ECG biometric using 2D Deep Convolutional Neural Network

Siddartha Thentu, Renato Cordeiro, Youngee Park, and Nima Karimian
Deportment of Computer Engineering
San Jose State University
San Jose, California, USA

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***Abstract*—We propose a novel multi-scale continuous wavelet transform feature method to accurately obtain micro-texture and multi-scale ECG characteristics and demonstrate how it could benefit from the state-of-the-art deep convolutional neural network techniques. In other words, we performed transfer learning with popular CNN architectures such as InceptionV3, VGG16, VGG19, Inception ResNetV2, MobileNetV2, and Xception which have been trained on the ImageNet. Our proposed ECG biometric framework achieves an average identification rate of 99.96% on CEBDB, 99.47% on PTB dataset with 290 subjects. We also evaluate the effectiveness of the proposed algorithm with the other two public ECG datasets with diverse behaviors.**

I. Introduction

The popularity of the biometric systems by the consumer continues to grow and demonstrates how it can be successfully leveraged to meet the insatiable consumer demand for practical dexterity. Today, wearable devices and smartphones are equipped with powerful advanced biometric technologies such as fingerprint and face recognition. The widespread adaptation of fingerprint and facial biometrics holds the promise of a more secure way to prove identity but comes with various drawbacks such as presentation attacks [21]. One concern is whether biometrics can be leveraged successfully in different situations. Due to the outbreak of the COVID-19 pandemic grips from all over the globe, most of the people who use face biometric verification for different applications are encountering recognition obstacles due to wearing face masks to prevent the spread of viruses. Many people are entering the bank, shopping center, airport with their faces covered, resulting in unlocking their phones, unauthorized boarding pass using CLEAR, or making a biometric mobile transactions almost impossible. Moreover, spoofing concerns will invariably arise, too [16], [17], [29], [32]. Unlike other biometrics, ECG-based biometric offers intrinsic aliveness characteristics, difficult to spoof, and relatively easy to measure [10], [13].

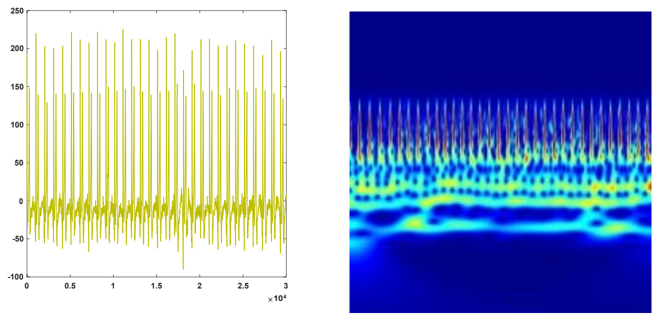
While ECG-based biometric authentication offers several benefits, several limitations are encountered. The ECG signals contain a lot of timing information and they are very sensitive to noises [12]. Thus, it could change based on the subject's prior activities, sensor quality, environment, and other factors. Hence, handcrafted feature extraction such as the fiducial feature extraction technique may not be the best approach. On the other hand, with the advent of deep learning, facial and fingerprint recognition have greatly benefited from transfer learning from state-of-the-art CNN architectures, while ECG biometrics are lacking behind due to 1 dimensional signal. Therefore, we propose a novel continuous wavelet transform feature extraction for ECG biometric identification based on the 2D representation of the image. Our proposed technique avoids fiducial feature extraction and highly customized feature engineering. In addition, our novel proposed method not only provide deep information about both the timing and frequency domain but also is compatible with transfer learning due to the image structure of the ECG.

In short, the novelty and contributions of the paper are as follows:

1) **A novel 2D representation of ECG**: We propose a novel multi-scale continuous wavelet transform feature method to accurately obtain micro-texture and 2D representation of an ECG characteristics in order to take advantage from mature field of computer vision to ECG biometrics such as 2D convolution, max-pooling, and transfer learning.
2) **Image based ECG biometric identification using transfer learning**: We employed deep CNN architecture such as Xception, VGG19, VGG16, mobilenetv2, Inception architecture to evaluate the ECG-based biometric identification using the converted 2D representation of ECG. Our proposed deep mobilenetv2 CNN framework achieves 98.21% accuracy with 0.06% EER.
3) **Effectiveness of proposed technique**: Extensive experiments are conducted on four public ECG datasets in order to evaluate the proposed techniques. The results demonstrate that the proposed non-hand crafted feature extraction outperforms several state-of-the-art methods.

