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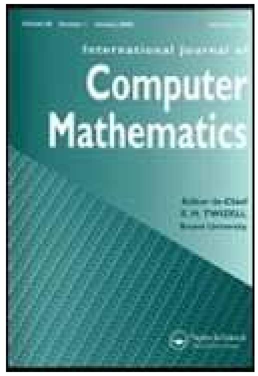

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A Topology Preserving System for Environmental Models Forecasting - CMMSE 2009

Emilio Corchado[a], Aitor Mata[a*] , Bruno Baruque[b], Juan M. Corchado[a] and Belén Pérez-Lancho[a]

[a]*Department of Computing Science and Automation, University of Salamanca, Spain*;
[b]*Department of Civil Engineering, University of Burgos, Spain*

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This intertidisciplinary study presents a novel mathematical simulation model based on an algorithm for summarization of Self-Organizing Maps ensembles applied under the Case-Based Reasoning methodology to perform forecasting tasks. This methodology represents a knowledge extraction frame, where past information is used to generate new solutions to new problems. The novel summarization algorithm based on topology preserving models organizes the stored information simplifying the retrieval of the most useful information from the case base. This algorithm is used to organize the case base and to improve the speed and efficiency of the retrieval phase of the CBR cycle within the explained predicting system. The developed mathematical system was applied to a real case of study: a forest fire forecasting data set. Forest fires represent an environmental risk that should be predicted in order to avoid further damages. This novel system was able to predict the future situation of geographic areas after a forest fire had been originated.

Keywords: Case-Based Reasoning, Forest Fires, Topology Preserving Models, Self-Organizing Maps, Ensemble Fusion, Mathematical Simulation.

1. Introduction

In this study the Case-Based Reasoning (CBR) [22] methodology is applied as it is able to use past information in order to generate useful knowledge that may be used to solve new problems. These kind of systems should organize the information handled in order to improve the way that information is used. When the amount of information stored in a CBR system grows, the results obtained are generally better. But the growth of the case base (internal structure where the data is accumulated) also implies a more dificult retrieval process, where more information has to be considered in order to obtain the best possible collection of data.

The summarization algorithm presented in this study is called Weighted Voting Summarization of SOM ensembles (WeVoS-SOM) [3], which represents the organizing system of the internal structure of the data in the CBR system. This type of inner organization makes it easier to locate the new data that is introduced in the system and to retrieve the needed information to solve new problems. This algorithm serves to organize the case base according with the data stored in it. Similar information will be stored close one to another and so, the retrieval of similar elements will be easier and faster. The combination of the generalization power of the CBR methodology together with the organizational capabilities of the

*Corresponding author. Email: aitor@usal.es

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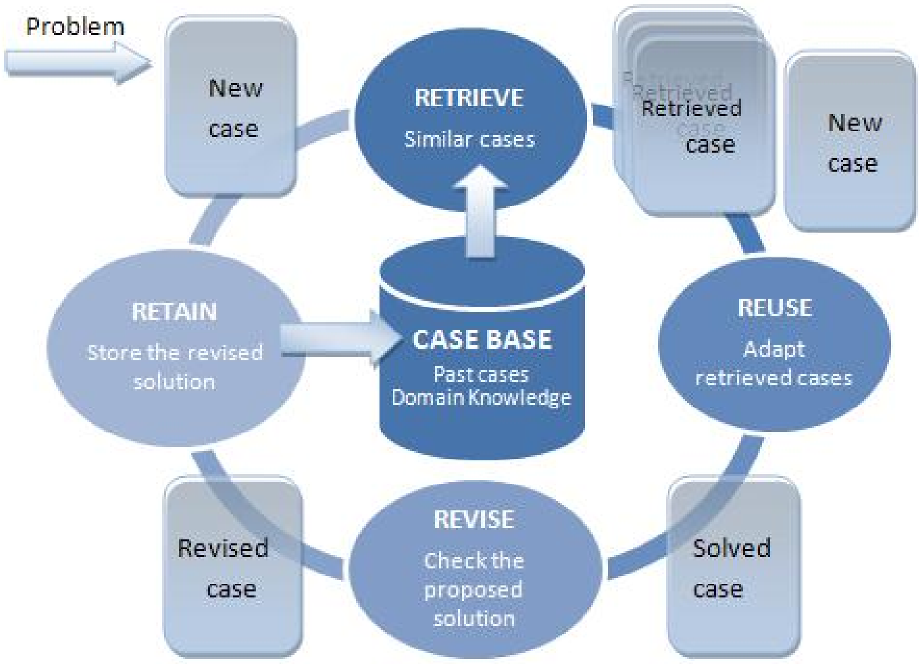

Figure 1. Basic CBR structure.

