WiFi Sensing of the Environment

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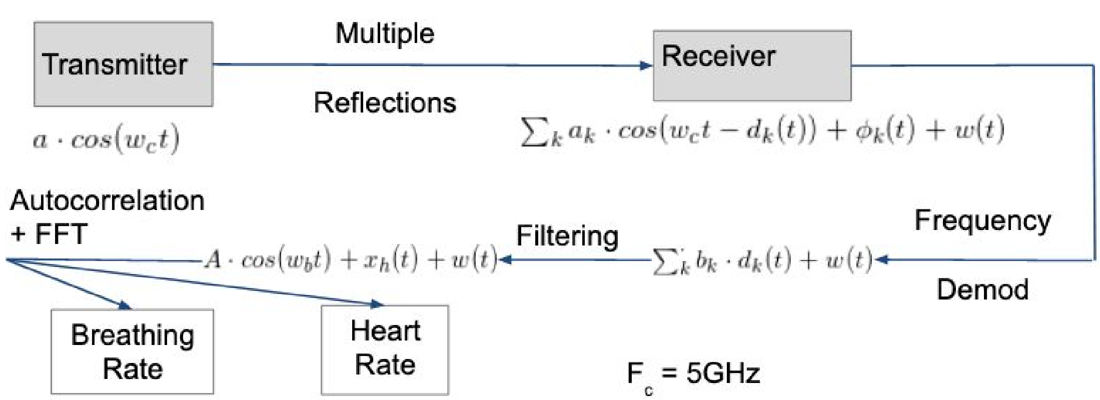
Introduction

The current generation is faced with a multitude of health issues, right from obesity to the extremes of heart problems. This situation urges us to be self-conscious about our health. With the growing technology and the subsequent rise of smart devices, this demand can be satisfied using smart watches/bands. An appropriate replacement of the traditional wrist watch, these devices additionally provide us with inputs on our vital health metrics like steps heart rate, blood pressure, sleep pattern and others. But these digital health aids have their drawbacks which include giving inaccurate data on the health vitals, discomfort caused due to continuous wearing of these devices, even during sleep and a limited battery life, thus needing daily charge. Through our current research, we propose a novel solution of acquiring the health vitals **without the use of wearables**, which solves the problems of the discomfort caused and the everyday charging and positively moves in the direction to get precise health related data.

Concept & Theory

The main idea behind the proposed solution is the use of high frequency signals along with the concepts of signal processing, to obtain the very low frequency components from the received signals, corresponding to the **heart rate** as well as the **breathing rate**.

We will elaborate this using a block diagram:



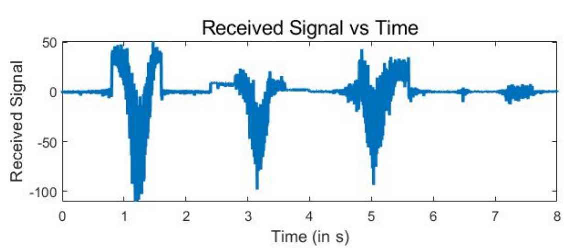
Transmitter: We send high frequency (here, 5GHz) signals from this end.

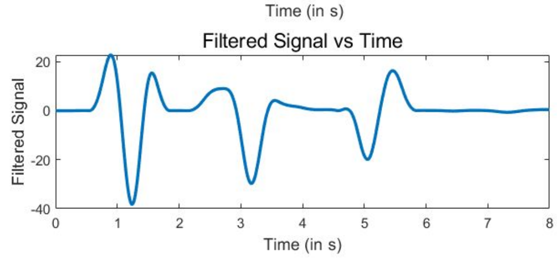
Mathematical Representation: $x(t) = a\cos(w_c t)$, where $w_c = 2\pi f_c$

Receiver: After multiple reflections from the surrounding environment including the human being, we receive a delayed version of the transmitted signal along with a phase shift and additional noise; Mathematical Representation: $r(t) = \sum_k a_k \cos(w_c t - d_k(t)) + \Phi_k(t) + w(t)$, where the index 'k' represents the k^{th} path and $d_k(t) = \tau_k(t) w_c$,where $\tau_k(t)$ is the delay along the k^{th} path

Frequency Demodulation Output: We can see that the main information is in the overall phase of the received signal. Thus, we perform F.M Demodulation, to extract this useful information. We see that the term $\Phi_k(t)$ is very slow varying and thus, on performing DC shift on the received signal, we can assume $\Phi_k(t) \sim 0$. Mathematical Representation of F.M Demodulated Signal: $y(t) = \sum_k b_k d_k(t) + w(t)$, which represents a scaled version of the useful information along with noise

