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TWO-STAGE BIOMETRIC AUTHENTICATION METHOD USING THOUGHT ACTIVITY BRAIN WAVES

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Brain waves are proposed as a biometric for verification of the identities of individuals in a small group. The approach is based on a novel two-stage biometric authentication method that minimizes both false accept error (FAE) and false reject error (FRE). These brain waves (or electroencephalogram (EEG) signals) are recorded while the user performs either one or several thought activities. As different individuals have different thought processes, this idea would be appropriate for individual authentication. In this study, autoregressive coefficients, channel spectral powers, inter-hemispheric channel spectral power differences, inter-hemispheric channel linear complexity and non-linear complexity (approximate entropy) values were used as EEG features by the two-stage authentication method with a modified four fold cross validation procedure. The results indicated that perfect accuracy was obtained, i.e. the FRE and FAE were both zero when the proposed method was tested on five subjects using certain thought activities. This initial study has shown that the combination of the two-stage authentication method with EEG features from thought activities has good potential as a biometric as it is highly resistant to fraud. However, this is only a pilot type of study and further extensive research with more subjects would be necessary to establish the suitability of the proposed method for biometric applications.

Keywords: Authentication; biometric; electroencephalogram; thought activities.

1. Introduction

Authentication of individuals, which is different from identification, has become an important issue with the advent of internet banking and e-commerce. It is also crucial in ensuring security while access to confidential resources or locations is granted. The common authentication approaches are those based on personal identification number (PIN) and password. However, these can be easily compromised by methods such as ‘shoulder surfing’. Therefore, biometric approaches based on the physical and behavioral traits of humans have been proposed.

The most common and widely used biometric is the fingerprint;[1,2] though in recent years, numerous alternative biometric methods to replace or augment the fingerprint technology have emerged. These other biometric methods are like voice,[1] palmprint,[3] hand geometry,[4] iris,[5] face,[6] ear force fields,[7] heart signals,[8] odor,[9] and brain signals.[10–13]

However, using electroencephalogram (EEG) during imagined activities as a biometric is a new approach. There have been other types of EEG signals that have been studied for biometric applications.[10–12] In Ref. 10, alpha rhythm EEG signals were used to classify four subjects, while in another study,[11] autoregressive (AR) modeling of EEG obtained when the subjects had their eyes open or closed were used as a biometric. Visual evoked potentials recorded while subjects perceived a picture were used in Ref. 12 to identify the subjects. However, this method required 61 channels, which was cumbersome and also required the individuals to perceive a visual stimulus, which could be considered a drawback for the visually impaired.

In a previous study,[14] it has been shown that classification of EEG signals during thought activities is a suitable technique for use in the design of Brain

Computer Interfaces (BCIs) to aid the disabled to communicate or control devices. BCIs are also useful for hands-off menu activation, which could be used by the general public. In the study in Ref. 13, the same approach but using different feature extraction and classification methodologies was proposed to identify the individuality of the subjects.

Until now, these studies on using electrical activity of the brain as biometric concentrated on identification of a user from a pool of users. In this study, authentication of the user using EEG extracted during thought activities is explored rather than identification. Though the same dataset as used in Ref. 13 are used here, the feature extraction methodology here includes the features from nonlinear measures and further, a novel two stage authentication procedure is proposed which gives improved accuracy as compared to existing authentication methods that adjusts a single threshold to balance false accept error (FAE) and false reject error (FRE). FAE is the error made by the authentication system when wrongly accepting an impostor as client while FRE error is made when wrongly rejecting a client as impostor. Client is the actual user claiming the identity while impostor is the user claiming another person's identity.

2. Data

EEG data from five subjects were used in this study. The data were collected by Keirn and Aunon[15] and are publicly available.[16] The description of the data and recording procedures are as follows. The subjects were seated in noise controlled room. An electrode cap was used to record EEG signals from positions C3, C4, P3, P4, O1 and O2 defined by the 10–20 system of electrode placement (as shown in Fig. 1). The impedances of all electrodes were kept below $5\,\mathrm{K}\Omega$ and measurements were made with reference to electrically linked mastoids, A1 and A2. The electrodes were connected through a bank of amplifiers with analog band-pass filters set from 0.1 to 100 Hz. The data were sampled at 250 Hz with 12-bit precision. The system was calibrated before each recording. Signals were recorded for ten seconds during each of the five imagined activities and each activity was repeated for different day sessions.

