ECG Signal Monitoring using One-class Support Vector Machine

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Abstract: - In this paper we proposed an ECG(electrocardiogram) signal monitoring system working on a ZigBee based wireless sensor network. An ECG signal acquisition module is implemented on a wireless platform that can acquire heart signals from ECG sensors and do wirelessly transmit the acquired heart signals based on a ZigBee protocol. Moreover, the ECG signal acquisition module is accompanied by an ECG signal monitoring module implemented in a host PC, which analyzes transmitted ECG signals from the ECG signal acquisition module and generates monitoring signals indicating normal and abnormal states. The proposed ECG signal monitoring system operating based on wireless communication of these two modules is aimed to be developed as a personalized heart signal processing system. In order to develop such a personalized system, a generic feature extraction method and an OCSVM (one-class support vector machine) classifier are applied. A histogram technique and a principal component analysis method are considered for generating features with general characteristics by extracting initial features and refined features from input ECG signals, respectively. Moreover, OCSVM is considered for developing a personalized heart signal classifier working for discriminating abnormal heart signals from normal heart signals aimed at a personalized system operating. For performance verification of the proposed system, experiments using supraventricular arrhythmia and normal ECG signals of MIT-BIH DB are conducted. The proposed system correct classification rates of 93.3% and 92.6% for normal ECG signals and supraventricular arrhythmia ECG signals, respectively. Theses experimental results shows that the proposed system outperforms compared with different approaches with other classifiers.

Key-Words: - ECG signal monitoring, One-class support vector machine, Principal component analysis

1 Introduction
Ubiquitous sensor network (USN) is widely applied for remote monitoring systems such as a ubiquitous health monitoring system, a natural disaster monitoring and prevention system, a security system, etc [1-3]. Among them, a health monitoring system is under consideration as a hot issue for saving old people or specific patient from emergency situations by automatically indicating health emergency and promptly informing or providing a proper emergency treatment. For a health monitoring system, ECG signal monitoring is widely used in clinical practice [4], which is measuring the electrical activity of the heart. Most of the algorithms processing ECG signals are focused on indicating a specific feature for diagnosis, which works well in many applications [4-7]. However, in some cases, it is very hard to find an essential characteristic feature for indicating an occurrence of abnormal symptom. Therefore, it is needed to develop a generic feature extraction method for monitoring any emergency situation by detecting abnormal ECG signals having different characteristic features compared with ECG signals obtained during normal states. Analysis of the ECG signals is of the great importance in the detection of cardiac anomalies. One of the most important ECG components is the QRS complex, which is associated with electrical ventricular activation. ECG pattern recognition can be divided into a sequence of stages; starting with feature extraction from the occurring patterns, which is the conversion of the patterns to features that are regarded as a condensed representation. In this paper, we proposed a new wireless sensor network platform for monitoring ECG signals. The proposed platform consists of two wireless sensor nodes and a personal computer (PC). One of two wireless sensor nodes works for both sensing ECGs and transmitting ECG signals to another sensor node in wireless. The other sensor node receives ECG signals and sends ECG signals to a PC in serial. ECG signal monitoring is occurred in the PC by the proposed ECG signal analysis and classification module. Wireless communication is conducted by ZigBee protocol operated by a communication chip in the sensor node.

Many non-linear approaches and time-frequency approaches are introduced for ECG signal processing for providing stable and effective rhythm detection [8-11]. Oswoski proposed an hierarchical system that combines multilayer perceptron(MLP) and another artificial neural network [12].

In this paper, we proposed an ECG signal monitoring module which extracts generic features from transmitted
ECG signals and discriminate each ECG signals as normal and abnormal. For feature extraction, the histogram of 1st derivative of transmitted ECG signals is considered in conjunction with a principal component analysis (PCA). In order to efficiently analyze the patterns of ECG signals using the extracted features, we have considered a support vector machine (SVM) which can make the optimal threshold for discriminating two different reflected signals [13, 14]. The SVM may show a robust performance in discriminating ECG signal patterns as normal and abnormal. However, we need enough data, normal and abnormal signals, to utilize for constructing active classifier such as the SVM. Unfortunately, it is hard to personally collect enough abnormal ECG signals caused by various factors. On the other hand, normal ECG signals can be easily collected. Therefore we considered the one-class SVM (OCSVM) since it is well known that the OCSVM can design an optimal classifier by properly describing one class data distribution in the feature space [13, 14]. The OCSVM is trained only using normal ECG signals that can make an optimal model for properly representing the distribution characteristic of normal ECG signal patterns. Moreover, in order to reflect non-linearity of ECG signals, we designed OCSVM as the nonlinear classifier by applying kernel function to the input features. For verifying the performance of the proposed model, the proposed model was applied to discrimination of ECG signals caused by the supraventricular arrhythmia symptoms from normal ECG signals. The ECG signals used in the experiments are obtained from MIT-BIH database.

