FERST: A Full ECG Reception System for User Authentication using Two-stage Deep Learning

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***Abstract*—We are being increasingly surrounded by electronic devices that need reliable authentication before they can be accessed. While typed passwords, face and fingerprint-based authentication are popular today, we explore the possibility of using additional bio-origin signals, especially electrocardiogram (ECG) signals that can be collected without an active engagement and attention of the human user. Our proposed approach, abbreviated as FERST, uses a two-stage deep learning framework for signal processing and classification. The acquired and pre-equalized ECG signal is transferred from a wearable device through arm-wrist-palm galvanic coupled channel. The first part of the reception framework consists of a denoising autoencoder (DAE) that filters this noisy ECG signal. Then, the second stage includes a convolutional neural network (CNN) to classify and authenticate the denoised ECG signal as present/absent in a prior database used for training. The overall design goal of our approach is to achieve acceptable authentication performance with simple hardware, which further decreases network complexity and enables miniaturization of the end-to-end system. Results reveal that the FERST provides (i) 82% improvement in inference time relative to state-of-the-art adaptive filtration methods, (ii) outperforms the state-of-the-art with 99.7% classification accuracy on a standardized ECG library dataset and (iii) a relatively high classification accuracy of 99.2% for different arm-wrist-palm channel dimensions.**

***Index Terms*—ECG, signal denoising, deep learning, convolutional neural network**

I. Introduction

The explosive growth of connected Internet of Things (IoT) and smart wearables have transformed the way humans access information and interact with the environment. With simple gestures and voice commands, we can now control Internet-linked appliances on the other side of the world. While such freedom has the potential to dramatically enhance quality of life, it also raises concerns of misuse, especially, in context of the dangers of unauthorized access of these very devices. Thus, any secure IoT framework now uses an authentication step, through which the legitimate user is verified before allowing access to its controllable features.

Approach and motivation: There are several methods for authentication in use today, with the most popular being typed passwords. While such passwords can be made reliable and strong by increasing the length, non-standard combinations of regular and special characters, this requires the user to actively type in the password. Furthermore, it assumes the device is capable of supporting a virtual or physical keyboard. Other forms of authentication use biometrics, such as fingerprints, iris scans and face recognition. Apart from the requirement of specialized fingerprint sensors and cameras, there have been reported cases of intentional 'eavesdropping', where the prints are lifted off object surfaces [1], and face and iris recognition are compromised through high-resolution photos [2]. Finally, as in the case of fingerprints, these methods also require focused effort on behalf of the human user. Thus, we are motivated to further study other bio-origin signals, such as ECG, which are easy to obtain, offer discriminative properties suitable for user authentication, and most importantly, do not require an active effort as part of the authentication. Our hypothesis is that a mere touch as part of normal device interaction, for example, typing on a keyboard, will authenticate the user in real time.

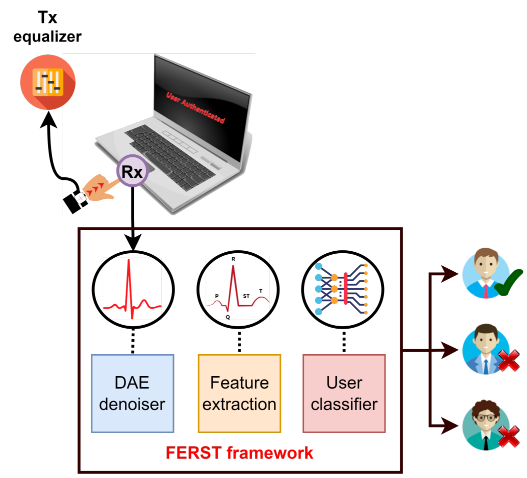

Fig. 1. An overview of proposed FERST ECG reception system architecture for user authentication for a noisy ECG input.

Unique properties of ECG: ECG signal captures the state of the heart's electrical conduction, easily acquired through non-invasive techniques. The characteristic features of ECG include the P-wave and QRS complex which capture the atrial and ventricular depolarization actions, respectively. ECG can be recorded at various locations [4], although the wrist location offers easy access. This signal must then propagate to the authentication point without being compromised en-route. One way to achieve this is by leveraging the galvanic coupled channel [3] that leverages the conductive properties of the human body channel that include skin and muscles. This confines the energy propagation within the body channel, making eavesdropping infeasible even at close proximity. We note that ECG signals collected at the wrist are noisy compared to other locations closer to the heart. Hence, we need to take into account the signal distortions caused by so called baseline wander (BW), muscle artifact (MA) and electrode motion (EM).

