ARTIFICIAL NEURAL NETWORKS FOR DIAGNOSES OF DYSFUNCTIONS IN UROLOGY

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Abstract: In this article we evaluate the work out of artificial neural networks as tools for helping and support in the medical diagnosis. In particular we compare the usability of one supervised and two unsupervised neural network architectures for medical diagnoses of lower urinary tract dysfunctions. The purpose is to develop a system that aid urologists in obtaining diagnoses, which will yield improved diagnostic accuracy and lower medical treatment costs. The clinical study has been carried out using the medical registers of patients with dysfunctions in the lower urinary tract. The current system is able to distinguish and classify dysfunctions as areflexia, hyperreflexia, obstruction of the lower urinary tract and patients free from dysfunction.

1 INTRODUCTION

Nowadays, the urologists have different tools available to obtain urodynamical data. However, it still remains very complicated to make a correct diagnosis: the knowledge concerning the origin of the detected dysfunctions depends mainly on acquired experience and on the research, which is constantly carried out within the field of urology. The specialists in urology are quite often dealing with situations that are poorly described or that are not described in the medical literature. In addition there are numerous dysfunctions whose precise diagnoses are complicated. This is a consequence of the interaction with the neurological system and the limited knowledge available on how this operates.

Various techniques are used to diagnose dysfunctions of the lower urinary tract (LUT), which entail different degrees of invasiveness for the patient (Abrams, 2005). A urological study of a patient consists of carrying out various costly neurological as well as physical tests like flowmetry and cystometry examinations with high degrees of complexity and invasiveness. This project is intended to aid the specialist in obtaining a reliable diagnosis with the smallest possible number of tests. To this end we propose the use of artificial neural networks (ANNs) since these present good results for classification problems (Begg, 2006). The reason why we decided to apply ANNs instead of other artificial intelligence (AI) methods for the support of medical diagnosis is due to the fact that ANNs can be trained with appropriate data learning in order to improve their knowledge of the system. In comparison to other techniques or other (more classical) approaches such as rules based systems or probabilities, ANNs are more suitable for medical diagnosis. On one hand, rules based systems (MYCIN system (Mycyn, 1976)) contain ”if-then” rules where the ”if” side of any rule is a collection of one or more conditions connected by logical operators such as ”AND”, ”OR” and ”NOT”. On the other hand, other systems such as probability systems calculate measures of confidence without the theoretical underpinnings of probability theory. These formal approaches based on probability theories are precise but can be awkward and non-intuitive to use.
Therefore, in medical diagnosis, we use the advantages of ANNs, which are considered as a method of disease classification. This classification has two divergent meanings. We can have a set of registers, vectors or data with the aim of establishing the existence of classes or clusters. In contrast, we can know with certainty that there exist some classes, and the aim is to establish a rule able to classify a new register into one of these classes. The first type is known as Supervised Learning and the second one is known as Unsupervised Learning (or Clustering). We believe that the accuracy of the diagnosis in medicine and, in particular, in urology will be improved by using these types of architectures (one supervised and two unsu-

pervised).

With the system of aid to the diagnosis major benefits are obtained both for the patient, by avoiding painful tests, and for the medical centres by avoiding expensive urodynamical tests and reducing waiting lists.

Although the use of ANNs in medicine is a rather recent phenomenon, there are many applications deployed as in the field of diagnosis, imaging, pharmacology, pathology and of course prognosis. ANNs have been used in the diagnosis of appendicitis, back pain, dementia, myocardial infraction (Green, 2006), psychiatric disorders (Peled, 2005)(Politi, 1999), acute pulmonary embolism (Suzuki, 2005), and temporal arteries.

In Urology, prostate cancer serves as a good example of the usability of ANNs (Remzi, 2001)(Batuello, 2001)(Remzi, 2004). However our work is more related with the neurological part which is less explored (Gil, 2006)(Gil, 2005)(Ruiz, 2005).

In this paper we describe the implementations of ANN based systems aiming at support diagnoses of dysfunctions of the LUT. The remaining part of the paper is organized as follows: first, we give a brief description of the employed neural network architectures. Next we describe the design of our proposal and the training of the ANNs by the available data. Then we describe the subsequent testing carried out in order to analyze the results. Finally we draw the relevant conclusions.

2 NEURAL NETWORK ARCHITECTURES

We have tested three different neural network architectures, two unsupervised ANNs and one supervised ANN. The goal is to obtain a system that supports the diagnoses of the dysfunctions of the LUT. The classification in the maps of the unsupervised ANNs and the output from the supervised ANN will assist the urologist in their medical decisions.

