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EEG signal analysis for the assessment and quantification of driver's fatigue

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ABSTRACT

Fatigue in human drivers is a serious cause of road accidents. Hence, it is important to devise methods to detect and quantify the fatigue. This paper presents a method based on a class of entropy measures on the recorded Electroencephalogram (EEG) signals of human subjects for relative quantification of fatigue during driving. These entropy values have been evaluated in the wavelet domain and have been validated using standard subjective measures. Five types of entropies i.e. Shannon's entropy, Rényi entropy of order 2 and 3, Tsallis wavelet entropy and Generalized Escort-Tsallis entropy, have been considered as possible indicators of fatigue. These entropies along with alpha band relative energy and $(\alpha+\beta)/\delta_1$ relative energy ratio have been used to develop a method for estimation of unknown fatigue level. Experiments have been designed to test the subjects under simulated driving and actual driving. The EEG signals have been recorded along with subjective assessment of their fatigue levels through standard questionnaire during these experiments. The signal analysis steps involve preprocessing, artifact removal, entropy calculation and validation against the subjective assessment. The results show definite patterns of these entropies during different stages of fatigue.

1. Introduction

Fatigue is a complex state which manifests itself in the form of lack of alertness and reduced mental or physical performance, often accompanied by drowsiness (Lal & Craig, 2001). In transportation systems, it is a major cause of fatal road accidents. Earlier research has established that fatigue is responsible for 20–30% of total road fatalities (Lal, Craig, Boord, Kirkup & Nguyen, 2003).

The symptoms of fatigue are non-specific: generally it manifests in the form of drowsiness, tiredness or weakness. Fatigue leads to severe deterioration in the vigilance level of the human driver eventually making them commit mistakes. The detection and quantification of fatigue can help researchers to build instruments that will help in early assessment of fatigue level on-board. There has been considerable research to detect fatigue from several measurements. Most of them involve:

(i) Subjective measurements based on questionnaires,
(ii) Psychomotor tests based on reaction time and concentration,
(iii) Measurement of ocular parameters like saccadic movement, Percentage Closure of Eyes (PERCLOS)
(iv) Measurement of physiological variables like Electroencephalogram (EEG), Electrooculogram (EOG), Electromyogram (EMG), Electrocardiogram (ECG)

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Few authors have also suggested methods based on steering grip pressure, skin conductance, Blood Volume Pulse (BVP), etc. (Cai & Lin, 2007; Healey & Picard, 2005).

Subjective tests are based on standardized questionnaires and helps in self assessment of fatigue. A number of such questionnaires are reported in literature (Stanford Sleepiness Scale, Piper Fatigue Scale, Epworth Sleepiness Scale). Psychomotor tests include performance assessment of the subject based on some predefined tasks. It has been observed that *the reaction time* and *error* during *audio-visual response test* of a subject increase as the fatigue level of the person increases (Caldwell, Prazinko, & Caldwell, 2003; Milosevic, 1997).

Eye movement and percentage closure of eyes (PERCLOS) are two important parameters for detecting drowsiness. It has been observed that eye movement decreases while blink rate increases as a person enters into the state of fatigue (Lal & Craig, 2001). Different techniques have been developed for measurement of eye movement and blink rate using facial image of the subject (Papadelis et al., 2007; Singh & Papanikolopoulos, 1999). Many researchers have used PERCLOS for non-intrusive fatigue detection (Dinges, Mallis, Maislin, & Powell, 1998; Eriksson & Papanikolopoulos, 1997; Ji, Zhu, & Lan, 2004).

A number of studies on ECG have shown a reduction in heart rate and change in the heart rate variability during fatigue (Ishbashi et al.,1999; Jeong, Lee, Park, Ko, & Yoon, 2007). Research on EMG reveals that when a muscle becomes fatigued, its stiffness changes, the amplitude of the EMG signal increases, and the spectrum shifts towards lower frequencies (Knaflitz & Molinari, 2003; Park & Meek, 1993).

Amongst a number of indicators that can be used for fatigue detection, EEG is considered to be the most significant and reliable. EEG is a record of electric potential from the human scalp, which is a result of excitatory and inhibitory post-synaptic potentials generated by cell bodies and dendrites of pyramidal neurons (Lal & Craig, 2001). It is closely associated with mental and physical activities. For different activities the EEG recording may be different either in terms of magnitude or in terms of frequency or both.

