Performance Analysis Between Feature Extraction and Fusion in Familiar and Unfamiliar Typing Biometric Authentication

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Abstract. The brain signals recorded by EEG devices are largely developed in for biometric authentication purposes. Those signals are very informative and reliable to be classified using signal processing. In this paper, the feature extraction and feature fusion are further studied to observe their performance towards the typing tasks. The signals are pre-processed to eliminate the unwanted noise present in the signals. The feature extraction method such as Welch’s method, Burg’s method and Yule Walk’s method are applied to extract the mean, median, standard deviation and variance in the data. Nonlinear feature such as fuzzy entropy is also been extracted. The extracted features are further classified by using k-Nearest Neighbour (k-NN), Random Forest (RF) and Ensemble Bagged Tree (EBT). The performance of feature extraction and feature fusion through concatenation are recorded and compared. For comparison, the feature fusion shows a better performance accuracy rather than feature extraction. The highest percentage accuracy was produced by Burg’s method for frontal-parietal lobes feature fusion which is 95.94% using Ensemble Bagged Tree (EBT).

1. Introduction
Over the past years, researches on biometrics using electroencephalogram (EEG) has been gaining popularity from previous researchers [1]. This situation is due to the brain signals characteristics that are difficult to steal or imitate [2]. As it is known, biometric is the measurement and statistical analysis of people’s physical and behavioural characteristics. It is mostly used to identify individuals that are kept under surveillance [3]. Existing conventional biometrics for human authentication such as fingerprints and face recognition method is used by the companies and government to maintain the security and to access the control system [4].

The problem arises when the cracking security system is becoming easier with the advances of the computer hardware and the growth of the Internet that will make the data become less protected. As the data volumes are getting larger by day, the access control to the data is getting much easier [5]. So, the data contained in the system must be fully secured. Also, a person’s identification is important in many application and the hike in credit card fraud and identity theft in recent years indicate that this is an issue of major concern in wider society [6]. As such, password and PIN that demands a high level of security
with performance. This is because the use of a password in a knowledge-based user authentication technique is risky, because of the possibility of off-line guessing attacks.

The password is also unsafe as pressing the password in a public place, monitored by video cameras, may lead to password theft. For example, an attacker may observe when the user withdraws money from an ATM, or by using a camera that records the PIN code, or even using a thermal camera to know the touch used to enter the PIN code [7]. After authentication, a thermal camera captures the heat traces left on the surface of a mobile device throughout a thermal attack. To reorganize the password, these traces are retrieved and used. The order of entry of the PIN and patterns would also be leaked [8].

The current user authentication has used fingerprint, gait, and facial recognition as a medium to authenticate the user to a system. However, the existing method of biometric authentication such as fingerprint identification may have its own limitations. The acceptable fingerprint image is determined by some factors, for example, skin condition, sensor condition, and poor user cooperation [9].

In this study, a typing biometric is performed. It is one of the behavioural biometrics. This study used the electroencephalogram (EEG) to extract the brain signals while the users type in order to check the familiarity of the users to their own password and others’ password. The brain (EEG) signals collected will be analysed to verify that the password should be something that the genuine user could easily type, but other users should not be equally fluent in typing it. This research requires the use of brain signals as the brain signals are very unique.

2. Related Work

Authentication in security systems is very significant in our daily life as it avoids unauthorized access to valuable resources. There are several types of research done by using EEG based authentication. Research done by [10] used the cognitive and memory performance during human user authentication in an image-based password system where the sequential learning of image sequences was utilized. They applied the image sequence-based user authentication system and analysed the interpretation of sequence learning behaviours among users. Users have presented an image library of several themed sets of image sequences and were asked to arrange them on another grid, allowing the user’s choice of theming the sequences. The users were assessed on the system and EEG recordings while training (‘generating the password’) and authentication were recorded.

In research done by [11], the researchers asked the system used to visualize a number while corresponding EEG signals are captured. Captured signals were used to train the system, compared in the authentication process. Visual and audio stimuli also had been used in EEG based authentication by [12]. The researchers presented an EEG-based biometric authentication system employing brain patterns in response to a number of visual or auditory stimuli by seeing/hearing self, familiar and unfamiliar faces/voices.

