ECG Monitoring System Integrated With IR-UWB Radar Based on CNN

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This work was supported in part by the National Science Foundation of China under Grant 61601046, in part by the EU FP7IRSES Mobile
Cloud Project under Grant 612212, in part by the 111 Project under Grant B08004.

ABSTRACT In the demand for protecting the increasing aged groups from heart attacks, the improvement
of the mobile electrocardiogram (ECG) monitoring systems becomes signi_cant. The limitations of the
arrhythmia classi_cation in these systems are the lack of ability to cope with motion state and the low
accuracy in new users' data. This paper proposes a system which applies the impulse radio ultra wideband
radar data as additional information to assist the arrhythmia classi_cation of ECG recordings in the slight
motion state. Besides, this proposed system employs a cascade convolutional neural network to achieve an
integrated analysis of ECG recordings and radar data. The experiments are implemented in the Caffe platform
and the result reaches an accuracy of 88.89% in the slight motion state. It turns out that this proposed system
keeps a stable accuracy of classi_cation for normal and abnormal heartbeats in the slight motion state.
INDEX TERMS Electrocardiography, ultra wideband radar, neural networks.

I. INTRODUCTION

Heart disease is the leading cause of death in chronic diseases.
There is a high incidence of heart disease among middle-aged
and elderly groups. As the aging population keeps in growth,
it becomes signi_cant to protect aging groups from heart
attacks. The sudden onset of heart attacks aggravates the dif-
_culty of treatment. The dynamic electrocardiogram (ECG)
mornitoring system is an effective means to prevent heart
diseases. This monitoring system tracks the activity of hearts
in the ECG for a long time and therefore is able to capture
incidental arrhythmias and sudden cardiac diseases. Besides
such monitoring system ful_lls the increasing demand for

ubiquitous heart healthcare by the usage of the mobile Internet of Things (IoT).

Under the architecture of the IoT, the traditional ECG monitoring system [7] consists of the sensing layer, the network layer and the application layer. In the sensing layer, diverse wearable medical devices are connected by wireless data communication technology to form a wireless sensor network [18]. The application layer serves as an analyzer for the detection of arrhythmias by applying various algorithms. Existing traditional methods for the classi_cation of arrhythmias in the ECG include the wavelet transform [15], the frequency analysis [19], the support vector machines [16] and the mixture-of-experts method [17]. Speci_cally, the wavelet transform method is used in the ECG denoising by setting special thresholds to the third layer of the wavelet decomposition. Due to the correlation between the peak of the wavelet decomposition and the peak of the R wave in ECG recordings, the wavelet transform method makes contributions as well in locating the R wave. In one word, these traditional algorithms depend on the special features extracted from the waveform of ECG. Besides they are restricted to speci_c thresholds which usually vary in different datasets. Thus the performance of these approaches not only is subject to the interference of noises but also decreases in new datasets.

So as to accurately classify new patients' ECG recordings, approaches based on neural networks (NNs) are applied. In these approaches, NNs serve as a common classi_er for arrhythmias [1], [2], a detector for heartbeat recognition [3], or an extractor for not predesigned features before classi_cations [4]. Due to the ability to automatically acquire features from ECG recordings, NNs-based methods are deployed in a hybrid mobile-cloud solution [5] for ECG monitoring. In such a hybrid mobile-cloud solution, NNs periodically learn new features from speci_c users' ECG recordings in the cloud so that the NNs can be more _tting to speci_c users. The NNs trained for speci_c users take the individual differences into account and therefore improve the accuracy of ECG annotation dramatically. So far many efforts have been made in proposing patient-speci_c methods for arrhythmia

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classi_cation in the dynamic electrocardiogram (ECG) monitoring systems [20].

