Comparative of Dynamic Tuning Algorithms For Dynamic-Fuzzy Cognitive Maps

Márcio Mendonça, Ivan Rossato Chrún
Laboratório de Automação e Sistemas de Controle Avançado (LASCA)
Universidade Tecnológica Federal do Paraná
PR/Curitiba, PR
mendonca@utfpr.edu.br/ivanchrun@gmail.com

Adailton S. Borges, Márcio A.F. Montezuma
Programa de Pós-Graduação em Engenharia Mecânica (PPEGEM)
Universidade Tecnológica Federal do Paraná
Cornélio Procópio, PR
montezuma@utfpr.edu.br/adailton@utfpr.edu.br

Abstract— This work develops a knowledge-based system to autonomous navigation using Dynamic-Fuzzy Cognitive Maps (D-FCM) used to model decision tasks and/or make inference in the robot or mobile navigation. Fuzzy Cognitive Maps is a tool that modeling qualitative structured knowledge way through concepts and causal relationships. The proposed model allows representing the dynamic behavior of the mobile in presence of environment changes. A brief review of correlated works in the navigation area by use of FCM is presented. Some simulation results are discussed highlighting the ability of the mobile to navigate among obstacle in navigation environment (with unexpected and surprise obstacles). Objective this work is a comparative with Fuzzy Logic, Hebbian and Reinforcement learning for dynamic tune of D-FCM. For these comparative same two different types’ scenarios with and without noise are realized.

Keywords— mobile robot navigation; fuzzy cognitive maps; dynamic-fuzzy cognitive maps; intelligent decision systems; fuzzy logic

I. INTRODUCTION

The Fig. 1 show images a real problem using a commercial robot (Curumin/XBOT) “Yellow Robot” and kid/XBOT) “Green Robot” as an explorer robot and mobile obstacle respectively, in the real generic environment with static and dynamic obstacles. In this generic scenario, the black tubes are static obstacles. This real experiment used a domestic language block program for avoid obstacles. However, if change in position or velocity of the robots or obstacles, its necessary a new program. This necessity is a motivation of create an agent autonomous.

The first experiments (simulations) will be multi-objective. Beyond the obstacles suggested in Fig. 1, targets should be reached. Unexpected obstacles will be added in scenarios to increase the complexity and diversity.

Autonomous Systems have the ability to perform complex tasks with a high degree of success [1]. In this context, the complexity involved in the task of trajectory generation is admittedly high and, in many cases, requires that the autonomous system is able to learn a navigation strategy through interaction with the environment [2].

An autonomous robot navigation system usually consists of an intelligent mobile robot and various sensors to detect the outside world [3]. Researches in autonomous navigation are in stage of ascent. Autonomous systems have the ability to perform complex tasks with a high degree of success [1]. Complex robotic tasks such as trash collection using autonomous robots can be broadly applied to a variety of fields such as product transferring in manufacturing factory, rubbish cleaning in office, and bomb searching on battlefield, etc. Such robots should be able to cope with the large amount of uncertainties existing in the physical environment [4].

In this context, the complexity involved in the task of trajectory generation is admittedly high efficient and, in many cases, requires that the autonomous system is able to learn a navigation strategy through interaction with the environment [2].

There is a growing interest in the development of autonomous (agents) robots and vehicles, mainly due to the great diversity of tasks that can be handled by them, especially those that endanger human health and/or the environment [5][6][7][8]. As examples, we can cite works that describes an autonomous mobile robot for use in welding [9], exploration environment [10], underwater [11][12] and others. As an example, we can cite [13], which describes an autonomous mobile robot for use in agriculture, in order to replace the human worker, through inhospitable activities as spraying with insecticides.

The problem of mobile robots control comprises two main sub problems: 1) navigation, determining of robot/vehicle position and orientation at a given time, and 2) guided tours, which refers to the control path to be followed by the robot/vehicle [14].

This work specifically proposes by decentralized control, achieving robot motion coordination by individual robot controllers. The development of an autonomous navigation system that uses heuristic knowledge about the behavior of the robot/vehicle in various situations, modeled
by fuzzy cognitive maps [15]. In this case, the robot/vehicle determine a planning or generation of sequences of actions in order to reach a given goal state from a predefined starting state.

