Fold Electrocardiogram Into a Fingerprint

Po-Ya Hsu
University of California, San Diego
p8hsu@ucsd.edu

Po-Han Hsu
University of California, San Diego
p6hsu@ucsd.edu

Hsin-Li Liu
Central Taiwan University of Science and Technology
101106@gtrial.ctust.edu.tw

Abstract

Electrocardiogram (ECG) has become a popular biometric to study since it is highly secured against spoofing attack. In this study, we address the issues of hard-required ECG data length and neglected causality when performing ECG identity matching tasks. First, we propose an ECG image generation algorithm that is able to handle any specified number of ECG heartbeats. Such an algorithm uses detected R-peaks as ***folding*** *points and projects ECG data onto a two-dimensional image, which overcomes the challenge of hardly-required fixed length and truncated ECG. Second, we leverage transfer learning and perform across-session testing. We construct the ECG identification models based on the pretrained AlexNet and ReseNet18 models. Our ECG biometric models are trained on the past ECG data and their performances are evaluated on future ECG data. Furthermore, we develop a voting strategy that is able to detect anomaly ECG heartbeats. Our novel ECG image generation approach shows itself to be competitive. Such method has been evaluated on the MIT-DB and ECG-ID datasets. We observe satisfying results of the proposed models in both datasets: 100% on the MIT-DB and 94.4% on ECG-ID. More importantly, our method is available to generate satisfying results by using a single ECG beat to conduct identity matching task: 100% on the MIT-DB and 91.7% on ECG-ID. In addition, qualitative analysis presents the perceptual uniqueness of ECG between individuals. We believe that the proposed ECG biometric system is promising to identify humans with short ECG sequence.*

1. Introduction

In modern society, biometric systems have been widely applied to human identification to achieve high level security. A standard biometric system is illustrated in Figure 1. Typical biometric systems process the data, extract their features, and evaluate the matching score between the query and the database to determine the subject's identity. Nowadays, fingerprint, face, and iris are commonly used biometrics [11]. However, all the aforementioned biometrics are vulnerable to spoofing attacks [35]. For example, fingerprints left on an object can be recreated with latex; iris images can be fooled with contact lenses; facial recognition can be cracked by high-resolution stolen photos.

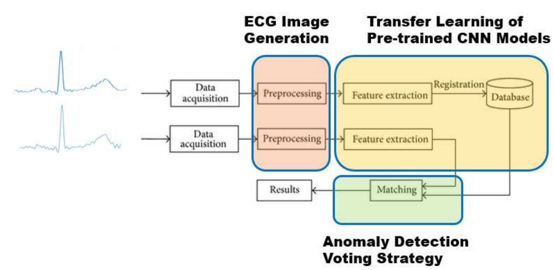


Figure 1. Schematics of a standard biometric system and our contributions. Standard biometric systems process the data, extract the features, and evaluate the matching score between the query and the database to determine the subject's identity. Red box represents our contributions of novel ECG data pre-processing technique. Yellow box stands for extracting features from transfer learning of the pre-trained CNN models. Green box stands for our contribution of devising a voting strategy that is aware of anomaly.

To circumvent the intrinsic issues in external biometrics, electrocardiogram (ECG) has gained its popularity as a biometric in recent years. ECG is a continuous measure of electrical depolarization and repolarization throughout cardiac activities; moreover, quasi-periodicity is observable in ECG. An individual's ECG is influenced by that individual's cardiovascular system, and the uniqueness of ECG has been reported in several studies [3, 18]. ECG shows several advantages as a biometric: (1) difficult to be stolen; (2) able

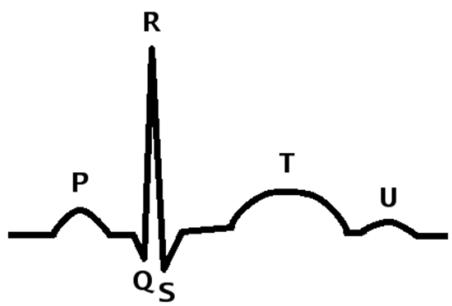


Figure 2. Illustration of a typical ECG waveform. P, Q, R, S, T, and U waves are fiducial points that are commonly observed in healthy subjects.

to indicate liveness; (3) easy to acquire.

Numerous feature extraction and pattern recognition techniques have been proposed for ECG, and they can be classified into two categories: fiducial and non-fiducial strategies.