The convolutional neural network (CNN) is useful in one dimensional data as well as two dimensional data. The research in employing the CNN to the ECG [4] not only veri_es the validity of CNNs in the application of one dimensional signals but also enables the CNN to adapt to different resolution. There exists another method [13] to apply the CNNs to ECG recordings by combining eight leads of ECG recordings into a two dimensional matrix. This method puts forward a CNN named LCNN (leads convolutional neural network). In the LCNN, the sliding range of the convolutional kernels is restricted according to the rule that one _lter cannot be shared by different leads of ECG recordings. By this adjustment, this method increases the accuracy of the ECG classi_cation greatly. However the application of this method is limited by the requirement of multi-lead inputs.

The reason why the ECG monitoring system reduces the death rate of elderly heart diseases lies in its ability to dynamically record ECG signals for a long time. Some rare phenomena of arrhythmia are captured by the ECG monitoring system. However the dynamic ECG recordings also suffer from the motion artifacts generated by the muscular activity. Although some algorithms, such as the adaptive _ltering method [21] and the blind source separation method [22], have been proposed to suppress the motion artifacts, it is still dif_cult to clearly remove the motion artifacts. In the demand for detecting arrhythmia in the motion state, the Impulse Radio UltraWideband (IR-UWB) radar is employed in the monitoring system as an auxiliary measurement. Some papers [29] are dedicated to combine the ECG platform with the IR-UWB radar for the arrhythmia diagnosis. However the corresponding research works on the simultaneous acquisition of multi signals rather than how the IR-UWB radar contributes to cardiovascular diagnostics. The IR-UWB radar does not only provide a non-contact detection but also avoids the electrical interference. The clinical use of the IR-UWB radar includes measurements in the heart rate, the respiration rate and the blood pressure. It has been proven that deep neural networks designed for analyzing the integrative data from multi-platforms achieve better performance [6].

This paper proposes a monitoring system for analyzing data synthesized by ECG recordings and IR-UWB signals. In addition to an acquisition module for multi biological data, this system is designed on a cascade CNNs module to distinguish normal and abnormal heartbeats. The acquisition module handles the synchronizing problem by making use of timestamps and features of ECG signals and heartbeat

signals acquired from the radar signals. The _rst stage of the cascade CNN module extracts un-predesigned features from ECG data and radar data separately by different CNNs, and the second stage of the cascade CNN module deploys these integrated features to tag heartbeats by normal labels or abnormal labels. Given that ECG data and heartbeat data extracted from radar data are one dimensional data, convolutional kernels in the _rst stage of cascade CNNs are one dimensional correspondingly. Convolutional kernels in the second stage are bidimensional. The reason why the two isolated CNNs are devised in the _rst stage is due to the different data structures of ECG data and heartbeat data determined by sampling rates of acquisition platforms. The proposed system is supposed to achieve good accuracy of arrhythmia classi_cation in some motion states, taking the driving case or bicycling indoor case for instance.

The contribution of this proposed system is dedicated to two improvements of traditional monitoring systems [7]. (1) One improvement is made to achieve stable accuracy of classi_cation in dynamic monitoring by the assistant measurement of the IR-UWB radar. (2) The proposed system makes the _rst effort to combine the cascade CNNs with the integrated analysis of ECG recordings and the IR-UWB data. (3) Based on the above two points an ECG monitoring system is built up.

The rest of this paper is arranged in the following architectures. Section 2 describes the architecture of the proposed system. Methods of radar signal processing for separating heartbeats from respirations and the structure and training methods of the cascade CNNs are detailed in Section 3. Both experimental settings and results are displayed in Section 4. Section 5 concludes this paper in summary.

II. SYSTEM ARCHITECTURE

As the architecture elaborated in Figure 1 shows, the proposed monitoring system contains two signi_cant parts, the acquisition module and the cascade CNNs module.

