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Fuzzy Cognitive Maps Tool for Scenario Analysis and Pattern Classification

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***Abstract*—After 30 years of research, challenges and solutions, Fuzzy Cognitive Maps (FCMs) have become a suitable knowledge-based methodology for modeling and simulation. This technique is especially attractive when modeling systems that are characterized by ambiguity, complexity and non-trivial causality. FCMs are well-known due to the transparency achieved during modeling tasks. The literature reports successful studies related to the modeling of complex systems using FCMs. However, the situation is not the same when it comes to software implementations where domain experts can design FCM-based systems, run simulations or perform more advanced experiments. The existing implementations are not proficient in providing many options to adjust essential parameters during the modeling steps. The gap between the theoretical advances and the development of accurate, transparent and sound FCM-based systems advocates for the creation of more complete and flexible software products. Therefore, the goal of this paper is to introduce FCM Expert, a software tool for fuzzy cognitive modeling oriented to scenario analysis and pattern classification. The main features of FCM Expert rely on Machine Learning algorithms to compute the parameters defining the model, optimize the network topology and improve the system convergence without losing information. On the other hand, FCM Expert allows performing WHAT-IF simulations and studying the system behavior through a friendly, intuitive and easy-to-use graphical user interface.**

***Index Terms*—Fuzzy Cognitive Maps, Software Tool, Scenario Analysis, Pattern Classification, Machine Learning Algorithms.**

I. Introduction

Fuzzy Cognitive Maps (FCMs) were presented by B. Kosko as a knowledge-based methodology for modeling and simulating dynamic systems [1]. FCMs are in fact, a kind of combination of fuzzy logic, neural networks and cognitive mapping, serving as a way to represent knowledge of systems that are characterized by uncertainty, causality and complex processes. From a structural point of view, an FCM may be represented by fuzzy directed digraphs with feedback, seen as a collection of neural processing units and signed weighted relations. Using this methodology, a system could conveniently be modeled in terms of concepts (e.g. variables, objects or entities) and causal relations between these concepts. Each concept is characterized by its activation degree, which denotes to what extent this variables influences the others. The fuzzy approach allows us to have degrees of causality, represented as links between the concepts [2]. The fuzzy nature of FCMs is confined to the network construction phase where experts define the causal relations using linguistic terms. After that, no explicit fuzzy operations are used.

Since FCMs allow feedback in their connections, we can explore the system dynamics by describing the effect of specific changes over the whole causal network. Therefore, during the inference phase, the FCM calculates the activation value of all concepts at each discrete-time step according to the standard McCulloch-Pitts model [3]. After a number of discrete-time steps, an FCM may arrive to three possible states: a fixed-point, a cyclic state or a totally chaotic behavior. The former scenario implies that a hidden pattern was discovered [4], while the last ones suggest that the FCM is unable to confidently recognize the target pattern. However, in scenarios devoted to time series forecasting, the convergence to a fixed-point attractor becomes a serious drawback since the FCM-base forecaster is unable to fit the expected values during time.

FCMs have received increasing attention among researchers and both practical and theoretical results have been introduced. Some representative application fields include: decision making [5], system control [6], engineering [7], protein modeling [8], transport management [9], intrusion detection [10], etc. Also, Papakostas et al. [11] introduced FCM-based classifiers as *light grey box models*, being used for classification tasks. In order to construct an accurate FCM-based classifier from historical data, the estimation of several parameters is required, and we believe in the power of Machine Learning to do so. This opens up the need for a suitable software platform to execute loads of work. Nevertheless, the scientific literature shows just a few software products capable of drawing FCMs and performing very simple simulation tasks, and these tools cannot be used for solving pattern classification problems anyway due to the absence of experimentation facilities.

With the goal of filling this important gap, in this paper, we present a Java software tool that allows designing, learning and simulating FCM-based systems. FCM Expert[1] extends a previous specific-purpose software tool called FCM Tool, which was developed by León et al. [12] to address a decision-making problem concerning public transportation in Belgium (2008-2012). The key advantages of FCM Expert rely on the inclusion of several experimentation facilities and Machine Learning algorithms, which are supported by a friendly visual

[1]www.fcmexpert.net

interface. Overall, the most attractive features of FCM Expert can be concisely summarized as follows:

- Experimentation options to configure the FCM model and perform WHAT-IF simulations as a tool supporting the analysis of hypothetical scenarios.
- The possibillity to model pattern classification problems by using different architectures [11]. To encourage the compatibility with other Machine Learning software, FCM Expert uses the well-known Attribute Relation File Format (ARFF) to handle historical data.
- The inclusion of supervised and unsupervised Machine Learning algorithms to estimate the weight set, optimize the network topology without losing relevant information and improve the convergence of the FCM-based system being modeled. These algorithms rely on population-based heuristic search methods, which are capable of computing near-optimal solutions in a reasonable execution time, thus ignoring analytically properties of the error function such as continuity, convexity or differentiability.
- Several visualization options oriented to model, adjust and exploit the FCM-based system. Some of such options include real-time visualization of the learning progress (error minimization), analysis of fixed-point attractors and graphical simulations of new virtual scenarios to support the decision-making process.

