A REAL-TIME RESPIRATORY PATTERN CLASSIFICATION SYSTEM BASED ON EDGE COMPUTING FOR 60 GHZ MMWAVE RADAR

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ABSTRACT

Millimeter wave radar can be used for monitoring vital signs of personnel under non-contact conditions, and has stronger anti-interference and privacy capabilities. This article proposes a method based on the 60GHz FMCW millimeter wave radar system, which utilizes an improved ResNet50 network to classify six respiratory patterns of the human body (Eupnea, Tachypnea, Bradypnea, Biots, Cheyne Stokes, and Central Apnea) based on the echo waveform. This method demonstrates high accuracy and robustness in respiratory classification in complex environments; In addition, we also use the network reasoning optimization method to deploy it on edge computing devices; According to the experiment, when the refresh rate of edge computing system is 20Hz, the recognition accuracy of this method is up to 95.25%, which verifies the accuracy and robustness of this method.

***Keywords*-** mmWave, vital sign, edge computing, ResNet, real-time

1. INTRODUCTION

In recent years, living standards have gradually improved, and more and more people have begun to pay attention to their physical health. Human respiration is a relatively easy to obtain and extremely important vital sign, which can greatly reflect whether the human body is healthy. Traditional respiratory measurement instruments are mostly wearable, and long-term use will bring great inconvenience to users. Millimeter wave radar can detect chest displacement caused by human respiration by emitting electromagnetic waves, so we can judge the respiratory status of the human body based on the echo and achieve non-contact vital sign monitoring.

With the development of millimeter wave radar technology, there is an increasing amount of research using it for non-contact vital sign detection[1, 2] and respiratory status judgment. In 2013, Nijsure et al. [3] classified respiratory patterns by monitoring respiratory changes with an accuracy rate of 81%. In 2016, Rahman et al. [4] extracted memory density features from respiratory waveforms and classified the respiratory patterns of three experimental subjects. However, these traditional classification methods are all based on artificial features and cannot exhibit the same robustness in complex environments. Therefore, some researchers have begun to apply deep learning methods to respiratory signal classification. In 2020, the Seong Hoon Kim team[5] achieved classification of five respiratory patterns using a one-dimensional convolutional neural network, with an average accuracy of 95.8%.

By performing clutter filtering, target localization, phase unwrapping, signal separation, and frequency estimation on the echo signal of millimeter wave radar, we can obtain the breathing waveform of the monitoring target, which can further classify breathing patterns and determine abnormal breathing. When classifying breathing patterns, we face three challenges. Firstly, although there are many research methods that can achieve high accuracy classification, these methods do not use a large number of samples to train the network and evaluate the robustness of experimental methods. Secondly, in breathing patterns, except for Eupnea, all belong to abnormal breathing patterns. Therefore, when simulating abnormal breathing patterns, we cannot use traditional single harmonic simulation models or periodic pulse simulation models. The final challenge is to achieve real-time monitoring of vital signs, which means that we need to collect, analyze, and store data frame by frame. If the model we use is redundant or the algorithm is complex, it will be difficult to monitor in real time due to the limitations of edge device computing power. To address the aforementioned issues, this paper proposes a respiratory pattern classification method based on an improved ResNet50 network. This method can classify six breathing patterns in a real-time edge computing device with a refresh rate of 20Hz per frame, and the recognition accuracy rate is as high as 95.25%. In random populations and complex environments, the average recognition accuracy rate is 88.31%, indicating that this method has high accuracy and robustness.

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2. METHOD

Fig. 1. shows the overall framework of the REAL-TIME RESPIRATORY PATTERN CLASSIFICATION SYSTEM. The system consists of three parts: radar device, data transmission device DCA1000, and real-time signal edge processing system.