Limitations of existing ECG authentication systems: Despite vast strides in the area of ECG authentication [6], there are several open challenges in terms of effective noise reduction in the captured signals and reducing classification complexity. Previous works either use classical signal processing for ECG denoising [6] or filtered ECG signals to validate their system design [5]. Works that propose novel denoising methods are limited to a single noise-source or require reference signals in their system implementation. These methods are difficult to incorporate within wearables that only support single-lead ECG reception. As opposed to these approaches, FERST enables a full-ECG reception system that takes into account realistic ECG acquisition and reception artifacts. It considers the system efficiency (inference speed), suppression of major ECG noise types, and ensures high classification accuracy.

FERST for user authentication: Fig. 1 represents an high-level overview of the authentication process for a noisy ECG input. The proposed system comprises three main stages: preprocessing, feature extraction, and user authentication. The first stage includes a deep learning based denoiser that aims to efficiently suppress major ECG noise types, normalize ECG waves and enable a simple system architecture. This in turn helps to speed up processing speed and accuracy. The second stage extracts discriminative ECG features for the eventual classification step. The user authentication stage classifies test subjects according to their ECG signal similarity percentage with signals in an existing database.

The main contributions of this paper are as follows:

- We propose a full ECG reception system for user authentication that uses two-stage deep learning: the first denoises the ECG signal using denoising autoencoders (DAE), while the second ensures accurate classification through signal pattern matching.
- We propose a deep learning based denoiser that outperforms the state of the art in terms of denoising inference time and filtration accuracy.
- We demonstrate an optimized testing pipeline using denoised ECG signals that yields an overall 99.7% classification accuracy, considering a dataset of signals imported from MIT-BIH and QT databases.
- We consider the variations between people in the arm-wrist-palm channel dimensions and our FERST system shows a relatively high authentication accuracy of 99.2%.

II. Related Work

Signal processing methods have been widely used for filtering and denoising ECG signals for various clinical applications. Discrete Wavelet Transform (DWT) is a method used for noise suppression [7]. Despite its good performance in terms of filtration, DWT may contribute to fluctuations and amplitude attenuation in the final filtered signal. In [8], the Empirical Mode Decomposition (EMD) is proposed for ECG denoising, which aims to decompose signals into intrinsic mode functions (IMFs). However, this technique may suppress the unique ECG QRS complexes due to wrong discrimination with high frequency noise.

More recently, neural networks have been used for enhancing ECG signals by minimizing root-mean-squared error (RMSE) and percentage root-mean-squared difference (PRD) for use cases such as arrhythmia prevention and detection and the overall examination of the cardiac tissue [11]. More specifically, DAEs are used as an alternative to adaptive filtering, to avoid the need for a reference signal. For biometric authentication, we wish to acquire ECG on the wrist with single-lead electrodes. Thus, adding a reference signal increases the complexity of the system [10]. Deep neural networks (DNNs) have been used to analyze ECG signals for clinical objectives, for example to identify the occurrence of one or more of six different abnormalities on 12-lead ECG signals [12]. For single-lead ECG signals, [13] proposes two CNNs used to classify arrhythmia for emergencies when no physicians available.

The work that comes closest to our approach is [14] that proposes a wearable authentication device with a trained neural network classifier combining ECG and fingerprint data. While it aims to identify a user by classifying the QRS segment of the ECG signal, unlike FERST, [14] does not use DNNs for denoising and pre-processing the ECG signals, and also bases the final authentication decision on more than one biometric.

III. FERST System Architecture

An ECG-based authentication system is composed of data acquisition, feature extraction, and pattern matching with signals present in an existing database. We first recall the main noises that contaminate the ECG wave. The common ECG artifact is the baseline wander (BW) which emerges from breathing or movement. Muscle activities generally cause muscle artifact (MA). Electrode motion (EM) arises from the variations in electrode-skin impedance due to skin stretching.

