Detection Method for Human Respiration Waveform in Sleep State Based on IR-UWB

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***Abstract*—Detecting human respiration waveform in sleep is crucial for intelligent healthcare and medical applications. Traditional contact methods are inconvenient. This study proposes an IR-UWB-based method. It uses the periodic changes in wireless pulse signal propagation caused by chest undulation during sleep. The method generates a refined respiration waveform for real-time output and high-precision respiratory rate estimation. It proposes a respiration energy ratio indicator and uses vector projection and signal selection methods. A variational encoder-decoder network is employed for waveform recovery. Experiments show high similarity to commercial belts, with an average error of 0.229 bpm in respiratory rate estimation.**

Keywords: wireless sensing; respiration waveform detection; IR-UWB; I/Q signal; variational encoder-decoder

I. Related Work on Respiration Detection Technology

The detection technology of vital sign signals in the sleep state is of great significance in the fields of human health analysis and disease diagnosis, and has received extensive attention from researchers [1], [2]. The existing respiration detection technologies can be divided into contact and non-contact types. The contact type causes discomfort to users and affects their breathing habits and perception results, so the focus is on non-contact methods. Non-contact methods can be further classified into perception methods based on computer vision, sound signals, and wireless radio frequency signals. The methods based on computer vision and sound signals are susceptible to environmental interference and privacy leakage issues, and the non-contact respiration perception technology based on wireless radio frequency signals is gradually emerging.

The human respiration perception work based on WiFi [3], [4] signals has problems such as narrow bandwidth and coarse perception spatial resolution. The human respiration perception work based on radio frequency (RF) signals includes the research of Zhai et al. [5], Pi-ViMo [6], etc., which can achieve fine-grained respiration perception. The IR-UWB (impulse radio-ultra wide band) [7], [8] technology is more suitable for home use, and related work has verified its feasibility in respiration perception, but factors such as the position of the equipment and the orientation of the person during sleep can reduce the perception accuracy. This paper proposes an IR-UWB-based method for detecting human respiration waveforms in sleep and designs the SleepBreather system. Fig. 1 shows the schematic. This method can obtain the respiration reflection area and combine signal projection and a deep learning model to detect fine-grained respiration waveforms.

II. Basic Knowledge

Each frame of the impulse radio-ultra wide band (IR-UWB) signal is modulated by a baseband Gaussian pulse through a cosine carrier, and the received signal is a superposition of multipath signals. The received baseband signal frame sequence can be obtained through low-pass filtering.

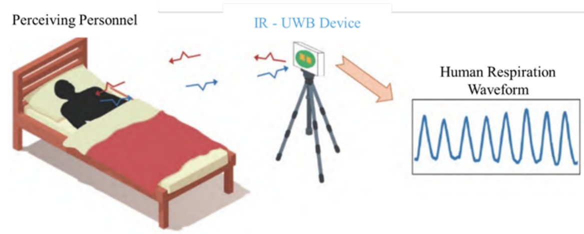

Fig 1. Schematic Diagram of the Human Respiration Waveform Detection System in the Sleep State Based on IR-UWB Technology

The received frame sequence of the IR-UWB device is a two-dimensional signal pulse response matrix. After eliminating the direct current component, human respiration will cause the I/Q complex plane signal to show a periodic arc-like change. However, there are limitations in extracting human respiration characteristics using only the amplitude, phase, I signal, or Q signal of the IR-UWB radar alone.

III. Detection Method for Human Respiration Waveform in Sleep State Based on IR-UWB

A. System Framework

The framework diagram of the detection method for human respiration waveforms in the sleep state based on IR-UWB is shown in Fig. 2. This method includes obtaining the original I/Q signal matrix by the IR-UWB terminal, obtaining the human reflection area by the respiration position estimation module, generating the respiration characteristic waveform by the projection signal generation module, and generating the human respiration waveform consistent with the respiration belt [9] by the respiration signal fitting module using the variational encoder-decoder model.

B. Respiration Position Estimation

This paper proposes the respiration power ratio (RPR) based on distributed Doppler shift to determine the center of the human reflection area for adaptive sleep respiration perception. The calculation method of the respiration energy ratio RPR is as follows:

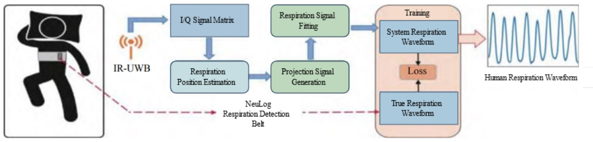

Fig 2. Framework Diagram of the Detection Method for Human Respiration Waveform in Sleep State Based on IR-UWB.