II. Literature Review

The search for ECG-based biometric began with 12 leads recording studies by Biel et.al [2] just two decades ago. These initial studies inspired follow-up work exploring handcrafted feature extraction for ECG biometric recognition. Since there was no specific database for ECG-based biometric, most of the work performed analysis on the public database from Physionet [1] that is known to identify cardiac abnormalities. Later work, different public databases are applied for ECG-based biometric recognition. In 2005, Lugovaya et.al [20] introduced the ECG-ID database with 90 subjects for the biometric study and they found that the ECG trait is inherently



(a) (b)

Fig. 1. Multiple heartbeats from ECG signal, (a) ECG in the time domain and (b) 2D representation of ECG image after applying continuous wavelet transform which provides timing, and frequency information.

difficult to be cloned. It has also been demonstrated ECG-based biometric recognition can be performed using a single lead which is suitable for mobile and wearable devices [11]. While physiological biometrics such as fingerprint and faces offer accurate and fast recognition, they are easily observable and can be easily obtained and spoofed by adversaries. Considering that ECG is a vital signal and motivated by its inherent liveness, Caused that biometric community to combine it with a fingerprint liveness detection algorithm [15]. However, the most drawback of ECG-based biometric is that there was no large population size of database with diverse attributes such as healthy, unhealthy, age, and weight. Moreover, most of the existing work falls into a handcrafted technique rather than standard methods. Although deep learning is being widely adopted for computer vision, less research has been prominent in ECG-based recognition. We summarized the most relevant deep learning ECG biometric approach that has been explored.

Hong et.al [9] utilized Inception-v3 CNN model by transferring ECG into an image using spatial correlation image. The model classifies all the subjects of the PTB dataset and obtained a 97.84% identification rate. Labati et.al [18] proposed a (1D)-CNN model, comprising six convolutional layers, three max-pooling layers, one dropout layer, a fully connected layer, and a Soft-max layer. The PTB database with only 52 subjects (healthy) was considered and achieved 2.90% EER. Kim et.al [14] used the resnet-ve-152, inception-resnet-v2, inception-v4, and inception-v3 and 2-D coupling image generated from three sequential cycles of the ECG signal. The MIT-BIH normal sinus rhythm database and PTB database with 100 subjects out of 290 subjects were used and the identification rate of 98.45% was reported.

Chu et.al [5] proposed a parallel multi-scale one-dimensional residual network contains an input layer, a pre-processing convolutional block, three parallel residual blocks, embedding fully connected layer, and an extra fully connected layer. Three public datasets including the ECG-ID, PTB, and MIT-BHI with an accuracy of 97.7%, 99.33.%, and 94.74% is reported, respectively. Zhang et.al [33] proposed to use a multi-resolution CNN for identification. They used wavelet and autocorrelation instead of feeding raw ECG as an input to the CNN for identification. Moreover, CNN was designed as a group dedicated to CNN. Li et.al [19], proposed a 1D F-CNN model, comprising three Convolution layers, two Pooling layers, and three fully-connected layers. ECG biometric identification has been implemented on six public databases with an average of 95.2% identification rate. Luz et.al [6] proposed a combination of raw ECG and its spectrogram and CNN for biometric authentication. They used three public databases and evaluate their proposed system based on the DET curve and equal error rate. Zhao et.al [34] propose ECG identification with S-transform—GST and CNN. They applied a GST on the ECG signal and generate an image for the input of CNN. The best result on identification has an accuracy of 96.63% and does not report experiments on authentication.

