Parameter tuning for accurate heart rate measurement using Wi-Fi signals

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***Abstract*—Heart rate monitoring is crucial for detecting possible changes in human health. Therefore, in recent years, the development of applications and devices that monitor vital signs has evolved significantly. This work proposes a non-contact approach to heart rate monitoring through the processing of channel state information from a commodity Wi-Fi network. Various settings for signal processing parameters were evaluated. The experimental analysis counted on over 50 participants, each performing 17 different positions and activities. Results confirm that it is possible to achieve accurate heart rate detection for each position or activity, provided proper parameter configuration.**

***Index Terms*—Channel state information, CSI, Wi-Fi, Heart rate.**

I. Introduction

In the last decade, health monitoring systems have evolved rapidly, demonstrating significant potential to change the way healthcare is provided [1]. As a result, contact-free vital signs monitoring, such as heart rate and respiration, has been receiving significant attention [2]. These vital signs can explain medical conditions such as cardiovascular disease, sleep disorders, or health abnormalities. Most traditional methods of monitoring vital signs require a person to wear special devices such as a capnometer [3] or a pulse oximeter [4]. However, these technologies are not practical and uncomfortable to use. Wi-Fi technology is widespread, and applying this technology to health monitoring can be contact-free, non-contact, and low-cost [2].

Most Wi-Fi transmissions utilize Orthogonal Frequency Division Multiplexing (OFDM) modulation. OFDM divides the transmission channel into subcarriers, and Channels State Information (CSI) could be collected from some OFDM subcarriers. CSI data can express the distortions caused by the human body in transmitted Wi-Fi signals. Section III will present how CSI data can be processed and used to estimate heart rate.

In this article, we evaluate the accuracy of heart rate monitoring through Wi-Fi networks. Our proposal involves tuning the parameters used to process the collected CSI data of 59 participants submitted to 17 different positions/activities. Experiments are based on an early version of the publicly available eHealth CSI dataset [5]. Although this dataset has over 120 participants to this date, at the time this work started, only 59 participants were available. The dataset creation was previously submitted and approved by the Research Ethics Committee, affiliated with the National Health Council of the Brazilian Ministry of Health. Data collection was authorized under CAAE reference number 54359221.4.0000.5243 [5]. In addition to the CSI data, the dataset also contains heart rate measurements obtained with a smartwatch.

The major contributions of this work are summarized as:

- Propose a Wi-Fi signal processing pipeline consisting of (i) a moving average filter to achieve better signal cleanup, (ii) a bandpass filter to obtain the frequency range where the heart rate is present, (iii) a Principal Component Analysis (PCA) to reduce the dimension of the CSI data, (iv) a Fast Fourier Transform (FFT) to obtain the amplitude peaks in the signal used to estimate the heart rate, and finally (v), the estimation of the heart rate as an average of the frequency peak values corresponding to the highest intensities.
- Find the set of parameter configurations for the filters utilized in the Wi-Fi signal processing pipeline that provide the most accurate heart rate measurements for each of the 17 different positions/activities — the reference heart rate value is obtained with a smartwatch. Namely, we tune (i) the sliding window parameters for the moving average filter, (ii) the maximum and minimum cutoff frequencies of the bandpass filter, and (iii) the number of frequencies in the FFT.
- Analyze the feasibility of accurately measuring the heart rate through Wi-Fi signal processing for a wide range of positions/activities, identifying possible limitations of the technology.
- Compare the best parameter settings for each position/activity to identify similarities and discrepancies. Positions/activities sharing the same (or similar) parameters broaden the application scenarios of this technology.

The remainder of the text is organized as follows. Section II presents recent related work. In Section III, we present the proposed methodology. Section IV presents the obtained results. Finally, Section V provides some conclusions and final remarks.

II. Related Work

Several studies have considered using CSI for heart rate monitoring in the literature. The CardioFi system [6] proposes a new selection of subcarriers that allows to amplify and detect the heart rate in subcarriers that are less affected by multipath propagation. However, this work must be extended to enable its use in real-time medical applications.

