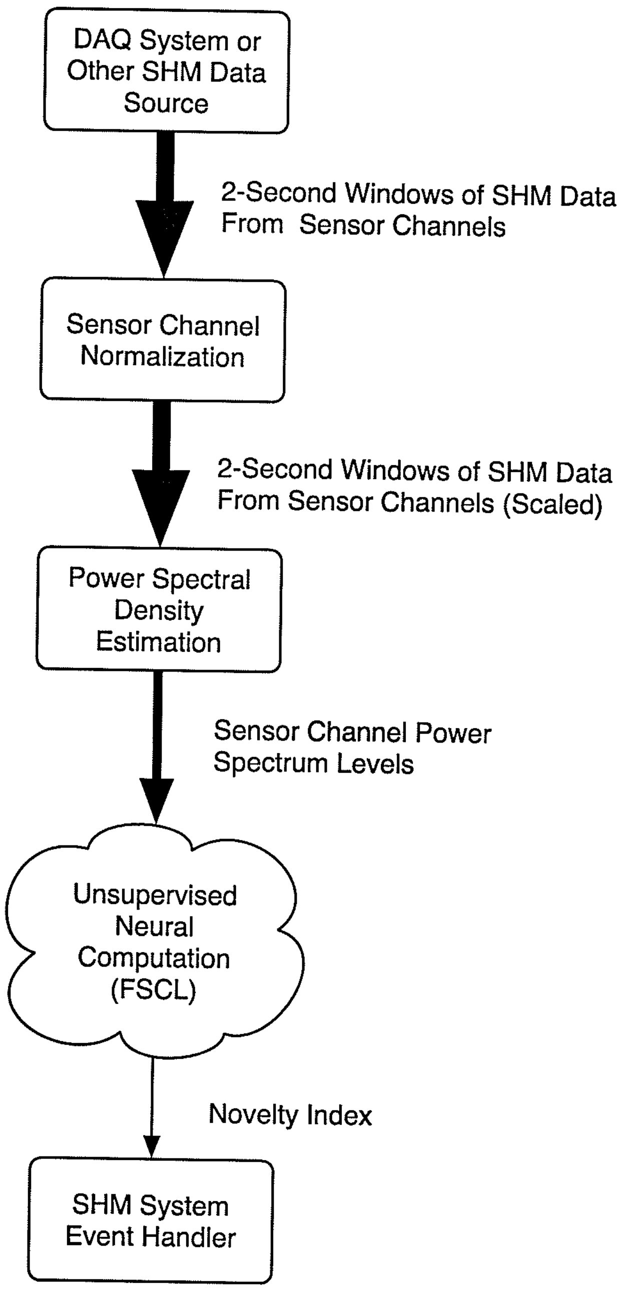

Figure 4: EID System Using Unsupervised Neural Computation

3.1.3 Normalization of Measurment Values

Once the SHM data in separated into 50% overlapping, 2-second windows, it is normalized to give each channel equal influence in the neural computing process. The mean value of each channel, over the window, is calculated and subtracted from each data sample. This is done to make the EID system insensitive to slow trends in sensor output (such as daily thermal cycles). Each sensor measurement is also scaled by a normalization value, forcing sensor values to range approximately between plus one and minus one. This scaling is mainly an effort to reconcile the different units of measure used by different sensor types. (For example, microstrain vs. g's)

3.1.4 Power Spectral Density Estimation

The third step in the EID system is a power spectral density estimation, of each channel across the data in a 2-second window. A power spectral density is used instead of a standard FFT operation since signal phase is arbitrary. This step reduces the number of data points involved by a factor of two. The power spectral density estimation was originally an attempt to help characterize the natural frequencies of structures. In section 4 we see the EID system (in its current configuration) is not especially sensitive to the natural frequencies exhibited by structures. The power spectral density estimation is useful however, to help the neural computing system characterize noise levels on sensor channels.

3.1.5 Unsupervised Neural Computation

The power levels of each sensor channel, at each frequency are presented to the neural computing system for assessment. The channel power spectrum levels define a point in a high dimensional space. (Figure 3 depicts a 2-D neural computation space. The Golden Boy, for example, has 37 sensor channels sampled at 32Hz. 2-second windows of Golden Boy SHM data result in a 1184-

dimensional space.) For the experiments in this thesis, eight learning units are used. The learning units characterize the SHM system output state, and generate a "Novelty Index" (NI) value for each 2-second window of SHM data.

3.1.6 EID System Output: A Novelty Index

The main output of the EID system is a single NI value associated with each window of SHM system sensor readings. (This is the same NI described in equation 4.) Plotting the NI values versus time reveals "novel sensor events" as spikes against a background of "mundane sensor events". When sensor channels exhibit any activity over a 2-second window, the EID system's output will jump to several times, several hundred times, or several thousand times its mean output value.

3.1.7 SHM System Event Handler

Finally, a process or application makes use of NI values. This thesis has briefly described some of the applications of an EID system such as data decimation, and optimizing usage of communications resources. These applications are not explored in detail.

3.2 System Apparatus and Implementation Notes

The EID system was implemented using the PERL programming language with commodity PC hardware. An EID program interacts with a database of SHM measurements hosted by a MySQL database server. The EID program reads SHM measurement values from a data table, performs analysis and writes a NI value to a separate table. The database also hosts tables which store the learning unit weight vectors and normalization values used in the EID process. Figure 5 diagrams the interaction of the EID application with SHM data and other tables.

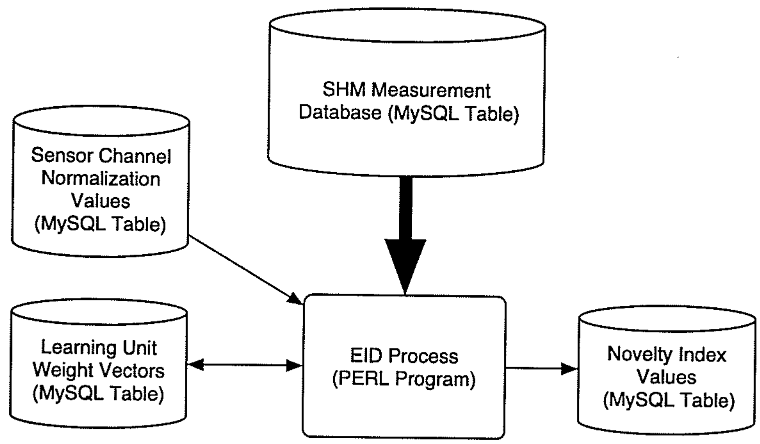

Figure 5: EID System Data Flow and Data Structures

The EID program is designed to be largely self-configuring. The process requires only a database table of SHM measurements. It checks for the existence of a table containing normalization values. If the normalization table does not exist, it is created by calculating a standard deviation for each sensor channel from the first two hours of SHM data. Once the normalization table is created, it is reused and not modified.

The EID program also checks for the existence of a learning unit weight vector table and creates it as required. Weights are initialized randomly. The FSCL process allows the EID program to update the weights with every window of SHM data, and the EID program stores modified weight vectors back in the database table periodically. When the EID process is run subsequent times, it benefits from the weights stored previously. NI values are stored in a separate database table. This table is also created as required. NI values are keyed by the date and time of the associated window of SHM data.

PERL was chosen for its flexibility and robust support for database interaction. Despite being a high-level, interpreted computer language, PERL proved to be capable of performing SHM data manipulation tasks. The current EID system implementation is portable, and has run successfully on Linux, MacOS X, and FreeBSD. Some minor modification of path variables would be required to run the software on MS Windows.

The execution speed of the EID system was not formally characterized. It was found however, that a 450 MHz Pentium III desktop computer, running the EID software while hosting the SHM data, was able to process Taylor Bridge SHM data (14 sensor channels with 32 Hz sampling) at about five times real-time speed. (Each unit of SHM data took one fifth as long to process as collect.) A more current desktop computer, with an AMD AthlonXP 2500+ (1.8Ghz) processor was able to process the same data set at about 30 times real-time speed. One might expect that the FFT operation is the most time-consuming operation in the EID system. Experimentation with the simplified EID system (described in Section 4) indicates that the main obstacle to increased performance is in fact the large number of database calls in the current EID program implementation. The current implementation presents opportunities for optimization.

