Human Reliability Estimation Using Physiological Behaviour

Thesis to be submitted in partial fulfillment of the requirements for the degree

of

Master of Technology in Computer Science and Engineering

by

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CERTIFICATE

This is to certify that we have examined the thesis entitled **Human Reliability Estimation Using Physiological Behaviour**, submitted by **Abhishek Topwal**(Roll Number: *21CS60R01*) a postgraduate student of **Department of Computer Science and Engineering** in partial fulfillment for the award of degree of Master of Technology in Computer Science and Engineering. We hereby accord our approval of it as a study carried out and presented in a manner required for its acceptance in partial fulfillment for the Post Graduate Degree for which it has been submitted. The thesis has fulfilled all the requirements as per the regulations of the Institute and has reached the standard needed for submission.

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ABSTRACT

Human Reliability tells us the probability of conducting a specific tasks by a subject with satisfactory performance. Due to highly dynamic nature of human behaviour, estimating Human Reliability is a complex task. By using the physiological behaviour of a human, estimating Human reliability can be accomplished. We have used the brain electroencephalogram (EEG) signals to classify the human behaviour using different parameters. Our approach considers different human behaviour as different states and find the probabilities of the errors made in these states.

Keywords: Human Reliability, Brain-Computer Interface

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Chapter 1

Introduction

Human reliability refers to the likelihood of successful human performance within specified time frames and environmental conditions. Human performance can be affected by many factors such as age, state of mind, physical health, attitude, emotions, propensity for certain common mistakes, errors and cognitive biases [9]. Human reliability assessment allows to avoid human errors as well as tell about the human contribution to the resilience of systems. The concept of **Human Reliability Analysis (HRA)** allows us to understand the human side of a man-machine interaction in a better way. Due to highly dynamic nature of human behaviour, the reliability of the system remains questioned. Thus, to improve on the factor of human reliability, there is a need of improvement in understanding of human cognitive behaviour.

The main reasons of human errors can be categorizes as internal factors and external factors. Internal factors include workload, stress, experience etc. while external factors include task conditions, training etc. Since, the performance of the subject depends on such factors, these are popularly known as **Performance Shaping Factors (PSFs)**. Considering these factors, different HRA methods have established methodologies to evaluate **Human Error Probability (HEP)**. Due to unpredictable nature of human behaviour, it becomes difficult to predict HEP and comment about the reliability of the subject.

1.1 Motivation

The concept of Human Reliability Analysis (HRA) reflects an understanding that people and systems are not error-proof. Hence, human reliability estimation for a given task can help us not only to avoid human errors but to also comment about the performance of the subject. It also gives the freedom to focus on a user-centered design, as well as increases the probability to develop an error-tolerant design. Moreover, estimating reliability using quantitative measures related to utilization of physiological parameters such as EEG signals leads to a highly correlated approach with the changes in subject cognitive state. Measures such as heart rate, blood pressure etc. can also be included to extend the features utilized to quantify the cognitive states.

Traditionally, human cognitive behaviours have been analyzed using questionnaires, which are qualitative approaches and are mostly subjective. Since, human behaviour is very complex and is affected by various factors, it becomes very difficult to predict or simulate human behaviour. Moreover, methods of evaluation like questionnaires depends highly on the expert and remains specific to the context only.

Methods using physiological parameters are objective and provides a measure for quantitative performance. The widely used physiological parameters are ECG (Electrocardiogram), EOG (Electrooculogram), Heart Rate, Eye blinking, and Heart Rate Variability (HRV). Our approach for the quantitative analysis uses Electroencephalogram (EEG) signals. It allows us to extract the underlining indices and features from EEG signals.

1.2 Problem Statement

Since EEG records brain activity in real time as well as it has a High temporal resolution which allows it to determine the rapidly changing patterns of brain activity and hence the underline mental function. EEG signals provides the temporal resolution in the millisecond range. Therefore the potential of EEG can be utilized to explore certain parameters which can be incorporated into the proposed HEP evaluation model.

In complex working environment, there are certain characteristics of human nature which gets accentuated. These can be stress, limited working memory, limited attention resources, fatigue etc [9]. The human specific factors like the ones mentioned above will make the proposed approach independent to the subject as well as dynamic in nature. The barrier lies in estimating these complex parameters which are highly variable and changes w.r.t subject. By applying various machine learning and deep learning techniques on EEG signals, the level of the mentioned parameters can be estimated and used to analyze the performance of the subject. An experiment needs to designed such that it involve components to carefully invoke the parameters on different levels such that analysis on them reflects the performance of the subjects. The approach will help in developing a system containing ensemble of various classification models which can determine the level of various human PSFs and estimate the reliability of the subject.

