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A New Approach of Dynamic Fuzzy Cognitive Knowledge Networks in Modelling Diagnosing Process of Meniscus Injury ⋆

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Abstract: A new approach of Dynamic Fuzzy Cognitive Knowledge Networks is presented. This is an evolutionary type of Fuzzy Cognitive Maps (FCM) that arose from the need for updating classic methodology in order to overcome its drawbacks, concerning the single calculation rule, stability and real time problems and expand its use in a variety of applications. This new approach is being tested for its accuracy in Decision Support Systems in medicine, trying to model knee injuries by using 17 real cases of patients. The new proposed model is able to diagnose meniscus injuries and to distinguish between acute and degenerative injury. Subsequently we observe the evolution of the injury by administering a proposed treatment by the physician. Results of this new method, which are presented in detail, are very satisfactory for both two levels and treatment stage, and in total agreement with Magnetic Resonance Imaging outcomes. The whole methodology is the outcome of a close collaboration between engineers and medical doctors and is significant because it is a promising tool which sets aside the main disadvantages of Fuzzy Cognitive Maps and allows us a wide use in many real time problems.

Keywords: Fuzzy Control, Dynamic Fuzzy Cognitive Knowledge Networks, Meniscus Injuries

1. INTRODUCTION

Fuzzy Cognitive Map (FCM) is a modelling method that works efficiently even with missing data. Experts, for each case study, support with their knowledge the developed FCMs. They have been used in a large range of applications supporting decision systems in medicine (Kannappan et al., 2011), economy (Ginis, 2015), zero energy buildings (Vergini et al., 2012), education (Cole and Persichitte, 2000) etc. The basic calculation rule that computes the value of each concept at every simulation step is the following (Kosko, 1986)

$$A_i(n+1) = f(k_2 A_i(n) + k_1 \sum_{j=1, j\neq i}^{N} A_j(n) w_{ji}) \quad (1)$$

$A_i(n+1)$ is the value of the concept C_i at the iteration step n+1, $A_j(n)$ is the value of the concept C_j at the iteration step n, w_{ji} is the weight of interconnection from concept C_j to concept C_i and f is the sigmoid function. "k_1" expresses the influence of the interconnected concepts in the configuration of the new value of the concept A_i and k_2 represents the proportion of the contribution of the previous value of the concept in the computation of the new value (Groumpos, 2010).

Nevertheless, there are some drawbacks that should be overcome. The existing idea of a single calculation rule for all the concepts creates problems. Firstly all concepts are treated in the same way. That causes a big issue in which we should define initial values for the output on advance. This makes our tool difficult to use because we want a final unknown diagnosis, and the procedure of random definition of the output values complicate the method and affects the entire process. In addition changes in the values of concepts affect the system in a way that is difficult to be predicted and could not be imported in real time into the model to be tested. Also there is a high degree of difficulty to adjust each different problem to this existing model. Another important aspect is the analysis of the evolution of the resulting networks through time (Bourgani et al., 2014). In addition FCMs have stability problem regarding real world systems (Carvalho and Tomé, 2002). These reasons are enough to examine the possibility of a new, more comprehensive and flexible model. In order to model behavior of a nonlinear dynamic system, a new type of Dynamic Fuzzy Cognitive Knowledge Networks (DFCKN) is developed, which is focused on dynamic aspects of our variables. We use 'Cognitive Knowledge' because we want to emphasize in the existing knowledge

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extracted by experts and exploited, so as to generate new knowledge through cognitive process. As far as networks are concerned, cognitive maps form an extensive network (Papageorgiou and Stylios, 2008).

In this new model the new calculation rule should be comprised by two equations. These equations will consist not only of the inputs and outputs of the system but also the states. The dynamic combination of the three concepts, States, Inputs and Outputs will consist the Dynamic Fuzzy Cognitive Knowledge Network. The combination of the three concepts in two new, different equations, extracted and following the basic rules of fuzzy modelling, will be the core of the new approach, which will be applied in modelling the diagnostic procedure of meniscus injury and tested in 17 real patients. After the distinction between acute and degenerative injury, we examine the influence of daily analgesics in the evolution of the injury through time.