Specifically, this work proposes the development of an autonomous navigation system that uses heuristic knowledge about the behavior of the robot/vehicle or agent in various situations; modeled by fuzzy cognitive maps (FCM), in a similar way to the work in [16].

Through cognitive maps, beliefs or statements regarding a limited knowledge domain are expressed through language words or phrases, interconnected by simple relationships of cause and effect (question/non-question). In the proposed model, the FCM relationships are dynamically adapted by rules that are triggered by the occurrence of special events. These events must change mobile behavior. There are various works in the literature that model heuristic knowledge necessary for decision-making in autonomous navigation, by means of fuzzy systems [17][18][19][20][21][22]. In a similar way, the approach proposed in this paper build qualitative models to mobile navigation by means of fuzzy systems. However, the knowledge is structured and built as a cognitive map that represents the behavior of the mobile.

Thus, the proposed autonomous navigation system must be able to take dynamic decisions to move through the environment and sometimes it must change the trajectory because of an event. For this, the proposed FCM model must aggregate discrete and continuous knowledge about navigation. Actions such as the decision to turn left or right when sensors accuse obstacles and accelerate when there is a free path are always valid control actions in all circumstances. In this way, this type of action is modeled as causal relationship in a classical FCM.

However, there are specific situations, such as the need to maintain a trend of motion mainly in curves when the vehicle is turning left and sensors to accuse a new obstacle in the same direction. Due to inertia and physical restrictions, the mobile cannot abruptly change direction; this type of maneuver must be carefully executed. In this context, some specific situations should also be modeled on the map by causal relationships and concepts, but they are valid just as a result of a decision-making task caused by ongoing events. To implement such a strategy, new type of relationships and concepts will be added to the FCM classic model.

This new type of FCM in which the concepts and relationships are valid because of decision driven by events modeled by rules and is called Dynamic-FCM. Specifically, [16] presents a type of D-FCM, which aggregates the occurrence of events and other facilities that makes appropriate this type of cognitive map, for the development of intelligent control and automation in an industrial environment.

The remainder of the paper is organized as following. Session 2 introduces Fuzzy Cognitive Maps concepts and provides a brief review of its application in autonomous navigation. Session 3 describes the proposed D-FCM and develops the autonomous navigation system. Session 4 presents real environment, and same simulation results obtained with the proposed navigation system and fuzzy logic navigation system and session 5 concludes the paper and suggests future works.

II. FUZZY COGNITIVE MAPS

Cognitive maps were initially proposed by Axelrod [23] to represent words, thoughts, tasks, or other items linked to a central concept and willing radially around this concept. Axelrod developed also a mathematical treatment for these maps, based in graph theory, and operations with matrices. These maps can thus be considered as a mathematical model of "belief structure" of a person or group, allowing you to infer or predicting the consequences that this organization of ideas represented in the universe.

This mathematical model was adapted for inclusion of fuzzy logic uncertainty through by Kosko [15] generating widespread fuzzy cognitive maps. Like the original, FCMs are directional graph, in which the numeric values are fuzzy sets or variables. The "graph nodes", associated to linguistic concepts, are represented by fuzzy sets and each "node" is linked with other through connections. Each of these connections has a numerical value (weight), which represents a fuzzy variable related to the strength of the concepts through cause-effect. The concepts of a cognitive map can be updated through the iteration with other concepts and with its own value.

For reasoning about cause-effect relationships, a Bayesian Network (BN) or structural equation model might be appropriate, but these approaches are limited in that the former does not allow for feedback between nodes and the latter is used to confirm a hypothesis about an existing causal structure rather than learn one from observational data. Fuzzy cognitive maps are a relatively young methodology for modeling the cause-effect relationships of complex (nonlinear) systems where the causal structure of the system is represented as a signed, directed cyclic graph with feedback [24].