1.3 Organization of the Report

The rest of the report is in the following manner:

- **Chapter 2** contains the Literature Review of similar work done related to the problem statement.
- **Chapter 3** contains the proposed approach and the description of the model used to estimate the Human Reliability.
- **Chapter 4** discusses about the components and guidelines related to the experiment.
- **Chapter 5** discusses the further work to be done.

Chapter 2

Background

2.1 Literature Review

Humans have a major contribution to operate any system in a smooth and systematic manner. However, the actions performed by humans are always prone to error and make the system vulnerable in nature. This may disrupt the overall performance of a system. To tackle these issues, Human Reliability Assessment is used. It helps in examining the human factors and the risks associated with them in a workplace. This method was originated in US Nuclear Energy Development Programme as a part of another assessment known as probabilistic risk assessment (PRA) [16]. The Human Error Probability(HEP) estimation was first used in Technique for Human Error Rate Prediction (THERP) [21]. However, the issue with these first generation methods involves the exclusion of internal and external human factors which are known to affect the performance. Human factors involves the consequences of workload, psychological issues, stress etc. [3] etc. Various research has shown that the decision making is influenced by systematic influences that can't be categorized as omissions or commissions [5].

In various HRA approaches, the estimation of human reliability is improved by inclusion of relevant Performance Shaping Factors or by evaluating values of PSF multiplier from empirical data [6]. Several studies have concluded that PSFs such as sleep duration and fatigue effects the performance of the subject directly and hence are included in various HRA models. [7]. Recent studies have been trying to incorporate the realistic empirical data and probabilistic values by replacing the traditional approach of relying on expert opinions [6]. Kim et al. proposed an important approach utilizing the statistical methods to estimate human error probabilities [11].

There has been various approaches which have utilized various features of EEG signals. In [2], power distribution and event-related brain potential (ERP) have been utilized to assess specific mental tasks, e.g. arousal level and cognitive depth. The studies have also found that in case of drop of arousal of the subject, the EEG waves shift from a fast and low amplitude nature to a slow and high amplitude one [12]. The studies have also found that in case of decreased alertness, an increase in low-frequency alpha and theta activity in cortical activation [4]. Hence, using the power of alpha and theta band, we can make a good estimation of fatigue that the subject experience. One of the components of ERP, the P300 which is defined as the most positive peak in a window between 200 and 500 millisecond have been used in identification of the depth of cognitive information processing. It has been reported that as the difficulty of the task increases, the amplitude of the P300 decreases [13]. In [18], a method known as Person-Specific Human Error Estimation (P-SPHERE) is given which evaluates utilizes the concept of Human Error Probability by also taking into consideration the dynamic nature of human behaviour through the EEG signals. It uses various user performance shaping factors (PSFs) to model human behavior.

For the purpose of Human Reliability Estimation, there are several existing methods that uses PSFs but there still remains a scope for further research. The reasons are:

1. The PSFs values and there multipliers either depends on the domain of the work or are determined by the assigned experts.

2. Less Attention is paid to the dynamic nature of the human behaviour.

3. Less studies that solely focus on the physiological parameters to estimate Human Reliability.

Chapter 3

Methodology

3.1 Proposed Approach

Human Performance is known to be affected by various PSFs. These can be used to estimate the human performance even when the nature of human performance is dynamic and subjective. To find the human error probability efficiently, the factors are considered under different categories which appears in the workplace. The PSFs are divided into four categories on the basis of the impact on the working of an individual [18]. The categories are:

- **Environmental Factors -** Work Shifts, Work Processes
- **Human Factors -** Skill, Fitness for Duty
- **Task Oriented Factors -** Task Frequency, Task Complexity
- **Organisational Factors -** Procedures, Training

Among the above factors, some of the factors remain same for different subjects for a given task. But Human Factors vary among the individuals and can be used to differentiate between the Human Performances. In the category of Human Factors, the component of Fitness for Duty comprises of parameters like Mental Workload, Vigilance, Anxiety, Working Memory etc. These parameters directly affects the performance of the individual and hence are useful in determining the reliability of the subject. Our approach focuses on determining the PSFs for the above mentioned Human Factors using the physiological behaviour of the subject captured using EEG signals. Our approach is based on the P-SPHERE (person specific human error estimation) approach as mentioned in [18]. The P-SPHERE approach takes in consideration all the above mentioned PSF categories, but our approach will only be depending on the physiological based parameters to evaluate HEP.