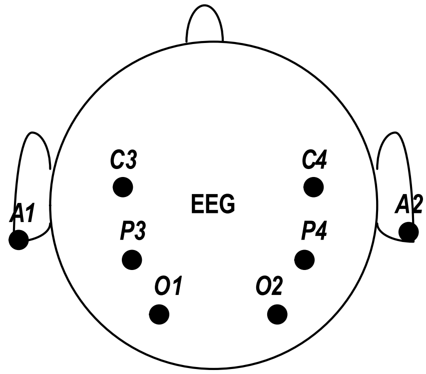

Fig. 1. Electrode placement.

These imagined activities are as follows:

2.1. *Baseline activity*

The subjects were asked to relax and think of nothing in particular.

2.2. *Math activity*

The subjects were given non-trivial multiplication problems, such as 79 times 56 and were asked to solve them without vocalizing or making any other physical movements. The activities were non-repeating and designed so that an immediate answer was not apparent. The subjects verified at the end of the activities whether or not he/she arrived at the solution and no subject completed the activity before the end of the 10 s recording session.

2.3. *Geometric figure rotation activity*

The subjects were given 30 s to study a particular three-dimensional block object, after which the drawing was removed and the subjects were asked to visualize the object being rotated about an axis. The EEG signals were recorded during the imagined rotation period.

2.4. *Letter composing activity*

The subjects were asked to mentally compose a letter to a friend without vocalizing. Since the activity was repeated for several times the subjects were told to continue with the letter from where they left off.

2.5. *Visual counting activity*

The subjects were asked to imagine a blackboard and to visualize numbers being written on the board sequentially, with the previous number being erased before the next number was written. The subjects were instructed not to verbalize the numbers but to visualize them. They were also told to resume counting from the previous activity rather than starting over each time.

Keirn and Aunon[15] specifically chose these activities since they involve hemispheric brainwave asymmetry (except for the baseline activity).

3. Feature Extraction

In this study, each of the EEG signal was segmented into 20 segments with length 0.5 s, so each EEG segment was 125 data points (samples) in length. Since there were 10 sessions, each thought activity gave 200 segments. The EEG segments were referenced to the common reference (i.e. centered to zero mean across all the channels) and also were centered to zero mean in each of the channel. The preliminary results indicated that both these operations decreased the classification error and hence were adopted. Elliptic Finite Impulse Response (FIR) filter was used to high-pass filter the EEG signals above 0.5 Hz (to reduce baseline noise). The filter specifications were: 30 dB minimum attenuation in the stop-band with 0.5 dB ripple in the pass-band. Elliptic filter was used because of its low order as compared to other FIR filters like Butterworth. Forward and reverse filtering were performed to ensure that there would be no phase distortion.

3.1. *Autoregressive coefficients*

The EEG signals were subjected to feature extraction using AR modeling:

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + e(n), \tag{1}$$

where p is the model order, $x(n)$ is the signal at the sampled point n, a_k are the real valued AR coefficients and $e(n)$ represents the error term independent of past samples. In this paper, Burg's method[17] was used to estimate the AR coefficients. In computing AR coefficients, order six was used because other researchers[14,15,18] have suggested the use of order six for AR process for thought activity classifications. Therefore, six AR coefficients were obtained for each channel, giving 36 features for each EEG segment for a thought activity.

3.2. *Channel spectral powers and inter-hemispheric channel spectral power differences*

Next, Elliptic filters with similar specifications as used earlier were utilized to extract EEG in three spectral bands: alpha, beta and gamma. Delta and theta bands were ignored since there is seldom any EEG of interest in these low frequencies during any thought activity. The frequency ranges of each bands were alpha (8–13 Hz), beta (14–20 Hz) and gamma (21–50 Hz). Channel spectral power in each band was computed using the variance of the filtered output. Next, inter-hemispheric channel spectral power differences in each spectral band was computed using

$$Power_{difference} = (P_1 - P_2)/(P_1 + P_2), \tag{2}$$

where P_1 is the power in one channel and P_2 is the power in another channel in the same spectral band but in the opposite hemisphere. Overall, this gave 18 channel spectral powers and 27 inter-hemispheric channel spectral power differences (nine spectral power differences for six channels in opposite hemispheres × three bands) for each thought activity.

