An End-to-End Convolutional Neural Network for ECG-Based Biometric Authentication

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Abstract

Aiming towards increased robustness to noise and variability, this paper proposes a novel method for electrocardiogram-based authentication, based on an end-to-end convolutional neural network (CNN). This network was trained either through the transfer of weights after identification training or using triplet loss, both novel for ECG biometrics. These methods were evaluated on three large ECG collections of diverse signal quality, with varying number of training subjects and user enrollment duration, as well as on cross-database application, with or without fine-tuning. The proposed model was able to surpass the state-of-the-art performance results on off-the-person databases, offering 7.86% and 15.37% Equal Error Rate (EER) on UofTDB and CYBHi, respectively, and attained 9.06% EER on the PTB on-the-person database. The results show the proposed model is able to improve the performance of ECG-based authentication, especially with off-the-person signals, and offers state-of-the-art performance in cross-database tests.

1. Introduction

Biometric recognition aims to dismiss the use of external credentials for identification and authentication of individuals in favor of their intrinsic characteristics [16, 18]. Biometric systems avoid the possibility of credentials getting lost or being stolen or discovered by attackers [2]. However, the variability of biometric traits grants these systems a fuzzy nature (matching is not binary as in the comparison of an input password with its stored version), which enables attackers to try to unlawfully gain access by mimicking users' traits [14, 32].

The electrocardiogram (ECG) has been gaining traction as a biometric system, and recent studies show ECG-based biometric systems are significantly more difficult to successfully attack than those based on other traits [12, 17]. Besides carrying enough personal information for robust recognition, the ECG's hidden nature and inherent liveness information make it more difficult to unlawfully capture and inject into the system [23, 29].

Initially, research in ECG-based biometrics was mainly focused on on-the-person signals (from medical acquisition settings, using several wet electrodes on the chest and limbs) [4, 5, 21]. However, it has since evolved towards higher acquisition comfort, using off-the-person signals (acquired in less obtrusive ways, using dry electrodes on the fingers, palms, or wrists) [10, 20, 26, 28, 31, 33].

However, ECG signals are greatly influenced by noise and variability [22, 24], especially in off-the-person settings, which require more robust recognition approaches. Although researchers have recently started to use deep learning techniques to achieve better performance and robustness [13, 27, 30, 38, 39], current deep approaches still rely on separate predefined feature transforms and/or noise removal techniques, which are not optimized for the task at hand and therefore limit the achievable performance.

This work proposes a method for authentication using short ECG segments that, consisting on an end-to-end convolutional neural network (CNN), dismisses all separate processes of denoising or preparation. The main advantage of using an end-to-end model is that the network is granted complete control over the robustness to signal noise and variability. Besides the use of triplet loss, this work introduces the technique of weight transfer from a similar model trained for identification. This aimed to assess whether parameters optimized for identification tasks would offer performance benefits in authentication.

The proposed network and both training methodologies were extensively evaluated on three ECG collections, that include on-the-person and off-the-person signals with varying signal quality, multi-session recordings from several subjects, and influence of emotions, posture, and exercise. This evaluation included the assessment of the trained model's applicability to other signal collections, through cross-database tests using transfer learning and fine-tuning.

