Haptic System to Alert Users Before Impending Human Errors

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***Abstract*— High performance cognitive environments such as surgery or driving pose extensive constraints on efficient perception of salient information. In such environments it is beneficial to track physiological signals from the operator and predict errors and their type before they occur and alert the operator to take preventive action. The challenge lies in interpreting complex neural data obtained through sensors such as EEG signals and subsequently alerting the subject to possible errors. This paper presents a EEG based analysis system coupled with a haptic glove and visual feedback based alert system to provide such functionality. The haptic glove was made from six vibratory motors placed on fingers and palm. The EEG system consisted of a Bluetooth EEG cap that monitored attention distraction and drowsiness. Results show that the hand based system for delivering visio-haptic signals to alert users to impending errors can help in avoiding human errors.** *(Abstract)*

Keywords-Ambient Haptics, Cognitive Alerts, Glove based system

I. INTRODUCTION

High cognitive load environments pose a challenging problem for human computer interaction designers. These environments require sophisticated decision making and reasoning capability under time constraints and usually in the presence of noise and other artifacts. Human error in high performance cognitive environment can often cause significant damage and unfortunately is very prevalent. For example, in medical environments which are widely recognized to be high cognitive load environments a large number of errors are reported each year, many of which lead to fatalities. Error management, recovery and mitigation are hence an important part of technology based interventions in these environments.

One of the major challenge lies in monitoring the environment and human operator. Monitoring environments has traditionally been accomplished by human observers. There is significant literature in the psychological realm on using observations, interviews and propositional analysis for monitoring environments and especially cognitive environments. However, lately technological solutions for monitoring environments have been gaining momentum. Advent of computer vision technology, radio frequency identification tags has allowed for institutions and agencies to develop automated monitoring systems for the environments. Such systems aim to capture variations in an environment in an automated manner that may reasonably predict or indicate errors. Monitoring the human operator often requires specialized solutions that go beyond environment monitoring. Often humans do not exhibit percievable changes through environment monitoring and by the time a perceivable change is seen error may well have occurred. It is hence required to develop systems that can monitor an individual through other means. One such methodology lies in observing a user action in an environment and then developing causal models and predictive models for errors based on that action. An example of this type of monitoring would lie in communication graphs that show individuals as nodes and edges as being communication lines. Such graphs can often be useful in predicting communication errors which are very common in high risk cognitive environments. Another type of monitoring lies in employing physiological and cognitive signals from human operators. These systems aim to go beyond observable parameters and enable tracking of factors such as fatigue and experience.

An operators' mental state is an important variable in error prediction and monitoring. However the challenge lies in development of robust models of errors based on physiological modeling. Electroencephalography (EEG) based systems that record electrical potential from the scalp are increasingly gaining popularity as a means to monitor neural activity. In this paper we propose a model that automatically determines levels of workload, distraction, and drowsiness and models their temporal variations to determine the type of error. There are devices that use physiological means other than EEG to measure workload. This includes using a head mounted eye-tracker to measure pupil size and galvanic skin response biosensors to measure skin conductance, measuring respiration rate, heart rate, eye blinks, and eye fixation fraction. Iqbal et al. [1] used pupil size to measure mental workload during reading, mathematical reasoning, searching, and object manipulation tasks and found out that pupil size increases with cognitive tasks and decreases back to normal levels after completion of a task. Khawaja et al. [2] used skin conductance to measure workload during a reading and comprehension task and found it to be directly proportional to cognitive workload. Wierwille et al. [3] used 16 measures which 5 included physiological measurements such as respiration rate (RR) , heart rate (HR), pupil diameters (PD), eye blinks (EB), and fixation fraction (FF) and found out that FF is the only one that produces changes and is reliably able to discriminate between high and low levels of workload.

