ECG based person authentication using empirical mode decomposition and discriminant analysis

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Abstract. Person identification or authentication through biometric features has been widely applied for basic access and high-level security. But conventional biometrics such as fingerprints and irises tend to be easily faked or duplicated. Therefore a new biometric modality is needed to overcome that problem. In this paper, we simulate a new model of biometric systems using physical signals of the body. The proposed biometric system is based on ECG signals as a characteristic of each subject. A total of 110 raw ECG signals with a duration of 5 seconds from 11 participants were demonstrated in the proposed system. Empirical mode decomposition (EMD) and statistical analysis are used for feature extraction. Discriminant analysis with cross-validation was applied to test the performance of the proposed method. In this research, the highest accuracy of 93.6% was obtained using subspace discriminant in the scenario of all feature attributes as predictors.

1. Introduction

Biometric systems have been widely applied for a long time for personal identification. Conventional biometric systems based on physical characteristics such as fingerprints, face patterns, iris, and hand geometry tend to be easily duplicated. So it is less suitable for applications that require a high level of security. One alternative biometric modality that has received much attention recently is biosignal based biometrics. Biometrics using electroencephalogram (EEG) and electrocardiogram (ECG) waves are candidates for biometric applications.

Research on brain signals proved that each individual has a unique EEG wave so that EEG become popular as a subject for biometric identification. So far most research had been discussed, [1] in this paper, EEG signals were acquired from 50 subjects to classify 4 biometric tasks there was a spell, math, relax, and read using FNN (Feedforward neural network) and RNN (Recurrent neural network) the result obtained 95 % of accuracy. Another research by Rig Das et al [2] had been presenting use CNN (convolutional neural network (CNN) method acquired from 40 subjects, the result showed high accuracy. Another high accuracy also achieved by Marcos et.al [3] which experimented in the time-frequency domain and by Isuru et.al [4] which was using Linear Discriminant Analysis (LDA) as a classifier. Robertas et al [5] presented EEG based biometrics combined with cryptographic authentication based on fuzzy scheme and BCH (Bose Chaudhuri Hocquenghem) code, the experimental result had shown 87 bits of the error to calculate biometric system from 42 subjects of EEG dataset. However, biometric identification based EEG signals still faces the problems [6-9] such as robustness, privacy because EEG signals contain sensitive information about the enrolled users [10], ergonomics
and security if used as person identification in BCI (Brain-Computer Interface) applications because it tendencies could be random, has had high intra-individual variance and signal retrieval was relative difficult.

Another challenge is to use an electrocardiogram (ECG) as a biometric modality, the advantages of ECG because it offers a number of benefits such as [11,12]; the inherent inter variability is the solution for the security system, ECG is less affected by noise environment than face or voice recognition. Most of the research use ECG based method both for identification and authentication approach [13], through IoT technology Ahmed [14] had been presented ECG feature to identify a person using DCT with 97.78% of accuracy but the subjects were carried out from MIT-BIH database, while Susana et.al was use PTB database achieved 98% of accuracy [15]. Another study that was using DCT as a feature method with different database shown that noise over the ECG signals significantly decreased their quality [16]. Same as Ahmed [14], Sellami et.al [17] was use MIT-BIH database achieved an accuracy of 90% using DWT. Mariusz [18] also use the MIT-BIH database conducted that LDA, KNN, and MLP achieved high accuracy.

There were a number of experimental with high accuracy of both identification and or authentication use ECG based method, but most of them were use MIT-BIH, PTB, and QT database. Different from them, our previous research was conducted using a dataset from self-collected sources (ten adult people as subjects) had taken from a one-lead ECG machine [19]. This study was processed using the SampEn (Sample Entropy) and Hjorth Descriptor as feature methods and SVM (Support Vector Machine) algorithm as the classifier, the results achieved 93.8% of accuracy. As a continuation, in this research proposed 11 subjects of ECG signals consists of men and women using EMD (Empirical mode decomposition) as feature method and DA (Discriminant Analysis) as a classifier. From seven classifier methods [18] LDA conducted a high accuracy, based on that in this research was to choose LDA as the algorithm of DA.

2. Material and Method

2.1 ECG Data

Participant's ECG data were acquired using a single lead ECG machine from a previous study [20]. A total of 11 adult subjects consisting of 8 men and 3 women became participants in this study. The recording was done for 60 seconds while sitting resting without doing any activities. Before recording, these subjects also did not carry out heavy activities. Participants also do not have a history of heart disease or high blood pressure.

