

Detection of Faulty Measurements in WBANs using Gaussian Mixture Model and Ant Colony

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Abstract

Wireless sensor networks are subject to different types of faults and interferences after their deployment. Abnormal values reported by sensors should be separated from faulty or injected measurements to ensure reliable monitoring operation. The aim of this paper is to propose a lightweight approach for the detection and suppression of faulty measurements in medical wireless sensor networks. The proposed approach is based on the combination of statistical model and machine learning algorithm. We begin by collecting physiological data and then we cluster the data collected during the first few minutes using the Gaussian mixture decomposition. We use the resulted labeled data as the input for the Ant Colony algorithm to derive classification rules in the central base station. Afterward, the derived rules are transmitted and installed in each associated sensor to detect abnormal values in distributed manner, and notify anomalies to the base station. Finally, we exploit the spatial and temporal correlations between monitored attributes to differentiate between faulty sensor readings and clinical emergency. We evaluate our approach with real and synthetic patient datasets. Our experimental results demonstrate that our proposed approach achieves a high rate of detection accuracy for clinical emergency with reduced false alarm rate when compared to robust Mahalanobis distance.

Keywords

Anomaly Detection, Wireless Sensors Networks, Ant Colony (AC), Gaussian Mixture Model (GMM), Healthcare monitoring

1. Introduction

The Medical Wireless Sensor Networks (WSNs) or Wireless Body Area Networks (WBANs) are a set of wearable or implantable biomedical sensors with wireless transmission capabilities, used to collect vital signs (pulse, heart rate, blood pressure, oxygen saturation, body temperature, glucose level, galvanic skin ratio, electrocardiogram, electromyogram, etc.) from the monitored patients (Crosby, Ghosh, Murimi, & Chin, 2012), and to transmit collected data toward a central device (smartphone or tablet) (Movassaghi, Abolhasan, Lipman, Smith, & Jamalipour, 2014).

These sensors measure and transmit physiological data in real time, and allow remote and continuous health monitoring (in-home or in-work) over an extended period of time (Otto, Milenkovi, Sanders, & Jovanov, 2005). These sensors minimize the need of caregivers and allow monitored patient to continue living independent life. Their usage leads to the modernization of the way in which healthcare services are deployed and delivered. WSNs may also resolve the shortage of nursing for assisting elderly people in-home. Several clinical situations could be prevented or better monitored using WBANs, where the collected data in real-time can be used to follow the evolving state of remotely monitored patient, to early detect clinical emergency situation and to quickly react by taking the appropriate actions to save the life of the monitored patient (Ko, et al., 2010).

WBANs provide a mobile healthcare system used for remote and in-home monitoring, where the physiological data collected by sensors are transmitted to Local Processing Unit (LPU), which has more processing power, battery and transmission capabilities than sensors. The LPU must process collected measurements in real time, and raise an alarm for healthcare center (or family, neighbor, etc.) when it detects clinical emergency, in order to let them react by taking the necessary actions.

Therefore, pervasive healthcare services require the development of real-time applications for the detection of emergency situations, such as the detection of myocardial ischemia which precedes the heart attack (or infarction). The early detection prevents serious complications and damage of the heart by therapies using anticoagulants or Percutaneous Coronary Intervention (PCI) that reestablish the normal flow of blood in the obstructed coronary artery.

WBANs reduce healthcare cost and improve the usage of occupied beds in hospital by enabling the monitoring of chronic and long term diseases outside institutions. They also enhance the life of monitored patients by allowing them to move freely and to achieve their daily life activities while being monitored. However, the use of WBANs is susceptible to several problems which range from reliability to security threats after deployment.

Sensors are subject to hardware and software faults, which are due to various reasons such as damaged device, calibration, battery exhaustion, or dislocation. Furthermore, with the small size of sensors and their underlying constrained resources, such as limited processing power, small memory and restricted transmission range, their transmitted data are extremely vulnerable to radio interference, environmental noise, function fault, breakdown, faulty measurements from badly attached sensor and malicious behavior. Consequently, the collected measurements are affected by noise and errors and have low quality and reliability.

The transmission of faulty measurements consumes energy of constrained sensors, and they might trigger a false alarm. Faulty measurements reduce the reliability and the accuracy of diagnosis results, and they affect the credibility of such monitoring system and prevent its deployment, where reliability is extremely important to ensure accuracy in the medical domain (Sahoo, 2012).

The use of WSNs in medical field has stringent requirements in terms of reliability and security. Security issues in WSNs should consider not only technical issues, but also social issues which might break the privacy of patient life. For example, the collected measurements might be accessed by an attacker which may (i) modify data, (ii) inject false data or (iii) replay previously registered data to threat patient's life. As the LPU must process the measurements in real-time to detect clinical deterioration, faulty measurements or maliciously injected data must be detected and isolated to increase the reliability of such monitoring system and to reduce false alarms.

Intrusion Detection Systems (IDS) are classified into two categories: misuse and anomaly detection. Misuse detection techniques are signature-based for detecting malicious traffic, and these signatures are not currently available for medical WSNs. In fact, most of malicious activities are the results of some assumptions and unknown signature attacks would be serious problem for WSNs. Anomaly Detection (AD) techniques measure the deviations between actual and pre-established normal model. Afterward, AD flags measurements that deviate from normal profile as anomalies. Although various IDS for wired and ad hoc

networks are mature enough today, they cannot be applied directly in WSNs because of the vast difference in sensor's resources, such as limited memory, small processing power, low transmission range, etc.

Several anomaly detection approaches have been proposed as solutions for these challenging problems which could severely affect the diagnosis results and pose a life-threatening risk. Despite the increasing interest in health monitoring, existing approaches for the detection of clinical deterioration using WBANs still suffer from the high number of false alarms. It is important to design a reliable detection algorithm that is able to differentiate between two types of changes in sensors' readings: (i) an emergency situation which causes changes in many physiological measurements, and (ii) faulty or injected measurements by malicious users. Abnormal data from these two types will deviate from the normal data profile and will trigger false alarms for healthcare professional. To reduce the high rate of false alarms caused by faulty measurements, it is important to provide a mechanism able to detect any abnormal deviations, and to distinguish between an emergency situation and sensor fault.

In this paper, we propose a solution to detect and insolate faulty measurements, and to enhance the reliability of healthcare monitoring using WBANs. Our proposed approach is based on machine learning algorithm and statistical model to detect abnormal data. First, we use Gaussian Mixture Model (GMM) decomposition to learn the statistical regularities of collected measurements. Then based on obtained labeled data, the Ant Colony (AC) is used to discover the set of classification rules for normal class. The derived rules by AC are the normal range for each monitored physiological attribute, and will be used to detect all abnormal measurements that deviate from the regular data.

