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A Review on Features used for EEG-based Mental Fatigue Detection

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Abstract: Mental Fatigue has become a one of the major concerns among public safety and health since it has led to large number of occurrences of road accidents, work place injuries etc. Mental fatigue related accidents may lead to death or severe injuries making one unable to lead a normal life. Given the importance of this issue, mental fatigue monitoring has been attempted (i) subjectively via self-assessments, (ii) behaviourally via monitoring of eye blinks, head movement, yawning, (iii) physiologically via Electroencephalogram (EEG), Electrooculogram (EOG), Electrocardiogram (ECG) etc. and (iv)vehicular based parameters like reaction to lane deviation, pressure on accelerator etc. Recent investigations have reported that EEG-based mental fatigue detection is more reliable and can be extended not only for driver drowsiness detection but also in other industries involving continuous and monotonous work which are prone to fatigue related accidents. This paper reviews, different EEG features that has been used in the recent studies and try to identify those features that best depict the change in an individual vigilance state.
Keywords: Mental Fatigue, Driver Drowsiness Detection System, EEG, EEG Features, workplace fatigue.

I. INTRODUCTION

Mental fatigue is one of the major causes for workplace injuries and road accidents, hence fatigue has been widely accepted as a significant factor in a variety of transportation accidents and workplace hazard. Mental fatigue can be defined as a state marked by reduced efficiency and a general unwillingness to work as result of feeling tired, sleepy. The major cause for mental fatigue is insufficient sleep, engaging in a demanding or monotonous job for a prolonged duration of time. The effects of mental fatigue can take a toll on many aspects of a person's life like poor work performance and reduced productivity and hence, today it has become a major concern in public safety, health and quality of life. 4,552 accidents, 1,796 deaths and 4,685 injuries are reported by [1] to direct consequence of fatigue driving. 13% of workplace injuries are mainly due to mental fatigue [2]. Given the importance of this issue, it has become one of the important areas of research and many methods have been attempted.

Subjective-based Detection, where the driver is asked to assess his mental fatigue state, hence this method is purely dependent on driver's judgement. Standard questionnaires like Stanford Sleepiness Scale, Groningen Sleep Quality Scale, Karolinska sleepiness scale (KSS etc. are used which consists of set of questions to find the fatigue level. This method will be unreliable when the driver is a poor judge of his/her mental state, or driver may not be sincere about his judgement.[3]

Vehicular-based Detection, where the number of parameters such as speed of the vehicle, lane deviation, pressure on accelerator, pressure on steering wheel etc. are monitored continuously to detect and monitor mental fatigue. A threshold is pre-defined, against which the metrics are compared to conclude the mental state of the driver. The disadvantage of this method is that it is difficult to generalize a method due to change in vehicular types, experience of the driver, driving and road conditions. This measurement metrics can also be influenced by driver behaviour and may lead to wrong detection.[3]

Behavioural-based Detection, where the detection of mental fatigue is based on behaviour of the driver like yawning, eye blinks, head movement, eye movements. The disadvantage of this method is sensitivity of the camera used for monitoring the behaviour to surrounding light.[3]

But these methods are focussed on driver drowsiness detection which are behavioural based and vehicular based. But when monitoring in workplace is considered, subjective based method is subject biased and hence this led to exploration of physiological signals [3].

Physiological Signals-based Detection, where the detection of mental fatigue is based on change in features of physiological signals w.r.t change in vigilance state. Many studies have shown that there exists correlation between physiological signals and vigilance state. Physiological signals like Electroencephalogram (EEG), Electrooculogram (EOG), Electrocardiogram (ECG), and Electromyogram (EMG) are used to detect mental fatigue. Among these signals, EEG is most reliable to detect mental fatigue. Among the many physiological signal's EEG is more popular due to its direct relation to mental state A person tends to fall asleep when he/she feels fatigue and this is reflected by change in EEG wave patterns due to the established fact that, particular EEG wave

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bands are dominant during particular stages. We know that standardized sleep stage scoring is based on EEG criteria [4] i.e. change in frequency and amplitude of EEG waves and the same knowledge is being utilized for mental fatigue monitoring that is capturing the features during the transition from alert to sleep state.

Mental fatigue monitoring systems based on EEG is developed where the detection is either based on thresholding [14,15] or using machine learning algorithms [8-13], [16-21]. The core step in both of these methods is feature extraction for successful classification results. Hence it is important to identify features that can successfully bring out the hidden information with in the EEG signals and thus enable to help distinguish between the different mental state of an individual.

Thus, this paper aims at reviewing various EEG features that has been investigated for mental fatigue detection and identify their practicality via their advantages and disadvantages.

II. MENTAL FATIGUE DETECTION BASED ON EEG SIGNALS

Mental Fatigue is highly correlated with drowsiness, a transitional state between wake and sleep. This change in mental state is reflected by change in EEG wave pattern i.e. EEG amplitude and frequency. It has also been documented that the mental fatigue is associated with significant changes in delta, theta, and alpha and beta activity [38]. Thus, extraction of suitable features that trap the transition between wake and sleep enables developing a system for fatigue detection.

