Extracting Vital Signs from Continuous Wave Radar based return signals using Discrete Wavelet Transform and Empirical Mode Decomposition

Shreya Ramakanth[1], Rohit H.R[1], Saraswathi K[2]

[1] UG Student, Dept. of Telecommunication Engineering, R.V College of Engineering, Bangalore, India
[2]Associate Professor, Dept. of Telecommunication Engineering, R.V College of Engineering, Bangalore, India

---

Abstract - *Continuous Wave (CW) Radars play a significant role in detecting vital signs of a human within a certain distance and hence are able to trace victims who are buried under collapsed buildings or target fugitives behind walls. The algorithm proposed in this paper consists of Discrete Wavelet Transform (DWT) followed by Empirical Mode Decomposition (EMD) which helps to detect the heartbeat rate and respiratory rate of the target. DWT helps to reduce complexity and increase computation speed while EMD helps in removing high frequency noise. The final calculated results show that the proposed algorithm never fails to detect the presence of a human.*

Key Words*: *CW radar, DWT, EMD, Vital Signs

1.INTRODUCTION

Life detecting radars combine the use of radar technology and biomedical signal processing. Using this combination, algorithms are framed to detect the presence of life after an earthquake and as warning system for approaching targets. By monitoring cardio-pulmonary rates one can diagnose patient's condition in hospitals. The two main classifications of life detecting radars that are based on the type of waveform utilization are Continuous Wave (CW) radars and Pulsed radars [1]. CW radar systems emit stable frequency radio energy, are automated and can be manufactured easily.

The emitted CW Radar signal is partly absorbed and partly reflected by the human body. These reflected signals possess Doppler and micro Doppler effects due to the frequency modulation caused by walking, respiration and heartbeat [2]. The Doppler effects can be observed by the shift in the carrier frequency of the return signal due to the movement of target with constant velocity while deviations from the center frequency due to minor displacements are the effects of micro Doppler theory [3].

Previously, vital signs were detected using wearables and on body antennas to monitor a human's vitals [4]. As technology advanced, non-contact vital sign detection proved its importance during man hunts. Short time Fourier transform (STFT) and correlation blocks are most commonly used to detect these vital signs [1,5]. Maaref et al., [6] subtracted the return signal from the transmitted signal to eliminate the fixed echoes. Singular value decomposition was performed to reduce the noise caused due to obstruction. A new algorithm [8] which is a combination of filtering, decomposition in the time domain and auto correlation was introduced. This algorithm [8] uses a set of short time windows and autocorrelation blocks to reduce the impact of noise on the signal. This noise reduction technique has a complexity of Ø (N) * Ø (NlogN) which is high. The proposed algorithm aims at detecting and extracting both the heartbeat rate and respiratory rate with reduced complexity.

This paper describes a less complex yet significant approach to vital sign detection where the simulated return signal mentioned in Section 2 is passed through preprocessing blocks prior to DWT and EMD. Section 3 and Section 4 give a brief account on DWT and EMD respectively. The detailed explanation of the proposed algorithm is mentioned in Section 5 followed by the Results in Section 6. The paper, methodology and results are concluded in Section 7.

2. RETURN SIGNAL MODEL

The distance ($d_r(t)$) from the radar antenna and the human target; and the time delay ($\tau(t)$) due to the response from the life activity [7, 11] can be expressed as equations (1) and (2).

$$d_r(t) = d_0 + r(t) = d_0 + a_r \sin(2\pi f_r t) + a_h \sin(2\pi f_h t) \quad (1)$$

$$\tau(t) = \frac{2 d_r(t)}{c} \quad (2)$$

where d_0 represents the distance of the center of human chest from the radar antenna; the displacement due to respiration is a_r and due to the heartbeat is a_h; the frequencies of both the afore mentioned movements are f_r and f_h respectively; c represents the speed of light. The time domain representation of the complex valued return signal is generated using equation (3).

$$R(t) = A\cos\left(2\Pi f_c t + \frac{2d_0}{c} + \frac{2a_r}{c} \sin 2\Pi f_r t + \frac{2a_h}{c} \sin 2\Pi f_h t\right) \quad (3)$$

The frequency of heartbeat (f_h) corresponding to 54-120 beats per minute is given by 0.9 Hz to 2Hz and the frequency of human respiration (f_r) is anywhere between 0.1Hz and 0.8Hz.