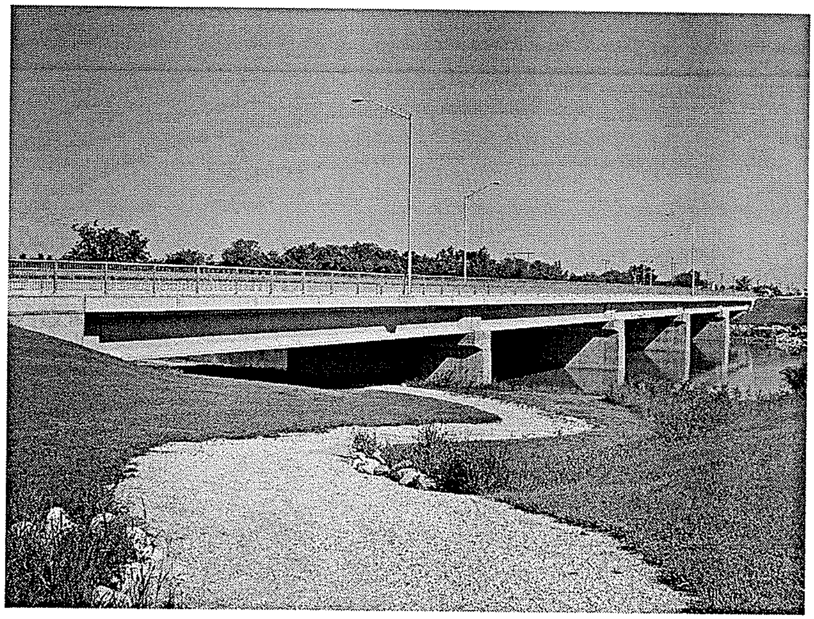

Figure 6: Taylor Bridge, Headingley, Manitoba, Canada

4 EID System Performance Characterization

The EID approach presented in this thesis has been evaluated with three separate structures. These include two bridges, the Taylor Bridge in Headingley, Manitoba, Canada (Figure 6) and the Portage Creek Bridge in Victoria, British Columbia, Canada (Figure 7). The third structure is a public statue, the Golden Boy (Figure 8), which is a 5m tall gilded bronze statue mounted at the pinnacle of the main government building in Winnipeg Manitoba, Canada 77m above grade. These three structures are equipped with mechanical and fiber optic strain gauges, temperature sensors, and accelerometers. Data acquisition (DAQ) equipment is used to continuously monitor the structures taking measurements 32 times per second.

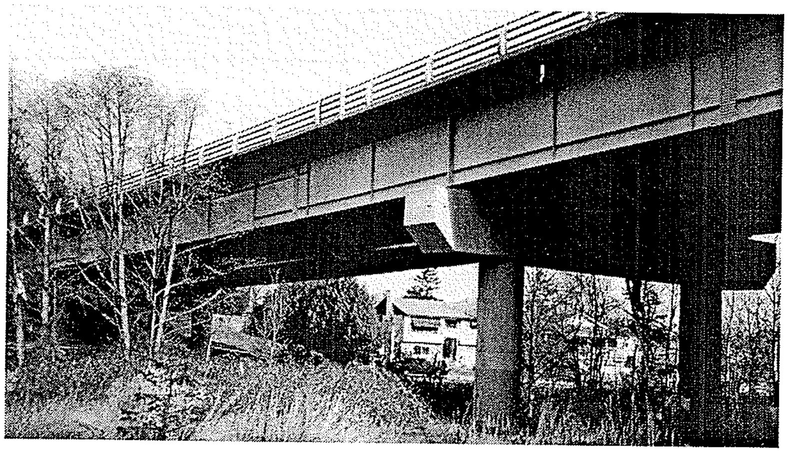

Figure 7: Portage Creek Bridge, Victoria, British Columbia, Canada

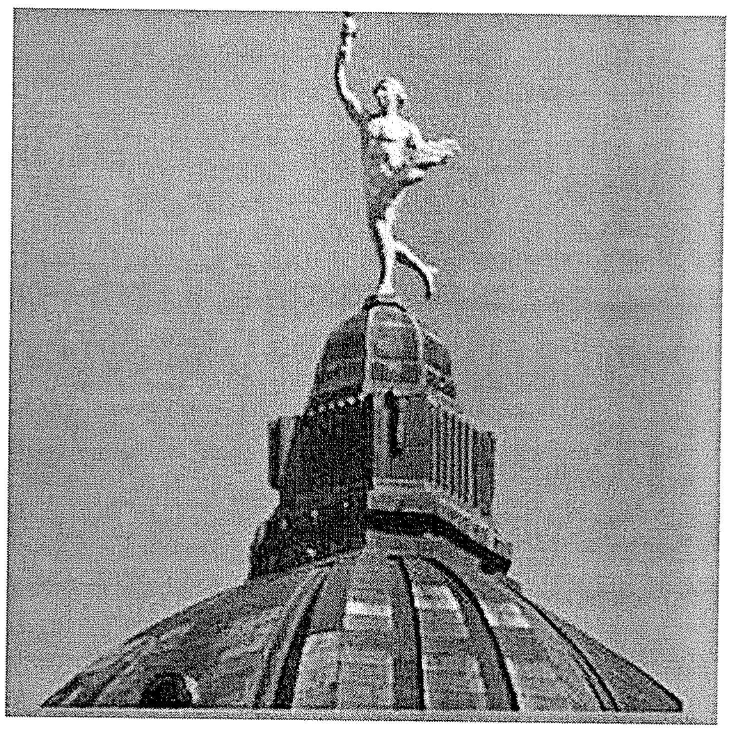

Figure 8: The Golden Boy, A Statue in Winnipeg, Manitoba, Canada

The Taylor Bridge is equipped with 12 strain gauges, and two temperature sensors. The strain gauges are located on the bridge's girders. Six of the gauges are located mid-span, and six are located near supports. The mid-span sensors are naturally more active then the support sensors. The Taylor Bridge's 14 sensor channels, sampled at 32 Hz, taken in two-second windows results in 448-dimensional input vectors after being normalized and Fourier transformed. The primary source of excitation of the Taylor Bridge is vehicle traffic. Since the bridge is not located on a busy route, vehicle traffic is relatively sparse. Taylor Bridge sees a few heavy trucks on a daily basis.

The Portage Creek Bridge is equipped with 30 strain gauges, two 3-axis accelerometers, and one temperature gauge. The Portage Creek Bridge's 37 sensor channels, sampled at 32 Hz, taken in two-second windows results in 1184-dimensional input vectors after being normalized and Fourier transformed. The Portage Creek Bridge's sensors are all located on support columns. The bridge sees lots of commuter traffic on a regular basis. It is also located in a region subjected to seismic activity.

The Golden Boy is equipped with five strain gauges, two 3-axis accelerometers, and one temperature gauge. The Golden Boy's 13 sensor channels, sampled at 32 Hz, taken in two-second windows results in 416-dimensional input vectors after being normalized and Fourier transformed. The Golden Boy's principal source of excitation is the wind. It has a natural frequency near 3 Hz. As one might expect, the Golden Boy tends to oscillate more on windier days.

Table 1: Summary of SHM System Sensors

Structure Name	Strain Gauge Count	Accelerometer Channel Count	Temperature Sensor Count	Input Vector Dimensionality
Taylor Bridge	12	0	2	448
Portage Creek Bridge	30	6	1	1184
Golden Boy	5	6	2	416

