Detection and Isolation of Faulty Measurements in Medical Wireless Sensor Networks

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***Abstract*—In this paper, we propose a new framework for online detection and isolation of faulty measurements reported by medical wireless sensors. In our proposed framework, each sensor applies the non-seasonal Holt-Winter algorithm to detect any deviation in the time series associated with its measurements, and it will only transmit the detected abnormal values to the portable collection device (smart phone), in order to reduce the consumed energy of data transmission. As the physiological parameters are heavily correlated, the faulty measurements are usually uncorrelated with values of other sensors. Therefore, the collection device uses this correlation and its global view on the number of received deviations, to decide whether to raise an alarm for an emergency situation or to discard reported faulty measurements. Our main objective is to reduce false alarms triggered by faulty measurements. We apply our proposed approach on real physiological data set, and we prove its ability to achieve good detection accuracy with a low false alarm rate.**

***Index Terms*—Wireless Sensor Networks, Faulty Sensor, Interference, Signal Fading, Malicious Attacks, Anomaly Detection.**

I. Introduction

Wireless Sensor Networks (WSNs) are a set of autonomous sensors with wireless transmission capabilities. In medical applications, these sensors are attached to or implanted in the body of a patient to collect various vital signs from the monitored patients, such as heart rate, oxygen saturation, body temperature, etc. These devices continuously transmit the collected data to Local Processing Unit (LPU), such as Smart Phone, Tablet, etc. The LPU processes the received data and must raise an alarm to the healthcare professionals while detecting a clinical deterioration of monitored patients, to quickly react [1]–[4] by taking the appropriate actions [5].

WSNs have enhanced the quality of life by: (i) reducing the healthcare costs (overcapacity, waiting, sojourn time, number of nurses, etc.), (ii) providing mobility and freedom for monitored patient. However, the small size and weight of these sensors lead to limited energy, memory, small processing power and transmission range. Due to their constrained resources, they are susceptible to various sources of errors [2], [6], such as faulty measurements, badly attached sensors, malfunction, communication interferences, malicious attacks, battery depletion, compromised sensor, etc. Consequently, sensor readings are unreliable and inaccurate [7]–[9], and this lead to a large number of false alarms and unnecessary intervention of medical emergency team. Therefore, to reduce the false alarm rate, it is important to detect and isolate the faulty measurements and the maliciously injected data, without reducing the detection accuracy of the monitoring system for a medical emergency [10].

Several anomaly detection approaches have been proposed [11], [12] as solutions to increase the reliability of the monitoring system using WSNs. However, most of existing solutions assume that neighbor sensors measure the same parameters and exploit this redundancy to detect anomalies or outliers. In health monitoring, it is impractical to use redundant sensors for measuring the same parameter, and the existing approaches are inappropriate in such applications. Therefore, it is important to design a reliable anomaly detection algorithm, which is adequate with the constrained resources of sensors, and able to distinguish between faulty measurements and clinical emergency.

The second objective of this paper is to minimize energy consumption by wireless transmissions. In [13], the authors show that the ratio between communication and computation energy consumption ranges from 10^3 to 10^4. Hence, to prolong the lifetime of the sensors, it is desirable to reduce communications between sensors and LPU to save energy. Most of the time, the sensor measurements are normal and anomalies are rare. Therefore, the energy consumption can be reduced by only transmitting the abnormal measurements.

In this paper, we propose a solution to enhance the reliability of collected data in medical WSNs and to early detect emergency situations. The proposed approach performs forecasting and change point detection in each sensor to locally detect abnormal values. In order to reduce the communications overhead and energy consumption, only abnormal measurements are transmitted by sensors to LPU. The LPU takes the final decision to raise an alarm or to discard the received data according to the number of deviated attributes.

Our proposed approach for anomaly detection is based on the use of non-seasonal Holt-Winters (HW [14]) forecasting to detect abnormal values in the time series associated with its measurements. Each sensor uses double exponential smoothing of past values to predict the m future values. When the difference between predicted and measured values exceeds a dynamic threshold, the sensor sends the associated

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measurement to LPU.

In medical context, a clinical emergency leads to coherent changes in many physiological parameters. The correlation between monitored attributes should be exploited to make the difference between faulty measurements and clinical emergency. When a sensor detects an abnormal value, it transmits the value to the LPU that exploits the correlation among monitored attributes to decide wether to raise a medical alarm or to discard received values.

