Toward An IoT-based Expert System for Heart Disease Diagnosis

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Abstract

IoT technology has been recently adopted in the healthcare system to collect Electrocardiogram (ECG) signals for heart disease diagnosis and prediction. However, noises in collected ECG signals make the diagnosis and prediction system unreliable and imprecise. In this work, we have proposed a new lightweight approach to removing noises in collected ECG signals to perform precise diagnosis and prediction. First, we have used a revised Sequential Recursive (SR) algorithm to transform the signals into digital format. Then, the digital data is proceeded using a revised Discrete Wavelet Transform (DWT) algorithm to detect peaks in the data to remove noises. Finally, we extract some key features from the data to perform diagnosis and prediction based on a feature dataset. Redundant features are removed by using Fishers Linear Discriminant (FLD). We have used an ECG dataset from MIT-BIH (PhisioNet) to build a knowledge-base diagnosis features. We have implemented a proof-of-concept system that collects and processes real ECG signals to perform heart disease diagnosis and prediction based on the built knowledge-base.

1 Introduction

Electrocardiogram (ECG) signals are the data measured from patients' heartbeats by electronic devices. Generated by cells in the heart, ECG signals reflect all activities in these cells. Therefore, ECG signals are the most valuable data used in the heart disease diagnosis [Blackburn *et al.*, 1960].

Nowadays, ECG signals can be measured automatically by sensors instead of the conventional discrete measurement [Hassanalieragh and Moeen, 2015; Pantelopoulos *et al.*, 2010; Paradiso *et al.*, 2005; Milenkovi *et al.*, 2006; Bazzani and Marco, 2012; Benharref *et al.*, 2014]. The data collected by the sensors can be transmitted to a cloud-based system to perform preliminary automatic diagnosis based on a knowledge-base without medical experts. A knowledge-base is initially built using a large sample dataset, and then can frequently be updated by specialists to improve the accuracy of the prediction.

The overall aim of our work is to develop such an eco-expert system using Internet of Things (IoT) technology. As data can be collected in real-time and transmitted to the cloud for analysis, the proposed expert system will help patients to detect their possible heart diseases before seeing their doctors. This system can also support the physicians to perform treatment for their patients for a minimum period.

However, there are several significant research challenges in building such expert systems. First, noises always appear in the ECG signals, making the data imprecisely or even unreadable. Second, building a knowledge-base to be used in heart disease diagnosis and prediction is not a trivial task. Finally, ECG signals must be extracted with some key features to match with the knowledge-base for accuracy prediction.

In this paper, we have proposed a lightweight approach to solving above mentioned challenges. We have developed a combined data processing algorithms to collect "clear" ECG signals from sensors. In particular, we have adopted the Sequential Recursive (SR), Discrete Wavelet Transform (DWT), and Fishers Linear Discriminant (FLD) algorithms and combined them to remove noises from raw ECG data. Based on these algorithms, we have proposed a novel computational model to extract precise features and perform diagnosis and prediction by matching with the ones developed in the knowledge-base. We have also built a knowledge-base from a public heart disease dataset (MIT-BIH [MIT-BIHArrhythmiaDatabase, 2016] from Boston's Beth Israel Hospital) and evaluated our proposed diagnosis system using this knowledge-base.

In summary, the main contributions of this paper include:

- We have proposed combined algorithms to remove noises from ECG signals received from sensors.
- We have developed a mechanism to automatically extract information related to heart disease from filtered ECG signals.

- We have implemented a proof-of-concept heart disease diagnosis system based on a large dataset. The system has been validated by a real data collected from the human through ECG sensors.

The rest of the paper is organized as follows. In the next section, we discuss the related work and motivate our contributions. Section 3 describes the background of this research including knowledge-base of ECG, data processing, Sequential Recursive (SR) algorithm, features extraction using Discrete Wavelet Transform (DWT), arrhythmias classification using Fishers Linear Discriminant (FLD). Section 4 presents our approach to building a computational model using combined algorithms to filter data. Classifying and extracting heart disease features for matching with knowledge-base are also described. In Section 5, we illustrate our experimental results. We discuss and summarize our contributions in Section 6.

