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A Pervasive Energy-Efficient ECG Monitoring Approach for Detecting Abnormal Cardiac Situations

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Abstract—Mobile and pervasive ECG monitoring systems require continuous connectivity with server-side ECG analyser for instantaneously detecting abnormal cardiac situations. Normally, these systems generate a large amount of data, resulting in a high energy expenditure with data transmission on pervasive ECG platform. In this context, data reduction mechanisms can be applied for saving transmission energy of pervasive ECG monitoring devices, maximizing the availability and confiability of ECG monitoring systems. This paper proposes an pervasive energy-efficient ECG monitoring approach for detecting abnormal cardiac situations for ubiquitous health systems. The data reduction approach based on error prediction maximize the life time of pervasive ECG monitoring device by gathering and reducing heart signal before sending it to server-side ECG analyzer application. Moreover, Pearson's Coefficient (correlation rate) is applied on the proposed data reduction approach, enhancing the quality of monitored heart signal.

I. INTRODUCTION

Pervasive health monitoring systems are sensor-based platforms able to check vital signal of person, at anytime and anywhere [12], [13], [14], [3]. For exemple, these mobile sensor-rich biological monitoring systems can be equipped with ECG sensor for continuously tracking heart disease. Usually, ECG gathered data is locally stored on the pervasive monitoring platform for later analysis, or is continuously sent for server-side analyzer application. In fact, there is a huge demand for continuous ECG monitoring systems, requiring real-time response, high availability and confiability.

However, these resource-constrained real-time monitoring platform (e.g., ECG continuous monitoring systems) usually generate a large volume of data, expending a lot of energy from mobile monitoring device that are powered by batteries [15]. Also, pervasive ECG monitoring systems have severe physical constraints, such as memory capacity, computational power, and energy autonomy [16], [17]. The energy consumption of monitoring systems is mainly associated with three operations: i) sensing fuctions, ii) data processing, and iii) communication [18]. In fact, the energy spent in sensing varies according to the sensor type and application nature. For

instance, the sporadic sensing (e.g., blood sugar monitoring) consumes less energy than the constant event monitoring, such as heart disease tracking. Therefore, a data reduction mechanism is essential for save energy, but it should be concerned with the quality of information generated after compression [4], [5], [3], which adds application error.

The focus of this work is to maximize the lifetime of ECG monitoring systems, by saving transmission data energy. This paper proposes a predictive data reduction mechanism (Adaptive Simple Linear Regression - ASLR) to extend the lifetime of pervasive ECG continuous monitoring systems.

The proposed ASLR approach compress heart data gathered from pervasive ECG monitoring platform before sending it to server-side ECG analyser application. The pervasive ECG monitoring system is based on the Arduino Platform¹, which was integrated with our Context Manegment Framework (CxtMF) for constructing context-aware healthcare applications, such as ECG monitoring systems (for more information about the CxtMF, please refer to [4], [3]). The proposed ECG pattern classification is constructed on the CxtMF, which is able to classify ECG signal as normal and abnormal heart condition.

ASLR uses a basic mechanism of prediction, which is based on the history of vital signal raw data collected by ECG monitoring platform. By using the proposed ASLR approach, the ECG monitoring platforms should to produce coefficients that models the sample set from the reading window. Thus, instead of send all gathered samples, the monitoring platform send to the server-side analyser application only the coefficients that represents the line, i.e., the set of reading values [15]. The production of the coefficients are controlled by the error between the real and estimated value. Thus, we have a mechanism that can adjust the sample windows used on the model. Based on the received coefficients (models), the server-side application is able to reconstruct the sample set

¹<http://www.libelium.com/130220224710/>

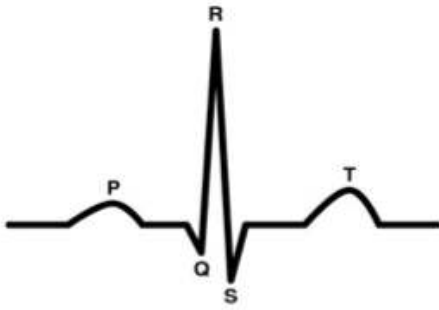


Fig. 1. Representation of a normal electrocardiographic wave.

of ECG gathered data. The quality of ECG gathered data is enhanced by using Pearson's Coefficient (correlation rate) in the proposed ASLR approach.

