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ORIGINAL PAPER

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Neural network classification of late gamma band electroencephalogram features

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Abstract This paper investigates the feasibility of using neural network (NN) and late gamma band (LGB) electroencephalogram (EEG) features extracted from the brain to identify the individuality of subjects. The EEG signals were recorded using 61 active electrodes located on the scalp while the subjects perceived a single picture. LGB EEG signals occur with jittering latency of above 280 ms and are not time-locked to the triggering stimuli. Therefore, LGB EEG could only be computed from single trials of EEG signals and the common method of averaging across trials to remove undesired background EEG (i.e. noise) is not possible. Here, principal component analysis has been used to extract single trials of EEG signals. Zero phase Butterworth filter and Parseval's time-frequency equivalence theorem were used to compute the LGB EEG features. These features were then classified by backpropagation and simplified fuzzy ARTMAP NNs into different categories that represent the individuality of the subjects. The results using a tenfold cross validation scheme gave a maximum classification of 97.33% when tested on 800 unseen LGB EEG features from 40 subjects. This pilot investigation showed that the method of identifying the individuality of subjects using NN classification of LGB EEG features is worth further study.

Keywords Backpropagation · Biometrics · Electroencephalogram · Late gamma band · Principal component analysis · Simplified fuzzy ARTMAP · Subject identification

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1 Introduction

Electroencephalogram (EEG) signals are electrical oscillations in the range of microVolts that are believed to be generated from the neurons in the cortex of the brain (Misulis 1994). In general, EEG signals are used for clinical studies and could be divided into spontaneous or evoked types. In this paper, the EEG signals are used for a different purpose other than clinical. The features computed from the evoked EEG signals are investigated as a possible tool to identify the individuality of subjects.

The most common method of identifying individuals is through the use of fingerprints (thumbprints) (Pankanti et al. 2000, 2002). However, in recent years, alternative biometric methods to replace or augment the fingerprint system have been proposed. Some of these methods are like electrocardiogram (Biel et al. 2001), palmprints (Duta et al. 2002), hand geometry (Jain et al. 1999), iris (Daugman 1999) and face (Samal and Iyengar 1992).

The use of EEG signals for the purpose of identifying individuals is relatively new as compared to the other biometrics. Very few research work have been published using brain signals as a biometric tool to identify individuals. The method proposed by Poulus et al. (1999) used autoregressive (AR) modeling of EEG signals and linear vector quantization neural network (NN) to recognize an individual as distinct from other individuals with 72–80% success. However, the method was not tried to recognize each individual in a group. Paranjape et al. (2001) proposed a method using AR modeling of EEG with discriminant analysis to identify individuals with classification accuracy ranging from 49% to 85%. Both the methods used EEG signals recorded while the subjects were resting with eyes closed (Poulos et al. 1999) and with eyes open or closed (Paranjape et al. 2001).

In this paper, late gamma band (LGB) EEG features are computed and these features are used by backpropagation (BP) and simplified fuzzy ARTMAP (SFA) NN

classifiers to identify the individuality of the subjects. There are other common frequency bands in EEG signals like δ (0–3 Hz), θ (4–7), α (8–13), β (1–29 Hz) but these bands have been studied for medical and clinical purposes only. In general, gamma band EEG is evoked as early, middle or late in response to external stimulus. It has been reported that early gamma responses occurs around 90 ms (Tallon-Baudry et al. 1996), 95 ms (Tallon-Baudry et al. 1997) and 100 ms (Basar et al. 1999), while middle gamma responses occur around 190 ms (Tallon-Baudry et al. 1997). Late gamma responses occurs after 280 ms (Tallon-Baudry et al. 1997, 1998) or 300 ms (Basar et al. 1999). The early and middle gamma responses are time-locked but they do not vary with simulation type (Tallon-Baudry et al. 1996, 1997). The LGB responses are not time-locked, but they are suitable for the proposed method because these evoked responses are related to attention and feature binding ability (Basar et al. 1995; Basar et al. 1999; Tallon-Baudry et al. 1997).