The rest of this paper is organized as follows: in Section II we briefly formalize the mathematical theory behind FCM-based systems, whereas in Section III we examine existing software tools related to FCM-based modeling. In Section IV, we present the main functions and general architecture of FCM Expert. Section V, Section VI and Section VII describe the algorithms implemented into FCM Expert, as the most advanced features of FCM Expert. Section VIII is devoted to the tool support, while Section IX provides concluding remarks and future research and implementation goals.

II. Fuzzy Cognitive Maps

In general terms, FCMs can be understood as recurrent neural networks with interpretable features that have been widely used in modeling tasks [1]. They consist of a set of neural processing entities called concepts (neurons) and the causal relations among them. The activation value of such neurons regularly takes values in the $[0, 1]$ interval, so the stronger the activation value of a neuron, the greater its impact on the network. Also, connected weights are relevant in this scheme. The strength of the causal relation between two neurons C_i and C_j is quantified by a numerical weight $w_{ij} \in [-1, 1]$ and denoted via a causal edge from C_i to C_j.

There are three types of causal relationships between neural units in an FCM, being detailed as follows:

- If $w_{ij} > 0$ then there is a *positive causality*, so an increase (decrement) on C_i produces an increment (decrement) on the effect C_j with intensity $|w_{ij}|$.
- If $w_{ij} < 0$ then then there is a *negative causality*, so an increase (decrement) on C_i produces an decrement (increment) on C_j with intensity $|w_{ij}|$.
- If $w_{ij} = 0$ then there is no causal relation.

Equation (1) formalizes the original Kosko's activation rule, with $A^{(0)}$ as the initial state. The rule is iteratively repeated until a stopping condition is met. A new activation vector is calculated at each step t and after a fixed number of iterations, the FCM will be at one of the following states: (i) equilibrium point, (ii) limited cycle or (iii) chaotic behavior [4]. The FCM is said to have converged if it reaches a fixed-point attractor, otherwise the updating process terminates after a maximum number of iterations T is reached.

$$A_i^{(t+1)} = f\left(\sum_{\substack{j=1\\ i\neq j}}^{M} w_{ji} A_j^{(t)}\right) \tag{1}$$

In the above neural inference rule, $f(\cdot)$ denotes a monotonically non-decreasing function used to clamp the activation value of each concept to the allowed interval. Among other possibilities, the five functions most extensively used based on existing literature are depicted as follows:

- *The bivalent function*

$$f_1(x) = \begin{cases} 1, & x > 0 \\ 0 & x \leq 0 \end{cases} \tag{2}$$

- *The saturation function*

$$f_2(x) = \begin{cases} 0, & x \leq 0 \\ x, & 0 < x < 1 \\ 1, & x \geq 1 \end{cases} \tag{3}$$

- *The trivalent function*

$$f_3(x) = \begin{cases} -1, & x < 0 \\ 0, & x = 0 \\ 1, & x > 0 \end{cases} \tag{4}$$

- *The hyperbolic function*

$$f_4(x) = \frac{e^{2x} - 1}{e^{2x} + 1} \tag{5}$$

- *The sigmoid function*

$$f_5(x) = \frac{1}{1 + e^{-\lambda(x-h)}} \tag{6}$$

Equation (1) shows an inference rule widely used in many FCM-based applications, but it is not the only one possible. Stylios and Groumpos [13] proposed a modified inference rule, found at Equation (7), where neurons also take into account its own past value. This rule is preferred when updating the activation value of independent neurons, i.e., neurons that are not influenced by any other neural processing entities.

$$A_i^{(t+1)} = f\left(\sum_{\substack{j=1 \\ i\neq j}}^{M} w_{ji}A_j^{(t)} + A_i^{(t)}\right) \tag{7}$$

Another rule proposed in [14] is used to avoid the conflicts emerging in the case of non-active neurons. The re-scaled inference depicted in Equation (8) allows dealing with scenarios where there is not information about an initial neuron-state and helps preventing the saturation problem.

$$A_i^{(t+1)} = f\left(\sum_{\substack{j=1 \\ i\neq j}}^{M} w_{ji}(2A_j^{(t)} - 1) + (2A_i^{(t)} - 1)\right) \tag{8}$$

If the network is able to converge, then the system will produce the same output towards the end, so the activation degree of neurons will remain unaltered (or subject to infinitesimal changes). Convergence is often desired in pattern classification and scenario analysis, whereas it becomes a serious problem when modeling time series problem.

