International Journal of Computer Applications (0975 – 8887)
Volume 57– No.22, November 2012

Robust Implementation of ALFIS for Prediction of Medical Information System

Sindhu.M
Assistant Professor
Pollachi Institute of Engineering and Technology
Pollachi

S.Venkatesh
Assistant Professor
Pollachi Institute of Engineering and Technology
Pollachi

A. Mary Benita
PG Scholar, Dept of IT
SRM University
Kattankulathur, Chennai

ABSTRACT
The institute of medicine has long recognized Problems with health care quality and for more than a decade has advocated using health information technology to improve quality. The fuzzy cognitive map has gradually emerged as a concrete paradigm for knowledge representations, and simulation conditions are applicable, to numerous research and application field. However we have proposed efficient methods to determine clustering based investigated systems, for medical decision making. The manually developed models have a substantially shortcoming due to difficulties in assessing its reliability. In this paper we proposed a fuzzy logical network that enhances the learning ability of FCM. Our approach discusses the inference mechanisms of conventional FCM in the determination of membership functions. FCM models of investigations system can be automatically constructed from medical data using our approach. In the employed fuzzy logical networks the concept of mutual subset used to describe the casualties which provide more transparent interpretations in FCM. The effectiveness of the proposed approach in prediction of jaundice using clustering is demonstrated through numerical simulation.

General Terms
Artificial Intelligence, Medical decision making system.

Keywords
FCM, IFS, IFCM, Clustering, Inference mechanism.

1. INTRODUCTION
Medical diagnostics investigations are complicated to find out the decision making in Medical Diagnosis is the result of logical reasoning. Medicine was one of the first fields in which Lotfi zadeh's fuzzy set theory [1] applied .However in the 20^{th} century there have been and still are philosophers of science who pointed out that there is a need for the new methods in medical science and, that there is an inadequacy of conventional scientific methods for dealing with medical knowledge. Even philosophers in the first half of the 20th century were not aware of fuzzy sets. After 1970 its formal introduction the use of fuzzy concepts are extended from the philosophy of medicine to the technology of medicine. The beginnings of the development of Artificial intelligence systems in medicine can be traced back to very early research projects such as a marginal punched card system and a mathematical model in the 1950's.For more than a decade the medical decision making and the extension of FCM is the foremost research objectives, revolutionary modeling approaches based on the Bayesian logic [3] have appeared from the time when the late 1950's. Soon after fuzzy logic has been used to Model the innate uncertainty present in the real world medical decision making. With the approaches of Zadeh, Sanchez, and Adlassing to be the most predictable ones. Till recently considerable results obtained in modeling. Medical decision making with artificial cognitive structures has been among the leading research objectives. Towards this direction substantial results providing indications on the applicability of such structure for practical decision support have been obtained by FCM based on fuzzy logic [13]. Kosko introduces the theory ofFCM, on the basis of Axelrod work on cognitive maps. FCM's are trouble free and appropriate to explicitly encode the knowledge and experience accumulated on the operation of a complex system. Once constructed for a particular domain, FCM allows quantitative simulation of a system, using concepts and the relationships between them, while considering the degree of uncertainty that may characterize these relationships in the real world by using fuzzy logic. Regarding the inference networks FCM is a directed graph, consists of a nodes and Directed weighted arcs that interconnect nodes and can be used any type of shortest path to find out feasible solution in the network, that's why we can find out the destination address through this algorithm easily. This paper presents new efficient shortest path algorithms to solve single origin shortest path problems
in FCM. The effectiveness of the proposed approach in prediction of jau
(SOSP problems) and multiple origins shortest path problems (MOSP problems) for hierarchically clustered data networks. To solve an SOSP problem for a network with n nodes, the distributed version of our algorithm reaches the time complexity of O (log (n)), which is less than the time complexity of O (log 2 (n)) achieved by the best existing algorithm. To solve an MOSP problem, our algorithm minimizes the needed computation resources, including computation processors and communication links for the computation of each shortest path so that we can achieve massive parallelization. The time complexity of our algorithm for an MOSP problem is O (m log(n)), which is much less than the time complexity of O (M log2 (0)) of the best previous algorithm. Here, M is the number of the shortest paths to be computed and m is a positive number related to the network topology and the distribution of the nodes incurring communications, m is usually much smaller than M. Our experiment shows that m is almost a constant when the network size increases. Accordingly, our algorithm is significantly faster than the best previous algorithms to solve MOSP problems for large data networks.

The application of generalizations of conservative fuzzy sets such as the IFS have this been already provided indications for their applicability in the province. We investigate the use of IFS as a method for constructing an FCM model in the presence of imperfect facts and imprecise knowledge. IFS comprise of elements characterized by both membership and non membership value. Membership value indicates the degree of belongingness to the set, Non membership value indicate an element that does not belongs to the set. Original FCM has two significant drawbacks. Till recently MIAO, Liu and SATAR [12] have made research about the extension of FCM and inference properties of FCM. FCM lack effective methods to determine system states and they are limited to the fuzzy domain which makes difficult to compare inference results with real data and it greatly depend on expert knowledge.

