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BRAINWAVE BASED AUTHENTICATION SYSTEM: RESEARCH ISSUES AND CHALLENGES

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ABSTRACT:

Despite extensive research conducted in authentication system, security issues are still a challenging task. The most common authentication mechanism is Username and Password. Due to its lack of efficacy, it has been proved as weak method for authentication. In the recent years, Biometric authentication methods have been receiving increasing attention. The design of the biometric system requires human biological physical characteristics such as fingerprints, ear, face, and plamprint etc. The general problems of these characteristics are its easy acquisition process therefore the numbers of attack vectors are associated with them. To reduce the chances of attacks in authentication system research has taken the direction to brainwaves based authentication system which is an alternative method. The objective of this article is to summarize and presents a comprehensive review of well known methods used in brainwave authentication system and identify the research topics and application which are at forefront of this exciting and challenging field.

Keywords: *Cognitive biometrics, EEG, Biometry, Biometric authentication, Brainwaves based authentication system*

[1] INTRODUCTION

The society is transforming into the digital world and every individual are now living with digital identities. Digital identities are having intensive that should be pre-recorded to help machine for user authentication. In fig 1 we have explained various user authentication techniques which are helping the user of digital infrastructure to secure the vital information from the unauthorized access. **Figure1** emphasizing the flow of Authentication.

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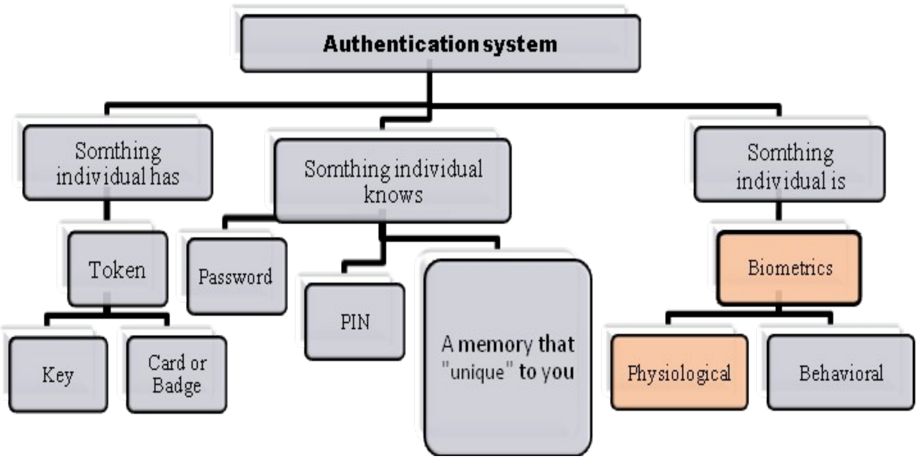

Figure 1 Emergence of authentication system

One of most popular authentication protocol being used in the digital world is "Biometrics" which takes user's physical and behavioral characteristics as an input for the authentication procedure that has unique potential to classify individual from others. According to the study, each biometrics is evaluated in seven factors: Each biometrics is evaluated in seven factors: universality, uniqueness, permanence, measurability, performance, acceptability, and circumvention**. [A.K Jain et al]**

Biometrics systems which are based on fingerprints, Iris, plamprint, retina, and face are widely used in diversity of area for user authentication; these approaches are gaining much popularity in the technology world. Unfortunately, they have caught with some abatement which degrades its performance. **[Ratha et. al. 2001]** has found that when information flows from source to destination within the architecture of Biometric system, there is various prone area where an attacker can attack easily. According to his outcome of the research, eight significant attack vectors are pointed out which are drawn in below figure 2.

