Applications of TVF-EMD in Vital Signal Detection for UWB Radar

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When using pulsed ultra-wideband radar (UWB) noncontact detection technology to detect vital signs, weak vital signs echo signals are often covered by various noises, making human targets unable to identify and locate. To solve this problem, a new method for vital sign detection is proposed which is based on impulse ultra-wideband (UWB) radar. The range is determined based on the continuous wavelet transform (CWT) of the variance of the received signals. In addition, the TVF-EMD method is used to obtain the information of respiration and heartbeat frequency. Fifteen sets of experiments were carried out, and the echo radar signals of 5 volunteers at 3 different distances were collected. The analysis results of the measured data showed that the proposed algorithm can accurately and effectively extract the distance to the target human and its vital signs information, which shows vast prospects in research and application.

1. Introduction

In recent years, the use of pulsed ultra-wideband radar for human noncontact vital sign measurement has become a research hotspot [1–5] and its related research results are widely used in those fields: vital sign signal detection [6, 7], medical treatment [8, 9], public safety [10–12], through-wall imaging [13, 14], indoor positioning [15], and moving target detection [16, 17]. The weak vital signal generated by the target’s micromovement is submerged in strong noise. Therefore, it is particularly important to select a suitable and appropriate signal processing algorithm for the extraction of breathing and heartbeat signals [18–20].

Many vital sign detection techniques have been adopted in the literature [21–30]. In [21, 22], a combination of fast Fourier transform (FFT) and Hilbert transform (HHT) is used to analyze the time-frequency characteristics of respiratory signals. In [23], the researcher studied a new type of dual-frequency pulsed ultra-wideband radar with low center frequency, and an adaptive clutter elimination method to eliminate respiratory clutter is proposed. Tracking methods are used to extract vital sign signals, but it is not suitable for long-distance and low SNR environments [24]. In [25], the morphological filtering method is used to analyze the time-domain signal of UWB radar to extract the human heart rate. In [26], human breathing motion detection based on Short-Time Fourier Transform (STFT) and Singular Value Decomposition (SVD) is studied for three different media. The nonstationary and nonlinear signals caused by the micromotion of the human target are separated by SVD to improve the detection performance of the ultra-wideband radar under the condition of a low signal-to-noise ratio [27]. In [28], empirical mode decomposition (EMD) is used to adaptively decompose radar echo signals into Intrinsic Mode Function (IMF). By analyzing the energy spectrum characteristics of each IMF, respiratory and heartbeat signals are reconstructed in the time domain. Based on the ideas in [28], ensemble empirical mode decomposition (EEMD) is used to improve the modal mixing problem in EMD [29]. However, the introduction of white noise in the decomposition process may cause a change in amplitude and cause reconstruction errors, and the decomposed IMF component has modal aliasing in the low-frequency band. At the same time, the Higher Order Cumulant (HOC) of
the reconstructed signal is calculated and the Fast Fourier Transform (FFT) is carried out on the Cumulant, which has higher SNR and frequency estimation accuracy than the direct FFT. In [30], Variational Mode Decomposition (VMD) is used to suppress mode mixing, but the decomposition level needs to be determined according to the number of targets in the detection scene.

In the algorithm proposed above, the respiratory frequency and the heartbeat frequency are obtained by Fourier spectrum analysis of a single frame signal. However, when the sampling frequency is fixed, the longer the time series, the better the frequency spectrum. Thus, long-term objective data is required, but the efficiency of the radar is reduced. In addition, among all the methods that improved EMD, such as EEMD and Complete Ensemble Empirical Mode Decomposition of Adaptive Noise (CEEMDAN), and that are derived from it to reduce noise by dividing high and low-frequency components, most of them only perform noise reduction processing on the high-frequency components in the components and ignore a small amount of noise in the low-frequency components. However, the direct use of such for reconstruction will seriously affect the frequency estimation accuracy, and it is difficult to obtain a satisfactory decomposition effect.

Aiming at the above-mentioned shortcomings, a new method is proposed to accurately estimate the frequency of respiration and heartbeat and the human target range. This method estimates the distance between the human target and the radar by the range-frequency matrix which is obtained by continuous wavelet transform of variance of slow time direction data of radar echo matrix. Selecting and recombing these signals on adjacent distance gates based on the largest signal amplitude in the range-frequency matrix of the variance, more vital sign information can be obtained than a single frame signal, and the observation time can be reduced. The TVF-EMD algorithm is used to adaptively decompose the combined radar echo signal into IMFs. According to the energy percentage of each IMF in the breathing and heartbeat frequency bands, the respiratory and heartbeat signals are reconstructed and FFT is performed on them to obtain the frequency of respiratory and heartbeat. The measured data processing results show that the proposed algorithm overcomes the modal mixing problem and can accurately and effectively extract the distance and vital signs information of human targets.

For the convenience of research, the human body’s micromovement can be approximated as several groups of simple harmonic motions, and the instantaneous distance from the antenna to the surface of the human thoracic cavity can be expressed as [31, 32]

\[
d(t) = d_0 + c(t) = d_0 + A_r \sin(2\pi f_r t) + A_h \sin(2\pi f_h t + \Delta) + \text{res}(t),
\]

where \(A_r\) is the micromovement amplitude of human respiration, \(f_r\) is the frettng frequency of human respiration, \(A_h\) is the micromovement amplitude of human heartbeat, \(f_h\) is the frettng frequency of human heartbeat, \(\Delta\) is the phase difference between the start point of the heartbeat and the start point of the respiration, and \(\text{res}(t)\) is the distance change caused by other human body’s micromovement except respiration and heartbeat.

