Wireless Radar Breath Detection with Empirical Mode Decomposition Method

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Physiological signal processing can be applied to emergency rescue and healthcare monitoring with an understanding of health status. Existing works have demonstrated the capacity of extracting respiratory signal with continuous-wave radar. Current breath detection adopts time-frequency transform and statistical pattern recognition method, which requires a lot of efforts to collect data. This paper proposes a method of respiratory detection that uses empirical mode decomposition for de-noising and I/Q (In-phase and Quadrature) signal demodulation. With domain-knowledge, the proposed method does not require a large dataset and processes signals in time domain to improve calculation efficiency. To verify the performance of the proposed method, experiments of detecting and recording breath signal from human participants were conducted. The accuracy of breath detection of the methods was obtained to assess performance. Waveshape distortion affects health monitoring judgement. To assess the degree of waveshape distortion of extracted respiratory signal, comparing waveshape between extracted signal and base signal was conducted. This finding could be used to aid the breath monitoring remotely at home to identify potential illness related to breath like apnea caused by brain.

CCS CONCEPTS • Human-centered computing ~ Ubiquitous and mobile computing • Hardware ~ Communication hardware, interfaces and storage ~ Signal processing systems

Additional Keywords and Phrases: Signal Processing, Noise Reduction, Radar, Breath Detection

1 INTRODUCTION

Breath detection has been an important sub-branch of physiological signals monitoring, which contributes health status assessment. From the medical perspective, respiratory signals can reflect various kinds of illness including hypertension, from technical perspective, accurately extracted breath signals can be further processed to obtain more information such as sleeping disorder. For breath detection, solutions like wearable sensors and camera monitoring have been proposed [1,2]. Discomfort arising from wearable sensors and potential privacy intruding of cameras prevent such solutions from being applied widely, because traditional respiratory signal detection like wearable sensors requires patients to take part into precious, time-consuming C14 breath detection at the hospitals. As a result, the demanding for compact and non-contact monitoring of health status at home is raised.

Existing works have demonstrated health status tracking [3] with electronic waves. To have a good and excellent electronic wave processing device, radar had been adopted as an integrated platform for health status tracking in existing works [1, 2]. The main principle behind above researches is modulation, i.e. the process of carrying a physical parameter with a signal. The tiny movement of human chest can be modulated onto the electronic waves as phase when reflection happens. Thus, how to modulate respiratory information onto radar electronic waves and de-modulate the respiratory information off electronic waves is the key. Specifically in this paper, Frequency Modulated Continuous Wave (FMCW) radar modulates the phase information. However, as researches in prior papers adopted time-frequency analysis to extract phase information, the aliasing arising from windowing Fourier Transform could occur and affects accuracy. This paper extracts phase information without converting signal into frequency domain.

N. E. Huang [11] in 1998 proposed a kind of decomposition algorithm Empirical Mode Decomposition (EMD) for analyzing temporal signals without domain transformation. The novelty of this paper mainly lies on the application of EMD empirical mode decomposition into the respiratory signal detection, which directly processes the phase of radar signal for breath identification without time-consuming transformation. EMD decomposes the signal into a set of time-domain signals of equal length, from which the frequency and amplitude information can be acquired. By decomposing the signal into different IMF components, the active noise generated from electrical interference can be eliminated. The de-noised mixed radar signal is just the needed breath signal.

The paper is organized in the following ways. The introduction of this field, related literature and principle of hardware which lays foundation for the further signal processing are discussed in the Background. The signal processing algorithms including EMD empirical mode decomposition, and its application of the signal processing are discussed in Design and Implementation. The validation experiment that evaluates the overall performance of the detection is in Experiments. Conclusion concludes the whole paper and discusses the areas that can be improved further and how this research could be applied to some other fields.

2 BREATH SIGNAL DETECTION

2.1 Respiratory Signals Detection with Radar Signal

The chest cavity rises and falls as the body exhales and inhales, caused by contraction and expansion of the lungs and diaphragm muscles. Studies have shown that these chest fluctuations can be measured in centimeters [4,5] and can therefore be considered as minor movements. This tiny movement is also regular in term of frequency, respiratory rate mainly lies between 12 and 20 bpm [6]. Hence, detecting the breath focuses on how to perceive this tiny regular movement.

