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Identifying Visual Evoked Potential (VEP) Electrodes Setting for Person Authentication

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Abstract

Over recent years, person authentication using Electroencephalograms (EEG) signals has become more significant to researchers due to its uniqueness and security. EEG signals such as Visual Evoked Potential (VEP) had been used in the past literature for person authentication purposes. However, different sets of electrode channels were used in various VEP research. There is no consensus on the selection of EEG electrodes, particularly in person authentication research. Thus, this paper aims to investigate the best set of electrode channels for person authentication using VEP. Feature extraction methods such as coherence, cross-correlation and mean of amplitude were used for the purpose of classification. The performance measurement were based on the accuracy and area under ROC curve (AUC) values using Fuzzy-Rough Nearest Neighbour (FRNN) classifier proposed in our earlier work. An Anderson-Darling test in MATLAB was carried out to test the normality distribution of the results and the Wilcoxon sign-ranked test was used to perform statistical test. The results show that the set of eight channels from the occipital area perform better compared to the set of three channels and nine channels. The future research work will focus on investigating the performance of each parietal occipital and midline channels to obtain the best reduced set.

Keywords: *Person Authentication, Electroencephalograms, Visual Evoked Potential.*

1 Introduction

Over the recent years, person authentication is increasingly catching researchers' attention. It involves either confirmation or denial of the identity that the user is claiming. An identity authentication system has to deal with two kinds of events: either the person claiming a given identity is the one who are claims to be (client), or he is not (impostor). It is essential in ensuring security for access to highly restricted areas.

Traditional methods such as knowledge-based, e.g. password and token based, e.g. signature, are the weak authentication methods as they can be forged, stolen, forgotten and guessed easily. The use of Personal Identification Number (PIN) is actually denotes the automatic identification of the PIN, not necessarily identification of the person who has provided it. However, there are widely used nowadays due to its low cost and user's familiarity [1].

Biometric authentication methods were introduced to overcome traditional authentication methods. Biometric authentication methods measure behavioral and/or physiological characteristics (e.g. fingerprints, voice, face, iris and hand geometry). Nevertheless, these modalities are less promising due to the advancement of technologies.

Fingerprint authentication system is the most popular among the other authentication system. However, it does not seem suitable for high security environments. Some common household articles (e.g. gelatin) can be used to make artificial fingers to access security systems. Besides, fingerprint authentication system is depending on the surface of the finger. It is unable to get fingerprint perfectly if the people with certain physical disabilities or severe injuries such as missing hands or burnt fingers and thus increasing false rejects. Facial recognition model is less promising because human face structure evolves and changes as the person grows old. The facial recognition model faced the issues like the occurrence of identical twins and the family resemblance. It also affected by lighting, facial expression, head orientation, resolution and the form of hair of an individual. Voice recognition acts as biometric authentication but it seems to suffer from several shortcomings. Voice can be easily recorded and may change over time because of health, emotional state and age. Therefore, it is inherently unreliable for high security. Iris recognition is sensitive to body motions. The equipment required for data acquisition and parsing is costly [2]. Besides, the user is expected to stand in the fixed position in front of the camera. Hand geometry recognition was popular in 10 years ago but it is seldom used because it is less unique. This recognition system measures and records the length and height of the fingers, shape of the knuckles, distance between joints and the surface area of the hand.

The existing biometric authentication systems discussed above have highlighted the shortcomings for high security or restricted area. Thus, a biometric authentication using electroencephalograms (EEG) signals was introduced to overcome the shortcomings as it is more suitable to use in a high security or restricted area.

Recently, person authentication using EEG signals is popular among the researchers [1–7]. Person authentication using brainwaves particularly aims to differentiate client from imposter based on the distinctive features hidden in the EEG signals. EEG signals are brain activities in a form of ionic current which flows across the brain's neurons. These signals can be recorded using non-invasive electrodes mounted on the scalp.

The advantages of using brain electrical activity in EEG signals is the EEG signals are unique for each individual since the signals are only transmitted in live condition. Every individual will has various pattern of brain wave even if they are doing the same activity or task. Hence, it is impossible to be forged and mimicked by unauthorized people to steal the sensitive information. Additionally, the EEG signals are confidential, as it is safe from shoulder surfing attacks since the brain activities are something that cannot be seen directly. EEG signals can be easily affected but they cannot be easily reproduced under conditions of stress, anxiety, fatigue, drowsiness, medication, etc. [8]. An invader cannot force the person to reproduce his or her mental pass-phrase due to the EEG signals is sensitive to stress and the mood of person [7]. The EEG signal is not exposed and it is difficult to fake the process in which this resulting to a very secure authentication system [9]. Therefore, EEG signals are reliable and believable to be used as person authentication.