Device acquisition of ECG signals that the user has a 10-bit ADC resolution with a 100 Hz sampling rate. Raw ECG signals sent in the decimal form via serial communication are then stored in the .txt format by personal computers. Each ECG signal segment that is processed must have a QRS complex component if not, the segment will be excluded. ECG signals from two participants can be seen in Figure 1 where visually indicate a difference.

![Figure 1. Graph the typical ECG signal from two participants](image-url)
In order to test the performance of the proposed method relating to the intra-individual ECG wave variance, the raw data from each subject was divided into 10 segments of the total recorded data. Each segment has a duration of 6 seconds with a 50% overlap. Thus the total number of ECG signals observed in this study is 110 (11 subjects x 10 ECG segments).

2.2. Empirical Mode Decomposition

Empirical mode decomposition (EMD) is one method to decompose signals into several constituent parts. EMD can decompose signals based on the amplitude and frequency of the information signal at a certain moment [21]. EMD is very commonly applied to non-stationary and non-linear signals or tends to be random. EMD decomposes the signal into a number of intrinsic modes or what is called Intrinsic Mode Function (IMF) and another part is residual. Mathematical equations are expressed as follows:

\[ x(t) = \sum_{i=1}^{IMF} IMF_i(t) + r(t) \]  

With \( x(t) \) is the original signal, \( IMF_i(t) \) is IMF data and \( r(t) \) is monotonous residue. The steps to get the IMF from the signal \( x(t) \) are as follows:

1. Calculate local maxima and minima a series of signals \( x(t) \).
2. Estimating the signal envelope by interpolating all local maxima to get the upper envelope and all local minima to get the bottom envelope.
3. Calculate the average for local maxima and minima so that the mid-value \( m(t) \) is obtained.
4. Calculate candidates IMF \( I(t) = x(t) - m(t) \).
5. The IMF is obtained if it meets the following two criteria: 1) The number of zero crossings and extrema points must be the same or different at least once. 2) The average envelope must be zero at all points.
6. Repeat steps 1-5 to get some IMF and finally produce a residue with monotonous values.

The results of the IMF decomposition iteration which at a higher level will tend to have monotonous values so that the information contained is also less. Therefore, in this research, the IMF analyzed as a statistical feature is IMF-1 to IMF-5.

2.3. Calculation of Statistical Features

Simple statistical computing is used to calculate the features of each IMF (IMF-1 to IMF-5). These statistical features are mean, variance, skewness, kurtosis, and entropy. These features are the main characteristics for distinguishing one subject from another.

a) Mean

The mean represents the average value of the time-series data of each IMF which expressed in the following equation:

\[ \mu = \frac{1}{N} \sum_{i=1}^{N} n \]  

b) Variance

Variance represents the distribution characteristics of the data series expressed by the following equation:
\[ \sigma^2 = \frac{1}{N-1} \sum_{i=1}^{N} (n - \mu)^2 \]  

(3)

c) Skewness
Skewness shows the slope level of the curve of the observed data series. Skewness is calculated based on the following equation:

\[ Skew = \frac{N}{(N-1)(N-2)} \sum_{i=1}^{n} \left( \frac{n - \mu}{\sigma} \right)^3 \]  

(4)

d) Kurtosis
Kurtosis is the degree of sharpness of a distribution. Kurtosis is calculated by the following equation:

\[ Kurt = \sum_{i=1}^{n} \left( \frac{n - \mu}{n\sigma} \right)^4 \]  

(5)

e) Entropy
In information theory, entropy describes the information content of a message. High entropy values are associated with random information content. Entropy is calculated by the following equation:

\[ H(x) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i) \]  

(6)

2.4. Discriminant Analysis

Discriminant Analysis (DA) is one of the classification methods based on statistical computation. Discriminant analysis that commonly used is Linear Discriminant Analysis (LDA) also known as Fisher's Linear Discriminant [22]. LDA is a classification method with a combination of mathematical and statistical operations calculations that impose separate statistical properties for each object. The LDA method aims to find linear projections (commonly referred to as "fisher image") to maximize the between-class covariance matrix while minimizing the within-class covariance matrix so that members in the class are more dispersed and can eventually increase the success of the classification.

