A Lightweight Anomaly Detection Framework for Medical Wireless Sensor Networks

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***Abstract*—In this paper, we focus on online detection and isolation of erroneous values reported by medical wireless sensors. We propose a lightweight approach for online anomaly detection in collected data, able to raise alarms only when patients enter in emergency situation and to discard faulty measurements. The proposed approach is based on Haar wavelet decomposition and Hampel filter for spatial analysis, and on boxplot for temporal analysis. Our objective is to reduce false alarms resulted from unreliable measurements. We apply our proposed approach on real physiological data set. Our experimental results prove the effectiveness of our approach to achieve good detection accuracy with low false alarm rate.**

***Index Terms*—Wireless Sensor Networks, Fault detection, Security, Anomaly detection, Haar wavelet**

I. Introduction

Wireless Body Area Networks (WBANs) are composed from a set of small sensors with constrained resources, attached or implanted into the body of the patient to collect vital signs, while offering freedom to move for patients with long-term diseases [1]. These devices are used to continuously monitor patients or elderly people in home or in hospital, and transmit collected data to a portable collection point (e.g. smart phone) with more processing and transmission power.

The collection point may process the received data locally, and transmit them to DataBase server for storage. It is also responsible for raising medical alarms for caregivers or healthcare professionals, when detecting anomaly in the physiological data of monitored patients, to quickly react [2], [3], [4] by taking the appropriate actions. The deployment of Wireless Sensor Networks (WSNs) for patient monitoring will reduce the healthcare costs (overcapacity, waiting and sojourn time, number of nurses, etc.), and help people with cardiac and pulmonary insufficiencies, Diabetes, Alzheimer or Asthma.

Medical sensors with wireless transmission are available in the market (MICAz, TelosB, Imote2, Shimmer [5], etc.). For example, ECG wireless sensor is connected to three electrodes placed on the chest for real time monitoring. Many other devices are available to monitor vital signs, such as glucose level, blood pressure, cardiac and respiratory activity, skin temperature, oxygen saturation, etc.

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The pulse oximeter is used to measure the pulse and blood oxygenation ratio (SpO2), through the use of infrared light and photosensor. These valuable information can be exploited to detect asphyxia, insufficient oxygen (hypoxia) or pneumonia. Normal SpO2 ratio is larger than 95%. When this ratio is lower than 90%, an emergency alarm must be triggered due to respiratory failure.

Sensor readings are unreliable and inaccurate [6], [7], due to constrained sensor resources, which make them susceptible to various sources of errors. For example, additional environmental light (fluorescent lighting) may affect the functioning of pulse oximeter, and cause faulty measurements.

Abnormal values may be resulted from many reasons in WSNs [8], 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. Therefore, an important task is to detect abnormal measurements (outliers) that deviate from other observations, and to distinguish between sensor faults and emergency situation to reduce false alarms.

Various anomaly-based detection techniques for sensor fault identification and isolation have been proposed and applied [9], [10], [11], [12]. Distributed detection techniques identify anomalous values at individual sensors to prevent the transmission of erroneous values and reduce energy consumption. These techniques require resources that are not available in sensors, and their accuracy is lower than centralized approaches, which have global view for spatio-temporal analysis.

Physiological parameters are correlated in time and space, and correlation must be exploited to identify and isolate faulty measurements, in order to ensure reliable operation and accurate diagnosis result. Usually, there is no spatial or temporal correlation among monitored attributes for faulty measurements.

In this paper, we propose a lightweight fault detection and isolation approach to reduce the false alarms, by removing the underlying outliers from faulty sensor measurements. We consider a general deployment scenario, where many sensors are attached to the patient, and are used to monitor different physiological attributes. The collected data are transmitted to a

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portable device (smart phone) for processing.

The proposed approach is based on Haar wavelet, Hampel filter and boxplot, and is intended to work on smart phone. This approach provides online anomaly detection with reduced memory and complexity, and without using a predefined fixed threshold or labeled training data. The Haar wavelet and Hampel filter are used to detect spatial deviation between correlated attributes, and the boxplot is activated for temporal analysis, only when spatial deviations are detected.

