손실 값을 갖는 유비쿼터스 헬스케어 환경에서 신경망을 이용한 에이전트 기반 증상 패턴 분류☆

Symptom Pattern Classification using Neural Networks in the Ubiquitous Healthcare Environment with Missing Values

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요 약

무선선서네트워크의 주요 응용분야 중 하나가 유비쿼터스 헬스케어 시스템이다. 하지만 무선센서네트워크가 가지고 있는 과제중의 하나는 데이터 중에 나타나는 높은 손실 율이다. 바이오 센서로부터 들어오는 데이터는 기지국에 도착되지 않을 수 있으며, 이 값은 손실 값(missing value)이 된다. 본 논문은 기지국에서 데이터를 수집하고, 손실 값을 처리한 후, 증상 패턴에 따라 건강상태를 분류하여, 비상시에 적절한 행동을 취할 수 있도록 하는 헬스케어 모니터 에이전트(HMA)를 제안한다. 이 에이전트는 유비쿼터스 헬스케어 환경에 적용되며, 건강상태를 인지하기 위한 증상패턴으로 바이오 센서 및 환자의 가족력으로부터 생성된 데이터를 사용한다. 손실 값이 나타나면 HMA는 분류하기 전에 증상패턴의 손실 값을 채우기 위한 예측 알고리즘을 수행한다. 시뮬레이션 결과 HMA를 사용한 예측알고리즘이 다른 방법들에 비해 더 정확하게 증상패턴을 분류함을 보여 주었다.

ABSTRACT

The ubiquitous healthcare environment is one of the systems that benefit from wireless sensor network. But one of the challenges with wireless sensor network is its high loss rates when transmitting data. Data from the biosensors may not reach the base stations which can result in missing values. This paper proposes the Health Monitor Agent (HMA) to gather data from the base stations, predict missing values, classify symptom patterns into medical conditions, and take appropriate action in case of emergency. This agent is applied in the Ubiquitous Healthcare Environment and uses data from the biosensors and from the patient's medical history as symptom patterns to recognize medical conditions. In the event of missing data, the HMA uses a predictive algorithm to fill missing values in the symptom patterns before classification. Simulation results show that the predictive algorithm using the HMA makes classification of the symptom patterns more accurate than other methods.

☞ KeyWords : pattern classification, neural network, ubiquitous healthcare, missing values, 패턴분류, 신경망, 유비쿼터스 헬스케어, 손실값

1. Introduction

People need efficient service in almost everything especially when it comes to a person's health. With the lack of hospital beds in a world being populated more and more each year, some people who have certain conditions opt to just stay home where they feel secured and relaxed. In some cases, it is advisable for some patients to do some activities to be able to relax and forget that they are sick. Others,

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although bothered with chronic disease, can still go on doing the things they love such as sports. But these patients have to be carefully and not pushing their bodies to the limit. This is where the bio-sensors come in. They range from sensors able to be worn easily, up to sensors embedded into household furniture as discussed in [1]. While other studies of ubiquitous healthcare are limited to home implementation [2], the need for mobility is quickly rising with the advancement of technology today. Most importantly, recent developments suggest that these sensors can be implemented in almost anything and anywhere.

Providing information wirelessly and automating services based on the context information from user profiles in the environment of the ubiquitous computing concept has emerged as of late. The use of software programs guided by rules on performing their tasks is just one of the many considerations in the environment being discussed. In [3], Agent technology is mostly used to automate the tasks in the ubiquitous environment. These researches bring up the convenience of living by making the possible interactions to objects in real environment. Though, there are some challenges that most researchers encounter in designing a transparent ubiquitous system such as limited resources that allow only a partial function of system, providing large amount of information, and adding additional features. One of these is the limitation of middleware for mobile and ubiquitous environment that purposely provides the transparency of services to mobile devices as proposed in [4, 5]. This technology provides an abstraction layer between applications and the underlying network infrastructure and it also keeps the balance between the application's QoS requirements and the network lifetime.

In order to achieve higher quality of service for the ubiquitous healthcare environment, we need early detection of illnesses and higher response time in case of emergencies. Some techniques and algorithms are integrated to the agent-based healthcare system for medical diagnosis. Neural network is a common technique for medical diagnosis [6, 7]. Successful application examples show that neural diagnostic systems are better than human diagnostic capabilities. Furthermore, neural network are used to analyze medical images [8, 9]. These research articles survey various approaches and techniques to improve diagnosis in medical images, including mammography, ultrasound and magnetic resonance imaging.