WeVoS-SOM algorithm generates a hybrid system that has been used to generate predictions in a natural environment such as forest fires. Historical data have been used to check the correction of the system, where the predictions generated were compared with the actual past data. Following the introduction, this research will briefly explain the Case-Based Reasoning (CBR) methodology and Self-Organizing Maps (SOM). Then the summarization algorithm is presented followed by a description of the developed system. Finally, some results of the application of the system to the forest fire case study are shown.

2. The Applied Methodology

The origins of *Case-Based Reasoning* [22] are rooted in knowledge based systems. CBR systems solve new problems by acquiring the required knowledge from previous situations [1]. The main element of a CBR system is the case base, a structure that stores the information used to generate new solutions.

The learning capabilities of CBR systems lie within their very structure, which is composed of four main stages [2]: *retrieve, reuse, revision and retain*. Those four phases create a methodology that allow this kind of systems to acquire knowledge from past information; new problems can be solved by reusing past solutions applied to past problems. When a new problem comes into the system, it is necessary to solve it. So, the first stage, called *retrieve*, consists of searching the case base to find those cases that are most similar to the new problem to be solved. Once a set of similar cases is extracted from the case base, they are *reused* by the system. In this second stage (*reuse*), the selected cases are adapted to the new problem; the solutions stored in the case base regarding those retrieved cases are adapted to solve the new one. After applying the new solution to the problem, that solution is *revised* to check its performance and validity. If it is an acceptable solution, then it is *retained* by the system and could eventually serve as a solution to future problems. Those four main phases can be graphically seen in *Figure 1*.

As a methodology [22], CBR has been used to solve a great variety of problems. It is a cognitive structure that can be easily applied to solve problems such as those related to soft computing, since the procedures used by CBR are quite easy to assimilate by soft computing approaches. CBR has also helped to create applications related to quite different environments. Different kinds of neural networks such as ART-Kohonen [23] or Growing Cell Structures [5] have been combined with CBR to automatically create the inner structure of the case base. Some effort has also been devoted to the case-based maintenance issue [12]. It has also been used to generate plans by using different mathematical models [17].

It is easy to understand that the *case base* is one of the key elements of a CBR system. It is crucial to dispose of a great amount of data, but properly organized. The quantity is important, but if there is no order within the stored cases, it could become impossible to obtain all the knowledge that such an accumulation of data may offer. This is why an algorithm like the WeVoS-SOM, which will be explained next, is so useful to CBR systems.

3. Self-Organizing Maps

Among the great variety of available mathematical tools for multi-dimensional data visualization, several of the most widely used ones are those belonging to the family of the topology preserving maps [9]. The main purpose of this family of algorithms is to produce low dimensional representations of high dimensional datasets, while maintaining the topological features of the input space.

The Self-Organizing Map algorithm [9] is probably the best known of the techniques. It is based on a type of unsupervised learning called competitive learning, an adaptive process in which the neurons in a neural network gradually become sensitive to different input categories or sets of samples in a specific domain of the input space [8]. As a result of the learning process, i.e. the presentation of all input vectors and the adaptation of the weight vectors, the SOM generates a mapping from the input space $\Re^n$ onto the lattice U, in such a way that the topological relationships in the input space are preserved in U as much as possible. If the winning neuron as well as its neighbors on the lattice are both allowed to learn, that is to adapt their characteristics to those presented as the input, neighboring neurons gradually specialize to represent similar inputs, and the representations become ordered on the map lattice.

