Evaluating heart rate prediction accuracy focusing on different body parts using COTS Wi-Fi devices

PETRAS BAUBLYS, University of Twente, The Netherlands

ABSTRACT

Heart disease is the leading cause of death in middle-upper-income countries, which makes heart and heartrate tracking technologies and methods a vital part of human health monitoring. Past research was able to track a subject's heart rate from Wi-Fi's Channel State Information (CSI) by focusing the signals on their chest. However, antennas in a dynamic environment can not always focus on the subject's chest. Therefore, this research aims to analyze the possibility of heart rate tracking using existing signal processing algorithms by focusing the Wi-Fi signals on a sitting subject's chest, neck, thighs/hips, and back of the knees. This is done by testing the best antenna positioning and orientation to focus the signals on a specific body area. The findings are then used to target the different mentioned body areas. The data collected from five test subjects shows that existing heart rate-tracking algorithms best predict the heart rate from the chest area followed by the thighs/hips, whereas the neck and back of the knees perform the worst. Furthermore, based on the collected data and wave propagation theory, it is found that the most important characteristic of a body area is its surface area for heart rate prediction accuracy.

Additional Key Words and Phrases: Channel State Information, health sensing, heart rate monitoring.

1 INTRODUCTION

According to the WHO, the number one leading cause of death is ischemic heart disease, which causes about 12.8% of deaths [7]. With heart disease being more prevalent in older people [10], invasive HR (heart rate) tracking techniques might not be applicable as they might not suit their lifestyle. Wearable trackers might not be comfortable to wear while sleeping or be forgotten after the user has taken them off.

In recent years nontraditional pervasive HR tracking methods have been emerging including video-based HR tracking [11], Millimeter Wave Radar HR tracking [16], and Wi-Fi signal-based HR tracking [9]. All these approaches have their upsides and downsides.

Video-based HR tracking's biggest drawback is the need for light to record video, making it unusable in low light conditions for example when the users would like to sleep.
Millimeter wave radars are expensive and specialized equipment that is not easily accessible on the market, thus making some users unable to afford such solutions.

Wi-Fi signal-based tracking does not incur the aforementioned downsides that video-based and mm-wave radar have. It can be used in any lighting conditions and Wi-Fi equipment is cheap and easily purchasable. These factors would seem to make it ideal for the mass adoption of HR tracking applications.

However, Wi-Fi-based tracking suffers from reliability and robustness issues. Different body positions and locations of the receiver, transmitter, and subject all greatly influence how the Wi-Fi signal bounces, thus greatly affecting the reliability of CSI data [13] for HR predictions. The main challenge comes from the tools used, CSI was created to describe the propagation of the signal through a multipath environment and not to monitor hardly noticeable physical changes in the environment as someone's heartbeat. However, signal propagation theories as the Fresnel zone theory can be leveraged to assist. Using Fresnel's theory, the effects of small environmental changes on CSI data can be amplified and small unnoticeable heartbeat movements magnified to a noticeable change in the CSI data [13].

The current research about CSI HR tracking revolves around tracking chest movements of a subject that are generated by the systole and diastole phases of cardiac cycles. This paper expands the research by diverting from the chest area and trying to record HR signals from different body areas. Exploring the possibility of tracking a subject's heart rate from various body areas would make it possible to create more robust solutions that do not require the user to sit or lay down in one specific position and strive toward more general heart-rate-tracking systems. It may be possible to track the heart rate on different body parts because the systole phase of the cardiac cycle creates pressure in the Aorta and the attached Arteries, which expand and contract them [8] which then expand and contract the surrounding tissues, creating micro-physical pulsations. These periodic micro-physical pulsations might be noticeable in the CSI data. This research aims to target this effect and discover the feasibility of predicting the subject's HR by focusing the Wi-Fi signals on different body areas. This aim gave rise to the following **Research Question**:
How accurately can the human heart rate be tracked using CSI data from commodity Wi-Fi devices focusing the signals at their neck, thighs/hips, and back of the knees compared to their chest?

To create adequate tests for each of the body areas, test environments had to be optimized to target each body part for an accurate representation of its performance. This need gave rise to a **sub-research question:**
What antenna orientation and position relative to the subject's targeted body part yields the most accurate heart rate predictions?

2 RELATED WORKS AND PRELIMINARIES

This section discusses the related works in the field of pervasive heart rate tracking systems and goes in-depth about the theories and technologies used for CSI heart rate tracking in this paper.

