Agent-based intelligent medical diagnosis system for patients

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Abstract.
BACKGROUND: According to the analysis of the challenges faced by the current public health circumstances such as the sharp increase in elderly patients, limited medical personnel, resources and technology, the agent-based intelligent medical diagnosis system for patients (AIMDS) is proposed in this research.
OBJECTIVE: Based on advanced sensing technology and professional medical knowledge, the AIMDS can output the appropriate medical prescriptions and food prohibition when the physical signs and symptoms of the patient are inputted.
METHODS: Three core modules are designed include sensing module, intuition-based fuzzy set theory/medical diagnosis module, and medical knowledge module.
RESULTS: The result shows that the optimized prescription can reach the desired level, with great curative effect for patient disease, through a case study simulation.
CONCLUSION: The presented AIMDS can integrate sensor technique and intelligent medical diagnosis methods to make an accurate diagnosis, resulting in three-type of optimized descriptions for patient selection.

Keywords: Intuitionistic fuzzy set theory, sensing technology, intelligent medical diagnosis, agent, medical knowledge

1. Introduction

According to the latest Chinese census data (http://usa.chinadaily.com.cn/epaper/2013-12/19/content_17184843.htm), it shows that the elderly (greater than or equal to 60 years old) account for 13.26% of the total population, namely 1.5 billion. It means that China has stepped into an aging society. As a fact, with the decay of the old body function, the elderly becomes a high incidence of disease crowd. Therefore, in China, current medical treatment mode should be investigated by considering the following serious challenges.

(1) Based on medical actuality, limited medical personnel, resources and technology cannot meet the requirements of the current diseases diagnosis. Therefore, patients may not get enough time and effective treatment from the doctors, and the patients' satisfaction of diagnostic services is low. Moreover, due to the different level of the doctors, it impacts the rationality of diseases medication and the accuracy of the medical diagnosis.

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(2) With the patients increasing sharply in the aging society, it will result in the medical staff works the whole day under high-intensity load, and the human factors increase chance of misdiagnosis from several aspects, for example medical staffs' crossness, negative emotion and fatigue-proof working. Beyond that, each patient gets relatively insufficient effective clinic service time with a large number of patients, resulting in the cure for the disease show hysteresis and retardance.

(3) Appearing a series of nervous relationship events between patients and medical staffs makes the negative effects on both the diagnosis of patients and medical staffs' working. It is a fact that a part of medical staffs gain wrongful profits in the process of prescription drugs, augment additional medical diagnosis flow simultaneously. It will aggravate the burden of patients and destroy the image of doctors.

Over the past few years, the increasing attention on severe challenges in medical diagnosis process such as sharply increased elderly patients, limited medical personnel, has led to a number of contributions in the areas of the intelligent medical diagnosis methods. The early contributions can be found on the neural networks, it provides a new significant way for intelligent medical diagnosis. Based on this idea, artificial neural networks have been applied in the diagnosis of: (i) pancreatic disease [1], (ii) gynecological diseases [2], (iii) early diabetes [3], (iv) colorectal cancer [4], and (v) multiple sclerosis lesions [5]. While this kind of method to set up the achievements of medical diagnostic system is still limited, the main reasons are that the learning algorithm cannot calculate the right results when the required algorithm to set up neural network model solves the larger, multi-features disease diagnosis problems. In a novel perspective, Nikovski et al. [6] constructed the bayesian network medical diagnosis system from the incomplete and partially correct numerical probabilistic information by introducing domain-dependent constraints, to solve the problem of determining the combined influences of several diseases on a single test result for individual diseases. While it is a fact that this method encounters the following conditions as more network nodes, complex network structure, high uncertainty relationship between parameters and node, the feasibility and calculation performance will descend greatly. Therefore, it is suitable to diagnose for few symptoms. Recent published methods in the intelligent medical diagnosis include an improved genetic algorithm procedure to optimize parameter and select feature of the multi-layer perception network in medical diagnosis of diabetes, heart and cancer [7]. Chattopadhyay et al. [8] proposed a CBR-based expert system that uses the K-nearest neighbor (KNN) algorithm to search k similar cases based on the Euclidean distance measure to enhance diagnostic accuracy for complex diseases. Nonetheless, expert system has little applied value due to the defects in the production structure and serial working manners. And Qasem et al. [9] presented an adaptive evolutionary radial basis function (RBF) network algorithm to provide an effective means to solve multi-objective RBF network for medical disease diagnosis.