(1) By calculating the Doppler shift value of each range bin, since the normal human respiration frequency is 10–37 bpm, and the data segmentation of this method is 20 s, the adopted respiration frequency range is -15 15 Hz. Calculate the energy sum within the respiration frequency range:

$$E_{\text{resp}} = \sum_{f=-15}^{15} |X(f)|^2 \tag{1}$$

(2) Calculate the energy sum reflected by normal human activities in the same way. Since the frequency range affected by human activities is usually within 50 Hz, calculate the energy sum of human activity reflections within -50 50 Hz:

$$E_{\text{act}} = \sum_{f=-50}^{50} |X(f)|^2 \tag{2}$$

(3) By comparing the energy sum within the respiration frequency range with the energy sum reflected by human activities, the corresponding respiration energy ratio RPR can be obtained:

$$\text{RPR} = \frac{E_{\text{resp}}}{E_{\text{act}}} \tag{3}$$

C. Projection Signal Generation

After obtaining the reflected signal of the human respiration area, it is necessary to further extract features that conform to the human respiration pattern from the reflected area signal. The specific extraction method includes signal offset, filtering, projection, and weighted combination. By adding a static offset vector to make the I/Q signal phase continuous, using Hampel filtering to eliminate outliers, using the vector projection method based on the I/Q complex plane to extract the human respiration characteristic signal, and solving the problem of the bidirectionality of the signal projection, finally, the weighted sum is used to generate the respiration characteristic sequence.

D. Experimental Verification and Result Analysis

This paper uses a variational encoder-decoder model to extract fine-grained human respiration waveforms from nonlinear mixed signals. The model consists of an encoder, a decoder, and a loss function, which can make the generated respiration waveform smoother and avoid overfitting.

1) Experimental Setup: This method uses the Novelda X4M05 IR-UWB single-transmitter single-receiver terminal, a notebook, a camera, and the NeuLog commercial respiration detection belt for the experiment, performs data processing based on Matlab 2021b and Python 3.8.12, and recruits 8 volunteers to conduct the test in a room of about 30m^2.

2) Evaluation Metrics: The waveform similarity is used to evaluate the similarity between the recovered respiration waveform and the real respiration waveform. The calculation method is as follows:

$$\text{Similarity} = \frac{\sum_{i=1}^{n}(y_{\text{pred},i} - \bar{y}_{\text{pred}})(y_{\text{true},i} - \bar{y}_{\text{true}})}{\sqrt{\sum_{i=1}^{n}(y_{\text{pred},i} - \bar{y}_{\text{pred}})^2 \sum_{i=1}^{n}(y_{\text{true},i} - \bar{y}_{\text{true}})^2}} \tag{4}$$

The human respiration rate is calculated through the peak-finding algorithm and the peak interval time. The specific calculation method is as follows:

$$\text{RR (bpm)} = \frac{60 \times N}{T} \tag{5}$$

where N is the total number of peaks extracted in one breathing segment, and T is the duration of the segment (in seconds).

3) Overall Performance: The method in this paper has high waveform similarity and small estimation error of the respiration rate, indicating that the method is effective and accurate.

4) Influence of Experimental Environment Parameters: Different users have different physical constitutions and sleep habits, but this method can maintain stable and high-precision respiration detection results for different people; a perception distance of 1–3m can achieve high-precision respiration waveform acquisition; the similarity of the respiration waveform is the highest in the central area of the radio frequency antenna; this method can ensure the robustness of the waveform detection in different sleep postures. The detection results of the respiration waveform similarity corresponding to the changes of different experimental environment parameters are shown in Fig. 3.

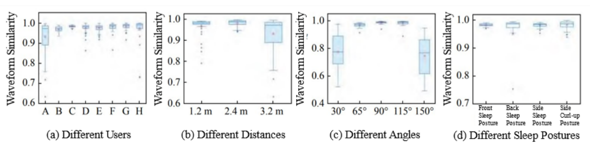

Fig 3. Influence of Experimental Environment Parameters.

5) Influence of Learning Model Parameters: Different numbers of training set samples have little impact on the waveform recovery results, and the hidden channel dimension has little impact on the accuracy of respiration waveform detection. After comprehensive consideration, a one-dimensional convolutional variational encoder-decoder network model with 256 hidden channels is used for human respiration waveform recovery. The detection results of the respiration waveform similarity corresponding to the changes of the learning model parameters are shown in Fig. 4.

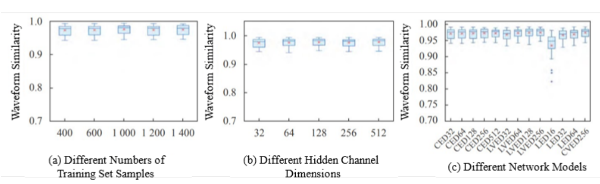

Fig 4. Influence of Deep Network Model.

IV. Conclusion

This paper proposes a detection method for human respiration waveforms in the sleep state based on the IR-UWB technology. Through a large number of experiments, the test results show that the average similarity of the human respiration waveforms generated by this method in the sleep state is 0.96, and the average error of the estimated human respiration rate is 0.229 bpm, which verifies that this method can achieve high-precision and robust detection of human respiration waveforms in the sleep state. In the future, we will focus on deploying in more scenarios and expanding the signal feature extraction method to realize the detection of more vital indicators.

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