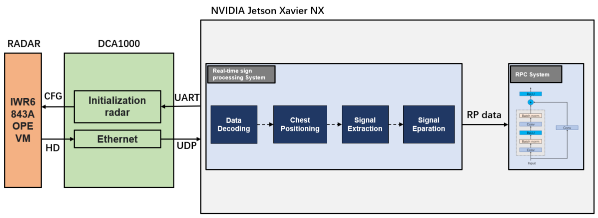

Fig. 1. Processing flow of system

The system is a radar signal processing platform that utilizes NVIDIA Jetson Xavier NX for real-time signal processing. It acquires signals from the IWR6843AOPEVM radar module via the DCA1000 acquisition module and transmits the signals to the Jetson Xavier NX over Ethernet using the UDP protocol. There, the data is decoded and chest localized to extract relevant signals. Subsequently, the extracted phase signal is decomposed by VMD to obtain the time domain diagram of the respiratory signal and forwarded to the Respiratory Pattern Classification (RPC) system based on ResNet50 for processing, thereby achieving classification and identification of respiratory waveforms and achieving real-time monitoring of the target's respiratory pattern.

2.1. MIMO Radar System

IWR6843AOPEVM is a radar system with a main frequency of 60GHz and an operating bandwidth of 4GHz. It has three transmit antennas and four receive antennas that can simultaneously measure azimuth and elevation energy at low range resolution. IWR6843AOPEVM can transmit LVDS radar data packets through the HD interface, which can improve real-time data transmission efficiency. The radar is shown in Fig. 2.

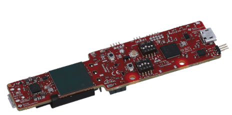

Fig. 2. IWR6843AOPEVM

2.2. Data Transmission System

The DCA1000 Evaluation Module (EVM) is designed for real-time data capture and streaming from Texas Instruments' AWR and IWR radar sensor EVMs. It can handle two and four lanes of LVDS traffic for efficient data transfer. Data captured by the DCA1000 can be transmitted to edge computing platforms via a high-speed 1 Gbps Ethernet connection. This setup enables the capture and visualization of radar data and facilitates further signal processing and data inference efforts on the edge computing platform, it is shown in Fig. 3.

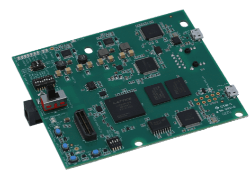

Fig. 3. DCA1000EVM

2.3. Edge Computing System

NVIDIA NX mobile development platform (NVIDIA Jetson Xavier NX) is the latest high-tech artificial intelligence AI edge device launched by NVIDIA in 2020. The purpose of this product is to promote the marginalization of artificial intelligence algorithms and eliminate over-reliance on the network environment. The NVIDIA NX mobile development platform is a platform that provides excellent computing speed and energy efficiency for deep learning algorithms. It is equipped with NVIDIA's dedicated deep learning GPU, including up to 8 GB of memory, 59.7GB/s memory bandwidth, and a variety of Standard hardware connection interface can be easily integrated with products of different types and shapes. The product appearance is shown in Fig. 4.

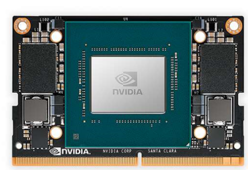

Fig. 4. NVIDIA Jetson Xavier NX

In addition to the advantages of the above-mentioned product hardware, unlike other edge computing devices, the biggest advantage of NVIDIA's high-performance edge AI devices is that NVIDIA's GPU can be used to accelerate the inference process of the entire algorithm model. In this article we implement accelerated optimization of our model through the TensorRT framework.

2.4. Variable Respiratory Simulation Model

Breathing pattern is an indicator of the human breathing mechanism, which is affected by elements such as respiratory rate, depth, rhythm and body movement. For Normal breathing (called Eupnea) is characterized by an average respiratory rate of 0.2Hz-0.33Hz, maintaining a standard depth and rhythm. On the other hand, deviations in any of these aspects can mean abnormal breathing. These irregular patterns often indicate physiological problems, emotional states, or stress levels and are valuable for clinical evaluation. Respiratory conditions and typical signs of the six modes, namely Eupnea, Bradypnea[6], Tachypnea, Biot, Cheyne-Stokes[7], and Central Apnea, are listed here, while their representative waveforms are depicted in the Fig. 5.

