Radar detection of multi-target vital signs based on blind source separation

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Abstract. Radar non-contact monitoring of vital signs has a broad application prospect in clinical monitoring. Aiming at the problem of strong interference in non-contact vital signs detection (Such as multi-target, random body motion), a blind source separation (BSS) signal detection method based on Fast-ICA is proposed to reduce the interference of multi-target. In this algorithm, entropy is used to evaluate the non Gaussian property, and the appropriate transformation matrix is selected, according to the statistical independence of the signals, the source signals are separated from the observed mixed signals. On this basis, the traditional blind source separation process is improved, and the wavelet transform preprocessing algorithm based on translation invariant is added to suppress the interference of static clutter. The feasibility of this method is verified by simulation experiments.

1. Introduction

Monitoring human vital signs (such as heart rate and respiratory rate) is very important to save lives. Many sudden diseases usually lead to abnormal cardiopulmonary activities [1-3]. With the development of technology, the hardware design is constantly improved, at the same time, the signal processing methods are also increasingly rich. However, the research on multi-target signal processing method is relatively less. Reference [4] proposes to use the traditional clean algorithm to calculate the channel impulse response by subtracting the convolution of the received signal from the clutter, but the frequency information corresponding to the component to be removed is required to be known.

In this paper, blind source separation (BSS) signal processing technology is proposed to deal with the interference caused by multiple targets[5,6]. Because the traditional blind source separation (BSS) can't distinguish the life signal from the clutter signal, a method based on wavelet transform is proposed to preprocess the observed signal to remove the static clutter, and then the fast ICA based BSS is used to get the estimation of each target source signal, which can provide more accurate target information for the later target vital signs detection in order to improve the recognition accuracy.

2. Non contact vital signs detection model based on Radar

2.1. human thoracic motion model

Vital signs signal comes from periodic motion caused by respiration and heartbeat, which is usually approximate to harmonic motion [7]. The instantaneous distance from the radar antenna to the chest is as follows:

\[ d(t) = d_0 + \Delta d(t) = d_0 + \Delta_1 \sin(2\pi f_1 t) + \Delta_2 \sin(2\pi f_2 t) \] (1)
In formula (1), $d_0$ is the average distance from the radar transceiver antenna to the chest vibration center of the target, $\Delta d(t)$ represents the chest vibration amplitude, $\Delta_1$, $\Delta_2$, $f_1$, $f_2$ represent the breathing amplitude and heartbeat amplitude, breathing rate and heartbeat rate of the target respectively. The time delay of the received signal reflected by the human body on the time axis is:

$$\tau_d(t) = \frac{2d(t)}{c_0} = \frac{2(d_0 + \Delta_1 \sin(2\pi f_1 t) + \Delta_2 \sin(2\pi f_2 t))}{c_0}$$

$$= \tau_0 + \tau_1 \sin(2\pi f_1 t) + \tau_2 \sin(2\pi f_2 t)$$

(2)

Where $c_0$ is the speed of light.

### 2.2. Signal Model

This paper uses FMCW radar to detect life signal, and the radar waveform is sawtooth wave. The working principle of FMCW radar is shown in Figure 1. The transmitted signal is reflected on the target and received with time delay $\tau_d$, which depends on the distance $d(t)$ between the radar and the target.

![Working principle of FMCW Radar](image)

Radar transmitting signal:

$$S_T(t) = \cos(2\pi f_c t + \pi \gamma t^2 + \varphi)$$

(3)

In equation (3), $f_c$ is the center frequency of the signal, $\gamma$ is the slope of the sawtooth wave, and $\varphi$ is the initial phase. Compared with the transmitted signal, the received signal contains a time delay $\tau_d$.

$$S_R(t) = A_R S_T(t - \tau_d(t))$$

(4)

