Agent-Based Intelligent Decision Support for the Home Healthcare Environment*

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Abstract. This paper brings together the multi-agent platform and artificial neural network to create an intelligent decision support system for a group of medical specialists collaborating in the pervasive management of healthcare for chronic patients. Artificial intelligence is employed to support the management of chronic illness through the early identification of adverse trends in the patient's physiological data. A framework based on software agents that proxy for participants in a home healthcare environment is presented. The proposed approach enables the agent-based home healthcare system to identify the emergent chronic conditions from the patterns of symptoms and allows the appropriate remediation to be initiated and managed transparently.

1 Introduction

Medical care problems are quite complex, and the solution of a problem involves the coordination of the efforts of different individuals with different skills and functions. This study focuses on the coordination of a group of specialists collaborating as a medical team for a patient with multiple chronic conditions. In critical situation such as healthcare management, the risk of making incorrect decision based on incomplete or outdated information is very high. Providing decision support to a medical group having potentially conflicting views in a time-critical situation represents a very important and innovative area for research. The use of artificial intelligence to support decision making have been demonstrated successfully in previous studies [1].

This paper brings together mobile software agents and artificial neural network into a real-time decision support system for pervasive healthcare management. Specifically, we propose the use of mobile agents that automate the process of obtaining data from physiological sensors and use the neural network in a decision support system to coordinate a group of medical specialists. We choose the multi-agent platform as the key enabling technology because it offer a

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general framework in which distributed, real-time decision support applications can be implemented more efficiently [2], [3].

The literature indicates that agent-based applications in the medical domain have recently become popular [3]. In other studies intelligent home healthcare systems showed promising results in improving the delivery of care to chronic patients particularly those receiving care in their homes. A recent medical study reported that the average age in most societies is growing higher with more people belonging to higher age groups nowadays [4]. These findings highlight the urgent need to develop better ways to deliver home health care particularly to the elderly [5].

Remediation is time-critical due to the fragile health of chronic patients. The emergent adverse condition needs to be identified as quickly and accurately as possible. In this paper we use the artificial neural network (ANN) to recognize classes of medical conditions from the symptom patterns. Our goal is to enable the system to notify the appropriate medical specialist and provide the relevant patient data when the adverse condition arise. Intelligent software agents are used in a decision support system to coordinate the group of medical specialists. By coordinating the emergency medical care, the proposed system can potentially improve the patient's safety and avoid additional costs that arise from unnecessary trips to the emergency room that result from false alarms. The use of a home healthcare system can increase the number of patients that can be safely assigned under the care of a specialist [6]. This approach could save medical funds as well as alleviate the shortage of medical personnel in some hospitals.

2 Related Works

2.1 Intelligent Decision Support System

Intelligent decision support system enables medical practitioners to obtain information more quickly and make more accurate diagnosis and treatment decisions. Foster [7] presented an overview into the current research on agent-based decision support system (DSS) in the medical domain. The advantage of intelligent DSS over plain DSS is the use of artificial intelligence that gives it a wider range of decisions including those that involve uncertainty. IDSS in medicine includes diagnosis assistants, treatment recommendation systems and patient history examination systems[7]. Frize [8] identified some important applications of ANN to various medical problems with a particular focus on the Intensive Care Unit (ICU). The study reported significant improvements in the management of resources and the quality of the medical services in a hospital. The current work extends the use of IDSS as diagnosis assistant into a coordination assistant for a group of medical specialists. The proposed healthcare system is intended for patients that require continuous monitoring - whose health conditions are too grave that rapid recognition of the medical condition from the symptom patterns obtained from medical sensors is vital to the survival of the patient.

2.2 Multi-agent Systems

Multi-agent system (MAS) is based on autonomous agents that interact with each other and their environments. A MAS is a loosely coupled network of problem solvers that interact to solve problems beyond the capabilities or knowledge of the individual problem solver. The software agents are autonomous and usually heterogeneous. In the multi-agent platform, the individual agent has a limited view point with incomplete information or capabilities for solving the problem, there is no global control, data are decentralized, and computation is asynchronous.