Meanwhile, Ahn et al. [10] developed an interview chart with interval fuzzy degrees based on the relation between symptoms and diseases (three types of headache) and utilized the interval-valued intuitionistic fuzzy weighted arithmetic average operator to aggregate fuzzy information from the symptoms. Then they proposed a new approach for medical diagnosis of headache using the distance between interval-valued intuitionistic fuzzy sets. Szmidt et al. [11] presented a new approach for medical diagnosis by employing intuitionistic fuzzy sets. By looking for the smallest distance between symptoms that are characteristic for a patient and symptoms describing illnesses considered making a diagnose of the disease. Thought efficiently constructing fuzzy probabilistic mapping between input membership function, and determining an effective set of input features, Majid et al. [12] proposed an intelligent system based on fuzzy probabilities for medical diagnosis, in particularly aphasia diagnosis. Recent results described in the literatures prove that medical diagnostics elaboration many times is a distributed and
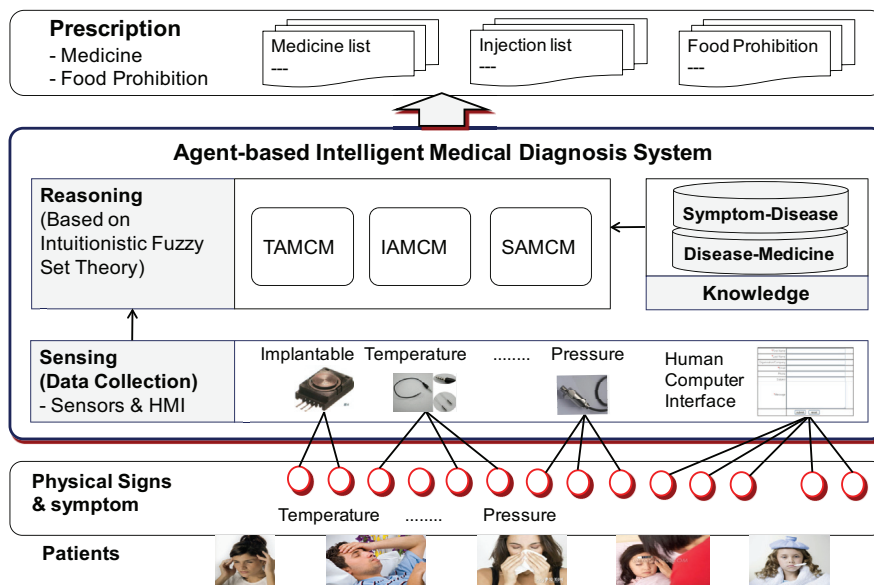
Fig. 1. Overall architecture of AIMDS.

cooperative work, which involves more medical human specialists and different medical systems [13]. Horacio et al. [14] presented an agent-based distributed decision support system for the diagnosis and prognosis of brain tumors developed by the HealthAgents project. Zhang et al. [15] applied multi-agent system for identifying and optimizing the exceptions of the production system. Simultaneously, there are some other methods applied in medical diagnosis. For example, Gupta et al. [16] proposed an optimal feed forward back propagation algorithm to improve medical diagnosis and treatment for the practitioners of medicine. Recent developments in wireless sensors have created a new era of the internet of things (IoT) [17], which can be used to automatically capture the real-time data of the physical signs and symptoms of the patient.

Although the significant contributions of the above methods and theories for medical diagnosis, how to integrate the sensor technique and intelligent medical diagnosis method has not been widely considered and systematically studied.

This paper focuses on how to effectively solving the current serious challenges existing in medical diagnosis process and proposing an innovatory medical diagnosis way by integrating the sensor technique and intelligent medical diagnosis methods. The aim of this paper is to construct an Agent-based Intelligent Medical Diagnosis System (AIMDS) for patients, and the proposed AIMDS will integrate the sensor technology and artificial intelligence to provide correct prescription for patients. In the AIMDS, the important information (symptoms and physical signs) of patients will be captured by the sensors and human-computer interface, then, the intuitionistic fuzzy set theory and the symptom-disease knowledge are used to diagnose a patient's condition. Finally, the disease-medicine knowledge is responsible for outputting the appropriate medical prescription.

2. Overall architecture of AIMDS

The overall architecture of AIMDS is shown in Fig. 1. The input of AIMDS is the physical signs and

symptoms of the patient, and the output is the appropriate medical prescription and food prohibition. As seen in the middle of Fig. 1, three core modules are designed in the AIMDS. They are sensing, reasoning and knowledge.

The sensing module consists of sensors (e.g., temperature sensor, velocity sensor, pressure sensor) and human-computer interface. The sensors are used to capture the physical signs of the patient, for example body temperature, blood pressure. The human-computer interface is used to capture the symptoms of the patient, for example fever, cough, headache.

The reasoning module is an intelligent medical diagnosis model based on intuitionistic fuzzy set theory. The intuitionistic fuzzy sets of the physical signs and symptoms of the patient and the relevant diseases are defined as Set A and Set B respectively. Then correlation coefficient of Set A and Set B is captured by three kinds of correlation measure calculation methods. It is a probability of the relevant diseases. The diagnosis corresponding to the maximal probability is identified finally.

The knowledge module is used to establish the field knowledge to support the reasoning module. Two types of knowledge namely symptom-disease knowledge and disease-medicine knowledge are designed in the knowledge module, it can be continuously updated according to the experts.

The designed AIMDS can be developed as an ATM (Automatic Teller Machine). It can be easily installed at the elderly communities. The patient can use it like using the ATM.

Agent-based intelligent medical diagnostic procedure is composed of the following seven steps.

First, establish symptom-disease matched knowledge database. The knowledge database describes the membership of symptoms and diseases.

Second, construct disease-medicine matched knowledge database. The knowledge database contains drug information and applicable prescription associated disease knowledge sets. Drug information comprises drug information of ontology and rules of the classification information.

Third, enter patient's information via human-computer interaction, including physical signs, clinical symptoms, medical history and auxiliary examination results.

Fourth, classify and tidy entered information and input. The acquired information from the human-computer interface section is classified and tidied in the time sequence, as the parameters input of the theory of intuitionistic fuzzy diagnosis model and is stored.

Fifth, establish agent-based the theory of intuitionistic fuzzy diagnosis model. Three kinds of methods for calculating the correlation coefficient are proposed: the general calculation method of the correlation coefficient, improved new calculation method of the correlation coefficient and the calculation method of the correlation coefficient based on set theory.

Sixth, calculate intuitionistic fuzzy correlative measure and output. The content entered in human-machine interface is inputted into the diagnosis model. The diagnosis is outputted in the model of terminal.

Seventh, match optimization scheduling and output correct prescriptions of diseases. The diagnosis is inputted into the disease-medicine knowledge database. After that, the correct prescription of disease is scheduled optionally and outputted by searching the highest matched-degree drugs for disease in the disease-medicine knowledge database. Figure 2 represents the specific medical diagnostic flow.

