# Sensor Fault and Patient Anomaly Detection and Classification in Medical Wireless Sensor Networks

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***Abstract*—Wireless Sensor Networks are vulnerable to a plethora of different fault types and external attacks after their deployment. We focus on sensor networks used in healthcare applications for vital sign collection from remotely monitored patients. These types of personal area networks must be robust and resilient to sensor failures as their capabilities encompass highly critical systems. Our objective is to propose an anomaly detection algorithm for medical wireless sensor networks. Our proposed approach firstly classifies instances of sensed patient attributes as normal and abnormal. Once we detect an abnormal instance, we use regression prediction to discern between a faulty sensor reading and a patient entering into a critical state. Our experimental results on real patient datasets show that our proposed approach is able to quickly detect patient anomalies and sensor faults with high detection accuracy while maintaining a low false alarm ratio.**

***Index Terms*—Wireless Sensor Networks, Sensor Faults, Personal Area Networks, healthcare and remote patient monitoring, sensor management and regression tool framework**

## I. Introduction

With current medical procedures and the healthy lifestyles of many, the average lifetime expectancy is ever increasing [1]. Doctors are able to better diagnose and treat patients while the ability of individuals to cope and recover from illnesses is staggering. Technological advances incorporated with vast and accurate knowledge of the human anatomy have allowed healthcare professionals the ability to handle almost any scenario they encounter in individuals at hospitals and emergency treatment facilities [1], [2]. As the average individual lifetime expectancy has increased, this has also directly impacted our planets population and as such, a shortage of qualified healthcare professionals to treat the sick and needy has become an issue.

Scientists and researchers have developed numerous solutions to this problem, one of which allows patients to be remotely monitored utilizing networks of wireless sensors which relay, in real time, patient information to doctors and healthcare providers. Advances in sensor technologies and high throughput networks continue to refine the accuracy and increase the integrity and public trust of these systems. As a direct result, more individuals elect to utilize these systems as they allow greater freedom and mobility while maintaining the quality of care equivalent to direct medical interaction and attention found previously only in hospitals, clinics, and other specialized care facilities.

In medical applications, implementations of specialized Wireless Sensor Networks (WSN), known as personal area networks (PAN) and wireless body area networks (WBAN), are comprised of numerous small devices attached to or implanted in the body of a patient. In current days, many existing medical wireless devices are used to collect various patient metrics and vital signs, such as Heart Rate (HR), pulse, oxygen saturation (SpO2), Respiration Rate (RR), Body Temperature (BT), ElectroCardioGram (ECG), ElectroMyoGram (EMG), Blood Pressure (BP), Blood Glucose Levels (BGL) and Galvanic Skin Response (GSR).

These networked sensors accumulate and transmit collected data to a central device (i.e. base station, PDA, smart phone) for processing and storage, which then may be used for alarms upon detection of anomalies and clinical deterioration [2]. The use of PANs and WBANs has been extended to monitor individuals having chronic illnesses (i.e. cardiovascular, Alzheimer's, Parkinson's, Diabetes, Epilepsy) where these networks have enhanced the quality of life by providing mobility, while continuously collecting and relaying critical physiological data to their associated healthcare providers, e.g. long-term monitoring of patient recovery from surgical procedure after leaving the hospital.

These types of Personal Area Networks (PAN), while extremely useful, are not without problems such as faulty measurements, hardware failure, and security issues. These networked small, lightweight wireless sensing devices also have additional drawbacks such as reduced computational power and limited capacity and energy resources. Sensor measurements from these networks are prone to a variety of other types of anomalies including environmental noise, constant faults resulting from bad sensor connections, energy depletion, badly placed sensors, malicious attacks through data injection, modification or replay attacks which may cascade and directly affect the collection point leading to unexpected results, faulty diagnosis, and a reduction in public trust of these systems.