Pinto et.al [25] proposed a (1D)-CNN model, comprising four convolutional layers, three max-pooling layers, two fully connected layers, and a triplet loss for authentication. 7.86%, 15.37%, and 9.06% equal error rate on three public databases reported on UofTDB, CYBHi, and PTB respectively. Ranjan et.al [26] convert the ECG segment into an image and used the 2D CNN model for identification purposes. They report an EER of 2% on the ECG-ID database for identification. *However, the main challenge with existing works are not only most of the subjects are excluded, but also the databases were limited in terms of diversity of population size. Moreover, the ECG waveform also contains a lot of timing and frequency information in which have not been studied in the past. In this study, we go beyond the timing information provided from the original ECG and explore uncovered characteristics of ECG. Specifically, we applied continuous wavelet transform to take advantage of timing and frequency together and convert it to a 2D representation image in order to get the benefit of the state-of-the-art deep learning techniques.*

III. Our Proposed Method

ECG signals can be measured using non-invasive and low-cost sensors. Due to non-stationary characteristics, it demonstrates time-varying morphological content and influence from different environmental conditions such as noise and artifacts such as power line interface, baseline drift, motion artifacts, arrhythmia, electromyography (EMG), and intra-user variability. Apart from the handcrafted feature extraction or non-handcrafted, the filtering is a major pre-processing step that can not be eliminated due to its impact on performance. *Unlike face and fingerprint biometrics, the ECG signal is a more non-stationary signal and it is affected by the aforementioned environmental noises that can not be handled by deep learning without pre-processing.* ECG comprises three almost immediately distinguishable waves: the P wave, the QRS complex, and the T wave, and it is continuously repeated. In order to speed up enrollment and authentication, one cycle of ECG that has all three waveforms is sufficient. ECG segmentation not only reduces the template size but also due to the fewer data processing, the power consumption of the device is maintained.

Authors	Database	NS	F	EER	Id	SE
Hong et.al [9]	PTB	200	CNN (Inception)	–	98.1%	Y
Labati et.al [18]	PTB	52	CNN	2.90%	100	Y
Kim et.al [14]	PTB	52	CNN (Inception)	–	98.45%	Y
	MIT-BIH	18			99.2%	
Chu et.al [5]	ECG-ID	90	CNN	2%	98.24%	Y
	PTB	290		0.59%	100%	
	MIT-BIH	48		4.74%	95.99%	
Zhang et.al [33]	CEBSDB	20	CWT CNN	–	99%	N
	STDB	28			90.3%	
	MITDB	47			91.1%	
	NSRDB	18			95.1%	
	AFDB	23			93.9%	
	WECG	22			95.5%	
	VFDB	22			86.6%	
	FANTASIA	20			97.2%	
Li et.al [19]	CEBSDB	20	Cascaded CNN	–	93.1%	N
	NSRDB	18			91.4%	
	STDB	28			92.7%	
	AFDB	23			89.7%	
	FANTASIA	20			99.9%	
Luz et.al [6]	CYBHi	65	CNN	13.93%	–	Y
	UofTDB	1019		14.27%		
Zhao et.al [34]	ECG-ID	90	CNN		96.63%	N
Pinto et.al [25]	UofTDB	1019	CNN	7.86%	–	Y
	CYBHi	126		15.37%		
	PTB	290		9.03%		
Ranjan et.al [26]	Private	800	CNN	2.0%		N

TABLE I

SUMMARY OF THE STATE-OF-THE-ART APPROACHES FOR ECG BIOMETRICS. NS - NUMBER OF SUBJECTS, F - FEATURE EXTRACTION, EER - EQUAL ERROR RATE, ID - IDENTIFICATION RATE, SE - SUBJECT EXCLUSIVE, CNN - CONVOLUTIONAL NEURAL NETWORK.

A. Segmentation

An ECG signal is formed by a series of waveforms including P, Q, R, S, and T peaks in a periodic format which represent the sequence of depolarization and repolarization. One sequence of ECG signals that comprises the aforementioned peaks is called the ECG segment in which provide the same information over time. Since, each ECG segment contains same information of the signal,it is not efficient to repetitively read correlating signals. By segmenting ECG signal into the one cycle of waveform, not only the size of data used for biometric template is decreased, but also the processing time and power consumption will be degraded. To segment ECG signal, Pan-Tompkins [23] technique has been utilized to identify R-peak. Upon successful completion of R peak detection, the ECG signals are isolated into ECG beats (segments). We used fixed length segmentation with $n = 0.16s$ and $n^l = 0.41s$ where n and n^l are the time periods before and after the R peaks.