3. Methods

The AIMDS uses the theory of intuitionistic fuzzy sets to diagnose. Three diagnosis methods are designed in the reasoning of AIMDS, and they will be described in this section.

Table 1
Symptom-disease matched knowledge base

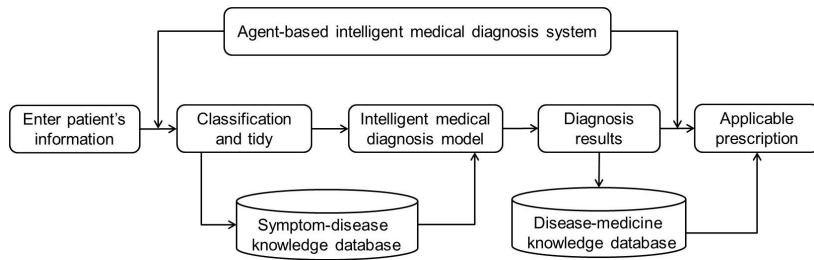|	Disease 1	Disease 2	Disease 3	...	Disease j	...	Diseases n
Symptom 1	(μ_{11}, ν_{11})	(μ_{12}, ν_{12})	(μ_{13}, ν_{13})	...	(μ_{1j}, ν_{1j})	...	(μ_{1n}, ν_{1n})
Symptom 2	(μ_{21}, ν_{21})	(μ_{22}, ν_{22})	(μ_{23}, ν_{23})	...	(μ_{2j}, ν_{2j})	...	(μ_{2n}, ν_{2n})
Symptom 3	(μ_{31}, ν_{31})	(μ_{32}, ν_{32})	(μ_{33}, ν_{33})	...	(μ_{3j}, ν_{3j})	...	(μ_{3n}, ν_{3n})
...	...	...	...	...	...	...	...
Symptom i	(μ_{i1}, ν_{i1})	(μ_{i2}, ν_{i2})	(μ_{i3}, ν_{i3})	...	(μ_{ij}, ν_{ij})	...	(μ_{in}, ν_{in})
...	...	...	...	...	...	...	...
Symptom n	(μ_{n1}, ν_{n1})	(μ_{n2}, ν_{n2})	(μ_{n3}, ν_{n3})	...	(μ_{nj}, ν_{nj})	...	(μ_{nn}, ν_{nn})

Fig. 2. A flow diagram of agent-based intelligent medical diagnosis system for patient.

3.1. Knowledge database

3.1.1. Symptom-disease matched knowledge database

The constructed symptom-disease matched knowledge database is composed of universal symptom information, disease information and membership correlation sets of symptoms and diseases. This knowledge database integrates medical experts' knowledge and their large amount of clinical experience, and also extracts relatively medical knowledge based on the symptoms of disease diagnosis from the authoritative medical institutions and books.

A framework of symptom-disease matched knowledge database is presented to describe the mapping relationship of symptoms and diseases, which includes three sub-sets. The first sub-set contains symptom set and detected information set. Symptom sets are patient's symptoms such as headache, diarrhea, cough and choking sensation in the chest and so forth. The detected information sets are physical signs captured by sensors. The second sub-set is a disease diagnosis set, which describes universal diseases such as viral fever, dysentery, typhoid fever. The third sub-set is an intuitionistic fuzzy number set, which describes membership and nonmembership of each symptom and related diseases by utilizing a set of parameters: (μ, ν). The parameter μ and ν respectively represents the membership and nonmembership of each symptom and related diseases.

We establish symptom-disease knowledge database as showed in Table 1. Table 1 lists the almost all of the symptoms and diseases as well as their membership in daily life. The first column represents the symptom variables, and the first row represents the diseases variable in the Table 1. The parameter set (μ_{ij}, ν_{ij}) is the intuitionistic fuzzy number of symptom i and disease j. Here, μ_{ij} represents the probability of the symptom i belongs to the disease j, and ν_{ij} represents the probability of symptom i does not belong to disease j.

3.1.2. Disease-medicine matched knowledge database

Disease-medicine matched knowledge database includes the medicine knowledge and disease knowledge, which are introduced in the following sections in detail.

Table 2
Physical sensor applied in the biomedical field

Name	Purpose
Velocity sensor	Bloob flow velocity, micturition speed, production speed, etc.
Vibration sensor	A variety of physiological pathology, heart sounds, pulses, tremor, etc.
Force sensor	Muscle contraction force, Twisted together, etc.
Pressure sensor	Blood pressure, intraocular pressure, heart pressure, etc.
. . .	. . .
Temperature sensor	Body, mouth, skin, blood temperature, etc.

Medicine knowledge is made up of the drug ontology knowledge and rules of drug classification. Here, the drug ontology knowledge mainly includes drugs in both Chinese and English name, price, composition, property, attending function, usage and dosage, specification, adverse reaction, contraindication, matters needing attention, the production enterprise and drug interaction.

According to the rules of drug classification, drugs are classified in the light of different attributes of drugs and labeled detailedly. The specific content of the drug classification is listed as follows. First of all, drugs are divided into antibiotic drug and the non-antibiotic. Then drugs are divided into digestive system drugs, respiratory drugs, heat-clearing and detoxifying drugs, vitamins and minerals and so on according to the function and use. Moreover, drugs are split into Chinese traditional medicine and Western medicine on the basis of property and composition. The most important rule of drug classification is the usage and dosage, and it plays an integral role in pushing the prescription of medicine. Based on this rule, drugs are split into injection and oral drug.

