ECG based Human Identification using Short Time Fourier Transform and Histograms of Fiducial QRS Features

Abdullah Biran[1] and Aleksandar Jeremic[2]
[1]Department of Biomedical Engineering, McMaster University, Hamilton, Canada
[2]Department of Electrical Engineering, McMaster University, Hamilton, Canada

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Abstract: Human identification from the biological signal the Electrocardiogram (ECG) has been demonstrated in several studies. In this paper, we present a new technique for personal identification using short time Fourier transform (STFT) and histograms of four fiducial QRS features. We examined the applicability of our methodology on 162 ECG records of 81 subjects from the publicly available ECG ID data base. Our experiments show that the normalized Euclidean STFT distance can identify individuals with 95 % accuracy. Hence, with fusing six histogram distances computed from the QRS fiducial features and applying majority voting, the identification accuracy increases up to 100 %. These findings indicate that ECG is sufficiently unique signal and can be useful as biometric identifier.

1 INTRODUCTION

Biometrics are potentially helpful to recognize any identity as they rely on the individual intrinsic characteristics and they require the physical appearance of the person. However, with increasing demand on security requirements of biometrics, where the main focus here is to consider a biometric that cannot be stolen, ECG is an emerging biometric modality and it achieves such goal as it is a vital sign. In addition, it has robust advantages including universality, hidden nature and simple acquisition (Joao, S. Cardoso, & Lourenco, 2018)

Existing ECG based human identification systems are generally divided into two groups: fiducial points based and non-fiducial feature based (Joao, S. Cardoso, & Lourenco, 2018). Fiducial based systems depend on locating heartbeat waveform points, onsets and offsets, and then it extracts different amplitude and distance features. Whereas in non-fiducial methods, features are extracted without relying on fiducial points such as using autocorrelation and wavelet coefficients algorithms (Chun Chi , Peng Tzu, & Pie Lun, 2019).

Adrian et al. have proposed a method for human identification using wavelet-based distance measure (D.C. Chan, M. Hamdy, Badre, & Badee, 2008). Saiful et al. proposed another method based on heartbeat morphology features (Islam, Alajlan, Bazi, & S. Hichri, 2012). Lin et al developed an algorithm based on non-linear Lyapunov exponents, root mean square (RMS) and support vector machine (SVM) (Lin, Chen, Lin, Yang, & Chiang, 2014). Furthermore, Gutta and Cheng applied discrete cosine transform (DCT) and autocorrelation techniques for extracting non-fiducial ECG features (Gutta & Cheng, 2016). In contrast, Arteaga-Falconi et al proposed a numerical based algorithm to extract fiducial based time and amplitude features (Arteaga-Falconi, Al Osman, & El Saddik, 2016).

Liu et al. proposed a multi scale autoregressive model method (MSARM) for human identification using ECG (Liu, et al., 2018). Moreover, Sidek et al. examined the feasibility of ECG signal as biometric modality in abnormal cardiac conditions (Sidek, Khalil, & F. Jelinek, 2014). Furthermore, Odinaka et al. presented a multibiometric identification system based on combining both the electrical originating signal, the ECG, and the laser Doppler vibrometry (LDV) (Odinaka, A. O'Sullivan, J. Sirevaag, & W. Rohrbaugh, 2015).

In this paper, we present a method which identifies individuals from their ECGs. To illustrate, the main identification process starts by calculating the normalized Euclidian STFT distance. Then, six histogram distances computed from four fiducial QRS features are fused to create multi-channel identification

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process. Finally, majority voting is applied. Figure 1 shows the block diagram of this work.

