DECISION SUPPORT SYSTEM FOR DIAGNOSING DYSFUNCTIONS IN THE LOWER URINARY TRACT

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Abstract: In this article the development of a decision support system for medical diagnosis using self organizing artificial neural networks is proposed in order to classify/predict the dysfunctions of the lower urinary tract. This new tool is meant to help the urologists in obtaining an automatic diagnosis for complex multi-variable systems, and to avoid painful and costly medical treatments. The clinical study has been carried out using the medical journals of patients with dysfunctions in the lower urinary tract. The system is able to distinguish (and classify) the following dysfunctions: Effort incontinence, bladder instability, obstruction of the lower urinary tract or the presence of no dysfunction at all. The results of the experiments display a high percentage of certainty of about 90 %.

Introduction

Despite the different tools available to the urologists to obtain the urodynamical data, it still remains very difficult to deliver a correct diagnosis: the knowledge concerning the origin of the detected dysfunctions depends mainly on already acquired experience and on the research which is constantly carried out within the field of urology. The experts are often confronted to situations that are not described in the medical bibliography or that are poorly described. Also, the dysfunctions whose exact diagnoses are complicated to deliver are numerous as a consequence of the interaction with the neural system and the limited knowledge available on how it operates. During the last five years, the amount of research whose aim is to study the neural control of the lower urinary tract has risen. This fact is clearly reflected at the European congress I.C.S. (International Continence Society). In 2001, 28 studies related to neurology were presented whereas 91 studies including the organisation of a symposium on neurology were presented at the congress in 2005. We are facing an arduous task that requires progress towards a solution and at the same time, it will be necessary to suggest new models and methods to solve other problems both for the biological systems as for other environments and disciplines.

For the purpose of diagnosing dysfunctions of the lower urinary tract (LUT), various techniques which entail different degrees of invasiveness of the urological patient exist [1] [2]. A urological study of a patient consists of carrying out various costly tests (physical, neurological, flowmetry and cystometry examinations) with a high degree of complexity and of invasiveness. This project is intended to aid the specialist in obtaining a reliable diagnosis with the smallest possible number of tests. This way, major benefits are obtained both for the patient, avoiding him useless and painful tests and for the medical centres, as urodynamical tests are expensive.

Decision support systems (DSS) in medicine can be viewed as intelligent advisors, or sources of second opinion. Their typical life cycle often consists of defining a problem on which to focus, gathering the corresponding retrospective data, and constructing the predictive model. The decision support system has to be immediately accessible providing the useful data in accordance with the situation [3] [4]. The range of techniques used as tools for the DSS is very wide, covering everything from traditional statistics and expert systems to more emerging fields such as Artificial Neural Networks (ANN), Fuzzy Inference Systems (FIS) [5] and other technologies within Soft Computing [6].

Because of the high degree of heterogeneity of the information gathered in a urological study (qualitative and quantitative parameters, boolean data, multi-value information etc.) we have based our DSS on artificial neural networks, in particular on Self-Organizing Maps (SOM) [7]. Kohonen's Self-Organizing Maps have demonstrated their validity as components for prediction, classification and diagnostics of medical signals and data within various specialities [8] [9] [10] [11].

The SOM can be used combined with other methods [12] or/and by clustering cases with similar properties together [13] .

In the present article, a system for aiding in diagnosing dysfunctions of the LUT is implemented. The remaining part of the paper is organized as follows: First, it describes the design of a DSS. Next, it describes the training of it by means of the available data and the subsequent testing carried out with new data in order to analyse the results. Finally, the relevant conclusions are drawn.

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The design of the system

Decision support applications within medicine have rapidly evolved over the last 40 years. Research into the methodology of developing expert systems has brought together the fields of artificial intelligence, computer science, mathematics, cognition, and even systems that model genetic and evolutionary development of biological systems. The complexity of these systems have ranged from simple algorithms using predicate logic (or set theory to machine learning and neural networks) to systems that integrate automated decision support with other disparate clinical information systems.

A DSS in medicine is a system that aids the specialist in the determination of the diagnosis based on findings and test results. The DSS can be divided into 2 different types of components: the knowledge component and the information system component. Methods from software engineering, knowledge engineering and management are combined into a dynamic development cycle that allows stepwise update and refinement.

The developed DSS is composed of 3 blocks in a composition as shown in figure 1.

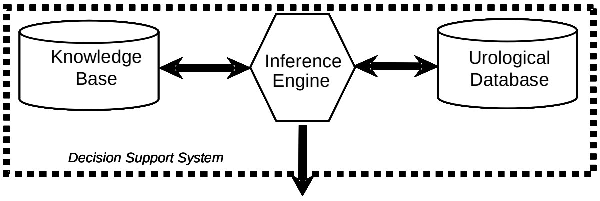

Figure 1: Diagram of the decision support system.

