A new associative classification approach to Parkinson pre diagnosis

Rogelio Ramírez-Rubio, Sonia L. Valencia-Ortíz, Mario Aldape-Pérez, Cornelio Yáñez-Márquez, and Oscar Camacho-Nieto

Centro de Innovación y Desarrollo Tecnológico en Cómputo (CIDETEC)
Instituto Politécnico Nacional (IPN)
Ciudad de México, México

http://www.aldape.mx

Abstract. In this paper Parkinson Disease pre diagnosis is addressed from a different perspective using associative models. Associative memories are mathematical models used to recognize and classify instances. In the present paper we address Parkinson classification problem using an autoassociative memory and the smallest normalized difference criteria. Parkinson Disease symptoms begin slowly, typically on one side of the body and then both sides are affected. It is important to diagnose this disorder as soon as possible in order to reduce its consequences. In this paper, a set of well-known classifiers are compared in order to have a fair classification performance comparison.

Keywords: Associative models, CHAT, Parkinson Disease, Pattern Recognition.

1 Introduction

Associative models have been used mainly to perform pattern recognition, but they are also useful to perform classification tasks. It has to be mentioned that associative memories in its autoassociative mode have not been widely used in classification tasks. In this paper we propose an algorithm that uses an autoassociative memory as its first step and smallest normalized difference criteria as its second step. Parkinson Disease has been addressed with many classification algorithms and diagnosis tests [1,2,3].

Parkinson Disease is a type of movement disorder. It occurs when nerve cells (neurons) do not produce enough of an important chemical in the brain called dopamine. Some cases are genetic, but most do not seem to occur between members of the same family. Symptoms begin slowly, in general, on one side of the body. Then affect both sides [4]. Some symptoms are:

– Trembling hands, arms, legs, jaw and face

- Stiffness in the arms, legs and trunk
- Slowness of movement
- Balance and coordination problems

Parkinson Disease is a neurological disorder with evolving layers of complexity. It has long been characterized by the classical motor features of Parkinsonism associated with Lewy bodies and loss of dopaminergic neurons in the substantia nigra. However, the symptomatology of Parkinson's disease is now recognized as heterogeneous, with clinically significant non-motor features [5].

Normal maintenance of human motivation depends on the integrity of subcortical structures that link the prefrontal cortex with the limbic system. Structural and functional disruption of different networks within these circuits alters the maintenance of spontaneous mental activity and the capacity of affected individuals to associate emotions with complex stimuli. The clinical manifestations of these changes include a continuum of abnormalities in goal-oriented behaviors known as apathy. Apathy is highly prevalent in Parkinson's disease (and across many neurodegenerative disorders) and can severely affect the quality of life of both patients and caregivers. Differentiation of apathy from depression, and discrimination of its cognitive, emotional, and auto-activation components could guide an individualized approach to the treatment of symptoms [6].

The paper is organized as follows. A succinct description of associative memories fundamentals is presented in Section 2. Section 3 provides a concise description of the most important characteristics of Alpha-Beta Associative Memories. In Section 4 our proposal foundations are presented. In Section 5 classification accuracy results achieved by each one of the compared algorithms using Parkinson Disease dataset are presented. Finally, our proposal advantages, as well as some conclusions will be discussed in section 7.