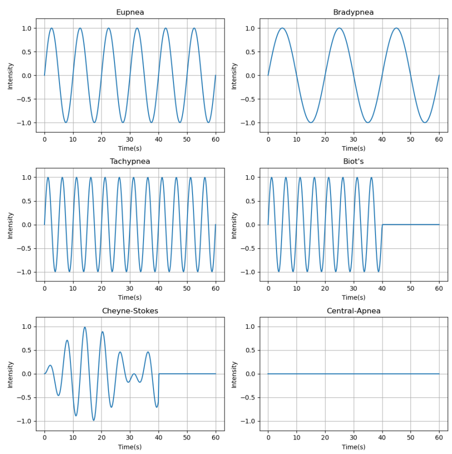

Fig. 5. Waveforms Of Six Respiratory Patterns

Respiratory movement is a cyclic movement, which consists of two processes: inhalation and exhalation, which are reflected in the rise and fall of the waveform respectively. Typically, non-contact measured respiratory signals can be approximated as sinusoidal waves. The actual measured respiratory signal, especially the respiratory signal measured by non-contact sensors such as radar equipment, is easily biased due to environmental changes, causing the respiratory signal amplitude and frequency to fluctuate within a certain range. In addition, due to the influence of body movement during measurement, the signal is prone to longitudinal and tilt deviations. Taking into account the above possible deviations, the actual measured respiratory signal can be defined as[1]

$$S_{breath}(t) = Asin(wt) + Bx + C \tag{1}$$

In the formula, t is a variable time, used to represent the change of signals belonging to the same breathing pattern; A is the breathing depth; W is the breathing frequency; B and C are the longitudinal deviation and tilt deviation of the breathing signal respectively. For training data, except for Eupnea which contains real respiratory waveform and simulation waveform, other respiratory patterns use a variable amplitude and frequency respiratory simulation model (VRSM), The simulation results are shown in Fig. 6.

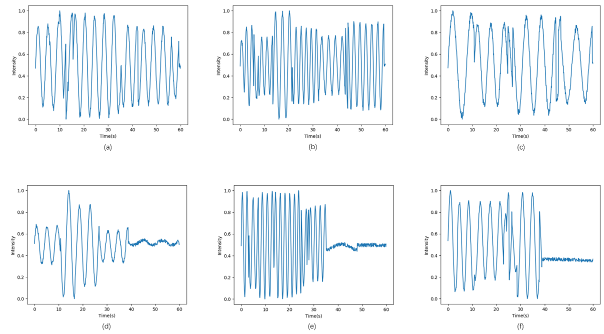

Fig. 6. The simulated signals generated by VRSM. (a) Eupnea (b) Tachypnea (c) Bradypnea (d) Biots signal (e) Cheyne-Stokes (f) Central-Apnea

2.5. Respiratory Pattern Classification System

ResNet50 is divided into 5 stages. The structure of Stage 0 is relatively simple and can be regarded as preprocessing of INPUT. The last four Stages are composed of Bottlenecks and have similar structures.