Experimental results, on a real medical data set, show that our proposed approach is accurate in detecting anomalies in physiological parameters, and is reliable in term of reduced false alarm rate with the presence of inconsistent data in monitored attributes.

The rest of this paper is organized as follows. Section II surveys related work. Section III briefly reviews related techniques and presents our approach for anomaly detection. Section IV presents our experimental results. Finally, Section V concludes the paper.

II. Related work

Several medical applications for WSNs have been proposed for health monitoring. Authors in [13] propose an accelerometer based method to detect patient inactivity in home and to trigger an alarm for long time immobile patient. Other approach in [14] deals with wearable accelerometer to detect the fall of elderly people under remote monitor.

Various architectures for vital sign monitoring have been proposed, such as CodeBlue [15], LifeGuard [16], AlarmNet [17], MEDiSN [3], Medical MoteCare [18], Vital Jacket [19], etc. A survey of medical applications using WSNs is available in [1], [20].

However, collected data by WSNs have low quality and poor reliability. Different approaches for anomaly detection have been applied. Authors in [21] 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. They focus on detecting three fault categories: short, noise and constant. The authors found no best class of detection methods suitable for every type of anomaly. Rule-based methods require calibrating and tuning threshold parameter, learning methods require training phase, estimation methods cannot classify faults, and time series analysis has the highest false positives.

Authors in [22] propose an approach based on Support Vector Machine (SVM) and k-nearest neighbor (KNN) for anomaly detection in WSNs. Authors in [23] use an unsupervised approach for anomaly detection in WSNs, which is based on Discrete Wavelet Transform (DWT) and Self-Organizing Map (SOM). The DWT is used to reduce the size of input data for SOM clustering.

Authors in [10] propose a distance based method to identify insider malicious sensors, while assuming neighbor nodes monitoring the same attributes. Each sensor monitors its one hop neighbors and uses Mahalanobis distance between measured and received multivariate instances to detect anomaly. Authors in [24] propose a voting based system to detect events. Authors in [9] propose a failure detection approach for WSNs, which exploits metric correlations to detect abnormal sensors and to uncover failed nodes.

Authors in [11] propose a score parameter for anomaly detection in collected data by sensors. This parameter is based on Hampel filter and KDE (Kernel Density Estimator). Authors in [7] note that only limited research uses spatial and temporal correlation for outlier detection. The temporal dependency means that the current attribute measurement depends on readings at the previous time instants, while the spatial dependency means that the observations from different attributes are correlated.

In health monitoring, the physiological parameters are heavily correlated. To increase the anomaly detection accuracy, the spatio-temporal dependencies must be exploited to distinguish between errors and medical emergencies, where measurements tend to be correlated in time and space, and errors are usually uncorrelated from other attributes.

In this paper, we propose a simple and light approach for online anomaly detection in collected data by medical wireless sensors. The proposed approach is based on discrete Haar wavelet transform and Hampel filter for spatial analysis, and boxplot for temporal analysis. The objective is to reduce false alarms resulted from faulty measurements, in order to enhance the reliability and the accuracy of patient monitoring systems.

III. Proposed approach

We consider a medical deployment scenario for continuous monitoring, with N sensors $(S_1, \ldots, S_N)$ are attached or weared by the patient (as shown in Fig. 1). These sensors are used to gather vital signs, and to transmit collected data to portable device for processing. Each sensor monitors one or many attributes, e.g. pulse oximeter monitors the pulse and SpO2. We denote the collected measurements at the given time instant t by $X_t = (x_{1t}, x_{2t}, \ldots, x_{pt})$, where p is the total number of monitored attributes ($p \geq N$).