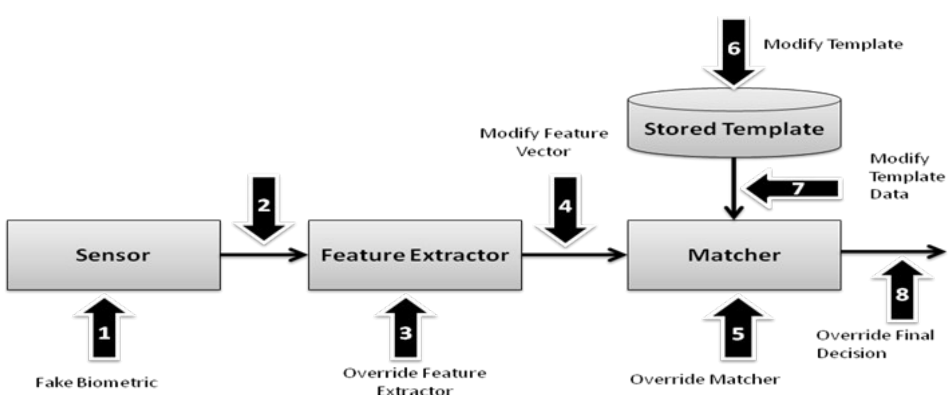

Figure 2 Ratha's framework of Various Attacks Vector **[Ratha et. al. 2001]**

Table 1 Description of attack vectors

Attack Vectors	Description
Fake Biometric	At this point attacker can submit a fake biometric trait and can gain access to information.
Override feature extractor	At this point attackers are able to modify the data and provide the further processing.
Override matcher	This threat vector could attack where matching software works and manipulate the result and falsely produce the result.
Modify feature vector	At this stage modifications are possible with various algorithms in feature vector which are extracted from the genuine biometric trait.
Modify template	This threat vector could modify the template by the reconstruction samples**.**
Modify template data	In the threat unauthorized changes are made as templates are modified, replaced or added to the system for further processing
Override final decision	This type of attack overrides the decision data or injects a false acceptance between the system and the end device. **[Ratha et. al. 2001]**

[2] THE SURVEY

In the view of above mentioned Ratha's described framework of attack vectors in biometric systems, this article organized as follows: How Brainwaves would be helpful for next generation biometric system and what are different methods have been used for signal preprocessing, feature extraction and classification. Furthermore ,we are also showing strength of brainwave to become a secure technique for authentication system, what are different methods have been used so far for its preprocessing, feature extraction and classification.

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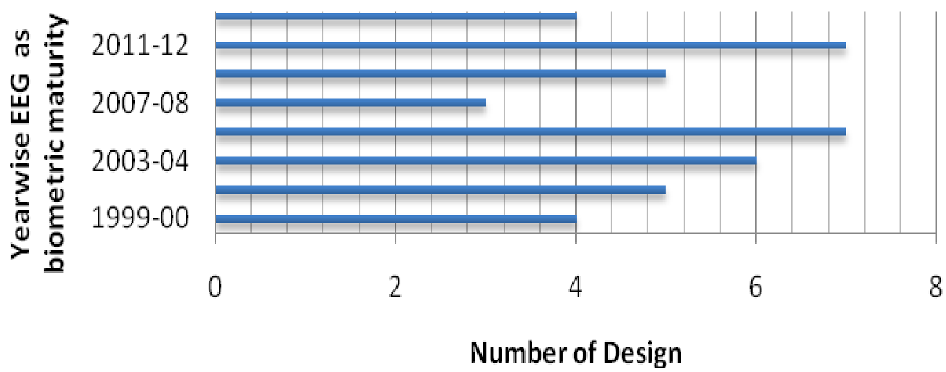

Figure 3 The Increasing research trend in EEG as biometric

2.1 Brainwaves as Privacy protection technique: *"A privacy protection technique which uses human's cognition brainwaves is called Brainprint biometric system or cognitive biometrics."* For designing a cognitive biometric system we have to have one most important tool is being used in clinical area to track electrical activities of brain i.e. Electroencephalogram (EEG). It is combination of three terms '*Electro*' which means the electrical activity, '*encephalo*' which means a brain, and '*graph*' which means the picture. Hence, it is a tool to record the picture of brain's electrical activity for the different intention such as health and medical application and Brain computer Interface (BCI) Brainwaves signals are usually decomposed in several frequency bands. Each band contains signals associated with particular brain activities **(Basar et al., 1995).** The standard EEG signal consists of a number of underlying oscillating frequency spectrum are: 0.5–3.5 Hz (d), 4–7 Hz (q), 8–15 Hz (a), 15–30 Hz (b), 30-70 Hz or around 40 Hz (g).