According to systemic review of [7], two categories of automatic breath detection methods are prevalent among the medical and technical field. One kind of these is to attach sensors to human skin to perceive needed physiological signals for respiratory signals detection, such as moisture detectors, face masks and bioimpedance electrode sensors. These sensors can receive necessary signals related to respiratory efforts like changes of moisture and convert them into respiratory signals. The attached-skin sensors can cause inconvenience reported in some cases [8,9] such as for infants, hence non-contact detection of respiratory movement should be proposed. The non-contact detection makes use of other indicators such as chest movement during breath to perceive breath with the use of radars and cameras. The proposed method in this paper falls into the category of contact-less detection mentioned above.

Human respiratory movement can cause changes for radar electronic waves in terms of amplitude, frequency and phase. Based on these three features, different kinds of radar systems are developed [12], e.g. Doppler radars [13], interferometric radars [14,15], video impulse radars [16,17], millimeter-wave radar [18] are used respectively to detect human health status. The proposed method in this paper adopts a type of millimeter-wave radar to detect human breath since millimeter-wave radar yields high resolution of localization to modulate chest tiny movement onto electronic waves.

2.2 Signal Processing of Respiratory Signals Detection

The breath signal is temporally periodic and only has finite non-zero values within a range (time-limited). To exploit the periodicity and time-limited characteristic, researchers in [4] used auto-correlation function which is 1-D filtering with the signal itself as kernel in time-domain as illustrated below:

$$R_{xx}(\tau) = \int x(t) \cdot x(t+\tau)\, d\tau$$

to extract breath information from radar signal. This method is generalized, not device-specific, since breath signals generated from any kind of device have temporal periodicity and time-limited feature. Other researchers in [5] uses modulation of amplitude for identifying breath information, where filtering must be sophisticated enough to filter the noise spectrum and preserves breath signal spectrum, because the breath signal amplitude information is hidden by active radar noise, this causes the noise spectrum cover the signal spectrum. And ChongYu Wei [10] adopted statistical pattern recognition approach to solve the problem, which involves pattern vector construction and distance measurement. But this method requires a large amount of data to construct pattern vectors vocabulary.

This paper adopts In-phase and Quadrature signal (I/Q) demodulation. The method closely relies on the characteristic proprieties of Frequency Modulation Continuous Wave radar that is I/Q modulation, this enables the phase information to be directly obtained by I(t)/Q(t), but the serious question is the noise. The white and pulse noise from internal system and external environment affect hide phase information as illustrated in the below Figure 1. The noise expands into all frequencies bins which hides the breath signal. In this case, this paper applies EMD empirical mode decomposition to denoise.