Section 2 describes the overview of the proposed wireless sensor network for ECG signal monitoring. Section 3 and 4 describes the proposed ECG signal monitoring module and experiments, respectively. Conclusion and discussion will follow in Section 5.

2 System Overview

Fig. 1 shows the proposed wireless sensor network for ECG signal monitoring. One ZigbeX mote (ZigbeX 1 in Fig. 1) as a wireless sensor node plays a role for sensing ECG signals and wirelessly transmitting sensed ECG signals to another ZigbeX mote (ZigbeX 0 in Fig. 1) in every 256 ms. Each radio communication is conducted by 250kbps transmission rate using a 2.4GHz frequency band by the CC2420 wireless communication chip in ZigbeX mote. In addition, three ECG sensors are applied for obtaining ECG signals from human body. The second ZigbeX mote (ZigbeX 0 in Fig. 1) sends the transmitted ECG signals from ZigbeX 1 to a PC in serial. Then the transmitted ECG signals are analyzed by the ECG signal monitoring module implemented in a PC.

3 Proposed ECG Signal Monitoring Module

Fig. 2 shows a procedure of the proposed ECG signal monitoring module, which mainly consists of two parts. One is a feature extraction part from the input signals, and the other is a recognition part implemented by an OCSVM algorithm.

3.1 Feature Extraction

In this paper, we adapted a feature extraction model having more general characteristics for representing ECG signals in time domain applied in our previous model [15]. As shown in Fig. 3, 1st derivative of input signals is applied to extract primitive features of the ECG, which is calculated by Eq. (1):

$$dS(t) = S(t + \Delta t) - S(t)$$

(1)

where S(t) and \( \Delta t \) are an amplitude of raw input ECG signal at time t and a sampling time, respectively. The 1st derivative of input signals can generally represent simple patterns of time-series signals. Therefore it is natural that the 1st derivative of input signals can be used for describing general features of target signals. For generating more generic feature representation, a histogram approach is applied for 1st derivative signals.
For generalization, before obtaining the histogram, normalization of signal amplitudes is processed by Eq. (2):

$$nS(t) = \frac{dS(t)}{\text{max} \{ |dS(t)| \text{ for } \forall t \}}$$

Then quantization of the normalized 1st derivative signals follows before obtaining the histogram of the normalized 1st derive signals in order to make every histogram features have the same dimension. The quantized signals of the normalized 1st derivative signals are obtained by Eq. (3):

$$qS(t) = \frac{\text{max}_nS - nS(t)}{\text{max}_nS - \text{min}_nS} \cdot 100 \text{ mod } \text{n\_levels} \quad (3)$$

where max_nS and min_nS are a maximum value and a minimum value among the amplitudes of the total normalized signals, respectively. And n_levels in Eq.(3) is the number of quantized levels and the ‘mod’ operator calculates the quotient after division, which is used as a quantized index. From the quantized signals, the histogram, hS(i), is obtained by Eq.(4):

$$hS(i) = \# \text{ of } qS(t), \text{ where } qS(t) = i \quad (4)$$

In general, the histogram can represent statistical characteristics of extracted features, which makes the extracted features have more robustness against noise or disturbance of input signals than directly using the raw input signals. Moreover, in order to extract more important features from the histogram features as well as reduce dimensionality of the features, some eigenvectors with large eigen-values obtained by PCA are applied to the obtained histogram features. The number of eigen-vectors selected for transformation of features is decided by Eq. (5), which is the ratio between summation of the eigenvalues corresponding to the selected eigen-vectors and summation of all the eigenvalues. PCA is a well-known process for extracting essential features in a point of considering 2nd order statistics and reducing dimensionality of a high-dimensional feature space.