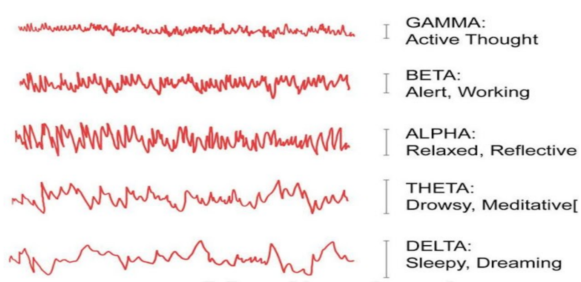

Fig4. EEG frequency bands

This last one, gamma band, has been related to cognitive functions such as attention, learning, visual perception and memory **(Keil et al. , 1999)**. In addition, brain signal can also play the vital role in the area of authentication as per genetic science it has been published that every brain has different signal pattern while visualization, cognition and in any attention that would be a vital trait to distinguish the identification of human. For acquisition of EEG signals, the 10-20 system is well known an international standard method to describe the location of electrode deployment. Many of the work towards the brain related research has been with this standard and some of the works had added the more electrodes as per their requirements. It is important to take into account the willingness to use the system by the users. If the system requires the use of several electrodes, it might take long time to set up. Also the use of wet electrodes (i.e. placed

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with conductive gel) makes these types of systems somehow invasive. Fig 3 shows the location of the electrode's place over scalp and table 2 describes the available devices designed in10- 20 system.

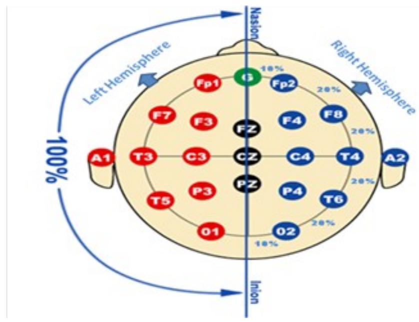

Figure 3: Electrode placement method in 10-20 system

Table 2 Available EEG devices based on 10-20 system

EEG Device	*No. of Channels*
EMOTIV[13]	14
ENOBIO[14]	8 or 20
BIOSEMI[15]	From8 to256
MINDWAVE Mobile[16]	1
MINDWAVE[17]	1
MINDSET[18]	1

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[3] DIFFERENT NEUROMECHANISMS:

The neurological mechanisms of brain are responsible for emissions the electrical signals and these signals are categorized in five major group of neuromechanism are being used so far to develop a brainwaves authentication system. These categories are P300, VEP, SCP, and activity of neural cell (ANC). In this paper we are including one another neuromechanism is the Energy of brain signal which have been described below:

- **Slow cortical potentials:** Slow cortical potential is one of the slowest neuromechanism of the brain signal, it basically observed when subject does the non-movement task, it response started from 300 sec to several sec. In the view of its characteristics we can say that it is able to give mechanism for excitatory mobilization **.[Neumann et al 2003]**

- **P300 evoked potential:** Evoked potential are quite infrequent and particularly generated by auditory, visual, and somatosensory stimuli. Parietal cortex region of the brain is responsible to emit P300 at 300ms after any of above stimuli is received. P300 is actually a peak of the waveform at 300ms **[Kubler et al 2001a]**

- **Visual evoked potentials (VEP):** Visual Evoked Potential is a brain signal generated when sail changes happen in brain. These small changes is basically generated from the visual stimulus such as flashing lights and its quality depends on type of visual stimulus presented respectively at a rate of 5 -6 Hz or greater. The electrical response generated from visual pathways with continuous oscillation is called SSVEP, a distinction of VEP. SSVEP is highly dependent on repetition rate of the stimulation.**[Kubler et al 2001a].**Generation of VEP's for medical purpose the well known set of images dataset have been used **[Snodgrass and Vander et al]** and it contains 260 pictures.