However, because LGB EEG are not time-locked i.e. they occur with differing latency between trials, it is necessary that these features are computed from single trials of EEG signals. The common method of signal averaging between trials to remove unrelated background EEG (i.e. noise) cannot be used here because the LGB EEG will disappear during averaging. Therefore, in this study, principal component analysis (PCA) (Jolliffe 1986) is employed to extract single trials of EEG signals. Next, zero-phase Butterworth filter and Parseval's time-frequency equivalence theorem are used to compute the LGB EEG features. These features are used by two NNs: BP (Rumelhart and McCelland 1986) and SFA (Kasuba 1993) to classify into different categories that represent the individuality of the subjects.

The data set used here is actually part of a larger experimental study aimed at studying the differences in EEG signals extracted during visual evoked responses between alcoholics and non-alcoholics (Palaniappan et al. 2002; Zhang et al. 1997). In (Palaniappan et al. 2002; Zhang et al. 1997), the authors studied the electrophysiological differences related to short-term memory between alcoholic and non-alcoholic subjects. Their stimuli consisted of two pictures presented with a short interval, suitable to study short-term memory. The subjects were asked to remember the first picture and the second picture was shown either as the same or different picture. The subjects denote whether the second picture was the same or different by pressing a mouse button.

Here, we merely used part of this data from randomly chosen 40 non-alcoholics subjects, where only the data from first picture shown was used. The first picture shown will evoke potentials in the brain that are related to memory. Our point here is that different subjects will have different memory processes and this could be used as a tool to characterize the individually of the subject. Even if some parts of the brain are evoked with similarity between the subjects, it is unlikely that different individuals will evoke similar brain patterns across all parts of the brain (i.e. across all 61 channels).

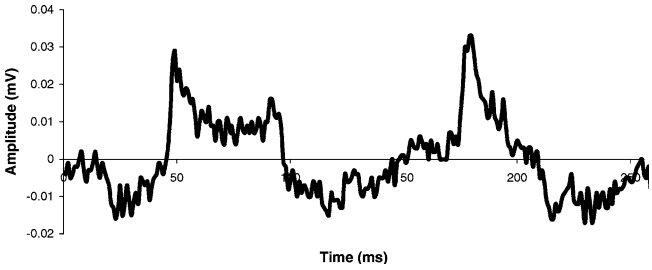

Fig. 1 An EEG signal

2 EEG data

In this study, EEG signals (see Fig. 1 for an example) were recorded from 61 active electrodes[1] while the subjects perceived a visual stimulus in the form of a picture. The electrodes were located at standard sites (see Fig. 2) following an extension of the Standard Electrode Position Nomenclature, American Encephalographic Association. The active 61 electrodes are inside the hexagon while the three reference electrodes are outside the hexagon. The pictures were obtained from Snodgrass and Vanderwart picture set (Snodgrass and Vanderwart 1980). These pictures were black and white line drawings executed according to a set of rules that provide consistency of pictorial representation and were easily named, i.e. they have definite verbal labels. These pictures were standardized according to variables of central relevance to memory and cognitive processing. Figure 3 shows some of these pictures where a wooden fence, shirt button, envelope and shirt hanger are shown.

Forty subjects participated in the study. The subjects were seated in a reclining chair located in a sound attenuated RF shielded room. The signals were hardware band-pass filtered between 0.02 Hz and 50 Hz and sampled at 256 Hz. The subjects were asked to recognize and remember the stimulus. The stimulus was shown for 300 ms using a computer display unit located at 1 m from the subject's eyes. There was an inter-trial interval of 5.1- and 1-s EEG measurements after each stimulus onset was stored. The 1 s recording is inclusive of the 300 ms when the stimulus was shown. This was repeated for 40 trials, i.e. EEG recordings were conducted for forty different picture stimuli. Figure 4 shows an example of the stimulus presentation. EEG recordings for 40 such picture presentation trials were used in this study, giving a total of 1,600 EEG signals.

