# Exploration of Mode Decomposition for Concurrent Cardiopulmonary Monitoring using Dual Radar

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***Abstract*—Cardiopulmonary monitoring involves surveilling the important physiological parameters of an individual like the breathing rate (BR) and the heart rate (HR). This paper uses a simple, off-the-shelf dual multifrequency Continuous Wave (CW) radar setup to monitor the BR and HR of a static individual. The source separation problem of extracting the HR signal in presence of a higher amplitude BR signal poses a huge challenge and has been effectively solved by using an optimal channel selection process and the Variational Mode Decomposition (VMD) algorithm in this paper. Frequency extraction from the nonstationary signal modes produced by VMD has been performed by using the Fourier-Bessel transform to extract precise frequency information. Results show that the proposed system is accurate and outperforms other existing mode decomposition methods like Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD) with a mean absolute error of 5.1 $\pm$5.4 with respect to the number of heartbeats per minute and an accuracy of 95.87%($\pm$4.9) with respect to the number of breaths per minute.**

***Index Terms*—Continuous Wave (CW) radar, breathing rate, heart rate, vital signs, Variational Mode Decomposition, Fourier-Bessel transform**

## I. Introduction

Microwave Doppler radars have been at the forefront of the unobtrusive sensing paradigm in recent times for a large number of commercial and research applications like vibration detection and characterisation [1], [2], gesture recognition [3], [4] and non-pervasive vital signs monitoring [5]–[7]. Several radar systems are widely used for such applications like Continuous Wave (CW), Frequency Modulated Continuous Wave (FMCW), Stepped Frequency Continuous Wave (SFCW) and Ultra Wide Band (UWB) radars. Non-contact vital signs monitoring, especially, has received much attention due to its potential use in scenarios like elderly and infant care and monitoring. The unobtrusive sensing capability of these systems helps preserve the privacy of individuals, while at the same time removing the burden of physically wearing on-body sensors. Concurrent detection of the breathing rate (BR) and the heart rate (HR) from such radars form a source separation problem, as the obtained BR and HR signals are composite in nature. Radars receive the signature of the chest wall movement of an individual, which occurs as a combined result of respiration and heartbeat. The captured signal has these components fused together. The BR and HR signals occupy closely spaced ranges in the frequency domain: 0.12-0.5Hz and 1-2Hz respectively. While FMCW and UWB systems are known to facilitate easier separation of BR and HR from the composite signals [8], they are more complex than CW systems in terms of hardware and signal processing techniques and are thus not considered in this work. The source separation problem for CW radars can be challenging [9] due to the non-stationarity of the obtained signals as well as the presence of several intermodulation terms among them. Moreover, the amplitude of the heart signal is around 30 times less than that of the respiratory signal as a result of lower displacement of the chest wall cavity for the beating heart. This makes correct observations of the HR extremely difficult. In this paper, we propose solving this problem of concurrent BR and HR detection by exploring mode decomposition techniques.

The source separation problem has been tackled in most prior art by using techniques like Independent Component Analysis, Principal Component Analysis or filtering followed by the Fast Fourier Transform. Independent component analysis has been used in [10] to treat the BR and HR signals separately and process them. [11] uses the standard BSS technique to separate the BR and HR. However the low HR amplitude and the presence of BR harmonics in a noisy environment makes these techniques unsuitable for most applications. Mode decomposition is another approach to segregate a composite signal into its constituent components. Empirical Mode Decomposition (EMD) was one of the first mode decomposition techniques, introduced by Huang et al. [12]. EMD involves iteratively breaking down a signal into its mode functions by subtracting the mean of its extreme envelopes at every iteration. At every such iteration, the property that the number of zero crossings of the signal is one less than or equal to the number of extrema is maintained. Despite being robust in its approach, EMD suffered from issues like mode-mixing and noise sensitivity. The Ensemble Empirical Mode Decomposition (EEMD) was developed later by Wu et al. [13] and is a variation of EMD that is resistive to white noise. EEMD takes in a noise deviation value as a parameter and iteratively sifts an ensemble of white noise-added signal to accept the mean as the final result. Variational Mode Decomposition (VMD) by Dragomiretskiy et al. [14] is another relatively new decomposition technique that is used to split a composite signal into a discrete number of sub-signals or modes, with each mode having a certain specific

band spread around a center frequency. It is non-recursive in nature and avoids the drawbacks of the other techniques.