3. DISCRETE WAVELET TRANSFORM

The frequency range that is necessary to detect vital signs is from 0Hz to 5Hz. Hence, it is helpful to apply DWT on the simulated return signal as it limits the frequencies that are greater than 5Hz. By using the approximation coefficients, it not only removes unwanted higher frequencies but also increases the speed of processing.

As given in figure 1, on applying DWT the input signal is passed through a series of low pass and high pass filters which give approximation coefficients and detailed coefficients respectively. At every level these filters are followed by down sampling blocks because half the frequencies are removed and so according to the Nyquist's Criteria half the samples are discarded. The filter bank coefficients at every level are computed by shifting and scaling the mother wavelet by powers of two. In wavelet decomposition, the discrete signal $x(n)$ is represented as given in equation (4).

$$\begin{aligned} x(n) &= cD_1 + cA_1 \text{ : level 1} \\ &= cD_1 + cD_2 + cA_2 \text{ : level 2} \\ &= cD_1 + cD_2 + cD_3 + cA_3 \text{ : level 3} \\ &\vdots \\ &= \sum_{j=1}^{N} cD_j + cA_N \text{ : level N} \end{aligned} \quad (4)$$

where, cD_j and cA_j, the detailed and approximation coefficients at the j^{th} level of decomposition are given by equation (5).

$$\left.\begin{aligned} cD_j &= (cA_{j-1} * HP) \downarrow 2 \\ cA_j &= (cA_{j-1} * LP) \downarrow 2 \\ cA_1 &= (x * LP) \downarrow 2 \end{aligned}\right\} \quad (5)$$

The lowpass filter coefficients are represented as LP and highpass filter coefficients are represented as HP and are designed based on the mother wavelet.

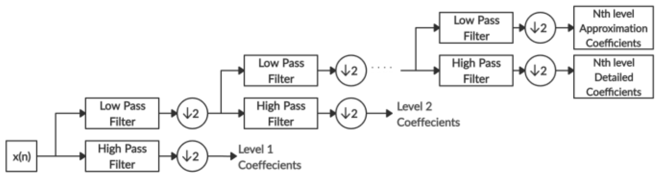

Fig - 1. Block Diagram for implementation of DWT.

The levels of decomposition [9] needed to achieve the requirement of the algorithm is given by equation (6).

$$N < \left\lfloor \frac{\log\left(\frac{F_s/2}{5}\right)}{\log 2} \right\rfloor \quad (6)$$

where Fs is the sampling frequency of the CW radar.

4. EMPIRICAL MODE DECOMPOSITION

Along with a given advantage that EMD does not require any predefined functions, it also reduces noise in the signal. The range of frequencies that needs to be concerned for this application is low and so when a signal is decomposed into a set of IMFs, the highest frequencies which usually lie in the first IMF are mostly dealing with noise. Hence, the first IMF which is a result of EMD applied on the approximation coefficients is ignored and the vital sign extraction algorithm is continued.

EMD decomposes a signal into the residual and a set of Intrinsic Mode Functions (IMFs). These IMFs are results of a series of sifting process and satisfy two conditions: (a) the number of maxima and minima differ by at most 1 and (b) the mean envelope of the IMF is zero. The first IMF contains the highest frequencies in the N^{th} level approximation coefficients and each subsequent IMF consists of the lower frequencies. The sifting process follows the steps as described [10]. Assuming a signal $y(n)$ which is discretely sampled,

Step 1: Find all the maxima, $ymax(n)$, and minima, $ymin(n)$ of the input signal $y(n)$.
Step 2: Insert a cubic spline through $ymax(n)$ and $ymin(n)$ to get the upper and lower envelopes.
Step 3: Determine the mean of the lower and upper envelopes, $m(t) = (ymax(n) + ymin(n))/2$.
Step 4: Subtract the mean from the original to obtain the residual. Let $d(n) = y(n) - m(n)$.
Step 5: If $d(n)$ satisfies the criteria of an IMF, then let $imf_k(n) = d(n)$ and increase k by 1. Subtract to get the residual $r(n) = y(n) - d(n)$. If $r(n)$ does not satisfy the criteria of an IMF, shifting is repeated until the residual no longer has any useful frequency information.
The original signal is equal to sum of its individual parts. Assuming there are N IMF's and a final residual $r_N(n)$, the input signal can expressed as given in equation (7).

$$y(n) = \sum_{k=1}^{N} imf_k(n) + r_N(n) \quad (7)$$

5. PROPOSED ALGORITHM

To accurately estimate the vital signs of a human body, this section presents an algorithm for automatic estimation and detection of the heart rate and respiratory rate. Figure 2, is the block diagram of the proposed algorithm which is less complex and highly accurate in detecting the presence of human life.