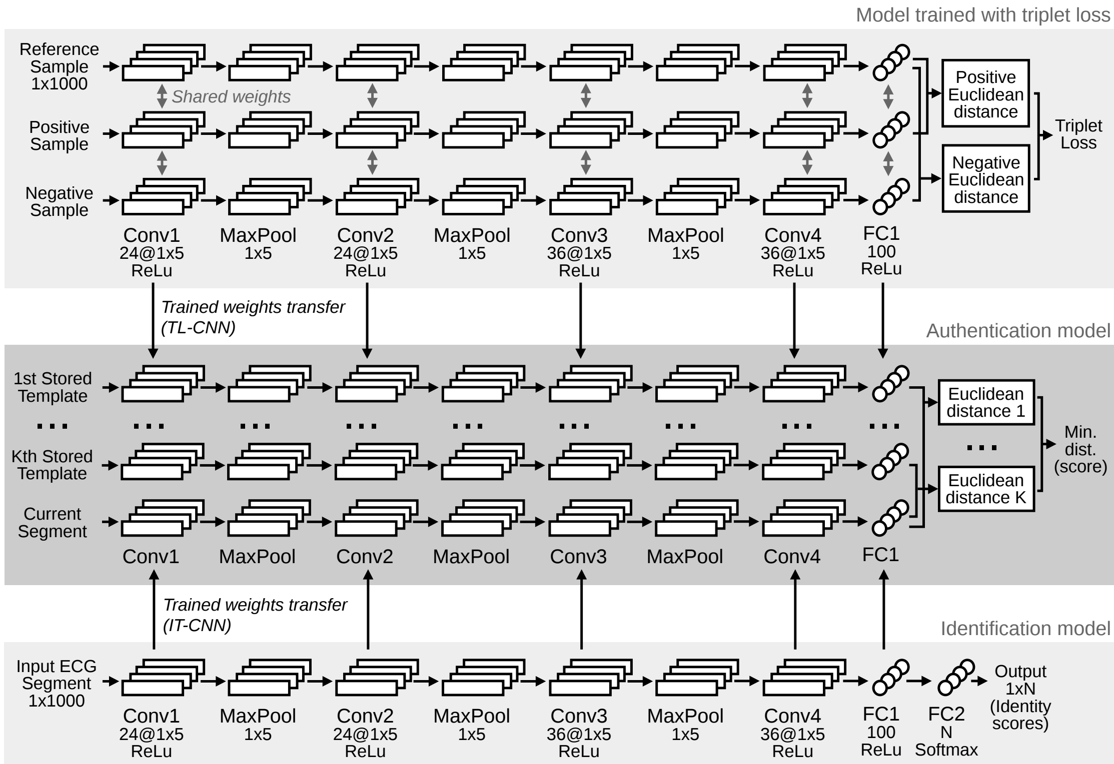

Figure 1. Schemes illustrating the proposed authentication model, including the weight transfer between networks for both proposed training methodologies (the input shape 1×1000 refers to the five-second length of the segments used in this work, 1000 samples at 200 Hz sampling frequency).

2. Proposed Methodologies

The proposed method for ECG biometric authentication is based on a CNN (see Fig. 1, darker gray). All enrolled users have one or more fixed-length ECG segments (templates) stored in the system, that have been blindly segmented (without requiring any process of reference point detection) from a recording obtained upon enrollment.

When a user claims to be an enrolled individual, the model receives and processes, simultaneously, the K stored templates of the claimed identity and 1 current segment of the user. The comparison between the processed current segment and each of the K stored templates allows the model to output a dissimilarity score, which can be used to accept or reject the identity claim.

After sample-wise normalization to zero mean and unit variance, the processing of each input segment or template starts with a succession of convolutional and pooling layers. As visible in Fig. 1, four unidimensional convolutional layers are alternated with three max-pooling layers. All have 1×5 filters, and the convolution is performed with unit stride and no padding. The first two convolutional layers hold 24 feature maps, while the last two hold 36.

The second part of the network is composed by a fully-connected layer. The outputs of this fully-connected layer for each stored template ($\mathbf{a}$) and for the current segment ($\mathbf{b}$) are compared using normalized Euclidean distance [37] (see Eq. (1)), using their variance (Var) so the output lies in $[0, 1]$. Among the K distances computed, the minimum is output as the final dissimilarity score for authentication.

$$d(\mathbf{a}, \mathbf{b}) = \frac{Var(\mathbf{a} - \mathbf{b})}{2\left(Var(\mathbf{a}) + Var(\mathbf{b})\right)}. \quad (1)$$

2.1. Model Training

The weights for the authentication model layers are transferred either from a model trained for identification or from a model trained using triplet loss (see Fig. 1). The training methodology of transferring weights from an identification model aimed to take advantage of the training process of identification deep neural networks and assess how it could benefit a neural network for authentication. On the other hand, triplet loss has been recently and successfully used in biometrics, for authentication, and other similar tasks [7, 8, 11].

