Fuzzy Cognitive Map

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Fuzzy logic-based hybrid knowledge systems for the detection and diagnosis of childhood autism

Sahar Qazi, Khalid Raza, in Handbook of Decision Support Systems for Neurological Disorders, 2021

4.3.3 Fuzzy cognitive maps

Fuzzy cognitive maps (FCMs), first proposed by Ref. [54], are one of the hybridizations of fuzzy logic and cognitive mapping. FCMs are basically fuzzy graph structures used to represent causal reasoning in the form of diagraphs consisting of nodes and weighted edges. An FCM with a nonlinear Hebbian learning model was proposed previously for autism prediction and has successfully achieved a reliable classification accuracy of 79.9% [55]. Another study by the same group [56] looked at FCM ensembles and their application in autism prediction. They discerned that the FCM ensemble outperformed a single FCM when used with a nonlinear Hebbian learning model, which achieved an accuracy of 89.4%. Puerto et al. [57] proposed a multilayer FCM model for ASD (MFCM-ASD) diagnosis based on standard behavior assessments such as Autism Diagnostic Observation Schedule 2nd Edition (ADOS2), and ADI-R. The MFCM-ASD model outperforms the conventional FCM. Table 4.1 summarizes fuzzy-based models used to detect and assess the severity of childhood autism.

Table 4.1. Fuzzy-based models employed to diagnose and assess severity in ASD.

S. no.	Fuzzy-based model	Description	Datasets	Accuracy (%)	References
1.	Fuzzy logic model	A TSK-type fuzzy model	EEG dataset	70–97	[44]
2.	Functional fuzzy model	A TSK-type inferencing model that employs a single input/single output first-order fuzzy functional model	100 real-world cases	98	[45]
3.	Fuzzy logic model	A simple fuzzy logic framework	Autism—UCI dataset	99	[58]
4.	FIS and ANFIS	Compared to the prediction accuracy of FIS and ANFIS	–	ANFIS outperforms FIS	[53]
5.	Neuro-fuzzy model	The fuzzified values are fed to the neural network for training	Questionnaire based	85–90	[50]
6.	Neuro-fuzzy model	A coadunation of the ANN and fuzzy logic	18,000 ASD subjects	95.7	[78]
7.	Neuro-fuzzy model	A three-layered model; the first two represent the FIS and the last layer is represented by a single neuron performing binary classification	701 subjects	98.4	[49]
8.	Fuzzy synchronization likelihood-wavelet (fuzzy SL)	Fuzzy-based SL method based on EEG	EEG datasets	95.5	[52]
9.	Fuzzy expert system	Three severity levels were considered: Mild, moderate, and severe	Interview with psychologist and 36 questionnaires from parents/teachers	NA	[59]
10.	Hierarchical fuzzy expert model	The hierarchical fuzzy expert system designed deploying IF-THEN rules based	80 (40 each) subjects categorized as autistic and normal	99	[47]

		on the experiences of specialists and autistic and normal subject groups			
11.	FCMs	FCM ensemble with non-linear Hebbian learning model	40 subjects	89.4	[56]
12.	MFCMs	MFCMs proposed to increase the prediction accuracy	ADOS2 and ADI-R	84.2	[57]

ADI-R, Autism Diagnostic Interview, Revised; *ADOS2*, Autism Diagnostic Observation Schedule 2nd Edition; *ANFIS*, adaptive neuro-fuzzy inference system; *ANN*, artificial neural network; *ASD*, autism spectrum disorder; *EEG*, electroencephalography; *FCMs*, fuzzy cognitive maps; *FIS*, fuzzy inference system; *MFCMs*, multilayer fuzzy cognitive maps; *TSK*, Takagi-Sugeno Kang.