Many sensor network applications, such as environmental monitoring or location systems, do not require data delivery guarantees as they can tolerate occasional data loss. However, other sensor network application classes, such as industrial monitoring or medical motoring require delivery guarantees as they are more sensitive to packet loss. Due to the inherent instability and energy constraints of sensors, sensor nodes are prone to failures. It would thus be useful to determine which set of nodes or which areas within the network are experiencing high loss rates. Such information is potentially valuable to the design of fault tolerant protocols or monitoring mechanisms, so that the problem areas may be re-deployed, and critical data may be rerouted to avoid these areas (or nodes) suffering high loss rates. These are just a few of the many possible applications of per node loss rate information to streamline the data flow or enhance the reliability of large-scale sensor networks.

In this paper, we propose the Health Monitor Agent (HMA) to collect data from the biosensors, recognize medical conditions. The proposed agent is used for the ubiquitous healthcare system based on the previous framework [10]. The framework considers the distributed software and hardware which provides services and the limited resources to the services by means of mobility middleware. The proposed agent is implemented in the framework to monitor patients and provide necessary services in case of emergency. For the detection of abnormal health condition, we use the multilayer perceptron (MLP) architecture with two hidden layers. The symptom patterns (interchangeably used with input patterns in this study) are trained using the backpropagation neural network. The HMA gathers data from the biosensors and medical history of the patient. In the event of a missing data from the biosensor, the HMA performs a predictive algorithm to provide data based on other known values. Simulation results show that the accuracy of the backpropagation neural network is high and at the same time shortens delay time of classification without the need of querying the biosensor for a reading.

2. Related Works and Background

2.1 Agent-based Healthcare System

Healthcare automation using software agent plays a crucial role on disseminating correct information to healthcare proponents and providing immediate medical services. Home healthcare services are previously researched to provide information to physicians the necessary diagnosis to patients and continuous monitoring of patient to acquire immediate response and save lives in critical conditions. Agent-based intelligent decision support is proposed for the home healthcare environment [11] where the multi-agent platform is combined with artificial neural network for the intelligent decision support system in a group of medical specialists collaborating in the pervasive management of care for a patient. Mobile agents are used to serve the collaboration of services for mobile users [12]. An agent is an autonomous, social, reactive and proactive entity, sometimes also mobile. Since telemedicine is grounded on communication and sharing of resources, agents are suitable for its analysis and implementation, and these are adopted for developing a prototype telemedical agent. In [13], mobile agents were used in data mining for diagnosis support in ubiquitous healthcare.

2.2 Neural Networks in Healthcare

Artificial neural network (ANN) is a computational system consisting of a set of highly interconnected processing elements, called neurons that process information as a response to external stimuli. A neuron contains a threshold value that regulates its action potential. Neural networks have been applied in the medical domain for clinical diagnosis [6], image analysis and interpretation [14], and drug development [15].

In [16] neural networks were used for automatic detection of acoustic neuromas in MR images of the head. Neural networks were utilized and supported by more conventional image processing operations. The prototype system developed as a result of the study achieved 100% sensitivity and 99.0% selectivity on a dataset of 50 patient cases. In [17], neural networks were used for breast cancer detection. A comprehensive list and overview of various research works on the uses of neural networks in the medical domain is presented in [18].

2.3 Missing Data Handling Techniques

The quality of training data for knowledge discovery in databases (KDD) and data mining depends upon many factors, but handling missing values is considered to be a crucial factor in overall data quality. Today real world datasets contains missing values due to human, operational error, hardware malfunctioning and many other factors. The quality of knowledge extracted, learning and decision problems depend directly upon the quality of training data. There are varieties of approaches to deal with missing data. The most common method is to omit cases with missing values. Since deleting data may waste valuable data points, missing values are often filled. For this, association rules are widely used to predict missing values. A novel Hybrid Missing values Imputation Technique (HMiT) using association rules mining and hybrid combination of k-nearest neighbor approach was used in [19]. In [20], the possible value of a missing data is guessed according to related association rules. The use of an association rule algorithm in data mining and the processes of handling missing data in a distributed database environment is discussed in [21]. And in [22], a solution to improve the data cleansing ordinal association rules technique by approximation of the missing data.

