Machine Learning-Based Smart-Textile for COVID-19 Monitoring

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Keywords: Signal Processing, Wearable and Mobile Devices, Artificial Intelligence, Health Monitoring Device, COVID-19.

Abstract: We propose a new low-cost wearable system to guaranty patient mobility and robust monitoring of COVID-19 using physiological signals. Considering the correlation between two key signals (ECG and PPG), the proposed wearable system will integrate an Variational AutoEncoder (VAE) with self-attention block to reconstruct robust ECG, PPG Red and IR signals from a noisy ECG time series. The model performance is evaluated using the Mean Square Error (MSE), the root-mean-square error (RMSE), Mean Absolute Error (MAE) and the Signal-to-Noise Ratio (SNRoutput) for the signals. With a low MSE, RMSE and MAE, as well as good SNR, the model can generate robust and clean data from the noisy ECG waveform measured by the wearable system. we believe that the proposed wearable system can not only help to provide robust online COVID-19 symptoms monitoring but also for other applications.

1 INTRODUCTION

Three years after its emergence in late 2019, severe acute respiratory syndrome coronavirus 2 (Sars-CoV-2) or COVID-19 infected more than 630 million people, causing more than 6 million deaths (2023). However, the symptoms of COVID-19 patients differ from one variant to another in this long duration. For all reported variants and all periods, the most serious symptoms are shortness of breath (blood oxygen level<92%) and heart failure (heart rate>90 bpm) (Dhadge and Tilekar 2020, 2021). Although the intensity of infection and symptoms have attenuated thanks to the vaccination and follow-up of barrier gestures, we are still far from the termination of the pandemic. This is mainly due to the high infection rate, the proliferation of its variants that can escape from vaccination coverage, and the inability to detect the virus in real-time and thus, control its proliferation. This situation promotes the emergence of remote monitoring and diagnosis tools using the IoT (Internet of Things), including wearable systems (Cacovean, Ioana et al. 2020, Nasajpour, Pouriyeh et al. 2020, Pozo and Berrezueta Guzman 2020). Wearable monitoring systems effectively reduced the pressure of medical resources (e.g., medical doctors, healthcare staff, devices, materials, etc.). They perform real-time detection of basic symptoms of COVID-19 by monitoring skin temperature, blood oxygen saturation level and heart rate(Cacovean, Ioana et al. 2020, Nasajpour, Pouriyeh et al. 2020). The SpO_2 and the heart rate are computed from PPG signals (red light and infrared light) and ECG signal respectively. Despite their advantages, several limitations are observed: 1) Physiological signal (ECG, PPG_{Red} and PPG_{IR}) are highly sensitive to noises (Chen, Li et al. 2017, Chatterjee, Thakur et al. 2020): Noise induced by patient motion (motion artifacts), respiration (Baseline wander) and by the sensors itself (Powerline Interference). The lack of robustness against noises affects SpO_2 and heart rate computation accuracy. 2) The patient daily activities are heavily obstructed by the positioning of the pulse oximeter or PPG sensor (tip of the finger); 3) The most robust wearable sensors are not easily affordable. The ECG and PPG signals are intrinsically correlated since the variation of the peripheral blood volume is influenced by the left ventricular myocardial activities. Unlike pulse oximeter or PPG sensor, the optimal positioning of heart monitor sensor does not obstruct patient daily activities and provide useful signals. Our idea is to design and implement an effective low-cost wearable system coupling with a supervised learning model, to

Marc Junior, N., Zeng, X., Koehl, L., Tao, X., Dassonville, F. and Dumont, N.
Machine Learning-Based Smart-Textile for COVID-19 Monitoring.
DOI: 10.5220/0012466200003657

In *Proceedings of the 17th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2024) - Volume 1*, pages 172-180
ISBN: 978-989-758-688-0; ISSN: 2184-4305

monitor the patient's symptoms and make appropriate decision support in real-time. The supervised learning model learns the representation of clean ECG signal and corresponding PPG signals (Red and IR) from a single measured noisy ECG signal. The clean signals can be used for accurate heart rate and SpO_2 estimation.

The rest of this paper is organized as follows. Section 2 gives an overview of the related works. Section 3 offers a description of the proposed wearable system. In Section 4, we analyze the results obtained and discuss about the implication of our work. A conclusion and future perspectives are given in Section 5.