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Advanced Methods of Risk Assessment and Management

Hirushie Karunathilake, ... Rehan Sadiq, in Methods in Chemical Process Safety, 2020

4.1.2 Multi-objective fuzzy cognitive map with MADM

MOFCM-MADM technique integrates FCM with multiple risk-oriented objectives and different weighting scenarios in TOPSIS. This technique prioritizes and evaluates failure modes with respect to the triple risk factors in three main steps as follows (Bakhtavar & Yousefi, 2018).

- *Step 1*: Failure modes are recognized and considered as risk alternatives (*Ri*), and the fuzzy degrees of occurrence probability (*Dp*), severity (*Ds*), and detection (*Dd*) are determined for each failure mode through the scale given in Table 1. Besides, the main objectives (goals) of the system (such as maximizing safety, minimizing stoppage in operation, and minimizing operational and capital costs) are defined.
- *Step 2*: A specific FCM is designed to investigate causal relationships among the failure modes in the presence of the risk factors and considered multiple

objectives (Fig. 2). The figure indicates a cognitive map that considers the effects of risk factors on each failure mode and the failure modes on the management objectives (goals) during the risk evaluation process. Accordingly, the multi-objective FCM model consists of the following steps:•*Step 2.1*: Concepts (failure modes, risk factors, and objectives) are considered as the map nodes in the system.•*Step 2.2*: The initial matrix of causal relationship weights is considered by determining the causal relationship between every two concepts based on expert opinions. Accordingly, the specific cognitive map is designed. Fig. 2 indicates a sample cognitive map representing three different sets of required nodes (failure modes, risk factors, and objectives). In this figure, the risk factors' nodes are linked to each failure mode by a weight of 1. Because the amounts of the risk factors' concepts should be entirely given to any failure mode. Other causal relationships and weights between other every two concepts (Wij for $i = (1, 2, \ldots, m)$ and $j = (1, 2, \ldots, n)$) should be specified by expert opinions.•*Step 2.3*: Scenarios are made, and the values of the nodes are calculated through obtaining a sustainable structure of the cognitive map. In each scenario, one failure mode is assumed to occur, and a value of 1 is assigned to its related concept accordingly. Therefore, the values of the triple risk factors are normalized between 0 and 1. For this purpose, after determining the values of a certain node, the values for other nodes related to that node can be calculated by Eq. (10); where, $Ai(k+1)$ is the value of concept i in iteration $k + 1$, f is transformation function, and $Ai(k)$ is the value of concept i in iteration k. A hybrid learning algorithm of nonlinear Hebbian and differential evolution could be used to improve the precision of the final weights of concepts when the initial causal relationship matrix is completed based on expert opinions. Using the learning algorithm, the dependency on expert opinions could be decreased, and the structure of FCM could be improved. The output of the three concepts resulted by running the hybrid algorithm in each scenario indicates the effect degree of each failure mode on the system objectives.

(10)

- *Step 3*: A single or hybrid MADM technique (Fig. 1) is applied to prioritize failure modes as alternatives with respect to the system's multiple objectives (as criteria). Notably, the designed FCM in Step 2 results in the weights of the failure modes with respect to objectives, which is considered as a decision matrix. Before doing any process by a MADM technique on the FCM-based decision matrix, the matrix is normalized. TOPSIS or GRA-TOPSIS, for example, could be applied for risk prioritization. As a result of the prioritization, the failure mode with the highest value represents the most critical failure mode (risk), which needs high consideration by the system management. As pointed out by

Bakhtavar and Yousefi (2018), different weighting scenarios could be regarded for the objectives with different importance to cover the different opinions of any system management policy.