Our motive is, improving FCM by automatically identify membership functions for the investigated systems and to determine the states of investigated systems and how to quantify the causalities in the FCM. By using clustering methods .In order to deal with this difficulty first attempt to learn FCM using Hebbian law, non linear Hebbian learning algorithm. However in proposed approaches causalities needed to be quantified are not exactly consistent with the conventional FCM, also lack clear mathematical interpretations. To overcome the drawbacks and we employ FCM to implement prediction by using preprocessing of clustered raw dataset which makes prediction more complex.

In this paper we propose a fuzzy logical network that equips the inference mechanisms of original FCM with the automatic identification of membership functions and quantification of causalities. When the amount of data is available our approaches able to construct FCM for complex system with less expert knowledge [12] [13]. In addition our approach make it possible to compare the inference results with real data such as prediction of disease, by using mutual subset hood to define and describe causalities in the investigated systems also it provides clear mathematical interpretation on causalities and easy to understand. In this a factor of hesitancy is introduced into the weights of the FCM providing an additional cue to the cause effect relationships among concepts. Fuzzy clustering can be considered the most important unsupervised learning algorithm and fuzzy c-mean is the most popular fuzzy clustering method among different fuzzy clustering algorithms. The aim of this paper is to achieve an improved clustering performance for a given document collection and to improve retrieval performance for information research. FCM algorithm shows the superior nature in terms of convergence rate. Experimental results show the promising results for the modified FCM algorithm. This is the first approach to a mathematical formulation of IFCM enabling decision making in medicine through automated knowledge representation and reasoning.

The rest of this paper is organized as follows; Section II describes the representation of FCMs and stresses the motivation of our works, and its structures. Section III proposes the fuzzy logical network and discusses the corresponding functionalities and operations of network inference mechanisms. Section IV gives the detailed description of learning algorithm which is employed to tune the related parameters in the proposed fuzzy logical network by using ALFIS. In this section we enhance the learning ability of FCM. Our approach discusses the inference mechanisms of conventional FCM in the determination of membership functions. FCM models of investigations system can be automatically constructed from medical data using our approach To evaluate the performance, we employed ALFIS in the IFCM of fuzzy logical networks, in that the concept resolves pitfalls which provide more transparent interpretations in FCM. The effectiveness of the proposed approach in prediction using clustering is demonstrated through numerical simulation. Section V presents two applications in prediction of jaundice severity assessment and compares the results of the experiment with other models. Section VI provides construction of DM model. Finally VII concludes the paper.

2. RELATED WORK

2.1 FUZZY COGNITIVE MAPS

Intuitively, an FCM is a signed directed graph that represents a causal system with uncertain and incomplete causal information. The human experience and knowledge on the complex systems are embedded in the structure of FCMs and the corresponding inference process.

2.1.1 Genesis of FCM

FCM is developed from CMs [3]. The research about CMs sprung from findings in physical-psychological experiments that tried to trace and interpret the functionalities of various mental and cognitive tasks, abilities, and phenomena in animals and humans. Tolman [20] and Axelrod [3] described them in the formal and systemic manner. In detail, a CM represents a causal system that consists of a set of concepts and causal-effect relationships (causalities) among these concepts. By describing the causalities and the state information of concepts, CM reveals the impacts produced by the changes in all elements of the entire system. As far as CM structure is concerned, links between nodes may obtain only binary values, which are +1 and −1. The nodes may take the value −1, 0, and +1. Practically, node value +1 represents an increase of the concept state, and node value −1 means a decrease of the corresponding concept state. In order to overcome the drawbacks of the binary logic that CMs enclose, Kosko[1], [2] extended CMs to FCMs by introducing fuzzy values to quantify the concept states and the strength of causalities.

2.1.2 Fundamental of Structures

As an extension to CMs, FCMs incorporate fuzzy logic principles into CM theories and, therefore, provide a more realistic and accurate representations for the real causal systems than CMs do. An FCM is a signed directed graph with feedbacks, as shown in Fig. 1, which consists of a collection of nodes and directed-weighted arcs interconnecting the nodes. In FCMs, nodes represent the concepts that are abstracted from real-causal systems. Directed-weighted arcs denote the causal relationships among concepts. In FCMs, concepts C_i (i = 1, 2. . . N) represent a set of research objects with a semantic meaning that forms the investigated causal system, where N denotes the number of concepts in a given FCM. The active degree of concept C_i is described by state value s_i [0, 1], which changes over time in inference process. Therefore, concept states describe the behavioral characteristics of the system. The causal relationship between concept C_i and C_j in an FCM is represented by a directed arc pointing from C_i to C_j .In general, the weight w_{ij} associated with the arc connecting C_i with C_j takes the value in the interval [−1, 1], thus describing the type and magnitude of the corresponding causality. The weights with high absolute values signify strong cause-effect relationships among the concepts. In practice, the following conditions hold.