We propose a novel setup for the simultaneous detection of BR and HR by using mode decomposition. We employ a multi-frequency dual CW radar to capture the perturbations of the chest wall. The quality of the signals captured is then checked for both radars and an optimal radar channel is selected for BR and HR information retrieval. The optimal channel signal is then subjected to the VMD algorithm and the modes corresponding to respiration and heartbeats are extracted. From these modes, the correct centroidal frequencies are evaluated by taking their Fourier-Bessel (FB) transforms. The entire pipeline is designed such that precise detection of the BR and HR is achieved at minimal cost and labour.

The paper is organised as follows. Section 2 explains the overall methodology for finding the BR and HR simultaneously. It is followed by the experimental setup in Section 3. Results are examined in Section 4 and concluded in Section 5.

## II. Methodology

Fig. 1 shows the overall structure of the proposed approach to obtain the BR and HR concurrently. A dual CW radar setup is used to capture the physical data by placing it in front of a human subject. Data from each radar is first preprocessed individually and then passed onto an Optimal Channel selection block. The Optimal channel selection block chooses the optimal channel from the dual channel setup for extraction of the breathing rate and heart rate information. Following the selection, VMD is used to break up the composite signal into its constituent modes. A selection is next performed on the obtained modes to select the most appropriate ones for BR and HR detection. The final BR and HR are determined by taking a Fourier-Bessel transform on the selected modes.

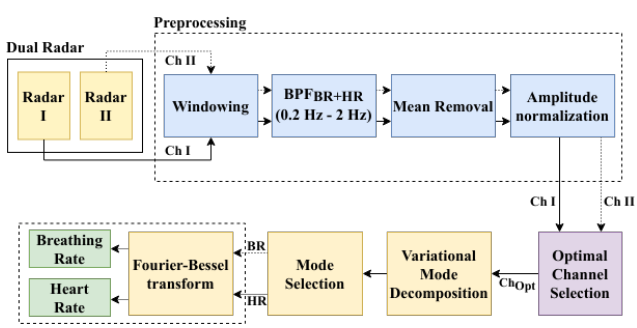


Fig. 1. Block diagram for concurrent cardiopulmonary monitoring

### A. Dual Radar setup

The dual radar setup consists of two CW radars physically spaced apart and working in the 10.525GHz and 24GHz bands. A nominal distance of 1 - 2 metres is maintained between the radar setup and the human subject. The 24GHz radar is more sensitive to picking up minor displacements in its field of view than the 10GHz radar, but also picks up more noise as a result. The outputs of the radars are fed into the preprocessing block.

### B. Preprocessing

The incoming signal from the dual radars is sampled at 64 samples per second and windowed into 60 second sequences. The windowed sequences are subsequently filtered by a fourth order Butterworth bandpass filter with cutoff frequencies at 0.2Hz and 2Hz. This range of frequencies ensures that the signal only contains the composite BR and HR signals in it. The sequences are then mean corrected and amplitude normalized before being fed into the next block.

### C. Optimal Channel Selection

Following the work described in [15], the dual channel data is checked for optimality and a single channel is finally selected for further processing. [15] selects a single channel from two parallel channels based on characteristics of the sequence like the peak to peak value, the autocorrelation of the sequence and the variance of the peak positions in the sequence.

