Filtering Parameters Selection Method and Peaks Extraction for ECG and PPG Signals

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***Abstract*—With the growth of electronic E-health, wearable devices have highlighted due to its practicality and comfort in sensing of the personal data. Those devices gather biosignals for heart rate measurements, blood oxygenation checks, and identification. From sensors in the devices, electrocardiogram (ECG), photoplethysmogram (PPG) generate unique identifiers for use in identifying people, just like fingerprint, faceid, iris, among others. Every process with sensors has noises, electromagnetic waves, and movement that can interfere with the system when identifying, analyzing, and checking the individual. From this, filtering is an indispensable step in any process. The identification is divided into stages, and the main and essential is the filtering because where preprocessing starts. Thus, this work proposes a method of select filtering parameters for ECG and PPG signals and peaks extraction to the purpose the apply them for any dataset, following a sequence of steps, filtering, characteristics extraction (Peaks) and to affirm our model the correlation between filtered and raw waves performing a wave overlap. It is achieving an 80% correlation between raw waves and filtered waves.**

***Index Terms*—Filtering, Peaks Extraction, Wearable Devices.**

I. Introduction

In the last few years, the proliferation of smart wearable devices increased at a mass industrial level, (particularly smartwatches and bracelets), which enabled to capture vital and non-vital functions, such as body accelerations, electrocardiogram (ECG), photoplethysmogram (PPG), bio-impedance, and others [1]. However, the sensors suffer several limitations, such as noisy signals and interference occurring over the collect of signals. Particularly, ECG sensors suffer problems related to electromagnetic signals and electrical signals at the time of signal capture of the individual. On the other hand, PPG sensors also pick up noise, interference, and depending on the type of sensor used. The hardware can also influence the performance of signal capture of the individual [2]. In this context, filtering applied in the processing of ECG and PPG signals must be adjusted to filter type chosen for the signal [3]. Therewith, making it inevitable for all types of processing signals on wearable devices to establish the optimal filter.

In general, heart rate pre-processing follows the use of filters, either in hardware or software. Hardware filters have the advantage of being designed to extract specific data (*e.g.*, data related to cardiac variation or respiration), being more efficient. However, they are usually limited and little flexible as to the data treated, restricting the frequency range that they act [1]. The software filters limit the amplitude of the collected signal in a similar way to the hardware filters, but through mathematical calculations implemented in software. In addition, the chosen filter should consider the computational limitation of the wearable devices, being priority filters with low computational complexity [2].

Although the usage of values measured from ECG and PPG signals is a reality, the use of practice on the identification step in wearable devices is a non-trivial task. The wave obtained from the ECG and PPG signals allows the extraction of different user unique characteristics. The main ones being the number of peaks during a time interval, the valley shape, and the peak shape, the wave amplitude, and the distance between the peak and the valley of the wave [2]. Peaks extraction consists of obtaining the characteristics of the ECG and PPG signals. Detecting the highest amplitudes of filtered waves of each biosignal is of extreme importance since it is a characteristic of human identification [3]. Current works [1], [4]–[6] have proposed filtering and character extraction from ECG and PPG signals. Identification of people, analyze to select parameters filtering and classification. However, they prioritize a single parameter for both signals or only work with a single signal type being either ECG or PPG.

In this paper, we present a method to select filtering parameters to handle of ECG and PPG signals, which is used to evaluate the filtering and peaks extraction with ECG and PPG signals. The purpose here is to determine an easy-to-handle configuration independent of the dataset addressed and optimization of the ECG and PPG signal filters. We conclude that for filtering the ECG and PPG signals, the order of filter directly influences the amplitude of these signals. The normalization of the signals corresponds to changes in magnitude and sampling rate in the correlation of signals. The longer the signal period, the greater the capture of both signal noise and electromagnetic interference. The results indicated more precise adjustments in the filtering parameters and peak extraction. We obtain 80% correlation between all raw signal and filtered signal for peak extraction. ECG and PPG signals can not use with a single parameter in filtering, due to the way sensors pick up signals and the type of sensors are different.