EEG signals such as Visual evoked potential (VEP) had been used in the past literature for person authentication purposes. VEP is the evoked response to visual stimulus [1]. The brain activities typically recorded from the occipital scalp when the brain responses to visual stimuli. However, different sets of electrode channels were used in various VEP research. There is no consensus on the selection of EEG electrodes, particularly in person authentication research. Thus, this paper aims to investigate the stronger electrodes position in response to visual stimulation. It is essential step before do experiment on visual stimuli.

The rest of the paper is organized as follows. Section II describes literature review on electroencephalograms (EEG) signals and visual evoked potential (VEP) in person authentication. Section III presents the experiment including the data description and preparation, feature extraction and the description of FRNN classifier. Section IV depicts the result and discussion while section V draws conclusion and the direction of the future work.

2 Literature Review

Several types of signals can be produced by brain activities includes electrical, magnetic and metabolic signals [10]. These activities can be recorded using both invasive and non-invasive methods. The invasive method requires surgical intervention for installing permanent implant devices in the brain. This brings some serious risks to the subjects and hence it is not feasible for biometric application. In contrast, non-invasive method does not involve any surgical intervention or physical damage. Non-invasive methods are widely used nowadays for medical applications. EEG is a simplest non-invasive method to record brain electrical activity [11]. EEG waves can be represented as a signal over time and it can detect changes over milliseconds. Besides, EEG is more practical, portable and faster to use and hence it is feasible for biometric application.

EEG analysis can be carried out in various design paradigms according to the purpose of classification. An implementation of EEG signals in authentication system [12] was designed using pass-thoughts. It has shown reliability and achieved good performance since EEG signals are unique and impossible to duplicate. EEG capturing devices are usually expensive, but an EEG authentication system based on a low cost EEG headset was proposed by [13]. Marcel and Millan [7] obtained highest accuracy of 93.40% for person authentication with a dataset of nine normal subjects performing three tasks during twelve non-feedback sessions over three days, which is four sessions per day. The three tasks are left hand movement, right hand movement and words generation beginning with the same random letter. On the other hand, research work in [14] achieved 94.18% in average classification accuracy where a dataset of 61 channels placed on the scalp is taken from 20 subjects. The BCI competition 2003 dataset with the EEG recording from a 64 channels and sampled in 250 Hz [15] was also tested for authentication purposes. The classification results ranged from 75% to 85%. Different mental tasks i.e. reading, relaxing and performing multiplication were studied for an authentication model [3]. All three mental tasks attained very high accuracy rate with little difference among them. The multiplication task leads with 97.5%, followed by reading task with 97.3%, and the relaxing task with 94.4% in accuracy. Hu [16] used motor imagery for biometric authentication system. The task was to perform imagery left hand, right hand, foot or tongue movements according to a cue. The selected channels for motor imagery were C3, C4, P3, P4 O1 and O2 for further analysis. The research work in [17] proposed a multimodal biometrics system by combining two unimodal modalities that is fingerprint and EEG. The EEG data acquired from 20 individuals recorded non-invasively from the scalp. For building authentication system in [17], the authors considered 7 occipital channels from the 32 available channels in the dataset.

EEG signals are commonly categorized into six basic rhythms. The standard EEG frequency bands are: Gamma (γ) – [30, 40] Hz, Beta (β) – [13, 30] Hz, Mu (μ) – [8, 13] Hz, Alpha (α) – [8, 12] Hz, Theta (θ) – [4, 8] Hz and Delta (δ) – [0.5, 4] Hz. There is a particular area that produces stronger electrical activity for each particular brain activity. EEG signals are multi-channel signals, where each channel corresponds to a specific location on the scalp. In this study, we would like to identify the stronger electrodes position in response to visual stimulation.

VEPs are the brain activity responses to visual stimuli, which include different components such as color, texture, motion, objects and etc [17]. VEPs are the operational measurement of the visual journey from the retina to visual cortex of the brain using the optic nerves. From the literature review on the VEP, there are few sets of number of electrode channels used to measure VEP. The electrodes placement on the scalp is shown in the Figure 1.

