A Survey about Fuzzy Cognitive Maps Papers (Invited Paper)

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***Abstract*— In this paper we present different results and studies around the world about the Fuzzy Cognitive Maps. This technique is the fusion of the advances of the fuzzy logic and cognitive maps theories. At this moment, there are several applications in different domains (control, multiagent systems, etc.) and new works (dynamical characteristics, learning procedures, etc.) to improve the performance of these systems. In this paper, we present a survey of different work about this topic.** *Copyright © 2004-2005 Yang's Scientific Research Institute, LLC. All rights reserved.*

***Index Terms*— Cognitive maps, fuzzy logic, neural networks.**

I. INTRODUCTION

DECISION makers and policy proponents face serious difficulties when approaching significant dynamic systems. Modeling a dynamic system can be hard in a computational sense. In addition, formulating a mathematical model may be difficult, costly, even impossible. These approaches offer the advantage of quantified results but suffer from several drawbacks. First, developing the model typically requires a great deal of effort and specialized knowledge outside the domain of interest. Secondly, systems involving significant feedback propagates casual influences in complicated chains may be nonlinear, in which case a quantitative model may not be possible. Finally. numerical data may be hard to come by or uncertain. Efforts to communicate an understanding of the system and propose policies must rely on natural language arguments in the absence of formal models (qualitative approach). Fuzzy Cognitive Maps (FCM) are a qualitative alternative approach to dynamic systems, where the gross behavior of a system can be observed quickly and without the services of an operations research expert.

FCMs were proposed by Kosko to represent the causal relationship between concepts and analyze inference patterns [22, 23, 24, 25, 26]. FCM were originally proposed as a means of explaining political decision making processes. FCMs are hybrid methods that lie in some sense between fuzzy systems and neural networks. FCMs combine the robust properties of fuzzy logic and neural networks. FCMs represent knowledge in a symbolic manner and relate states, processes, policies, events, values and inputs in an analogous manner. Once constructed, an FCM of a domain allows to perform a qualitative simulation of the system and experiment with the model. Compared either experts system and neural networks, it has several desirable properties such as: it is relative easy to use for representing structured knowledge, and the inference can be computed by numeric matrix operation instead of explicit IF/THEN rules. FCMs are appropriate to explicit the knowledge and experience which has been accumulated for years on the operation of a complex system. FCMs have gained considerable research interest and have been applied to many areas. This paper presents a survey of different works about FCMs.

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II. FUZZY COGNITIVE MAPS

At first, Axelord used cognitive maps as a formal way of representing social scientific knowledge and modeling decision making in social and political systems [4]. Then, Kosko enhanced cognitive maps considering fuzzy values for them [22, 23, 24, 25]. A FCM describes the behavior of a system in terms of concepts, each concept represents a state or a characteristic of the system. A FCM can avoid many of the knowledge-extraction problems which are usually posed by rule based systems. The classical knowledge representation in expert system is made through a decision tree. This form of knowledge presentation presents problems such as: impossibility of larger trees have dynamic behavior; impossibility of trees have performance in real time, and so for.

A FCM illustrates the whole system by a graph showing the cause and effect along concepts. Particularly, a FCM is a fuzzy signed oriented graph with feedback that model the worlds as a collection of concepts and causal relations between concepts. Variable concepts are represented by nodes in a directed graph. The graph's edges are the casual influences between the concepts. The value of a node reflects the degree to which the concept is active in the system at a particular time. This value is a function of the sum of all incoming edges multiplied and the value of the originating concept at the immediately preceding state. The threshold function applied to the weighted sums can be fuzzy in nature. Moreover, concept values are expressed on a normalized range denoting a degree of activation rather than an exact quantitative value. These facts of FCMs are taken from the fundamentals of fuzzy logic. The threshold function serves to reduce unbounded inputs to a strict range. This destroys the possibility of quantitative results, but it gives us a basis for comparing nodes – on or off, active or inactive. This mapping is a variation of the "fuzzification" process in fuzzy logic. Fuzzification gives us a qualitative model and frees us from strict quantification of edge weights.

The causal relationships are expressed by either positive or negative signs and different weights.

