ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

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www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940www.ijsem.org

Vol 6, Issuse.3 Aug 2018

Low recurrence ECG signal based Biometric Distinguishing proof

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Abstract— When it comes to contemporary information systems, security is the biggest issue we face. This may be accomplished by employing the most precise methods of verification and identification. Biometric signals play a pivotal part in all of the approaches. It is shown that the application of Laplace transform to the system, input, and output matrices leads the transfer function of satellite orbit. Consideration of small signal variation in the input and output matrices gives the control characterization of the satellite orbit.

INTRODUCTION

Analyzing a person's heartbeat might provide valuable information about their personality. An Electrocardiogram (ECG) may be used to check the functional condition of a person [1]. Education systems may benefit greatly from functional state analysis, in the design of individualized educational programs, for example. An adaptive learning interface based on ECG data is built using methods in [1], which include the measurement of heart rate variability as well as the evaluation of stress express and centralization indices. ECG signals are regarded unique enough to be used for biometric identification and verification. In order to prevent unauthorized access to the source data, many systems supply data stored in their memory banks. A variety of biometric identification and assessment techniques have been effectively deployed in a wide range of information systems. For example, a person's capacity to retain and recall information like their login and password may be assessed using cognitive ability procedures. USB tokens, RFID tokens, and other forms of personal identification are part of the second main category. It is anticipated that biometric techniques of identification and verification would have the greatest

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future potential. The uniqueness of a person's biometric data may be utilized to construct algorithms. With biometric data analysis, people don't need to remember any more information or maintain the concept of carrying about a smart card since they provide all of the information necessary for their own identification and verification. It is feasible to identify a person using a combination of various biometric markers (for example, ear recognition, face recognition, and gait recognition). A person's cognitive capacities or functional status may be determined if eye tracking data is utilized in combination with ECG signal analysis. [7, 8] In the human heart, the depolarization of the right and left ventricles occurs in a recursive pattern known as the QRS complex.

Many additional waveforms outside the QRS complex are used to describe signals [9], including P, T and U waves. The R-peak (or R-wave) of the fragment is a notable characteristic and an upward deflection. P-wave followed by lower deflection, then a lower deflection Q-wave This wave occurs after the R peak whenever the ventricles or Purkinje fibers repolarize (T-wave) (U-wave). Classification algorithms based on the ECG signal may be used to identify an individual. There are a number of them. For the biometric approach in [10], researchers employed a 1000 Hz device to capture data from 60 persons, and then used discrete wavelet transformation to derive the relevant attributes. [10] Adjusting the rank level number may boost the 90.8 percent identification accuracy to 100%. The results were accurate. Researchers in [9] classified data using neural networks. To detect ECG data captured at a 500 Hz rate, researchers utilized a variety of techniques. QT interval analysis yielded 97% identification accuracy, whereas QRS complexes yielded 99.1 percent.

The authors of [9] used a neural network method called "deep neural nets" in their experiment. A custom-built approach was employed to extract QRS complexes from the 500 Hz signals in order to guarantee the datasets had an error rate of 0.05 percent. Thanks to significant technological advancements, a broad variety of biometric signals may now be evaluated using instruments that are typically customized for each signal type. So, since there are so many different sampling rates, the data collected varies greatly in quality. As technology becomes more complex, so does the price of devices with high sampling rates, therefore it's crucial to keep this in mind. Most identification and verification techniques that employ low frequency equipment are not able to get high-accuracy results because of the lack of measurements. Due to this, protocols for high and low frequency devices must be designed to provide accurate identification results.

I. BIOMETRIC IDENTIFICATION APPROACH

Biometric identification is now based on analyzing biometric signal repeating fragments, which is a novel approach. Signals may be identified by include the items that appear often. The method is based on extracting pieces that are unique to each signal and may be used to identify it.

A. *Features of the biometric signal*

Let's begin by defining a collection of characteristics that may identify a certain portion of the signal, and hence the whole signal. The QRS complexes in a person's heart rate are what make a cardiogram a periodic biometric signal. Figure 1 shows an illustration of the signal.