III. Examining software tools related to Fuzzy Cognitive Maps

Most of the FCM papers exhibit theoretical contributions or practical applications related to FCMs application, but less is usually found about well-defined software for handling FCM-based systems. Moreover, the existing software implementations fail in providing advanced options to adjust the model parameters. The absence of such features leads to a gap between the recent theoretical advances on FCMs research and the development of accurate and mathematically sound FCM-based systems. In this section, we review the most representative software tools for FCMs we have found.

We begin with FCM Modeler [15], a desktop implementation aiming to model generic FCMs. It involves a simple graphical user interface offering support for group decision making on a qualitative static model. It intended to be a general modeling tool, but regrettably the project never evolved into that. The authors also advocated for including a basic Machine Learning algorithm for adjusting the weight set.

A similar approach, FCM Designer [16] was also found during our survey. This tool allows adapting the inference rule by selecting the transfer function and the stopping criterion. The key drawback of this implementation relies on the lack of learning algorithms to compute the parameters that characterize the system. In spite of this limitation, several modeled scenarios were found using this software tool, including the use of FCM for simple tasks related to supervision and control. In a similar line, FCM-Analyst [17] facilitates the simulation and implementation of FCMs with basic drawing supported and options for configuring the transfer function. This feature was interesting as they offer an editor that is able to recognize equation supporting different functions.

FCM Tool [12] is a Java software tool that allows designing complex FCM-based models through an interactive graph visualization. It allows analyzing scenarios and customizing the FCM reasoning process. Likewise, FCM Tool provides a population-based learning algorithm based on Swarm Intelligence to learn the weight set from historical data. Another relevant feature is the inclusion of aggregation operators for combining several FCM-based systems into a single knowledge-based representation. As FCM Tool was designated to address a specific decision-making problem, this implies that its algorithms could not be used for solving more generic pattern classification applications. On the other hand, FCM Tool uses specific files for handling historical data, which are generated by an *Automated Knowledge Engineer* implementation, such features contribute to the lack of generality.

Another promising software tool recently proposed is Mental Modeler [18], which comprises a web-based interface to support individuals and communities to capture their knowledge in a standardized format for scenario analysis. This software tool was developed to support group decision-making, allowing domain experts to collaboratively represent and test their assumptions about a system. Mental Modeler can be mainly used by non-IT people, usually experts or stakeholders in a given domain who need to design a simple cognitive map and simulate its behavior for some scenarios. The key drawbacks of this FCM implementation relies on the lack of learning methods and its limited experimenting options.

More recently, the Java Fuzzy Cognitive Maps (JFCM), an open source library for fuzzy cognitive mapping modeling was presented [19]. The library is small and simple, but can be used to create a variety of cognitive networks. The JFCM library allows loading networks from XML files, thus increasing its portability. The idea behind the library is to create reusable modules that could be used when needing FCM solutions in a given problem. Interacting with this library requires to reuse and modify the source code to model specific features, which becomes a limitation for non-expert users.

Finally, in our study we found the Intelligent Expert System based on Cognitive Maps (ISEMK) [20] that allows modeling decision support systems based on FCMs and neural networks. ISEMK includes a multi-step gradient learning algorithm and two evolutionary search methods (e.g., Real-Coded Genetic Algorithm) for adjusting the FCM model. Moreover, it includes two learning algorithms for multi-layer neural networks used in time series forecasting, while it supports the visualization of results through an adequate graphical interface. This software however is mostly focused on time series forecasting, which reduces its usability in more generic domains.

When comparing among the surveyed software tools for several features, we can conclude that FCM Designer, Mental Modeler, FCM-Analyst and FCM Tool provide to the experts an appropriate graphical support when analyzing scenarios and experimenting new situations; JFCM is suitable for developing FCM modules that could be reused in more complex solutions, while ISEMK resulted in the best implementation for time series forecasting. The surveyed software tools lack advanced algorithms and experimentation options, making this a strong motivation for introducing FCM Expert. Furthermore, none of these software products allow handling pattern classification problems, which reduce their usability when investigating new FCM-based solutions in this domain.

IV. Architecture and Features of FCM Expert

As mentioned, FCM Expert is a software tool for designing FCM-based systems. This software is written in Java language and comprises more than 25,000 source code lines, which are distributed in 120 source files. These files are organized in five global packages (i.e., *Network*, *Algorithms*, *Learning*, *Software* and *Resources*) and several sub-packages. Figure 1 shows the structure of the packages in FCM Expert, including primary packages and some sub-packages.