3.3. *Inter-hemispheric channel linear complexity*

For a certain C number of channels (C-channel) signals, linear complexity[19] is defined as:

$$\Omega = \exp\left(-\sum_{i=1}^{C} \xi_i \log \xi_i\right) \tag{3}$$

where the eigenvalues, λ are computed from the covariance of the C-channel EEG matrix and normalized using

$$\xi_i = \lambda_i \Big/ \sum_{i=1}^{C} \lambda_i. \tag{4}$$

Roughly, the linear complexity, Ω measures the amount of spatial synchronization. Large values of Ω indicate low correlation between the signals in the channels and vice versa. Here, Ω is computed to measure the inter-hemispheric channel linear complexity for each spectral band where the two channels used were one each from the opposite hemispheres. There were nine inter-hemispheric channel linear complexity values times three bands, totaling 27 for each thought activity.

3.4. *Non-linear complexity*

It has been shown recently that this dataset exhibits a mixed property of linearity and non-linearity, i.e. some thought activity EEG signals are more linear while others are more non-linear using Delay Vector Variance method.[20] Hence, it would be appropriate to include non-linear measures as well. Approximate entropy is a measure that has been used successfully to quantify the complexity of the EEG signal. It is obtained by

$$ApEn(m, r, n) = \frac{1}{N-m} \sum_{i=1}^{N-m} \operatorname{In} C_i^{m+1}(r) - \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \operatorname{In} C_i^{m}(r), \tag{5}$$

where $C_i^m(r)$ is the correlation integral with embedding dimension m and time lag of 1 that is obtained from

$$C(r) = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \Theta(r - |x_i - x_j|), \tag{6}$$

where x_i and x_j are data points in the EEG signal, N is the length of the EEG signal, r is the threshold radial distance around point x_i, while Θ is the Heaviside function.

In this study, m is set to 2 and r is set to 0.15% of the standard deviation of the EEG signal. These values were chosen based on the previous studies[21,22] that indicated good statistical validity of approximate entropy. There were six approximate entropy values for each band, totaling 18 values (from three bands) for each thought activity.

3.5. *Principal Component Analysis*

The standard Principal Component Analysis (PCA) was used to reduce the feature size. In this work, the principal components that contributed to 99.99% of the total variance were retained. This variance value to be retained was obtained after some preliminary simulations. The reduced feature size was 11.

4. Two-Stage Authentication

4.1. *Initial setting of the data*

The data consisted of 1000 feature vectors (from 200 segments for each activity × 5 subjects), each with length 126 for each thought activity. When a subject was being considered for authentication, 200 feature vectors from the subject were treated as client data while the rest 800 feature vectors were treated as impostor data. This data were split into

- Train patterns using 50 randomly selected client feature vectors,
- Validation patterns using 50 randomly selected client feature vectors (with no overlap to train patterns),
- Test patterns using 100 remaining client feature vectors and all 800 impostor feature vectors.

4.2. *Threshold computation*

An important step in this proposed two stage authentication is the computation of two thresholds, Th_1 and Th_2. The Th_1 will be useful in reducing FAE, i.e. reducing the error of wrongly accepting impostors as clients while Th_2 will be useful in reducing FRE, i.e. reducing the error of wrongly rejecting the clients as impostors. The following procedures describe the steps to compute these two thresholds.

The Manhanttan (city block) distances D, were computed between 50 validation patterns and 50 training patterns. Next, Dmax and Dmin, the maximum and minimum of these validation-training distances for each validation pattern were computed. Thresholds, Th_1 and Th_2 were obtained using

$$Th_1 = \min(D \min), \quad Th_2 = \max(D \max). \tag{7}$$

The Dt, Manhanttan distances of the 800 test patterns from the 50 training patterns were computed. Next, maximum and minimum of these Dt, Dtmax and Dtmin were computed.

4.3. *Authentication stage one*

The threshold Th_1 was used to determine whether each pattern was client or impostor using the rule that the test pattern belonged to the client category if $Dt \max < Th_1$. Else, the test pattern was detected as possibly from the impostor category. The focus of this authentication stage was to reduce FAE only. No doubt, the FRE would be very high but the 2nd stage authentication would solve this problem.