The update of the inter-neuronal weights of this kind on network is governed by Eq. 1:

$$w_k(t+1) = w_k(t) + \alpha(t)\eta(v,k,t)(x(t) - w_k(t)) \tag{1}$$

where w_k is the winning neuron, also called best matching unit (BMU); $\alpha(t)$ is the learning rate of the algorithm; $\eta(v,k,t)$ is the neighborhood function (usually, the Gaussian function or a difference of Gaussians) in which v represents the position of the winning neuron in the lattice, k represents the positions of the neurons in the neighborhood of this one, and x is the network input.

4. Topology preserving architectures based on Fusion Models

Case-Based Reasoning systems are highly dependent on stored information. The new algorithm presented here, *Weighted Voting Summarization of SOM ensembles (WeVoS-SOM)* is used to organize the data that has accumulated in the case base. It is also used to retrieve the most similar cases to the proposed problem. Neural network ensembles represent a learling paradigm that improves the classification and generalization performance of the networksLEE10.

The main objective of the new WeVoS-SOM [3] is to generate a final map processed unit by unit. Instead of trying to obtain the best position for the units of a single map trained on a single dataset, it aims to generate several maps over different parts of the dataset. It then obtains a final summarized map, calculating by consensus which is the best set of characteristics vector for each unit position in the map. In order to perform this calculation, the meta-algorithm must first obtain the *quality* [18] of every unit that composes each map, so that it can relay in some kind of informed resolution for the fusion of neurons.

The final map obtained is generated unit by unit. The units of the final map are first initialized by determining their centroids in the same position of the map grid in each of the trained maps. Afterwards, the final position of that unit is recalculated using data related to the unit in that same position for each of the maps of the ensemble. A sort of voting process is carried out for each unit, as shown in Eq. 2:

$$V(p,m) = \frac{|x_{p,m}|}{\sum_1^M |x_p|} \cdot \frac{q_{p,m}}{\sum_1^M q_p} \quad (2)$$

where $V_{p,m}$ is the weight of the vote for the neuron included in map m of the ensemble, in its position p. M is the total number of maps in the ensemble, $b_{p,m}$ is the binary vector used for marking the dataset entries recognized by the neuron in position p of map m, and $q_{p,m}$ is the value of the desired quality measure for the neuron in position p of map m.

The final map is fed with the weights of the units of all composing ones, as with the data inputs during the training phase of a SOM. In this case, the BMU is not calculated among all the units of the final map: the "homologous" unit in the final map is used as the BMU. Therefore, the weights of the final unit will be adapted towards the weights of the composing unit. The difference of the updating performed for each "homologous" unit in the composing maps depends on the quality measure calculated for each unit. The higher the quality (or the lowest error) of the unit of the composing map, the stronger the unit of the summary map that will be updated towards the weights of that neuron. The summarization algorithm will consider the "more suitable" weights of a composing unit to be the weights of the unit in the final map according to both the number of inputs recognized and the quality of adaptation for the unit (Eq. 2). With this new approach it is expected to obtain more faithful maps to the inner structure of the dataset.

Algorithm 1 generates a structure where similar data are placed close together, with a clear relationship between the distribution of the initial data and the structure obtained by the algorithm. This relationship between *reality* and *inner structure* is quite useful to a CBR system, where the stored information must be used in future situations to obtain future solutions.

The following section explains the system developed combining the CBR methodology and the WeVoS-SOM algorithm, focusing on the main phases of the CBR

Algorithm 1 WeVoS

Input: Set of trained topology-preserving maps: $M_1...M_n$, training data set: S
Output: A final fused map: M_{fus}

```
Select a training set S = ⟨(x_1, y_1) ... (x_m, y_m)⟩
train several networks by using the bagging meta-algorithm : M_1...M_n
procedure WEVOS(M_1...M_n)
    for all map M_i ∈ M_n do
        calculate the quality/error measure chosen for ALL neurons in the map
    end for
                                        ▷ These two values are used in Eq. 2
    calculate an accumulated total of the quality/error for each position Q(p)
    calculate recognition rate for each position B(p).
    for all unit positions p in M_i do
        initialize the fused map (M_fus) by calculating the centroid (w_c) of the
        neurons of all maps in that position (p)
    end for
    for all map M_i ∈ M_n do
        for all unit positions p in M_i do
            calculate the vote weight (V_{p,M_i}) using Eq. 2.
            feed the weights vector of neuron w_p into the fused map (M_fus) as
            if it was an input to the network. The weight of the vote (V_{p,M_i}) is used as the
            learning rate (α). The position of that neuron (p) is considered as the position
            of the BMU (v).
        end for
    end for
end procedure
```

