33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Health Status Detection for Patients in Physiological Monitoring

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***Abstract*— A primary difficulty in physiological monitoring is detecting changes of health status for patients. In order to address this difficulty, we propose a new framework in patient-specific physiological monitoring by defining a density ratio using the training density and testing density to denote the changes of patient status, such as health, sub-health and abnormalities. We use a Least Square-based algorithm to estimate density ratio parameters without involving density estimation. For verifying the availability and efficacy of the proposed framework, we apply our approach to physiological monitoring data (11901 beats) from the Physionet database to do the pilot experiments. Results demonstrate that the approach is effective in detecting the patient status.**

I. Introduction

In hospital or home healthcare, preventative intervention is very important in physiological monitoring, especially for the elderly and for patients who have cardiovascular disease history. For example, during surgery, patients may experience acute physiological disturbance and physiological instability, which may lead to death [1]. These adverse events often occur with minimal warning, which can prevent a timely and effective intervention before coming dangerous [2]. Thus, there is a great need for patient monitoring systems to perform automatic identification of patient status. Different methods have been developed for detecting patient deterioration and prompting staff intervention. Among them, novelty detection method is the most promising approach. The works on statistical approaches to novelty detection are reviewed in [3], [4]. The goal of novelty detection is to learn the density of training data and to give an alarm for new points which fall in low density areas

In [5] – [7] authors recently developed a data fusion based patient monitoring system, identifying abnormalities in a patient's vital signs based on a probabilistic model of normality, learned from a large sample of data previously collected. This motivates the use of vital signs to provide early warning of patient deterioration. [8] Employs the similar method to predict deterioration in dialysis patients. In paper [9], this type of method also has been proven effective in the early identification of critically ill patients. In above papers, the applied methods belong to KDE-based method, which use training density into biomedical monitoring. However, training density is not accessible in practice and density estimation is known to be a difficult problem and Threshold is hard to be determined in the tail of training data distribution. Thus, using densities to describe patient status may not be promising in practice.

In order to address above limitations, we propose a new framework into patient-specific physiological monitoring by defining density ratio using the training density and testing. We can give score for every beat and label every beat to denote the changes of patient status, such as health, sub-health and abnormalities.

The organization of this paper is as follows. In section II, we propose the framework for patient status monitoring system and convert it into density ratio estimation problem. In section III, we give the mathematical algorithm to show how to estimate the density ratio values using least squares method. In section IV, we present some experiments results to illustrate the usefulness of our approach which is followed by the conclusions and future work in section V.

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II. APPROACH TO HEALTH STATUS DETECTION

In this section, we propose the framework for patient status monitoring system and convert it into density ratio estimation problem.

Fig.1 shows the framework for patient status monitoring system to detect abnormal event. The key idea of our approach is to use the ratio of training and testing data density as health status index to denote the changes of patient status. Here we use blue color to denote the health status, green color to denote the sub-health status and red color to denote abnormalities status. Patients in the green status, mean patients' health are in the degenerating state, which is a predictive alert to make the patients or doctor pay attention to monitoring in the future.

Illumined by the density definition from papers [10], [11], here we can define our two sets of samples: training dataset $\{x_j^{tr}, x \in \mathbb{R}^d\}_{j=1}^{n_{tr}}$ and testing dataset $\{x_i^{te}, x \in \mathbb{R}^d\}_{i=1}^{n_{te}}$ in the d-dimensional domain ($D \in \mathbb{R}^d$). All samples in the training dataset $\{x_j^{tr}, x \in \mathbb{R}^d\}_{j=1}^{n_{tr}}$ are normal, while some anomalies are in the testing dataset $\{x_i^{te}, x \in \mathbb{R}^d\}_{i=1}^{n_{te}}$. We suppose training samples $\{x_j^{tr}, x \in \mathbb{R}^d\}_{j=1}^{n_{tr}}$ are independent and identically distributed (i.i.d.) following a training data distribution with nonnegative density- $p^{tr}(x)$, and testing samples $\{x_i^{te}, x \in \mathbb{R}^d\}_{i=1}^{n_{te}}$ are i.i.d. following a test data distribution with strictly positive density-$p^{te}(x)$. Via above two densities, the density ratio can be defined by [10] - [12]:

$$\mathrm{r(x)} = \frac{\mathrm{p^{tr}(x)}}{\mathrm{p^{te}(x)}} \tag{1}$$

Here, we propose the following inequality to denote the three statuses of patients:

$$\begin{cases} \mathrm{r(x)} = \frac{\mathrm{p^{tr}(x)}}{\mathrm{p^{te}(x)}} > T_1 & \text{(a)} \\ \mathrm{T_2} < \mathrm{r(x)} = \frac{\mathrm{p^{tr}(x)}}{\mathrm{p^{te}(x)}} < T_1 & \text{(b)} \\ \mathrm{r(x)} = \frac{\mathrm{p^{tr}(x)}}{\mathrm{p^{te}(x)}} < T_2 & \text{(c)} \end{cases} \tag{2}$$

Inequality (a) means patients are healthy, the inequality (b) means patients in the sub-health status, and inequality (c) means patients are abnormal. Where T_1=Threshold$_1$, T_2=Threshold$_2$, which can be determined by doctors according to different patient's situation.