Eye blink contamination is a common problem associated with EEG recordings. Eye blinks caused by eye muscles give very high readings in EEG signals and could distort the information from the brain completely. Therefore, they have to be removed or reduced. Here, eye blink EEG signals that exceed 100 μV were assumed to be contaminated by eye blinks (Misulis 1994) and

[1]Actually the recording is conducted using 64 electrodes but three electrodes serve as references.

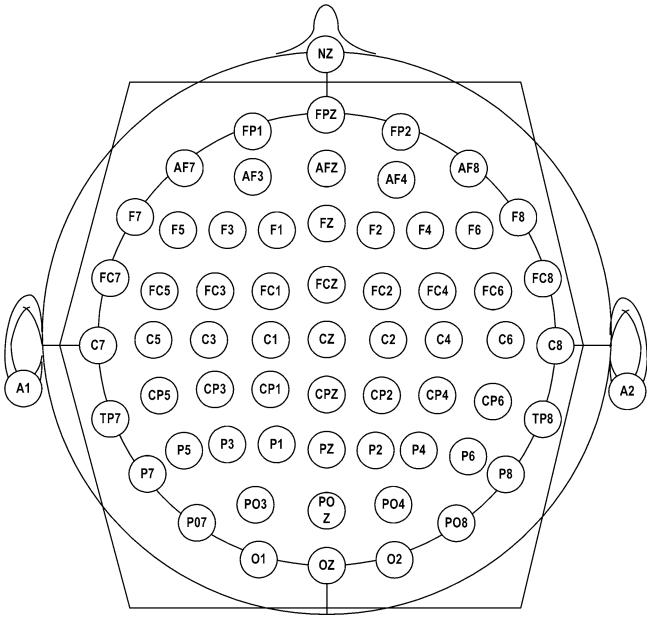

Fig. 2 The location of electrodes (active channels inside hexagon)

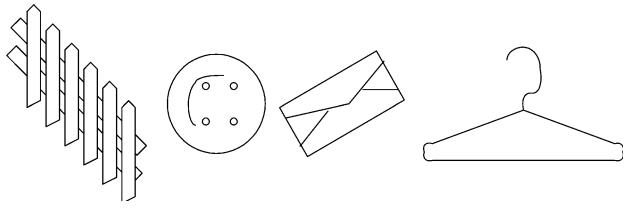

Fig. 3 Examples of pictures from Snodgrass and Vanderwart set

were discarded. A total of 40 eye-blink free EEG signals for each subject were stored. Next, the amplitudes of the EEG signals were adjusted to a mean value of 0.

3 LGB EEG feature extraction

Principal component analysis was applied to the 61 channel EEG signals and principal components (PCs) were computed. PCA uses eigen analysis, which involve covariance computations and the stimulus related EEG signals are correlated from channel to another during stimulus perception. Therefore, the first few PCs represent a large proportion of the desired EEG signal related to the stimulus, while the rest represent noise (i.e. undesired background EEG). As mentioned earlier, the recorded EEG signal will consist of stimulus related potentials and the background EEG (note that the brain is also performing other functions while the stimulus is being perceived). The background EEG is many times higher than the stimulus related EEG causing difficulty in analysing the stimulus related EEG signal. The common method of solving this problem is to use ensemble averaging from a certain number of trials, where the background EEG will be reduced as compared to the stimulus related EEG signals. However, this procedure requires numerous trials and analysis from single trials of EEG signals cannot be performed. Furthermore, LGB EEGs are not time-locked to the stimulus onset and therefore will disappear when averaged. Therefore, in this paper, we analyse single trial EEG signals where PCA has been used to reduce the background EEG.

