Reliable Vital Sign Collection in Medical Wireless Sensor Networks

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***Abstract*—The aim of this paper is to propose a new approach for the detection and isolation of faulty measurements in medical wireless sensors 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, which are used to detect abnormal values. Finally, we exploit the spatial correlation between monitored attributes to differentiate between faulty sensor readings and emergency situations. Our experimental results on real patient dataset show that our proposed approach achieves a high level of detection accuracy, which in turn proves the effectiveness of this approach in enhancing the reliability of medical wireless sensors networks.**

***Index Terms*—Anomaly Detection, Wireless Sensors Networks, Ant Colony (AC), Gaussian Mixture Model.**

I. Introduction

Medical Wireless Sensor Networks (WSNs) are composed of distributed autonomous sensors with wireless transmission capabilities, and used to collect various vital signs from the monitored patients. Each sensor is able to monitor one or more physiological parameters (heart rate, blood pressure, oxygen saturation, activities) or some environmental parameters (location, temperature, humidity, light, etc.). These sensors are attached to (or implemented in) the body of the patient for continuous health monitoring over an extended period of time [7], and their usage leads to the modernization of the way in which healthcare services are deployed and delivered.

As WSNs are used for remote and in-home monitoring (telemedicine), the physiological data collected by sensors are transmitted to Local Processing Unit (LPU), such as SmartPhone, Tablet, etc. The LPU has more processing power, battery and transmission capabilities than sensors. The LPU must process collected measurements in real time, and raise an alarm for the healthcare center when it detects any abnormal measurements or emergency situation, in order to take the necessary action [7].

While medical wireless sensor networks add more convenience by allowing monitored patients to move, its services are vulnerable to several problems which range from reliability to security attacks after deployment. Sensors are susceptible 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 transmission power, their transmitted data are subject to radio interference, environmental noise, badly attached sensor and malicious behavior. Consequently, faulty measurements received by the LPU might trigger a false alarm, threat the life of monitored patient, and reduce the accuracy of diagnosis results. These measurements affect the credibility of such monitoring application, where reliability is extremely important to ensure accuracy in the medical domain [9].

Several anomaly detection approaches have been proposed as solutions for these challenging problems which could severely affect the diagnosis results and pose a life-threating risk. In health monitoring, 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 at least two physiological measurements, and (ii) faulty measurements or injected values by malicious users. Abnormal data from these two types will deviate from the normal data profile and will lead to raised false alarms for healthcare professional. Therefore, in order 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 enhance the reliability of medical WSNs. 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) discovers the set of classification rules, which will be used to detect all abnormal measurements that deviate from the regular data. In such case, we 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 II reviews related work for fault detection and isolation in WSNs. Section III briefly reviews related techniques used in our proposed approach. Section IV presents our proposed approach. In section V, we present our results from experimental

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evaluation. Section VI concludes this paper.

II. Related work

The medical WSNs provide remote and continuous monitoring of patients in a modern and comfortable way. One of the proposed monitoring systems is CodeBlue [5], which is able to monitor the heart rate, Pulse, SpO2 and ECG. It transmits the collected data to the healthcare professionals for further analysis, through the use of base station (LPU).

However, the measured and collected data by sensors are often unreliable and inaccurate [11]–[13]. They are affected by interference, error, noise, missing values, inconsistent readings, etc. Several approaches for the detection of faulty measurements/sensors have been proposed in the literature.

Authors in [4] 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.

Authors in [3] 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 decision will be aggregated using a weighted majority algorithm to obtain the final decision.

Authors in [2] 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 subsequence and its nearest non-self match. They consider as anomalies the subsequence with the largest distance.

Authors in [1] 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.

The authors in [4] 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. However, hybrid approaches may threat the life of monitored patient when the faulty sensor is not able to raise an alarm for the central collection point. In this paper, we will use a centralized approach to enhance the detection accuracy of monitoring result.

In this paper, we provide an approach for reliable vital sign collection in medical WSNs. 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, which will be applied on each received record to classify measurements into 2 classes: normal or abnormal. Finally, we will exploit the correlation between monitored attributes to make a detection decision, and to reduce false alarms triggered by faulty measurements.

III. 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 [6], [10].

A. Gaussian Mixture Models (GMM)

GMM is used to model unknown probability density function by a weighted mixture of J Gaussians distribution in the form:

$$p(Y_{t_m}) = \sum_{i=1}^{J} P_i.N(m_i, \Sigma_i) \quad \text{where} \quad \sum_{i=1}^{J} P_i = 1 \qquad (1)$$

Where m_i and Σ_i represent the mean and the covariance matrix, and 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 [10] 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. To obtain a hard clustering, we use the maximum value of the cluster probability $Class = max(cp_k)$.

