

Cellular Fuzzy Networks

Koosha Sadeghi Oskooyee¹, Mohammad Mansour Riahi Kashani², and Mehrdad Jangjou³

^{1,2}Dept. of Computer Engineering,
Islamic Azad University, North Tehran Branch,
Tehran, Iran

³Dept. of Computer Engineering,
Islamic Azad University, U.A.E. Branch,
Dubai, Emirates

e-mail: {¹K_Sadeghi_Oskooyee, ²M_Riahi_Kashani}@iau-tnb.ac.ir, and ³Mehrdadjangjou@live.com

Abstract—A formal representation of the mutual information processing among the cognitive processes of the brain provides a real impression of the mechanisms of a Natural Intelligence (NI) system. The nature of information processing in the human brain is fuzzy. In this article, a new formal model, namely Cellular Fuzzy Networks (CFNs), is introduced to model the real characteristics of NI-Systems and especially the human mind. CFNs can effectively manipulate the interactions among natural concepts in an NI-system. The detailed definitions of CFNs and related theorems are provided. Then, CFNs are exploited to model a feasibility analysis of the human brain in the cognitive process of decision making. Finally, it is posited that CFNs have great potential to be applied in modeling the complex interrelationships in large-scale natural systems.

Keywords- *Cognitive informatics; natural intelligence system; fuzzy sets theory; cellular fuzzy networks; human mind*

I. INTRODUCTION

The contemporary form of cybernetics is known as Cognitive Informatics (CI), which attempts to discover the mechanisms of natural intelligence and the cognitive processes of the brain [1]. CI applies many disciplines such as philosophy, physiology, psychology, and computer science to study the human brain as the most complicated organism in the universe [2, 3]. Natural intelligence, like other natural phenomena, is involved with vague concepts. An average brain in daily life thinks and proceeds with imprecise information and facts, and the nature of information processing in the human brain is fuzzy. Fuzzy sets theory provides a formal method to capture and process vague data from the natural world in a precise form [4].

The human brain proceeds through nonstop performance causal relationships among cognitive functions. Imitation of the real characteristics of the human mind requires the composition of an ultimately accurate harmony among the cognitive functions of the brain [5]. Subsequently, analyzing the complex interactions among a set of cognitive processes requires a formal method that can be easily adapted to the nature of information processing in an NI-System. The method can be exploited more effectively as one of the most vital issues in CI and AI research through the representation of mind flows [6].

In this paper, the concept of CI is used to make a relevant connection between psychological studies of NI and methodological models in computer engineering to develop a casual network in light of fuzzy sets theory. In this way, a new concept of cellular fuzzy networks is proposed to manipulate the mutual information processing among cognitive processes of the brain. The idea comes from the theorems of Cellular Bayesian Networks (CBNs) proposed in [7] and the fuzzy sets theory. Actually, CFNs acquire and merge the structure and mathematical background of CBNs and the principles of fuzzy inference systems [8].

This paper is arranged as follows: in Section II, a brief description of fuzzy sets theory is proposed, and then in Section III the cellular fuzzy network is developed on the basis of casual network and fuzzy sets theory. In Section IV, feasibility testing in NI-systems is modeled and simulated according to CFN in a MATLAB workspace. In this case, the psychological models for integrating new information into the existing knowledge are exploited to manipulate the feedback information to the NI-system. Finally, the paper is concluded in Section V.

II. FUZZY SETS THEORY

In cognitive psychology, vagueness and uncertainty regarding perception are properties of concepts which are inevitable in human thought processes. The origin of fuzzy concepts is due partly to the fact that the nature of information processing in the human brain is fuzzy.

The theory of fuzzy sets was proposed by L.A. Zadeh and provides an efficient basis for the model the cognitive capabilities of the human brain under uncertain circumstances. Currently, fuzzy sets is an extension of the classical notion of sets in which the membership of elements or objects in a set is assessed in binary terms according to a bivalent condition [9, 10]. In contrast, fuzzy sets theory permits the gradual assessment of the membership of elements in a set, which is determined by a membership function valued in the real unit interval [0, 1].

