Data abnormal detection and classification in wireless body area networks using Convolutional Neural Networks

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***Abstract*—Wirekess body area network(WBAN) has become a promising type of networks to efficiently collecting as well as analyzing human physiological information. These collected data are then transformed to outside database support real-time monitoring or other health applications. However , due to the resource constrained of the networks, the monitored data needs to be analyzed for automatic detection of physiological changes indeed trigger an alarm of patient health degradation. Moreover, false alarm result by abnormal changes or faulty measurements should be classified to reduce unnecessary medical intervention..In this paper, we propose a novel framework for data abnormal detection and classification on real-time ECG signals to distinguish faulty measurements form clinical emergency. Our work is based on adaptive 1-D convolutional neural networks(CNNs). We use small common ECG dataset to build a dedicated CNN models offline, which can be used to classify possibly long ECG data stream in a fast and accurate manner, such a solution can conveniently be used for real-time monitoring and early alert system in WBANs.The state-of-the-art performance on efficiency and accuracy for ECG classification over real dataset is achieved by the proposed method.**

***Index Terms*—Wireless Body Area Networks; abnormal detection; faulty detection; convolutional neuron network**

I. Introduction

With the rapid development of electrical devices and wireless communications technologies, wireless body area networks can provide real-time monitoring and diagnosis services from human body to users and doctors without causing any discomfort and interrupting their daily lifestyle[1]. WBANs consisted of a collection of low-power, miniaturized, and lightweight sensor nodes that can be implanted in or on the human body to monitor real-time physiological parameters. These collected data are further transmitted to the remote database by one resource rich hub (mobile phone or PDA) for various medical and healthcare applications[2].

Since the criticality of WBAN applications and the heterogeneity of the deployed sensor devices confirm that WBAN has special characteristics that impose key challenges in designing an efficient and resilient WBAN. For instance, a WBAN has to be reliable as any fault of the collected data could be life threatening for the person dependent on this technology[3-5]. Most of the collected data are related to the chronic diseases,which must be continuously analyzed for automatic detection of physiological changes.The in-network processing of collected data from different sensors allows to raise an alarm upon detection of unusual change associated with potential diseases, and quickly warn healthcare professionals to prescribe the appropriate medical care[6].

However, the small size and little energy resource of sensor node, makes them susceptible to various sources of environmental noise, and malfunctions. Besides, signal fadingmalice data attackmay also lead to unreliable results. Real time monitoring with lightweight algorithm is required to detect and classify the abnormal changes among medical data for further use[7].

Many of the researchers investigated the statistical characteristics of the abnormal detection models to support patient healthy monitoring[8-10]. They focus on distributed detection techniques to identify anomalous values at individual sensor in order to prevent the transmission of abnormal data and reduce system energy consumption. One major problem of these methods is that WBAN sensors can not provide available resources supporting abnormal data process for each of the sensors implanted in the human body shall be single-functioned.

In this regard, some author in [11-13] proposed lightweight algorithm based on the time and spatial correlations between physiological parameters of patients in wireless and they derive a reference record(or normal profile) and measure the distance between measured and reference records to detect anomalies. However, these methods can not perform well when there suddenly comes a new type of abnormal data , because they have to spend time on rebuilt the reference profile. Farrukh et al[14], gives a new solution on anomalies detection and identify in ECG signals for WBAN-based healthcare environments using a simplified markov model. By these methods, the new changes of the ECG data can be learned and the system will inform medical personnel by raising an alarm in the hospital systems. Although many researches gained almost

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optimal results for ECG segmentation and various filtering methods were proposed, there is still room for improvements in the steps related to abnormal classification (ECG feature extraction and classification algorithms) Recent works on skin cancer diagnosis [15-16] and classification of real-time patient-specific ECG signals [17] by CNN have gained great success, which demonstrates the great power of CNN for disease diagnosis and abnormal classifications. Generally, ECG signals are also shown as photographs which can be easily combined with CNN as normal images. What is more, to make the ECG detection more practical, an ECG based abnormal detection and classification system should be fast, or in real-time, which means it can be embedded in the popular WBANs.