The rest of the paper is organized as follows. Section II

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shows the state-of-the-art about Filters and Classifiers with ECG and PPG. Section III details our method to select filtering parameters to handle of ECG and PPG signals, which is used to evaluate the filtering and peaks extraction with ECG and PPG signals. Section IV discusses the results achieved. Section V concludes the paper and discusses future works.

II. Related Work

Previous studies trying to show a way of using parameters for filtering and peaks extraction on ECG and PPG signals. Many ways of filtering with ECG, PPG, and the two signals together propose to adjust parameter values used in biometric signal filters. Hence, we investigated methods existing in the literature to filter, and peaks extraction on ECG and PPG signals typically works follow approach on analysis with both signals.

Birrenkott et al. [4], the approach using parameters for filtering on ECG and PPG specifically calculate respiratory modulation robustness. Example of an explicit quality index for extracted respiratory modulations. The work expands the concept by developing novel respiratory quality indices (RQIs) and fusing them into a single robust RQI that can be used to facilitate improved fusion of respiratory estimates from multiple sensors and modulations. Specifically calculates respiratory modulation (RM) robustness. To find the RM was filtered using a 5th-order Butterworth bandpass filter between 0.083 Hz and 1.000 Hz (representing 5 to 60 brpm) and downsampled to 4 Hz for each modulation obtaining 50% correlation between the raw waves and the filtered waves.

Nakayama et al. [2] presents the BEAT system that provides secure, continuous, non-intrusive authentication without the need for additional user actions. The BEAT system uses vital signals related to heart rate and collected from PPG (photoplethysmogram) sensors to authenticate users. It uses filtering after capture by the sensors used. The sensor works in a range between 1 and 50Hz, signal values captured outside the range are disregarded. Yongbo et al. [1] investigated filter orders to improve the morphology of the PPG waveforms. Each set of filter orders included ten-valued that sequentially increased at a fixed rate. A total of 90 filter configurations were produced, which helped to determine the optimal filter order. Note that the filters designed in the filter study were all digital filters and not hardware filters.

Charlaton et al. [5] created respiratory rate algorithms to determine how closely algorithms agreed with a gold standard RR measure when operating under ideal conditions. Secondary aims were: (i) to compare algorithm performance with IP, the clinical standard for continuous respiratory rate measurement in spontaneously breathing patients; (ii) to compare algorithm performance when using ECG and PPG; and (iii) to provide a toolbox of algorithms and data to allow future researchers to conduct reproducible comparisons of algorithms and divided into three stages, being two of the stages, namely 'extraction of respiratory signals' and 'RR estimation'. In the first stage, they used the Butterworth bandpass filter between 4 and 60 bpm for ECG and PPG signals obtaining a 60% correlation between the waves. Using the same filtering parameters for ECG and PPG signals represent waves outputs so different in reference from raw signals, therewith, extract characters is committed by the lack of correlation between the waves.

Liang et al. [1] analyzed the filtering performance of the PPG signal, adopting three categories of signal quality (SQ). To compare the filter types calculates the SQ of the filtered PPG signals, the five orders of each filter type calculate an average SQ for each one. This work only addresses filtering in PPG signals, which makes it impossible to apply its filter parameters in ECG signals, since the waveforms need to be parameterized according to their structure, obtaining a 75% correlation between the raw waves and the filtered waves but just PPG signal. Recent studies report the need for new approaches to filtering on ECG and PPG signals because techniques based on unique filter parameters and peaks extraction are not effective [6]. In this way, biosignals parameterization has a lot of attention in recent studies. In general, templates focus on the same parameters filter or just one biosignal. Moreover, to the best of our knowledge, the existing approaches do not consider exact parameters filter to such kind of filter on such type of biosignal, ECG, or PPG.