1. **Fiducial Strategies:** Figure 2 shows that a typical ECG waveform contains fiducial points, namely, P, Q, R, S, T, and U waves. Based on the prior knowledge, researchers extract features such as the amplitude and the slope composed of these fiducial points [13, 24, 28]. The features selected from the QRS complex have been the most popular in the proposed ECG biometric systems because the QRS complex tends to be stable against physical and emotional variations [31]. The performance of fiducial methods depends on not only the existence but also the accurate acquisition of the fiducial points.

2. **Non-Fiducial Strategies:** To generalize the ECG identification models, researchers have suggested non-fiducial methods. Such techniques do not rely on the hand-crafted feature sets. Commonly used approaches are automatic segmentation of ECG waveforms followed by a machine-learning (ML) or deep-learning (DL) model [26, 29].

Non-fiducial strategies have attracted attention recently since ML and DL have shown promising results in accomplishing identity and image recognition tasks [7, 14, 9].

Several non-fiducial methods have been proposed in literature. For example, one-dimensional convolution neural network (1D-CNN) models have been proposed by Chen and Chen [4], Wu *et al*. [32], and Zhang *et al*. [34]. Besides CNN, one-dimensional recurrent neural network (1D-RNN) models have also been proposed by a number of researchers, including Lynn *et al*. [17], and Salloum and Tsai [25]. Other ECG identification approaches include sparse representation method proposed by Li *et al*. [15] and 2D-CNN methods proposed by Ranjan [23] and Byeon *et al*. [2].

While the aforementioned methods present promising ECG identification systems, we discover two issues that could possibly lie in the proposed methods. First, the segmentation of ECG requires to be an empirically fixed number. For example, in Salloum and Tsai's work [25], the length of the ECG waveform is forced to be 251 samples for the MITDB dataset and 301 for the ECG-ID dataset; both require the R-peaks positioning at the center. Similar ECG segmentation procedure has been adopted by Lynn *et al*. [17], but they stack and concatenate ECG heartbeats. In Chens' work [4], 251 samples have to be acquired from one ECG beat with the R-peak standing at the 71^{th} position. Generally speaking, some one-dimensional neural network models can only handle data of fixed length and position, which might not be generalizable for extreme ECG data.

Another issue is pointed out by a comparative analysis of ECG biometric systems conducted by Odinaka *et al*. [20]. In their paper, the authors indicate that a reliable ECG identification model should be trained on past ECG data and perform identity testing on future ECG data, instead of training and testing the ECG data within the same period. To be more specific, one should build an ECG identification model and conduct across-session tests instead of within-session tests. Some of the aforementioned works have reported within-session results [17, 25, 34], which could possibly bias the evaluation.

In this work, we address the two issues through a combination of approaches as shown in Figure 1. First, we propose an ECG image generation algorithm that is able to handle any specified number of ECG heartbeats. Such an algorithm uses detected R-peaks as folding points and projects ECG data onto a two-dimensional image, which overcomes the challenge of hardly-required fixed length and truncated ECG. Second, we perform across-session testing. We construct the ECG identification models by using the past ECG data and evaluate their performance on future ECG data. We leverage transfer learning of pre-trained CNN models to efficiently build the ECG biometric system. Furthermore, we develop a voting strategy that is able to detect anomaly ECG heartbeats.

The rest of the paper is organized as follows. We first review the relevant literature in Section 2 and then present our ECG image identification models in Section 3. Subsequently, in Section 4, we describe the two public ECG datasets, MITDB and ECG-ID, which are used to evaluate the performance of the proposed identification models. Next, we present and discuss our experiments and results in Section 5. Finally, we conclude our work in Section 6.

2. Related Work

Numerous works have been proposed to recognize the patterns of ECG waveforms, and on a large scale, they can be classified by the approaches being either fiducial or non-fiducial.

For fiducial approaches, researchers first extract the features from ECG waveforms and then apply machine learning classifiers to accomplish ECG biometric tasks. The features are often extracted first by labeling the characteristic points (P, Q, R, S, T, and U waves depicted in Figure 2) and then computed based on the algorithms devised by the researchers. For instance, Biel *et al*. combine 10 fiducials together with PCA and use generative model classifier to perform ECG biometric tasks [1]. Biel *et al*.'s model demonstrates an identification rate of 100% on 20 subjects with ECG collected through multiple days. Shen extract 17 fiducials from ECG waveforms and apply k-nearest neighbor (kNN) classifier to do identity matching [27]. Shen reports an identification rate of 95.3% on 168 subjects with ECG data collected on a single day.