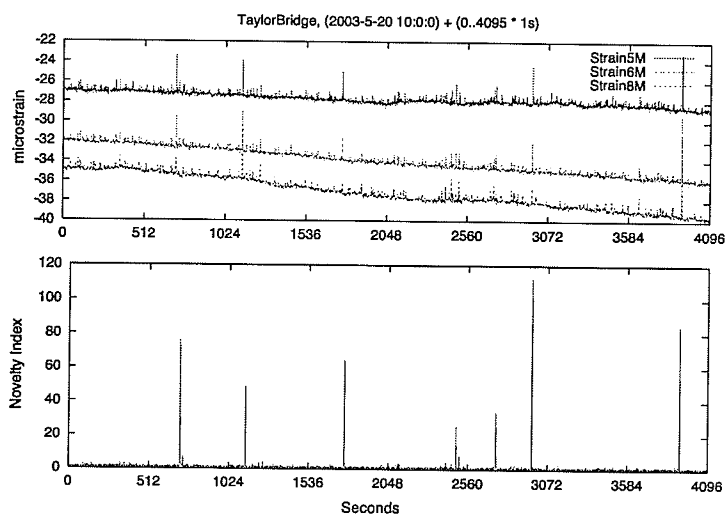

Figure 9: Typical Sensor Output and Novelty Plot from Taylor Bridge EID System

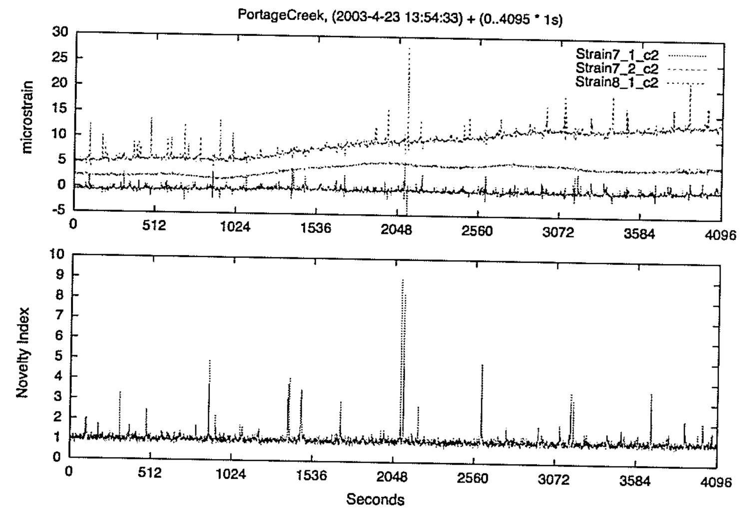

Figure 10: Typical Sensor Output and Novelty Plot from Portage Creek Bridge EID System

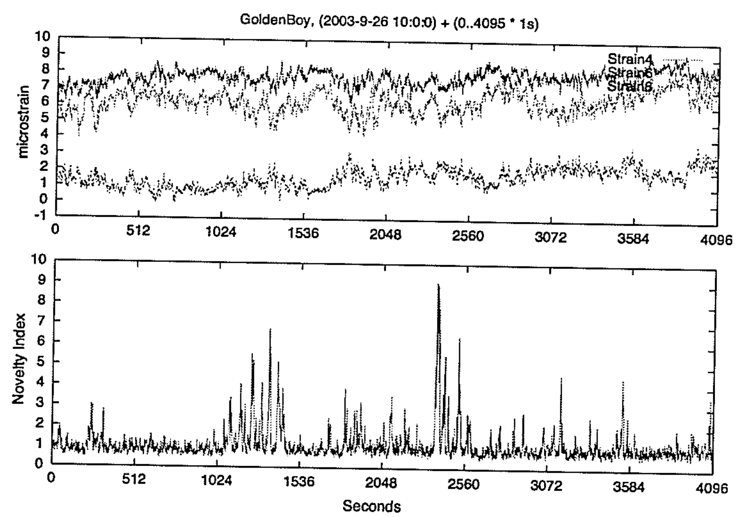

Figure 11: Typical Sensor Output and Novelty Plot from Golden Boy EID System

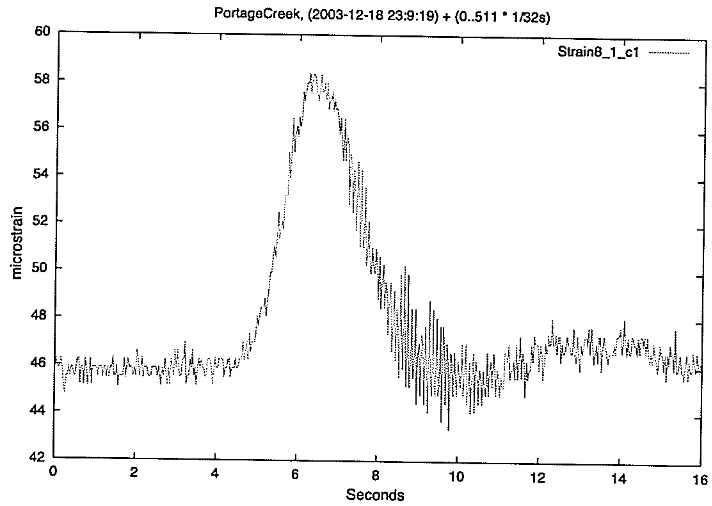

Figure 12: A Simple SHM Event

4.1 EID System Behaviour

Figures 9, 10, and 11 show some typical EID system output plots (bottom), with a few sensor channels (top). Note that spikes in the EID system output correspond to those in the sensor channel plots. The output of the EID system can be considered an assessment of the state of the structure at any time. Structural events result in spikes in the EID system output. Note that in Figure 11, the EID system output is more erratic, reflecting the gusty nature of the wind which excites the Golden Boy.

Figures 12, and 13 show examples of some SHM events the EID system is able to identify. Figure 12 is a simple event, where a strain gauge's measurements have changed by several microstrain in a few seconds. Figure 13 shows a more complex event where several strain gauge outputs have oscillated by several microstrain in a few seconds. The EID system is capable of identifying many types of such sensor events. The system is sensitive to events which cause

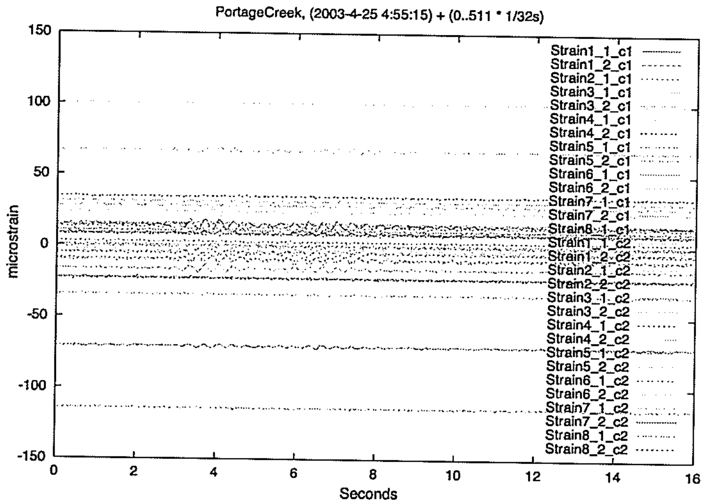

Figure 13: A More Complex SHM Event

changes in the power spectra of the SHM sensors channels. Any change in one or more sensor channels' measurements over one window of SHM data (2 seconds) will affect the output of the EID system.

4.2 EID System Sensitivity

Having briefly explored the kinds of SHM events which can be identified by the EID system, it is desirable to characterize precisely the sensitivity of the system. In order to determine the sensitivity of the EID system, samples of SHM data were artificially modified by adding sinusoidal signal components to them. The reaction of the EID system to the addition of different sinusoidal signals to its inputs is plotted in Figures 14 through 18. Note that the EID system output has been normailized in Figures 14 through 18 so that an "average" or "mundane" event is scaled to unity. This scaling gives some basis for comparing the EID system output across various structures. Table 2 summarizes the results of the tests.

Figure 14 explores the EID system's sensitivity with Taylor Bridge's SHM system. The eight curves plotted show how the EID system's output varies with the addition of different signals. Although the plot is crowded with eight different curves, they are labelled on the plot in the order in which they appear. The steepest, tightest curve on the left side of the plot is the Taylor Bridge's EID system response to a 10 Hz sinusoidal signal added to the six strain gauge channels located near the span supports. The curve furthest to the right represents the Taylor Bridge's EID system response to a 4.5 Hz sinusoidal signal added to the six strain gauge channels located mid-span.

The sinusoidal signals were added to a set of 10 baseline 2-second windows of SHM data, previously identified by the EID system as "mundane". An average of the EID system's response across these 10 modified windows is shown in the sensitivity plots.

The minimum EID system output level required to designate an "event" was chosen (somewhat arbitrarily) to be 1.5. Some basis for this decision can be found be examining the EID system output levels in Figure 20. The EID system output only rarely exceeds a value of 1.5.

As can be expected, the Taylor Bridge's EID system is more sensitive to the excitation of many channels at once, than to the excitation of a single sensor channel. Also as expected, the Taylor Bridge's EID system is more sensitive to excitation of the strain change located near the supports, than those located mid-span. The system's insensitivity to the frequency of sinusoidal excitation was unexpected. The Taylor Bridge has a natural frequency near 4.5 Hz, but the EID system is only very slightly less sensitive at this frequency.

Table 2: Summary of EID System Sensitivity

Structure Name	Minimum Strain Event Detectable	Minimum Accelerometer Event Detectable
Taylor Bridge	$0.75\mu\varepsilon$	NA
Portage Creek Bridge	$12.5\mu\varepsilon$	$0.0045g$
Golden Boy	$1.25\mu\varepsilon$	$0.0020g$

Figure 15 shows the Portage Creek Bridge's EID system response to sinusoidal excitation of some of its (30) strain gauges. Note the variation in sensitivity from the "Docile" to the "Active" strain gauges. This variation in sensitivity is due to different normalization (scaling) values allocated to each sensor channel during the initial calibration of the EID system. The calibration process indicated the EID system should expect more activity on the strain gauge channel denoted "Active" than the one denoted "Docile", and has compensated accordingly.