A non-invasive device called pulse oximeter, measures the amount of infrared light reflected by the photo-sensor, to

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978-1-4673-3122-7/13/$31.00 ©2013 IEEE

measure SpO2 and pulse. This device provides information about cardiovascular system (asphyxia, hypoxia or insufficient oxygen and pneumonia). Normal SpO2 ratio is larger than 95%. When this ratio is lower than 90%, an emergency alarm must be triggered due to lung problems or respiratory failure.

An improperly attached device or an external fluorescent light may cause inaccurate reading. In [3], the authors found that the sensing components were the first source of unreliability in medical WSNs, not networking issues. Abnormal values may be resulted from many reasons in WSNs, such as hardware faults, corrupted sensors, energy depletion, calibration, electromagnetic interference, disrupted connectivity, compromised sensors, data injection, patient with sweating, detached sensor, heart attacks or health degradation, etc.

Faulty measurements from sensors negatively influence the measured results and lead to diagnosis errors. Furthermore, they may threaten the life of a patient after alerting emergency personnel for code blue. Therefore, an important task is to detect abnormal measurements that deviate from other observations, and to distinguish between sensor faults and emergency situation to reduce false alarms.

Over time, these networks accumulate vast amounts of historical data about an individual. Due to the enormity of information, it often becomes difficult to observe and extract sensor metric correlations and to distinguish between a patient entering a critical state and faulty hardware. Therefore, an anomaly detection mechanism is required to identify abnormal patterns and to detect faulty data.

In contrast to signature based intrusion detection systems, where signatures are required to detect attacks, anomaly based systems [4] look for unexpected patterns in data measurements received from sensors. The abnormal pattern is a deviation from a dynamically updated normal model for sensed data, and is more adequate for WSNs given the lack of attack signatures. It is also important to note that anomaly based systems face challenges related to the training phase as it is difficult to find normal data to establish an appropriate normal profile.

In this paper, we focus on anomaly detection in medical wireless sensor readings, and we propose a new approach based on machine learning algorithms to detect abnormal values. First we use J48 [5] decision tree algorithm to detect abnormal records, and when detected, we apply linear regression [6] to pinpoint abnormal sensor measurements in an abnormal record. However, physiological attributes are heavily correlated, and changes occur typically in at least two or more parameters, e.g. in Atrial Fibrillation (AF) & Asthma disease, the heart rate and respiration ratio increase simultaneously.

Our proposed solution is intended to provide reliability in medical WSNs used for continuous patient monitoring, where we detect anomalies in a patient's health, and differentiate between the individual entering a critical health state and faulty readings (or sensor hardware). We seek to reduce the false alarm rate triggered by inconsistent sensors readings.

The rest of this paper is organized as follows. In section II, we review related work on anomaly detection and machine learning algorithms used in medical WSN. Section III describes briefly linear regression and decision tree algorithm (J48) used in our detection system. The proposed approach is explained in section IV. In section V, we present our results from experimental evaluation, where we conduct performance analysis of the proposed solution over medical dataset. Finally, we conclude the paper in section VI.

## II. Related work

WSNs are becoming a major center of interest as they provide many viable solutions to avoid unnecessary casualties in many fields such as military, civil protection or medicine. Various vital sign monitoring systems have been proposed, developed and deployed, such as MEDiSN [7] & CodeBlue [8], [9] for monitoring HR, ECG, SpO2 and pulse, LifeGuard [10] for ECG, respiration, pulse oximeter & BP, AlarmNet [11] & Medical MoteCare [12] for physiological (pulse & SpO2) & environmental parameters (temperature & light), Vital Jacket [13] for ECG & HR. A survey of medical applications using WSNs is available in [14], [15]. Many approaches for anomaly detection in WSNs have been proposed to detect abnormal deviation in collected data, and to remove faulty sensor measurements. Authors in [16] propose an algorithm for the identification of faulty sensors using the minimum and the maximum values of the monitored parameters. Any received measurement outside the [min-max] interval is considered an outlier or inconsistent data. In medical applications, we can not assume that all patients will have the same attribute interval ranges as the min-max values depend on sex, age, weight, height, health condition, etc.