- **Acknowledge to mental task:** Response different mental task such as arithmetic expression, multiplication problem, imagination of 3D object and mental visual counting can give us distinct pattern of signal over different region of the brain. [**Kubler et al 2001a]**

- **Activity of Neural cell:** This neuromechanism states that the firing rates of the neuron in the region of motor. The rate of firing neuron of each person can lead to a good parameter for authentication **[Donoghue 2002 ,Olson et al 2000]**

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- **Complex Neuromechanism:** This sort of system has combination of numerous neuromechanism i.e. combo of neuromechanism as two or more classes above mentioned.

- **Energy of the brain:** Energy of brainwaves at different frequencies can give different information to make an authentication paradigm. **[Ramaswamy Planiappan et. al]**.

3.1 Advantage of brain signal over conventional authentication system

1. It is not exposed and it is very difficult to fake resulting in a very secure authentication system

2. As brain signals are dependent on the mood and stress on the subject making it difficult to get them by force.

3. As EEG can be recorded continuously, it allows for continuous authentication

4. It can also be used for aliveness control, since, only live people have an EEG.

5. The brain signals are related with the subject's genetic information making them unique for each individual and are stable over time.

[4] HOW BRAINWAVE BASED BIOMETRIC SYSTEM WORKS?

Just as a hand is an organ for grasping, and an eye for seeing the brain is an organ for cognitive task or thinking and EEG is well known tool by which we can track our brain's electrical activities to get the information about the cognitive task. According to neurologists, EEG signal varies for every subject while person during same cognitive task such as thinking about visual object, counting the visual object and solving some arithmetic expression etc. This property of brain pattern satisfies all necessary requirements to become a biometric system.

Brainwave based Biometric system allows individual to provide brainwave pattern as input to the system for authentication of user just by doing any cognition task like some thought about doing something or thinking of any arithmetic calculation. This

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positive change becomes too fruitful when we consider the user like one who is suffering from physical disabilities.

