Anomaly Detection in Medical WSNs Using Enclosing Ellipse and Chi-square Distance

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***Abstract*—In this paper, we propose an Anomaly Detection (AD) approach for medical Wireless Sensor Networks (WSNs). This approach is able to detect abnormal changes and to cope with unreliable or maliciously injected measurements in the network, without prior knowledge of anomalous events or normal data pattern. The main objective is to reduce the false alarms triggered by abnormal measurements. In our proposed framework, each sensor applies the Exponentially Weighted Moving Average (EWMA) for one-step forecasting. To reduce the energy consumed by periodic data transmission to the Local Processing Unit (LPU), the sensor transmits only when the data point (measured, expected) falls outside the dynamically updated ellipsoidal region enclosing the normal data. The LPU exploits correlation and uses chi-square distance for spatial analysis before raising a medical alarm. We evaluate our approach on real medical data set. Experimental results through computer simulation demonstrate that our proposed approach can achieve a good detection accuracy with low false alarm rate (less than 4%).**

***Index Terms*—Wireless Body Area Networks, Security, Intrusion Detection, Healthcare monitoring**

I. Introduction

Wireless Sensor Networks are used in healthcare monitoring to collect physiological data from patients. They are composed from a set of sensors with wireless transmission capabilities, used to collect vital signs from monitored patient or from elderly people. Collected data by sensors are transmitted to a LPU (e.g., SmartPhone, Tablet, etc.) for preprocessing, and for raising a medical alarm for caregivers when detecting abnormal changes in gathered vital signs. This allows real time monitoring and early detection of clinical deterioration [1], [2].

These small devices will improve the life quality of patients having long term disease by allowing in-home and remote monitoring. Wearable and in-body medical sensors are available in the market (Shimmer [3], etc.), and existing devices are able to collect many vital signs, e.g., body Temperature (T°), Heart Rate (HR), Blood Pressure (BP), Blood Glucose Level (BGL), blood oxygenation (SpO2), Pulse, ElectroCardioGram (ECG), ElectroMyoGram (EMG), etc.

There are many application areas for these devices in real time monitoring, such as kinematic & rehabilitation assessment, remote patient monitoring, environmental & exposure to radiation, elderly care, glucose monitoring and insulin injection, nerve disorders such as Epilepsy, Parkinson and Alzheimer monitoring.

The use of WSNs will reduce the healthcare costs (such as overcapacity, sojourn time, number of nurses, etc.), and allow in-home and remote monitoring. However, these tiny devices with their limited resources are susceptible to environmental noise, interference, disrupted connectivity, short hardware fault, inconsistent measurements, malicious attacks through the injection of bogus and false data in the network [4] which may lead to unreliable measurements [5]. These inconsistent measurements heavily affect the result in the central device (LPU or SmartPhone), and lead to inaccurate diagnosis results and unreliable monitoring systems.

Medical applications have strict requirements for reliability, security and privacy [2]. The sensor measurements should be accurate to avoid false alarms and miss detections. Anomalous data (also called outliers) from badly attached or malicious sensors must be identified and isolated to ensure reliable operation. Authors in [1] show that the medical WSNs will be rejected by healthcare professionals and patients if results are not reliable.

In general, anomaly detection algorithms in sensor measurements can be classified into two approaches: parametric and non-parametric. In the parametric approach, the data distribution is supposed to be known a priori, but this assumption is unrealistic in medical applications, where many physiological parameters are highly dynamic and do not have a matching statistical distribution. The non-parametric approach does not require any prior knowledge on the data distribution, and uses distance or density-based methods to detect deviations in data pattern on the fly. This approach needs little or no prior knowledge to build an initial model, and data from a sliding window are used to dynamically update the initial model. Our detection scheme adopts the anomaly based approach.

In this paper, we propose a hybrid scheme to accurately identify abnormal measurements in the data gathered by medical WSNs. We consider a scenario where many sensors are attached to the patient, in order to monitor several physiological parameters, and they transmit only the suspicious abnormal data to the LPU for further processing. The LPU exploits the spatial correlation between attributes to raise medical alarms to caregivers only when the patient health degrades. We seek to detect and to remove outliers in order to reduce false alarms triggered by malicious or inconsistent sensor readings which significantly deviate from the normal data pattern.

