Contactless Heartbeat Estimation with FMCW Radar

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Measuring heart rate is usually done with the use of invasive technologies, such as an electrocardiogram which uses electrodes. However, this may not always be the optimal method. Non-invasive methods for measuring heart rate are often preferred due to their simplicity and reduced discomfort for the individual. Using Millimetre-wave frequency modulated continuous wave radars (FMCW) to detect chest movements and extract vital signs is a promising possible alternative due to its non-invasive nature. In this paper we use Fast Fourier transformations, the Savitzky–Golay filter, Elliptic filters, and the Kalman Filter to explore the feasibility of real-time contactless heart rate estimation using FMCW radar. Across all datasets, using a 2.5s monitoring window, an average Mean Absolute Percentage Error (MAPE) of 5.56% was achieved. Remarkably, on an individual dataset, the MAPE reached an impressive low of 3.41%, highlighting the robustness of the approach in advancing real-time contactless heart rate estimation with FMCW radar.

Additional Key Words and Phrases: Frequency Modulated Continuous-Wave Radar, Heart Rate Estimation, Kalman Filtering, Non-Invasive Vital Sign Monitoring, Savitzky-Golay Filter, Signal Pre-processing

1 INTRODUCTION

Monitoring an individual's heart rate can be a crucial indicator for assessing their overall health. The significance of monitoring an individual's heart rate extends beyond assessing overall health. For instance, it can play an important role in early detection of cardiovascular conditions. This quite significant, since cardiovascular diseases are the most common cause of death in the entire world [3]. It is possible to detect potential heart issues by monitoring the heart rate of a person [9].

In the context of our research, contact-based measurements play an important role in assessing vital signs, particularly focusing on the heart rate. These measurements require direct physical contact with the subject, with an electrocardiogram's electrodes being example. While we do not delve further into these contact-based techniques in this paper, it is essential to acknowledge their importance in the broader field. Numerous studies, have extensively explored and validated the effectiveness of contact-based measurements in monitoring the heart rate [7], [8] [5]. By citing these established works, we place our research in the context of existing knowledge, laying the groundwork for our examination of FMCW Radar in the following sections.

Monitoring vital signs is utilized across various sectors. Non-contact vital sign monitoring based on thermal imaging, camera imaging, and radar has experienced in increase in interest. Non-contact monitoring is the preferred method due to its non-invasive nature. Radar has various advantages over imaging-based monitoring, including protecting the personal privacy, reliability, and low complexity [1] [6].

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Among non-contact methods, Frequency Modulated Continuous-Wave (FMCW) radar stands out, offering detailed information by dividing the acquired radar signal into multiple ranges. This makes it a promising tool for monitoring vital signs, including heart rate. Within our study we leverage FMCW radar as a crucial component for monitoring heart rate. FMCW radar is technique that continuously modulates the frequency of the signal it transmits, allowing for precise measurement of the heart rate of an individual. In existing literature the efficacy of FMCW radars in diverse applications has been investigated and validated, including heart rate and respiration rate measurement.[4].

Currently, there is no accurate real-time method for measuring heartbeats without contact. Unlike [2], which uses a 10-second window, the newly proposed approach uses a 2.5-second window, greatly improving real-time processing.

In this research, we propose a novel algorithm utilizing the elliptic filter, Fourier transformations, and the Kalman filter. Our approach aimed to optimize real-time heart rate estimation using FMCW radar. The heart rate reference values were obtained from the Polar H10 Heart Rate Sensor, and the AWR16422 radar from Texas Instruments was utilized in our study. By doing so, we aim to contribute valuable insights into the enhancement of real-time heart rate estimation. Our approach is dedicated to advancing the field of non-contact heart rate monitoring towards real-time, paving the way for improved applications in healthcare, surveillance, and various other domains.

2 PRELIMINARIES

FMCW radar is a helpful technology in vital signs monitoring due to its ability to detect object position and movement remotely. FMCW radar generates and sends out a signal that is called a chirp. A chirp is a transmission which frequency increases linearly over time. Of this chirp a number of samples are taken depending on the chirp duration and sample rate. The emitted signal is then reflected of an object, such as the human chest. This reflected signal is mixed with the original transmitted signal and the resulting signal is called an IF signal. The IF signal is a sinusoid with the frequency equal to the differences of the input sinusoids (transmitted and reflected signal) and the phase is equal to the difference of the phase of the input sinusoids. By keeping track of the phase changes over time it is possible to extract information regarding the movement of the object on which the signal was reflected. This can be done to determine the chest displacement of the target.