EEG is recording of electrical activity of the brain. The EEG is recorded using electrodes, these are mostly non-invasive (electrodes attached to surface of scalp) or invasive depending on application. The EEG signal of a healthy adult has an amplitude of 10µV to 100µV [5]. Depending on the behavioural state, the frequency varies up to 600 Hz [6]. The variations of amplitude and frequency has significant diagnostic value, more evidently the frequency variations are direct reflection of change in mental states. The five prominent EEG waves that have clinical importance are Delta, Theta, Alpha, Beta and Gamma. Delta waves with frequency less than 4 Hz are dominant during deep sleep, theta waves with frequency ranging from 4 to 8 Hz are dominant in drowsy condition, alpha waves with frequency ranging from 8 to 13 Hz are present during relaxed state, the beta waves with frequency ranging from 13 to 30 Hz are prominent during high concentration and attention and gamma waves with frequency greater than 30 Hz are present during highly active state. The idea behind EEG based mental fatigue detection system is to capture the features that relate to these above-mentioned criteria. The basic building blocks of EEG based mental fatigue system is presented in Fig 1.

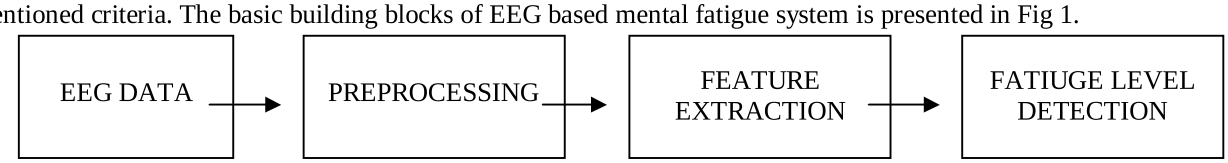

Fig. 1 General block diagram for EEG-based mental fatigue detection

A. EEG Data

The EEG data is either obtained from a reputed online database like Physionet, CAP [7] or collected in real-time by designing application specific paradigm like driver simulation test [] etc. The data required for developing of a fatigue detection model should be diverse in nature, large in number representing all the classes required to be found. The data is collected using scalp electrodes placed according to 10-20 standard electrode system.

B. Pre-Processing

The data acquired are generally contaminated by surrounding artefacts and hence pre-processing becomes essential. Pre-processing like notch filter, band pass filter, wavelet denoising, Independent component analysis are most commonly used.

C. Feature Extraction

Once the data is processed next comes the crucial step which is feature extraction which may be time domain, frequency domain or non-linear features. The features extracted should be independent and descriptive of the labels one is looking for. The features should not only be a good representative of all classes but should be computationally inexpensive and should not consume more time if the model needs to be extended in real-time. The next section gives a detailed discussion about the features used.

D. Fatigue Level Detection

Once the features are extracted, either by identifying a threshold or by the aid of machine learning algorithms fatigue detection is accomplished. SVM, Neural networks are most commonly used learning algorithms.

III. FEATURES FOR EEG-BASED MENTAL DETECTION

Features are illustrations of the hidden information in the signal. The features extracted should be representative of the information one is trying to find and independent. Hence feature extraction is a crucial step in any signal processing applications and number of techniques have been developed to extract suitable features from the signal. In this case, the features extracted from the EEG signal should effectively represent alert and drowsy state. The features extracted in sleep stage classifications are also studied since detection of fatigue level is correlated with transition from wake to alert state. The three main categories of features identified are, (i) time-domain features, (ii) frequency-domain features and (iii) N=non-linear features.

A. Time Domain Features

The time domain features represent change in statistical properties of a signal. These are indicated by change in morphological properties of the signal. Time domain features are one of the easiest features to compute. They inexpensive both computationally and in time. They are less complex since no additional data processing like sampling, Fourier transform etc. are required. Some of the wide-spread time domain features used are,

1) *Statistical Moments:* The simplest features of time domain are the statistical moments. Mean, Standard Deviation, Skewness, Kurtosis are the most common features extracted.
2) *Hjorth Parameters:* It is measure of statistical properties in terms of Activity which represents the power of signal and id defined as variance of a signal, Mobility which represents the mean frequency of the signal and Complexity that represents frequency change**.** The Hjorth parameters are is given by,

$$\text{Activity} = \text{Var}(x) \tag{1.1}$$

$$\text{Mobility} = \sqrt[2]{\frac{\text{Var}(x')}{\text{Var}(x)}} \tag{1.2}$$

$$\text{Complexity} = \frac{\text{Mobility}(x')}{\text{Mobility}(x)} \tag{1.3}$$

where Var(x) and Var(x’) represents variance of input signal x and variance of its first derivative.