Fuzzy sets theory can be used in a wide range of domains in which information is incomplete or imprecise, such as bioinformatics [11]. In this way, fuzzy sets theory provides fuzzy production rules in order to reason and infer properly

with real world information. Fuzzy systems apply linguistic identifiers and rules to mimic NI-System behaviors and thought mechanisms more effectively.

III. CELLULAR FUZZY NETWORKS

In this section, cellular fuzzy networks and their related theorems are defined and explained in detail to determine a formal framework for representing an accurate depiction of the information flow in an NI-system.

A *causal network* is an acyclic digraph arising from an evolution of a substitution system, and representative of its history. In the evolution of a multi-way system, each substitution event is a vertex in a causal network. The existence of an edge between two vertices in the casual network indicates the order of the corresponding events, which are related by causal dependence. More precisely, the edge is a directed edge leading from the past event to the future event [11]. In a causal network, if the variables A and B become the parents of the variable C independently, there is no information on how impacts from variable A and variable B interact, and more specification is required. In addition, causal networks do not support the domain to be modeled contains feedback cycles. In this way, to eliminate these restrictions, some modifications to the structure of causal networks are performed according to the following definitions.

Definition 1. A *Fuzzy Network* (FN) is a fuzzy graphical model that represents a set of natural variables and their causal dependencies via a Directed Acyclic Graph (DAG). More particularly, an FN is a kind of casual network with the following characteristics:

- There is a set of variables and a set of directed edges between the variables;
- Each set contains a finite set of mutually exclusive states;
- The variables coupled with the directed edges construct a directed acyclic graph;
- Each variable A with parents $B_1, B_2 \dots B_n$ is associated with a set of fuzzy production rules table comprised of the fuzzy rules in the form of IF B_1 AND B_2 AND... B_n THEN A .

In fact, each node in an FN presents a fuzzy inference system. If the variable A has no parent, then the table can be replaced by the degree of membership. A fuzzy network provides a graphical model of information passing among nodes to mimic the behaviors of an NI-system.

In a directed acyclic graph $G = (V, E)$, a node $C \in V$ is called a *center node* if and only if for any node $X \in V \setminus \{C\}$, the condition $\langle X, C \rangle \in E$ is satisfied. For example, in Fig. 1, the node n_3 in graph G_1 and the node n_2 in G_2 are the center nodes in their graphs, respectively. A directed acyclic graph is a *centered graph* if and only if it has only one center node, and there are no edges ending at non-center nodes [7].

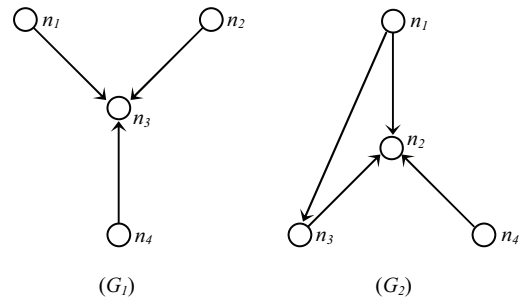


Figure 1. The sample graphs

For example, graph G_1 is a centered graph, and graph G_2 is not due to its containing extra edges between non-center nodes. The center node of a centered graph is specified shortly to $C(G)$. Hence, in Fig. 1, we have $C(G_1) = n_3$.

Definition 2. A *cellular fuzzy network* is a pair (G, R) , where $G = (V, E)$ is a centered graph, and R is a set of fuzzy production rules for the center node of G given its parents. For convenience, the center of G is also called, $C(G)$, the center of the CFN, short for C (CFN).

