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Using Fuzzy Concept Lattice for Intelligent Disease Diagnosis

CAIFENG ZOU[1,2], (Student Member, IEEE), AND HUIFANG DENG[1]
[1]School of Computer Science and Engineering, South China University of Technology, Guangzhou 510006, China
[2]College of Information Engineering, Guangdong Mechanical and Electrical College, Guangzhou 510515, China

Corresponding author: H. Deng (hdeng2008@gmail.com)

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ABSTRACT This paper proposes a novel intelligent disease diagnosis method based on fuzzy concept lattice. Symptoms and the corresponding extents (e.g., frequency, severity, and duration) of each disease can be extracted to form a fuzzy concept lattice. The fuzzy concept lattice of the symptoms and their extents to be diagnosed needs to be constructed to match the fuzzy concept lattice of possible diseases. The similarity between the above two types of concept lattices can be calculated and used to aid for effective diagnosis. Naturally, the disease with the largest similarity is the finding of intelligent diagnosis. In the future, more efficient fuzzy concept lattice construction method and update algorithm will be explored, which are presumed to be very complicated.

INDEX TERMS Fuzzy concept lattice, fuzzy formal context, intelligent disease diagnosis, similarity.

I. INTRODUCTION

Health care sector is currently faced with many challenges [1], [2], such as chronic diseases, disease prevention, dear medical expenses, etc [3]. In order to cope with various challenges, medical institutions must take medical data as resources, analyze the data, get valuable information, and thus improve the treatment effect and reduce the cost [4], [5]. Data mining and data analysis can help doctors to make accurate clinical diagnosis, effective prediction of disease outbreak, useful personalized treatment, etc. In the era of Internet of Everything, the data increase exponentially. Medical data have become indispensable and important resources. The traditional manual data analysis methods are no longer able to meet the requirements. Efficient computer-based intelligent data analysis methods have become indispensable.

Data sources from healthcare sector include hospital information system (HIS), users' physical sign data collected by various devices [6], [7], implicit health information in social networks, and so on [8], [9]. Data processing technologies in the healthcare community include data fusion, classification, clustering, association rule mining, machine learning, simulation, visualization, etc [10], [11]. Among them, the aim of association rule mining is to find relationships among the variables; the purpose of cluster analysis is to divide the data into several small data sets according to the similarity of data; the goal of visualization is to present data through images, animations and other intuitive ways [12].

'Concept' is defined as the basic unit consisting of extensions and intensions. Formal Concept Analysis(FCA) was proposed by Wille, a famous German scientist, in 1982 [13]. Wille proposed the basic idea of constructing the corresponding concept lattice by binary relation, and established a theoretical basis for development of Formal Concept Analysis (FCA).

FCA emphasizes human cognition, and provides an effective data analysis and knowledge representation method. Concept lattice, as the key data structure of FCA, is a kind of external cognitive means. Concept lattice consists of some formal concept nodes, which involve extension and intension part [14]. The intension of the concept is the set of common attributes of all the objects in the extension, and the extension of the concept is the largest set of objects that can be determined by the intension [15]. Concept lattice is a highly simplified description of the objective world, which reveals the relationship between concepts, and has good mathematical properties. Concept lattices can be graphically represented as labeled line diagrams, named Hasse diagrams, which facilitate data visualization.

II. RELATED WORK

The related work includes formal context, concept lattice, Hasse diagram, fuzzy concept lattice, intelligent disease diagnosis, and so on [16].

A. FORMAL CONTEXT

Formal context $K(U, A, I)$ is composed of an object set U, an attribute set A, and their binary relation I, i.e. $I \subseteq U \times A$. If $(x, a) \in I$, then xIa indicates that object x possesses attribute a. Formal context can also be shown as a two-dimensional data table, where the row indicates object, and the column indicates attribute.

$$\text{When given } \begin{cases} X^* = \{a | a \in A, \forall x \in X, xIa\}, X \subseteq U \\ B^* = \{x | x \in U, \forall a \in B, xIa\}, B \subseteq A \end{cases}$$

if $\exists X^* = B$ and $B^* = X$, then (X, B) is regarded as a formal concept [17]. X represents the extension of the concept (X, B), which shows the set of all objects in this concept. B represents the intension of the concept (X, B), which shows the set of the common attributes for all objects in this concept. For instance, $C((2, 3,4), \{a, c\})$ shows that the concept C involves three objects 2, 3 and 4. The set of the common attributes of these three objects is $\{a, c\}$.

