EEG-Based Biometric Authentication for Brain Computer Interfaces

DAS Abhishek
Department of ECE, CMU
addas@andrew.cmu.edu

SHANNON Keith
Department of ECE, CMU
kshannon@andrew.cmu.edu

BANALA NITHYANANDAM Revanth
Department of ECE, CMU
rbanalan@andrew.cmu.edu

Abstract

Authenticating users has always been an integral part of security systems. Despite the fact that Biometric Authentication has long been the gold standard for security, with advancing technology, even the biometric authentication techniques are not safe from forgery and deception. A significant step would be Biometric Authentication using the few channels of Electroencephalogram (EEG) data available in brain computer interfaces (BCIs). Authentication could be done quickly and effortlessly capturing a predefined brain state which is impossible to evoke by insistence or coercion nor can be replicated by a non-living brain, because every human brain has a distinctive neural signature. We have modelled an offline biometric authentication model starting with 64 channels that can be reduced to 5 best channels that accurately identify the subjects with an accuracy of 95% that can be used for the implementation of an online model using the MUSE headset.

1 Introduction

Authenticating users has always been ubiquitous to security systems to verify the user credentials and privileges in order to gain access to the system. Not withstanding the fact that there are various types of authentication - knowledge-based (in the form of username- password pairs), possession-based(in the form of smart cards, RFID Tags) and biometric authentication (Fingerprints and IRIS Scanners); it becomes a key issue to safeguard these modes of authentication as they can easily be replicated and stolen. Biometric authentication has long been the gold standard for security as physical devices can be misused, stolen and damaged while conventional authentication techniques are prone to being hacked or easily forgotten. With the advancing technology, even the biometric authentication techniques are not safe from forgery and fake replicas as fingerprints can be easily duplicated while iris scans can be deceived by high resolution images. This clearly poses a new problem to innovate new robust techniques that can safeguard authentication from the above unauthorized access to security systems. [1]

The use of EEG biometrics, for the purpose of automatic people recognition, has received increasing attention in the recent years. Biometric authentication based on Electroencephalograph (EEG) data would be a significant step forward in the field of brain computer interfaces (BCIs), as it would allow users to avoid the step of manual authentication. The human brain is a complex interconnected system with a distinctive pattern formed by these neural connections, allowing EEG to be used for distinguishing and identifying the neural signature of every brain. Using EEG as a biometric trait has many potential advantages over traditional biometrics as it captures a predefined brain state which authenticates a system and is impossible to evoke by insistence or coercion. No non-living brain can produce an EEG, which prevents breaching an authentication system by assassinating a user. Even though most other biometric traits are visible, EEG biometrics are invisible, making them uncapturable by other parties.

While EEG authentication had been achieved securely on 64 channel devices, most commercial devices have 2 to 5 channels. Our objective is to achieve the same level of secure authentication on as few channels as possible.

2 Background Study

Brain-computer Interfaces (BCIs) are control and communication systems based on acquisition and processing of brain signals to control a computer or an external device. One of the most popular techniques used for neuro-imaging is Electroencephalography (EEG). EEG signals provide relevant information about individual differences related to anatomical and functional traits of the human brain, as established by previous studies, hence distinctively identifying the human brain. [2] Feature extraction over EEG signals for BCI systems is crucial to the classification performance.

A crucial part of the problem is capturing variation between users with the minimal amount of data. The traditional EEG extraction methods use a skull-cap with around 64 EEG channels which becomes cumbersome while extracting the data as well as processing it. This is a dimensional reduction problem, reducing the 64 sensors to less than 10. This reduction can be accomplished by reducing the dimensionality of the EEG data, then finding a set of sensors which captures the best variation in this reduced space. From previous studies, it is evident that choosing the Frontal region of the brain yields a higher recognition accuracy than the other regions. This condenses the problem by reducing the number of electrode channels actually needed for the implementation of the project - which in our case, is 5 electrode channels in the Frontal region.