B. Two-Dimensional Representation of ECG

A 2D representation of ECG instead of the 1D signal provides more opportunity to integrate many properties from the computer vision field into ECG biometric domains including 2D convolution and max-pooling, transfer learning, larger filter sizes. To generate a 2D representation of an ECG signal, the entire user's ECG is segmented into heartbeats using fixed-length segmentation described in Section III-A. Then, a continuous wavelet transformation function with Morse wavelets is applied to the ECG signal corresponding to each user. The resulting coefficients are transformed into RGB format which creates the 2D representation of the ECG signal.

$$\Psi_{P,\gamma}(\omega) = U(\omega)a_{P,\gamma}\omega^{\frac{P^2}{\gamma}} e^{-\omega^{\gamma}} \quad (1)$$

where $U(\omega)$ is the unit step, a $a_{p,\gamma}$ is a normalizing constant, p^2 is the time-bandwidth product, and γ characterizes the symmetry of the Morse wavelet. After converted 2D representation of the ECG signal, we then resized into the 224×224 or 299×299 dimension to get uniformity in the shape of input.

IV. EXPERIMENTAL SETUP

A. Evaluation metrics

To evaluate the performance of our ECG based biometric algorithm, we conducted the experiments with three error rates: false positive/accept rate (*FPR/FAR*), true positive/accept rate (*TPR*), and equal error rate (*EER*). *FPR* is the probability that the biometric system incorrectly rejects an authorized user by an access attempt whereas *FAR* is the probability that the biometric system accepts an unauthorized user and allow them to access attempt incorrectly. Both *FRR* and *TPR* can be traded-off with each other in order to find the optimal and desired *EER*. *EER* is the location on the receiver operator characteristic (ROC) curve where the *FAR* and *FRR* are equal. We also used identification rank which is defined as the user's correct identity corresponding to the top t matches with N enrolled identity, where the ($1 \leq t \ll N$).) We also evaluate our system using identification Rate or accuracy where it is defined as a portion of correctly identified subjects.

B. Database

To evaluate our proposed ECG biometric system, four public ECG databases has been examined in this study. The databases offer different size, status of condition, length and etc. The summary of databases information can be found in Table II.

PTB Diagnostic ECG Database (PTB): This database was obtained by the Physikalisch-Technische Bundesanstalt (PTB), National Metrology Institute of Germany [3]. The database is collected from non-commercial sensors. Overall, 290 subjects participated in the study with various profile information such as gender, age, healthy, unhealthy, different lengths with the sample rate of 1 kHz.

Combined measurement of ECG, breathing, and seismocardiograms database (CEBSDB): CEBSDB database [8] only contain healthy subjects. Moreover, compared to other databases, only 20 subjects has been participated. Each ECG data recorded at a sampling frequency of 5 kHz

Arrhythmia Database (MITDB): The *MITDB* [22] is an ECG database that was collected in the laboratories at Boston's Beth Israel Hospital and MIT. It contains 48 half-hour ECG recordings from 47 subjects. The recordings were digitized at 360 samples per second per channel with an 11-bit resolution over a 10 mV range.

ECG identification database (ECG-ID). The *ECG-ID* were recorded for biometric identification purpose [20]. Each raw ECG record was acquired for about 20 seconds with a

Dataset	# Subjects	Sample Rate (Hz)	Type	Health state
PTB	290	100	Public	Healthy/Myocardial infarction
ECG-ID	90	500	Public	Arrhythmia
MITDB	47	360	Public	Healthy
CEBSDB	20	10,000	Public	Healthy

TABLE II

THE SUMMARY OF THE FOUR DATA SETS ADOPTED IN OUR EXPERIMENTS.