The main advantage of the FCM is the simplicity of design and thus possibility to create quick model prototypes, even for systems, which we have limited knowledge about. This way, it is possible even for non-experts to identify the crucial relations within the system internals [25]. In this context, a FCM uses a structured knowledge representation through causal relationships being calculated mathematically from matrix operations, unlike much of intelligent systems whose knowledge representation is based on rules if-then type. However, due to this "rigid" knowledge representation by means of graph and matrix operation, the FCM based inference models lack robustness in presence of dynamic modifications not a priori modeled [26]. To circumvent this problem, this article develops a new type of FCM in which concepts and causal relationships are dynamically inserted into the graph from the occurrence of events. In this way, the dynamic fuzzy cognitive map model is able to dynamically acquire and use the heuristic knowledge. The proposed D-FCM and its application in autonomous navigation will be developed and validated in the following sections.

A. FCM in Autonomous Navigation

As some related works which use cognitive maps in the robotics research area can be found in the literature. Among them, we can cite the work in [20] that employs...
probabilistic FCM in the decision-making of a robot soccer team. These actions are related to the behavior of the team, such as kick the ball in presence of opponents. The probabilistic FCM aggregates a likelihood function to update the concepts of the map.

Other example, Pipe [21] uses Potential Field and a Cognitive Maps to guide an autonomous robot. Other related works of robotics intelligent navigation based on FCM can be found in [27]. Other developments in the FCM are known in the literature as ED-FCM (Event Driven – Fuzzy Cognitive Maps) [28], E-FCM (Extended-Fuzzy Cognitive Maps) [29], RB-FCM (Rule Based – Fuzzy Cognitive Maps) [30], the DCN (Dynamic Cognitive Map) [31], Temporal Granularity in Fuzzy Cognitive Maps [32], Papageorgiou and Salmeron [33] presented a recent survey with major variations of FCM classic in recent years that suggests low computational complexity.

Despite of the use of a known trajectory, actions are necessary due to errors and uncertainties inherent in the displacement of the robot, such as slippage, reading errors of the sensors, among others. A review of other related works employing intelligent navigation in robotics can be found in [23]. This paper also presents a Cognitive Map to implement a 3D representation of the environment where an autonomous robot must navigate. The described architecture use a previously stored neural network based model to implement adjustments and course corrections of the robot in presence of noise and sensor errors. Similar to these works, we also use a fuzzy cognitive map to navigation tasks.

III. THE D-FCM MODEL

The development of a FCM model follows the steps listed in table 1. In the step 1, we identify 3 inputs related to the description of the environment (presence of obstacles) and 3 outputs describing the mobile’s movements: turn left, turn right and move forward. The three inputs take values from the three sensors located at left, right and front side of the mobile.

Arcs representing the actions of acceleration (positive) and braking (negative) connect these concepts. Three decisions are originally modeled, if left sensor accuses an obstacle in this position, the vehicle must turn to the right side and equally if the right sensor accuses an obstacle in the right side, the vehicle turns to the other side. The direction change decision implies smoothly vehicle deceleration. The third decision is related to a free obstacle environment; in this case, the mobile follows a straight line accelerating smoothly.

The initial FCM after execution of steps 1 to 4 is showed in Fig. 2. The input concepts are SL (left sensor), SR (right sensor) and SF (frontal sensor) and the output concepts are OutLeft, OutRight and OutFront. The values of the concepts are the readings of the corresponding sensors. As a fuzzy number, these values are normalized into the interval [0, 1]. The relationships among these concepts modeled by weights w1 to w5, which are computed. It is worthwhile to note in Fig. 2, that the concepts O.L. (-1) and O.R. (-1) are the values of the concepts in the previous state. This representation is equivalent to insert negative values (-1) in the corresponding diagonal positions of matrix W.

We choose to retain this representation to highlight that some concepts has memory. In this case, the mobile can remember the actions taken to turn left or right and a zigzag motion is prevented. As a result, the mobile can maintain a movement trend.

In order to model the adaptation ability, we introduce 3 new concepts into the FCM associated to an “intensity” of motion (acceleration or braking) at each direction. There are left factor, right factor and front factor, as shown in Fig. 2. The factor concepts have their values changed according to the current condition of the vehicle motion and the occurrence of events. These events are modeled by the weights ws in Fig. 2, which are obtained by applying the rules of type IF-THEN based on linguistic terms.