2. DYNAMIC FUZZY COGNITIVE KNOWLEDGE NETWORK

The new proposed system uses the basic theory of FCM with the difference that the system main variables are not treated in the same way. FCM are specialized in complex systems and are suitable for medical decisions because they model the human thinking, using a reasoning process that can include uncertain descriptions. The procedure of constructing the FCM is remaining the same. First of all experts should define all together the basic system variables. But the main change is that after this procedure, variables should be divided into three categories:

- Fuzzy States
- Fuzzy Inputs
- Fuzzy Outputs

The fuzzy inputs concern signals that stimulate the system. The fuzzy states of a dynamic system refer to a minimum set of variables, known as state variables, which fully describe the system and its response to any given set of inputs. The fuzzy output variables constitute those that we should examine their behaviour. In that way we take into consideration what exactly each concept does. We no more treat outputs in the same way as inputs and inputs are separated from states. The mathematical description of the system and the combination of initial states and inputs are sufficient to provide information about both the future states and outputs. Mathematically the standard form of the new model is described by the system general equations (Yu, 2005),(Rowell, 2002):

$$\mathbf{x}(k+1) = f[A\mathbf{x}(k) + B\mathbf{u}(k)] \tag{2}$$

$$\mathbf{y}(k) = f[C\mathbf{x}(k) + D\mathbf{u}(k)] \tag{3}$$

where x(k)$\in$ R^n is a state vector, u(k)$\in$ R^r is an exogenous known input vector, y(k) $\in$ R^m is the output vector in time unit "k". "k" is the discrete instant of time that input and state vectors are defined. This is in stark contrast with "n" variable in equation (1). The latter expresses the iteration steps until convergence. In the new model the number of iteration steps depends on the samples defined by "k". Each sample adds a new iteration step. The state variables are an internal description of the system and in combination with the system inputs are sufficient for computing the output. Figure 1 illustrates the system structure.

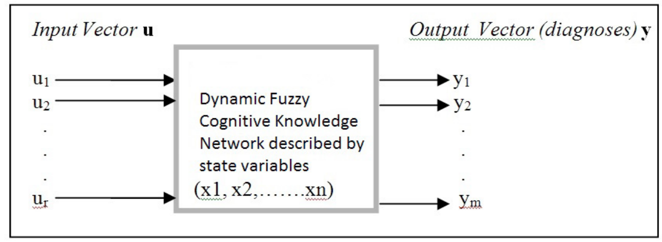

Fig. 1. System states, inputs and outputs

Matrices A, B, C and D contain constant coefficients that describe our system. Function f is a nonlinear activation function and is intentionally omitted because the aim of this paper is to test the conclusions from the new separated fuzzy equations. So we use a linear model and in order to interpret the output we use a set of fuzzy rules since the nature of medical problems and decisions does not require a precise numeric interpretation of the output between 0 and 1, but an ambiguous interpretation that simply determines whether the patient is healthy.

Arrays A, B, C and D are the connection weight matrices, associated with the fuzzy state, input and output vectors. More specifically, array A is a weight matrix that connects the states between them and it corresponds to the weight matrix of classic FCM but now it connects only the states of the system. Array B is a new weight matrix which represents how each input influences the states one by one. Array C is the weight matrix of the interrelationship between the states and the outputs and array D depicts the influence of the inputs to the outputs respectively. Arrays A, B, C and D must be decided by experts, describing the linguistic interrelationships between vectors. The exact procedure is the same as in the construction of a classic Fuzzy Cognitive Map (Groumpos, 2010). Experts should define all these interconnections in their natural language using linguistic variables and after a defuzzification method of Center of Area, the arrays will be filled with numeric values.