To minimize the communication overhead by the transmission of abnormal data, the LPU transmits the derived rules to sensors. Each sensor applies the associated rule and transmits alarms to LPU only when data lie outside the range defined by the AC rule. Therefore, there is a reduction in data transmission and energy consumption in the network compared to centralised approach, where the whole collected measurements must be transmitted to the LPU, and anomaly detection is impractical with the overwhelming amount of collected data.

In our distributed case, the LPU still has a global overview of abnormal data through received alarms and can exploit correlation between monitored attributes to take a detection decision and to reduce the number of false alarms.

The remaining of this paper is organized as follows. Section 2 reviews related work for fault detection and isolation in WSNs. Section 3 reviews Gaussian Mixture Model and Ant Colony classification algorithms used in our proposed approach. Section 4 presents our proposed approach. In section 5, we present our results from experimental evaluation over real and synthetic physiological datasets. Finally, section 6 concludes this paper with a discussion of the results and plans for future work.

2. RELATED WORK

The remote healthcare monitoring using WBANs has recently gained momentum as powerful architecture for improving the quality of life for patients and for reducing the healthcare costs.

One of the proposed monitoring systems is CodeBlue (Malan, Fulford-jones, Welsh, & Moulton, 2004; Havard Sensor Networks Lab, 2013), which is able to monitor the Heart Rate (HR), Pulse, SpO2 and ElectroCardioGram (ECG). It transmits the collected data to the healthcare professionals for further analysis, through the use of base station (LPU). Other medical monitoring systems are: MEDiSN (Ko, et al., 2010), LifeGuard (Montgomery, et al., 2004), AlarmNet (Wood, et al., 2006), Medical MoteCare (Navarro, Lawrence, & Lim, 2009), Vital Jacket (Cunha, et al., 2010). Some comprehensive survey studies of medical applications using WSNs are available in (Alemdar & Ersoy, 2010; Grgic, Žagar, & Križanovic, 2012).

Various other monitoring systems using WBANs have been proposed for the detection of specific event, such as: epileptic seizure detection (Cuppens, Lagae, Ceulemans, Huffel, & Vanrumste, 2010), fall detection (Lee, Kim, Son, & Lee, 2007), myocardial ischemia (Romero, Ringborn, Laguna, Pahlm, & Pueyo, 2011), myocardial infarction (Bradley, et al., 2012; Sun, Lu, Yang, & Li, 2012), kinematics (Toffola, Patel, Ozsecen, Ramachandran, & Bonato, 2012), Sleep Apnea (Bsoul, Minn, & Tamil, 2011), etc.

However, the measured and collected data by sensors are often unreliable and inaccurate (Zhang, Meratnia, & Havinga, 2010; Wang, Fang, Xing, & Chen, 2011; Zhang, et al., 2012). They are affected by interference, error, noise, missing values, inconsistent readings, maliciously injected, etc. Several approaches for the detection of faulty measurements have been proposed in the literature. Authors in (Zhang, Meratnia, & Havinga, 2010; Xie, Han,

Tian, & Parvin, 2011) provide surveys for outlier detection techniques in WSNs, and compare existing techniques.

Authors in (Jurđak, Wang, Obst, & Valencia, 2011) define the common types of anomalies in WSNs, and classify them into three types: network anomalies, sensor anomalies and data anomalies. Their detection can be achieved by building a model to represent normal data, and any heavy deviation from the established normal profile will be considered as anomaly. Usually, normal measurements follow the same distribution and abnormal values (outliers) are generated by other distribution or require changes in statistical parameters.

Authors in (Abduvaliyev, Pathan, Zhou, Roman, & Wong, 2013) survey recently proposed approaches on IDS in WSNs, and include the significant advancements in this area. They present a classification of IDS into 3 categories based on their detection techniques: misuse detection, anomaly detection and specification-based detection. They also present a comparison between existing approaches in terms of energy efficiency, accuracy and memory requirements. They note the importance of the tradeoff between resources consumption (energy and memory) and detection accuracy, where the required computational power by some approaches to achieve good detection accuracy, are not available in the sensors.

Authors in (Curiac & Volosencu, 2012) propose an algorithm to detect faulty measurements on the LPU of WSNs. They use five different classifiers, each of which classifies the sensed data as normal or abnormal. All individual decisions will be aggregated using a weighted majority algorithm to obtain the final decision.

Authors in (Siripanadorn, Hattagam, & Teaumroong, 2010) use an unsupervised approach (data mining or clustering) for anomaly detection in WSNs. Their proposed approach is based on Self-Organizing Map (SOM) and Discrete Wavelet Transform (DWT). The DWT is used to reduce the size of input data for SOM clustering. Experimental results over synthetic traces show that this method is able to detect anomalies accurately, but the required processing and storage cost caused by SOM and Wavelet may prevent its usage for real time detection with the constrained resources in WSNs.

Author in (Zhu, 2011) uses machine learning approach (or supervised classification) to automatically detect anomalies in the Blood Glucose Level (BGL) of monitored patients. The normal daily measurements of the patient are used to train the Hidden Markov Model

(HMM) by estimating the transition and output probabilities. In test phase, if the likelihood of measured value is lower than output in HMM, it is considered as an anomaly. However, experimental results are conducted by simulations, and the author doesn't evaluate the complexity and the feasibility of parameter estimations in a real world scenario.

Authors in (Chuah & Fu, 2007) proposed an Adaptive Window-based Discord Discovery (AWDD) scheme, which is based on time series analysis to detect abnormal heartbeat. Their algorithm is accomplished in two passes with adaptive window size. They compared two subsequences of different lengths, and they use Euclidean Distance to measure the divergence between one of the subsequences and its nearest non-self-match. They consider as anomalies the subsequence with the largest distance.

Authors in (Chang, Terzis, & Bonnet, 2009) also use machine learning model (Neural Networks) for anomaly detection in WSNs. They build a distributed algorithm for fault and event detection. Their proposed approach is based on two stages: (i) training phase where nodes are trained by Echo State Networks (ESN) to build a model for normal data, (ii) detection phase where measurements that significantly deviate from their predicted values by ESN are considered as anomalies.

Authors in (Zhang, Ren, Gao, Yan, & Li, 2009) propose a distributed fault detection scheme for WSNs. They identify faulty sensor based on the similarity test of neighboring nodes and dissemination of the decision made at each node. Each sensor has NT table which contains certain information about its neighbors, such as node ID, similarity coefficient and current state. The sensor will be considered as faulty when its current state in NT table is faulty, or if the similarity coefficient is less than threshold.