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The use of fuzzy logic techniques to improve decision making in apparel supply chains

L. Wang, ... L. Koehl, in Information Systems for the Fashion and Apparel Industry, 2016

2.3.3.2 Computation of the relevancy degree REL(t_i, D)

From *Experiment III*, we have acquired the consumer data taken from $\{R_1,\ldots, R_5\}$, which characterize the relations between the desired fashion themes t_i's ($i = 1,\ldots, n$) and the sensory descriptors d_j's ($j = 1,\ldots, m$). In our study, this generalized relation is modeled using a fuzzy cognitive map. A fuzzy cognitive map [29] is a cognitive map within which the relations between the elements (eg, concepts, events, project resources) of a "mental landscape" can be used to compute the "strength of impact" of these elements. Fuzzy cognitive maps are signed fuzzy digraphs [20]. Any causal relation between two concepts is usually uncertain and varies between "positive and certain response" and "negative and certain response." Fuzzy cognitive maps offer a good approach to the stimulation and aggregation of generalized human perceptions provided by multiple evaluators [30]. A fuzzy cognitive map can effectively represent data provided by different consumers, which may be inconsistent.

Next, we aggregate the results of all the z consumer evaluators ec_k ($k = 1,\ldots, z$) and obtain a possibility distribution characterizing the relation between each fashion theme t_i and each sensory descriptor d_j. This relation aggregating all the z consumers can be expressed by a fuzzy value distributed on the set $\{R_1,\ldots, R_5\}$, ie:

where $NB_{ij}(R_k)$ ($k = 1,\ldots, 5$) is the number of evaluators selecting the linguistic value R_k when evaluating the relation between t_i and d_j. Evidently, the sum of all components of REL(t_i, d_j) is 1.

The ($m \times 5$)-dimensional fuzzy matrix REL(t_i, D) characterizes the fuzzy relation between a fashion theme t_i and all the sensory descriptors.

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Large Scale Systems and Fuzzy Cognitive Maps: A critical overview of challenges and research opportunities

Peter P. Groumpos, in Annual Reviews in Control, 2014

4.3 Neural network nature of Fuzzy Cognitive Maps

Fuzzy Cognitive Maps as been described is a hybrid methodology, because it utilizes characteristics of fuzzy logic and neural networks. The development and construction of FCMs have shown their fuzzy nature. Learning rules, used in Neural Networks theory, they are used to train the Fuzzy Cognitive Map. Parameter learning of FCM concerns the updating of connection weights among concepts. The construction of FCM is based on experts who determine concepts and weighted interconnections among concepts. This methodology may lead to a distorted model of the system because human factor is not always reliable. In order to refine the model of the system, learning rules are used to adjust weights of FCM interconnections.

The Differential Hebbian learning rule has been proposed to be used in the training of a specific type of FCMs. The Differential Hebbian learning law adjusts the weights of the interconnection between concepts t grows a positive edge between two concepts if they both increase or both decrease and it grows a negative edge if values of concepts move in opposite directions. Adjusting the idea of differential Hebbian learning rule in the framework of Fuzzy Cognitive Map, the following rule is proposed to calculate the derivative of the weight between two concepts.

(24)

where

Appropriate learning rules for Fuzzy Cognitive Maps need more investigation. These rules will give FCMs useful characteristics such as the ability to learn arbitrary non-linear mappings, capability to generalize to situations the adaptability and the fault tolerance capability of a complex dynamic system.

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Evaluation of Electrical Energy Storage (EES) technologies for renewable energy: A case from the US Pacific Northwest

Jisun Kim, ... Tugrul U. Daim, in Journal of Energy Storage, 2017

3.7.3 Fuzzy Cognitive Maps (FCM)

Fuzzy Cognitive Maps (FCM) is an emerging technique for knowledge elicitation and data synthesis. The technique can capture the cause and effect relationships that subject matter experts believe to exist about a problem. The unquestionable advantages of FCMs lie in the simplicity and adaptability to a certain application domain.

However, it seems that their further development and is somewhat constrained by deficiencies that are present in their underlying theoretical framework. Disadvantages related to the manual development recently encouraged researchers to work on semi-automated or automated tools for learning FCM models from historical data [297].