The urological database (DB) is the result of urological studies during various years carried out in close collaboration with urologist [14] [15]. This DB is obtained by converting the medical journals of patients into registers. The motor of inference is the heart of any support system and in our case it creates the knowledge database with the information which is provided by the DB.

The knowledge base is composed of the database of the patients that has become a part of the knowledge when the motor of inference has decided it.

SOM will be used as a motor of inference that allows classifying and predicting. They represent a type of neural network of unsupervised learning. SOM use the competitive learning where cells/neurons are competing against each their neighbours. One of the cells becomes the "winner" with full activity and then suppresses the activity of the remaining cells.

SOM is composed of neurons located in a two-dimensional matrix. With every node of the SOM, a parametric model vector also called reference vector $m_i = (m_{i1}\ m_{i2} \ldots m_{in})$ is associated, where n is the dimension of the input vectors. In our case they are the n-fields of each observation of a pattern or a patient i-register.

The input vectors, that in our case are the registers of the patients, are mapped into the neighbours cells in the map. If they have similar values or they match the same dysfunction, they then map the same neuron.

The proposed DSS has been implemented in the programming language C++, following the algorithms of the self-organizing maps of Kohonen. It has to define the parameters of the arrays to construct the matrix in the input dimension and the size of the reference vector in order to be able to read the database of patients which is the objective of our motor of inference.

The network settings

The Kohonen network used as a classifier is organized as follows in the figure 2.

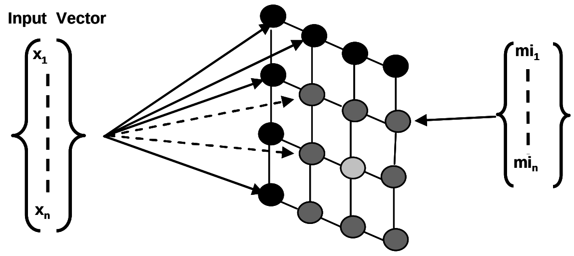

Figure 2: The Kohonen network.

Each node of the network is associated to a vector in the input space. The 'winner' modifies the weights of the whole 'neighbourhood'.

One-dimensional input vector α of length N (N equal 21. table 1), representing important parameters from a sample of the input space.

Two-dimensional map with neurons (nodes), where each neuron is connected to each parameter from the input vector by a weighted connection. The result is an input vector that is fully connected to a topological map consisting of 2500 neurons (M x M, M being 50). Thus, there are N x M x M weighting factors. The connection weights are initialized randomly according to a uniform distribution between -1 and 1.

The network was implemented in C++ code. The training of the SOM is basically done by running the training data over and over again in order to adjust the weighting coefficients. Various numbers of training cycles were applied until no further improvement (better prediction results, on the average) was noticed. The training algorithm of the Kohonen network was done during 2000 cycles and it employs the competitive and unsupervised method ('self-organizing maps'). It proceeds as follows:

1. A learning example (vector with N parameters) is presented at the input.

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2. At each iteration t, the 'similarity' is calculated between each node n and the input vector α by computing a simple Euclidean distance δ_n:

$$\delta_n(t) = \min \left|\vec{\alpha}_k - W_{kn}(t)\right| \qquad (1)$$

This 'winner' neuron has been obtained via a competitive process among the neurons and it is defined as the neuron with the closest reference vector to δ.

3. The node with the minimum distance is selected: i.e. the 'winner'.
4. The winner node's weights and also its close neighbours in the map are adapted as follows:

$$W_{kn}(t+1) = W_{kn}(t) + c(t)h(t)\left[\vec{a}_k - W_{kn}(t)\right] \qquad (2)$$

Where:

- $W_{kn}(t+1)$ and $W_{kn}(t)$ are the weighting factors between input feature (parameter) k and node n at iteration t and t + 1;
- α is the current input vector;
- c(t) is the learning rate
    - c(t=0)=1.0 at start, with c decreasing each cycle t:
    - c(t+1) = c(t) –0.001

$$h(t) = \begin{cases} 1.0 \; for \left|(i,j) - (i_{\min}, j_{\min})\right| \le rc(t) \\ 0.0 \; for \left|(i,j) - (i_{\min}, j_{\min})\right| > rc(t) \end{cases} \qquad (2)$$

- h(t) is the neighbourhood function:

Where r is a constant and (imin, jmin) are the coordinates of the winning node. The net result is that learning is not restricted to adapt the weight correction of the 'winner' node alone, but also to all 'neighbour' nodes where h(t) is different from 0. The neighbourhood function h(t) defines a dynamic square region on the output node map. In our configuration, r has been given the value of 2 (in both directions, X-axis and Y-axis).
h(t) determines the set of neurons in the layer that change their weigths. This two parameters (h and c) deerease gradually with the number of adaptation steps.