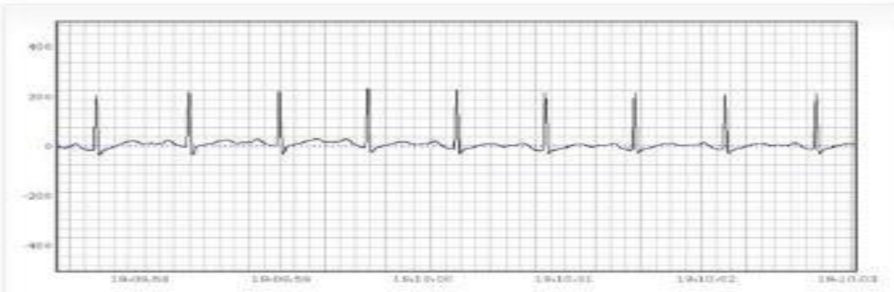

Figure 1. An example of ECG signal

There are many biometrics studies that use QRS complexes because of the unique information they provide about a person's cardiovascular system, which makes it possible to use these complexes to identify a specific individual. The functional state of a person can be determined by measuring the QRS complex [1]. Biometric signals can be studied using the developed approach that assumes a QRS complex as well as the surrounding P, T, and U waves. A low-frequency signal-specific approach should take into account the enclosing complexes as well. There will be a lack of measurements in this case because the device only has a limited number of discrete points. This will prevent accurate identification results from being obtained. See Fig. 2 for a visual representation of the assumed signal's partial pattern.

To ensure that the results are similar, each fragment is analyzed using a unique coordinate system. To construct the coordinates for an ECG fragment, the R-peak is used. It is first determined that R peaks and QRS complexes are present in the acquired signal by employing the Pan-Tompkins method [12]. A QRS fragment, including P, T, and U waves, is then recovered from the signal using the location of the observed R-peak. All pieces are considered to be in the same coordinate system, although each fragment has its own unique system. This coordinate system, which has temporal units of milliseconds and millivolts (mV), has a single fragment whose start and last points are Aj and Bj, respectively. An R-peak coordinate identifies the location at which a fragment is at its starting point in time. Figure 3 shows the coordinate system in use.

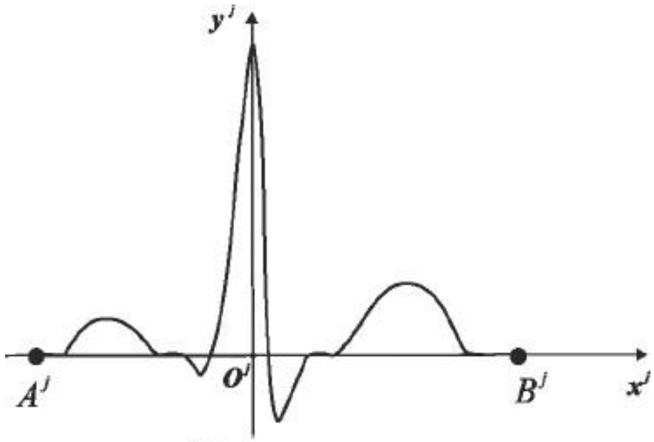

Figure 3. $O^jx^jy^j$ coordinate system of the fragment

Using the device's discrete signal, an approximation may be performed to restore continuous signal characteristics. The characteristics of the considered fragment are derived using a Taylor series approximation. Using the following formula, one may approximate the signal.

