METHOD FOR ISOLATING THE PATIENT AND IoT ABNORMALITY USING A BAYESIAN NETWORK

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ABSTRACT

In recent years, Internet of Things (IoT) systems have become widespread. In the medical and health fields, the number of systems that use IoT to detect and diagnose patient abnormalities is increasing. Even if an abnormality in a patient is detected by such a system, it may actually be due to an abnormality in a component, such as the IoT. Therefore, when an abnormality in a patient is detected, we have developed a method to determine whether the abnormality is a patient abnormality or an abnormality in any part of the detection system using a Bayesian network. In addition, it was confirmed that by applying this method to a patient abnormality detection system using an under-sheet-type multi-vital IoT monitor in hospital, it is possible to isolate the cause of the abnormality appropriately and efficiently.

KEYWORDS

Bayesian Network, Medical IoT, Patient Abnormality, Cause Isolation

1. INTRODUCTION

In recent years, Internet of Things (IoT) systems have become increasingly widespread. In the medical and health fields as well, systems that use IoT to detect and diagnose patient abnormalities are increasing. Even if an abnormality in a patient is detected by such a system, the abnormality may actually be due to an abnormality in a component, such as the IoT. Therefore, when an abnormality in the patient is detected, it is necessary to have a method by which to determine whether the cause is an abnormality in the patient or any of the component abnormalities. The authors have developed a method for isolating the cause using a Bayesian network. At the same time, we have solidified the concept of a system referred to as the Integrated Abnormality Detection/Guide System, which is the target of the proposed method. This system consists of a patient abnormality diagnosis subsystem and an abnormality cause isolation subsystem. The patient abnormality diagnosis subsystem indicates to a nurse the patient to be treated first, and the abnormality cause isolation subsystem indicates to the remote maintenance (RM) personnel the component to be maintained next.

An experiment was conducted in which the proposed method was trial-applied to the abnormality cause isolation subsystem, targeting the under-sheet-type multi-vital IoT monitor as an IoT component for detecting patient abnormalities. As a result, it became clear that the proposed method can appropriately and efficiently isolate the cause of an abnormality.

Various methods have been proposed (for example, Lo, Flaus and Adrot (2019), Cai, Huang and Xie (2017), Chiremsel, Said and Chiremsel (2016), Tanwar (2020), Sasaki et al. (2018)) including methods using a Bayesian network, for isolating components that cause abnormalities when there is an abnormality in the system. However, there has been no proposal of a method for isolating the cause using a Bayesian network for medical IoT systems that monitor patient abnormalities.

In addition, in order to properly respond to the requirements of the system, the proposed method has the following characteristics.

(Characteristic 1) The proposed method has a mechanism that does not require an inappropriate flow of information, such as patient privacy information between the nurse, who is the manager of abnormal information, and RM personnel.
(Characteristic 2) If each patient or component is treated as one node of the Bayesian network, then the model becomes complicated, and the calculation takes time due to the large number of nodes. Therefore, the proposed Bayesian network treats them as one node or two nodes and identifies which patient or which component with which the node is associated before and after the calculation.

(Characteristic 3) In the proposed method, it is presumed that abnormal alerts may be issued for many patients at the same time due to component abnormalities. Therefore, we decided to treat the abnormal alarm of one patient and the simultaneous abnormal alarm of one or more other patients as separate nodes. By doing so, it can be expected that the cause of the failure can be appropriately and efficiently isolated.

The remainder of this paper is structured as follows. In Section 2, we introduce an overview of a Bayesian network and the Waikato Environment for Knowledge Analysis (Weka) program used for its modeling and simulation, whereas Section 3 outlines the under-the-sheet-type multi-vital IoT monitor used as an example medical IoT system in the present study. Section 4 describes the integrated monitoring/abnormality guide system concept, and Section 5 describes the Bayesian-based network abnormality cause isolation method and its trial application results. Finally, we conclude the present paper in Section 6.

2. OVERVIEW OF THE BAYESIAN NETWORK AND WEKA

A Bayesian network is defined in Nguyen and Do (2009) as “a probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph (DAG).”

The example of a sprinkler is often used to explain a Bayesian network, as shown in Figure 1. The Bayesian network in this figure is composed of nodes and edges that represent causal relationships, and a conditional probability table (CPT) is provided for each node. These CPTs describe the probability for each condition composed of the values taken by the parent (upstream) node.

In the figure example, T represents true, and F represents false. Moreover, there are three nodes: RAIN (whether it has rained), SPRINKLER (whether the sprinkler has operated), and GRASS WET (whether the lawn is wet). In addition, edges (arrows) are drawn for each of these nodes. The edge from RAIN to SPRINKLER represents the cause and effect that “raining or not raining affects the probability that the sprinkler will operate”. From the bottom line of the CPT in the upper-left corner of the figure, it can be seen that the “probability that the sprinkler will operate when it rains” is 0.01 (1%). Since it is useless to operate a sprinkler on a rainy day, the strongest assumption is that the sprinkler will not be operated under such conditions.
The structure modeling and probability of such a Bayesian network can be obtained by inputting data or can be determined by human subjective judgment. In the present study, the human subjective judgment method is adopted because this method targets a system that will be operated in the future.