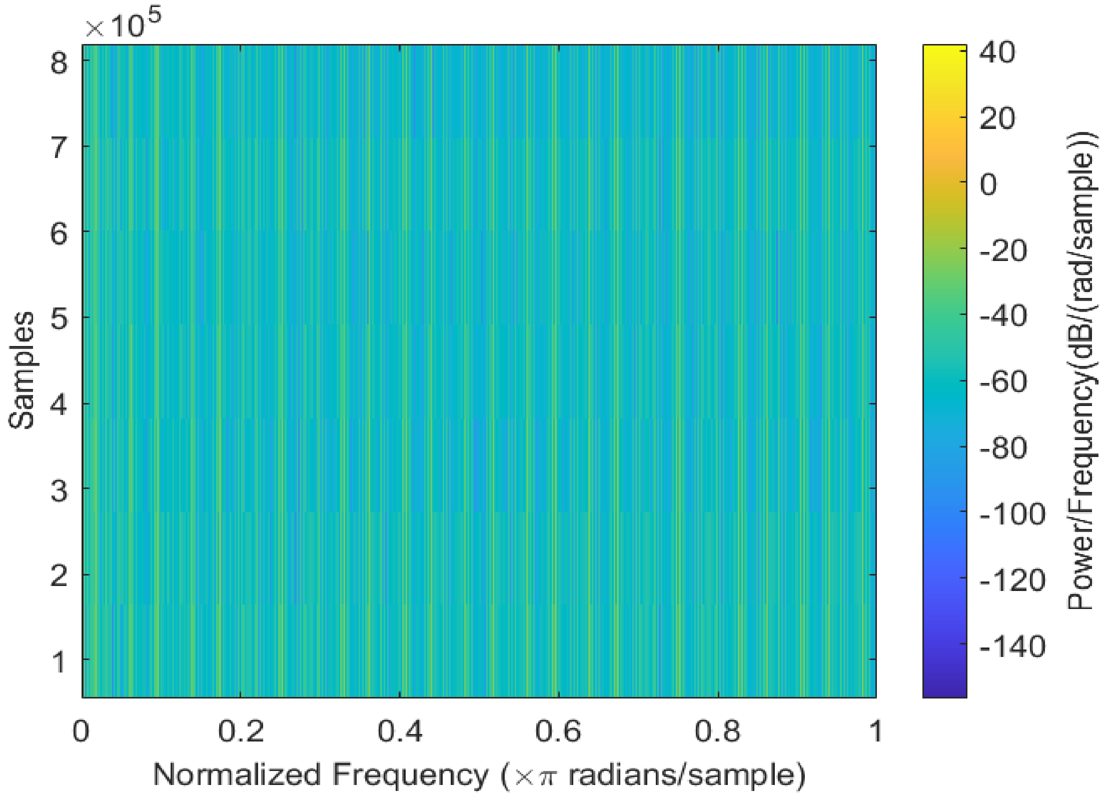

Figure 1. Spectrogram of $y(t)$ from I/Q Demodulation

2.3 FMCW Radar Fundamentals

This paper selects radar board RKB1102I produced by Sgrsemi™ in Shanghai. The reason why this specific type of radar is chosen lies on the fact that it is small, compact and economic friendly. The power is 0.561 watt which consumes electricity so less so that laptop can support it without referring to any extra external resources. This feature enables the same cable to transmit data and electricity simultaneously. Although some parameters are not excellent such as the distance detection accuracy, the overall performance is enough to support the function of radar.

RKB1102I is a kind of frequency modulation continuous wave radar. Frequency modulation means that the frequency of waves is a specific function versus time. Sine function and linear equation are common functions used to modulate frequency. In this paper, linear equation is used to modulate frequency and the frequency versus time of this radar is shown in Figure 2, where Transmitted signal is emitted signal and Received signal is reflected electronic waves captured by two channels.

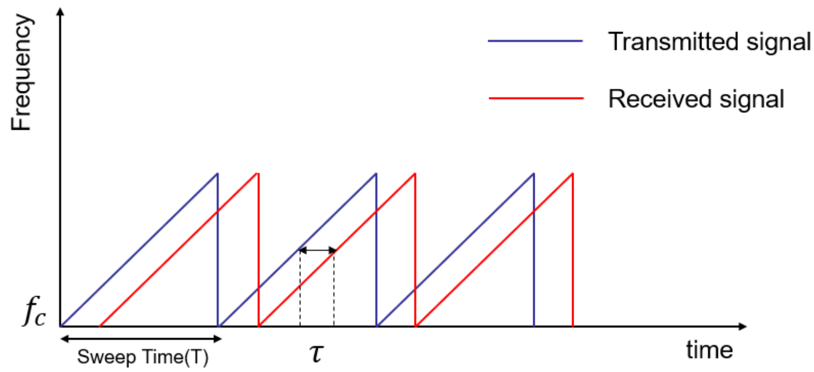

Figure 2. Frequency versus time of waves emitted

3 DESIGN AND IMPLEMENTATION

This section introduces the concrete implementation for respiratory signal breath detection. The detailed processing of radar signal into signals containing breath signal is in subsection 3.1. The subsection 3.2 specifically introduces EMD based respiratory signal detection principle.