The algorithm that describes the new model in detail, adjusted in medical diagnosis follows:

Step 1: Ask experts to define the basic concepts

Step 2: Experts separate them into Fuzzy States, Inputs, and Outputs

Step 3: Experts construct weight matrices between Outputs-States, States-States, Outputs-Inputs, States-Inputs, using fuzzy variables

Step 4: Convert weight matrices into numeric values using a defuzzification method

Step 5: Detect initial states in time unit "k" (Patients Initial Symptoms)

Step 6: Compute Initial Output in "k" from equation (3) $\rightarrow$ Diagnosis

Step 7: According to diagnosis, physicians propose Treatment

Step 8: Treatment is a new Input in our system in time variable "k"

Step 9: Compute new States in time unit "k+1" with equation (2)

Step 10: Compute new output in "k+1" according to equation (3)

Step 11: Renew the new input value in "k+2"

Step 12: Repeat steps 9-11 until desired time unit

3. MODELLING MENISCAL TEAR USING DFCKN

Immediate diagnosis and treatment is of the utmost importance in medicine. In knee injuries physicians are forced to use the solution of MRI in order to have verified results. Is this method necessary though? A new integrated tool that would work supportively to the physician has to be implemented in order to make the right decision. This paper models the diagnostic process of meniscus injury using DFCKN and constitutes an extension of paper of Anninou et al. (Anninou et al., 2016) that used the classic theory of Fuzzy Cognitive Maps. Apart from these the evolution of the disease through time with the proper treatment is examined for the first time.

The model will be consisted of two levels. In the first level we decide if the patient has meniscus tear and if the answer is positive the final diagnosis in the second level concerns the distinction between acute and degenerative injury.

In the first level the output vector is Meniscal Tear (MT) and a high value of that corresponds to a positive result according to equation (3).

The output is directly depended on the states. This specific output is not affected by any input and therefore matrix D is zero and equation (3) is being transformed to (4).

$$\mathbf{y}(k) = C\mathbf{x}(k) \tag{4}$$

The system states x(k) are comprised of the patients symptoms at the specific time of the examination and their initial values could be on or off, so they take two values, 0 or 1 (Kandasamy and Smarandache, 2003). All possible symptoms are the following 13: Clicking, Catching, Giving way / weakness, Localized pain, Episodic pain, Pain with activity, Pain with pivoting/twisting, Change in quality/pattern of pain, Locking, Acute swelling, Subacute swelling, Weight bearing, Continued in athletic activity, and they have been explained in (Anninou et al., 2016).

The state vector is a vertical vector consisting of the following elements: C1, C2, C3, C4, C5, C6, C7, C8, C9, C10, C11, C12, C13.

The way that the 13 states interact with the output has been decided by experts and after the defuzzification method of Center of Area (CoA) it is illustrated in matrix C.

$$C = [0.75\ 0.375\ 0.375\ 0.75\ 0.5\ 0.75\ 0.875\ 0.25\ 0.875\ 0.25\ 0.675\ 0.5\ 0.5]$$

Instead of the sigmoid function f that used in FCM to transform the output into the interval [0,1] in combination with an interpretation criterion in order for the output to be fully understandable, we now use fuzzy rules to immediately transform the numeric value to a fuzzy variable,because of the nature of medical problems that demand an explicit linguistic interpretation. Fuzzy rules resulted from the entire bandwidth spectrum of the output value and are the following:

- IF the output is between 0-3.0125 THEN the output fuzzy variable is "Low".
- IF the output is between 3.0126-6.025, THEN the output fuzzy variable is "Medium"
- IF the output is between 6.026-9.0375, THEN the output fuzzy variable is "High"
- IF the output is between 9.0376-12.05, THEN the output fuzzy variable is "Very High"

If the fuzzy variable is High or Very High then the patient suffers from meniscal tear. In the first case with variable Low, the patient is healthy and when the fuzzy variable is Medium we need extra information to conclude to a decision. This information concerns clinical examination results (Tests) (Anninou et al., 2015) that influence the output and the final decision. Possible Tests are: Mcmurrey's test, Thessal's test (20° knee flexion), Steinmann's I test, Joint Line Tenderness, Ege's test, Childress' test, Appley's test. So the second fuzzy rule is translated as follows:

- IF Meniscal Tear is Medium AND one or more tests from the list: T1, T2, T3, T4, T5, T6 are positive THEN the patient suffers from meniscal tear. IF Meniscal Tear is Medium AND only test T7 is positive THEN the patient does not suffer from meniscal tear.