The training process requires specific structural changes to the model, which are illustrated in Fig. 1 and described below. In all cases, during training, the optimizer used was Adam [19] with an initial learning rate of 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$, and no decay. Dropout [35] and data augmentation (random permutations, as in [30]) were used to prevent overfitting. After training, the weights are transferred to the respective layers on the authentication model.

2.1.1 Transfer from Identification Network (IT-CNN)

In the case of identification training (IT-CNN), the model is structured to receive 1 input segment and contain one additional fully-connected layer (FC2), using softmax activation, that will output N scores. It is trained for identification with data from N identities (following the work of Pinto *et al.* [30]).

After receiving a training segment, considering its true label and the network's output, the sparse categorical cross-entropy loss [1, 9] is computed and used during training to ultimately prepare the model to adequately discriminate the subjects.

2.1.2 Triplet Loss Training (TL-CNN)

To be trained using triplet loss (TL-CNN), the authentication model, which has $K+1$ inputs and 1 output, is restructured to receive 3 inputs and offer 2 outputs. The three inputs are the reference template, a positive template (whose identity is the same as the reference), and a negative template (of a different identity). The network processes each input and computes the dissimilarities between the reference and the positive template (p) and between the reference and the negative template (n).

Using adequate triplets of signal segments, the goal is to minimize p and maximize n. Hence, the model is trained using triplet loss [7], which can be computed for each triplet of inputs through the function:

$$l(p, n) = \max(0, \alpha + p - n), \qquad (2)$$

where α controls the margin to be enforced between the scores of positive and negative pairs (in this work, $\alpha = 0.5$). This margin eases the choice of an effective threshold for the purpose of authentication.

3. Evaluation Details

In this work, one of the main concerns was ensuring the performance results were as realistic as possible. To achieve this, all databases were split between training subjects and testing subjects, to ensure the model can be trained and applied on data from two entirely different set of subjects. Furthermore, cross-database tests were performed to ensure the model can generalize to other population samples and acquisition settings. Subject enrollment was limited to realistic durations (5, 10, 15, or, at most, 30 seconds of the first data from each subject).

3.1. Data and Reference Methods

The three selected databases were UofTDB [36], CYBHi [34], and PTB [6, 15]. UofTDB (off-the-person, 1019 subjects) was used for most experiments due to its intermediate but realistic signal quality. The PTB (on-the-person, 290 subjects) and CYBHi (off-the-person, 128 subjects) databases were used to assess performance in better and worse signal quality settings, respectively. To match UofTDB, CYBHi and PTB signals were resampled to 200 Hz. For PTB, only Lead I signals were used.

Three literature methods were used as reference: the AC/LDA method, proposed by Agrafioti *et al.* [3]; the Autoencoder method, proposed by Eduardo *et al.* [13]; and the DCT method, proposed by Pinto *et al.* [30, 31] (adapted for authentication, using cosine distance normalized to $[0, 1]$ for matching).

3.2. Evaluation Procedures

The proposed and implemented methods were evaluated across four procedures, as detailed below, using as metric the Equal Error Rate (EER, see [29] for more details). Here, each signal segment used as input for the proposed model was five seconds long (1000 samples at 200 Hz sampling frequency).

On single-database procedure *P1*, the proposed model was evaluated on UofTDB data, and compared with the aforementioned reference state-of-the-art methods. The last 100 subjects were reserved for training, while the data from the remaining 919 subjects were used for testing. The number of enrollment templates was varied between 1, 2, 3, or 6 five-second segments.

Procedure *P2* aimed to study how the performance is affected by the number of subjects used to train the model. Instead of the original 100 subjects, training was performed using the 20, 50, or 150 last subjects of UofTDB, and the remaining 999, 969, or 869 subjects, respectively, were used for testing.

Cross-database procedure *P3* was designed to assess the proposed model's applicability to signals from other databases. The proposed model, previously trained on 100 subjects from UofTDB, was directly tested on data from CYBHi and PTB, without fine-tuning.

At last, on procedure *P4*, the goal was to assess the performance benefits brought by fine-tuning. As in *P3*, the proposed model trained on UofTDB data (from 100 subjects), was fine-tuned to CYBHi/PTB data (from 20 subjects). This was compared to the model directly trained, from scratch, on data from CYBHi or PTB (from 20 subjects, following *P1*). With 20 subjects reserved for training, the tests on $P4$ were performed for 108 (CYBHi) or 270 (PTB) subjects.