III. Filtering Parameters Selection and Peaks Extraction Method

This section details our method to select filtering parameters to handle of ECG and PPG signals. Showing how we perform the peaks extraction in filtered waves. The validation of the filtering parameters selection method between the raw waves and the filtered waves utilizing correlation. Initially, we show the datasets used on a method, after how ECG and PPG signals are captured on the body. Its followed for that kinds of filters we utilized on analyze of biosignals, the form of peaks extraction. Finally with correlation, we see in Figure 1 the division of the steps for the filtering parameters selection method and peaks extraction for ECG and PPG signals. In the gray blocks, we see the generated data used for the method and in the other blocks, the techniques that are of extreme necessity for the processing of the ECG and PPG signals. Being the first block of the signals coming from datasets. The second third and fourth are in flat the techniques apply to generate data. The final block is part of data that we generated after to apply the method in the signals with the intention to identify people.

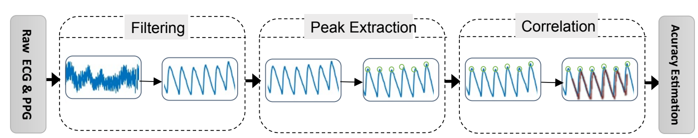


Fig. 1: Filtering Parameters Selection Method and Peaks Extraction for ECG and PPG Signals

A. ECG and PPG Signals

The distribution of blood within the body changes during each cardiac cycle due to the pulsatile flow of blood from the heart [7]. Each cardiac cycle consists of two phases; systole, the period of ventricular contraction and blood ejection in the arteries, and diastole during which the ventricles are relaxed and filled with blood [8]. The ECG signal is a record of electrical potentials generated by the heart, and it is conventionally measured with electrodes attached to the chest wall. Figure 2 shows the major electrical events of a single heartbeat, which are P wave, QRS complex and T wave; P wave corresponds to the atrial depolarization, QRS complex to the ventricular depolarization and T wave to the ventricular repolarization [9].

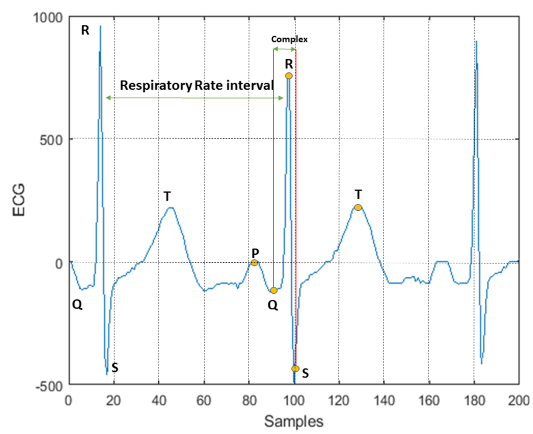


Fig. 2: Illustration of the six ECG Signal waves

In a typical PPG measurement, only a light source to illuminate the skin and a photo-detector to measure the variations of light intensity associated with changes in blood volume, are required [10]. PPG usually operates at a green, red, or near-infrared wavelength and has a fundamental frequency of around 1 Hz, depending on heart rate. The PPG pulse waveform consists of two phases, the anacrotic phase being the rising edge of the pulse and the catacrotic phase being the falling edge of the pulse. Figure 3 shows the first phase is concerned with systole and the second phase with diastole and wave reflections from the periphery [11]. Also, the dicrotic notch is usually seen in the catacrotic phase of subjects with healthy compliant arteries [11]. With all the capture factors in the preprocessing filtering removes problems that the sensor may have picked up, such as noise and electromagnetic waves that impair the correct reading of the signal.