For non-fiducial methods, we can split the techniques into ML and DL. For ML tactics, researchers extract non-fiducial features first and then perform identity matching with ML algorithms. For DL strategies, researchers combine the feature extraction and matching score computation together in a neural network model; or, they may leverage DL model as a feature extractor and perform classification task with other ML/DL classifiers.

For ML example, Ye *et al*. extract non-fiducial features with independent component analysis and discrete wavelet transform and utilize support vector machine of radial basis kernel to classify the subjects [33]. An identification rate of $> 80\%$ has been reported by Ye *et al*. on 65 subjects with ECG data measured on the same day. Ghofrani and Bostani choose autocorrelation and period transform as their weapon to extract non-fiducial features [5]. Then, they complete ECG biometric tasks with kNN and achieve an identification rate of 100% on 12 subjects.

For DL example, Salloum and Tsai build one hidden layer 1D-RNN with different functional units and evaluate the performance of the models on the ECG-ID and MITDB datasets. Their best identification rate is 100% for both datasets with long short-term memory (LSTM) chosen, which outperforms gated recurrent units. Moreover, the sequence length is required to be nine consecutive heartbeats [25]. Wu *et al*. combine 1D-CNN and RNN together and demonstrate identification rates of 99.70% and 97.54% on the MITDB and ECG-ID datasets, respectively. Zhang *et al*. develop a multi-resolution 1D-CNN which has archietecture similar to AlexNet and achieve an identification rate of 91.1% on the MITDB dataset.

For fiducial methods, the identification rate is influenced by the accuracy of extracted fiducial features, and for non-fiducial methods, depends on the structure of learning models and ECG data representation. We aim at developing a non-fiducial ECG identification technique that can address the data segmentation issue.

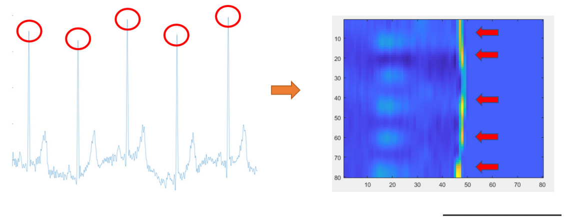


Figure 3. Demonstration of folding a raw signal into a two-dimensional ECG image. On the left, we present a raw ECG sample with five heartbeats; on the right, we draw the image of the ECG sample, which is generated by our folding approach. The five R-peaks are denoted in red circles and arrows on the left and right plots.

3. Using ECG image to identify humans

In this section, we present our ECG image identification system. There are four steps in building the whole system. First, we detect the R-peaks of ECG signals. Second, we generate a two-dimensional image for each segment of ECG signals. Third, we perform transfer learning to fine-tune the identification model parameters. Last, we use voting strategy to identify the subjects.

3.1. Detecting ECG R-peaks

Our first step is to detect each ECG beat from the raw signals. To complete this task, we use the Pan-Tompkins algorithm to detect the R-peaks of the raw signals [21]. Pan-Tompkins algorithm is a real-time and state of the art R-peaks detection method. It detects R-peaks by processing the raw signal through filtering and automatic thresholding. According to Pan and Tompkins's paper [21], the Pan-Tompkins algorithm can correctly detect 99.3% R-peaks in MITDB.

3.2. Generating 2D ECG Image

Figure 3 showcases the raw ECG signal and its generated ECG image. We develop an ECG image generation algorithm that can handle varying numbers of ECG beats. To explain the image generation procedure, we denote the detected R-peaks as R_i, where symbol i stands for the position of the R-peaks. Given a sequence of N R-peaks $\{R_{i_1}, R_{i_2}, R_{i_3}, ..., R_{i_N}\}$ in ascending order, we compute the midpoints between each two consecutive R-peaks and create a new sequence $\{R_{j_1}, R_{j_2}, R_{j_3}, ..., R_{j_{N-1}}\}$, in which j_k is the midpoints of the k^{th} and $k+1^{th}$ R-peaks.