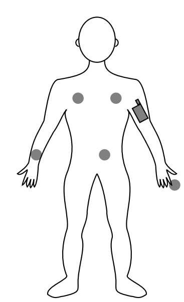

Fig. 1. Vital signs in real time remote monitoring

The collected data on the smart phone must be processed in real time for online anomaly detection. These measurements are probably of low quality and reliability, due to constrained resources of sensors and the deployment context (sweat, detached, damaged sensors, interrupted communications, etc.).

The accuracy of this monitoring system relies on the data, where faulty measurements trigger false alarms for caregiver. Therefore, to increase the accuracy of diagnosis result, faulty observations must be detected and isolated in order to reduce the false alarms and to prevent fault diagnosis.

Our proposed approach is based on three steps: Discrete Haar Wavelet transform (DWT), Hampel filter and Boxplot. The DWT and Hampel filter are used to detect spatial deviations, and the boxplot is used for temporal analysis, to pinpoint suspects underlying attributes, which are responsible for the detected deviation. The objective is to reduce false alarms and to raise alarms only when patient health degrades (respiratory failure, cardiac arrest, etc.).

The architecture of the proposed sequential approach is shown in Fig. 2, where the three algorithms (DWT, Hampel, Boxplot) are applied on every instance to raise alarms only when the patient enters in critical phase.

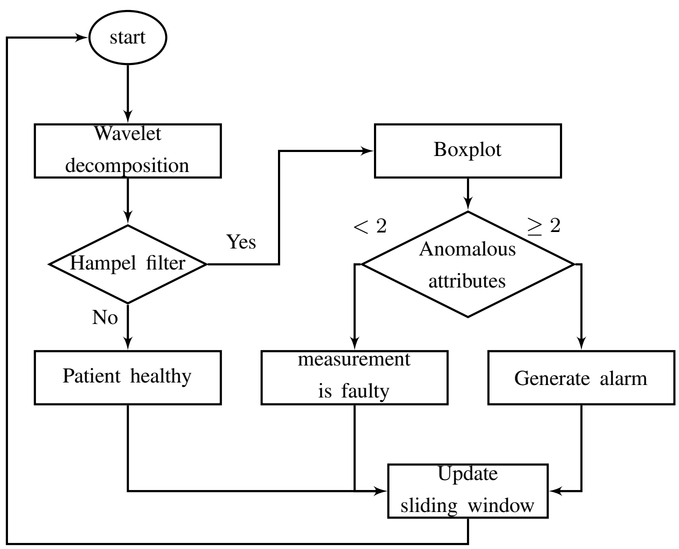

Fig. 2. Flow diagram of the implementation

A. Discrete wavelet transform

The discrete Haar wavelet transform is used to divide the observations in the vector X_t into two parts: approximation A_t and detail D_t signals. Approximation signal (A_t) is the filtering result of input signal through Low Pass Filter (LPF) and Inverse Low Pass Filter (ILPF), and detail signal (D_t) is the filtering result through High Pass Filter (HPF) and Inverse High Pass Filter (IHPF) as shown in Fig. 3.

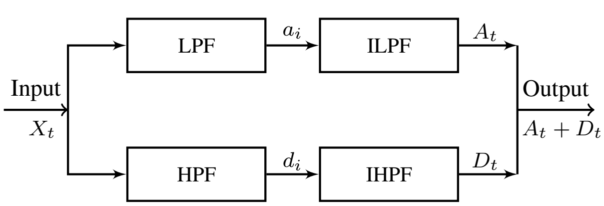

Fig. 3. Filters used in the Haar transform

Observations in X_t can be reconstructed as the results of inversion filters. We use the Haar wavelet as it is the simplest form of discrete wavelet transform (the smallest computational cost), with only two coefficients $\{l_0 = l_1 = 1/\sqrt{2}\}$ for LPF, and $\{h_0 = -h_1 = 1/\sqrt{2}\}$ for HPF [25]. The signal can be expressed using the matrix L & H with dimension $p/2 \times p$:

$$L = \begin{pmatrix} l_0 & l_1 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & l_0 & l_1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 0 & l_0 & l_1 \end{pmatrix}$$