Step 1: Convert the complex values return signal into its analytic form.

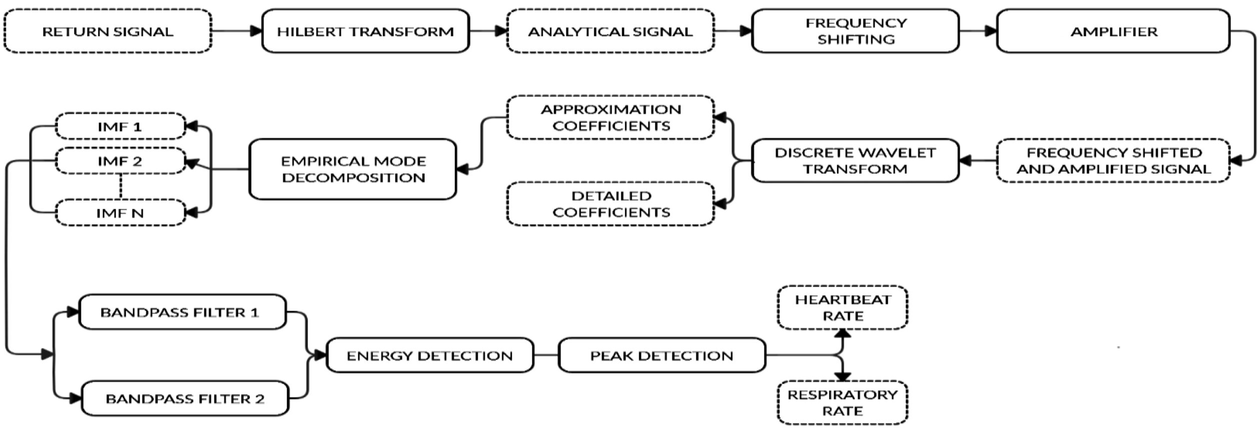

Fig - 2. Block Diagram of the proposed algorithm.

Step 2: Shift the center frequency of the signal and amplify it.
Step 3: Extract the approximation and detailed coefficients by applying Discrete Wavelet Transform (DWT) on the amplified signal.
Step 4: Perform Empirical Mode Decomposition (EMD) on the Nth level approximation coefficients to get the Intrinsic Mode Functions (IMFs).
Step 5: Pass the IMFs into two Band Pass Filters (BPFs) with cutoff frequencies corresponding to the range of vital signs.
Step 6: Calculate the energy of each of the outputs from both the BPFs.
Step 7: Select one IMF from each of the filter outputs based on the threshold.
Step 8: Estimate the vital signs using peak detection on the selected IMFs.

Table-I: Specifications of proposed algorithm.

Parameters	Values
Frequency of Radar (f_c)	1GHz
Frequency of respiration (f_r)	0.7Hz
Frequency of heartbeat (f_h)	1.7Hz
Distance between the radar and the center of human chest (d0)	1m

In step 1, a complex valued return signal as shown in figure 3 is converted into its analytic form using the Hilbert transform. The Hilbert Transform helps remove the negative frequency components and hence simplifies the composition of frequency without the loss of any information. The frequency domain representation of the analytical signal.

In step 2, the analytic signal is shifted from the center frequency at fc (fc represents the radar frequency around which the micro Doppler effects are seen) to 0 Hz and further amplified since the signal strength is not high enough due the small displacement of the thoracic cavity.

In steps 3, DWT is applied on the amplified signal shown in figure 4. As given in section 3, DWT helps to limit the frequency band larger than 5Hz. The levels of decomposition [9] to be performed is given by (6). The Nth level approximation coefficients vector is used for further analysis.

In step 4, EMD explained in section 4 is performed on the approximation coefficients to calculate the IMFs as shown in figure 5. Two of the total number of IMFs must contain fr and fh.