In general, a FCM functions like associative neural networks. A FCM describes a system in a one-layer network which is used in unsupervised mode, whose neurons are assigned concept meanings and the interconnection weights represent relationships between these concepts. The fuzzy indicates that FCMs are often comprised of concepts that can be represented as fuzzy sets and the causal relations between the concepts can be fuzzy implications, conditional probabilities, etc. A directed edge E_{ij} from concept C_i to concept C_j measures how much C_i causes C_j. In simple FCMs, directional influences take on trivalent values $\{-1, 0, +1\}$, where -1 indicates a negative relationship, 0 no causality relationship, and $+1$ a positive relationship. In general, the edges E_{ij} can take values in the fuzzy causal interval $[-1, 1]$ allowing degrees of causality to be represented:

- $E_{jk} > 0$ indicates direct (positive) causality between concepts C_j and C_k. That is, the increase (decrease) in the value of C_j leads to the increase (decrease) on the value of C_k.
- $E_{jk} < 0$ indicates inverse (negative) causality between concepts C_j and C_k. That is, the increase (decrease) in the value of C_j leads to the decrease (increase) on the value of C_k.
- $E_{jk} = 0$ indicates no relationship between C_j and C_k.

Because the directional influences are presented as all-or-none relationships, FCMs provide qualitative as opposed to quantitative information about relationships. In FCM nomenclature, model implications are revealed by clamping variables and using an iterative vector-matrix multiplication procedure to assess the effects of these perturbations on the state of a model. A model implication converges to a global stability, an equilibrium in the state of the system. During the inference process, the sequence of patterns reveals the inference model. The simplicity of the FCM model consists in its mathematical representation and operation. So a FCM which consists of n concepts, is represented mathematically by a n state vector A, which gathers the values of the n concepts, and by a $n \times n$ weighted matrix E. Each element E_{ij} of the matrix indicates the value of the weight between concepts C_i and C_j. The activation level A_i for each concept C_i is calculated by the following rule:

$$A_i^{\text{new}} = f\left(\sum_{j=1}^{n} A_j^{\text{new}} E_{ji}\right) + A_i^{\text{old}}. \tag{1}$$

A_i^{new} is the activation level of concept C_i at time $t+1$, A_j^{old} is the activation level of concept C_j at time t, and f is a threshold function. So the new state vector A, which is computed by multiplying the previous state vector A by the edge matrix E, shows the effect of the change in the activation level of one concept on the other concepts. FCM can be used to answer a "what-if" question based on an initial scenario that is represented by a vector $S_0 = \{s_i\}$, for $i = 1 \ldots n$, where $s_i = 1$ indicates that concept C_i holds completely in the initial state, and $s_i = 0$ indicates that C_i does not hold in the initial state. Then, beginning with $k = 1$ and $A = S_0$ we repeatedly compute A_i. This process continues until the system convergence (for example, when $A_i^{\text{new}} = A_i^{\text{old}}$). This is the resulting equilibrium vector, which provides the answer to the "what if" question.

The development of a FCM often occurs within a group context. The assumption is that combining incomplete, conflict opinions of different experts may cancel out the effect of oversight, ignorance and prejudice. An expert draws a FCM according to his experience. That is, each expert provides its individual FCM matrix, which is then synthesized into a group FCM matrix. The group matrix (E^G) could be computed as:

$$E_{ji}^G = \max_t \left\{E_{ji}^t\right\}, \forall t = 1 \text{to number of experts (NE)}. \tag{2}$$

or

$$E_{ji}^G = \sum_{t=1}^{NE} b_t E_{ji}^t$$

where E_{ji}^t is the opinion of the expert t about the causal relationship among C_j and C_i, and b_i is the expert's opinion credibility weight.

In a distributed system, a FCM is constructed for each subsystem. Then all FCM are combined in one augmented matrix E for the whole system. The unification of the distinct FCMs depends on the concepts of the segmental FCM. If there are no common concepts among different maps, the combined matrix E is constructed according to the equation (3) and the dimension of the matrix E is the total number of distinct concepts in all the FCMs.

$$E = \begin{bmatrix} E_1 & 0 & 0 & 0 \\ 0 & E_2 & 0 & 0 \\ 0 & 0 & E_3 & 0 \\ 0 & 0 & 0 & E_4 \end{bmatrix} \tag{3}$$

III. State of Art

FCMs have gradually emerged as a powerful modeling and simulation technique applicable to numerous research and application fields. A useful tool for causal reasoning is the language of FCMs developed by political scientists to analyse, predict and understand decisions An excellent source for FCMs is Bart Kosko's Fuzzy Engineering [25]. In general, FCM have been found useful in many applications: administrative sciences, game theory, information analysis, popular political developments, electrical circuits analysis, cooperative man–machines, distributed group-decision support and adaptation and learning, etc. [12, 13, 25, 44].