2 RELATED WORKS

Many researchers in IoT and artificial intelligence have developed various tools for monitoring and detection of the virus infection. a number of wearable systems with tiny sensors integrated into garments or accessories have been used to measure physiological parameters (e.g., skin temperature, heart rate, and SpO_2) of infected patients (Cacovean, Ioana et al. 2020, Nasajpour, Pouriyeh et al. 2020, Pozo and Berrezueta Guzman 2020). Skin temperature is estimated thanks to temperature sensor, SpO_2 level is estimated from PPG signals (Red and IR) measured by pulse oximeter sensor, and heart rate is estimated from ECG signal measured by heart monitor sensor. These wearable systems will enable the detect the gravity of symptoms by checking measured parameters values (e.g., the skin temperature>38°C , corresponding to high fever, SpO2<92% associate to shortness of breath, and heart rate>90 bpm associate to heart failure). The wearable systems allow a quick monitoring of infected wearer's health state with real-time data acquisition.

Despite these advantages, the current wearable systems have several drawbacks: 1) Raw ECG signals and PPG signals are highly sensitive to noises (Chen, Li et al. 2017, Chatterjee, Thakur et al. 2020) (Motion artifacts, powerline interference, Baseline wander). Without a pre-processing step, the signals cannot be exploited for heart rate and SpO_2 estimation; 2) The patient daily activities are heavily obstructed by the positioning of the pulse oximeter sensor (the tip of the finger is the optimal position for SpO_2 monitoring, the patient need to stay still for an optimal measurement) ; 3) Wrist-based wearable system, while more robust and less restraining than traditional wearable systems, appears to be less accurate (They incorporate wrist-based pulse oximeter sensor, which are less accurate than finger-based pulse oximeter (Lee, Ko et al. 2016)) . They are also not easy affordable (the average smart-watch price is higher than 150$). Since the peripheral blood volume variation is linked to left ventricular myocardial activities, it is easy to establish a correlation between The PPG and ECG signals. By using GAN, (Zhu, Tian et al. 2019, Sarkar and Etemad 2021, Vo, Naeini et al. 2021) estimate the waveform of the ECG signal using PPG measurements by learning a signal model related to ECG and PPG. Despite the good results obtained, the models are not trained to handle noisy PPG signals. Therefore, generated ECG and PPG signals are still sensitive to noise.

In this context, the proposed system has been developed to overcome the daily activities obstruction caused by the pulse oximeter sensor and the signals (ECG, PPG_{Red} and PPG_{IR}) vulnerability against noise. We propose a low-cost smart textile coupling with a supervised learning model. Instead of learning ECG waveform representation from PPG waveform, the model will learn three waveforms representation (ECG, PPG_{Red} and PPG_{IR}) from a noisy ECG waveform. In the next section, we describe the overall system, the supervised learning method for PPG signals generation, and the experimental results.

3 MATERIAL AND METHODS

The architecture of our wearable system is heavily based on (Tao, Huang et al. 2018). The proposed electronic textile measured ECG signal and skin temperature and transmit the data to a mobile application thanks to the Bluetooth Low Energy (BLE) protocol. BLE allows a lower power consumption than other wireless transmissions protocol (Bluetooth, Zigbee) and improves the system energetic autonomy. The mobile application by using the proposed supervised model, reconstruct from the noisy ECG signal measured by the wearable device, three clean signals:

- ECG signal: The ECG signal will be use to estimate the heart rate.
- PPG Red and IR signals: The two signals will be used to estimate the SpO_2.

By checking the heart rate, SpO_2 and skin temperature values (skin temperature>38°C, SpO2<92% and heart rate>90 bpm), the system allow a quick monitoring of the wearer health state in real-time.
The generated waveforms, heart rate, SpO_2, skin temperature and COVID-19 patient state are shown

on the mobile application. Figure 1 shows the adopted architecture.

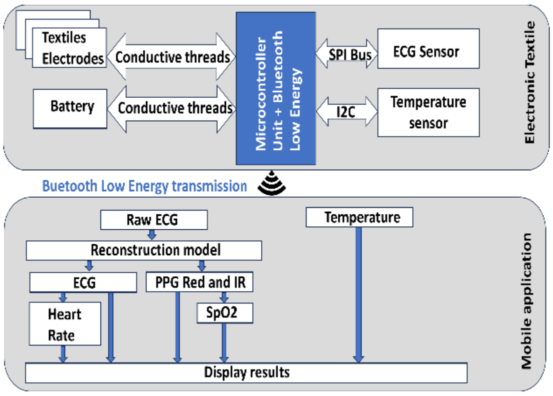

Figure 1: Wearable system architecture.