EEG is better than above listed devices because in addition to workload EEG can measure subtle shifts in alertness and attention that can be identified and quantified on a second by second basis. EEG shifts are related to task complexity and task difficulty [4]. EEG is better than pupil response system used by Iqbal et al. [1] in that it is not affected by headband slip and vibration. The disadvantage of using EEG is that a baseline test is required before values of workload, distraction, and drowsiness can be measured. However only a single baseline session can serve to provide the basis for multiple sessions and hence baseline needs to be collected only in the beginning of the experiments.

Providing feedback to the user is important and helps the user and system to recover sooner from errors produced. Feedback can be provided in audio, visual, haptic modalities. This study focuses on visio-haptic mode of providing feedback. Specifically we developed a multipoint hand haptic feedback system to provide vibratory input on the physiological state of the operator to the operator themselves. This system provided a ubiquitous method to give users feedback on their own state. We developed a system for users to select *hapticons* that represent different events in their mental states. *Hapticons* are haptically delivered signals associated with certain pieces of information. These hapticons helped users get feedback when error prone situations were being observed and alerted them to take measures to avoid errors.

II. Related Work

The use of electroencephalography (EEG) has been around for several decades and doctors have used it for several clinical applications. Today the typical EEG device for scientific use including the one used in our experiment is wireless and the electrodes make contact with the scalp though gel which is dispersed through the cap. The EEG cap does not need any tape to keep it secure on the head; instead straps are used to make sure the cap is snug. Digitization has eliminated the need for paper and ink and storage of EEG records. Every time a records needs to be examined, it can simply be recreated on a computer and manipulated by software to remove artifacts created, which was not an option with the paper and ink EEG devices. The amount of artifacts is monitored and the technician is notified accordingly. Also the signal is amplified close to the sensors and sent to a computer. Operating the EEG cap and the software that is provided for EEG monitoring is easy to learn compared to the older EEG devices. These factors have enabled a rapidly growing use of EEG devices in human computer interaction.

Using the digital EEG device extensive research has been done. Berka et al [5] has created an integrated hardware and software solution for acquisition and real-time analysis of EEG to monitor indexes of alertness, cognition, and memory. Three experiments were performed to identify EEG indices with changes in cognitive workload: The warship commander task [5], a cognitive task with three levels of difficulty and consistent sensory inputs and motor outputs, and an image learning and recognition memory task. For each of the experiments, sensor headset receives six channels of EEG data using bipolar or unipolar montage. The data is sampled at 256 samples per second with a band pass from 0.5 Hz to 65 Hz obtained digitally. To decontaminate artifacts, 60 Hz notch filter is applied to all EEG channels and three sets of filtered EEG data are derived using FIR filters. For each epoch of the four class model derived with data from three baseline tasks, five variables were computed: the logged PSD, the relative power compared to total power, and the z scores for Eyes Open, Eyes Closed, and Psychomotor Vigilance Task. The study showed that the percentage of high vigilance classifications during Warship Commander Task decreased as participants gained more training. The results from the warship task showed that the B-Alert indices are related to cognitive effort associated with task difficulty and not to the number sensory inputs or the amount of motor input required for the levels. The three-level cognitive task evaluated the EEG indices without the sensory and motor confounds associated with workload levels in the warship task. For the image learning and recognition memory task, it was confirmed that the percentage of high vigilance was significantly higher during the image memorization period compared to the recognition period [2]. These experiments showed that it is possible to monitor cognitive states of users through EEG in common human computer interaction tasks.

Significant work has been done in the area of error classification using EEG. Lotte et al [6] reviewed the various classifiers that have been used as linear classifiers and non-linear classifiers. The first group consists of linear discriminant analysis and support vector machines. The second group consists of artificial neural networks, hidden markov models (HMMs), and Bayesian quadratic classifiers [6].

Guger et al. [7] performed experiments for detection of left or right hand movement by EEG signals. The algorithm used for classifying hand movement was linear discriminant analysis in an adaptive auto regression model. Subjects imagined left or right movement without actually moving their hands and arms after the presentation of an arrow pointing to the left or right of the screen. The classification result was provided as feedback. After several sessions with feedback the classification accuracy for detecting errors became 70-95% [7]. Another study done using linear classification was to predict laterality in single trails of EEG. Subjects were asked to respond to targets with the right index finger and non targets with the left index finger. Error potentials from the EEG runs were classified and more than 85% of errors were detected within 300ms after response in seven out of eight subjects [8]. Also error related negativity related to human responses has been detected using linear classification algorithms particularly linear discriminators. The rate of correct detection of the ERN for offline processing has been 79% within 100ms for the study [9].