Driving involves various functions such as movement, reasoning, visual and auditory processing, decision making, perception and recognition. It is also influenced by emotion, anxiety and many other psychological factors (Lal & Craig, 2001). All the physical and mental activities associated with driving are reflected in EEG signals. This is the reason for considering this signal as a reliable indicator of fatigue.

Several methods are used in literature to quantify the EEG signal. These quantifications involve calculation of features like energy (Jap, Lal, Fischer, & Bekiaris, 2009; Siemionow, Fang, Calabrese, Sahgal, & Yue, 2004) and entropy (Papadelis et al., 2006) in different bands of signals and their interactions. Classical methods to quantify EEG signal (such as Fourier Transform) is generally based on power spectral analysis. Such type of analysis assumes that the signal is stationary within the analysis window. But, EEG signal is highly non-stationary in nature and is very difficult to find its complete statistical characteristics either in time domain or frequency domain (Shuren & Zhong, 2004) rendering most of the classical methods inadequate for analysis. In recent times, Wavelet Transform has been used in EEG signal analysis for detecting epilepsy (Yamaguchi, 2003), brain injury (Al-Nashash et al., 2003), or micro-arousal in sleep (Glavinovitch, Swamy, & Plotkin, 2005), etc. It provides a multi-resolution time-scale representation of the signal and is considered as a potential tool for study of non-stationary signals. It offers good time resolution at high frequencies and good frequency resolution at low frequencies (Daubechies, 1990; Mallat, 1999).

The paper presents characterization of the EEG signals in the wavelet domain using various entropy measures. The EEG signals are collected from 30 subjects under varying experimental conditions representing different levels of fatigue. The features are based on basic index which is the property of an individual band, ratio index which presents the combined property of a number of bands, and entropies which is a measure of information content. Subjective self assessments have been used to establish the level of fatigue and also as a confirmatory test for the proposed method.

the paper has been organized as follows:

Section 2 describes the experiment design and data collection. In Section 3, the methodology of analysis has been described. This includes signal preprocessing, artifact removal, calculation of entropy and development of a scale for an unknown fatigue level. Section 4 describes the results along with discussions.

2. Experiment design

Different sets of experiments were conducted using a 32-channel Polysomnograph machine to collect EEG data from various subjects in actual and simulated driving scenario. The EEG signals were recorded in the laboratory as well as on the test sites at suitable instants during the experiments. The following paragraphs depict our experiments and collection of data.

2.1. Subjects and experiment design

The entire set of experiments has been divided into three categories.

2.1.1. Experiment 1: actual driving and driving related psychomotor vigilance tests

Experiment 1 was conducted on 21 healthy male participants (professional drivers) between ages 25 and 35. They were asked to drive for 1 h in a busy traffic followed by a computerized subjective test. Then a set of psychomotor tests i.e. Complex Reaction Time Test, Action Judgment Test, Speed Distance Judgment Test, Glare and Vision test were conducted

(Chakraborty, 1998). All the test set-ups were designed to simulate different types of actual driving activities and are used to evaluate the driver's skill and performance. The EEG data collected before the commencement of the entire process of experiment was labeled as 'Level 1'. On the other hand the EEG data recorded at the conclusion of the entire procedure was labeled as 'Level 2'. All these tests were conducted at specialized laboratory facilities located at Central Road Research Institute (CRRI), New Delhi, India.

2.1.2. Experiment 2: simulated driving tasks with sleep deprivation

Twelve healthy male subjects have been chosen in the age group of 20–35 years for this experiment. All the subjects were reported to have no disorders related to sleep. They were asked to refrain from any type of medicine and stimulus like alcohol, tea or coffee during the experiment.

The entire experiment was divided into a number of identical stages. Each stage started with condition monitoring of each subject by a medical practitioner. After the subject was declared fit, he was asked to perform some predefined tasks. These were: physical exercise on a tread mill for 2–5 min to generate physical fatigue; simulated driving for about 30 min to generate physical, visual, and mental fatigue; auditory and visual tasks for 15 min to generate mental and visual fatigue; finally the computerized game related to driving for about 20 min. A single stage of experiment lasted for about 3 h. The experiment was continued for about 36 h.

Three minute EEG data were recorded at the beginning of the experiment and at the final phase of each stage when the subjects were playing the computer game.

2.1.3. Experiment 3: actual driving tests for validation

Seven healthy male subjects (professional drivers) have been chosen for validating the estimation method under actual driving condition. The details are given in Table 1 (Section 4.3).

