A Cloud-Based Platform for ECG Monitoring and Early Warning Using Big Data and Artificial Intelligence Technologies

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Abstract. The prevalence of heart failure is increasing and is among the most costly diseases to society. Early detection of heart disease would provide the means to test lifestyle and pharmacologic interventions that may slow disease progression. However, the massive medical data have the following characteristics: real-time, high frequency, multi-source, heterogeneous, complex, random and personality. All of these factors make it very difficult to detect heart disease timely and make heart-warning signals accurately. So big data and artificial intelligence technologies are introduced to the field of health care, in order to discover all kinds of diseases and syndromes, and excavate valuable information to provide systematic decision-making for the diagnosis and treatment of heart. A cloud-based platform for ECG monitoring and early warning - HeartCarer is created, including a personalized data description model, the evaluation strategy of physiological indexes, and warning methods of trend-similarity about data flow. The proposed platform is particularly appropriate to address the early detection and warning of heart, which can provide users with efficient, intelligent and personalized services.

Keywords: Heart failure · Massive medical data · Big data · Early detection and warning · Cloud-based platform

1 Introduction

Heart failure (HF) prevalence is increasing and is among the most costly diseases to Medicare [1–3]. HF affects approximately 5.7 million people in the United States, and about 825,000 new cases per year with 33 billion total annual cost [4,5]. The lifetime risk of developing HF is 20% at 40 years of age [4,6,7]. HF has a high mortality

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rate: 50% within 5 years of diagnosis [8,9] and causes or contributes to approximately 280,000 deaths every year [10,11]. Approximately 20–30% patients are readmitted after 30 days and nearly 50% are readmitted within the next six months. Moreover, with the aging of the population, this tendency will continue to increase [12–14]. There has been relatively little progress in slowing progression of HF severity largely because there are no effective means of early detection of HF to test interventions. Early detection of heart disease would provide the means to test lifestyle and pharmacologic interventions that may slow disease progression.

However, the massive medical data have the following characteristics: real-time, high frequency, multi-source, heterogeneous, complex, random and personality. Most of the data are collected from sensors, video, cameras etc. at the low level. The result for processing systems is a very diverse collection of different types and formats of data. Processing and aggregation of these data is a major challenge especially when analyzing in real-time large streams of physiological data such as electrograph (EEG) and electrograph (ECG). All of these factors make it very difficult to detect heart disease timely and make heart-warning signals accurately.

So big data and artificial intelligence technologies are introduced to the field of health care, in order to discover all kinds of diseases and syndromes, and excavate valuable information to provide systematic decision-making for the diagnosis and treatment of heart. In this paper, a cloud-based platform for ECG monitoring and early warning - HeartCarer is created based on big data and artificial intelligence technologies.

This research topic comes from a real research project. In this study, data resulting from the HeartCarer telemonitoring study was employed. The records are composed of biosignals collected on a daily basis, in particular, before the occurrence of one event, together with its prediction (decompensation HF and normal condition). The proposed platform is particularly appropriate to address the early detection and warning of heart, which can provide users with efficient, intelligent and personalized services.

The main contributions of this paper are summarized as follows:

- We proposed a personalized data description model;
- We proposed the evaluation strategy of physiological indexes, and warning methods of trend-similarity about data flow;
- A cloud-based platform for ECG monitoring and early warning is created.

2 Related Work

The goal of prediction is to analyze the relationships among existing data and detect abnormalities, so as to make corresponding early warnings. Computer-assisted methods, such as medical data mining or medical knowledge discovery, are effective tools for predicting disease and are used to explore hidden relationships among massive data sets.