Author in (Jiang, 2009) proposes another distributed scheme to divide sensors into 2 types: normal and faulty. However, distributed detection schemes assume that neighbor nodes are measuring the same attributes. Each sensor monitors its one hop neighbors and uses local comparisons between measured and received data, and some thresholds are used to detect faulty measurements and to prevent their transmission. However, it is impractical to use redundant sensors in healthcare monitoring. Furthermore, distributed detection techniques require resources that are not available in medical sensors, and their accuracy is lower than centralized approaches, which have a global view on collected data from multiple sensors. Authors in (Jurdak, Wang, Obst, & Valencia, 2011) classify the anomaly detection approaches in WSNs into 3 categories: centralized, distributed and hybrid. They found that a hybrid

approach that locally detects problems and then triggers more involved analysis in the centralized collection point is most suitable for anomaly detection. In this paper, we will use a hybrid approach to reduce the energy consumption and to enhance the detection accuracy of monitoring results. For further information of existing technologies, several comprehensive surveys on anomaly detection in WSNs are available in (Chandola, Banerjee, & Kumar, 2009; Xie, Han, Tian, & Parvin, 2011; Abduvaliyev, Pathan, Zhou, Roman, & Wong, 2013).

A common problem in majority of existing anomaly detection approaches is the ignorance of both spatial and temporal correlation between monitored physiological attributes. Mostly they focus on temporal correlation without considering spatial relationship among attributes.

In this paper, we provide a distributed approach for reliable vital sign collection in medical WSNs. The aim is to reduce false alarms triggered by faulty or maliciously injected measurements. We use GMM decomposition to cluster the collected data in the first few minutes, and the resulted labeled data are used by the AC to derive classification rules. The LPU transmits the rules to sensors, which apply associated rule on each sensed data to classify measurements into 2 classes: normal or abnormal. Sensors communicate only abnormal data to LPU in order to reduce energy consumption by communication overhead. As the LPU has a global view on abnormal data, it exploits the correlation between monitored attributes to make a detection decision, and to reduce false alarms triggered by faulty measurements.

3. Background

In this section, we briefly survey the Gaussian Mixture Models (GMM) and Ant Colony Optimization (ACO) classifier used in our proposed approach. For detailed information about these algorithms, reader may refer to the papers (Martens, et al., 2007; Theodoridis, Pikrakis, Koutroumbas, & Cavouras, 2010).

A. Gaussian Mixture Model (GMM)

Gaussian Mixture Model (GMM) is used to model unknown probability density function by a weighted sum of J Gaussian distributions in the form:

$$p(Y_{t_m}) = \sum_{i=1}^J P_i \cdot p(Y_{t_m} / i) = \sum_{i=1}^J P_i \cdot p(Y_{t_m} | m_i, \Sigma_i) \quad \text{where} \quad \sum_{i=1}^J P_i = 1 \quad (1)$$

Where $p(Y_{t_m}/i)$ models the i^{th} cluster specified by its mean m_i and its covariance matrix Σ_i , P_i is the probability that data vector Y_{t_m} is generated by the component i . To cluster the data into 2 ($J = 2$) classes (normal & abnormal), we use the iterative generalized mixture decomposition algorithm (Theodoridis, Pikrakis, Koutroumbas, & Cavouras, 2010) which adjusts the parameters m_i , Σ_i and P_i with respect to an initial estimate, and terminates when no significant change in these values between two successive iterations. It returns the posteriori probability that the vector Y_{t_m} stems from the distribution associated with the i^{th} cluster (cp_k). To obtain a hard clustering, we use the maximum value of the cluster probability $\text{Class} = \max(cp_k)$.

B. Ant Colony Classifier

Ant Colony Optimisation (ACO) is a meta-heuristic algorithm inspired from the behaviour of ants to find the shortest path toward the food. ACO has been applied to build a classification rules in machine learning domain, where it uses a set of labeled training data to infer the classification rules.

Ant Colony (AC) classifier is inspired from the collective behavior of the real ants which communicate together in an indirect manner by depositing a substance called pheromone (Martens, et al., 2007). In fact, Ants go out from their colony looking for food (as shown in Figure 1), with their colony as start point and their destination (the food) as their stop point.

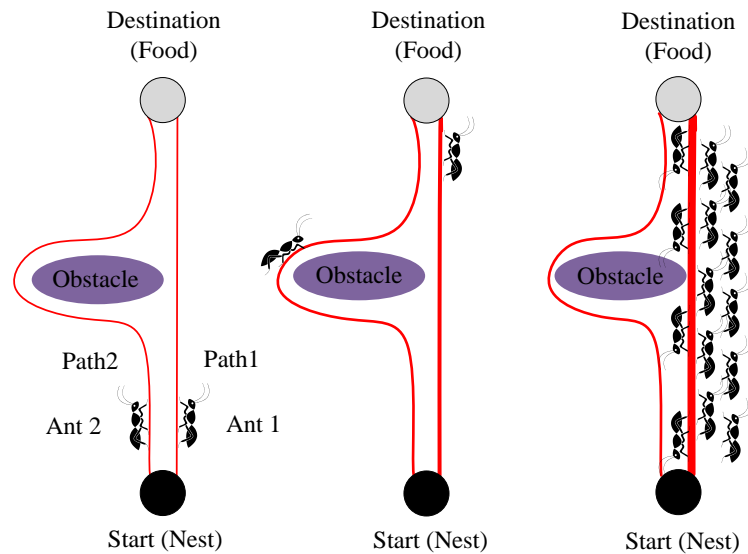


Figure 1. Ants behaviour

Initially, the ants start searching for the food in a random manner, and they might face some obstacles and barriers which make them take a decision to search for alternative paths. Furthermore there will be a disparity between the lengths of paths. So the goal of ants is not limited to reach the destination (food), but to reach the destination using the shortest path. In Figure 1, Ant 1 and Ant 2 start from the nest and deposit pheromone on the paths while searching for the food. Ant 1 reaches the destination (food) earlier than Ant 2 and thus it goes back to the start point. This causes reinforcement of the amount of pheromone in path 1 (shortest path), which attracts other ants to pass through this path. The path will be used by other ants which in turn drop some amount of pheromone. After some amount of time, all ants converge to path 1 as the shortest path between Nest and Food.