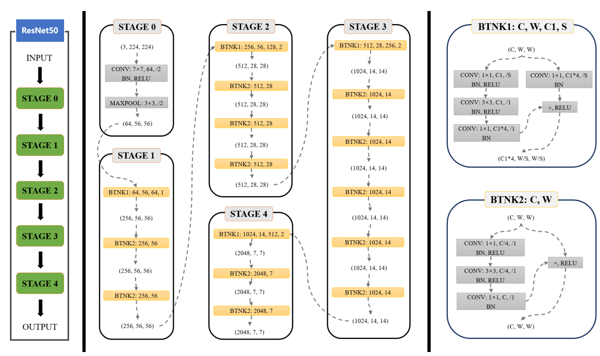

Fig. 7. ResNet50 overall structure

(3,224,224) refers to the number of channels (channel), height (height) and width (width) of the input INPUT, that is (C, H, W). Since the input height and width are equal, they are represented by (C, W, W). The first layer in this stage includes 3 sequential operations, where CONV is the abbreviation of convolution, 7×7 refers to the size of the convolution kernel, and 64 refers to the number of convolution kernels (that is, the number of channels output by the convolution layer) . BN is the abbreviation of Batch Normalization, which is often referred to as the BN layer. RELU refers to the ReLU activation function. The second layer in this stage is MAXPOOL, which is the maximum pooling layer. Its kernel size is 3×3 and the step size is 2. (64,56,56) is the number of channels, height and width of the stage output, where 64 is equal to the number of convolution kernels in the first convolutional layer of the stage. Generally speaking, the respiratory time domain waveform is passed through the convolution layer, BN layer, ReLU activation function, MaxPooling layer and four Stages according to the input image of (3,224,224), and the output feature map with the shape of (2048,7,7) is obtained, then the obtained output will be flattened and passed through the fully connected layer to obtain the classification result.

3. EXPERIMENTATION AND EVALUATION

When collecting real Eupnea samples, the working bandwidth of the mmWave radar system is set to 4 GHz, and 20 frames are collected per second, each frame contains 126 Chirps, and each Chirp samples 16 points. A training sample is constituted by breathing waveform pictures with intervals of 20 frames. In the way of mixing simulation samples and real samples, there are a total of 3600 samples in Eupnea. For the other five kinds of abnormal respiratory pattern samples, a total of 1000 samples were generated for each pattern. Finally, the data set contains 8600 samples to complete the training, among which the samples are divided into training set, verification set and test set according to the ratio of 6:2:2.

In the training process, set the learning rate to 0.002, the loss function to the cross-entropy loss, and the batch size to 32, and train network about 50 epochs in total. By observing the loss curve and accuracy curve during the experiment, it can be found that at about 30 epochs, the loss drops below 0.1 and becomes stable. At last it achieves the accuracy of 95.25% on the test set.The Confusion matrix of ResNet50 method is shown in Fig. 8.

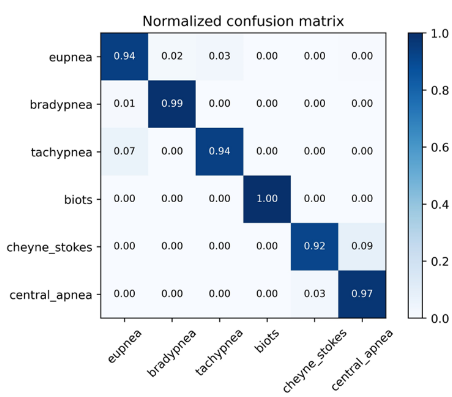

Fig. 8. Result of ResNet50

In order to further verify that the system proposed in this paper can be applied to real complex environments, the whole model is pruned and deployed on an edge computing device. The robustness of the proposed method is verified by real-time flow data collected by mmWave radar. The environment is more complex, including the collection of volunteers' breathing waveforms in outdoor, office, teaching building and other places, and the 600 samples generated in these complex scenes are saved as a new test set called TEST SET 2. Based on these data sets, the proposed method is compared with the support vector machine model based on four artificial features. The accuracy of experimental results are given in Table 1.

Table 1. Experiment results.

Model	TEST SET 1	TEST SET 2
ResNet50	95.25%	88.31%
SVM	90.00%	74.67%

4. CONCLUSION

This paper proposes a method to classify breathing patterns based on the 60GHz FMCW millimeter wave radar system and the improved ResNet50 network, which is deployed on edge computing devices. Experiments show that when the refresh rate of the edge computing system is 20Hz, the classification accuracy of the method for six breathing patterns is as high as 95.25%, and 88.31% in random crowds and complex experimental environments. It proves that the performance of the method is better than the machine learning method based on artificial features, and it has the advantages of fast processing speed, edge deployment, real-time classification and high robustness.

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