A. System Overview

The general block diagram of the FERST ECG authentication system is shown in Fig. 2. The preprocessing stage includes ECG signal filtration and normalization. The normalized ECG wave enters the feature extraction stage to get prepared for the eventual user classification. Equation 1 represents the mathematical model of a real ECG signal:

$$X_{\texttt{ECG}}(t) = A_0 + \sum_{n=1}^{N} \sum_{j \in J} \alpha_j(n) \cos(\omega(n - \tau_j)n) \qquad (1)$$

Where N represents the number of pulses or *heartbeats* per timestamp t, j is an event $[P, Q, R, S]$ that is incident at the time τ_j, $A_0 = \sum_{j \in J} A_j$ represents ECG waveform from the line of zero voltage and $\alpha_j(n)$ is the Fourier coefficient.

The FERST system consists of a transmitter and a receiver where the transmitter acquires ECG, pre-equalizes and transmits it through arm-wrist-palm channel. FERST receiver processes the acquired signals for authentication.

B. FERST Transmitter

- **Galvanic coupling channel:** By coupling weak electric signals at low (sub-MHz) frequencies to human tissue,we send information through the arm-wrist-palm channel (around 10 cm). The modulated ECG signal is confined in the human tissue, and is transmitted through the galvanic coupling channel to be decoded and demodulated at the RX. An AWGN noise is added to the ECG signal to emulate realistic body channel conditions.
- **Equalizer:** Once the ECG signal is acquired via a wearable device, a simple pre-equalizer is applied to the signal to compensate the estimated human body channel attenuation and to avoid noise enhancement issue. We utilize the equivalent circuit done in [3] to apply a zero forcing (ZF) pre-equalizer using the known average channel body dimensions. Then, the ECG signal is transmitted through human tissues using galvanic coupling for reception.

C. FERST Full Reception Receiver

Our proposed receiver consists of the following three stages:

- **ECG denoising:** In order to eliminate the effect of the three major noise types on ECG signal (as mentioned in Sec. I), an efficient deep learning method is used for optimizing this task. A Denoising Autoencoder (DAE) based on a fully convolutional network (FCN) method is used to attain highest accuracy results and least validation loss. DAE comprises of a back-to-back encoder and decoder. It aims to reconstruct a clean or filtered signal from its noisy version. The encoder takes the contaminated input signal and down samples it to map to a hidden representation defined by the code layer. Then the decoder uses a non-linear transformation to map the code layer version to its new reconstruction output. The rationale behind using the FCN instead of the traditional convolutional neural network (CNN) is that the former discards the fully connected layer to get a simpler network with low computational complexity. Furthermore the ECG wave is normalized to compensate the effect of the change in ECG frequency due to different environmental conditions (for e.g., after vigorous exercise) and also take into account the difference in input data range.
- **Feature extraction:** The normalized ECG wave enters feature extraction and selection stage where we extract the P-wave and QRS complex interval. These are the most discriminative and informative features of the signal for user authentication. This stage aims to enhance user's uniqueness from his/her ECG heartbeat.
- **User classification and authentication:** An 8-layer CNN is used to finally identify a user who has permission for accessing a device. An 'accept' or 'reject' decision is made according to the percentage of ECG similarity with signals in the registered database.

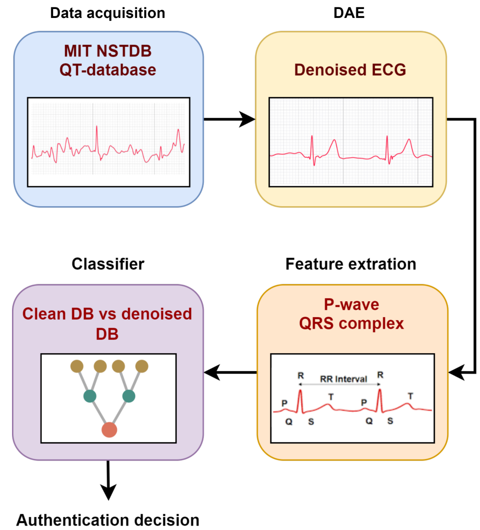

Fig. 2. The proposed FERST ECG reception system architecture for user authentication for a noisy ECG input.

IV. FERST Framework

In this section, we discuss different steps and components of the proposed FERST framework.