2.2. Acquisition of EEG data

Driving is a complex task involving simultaneous activities of different parts of the brain. Different lobes of the brain are related to various functionalities. The frontal lobe is associated with planning, reasoning, movement, emotion and problem solving. The parietal lobe is associated with movement, recognition, perception of stimuli whereas temporal lobe is associated with recognition and perception of auditory stimuli, memory, and speech. This makes the spatial placement of electrodes in EEG recordings a critical parameter. Using the International 10–20 electrodes placement system, the number of EEG channels used can be as high as 19 (Lal et al., 2003) or as low as 4 (Schier, 2000).

In this work, thirteen scalp electrodes were used in addition to reference and ground to collect the signals from locations Fp1, Fp2, F3, F4, T3, T4, C3, C4, P3, P4, O1, O2, and CZ following the international 10–20 system. The sampling frequency was kept at 256 Hz with 16 bit A/D conversion.

The experiment was performed in compliance with the relevant laws and institutional guidelines. The subjects were asked to file written consents prior to the experiment.

2.3. Collection of subjective data

During the above experiments the drivers were requested to give subjective feedback, the methodology of which has been explained in Section 3.5. This feedback is instrumental in establishing the correlation between the feature-based analysis and actual subjective fatigue, and developing a scale for estimating the unknown fatigue level.

3. Methodology

The method of data analysis involves preprocessing, artifact removal, and computation of features based on Discrete Wavelet Transform for estimation of fatigue. The preprocessing stage includes filtering and normalization followed by artifact removal using wavelet based thresholding.

3.1. Preprocessing

The raw EEG data is contaminated with numerous high frequency and low frequency noise known as artifacts. The high frequency noise is due to atmospheric thermal noise and power frequency noise. The low frequency noise is mainly due to eye movements, respiration and heart beats. They are characterized by amplitude in the millivolt range (whereas the actual EEG is in microvolt range) in the frequency band of 0–16 Hz (Krishnaveni, Jayaraman, Aravind, Hariharasudhan, & Ramadoss, 2006). The raw EEG containing this noise at both ends of the spectrum was first processed using a band pass filter with cutoff frequencies of 0.5 Hz and 30 Hz followed by normalization. Normalization ensures removal of any unwanted biases that may have crept into experimental recordings. The in-band artifacts were then removed using a wavelet based technique as will be explained in the subsequent paragraphs.

3.2. Artifact removal using discrete Wavelet Transform

Wavelet Transform is a useful tool for time frequency analysis of neurophysiological signals. *Wavelets* are small wave like oscillating functions that are localized in time and frequency (Daubechies, 1990; Mallat, 1999).

In discrete domain, any finite energy time domain signal can be decomposed and expressed in terms of scaled and shifted versions of a mother wavelet $\psi(t)$ and a corresponding scaling function $\phi(t)$. The scaled and shifted version of the mother wavelet is mathematically represented as

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^j t - k), \quad j,k \in Z \tag{1}$$

A signal $S(t)$ can be expressed mathematically in terms of the above wavelets at level j as

$$S(t) = \sum_k s_j(k)\phi_{j,k}(t) + \sum_k d_j(k)\psi_{j,k}(t) \tag{2}$$

where $s_j(k)$ and $d_j(k)$ are the approximate and detailed coefficients at level j. These coefficients are computed using filter bank approach as proposed by Rioul and Vetterli (1991).

The original signal $S(t)$ is first passed through a pair of high pass and low pass filters. The low frequency component approximates the signal while the high frequency components represent residuals between original and approximate signal. At successive levels the approximate component is further decomposed. After each stage of filtering, the output time series is down-sampled by two and then fed to next level of input.

The features extracted from the wavelet decomposition depend primarily on the type of mother wavelet chosen. It is known that the best results are obtained when there is a close resemblance between the signal and the mother wavelet. The Daubechies family of wavelets has a compact support with relatively more number of vanishing moments (Mallat, 1999). This makes it a suitable candidate for signal compression and characterization. By repeated simulation and test we found that the dB4 (Daubechies family) is most suitable for the EEG signals in our case.

In this work, the signal has been decomposed into four levels in which the detail component at level-1 approximately represents beta (β) band (15–30 Hz), detail component at level-2 represents alpha (α) band (8–15 Hz), detail component at level-3 represents theta (θ) band (4–8 Hz) whereas the detail component at level-4 (δ_2:2–4 Hz) along with approximate (δ_1:0.5–2 Hz) component represent the delta (δ) band (0.5–4 Hz) of the EEG signal.