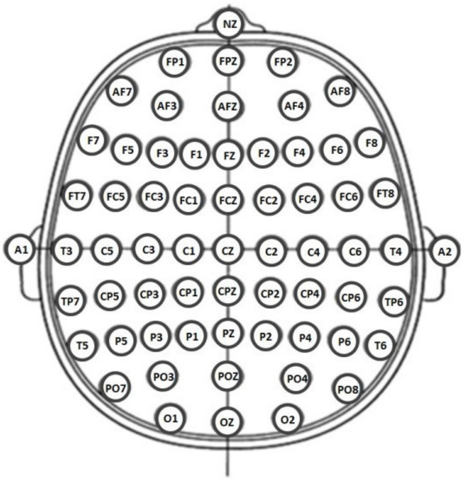

Fig. 1: 64 Channels EEG Electrode Placement

The authors in [18] have considered lateral and midline electrodes for different specialized and extended VEP protocols such as pattern-reversal stimuli, pattern onset/offset stimuli and flash stimulus [18]. The VEP channels included in [18] are FPZ, FZ, OZ, CZ and PZ for midline electrodes and O1, O2, OZ, PO7 and PO8 for lateral electrodes. Our earlier research works in [5] and [6] have considered midline and lateral electrodes to build person authentication application. However, there was a research work in [19] had considered eight occipital channels to build their biometric authentication application. The eight occipital channels were PO3, PO4, POZ, PO7, PO8, O1, O2 and OZ. Besides, another set of VEP electrode channels used in [20] were O1, OZ and O2. These are the electrode channels located at primary occipital area. Thus, we compared the performance of three sets of data.

A classifier is needed to evaluate the performance of the three sets of data. Fuzzy-Rough Nearest Neighbour (FRNN) classifier was used to perform classification and the accuracy and AUC were used to measure the performance of the three sets of data. FRNN was first introduced by Jensen and Cornelis [21] and had been proposed in our earlier work [5-6] for person authentication modelling.

3 Experimentation

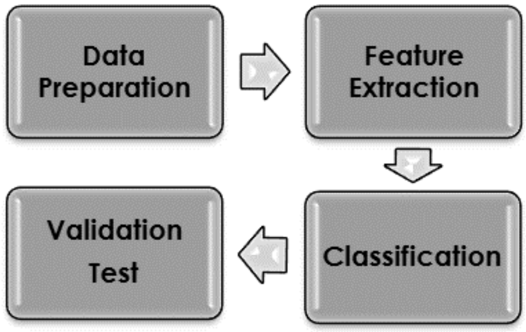

Fig. 2: Block Diagram of Processes of the Experiment

3.1 Data Description and Preparation

In this study, an EEG dataset downloaded from UCI Machine Learning Repository was used. It consists of three versions of data with different size, i.e. small (1 subject), large (10 subjects) and full dataset (122 subjects). Large dataset were used in this study and it consists of 10 subjects with 64 channels electrode placement. Each individual is completed with a total number of 60 trials and sampled at 256 Hz (3.9 msec epochs). The subjects were asked to recognize a picture as the picture presented on a white background at the center of the computer monitor and located 1 meter away from the subject's eyes. Due to many redundant trials in one of the subjects in large dataset, it was replaced by another subject from the full dataset. This is vital to ensure the prediction ability is not influenced by the same data in both training and testing phase.

Instead of treating the classification as a ten-class problem, the classifier was trained with only two classes, i.e. the client and the imposter. The data was split into 80% for training and 20% for testing. For training data, 16 trials of S1 object and 32 trials of S2, both match and not match will be selected. On the contrary, there are 4 trials of S1 object and 8 trials of S2, both match and not match will be selected for testing data. The purpose of splitting the data into two, i.e. S1 object and S2, cases is because the EEG signals are different. The EEG signals in S2 match and not match involves analysis of the picture whether it is match and not match with the previous picture. This is different from the EEG signals as the S1 object does not involve such analysis.

In this study, we have considered three sets of data with different channels (i.e. 3, 8 and 9 electrode channels) to build our person authentication application. All these channels have been proven good and able to provide stronger signals in response to VEP.

3.2 Feature Extraction

Raw EEG data are non-stationary, noisy, complex and difficult to analyze. Thus, it is a vital process to extract the relevant information or characteristics from the EEG signals. Feature extraction stage involves the transformation of the raw signal from the data into a relevant data structure which is known as feature vector. All the feature vectors that extracted will be used as input attributes for the classification purpose. Different features provide different discriminative power for different subjects. Most of the authentication system will make use of features combination architecture. The results were able to demonstrate the significant improvement in the system performance [16]. Three feature extraction techniques are used in this research-coherence, cross-correlation and mean of amplitude.