2 Related Work

Expert systems for heart disease diagnosis have been studied in the literature. For example, ECG signal analysis can be recognized and classified by neural networks [Kiranyaz *et al.*, 2016]. Neural networks use a large number of neural units; each neural unit has relations with others, the number of relationships depends on the structure of the system. The neural network combines multilayer feed forward network with back propagation learning algorithm [Patel and Joshi, 2013]. Although the system can learn during runtime, some parameters are still chosen in ranges, which are dependent on the experience of the users when they deploy the system. A more advanced system is proposed by adding one more step to classification the arrhythmias [Khemphila and Boonjing, 2011]. The method is to use the production data from *multi layer feed forward network with back propagation learning algorithm* and *doctor's expertise, experience* to give the clinical diagnosis. However, these systems only support the physicians yet do not provide the automatic diagnosis.

Fuzzy support vector machine (FSVM) is another method using techniques of pattern recognition to decide the acceptable recorded signals. FSVM is frequently used to assess the quality of ECG analysis processing [Zhang and Ya-tao, 2014].

Classification of heart disease features was also well studied. In [Rani, 2011; Das *et al.*, 2009], a database from Cleveland was used to build the training and testing classification. However, the diagnosis and analysis of input data were not studied.

On the other hand, Wireless Body Area Network (WBAN) technologies have been recently introduced and adopted in healthcare systems. WBAN automatically measures users' parameters such as blood pressure, brain activities, ECG and other, and transmits the collected data to the cloud for analysis. Users, medical staffs, and other stakeholders can access, analyze and visualize data depend on their right. WBAN is considered as an IoT-based system in healthcare and has recently been studied [Hassanalieragh and Moeen, 2015; Pantelopoulos *et al.*, 2010; Paradiso *et al.*, 2005; Milenkovi *et al.*, 2006; Bazzani and Marco, 2012; Benharref *et al.*, 2014]. As discussed in [Soni *et al.*, 2011], IoT-based data contain *'rich information'* but *'poor knowledge'*. Several data-mining methods for extracting data from the massive volume healthcare database were proposed in [Soni *et al.*, 2011].

In this work, we aim to contribute to filling the gap by introducing an IoT-based framework that combines data acquisition, extraction, classification. We will also build a frequently update knowledge-base to perform feature matching for heart disease diagnosis and prediction. In the next section, we present the background needed for this work.

3 Background

In this section, we describe the overview of the electrocardiogram signal and related algorithms to process the data.

3.1 Electrocardiogram

Electrocardiogram signal (ECG) is an electrical signal that is frequently measured by three poles, also known as electrodes, placed on the skin. These electrodes capture electrical signals produced by heart muscles electrophysiological during the heartbeat.

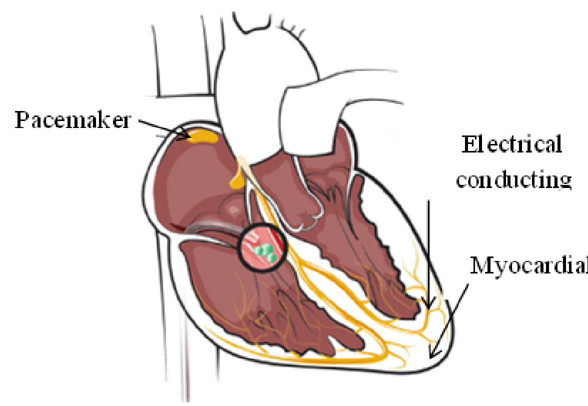

Figure 1: The cells in construction of heart

ECG signals are generated by cells in the heart. The structure of the heart constructed by three kinds of cells: pacemaker, electrical conducting, myocardial. Figure 1 depicts the cells in the construction of heart. Pacemaker cells produce electrical that provides power for all activities of heart. Electrical conducting cells transmit the power from the source to remote regions of the heart. Myocardial cells work likely to the engine of a mechanical system. Therefore, for any issue relevant to these cells will be reflected through the electrical signals (ECG). Parameters in ECG signals such as phase time cycles, peak magnitudes can be used to diagnose types of heart diseases [Blackburn *et al.*, 1960].