The matrix H has the same structure by replacing the scale coefficients l_0 and l_1 by $h0$ and $h1$ respectively. The approximation and detail coefficients are obtained as:

$$a_i = L \times X_t^T = \frac{x_{2i-1,t} + x_{2i,t}}{\sqrt{2}} \qquad i \in [1, p/2] \tag{1}$$

$$d_i = H \times X_t^T = \frac{x_{2i-1,t} - x_{2i,t}}{\sqrt{2}} \qquad i \in [1, p/2] \tag{2}$$

The approximation A_t (average) and detail D_t (fluctuation) signals are calculated as follows:

$$A_t = a^t \times L = \sum_{i=1}^{p/2} L_{it} \times a_i \qquad t \in [1, p] \tag{3}$$

$$D_t = d^t \times H = \sum_{i=1}^{p/2} H_{it} \times a_i \qquad t \in [1, p] \tag{4}$$

To detect abnormal deviations between monitored attributes, we monitor the energy of fluctuation signal (D_t) with respect to the total energy of both signals as it has been proposed in [26] for stealth attack detection in VoIP:

$$E_i = \frac{\sum_{t=1}^{p} (D_t)^2}{\sum_{t=1}^{p} (A_t)^2 + \sum_{t=1}^{p} (D_t)^2} \tag{5}$$

The energy ratio signal (E_i) will increase when one or more attributes change. Statistical based parameters, such as mean (μ) and standard deviation (σ) have been widely used as dynamic threshold to detect deviations (z-score or $\mu \pm k\sigma$). At a confidence level of 95%, the associated value of k is 1.96, and 99% of observations fall within $k = 2.57\sigma$ from μ, and 99.73% of observations fall with 3σ from μ.

To detect deviations in energy time series ($E_t = \{E_1, \ldots, E_n\}$), we use a sliding window of last w observations (as shown in Fig. 4) to estimate statistical parameters (μ & σ) used in the z-score rule. However, the data in sliding window may contain outliers, which distort and skew the means and the variance toward them, and affect the detection performance. Contaminated data have two underlying effects: masking and swamping problems. Masking occurs when outliers are masked and are not detected, and swamping occurs when normal observation is detected as abnormal (inversion). To avoid these problems, we use robust Hampel filter instead of z-score to detect deviations in energy time series (E_t).

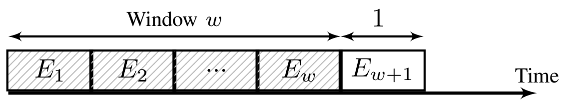

Fig. 4. Sliding window used to estimate statistical parameters

B. Hampel Filter

The Hampel filter is a sliding window implementation of the Hampel identifier, proposed as robust alternative to outlier sensitive z-score. To provide robust method for estimating μ and σ in contaminated data, Hampel proposes the use of median and Median Absolute Deviation (MAD) as outlier resistant parameters. We use a sliding window containing the prior w values of energy ratio $E_i^w = \{E_{i-w}, \ldots, E_i\}$, and we compute the median and the scale (MAD) of E_i^w as follows:

$$\phi_w = median(E_i^w) \tag{6}$$

$$S_w = 1.4826 \times median\{|E_i^w - \phi_w|\} \tag{7}$$

After replacing the mean μ by the median ϕ_w, and the standard deviation σ by S_w, the z-score is used to test if the new value E_{i+1} is abnormal:

$$|E_{i+1} - \phi_w| \geq k \times S_w \tag{8}$$

With k is a threshold value ($k = 1.96$ in our experiments). However, the data in sliding window have zero or near zero MAD under normal condition [11], and we use $S_w = max(S_w, c_1)$ to eliminate false alarms. c_1 is a predefined constant greater than zero.