As the wireless transmission consumes a lot of sensor's energy with respect to computation, our second objective is to reduce energy consumption by wireless transmission and to prolong the lifetime of the sensors. Most of the time, the sensor measurements are normal and anomalies are rare. Therefore, in-sensor processing is required to detect abrupt temporal deviations, and to transmit only suspect measurements to the LPU for further analysis of spatial correlations in order to distinguish between faulty measurements and illness indicators.

The proposed approach achieves distributed lightweight computing to prolong the lifetime of sensors, where each sensor performs local detection by forecasting the current value using EWMA, and by transmitting only data points (measured, estimated) located outside the dynamically updated normal region (ellipse) to the LPU.

The LPU has a global view on the gathered data and can exploit the spatial correlation between monitored attributes to distinguish between clinical emergency and faulty measurements, and therefore reduces false alarms by discarding received faulty measurements. It applies chi-square distance to measure the deviation between the forecasted and observed values before raising a medical alarm. We have applied our AD approach on real physiological data sets with anomalies. Our experimental results through computer simulation show the effectiveness of our proposed approach for an accurate detection with a low false alarm rate.

The rest of this paper is organized as follows. Section II reviews the related work. Section III describes the proposed approach for the anomaly detection system. In Section IV, experimental results are presented to demonstrate the effectiveness of the propose approach. Finally, Section V concludes the paper.

II. Related works

Several architectures for medical WSNs have been proposed and deployed to monitor patients and to raise alarm in case of medical emergencies, such as MEDiSN [6], CodeBlue [7], LifeGuard [8], AlarmNet [9], Vital Jacket [10], etc. A survey of medical applications using WSNs is available in [11].

Sensor nodes could easily be compromised and can inject falsified values. The collected data by WSNs have low quality and reliability [12] due to their limited resources and their vulnerabilities. Therefore, anomaly based intrusion detection systems are used to build a normal data model, and detect unusual deviations. Several anomaly detection approaches for WSNs have been proposed to detect abnormal deviation in collected data, and have been analyzed in terms of their detection accuracy and false alarm ratio [13]. Machine learning algorithms for classification and clustering techniques have been applied, such as K-means, k-Nearest Neighbor (KNN), Artificial Neural Networks (ANN), Support Vector Machine (SVM [14]), Self-Organizing Map (SOM), Wavelets [15], etc.

SVM provides the optimum solution with relatively large computational complexity for calculating the hyperplane. Unfortunately, all the previous schemes are centralized on the LPU and not adequate with the constrained resources of sensors. We refer to [4], [16] for further details and discussions of AD in WSNs.

Authors in [17] propose a score based approach for anomaly detection in WSNs. This approach is based on Hampel filter and Kernel Density Estimator (KDE) to identify outliers, but it does not take into account the correlation between attributes. Therefore, to increase the 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.

Recently, authors in [12] note that only limited research makes explicit use of spatial and temporal correlation for outlier detection. Most existing AD approaches [18], [19] assume redundant deployment and use majority voting scheme to differentiate between malicious and emergency events, which is an unrealistic scenario in healthcare monitoring.

Unlike existing techniques, our work addresses distributed (or in-network) AD to reduce the data transmission and the underlying energy consumption, and relies on centralized correlation analysis to distinguish between faulty measurements and clinical emergency. Uncorrelated measurements are discard to reduce false alarms .

III. Proposed approach

We consider a general medical deployment scenario, where N wireless motes $(S_1, \ldots, S_N)$ are placed on the patient body (as shown in figure 1), and they are used to collect vital signs and to transmit collected data to the SmartPhone attached to the patient for further processing. Let $X_j = \{x_{1,j}, x_{2,j}, \ldots, x_{p,j}\}$ denote the measured values by sensor j. Usually, sensor measurements are transmitted to the SmartPhone every discrete time interval T. However, the energy consumed by transmission ranges from 10^3 to 10^4 times the energy used by computation [20]. Also transmitting normal measurements that occur in the most of time is useless. Therefore to save energy, each sensor must transmit only values that deviate from other.