These rules represent some decisions such as if the mobile is turning right because the left sensor has detected an obstacle and suddenly the right sensor also detects an obstacle then the factor right is small (ws3). The default value to factor concepts is one. If any rule is triggered the weights ws are null. Finally, the outputs of the D-FCM are the product between the factor concepts and the output of classical FCM (OutLeft, OutRight and OutFront).

<table>
<thead>
<tr>
<th>TABLE I. BUILDING FCM MODELS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Step 1:</strong> Identification of concepts and their roles (input, output, and selection), their interconnections, and/or selection of relationships determining their causal nature (positive, negative, neutral).</td>
</tr>
<tr>
<td><strong>Step 2:</strong> Initial data acquisition, through expert opinion and/or analysis of a mathematical model, or data analysis.</td>
</tr>
<tr>
<td><strong>Step 3:</strong> Submission of data concerning the views of various experts’ to a logical fuzzy system that has as output the values of FCM weights.</td>
</tr>
<tr>
<td><strong>Step 4:</strong> Treatment of information, adaptation and optimization of FCM by adjusting their answers to the desired output.</td>
</tr>
<tr>
<td><strong>Step 5:</strong> Validation of FCM model that is tested in the operation conditions of the system modeled.</td>
</tr>
</tbody>
</table>

In conclusion, the proposed D-FCM navigation system confers to the robot/vehicle the following behavior:

- The mobile is autonomous and it moves into unknown environment from an origin point to an end point.
- If an obstacle is detected by the sensors in front, left and/or right positions the mobile must take a decision about new direction to follow.
- Default navigation position is in a straight line with constant speed, i.e. lateral movements are used only as a result of obstacle detection.
- When the mobile is in motion and the sensors do not identify any obstacle, the mobile accelerates smoothly and then it remains in a constant speed.
- Motion trend corresponds to an average between the current movement values and the values in immediately before instant, which prevents any sharp changes in direction of the mobile navigation.
- When the mobile is turning in left or right direction and the opposite sensor detects an obstacle, the motion trend is maintained but the mobile is softly breaking until to reestablish a straight movement.
Intelligent control architecture to the navigation system is shown in Fig 3. The input interface read the sensor measurements, which are inversely proportional to the distance of obstacles. The D-FCM is the inference engine that gathers the input data and the knowledge (values of weights w and ws) to take a decision about the movement of the mobile agent. The rule base block represents the heuristic knowledge to take decision in presence of conflicting events. The causal relationship block represents the structured knowledge about navigation. Thus, according to the inference result, control actions sent to the actuator by means of an output interface.

In this paper, three methods are used for tune D-FCM, but the three methods are described briefly. The three methods used to update the intensity of causal relationships in a deterministic way according to the variation or error in the intensity of the concept or input variable. In [3], a similar proposal for FCM dynamic tuning in uses Reinforcement Learning Algorithm (Q-learning). These conditions are motivations for work, which are also used for decision support based on the principle of causal discovery in the presence of uncertainty and incomplete information in dynamic scenarios.

For use in autonomous agents, a Reinforcement Learning Algorithm (Fig. 4) based on heuristic rules is implemented. In this case, a policy is used in the states mapping action, i.e., determine what action should be performed when the mobile robot (agent) is in a st state; thus, defining the agent behavior over time. This algorithm uses the experience of each state transition to update an element of a table, which stores the steps of evolution of the algorithm.

\[ Q(s, a, t + 1) = Q(s, a, t) + \alpha [r + \gamma \max Q(s', a') - Q(s, a, t)] \]

This equation, denoted by Q, has an input, Q (s, a), for every pair of states and actions a. After st transition, st+1, this algorithm performs the update and get a reward r, the management of the penalties is made by a policy (rule base, in the proposed D-FCM) and some parameters, e.g., \( \alpha \) is a positive parameter that determines the step size. Under appropriate conditions, this algorithm converges when establishing a policy that applies rewards and punishments according to environmental changes [35].