Figure 17 shows the Golden Boy's EID system's response to stimulation of its strain gauge channels. 3 Hz and 10 Hz frequencies were chosen to test the EID system's response to characteristic and non-characteristic frequency events. The Golden Boy has a natural frequency near 3 Hz, and does not usually exhibit an 10 Hz oscillation. It was hoped that the EID system would be able to discriminate between events exhibiting the Golden Boy's natural frequency, and those which do not. Figure 17 shows the system does discriminate, although not significantly. Figure 17 shows the Golden Boy's EID system is only slightly less sensitive to event which exhibit 3 Hz oscillations.

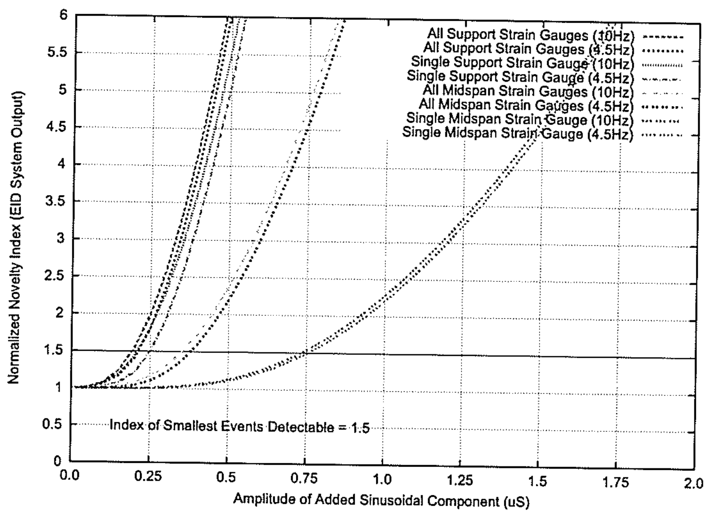

Figure 14: Sensitivity of Taylor Bridge's EID System to Sinusoidal Excitation of Strain Gauge Channels

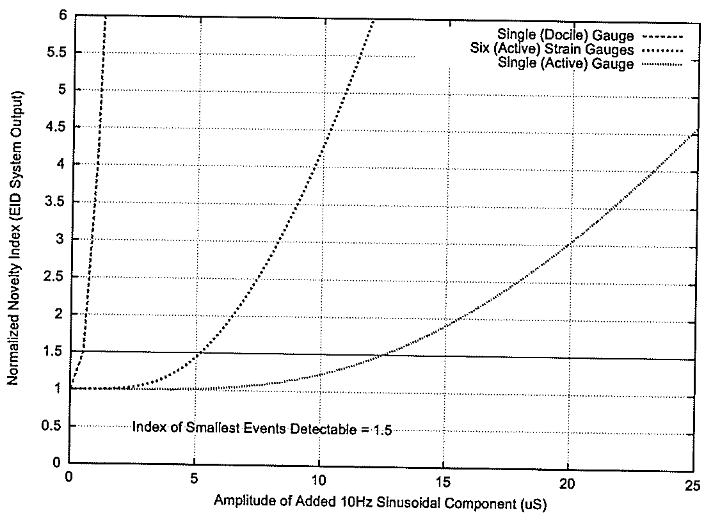

Figure 15: Sensitivity of Portage Creek Bridge's EID System to Sinusoidal Excitation of Strain Gauge Channels

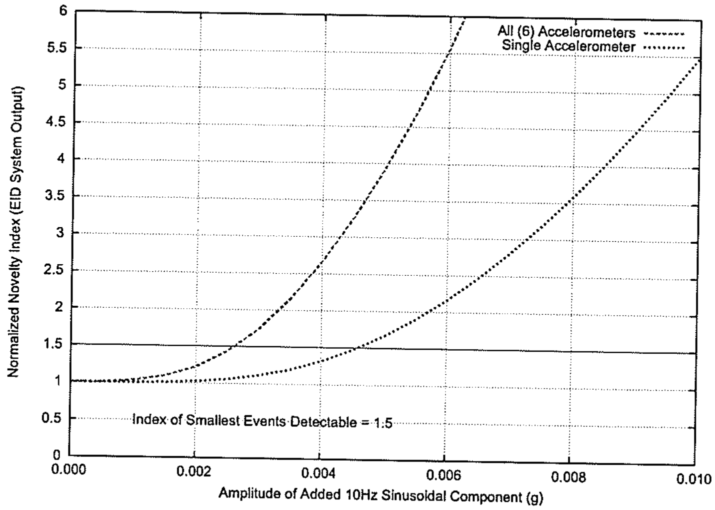

Figure 16: Sensitivity of Portage Creek Bridge's EID System to Sinusoidal Excitation of Accelerometer Channels

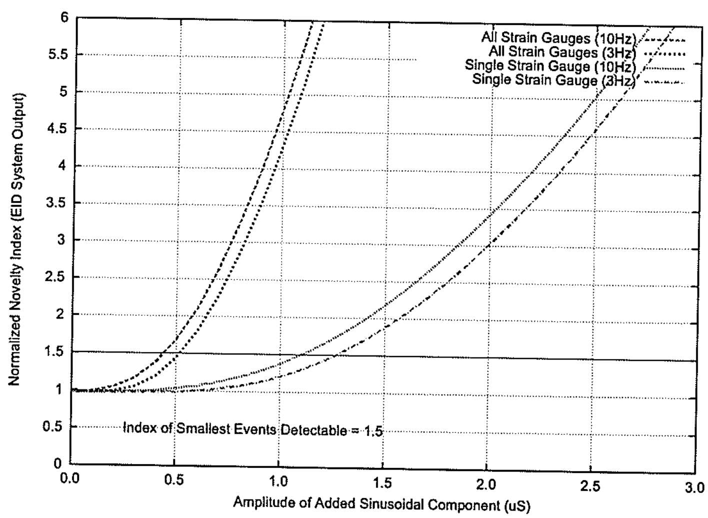

Figure 17: Sensitivity of Golden Boy's EID System to Sinusoidal Excitation of Strain Gauge Channels

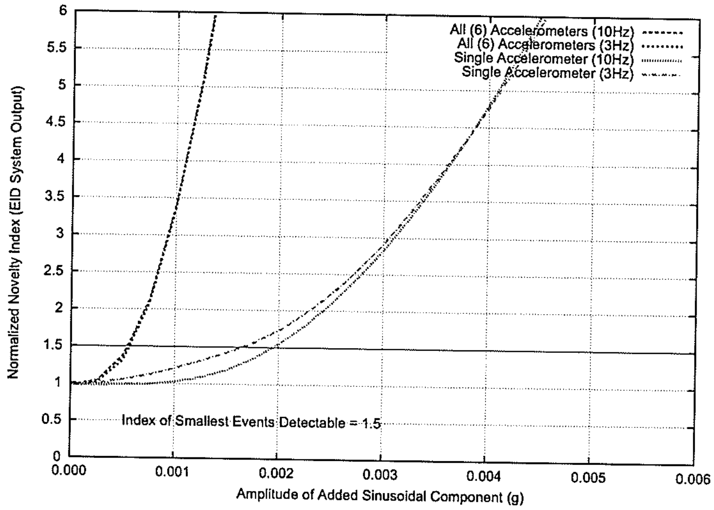

Figure 18: Sensitivity of Golden Boy's EID System to Sinusoidal Excitation of Accelerometer Channels

4.3 Comparing the EID System to a Simplified Approach

We have seen that an unsupervised neural computing approach to EID can be effective. Some may argue that the approach is too complicated, and that similar functionality might be gained using a simplified approach. The most common output state of the Taylor Bridge, Portage Creek Bridge, and Golden Boy SHM systems is a mundane state which represents very little activity. This mundane state is characterized by flat power spectra on each channel. In the time domain, such mundane windows of SHM data are flat unchanging sequences of sensor measurements. This most common, mundane output state represents the origin in the EID system's multi-dimensional neural computation space.

The power density estimation step of our EID system is computationally intensive. An EID system could be made more computationally efficient without it. Estimating the signal power on a sensor channel can be achieved in a much cruder way by subtracting the minimum sensor value from the maximum sensor value in a window of SHM data. Since the EID system does not seem to characterize the natural frequencies of the structures tested previously, such crude power level estimation might be appropriate.

