Fuzzy Cognitive Map based approach for assessing pulmonary infections

E.I. Papageorgiou[1,*], N. Papandrianos[2], G. Karagianni[3], G. Kyriazopoulos[3] & D. Sfyras[3]

[1]Department of Informatics & Computer Technology, Technological Educational Institute of Lamia, 3rd Km Old National Road Lamia-Athens, 35100 Lamia, Greece
epapageorgiou@teilam.gr
[2]Department of Nuclear Medicine, University General Hospital of Patras, 26500 Patras, Greece, nikpapan@upatras.gr
[3]Department of Intensive Care Unit, Lamia General Hospital, 35100 Lamia, Greece
gikaragianni@yahoo.gr;dimitriosfyras@yahoo.gr

The decision making problem of predicting infectious diseases is a complex process, because of the numerous elements/parameters (such as symptoms, signs, physical examination, laboratory tests, cultures, chest x-rays, e.t.c.) involved in its operation, and a permanent attention is demanded. The knowledge of physicians according to the physical examination and clinical measurements is the main point to succeed a diagnosis and monitor patient status. In this paper, the Fuzzy Cognitive Mapping approach is investigating to handle with the problem of pulmonary infections during the patient admission into the hospital or in Intensive Care Unit (ICU). This is the first step in the development of a decision support system for the process of infectious diseases prediction.

1. Introduction

During the last years, an enormous number of decision support systems (DSS) for diverse medical problems have been developed. The traditional medical expert systems [1], were equipped with a rule knowledge base supplied by the domain experts (physicians). On the basis of rules inserted in the expert system, it is possible to classify new instances of medical observations by matching symptoms to the conditional part of a rule and then to perform forward and backward reasoning to achieve the diagnosis or construct a therapy plan. In our opinion, one of the main disadvantages for the application of the classic rule-based knowledge representation in medical DSS is its limitation of representing some of the more complex associations that may be experienced within the medical data. For example, in a rule-based DSS, the representation of the complex phenomenon of causality [2] is, in fact, left to the interpretation and expertise of the doctor.

There are a vast number of knowledge-representation methods that can be considered, in general, as exemplification of the conceptual modeling approach. The best-known of them are ontologies and semantic networks that are able to express concepts and relationships among them. Maybe less known in computer science are fuzzy cognitive maps (FCMs).

FCM is a soft computing technique capable of dealing with situations including uncertain descriptions using similar procedure such as human reasoning does [3,4]. FCMs are originated from cognitive maps and are used to model knowledge and experience for describing particular domains using nodes-concepts (representing i.e. variables, states, inputs, outputs) and the relationships between them in order to outline a decision-making process.

In this work, the process of making medical diagnoses is our primary attention. The FCM approach is used as a first step, to model a physician-expert's behavior in the decision making [5]. The behavior to be modeled is centered in the decision making process, whose reasoning implies to reach a predefined goal, coming from one or more initial states. Therefore, the reasoning system will be more efficient when a least number of transitions to reach the final goal are achieved. They have been used in many different scientific fields for modeling and decision making and a special attention given in medical diagnosis and medical decision support through the recently works [6-8].

FCM was chosen because of the nature of the application problem. The prediction of infectious diseases in pneumonia is a complex process with sufficient interacting parameters and FCMs have been proved suitable for this kind of problems. To the best of our knowledge, no any related work has been done till today on implementing FCMs to handle with the specific problem of defining factors as well as their complex cause-effect relationships that affecting infectious diseases and/or adverse events in Intensive Care Unit. Therefore, this is the first step in the development of an expert system tool that will help in decision making process in medicine, through the design of the knowledge representation and the design of reasoning with FCM to automate the decision.

2. Main aspects of Fuzzy Cognitive Maps

A FCM is a representation of a belief system in a given domain. It comprises of concepts (C) representing key drivers of the system, joined by directional edges of connections (w) representing causal relationships between concepts. Each connection is assigned a weight w_{ij} which quantizes the strength of the causal relationship between concepts C_i and C_j [3]. A positive weight indicates an excitatory relationship, i.e. as C_i increases C_j increases while a negative weight indicates an inhibitory relationship, i.e. as C_i increases C_j decreases. In its graphical form, A FCM provides domain knowledge as a collection of "circles" and "arrows" that is relatively easy to visualize and manipulate. Key to the tool is its potential to allow feedback among its nodes, enabling its application in domains that evolve over time. It is particularly suited for use in soft-knowledge domains with a qualitative rather than a quantitative, emphasis. The tool is said to be semi-quantitative, because of the quantification of drivers and links can be interpreted in relative terms only [4].

