Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
© 2025 SCPE. Volume 26, Issues 3, pp. 1496–1503, DOI 10.12694/scpe.v26i3.4328

MULTI-TARGET VITAL SIGN DETECTION BY FUSION OF BIOLOGICAL RADAR AND CONVOLUTIONAL NEURAL NETWORK

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Abstract. In order to address the increasing demand for vital sign detection, the author proposes a multi-target vital sign detection research that combines biological radar and convolutional neural network. Based on the fundamental architecture of convolutional neural networks (CNNs), the author combines classification-based CNN object detection techniques to develop a biological radar multi-target vital sign detection platform. The feasibility of this approach is confirmed through experiments, demonstrating the integration of biological radar and CNNs for multi-target vital sign detection. The experimental results indicate that the biological radar achieves a recognition accuracy of 96.1%, proving the effectiveness of the biological radar detection algorithm. The research on multi-target vital sign detection based on the fusion of biological radar and convolutional neural network is an effective auxiliary method that can provide reference for relevant researchers.

Key words: Biological radar, Convolutional neural network, Multi objective, Vital sign detection

1. Introduction. In recent years, with the in-depth research and popularization of artificial intelligence algorithms represented by convolutional neural networks, intelligent electronic devices and related application scenarios have become ubiquitous, such as object detection, facial recognition, smart healthcare, etc. CNN achieves high accuracy in model prediction at the cost of high computational complexity by increasing the network structure. Some application scenarios that require high real-time performance not only demand high accuracy of the network, but also require high processing speed of the network [1]. Human vital signs primarily consist of physiological parameters such as heart rate, respiratory rate, body temperature, and blood pressure. These metrics are essential for assessing an individual's health status. Heart rate indicates the number of heartbeats per minute, whereas respiratory rate refers to the number of breaths taken per minute. For healthy adults, the normal respiratory rate ranges from 12 to 20 breaths per minute, and the typical heart rate ranges from 60 to 100 beats per minute. The commonly used detection methods for life signals nowadays include electrocardiography (ECG), photoplethysmography (PPG), and other detection methods that require direct contact with the human body. However, in some special situations such as burns, infectious diseases, and psychiatric patients, the use is restricted. To address emerging needs, research on non-contact vital sign detection technology has garnered significant attention. This technology primarily monitors vital signs using methods such as infrared, electromagnetic waves, and video [2,3].

Non contact vital sign detection does not require physical contact with the target being tested, and can detect distant targets. It not only avoids the constraints of cumbersome wiring harnesses and electrodes, expands its application range, but also avoids psychological pressure on the target during the testing process, making the detection results more realistic. It has a wide range of applications in home and medical health monitoring, driver life status monitoring, and other fields. As an emerging physiological signal detection method, microwave biological radar can detect vital sign signals such as human heart and lung activity. Compared with traditional methods such as electrocardiogram and pulse, microwave biological radar technology is not only non-contact, but also has good penetrability, which can penetrate obstacles such as clothing and bedding for detection. These advantages make microwave biological radar technology have potential applications in medical diagnosis, health monitoring, disaster rescue and other fields. This study aims to combine biological radar and CNN technology

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to achieve accurate detection and analysis of multi-target vital signs, providing new technological solutions for fields such as medical diagnosis and health monitoring [4].

2. Literature Review. With the continuous development of medical technology, there is an increasing demand for the application of vital sign signal monitoring in scenarios such as infant monitoring and smart elderly care. Traditional vital sign detection methods such as electrocardiogram monitors, smart bracelets, oximeters, etc. require contact with the patient's body, which is not only inconvenient but also prone to cross infection. Biological radar is a new concept radar technology that mainly focuses on the human body as the detection object. It can detect signals such as breathing, heartbeat, and body movement of the human body in a non-contact manner, and has become a research hotspot at home and abroad in recent years. Compared with traditional contact detection, biological radar can reduce the discomfort and psychological burden caused by electrodes, wires, sensors, etc. on the human body, and has broad application prospects in the field of social medicine. Liu, J. et al. introduced a convolutional neural network leveraging multi-scale feature fusion to enhance the integration quality of multimodal medical images. The findings show that this method outperforms other state-of-the-art techniques across most metrics [5]. Zhang, A. et al. developed a multimodal fusion convolutional neural network (MFCNN) that employs a dual-stream convolutional neural network (CNN). This network extracts shared information from surface electromyography (sEMG) and accelerometer signals from various subjects [6]. Mohan, R. et al. designed a convolutional neural network called MIDNet18, a tailored medical image analysis and detection network, to diagnose various lung diseases using chest CT images. The MIDNet-18 CNN architecture has simplified model construction, minimal complexity, simple techniques, and high-performance accuracy, and can classify binary and multi class medical images [7].