As physiological parameters are heavily correlated, and faulty measurements are spatially unrelated with other attributes, the time series analysis of energy ratio E_t can only detect spatial deviations, without any information of the underlying attributes responsible of the occurred change. To identify the abnormal attributes, we activate the univariate boxplot only after the detection of spatial anomaly. The boxplot is used to check temporal deviation in each attribute with low computational complexity. If the number of underlying attributes is smaller than r ($r = 2$ in Fig. 2), we consider the measurement of this attribute is faulty and we discard the alarm. In the other case, we raise an alarm for caregiver to quickly react for the patient health degradation.

C. Box-and-Whisker plot

The Box-and-Whisker plot or boxplot is a simple and robust outlier detection method. Let $X_i^w = \{x_{i,t-w}, \ldots, x_{i,t}\}$ represents a temporal sliding window of the last w values for the i^{th} monitored attribute. The lower quartile (Q_1 is the 25th percentile) and the upper quartile (Q_3 is the 75th percentile) of X_i^w are used to obtain robust measurements for the mean $\hat{\mu} = (Q_1 + Q_3)/2$, and the standard deviation is replaced by the interquartile range $\hat{\sigma} = IQR = Q_3 - Q_1$. A measurement is considered as abnormal (Fig. 5) if the following condition is satisfied:

$$x_{i,t} \leq Q_1 - 1.5.(Q_3 - Q_1) \ \vee \ x_{i,t} \geq Q_3 + 1.5.(Q_3 - Q_1) \tag{9}$$

The univariate boxplot is applied on every attribute, and an alarm variable is incremented for detected deviation in each attribute, and when the value of this variable is greater or equal to r, we raise an alarm. For clarification, when the heart rate and respiration rate increase, and the SpO2 decreases, a medical intervention is required. In the other case, the measurements are considered faulty and no alarm will be raised.

We use a value of $r \geq 2$ in our experiments, as the probability that many sensors are faulty in the same time instant is low. We also consider that the physical check for sensors is necessary when more than r sensors report abnormal values. The proposed method is presented in algorithm 1.

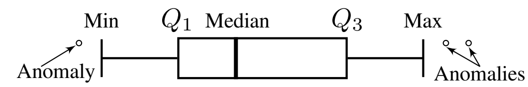

Fig. 5. Boxplot

Algorithm 1 Anomaly Detection Approach

Apply Haar DWT to get A_t & D_t
Calculate Energy ratio E_i
Estimate $median$ & MAD for the last w values of E_i
if $|E_{i+1} - median(E_i^w)| \geq k \times S_w$ **then**
  for all x_{it} **do**
    if $((x_{it} \leq Q_1 - 1.5.IQR) \ || \ (x_{it} \geq Q_3 + 1.5.IQR))$ **then**
      $Alarm$++
    end if
  end for
  if $Alarm \geq r$ **then**
    Raise an alarm for caregiver
  end if
end if

IV. Experimental results

To evaluate the performance of the proposed approach, we conduct many experiments using real medical dataset from he Physionet database [27], where each record contains 8 parameters (Blood Pressure, C.O., Heart rate, Pulmonary Artery Pressure, Pulse, RESP, SpO2, Body temperature). We apply our approach on this trace before and after injecting synthetic anomalies at different instants. We use a sliding window of width $w = 10$ to reduce memory requirement, and we set $k = 1.96$ and $r = 2$.

We begin by showing the variations of physiological attributes in the used dataset. The variations of the heart rate and respiration rate (in breaths per minute) are shown in Fig. 6. We can visually identify 4 anomalies (spikes) in the heart rate, where one observation falls down to zero and others are less than 25bpm (beat per minute). Similarly, the respiration ratio falls to zero in two observations. The variations of the pulse and the temperature are shown in Fig. 7. The temperature is constant during the monitoring time, but the pulse exhibits 4