3. Ubiquitous Healthcare Framework, Components, and Environment

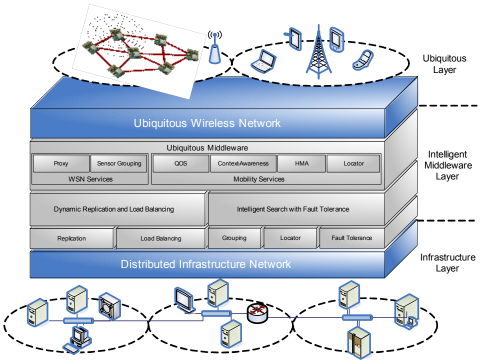
3.1 The Ubiquitous Healthcare Framework and its Components

This paper uses a ubiquitous and intelligent design, which is an upgrade of the one used in [10], to propose an agent for the early recognition of medical conditions. In Figure 1, the ubiquitous layer consists of software and hardware components utilizing the resources on the ubiquitous environment. In this layer, hardware components are mobile devices, wireless sensors and embedded devices while software components are agents and primitive commands to communicate with the services. The mobile and wireless devices are classified into two; 1) object-oriented and 2) proxy controlled devices. The object oriented devices have enough processing power to host objects in able to interact with the distributed object system seamlessly while the proxy controlled has no capability to host an object but only provide a proxy within the system to access its primitive controls.

The framework also consists of a middleware that supports mobility in which it focuses on the limited resources of the system like mobile devices. The adaptive ubiquitous middleware is presented which is another sub layer between the intelligent middleware layer and ubiquitous layer that provide services to support mobility. The intelligent middleware layer acts as the primary middleware where services are transparently operating on serving the clients. Interaction of clients from ubiquitous layer and services are handled by this layer. Users and administrators do not need to know the configuration on how to find, where to find, and how to manage the resources while transparently executes services. The service functions are influenced by the adaptive module in able to interact correctly with services in goal of optimizing the performance of tasks.

3.2 The Ubiquitous Healthcare Environment

This section describes the expected deployment of the Health Monitor Agent in the Ubiquitous Healthcare Environment. In Figure 2, the healthcare environment is shown where there are three locations interconnected by the overlapping of local wireless range. The ubiquitous healthcare center manages and updates a patient's location and stores health records from each hospital. The remote locations of the patients are updated every time they move to another location by the base station within range.



(Figure 1) Ubiquitous Healthcare Framework

Replication service. This performs the replication of an agent and deployment of the mobile agent through the base stations. The replication service communicates to locator for request of service.

Load Balancing service. The load balancing agent is responsible for load distribution. The load balancing service coordinates with the sub-components of the group which determines the object replicas in distributing the loads.

Grouping manager. This manages the grouping of agents in the base stations. The group manager decides the migration based on the balanced clustering proposed in [10].

Locator service. This locates the appropriate physician that monitors the patient using mobile devices. The classification of the appropriate patient to physician agents is the main purpose of the locator service.

Fault Tolerance. This service ensures that the application continues to run appropriately and efficiently in the likely event of errors.

The infrastructure layer is networks of different computers that are powerful for storing data and processing transactions within the system, like PCs and servers. These computers are communicating in wired network system to provide massive information exchange between the systems. The intelligent middleware layer presents an overlay communication of software components that are hosted by hardware devices in the ubiquitous and infrastructure layers. The new services for the adaptive ubiquitous middleware that are currently being designed are the following:

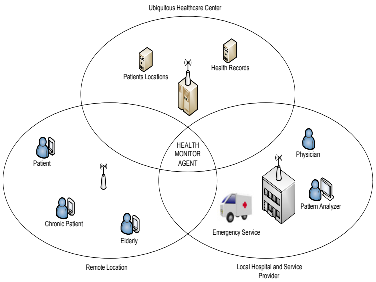
Proxy Service. Because ubiquitous devices like sensors and embedded system are limited in resources to integrate with ORB, this service provides a proxy for the devices in the system for efficient integration to the middleware system. This is also influenced by the adaptive system.

Sensor Grouping. This service is in-charge of the sensor groupings and selecting the sink node for data transmission in the ubiquitous healthcare environment.

QoS manager. This implements the efficient coordination of the services to ensure that the application meets the needs of clients in the ubiquitous healthcare environment.

Context-Aware Service. Application based on context-awareness are supported by this service. Unlike the classical distributed system, the physical location of the resources is necessary for the knowledge of users. This also supports the location transparency of services where it finds the needed service within the system. It includes the knowledge of each service functions to perform the search.