To tackle these challenges and establish a foundation for multi-target vital sign detection, the author suggests a study focused on detecting multiple vital signs through the integration of biological radar and convolutional neural networks. Non-contact vital sign detection technology offers a valuable supplementary method for health monitoring. Developing a device for detecting human vital signs using microwave radar technology. Design a continuous wave radar circuit based on the Doppler principle to detect human micro motion signals; Using short-time Fourier transform and interpolation algorithm to extract human heart rate and respiratory rate parameters; Introducing embedded platforms to achieve miniaturization design and integration of devices; Develop embedded signal processing software to achieve real-time signal processing, recording, and display. With the growth of training data and advancements in machine performance, convolutional neural network-based object detection has surpassed the limitations of traditional methods, becoming the leading algorithm in contemporary object detection.

3. Research Methods.

3.1. Convolutional Neural Networks.

3.1.1. Basic Structure of Convolutional Neural Networks. Convolutional neural networks were proposed by Professor LeCun at the University of Toronto in Canada. The earliest convolutional neural networks were used as classifiers, mainly for image recognition [8]. In Figure 3.1, a convolutional neural network (CNN) is depicted as a hierarchical model comprising essential components: an input layer, convolutional layers, pooling layers, fully connected layers, and an output layer. CNNs are specialized for image processing, leveraging weight-sharing through convolution to extract features in the convolutional layers. This architecture enables the network to progressively extract hierarchical features from low-level to high-level representations. These high-level features are then classified using fully connected and output layers, producing one-dimensional vectors that categorize the input image. Thus, CNNs can be conceptually divided into a feature extractor (input, convolutional, and pooling layers) and a classifier (fully connected and output layers), each contributing distinct functions in the image recognition process.

3.1.2. Classification based Convolutional Neural Network Object Detection. Traditional object detection methods involve a sequence of steps: preprocessing, window sliding, feature extraction, feature selection, feature classification, and post-processing. In contrast, convolutional neural networks (CNNs) encompass the capabilities of feature extraction, selection, and classification within their architecture. This integrated approach enables CNNs to streamline object detection tasks by reducing the need for separate preprocessing steps