2 Associative Memories

An associative memory $\mathbf{M}$ is a mathematical model that relates input patterns and output patterns. Each input vector $\mathbf{x}$ forms an association with its corresponding output vector $\mathbf{y}$. For each γ integer and positive, the corresponding association will be denoted as: $(\mathbf{x}^\gamma, \mathbf{y}^\gamma)$. An associative memory $\mathbf{M}$ is represented by a matrix whose ij-th component is m_{ij}. An associative memory $\mathbf{M}$ is generated from an *a priori* finite set of known associations, called the fundamental set of associations. If μ is an index, the fundamental set is represented as: $\{(\mathbf{x}^\mu, \mathbf{y}^\mu) \mid \mu = 1, 2, ..., p\}$ with p as the cardinality of the set. The patterns that form the fundamental set are called fundamental patterns. If it holds that $\mathbf{x}^\mu = \mathbf{y}^\mu \; \forall \mu \in \{1, 2, ..., p\}$, $\mathbf{M}$ is autoassociative, otherwise it is heteroassociative; in this case, it is possible to establish that $\exists \mu \in \{1, 2, ..., p\}$ for which $\mathbf{x}^\mu \neq \mathbf{y}^\mu$. If we consider the fundamental set of patterns $\{(\mathbf{x}^\mu, \mathbf{y}^\mu) \mid \mu = 1, 2, ..., p\}$ where n and m are the dimensions of input patterns and output patterns, respectively, it is said that $\mathbf{x}^\mu \in A^n$, $A = \{0, 1\}$ and $\mathbf{y}^\mu \in A^m$. Then the j-th component of an input pattern $\mathbf{x}^\mu$ is $x_j^\mu \in A$. Analogously, the i-th component of an output pattern $\mathbf{y}^\mu$ is represented as $y_i^\mu \in A$. Therefore, the fundamental input patterns and output patterns are represented as follows:

$$\mathbf{x}^\mu = \begin{pmatrix} x_1^\mu \\ x_2^\mu \\ \vdots \\ x_n^\mu \end{pmatrix} \in A^n \qquad \mathbf{y}^\mu = \begin{pmatrix} y_1^\mu \\ y_2^\mu \\ \vdots \\ y_m^\mu \end{pmatrix} \in A^m$$

A distorted version of a pattern $\mathbf{x}^\gamma$ to be recalled will be denoted as $\widetilde{\mathbf{x}}^\gamma$. An unknown input pattern to be recalled will be denoted as $\mathbf{x}^\omega$. If when an unknown input pattern $\mathbf{x}^\omega$ is fed to an associative memory $\mathbf{M}$, happens that the output corresponds exactly to the associated pattern $\mathbf{y}^\omega$, it is said that recalling is correct.

3 Alpha-Beta Associative Memories

Alpha-Beta Associative Memories were first introduced in [7]. Alpha-Beta Associative Memories mathematical foundations are based on two binary operators: α and β. Alpha operator is used during the learning phase, while Beta operator is used during the recalling phase. The mathematical properties within these operators, allow the $\alpha\beta$ associative memories to exhibit similar characteristics to the binary version of the morphological associative memories, in the sense of: learning capacity, type and amount of noise against which the memory is robust, and the sufficient conditions for perfect recall [8]. First, we define set $A = \{0, 1\}$ and set $B = \{0, 1, 2\}$, so α operator is defined as in Table 1 and β operator is defined as in Table 2. These two binary operators along with maximum ($\vee$) and minimum ($\wedge$) operators establish the mathematical tools around the Alpha-Beta model [9]. The definitions of α and β exposed in Table 1 and Table 2 , imply that: α is increasing by the left and decreasing by the right, β is increasing by the left and right, β is the left inverse of α, see Table 3. A summary of the mathematical properties of α and β operators are shown in Table 4 and Table 5.

According to the operator that is used during the learning phase, two kinds of Alpha-Beta Associative Memories are obtained. If maximum operator ($\vee$) is used, Alpha-Beta Associative Memory MAX type will be obtained, denoted as $\mathbf{M}$; analogously, if minimum operator ($\wedge$) is used, Alpha-Beta Associative Memory min type will be obtained, denoted as $\mathbf{W}$ [7].

In order to understand how the learning and recalling phases are carried out, some matrix operations definitions are required.

Table 1: Alpha Operator.

$\alpha : A \times A \longrightarrow B$

x	y	α(x,y)
0	0	1
0	1	0
1	0	2
1	1	1

Table 2: Beta Operator.