Next, research by [13] had an approach of authentication through EEG signals by motor imagery. The subjects were asked to visualize three objects which were blue colour paper, own identity card, and other people’s identity card. Each object was visualized for 20 seconds and the EEG signals collected were analysed. EEG based authentication also developed in terms of memorability [14]. The researchers investigated the relationship between users’ perceptions of the memorability of a number of passwords and the users’ EEG data collected using BCIs when presented with these passwords. The participants were presented with five passwords appearing one at a time. Then, the passwords were shown in one grid, and participants were asked to rank them based on how they think each password measured.

3. Data Acquisition

In this study, the experimental data is recorded by using EEGO sports device (ANT Neuro, Enschede, The Netherlands). The data contains EEG signals collected from thirty subjects, each of which performed two sets of familiar and unfamiliar typing tasks (each set has duration of 180 seconds).

Type of typing tasks:
1. Familiar: Typing of their own name (first and last name).
2. Unfamiliar: Typing of other person’s names (first and last name) twice.
The electrodes are placed as shown in Figure 1 and the measurements are made with reference to electrically linked mastoids, M1 and M2.

![Figure 1. Electrode placement](image)

The EEGO sports device has been used to record the brain signal that included 32 channels namely Fp1, Fpz, Fp2, GND, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, M1, CP5, CP1, CPz, CP2, CP6, M2, P7, P3, Pz, P4, P8, POz, O1, Oz and O2 according to the international 10-20 system as in Fig 1. The sampling frequency is set to 512 Hz. Therefore, for a given task and a subject – 92,160 samples (512 Hz × 180 s) per channel are recorded (for the whole trial).

4. Methodology
An overview block diagram representing the methodology is shown in Figure 2.

![Figure 2. Overview block diagram](image)

4.1. Pre-processing
Recorded raw EEG signals have amplitudes in microvolts and contain frequency components up to 100 Hz. Thus, pre-processing is required which includes removal of artefacts. Independent Component Analysis (ICA) is used to remove eye blink and movement artefacts through the use of EEGLAB [15]. The removal of eye blinks is done to a certain channels that contain spikes which represents the eye blink artefacts. The algorithm implemented in this thesis is runica(), a function for automated infomax ICA decomposition the EEGLAB toolbox [16].

Notch filter with 50 Hz cut-off frequency has been applied to remove power line noise [17] which comprising of lower frequency line noise and harmonics [18]. The highest frequency that can exist in the sampled data is known as the Nyquist frequency which is equal to half the sampling rate. Nyquist Frequency also plays a major role in determining the higher cut-off frequency [19]. Butterworth bandpass filter was applied to separate the signals into gamma frequency band (30Hz-100Hz) [20].
4.2. Feature Extraction

For feature extraction method applied in this study are Burg’s method, Welch’s method and Yule-Walker method to extract mean, median, standard deviation and variance from the signals in each channel. Burg technique performs the minimization of the forward and backward prediction errors and estimates the reflection coefficient. The primary advantages of the Burg method are resolving closely spaced sinusoids in signals with low noise levels, and estimating short data records, in which case the Auto Regressive (AR) power spectral density estimates are very close to the true values [21]. Equation (1) shows that Burg Method varies from Yule-Walker Method in the way the PSD, $P_B(f)$, is acquired, as appeared in the accompanying condition:

$$P_B(f) = \frac{E_p}{\left| 1 + \sum_{k=1}^{1_p} a_p e^{-2\pi i f} \right|^2}$$

where $E_p$ denotes the total least square error and it is the sum of the forward and backward prediction errors.

Welch’s method is a non-parametric method. The signal is divided and sequenced into segments which also reduces noise. The signal to noise ratio for Welch’s method is high. It reduces in the estimated power spectra in exchange for reducing the frequency resolution [22]. The Welch Power Spectrum that mean average of the periodogram for each interval is expressed in equation (2):

$$P_{xx}(f) = \frac{m^p}{\left| 1 + \sum_{l=1}^{m^p} \delta_p(l) e^{-j2\pi f l} \right|^2}$$

where, $p$ is model order, $m^p$ denotes the total least mean square error and it is the summation of forward and backward prediction errors.