Assuming that other objects around the antenna and the human body are stationary except the human body, the impulse response of the radar channel can be expressed as

\[
h(t, \tau) = a_r \delta(t - \tau_{r}(t)) + \sum_s a_s \delta(t - \tau_{s}(t)),
\]

where \(\tau\) is the fast time of signal transmission, which can be used to characterize distance information, \(t\) is the slow time of signal acquisition, \(\sum_s a_s \delta(t - \tau_{s}(t))\) corresponds to the surrounding stationary objects, and \(a_r \delta(t - \tau_{r}(t))\) corresponds to the human body’s micromovement. \(\tau_{r}(t)\) can be expressed as

\[
\tau_{r}(t) = \frac{2d(t)}{v} = \tau_0 + \tau_r \sin(2\pi f_r t) + \tau_h \sin(2\pi f_h t + \Delta) + \tau_{\text{res}}(t),
\]

where \(v\) is the propagation velocity of electromagnetic waves. By the above formula, \(\tau_0 = d_0/v, \tau_r = A_r/v, \tau_h = A_h/v, \tau_{\text{res}}\) is the change of time delay caused by the micromovements of the human body except for the respiration and heartbeat. Consider the case of only one living body. For impulse UWB radar, assuming the transmitted signal \(s(\tau)\), the received signal can be expressed as

\[
R(\tau, t) = s(\tau) \times h(t, \tau) = a_r s(\tau - \tau_{r}(t)) + \sum_s a_s s(\tau - \tau_{s}(t)) + \sum_s a_s s(\tau - \tau_{s}(t)).
\]

The discrete matrix \(R(m, n)\) is the MxN-order echo matrix carrying the human target information, and the signal acquisition slow time \(t\) is discrete, with \(t = nT_r, (n = 1, 2, \cdots, N),\) and \(T_r\) is the pulse repetition time. Similarly, the signal transmission fast time \(\tau\) is discrete, with \(\tau = m\delta_T, (m = 1, 2, \cdots, M),\) and \(\delta_T\) is the fast time sampling interval.

\[
R(m, n) = a_r s(m\delta_T - \tau_{r}(nT_r)) + \sum_s a_s s(m\delta_T - \tau_{s}(t)).
\]
Assuming that the transmitted signal pulse width is $T_w$, in order to avoid frequency aliasing and distance ambiguity, the pulse repetition time $T_s$ must meet the Nyquist sampling rate to ensure that all target echoes within a pulse period fall in the receiving window:

$$2T_s f_0 \leq 1, \quad T_w + \max \{r_v(t)\} - \min \{r_v(t)\} < T_s.$$  \hfill (6)

$R(m, n)$ is the radar echo matrix that carries the vital information of the human target, which not only contains the human respiratory and heartbeat signals but also contains a lot of clutter and noise. The mathematical modeling process of vital sign signals is illustrated in the schematic diagram shown in Figure 2. The dotted line in Figure 2 is the location scope of the human target.

### 2.1. Vital Sign Signal Detection Algorithm

In this section, the algorithm is proposed to obtain vital information by the radar echo matrix. Each implementation of this algorithm is shown in Figure 3. It contains of three parts: signal preprocessing, range detection and echo selection, and vital sign signal extraction.

### 2.2. Signal Preprocessing

In the radar echo matrix, due to the direct coupling of the radar antenna and the reflection and scattering of the radar wave by the ruins, there is usually a strong background clutter, which usually exhibits low frequency or DC components, and a linear and gradual trend.

#### 2.2.1. Range Profile Subtraction

The simplest and most direct way to remove background clutter from the radar echo matrix is to subtract each radar echo signal from the previous radar echo signal. In this process, the components that remain constant during the scanning process will be eliminated.

For the radar echo matrix $R(m, n)$, assuming that $Y_j$ is the fast time series, $j = 1, 2, 3, \cdots, N$, $N$ is the number of sampling points in the scanning time, and the result of the range profile subtraction method is as follows:

$$Y'_j = Y_{j+1} - Y_j.$$  \hfill (7)

#### 2.2.2. Time Mean Subtraction

The background clutter caused by stationary objects in the detection scene can be approximated by the DC component, and time mean subtraction (TMS) is used to estimate this component [33]:

$$\bar{S} = \frac{1}{M \times N} \sum_{m=1}^{M} \sum_{n=1}^{N} R[m, n].$$  \hfill (8)

The result of eliminating static clutter is as follows:

$$\Omega_{M \times N} = R_{M \times N} - \bar{S}.$$  \hfill (9)

#### 2.2.3. Linear Trend Suppression

In the real detection environment, in the process of data acquisition, the radar echo data is affected by the time jitter and drift of the trigger unit in the radar system and shows a linear trend with slow time changes. To eliminate the linear trend, the linear trend suppression (LTS) method is adopted:

$$W = \Omega^T - X (X^TX)^{-1}X^T \Omega^T,$$  \hfill (10)

where $X = [x_1, x_2]$, where $x_1 = [1, 2, \cdots, N]^T$ and $x_2 = [1, 1, \cdots, 1]^T$.