Artificial neural networks are the next step when it comes to better classification of EEG signals and reduced error rates using non linear classifiers. Pfurtscheller et al. [10] conducted the same experiment mentioned in [7] with band power learning vector quantization, a type of neural network based classification and the results with delayed feedback provided minimal online classification errors of 10%,13%,14%, and 17 % across four subject after several sessions. A more recent study done by Subasi et al. [11] used multilayer perception neural networks (MLPNN) in classifying EEG signals for a novel and more reliable classifier. The MLPNN used consisted of one input layer, one hidden layer with 21 nodes and an output layer. The classification accuracy of the MLPNN with Levenberg-Marquart algorithm was 93% in predicting normal versus epileptic data.

HMMs have recently become known because of the success they achieved in solving speech recognition. The use of HMMs in Brain Computer Interfaces (BCI) can build on that success because error classification using EEG is similar to speech recognition. The similarity is that both can be appropriately modeled using a stochastic approach rather that a deterministic approach. HMMs were used in a single trial EEG data and compared to Fishers linear discriminant classification and proved to have a lesser error rate [12]. Also HMMs were used in another study in a form of a temporal hidden markov tree to improve the detection of error related negativity [9]. Zhong and Ghosh [13] have proven that multivariate HMMs based on multiple channels of EEG can better capture data from multiple electrodes placed on the same head. They also used coupled HMMs to further improve error rate reduction. Rosen et al [14] applied Discrete HMMs to classify hand movement into expert and novice surgeons groups. The classification accuracy of their model was 87.5%.

The above mentioned algorithms and systems work with high resolution EEG data. However in many cases this type of resolution and data is not available. Our domain lies in developing augmented human computer interfaces that utilize low resolution EEG data for enabling preventative decisions. This is fundamentally a different problem and requires different pattern recognition solutions.

Feedback through haptic interfaces has been an active research area [15-18]. Research involves probing the placement of haptic devices, investigating stimulus response compatibility, type of haptic signals, the duration of haptic signals and the number of haptic feedback devices. A key element pertaining to this research is investigating these factors for applying haptics in a complex environment. Complex environments are characterized by several confounding factors that complicate application of any technological interventions. In general due to the emergent nature of complex environments, any technological intervention has to adapt to a users' preference and styles. Further, the user attentional focus should not be disturbed by feedback. In research done by Kahol et al. [19], it was shown that haptic feedback actually is feasible for complex environments as it does not disturb a users' attention and gives feedback in a natural and ubiquitous manner. However, it is yet to be determined whether haptic feedback can actually serve as a feedback on users' own mental state. A key issue is to see if the feedback helps subjects correct their behavior or does the feedback affects the operator in a detrimental manner. This is also true when considering multimodal systems that involve vision and haptics.

III. CONCEPTUAL FRAMEWORK

Figure 1 represents the overall framework for the Error Classification and Feedback System. EEG is employed to provide a