2.1 Supervised ANN - Multilayer Perceptron

A typical Multilayer perceptron (MLP) network consists of three or more layers of neurons: an input layer that receives external inputs, one or more hidden layers, and an output layer which generates the classification results (Jiang, 2006)(Fig. 2). Note that unlike other layers, no computation is involved in the input layer. The principle of the network is that when data are presented at the input layer, the network neurons run calculations in the consecutive layers until an output value is obtained at each of the output neurons. This output will indicate the appropriate class for the input data.

The architecture of the ANN (MLP) consists of layer 1, with the inputs that correspond to the input vector, the layer 2, with the hidden layer and the layer 3 which are the outputs (the 3 diagnoses of the LUT) and the learning used is backpropagation and the algorithm runs as follows:

All the weight vectors m are initialized with small random values from a pseudorandom sequence generator. The following steps are repeated until convergence (i.e. when the error E is below a preset value): Update the weight vectors m_i by

$$m(t+1) = m(t) + \Delta m(t) \quad (1)$$

where

$$\Delta m(t) = -h\partial E(t)/\partial m \quad (2)$$

Compute the error E(t+1).
where t is the iteration number, m is the weight vector, and h is the learning rate. The error E can be chosen as the mean square error function between the actual output y_j and the desired output d_j:

$$E = \frac{1}{2}\sum_{j=1}^{n_j}(d_j - y_j)^2 \quad (3)$$

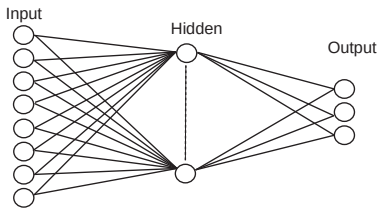

Figure 1: The architecture of the MLP.

2.2 Unsupervised ANN - Kohonen's Self-Organizing Maps

Kohonen's Self-Organizing Map (SOM) is composed of neurons located in a two-dimensional matrix (Kohonen, 1988)(Kohonen, 1990)(Kohonen, 2000). There is a weight vector, $m_i = (m_{i1\ i2}\ ...\ m_{in})$ associated with every neuron in the SOM, 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 in the register.

The SOM is used as a classifier and is organized as indicated in figure 1.

In the fully trained network each neuron is associated with a vector in the input space. The SOM is a soft competitive neural network, which means the winner neuron, i.e. the neuron with the weight vector that is closest to the current input vector according to some measure (dot product in our implementation), gets its weight vector updated so that it becomes more similar to the input vector. The neurons in the vicinity of the winner neuron also get their weight vectors updated but to a lesser extent. Usually a Gaussian function of the distance to the winner neuron is used to modify the updating of the weight vectors. The trained SOM is a projection of the input space, which preserves the topological relationships of the input space. The training of the SOM works as follows:

At time step t an input signal $x \in \mathrm{R}^n$ activates a winner neuron c for which the following is valid:

$$\forall i : x^T(t)m_c(t) \geq x^T(t)m_i(t) \tag{4}$$

The weights are updated according to:

$$m_i(t+1) = \begin{cases} \frac{[m_i(t)+\alpha(t)x(t)]}{||m_i(t)+\alpha(t)x(t)||} & if \quad i \in N_c(t) \\ m_i(t) & if \quad i \notin N_c(t) \end{cases} \tag{5}$$

where $N_c(t)$ is the neighbourhood of the neuron c at time t and $0 < \alpha(t) < \infty$.

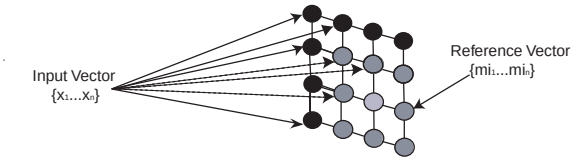

Figure 2: The Kohonen SOM.

2.3 Unsupervised ANN - Growing Cell Structures

It has been pointed out that the predefined structure and size of Kohonen's SOM bring limitations to the resulting mapping. One attempt to solve this problem is the growing cell structures (GCS) (Fritzke, 1993)(Fritzke, 1997), which has a flexible and compact structure, a variable number of elements and a k-dimensional topology where k can be arbitrarily chosen.

In principle, the adaptation of a weight vector in the GCS is done as described in the previous section (SOM), i.e. determine the best matching neuron, adjust its weight vector and the weight vectors of its topological neighbours. However, there are two important differences when compared to the SOM, namely that the adaptation strength is constant over time, and that only the best matching neuron and its direct topological neighbours are adapted.

The GCS estimates the probability density function $P(x)$ of the input space by the aid of local signal counters that keep track of the relative frequency of input signals gathered by each neuron. These estimates are used to indicate proper locations to insert new neurons. The insertion of new neurons by this method will result in a smoothing out of the relative frequency between different neurons. The advantages of this approach is that also the topology of the network will self-organize to fit the input space and the proper number of neurons for the network will be automatically determined, i.e. the algorithm stops when a certain performance criterion is met. Another advantage is that the parameters are constant over time.