5. The procedure is repeated from step 1 for the next iteration t.

Experimentation

An exhaustive urological exploration with 21 different measurements has been carried out with 250 patients with dysfunctions of the lower urinary tract in order to create a database. The data has been analysed and processed before entered into the network in order to ensure its homogeneity. With this information, a database of these patients was created with the Standard Query Language (SQL). These 250 registers contribute to the full knowledge adding different values to delimit the ranks of each measure. Each of these registers contains the information measured in 21 fields showed in Table 1. For this reason, this database plays a crucial part in order to obtain the knowledge base of our system.

Table1: Fields discretized for the urological database.

Neurological Physical Examination	
Perineal and perianal sensitivity (1-4)	Anal tone(1-2)
Voluntary control of the anal sphincter (1-4)	Age (1-4)
Sex (1-2)	Bulbocavernosus Reflex (1-4)
Free Flowmetry	
Volume of urine (1-4)	Post void residual (1-4
Maximum flow rate (1-4)	Micturition time (1-4)
Cystometry	
Bladder storage (1-4)	Detrusor pressure during filling (1-4)
First sensation of bladder filling (1-4)	
Test Detrusor pressure /Micturition flow	
Detrusor contraction (1-3)	Abdominal pressure (1-2)
Volume of urine in micturition(1-4)	Post void residual (1-4)
Maximum pressure Detrusor (1-4)	Maximum flow rate (1-4)
Average flow rate (1-4)	Micturition time (1-4)
Diagnosis	
Diagnosis (Effort Incontinence - Bladder Instability – Obstruction of the LUT – No dysfunction)	

The processing of analysing the data was necessary due to its diversity. It has shown to be necessary to revise, adapt and filter the medical journals collected by several doctors in order to ensure the correct homogeneity the database requires. Also, the true nature of the patients heterogeneous data such as age, sex, volume of urine, time of micturition etc., lead to data of such a high degree of diversity that discretization becomes inevitable when applied to a neural network unable to assimilate it.
With the assistance of specialists within the field of urology, a range of values for each field of the database has been created. For example in Table 1, the values given to the volume of urine of the section of the Free Flowmetry lies between 0 and 500. The discretization applied is between 1 and 4: 0 - 150 :1 , 150 - 300 :2 , 300 - 500 :3, 500 - ≤ : 4 .

In order to carry out the training of the system, 200 entries of the database are randomly taken. These data are the fields of each pattern which indicate the dimensionality of the reference vector. Each patient is a pattern in the input of the net and they model the matrix, specifically the patterns around the reference vector by the weights of each of them. After the map has been trained by means of the database of patients, it is possible to identify different areas which locate the specific dysfunctions as shown in figure 3. It discerns (and classifies) between the dysfunctions of effort incontinence (1), bladder instability (2), obstruction of the lower urinary tract (3), or the presence of no dysfunction at all (0).

The topology of the map is determined by the quantity of cells which it comprises. In our case, it is of 50x50. This size is due to the number of the registers/patterns entered to the net and the number of areas to be classified. Other sizes were tested; in particular 10x10 and 25x25 and their results were lower. The reason is that when working with multivariable data, every dysfunction can not be located only in one place. In other words, a huge net is needed in order to have a lot of neurons which can be labelled with many different reference vectors. Sometimes, even some of these neurons with theirs reference vectors only collect one pattern in the training but it is different to another neuron with the same dysfunction. After the map has been trained by means of the database of patients, it is possible to identify different areas which locate the specific dysfunctions as shown in figure 3.

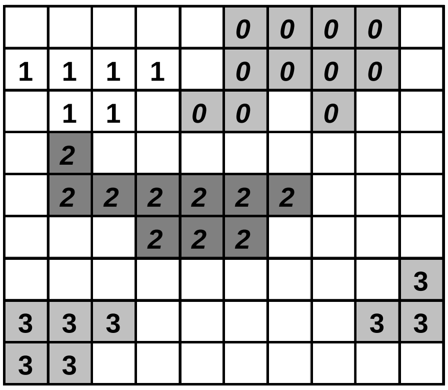

Figure 3: Representation of Kohonen map clustering the different dysfunctions

The Kohonen map shows that the data relating to the patients are grouped in specific areas each relating to the corresponding urinary disease. Likewise, it is possible to check how the map has classified the diseases 1, 2 and 3 as well as the disease free 0 in well defined zones. Thus, when one is dealing with multi-variable problems, one must be very precise in the collection of data of an exploration performed on a patient. An error in the data collection can lead to a misleading diagnosis.

