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EEG Based User Identification and Verification Using the Energy of Sliced DFT Spectra

Hend A. Hadi[1], Dr. Loay E. George[2]

[1, 2]College of Science, Computer Science Department, Baghdad University, Baghdad, Iraq

Abstract: ***Electroencephalogram signals reflect the electrical activity of the brain; EEG signal is the measurement of voltage fluctuations coming from ionic stream within the neurons of the brain. They have been explored in medical researches to diagnose some brain diseases such as Alzheimer's and epilepsy, and have been used in Brian computer interface (BCI) applications. Recently EEG signals are being investigated for identification and verification applications because they show evidence against falsification or replication since the brain activity of people is distinctive. In this paper a promising EEG-based identification and verification system is presented. A feature set based on the energy distribution of Fourier accumulative components is proposed, and some Euclidean distance measures are used for matching. This system was tested on the EEG public CSU dataset which was collected from 7 healthy volunteers. The attained identification results are encouraging with best recognition result is (100%), the tested feature sets were extracted under the condition "they should extract from single task & signal channel". The verification results indicated that the minimum achieved HETR is (0.4%), these results are considered competitive when compared with the results of other recently published works. The adopted condition "one channel per single task" was aid to achieve less computational complexity and, consequently, little execution time is required.***

Keywords: EEG signal processing, Discrete Fourier transform, Energy features

1. Introduction

EEG signals draw the attention of researchers because they can lead to distinctive features about the user identity. Also, they are robust against falsification or replication. Other Biometrics such as fingerprint, hand geometry, facial features, and voice characteristics can be forged using spoof attack. Due to the development of biomedical instrumentation these signals are acquired easily using portable devices with dry electrodes. EEG signals are measured with the electrodes placed on different places of the scalp (Abo-Zahhad, Ahmed and Abbas 2015), (Rodrigues, et al. 2016).The first proposed works that studied the EEG signals as biometric was by Poulos et al.(Poulos, et al. 1999), (Poulos, Rangoussi and Alexandris 1999), (M. Poulos, et al. 1999).Then, this research area had received big interests due to its potential in biometrics systems.

(Palaniappan 2006) proposed the use of AR coefficients, channel spectral powers, differences of inter-hemispheric channel spectral power, inter-hemispheric channel linear and non-linear complexity for feature extraction after filtering the signals using Finite Impulse Response (FIR) filter, and then he reduced the feature vector size using Principal Component Analysis (PCA), also he used Linear Discriminant Classifier (LDC) to classify5 subjects and achieved recognition rate up to (100%) with features combined from Rotation, Math., Letter, Baseline tasks.

(Palaniappan 2008) Proposed same system in (Palaniappan 2006) for subject authentication and achieved best accuracy with FAR and FRR both zero. (Kumari and Vaish 2016) Proposed a system based on the fusion of features from different mental tasks using Canonical Correlation Analysis (CCA). They used Empirical Mode Decomposition (EMD) and information theoretic measure with statistical measurement for feature extraction, then classified the 7 subjects using Linear Vector Quantization (LVQ) neural network and its extension LVQ2;they achieved best recognition rate (96.05%).

(Bajwa and Dantu 2016) Proposed to use EEG signals for both authentication and cryptographic key generation; they used Fast Fourier Transform (FFT) to decompose the signal into frequencies that make it up, and then they used Daubechies (Daub8) to break the signal into to obtain the five major rhythms that composes the brain signal, then they compute the energy of each sub band to obtain the relevant features. Two type of classifiers Support Vector Machine (SVM) and Bayesian network were used, and the best achieved accuracy was (100%). While in this work the DFT spectra of the signal is partitioned into slices, then the average energy of each slice is determined to obtain the relevant features without the need for wavelet decomposition step.

However the researches on EEG-based recognition have faced complications in feature extraction and their combination or in the fusion steps to select the best features for classifiers, they used features extracted from different channels and tasks, and then they tried to use features fusion to generate final feature vector.