Another key problem in the design is the feature extraction from the EEG Signals. From [4], previous studies have approached the feature problem using two techniques - Wavelet Transform and Power Spectral Density formulation and feature extraction. We intend to build on the existing work and implement a more real-time robust model for EEG Data feature extraction, classification and validation.

3 Dataset

Physionet's EEG Motor Movement/Imagery Dataset was used for the implementation of the offline model. [3] The EEG data corresponds to two baselines - Eyes Open (EO) and Eyes Closed (EC), each recorded for 1 minute each for 109 subjects. In each condition, subjects were comfortably seated on a reclining chair in a dimly lit room. During EO, they were asked to avoid ocular blinks in order to reduce signal contamination. The data was collected over a 64-channel skull-cap and sampled at a frequency of 160 Hz. The data was segmented into 6 epochs (5 - training, 1 - testing) of 10s on which PSD and Spectral Coherence were used to extract features, to illustrate versions of the same state of mind.

4 System Design and Implementation

Our objective was to achieve the accuracy of the 64 channel EEG systems on a small subset of channels. To accomplish this, we used the full dataset of 64 channels to validate the subsets of channels with best identifying accuracy. Then, rather than run the same algorithm on this subset, we used the 64 channel data to generate a feature map, projecting signals from the subset of channels onto the connections most significant in the full dataset. This leads to the two algorisystem comprises two models - the offline and online models. The offline model uses of Physionet's 64-channel EEG data in order to find the best feature subspace that will be used for the verification of the online model that uses the MUSE headset with 5-channels whose data will be projected onto the feature subspace for feature extraction, classification and biometric authentication.

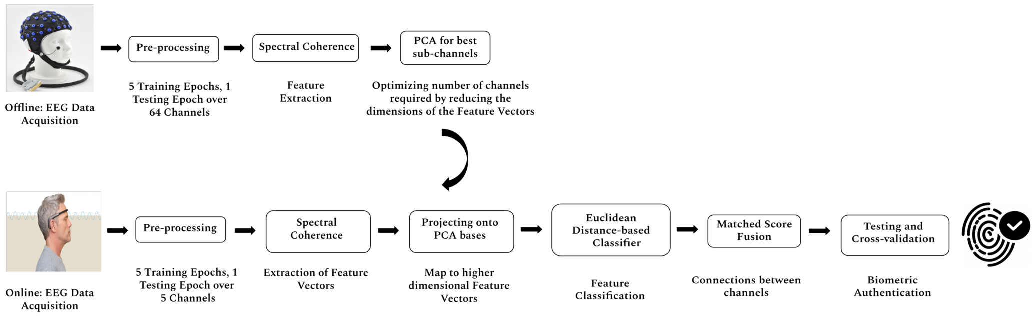

Figure 1: EEG-based Biometric Authentication using Spectral Coherence

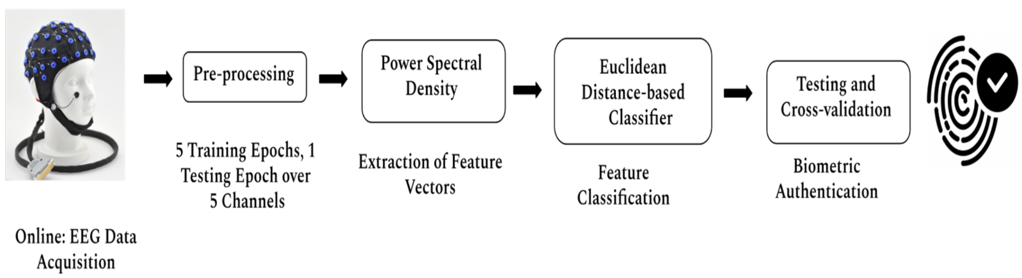

Figure 2: EEG-based Biometric Authentication using Power Spectral Density

As shown in the above figure, the key implementation involves the following sections:

4.1 Preprocessing of EEG data

The EEG data was down-sampled to 100Hz by applying an anti-aliasing low-pass filter in order to keep the bandwidth 50Hz for the feature extraction as the important frequency bands lie within the 0-40 HZ range. The data was divided into 6 epochs of 10s each where 5 were used as training data and the other one was used for testing the model.