Unsupervised neural networks are capable of characterizing complex patterns in neural computation spaces. It may seem superfluous to use a neural network to characterize the output state of an SHM system which amounts to a multi-dimensional zero-crossing. Such an output state could be more simply modelled with a multi-dimensional zero-vector.

These ideas lead to the concept of a simplified event identification system (S-EID) which does not use an FFT for power spectral density estimation, and does not use a neural network to characterize the common, mundane output state of an SHM system. Figure 19 depicts a S-EID system to help explore the costs and benefits associated with the EID system central to this thesis. Key aspects of the S-EID system are discussed below.

4.3.1 Normalization of Measurment Values

Just as with the EID system, SHM data is normalized to give each channel equal influence in the S-EID system. Scaling is still useful to reconcile the different units of measure used by different sensor types.

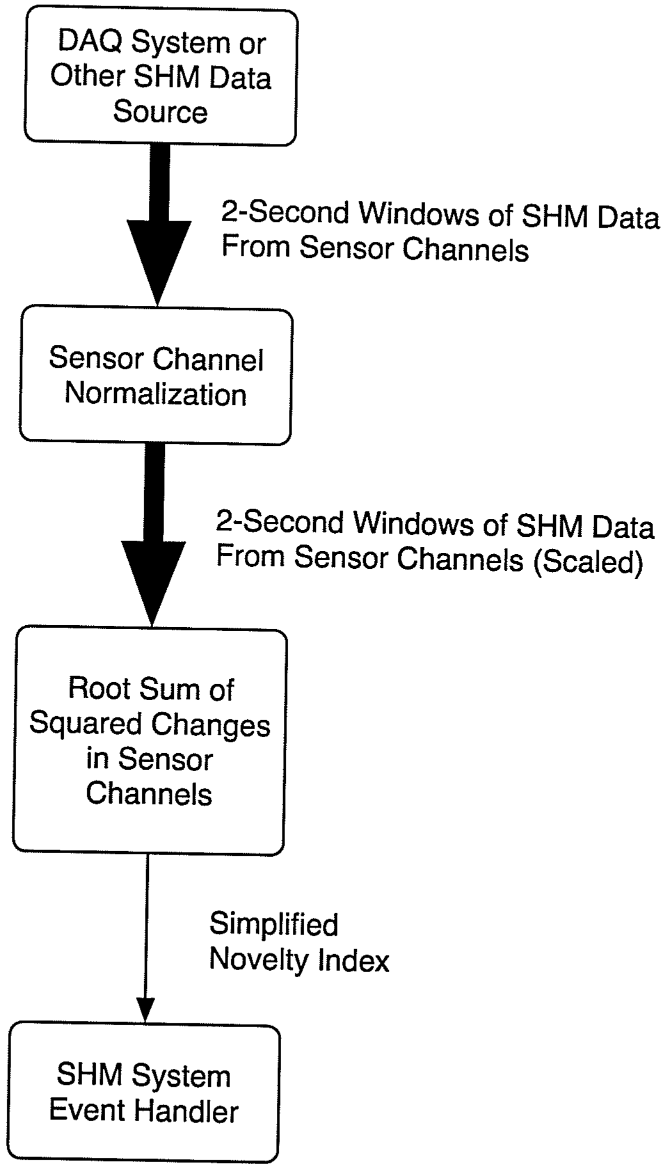

Figure 19: Simplified EID (S-EID) System Without Power Spectral Density Estimation or Neural Computation

4.3.2 Root Sum of Squared Changes in Sensor Channel Outputs

Instead of performing a power spectral density estimation and neural network analysis on windows of SHM data, the S-EID system assumes that the common, mundane output state of all SHM systems is a state of inactivity. The S-EID system assumes that any changes in the channel outputs in a window of SHM data represents an event of interest.

A range of values for each sensor channel is calculated for the 2-second window of SHM measurements. Each sensor range value is squared, and summed. The root of the sum is taken, resulting in a "Simplified Novelty Index" (SNI). Each window of SHM measurements is associated with a SNI value, used as an an output from the S-EID system:

$$SNI = \sqrt{(Ch1_{max} - Ch1_{min})^2 + \ldots + (ChN_{max} - ChN_{min})^2} \tag{5}$$

4.3.3 S-EID System Output: A Simplified Novelty Index

The main output of the S-EID system is a SNI value (analagous to the EID system's NI) associated with each window of SHM system sensor readings. Just as with the EID system, plotting the SNI values versus time reveals "novel sensor events" as spikes against a background of "mundane sensor events". The main difference is the S-EID turns out to be less sensitive than the EID system to SHM events. Figures 20 and 21 show EID and S-EID system output from analysing the same Portage Creek Bridge SHM data. Note the peaks in the EID system output plot are much more pronounced.

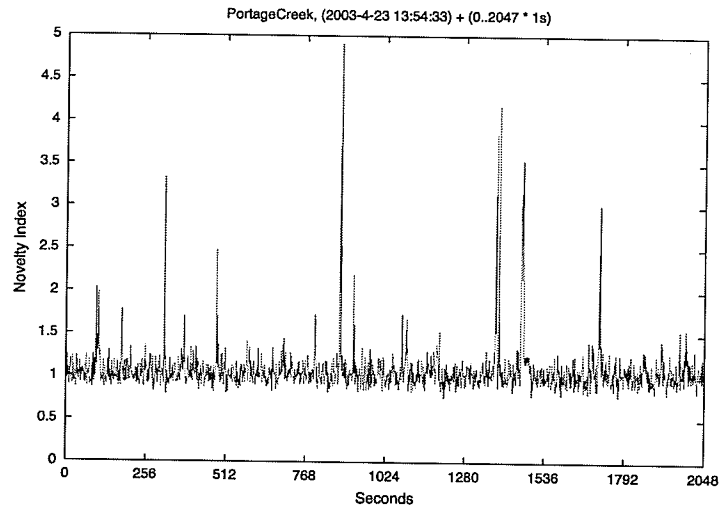

Figure 20: EID System Output

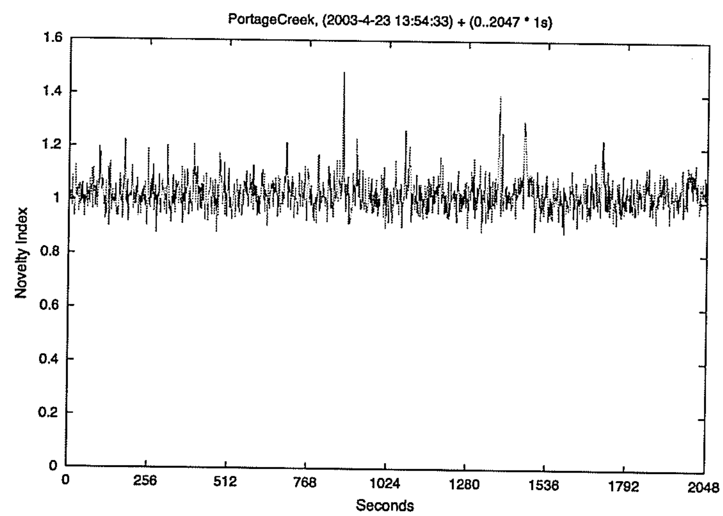

Figure 21: S-EID System Output

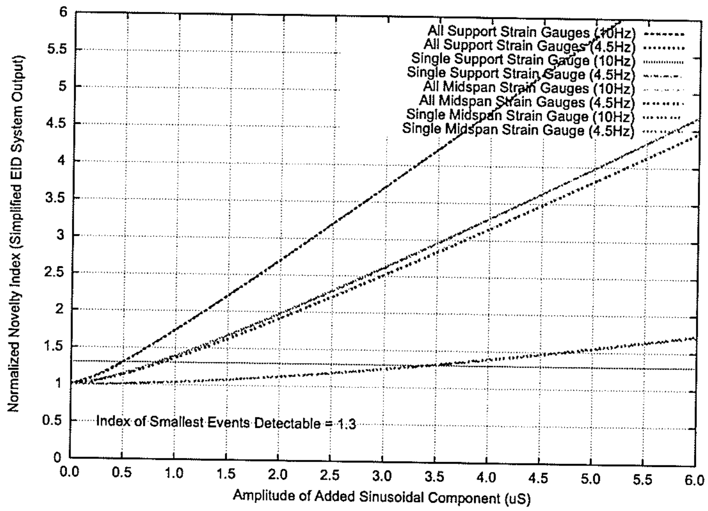

Figure 22: Sensitivity of Taylor Bridge's S-EID System to Sinusoidal Excitation of Strain Gauge Channels

4.4 S-EID Vs. EID System Performance.

Figures 20 and 21 seem to indicate that the original EID system is more sensitive to SHM events than the S-EID system. The same tests as performed on the EID system in section 4.2, where performed on the S-EID system. The results are shown in Figures 22 to 26. A summary of the test results is shown in Table 3. There is one difference in how the test results were interpreted for the S-EID system. The minimum normalized S-EID system output used to designate an SHM event was reduced from 1.5 to 1.3 since the range of output values for "mundane SHM system outputs" is slightly narrower for the S-EID system than the EID system. Figures 20 and 21 shows the narrower range of output values for "mundane events" with the S-EID system.