Covariance matrix within the class (\(S_W\)) and covariance matrix between class (\(S_B\)) are defined as:

\[ S_W = \sum_{i=1}^{c} \sum_{x_k \in X_i} (x_k - \mu_i)(x_k - \mu_i)^T \]  

(7)

\[ S_B = \sum_{i=1}^{c} N_i (\mu_i - \mu)(\mu_i - \mu)^T \]  

(8)

Where \(x_k = k\)-th features, \(c = \) number of classes, \(N_i = \) number of features for \(i\)-th class, \(\mu = \) total mean for all the features, \(\mu_i = \) mean of feature for \(i\)-th class.
In order to minimize within-class covariance matrix in the class (SW) while the covariance matrix between classes (SB) is maximized, an eigenvector (V) will be sought so that the ratio equation (9) becomes maximal:

\[
\frac{\det(V_S W V^T)}{\det(V_S W V^T)}
\]

(9)

So that produces a solution:

\[
S_B V = \lambda S_W V
\]

(10)

Then find the eigenvalue (\(\lambda\)) and eigenvector (V) from the equation covariance matrix (10) as in equation (11).

\[
cov = S_B S_W^{-1}
\]

(11)

LDA is widely used for pattern recognition, such as face recognition [23], emotion recognition [24], or gait analysis [25].

To test the performance of the proposed method in the context of discrimination based on mean, variance, skewness, kurtosis and entropy values, discriminant analysis was combined with cross-validation. Cross-validation divides test data and training data randomly without over-fitting. The total number of features is 25 (IMF 5 and 5 statistical features). The performance of this system is calculated as the response rate correctly classified as accuracy. The calculated accuracy is the average of each cross-validation iteration. Accuracy is expressed by the following equation:

\[
Accuracy = \frac{TP + TN}{TP + TN + FP + FN}
\]

(12)

TP and TN represent the number of true positive and true negative, FP and FN are the numbers of a false-positive and false-negative.

3. Result and Discussion

The results of the raw signal decomposition by EMD are shown in Figure 2 which consists of an EEG signal segment with the following 6 seconds duration with the IMF (IMF-1 to IMF-5). Figures 2 (a) and (b) are the result of signal processing of the same subject but different segments. Visually, it shows the results of decomposition with a similar pattern. This shows that intra-individual variants are relatively small so that ECG waves have a consistent pattern to be used as biometrics. Figure 2 (c) is an ECG signal and decomposition results from different subjects. In the results of decomposition, it visually shows differences with the subjects in Figures 2 (a) or (b) especially the IMF-3, IMF-4, and IMF-5. These results have also been confirmed in other subjects where decomposition results show unique characteristics between subjects. Thus, this analysis provides sufficient evidence that the ECG between one subject and another has a different pattern so that it can be used for biometric purposes.

Calculation of statistical features is then applied to each IMF. Each ECG signal observed has 25 features (5 IMF x 5 statistical features). The average value of the statistical features of each subject is presented in Table 1 and Figure 3. Table 1 presents the statistical features of decomposed signals from subjects. The statistical feature shows that there are differences in characteristics between one ECG wave and another. However, it should be noted that the higher the decomposition level, the smaller the standard deviation will be given, this is an indication that the decomposition results are increasingly monotonous. The visual difference in features is shown in Figure 3.
Figure 2. ECG and IMF signals (a) subject-1 segment 1 (b) subject-1 segment 2 (c) subject-2

Table 1. Statistical features (a) IMF-1 (b) IMF-2 (c) IMF-3

|       | IMF-1 | IMF-2 | IMF-3 |
|-------|-------|-------|-------|
| Mean  |       |       |       |
| Subject-1 | -0.59 | 211.27 | -0.42 |
| Subject-2 | -0.49 | 162.44 | -0.12 |
| Subject-3 | 2.00  | 495.32 | 0.19  |
| Subject-4 | -0.28 | 136.61 | -0.01 |
| Subject-5 | -0.38 | 520.28 | -0.20 |
| Subject-6 | 1.14  | 200.09 | 0.39  |
| Subject-7 | 2.52  | 1482.80 | 0.19 |
| Subject-8 | 2.19  | 1171.14 | 0.46 |
| Subject-9 | 1.20  | 442.84 | 0.06  |
| Subject-10 | 0.29  | 188.98 | 0.08  |
| Subject-11 | -0.17 | 828.22 | -0.23 |
| Std. Dev | 1.17  | 450.92 | 0.27  |
| Subject | IMF-2 | IMF-3 |
|---------|-------|-------|
|         | Mean  | Var.  | Ske.  | Kurt. | Ent.  |
| Subject-1 | 0.21  | 185.72| 0.23  | 9.33  | 2.16  |
| Subject-2 | 0.05  | 93.67 | -0.10 | 5.96  | 1.80  |
| Subject-3 | -0.60 | 316.02| -0.04 | 4.66  | 1.99  |
| Subject-4 | 0.36  | 49.27 | 0.13  | 6.52  | 3.16  |
| Subject-5 | -0.25 | 382.02| 0.00  | 7.38  | 1.70  |
| Subject-6 | -0.50 | 125.13| 0.01  | 4.82  | 2.29  |
| Subject-7 | -0.75 | 1416.26| 0.10 | 3.83  | 1.54  |
| Subject-8 | 0.47  | 451.74| 0.06  | 4.36  | 2.15  |
| Subject-9 | -0.21 | 202.83| 0.00  | 5.21  | 2.21  |
| Subject-10| -0.20 | 112.86| -0.03 | 5.64  | 2.80  |
| Subject-11| -0.98 | 454.93| -0.05 | 5.96  | 1.73  |
| Std. Dev  | 0.46  | 383.63| 0.10  | 1.55  | 0.49  |