In a CFN, each node acts as a fuzzy inference system, following five steps: (1) fuzzification of the input variables from the parents, (2) application of the fuzzy operator (AND or OR) in the antecedent, (3) implication from the antecedent to the consequent, (4) aggregation of the consequents across the rules, and, finally, (5) defuzzification and the outputs their passing onto the childs. For any two given cellular fuzzy networks $F_1 = (G_1, R_1)$ and $F_2 = (G_2, R_2)$, if $C(B_1) \neq C(B_2)$, the *union* $F = F_1 \cup F_2$ of the CFN F_1 and CFN F_2 is a pair (G, R) , where G is the union of G_1 and G_2 , and R is the union of R_1 and R_2 . As shown in Fig. 2, two fuzzy cells (i.e. F_1, F_2) are linked through their center nodes (i.e. n_2, n_4) with directed edges. The union of two CBNs is also a graph model but according to the definitions it is no longer a CBN.

Definition 3. A *Cellular Fuzzy Networks* (CFNs) is a union, $CFNs = F_1 \cup F_2 \cup \dots \cup F_n$, where F_i ($i = 1, \dots, n$) is cellular fuzzy network, and they are subject to the following constraints:

$$C(F_i) \neq C(F_j), 1 \leq i < j \leq n \quad (1)$$

and

$$C(F_i) \in (\bigcup_{i \neq j} V_j), i = 1, \dots, n, \quad (2)$$

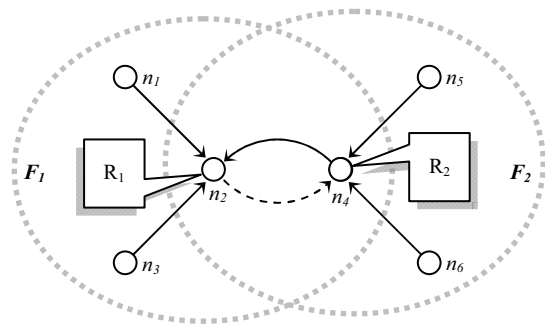


Figure 2. The union of cellular fuzzy networks (F_1 and F_2)

where V_j is the node set of F_j . The first constraint indicates the uniqueness of every cell in the networks and the second constraint indicates that the center nodes are the only path for connection among the cells. CFNs can be developed like fractals by substituting every node with CFNs and so on. This attribute makes CFNs more flexible to model natural systems with dynamic scales.

IV. THE NATURAL INTELLIGENCE SYSTEM

An artificial mind system attempts to imitate cognitive mechanisms of the human brain in dealing with a wide variety of physical and mental incidents in the natural world. In cognitive psychology, vagueness and uncertainty are inevitable in human thought processes [12]. In many everyday situations, an average person thinks largely in an intuitive and associative manner, which is calculated or identified by qualitative or verbal measures within the range of interpretation for a given phrase. Particularly, it is recognized that people’s internal representations of uncertainty are verbal.

Human brain as the most complex organism in the universe is the faculty of any kind of intelligent behaviors. Human behavior is directly generated by behavioral intensions, which are controlled by the attitude consisting of personal experiences and social norms [7].

Attitude or perceptual feasibility in which uncertainty is a substantial issue generally focuses on decision making processes. Attitude has a considerable impact on behavior and influences the ways a person thinks and feels. The direct relationship between attitude and behavior intention is shown in Table II. Furthermore, attitude of a person is affected by the environmental results of the related behavior. In this case, in order to manage the feedback of new information, in [18], a psychological model was developed which adjusted membership functions toward predicting the impact of new information on the existing body of knowledge. According to this model, newly acquired information from the environment about the possibility of doing an action has an impact on the modification of the perceptual feasibilities, as can be seen in Table I.

Now, the interactions between perceptual feasibility and behavior intention [18] as two fuzzy concepts in an NI-Sys are modeled with CFNs. Fuzzy concepts are characterized by generalized bell-shaped membership functions according to prevalent psychological and linguistic disciplines, as seen in Fig. 3 [8]. Psychological experiments [19] indicate that the amount of above-mentioned specifications is sufficient for practical purposes. As shown in Fig. 4, a CFNs model is developed which accounts for the verbal thinking orientation for decision making, or behavior modeling through logically describing the imprecision of the mind’s activities ([10], [19]).