In order, other algorithm to dynamic adapt the D-FCM weights we use the Hebbian Learning Algorithm for FCM that is an adaptation of the classic method (Kosko, 1986) [16]. Different proposals and variations of this method applied in tuning or in learning for FCM are known in the literature [36].

\[ W_i(k) = W_{ij}(k - 1) + \gamma \Delta A_i \]

where: \( W_i (k) \) is a new value of the weight, old value \( W_i (k-1) \), \( \gamma \) forget factor and error \( \Delta A_i \).

In this case, the application of hebbian learning provides control actions as follows: if an obstacle to the right is nearest, the causal relationship of exit turn left increases and consequently increases its control action. The others action have same behavior. Forgetting factors obtained from empirical mode. Finally minimum and maximum limits were placed due to the application of the method is to tune the dynamic D-FCM; thereby varying the intensity of causal relationships should be within a clearly defined range. This range is defined by closed intervals \([0.35, 0.65]\) for WF; \([0.6, 1]\) for WE; and \([0.6, 1]\) for WD. These values obtained empirically by observing the dynamic behavior of the mobile agent.

where: \( W_f \) is the weight related to front proximity sensor; \( W_k \) is the weight related to left proximity sensor; and \( W_p \) is the weight related to the right proximity sensor.

The Fuzzy system is implemented for tune FCM, in this work is type Mandani with 3 inputs, 3 outputs and employs 23 rules for abstraction of the same heuristic logic.
navigation controller inserted in the D-FCM. The inputs are the sensors, right, left and front and outputs are turning right, left and accelerate. In this context, the work in [37] is similar, therefore, presents a Fuzzy Control strategy similar, but only to calculate the desired speed mobile using 8 rules and input variables as the turning angle and distance of the obstacle. This tune is inspired in Fuzzy Cognitive Networks (FCN), because the causal knowledge of the dynamic behavior of the system is stored in the structure of the network and in the interconnections that summarize the correlation between cause and effect [38]. An example, of a Fuzzy System surface is shown in Fig. 5. In this figure, the inputs are the right and left sensors and the output is the concept turn right.

These rules were implemented in the paper it is intuitive way according to heuristic D-FCM. For example:

- IF the right sensor is strong THEN turn left strong.
- IF the right sensor is weak THEN turn left weak.
- IF right sensor and frontal sensor very strong THEN weak accelerate and turn left very strong
- IF right, left and frontal sensor weak THEN accelerate Strong.

The graphic shows the dynamic trajectory made by the robot. The apparent flaws in the trajectory represent the speedup, when sensors do not "see" an obstacle. In all experiments, we consider that the robot successfully attains the target point if its final position is into a horizontal interval [-8, +8] around the desired end area.

**Figure 6.** Noise included in the controllers

In the every scenario, example (Fig. 7 and 8), there is a critical situation with a surprise obstacle around the position y=100. In the first experiment (Fig. 7) the robot must to take the decision of moving straight, passing between the two obstacles and immediately to turn left to avoid a frontal barrier and to attain the target point. In second experiment (Fig. 9), one dynamic obstacle is in the scenario, starting about in position (10, 83) and finishing about in position (3, 83). Fig. 9 shows all maneuvers decisions made by the robot.

In both cases, the robot motion trend is to move straight to the end, the robot takes the correct decision to turn in order to avoid a collision but it also maintains the motion trend of follow a straight line. In Fig. 7 the D-FCM with RL reached all objectives, collected the targets and avoided the obstacles, especially the surprise obstacle. Fig. 7b shows the
dynamic adjustment of the low-level causal relationships (turns left, right, accelerate).

In Fig. 8, the D-FCM using RL (with noise) reached all objectives, collected targets and avoided the obstacles, especially the surprise obstacle. Fig. 8b shows the dynamic adjustment of the low-level causal relationships. It is observed that: Actions of reinforcement learning algorithm follows a sensor variation trend.

In Fig 9, there was a change in the environment; the critical point is a moving obstacle (such as another robot). The robot was able to reach reached all objectives, particularly in the critical case of this scenario. And Fig 9b shows the dynamic performance of the RL.