3.2.1 Coherence

Coherence is a feature used to measure the degree of linear correlation between two signals. The correlation between two time series at different frequencies can be uncovered by coherence. Coherence is normally used for analyzing the condition of different cognitive disorders. It has been proved that EEG-based coherence analysis can be used in biometrics [11]. The range values for the magnitude of the squared coherence. The range value for the magnitude of the squared coherence estimate is between 0 and 1, which quantizes how well x corresponds to y at each frequency. The value of 0 for the coherence function means the independence between two signals. The value of 1 for the coherence function means the complete linear dependence. The formula of coherence given as follow:

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)} \tag{1}$$

where, $C_{xy}(f)$ is a function of the power spectral density, $(P_{xx}\ and\ P_{yy})$ of x and y and the cross-power spectral density P_{xy} of x and y.

3.2.2 Cross-Correlation

The main idea of the cross-correlation, also known as sliding dot product is to measure the similarity of two channels. Cross-correlation is used to find occurrences of a known signal in unknown one. Additionally, it is a function of the relative delay between the signals which can be applied in pattern recognition and cryptanalysis. Two input signals will be used to compute the cross-correlation:

- Channel 1with itself: ρ_X
- Channel 2 with itself: ρ_Y
- Channel 1 with channel 2: ρ_{XY}

The correlation ρ_{XY} between two random variables x and y with expected values, μ_x and μ_y and standard deviation, σ_x and σ_y is given as:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E\big((X-\mu_X)(Y-\mu_Y)\big)}{\sigma_X \sigma_Y} \tag{2}$$

where, $E(X)$ is the expectation operator, and $cov(X)$ is the covariance operator.

3.2.3 Mean of Amplitude

Mean, also known as average is the sum up of all EEG potential value and divides by the number of samples. The expression of the mean is given in the equation as follows:

$$\bar{x} = \frac{1}{n} \cdot \sum_{i=1}^{n} x_i \tag{3}$$

where, n is the number of data and x_i is the value of data.

3.3 Fuzzy-Rough Nearest Neighbour (FRNN) Classifier

In this study, fuzzy-rough nearest neighbor (FRNN) classifier, proposed in our previous work is used to evaluate the performance for each set of data. FRNN is a fuzzy-rough version of WEKA data mining tools. FRNN classifier was first introduced by Jensen and Cornelis [21]. FRNN classifier is an algorithm which combined the strength of fuzzy sets, rough sets, and nearest neighbours classification approach motivated by human decision making. In FRNN algorithm, the nearest neighbours are used to construct the fuzzy lower and upper approximations to quantify the membership value of a test object to determine its decision class, and test instances are classified based on their membership to these approximations. FRNN classification approach was used in [5] and [6] have gained good results for person authentication using EEG signals.

Fuzzy logic connectives play important role in the development of fuzzy-rough set theory. A triangular norm (t-norm), T is any increasing, commutative and associative $[0,1]^2 \rightarrow [0,1]$ mapping satisfy $T(1,x) = x$, for all x in $[0,1]$. On the other hand, an implicator is any $[0,1]^2 \rightarrow [0,1]$ mapping 1 satisfy $1(0,0) = 1, 1(1,x) = x$, for all x in $[0,1]$. In [21], they have use Kleene-Dienes implicator for x, y in $[0,1]$.

Various types of performance measurements like accuracy, recall, precision and area under Receiver Operating Characteristics (ROC) curve (AUC). Accuracy and AUC were selected based on literature review. The formula of accuracy is as in equation below:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{4}$$

Although accuracy is commonly used to analyze results, but it is not a good performance measurement at all the times because it provides less meaningful information by omitting false positives in its measurement. False positives provide useful information on tolerance up to a certain extend. In addition, AUC is gaining more popularity for judging classifier properties by providing a graphical method. It is very useful performance measure by calculating AUC learning curves for very large data sets. It is cannot be denied that AUC curves are provided very meaningful of both theoretical and empirical justification. AUC is found to have a more discriminating value and statistically consistent compared to the accuracy.