The remainder of the paper is organized as follows: Section 2 gives an overview on electrocardiogram data. Section 3 presents the proposed data reduction approach as well as the proposed ECG pattern classification approach. Section 4 presents the methodology and Section 5 the discuss about experimental results. Finally, we conclude the paper and discuss future work in Section 6.

II. ELECTROCARDIOGRAM OVERVIEW

Electrocardiogram (ECG) is an exam which records electrical pulses generated during the cardiac activity and, thus, aids the diagnosis of heart disease and other diseases, not only related to the circulatory system [20]. Among the main diagnoses, can be highlighted diseases²: arrhythmias, overload, areas electrically inactive, neurological diseases and congenital diseases. It is responsibility of surgeons, general practitioners and emergency care physicians, the interpretation of ECG signals. The heart activity produces currents that radiate through the surrounding tissue to the skin. ECG electrodes are attached to the skin to capture that heart's electrical activity (electrical currents). The equipment converts that current into waves which represents the heart depolarization and repolarization cycle [19]. A ECG Complex represents the electrical events occurring in the cardiac cycle and consists of five waves denominated by the letters P, Q, R, S and T. The letters Q, R and S are considered a unit, namely, the QRS Complex. P wave is the first component of a normal ECG (Figure 1) and represents the atrial depolarization. A normal P wave has the following characteristics:

- Location: Precedes the QRS complex;
- Width: 2 to 3 mm in height;
- Duration: 0.06 to 0.12 seconds;
- Configuration: Generally rounded up.

PR interval is from the beginning of the P wave to the beginning of the QRS complex and takes between 0.12 and 0.20 seconds. QRS complex comes shortly after the P wave

(Figure 1) and represents the depolarization of the ventricles. A normal QRS complex has the following configuration:

- Location: After the PR interval;
- Width: 5 to 30 mm in height;
- Duration: 0.06 to 0.10 seconds or half the PR interval;
- Configuration: Q waves (deflection below the baseline), R (first positive deflection following the Q wave) and S (first negative deflection after the R wave).

ST segment, also known as J point represents the end of ventricular depolarization and the beginning of ventricular repolarization. This segment under normal has the following characteristics:

- Location: extends from the S wave to the beginning of the P wave follows;
- Deflection: Generally isoelectric (neither positive nor negative);
- Amplitude: Can range from -0.5 to 1 mm.

T wave represents ventricular repolarization. It has the following characteristics:

- Location: Follows the S wave;
- Width: 0.5 to 10 mm;
- Setup: Typically rounded and smooth;
- Deflection: Generally up, but may appear reversed in some derivations.

QT interval is from the beginning of the QRS complex to the end of T wave. This range varies with age, sex and heart rate. Usually takes from 0.36 to 0.44 seconds. Heart rate is the number of times the complete cycle (the start of a P wave to the beginning of another wave P) occurs per minute. The reference values for adults is 60-100 bpm (beats per minute) at rest [19]. On the other hand, heart rate is the distance between R wave peaks from two successive QRS complexes. If all those distances are in the same size range, the rhythm is normal. Furthermore, in order to that a wave electrocardiographic be diagnosed as normal, it must meet the following five characteristics [19]:

- Regular rhythm;
- Normal frequency;
- A P wave for every QRS complex and all the P waves and QRS complexes similar in size and shape;
- PR and QT intervals normal;
- T waves up and rounded.

Based on all those characteristics, ECG gathered data can be separated into two basic groups: normals and abnormal. In fact, any ECG wave that does not meet those five basic requirements will have an abnormal diagnosis. Therefore, our proposed ECG classification solution is taking into account these considerations for classifying heart signal in normal and abnormal cardiac situation.