Knowledge sets of applicable prescriptions associated with diseases are formed by extracting useful information from authoritative books and periodicals, and integrating famous medical expert knowledge and their clinical experience. Judging by diagnostic result, three-type medicine prescriptions are pushed by transferring the knowledge sets. The first optimized pushed prescription is the oral drug; The second is the injection, and the third is a portfolio of oral drug and injection.

Compared with the first prescription, the latter two have advantages including shorter healing time, more significant curative effect. They could also reduce the patient's pain effectively, but the price is relatively high. At the same time, the latter two mainly focus on more severe diseases.

In addition, in the opinion of dietotherapy, we collected and analyzed matters needing attention involving in each drug. Food prohibition related to drugs is enumerated in the prescription.

3.2. Patients' information input with the human-computer interface

With the rapid development of sensor, computer technology, sensor network and speech recognition technology, related technologies are applied in the biomedical field and promote the invention of physical sensors. At present, physical sensors applied in the biomedical field are divided as shown in the Table 2 in term of purpose and function.

Heterogeneous physical sensors installed at autonomic diagnostic equipment detect the individual physical signs including body temperature, blood pressure and others, and is entered and stored in the form of the semi-structured data in the first human-computer interface. In the second, the contextual model of dialogue between patient and doctor is simulated by speech recognition technology. Computer takes place of the role of the doctor. Patients describe their symptoms to form symptom sets. Symptom sets include headache, fever, diarrhoea, cough and others, and are entered and stored in the form of the structured data. Here, it is to be highlighted that the primary and secondary relationship of patients' symptoms are arranged in descending order according to the time sequence of inputted symptoms. It is

often the case that the patient usually describes the main symptoms firstly, and then a minor. Auxiliary examination results information is inputted including blood tests, urinalysis and others in the third, and is stored in the form of semi-structured data.

Semi-structured and structured data is classified in a specific regulation. Any symptoms of illness have the occurred site of lesions. The human body is composed of eight systems (movement, digestive, respiratory, urinary, reproductive, endocrine, nervous and circulatory system). Based on aforesaid facts, disease is divided into the nine categories. It is greatly convenient to suit the remedy to the case.

3.3. Correlation measure modeling of intuitionistic fuzzy set

First, introduce the concept, definition and property of the intuitionistic fuzzy set as well as its extensions.

Definition 1. Assumed that X is a nonempty set, $A_j = \{\langle x_i, \mu_{A_j}(x_i), \nu_{A_j}(x_i) \rangle \mid x_i \in X\}$ represents an intuitionistic fuzzy set.

Where $\mu_{A_j}(x_i)$ and $\nu_{A_j}(x_i)$ respectively describes the membership and nonmembership of element x_i corresponding to the set A_j.

Property: the value range of $\mu_{A_j}(x_i)$ is [0, 1]. And it is the same for $\nu_{A_j}(x_i)$. Furthermore, for both $\mu_{A_j}(x_i)$ and $\nu_{A_j}(x_i)$, they meet some function relations as follows:

$$0 \leqslant \mu_{A_j}(x_i) + \nu_{A_j}(x_i) \leqslant 1, x_i \in X, \quad \pi_{A_j}(x_i) = 1 - \mu_{A_j}(x_i) - \nu_{A_j}(x_i), \quad x_i \in X.$$

Where $\pi_{A_j}(x_i)$ is the degree of hesitation or the degree of uncertainty corresponding to the element x_i and the set A_j.

Definition 2. The intuitionistic fuzzy number α is a vector (μ_α, ν_α), such that $s(\alpha) = \mu_\alpha - \nu_\alpha$.

Where $s(\alpha)$ is the scoring function corresponding to the intuitionistic fuzzy number α. The scoring value of the intuitionistic fuzzy number is related to the d-value of the membership μ_α and the nonmembership ν_α directly. The greater the d-value, the greater the scoring value.

Then $h(\alpha) = \mu_\alpha + \nu_\alpha$, where $h(\alpha)$ is the accuracy function corresponding to the intuitionistic fuzzy number α. Where h represents the accuracy function and $h(\alpha)$ is the accuracy value. The greater the accuracy value, the greater the accuracy.

After that, the function relationship of the degree of hesitation and the accuracy can be determined. The equation $h(\alpha) + \pi_\alpha = 1$ represents the function relationship, so the smaller the degree of hesitation, the greater the accuracy.

3.3.1. Traditional correlation measure calculation method

Gerstenkom and Manko [18] proposed a calculation formula for the correlation measure of the intuitionistic fuzzy set as

$$\rho(A_1, A_2) = \frac{c(A_1, A_2)}{(c(A_1, A_1) \cdot c(A_2, A_2))^{1/2}} \tag{1}$$

Where $\rho(A_1, A_2)$ represents the correlation coefficient of the intuitionistic fuzzy set A_1 and A_2. The molecule can be represented by the expression and it is $\sum_{i=1}^{n}(\mu_{A_1}(x_i) \cdot \mu_{A_2}(x_i) + \nu_{A_1}(x_i) \cdot \nu_{A_2}(x_i))$.

Meanwhile, the correlation coefficient $\rho(A_1, A_2)$ has following property. First, the value range of $\rho(A_1, A_2)$ is a closed interval of 0 to 1; second, if $A_1 = A_2$, then $\rho(A_1, A_2) = 1$; third, if A_1 exchanges the position with A_2, then $\rho(A_1, A_2) = \rho(A_2, A_1)$.