$\beta : B \times A \longrightarrow A$

x	y	β(x,y)
0	0	0
0	1	0
1	0	0
1	1	1
2	0	1
2	1	1

Definition 1. *Let n and m be integer and positive numbers that represent the dimension of input patterns and output patterns, respectively.* $\alpha \max$ *Operation is defined according to the following expression:*

$$P_{mxr} \nabla_{\alpha} Q_{rxn} = \left[f_{ij}^{\alpha} \right]_{mxn} \tag{1}$$

where $f_{ij}^{\alpha} = \vee_{k=1}^{r} \ \alpha(p_{ik}, q_{kj})$

Definition 2. *Let n and m be integer and positive numbers that represent the dimension of input patterns and output patterns, respectively.* $\beta \max$ *Operation is defined according to the following expression:*

$$P_{mxr} \nabla_{\beta} Q_{rxn} = \left[f_{ij}^{\beta} \right]_{mxn} \tag{2}$$

where $f_{ij}^{\beta} = \vee_{k=1}^{r} \ \beta(p_{ik}, q_{kj})$

Definition 3. *Let n and m be integer and positive numbers that represent the dimension of input patterns and output patterns, respectively.* $\alpha \min$ *Operation is defined according to the following expression:*

$$P_{mxr} \mathit{\Delta}_{\alpha} Q_{rxn} = \left[f_{ij}^{\alpha} \right]_{mxn} \tag{3}$$

where $f_{ij}^{\alpha} = \wedge_{k=1}^{r} \ \alpha(p_{ik}, q_{kj})$

Table 3: Operators Properties.

$\beta[\alpha(x,y),y] = x$
$\beta[\alpha(x,y),x] = x$
$\beta[\alpha(x,x),y] = y$

Table 4: Alpha Operator Properties.

$\alpha : A \times A \longrightarrow B$

$\alpha(x,x) = 1$
$(x \leq y) \longleftrightarrow [\alpha(x,y) \leq \alpha(y,x)]$
$(x \leq y) \longleftrightarrow [\alpha(x,z) \leq \alpha(y,z)]$
$(x \leq y) \longleftrightarrow [\alpha(z,x) \geq \alpha(z,y)]$

Definition 4. *Let n and m be integer and positive numbers that represent the dimension of input patterns and output patterns, respectively. $\beta \max$ Operation is defined according to the following expression:*

$$P_{mxr} \varDelta_\beta Q_{rxn} = \left[f_{ij}^{\beta} \right]_{mxn} \tag{4}$$

where $f_{ij}^{\beta} = \wedge_{k=1}^{r} \beta(p_{ik}, q_{kj})$

Whenever a column vector of dimension m is operated with a row vector of dimension n, both operations ∇_α and $\varDelta_\alpha$, are represented by $\oplus$; consequently, the following expression is valid:

$$\mathbf{y} \boldsymbol{\nabla}_{\boldsymbol{\alpha}} \mathbf{x}^t = \mathbf{y} \oplus \mathbf{x}^t = \mathbf{y} \boldsymbol{\Delta}_{\boldsymbol{\alpha}} \mathbf{x}^t \tag{5}$$

If we consider the fundamental set of patterns $\{(\mathbf{x}^\mu, \mathbf{y}^\mu) \mid \mu = 1, 2, ..., p\}$ then the ij-th entry of the matrix $\mathbf{y}^\mu \oplus (\mathbf{x}^\mu)^t$ is expressed as follows:

$$\left[\mathbf{y}^\mu \oplus (\mathbf{x}^\mu)^t \right]_{ij} = \alpha(y_i^\mu, x_j^\mu) \tag{6}$$

3.1 Learning Phase

Find the adequate operators and a way to generate a matrix $\mathbf{M}$ that will store the p associations of the fundamental set $\left\{ \left(\mathbf{x}^1, \mathbf{y}^1\right), \left(\mathbf{x}^2, \mathbf{y}^2\right), ..., \left(\mathbf{x}^p, \mathbf{y}^p\right) \right\}$, where $\mathbf{x}^\mu \in A^n$ and $\mathbf{y}^\mu \in A^m$ $\forall \mu \in \{1, 2, ..., p\}$.