Table 1. Procedure *P1*: EER results (%) when trained with data from 100 UofTDB subjects and tested with 919 UofTDB subjects (in italics: proposed methods; in bold: best results).

	Enrollment duration			
Method	***5 s***	***10 s***	***15 s***	***30 s***
IT-CNN	**13.70**	**10.92**	**9.52**	**7.86**
TL-CNN	13.93	11.89	10.90	9.94
AC/LDA [3]	30.27	17.90	16.55	15.82
Autoencoder [13]	21.82	19.68	18.84	17.09
DCT [30, 31]	23.05	20.41	18.55	17.38

Table 2. Procedure *P1*: Mean and standard deviation of the EER results (%) obtained on 100 random data divisions (in italics: proposed methods; in bold: best results).

	Enrollment duration			
Method	***5 s***	***10 s***	***15 s***	***30 s***
IT-CNN	$\mathbf{11.3 \pm 0.14}$	$\mathbf{9.4 \pm 0.12}$	$\mathbf{8.4 \pm 0.14}$	$\mathbf{7.0 \pm 0.14}$
TL-CNN	11.6 ± 0.16	10.3 ± 0.11	9.7 ± 0.14	8.7 ± 0.11
AC/LDA	17.7 ± 0.18	15.6 ± 0.17	14.6 ± 0.17	13.3 ± 0.31
Autoenc.	18.4 ± 0.17	16.3 ± 0.14	15.9 ± 0.16	13.8 ± 0.12
DCT	21.2 ± 0.16	18.6 ± 0.15	16.4 ± 0.14	15.5 ± 0.21

4. Results and Discussion

4.1. Evaluation Procedure P1

The results obtained on the single-database procedure *P1* are presented in Table 1. In all cases, the IT-CNN model, which used weights trained for identification, attained better results than TL-CNN, which was trained using triplet loss. With 30 seconds of user enrollment, IT-CNN achieved 7.86% EER, while TL-CNN offered 9.94% EER in the same circumstances.

When considering shorter enrollment recordings (5 s, 10 s, and 15 s), the performance of both proposed methods worsens, but always remained below 14% EER. It is noteworthy that IT-CNN presented a wider advantage over TL-CNN with more enrollment data, which may denote it takes better advantage of the availability of data.

Among the reference methods, AC/LDA presented the best results in most settings. When compared with these results, both proposed methods offered consistently lower EER. Considering the best reference method for each enrollment duration, IT-CNN attained an EER reduction around $7 - 8\%$, which can be regarded as a significant improvement over the state-of-the-art.

Among other state-of-the-art works, Luz *et al*. [27], under similar settings, reported a performance of 14.27% EER with UofTDB data. All IT-CNN and TL-CNN performance results are better, even when considering only 5 seconds of enrollment (much less than what was used by Luz *et al*.).

Moreover, Louis *et al*. [25] reported 7.89% EER, but only using single session data from 1012 UofTDB subjects. Using only data from subjects with more than one session (82 subjects), Louis *et al*. reported 10.10% EER, while Komeili *et al*. [20] reported 6.9% EER. Although the evaluation settings are different, the proposed method's results are aligned with these (7.86% for IT-CNN with 30 s enrollment).

The statistical significance of the results was assessed, repeating the evaluation on one-hundred random subject data divisions between enrollment and testing (Table 2). Overall, the results were better, as this test is arguably less realistic than the remaining tests performed in this study (a real biometric system will always use the very first data of a subject for enrollment). Applying a paired two-sided *t*-test to the EER estimates, the results of the proposed methods IT-CNN and TL-CNN were significantly different in all cases (the differences are statistically significant at the 1% level), not only from each of the implemented state-of-the-art methods, but also between themselves.

Additionally, the outputs of the network for five-second training segments from different subjects were visualized (see Fig. 2). These are, effectively, the feature vectors used for the authentication decision. It is possible to observe that, despite the blind segmentation and the noise and variability carried by each five-second segment, the trained network was able to represent each input segment in a way that maximizes similarity with other segments from the same subject. Although some variability is still present, it is reduced to a manageable level for the biometric authentication task, and the differences between the subjects output patterns are noticeable even through a simple visualization of the plots.