4.2 Feature Extraction

Features extraction proceeds in the following way: the power spectral density(PSD) of each channel, $S_i(\omega)$, and the cross spectral density of each pair of channels, $S_{ij}(\omega)$, are computed. Along with these the "brain waves" or features from the wavelet transform also used to find the best frequency bands with optimal distinctive capabilities. The results after classifying the features obtained by PSD and Spectral Coherence are compared to choose the best Feature extraction algorithm.

4.2.1 Wavelet Transform

The Wavelet Transformation ideally separates the EEG into various frequency bands which helps us to isolate the “band levels” or “features” and then choose the best features for classifying the EEG signals. Decomposition is made by employing two sets of functions, called scaling and wavelet functions, which are associated with low-pass filters and high-pass filters, respectively.

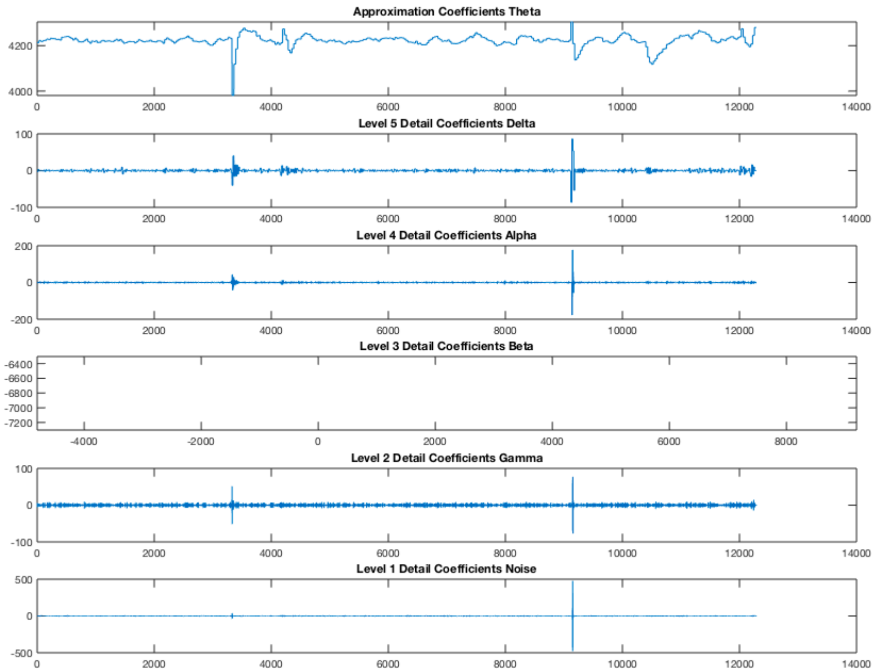

Figure 3: Wavelet transform of the EEG-data

The above figure illustrates the various frequency bands also called "brain waves". Each frequency band has a special physiological implication.

- Delta Waves (0-4Hz) - These lie in the lower-most part of the wavelet transform and are often associated with deep levels of relaxation and restorative sleep and many of our unconscious bodily functions such as regulating the cardiovascular and the digestive systems.
- Theta Waves (4-8Hz) - The Theta waves are known as the ‘suggestible waves’, because of their prevalence when one is in a trance or hypnotic state. Theta waves are often involved in a relaxed brain state, so would seem active when the user is still conscious but in a "relaxed" state.
- Alpha Waves (8-13Hz) - These waves form the ‘frequency bridge’ between our conscious thinking (Beta) and subconscious (Theta) mind. They help to stay calm and work towards the higher levels of relaxation, but when a person is in a conscious state of mind, these are inhibited by the higher frequency beta waves.
- Beta Waves (13-40Hz) - Beta waves comprise the majority of the meaningful "brain wave" spectrum as they are associated with conscious states of cognitive reasoning, thinking. Studies have also shown that the alpha waves are suppressed by the brain in case of heightened beta-wave activity, which could play an important role in the biometric authentication process as the user is often in a conscious eyes closed state where inherent cognitive thinking can suppress the alpha waves.
- Gamma Waves (40-100Hz) - These lie in the upper-most parts of the wavelet transform and are often associated with processing more complex tasks in addition to healthy cognitive function. Gamma waves are found to be important for learning, memory and processing and they are used as a binding tool for our senses to process new information.