B. Filtering

Pre-processing of wearable devices is required as they are vulnerable to different sources of noise, such as electromagnetic interference, excessive brightness, and sudden user movements in regions close to the sensor. However, the sensors with filters in hardware are limited and little flexible as to the data treated, restricting the frequency range that they act. For example, a PPG sensor in hardware designed to operate in the frequency range between 0 and 125 Hz provides values between 1 and 50 Hz, with the values above and below the filter being discarded. If the sensor does not have hardware

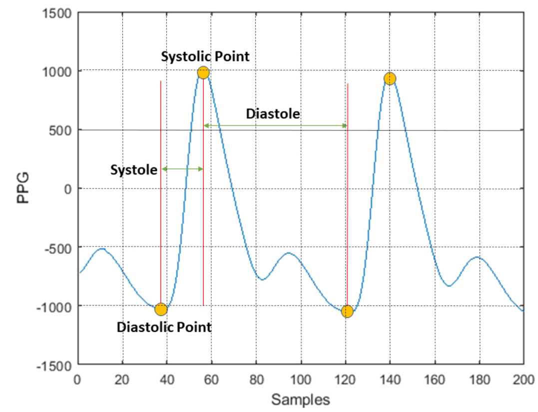


Fig. 3: Illustration of the two PPG Signal waves

filters, the data of all the frequency bands captured by the sensor will be available for consultation. However, in addition to being a large volume of data, many of the data obtained are unnecessary. Especially those obtained at very high and very low frequencies, being noise [2].

The ECG and PPG signals filtered according to the parameters in Table I applied on the whole signal for the removal of the power line interference, motion artifacts, baseline wanders. The Table I defines the parameters we use in filtering, filter type, filtering order for signal, cut frequency or scale are parameters to define about signal pickup frequency of the sensor, the sample rate of signal type. Thus, it creates parameter models for filtering applied on the ECG and PPG signals, which aids for the extraction of signal peak characteristics. We applied the Butterworth and Modwt filters, which are widely employed in wearable devices. In the Butterworth, we have a magnitude response that is maximally flat in the passband and monotonic overall. This smoothness comes at the price of the decreased roll-off steepness. The algorithm for filtering is divided into five-steps [12]:

1) It finds the lowpass analog prototype poles, zeros, and gain using the function buttap.
2) It converts the poles, zeros, and gain into state-space form.
3) If required, it uses a state-space transformation to convert the lowpass filter into a bandpass, highpass, or bandstop filter with the desired frequency constraints.
4) For digital filter design, it uses bilinear to convert the analog filter into a digital filter through a bilinear transformation with frequency prewarping. Careful frequency adjustment enables the analog filters and the digital filters to have the same frequency response magnitude.
5) It converts the state-space filter back to its transfer function or zero-pole-gain form.

The Modwt implements the circular convolution directly in the time domain. This implementation of the MODWT performs the circular convolution in the Fourier domain. The wavelet and scaling filter coefficients at level j are computed by taking the inverse Discrete Fourier Transform (DFT) of a product of DFTs. The DFTs in the product are the signal's DFT and the DFT of the jth level wavelet or scaling filter [13].

Let H_k and G_k denote the length N DFTs of the MODWT wavelet and scaling filters, respectively. Let j denotes the level of the filter, and N denotes the sample size. The jth level wavelet filter can be computed based on Eq. 1.

$$H_{j,k} = H_{2^{j-1}kN} \prod_{m=0}^{j-2} G_{2^{m}kN} \tag{1}$$

The j^{th} level scaling filter is Eq. 2.

$$G_{j,k} = \prod_{m=0}^{j-1} G_{2^{m}kN} \tag{2}$$

C. Peaks Extraction

There are a number of methods for extracting the respiratory-induced variation, which relies on the identification of the peaks and troughs of the ECG and PPG waveforms. The wave obtained from the ECG and PPG dosage allows the extraction of different unique characteristics of the user, the main ones being the number of peaks during a time interval, the valley shape, and the peak shape, the wave amplitude, and the distance between the peak and the valley of the wave.