As the wavelet coefficients represent the correlation of signal with the mother wavelet, the signal will generate high amplitude coefficients at places where artifacts are present. These coefficients can be eliminated using a simple thresholding technique. The threshold can be computed as:

$$T_j = mean(C_j) + 2 \times std(C_j) \tag{3}$$

Here C_j is the wavelet coefficient at jth level of decomposition. If the value of any coefficient is greater than the threshold it is reduced to half (Kumar, Arumuganathan, Sivakumar, & Vimal, 2008). This generates a new set of wavelet coefficients for signal without artifacts.

The EEG based parameters have been computed with an 8 s window with 50% overlapping between successive windows.

3.3. Wavelet relative energy and ratios

The energy at a particular level of decomposition j, which may correspond to any of the wave group, i.e. δ, θ, α, β can be expressed as

$$E_j = \sum_{k=1}^{L} [C_j(k)]^2 \tag{4}$$

where $C_j(k)$ is the wavelet coefficient (approximate or detailed). L is the total number wavelet coefficients at the jth level. Hence the relative energy of a particular band represented by the resolution level j is given by

$$p_j = \frac{E_j}{\sum_j E_j} \tag{5}$$

These relative energy parameters form the basic energy indices can be used as features for the classification of fatigue. However many a times it has been observed that these indices do not show a substantial change under mild fatigue. Therefore ratio indices are proposed to enhance the contrast among different levels of fatigue (Eoh, Chung, & Kim, 2005). These ratio indices include ratios of relative energies of various wave groups.

In this paper we also propose four different entropic measures i.e. Shannon, Renyi, Tsallis and Generalized Escort-Tsallis Entropy as the features to improve the classification in the presence of uncertainties associated with these energy bands.

3.4. Wavelet entropy

Entropy serves as a measure of information (Blanco, Figliola, Qiuroga, Rosso, & Serrano, 1998; Glavinovitch et al., 2005). The Shannon's entropy (*SE*) is a disorder quantifier (Shannon, 1948) and is a measure of flatness of energy spectrum in the wavelet domain. It is defined as

$$SE = -\sum_j p_j \cdot \log(p_j) \tag{6}$$

The significance of this entropy can be best understood in terms of probabilistic concept. A signal having very high energy content in a particular wave group of EEG accentuates the fact that it is predominantly composed of particular frequency band. The concentration of energy in a particular frequency band indicates lack of randomness in terms of frequency of that particular signal. Hence the entropy value will be lower for such signals. On the other hand uniform distributions of energy in all the wave groups indicate the presence of randomness associated with the signal resulting in higher entropy value.

Another statistical measure closely related to *SE* is Rényi entropy (*RE*) (Renyi, 1961). The basic definition of *RE* is given by

$$RE = \frac{1}{1-q}\log\left[\sum_j p_j^q\right] \tag{7}$$

where p_j is the relative energy as described earlier and $q \in \Re$ is known as the *entropic index*. The parameter q confers generality to this information measure. In the present study we have used $q = 2$ and 3 to calculate 2nd and 3rd order entropy.

Both *SE* and *RE* are extensive property of a system (Tong, Bezerianos, Paul, Zhu, & Thakor, 2002). Earlier studies have shown that *SE* and *RE* work well on signal exhibiting short range interaction (Bezerianos, Tong, & Thakor, 2003; Renyi, 1961; Tong et al., 2002; Torres & Gamero, 2000).

Further search for disorder quantifiers brings out non-extensive entropies like Tsallis wavelet entropy (*TsE*) (Tsallis, 1988) and Generalized eScort-Tsallis entropy (*GenTsE*) (Poja, Hornero, Abasolo, Fernandez, & Escudero, 2007). The major point of disparity between extensive and non-extensive entropy lies in the proficiency of the latter in dealing with signals exhibiting long range interactions. *TsE* is a non-logarithmic parameterized entropy defined by Tong et al. (2002) as

$$TsE = \frac{1}{q-1}\sum_j [p_j - p_j^q] \tag{8}$$

where $q \in \Re$ is an embodiment of degree of non-extensivity. The variable parameter q, confers the control of modifying the entropy in concordance with the nature of the signal. Low values of q work well with signals having long range interaction, whereas high q are used with signals plagued with spikes and sudden abrupt changes. In this study we have used $q = 2$ for *TsE*.