In this paper, we propose a novel framework for data abnormal detection and classification on real-time ECG signals to distinguish faulty measurements form clinical emergency. Our work is based on adaptive 1-D convolutional neural networks(CNNs). CNNs are now common used for the deep learning task, such as object recognition in large image achieves while achieving the state-of-art performance, ECG signals are also shown as photographs which can be easily combined with CNN as normal images. As far as we know, this work is the first to combine ECG classification and faulty measurements detection under real-time monitoring WBANs. Finally, we evaluate the efficiency and energy consumption of the two strategies and show the influence of the parameters on the selection strategy.

The rest of this paper is organized as follows. Section 2 introduces the system models. We present the details of the ECG data processing in Section 3. Section 4 conducts performance evaluation and discussion about the results. Finally, we conclude this work in Section 5.

II. ECG DATA PROCESS

In this study,we used the 2017 Physionet Challenge(https://www.physionet.org/challenge/2017/) dataset for the performance evaluation of the proposed abnormal detection method. We trained our CNN on the publicly available training dataset(n=8528), holding out a 10% development dataset for early stopping.

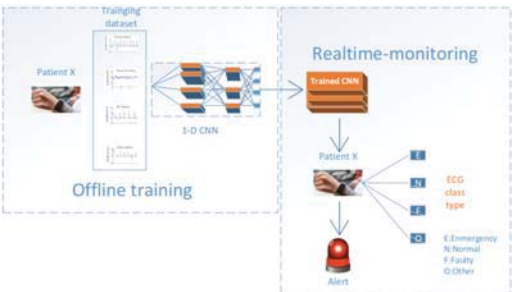

Fig. 1. Data processing

For the test dataset, 30-s records of each rhythm were sampled in a similar manner to achieve a greater representation of rare rhythms; however, the test dataset included only a single record per patient. The training, development, and test dataset had completely disjointed sets of patients.

In this paper, we consider a classic WBAN system, which contains one hub and N wireless body sensors.Generally, the hub (such as a PDA and a mobile phone) has a large battery and it is easy to recharge or replace the battery. We use small common ECG dataset to build a dedicated CNN models offline, which can be used to classify possibly long ECG data stream in a fast and accurate manner.Our trained CNN will be apply on the hub to detect and classify abnormal data in real-time monitoring process as shown in Fig.1.

III. PROPOSED 1-D CNN METHOD

In this section,we present the data abnormal detection and classification with 1-D CNN method. CNNs are hierarchical neural networks which consists of convolotional layers alternate with subsampling layers, following with a full connected layers, which are identical to multilayer perceptions(MLP). With the proper training, the convolutional layers of CNNs can learn to extract ECG beats features, while the MLP layers performing the classification task to produce the final class vectors of each beat. This part we first introduce an overview of the traditional CNNs developed for a 2-D image classification, then we shall highlight the differences between 1-D CNNs and 2-D CNNs along with BP formulations.

A. About Forward-propagation

CNNs are now common used for the deep learning task, such as object recognition in large image with two or more dimensions achieves while achieving the state-of-art performance, ECG signals are also shown as photographs which can be easily combined with CNN as normal images.

In CNN, convolutional layers are responsible for extracting various features by convoluting the input images or feature maps produced by intermediate layers with the fifilters.During the forward propagation(FP), the input map of next layer neuron will be obtained by the cumulation of the final output maps of the pervious layer neurons convolved with their individual kernels as follows:

$$x_k^l = b_k^l + \sum_{i=1}^{N_{T-1}} conv2D(\omega_{ik}^{l-1}, s_i^{l-1}) \qquad (1)$$

where x_k^l is the input,conv2D is a regular 2-D convolution without zero padding on the boundaries, b_k^l is the bias of the kth neuron at layer l, and $s_i^{l-1}$is the output of the ith neuron at layer l-1. ω_{ik}^{l-1} is the kernel (weight) from the ith neuron at layer l-1 to the kth neuron at layer l. To accomplish BP training, there are three more elements that are stored for each neuron: the delta error Δ_k^l , downsampled delta error Δ_{sk}^l , and, finally, the derivative of the intermediate output f'(x_k^l).