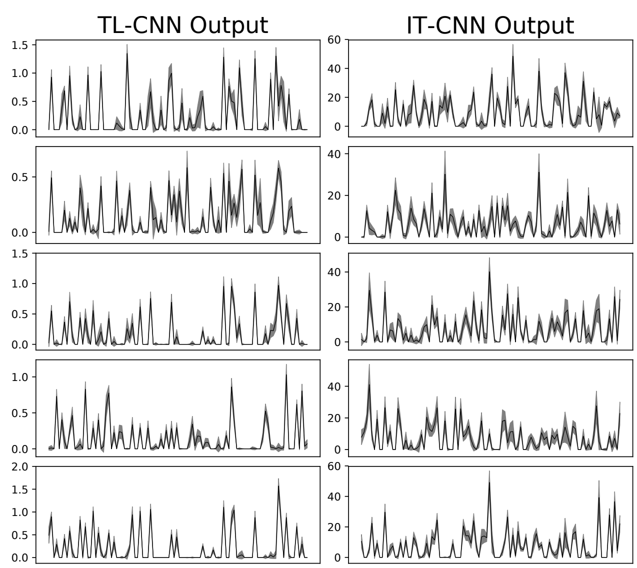

Figure 2. The network outputs for all training samples of five example subjects of UofTDB (each row). The average output feature vector is presented as a black line, and the standard deviation as a grey area.

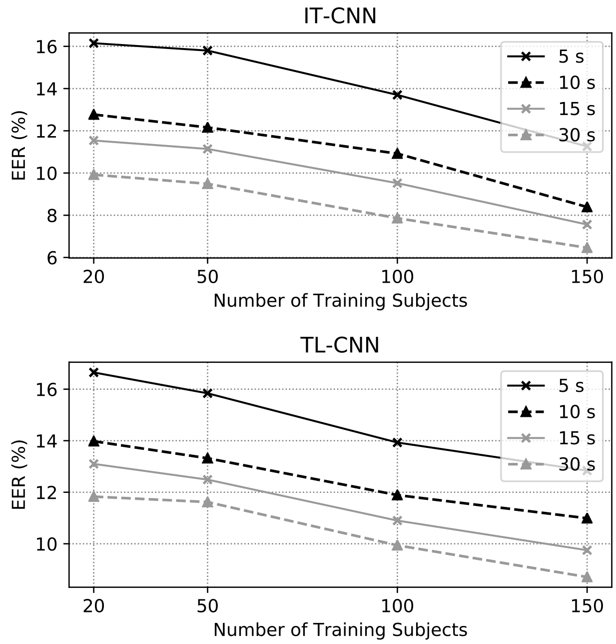

Figure 3. Procedure *P2*: EER evolution with number of subjects reserved for training, for diverse enrollment durations, for the proposed methods IT-CNN and TL-CNN.

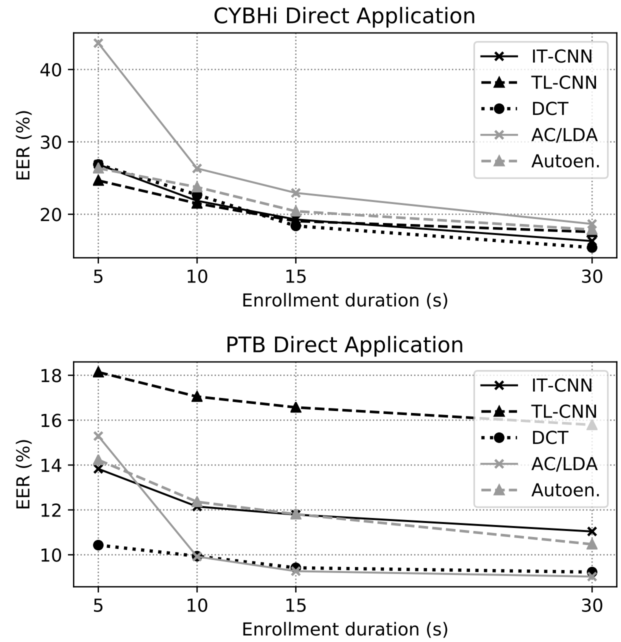

Figure 4. Procedure *P3*: EER for the proposed methods IT-CNN and TL-CNN when trained with UofTDB data and directly applied to CYBHi or PTB, and comparison with state-of-the-art methods.