3.1 Phase Modulation Principle

As discussed in Background, the frequency of transmitted signal increases linearly and can be expressed as $f(t) = f_c + \alpha t$, where f_c is initial frequency and α is the modulation slope.
To calculate the phase of the signal $\mu(t)$, transmitted frequency $f(t)$ is integrated over one sweep time.

$$\mu(t) = 2\pi \int_0^t f(t)dt = 2\pi\left(f_c t + \frac{\alpha t^2}{2}\right) + \varphi_0.$$

Since voltage-controlled oscillator outputs cosine signals, thus the transmitted signal $x_{tx}(t)$ is expressed as follows:

$$x_{tx}(t) = A\cos\big(\mu(t)\big) \ = A\cos(2\pi(f_c t + \frac{\alpha t^2}{2}) + \varphi_0)$$

where t is in the range of [0, T]. The signal is transmitted periodically. To extend the expression to any time, substitute t with $nT + t_s$. Then $x_{tx}(t)$ is expressed as follows:

$$x_{tx}(t) = A\cos(2\pi(f_c(nT + t_s) + \frac{\alpha t^2}{2}) + \varphi_0).$$

Assuming the physical object is located in the position at a distance R away from radar, the radial speed is v. Then delay $\tau = 2(R + v(nT + t\_s))/c$ .Hence the received signal $x_{rx}(t)$ is expressed as $x_{tx}(t-\tau) = B\cos\big(\mu(t-\tau)\big)$.
According to the structure of the radar, the received signal and transmitted signal are multiplied together by a multiplier before output. The multiplied signal $x_{mx}(t)$ is as follows:

$$x_{mx}(t) = x_{rx}(t) \cdot x_{tx}(t).$$

A low passing filters the signal and small frequency components are eliminated, thus $x_{mx}(t)$ is simplified into:

$$x_{mx}(t) = x_{mx}(t_{s,}n) = \frac{AB}{2}\cos(2\pi \cdot (\frac{2\alpha R}{c} + \frac{2f_c v}{c}) \cdot t_s + 2\pi \cdot \frac{2f_c v}{c} \cdot T \cdot n + \frac{4\pi f_c R}{c}).$$

Considering the respiratory detection problems, since the participant is static, the radial velocity is zero. Hence, the output signal is:

$$x_m(t_s) = \cos(2\pi f_b \cdot t_s + \frac{4\pi f_c R}{c})$$

where $x_m(t_s)$ takes t_s in the range of [0, T] and T is the period time (sweep time) of chirp signal, $2\pi f_b$ is the frequency of output signal and $f_b = 2\alpha R/c$ with R being the distance between the radar and the object, $2\alpha/c$ is a constant variable.

When the participant is in a fixed position in front of the radar with a distance of R, the frequency of each $x_m(t_s)$ is constant. Because range accuracy is $\frac{c}{2\alpha}$, according to parameters of radar, range accuracy is 15 centimeters. The amplitude of respiratory signal is much less than range accuracy thus the frequency of each chirp is constant. $4\pi f_c R/c$ is the initial phase of chirp signal and determined by R. Periodic changes of R affects initial phases of each $x_m(t_s)$. R is introduced into $x_m(t_s)$ by the delay time $\tau = 2(R + vt)/c$ and is initial distance between human chest and radar at the instance when a chirp begins. This means initial phase of each chirp is a sample of distance.

3.2 Principle of Empirical Mode Decomposition for Breath Detection

EMD Empirical Mode Decomposition is a kind adapting signal processing approach for non-stationary and non-linear signal. It is data-driven and un-supervised processing and decomposes original signal $y(t)$ into a series of zero-mean Intrinsic Mode Functions (IMF) and a residual, where each IMF component conforms to the following criterion:

a. The number of local maximum and local minimum differs at most by one.

b. Each IMF has zero mean value.

The original can be represented by IMF and residual as followings:

$$y(t) = \sum_{n=1}^{N} Y_n + R$$

, where Y_n is the order n-th IMF and R is the residual. Each Y_n is frequency modulated and represents a domain frequency component in original signal $y(t)$. The higher the n and the lower the frequency is. Hence, denoising can be implemented by direct thresholding on IMFs. If noise frequency is much higher than useful signal, by removing some low orders of IMF components can reconstruct the filtered signal. The reconstruction is as follows:

$$y'(t) = \sum_{n=L}^{N} Y_n + R$$

where $y'(t)$ is the filtered signal and L is the order that begins to contain useful information without noise.

