ECG Based Biometric using Wavelet Packet Decomposition

Sugondo Hadiyoso, Achmad Rizal, Inung Wijayanto

Abstract: Biometric technology has been commonly used for authentication. Fingerprint or iris become one of the biometrics that is widely applied. However, this type of biometrics tends to be easily falsified and damaged. So it is misused for manipulating actions and even crime. Therefore a new biometric method is needed to overcome this problem. One potential modality is biometrics based on an electrocardiogram (ECG) signal. This research simulates a one-lead ECG waveform for person authentication. ECG waves were taken from eleven healthy adult volunteers with a length of 60 seconds. ECG waves from each person are segmented into 10 sections so that a total of 110 ECG waves are used for person authentication simulations. All noise of the ECG waves was removed using a bandpass filter to reduce artifacts and high-frequency noise. Wavelet packet decomposition (3 Level) was applied to decompose the signal in several intrinsic parts so that typical wave information can be retrieved. Entropy-based feature extraction applied to all decomposed signals. A total of 14 entropy features have been calculated and used as predictors in the classification process. Validation and performance tests are carried out by cross-validation combined with linear discriminant analysis and support vector machines with five scenarios. The proposed method provides the highest accuracy of 71.8% using discriminant analysis and cubic support vector machine. The best accuracy value was achieved if all entropy features from all wavelet decomposition levels are used as predictors in the classification process. This research is expected to be a reference that ECG has the potential to become a future biometric modality.

Keywords*: *ECG, person authentication, wavelet, decomposition

I. INTRODUCTION

Person authentication based on measurement of biometric parameters has long been used. Biometrics has been commonly applied to security systems, presence systems, forensics, access control, and others. The advantage of biometrics for person authentication applications is that they do not need tags, which made this more efficient. The fingerprint-based biometric system is one of the most commonly used applications. Fingerprints have become the most popular and have long dominated the application of biometrics for various purposes. However, this type of biometrics tends to be easily falsified so that it is potentially misused for a crime. Bio signal-based alternative techniques began to attract the attention of many researchers to be applied to new biometric systems. Among biosignal modalities, electrocardiogram (ECG) waves are one of the new biometric methods that are starting to be proposed [1].

The hypothesis that each person has a unique ECG waveform [2] so that it can be used in person authentication applications [3]. Several studies related to biometric ECG simulations have been carried out by several researchers. Research by Belgacem, et al., simulates person authentication based on ECG and electromyogram (EMG) signals analysis [2]. They have used Fourier transforms for the extraction of features of the two signals. Although this research provides high accuracy, the use of EMG makes resources wasteful. Another study by Yue Zhang et al. simulates ECG biometric for 254 subjects. This study resulted in an accuracy of up to 98.87% [4]. Ahmed et al. [5], Sellami et al. [6], and Mariusz [7] also simulate an ECG biometric. They use the MIT-BIH database. Research [5], [6] achieved an accuracy of >90%, each of these studies using Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT). Mariusz proposed linear discriminant analysis and claimed to have high accuracy [7]. The primary purpose of some of the studies mentioned is to choose the best method to produce high accuracy. Although we cannot compare the result directly because the datasets used are different, at least this research can be mutually reinforcing so that in the end, an ECG can be widely used for biometric applications.

In this paper, an ECG signal based person authentication system has simulated. This is part of our research, wherein previous studies, the time-series approach was applied and resulted in an accuracy of >90% [9]. The feature extraction method with the wavelet approach was trialed in this new work for the same dataset. Wavelet packet decomposition was applied in this study to produce an ECG wave feature vector. Performance tests are performed using cross-validation and classifier algorithms to get accuracy in-person authentication.

II. MATERIAL AND METHOD

A. ECG Recording

Analog ECG waves were recorded using a one-lead ECG machine with Arduino for digitization. The recording duration was 60 seconds, with a sampling frequency of 100 Hz. The ECG machine used had a resolution of 10 bits so that the resulting decimal values range from 0 to 1023. A total of 11 healthy adults were participants in this study.

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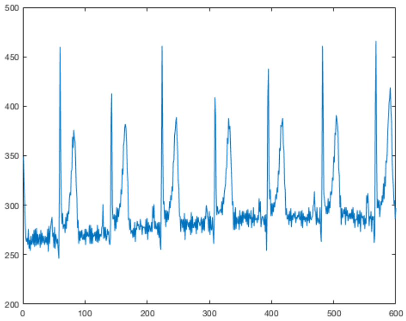
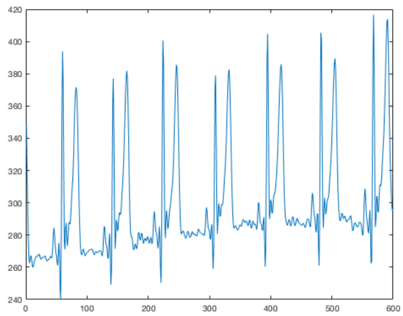
All participants were in a relaxed condition, sitting in a chair, and not doing substantial physical activity before recording. All recorded data were saved in .txt format for further processing.