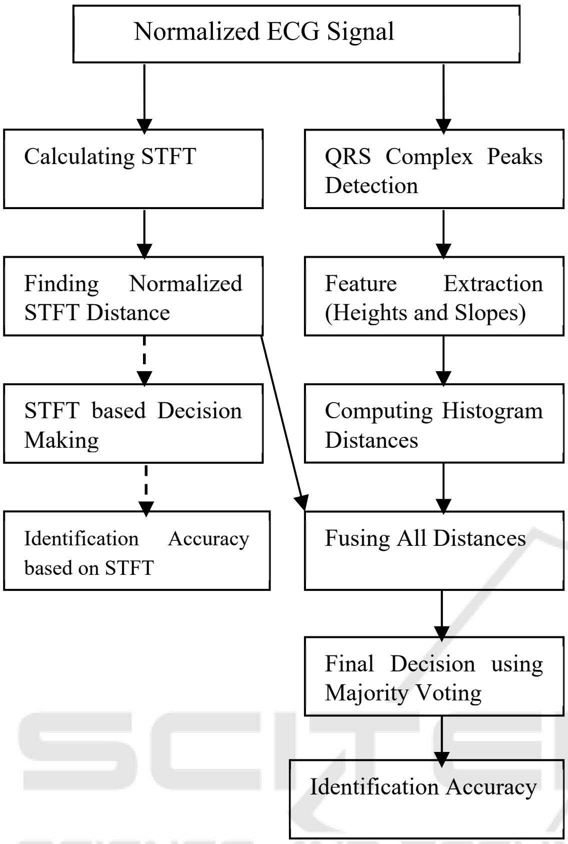

Figure 1: Block diagram of the proposed methodology.

2 PROPOSED METHODOLOGY

2.1 Short Time Fourier Transform (Non-fiducial Technique)

Short Time Fourier Transform (STFT) converts the time segment of any signal to its frequency components. It provides accurate results about all the frequencies that exists in a signal. Its strength in the signal processing field makes it excellent tool to distinguish between different signals. Since ECG signal is believed to be unique, its frequency components should vary between different subjects (V. Oppenheim & W. Schafer, 1989).

2.1.1 Calculating STFT

In a preprocessing stage, the main ECG signals of 81 subjects were normalized before applying STFT and then each normalized ECG signal $X \in R^{1xl}, X = [X(1), X(2), ., X(l)]$ was divided equally into two types, the training set $Xt \in R^{1xh}$, $Xt = [X(1), X(2), \dots, X(h)]$ and test set $Xe \in R^{1xh}, Xe = [X(h+1), X(h+2) \dots, X(2h)]$, where $h = l/2$. Signal normalization is the process of changing the range of the amplitudes to simplify the analysis. The selected range is 0 to 1 where 0 refers to the minimum and 1 refers to the maximum amplitudes in the ECG. Equation (1) is used to normalize the signal:

$$X(m) = \frac{X(m) - Min(X)}{Max(X) - Min(X)} \quad (1)$$

where $X(m)$ is the ECG signal and $m = 1,2,3,.,l$ is the sample number

Then, the STFT is calculated to find the frequency components using Equation (2):

$$X(k) = \sum_{n=o}^{N-1} X(n) e^{j\left(\frac{2\pi}{N}\right)kn} \quad (2)$$

where N is the window length of the STFT and k is the sampling frequency. In this work, we only considered using magnitudes of the frequency components.

2.1.2 Finding Normalized Euclidian STFT Distance

Following the commonly used algorithms in using ECG for human identification, the intrinsic value that is considered to distinguish between subjects using their ECGs is the minimum distance between the training set and test set. In other words, such distance should be as large as possible when it is calculated between data sets of different subjects. However, it should be the smallest distance when both the training and test tests belong to the same subject.

The Euclidian distance is defined in Equation (3) as.

$$D = \sqrt{\sum (Xt(ir) - Xe(jr))^2} \quad (3)$$

Where, $i = 1,2,3,.,81$ and $j = 1,2,.,81$ are subject indices, and r is the record number.

However, we propose to use normalized signal:

$$D = \sqrt{\sum \left(\frac{Xt(ir)}{std(Xt(ir))} - \frac{Xe(jr)}{std(Xe(jr))}\right)^2} \quad (4)$$

where std refers to the standard deviation based on the results presented in (Li & Jeremic, 2017). This will further enhance the identification process as there might be some individuals who have similar frequency components. Thus, by normalizing the values, such similarity decreases and the performance of the identification process increases.

2.1.3 STFT Decision Making

The STFT based identification process depends on finding the distance between a test set to the training set of all subjects using Equation (4). Then, the decision is made when the minimum distance is found where the expectations are that the shortest distance is between the test and the training sets of the same person.

2.2 QRS Peaks and Features (Fiducial Technique)

Fiducial points refer to finding the maxima, minima, onsets and offsets of the ECG waveform (Chun Chi , Peng Tzu, & Pie Lun, 2019). Since most of the information are found in the QRS complex, which is the largest wave in the heart beat, we developed an algorithm to extract the Q, R and S peaks. After these points are determined, a number of features can be extracted including heights or slopes between these peaks.