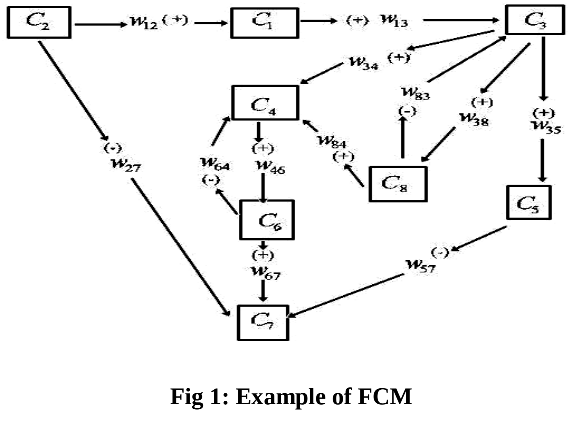

Fig 1: Example of FCM

1) 1 > w_{ij} ≥= 0, which indicates that the increase (decrease) in the value of C_i leads to an increase (decrease) in the value of C_j .
2) 0 > w_{ij} ≥= −1, which indicates that the increase (decrease) in the value of Ci leads to decrease (increase) in the value of C_j .
3) w_{ij} = 0, which indicates that there is no causal relationship between C_i and C .

As mentioned previously, our approach is proposed only to improve original FCMs proposed by Kosko [1]. Therefore, a concept cannot cause itself, and there is no causal relationship between a concept and itself. Therefore, for all the concepts in an FCM, there will be w_{ii} = 0. For the sake of simplicity, the weights in an FCM can be represented by a matrix.

$$w = \begin{pmatrix} \bullet & \cdots & W_{1,N} \\ \vdots & \ddots & \vdots \\ W_{N,1} & \cdots & \bullet \end{pmatrix}^n \times \begin{pmatrix} \bullet & \cdots & W_{1,N} \\ \vdots & \ddots & \vdots \\ W_{N,1} & \cdots & \bullet \end{pmatrix}^n$$

2.1.3 *Inference Mechanism of Fuzzy Cognitive Map*

The detailed inference mechanism of the original FCMs was introduced in many publications [1], [10]. Briefly, the process is to keep updating the state values of concepts in a discrete-time manner based on a given weight matrix W and the initial-state information of a particular system. The inference mechanism of FCMs is described by the following formula:

$$\begin{cases} S(t) = \left(si\ (t)\right)1 \times N \\ s_i(t+1) = f\left(\sum_{j=1}^{N} s_i(\mathrm{t}) \times w_{\mathrm{ji}}\right), +f\left(\sum_{j=1}^{N} s_i(\mathrm{t}) \times w_{\mathrm{ji}}\right) \end{cases}$$
$$= 1, 2, \ldots, N$$

Where t is the iteration step, and $s_i(t)$ indicates the state value of concept Ci at iteration t. Correspondingly, S(t) indicates the system state at iteration t, and f is a threshold (transformation) function. The inference process of an FCM can be regarded as an iterative process that applies the scalar product and threshold unction to generate the discrete-time series of system state until the following requirements on convergence are satisfied.

1) A fixed-point equilibrium is reached. In this case, S (t0+1) = S (t0)(t0 T), where S(t0) is the final state.

2) A limited cycle is reached. In this case, S(t0 +ΔT) = S (t0) (t0 T), where S(t0) is the final state. This case means that the system falls in a loop of a specific period, and after a certain number of inference steps ΔT, it reaches the same state S (t0).

3) Chaotic behavior is exhibited [21], [22].

2.1.4 Fuzzy Clustering

Fuzzy clustering relevant for information retrieval. as a document might be relevant to multiple queries, this document should be given in the corresponding response sets ,otherwise ,the user would not be aware of it ,Fuzzy clustering seems a natural technique for document categorization there are two basic methods of fuzzy clustering[4] ,one which is based on fuzzy c-partitions, is called a fuzzy c-means clustering method and the other, based on the fuzzy equivalence relations, is called a fuzzy equivalence clustering method.

2.1.5 Clinical Data Collection

The design conception of patient-centered is fully reflected in this model. We give an example of diagnose disease to analyze the effectiveness of the work process. As for a patient, there are mainly two ways to access the medical information system, which are remote and local. We give an authentication agent to every patient. And this agent is used as the only identity for extracting data in HIM.