Health Monitor Agent. The proposed agent that is able to move from base station to base station, gather data from the biosensors, predict missing values, and use the nearest pattern analyzer to the classifications of symptom patterns.

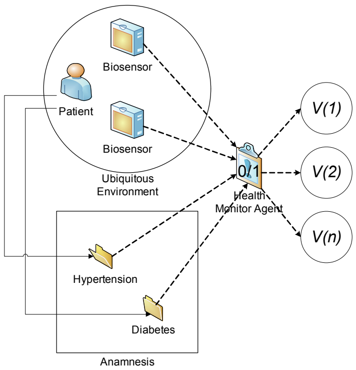


(Figure 2) Ubiquitous healthcare for mobile patients

If there are emergency cases detected, the nearest hospital is contacted to dispatch an ambulance to the location of the patient. That hospital may also gather previous health records of the patient from the healthcare center. The health monitor agent (HMA) collects biosensor readings and the patient's medical history then uses the nearest pattern analyzer for classification. The pattern analyzer holds information about all known and currently active diseases within its area.

4. Missing Data Handling and Symptom Pattern Classification

4.1 Data Collection and Prediction of Missing Values using the Health Monitor Agent



(Figure 3) The Health Monitor Agent gathers data from the biosensors and the patient's medical history

Figure 3 illustrates the values being acquired to be used collectively as input patterns to be classified. Each sensor attached to the patient monitors a different vital sign e.g. heart rate, blood pressure, ECG, glucose (blood sugar) level, etc. The Health Monitor Agent collects these data and compares each biosensor reading to a specific threshold range. Each biosensor reading has its own unique threshold range to determine if the reading is normal or not. For a reading that fails to reach or exceeds the threshold value, 1 is assigned as one of the values in the input pattern. For normal readings that are within range, 0 is assigned. Also, since some health conditions are hereditary, family background on these conditions are also considered. 1 is assigned if the patient has a history of that illness in the family, and 0 if none. Simply put, 1 denotes a presence of the symptom, and 0 if it is absent.

It is assumed that biosensor readings are sent to the HMA periodically. In the event that a biosensor fails to send data, the HMA fills the missing value in the input pattern with a prediction based on known values. Biosensor readings, along with the Anamnesis or more commonly known as the medical history of the patient, are related to each other in a way that some variables are affected by others. In simple terms, if a patient has a history of diabetes in the family, it is possible that he will also have a high glucose level. If he has hypertension in the past, then it is more likely that his blood pressure will be high. We analyze this relationship based on regression analysis to provide a realistic and more accurate input pattern using Equation 1 where y is the dependent variable, x is the independent variable, and β are unknown parameters.

$$y = f(x, \beta) \tag{1}$$

In statistics, regression analysis refers to techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables. More specifically, regression analysis helps us understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. Most commonly, regression analysis estimates the conditional expectation of the dependent variable given the independent variables — that is, the average value of the dependent variable when the independent variables are held fixed. Equation 2 represents the dependent variable y_i as a linear function of one independent variable x_i subject to a random disturbance or error u_i.

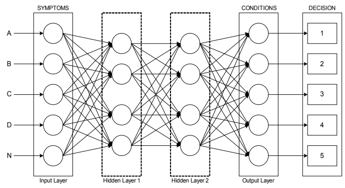
$$y_i = \beta_0 + \beta_1 x_i + u_i \tag{2}$$

In this paper, the independent variables refer to the medical history and the known biosensor readings. And $\hat{y}_i$ is the estimation of the missing value that will be used in the symptom pattern. The task of estimation is to determine regression coefficients $\hat{\beta}_0$ and $\hat{\beta}_1$, estimates of the unknown parameters β_0 and β_1 respectively. Equation 3 shows the form of the estimated equation.

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i \tag{3}$$

Many diseases are hereditary and can be passed down from parent to child. In some cases, disease may skip a generation and although one's children may not be afflicted, the grandchildren may suffer the effects of illness. Therefore, one of the factors that could greatly affect a patient's current medical condition is through his genetic heredity. We base the predictive algorithm on this fact.

This paper proposes the Health Monitor Agent which uses neural network to classify input patterns collected from the biosensors and the patient's medical history. The architecture of the proposed agent is shown in Figure 4. Biosensor readings and medical history which form the symptom patterns are used as input signals in the input layer. The internal layer consists of two hidden layers of the MLP structure while the output layer consists of the classes of conditions. Lastly, we include the decision layer that is connected to the class. This determines the necessary action that is needed to be done based on the current condition of the patient.