B. Ant Colony Classifier

Ant Colony (AC) classifier is a machine learning algorithm, inspired from the collective behavior of the real ants which communicate together in an indirect manner by depositing a substance called pheromone [6]. In fact, ants go out from their colony looking for food, with their colony as start point and their destination (the food) as their stop point. Initially, the ants start searching for the food in a random manner, and they might face some obstacles and barriers which obligate them to search for alternative paths. Furthermore there will be a disparity between the lengths of paths. The goal of ants is not limited to reach the destination (food), but to reach the destination using the shortest path. We denote by S the shortest path between the Nest and the Food, after some amount of time the amount of pheromone in path S will be reinforced. The pheromone in path S attracts other ants to pass through it, and all ants will go through the path S 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 & $\ldots$ & Y_n), where each term is a condition (Y_i, operator, value). For clarification, an example of a term when monitoring the Heart Rate (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* $(HR < 120))$ *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 1) 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 $(V_1, V_2, \ldots, V_n)$ represent n attributes (e.g., HR, Pulse & SpO2 used in our experiments), 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, SpO2) are duplicated in (HR', Pulse', 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.

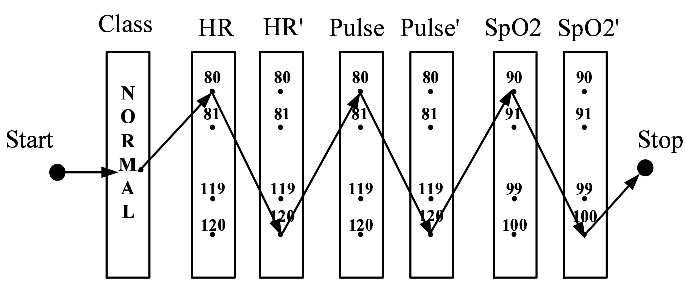

Fig. 1. WSN in medical scenario

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 [6].

Algorithm 1 Ant Colony algorithm

TrainingSet= {all training cases};
DiscoveredRulesList=[];
while (Not early Stopping) **do**
  Initialize all path to pheromone level τ_{MAX}
  while (Not converged) **do**
    Let ants run from start to end;
    Update the pheromone of all trails;
    An ant incrementally constructs a classification rule;
    Prune the just-constructed rule;
  end while
  Choose the best rule out of all constructed rules;
  Add the chosen rule to DiscoveredRuleList;
  TrainingSet = TrainingSet - {cases correctly covered by the chosen rule};
end while

IV. Proposed Approach

We consider a real deployment scenario where many sensors are attached to the body of the monitored patient as shown in figure 2. These sensors collect many physiological parameters (HR, Pulse and SpO2) and transmit the collected data to the LPU (smart phone) for real time processing. The LPU sends the collected data to the monitoring center for storage, and it processes data before their transmission, in order to detect heavy deviations in monitored parameters, and to raise an alarm for healthcare professionals upon detecting an emergency situation.

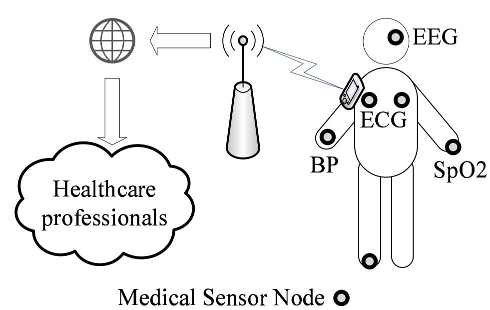

Fig. 2. WSN in medical deployment scenario

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 id. We denote by $Y_k = \{y_{1,k}, y_{2,k}, \ldots, y_{m,k}\}$ 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 :

$$Y = \begin{array}{c c} & \begin{array}{cccc} Y_1 & Y_2 & \cdots & Y_n \end{array} \\ \begin{array}{c} Y_{t_1} \\ Y_{t_2} \\ \vdots \\ Y_{t_n} \end{array} & \begin{pmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,n} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m,1} & y_{m,2} & \cdots & y_{m,n} \end{pmatrix} \end{array} \quad (2)$$

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 are used to collect physiological measurements and to cluster them into 2 categories (normal & abnormal) using generalized mixture decomposition algorithm [10]. 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

```
i = 0
for i ≤ n do
    Calculate the Lower Bound (LB_i)
    Calculate the Upper bound (UB_i)
end for
if (((LB_1 ≤ y_{i,1} ≤ UB_1) & ... &(LB_n ≤ y_{i,n} ≤ UB_n))
then
    Class = normal
else
    Class = abnormal
end if
```

Generated rules by AC are applied on each received record to detect abnormal measurements. As physiological parameters are heavily correlated, the change is usually reflected in many measurements. Therefore, to discriminate patient health degradation from faulty measurements, we raise an alarm for healthcare professionals only when at least k measured values are outside the dynamically established interval (LB_i, UB_i) by AC.

V. 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 the Physionet [8], which has 31364 records, and each record contains 3 attributes: HR, Pulse & SpO2.

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 decomposition, in order to derive dynamic interval for normal values of the monitored attributes. To enhance the accuracy of the clustering algorithm, 10 predefined abnormal records are added to the data to ensure the presence of two classes, and the clustering procedure is applied every 15 minutes to update the normal interval values.

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. The dynamically established intervals by the training phase of AC for each monitored attribute are: HR & pulse are inside the interval $[60, 120]$, and the SpO2 $\in [92, 100]$.