IV. FREQUENCY DOMAIN FEATURES

Frequency domain features are versatile features which are repeatedly utilized for describing changes in EEG signals. The most commonly used feature in EEG analysis is Power Spectral Density (PSD).

A. Power Spectral Density (PSD): This represents the distribution of signal energy over frequency. This gives information about the frequency at which the average power of the signal is accumulated. In case of EEG analysis, it is known that delta band is prominent during sleep stage, theta during drowsy, alpha and beta during wake stage. Thus, computing the PSD of the EEG, one can find which EEG sub-band has stronger variations and indirectly find the mental state. Welch Periodogram is the most commonly used method to estimate PSD. It is improved version of periodogram and Bartlett’s method. The main advantage of this method is that it reduces noise in the PSD estimated. The feature that sets Welch different from Bartlett’s and standard periodogram is the windowing of overlapped time segments. The periodogram of this windowed segment gives the PSD which is computed as square of absolute value of FFT. Some of the studies have also used PSD of selective bands, only those band EEG that represent the state transition from alert to drowsy prominently are chosen.

B. The other frequency domain features include Fast Fourier transform coefficients, Wavelet Transform Coefficients.

V. NON-LINEAR FEATURES

Non-linear features of EEG due to its randomness and complex patterns can be used to effectively classify EEG into different mental states. The most commonly used non-linear features are,

1) *Entropy:* Entropy measures the randomness of the signal. It is observed that the EEG pattern is more random when alert than in drowsy and sleepy state. Spectral Entropy, Approximate Entropy, Sample Entropy are different kind of entropy measures employed.

2) *Higuchi Fractal Dimension:* This gives the measure of complexity of the signal. This feature is extensively used in EEG analysis. This can be used to effectively differentiate between alert and sleep stages. Among different methods used to calculate the fractal dimension, Higuchi's method deliver's more accurate results.

Table I
Various Eeg Features Extracted For Mental Fatigue Detection

Features	Findings
Power Spectral Density (PSD)	Most commonly used feature extracted from EEG. Normally the PSD of the EEG bands are used as feature as it is observed that different EEG bands dominate during different stages of sleep.
Statistical features	Wide range of features like mean, median, standard deviation, kurtosis, max/min amplitude etc. can be used as change in statistical properties can be observed w.r.t to change in mental states. These features are easy and quick to compute, but are highly sensitive to noise.
Entropy	Represents irregularity. EEG becomes less random when one falls to sleep. These features provide good classification result but they consume more time for computing.
Fractal Dimension	It describes the complexity of the signal and gives structural information of the signal. This feature can be used as EEG exhibits fundamental difference in their pattern during different mental states.
Hjorth parameters	The Hjorth parameters (activity, mobility and complexity) provides information about signal power, mean frequency and change in frequency w.r.t to change in mental states.

The summary of various features used for EEG-based mental fatigue detection is presented in Table 1. Normally these features are not used individually, they are combined with other features in order to enhance the result. Below table (Table 2) lists gives comparison of performance w.r.t feature used.

Table II
Comparision Of Performance Bsed On Eeg Features Extracted

Ref	Feature Extracted	Performance
[8]	Logarithmic power	Acc=80%
[9]	PSD	Acc=75.3%
[10]	FFT	Acc(drowsy)=86.5% Acc(alert)=83%
[11]	PSD-based indices	NA
[12]	PSD	Acc=79%(feature-based) Acc=83%(ML-based)
[13]	PSD	Acc=90%
[14]	PSD	NA
[15]	Statistical features, Log variance and PSD	NA
[16]	Sub-band PSD (1 – 4 Hz) and (9 – 11 Hz) and ratio of PSD	Acc = 98.01%
[17]	Average amplitude, variance, spectral powers, coherence, fractal exponent, prediction error	Acc=74%
[18]	Dominant frequency, Average power, Centre of gravity frequency, Frequency Variability	Acc= 90%
[19]	Hjorth parameters, PSD	Acc = 93.21% (max with SVM classifier)
[20]	Entropy, Fractal Dimension, Detrended fluctuation analysis	Acc = 81%
[21]	Statistical features	Acc= 94.14% (using bagging)

VI. CONCLUSIONS

In this paper a brief review of various features extracted for EEG-based mental fatigue detection is presented. It can be observed that Power Spectral Density is the most common feature that is used. PSD throws information about the relative energy in each band of EEG and as it has been proved that each mental state is dominated by a particular EEG band PSD becomes most promising feature for mental fatigue detection. Even though EEG based detection is reliable in terms of features extracted it is not that easy to implement in real-time. It may cause discomfort to the user if the electrodes are attached and would hinder their work and hence face reluctance and thus, failing its purpose. More investigation is required in developing systems that utilizes less electrodes and abide to the concept of wear and forget. The features extracted are experimented only in offline and its feasibility in the field is not addressed in the literature. On a final note, the features extracted should be robust, flexible, easy to integrate with other EEG acquisition devices.

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