3.1 Wearable Device

The microcontroller unit used is an Arduino Nano 33 BLE Sense. It integrates a SoC ARM ® Cortex ® - M4 32-bit processor with a clock speed of 64 MHz. It also integrates a high-performance professional grade Bluetooth smart radio transceiver to ensure the bidirectional communication between the wearable system and the mobile device.

The heart monitor sensor used was AD8232 (Texas Instruments), connected to the microcontroller via analogic pin.

The temperature sensor was integrated into MPU-6050 chip, connected to the microcontroller via inter-integrated circuit (I2C) bus.

Five pads were designed to realize the interconnections using conductive threads to peripherals. Two of them in form of snap button were used to connect a battery and three of them were considered as textile knitted electrodes to connect with the heart monitor sensor. The conductive surface dimension of knitted electrode was 3 cm × 5 cm. The thread used for knitting the textile electrodes was sliver-plate polyamide thread (Shieldtex 234/34-2 ply HCB, Statex Produktions + Vertries GmbH), with a linear resistance of less than 100 $\Omega.m^{-1}$. The conductive thread between the sensors and the electrodes is made of copper wires (Elektrisola, Switzerland), and Lendzing Pro_len R PTFE (Polytetra_uoroethylene) monofilament (Lenzing Plastics GmbH, Austria) (Ismar, Tao et al. 2020).

The sampling frequency for heart monitor sensor was set to 128 Hz for two reasons: 1) The developed supervised learning model input length must be a power of 2; 2) Sampling frequency above 125 Hz are suitable for time-domain analysis and heart-rate computation (Kwon, Jeong et al. 2018). The skin temperature was set to 1 Hz (Skin temperature evolution is slower than ECG signal evolution). The wearable prototype is represented by Figure 2.

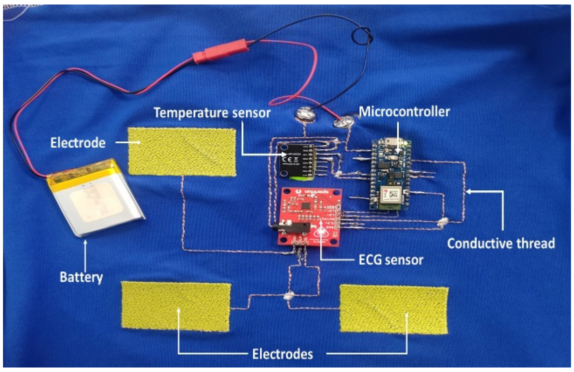

Figure 2: Smart textile prototype.

3.2 Signal Reconstruction Model

One of the main highlights of our contribution is the signal reconstruction model developed. As we mentioned earlier, a pulse oximeter integration in a wearable t-shirt is highly difficult, since the sensor placement is not optimal. It is a known fact that PPG signals and ECG signals are heavily correlated. Indeed the peripheral blood volume change (describes by PPG signals) is influenced by cardial muscles contraction and relaxation (which are describes by the ECG signal). In addition, the PPG signal peak-to-peak and the R-R peak are correlated, as describes by Figure 3.

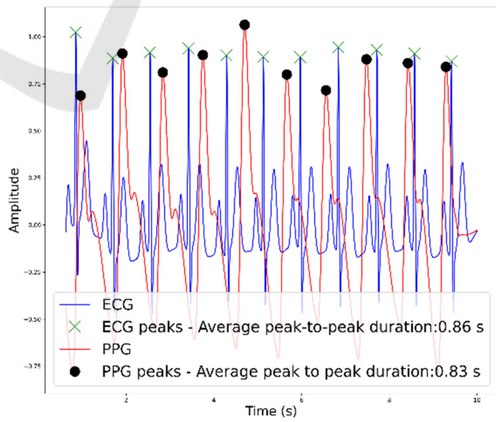

Figure 3: R-R peak and PPG peak-to-peak correlation.