Moreno [6] listed the critical areas in the health care domain where the capabilities of multi-agent systems can be particularly useful: distribution of knowledge; coordination of medical personnel; and the immediate delivery of diagnosis and treatment.

2.3 FIPA and JADE

The Foundation for Intelligent Physical Agents (FIPA) promotes the establishment of standard specifications in agent technology [9]. The Agent Communication Language (ACL) is the main output of FIPA. Common patterns of agent conversations have been formalized into interaction protocols that provide agents with a library of patterns to achieve common tasks [10]. Java Agent Developer Framework (JADE) is a middleware for the development of distributed multi-agent applications based on the peer-to-peer communication architecture that complies with FIPA standards. The intelligence, initiative, information, resources and control of agents can be fully distributed on mobile terminals as well as on computers in the fixed network. We refer the reader to [10], [11] and [12] for the details of the platform services in JADE.

2.4 Homecare Monitoring Systems

There are many commercial solutions related to homecare monitoring systems mentioned in [13]. These solutions usually rely on medical call centers, transmit their data through telephones and are based on proprietary technology. Several examples of these systems are discussed in [7]. The physiological data that can be monitored include blood pressure, pulse, oxygen saturation, temperature, ECG, respiration among others.

In [14] a home health care system consists of several diagnostic peripherals such as a blood pressure monitor, glucose meter, spirometer and pulse oxymeter. Clinical data from the unit is streamed to a centralized workstation. The coordination is manually performed by a nurse who reviews the data, performs assessment of the patient's health and coordinates the necessary intervention including sending alerts and relevant medical data to the appropriate specialist involved in the collaborative care of the patient.

According to [4], the top five chronic conditions are diabetes, coronary heart disease, congestive heart failure and chronic obstructive pulmonary disease. Patients of various ages particularly the elderly tend to have multiple conditions cutting across many individual diagnostic categories. Up to 45% of the highest risk segments have five or more distinct diagnoses, each of which can be the focus of condition-specific disease management. For the current work, we limit our definition of medical sensors to include only those that can detect the abnormal medical condition or symptom from the physiological signals.

2.5 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 in 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 [15], image analysis and interpretation [16], and drug development [17]. In [18] 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. A comprehensive summary of various research works on the uses of neural networks in the medical domain is presented in [14].

3 Agent-Based Intelligent Home Health Care System

The current work focused on the coordination and decision support features of the healthcare system. We use a software agent as proxy for each participant in the system: medical sensors, the patient and the medical specialists. The proxy agents are of three types: sensor agent, patient agent and doctor agent respectively. The sensor agents handle retrieval of information from health sensing devices. These agents perform the required analysis on the sequential data from the sensors. The framework supports the dynamic configuration of sensor agents according to the symptoms that need to be monitored. The doctor agent is a mobile agent that migrates from the native environment in the doctor's clinic computer to the local environment of the multi-agent healthcare system. The patient agent coordinates the interaction of the other agents. It invokes the sensor agent to check the physiological data for the presence of abnormal condition or the symptom that the sensor agent reports back as a binary value. The patient agent contains the neural network code that enables it to recognize the medical condition and send notifications and relevant medical information to the appropriate medical specialist.

3.1 Software Agent as Proxy

Figure 1 presents the framework of the proposed multi-agent home healthcare system. The patient and sensor agents are local agents in the home health care system while the doctor agents are mobile that migrate from the clinic computer of the respective specialists. Our goal is to make the network more efficient by enabling the software agents to process the data locally and send only the results to their host systems thus avoiding unnecessary transmission of raw sensor data. Our proposed healthcare system aims to support a collaborating medical team that consists of individual specialists assigned to one or more medical conditions that requires continuous monitoring.