EEG-based biometric system must be applicable and usable by making the number of electrodes and tasks that required as less as possible to reduce the Difficulties of EEG signal acquisition from the scalp of the user, as well as the complexity of the system, and the processing time should reduce by using feature extraction methods and classifiers with less computational complexity (Abo-Zahhad, Ahmed and Abbas 2015).

In this paper the use of lowest number of tasks and channels (i.e., one channel per task) was tested to achieve high recognition rates without need to features fusion step, this keep the required computational complexity as low as possible. The discrete Fourier transform is applied, and a set of mean energy values each taken for certain partition of the frequency spectra is proposed to be the feature vector, then the intra/enter scatter analysis is performed for best discriminating feature selection is performed, and the normalized Euclidean distance measure is used.

2. Materials and Methods

The general layout of the proposed EEG-based identification and verification system is shown in Figure 1. The main stages of the both operation phases are:

1) Feature extraction stage.
2) Feature analysis and selection stage.
3) Matching.

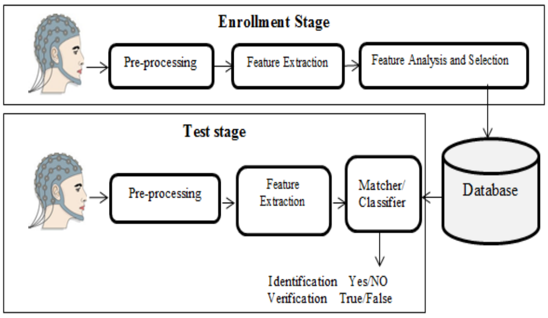

Figure 1: Block diagram of general EEG I/V system

The major task of feature extraction is to extract the best features from the basic component of the signal to represent each subject class. The task of feature analysis and selection stage is to select the most discriminative features.

In matching stage some Euclidean distance measures are applied to test samples and identify subjects.

Dataset

In this paper the EEG CSU dataset was used it was collected by Keirn and Aunon (Keirn and Aunon 1990); which is available at (Colorado State University Brain-Computer Interfaces Laboratory 1989). It is a small dataset of seven healthy volunteers, the EEG signals recorded while each one was performing some mental tasks. These tasks are: Baseline task, Letter composing task, mathematics task, rotation task, counting task. Signals were recorded from the positions C3, C4, P3, P4, O1 and O2. The EEG signals were sampled for 10second time interval using sampling rate 250 sample/sec (Abo-Zahhad, Ahmed and Abbas 2015). The tasks are:

- In Baseline task the subjects do nothing they are just be relax with open eyes or closed eyes (Keirn and Aunon 1990).
- In mathematics task they asked to do some mathematical multiplication problems without pronounce or doing physical activities (Keirn and Aunon 1990).
- In letter composing task the volunteers asked to compose letters mentally without vocalizing.
- In geometric rotation of figure task the volunteers study a three dimensional object for (30 sec), and then imagined the rotation of this object around a particular axis (Keirn and Aunon 1990).

In counting task the volunteers asked to visually count a series of numbers (Keirn and Aunon 1990).

Table 1: Number of samples for each subject

Class No.	No. of Samp.	Class No.	No. of Samp.
1	10	5	15
2	5	6	10
3	10	7	5
4	10 or 9		

Table 1 shows the number of samples for each class. (Note: subject 4 has 9 samples for the letter-composing task because of an error occurred in the dataset) (Kumari and Vaish 2016), (Keirn and Aunon 1990).

Features Extraction Stage

In this stage a set of key features are extracted from EEG signal for accurate recognition of subject classes. Features are extracted from the energy distribution of Fourier alternating components (AC).