Karaolis [17] developed a data mining system for assessing heart-related risk factors using association analysis based on the Apriori algorithm. The results show that smoking is one of the major risk factors that directly affect coronary heart disease. The literature [18] uses Doppler radar to monitor the heartbeat and respiration of the elderly at night and excludes the abnormality of the elderly's body motion. The monitoring results are used to monitor the occurrence of respiratory disorders in the elderly during sleep. By monitoring the physical parameters of electrocardiogram, blood oxygen saturation, blood pressure, and weight of the elderly, combined with daily activities and walking, liturature [19] determines whether there is chronicity heart failure threshold by judging each elderly's individualized threshold. Karlberg and Elo [20] analyzed data on ischemic heart disease (IHD) and coronary risk factors in the population. Calculations show that the age-specific rate of acute myocardial infarction (AMI) is only slightly different, and the incidence of angina is 3 to 10 times higher in people older than 50 years. Kunc [21] presented a simulation result that can be used to assess coronary heart disease, congestive heart failure, and end-stage renal disease in Slovenia. CoCaMAAL is a middleware-centric, cloud-based solution [16] that proposes different methods for handling various types of data such as vital signs, activity logs, and location logs. However, these systems are often only suitable for a certain application point, only consider a single context, and the efficiency of real-time processing is not high.

The assessment of similarity between time series is a central concept in knowledge discovery and generally consists of evaluating the similitude between two different time series. Two main groups of algorithms can be identified: time domain and transform-based methods. The former work directly with the raw signals (eventually with some preprocessing) and the main goal is to derive a measure (scalar) based on the comparison of the original time series. Euclidean distance for signals with the same length and dynamic time warping technique for signals with different lengths, are well-known examples of such algorithms [22]. Due to the high dimensionality of time series, most of the approaches perform dimension reduction on original data (transformed-based methods). This second group includes, among others, discrete Fourier transform [23] and singular value decomposition [24]. Other authors used the principal component analysis (or Karhunen Loeve transform) [23], while others applied methods based on discrete wavelet transform [25].

In summary, the existing research work has various deficiencies and cannot meet the needs of early detection and prediction of heart failure. Therefore, this paper proposes a Bayesian-based personalized event description model, a data stream trend similarity assessment strategy based on time series. In addition, based on the open prediction and early warning platform for heart failure, the proposed theory and method are validated.

3 System Overview and Methodology

3.1 System Architecture

A context aware cloud-based platform - HeartCarer is proposed here for ECG monitoring and early warning. This platform makes it possible for third-party systems to provide high level monitoring data and obtain detection and prediction services from the system. User can work with the system to define their preferences regarding the input and output of the system. The proposed platform architecture is shown in Fig. 1.

Researchers and engineers working with real-time signals perform similar preprocessing and processing steps prior to making inferences. The collected data can be used both in real-time and off-line to derive multiple inferences about the patients condition. However, applications in the healthcare domain are fairly limited due to the

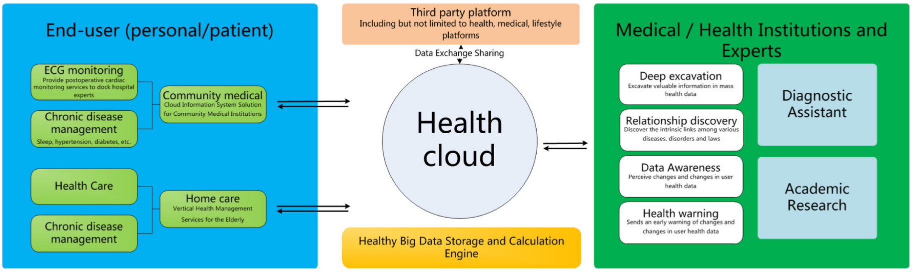

Fig. 1. The framework of the platform

processing and network demands on the supporting infrastructure. A real-world health-care application requires analyzing high-resolution sensor data in real time as well as data from other sources simultaneously, for many users at the same time. Processing the whole data on single machine locally is not practical due to computational limitations, reliability, scalability, failure/recovery and power consumption concerns.

To address this issue of application dependent implementations there is a need for processing platforms that are efficient enough to operate under real-world hardware and software constraints. Also, at the same time to be general enough to support different problems and applications. This work suggests an architecture that tries to solve this problem using intelligent distribution of the computational load using a publication/-subscription scheme. In this regard, the projects goal is to design and test an architecture which can scale to handle very large number of users and can act as a platform for processing real-time health analytics/inferences.