B. CONCEPT LATTICE

Concept lattice theory is an effective tool for knowledge representation and discovery. It is mainly used in cognitive computing, machine learning, pattern recognition, expert systems, decision analysis, web search and other fields. Concept lattice [18] essentially describes the association between objects and attributes.

One kind of partially ordered relationship can be established between the nodes of concept lattice. If $C_1(X_1, B_1)$, $C_2(X_2, B_2)$ satisfies $X_1 \subseteq X_2$ or $B_2 \subseteq B_1$, then $C_1(X_1, B_1)$ is called a sub-concept, and $C_2(X_2, B_2)$ is called a parent concept, which can be expressed as $C_1(X_1, B_1) \leq C_2(X_2, B_2)$. The relationship $\leq$ is called the partial order of concepts. For all concepts in a formal context, the set of partial orders produces the concept lattice $L(U, A, I)$, which is unique for a specific formal context $K(U, A, I)$.

C. HASSE DIAGRAM

Hasse diagram [18] is the visual representation of concept lattice, which effectively shows the partially ordered relationships of all concepts in the concept lattice. Each node in the Hasse diagram represents a concept, and the connections between the nodes indicate the generalization-specialization relationships. The positions of the nodes in Hasse diagram are arranged from bottom to top according to their orders. For the partially ordered set $(S, \leq)$, if y covers x (that is, $x < y$ and $\neg\exists z(x < z < y)$), then the line from x up to y is added.

D. FUZZY CONCEPT LATTICE

There are many vague concepts in people's thinking, such as young, big, warm, evening, etc. In the real world, there are a lot of fuzzy phenomena [19]. Fuzzy theory and FCA can be combined to deal with uncertain information. In 1994, A. Burusco and R. Fuentes proposed the fuzzy concept lattice theory [20], which is the combination of concept lattice and Zadeh fuzzy set theory [21], [22].

Liu et al. [23] and Qiang et al. [24] discussed the construction algorithms and applications of fuzzy concept lattice. Jaoua and Elloumi [25] took advantage of implication operator to generate the fuzzy concept lattice, studied the concept lattice with varying accuracy, and introduced the variable threshold concept lattice. Tho et al. [26] studied the combination of the fuzzy set theory and FCA, and discussed the technique of fuzzy formal concept analysis (FFCA). This technique can be used to calculate the similarity between the fuzzy formal concepts. Sun and Qin [27], Liu et al. [28] used residual implication and different implication operators to generate fuzzy concept lattice. Sun et al. [29] discussed an fuzzy concept generation method based on alternate objects and attributes. Chen et al. [30], Chen and Luo [31] studied the generation approach of interval-valued fuzzy concept lattice.

E. INTELLIGENT DISEASE DIAGNOSIS

Intelligent medical diagnosis is the goal the expert system attempts to achieve [32]. Some meaningful works have been done by researchers. Miller et al. [33] developed the famous Internist-I internal medicine computer aided diagnosis system. Barnett et al. [34], at Harvard Medical School, developed the interpretation software, including about 2200 kinds of diseases and 5000 kinds of symptoms. Umbaugh et al. [35] developed a skin cancer aided diagnosis system. Provan and Clarke [36] constructed a decision support system to help diagnose the chronic abdominal pain. Keith and Greene [37] developed an intelligent CTG analysis system, which is a combination of digital algorithms and artificial neural network methods. Birndorf et al. [38] developed a diagnostic expert system for anemia. Wells et al. [39] developed a knowledge based system for breast cancer treatment planning. Recently some researchers have carried out a wide range of research in the field of intelligent diagnosis of diseases. The fields of expert system and concept lattice have also achieved good results. The application of concept lattice in medical field is worthy of further research.