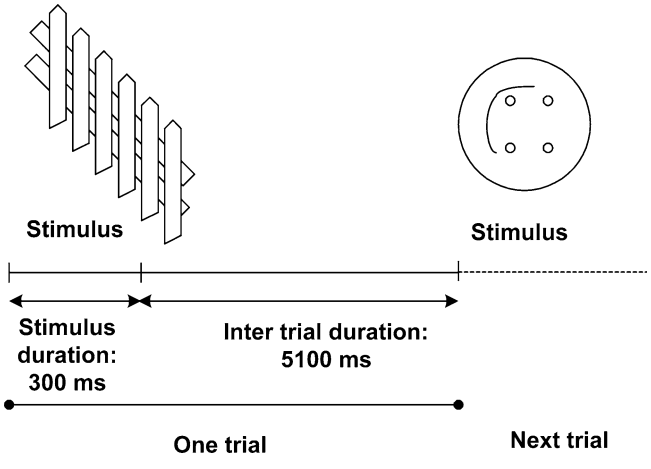

Fig. 4 Example of stimulus presentation

The PCA method is as follows. Compute the covariance of matrix **z**, the extracted signal using:

$$\mathbf{R} = \mathbf{E}(\mathbf{z}\mathbf{z}^{\mathbf{T}}). \tag{1}$$

Next, compute **V** and **D**, where **V** is the orthogonal matrix of eigenvectors of **R** and **D** is the diagonal matrix of its eigenvalues, $\mathbf{D} = diag(d_1,\ldots,d_n)$. The PCs are now computed using

$$\mathbf{y} = \mathbf{V}^{\mathbf{T}}\mathbf{z}^{\mathbf{T}}. \tag{2}$$

In this work, Kaiser's rule is used to select the number of PCs to be used [Jolliffe 1986). Using this method, PCs with eigenvalue more than 1.0 are considered to be part of the stimulus related EEG subspace, while the rest is considered to be part of the background EEG noise subspace. The single trial stimulus related EEG signals can now be reconstructed from the selected PCs using

$$\tilde{\mathbf{z}} = \hat{\mathbf{V}}\hat{\mathbf{y}}, \tag{3}$$

where $\hat{\mathbf{V}}$ and $\hat{\mathbf{y}}$ are the eigenvectors and PCs corresponding to eigenvalues more than 1.0.

Next, a forward and reverse digital Butterworth filter was applied to obtain EEG signals in the gamma band range of 30–50 Hz. Butterworth filter is a type of infinite impulse response (IIR) filter, which has the advantage of sharp-roll off but is disadvantageous in terms of phase distortion. Here, forward and reverse filtering was performed to remove the non-linear phase effects of the Butterworth filter. MATLAB's[2] *filtfilt*

[2]The Mathworks Inc.

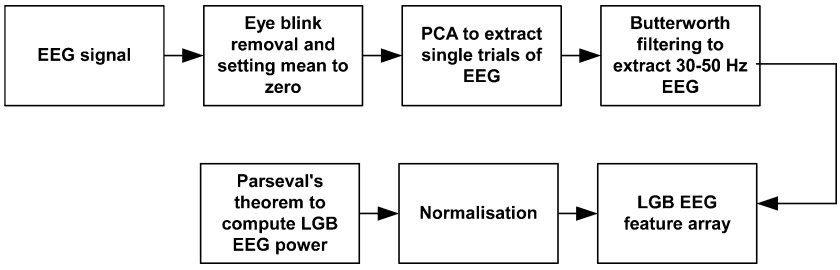

Fig. 5 LGB EEG feature extraction

function was used for this purpose, where the non-linear phase effects were completed removed. Order 10 was chosen because it gave a minimum stopband of 30 dB at 25 Hz and 55 Hz. Because LGB is the interest of the study, only the filtered EEG signals from 280 ms onwards were stored for analysis. Variance was computed and according to Parseval's time-frequency equivalence theorem, the computed variance represents the spectral power of the LGB EEG. This is because the power (i.e. energy) of the signal is equal to variance of the signal since we have set the mean to 0 earlier. Using Parseval's time-frequency equivalence theorem circumvents the need to perform spectral analysis to compute the spectral power. Using this method, the spectral power could be computed in the time domain itself. This process was repeated for all the 61 channels. LGB spectral powers were normalized with the total spectral power from all the 61 channels. These normalized LGB spectral powers were concatenated into one feature array. Figure 5 shows the steps involved in the feature extraction.