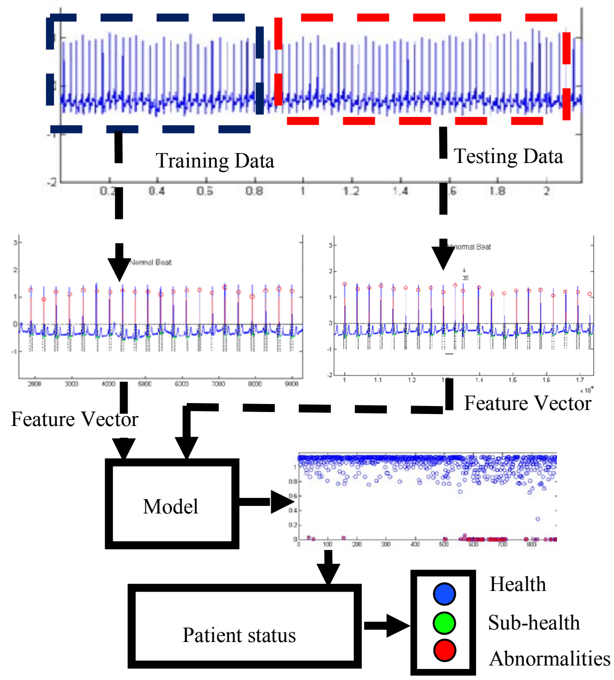

Fig.1 The framework for patient status monitoring system

In order to quantify the status of patients, a Patient Status Index (PSI) is defined to generate alerts during periods of abnormal physiology:

$$\text{Patient Status Index(PSI)} = \mathrm{r(x)} = \frac{\mathrm{p^{tr}(x)}}{\mathrm{p^{te}(x)}} \tag{3}$$

Alerts are generated when the PSI is below the Threshold$_2$ (T_2) -density ratio values. In real situation, the density ratio r(x) is usually unknown, so the key issue of our approach is accurately estimating r(x). In the following part, we will show the algorithm about how to estimate density ratio values.

III. DENSITY RATIO ESTIMATION ALGORITHM

In this section, we give the mathematical algorithm to show how to estimate the density ratio values using least squares method.

First let us model the density ratio r(x) by the following linear model [10]:

$$\tilde{r}(x) = \sum_{l=1}^{b} \alpha_l \, \varphi_l(x) \tag{4}$$

Where $\{\alpha_l\}_{l=1}^{b}$ are parameters to be learned from data sampl es and $\{\varphi_l(x)\}_{l=1}^{b}$ are basis functions such that $\varphi_l(x) \geq 0 \; for \; all \; x \in \mathbb{R}^d \; and \; for \; l = 1,2,\cdots,b$

In the following we will modify the algorithm proposed by papers [10] – [12] and link [13], [14] in order to make it adapt to our approach. Using the estimated density ratio model (4) we can get the squared error equation by

$$J = \int \left(\tilde{r}(x) - r(x)\right)^2 dx = \int [\tilde{r}(x)^2 - 2r(x)\tilde{r}(x) + r(x)^2]dx$$

$$= \int [\tilde{r}(x)^2 - 2\tilde{r}(x)\frac{p^{tr}(x)}{p^{te}(x)} + r(x)^2]dx$$

$$= \int \{[\textstyle\sum_{l=1}^{b} \alpha_l \varphi_l(x)]^2 - 2[\sum_{l=1}^{b} \alpha_l \varphi_l(x)]\frac{p^{tr}(x)}{p^{te}(x)} + r(x)^2 \}dx \qquad (5)$$

The third term in above is constant, so we can only focus on the first and the second term-inconstant term. The parameters $\{\alpha_l\}_{l=1}^{b}$ are determined so that the squared error equation (5) can be minimized [10] - [12]:

$$\min_{\{\alpha_l\}_{l=1}^{b}} [\alpha^T H_{te}\alpha - h_{tr}\alpha] \qquad (6)$$

Where $H_{te} = \frac{1}{n_{te}}\sum_{i=1}^{n_{te}} \varphi_l(x_i^{te})\varphi_m(x_i^{te})$

$$h_{tr} = \frac{1}{n_{tr}}\sum_{j=1}^{n_{tr}} \varphi_l(x_j^{tr})$$

We can use l_1-regularizer $1_b^T\alpha$ or l_2- regularizer $\alpha^T\alpha$ as regularization parameter [10] to solve above minimization equation.

IV. EXPERIMENTS EVALUATION

In this section, we do pilot experiment and report the results of patient health status detection for selected patients from MIT-BIH Arrhythmia Database.

The training and testing data employed to verify the availability and efficacy of the proposed diagnosis system are selected from MIT-BIH Arrhythmia Database [15], [16]. Here, we have one criterion to select patient records in our experiment. The record, where the duration of continuous normal data is longer than 6.30 minutes, can be selected as our database. So there are totally 10 records from 10 patients are satisfied.