Step 1. For each fundamental pattern association $\{(\mathbf{x}^\mu, \mathbf{y}^\mu) \mid \mu = 1, 2, ..., p\}$, generate p matrices according to the following rule:

$$\left[\mathbf{y}^\mu \oplus (\mathbf{x}^\mu)^t \right]_{mxn} \tag{7}$$

Table 5: Beta Operator Properties.

$\beta : B \times A \longrightarrow A$

$\beta(1, x) = x$
$\beta(x, x) = x, \forall x \in A$
$(x \leq y) \rightarrow [\beta(x, z) \leq \beta(y, z)]$
$(x \leq y) \rightarrow [\beta(z, x) \leq \beta(z, y)]$

Step 2. In order to obtain an Alpha-Beta Associative Memory MAX type, apply the binary MAX operator ($\vee$) according to the following rule:

$$\mathbf{M} = \vee_{\mu=1}^{p} \left[\mathbf{y}^{\mu} \oplus (\mathbf{x}^{\mu})^{t} \right] \tag{8}$$

Step 3. In order to obtain an Alpha-Beta Associative Memory min type, apply the binary min operator ($\wedge$) according to the following rule:

$$\mathbf{W} = \wedge_{\mu=1}^{p} \left[\mathbf{y}^{\mu} \oplus (\mathbf{x}^{\mu})^{t} \right] \tag{9}$$

Consequently, the ij-th entry of an Alpha-Beta Associative Memory MAX type is given by the following expression:

$$\nu_{ij} = \vee_{\mu=1}^{p} \alpha(y_i^{\mu}, x_j^{\mu}) \tag{10}$$

Analogously, the ij-th entry of an Alpha-Beta Associative Memory min type is given by the following expression:

$$\psi_{ij} = \wedge_{\mu=1}^{p} \alpha(y_i^{\mu}, x_j^{\mu}) \tag{11}$$

3.2 Recalling Phase

Find the adequate operators and sufficient conditions to obtain the fundamental output pattern $\mathbf{y}^{\mu}$, when either memory $\mathbf{M}$ or memory $\mathbf{W}$ is operated with the fundamental input pattern $\mathbf{x}^{\mu}$.

Step 1. A pattern $\mathbf{x}^{\omega}$, with $\omega \in \{1, 2, ..., p\}$, is presented to the Alpha-Beta Associative Memory, so $\mathbf{x}^{\omega}$ is recalled according to one of the following rules.

Alpha-Beta Associative Memory MAX type:

$$\mathbf{M} \Delta_{\beta} \mathbf{x}^{\omega} = \wedge_{j=1}^{n} \beta(\nu_{ij}, x_j^{\omega}) = \wedge_{j=1}^{n} \left\{ \left[\vee_{\mu=1}^{p} \alpha(y_i^{\mu}, x_j^{\mu}) \right], x_j^{\omega} \right\}$$

Alpha-Beta Associative Memory min type:

$$\mathbf{W} \bigtriangledown_{\beta} \mathbf{x}^{\omega} = \vee_{j=1}^{n} \beta(\psi_{ij}, x_j^{\omega}) = \vee_{j=1}^{n} \left\{ \left[\wedge_{\mu=1}^{p} \alpha(y_i^{\mu}, x_j^{\mu}) \right], x_j^{\omega} \right\}$$

Without dependence on the Alpha-Beta Associative Memory type used throughout the recalling phase, a column vector of dimension n will be obtained.

Remarks

- Advantages
  One of the biggest advantage of Alpha-Beta Associative Memories is that this mathematical model recalls the fundamental set completely, if it is trained in auto-associative mode. This implies that all the fundamental patterns that are used along the learning phase will be retrieved without errors. The proof of the theorem that guarantees the complete recovery of the fundamental set can be found in [7].
- Disadvantages
  The main disadvantage with this mathematical model is that it only works with binary patterns, so in case you want to work with patterns with real components, each component has to be binary coded. As a consequence, data processing complexity is increased. It should be noted that this mathematical model is very robust to additive or subtractive noise in input patterns [7], however, this model has low classification performance when you have mixed noise in input patterns [7]. These associative memories have been widely used in many applications but the fundamental input patterns had to be coded using the Johnson-Möbius Modified Code [7]. This type of coding mantains the order relation between patterns. As a result noise type is preserved and performance is improved, but also processing complexity is increased.