$A_R$ is the amplitude of the received signal. In the next step, the transmitted and received signals are multiplied by a mixer to obtain an intermediate frequency signal:

$$S_{IP}(t) = S_T(t) \times S'_R(t)$$

$$= \frac{A_R}{2} \left[ \cos(2\pi \gamma \tau_d^2 - 2\pi \gamma \tau_d + 4\pi f_c t - 2\pi f_c \tau_d + \pi \gamma \tau_d^2 + 2\varphi) + \cos(2\pi \gamma \tau_d - \pi \gamma \tau_d^2 + 2\pi f_c \tau_d) \right]$$

(5)

The difference frequency signal contains the complete information of the object in the scene, and the former sum frequency signal is filtered by low-pass filter, and the latter difference frequency signal is left. The frequency $2\pi \gamma \tau_d$ of the difference frequency signal $S_M(t)$ is only related to the round-trip delay, and the distance $R$ between the radar and the target can be determined by detecting the difference frequency [8]. FFT is used for the difference frequency signal to obtain the spectrum of the difference frequency signal. Its different peaks correspond to the objects in different ranges of the difference frequency signal. This FFT displays the distance information, it is also called distance FFT.

### 3. Multi Target Vital Signs Separation and Detection Algorithm Based on Blind Source Separation

#### 3.1. Wavelet Transform Preprocessing

Wavelet transform can effectively distinguish the abrupt part of the signal and the noise at different decomposition levels by analyzing the time-frequency of the signal, so as to realize the de-noising of
the signal [9]. Based on the good denoising performance of wavelet threshold method, wavelet threshold
is used to denoise the signal $S_M(t)$ with noise difference frequency of FMCW radar, and the useful
signal is kept to the maximum extent. The specific steps are as follows:
1) Wavelet decomposition is performed on the noisy difference frequency signal, and the appropriate
wavelet basis and decomposition level $j$ are selected to obtain the corresponding wavelet
coefficients $w_{j,k}(j,k \in Z)$ of different decomposition levels.
2) The wavelet coefficients of each layer after decomposition are processed by threshold quantization,
and the appropriate threshold function and threshold are selected to quantize the corresponding
wavelet coefficients. The wavelet coefficient $w_{j,k}$ is compared with the critical threshold. If the
wavelet coefficient $w_{j,k}$ is greater than the critical threshold, the wavelet coefficient $w_{j,k}$ is retained,
or the estimated wavelet coefficient $\hat{w}_{j,k}$ is obtained by translating and contracting to zero according
to a fixed quantity; if the wavelet coefficient $w_{j,k}$ is less than the critical threshold, the wavelet
coefficient is set to zero and cleared.
3) The quantized wavelet coefficients are used to inverse transform the signal wavelet, and then the
processed wavelet is reconstructed to get the denoised signal.

3.2. principle and method of blind source separation
The main purpose of this paper is to propose a simple, compact and accurate unsupervised blind source
separation (BSS) method, which is based on Fast ICA algorithm to realize the separation of multi-target
vital signs signals, decompose the echo signal processing, and complete the separation of observed
signals according to the statistical independence of signals [10].

By solving the separation matrix, blind source separation can recover the source signal from the
observed mixed signal only according to the statistical independence of the signal. The basic BSS model
is shown in Figure 2, which is divided into mixing process and separation process. The observed signal
$x(t)$ of the sensor comes from the linear mixture of the source signal $s(t)$ and contains additive noise
$n(t)$. Its mathematical model is $x(t) = As(t) + n(t), t = 1, 2, \cdots, T_0$.

![Figure 2. Basic BSS model](image)

Fast fixed point algorithm (fast ICA) is used for separation: the principle of separation is to separate
single signal source by finding the separation matrix $W \approx A^T$ and estimating $h_n$. In our method, BSS
adopts FastICA based on the maximization of negative entropy:

$$J(x) = H(x) - H(x)$$

In equation (6), $x_0$ is a Gaussian random variable with the same variance as $x$, and $H(\cdot)$ is the
differential entropy of the random variable.