It is noted that the actual implementation of EMD varies. The above criterion of IMF is too strict to follow in real world because not all signals have above proprieties. In this paper, the EMD is implemented by built-in function EMD in MATLAB. The algorithm of EMD function in MATLAB is shown in Figure 3. In the following algorithm, the soft stop sifting criterion added including SiftRelativeTolerance (Cauchy-type) are all set to be the default value. The Cauchy-type value is to control whether the above IMF criterion are strictly followed or not.

Algorithm 1: Empirical Mode Decomposition

Input: Initial signal $x(t)$, Current sift iteration number i, Current IMF number k
Output: A set of $IMF_k(t)$
$i = 0$;
$k = 0$;
$r_i(t) = x(t)$;
while *Energy Ratio of* $r_i(t)$ <= *MaxEnergyRatio and Total number of local extrema of* $r_i(t)$ >= *MaxNumExtrema and* k <= *MaxNumIMF* **do**
    $flag = 0$;
    $r_iPrev(t) = r_i(t)$;
    while $flag$ == *0* **do**
        Sift $r_iPrev(t)$ to obtain $r_iCur(t)$;
        if *Relative tolerance of* $r_iCur(t)$ < *SiftRelativeTolerance or* $i + 1$ > *SiftMaxIterations* **then**
            An IMF has been found: $IMF_k(t) = r_iCur(t)$;
            k++;
            $r_i + 1(t) = r_i(t)\ \ r_iCur(t)$;
            i++;
            $flag = 1$
        else
            $r_iPrev(t) = r_iCur(t)$

Figure 3. Decomposition Algorithm of EMD function

During I/Q modulation, the output signal of radar is as follows:

$$x_m(t_s) = (2\pi f_b \cdot t_s + \Phi) = cos(2\pi f_b \cdot t_s)cos(\Phi) - sin(2\pi f_b \cdot t_s)sin(\Phi).$$

The phase draws movement of human chest reflecting respiratory effort. Hence obtaining the phase information is required and this can be completed by simply dividing $I(t)$ by $Q(t)$. Assuming phase signal is represented as $y(t)$, $I(t) = sin(\Phi)$ and $Q(t) = cos(\Phi)$, so the phase signal is as follows:

$$y(t) = I(t) / Q(t).$$

But phase signal is sensitive and white noise plus pulse noise can hide the useful information, hear beating frequency is much higher than respiratory rate which acts as noise too. The following Figure 4 shows $y(t)$ signal with noise.