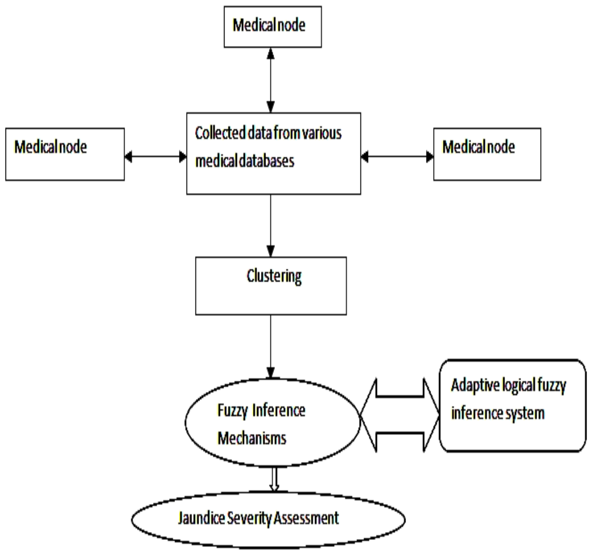

Fig 2: Construction of the Decision Making Model

3. NETWORK INFERENCE MECHANISMS

A number of network path delay, loss, or bandwidth inference mechanisms have been proposed over the past decade. Concurrently, several network measurement services have been deployed over the Internet and intranets. We consider inference mechanisms that use: $o(N)^2$

1) For which measurement request patterns would using an inference mechanism be advantageous?
2) How does a measurement service determine the set of hosts that should utilize inference mechanisms, as opposed to those that are better served using direct end-to-end measurements?

We explore three solutions that identify groups of hosts which are likely to benefit from inference. We compare these solutions in terms of effectiveness and algorithmic complexity. results with synthetic data sets and data sets from a popular peer-to-peer system demonstrate that our techniques accurately identify host subsets that benefit from inference, in significantly less time than an algorithm that identifies optimal subsets. The measurement savings are large when measurement request patterns exhibit small-world characteristics, which is often the case.

3.1 Adaptive Logical Fuzzy Inference System Basic Principle

ALFIS is a kind of commonly used fuzzy inference model based on the T-S model which is proposed by Takagi- Sugenon. It is a nonlinear model which is fit to express the dynamic characteristics of complex systems. The Fuzzy Inference System is mainly based on the experiences and knowledge of the experts or the operators but not on the models of the objects, while ANFIS has been widely used to forecasting flied because of the easy expressment of human knowledge in fuzzy logic and the nonlinear approximation capacity of the neural network and so on.

The model is expressed by a set which contains m fuzzy rules and the i -th fuzzy rule can be described as:

4. BASIC ARCHITECTURE OF ALFIS

R^i :if$(x_1\ is\ A_1^i), (x_2\ is\ A_2^i) \cdots (x_n\ is\ A_n^i)$ Then $f^{i=g(x_1,x_2\cdots x_n)}i= 1,2 \cdots m$

In this section we present the basic theory of ALFIS. Lately, artificial logical Network and fuzzy inference system have been widely used in many applications to solve complex nonlinear problem. Fuzzy Neural network, while fuzzy logic performs an inference system under cognitive uncertainty, logical networks possess the ability of learning, adaption, fault tolerance and generalization. Combinations of the two create system called fuzzy neural system. ALFIS is such system. Both fuzzy system and neural system are used in ALFIS [5].ALFIS consists of if-then rules and many input-output. Assume ALFIS has two inputs(x and y) and one output z. A typical rule set with if-then can be expressed as: If x is A1 and y is B1 then f = p*x + q*y + r (.where p, r, q are output parameters. The architecture of ALFIS can be seen in fig 1.