TScIT 41, July 5, 2024, Enschede, The Netherlands

2.1. Wi-Fi OFDM and CSI protocols

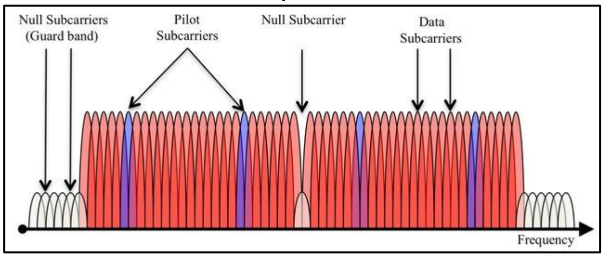

Fig. 1. Wi-Fi OFDM channel data encoding in different frequencies representation. (Taken from [2])

Orthogonal frequency-division multiplexing (OFDM) is a data encoding technique that encodes a byte stream into multiple subcarrier frequencies. This enables the data stream to handle subpar channel conditions. The standard Wi-Fi signal is usually divided into 64 different subcarriers as seen in Fig. 1. Out of the 64 subcarriers 12 are used as Guard bands, 4 as pilots (for phase and frequency training and tracking), and only 48 carry data [2].

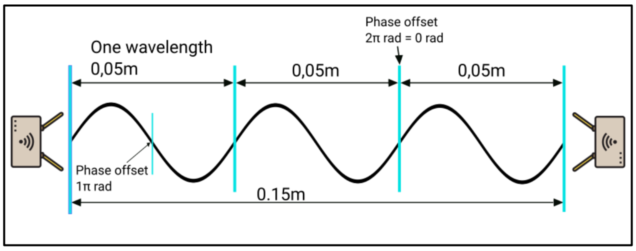

Fig. 2. Phase offset illustration with wave propagation.

An estimate of how the subcarrier travels through a complex environment is calculated for each data-carrying and pilot subcarrier. This calculation is called its channel state information (CSI) which is composed of two values that represent the amplitude change and the phase shift the signal experienced when traveling from the transmitter to the receiver [12]. CSI can be better understood by this formula:

$$R = H * T + n$$

R and T represent received and transmitted signals, n being noise, and H representing the CSI matrix. Changes in the CSI data represent changes in the environment the Wi-Fi signal propagates through. This environment representation in CSI data has been used in numerous human sensing applications including fall detection [4], driving fatigue [3], gestures [1] and many more. For heart rate tracking, only the phase shift part of CSI data is used as it is more sensitive than the amplitude.

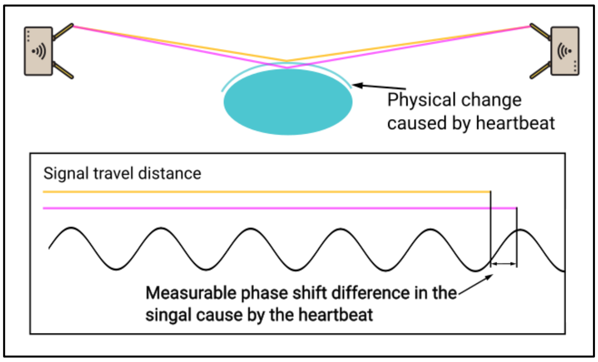

Fig. 3. Heart-beat induced phase shift difference on the signal.

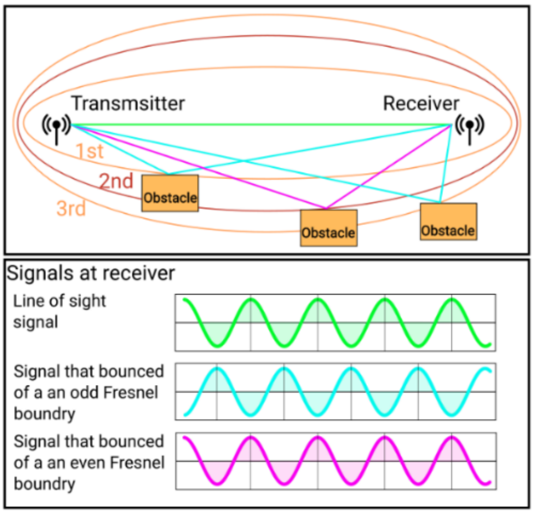

Fig. 4. Fresnel zone boundaries affect the signal phase shift

A signal experiences a phase shift as it travels through the environment, after traveling one sinusoidal cycle (one wavelength) the offset is again zero as shown in Fig. 2. Small environmental changes create a phase shift in the signal which can be detected in CSI data. Fig. 3 represents how the contraction and expansion of a subject's chest caused by the heartbeat creates a phase shift in the received signals.