#### 2.2.4. Automatic Gain Control

The amplitude of the radar echo signal caused by the micromovement of the human target is mainly related to the lateral distance of the human thoracic cavity and the relative distance between the human target and the radar. The multipath effect in the actual detection environment will also interfere with the target echo. Therefore, automatic gain control (AGC) is used to enhance the weak vital sign signals in the slow time direction, thereby further improving the signal-to-noise ratio.
and the corresponding gain coefficient is calculated according to the energy in the selected time window $2\lambda + 1$, where $\lambda$ depends on the length of the window, so as to realize the adaptive control [34]. Take the $n_1$th frame echo signal $r(\tau, n_1)$ as an example:

$$g_{\text{mask}}(\tau, t) = \frac{2\lambda + 1}{\sqrt{\sum_{k=\lambda}^{\lambda+\lambda} r(\tau_k, t)^2}},$$

where $g_{\text{mask}}(\tau, t)$ represents the gain coefficient and $r_E(\tau, t)$ is the signal after AGC processing.

2.3. Range Detection and Echo Selection. UWB life detection can usually be divided into two ranges: a range with human targets and a range without human targets, so the main purpose of this section is to find the range that contains the most obvious human vital sign signals. In the radar echo matrix, the background clutter does not change with time, and the only thing that changes is the human body’s
micromovement if there is person in the detection environment, which means there is only one data related to human body’s micromovement that fluctuates. To determine the distance range that contains the most obvious vital sign signals in the radar echo matrix $W$, it is necessary to analyze the statistical characteristics of the slow-time direction data (for example, kurtosis [30], standard deviation [35], and variance [26]). Time domain signals can be divided into dimensionless eigenvalues and dimensionless eigenvalues according to whether they are dimensionless. Dimensional characteristic values include maximum value, minimum value, peak-to-peak value, mean value, variance, mean square value, and root mean square value. In this paper, we determine the human target location by analyzing standard deviation, variance, and peak-to-peak value of the slow-time direction data.

For fast time series $n$, the SD is given by

$$SD[n] = \sqrt{\frac{\sum_{m=1}^{M} (W[m, n] - \mu[m, n])^2}{M - 1}}.$$  \hspace{1cm} (12)

Also, the variance can be calculated:

$$V[n] = \frac{\sum_{m=1}^{M} (W[m, n] - \mu[m, n])^2}{M - 1}.$$  \hspace{1cm} (13)

The peak-to-peak value can be calculated:

$$PK[n] = \max |W[m, n]| - \min |W[m, n]|.$$  \hspace{1cm} (14)
where \( m = 1, 2, \cdots, M \) and \( \mu \) is the mean value used to describe the stable component (DC component) of the signal.

A volunteer is used as the test object, and the results of calculating the standard deviation, variance, and peak-to-peak value of the data at 1 m from the antenna are shown in Figure 4. From Figure 4, we can see that the standard deviation, variance, and peak-to-peak value results in the human target range are larger than those in the nonhuman target range, which provides a data basis for human target positioning.

To obtain accurate position information of human target, continuous wavelet transform was performed on the calculated standard deviation, variance, and peak-to-peak values to obtain the range- (fast time) frequency

\[
P_{p0} - 0.5 \times P_{th0} \quad P_{p0} \quad P_{p0} + 0.5 \times P_{th0}
\]

where \( P_{p0} \) is the human target position.

Figure 6: The schematic diagram of this part of the algorithm.

Figure 7: UWB radar system.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>-10 dB lower limit cut-off frequency</td>
<td>0.45Ghz</td>
</tr>
<tr>
<td>-10 dB upper limit cut-off frequency</td>
<td>3.55Ghz</td>
</tr>
<tr>
<td>Output power</td>
<td>-14 dBm</td>
</tr>
<tr>
<td>Fast time domain sampling frequency</td>
<td>39GHz</td>
</tr>
<tr>
<td>Slow time domain sampling frequency</td>
<td>152.6 Hz</td>
</tr>
<tr>
<td>Fast time domain sampling length</td>
<td>512</td>
</tr>
<tr>
<td>Radar transmitted waveform</td>
<td>First order Gaussian pulse waveform</td>
</tr>
<tr>
<td>Pulse repetition frequency</td>
<td>48 MHz</td>
</tr>
<tr>
<td>Equivalent distance resolution</td>
<td>4 mm</td>
</tr>
<tr>
<td>Vivaldi antenna gain</td>
<td>6dBi</td>
</tr>
</tbody>
</table>
characteristics. For the fast index \( n \), continuous wavelet transform of the variance \( V[n] \) is defined as follows:

\[
W_{V[n]}(a,b;\psi) = \int_{-\infty}^{\infty} V[n](\tau)\psi_{a,b}(\tau)d\tau, \quad a > 0. \tag{15}
\]

Function \( \psi_{a,b}(t) \) is generated by the basic wavelet function \( \psi(t) \) through translation and expansion:

\[
\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), \quad a, b \in R, \tag{16}
\]

where \( a \) is the scale parameter; also known as the scale factor (stretching factor); \( b \) is the positioning parameter, also known as the time translation factor; and \( 1/\sqrt{a} \) is the normalization constant, which is used to ensure the conservation of energy during the transformation process.

The wavelet coefficient \( W_{V[n]}(a,b;\psi) \) obtained by the wavelet transform is used to obtain the instantaneous frequency \( \omega_{V[n]}(a,b) \):

\[
\omega_{V[n]}(a,b) = -\frac{i}{2\pi} \frac{\delta W_{V[n]}(a,b;\psi)}{\delta b}. \tag{17}
\]

After formula (17) is calculated, the range- (fast time) scale plane \( (b,a) \) can be converted to the range- (fast time) frequency plane \( (b,\omega_{V[n]}(a,b)) \).