III. FUZZY CONCEPT LATTICES BASED ON DISEASE

According to the general process of clinical medical diagnosis, fuzzy concept lattices can be used in medical information retrieval and disease diagnosis.

A. FUZZY FORMAL CONTEXT OF DISEASE

The symptoms and the corresponding extents of each disease can be extracted to form a fuzzy formal context $K(U, A, I)$, where U indicates a set of symptoms of the disease, A indicates a set of the corresponding extents of symptoms, and I is a membership function, $U \times A \rightarrow [0,1]$. The extent of a symptom mainly includes the frequency at which it occurs, the severity the patient suffers it, and the duration it lasts.

In the fuzzy formal context $K(U, A, I)$, for each $a \in A$, $\varphi_a (0 \leq \varphi_a \leq 1)$ is given. Suppose $\theta K = (U, A, I_\theta)$, and I_θ is defined as:

$$I_\theta(u,a) = \begin{Bmatrix} I(u,a), \ if \ I(u,a) \geq \theta\varphi_{ai} \\ 0, \ if \ I(u,a) < \theta\varphi_{ai} \end{Bmatrix}$$

The fuzzy concept $C_i = (U_i, A_i)(i = 1, \ldots, n, n$ is the number of the fuzzy concepts), $U_i \subseteq U, A_i \subseteq A$, satisfies:

$$\forall U_i \subseteq U, g(U_i) = \{a | \forall u \in U_i, I(u,a) \geq \theta\varphi_{ai}\}$$
$$\forall A_i \subseteq A, g(A_i) = \{u | \forall a \in A_i, I(u,a) \geq \theta\varphi_{ai}\}$$

Table 1 shows the fuzzy formal context of the common cold. Suppose φ_{ai} is the average value of each column, and $\theta = 0.8$. The values over $\theta\varphi_{ai}$ in each column keep the original value, otherwise take zero value. Then the objects whose corresponding attribute values are over $\theta\varphi_{ai}$ are merged, and the fuzzy formal concepts of the common cold are obtained as shown in Table 2.

TABLE 1. The Fuzzy Formal Context of the Common Cold

	Frequency			Severity		Duration	
Symptom	a	b	c	d	e	f	g
1	0.1	0.1	**0.8**	0.2	**0.8**	0.2	**0.8**
2	0.1	**0.7**	0.2	0.1	**0.9**	0.2	**0.8**
3	**0.8**	0.1	0.1	**0.8**	0.2	**1.0**	0.0
4	**0.7**	0.2	0.1	**0.7**	0.3	**0.8**	0.2
φ_{ai}	0.43	0.28	0.3	0.45	0.55	0.55	0.45
$\theta\varphi_{ai}$	0.34	0.22	0.24	0.36	0.44	0.44	0.36

Note: 1- fever, 2- headache, 3- runny nose, 4- cough, a- high frequency, b- medium frequency, c- low frequency, d- severe, e- non-severe, f- long, g- short. Suppose $\theta = 0.8$.

TABLE 2. The Fuzzy Formal Concepts of the Common Cold

Fuzzy Concept	Fuzzy Concept	Fuzzy Concept	Fuzzy Concept
({1},{c,e,g})	({2},{b,e,g})	({3,4},{a,d,f})	({1,2},{e,g})

B. FUZZY CONCEPT LATTICE BASED ON DISEASE

The symptoms of the disease can be regarded as objects, and the extents of symptoms can be regarded as attributes. The pair of object-attribute (i.e., symptom-extent) can be defined as the concept. Then the fuzzy concept lattice can be obtained. Fig. 1 shows the fuzzy concept lattice corresponding to Table 1.

IV. INTELLIGENT DISEASE DIAGNOSIS BASED ON FUZZY CONCEPT LATTICE

The fuzzy concept lattice of the symptoms and their extents to be diagnosed need to be constructed to match the fuzzy concept lattice of possible diseases. The most probable disease of the patient to be diagnosed can be presumed then.