Basically, telemonitoring involves the transfer of physiological data and symptoms from patients at home (anytime and anywhere) to health-care providers. This allows more frequent assessment of a patients HF status and earlier recognition of hemodynamic deterioration than would be possible in common clinical practice. In effect, remote monitoring allows professionals to play a proactive role in daily care by implementing more effective and personalized therapies.

The methodology is based on a trend similarity measure, followed by a predictive procedure. The similarity scheme combines the Haar wavelet decomposition, in which signals are represented as linear combinations of a set of orthogonal bases, with the Karhunan-Loeve transformation (KLT), which allows for the optimal reduction of that set of bases. The trend similarity measure is then indirectly calculated by means of the coefficients obtained in both time-series description. The prediction strategy assumes that trends of physiological data common to patients with similar disease progression may have prognostic value in the prediction process. Therefore, using an approach similar to the k-nearest neighbor (k-NN), an estimation of the biosignals future values is performed, supported on a set of similar time series previously identified in the historical dataset.

3.2 Data Sample Collection

The strategy is evaluated using physiological data resulting from HeartCarer, which is a home telemonitoring system aimed at the supervision of HF patients, enabling intervention when appropriate. This is done by monitoring physiological body signs with wearable technology, processing the measured data and giving recommendations to the patient. Professional users of the system can use the measured data to give user feedback.

Table 1. Description of properties in the dataset

S. no	Properties	Description
1	Age	Age in years
2	Sex	Sex (1 = male; 0 = female)
3	Weight	Weight of the corresponding patient
4	Waist circumference	Male > 40 in. and female > 35 in.
5	Smoking	If yes = 1 and no = 0
6	CP Type	Chest pain type
7	Systolic BP	Systolic blood pressure in mm/Hg
8	Diastolic BP	Diastolic blood pressure in mm/Hg
9	Serum cholesterol	Serum cholesterol in mg/dl
10	Fasting blood sugar	Fasting blood sugar >120 mg/dl
11	Restecg	Resting electrocardiographic results
12	Thalach	Maximum heart rate achieved
13	Exang	Exercise induced angina
14	Old peak	ST depression induced by exercise relative to rest
15	Slope	The slope of the peak exercise ST segment
16	Ca	Number of major vessels (0–3) colored by fluoroscopy
17	Thal	3 = normal; 6 = fixed defect; 7 = reversible defect

This system was used in a clinical observational study carried out with 168 patients from six clinical centers in China. The trial had an enrolment phase of 9 months with 12 months of patient follow up. During the clinical study, patients were requested to daily measure (during the morning period approximately at the same hour), weight, blood pressure, and, using a vest, the heart rate, and bioimpedance. Also the heart rate, respiration rate, and activity were monitored during the night by means of a bed sensor. Moreover, they were requested to complete two questionnaires of symptoms and mood/-general well-being each day. The measured properties are shown in Table 1. From the 168 patients recruited, 132 (78%) were considered analyzable, that is, with more than 30 days of telemonitoring measurements. Additionally, HF related events were recorded. Six cardiologists have analyzed the data, identifying which patients had experienced a decompensation event requiring hospitalization (47 patients) and which patients had not (85 patients).

The obtained results suggest, in general, that the physiological data have predictive value, and in particular, that the proposed scheme is particularly appropriate to address the early detection of HF decompensation.

4 Personalized Data Description Model

Each time a patient is admitted to the hospital the reason for the admission, as determined by the medical practitioner in primary charge during the admission, is recorded in the patients medical history. This is performed using a standardized international $'codebook'$, the International Statistical Classification of Diseases and Related Health Problems (ICD) [31], a medical classification list of diseases, injuries, symptoms, examinations, physical, mental or social circumstances issued by the World Health Organization. The ICD has a tree-like structure; at the top-most level codes are grouped into 12 chapters, each chapter encompassing a spectrum of related health issues. A disease progression is seen as being reflected by a patients admission history $H = a_1 \rightarrow a_2 \rightarrow \ldots \rightarrow a_n$ where a_i is a discrete variable whose value is an ICD code corresponding to the ith of n admissions on the patients record. The parameters of the underlying firstorder Markov model are then learnt by estimating transition probabilities $p(a^{‘} \rightarrow a^{“})$ for all transitions encountered in training (the remaining transition probabilities are usually set to some low value rather than 0). The model can be applied to predict the admission a_{n+1} expected to follow from the current history by likelihood maximization:

$$a_{n+1} = arg \max_a p(a_n \rightarrow a) \tag{1}$$

Alternatively, it may be used to estimate the probability of a particular diagnosis a^* at some point in future:

$$p_f(a^*) = \sum_a [p(a \rightarrow a^*) p_f(a)] \tag{2}$$

or to sample the space of possible histories:

$$H^{‘} = a_1 \rightarrow a_2 \rightarrow \ldots \rightarrow a_n \dashrightarrow a_{n+1} \dashrightarrow a_{n+2} \ldots \tag{3}$$

Our aim is to predict the probability of a specific admission a following the patient history H:

$$p(H \rightarrow a|H) \tag{4}$$

A history H is represented using a history vector $v = v(H)$ which is a fixed length vector with binary values. Each vector element corresponds to a specific admission code (except for one special element explained shortly) and its value is 1 if and only if the corresponding admission is present in the history:

$$\forall a \in A. v(H)_{i(a)} = \begin{cases} 1 : \exists j. H = H_1 \rightarrow a_j \rightarrow H_2 \wedge a = a_j \\ 0 : otherwise \end{cases} \tag{5}$$

where A is the set of admission codes, $i(a)$ indexes the admission code a in a history vector, and $H_{1,2}$ may take on degenerate forms of empty histories.

The disease progression modelling problem at hand is thus reduced to the task of learning transition probabilities between different patient history vectors:

$$p(v(H) \rightarrow v(H^{`})) \tag{6}$$

It is important to observe that unlike in the case of Markov process models working on the admission level when the number of possible transition probabilities is close to n_a^2, here the transition space is far sparser. Specifically, note that it is impossible to observe a transition from a history vector which codes for the existence of a particular past admission to one which does not, that is:

$$v(H)_{i(a)} = 1 \wedge v(H^{`})_{i(a)} = 0 \Rightarrow p(v(H) \rightarrow v(H^{`})) = 0 \tag{7}$$

5 Data Flow Trend Similarity Measure Method

The correlation between a patient p_j and a data e_0 is the log function of the probability of abnormality in physiological index e_0 divided by the probability of no abnormality in e_0.

$$corr(e_0, p_j) = log \frac{Pr(F_0|F_{j,1}, F_{j,2}, ..., F_{j,k})}{Pr(F_0^c|F_{j,1}, F_{j,2}, ..., F_{j,k})} \tag{8}$$

$corr(e_0, p_j)$ indicates the relationship between p_j and e_0. The higher $corr(e_0, p_j)$ is, the more relevant e_0 is to patient j, and with the greater probability that patient j is abnormal in data e_0. We can simplify the calculation of $corr(e_0, p_j)$ as follows.

$$corr(e_0, p_j) = log \frac{Pr(F_0)}{Pr(F_0^c)} + \sum_{i=1}^{k} \frac{logPr(F_{j,i}|F_0)}{Pr(F_{j,i}|F_0^c)} \tag{9}$$

To future simply the above formula, we make use of the characteristic of our data. Since a data has only two states normal or abnormal, i.e. F_0 or F_0^c, using the property of probability, $Pr(F_0^c)$ and $Pr(F_{j,i}|F_0^c)$ in (9) can be eliminated in $corr(e_0, p_j)$, as shown below.

$$log \frac{Pr(F_0)}{1 - Pr(F_0)} + \sum_{i=1}^{k} log \frac{Pr(F_{j,i}|F_0)(1 - Pr(F_0))}{Pr(F_{j,i} - Pr(F_{j,i}|F_0^c)Pr(F_0))} \tag{10}$$