In machine learning, AC is applied over labeled training to discover the classification rules, such that each path discovered by the artificial ants represents one candidate classification rule. These rules are of the form: *if "rule antecedent" then "rule consequent"*. The condition "*rule antecedent*" stands for a conjunction of terms ($Y_1 \& Y_2 \dots Y_n$), where each term is a condition (Y_i , operator, value). For clarification, an example of a term when monitoring the HR of a patient, the term is: ($HR < 60$). The "*rule consequent*" is the discovered class where their attributes satisfy all the terms in the "*antecedent rule*". An example of the rule:

```
if ((HR > 60) and (HR < 100))  
then  
    class = normal  
else  
    class = abnormal
```

In AC, artificial ants are used to explore the environment, which is represented by a directed acyclic graph G with a vertex group for each attribute. To build the graph G , we apply the following procedure over 3 physiological data (HR, Pulse and SpO2):

1. All ants begin in the start vertex and walk through their environment to the stop vertex.
2. A vertex group (Class in Figure 2) contains only one vertex (i.e., normal class in our study) that is used to extract a rule for normal data. The abnormal class will be the result of negating the final established rule for the normal class (the else clause).
3. Vertex groups (V_1, V_2, \dots, V_n) represent n attributes (e.g., HR, Pulse and SpO2), where V_i contains the data measurements in normal class from the i^{th} attribute.

4. To derive an interval for normal data, such as the case for normal $HR \in [60 - 100]$, the vertex groups (HR, Pulse and SpO2) are duplicated in (HR', Pulse' and SpO2'). The first vertex group is used to derive the lower bound, and the duplicated vertex group is used to derive the upper bound for each attribute.
5. To avoid conflict in rule construction (e.g. $HR \geq 90$ and $HR \leq 80$), the edge between two vertices in the same attribute must be removed if the first vertex has a higher value than the second one.

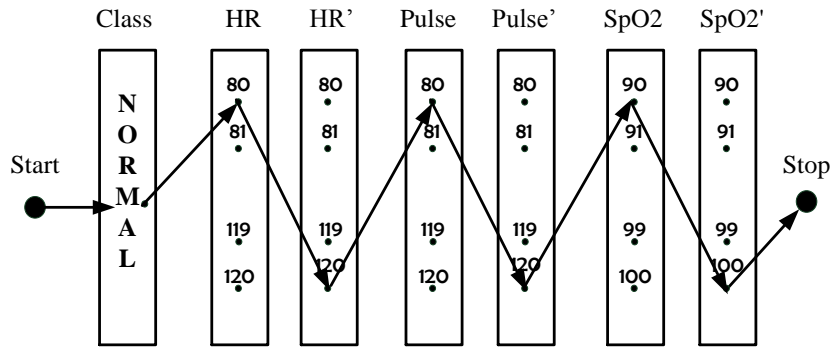


Figure 2. Rule construction using Ant Colony

After building the graph using only the records in normal class as training data, the classification is done by two nested loop as given in algorithm 1. AC starts by the outer loop where a classification rule will be discovered in each iteration. The pheromone level in all paths will be initialized to τ_{MAX} in order to assign equal probabilities for an ant to choose between edges. This loop will be repeated until satisfying the early stopping condition, that is to say, that loop will be repeated until the number of uncovered cases is smaller than the threshold predefined by a user.

In the interior loop, an ant begins from the start vertex with an empty rule and walks through the environment to the stop vertex. Incrementally, it constructs the candidate rule by adding one term at a time. The probability of path selection among vertices is based on the pheromone and heuristic values. The pheromone level is an indication of the number of ants passing through this path, and the heuristic level gives each vertex an importance in the problem domain, the higher the heuristic value the higher probability for the edge to be chosen. For more information about AC classifier, reader may refer to (Martens, et al., 2007).

Algorithm 1. Ant Colony algorithm

```
1: TrainingSet = {all training cases}
2: DiscoveredRulesList=[];
3: while (Not early Stopping) do
4:   Initialize all path to pheromone level  $\tau_{MAX}$ 
5:   while (Not converged) do
6:     Let ants run from start to end;
7:     Update the pheromone of all trails;
8:     An ant incrementally constructs a classification rule;
9:     Prune the just-constructed rule;
10:  end while
11:  Choose the best rule out of all constructed rules;
12:  Add the chosen rule to DiscoveredRuleList;
13:  TrainingSet = TrainingSet - {cases correctly covered by the chosen rule};
14: end while
```

4. Proposed approach

We consider a real deployment scenario where many sensors are attached to the body of the monitored patient as shown in Figure 3. These sensors collect several physiological parameters (HR, Pulse, Blood Pressure, Respiration rate, SpO₂, etc.) and transmit the collected data to the LPU (smart phone) for real time processing. The LPU may send the collected data to remote monitoring center for storage, and it processes data in real-time, in order to detect heavy deviations in monitored parameters, and to raise medical alarm for healthcare professionals upon detecting an emergency situation.

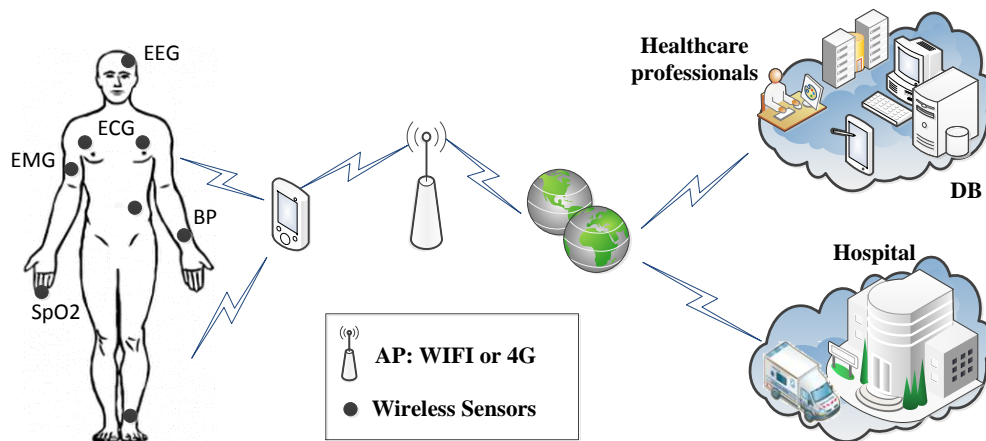


Figure 3. WSN in medical deployment scenario

Let $Y = (y_{i,j})$ denotes the set of collected measurements by n sensors during the last m minutes, where i represents the time instant, and j represents the sensor identifier (id). We denote by $Y_k = \{y_{1,k}, y_{2,k}, \dots, y_{m,k}\}$ the time series associated with the k^{th} sensor, and by Y_{t_i} the record at time instant t_i . Y_{t_i} is a line and Y_k is a column in the data matrix Y given by the following equation :

$$Y = \begin{matrix} & Y_1 & Y_2 & Y_3 & \cdots & Y_n \\ \begin{matrix} Y_{t_1} \\ Y_{t_2} \\ \vdots \\ Y_{t_m} \end{matrix} & \begin{bmatrix} y_{1,1} & y_{1,2} & y_{1,3} & \cdots & y_{1,n} \\ y_{2,1} & y_{2,2} & y_{2,3} & \cdots & y_{2,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ y_{m,1} & y_{m,2} & y_{m,3} & \cdots & y_{m,n} \end{bmatrix} \end{matrix} \quad (2)$$