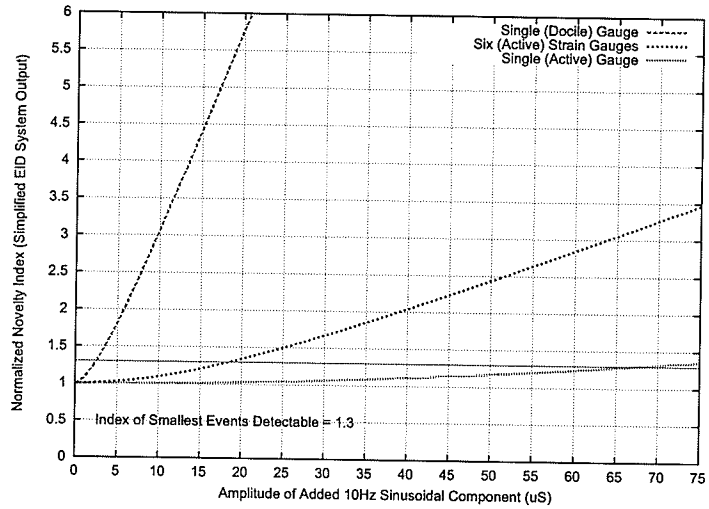

Figure 23: Sensitivity of Portage Creek Bridge's S-EID System to Sinusoidal Excitation of Strain Gauge Channels

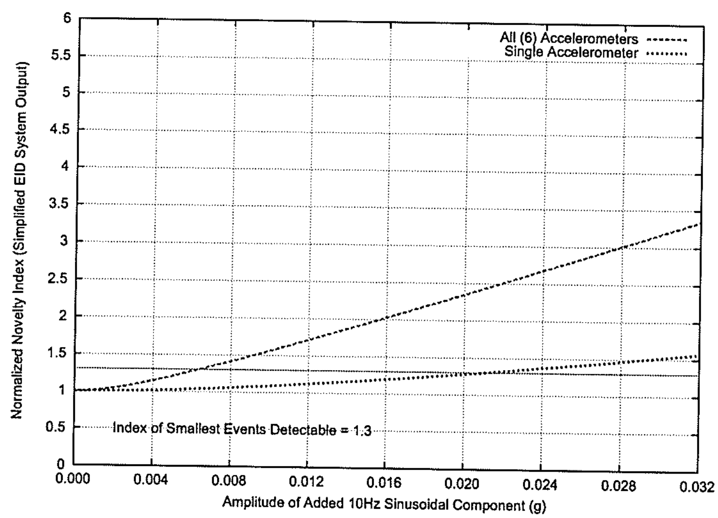

Figure 24: Sensitivity of Portage Creek Bridge's S-EID System to Sinusoidal Excitation of Accelerometer Channels

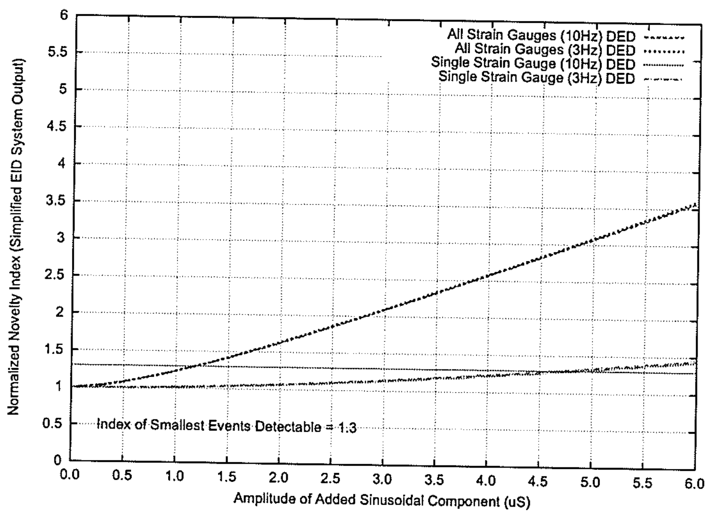

Figure 25: Sensitivity of Golden Boy's S-EID System to Sinusoidal Excitation of Strain Gauge Channels

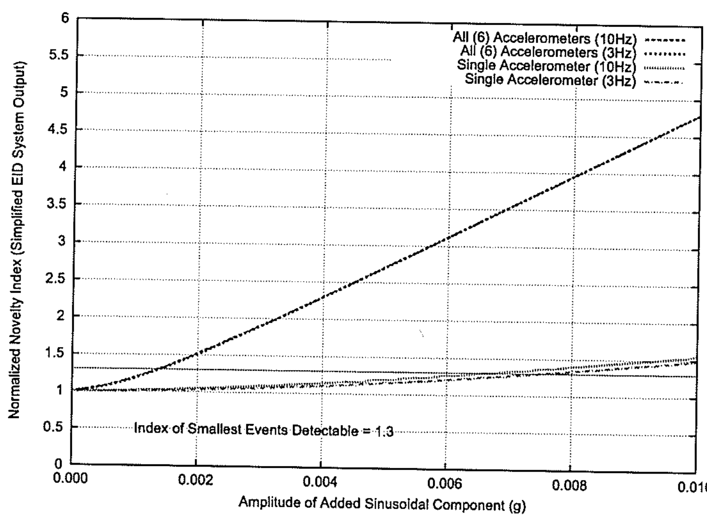

Figure 26: Sensitivity of Golden Boy's S-EID System to Sinusoidal Excitation of Accelerometer Channels

Table 3: Summary of EID Vs. S-EID System Sensitivity

Structure Name	Min. Strain Event EID	Min. Strain Event S-EID	Min. Accel. Event EID	Min. Accel. Event S-EID
Taylor Bridge	$0.75\mu\varepsilon$	$3.4\mu\varepsilon$	NA	NA
Portage Creek Bridge	$12.5\mu\varepsilon$	$70\mu\varepsilon$	$0.0045g$	$0.021g$
Golden Boy	$1.25\mu\varepsilon$	$4.75\mu\varepsilon$	$0.0020g$	$0.075g$

Figures 22 to 26 show that the S-EID system is less sensitive to events than the EID system. Notice that although the EID system showed only a slight ability to discriminate between events exhibiting different frequencies, the S-EID system is completely insensitive.

In some sense the S-EID system behaves purely as an aggregate SHM sensor channel power meter. The simplified approach of the S-EID system may be appropriate for use with the SHM systems of the Taylor Bridge, Portage Creek Bridge and Golden Boy. It is important to remember that the S-EID system inherently assumes that a "mudane event" is one which exhibits little or no signal power on the sensor channels, and that a "novel event" of interest is one which exhibits higher signal power levels. Although this may be a reasonable assumption for the test structures in this thesis, it may not be in general. One need only image a structure whose "mundane" state of existence exhibits non-zero power spectra on its SHM sensor channels and the S-EID approach would become useless. Such a structure could be as simple and commonplace as a bridge under moderate 24-hour traffic.

Having explored two event identification systems, it may not be immediately apparent why the EID system is more sensitive than the S-EID system. It makes more sense if we consider the S-EID system in a neural computing context. The S-EID system can be thought of as a neural computing system with a single learning unit located at the origin of the multi-dimensional neural computing space. The S-EID system's conceptual single learning unit is not updated, and does not learn. Strictly speaking, the S-EID system is in no-way a neural computing system, but the analogy is useful for visualization purposes. Functionally this description is accurate.

Figure 27 shows conceptually how the EID system characterizes the SHM system output in a noisy environment. Figure 28 shows how the S-EID system characterizes the same output. The S-EID system is not able to adapt to noise on the sensor channel outputs in any way. The EID system is perfectly capable of characterizing a noise envelope for "mudane" SHM output states.