The discrete Fourier transform (DFT) decomposes the input signal, has the length N, into two sets of signals which are contain the Sine or Cosine series of the input signal. (Abo-Zahhad, Ahmed and Abbas 2015)(Smith and others 1997). Power spectra consist of the sine and cosine components and consists of different frequencies, high frequencies are concentrated at the end of the transformed components, while the low frequencies at the beginning of the signal. Power spectra contain DC and AC coefficients, DC is the coefficient at the first position and represents the average of the signal, while AC components represent the alternating components of the input signal and used to extract the main features that are used to recognize each class (Smith, et al., 1997). Although DFT is slower than FFT, but it is more suitable for signals whose length is not power of two. Since, the length of processed EEG signal is not power of two, so in this paper a quick DFT algorithm has been used to speed the mapping task from time to the frequency domain (i.e., DFT). The Fourier transform an EEG signal is applied using the following general mapping equation (Gonzalez and Woods 2002).

$$F(u) = \frac{1}{N}\sum_{n=0}^{N-1} s\,(n)\; e^{-j2\pi un/N} \qquad (1)$$

Where the $F\,(u)$ is the u^{th} coefficient of the DFT; $u=0, 1, 2, \ldots N$. The real part is given by the following equation:

$$R(u) = \frac{1}{N}\sum_{t=0}^{N-1} S(t)\cos\left(\frac{2\pi tu}{N}\right) \qquad (2)$$

While the imaginary part is given by the equation:

$$I(u) = -\frac{1}{N}\sum_{t=0}^{N-1} S(t)\sin\left(\frac{2\pi tu}{N}\right) \qquad (3)$$

Then, the power spectra can be obtained using the following equation:

$$F(u) = \sqrt{R^2(u) + I^2\,(u)} \qquad (4)$$

The obtained Fourier AC coefficients of the power spectra are divided into number of slices and the energy of each slice is calculated by taking the average of it, the average is computed by dividing the summation of the squared Fourier coefficient of this slice by the number of that coefficients as follows(Abbas and George 2014):

$$e(k) = \frac{1}{m} \sum_{i=s}^{s+m-1} |F\ (i)\ |^2 \quad k = 1,..N. \qquad (5)$$

Where $e(k)$the energy of k^{th} slice; m is the slice length, and N is the number of energy slices, is the offset index of the first coefficient belongs to k^{th} slice, m is number of coefficients of this slice. By taking the advantage of the Fourier power spectrum symmetry (Gonzalez and Woods 2002) we've calculated the energy of slices for the first half of it only. Figure 2 shows the Raw EEG signal belongs to subject1, as an example. While Figure3 shows the power spectrum of the raw EEG signal after applying DFT.

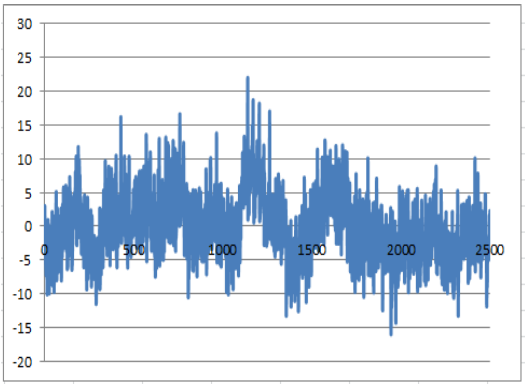

Figure 2: Raw EEG signal.

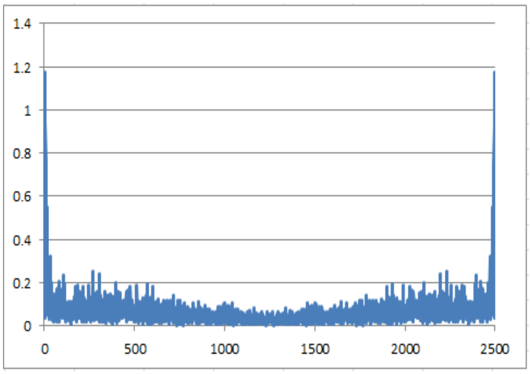

Figure3: Fourier power spectrum of the Raw EEG signal.