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B. About Back-propagation

The errors which we propagate backwards through the network can be thought of as sensitivities of each unit with respect to perturbations of the bias.Once the first BP is performed from the next layer, l+1, to the current layer, l, then we can further BP it to the input delta. Then the delta error can be write as:

$$\Delta_k^l = \frac{\partial E}{\partial x_k^l} = \frac{\partial E}{\partial y_k^l}\frac{\partial y_k^l}{\partial x_k^l} = up(\Delta_{sk}^l)\beta f'(x_k^l) \tag{2}$$

where β=$(ssx, ssy)^{-1}$ since each pixel of s_k^l was obtained by average ssx,ssy number of pixels of the intermediate output y_k^l. ssx shall be the subsample factors[7].

The delta rule for updating a weight assigned to a given neuron is just a copy of the inputs to that neuron, scaled by the neurons delta. In vector form, this is computed as an outer product between the vector of inputs (which are the outputs from the previous layer) and the vector of sensitivities. if the output of the kth neuron at layer l, contributes a neuron i in the next level with a weight, ω_{ik}^{l-1}, that next layer neurons delta, Δ_l^{l+1}, will contribute with the same weight to form lk of the neuron in the previous layer l, this means:

$$\frac{\partial E}{\partial s_k^l} = \sum_{i=1}^{N_{T-1}} \Delta_l^{l+1} \tag{3}$$

where

$$x_i^{l+1} = ... + s_k^l * \omega_{ik}^l + ... \tag{4}$$

where $*$ is the conv2D operator without zero padding.

C. About convolutional layers

At a convolution layer, the previous layers feature maps are convolved with learnable kernels and put through the activation function to form the output feature map. Each output map may combine convolutions with multiple input maps. In general, we have that:

$$x_k^l = f(\sum_{i \in M_k} x_i^{l-1} * k_{ik}^l + b_k^l) \tag{5}$$

where $M_k$represents a selection of input maps,Each output map is given an additive bias b, however for a particular output map, the input maps will be convolved with distinct kernels. That is to say, if output map j and map k both sum over input map i, then the kernels applied to map i are different for output maps j and k.

The back propagation algorithm says that in order to compute the sensitivity for a unit at layer l, we should first sum over the next layers sensitivies corresponding to units that are connected to the node of interest in the current layer l , and multiply each of those connections by the associated weights defined at layer l + 1,In the case of a convolutional layer followed by a downsampling layer, one pixel in the next layers associated sensitivity map δ corresponds to a block of pixels in the convolutional layers output map.

The weights multiplying the connections between the input patch and the output pixel are exactly the weights of the (rotated) convolution kernel. This is again efficiently implemented using convolution:

$$\Delta s_k^l = \sum_{i=1}^{N_{T-1}} conv2Dz(Delta_l^{l+1}, rot180(\omega_{ik}^l)) \tag{6}$$

where rot180(.) rotates the kernel,ω_{ik}^l,180 are perform a full convolution with zeri padding to boundary of the Δ_i^{l+1}.

We give the sensitivity of bias as follow:

$$\frac{\partial E}{\partial x_k^l} = \sum_m \sum_n \Delta_k^l(m,n) \tag{7}$$

where (m,n) donate the output pixel.