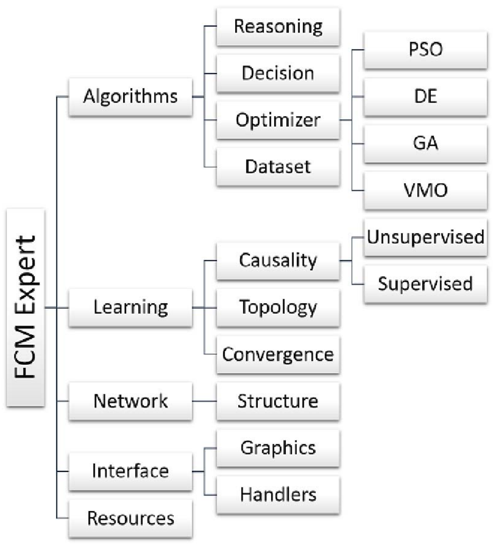


Fig. 1. Packages tree of the FCM Expert software tool.

In a rough picture, FCM Expert involves three groups of functions that are distributed in five menus: *File*, *Edit*, *Build*, *Run* and *Reset*. The first group is oriented to the design of the FCM-based model, where the expert (user) in a given domain can model a complex system (visual options do not require deep expertise in Mathematics or Computer Science). The second group comprises Machine Learning algorithms for adjusting the model parameters and optimizing its performance. Finally, the third group includes procedures for exploiting the FCM-based system, as a tool for supporting decision-making processes. Figure 2 shows the main window of FCM Expert displaying a real case study concerning the resistance mechanism of HIV mutations to existing inhibitors [21].

Also, FCM Expert allows designing an FCM-based system from scratch. This can be done by manually drawing the network structure or importing the weight matrix from a CSV file (see Figure 3). This last option includes a heuristic layout procedure for efficiently drawing the network topology, which minimizes both the distance between concepts and the cuts between graph edges and concepts.

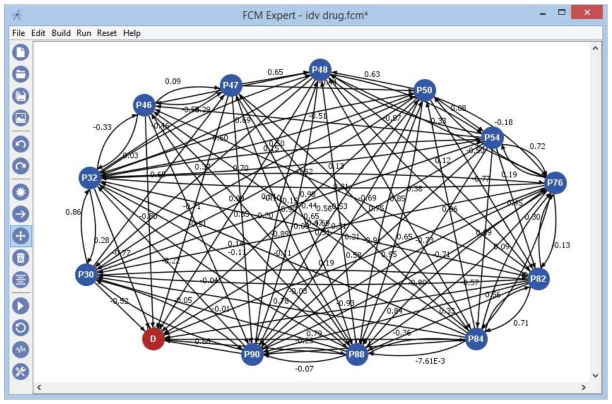
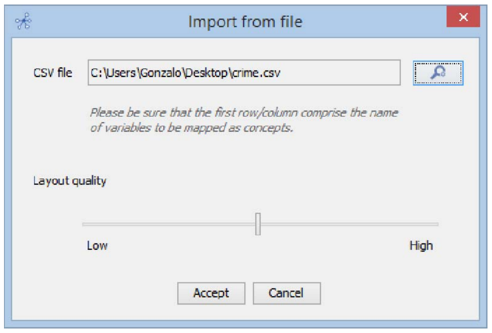


Fig. 2. Snapshot of the proposed FCM Expert.



Import from file

CSV file C:\Users\Gonzalo\Desktop\crime.csv

Please be sure that the first row/column comprise the name of variables to be mapped as concepts.

Layout quality

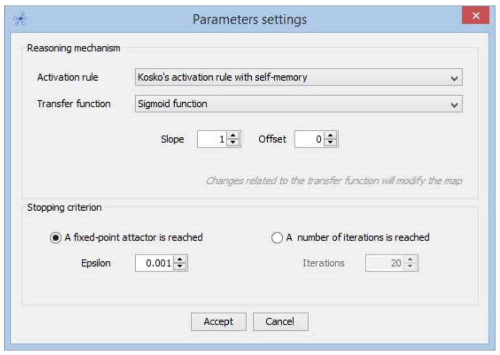
Low High

Accept Cancel

Fig. 3. Dialog to build an FCM-based network from a CSV file.

Other options however require more expertise as they were conceived for supporting the FCM research community. For example, Figure 4 illustrates how to configure the parameters related to the FCM reasoning: *the inference rule*, *the transfer function* and *the stopping criterion*.