4 SND Associative Memory

In this section, Smallest Normalized Difference Associative Memory (SNDAM) theoretical foundations are presented. In order to eliminate Alpha-Beta Associative Memories disadvantages, we have to extend Alpha and Beta operators to $\mathbb{R}$ domain. Alpha operation has only one case of application; however, Beta operation has two cases according to the type of memory that is built in the training phase (MAX or min).

Definition 5. *Alpha operation* $\alpha_{\mathbb{R}} : \mathbb{R}\ x\ \mathbb{R} \to \mathbb{R}$ *is defined as follows:*

$$\alpha_{\mathbb{R}}(c, d) = c - d + 1 \tag{12}$$

Definition 6. *Beta* MAX *operation* $\beta_{\mathbb{R}}^{\vee} : \mathbb{R}\ x\ \mathbb{R} \to \mathbb{R}$ *is defined as follows:*

$$\beta_{\mathbb{R}}^{\vee}(c, d) = \begin{cases} d - |c| - 1 & if\, c \neq d \\ c & if\, c = d \end{cases} \tag{13}$$

Definition 7. *Beta* min *operation* $\beta_{\mathbb{R}}^{\wedge} : \mathbb{R}\ x\ \mathbb{R} \to \mathbb{R}$ *is defined as follows:*

$$\beta_{\mathbb{R}}^{\wedge}(c, d) = \begin{cases} c - |d| - 1 & if\, c \neq d \\ c & if\, c = d \end{cases} \tag{14}$$

It is important to note that when an Alpha-Beta Associative Memory is trained in auto-associative mode, the main diagonal of the learning matrix has only 1's. As a consequence, complete recalling of the fundamental set is guaranteed (see Equation 15). The proof of the theorem that guarantees that an Alpha-Beta Associative Memory recovers completely the training set, appears in [7].

$$\alpha_{\mathbb{R}}(c, c) = c - c + 1 = 1, \forall c \in \mathbb{R} \tag{15}$$

4.1 Algorithm

Once we have extended Alpha and Beta operators for real values, we can describe the algorithm in both of its phases: training and recalling. The proposed algorithm consists of two stages. In the first stage, an associative memory is built, while in the second, the smallest normalized distance is applied to the recovered pattern in order to assign a class label.

Definition 8. *Let p be the cardinality of the fundamental set of associations and let n be the dimension of fundamental input patterns $\mathbf{x}^{\mu}$. Let $\mathbf{x}^{MAX}$ be the vector that stores the maximum value $\forall j \in \{1, 2, ..., n\}$, according to the following expression:*

$$x_j^{MAX} = \bigvee_{\mu=1}^{p} x_j^{\mu} \tag{16}$$

Training phase Find adequate operators and a way to generate an associative memory $\mathbf{M}$ that will store p associations of the fundamental set. Let p be the cardinality of the fundamental set of associations and let n be the dimension of fundamental input patterns, whose n components are in $\mathbb{R}$ domain.

1. In order to build an Alpha-Beta Associative Memory MAX type, use Equation 17, similarly, if you want to build an Alpha-Beta Associative Memory min type, use Equation 18.

$$\mathbf{M} = \bigvee_{\mu=1}^{p} \left(\alpha_{\mathbb{R}}\left(\mathbf{x}^{\mu}, \mathbf{x}^{\mu}\right)\right) \tag{17}$$

$$\mathbf{M} = \bigwedge_{\mu=1}^{p} \left(\alpha_{\mathbb{R}}\left(\mathbf{x}^{\mu}, \mathbf{x}^{\mu}\right)\right) \tag{18}$$

   Where $\bigvee$ is the maximum operator and $\bigwedge$ is the minimum operator. After this step, we get an associative memory $\mathbf{M}$.
2. Search for the highest absolute value of each component, using the maximum vector $\mathbf{x}^{MAX}$ as stated in Equation 16.