If a Bayesian network can be modeled in this manner, then it is possible to obtain the probability value of the event “cause” when the “result” is known. For example, when the lawn is found to be wet, the probability of rain can be calculated. This probability value is sometimes called the posterior probability. In addition, when the result is known, both the knowledge and the event probability that causes the knowledge are obtained. This is sometimes called a simulation.

As defined in Holmes, Donkin and Witten (1994), Weka is machine learning software developed at the University of Waikato in New Zealand that is written in Java. Since one of the machine learning functions is a Bayesian network, Weka can be used to model and simulate a Bayesian network.

3. OVERVIEW OF THE UNDER-SHEET-TYPE MULTI-VITAL IOT MONITOR

The IoT component targeted here is an under-sheet-type multi-vital IoT monitor (See Figure 2) shown in Takano and Ueno (2019). Monitoring is performed by installing the sensor under the bed sheet of the patient and using the sensor to measure his or her electrocardiogram, whether he or she is in or out of bed, his or her breathing condition, blood pressure, etc. The sensor also alerts the nursing staff if the sensor detects any abnormalities. This monitor can be used in hospitals and long-term care facilities.

In typical systems of this type, even if a patient abnormality alert has been issued, the alert is often traced to a component abnormality, such as a hardware failure, a program bug, a program change caused by a virus, or something similar. Therefore, a mechanism that can distinguish between patient and component abnormalities is needed, and if the cause of an abnormality is found to be component-related, then the same mechanism should be capable of estimating the cause and identifying the components that are most likely to be responsible for the alert.

4. CONCEPT OF INTEGRATED MONITORING/ABNORMALITY GUIDE SYSTEM

The integrated monitoring/abnormality guide system based on the proposed method for the under-sheet-type multi-vital IoT monitor proposed herein is designed for in-facility and RM servers and will be configured as shown in Figure 3. This system will be operated as follows:
The patient monitoring function of each under-sheet-type multi-vital IoT monitor (hereinafter referred to as the IoT monitor) in the hospital is used to measure the electrocardiogram, blood pressure, respiratory status, bed leaving status, and so on, of the patient. The result is then sent to the in-facility server by LAN together with the component ID.

(2) The in-facility server uses the patient abnormality diagnosis function to determine whether a patient has an abnormality based on the measurement results of the vital data of the patient.

(3) If it is determined that there is an abnormality, then the component ID used by the patient with the abnormality is sent to the RM server.

(4) At the same time, an alert including the component ID, the corresponding room number, the patient ID, the type of abnormality, etc., is sent to the terminal of the corresponding nurse using wireless LAN.

(5) When a warning indicating the abnormality of the patient arrives, the nurse goes to the corresponding patient and checks whether there is any abnormality. If the patient is normal, then input the following information from the nurse terminal into the in-facility server:
   (a) There was a patient abnormality alert, but there was no patient abnormality.
   (b) The component ID corresponding to the target patient.

(6) The in-facility server sends the input result from the nurse to the RM server.

(7) The RM server has an abnormality cause isolation subsystem using Weka based on the Bayesian network. If a false alert about the abnormality of a patient is received, then the posterior probability of failure of each component in situations in which the results are known is calculated.

(8) The subsystem notifies the RM personnel of the component ID with a large posterior probability value that causes it as the component to be maintained next. The RM personnel checks whether the component is abnormal or normal and inputs the status to the system.

The methods described in (7) and (8) will be explained in more detail in the next section.

Here, the abnormality of the patient was not sent to the RM server, although (a) a patient abnormality alert was raised for the patient (despite the patient being normal), and (b) the component ID of the component used for the patient is input. This prevents patient privacy information that RM personnel should not know from being sent to the RM server. This corresponds to Characteristic 1 mentioned in Section 1.

Figure 3. Configuration of the integrated monitoring abnormality guide system
5. **BAYESIAN-NETWORK-BASED ABNORMALITY CAUSE ISOLATION METHOD AND ITS TRIAL APPLICATION RESULTS**

5.1 Proposed Method

In this section, we provide a more detailed explanation of the functions of the abnormality cause isolation subsystem implemented in the RM server of the proposed integrated monitoring/abnormality guide system (see Figure 3). This subsystem consists of (a) an input processing unit, (b) a Bayesian network processing program, and (c) a display unit. Here, Weka is used as the Bayesian network processing program.

As a result, we modeled the Bayesian network as shown in Figure 4. There are nine nodes in this model. The following five causes are the causes of abnormalities: ① Abnormality of the in-facility server, ② Patient abnormality using IoT monitor i, ③ Patient abnormality using IoT monitor j, ④ Output error of IoT monitor i, ⑤ Output error of IoT monitor j. The results are ⑥ Abnormal alert for a single patient and ⑦ Simultaneous abnormality alerts for multiple patients. The conditional probability tables of the nodes are described in Figures 5 and 6. These values are based on the following assumptions.

