Application of SHM Pattern Recognition to Assess Decision Making of Humans in the Loop

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ABSTRACT

Structural health monitoring (SHM) techniques have traditionally been applied to mechanical, aerospace, and civil structures to identify loading and damage patterns. However, human operators in the loop play an important role in the operational performance of aircraft and other structural systems. The increased availability of sensors such as EEG, skin conductance, and eye-tracking systems are creating an opportunity to develop SHM techniques for assessing neuro-physiological factors that influence human decision-making. The parallels between the structural dynamic response of a system to an excitation source and the response of a human to the presentation of a scenario suggests that SHM algorithms can be used to interpret neuro-physiological signals. As in traditional SHM, where the system's dynamic response is measured to characterize the system's state of health, the measured response of a human during decision-making can capture information about the human's mental state, including levels of fatigue, engagement, workload, and other human factors. The ability to monitor the human's mental state in real-time could also enable predictions of human susceptibility to poor decision-making and to trigger an appropriate intervention to prevent human errors.

In this work, EEG, eye-tracking, and skin conductance data are acquired from multiple subjects while performing the Stroop test, a standard test designed to induce errors, under varying degrees of time pressure. Time pressure is induced by progressively reducing the time-to-answer allowed for each set of questions. The data is then analyzed using pattern recognition techniques including principal component analysis and the least squares complex exponential (LSCE) parameter estimation algorithm. Results from the principal component analysis identify the modes which dominate the response during decision-making. These modes are compared to the modes identified while the subject is at rest. Next, LSCE is applied to identify model parameters that can be used to perform a one-step-ahead prediction of the neuro-physiological variables. The LSCE approach allows data from the different sensor

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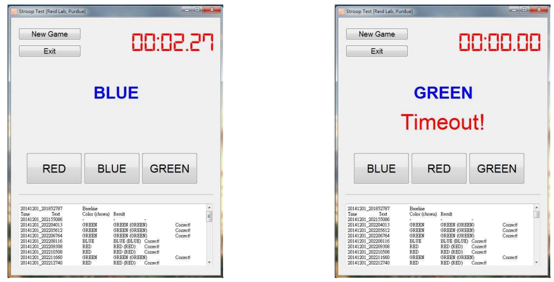
types to be analyzed simultaneously. Results show that model error is reduced as the time pressure is increased.

INTRODUCTION

Traditionally, structural health monitoring (SHM) techniques have focused on monitoring mechanical, aerospace, and civil structures to identify loading and damage patterns. However, as the availability of human-monitoring sensors increases, so, too, do the opportunities to extend SHM to assess human and human-machine performance. Just as being able to detect the initiation of a crack in an airplane wing can prevent the degradation of the aircraft's performance, detecting the onset of fatigue, stress, or distraction in a human operator may help prevent human mistakes and poor decision making. Many parallels can be drawn between monitoring the state of a structure and monitoring the state of a human operator. First, SHM of a traditional structure typically involves a source of excitation, such as an applied force or an acoustic excitation. In human monitoring, the subject's brain is excited by the presentation of a question or task. The measured response of a structure is often affected by its physical properties, environment, and boundary conditions. The response of a subject's brain is affected by the person's current mental state (i.e. level of fatigue, perception of pressure, etc.), the difficulty of the task, and the environment. A structure can be monitored using data from a variety of sensors including accelerometers, strain gauges, lasers, etc. A human can be monitored using heart rate monitors, EEG sensors, skin conductance sensors, eye-tracking systems, etc. Finally, successful SHM of traditional structures requires pattern recognition to identify features of the data that indicate the presence of damage. The goal of this work is to extend this SHM pattern recognition approach to the analysis of neuro-physiological data acquired from human subjects.

Analyzing neuro-physiological data to determine the human state is a growing area of interest, especially with the continual development of smart human-machine teams [1]. EEG data has been analyzed to identify fatigue [2], workload [3], and perceived error [4]. Typical analysis methods include processing time data to identify even-related anomalies, comparing magnitudes of response spectra in certain frequency bands, and using classifier methods such as machine learning. In this work, pattern recognition techniques including principal component analysis (PCA) and the least squares complex exponential (LSCE) parameter estimation algorithms are applied to the neuro-physiological data to investigate the effectiveness of traditional SHM techniques in identifying changes in a human's state. PCA and the related independent component analysis have been applied to EEG data, but these techniques are typically used to eliminate unwanted artifacts such as eye blinks and muscle movements from the data [5, 6]. The LSCE technique will be used here to formulate a data-based model of the EEG data. In the following sections, the procedure for acquiring data from human subjects, the approach to the data analysis, the results of the data analysis, and conclusions will be presented.