Fig. 1 shows a fuzzy cognitive map consisting of a number of concepts, some of them are input concepts and the rest are decision (output) concepts, as well as their fuzzy interactions. The main objective of building a fuzzy cognitive map around a problem is to be able to predict the outcome by letting the relevant issues interact with one another.

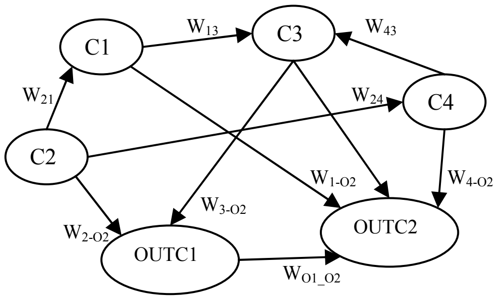

Fig. 1. A generic FCM model for decision making

The concepts C_1, C_2, … C_n, (where *n* is the number of concepts in the problem domain) represent the drivers and constrains that are considered of importance to the issue under consideration. The link strength between two nodes C_i and C_j as denoted by W_{ij}, takes values within [-1,1]. If the value of this link takes on discrete values in the set {-1, 0, 1}, it is called a simple or crisp FCM. The concept values of nodes C_1, C_2, … , C_n together represent the state vector ***V***. The state vector takes values usually between 0 and 1. the dynamics of the state vector is the principal output of applying a FCM. To let the system evolve, the state vector *V* is passed repeatedly through the FCM connection matrix *W*. This involves multiplying *V* by *W*, and then transforming the result as follows:

$$\mathbf{V} = f(\mathbf{V} + \mathbf{V} \cdot \mathbf{W}) \qquad (1)$$

or

$$V_i(t+1) = f(V_i(t) + \sum_{\substack{j \neq i \\ j=1}}^{N} V_j(t) \cdot W_{ji}) \qquad (2)$$

where $V_i(t)$ is the value of concept *Ci* at step *t* , $V_j(t)$ is the value of concept *Cj* at step *t*, *Wji* is the weight of the interconnection from concept *Cj* to concept *Ci* and *f* is the threshold function that squashes the result of the multiplication in the interval [0, 1], [9]. We use the function *f*(x): $f(x)=1/(1+\exp(-mx))$ (3)
where *m* is a real positive number (*m*=1) and *x* is the value $V_i(t)$ on the equilibrium point.

2.1 Construction of Fuzzy Cognitive Maps

Usually, a group of experts, who operate, monitor, supervise and know the system behaviour, are used to construct the FCM model. The experts, based on their experience, assign the main factors that describe the behaviour of the system; each of these factors is represented by one concept of the FCM. They know which elements of the systems influence other elements, thus they determine the negative or positive effect of one concept on the others, with a fuzzy degree of causation for the corresponding concepts. The development methodology extracts the available knowledge from the experts by a form of fuzzy "if-then" rules. The following form of rules is assumed, where **A, B** and ***C*** are linguistic variables:

*IF value of concept C_i is **A** THEN value of concept C_j is **B** and thus the linguistic weight e_{ij} is **C** (from the set T(influence*))

Each interconnection associates the relationship between the two concepts and determines the grade of causality between the two concepts. The causal inter-relationships among concepts are usually declared using the variable *Influence* which is interpreted as a linguistic variable taking values in the universe U=[-1,1]. Its term set T(influence) is suggested to comprise twelve variables. Using twelve linguistic variables, an expert can describe in detail the influence of one concept on another and can discern between different degrees of influence. The twelve variables used here are: *T(influence)* = {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}.

Then, the linguistic variables ***C*** proposed by the experts for each interconnection are aggregated using the SUM method and so an overall linguistic weight is produced which is defuzzified with the Centre of Gravity method and finally a numerical weight for W_{ij} is calculated. Using this method, all the weights of the FCM model are inferred.