Filtered Output: We have prior information that the health metrics will correspond to very low frequencies and thus, we need to perform low pass filtering on y(t). We can use FIR/IIR filters with cut-off frequency < 2Hz but as we checked the output from this filter, we found dominating higher frequency range outputs which could be probably due to the transition width between the pass band and stop band frequency. Keeping this in mind, we found through continuous experiments that, the moving average filter almost satisfies the needs of the desired low-pass filter. It takes data corresponding to a particular window length and averages it out, thus removing the high frequency components and then slides the window, thus leading to an overall smoothing of the received data. This helps us to average out the overall noise and gives us a cleaner data.





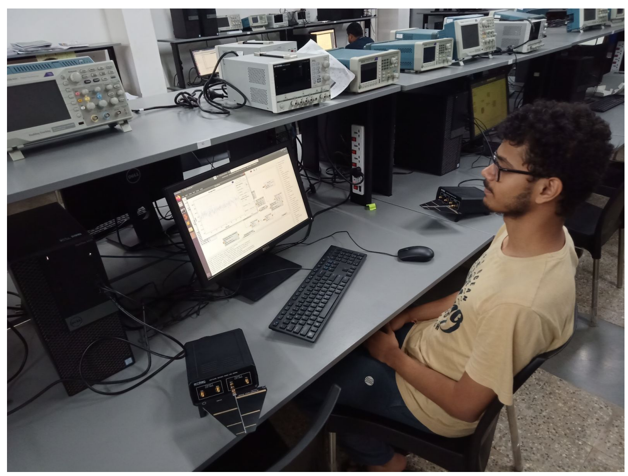
Mathematical Representation: $y_f(t) = y_f(t-1) + \bar{y}(t)$; Thus, $y_f(t) \approx \sum_k a_k d_k(t) + w_1(t) = a_0 d_b(t) + a_1 d_h(t) + \bar{w}(t)$; $d_b(t) \rightarrow$ delay caused by breathing; $d_h(t) \rightarrow$ delay caused by heart beats.

Post-Processing Output: At this point of time, we have the appropriate information needed to calculate the required metrics. But, we have a lot of samples to perform the processing, which makes the overall process difficult. Thus, we perform downsampling i.e take every m^{th} sample, where 'm' is the downsampling rate. We adaptively adjusted this rate such that we can work on the clean, processed data and get the slow varying signal out of the original signal.

Mathematical Representation: $y_{fd}(t) = y_f(m*t)$

Final Output: In the final stage, we calculate the power spectral density i.e squared magnitude of the Fourier Transform of the autocorrelation of the downsampled signal. This gives us accurate peaks around the very low frequency components corresponding to the breathing and heart rate.