(a) (b)

Figure 1: Screen shots of the computer-based Stroop test. (a) A congruent question with a 3-second timer. (b) An incongruent question. The participant has run out of time.

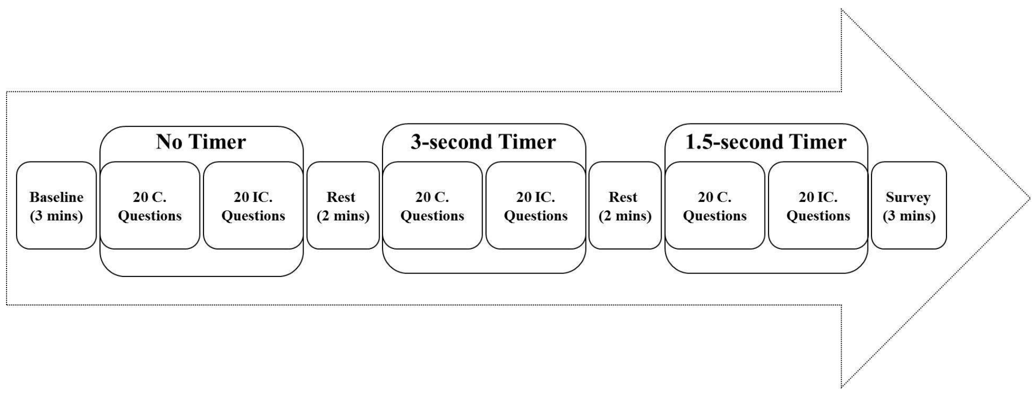


Figure 2: The experimental procedure. C: congruent; IC: incongruent.

EXPERIMENTAL PROCEDURE

Computer-Based Stroop Test

In order to acquire responses from human subjects that could be used to assess the decision making process, a test was designed to induce mistakes and stress caused by time pressure. The test was based on the Stroop test. The Stroop test [7] is a standard test in which a subject is required to identify the color of the font of a word presented to them. To induce errors, the word itself is the name of a color, which may or may not be the color of the font. To make the question colors easy to distinguish, only primary colors (red, blue, and green) were included, which is consistent with established Stroop test protocols [7]. Two types of questions were used during testing: congruent and incongruent. Congruent questions are cases when the word presented is the same as the color of the font. Figure 1a shows an example of a congruent question where the word blue is shown written in blue font. (The correct answer is blue.) Incongruent questions are cases when the word presented is the not the same as the color of the font. Figure 1b shows an example of an incongruent question where the word green is written in blue font. (The correct answer is blue.)

The test contained three sets of questions separated by rest periods, as shown in the flowchart in Figure 2. In each set, forty questions were presented to the subject.

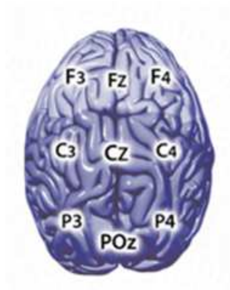


Figure 3: Locations and labels of data channels acquired using the B-Alert system [10].

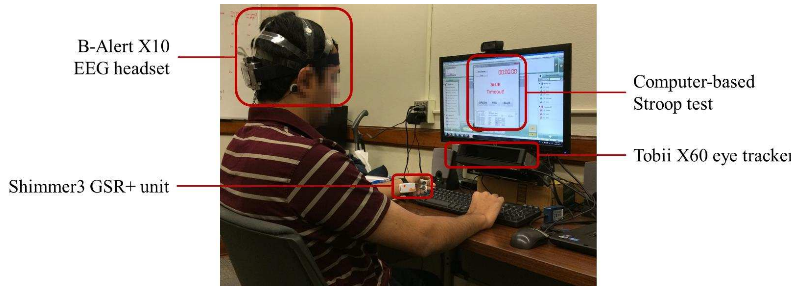


Figure 4: A participant wears the GSR sensor on the left (non-dominant) wrist and the EEG head set, and uses the keyboard to do the computer-based Stroop test. The eye-tracking system is mounted under the screen monitor for tracking the participant's pupils.