2.2.1 QRS Complex Peaks Detection

The R peaks are commonly-known to be the highest peaks in the normal ECGs. Thus, if a specific threshold is optimized, they can be localized. However, such threshold differs between subjects as well as it also depends on the heart rate. Therefore, the R peaks extraction process starts by finding all peaks of amplitudes above 0.5 in a range of thresholds $T \in R^{1xg}$, $T = t1, t2, t3, ., tg$. Then the R-R intervals be-

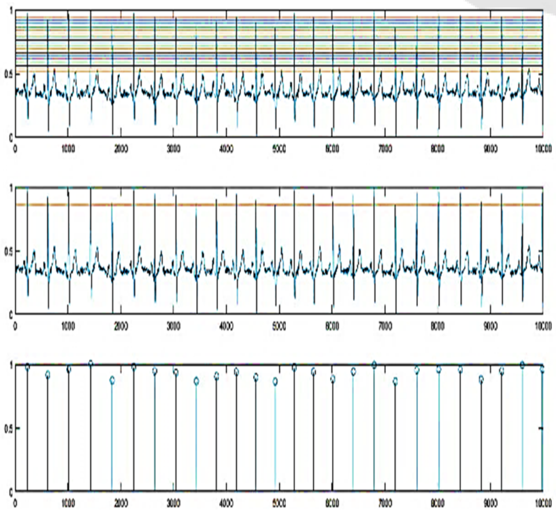

Figure 2: Automatic detection of the R peaks. In the top image, all the possible thresholds are found, at the middle image, only one optimized thresold is selected, in the bottom image, all the R peaks are extracted.

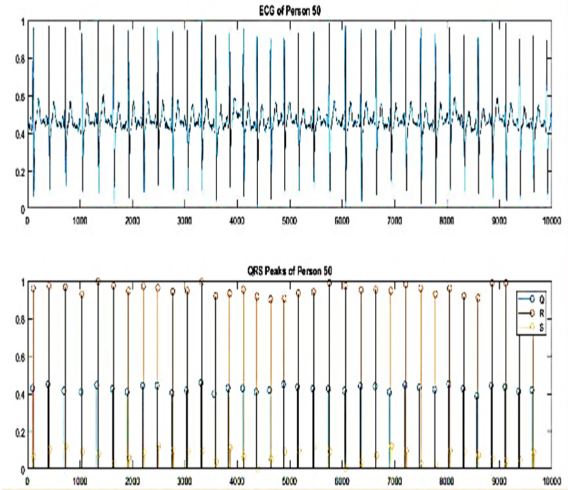

Figure 3: Automatic detection of the Q and S peaks. In the top image, the normalized ECG is shown, in the bottom image, Q,R and S peaks are detected.

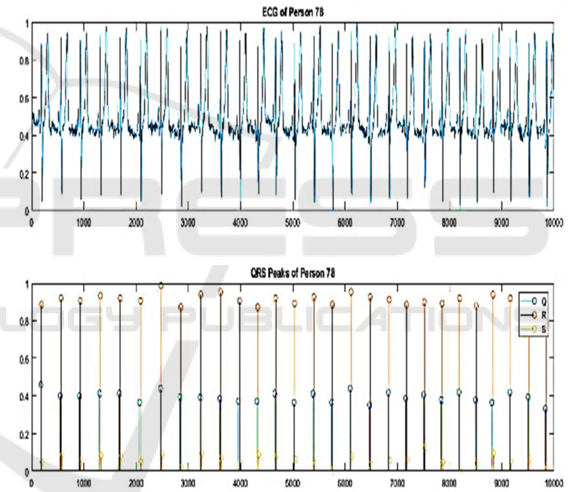

Figure 4: Automatic detection of the QRS complex peaks. In the top image, the normalized ECG is shown, in the bottom image, Q, R and S peaks are detected.

tween the extracted peaks in each threshold is computed. In order to find the proper threshold $topt$, the algorithm automatically selects the threshold that has the lowest standard deviation between R-R intervals. Figure 2 shows an example of the automatic detection of R peaks. Regarding the Q and S peaks, there were located as the minimum peaks in right and left of each R peak. Figure 3 shows an example of the Q and S peaks detection.