Once we have the R-peak and midpoint sequences, we generate the image in the following procedure:

$$X[k,:] = \begin{cases} D[R_{j_{\lceil k/2 \rceil}} : 1 : R_{i_{\lceil k/2 \rceil + 1}}], & \text{if } k\%2 = 1 \\ D[R_{j_{\lceil k/2 \rceil + 1}} : -1 : R_{i_{\lceil k/2 \rceil + 1}}], & \text{otherwise} \end{cases} \tag{1}$$

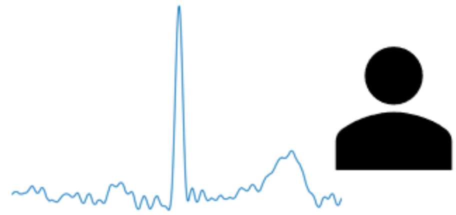
where $X[k,:]$ represents the k^{th} row of the generated image X, and D is the ECG data. For the odd number of row, we project the ECG data from the midpoint to the R-peak onto the row in sequential order; as for the even number of row, we project the ECG data from the R-peak to the next midpoint in reverse order. Here, we directly treat each pixel as one time-point, and the pixel's value represents the corresponding ECG voltage. Since the period of heartbeats ranges from $0.5 - 2$ Hz, we guarantee the image size is bounded by $2(N-1) \times 2f_s$, where f_s is the data sampling rate and N being the number of the ECG beats.

3.3. Building ECG Identification Models

Unlike conventional biometric identification system, we combine feature extraction and matching distance evaluation together by using the pre-trained deep learning models. In this research, we select ResNet18 [8] and AlexNet [12] as our pre-trained networks to conduct transfer learning since they are known for the abilities to extract informative features from images. For each network, we change the input size to $M \times M \times 1$ and output size to C in which $M \times M$ is the size of the ECG image and C is the number of subjects to identify.

Model	CNNs	Dataset	# ECG Beat
a	AlexNet	ECG-ID	1
b	AlexNet	ECG-ID	2
c	AlexNet	ECG-ID	3
d	AlexNet	ECG-ID	4
e	AlexNet	ECG-ID	5
f	AlexNet	MIT-DB	1
g	AlexNet	MIT-DB	2
h	AlexNet	MIT-DB	3
i	AlexNet	MIT-DB	4
j	AlexNet	MIT-DB	5
k	ResNet18	ECG-ID	1
l	ResNet18	ECG-ID	2
m	ResNet18	ECG-ID	3
n	ResNet18	ECG-ID	4
o	ResNet18	ECG-ID	5
p	ResNet18	MIT-DB	1
q	ResNet18	MIT-DB	2
r	ResNet18	MIT-DB	3
s	ResNet18	MIT-DB	4
t	ResNet18	MIT-DB	5

Table 1. Models Tested in this work.



Model	Model Output	Result
1 Beat	Subject 1	Subject 1
2 Beats	Subject 1	Subject 1
3 Beats	Subject 2	Anomaly

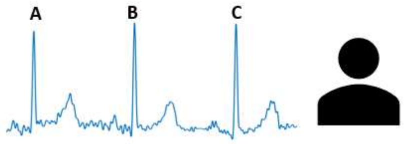
Figure 4. Demonstration of the subject identification result of one ECG beat.

Table 1 displays all the models built in the current research. For each ECG sample, we are free to select the heartbeat number and generate the ECG image by using the approach introduced in 3.2. Therefore, for each given length (defined by heartbeat counts) of data sample, we trained an identification model. For example, X-HB model means an identification model for input images of X consecutive heartbeats. In this study, we built the models for sequence length varying from one to five for each dataset.

3.4. Voting for Identification

We adopt anomaly detection and majority vote in final identification decision. Suppose we trained 1-HB, 2-HB, and 3-HB models, for each testing heartbeat, we would have three identification results computed by each model, respectively. Then, we claim the testing heartbeat to be anomaly if any two results differ from each other. In other words, a heartbeat is valid only if it shows identical identity across all the identification models. For each recording, we first sift the valid heartbeats and then use majority vote to determine the identity of the subject. The identification rate is calculated by the number of correct prediction made divided by total prediction number.