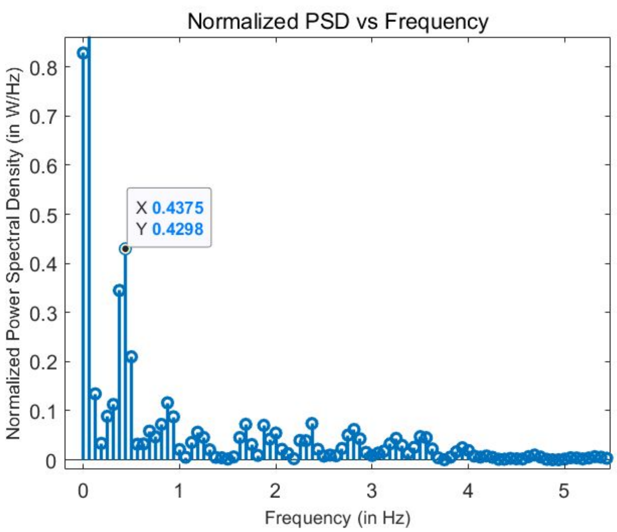
<u>Experimental Setup</u>

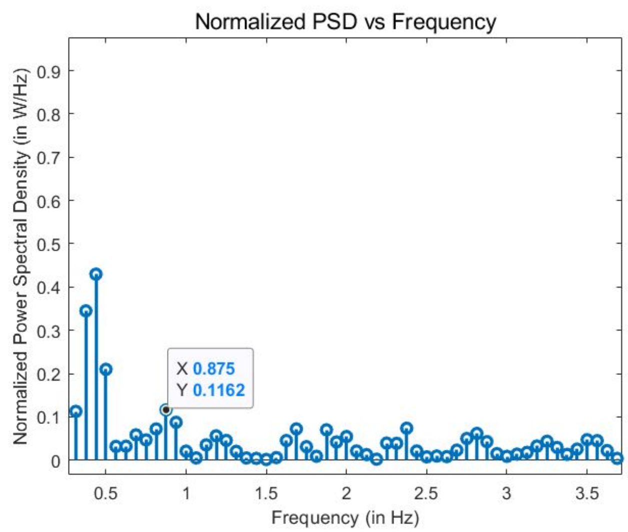


We used Software Defined Radios(SDR) and antennas (as shown in the image on the left) for the purpose of transmitting and receiving signals. We used the GNU Radio software to interface the hardware with the software, thereby processing and logging the data, which could then be used for further analysis. We had to perform most of the processing offline as we had a resource constraint with respect to the SDR. This offline processing was done in MATLAB and Python. The above figure on the right shows me, breathing normally and collecting the required data. We had to breathe heavily for the directed antennas to detect the change and thus, give us the breathing and heart rate.

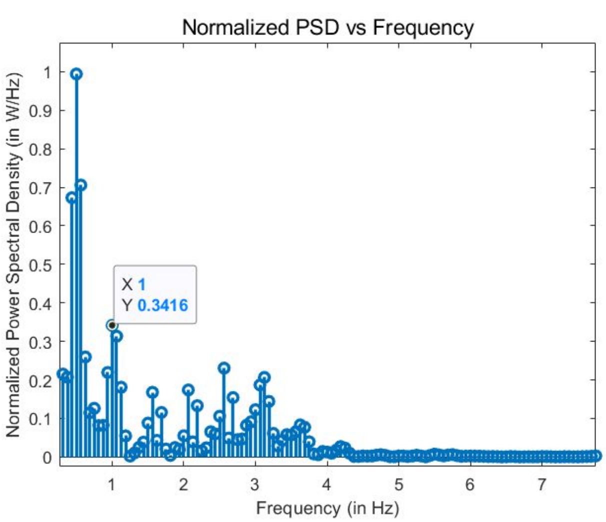
<u>Results</u>

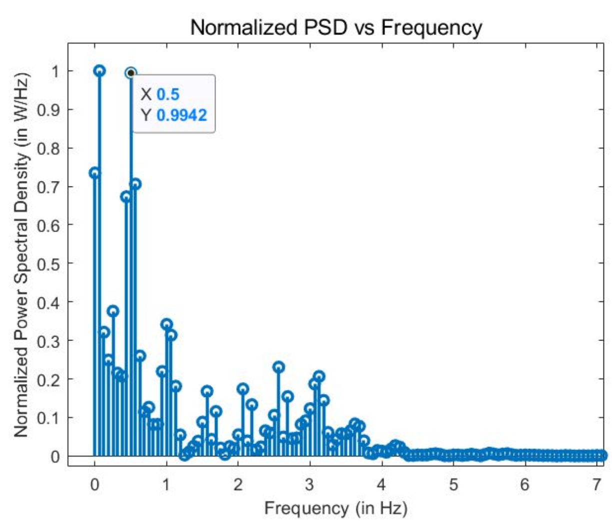
Breathing Rate and Heart Rate in Normal Conditions





Breathing Rate and Heart Rate after Running





Theoretical vs Practical Calculation of Breathing & Heart Rate

Category	Actual Breathing Rate (breaths/min)	Actual Heart Rate (beats/min)	Breathing Rate - Our Method (breaths/min)	Heart Rate - Our Method (beats/min)
Normal - 1st	25	65	~ 26	~ 53
After Running	29	78	30	60
Normal - 2nd	20	70	~ 19	~ 57
After Running (Controlled Breathing)	24	92	~ 25	~ 82

Conclusion

Here, the actual breathing rate was calculated by manually counting the number of breaths taken in a minute, through a timer. Also, the actual heart rate was calculated by wearing a smart device. As we can see, through our method, the breathing rate can be measured accurately and the heart rate can be measured with an additional error. This error is mainly due to the fact that the antennas are not very sensitive to very low amplitude signals and the hardware adds an additional error

Future Work

- Use of better hardware to accurately measure the heart rate
- Estimating the sleep pattern using Machine Learning algorithms
- Performing multi-user health metric estimation
- Gesture Recognition for personalized user experience

References

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