**Figure 3.** The average value of the "variance" feature of each subject
The next step is the performance validation of the proposed method using a classification algorithm. Linear discriminant and subspace discriminant was used in this research. There are two scenarios in order to get the best performance, the first scenario is to use one attribute as a predictor and use all attributes as predictors. The results of each test scenario are shown in Table 2.

**Table 2. Accuracy of each scenario**

| Classifier         | Mean | Var. | Ske. | Kurt. | Ent. | All  |
|--------------------|------|------|------|-------|------|------|
| Linear discriminant| 59.1 | 75.5 | 24.5 | 48.2  | 71.8 | 91.8 |
| Subspace           | 57.3 | 72.7 | 24.5 | 45.5  | 70   | 93.6 |

**Table 3. Confusion matrix (accuracy 93.6%)**

| Predicted Subject (Sn) | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 | S11 |
|------------------------|----|----|----|----|----|----|----|----|----|-----|-----|
| **TOTAL**              |    |    |    |    | 9  | 7  | 1  | 2  |    |     | 1   |
| S1                     | 10 | 10 |    |    |    |    |    |    |    |     |     |
| S2                     |    |    | 10 | 10 |    |    |    |    |    |     |     |
| S3                     |    |    | 9  | 7  | 1  | 2  |    |    |    |     | 1   |
| S4                     |    |    | 10 |    |    |    |    |    |    |     |     |
| S5                     |    |    |    | 2  | 7  | 1  |    |    |    |     | 10  |
| S6                     |    |    |    |    | 10 |    |    |    |    |     |     |
| S7                     |    |    |    |    |    | 10 |    |    |    |     |     |
| S8                     |    |    |    |    |    |    | 10 |    |    |     |     |
| S9                     |    |    |    |    |    |    |    | 10 |    |     |     |
| S10                    |    |    |    |    |    |    |    |    | 10 |     |     |
| S11                    |    |    |    |    |    |    |    |    |    | 10 |     |

Validation results on the performance of the proposed method showed the highest accuracy of 93.6%. Confusion matrix was confirmed through Table 3. The best results are achieved with the scenario that all feature parameters are used as predictors. Test scenarios with one predictor showed significantly lower accuracy. This shows that each predictor especially variance has a significant effect on accuracy. The subspace discriminant shows that the performance was slightly higher than linear discriminant, referring to the subspace discriminant properties which are suitable for multi-class cases. Although this study has not obtained 100% accuracy results, this study confirms previous research, the proposed method is currently able to provide comparable accuracy with a greater number of subjects and data.

4. Conclusion

In this paper, a biometric-based person authentication simulation has been discussed with ECG signals as the main modality. In this preliminary study, we conducted a simulation of 11 people. The ECG signal was taken using a one-channel ECG machine with 10-bit resolution and sampling frequency of 100 Hz. The recording was done in a relaxed rest condition, sitting on a chair with a duration of 1 minute. The raw signal was segmented into 10 segments with a duration of 6 seconds and overlapping 50%. Segmentation aims to get more test data and training data. The total number of ECG waves observed was 110. All ECG waves were then decomposed using EMD. Statistical features (mean, variance, skewness, kurtosis, and entropy) are calculated for each IMF (IMF-1 to IMF-5). Discriminant analysis was applied to validate and test the performance of the proposed feature extraction method. The highest accuracy achieved was 93.6%, using subspace discriminant with the scenario of all predictors used. Each predictor or feature has a significant impact on the accuracy of detection.

Although this preliminary study is quite successful in simulating ECG-based biometrics, it still has limitations. These limitations are the lack of a number of subjects, the simulation is still done offline and the number of features is relatively large. Future research is required to be able to meet these limits. In a short period, subsequent research will involve more subjects. Validation testing on a number of subjects that are not in the database also needs to be done. Thus, strengthening research on the
application of ECGs for biometric purposes can be sustainable in the hope that it can be applied widely, especially at high-level security access.

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