ECG can be measured by sensors. The output of these ECG sensors is analog signals. These signals need to be converted to digital data to be able to processed. Normally, ECG will go through an Analog-to-Digital Converter (ADC) and then to other Microcontrollers (MCU). Data processed by MCU then is stored in cloud helping for the database of healthcare systems.

3.2 Data processing algorithms

In this work, we propose a model to process the ECG signals from sensors. The model adopts a number of data processing algorithms. In this subsection, we briefly describe these related algorithms used in Section 4.

Finite Impulse Response (FIR)

Finite Impulse Response (FIR) filter is an algorithm that removes noises in digital signals. FIR filter can briefly be described as function below [Oppenheim *et al.*, 1983].

$$\begin{aligned} y[n] &= b_0 x[n] + b_1 x[n-1] + ... + b_N x[n-N] \\ &= \sum_{i=0}^{N} b_i x[n-i] \end{aligned} \tag{1}$$

where,
x[n]: The input signal;
y[n]: The output signal;
N: The filter order;
$b_i, i = 0 \to N$: The value of the impulse response at the i^{th} instant, it is also a coefficient of the filter.

Sequential Recursive Algorithm - SR

With the characteristics of ECG, time series represent for the object that need to be analyzed. For a long time, time series investigating belong to the scope of medical diagnoses.

The signal y at time n can be estimated via the data from beginning to $(n-1)$. To obtain $y[n]$, factor θ decides the quality of the estimating operation [Ifeachor and Jervis, 2002; Godambe, 1991].

$$\begin{aligned} y[n] &= \sum_{i=1}^{n} \theta_i . y[k-1] + e[k] \\ &= [y[k-1] \cdots y[k-n]] . [\theta_i \cdots \theta_n]^T + e[k] \\ &= \mu[k]^T . \theta + e[k], e[k] \simeq NID[0, \sigma_e^2] \end{aligned} \tag{2}$$

where,
$y[k]$: Signal at time k;
$\mu[k]$: Regression vector at time k;
θ: Prediction parameter vector;
$e[k]$: The error at time k.

Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) using technique of discretely sampling where all signals such as numerical, functional analysis based on any wavelet is discretely separated, both frequency and location information stored in the signal are captured [Akansu *et al.*, 2010; Akansu and Haddad, 2001].

$$a^t[n] = \sum_k a^{t-1}[n] g[2n-k] \tag{3}$$

$$d^t[n] = \sum_k a^{t-1}[n] h[2n-k] \tag{4}$$

$a^t[n]$: Coefficient of the approximation;
$d^t[n]$: Detail vector;
$g[.]$: Low-pass wavelet filter;
$h[.]$: High-pass wavelet filter.
Both $g[.]$ and $h[.]$ represent for down-sampling by two $[2n-k]$.

Fisher's Linear Discriminant

Fisher's Linear Discriminant (FLD) is a method for pattern recognition, machine learning, and statistics. It operates by the way of finding a linear combination of features which represent for separated classes of objects or events, the number of classes depends on the characteristics of the signal. The combination helps to reduce the redundancy features which are duplicated or not necessary, it makes the classification less complicated [McLachlan, 2004; Haghighat *et al.*, 2016]. Equation (5) illustrates this algorithm.

$$S_w = \sum_{t=1}^{n} \sum_{x \in C_t} (x - \bar{x}_t)(x - \bar{x}_t)^T \tag{5}$$

where,
S_w: The intra-class matrix;
$\bar{x}_t$: The mean vector of the t^{th} class;
x: Data vector that belong to training feature data set.

4 Proposed Model for Data Processing and Diagnosis

We propose a model that contains several modules and steps. First, we develop several filter modules to remove noises in raw ECG signals collected from sensors. Next, we adopt the SR algorithm to process the filtered ECG data, and compare with an ECG knowledge-base to produce data for the feature extraction module. Extracted features are the input for the classification module that performs diagnosis. In the next subsections, we describe these modules in detail.