(Figure 4) Network structure of the Health Monitor Agent

4.2 Classification of Symptom Patterns using the Backpropagation Neural Network

Considering that the training of patterns take much time and require a device with stronger computing power than a mere sensor with lesser computational capability, the patterns are sent to a base station where the computations will be done. And to explain how the symptom patterns are used as input signals, we assume that each biosensor and medical attribute acts as a neuron. The action of a potential neuron is determined by the weight associated with the neuron's inputs in Equation 4. A threshold modulates the response of a single neuron to a particular stimulus confining such response to a predetermined range of values.

$$z = \sum_{i=1}^{n} x_i w_i \tag{4}$$

Equation 5 defines the output y of a neuron as an activation function f of the weighted sum of n+1 inputs. The output is configured by the medical expert and is not discussed in detail by this paper. This equation is done for both hidden layers in the architecture. The threshold is incorporated into the equation as the extra input in Equation 6.

$$y = f\left(\sum_{i=0}^{n} x_i w_i \right) \tag{5}$$

$$f(x) = \begin{cases} 1 if \sum_{i=0}^{n} x_i w_i > 0 \\ 0 if \sum_{i=0}^{n} x_i w_i \le 0 \end{cases} \tag{6}$$

The output produced by a neuron is determined by the activation function. This function should ideally be continuous, monotonic, and differentiable. With these features in mind, the most commonly chosen function is the sigmoid which is shown in Equation7. The accuracy of the response is measured in terms of an error E defined as the difference between the current and desired output in Equation 8.

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{7}$$

$$E = \tfrac{1}{2} \sum_j \left(t_{pj} - o_{pj} \right)^2 \tag{8}$$

The error E is propagated backwards from the output to the input layer. Appropriate adjustments are made by slightly changing the weights in the network by a proportion of the overall error E.

After weights are adjusted, the examples are presented again. The error is again calculated and weights are adjusted and the process is repeated until the current output is satisfactory or the network cannot improve further.

We present the input-output pair p and produce the current output o_p. We then calculate the output of the network and calculate the error for each output unit for a particular pair using Equation 9.

$$\delta_{pj} = \left(t_{pj} - o_{pj} \right) f'\left(net_{pj} \right) \tag{9}$$

In Equation 10, we calculate the error by the recursive computation of δ for each of the hidden units j in the current layer. Where w_{kj} are the weights in the k output connections of the hidden unit j, δ_{pk} are the error signals from the k units in the next layer and $f'(net_{pj})$ is the derivative of the activation function. Then we propagate backwards the error signal through all the hidden layers until the input layer is reached.

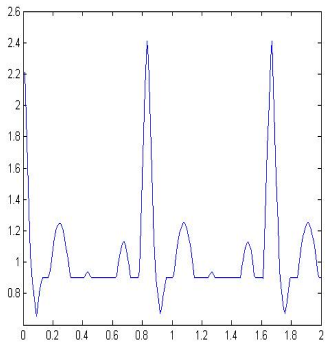
$$\delta_{pj} = \sum_k \delta_{pk} w_{kj} f'\left(net_{pj} \right) \tag{10}$$

Finally, we repeat the steps for Equations 9 and 10 until the error is acceptably low. After the structure of the neural network is trained, the base station sends this information back to the health monitor agent and then uses the structure for recognizing medical conditions. In detection of such conditions, actions are taken such as dispatching an ambulance or providing immediate precautions.

5. Implementation Results

5.1 Environment

The simulation environment of the proposed system consists of multi-agents created in the JADE agent platform. A single PC was used as environment for the agents because this approximates the expected actual deployment configuration of the ubiquitous healthcare system. We programmed the BPNN in Java and put the functionality in a JADE agent.

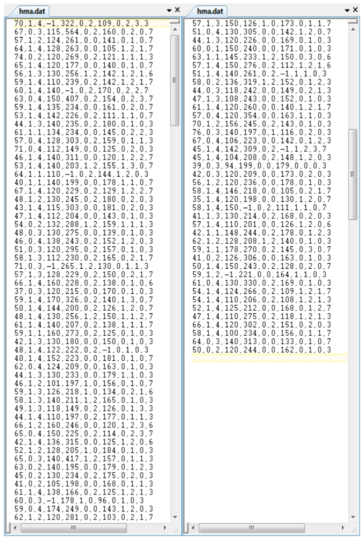


(Figure 5) A reading from an ECG simulator using MATLAB

As explained in the previous section, some values that will be used as input patterns in the backpropagation neural network are taken from biosensors. There are a lot of medical instruments that are already being used as biosensors like the sphygmomanometer, pulse meter, glucose meter, and ECG among others.