Based on [16], we proposed a new-extended formula to apply in the medical diagnosis as

$$\rho(A_0, A_j) = \frac{c(A_0, A_j)}{(c(A_0, A_0) \cdot c(A_0, A_j))^{1/2}} \tag{2}$$

Where $c(A_0, A_j) = \sum_{i=1}^{n} \left(\mu_{A_0}(x_i) \cdot \mu_{A_j}(x_i) + \nu_{A_0}(x_i) \cdot \nu_{A_j}(x_i) \right)$.

Next, we assume that if $X = \{x_1, x_2, \ldots, x_n\}$ is a limited set of the symptoms, then $A_o = \{\langle x_i, \mu_{A_0}(x_i), \nu_{A_0}(x_i) \rangle | x_i \in X\}$ and $A_j = \{\langle x_i, \mu_{A_j}(x_i), \nu_{A_j}(x_i) \rangle | x_i \in X\}$ are defined as the intuitionistic fuzzy sets, which respectively describe membership of patient's symptoms and that of symptoms and diseases. Finally, correlation measure equation is obtained as Eq. (2).

3.3.2. Improved new correlation measure calculation method

In this section, an improved new correlation measure calculation method is proposed, which is similar to the abovementioned formula. However this method takes account of all the data as a whole in the view of absolute value of membership and nonmembership.

Equation of the presented calculation method is

$$\rho(A_0, A_j) = \frac{1}{2n} \sum_{i=1}^{n} \left(\frac{\Delta\mu_{\min} + \Delta\mu_{\max}}{\Delta\mu_i + \Delta\mu_{\max}} + \frac{\Delta\nu_{\min} + \Delta\nu_{\max}}{\Delta\nu_i + \Delta\nu_{\max}} \right) \tag{3}$$

Where

$$\Delta\mu_i = |\mu_{A_0}(x_i) - \mu_{A_j}(x_i)|, \quad \Delta\nu_i = |\nu_{A_0}(x_i) - \nu_{A_j}(x_i)|,$$

$$\Delta\mu_{\min} = \min_i\{|\mu_{A_0}(x_i) - \mu_{A_j}(x_i)|\}, \quad \Delta\nu_{\min} = \min_i\{|\nu_{A_0}(x_i) - \nu_{A_j}(x_i)|\},$$

$$\Delta\mu_{\max} = \max_i\{|\mu_{A_0}(x_i) - \mu_{A_j}(x_i)|\}, \quad \Delta\nu_{\max} = \max_i\{|\nu_{A_0}(x_i) - \nu_{A_j}(x_i)|\}.$$

Generally, the clinical manifestation of the disease can show up different symptoms. As a result, the importance of all the symptoms can also be different. Here, each symptom should be given different weight. Eq. (3) can be generalized as

$$\rho(A_0, A_j) = \frac{1}{2} \sum_{i=1}^{n} \omega_i \left(\frac{\Delta\mu_{\min} + \Delta\mu_{\max}}{\Delta\mu_i + \Delta\mu_{\max}} + \frac{\Delta\nu_{\min} + \Delta\nu_{\max}}{\Delta\nu_i + \Delta\nu_{\max}} \right) \tag{4}$$

Where $\omega = (\omega_1, \omega_2, \ldots, \omega_n)^T$ is a weight vector of $x_i (i = 1, 2, \ldots, n)$. $\omega_i \geqslant 0 (i = 1, 2, \ldots, n)$ and $\sum_{i=1}^{n} \omega_i = 1$. In particular, as we said in the Section 3.2, the permutation of the weight is $\omega_1 \geqslant \omega_2 \geqslant \ldots \geqslant \omega_n$, and not all equal.

3.3.3. Correlation measure calculation method based on set theory

We considered from the point of view of set theory, and presented a correlation measure calculation method of intuitionistic fuzzy set based on set theory.

Equation represented the correlation coefficient of set A_0 and set A_j is

$$\rho(A_0, A_j) = \frac{\sum_{i=1}^{n} \left(\mu_{A_0}(x_i) \cdot \mu_{A_j}(x_i) + \nu_{A_0}(x_i) \cdot \nu_{A_j}(x_i) \right)}{\max \left(\sum_{i=1}^{n} (\mu_{A_0}^2(x_i) + \nu_{A_0}^2(x_i)), \sum_{i=1}^{n} (\mu_{A_j}^2(x_i) + \nu_{A_j}^2(x_i)) \right)} \tag{5}$$

To measure the probability of symptom associated with disease, we presented three kinds of correlation measure calculation methods from different viewpoints. During the process of medical diagnosis, we selected a disease corresponding to the maximal probability as the diagnosis.

Table 3
Symptoms and physical signs of the patient

Symptom set	Physical sign set
Fever	1. Body temperature: 38.5 Celsius degree
Headache cough	2. The number of white blood cell is greater than the normal value.
Weakness pharyngodynia diarrahea	3. Lymphocyte rate is greater than the normal value.

Table 4
Intuitionistic fuzzy number of symptoms and physical signs

Symptom and physical sign	Intuitionistic fuzzy number
Body temperature: 38.5 C	(1, 0)
White blood cell: High	(1, 0)
Fever	(0.8, 0.1)
Headache	(0.7, 0.2)
Cough	(0.4, 0.2)
Weakness	(0.3, 0.4)
Pharyngodynia	(0.4, 0.1)
Diarrahea	(0.3, 0.2)