Authors in [17] propose a hierarchical (cluster based) algorithm to detect outliers from compromised or malicious sensors. The proposed method is based on transmission frequency, and KNN distance between received values from different sensors. However, it is impractical in medical applications to put redundant sensors for monitoring the same parameters. A simple prediction and fault detection method for WSNs was proposed in [18]. The proposed algorithm is based on the detection of deviation between reference and the measured time series. The proposed approach uses a predefined threshold and has been evaluated on 3 types of faults: short time, long time and constant fault.

Authors in [19] explore four classes of methods for fault detection: rule-based, estimation-based, time series analysis, and learning based methods. They investigate fixed and dynamic threshold, linear least squares estimation, Auto Regressive Integrated Moving Average (ARIMA), Hidden Markov Model (HMM), etc. The authors found no best class of detection methods suitable for every type of anomaly.

Data mining techniques and machine learning algorithms have also used in WSNs to detect anomalies in multidimensional data. For example, Naïve Bayes [20], Bayesian network [21], Support Vector Machine (SVM [22]), Self-Organizing Map (SOM [23]) which is based on neural networks.

Authors in [24] propose the use of logistic regression modeling with a static threshold to evaluate the reliability of a WSN in the industrial field with a large number of sensors, and without updating the training model to be able to identify the cause of a potential loss of reliability. On the same scale of large sensor networks, authors in [5] propose a diagnosis method based on the enhanced $C4.5$ ($J48$ or decision tree algorithm) which merges the local classifiers into a large spanning tree to answer for the whole network accuracy. Another type of WSN deployment is presented in [20], which shows how to monitor the physical activity of a person using Sun SpOT sensors attached to the thighs. Authors use naïve Bayes based machine learning algorithm to determine if the person is sitting, standing, lying or walking. However, they do not take in consideration that the values can be corrupted due to faulty hardware. Similarly, the authors in [25] present a system capable of discerning between mental stress states from relaxation states using logistic regression based on the heart rate variability.

In this paper, we will use decision tree (J48) and linear regression algorithms to detect abnormal record and to pinpoint abnormal sensors reading. J48 is used to classify records and to reduce temporal complexity, and linear regression is used to predict current values. As physiological parameters are correlated, if only one monitored attribute deviates from estimated value, we classify the reading as faulty and perform data cleaning, and in the other cases, we trigger an alarm for patients entering into a critical state.

## III. Background

We consider medical wireless motes attached to patient in order to monitor many physiological parameters, as depicted in figure 1. These sensors transmit the collected data to the base station (smart phone) for real time analysis and for alerting healthcare professionals when required. The base station may also transmit collected data for remote/local DB for storage. The base station has higher computation power, memory storage and larger transmission range than sensors. Collected data is analyzed at the base station before transmission to detect anomaly and raise alarms when a patient enters a critical state.

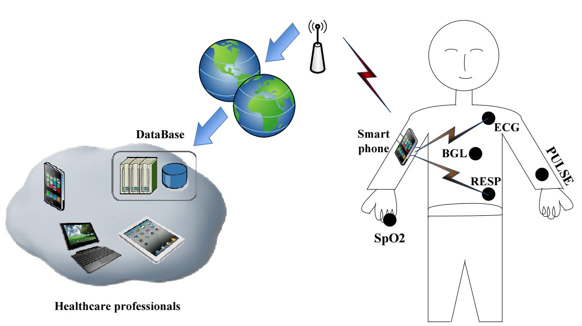


Fig. 1. WSN for collecting vital signs & raising alarms.