The rest of this paper is organized as follows. In section II, we review related work on fault detection and isolation in WSNs. Section III briefly reviews the non-seasonal Holt-Winter and presents our proposed framework for faulty measurements detection and isolation. In section IV, we present our experimental results over real medical dataset. Finally, section V concludes the paper with a discussion of the results and suggested future directions.

II. Related work

Several architectures have been proposed and deployed for remote monitoring of vital signs using WSNs, such as CodeBlue [15], LifeGuard [16], AlarmNet [17], MEDiSN [3], etc. Recent surveys of medical applications using WSNs are available in [18], [19].

Many platforms for medical wireless sensors are available in the market (i.e. MICAz, TelosB, SunSpot, IRIS, Imote2, Shimmer, etc.), and are able to collect many vital signs.

However, collected data by WSNs usually have low quality and poor reliability [6], [8], [9]. They are affected by interference, errors, incorrect readings, environmental noise, missing values, inconsistent readings, damaged sensors, etc. Several approaches for the detection of faulty measurements/sensors have been proposed in the literature. Authors in [6] provide a survey for outlier detection techniques in WSNs, and compare existing techniques. Single spike readings, longer duration spike as noisy readings, as well as anomalous constant reading have been observed in medical WSNs. Faulty measurements can be classified into 3 categories [20]: short, noise & constant.

Different approaches for anomaly detection have been proposed and applied to detect inconsistent measurements in collected data. Several algorithms based on machine learning (classification) or data mining (clustering) have been investigated, such as Naïve Bayes (NB), decision tree (C4.5), K-Nearst Neighbor (KNN), Self-Organizing Map (SOM) and Support Vector Machine (SVM). SVM provides the optimum solution with the lowest computational complexity. However, all these supervised techniques required labeled training data to build the classification model. This training data set is hard to build, and most of the time, it contains skewed classes where most of the training data belong to one class.

To resolve the problem of labeled and unskewed training data, data mining (unsupervised) techniques group similar data in one cluster, and flag small-size clusters (containing less than $t\%$ of total values) as abnormal. The widely used algorithms [21] are K-means, hierarchical clustering, Fuzzy C-means and GMM. However, clustering methods assume that anomalous data can be clearly distinguished from normal data. Compared to the normal data, the abnormal data rarely happen.

Authors in [20] investigate different approaches for anomaly detection in WSNs, such as rule-based methods, estimation methods, time series analysis methods and learning based methods. They apply different methods, such as 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 detecting every type of anomaly. Different classifiers may fail on different data patterns.

Authors in [12] 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 [8] note that only limited researches use 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 this paper, we provide a framework for reliable vital sign collection in medical WSNs. We focus on change point detection in each sensor readings. The change point detection algorithms look for time instant where the data distribution changes, i.e. data follows distribution $f(\theta_1)$ before the change and another distribution $f(\theta_2)$ after the change.

We use the non-seasonal holt-winter for change point detection, as it is adequate with the constrained memory and processing power of sensors. This simple approach appears to be promising in our experiments. HW doesn't assume a specific distribution for values in time series (non-parametric). It uses the past observations to predict future values with good accuracy and reduced computational complexity. When the difference between forecasted and measured values falls outside the confidence interval (or greater than threshold), measured value will be transmitted to the LPU which exploits the correlation between monitored attributes before raising an alarm for healthcare professionals.

III. Proposed Approach

We consider a real deployment scenario for patient monitoring, where n sensors $(S_1, \ldots, S_n)$ are attached or weared by the patient (as shown in figure 1), and used to monitor many physiological parameters. The sensors only transmit measurements that significantly deviate from other to the LPU (Smart Phone) which is responsible to raise an alarm for caregivers when clinical emergency is detected.

Let $X_j = (x_{i,j})$ denotes the time series associated with the collected measurements by the sensor with id j. i represents the time instant. With reference to t we define two windows on each sensor: $X_j^{(p)}$ the past data, $X_j^{(f)}$ the future part predicted using the original time series X_j:

$$X_j^{(p)} = (x_{1,j}, \ldots, x_{t-1,j}) \tag{1}$$

$$X_j^{(f)} = (x_{t,j}, \ldots, x_{t+m,j}) \tag{2}$$

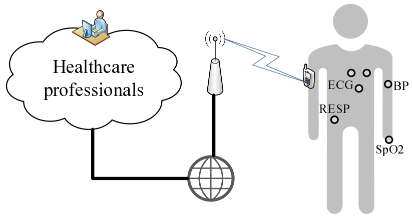

Fig. 1. WSN in medical deployment scenario

The m-step values in the future part (future window) of the signal ($X_j^{(f)}$) will be predicted using the non-seasonal HW forecasting algorithm (single exponential smoothing with linear trend). The m-step ahead forecasts of $x_{i,j}$ take into account the trend as given in the following equations:

$$\hat{x}_{i+m,j} = L_{i-1,j} + m \times T_{i-1,j} \tag{3}$$

Where $L_{i,j}$ and $T_{i,j}$ are calculated as follows:

$$L_{i,j} = \alpha x_{i,j} + (1-\alpha)\left(L_{i-1,j} + T_{i-1,j}\right) \tag{4}$$

$$T_{i,j} = (1-\beta)\, T_{i-1,j} + \beta\left(L_{i-1,j} + L_{i-2,j}\right) \tag{5}$$

The reference, test and forecasted windows are shown in figure 2. The reference window contains past measurements ($X_j^{(p)}$), which will be used to predict the values in forecasted window ($\hat{X}_j^{(f)}$). The measured values after the time instant t are in ($X_j^{(f)}$).

To detect deviations in the future window, we use the difference between the predicted $\hat{x}_{t+i,j}$ and the measured values $x_{t+i,j}$ to get the residual time series $R_j^{(f)}$:

$$\begin{aligned} R_j^{(f)} &= \left(|\hat{x}_{t+1,j} - x_{t+1,j}|, \ldots, |\hat{x}_{t+m,j} - x_{t+m,j}|\right) \\ &= \left(r_{1,j}, r_{2,j}, \ldots, r_{k,j}\right) \end{aligned} \tag{6}$$

The absolute residual value will increase for inconsistent

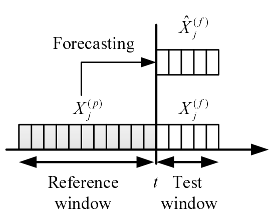

Fig. 2. Reference, test and forecasted windows

measurement with predicted value. To detect deviations, we use the statistical parameters, such as the mean (μ) and standard deviation (σ) to calculate a dynamic threshold as established in z-score ($\mu \pm k\sigma$). At a confidence level of 95%, the associated value of k is 1.96.

To detect deviations in the residual time series ($R_j^{(f)} = (r_{1,j}, r_{2,j}, \ldots, r_{k,j})$), we use a sliding window of last m observations (as shown in figure 3) 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. Therefore, we replace the mean μ by the median, and the standard deviation σ by Median Absolute Deviation (MAD) in the z-score:

$$\mu_t = median(r_{t-m,j}, \ldots, r_{t,j}) \tag{7}$$

$$\sigma_t = 1.4826 \times median\{|r_{t-m,j} - \mu_t|, \ldots, |r_{t,j} - \mu_t|\} \tag{8}$$

After replacing the mean μ by the median μ_t, and the σ by σ_t,

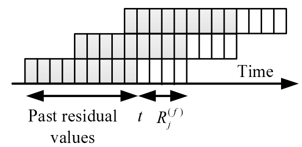

Fig. 3. Sliding window for residual

the z-score is applied to test if the values in the test window are normal or abnormal:

$$|r_{t+i} - \mu_t| \geq k \times \sigma_t \tag{9}$$

Where k is a threshold value ($k = 1.96$ associated with $p - value < 0.05$). Essentially, we can take a low value of the threshold to detect any small deviations, and faulty measurements will be filtered in the LPU. However, for a small threshold, small deviations will induce the transmission of measured value to the LPU, and thus consuming more energy.

As the residual values in the sliding window have zero or near zero median and MAD under normal condition [12], we use $\sigma_t = max(\sigma_t, c_1)$ to eliminate false alarms. c_1 is a predefined constant greater than zero.

To make the difference between faulty measurements and clinical emergency situation in LPU, we exploit the correlation among monitored parameters. When more than p sensors detect the change in their time series, they transmit the abnormal data to LPU that will raise a medical alarm. In the other case, it is a symptom of possible fault and we discard the received measurements. The choice of p is a tradeoff between detection accuracy and false alarm rate. A small value of p induces a large number of false alarms, and a large value of p may lead to miss detection and thus may threat the life of patient.