The proposed software implements the three inference rules (see Equations (1), (7) and (8)) and the five transfer functions earlier mentioned (see Equations (2), (3), (4),(5) and (6)). This suggests that the concepts can take values in $[-1, 1]$ or $[0, 1]$, hence providing flexibility during the modeling phase.



Parameters settings

Reasoning mechanism

Activation rule: Kosko's activation rule with self-memory

Transfer function: Sigmoid function

Slope 1 Offset 0

Changes related to the transfer function will modify the map

Stopping criterion

● A fixed-point attractor is reached ○ A number of iterations is reached

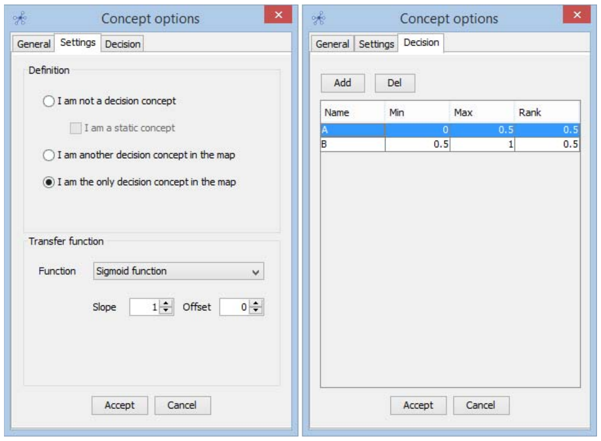
Epsilon 0.001 Iterations 20

Accept Cancel

Fig. 4. Configuration of the FCM reasoning process (settings).

Unlike other tools, our software allows handling different architectures for both scenario analysis and pattern classification. In the first case, the FCM does not comprise a decision concept, whereas in the second case we implement two different FCM architectures for pattern classification defined in [22] that differ in the number of decision concepts.

The *single-output architecture* uses a single decision concept such that classes are defined as closed partitions of the decision space, while in the *class-per-output architecture*, each class is defined by an output neuron. Figure 5 shows how to specify the role of each neuron in an FCM-based network. Observe that each neuron may use its own transfer function when updating its activation values. In this example, we show how to configure the decision table in a single-output architecture for a two-class (binary) classification problem.



Concept options

General | Settings | Decision

Definition

- ○ I am not a decision concept
- ☐ I am a static concept
- ○ I am another decision concept in the map
- [✓ I am the only decision concept in the map]

Transfer function

Function: Sigmoid function

Slope: 1 Offset: 0

Accept Cancel

Concept options

General | Settings | Decision

Add Del

Name	Min	Max	Rank
A	0	0.5	0.5
B	0.5	1	0.5

Accept Cancel

Fig. 5. Configuration of parameters for the selected concept.

FCM Expert allows performing WHAT-IF simulations by directly modifying the activation values of each concept and next running the inference process. This generates a plot and a table (see Figure 6) with the activation value of each concept at each iteration-step for the specified stimulus.

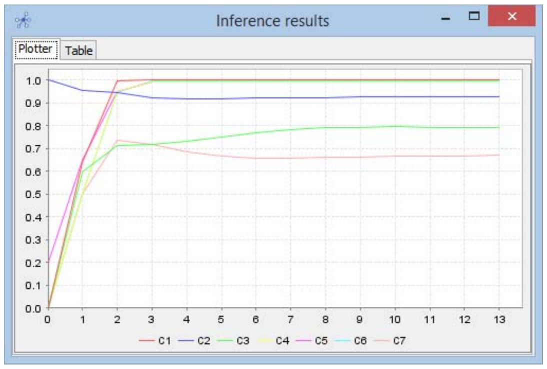
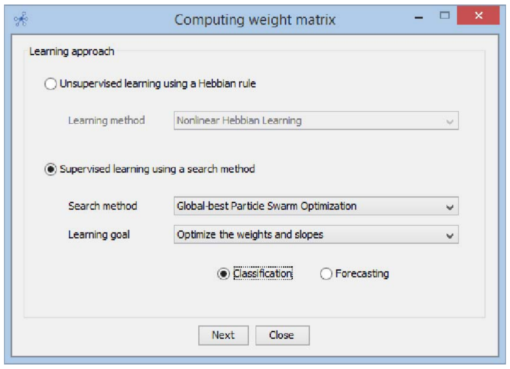


Fig. 6. Dialog summarizing the FCM inference process.

As an additional feature, FCM Expert allows performing simulations in a visual mode where the size of each concept is determined according to its activation value. Other interesting feature is the aggregation of multiple FCM-based systems into a single knowledge-based structure. In the next sections, we describe the learning algorithms implemented, which comprise one of the main advantages over other software tools found in the surveyed literature.