4.4. *Authentication stage two*

This stage was used only for those test patterns that were detected as impostors in the earlier stage.

The threshold Th_2 was used to determine whether the test patterns detected as impostors from 1st stage authentication were really clients or impostors. Client was detected if $Dt\min < Th_2$. Else, it was impostor. The focus of this stage was to reduce FRE.

4.5. *FRE and FAE computation*

Next, FRE and FAE were computed using

$$
\begin{aligned}
\text{FRE} = {} & (\text{no. of client patterns incorrectly} \\
& \text{detected as impostor patterns}/100) * 100\%, \\
\text{FAE} = {} & (\text{no. of impostor patterns incorrectly} \\
& \text{detected as client patterns}/800) * 100\%.
\end{aligned} \tag{8}
$$

It should be noted here that there was no overlap between the test, validation or training patterns. This was no ensure that accurate FRE and FAE would be reflected. A modified four-fold cross validation (CV) was conducted to ensure the reliability of the results. These steps were repeated four times with different train, validation and test patterns from client feature vectors. Test feature vectors from impostor data remained the same. The averaged FAE and FRE from CV were stored. These steps were repeated for every thought activity and for every subject. Figure 2 shows a block diagram of computation of the thresholds while Fig. 3 shows a block diagram of the authentication procedure.

5. Results and Discussion

Tables 1 and 2 show the results of the experimental study. As mentioned earlier, the FAE and FRE were obtained using the two-threshold procedure with CV. Table 1 shows the results using all the 126 features. All the subjects gave perfect accuracy in rejecting impostors (i.e. zero FAEs) for any thought activity. FREs for most of the subjects for the different thought activities were also zero except for subject 5 that gave 1.5% and 0.75% for counting and mathematics activities and subject 1 that gave 1.0% for letter activity. The best thought activity was either counting or rotation since both FAE and FRE were zero for both these activities for all the subjects.

Table 2 shows the FRE and FAE results using only the 11 features from PCA. As can be seen by comparing Tables 1 and 2, the error values are not very much increased by using the reduced feature set and as such, the reduced feature set could be used in future studies. The rotation activity gave the best performance with zero FRE and FAE for all the subjects.

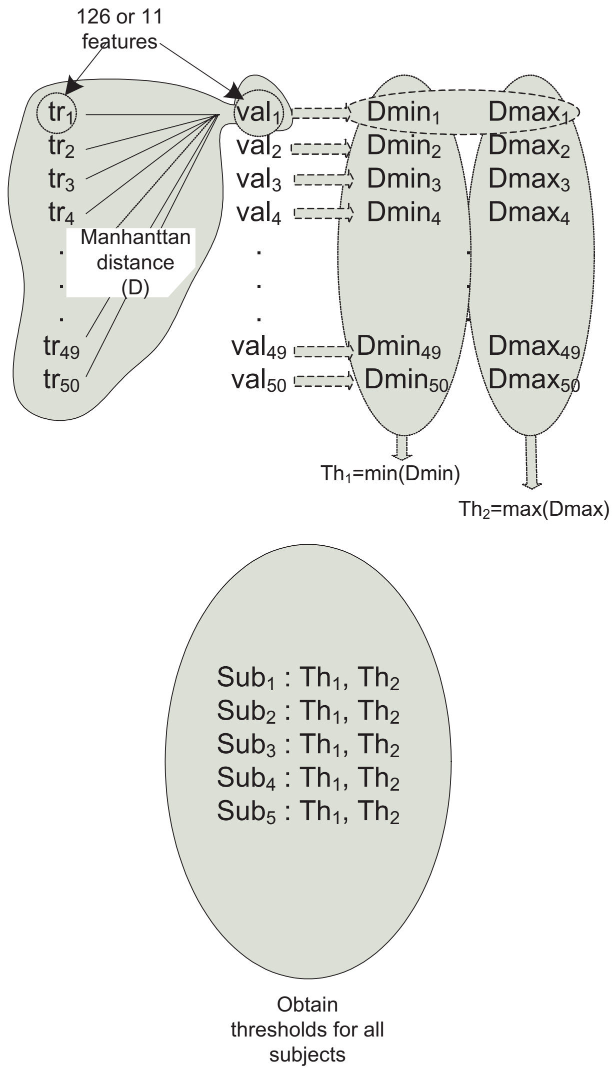

Fig. 2. Computing the thresholds.