Similarly, the range- (fast time) frequency characteristics of standard deviation and peak-to-peak value can also be obtained. The corresponding CWT results of the standard deviation, variance, and peak-to-peak value with a human target at 1 m from the antenna are shown in Figure 5. As is shown in Figure 5, for the obtained fast time-frequency matrix, the range axis corresponds to the fast time, compared to the standard deviation and peak-to-peak value; the position of the human target is more obvious in the range-frequency matrix of the variance. So, we choose to determine the range with human targets based on the range-frequency matrix of the variance. The position of the human target \( P_{pos} \) can be determined by finding the point with the largest signal amplitude; then, get the range information of the human target:

\[
\text{Range} = \frac{v \times P_{pos} \times \delta T}{2}. \tag{18}
\]

In traditional methods, the extraction of vital sign signals is often obtained by decomposing and reconstructing a single frame signal in the slow time direction. When the sampling frequency is fixed, the longer the signal acquisition time is, the richer the vital sign information contained in the signal, and the better the result of spectrum analysis, so a lot of time will be wasted, which greatly reduces the efficiency of the radar. The human vital sign signals are distributed on adjacent distance gates. The following are the reasons: (1) radar emission has a certain trajectory; (2) the lateral distance of the human thoracic cavity is close to 30-40 cm, so there may be multiple radar scattering points in the thoracic cavity at the same time; (3) the human target
has swung slightly [36]. Selecting and recombining these signals on adjacent distance gates based on the point with the largest signal amplitude in the range-frequency matrix of the variance, more vital sign information can be obtained than a single frame signal, and the observation time can be reduced.

Suppose $D_{tho}$ is the lateral distance of the human thoracic cavity; then, according to the sampling interval $\delta_T$ in the fast time direction, the number of points occupied by the human thoracic cavity distance in the received pulse can be calculated:

$$P_{tho} = \frac{2D_{tho}}{v\delta_T},$$

where $v = 3 \times 10^8$ m/s. Use $\psi$ to denote the vital sign signal matrix, which can be expressed as

$$\psi = W \left[ \left( \frac{P_{pos} - P_{tho}}{2} \right) : \left( \frac{P_{pos} + P_{tho}}{2} \right) \right],$$

$$0 \leq P_{pos}, P_{tho} \leq M, n = 1, 2, \ldots, N.$$  

The vital sign signal vector $\zeta(t)$ is obtained by arranging the echo signals of the adjacent distance gates at the position $P_{pos}$ of the human target into rows and recombining them. The schematic diagram of this part of the algorithm is shown in Figure 6.

2.4. Vital Sign Signal Extraction. For the vital sign signal vector $\zeta(t)$, the EMD method decomposes it into a set of IMFS:

$$\zeta(t) = \sum_{j=1}^{n} \text{imf}_j(t) + r(t),$$

where $\text{imf}_j(t)$ represents the $j$th IMF component and $r(t)$ represents the residual of $\zeta(t)$.

Screening a set of IMF components includes the following two steps: (1) estimate the local mean $m(t)$, and (2) recursively subtract $m(t)$ from the input data until IMF is generated. Therefore, IMFs decomposed by EMD have two shortcomings: high sampling rate is required, and if it is too low, the results may be invalid; stopping criterion is
too rigid. To solve the above problems, the TVF-EMD method proposes the use of the local narrow-band signal of the Hilbert spectrum instead of the IMF as the iteration stop condition [37]. The analysis steps are as follows.

2.4.1. Find the Local Cut-Off Frequency. In the TVF-EMD method, the B-spline approximation can be regarded as a unique form of low-pass filtering, and the signal in its space is defined as follows:

$$g_m^n(t) = [p^m_n \times x]_{\downarrow m} \times b_m^n(t).$$

(22)

where $[.]_{\downarrow m}$ is the downsampling operation, $m$ is the node, and $p_m^n$ is the prefilter.

Figure 10: Linear trend suppression processing result.

Figure 11: Comparison results before and after slow time filtering.
The node $m$ determines the local cut-off frequency of the B-spline time-varying filter, and the cut-off frequency depends on the time to perform the time-varying filtering on the signal. The steps to construct a B-spline time-varying filter are as follows:

1. Use Hilbert transform to calculate the instantaneous amplitude $A(t)$ and instantaneous phase $\phi(t)$ of the input signal $\zeta(t)$:

$$A(t) = \sqrt{\zeta^2(t) + \zeta'\zeta(t)},$$  \hspace{1cm} (23)

$$\phi(t) = \arctan \left( \frac{\zeta(t) + \zeta(t)}{\zeta(t) + \zeta(t)} \right),$$ \hspace{1cm} (24)

where $\zeta(t)$ is the Hilbert transform of $\zeta(t)$.