Tables I and II indicate the production rules of the fuzzy inference system on each node in the model in Fig. 4. As mentioned before, some natural and psychological attributes are extracted for the purpose of defining fuzzy rules. In fact, in the proposed model, perceptual feasibility is in charge of the evaluation or belief of a person about the difficulty of carrying out a designated behavior.

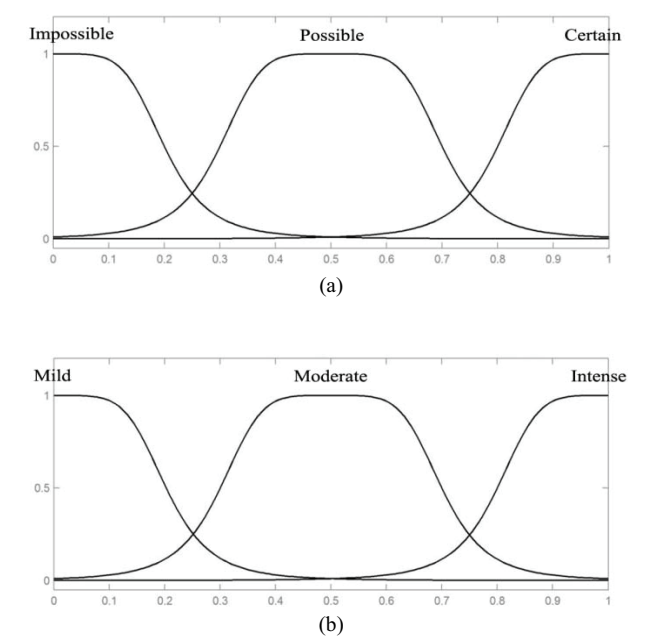


Figure 3. Diagrams of the membership functions of (a) feasibility analysis, and (b) behavior intention

For simulation, the fuzzy logic toolbox of Matlab was used to describe each node (in Fig. 4) efficiently as a fuzzy inference system and the plots of the fuzzy inference systems are shown in Figs. 5 and 6 [14]. In Fig. 5, the effect of the outcome of the behavior (i.e. the feedback) on the current belief about the feasibility of success in carrying out the behavior can be seen.

TABLE I. THE EFFECT OF FEEDBACK OF NEW INFORMATION ON OLD KNOWLEDGE

	New information		
	Impossible	Possible	Certain
Old knowledge			
Impossible	Impossible	Impossible	Possible
Possible	Impossible	Possible	Certain
Certain	Possible	Certain	Certain

TABLE II. THE EFFECT OF A FEASIBILITY ANALYSIS ON BEHAVIOR INTENTION

Feasibility analysis	Behavior intention
Impossible	Mild
Possible	Moderate
Certain	Intense

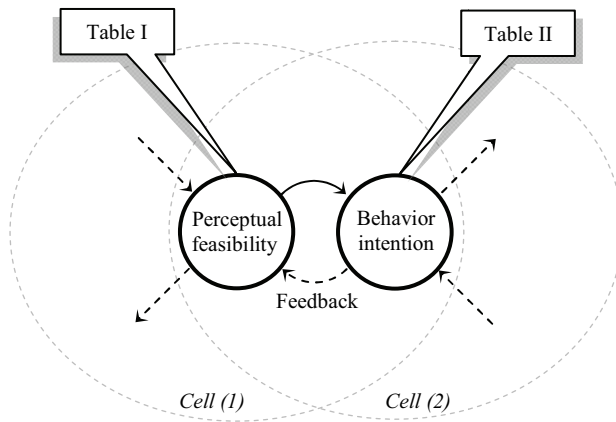


Figure 4. CFNs model of the interactions between feasibility analysis and behavior intention

In this case, the fuzzified inputs from the natural world are processed through IF-THEN rules and the Mamdani's max-min composition [17]. The simulated CFNs model provides a formal explanation for the mechanism and relationship between attitude and behavior. Also, it can be used for describing the way attitude helps to regulate the behavioral intention with a positive or negative judgment.