### D. Variational Mode Decomposition

The filtered and preprocessed sequence is next decomposed into its constituent modes using VMD. VMD decomposes an input sequence $u$ into a discrete number of modes $m_k$ that have specific sparsity characteristics which can be reused to reconstruct the original sequence $u$. These are known as Intrinsic Mode Functions (IMF). Each mode is mostly compact around a center mode frequency $\omega_k$ which is evaluated during the decomposition. The constrained variational problem is described as:

$$\min_{\omega_k, m_k} \sum_{k=1}^{K} ||\partial(t)[\delta(t) + \frac{j}{\pi t} \times m_k(t)]exp(-j\omega_k t))||_2^2 \quad (1)$$

so that $\sum_{k=1}^{K} m_k = u$, where $K$ is the total number of modes, $\delta(t)$ is the Dirac distribution function and $m_k$ and $\omega_k$ are the individual modes and their center frequencies respectively.

The variational problem expressed in (1) is solved by using an optimization technique called Alternating Direction Method of Multipliers (ADMM) to find out the $\omega_k$'s and the mode functions centered on those frequencies in an iterative manner. In the frequency domain, the expression for $\hat{m}_k^{n+1}(\omega)$ can be obtained as:

$$\hat{m}_k^{n+1}(\omega) = \frac{\hat{u}(\omega) - \sum_{i \neq k} \hat{m}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k)^2} \quad (2)$$

$\omega_k$ is updated as:

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |\hat{m}_k(\omega)|^2 d\omega}{\int_0^\infty |\hat{m}_k(\omega)|^2 d\omega} \quad (3)$$

The Lagrangian multipliers $\lambda$ are updated as:

$$\hat{\lambda}^{n+1} = \hat{\lambda}^n + \tau \left( \hat{u}(\omega) - \sum_{k=1}^{K} \hat{m}_k^{n+1}(\omega) \right) \quad (4)$$

The iterative process is terminated when Equation (5) is satisfied.

$$\frac{\sum_k ||\hat{m}_k^{n+1} - \hat{m}_k^n||_2^2}{||\hat{m}_k^n||_2^2} < \epsilon \quad (5)$$

Here $\alpha$ and $\tau$ dictate the bandwidth constraint and the noise tolerance of VMD respectively, while $\epsilon$ is the tolerance of convergence. Equations (2) and (3) are updated continuously until convergence is achieved. The $m_k(\omega)$'s are then retransformed back into the time domain to obtain the $K$ decomposed modes.

In this work, the optimal channel sequence is broken up into 8 modes ($K = 8$) using VMD. $\alpha$ is supplied a value of 11000 and $\tau$ is set to 0. The $\omega$'s for the 8 modes are initialized uniformly and a tolerance of $10^{-7}$ is fixed for convergence.

### E. Mode Selection

VMD splits up the composite BR and HR signal into several modes. For an ideal composite signal containing frequencies corresponding to the BR and HR signals only, two sharp peaks should be produced in the frequency spectra. The presence of noise in the obtained composite signal does not guarantee the presence of such pure frequencies. The mode selection in VMD thus becomes critical in such a scenario. With the parameters specified in the previous subsection, it is observed that the first mode obtained corresponds to the respiration signal while the sixth mode corresponds to the heartbeat signal in VMD.

### F. Fourier-Bessel Transform for BR and HR detection

For simultaneous detection of the BR and HR from the selected VMD modes, the Fourier-Bessel (FB) transform is considered a better alternative than conventional frequency extraction techniques like the Fast Fourier transform (FFT) because of its inherent ability to handle nonstationary signals [16].This is because of the presence of the Bessel basis functions that decay over time, unlike the sinusoidal basis functions as used in Fourier expansions. The Fourier-Bessel transform of order $p$ of a signal $x(n)$ is given as:

$$F_p(k) = \int_0^\infty x(n) J_p(kn) n dn \tag{6}$$

where $J_p$ is the Bessel function of the first kind of order $p$.