- Patient Abnormality Occurrence Probability > IoT Monitor Abnormality Occurrence Probability > Server Abnormality Occurrence Probability

![Figure 4. Abnormality cause isolation subsystem](image)

![Figure 5. Conditional probability table (1)](image)

![Figure 6. Conditional probability table (2)](image)
In Bayesian networks, the conditions for entering one child node from multiple parent nodes are represented by OR conditions. However, considering simultaneous failures, it is necessary to use AND conditions, as in \( \oplus \) and \( \oplus' \). Therefore, we decided to introduce the pseudo-conditional probabilities shown in the lower-right corner of Figure 5, referring to the method described in Reference [3]. This is to achieve Characteristic 3, as described in Section 1.

In addition, since one hospital has many patients and many monitors corresponding to each patient, treating them as a node complicates the model and takes time to calculate. Therefore, the Bayesian network model considered herein uses a method of treating them as one or two nodes and associating the node as an individual patient or component before and after calculation. This is to achieve Characteristic 2, as described in Section 1.

### 5.2 Application Results

The output results regarding the prior probabilities of each node are as shown in Figure 7 when the above Bayesian network structure and conditional probabilities are input to Weka. Here, \( T \) represents the probability of occurrence in the case of True, and \( F \) represents the probability of occurrence in the case of False. Node \( \oplus \) is described as T0200, which indicates that the probability of being True is 0.02, i.e., 2\%, and indicates that the probability of being False is 0.98, i.e., 98\%.

In addition, the posterior probabilities of each node calculated using Weka when there is an abnormality alert for a single patient, as shown in node \( \oplus \), are as shown in Fig 8. Here, among nodes \( \oplus, \oplus', \) and \( \oplus'' \), which are the inputs to node \( \oplus \), the posterior probability is the largest for \( \oplus' \) Patient abnormality using IoT monitor i, as shown in Figure 8, and the value of the probability is 61.85\%.
In this situation, if the nurse confirms that there is no abnormality in the patient corresponding to IoT monitor i, the state of node ② can be fixed as False. Therefore, the probability of occurrence of other nodes is as shown in Figure 9. From this, it can be seen that, among the nodes ① and ④, the node with the highest posterior probability is the output error of IoT monitor i in ④. Let the RM personnel know this result and perform maintenance of IoT monitor i.

Furthermore, if simultaneous abnormality alerts for multiple patients of node ② occur, then the post-occurrence probabilities of the other nodes are as shown in Figure 10. Among nodes ①, ⑥, and ⑦, which are directly connected to node ②, the largest abnormality is that of the in-facility server of node ④, and the value of the probability is 2%. Notify the RM personnel of the result in this case and have the personnel perform maintenance.

5.3 Considerations

(1) The order of these patients and components to check next is consistent with the engineer's intuition. Therefore, this method can be considered to be appropriate. We also found that the calculations were completed instantly and were efficient.

(2) We attempted to determine what kind of components and patients should be checked next by changing the probability of patient abnormality and the probability of component abnormality in various ways. When multiple patient abnormality alerts are issued, the component to be checked next changes from the in-facility server to multiple corresponding patients when the in-facility server abnormality probability is less than half of the current estimated value. Similarly, the same result is obtained when the probability of abnormality of the patient is equal to or greater than 1.5 times the current estimated value. By carrying out such sensitivity analysis, the measures to be taken under various preconditions can be seen.

(3) The current method is to check the patient for abnormalities first, based on the concept of patient safety first. However, if reducing the burden on the nurse is desired in order to balance safety and efficiency, it is possible to make a decision in the abnormality cause isolation subsystem first and to determine whether the patient is likely to have an abnormality. Therefore, as shown in Figure 10, if an abnormality occurs in multiple patients at the same time, then there may be a method of first checking the in-facility server that is likely to be the cause.

6. CONCLUSIONS AND FUTURE RESEARCH

(1) For an IoT system that detects patient abnormalities, we developed a method that uses a Bayesian network to isolate whether patient abnormality alerts are really due to patient abnormalities or component abnormalities.

(2) The proposed method also realizes the three characteristics described in Section 1 and is consistent with practical requirements.

(3) By applying the proposed method to a patient abnormality detection/guide system for under-sheet-type multi-vital IoT monitors, it was confirmed that the cause of the abnormality can be appropriately and efficiently isolated.

In the future, we would like to apply the proposed method to the actual field on a trial basis in order to make the probability of occurrence on the causal side more realistic. In addition, we would like to perform more precise modeling by classifying patient abnormalities as (a) electrocardiogram abnormalities, (b) blood pressure abnormalities, (c) respiratory abnormalities, or (d) bed-leaving abnormalities.

REFERENCES