B. Biometric Identification Approach

There are two methods of recognizing the biometric signals acquired by comparing the collected data in this manner. However, the initial steps of both algorithms are the same. As seen in Fig. 4, the algorithm's flow diagram. An initial stimulus presentation that affects a person and allows for the collection of the relevant biometric data is required in order to begin data collection in this area

$$x^j(t_i+\tau) = x^j(t_i) + \frac{\left(x^j(t_i)\right)^1}{1!}\tau + \frac{\left(x^j(t_i)\right)^2}{2!}\tau^2 + \cdots + \frac{\left(x^j(t_i)\right)^m}{m!}\tau^m + \cdots \qquad (1)$$

$$i = 2,3,4,5, \tau = t - t_i$$

$$\left(x^j(t_i)\right)^m = \frac{\nabla^m x_i^j}{\square^m} + O(\square) \qquad (2)$$

Using electrocardiographic signals as the focus of this study, it can include any visual items, electrical tests, or writings. Devices that record ECG data are used to acquire this data when the stimulus is being given to a person. A dataset in storage is a representation of a gathered signal. For a person, a class pattern is formed by the collection of datasets. Each dataset is linked to a ten-item feature list for r^{th} analysis $\varsigma = \{\varsigma_{r,1}, \varsigma_{r,2}, \dots, \varsigma_{r,10}$ that are computed for it.

1) Point-to-point algorithm

The point-to-point method is based on comparing two datasets side-by-side. It's predicated on figuring out how far apart two distinct datasets are. A feature's distance between datasets is the initial stage in the process. According to Kolmogorov-Smirnov test probabilities, the distance is based on a comparison of feature value distributions in two sets of data in order to determine their likelihood:

$$d(\varsigma_{r,t},\varsigma_{q,t}) = -\ln\left[p\left[K \geq \sqrt{\frac{n_r n_q}{n_r + n_q}} D'_{r,q}\right]\right]$$

where K is a random variable with Kolmogorov distribution, and Kolmogorov- Smirnov test statistic for the featureodatasets f the, areempiric is datasets, n_r and n_q are the number of r^{t} and q^{t} fragments in the datasets.

$\varsigma'_{q,n}(\varsigma)|$

i^{t}

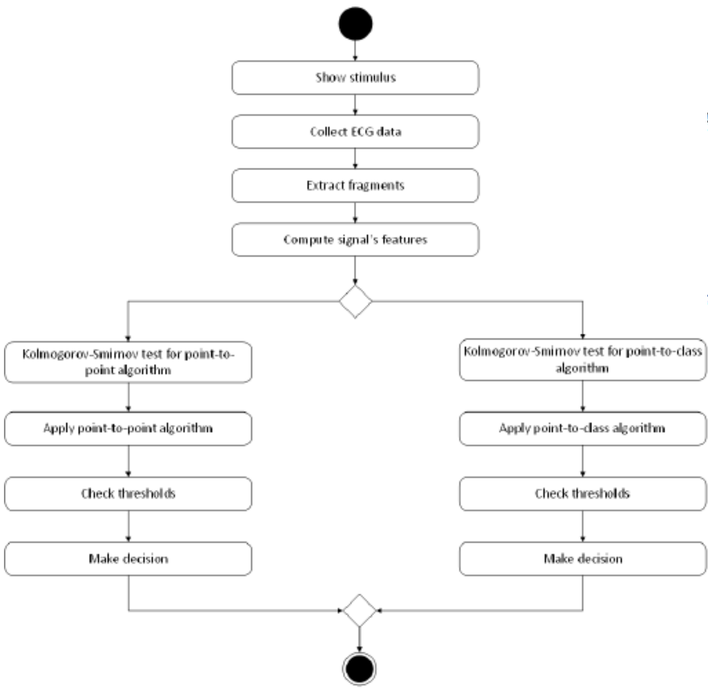

Figure 4. A scheme of identification algorithm

Step 2 is to determine the distance between data points. This number is the sum of all the distances depending on several features:

$$d(\varsigma_r,\varsigma_q) = \sum_{i=1}^{10} d(\varsigma_{r,t},\varsigma_{q,t}) \quad (4)$$

It is therefore possible to determine how far a dataset is from a specific class.