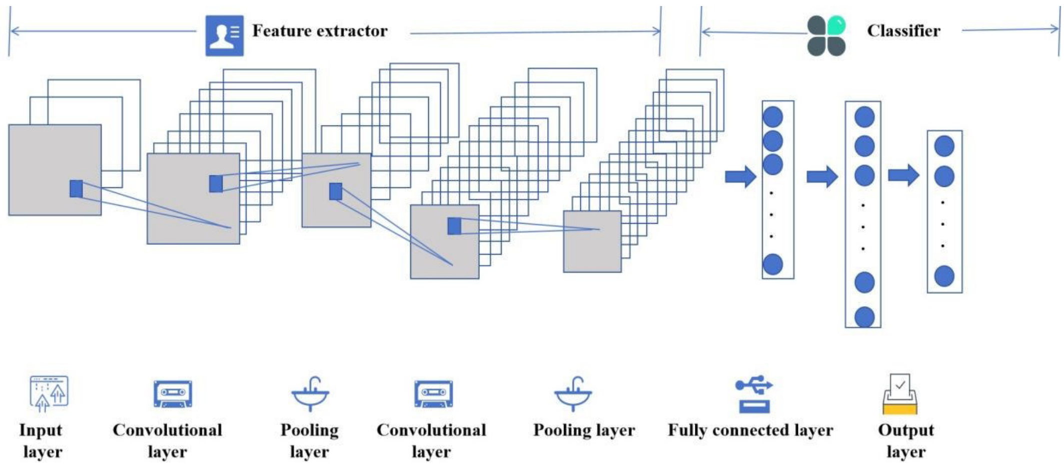

Fig. 3.1: Basic Structure of Convolutional Neural Network

and directly processing raw data to classify objects effectively [9]. Convolutional neural networks (CNNs) are capable of directly classifying candidate regions generated by sliding windows, a method known as classification-based CNN object detection. Unlike traditional object detection methods with multiple steps, this approach simplifies the process to three main steps: sliding windows, image classification, and post-processing, where sliding windows and post-processing methods are predefined. As a result, research in this area predominantly centers on enhancing CNNs' abilities in feature extraction, selection, and classification to improve the overall accuracy of image recognition.

Researchers have developed algorithms to extract sub-images containing specific semantic information from the target image, thereby reducing the number of candidate regions. These regions vary in size and represent distinct semantic meanings. By employing convolutional neural networks (CNNs) for classification and recognition, this approach enables the detection of objects across multiple scales and classes. This method significantly enhances the efficiency of object detection by focusing computational efforts on relevant and meaningful regions within the image [10]. In the evolution of object detection methods, researchers are exploring new approaches to enhance accuracy by reconfiguring convolutional neural networks (CNNs) as regressors. Instead of relying solely on classification, these methods treat the entire image as a potential candidate region. This involves directly inputting the image into the CNN to regress and pinpoint the precise position information of the target within the image itself. This approach represents a shift towards more holistic and integrated methodologies in CNN-based object detection [11].

3.1.3. SIMD Computing Acceleration Method for Convolutional Networks Based on ARM Processor. ARMv8 has 32 128 bit registers, and the author uses embedded assembly programming based on ARMv8 to implement the design of SIMD convolution accelerator. One instruction is used to perform multiplication and accumulation operations on 8 sets of data [12]. Table 3.1 lists several common instructions, namely addition, subtraction, multiplication, multiply accumulate, data load, and store instructions.

3.2. Bioradar Multi target Vital Signs Detection Platform.

3.2.1. Composition and Detection Principle of Experimental Platform. Figure 3.2 shows the overall structure of the experimental platform, which mainly includes the biological radar sensor, radar baseband signal conditioning circuit, MSP430F 5529LaunchPad experimental board, and upper computer data processing system. Through the experimental platform, non-contact respiratory and heartbeat signals can be collected, processed, and analyzed. The experimental steps are as follows: One is that the biological radar sensor emits high-frequency continuous microwaves to the human body; The second is to use the radar baseband signal conditioning circuit to perform DC offset correction, filtering, and amplification processing on the signal output by the radar sensor, filter out noise in the signal, and preserve the effective frequency components of the

Table 3.1: Several Common SIMD Instructions

op	Output operands	Input operands
add	v0.8h,	v0.8h,v8.8h
sub	v0.8h,	v0.8h,v8.8h
mul	v0.8h,	v0.8h,v8.8h
mla	v0.8h,	v0.8h,v8.8h
1d4	{v0.8h,v1.8h,v2.8h,v3.8h}	[%0]
st4	[%2]	{v0.8h,v1.8h,v2.8h,v3.8h}

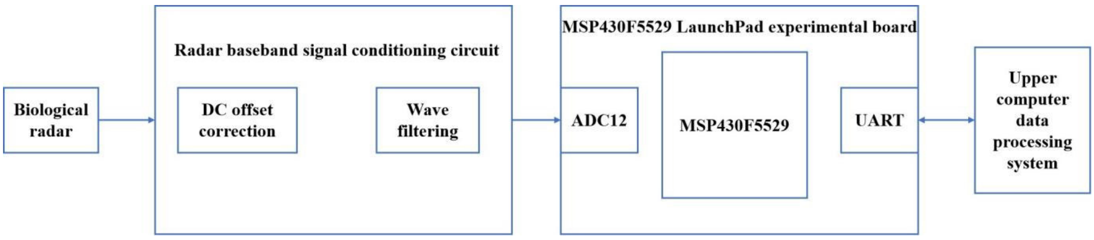

Fig. 3.2: Overall structure of experimental platform

body motion signal; The third is to use the MSP430F5529 LaunchPad experimental board to collect and process the body motion signals output by the conditioning circuit, and transmit the processing results to the upper computer data processing system through a serial communication interface. The upper computer data processing system, often developed using MATLAB or LabVIEW, serves to process and analyze collected body motion signals. Its primary function includes extracting respiratory and heartbeat signals from the gathered data.