Features Analysis and Selection Stage

Then, the extracted features vector is fed as input to the feature analysis stage to select the best discriminative features with lowest intra distance and highest inter distance for the seven subjects this operation in turn lead to reduce the feature vector size (Mohammed and George 2015). For supervised dimensionality reduction the Linear Discriminative Analysis (LDA) that is based on traditional statistical methods is used to reduce the extracted feature vector size by selecting features which minimize the intra-class distances and maximized inter-classes distances(James and Dimitrijev 2012)(Boulgouris, Plataniotis and Micheli-Tzanakou 2009).

Matching Stage

In this stage the degree of similarity between extracted pattern and stored template is calculated. Two Euclidean distance measures were used in this work, the first is the normalized mean absolute difference (as in Eq. 6) and the normalized mean square difference (as in Eq. 7) (Pratt 2001):

$$nMAD\ (S_i, T_j)\ = \sum_{k=1}^{\#features} \frac{|s_i(k) - t_j(k)|}{\sigma_j(k)} \qquad (6)$$

$$nMSD(S_i, T_j) = \sum_{k=1}^{\#features} \left(\frac{(s_i(k) - t_j(k))}{\sigma_j(k)} \right)^2 \qquad (7)$$

Where the $s_i$is the sample of i^{th} class, T_j is the template of j^{th} class and σ_j is the standard deviation of j^{th} template.

3. Result and Discussion

The performance of the proposed system was tested on CSU dataset, various feature combinations were tested, each set of features are extracted from single task and channels. The best attained system recognition rate was up to (100%) for some feature sets for identification for all seven subjects. The results of the tests are described in details in the following sections:

Identification Results

In identification mode the input pattern is compared with all stored templates, and the system accuracy is measured using Correct Recognition Rate (CRR) which is the ratio of the number of correctly classified samples to the total number of tested samples (Abbas and George 2014). The main parameter of the proposed system affects the recognition rate is the number of slices to which the spectra of EEG signal is divided. Table 2 indicates that the results for the 6 cases are relatively approximate but the best case is when the slice numbers is equal to 45. The slice numbers less than 45 gives less recognition rates (Note: the nMAD was used in this test).

Table2: CRR for different number of slices

Feature sets	No. of Slices					
	42	43	44	45	46	47
C3-Base	98.5%	100%	100%	100%	100%	100%
C3-Lett	98.4%	96.9%	100%	96.9%	96.9%	98.4%
C3-Rot	96.9%	95.4%	96.9%	96.9%	96.9%	96.9%
C3-Count	96.9%	98.5%	100%	100%	98.5%	100%
C4-Rot	96.9%	98.5%	98.5%	98.5%	98.5%	98.5%
P3-Base	100%	98.5%	100%	100%	98.5%	100%
P3-Mult	100%	100%	100%	100%	100%	98.5%
P3-Rot	96.9%	96.9%	98.5%	98.5%	98.5%	98.5%
P4-Base	100%	98.5%	100%	100%	100%	95.3%
P4-Mult	98.5%	98.5%	98.5%	100%	100%	100%
P4-Lett	96.9%	95.3%	96.9%	96.9%	96.9%	100%
P4-Count	100%	100%	100%	100%	100%	100%
P4-Rot	100%	100%	100%	100%	100%	100%
O1-Base	100%	100%	100%	98.5%	100%	100%
O1-Mult	98.5%	96.9%	96.9%	98.5%	96.9%	96.9%
O1-Count	95.4%	96.9%	95.4%	96.9%	96.9%	95.4%
O1-Rot	96.9%	98.5%	95.4%	100%	98.5%	96.9%
O2-Base	98.5%	98.5%	98.5%	98.5%	100%	100%
O2-Mult	98.5%	98.5%	98.5%	100%	100%	98.5%
O2-Rot	98.5%	98.5%	98.5%	98.5%	96.9%	96.9%

Table 3 shows the CRR for the best 20 feature sets when the system was trained using nMAD distance measure and Figure 4 show the data-chart of that results, while Table 3 shows the CRR when nMSD is used and the data-charts of this results are showed in Figures 4 and 5, respectively. Table 5 shows the confusion matrix for the P4-Rot feature set.