III. PERVASIVE ENERGY-EFFICIENT ECG MONITORING APPROACH

This section outlines the proposed approach by describing the data reduction mechanism based on the Pearson's Coefficient (correlation rate) which reduces the error generated by

²<http://www.heart.org/>

Adaptive Simple Linear Regression (ASLR). Furthermore, we present the electrocardiogram classification mechanism, which uses the following techniques: Machine Learning, Support Vector Machines, Stepwise Algorithm, and Cross-Validation.

A. Adaptive Simple Linear Regression Based on Pearson's Coefficient

Simple Linear Regression (SLR) is a technique to modeling the relationship between a scalar dependent variable Y and one explanatory or independent variable named X . SLR, basically, is based on least squares. In that case, each ECG sensor node calculates α and β by using as the independent variable, a counter that represents the time. The dependent variable to be predicted is the monitored physical variable (ECG signals for instance). In our adaptive scheme, the ECG sensor adjust the window of samples based on correlation coefficient. In that case, α and β are computed from samples based on Pearson's Coefficient, according Equation (1). Pearson's Coefficient shows the level of intensity between two variables and the direction from that correlation (positive or negative). Value of coefficient can be in range $[-1, +1]$.

$$r = \frac{n \sum_{i=1}^n x_i y_i - (\sum_{i=1}^n x_i)(\sum_{i=1}^n y_i)}{\sqrt{[n \sum_{i=1}^n x^2 - (\sum_{i=1}^n x_i)^2] [n \sum_{i=1}^n y^2 - (\sum_{i=1}^n y_i)^2]}} \quad (1)$$

where r represents the relationship between two one-dimensional vectors X and Y , to be compared in terms of its correlation. It contains window of samples of two variables, $X = x_1, x_2, \dots, x_i$ and $Y = y_1, y_2, \dots, y_i$, where $i = 1, \dots, n$ and n is the number of samples (window size). \bar{X} and \bar{Y} represent the average of samples of each variable vector.

Value of coefficient can be played as follows: if value is +1, then there is perfect positive correlation between the two variables; if value is -1, then there is perfect negative correlation between two variables. In other hand, if value is 0, then there is no correlation or correlation is non-linear. In our case, the better results on performance evaluation from prediction (low error) were got when Pearson's Coefficient ranged between $[0.6 - 1]$. The mechanism is done as described below and pictured in Figure 2:

- Step #1: the sensor node takes one measurement from the interested variable, for instance, the ECG signals, which named ECG;
- Step #2: if the node is in training mode, it adds the ECG in an internal buffer and sends this value to ECG server-side analyser application. After that, the node checks if the buffer is full. If it is true, the node goes to Step #3; otherwise returns to Step #1; if the node is not in training mode goes to Step #4;
- Step #3: the buffer is full. The pearson value is calculated; if the Pearson's Coefficient is less than a specific threshold, then the coefficients of linear regression is generated. We named Model. The model is sent to the ECG analyser. Finally, the buffer is cleared and Training Mode is set to False; returns to Step #1;

- Step #4: the node is not in Training mode. In this Step, the node estimates the measured value, based on the Model (linear regression coefficients). The error (the absolute difference between the Value and the estimated Value) is computed;
- Step #5: if error reach a specific threshold, the Value is sent to the ECG analyser and the node enters Training Mode;

The five steps are summarized in Algorithm 1 below:

```

Training_Mode = True;
while true do
    ECG = readECG();
    if Training_Mode then
        Buffer.add(ECG);
        send(ECG);
        if Buffer.isFull then
            P = calculatePearson(Buffer);
            if P < PEARSON_THRESHOLD then
                Model( $\alpha$ ,  $\beta$ ) = linearRegression(Buffer);
                send(Model);
                Training_Mode = False;
                Buffer.Clear;
            end
        end
    else
        ECG_Estimated = generate_value(Model, ECG);
        Error = abs(ECG - ECG_Estimated);
        if Error  $\geq$  ERROR_THRESHOLD then
            send(ECG);
            Training_Mode = True;
        end
    end
end

```

Algorithm 1: SLR based on Pearson's Coefficient

B. Machine Learning

In general, machine learning solutions can be divided into supervised and unsupervised learning approaches³. In supervised learning approach, systems need to know the environment by examples of input-output. The learning will be by reinforcement, which occurs by continuous interaction with the environment in order to minimize the performance. In unsupervised learning solutions, there are not examples of desired output values. In this case, the task searches from the input data to create some understanding of the data and generate an internal representation able of encoding the input characteristics in new classes, separating it into groups correctly. For this work, we are using supervised learning approach, providing to ECG monitoring system with all required data for learning cardiac situations.

