Implementation of an Expert System to Diagnose Spinal Diseases

Miguel F. Rocha
ESIME, Instituto Politécnico Nacional, U.P. A.L. Mateos, G. A. Madero, México D.F. 07738, México.
Email: mrocha@ipn.mx.

Leonardo Orozco, M. Rosario Osnaya, Darío R., Rafael Navarrete, M. I. Rocha G., and E. Andrade
ESIME, Instituto Politécnico Nacional, U.P. A.L. Mateos, G. A. Madero, México D.F. 07738, México.
Grupo de Fenómenos Ondulatorios, Departamento de Ingeniería Electrónica, Universidad Politécnica de Valencia, España.
Instituto de Física, Universidad Nacional Autónoma de México.
Email: mrocha@ipn.mx., marocga@doctor.upv.es, andrade@fisica.unam.mx

***Abstract*—Sometimes medical human specialists may be affected by fatigue which may impact in their professional response. The spine consists of 26 bones called vertebrae, the vertebrae protect the spinal cord and allowed to stand and remain in an upright position. The objective of this paper is to implement an Expert System (ES) to diagnose spinal diseases by means of Morphological Hetero-Associative Memories and compare it with other approaches proposed previously in the literature. The implemented expert system based on Morphological Hetero-Associative Memories is able to diagnose normal status, disk hernia or spondylolisthesis, with a degree of reliability of up to 87.74% for a given TR of 100%.**

***Index Terms*—expert system, morphological hetero-associative memories.**

I. Introduction

The spine consists of 26 bones called vertebrae. The vertebrae protect the spinal cord and allowed to stand and remain in an upright position. There are several problems that can alter the structure of the spine or injure the vertebrae and the surrounding tissue. Including: Infections, Injuries, and Tumors. These diseases affect the world population in a large scale. Fortunatelly, human specialists are able to diagnose these diseases. Spinal diseases affect the world population in a large scale. Fortunatelly, human specialists are able to diagnose these disease However,sometimes human specialists cannot attend all the existing pacients. In fact, fatigue can affect the response of the specialists and, if the human specialist resigns, retires or dies, then his knowledge is missed. Therefore, a Medical Expert System is usefull to to diagnose diseases without fatigue or emotions [1]. For these reasons we propose a tool to offer a second medical opinion in the spinal diseases area. The objective of this paper is to implement an Expert System (ES) to diagnose spinal diseases by means of Morphological Hetero-Associative Memories and compare it with other approaches proposed previously in the literature [2]-[4].

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A. Expert System

An ES is a system able to emulate the decision making ability of human specialists [5]. Fig. 1 shows the basic architecture of an Expert System. Knowledge Base is composed by all the available information about the field of the application in form of rules. Moreover, working memory is used to introduce some information about a particular problem (Fact) to the ES; then, the Inference engine contrasts the particular fact with rules contained in the Knowledge Base; that is to say, it makes inferences by deciding which rules are satisfied by facts and executes the rule with the highest priority.

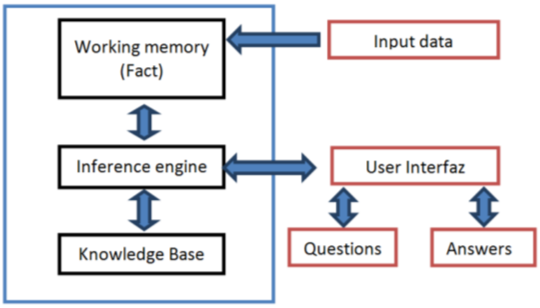

Figure 1. .Architecture of an expert system.

For the Knowledge Base of the proposed ES we used a “Vertebral Column Data Set” which is a data set with 310 instances that contains values for six biomechanical features used to classify orthopedic patients into 3 classes: normal, disk hernia or spondylolisthesis [6]. Furthermore Morphological Hetero-Associative Memories are used as Inference engine.

B. Morphological Associative Memories

Morphological associative memories are structures that associate input patterns to output patterns.