The collected measurements for physiological parameters are represented by data matrix $X = (X_{ij})$ where $i$ is the time instance, $j$ represents the monitored parameter. We denote by $X_k = (X_{1k}, X_{2k}, \ldots, X_{tk})$ the time series associated with each parameter. $X_k$ is a column in the data matrix $X$ given in equation 1.

$$X = \begin{array}{c} \\ t_1 \\ t_2 \\ \vdots \\ t_m \end{array} \begin{array}{c} \begin{array}{ccccc} X_1 & X_2 & X_3 & \cdots & X_n \end{array} \\ \left[ \begin{array}{ccccc} x_{11} & x_{12} & x_{13} & \cdots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & \cdots & x_{mn} \end{array} \right] \end{array} \quad (1)$$

To detect abnormal values, we use decision tree algorithm (J48) to classify records (or line) as normal or abnormal. When an abnormal record is detected, the linear regression algorithm is used to predict current measurements for each parameter, and when the difference between predicted and current value is larger than threshold, a correlation analysis is conducted to differentiate between faulty sensor and patient health degradation.

In the rest of this section, we briefly review decision tree (J48) and linear regression algorithms used in our approach. For detailed information about these algorithms, please refer to [6].

### A. Decision tree J48

J48 [5] is a decision tree algorithm used in classification, where attributes are represented by nonterminal nodes, and terminal nodes represent decision outcome. In our model, the tree nodes are the monitored physiological attributes and the leaf nodes are the class (normal & abnormal). To build the tree nodes from root to leafs, the Gain Ratio ($GR$) of each attribute is calculated as:

$$GR(X, X_k) = \frac{IG(X, X_k)}{SI(X, X_k)} \quad (2)$$

The Information Gain $IG(X, X_k)$ in equation 2 of an attribute is given by:

$$IG(X, X_k) = H(X) - \sum_{x_{ik} \in X} \frac{|x_{ik}|}{|X|} H(x_{ik}) \quad (3)$$

Where $H(X)$ is the entropy of the association between a training record and the nominal class (normal or abnormal), and $x_{ik}$ are the values taken by the attribute $X_k$. As the information gain does not take into account the division of information between the two classes, it is necessary to calculate the splitting of the information for each $x_{ik}$:

$$SI(X, x_{ik}) = -\sum_{c=1}^{n} \frac{|x_{ik}|}{|X|} \log_2 \frac{|x_{ik}|}{|X|} \quad (4)$$

Where $n$ is the number of classes, and $SI(X, x_{ik})$ is the entropy of the apparition of the $x_{ik}$ within each class. Therefore, by calculating the gain ratio for each attributes, we will be able to hierarchically distribute those attributes into the tree nodes.

### B. Linear regression

Linear regression is a statistical method which models a dependent variable $y_{ik}$ using a vector of independent variables $x_{ik}$ called regressors. The model itself is represented by:

$$y_{ik} = C_0 + C_1 x_{i1} + C_2 x_{i2} + \cdots + C_n x_{in} \quad (5)$$

Where $y_{ik}$ is the dependent variable in instance $i$, $x_{ik}$ are the regressors and $C_n$ are the coefficients of the regressors (weights). These coefficients are calculated in the training phase as the covariance of $X_k$ and $Y_k$ is divided by the variance of $X_k$.

$$C_k = \frac{Cov(X_k, Y_k)}{Var(X_k)} = \frac{\sum \left(x_{ik} - \bar{X}_k\right)\left(y_{ik} - \bar{Y}_k\right)}{\sum (x_{ik} - \bar{X}_k)} \tag{6}$$

The linear regression is used to predict the value of $y_{ik}$ by using other attributes in the same instance $x_{ij|j \neq k}$, and to compare the predicted ($y_{ik}$) with the actual value of $x_{ik}$ to find if it fits within a small margin of error.

## IV. Proposed Approach

We consider a general scenario for remote patient monitoring, as shown in figure 1, where many wireless motes with a restricted resources are used to collect data, and a portable collection device (e.g. smart phone) with higher resources and higher transmission capabilities than motes, is used to analyze collected data, and to raise alarms for emergency team when abnormal patterns are detected. We seek to detect abnormal values, in order to reduce false alarms resulted from faulty measurements, while differentiating faults from patient health degradation.