Table 5
Symptom-disease matched knowledge set

	Dysentery	Influenza	Migraine	Enteritis	Pharyngitis
Body temperature: 38.5C	(0.5, 0.0)	(0.5, 0.1)	(0.5, 0.0)	(0.3, 0.3)	(0.3, 0.2)
White blood cell: High	(0.4, 0.2)	(0.6, 0.1)	(0.5, 0.3)	(0.1, 0.5)	(0.2, 0.8)
Fever	(0.4, 0.3)	(0.7, 0.0)	(0.2, 0.6)	(0.2, 0.7)	(0.2, 0.6)
Headache	(0.1, 0.7)	(0.5, 0.4)	(0.9, 0.0)	(0.2, 0.7)	(0.3, 0.3)
Cough	(0.3, 0.1)	(0.5, 0.1)	(0.0, 0.5)	(0.0, 0.7)	(0.5, 0.2)
Weakness	(0.5, 0.0)	(0.4, 0.2)	(0.3, 0.3)	(0.3, 0.2)	(0.0, 0.7)
Pharyngodynia	(0.3, 0.3)	(0.6, 0.2)	(0.1, 0.5)	(0.0, 0.6)	(0.8, 0.0)
Diarrahea	(0.3, 0.4)	(0.1, 0.3)	(0.0, 0.8)	(0.6, 0.0)	(0.0, 0.6)

Table 6
Correlation coefficient of symptom and disease

	Dysentery	Influenza	Migraine	Enteritis	Pharyngitis
Method A	0.7421	0.9142	0.6871	0.4370	0.5525
Method B	0.7097	0.8961	0.6642	0.7440	0.7327
Method C	0.5267	0.7277	0.6132	0.3715	0.4961

4. Results and case study

For the sake of simple expression, we defined the three-type correlation measure calculation methods of intuitionistic fuzzy set as Method A, Method B and Method C respectively. They are the traditional correlation measure calculation method, an improved one and the one based on set theory respectively.

Once a member of our team was ill, he utilized the established AIMDS to make a diagnostic testing. And a prescription was pushed. This process took him seven minutes. Then he saw a doctor who is a famous medical expert again. And he also got a prescription.

To illustrate the effectiveness of AIMDS, the diagnostic process was simulated by utilizing recorded messages about the member again. Table 3 describes the information of symptoms and physical signs about the member.

Table 4 describes the intuitionistic fuzzy number of the member's symptoms and physical signs. Next, these recorded symptoms and physical signs are entered into the symptom-disease matched knowledge database. And the diagnostic set is constructed by ergodic search and function call, which is dysentery, influenza, migraine, enteritis, pharyngitis. Then symptom-disease matched knowledge set is also formed as showed in Table 5.

In this section, we assumed that the importance of each symptom is the same, namely parameter variables of symptoms have same weights. Then parameter variables are substituted into Eqs (2), (3) and

Table 7
The detailed information of prescriptions

	Oral drugs	Injection	Portfolio of oral drug and injection
Drug name	Lianhuaqingwen Capsule	Ribavirin injection	Ribavirin injection
	Virus particles	Shuanghuanlain Injection	Sodium chloride injection
	Vitamin C tablets	Sodium chloride	Compound amantadine Tablets
	Cydiodine buccal Tablets	Injection	Cydiodine buccal tablets
Food Prohibition	Alcohol, tobacco, spicy food, stodge, fishy food. etc		

(5) severally. The correlation coefficients were obtained. Table 6 describes the correlation coefficients achieved by different calculation methods. It represents the probability distribution of disease's occurrence corresponding to the symptoms and physical signs. The greater the probability value, the greater the chance of disease occurrence. The result shows that the influenza has the maximal probability value in each calculation methods, which is 0.9142, 0.8961, and 0.7727. Hence, the member of our team was diagnosed with influenza.

Next, the influenza was entered into the disease-medicine matched knowledge database. Three kinds of the optimized prescriptions were pushed. And outputted prescription also contains food prohibition and matters needing attention. Table 7 lists the detailed contents of prescriptions.

Meanwhile, we also listed the prescription of the member of our team prescribed by a famous medical expert. The content of the prescription is Virus Particles, Compound Amantadine Tablets, Lianhuaqingwen Capsule, Shangfengting Capsule, Jingsangzi Lozenge and Vitamin C Tablets. We made a minute and comparative contrast analysis in the following section. Here, we supposed the prescription prescribed by AIMDS and the famous medical expert as Prescription A and Prescription B respectively.

5. Discussion

This study illustrates the value of agent-based intelligent medical diagnosis system (AIMDS) for patients to push the optimized prescription. Utilizing advanced sensing technology and synthesizing authoritative medical knowledge to construct an AIMDS, AIMDS can provide a good platform for disease diagnosis and play an integral role in solving the existing problems in medical diagnosis, as discussed below.

Advanced sensing technology was applied into the biomedical field to pave a feasible approach for detecting the patient's physical signs. Compared with traditional medical diagnosis, it costs less time to acquire more abundant and comprehensive information of physical. This technology is considered to be well-suited to link the physical and virtual world.