Regarding how to develop the knowledge, machine learning can also be divided into Learning by Discovery, Learning

³<http://mitpress.mit.edu/books/foundations-machine-learning-0>

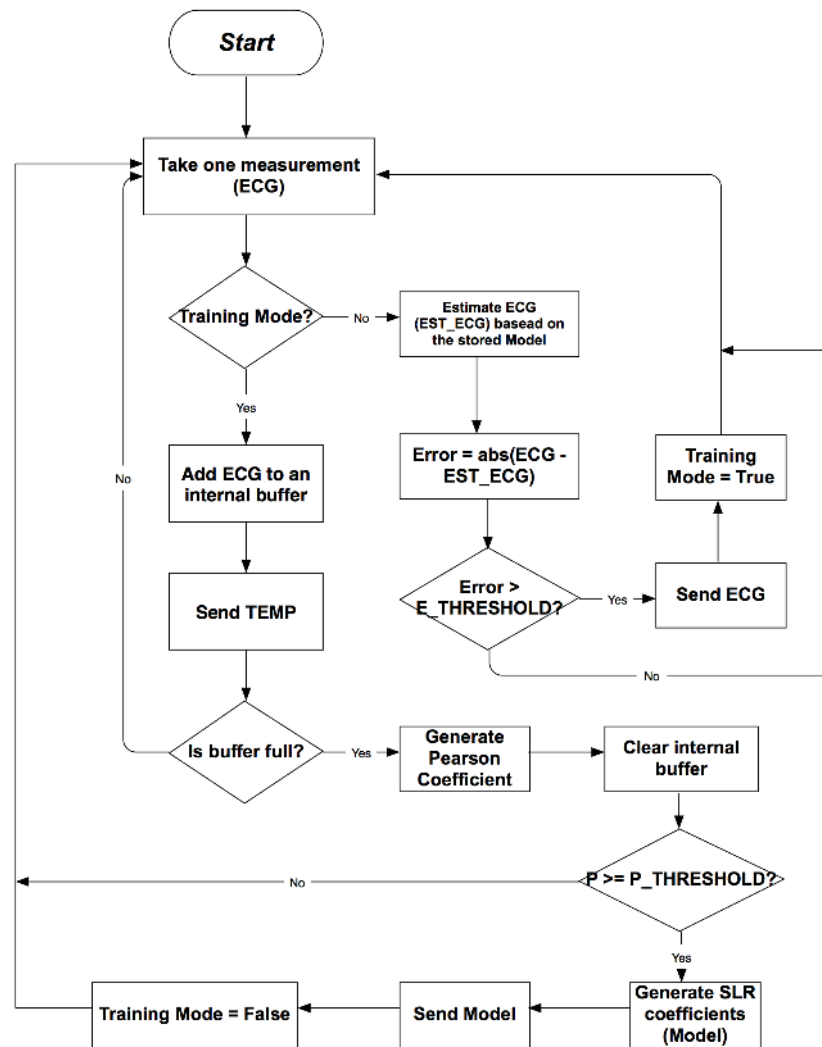


Fig. 2. Flowchart of the Algorithm of Data Reduction on SLR Adaptive

by Generalization and Learning by Analogy. These types of learning are discussed below:

- Learning by Analogy: is the ability to induce from a similar concept;
- Learning by Discovery: without a priori knowledge and without the assistance of someone who has knowledge, learn new concepts and facts;
- Learning by Generalization: objective produces generic and comprehensive knowledge from existing information.

Learning by Generalization can be subdivided into:

- Deductive Learning: try to learn new information that are valid consequences of something already known, such as explanation-based learning;
- Inductive Learning: It is based on inductive inference from facts provided by a teacher or environment. The system attempts to induce a rule from a set of observed instances.