4.2.2 Power Spectral Density

The Power Spectral Density (PSD) describes how the power of a signal is distributed in frequency. Since signal with nonzero average power is not square integrable, the Fourier transforms do not exist in this case. The PSD is the Fourier transform of the autocorrelation function of the signal. The power of a signal in a given frequency band is calculated by integrating over positive and negative frequencies. [2] PSD is computed using Welch's average periodogram using the following parameters: Hanning window of 100 samples, overlap of 50 samples, 100 nfft data points for 51 elements. Once the PSD is computed, we choose only 40 elements as "brainwaves" convey most information within the freq bands of 1-40Hz. Hence using PSD for feature extraction we have 64 feature vectors each having 40 elements corresponding to the frequency bands of the brain waves.

4.2.3 Spectral Coherence and Dimensionality Reduction using PCA

Features extraction proceeds in the following way: the power spectral density of each channel, $S_i(\omega)$, and the cross spectral density of each pair of channels, $S_{ij}(\omega)$, are computed. The connection coherence at a given frequency, for a pair of channels, is defined as:

$$C_{ij}(\omega) = \frac{S_i(\omega)S_j(\omega)}{S_{ij}(\omega)}$$

A frequency spacing of 1 Hz is used, from 1 Hz to 40 Hz, to give adequate coverage of the significant bands in EEG activity. This gives 40 features for each pair of channels, which form a feature vector ϕ_{ij}. Thus the 1540 pairs of channels each have an associated feature vector.

The dimensionality of the feature vectors using Spectral Coherence is very large for a real-time practical implementation of the system. Hence, there arises a dimensionality reduction problem. Hence, Principal Component Analysis is used for finding the principal components corresponding to the highest eigenvalues. These represent the best subspace of the feature vectors that can be used for the online implementation of the model. Another important thing to note is that the MUSE headset has 5 channels, which are a subspace of the original 64-channels of the offline model. Hence for the online model, we collect data from the MUSE headset and project it onto the best feature space found using PCA. This ensures that we have a few meaningful channels and a responsive real-time model that can still manage a good accuracy compared to the 64-channel model.

4.3 Feature Classification

The classification is done using a minimum distance classifier - Euclidean Classifier. The feature vectors of the 5 training samples are averaged to give the mean of each class, $\mu_m(i, j)$. For a given feature vector, classification uses the Euclidean distance from subject n to a given class m:

$$d_{m,n}(i, j) = \|\phi_n(i, j) - \mu_m(i, j)\|$$

the combined score for all 1540 feature vectors is given by:

$$score = \sum_{i,j}^{1540} (1 + d_{m,n}(i, j))^{-1}$$

which is the same score by other groups [4], but with the addition of a constant. This prevents unbounded values and improves accuracy by limiting score contribution.

Using the greatest score as a classifier, 100% accuracy is achieved on the test set. However, performs drops as fewer channels are used, dropping below 50% at five channels. To avoid this and recover some of the 64 channel accuracy, we create a feature map from the subset of channels (10 feature vectors for 5 channels) to the 1540 feature vectors.

We define $\rho_m(\omega)$ as the vector of all values of $\mu_m(i, j)[\omega]$. This vector has 1540 features, one for each connection. Principle component analysis is then used to create the feature map. For a particular ω, the covariance matrix of $\rho_m(\omega)$ is computed. The eigenvectors v_k corresponding to the greatest eigenvalues λ_k indicate which channels are of greatest identifying significance. For identification using 10 connections, the first 10 eigenvectors form the matrix:

$$P(\omega) = [\lambda_1 * v_1 ... \lambda_{10} * v_{10}]$$

which has dimensions 1540 x 10. Then, features from the subset of connections are mapped by defining

$$A_n = [\phi_n(1, 2) - \mu_m(1, 2), \phi_n(1, 3) - \mu_m(1, 3) ... \phi_n(4, 5) - \mu_m(4, 5)]$$

and finally multiplying: $F_n = A_n * P(\omega)^T$. F_n is a 40x1540 matrix, and the distances dm, n are given by the Euclidean norm of each column.