The first twenty questions were congruent and the second twenty questions were incongruent. During the first set, no timer was imposed and subjects were allowed to take as much time as needed to answer each question. During the second set, a three second timer was imposed. During the third set, a 1.5-second timer was imposed. Before each set of questions, subjects were given a rest period during which they listened to Bach's Harpsichord Concerto No. 5 in F Minor BWV 1056, which meets the criterion for being of a relaxing nature [8]. To conclude the test, participants answered a short survey about their previous experience with the Stroop test and their perception of time pressure during the test.

Participants used arrow keys (left, down, and right) to answer questions. The setup was intuitive, so participants could answer as quickly as possible when they figured out the answer. The result of each question showed on the screen for 0.5 seconds. If the participant did not answer in time, a ”timeout” warning was displayed and the answer was recorded as incorrect for that question.

Instrumentation

Three types of sensors were used in the experiment. A B-Alert X10 EEG headset system (Advanced Brain Monitoring, Inc., USA), a Shimmer3 GSR+ Unit (Shimmer, USA), and a Tobii X60 eye tracker (Tobii Technology, USA) were utilized to collect brain waves, galvanic skin response, and pupil dilation, respectively. All data collection was performed and synchronized through iMotions Attention Tool (iMotions, Inc., USA) on a Windows 7 operating system. B-Alert X10 is a 9-channel EEG system, which records brain waves from mid-line and lateral sites on the scalp including Fz, Cz, POz, F3, C3, P3, F4, C4, P4 (Figure 3). Participants' skin resistances between 2 electrodes attached to the index and the middle fingers of the non-dominant hand were monitored by the Shimmer 3 GSR+ Unit using a 52 Hz sampling frequency. Skin resistance fluctuates in response to external or internal stimuli [9]. The proposed experiment is a computer-based test, so a Tobii X60 eye tracker was mounted on the screen to track how participants' pupil dilation responded to stimuli on the screen monitor. Figure 4 shows the experimental setup of the EEG headset, the GSR sensor, and the eye-tracking system.

Subjects

The study protocol was approved by the Institutional Review Board on human investigation. Subjects were adult volunteers who agreed to join the study after passing a pre-screening and providing a written consent form. Results from nine subjects are presented here.

DATA ANALYSIS METHODS

The nine channels of EEG data described above were acquired from each of the nine subjects. The time histories of each channel of data were post-processed within the b-Alert software to remove artifacts such as eye blinks, muscle movements, and other data contaminates. The raw (decontaminated) time histories were then partitioned by question. The length of time for each question was defined as the time between mouse clicks used to answer consecutive questions. When necessary, data was linearly interpolated so that the number of points in each time history was equal.

Two methods traditionally applied to time series data of dynamic systems were applied to the EEG data sets. First, principal component analysis (PCA) was applied to identify differences across data sets acquired under different testing conditions (i.e. timer lengths). Independent component analysis (ICA) is often used in EEG analysis instead of PCA because of its ability to detect and remove artifacts in the data such as eye-blinks [6]. ICA has also been shown able to correlate brain activity to behavioral phenomena including workload [11] and drowsiness [12]. PCA is chosen here in order to investigate its ability to distinguish relatively long time histories acquired under different test conditions. Further, training data is not necessary to perform the PCA analysis presented here.

The second method is the least squares complex exponential (LSCE) parameter estimation technique. The purpose of applying this technique to the EEG data is to investigate the ability of the LSCE algorithm to identify a model for the data and then to use that model to make a one-step-ahead prediction of the data. Both the PCA and the LSCE analysis are described in the following sections.

Principal Component Analysis

Principal component analysis (PCA) uses singular value decomposition to identify principal values and vectors of a data set. The magnitude of the principal values indicate the contribution of the corresponding vector in describing the data. In this work, PCA was applied to the set of EEG time histories acquired from the bAlert system. Data from the nine data channels (F_3,F_Z,F_4,C_3,C_Z,C_4,P_4,PO_Z,P_4) shown in Figure 3 were compiled into a single matrix, Q, as follows:

$$Q = \begin{bmatrix} F_3(t_1) & F_Z(t_1) & F_4(t_1) & C_3(t_1) & C_Z(t_1) & C_4(t_1) & P_3(t_1) & PO_Z(t_1) & P_4(t_1) \\ F_3(t_2) & F_Z(t_2) & F_4(t_2) & C_3(t_2) & C_Z(t_2) & C_4(t_2) & P_3(t_2) & PO_Z(t_2) & P_4(t_2) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ F_3(t_N) & F_Z(t_N) & F_4(t_N) & C_3(t_N) & C_Z(t_N) & C_4(t_N) & P_3(t_N) & PO_Z(t_N) & P_4(t_N) \end{bmatrix} \tag{1}$$

where N is the number of data points in the selected data set. Singular value decomposition was then applied to the covariance of the matrix Q to identify the singular (principal) vectors (v) and the singular (principal) values (SV):

$$[v, SV, v] = \text{svd}(\text{cov}(Q)). \tag{2}$$

The singular values were used to identify which vectors contribute most to the overall measured response. The corresponding vectors were then studied to identify whether the data channels were affected by the changing conditions of the test.