From the concept of conditional probability, we know that a joint probability is

$$Pr(F_{j,i}|F_0) = Pr(F_{j,i}|F_0)Pr(F_0) \tag{11}$$

Then we can further simplify

$$corr(e_0, p_j) = (k-1)log \frac{1-\alpha}{\alpha} + \sum_{i=1}^{k} log \frac{\beta_{j,i}}{\gamma_{j,i} - \beta_{j,i}} \tag{12}$$

where

$$\alpha = Pr(F_0) = \frac{number of exceptional events}{number of events} \tag{13}$$

$$\gamma_{j,i} = Pr(F_{j,i}) = \frac{number of events that F_{j,i} holds}{number of events} \tag{14}$$

$$\beta_{j,i} = Pr(F_{j,i}|F_0) = \frac{Pr(F_{j,i}, F_0)}{Pr(F_0)} = \frac{1}{\alpha}\frac{number of events that both F_0 and F_{j,i} holds}{number of events} \tag{15}$$

We also apply smoothing techniques for the above formula. The next step is ranking $corr(e_0, p_j)$ with respect to all the data in descending order. The higher a data in the list, the more possible that p_j is abnormal in related to this data.

6 System Demonstration

The basic vital sign data in this system comes from the cooperative medical institutions. The real-time ECG data is collected using the 12-lead ECG monitoring equipment-HeartView 12BT- from Israeli Aerotel Medical System. This device supports two transmission modes of Bluetooth and voice. The transmission mode of Bluetooth means that the HV device can transmit the detected ECG data to the external Bluetooth media in real time through Bluetooth. The voice transmission mode refers to that the device can convert the ECG data into sound signals for transmission to the remote ECG monitoring center. Then the ECG center will restore the ECG based on the received voice signals. In this system, we use Bluetooth as the transmission channel, and send the ECG data to a corresponding APP first. From the APP to the ECG monitoring cloud center, the ECG interpretation and screening are performed by the automatic interpretation system.

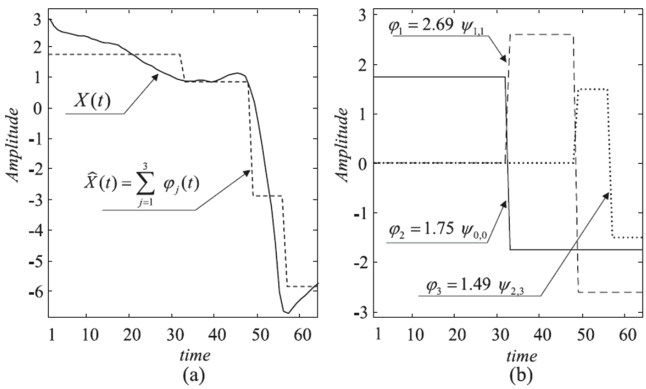

Fig. 2. Signal approximation using the Haar WaveletKLT decomposition scheme. (a) Actual signal and approximation (dashed line). (b) Specific wavelet bases used in the approximation.

As can be seen in Fig. 2, the main characteristics of the signal are captured using only three bases. Although it is possible to obtain small approximation errors (by increasing the threshold ε, and thus, the number of bases), it should be noted that this is not the main focus of the proposed scheme. Effectively, the final goal is to identify the main characteristics of the signal, that is, the main trends or behavior.

In this particular case, the most important basis is $\varphi_1(t) = 2.69\psi_{1,1}$ (largest coefficient). This means that the highest variation in the signal occurs between the instants, as can be confirmed by inspecting Fig. 2(a). Moreover, the second basis, $\varphi_2(t) = 1.75\psi_{0,0}$, is the one that reflects the contribution of the complete signal. Since the coefficient has a positive value, it can be concluded that the signal presents a global positive variation, that is, the mean of the first half, instants, is higher than the mean of the second half, instants. Finally, a similar conclusion can be drawn for the third basis, $\varphi_3(t) = 1.49\psi_{2,3}$. In fact, in the corresponding time region, instants, the signal presents a significant variation from a higher to a lower value, and thus, the coefficient has a positive sign.