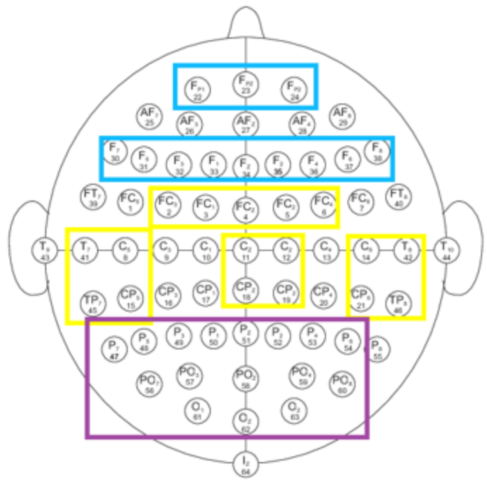

Figure 4: Frontal, Temporal and Parieto-Occipital regions shown in blue, yellow and purple respectively

The matched score fusion technique elucidated above is used for the testing the model and helps validate the identity of the user based on EEG.

5 Results and Discussion

We repeated the results of [4], achieving similar levels of accuracy for eyes open and closed, using both PSD methods and cross coherence. When applying the feature map generated offline, we achieved slightly over 90% accuracy using only 5 channels. In addition, we were able to achieve 100% accuracy using only 11 channels.

5.1 Dimensionality Reduction

Looking at the feature map, the principle components can be computed for any frequency. Thus we found the maps at all 40 frequencies and compared classification accuracy. In figure 5, we show the variance accounted for by the first 3 principle components of the feature maps. There is a minimum at 10 Hz, corresponding with the accuracy of these frequencies. This validates the use of principle components for feature mapping.