We provide an example to elucidate the introduced identity matching strategy in Figures 4 and 5. To simplify the explanation, we consider the case of ECG beats with models trained on sequence length varying from one to three. In Figure 4, we display the outputs and identity matching results of three models from the same ECG beat. If we iden-



Model	Result of A	Result of B	Result of C	Voting
1 Beat	Subject 1	Subject 1	Subject 2	Subject 1
2 Beats	Subject 1	Subject 1	Anomaly	Subject 1
3 Beats	Anomaly	Subject 1	Anomaly	Subject 1

Figure 5. Demonstration of the subject identification result of three ECG beats using our voting strategy.

tify the subject based on a single ECG beat, we only need to take the output of 1-HB model into account; if we identify the subject using two consecutive ECG beats, then we take outputs from 1-HB and 2-HB models into consideration. In Figure 4, both 1-HB and 2-HB generate the same identity output; therefore, the subject identity is matchable. Finally, if we recognize the subject with three consecutive ECG beats, then we take all three outputs into consideration. Since the output of the 3-HB model deviates from 1-HB and 2-HB models, we mark the ECG heartbeat as anomaly.

Following the anomaly detection of single ECG beat, we perform majority voting to finalize the identity matching of the subject. In Figure 5, we consider a sequence of three ECG beats. For 1-HB model, we conduct majority vote without ambiguity. Considering the results of two consecutive ECG beats, we observe one anomaly and two identical matchings; as a result, we match the subject to subject 1. Finally, for three consecutive ECG beats, we arrive at two anomalies and one successful subject match. We still match the subject to subject 1 since we do not take anomalies into account when voting.

4. Datasets

We ran our identification models on two publicly available datasets that are often used for ECG biometric system evaluation: MITDB [19] and ECG-ID [16]. Both datasets are downloadable from PhysioNet database [6].

The MITDB dataset contains 48 two-channel 30-minute recordings of ECG measured from 47 subjects (25 male and 22 female) diagnosed of arrhythmia. Only one subject has two recordings. Every recording is sampled at a frequency of 360 Hz with 11-bit resolution over a 10 mV range.

The ECG-ID dataset contains 310 one-channel recordings of ECG obtained from 90 subjects (44 male and 46 female). Each subject has various number of recordings, which ranges from one to twenty. Some subjects have recordings collected on the same day, while the others have recordings measured over 6 months. All the recordings have length of 20 seconds sampled at 500 Hz with 12-bit resolution over 10 mV range. The ECG-ID is mentioned as a challenging dataset by several previous works [15, 23, 32].

5. Experiments

5.1. Experimental Setup and Implementation

We aim at using the past ECG to verify the identity of future ECG; as a result, we choose to follow the experiment settings in [32] for the MITDB dataset and [22] for the ECG-ID dataset. For the MITDB dataset, we use the first 70% of heartbeats as training and the rest as testing for all 47 subjects. Concerning the ECG-ID dataset, we select the same 12 subjects (id: 3, 10, 24, 25, 30, 32, 34, 36, 52, 53, 59, 72) who have recordings collected on multiple days as Patro et al. did [22]. We train our identification models on the first two recordings and test them on the following three recordings.

We conduct all the experiments with MATLAB R2019B. For image generation, we set the image size as $2(N-1)\times f_s$ and resize the image to 80×80 to train the models. For training process, we use adam optimizer [10] with learning rate 0.0001. Based on the size of the two datasets, we set the mini-batch size to 20 for the ECG-ID dataset and 100 for the MIT-DB dataset. We found that 20 epochs were enough for the models to converge, so we set 20 as the number of the epoch for our experiments.

5.2. Identification of ECG Image

We show the performance of each model in Table 2, in which the plus sign stands for adopting the voting strategy introduced in 3.4. Considering the MITDB dataset, our model performs very well with an identification rate of 100% in all number of ECG. We think there are two reasons that can explain such good results. First, we have sufficiently large data sample during the training process for the MIT-DB dataset. Second, although we used the past ECG to predict the future, the recording is still the same one for each individual. As for the ECG-ID dataset, interesting results have shown. Single beat and five consecutive beats produce the best results in both AlexNet and ResNet18 transfer learning models. In addition, ResNet18 trained with five consecutive beats achieves the best performance with an identification rate of **94.4%**. This indicates that two and three consecutive beats are prone to identity matching errors than single beat does. Such a phenomenon might be induced by short-term bad ECG data acquisition. Nevertheless, keep adding beat numbers on top of three consecutive beats pulls back to good results.