3.4 Validation Test

An Anderson-Darling test in MATLAB was carried out to test the normality distribution of the results. The Anderson-Darling test [22] is modified from Kolmogorov-Smirnov (K-S) test. By comparing to the (K-S) test, Anderson-Darling test gives more weights to the tails of the distribution. The Anderson-Darling test calculates the critical values for specific distribution. This gives the benefit of allowing a more sensitive test. Anderson-Darling tends to be more effective in detecting departures in the tail of distribution. The departure tail of distribution is very important especially in the analysis of capability. The Anderson-Darling test is calculated as:

$$W_n^2 = n \int_{-\infty}^{\infty} [F_n(x) - F^*(x)]^2 \psi\, (F^*(x) dF^*(x) \tag{5}$$

Where, $\psi =$ non-negative weight function which can be defined from

$$\psi = F^*(x)(1 - F^*(x))^{-1} \tag{6}$$

The normality distribution of the data have to determine before perform a statistical test. A statistical test is performed to determine the confidence level of the dataset that can be in reaching conclusions. Parametric test is chosen when the data are normally distributed while non-parametric test will be chosen when the data are not normally distributed. Parametric test such as Z test, paired-sample t-test or F test will get higher accuracy when the data are normally distributed. At the same time, if the data are normally distributed and a non-parametric test is performed, then the results will not be as accurate as the parametric test [23].

A statistical test, Wilcoxon signed-rank test was used to determine whether there is a significantly different between median values of three channels, eight channels and nine channels model based on their classification accuracy and AUC. Wilcoxon signed-rank test is a non-parametric test that widely used in statistical testing when the data are not normally distributed. It is more powerful in detecting a difference between the two samples [24]. In Wilcoxon signed-rank test, the null hypothesis will be rejected when the p-value is less than 0.05 and there is a significantly different between the paired samples. In contrast, the null hypothesis will be accepted when the p-value is greater than 0.05 and there is no significantly different between the paired samples.

4 Results and Discussion

The experimental data were preprocessed in the same ways as mentioned in the previous section. The same classification method and performance measures were used to ensure a fair comparison on different set of data. Table 1 shows the classification performance for three, eight and nine channels in FRNN modeling.

The highest average classification accuracy and AUC was eight channels, it achieved 91.67% in accuracy and 0.920 in AUC. In contrast, the lowest average classification accuracy and AUC was three channels, it achieved 85.17% in accuracy and 0.670 in AUC. According to [25], the correct classification rate is illustrated as perfect classification when the AUC is 1 and a random classification when the AUC is 0.5 based on the positive rate. On the other hand, the classification performance of nine channels is slightly lower than the classification performance of eight channels but higher than the classification performance of three channels. The classification accuracy and AUC are 90.17% and 0.904 respectively.

The accuracy in the set of eight channels and nine channels were 91.67% and 90.17% respectively, which is slightly higher than the set of three channels with 85.17 in accuracy. Meanwhile, the AUC in the set of eight channels and nine channels were 0.920 and 0.904 respectively, which is higher than set of three channels with 0.670 in AUC. From the results obtained in Table 1, we noticed that the difference in AUC is larger than accuracy. It is because the False Positive Rate (FPR) takes into account in AUC. The larger value of FPR shows the lower value of AUC. The values of True Positive Rate (TPR) and False Positive Rate (FPR) between three, eight and nine channels were shown in Table 2.

Table 1: Comparison of Accuracy and AUC between 3, 8 and 9 Channels in FRNN Modeling

Person	**3 Channels**		**8 Channels**		**9 channels**	
	Accuracy	**AUC**	**Accuracy**	**AUC**	**Accuracy**	**AUC**
1	86.67	0.755	85.00	0.910	87.50	0.924
2	86.67	0.607	88.33	0.856	86.67	0.788
3	88.33	0.772	93.33	0.921	88.33	0.922
4	66.67	0.465	88.33	0.795	80.83	0.704
5	90.00	0.729	95.83	0.978	93.33	0.954
6	86.67	0.633	90.00	0.940	88.33	0.924
7	84.17	0.509	93.33	0.914	99.17	1.000
8	86.67	0.613	94.17	0.966	90.83	0.895
9	83.33	0.673	94.17	0.945	90.00	0.936
10	92.50	0.939	94.17	0.979	96.67	0.990
Average	**85.17**	**0.670**	**91.67**	**0.920**	**90.17**	**0.904**