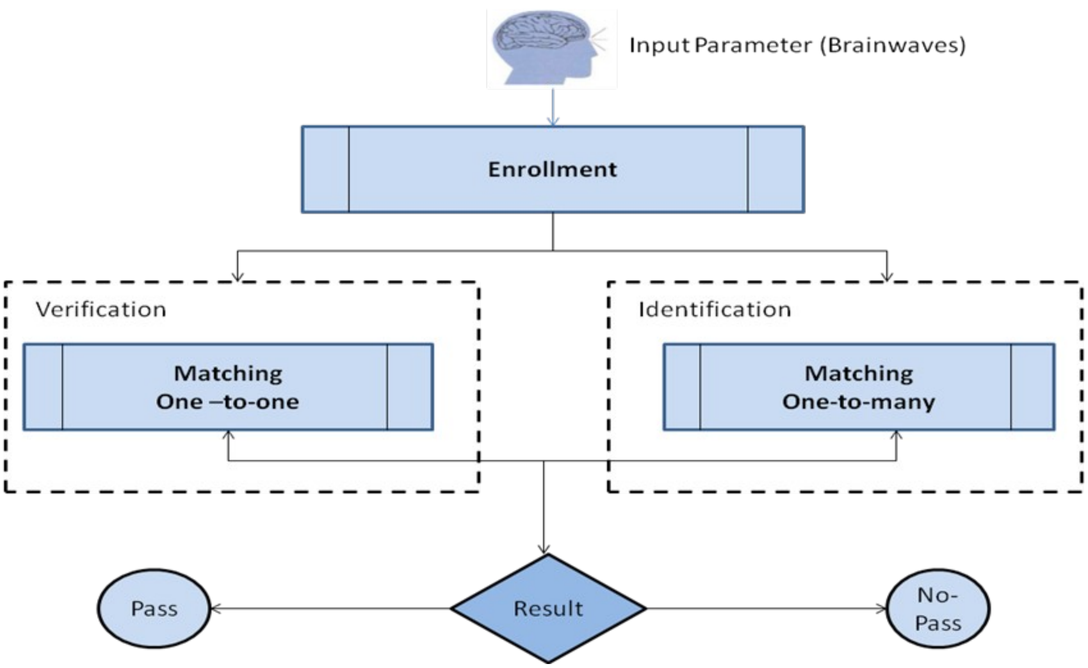

Figure 4 Flow chat of brainwaves based authentication system

Table3 Past researches have used above mentioned Methods for signal processing

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Methods	**Authors**	**No. of channels**	**Data Size**	**Frequency Range**
Sum and Difference(SD) FIR	R. Planiappan et al 2007	61	10	32-48Hz(Gamma)
Butterworth IIR	R. Planiappan 2005	61	20,40	30-50Hz, 30-70Hz(Gamma)
Elliptic IIR Filter	R. planiappan2005, Corey Ashby et al 2011	61,7	20,10	30-50Hz(Gamma)
Band Pass Butterworth filter	R. Planiappan, A. Zúquete	61,4	10	Centered at 40Hz, 50-40Hz(Gamma)
Band pass filter , Notch filter	Shih-Chung Chen Gonzalo Safont et.al , HU Jian-feng et al	8,4,6	5,70(50-genuine, 20 intruder),3	{1~30Hz, 60Hz(Gamma)},{5-70Hz},{1- 50Hz}

The above depicted picture describes the information flow of biometric system while doing identification process and authentication process as well. In identification simple takes the input from desired sensor and the system conducts the one-to-many schema to establish the person identity whereas, an authentication process first users need to go through the enrollment process then system conducts one-to one comparisons to establish the identity of the user before the system is able to verify the specific biometric of the person. An authentication process consist two types of attempts 1) Genuine Attempt (True identity) and 2) imposter attack (False identity).

Like other biometric system, the brainwave based biometric system has three major phases:

Phase I Signal preprocessing

Phase II Feature Extraction

Phase III Classification

Phase I: Signal Pre-processing Methods -The signal preprocessing is the most important stage of overall brainwaves based authentication as raw brainwaves are very difficult to understand and extract the meaningful information from it. Hence, it need conditioning and pre-processes the signal. In order to preprocess the signals there are various filtering techniques have been applied in the area brainwaves based authentication system which are shown below:

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- **Finite impulse response**: A digital filter that has an impulse response which reaches zero in a finite number of steps are called finite impulse response (FIR) filter. A FIR filter can be implemented non- recursively by convolving its impulse response with the time data sequence it is filtering.

- **Butterworth Filter**: The well known analog filter is Butterworth which main characteristics are that the pass band is maximally flat. There are no variations (ripples) in the pass band. The magnitude response of LP

Butterworth filter is given by:

$$|H(\Omega)|^2 = \frac{1}{1+\left[\frac{\Omega}{\Omega c}\right]^{2N}}$$

$|H(\Omega)|^2$ =magnitude of LPF

N-Order of filter that means the no of stages used in the design of analog filter

- **Elliptic Filter**: An elliptic filter is a signal processing filter with equalized ripple (equi-ripple) behavior in both the pass band and stop band and also it offers steeper rolloff characteristics than butterworth. The response of elliptical filter satisfies: $|H(j\omega)|^2 = \frac{1}{1+c^2 R_n^2(\omega, L)}$

Where is $R_n(\omega, L)$ an n^{th} order chebyshev rational function with the ripple parameter L. Elliptical filter sometimes known as *cauer* filter

- **Others filter :**The filter like sum and difference (SD) and band pass filter is a filter that passes frequencies within certain range and rejects (attenuates) frequencies outside the range and it also known as Sum and Difference (SD) filter which basically calculates the sum and differences of the out of filters (low pass, high pass and band pass).