The front-end antenna of the continuous wave biological radar emits high-frequency continuous microwaves to the human body [13]. When the microwave irradiates the human body, the chest wall micro motion caused by respiratory movement and heart beat modulates the reflected echo signal in phase and frequency. After signal amplification, filtering and other processing, respiratory, heartbeat and other signals are extracted from the echo signal.

Microwave biological radar provides a non-contact and penetrating means of detecting biological motion information [14]. Among them, continuous wave radar uses the Doppler effect of electromagnetic waves to detect the displacement, velocity and other motion information of targets, with a simple structure and easy processing of received signals. Continuous wave biological radar emits continuous electromagnetic waves towards human targets, while receiving echoes reflected from the human body surface. By changing the frequency or phase of the echo signal, micro motion information on the body surface is extracted and calculated [15]. Due to the higher frequency of electromagnetic waves, the stronger the reflection at the interface between human skin and air, but at the same time, the reflection on obstacles such as clothing and bedding will also increase. In order to achieve higher detection accuracy and reduce the power of clutter, biological radar usually uses a carrier frequency of (2.4-60) GHz. In terms of physiology, the micro motion information on the human body surface can reflect certain physiological activities of the human body, such as detecting chest wall vibrations to obtain heart and lung activity related information such as breathing and heartbeat. The amplitude of surface mechanical vibration caused by normal human heartbeat movement is about 0.6 mm; The amplitude generated by respiration is around (4-12) mm. If a 10GHz frequency band biological radar is used to detect chest wall motion, every 1mm displacement of the chest wall will cause a maximum phase shift of 25.2. Therefore, theoretically, although the amplitude of chest wall vibration is small, the phase shift reflected in the radar baseband can still be distinguished when the carrier frequency is high enough [16].

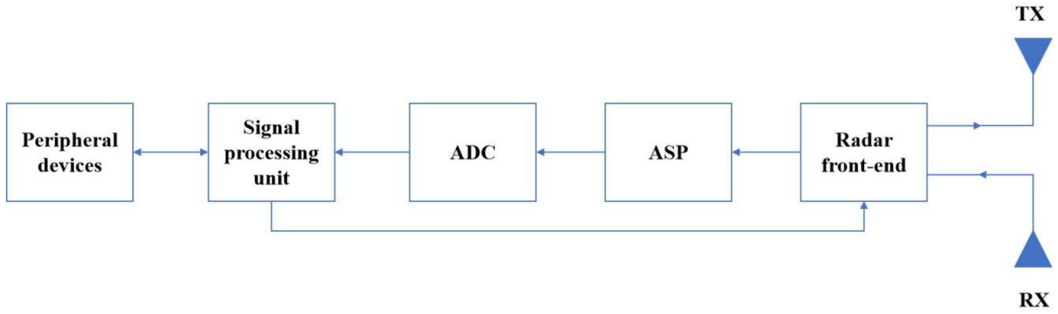

Fig. 3.3: System Principle Block Diagram

The sine signal generated by the oscillator is represented as the radar transmission signal by formula 3.1:

$$T(t) = A_T cos(2\pi f t + \phi(t)) \tag{3.1}$$

The distance traveled by the transmitted signal to become the received signal is represented by formula 3.2:

$$R(t) = A_R cos[2\pi f t - \frac{4\pi d_0}{\lambda} = \frac{4\pi x(t-d(t)/c)}{\lambda} + \phi(t - \frac{2d_0}{c} - \frac{2x(t-d(t)/c)}{c} + \theta_0)] \tag{3.2}$$