3. Fuzzy Cognitive Map approach to assess pulmonary infections

The FCM is suitable technique to cope with complex decision making tasks such as the prediction of infection, the severity of infectious disease and the therapy plan acceptance. It is simple, no time consuming and exploits experience and accumulated knowledge from experts.

A large number of parameters, factors, constraints and different conditions exist in the complex problem of pulmonary infections [10,11]. For the problem of pneumonia, a number of typical symptoms are associated including fever (80%) often accompanied by chills or hypothermia in a small group of patients, altered general well-being and respiratory symptoms such as cough (90%), expectoration (66%), dyspnea-shortness of breath (66%), pleuritic pain-a sharp or stabbing pain, experienced during deep breaths or coughs (50%), and hemoptysis-expectoration of blood (15%). The initial presentation is frequently acute, with an intense and unique chill. Productive cough is present and the expectoration is purulent or bloody. Pleuritic pain may be present.

Physical examination reveals typical findings of pulmonary consolidation-bronchial breath sounds, bronchophony, crackles, increased fremitus, dullness during percussion, tachypnea-increased respiratory rate, tachycardia-high heart rate (pulse should increase by 10 beats per minute per degree Celsius of temperature elevation) or a low oxygen saturation, which is the amount of oxygen in the blood as indicated by either pulse oximetry or blood gas analysis. In elderly and immunocompromised patients, the signs and symptoms of pulmonary infection may be muted and overshadowed by nonspecific complaints. If pneumonia is suspected on the basis of a patient's symptoms and findings from physical examination, further investigations are needed to confirm the diagnosis. From the lab tests only the WBC have been considered as the most important one to increase mainly the risk of infection. These data provide a logical basis for evaluation the risk of infection and the need for intensive care.

Three physicians-experts were pooled to define the number and type of parameters-factors affecting the problem of pulmonary infection. Two of the physicians were from the General Hospital of Lamia, and one from the University General Hospital of Patras, Greece. The factors are represented in Table 1 and are well documented in bibliography. These factors assign the main variables that play an important role in the final diagnostic decision about the risk of pulmonary infection and are the concepts of the FCM. The concept values can take two, three, four or five possible discrete or fuzzy values, as shown in Table 1.

These 26 concepts are the factor concepts representing the main variables that physicians in ICU usually take into consideration in assigning the existent and the grade of the infection. The output (decision) concept (OUT-C) represents the risk of pulmonary infection in percentage and takes *five fuzzy values (very low, low, moderate, high, very high).*

Table 1: Factor concepts coding pulmonary infection

Concepts	*Type of values*
C1: Dyspnea	Four fuzzy values (no dyspnea, less serious, moderate serious, serious dyspnea state)
C2: Cough	Three fuzzy values (no cough, non-productive and productive)
C3: Rigor/chills	Two discrete values (exist or no)
C4: Fever	Six Fuzzy values (hypothermia (34-36^0), no fever (36-38,4^0), low grade (38.5-38.9^0), moderate, high grade (39.5-40.9^0), hyperpyrexia (>41^0))
C5: Loss of appetite	Two discrete values (0,1)
C6: Debility	Four fuzzy values (no, small, moderate, large)
C7: Pleuritic pain	Two discrete values (0, 1)
C8: Heamoptysis	Two discrete values (0, 1)
C9:Oxygen requirement	Four fuzzy values (no need of oxygen, low, medium and high)
C10: Tachypnea	Four fuzzy values (normal (12-24), moderate (25-38), severe (35-49) and very severe (>50))
C11:Acoustic characteristics	Three fuzzy values (no rales, localized and generalized)
C12:GCS	Three fuzzy values: (Severe altered mental status, GCS ≤ 8 , Moderate, GCS 9 - 12 , Minor altered mental status, GCS ≥ 13)
C13: Systolic Blood Pressure	Seven fuzzy values (Hypotension <90, Optimal <120 , Normal <130, High-normal 130-139, Grade 1 hypertension 140 – 159 Grade 2 hypertension 160-179 Grade 3 hypertension >/=180 *(British hypertention society)*
C14: Diastolic blood pressure	Seven fuzzy values (Hypotension <60, Optimal <80, Norma l<85, High-normal 85-89, Grade 1 hypertension 90-99 Grade 2 hypertension 100-109, Grade 3 hypertension >/=110 *(British hypertention society)*
C15: Tachycardia	Four fuzzy values (low (less than 80 beats/min), normal (90-110), moderate sevre (110-140), severe (>140))
C16:Radiologic evidence of pneumonia	Two discrete (exist or no)
C17: Radiologic evidence of	Two fuzzy values (presence, absence)