The estimation of power spectral density (PSD) using Yule–Walker method is basically on creating a biased estimate of the signals’ autocorrelation function and solving the least squares minimization of the forward prediction error [23]. The equation for Yule Walker method is expressed as in equation (3):

$$P_{yw}(f) = \frac{\sigma^2wp}{\left| 1 + \sum_{k=1}^{p} \delta_p(k) e^{-j2\pi f k} \right|^2}$$

Where, $p$ is model order, $\sigma^2wp$ the estimated minimum mean square error is for the $m$-th order predictor.

Other than linear features using Power Spectral Density (PSD), the nonlinear fuzzy entropy (FuzzyEn) also has been extracted from each channel. FuzzyEn is a refined algorithm for SampEn based on fuzzy logic. It does not count on the absolute probability of similar vectors according to the hard thresholding criterion as applied in Sample Entropy (SampEn). Instead, FuzzyEn estimates the probability that two vectors are similar based on the fuzzy membership function [24]. The calculation of FuzzyEn value in the time-series $\{u(i)\}$ can be calculated by using this formula in equation (4):

$$FuzzyEn(m, \tau, r) = -ln \frac{\sum_{i=1}^{N-mr} A_i^{(m+1)}(r)}{\sum_{i=1}^{N-mr} A_i^{(m)}(r)}$$

where $A$ is fuzzy set, $m$ is embedding dimension, $\tau$ is time lag and $r$ is threshold.
4.3. Feature Fusion

The combination of various feature information in order to achieve more significant information is referred as feature fusion. Different methods of feature fusion can result in different results. Selecting a right fusion method help to improve the performance.

In this study, the features extracted are fused through concatenation into a fixed length feature vector. The concatenation fusion involves the fusion of different brain lobes. For instance, two groups of channels were used in concatenation which are (Fp1-Fpz-Fp2-F7-F3-Fz-F4-F8-FC5-FC1-FC2-FC6) and (P7-P3-P4-P8-POz), which represent the frontal lobes and parietal lobes respectively. This feature brain lobes fusion is developed for every feature using Welch’s method, Burg’s method, Yule Walker’s method and fuzzy entropy features.

4.4. Classification

There are several classifiers involved in this classification stage such as k-Nearest Neighbour (k-NN), Random Forest (RF) and Ensemble Bagged Tree (EBT). Those classifiers are able to classify feature extraction and feature fusion in this study. k-NN classifier uses a distance of features in a data set to assign which data belongs to which group. A group is formed when the distance within the data is close while many groups are formed when the distance within the data is far. k-NN classifies by comparing a testing data with a training data. An object is classified by a majority vote of its neighbours, with the object being assigned to the class most common among its k nearest neighbours. The value of k varies in order to find the match class between training and testing data [25]. If k equal 1, then the object is simply assigned to the class of nearest neighbour. A commonly used distance metric is Euclidean distance, d defined as in equation (5) below:

\[ d(X_i, X_j) = \sqrt{\sum (X_i - X_j)^2} \]  

where, \(X_i\) and \(X_j\) represents the training and testing data respectively. In this work, the value of k was chosen as 1. The classification accuracy can be measured as in Equation (6):

\[ \text{% Accuracy} = \frac{\text{Number of correctly classified samples}}{\text{Total number of tested samples}} \times 100 \]  

Random Forest classifier contains of a set of a tree-structured classifiers where tree is grown with the training dataset. Random vectors are independently distributed and input vector is for which each tree casts vote. Bagging technique is done to produce training data for individual tree and Gini Index \(G_i\) is used for random split selection [26]. The \(G_i\) estimates the degradation of the data sample and can be computed using Equation (7) as below:

\[ G_i(t) = 1 - \sum_{j=1}^{J} p^2(j|t) \]  

where, \(p(j|t), \{ j = 1, 2, .. J\}\) gives the estimated class probabilities for J number of classes. The classification based on leaf node samples is performed with posterior probabilities.

The Ensemble Bagged Tree (EBT) classifier uses bootstrap resampling to break the training data into subsets. Every decision tree is built by using each subset as training data. The number of the built decision tree is defined by the bootstrapping number. The outputs of the decision trees are then added to the majority voting process [27].

Training and testing data using 10-fold cross-validation methods are created in order to evaluate the efficiency of the proposed classifiers. It helps to reduce the method's bias. The feature matrix set is divided into 10 mutually exclusive subsets of approximately equal size in a 10-fold cross-validation.
procedure and the process is repeated for 10 times (folds). One of the subsets is used as a test set each time and the remaining 9 subsets are assembled to form a training set. Next, it measures the average accuracy of all 10 trials for all thirty subjects. In this research, the training set is used to train the classification model and the test set is used to evaluate the model’s performance. Since each trial contains 1 dataset (for one task), we have a total of 30 datasets per task. This gives 1 dataset per task = 2 tasks = 2 datasets for training/testing per person.