4.1 Noise removal

As mentioned, ECG signals are very sensitive to noises that make the collected data unreadable. To filter and remove noises, we have performed several steps and algorithms as follows. First, we propose a simple raw filter module, developed in a micro-controller, to filter the raw data so that they can be readable for the next step. Next, we implement the Low and High pass filters because ECG signals are sensitive to low and high-frequency noises. We use the FIR filter algorithm (c.f. Section 3) for the both filters. These FIR-based filters

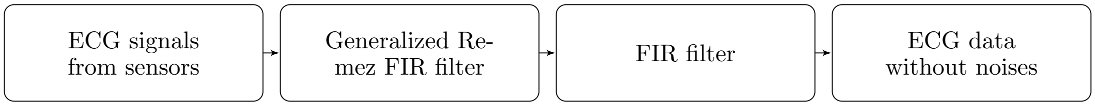

Figure 2: Structure of Low/High pass filter

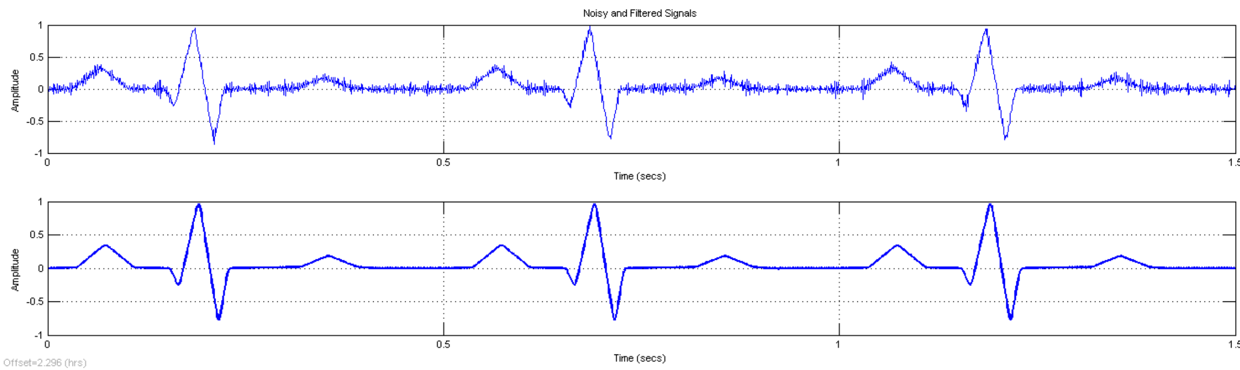

Figure 3: ECG signal with and without noise

are the primary processor to remove noises, as illustrated in Figure 2. **Defined Parameters** integrated in block *Generalized Remez FIR filter* have threshold parameters such as pass-threshold, stop-threshold, and other corresponding ones. Depending on the values of pass-threshold and stop-threshold parameters; diagram in Figure 2 is defined as Low or High pass filter respectively.

The output of these filters is ECG data without noises that can be used for the next module for analysis and classification. Figure 3 illustrates the ECG signals with and without noises, before and after passing through Low and High pass filters. In the real implementation, the values of parameters of FIR filter are calibrated to reach the best fit.

4.2 Sequential Recursive Algorithm for Data Processing

We propose a data processing adaptive model using the Sequential Recursive (SR) Algorithm, depicted in Figure 4. The core of this adaptive model is the block Model (SR algorithm) in the figure. ECG signals of each patient have different characteristics. To handle this, our proposed model will perform automatic adjustment to get the best match based on: (1) the backward step n in the previous block, and (2) the gap between the measurement signal and estimation signal. With this proposed model, the algorithm can perform quick convergence to generate the best fit model for a particular ECG data from each patient.

As mentioned, raw ECG signals contain not only pure signals but also noises $v(t)$ as showed in Figure 4. Noises come from the environment, measurement, system noises, etc. The model is built based on the knowledge-base integrated with SR algorithm, which uses the previous cycles of the ECG data to predict the signal at time (k).