For all types of learning, the set of all rules defined for the solution of a learning problem is named learning algorithm.

There are a range of algorithms that offer advantages and disadvantages depending on the problem to which it are applied.

C. Support Vector Machines

Support Vectors Machines (SVM) is a technique for optimal binary classification (two classes), but it was extended to support regression and classification problems of multiple classes. SVM is a particular case of kernel-based methods, which maps feature vectors into a high dimensional space by using some kernel function, and then for this new linear space creates a optimal hyperplane separating the classes. The solution is optimal in the sense that the margin between the hyperplane and the closest feature vectors of the two classes is maximal. The feature vectors that are closest to the hyperplane are named support vectors, meaning that the position of other vectors do not affect the hyperplane.

SVM algorithms were developed to solve classification problems and has been successfully used in pattern recognition applications, such as text categorization, categorization of

SPAM, handwritten character recognition, texture recognition, gene expression analysis, object recognition in 3 dimensions, and so on. Basically the operation of an SVM can be described as follows: given two classes and a set of points belonging to these classes, the SVM determines the hyperplane that separates points in order to place the highest points of the same class the same side while maximizing the distance of each class to hyperplane. The distance from one class to a hyperplane is the shortest distance between it and the points of this class and is named separation margin.

IV. METHODOLOGY

This section describes how our ECG continuous monitoring system works by using the ECG classifier on server-side ECG analyser application and data reduction techniques.

A. Applying Data Reduction on ECG Gathered Data

Before automatically classify exams by the ECG classifier on the server-side ECG analyser application, the pervasive ECG monitoring platform gathers ECG data for tracking vital signs (see Figure 3). The device consists of ECG sensors which monitor in realtime the patient conditions. That information is then compressed by coefficients of linear regression function, which are then sent to the server-side application through a ZigBee radio. When the ECG analyser application receives the coefficients, it is converted to ECG signals. Then these ECG signals are classified as normal or abnormal, automatically.

B. ECG Classification

This section describes all the steps and procedures of the methodology used to find the proper ECG classification. Essentially, the steps of this methodology performs the following actions:

- Acquisition;
- Training;
- Classification.

Acquisition is the first step for gathering ECG data from pervasive ECG monitoring platform.

In training step, the method of samples partitioning leave-N-Out method is used (to describe this method is beyond the scope of this work). Lastly, the classification step analyzes all the features of detected in the ECG signals, classifying the ECG data as normal or abnormal through the classifier SVM.

V. EXPERIMENTAL RESULTS

In order to evaluate the ECGs diagnostic methodology were performed some experiments. This section shows and discusses the experimental results obtained according to the used approach. One hundred (100) of ECG gathered data were selected randomly by attending only to the condition that these hundred ECG data, fifty (50) were considered normal and fifty (50) abnormal. Experiments were performed with the goal of minimizing the processing time without affecting the final result.

In this step, the candidates were divided into five (5) groups. This division aims to use the technique leave-N-out,

TABLE I
EXPERIMENTAL RESULTS WITH THE TECHNIQUE LEAVE-N-OUT

Group	Accuracy	Sensibility	Specificity
1	70%	70%	70%
2	80%	70%	90%
3	95%	90%	100%
4	95%	90%	100%
5	80%	70%	90%
Average	84%	78%	90%

where all groups are trained and tested, thus avoiding biased experiments. Follows, in the table below, the results for each group.

Group 1 achieved the correct diagnosis of fourteen (14) from twenty (20) tested exams, where the ten (10) normal, seven (7) were diagnosed correctly and three (3) incorrectly. The same occurred for the ten (10) abnormal in that group. Groups 2 and 5 had a slight improvement in accuracy where sixteen (16) out of twenty (20) exams were correctly diagnosed, and has been kept the same for seven (7) correct diagnoses to abnormal, and an increase to nine (9) correct diagnosis from ten (10) normal. Groups 3 and 4 were the ones that achieved the most significant results. The rate was nine (9) hits from twenty (20) exams, only one error for abnormal cases of the two groups. In the end, was obtained a average of 84% from accuracy, 90% from specificity and 78% from sensitivity. Results show that, in certain ECG signal particularly abnormal, the tests for the diagnosis from ECG failed to include the exams in set of regions of interest. This suggests that the way for obtaining the region of interest (complex P, Q, R, S and T) can be improved especially in the choice of abnormal complex exams, since there are several different standards, directly affecting the diagnosis sensitivity and reducing the accuracy.