The proposed approach is based on decision tree and linear regression. It builds a decision tree and looks for linear coefficients from normal vital signs that fall inside restricted interval range of monitored attributes. In the rest of this paper, we focus only on the following vital signs: HR $\in [80-120]$, pulse $\in [80-120]$, respiration rate $\in [12-30]$, SpO2 $\in [90-100]$, T° $\in [36.5-37.5]$. Attributes values that fall outside these (restricted) normal intervals are considered abnormal. HR and pulse reflect the same attribute from different sensors, where pulse is obtained from the pulse oximeter and HR is measured as the number of interbeat intervals (R-R) in ECG signal.

**Algorithm 1** Detection Algorithm

**for each** received record $R_i$ during $T$ **do**
  Classify $R_i$ using J48;
  **if** Class($R_i$) == '*ABNORMAL*' **then**
    **for each** $x_{ik}$ **do**
      $\hat{x}_{ik} = \sum_{j=1, j\neq k}^{n} C_j x_{ij}$
      $ctr+ = (|x_{ik} - \hat{x}_{ik}| \geq 0.1 * \hat{x}_{ik})\ ?\ 1 :\ 0$
    **end for**
    **if** $ctr \geq 2$ **then**
      *Raise alarm for healthcare*;
    **end if**
  **end if**
**end for**

Equation 7 shows the residual threshold used to detect abnormal measurement:

$$e_i = |x_{ik} - \hat{x}_{ik}| \geq 0.1 * \hat{x}_{ik} \tag{7}$$

The proposed approach is based on two phases: training and detection. In the training phase, machine learning methods generate a model to classify data, and in the testing phase, inputs are classified as abnormal if they deviate from established model. The J48 decision tree model (built using training data within restricted intervals) is used in our approach to classify each received record as normal or abnormal. In our experiments, the decision tree was the most efficient classification algorithm. The tree model is a set of rules (if-then) which is inexpensive to build, robust, and fast in processing as it is based on numerical comparisons for classification. Furthermore, abnormal instances detected by J48 will only trigger the forecasting with linear regression, and this is why we use restricted small intervals for monitored attributes in the training phase.

If a record is classified as abnormal by J48, we recursively assume that an attribute ($x_{ik}$) is missing, and the coefficients of linear regression are used to estimate the current value for this attribute ($\hat{x}_{ik}$) with respect to the others ($x_{ij|j\neq k}$), as given in equation 8 for heart rate estimation:

$$\hat{HR}_i = C_0 + C_1 Pulse_i + C_2 RESP_i + \cdots + C_5 T_i \tag{8}$$

If the Euclidian distance between current ($HR_i$) and estimated ($\hat{HR}_i$) values is larger than the predefined threshold (10% of estimated value) for only one attribute, the measurement is considered faulty and replaced by estimated value with linear regression. However, if at least two readings are higher than the threshold, we trigger an alarm for response caregiver emergency team to react, e.g. heavy changes in the HR & reduced rate of SpO2 are symptoms of patient health degradation and requires immediate medical intervention. We assume that the probability of many attributes (2 in our experiments) being faulty is very low.

The J48 is used to reduce the computation complexity, and to prevent the estimation of each attribute for each instance on the base station. J48 is based on few comparisons for classification, and the combination of both approach for fault detection and classification is used. Sliding window is not used in our experiments to reduce the complexity. When the model is well specified with the training data, updating or rebuilding the model requires additional complexity (temporal & spatial) without large impact on the performance.

## V. Experimental results

In this section, we present the performance analysis results of the proposed approach for anomaly detection in medical WSN. Afterward, we conduct analysis to study the impact of decision threshold on true positive and false alarm ratio. We used real medical dataset from the Physionet database [26], which contains 30392 records, and each record contains 12 attributes (ABPmean, ABPsys, ABPdias, C.O., HR, PAPmean, PAPsys, PAPdias, PULSE, RESP, SpO2, T°). We only focus on 5 attributes: HR, PULSE, RESP, SpO2 & T°. The variations of Heart Rate (in beat per minute - bpm), Pulse and Respiration rate are presented in figure 2. Figure 3 shows the variations of SpO2 (oxygenation ratio) and the body temperature (constant value: 37°C).