4 SFA and BP NNs

Two NN architectures: SFA (Kasuba 1993) and BP (Rumelhart and McCelland 1986), were used to classify the LGB EEG features into the corresponding categories that represent the individuality of the subjects and their performances were compared. NN architectures were considered here because of their ability to give high classification accuracies. SFA is relatively new as compared to BP. SFA is advantageous as compared to BP due to its high-speed training in fast learning mode and incremental learning abilities. SFA consist of two modules: Fuzzy ART and Inter ART mapping. The Fuzzy ART module receives the input features and outputs the particular category node. The category node is linked to the corresponding class (i.e. the individuality of the subject in this case) through the Inter ART mapping module. Inter ART mapping module works by increasing the vigilance parameter (VP) of Fuzzy ART by a minimal amount to correct a predictive error at the category layer. Figure 6 shows the SFA as used in this study.

4.1 Fuzzy ART

Fuzzy ART system has three different layers: F_0, F_1 and F_2 consisting of nodes. Input layer F_0 nodes represent a current input vector and F_0 activity vector is denoted by $I = (I_1,\ldots,I_M)$, with each component I_i in the interval [0, 1], $I = 1,\ldots,M$. F_1 layer consists of a one to one

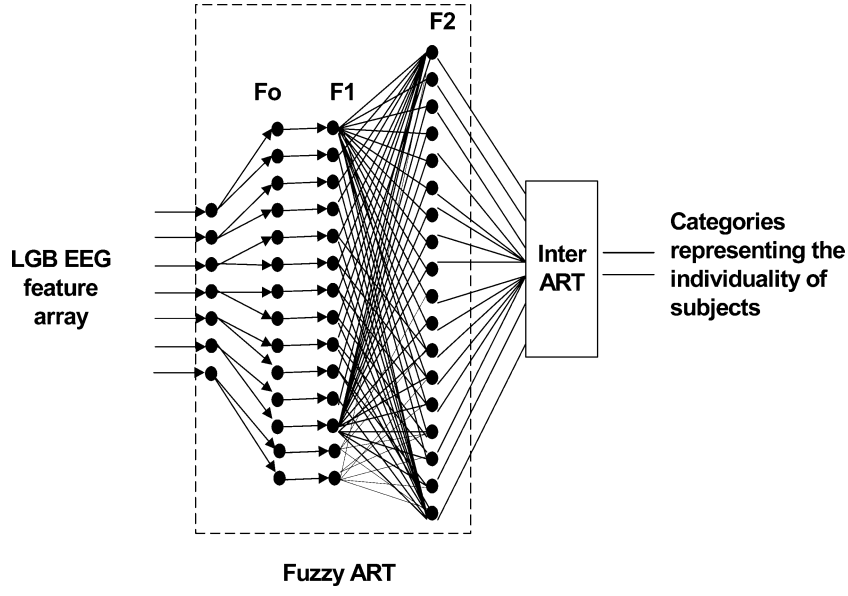

Fig. 6 SFA as used in the study

connecting nodes with F_0 layer and is connected to output layer F_2 nodes through a weight vector. F_1 activity vector is denoted by $x = (x_1,\ldots,x_M)$ and the F_2 activity vector is denoted by $y = (y_1,\ldots,y_M)$. For each F_2 category node j ($j=1,\ldots,N$), there is a weight vector associated with layer of F_1 nodes, $w_j = (w_{j1},\ldots, w_{jM})$ of adaptive weights. Initially we have

$$w_{j1}(0) = \cdots = w_{jM}(0) = 1 \tag{4}$$

which means that each category is uncommitted.