The features are extracted from the sequence of records then converted into data samples in the training dataset and testing dataset. Here, we extracted 10 features from ECG signal. The features lists are shown in Table I. The numbers of involved heart beats are listed in table II. Clearly, it is a large scale experiment, containing totally 11,901 beats.

Here, we show the results for some selected patients due to page limitation. In the following Fig. 2, Fig.3, we use blue circle symbols to denote healthy samples, green triangle symbols to denote sub-healthy samples and red star symbols to denote abnormal samples.

TABLE I

DESCRIPTION FOR EXTRATED FEATURES

Feature symbol	Feature description
RR	The time duration between the adjacent beat R peak
QRS-dur	The time duration between *Q* and *S* in a QRS complex
TeSend	The time duration between *S* end and *T* end
H-QR	The amplitude between *Q* and *R* in a QRS complex
H-RS	The amplitude between *R* and *S* in a QRS complex
RP	The time duration between P and R
TR	The time duration between T and R
QsPstart	The time duration between Q start and P start
H-PR	The amplitude between *R*and *P* in the same beat
H-RT	The amplitude between *R* and *T* in the same beat

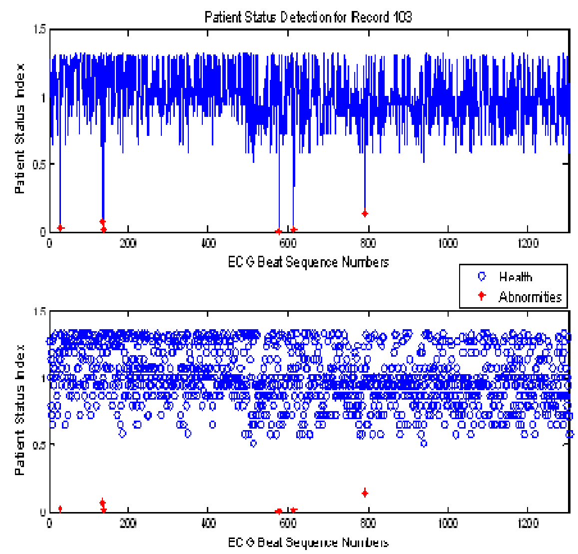

Fig.2 Patient Status Detection for patient 103

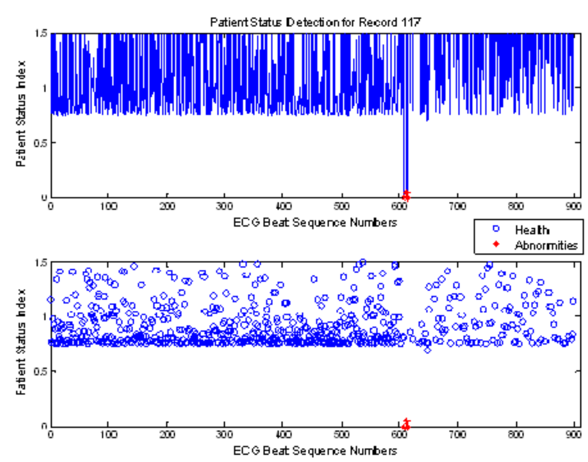

Fig.3 Patient Status Detection for patient 117

The sensitivity (Se) and specificity (Sp) for the ten patients are shown in table II when selecting 0.5 and 0.2 as the two thresholds. The experimental results for the ten patients datasets showed that our approach work very well in terms of specificity and sensitivity. From the table II we can see Patient record 234, exhibited poor performance, this is because there are many noises in this record, and those noises can be regarded as anomaly when performing our approach.

TABLE II

SENSITIVIRY AND SPECIFICITY FOR THE TEN PATIENTS

(T1=0.5, T2=0.2)

Record	Test Beat Numbers	Sensitivity (Se)	Specificity (Sp)
101	1153	**100%**	99.83%
103	1302	**100%**	99.69%
112	1597	**100%**	99.12%
113	1354	**100%**	99.78%
115	1179	**100%**	**100%**
117	912	**100%**	99.78%
121	890	**100%**	94.65%
122	1065	**100%**	**100%**
123	1165	**100%**	**100%**
234	1284	88.68%	98.15%
Total	**11901**	**98.87%**	**99.10%**

V. CONCLUSIONS AND FUTURE WORKS

In this paper we propose a new framework into patient-specific physiological monitoring by defining density ratio using the training density and testing density to denote the changes of patient status, such as health, sub-health and abnormalities. We use Least Square-based algorithm to estimate density ratio parameters without involving density estimation which is more advantages than approach using non-parametric technique to estimate density. The results of experiments show that it is possible to detect the changes of health status during physiological monitoring.

In the future, we will further apply this approach in longer time records and more patients, try to find more effective algorithm to estimate density ratio values and apply it in health status detection for physiological monitoring. In addition, other measures capable of characterizing the different physiological phenomena (such as respiratory rate, oxygen saturations, blood pressure and temperature) will be investigated and assessed for their added value with respect to the predictive capability of the health status index.

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[16]http://www.physionet.org/