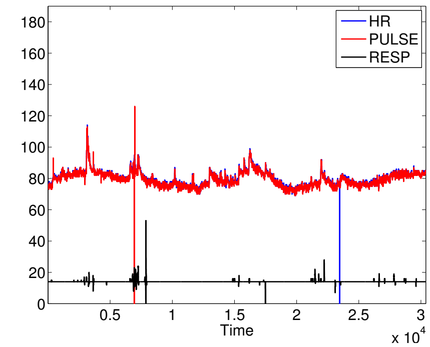


Fig. 2. Heart rate, pulse & respiration rate

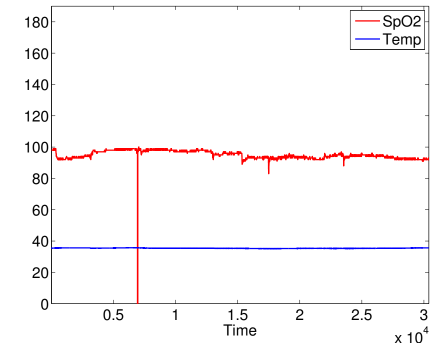


Fig. 3. Oxygenation ratio & body Temperature

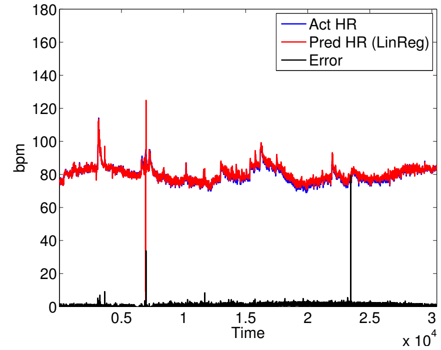


Fig. 4. Linear regression classifier

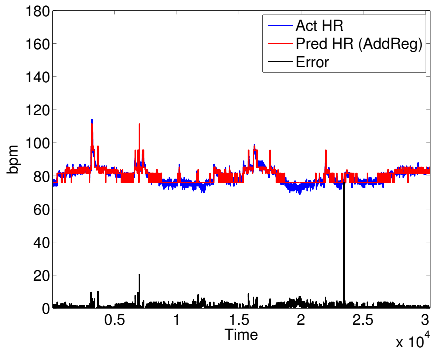


Fig. 5. Additive regression classifier

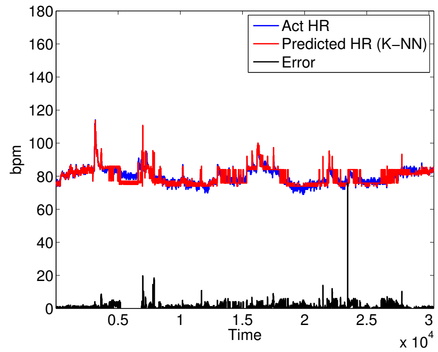


Fig. 6. KNN classifier (k=3)

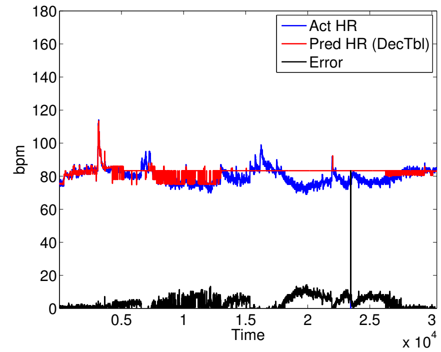


Fig. 7. Decision table classifier

Figure 4 shows the actual, predicted and difference between actual and predicted values (error) for HR with linear regression. To test the efficiency of the used algorithms, we compare the results (actual, predicted & error) with different classifiers though the use of WEKA [27] tool: Decision Table, Additive Regression & KNN for $K = 3$.