IV. Experimental results

In this section, we present the application results of the proposed framework for faulty measurement detection and isolation in medical WSNs. We use a real medical dataset from the Physionet database [22] (MIMIC Database). The dataset contains 7 attributes: Mean Blood Pressure (BPmean), Systolic Blood Pressure (BPsys), Diastolic Blood Pressure (BPdias), Heart Rate (HR), PULSE, Respiration rate (RESP) and Oxygenation ratio (SpO2). We use only the first 20000 records from 5 attributes: BPmean, HR, PULSE, RESP, SpO2. We set values as follows: $m = 10$, $k = 1.96$, $p = 2$, $\alpha = 0.3$, $\beta = 0.7$ and $c_1 = 3$.

The variations of BPmean, HR, PULSE, RESP and SpO2 are presented in figures 4, 5, 6, 7 and 8 respectively. The BP

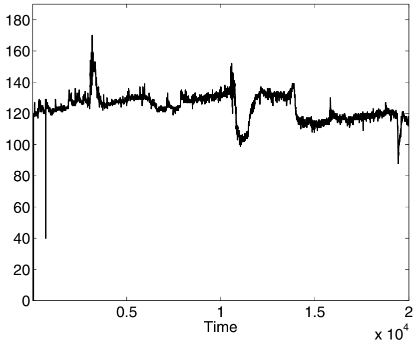

Fig. 4. Blood Pressure

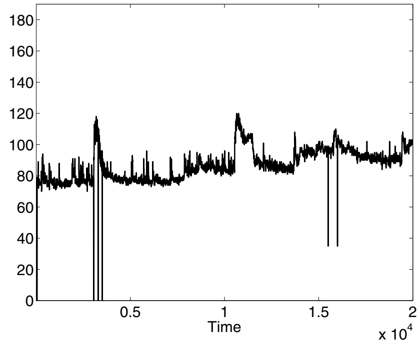

Fig. 5. Heart Rate

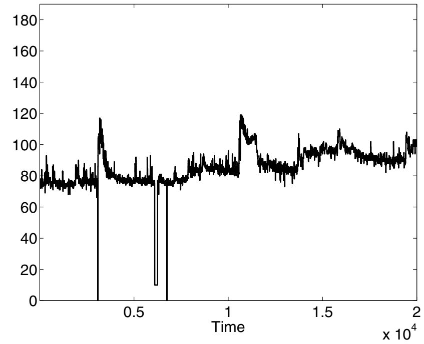

Fig. 6. Pulse

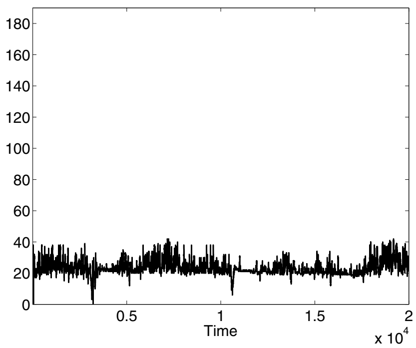

Fig. 7. Respiration Rate

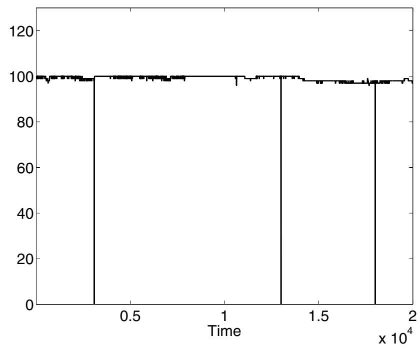

Fig. 8. Oxygenation ratio

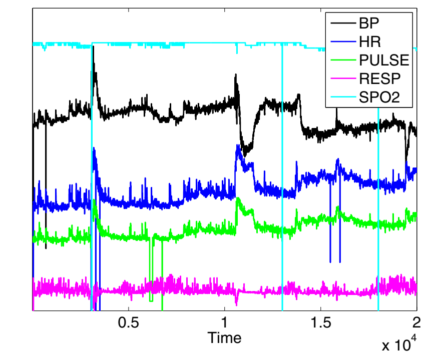

Fig. 9. Variations of 5 parameters

is measured in millimeters of mercury (mmHg) with normal values $\in [90 - 140]$. The HR and PULSE are in beat per minute (bpm) with normal values for a healthy adult in rest $\in [60 - 100]$. The respiration is measured in respiration per minute (rpm) and the SpO2 is the percentage of oxygen in the blood with normal values $\in [95\% - 100\%]$. As physiological parameters are not the same for whole people and they depend on many parameters (sex, age, weight, activity, etc.), the use of static interval for anomaly detection heavily depends on many additional dynamic parameters (environmental, ages, activities, etc.), and these parameters are not easy to set dynamically.