B. ECG Pre-processing

Raw ECG signals contain large amounts of noise, exceptionally high-frequency noise, as shown in Figure 1 (a). Therefore, we have applied a digital filter to remove this noise. The filter design used is an infinite impulse response (IIR) low pass filter (LPF) with a cutoff frequency of 50 Hz. After the signal was processed using this filter, we can see in Figure 1 (b) the ECG waves are smoother. The purpose of applying this filter is so that we get noise-free ECG waves (close to ideal ECG waves) to maximize the results of computing in the next process. Signal segmentation with 50% overlap was applied to get more training data. Each ECG record was segmented into ten waves so that the total ECG waves which observed were 110 waves.



(a)



(b)

Fig. 1. ECG signal (a) raw data (b) low pass filtered ECG signal

C. Wavelet Packet Decomposition

A wavelet method was said as a suitable technique to analyze a non-stationary signal such as ECG. A discrete signal $x[k]$ decomposed into a set of wavelet coefficients using Discrete Wavelet Transform (DWT) by shifting the mother wavelet [10]. Mother wavelet or basic wavelet shape was a function which has a various amplitude in a certain period and localized in both time and frequency. DWT process started by deciding the wavelet scale levels (decomposition levels) n_m. The $x[k]$ passed through a high-pass and a low-pass filter in the initial state $n=1$. This process generates two forms of signal, the Detail (D_n) and Approximation (A_n) described as:

$$D_j = \sum_k x[k].h[2.i-k] \quad (1)$$

$$A_j = \sum_k x[k].l[2.i-k] \quad (2)$$

The next step is by the processed the approximation (A_n) as the next $x[k]$ while n increasing by 1. Those procedures were repeated until they reached the maximum decomposition levels (n_m).

Wavelet Packet Decomposition is the extension of DWT. It worked by using the mother wavelet transform the signal $x[k]$ [11]. WPD decomposed a signal into a multi-resolution signal by decomposing both the approximations and the detail signals [12]. The topology of WPD shown in Figure 2 The number of wavelet coefficient produced by this process is different from DWT. For n levels, WPD produced 2^n number of wavelet coefficient, while DWT only produced $n+1$. WPD produce better frequency resolution than DWT, which can provide valuable information in higher frequency component [13], [14]. In this study, we used three levels of decomposition.

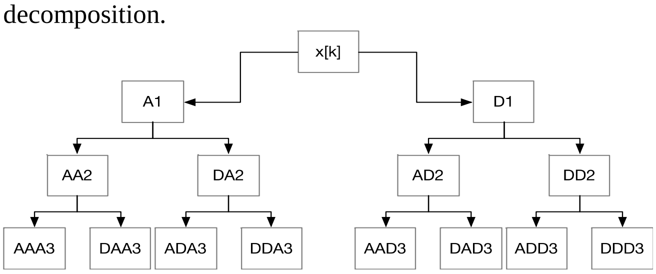


Fig. 2. WPD topology

D. Support Vector Machine (SVM)

Support Vector Machine (SVM) used the class separation concept, which said as one of the most satisfying and advanced classifiers. This classification method has been used in many problems [15], included the nonlinear relationship, small size sample, and more than one step of classification [16]. SVM produces an imaginary separator called as hyperplane, which presumes new examples [17]. The kernel function used and nonlinear problems are converted to linear classification problems by increasing the dimensions.

This research used six types of SVM kernels and 5-fold cross-validation for dataset training and testing specification. The general function of SVM described in Eq. 3.

$$y_i[(w \cdot x_i)+b]-1 \geq 0 \quad (3)$$

with $i=1,2,\cdots,l$ and $y_i \in -1,+1$ as the category or class identifier. The modification of objective function can change the identifier into a dual problem by using a Lagrange multiplier as:

$$\min Q(a) = \frac{1}{2}\sum_{i,j=1}^{l} a_i a_j y_i y_j \cdot K(x_i,x_j) - \sum_{i=1}^{l} a_i \quad (4)$$

The corresponding Lagrange multipliers for each value defined as a_i and the selected kernel function defined as $K(x,y)$ which can be written as:

$$K(x,x_i) = \frac{\exp(-|x-x_i|^2)}{g^2} \quad (5)$$

Linear SVM

The first kernel used in this research was linear SVM. Linear SVM used the weight of the SVM model before. The separation concept between positive and negative values was considered by seeing the weight vector as the normal to the hyperplane [18]. Linear SVM plays an essential role in the decision function. Therefore, it is essential to find out the training selection effects on the final classifier performance [19]. The algorithm is defined as:

$$\min \frac{1}{m} \sum_{i=1}^{m} x_i + \frac{1}{C} \sum_{i=1}^{m} a_i \tag{6}$$

with $\xi_i \geq 0, i = 1, \cdots, m$ were stack variables.