complicated pneumonia	
C18: pH	Three fuzzy values (Acidosis <7.35, Normal 7,35 – 7,45 , Alkalosis >7.45)
C19:pO2	Two fuzzy value (*normal* 70-100mmHg, *hypoxia* is every value under normal)
C20: pCO2	Three fuzzy values: (normal 35-45mmHg , hypocapnia <35 mmHg , hypercapnia >45mmHg)
C21: sO2%	Two fuzzy values: (normal >95%, hypoxia <95%)
C22: WBC	Three fuzzy values: (Normal 4,3 - $10x10^3$/µl leukocytosis>$10x10^3$/µl, leukopenia<1000/µl)
C23: Immunocompromise	Two fuzzy values: (presence, absence)
C24: Comorbidities	Two discrete values: (presence=1, absence=0)
C25: Age	Three fuzzy: (Young, middle age, older)
OUT-C: Risk of pulmonary infection	Five fuzzy values: (very low, low, moderate, high, very high)

After the description of FCM concepts, each expert was asked to define the degree of influence among the concepts and to describe their interrelationship using an IF—THEN rule, assuming the following statement where Ci and Cj are all the ordered pair of concepts:

IF a {no, very small, small, medium, large, very large} change occurs in the value of concept Ci **THEN** a {no, very small, small, medium, large, very large} change in value of concept Cj is caused. **THUS** the influence of concept Ci on concept Cj is *T(influence).*

Then, experts inferred a linguistic weight to describe the cause and effect relationship between every pair of concepts. To illustrate how numerical values of weights are produced, the three experts' suggestions on how to indicate the interconnection between concept C_{22} (number of white blood cells) and concept OUT-C (risk of pulmonary infection) are shown below:

1st expert:
IF a small change occurs in the value of concept C_{22}, THEN a medium change in value of concept OUT-C is caused.
Infer: The influence from C_{22} to OUT-C is positive medium.

2nd expert:
IF a small change occurs in the value of concept C_{22}, THEN a large change in value of concept OUT-C is caused.
Infer: The influence from C_{22} to OUT-C is positive high.

3rd expert:
IF a very small change occurs in the value of concept C_{22}, THEN a large change in value of concept OUT-C is caused.
Infer: The influence from C_{22} to OUT-C is positive very high.

These linguistic variables (medium, positive strong and positive very strong) are summed and an overall linguistic weight is produced, which with the defuzzification method of CoG is transformed into the numerical value of $W_{22\text{-}OUTC}=0.617$.

The 26 identified concepts (Table 1) keep relations with each other, in order to characterize the process of predicting the risk of pulmonary infectious diseases and to provide a first front-end decision tool about the prediction of pulmonary infection. All the corresponding relations between concepts are given in the following Table 2.

Table 2: Linguistic weights assigned by each one of three experts and the produced numerical weight

	OUT-C First Expert	*OUT-C Second Expert*	*OUT-C Third expert*	*Numerical weight*
C1-Dyspnea	Very weak	medium	weak	0.311
C2-Cough	v. weak	med	Very weak	0.2
C3-Rigor	weak	med	weak	0.345
C4-Fever	med	weak	strong	0.448
C5-appetite	v. weak	weak	v. weak	0.20
C6-debility	Med	Med	med	0.50
C7-chest pain	v. weak	weak	v. weak	0.15
C8- hemoptysis	strong	Very strong	strong	0.691
C9-ox.req.	weak	med	weak	0.345
C10-tachypnea	v.weak	v.weak	weak	0.20
C11- rales	weak	weak	v.weak	0.260
C12- GCS	Neg.med	Neg.weak	Neg.med	-0.455
C13-systolic	med	strong	strong	0.584
C14-diastolic	weak	strong	strong	0.50
C15-heart rate	weak	med	med	0.40
C16-infiltrate	med	strong	strong	0.584
C17-rad. complicated evidence	strong	v. strong	v. strong	0.740
C18-pH	weak	v.weak	v.weak	0.20
C19-PO2	v.weak	v.weak	weak	0.20
C20-pCO2	v.weak	v.weak	weak	0.20
C21-sO2	weak	med	weak	0.345
C22-WBC	strong	v.strong	med	0.617
C23-immunoc	weak	weak	med	0.345
C24-comorbid	weak	strong	strong	0.50
C25-Age	med	med	weak	0.40