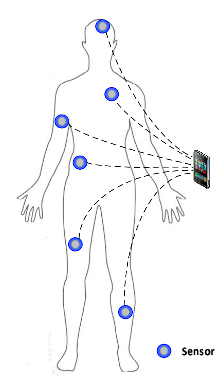


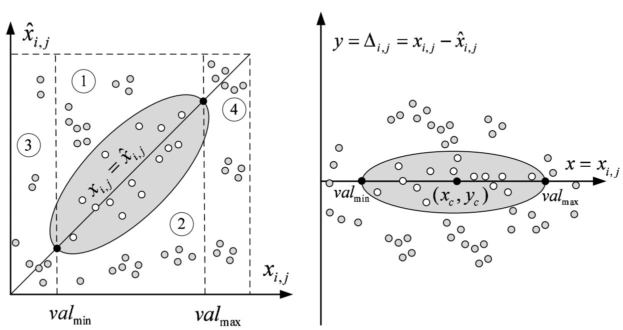
Fig. 1. Vital signs monitoring in real time

To achieve this purpose, each sensor is designed to process its measurements in a distributed manner using a lightweight method adequate with its constrained resources. In our approach, each sensor j uses the EWMA to predict the current value ($\hat{x}_{i,j}$) as:

$$\begin{aligned} \hat{x}_{i,j} &= \hat{x}_{i-1,j} + \alpha \left(x_{i-1,j} - \hat{x}_{i-1,j} \right) \\ &= (1-\alpha)\, \hat{x}_{i-1,j} + \alpha x_{i-1,j} \end{aligned} \tag{1}$$

The forecast of an observation at time instant i depends on the $(i-1)^{th}$ observation and its forecasted value. The choice of the weight α ($0 \le \alpha \le 1$) is a key factor to determine the convergence speed. A large value of α induces a quick updating to the change in the monitored attributes, and a small value induces less dependency on the recent measurement. As physiological parameters (e.g., T°, HR, PULSE, SpO2, Respiration, etc.) change slowly between two consecutive intervals, we use a value of $\alpha = 0.1$ to reduce the response rate of the current estimate to a change in the measurement.

After forecasting the current value, each sensor compares the forecasted ($\hat{x}_{i,j}$) with the measured value ($x_{i,j}$) to detect deviation from normal profile, and transmit only the abnormal measurement to the SmartPhone. Normal data points $(x_{i,j}, \hat{x}_{i,j})$ must be near the line $y = x$ (as shown in figure 2(a)), and abnormal data points have significant deviations between measured and estimated values (far from the line $y = x$).



(a) Ellipse enclosing normal data (b) Ellipse enclosing residual data

Fig. 2. Ecnclosing data with an ellipse.

We distinguish 4 patterns for abnormal values: (1) $\hat{x}_{i,j} > x_{i,j} + \xi$, where ξ represents an accepted estimation error (2) $\hat{x}_{i,j} < x_{i,j} + \xi$, (3) $x_{i,j} \wedge \hat{x}_{i,j} < val_{\min}$, (4) $x_{i,j} \wedge \hat{x}_{i,j} > val_{\max}$ ($val_{\min}$ & $val_{\max}$ are the lower and upper bound for the monitored attribute). The 4 regions are depicted in figure 2(a), where x-axis refers to the measured values, and y-axis refers to the estimated values. When referring to HR, normal values are inside the interval $[60 - 120]$ beats per minute (bpm).

The estimated error varies ξ with respect to measured and estimated values, where it must be small near the lower and upper bound. Many researchers have investigated the minimum ellipse englobing the whole data, e.g., Minimum Volume Ellipsoid (MVE [21]), Orthogonalized Gnanadesikan-kettering (OGK [22]), Minimum Covariance Determinant (MCD [23]), Fast-MACD [23] and Deterministic MCD (DetMCD [23]), etc.