GenTsE (Poja et al., 2007) is defined as

$$GenTsE = \frac{1}{q-1}\left[1 - \left(\sum_j p_j^{1/q}\right)^{-q}\right] \tag{9}$$

Where q is the entropy parameter similar to that of *TsE*. It shares its non-extensive properties with *TsE* but differs in its treatment of probability distributions. The probability distribution is modified to generate an escort distribution of order q. Such modifications in probability distributions help one to reveal information that was interred in the original distribution. The q value for this study was taken to be 2.

3.5. Subjective assessment

The subjective assessment of fatigue is based on questionnaire. A set of questions has been selected from standard sleepiness scales (Stanford Sleepiness Scale, Piper Fatigue Scale, Epworth Sleepiness Scale) for the purpose (Appendix A). The questions were asked through an interactive session. Subject's self assessment has been used for final fatigue level assessment on a scale 1–10 with 10 being most fatigued.

3.6. Fatigue scale: estimation of fatigue level

The above parameters have been computed from the *EEG* records of the subjects at different levels of fatigue based on a subjective assessment, as specified in Section 3.5. This helped to find a method for scaling and estimating unknown fatigue level from the *EEG* records. The following procedure is followed to establish the proposed entropy measures as the indicator of fatigue:

Step 1: Selection of important *EEG* parameters those are most coherent with the self assessed fatigue at different levels.
Step 2: For every subject, plot each parameter value with respect to self-estimated fatigue levels and fit a polynomial.
Step 3: Estimate the unknown fatigue level from each of the above curves.

Step 4: Compute the mean and variance of the estimated values.
Step 5: Eliminate those estimations which cross a predefined threshold value. Find the mean estimation of all other measurements.

4. Results and discussions

4.1. Energy-based analysis

The relative wavelet energy for the α band was calculated directly from the discrete wavelet coefficients as explained in Section 3.3. Fig. 1 shows the relative wavelet energy of the α band of two subjects; one from each type of experiment, for different stages of fatigue. It has been observed that the α energy increases with the level of fatigue.

It has already been discussed that sometime the basic energy indices do not show a substantial change under mild fatigued condition and suitable ratio parameters may be better in differentiating such fatigue levels. In this study we observed increase in the value of α relative wavelet energy and β relative wavelet energy and a dip in energy in the low frequency δ band for most of the subjects. This observation led to the choice of ratio index $(\alpha + \beta)/\delta_1$ in this study. The values of this ratio parameter at different fatigue levels are shown in Fig. 1. We have observed such variation in most of the subjects from all types of experiments.

The physical interpretation of these observed variables can be best understood in terms of energy spectrum. In normal state the driver's energy spectrum is primarily composed of low frequency δ waves. At the onset of fatigue the spectral energy shifts from low frequency bands to high frequency α and β bands. This observation led to the choice of a ratio index $(\alpha + \beta)/\delta_1$ which amplifies the increase in relative wavelet energies in high frequency bands and simultaneous decrease in relative wavelet energy in low frequency bands.

Fig. 1 also show the correspondence between energy based parameters and subjective assessment at successive stages. Such observation has also been observed in other experimental results.

4.2. Entropy analysis

Entropy analysis helps us to capture the essence of spectral energy distribution changes in a broader perspective. It has been observed from the energy and ratio analysis that, the fatigue manifests itself as change in energies in different frequency bands. Wavelet entropies take into account these relative energies (probabilities) of different frequency bands and hence project out as single valued quantifiers for study of changes in energy distribution.

The entropy analysis of two subjects is shown in Fig. 2. An increasing trend has been observed in entropy values with fatigue at successive stages. A closer look at the graph elucidates that the extensive entropies (*SE* and *RE*) have better performance than the non-extensive ones in classifying the fatigue stages.