Consider $\boldsymbol{x} \in \mathbf{R}^{\mathbf{n}}$ as an input pattern and $\boldsymbol{y} \in \mathbf{R}^{\mathbf{n}}$ as an output pattern. An association between input pattern $\boldsymbol{x}$ and output pattern $\boldsymbol{y}$ is denoted as $(\boldsymbol{x}^{\xi},\boldsymbol{y}^{\xi})$ where ξ is the

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corresponding association. Associative Memory (AM), **W,** is represented by a matrix whose components, w_{ij}, can be seen as the synapses of the neural network. If $x^\xi = y^\xi$ $\forall \xi=1,\ldots,k$, then **W** is auto-associative, otherwise it is hetero-associative.

A distorted version of a pattern **x** to be recuperated will be denoted as $\bar{x}$. If an AM, **W,** is fed with a distorted version of $\mathbf{x}^\xi$ and the output obtained is exactly $\mathbf{y}^k$, it is sadi that recalling is robust.

A Morphological Associative Memories (MAM) that will recall the pattern ***y*** when presented the pattern ***x*** is givenby:

$$W = y \vee (-x)^t = \begin{pmatrix} y_1 - x_1 & \ldots & y_1 - x_n \\ \vdots & \ddots & \vdots \\ y_m - x_1 & \ldots & y_m - x_n \end{pmatrix} \quad (1)$$

Since **W** satisfies the equation $W \vee x = y$, that is to say:

$$W \vee x = \begin{pmatrix} \bigvee_{i=1}^{n} (y_1 - x_i + x_i) \\ \vdots \\ \bigvee_{i=1}^{n} (y_m - x_i + x_i) \end{pmatrix} = y \quad (2)$$

Equation 1 represents **W** that is called max product of ***y*** and ***x***. Also it is possible to denote the ***min*** product of ***y*** and ***x*** using operator $\wedge$.

For a given set of pattern associations $\{(x^\xi, y^\xi); \xi = 1,\ldots,k\}$ a couple of pattern matrices ***(X,Y)*** is defined, where $X = (x^1,\ldots,x^k)$, $Y = (y^1,\ldots,y^k)$. With each pair of matrices ***(X,Y)***, two natural morphological *mxn* memories $\mathbf{W}_{xy}$ and $\mathbf{M}_{xy}$ are defined by:

$$W_{XY} = \bigwedge_{\xi=1}^{k} [y^\xi \vee (-x^\xi)] \quad (3)$$

and

$$M_{XY} = \bigwedge_{\xi=1}^{k} [y^\xi \vee (-x^\xi)] \quad (4)$$

From this definition it follows that

$$y^\xi \wedge (-x^\xi)^t = y^\xi \vee (-x^\xi)^t \quad (5)$$

Which implies that $\forall \xi=1,\ldots,k$

$$W_{XY} \leq y^\xi \wedge (-x^\xi)^t = y^\xi \vee (-x^\xi)^t \leq W_{XY} \quad (6)$$

In terms of equation 2, 3 and 4, this last set of inequalities implies that $\forall \xi=1,\ldots,k$

$$W_{XY} \vee X \leq Y \leq M_{XY} \wedge X \quad (7)$$

MAMs are robust to additive noise or subtractive noise, but, not both, that is to say mixed noise. While MAM $\mathbf{W_{XY}}$ is robust to subtractive noise, MAM $\mathbf{M_{XY}}$ is robust to additive noise [7], [8].

II. Methodology

To obtain an inference engine it is necessary to find MAM $\mathbf{M_{XY}}$ and $\mathbf{W_{XY}}$. First, we select a value for ***a*** and ***b*** coefficients because by means of them it is possible to build ***y*** patterns. The proposed structure for ***y*** patterns is shown in equation 8. If $i = \xi$, then $y^\xi_i = a$, otherwise, $y^\xi_i = b$.

$$y^\xi = \begin{pmatrix} y_1^\xi \\ y_2^\xi \\ \vdots \\ y_i^\xi \\ \vdots \\ y_m^\xi \end{pmatrix} \quad (8)$$

Meanwhile, each ***x*** pattern is composed by an instance of“Vertebral Column Data Set”. Therefore ***x*** patterns are composed by six biomechanical features of an instance. The proposed structure for ***x*** patterns is shown in equation 9.

$$x^\xi = \begin{pmatrix} x_1^\xi \\ x_2^\xi \\ \vdots \\ x_j^\xi \\ \vdots \\ x_n^\xi \end{pmatrix} \quad (9)$$

Applying equations 3 and 4 led us to both MAMs, and therefore, inference engine is completed.