We seek to detect abnormal values on the portable device (LPU), and to discriminate between faulty measurements and patient health degradation, in order to reduce the false alarms resulted from faulty measurements. Our proposed approach to detect abnormal values is based on two phases: training and classification. In training phase, the first few minutes into 2 categories (normal & abnormal) using generalized mixture decomposition algorithm (Theodoridis, Pikrakis, Koutroumbas, & Cavouras, 2010). In classification phase, we applied Ant Colony (AC) classifier over labeled data to generate the classification rules as given in algorithm 2.

Algorithm 2. Classification using Ant Colony algorithm

```

1:  $i = 0$ 
2: for ( $i = 1; i \leq n; i++$ )
3:   Calculate the Lower Bound ( $LB_i$ )
4:   Calculate the Upper bound ( $UB_i$ )
5: end for
6: if ( $(LB_1 \leq y_{i,1} \leq UB_1) \& \dots \& (LB_n \leq y_{i,n} \leq UB_n)$ )
7: then
8:   Class = normal
9: else
10:  Class = abnormal
11: end if

```

To achieve this task, the generated rules by AC are applied on each received value to detect abnormal measurements and to assign one class to the whole record (normal and abnormal).

The rule is a logical conjunction of many conditions, and abnormal class is assigned if at least one attribute is outside the derived range. As this approach is centralized, all the sensor measurements must be communicated to LPU in order to apply the anomaly detection algorithm.

To reduce energy consumption by the transmission of normal measurements and extend the lifetime of the wireless sensors, it will be more efficient to perform in-network detection of abnormal measurements and to transmit only alarms associated with abnormal measurements to the LPU for further processing and correlation analysis. However, the GMM and rules extraction using ACO require resources not available in the sensors. These algorithms run on the LPU, which transmits the discovered rules for sensors in order to achieve distributed anomaly detection. As a rule takes the form of "if $(LB_n \leq y_{i,n} \leq UB_n)$ then Class = normal", it can easily be installed and applied in the sensor.

Instead of transmitting collected data to the LPU, the sensor applies the received rule and transmits only alarms when detecting a measurement outside the range. If the sensed value by S_i lies outside the range $[LB_i, UB_i]$ determined by AC rule for this attribute, then the sensor transmits an alarm for the LPU. LPU maintains a sliding window for raised alarms by each sensor and a final decision window as shown in Figure 4.

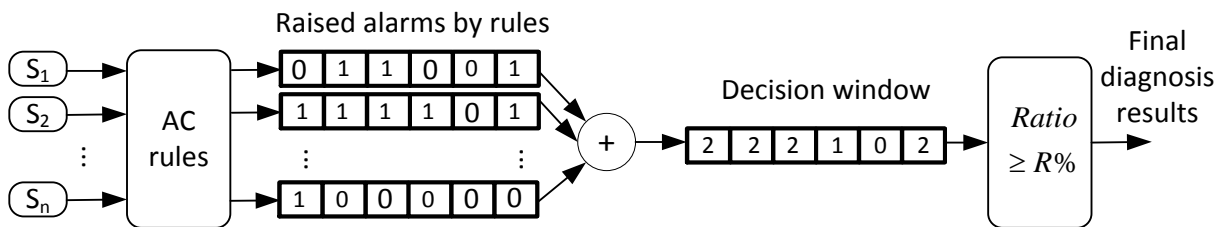


Figure 4. LPU processing for medical alarm

The slot value in the associated sliding window is set to 1 to indicate abnormal value for this attribute. As the LPU has a global vision of whole detected anomalies (or raised alarms), it can update the alarm decision window. The alarm flags in whole windows are added to get final decision window. The raised medical alarm is based on the values in decision window, and it is not triggered by each alarm transmitted by individual sensor.

As physiological parameters are heavily correlated, the change is usually reflected in many measurements. Therefore, to discriminate between clinical emergency and faulty measurements, we use a sliding window of length T timeslots, where each slot contains the

sum of raised alarms by sensors (as shown in Figure 5). If at least p of T values, or more specifically, when the percentage of slots with values $\geq k$ is larger than $R\%$ ($Nb(slot \geq k) \geq R\%$) in decision window ($k = 2$ in Figure 5), a medical alarm is triggered for healthcare professionals. In fact, physiological change persists over considerable slots while faulty measurements are transient. Furthermore, a long term anomaly does not necessary mean clinical emergency and this is why a correlation between k attributes in sliding window is considered instead of change point-based techniques. The organisation chart showing the main blocks used in our distributed approach is shown in Figure 6. The pseudo code of the distributed approach for clinical emergency detection is given in algorithm 3. Faulty and transient variations are detected and isolated to reduce false alarms.

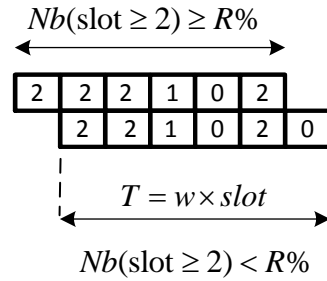


Figure 5. Sliding window

Algorithm 3. Distributed anomaly detection

1: **Initialization**

2: LPU extracts the classification rules

3: LPU transmits rules to sensors

4: **end initialization**

5: each sensor (S_i) applies the rules to detect local abnormal values

6: each sensor sends only locally raised alarm to the LPU

7: LPU updates the decision window

8: **if** ($Nb(slot \geq 2) \geq R\%$)

9: **then**

8: Raise alarm for healthcare professionals

9: **end if**

5. Experimental results

In this section, we present the experimental results of the proposed approach for anomaly detection in medical WSNs. Afterward, we conduct performance analysis experiments to

analyze the impact of window size on the detection accuracy and false alarm ratio. In our experiments, we use real medical dataset from MIMIC II Database, available in Physionet (Physionet, 1999; Goldberger, et al., 2000). The original patient record contains 131249 lines for monitoring duration of 37.5h, and each line contains 14 attributes: time, ABPmean, ABPsys, ABPdias, C.O., HR, PAPmean, PAPsys, PAPdias, PULSE, RESP, SpO2 and Tblood. The dataset is annotated with alarm instant for each abnormal attributes.