D. changes for 1-D CNN implementation

There are some differences between the 2-D and 1-D CNNs. The main difference is the 1-D arrays used in each neuron for its kernels (weights), input and output elements for both FP and BP rather than 2-D matrices. So that during both FP and BP runs, 1-D array manipulations such as conv1D and reverse will be performed instead of 2-D matrix operations, such as conv2D and rot 180.For example, the input map of the neuron can be now expressed as:

$$x_k^l = b_k^l + \sum_{i=1}^{N_{t-1}} conv1D(\omega_{ik}^{l-1}, s_i^{l-1}) \tag{8}$$

The inter-BP delta error of the output s_k^l given in (6) can now be expressed for 1-D as:

$$\Delta s_k^l = \sum_{i=1}^{N_{t+1}} conv1Dz(Delta_l^{l+1}, rev(\omega_{ik}^l)) \tag{9}$$

where rev(.) reverses the array, and conv1Dz(.,.) performs full convolution in 1-D with k-1 zero padding.

IV. Performance Evaluation

In this section, we investigate the performance of the proposed data abnormal detection and classification algorithm in terms of computational complexity and receive opreating characteristic curves , we present the overall results obtained from the classification experiments and perform comparative evaluations against several state-of-art techniques in this field.

TABLE I
ECG signal classification results.

type	Precision	Recall	F1-score	Support
Normal	0.882	0.908	0.895	512
Emergency	0.791	0.828	0.809	64
Faulty	0.882	0.536	0.667	28
Other	0.781	0.759	0.770	249

A. simulation setup

We implanted the proposed 1-D CNN on a computer device I6-4670 CPU at 3.60GHZ. Actually, all the training and test stages can be executed fast enough. In the training stage for CNN, 8000 samples can be processed per second. That is to say, only seven seconds are needed for training one epoch. And the CNN can be trained in 90mins. Notably, once the CNN is trained, it can be used for any individual forever, so the training time of CNN can be neglected.

B. simulation results

Classification performance is measured using the two standard metrics:sensitivity (Sen), specificity (Spe),while Sensitivity is the rate of correctly classified abnormal among all abnormal, Sen = TP/(TP+FN); Specificity is the rate of normally classified normal among all normal, Spe = TN/(TN+FP).

We plotted receive opreating characteristic curves(ROCs) and F1 scores(which is the harmonic mean of the positive predictive value and sensitivity) for the sequence- level analysis of four example classes: Normal; Emergency; Faulty and other. We use 853 samples be the test dataset and give the precision-recall rater and F1-scores in TABLE I,which support means the number of each sample.

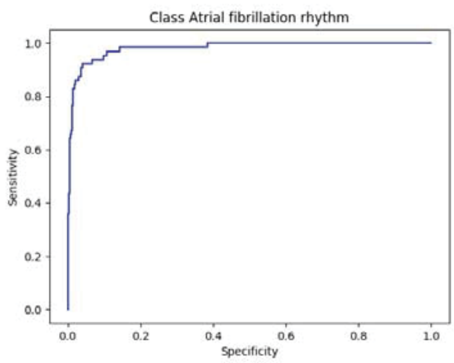

Fig. 2. ROC of emergency type ECG

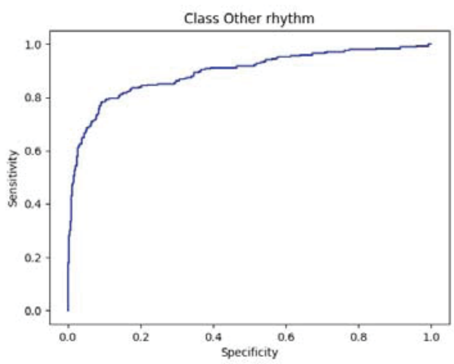

Fig. 3. ROC of other type ECG

Several interesting observations can be made from the results in Table I. First, for faulty measurements detection, precision and recall rates are comparably lower than normal detection, while a high-specificity performance is achieved. The reason for the worse classifier performance in detecting faulty is that faulty class is underrepresented in the training data, and, hence, Some beats are misclassified as normal beats. Moreover, on several patients, particularly on the test dataset. The test data from the first 30s interval and the common data of 200 beats extracted randomly from the training dataset do not successfully characterize most of the faulty and some of the emergnecy beats.