cycle. The WeVoS-SOM algorithm will be used in the creation of the case base and to improve the retrieval and then, some other artificial intelligence techniques will be used to adapt the retrieved cases to generate a new solution.

5. Mathematical system for forecasting tasks

CBR have already been used to generate predictions in complicated environments where different parameters were involved [4]. In this study, the CBR methodology is used in combination with a summarization of SOM ensembles algorithm, in order to improve its results. The WeVos-CBR system presented is able to generate predictions using past information as a source of knowledge to solve new problems. The available information is divided into cases that are stored in the case base. Those cases are structured, using the WeVoS-SOM algorithm.

When a new problem comes to the system, to be solved, the most similar data to the problem is retrieved from the case base. The inner organization of the case base is developed by using the WeVoS-SOM algorithm. So, when retrieving the elements most similar to the one that is introduced in the system as a problem, the speed of the retrieval phase is faster, being the information stored by terms of its internal similarity. The retrieved cases are used to generate the new solution by feeding a Growing Radial Basis Function (GRBF) neural network [7], which is trained to generate solutions. The training of the GRBF network is done by using the data that is used to create the case base.

If the solution generated is good enough to be proposed to the user, then it is also stored in the case base, to serve as new data to solve new problems. This entire process, which covers the four main phases of the CBR cycle previously explained, is covered in the next sub-sections.

5.1 *Case base creation and retrieval*

When the case base is created the WeVoS-SOM algorithm is used to structure it. The graphical capabilities of this novel algorithm are used on this occasion to create a model that represents the actual variability of the parameters stored in the cases. At the same time, the inner structure of the case base will make it easier to retrieve the cases most similar to the problem cases introduced in the system.

The WeVoS-SOM algorithm is also used to retrieve the cases most similar to the problem introduced in the system. That process is performed once the case base is structured, thus keeping the original distribution of the available variables. When a new problem enters the system, its virtual position into the inner structure of the case base is calculated. The system tries to store the problem into the case base, as if it were a solution. That virtual allocation serves to calculate the position of the problem into the case base, and to retrieve those elements that are located close to that virtual position. Those retrieved cases are used in the next stage to generate the solution.

5.2 *Reuse phase*

After retrieving the cases most similar to the problem from the case base, those cases are used to obtain a solution. *Growing RBF networks* [7] are used to generate the predicted solution corresponding to the proposed problem. The selected cases are used to train the GRBF network. This adaptation of the RBF [16] network lets the system grow during the training phase in a gradual way, increasing the number of elements (prototypes) that work as the centers of the radial basis functions. The error definition for every pattern is shown below:

$$e_i = l/p \cdot \sum_{k=1}^{p} ||t_{ik} - y_{ik}|| \tag{3}$$

Where t_{ik} is the desired value of the k^{th} output unit of the i^{th} training pattern, y_{ik} are the actual values of the k^{th} output unit of the i^{th} training pattern. After the creation of the GRBF network, it is used to generate the solution to the introduced problem. The solution will be the output of the network using the retrieved cases as input data.