Figure 5 shows the results with additive regression tree, where the error is higher than linear regression. Figure 6 shows the results for KNN which is more computationally expensive and has an error higher than additive regression. Figure 7 shows the results of the decision table classifier, which had the worst results of all these classifiers. Figure 8 shows the mean absolute error for each of these classifiers, where decision table achieves the prediction with the highest mean error rate, followed in descending order by KNN, additive and linear Regression. Linear regression had the lowest error percentage and the best overall performance out of the three classifiers, which is why we use this classifier in the rest of this paper.

Figure 9 shows the raised alarms by our proposed approach. The first alarm is raised when reported values for pulse and SpO2 are abnormal in the same instant (both attributes are measured by the same sensor). The second alarm is triggered by the abnormal values of the HR attribute. These abnormal values are visible in figures 4 & 5 when corresponding attributes suddenly fluctuate or decrease to zero.

To evaluate the performance of the proposed approach, we used the ROC (Receiver Operating Characteristic) to show the relationship between the true positive rate (Eq. 9) and the false positive rate (Eq. 10).

$$TPR = \frac{TP}{TP + FN} \tag{9}$$

Where $TP$ is the number of true positives, and $FP$ is the number of false positives. The false positive rate (FPR) is defined as :

$$FPR = \frac{FP}{FP + TN} \tag{10}$$

The ROC curve is used for accuracy analysis when varying the value of the decision threshold. In general, a good detection algorithm must achieve a high detection ratio with the lowest false alarm rate. Figure 10 shows the ROC for the proposed approach where the first nominal classifier is J48, Logistic regression, NaïveBayes & Decision Table respectively. The J48 classifier achieves the best performance with TPR=100% and FPR=7.4%. These results demonstrate that our proposed approach can achieve very good accuracy for detecting motes anomalies.

## VI. Conclusion and Perspectives

In this paper, we proposed a new framework which integrates decision tree and linear regression for anomaly detection in medical WSNs. The proposed approach achieves both spatial and temporal analysis for anomaly detection. We have evaluated our approach on real medical data set with many (real and synthetic) anomalies. Our experimental results demonstrated the ability of the proposed approach to achieve low false alarm rate with a high detection accuracy.

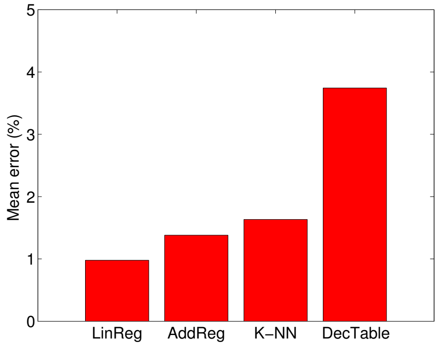


Fig. 8. Mean error rate with # classifiers

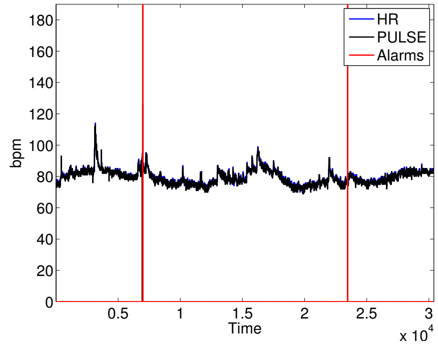


Fig. 9. Raised alarms

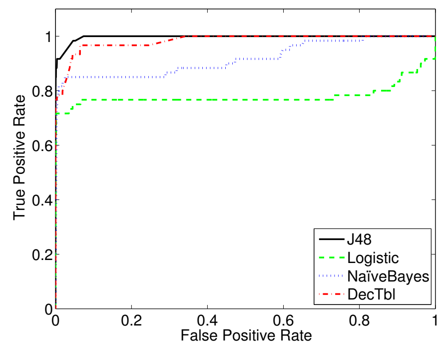


Fig. 10. ROC

We are currently investigating the performance of the proposed approach on real medical wireless sensor traffic using Shimmer platinum development kit [28].

## VII. Acknowledgments

This research was supported by Korea Science and Engineering Foundation, under the World Class University (WCU) program.

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