Similar to (Zhu, Tian et al. 2019, Sarkar and Etemad 2021, Vo, Naeini et al. 2021), we propose to use the correlation between ECG and PPG signals for signal reconstruction.

Unlike the other contributions however, instead of reconstruct ECG signal from PPG signal, the model developed reconstruct from a noisy ECG signal, three clean signals: A clean ECG signal, a clean PPG_{Red} signal, and a clean PPG_{IR} signal.

3.2.1 Data Description and Pre-Processing

The pre-processing consists of creating a new dataset from existing datasets. The dataset use must contains the three signals (ECG, PPG_{Red} and PPG_{Ir}) Two publics datasets with ECG signals, PPG_{Red} signals and PPG_{IR} signals matched our criteria:
The BIDMC dataset (Pimentel, Johnson et al. 2016) and Pulse Time Transit (PPT) dataset (Mehrgardt, Khushi et al. 2022). All the datas were recorded during human study, using wearable heart monitor sensor AD8232 (The same sensor we use for our smart textile) and pulse oximeter MAX30100. Five steps were followed for data pre-processing.

- **PPG Signal Red Retrieval**

BIDMC provide ECG signal, PPG_{IR} signals and SpO_2 level. PPG_{Red} signals of BIDMC were reconstructed using the correlation between the SpO_2 level and the ratio of ratios R, defined by the equation 2:

$$R = \frac{\left(\frac{AC_{Red}}{DC_{Red}}\right)}{\left(\frac{AC_{Ir}}{DC_{Ir}}\right)} \quad (1)$$

where AC represents the signal amplitude and DC the signal baseline.

The correlation between R and SpO_2 is described by the equation 3 from (Tang, Li et al. 2022), with a maximum error below 4%, and a confidence level above 95%:

$$SpO2 = 11.78\ R3 + 55.92\ R2 + 28.84\ R + 97.12 \quad (2)$$

By normalizing PPG_{Red} and PPG_{IR} signals baseline value ($DC_{RED} = DC_{IR}$), we can retrieve AC_{RED} from AC_{IR}, and thus the PPG_{Red} signal.

The resulting ECG-PPG data from BIDMC and PPT were combined to form a large multi-corpus.

- **Signal Resampling and Filtering**

Signals were resampled using an interpolation technique where the sampling rate for all ECG-PPG records became 128 Hz. A bandpass FIR-filter, as well as Butter worth filter (Jagtap and Uplane 2012, Vidhya and Jerritta 2022), were applied to the ECG and PPG signals. Each signal is split into intervals of 4 seconds each with 1 second of overlapping to avoid data loss.

- **Minmax Normalization.** In order to prevent outlier, min-max normalization was applied in each signal to ensure that the network data inputs all lie within the same range.

To preserve the Ratio of Ratios, each PPG_{Red} and PPG_{IR} signal has been normalized as follows:
For each sample x_{red} and x_{ir}, respectively of a PPG_{Red} signal red and the corresponding PPG_{Ir} signal ir, the normalized values are:

$$x_{rednorm} = \frac{x_{red} - \max(red)}{\max(ir) - \min(ir)} \quad (3)$$

$$x_{irnorm} = \frac{x_{ir} - \max(ir)}{\max(ir) - \min(ir)} \quad (4)$$

- **Data Augmentation**

While the obtained signals can be considered as more than enough (10 000 signals of each category), a data augmentation has been performed to prevent overfitting or underfitting. A GAN model was used to the task (Li, Ngu et al. 2022). The proposed architecture is divided into two parts: A generator, which generate synthetized signals by mapping real signals features, and a discriminator which make sure the generate signals are close as possible to real signals. can generate multi-category synthetic time-series. The model has been trained with our dataset to generate more ECG and PPG signals. We were able to generate 120 323 signals of each category (ECG, PPG_{Red} and PPG_{Ir})

- **Input Signal Dataset Creation**

An input dataset of noisy ECG signals was created by adding a random combination of the three main ECG noises (motion artifacts, powerline interference, baseline wander) to the ECG signals.
Each noise signal can be described by the equation:

$$N(t) = A.\sin(2\pi f t + \psi) \quad (5)$$

With A, the signal amplitude, f the frequency in Hz and ψ the phase between [-π,π].

The noise signal is generated by randomly variates A, f and ψ. Baseline wander is a low frequency noise of 0.5 Hz. Powerline Interference is a low frequency noise of 50 Hz and motion artifact is a low frequency noise between 0.5 and 300 Hz.