Quadratic SVM

The second kernel had attractive approximation properties. The quadratic kernel mentioned easy to learn since it was simpler than linear SVM [20]. It used the general case of the linear SVM kernel, and it can be assumed that $\sum = \sum_1 = \sum_2$ while the algorithm based on quadratic programming. This condition needs to be solved in the training of SVM [21].

Cubic SVM

This kernel has better interoperability and more flexible than Linear SVM. Furthermore, this kernel suitable for computation with low memory space. The hyperplane separated classes in the best possible ways in the multidimensional space [22]. The cubic kernel described as:

$$k(x_i, x_j) = (x_i^T x_j)^a \tag{7}$$

Fine Gaussian SVM

Fine Gaussian SVM used the number of predictors (P). The subtle distinction between classes was made together associated with a Gaussian kernel [23]. The kernel scale used was $\sqrt{\frac{p}{4}}$.

Medium Gaussian SVM

This SVM kernels used the Gaussian kernel to make a relatively lower distinction between classes [23]. The kernel scale used was P which calculated as $\sqrt{P}$.

Coarse Gaussian SVM

The coarse Gaussian SVM set the coarse distinction between classes with the kernel scale of $\sqrt{P * 4}$. Similar with the other Gaussian kernel, the Gaussian kernel also used.

E. Linear discriminant analysis

Linear Discriminant Analysis (LDA) is a form of Fisher's linear discriminant application, is one of the statistical analysis-based classification methods commonly used in separating two or more classes of objects. LDA works linearly by separating object classes. In this study, discriminant analysis is used to differentiate more than two classes based on the number of subjects used in biometric simulations. In this case, where there are more than two classes, the LDA used is developed to find subspaces that contain all class variations. Suppose that each of classes (C) has a mean μ_i and the same covariance Σ. Then the covariance matrix within class (S_W) and covariance matrix between class (S_B) are defined as:

$$S_W = \sum_{i=1}^{c} \sum_{x_k \in X_i} (x_k - \mu_i)(x_k - \mu_i)^T \tag{8}$$

$$S_B = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^T \tag{9}$$

Where x_k = k-th features,
c = number of classes,
N_i = number of features for i-th class,
μ = total mean for all the features,
μ_i = mean of feature for i-th class.

III. RESULT AND DISCUSSION

In this study, three levels of wavelet packet decomposition were calculated. Each level of decomposition produces a signal of 2^n, where *n* is the decomposition level. So the total decomposition signal observed in this study is 14 signals. Figure 3 below is the result of signal decomposition of one subject. All decomposition signals then calculate for their entropy values to measure the information degree of the signal. Entropy is calculated using the function in Matlab. Figure 4 shows the average entropy of each decomposed ECG wave. Intuitively we can see that the value of entropy differs from one subject to another, even though in some features, the differences are very subtle.

The next stage is the performance test of the proposed feature extraction method. Cross-validation will divide the test data and training data randomly, then the person authentication process was carried out by the classifier. There are several test scenarios applied, in this study is to change the combination of vector features and the use of various classifier algorithms. The goal is to get a combination of features that can provide the highest accuracy. A description of these test scenarios is as follows:

1. Entropy decomposition level 1 as the predictor.
2. Entropy decomposition level 2 as the predictor.
3. Entropy decomposition level 3 as the predictor.
4. Entropy decomposition level 1 and 2 as the predictor.
5. Entropy decomposition level 1, 2, and 3 as the predictor.