According to the diagnosis if the patient has meniscal tear we continue to the next level FCM so as to understand the exact injury between acute and degenerative. In that second level we have to take into consideration the Risk Factors, which are attributes, characteristics or exposures that increase the likelihood of a person developing a disease, in order to check if they are susceptible to acute or degenerative meniscal tears respectively. The total Risk Factors are: R1: Sport activity / high Tegner score (soccer), R2: Systemic laxity ($>$ 1 score in Beighton scale), R3: History of previous injury/ surgery, R4: Time From initial ACL Injury $> 2-5$ years, R5: Lifting weight routine, R6: Age $>$ 60 years old, R7: Male gender, R8: Work related/ frequently kneeling-squatting, R9: Using stairs frequently, R10: BMI $\geq$ 25 kgr/ m^2, R11: Standing / walking routine, R12: Chronic recurring pain and swelling after exercise, R13: Minor trauma/Insignificant traumatic injury / unable to recall traumatic event, R14: Quads wasting / VMO assymetry, R15: Pain / symptoms bilaterally present, R16: Vaguer / more subtle symptoms (no knee block), R17: Knee OA present (Snoeker et al., 2013).

The output vector now has two values: Acute Injury and Degenerative Injury. In this specific level, states of the system are a vertical vector consisting of Risk Factors: R1, R2, R3, R4, R5, R6, R7, R8, R9, R10, R11, RF. In addition D is a zero matrix because the output is influenced only by the states at this level too. So we use equation (4).

$$y(k) = \begin{bmatrix} Acute \\ Degenerative \end{bmatrix} \tag{5}$$

The last value RF depends on the value of the six risk factors between R12-R17. If one at least of the values of R12-R17 is activated then RF=1. But if all values are zero then "RF"=-1. According to the following matrix C, if RF=1 a very high positive weight is added to degenerative injury and a very high negative weight to the acute one. That introduces competitiveness to our system and means that if one or more risk factors between R12-R17 are activated then we have low possibility of the final diagnosis to be acute injury. If RF=-1 the reverse process is performed.

$$C = \begin{bmatrix} 0.75 & 0.75 & 0.75 & 0.75 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & -0.75 \\ -1 & -1 & -1 & -1 & 0.75 & 0.75 & 0.75 & 0.75 & 0.5 & 0.5 & 0.5 & 0.75 \end{bmatrix}$$

Competitiveness is very useful in medical decision support systems, where we need a dominant output over all the other possible diagnoses.

We are now ready to examine the model with 17 real case studies from General University Hospital of Patras.

4. SIMULATION RESULTS

4.1 1st Patient

In order to fully understand the method, the diagnosis procedure of the first patient will be presented analytically.

Patient 1 had symptoms: C1, C4, C6, C7, C11. Positive tests were: T1, T2, T3, T4, T5, T6.

According to (4) the arising output value is 3.8 which corresponds to the fuzzy variable 'Medium'. So we have to examine the Test results. According to the positive tests and the second fuzzy rule the patient suffers from meniscal tear.

Now we examine first patient risk factors arose from his examination. He is positive to: R1, R3, R4, R6, R7, R8, R9, R10, R12, R14, R16, R17. First of all we observe that we have activated values between R12 to R17. That means that RF=1. According to equation (4) the output values are the following:

$$y(k) = \begin{bmatrix} -1.5 \\ 1 \end{bmatrix} \qquad (6)$$

Consequently the accurate diagnosis for patient 1 is Degenerative Injury. The competitiveness reduced significantly the value of one concept and helped us conclude to one final decision.

4.2 Overall Patients

The overall data collected by the 17 real patients arrived at University Hospital of Patras having knee injuries are presented in the Table 1. According to the first level analysis, using the second and third column of Table 1, with symptoms as states and test results as additional data, we compute the first level output in the last column using a linguistic variable extracted by fuzzy rules.