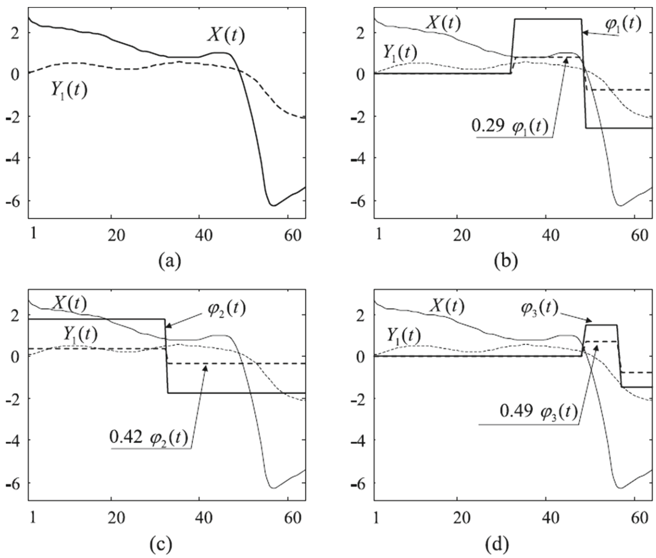

Fig. 3. Comparision of the two signals. (a) Signals to be compared, (b) first basis, (c) second basis, and (d) third basis.

The first signal to be compared, $Y_1(t)$, is described as (16) and shown in Fig. 3. In the second, Fig. 4, the same template, $X(t)$, is compared with the signal $Y_2(t)$, described as (17).

$$\hat{Y}_1(t) = \sum_{j=1}^{3} \alpha_j \varphi_j(t) = 0.29\varphi_1(t) + 0.42\varphi_2(t) + 0.49\varphi_3(t) \tag{16}$$

$$\hat{Y}_2(t) = \sum_{j=1}^{3} \alpha_j \varphi_j(t) = -0.93\varphi_1(t) - 0.49\varphi_2(t) + 0.21\varphi_3(t) \tag{17}$$

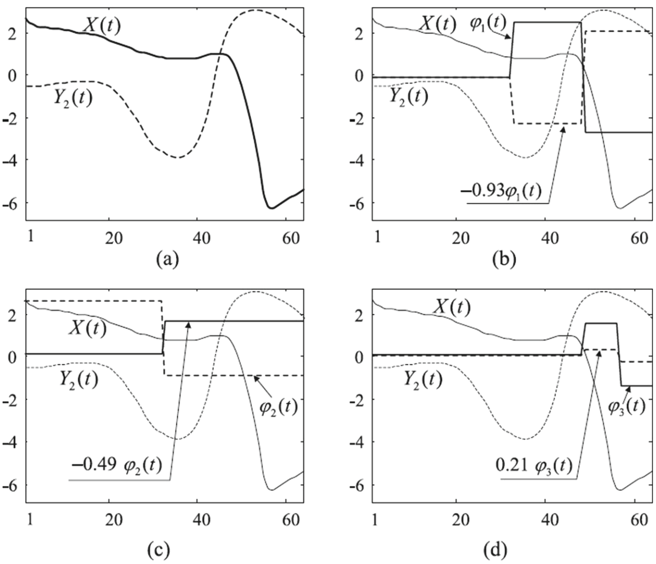

Fig. 4. Comparision of the two signals. (a) Signals to be compared, (b) first basis, (c) second basis, and (d) third basis.

In the first case, all the coefficients $\alpha_j(j = 1, 2, 3)$ are positive, thus having the same sign as the coefficients of the template (all equal to 1). From this simple statement, it can be concluded that template and signal present the same behavior, i.e., the same temporal trend (as can be observed in Fig. 3(a). As result the similarity measure, defined as (23), is $S_T(\Gamma, \Omega) = 1$. In the second example, it is observed that the first two coefficients are negative and the third is positive. Thus, it may be concluded that, in global terms, they do not present the same behavior (this can be observed for some intervals of the signal in Fig. 4(a). The similarity measure is in this case $S_T(\Gamma, \Omega) = 1/3$.