V. Computing the FCM parameters

Learning methods for computing the weight set are pivotal when designing an FCM-based system. The most prominent algorithms for FCM learning may be gathered into two large groups [23]: unsupervised and supervised models. Figure 7 displays how to select the learning approach in FCM Expert, as a first step towards learning the weight set.



Computing weight matrix

Learning approach

- ○ Unsupervised learning using a Hebbian rule
  - Learning method: Nonlinear Hebbian Learning
- [✓ Supervised learning using a search method]
  - Search method: Global-best Particle Swarm Optimization
  - Learning goal: Optimize the weights and slopes
  - [✓ Classification] ○ Forecasting

Next Close

Fig. 7. Settings for the weight estimation algorithm.

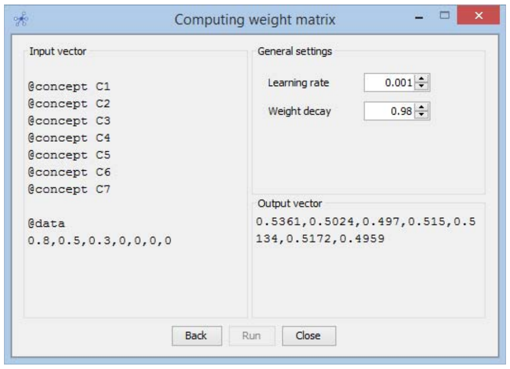
According to [23], the unsupervised learning algorithms are convenient to fine-tune the weight set with a small deviation from the initial configuration. However, these algorithms lack generalization capabilities, hence they are not advised when solving pattern classification problems; instead we may use heuristic (supervised) learning algorithms.

A. Scenario analysis

Unsupervised learning of FCM is based on the Hebbian law to iteratively adjust the causal weights by using a single representative pattern as training data. Hebbian-based learning was initially applied on the training of artificial neural networks, however, recently this approach has been successfully used for training FCM-based systems. The key feature of this learning rule is that the change of a synaptic is computed by taking into account the presynaptic and postsynaptic signals flow towards each neural processing unit.

The proposed software tool includes the following Hebbian-type algorithms: the *Differential Hebbian Learning* [24], the *Balanced Differential Algorithm* [25], the *Nonlinear Hebbian Learning* [26] and the *Improved Nonlinear Hebbian Learning* [27]. In these learning algorithms, the expert must specify two parameters related to the weight decay and the learning rate. Figure 8 portrays graphical interface to capture the training example (i.e. an activation vector) and visualize the response vector obtained after adjusting the weights.

It should be mentioned that the adjusted weights partially preserve their physical meaning, which is often desired when performing WHAT-IF simulations. Of course, the requirement

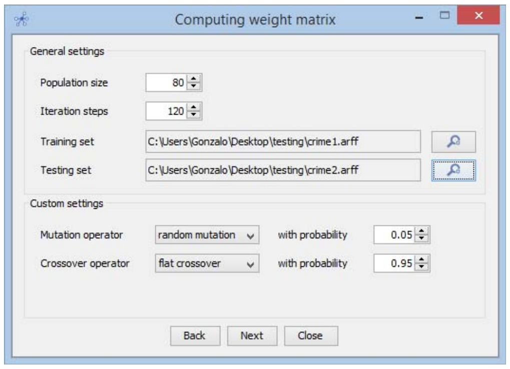


```
@concept C1
@concept C2
@concept C3
@concept C4
@concept C5
@concept C6
@concept C7

@data
0.8,0.5,0.3,0,0,0,0
```

Learning rate 0.001
Weight decay 0.98

```
0.5361,0.5024,0.497,0.515,0.5
134,0.5172,0.4959
```

Fig. 8. Unsupervised learning of the weight matrix.



Population size 80
Iteration steps 120
Training set C:\Users\Gonzalo\Desktop\testing\crime1.arff
Testing set C:\Users\Gonzalo\Desktop\testing\crime2.arff
Mutation operator random mutation with probability 0.05
Crossover operator flat crossover with probability 0.95

Fig. 9. Settings for the Real-Coded Genetic Algorithm.

of experts' knowledge is a serious drawback. The flexibility on data requirements of these algorithms is the key aspect behind their poor generalization capability.

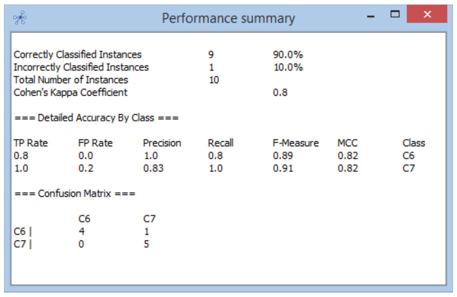
B. *Pattern classification*

In the context of FCM-based classifiers, the learning goal is to compute, in a supervised fashion, a weight matrix minimizing the dissimilarity between the expected outputs and the predicted ones. Unlike Hebbian-based procedures, supervised learning approaches use a set of training instances instead of using a single example. FCM Expert also allows optimizing the parameters attached to the sigmoid transfer function. The algorithm computes a custom transfer function for each concept hoping to increase the overall prediction rates. The software allows including expert knowledge related to causal relations during learning, therefore the resulting FCM model is no longer a black-box! The optimization process may be performed by using a variety of heuristic search methods.