Graphically the numeric values of outputs are illustrated in Fig.2.

As far as the second level results are concerned for the total patients, they are presented in Table 2 and Fig. 3.

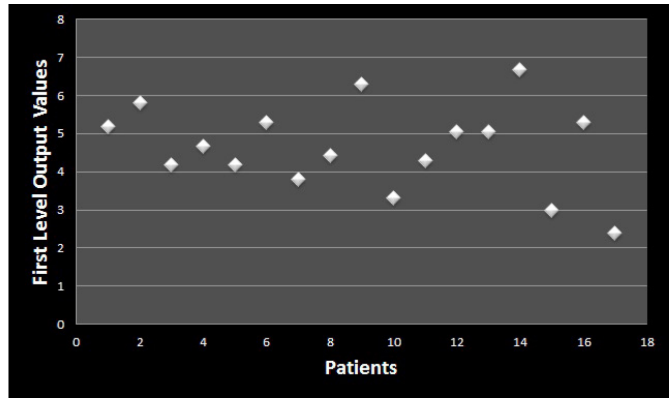

Fig. 2. Meniscus Tear Diagnosis

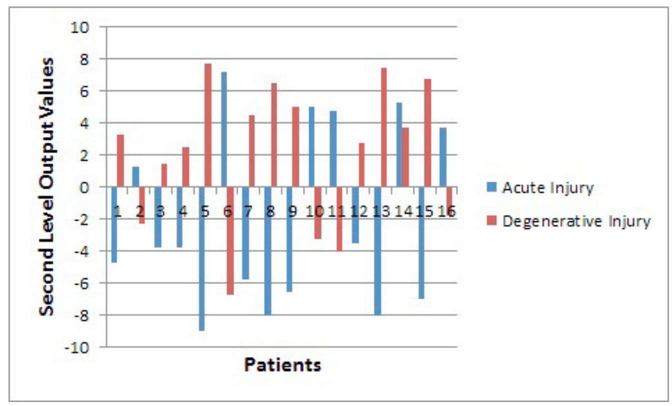

Fig. 3. Final Diagnoses

5. TREATMENT STAGE-SIMULATION RESULTS

All this aforementioned methodology is used in order to compute the output at the specific time unit k, that patient arrived at hospital and wanted a diagnosis. But after this diagnosis, the physician proposes an external intervention, a treatment, so the existing states of the system are updated. Therefore in (k+1) time unit the new states are computed by (2) and the new output is as follows:

$$\mathbf{y}(k+1) = C\mathbf{x}(k+1) + D\mathbf{u}(k+1) \qquad (7)$$

The input is the proposed treatment that influences patients symptoms, and after the computation of the new states, we compute the new output y(k+1) by using x(k+1) instead of x(k). Treatment is steady but its influence to patient, changes through time. For knee injuries, nonoperative treatments are often proposed, including supervised sessions of physical therapy with scope for individual adaptation thrice a week during the first 6 weeks and then at least twice a week for further 6 weeks under supervision of a musculoskeletal physiotherapist. It needs 6 weeks for the patient to respond. The number of time steps we need in order to complete the treatment stage is exactly the same as the time that patient would go to physician for re-examination. More specifically we will check the influence of the method proposed by the physicians that concerns Daily analgesics (NSAIDs) that were administered for those 6 weeks and then as required during the follow-up. In case of contraindications to nonsteroidal anti inflammatory drugs (NSAIDs), paracetamol 4 g/day in di-