In step 5, the first IMF is discarded and each of the other IMFs is passed through two BPFs with cutoff frequencies 0.1 to 0.8Hz and 0.9 to 2Hz which correspond to the respiratory rate and heartbeat rate respectively [9] as shown in figure 6.

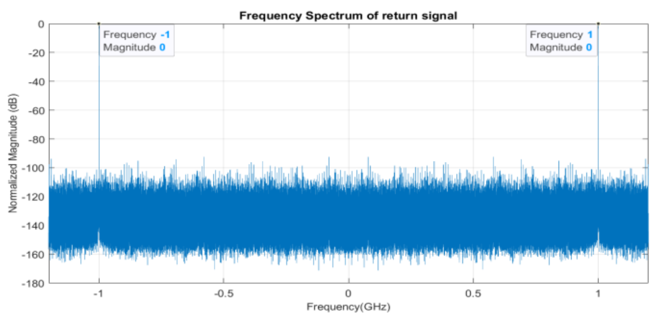

Fig - 3. Frequency Spectrum of the complex valued return signal.

In steps 6 and 7, the energy of each output from the BPFs are calculated using equation (8). IMFs with energy peaks above the threshold value are selected for further processing. This energy detection helps in selecting the IMF that has the highest signal strength in the range corresponding to the respectively vital signs as shown in figure 7.

$$E = \sum_{-\infty}^{\infty} |x[n]|^2 \quad (8)$$

In step 8, the 2 IMFs that have been selected after energy detection are converted into their frequency domain representation to calculate fr and fh that correspond to frequencies with the maximum magnitude.

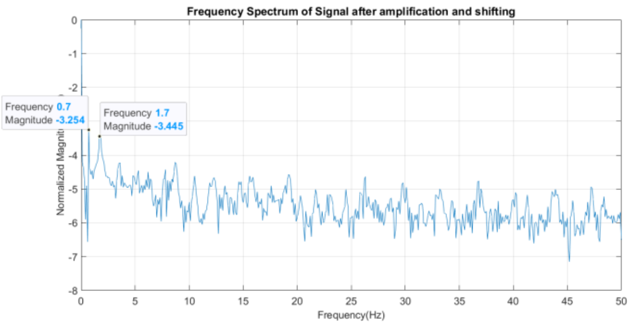

Fig - 4. Frequency Spectrum of signal after amplification.

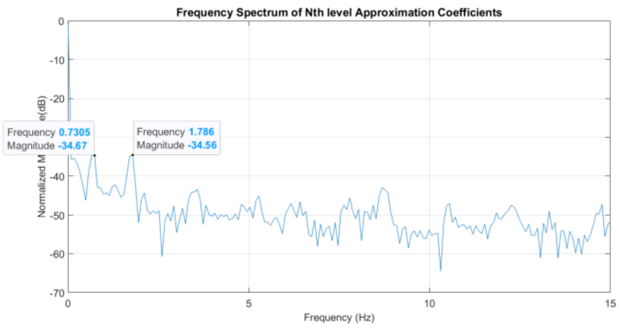

Fig - 5. Frequency Spectrum of the Nth level approximation coefficients.

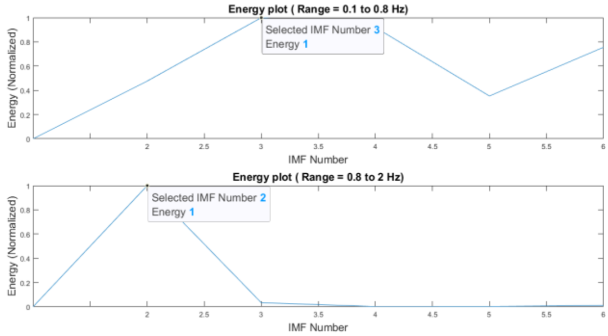

Fig - 7. Energy plots of the bandpass filtered IMFs.

6. VERIFICATION WITH RETURN SIGNAL

The specifications used in generating the CW radar return signal is given in Table 1. The mother wavelet used while performing DWT is the 'Daubechies' wavelet of the order 45 and 16 levels of decomposition was required to limit the signal to 5Hz. It can be observed in figures 8 and 9 that the maximum peaks of the frequency spectrum of selected IMFs are at 0.6493Hz and 1.786Hz which are approximately equal to the initially used frequencies of respiration and heartbeat respectively.