PhaseBeat [2] estimates the heart rate using the phase difference of two or more receiving devices. In the proposal, the authors experiment with different distances and obtain a phase difference according to its stability and periodicity. However, heart rate monitoring still needs optimization in these scenarios. More recently, PhaseBeat has been extended [7] and showed that the CSI phase difference is more robust in scenarios with varying distances, obstacles, and orientations. Dynamic time-warping has also been explored to detect changes in the movement of the Wi-Fi wave affected by heart rate [8].

WiHeath [9] estimates the heart rate using CSI samples collected from the Intel 5300 NIC. They used a median filter to mitigate samples that have a significant difference from the other neighboring ones, and a low-pass filter to remove high-frequency noise that cannot be caused by chest movement. They achieved average estimation error under 0.6 bpm and 6 bpm, but the experiment was conducted with just 3 participants.

CSI has been also used to track the heart rate during sleep [10]. The algorithm utilizes information from the channel in the temporal and frequency domains to estimate the heart rate. Later, the work evolved to estimate the heart rate in scenarios with extended distances between the Wi-Fi device and the access point, non-line-of-sight situations (NLOS), and 6 different sleep postures [11].

Note that most previous works focus on varying distances of the Wi-Fi device and the presence of obstacles. While some works consider subjects sleeping in a few different postures, there is no work investigating the influence of many different human positions/activities on the accuracy of heart rate estimation. The present work fills this gap in the literature.

III. Proposed Methodology

The architecture of our solution consists of three phases: CSI data collection, processing pipeline, and parameter tuning. Fig. 1 depicts the wireless scenario and proposed methodology. The following details each of the steps involved in the process.

A. Collection

In this section, we briefly recall the CSI data capture process used to create the publicly available eHealth CSI dataset [5]. The reader can refer to the original publication for a detailed description of the construction of the dataset. The present work uses an early version of this dataset which contains only 59 participants; this is a highly active project and the number of participants rapidly grows over time. We emphasize here that all participants are anonymous and that the dataset creation was previously submitted and approved by the Research Ethics Committee, affiliated with the National Health Council of the Brazilian Ministry of Health.

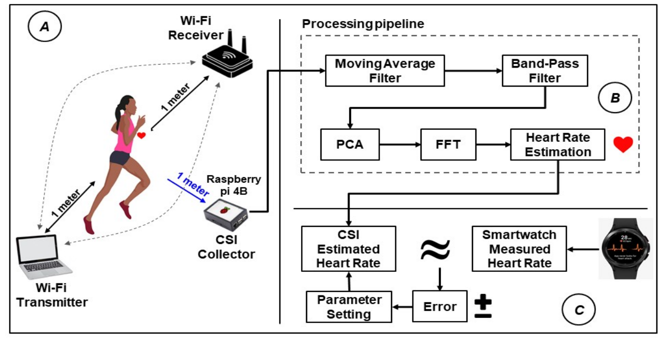

Fig. 1. Proposed methodology.

As can be seen in Fig. 1, our CSI data collection setup consists of a Wi-Fi transmitter (a laptop), a Wi-Fi receiver (a router), and a CSI collector (a Raspberry Pi 4B). The distance between the participant and all equipment was approximately maintained at 1m.

A traditional Wi-Fi network was used to collect CSI data, in which a Wi-Fi client sends *pings* to the router. The network was configured in the 5GHz band and used a channel with 80MHz bandwidth, resulting in a total of 256 subcarriers. Of these, only 234 subcarriers are considered, since the rest are intended for signaling and band separation. Then, a *Raspberry* Pi 4B with its network card in monitor mode, running the Nexmon-CSI firmware [12] was used as a *CSI collector*, and it captures and collects data in an interval of 0.12 seconds.