3.2.2 Deep Learning Model

The deep learning model architecture described in Figure 4. The model architecture present as an Autoeoncoders and can be divide in two neural networks: An encoder and a decoder.

The encoder role is to learn efficient data encoding from the signals and pass it into a bottleneck architecture. In other words, the encoder estimates a compressed version of the input signal by learning his features. For this reason, we choose a CNN as an encoder since the convolutional Layers can easily extract the signals features. Each convolutional block consists of:

- **A convolution operation**, to allow feature extraction. The equation (6) describes the convolution operation.

$$y_i = \sum_{j=0}^{h} x(i-j).w_j + b_j \qquad (6)$$

When h corresponds to the filter kernel, w_j the filter weights and b_j the biases, y_i the feature extracted and x the signal.

- **A layer normalisation,** to avoid outlier, speed up the model training, reduce bias and avoid gradient exploding (Ba, Kiros et al. 2016). By using the layer normalization, we ensure that all the signal features lie withing the same range.

The activation function used is LeakyReLU. LeakyReLU has been chosen for his efficient computation, a better gradient propagation, and help to better handle the vanishing gradient problem, since it allows a small positive gradient when the unit is not active.

The decoder role is to establish to relationship between the reduce representation and the desired output signals, by minimizing the reconstruction error (the error between the signals obtained and the real signals). The decoder network architecture is the same as the encoder network architecture, except for using deconvolutional layer for the data mapping between the reduce representation and the signals. The deconvolution operation is describes by:

$$\tilde{y}_i = \sum_{j=0}^{h} y_i(i-j).w'_j + b'_j \qquad (7)$$

When h corresponds to the filter kernel, w'_j the filter weights and b'_j the biases, $\tilde{y}_i$ the estimated output and yi the reduced representation sample.

Skipped connection with self-attention block between layers of the encoder and layers of the decoder are used for two reasons: Avoiding gradients vanishing are helping to further learn the correspondence between the signals.

The kernel size and the number of filters has been chosen empirically to have the smallest and efficient model possible (The target device is an edge device).

To our best knowledge, this is the first proposition of ECG, PPG_{Red} and PPG_{Ir} signals reconstruction from a noisy ECG signal.

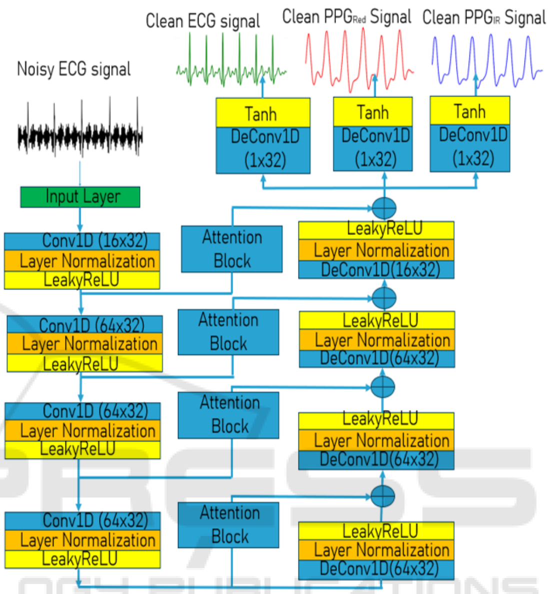

Figure 4: Model Architecture.

3.3 Implementation Details

The TensorFlow library is used for model training and evaluation. The Adam optimization method is used for training, with a cyclical a learning rate between 10^{-6} and 10^{-4}.

The learning rate decayed exponentially with a decay factor of 0.95. Other training parameters include the batch size (128) and the number of epochs (100). To guarantee the best performances, the model has been trained using a k-fold cross validation with 5 iterations. For each iteration, 80% of data were using for training, 10% for validation, and 10% for the test.

In this study, the Mean Square Error (MSE), the Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) are used as qualitative performances estimators for all signals.