3.2 Performance Shaping Factors

In various HRA methods, to quantify the probability of human error, different PSF are utilized. These PSFs are systematically evaluated such that the possible sources of human errors can be identified. The strength of the PSFs changes while performing a task due to change in human behaviour, task demands etc. This alteration is also observed in the performance of the subject. Hence to estimate HEP using PSFs, the definition of different PSF levels should be given.

Factors influencing human performance	Levels	Definition
Mental Workload	High	The subject is performing low due to increase in error rate as well as high response time. The Subject experiences extreme difficulty in performing the task.
	Nominal	The Subject can perform in an optimal way. The error rate in this state is minimum and the productivity is higher.
	Low	The task requires less effort and hence the subject is experiencing minimum difficulty and less mental workload.

Table 3.1: Levels and definition for the PSF Mental Workload [18]

3.2.1 Multiplier Evaluation for the considered PSFs

Our approach considers each subject's performance independently, hence the evaluation of multiplier should be done independently for each subject based on the performance. The gathered data is used to estimate the transition probabilities for a subject changing its level of PSFs. At the same time, probabilities are also calculated for committing an error in that particular state. To derive the multiplier values for the PSFs, we have used the principle of Continuous Time Markov Chain (CTMC) Model. The CTMC model is applied to random processes which exist in discrete state space but can change their values at any instant of time. Also, the future state

Factors influencing human performance	Levels	Definition
Vigilance	High	The Subject is keenly performing the task by using high alertness observing any danger or critical events[14].
	Nominal	The Subject is actively performing the task. This subject is showing a good reaction time and the frequency of missed events is low.
	Low	The Subject is observed to lack attention leading in frequent errors.

Table 3.2: Levels and definition for the PSF Vigilance [18]

Factors influencing human performance	Levels	Definition
Anxiety	High	The subject seems to be nervous making more errors and hence giving a poor performance. The subject is indecisive and shows absenteeism.
	Nominal	The subject is well aroused and not in a state of over-stressed and unhappy can give a high quality performance.
	Low	The subject seems to lack motivation and is reaching a state of boredom.

Table 3.3: Levels and definition for the PSF Anxiety [18]

Factors influencing human performance	Levels	Definition
Working Memory	High	The subject can control, regulate and actively maintain the task related information.
	Nominal	The subject can actively maintain the task-relevant information.
	Low	The subject is not able to hold and use the required information.

Table 3.4: Levels and definition for the PSF Working Memory

of the model depend only on the current state and not on the previous states. The CTMC model imitate the highly dynamic nature of humans as the state of a person can make transition from any state to the other at any instant of time. The model also reflects the human behaviour in a way that it his highly correlated to the present state and not on the history of the states to reach the current state.

The multipliers are evaluated in 2 steps [18]:

- Evaluate the probability of the subject of being in one of the defined states or levels of the PSFs.
- Evaluate the probability of the error made by the subject while being in one of the defined states.

Depending on the individual performing the task, these PSFs can change from one level to another. The levels can be categorised as:

- Nominal State (st = NO) is the base state.
- Positively Affecting State (st = PF) is the state in which the individual performs the task in a performance improving scenario.
- Negatively Affecting State (st = NF) is the state in which the individual performs the task in a performance degrading scenario.

We would consider the probability of the errors separately in two states as:

- Error-Free State (st = NE) where the subject does not commit any error.
- Error-Occurrence State (st = EO) where the subject takes a wrong decision or performs a delay in action or performs an incomplete task.

3.2.2 Transition Rate Computation

Let α be the rate at which the PSF leaves state i and P_{ij} is the probability that the PSF goes to state j. Let a_{ij} be the transition probability from state i to state j. We can find the steady-state probabilities $[P = P_0, P-1, \ldots, P_r]$ using the transition probability of each state using the matrix equation,

$$\begin{bmatrix} P_0 & P_1 & \dots & P_r \end{bmatrix} \cdot \begin{bmatrix} a_{00} & a_{01} & a_{02} & \cdots & a_{0r} \\ a_{10} & a_{11} & a_{12} & \cdots & a_{1r} \\ \vdots & \vdots & \vdots & \vdots & \\ a_{r0} & a_{r1} & a_{r2} & \cdots & a_{rr} \end{bmatrix} = \begin{bmatrix} P_0 & P_1 & \dots & P_r \end{bmatrix}$$

Once steady state probabilities are computed, the steady state probabilities are multiplied with the error occurrence probability to get the corresponding multiplier for the PSFs.