2. Determine the maximum $\{t_{\text{max}}\}$ and minimum $\{t_{\text{min}}\}$ of $A(t)$.

For multicomponent signals, the analytic signal $z(t)$ can be expressed as the sum of the two signals:

$$z(t) = \bar{\zeta} (t) + \tilde{\zeta} (t) = a_1 e^{i \phi_1 (t)} + a_2 e^{i \phi_2 (t)}.$$ \hspace{1cm} (25)

We can get the following:

$$A^2(t) = a_1^2(t) + a_2^2(t) + 2a_1(t)a_2(t) \cos [\phi_1(t) - \phi_2(t)],$$ \hspace{1cm} (26)

$$\phi'(t) = \frac{1}{A^2(t)} \left\{ \phi'_1(t) \left( a_1^2(t) + a_1(t)a_2(t) \cos [\phi_1(t) - \phi_2(t)] \right) \\
\quad + \phi'_2(t) \left( a_2^2(t) + a_1(t)a_2(t) \cos [\phi_1(t) - \phi_2(t)] \right) \\
\quad + \frac{1}{A^2(t)} \left[ a'_1(t)a_1(t) \sin [\phi_1(t) - \phi_2(t)] - a_2^2(t)a_1(t) \sin [\phi_1(t) - \phi_2(t)] \right] \right\},$$ \hspace{1cm} (27)

where $a_i(t)$ and $\phi_i(t)$ are the instantaneous amplitude and instantaneous phase of the $i$th component, respectively.

Assuming that the local minimum of $A(t)$ is obtained at $t_{\text{min}}$, then

$$\cos [\phi_1(t_{\text{min}}) - \phi_2(t_{\text{min}})] = -1.$$ \hspace{1cm} (28)

Substituting formula (26) into formulas (23) and (24), we can get the following:

$$A(t_{\text{min}}) = |a_1(t_{\text{min}}) - a_2(t_{\text{min}})|,$$

$$\phi'(t_{\text{min}})A^2(t_{\text{min}}) = \phi'_1(t_{\text{min}}) [a_1^2(t_{\text{min}}) - a_1(t_{\text{min}})a_2(t_{\text{min}})] \\
\quad + \phi'_2(t_{\text{min}}) [a_2^2(t_{\text{min}}) - a_1(t_{\text{min}})a_2(t_{\text{min}})].$$ \hspace{1cm} (29)

According to the derivative operation, $A'(t_{\text{min}})$ is obtained; then

$$A(t_{\text{min}}) = |a_1(t_{\text{min}}) - a_2(t_{\text{min}})|.$$ \hspace{1cm} (30)

Thus, the maximum value $\{t_{\text{max}}\}$ and minimum value $\{t_{\text{min}}\}$ of $A(t)$ are obtained.

3. Calculate $a_1(t)$ and $a_2(t)$. Make

$$\beta_1(t) = |a_1(t) - a_2(t)|,$$

$$\beta_2(t) = a_1(t) + a_2(t).$$ \hspace{1cm} (31)

It can be obtained from formula (26):

$$\beta_1(t_{\text{min}}) = A(t_{\text{min}}) |a_1(t_{\text{min}}) - a_2(t_{\text{min}})|,$$

$$\beta_1(t_{\text{max}}) = A(t_{\text{max}}) |a_1(t_{\text{max}}) + a_2(t_{\text{max}})|.$$ \hspace{1cm} (32)

Since $a_1(t)$ and $a_2(t)$ are slowly varying components, $\beta_1(t)$ and $\beta_2(t)$ can be estimated separately by interpolation of $A(t_{\text{min}})$ and $A(t_{\text{max}})$. Therefore, $a_1(t)$ and $a_2(t)$ can be calculated by formulas (32) and (33):

$$a_1(t) = \frac{|\beta_2(t) + \beta_1(t)|}{2},$$ \hspace{1cm} (35)

$$a_2(t) = \frac{|\beta_2(t) - \beta_1(t)|}{2}.$$ \hspace{1cm} (36)

4. Calculate $\phi'_1(t)$ and $\phi'_2(t)$. Make

$$\eta_1(t) = \phi'_1(t) [a_1^2(t) - a_1(t)a_2(t)] + \phi'_2(t) [a_2^2(t) - a_1(t)a_2(t)],$$ \hspace{1cm} (36)

$$\eta_2(t) = \phi'_1(t) [a_1^2(t) + a_1(t)a_2(t)] + \phi'_2(t) [a_2^2(t) + a_1(t)a_2(t)].$$ \hspace{1cm} (37)
respectively, and it is necessary to reconstruct to obtain a new signal \( f(t) \):

\[
f(t) = \cos \left[ \int \beta_{\text{avg}}(t) \, dt \right].
\]

(41)

It can be obtained from formula (27):

\[
\eta_1(t'_{\text{min}}) = \phi_1^t(t'_{\text{min}}) \left[ a_1^2(t'_{\text{min}}) - a_1(t'_{\text{min}})a_2(t'_{\text{min}}) \right]
+ \phi_2^t(t'_{\text{min}}) \left[ a_2^2(t'_{\text{min}}) - a_1(t'_{\text{min}})a_2(t'_{\text{min}}) \right],
\]

\[
\eta_2(t'_{\text{max}}) = \phi_1^t(t'_{\text{max}}) \left[ a_1^2(t'_{\text{max}}) + a_1(t'_{\text{max}})a_2(t'_{\text{max}}) \right]
+ \phi_2^t(t'_{\text{max}}) \left[ a_2^2(t'_{\text{max}}) - a_1(t'_{\text{max}})a_2(t'_{\text{max}}) \right].
\]

(38)