Least Squares Complex Exponential Method

In dynamic systems analysis, the least squares complex exponential (LSCE) method [13] is used to identify modal parameters from time histories acquired from multiple input-output pairs. In this work, the LSCE method is extended to analyze EEG data acquired from human subjects. The purpose of the LSCE method is to identify the parameters, α_k, such that

$$\sum_{k=0}^{m} \alpha_k h_n(t_{i+k}) = 0 \tag{3}$$

where m is the model order, $h_n(t)$ is an impulse response function, n indicates the data channel of interest, and i is an arbitrary starting index within the time vector, t. Note that the index i must be selected such that $i + m$ is within the bounds of the data. Because an impulse response function could not be directly determined from the data acquired from the EEG sensors (impulse response function calculations require the input force to be measured), an operational impulse response function was used instead. As detailed in [14], the operational impulse response function of a time history, $x(t)$, is the positive lags of the autocorrelation function, R_{xx}. The operational impulse response function will be denoted as $\hat{h}(t)$, with the $\hat{}$ distinguishing it from the standard impulse response function. After substituting in the operational impulse response function, normalizing the α_k terms by α_m, and rearranging, Equation 3 becomes

$$\alpha_0 \hat{h_n}(t_{i+0}) + \alpha_1 \hat{h_n}(t_{i+1}) + \cdots + \alpha_{m-1} \hat{h_n}(t_{i+m-1}) = -\hat{h_n}(t_{i+m}) \tag{4}$$

Equation 4 has $m - 1$ unknowns, and, therefore, more equations are necessary in order to determine the values for the α_k's. The additional equations come from the N different data channels as well as altering the starting index i within the same data stream:

$$
\begin{bmatrix}
\hat{h_1}(t_0) & \hat{h_1}(t_1) & \dots & \hat{h_1}(t_{m-1}) \\
\hat{h_1}(t_1) & \hat{h_1}(t_2) & \dots & \hat{h_1}(t_m) \\
\vdots & \vdots & \vdots & \vdots \\
\hat{h_1}(t_{m-1}) & \hat{h_1}(t_m) & \dots & \hat{h_1}(t_{2m-2}) \\
\hat{h_2}(t_0) & \hat{h_2}(t_1) & \dots & \hat{h_2}(t_{m-1}) \\
\hat{h_2}(t_1) & \hat{h_2}(t_2) & \dots & \hat{h_2}(t_m) \\
\vdots & \vdots & \vdots & \vdots \\
\hat{h_2}(t_{m-1}) & \hat{h_2}(t_m) & \dots & \hat{h_2}(t_{2m-2}) \\
\vdots & \vdots & \vdots & \vdots \\
\hat{h_N}(t_0) & \hat{h_N}(t_1) & \dots & \hat{h_N}(t_{m-1}) \\
\hat{h_N}(t_1) & \hat{h_N}(t_2) & \dots & \hat{h_N}(t_m) \\
\vdots & \vdots & \vdots & \vdots \\
\hat{h_N}(t_{m-1}) & \hat{h_N}(t_m) & \dots & \hat{h_N}(t_{2m-2})
\end{bmatrix}
\begin{bmatrix}
\alpha_0 \\ \alpha_1 \\ \vdots \\ \alpha_{m-1}
\end{bmatrix}
=
\begin{bmatrix}
\hat{h_1}(t_m) \\
\hat{h_1}(t_{m+1}) \\
\vdots \\
\hat{h_1}(t_{2m+1}) \\
\hat{h_2}(t_m) \\
\hat{h_2}(t_{m+1}) \\
\vdots \\
\hat{h_2}(t_{2m+1}) \\
\vdots \\
\hat{h_N}(t_m) \\
\hat{h_N}(t_{m+1}) \\
\vdots \\
\hat{h_N}(t_{2m+1})
\end{bmatrix}. \qquad (5)
$$

After solving Equation 5, the α_k and $\hat{h_n}$ values were substituted into Equation 3 and the mean percent error over different groups of questions was calculated. The results of these analyses will be presented in the next section.