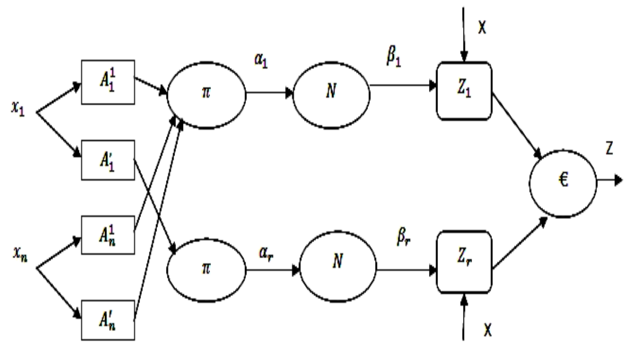

Fig 3: The architecture of ALFIS

5. ALFIS AND IFCM FOR PREDICTION OF JAUNDICE SEVERITY ASSESSMENT

Jaundice is not a disease but rather a sign that can occur in many different diseases. Jaundice is the yellowish staining of the skin and sclera (the whites of the eyes) that is caused by high levels in blood of the chemical bilirubin. The color of the skin and sclera vary depending on the level of bilirubin. When the bilirubin level is mildly elevated, they are yellowish. When the bilirubin level is high, they tend to be brown. Bilirubin comes from red blood cells. When red blood cells get old, they are destroyed. Hemoglobin, the iron-containing chemical in red blood cells that carries oxygen, is released from the destroyed red blood cells after the iron it contains is removed. The chemical that remains in the blood after the iron is removed becomes bilirubin. The liver has many functions. One of the liver's functions is to produce and secrete bile into the intestines to help digest dietary fat. Another is to remove toxic chemicals or waste products from the blood, and bilirubin is a waste product. The liver removes bilirubin from the blood. After the bilirubin has entered the liver cells, the cells conjugate (attaching other chemicals, primarily glucuronic acid) to the bilirubin, and then secrete the bilirubin/glucuronic acid complex into bile. The complex that is secreted in bile is called conjugated bilirubin. The conjugated bilirubin is eliminated in the feces. (Bilirubin is what gives feces its brown color.) Conjugated bilirubin is distinguished from the bilirubin that is released from the red blood cells and not yet removed from the blood which is termed unconjugated bilirubin. Jaundice occurs when there is 1) too much bilirubin being produced for the liver to remove from the blood.(For example, patients with hemolytic anemia have an abnormally rapid rate of destruction of their red blood cells that releases large amounts of bilirubin into the blood), 2) a defect in the liver that prevents bilirubin from being removed from the blood, converted to bilirubin/glucuronic acid (conjugated) or secreted in bile, or 3) blockage of the bile ducts that decreases the flow of bile and bilirubin from the liver into the intestines. (For example, the bile ducts can be blocked by cancers, gallstones, or inflammation of the bile ducts). The decreased conjugation, secretion, or flow of bile that can result in jaundice is referred to as cholestasis: however, cholestasis does not always result in jaundice. By using ALFIS the uncertainty present in the decision making has been resolved and also it overcomes the disadvantages of FCM and IFCM. The drawback of IFCM is missing the input values while determining the decision. ALFIS exhibits much more robustness to the uncertainties involved with in the input and output datasets. It’s shown that

ALFIS can be successfully applied into IFCM to resolve uncertainties, so that robust model can be obtained from some non-dominated ALFIS models.

6. CONSTRUCTION OF THE DECISION MAKING MODEL

The IFCM model for jaundice severity assessment has been designed with the contribution of three medical experts according to the methodology described in Section II. A total of N =34 concepts were identified. The concepts Ci , i = 1, 2, .., 34, are presented in Table I, along with the considered set of linguistic values and the respective real discrete values or intervals comprising the respective universes Ui . The fuzzy membership functions used are triangular, centered at each bounded interval, or trapezoidal for the unbounded intervals. Concepts C1-C33 comprise the model's input, whereas C34 represents the model's output. An indicative example of the membership functions considered in the construction of the IFCM model is presented in Fig. 2, for concept C34 .The influences between the concepts have been fuzzified using the twelve ι = 12 linguistic variables {―negatively very strong, negatively strong,||―negatively medium,|| ―negatively weak,|| ―negatively very weak,|| ―zero,||―positively very weak,||―positively weak, ||―positively medium, ||―positively strong,||―positively very strong,|| ―positively very very strong||} from fuzzy set I, and the hesitancies between the concepts have been fuzzified using h 6 linguistic variables {―zero,|| ―very low,||―low,|| ―medium, high,|| ―very high||} between the concepts. The opinions of the experts for the determination of the influence and hesitancy weights, and the obtained weight values are presented in Table II (where the linguistic values have been abbreviated due to space limitations). The aggregation of the corresponding membership functions has been performed by the fuzzy sum aggregator, whereas the real weight values have been obtained with the centre of gravity defuzzification method [31].The choice of these methods has been motivated mainly by their simplicity. In Fig. 4, we indicatively present the aggregated membership, nonmember ship, and hesitancy functions (7) corresponding to the IFCM edge directed from C16 to C34. This figure visually validates that the inequality in (4) holds, and shows that the nonmember ship is not necessarily symmetric to the membership function. The concepts along with the estimated influence of each other and the hesitancy in the expression of this influence, model the experts' knowledge on the decision-making task under study.

6.1 LOCAL MEDICAL PROCESS

The work process of local medical process can be described as following.

Step1: Use registration agent to enter OIS. Step2: Outpatient doctor diagnosis and the patient information enter EMRS. If the patient is without hospitalization, the medical data are stored in EMRS, and then they are sent to center database after the whole treatment process is finished.

Step3: The patient need hospitalize and the medical data temporarily are stored in EMRS, LIS, and PACS. When the patient get well and leave hospital, these medical data are sent to center database. The registration agent contains the information of certification and medical insurance. In the actual operation, it is a specific physical card. The patient may use this card to inquiry its clinic records including cost inventory in the medical system. The work efficiency is greatly improved and distributed database based agent bring great convenience for system construction and implementation.