$$\arg \max \left\{ \frac{\sum_{i=1}^{n} \lambda_i}{\sum_{i=1}^{N} \lambda_i} > \theta \right\}, \lambda_1 > \lambda_2 > \cdots > \lambda_N \quad (5)$$

### 3.2 ECG signal discrimination using OCSVM(One-Class Support Vector Machine)

As mentioned in the previous section, it is hard to gather enough abnormal ECG signals from human body under different corresponding emergency states. Therefore we considered the classifier to be trained using only normal ECG signals, which are easily collected from human body in a normal status. For this purpose, an OCSVM is applied to design an optimal hyper-plane for discriminating abnormal ECG signals from normal ECG signals. It is well known that the SVM is a powerful binary classification method from previous studies [16-20].

In the two-class SVM, the linear hyper-plane is determined by Eq. (6)

$$f(x) = \langle w \cdot x \rangle + b \quad (6)$$

where x is observed data point, w is the normal vector and b is a bias term. These two parameters, such as w and b, define a boundary that maximizes the margin between data samples in two classes. The data samples, which are used to design the optimal decision boundary, are called support vector. Depending upon the sign of the function f, an input x is classified into either of the two classes. That is, if f(x) < 0 x is classified as its own class, otherwise it is indicated as an element of the outlier class. When we can have enough training data from two classes to be classified, SVM can properly generate an optimal hyper-plane for discriminating two classes. In some cases, however, it is hard to obtain enough training data from both two classes and we can have enough training data from only one class. That is, SVM cannot be applied to two class classification problem.

In such a problem, it is well known that the OCSVM can design an optimal classifier based on properly describing one class data distribution in the feature space [19]. The OCSVM algorithm maps input data into a high dimensional feature space (via a kernel) and iteratively finds the maximal margin hyperplane which best separates the training data from the origin. The OCSVM may be viewed as a regular two-class SVM where all the training data lies in the own class, and the origin is taken as the only member of the outlier class.

Therefore, the OCSVM generates a model for representing the distribution of features of normal ECG signals which is easily obtained rather than abnormal ECG signals. Because of nonlinear characteristic of ECG signals we need to consider the nonlinear classification method instead of linear hyper-plane as in Eq. (6). By applying kernel function to transform input data into a high dimensional feature space, we can design the nonlinear decision boundaries. The kernel function plays...
a role for transforming a nonlinear problem into a linear problem [19, 20]. The transform function is written by Eq. (7)

$$\phi : X \rightarrow R^N$$  \hspace{1cm} (7)

where input space X is transformed by to a high dimensional feature space, we can define the kernel function as Eq. (8)

$$K(x, x) = \phi(x) \phi(x)^T$$  \hspace{1cm} (8)

We can design the nonlinear decision boundary using Eq. (9) from combination of Eqs. (6) and (8)

$$f(x) = \mathbf{w} \cdot \phi(x) + b$$  \hspace{1cm} (9)

where \( f(x) \) has nonlinear characteristic by using kernel function to transform input data to high dimensional feature space and we applied the Gaussian kernel function. Gaussian kernel function is determined by Eq. (10)

$$K(x, y) = \exp(-\frac{1}{2\sigma^2} ||x - y||^2)$$  \hspace{1cm} (10)

where \( \sigma^2 \) is a variance which means the width of Gaussian kernel function.

The optimization problem of OCSVM using kernel function is equivalent to solve the dual quadratic programming problem as in Eqs. (11) and (12)

$$\min_\alpha \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j K(x_i, x_j)$$  \hspace{1cm} (11)

$$0 < \alpha_i < \frac{1}{r}, \sum_i \alpha_i = 1$$  \hspace{1cm} (12)

where \( \alpha_i \) is a Lagrange multiplier at ith data out of total number of data, \( r \) is a parameter that controls the trade-off between maximizing the distance of the hyper-plane from the origin and support vector, l is the number of learning data. From solving this problem, we can obtain the optimal nonlinear decision boundaries.

4 Experimental Results

Fig. 3 shows the acquired ECG signals transmitted from one wireless sensor node (ZigbeX 1 in Fig. 1) sensing ECG signals using ECG sensors through another sensor node (ZigbeX 0 in Fig. 1) communicating in wireless with the ZigbeX 1 sensor node. The proposed sensor network successfully transmits ECG signals from the sensing sensor node to the final destination of PC through another sensor node in wireless.