Each participant performed a predefined protocol with 17 different positions and/or movements, for 1 minute in each position, during the CSI data capture. The positions and/or movements are:

1) sitting facing the collector and the Wi-Fi devices on each side of the participant.
2) sitting in front of the device alternating breathing.
3) alternating the position of sitting and standing in front of the picker.
4) back to the collector and with the Wi-Fi devices on each side of the participant
5) with their back to the device alternating breathing
6) standing facing the collector and the Wi-Fi devices on each side of the participant.
7) standing in front of the device and alternating breathing.
8) standing with back to the collector and the Wi-Fi devices on each side.
9) standing with back to the device and alternating breathing.
10) lying on the stretcher with the belly on top and side of

the collector.

11) lying on the stretcher with the belly on top and alternating breathing.
12) lying on the stretcher face down and side to the collector.
13) lying on the stretcher face down and alternating breathing.
14) alternating lying on your back on the side of the collector and standing facing the collector.
15) walking position (act of walking in place) facing the collector.
16) running position (the act of running in place) in front of the collection.
17) sweeping position (the act of sweep) in the indicated area.

During the CSI data collection, the heart rate was also measured in parallel using a Samsung Galaxy Watch4 smartwatch. This device was used to measure and compare the estimated results through Wi-Fi CSI signals. Specifically, in this work, the measurements obtained via the *smartwatch* are considered as *ground truth* (GT); that is, the estimated measurements are compared to the *smartwatch* measurements so that it is possible to assess how far the values obtained from CSI are from the smartwatch reference.

Notice, however, that even such smartwatch devices are not completely accurate. According to a study reported in [13], these devices can reach up to 95% accuracy compared to the results generated by an electrocardiogram.

It should be mentioned that the data obtained from the *smartwatch* are also available in the *eHealth CSI dataset*.

B. Processing pipeline

In order to improve the performance of the proposed system, signal processing techniques are used [14] to reduce noise and remove *outliers*. In Fig. 1, the diagram with the main stages of the processing is presented in summary form.

1) Moving average filter: Often, to eliminate or reduce some undesirable noise in a signal, it is necessary to filter it. The moving average filter aims to smooth and reduce the noise present in the signal. It is not just an average of an isolated set of values. By using fixed coefficients, the moving average filter produces a smooth low-pass filter that reduces undesired high-frequency signals.

2) Bandpass filter: After using the moving average filter, the bandpass filter is applied to delimit the frequency bands of interest, removing the irrelevant part of the signal. The bandpass filter used is directly related to the system is intended application. For estimating the heartbeat, the frequency range of interest for this project corresponds to the range between 0.6Hz and 3.67Hz, i.e., between 36bpm and 220bpm.

3) PCA (Principal Component Analysis): After the preprocessing step, the amount of data represented in the signals received on each of the 234 subcarriers represents a large volume. To reduce the dimension of the CSI data, PCA is a frequently adopted technique. When PCA is applied in a set of received signals, a linear transformation (base change) is performed on the data so that the first component represents the dimension of the highest variance of the data. We used only the first component obtained for the following steps.

4) FFT (Fast Fourier Transform): After the PCA, the fast Fourier transform (FFT) converts the signal from the time domain to the frequency domain. From the result of the PCA, which transformed the collected CSI dataset into a single component, the FFT will result in a discrete set of values within the frequency range of interest filtered through the bandpass filter.

5) Heart rate estimation: The previous step outputs a set of frequency values and their respective intensity, representing the signal strength at that specific frequency. In order to obtain the estimated heart rate value, an average is performed between frequency peak values corresponding to the highest intensities. Then, we obtain the frequency in Hertz of the beats per minute (bpm) value by simply calculating the conversion from Hz to bpm, given that 1Hz represents 60 bpm.

C. Parameter tuning

In order to increase the accuracy of the heart rate measurement, we propose changing the limits of the cut-off frequencies of the band-pass filter, the number of peaks used in the estimation process, and also the moving average window size. By doing this, we find the configuration that yields the best results.

IV. Experiments and Results

In this section, we propose and analyze the effect of using different parameter configurations related to the processing of the collected signal on heart rate measurements through the CSI signal. The proposed procedure is described next.