A. ACQUISITION MODULE

The ECG signal acquisition platform is built on the ECG sensor chip BMD101 and additional Bluetooth module. Although the BMD101 sensor chip only acquires one lead of ECG signals, it is enough for the classi_cation of normal and abnormal heartbeats. The NVA-R661 radar module is employed as the acquisition module for heartbeats signals. Given the fact that the transmitting power of this radar is lower than one tenth of the transmitting power of WiFi, it will not bring severe harm to human body. The sampling rate

of the ECG sensor is 512 Hz while the heartbeats sampling rate of the radar module is merely 38 Hz when the coverage radius of radar is set to 2 meters. Because this difference in sampling rates, the length of ECG recordings differs from that of the heartbeat data and therefore the two CNNs are designed respectively for them.

B. CASCADE CNNS MODULE

Although both ECG signals and heartbeats signals from radar data describe the same heartbeat, they possess different features which should be learned through independent CNNs. Speci_cally, ECG recordings carry the bio-electrical features of heartbeats, for instance, the intervals between ventricular depolarization and repolarization. The radar data carry physical features of heartbeats, such as the amplitude of the heart movement and the intervals between heart beats.

FIGURE 1. Architecture of proposed monitoring system.

These features complement each other which is meaningful in situation that one of the ECG data and the radar data is badly interfered. After the features of ECG signals and heartbeat signals are captured separately by the two isolated CNNs, another CNN integrates these features together and then learns to increase the accuracy of the classi_cation. The _nal part of this system comes down to the development of an application for real-time computing with well-trained CNNs and dynamically displaying the results of the detection.

III. METHODS

A. UWB RADAR SIGNAL PROCESSING

Great progress has been made in the application of IR-UWB radar in the vital sign measurements, such as detecting the respiratory rate and the heart rate from multi-targets [23] or behind walls [24]. Due to the fact that heartbeat signals suffer from the interference of respiration signals and their harmonics, it is primary to separate the heartbeat signal from the respiration signal. The algorithms which have emerged as the demand requires include the approximation method by linear function or parabolic function [25], the canceling _lter for breathing harmonics [26], the improved ensemble empirical mode decomposition [27], etc.

The IR-UWB radar has high spatial resolution and strong penetrability, which make it suitable for detecting the moving chest cavity. For the radar part of the synchronous acquisition system, the received signals are stored in a matrix. So as to get the heartbeat signals, signal processing methods are applied to the received signals by the radar.

In the received signal matrix, the time along each row is called fast time _ , while the time along each column is the slow time *t*. Each row shows the changing sampled signals, while each column represents a different position away from the radar. Received signals contain the Direct Current (DC)

FIGURE 2. Procedure of radar signal processing.

component, which is static, and does not change with the changing time *t*. So the DC component is calculated by just taking the average by rows in the signal matrix, and then is deducted by the raw signals [8]. Actually, the parameter setting of the radar chip controls the frequency range of the received signals. Using a band pass _lter is helpful to further get the target signal in the known frequency range.

Principal Component Analysis (PCA) is usually used in extracting the main characteristics component of data [9]. Because the clutter signal is re_ected from static background environment, the clutter signal changes little on the same time point, i.e., the same column of the radar matrix. The energy of clutters is usually larger than the energy of re_ected signals from the moving chest cavity. By Singular Value Decomposition (SVD), shown in formula (1), the re_ected signal matrix is decomposed [10].

$$R \text{ D } USV^T \quad (1)$$

In this formula, S is composed by the non-negative singular values of R. All elements in S are zero except for the elements on diagonal, and the diagonal elements are the non-negative singular value arrayed in descending order, which could be represented by $S_{1;1} > S_{2;2} > S_{N;N}$. Since the components sequentially array with the amount of energy in order, the energy of signal is mainly distributed in the _rst few singular values. So for a speci_c energy percentage, the number of

FIGURE 3. Raw radar data and filtered radar data by the PCA filtering.
(a) Raw radar data; (b) Filtered radar data.

components is ensured. Set these singular values to be zero, and then the corresponding energy is removed. After the SVD and the reconstruction, the main energy of the clutter signals is removed, and the reconstructed matrix would have a higher signal noise ratio. Figure 3 shows the radar signals after PCA _ltering.