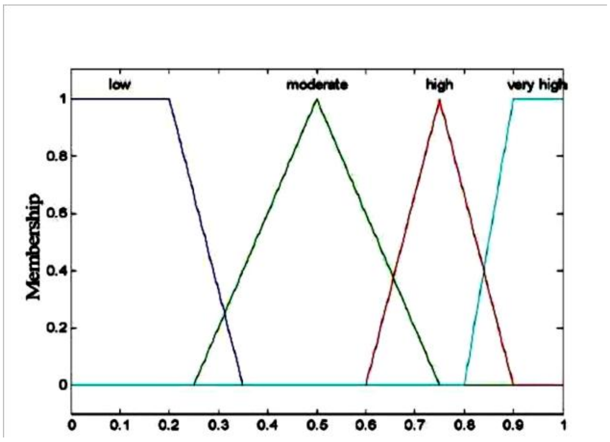

Fig 4: Severity of jaundice

Fig.4 Membership functions of the fuzzy sets Ln^{C34} , n = 1, . . . , 5,corresponding to the linguistic values used for the decision (output) concept C34 .

Table I
Concepts of the IFCM Model and the values

Concept	Linguistic Values(Real values
C1:Dyspnea	—no dyspnea||(0-0.15), —less serious||(0.1-0.5), —moderate||(0.3-0.7), —serious dyspnea||(0.5-1)
C2: Cough	—no cough||(0,0.15), —non productive||(0-0.3) —productive||(0.4-1)
C3: Rigor/chills	—no||(0),||yes||(1)
C4: Temperature	—hypothermia||(34-36) —normal(36-38.4)||,||low||(38.5,38.9), —moderate||(38.9,39.5),||high||(39.5-40.9),||hyperpyrexia||(>41)
C5: Loss Of appetite	—no||(0),||yes||(1)
C6: Debility(NYHA)	—no||(1),||small||(2), ||moderate||(3), ||large||(4)
C7: Abdominal pain	—no||(0),||yes||(1)
C8: Fatigue	—no||(0),||yes||(1)
C9: Dark yellow Urine	—no||(0),||low||(2-4),||medium||(4-15) —high||(mechanical ventilation, MV)
C10:Tachypnea	—normal||(12-24),||moderate||(2538), ||severe||(35-49,||very severe||(>=50)
C11:Acostic characteristics	—no||(0),||yes||(1)
C12: Mental status (Glascow Comma Scale)	—severe||(<=8),||moderate||(9-12), —minor||(>=13)
C13: Systolic blood pressure (mmHg)	—hypotension||(<90),||optimal||(<120), —normal||(<130), —high-normal||(130-139), —grade-1 hypertension||(140-159), —grade-2 hypertension||(160-179), —grade-3 hypertension||(>=180)
C14:Diastolic blood pressure(mmHg)	—hypotension||(<60),||optimal||(<80), —normal||(<85) —high-normal||(85-89), —grade-1 hypertension||(90-99), —grade-2 hypertension||(100-109), —grade-3 hypertension||(>=110)
C15:Tachycardia(beats/min)	—low||(<80),||normal||(90-110), —moderately severe||(110-140), —severe(>140)
C16:Radiological evidence of jaundice	—no||(0),||yes||(1)
C17:Radiological evidence of complicated Jaundice	—no||(0),||yes||(1)
C18:Acidity(pH)	—acidosis||(<7.35), —normal||(7.35-7.45) —alkalosis(>7.45)
C19:Partial pressure of Oxygen	—normal|| (70-100),||hypoxia||(<70) (PO2 in mmHg)
C20: Partial pressure of carbon dioxide ($_pO_{2 \text{ in mmHg}}$)	—normal||(35-45) ,||hypocapnia||(<35) —hypercapnia||(>45)

C21:Oxygen saturation(sO_2 %) C22:White blood cells(WBC) (count/µ1)
C23:Immunocompromise
C24:Comorbidities
C25:Age

C26:Sputum culture
C27:Bronchial secrets culture C28:Blood culture
C29:Change in stool colour C30:Mantoux
C31:Gram stain(+/_)
C32:Urinary antigen test
C33:Pathogen sensitivity(ACDP)

C34:Severity of Jaundice

—normal||(>95),||hypoxia||(<95)
—leukopenia||(<1000),||normal (4.3-10*10^3),||leukocytosis||(>10*$10^{3)}$
—no||(0)
,||yes||(1)
—no||(0),
||yes||(1)
—young||
(1-130),||
middle edged||(31-55),||
old
||(56-100)
—negative||(-1),||positive||(1)
—negative||(-1),||positive||(1)
—negative||(-1),||positive||(1)
—negative||(-1),||positive||(1)
—negative||(-1),||positive||(1)
—negative||(-1),||positive||(1)
—negative||(-1),||positive||(1)
—low||(2),||medium||(3),||high||(4)
(Advisory Committee on Dangerous Pathogens ,ACDP)

—low||(00.35),
||moderate||(0.2-50.75),
—high||(0.5-0.8),||very high||(0.7-1)