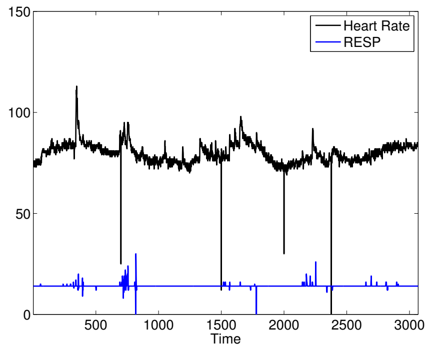

Fig. 6. Heart rate & respiration

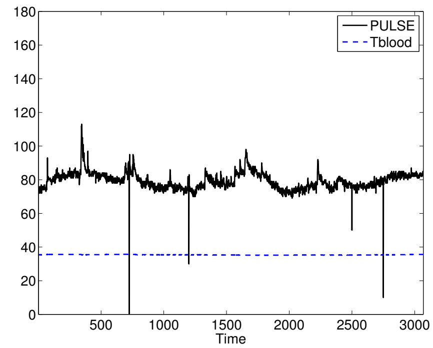

Fig. 7. Pulse & temperature

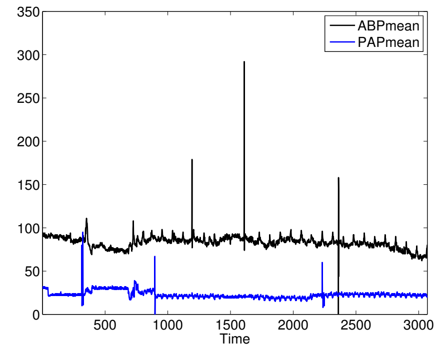

Fig. 8. Blood & pulmonary artery pressure

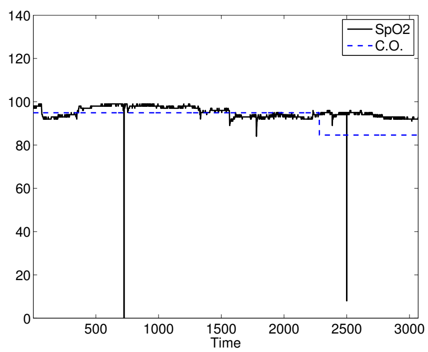

Fig. 9. SpO2 & C.O.

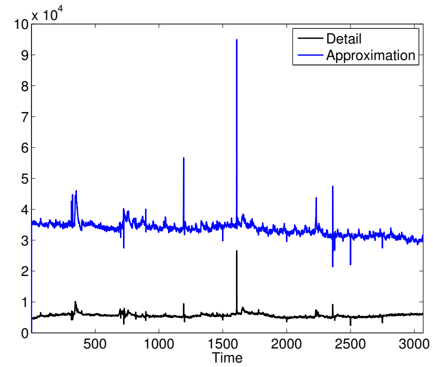

Fig. 10. Energy of Approximation & Detail

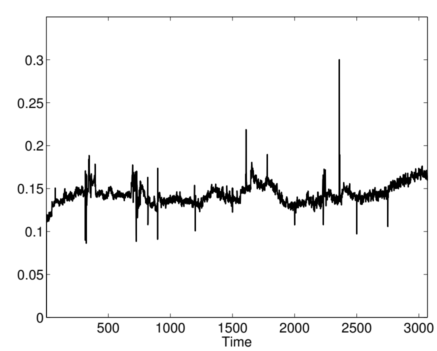

Fig. 11. Energy ratio

anomalies at different time instants in the heart rate. Usually, the heart rate and the pulse must have the same values and must show the same variations, as they represent the same attribute monitored through two different sensors. However, they don't superpose on anomalies when drawing them in the same figure, and different deviations on different time instant appear clearly when comparing Fig. 6 & Fig. 7.

Fig. 8 shows the variations of the Pulmonary Artery Pressure (PAPmean) and Blood Pressure (BPmean) for the monitored patient. BPmean is calculated from the systolic and diastolic blood pressure, and analogously for the PAPmean. Fig. 9 shows the variations of the SpO2 and the C.O., where the normal values of SpO2 must be within the range of [95%-100%], and a lower value is synonym of asphyxia, lack of oxygen and heart disease. In Fig. 9, we can notice two abnormal readings with zero or near zero values for SpO2 followed by normal values.