In the signal matrix, all columns correspond to different positions. Since the environment is static, the columns of moving chest cavity correspond to a maximum variance. So calculate the variance of each column of the signal matrix, and _nd the maximum variance peak. Then the column of the moving chest cavity could be detected [11].

After ensuring the location of the moving chest cavity, the heartbeat signals should be separated from the mixed signals, which are composed by respiration signals and heartbeat signals. Empirical Mode Decomposition (EMD) decomposes the signal into a series of Intrinsic Mode Functions (IMF), according to the character of the signal itself. Each IMF shows the oscillation character of signal in a different frequency scale. Ensemble Empirical Mode Decomposition (EEMD) is an improved algorithm based on EMD, with random white noises added to the original signals, and then, to process the signals by EMD for several times, all the decomposed IMFs are averaged to be the _nal IMF, as the basis function of original signals [12].

Sort the IMF components in the order from high frequency to low frequency, of which the lower-order IMF represents faster oscillation and higher-order IMF represents slower oscillation. Calculate the energy on the whole frequency band E_{Total} and the energy on the heartbeat frequency band ([0.8Hz, 2.5Hz]) E_{Heart} for each IMF respectively. According to the energy ratio of E_{Heart} to E_{Total} , the certain IMF with the maximum energy ratio could be selected to reconstruct the heartbeats signal. Figure 4 illustrates the heartbeats signal extracted by the EEMD method.

B. TIME ALIGNMENT

As the ECG signals and radar signals are obtained from distributed platforms, it is the primary work to align the time of these two signals. Even though the BMD101 sensor and the radar module start simultaneously, it costs them time

FIGURE 4. Heartbeats signal extracted by the EEMD method.

FIGURE 5. Time alignment in resting state. The R wave is marked in this figure.

differently to set up before working. Thus, in this sensor network, the receipt time marked with timestamp is chosen as the standards for time alignment. Figures 5 and 6 show the result of synchronization that the peak of heartbeat signals corresponds to the R wave in the ECG signals. One heartbeat in ECG waveform consists of _ve waves, among which the R wave is the highest one.

The upper line in Figure 5 is the ECG signal and the lower line is the heartbeat signal from radar signals which is magni_ed one thousand times. The positive part of the vertical axis is in mV unit and the negative part of the vertical axis is in mm unit.

C. IMBALANCED DATASETS PROCESSING

Usually the normal heartbeats exceed the abnormal heartbeats greatly in quantity, which reveals the imbalance of ECG datasets and the radar datasets. Subsequently the accuracy of

majority class is greater than that of minority class. Two kinds of methods have been proposed to handle the imbalance of datasets in order to suppress the in_uence of majority class to the classi_cation accuracy. One is to increase the minority or decrease the majority on the datasets sides, while the other one is to add weights to the classi_er. According to the result in [13], the over-sampling method performs better than the weighted classi_er method in the use of the CNNs.

FIGURE 6. Time alignment in motion state.

As to the periodic signal, such as the ECG signals or the heartbeats signals, one over-sampling method increases the number of samples by moving the starting points of samples in a period. Besides, adding noises to the ECG signals contributes to a higher accuracy of classi_cation in CNNs. These added noises are made similar to the baseline drift and the power-line interference obeying a rule that these noises can be removed. These two methods are applied in the proposed system.

FIGURE 7. Structure of cascade CNNs.

D. CNN DESIGNED FOR INTEGRATED ANALYSIS

The _owchart depicted in Figure 7 shows the process of integrated analysis. The _rst stage of the cascade CNNs consists of two 1-D CNNs. Each of the 1-D CNNs designed for ECG signals and radar signals has three convolution layers and each convolution layer is followed by a pooling layer. After the responses of the _rst stage are generated, the extracted features are incorporated to the second stage to classify heartbeats into different categories. The second stage contains one traditional CNN with one convolution layer and two-layers multilayer perceptron (MLP).