TABLE II
INFLUENCE AND HESITANCY WEIGHT VALUES

Relation (from-to)	**Linguitic Weights (I*nfluency(Hesitancy))]***			**Real weights**	
	First	**Second**	**Third**	**Influence**	**Hesitancy**
C1-C34	v-weak (v-low)	medium (v.low)	weak (v.low)	0.311	0.100
C2-C34	weak (v-low)	medium (v.low)	v-weak (v.low)	0.250	0.123
C3-C34	weak (v-low)	medium (low)	weak (v.low)	0.345	0.151
C4-C34	medium (v-low)	weak (v-low)	strong (zero)	0.448	0.070
C5-C34	v-weak	weak	v-weak	0.200	0.500
C6-C34	medium	medium	medium	0.500	0.500
C7-C34	v-weak (v-low)	weak (low)	v-weak (v-low)	0.150	0.123
C8-C34	strong (low)	medium (v-low)	strong (v-low)	0.584	0.123
C9-C34	weak	medium	weak	0.345	0.500
C10-C34	weak	weak	weak	0.300	0.500
C11-C34	weak	weak	V-weak	0.200	0.500
C12-C34	n.medium	n.weak	n.medium	-0.455	0.500
C13-C34	medium (v-low)	strong (low)	medium (low)	0.584	0.151
C14-C34	weak (v-low)	strong (v-low)	strong (v-low)	0.500	0.100
C15-C34	weak	medium	medium	0.400	0.500
C16-C34	medium (v-low)	strong (zero)	strong (low)	0.584	0.100
C17-C34	strong (zero)	v-strong (v-low)	v-strong (low)	0.740	0.100
C18-C34	weak	V-weak	V-weak	0.200	0.500
C19-C34	n.weak	n.medium	n.medium	-0.430	0.500
C20-C34	v-weak	V-weak	weak	0.200	0.500

C21-C34	n.weak (v-low)	n.medium (low)	n.medium (low)	-0.430	0.183
C22-C34	strong (v-low)	strong (v.low)	medium (v.low)	0.584	0.100
C23-C34	weak (v-low)	weak (v.low)	medium (low)	0.345	0.151
C24-C34	weak	strong	strong	0.500	0.500
C25-C34	medium	medium	weak	0.400	0.185
C26-C34	strong	strong	v-strong	0.700	0.100
C27-C34	strong (v-low)	v-strong (low)	strong (v.low)	0.700	0.151
C28-C34	strong	strong	strong	0.600	0.160
C29-C34	strong (low)	strong (low)	strong (low)	0.700	0.100
C30-C34	medium	weak	medium	0.400	0.250
C31-C34	v-strong	v-strong	v-strong	0.756	0.151
C32-C34	strong (v-low)	strong (v-low)	strong (low)	0.750	0.151
C33-C34	v-strong (v-low)	v-strong (v-low)	strong (low)	0.780	0.141
C16-C4	medium	medium	medium	0.500	500
C22-C12	n.weak (v-low)	n.weak (v.low)	n.medium (low)	-0.345	0.121
C4-C22	strong (v-low)	strong (v-low)	strong (low)	0.250	0.151
C4-C5	weak	V-weak	weak	0.300	0.258
C4-C15	weak	V-weak	weak	0.300	0.255
C21-C1	n.weak (v-low)	n.weak (low)	n.medium (v-low)	-0.345	0.121

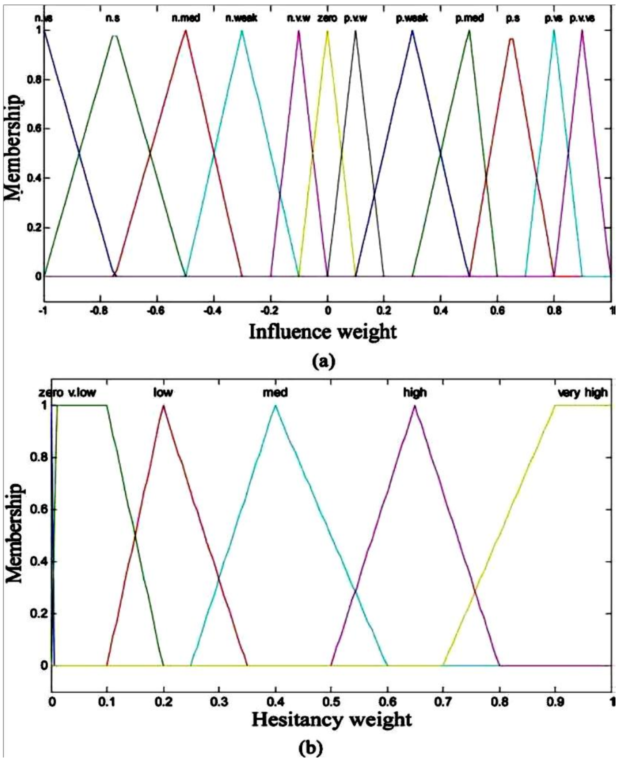

Fig 4.1 (a) Membership functions corresponding to the linguistic variables describing the influence of one IFCM concept to another. (b)Membership functions corresponding to the linguistic variables describing the hesitancy in the expression of the influence of one IFCM concept to another.