The essence of FastICA algorithm is to select an appropriate transformation matrix $W$ to maximize
the value of negative entropy $J(W^T x)$. Because when the mean value is 0 and the variance is 1, solving
the maximum value of $J(W^T x)$ can be equivalent to solving the maximum value of $E(GW^T x)$. Therefore, before the algorithm starts, two steps of centralization and whitening are needed to preprocess, so that the problem can be transformed into solving the maximum value of $E(GW^T x)$ under the condition of satisfying $E(GW^T x) = |W|^2 = 1$.

4. Simulation analysis

In order to verify the feasibility and advantages of blind source separation algorithm, the algorithm simulation test is carried out firstly. Suppose the respiratory and heartbeat parameters of the two targets are shown in Table 1, and the combined signal is shown in Figure 3. The first line is the mixed time domain diagram of the two targets added with Gaussian white noise, and the last line is the spectrum diagram of the mixed signal.

Table 1. Simulation signal parameters

| Target   | Respiratory rate /Hz | Respiratory amplitude /m | heart rate /Hz | Heart rate range /m | Signal to noise ratio /dB |
|----------|----------------------|--------------------------|----------------|---------------------|--------------------------|
| Target 1 | 0.3                  | 0.01                     | 1.1            | 0.001               | 5                        |
| Target 2 | 0.4                  | 0.01                     | 0.9            | 0.001               | 5                        |

The BSS algorithm is used to process the signal, and the results are shown in Figure 4. In Figure 4, the first line is the original signal of vital signs of two targets; In the second line, the original signal passes through a random mixture matrix and then Gaussian white noise is added to get two noisy mixed signals; in the third line, the separation result is obtained by using only the traditional blind source separation algorithm; in the last line, the separation result is obtained by using FastICA algorithm after denoising with wavelet transform proposed in this paper. It can be seen directly from the figure that only using the traditional blind source separation algorithm for separation, the separation effect is poor, the separated target signal has been lost and blurred, and the effect of signal separation after de-noising is significantly better than that of direct separation.
The separated target is separated and FFT transformed to obtain the spectrum. According to the respiratory and heartbeat frequency bands, the effective respiratory and heartbeat frequency information is obtained. As shown in Figure 5, there are two peaks on the two component spectrum. The first peak corresponds to the respiratory rate of the target, and the second peak corresponds to the heartbeat rate of the target. The respiratory rate of target 1 is 0.3027 Hz (18 beats/min), and the heart rate is 1.104 Hz (66 beats/min), which is consistent with the preset respiratory rate of target 1 (0.3 Hz) and heart rate of target 2 (1.1 Hz); the respiratory rate of target 2 is 0.4004 Hz (24 beats/min), and the heart rate is 0.8984 Hz (54 beats/min), which is the same as the preset respiratory rate of target 2 (0.4 Hz) and heart rate (0.9 Hz). Therefore, after the BSS algorithm of wavelet de-noising, the multi-target vital signs signal separation is successfully realized, and the time-domain waveform recovery is very good. The simulation results show that the method is feasible and effective in the noisy environment.
5. Conclusion
Aiming at the problem of multi-target strong interference in non-contact vital signs detection, the echo signal model of radar system is established, and a blind source separation algorithm based on FastICA is proposed. Considering the influence of actual noise environment, the traditional blind source separation processing flow is improved, and the wavelet transform preprocessing algorithm based on translation invariant is added, so as to suppress the interference of environmental static clutter. In order to obtain more accurate noise variance, the algorithm uses high frequency coefficient sliding window method instead of the original high frequency coefficient median method, which greatly improves the separation quality of blind source separation algorithm. In this paper, the entropy value is used to evaluate the non Gaussian property of the separation algorithm, and the appropriate transformation matrix is selected to maximize the negative entropy value. The vital signs information of each target can be obtained by processing the transformation matrix. The blind source separation algorithm based on FastICA can separate the signals without destroying the details of other signals, which solves the problem of weak breathing signal loss in traditional separation methods questions. Simulation results show that the proposed algorithm can effectively separate the multi-target vital signs signals in noisy environment.

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