The Growing RBF pseudocode is as follows:

```
(1) Calculate the error, e_i (Eq. 3) for every new possible
    prototype.
    • If the new candidate is not among those selected and the
      error calculated is less than a threshold error, then the
      new candidate is added to the set of accepted prototypes.
    • If the new candidate already belongs to the accepted ones
      and the error is less than the threshold error, then
      modify the weights of the units in order to adapt them to
      the new situation.
(2) Select the best prototypes from the candidates:
    • If there are valid candidates, create a new cell centred
```

```
      on the valid candidate...
    • Else, increase the iteration factor. If the iteration
      factor reaches 10% of the training population, freeze the
      process.
(3) Calculate global error and update the weights.
    • If the results are satisfactory, end the process.
    • If not, go back to step 1.
```

5.3 *Revision and retention phases*

Explanations are used in order to verify the precision of the proposed solution [20]. These *explanations* represent an automatic way of clarifying the solutions proposed by a CBR system by justifying the system's proposal. In this case, to generate the explanations, the retrieved cases are used once again. The selected cases have their own future associated situation. If the case and its solution are considered as two vectors, the distance between them can be measured by calculating the evolution of the situation in the conditions under consideration. If the distance between the proposed problem and the solution given is smaller than the distances obtained from the selected cases, then the proposed solution is considered to be a good one. This is how the system explains and justifies the proposed solution.

The distances are calculated considering the sign of the values without using its absolute value. This decision is justified by the fact that is not the same to move to the north than to the south, even if the distance between two points is the same. If the prediction is considered correct, it will be stored in the case base and can then be used in next predictions for obtaining new solutions. It will have the same category as the historical data previously stored in the system.

Next, the pseudocode of the automatic explanations process is showed:

```
(1) For every selected case in the retrieval phase, the distance
    between the case and its solution is calculated.
(2) The distance between the proposed problem and the proposed
    solution is also calculated.
(3) If the difference between the distance of the proposed
    solution and those of the selected cases is below a certain
    threshold value, then the solution is considered as a valid
    one.
(4) If not, the user is informed and the process goes back
    to the retrieval phase, where new cases are selected from the
    case base.
(5) If, after a series of iterations the system does not produce
    a good enough solution, then the user is asked to consider
    the acceptance of the best of the generated solutions.
```

When inserting a new case in the case base, Fast Iterative Kernel PCA is used for reducing the number of variables used and adapting the data generated by the system. The adaptation is done by changing the original variables into the principal components previously chosen by the system. The internal structure of the case base also changes when a new case is introduced. The *WeVoS-SOM* system related with the case base structure controls its growth. The *WeVoS-SOM* system grows and improves its capability of generating good results as new knowledge is introduced in the system.

Figure 2. Image of the Gestosa experiments.

Table 1. Variables stored in the case base.

Variable	Definition	Unit
Longitude	Geographical longitude	Degree
Latitude	Geographical latitude	Degree
Date	Day, month and year of the analysis	dd/mm/yyyy
Bottom pressure	Atmospheric pressure in the area	Newton/m^2
Temperature	Celsius temperature in the area	^{o}C
Area of the fires	Surface covered by the fires present in the analyzed area	Km^2
Meridional wind	Meridional direction of the wind	m/s
Zonal wind	Zonal direction of the wind	m/s
Wind strength	Wind strength	m/s

6. A Real Case Study

Forest fires are a very serious hazard that, every year, causes significant damage around the world from an ecological, social, economical and human point of view [13]. These hazards are particularly dangerous when meteorological conditions are extreme with dry and hot seasons or strong winds, as can be found, for example, in the Mediterranean areas where fire is a recurrent factor. Fires represent a complex environment, that involves multiple parameters. There are different approaches to the forest fire problems, including all the main phases existing in the evolution of this kind of problem. The causes that produce forest fires are many, and the great majority are related in one way or another to human factors (more than 90% of forest fires are provoked by human action); in addition, fires in degraded forests are worse than those that occur in forests that are more intact.

The WeVoS-CBR system presented here was applied to generate predictions in a forest fire scenario. Forest fires represent a great environmental risk. The main approaches that have been used to solve this problem begin with the detection of the fires [15], where different techniques have been applied. Once the fire is detected, it is important to generate predictions that should assist in making a decision in those contingency response situations [6]. Finally, there are complex models that tackle the forest fire problem by trying to forecast its evolution and to minimize its associated risks [19].

The data used to check the WeVoS-CBR system were a subset of the available data that had not been previously used in the training phase. The predicted situation was contrasted with the actual future situation as it was known (historical data was used to train the system and also to test its correction). The proposed solution, in most of the variables, had a near 90% accuracy rate.