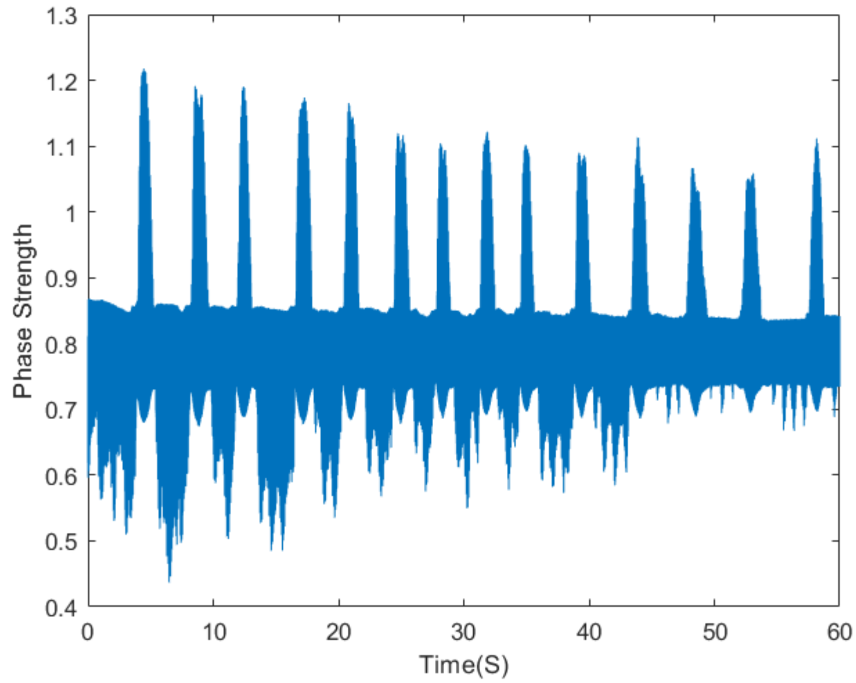

Figure 4. Phase Signal $y(t)$ from I/Q Demodulation

The noise source is multiple and complex which make the signal non-stationary. Internal electronic devices including voltage control oscillator is not stable and produce signals without linear frequency modulation. And as shown in Figure 1, the noise leakage can occur in the divider causing serious noise and out-of-phase. External environment also produces several kinds of noise including white gaussian noise. All these are added to the sensitive phase signals and hide useful information.

To analyze the frequency components, applying Short Time Frequency Transform to get the spectrogram of $y(t)$, the noise with strong power expands into all frequency bins thus EMD empirical mode decomposition is proposed to denoise $y(t)$ signal, since EMD separates $y(t)$ into different modules with different orders of frequencies. And as discussed in the above section, EMD derives IMF components with equal number of cross-zeros and peaks, and this property is just the characteristics of regular breath signal which oscillates around a mid-value.

With using the default stop criterion of MATLAB EMD function illustrated in Figure 3, and by setting the interpolation for constructing envelops as piecewise-cubic Hermite interpolating polynomials, the original signal $y(t)$ is decomposed as illustrated in Figure 5.

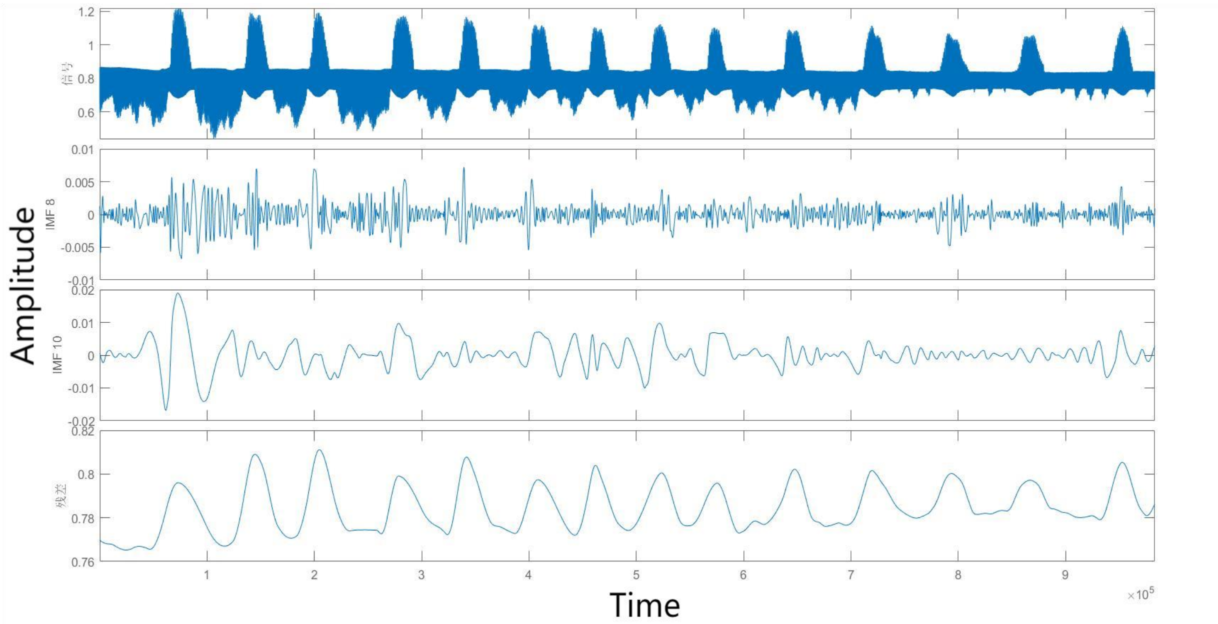

Figure 5. EMD Analysis of $y(t)$ from I/Q Demodulation

To decide on what IMFs are noise information components and to separate the useful phase IMFs to reconstruct the signal, the direct thresholding is adopted. To measure the power strength of each frequency component (IMF), this paper selects mean envelope energy as indicator.

$$Mean\ Envelope\ Energy = \sqrt[2]{(Uper\ Envelope\ Energy + Lower\ Envelope\ Energy)}$$

If the mean envelop energy is high, it means the corresponding IMF component is a domain component in the original signal. Since noise is much higher than phase information, the IMF components with strong mean envelope energy are discarded.