Table 2: Values of TPR and FPR between 3, 8 and 9 Channels in FRNN Modeling

Person	3 Channels		8 Channels		9 channels	
	TPR	FPR	TPR	FPR	TPR	FPR
1	0.867	0.385	0.850	0.313	0.875	0.236
2	0.867	0.830	0.883	0.606	0.867	0.756
3	0.883	0.680	0.933	0.452	0.883	0.606
4	0.667	0.704	0.883	0.606	0.808	0.688
5	0.900	0.604	0.958	0.227	0.933	0.304
6	0.867	0.830	0.900	0.381	0.883	0.531
7	0.842	0.832	0.933	0.378	0.992	0.001
8	0.867	0.830	0.942	0.377	0.908	0.751
9	0.833	0.685	0.942	0.229	0.900	0.381
10	0.925	0.379	0.942	0.229	0.967	0.226
Average	**0.852**	**0.676**	**0.917**	**0.380**	**0.902**	**0.448**

A statistical test was performed to test the significance difference between the three sets of data. However, normality test must be performed in the earlier stage to test the normality distribution of the results. Among all the results obtained, only the accuracy of three channels and AUC of nine channels are not normally distributed. Thus, we have to use non-parametric test to validate the results. Table 3 shows the statistical test using SPSS Statistics 17.0.

According to the Wilcoxon signed-rank test in Table 3, the *p*-value between the accuracy of three channels and eight channels is 0.011 and the accuracy of the three channels and nine channels is 0.012, which are lower than the significance value, 0.05. Thus, the statistical test is to reject the null hypothesis. In other words, the accuracy of three channels and eight channels are significantly different. From the mean value shown in Table 3, it is clearly proved that the accuracy of eight channels is higher than accuracy of three channels. Besides, the accuracy of three channels and nine channels are significantly different. From the mean value shown in Table 3, it is proved that the accuracy of nine channels is higher than accuracy of three channels.

Comparatively, AUC is another performance measurement used in this research. As the computed *p*-value, 0.005 is lower than the significance level, 0.05, the test reject the null hypothesis. Thus, the AUC of three channels and AUC of eight channels are significantly different. The AUC of three channels and nine channels are also significantly different. From the mean value shown in Table 3, we can conclude that the AUC of eight channels and nine channels are performing better than the AUC of three channels.

Table 3: Wilcoxon Signed-Rank Test for Comparison of Classification Performance for 3, 8 and 9 Channels

	Mean	Standard Deviation	Min	Max	p-value (2-tailed)	Null Hypothesis	Statistical Test
Accuracy 3 Channels	85.17	7.013	66.67	92.50	0.011	Reject	Significantly different
Accuracy 8 Channels	91.67	3.514	85.00	95.83			
Accuracy 3 Channels	85.17	7.013	66.67	92.50	0.012	Reject	Significantly different
Accuracy 9 Channels	90.17	5.240	80.83	99.17			
Accuracy 8 Channels	91.67	3.514	85.00	95.83	0.283	Accept	Significantly no different
Accuracy 9 Channels	90.17	5.240	80.83	99.17			
AUC 3 Channels	0.670	0.137	0.465	0.939	0.005	Reject	Significantly different
AUC 8 Channels	0.920	0.058	0.795	0.979			
AUC 3 Channels	0.670	0.137	0.465	0.939	0.005	Reject	Significantly different
AUC 9 Channels	0.904	0.091	0.704	1.000			
AUC 8 Channels	0.920	0.058	0.795	0.979	0.285	Accept	Significantly no different
AUC 9 Channels	0.904	0.091	0.704	1.000			

In addition, both the accuracy and the AUC of eight and nine channels are not significantly different. The p-value between the accuracy is 0.283 and the AUC is 0.285, which are higher the significance level. Hence, there is no significant difference between the accuracy of eight channels and nine channels. All the three sets of data consist of O1, OZ and O2; it is because these are the primary occipital region. Nevertheless, these are not enough to build the person authentication application. The validation results showed that both eight and nine channels were performed better than three channels. It is because the VEP signals do not depend on primary occipital region only. The visual cortex also includes the parietal occipital site. Therefore, we gained better results by including the parietal occipital channels.

5 Conclusion

In this paper, we have investigated the performance of the set of three channels, eight channels and nine channels. It can be concluded that using only the primary occipital channels, i.e. O1, OZ and O2 are less promising in person authentication classification. Additional channels from the parietal occipital and midline has proven to increase the classification performance. The FRNN model performed slightly better in term of accuracy when it combines with the additional channels. However, a large difference in the AUC was observed between the primary occipital channels in opposite to the set of eight channels and the set nine channels. However, the lesser the number of VEP electrodes needed, the more convenient the person authentication application setup is. Thus, the future work will focus on investigating the performance of each parietal occipital and midline channels to obtain a best reduced channels set.

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