A lower FAE is generally accepted as more important than corresponding FRE as it is more important to prevent any impostors from cheating as clients rather than having some clients turned away as impostors. The zero FAEs result for any thought activity for all the subjects show that the proposed authentication procedure could prevent any impostors from cheating as clients, while maintaining a high level of client detection.

Currently, the uniqueness of EEG biometric has not been proven and one may be tempted to raise this question when EEG is used as a biometric. But then,

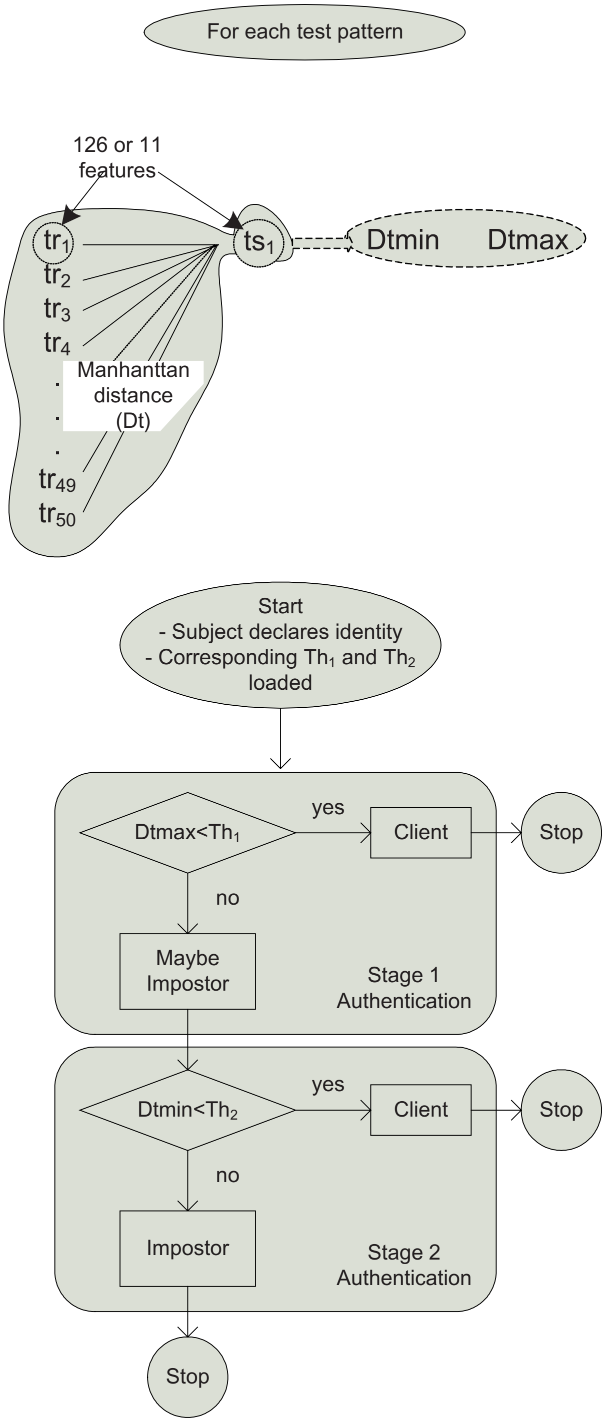

Fig. 3. Authentication procedure.

this is the case for any biometric, even fingerprints where the individuality has been challenged.[2] And what is more central to a person's identity than their brain state? DNA is a good alternative but unfortunately cannot be implemented close to real-time, i.e. in a matter of seconds. The central theme of this study is to draw interest on an approach that is least possible (practically) to be compromised in the data collection stage (any system can be compromised in the data processing stage but this is a separate issue).

EEG signals are generally distinctive, however the procedures of extracting features to normalize intra-subject variation in time causes some loss of distinctiveness, which is why the results obtained for some thought activity are not error free.

At the moment, the data collection is slightly cumbersome but still practically possible for high-security applications as only a few channels are used (a simple headband with disposable electrodes would be a solution). Also, the current research into dry electrodes, when successful would make it possible to record EEG as quickly and simply as fingerprint scanners/facial image capturing camera etc.