The MSE represented the standard deviation between the output predicted by the model and the actual output. The MSE is defined as:

The MSE describes the standard deviation between the output predicted by the model and the actual output. The MSE is defined as:

$$MSE = \frac{1}{N}\sum_{i=0}^{N}(x_i - \hat{x}_i)^2 \tag{8}$$

The RMSE is the squared value of the MSE. It can be define as the variance between the predicted output and the desired output. A smaller value of RMSE corresponds to a smaller difference and better performance. The RMSE is formulated as follows:

$$RMSE = \frac{1}{N}\sqrt{\sum_{i=0}^{N}(x_i - \hat{x}_i)^2} \tag{9}$$

The MAE is defined as the absolute difference between the predicted output and the desired output. A smaller value of MAE corresponds to a smaller difference and better performance. The MAE is formulated as follows:

$$MAE = \frac{1}{N}\sum_{i=0}^{N}|x_i - \hat{x}_i| \tag{10}$$

Other used qualitative performances are the Signal to Noise. The SNR is widely defined as the ratio of signal power to noise power. In other terms, SNR quantify the robustness of the signal against noise (A higher SNR means a more robust signal against noise). The SNR in decibels (dB), is described as the following expression:

$$SNR_{out} = 10\log_{10}\left(\frac{\sum_{i=1}^{N} {x_i}^2}{\sum_{i=1}^{N}(\hat{x}_i - x_i)^2}\right) \tag{11}$$

N is the signal length, x_i is a sample value of the original signal at time i/N, $\hat{x}_i$ is a sample value of the denoised waveform at time i/N.

4 RESULTS

4.1 Cross Validation Results

Table 1 regroups the best cross-validation model metrics. The results confirm our model can accurately reconstruct both PPG waveforms and ECG waveform form a noisy ECG waveform. Indeed, the MSE, RMSE and MAE show that our model can reconstruct the signals with a minimal error. The SNR for each signal shows that the reconstructed signal is robust against noise.

Table 1: Model performances.

Metrics	ECG signal	PPG_{Red} signal	PPG_{IR} signal
MSE	$1.1.10^{-3}$	$2.7.10^{-3}$	$6.3.10^{-3}$
RMSE	0.033	0.0519	0.0794
MAE	0.0185	0.0297	0.0466
SNRout(dB)	18.39	11.10	12.97

4.2 Real-Time Demonstration

4.2.1 Offline Demonstration

To confirm the model efficiency and reliability, we aim to recorded at the same time, noisy signals using our wearable device and the PPG signals. Five volunteers (Three male and two female) aged between 20 and 25 years participated to the experiment. The PPG_{Red} and PPG_{IR} signals are recorded from the pulse oximeter sensor MAX30102. The PPG recording was done by placing the pulse oximeter sensor at the tip of the finger. Both ECG and PPG are recorded at the same time. The experiment duration was 5 minutes for each volunteer. The model was applied to the recorded data to reconstruct the three signals.

Figure 5 shows ECG and PPG signals reconstruction from the noisy ECG signal. The figure shows that the model reconstructed ECG and PPG signals correctly. The reconstructed PPG signals are also robust against noises as shows in Table 2.

Table 2: SNR improvement in reconstructed signals.

	Reconstructed ECG	Reconstructed PPG Red	Reconstructed PPG Ir
SNR(dB)	13.27	8.71	5.36

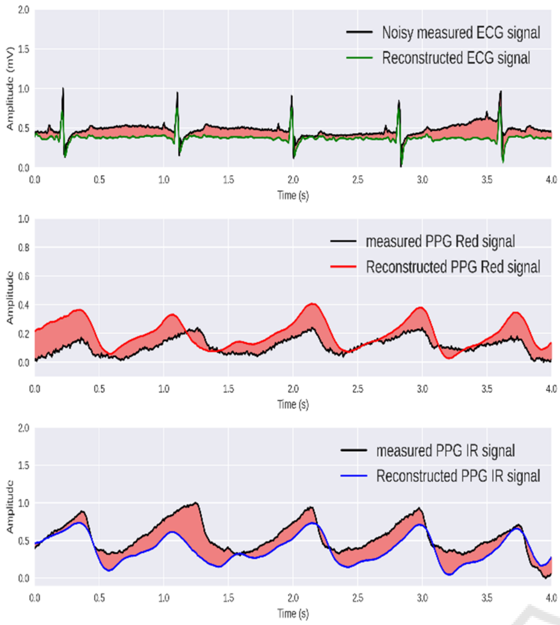

Figure 5: Comparison between reconstructed signals and real signals.