The individual modes obtained after mode selection for the BR and HR processes are processed using the FB transform of zeroth order ($p = 0$). Detecting the peak in the FB spectrum provides the centroidal frequency in the selected VMD mode, from which the BR and HR can be directly computed. It has been observed that closely spaced and low amplitude frequencies can be detected with superior precision with the FB transform than a Fourier method like FFT, especially in the presence of larger sidelobes, as has been discussed in the Results section.

## III. Experimental Results and Discussion

### A. Experimental Setup

Data was collected from the dual radar setup via a Raspberry Pi 3B+ module and a GUI developed using Python. The subjects were made to sit 1.5 metres in front of the radar setup, typically wearing two layered clothing. They were told to rest for 5 minutes before data was collected for 1 minute while breathing normally. During data collection, the subjects were advised to restrict sudden movements to avoid motion artifacts. Ten such subjects belonging to the age group of 25-35 years and including both men and women were selected for data collection. Video recording to count the number of chest wall movements and a pulse oximeter served as the ground truth for the BR and HR respectively. Fig. 2 shows the experimental setup used.

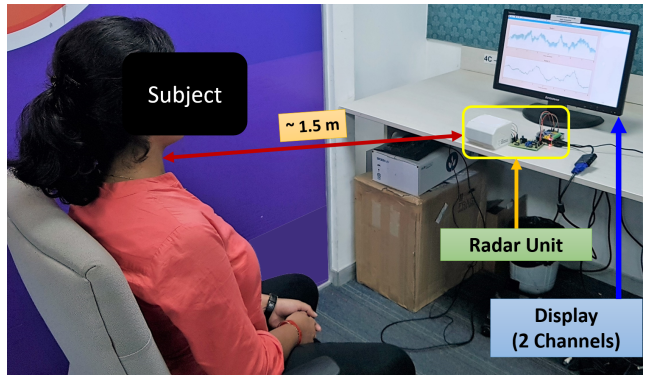


Fig. 2. Experimental setup for concurrent BR and HR detection

### B. Results

The VMD algorithm could effectively segregate the BR and HR frequencies even in the presence of substantial noise. Fig. 3 shows the different decomposed modes for a signal supplied with a bandwidth constraint parameter ($\alpha$) value of 11000 and a tolerance of $10^{-7}$. As can be seen, VMD is able to effectively segregate the filtered composite signal into clean sub-signals. The first IMF corresponds to the respiration signal and the sixth IMF corresponds to the heartbeat signal. Fig. 4 shows the BR per minute computed from the first mode using the FB transform in comparison with the actual BR as observed from the video recordings. The BR is detected with an accuracy of 95.87($\pm$4.9)%. Table I shows the detected heart rates from the sixth mode using the FB transform for all subjects. The results have been compiled for VMD, EMD and EEMD. For this work, EEMD was carried out with a noise deviation value of 0.3. It is seen that VMD performs better in most cases than EMD or EEMD - the HR Mean Absolute Error (MAE) calculated with respect to the number of heartbeats per minute is substantially lower for VMD ($5.1 \pm 5.4$) than that for EEMD ($11.2 \pm 12.6$) or EMD ($14.9 \pm 16.5$).

The advantage of using FB transform over traditional Fourier transforms like the FFT is highlighted in Fig. 5. It is seen that certain sidelobes present in the signal hinder correct peak detection for HR retrieval when using FFT. FB, however generates more sharper peaks at the BR and HR frequencies, leading to easier detection of the same. Table II shows a comparison of the peak frequency detection using the FFT and FB techniques. It is seen that the FB technique outperforms the FFT technique in all cases.