A. Experiment setup

We propose sixteen different parameter configurations and use them to find the best parameters to increase the accuracy of the estimated heart rate when the individuals are performing each position/activity. The parameters tested are detailed below:

- The minimum and maximum frequencies of the bandpass filter that delimits the captured signal to be analyzed: some studies, such as [14], treat scenarios with values between 0.6Hz to 3.67Hz, equivalent to the range of 36 to 220 beats per minute. We have tested values between 1Hz and 2.5Hz which is equivalent to the range of 60 to 150 bpm, between 1.5Hz and 3.67Hz, and also between 0.6Hz and 3.67Hz.
- Number of FFT peak frequencies (k): represents the number of frequencies corresponding to the energy peaks we found in the FFT processed signal, which we use to calculate the average frequency that we convert into beats per minute. We test 1, 2, 3, and 4 peaks.
- Moving average sliding window size: more significant data smoothing can be obtained by increasing the value

of this parameter, however, at the expense of a longer processing time. We test values 3 and 10.

Table I shows the combinations of the abovelisted configurations parameters tried in this work.

TABLE I
PROPOSED CONFIGURATIONS

Parameters Config.	Bandpass frequencies [Hz]	Number of FFT peaks (k)	Moving Average Window size
1	0.6/3.67	1	10
2	0.6/3.67	2	10
3	0.6/3.67	3	10
4	0.6/3.67	4	10
5	1/2.5	1	10
6	1/2.5	2	10
7	1/2.5	3	10
8	1/2.5	4	10
9	1.5/3.67	1	10
10	1.5/3.67	3	10
11	1.5/3.67	1	3
12	1.5/3.67	3	3
13	0.6/3.67	1	3
14	0.6/3.67	3	3
15	1/2.5	1	3
16	1/2.5	3	3

The estimated BPM values were compared with those obtained with the smartwatch (considered as ground truth - GT) to evaluate the effectiveness of the proposed configurations. The mean difference between the results of executing the Wi-Fi CSI estimator and the data collected with the smartwatch was taken as a performance measure. The smaller the mean difference value, the smaller the estimation error.

B. Discussion of results

In this section, we present the results obtained using the CSI data for each of the the 17 positions/activities available in the eHealth dataset [5]. Table II summarizes the results.

Table II presents the best configuration that achieves the lowest mean error, considering each of the 17 positions.

For each position (first column - Position), the heart beat value of each participant was estimated and we present the mean of the BPM considering the 59 individuals in the fourth column (Average BPM CSI). Also, we present in the fifth column (Average BPM GT) the mean BPM obtained from the smart watch (GT) considering the 59 individuals. Finally, in the sixth column we present the mean error between the CSI estimation and GT. The best configuration for each position is shown in the third column.

As we can notice from the obtained results, it doesn't matter whether the person is facing forward or backwards or whether breathing is alternated or not, whenever the individual is **sitting**, the best parameters are from configuration 5. We can also identify the same behavior when it comes to **standing** position, in which the best configuration is always number 8. When it comes to **lying** positions, we can see that the best configuration for the majority of the cases is number 4.

When walking position face the collector (position 15), and also when alternating the position of sitting and standing (position 3), configuration 8 is also recommended.

For moving positions 16 and 17, running and sweeping, configurations 14 and 16, both with smaller moving average window sizes, are recommended respectively.

As we can see, the smallest errors, highlighted in bold, were obtained for positions in which the individual is in static positions: either sitting or lying. In these cases, it is observed that an adequate configuration of the parameters minimizes the estimation error.

For a more detailed study, we can also analyze the obtained results from a dispersion point of view in Fig. 2 and Fig.3.

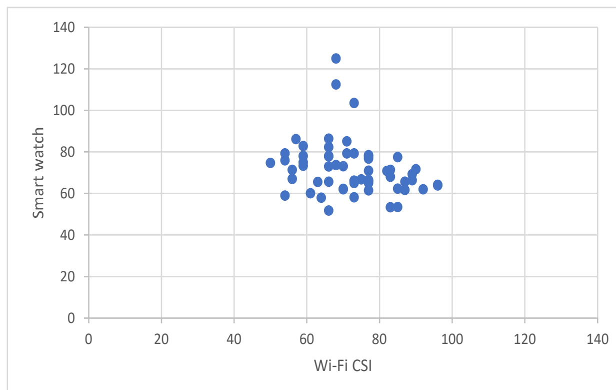

Fig. 2. Dispersion of position 11 configuration 3 Wi-Fi CSI and smartwatch.

