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EXTENDED ABSTRACT

A37 Processing and Extraction of Arterial Pulse Waves - comparison between manual and clustering based selections

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Introduction

According to the World Health Organization (WHO) cardiovascular diseases (CVDs) are the prime cause of death in developed countries, and consequently worldwide organizations have been gathering efforts to evolve strategies to counteract this trend [1]. An early diagnosis or a CVD risk assessment is crucial in preventing the development of severe complications. This can be done by monitoring and preventing hypertension, which is the leading cause of CVD's, being many times asymptomatic.

One way to assess hypertension organ damage is by evaluating arterial stiffness, which is normally done by determining the carotid-femoral pulse wave velocity (PWV) [2]. Other methods have been investigated in order to assess central hemodynamics and stiffness using only the arterial pulse wave morphology. The optical fiber sensor developed and clinically evaluated in [3,4] allows a non-invasive, rapid and easy way of accessing central hemodynamic parameters through the acquisition of the arterial pulse wave morphology at the carotid artery.

The acquired signals hand-helded devices, such as the one that was mentioned above, is that they are easily tainted with random noise, whether by movements of the patient or the medical professional using the device. Another potential source of noise is due to the optical nature of the device, since the signal baseline depends highly on how the device is placed in relation to the reflective surface, and the amplitude of the waveforms depend on where the reflective surface is placed on the patient (exactly placed on top of the artery or slightly to the side).

The present work had the main goal of developing a completely automatic algorithm to retrieve, from the raw data of the optical sensor, the individual arterial pulse waveforms with the higher signal-to-noise ratio and calculate the beat-by-beat hemodynamic parameters. These waveforms and parameters could then be presented to the cardiology specialist for analysis or used to train machine learning algorithms that would help classify the risk for CVDs. The latter being the end goal of this project.

Methods

Arterial pulse waves were acquired in 71 hypertensive patients with the referred optical device, from the hypertension consultation from Centro Hospitalar do Baixo Vouga. Raw data were acquired, with a sampling rate of 500 Hz, in each patient, until a steady and high-quality arterial pulse sequence was achieved, being the quality of the waves assessed by a specialist.

The data acquisition started with the finding of the best location for the sensor application which corresponds to the carotid location presenting the higher pulsatility. Once that place is found, a high reflectance adhesive is attached to the skin, being this location monitored during all the acquisition. This process usually takes around 20s. Once the signal acquisition has stabilized, there is noise interference due to patient movement or other physiological variables. It should be noted that to acquire the data it is necessary to exert some pressure on the carotid artery and that the lack of bone support sometimes makes the process of signal stabilization difficult. In this way, the existence of additional noise on carotid arterial pulses is predictable.

For filtering and extracting pulse waves from the raw data, various signal filters and processing techniques have been implemented, as shown in Figure 1.

Large oscillations related to the process of finding the carotid pulse wave correspond to low frequency data, close to 0 Hz corresponding to non-periodic baseline drifts. Thus, it was necessary to create a filter

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The authors declare no conflict of interests.

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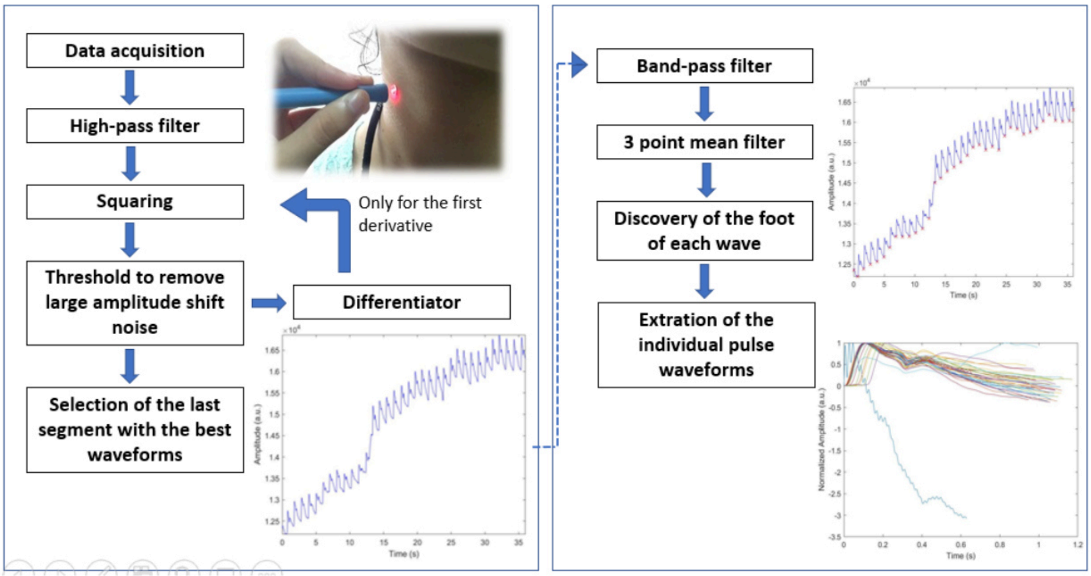

