Principal Component Analysis for Heart Rate Measurement using UWB Radar

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Abstract

This paper proposes a signal processing approach based on principal component analysis (PCA) for monitoring heart rate using an ultra-wideband impulse (UWB) radar. Vital signals including respiration and heart rate is measured by a UWB radar, and then compressed and projected on the main principal component. This projection helps to significantly improve the signal-to-noise ratio in comparison to other conventional methods such as direct fast Fourier transform and complex signal decomposition. Thus, an accurate measurement of heart rate can be obtained. The proposed approach can help improve about 10 dB of heartbeat signal.

Keywords: UWB radar, Vital sign, Remote sensing, PCA

1. Introduction

Ultra-wideband impulse (UWB) radars have shown promising results for indoor applications such as target localization, human detection, fall detection, human gait analysis, and vital sign detection [1-6]. The main characteristics of UWB radars behind their interesting applications are: 1) a wide bandwidth (>500 MHz), which provides a high spatial resolution; 2) low power (e.g., -41.3 dBm/MHz for a bandwidth between 3.1–10.6 GHz by the FCC rule); and 3) the ability to penetrate objects (e.g., wall, wood, soil, and human body). The use of UWB radars for non-contact vital sign detection, including respiration and heart rate, has received significant attention [7–14]. UWB radars measure vital signs by measuring a small motion of the thorax, which is caused by breathing and heartbeats. However, the motion of the thorax caused by heartbeats is very small, in order of over the second harmonic frequency of respiration, and the signal can be easily perturbed by noise [10].

Various signal processing algorithms have been proposed to extract respiration and heartbeat signals from noisy signals. The singular value decomposition (SVD) method has been used to remove wall and other static object signals for enhancing the signal-to-noise ratio (SNR) [15,16]. Fast Fourier transform (FFT) is used to estimate respiration and heart rate, following which a higher-order cumulant (HOC) model is used to reduce the harmonic frequencies of respiration [17]. Wavelet transforms (WTs) are also used to extract the heartbeat signal from a signal mixed with respiration based on a prior knowledge of the range of heart rate [18]. Ensemble decomposition modes and their variations (EMDs) efficiently decompose a non-stationary signal into different frequency components, thus accurately obtaining a heartbeat signal [18]. HOC, WTs, and EMDs typically follow the vital signal decomposition step.
Complex signal decomposition (CSD) or arctangent decomposition (AD) are commonly used for direct sampling for vital signal decomposition, and are used to construct vital signals from a raw signal with less errors. AD extracts the phase signal from an I/Q signal, which is related to the thorax displacement. However, a hardware calibration process needs to be applied for an accurate phase extraction. CSD combines two I/Q channel signals into a single complex signal, which is proven to reduce hardware error, such as jitter in the FPGA clock, thus enhancing the SNR [19]. Therefore, CSD can also be applied for directly sampling radio frequency (RF) signals (direct RF) with sampling frequencies higher than the impulse signal’s Nyquist frequency. In CSD, electromagnetic wave propagation is compressed by transferring the signal in a time domain to a frequency domain.

The signal processing algorithm proposed in this paper uses PCA to enhance SNR. PCA is used to compress the pulse signal at a person’s location, thus improving the vital signal’s SNR. In PCA, the vital signal is projected onto its first PC, which contains the most vital information with minimum noise. Heart rate is then accurately calculated by a chirp z-transform (CZT), which provides a higher frequency resolution than the conventional FFT method. The performance of the proposed method is compared with that of the direct FFT sampling method and direct RF method.

2. Principle of UWB Radar for Vital Sign Measurement

2.1 UWB Radar Signal Model

The RF signal is directly sampled with a sampling frequency higher than the Nyquist frequency criterion. We denote $\tau$ as the fast sampling time (fast time) and $t$ as the slow sampling time (slow time). Usually, $\tau$ is in the order of nanoseconds and $t$ is in the order of milliseconds. In addition, $\nu$ and $f$ denote the FFT component in fast and slow time, respectively. The distance between the person at a nominal distance $d_0$ (with respect to $\tau_0$) and the radar receiver is the sum of respiratory and cardiac activities, $d(t)$, and is expressed in Eq. (1).