The above conceptual comparison is not fair since it ignores the fact that the EID system performs a power spectral density estimation on the windows of SHM data. Further experimentation would be required to completely and discretely characterize the costs and benefits of the power spectral density estimation and neural computing aspects of the EID system. The importance of the conceptual comparison is to illustrate the EID system's capability, and the S-EID system's inability to characterize noisy SHM outputs.

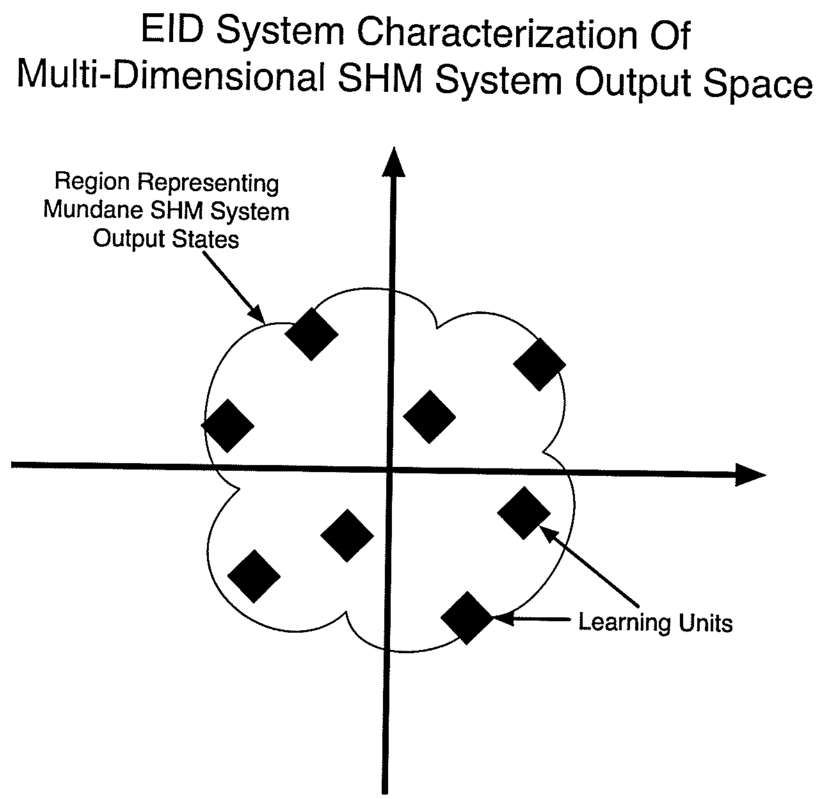

Figure 27: EID Model of SHM System Output

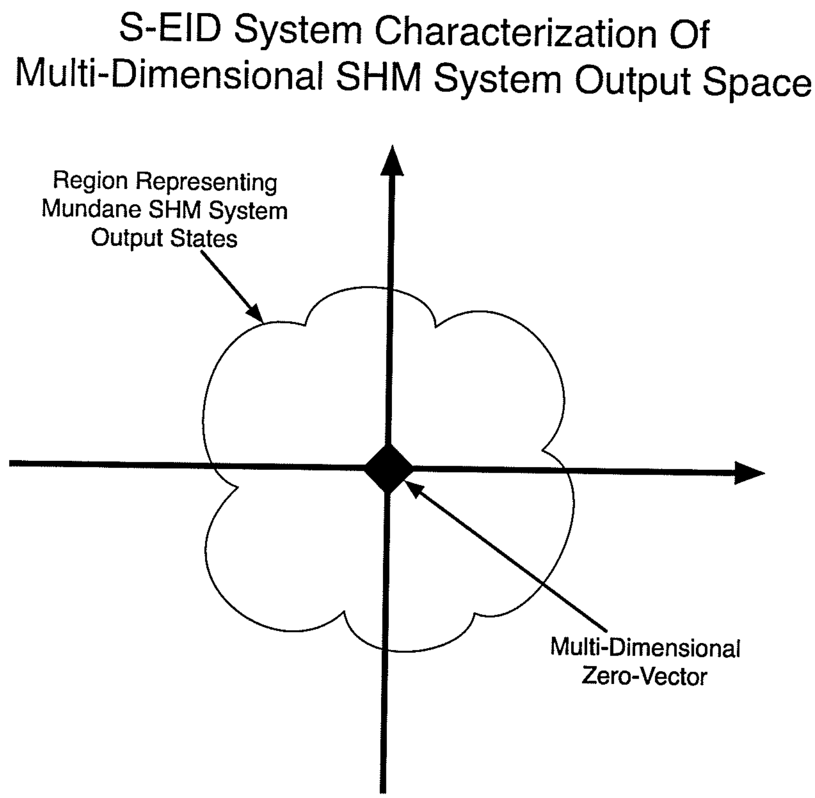

Figure 28: S-EID Model of SHM System Output

Table 4: Seismic Events at Portage Creek Bridge

Event	Earthquake Time (UTC)	Event Time	Δ Time	Event Duration	Maximum Δ Strain
1	2003-12-19 05:33	2003-12-18 23:13	19m 30s	~11s	$13\mu\varepsilon$
2	2004-01-01 15:12	2004-01-01 08:56	15m 40s	~23s	$10\mu\varepsilon$
3	2004-04-25 10:02	2004-04-25 04:55	6m 40s	~19s	$12\mu\varepsilon$

5 Seismic Events Affecting Portage Creek Bridge

This section discusses some events affecting the Portage Creek Bridge which are believed to be a result of seismic activity. Table 4 summarizes some of the properties of these events. The second column shows the times at which seismic activity was recorded by the Ministry of Transporation of British Columbia, near the Portage Creek Bridge. The third column shows the times at which activity was detected by the EID system. The discrepancies between the time stamps are believed to be anomalies of the Portage Creek Bridge's data acquisition system. The duration of the events, and the maximum change in strain incurred by the bridge's strain gauges are shown to reference the strength of the events. The event duration was estimated by examining the frequency spectra of the sensor channels for activity around the times of the events.

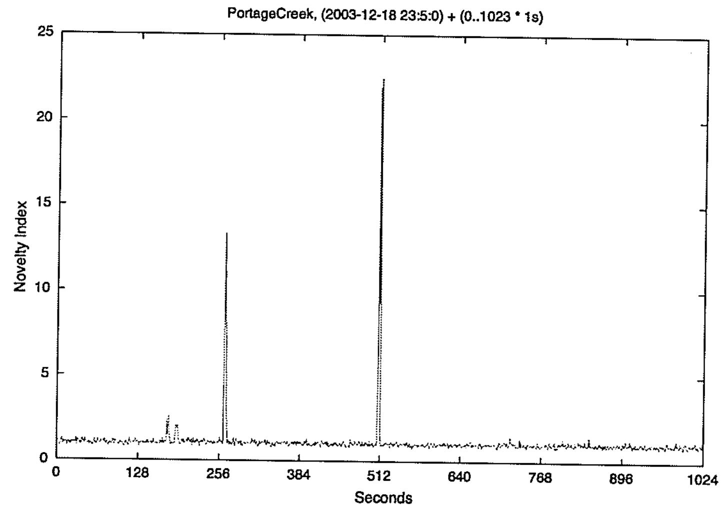

Figure 29: Seismic Event 1 - Identified by EID System (Center Peak)