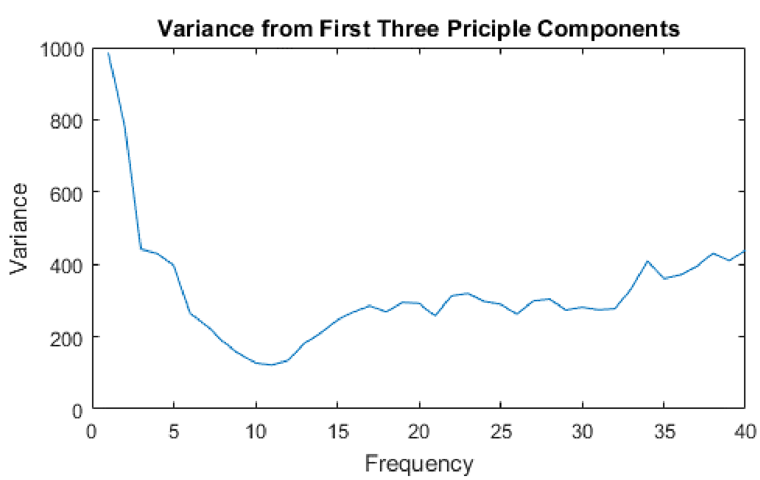

Figure 5: Variance from the first three principle components

5.2 Wavelet Transform

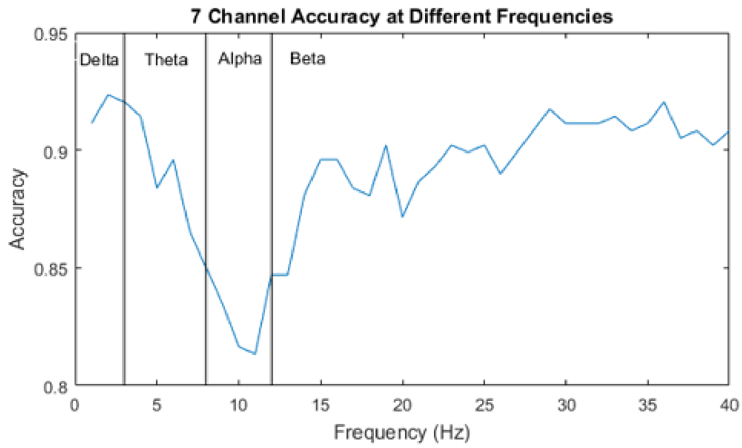

Figure 6: Seven channel accuracy at different frequencies

As can be seen in figure 6, the Delta and Beta bands perform the best, while there is a significant drop around Alpha frequencies. The alpha frequencies correspond to the electrical activity of pacemaker cells, and hence the power spectrum has a peak around 10 Hz. This activity seemingly does not differ significantly enough between people to be useful for authentication. This is a direct consequence of the "Alpha-blocking" phenomenon that occurs due to a heightened Beta wave activity.

5.3 Power Spectral Density vs Spectral Coherence

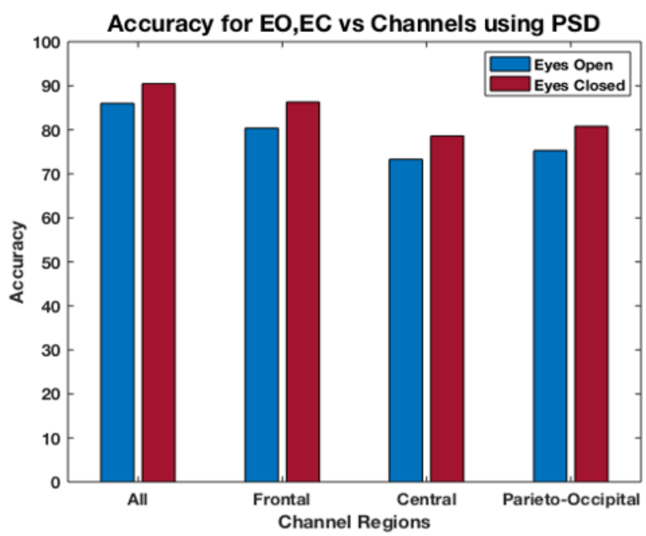

Figure 7: Accuracy for EO, EC v/s Channel regions using Power Spectral Density

Using Power Spectral Density for feature extraction, we obtain an accuracy of around 90% for Eyes Closed and 85% for Eyes Open baselines using all 64-channels. Accuracy for eyes closed is better than eyes open, as eyes closed resting states interrupt the visual processing while enhancing endogenous and autonomic related brain activity. We also notice a optimal performance in the channels in the Frontal region compared to the Central and Parieto-Occipital regions.

Spectral Coherence performs much better than Spectral Density, both at low and high channel numbers. Coherence quantifies how regions of the brain connect, characterizing brain structure, and performs better even with the same number of features. Spectral Coherence achieves an accuracy of over 90% for a 5 channel model. Hence we moved forward with Spectral Coherence for the online model using the MUSE Headset.

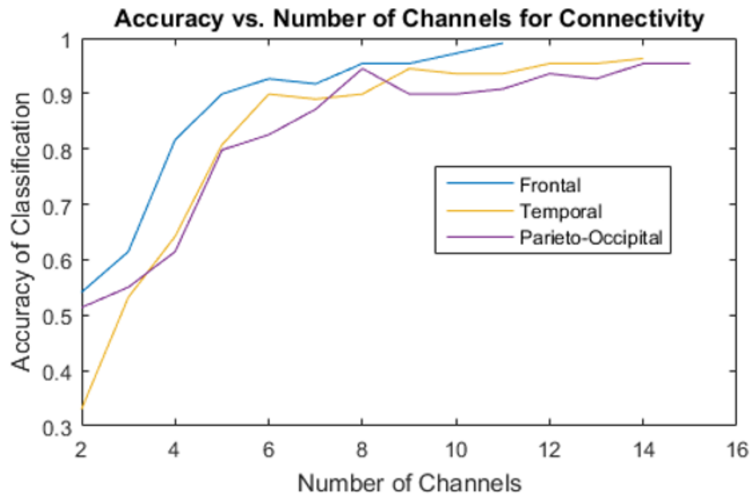

Figure 8: Accuracy v/s Number of channels used for connectivity

5.4 Best Feature subspace

To validate the use of a MUSE headset, we searched for the closest subspace of connections created by any 5 channels to the 10 most significant principle components. Shown in figures 9 and 10 below, the most significant subset was found at low and high frequencies for 2, 3, and 5 channels. These results indicate that which channels provide the greatest information may differ at different frequencies, but that overall frontal and temporal channels are the most significant. These are the channels involved in a MUSE headset, and so there is good reason to believe this approach will work.