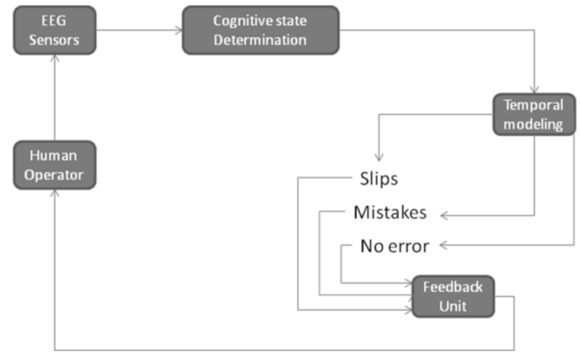

Figure 1. Conceptual Framework

feedback system that can analyze cognitive state using temporal classification of errors into slips and mistakes. Broadly, errors can be classified into two categories: *procedural errors* and *proficiency errors*. Procedural errors are those that occur while carrying out prescribed or normative sequences of action, while proficiency errors are related to a lack of skills, experience or practice [20]. A slip is a procedural error which occurs due to perceptual reasons where in a subject may not pick up cues or may inadvertently forget some details. Slips are the consequences of execution problems meaning that the plan is correct but the execution is wrong because the action is not appropriate to the intention. A mistake is a cognitive error that occurs due to lack of knowledge [21]. Mistakes can classified as proficiency error and are due to planning problem meaning that the action is executed according to plan and intention but the plan is wrong. An automated classification system that can categorize errors into slips and mistakes could prove to be a highly useful tool in high cognitive load environments.

EEG provides a reliable physiological signal used in conjunction with the temporal classifier, hidden markov models, to be able to predict errors and their type before they occur and alert the user to take preventive action. Section A explains EEG data capture device worn by the human operator and the setup procedure for each experiment. Section B examines the cognitive state determination and how workload, distraction, and drowsiness levels are determined. Section C explains how temporal modeling was used to classify slips, mistakes, and non errors. Section D examines the methodology for feedback unit used in the systems.

A. EEG Capture Device.

A battery powered wireless EEG sensor headset B-Alert was used to acquire six channels which included bipolar recordings form F3F4, FzPO, CzPO, FzC3, C3C4, and F3Cz. The EEG head set was connected via Bluetooth to the B-Alert EEG monitoring system to monitor levels of distraction, drowsiness, workload, and engagement. The first procedure done in testing was to acquire baseline EEG data. The subject participated in three tests: the first being a 20 minute 3-choice vigilance task (3C-VT). Second, a 5-min test with eyes open (EO) and last, a 5 min test with eyes closed (EC). The data received in these test was analyzed by the B-Alert EEG software and data quality was accessed. The three parts of the baseline test account for the individual differences in brain patterns. This helped account for different users. It may be noted that baseline are needed only once per subject.

B. Cognitive State Determination

Cognitive state changes were identified by using an algorithm based on linear and quadratic discriminant function analyses. The algorithm is defined in [4] in detail but we briefly present the system. The EEG signal from the 7 channel system is denoised using Gaussian smoothing. After the smoothing we need to decontaminate the EEG signal and reject EEG signals during eye blinks and excessive movement activity. Wavelet analyses are applied to detect excessive movements and to identify and decontaminate eye blinks. Thresholds are developed for application to the wavelet power in the 64 – 128 Hz bin to identify epochs that should be rejected for excessive movement. The wavelets eye blink identification routine uses a two-step discriminant function analysis. The discriminant function analysis classifies each data point as a control, eye blink or theta activity. Multiple data points that are classified as eye blinks are then linked and the eye blink detection region is established. Decontamination of eye blinks is accomplished by computing mean wavelet coefficients for the 0-2, 2-4 and 4-8 Hz bins from nearby non-contaminated regions and replacing the contaminated data points.

The EEG signal is then reconstructed from the wavelets bins ranging from 0.5 to 64 Hz. Zero values are inserted into the reconstructed EEG signal at zero crossing before and after spikes, excursions and saturations. EEG absolute and relative power spectral density (PSD) variables for each 1-second epoch using a 50% overlapping window are then computed. The PSD values are scaled to accommodate the insertion of zero values as replacements for the artifact. These PSD of these wavelets have proven utility in tracking both phasic and tonic changes in cognitive states, in predicting errors that result from either fatigue or overload and in identifying the transition from novice to expert during skill acquisition. We impose thresholds on PSDs to determine levels of attention, distraction and drowsiness. The thresholds were provided by the manufacturers and were calculated based on several experiments.