Model	Identification Rate
a	88.89%
a+b	83.33%
a+b+c	83.33%
a+b+c+d	91.7%
a+b+c+d+e	91.7%
f	100%
f+g	100%
f+g+h	100%
f+g+h+i	100%
f+g+h+i+j	100%
k	91.7%
k+l	88.9%
k+l+m	88.9%
k+l+m+n	91.7%
k+l+m+n+o	94.4%
p	100%
p+q	100%
p+q+r	100%
p+q+r+s	100%
p+q+r+s+t	100%

Table 2. Performance of the models in this work.

Model on MIT-DB	Identification Rate
1D-CNN + LSTM [32]	99.70%
Ours [AlexNet and ResNet18]	**100%**
Model on ECG-ID	**Identification Rate**
Fiducial [22]	88.9%
PCANet + SVM [30]	**94.4%**
Ours [ResNet18-5 beats]	**94.4%**

Table 3. Comparison to the state of the art.

5.3. Comparison to the state of the art

We compare the performance of our model to the state of the art in Table 3. Our model shows its competency in both datasets. In MIT-DB dataset, most published results demonstrate outstanding identification results. As to the ECG-ID results, it appears that non-fiducial methods such as ours and Wang *et al.* [30] are likely to explore the features for better identity matching. The reasons could be due to the short and varying states of the ECG data in the ECG-ID dataset. We investigate into the mis-classified subject and discover that both our model and Wang *et al.*'s falsify two recordings of subject 72 as subject 59. Given the fact that two models arrive at the same mis-classification, it seems reasonable to conclude that the two recordings of subject 72 are susceptible to be categorized as subject 59.

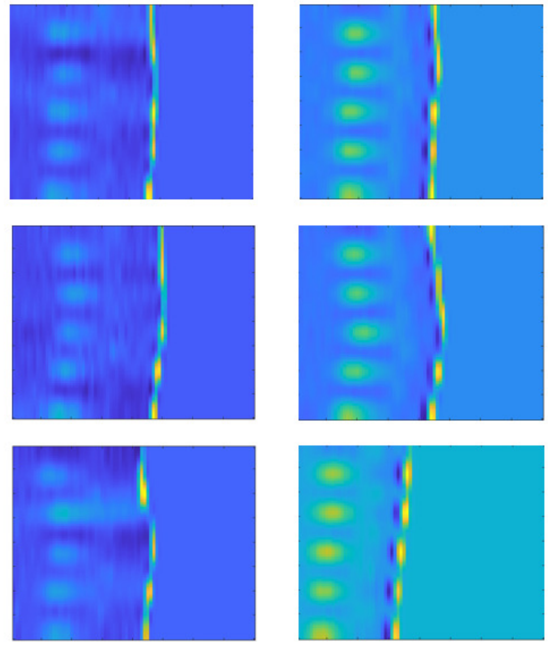


Figure 6. Demonstration of ECG image generated from two subjects in the ECG-ID dataset. All the images are constructed from five consecutive ECG beats. Three figures on the left plot ECG image of subject 3, while three figures on the right plot ECG image of subject 72. The first two rows are recordings in the training set; the last row shows ECG image in the testing set.

5.4. Qualitative Results of ECG Image

Figures 6 and 7 demonstrate the ECG images generated from two different subjects within the ECG-ID dataset and the MIT-DB dataset, respectively. We observe not only the perceptual difference between each two subjects but also the visual similarity between different recordings of the same subject. Focusing on the ECG-ID dataset, we are able to tell that subject 72 has either larger P wave or T wave compared to subject 3, whereas subject 3 has a sharper R-peak. In addition, the testing data of subject 2 differs from its training data more than subject 3 does. Shifting the attention to the MIT-DB dataset, we observe the differences of heart rate between subject 100 and subject 234. Subject 234 has a higher heart rate compared to subject 100 because it displays shorter folding segment. Furthermore, arrhythmic heart beats are clearly shown in the testing data of subject 100, in which the folding ECG segments have observable different lengths. In summary, the qualitative results showcase that ECG could be a promising biometric.