By using DWT as a replacement in the algorithm [8] there was a decrease in the complexity by a factor of Ø (NlogN). The reduction in number of samples due to DWT also leads to a decrease in the order of the BPFs and hence increases the computation speed. Table 2 shows the tabulated results of the specifications taken initially and the extracted values after implementation of the proposed algorithm. Therefore, the proposed algorithm is efficient in detecting vital signs of humans.

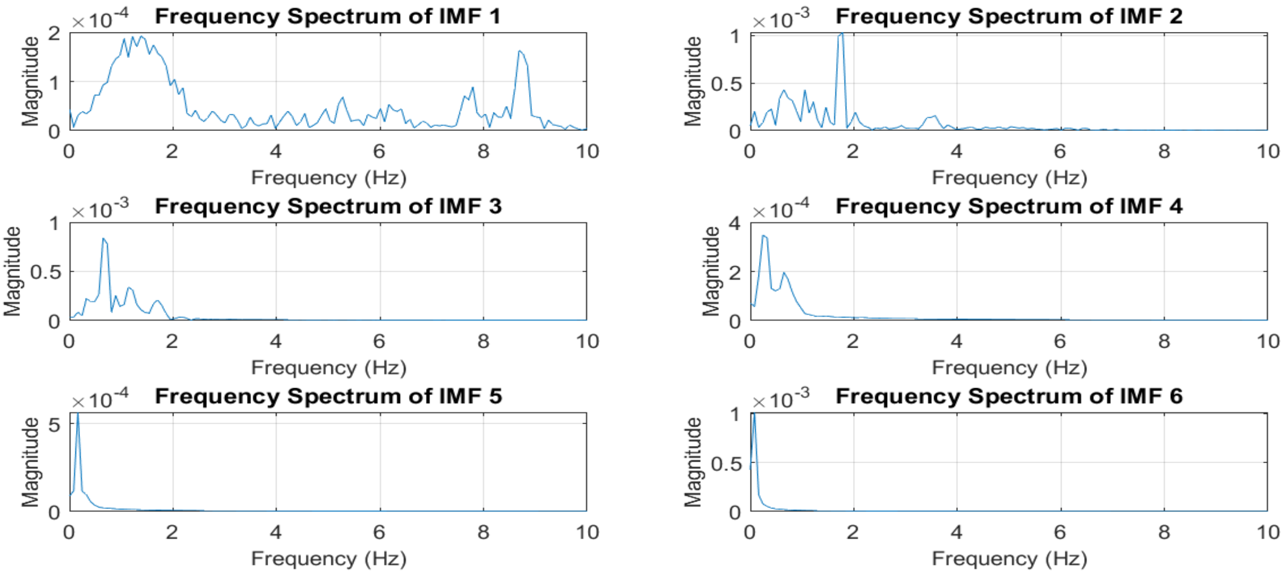

Fig - 6. Frequency Spectrum of all the IMFs.

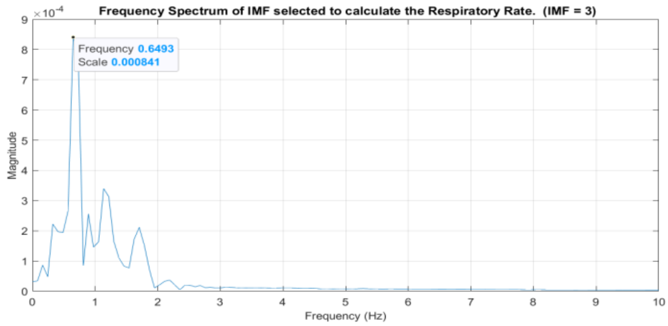

Fig - 8. Frequency Spectrum of IMF selected to calculate the Respiratory Rate.