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A survey on computational intelligence approaches for predictive modeling in prostate cancer

Georgina Cosma, ... A. Graham Pockley, in Expert Systems with Applications, 2017

3.2.3 Evolutionary Fuzzy Cognitive Maps

A Fuzzy Cognitive Map (Kosko, 1986) is an extension of cognitive maps which inherited the main aspects of fuzzy logic and Artificial Neural Networks for graphically representing the reasoning behind a given domain of interest. Fuzzy Cognitive Maps describe a system using nodes/concepts (variables, states) and signed fuzzy relationships between them. Although the Fuzzy Cognitive Map bears a resemblance to an Artificial Neural Network, it is a conceptual network and therefore the nodes and arcs within the Fuzzy Cognitive Map are able to follow semantical interpretation. The advantage of Fuzzy Cognitive Maps over Artificial Neural Networks is that knowledge about the casual dependencies within the domain of interest is transparent and hence it can be easily interpreted by humans. However, a limitation of Fuzzy Cognitive Maps is that they are constructed manually, and therefore it may not be feasible to apply them when dealing with data comprising of a large number of variables. In order to address this limitation, Froelich, Papageorgiou, Samarinas, and Skriapas (2012) proposed an evolutionary Fuzzy Cognitive Map approach which is capable of learning Fuzzy Cognitive Maps. The proposed evolutionary Fuzzy Cognitive Map was applied to predict a patient's state after a period of time following a suggested therapy plan. The evolutionary Fuzzy Cognitive Map was applied to a small dataset comprising of 40 patients suffering with prostate cancer. The results revealed that the evolutionary Fuzzy Cognitive Map outperformed the basic Fuzzy Cognitive Map. Although it is difficult to determine the reliability of the results given the small dataset, it is important to appreciate that the authors gave appropriate thought to the validation of the results in order to ensure reliability of findings. They applied two methods to validation - method 1: the data were divided into learning and testing sets of the same cardinality (the learning set contained records of 20 patients, the remaining 20 records constituted the testing set); and method 2: the leave-one-out cross validation (LOOCV) method was applied. The results revealed that both validation methods returned very similar results, and this may not have been the case if a larger dataset was utilised.

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Causal knowledge and reasoning by cognitive maps: Pursuing a holistic approach

Alejandro Peña, ... Agustín Gutiérrez, in Expert Systems with Applications, 2008

Fuzzy CM provide different gray levels for the values of concepts and causal relations through: Crisp sets, like {0, 1} or {–1, 0, 1}, continues values, into a range [0, 1] or [–1, 1], and fuzzy values, like {low, high, …} by membership functions. Prior to start the simulation process, the values associated to concepts are estimated and represented into a vector (*V*), whilst the values for the causal relations are stored in an adjacency matrix (*W*) of *n* ⯑ *n* concepts. Afterwards the inference process is carried out along discrete steps, from $t = 0$, $t = 1$, $t = 2$,… At each step (*t*), new values for the concepts (*V*(*t*)) are estimated based on the fuzzy causal influences; whereas the adjacency matrix remains fixed. The new value for each concept (*vi*(*t*)) is stemmed from the normalization of rough influence value (s_i) by (9_a). Value s_i represents the sum of the concepts' values inputs (*vj*(t – 1)), whose edges arrive to *i*, multiplied by the corresponding relation weight *wij*, as in (9_b). According to the nature of the concepts' values, a threshold function (u) is applied to s_i in order to normalize the final value to a bipolar crisp value in {0, 1} by (10_a), a tripolar crisp value in {−1, 0, 1} through (10_b), a discrete value in the continue range [0, 1] through (11_a) or a discrete value in the continue range [−1, 1] by means of (11_b); where: c is critical in determining the degree of fuzzification of the function, so it is advisable a value $c = 5$ (Mohr, 1997). The equilibrium state of a Fuzzy CM is easily detected by comparing two successive patterns of states concepts, composed by one or more state vectors. If they are identical, then the map has reached an equilibrium state and the execution ends. Thus, a fuzzy CM with discrete threshold functions, as (10_a) or (10_b), will either converge to a limit cycle or reach an equilibrium state, due to these functions force fuzzy state vectors to non-fuzzy values. Whereas, a fuzzy CM using the logistic signal threshold function, as (11_a) or (11_b), with lacks of feedback flows may be checked for stability in terms of the eigenvalues of the edge connection matrix. However, a fuzzy CM may become nonlinear under complex feedback dynamics (Mohr, 1997).