As a result, CFNs provide relevant specifications to freely determine the relationships among fuzzy inference systems, whether as aforementioned, a causal network has some restrictions in this way, such as a lack of information on how impacts from parent systems interact, and also the domain which contains feedback cycles are not supported. In addition, the model can be easily expanded to cover other factors involved in forming behavior in natural intelligent systems, like emotion and motivation. The designed CFNs can be used to control the behavior of an intelligent system with autonomous decision making ability according to the rules of feedback information and natural intelligence [15, 16].

V. CONCLUSION

A formal method is required to analyze the complex interactions among a set of cognitive processes of the brain

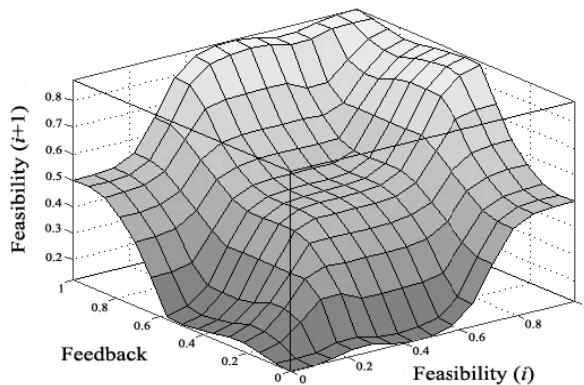


Figure 5. Surface plot of the fuzzy inference system of the left node in the CFNs model (in Fig. 4) that illustrates the influence of feedback as new information on the current feasibility analysis

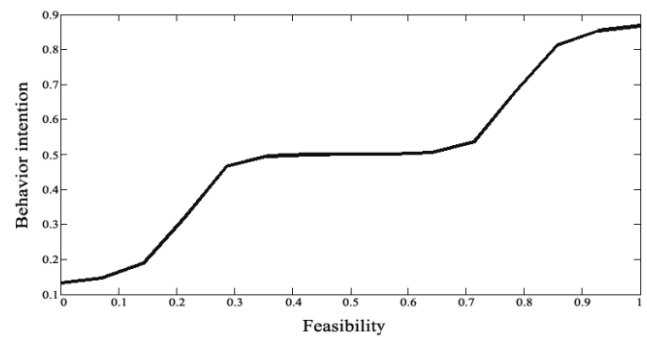


Figure 6. The plot of the fuzzy inference system of the right node in the CFNs model (in Fig. 4) that illustrates the influence of the feasibility analysis on the behavior intention

that can be easily adapted to the nature of information processing in a natural intelligence system. The brain works continuously through a life time; in such a dynamic organism, considering the effects of every stimulus and process becomes very complicated.

In the present work, a new concept of cellular fuzzy networks is proposed to model the real characteristics of NI-Systems, especially those of the human mind. The detailed definitions of CFNs and related theorems are provided. Subsequently, CFNs are exploited to model the feasibility analysis of the human brain in the cognitive process of decision making and behavior intention. The proposed model can be applied to simulate the transmission of mind flows toward implementing an intelligent humanoid behavior mechanism and other mental phenomena as well. The model offers the real possibility of humanoid behavior through developing an artificial mind system and future generation intelligent systems.

The authors propose future research on the theme, including the concepts of learning and inference in cellular fuzzy networks. CFNs have great potential to be applied to model the complex interrelationships in large-scale natural systems. Finally, it is expected that such methods will be able to establish more natural characteristics of the human mind and brain in the operation of artificial intelligence systems.