$$d(t) = d_0 + d_r \sin(2\pi f_r t) + d_h \sin(2\pi f_h t),$$

where $d_r/f_r$ and $d_h/f_h$ are the amplitude and frequency of respiratory activity and cardiac activity, respectively. The signal received at the radar receiver can be modeled as Eq. (2) [19]:

$$v(t, \tau) = \sum_i A_i(p(\tau - \tau_i) + A_d(p(\tau - \tau_d(t))), \quad (2)$$

where $p(t)$ is the collected pulse with a carrier of frequency $\nu_c$; $A_i$ and $\tau_i$ denote the strength and delay time of multipath components; and $A_d$ and $\tau_d$ denote the amplitude of the collected pulse and time-of-arrival from the person, respectively [12,19]. $\tau_d$ is the time of the two-way fly, which can be calculated using the relationship between distance $d(t)$ and speed of light $c$, as shown in Eq. (3).

$$\tau_d(t) = 2d(t)/c = \tau_0 + \tau_r \sin(2\pi f_r t) + \tau_h \sin(2\pi f_h t), \quad (3)$$

where $\tau_r$ and $\tau_h$ are the time delay amplitudes of respiratory and cardiac activities, respectively, and $\tau_0$ is the nominal time delay at the person’s location. Static objects, transmitter and receiver antenna interference, and stationary parts of the person’s body can produce multipath components, which are the DC component in the signal $x_d(t, \tau)$. This DC signal can be simply removed by removing the background using a mean subtraction, or by running an average filter or an SVD filter [15, 16]. Finally, the signal of respiratory and cardiac activities at the receiver can be expressed by Eq. (4).

$$x_d(t, \tau) = A_d(p(\tau - \tau_d(t))), \quad (4)$$

2.2 Direct FFT Method

The respiration and heart rate can be obtained by directly applying FFT in the slow-time direction. The FFT in fast time $\tau$ can be expressed in Eqs. (5) and (6) [12, 19], where $P(\nu)$ is the FFT of pulse $p(t, \tau)$ in the fast-time direction $\tau$; $J_k(\beta_r\nu)$ and $J_l(\beta_h\nu)$ are Bessel functions with $\beta_r = 2\pi f_r$, and $\beta_h = 2\pi f_h$. $C_{kl}$ is a constant value. It is proven that the maximum of $X(f, \tau)$ is at $\tau = \tau_0$ [12]. The discrete frequency resolution of the FFT is $fs/N$, where $N$ is the number of signal samples. For a rapid measurement of vital signals, $N$ should be small (e.g., 512 samples); therefore, the frequency resolution is low. Thus, we use CZT instead of FFT, which zooms in on an interesting bandwidth of the vital signal. The frequency resolution is then $(f_{max} - f_{min})/N$, where $f_{min}$ and $f_{max}$ are the limited frequency bandwidths of the respiration signal (e.g., 0.1-3.0 Hz).

$$X(f, \tau) = A_d \sum_{k=-\infty}^{k=+\infty} \sum_{l=-\infty}^{l=+\infty} C_{kl}\delta(f - kf_r - lf_h), \quad (5)$$
\[ C_{kl} = \int_{-\infty}^{+\infty} P(v) J_k(\beta_r v) J_k(\beta_h v) dv. \] (6)

### 2.3 Complex Signal Demodulation

In the CSD method, the signal \( v_d(t, \tau) \) is first transferred to the frequency domain by FFT in the fast-time direction for the extraction of phase variation, and then another FFT in the slow-time direction is applied to extract respiration and heart rate. The FFT of \( v_d(t, \tau) \) in the fast-time direction can be expressed by Eq. (7). At \( \nu = 0 \), Eq. (7) becomes Eq. (8), which is then an FFT in the slow-time direction for finding the respiration and heart rate, as expressed before. The CSD method can help reduce the intermodulation of respiration and heart rates, and a jitter signal can be generated in hardware [19].

\[
X(t, \nu) = A_d P(\nu + \nu_c) e^{\nu_c} \exp[\nu_c \nu_c c / \nu_c \sin(\nu_c t)]
+ 4 \pi d_h c / \nu_c \sin(\nu_c t) + 2 d_0 c / \nu_c.
\] (7)

\[
X(t, 0) = A_d P(\nu_c) \cdot \exp[4 \pi d_h c / \nu_c \sin(\nu_c t)]
\] (8)

### 3. PCA based Method

PCA is used in several applications for noise reduction, data compression, and pattern recognition [22]. PCA derives the input data variables into a small number of decorrelated linear combinations while retaining as much information as possible from the original variables. The basic idea of PCA is to find PCs of the data variables that are orthogonal to each other. The received signal of the UWB radar is formed in the 2D matrix, \( X_{i,j} \), whose dimension is \( N \times M \). Here, \( i = 1, 2, \ldots, N \) and \( j = 1, 2, \ldots, M \) denotes the fast and slow time indices, respectively. It is assumed that \( i \) is the index of the variables, \( j \) is the index of observations in the PCA analysis. A simple coherent signal process, that is, a moving average for improving signal quality, is performed before applying PCA, as expressed in Eq. (9). Here, \( 2R + 1 \) is the size of the sliding window in the slow-time direction.