8. CONCLUSIONS AND FUTUR WORK

The area of Medical Decision Support Systems (MDSS) is characterized by complexity requiring the investigation of new advanced methods for modeling and development of sophisticated systems, which must adequately take into consideration the needs of medical practitioners. We investigated a novel approach to the construction of a cognitive map based on intuitionistic fuzzy logic for modeling uncertain imprecise, and/or incomplete medical knowledge.The comparative advantage of the proposed ALFIS over the conventional FCM model is that it can incorporate additional information regarding the hesitancy of the experts in the definition of the cause-effect relations between the concepts involved in a domain. The proposed model was
experimentally evaluated in comparison to previous models for decision making on jaundice severity assessment. By being intuitive, an ALFIS is capable of modeling real-world medical
Decision-making tasks closer to the way humans perceive them. It is easily understandable, even by a nontechnical audience, and each of its parameters has a perceivable meaning.

1) Intuitionistic fuzzy logic improves the knowledge elicitation and, consequently, the FCM-based decision making.

2) The decision-making performance of ALFISs is more robust than the conventional FCM and the preliminary ALFIS approaches in the presence of incomplete data. Future work includes the application of the proposed decision-making model in various domains, exploration of alternative approaches to the exploitation of intuitionistic fuzzy logic in even more effective modeling of medical
Knowledge and decision making.

9. REFERENCES

[1] Babushka Fuzzy Modeling for Control K1uwer Aca.Pub London (1998).

[2] Bezdek C et al, FCM Fuzzy c-means clustering algorithm Computers and Geoscience, 1984, 10(2-3), l91-203.

[3] Hammouda M, Web Mining: Identifying Document Structure for Web Document Clustering Master's Thesis, Department of Systems Design Engg , Canada (2002).

[4] Kanjani Parallel Nonnegative Matrix Factorization for Document Clustering CPSC-659 spring (2007)

[5] Mendes ES et al, A Scalable Hierarchical Fuzz Clustering Algorithm for Text Mining, UK.

[6] Grira M et al, Unsupervised and semi-supervised clustering: a brief survey (2004)

[7] Guh et al Cure: an Efficient Clustering Algorithm for Large Databases Proceedings of the 1 998 ACM SIGMOD Int.Conf. On Mgt of data ACM Press,(1998) 73-84.

[8] Change HH Intelligent Agent’s Technolog Characteristics Applied to Online Auctions Task A Combined Model of TTF and TAM Technovation 28 (9), 564-577, 2008.

[9] Kahramanli H et al Design of a Hybrid System for the Diabetes and Heart Diseases Expert Systems with Applications 35(1-2) 82-89, (2008).

[10] Grant P A new A approaches to Diabetic Control:Fuzzy Logic and Insulin pump Technology Medical Engineering & Physics 29(7)824-827, (2007).

[11] Hayashi K et al, Simulator for Studies of Fuzzy Control Methods Fuzzy Sets and Systems 93, 137-144(1998).

[12] Guillaume S, Designing Fuzzy Inference System From Data: An Interpretability Oriented Review, IEEE Transaction on Fuzzy Systems, 9(3), 426-443, (2001)

[13] Balasko B et al, Fuzzy clustering and data analysis toolbox for use with MATLAB(2010).

[14] Mamdami EH et al An Experirnalment in linguistic Synthesis with a Fuzzy Logic Controlle, Int.Jou. of Man-Machine Studies, 7(1)1-13(1975).

[15] Acampora G et al Using FML and Fuzzy Technology in Adaptive Ambient Intelligence Environments Int.Jou. Of Computational Intelligence Research, 1(2)171-182 (2005).

[16] Ross TS Fuzzy Logic with Engineering Applications, McGraw Hill Int. Ed (1997).

[17] Saade JJ A Unifying Approach to Defuzzification and Comparison of the outputs of Fuzzy Controllers IEEE Translation on Fuzzy Systems,4(3)227—237, (1996).

[18] Zadeh LA, Outline of a New Approach to the Analysis of the complex Systems and Decision Processes, IEEE Trans. Systems, Man and Cybernetics, 3(28-44), Jan 1973.

[19] Jang JSR et al,Neuro-fuzzy Modeling and Control, Proceedings of the IEEE, 83(3), 378-406(1995).

[20] Acampora G et al Fuzzy Control Interoperability and Scalability for Adaptive Domotic Framework, IEEE Transactions on Industrial Informatics1 (2)77-111,(2005).

[21] Czogala E et al, Fuzzy and Neuro-Fuzzy Intelligent Systems, Physica-Verlag,(2000).

[22] Lee CS et al, Ontology-based intelligent healthcare agent and its application to respiratory waveform recognition Expert Systems with Applications, 33(3),606-619(2007).

[23] Lee CS et al Automated Ontology construction for Instructed Text Document Data & knowledge Engineering 60(3) 547-566(2007).