Table 3: CRR for each feature set using nMAD

Feature set	CRR	Feature set	CRR
C3-Base	100%	P4-Lett	96.9%
C3-Lett	96.9%	P4-Rot	100%
C3-Rot	96.9%	P4-Count	100%
C3-Count	100%	O1-Base	98.5%
C4-Rot	98.5%	O1-Mult	98.5%
P3-Base	100%	O1-Rot	96.9%
P3-Mult	100%	O1-Count	100%
P3-Rot	98.5%	O2-Base	98.5%
P4-Base	100%	O2-Multi	100%
P4-Mult	100%	O2-Rot	98.5%

Table 4: CRR for each feature set using nMSD

Feature set	CRR	Feature set	CRR
C3-Base	98.46%	P4-Lett	96.88%
C3-Mult	96.92%	P4-Rot	100%
C3-Rot	96.92%	P4-Count	100%
C3-Count	98.46%	O1-Base	100%
P3-Base	100%	O1-Mult	98.46%
P3-Mult	100%	O1-Rot	96.92%
P3-Rot	98.46%	O1-Count	100%
P3-Count	98.46%	O2-Base	100%
P4-Base	100%	O2-Mult	100%
P4-Mult	98.46%	O2-Rot	98.46%

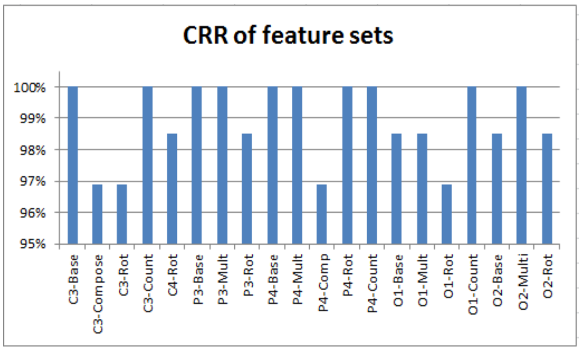

Figure 1: CRR data-chart using nMAD

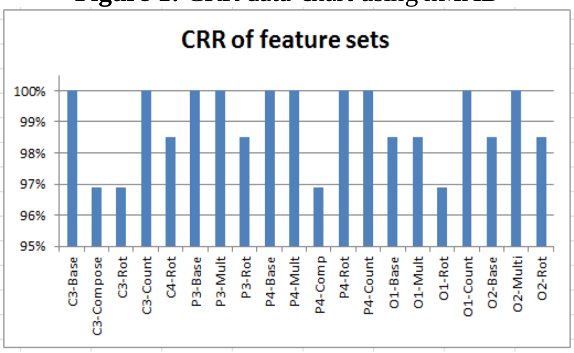

Figure 2: CRR data-chart using nMSD

Table 5: Confusion matrix for P4-Rot feature set

	S1	S2	S3	S4	S5	S6	S7
S1	100%	0%	0%	0%	0%	0%	0%
S2	0%	100%	0%	0%	0%	0%	0%
S3	0%	0%	100%	0%	0%	0%	0%
S4	0%	0%	0%	100%	0%	0%	0%
S5	0%	0%	0%	0%	100%	0%	0%
S6	0%	0%	0%	0%	0%	100%	0%
S7	0%	0%	0%	0%	0%	0%	100%