IMF number	Mean Envelope Energy ($\times 10^{-4}$)
IMF1	1.4
IMF2	8.7
IMF3	1.3
IMF4	2.8
IMF5	1.9
IMF6	7.4
IMF7	5.9
IMF8	3.4
IMF9	1.1
IMF10	3.2

Table 1. Mean Envelope Energy Distribution

As shown in the Table 1, the first five components are discarded because of the large energy and low order. The low order means these IMF components are modulated with much higher frequency which are noise signals. The next four orders are discarded by checking the waveform in the Figure 5 that these components are still noise information although their energy are still small. Hence, the reconstructed respiratory signal $y'(t)$ is as follows:

$$y'(t) = Y_{10} + R.$$

The reconstructed signal $y'(t)$ has strong DC components that impairs the filtering of $y'(t)$ to obtain smooth signal. The DC component doesn't affect respiratory signals at all because only the shape of waveform takes effect during the counting of respiratory rate. Thus, DC component of $y'(t)$ is removed. Assuming first value of $y'(t)$ is Q and $y''(t)$ is the signal whose DC component is removed, then it is expressed as follows:

$$y''(t) = y'(t) - Q.$$

The DC-removed signal $y''(t)$ is shown in the B of Figure 6. But there are still noise caused by heart beating which can cause fluctuations along the respiratory signals. By applying Butterworth filtering to $y''(t)$, the final clean respiratory signals are extracted in the C of Figure 6.

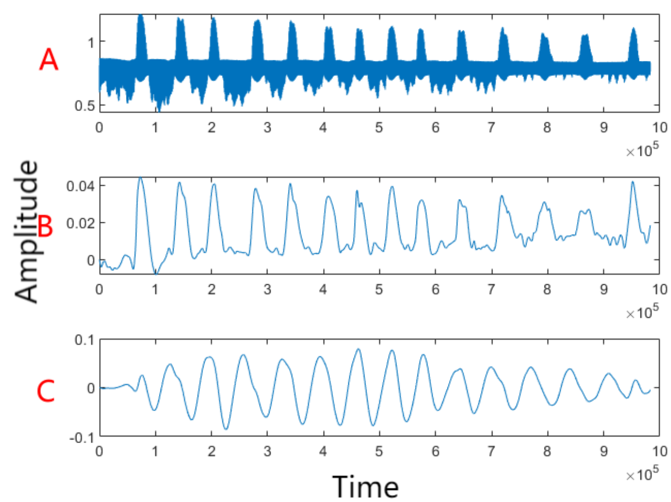

Figure 6. A: Original IQ Signa. B: DC-Removed Reconstructed Signal. C: Filtered DC-Removed Reconstructed Signal

4 EXPERIMENTS

This section introduces the experiments and results of the proposed method. The first subsection is about settings of experiment about environment and parameters. The second subsection is about the evaluation of EMD method.

4.1 Experiments Settings

The experiment setting is as follows: the participant is fixed into a static position in front of the radar with distance no more than 40 centimeters. The radar board is parallel to the human chest and placed towards abdomen-thorax, it is fixed onto the wall to have a stable position. One-minute-long radar signals are collected and transmitted simultaneously to the serial port of computer. The radar is connected to the computer next to the participant with USB cable, which provides power and acts as data transmission cable. Once the one-minute timer is off, the serial port no longer accepts signals and reserves the raw data for further processing.

The Figure 11 shows the experiment surroundings and data receiving windows.