[35, 37, 38] investigate the implementation of the FCM in distributed and control problems. Particularly, FCMs have been used to model and support a plant control system, to construct a system for failure modes and effect analysis, and to model the supervisor of a control system. [11] investigates FCM for modeling and controlling Supervisory Control Systems. An FCM represents the whole system in a symbolic manner, just as humans have stored the operation of the system in their brains, thus it is possible to help man's intention for more intelligent and autonomous systems. The implementation of FCM in a process control problem is illustrated, and a model for supervisors of manufacturing systems is discussed. The application of FCMs for modeling the Supervisor may contribute in the development of more sophisticated systems.

The development of a novel soft computing approach to model the supervisor of manufacturing systems, based on FCMs, is described by Stylios and Groumpos in [40], and it is used to model the behaviour of complex systems. The description and the construction of FCMs are examined, a new methodology for developing FCMs is proposed and an example the FCM for a simple plant is developed. A hierarchical two-level structure for supervision of manufacturing systems is presented, where the supervisor is modelled as a FCM. The FCM model for the failure diagnosis part of the supervisor for a simple chemical process is constructed.

Hadjiski et al. consider an approach to design adequate models for plants with large uncertainties [17]. Hybrid modelling schemes are described combining Fuzzy Logic, Neural Network and Statistical models. Several methods of aggregation are proposed: (i) Fuzzy gain scheduling of particular parameters of the First Principles model by most important input factors; (ii) Weighted sum of output signals from First Principles gain scheduled model and Fuzzy Logic model; (iii) A hybrid architecture for Hammerstein type model. A FCM is used to aggregate Separate Models and to fit more precisely the plant behaviour at different operational conditions. The presented methods are applied to the modelling of Steam Boiler Mill-Fan.

In [36] is described a decision engine for an intelligent intrusion detection system that fuses information from different intrusion detection modules using a causal knowledge based inference technique. The task of an intrusion detection system is to protect a computer system by detecting and diagnosing attempted breaches of the integrity of the system. A robust intrusion detection system for a computer network necessarily use multiple sensors, each providing different types information about some aspect of the monitored system. In addition, the sensor data will often be analyzed in several different ways. FCMs and fuzzy rule-bases are used to support the causal knowledge acquisition and reasoning processes.

In [37] is introduced a formal technique based on FCM to represent different types of knowledge in a group of agents. FCMs model the possible worlds as collection of classes and causal relations between classes. In [30] is presented an integrated process for rating of the intensity of causal relationship generating mean FCMs, assessing group consensus, and supporting the building of group consensus. In [23] they propose an extension of the FCM where each concept can have its own value set, depending on how precisely it needs to be described in the network. The value set can be a binary set, a fuzzy set, or a continuo interval. In addition, the procedure of how the causes take effect is modeled by a dynamic system.

In addition, FCMs can be used like decision makers system. In [18] is proposed that the ontological FCM framework shares knowledge between heterogeneous businesses by using O-Repository. As an example, they shown that O-FCM's of food company and logistics company can be augmented. In conclusion, decision makers of each business can be supported by instantaneous responses of O-FCM. In [19] they identity the maximum utilization time period of a route and estimate its overall utility rate using a tool to analyze the data based on FCMs. They obtain the simple signed FCMs of an experts opinion and form the corresponding connection matrix. They have developed a Java program to study the model implications. They illustrate and check the validity of their research model using real data from the Pallavan transport corporation. They have given several suggestion from their study, for example, operation of more number of trips in the time periods 8am to 10am, gives beneficial results.