Peaks extraction consists of obtaining the characteristics of the ECG and PPG signals to detect the highest amplitudes of the filtered waves of each biosignal since the characteristic is of crucial importance for human identification [3]. We note that the number of peaks and troughs, respectively, need to be different. Indeed, it is often the case that peak-trough detection algorithms fail to identify peaks or troughs in noisy signals or identify spurious peaks or troughs. Thus, we developed an algorithm to detect the standard peak for both filtered ECG and PPG signals. The algorithm deals with the steps shown in Figure 1. The steps were divided into codes to analyze the entire PPG and ECG signal. For each step, apply the appropriate algorithm created each part of the method.

D. Correlation

We use the correlation to verify if the proposed model is correct. In the correlation, the waves are superimposed on each other and analyzed. It is affirming if it is possible to extract the peaks from filter waves. Thus, the raw waves are superimposed on the filtered waves for analysis if they are positioned correctly in relation to time and samples. Whereas for extraction of peaks in raw waves and filtered waves need to be associated correctly. From the analysis of the selected model, it was possible to obtain an 80 % correlation between the waves, according to the selection model for the filtering parameters. The correlation of two discrete-time sequences. Correlation measures the similarity between a vector x and shifted (lagged) copies of a vector and as a function of the lag. If x and y have different lengths, the function appends zeros to the end of the shorter vector, so it has the same length as the other, Making a similarity of waves [14].

IV. Analysis

This section describes our evaluation methodology. We take into account the steps of filtering, peaks extraction, and correlation, and discussed the results obtained.

A. Methodology

The results obtained from the application of the method of select filtering parameters will be presented, in each step, Filtering, Peaks Extraction, and Correlation in the ECG and PPG signals with the datasets. We consider two independent, publicly-available datasets: MIMIC-II [15] and CapnoBase [16]. Both Datasets contain simultaneous PPG and ECG waveforms. The MIMIC II dataset consisted of the same 53 subjects. One eight-minute segment was extracted between the t = 60 and t = 68 minutes of the recording [4]. The CapnoBase dataset consisted of the same 42 subjects. One high-quality, eight-minute segment of data, taken during elective surgery or routine anesthesia, was available for each subject [16]. We implemented and analyzed the method using the MATLAB software framework, v.R2017a (Math-works, USA), and designed to function on every single window (independently of the others).

B. Results

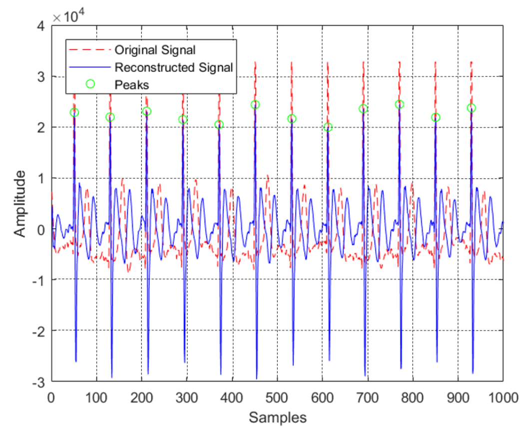
Figures 4a and 4b show the original, reconstructed, and peaks of ECG signal. Filtering regulates the higher peaks of the waves, thus facilitating the removal of the peaks. By parameterizing the data from the raw wave, we were able to adjust the filtered wave. The QRS complex corresponds to ventricular depolarization. It is larger than the P wave because the muscle mass of the ventricles is greater than that of the atria, the signals generated by the ventricular depolarization are stronger than the signals generated by the atrial repolarization. As previously said, the ECG signal composts six waves, with peaks in the highest amplitude waves being one of the most relevant characteristics for identifying people. Hence, the wave analysis is necessary to ensure the removal of the peaks with efficiency, and thus being able to correlate it in the future.