A. Data Acquisition

The first step of any user authentication system is data acquisition. FERST framework works on the ECG signals acquired from the wrist of a person. We denote such acquired ECG signals as $X_{\texttt{ECG}}(t)$ collected at timestamp t.

Representation of ECG inputs and outputs: We define the data matrix of the acquired ECG signal as: $X_{\texttt{ECG}}(t) \in \mathbb{R}^{d_0^{\texttt{ECG}} \times d_1^{\texttt{ECG}}}$, where $(d_0^{\texttt{ECG}} \times d_1^{\texttt{ECG}})$ represents the dimension of the ECG signal. We represent the pool of participating people of $\mathcal{P}$ via binary label matrix $Y_{\texttt{ECG}} \in \{0,1\}^{|\mathcal{P}|}$.

B. FERST Deep Learning based Denoiser

We propose a denoising autoencoder (DAE) based on deep learning models to filter the subject's noisy ECG signal and prepare it for the classifier. This model utilizes the FCN described in [18] to generate a clean ECG image output from a received noisy ECG signal. The network architecture of the proposed DL denoiser is shown in Fig. 3. We also remove the pooling layers except for the code layer. The encoder of the deep learning denoiser comprises of a series of six layers sharing the same kernel size of 3. Each layer performs three operations on the noisy ECG input: convolution, batch normalization, and activation. The convolution operation aims to use the kernel to shift through the pixels in the whole ECG image. Batch normalization is utilized to increase the training speed and balance the weights of the neural network during training. The exponential linear units (ELU) are used for activation after normalization instead of the common rectified linear units (ReLU) to further improve the classification accuracy and lower the overall system computational complexity. The

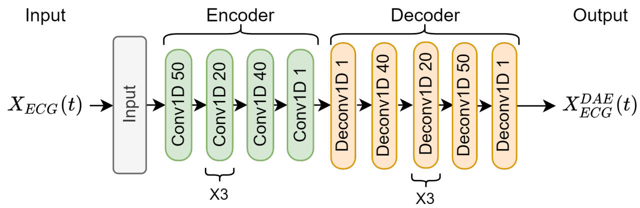

Fig. 3. Deep learning based denoising autoencoder (DAE).

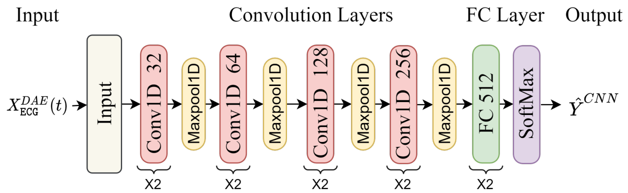

Fig. 4. CNN for user ECG classification.

number of filters is changed with different feature maps and a single filter is used to down-sample the ECG image to get a compressed low dimensional version in the code layer. Note that the decoder has a symmetrical effect to the encoder with the deconvolutional layers replacing the convolutional layers.

Denoiser modeling: The input dimension of the original ECG signal $X_{\mathtt{ECG}}(t)$ is $(d_0^{\mathtt{ECG}}, d_1^{\mathtt{ECG}})$, where $d_1^{\mathtt{ECG}} = 144$ and $d_2^{\mathtt{ECG}} = 224$. We use the original ECG signals for training and testing of the denoising autoencoder. This generates denoised ECG signal $X^{\mathtt{DAE}}_{\mathtt{ECG}}(t)$ from the original noisy ECG signal $X_{\mathtt{ECG}}(t)$, where α is linear activation, and $F^{\mathtt{DAE}}_{\theta}(.)$ denotes the denoising autoencoder.

$$X^{\mathtt{DAE}}_{\mathtt{ECG}}(t) = \alpha(F^{\mathtt{DAE}}_{\theta}(X_{\mathtt{ECG}}(t))) \qquad F^{\mathtt{DAE}}_{\theta} : \mathbb{R}^{d_0^{\mathtt{ECG}} \times d_1^{\mathtt{ECG}}} \mapsto \mathbb{R}^{d_0^{\mathtt{ECG}} \times d_1^{\mathtt{ECG}}}$$

C. Feature Extraction

The main goal of feature extraction stage is to promote the uniqueness of each user from his/her segmented heartbeat. In this study, we extract the informative ECG fiducial features to express the individual's heart structure. ECG P wave and QRS complex are used specifically to perform authentication thanks to their robustness against noise and user variability.