Fig. 3 ECG signals finally transmitted at PC from ECG signal sensing sensor node through another sensor node

In order to verify the proposed generic feature extraction method, we apply the proposed model to indicate supraventricular arrhythmia symptoms using some chosen ECG recordings of supraventricular arrhythmias in the MIT-BIH arrhythmia database. Normal ECG data are obtained from Physiobank database[21, 22]. The sampling rate of all the ECG signals obtained from the MIT-BIH arrhythmia database and Physiobank database is 125Hz. Supraventricular arrhythmia is a type of arrhythmias that cause the heart to pump blood less effectively [23]. Supraventricular arrhythmias occur in two upper chambers of the heart called the atrium. Arrhythmias cause nearly 250,000 deaths each year [23]. As many as 2 million Americans are living with atrial fibrillation, a type of arrhythmia, which is a very common long term arrhythmia [23]. A normal heart beats between 60 and 100 times a minute. However, in atrial fibrillation, the atria (upper lobes of the heart) beat 400 to 600 times per minute [23]. Therefore, the statistical features of ECG signals caused by supraventricular arrhythmia, such as the histogram of 1st derivative signals, may show different characteristics compared with ECG signals caused by normal heart.

Fig. 4 show raw ECG signals for normal & abnormal signals, respectively.

Fig. 4 Raw ECG signals for normal state (a) and supraventricular arrhythmia (b)
Fig. 5 shows the histograms of the normalized 1st derivatives for normal and abnormal signals, respectively. Fig. 6 shows a projection result of the histogram features onto two principal components obtained from PCA. In order to generate input features for the OCSVM classifier, 48 ECG signals are used for training data. Fig. 7 shows training data distribution of OCSVM and its support vectors and Fig. 8 shows classification results for each test ECG data by OCSVM. In Fig. 8, from # 1 to # 15 in test ECG data are normal ECG signals and the others (#16 ~ #42) are abnormal ECG signals for test. Fig. 8 shows that the proposed model fails to correctly classify one normal ECG signal among 15 normal signals and two abnormal ECG signals among 27 abnormal signals. Table 1 shows the performance of the proposed classification model. 42 ECG signals are used for testing the proposed classification model, which are not used for training. The proposed model correctly classify with 93.3% accuracy for normal ECG data and also shows plausible performance for abnormal ECG data with 92.6% correct classification rate.

Table 1. Performance of the proposed classification model for test data

<table>
<thead>
<tr>
<th>Classifier</th>
<th>data</th>
<th># of total signals</th>
<th># of correctly classified signals</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>K-means</td>
<td>Normal ECG</td>
<td>15</td>
<td>13</td>
<td>86.7%</td>
</tr>
<tr>
<td></td>
<td>abnormal ECG</td>
<td>27</td>
<td>24</td>
<td>88.9%</td>
</tr>
<tr>
<td>MLP</td>
<td>Normal ECG</td>
<td>15</td>
<td>15</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>abnormal ECG</td>
<td>27</td>
<td>24</td>
<td>88.9%</td>
</tr>
<tr>
<td>OCSVM (proposed)</td>
<td>Normal ECG</td>
<td>15</td>
<td>14</td>
<td>93.3%</td>
</tr>
<tr>
<td></td>
<td>abnormal ECG</td>
<td>27</td>
<td>25</td>
<td>92.6%</td>
</tr>
</tbody>
</table>

We compared the performances of the three different classifiers such as k-means, MLP and OCSVM. As shown in Table1, OCSVM shows the most plausible performance for both normal and abnormal ECG signals among three different cases.
5 Conclusion
We proposed an ECG signal monitoring system prototype, which is operating in a wireless sensor network platform using commercial sensor node motes working under ZigBee protocol. In the proposed system, a proposed OCSVM based ECG signal classification model is successfully monitoring the normal and abnormal ECG signals. The proposed system can apply to a health monitoring system for emergency treatment of heart patient. In addition, the proposed model can be utilized for a personalized heart emergency detector since the applied signal monitoring approach is appropriate for adaptively working for each individual person. As further works, we are considering to develop more complex sensor networks for health monitoring which can play a role for a large scale health emergency system as well as a personalized monitoring system.

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