These heart rate-induced periodic phase shifts have already been used in studies to monitor a subject's heart rate. PhaseBeat [14] used a Wi-Fi 5 GHz signal to track the HR of its subject in different poses (standing, sitting, laying) and variant positions in the room. They switched to a directional antenna at the transmitter to improve received data accuracy and use a 400Hz sampling rate.

CSI data is not only a Wi-Fi-based technology as other technologies use it for sensing applications. Using millimeter-wave radar [16] researchers achieved an average of 1.281 mean absolute error. They further took the research to estimate the subject's breathing and heart rates with an obstructed LOS from the radar to the subjects with a cardboard obstacle, which still yielded high accuracy results.

2.1. Fresnel Zones

Fresnel Zones and boundaries always have a strong effect on propagating signals and must be considered when dealing with signal propagation through a medium. Fresnel Zones are concentric ellipses with their foci points being the transmitter and the receiver. These Zones and boundaries can be used to calculate the phase shift of the signal that it experiences when bouncing off a surface before reaching the receiver.

A signal bouncing off a surface that is located at any odd-numbered Fresnel boundary before reaching the receiver experiences a phase shift of 180 degrees as seen in Fig. 4 in blue. A signal bouncing off an even-numbered Fresnel boundary experiences a 360-degree phase shift, which is also a 0-degree shift, as seen in the pink signal. In each Fresnel zone, this 180-degree phase shift happens gradually from one boundary to another. The boundaries of the Fresnel zones are most interesting because the received signal is either 0 degrees out of phase or 180 degrees out of phase which greatly influences the received signal's amplitude.

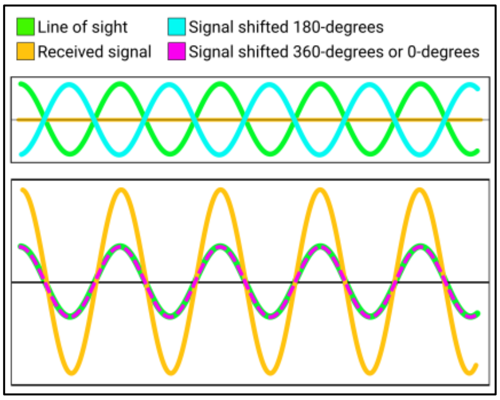

Fig. 5. Addition of differently offset signals.

If a signal arrives 180 degrees out of phase at the receiver it completely cancels out the LOS signal, making it look like no signal arrived at the receiver as shown in the upper image of Fig. 5. Whereas if the signal is 360 degrees out of phase it is perfectly aligned with the original signal and so will double the signal amplitude, making it look like a powerful signal has arrived at the receiver as shown in the lower diagram of Fig. 5.

Current research has explored how the location of a subject relative to Fresnel zones affects the accuracy of sensing applications. The studies [13] explores how placing the subjects in different positions and orientations relative to Fresnel zones influences the sensitivity and reliability of CSI data for the subjects' breathing predictions. Their findings show that the positions and orientation of subjects are highly influential to how sensitive and accurate the CSI measurements are based on whether the subject is in the Fresnel zone center or boundary.

3 DATA COLLECTION

This section first discusses the devices used for data collection during the tests. Secondly, it details the tests done to optimize antenna placement and rotation regarding the subject's position. Lastly, it details the testing environment.

3.1 Devices

3.1.1 Nuc Box-1220P minicomputers

For the collection of CSI data, two mini Nuc Box-1220P were used and throughout this paper are referred as nodes. The nodes were equipped with a 6-core i3-1220p processor, an AX211 chip, a 2x1 MIMO network card, with 64 GB memory, and dual Wi-Fi antennas. The nodes used a frequency of 6 GHz for the tests.

It was chosen to configure the devices to run on 400Hz CSI data transmission and collection frequency because it was found that lower frequencies produced less accurate heart rate predictions and higher frequencies did not yield considerable gains [14]. After initial data analysis, it was determined that the devices ran at a reduced 336Hz frequency rate. However, due to the positive results obtained from the pilot test after switching the pre-processing algorithm to 336Hz frequency, this discrepancy was not investigated more thoroughly, as it did not have a substantial effect on the study. The 400Hz input frequency was kept, but data was analyzed as if it was 336Hz.

3.1.2 Huawei watch fit 2.

For the ground truth HR measurements, the Huawei Fit 2 watch was used in exercise mode to monitor the HR of the sitting subjects. According to independent research [5] the Huawei Fit 2 watch is in 0.99 correlation with the Polar H10 Heart-Rate tracker which is an industry standard.