6. Conclusion

We contribute a novel ECG image generation approach that is able to generate competitive ECG biometric mod-

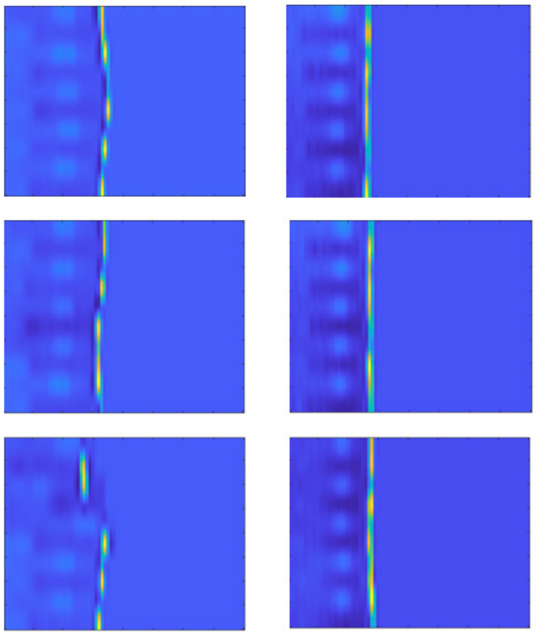


Figure 7. Demonstration of ECG image generated from two subjects in the MIT-DB dataset. All the images are constructed from five consecutive ECG beats. Three figures on the left plot ECG image of subject 100, while three figures on the right plot ECG image of subject 234. The first two rows are recordings in the training set; the last row shows ECG image in the testing set.

els by leveraging transfer learning method. Such approach has been evaluated on MIT-DB and ECG-ID datasets. We observe satisfiable results of the proposed models in both datasets: 100% on the MIT-DB and 94.4% on ECG-ID. In addition, qualitative results demonstrate the uniqueness of ECG in each subject. More importantly, our method also generate satisfying results by using a single ECG beat to conduct identity matching task.

References

[1] Lena Biel, Ola Pettersson, Lennart Philipson, and Peter Wide. Ecg analysis: a new approach in human identification. *IEEE Transactions on Instrumentation and Measurement*, 50(3):808–812, 2001. 3

[2] Yeong-Hyeon Byeon and Keun-Chang Kwak. Pre-configured deep convolutional neural networks with various time-frequency representations for biometrics from ecg signals. *Applied Sciences*, 9(22):4810, 2019. 2

[3] Carlos Carreiras, André Lourenço, Hugo Silva, Ana Fred, and Rui Ferreira. Evaluating template uniqueness in ecg biometrics. In *Informatics in Control, Automation and Robotics*, pages 111–123. Springer, 2016. 1

[4] Ying Chen and Wenxi Chen. Finger ecg based two-phase authentication using 1d convolutional neural networks. In *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 336–339. IEEE, 2018. 2

[5] Nahid Ghofrani and Reza Bostani. Reliable features for an ecg-based biometric system. In *2010 17th Iranian Conference of Biomedical Engineering (ICBME)*, pages 1–5. IEEE, 2010. 3

[6] Ary L Goldberger, Luis AN Amaral, Leon Glass, Jeffrey M Hausdorff, Plamen Ch Ivanov, Roger G Mark, Joseph E Mietus, George B Moody, Chung-Kang Peng, and H Eugene Stanley. Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals. *circulation*, 101(23):e215–e220, 2000. 5

[7] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016. 2

[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016. 4

[9] Po-Ya Hsu and Chester Holtz. A comparison of machine learning tools for early prediction of sepsis from icu data. In *2019 Computing in Cardiology (CinC)*, pages Page–1. IEEE, 2019. 2

[10] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014. 5

[11] Teddy Ko. Multimodal biometric identification for large user population using fingerprint, face and iris recognition. In *34th Applied Imagery and Pattern Recognition Workshop (AIPR'05)*, pages 6–pp. IEEE, 2005. 1

[12] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012. 4

[13] Nancy Laplante, Phillip A Laplante, Jeffrey Voas, and Jane Cleland-Huang. Caring: An undiscovered" super-ility" of smart healthcare. *IEEE software*, 33(6):16–19, 2016. 2

[14] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. *nature*, 521(7553):436–444, 2015. 2

[15] Rui Li, Gongping Yang, Kuikui Wang, Yuwen Huang, Feng Yuan, and Yilong Yin. Robust ecg biometrics using gnmf and sparse representation. *Pattern Recognition Letters*, 129:70–76, 2020. 2, 5

[16] Tatiana S Lugovaya. Biometric human identification based on ecg. *PhysioNet*, 2005. 5

[17] Htet Myet Lynn, Sung Bum Pan, and Pankoo Kim. A deep bidirectional gru network model for biometric electrocardiogram classification based on recurrent neural networks. *IEEE Access*, 7:145395–145405, 2019. 2