Table 1. Data Collected By 17 Patients and Meniscal Tear Diagnosis

Patients	**Symptoms**	**Positive Tests**	**First Level Diagnosis**
1	C1, C4, C6, C7, C11	T1,T2,T3,T4,T5,T6	Medium
2	C1,C2,C4,C6,C7,C11	T1,T2,T5,T6	Medium
3	C1,C3,C4,C6,C7,C11	T1,T2,T5	Medium
4	C1,C4,C6,C7,C11	T2,T3,T4,T5,T6	Medium
5	C1,C2,C4,C6,C7,C11	T2,T3,T4,T6	Medium
6	C2,C4,C7,C11,C12,C13	T1,T2,T3,T5,T6,T7	Medium
7	C1,C2,C3,C4,C7,C11	T2,T4,T5	Medium
8	C2,C4,C6,C7,C11,C12,C13	T1,T2,T5,T7	Medium
9	C1,C2,C4,C5,C6,C7,C11	T3	High
10	C1,C3,C4,C5,C11	T2,T3	Medium
11	C1,C2,C4,C7,C11	T1,T2	Medium
12	C1,C2,C3,C4,C5,C7,C11	T1,T2,T3,T4,T7	Medium
13	C1,C2,C3,C4,C5,C6,C7,C11	T1,T2,T3,T4,T7	Medium
14	C1,C2,C3,C4,C5,C6,C7,C11	T1,T2,T3,T4,T7	High
15	C1,C2,C6,C11	T1,T2,T3,T4,T5	Medium
16	C1,C2,C3,C6,C7,C11,C12,C13	T1,T2,T4,T5	Medium
17	C1,C2,C3,C7	T7	Low → HEALTHY

Table 2. Accurate Diagnosis of 17 Patients

Patients	**Risk Factors**	**Acute Injury**	**Degenerative Injury**	**Final Diagnosis**
1	R1,R3,R4,R5,R6,R7,R8,R9,R10,R12,R14,R16,R17	-4.75	3.25	Degenerative
2	R1,R3,R4,R6	1.25	-2.25	Acute
3	R1,R3,R4,R6,R8,R12,R13,R14,R16	-3.75	1.5	Degenerative
4	R1,R3,R4,R6,R7,R8,R10,R11,R12,R14,R16	-3.75	1.5	Degenerative
5	R6,R7,R8,R10,R11,R12,R13,R14,R15,R16,R17	-9	7.75	Degenerative
6	R6,R7,R8,R10	7.2	-6.75	Acute
7	R1,R3,R4,R6,R8,R9,R10,R11,R12,R13,R14,R15,R16,R17	-5.75	4.5	Degenerative
8	R6,R7,R8,R9,R12,R13,R14,R15,R16	-8	-6.5	Degenerative
9	R3,R4,R6,R8,R9,R10,R12,R13,R14,R15,R16,R17	-6.5	5	Degenerative
10	R8,R9	5	-3.25	Acute
11	R1,R6,R8	4.75	-4	Acute
12	R3,R4,R5,R8,R9,R11,R13,R14,R17	-3.5	2.75	Degenerative
13	R5,R7,R8,R9,R10,R11,R13,R14,R15,R16,R17	-8	7.5	Degenerative
14	R1,R3,R4,R5,R7,R8,R9,R10,R11	5.25	-3.75	Acute
15	R6,R8,R9,R10,R11,R13,R14,R15,R16,R17	-7	6.75	Degenerative
16	R1,R5,R7, R8,R9,R10,R11	3.75	-1.75	Acute

vided doses combined with tramadol sustained release 100 mg at night was used. The goal of rehabilitation is to regain good knee control, range of motion (ROM),flexibility, and muscle strength and thereby to improve knee function.

Patient needs 4 re-examinations during these 6 weeks. These would be the 4 time steps, k+1, k+2, k+3, k+4, for our algorithm. The way that this "input" interacts to the patient in relation to time has a discrete time function illustration, where in "k+1", input is very low and corresponds to u=0.1, in the next selected time variable k+2 the input is u=0.5, in the third iteration of the algorithm k+2, u has its highest value (u=1) and keep it for the last iteration in the final step k+3. Matrix A expresses the interrelationships between states with each other and matrix B the influence between input and states, namely between treatment and symptoms. Experts defined these relationships with linguistic variables and after the defuzzification method, the two numeric matrices are as follow.