The MAE for Heart Rate Variability (HRV) calculated using RR intervals for the three mode decomposition methods are shown in Fig. 6. It can be seen that VMD consistently

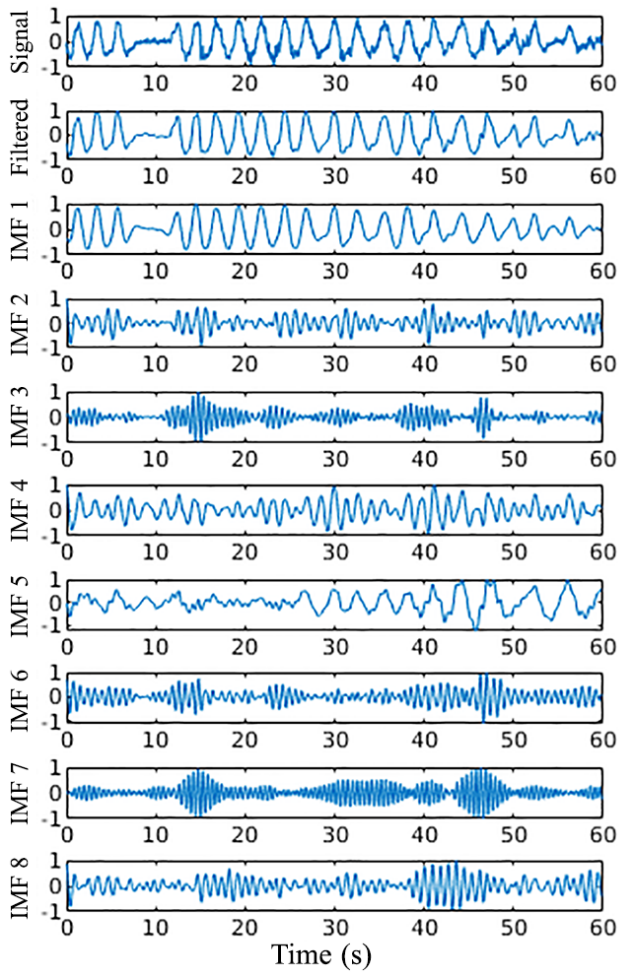


Fig. 3. Mode decomposition using VMD

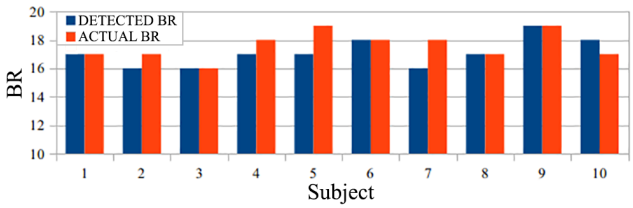


Fig. 4. BR computed from the first IMF using VMD

TABLE I
MODE DECOMPOSITION FOR HR

| Subject | VMD HR MAE | EEMD HR MAE | EMD HR MAE |
|---|---|---|---|
| 1 | 0.231 | 38.906 | 46.88 |
| 2 | 0.878 | 14.531 | 33.75 |
| 3 | 13.669 | 11.25 | 22.5 |
| 4 | 1.233 | 0.0 | 0.47 |
| 5 | 2.016 | 2.344 | 1.88 |
| 6 | 5.145 | 15.0 | 26.19 |
| 7 | 11.69 | 0.469 | 12.19 |
| 8 | 0.522 | 2.344 | 0.0 |
| 9 | 3.665 | 3.281 | 3.28 |
| 10 | 12.748 | 24.844 | 1.88 |