Since \( a_1(t), a_2(t), \phi_1'(t), \) and \( \phi_2'(t) \) are slowly changing components, \( \eta_1(t) \) and \( \eta_2(t) \) can be estimated by interpolation of \( \phi_1'(t'_{\text{min}})A_1^2(t'_{\text{min}}) \) and \( \phi_2'(t'_{\text{max}})A_1^2(t'_{\text{max}}) \), respectively, and \( \phi_1'(t) \) and \( \phi_2'(t) \) can be obtained by formulas (36) and (37):

\[
\begin{align*}
\phi_1'(t) &= \frac{\eta_1(t)}{2a_1^2(t) - 2a_1(t)a_2(t)} + \frac{\eta_2(t)}{2a_1^2(t) + 2a_1(t)a_2(t)}, \\
\phi_2'(t) &= \frac{\eta_1(t)}{2a_2^2(t) - 2a_1(t)a_2(t)} + \frac{\eta_2(t)}{2a_2^2(t) + 2a_1(t)a_2(t)}.
\end{align*}
\]

(39)

(5) Calculate the cut-off frequency.

\[
\phi'_{\text{avg}}(t) = \frac{\phi_1'(t) + \phi_2'(t)}{2} = \frac{\eta_3(t) - \eta_1(t)}{4a_1(t)a_2(t)}.
\]

(40)

(6) Solve the intermittent problem.

The intermittent components in the signal may affect the local cut-off frequency. In order to solve this problem, it is necessary to reconstruct to obtain a new signal \( f(t) \):

\[
\theta(t) = \frac{B(t)}{\phi_{\text{avg}}(t)},
\]

(42)
Figure 15: Resurrected respiratory signals and heartbeat signals. (a) The resurrected respiratory signal. (b) The resurrected heartbeat signal.

Figure 16: Spectrum of respiratory signal. (a) The amplitude spectrum of the respiratory signal. (b) The power spectrum of the respiratory signal.
where $B_L(t)$ is the instantaneous bandwidth of Loughlin, $\varphi_{avg}(t)$ is the weighted average instantaneous power, and the calculation formula is follows:

$$B_L(t) = \sqrt{\frac{[a_1^2(t) + a_2^2(t)]}{a_1^2(t) + a_2^2(t)} + \frac{a_1^2(t) a_2^2(t) [\varphi_1'(t) - \varphi_2'(t)]^2}{[a_1^2(t) + a_2^2(t)]^2}}.$$  

$$\varphi_{avg}(t) = \frac{a_1^2(t) \varphi_1'(t) + a_2^2(t) \varphi_2'(t)}{a_1^2(t) + a_2^2(t)}.$$  

(43)

Given a threshold $\varepsilon$, when $\theta(t) \leq \varepsilon$, the signal can be regarded as a local narrow-band signal.

The principle of the TVF-EMD algorithm for extracting respiratory and heartbeat signals is as follows: the important components of vital sign signals are concentrated in the low frequency range (respiratory frequency band is 0.1~0.8 Hz, and heartbeat frequency band is 0.8~2.5 Hz). Only part of the IMFs in the vital signal spectrum are used to reconstruct the respiratory and heartbeat signals. Assuming that the human body echo signal is decomposed into $n$ IMFs by TVF-EMD, the energy percentage of respiration and heartbeat is calculated for each IMF in the frequency domain [38], as follows:

$$\frac{E_r(j)}{E(j)} > \delta_r,$$  

$$\frac{E_h(j)}{E(j)} > \delta_h.$$  

(44)

$E(j)$ is the frequency domain energy of the $j$th IMF; $E_r(j)$ and $E_h(j)$ are the energy in the respiratory and heartbeat frequency bands of the $j$th IMF, respectively; $\delta_r$ and $\delta_h$ are the thresholds for judging the energy ratio of respiratory and heartbeat, respectively. Reconstruct the IMF components judged to meet the requirements into respiration and heartbeat signals:

$$S_r(t) = \sum \text{IMF}(t),$$  

$$S_h(t) = \sum \text{IMF}(t).$$  

(45)

3. Experiment and Results

3.1. Ultra-Wideband Radar System and Experimental Setup. The composition of UWB radar is shown in Figure 7. The ultra-wideband radar system used in the experiment is NVA 6100 pulse ultra-wideband radar. The data collected by the radar system is sent to the computer through the USB interface for data collection and subsequent signal processing. After the transmitted signal is scattered by the target, the signal is sampled by the echo acquisition module and then converted into a digital signal by an analog to digital converter (ADC) and stored by a field programmable gate array (FPGA). The real-time sampling frequency of ADC is higher than the high-speed sampling rate of 30GS/s, where the parameter most closely related to our detection algorithm is the sampling rate. From Table 1, the fast time domain sampling frequency of the radar system is 39 GHz, and the slow time domain sampling frequency is 152.6 Hz.
To verify the effectiveness of the algorithm, we designed an experiment based on an ultra-wide band radar system. Figure 8 is the test scene, with the radar 0.5 meters above the ground. The metal railings and equipment in the test scene may affect the accuracy of vital sign signal extraction. Five volunteers conducted tests at 0.35 m, 1 m, and 1.5 m from the radar. During the experiment, the volunteers maintained normal breathing and normal heartbeat and sat next to the radar. The volunteer participating in the experiment in the picture is a healthy adult male student (181 cm, 83 kg).

4. Result Analysis

4.1. Performance of Signal Preprocessing Algorithm. In this section, the signal preprocessing performance is discussed with the experimental data of the first volunteer standing at 0.35 m from the radar. Figure 9(a) is the original radar data. Figure 9(b) shows the result of RPS removing background clutter. Figure 9(c) shows the result of TMS removing the DC component. The vital sign signal is relatively weak. The result obtained by using AGC is shown in Figure 9(d). Compared with the result shown in
Figure 9(a), the vital signal gradually increases in the echo matrix.