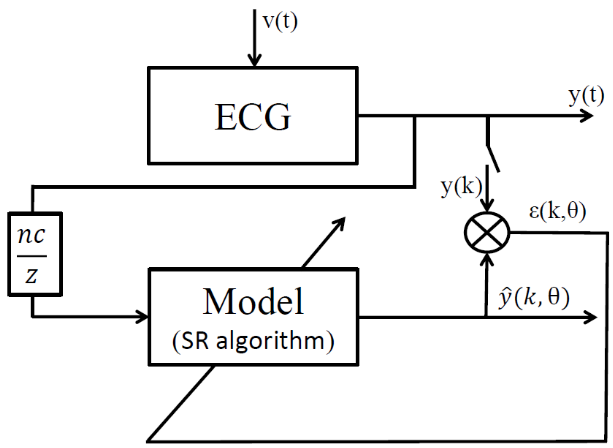

Figure 4: Our proposed model using the SR algorithm

The signal produced by Block Model can be considered as the standard signal which is compared to the real signal at time (k), along with the prediction period. The SR algorithm receives two inputs: (1) data from ECG knowledge-base such as MIT-BIH, and (2) real ECG data captured from patients after being filtered by the filter module. These datasets will be analyzed and stored so that if the difference between them (by subtraction) is greater than a threshold, the data is generated as the output data for the feature extraction module.

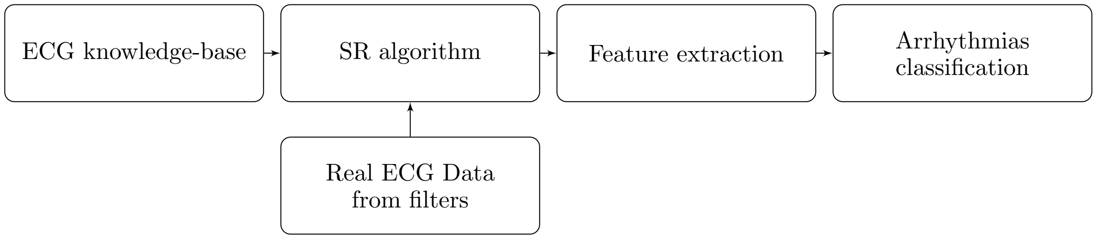

Figure 5: SR algorithm and feature extraction modules in the system

4.3 Feature Extraction and Classification

Processed data from the SR algorithm will be the input for our feature extraction module, illustrated in Figure 5. We adopt the DWT algorithm described in Section 3 to perform this feature extraction. The DWT is used to detect R-peak and capture the center of R-peak, which is the top of each cycle of ECG signal. The DWT gives a flexible time-frequency localization, an appropriate transform domain where the classification system operating.

DWT processes the signal based on the decomposition using an orthonormal. Wavelets have its energy carrying and the magnitude values depending on the concentration representing in time. Their energy spectrums are concentrated around low frequencies [Mahmoodabadi and Abolhasani, 2005].

The decomposition repeatedly implements on the approximation signal to get the second detail and approximation signal. Therefore, discrete wavelet domain gives a multiresolution analysis [Majumder *et al.*, 2008]. The level of each implementation can be adjusted to achieve the appropriate quality, depending on the characteristics of signals. To clearly get the information from the low frequency, the level of decomposition is taken to be high value [Thakor *et al.*, 1984].

Depending on the energy concentration, the decompositions are chosen to comprise and evaluate. Therefore, the R-peaks are captured based on the maximum amplitude points. The accuracy of the feature extraction module mainly depends on the accuracy of R-peaks detection [Thakor *et al.*, 1984].

The final step is the classification for heart disease diagnosis. To employ the arrhythmias classification, we adopt the FLD algorithm described in Section 3. The FLD algorithm helps to reduce the dimension space, where some features are not necessary; and helps to classify the heart disease in the end of the SR data flow.

In equation (5) (c.f. Section 3), we have n classes for the feature vectors x, S_w is the intra-class matrix, C_t is class t, $\bar{x}_t$ is the mean of vectors x, which we obtain equation (6)

Re-write equation (5) with m_t is the number of vectors of class C_t, $\bar{x}$ is the mean of x.

$$S_b = \sum_{t=1}^{n} m_t \big(\bar{x}_t - \bar{x}\big)\big(\bar{x}_t - \bar{x}\big)^T \tag{6}$$

where,
S_b: The between-class matrix;
m_t: The number of vectors of class C_t;
$\bar{x}_t$: The mean of vector x;
$\bar{x}$: The mean vector of all fault samples.