Specifically, to avoid errors occurring at the instance when the radar is switched on, participant is asked to hold breath before experiment start and begin to breath until 2 seconds after radar is working. During last 2 seconds in one minute, the participants were asked not to breath either to avoid aliasing. During the experiment, the number of breaths is counted by the participant himself.

4.2 EMD Method Evaluation

To verify the results of EMD-based method, two indicators are needed. One is the error rate to verify whether the proposed method can detect the correct respiratory rate or not. The second indicator is to assess the waveform shape of respiratory signals generated by EMD method. The second indicator is required and meaningful because the waveform of signals from EMD method are often distorted in terms of amplitude. This is caused by two sources. One is from the mode mixing problem in decomposing the original signal, this can cause the amplitude of IMF components distorted thus affecting the final waveform shape of respiratory signal. The other source is the noise, noise is distributed in all frequencies as shown in the Figure 5 and cannot be eliminated in the low order IMF components, so the final filtered signals is still distorted. The mode mixing problem is much more serious because envelope construction method has strong effect. Error rate is as follows:

$$error\ rate = \frac{1}{N} \cdot \sum_{n=1}^{N} (|b_n - a_n|/a_n)$$

where a_n is the actual number of breath, and b_n is the detected number of breath.

And to assess the waveform shape is meaningful in medical field since this can reveal the function of lung muscle. The waveform shape indicator is the cross-correlation number between two respiratory signals generated by EMD and STFT method (as a reference). The reason why the respiratory signal from STFT method is selected as basis is because the phase from STFT method reveals chest movement, and the higher similarity means the more accuracy the shape from EMD is. Waveform from STFT method is right since the rightness emphasizes on the relative position between consecutive data points in the digital sequence. Although the absolute value of each data point in the sequence generated from STFT method is not right, the relative position is right because these points are calculated from the same frequency bin.

The waveform indicator R is as follows:

$$R = \left| \frac{\sum_{i=1}^{N}(x_i - \bar{x})\,(y_i - \bar{y})}{\sqrt[2]{\sum_{i=1}^{N}(x_i - \bar{x})(x_i - \bar{x})}\sqrt[2]{\sum_{i=1}^{N}(y_i - \bar{y})(y_i - \bar{y})}} \right|$$

where R is between [0,1], x_i is the series of respiratory signal from STFT method and y_i is the series of respiratory signal from EMD method. Higher R means greater resemblance and better performance.

The experiment has been conducted in various scenarios in terms of rate and distance. The predefined rate is 14, 16 and 18 bpm respectively. The detection distance ranges from 10 cm to 40 cm.

The overall accuracy is 94.87%. Selecting waveforms in STFT method as basis, the overall R is 0.4472.

The indicator R is just a numerical value which cannot illustrate whether the results are good or not. According to the used experience in applied statistics and definition of cross-correlation coefficient, correlation coefficients between 0.7 and 0.9 indicate variables which can be considered highly correlated. Correlation coefficients between 0.5 and 0.7 indicate variables which can be considered moderately correlated. Correlation coefficients between 0.0 and 0.5 indicate variables which can be considered weakly correlated. Thus, the following table is used to assess the performance more specifically.

R Value	Performance
[0, 0.5]	Bad
(0.5, 0.7]	Medium
(0.7, 1.0]	Good

Table 2. Relations between R and Performance

The indicator of EMD method which falls into 'Bad' category which means the waveform shape of respiratory signal from EMD method is distorted badly and need further improvements.

5 CONCLUSION

This paper proposes EMD Empirical Mode Decomposition to extract respiratory signals from Frequency Modulation Continuous Wave Radar. The performances in terms of accuracy is 94.87% which validates the feasibility of being applied into respiratory rate monitoring. But the EMD method cannot reveal the respiratory effort according to the human chest movement. This is the result of distorted amplitude of EMD method, originating from mode mixing problem. This is intrinsic problem in EMD and can be avoided by VMD Variational mode decomposition. And the extracted respiratory signal in time domain can be used for further medical detection such as central sleep apnea part detection.

Hence, in the future work includes the VMD (Variational Modal Decomposition) signal processing for better extraction of breath signal in terms of shape because VMD avoids component aliasing problems of EMD, and the application of time-domain respiratory signals into the central sleep apnea detection.

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