Recalling phase After we have trained our associative memory and found the $\mathbf{x}^{MAX}$ vector, execute the following steps:

1. Recall pattern $\mathbf{y}$ from an unknown input pattern $\tilde{\mathbf{x}}$ using Equation 19 or Equation 20:
$$\mathbf{y} = \bigwedge (\beta(\mathbf{M}, \tilde{\mathbf{x}})) \tag{19}$$
$$\mathbf{y} = \bigvee (\beta(\mathbf{M}, \tilde{\mathbf{x}})) \tag{20}$$
Where $\bigvee$ is the maximum operator and $\bigwedge$ is the minimum operator
2. Compute the normalized difference $\boldsymbol{\delta}^{\mu}$ between the recalled pattern $\mathbf{y}$ and the fundamental input patterns $\mathbf{x}^{\mu}$, $\forall \mu \in \{1, 2, ..., p\}$ as stated in Equation 21
$$\boldsymbol{\delta}^{\mu} = \sum_{i=1}^{n} \frac{|y_i - x_i^{\mu}|}{x_i^{max}} \tag{21}$$
3. Obtain the smallest normalized difference value $\boldsymbol{\delta}^{\mu}$ in order to identify μ
4. Use μ value to assign the class label of the pattern $\mathbf{x}^{\mu}$ to the recalled pattern $\mathbf{y}$.

5 Experimental Phase

Throughout the experimental phase, Parkinson Disease Dataset was used as test set to estimate the classification performance of each one of the compared algorithms. These dataset was taken from the UCI machine learning repository [10], from which full documentation can be obtained. SNDAM performance was compared against the performance achieved by the twenty best-performing algorithms of the seventy-six available in WEKA 3: Data Mining Software in Java [11].

5.1 Parkinson Dataset

This database was created by Max Little of the University of Oxford in collaboration with the National Centre for Voice and Speech, Denver, Colorado, who recorded the speech signals. The original study published the feature extraction methods for general voice disorders. This dataset is composed of a range of biomedical voice measurements from 31 people, 23 with Parkinson's disease (PD). Each column in the dataset is a particular voice measure, and each row corresponds to one of 195 voice recording from these individuals (”name” column). The main purpose of this dataset is to discriminate healthy people from those with PD, according to “status” column which is set to 0 for healthy and 1 for PD.

Table 6: Classification accuracy was computed using Stratified 10-Fold Cross Validation.

Algorithm	% Accuracy
1. AdaBoostM1	85.12
2. Bagging	87.69
3. BayesNet	80.00
4. Dagging	85.12
5. DecisionTable	83.58
6. DTNB	85.12
7. FT	84.61
8. LMT	86.15
9. Logistic	86.66
10. MultiClassClassifier	86.66
11. NaiveBayes	69.23
12. NaiveBayesSimple	69.23
13. NveBayesUpdateable	69.23
14. RandomCommittee	90.76
15. RandomForest	90.76
16. RandomSubSpace	88.7
17. RBFNetwork	84.10
18. RotationForest	90.25
19. SimpleLogistic	84.61
20. SMO	87.17
★ SNDAM	92.22

6 Results

The experimental phase was conducted with twenty algorithms. All of them are different pattern classification methods, executed in WEKA environment [11]. The algorithms accuracy is shown in Table 6. The cross validation method was the Stratified 10-Fold Cross Validation [12] in order to do an objective comparison.

The first twenty algorithms were tested because all of them represent multiple ways of classification and are widely used in pattern recognition tasks. It is worth to say there are other classification algorithms and previous work in associative classifications algorithms as can be seen in [13,14,15], notwithstanding our proposal achieve the highest classification accuracy, specifically, it has an advantage of 22.99% in comparison with NaiveBayes, NaiveBayesSimple, and NveBayesUpdateable (whose results were the worst in our test), likewise, it has an advantage of 1.46% in comparison with RandomCommittee and RandomForest (whose results are the best in our test, except for our proposal).