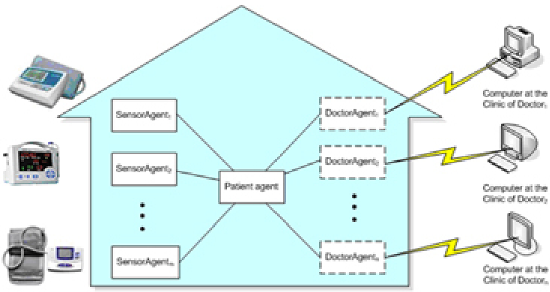

Fig. 1. Framework of the Multi-Agent Home Health Care System

We used the JADE platform for the implementation of the agent-based home healthcare system. The sensor agent registers a *medical-sensing* service that enables the patient agent to locate and subscribe to the service. Figure 2 shows the architecture of the proposed healthcare system based on the JADE platform. Each agent has a communication module which handles the exchange of data with other agents. The sensor agent uses the symptom detection module to determine the state of physiological data. The patient agent uses the neural network to classify the symptoms into the specific medical condition. The doctor agent uses the remediation management module to perform tasks such as sending the medical data to the approriate specialist.

Figure 3 shows the details of the data flow and individual functions of the component agents. Each sensor agent sends the medical data in the form of an ACL message to the patient agent. The sensor agent performs the analysis to detect the symptom based on the data from the medical sensor. *Symptom* refers to the state of the physiological data, such as heart rate which is not within the threshold considered to be normal. Each sensor agent need to be initialized with the threshold value for the particular physiological data to be able to detect the symptom. Various approaches to process the sensor data to detect the symptom are proposed in other studies [19], [20], [21]. To implement the proposed healthcare system, this study assumes that a suitable method for detecting the symptom is selected from among those presented in other studies. The patient agent provides the intelligent decision support for the medical specialists by performing the following tasks:

1. Trigger sensor agents to test for the presence of symptoms;
2. Process the inputs from sensor agents using the neural networks to recognize the medical condition from the symptom patterns; and
3. Send alerts and relevant data to the appropriate medical specialist when a medical condition is found.

The doctor agent is a mobile agent that transports the medical data from the local node of home health care environment to its host computer in the doctor's clinic. It performs other tasks such as handle the communication between the doctor and the patient and manages other remediation tasks such as the adjustments in the dosage of medication.

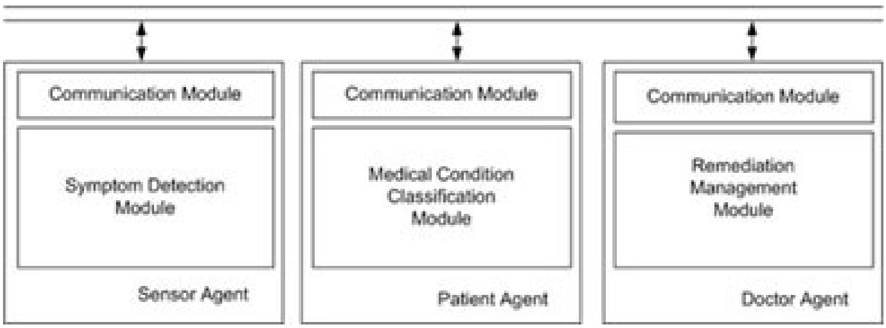

Fig. 2. Architecture of the Home Healthcare System

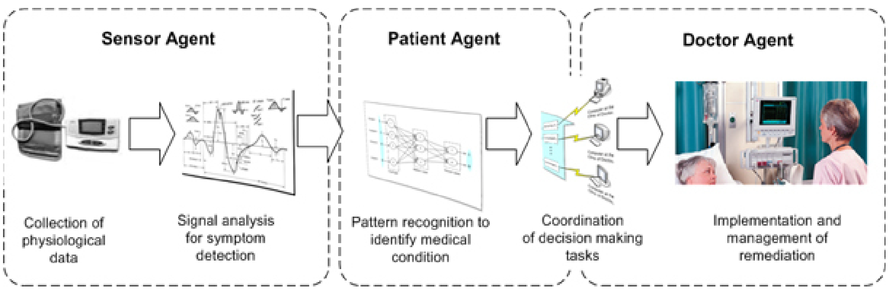

Fig. 3. Data Flow and Functions of the Component Software Agents

4 Recognizing Chronic Conditions from Symptom Patterns

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 to approximate the expected actual deployment configuration of the health care system. We programmed the ANN in Java and put the code in a JADE agent. Fig. 4 is a simplified model of the multi-layer neural network showing the neurons in the input, hidden and output layers. The input signal from the individual sensor agent is a binary value where the value 1 indicates that the symptom is detected by the sensor.