3.2 Antenna Placement

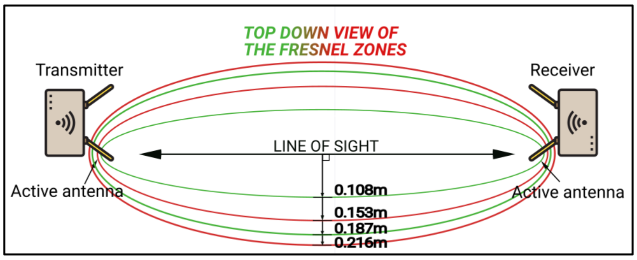

Fig. 6 Fresnel zone visualization from the top-down view of horizontal router placement.

This section discusses the theory followed for the placements of antennas, the nodes' limitations in terms of antenna placements, our defined antenna orientations, and the ways it was measured where the subjects sit relative to the antennas.

Based on the findings in [13] the best subject placement is inside Fresnel zones and not on the boundaries of them. It is theorized that signals bouncing off Fresnel zone boundaries and close to them have a small phase shift relative to the LOS signal which makes it have a big effect on the signal amplitude as shown in Fig. 5. However, it induces a low phase shift effect, making the CSI data accuracy low for HR tracking. However, movements and physical changes inside Fresnes zone centers have more noticeable changes in the received signal, because of the more differentiable phase shift. Furthermore, it was found that the Fresnel zones closer to the LOS of the signal have a greater effect on the received signal, as an example movements in zone 1 are more noticeable than in zone 13. Regarding these findings, two initial antenna placement testing methods have been tried: *parallel* and *perpendicular* antenna placements in reference to the subject's body surface. Parallel placement puts one antenna closer to the subject, and one further away from them, perpendicular antenna placement places both antennas at the same distance from the subject's body, but at different positions.

One limitation imposed by the nodes is relative antenna placement. As both of its antennas are built inside the device their relative placement could not be changed. The distance was estimated to be 10 cm and considered in further calculation.

The distance from the antennas is calculated as the perpendicular distance from the imaginary line that is drawn between the transmitter and receiver antennas (LOS path) as shown in Fig. 6.

Because of the hardware used this study was working with the limitation that the antennas had to be 10 cm apart, which made *perpendicular antenna placement* more difficult. Nonetheless, Fresnel zone centers were calculated, and a distance was chosen that would put the research subject inside both antennas Fresnel zone centers. The distance from the antenna closer to the research subject was calculated to be 13cm (the center between the 1st and 2nd Fresnel boundaries.) That then puts the further away antenna at a distance of 23cm from the subject, which is almost perfectly the center of the 4th and 5th Fresnel zones which is 22.5cm.

Parallel Antenna placements: antennas were placed parallel to the body's surface 13cm away from the subject between the 1st and the 2nd Fresnel zone boundaries.

For the comparison of the performance of the two antenna orientation methods, the difference between the abdomen distance and the chest distance needs to be discussed. This distinction was made because it was necessary to accurately define how the test subject should be positioned in reference to the antennas. People may have different distances to their abdomen or chest to the antenna LOS due to different physiques, which is why the abdomen distance is measured from their abdomen and the chest distance from the chest's most protruding part, for HR measurements from the chest area.

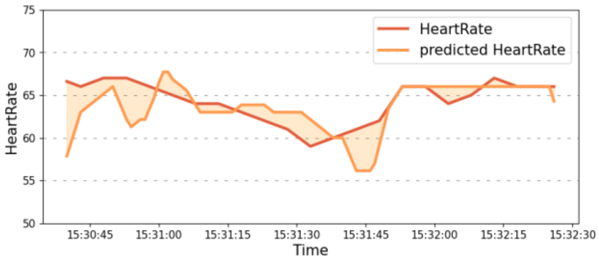

Fig. 7. Heart rate prediction in the pilot test from the abdomen distance with Parallel Antennas

The conducted pilot tests on different antenna positions relative to the chest revealed that the best antenna orientation is parallel to the focused body part and measuring from the "abdomen" distance. Fig. 7 shows HR predictions compared to the ground truth with the optimized settings for the chest area. These results are further elaborated on in Section 5.