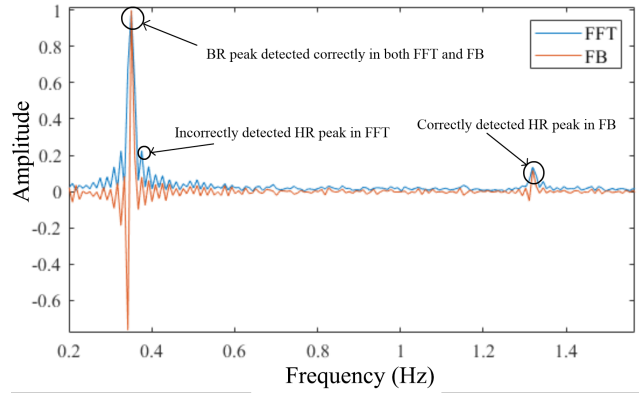


Fig. 5. Peak detection in FFT and FB techniques

TABLE II
HR MAE USING FB AND FFT

| Subject | VMD HR MAE using FB | VMD HR MAE using FFT |
|---|---|---|
| 1 | 0.231 | 0.4688 |
| 2 | 0.878 | 9.8438 |
| 3 | 13.669 | 13.6938 |
| 4 | 1.233 | 1.9781 |
| 5 | 2.016 | 2.8751 |
| 6 | 5.145 | 5.2812 |
| 7 | 11.690 | 11.689 |
| 8 | 0.522 | 1.213 |
| 9 | 3.665 | 3.879 |
| 10 | 12.748 | 24.8438 |

generates lesser MAE $(0.48 \pm 0.34)$ compared to the other two methods for all subjects.

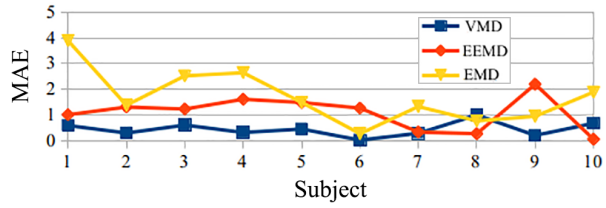


Fig. 6. HRV MAE for different subjects (lower is better)

### C. Comparison with existing work

Application of VMD along with FB to detect the BR and HR from CW radars is sparse in literature. Authors in [17] have used a UWB radar along with VMD and FFT to detect the BR and HR frequencies. [18] uses a 24GHz CW radar with horn antennas which requires initial calibration. No quantitative results have been reported in these work. Background noise removal and clutter filtering, followed by a maximum distance gate selection has been attempted in [19] to detect the vital signs of subjects placed in front of a radar and behind concrete walls. VMD coupled with time-frequency analysis (utilizing the Hilbert spectrum) has provided a maximum accuracy of 91%. Similar sensor motion artifacts removal in a microwave radar system to capture the vital signs has been reported in [20] and [21]. In [22], authors have used a combination of

permutation entropy and EEMD to track a subject and obtain vital signs from a UWB radar, for both direct and through-wall applications. The reported results show that the tracking works well, but the vital signs detection has not been compared to any existing ground truth. An EEMD-PCA combination has been proposed in [23] to determine vital signs under the condition of strong close reflected interferences using a FMCW radar. Yin et al. [24] describes the HEAR algorithm that achieves continuous monitoring with compensation for body movement that builds upon the VMD algorithm. A minimum error rate of 4.6% is reported. Vital sign tracking in a car has been reported in [25] which directly utilises the VMD algorithm. It adopts a location based approach and has reported a maximum accuracy of 92.66%. EMD-ICA has been used as a source separation tool in [26] to separate BR and HR frequencies; however no exhaustive results have been reported. Compared to the above mentioned works, this paper has implemented a novel yet simple approach to solve the source separation and concurrent detection problem of BR and HR that works on signals generated from simple, off-the-shelf, cost effective CW radars. Apart from being accurate (more than 94% accuracy for BR as well as HR), our entire system can work out of the box, does not require external calibration and most importantly, has been tested on external cohort.

## IV. Conclusion

This paper has presented a multifrequency dual CW radar system to capture the vital signs of static subjects placed at distances of one to two metres from the radar setup. The proposed system uses optimal channel detection to identify the proper channel for breathing rate and heart rate information extraction. Variational Mode Decomposition has been used to separate the breathing rate and heart rate signals and a Fourier-Bessel transform is performed to detect the frequencies of the separated signals. The EMD and EEMD methods of mode decomposition has also been investigated. The VMD-FB system has superior performance, indicated by a lower detected heart rate MAE as well as better HRV, even in the presence of external noise. Our future work will mainly emphasize on detecting vital signs using the proposed low cost setup for moving subjects.

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