Table 2. Percentage of good predictions obtained with different techniques.

Number of cases	RBF	CBR	RBF+CBR	WeVoS-CBR
500	43%	42%	46%	46%
1000	46%	48%	53%	61%
3000	54%	58%	62%	75%
5000	63%	66%	76%	86%

To create the cases, the geographical area being analyzed was divided into small squares, each of which was considered a case, with its associated parameters shown in *Table 1*. The squares determine the area to be considered in every case. The problem is represented by the current situation of the area (all its parameters and the presence, or lack thereof, of fire). The solution is represented by the situation in that area in a future moment (same location but parameters changed to those for the next day -or the next step, if less than a day is considered in every step-). The data used are part of the SPREAD project, in particular the Gestosa field experiments that took place in 2002 and 2004 [21]. The experiments of the Gestosa field began in 1998 and finished in December 2004. They were aimed at collecting experimental data to support the development of new concepts and models, and to validate existing methods or models in various fields of fire management. An image of those experiments is shown in *Figure 2*. The study area is located in central Portugal (Gestosa, 40^o 15'N, 8^o 10'O) in a hillside of Serra de Lousa, whose altitude is between 800 and 950m above sea level. To protect the safety of the burns and carry out different sorts of tests and measurements, the terrain was divided into dedicated plots with even shape and dimensions, separated by firewalls to limit fire spread and to keep it inside the desired boundaries during each burn. The experimental burning plots were established in forest service lands, within the perimeter of the Gestosa forest. The experimental plots were generally located together, in the same vegetation mosaic, which consists of shrub with some isolated *Pinus pinaster* trees. Three arboreal species are dominant in the area: *Erica umbellate*, *Erica australis* and *Chamaespartium tridentatum*.

The case base should be created using valid historical data and following the WeVoS-SOM algorithm. This is how similar information will be stored close one to another to generate a fast and accurate retrieval of the cases most similar to the problem to be solved. When those cases have been retrieved from the case base, always according with the data introduced in the system as a problem, they are used to generate a new solution. That new solution is created by feeding the GRBF neural network with the problem to be solved and with the similar cases retrieved from the case base. Those retrieved cases will be connected with their solutions, which are the future situations. Those future situations will be adapted by the GRBF network to generate the new solution.

Table 2 shows a summary of the results obtained, with a comparison of the different techniques. It shows the evolution of the results along with the increase in the number of cases stored in the case base. The percentages showed in the table represent the accurate predictions generated by the applications used for comparison and by the WeVoS-CBR system. All the techniques analyzed improved their results when the number of elements stored in the case base is increased. In the initial phases, when the amount of information was not big enough, the difference between the WeVoS-CBR system and the rest of the applications was not significant. But, when the number of information available grew bigger, the results generated by using the WeVoS-CBR system became quite better. Having more cases in the case base makes it easier to find cases similar to the proposed problem, thus allowing the solution to be more accurate.

The *"RBF"* column represents a simple Radial Basis Function Network [16] that is trained with all the available data. The network gives an output that is considered directly a solution to the problem. The *"CBR"* column represents a pure CBR system, with no other techniques included. The cases are stored in the case bases and retrieved by applying the Euclidean distance. The most similar cases are selected and, after applying a weighted mean according to the similarity, a solution is proposed. The *"RBF+CBR"* column corresponds to the possibility of using a RBF system combined with CBR. The retrieval from the CBR is done by the Manhattan distance, and the RBF network works in the reuse phase, adapting the selected cases to obtain the new solution. The results of the *"RBF+CBR"* column are normally better than those of the *"RBF"*, mainly because of the elimination of useless data to generate the solution. Finally, the *"WeVoS-CBR"* column shows the results obtained by the proposed system, obtaining better results than the three previous analyzed solutions.

The predicting capabilities of the system presented in this study have been demonstrated in previously known conditions, and showed better results than previously used techniques. *Table 2* illustrates how the use of a combination of techniques within the WeVoS-CBR system makes it possible to obtain results 17% better (on average) than when using the CBR alone, and also 11% better (also on average) than using isolated techniques, without the integration feature produced by the CBR. This model may be used in other areas if historical data are available or if this historical data can be generated by experts.