RESULTS

Singular vectors were determined from data for each question. Figure 5 shows the nine mean singular vectors identified from data acquired from Subject 1 with varying levels of time pressure. In general, these results are representative of all the subjects. The first three to four singular vectors determined from data from each subject showed little variation across the data sets acquired with different length timers. There were noticeable differences in the remaining singular vectors, however, no clear trends were identified across the results from all nine subjects. Further, when singular vectors determined from data from the rest period were compared to those determined from data acquired while the subject was actively answering questions, no clear distinction was evident. These results suggest that PCA of raw (decontaminated) EEG signals may not be an effective analysis technique. Future work will be conducted to understand if pre-processing the data (i.e. filtering, component identification using independent component analysis, etc.) improves the results of PCA.

The parameters of the least squares complex exponential model shown in Equation 5 were estimated for data acquired for each question. The mean percent error between the model and the measured data was calculated. These results were then sorted in two different ways. First, results were sorted into three groups based on the length of the timer imposed for each question. Figure 6 shows the mean percent error for each of the three groups of data for each of the nine subjects. Secondly, the results were sorted into two groups based on the type of question, congruent or incongruent, that was presented. Figure 7 shows the mean percent error for these two groups of data for each of the nine subjects. When sorted by timer length, Figure 6 shows that the model is generally more accurate as the length of the timer decreases. One possible explanation for this trend is that when the timer length is short, the subject is more engaged, and the data is more consistent and better modeled using LSCE. On