D. FERST Deep Learning based Classifier

The last stages of the ECG Authentication system are classification and pattern matching. We first create a database of denoised ECG segmented images for each person. Every image includes one QRS complex (one beat) for image comparison and user authentication with the key metric being similarity of the signal features with those contained in the existing database. The proposed convolutional neural network (CNN) is composed of a series of 8 layers, all of which share the same kernel size and ReLU activation function. Each layer has an independent number of filters for feature extraction, followed by ReLU activation.The last flattened dense layer is utilized along with the *SoftMax* function to determine the final class probability.

CNN modeling: The denoised ECG signals ($X^{\mathtt{DAE}}_{\mathtt{ECG}}(t)$), generated from the DAE are used for training and testing the CNN classifier along with one hot representation, $Y_{\mathtt{ECG}} \in \{0, 1\}^{|\mathcal{P}|}$, of the ground truth information of the original ECG signals. The proposed CNN-based classifier predicts the probability of each class from (2) using the denoised ECG signal $X^{\mathtt{DAE}}_{\mathtt{ECG}}(t)$, where γ is *Softmax*, and $F^{\mathtt{CNN}}_{\theta}(.)$ denotes the classifier CNN.

$$\hat{Y}^{\mathtt{CNN}} = \gamma(F^{\mathtt{CNN}}_{\theta}(X^{\mathtt{DAE}}_{\mathtt{ECG}}(t))) \qquad F^{\mathtt{CNN}}_{\theta} : \mathbb{R}^{d_0^{\mathtt{ECG}} \times d_1^{\mathtt{ECG}}} \mapsto \mathbb{R}^{|\mathcal{P}|} \quad (2)$$

As shown in Fig. 5, we train the CNN with $X^{\mathtt{DAE}}_{\mathtt{ECG}}(t)$ using *categorical cross-entropy* loss for 100 epochs with stochastic gradient descent optimization. During the testing phase, we process the denoised ECG signals and feed them to the trained CNN model. The predicted class index, $\hat{k}$, from the probability vector, $\hat{Y}^{\mathtt{CNN}}$, is determined as (3).

$$\hat{k} = \underset{0 \le \hat{k} \le len(\mathbb{I}^{\mathtt{CNN}})}{\arg\max} \; (\hat{Y}^{\mathtt{CNN}}) \qquad (3)$$

E. Authentication Procedure

The denoised ECG dataset is split into a training and testing set. Both sets include sequences of size $1 \times N$, where N is the total number of samples in the ECG waveform. After the one-hot encoding, $Y_{\mathtt{ECG}}$, the Softmax function is used to get a measured class probability. After completing the training, the ECG test sequence is injected for evaluation. The user is authenticated only if the predicted class index $\hat{k}$ has the maximum probability in all classes.

V. Experimental Evaluation

We validate the FERST framework on widely used PhysioNet datasets. We use Keras 2.2.5 with Tensorflow backend (version 2.8.0) for the implementation. Furthermore, we use different evaluation metrics that capture the individual performance of the denoiser and the classifier blocks.

A. Validation Datasets

To validate the proposed framework, we use publicly available PhysioNet datasets such as QT database [15], Arrhythmia database (MIT-BIH) [16] and the Noise Stress Test Database (NSTDB) [17]. The QT database contains over hundred ECG recordings of 15-min length, each with end-markers for QRS from 30 to 50 selected beats. The MIT-BIH NSTDB database comprises of 12 half-hour ECG recordings digitized at 360 samples per second per channel and 3 recordings that contain the three main ECG noises: baseline wander, muscle artifact, and electrode motion. During validation of CNN classifier, the denoised database is used for pattern matching and authentication purposes.

B. Evaluation Metrics

To evaluate the denoiser performance, we use maximum absolute distance (MAD), Percentage root-mean-square difference (PRD), and cosine similarity metrics. For CNN classifier evaluation, we are using accuracy for comparison with state-of-the-art.

C. FERST Transmitter Settings

To estimate body channel attenuation, we use typical arm-wrist-palm thickness values and average lengths as an input to the equivalent circuit in [3]. A simple ZF pre-equalizer is then applied to compensate anticipated channel distortion and improve authentication accuracy.