To study the response of the inference engine, we propose to select some instances of “Vertebral Column Data Set”. To build the inference engine, and the other instances that were used to test it. In other words, some instances of “Vertebral Column Data Set” were used for the Knowledge Base and the rest were used towork the Memory. Then the *Training Rate*(*TR*)was defined as a parameter to determine the number of instances used to build theKnowledge Base. The *TR* is applied for each class of “Vertebral Column Data Set”. For example, if there are 100 instances classified as normal, 60 instances as disk hernia and 150 as spondylolisthesis; for a *TR* of 50%, the Knowledge Base is built with 50 instances classified as normal, 30 instances as disk hernia and 75 as spondylolisthesis. All of them are selected randomly and to select the same instance is not allowed.

We considered three subsets of *y* patterns, each one associated to a different class: normal, disk hernia or spondylolisthesis. The amount of *y* patterns associated with a class depends on *TR* and on the total amount of instances by class. For the mentioned example, the normal class was associated with a subset of *y* patterns given by $Y_1 = (y^1,\ldots,y^{50})$, the disk hernia class was associated with subset of ***y*** patterns given by $Y_2 = (y^{51},\ldots,y^{80})$, and finally, the spondylolisthesis class was associated with subset of ***y*** patterns given by $Y_3 = (y^{81},\ldots,y^{155})$. Of course, the set of ***y*** patterns remains the same, that is to say, $Y = (y^1,\ldots, y^{155})$ or $Y = (Y^1, Y^2\ Y^3,)$.

To test the engine inference ***x*** pattern from Working Memory was presented to inference engine ***a*** and ***y*** pattern is obtained. Consequently, it was possible to identify its associated class by means of the position of a coefficients. In other words, according to equation 8, the position of the ***a*** coefficient ($i \ni y^{\xi}_{i}=a$) determinates the number of associations ξ and therefore the subset of ***y*** patterns which was associated with a class. If the given class is the same as the "Vertebral Column Data Set", then, it means a robust recalling, otherwise, it was a mistake. After feed the inference engine with the complete set of instances contained in the Working Memory, the amount of instances with robust recalling were counted.

III. Results and Discussion

The proposed Expert System was implemented in "C#" language.

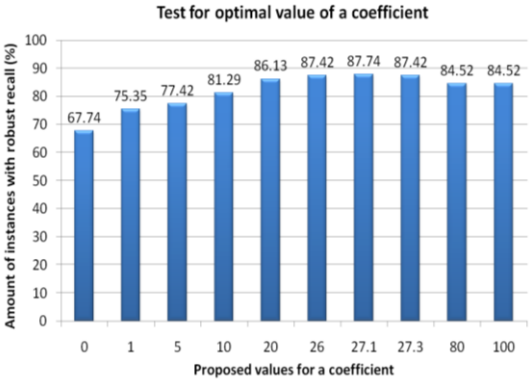

Figure 2. Tests for optimal value of a coefficient.

To obtain the optimal value for ***a*** and ***b*** coefficients, we proposed 100% as Training Rate with a constant parameter. Thereby, different values for ***a*** and ***b*** were tested. The goal was to find those which produced the highest amount of instances with robust recalling. Fig. 2 shows some tests; ***x***-axis represents the proposed value for ***a*** coefficient and ***y***-axis represents the amount of instances with robust recalling in percentage produced by ***a*** coefficient. It was found that the value for the ***b*** coefficient is not involved in the result as long as ***a*** is greater than ***b*** for M_{XY} and, similarly, ***a*** is less than ***b*** for W_{XY}. In both cases the value for the ***b*** coefficient was zero.

In this particular case all the instances of "Vertebral Column Data Set" were used for the Knowledge Base and likewise all of them were used for the Working Memory. For the given database it was found that the best value for the ***a*** coefficient is 27.1, since it produces 87.4% of instances with robust recalling.

We studied the response of the Expert System with the optimal value of the ***a*** coefficient as a constant parameter, but this time we tested with different values of *Training Rate*. This means that for a given *TR*, some instances of "Vertebral Column Data Set" were used for the Knowledge Base and the rest of them were used for the Working Memory, except for a *TR* of 100%. It is shown in Fig. 3, that the *x*-axis represents the proposed *Training Rate* in percentage and the *y*-axis represents the amount of instances with robust recalling in percentage.