More explicitly, we implemented several population-based optimizers including *Particle Swarm Optimization* [28], *Differential Evolution* [29], *Real-Coded Genetic Algorithm* [30] and *Variable Mesh Optimization* [31]. The advantage of using heuristic methods relies on their ability for estimating near-optimal solutions, therefore ignoring analytic (often unknown) properties of the error function to be optimized.

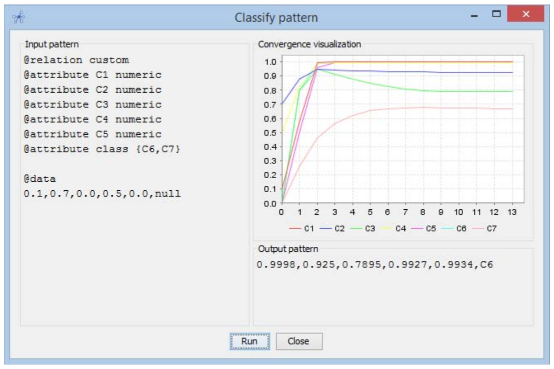
Figure 9 shows, as an illustrative example, how to configure the parameters related to the Real-Coded Genetic Algorithm. The expert may provide to the learning algorithm a separated testing set in order to evaluate the generalization capability of the learned model, which is a pivotal aspect in pattern classification scenarios. F-measure, accuracy, Kappa coefficient and the confusion matrix are some of the statistics used to assess the quality of the FCM-based classifier (see Figure 10). Once the supervised learning process is completed, we can use the learned FCM model to determine the most likely decision class for unseen instances (see Figure 11).

Recently, Nápoles et al. [32] surveyed the key advances and challenges on FCM-based classifiers. Although the road towards computing truly causal, interpretable FCM classifiers is still narrow, we believe that FCM Expert comprises useful options for supporting new researches in this field.



```
Correctly Classified Instances     9      90.0%
Incorrectly Classified Instances   1      10.0%
Total Number of Instances          10
Cohen's Kappa Coefficient                 0.8

=== Detailed Accuracy By Class ===

TP Rate   FP Rate   Precision   Recall   F-Measure   MCC    Class
0.8       0.0       1.0         0.8      0.89        0.82   C6
1.0       0.2       0.83        1.0      0.91        0.82   C7

=== Confusion Matrix ===

          C6        C7
C6 |      4         1
C7 |      0         5
```

Fig. 10. Statistics used to asses the quality of an FCM-based classifier.



```
@relation custom
@attribute C1 numeric
@attribute C2 numeric
@attribute C3 numeric
@attribute C4 numeric
@attribute C5 numeric
@attribute class {C6,C7}

@data
0.1,0.7,0.0,0.5,0.0,null
```

```
0.9998,0.925,0.7895,0.9927,0.9934,C6
```

Fig. 11. Classifying new instances with an FCM-based classifier.

VI. Optimizing the Network Topology

Sometimes, we need to handle FCMs with very complex network structure as a result of modeling a physical system comprised of a large number of variables. In these situations, some concepts/variables could be superfluous or even contradictory due to the uncertainty and subjectivity attached to human reasoning and modeling, thus negatively affecting both the system performance and interpretability.

Aiming at overcoming this issue, Nápoles et al. [21] proposed a reduction algorithm for optimizing the network topology on FCM-based systems, without losing relevant information. The learning goal of this algorithm is to find the minimal subset of concepts capable of preserving, in some extent, the original system performance. Since we are mainly focused on FCM-based systems used in pattern classification scenarios, the performance could be measured as the number of patterns positively recognized by the system under investigation. Finding this minimal subset involves a difficult combinatorial problem defined by a search space comprised of 2^{M-1} solutions, with M being the number of concepts in the network.

The proposed implementation offers the possibility to select and configure the search method and the threshold for accuracy. This algorithm will not produce models with prediction rates below that threshold; therefore the algorithm may get trapped into local optima. The more strict the threshold, the more likely the algorithm to get trapped into a local optimum.