3.2.3 Human Error Probability Calculation

The steps to evaluate Human Error Probability (HEP) is as follows:

- Using the Continuous Time Markov Chain approach as discussed in Section 3.2.1 evaluate the considered PSFs.
- Perform the union of all the multipliers to get the error contribution from the factors.

$$\begin{aligned} P(HF) &= P(MW) \cup P(V) \cup P(WM) \cup P(A) \\ HEP &= P(HF) \end{aligned} \tag{3.1}$$

where, MW = PSF Multiplier for Mental Workload, V = PSF Multiplier for Vigilance, WM = PSF Multiplier for Working Memory, A = PSF Multiplier for Anxiety.

3.3 Classification Approaches

There are various Machine Learning and Deep Learning Techniques available for the classification of the considered PSFs. The acquired EEG signals are first processed for artefacts and noise removal and then various features are extracted. These features are then used for classification.

3.3.1 Mental Workload

The dataset used for the classification of Mental Workload was generated by previous students in the HCI-BCI Lab of IIT-KGP. The EEG data is collected from 8 subjects

S.No.	Features	Short Description
1	Coefficient of Variation	a statistical measure of the deviation of a variable from its mean, standard deviation divided by mean
2	Skewness	A measure of asymmetry of the distribution
3	Kurtosis	A measure of flatness of the distribution
4	Fractal dimension	Nunmber of points
5	1st Diff Mean	Mean value of the first derivative of the signal
6	1st Diff Max	Maximum value of the first derivative of the signal
7	Mean absolute correlation	Mean value of auto-correlation or cross-correlation function
8	2nd Diff Mean	Mean value of the second derivative of the signal
9	2nd Diff Max	Maximum value of the second derivative of the signal
10	Hjorth Components	The parameters are normalised slope descriptors (NSDs) used in EEG.
11	Zero Crossing	Number of zero crossings in a signal
12	Min-Max Number	Number of local minima and maxima
13	Amplitude Range	The difference between the maximum positive and maximum negative Amplitude values

Table 3.5: Time Domain Features

working on 3 different levels of Solidworks [20] models using a 14-channel Emotiv EEG device at a channel frequency of 128 Hz.

The task is to classify the 1 second epoch of the EEG signals into 3 levels of Low, Nominal or High. For the purpose a feature matrix is made consisting of various time domain and frequency domain features.

The feature extraction matrix is created using the above features for every Epoch of the EEG signal along with the target level. Various Machine Learning models are used for the classification. The results are depicted in table 3.8

We can observe in 3.8 that the applied Machine Learning Models are able to classify the given EEG signals considerably well.

S.No.	Features	Short Description
1	Wavelet Coefficient of Variation	Coefficient of Variation
2	Wavelet Total Energy	Total Energy
3	Min and Max Wavelet Value	Minimum and Maximum Wavelet Value
4	Mean Wavelet Value	Mean Value
5	Median Wavelet Value	Median Value
6	STD Wavelet Value	Standard Value
7	Wavelet Skewness Value	A measure of asymmetry of the distribution
8	Wavelet Kurtosis Value	A measure of flatness of the distribution
9	Wavelet Band	Relative Energy
10	1st Diff Wavelet Mean	Mean value of the 1st derivative
11	1st Diff Wavelet Max	Maximum value of the 1st derivative
12	2nd Diff Wavelet Mean	Mean value of the 2nd derivative
13	2nd Diff Wavelet Max	Maximum value of the 2nd derivative
14	Wavelet Zero Crossing	Zero Crossing

Table 3.6: Wavelet Features

S.No.	Features	Short Description
1	Spectral Entropy	A measure of its spectral power distribution
2	Shannon Entropy	A measure the uncertainty of a random process
3	FFT Delta Power	0.1 - 3 Hz frequency
4	FFT Theta Power	3 - 7 Hz frequency
5	FFT Alpha Power	7 - 12 Hz frequency
6	FFT Beta Power	12 - 30 Hz frequency
7	FFT Gamma Power	30 - 40 Hz frequency
8	FFT Whole Power	0.1 - 40 Hz frequency
9	FFT DT RATI)	DELTA / THETA
10	FFT DA RATIO	DELTA / ALPHA
11	FFT TA RATIO	THETA / ALPHA
12	FFT DTA RATIO	(DELTA + THETA) / ALPHA
13	FFT SEF	Spectral edge frequency (95 % of the total spectral power resides)