4.2. Evaluation Procedure P2

On the single-database procedure *P2*, the number of UofTDB subjects reserved for training was varied (Fig. 3). In all cases, an increase in the number of training subjects resulted in performance improvements. The best results were obtained with 150 training subjects and 30 seconds enrollment, with 6.46% EER and 8.71% for IT-CNN and TL-CNN, respectively. Nevertheless, even with just 20 training subjects, IT-CNN offered performance under 10% EER (9.92%, with 30 s enrollment).

As on *P1*, it was noticeable that the performance advantage of IT-CNN over TL-CNN was greater when more data was available, either for model training or user enrollment. For example, the EER difference between IT-CNN and TL-CNN grew from 0.5% to 2.25% when increasing the number of training subjects from 20 to 150 and the enrollment duration from 5 to 30 s.

Despite this, one could expect the IT-CNN method to perform better than the state-of-the-art, even under scarce data conditions. Based on the results, when pre-trained with only 20 subjects with 10 s enrollments, IT-CNN should offer an EER lower than 13% on a population of nearly one thousand individuals.

4.3. Evaluation Procedure P3

On *P3*, the proposed methodologies were directly applied to CYBHi and PTB, after training on data from 100 UofTDB subjects (Fig. 4).

On CYBHi, IT-CNN offered better performance than TL-CNN when using 30 s enrollment (16.30% against 17.56% EER). However, with reduced enrollment duration (5 s), TL-CNN performed better (24.66% against 26.89% EER). This reinforces the idea that TL-CNN is better in scarce data situations, while IT-CNN takes better advantage of a greater availability of data. On PTB, IT-CNN was, in all cases, the most successful proposed method (13.83% EER with 5 s enrollment).

Among the state-of-the-art methods, AC/LDA behaved as on *P1* (see Table 1), offering the worst results when using 5 s enrollment, but sharply improving with more enrollment data, offering the best result on PTB (9.03% EER). DCT presented the best result in CYBHi (15.40% EER), while IT-CNN offered the second-best result (16.30% EER). Both proposed methods were, in general, worse than the state-of-the-art on the PTB database.

4.4. Evaluation Procedure P4

On procedure *P4*, the model was trained with CYBHi/PTB data and compared with the state-of-the-art (Fig. 5) and when trained with UofTDB data and fine-tuned to CYBHi/PTB (Fig. 6).

Directly trained on CYBHi data, TL-CNN attained 20.04% EER, but it offered 17.56% EER if trained with UofTDB data, and further improving to 15.37% EER if fine-tuning is performed. TL-CNN was able to attain better

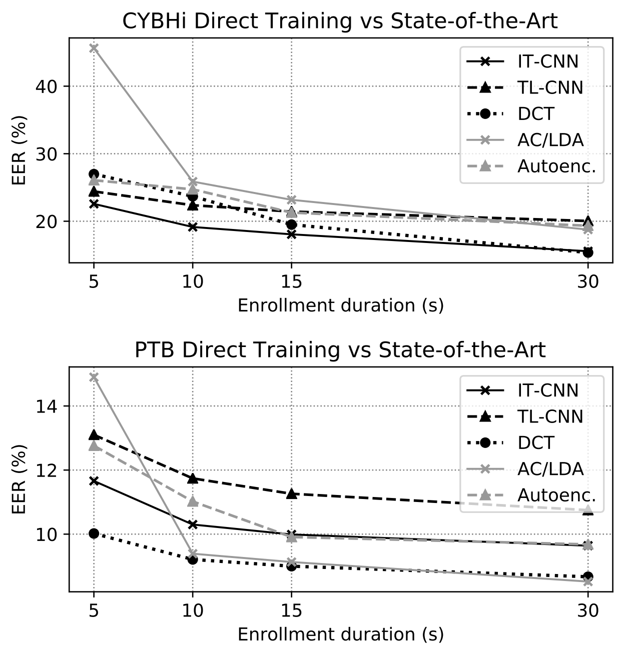

Figure 5. Procedure *P4*: EER for the proposed methods IT-CNN and TL-CNN when directly trained with CYBHi or PTB data from 20 subjects, and comparison with state-of-the-art methods.