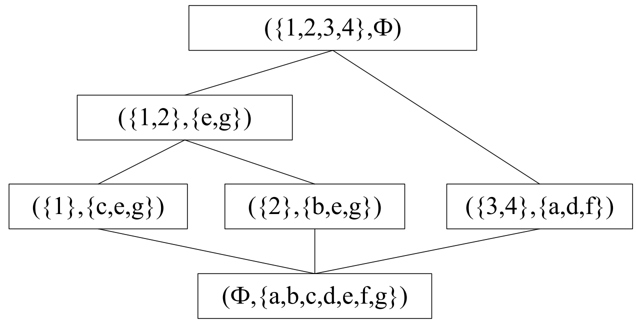

FIGURE 1. The fuzzy concept lattice of the common cold.

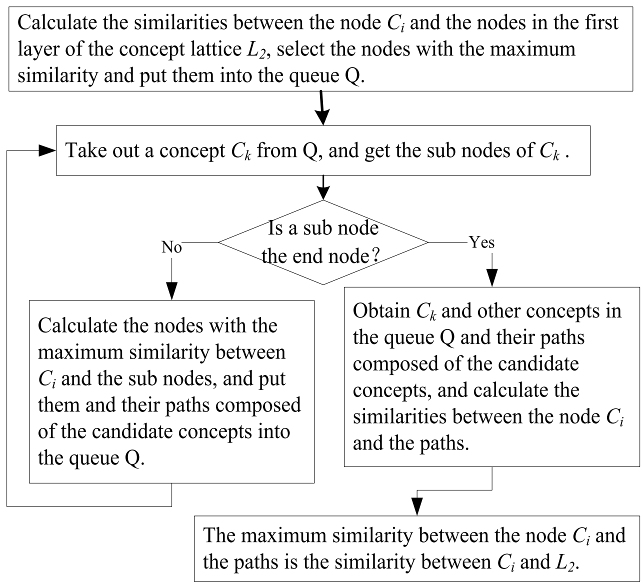

FIGURE 2. Calculation of the similarity between the node C_i and the concept lattice L_2.

A. SIMILARITY BETWEEN TWO CONCEPT NODES

For two concepts $C_1 = (U_1, A_1)$ and $C_2 = (U_2, A_2)$ in one or more formal contexts, let r be the maximum value of the cardinalities of U_1 and U_2, and m be the maximum value of the cardinalities of A_1 and A_2, i.e.,

$$r = \max(|U_1|, |U_2|); m = \max(|A_1|, |A_2|)$$

Then the similarity between two concepts $C_1 = (U_1, A_1)$ and $C_2 = (U_2, A_2)$ can be calculated as follows:

$$Sim(C_1, C_2) = \begin{cases} \frac{|U_1 \cap U_2|}{r} \times p + \frac{|U_1 \cap U_2|}{r} \times \frac{|A_1 \cap A_2|}{m} \\ \quad \times (1-2p) + \frac{|A_1 \cap A_2|}{m} \times p, \ U_1 \cap U_2 \neq \emptyset \\ 0, \ U_1 \cap U_2 = \emptyset \end{cases}$$

Wherein p is a weighting factor $(0 \leq p \leq 0.5)$.

B. SIMILARITY BETWEEN CONCEPT NODE AND CONCEPT LATTICE

The similarities between a concept node C_i of one concept lattice L_1 and concept nodes in each layer of another concept lattice L_2 can be calculated. Then the concept nodes with the

TABLE 3. The Fuzzy Formal Context of the Symptoms of a Patient

	Frequency			Severity		Duration	
Symptom	a	b	c	d	e	f	g
1	**0.6**	0.2	0.2	**0.7**	0.3	**0.7**	**0.3**
2	0.2	**0.3**	**0.5**	**0.4**	**0.6**	0.4	**0.6**
4	0.2	**0.5**	**0.3**	0.3	**0.7**	**0.8**	0.2
φ_{ai}	0.33	0.33	0.33	0.47	0.53	0.63	0.37
$\theta\varphi_{ai}$	0.26	0.26	0.26	0.38	0.42	0.50	0.30