Our study is the first comprehensive demonstration of a deep learning approach to perform abnormal detection and classification across a broad range of the common and important patient health monitoring. CNN performance on the test dataset (n=853) demonstrated overall F1 scores that were among those of the best performance from the competition[24],with a class average F1 of 0.78.

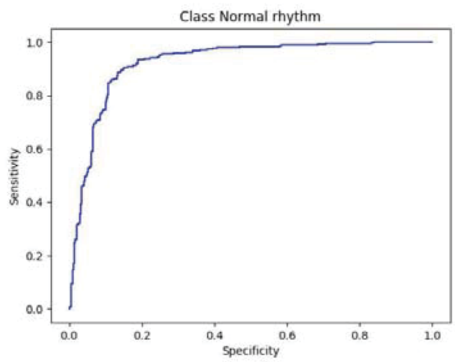

Fig. 4. ROC of normal type ECG

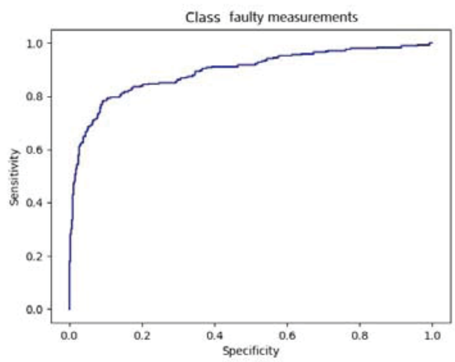

Fig. 5. ROC of faulty type ECG

C. computational complexity

The most important advantage of the proposed system is its significantly low computational cost for the beat classification. Specifically, for the single-CPU implementation, the total time

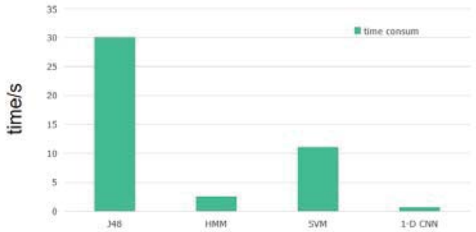

Fig. 6. Time consuming of new abnormal detection

for a FP of a single beat to obtain the class vector is about 0.58 and 0.74 m sec for 64 and 128 samples beat resolutions. To prove the effectiveness of our proposed approach for WBANs, we compare our approach with several existing algorithms, such as SVM and J48 from machine learning based approaches,and hidden markov models(HMM).Fig 6 contains the time consuming of detect processing. We found that the performance of HMM is very close to our proposed approach achieving a fast react time, which means a fast,low computational with a superior calssication performance. It is important to note that classification algorithms with hand-craft feature extraction such as J48 do not perform well in our experiment because it has to rebuild the entire tree from scratch to update the classification model, where this operation took 30 seconds in our experiments.

V. Conclusion

In this paper, we proposed a lightweight data abnormal detection and classification system with 1-D CNN that are able to distinguish faulty measurements form clinical emergency. Such a compact implementation, for each patient over a simple CNN, not only negates the necessity to extract hand- crafted manual features, or any kind of pre- and postprocessing, also makes it a primary choice for a real-time implementation for heart monitoring and anomaly detection. Besides the speed and computational efficiency achieved, the proposed method only requires 1-D convolutions (multiplications and additions) that make any hardware implementation simpler and cheaper.

Our approach is suitable for real-time detection and isolation of faulty measurements with low computational complexity and storage requirement. We have tested our proposed approach on real physiological dataset publicly available on the Physionet Web site. The conducted experimental results demonstrate the efficiency and the accuracy of our approach, showing its ability to identify faulty measurements and reduce the number of false alarms.

VI. Acknowledge

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