For each input I and F_2 node j, the choice function T_j is defined by

$$T_j(I) = \frac{|I \wedge w_j|}{\alpha + |w_j|} \tag{5}$$

where the fuzzy AND operator $\wedge$ is defined by

$$(p \wedge q)_i = \min(p_i, q_i) \tag{6}$$

and the norm $|.|$ is defined by

$$|p| = \sum_{i=1}^{M} |p| \tag{7}$$

for any M-dimensional vectors p and q. For simplicity, let, $T_j\ (I)$ in Eq. 2 be denoted as T_j when the input I is fixed. A category choice is made when one F_2 node becomes active at a given time. The category choice is indexed by J, where

$$T_J = \max\{T_j : j = 1,\ldots,N\} \tag{8}$$

If more than one T_j is maximal, the category with a smaller index is chosen.

Resonance occurs if the match function, $|I\wedge w_J| \,/\, |I|$ of the chosen category meets the vigilance criterion:

$$\frac{|I \wedge w_J|}{|I|} \geq \rho \tag{9}$$

With resonance, learning starts, as explained below. Mismatch reset occurs if

$$\frac{|I \wedge w_J|}{|I|} < \rho \tag{10}$$

then the value of the choice function T_J is set to 0 and a new index J is chosen by Eq. 5.

The search process continues until the chosen J satisfies Eq. 6. Once the search is completed, the weight vector w_J is updated according to the equation

$$w_J^{(\text{new})} = (I \wedge w_J^{(\text{old})}) \tag{11}$$

where fast learning is used.

Proliferation of categories in Fuzzy ART is avoided if the inputs are normalised using the method of complement coding. Therefore the complement coded input I to the field F_1 is the $2M$ dimensional vector

$$I = (\mathrm{a}, \mathrm{a}^{\mathrm{c}}) \quad \text{where } a_i^c = 1 - a_i \tag{12}$$

Where complement coding is used, the initial condition in Eq. 11 is replaced by

$$w_{j1}(0) = \cdots = w_{j,2M}(0) = 1 \tag{13}$$

4.2 Inter ART

As mentioned earlier, SFA consists of Fuzzy ART module and an Inter ART module. Fuzzy ART takes in the input features of the patterns to be classified. The Inter ART module will create mappings between the Fuzzy ART module and the output category representing the individual to correctly learn to predict the classification patterns. For all the input patterns presented, it creates a dynamic weight link that consists of a many to one or one to one mapping between the output layer F_2 of Fuzzy ART and output category. Note that every time a one to many mapping from Fuzzy ART to output category is triggered, an error correcting mechanism called match tracking occurs which will increase the VP of Fuzzy ART, ρ to a value slightly higher than

$$\frac{|I \wedge w_J^a|}{|I|} \tag{14}$$

where J is the index of the active F_2 node.

This is to avoid any confusion in mapping, and hence predictions. When this occurs, Fuzzy ART search leads either to another category that correctly predicts the target or to an uncommitted new category and the dynamic weight link between the Fuzzy ART modules are updated. After this, ρ is set back to the earlier (baseline) VP value. This process is continued until all the training patterns have been presented. The testing stage works in the same principle except that there will be no match tracking. This is since the input presented to Fuzzy ART will output a category with highest value that refers to the predicted class. Further details of SFA could be found from (Kasuba 1993).