Some more linguistic relationships among concepts exist which are not included in the above Table 2. There is one influence from concept C16-(describe the radiology evidence) towards concept C4 representing “fever”. This influence from C16 to C4 is medium. Also there are influences from C25 (Age) to C12 (GCS), from C4 to C22 (WBC), from C4 to C5 (loss of appetite), from C4 to C15, from C21 to C1, from C21 to C10, from C21 to C9, from C21 to C19, from C19 to C1, from C19 to C10, from C19 to C9, from C20 to C1, from C20 to C18. The influence from C25 (Age) to C12 (GCS) is negatively weak (-0.4). The influence from C4 to C22 is strong (0.7). The influence from C4 to C5 is low and the produced numerical weight is equal to 0.3.

The same approach was used to determine all the weights of the FCM. Figure 3 illustrates the FCM model for predicting the risk of pulmonary infection with the assigned numerical values of weights.

The proposed method based on FCMs for predicting pulmonary infection provides a framework within which physicians evaluate a series of traditional diagnostic concepts (symptoms, signs, laboratory tests, chest x-rays, risk and other factors). The way the FCM prediction model is designed increases the objectivity of the diagnostic process by taking into account the different physicians’ opinions regarding the interplay of factor and selector variables in the diagnostic output/decision. Using these variables, the FCM model predicts the risk percentage of the pulmonary infection.

In the next section, two different case studies have been considered for the model simulation and the operation of the FCM tool for the specific approach is evaluated and summarized.

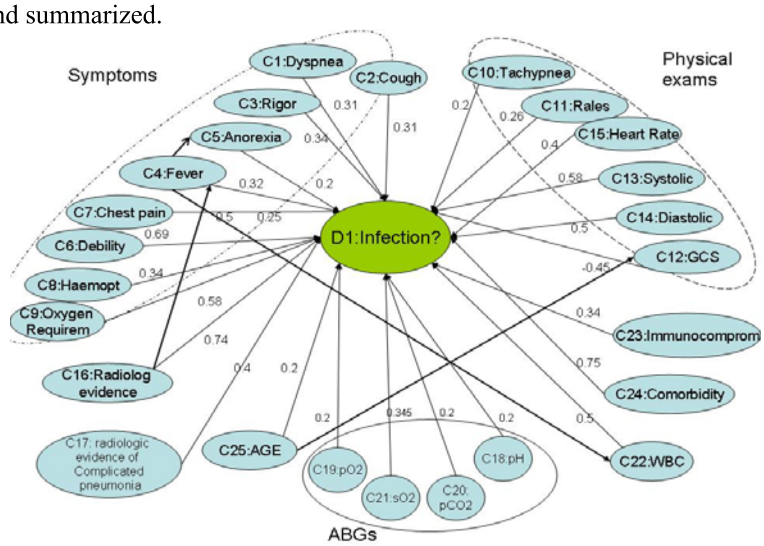

Figure 3. The FCM model for assessing the risk of pulmonary infection

4. Simulations for two case studies

In each of the test scenarios we have an initial vector ***Vi***, representing the presented events at a given time of the process, and a final vector **V**_f, representing the last state that can be arrived at.

For the interpretation of the results, an average only for the output value of the decision concept OUT-C is computed according to the following criteria:

$$R(x)=\begin{cases} 0, x\leq 0.5 \\ \dfrac{x-0.5}{0.5}\times 100\%, 0.5<x\leq 1 \end{cases}$$

where 0 represents the characteristic of the represented process by the concept is null, and 1 represents, the characteristic of the process represented by the concept is present 100%. For the specific approach, the function R(x) gives the risk of pulmonary infection in percentage. When R(value of OUT-C)=1, then the risk is 100%. The final value of decision concept D1 applying this criterion is denoted by OUT-C_f.