Table 3.7: Frequency Domain Features

Machine Learning Technique	Accuracy Obtained(%)
KNN	78.39
Random Forest	85.78
SVM(Linear Kernel)	83.77
MLP	88.51
LDA	80.6
Gaussian NB	55.54

Table 3.8: Mental Workload Classification Accuracy using different Machine Learning Techniques

3.3.2 Anxiety

To classify the PSF Anxiety, we have used the DASPS Database containing recorded Electroencephalogram (EEG) signals of 23 participants during anxiety elicitation by means of face-to-face psychological stimuli [1]. As shown in [1], anxiety is well elicited in 1 second, hence we have used the similar 1 second epochs as in Mental Workload classification.

The use of deep learning techniques like Convolutional Neural Networks has increased and has been effectively used for emotion detection [10, 17]. Since, deep learning based CNN extract increasingly more complex features of the data, they have shown better performance than the widely-used filter bank common spatial pattern algorithm

[19]. Moreover, it showed promising results for anxiety classification from EEG in Adolescents with Autism in [15].

Batch Size	Accuracy
16	86.83
32	84.79
64	83.49

Table 3.9: Results for Anxiety classification using EEGNet

Chapter 4

Experiment

4.1 Introduction

As discussed in the previous chapters, an experiment needs to be designed to get the required data for various PSFs level classification. The experiment needs to be designed in such a way that different physiological parameters of Mental Workload, Anxiety, Working Memory and Vigilance are invoked properly. It should include components to evoke all the above mentioned characteristics in the same environment for all the subjects. Moreover, the experiment should be conducted in an isolated environment to remove the interference in the EEG signals from any artefacts.

4.2 Multiple Attribute Task Battery

The Multi-Attribute Task Battery (MATB) is a aircraft tasks simulator designed to evaluate operator performance and workload. It requires the users to perform various tasks at the same time testing the mental workload and situation handling of the subject [8].

The MATB requires the subject to simultaneously perform tasks related to monitoring, resource allocation, tracking and dynamic resource management. These multitasking components of the MATB makes it suitable and consistent for various operational systems and makes it a useful method for various research related activities. The Multi-Attribute Task Battery (MAT Battery) was originally developed in the early 1990's at LaRC (Comstock & Arnegard, 1992) and re-implemented under Microsoft Visual Studio.NET (VS.NET) [8] .