For this, we compared the BPM obtained from the CSI with that collected by the smartwatch for all participants. In Fig. 2 we present the dispersion of the Wi-Fi CSI measure and the smartwatch measure considering position 11 and configuration 3.

In this case, the correlation index was -0.25. In addition, in Fig.3 we present the dispersion of the Wi-Fi CSI measure and the smartwatch measure considering position 13 and configuration 4. The Pearson correlation index was -0.20.

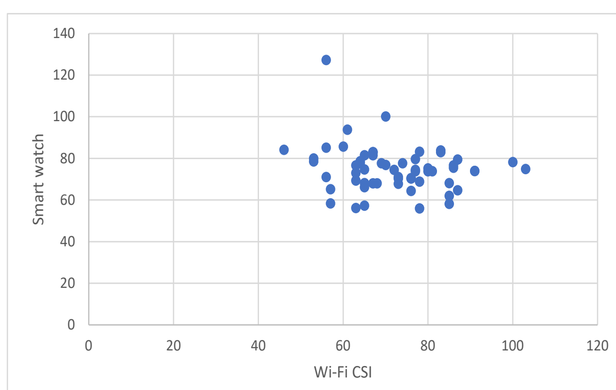

Fig. 3. Dispersion of position 13 configuration 4 Wi-Fi CSI and smartwatch.

TABLE II
BEST CONFIGURATIONS MEAN ERROR OF EACH BPM FOR EACH POSITION.

Position	Description	Best configuration	Average BPM CSI	Average BPM GT	Mean error[%]
1	Sitting facing the collector and the Wi-Fi devices on each side of the participant.	5	87.22	85.78	1.67
2	Sitting in front of the device alternating breathing.	5	86.61	86.32	**0.32**
3	Alternating the position of sitting and standing in front of the picker.	8	91.22	91.95	0.80
4	Sitting back to the collector and with the Wi-Fi devices on each side of the participant.	5	88.15	89.36	1.35
5	Sitting back to the device and alternating breathing.	5	88.54	85.94	3.02
6	Standing facing the collector and the Wi-Fi devices on each side of the participant.	8	90.83	95.12	4.51
7	Standing in front of the device and alternating breathing.	8	90.11	96.13	6.26
8	Standing with back to the collector and the Wi-Fi devices on each side.	8	89.69	96.06	6.62
9	Standing with back to the device, and alternating breathing.	8	90.23	96.97	6.94
10	Lying on the stretcher with the belly on top and side to the collector.	4	77.52	77.59	**0.35**
11	Lying on the stretcher with the belly on top and alternating breathing.	3	72.27	71.97	**0.47**
12	Lying on the stretcher face down and side to the collector.	4	75.59	76.83	1.61
13	Lying on the stretcher face down and alternating breathing.	4	72.13	74.99	3.81
14	Alternating lying on your back on the side of the collector and standing facing the collector.	4	77.69	79.73	2.55
15	Walking position (act of walking in place) facing the collector.	8	89.71	93.67	4.23
16	Running position (the act of running in place) in front of the collector.	14	111.39	109.596	1.59
17	Sweeping position (the act of sweep) in the indicated area.	16	103.59	108.19	4.25

In most cases, CSI estimation errors occur when CSI underestimates the BPM.

V. CONCLUSIONS

This work demonstrated the feasibility of accurately monitoring the heartbeat using CSI data from a conventional Wi-Fi network operating at 5 GHz. The proposed system is non-contact and low-cost. Experiments with 59 individuals in 17 distinct positions/activities made it possible to estimate the heart rate with parameter configurations in the Wi-Fi signal processing. The results showed that for each position/activity, a distinct configuration of the parameters is recommended. In future work, it is intended to adapt the system to detect the individual's position and then adaptively apply the appropriate parameters to monitor their heartbeat in real time.

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