	MITDB				CEBDB				PTB				ECG-ID			
Model	Id	EER	FRR	FAR	Id	EER	FRR	FAR	Id	EER	FRR	FAR	Id	EER	FRR	FAR
VGG16	95.83	0.17	4.17	0.09	99.93	0.007	0.08	0.004	97.43	0.017	4.05	0.009	96.42	0.08	3.46	0.04
VGG19	95.06	0.21	4.94	0.10	99.91	0.008	0.08	0.004	98.05	0.013	3.46	0.006	96.24	0.08	3.72	0.04
MOBILENET V2	97.45	0.14	2.55	0.01	99.96	0.008	0.05	0.003	99.47	0.003	0.85	0.001	97.52	0.05	2.49	0.02
INCEPTION V3	96.43	0.15	3.57	0.07	99.94	0.005	0.07	0.004	99.34	0.004	0.96	0.002	97.15	0.06	2.77	0.06
XCEPTION	96.77	0.13	3.23	0.07	99.93	0.008	0.06	0.003	99.31	0.005	1.14	0.002	96.88	0.07	2.98	0.03
INCEPTION RESNET V2	96.51	0.14	3.49	0.08	99.92	0.008	0.08	0.004	99.34	0.004	1.23	0.002	96.97	0.06	2.84	0.03

TABLE III

EXPERIMENT RESULTS USING DIFFERENT PUBLIC DATASETS SUCH AS MITDB, CEBDB, PTB, ECG-ID, AND STATE-OF-THE-ART DEEP CNN MODELS. METRICS ARE ID - IDENTIFICATION RATE, EER - EQUAL ERROR RATE, FRR - FALSE REJECT RATE, FAR - FALSE ACCEPT RATE.

sampling rate of 500 Hz and a 12-bit resolution. The first two records acquired from the same day were used for each subject. The database consists of 310 one-lead ECG recording sessions obtained from 90 volunteers during a resting state.

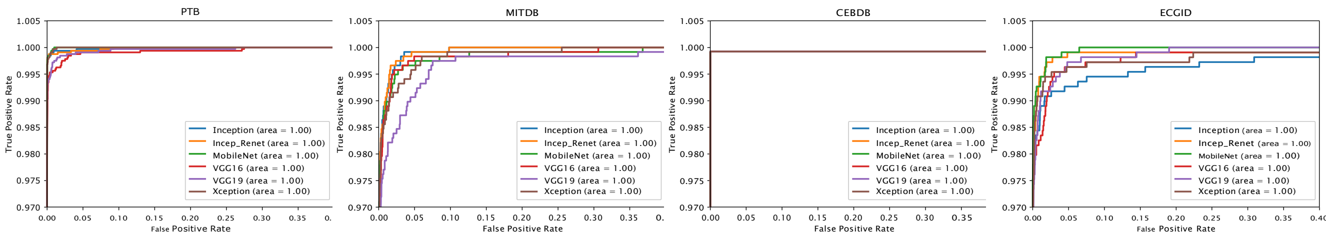
C. Experimental Configuration

Convolutional Neural Networks (CNN) have the capability to learn the features, eliminating the need for manual feature engineering. The only problem with neural networks is that they are data-hungry and to harness their true power, a relatively large number of data points are required. Usually, the biomedical dataset has fewer data samples, and hence transfer learning technique can be beneficial in such cases. Thus, we performed transfer learning with popular CNN architectures such as IncpetionV3 [31], VGG16 [28], VGG19 [28], Inception ResNetV2 [30], MobileNetV2 [27] and Xception [4]. While the aforementioned deep CNN architectures can obtain high performance on ImageNet, training deep CNN from scratch is difficult for 2D representation of ECG due to (i) it requires a huge amount of training data to deal with proper convergence; (ii) time-consuming process; (iii) it is most likely to suffer from overfitting problem. This motivated us to use transfer learning [24] to deal with the aforementioned drawbacks. In this paper, The ECG based biometric system has been trained on a large labeled dataset from ImageNet [7] with good results and thus has high generalization capabilities. In other words, we use the weights pre-trained on ImageNet to fine-tune our ECG-based biometric model to take advantage of the 2D structure input method on CNN. 2D image of ECG with a resolution of 224×224 was fed to the VGG and MobileNet architectures while a resolution of 299×299 was used for other models. The initial learning rate was set to $5e^{-3}$ with a polynomial decay of 0.01 for every epoch. A small batch size of 16 was used as smaller batches yield better results.