However, 19 of the subjects from the ECG ID database have different ECG shape, in which the T wave is the highest wave. To this purpose we developed a different method to detect the QRS complex peaks in these cases. The second method depends on finding the minimum peaks, S peaks, in a defined sliding window. Then, each R is determined by the highest peak left of each S peak while each Q is determined by the lowest peak left of each R peak. Figure 4 shows an example of QRS complex peaks detection of an ECG where T wave is higher the QRS Complex.

2.2.2 Feature Extraction

Features are special properties that describe how signals are distinctive. For, instance, the time delay between ECG peaks or waves, the distance between QRS complexes and the frequency components can provide particular details about any signal to investigate its uniqueness.

In this work, we arbitrarily propose four features: 1) the amplitude difference between Q and R peaks, 2) the amplitude difference between R and S peaks, 3) the rate of time change between Q and R peaks and 4) the rate of time change between R and S peaks.

Let c be the total number of beats, so, $Q \in R^{1xc}$, $R \in R^{1xc}$ and $S \in R^{1xc}$, where $Q = [q(1), q(2), \ldots \ldots q(c)]$, $R = [r(1), r(2), \ldots \ldots r(c)]$, and $S = [s(1), s(2), \ldots \ldots s(c)]$. The four features are then calculated using Equations (5), (6), (7) and (8) respectively.

$$QR(b)_{Height} = X(R(b)) - X(Q(b)) \quad (5)$$

$$RS(b)_{Height} = X(R(b)) - X(S(b)) \quad (6)$$

$$QS(b)_{Slope} = \frac{X(R(b)) - X(Q(b))}{R(b) - Q(b)} \quad (7)$$

$$RS(b)_{Slope} = \frac{X(S(b)) - X(R(b))}{S(b) - R(b)} \quad (8)$$

where $b = 1,2, \ldots, c$ refers to the beat number.

2.2.3 Computing Histogram Distances

We have combined the four extracted features in groups of two resulting in a total of six pairs. All the feature pairs are shown in Table 1. Then using Equation (3), the distance between each pair in the test set and its corresponding training sets were calculated. Therefore, a total of six histogram distances were measured. Similarly, to what we discussed in the STFT section, the minimum distance is expected to be when the two pairs belong to the same subject.

Table 1: Pairing the four features.

Combination	Features
C1	QR_{Height} , RS_{Height}
C2	QR_{Slope} , RS_{Slope}
C3	QR_{Height} , QR_{Slope}
C4	RS_{Height} , RS_{Slope}
C5	QR_{Height} , RS_{Slope}
C6	RS_{Height} , QR_{Slope}

2.2.4 Fusing All Distances

The normalized STFT based distance has shown excellent performance in individual recognition. Hence, to enhance the identification process, the fiducial based histogram distances were fused to create multi-channel-based identification process. Therefore, a total of seven decisions were made when every test set were examined to find its relevant identity.

2.2.5 Decision Making by Majority Voting

The final decision for every test set is made using majority voting algorithm, where the subject who has more votes from the seven decisions will be recognized as the correct or incorrect identity. For every test sample, if the smallest distance occurs between the training sample and test sample of equal subject indices, i = j, at each of the distance measurements, a subject is correctly identified, and a correct vote is obtained. In contrast, if the smallest distance happens between the training sample and test sample of unequal subject indices i ≠ j, at each of the distance measurements, a subject is incorrectly identified and a false vote is obtained. Then, the algorithm makes a final decision based on the maximum number of true votes and it determines if it is a right or wrong decision.

3 RESULTS

The publicly available ECG ID database from Physio Net were used to test the performance of the proposed methodology. The ECG records were measured using single lead for a duration of 20 seconds at 500 Hz sampling frequency from 44 men and 46 women whom age was between 13 to 75 years.

In this work, we selected 81 subjects and for every subject, two different records (r) were chosen. In the non-fiducial technique, each single record was divided equally into two sets where the first half is the training set and the second half is the test set. However, the fiducial based technique required higher training. Thus, each record was divided into 70% of n as training set and 30% of n as test set when the algorithm runs through the fiducial bath of the methodology.