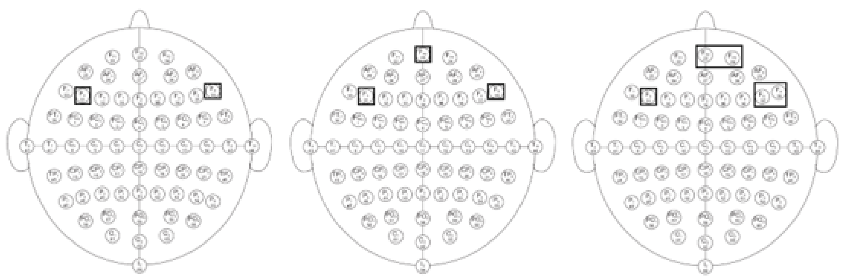
Figure 9: Best Channel subsets at high frequency

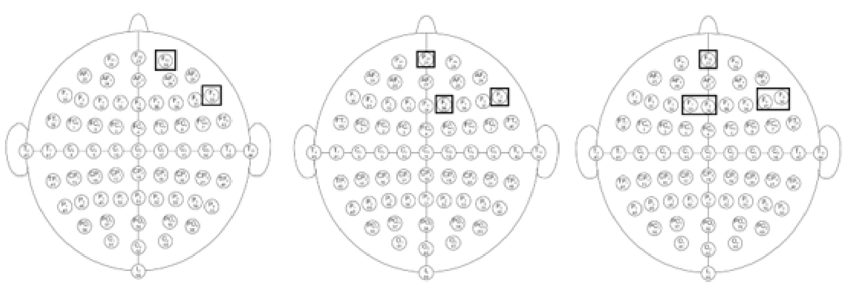
Figure 10: Best Channel subsets at low frequency

6 Conclusion

The most promising area of future research will be to combine authentication across the different frequency bands. Since feature maps can be computed at each frequency, we can form estimators based on the best components across the spectrum. In addition, authentication may improve when the alpha and theta bands are filtered out before hand. The dependence of accuracy on frequency, shown in figure 6, indicates that both filtering and combined frequency scores could improve performance.By finding high dimensional features from a full 64 channel EEG, we have improved the performance of authentication when using only the 5 channels on a commercial device. We have validated that using principle component analysis can find a good feature map from the few features generated by 5 channels to the full feature space of EEG connectivity. We found that the Spectral Coherence method was more effective than Power Spectral Density method for both low and high number of channels. This would mark an important milestone in the area of Brain Computer Interfaces as biometric authentication using EEG will redefine the authentication in security systems.

7 References

[1] J. Berkhout and D. O. Walter, "Temporal stability and individual differences in the human EEG: An analysis of variance of spectral values," IEEE Trans. Biomed. Eng., vol. BME-15, no. 3, pp. 165–168, Jul. 1968.

[2] Bower, J.M. & Beeman, D. (1995) *The Book of GENESIS: Exploring Realistic Neural Models with the GEneral NEural SImulation System.* New York: TELOS/Springer–Verlag.

[3] Hasselmo, M.E., Schnell, E. & Barkai, E. (1995) Dynamics of learning and recall at excitatory recurrent synapses and cholinergic modulation in rat hippocampal region CA3. *Journal of Neuroscience* **15**(7):5249-5262.

[4] La Rocca, Daria, et al. "Human brain distinctiveness based on EEG spectral coherence connectivity." IEEE transactions on Biomedical Engineering 61.9 (2014): 2406-2412.