Synthetic classes of medical conditions were created and paired with symptom patterns to form the input-output sets. We labeled conditions and symptoms

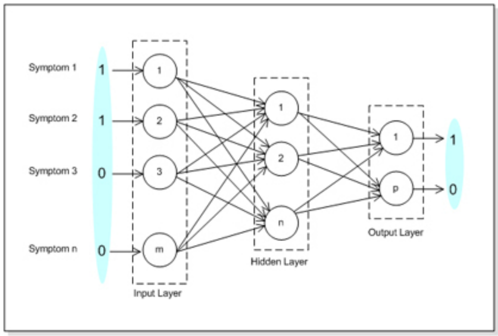

Fig. 4. The ANN is trained to recognize the medical condition from symptom patterns

and matched them together. For example we can state that condition1 exists if symptom1, symptom2 and symptom3 all exist. The existence of a symptom is represented by the binary value 1 in the sensor while 0 represents otherwise. The goal is to demonstrate that ANN can correctly recognize the chronic condition from the symptom patterns. To keep the models as close to the real medical conditions as possible, we observed the following rules:

1. When none of the symptoms exists, the patient's state of health is normal.
2. When all the symptoms exist, the patient is in critical state of health.
3. A medical condition has between 2 to 4 symptoms.
4. Two medical conditions may have overlapping symptoms but they differ in at least one.

Figure 5 shows an extracted portion of the training data used in our simulation. We choose the MLP with backpropagation training as the architecture of our ANN because the literature indicates that it is generally superior to other algorithms when used for classification tasks similar to this work [22].

	Input Signals											Target				
	V(1)	V(2)	V(3)	V(4)	V(5)	V(6)	V(7)	V(8)	V(9)	V(10)		T(1)	T(2)	T(3)	T(4)	T(5)
S(1)	1	1	1	0	0	0	0	0	0	0	C(1)	1	0	0	0	0
s(2)	1	1	1	1	0	0	0	0	0	0	C(1)	1	0	0	0	0
s(3)	1	1	1	0	1	0	0	0	0	0	C(1)	1	0	0	0	0
s(4)	0	0	1	1	1	0	0	0	0	0	C(2)	0	1	0	0	0
s(5)	0	1	1	1	1	0	0	0	0	0	C(2)	0	1	0	0	0
s(6)	0	1	0	1	1	0	0	0	0	0	C(2)	0	1	0	0	0
⋮											⋮					
s(16)	0	0	0	0	0	0	0	0	0	0	C(6)	0	0	0	0	0
s(17)	1	1	1	1	1	1	1	1	1	1	C(7)	1	1	1	1	1

Fig. 5. Extracted portion of the training data

The action potential of a neuron is determined by the weight associated with the neuron's inputs (Equation 1), a threshold modulates the response of s neuron to a particular stimulus confining such response to a pre-determined range of values. Equation 2 defines the output y of a neuron as an activation function f of the weighted sum of *n+1* inputs. The threshold is incorporated into the equation as the extra input. The output produced by a neuron is determined by the activation function. This function should ideally be continuous, monotonic and differentiable. The input data consists of the presence (or absence) of a symptom in a physiological data encoded as a binary value thus the applicable function is the step (Equation 3) or the binary sigmoid (Equation 4). If the desired output is different from the input, it is said that the network is hetero-associative, because it establishes a link or mapping between different signals; in autoassociative network the desired output is equal to the input.

In supervised learning, a feedforward ANN is trained with pairs of input-output examples. The accuracy of the response is measured in terms of an error E defined as the difference between the current and desired output (Equation 5) Weights are adjusted to minimize the overall output error.