\[
X(i, j) = \frac{1}{2R + 1} \sum_{i=2j-R}^{i+R} X(i, j).
\] (9)

In PCA, matrix \( X \) is first mean-centered by subtracting it from its mean, as expressed in Eq. (10). Then, the covariance matrix \( C \) of \( X \) is computed in Eq. (11), and its eigenvalues \( \lambda \) and eigenvectors \( \Lambda \) are computed using Eq. (12). The eigenvalues can be calculated by the SVD of the covariance matrix \( C \), as expressed in Eq. (13), where \( U \) contains eigenvectors in its column \( (\Lambda_i = U(:, i)) \) and \( S \) contains eigenvalues in its diagonal, \( \lambda = \text{diag}(S) \). Eigenvalues \( \lambda \) is arranged in a descending order, that is, \( \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_N \), and a higher value represents more information from the matrix signal \( X \) [20]. Finally, the two-dimensional vital signal \( X \) is compressed to a one-dimensional vital signal \( y_k \). A frequency transform based on CZT is then performed on \( y_k \) to obtain the respiration and heart rate.

\[
X = X - \frac{1}{M} \sum_{j=1}^{M} X(i, j),
\] (10)

\[
C = \frac{1}{M} XX^T,
\] (11)

\[
C = \Lambda \Lambda^T,
\] (12)

\[
y_k = U_i^T X.
\] (13)

### 3.1 Experimental Setup & Results of Conventional Methods

To demonstrate the effectiveness of the proposed method, a UWB radar with a center frequency of 4.3 GHz, a bandwidth of 550 MHz, and a sampling rate of 10 GHz was used. A healthy person sitting comfortably and breathing normally at 0.9 m was measured by the UWB radar. A photoplethysmography (PPG) sensor was attached to a finger during the experiment to measure heart rate as a reference. The UWB radar signal was recorded and processed in a block of 1024 samples in slow time, with respect to 22.8 s. The experimental setup is shown in Figure 1.

![Figure 1. Experimental setup.](image)
The raw signal $X$ was stacked in 2D with a size of $100 \times 1024$ samples, as shown in Figure 2(a). We observe the vital signal to exist within 0.2 m of the person’s location because of the thickness of the person’s body. Although the noise is significant, the respiration signal can still be clearly observed. The presence and location of the person can be estimated by using the standard deviation (std) of the signal in slow time, as shown in Figure 2(c). A maximum std represents the maximum quality of vital signal, as shown in Figure 2(b), which is then transformed into the frequency domain by CZT in Figure 2(d).

The CZT is zoomed in a range of 0-3.0 Hz, with respect to 0.0029 Hz (0.18 BPM), which is the normal frequency range of respiration rate (0.1-0.7 Hz) and heart rate (0.75-3.0 Hz). The maximum peak indicates the respiration rate (0.1787 Hz), the second maximum peak is a non-stationary signal, such as a slight movement of the person’s body or organs, the third maximum peak is the 2nd harmonic of the respiration signal, and the peak near 1 Hz is the heart rate (1.1777 Hz); however, it is not clear because of the high background noise. The reference PPG shows a heart rate of 1.1658 Hz.

Similarly, Figure 3 shows the signal of the CSD method. The quality of the vital signal was improved when compared to the direct FFT method because the FFT accumulates vital signals in the fast time by transforming it in the frequency domain. However, the heart rate signal (Figure 2(d)) is still difficult to detect because of the high background noise. It is noteworthy that the non-stationary signal is significantly reduced in the CSD method, which helps in the easier detection of respiration signals.

### 3.2 PCA Results

It is important to note that the vital signal has different phases at different distances (fast-time index), as shown in Figure 4(a). Thus, simply summarizing the entire signal in fast time is not suitable. Thus, an accumulation approach that uses PCA to project the signal onto eigenvectors that retain rich information of the original signal is recommended. As a distribution of 19 eigenvalues in Figure 4(b), the vital signal is represented mostly in the first eigenvalue (84.87%), followed by 7.36% in the second eigenvalue, and 4.38% in the third eigenvalue. Consequently, the projected signal (1D) of the vital signal (2D) on the first eigenvectors has the best quality, as shown in Figure 4(c).

The advantage of the PCA method over direct FFT and CSD methods is shown in Figure 5. All signals in the graphs in
Figure 4. The signals in PCA: a) input 2D vital signal, b) eigen-value distribution, and c) vital signal projected on the three principal components.