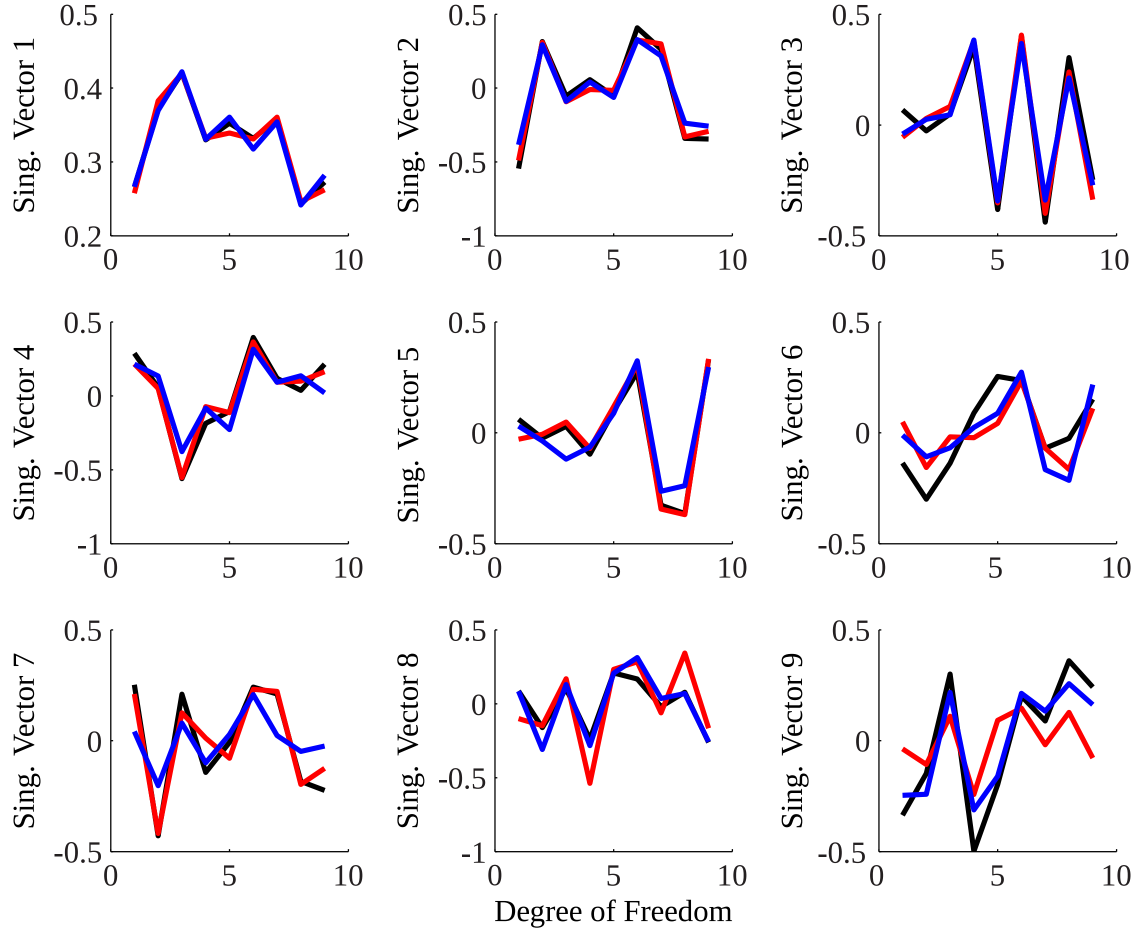


Figure 5: Singular vectors determined from data measured from Subject 1 with no timer (—), 3 second timer (—), and 1.5 second timer (—).

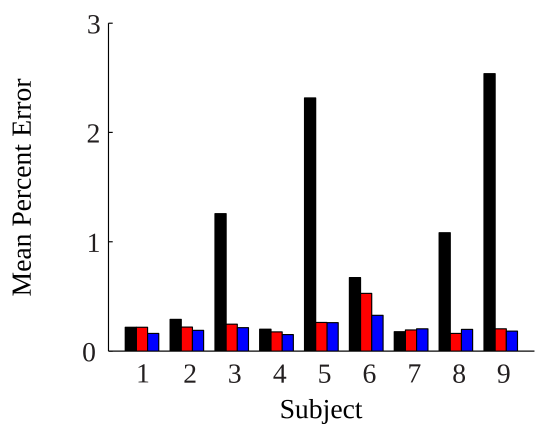


Figure 6: Mean percent error in LSCE model determined from data acquired with no timer (—), 3 second timer (—), and 1.5 second timer (—).

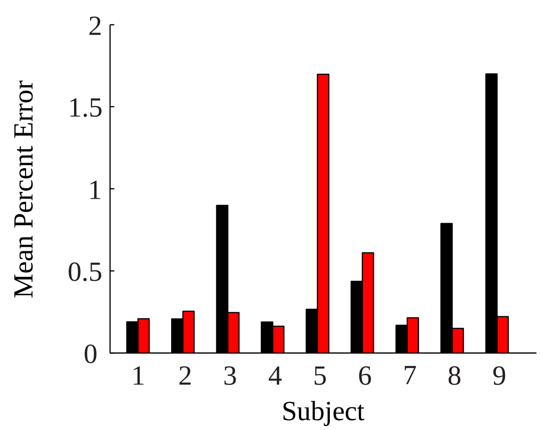


Figure 7: Mean percent error in LSCE model determined from data acquired from congruent (—)and incongruent (—) questions.

the other hand, when no timer is present, there is no penalty for loss of focus, distraction, or other changes in state of mind that may lead to errors in the LSCE model. Future work will correlate these initial findings with GSR and eye-tracking data to corroborate this hypothesis. When the data is sorted by question type, no consistent trend is present in the data. For some subjects (eg. 3, 8, 9), the results show more model error for data acquired from congruent questions while the results from other subjects (eg. 5, 6) show the opposite trend.

CONCLUSION

Principal component analysis (PCA) and the least squares complex exponential (LSCE) parameter estimation method were applied to EEG data measured from human subjects participating in a Stroop test experiment. These analysis methods were chosen in order to investigate their extension to a non-traditional SHM data domain. The parallels between traditional SHM of inanimate, dynamic systems and human state monitoring via neuro-physical data acquisition suggest that well-established SHM methods have the potential to be effective in this extended domain. Results presented here showed that the PCA analysis was not effective in distinguishing brain activity from subjects answering questions under varying degrees of time pressure. Furthermore, PCA was not effective in distinguishing brain activity from subjects actively answering questions compared to the brain activity when the subject was resting. It is possible that further pre-processing of the EEG data by using independent component analysis to generate time histories specific to parts of the brain or by filtering the data to include smaller frequency bands would improve the PCA results. Results from the LSCE parameter estimation method suggest that this modeling approach is effective. Mean percent model error from 99 percent of the questions was less than 5 percent. When results were sorted by timer length, mean percent model error increased as timer length decreased. Further work will investigate whether GSR and eye-tracking data support the hypothesis that model error increases as attention and engagement decrease and distraction increases.

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