REFERENCES

- [1] Y. Wang, W. Kinsner, and D. Zhang, "Contemporary Cybernetics and Its Facets of Cognitive Informatics and Computational Intelligence," *IEEE Transactions on Systems, Man and Cybernetics—part B: Cybernetics*, vol. 39, no. 4, Aug. 2009.
- [2] Y. Wang and Ying Wang, "Cognitive Informatics Models of the Brain," *IEEE Transactions on Systems, Man and Cybernetics—part: C, Applications and Reviews*, vol. 36, no. 2, pp. 203-207, Mar. 2006.
- [3] Z. Shi and J. Shi, "Perspectives on Cognitive Informatics," *Proceedings of the Second IEEE International Conference on Cognitive Informatics (ICCI'03)*, 2003.
- [4] X. Li, W. Yu, and F. Lara-Rosano, "Dynamic Knowledge Inference and Learning under Adaptive Fuzzy Petri Net Framework," *IEEE Transactions on Systems, Man and Cybernetics—part: C, Applications and Reviews*, vol. 30, no. 4, Nov. 2000.
- [5] G. Baci, Y. Wang, Y.Y. Yao, W. Kinsner, K. Chan and L.A. Zadeh (Eds.), "Perspectives on cognitive informatics and cognitive computing: Summary of the Panel of IEEE ICCI'09," *Proc. of the 8th IEEE Int.*

- Conf. on cognitive informatics (ICCI'09), IEEE CS Press, Kowloon, Hong Kong, pp. 9-27, Jun. 2009.
- [6] L. I. Perlovsky, "Neural Mechanisms of the Mind, Aristotle, Zadeh, and fMRI," IEEE Transactions on Neural Networks, vol. 21, no. 5, May. 2010.
 - [7] Y. Wang, Discoveries and Breakthroughs in Cognitive Informatics and Natural Intelligence, IGI global, pp. 428-435, Nov. 2009.
 - [8] J. C. Canales, X. Li, and W. Yu, "Fuzzy Knowledge Learning via Adaptive Fuzzy Petri Net with Triangular Function Model, Proceedings of the 6th World Congress on Intelligent Control and Automation, Dalian, china, Jun. 2006.
 - [9] G. Giangiacomo, "Effectiveness and Multivalued Logics". Journal of Symbolic Logic, Vol. 71, No. 1, pp. 137-162, 2006.
 - [10] P. D. Windschitl and G. L. Wells, "Measuring Psychological Uncertainty: Verbal Versus Numeric Methods," Journal of Experimental Psychology: Applied, vol. 2, no. 4, pp. 343-364, 1996.
 - [11] J. Pearl, Causality: Models, Reasoning, and Inference, Cambridge University Press, 2000.
 - [12] T. Hoya, Artificial Mind System – Kernel Memory Approach, Studies in Computational Intelligence (SCI), Springer-Verlag Berlin Heidelberg, Sep. 2005.
 - [13] L. R. Liang, S. Lu, X. Wang, Y. Lu, V. Mandal, D. Patacsil and D. Kumar, "FM-test: A Fuzzy-Set-Theory-Based Approach to Differential Gene Expression Data Analysis," BMC Bioinformatics, Jun. 2006.
 - [14] A. Che Soh, L. Guan Rhung, and H. Md. Sarkan, "MATLAB Simulation of Fuzzy Traffic Controller for Multilane Isolated Intersection," International Journal on Computer Science and Engineering, vol. 2, no. 4, pp. 924-933, 2010.
 - [15] D. Borrie, S. Isnandar, and C.S. Özveren, "Simulation of Complex Environments: The Fuzzy Cognitive Agent," IEEE Proceedings of the Sixth International Conference on Intelligent Systems Design and Applications (ISDA'06), 2006.
 - [16] K. S. Park, D. S. Kwon, M. Park, "A Design of the Mental Model of a Cognitive Robot," 16th IEEE International Conference on Robot & Human Interactive Communication, pp. 26 - 29, Aug. 2007.
 - [17] C. W. Hong, G. J. Choi, and D. S. Ahn, "Integrated Development Platform for Design of Fuzzy Inference System using RecurDyn and SIMULINK," SICE-ICASE International Joint Conference 2006, pp. 18-21, Bexco, Busan, Korea, Oct. 2006.
 - [18] Y. Wang, novel approaches in cognitive informatics and natural intelligence (Advances in Cognitive Informatics and Natural Intelligence), Information Science Reference, pp. 65-76, Dec. 2008.
 - [19] A. C. Zimmer, "A model for the interpretation of verbal predictions," International Journal of Man-Machine Studies, vol. 20, no. 1, pp. 121-134, Jan. 1984.