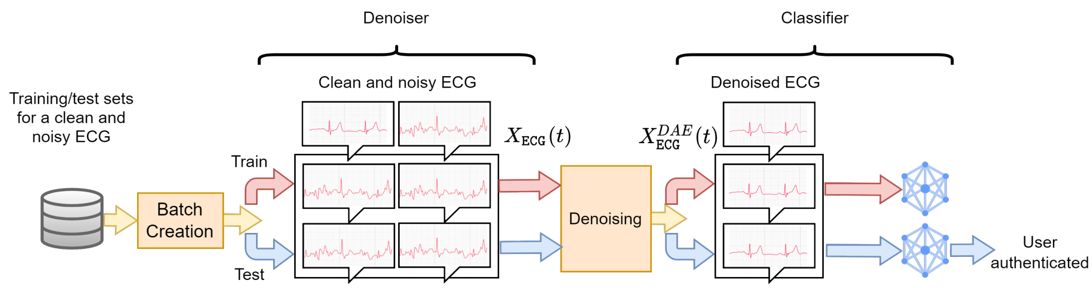

Fig. 5. The proposed FERST train/test pipeline.

TABLE I
TRAIN/TEST TIME FOR DIFFERENT ECG DENOISERS. FERST EXHIBITS 45% OF DECREASE IN TEST TIME COMPARED TO LANLD FILTER.

Method/Model	Train (GPU) h:m:s:ms	Test (GPU) h:m:s:ms
FIR filter	0	1:56:07.37
IIR filter	0	0:00:35.73
Multibrach LANLD [19]	2:53:34.81	0:00:11.08
FERST-DAE (proposed)	**0:58:32.28**	**0:00:06.76**

D. Validation of FERST Denoiser

In order to validate the performance of the denoising autoencoder, we compare it with the conventional adaptive filtration techniques commonly used in the state-of-the-art that have been applied for ECG [6].

For practical assessment, we also focus on the denoiser efficiency in terms of inference time and filtration accuracy. The lower the value of the inference time with accurate filtration, the better and faster the denoising performance. Additionally, it mitigates the chance for any possible attacks and eavesdropping with adversarial receivers. During testing, the ECG signals are contaminated with the common baseline wander and the white Gaussian noises.

•**Comparison with the state-of-the-art:** We see from Table I that the conventional IIR/FIR filters don't have GPU training time since they rely on CPU-based Scipy filters during run-time. Additionally, adaptive filters show the longest test time that makes the ECG authentication system prone to attacks and surrounding interference. As shown in Table II, adaptive filters result in the worst denoising performance, which necessitates a complex classifier to compensate the final authentication accuracy. Although multi-branch linear and non-linear dilated convolution approach described in [19] shows the best de-noising performance, our proposed technique shows filtration results very similar to LANLD [19], while at the same time it outperforms others in terms of both training and testing (inference) time. This makes the FERST authentication system better suited to mitigate the risk of possible attacks. The bar plot in Fig. 6 represents the improvement percentage in test time of different ECG denoisers relative to adaptive filters. It can be observed that our DAE approach shows the best timing performance among others with 82% and 45% decrease than IIR and LANLD [19] . Fig. 7 represents the ECG signal comparison between adaptive-filtered and DAE-filtered signals against a clean signal.

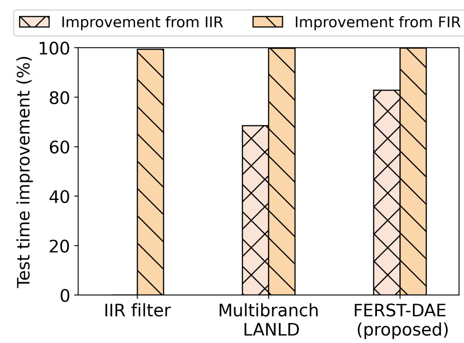

Fig. 6. Comparison between proposed FERST-DAE and state-of-the-art in terms of test time improvement. We observe 99.9% and 82.8% of improvement in FERST denoiser than the state-of-the-art FIR and IIR filters.