The inherent advantage of FMCW radar lies in its ability to capture minuscule displacements, translating these subtle motions into a distinguishable radar signal. In the context of vital signs monitoring, particularly heart rate estimation, FMCW radar makes use of the chest displacements caused by heartbeats. As the heartbeats, it generates tiny movements in the chest of the target. These displacements alter the radar signal, creating a pattern that correlates with the heartbeats.

3 SIGNAL PROCESSING

3.1 Pre-processing

After the radar captures the reflected signal and creates an IF signal, Fast Fourier Transformation (FFT) is applied on the data which converts a time domain signal into a frequency domain signal. This process, known as spectral analysis, decomposes the radar signal into its constituent frequency components. Afterward the output is stored in windows. We use this to detect the target and filter out all of the clutter. After that the phase changes are extracted out of the filtered data.

The captured data might contain noise or irregularities that could have an impact on the data analysis. For this reason the effect of Savitzky-Golay filter has been used to smooth the data and increase the precision of the phase changes. It works by fitting a polynomial to a window of adjacent data. Increasing the window size generally leads to a smoother output. However, too large a window size might lead to a loss of important features. A higher polynomial order allows for capturing more complex data. Yet, it also brings the risk of overfitting, making it more sensitive to noise. Both increasing the polynomial order and window size increase the computational complexity. After systematically testing uneven Savitzky-Golay window sizes ranging from 3 to 50 (equal to the sample window size) exploring combinations with polynomial orders from 1 to the respective Savitzky-Golay window size. It was found that a Savitzky-Golay window size of 13 and a polynomial order of 3 resulted in the highest accuracy.

3.2 Heartbeat filtering

Now that the phase changes have been extracted, the displacements caused by the heartbeats must be isolated. This is done with the use of a band-pass filter. In our case the elliptic filter. Meaning that it is able to achieve a faster transition between the pass-band. The elliptic filter's steep roll-off reveals its advantageous role in efficiently isolating heart-induced displacements from the extracted phase changes. The cut-off frequencies were initialized as 0.8 ... 3 Hz, which corresponds to a heart rate of 48 ... 180 bpm (beats per minute). It is essential to select appropriate cut-off frequencies for the band-pass filter. If the cut-off frequencies are too broad, the risk of obtaining unwanted frequencies is high. And in the case that the cut-off frequencies are too narrow, the chances of blocking the heart rate increases. The cut-off frequencies are updated as the windows are processed, shortening the range and leading to a more accurate filtering of the heartbeat. As the heart rate dynamics evolve, the adaptive adjustment of cut-off frequencies ensures the filter remains adaptable and responsive to varying physiological conditions. How this is done is explained in more detail in 3.4.

3.3 Heart Rate Estimation

After isolating the displacement from the heartbeats, we attempt to determine the heart rate within this data using Fourier transformations to identify the frequency in the data. This was done using the scipy.fftpack python library. Before performing the FFT we made use of zero padding. Zero padding involves adding zeros to the end of the input signal to increase the length of the signal. While zero padding enhances frequency domain analysis, it doesn't alter the time-domain characteristics of the signal. Due to the increased number of points in the signal, it leads to a finer frequency resolution in the Fourier Transform. This finer resolution enables a more precise identification of frequency components in the signal, contributing to improved accuracy in detecting the heart rate. The zero padding technique effectively provides a higher level of detail in the frequency domain, allowing for a more accurate determination of the heart rate frequency. The proposed algorithm makes use of zero padding with a factor of 2, effectively doubling the number of data points in the input signal.

3.4 Optimizing Heart Rate Estimation

Kalman filtering is employed in cases where observed values contain unpredictable errors. In this case the Kalman filter is applied on the observed heart rate values. The choice of Kalman filtering for optimizing heart rate estimation in this research is motivated by its effectiveness in handling observed values that contain unpredictable errors. In the context of heart rate estimation using FMCW radar, the observed heart rate values may be subject to noise or irregularities. The Kalman filter is designed as a constant acceleration model in this research, enabling it to adapt to changes in heart rate dynamics over time. This adaptive nature of the Kalman filter is particularly valuable when dealing with real-world data, where unexpected variations or errors in observed heart rate values can occur. By iteratively updating the heart rate estimates based on both observed values and the model's predictions, the Kalman filter contributes to the robustness and accuracy of the heart rate estimation process. The state vector used for this research is as follows:

$$x = \begin{bmatrix} h & \dot{h} & \ddot{h} \end{bmatrix}^T$$

Which is initialized as:

$$x = \begin{bmatrix} 60 & 0 & 0 \end{bmatrix}^T$$

Where $h, \dot{h}, \ddot{h}$ represents the heart rate in beats per minute, the first derivative, and second-order derivative respectively. In this research the Kalman filter is designed as a constant acceleration model. The state transition model is expressed as:

$$x_{k+1|k} = Ax_{k|k} = \begin{bmatrix} 1 & \Delta t & 0.5\Delta t^2 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix} x_{k|k}$$