Depending on the randomly selection of instances that were used for the Knowledge Base, our tests produced different percentages of instances with robust recalling. For this reason we made hundreds of tests to report the results with the highest score in Fig. 3. In Fig. 4 we report the arithmetic mean appliyed to 200 tests for each proposed *TR*; the *x*-axis represents the proposed *TR* in percentage and the ***y***-axis represents the arithmetic mean of instances with robust recalling in percentage.

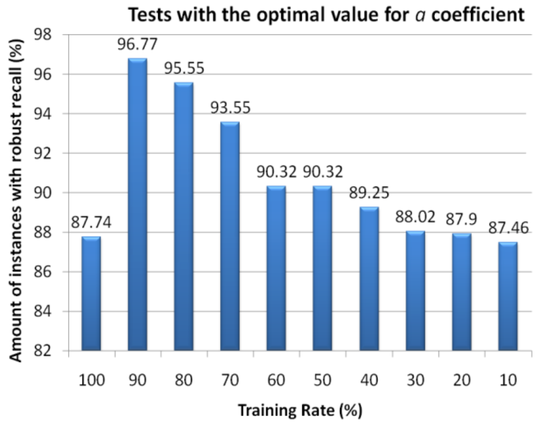

Figure 3. Tests with the optimal value for a coefficient with robust recall (%) and training rate (%)

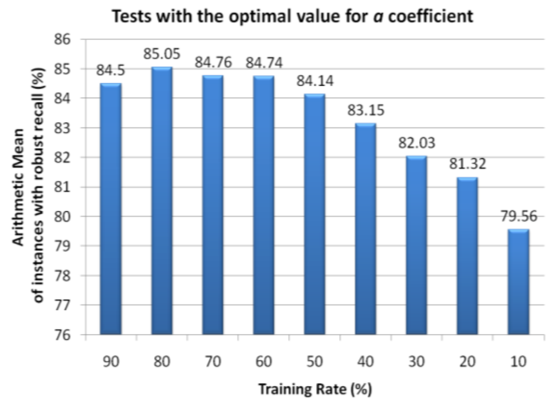

Figure 4. Tests with the op represents arithmetic with aritmetic mean.

TABLE I: Results of Some WEKA ́S(Waikato Environment for Knowledge Analysis) Classifiers and the Proposed ES

TR (%)	Amount of instances with robust recalling (%)			
	Multiclass classifier WEKA	Multilayer perceptron WEKA	Class classifier WEKA	MAM (Hetero-Associative)
90	83.87	90.32	87.09	96.77
80	80.64	83.87	80.64	95.55
70	83.87	80.64	78.49	93.55
60	83.87	87.09	78.22	90.32
50	81.93	83.22	81.93	90.32
40	84.40	83.87	75.80	89.25
30	86.17	86.17	77.41	88.02
20	85.08	82.66	77.82	87.90
10	77.06	82.79	73.83	87.46

Table I shows a comparison among some classifiers offered by WEKA (Waikato Environment for Knowledge Analysis) [9] and the Expert System based on Morphological Hetero-Associative Memories; all of them use "Vertebral Column Data Set" assourse for the Knowledge Base.

IV. CONCLUSIONS

The implemented Expert System based on Morphological Hetero-Associative Memories is able to diagnose normal status, disk hernia or spondylolisthesis, with a degree of reliability of up to 87.74% for a given *TR* of 100%.

Regarding some other classifiers offered by WEKA, their results are less than the proposed Expert System; in fact, the arithmetic mean of instances with robust recalling offered by the proposed Expert System is in most cases higher than the results of some classifiers offered by WEKA.

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Miguel F. Rocha obtains Degree in Physics and Mathematics, Nuclear Engineering; Assessors CONACYT, RCEA-01-18938-2010, his is Senior Member of IACSIT: 80340416; ARBITER, the Nuclear Instruments and Methods in Physics Research B; ARBITER CISCI 2008. Orlando, Florida, USA, Chief, Department of Radiation Protection and Head of Security Unit in nuclear power plants in the National Institute for Nuclear Research, Mexico Research Professor and Chair of the Academy of Physical ESIME, National Polytechnic Institute, Mexico; outreach work attendance at events or conferences, articles published in refereed journals (ISI), 21 Projects, 15 Research Group, 17 Research Visits, Directorate of Thesis;