3.1 Identification using the Normalized STFT Distance

The ECG is aperiodic signal as the time interval changes between its cycles. Thus, the STFT normalized distance measure performance depends on choosing the proper window size and the overlap percentage. In this work, we used a sliding window of 500 samples with a 75 % overlap.

Most importantly, human recognition based on the STFT normalized distance has shown excellent results with up to 95% of identification accuracy which is shown in Figure 5. As a result, we successfully identified 77 out of the 81 subjects. However, the remaining 4 subjects were not identified. This is because every subject may have an optimal window size. Although we repeated the experiment on the second record for all the subjects, the same identification accuracy is obtained.

3.2 Identification using QRS Complex Features

The six decisions based on the histogram distances are labelled as D1, D2, D3, D4, D5 and D6 as shown in Figure 6. These numbers stand for their corresponding feature combinations (C1 to C6). The identification process through these six decisions have shown good results. However, such technique requires larger training samples. This was expected as a result of the heart rate variability even within the same record which causes changes specially in the height features. As seen in Figure 7, the QRS complex peaks can vary within the same record. However, the change in the slope features is slight. For instance, the combination of slope features (C2) have the best performance as shown in Figure 6. It is also observed that at 80% training all the subject are correctly identified (D2) whereas in the combination of height features (C1) even at the same higher training percentage, the identification accuracy is 80% (D1).

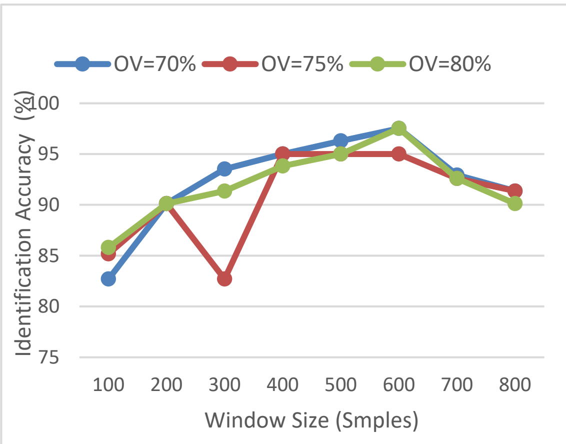

Figure 5: Identification accuracy curve based on the normalized STFT distance at different window sizes ranging from 100 to 800 samples at three different overlaps including 70%, 75% and 80%.

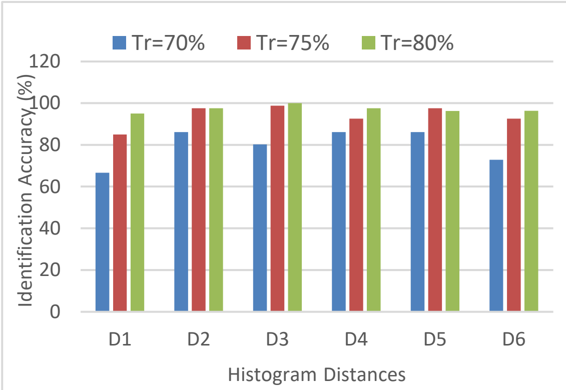

Figure 6: Identification accuracy based on the six histogram distances at different training percentages (Tr). The combination of the slope features has the best performance (D2).

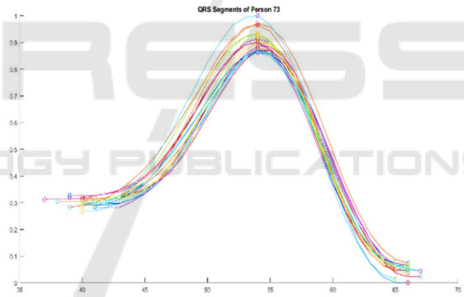

Figure 7: An example of the change in the QRS complex dimensions in the same record.

3.3 Fusing All Decisions and Applying Majority Voting

The non-fiducial based algorithms generally perform better than the fiducial techniques. However, the later methods can help in some cases to identify people who cannot be identified by the non-fiducial algorithms. Thus, all the seven measured distances are fused and majority voting is applied. As a result, the QRS complex features helped in identifying the four subjects who are not identified by the STFT normalized distance using majority voting. Therefore, the identification accuracy has increased from 95% (using only non-fiducial technique) to 100%, at 70% training set for the fiducial technique and 50% training set for the non-fiducial.