Figures 4c and 4d show PPG signal, filtered waves. We have observed the highest peaks to identify the peaks for analysis. With the identified peaks we can reference them to form the beginning and the end of each part of the filtered wave, thus forming each heart beat. PP signal constituted by two waves, generating peak and valley, systolic and diastolic respectively. To check the peaks, we analyzed the highest amplitude, systolic peak, since we were able to remove the necessary characteristics for both datasets used. We can observe that with the filtering step well done the filtered waves follow a pattern of amplitude thus facilitating in the detection of the peaks in the signal.

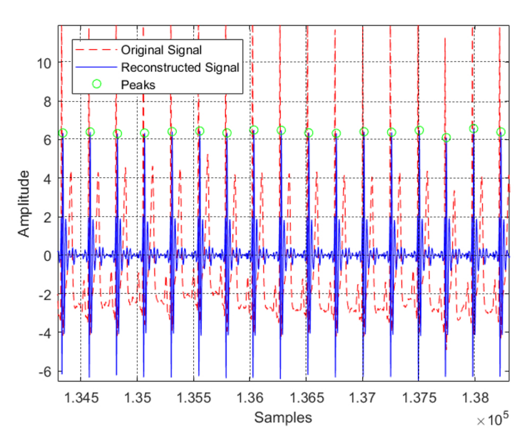
Correlation Step, the filtered waves will always follow the raw wave lines to act as an overlap of waves concerning

TABLE I: Filters with Unique Parameters for ECG and PPG Signals.

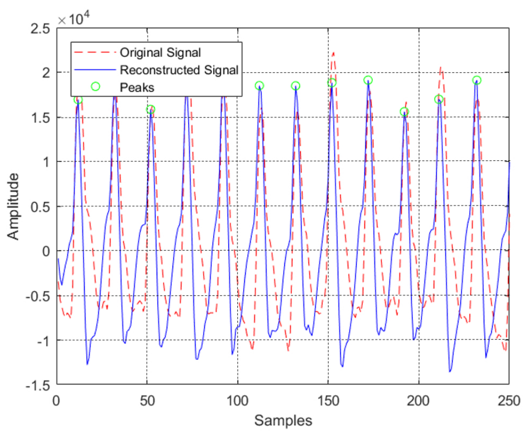
Filter	Order	Cut Frequency or Scale	Sample Rate	Signal
Butterworth	5°	[0.083hz 1.0Hz]	2.1	ECG-BIDMC
Butterworth	4°	[0.067hz 1.0Hz]	2.1	ECG-CAPNOBASE
Butterworth	3°	[0.083hz 1.0Hz]	3.1 - Downsample 4	PPG-BIDMC
Butterworth	3°	[0.083hz 1.0Hz]	3.1 - Downsample 4	PPG-CAPNOBASE
Modwt	9°	3 and 4	–	ECG-BIDMC
Modwt	9°	4 and 5	–	ECG-CAPNOBASE



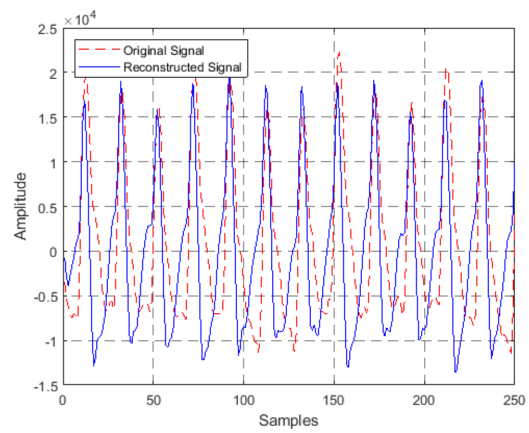
(a) ECG signal filtered for BIDMC dataset