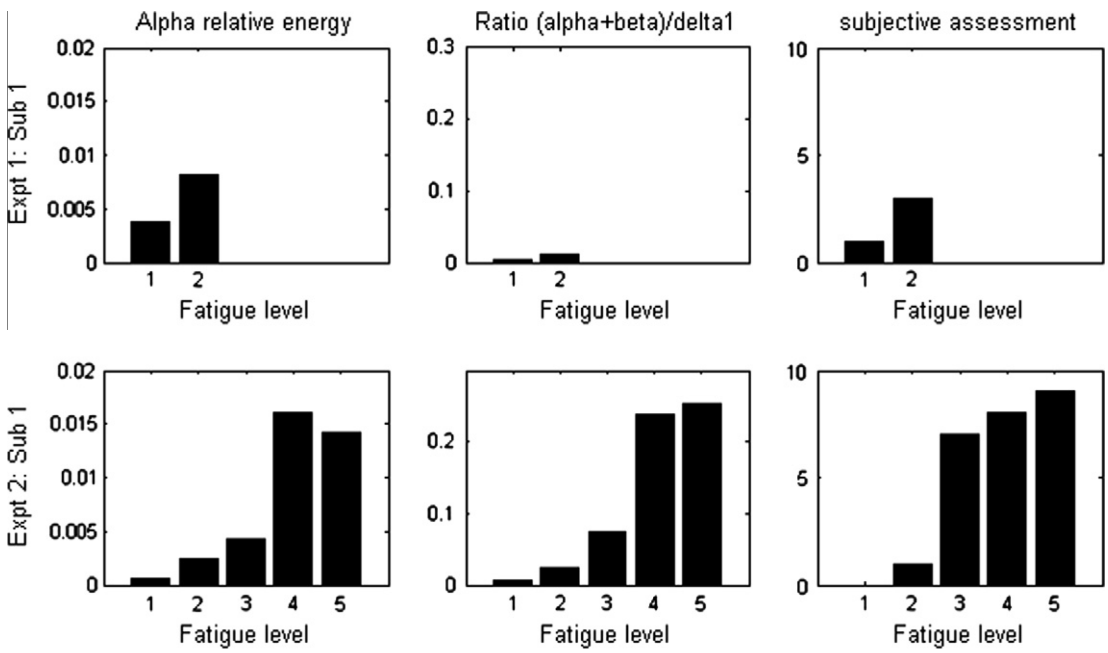

Fig. 1. Variation of α band relative energy, ratio $(\alpha + \beta)/\delta_1$ and subjective assessment of two subjects at various levels of fatigue.

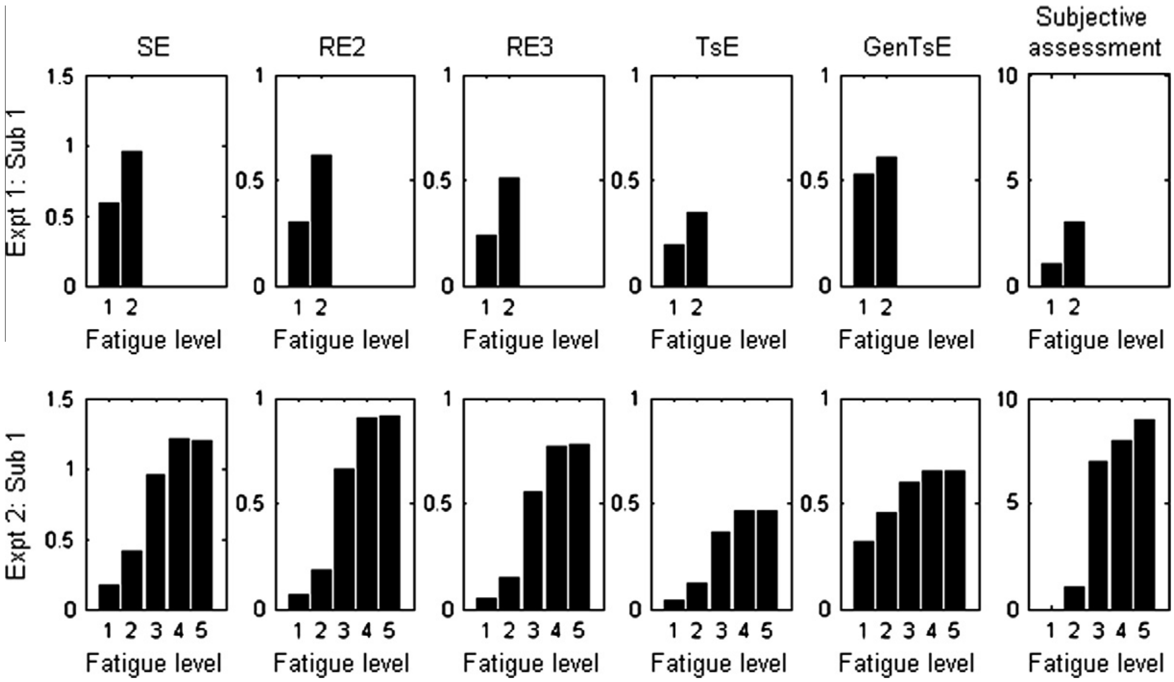

Fig. 2. Variation of different types of entropies of two subjects at various levels of fatigue.