Generally speaking, we extracted ≈ 40 segments from each user for the entire experimental dataset. *Note that some of the datasets may have more/fewer segments*. Then, each ECG segment is converted into a 2D image. Next, the 2D image dataset is split randomly into 75% for enrollment and 25% authentication sets with 5-fold cross-validation. By random we refer to random splits based on ECG segments rather than users to ensure balanced label distributions. Class weights were introduced to penalize the model more when classes with fewer samples were wrongly classified. For all the models, the top layer was removed and a Global Average Pooling layer, a dropout layer, two fully connected layers with ReLU activation, and a softmax layer were added. A dropout factor of 0.4 and an L2-regularization factor of $5e^{-4}$ was introduced to reduce any overfitting. The models were loaded with ImageNet weights and fine-tuned for our dataset. A stochastic gradient descent (SGD) with a 0.9 momentum was used as an optimizer for our models. Finally, the models were trained for a maximum of 100 epochs and were monitored using early stopping to halt training when validation loss starts increasing.

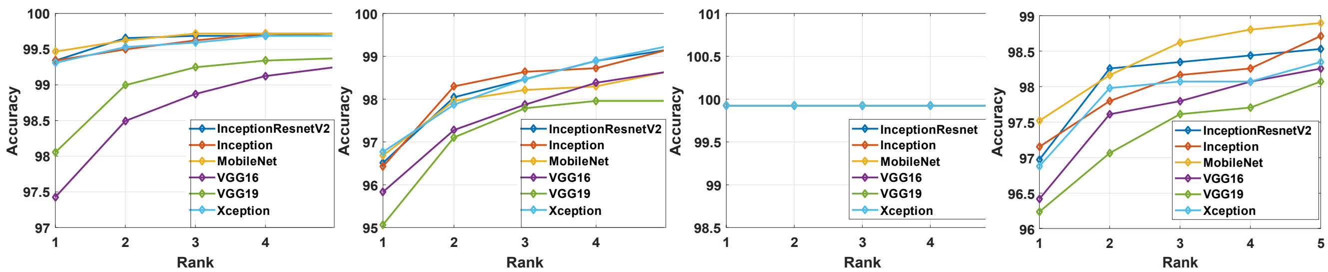
V. EXPERIMENTAL RESULTS

ROC curves are shown in Fig. 2 (a-d), TableIII. As shown in the results, the average identification rate from PTB are 97.43%, 98.0.5%, 99.47%, 99.34%, 99.31%, and 99.34% with EER of 0.017%, 0.013%, 0.003%, 0.004%, 0.005%, and 0.04% using VGG16, VGG19, MobileNet2, InceptionV3, Xception, and Inception ResNetV2 respectively. In contrast, the average identification from MITDB are 95.83%, 95.0.6%, 97.45%, 96.43%, 97.77%, and 96.51% with EER of 0.17%, 0.21%, 0.14%, 0.15%, 0.13%, and 0.14% using VGG16, VGG19, MobileNet2, InceptionV3, Xception, and Inception ResNetV2 respectively. Among different deep CNN model, MobileNetV2 seems to be a powerful tool for 2D CNN ECG biometric identification, achieve high identification rate. As expected, the CEBDB dataset obtains 99.92% identification rate and 0.008% EER for all types of CNN architecture since not only has 20 subjects but also all the users are healthy. VGG architectures are slow to train and the model weights are heavy. Depth wise and pointwise convolutions in MobileNet architectures make the model 32 times smaller than VGG while being faster and more accurate. Efficient and deeper models like InceptionV3, InceptionResNetV2, MobileNetV2, and Xception performed better than VGG architectures. How-



(a) (b) (c) (d)

Fig. 2. ROC curves for different non-crafted features extraction such as Inception, MobileNet, VGG16, VGG19, Xception. (a) PTB, (b) MITDB, (c) CEBSDB, (d) and ECG-ID.