Fig. 10 shows the variations of energy for approximation (A_t) and detail (D_t) signals obtained after applying the DWT on the 8 physiological attributes. The energy ratio (given in eq. 5) is shown in Fig. 11, and is used to detect spatial deviations through Hampel filter. The raised alarms by Hampel filter for spatial analysis are shown in Fig. 12, where we get a high number of false alarms. The prior application of data filtering techniques on each attribute may reduce the noise level by discarding anomalies and retaining good data, but it may also change the shape of variations, and discard interesting events.

We activate boxplot analysis only on instant with raised alarm by Hampel filter to achieve temporal analysis on each attribute. Only three alarms are raised after the application of boxplot (with $r = 2$) as shown in Fig. 13. It is important to note the difference between the number of raised alarms by Hampel (Fig 12) and thus transmitted to caregiver (Fig 13). However, the raised alarm on instant 2500 is a false alarm, and it is triggered by abnormal measurements in SpO2 and Pulse, which are measured by the same sensor (pulse oximeter). Therefore, increasing the value of r may discard this false alarm, as well as increasing the miss detection rate. The value of r is a tradeoff between detection accuracy and false alarms.

To conduct performance analysis of the proposed approach, we inject synthetic anomalies at different time instants on different attributes, and we use the Receiver Operating Characteristic (ROC) curve to show the impact of the threshold (k) on the true positive rate and the false negative rate. Fig. 14 shows the ROC for the proposed approach where we achieve 100% of detection rate with a false alarm rate of 7%.

V. Conclusion

In this paper, we propose a lightweight anomaly detection approach for medical WSNs. The proposed approach is based on Wavelet decomposition, Hampel filter and boxplot, and it is able to achieve spatial and temporal analysis, without prior knowledge of fault signatures. It is suitable for online detection and isolation for faulty or injected measurements with low computational complexity and storage requirement.

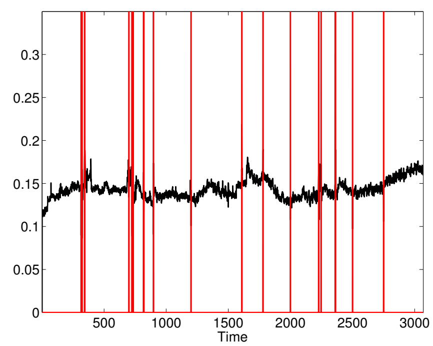

Fig. 12. Energy ratio & Hampel Alarms

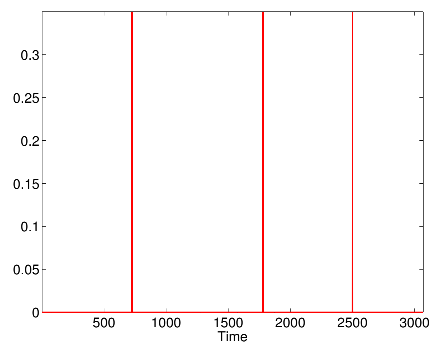

Fig. 13. Raised alarms by boxplot

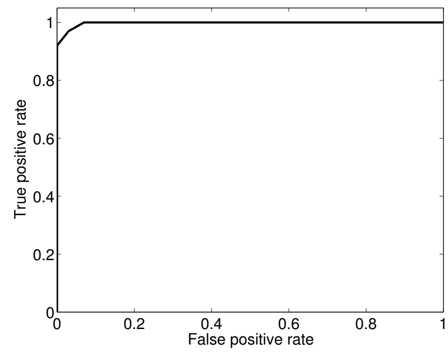

Fig. 14. Receiver Operating Characteristic (ROC)

We have tested the proposed approach on real physiological dataset. The experimental results prove that it can improve the efficiency and reliability, by identifying faulty measurements and reducing the number of false alarms. Our next task will be to apply this technique online using Shimmer platinum development kit [5] and to investigate a real implementation of distributed detection on sensors to reduce the wasted energy by the transmission of faulty measurements.

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