$$d(\varsigma_r, C_s) = \min_{q \in C_s}[d(\varsigma_r,\varsigma_q)] \quad (5)$$

Because the approach is meant to be used in actual systems, it's possible that impostors will gain access to it. Because of this, the system must be protected from such acts. For the purpose of reducing the number of classes to which a person's signal is subjected to comparison, we assume that thresholds for each class in the database have been calculated. For this, the formula is as follows:

$$d_s^+ = \max_{r \in C_s}[d(\varsigma_r, C_s/\{r\})] \quad (6)$$

d_s^+ $\quad$ $s^{t\square}$ $class\ (C_s)$

where is a threshold for an

Based on how many datasets that are closest to each other, the algorithm determines which class identifier should be assigned to each dataset. An evaluation dataset is regarded to be accurate if the number of datasets that are closest to a certain class meets a preset value.

2) Point-to-class algorithm

This technique differs from others in that we recalculate the distance between the datasets and the classes in question. The distance between two datasets is not taken into consideration by the point-to-class method. Each class's datasets are combined before the Kolmogorov-Smirnov test is run to assess if the observed dataset's distribution is similar that of the class as a whole. Bayes' theorem states that a dataset's distance from a Cs class is a function of:

$$d(\varsigma_r, C_s) = -\left[\ln\left[\frac{p(C_s)}{p(\varsigma_r)}\right] + \sum_{j=1}^{10}\ln[p(\varsigma_{r,j}|C_s)]\right] \quad (7)$$

$p(C_W)$

$p(\varsigma_r)$

ς_r

here is a probability of a dataset being related to the class C_s, is a probability of a dataset having a set of features $\varsigma_r, p(\varsigma_r)$ is a conditional probability of , given C_s. There is also a consideration for imposter access in the point-to-to-class procedure, which is why thresholds derived by (6) are also used.

II. EXPERIMENTAL RESULTS

Data from ECG recordings were used to examine the effectiveness of the new biometric identification method. The Pan-Tomkins filtering technique [12] was used to detect QRS complexes and then extract the appropriate fragments containing QRS complex, P, T, and U waves from the recorded data. First, the signal is decomposed into fragments, and then the characteristics needed to classify them are determined. Low frequency biometric signals are what we're aiming for with this method. It's important to note that the first signals were collected using a 125 Hz device, which has an intermediate sampling rate. An artificially reduced sampling rate of 30 Hz was achieved by removing every fourth point from the discrete presentation of the data in order to test the method on low-frequency sources. Both of the algorithms under consideration passed the examination with flying colors.

The (EER) values. According to FRR and FAR, which reveal how many datasets have been erroneously rejected and how many have been accepted, EER is built on the false rejection rate (FRR). FRR shows how many datasets have been rejected and how many have been accepted, while FAR shows how many impostors there are. Having computed the necessary characteristics for the 13 datasets, classification began. The same procedure for evaluating all of the existing classes was utilized throughout.

When evaluating both methods, one dataset from each class was picked to constitute the test set at each phase of evaluation. All of a class's datasets came together to produce its template. The methods were evaluated with a range of threshold values, from 0 to the farthest distance between classes and datasets currently available. There was 0.13 percent EER with the point-to-point method and 0.6 percent EER with point-to-class algorithm.

III. CONCLUSION

The study of electrocardiograms (ECGs) has recently spread to many other scientific fields. People's cardiograms give vital information about their functional state that may be used by educators to create intelligent systems based on the reactions of their body and central nervous system. ECG data may be tampered with using biometric identification, however this is the most probable approach. As shown below, eye tracking data may be used to analyze saccade fragments to disclose an individual's identity and ECG signals. Algorithms based on points and class assessments are included in the method. The ECG data utilized in the experimental assessment of the algorithms offers extremely accurate findings for a low-frequency signal. Algorithms that use points to connect were found to have an EER of just 0.13 percent, whereas algorithms that use classes to connect had an EER of just 0.60 percent For low frequency ECG data, we may infer that our technique provides reliable identification findings based on these results. A real-world information system is expected to be built using the method in the future when additional study is completed on data representation's practicality.

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