3.3 Experimental Setup

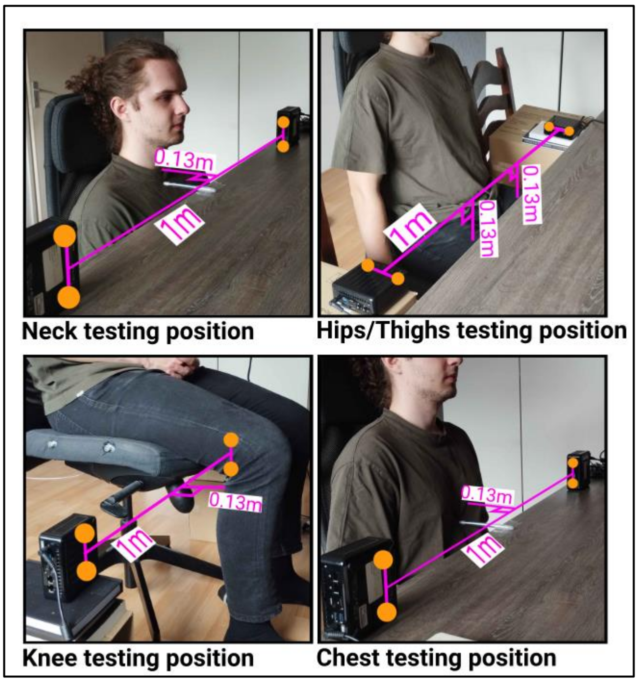

Fig. 8 Heart rate recording test setups.

After the initial pilot tests for algorithm and antenna placement analysis resulted in drastically different heart-beat prediction accuracies, rules had to be developed to obtain the best results from other body areas. Firstly, the antenna placement had to be parallel to the surface from which heart-rate data was extracted. Secondly, the surface of the subject's body should be 13 centimeters away from the LOS of the antennas (between the 1st and 2nd Fresnel boundary) as bigger and smaller distances degrade prediction accuracy. Thirdly to keep the same setup as the initial testing the distance between the transmitter and receiver nodes shall be 1 meter apart and the subject will be sitting on an office chair. The most accurate chest HR predicting setup is presented in the bottom right picture of Fig. 8.

These rules caused some interesting problems like antenna orientation for behind-the-knees data collection. As the subjects will have their knees halfway bent there is no obvious parallel surface from which to measure. Nonetheless, it was decided to keep the antennas parallel to the calves because the back of the thighs is hidden by the chair on which the subject is sitting, and the calves provided more exposed surface area. Based on anatomical research of active cardiovascular points in the human body [8] four body areas were chosen: chest, neck, hips/things, and behind the knees. All the different testing point setups are presented in Fig. 8. For each body area, about 1 minute and 30 seconds worth of usable data were collected from each test subject, meaning the recordings have been done for a longer time, but parts have been cropped out when there are big movements in the room the tests are held in.

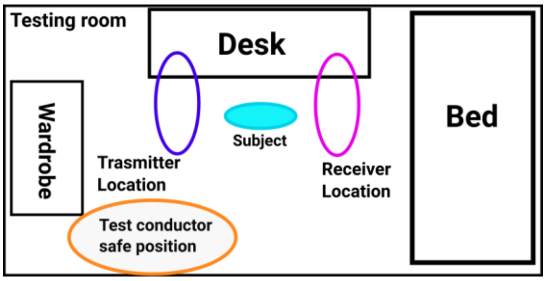

Fig. 9 Room test setup.

The tests were conducted on five different test subjects whose ages ranged between nineteen and twenty-two with average body builds. The tests were conducted in a small room of 5x3x3 meters, with a bed, table, and wardrobe. During the tests, two or three people were present in the room: one test subject and one or two people conducting the test: matching times and noting down each test's parameters. Based on Fresnel Zones theory a safe test conductor position was calculated to create the least interference in the received CSI data. The room test setup can be seen in Fig. 9.

4 METHODOLOGY

4.1 Signal Processing

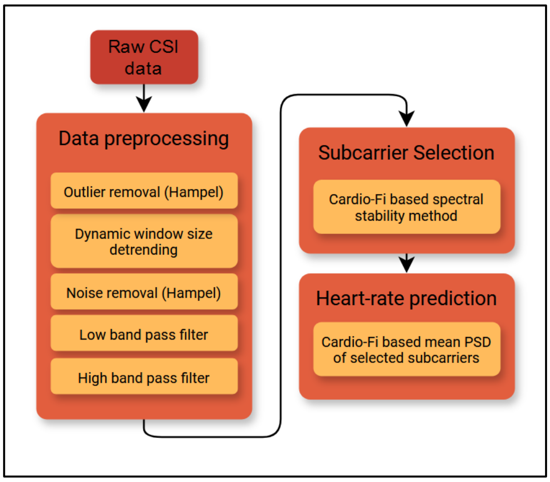

Fig. 10 Cardiofi's [6] Data processing pipeline.

The CSI data preprocessing and HR estimation algorithm follows the CardioFi's [6] used method that is demonstrated in Fig. 10. This method was chosen for several reasons. Firstly, it was demonstrated that their algorithm has a high accuracy for HR predictions with only a media error of 1.14 bpm. Secondly, the CardioFi [6] paper was written with great detail about the actual algorithm and parameters used to achieve the results, which made it simple to replicate even the custom parts of their algorithm as the dynamic window detrending and the spectral stability subcarrier selection algorithm.