Verification Results

Verification mode is different from identification mode; the input pattern is compared with the template of class subject that the user claims to be, so the role of verification is to confirm the claimant's identity (Palaniappan 2008). The Receiver Operating Characteristic (ROC) Curve organizing and visualizing the performance of verification system from the plots the FRR and FAR. To check the intersection point between FRR and FAR in which the Half Total Error rate (HTER) is obtained to evaluate the performance of the system. HTER is defined as the average rate of FRR and FAR, the definition of HTER is given by Eq. 10(Bajwa and Dantu 2016), the definitions of FAR and FRR are given by Eqs. 8and 9 respectively (Abbas and George 2014):

$$FAR = \frac{number\ of\ accpted\ imposter}{total\ number\ of\ imposter} \times 100\% \quad (8)$$

$$FRR = \frac{number\ of\ rejection\ genuine}{total\ number\ of\ genuine} \times 100\% \quad (9)$$

$$HTER = \frac{1}{2}\,(FAR + FRR) \quad (10)$$

The *Sensitivity* of system (or TAR) is given by Eq. (11), *Specificity* (or TRR) is given by Eq. (12), and the *Accuracy* of the system is given by Eq. (13) (Fawcett 2006):

$$TAR = \frac{number\ of\ accepted\ genuine}{total\ number\ of\ genuine} \times 100\% \quad (11)$$

$$TRR = \frac{number\ of\ rejected\ genuine}{total\ number\ of\ genuine} \times 100\% \quad (12)$$

$$Accuracy = \frac{TP + TN}{P + N} \quad (13)$$

Where TP means positives (or genuine) correctly accepted, TN means Negative (or imposter) patterns correctly rejected, P means all positive patterns and N means all negative patterns:

$$P + N = all\ patterns\ in\ the\ system \quad (14)$$

Table 6: Sensitivity, FRR, FAR, Specificity, Accuracy, and HETR for all feature sets using nMAD

Feature Set	TAR	FRR	FAR	TRR	RR%	HETR
C3-Base	97.14	2.86	3.35	96.65	96.70	3.11
C3-Lett	93.17	6.83	6.88	93.12	93.08	6.85
C3-Rot	92.38	7.62	6.91	93.09	92.97	7.26
C3-Count	90.95	9.05	9.17	90.83	90.77	9.11
C4-Rot	92.38	7.62	7.99	92.01	91.87	7.81
P3-Base	95.71	4.29	5.04	94.96	95.16	4.66
P3-Mult	97.14	2.86	4.21	95.79	96.04	3.53
P3-Rot	91.90	8.10	7.92	92.08	92.31	8.01
P4-Base	94.76	5.24	5.19	94.81	94.73	5.22
P4-Mult	91.43	8.57	9.09	90.91	91.21	8.83
P4-Lett	93.17	6.83	6.79	93.21	93.08	6.81
P4-Rot	99.05	0.95	2.91	97.09	97.36	1.93
P4-Count	94.29	5.71	5.19	94.81	94.73	5.45
O1-Base	91.43	8.57	7.87	92.13	92.31	8.22
O1-Mult	94.76	5.24	5.02	94.98	94.95	5.13
O1-Rot	89.52	10.48	10.78	89.22	89.45	10.63
O1-Count	93.33	6.67	6.52	93.48	93.41	6.59
O2-Base	94.76	5.24	6.00	94.00	94.29	5.62

O2-Mult	93.81	6.19	6.39	93.61	93.63	6.29
O2-Rot	91.43	8.57	9.53	90.47	90.55	9.05

In Table 6 P4_Rotate feature set achieved highest accuracy.

Table 7: Sensitivity, FRR, FAR, Specificity, HETR, and Accuracy for all feature sets using nMSD