VI. CONCLUSION

According to the World Health Organization (WHO), cardiovascular diseases kill 17 million of people each year around the world. Estimates suggest that in 2020, that number should increase to 25 million, which means that one every three people is the victim of cardiovascular diseases, which is a number six times higher than deaths from HIV. In Brazil, on average, 33% of the population dies every year victims of myocardial infarction or CerebroVascular Accident (CVA).

This paper provides a energy-efficient solution for automatic classification of ECGs in order to speed up the care of large number of patients who need to realize electrocardiographic exams in clinics and hospitals. That proposed solution is an energy-efficient ECG monitoring to detect abnormal cardiac conditions. It is composed of two mechanisms, which are responsible for: 1) collect ECG data of patients, but saving energy of ECG monitoring devices to increase its lifetime; and 2) classification of ECG exams automatically, from those data sent by the sensors devices to the ECG analyser application.

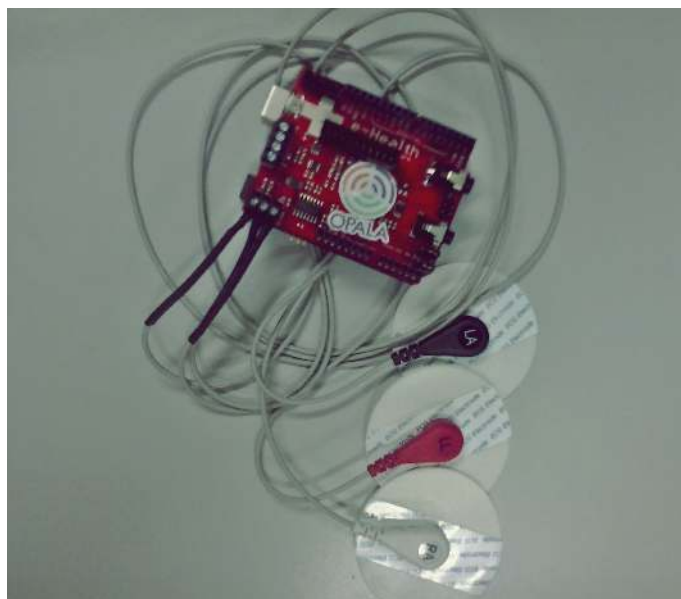


Fig. 3. ECG Sensors Device

REFERENCES

- [1] J. Zhu; M. Shen; K. Zhu, *An electrocardiogram classification method based on cascade Support Vector Machine*, Biomedical Engineering and Informatics (BMEI), 2011 4th International Conference on, Vol.3, pp.1640-1644, 15-17 Oct. 2011
- [2] F. Kiralj, *Basic Validation Procedures for Regression Models in QSAR and QSPR Studies: Theory and Application*, Journal of the Brazilian Chemical Society, Vol.20, No4, pp.770-787, 2009.
- [3] J. Bringel Filho, N. Agoulmine *Evaluation of Quality of Context Information in U-Health Smart Homes* In: IGI Global. (Org.). *Telemedicine and E-Health Services, Policies and Applications: Advancements and Developments*. Hershey PA: IGI Global, 2012.
- [4] J. Bringel Filho, A.D. Miron, I. Satoh, J. Gensel, H. Martin *Modeling and Measuring Quality of Context Information in Pervasive Environments*. In: 24th IEEE International Conference on Advanced Information Networking and Applications, 2010, Perth, Australia. AINA 2010. Los Alamitos, CA: ACM, 2010. v. 24. p. 690-697. .
- [5] J. Bringel Filho, N. Agoulmine *A Quality-Aware Approach for Resolving Context Conflicts in Context-Aware Systems* In: 9th IEEE/IFIP International Conference on Embedded and Ubiquitous Computing, Melbourne. EUC, 2011.
- [6] M. Niemeijer; M. Loog; M.D. Abramoff; M.A. Viergever; M. Prokop; B. van Ginneken, *On Combining Computer-Aided Detection Systems*, Medical Imaging, IEEE Transactions on, Vol. 30, Issue 2, 2011, pp.215-223.
- [7] F. Fraioli; G. Serra; R. Passariello, *CAD (computed-aided detection) and CADx (computer aided diagnosis) systems in identifying and characterizing lung nodules on chest CT: overview of research, developments and new prospects*, La radiologia medica, Vol.115, No3, Springer Milan, 2010, pp.385-402.