Figure 5. Comparison of PCA method with two conventional methods in the analysis of respiration and heart rate: a) vital signal extracted by the three methods, b) CZT of the vital signal, and c) CZT in heart rate range.

Figure 5 are normalized for easy comparison. The vital signal in Figure 5(a) shows a better contrast with the CSD method than with the direct FFT method. However, in both methods, the high-frequency noise signal had a higher influence on the vital signal; thus, a heartbeat signal could not be observed. The vital signal extracted by PCA, which is the projection on the first PC, was significantly improved than the other two methods. A heartbeat signal can be observed in the waveform signal. The signals in the frequency domain by CZT are shown in Figure 5(b) and magnified for heart rate in Figure 5(c). They show that the heart rate can be detected as a maximum peak in the PCA method but cannot be accurately detected in the direct FFT and CSD methods. The heart rate was measured by the reference PPG sensor at 1.1658 Hz (70 BPM), at 1.1816 Hz (1.36% errors) with the PCA method, at 1.5676 Hz (34.47%) with the CSD method, and at 3.2817 Hz (181.5%) with the direct FFT method.

The signal-to-noise (SNR) can be calculated using Eq. (15) [21], where $CZT_{hr}$ is the amplitude of the CZT transform of the fundamental respiration/heart rate. $CZT_{noise}$ is the amplitude of the CZT transform of the noise signal, which is in the frequency range of respiration/heart rate (0.10.75 Hz/0.75∼3.0 Hz), excluding the fundamental and harmonics of respiration/heart rate. The SNR of the heart rate was also improved by approximately 10 dB using the PCA method (17.27 dB) when compared to the direct FFT method (7.01 dB) and CSD method (6.45 dB). The SNR of respiration was improved by over 8 dB using the PCA method when compared to the other two methods. Table 1 summarizes the measurement results.

$$ SNR = 20 \times \log \left( \frac{CZT_{hr}}{1/N \sqrt{\sum CZT_{noise}^2}} \right). \quad (15) $$

### 3.3 Measurement Robustness

To verify the effectiveness and robustness of the proposed PCA method, a long measurement was performed. A window of 1024 slow-time samples of 22.8 s was slid over the measured data to extract heart rate using the PCA method and the other two conventional methods: direct FFT and CSD methods. A comparison of the calculated heart rates of the three methods along with the results of the reference PPG is shown in Figure 6. The PCA method shows a stable and accurate result when compared to the two conventional methods. The root-mean-square errors of the direct FFT, CSD, and PCA methods were

| Parameter          | Direct FFT | CSD  | PCA  | Ref. PPG |
|--------------------|------------|------|------|----------|
| SNR of respiration | 24.65 dB   | 28.7 dB | **36.30 dB** | -        |
| SNR of heart rate  | 7.01 dB    | 6.45 dB | **17.27 dB** | -        |
| Heart rate (Hz)    | 3.2817 Hz  | 1.5676 Hz | **1.181 Hz** | 1.1658 Hz |
| Error %            | 181.5%     | 34.47% | **1.36%**   |          |

Table 1. Measurement results of vital signal
53.07%, 36.36%, and 3.28%, respectively. The PCA method shows the most accurate and stable result among the three methods. However, this approach is still limited when a person is moving, as in the 0-16 s period.

A summary block diagram of the algorithm is shown in Figure 7. The raw UWB radar signal was stacked in the slow-time direction to build 2D matrix data. The person’s range could be detected by the standard variation values, as shown in Figs. 2 and 3. The vital range was selected at the person’s position, which is a 2D matrix data as the input of the PCA algorithm. Then, the principal component (first component) is extracted and selected from the PCA. The principal component will be transformed in a frequency domain using CZT, and the heartbeat frequency will be determined.

### 4. Conclusion

This paper proposes an accurate and stable measurement of heart rate using a UWB radar based on PCA. The PCA helps compress the UWB pulse signal, thus improving the SNR. The vital signal is transformed and analyzed in the principal component space. A projection on the first PC provides the best vital signal quality, containing the most information on vital signals (84.47%). Both the respiration signal and heart rate signal are improved to 8 dB-10 dB SNR using the PCA approach, when compared to the two conventional approaches: direct FFT and CSD. Thus, the measurement of heart rate is more accurate and stable, and is obtained with a root-mean-square error of 3.28% using the PCA, when compared to 36.36% and 53.07% for direct FFT and CSD methods, respectively. With these results, future studies can investigate the accuracy and robustness of the proposed method for different experimental conditions such as increased distances, through-wall measurement, and movement of the person.

### Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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