To obtain the data at time n, we apply the Rayleigh quotient. Rayleigh quotient [Horn and Johnson., 2012; Parlett, 1998] is a technique to get the eigenvalues providing for min-max operations of matrix multiplication. During classification progress, complicated matrix cannot be obtained from a series of multiplication operators if it is lack of using any technique like Rayleigh quotient. The role of Rayleigh quotient is vital; it decides the success of matrix operations.

5 Implementation and Experimental Results

We use data from MIT-BIH [MIT-BIHArrhythmiaDatabase, 2016] that were built at Boston's Beth Israel Hospital (Beth Israel Deaconess Medical Center) to develop the ECG knowledge-base to validate our proposed model. MIT-BIH data are divided into 3 files: Header file, Attribute file, Data file. The header file contains information relevant to personal info, properties of recorded data; attribute file coordinates with the data file to represent the characteristics of recorded data.

We have implemented a system to collect and analyze ECG signals. The data were recorded at 360 Hz, and the raw data results with noises are showed in Figure 6. Data after processing by our mechanism are shown in Figure 7, where vertical axis represents the beat (mV) and the horizontal axis represents the sample numbers. In Figure 7, incidents are detected and labeled as premature ventricular contraction (PVC). Near each incident, the R-peaks located closer than usual, it means that the period between R-peaks is shorter than usual. Iterative experiments show that recorded signals are stable and less affected by noise.

We use a sensor named AD8232 shown in Figure 8 to capture the ECG signals. This sensor is the single lead ECG, three electrodes, two poles adjustable high pass filter with fast restore capability, three poles adjustable low pass filter. The output signals from AD8232 is analog signals.