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

$$y = f\left(\sum_{i=1}^{n} x_i w_i\right) \tag{2}$$

$$f(x) = \begin{cases} 1 \text{ if } \sum_{i=1}^{n} x_i w_i > 0 \\ 0 \text{ if } \displaystyle\sum_{i=1}^{n} x_i w_i \leq 0 \end{cases} \tag{3}$$

$$f(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

$$f(x) = \frac{1}{2} \sum_{j} (t_{pj} - o_{pj})^2 \tag{5}$$

The error E is propagated backwards from the output to the input layer. The appropriate adjustments are made by slightly changing the weights in the network by a proportion d of the overall error E. After weights are adjusted, the inputs are presented again and the error is calculated, weights are adjusted and this procedure is repeated until the current output is satisfactory or the network performance cannot improve further. We used the backpropagation learning algorithm using the procedure in [14]:

1. Present the input-output pair p and produce the current output O_p.
2. Calculate the output of the network.
3. Calculate the error for each output unit for a particular pair using Equation 6.

$$\delta_{pj} = (t_{pj} - o_{pj}) f'(net_{pj}) \tag{6}$$

4. Calculate the error by the recursive computation of δ for each of the hidden units j in the current layer (Equation 7). 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 $f'j(net_{pj})$ is the derivative of the activation function. Propagate backwards the error signal through all the hidden layers until the input layer is reached.

$$\delta_{pj} = \sum_k \delta_{pk} w_{kj} f'\left(net_{pj}\right) \tag{7}$$

5. Repeat step 1 through 4 until error is acceptably low.

5 Experimental Evaluation

We trained the ANN using empirical models of chronic conditions and the matching sets of symptom patterns. We created 5 chronic conditions and each one is paired with a set of target outputs. We defined 2 additional conditions: the first, a normal healthy status when the outputs were all zero and the other, when all the outputs were 1, indicates the patient is in a critical state because all the symptoms were triggered. The training data consisted of 17 pairs of input and desired output patterns. Each chronic condition is matched with a set of 3 symptom patterns which were similar because they have similar symptoms but unique because they differ by at least one. This matching approximates real medical conditions that share some common symptoms. We created the test data consisting of 25 pairs of patterns that included the original 17 patterns used during training and new patterns that are different from the patterns already presented to the network.

We performed three runs of the simulation using higher epochs in successive runs to determine the performance of our ANN. An epoch is a single pass of the network through the full set of training data. Table 1 shows the performance of the network.

The ANN recognized all 17 patterns presented during training with 100% accuracy. At 5000 epochs, 22 patterns out of 25 were correctly identified. When we used higher epochs, the ANN recognized more test patterns correctly. The peak performance of the network was found at 96% generalization accuracy.

Table 1. Performance of the ANN across training epochs

Training Epochs	Training Accuracy	Generalization Accuracy
5000	100%	88%
25000	100%	92%
50000	100%	96%

6 Conclusions

This work contributes improvements to home healthcare systems particularly for critical-care patients that require continuous medical monitoring by a collaborating group of medical specialists. A framework based on software agents that proxy for participants in a healthcare environment was proposed. Neural networks were used to make the patient agent capable of intelligent decision support by being able to recognize symptom patterns that characterize certain chronic conditions. In this manner, we made the healthcare system capable of sending alerts and providing relevant medical data to the appropriate specialist responsible for the medical care of a specific chronic condition. Our simulation result indicates that ANN can recognize chronic conditions with very high accuracy. The implication is that future home healthcare systems can be enhanced with intelligent decision support in situations that require constant evaluation of the health status of a patient in critical care and the task of identifying the chronic condition from the symptoms of pattern can be safely delegated to a software agent. Using such systems, medical specialists can service more patients over a greater geographical area and be able to collaborate with colleagues from a broader spectrum of medical expertise.

Our future works will focus on improving the pattern recognition using other neural network algorithms or other adaptive systems. We will use domain-specific knowledge to perform the experimental evaluation using real-world data. Our platform that combines the multi-agent systems with the pattern recognition capabilities of neural networks will be used in other applications in other distributed environments.

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