7. Conclusions and future work

This work presents a mathematical modeling system applied to generate predictions about the evolution of forest fires in a certain area, taking different parameters into consideration. The system presented here uses data related to the problem of forest fires in order to generate predictions about it. That information is previously structured into the case base using the WeVoS-SOM algorithm. The system presented in this study uses different mathematical and artificial intelligence techniques to cover the four main phases of the CBR cycle.

The WeVoS-SOM algorithm used in this system is in charge of the organization of the case base and helps to better retrieve the most similar cases from the case base. The organization capabilities of this algorithm make it easier to create an internal structure within the case base and also to retrieve the cases from the case base that are most similar to the presented problem. Those improvements help the CBR system to generate better results; more accurate by using better information (more similar to the problem itself). The CBR system also generates solutions faster, by retrieving the similar cases easier from the case base, using the WeVoS-SOM algorithm to structure it.

The system presented in this study uses GRBF networks to generate a prediction using the cases retrieved from the case base. This evolution of the RBF networks generates a network better adapted to the data used to train it, and more coherent with the inner structure of the case base due to the application of the WeVoS-SOM algorithm.

Table 3 shows a multiple comparison procedure (Mann-Whitney test [14]) used to determine which models are significantly different from the others. The asterisk indicates that these pairs show statistically significant differences at the 99.0 confidence level. From the results on *Table 2*, it can be inferred that the WeVoS-CBR system presents statistically significant differences compared to the other models.

Future work will be focused on the application of different topology preserving

Table 3. Multiple comparison procedure among different techniques.

	RBF	CBR	RBF+CBR	WeVoS-CBR
RBF				
CBR	*			
RBF+CBR	*	=		
WeVoS-CBR	*	*	*	

models such as the ViSOM to improve the pattern recognition and clustering features of this system. Additionally, different case studies will be contemplated. It is also crucial to generalize the learning process, using new information to obtain a bigger case base that could generate better predictions in a wider range of situations. Another possible future improvement is to develop an on-line version that will include real time connection to data servers, providing information to predict future situations.

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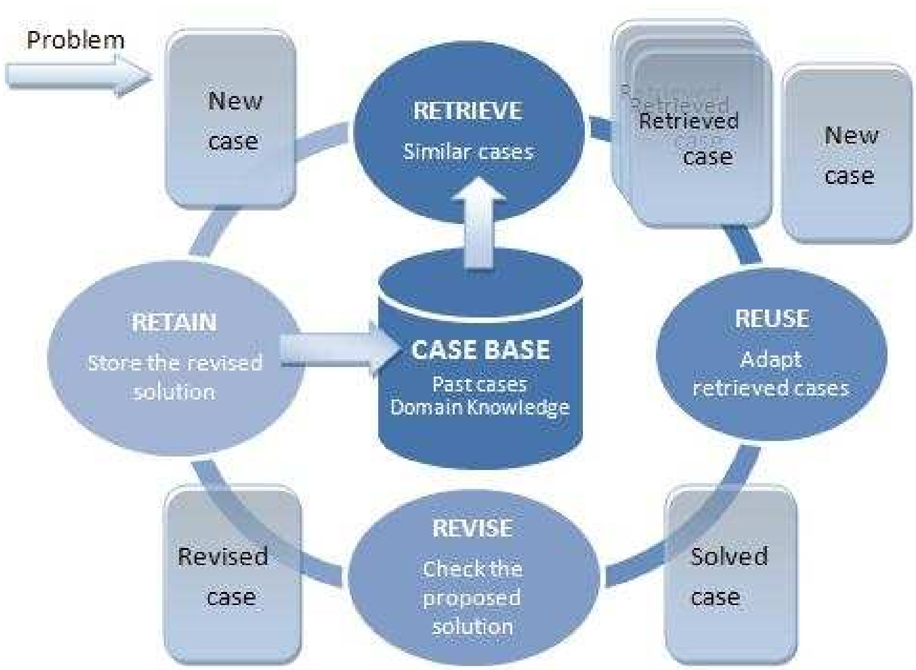

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