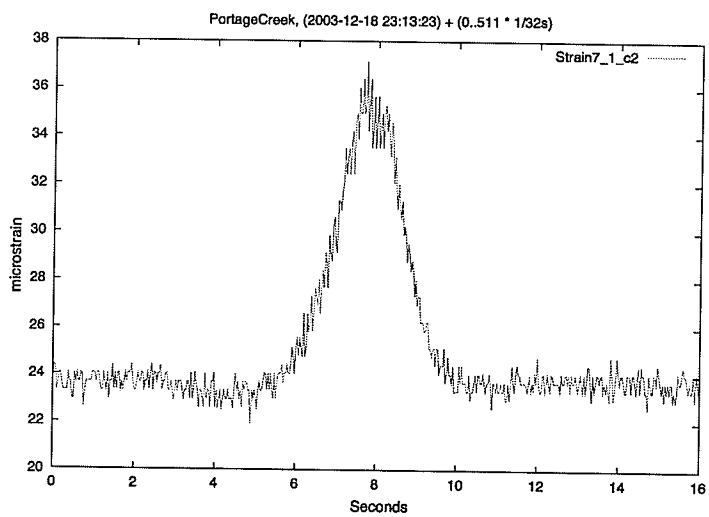

Figure 30: Seismic Event 1 - Most Active Strain Gauge

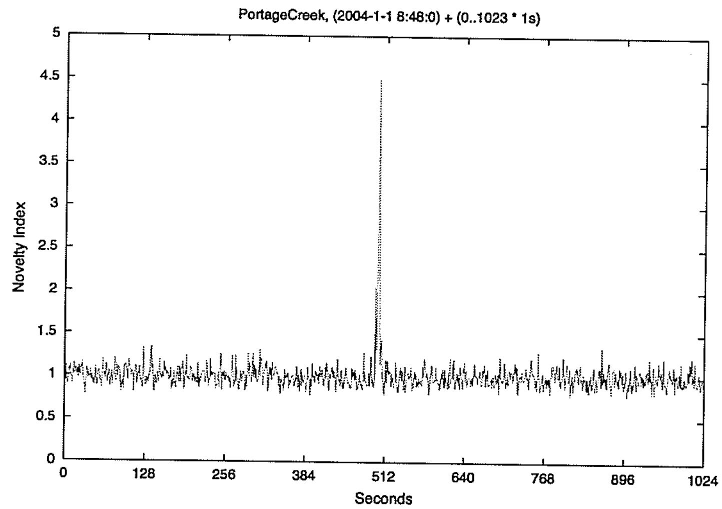

Figure 31: Seismic Event 2 - Identified by EID System

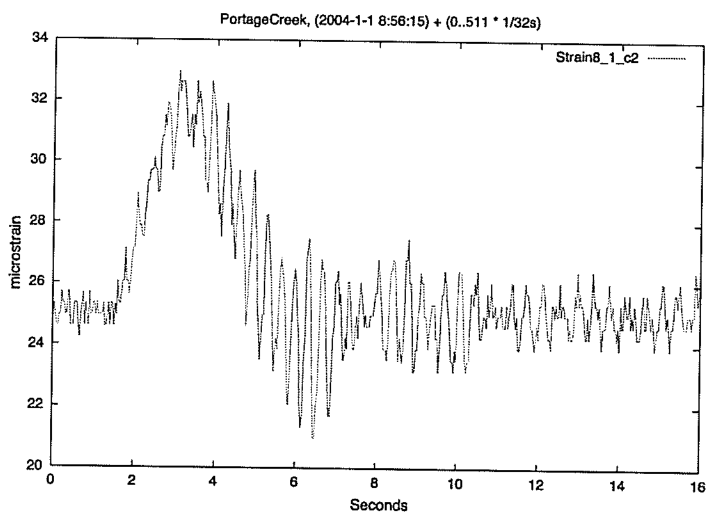

Figure 32: Seismic Event 2 - Most Active Strain Gauge

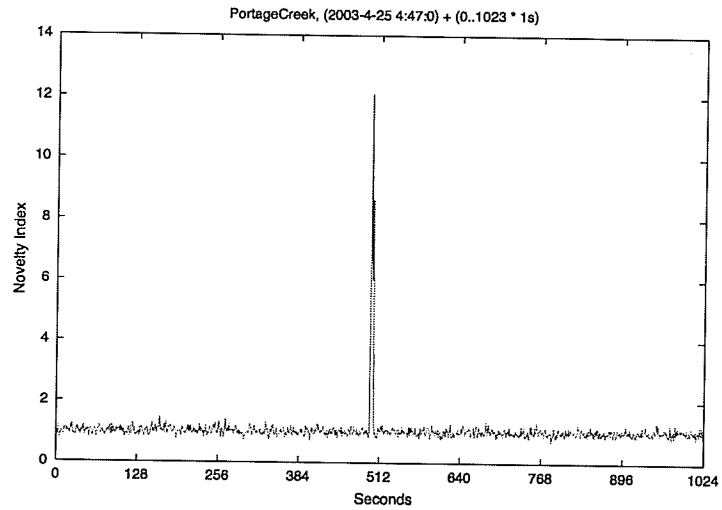

Figure 33: Seismic Event 3 - Identified by EID System

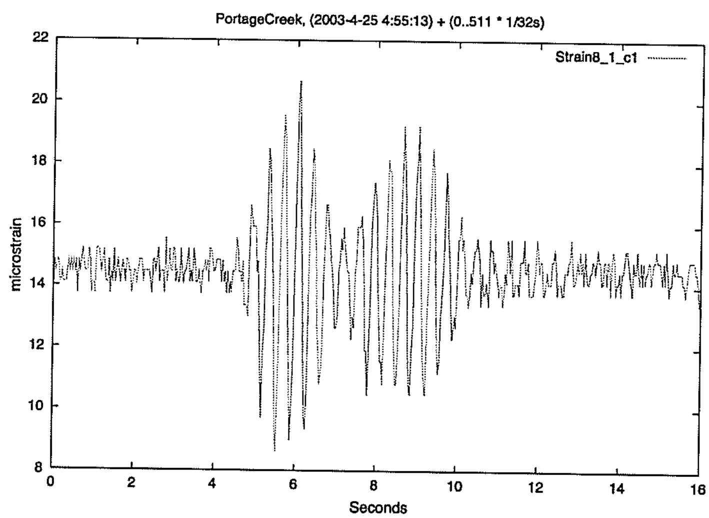

Figure 34: Seismic Event 3 - Most Active Strain Gauge

The EID system (in its present form) cannot distinguish between seismic and vehicular traffic events. In order to locate the above events, the EID system output was examined near the times of known seismic events. Those events identified by the EID system closest in time to the known seismic events are assumed to represent Portage Creek Bridge's response to seismic activity.

Using the EID system to help locate known seismic events in an SHM data set is a minor accomplishment. In the future, further research may enable an SHM system to classify, as well as identify events. A successful mechanism for classification would obviate the need to cross-reference EID system output against the times of known seismic events.

6 Conclusions and Future Work

This thesis has shown that an unsupervised neural computing approach can be very effective for event identification in SHM systems. The EID system described in this thesis is capable of identifying events in SHM data consisting of very small changes in sensor channel output values. In many cases the EID system is capable of identifying "sub-microstrain events."

The EID and S-EID system performance analysis showed that in some cases, a simplified approach to event identification may be appropriate. Despite being less sensitive, the S-EID system discussed in Section 4 proved to be capable of detecting many SHM events. In some cases, system simplicity may be more important than system sensitivity.

The importance of sensitvity adaptability in a noisy environment should not be underestimated. Despite the cost and complexity associated with the frequency-domain unsupervised neural computation approach outlined in this thesis, it may still be useful. A structural engineer may not normally be interested in being able to identify "one microstrain events" versus only "ten microstrain events", but SHM system installations offer diverse and varied scenarios.

One need only imagine an SHM site where key sensor locations are inaccessible, and engineers are required to locate sensors in "insensitive" locations. One could also imagine SHM scenarios where the stiffness of the structure, or nature of the stimulus were such that an SHM system event was represented by only very small deviations in sensor channel outputs. Signal levels associated with SHM systems may vary greatly depending on circumstances. Noise levels associates with SHM system sensors are a given phenomena. If the circumstances surrounding an SHM system require enhanced sensitivity, an approach such as the one outlined by the EID system may be required.

This thesis has explored techniques for SHM which are adaptable, versatile and self-configuring. We have also shown that meaningful SHM data processing is possible without detailed knowledge of the structure being monitored.

Future Work

Having explored and developed EID for SHM, a logical next step is to explore event classification. For example, an event classification system might be able to distinguish between a heavy truck, or an earthquake. Further sub-classification is also possible. An event classification system might be able to distinguish between a fast-moving light truck and a slow-moving heavy truck.

Preliminary experimentation shows that neural computing systems have potential for effective event classification. Ironically, there is also a monotonous aspect to SHM events, in that a given structure will tend to react similarly, to similar stimulus at different instances in time. Experimentation using neural computation to classify SHM events indicates it is possible to classify SHM event at least according to their "strength." Such classification may be immediately useful in implementing SHM systems which count SHM events to estimate levels of fatigue in civil structures.

One ambitious long term goal of SHM system research is to develop "Red-light, Green-light" SHM systems. Such a system would hypothetically monitor a structure with enough sophistication to make its own assessment of a structure's health. A "Green Light" assures structure owners that the structure is healthy, and a "Red Light" alerts owners that there is a problem which needs attention. Although such systems will require much further research to develop, it is exciting to imagine a structure which can assess and report its own health, in detail, or in summary, to its owners.

The more we explore data processing for SHM systems, the more research opportunities present themselves.

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