Note: 1- fever, 2- headache, 4- cough, a- high frequency, b- medium frequency, c- low frequency, d- severe, e- non-severe, f- long, g- short. Suppose $\theta = 0.8$.

maximum similarity in the layer are selected as the candidate nodes, and the sub concept nodes of the candidate nodes are calculated in turn. Through layer by layer recursion, one or more paths can be obtained. The similarity between the concept node C_i and the concept lattice L_2 is defined as follows [40]:

$$Sim(C_i, L_2) = \max\left(\frac{\sum_{C_k \in R_j} sim(C_i, C_k)}{n_j}\right)$$

Wherein R_j is a path composed of the candidate concepts ($j = 1, \ldots, s$, s is the number of candidate paths), n_j is the number of nodes in the path R_j, and C_k is a node in the path R_j ($k = 1, \ldots, t$, t is the number of nodes in the path R_j). The similarity between the node C_i and the path R_j is the average value of the similarities of C_i and all the candidate nodes in the path R_j. The calculation steps of the similarity between the node C_i and the concept lattice L_2 are shown in Fig. 2.

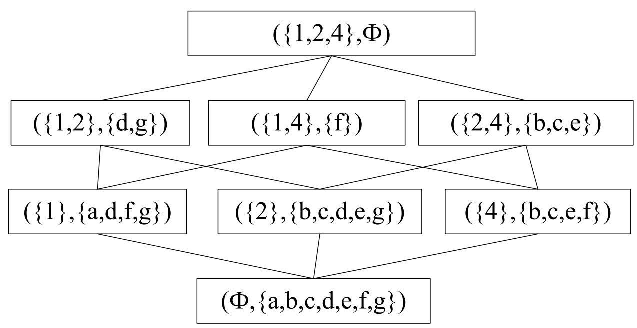

FIGURE 3. The fuzzy concept lattice of the symptoms of the patient.

C. SIMILARITY BETWEEN TWO CONCEPT LATTICES

The similarity of two concept lattices is regarded as the average value of the similarities of all nodes in the concept lattice L_1 and the concept lattice L_2 [40].

$$Sim(L_1, L_2) = \frac{\sum_{C_i \in L_1} Sim(C_i, L_2)}{n_1}$$

Wherein n_1 is the number of the concept nodes in L_1. Suppose the symptoms of a patient are shown in Table 3. The fuzzy

TABLE 4. Calculation of the Similarity of the Fuzzy Concept Lattices of the Patient's Symptoms and the Common Cold

Formal Concepts of the Patient's Symptoms	Formal Concepts of the Common Cold	Similarity	The Selected Nodes with the Maximum Similarity in Each Layer
({1},{a,d,f,g})	({1,2},{e,g})	0.25	selected
	({3,4},{a,d,f})	0	
	({1},{c,e,g})	0.4375	selected
	({2},{b,e,g})	0	
		$Sim(C_i, L_2) =$ (0.25+0.4375)/2= 0.229	
({2},{b,c,d,e,g})	({1,2},{e,g})	0.325	selected
	({3,4},{a,d,f})	0	
	({1},{c,e,g})	0	
	({2},{b,e,g})	0.7	selected
		$Sim(C_i, L_2) =$ (0.325+0.7)/2= 0.513	
({4},{b,c,e,f})	({1,2},{e,g})	0	
	({3,4},{a,d,f})	0.25	selected
		$Sim(C_i, L_2) =$ 0.25	
({1,2},{d,g})	({1,2},{e,g})	0.625	selected
	({3,4},{a,d,f})	0	
	({1},{c,e,g})	0.292	selected
	({2},{b,e,g})	0.292	selected
		$Sim(C_i, L_2) =$ (0.625+0.292)/2= 0.459	
({1,4},{f})	({1,2},{e,g})	0.125	
	({3,4},{a,d,f})	0.292	selected
		$Sim(C_i, L_2) =$ 0.292	
({2,4},{b,c,e})	({1,2},{e,g})	0.292	selected
	({3,4},{a,d,f})	0.125	
	({1},{c,e,g})	0	
	({2},{b,e,g})	0.458	selected
		$Sim(C_i, L_2) =$ (0.292+0.458)/2= 0.375	

concept lattice of the symptoms of the patient can be obtained as shown in Fig. 3.