Phase II Feature extraction: Extraction of appropriate features is an important subject of pattern recognition it transforms the input data into a set of features which are further used for classification process. The most important part is the quality selection of the features for the overall classifier, the accuracy directly determined by the choice of the features. The following set of features have used so far for the classification of EEG data.

- **Auto-Regression:** The Auto-regression of the EEG signal for each channel is assumed to be the output of an auto-regression system driven by white noise. Autocorrelation methods are used to fit a p[th] order AR model to the windowed input signal, x_t, by minimizing the forward prediction error in a least-square sense.**[Camillo Porcaro, Gelareh Mohammadi]**

  The AR model is represented by:

$$x_t = \sum_{i=0}^{q} c_i e_{t-i} + \sum_{i=1}^{p} a_i x_{t-i}$$

- **Auto covariance:** The Auto covariance of the signal could be a feature for EEG signal to distinguish from other. It can be used with different order:[23]

$$\mathrm{acov}_3(\tau) = E[\, X(t)X(t-\tau)X(t-2\tau)]$$

  being the lag and considered third order auto covariance of both channels grouped as a single feature. **[Corey Ashby et al 2011]**

- **Power spectral density (PSD):** The most demanding feature of EEG signal which distinguish the person from others. The Power spectral density function finds strength of the variations (energy) as a function of frequency. In other words, it gives at which frequencies are strong and at which frequencies variations are weak. **[Andr´ e Z et al 2010] [R. Palaniappan et.al 2002] [Se´bastien Marcel et al 2007]** [**John Chuang et al 2013]**

- **Energy spectrum density (ESD):** The energy spectral density describes how the energy (or variance) of a signal or a time series is distributed with frequency. If xt is a finite-energy signal, the spectral density Φω of the signal is the square of the magnitude of the continuous Fourier transform of the signal. ESD is computed as following: $\Phi_\omega = \left| \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} x_t e^{-j\omega t} dt \right|^2 = \frac{X_\omega X_\omega^*}{2\pi}$

  Where, ω is the angular frequency and X_ω^* is the continuous Fourier transform of X_t and X_ω is its complex conjugate.[**Muhammad Kamil Abdullah et al 2010**] **[HU Jian-feng et al 2010]**

- **Centroid frequency:** The Centroid frequency or spectral Centroid is a measure used to characterize the spectrum of the "Center off mass" of the frequency of interest:

$$f_{cntr} = \frac{1}{BW} \int_{f \in BW} \xi . P_X(\xi)\, d\xi$$

  BW is the bandwidth of the frequencies of the interest. The Centroid frequency of the channel is single feature**.[Gonzalo safont et al 2012]**

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- **Time reversibility:** Time reversibility is a measure of asymmetry due to time reversal

$$t_{rev}(\tau) = \frac{1}{\sigma_X^3} E\left\{\left[X(t) - X(t-\tau) \right]^3\right\}$$

-being the lag. The time reversibility values of both channels are a single feature. **[Gonzalo safont et al 2012]**

- **Interhemispheric power Difference:** The Interhemispheric power differences are actually shows each pair of electrodes in the left and right hemispheres. These difference are computed as :

$$Power_{Diff} = (P1-P2)/P1+P2$$

P1is power of one channel and P2 is the power of another channel in the same spectral band but in different hemisphere. **[Corey Ashby et al 2011]**

- **Interhemispheric channel linear complexity:** Interhemispheric linear complexity values are calculated as the entropy of the eigenvalues of the covariance matrix of Interhemispheric power differences. It measures the degree of spatial synchronization of data. **[Corey Ashby et al 2011]**