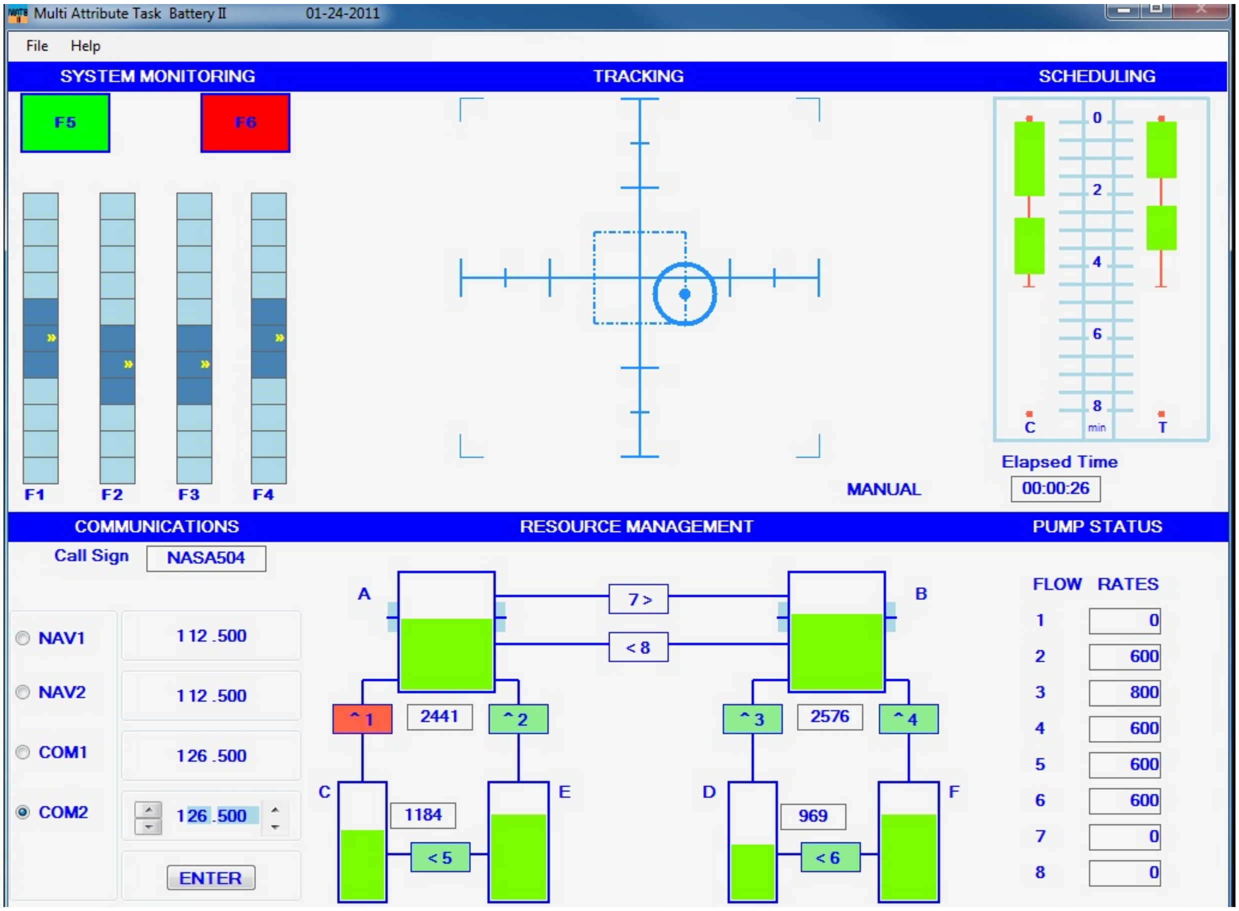

Figure 4.1: MATB Graphical User Interface

The different tasks which the subject has to perform and the physiological parameters invoked respectively are:

- **System Monitoring (SYSMON)**

  This task can be seen in the upper left window of the display. This part works similar to the gauges and lights of an aircraft. 2 lights are present in this section-green, red. The task also contains a four direction moving pointer dial whose deviation the user has to track. This task will test the vigilance levels of the subject. After some duration of the task, the subject will have to be more attentive to perform the task with less errors[8].

- **Tracking (TRACK)**

  The aim of this task is to simulate the manual control part of the flight using a Joystick. The subject keeps the target at the center of the window. This task will invoke the mental workload of the subject as well as the anxiety. Increasing the difficulty will lead in more mental workload as well as higher anxiety[8].

- **Communications (COMM)**

  This tasks simulates the instructions attending capability of the subject. The subjects are presented with some pre-recorded auditory messages after some intervals. By listening to the messages carefully, the subject has to determine the relevance of the message and respond to it accordingly. The response is provided by selecting the appropriate radio and frequency on the communications task window. This task involves the working memory and the vigilance characteristics of the subject[8]

- **Resource Management (RESMAN)**

  This task simulate the resource or fuel management demands of the aircraft. There are two tanks, A and B which are supposed to be maintained at 2500 units each. These are connected to eight pumps which can be turned On-OFF, hence controlling the level of A and B. Also, some cases may arise when there is a pump failure shown by red light. The amount of fuel in each tank is represented in green color. This task will include the vigilance and working memory parameter. [8].

In all the above tasks, the cases when the subject makes an error will lead to more anxiety in the subject.

Chapter 5

Further Work

We have decided a framework for the estimation of Human Reliability using Performance Shaping Factors such as Mental Workload, Vigilance, Anxiety and Working Memory utilizing the EEG signals of the subject. The framework takes different states of these PSFs as a state of Continuous Time Markov Chain. By using the probabilities of being in a state and the probabilities of making an error in that particular state, we are calculating the value of Human Error Probability.

To classify the state of PSFs using the EEG signals, the models have been built for Mental Workload and Anxiety. Similar models still needs to be built for Vigilance and Working Memory. Furthermore, the discussed experiment needs to be conducted to gather the data and check the correctness of the proposed approach.

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