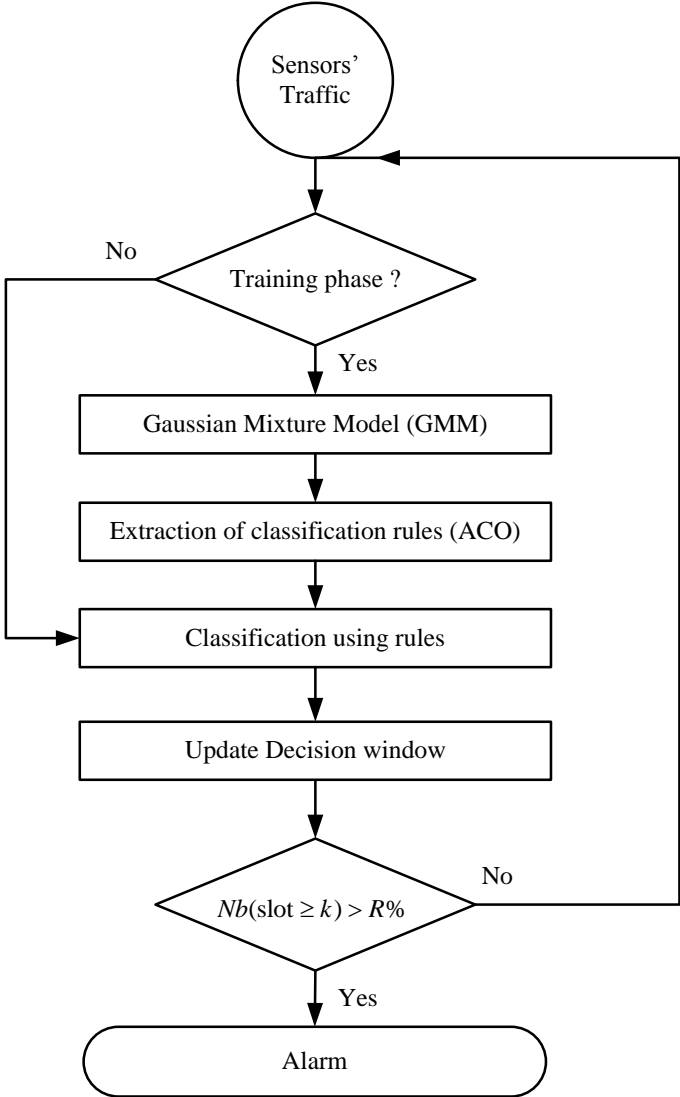


Figure 6. Architecture of the proposed approach for medical anomaly detection

We use the WFDB software package provided by Physionet to convert the binary data into ASCII, and we extract part of the dataset (~8,24h) where we focus only on 7 attributes (ABPmean, HR, PAPmean, PULSE, RESP, SpO2 and Tblood). We develop a program to read the measurements from the file and to transmit the data wirelessly to a Samsung galaxy 3 tablets with Android as operating system.

The variations of blood pressure (in mmHg), artery pressure (mmHg), heart rate (beats per minute - bpm), pulse (bpm), respiration rate ((breath per minute - bpm), SpO2 (%) and temperature (°C) are shown in Figures 7(a), 7(b), 7(c), 7(d), 7(e) and 7(f) respectively.

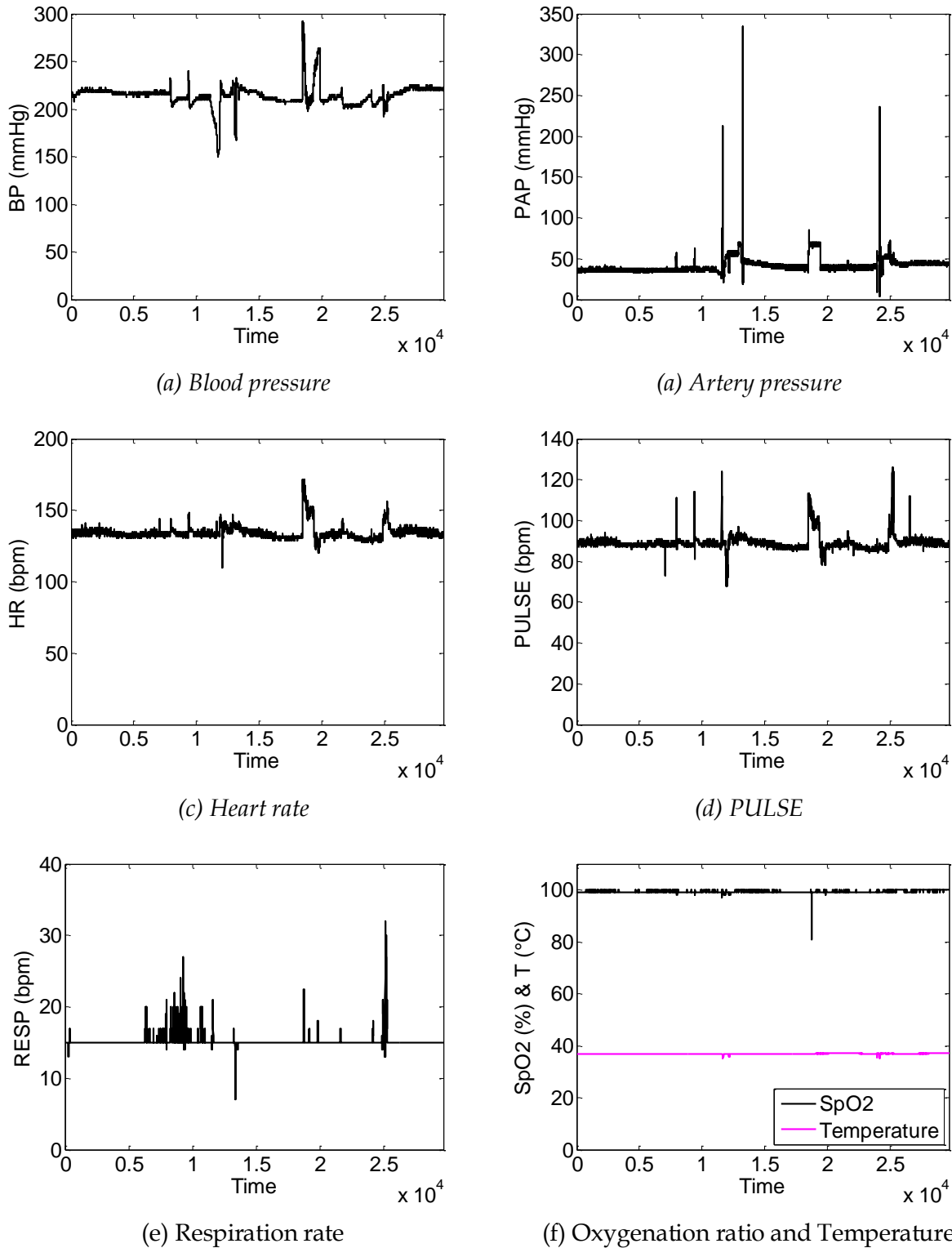


Figure 7. Blood pressure, Artery pressure, Heart rate, Pulse, Respiration, SpO2 and T°

HR and Pulse measure the same physiological parameter using two different devices, and usually they must present the same variations. However, when comparing Figures 7(c) and 7(d), they exhibit some differences (some spikes) at different time instants. The difference results from abnormal values measured by the sensors.