The received signal is mixed with the signal in the radar receiver and low-pass filtered to obtain the baseband signal output, which is expressed as formula 3.3:

$$B(t) \approx A_B cos[(\frac{4\pi d_0}{\lambda} - \theta_0) + \phi(t) - \phi(t - \frac{2d_0}{c}) + \frac{4\pi x(t)}{\lambda}] \approx A_B cos[\varphi(d_0) + \frac{4\pi x(t)}{\lambda}] \tag{3.3}$$

3.2.2. System Hardware Design. When extracting the target's cardiopulmonary activity information from the received signal of the biological radar, the useful signal frequency is between (0.2 10) Hz and the amplitude is weak. The front-end circuit of the continuous wave radar requires a sufficiently high signal-to-noise ratio, and performs DC offset correction, signal amplification, analog bandpass filtering, and analog-to-digital conversion on the down converted received signal. Then, various physiological parameter detection and extraction algorithms are used to obtain the required information. The system diagram of the vital sign detection device is shown in Figure 3.3.

The radar front-end uses equal amplitude sine wave transmission, zero intermediate frequency receiver structure, and the radar carrier operates in the frequency band of 10 GHz; The antenna used for transmission and reception is a microstrip antenna to save space; Analog signal processing circuit (ASP) is used to amplify, filter and level shift signals. The analog filter uses a lower cutoff frequency of 0.1 Hz to suppress DC offset and low-frequency noise, and an upper cutoff frequency of 100 Hz to prevent signal sampling aliasing; The analog-to-digital conversion uses a 16 bit high-precision ADC; The signal processing unit is an embedded platform used for digital signal processing and regulating the work of various interconnected units; At the same time, the signal processing unit is connected to various peripheral devices to achieve the output of vital sign results, including display, alarm, data storage, and communication with computers; On the other hand, it realizes user control signal input, including functions such as controlling the operation of the system, setting various system parameters, etc. [17].

3.3. Experimental research.

3.3.1. Detection experiment using analog signal source. The individual differences in human cardiovascular activity and the resulting surface vibrations vary with changes in body condition, posture, and environment. Therefore, in order to conduct quantitative, controllable, and reproducible experimental research, the author first used a device that simulates human chest wall vibration as the detection target [18].

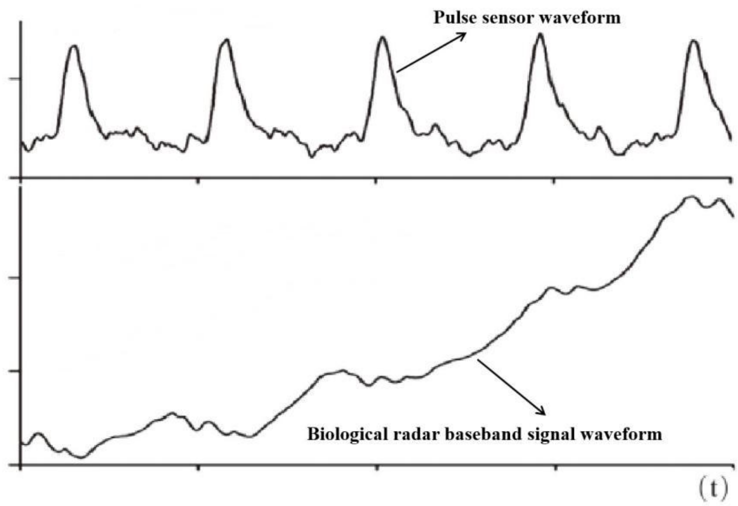

Fig. 3.4: Pulse sensor waveform and biological radar baseband signal waveform

The device reads in typical mechanical vibration waveform files generated by the computer on the surface of the human chest wall, converts them into vibration signals, and outputs them to simulate human cardiopulmonary activity. The vibration surface of the analog signal source device is covered with a metal layer to obtain strong electromagnetic wave reflection ability.

Referring to the physiological signal surface vibration parameters mentioned above, configure the analog signal source to send a sine wave with a vibration amplitude of 4 mm and a frequency of 1 Hz, and place it 50 cm away from the biological radar to obtain the baseband signal spectrum of the receiver. Both noise and useful signal energy are concentrated in the low frequency range, with a baseband signal amplitude of 10.64 dBmV at 1 Hz. Due to the nonlinearity of the demodulation system, harmonics appear in the spectrum. The system base noise is -94.64 dBmV, and the baseband signal signal-to-noise ratio is 98.36 dB.