[18] Mario Merone, Paolo Soda, Mario Sansone, and Carlo Sansone. Ecg databases for biometric systems: A systematic review. *Expert Systems with Applications*, 67:189–202, 2017. 1

[19] George B Moody and Roger G Mark. The impact of the mit-bih arrhythmia database. *IEEE Engineering in Medicine and Biology Magazine*, 20(3):45–50, 2001. 5

[20] Ikenna Odinaka, Po-Hsiang Lai, Alan D Kaplan, Joseph A O'Sullivan, Erik J Sirevaag, and John W Rohrbaugh. Ecg

biometric recognition: A comparative analysis. *IEEE Transactions on Information Forensics and Security*, 7(6):1812–1824, 2012. 2

[21] Jiapu Pan and Willis J Tompkins. A real-time qrs detection algorithm. *IEEE transactions on biomedical engineering*, (3):230–236, 1985. 3

[22] Kiran Kumar Patro and P Rajesh Kumar. Effective feature extraction of ecg for biometric application. *Procedia computer science*, 115:296–306, 2017. 5, 6

[23] Abhishek Ranjan. Permanence of ecg biometric: Experiments using convolutional neural networks. In *2019 International Conference on Biometrics (ICB)*, pages 1–6. IEEE, 2019. 2, 5

[24] Sairul I Safie, John J Soraghan, and Lykourgos Petropoulakis. Ecg biometric authentication using pulse active width (paw). In *2011 IEEE Workshop on Biometric Measurements and Systems for Security and Medical Applications (BIOMS)*, pages 1–6. IEEE, 2011. 2

[25] Ronald Salloum and C-C Jay Kuo. Ecg-based biometrics using recurrent neural networks. In *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 2062–2066. IEEE, 2017. 2, 3

[26] LN Sharma, RK Tripathy, and Samarendra Dandapat. Multiscale energy and eigenspace approach to detection and localization of myocardial infarction. *IEEE transactions on biomedical engineering*, 62(7):1827–1837, 2015. 2

[27] Tsu-Wang Shen, Willis J Tompkins, and Yu Hen Hu. Implementation of a one-lead ecg human identification system on a normal population. *Journal of Engineering and Computer Innovations*, 2(1):12–21, 2011. 3

[28] X Tang and L Shu. Classification of electrocardiogram signals with rs and quantum neural networks. *International Journal of Multimedia and Ubiquitous Engineering*, 9(2):363–372, 2014. 2

[29] Manal Tantawi, KENNETH Revett, ABDEL-BADEEH Salem, and Mohamed F Tolba. Ecg based biometric recognition using wavelets and rbf neural network. In *Proc. 7th Eur. Comput. Conf.(ECC)*, pages 100–105, 2013. 2

[30] Di Wang, Yujuan Si, Weiyi Yang, Gong Zhang, and Tong Liu. A novel heart rate robust method for short-term electrocardiogram biometric identification. *Applied Sciences*, 9(1):201, 2019. 6

[31] Yongjin Wang, Foteini Agrafioti, Dimitrios Hatzinakos, and Konstantinos N Plataniotis. Analysis of human electrocardiogram for biometric recognition. *EURASIP journal on Advances in Signal Processing*, 2008(1):148658, 2007. 2

[32] Bo Wu, Gongping Yang, Lu Yang, and Yilong Yin. Robust ecg biometrics using two-stage model. In *2018 24th International Conference on Pattern Recognition (ICPR)*, pages 1062–1067. IEEE, 2018. 2, 5, 6

[33] Can Ye, Miguel Tavares Coimbra, and BVK Vijaya Kumar. Investigation of human identification using two-lead electrocardiogram (ecg) signals. In *2010 Fourth IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS)*, pages 1–8. IEEE, 2010. 3

[34] Qingxue Zhang, Dian Zhou, and Xuan Zeng. Heartid: A multiresolution convolutional neural network for ecg-based biometric human identification in smart health applications. *Ieee Access*, 5:11805–11816, 2017. 2

[35] Zhidong Zhao, Yefei Zhang, Yanjun Deng, and Xiaohong Zhang. Ecg authentication system design incorporating a convolutional neural network and generalized s-transformation. *Computers in biology and medicine*, 102:168–179, 2018. 1