(9)

(10)

(11)

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MRI based medical image analysis: Survey on brain tumor grade classification

Geethu Mohan, M. Monica Subashini, in Biomedical Signal Processing and Control, 2018

3.2.1 FCM

A Unified Model based classification with FCM (UMCF) using Extended Hyperbolic Tangent (EHT) model (derived from logistic regression), Gaussian mixture model and fuzzy soft clustering technique is used in [82]. EHT quantifies the relationship between two variables. Soft clustering minimizes dissimilarities among objects of same cluster and similarity among different classes. Normal cells, edema and tumor were represented by using pixel value 0,100 and 255 respectively. The advantage of this work was that using EHT model reduces false positive and false negative.

For the classification of astrocytomas as WHO, high/low grade, [83] portrays the use of Fuzzy Cognitive Maps (FCMs). It models and represents the knowledge of experts like their expertise, experience, heuristic etc. The powerful properties of neural networks and fuzzy logic are blended into FCMs. It's grading ability and applicability was strengthened by the Activation Hebbian Algorithm (AHL). The most useful experience and knowledge of experts were extracted by AHL algorithm. FCMs benefits were the ample transparency and interpretability in the decision process and drawback was the convergence to undesired regions which was avoided by the use of suitable learning algorithms. Hence when new strategies were adopted, the learning algorithms recalculated the weights. To assess the tumor grade, experts usually utilize 8 histopathological features: cellularity, mitoses, apoptosis, the giant cells, the multinucleated cells, the necrosis, the vascular proliferation and the pleomorphism. These key characteristics encoded the degree of malignancy of the tumor. The experts could qualitatively explain the degree of causality among concepts and need not explain the causality relations by numerical values.

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Computational intelligence techniques for medical diagnosis and prognosis: Problems and current developments

Afzal Hussain Shahid, M.P. Singh, in Biocybernetics and Biomedical Engineering, 2019

4.2.6 Particle swarm optimization and fuzzy cognitive maps based

For modeling the complex systems, the fuzzy cognitive maps (FCMs) methodology was introduced by Kosko in 1986 [271]. It is able to express the causal interrelations between the main attributes which are responsible for the dynamic behavior of the systems. FCMs are a result of merging FL and ANNs and can represent both quantitative and qualitative data. Recently, it has been used extensively in medicine [272].

Salmeron et al. [273] used PSO and FCMs for the severity estimation of Rheumatoid Arthritis. The authors' claimed to be the first to use FCMs in the diagnosis of Rheumatoid Arthritis. The accuracy was found to be 90% which is very close to the experts. Earlier to this, many works have been done to address this disease [274–276]. However, the previous works have not considered: (i) the interrelationship between the diagnostic parameters and (ii) disease progression with the time element which helps in making better decisions. Also, the previous methods lack the transparency of the diagnostic knowledge and the explanation ability, which is very significant from the general physicians' perspective. Their model can work well in case of scarce data (available data may be limited) as opposed to ML algorithms which require a large amount of data. Furthermore, it consumes less time.

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Risk evaluation approaches in failure mode and effects analysis: A literature review

Hu-Chen Liu, ... Nan Liu, in Expert Systems with Applications, 2013

3.3.4 Fuzzy cognitive map

Pela´ez and Bowles (1996) applied fuzzy cognitive maps (FCMs) to model the behavior of a system for FMEA. The FCM was a diagram to represent the causality of failures with failure node and causal relation path. The path was described by using linguistic variables such as '*some, always, often*' and relative scales were assigned for each term. Then min–max inference approach was used to evaluate the net causal effect on any given node and weighted mean of maximum method was used as defuzzification technique to extract the resulting confidence values on linguistic variables.

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