For the detection of vital signs of real human targets, experimental results vary with factors such as the actual environment and subject status. The author fixed the distance between a single stationary human target and the biological radar at 30 cm, and used a pulse sensor to synchronously collect the pulse signal of the human target as a reference signal for heart rate recognition results, for comparative analysis. Figure 3.4 shows the comparison between the waveform of the pulse sensor and the waveform of the biological radar baseband signal, where the heartbeat signal of the biological radar baseband signal is superimposed with the larger amplitude respiratory signal. As shown in the figure, the biological radar simultaneously detects respiratory and heartbeat related information of human targets, where the heartbeat signal corresponds well with the reference signal; In addition, when using biological radar for the analysis and extraction of heartbeat signals, due to the strong baseline drift interference provided by respiratory signals, it is not easy to directly analyze using conventional heart rate measurement methods such as peak seeking or zero crossing detection in the time domain.

4. Results Analysis. In order to evaluate the accuracy of heart rate recognition using the aforementioned vital sign detection algorithm, an experiment was conducted to collect a signal containing changes in the target human heart rate, as shown in Figure 5, to obtain the heart rate recognition results of the biological radar and reference signal after passing through the detection algorithm. When the difference between the results obtained by the biological radar and the reference signal is less than 2%, it is considered that the biological radar recognition is correct. The calculation shows that for the data in Figure 4.1, the recognition accuracy of the biological radar is 96.1%. It can be seen from this that the effectiveness of the biological radar detection algorithm, in addition, the detection algorithm can quickly track and smoothly transition to changes in heart rate. Through experiments, it has been found that the biological radar detection system can effectively detect the respiratory and heart rate of the target in real time within a range of 90 cm from the target. When the

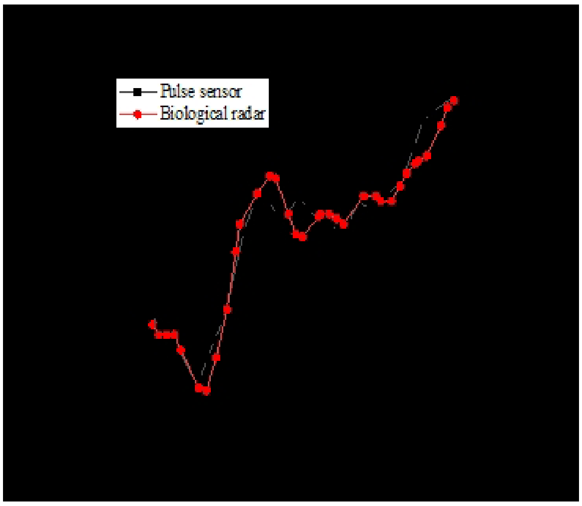

Fig. 4.1: Heart rate extraction results

distance is farther, due to the influence of noise in the actual environment, the noise power will be equivalent to the peak power of the heartbeat, causing fluctuations in the heart rate detection results and affecting the accuracy of heart rate recognition.

5. Conclusion. The current biological radar detection device needs to consider how to automatically adjust the phase shift constant in hardware, so that the demodulation point is near the optimal demodulation point to improve detection accuracy; In terms of algorithms, the tracking algorithm used can eliminate sudden strong interference signals but lacks sufficient suppression of continuous clutter interference, resulting in a decrease in the accuracy of actual human detection and recognition. Further research should not be limited to finding the highest spectral peak, but should attempt to use other in-depth spectral analysis algorithms. In order to address the increasing demand for vital sign detection, the author proposes a multi-target vital sign detection research that combines biological radar and convolutional neural network. The effectiveness of the method is verified through experiments.

Acknowledgement Fund project: Henan Province Science and Technology Research Project (232102210195)

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Edited by: Hailong Li
Special issue on: Deep Learning in Healthcare
Received: Jul 22, 2024
Accepted: Aug 27, 2024