An ECG (electrocardiogram) biosensor measures the electrical activity of the heart. It shows a series of waves that relate to the electrical impulses that occur during each beat of the heart. Medical experts then look at the readings for some irregularities. If the ECG readings indicate a problem in the patient's heart, then 1 is given as an input value. Figure 5 shows an ECG reading of a heart with a beat rate of 75 per minute. This was done using an ECG simulator that was developed in MATLAB [23]. The x-axis is in seconds while the y-axis is in millivolts. The waves in the figure interpret to be a typical or normal reading.

Electrocardiography is a starting point for detecting many cardiac problems, including angina pectoris, stable angina, ischemic heart disease, arrhythmias (irregular heartbeat), tachycardia (fast heartbeat), bradycardia (slow heartbeat), myocardial infarction (heart attack), and certain congenital heart conditions. In our simulation, we only focused on testing the neural network's ability to classify the symptom patterns as to the presence or absence of coronary heart disease. ECG readings are assumed to be configured by the experts.

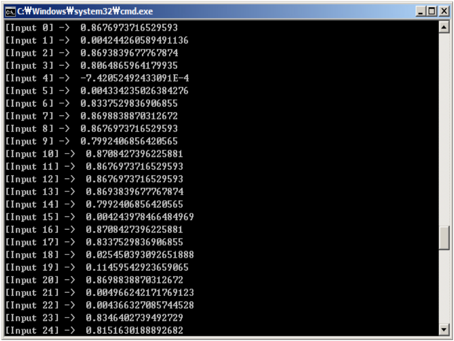


(Figure 6) Data with missing values collected by the health monitor agent

Figure 6 shows the data collected by the HMA from 100 patients. The values are of the patient's age, gender, chest pain type, blood pressure, cholesterol level, blood sugar, ECG result, heart rate, smoking habit, obesity (based on body mass index), genetics (degree of heredity), and physical activity. We chose these values because these are the most common high risks of having coronary heart disease. The patient's age, gender, chest pain type, smoking habit, obesity, genetics, and physical activity are data which can be collected from health records of the patient's most recent medical examination. While high blood pressure, cholesterol, blood sugar levels, and ECG reading irregularities are data which can be collected real-time through the biosensors. Patients over the age of 40 and patients with insufficient physical activity tend to have higher risk of coronary heart disease and thus assigned a value of 1. And data among the biosensors that exceeds the normal readings are also assigned 1. In Figure 6, -1 indicates a missing value and needs to be predicted by the HMA based on other known values. For example, a missing blood pressure reading can be predicted based on the patient's medical history of hypertension. Missing blood sugar readings may also be predicted depending on the patient's heredity of diabetes. And missing maximum heart rate values may be predicted based on the patient's lack of physical activity. We assume that among three examples, the presence of the latter will most likely lead to the presence of former. The HMA will then automatically assign 1 to the missing value and then proceed with the classification of the input pattern.

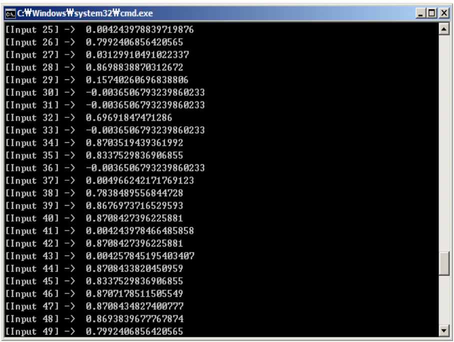
5.2 Results

To evaluate the efficiency of the algorithm, we randomly remove some missing values but only from data that were taken by the biosensors as we cannot predict the patient's age, gender, and other physical data based on any known values. Figure 7 shows the result of using the backpropagation neural network to train the input patterns and classifying them as whether the coronary heart disease is present or absent in the patient.