Figure 10 shows the result of using LTS to de-linearly trend slow-time data. LTS can effectively suppress the linear trend of radar echo signals and suppress the signals to the same level. Since the frequency range of human respiration is between 0.1 and 0.8 Hz and the frequency range of heartbeat is between 0.8 and 2.5 Hz, a bandpass filter is used to filter out high-frequency noise signals, and the filter is selected as a Butterworth filter. Figure 11 shows the result of using a Butterworth filter to remove high-frequency noise signals from slow-time data. The filtered signal can more clearly see the law of chest movement than before filtering. This method retains more vital sign information in the radar echo and filters out the noise in the surrounding environment.

4.2. Performance of Range Detection and Echo Selection Algorithm. The variance of the nonhuman target range is lower, and the variance of the human target range is higher. Figure 12 is the range-frequency matrix of the variance with volunteer A at 0.35 m from the radar. The estimated distance is 0.355 m, and the corresponding measurement error is 0.005 m.
4.3. Performance of the Vital Sign Signal Extraction Algorithm. In this section, we will take the data of volunteer A at 0.35 m as an example. According to the selection algorithm of the optimal distance gate and the width of the human thoracic cavity, the 10 rows of data near the 60th line of the optimal distance gate are selected for recombination. These signals contain the most obvious human sign signals, thus quite ideal as we further analyze the respiratory and heartbeat frequencies.

The result of TVF-EMD decomposition of the vital signs is shown in Figure 13. It can be seen from the figure that the signal is adaptively decomposed into a series of IMFs. Each IMF reflects the oscillation characteristics of different frequency scales in the signal, and the smaller the order, the higher the frequency of the IMF, and the larger the order, the lower the frequency of the IMF. This reflects the characteristics of the resolution of TVF-EMD decomposition.

Because the frequency band of human respiration is 0.1 Hz~0.8 Hz and the frequency band of heartbeat is 0.8 Hz~2.5 Hz, calculate the percentage of energy in the respiratory and heartbeat frequency bands in each IMF component, and the results are shown in Figure 14.

It can be seen from the Figure 14 that the percentage of energy occupied by IMF6, IMF7, and IMF8 in the respiratory frequency band reaches more than 90%, so these three IMF components can be used to reconstruct the respiratory signal. For heartbeat signals, IMF3 and IMF4 account for more than 90% of the energy percentage in the heartbeat frequency band, while other IMFs have a relatively small percentage of energy in the heartbeat frequency band, indicating that they contribute less to the reconstruction of the heartbeat signal. Therefore, the heartbeat signal can be reconstructed with IMF3 and IMF4. The reconstructed respiratory and heartbeat signals are shown in Figure 15, respectively.

After reconstructing the breathing and heartbeat signals, we can use the FFT method for frequency domain analysis. Figure 16 shows the results of frequency domain analysis of the reconstructed respiratory signal. From the figure, it can be estimated that the respiratory frequency of the

| Table 2: Analysis results at 0.35 m. |
|-----------------|---------|---------|---------|---------|
| Volunteer | Method  | \(F_r\) (Hz) | SNR\(_r\) (dB) | \(F_h\) (Hz) | SNR\(_h\) (dB) |
| A   | EEMD    | 0.36    | -4.10    | 1.18    | -4.29    |
|     | TVF-EMD | 0.35    | -3.55    | 1.17    | -3.80    |
| B   | EEMD    | 0.48    | -7.61    | 1.06    | -7.66    |
|     | TVF-EMD | 0.49    | -7.97    | 1.07    | -7.56    |
| C   | EEMD    | 0.36    | -4.31    | 1.21    | -5.84    |
|     | TVF-EMD | 0.36    | -3.57    | 1.22    | -4.85    |
| D   | EEMD    | 0.47    | -3.74    | 1.13    | -3.79    |
|     | TVF-EMD | 0.48    | -3.55    | 1.13    | -3.03    |
| E   | EEMD    | 0.42    | -6.30    | 1.03    | -9.69    |
|     | TVF-EMD | 0.42    | -6.24    | 1.04    | -9.13    |

| Table 3: Analysis results at 1.0 m. |
|-----------------|---------|---------|---------|---------|
| Volunteer | Method  | \(F_r\) (Hz) | SNR\(_r\) (dB) | \(F_h\) (Hz) | SNR\(_h\) (dB) |
| A   | EEMD    | 0.34    | -3.99    | 0.93    | -7.88    |
|     | TVF-EMD | 0.33    | -2.04    | 0.91    | -7.82    |
| B   | EEMD    | 0.39    | -4.11    | 1.29    | -5.88    |
|     | TVF-EMD | 0.38    | -4.12    | 1.29    | -4.91    |
| C   | EEMD    | 0.51    | -9.74    | 1.01    | -4.12    |
|     | TVF-EMD | 0.49    | -8.84    | 1.04    | -3.01    |
| D   | EEMD    | 0.39    | -9.44    | 1.08    | -3.34    |
|     | TVF-EMD | 0.38    | -9.73    | 1.09    | -4.71    |
| E   | EEMD    | 0.44    | -8.64    | 1.16    | -12.93   |
|     | TVF-EMD | 0.45    | -6.62    | 1.18    | -12.28   |