A stage wise analysis of the entropy values brings out the physical significance of this feature. As mentioned in energy and ratio analysis, the first stage *EEG* signal is basically composed of low frequency δ waves. Hence the entire energy distribution is skewed towards the lower frequencies. This represents a signal with lower disorder. Therefore, entropy values are lowest in case of first stage for all the entropies. As the fatigue level increases the energy in the α and β bands starts to increase. This leads to the flattening of the energy spectrum. Flattening of energy distribution means greater disorder, this leads to higher entropy values at later stages.

Among the above mentioned parameters relative α band energy is an already established indicator of fatigue (Lal & Craig, 2001; Rosso et al., 2001; Schier, 2000) and the others have been proposed from the above experimental analysis. It has been mentioned in the literature that α band relative energy increases as the fatigue level of a person increases. This has been observed in both actual (Experiment 1) as well as simulated (Experiment 2) driving experiments. For Experiment 1, the difference in fatigue level is less and α band relative energy failed to indicate that in four subjects (Subject numbers 3, 4, 8, 9). Whereas the ratio $(\alpha + \beta)/\delta_1$ failed in three subjects (Subject numbers 3, 4, 8) and the entropy parameters failed in only one subject (subject 4). The result of all the subjects from Experiment 1 has been shown in Appendix B. Thus proposed fatigue indicating parameters may be useful for the detection of fatigue in human subjects.

4.3. Estimation of fatigue level

A number of parameters have been identified in the previous sections which show a regular variation with increasing levels of fatigue. These parameters may be combined together to prepare a scale for the measurement of an unknown fatigue

Table 1
Comparison of estimated fatigue with self-estimation.

Subjects	State of the subject	Fatigue level	
		Estimation using proposed EEG based parameters	Subjective estimation based on questionnaire
1	Before driving	1.75	2
2	After driving for 10 h	7.2	6
3	After driving for 10 h	8.62	8
4	After driving for 10 h	7.24	7
5	After driving for 10 h	6.60	7
6	Before driving	1.1	1
	After driving for 10 h	6.3	3
	After driving for 10 h With sleep deprivation	9.6	10
7	After driving for 10 h	5.93	7

level. In this work five such parameters have been considered. These are (i) Relative α band energy, (ii) Shannon Entropy, (iii) Renyi Entropy of order 2, (iv) Renyi Entropy of order 3 and (v) $(\alpha + \beta)/\delta_1$ ratio. These parameters were selected depending on the results obtained in previous sections. This estimation method is based on the data of 17 professional drivers (except Subject numbers 3, 4, 8, 9) from experiments 1 and 12 subjects from Experiment 2.

For the validation of this estimation method 7 test subjects (professional drivers) have been considered. The estimated fatigue level of these subjects along with their self-estimated fatigue level has been given in Table 1. The results show that the estimated fatigue level using the proposed method is comparable with the self-estimated level in most cases.

5. Conclusions

In this paper we have investigated a number of fatigue indicating parameters based on higher order entropy measures of EEG signals in the wavelet domain. These parameters indicate the state of fatigue with more clarity as compared to ones proposed earlier (Jap et al., 2009; Papadelis et al., 2006). Through various experiments, we have established that these parameters vary in the same manner irrespective of simulated or actual driving conditions. However, the quantum of variation could not be found to be same in all the experiments and across all the subjects. This may be due to the nature of the induced fatigue and characteristics of individual subjects. We have also quantified the level of fatigue from these parameters after standardizing them with subjective assessment from the individual responses to a set of questions. This method can be used on board to quantify the level of fatigue in human drivers or human operators in safety critical human–machine interactions.

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Appendix A

Questionnaire for Subjective assessment of fatigue

1. Are you fatigue now? If yes, to what degree you are feeling fatigue? (Scale: 1–10)
2. How long have you been feeling fatigue?

15 m	30 m	1 h	1.5 h	2 h	3 h	4 h	More

3. To what degree your fatigue may affect your ability to work? (Scale: 1–10)
4. To what degree you are feeling sleepy now? (Scale: 1–10)
5. To what degree you are feeling able to walk normal? (Scale: 1–10)
6. To what degree you are feeling energetic? (Scale: 1–10)
7. To what degree you are feeling able to concentrate? (Scale: 1–10)
8. To what degree you are feeling able to think clearly? (Scale: 1–10)
9. What do you think is the main cause of your fatigue?