$$A = \begin{bmatrix} 0 & 0.5 & 0.375 & 0.5 & 0.375 & 0.375 & 0.375 & 0.375 & 0.375 & 0.375 & 0.375 & 0 & 0 \\ 0.5 & 0 & 0.5 & 0.375 & 0.375 & 0.375 & 0.75 & 0.75 & 0.75 & 0.375 & 0.375 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 & 0.5 & 0.5 & 0.375 & 0 & 0.75 & 0 & 0 & 0 & 0 \\ 0.5 & 0.375 & 0.375 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0.75 & 0 & 0.75 & 0 \\ 0.375 & 0.375 & 0.5 & 0 & 0 & 0.5 & 0 & 0 & 0.75 & 0 & 0 & 0.75 & 0 \\ 0.375 & 0.375 & 0.5 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0 \\ 0.375 & 0.75 & 0.75 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.375 & 0.75 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.375 & 0.75 & 0.75 & 0.5 & 0.75 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.675 & 0.675 & 0 & 0.75 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.375 & 0.375 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.375 & 0.375 & 0.375 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$B = [-0.1\ -0.1\ -0.1\ -0.1\ -0.3\ -0.3\ -0.3\ -0.3\ -0.3\ -0.3\ -0.3\ 0\ 0]$$

We observe that proposed treatment will significantly reduce symptoms C5-C11 if they exist. In case study 1 patient has symptoms C1, C4, C6, C7, C11. According to equations (3) and (7) the symptoms and the output (meniscus injury) are changing as in Table 3.

Table 3. Output Iterations

	Initial	"k+1"	"k+2"	"k+3"	"k+4"
Output	3.8	1.96	0.94	-0.31	0.1

We observe the fluctuation of output until the final application of the 6 weeks treatment as it is illustrated in the following figure.

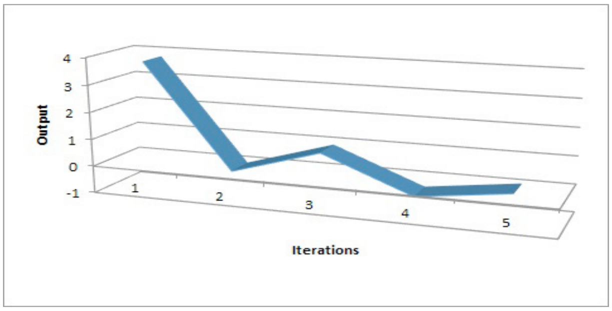

Fig. 4. Evolution of the output in 6 weeks (5 iterations)

The first patient manage to reduce symptoms and knee injury by following the treatment in a very strict way.

6. DISCUSSION OF THE RESULTS

In the examined sample 16 out of 17 patients suffered from meniscal tear. The first level output for patient 17 was LOW, so we did not have to proceed to the second level as he was healthy. More specifically during second level simulations, 10 cases were positive to degenerative injury and the rest 6 to acute injury. The first case (patient 1) was further analyzed in order to examine the influence of the daily analgesics (NSAIDs) through time in the course of patient. Considering that the first patient was following physician's orders, the results show full rehabilitation in his degenerative injury. Due to space limitation the rest patients treatment is not presented in the paper, as the methodology is the same.

7. CONCLUSIONS-FUTURE RESEARCH

This new modelling method helps us classify all concepts and makes it easier to influence them. Any external intervention in our system will be considered as a new input. States describe the system and their combination with the inputs could inform us about the outputs for any system. The interrelationships between these values must be decided by experts. In this paper the whole procedure of knee injury diagnosis was modelled and tested in 17 real cases. The results were verified by MRI results. But we went one step further in order to examine the influence of a proposed treatment. The choice of experts should be very careful because it is obvious that the whole model is based on them. The general methodology of the separation of concepts could be the core for the development of a wide range of applications, not only medical ones.

Future research concerns the use of a validation set to confirm the accuracy of the model. In addition, model could be evolved to an integrated advising software tool useful for physicians for real time clinical use, in order to diagnose meniscal tear and choose the appropriate treatment, observing the outcomes of each one.

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