Kardaras and Mentzas in [20] propose a framework for developing business metrics and discusses the suitability of FCMs to model and analyse the business performance indicators. Business metrics provide the basis for assessing business performance, identifying areas for improvement as well as benchmarking with the competition. Researchers and practitioners have stressed on the importance of assessing business performance, particularly with respect to business and Information Systems (IS) strategic planning as well as to business process re-engineering. However, currently available process effectiveness assessment approaches fall short to comprehensively represent the domain, to dynamically follow the business and technological advances as well as to enable stakeholders to express their beliefs. Their approach to developing business metrics considers an internal as well as an external organisational perspective while it recognises the strategic potential of Information Technology (IT). [16] shows how standard Geographical IS operations like the complement, union, intersection, and buffering of maps can be made more flexible by using fuzzy set theory. In particular, they present a variety of algorithms for operations on FCM, focusing on buffer operations for FCM.

In order to effectively understand how neophyte web users form the cognitive neurological networks that result in a mental pathway, or cognitive map, that makes more navigable the route to further information as well as the information they set out to find, in [29] is proposed a FCM model. The FCM that represents the opinions of experts on how users surf the web is introduced and compared to a markovian modeling of user's behavior. [29] shows that a viable FCM model can be developed to reveal cognitive and behavioral patterns of users on the web. An adaptive FCM was built to reflect their causal behavior in time. This change reflects the user's behavior as their knowledge of the web increases with time.

[21] describes the use of an FCM for analysing the diffusion process of a data warehouse in a bank. The process of building the FCM for simulating the data warehouse diffusion scenario is described. Analysis results obtained are presented and compared with the corresponding results obtained using a system dynamics methodology for modelling complex systems.

A novel approach is the use of FCMs as a computationally inexpensive way to ”program” the actors in a virtual world [13, 14, 24, 44, 45]. That is, FCM can structure virtual worlds that change with time. Simulations involving human actors might combine FCMs with expert systems in order to model the soft, emotional aspect of human decision making as well as the formal, logical side. A FCM links causal events, actors, values, goals, and trends in a fuzzy feedback dynamical system. A

FCM lists the fuzzy rules or causal flow paths that relate events. It can guide actors in a virtual world as the actors move through a web of cause and effect and react to events and to other actors. Experts draw FCM causal pictures of the virtual world. They do not write down differential equations to change the virtual world. Complex FCMs can give virtual worlds with ”new” or chaotic equilibrium behavior. Simple FCMs give virtual worlds with periodic behavior. In nested FCMs each causal concept can control its own FCM or fuzzy function approximator. This gives levels of fuzzy systems that can choose goals and causal webs as well as move objects and guide actors in the webs. FCM matrices sum to give a combined FCM virtual world for any number of knowledge sources. In complex FCMs the user can choose the dynamical structure of the virtual world from a spectrum that ranges from mildly to wildly nonlinear [45]. They use an adaptive FCM to model an undersea virtual world of dolphins, fish, and sharks. [34] lies within the interactive virtual stories telling scope and proposes the use FCMs as a tool to model emotional behavior of virtual actors improvising in free interaction within the framework of a “nouvelle vague” scenario. They show how FCMs can be delocalized on each agent level to model autonomous agents within a virtual world and describe the implementation carried out, starting from work in cognitive psychology and illustrate it by an improvisation between a shepherd, a dog and virtual sheep.

Sustainability of ecosystems and ecosystem conservation are increasingly accepted societal goals. However conservation projects of non-governmental organizations (NGOs) and governments also are prone to becoming impractical impositions on local people’s understanding of ecosystems? The Kizilirmak Delta is one of Turkey’s most important wetland complexes with rich biodiversity and critical habitat for globally endangered bird species. It is also one of the most productive agricultural deltas in Turkey. Individual stakeholders and [33] have drafted together 31 cognitive models of the social and ecological system. These models were converted to adjacency matrices, analyzed using graph theoretical methods, and augmented into social cognitive maps. Causal models were run based on neural network computational methods. “What-if” scenarios were run to determine the trajectory of the ecosystem based on the ecosystem models defined by stakeholders. Villagers had significantly larger numbers of variables, more complex maps, a broader understanding of all the variables that the Kizilirmak Delta, and mentioned more variables that control the ecosystem than did NGO and government officials. Villagers cognitive maps showed a large capacity to adapt to changing ecological and social conditions. They actively changed and challenged these conditions through the political process. Villagers were faced with many important forcing functions that they could not control. Most of the variables defined by villagers were related to agriculture and animal husbandry. Cognitive maps have served as a basis for discussion of the policies and management options. A villager-centered cognitive mapping approach is not only necessary because villagers resist conservation projects, or because top down projects that do not take local knowledge systems into account fail, but because it is the ethical and responsible way of doing ecosystem conservation.