As physiological parameters are not the same for whole people and are dependent on many parameters (sex, age, weight, activity, etc.), we started by clustering the collected data in the first few minutes using generalized mixture model, in order to derive dynamic interval for normal values of the monitored attributes. To enhance the accuracy of the clustering algorithm, we inject faulty record in the training data using values from outside the known normal interval of monitored attributes.

After data clustering, the data in normal cluster will be used by the AC to derive rules, which define the interval containing the normal values of each physiological attribute of the monitored patient. These rules will be applied in real time on each measured value by sensor for binary classification (normal & abnormal).

The variations of whole monitored physiological parameters are shown in Figure 8(a). The measurements that fall outside the established interval by AC will raise an alarm to the LPU. The red vertical lines in Figure 8(b) show the raised alarms for abnormal values in whole attributes to the LPU. Most of raised alarms in previous figure are false and they are triggered by benign deviation or faulty measurements. To reduce false alarms, and to differentiate between faulty sensor measurements and emergency situations, we exploit the correlation between physiological parameters and the filling ratio of sliding window. We consider clinical deterioration only if the changes occur in at least k attributes for w slots, where $k = 2$ in our experiments.

Figure 8(c) shows three areas of raised alarms to healthcare by our proposed approach. We obtained three alarms resulted from the deviations of many physiological parameters, instead of ten alarms when considering each attribute separately (e.g. deviations in HR, or in Pulse, or in SpO₂, etc.). In fact, a visual inspection in the variation of monitored attributes in figure 8(a) confirms the utility of these alarms.

The number of correlated attributes and the filling ratio of decision window for triggering an alarm are a tradeoff between false alarms and miss detection. In fact, a small number of

attributes leads to a large number of false alarms, and a large number may lead to miss detection and thus may threaten the life of monitored patient.

Figure 8(d) shows the raised medical alarm when increasing the size of decision window ($T = w \times slot$) from 2 minutes to 5 minutes (with $k = 2$). In fact, increasing value of w reduces the false alarms and decreases the detection accuracy of clinical emergency. A window size w equal to two minutes provides better detection, and it was chosen as a tradeoff between false alarms and detection accuracy.

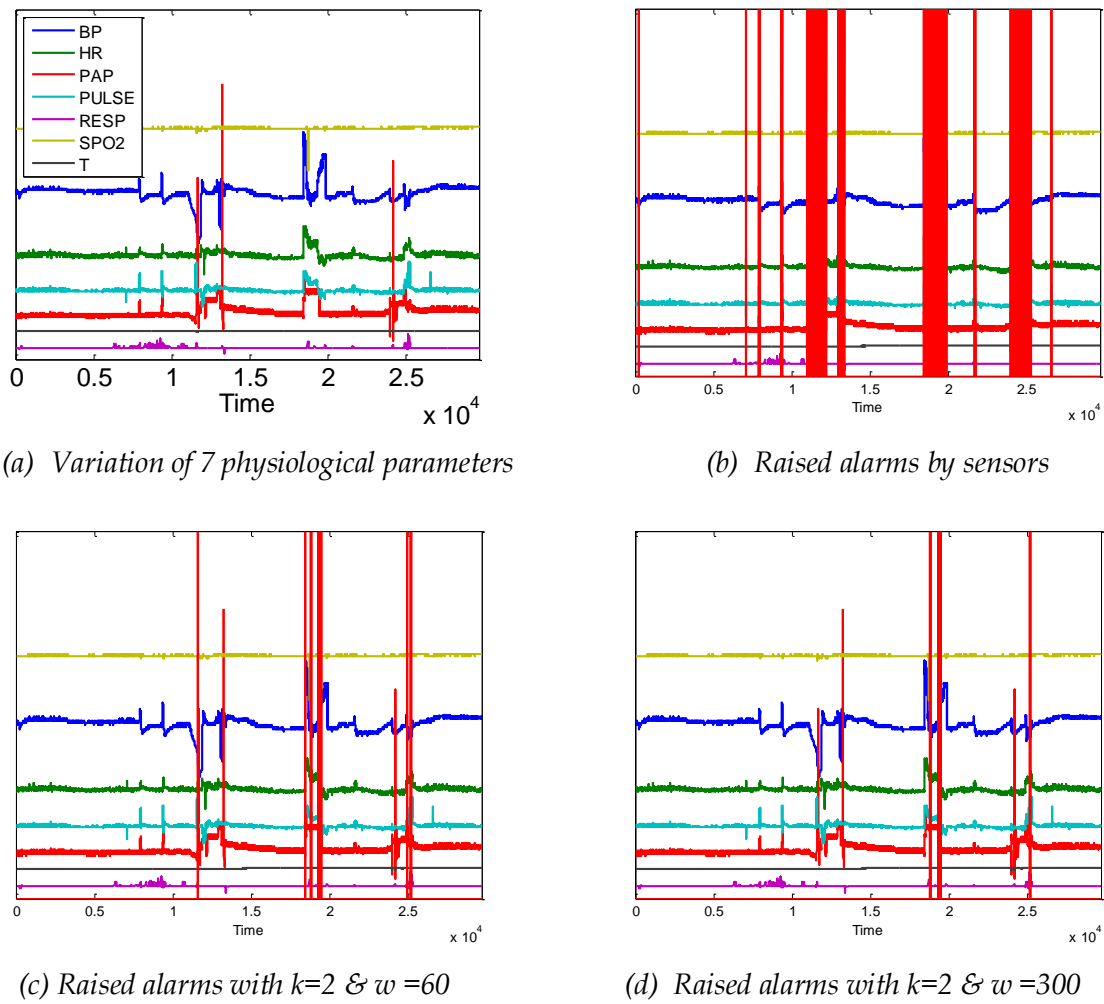


Figure 8. Physiological parameters and raised alarms

We compare our proposed scheme with the one proposed in (Liu, Cheng, & Chen, 2007), where Mahalanobis Distance (MD) is used to detect anomaly in gathered data by wireless sensors. The reason of using this approach in our comparison is that MD also calculates the distance between measurements by taking into account the correlation between monitored attributes:

$$MD_t = \sqrt{(X_t - \mu)^T \Sigma^{-1} (X_t - \mu)} \quad (3)$$

Where μ is the mean vector ($1 \times n$) and Σ is the covariance matrix ($n \times n$) of monitored n attributes. Σ is calculated by a robust estimation method (Orthogonalized Gnanadesikan-Kettenring -- OGK) which removes outliers during the estimation of covariance matrix by looking for a subset of training data without anomalies ($\hat{\mu}, \hat{\Sigma}$). Many robust estimation methods for covariance matrix of multivariate data have been proposed and used to remove outliers, e.g., Minimum Volume Ellipsoid (MVE), Minimum Covariance Matrix (MCD), Fast-MCD and deterministic MCD.

However, these robust estimation methods and the MD require additional memory and computation complexity (the inversion of covariance matrix Σ) when comparing to ACO rules. Furthermore, the robust estimations for $\hat{\mu}$ and $\hat{\Sigma}$ require resources not available on the LPU, nor in the sensor.

MD_t^2 follows chi-square distribution $\chi_{n,0.975}^2$ with n degrees of freedom and 97.5% quantile is used as the static threshold for anomaly detection by MD_t^2 (0.025 significance level for cut-off value). An alarm is triggered when the value of MD_t^2 is greater than the threshold ($\chi_{n,0.975}^2$). The results of applying robust MD over the used physiological dataset are shown in Figure 9(a) with the threshold $\sqrt{\chi_{7,0.975}^2} = 4.0016$ (horizontal red line). When comparing figures 8(c) and 9(a), we notice that both methods have good detection accuracy. However, robust MD triggers 4 additional false alarms when compared to our results in figure 8(c).

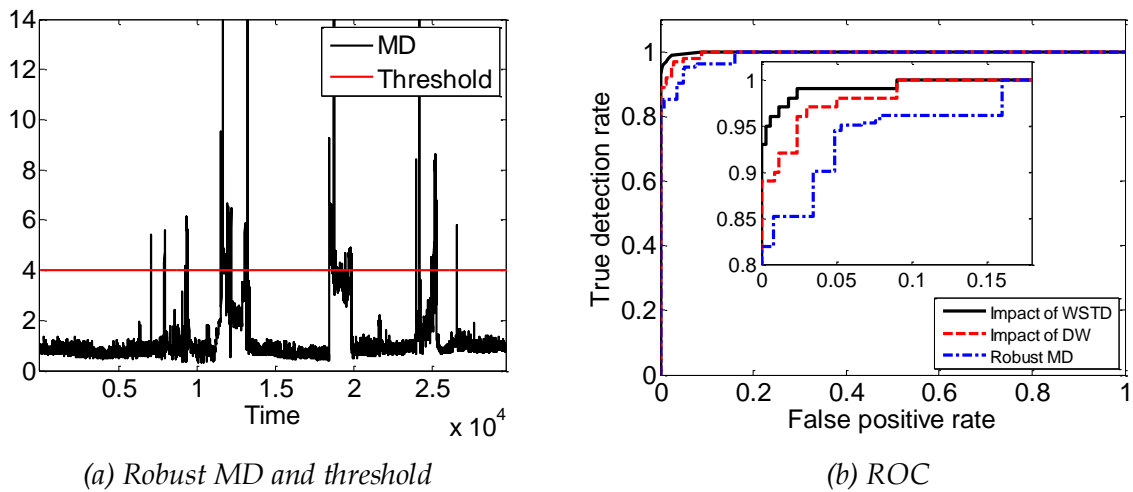


Figure 9. Performance analysis

To evaluate the performance of our proposed approach, we inject abnormal values at different time instants on different number of attributes, and we use the Receiver Operating Characteristic (ROC) curve to analyze the impact of the Window Size for Training Data (WSTD), as well as the impact of Decision Window (DW) size on the true detection and false alarm ratio. The ROC curve presented in Figure 9(b) shows the relationship between the detection rate (equation 4) and the false positive rate (equation 5) for both cases. The Detection Ratio (DR) is computed as the percentage ratio between the true positives and anomalous measurements.

$$DR = \frac{TP}{TP + FN} \quad (4)$$

Where TP is the number of True Positives, FN is the number of False Negatives, FP is the number of False Positives and TN is the number of true Negatives. The False Alarm Rate (FAR) is defined as the percentage ratio between the false positives and the actual normal measurements:

$$FAR = \frac{FP}{FP + TN} \quad (5)$$

A good detection mechanism must achieve a high detection ratio with the lowest false alarm rate. Figure 9(b) shows that our proposed approach can achieve a DR=100% with a FAR=9%. The performance of robust MD (Liu, Cheng, & Chen, 2007) was analysed over the same medical dataset and the result is presented in figure 9(b), where MD achieves a DR = 100% with a FAR = 16%. The performance of our proposed approach outperforms the robust MD and provides better result. Hence, our proposed approach is efficient in achieving low false alarm rate and high detection accuracy.

6. Conclusion and Perspectives

In this paper, we proposed a new distributed approach for reliable vital sign collection in medical WSNs with low communication overhead and energy consumption cost. The proposed approach aims to detect abnormal changes in monitored physiological parameters and to reduce false alarms triggered by faulty measurements. It is based on Gaussian Mixture decomposition and Ant Colony Classifier. The Gaussian decomposition is used to cluster the data. Based on the labeled data, the Ant Colony Classifier derives the classification rules for normal data in the LPU, and deduces the rules for abnormal values.

Derived rules are transmitted to sensors, which install the associated rule and transmit only alarms associated with abnormal measurements to reduce communication cost on the sensor and computational complexity on the LPU.

As abnormal records may result from clinical emergency or faulty measurements, we exploit the temporal and spatial correlation between the monitored physiological attributes to distinguish between faulty measurements and clinical emergency, in order to reduce the underlying false alarms. We applied our proposed approach and we evaluate the performance on real medical dataset with annotations. Our experimental results proved the effectiveness of our approach which can achieve a detection ratio of 100% with 9% of false alarms.

In the future work we intend to periodically adjust the parameters of the proposed model (k and w) based on knowledge from previous time windows. Another direction is to enhance the model by focusing on the detection of specific diseases.

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