6. Conclusion

In this paper, a novel method of authenticating individuals using classification of feature vectors from EEG signals recorded during thought activities has been proposed as a biometric tool. The features consisted of sixth order AR coefficients, channel spectral powers, inter-hemispheric channel spectral power differences, inter-hemispheric channel linear complexity and non-linear complexity (approximate entropy) values computed from six EEG channels that were recorded while the subjects performed different thought activities.

The drop in the number of features from 126 to 11 using PCA shows that the features have a high degree of redundancy (overlapping information). So, in future, it would be useful to study which are the most discriminatory features and using these would circumvent the requirement of using PCA to reduce the number of features.

A novel two-stage authentication procedure was used to verify the claimed individuality of the subject using the EEG feature vectors, where a modified four fold CV procedure was used to improve the reliability of the results. The perfect FRE and FAE verification accuracies over 1000 EEG feature vectors from five subjects for certain thought activities show promise for the method to be studied further as a biometric tool for individual authentication, especially for a small group. Currently, work in this direction is in progress. The method could be used as a uni-modal

Table 1. FRE and FAE using all the features. 'Sub' denotes subjects, 'Act' denotes the thought activities: b (baseline), c (visual counting), l (letter writing), m (maths multiplication) and r (object rotation).

Sub	S1		S2		S3		S4		S5	
Act	FRE	FAE	FRE	FAE	FRE	FAE	FRE	FAE	FRE	FAE
b	0	0	0	0	0	0	0	0	1.5	0
c	0	0	0	0	0	0	0	0	0	0
l	1.0	0	0	0	0	0	0	0	0	0
m	0	0	0	0	0	0	0	0	0.75	0
r	0	0	0	0	0	0	0	0	0	0

Table 2. FRE and FAE using the PCA reduced features. 'Sub' denotes subjects, 'Act' denotes the thought activities: b (baseline), c (visual counting), l (letter writing), m (maths multiplication) and r (object rotation).

Sub	S1		S2		S3		S4		S5	
Act	FRE	FAE	FRE	FAE	FRE	FAE	FRE	FAE	FRE	FAE
b	0	0	0.5	0	0	0	0	0	1.5	0
c	0	0	0	0	0	0	0	0	0.25	0
l	1.0	0	0	0	0	0	0	0	0.25	0
m	0	0	0	0	0	0	0	0	0.75	0
r	0	0	0	0	0	0	0	0	0	0

(stand alone) or in part of a multi-modal individual identification system and is mainly advantageous because of its fraud resistance (i.e. it is difficult to establish another persons exact EEG output).

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Appendix

A brief description on some of the key concepts used in this paper is as follows:

- Approximate entropy — a non-linear measure that measures the complexity of the EEG signal.
- Autoregressive (AR) — a linear model that is frequently used to represent EEG signal.
- Biometric — is the field where physical and behavioral traits of humans are used to identify/authenticate the individuality.
- Channel — EEG signals are normally recorded from a number of electrodes on the scalp and these are normally known as channels.
- Channel spectral powers — power (energy) of the EEG signal in a specific frequency (spectral) band.
- Client — is the actual user claiming the identity.
- Cross validation — training and testing with different non-overlapping subsets of the datasets to improve the reliability of the results.
- Electroencephalogram (EEG) — brain's electrical activity recorded at the scalp using electrodes.
- False accept error (FAE) — is the error made by the authentication system when wrongly accepting an impostor as client.
- False reject error (FRE) — is the error made when the system wrongly rejects a client as impostor.
- Features — representative values extracted from EEG signals using certain models (equations).
- Impostor — is the user claiming another person's identity.
- Inter-hemispheric channel linear complexity — measures the level of spatial synchronization of

the EEG signals from two channels (one from each hemisphere) in each spectral band.

- Inter-hemispheric channel spectral power difference — measures the difference in power between EEG signals from two channels (one from each hemisphere) in each spectral band.
- Segment — a part of the EEG signal from one channel.
- Session — denotes a time period of EEG signal recording.
- Spectral band — a band in a specific range of frequency. The common bands are delta, theta, alpha, beta and gamma.
- Thought activity — mental task performed by the subjects.
- Two stage authentication — a novel procedure where both FAE and FRE are minimised unlike single stage authentication where a compromise has to be made between minimization of FRE and FRE.

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