(a) (b) (c) (d)

Fig. 3. The CMC curve of the proposed approach using, MobileNet, VGG16, VGG19, Xception. (a) PTB, (b) MITDB, (c) CEBSDB, (d) and ECG-ID respectively.

ever, the boost in MobileNetV2's accuracy can be attributed to it's fewer parameters as more parameters might lead to over-fitting and deeper models might create optimization problems.

We also summarized the rank-t identification for different rank values using the cumulative match characteristics (CMC) curve in Fig. 3. The main purpose of Fig. 3 is to demonstrate the rank one accuracy of our proposed ECG based biometric identification from different datasets which indicates the value of TRP for $t = 1$. Since each dataset has a different number of users, thus the number of enrollment vary. Hence, instead of plotting the rank-t identification rate for $t = 1, 2, \cdot, N$, where N is the number of enrolled users, only rank-5 is depicted. As can be seen in this figure, in the PTB, the accuracy of rank-1 is as high as 96.3% using deep MobileNet architecture, while VGG16 and VGG19 are 97.47% and it reaches 99.3% in rank-5. Also, the average identification rate of MITDB starts with ≈ 97% and reaches 99% in rank-5. On the other hand, in the CEBDB dataset, the identification rate of rank-1 is ≈ 100% rate. In ECG-ID dataset, rank-1 starts at 97.5% using MobileNet technique and reaches ≈ 100% at rank-5. Similarly, the average identification rate starts at ≈ 96% and reaches 100% in rank-5.

VI. Conclusion

Most of the existing work on ECG biometric has been focused on handcrafted feature extraction and less attention has been paid to developing state-of-the-art non-handcrafted technique. One reason for that is that ECG is a one-dimension signal and thus cannot take advantage of mature fields such as computer vision, 2D convolution, and transfer learning. Thus, we developed a novel 2D representation of ECG using continuous wavelet transform to take advantage of timing and frequency together and convert it to a 2D image in order to get the benefit of the state-of-the-art deep learning techniques. Our proposed ECG biometric has been trained on a four public data sets including MITDB, CEBDB, PTB, and ECG-ID with more than 450 subjects. Our proposed ECG biometric framework achieves an average identification rate of 99.96% on CEBDB, 99.47% on PTB dataset with 290 subjects. We also evaluate the effectiveness of the proposed algorithm with another two public ECG datasets with diverse behaviors, such as a healthy and unhealthy ECG signal.

References

[1] Physiobank. http://physionet.org, 2018. [Online; accessed-2020].

[2] L. Biel, O. Pettersson, L. Philipson, and P. Wide. Ecg analysis: a new approach in human identification. *IEEE Transactions on Instrumentation and Measurement*, 50(3):808–812, 2001.

[3] R. Bousseljot, D. Kreiseler, and A. Schnabel. Nutzung der ekg-signaldatenbank cardiodat der ptb über das internet. *Biomedizinische Technik/Biomedical Engineering*, 40(s1):317–318, 1995.

[4] F. Chollet. Xception: Deep learning with depthwise separable convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1251–1258, 2017.

[5] Y. Chu, H. Shen, and K. Huang. Ecg authentication method based on parallel multi-scale one-dimensional residual network with center and margin loss. *IEEE Access*, 7:51598–51607, 2019.

[6] E. J. da Silva Luz, G. J. Moreira, L. S. Oliveira, W. R. Schwartz, and D. Menotti. Learning deep off-the-person heart biometrics representations. *IEEE Transactions on Information Forensics and Security*, 13(5):1258–1270, 2017.

[7] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pages 248–255. Ieee, 2009.

[8] M. A. García-González, A. Argelagós-Palau, M. Fernández-Chimeno, and J. Ramos-Castro. A comparison of heartbeat detectors for the

seismocardiogram. In *Computing in Cardiology 2013*, pages 461–464. IEEE, 2013.

[9] P.-L. Hong, J.-Y. Hsiao, C.-H. Chung, Y.-M. Feng, and S.-C. Wu. Ecg biometric recognition: template-free approaches based on deep learning. In *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 2633–2636. IEEE, 2019.