Several tools based on FCMs have been developed for different problems. For example, the Fuzzy Thought Amplifier (FTA) is a tool for constructing and exercising FMC [28]. In this work, they study the FCM squashing function and determine that this function reduces the summed input event values to the dynamic range of the state (the classical squashing function is the logistic function). For this reason, in the FTA many other forms are available: arc tangent, multiple step, expanding, etc. This rich set offers tools for a more stimulating environment for the thought modeling purpose of FCMs.

The FCModeler tool displays the known and uncertain biological information in a metabolic network using interactive graph visualization [15]. This tool displays the metabolic pathways interactively and uses graph-theoretic analysis tools to explore complex systems. The system also models pathway interactions and the effects of assumptions using a FCM-based modeling tool. The front end of the FCModeler tool is a Java TM interface that reads and displays data from a database of links and nodes. This algorithm searches for elementary circuits in the metabolic map to see if mathematical metrics can be used to find pathways and cycles. This algorithm finds existing pathways in the map as well as highlighting new relationships, oversights in the model, and misconceptions. Nodes of the map represent specific biochemicals such as proteins, RNA, and small molecules, or stimuli, such as light, heat, or nutrients. Edges of the map capture regulatory and metabolic relationships found in biological systems. These relationships are captured by domain experts and the biological literature. Families of interconnected cycles show how metabolic cycles/pathways interact with one another. Interactive graph display shows the biologist how the cycles fit together. The FCModeler tool uses fuzzy methods for modeling networks and interprets the results using FCMs. The FCModeler tool is intended to capture the intuitions of biologists, help test hypotheses, and provide a modeling framework for assessing the large amounts of data captured by RNA microarrays and other high-throughput experiments.

To improve the performance of FCM, several works have been proposed. Extensions to the FCMs theory are more than anything needed because of the feeble mathematical structure of FCMs and mostly the desire to assign advanced characteristics not met in other computational methodologies. Under this standpoint, four core issues are discussed and respective solutions are proposed in [27]; the first one concerns the case of multi-stimulus situations (parallel stimulation of many FCM concepts), the second one focuses on the design of a learning algorithm (using evolution strategies), and finally the generic real-world phenomena of conditional effects and synergies are properly modeled to support the inference mechanism of FCMs.

In [41] a new balance degree is proposed for better evaluation of the conflicts that exist in the graph of FCMs. The existence of two causal relations of opposite sign between two nodes makes the graph of the FCM imbalanced. The degree to which the whole digraph of the FCM is balanced or imbalanced is given by the Balance Degree. Various types of Balance Degree exist for signed directed graphs. They proposed a new type of Balance degree that is suitable for FCMs. The new degree is evaluated by exhaustively searching all the paths that are created in the graph and gives an indication of the dynamical behaviour that we should expect from the FCM. In [10] is shown how cognitive maps can be viewed in the context of relation algebra, and how this algebra provides a semantic foundation that helps to develop a computational tool using the language of cognitive maps.

Kosko explores the stability of a class of feedback fuzzy systems [26]. The class consists of generalized additive fuzzy systems that compute a system output as a convex sum of linear operators. Continuous versions of these systems are globally asymptotically stable if all rule matrices are stable (negative definite). So local rule stability leads to global system stability. This relationship between local and global system stability does not hold for the better known discrete versions of feedback fuzzy systems. A corollary shows that it does hold for the discrete versions in the special but practical case of diagonal rule matrices. The paper first reviews additive fuzzy systems and then extends them to the class of generalized additive fuzzy systems. The Appendix derives the basic ratio structure of additive fuzzy systems and shows how supervised learning can tune their parameters.

In [5], Carlsson and Fuller demonstrated that all the pertinent conceptual constructs of strategic management theory can be represented with a knowledge based support (KBS)-system with hyperknowledge properties. They show that FCMs can be used to trace the impact of the support and to generalize the experiences of the users. In addition, they show that the effectiveness and usefulness of this hyperknowledge support system can be further advanced using adaptive FCMs.