C. Error Prediction

Temporal modeling of the cognitive states was done using hidden markov models (HMMs). HMMs are probabilistic modeling tools employed for temporal sequence analysis, and have been widely used in gesture and speech recognition. Hidden markov models are doubly stochastic models that can be used to recognize any temporal or modeling sequence [22]. It is represented as a set of three sets of probabilities The Markov model is hidden because we don't know which state led to each observations which is the only element available to us for training our system.

We employed a continuous state HMM for the purposes of modeling errors. The states of the continuous HMM each have a mixture of probability density functions (pdf's) to represent the probability of observing certain multidimensional, continuous data. Mixtures of Gaussian (normal) pdf's are typically used to accurately model the state's membership in the space of observation vectors.

Mathematically, an HMM can be represented by

$$\lambda = (A, B, \Pi) \tag{1}$$

where A refers to a set of transition probabilities, B refers to the probability distributions in a state and refers to initial state probabilities. Baum Welch algorithm is employed for training an HMM. In our case, we employed two separate HMMs for the two types of errors namely slips and mistakes. In order to determine the class of a test sequence we employed the forward backward algorithm.

The HMMs were trained with one second epochs of distraction, attention and workload indices. We employed 2 second, 5 second, 10 second, 15 second and 30 second window before the errors for modeling errors. The HMMs had 4 states: the number of states being chosen empirically. Practically these windows will allow us to determine how soon we can predict that an error may happen. If an error can be predicted using 30 second window, then an operator could technically be warned 30 seconds before an error which can help them take precautionary measures.

D. Feedback Mechanism

In order to present feedback in real time we employed a custom haptic feedback glove. The glove contained a vibratory motor that can be programmed to present vibrations to the user. The glove contained six haptic motors: one for each finger and one for the palm. The feedback system can be programmed to give a variety of vibrations to convey to the user their performance.

In order to give haptic feedback using the six unit feedback system we developed a system that presents a temporal signal to different vibrator motors to provide feedback to the user. We used a variety of feedback schemes to alert users to slips or error occurrence. We developed an interface where users could decide on the type of hapticons to alert users for impending slips or mistakes. Examples of hapticons include, a constant signal, a haptic heartbeat that can be given to a single motor or a combination of motor, haptic bumps and friction signals.

We further augmented the feedback system with visual feedback through a color ball. The color ball on the monitor shows a visual representation of the mental state. The ball changes its color from green (no errors) to orange (slip) to red (mistake) to convey to the user feedback on their mental state. (Figure 2).

Figure 2. Visual and Haptic Feedback system.

IV. EXPERIMENTS AND RESULTS

We assembled a database of slips and errors in a simulation environment. The database included 80 samples of slips and 80 samples of mistakes and 80 samples of no errors event. EEG data from the database was processed as per the algorithm in section 3. Cognitive states were determined. We then employed a state vector to represent each one second epoch. Windows of two seconds, ten seconds, fifteen seconds and thirty seconds were taken before the occurrence of an event. Hidden markov models were chosen to have three states and three hidden markov models were trained; one for predicting slips, one for predicting mistakes and one for predicting no error event. 60 samples were employed for training and 20 samples were employed for testing the accuracy.

Figure 3 shows the results obtained by the HMMs for each of the time windows. The 15 second time window yielded the most favorable results. Post analysis showed that most misclassification of errors were between slips and mistakes and only a few errors were predicted to be non error events. Further many of the non-error events classified as errors were classified as slips. These results are consistent with EEG literature that suggests that slips are not a result of knowledge but occur due to distractions or missing perceptual cues [23]. In the case of the human operator missing perceptual cues, the slips and non-error events can be identical hence causing the misclassification.

The misclassification of mistakes as slips or vice verse suggests that a more robust approach may be needed to distinguish between the two models. One possible solution would be to add additional channels that may enable such analysis.

A. Feedback

In order to test the feedback system, we employed the following methodology. We chose the Tiger Woods Golf Game® as the virtual task. The game requires high vigilance from participants and it allows for both type of errors: slips and mistakes. We recruited 6 subjects for the study. Each participant played 18 holes. Out of all participants 3 were allowed to practice on even holes and 3 are allowed to practice on odd holes. The goal of practicing on every other hole is to differentiate between slips and mistakes mentioned in the introduction. Slips have a higher probability of occurring in holes were practice is allowed. Mistakes on the other hand, have a higher probability of occurring in holes were practice is not allowed.