[10] M. Ingale, R. Cordeiro, S. Thentu, Y. Park, and N. Karimian. Ecg biometric authentication: A comparative analysis. *IEEE Access*, 8:117853–117866, 2020.

[11] S. J. Kang, S. Y. Lee, H. I. Cho, and H. Park. Ecg authentication system design based on signal analysis in mobile and wearable devices. *IEEE Signal Processing Letters*, 23(6):805–808, 2016.

[12] N. Karimian, Z. Guo, M. Tehranipoor, and D. Forte. Highly reliable key generation from electrocardiogram (ecg). *IEEE Transactions on Biomedical Engineering*, 64(6):1400–1411, 2016.

[13] N. Karimian, M. Tehranipoor, D. Woodard, and D. Forte. Unlock your heart: Next generation biometric in resource-constrained healthcare systems and iot. *IEEE Access*, 7:49135–49149, 2019.

[14] J. S. Kim, S. H. Kim, and S. B. Pan. Personal recognition using convolutional neural network with ecg coupling image. *Journal of Ambient Intelligence and Humanized Computing*, pages 1–10, 2019.

[15] M. Komeili, N. Armanfard, and D. Hatzinakos. Liveness detection and automatic template updating using fusion of ecg and fingerprint. *IEEE Transactions on Information Forensics and Security*, 13(7):1810–1822, 2018.

[16] K. Kotwal, S. Bhattacharjee, and S. Marcel. Multispectral deep embeddings as a countermeasure to custom silicone mask presentation attacks. *IEEE Transactions on Biometrics, Behavior, and Identity Science*, 1(4):238–251, 2019.

[17] K. Kotwal, Z. Mostaani, and S. Marcel. Detection of age-induced makeup attacks on face recognition systems using multi-layer deep features. *IEEE Transactions on Biometrics, Behavior, and Identity Science*, 2019.

[18] R. D. Labati, E. Muñoz, V. Piuri, R. Sassi, and F. Scotti. Deep-ecg: convolutional neural networks for ecg biometric recognition. *Pattern Recognition Letters*, 126:78–85, 2019.

[19] Y. Li, Y. Pang, K. Wang, and X. Li. Toward improving ecg biometric identification using cascaded convolutional neural networks. *Neurocomputing*, 2020.

[20] T. Lugovaya. Biometric human identification based on electrocardiogram. *Master's thesis, Faculty of Computing Technologies and Informatics, Electrotechnical University 'LETI', Saint-Petersburg, Russian Federation*, 2005.

[21] S. Marcel, M. S. Nixon, and S. Z. Li. *Handbook of biometric anti-spoofing*, volume 1. Springer, 2014.

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

[23] J. Pan and W. J. Tompkins. A real-time qrs detection algorithm. *IEEE Transactions on Biomedical Engineering*, BME-32(3):230–236, March 1985.

[24] S. J. Pan and Q. Yang. A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22(10):1345–1359, 2009.

[25] J. Pinto and J. S. Cardoso. An end-to-end convolutional neural network for ecg-based biometric authentication. In *Proceedings of 10th IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS)*, 2019.

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

[27] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4510–4520, 2018.

[28] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

[29] C. Sousedik and C. Busch. Presentation attack detection methods for fingerprint recognition systems: a survey. *Iet Biometrics*, 3(4):219–233, 2014.

[30] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi. Inception-v4, inception-resnet and the impact of residual connections on learning. In *Thirty-first AAAI conference on artificial intelligence*, 2017.

[31] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1–9, 2015.

[32] S. Tirunagari, N. Poh, D. Windridge, A. Iorliam, N. Suki, and A. T. Ho. Detection of face spoofing using visual dynamics. *IEEE transactions on information forensics and security*, 10(4):762–777, 2015.

[33] Q. Zhang, D. Zhou, and X. Zeng. Heartid: A multiresolution convolutional neural network for ecg-based biometric human identification in smart health applications. *Ieee Access*, 5:11805–11816, 2017.

[34] Z. Zhao, Y. Zhang, Y. Deng, and X. Zhang. Ecg authentication system design incorporating a convolutional neural network and generalized s-transformation. *Computers in biology and medicine*, 102:168–179, 2018.