In the modeling exercise, we constructed three kinds of methods to calculate the correlation coefficient of symptoms and diseases. On the basis of Method A, Method B considers all the data as a whole to make a simulation, and it can lower effect of inequitable data on the accuracy of the diagnosis. Moreover, it is obvious that correlation coefficients calculated by Method C are less than the Method A and Method B (Fig. 3). It is the first reason that the denominator of Eq. (5) is equal to the maximum of c_0 and c_j, where c_0 represents cumulative sum of the square of membership and nonmembership in the set A_0. And c_j is the same corresponding to set A_j. Moreover, the membership of physical signs is equal to 1, for example body temperature and the number of White Blood Cells. Thus, the denominator is amplified
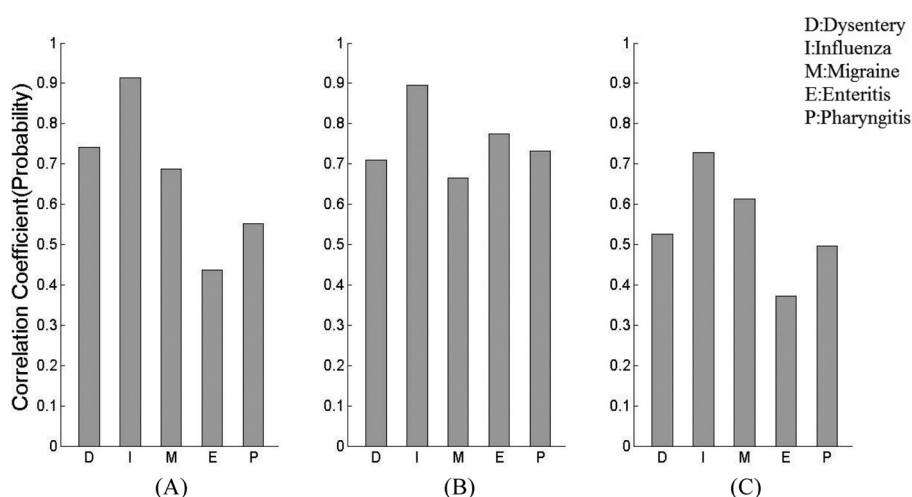
Fig. 3. The correlation coefficient of symptom and disease for the different methods (the probability distributions of diseases associated with symptoms): (A) the correlation coefficient corresponding to Method A; (B) the correlation coefficient corresponding to Method B; (C) the correlation coefficient corresponding to (C).

further. Then we analyzed the probability distributions as showed in the Fig. 3 and got an objective and correct diagnostic result.

We illustrated the practicality of AIMDS by examining the symptoms of the member of our team in the Section 4. The benign result shows that AIMDS can guide patients to choose an autonomic diagnostic pattern like ATM. Here, in order to fully demonstrate the advantages of AMIDS, we gave the contrast analysis of Prescription A and Prescription B.

As far as the desired curative effect of prescriptions, we consulted several famous medical experts and synthesized their evaluations. The conclusion is that two kinds of prescriptions have similar and good curative effects, and Prescription A is better than Prescription B in a sense. Prescription A has the characteristic of strong pertinence, but Prescription B may have a suspicion of repeated medication.

In prices, the cost of Prescription B is 64.9 yuan only drugs, while the Prescription A is 40.1 yuan. So the latter is in favor of reducing burden of patients. For time cost, Prescription A is obviously less than Prescription B.

At present, traditional medical diagnosis method is a way that doctors make a diagnosis combining their professional knowledge and clinical experience as well as auxiliary information detected by medical instruments. The proposed AIMDS takes place of the role of doctors, and it can overcome the impact from personal subjective factors and limited medical level of doctors to make a reasonable diagnosis. On the other hand, it is difficult to memory all matters needing attention of each drug for doctors. Doctors easily overlook the food prohibition related to drugs when they prescribe. Therefore, patients may eat taboo food. The curative effect can be decreased, even cause more serious consequences. We observed this problem and labeled the food prohibition in the Prescription A. The minutia plays a significant function in warning patients to notice food prohibition.

Additionally, the proposed diagnostic pattern is a quantitative analysis method instead of current qualitative analysis method in this paper. It can provide a scientific basis and a standard operating procedure. Xu [18] only considered the patient's symptoms as an intuitionistic fuzzy set, while we designed intuitionistic fuzzy set of symptom contained not only the symptoms, but also the information of physical signs such as body temperature, the number of white blood cell and others. The diagnostic contents

contained in the latter are more comprehensive. For example, the indicator of the number of white blood cell is closely related with virus infection in the clinical diagnosis.

Nevertheless, the value of AIMDS during diagnostic trial stages depends on accessibility of sample data from the actual clinical diagnosis. As is often the case with these types of studies, the data are not easily available due to safety and data confidentiality. For this bottleneck, we try to conduct in-depth and long-term collaborations with a famous medical institution and exchange the sample data. In addition, we actively encourage students of our school to use this system as an auxiliary test when they were ill. In this way, it can not only rich the sample data, but emonstrate the feasibility of AMIDS.

Several study limitations and modeling assumptions may have affected the outcome for correlation coefficients. First, we do not differentiate the importance of different symptoms in detail. And many diseases have the similar symptoms. Furthermore, the elderly may not describe their conditions correctly. Second, each symptom may have several expressions due to different language conventions of patients, so it is also a difficulty that how to normalize information of patients' symptoms. If the patient were suffering from a variety of diseases, they could not be identified simultaneously. Therefore, the misdiagnosis may occur. Additionally, the inequitable data may affect the effectiveness of the association coefficients.

Despite these limitations, our study highlights how AIMDS could provide powerful tools for patients' diagnosis. Conventional medical diagnosis pattern may not be sufficient to overcome the existing problems during the process of medical diagnosis. It must be emphasized that AIMDS based on intuitionistic fuzzy set theory cannot completely replace the doctors' role and function, and focuses more on diagnosis of common diseases.

6. Conclusions

In sum, our study highlights how agent-based intelligent medical diagnosis system (AIMDS) might synthesize advanced sensing technology, medical knowledge and mathematical modeling to structure intelligent medical diagnosis model. It is used to make a scientific diagnosis for patients' diseases. Considering Chinese status quo of medical care services such as sharply increased elderly patients, limited medical personnel, resources and technology, this approach would offer a new thought for solving above-mentioned challenges and could also aid in avoiding diagnostic errors caused by the doctor's factors.