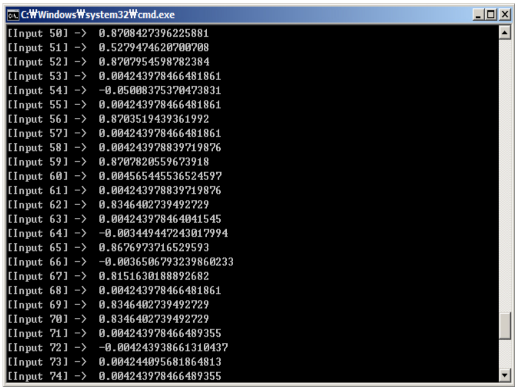


(a)

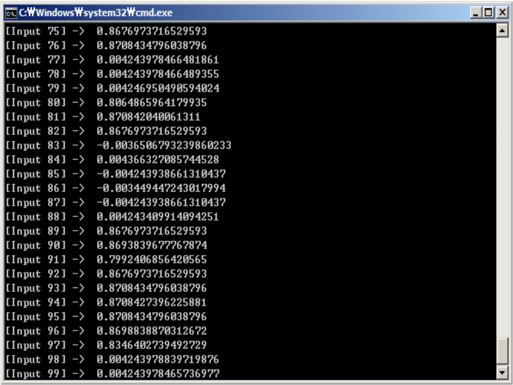
We configured our backpropagation neural network to run 10000 iterations, with 0.5 learning rate and 0.1 momentum. We then run our simulation 10 times to get the average accuracy of the bpnn in classifying the data with different number of missing values. First, we let the bpnn classify the data without predicting the missing values. Then we compared the performance of the bpnn when the HMA predicted the missing values. Table 1 shows the results.



(b)



(c)



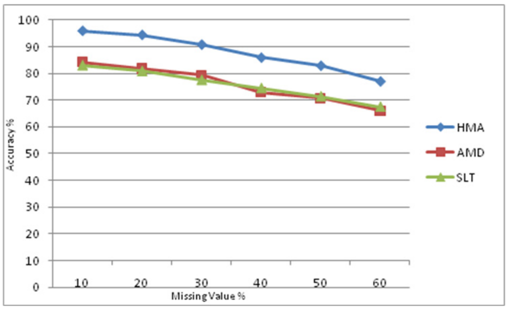
(d)

(Figure 7) Classification of input patterns using back propagation neural network (a,b,c,d)

Based on this table, the accuracy of the BPNN is high when missing values are predicted by the HMA. The algorithm for missing data (AMD) uses the mean of the variables, in this case the mean of all the present values for each category in the dataset with missing values, to fill the missing data of that category. While the standard learning technique (SLT) uses special symbols to ignore the missing value and classify the input patterns with only the known values. Figure 8 also shows these results.

(Table 1) Accuracy of the BPNN when missing values are supplied using different methods

Number of missing values	Using Standard Learning Technique (SLT) to ignore missing data	Using the Algorithm for Missing Data (AMD)	Using the predictive algorithm of the HMA
30	83.1%	84.3%	95.8%
60	80.9%	81.8%	94.3%
90	77.6%	79.3%	90.7%
120	74.5%	73.0%	85.9%
150	71.4%	70.7%	82.9%
180	67.5%	66.0%	77.1%



(Figure 8) Accuracy of classifying input patterns with different methods of supplying the missing values

6. Conclusion

This paper contributes improvements to the safety and efficiency of ubiquitous healthcare especially for patients that require continuous medical monitoring by a collaborating group of medical specialists. This is achieved by presenting the Health Monitor Agent (HMA) in the ubiquitous healthcare environment to provide early detection of illness and provide necessary services in case of emergency.

The HMA uses data collected from the biosensors and the patient's medical history as input patterns to determine the presence or absence of a medical condition. In the values that are collectively used as input patterns, 1 denotes the presence of the symptom, and 0 if it is absent. If a value is missing from a biosensor, that value is predicted by the HMA to have a complete symptom pattern to be classified. After interpreting the data, the HMA uses the nearest pattern analyzer to classify the symptom patterns into the correct medical condition. Once a medical condition is detected, the HMA suggests appropriate action ranging from providing ambulance to taking immediate precautions depending on the severity of the situation. Early detection of abnormal health conditions was aided by the backpropagation neural network. Simulation results show that even with missing data, the accuracy of the backpropagation neural network is higher when the missing value is predicted by the HMA using the proposed algorithm.

Future works in this paper will focus on how to improve the method of recognizing chronic conditions using other neural network algorithms and adaptive systems. There are other aspects in the ubiquitous healthcare environment that can be potentially enhanced by computation support using neural networks.

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