- **Coherence:** The coherence measures the relation between two time series at different frequencies. The coherence between two signal $C_{xy}(f)$, is a function of cross power spectral density $P_{xy}(f)$and the spectral density of each signal $P_x(f)$, $P_y(f)$ **.[Gonzalo safont et al 2012]**

$$C_{XY}(f) = \frac{\left|P_{XY}(f)\right|^2}{P_X(f)\,P_Y(f)}$$

- **Cross-correlation:** The well-known cross-correlation is a measure of the similarity of two signals, commonly used to find occurrences of a known signal in an unknown one. It is a function of the relative delay between the signals; it is sometimes called the sliding dot product, and has application in pattern recognition and cryptanalysis.[**Andr´ e Z ´ uquete et. al 2010**] **[Corey Ashby et al 2011]**
- **Fourier Transform:** The Fourier transform is way of the signal representation in frequency components. EEG bands of the interest are included: delta, theta, alpha, beta, and gamma. The Fourier transform of each channel was treated as a different feature **. [Gonzalo safont et al 2012]**

- **Wavelets transform:** Wavelet transform methods are using for decomposition of signal into wavelet analysis which co-efficient yield significant activity at the corresponding frequency **[Heinar A. Weiderpass et. at 2012][Muhammad Kamil Abdullah et al 2010]**

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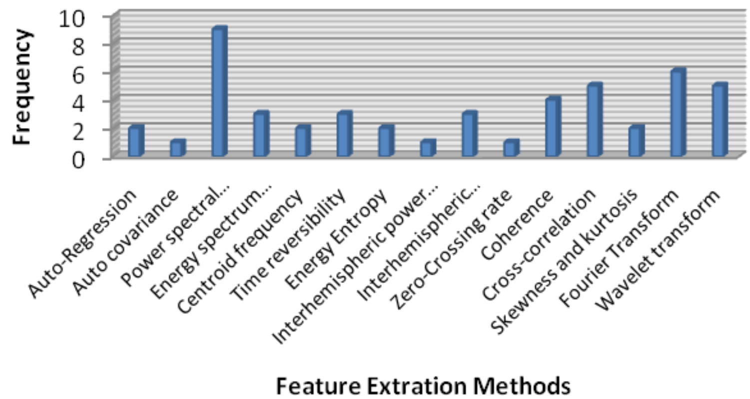

Figure 2 Number of design using above noted methods

Phase III Classification Methods:

Like feature extraction phase, classification stage is also a crucial part of any pattern recognition problem which is highly dependent on feature extraction stage. In order to choose most suitable classifier for a given set of features, the property of the available classifier must be chosen accordingly. A classification stage needs to be implemented in order to decide if the collected biometric sample belongs to the claimed subject or not (authentication mode) or in order to decide to whom this biometric sample belongs to (identification mode).The classification methods belong to the field of computational intelligence. This research field is indeed a very complex and broad one. In this review, we will present the methods that have been more used in brain based biometric system. In the following table, we show some of the most frequently used classification methods:

Table 4 Performance of Classification Methods

Classification methods	EEG Signals	Cognitive task	Author Name	Accuracy
Multi-layer back propagation neural network	C3,C4,P3,P4,O1 and O2	Motor Imaginary	HU Jian-feng	90%
Neural network	C3,P3 and C4 P4	Eye open and closed	Muhammad Kamil et al.	80%

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Elman neural network	All 61 channels	Simple white and black drawing of common object	Ramaswamy Palaniappan et. al	99.62%
Neural network with 10 times weight correction	32 (P300)	Number recognition from screen	Ramaswamy Palaniappan and Jenish Gosalia	90%
Simplified fuzzy ARTMAP (SFA), linear discriminant and K-nearest neighbor	VEP	Visual Object recognition	Ramaswamy Palaniappan et al.	96.50%
Simplified Fuzzy ARTMAP (SFA) neural network (NN)	VEP	Visual Object recognition	R Palaniappan; K V R Ravi	94.18%
competitive network	100 Channels	Motor Imaginary	Gelareh Mohammadi	80%to 100%
ENN and KNN.	VEP	Visual Object recognition	Ramaswamy Palaniappan et al	90%
K-Nearest Neighbors (KNN)	single-channel	Breathing Task, Simulated Finger Movement (finger), Sports Task (sport), Song/Passage Recitation Task, Eye and Audio Tone Task (audio)	John Chuang	90%