With Δt being the time between consecutive frames. The state observation model is as follows:

$$y_{k+1} = Hx_{k+1|k} = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} x_{k+1|ks}$$

The process noise covariance is modeled as:

$$Q = \begin{bmatrix} w_k & 0t & 0 \\ 0 & w_k & 0 \\ 0 & 0 & w_k \end{bmatrix}$$

where w_k is the process noise at time k, The algorithm works by processing each window and applying the band-pass filter with the initial cut-off frequencies. Then the heart rate is observed either via FFT. The observed value might be an outlier. These outliers are usually caused by the subject moving or signal interference. For this reason, the z-score of the new estimate is calculated and only considered if it does not qualify as an outlier, with the threshold

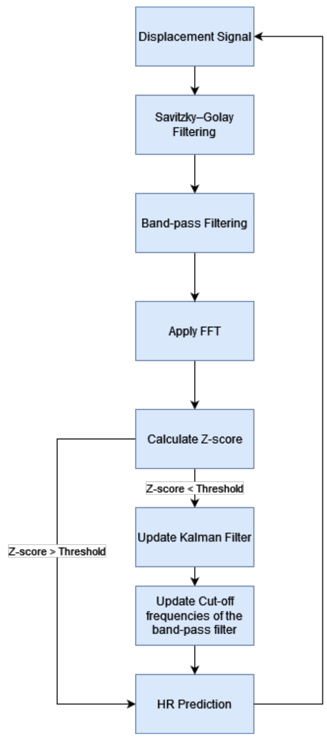

Fig. 1. Flow chart of the main part of the proposed algorithm.

set at 2.0. Only if the resulting value is not an outlier it is added to a list of observed values which is passed to the Kalman method, resulting in a list of estimates of the heart rate. In the case of an outlier we use the Kalman method to predict the next value. Finally the band-pass cut-off frequencies are updated, with the lower bound as the maximum of the current lower bound and the most recent estimate in bpm decreased by 10 converted to Hz. For the upper bound the minimum is taken of the current upper bound and the most recent estimate in bpm increased by 10 converted to Hz. The main steps of the algorithm can be seen in Figure 1.

4 EXPERIMENTAL SET-UP

The performance of the proposed algorithm was evaluated using the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE). In this evaluation we used 4 recordings of the same individual sitting on a chair in front of the radar. The experimental setup ensured a standardized testing environment for a comprehensive evaluation. With the radar being placed at chest height. During the recording the Polar H10 Heart Rate Sensor was utilized to serve as a reference value.

The radar was set up to face the subject at chest height at a distance of approximately 0.80 meters. The radar was oriented at a straight angle with the subject and forms a 90-degree angle with the ground. The only objects between the subject's chest and the radar were the clothing the subject was wearing during the recordings. This deliberate exclusion of any objects between the subject's chest and the radar, except for the clothing worn during recordings, minimizes interference, maintaining the purity of the captured signals for robust analysis. During the recordings the subject was instructed to sit still and not make any sudden movements. Ensuring the subject stays still during recordings avoids artifacts and provides a stable baseline for evaluating the radar's ability to capture subtle physiological variations.

To enhance the radar's capabilities, a careful consideration of parameters such as a ramp time of 50 microseconds, a frequency slope of $80000 * 10^9$ Hz/s, and a sample rate of 6250000 samples/s was employed. The window size was set at 50 frames contributed to the comprehensive data collection process. The parameters of the radar can be found in Table 1.