Figure 1- Block diagram of the processes used for filtering and extracting data.

that would eliminate this drift (applying a high-pass filter). For this, the *Matlab filterDesigner* tool was used and an IIR (Infinite Impulse Response) filter was created with a cutoff frequency of 0.05 Hz and a pass frequency of 0.5 Hz. The fact that the 0Hz frequency, corresponding to the DC component of the signal, was eliminated, allowed the signal to be centered at zero.

In order to eliminate large amplitude noise the signals were, after the first filter, normalized and then squared, increasing the discrepancy between normal amplitudes of the waveforms and noisy sections, this process was repeated for the first derivative obtained using a differentiator block: $y[n] = \frac{1}{8}(2x[n] + x[n-1] - x[n-3] - 2x[n-4])$, the $x[n]$ being the normalized signal and $y[n]$ the corresponding derivative.

It's important to note when the medical professional obtains the best waveforms the recording is stopped. So the original raw data is divided, using the large amplitude noise locations determined by empirical thresholds, into segments and these are analyzed from last to first. These segments can still be smaller amplitude noises, so we apply a continuous wavelet transform and determine the most prominent frequency, which for normal pulse waveforms must be between 0.5 and 2 Hz that corresponds to a normal heart beat frequency interval, if it's not in the interval the segment is considered noise.

After this step, a band-pass filter with a window between 0.1Hz and 50Hz, and a 3 point mean filter, to further eliminate high frequency noise. To remove the smaller baseline drifts inside the segment, we fitted a low order polynomial and subtracted it from the signal. The low order polynomial isn't capable of representing the intricate form of the individual waveforms, it’s only capable of depicting the larger signal fluctuations related with the baseline drifts. Subtracting it from the signal removes some of the baseline shifts.

The foot of each wave was determined through the local minimum point of the signal and then cut through the foot wave to get individual waveforms.

Now we have more “High-quality” pulse waveforms than noise affected ones so we can apply a clustering method to distinguish between them. The clustering method used was Kmeans with 2 clusters (Figure 2) and the cluster of the “High-quality” pulse waveforms was considered to be the one with most observations in it. The data fed into the Kmeans algorithm for each patient were the location of the maximum of the waveform and its derivative, the duration of the signal and the amplitude of the ending point of each individual pulse. These features were selected because they are critical points for distinguishing noisy waveforms from “good” waveforms. From this cluster 8,12 or 16 of the waveforms closer to the cluster center were chosen depending on the number of observations the clustering method was initialized with.

Results

The raw data acquired from one of the patients and the extracted pulse waveforms are represented in Figure 2. As we can see, there are several noisy waves that need to be removed.

The result of clustering is represented in 2 dimensions in Figure 3 and the results are in Figure 2 lower right. Not all the points of a cluster are chosen because even inside the cluster there are outliers, choosing the closest points prevents any outlier from making it out of the process.