4.2.2 Online Demonstration

An Android application was developed to receive, process, and display the data measured by the wearable system. This decision is motivated by two points : Using signal processing methods with ECG and PPG signals, in addition of increasing the microcontroller power consumption, do not provide enough satisfying results.; The current microcontrollers do not have enough memory to use Deep ML models. By using an Android application as a gateway since most current smartphones support Deep ML models (as TensorflowLite file), we achieve our goal to reconstruct ECG and PPG signals.

The wearable system measure ECG and skin temperature and send the data to the Android application using Bluetooth Low Energy. The sampling frequency used is 128 Hz for the ECG, and 1 Hz for the temperature. The android application receives the datas and extract the ECG signal and the skin temperature. The ECG signal and the temperature are stored , each to an array until the ECG signal duration is equal to 4 seconds. Then, the TensorflowLite model reconstruct the signals from the ECG signal received.

The reconstructed signals are used to estimate the heart rate (from the ECG signal), the SpO2 (from the PPG signals). The average skin temperature is estimated as the mean of the stored temperatures.

Heart rate and SpO_2 level are estimated from the generated signals. Heart rate is estimated from the equation (12). SpO_2 level is estimate from equation (2):

$$Hr = 60\frac{N}{T_r} \tag{12}$$

where N is the signal length in seconds, T_r is the R-peak interval length during N seconds.

Figure 6 shows that the Android application can successfully monitor in real-time skin temperature, ECG and PPG signals, and estimate heart rate and SpO_2.

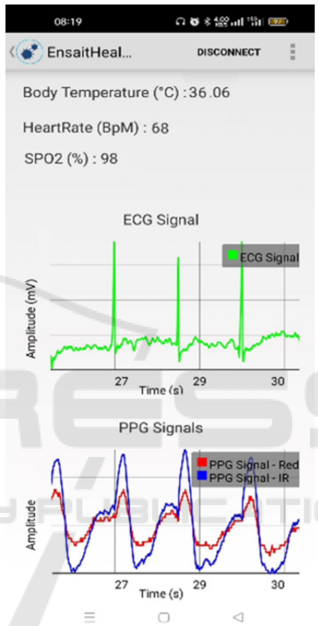

Figure 6: Real-time monitoring.

4.3 Discussions

We believe our proposed solution has the potential to make a significant impact in the healthcare and wearable domains, notably for continuous health monitoring. In addition to be lowcost, our proposed wearable system assures patient comfort and mobility, making it suitable for real-time and long-term monitoring. The integration of the proposed model offers many advantages to our system:

- A Real-time denoising of the ECG signal, ensuring continuous signal quality.
- The ability to generate robust PPG signals, eliminating the need for an oximeter. Initially design for COVID-19 monitoring, the current system can be used for other applications (Early diagnosis of cardiovascular diseases for example).

Despite its great performances, the current wearable system has some limitations:

- The current wearable systems mainly realize real-time detection for the basic symptoms of COVID-19 from skin temperature, blood oxygen saturation (SpO2) level, and heart rate. Since these symptoms are common with other diseases (e.g. Flu), it is impossible to distinguish COVID-19 from others without further investigation.
- Human study test must be conducted, to collect more data and assert the efficiency of the model and the proposed system. A cross-validation with practitioners is also collect more data and assert the efficiency of the model and the proposed system.

The model architecture must be less complex to be implemented directly to the microcontroller.

5 CONCLUSION AND PERSPECTIVES

This paper presents a novel textile-based wearable system for COVID-19 monitoring. By coupling to wearable system with an AI framework, we can obtain clean ECG signals and PPG signals for heart rate and SpO_2 level estimation. The proposed AI framework, reconstruct robust ECG and PPG signals from a single noisy ECG signal measured by the wearable device. The early experimental measures confirm our wearable system can be used in a real-time scenario. Considering that heart failure is one of the most prominent symptoms of COVID-19, we believe that the virus presence in the patient organism can affect the ECG waveform. Our next work will confuse on the implementation of an AI model that can distinguish ECG waveform from a healthy patient to a COVID-19. This information can improve greatly our current wearable system and help to monitor patient status in real-time.

ACKNOWLEDGEMENTS

This work was supported in part by the National National Research Agency (ANR) of France, Ecole Centrale Lille, and GEMTEX Research Laboratory under AI_Engineering_PhD@Lille grant.

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