The basic building block and also the initial configuration of the GCS is a k-dimensional simplex. Such a simplex is for $k = 1$ a line, for $k = 2$ a triangle, and for $k = 3$ a tetrahedron. In our implementation $k = 2$.

The self-organizing process of the GCS works as follows:

The network is initialized to contain k + 1 neurons with weight vectors $\mathrm{m}_i \in R^n$ randomly chosen. The neurons are connected so that a k-dimensional simplex is formed.

At time step t an input signal $x \in R^n$ activates a winner neuron c for which the following is valid:

$$\forall i : ||x - m_c|| \quad \geq ||x - m_i|| \quad , \tag{6}$$

and the squared distance between the input signal and the winner neuron c is added to a local error variable E_c:

$$\Delta E_c = ||x - m_c||^2. \tag{7}$$

The weight vectors are updated by fractions ε_b and ε_n respectively according to:

$$\Delta m_c = \varepsilon_b(x - m_c) \tag{8}$$

$$\forall i \in N_c : \Delta m_i = \varepsilon_n(x - m_i), \tag{9}$$

where N_c is the set of direct topological neighbours of c. A neuron is inserted if the number of input signals that have been generated so far is an integer multiple of a parameter λ. This is done by dividing the longest edge between the neuron q with the largest accumulated error and its connected neighbour f, and then removing the earlier connection (q, f) and connect r to all neighbours that are common for q and f. The weight vector for r is interpolated from the weight vectors for q and f:

$$m_r = (m_q + m_f)/2. \quad (10)$$

The error variables for all neighbours to r are decreased by a fraction α that depends on the number of neighbours of r:

$$\forall i \in N_r : \Delta E_i = (-\alpha/|N_r|) \cdot E_i, \quad (11)$$

The error variable for r is set to the average of its neighbours:

$$E_r = (1/|N_r|) \cdot \sum_{\iota \in Nr} E_i, \quad (12)$$

and then the error variables of all neurons are decreased:

$$\forall i : \Delta E_i = -\beta E_i \quad (13)$$

3 EXPERIMENTATION

An exhaustive urological exploration with 21 different measurements has been carried out with 200 patients with dysfunctions of the lower urinary tract in order to create a database. The data has been analyzed and processed before entered into the network to ensure that it is homogenized. These 200 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 the 21 fields showed in Table 1. For this reason, this database plays a crucial role in order to obtain the knowledge base of our system.

The table 1 shows the fields (every variable) of the urological database (their physical units and types of data). This table helps us to understand the dimension of the problem to deal with (different types of data, ranges and incomplete fields). The column direction of the table indicates the meaning for the ANN: all the fields are input for the system except the field diagnosis, which is the dysfunction of each register. There are three dysfunction and one output more for the diagnosis free of dysfunction.

Our database presents a diversity of ranks, values and types. For this reason it is better to start with a process of discretization in order to find a way to guarantee the homogeneity as a first step in the process of training of the ANN. It was adjusted and weighted with the help of the urologists, following their instructions and suggestions.

For example, some of the fields of the database are age, volume of urine and micturition time (as can be seen in table 1). As the differences among all these fields are huge, we created ranks in the values of the fields dividing them into subclasses in order to adjust the data input.

Table 1: The fields of the urological database.

Variable	Type of data	Values	Direction
Age	Numerical	3 85 years	Input
Sex	Categorical	Male, female	Input
Neurological Physical Examination			
Perineal and perianal sensitivity	Categorical	Partial, absence, normal, weak	Input
Voluntary control anal sphincter	Categorical	Partial, absence, normal, weak	Input
Anal tone	Categorical	Normal, relaxed	Input
Free Flowmetry			
Volume of urine	Numerical	7 682 ml	Input
Maximum flow rate	Numerical	4 58 ml/s	Input
Medium flow	Numerical	1 43 ml	Input
Post void residual	Numerical	0 550 ml	Input
Micturition time	Numerical	13 160 s	Input
Cystometry			
Bladder storage	Numerical	50 461 ml	Input
First sensation of bladder filling	Numerical	50 300 ml	Input
Detrusor pressure during filling	Numerical	2 30 cm H20	Input
Test pressure / flow			
Detrusor contraction	Categorical	Invol., Vol., Invol.-Vol.	Input
Volume of urine in micturition	Numerical	0 556 ml	Input
Maximum pressure Detrusor	Numerical	2 200 cm H20	Input
Average flow rate	Numerical	0 10 ml/s	Input
Abdominal pressure	Categorical	Yes, no	Input
Post void residual	Numerical	0 350 ml	Input
Maximum flow rate	Numerical	0 31ml/s	Input
Micturition time	Numerical	2 318 s	Input
Diagnosis			
Areflexia, Hyperreflexia, Obstruction of the LUT, No Dysfunction			Output

For instance:

Age: 0-20 (1), 21-50 (2), 51-65 (3), >65 (4)

Volume of urine: 0-150 (1), 151-300 (2), 301-500 (3), >500 (4)

The numbers between the parentheses are the discretized representations. As we can observe the difficulties are not only in the data ranks, but also in the

types of data, which complicates the process of data discretization.