To read analog signals from AD8232 then convert it to

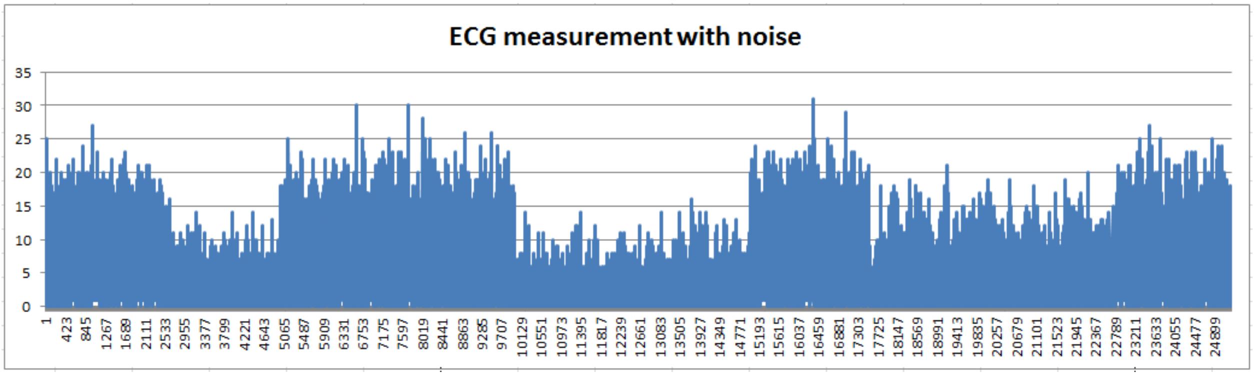

Figure 6: ECG measurement with noise

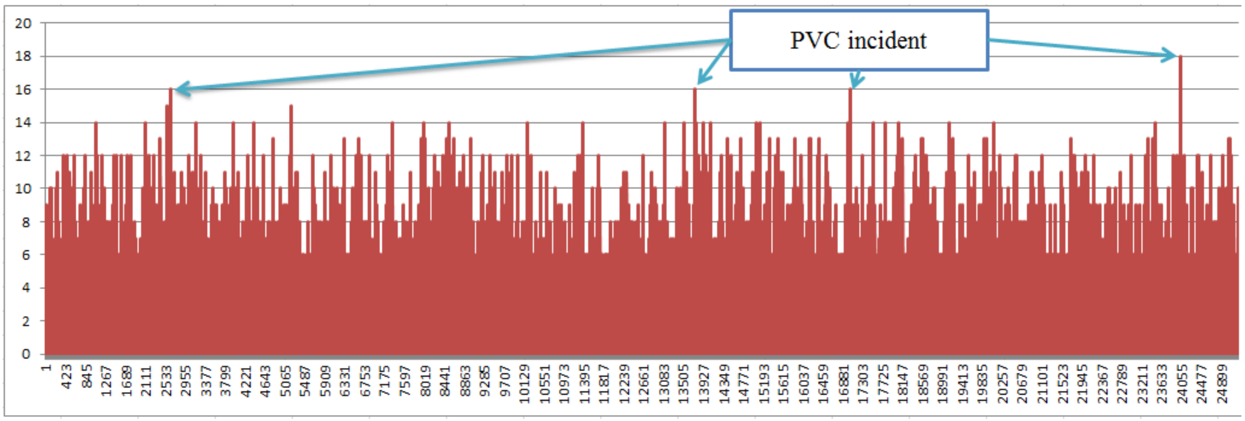

Figure 7: Recorded ECG signals with arrhythmia incidents (PVC)

digital signals, we develop a module on a microcontroller named STM32F4 shown in Figure 9. STM32F4 has 1MB Flash, 192KB SRAM; using ARM 32-bit $Cortex^{TM}$-M4F CPU with FPU, frequency up to 168 MHz. Raw production data from STM32F4 is processed by our proposed computational model and the algorithms introduced in the previous section.

The signal shown in Figure 6 represents the noises existing in the data. To remove noises, we have implemented the Kalman filter in microcontroller STM32F407VG, and implemented the FIR filter in Matlab R2013b to achieve the results as illustrated in Figure 7.

As demonstrated in the experimental results, the SR algorithm improves the quality of signals and makes them stable. We recognize that the SR algorithm not only has potential to make ECG extraction simpler but also reduces the suddenly rash or lost info, make ECG signals more stable. During the processing of ECG signals, the SR algorithm provides filters within calculations, reduces the duplications, and helps to improve the performance of microprocessors for implementation.

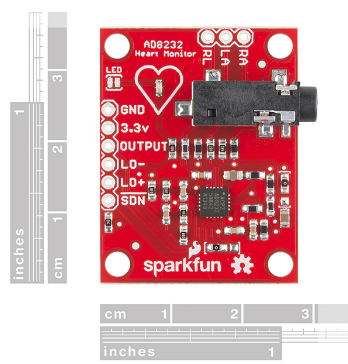

Figure 8: AD8232 - Heart sensor

6 Conclusion and Future Work

In this work, we have presented a lightweight approach to processing ECG signals from sensors in order to perform diagnosis based on a heart disease knowledge-base. Our preliminary results demonstrated that the proposed model can remove noises from raw ECG signals, extract

Figure 9: STM32F4 - Microcontroller

key features for performing diagnosis that can support patients for pre-treatment and physicians for treatment.

We have implemented a proof-of-concept prototype of the proposed model toward building an IoT expert system. However, there are several challenges to be addressed. These include the error detection and error correction of the collected data from sensors, online update of the knowledge-base to provide more precise diagnosis. We also need to validate our system with other independent validation mechanisms and datasets to ensure that the outcome of our model is precise. Furthermore, we have not investigated the security for the proposed system. Security is a very important factor in IoT-based systems as the data are transferred over the Internet. However, we leave these challenges for future research.

In future, we plan to develop a comprehensive IoT system that supports automatic data transmission to the cloud for automatic diagnosis and data-mining. We also plan to build a health social network where specialists can update the knowledge-base so that the disease diagnosis can be improved over the time. Our proposed model can be extended to other diseases such as high blood pressure, abnormal brain activities, measuring attention index, sleep index, pulse index, abnormal body temperature, daily physical activities, controlling cardiac fitness and stress index.

Acknowledgments

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