7. Summary

7.1. Background

It is a fact that China has stepped into an aging society. And the elderly becomes a high incidence of disease crowd with the decay of their body function. Therefore, in China, current medical treatment mode should be investigated by considering the serious challenges such as alarming medical actuality, tense doctor-patient relations. We proposed an agent-based intelligent medical diagnosis system (AIMDS) for patients to devote to improving the drawbacks of current medical treatment pattern.

7.2. Methods

We applied the intuitionistic fuzzy set theory to medical diagnosis. Advanced sensing technology was used to detect patients' signs and the symptoms were entered by human-computer interface. Three kinds

of correlation measure calculation methods based on intuitionistic fuzzy set theory were implemented to calculate the correlation coefficients of symptoms. Prescriptions and food prohibition were pushed in term of the diagnostic result.

7.3. Results

Our analyses indicate that the proposed correlation measure calculation methods based on intuitionistic fuzzy set theory reach the good effect of medical diagnosis. Additionally, the contrast analysis of Prescription A and Prescription B shows that they have a good and similar curative effect, but Prescription A has some advantages such as low consuming time, low cost. Food prohibition labeled in Prescription A can warn patients to pay more attention to their diets while taking drugs.

7.4. Conclusion

Our study demonstrates the feasibility and practicality of agent-based intelligent medical diagnosis system for patients. It also shows how presented AIMDS can integrate the sensor technique and intelligent medical diagnosis methods to make an accurate diagnosis, and push three-type of optimized descriptions for patients to choose. Through the contrast analysis of the different diagnostic results, it shows that the proposed AIMDS provides a powerful tool for solving the predicaments of current medical care service.

Acknowledgments

References

[1] Bartosch-Härlid A, Andersson B, Aho U, Nilsson J, Andersson R. Artificial neural networks in pancreatic disease. British Journal of Surgery. 2008; 95(7): 817-826.

[2] Siristatidis C, Chrelias C, Pouliakis A, Katsimanis E, Kassanos D. Artificial neural networks in gyneacological diseases: current and potential future applications. Medical Science Monitor. 2010; 16(10): 231-236.

[3] Shankaracharya, Odedra D, Odedra S, Vidyarthi A. Computational intelligence in early diabetes diagnosis: A review. The Review of Diabetic Studies. 2010; 7(4): 252-262.

[4] Spelt L, Andersson B, Nilsson J, Andersson R. Prognostic models for outcome following liver resection for colorectal cancer metastases: A systematic review. European Journal of Surgical Oncology. 2012; 38(1): 16-24.

[5] Mortazavi D, Kouzani A, Soltanian-Zadeh H. Segmentation of multiple sclerosis lesions in MR images: A review. Neuroradiology. 2012; 54(4): 299-320.

[6] Nikovski D, Constructing Bayesian networks for medical diagnosis from incomplete and partially correct statistics, IEEE Transactions on Knowledge and Data Engineering. 2000; 12(4): 509-516.

[7] Ahmad F, Mat Isa Nor A, Hussain Z, Osman MK. Intelligent medical disease diagnosis using improved hybrid genetic algorithm-multilayer perceptron network. Journal of Medical Systems. 2013; 37: 9934-9941.

[8] Chattopadhyay S, Banerjee S, Rabhi FA, Acharya UR. A case-based reasoning system for complex medical diagnosis. Expert Systems. 2013; 30(1): 12-20.

[9] Qasem SN, Shamsuddin SM. Radial basis function network based on time variant multi-objective particle swarm optimization for medical diseases diagnosis. Applied Soft Computing. 2011; 11(1): 1427-1438.

[10] Ahn JY, Han KS, Oh SY, Lee CD. An application of interval-valued intuitionistic fuzzy sets for medical diagnosis of headache. International Journal of Innovative Computing, Information and Control. 2011; 7(5): 2755-2762.

[11] Szmidt E, Kacprzyk J. An intuitionistic fuzzy set based approach to intelligent data analysis: An application to medical
      diagnosis. Recent Advances in Intelligent Paradigms and Applications Studies in Fuzziness and Soft Computing. 2003;
      113: 57-70.
[12] Majid MK, Mohammad-R AT, Nader J, Mahdi K. An intelligent system based on fuzzy probabilities for medical diag-
      nosis - A study in aphasia diagnosis. Journal of Research in Medical Sciences. 2009; 14: 89-103.
[13] Iantovics BL. Agent-based medical diagnosis systems. Computing and Informatics. 2008; 27(4): 593-625.
[14] Horacio GV, Mariola M, Margarida JS, Theodoros NA. HealthAgents: Distributed multi-agent brain tumor diagnosis
      and prognosis. Applied Intelligence. 2009; 30(3): 191-202.
[15] Zhang YF, Huang GQ, Sun SD, Yang T. Multi-agent based real-time production scheduling method for radio frequency
      identification enabled ubiquitous shopfloor environment. International Journal of Computers and Industrial Engineering,
      2014; 76: 89-97.
[16] Gupta A, Shreevastava M. Medical diagnosis using back propagation algorithm. International Journal of Emerging Tech-
      nology and Advanced Engineering. 2011; 1(1): 55-58.
[17] Zhang YF, Zhang G, Wang JQ, Sun SD, Si SB, Yang T. Real-time Information Capturing and Integration Frame-
      work of the Internet of Manufacturing Things, International Journal of Computer Integrated Manufacturing. 2014;
      DOI:10.1080/0951192X.2014.900874.
[18] Gerstenkom T, Manko J. Correlation of intuitionistic fuzzy sets. Fuzzy Sets and Systems. 1991; 44(1): 39-43.
[19] Xu ZS. On correlation measure of intuitionistic fuzzy sets. Lecture Notes in Computer Science. 2006; 4224: 16-24.