Two distinctive features of this learning algorithm should be highlighted. First, we use continuous search methods (e.g., Particle Swarm Optimization, Real-Coded Genetic Algorithm) to solve the constricted, combinatorial optimization problem. This can be achieved by discretizing the continuous space into non-homogeneous partitions, each denoting a specific state, where the size of each partition is heuristically determined. Second, the learning method recalculate the values of sigmoid parameters to compensate the alterations on the FCM topology. It is worth mentioning that this second feature is only applicable for FCM models using sigmoid neurons.

VII. Improving the system convergence

Most supervised learning methods reported in the literature do not accurately consider the FCM convergence into their learning scheme [33]. As a result, we obtain FCM-based model for scenario analysis and pattern classification with acceptable performance, but unable to converge to a fixed-point attractor. Ensuring the convergence to a fixed-point is often mandatory in decision-making scenarios where obtaining a non-oscillatory solution is expected, otherwise making a confident decision is not possible. In other domains (e.g., time series forecasting) the network convergence is less desirable.

To overcome this issue, Nápoles et al. [34] introduced a novel learning method to improve the convergence of sigmoid FCM-based classifiers, once the causal relations defining the system semantics have been defined. The algorithm computes the sigmoid parameters attached to each neural entity leading to improved convergence features. This involves a continuous optimization problem with $2M$ variables, with M being the number of neurons in the network.

FCM Expert implements this learning algorithm for both scenario analysis and pattern classification scenarios. Due to the fact that this algorithm is supervised, the expert must specify a set of examples where each attribute matches with a specific concept. Moreover, the expert must specify the accuracy level defining the expected deviation to the original responses. For simulation and experimentation tasks, real-time visualization (i.e., the error curve) is essential. Figure 12 shows this functionality, where the current parameters are used as seed in the learning procedure, allowing the inclusion of expert knowledge to guide the search process.

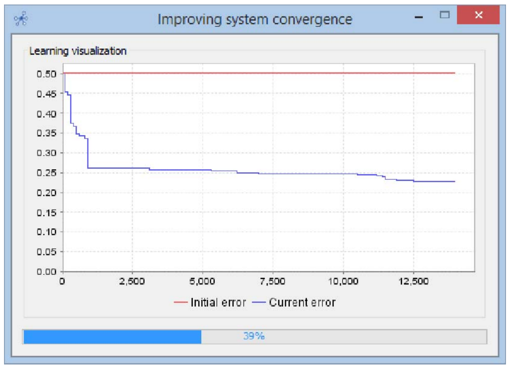


Fig. 12. Real-time visualization of error curve.

In a recent study, Nápoles et al. [35] analytically proved that, sometimes, under the weights constriction, the algorithm will be unable to improve the system convergence without harming the accuracy. Moved by this result, in [36] the authors proposed a supervised learning method for computing the weight set and the sigmoid parameters leading to convergence features from the beginning. This approach is specially useful when no constraint over the weight set exists, otherwise the method discussed in [34] should be adopted.

VIII. FCM Expert web support

The purpose of FCM Expert is to become a software tool supporting domain experts in the developing of FCM-based solutions. Likewise, we attempt equipping the research community with a software tool gathering key contributions to the FCM field. To accomplish this, FCM Expert can be downloaded by request through its website (www.fcmexpert.net)[2]. Additionally, we are working on the creation of a repository of FCM problems that researchers can use to test new contributions in a homogeneous framework. The web support also allows to report bugs, request the inclusion of new options and algorithms or simply ask for collaboration. Likewise, prominent contributors to the FCM theory will be invited to publish comments, being this another way to enhance connections in the community.

IX. Concluding remarks

Fuzzy Cognitive Maps have been extensively reported in literature for modeling real-life problems by recreating virtual scenarios. A weak point concerning this field is the lack of well-established software tools providing options for creation, simulation and experimentation using these useful structures. In this paper, we presented FCM Expert with the purpose of introducing to the scientific community a flexible software for modeling, learning and simulating FCM-based systems. FCM Expert is an object-oriented implementation organized in packages, with a compact and intuitive interface. Our software includes algorithms for computing the parameters defining the FCM model, optimizing the FCM topology and improving the convergence without losing information.

[2]Website under construction.

We have illustrated the existence of options for configuring the decision space, for analyzing new scenarios based on the modeled concepts and successive state vectors, for evaluating the convergence of the FCM-based system, among other options. These facilities have a graphical support that allows completely designing FCM-based systems with minimal effort. On the other hand, FCM Expert is a platform-independent software where the expert can mine the knowledge related to the system under analysis. Moreover, FCM Expert allows modeling a wide range of simulation and pattern classification problems with high flexibility. As part of the future research, we are currently developing other learning algorithms with stronger mathematical principles. Likewise, we are testing a new module with methods for time series forecasting.

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