| Table 4: Analysis results at 1.5 m. |
|-----------------|---------|---------|---------|---------|
| Volunteer | Method  | \(F_r\) (Hz) | SNR\(_r\) (dB) | \(F_h\) (Hz) | SNR\(_h\) (dB) |
| A   | EEMD    | 0.32    | -9.96    | 1.49    | -12.92   |
|     | TVF-EMD | 0.33    | -8.85    | 1.51    | -8.58    |
| B   | EEMD    | 0.36    | -2.96    | 1.04    | -3.47    |
|     | TVF-EMD | 0.35    | -3.77    | 1.05    | -3.41    |
| C   | EEMD    | 0.41    | -2.78    | 1.25    | -7.7     |
|     | TVF-EMD | 0.39    | -2.19    | 1.25    | -4.65    |
| D   | EEMD    | 0.41    | -6.48    | 1.27    | -8.12    |
|     | TVF-EMD | 0.40    | -4.10    | 1.28    | -4.37    |
| E   | EEMD    | 0.47    | -7.10    | 1.05    | -9.72    |
|     | TVF-EMD | 0.45    | -6.61    | 1.07    | -10.44   |

| Table 5: 0.35 m heartbeat frequency error. |
|-----------------|---------|---------|---------|
| Volunteer | Detected HR (Hz) | Reference HR (Hz) | Error |
| A   | 1.17     | 1.17    | 0       |
| B   | 1.07     | 1.16    | 0.01    |
| C   | 1.22     | 1.24    | 0.02    |
| D   | 1.13     | 1.13    | 0       |
| E   | 1.04     | 1.05    | 0.01    |

| Table 6: 1.0 m heartbeat frequency error. |
|-----------------|---------|---------|---------|
| Volunteer | Detected HR (Hz) | Reference HR (Hz) | Error |
| A   | 0.91     | 0.92    | 0.01    |
| B   | 1.29     | 1.29    | 0       |
| C   | 1.04     | 1.07    | 0.03    |
| D   | 1.09     | 1.13    | 0.04    |
| E   | 1.18     | 1.19    | 0.01    |

| Table 7: 1.5 m heartbeat frequency error. |
|-----------------|---------|---------|---------|
| Volunteer | Detected HR (Hz) | Reference HR (Hz) | Error |
| A   | 1.51     | 1.52    | 0.01    |
| B   | 1.05     | 1.07    | 0.02    |
| C   | 1.25     | 1.25    | 0       |
| D   | 1.28     | 1.27    | 0.01    |
| E   | 1.07     | 1.10    | 0.03    |
human body is 0.35 Hz, and the result obtained contains less clutter frequency components, the clutter is effectively suppressed, and the signal-to-noise ratio is high.

Figure 17 shows the results of frequency domain analysis of the reconstructed heartbeat signal. The human heartbeat signal is relatively weak and easily affected by the harmonics of the respiration and clutter. The FFT directly obtains the human heartbeat signal as 1.17 Hz.

Figures 18 and 19 are the effect diagrams of volunteer A’s vital sign signal extraction at 1.0 m and 1.5 m, respectively. From Figure 18(e), the estimated distance of 1.0 m is 1.045 m, and the error is 0.045 m. From Figures 18(h) and 18(i), the respiratory and heartbeat frequencies of volunteer A measured at 1.0 m from the radar are 0.33 Hz and 0.91 Hz, respectively. Similarly, From Figure 19(e), the estimated distance of 1.5 m is 1.525 m, and the error is 0.025 m. From Figures 19(h) and 19(i), the respiratory and heartbeat frequencies of volunteer A measured at 1.5 m from the radar are 0.33 Hz and 1.52 Hz, respectively.

Analysis of measured data shows that the proposed algorithm can accurately obtain human vital sign signals.

4.4. Performance Comparison

4.4.1. SNR Comparison. As shown in Tables 2–4, the radar echo signals collected by 5 volunteers at 0.35, 1.0 m, and 1.5 m are reconstructed results and signal-to-noise ratios after decomposition of EEMD and TVF-EMD, where $F_r$ is the respiratory frequency, $F_h$ is the heartbeat frequency, $SNR_r$ is the signal-to-noise ratio of the respiratory signal, and $SNR_h$ is the heartbeat signal ratio. Compared with EEMD, TVF-EMD effectively improves the signal-to-noise ratio of respiratory and heartbeat signals, with an average increase of 0.6340 and 0.9867, respectively.

4.5. Detection Error. Tables 5–7 show the errors of the heartbeat signal frequency and heartbeat reference signal extracted by the method in this paper at 0.35 m, 1.0 m, and 1.5 m, respectively. It can be seen from Tables 5–7 that the measurement error of this method is very small.

5. Conclusions

In this paper, a new vital sign detection algorithm based on impulse UWB radar is proposed. The range of the human target is obtained based on the continuous wavelet transform (CWT) technique, and the signal on the adjacent distance gate is selected and recombined based on the largest signal amplitude in the range-frequency matrix of the variance. The recombined signal is adaptively decomposed by the TVF-EMD algorithm. And reconstruct the respiratory and heartbeat signals in the time domain. Compared with EEMD, it improves the accuracy and real-time performance of signal separation and effectively improves the signal-to-noise ratio of respiratory and heartbeat signals. The experimental data analysis results show that this method accurately obtains the position, respiratory, and heartbeat frequency information of the human body, indicating the feasibility and effectiveness of introducing TVF-EMD into the separation processing and reconstruction of respiratory and heartbeat signals.

Data Availability

The test data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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