Suppose the weighting factor$p$ is set to 1/4, then the similarity of the fuzzy concept lattices of the patient's symptoms and the common cold is calculated as shown in Table 4. According to the calculation in Table 4, the result is $Sim_1 = (0.229 + 0.513 + 0.25 + 0.459 + 0.292 + 0.375)/6 = 0.353$.

D. INTELLIGENT DISEASE DIAGNOSIS BASED ON FUZZY CONCEPT LATTICE

An example of intelligent disease diagnosis based on fuzzy concept lattice is given. The possible disease sets include

TABLE 5. The Fuzzy Formal Context of the Viral Pharyngitis

	Frequency			Severity		Duration	
Symptom	a	b	c	d	e	f	g
1	**0.8**	0.1	0.1	**0.8**	0.2	**0.8**	0.2
2	0.3	**0.5**	0.2	**0.7**	**0.3**	**0.7**	**0.3**
3	0.0	0.1	**0.9**	0.1	**0.9**	0.1	**0.9**
4	**0.8**	0.1	0.1	**0.9**	0.1	**0.8**	0.2
5	**0.9**	0.1	0.0	**0.9**	0.1	**0.9**	0.1
φ_{ai}	0.56	0.18	0.26	0.68	0.32	0.66	0.34
$\theta\varphi_{ai}$	0.45	0.14	0.21	0.54	0.26	0.53	0.27

Note: 1- fever, 2- headache, 3- runny nose, 4- cough, 5- sputum, a- high frequency, b- medium frequency, c- low frequency, d- severe, e- non-severe, f- long, g- short. Suppose $\theta = 0.8$.

TABLE 6. The Fuzzy Formal Context of Pneumonia

	Frequency			Severity		Duration	
Symptom	a	b	c	d	e	f	g
1	**0.9**	**0.1**	0.0	**0.9**	0.1	**0.8**	**0.2**
4	**0.9**	**0.1**	0.0	**0.9**	0.1	**0.9**	0.1
5	**0.8**	**0.1**	**0.1**	**0.8**	**0.2**	**0.9**	0.1
φ_{ai}	0.87	0.1	0.03	0.87	0.13	0.87	0.13
$\theta\varphi_{ai}$	0.70	0.08	0.02	0.70	0.104	0.70	0.104

Note: 1- fever, 4- cough, 5- sputum, a- high frequency, b- medium frequency, c- low frequency, d- severe, e- non-severe, f- long, g- short. Suppose $\theta = 0.8$.

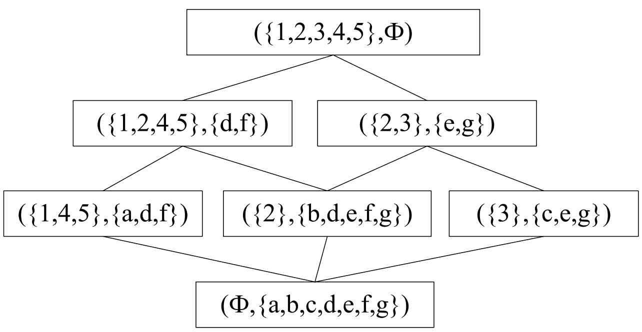

FIGURE 4. The fuzzy concept lattice of the viral pharyngitis.