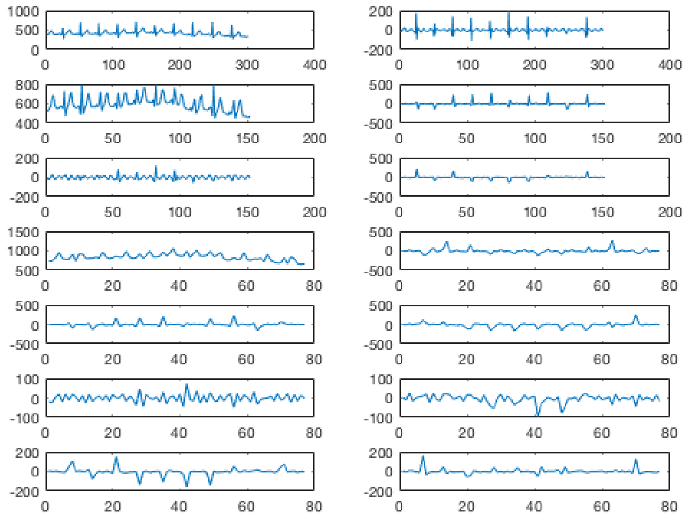


Fig. 3. Signal decomposition one of the subject

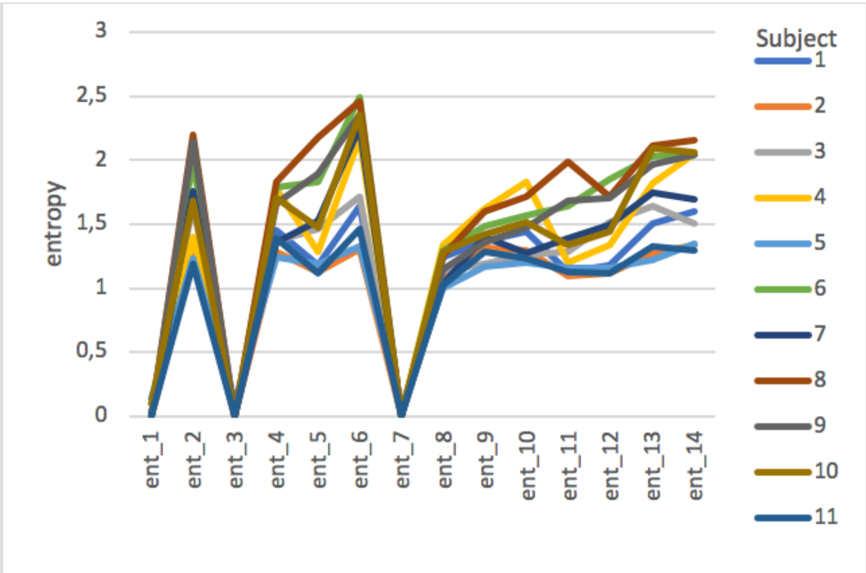


Fig. 4. The entropy value of each signal decomposition

The accuracy results of each scenario are presented in Table 1 below:

Table-I: Accuracy in each scenario (%)

	Ent (Level-1)	Ent (Level-2)	Ent (Level-3)	Ent (Level-1-2)	Ent (Level-1-2-3)
Linear discriminant	40.9	N.A	N.A	N.A	**71.8**
Linear SVM	42.7	54.5	47.3	59.1	70
Quadratic SVM	47.3	57.3	54.5	60.9	70
Cubic SVM	48.2	53.6	50.9	59.1	**71.8**

The test results show that this authentication system can provide the highest accuracy of 71.8% by Cubic SVM and Linear Discriminant. Testing scenarios using entropy at one level of decomposition yields accuracy below 60%. The best accuracy can be achieved if all vector features become predictors, this indicates if each feature has an essential role in the classification process. If in Figure YY intuitively shows the average differentiation of features which is quite significant between people, but if it is observed in more detail, there are entropy values that overlap between one person and another.

The results of this study are no better than previous studies [8] [9] which use a time series analysis approach with a higher number of features.

This is a challenge for the next job to combine more statistical features to get higher accuracy. Decomposition of higher-level wavelet packages can also be explored for future work because wavelets have excellent performance in ECG biometrics as reported in research [6].

IV. CONCLUSION

An ECG signal based person authentication system has been simulated in this research. 110 ECG waves from 11 participants were analysed using 3-level packet decomposition wavelets. Entropy was calculated at each level of decomposition as a feature vector. Performance and validation tests of the system are carried out through cross-validation and combined with classifiers including Linear Discriminant Analysis and Support Vector Machine. The highest detection accuracy achieved was 71.8% using LDA and cubic SVM in the scenario of all features being a predictor. This accuracy was lower than previous studies, this may be due to the entropy feature is not enough to characterize the signal so that the differentiation between ECG's person does not provide high accuracy. The next study will be calculated more diverse signal statistical parameters to complete the entropy analysis and mother wavelet variations so that it is expected to get high accuracy. Referring to previous studies [6], wavelets have the potential to be applied to ECG biometrics. Finally, this research will continue to be developed to find the best method for feature extraction and classification so that high accuracy is obtained. At the same time, this biometric application will be applied for real time authentication.

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