Considering the fact that ECG signals and heartbeat signals from radar data are one dimensional signals, it is appropriate to adopt 1-D convolutional kernels. In this situation the convolutional layer could be seen as a group of common _lters for unique features. During the forward propagation, the computation of 1-D convolutional layers could be expressed as,

x_k^l

D f (b_k^l C

X$_{i=1}^{N}$

$conv(w_k^{l-1}; y_i^{l-1})$); (2)

where x_k^l

is the kth feature map in layer l, b^l_k is the bias of kth feature map in the layer l, y^{l-1}_i is the ith feature map in layer $l-1$. w^{l-1}_k is the kth convolutional kernel from all the features in layer $l-1$ to the kth feature map in layer l. N is the total number of features in layer $l-1$. Symbol *conv* stands for the vector convolution and $f(:)$ is the activation function. Each kernel corresponds to a 1-D _lter added to the signal to extract an un-predesigned feature, generating a feature map. Considering the condition that the size of radar recordings is not as great as the size of ECG recordings, the two CNNs in the _rst stage are devised with different structures. Despite that these two CNNs have the same numbers of convolutional layers and pooling layers, the number of neurons in each convolutional layer of CNN1 are not equal to that of CNN2. With the aim to inputting the output features of the _rst stage into the second stage, the two CNNs in the _rst stage are supposed to produce 1-D features in the same sizes. The input of the CNN in the second stage are 2-D matrix made up by the same-size features generated by the CNNs in the _rst stage. Then in the second stage 2-D kernels are applied to learn the correlation between the two 1-D features from each CNN in the _rst stage. By combining these two 1-D features together, the integrated analysis classi_es multi biomedical recordings into correct categories even when either ECG recordings or radar recordings are destroyed. The outcome is attributed to the underlying correlation between these two 1-D features.

The CNN devised for ECG signals in the _rst stage is supervised pre-trained by a large amount of ECG signals from the Chinese cardiovascular disease database (CCDD) which has totally one hundred and _fty thousand ECG recordings. Every ECG recording in CCDD lasts for 10 to 20 seconds and contains 12 leads of signals. After being balanced in amount of abnormal and normal recordings by over-sampling methods, these ECG recordings could be used as training datasets.

IV. EXPERIMENTS

The radar data and ECG data are acquired by radar module NVA-R661 and BMD101 sensor chip, as shown in Figure 8. The tester stays in front of the IR-UWB radar with electrodes attached on arms. Totally 20 volunteers have participated in the data collection. The over-sampling method mentioned in the imbalanced datasets processing part is adopted to manip-

ulate these data.
The experiment on training CNNs is set up in the caffe [14], a framework for deep learning. To be speci_c, the CNN for ECG signals in the _rst stage of the cascade CNNs uses three kernels whose size are 1 _ 201, 1 _ 141, and 1 _ 141, and each pooling layer computes average pooling with the region size 1 _ 2. Before imported into the CNN, it is necessary to resample the ECG signals from 512 Hz to 200 Hz reducing redundant points and then ECG signals are devided into pieces every 1200 sampling points. The CNN for radar signals in the _rst stage employs the kernels with size 1_61,