4 CONCLUSIONS

ECG based human identification has shown promising results (David, Silva, Gamboa, Fred, & Figueiredo, 2013), (Zhang , Zhou, & Zeng, 2017), (Odinaka, et al., 2012). In this paper, we applied both fiducial and non-fiducial algorithms. Our preliminary results indicate that by measuring the STFT normalized distance, individuals can be identified with high accuracy. Furthermore, the identification accuracy increases after fusing histograms distances. Thus, features of QRS complex can play an effective role.

However, the size of training samples differs between the two techniques. Hence further algorithm development is needed in order to reduce it. Nonetheless, the height and slope features depend on the heart rate; therefore, QRS complex classification is needed to select the most effective beats which have an impact on the identification process. In contrast, finding the optimal window size is an important factor in the STFT based human identification.

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REFERENCES

Arteaga-Falconi, J., Al Osman, H., & El Saddik, A. (2016, March). ECG Authentication for Mobile Devices. *IEEE Transactions onInstrumentation and Mesurement, 65*, 591-600.

Chun Chi , W., Peng Tzu, C., & Pie Lun, H. (2019, May). Cancelable Biometric Recognition With ECGs: Subspace-Based Approaches. *IEEE Transactions on Forensics and Security, 14*, 1323-1336.

D.C. Chan, A., M. Hamdy, M., Badre, A., & Badee, V. (2008, February). Wavelet Distance Measure for Person IdentificationUsing Electrocardiograms. *IEEE Transactions on Instrumentation, 57*, 248-253.

David, C., Silva, H., Gamboa, H., Fred, A., & Figueiredo, M. (2013, February). Novel fiducial and non-fiducial approaches to electrocardiogram-based biometric systems. *Institution of Engineering Technology, 2*, 64-75.

Gutta, S., & Cheng, Q. (2016, March). Joint Feature Extraction and Classifier Design for ECG-Based Biometric Recognition. *IEEEJournal of Biomedical and Health Informatics, 20*, 460-468.

Islam, S., Alajlan, N., Bazi, Y., & S. Hichri, H. (2012, May). HBS: A Novel Biometric Feature Based onHeartbeat Morphology. *IEEEtransactions on Information Technology in Biomedicine, 16*, 445-453.

Joao, R. P., S. Cardoso, J., & Lourenco, A. (2018, June). Evolution, Current challenges, and Future Possibilities in ECG Biometrics. *IEEE Access, 6*, 34746-34776.

Li, H., & Jeremic, A. (2017). Semi-supervised Distributed Clustering for Bioinformatics - Comparison Study. *10th International Joint Conference on Biomedical Engineering Systems and Technologies, 4*, 259-264.

Lin, S.-L., Chen, C.-K., Lin, C.-L., Yang, W.-C., & Chiang, C.-T. (2014). Individual identification based on chaotic electrocardiogram signals during muscular exercise. *The Institution of Engineering*.

Liu, J., Yin, L., He, C., Wen, B., Hong, X., & Li, Y. (2018). A Multiscale Autoregressive Model-Based Electrocardiogram Identification Method. *IEEE Access*, 18251-18263.

Odinaka, I., A. O'Sullivan, J., J. Sirevaag, E., & W. Rohrbaugh, J. (2015, January). Cardiovascular Biometrics: Combining Mechanical and Electrical Signals. *IEEE Transactions on Information on Forensics and Security, 10*, 16-27.

Odinaka, I., Lai, P.-H., D. Kaplan, A., A. O'Sullivan, J., J. Sirevaag, E., & W. Rohrbaugh, J. (2012, December). ECG Biometric Recognition: A Comparative Analysis. *IEEE Transactions on Information on Forensics and Security, 7*, 1812-1824.

Sidek, K., Khalil, I., & F. Jelinek, H. (2014, November). ECG Biometric with Abnormal Cardiac Conditions in Remote Monitoring System. *ECG Biometric with Abnormal Cardiac Conditions, 44*, 1498-1509.

V. Oppenheim, A., & W. Schafer, R. (1989). *Discrete-Time Signal Processing.* New Jersey: Prentie-Hall, Inc.

Zhang , Q., Zhou, D., & Zeng, X. (2017). HeartID: A Multiresolution Convolutional Neural Network for ECG-Based Biometric Human Identification in Smart Health Applications. *IEEE Access, 5*, 11805-11816.