5. Experimental results and discussion

The experimental results are based on brain lobes and their feature fusion using proposed classifiers, k-NN, RF and EBT. Table 1 shows the percentage accuracy for each features based on brain lobes and their feature fusion using proposed classifiers.

| Brain lobes / Classifiers | Features   | Frontal (%) | Temporal (%) | Parietal (%) | Occipital (%) | Frontal-Parietal (%) |
|---------------------------|------------|-------------|--------------|--------------|----------------|-----------------------|
| k-NN                      | Welch      | 84.14       | 60.44        | 66.93        | 65.31         | 87.34                 |
|                           | Burg       | 76.25       | 58.79        | 64.32        | 64.18         | 80.28                 |
|                           | Yule Walk  | 81.58       | 59.61        | 64.64        | 63.85         | 84.56                 |
|                           | FuzzyEn    | 78.73       | 57.62        | 66.25        | 57.86         | 86.14                 |
| RF                        | Welch      | 89.45       | 69.59        | 77.32        | 73.85         | 92.01                 |
|                           | Burg       | 94.89       | 80.40        | 90.02        | 81.13         | 95.65                 |
|                           | Yule Walk  | 90.24       | 71.69        | 78.52        | 74.85         | 92.80                 |
|                           | FuzzyEn    | 81.35       | 59.48        | 70.67        | 61.69         | 87.62                 |
| EBT                       | Welch      | 90.53       | 70.59        | 78.35        | 73.48         | 92.98                 |
|                           | Burg       | 94.35       | 81.44        | 90.06        | 79.84         | 95.94                 |
|                           | Yule Walk  | 90.13       | 72.34        | 78.39        | 74.04         | 92.87                 |
|                           | FuzzyEn    | 82.64       | 60.38        | 72.07        | 61.93         | 88.77                 |

In order to investigate the most informative brain lobes that involved during typing tasks, the feature extracted are separated to four brain lobes/channels and the percentage accuracy were calculated in the proposed classifiers. The brain lobes consists of frontal, temporal, parietal and occipital brain lobes. Obviously in frontal and parietal lobes achieved the most significant brain lobes that are principally connected with feelings, critical thinking and movement [29]. Next, the frontal and parietal lobes features were fused together through concatenation in order to produce a better classification accuracy.

This fusion of frontal and parietal lobes features were able to show an increasing percentage of accuracy for Welch’s method, Burg’s method, Yule Walk’s method and Fuzzy Entropy in all classifiers. The frontal-parietal lobes feature fusion are compared by their percentage accuracy. Out of all classifiers, the RF and EBT classifiers obtained the most promising and significant values of percentage accuracy for all feature extraction method. The highest percentage accuracy were obtained by Burg’s method which are 95.65% and 95.94% for RF and EBT classifiers respectively whereas the least percentage accuracy obtained were fuzzy entropy which are 87.26% and 88.77% respectively.

Due to the nature of EEG signals from the brain that can discriminate between a user and an intruder in which the brain analyses the pattern of individual typing, it is suitable to have an EEG based authentication mechanism based on typing tasks. The user’s identity and information are verified through a typing task that is both familiar and unknown to the user. It is considered as a secure technique of distinguishing between users because EEG signals cannot be faked by intruders.
6. Conclusion
In general, the signal processing for feature extraction and feature fusion for typing biometric authentication were developed using EEG signals. In terms of 10-fold cross-validation accuracy, the percentage of feature extraction by using frontal-gamma features are the best for classifying the brain response during the typing tasks. The fusion of features also has been developed through concatenation for all types of method of feature extraction. The frontal and parietal lobes features for gamma bands are fused to achieve a better classification of percentage accuracy. The experimental results showed that the feature fusion are able to produce higher percentage accuracy than the feature extraction accuracy. Therefore, the typing tasks classification of fusion by concatenation can provide a greater way in the obtaining the significant and higher results in percentage accuracy for those proposed classifiers such as k-NN, RF and EBT classifiers.

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