FIGURE 8. Acquisition experiment settings.
1 _ 31, and 1 _ 21, and average pooling with the region size 1_2. The inputs of the CNN for radar signals are 10-second long heartbeat signals with 360 sampling points. The hidden layer in two-layers MLP contains 50 neurons and the output layer has one neuron. The setting of cascade CNNs, such as the number of feature maps and numbers of hidden neurons in two-layers MLP, are designed according to the LCNN mentioned in the introduction part. To verify the accuracy of the proposed system for single label classi_cation of normal or abnormal heartbeats, the LCNN is reproduced as a comparison. Table 1 displays the results under different proportions of abnormal recordings to normal recordings, i.e., the ratio of abnormal in the Table 1. In the below are three indicator parameters, accuracy, speci_city (Sp) and sensitivity (Se), which are computed for the evaluation of performance.
_ Accuracy - The proportion of ECG recordings and radar recordings classi_ed into correct categories.
_ Speci_city - The proportion of normal ECG recordings and normal radar recordings categorized as normal recordings.
_ Sensitivity - The proportion of abnormal ECG recordings and abnormal radar recordings categorized as abnormal recordings.
In addition, the method of paper [15] are reproduced as a comparison. This paper makes use of a MLP which contains three hidden layers. Results of this reproduction, which are elaborated as MLP3 in Table 1, show apparently decrease in accuracy and speci_city against the result whose accuracy and speci_city are 100 % as paper [15] presents. Methods in papers [15]_[17], [19], [28] mentioned in the introduction part perform the feature extraction and classi_cation separately while our proposed system combines these two process together by employing convolutional neural networks.

As demonstrated in [13], combining features extraction process and classi_cation process together avoids the errors generated in features extraction process.

Evidently shown in Table 1, the LCNN fails to distinguish the abnormal ECG recordings. This result con_rms the disability of the LCNN to keep well performance consistently in

TABLE 1. Compared experiments between LCNN and the cascade CNNs.

FIGURE 9. Comparison of LCNN and cascade CNNs in receiver operating characteristics curve.

a new dataset and the speci_c training dataset. The accuracy of the cascade CNNs increases as the ratio of abnormal recordings to normal recordings varies. Eventhough the effect of the imbalance dataset exists, the cascade CNNs still generates a high accuracy in the classi_cation.

Figure 9 illustrates the comparison of the LCNN and cascade CNNs in receiver operating characteristics (ROC) curve. The horizontal axis is the value of 1 □ *Se* and the vertical axis is the value of *Sp*. The area under ROC curve (AUC) in Figure 9 is a judging parameter correlated to the performance of classi_er. As apparently shown in Figure 9, the cascade CNNs performs better with a greater value of AUC than that of the LCNN.

In the second experiment, the classi_cation performance of LCNN and cascade CNNs in motion state are compared to verify the stableness of the proposed cascade CNNs. During the data acquisition, the testers are _rst allowed to speak or move slightly. Testing experiments are set with the ratio of abnormal 10=7 and results are listed in the Figure 10. The accuracy of the cascade CNNs varies in a range from the value in static state, proving the stable performance in a slight motion state. On the contrary, the accuracy of the LCNN keeps similar to the proportion of normal recordings to all recordings. In other words, the performance of the LCNN decreases dramatically in dataset consisting of motionless

FIGURE 10. Compared experiments of LCNN and cascade CNNs in motion state.

data and moving data. The outcome of the cascade CNNs adds proofs to the result that the usage of the radar data assists the classi_cation of ECG recordings effectively.

V. CONCLUSION

This paper proposes an integrated monitoring system based on the combination of ECG signals and radar signals from multi platforms. By applying a cascade CNN, this monitoring system extracts and combines features from ECG signals and radar signals for the comprehensive analysis. Due to the proposed cascade CNNs trained for integrated analysis of ECG

data and radar data, the proposed system is able to achieve stable performance in the slight motion state and _t to the individual differences, offering a personalized detecting service. Through the comparison experiment, it has been turned out that the proposed system has a better accuracy 91.31% in resting station on our collected dataset. Even in the slight motion state the cascade CNNs has an accuracy 88.89% on our collected dataset.

The future work is to modify the algorithm for _nding the proper column in which the heartbeat signal is less affected by the respiratory signal. Then the waveform shape of heartbeat signals separated from the radar matrix is reconstructed with less distortion. Besides, ECG recordings and radar data are to be acquired from more volunteers and imported to the cascade CNNs for further training.

ACKNOWLEDGEMENT

The gratitude is given to the provider of the CCDD, researchers in the Chinese Academy of Sciences, and the developer of the framework caffe. The authorswould also like to thank reviewers for their constructive comments.

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