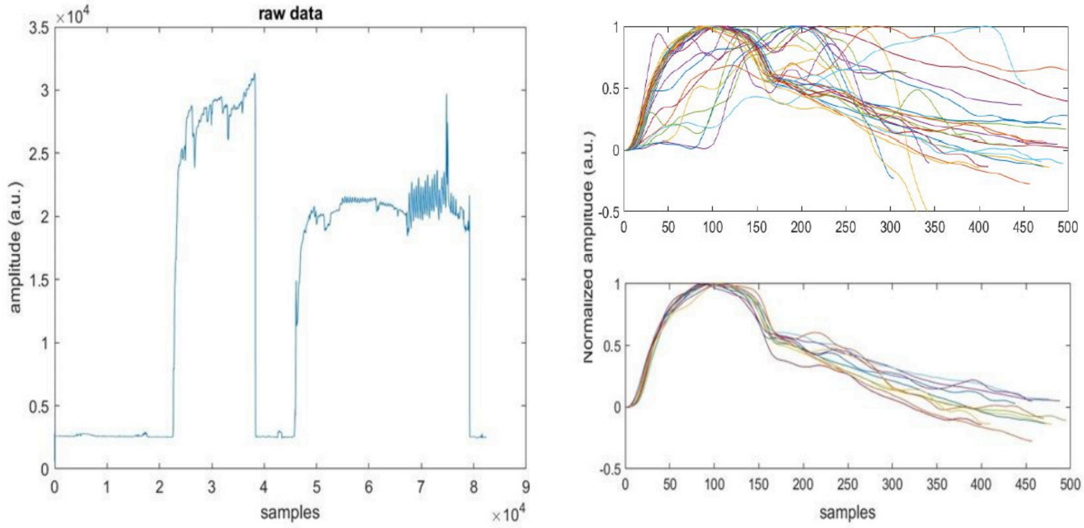

Figure 2 - Raw data (left) and waveforms before (upper right) and after (lower right) Kmeans cluster

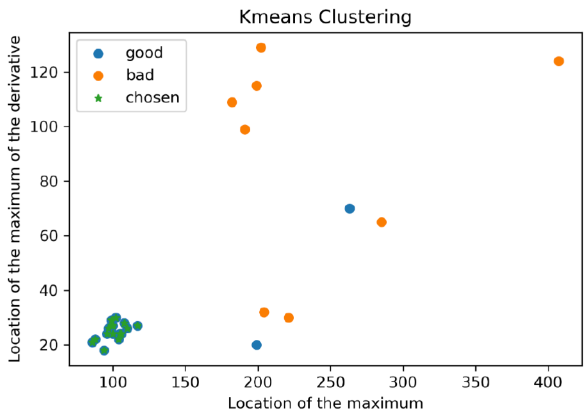

Figure 3 - Two dimensional representation of the Kmeans clustering, chosen waves are the 16 closest to the cluster center of the "good" waves that represents the least noisy waveforms.

As a reference for the clustering method, a manual selection of 'high-quality' pulse waves was made. The average pulse and the uncertainty area were calculated before selecting the best pulse waveforms, after manual selection and after the selection by the Kmeans algorithm. The results for the same patient of the previous figure are represented in Figure 4.

As shown in Figure 4, there is little to no discrepancy between manual and automatic procedures.

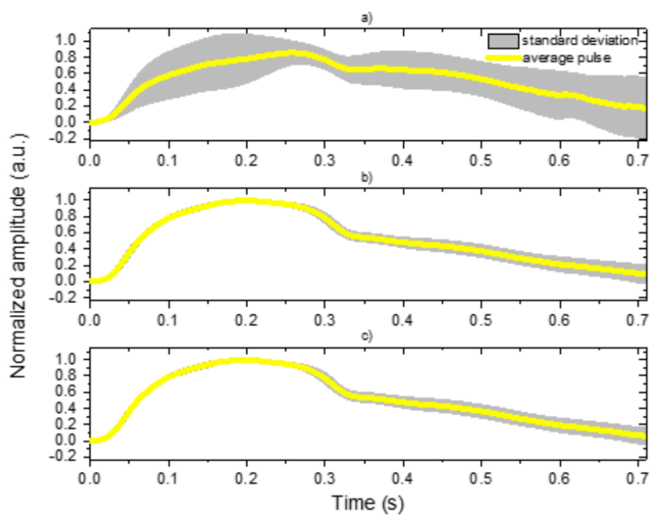

Figure 4 - Representation of the average pulse and the standard deviation for one patient, being: a) all waveforms after pre-processing the raw data; b) of waveforms left after a visual analysis and removal of noise tainted waveforms; c) of waveforms selected by the Kmeans algorithm.

Discussion

This paper provides a complementary automatic algorithm for an optical fiber sensor for retrieving arterial pulse waveforms and show that the results are on par with what is achievable by careful visual analysis. This method can save the time of a cardiology specialist by presenting only important waveforms and allow almost real time machine learning classification providing decision support. The algorithm failed in selecting waveforms for 2 patients in 71 getting a fail rate of 2.8%, which can be considered excellent preliminary results. With a bit more time the algorithm can be highly improved. More testing data is needed to confirm the results reported here. Future work involves the algorithm improvement and further testing in new patients and data acquisitions. Also, the algorithm will be applied in real-time data acquisition with the optical device.

Ethics committee and informed consent

The current research was approved by an independent ethics committee and subjects gave their informed consent before they were enrolled in the study.

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