However, the computational complexity of existing optimization methods prevents its use on the sensor. Therefore, to reduce the computational complexity, we look for the ellipse E enclosing the data points $(x_{i,j}, f(x_{i,j}, \hat{x}_{i,j}))$, where f is the residual function defined by $f(x_{i,j}, \hat{x}_{i,j}) = x_{i,j} - \hat{x}_{i,j}$. When using the residual, the center (x_c, y_c) of the ellipse E (eq. 2) will be located on the x-axis ($y_c = 0$ as shown in figure 2(b)) and thus reducing the calculation complexity associated with the rotated ellipse ($\theta = 45°$).

$$\frac{(x - x_c)^2}{a^2} + \frac{(y - y_c)^2}{b^2} = 1 \tag{2}$$

To find the major axis of the ellipse in figure 2(b), we use the Box-and-Whisker plot or boxplot. It is based on lower quartile (Q_1 is the 25th percentile) and the upper quartile (Q_3 is the 75th percentile) of X_j to detect abnormal values. Normal measurements must satisfy the following condition:

$$Q_1 - 1.5 \times (Q_3 - Q_1) \le \; x_{i,j} \le Q_3 + 1.5 \times (Q_3 - Q_1) \tag{3}$$

We denote by IQR the Interquartile range ($IQR = Q_3 - Q_1$). As the normal measurements must fall inside the interval $[Q_1 - 1.5 \times IQR, Q_3 + 1.5 \times IQR]$ defined in eq. 3, the width of the interval is equal to the length (L_E) of major axis of the ellipse ($2 \times a$) :

$$\begin{aligned} L_E &= \frac{Q_3 + 1.5IQR - Q_1 + 1.5IQR}{2} \\ &= 2IQR = 2a \end{aligned} \tag{4}$$

The length of the minor axis is calculated in the same manner over the residual time series ($IQR_\Delta = 2b$) resulted from the difference between the measured values X_j and the forecasted values $\hat{X}_j$ ($\Delta_{i,j} = x_{i,j} - \hat{x}_{i,j}$). The x-coordinate x_c of the ellipse center is in the middle of the interval and the y-coordinate (y_c) is zero:

$$\begin{aligned} x_c &= Q_1 - 1.5IQR + \frac{L_E}{2} \\ &= \frac{Q_1 + Q_3}{2} \\ y_c &= 0 \end{aligned} \tag{5}$$

When the difference $\Delta_{i,j}$ is outside the dynamically updated ellipse (eq. 6), the value is considered as abnormal and transmitted to the LPU. As normal data may change, the parameters of the ellipse (major & minor axis) are updated every T conditioned by maximum change ratio of 10%, i.e., the major and minor axis of the ellipse can not increase (or decrease) more than 10% of their previous values in two consecutive interval.

$$\frac{(x_{i,j} - x_c)^2}{IQR^2} + \frac{(\Delta_{i,j})^2}{IQR_\Delta^2} > 1 \tag{6}$$

The collected data are processed in real time on the LPU to detect anomaly and to raise alarms for caregiver only when patient health degrades (respiratory failure, cardiac arrest, etc.). Faulty measurements must be detected and isolated in order to reduce false alarms and prevent fault diagnosis.

Received values by the LPU may result from faulty measurements or clinical deterioration. Physiological parameters are correlated, and clinical deterioration induces changes in many parameters at the same time instant. The faulty measurements are usually not correlated with other attributes, and the probability that more than k sensors' measurements are faulty in the same time instant decreases when the number of received measurements by the LPU increases. Therefore, to distinguish faulty measurements from clinical deterioration, the LPU exploits this correlation and discards received data when $k < th$, where th is a threshold to trigger further processing ($th = 2$ in our experiments).

When more than k suspect measurements are received by the LPU, it applies the chi-square distance to detect abnormal deviations:

$$\chi_i^2 = \sum_{j=1}^{N} \frac{\left(x_{i,j} - \hat{x}_{i,j}\right)^2}{\hat{x}_{i,j}} \tag{7}$$

chi-square distance χ_i^2 must be low (near zero) for normal measurements. However, χ_i^2 will increase when the forecasted and measured values diverge in many attributes, and a large value of χ^2 implies abnormal measurements. Therefore, to identify clinical deterioration, we use the kernel Density Estimator (KDE), as a nonparametric method to estimate the Probability Density Function (PDF) of χ^2 . Let $\chi^2 = \{\chi_1^2, \chi_2^2, \ldots, \chi_n^2\}$ be the last n values of χ^2 having a common pdf $\hat{f}(x)$. The KDE estimates $\hat{f}(x)$ as:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - \chi_i^2}{h}\right) \tag{8}$$