Sleep deprivation	Long time	Monotonous road
Traffic	Mood	Others (mention)

10. What do you think is the best thing that can relieve your fatigue?

Music	Caffeine	Water	Rest	Other

11. Are you experiencing any other symptoms right now?

Head ache	Body ache	Head reeling	Others (mention)

12. Chance of dozing:
    (a) If allowed to read a newspaper inside the car. (Scale: 0–4).
    (b) If allowed to lie down for rest (Scale: 0–4).
    (c) If allowed to listen music (Scale: 0–4).
    (d) If allowed to drive in a long and monotonous road (Scale: 0–4).

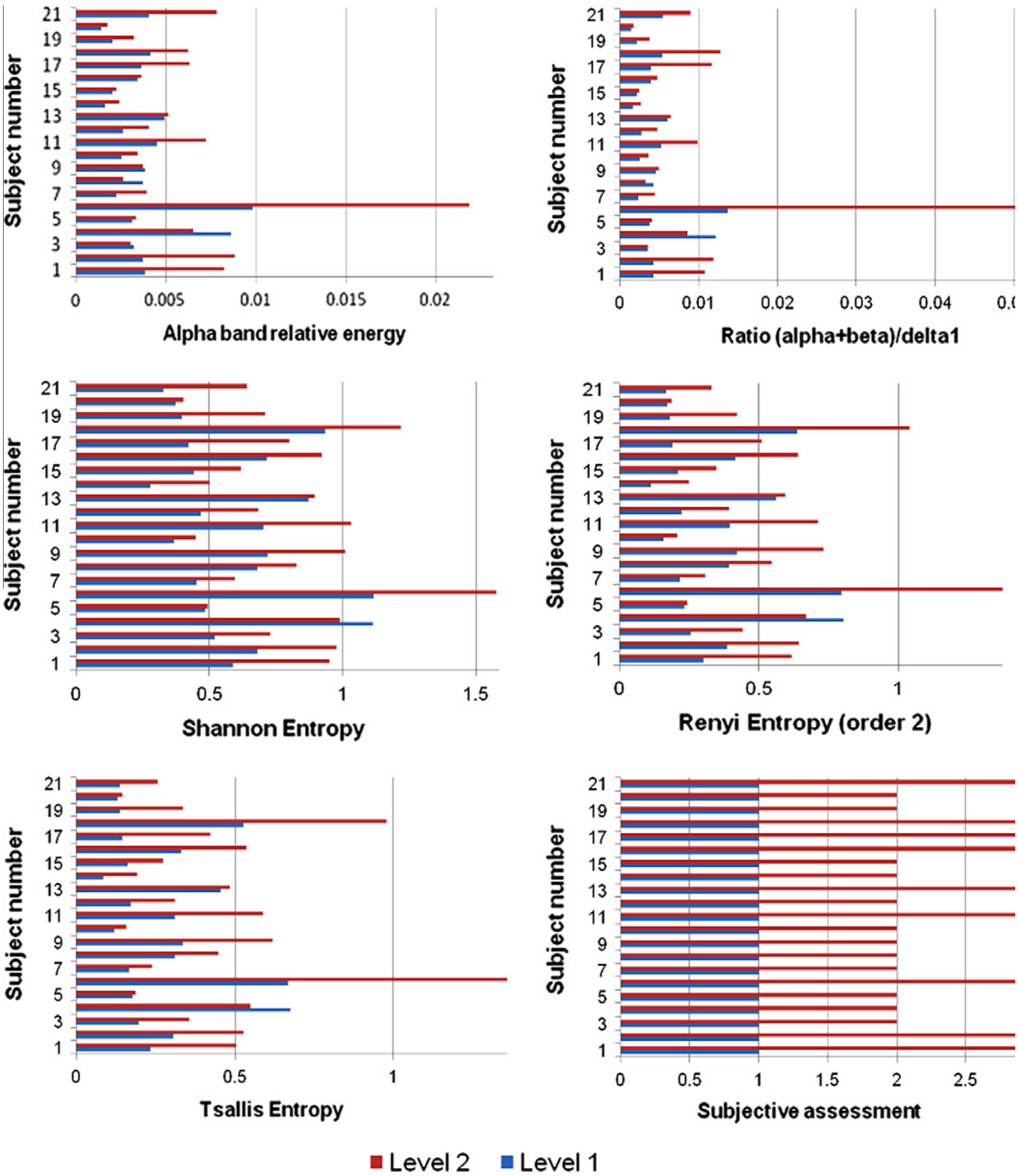

Fig. B1. Variation of different parameters at two levels of fatigue (Level 1 and Level 2) during Experiment 1.

Appendix B

See Fig. B1.

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