The purpose [2, 3] is to describe a FCM based on the random neural network model called the Random Fuzzy Cognitive Map (RFCM), and to illustrate its application in the modeling of process. This model is based on the probability of activation of the neurons/concepts in the network. Their model carries out inferences via numerical calculation instead of symbolic deduction. The arcs define dynamic relationships between concepts and describe the causal procedures. The experimental evaluation shows that their model provides similar results than previous fuzzy cognitive map and requires less iterations. In [1] is described an Adaptive Random Fuzzy Cognitive Map (ARFCM) based on the random neural network model. The ARFCM changes its fuzzy causal web as causal patterns change and as experts update their causal knowledge. They show how the ARFCM can reveal implications of models composed of dynamic processes.

Carvalho and Tomé propose a Rule Based Fuzzy Cognitive Maps (RBFCM) in [6]. RBFCM are proposed as an evolution of Fuzzy Causal Maps (FCM) that allow a more complete representation of cognition, since relations other than monotonic causality are made possible. Their structure is based on traditional fuzzy systems with feedback. It is potential to model the dynamics of qualitative real-world systems that include feedback links. They also provide guidelines to introduce time as an important qualitative entity in cognitive maps in [8]. That is, they introduce a coherent procedure to implicitly represent time in the RBFCM. Time is essential in the study of System Dynamics. In [7] is presented several stability issues regarding the modeling of the dynamics of qualitative real world systems, and the ability of RBFCM to provide a faithful modeling in what concerns the stability properties of those systems. It also introduces the concept of Intrinsic Stability as a necessary property of qualitative system dynamics modeling tools. An extension to RBFCM is presented in [9] to solve the main problem while trying to implement a RBFCM is the causal relation itself, since traditional fuzzy operations can not implement causality as it is usually defined in causal maps. [9] presents a method to implement Fuzzy Causal Relations. This method allows a great flexibility in the addition and removal of concepts and links among concepts, and introduces a new Fuzzy Operation that simulates the “accumulative” property of causal relations – the Fuzzy Carry Accumulation (FCA).

Concepts of bipolar fuzzy sets, fuzzy equilibrium, equilibrium energy, and stability are introduced for bipolar cognitive mapping, decision, coordination, and global regulation. Founded on Yin-Yang philosophy, bipolar fuzzy sets and fuzzy equilibrium bring dynamics into logical computation and provide a theoretical basis for bipolar information and knowledge fusion, clustering, and visualization. Equilibrium energy and stability measures provide perspectives and supports for strategic decision making, production control, and global regulation. In [43] basic ideas are illustrated with bipolar crisp and fuzzy cognitive maps in international relations. It is noted that the order of magnitude of a bipolar space resembles quantum interference and, therefore, bipolar logic may hold potential for quantum computing.

In general, the task of creating FCMs is made by experts in a certain domain but is very promising the automatic creation of FCMs form raw data. In [42] Vazquez presents a new algorithm (the Balanced Differential Algorithm) to learn FCMs from data. He compares the results obtained from the differencial Hebbian algorithm.

To enable the gradual learning of symbolic representations, a new fuzzy logical operator is developed by Oden [32] that supports the expression of negation to degress. As a result, simple fuzzy propositions become instantiable in a feedforward network having multiplicative nodes and tunable negation links. A backpropagation learning procedure has been straighforwardly developed for such a network and applied to effect the direct, incremental learning of fuzzy propositions in a natural and satisfying manner. Some results of this approach and comparisons to related approaches are discussed as well as directions for further extension. Finally, to overcome the lack of a concept of time and that they cannot deal with occurrence of multiple causes such as expressed by “and” conditions, in [31] is proposed the extended FCM. The features of this model are: weights having non-linear membership functions and conditional time-delay weights.

IV. Conclusion

There is a lot of application of FCMs in different domains. The notion of ”time” is very important for dynamical system. It is necessary more study about the introduction of the time in FCMs. In addition, the automated construction of FCM, using learning procedure, is a new field that must continue. The number of application, and the diversity of them, is very promising. In several domains, like control system because is an alternative to formal models. In other ones, because they can model complex situations like the virtual worlds and multiagent systems. We hope in the further more work to extend the utilization of FCM in other domains.

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