Where $K(.)$ is the kernel function and h is the bandwidth. We use the Gaussian kernel given by:

$$K(x - \chi_i^2) = \frac{1}{\sqrt{2\pi}} e^{-0.5\left(x-\chi_i^2\right)^2} \tag{9}$$

And the optimal bandwidth:

$$h_{opt} \approx \frac{1.06\sigma}{n^5} \text{ and } \sigma^2 = \frac{1}{n-1} \sum_{i=1}^{n} \left(\chi_i^2 - \mu\right)^2 \tag{10}$$

Where μ and σ are the mean and the standard deviation of the vector χ^2. To make the method robust to outliers, we replace the mean μ by the median Q_2 ($\mu = Q_2$), and σ by the Median Absolute Deviation (MAD) given by:

$$\begin{aligned} Q_2 &= median(\chi^2) \\ MAD &= 1.4826 \times median\{|\chi^2 - Q_2|\} \end{aligned} \tag{11}$$

In hypothesis testing, the KDE is used to estimate the probability of new observation, and when p-value (probability value) is less than threshold θ ($\theta = 0.05$), the null hypothesis is rejected and the chi-square value is considered as abnormal. Then a medical alarm is raised for the healthcare professionals. The sliding window of last n observations of χ^2 (shown in figure 3) moves one slot by removing the oldest value and adding the new one, and the new window is used as training data for estimating the PDF. However, the data in sliding window have zero or near zero values for chi-square in normal condition, and we use gaussian distribution with $\mu = 0$ & $\sigma = c_1$ ($N(0, c_1)$) as the minimal threshold for chi-square distance. c_1 is a predefined constant greater than 1.

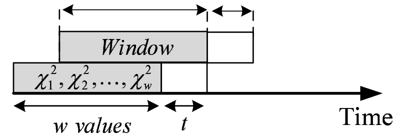


Fig. 3. Sliding window used for establishing normal profile

The alarm decision function is given by eq. 12, where a large value of χ_i^2 is synonym of large deviation between attributes.

$$A_i = \begin{cases} 1 & \textit{if } p\left(\chi_i^2\right) \leq 0.05 \\ 0 & \textit{Otherwise} \end{cases} \tag{12}$$

IV. Experimental results

In this section, we conduct experiments on the proposed approach for online anomaly detection in real medical data through computer simulation. We further compare and evaluate the performance of our proposed approach with robust Mahalanobis Distance (MD).

A. Simulation Setup

We use real medical dataset from the Physionet database [24], which contains ~ 45000 records, and each record contains 4 attributes (HR, Pulse, RESP, SpO2). We assume no prior knowledge about existing anomaly or faulty measurements in our approach that is applied on this dataset. We use a sliding window of 10 minutes ($T = 10$) to update the ellipse. This allows to reduce computational operations on the sensor (1 time every 10 minutes) and the underlying energy consumption. On the LPU, we set other parameters $w = 10$ and $\alpha = 0.1$.

The variations of HR (in beat per minute - bpm) are shown in figure 4, where we can visually identify abnormal measurement, a spike having a zero value. The heart rate can be extracted form ECG as the number of R-R intervals in one minute. The variations of the PULSE are presented in figure 5. Both figures exhibit the same variations (with abnormal values) as HR and PULSE represents the same physiological parameter measured using two different sensors. We can visually identify the zone of variations in both figures without being able to identify the reason behind these variations.

Figure 6 shows the variations of the respiration rate for the monitored patient, with two spikes falling down to zero, and figure 7 shows the variation of the blood oxygen saturation level (SpO2) or the percentage of oxygen in the blood. The value of this parameter must usually fall inside the interval $[95 - 100]$ in normal situation. However, measured values of SpO2 in figure 7 reach 80% for extended period of time and thus point to severe clinical deterioration (asphyxia).