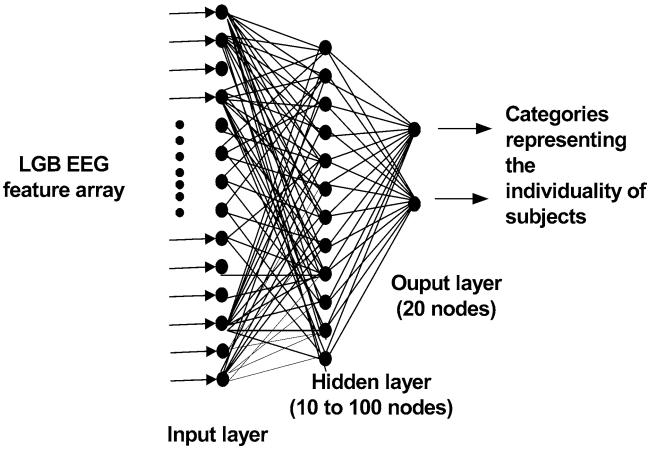

Fig. 7 BP network architecture

Table 1 Average classification results using tenfold cross validation scheme

Fuzzy ARTMAP		Backpropagation	
Vigilance parameter	Classification (%)	Hidden units	Classification (%)
0.0	81.54	10	89.83
0.1	82.11	20	94.83
0.2	82.04	30	95.00
0.3	82.64	40	96.83
0.4	81.96	50	95.33
0.5	81.88	60	96.00
0.6	81.94	70	97.33
0.7	82.64	80	96.83
0.8	82.08	90	95.67
0.9	85.59	100	96.33
Average	82.44		95.40

Backpropagation NN is multilayer perceptron NN type with a single hidden layer and trained by the BP algorithm (Rumelhart and McCelland 1986). Descriptions on BP NN could be found in common textbooks and will not be discussed here. Figure 7 shows the BP network architecture that is used in the study. The desired target output was set to 1.0 for the particular category representing the individual that was being trained, while for the other 39 categories, it was set to 0.

5 NN classification experiments and results

A total of 1,600 LGB EEG feature arrays from 40 subjects were used in the NN classification experiments. VP for SFA was varied from 0 to 0.9 in increments of 0.1[3], while the hidden units (HU) of the BP was varied from 10 to 100 in increments of ten. To validate the classification results, a tenfold cross validation scheme was implemented for both the SFA and BP. In this scheme, the data was split equally into ten sets with equal number of LGB EEG feature arrays, where the data was stratified across subjects, i.e. each part has equal number of feature arrays from each of the subjects. For training, five of these data sets (chosen randomly) were used, while the rest five data sets were used in testing. The classification experiments using this scheme were repeated ten times, each with different training and testing sets. Therefore, 20 (i.e. half of total) LGB EEG feature arrays from each subject were used in training, making a total of 800 LGB EEG feature arrays for training. The rest 800 LGB EEG feature arrays were used to test the performance of the NNs to identify the individuality of the subjects.

Table 1 shows the results of the classification experiments. The classification performances are tabulated using average of the tenfold cross validation scheme. It could be seen that the varying VP of SFA and HU of BP do not significantly influence the classification performances. The performance of BP (average 95.40%) was better than SFA (average 89.44%). The best performance of 95.40% was obtained for BP with 70 HU and for SFA, it was 85.59% for VP of 0.9. However, it must be noted that SFA training was much faster than BP training. But the classification (testing) time per feature array of 0.01 s was shorter for BP as compared to 0.03 s for SFA. Therefore, comparing both the classifiers, it could be concluded that BP is better in terms of classification accuracy and time. The training was conducted offline and therefore the higher computation time for BP during training is trivial.

With more data for NN training and improvements in signal processing techniques, it may be possible to increase the classification further.

[3]Note that VP could only vary from 0 to 1, so this range was chosen.

6 Conclusion

In this paper, a new method of identifying the individuality of subjects was proposed using LGB EEG features classified by NNs. The LGB EEG features have to be computed from single trials of EEG signals because they are not time-locked and PCA was employed for this purpose. Zero-phase Butterworth filter and Parseval's time-frequency equivalence theorem were used to obtain the LGB EEG features. Two NN architectures: SFA and BP were employed to classify the LGB EEG feature arrays, where the BP gave higher classification accuracy with lower classification time. This pilot study showed that the method of identifying subjects using LGB brain signals and NN is worth further study.

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