7 Conclusion

We can see that there are algorithms that cannot classify competitively (like NaiveBayes, NaiveBayesSimple, NveBayesUpdateable) because of their design. Also we can see that there are algorithms that can classify competitively and even more (like RandomCommittee, and RandomForest), but it's worth to say that our proposal has achieved the best performance in this Parkinson Disease classification, with an accuracy of 92.22%. We can say then that our proposal could be an interesting way to implement Parkinson pre diagnosis.

Acknowledgments The authors of the present paper would like to thank the following institutions for their economical support to develop this work: Science and Technology National Council of Mexico (CONACyT), SNI, National Polytechnic Institute of Mexico (COFAA, SIP, CIDETEC, and CIC).

References

1. Naranjo, L., Pérez, C.J., Campos-Roca, Y., Martín, J.: Addressing voice recording replications for parkinsonŠs disease detection. Expert Systems with Applications **46** (2016) 286 – 292
2. Rana, B., Juneja, A., Saxena, M., Gudwani, S., Kumaran, S.S., Agrawal, R., Behari, M.: Regions-of-interest based automated diagnosis of parkinsonŠs disease using t1-weighted {MRI}. Expert Systems with Applications **42**(9) (2015) 4506 – 4516
3. Castelli, M., Vanneschi, L., Silva, S.: Prediction of the unified parkinsonŠs disease rating scale assessment using a genetic programming system with geometric semantic genetic operators. Expert Systems with Applications **41**(10) (2014) 4608 – 4616
4. Kohonen, T.: Correlation matrix memories. IEEE Transactions on Computers **C-21**(4) (1972) 353–359
5. Lee, A., Gilbert, R.M.: Epidemiology of parkinson disease. Neurologic Clinics **34**(4) (2016) 955 – 965
6. Tokuchi, R., Hishikawa, N., Sato, K., Hatanaka, N., Fukui, Y., Takemoto, M., Ohta, Y., Yamashita, T., Abe, K.: Differences between the behavioral and psychological symptoms of alzheimer's disease and parkinson's disease. Journal of the Neurological Sciences **369** (2016) 278 – 282
7. Yánez-Márquez, C.: Associative Memories based on Order Relations and Binary Operators (In Spanish). PhD thesis, Instituto Politécnico Nacional (2002)
8. Ritter, G.X., Urcid, G., Iancu, L.: Reconstruction of patterns from noisy inputs using morphological associative memories. Journal of Mathematical Imaging and Vision **19**(2) (2003) 95–111
9. Yáñez-Márquez, C., Díaz-de-León., J.L.: Memorias asociativas basadas en relaciones de orden y operaciones binarias. Computación y Sistemas **6**(4) (2003)
10. Asuncion, A., Newman, D.: UCI Machine Learning Repository (2007)

11. Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., Witten, I.H.: The weka data mining software: An update. SIGKDD Explorations **11**(1) (2009) 10–18
12. Kohavi, R., John, G.H.: Wrappers for feature subset selection. Artificial Intelligence **97**(1) (1997) 273–324
13. Aldape-Pérez, M., Yánez-Márquez, C., Camacho-Nieto, O., Argüelles-Cruz, A.J.: An associative memory approach to medical decision support systems. Computer Methods and Programs in Biomedicine **106** (May 2012) 287–307
14. López-Yánez, I., Yánez-Márquez, C., Camacho-Nieto, O., Aldape-Pérez, M., Argüelles-Cruz, A.J.: Collaborative learning in postgraduate level courses. Computers in Human Behavior **51** (2015) 938–944
15. Aldape-Pérez, M., Yánez-Márquez, C., Camacho-Nieto, O., López-Yánez, I., Argüelles-Cruz, A.J.: Collaborative learning based on associative models: Application to pattern classification in medical datasets. Computers in Human Behavior **51** (2015) 771–779