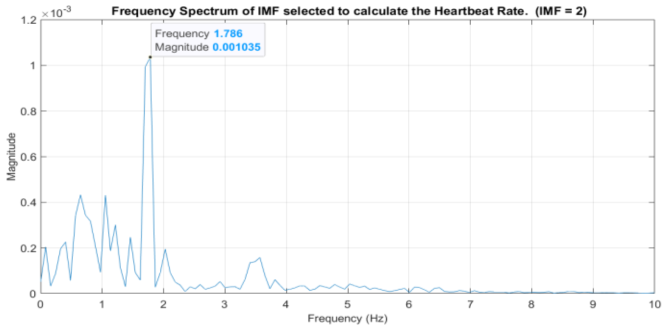

Fig - 9. Frequency Spectrum of IMF selected to calculate the Heartbeat Rate.

Table- II: Tabulated results of the specifications of heartbeat and respiration rates initially used and the extracted vital signs after implementation of the proposed algorithm.

Specifications of generated return signal		**Calculated using the proposed algorithm**	
fr (Hz)	**fh (Hz)**	**fr (Hz)**	**fh (Hz)**
0.7	1.7	0.65	1.79
0.2	1	0.16	0.97
0.5	1.5	0.49	1.46
0.7	1.8	0.65	1.79
0.4	1.2	0.41	1.22

7. CONCLUSION

This paper, presents an algorithm that helps to extract the respiratory rate and heartbeat rate of a human from CW radar return signals. The return signal is formed by frequency modulating the transmitted signal to have the shifts due to Doppler and micro Doppler effects. The signal is pre-processed prior to applying DWT, the amplified signal helps the lower frequencies to have significant signal strength.

By using DWT there is a reduction in complexity by a factor of Ø (NlogN). The decrease in the number of samples due to DWT also increases the computation speed. The IMFs extracted due to EMD have the respiration and heartbeat rates and are selected based on the energy in the bands corresponding to the vital signs, i.e., 0.1Hz to 0.8Hz for respiration rate and 0.9Hz to 2Hz for heartbeat rate. The final rates are calculated from the frequency spectrum of the selected IMFs.

REFERENCES

[1] Jian Lou and Yong Wang, "Implement of UWB Radar for Human Life Detection", *Applied Mechanics and Materials*, vols. 239-240, pp. 348-352, 2013.

[2] Xiaolin Liang, Jianqin Deng, Hao Zhang and Thomas Aaron Gulliver, "Ultra-Wideband Implusive Radar Through-Wall Detection of Vital Signs", *Scientific Reports*, 2018.

[3] V.C. Chen, F. Li, S.S. Ho, H. Wechsler, "Micro-Doppler Effect in Radar: Phenomenon, Model and Simulation Study", *IEEE Transactions on Aerospace and Electronic Systems*, vol. 42, no. 1, pp. 2-21, 2006.

[4] Tuba Yimaz, Robet Foster and Yang Ho, "Detecting Vital Signs with Wearable Wreless Sensors", *Senors (Basel, Switzerland)*, 2010.

[5] M Kemal Kiymik, Inan Guler, Alper Zizibuyuk and Mehmet Akin, "Comparison of STFT and Wavelet Transform Methods Indetermining Epileptic Seizure Activity in EEG Signals for Real-Time Application", *Computers in Biology and Medicine*, vol. 35, 2005.

[6] N.Maaref, P.millot, Ch.Pichot and O.Picon, "A Study of UWB FM-CW Radar for the Detection of Human Beings in Motion Inside a Building", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, no.5, 2009.

[7] Xialoin Liang et al., "Through-wall Human Being Detection using UWB Impulse Radar", *EURASIP Journal on Wireless Communication and Networking*, 2018.

[8] Liang Wang and Yong Wang, "A New Signal Processing Algorithm for Ultra-Wideband Radar Life Detection", *in Proceeding of Progress in Electromagnetics Research Symposium*, pp. 560-564, 2017.

[9] J.H Park, H. Lim and N.H Myung, "Modified Hilbert-Huang Transform and its Application to measured Micro Doppler Signatures from Realistic Jet Engine Signals", *Progress in Electromagnetics Research*, vol. 126, pp. 255-268, 2012.

[10] Denis Donnelly, "The Fast Fourier and Hilbert-Huang Transforms: A Comparison", *in Proceedings of IMACS Multiconference on Computational Engineering in Systems Applications*, pp. 84-88, 2006.

[11] Xiaoling Li, Bin Liu, Yang Liu, Jiawei, Jiarui Lai and Ziming Zheng, "A Novel Signal Separation and De-Noising Technique for Doppler Radar Vital Signal Detection", *Sensors,* 2019.