The results

The DSS has carried out a series of diagnosis which we subsequently will assess. When a new patient's register is introduced on the map it will match a neuron with the shortest distance to the characteristic pattern. This neuron is within an area with a specific dysfunction (0, 1, 2 or 3). This new entry will thus be diagnosed the same dysfunction as the neuron.

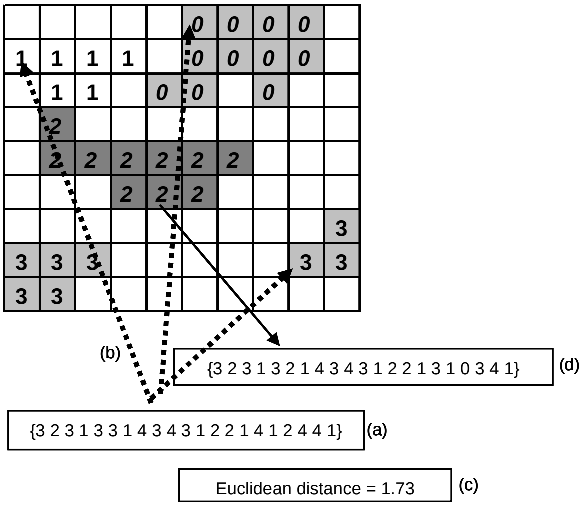

Figure 4: New input vector and its method of pattern recognition.

In the figure 4, ***a*** is the new pattern or input vector. This new input finds the shortest euclidean distance among all the neurons labelled (0, 1, 2 or 3) on the map. The discontinued lines ***b*** show some of these distances. At the end of the process the shortest distance ***c*** is localized in the neuron (5,6) in the coordinates of the matrix. The reference pattern of this neuron is ***d***. The resemblance of these two patterns is striking as the test pattern has matched it. This process has to be done for each new pattern.

Figure 5 is the result of the recognition process. From the graphics, it can be observed that effort incontinence and the disease free patients are the diagnosis with the highest degree of certainty with more than 90%.

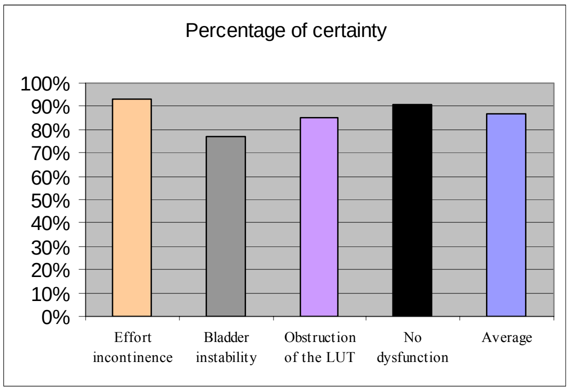

Figure 5: Percentage of certainty of the diagnosis classified according to disease.

This is due to the circumstance that the precision, with which the tests carried out were made, specifically within the field of cystometry, results in that the correctly measured value of these fields determines a diagnosis with a very low probability of error. The diagnoses of bladder instability and of obstruction of the LUT represent values of around 80% accuracy.

Conclusions

In the present article a DSS has been developed for the diagnosis of dysfunctions of the lower urinary tract with a degree of certainty of 90%. It has been observed that the SOM give very good results as concerns the recognition process of the urodynamical vectors of the patterns obtained from patients with urological dysfunctions. The system does not produce negative false. An ill patient will always be diagnosed as ill. Errors only take place when having to pinpoint similar dysfunctions.

The research constitutes the basis for further studies and research in the field of the system for aiding the diagnosis of dysfunctions in the LUT. In this regard we are considering the use of another type of unsupervised neural network such as the Growing Neural Gas (GNG) [16].

The system is of great help to the urologists as it permits them to eliminate tests with different variables and thus saving costs, time and pain for the patients.

A simple graphic interface which facilitates the entering of data by the user in order to train the learning of neural network (SOM or other type of network) should be created. In this way, it is possible to detect the significant relations between the multiple variables. This interface has recently been created and urologists have now started to use it. As a consequence, the collected data will be more precise and the discretization will be done when entering the medical journal of the patient. Time will therefore be saved, and the probabilities of errors will be reduced considerably.

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