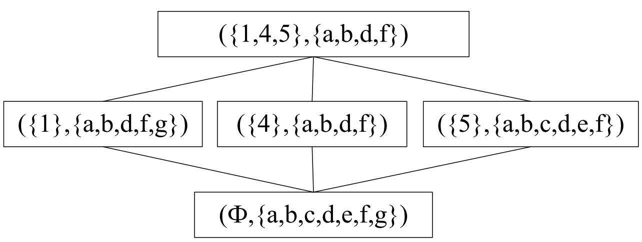

FIGURE 5. The fuzzy concept lattice of pneumonia.

the common cold, the viral pharyngitis, and pneumonia. The fuzzy formal context of the viral pharyngitis is shown in Table 5. The fuzzy formal context of pneumonia is shown in Table 6.

TABLE 7. Calculation of the Similarity of the Fuzzy Concept Lattices of the Patient's Symptoms and the Viral Pharyngitis

Formal Concepts of the Patient's Symptoms	Formal Concepts of the Viral Pharyngitis	Similarity	The Selected Nodes with the Maximum Similarity in Each Layer
({1},{a,d,f,g})	({1,2,4,5},{d,f})	0.25	selected
	({2,3},{e,g})	0	
	({1,4,5},{a,d,f})	0.396	selected
	({2},{b,d,e,f,g})	0	
		$Sim(C_i, L_2) =$ (0.25+0.396)/2= 0.323	
({2},{b,c,d,e,g})	({1,2,4,5},{d,f})	0.138	
	({2,3},{e,g})	0.325	selected
	({2},{b,d,e,f,g})	0.85	selected
	({3},{c,e,g})	0	
		$Sim(C_i, L_2) =$ (0.325+0.85)/2= 0.588	
({4},{b,c,e,f})	({1,2,4,5},{d,f})	0.156	selected
	({2,3},{e,g})	0	
	({1,4,5},{a,d,f})	0.188	selected
	({2},{b,d,e,f,g})	0	
		$Sim(C_i, L_2) =$ (0.156+0.188)/2 =0.172	
({1,2},{d,g})	({1,2,4,5},{d,f})	0.375	selected
	({2,3},{e,g})	0.375	selected
	({1,4,5},{a,d,f})	0.222	
	({2},{b,d,e,f,g})	0.325	selected
	({2},{b,d,e,f,g})	0.325	selected
	({3},{c,e,g})	0	
		$Sim(C_i, L_2) =$ (0.375+0.325)/2 =0.35	
({1,4},{f})	({1,2,4,5},{d,f})	0.375	selected
	({2,3},{e,g})	0	
	({1,4,5},{a,d,f})	0.361	selected
	({2},{b,d,e,f,g})	0	
		$Sim(C_i, L_2) =$ (0.375+0.361)/2 =0.368	
({2,4},{b,c,e})	({1,2,4,5},{d,f})	0.125	
	({2,3},{e,g})	0.292	selected
	({2},{b,d,e,f,g})	0.325	selected
	({3},{c,e,g})	0	
		$Sim(C_i, L_2) =$ (0.292+0.325)/2 =0.309	

The fuzzy concept lattice of the viral pharyngitis is shown in Fig. 4, and the fuzzy concept lattice of pneumonia is shown in Fig. 5.

TABLE 8. **Calculation of the Similarity of the Fuzzy Concept Lattices of the Patient's Symptoms and Pneumonia**