4.2 Signal Pre-processing

The signal preprocessing follows the algorithm and parameters disclosed in [6]. Firstly, the signal incoming into the two receiver antennas gets subtracted from one another to remove the random phase shift offset caused by the mismatched transmitter and receiver clock cycles. Secondly, from the subtracted signal as seen in Fig. 10 the preprocessing algorithm uses the first Hampel filter for outlier detection and removal. Then detrends the data using the dynamic window size algorithm introduced in [6] after which a second Hampel filter is used for noise removal. Once the data is cleaned and detrended low and high bandpass filters get applied to narrow down the frequencies present in the output to the expected heart-rate frequencies. This research deviates from [6] in the low and high band filter parameters and sets the cut-off frequencies from 0.7Hz to 2Hz corresponding to 42 and 120 beats per minute (bpm).

5.3 Subcarrier selection

For the subcarrier selection algorithm, this research replicated Cardiofi's [6] custom Spectral Stability based algorithm. It builds on the assumption that HR does not change quickly, so the subcarriers with the most stable HR predictions are considered the most accurate. The pilot test data revealed that the algorithm parameters were too strict and sometimes only selected one or two subcarriers as "stable enough". This made the heart-rate predictions very noisy and inaccurate as single subcarriers are unstable and need to be fused with other subcarriers to make the HR predictions more stable and accurate. The algorithm was modified to include at least 4 of the lowest noise subcarriers. Further modifications were done to include all subcarriers that are as stable as 1.6x times the stability of the most stable subcarrier compared to CardioFi's [6] 1.2x limit. These changes have significantly improved the accuracy of the test setup.

4.4 Heart-rate Prediction

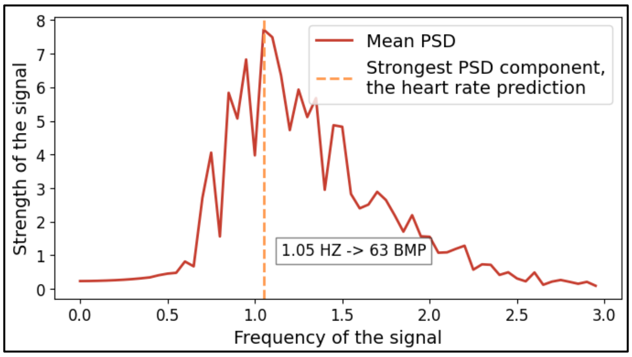

Fig. 11 Heart rate prediction from the mean PSD of selected subcarriers.

For heart-beat prediction, a mean PSD spectrum is calculated using a fast Fourier transform across all chosen subcarriers as in [6]. The final HR is estimated as the largest magnitude component in the mean PSD for a 20s window size as shown in Fig. 11.

5. RESULTS

5.1 Antenna Placement

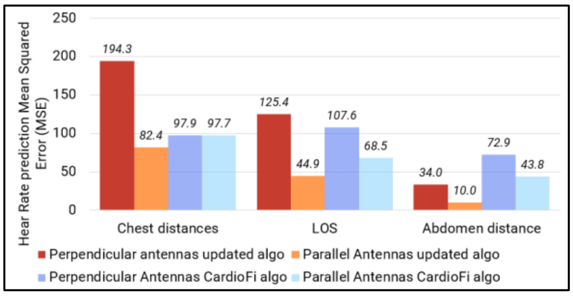

Fig. 12 Pilot test different antenna placement Mean Squared Error (MSE) of heart rate predictions.

The results of the initial antenna orientation and placement tests are represented in Fig. 12 The parallel antenna rotation is superior for chest area HR predictions at all distances from the human subject (chest, LOS, abdomen) as it produces the lowest MSE. It also shows better performance in both of the algorithms, the non-updated [6] and the updated algorithms show great improvements from using parallelly rotated antennas. Furthermore, the abdomen distance is the best for prediction accuracies as it produces the lowest MSE, meaning that the LOS of the antennas being placed 13cm away from the subject is the optimal distance.

With both antenna rotation and positioning optimized (vertical antennas and abdomen distance), the updated HR prediction algorithm yielded an MSE of 10,0 for HR predictions from the chest during the pilot test as shown in Fig. 12.