Table 1. Radar Parameters

Parameter	Value
number of samples	250
number of chirps	128
number of frames	1200
number of transmitters	1
number of receivers	1
ramp time	50 / 1000000 s
frequency slope	$80000 * 10^9$ Hz/s
sample rate	6250000 samples/s
window size	50 (number of frames)

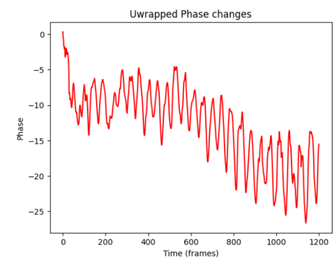

Fig. 2. Unwrapped Phase Changes

5 RESULTS

After applying the Savitzky-Golay (SG) filter on the unwrapped phase changes we were able to acquire smoother phase changes. A visual representation of the phase changes before applying the SG filter can be seen in Figure 2 and after applying can be seen in Figure 3. An example of a heart rate estimation can be seen in Figure 4. In this figure heart rate observations estimates of solely the FFT (yellow), FFT after Savitzky-Golay filtering (green), and Kalman filtering after both FFT and Savitzky-Golay filtering (red) are plotted along the reference value (blue). It is noticeable that a subtle distinction is observed between the yellow and green lines. It also reveals that the green line, indicative of FFT after Savitzky-Golay filtering, maintains sensitivity to outliers. In contrast, the red line, representing Kalman filtering after both FFT and Savitzky-Golay filtering, exhibits a reduction in sensitivity, resulting in a more stable and consistent measurement.

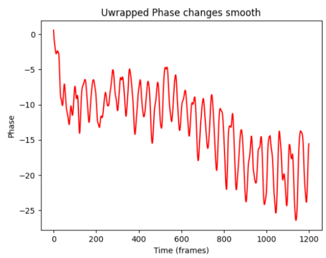

Fig. 3. Savitzky-Golay Filtered Unwrapped Phase Changes

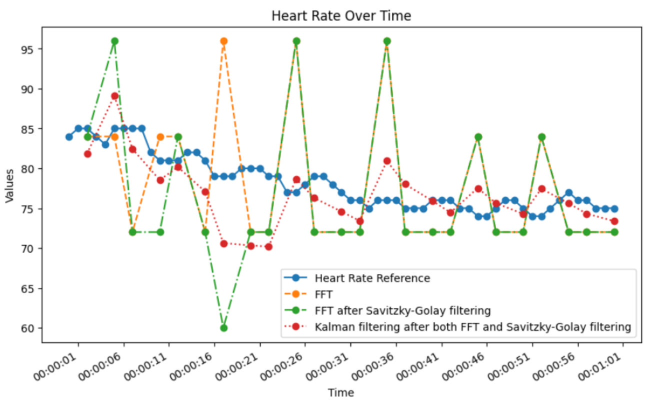

Fig. 4. Observed Heart Rate Over Time of Recording 3

Table 2. Experimental Results of the Proposed Algorithm

Recording	MAE	MAPE (%)
1	2.55	3.41
2	6.21	7.91
3	3.16	4.02
4	5.42	6.90
average	4.34	5.56%

The final performance of the algorithm on windows of 2.5 seconds can be seen in Table 2. Here we see that the MAE ranges from 2.55 bpm to 6.21 bmp with an average of 4.78 bmp. The MAPE ranges from 3.41% to 7.91% with an average of 5.56%.

6 CONCLUSION

In conclusion, this research introduces a novel approach for contactless heart rate estimation using Frequency Modulated Continuous-Wave (FMCW) radar. By leveraging advanced signal processing techniques such as elliptic filters, Fourier transformations, and the Kalman filter, the proposed algorithm optimizes real-time heart rate estimation with impressive results. The use of a 2.5-second window for real-time processing enhances the efficiency of the method compared to existing approaches using the same methods.

The study demonstrates the capability of FMCW radar to detect chest movements caused by heartbeats, offering a non-invasive alternative to traditional electrode-based methods. The evaluation of the algorithm's performance, using the Polar H10 Heart Rate Sensor as a reference, showcases an average Mean Absolute Percentage Error (MAPE) of 6.12%, indicating the robustness of the approach across different datasets.

Due to the small sample size of just 4 recordings used in this study, this limited sample size may not fully capture the diversity of physiological conditions and external factors that can influence the heart rate estimation. Future research should consider expanding the dataset to include a more diverse population, accounting for variations in age, gender, and activity levels, to ensure the algorithm's generalizability across a broader spectrum.

The inclusion of Fast Fourier Transformation and Savitzky-Golay filtering into the the pre-processing steps of the signal processing pipeline, contribute to the accuracy of heart rate estimation. The introduction of the Kalman filter further enhances the algorithm's adaptability to unpredictable errors in observed heart rate values.

Overall, this research provides valuable insights into the advancing of non-contact HR monitoring towards real-time monitoring. The achieved results underscore the effectiveness of the proposed algorithm, paving the way for advancements in real-time contactless heart rate estimation with FMCW radar technology. Notably, the implementation of a remarkably short window time in our algorithm stands out as an achievement, setting a new standard for real-time contactless heart rate estimation.

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