The next step is to run the experimentation. This has been performed by using cross-validation method. The data has been divided in five sets (S1, S2, S3, S4, S5) and the five experiments performed were:

Experiment 1-Training: T1, T2, T3, T4; Test: V (S5)
Experiment 2-Training: T1, T2, T3, T5; Test: V (S4)
Experiment 3-Training: T1, T2, T4, T5; Test: V (S3)
Experiment 4-Training: T1, T3, T4, T5; Test: V (S2)
Experiment 5-Training: T2, T3, T4, T5; Test: V (S1)

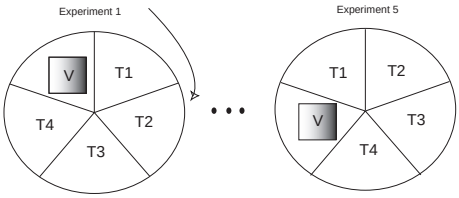

Figure 3: Cross Validation method.

This method is represented in figure 3. There are four data sets used for the process of constructing the model (the training data). The other set of data used to validate the model (the test data). The test data are chosen randomly from the initial data and the remaining data form the training data. The method is called 5-fold cross validation since this process has been performed five times.

The results of the Multilayer Perceptron with the backpropagation algorithm are of around 80% of accuracy. For the other networks, the unsupervised ones, the results are of 76% for the Growing Cell Structures and 74% for Kohonen's Self-Organizing Map. The MLP offers a slightly better performance than GCS and SOM. However the unsupervised ANNs give a useful visual information. This is the reason why we believe a hybrid system with supervised and unsupervised ANNs works properly incorporating the advantages of each ANN.

This comparative and its results with the three different types of ANNs not only has the goal of discovering which is the best neural network but also and mainly to find out relations between the dysfunctions (output of the network). As shown in figure 4 it will help the urologist to pay attention in some tests and its measures to increase the accuracy of the system. In this regard, it will be possible to eliminate some of the tests in order to save money, time and sometimes pain for the patients.

To measure the performance of the ANNs we proceed as follow: Once the ANNs have been trained there are some membership functions for each area, we take a test and we see in which area it is categorized. If the neuron has only input vectors of the same dysfunction the accuracy is 100% otherwise it depends on the mix of dysfunctions and it is another percentage (it incorporates the fuzzy logic idea since it measures the degree of membership to the categorized area). Moreover, a big advantage of using unsupervised ANNs , as we can see in figure 4, is the visual perception of the proximities of the different dysfunctions (their membership functions) categorized in areas to find out relations between similar inputs. The system does not produce negative false. This fact makes it highly reliable amongst the urologists.

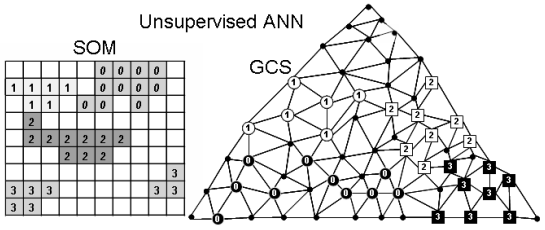

Figure 4: Evaluation of the unsupervised ANNs.

4 CONCLUSIONS AND FUTURE WORK

In this paper we have evaluated the performance of three different kinds of artificial neural networks, the Kohonen Self-Organizing Map, the Growing Cell Structures and the Multilayer Perceptron with the backpropagation algorithm, when applied to the categorization of urological dysfunctions. The ANNs were trained with data from a database with registers of different patients with urological dysfunctions.

The experiment starts with a stage of discretization of the urodynamical measures from a patient in order to provide them to the ANN and to determine if there are any of the three dysfunctions of the LUT or not. In case of finding a dysfunction it would determine what type of dysfunction or dysfunctions the patient could have.

The human expert is able to generalize by using his experience. This big advantage is compensated for ANNs by using graphs offering a visual perception. The frontiers between two dysfunctions help the urologist to discover resemblances. They can also help detecting similarities between fields or urodynamical samples.

In this work we obtained comments valuable from the urologists after using the system. They remarked

its advantages to give a more precise diagnosis and, therefore, to save time and money to the public health. Their comments encourage us to continue our work to develop a system that uses the diagnosis obtained as a result of the combined use of different neural networks. This gives an even more accurate diagnosis.

Next step is the use of data mining involving several steps such as pre-processing with sampling, cleaning and others learning methods as bayesian networks, decision trees, etc.

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