Formal Concepts of the Patient's Symptoms	Formal Concepts of Pneumonia	Similarity	The Selected Nodes with the Maximum Similarity in Each Layer
({1},{a,d,f,g})	({1,4,5},{a,b,d,f})	0.396	selected
	({1},{a,b,d,f,g})	0.85	selected
	({4},{a,b,d,f})	0	
	({5},{a,b,c,d,e,f})	0	
		$Sim(C_i, L_2)=$ (0.396+0.85)/2= 0.623	
({2},{b,c,d,e,g})	({1,4,5},{a,b,d,f})	0	
		$Sim(C_i, L_2)=0$	
({4},{b,c,e,f})	({1,4,5},{a,b,d,f})	0.292	selected
	({1},{a,b,d,f,g})	0	
	({4},{a,b,d,f})	0.625	selected
	({5},{a,b,c,d,e,f})	0	
		$Sim(C_i, L_2)=$ (0.292+0.625)/2= 0.459	
({1,2},{d,g})	({1,4,5},{a,b,d,f})	0.188	selected
	({1},{a,b,d,f,g})	0.325	selected
	({4},{a,b,d,f})	0	
	({5},{a,b,c,d,e,f})	0	
		$Sim(C_i, L_2)=$ (0.188+0.325)/2= 0.257	
({1,4},{f})	({1,4,5},{a,b,d,f})	0.313	selected
	({1},{a,b,d,f,g})	0.225	
	({4},{a,b,d,f})	0.25	selected
	({5},{a,b,c,d,e,f})	0	
		$Sim(C_i, L_2)=$ (0.313+0.25)/2= 0.282	
({2,4},{b,c,e})	({1,4,5},{a,b,d,f})	0.188	selected
	({1},{a,b,d,f,g})	0	
	({4},{a,b,d,f})	0.25	selected
	({5},{a,b,c,d,e,f})	0	
		$Sim(C_i, L_2)=$ (0.188+0.25)/2= 0.219	

The fuzzy concept lattice of the patient's symptoms needs to match the fuzzy concept lattices of possible diseases, and the corresponding similarities are calculated. According to the same calculation steps, the similarity of the fuzzy concept lattices of the patient's symptoms and the viral pharyngitis is calculated, which is $Sim_2 = (0.323+0.588+0.172+0.35+0.368+0.309)/6 = 0.352$, as shown in Table 7.

Then the similarity of the fuzzy concept lattices of the patient's symptoms and pneumonia is calculated, which is $Sim_3 = (0.623+0+0.459+0.257+0.282+0.219)/6 = 0.307$, as shown in Table 8. The disease with the largest similarity is the finding of intelligent diagnosis. Therefore the patient is most likely to suffer from the common cold.

V. CONCLUSION

This work proposes a novel intelligent disease diagnosis method based on fuzzy concept lattice. According to the general process of clinical medical diagnosis, fuzzy concept lattices can be used in medical information retrieval and disease diagnosis. Symptoms and their extents of each disease can be extracted to form a fuzzy formal context. The symptoms of the disease can be regarded as the objects, and the extents of symptoms can be regarded as the attributes. The fuzzy concept lattice of the symptoms and their extents to be diagnosed needs to be constructed to match the fuzzy concept lattice of possible diseases. Then the most probable disease of the patient to be diagnosed can be presumed. The similarity of the fuzzy concept lattices of the patient's symptoms and possible diseases can be calculated. The disease with the largest similarity is the finding of intelligent diagnosis.

In the future, we will take into account the weight values of the symptoms of each disease upon calculating the similarity of the fuzzy concept lattices, further explore more efficient fuzzy concept lattice construction method and update algorithm which are supposed to be highly complicated, and further study the intelligent disease diagnosis system based on concept lattice.

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CAIFENG ZOU (S'13) received the M.S. degree in computer application technology from Sun Yat-sen University, Guangzhou, in 2008, and the B.S. degree in computer science and technology from Shanghai University, Shanghai, in 2006. She is currently pursuing the Ph.D. degree in computer software and theory with the South China University of Technology, Guangzhou. She is currently a Lecturer with the Guangdong Mechanical and Electrical College, Guangzhou. Her current research interests include data mining, cloud computing, and internet of things.

HUIFANG DENG received the B.Sc. and M.Sc. degrees in China and the Ph.D. degree from the University College London. He is currently a Full Professor with the School of Computer Science and Engineering, South China University of Technology, Guangzhou, China. His current research interests include RFID technology and applications, Internet of Things, cloud computing, data science, information diffusion theory, social computing, computer simulation and modeling, service and advanced computing, massive parallel high-performance supercomputing, large-scale scientific supercomputing etc., He has authored or co-authored over 110 papers published in English, co-chaired over 10 international conferences outside China, and hosted China "863" and provincial-level key research projects.