The traditional AD methods look for deviation on the LPU and assume that whole gathered data by sensors are transmitted to the LPU for processing. As a first check for AD, we apply the chi-square distance (with forecasting) in our proposed

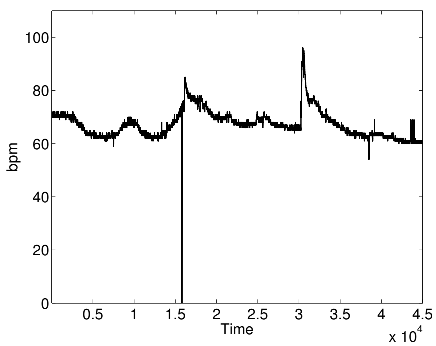


Fig. 4. Heart rate

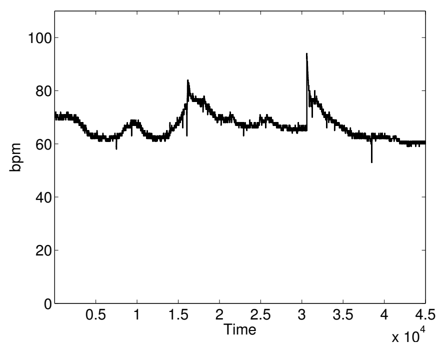


Fig. 5. Pulse

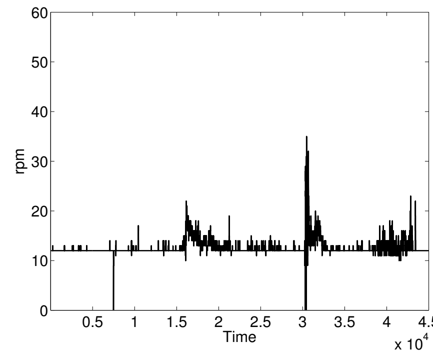


Fig. 6. Respiration rate

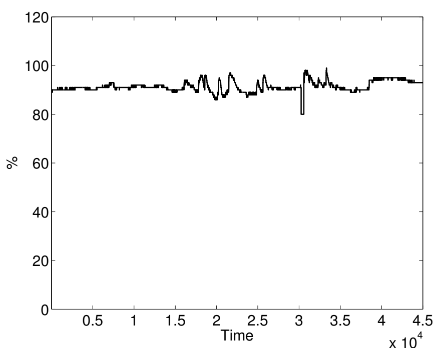


Fig. 7. Oxygenation ratio (SpO2)

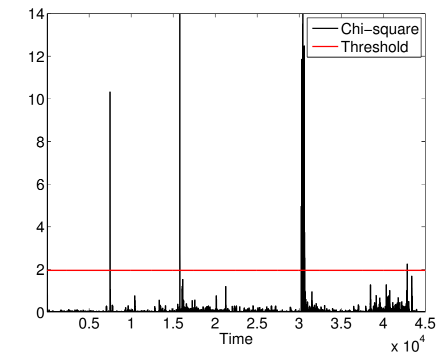


Fig. 8. Chi-square distance & threshold

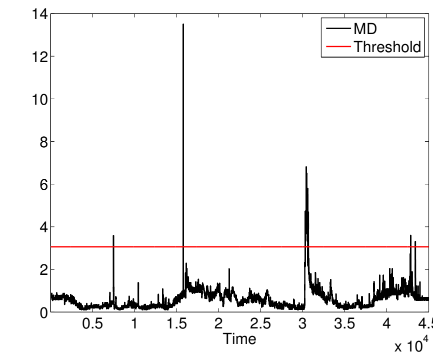


Fig. 9. Mahalanobis distance & threshold

scheme to detect abnormal deviations. Figure 8 shows the variations of chi-square and the associated threshold, where p-value of 5% is associated with a confidence level of 95% and a z-score 1.96. The four variations are clearly identified with their occurrence instants and durations.

B. Comparison with Robust MD

We compare our proposed scheme with the one proposed in [18], where the Mahalanobis Distance (MD) is used as a method for AD in gathered data by wireless sensors. MD calculates the distance between measurements by taking into account the correlation between monitored attributes:

$$MD_i = \sqrt{(X_i - \mu)^T \Sigma^{-1} (X_i - \mu)} \tag{13}$$

Where μ is the mean vector $(1 \times N)$ and Σ is the covariance matrix $(N \times N)$ of these N attributes calculated by a robust estimation method (OGK) which removes outliers from the Σ estimation by looking for a subset of training data without anomalies. However, MD requires additional complexity (the inversion of Σ) when comparing to chi-square, and the robust estimations for $\hat{\mu}$ and $\hat{\Sigma}$ require resources not available on the sensor.