Feature Set	TAR	FRR	FAR	TRR	RR%	HETR
C3-Base	97.62	2.38	2.60	97.40	97.36	2.49
C3-Mult	88.10	11.90	11.64	88.36	88.57	11.77
C3-Rot	92.38	7.62	7.69	92.31	92.31	7.65
C3-Count	92.38	7.62	7.61	92.39	92.31	7.61
P3-Base	96.19	3.81	3.90	96.10	96.04	3.85
P3-Mult	97.62	2.38	2.65	97.35	97.36	2.52
P3-Rot	96.19	3.81	3.19	96.81	96.70	3.50
P3-Count	88.10	11.90	9.43	90.57	90.55	10.67
P4-Base	93.33	6.67	7.01	92.99	92.97	6.84
P4-Mult	96.19	3.81	3.90	96.10	96.04	3.85
P4-Lett	94.60	5.40	5.20	94.80	94.64	5.30
P4-Rot	100	0	0.81	99.19	99.34	0.4
P4-Count	94.29	5.71	5.00	95.00	95.16	5.35
O1-Base	94.29	5.71	4.94	95.06	94.95	5.32
O1-Mult	92.86	7.14	6.61	93.39	93.19	5.32
O1-Rot	95.71	4.29	4.78	95.22	95.38	4.53
O1-Count	93.81	6.19	6.26	93.74	93.63	6.23
O2-Base	93.33	6.67	6.70	93.30	93.41	6.68
O2-Mult	94.29	5.71	5.87	94.13	94.51	5.79
O2-Rot	94.76	5.24	5.25	94.75	94.73	5.24

P4_Rotate feature set achieved highest accuracy as it is shown in Table 7, with accuracy (99.34) and HTER is (0.4) at threshold (21.6). Figure 6 shows ROC curve between FRR and FAR for the P4_Rotation set.

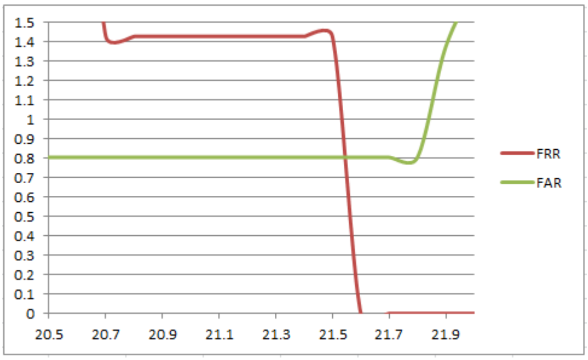

Figure 6: ROC curve for the P4_Rotation feature set using nMSD

Processing Time Results

The execution time is another parameter to evaluate the performance of the recognition system. Table 8 shows the average of processing time for each stage in milli-sec; the matching time is for one-to-many comparisons. The used computer was Intel® Core ™ i5-2450M CPU, with installed RAM (4GB), system type is windows7 (64bit), and the language was used is Microsoft visual C#.

Table 8: The average processing time results in msec.

Stage	Time in msec.
Feature extraction	13.359
Matching	0.013
Total	13.372

Comparison with Recently Published Works

Many works have been recently published in subject identification and verification using EEG signal. Here, a comparison is shown between some published works results on CSU dataset and our work results. Table 9 shows that our results is competitive when compared with the results of other published works, taking into account that the introduced work in this article has low computational complexity so is requires very little execution time; also the system uses EEG signal belong to single channel when subject applies certain single task.

Table 9: The comparison with other published works on CSU dataset based on Subjects number, channels used and tasks

Author	No. of Subjects.	mode	Ch.	Task	Acc. %
(Kumari and Vaish 2016)	7	I	6	2	96.05
(Bajwa and Dantu 2016)	7	V	6	1	100
(Palaniappan, 2008)	5	V	6	1	100 FAR=0 FRR=0
(Palaniappan, 2006)	5	I	6	3	100
Proposed work	7	I	1	1	100
Proposed work	7	V	1	1	RR=99.34 FAR=0.81 FRR=0

About the processing time most of the published works haven't mentioned it clearly.

4. Conclusion and Future work

In this paper, a fast and simple system is proposed for EEG-based identification and verification system of subjects, the proposed method uses the energy distribution of AC components of DFT power spectra for features extraction. The tests results indicated high performance for subjects' identification and verification modes. The test results showed that the proposed system achieved perfect recognition rate (i.e., 100%) for identification and 99.34% for verification when using minimum number of channels and tasks (i.e., one channel, single task) on CSU dataset.

Another feature extraction method based on wavelet transform can be applied to enhance the system for lowest complexity and also try to apply the proposed system on a larger data.

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