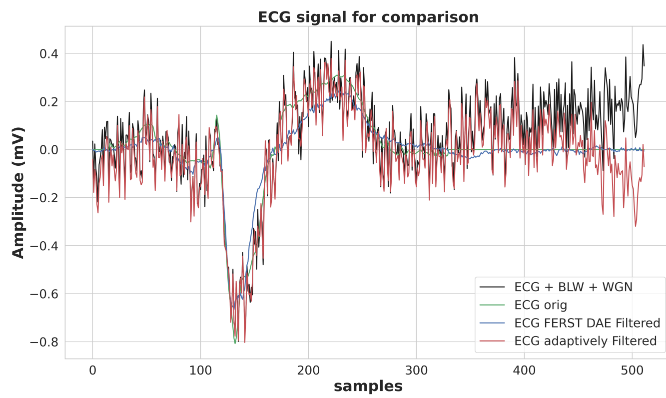

Fig. 7. Comparison between clean ECG signal, adaptive filtered and DL filtered ECG signal. FERST DAE filtered ECG (blue) shows the highest similarity with the original signal (green).

E. Validation of FERST Reception System

To validate the proposed FERST full reception system, we focus on some of the previous work done on ECG authentication using adaptive filtration. In this paper, we highlight the system efficiency of the whole ECG authentication reception system including the denoising and classification stages. The target is to achieve an efficient ECG authentication system with highest accuracy possible.

•**Comparison with the state-of-the-art:** We compare our approach with previous work in terms of accuracy percentage. We assume that the arm-wrist-palm channel here is pre-equalized with average body dimensions (10 cm), hence the effect of the IBC channel is compensated. As shown in

TABLE II
COMPARISON OF PERFORMANCE OF PROPOSED FERST DENOISER (FERST-DAE) WITH THE STATE-OF-THE-ART. MAD AND PRD IS LOWER THE BETTER, FOR COSINE SIMILARITY, HIGHER THE BETTER.

Method/Model	MAD	PRD	Cosine similarity
FIR filter	0.797 $\pm$0.541	74.129 $\pm$15.548	0.632 $\pm$0.185
IIR filter	0.747 $\pm$0.504	72.660 $\pm$15.650	0.651 $\pm$0.179
Multibrach LANLD [19]	0.372 $\pm$0.256	51.012 $\pm$29.760	0.899 $\pm$0.094
FERST-DAE (proposed)	**0.465 $\pm$ 0.306**	**52.327 $\pm$ 25.729**	**0.876 $\pm$ 0.118**

TABLE III
COMPARISON OF AUTHENTICATION PERFORMANCE OF FULL RECEPTION FERST WITH THE STATE-OF-THE-ART.

Papers	Added noise	Denoising	Classifier	Accuracy (%)
Patro *et al.* [20]	BW	LPF	SVM/RF	94.9 - 95.3
Diker *et al.* [21]	BW	BPF	DEA	97.5
Tirado-Martin *et al.* [22]	BW	BPF	MLP	97.78
FERST (proposed)	BW	**FERST-DAE**	**CNN**	**99.7**
FERST (proposed)	BW + AWGN	**FESRT-DAE**	**CNN**	**99.6**

Table III, FERST outperforms other state-of-the-art methods by obtaining 99.7% classification accuracy with 1.94% of improvement. This is because FERST achieves high fidelity in the filtration and accuracy in the classification stages, respectively. We then take into account the variations in the arm-wrist-palm channel dimensions and the corresponding final system accuracy. Table IV reveals a relatively high system accuracy even with changed IBC channel dimensions.

TABLE IV
COMPARISON OF THE CLASSIFICATION ACCURACY OF FERST SYSTEM WHEN DIFFERENT ARM-WRIST-PALM CHANNEL DIMENSIONS ARE USED.

Person	Arm-wrist-palm dimensions (cm)	Accuracy
Adult	$L_{arm} = 4.5, L_{wrist} = 1.5, L_{palm} = 9$	99.26%
Child	$L_{arm} = 1, L_{wrist} = 1.5, L_{palm} = 2.5$	99.21%

VI. CONCLUSIONS

This paper proposes FERST, a full ECG reception system that can be used to authenticate users for access to allowed devices. It considers the transmitted ECG signal from a wearable device through human tissues via galvanic coupled channel. FERST takes a step towards practical and efficient ECG classification by showing superior performance compared to the state-of-the-art in terms of denoising inference time and classification accuracy. Results show that acquired ECG can be confined to human body and at the same time can be precisely authenticated. Future work includes extending this system to continuously authenticate people in real time.

VII. ACKNOWLEDGEMENT

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