If the electrocardiogram is screened as invalid or abnormally abnormal electrocardiogram, the patient will immediately receive the interpretation result of the auto-response from the electrocardiographic monitoring center. If the electrocardiogram is not clearly answered after the interpretation, it will automatically form a pending task for the supervising doctor or ECG experts, as shown in Fig. 5. The expert will do the manual interpretation and processing of the ECG, as shown in Fig. 6.

The system can help experts screen and process 80% of ECG and interpretation time. Meanwhile, it saves patients a lot of treatment and waiting time.

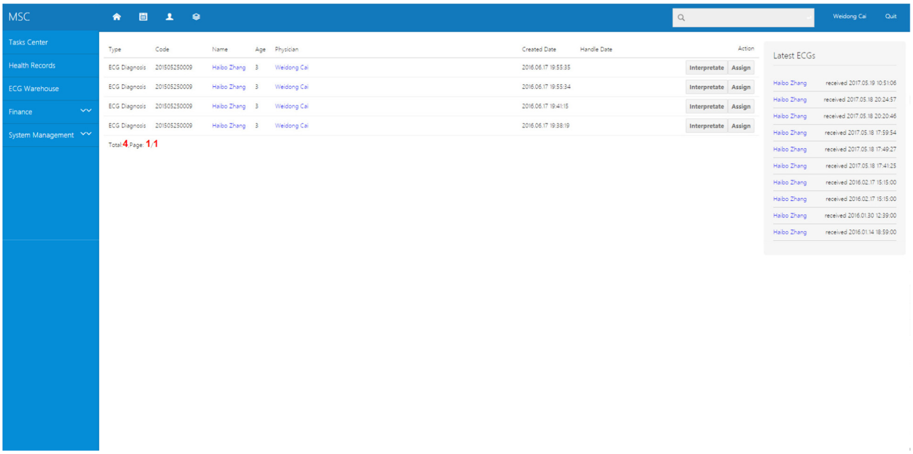

Fig. 5. The ECG monitoring cloud center

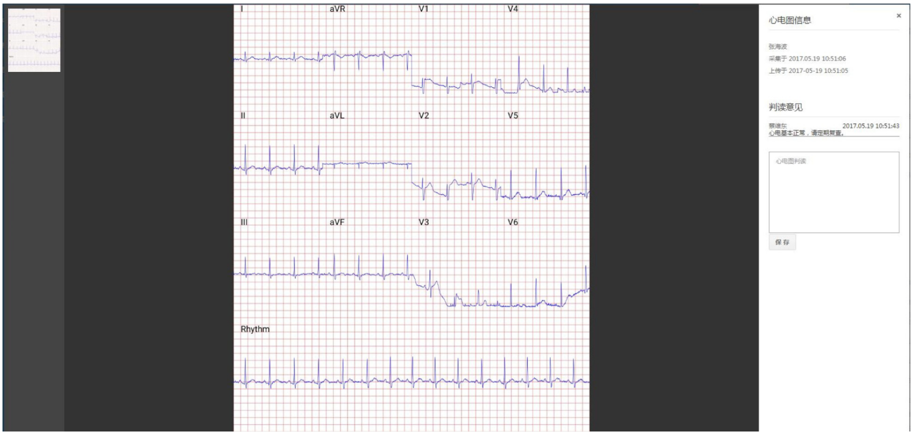

Fig. 6. The ECG

7 Conclusion

In conclusion, our study demonstrated that both unstructured and structured information can facilitate early detection of heart failure as early as two years prior to diagnosis. Through the introduction of big data and artificial intelligence technology, a cloud-based platform for ECG monitoring and early warning - HeartCarer is created. The proposed platform is particularly appropriate to address the early detection and warning of heart, which can effectively slow disease progression, save valuable rescue time for patients, reduce mortality, and provide users with efficient, intelligent and personalized services.

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