In addition, there are various works have been done by fusion of above mentioned methods to achieved better accuracy.

[5] CONCLUSION

In the biometric authentication using brainwave, we can assert that several methods have been applied to pre-process of the signal, feature extraction and to classify EEG biometric data. Which one is better? This is not an easy question to reply. From our point of view, for any brainwave based privacy protection system to perform well, both the feature extraction step and the classification step are very important. If the extracted EEG features are not discriminant, no classification method will be able to discriminate them. On the other hand, if the classification method is not properly trained, the system will not work even if the features are discriminant.

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Finally, there is an interesting book (Multivariate Decoding and Brain Reading. Lemm et al, 2010) where we can find a deep review of the most commonly used machine learning and pattern recognition techniques used in EEG data analysis. From this work, we have shown the scope of research in this emerging area.

[6] Open Issues and challenges for future work:

Despite of various methods have been applied during past few years on brainwave authentication system, there remains considerable need for additional work on this area. In this section we note some open challenges that deserve attention from researchers in this area:

- **Scalability in dataset:** Most designs in brainwave based authentication system have been talked about very small dataset therefore; it would be an interesting problem for future to investigate the potential of brainwaves for authentication task with large number of subjects.

- **Effect of Emotional state:** As we know that, brainwaves highly depending on states of neuron thus, it is important to study that what would be the response authentication system at time of subject's different emotions. Furthermore, most of the experiments have been considered only healthy subjects for development of authentication system therefore; it would be also a challenging task to see the system performance in case of subject's non-healthiness.

- **Novelty in techniques:** The research community should also devote most serious attention in novelty in methods to accomplish the authentication task using brainwaves which would able to give better accuracy in least time.

- **Electrode placement Paradigm:** In acquisition of brain signals, deployment of the electrodes at right position effects the quality of signal such as non-uniform or inappropriate spatial location may cause distortion in acquired signal. Therefore it is important to find out the extract spatial position from where we can get brainwave which would be helpful to extract unique features for authentication task.

- **Customization:** EEG device always come up with large number of electrodes so it is tough to keep everywhere thus, in future this would a good work if we could design a device as wearable as possible with less number of electrodes.

- **Robust against attacks:** As we know that choice of brainwave as object for authentication system to reduce the number of attack vectors which were associated with the conventional. Now it is important to look into further that how easy difficult to preserve the system from the intruder attack.

- **Selection of cognitive task:** Generation of brainwaves depends on type of cognitive tasks, so it would be a challenging task in future to find out the most appropriate task which would be fruitful for authentication task because duration of the task at the enrollment of the subject and at time of authentication process must be identical. For Instance at time of enrollment user plays cognitive task *"x"* mins time to set their password and at time of authentication he/ she may take "*x-1/x+2*" mins, which degrades the system performance or error in authentication hence it is important research further to find out most suitable tasks which are optimize for both duration of enrollment and authentication as well.

- **Multimodality:** To check brainwave feasibility in multimodality nature, so that we would also see its effectiveness with fusion capability with conventional biometrics such as face, iris, fingerprints, and Ear etc to develop highly secure method for privacy protection.

- **Usability:** The most important part of the work in future is to make the system usable as conventional systems of authentication like fingerprint, Iris, face and plamprint. To make brainwave system more usable research must have design a system with less number of electrodes, most suitable cognitive that would enough able to get distinguish pattern of every individuals and effective method etc.

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