(b) ECG signal filtered for CapnoBase dataset



(c) PPG signal filtered for BIDMC dataset

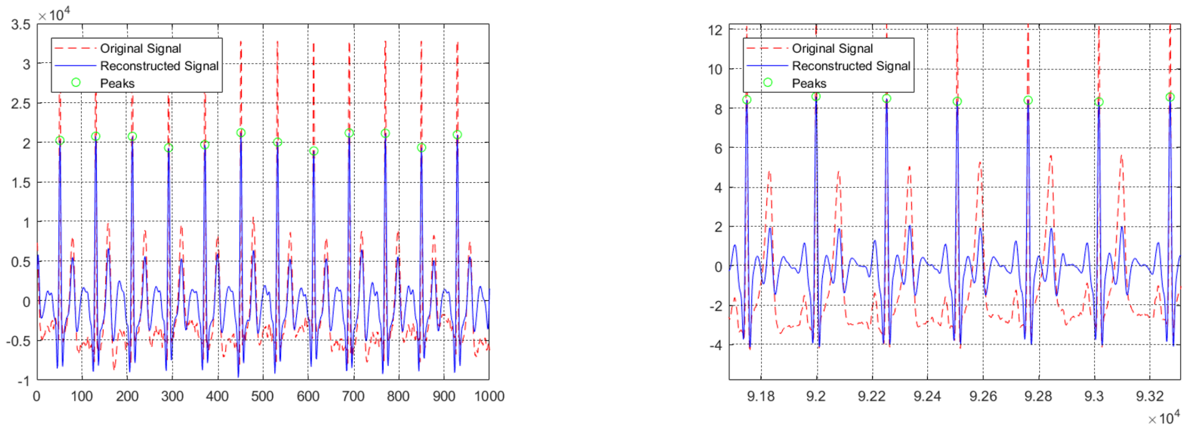


(d) PPG signal filtered for CapnoBase dataset

Fig. 4: Filtering, Peaks Extraction and Correlation of ECG and PPG Signals

time, extending the analysis to the entire wavelength that was analyzed. What is also to be analyzed, when passing filters in the ECG and PPG waves, there is a loss of correlation, since, in the raw waves, the noise interferes with the analysis. It is a necessary counterpoint in the relationship between the raw and filtered waves because a very low value can justify that the waves are not in the same time relation and very high value can show that the filtering was not effective. In this way, we can observe the Figures 5a and 5b on the ECG signals. Throughout the signal, the filtered waves follow the raw waves in relation to time but removing electromagnetic waves and waves that affect the signal, to establish a constant peak of peaks, so we can justify that the previous steps were performed correctly, parameterized according to the type and the metrics used for each ECG and PPG signal.

We conclude the filtering parameters (amplitude, cutoff frequency, sampling rate, and filter type) applied to signal correction and extraction peaks are independent sets of values, reaching 80 % correlation between the whole: raw signal and filtered signal with our parameters. All results seen at the filtering step require amplitude standardization. At the signal scale, the parameters adjustments follow along with the data set, defining from the signal type and metrics, and removing the electromagnetic waves and noise that affect the signal. The peak extraction step demands the verification of the filtered waves with the highest peaks according to the ECG or PPG signal performing the extraction. Lastly, correlation between the ECG signal and the PPG causes overlapping of



(a) (b)

Fig. 5: MODWT Filtering, Peaks Extraction and Correlation of ECG Signals

raw and filtered waves. Though, the time setting will ensure that all steps were done correctly, being that each step must be adjusted and parameterized according to the type and shape of the data set.

V. Conclusion

This work presented a new method of filtering parameters and extracting peaks with ECG and PPG signals. The evaluation of the employed model a set of parameter values that can be used in different datasets. From filtering steps, peak extraction and correlation according to the type of signal and metrics used, the results indicated 80% correlation between all raw signal and filtered signal to peaks extraction and the possibility of filtering out crude ECG and PPG waves and extracting and relating the waves. This work aims to help the research community to design parameters and values of filtration for use in biosynthesis. As future directions, we intend to investigate the impact of classification mechanisms on the identification in wearable devices. How much our parameters have influenced the improvement in the classification of other characteristics from PPG and ECG signals in wearable devices.

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