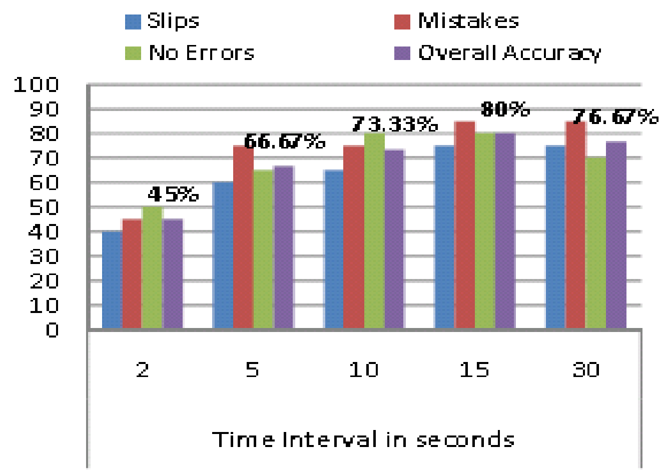

Figure 3. Results of EEG Analysis System

During the gaming sessions, subjects were given the feedback on whether they were about to make a slip or mistake through the visio-haptic system. We used the fifteen second window for the EEG analysis. We track the HMM's probability outputs from the forward backward algorithm. A continuous feedback on the probability of an error is provided with the visual system and the haptic system delivers discrete signals when the threshold of probability is reached. Empirically it was determined that a threshold of 0.6 was sufficient to allow subjects to take precautionary measures. Users were allowed to setup the hapticons to their preference. As all the participants were right handed, all the participants wore the glove in left hand. The visual feedback was provided by a screen kept on the side of the main screen on which the game was played.

The subjects played 10 holes (5 prone to slips and 5 prone to mistakes) with the feedback and 8 holes without feedback. ANOVA was performed on scores on holes with and without feedback. The results (Figure 4) showed that subjects performed statistically significantly ($p<0.05$) better on holes with feedback.

V. CONCLUSIONS

This paper presents an automated system for error classification based on human physiological measures namely

EEG. We use a multistage analysis algorithm that determines cognitive states and possible errors. Using this system it is possible to predict errors before they can happen and also reliably determine when an error has occurred. The feedback system uses visio-haptic sensations to enable users to self-correct their behavior in the case of possible error. The visual feedback provides a constant signal to enable users' to monitor their cognitive states while the haptic signal can serve as a discrete warning mechanism. Future work will involve further testing of the system and using this system in actual environments such as critical care environments and driving environments.

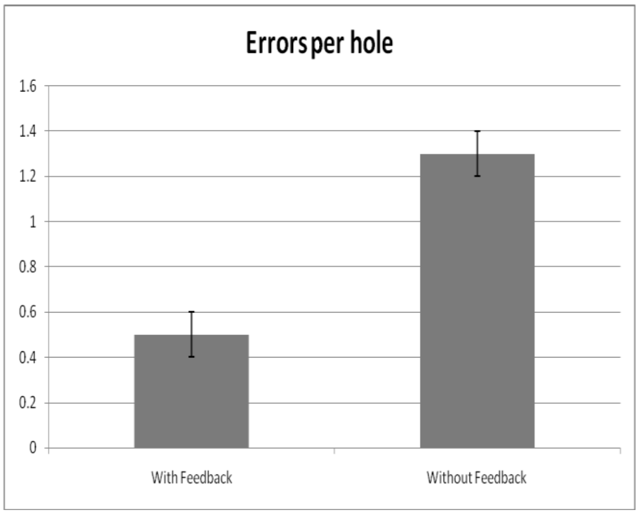

Figure 4. Results of Feedback Experiments with the Wii Golf Game.

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