Thus D1_f=R(*V*_f(26)). This criterion can be modified according with the expert judgment. The final vector **V**_f is the last vector produced in convergence region and the 26th value of this vector is the OUT-C_f, the final value of decision concept.

The algorithm used to obtain the final vector **V**_f is the following:

(1) Definition of the initial vector **V** that corresponds to the concepts identified in Table 1.
(2) Multiply the initial vector **V** and the matrix **W** defined by experts by the eq.(2).
(3) The resultant vector is updating using Eqs. (1)–(3).
(4) This new vector is considered as an initial vector in the next iteration.
(5) Steps 2–4 are repeated until $\mathbf{V}^{t} - \mathbf{V}^{t-1} \leq e = 0.001$.
The FCM performance is illustrated by means of simulation of three case scenarios in case of medium risk, high risk and very high risk of pulmonary infection.

First Scenario: For this scenario, an immunocompromised patient (C_{23}=1) has been considered, with high Fever (C_4=0.7), loss of appetite (C_5=1), high systolic blood pressure (C_{13}=0.7), with radiologic evidence present in chest x-rays (C_{16}=1) and small number of WBCs (C_{22}=0.4). Is infection existent and which is the probability risk of infection?

The initial concept vector is: **V1**=[0 0 0 0.7 1 0 0 0 0 0 0 0 0 0.7 0 1 0 0 0 0 0 0.4 1 0 0 0]. After the FCM simulation process described in previous five steps the system converges in a steady state with the final concept vector to be: **V1_f**=[0 0 0 0.7000 0.7163 0 0 0 0 0 0 0 0.7000 0 0 1.0000 0 0 0 0.7660 0 0.4000 1.000 0 0 0.9710].

The final value of decision concept V1_f(26)=0.9710, which following the above criterion (OUT-C_f=R(0.9710)) correspond to the 91,34% of risk, thus means that the risk of infection is very high according to the related fuzzy regions, initially prescribed.

Second Scenario: For this scenario, an old patient (C_{25}=0.8) has been considered, with altered mental status (C_{12}=0.4), with high oxygen requirements (C_9=0.8), and normal number of leukocytes-WBC (C_{22}=0). Is the infection existent and which is the probability risk of infection?

The initial concept vector is: **V2**=[0 0 0 0 0 0 0 0.8 0 0 0.4 0 0 0 0 0 0 0 0 0 0 0 0 0 0.8 0]. After the FCM simulation process described in previous five steps the system converges in a steady state with the final concept vector to be: **V2_f**=[0 0 0 0 0 0 0 0.8 0 0 0.559 0 0 0 0 0 0 0 0 0 0 0 0 0 0.8 0.748].

The final value of decision concept is V2_f(26)=0.7483, and following the above criterion, corresponds to the 49.66% of risk, thus means that the risk of pulmonary infection is medium according to the related fuzzy regions in concept description.

We have tested our system using data taken from real medical cases. Unfortunately, the presentation of the set of all contributed parameters and the entire FCM decision support module fall out beyond the scope of this paper. This is the first attempt to construct and present the FCM tool that will help on the prediction of risk in pulmonary infections.

Conclusions

The knowledge-based approach used in this work focuses on the soft computing technique of fuzzy cognitive maps to address the issue of pulmonary risk prediction. The modeling methodology using the FCM tool was applied as a part of decision support with a view to help medical and nursing personnel to assess patient status, assist in making a diagnosis, and facilitate the selection of a course of antibiotic therapy. It was demonstrated that FCMs can be a useful tool for capturing the physicians' understanding of the system and their perceptions on the medical requirements of the infectious diseases management. The main advantage of the proposed FCM tool in medical support is the sufficient simplicity and interpretability for physicians in decision process, which make it a convenient consulting tool in predicting the risk of infectious diseases. Our future work will be directed towards the insertion of other knowledge schemes into this approach, thus to enhance the performance of the suggested tool.

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