5.2 Different Body Area Prediction Accuracy

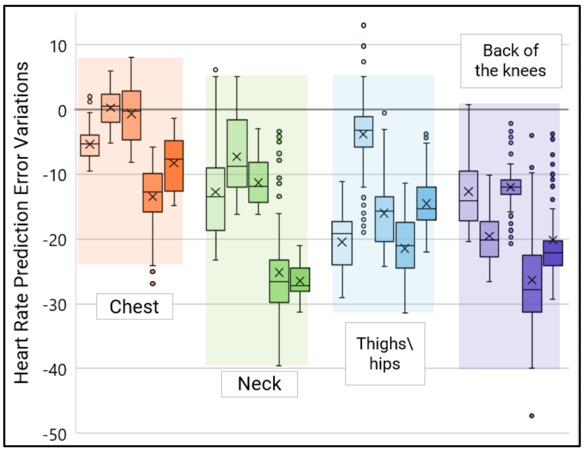

Fig. 13 Heart rate prediction error box chart.

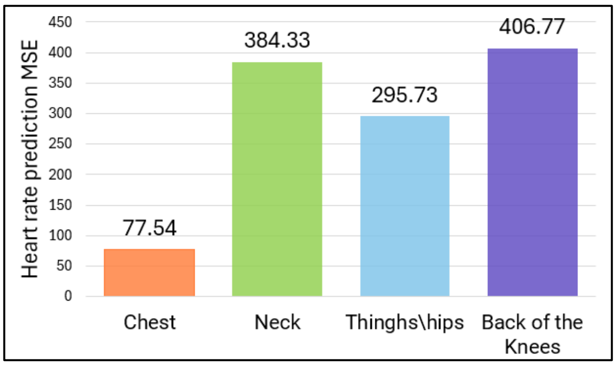

Fig. 14 MSE of heart rate predictions for different body parts.

The analysis of the results confirmed the initial assumption that the subject's chest is the best area for HR predictions. It had a considerably lower MSE of 77.54 compared to all the rest of the body areas. Furthermore, the chest had the lowest error variance as seen in Fig. 13 making it the most stable predictor.

The second-best area for heart rate prediction seems to be the thighs/hips. While it has a very high MSE of 295.73 it is still considerably lower than the neck with 384.33 and the back of the knees with 406.77. Furthermore, its variation in Fig. 13 is also lower than the neck and the back of the knees. While these results do not make it a good predictor, its performance is of interest for future research as it seems to be a possible predictor for a subject's HR.

Lastly, the neck and the back of the knees performed similarly, they both have the highest MSE for HR predictions and the widest variation spread, making them the worst areas for HR predictions. Further analysis of these results is in section 6.2.

6 DISCUSSIONS

6.1 Bias in The Algorithm

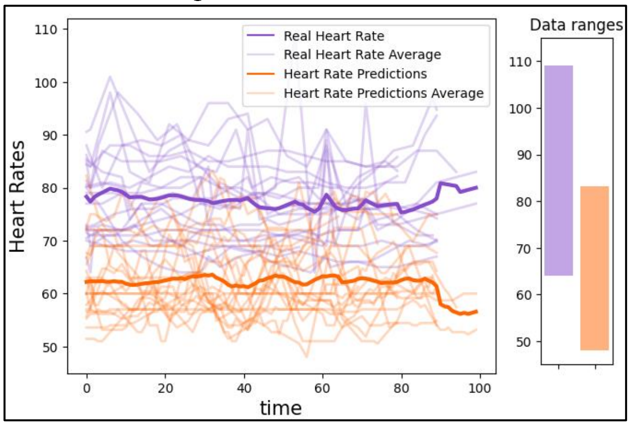

Fig. 15 All heart rate and heart rate plotted predictions.

From initial observations, it was noticed that the model's HR predictions were consistently lower than the corresponding ground truth as observed in Fig. 15. This underprediction was unexpected as the pilot tests did not exhibit such behavior. After further data review, it was found that the prediction algorithm is accurate if the subject's HR is around the 60-80 bpm limits. If the subject's HR is above 80 the algorithm can track HR trends, as when the subject's HR would increase or decrease the predicted values would rise and fall accordingly. This observation explains the high accuracy predictions during the pilot test as the pilot subject's HR was in a range of 60 to 70 bmp (Fig. 7) where the algorithm not only recognizes HR trends but also accurately predicts the subject's HR. The algorithm's lower prediction reasons are not understood and need further investigation.

6.2 Different body part predictor results.

As mentioned in section 5 the results did not correlate with initial expectations of what body parts would be good HR predictors. Original assumptions assumed that more strongly active cardiovascular areas covered with low amounts of tissues would perform better. However, the neck which contains large Carotid Arteries [15] only covered with small amounts of tissues yielded a high MSE of 384.33 and the biggest prediction error variance out of all other body parts as seen in Fig. 13 .Whereas the thighs/hips which in the sitting position cover their Femoral Arteries with large amounts of bodily tissues resulted in the second lowest MSE and second lowest variation of prediction errors.