MD_i^2 follows chi-square distribution $\chi^2_{N,0.975}$ with N degrees of freedom and 97.5% quantile is used as the threshold for anomaly detection by MD^2 (0.025 significance level for cut-off value). An alarm is triggered when the value of MD_i is greater than the threshold ($\chi^2_{N,0.975}$). The application results of robust MD over the physiological data are shown in figure 9 with the threshold $\sqrt{\chi^2_{4,0.975}} = 3.3382$ (horizontal line). When comparing figures 8 and 9, we notice that both cases have similar performance.

C. Performance Analysis when Using Enclosing Ellipse

The forecasting procedure and enclosing ellipse for AD are used to reduce the amount of transmitted data and to save energy. Sensors transmit only measurements falling outside the ellipse and the resulted chi-square variations are presented in figure 10. The false alarms associated with the faulty measurements in HR or in respiration rate have been discarded through correlation analysis. Only one medical alarm is raised for healthcare professionals (as shown in figure 11), and it is resulted from simultaneous changes in many physiological parameters at the same time instant. Curves in figure 11 are shifted to clarify the shape of their variations. We notice that the proposed scheme increases the detection accuracy and reduces the false alarm rate when compared to robust MD.

To evaluate the performance of the proposed approach, we synthetically inject 100 anomalies at different time instants in the different attributes in the used dataset. We used the ROC curve to show the impact of decision threshold (0-10%) on the true positive rate (equation 14) and the false negative rate (equation 15).

$$TPR = \frac{TP}{TP + FN} \tag{14}$$

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

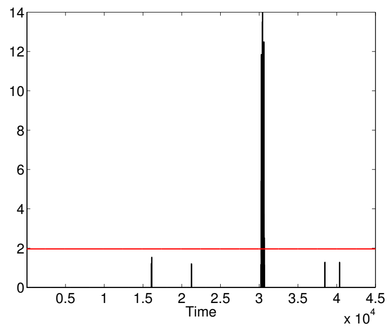


Fig. 10. Chi-square and threshold

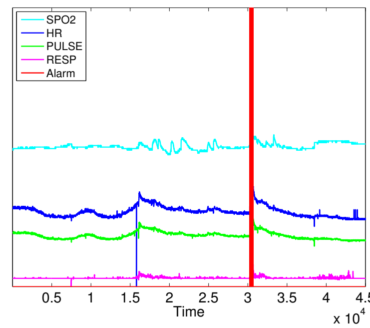


Fig. 11. Raised alarms

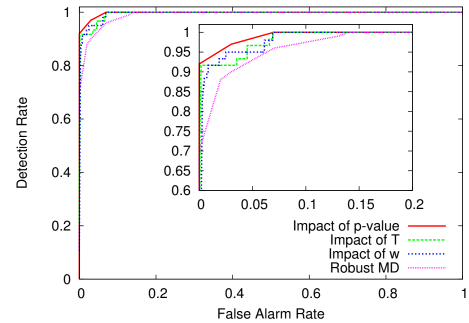


Fig. 12. Receiver Operating Characteristic (ROC)

defined as :

$$FPR = \frac{FP}{FP + TN} \tag{15}$$

Figure 12 shows the ROC for the proposed approach where the detection probability reaches 100% for a FAR of 4%. We also analyze in the same figure (figure 12) the impact of T and w parameters at the performance of our proposed scheme, and we show that our approach outperforms the robust MD scheme proposed in [18].

V. Conclusion

In this paper, we proposed an unsupervised approach for anomaly detection in medical WSNs. The proposed approach does not require a labeled training data nor threshold tuning. It is based on distributed forecasting using EWMA, and the transmission to the LPU of data points with large difference between forecasted and measured values. The LPU discards uncorrelated values and applies chi-square distance and KDE before raising a medical alarm. It is suitable for online detection and isolation for faulty or maliciously injected measurements with low computational complexity and storage requirement. We have evaluated the proposed approach using real medical data sets. Our experimental results show the effectiveness of our proposed approach in reducing the number of false alarms for medical emergency.

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