- [8] F. Melgani; Y. Bazi, *Classification of Electrocardiogram Signals With Support Vector Machines and Particle Swarm Optimization*, Information Technology in Biomedicine, IEEE Transactions on, Vol.12, Issue 5, 2008, pp.667-677.
- [9] A. Uyar; F. Gurgun, *Arrhythmia Classification Using Serial Fusion of Support Vector Machines and Logistic Regression*, Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, 2007, IDAACS 2007, 4th IEEE Workshop on, pp.560-565.
- [10] J.A. Nasiri; M. Naghibzadeh; H.S. Yazdi; B. Naghibzadeh, *ECG Arrhythmia Classification with Support Vector Machines and Genetic Algorithm*, Computer Modeling and Simulation, 2009, EMS '09, Third UKSim European Symposium on, pp.187-192.
- [11] N. Kohli; N.K. Verma; A. Roy, *SVM based methods for arrhythmia classification in ECG*, Computer and Communication Technology (ICCT), 2010 International Conference on, pp.486-490.
- [12] J. Smalls; W. Yue; L. Xi; C. Zehuang; K.W. Tang, *Health monitoring systems for massive emergency situations*, Systems, Applications and Technology Conference, 2009, LISAT '09, IEEE Long Island, pp.1-11.
- [13] A. Alahmadi; B. Soh, *A smart approach towards a mobile e-health monitoring system architecture*, Research and Innovation in Information Systems (ICRIIS), 2011 International Conference on, 2011, pp.1-5.
- [14] X. Haitao; T. Li; H. Ogai; Z. Xiaohong; T. Ottawa; S. Umeda; T. Tsuji, *The health monitoring system based on distributed data aggregation for WSN used in bridge diagnosis*, SICE Annual Conference 2010, Proceedings of, 2010, pp.2134-2138.
- [15] C.G.N. Carvalho; D.G. Gomes; N. Agoulmine; J.N. Souza, *Improving Prediction Accuracy for WSN Data Reduction by Applying Multivariate Spatio-Temporal Correlation*, Sensors, Vol.11, 2011, No11, pp.10010-10037.
- [16] I.F. Akyildiz; W. Su; Y. Sankarasubramaniam; E. Cayirci, *Wireless sensor networks: a survey*, Computer Networks, 2002, Vol.38, pp.393-422.
- [17] G. Anastasi; M. Conti; M.D. Francesco; A. Passarella, *Energy conservation in wireless sensor networks: A survey*, 2009, Ad Hoc Networks, Vol.7, No3, pp.537-568.
- [18] J. Yick; B. Mukherjee; D. Ghosal, *Wireless sensor network survey*, Computer Networks, 2008, Vol.52, pp.2292-2330
- [19] D.R. Adam, *Propagation of depolarization and repolarization processes in the myocardium-an anisotropic model*, Biomedical Engineering, IEEE Transactions on, Vol.38, Issue 2, 1991, pp.133-141.
- [20] P. Chulsung, P.H. Chou, B. Ying, R. Matthews, A. Hibbs, *An ultra-wearable, wireless, low power ECG monitoring system*. Biomedical Circuits and Systems Conference, 2006. BioCAS 2006. IEEE, vol., no., pp.241,244, Nov. 29 2006-Dec. 1 2006.