These rules will be applied in real time on each received record for binary classification (normal & abnormal). The measurements that fall outside the established interval raise an alarm. However, figures 3, 4 and 5 show the raised alarms for abnormal values in each attribute. Most of raised alarms in previous figures 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 we consider clinical deterioration only if the changes occur in at least k attributes, where $k = 2$ in our experiments.

Figure 6 shows the variation of the three attributes together, and figure 7 shows the 2 raised alarms by our proposed approach. We obtained two alarms resulted from the deviations in both HR & SpO2, instead of the 10 alarms when considering each attribute separately (e.g. deviations in HR, or in Pulse, or in SpO2). The first alarm is triggered when $HR = 35$ & $SpO2 = 80$ at the time instant 2443, and the second one is caused by abnormal values for $HR = 140$ & $SpO2 = 75$ around the time instant 15200. In fact, a visual inspection in the variation of HR & SpO2 in figures 6 confirms the utility of these alarms.

The number of correlated attributes for triggering an alarm is 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 threat the life of monitored patient.

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 on the true detection and false alarm ratio. The ROC curve presented in figure 8 shows the relationship between the detection rate (equation 3) and the false alarm rate (equation 4).

$$\text{Detection Rate} = \frac{TP}{TP + FN} \quad (3)$$

Where TP is the number of True Positives, and FP is the number of False Positives. The False Positive Rate (FPR) is defined as:

$$\text{False alarm rate} = \frac{FP}{FP + TN} \quad (4)$$

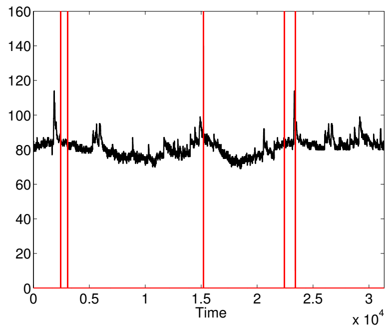

Fig. 3. Raised alarms for HR

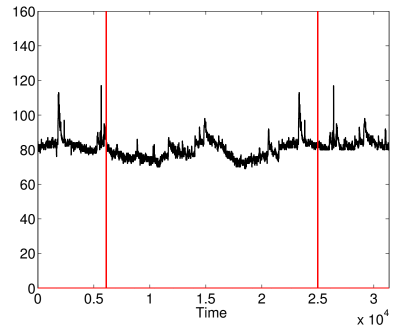

Fig. 4. Raised alarms for Pulse

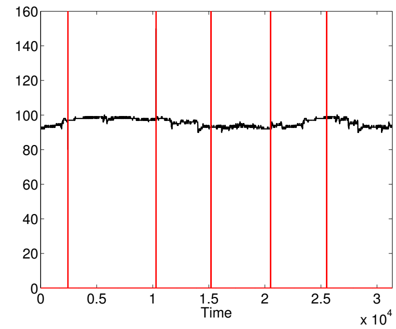

Fig. 5. Raised alarms for SpO2

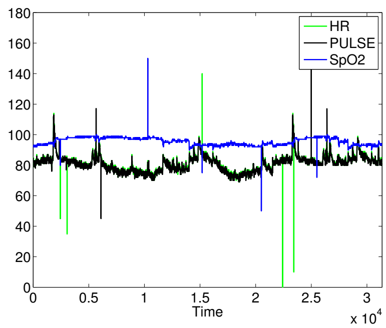

Fig. 6. HR & PULSE & SpO2

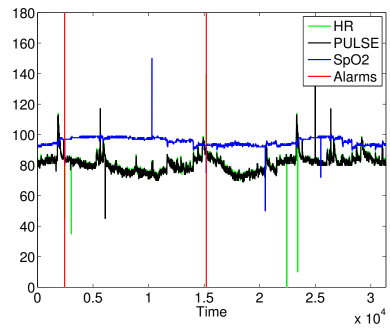

Fig. 7. Raised alarms

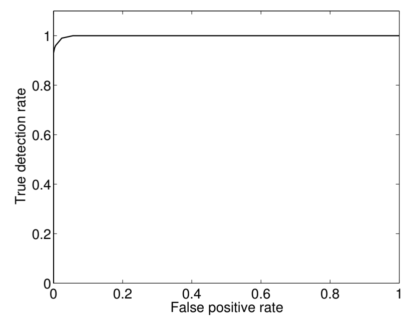

Fig. 8. ROC

A good detection mechanism must achieve a high detection ratio with the lowest false alarm rate. Figure 8 shows that our proposed approach can achieve a $DR = 100\%$ with a $FAR = 9\%$.

VI. Conclusion

In this paper, we proposed a new framework for the detection and isolation of faulty measurements in medical WSNs. The proposed approach 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, and deduces the rules for abnormal values. As abnormal records may result from clinical emergency or faulty measurements, we exploit the correlation between the monitored physiological attributes to pinpoint faulty measurements, and to reduce the underlying false alarms. We applied our proposed approach on real medical dataset, and we evaluate the performance using real data with synthetic anomalies. Our experimental results proved the effectiveness of our approach which can achieve a detection ratio of 100% with 9% of false alarms.

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