We can notice in figure 4 one abnormal value of BP falling to 40, and other variations associated with clinical change of the monitored patient. Furthermore, some values in HR and PULSE fall to zero in different time instant (shown in figures 5 and 6). In fact, HR and PULSE measure the same parameter using two different devices, and usually both curves must superpose. This is not the case when comparing both figures. The same goes for the RESP and the SpO2 in figures 7 and 8. We can visually identify abnormal variations of SpO2 with zero values (spikes) in figure 8.

To prove the correlation between monitored attributes, we show the variation curves of the 5 parameters in figure 9, where we can notice that clinical emergency induces changes in many parameters at the same time instant. However, there is no spatial correlation among monitored attributes for faulty measurements. It is important to note that some curves in figure 9 are shifted for clarifying the shape of their variations. We can visually distinguish 3 zones of clinical change (around 3500, 10500 and 19500 respectively).

Figure 10 show the variations of HR and the raised alarms by z-score for the abnormal deviations, that are detected in the residual time series associated with $|\hat{HR}_i - HR_i|$. The raised alarms in HR will trigger a transmission of abnormal values to LPU which exploits correlation among attributes to isolate faulty measurements. The medical alarms sent by LPU are shown in figure 11, where we can notice that alarms associated with unusual deviations in one sensor are discarded to reduce false alarms. When comparing the raised alarms in figure 10 and figure 11, we can observe the lack of some alarms (specially at the beginning and at the end), which are triggered by benign deviation or faulty measurements. In fact, when the change occurs in many sensors, a medical alarm is triggered by LPU. Otherwise, the measurement is considered to be faulty and will be discarded without raising any alarm. A visual inspection in the variation of monitored attributes in figure 10 confirms the accuracy of raised alarms.

To evaluate the performance of our proposed approach, we inject abnormal values at different time instants in the different attributes. We use the Receiver Operating Characteristic (ROC) curve to analyze the impact of detection threshold (k) on the detection accuracy and false alarm ratio. The ROC curve presented in figure 12 shows the relationship between the detection rate and the false alarm rate.

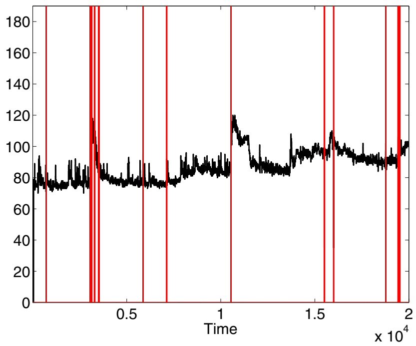

Fig. 10. HR & raised alarms

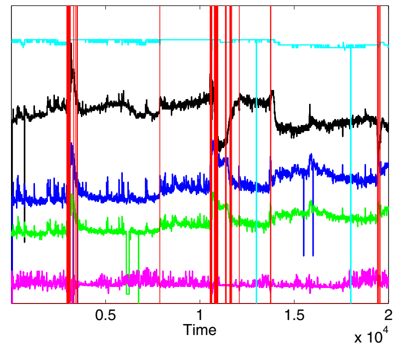

Fig. 11. Medical alarms by LPU

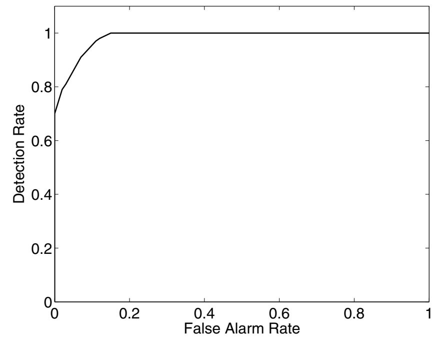

Fig. 12. ROC

A good detection mechanism should achieve a high detection ratio with the lowest false alarm rate. Figure 12 shows that our proposed framework can achieve a $DR = 100\%$ with a $FAR = 17\%$.

V. Conclusion

In this paper, we propose a sequential framework for the detection and isolation of faulty measurements in medical WSNs. The proposed approach is based on non-seasonal Holt-Winters forecasting and the z-score for faulty measurements detection, through the change point detection in the forecast error. It achieves spatial and temporal analysis before raising a medical alarm, to make the difference between faulty measurements and clinical emergency. The proposed framework reduces false alarms, and takes into account the computational complexity and energy consumption of medical sensors. We applied the proposed framework on a real medical dataset, and we evaluate the performance over the same trace with synthetic anomalies. Our experimental results show the accuracy of the proposed approach, where it can achieve a 100% of detection accuracy with low detection delay and with 17% of false alarms.

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