These initially strange results however seem to correlate with wave propagation theory. As stated in "3.2 Wi-Fi's CSI data" physical changes in the environment create a phase shift in the signal at the receiver. Stronger cardiovascular activity moves the surrounding tissues more, which resolves in a bigger phase shift at the receiver. However, a bigger phase shift is not enough to create ample change in the CSI data to make it an accurate predictor. If the phase-shifted signal has a low amplitude (is weak) it might be lost in the environment noise at the receiver.

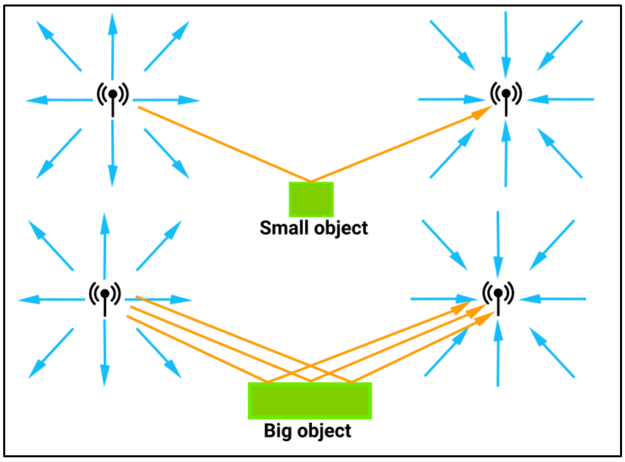

Fig. 16 Illustration of Wi-Fi waves bouncing off small and big obstacles in the environment.

The receiver combines all the received multipath signals and adds them together for CSI calculations, meaning larger surfaces that redirect more signals to the receiver will have a bigger effect on CSI calculations. As shown in Fig. 16 small objects might not redirect enough signal for them to be differentiated from the noise, while larger objects redirect more of the transmitted signal and will have a bigger effect on the CSI data.

Considering that more signal bounces of bigger surfaces it becomes quite apparent why the chest area and the thighs/hips are better HR predictors than the neck or the back of the knees. While the back of the knees and especially the neck have high cardiovascular activity, they do not have enough surface area to create a noticeable periodic phase shift in the received CSI data.

6.3 Algorithm's Slow Convergence

The tested algorithm demonstrated good performance following slow-changing trends in the heart rhythm of most test subjects.
However, the algorithm becomes unstable at HR predictions if a subject's HR is unstable and quickly changing. This is because it uses a large 20s window on the mean subcarrier PSD to estimate the subject's HR for accuracy reasons [6]. Fig. 13 is ordered in a way that for each body part, the test subjects are always in the same order from left to right. So, subject one is the first box on the left for the chest, neck, hips/thighs, and knees, subject 2 is the second box from the left, and so on. Subject 4 (2^{nd} box from the right) had the most sporadically changing and high HR, which caused the algorithm to underestimate the subject's HR and created the biggest prediction error variance on almost all test scenarios. This slowness of the algorithm to converge to a changed HR makes it not suitable for applications dealing with subjects whose heart rates while sitting are not stable.

6.4 Future research

For future work toward the robustness and reliability of Wi-Fi-based heart rate tracking technology, the shortcomings of this research should be addressed. Firstly, the bias in the algorithm to underpredict the heart rate skewed all results of our testing, to reveal the true potential of each body area, the tests should be redone with a non-underprediction algorithm. Furthermore, not only different heart rate predicting algorithms should be tried, but it would also be interesting to attempt to tune the heart algorithms for each body part.

7 CONCLUSIONS

This paper presented conducted research on CSI data heart rate measurement accuracy focusing on the Wi-Fi signal on different areas of the body: chest, neck, thighs/hips, and back of the knees. Firstly, it provides the theories leveraged to extract heart rate predictions from CSI data and to create the test setups. It describes devices and methods used to collect Wi-Fi CSI data, then details the algorithms used for signal pre-processing, subcarrier selection, and heart rate prediction. The experimental results showed that the chest is the best body part for heart rate prediction followed by the thighs/hips, while the neck, and back of the knees have the biggest MSEs and the widest variations in the prediction errors. Lastly, it has been found that the surface area of the body part has a strong influence on how accurate the heart rate predictions are and the underlying theory behind the finding.

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9 APPENDIX

During the preparation of this work, the author used Word to write and format the work, Grammarly as a spell checker, and Zotero as a reference tracker. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.