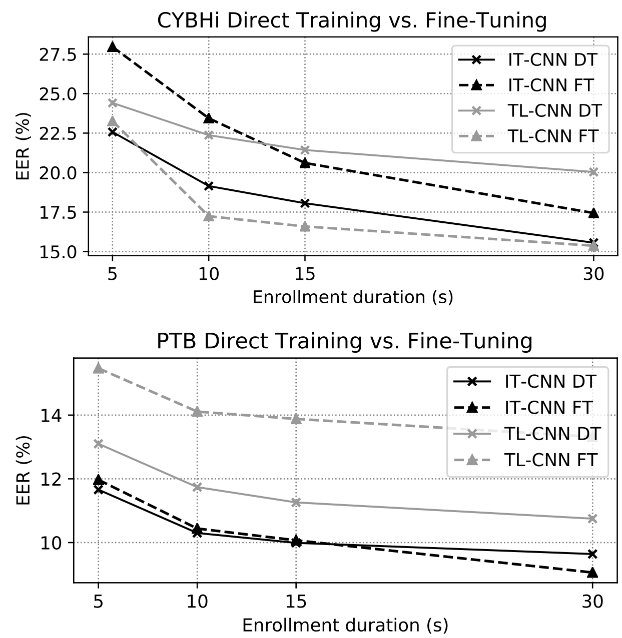

Figure 6. Procedure *P4*: EER for the proposed methods when (DT) trained, from scratch, with data from CYBHi or PTB, or when (FT) trained with UofTDB data and fine-tuned to CYBHi/PTB.

performance than IT-CNN in more difficult settings, once again indicating that this method may be better fitted for scarcer data or noisier signals.

On PTB, TL-CNN did not offer competitive results. For IT-CNN, fine-tuning (9.06% EER with 30 s enrollment) improved the results over direct application, but it was not enough to significantly improve over the results of direct training. Apparently, training with UofTDB data over-prepared the network for a degree of noise and variability that is not verified on PTB signals, which ultimately harmed its performance. An hybrid method where, before regular training, the neural network would be encouraged to mimic the behaviour of traditional methods, could be beneficial in cross-database settings.

Overall, the proposed methodologies presented more competitive results on CYBHi than on PTB, likely due to PTB signals' lesser noise and variability. Thus, while the proposed model has shown robustness to noise and variability on off-the-person settings, the state-of-the-art methods are more fitted to cleaner on-the-person signals.

5. Conclusion

In this work, an end-to-end model, based on a CNN, was proposed for biometric authentication using ECG signals. It was designed to use a set of stored templates of a claimed identity and an ECG segment of the current user, and output a dissimilarity score used to accept or reject the identity claim. The model was trained using triplet loss or by transferring weights from a similar model trained for identification.

The proposed model was successful in improving over the performance of state-of-the-art methods, especially in off-the-person signals, increasingly used on ECG-based biometrics. Using identification training has offered better performance than triplet loss when more training and enrollment data is available, and could bring benefits for other tasks or biometric traits. Both methods have shown the ability to overcome increased noise and variability of off-the-person signals, focusing on subject-specific signal patterns for accurate authentication. Nevertheless, further efforts should be devoted to improve performance and turn the ECG into a reliable alternative to common biometric traits.

Acknowledgments

This work was financed by National Funds through the Portuguese funding agency, FCT – Fundação para a Ciência e a Tecnologia within project "UID/EEA/50014/2019", and within the PhD grant "SFRH/BD/137720/2018".

The authors wish to acknowledge the creators and administrators of the databases UofTDB (University of Toronto, Canada), CYBHi (Instituto de Telecomunicações, Portugal), and PTB (Physikalisch-Technische Bundesanstalt, Germany), which were essential to the quality of this work.

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