In Fig. 10, a white noise, of approximately 1.5%, is inserted in the three sensors. The robot achieved similar results.

Fig. 11 is identical to the scenario of Figure 8; it is a premise to maintain the same conditions for the comparison of the algorithms. In this case, the H.L. reached all objectives, including the critical point. The D-FCM in Fig. 12 had a failure in the presence of noise, missed one target at the end of the path, due the difficulty of taking sequential decisions [28], necessary in mobile robotics; this difficulty can accumulate a series of error harming the trajectory of the robot, in special at the end of its route.

In Fig. 13, the D-FCM using Hebbian Learning (H.L.) Algorithm (without noise) reached all goals; however, in Fig. 14, with presence of noise, there were failures; the Agent (Robot) crashed into two obstacles (highlighted in the Fig. 14a). Note that the tuning actions vary directly to the intensity of the sensors.
In Fig. 15 and 16, the weights tuning is done by Classic Fuzzy, in the environment with unexpected obstacles. In Fig. 15, all objectives were achieved. However, in Fig. 16, a
noise is inserted in the sensors, causing a loss of a target (highlighted in the figure). In addition, it was observed similar behavior when tuning HL with proportional tune of the actions changing the intensity of the sensors. In other words, this learning algorithm provided a quicker response to change the sensors signals strengths.

Figure 15. a) D-FCM Architecture with Classic Fuzzy (unexpected obstacle) without noise b) dynamic tuning of the weights

Figure 16. a) D-FCM Architecture with weighted Classic Fuzzy (unexpected obstacle) with noise b) dynamic tuning of the weights

Figure 17. a) D-FCM Architecture with Classic Fuzzy Learning (mobile obstacle) without noise b) dynamic tuning of the weights

Figure 18. a) D-FCM Architecture with Classic Fuzzy Learning (mobile obstacle) with noise 1.5% b) dynamic tuning of the weights

The Fig. 17 and 18 are tuned by Classic Fuzzy. In Fig 17, without the noise, the D-FCM reached all goals. The worst performance in all experiments was obtained by the experiment in Fig. 18 with noise, in which several errors were committed in sequence, colliding with several and losing targets (highlighted in the figure). Some adjustments may be observed at Fig. 18b in particular. This suggests that the basic rules should be revised.
V. CONCLUSION

This paper developed an Autonomous Navigation System based on a new type or evolution of Fuzzy Cognitive Maps, named Dynamic Fuzzy Cognitive Map, D-FCM. The developed D-FCM approach adds new types of relationships and concepts into a classical FCM that allows modeling the human ability of to take decision in presence of random events. This approach is a contribution of this paper to the intelligent control area. It is not restricted to navigation systems and can be applied to model intelligent system needing to take decision on line.

It is observed that in a real robot, due to difficulties as precision sensors, ghost signal (in particular, ultrasound sensors), and others difficulties like noise (simulated white noise), uncertain in the measurements, it will be hardly possible to obtain similar results. However, with the variations of the scenarios with obstacles in difficulties positions, i.e., the spiral, suggest that the two hybrid architectures proposed can be used successfully for autonomous robots controllers.

In accordance with the results presented in this paper, we can conclude that the proposed D-FCM architecture constitutes a flexible and robust tool to navigation system able to process vagueness and uncertainty in environment. One of the main advantages of the proposed approach is that the knowledge acquisition and representation is simplified by the use of FCM models. Moreover, the resulting fuzzy cognitive maps are also easy to implement and run. Thus, it is easily embedded in a hardware robot.

The comparative between three proposal techniques for dynamic tuning D-FCM, Reinforcement Learning, Hebbian Learning e Classic Fuzzy Logic had similar results in two different scenarios without noise. Therefore, in scenarios with noise, a Reinforcement Learning with Heuristic Rules showed be a better option, because with noise this algorithm had almost optimal result unless collision and reach targets. The results of the RL algorithm for dynamic tuning showed a tendency in the variation of the sensors; while Hebb and Fuzzy algorithms have a direct influence from the sensors variations; because of these characteristics the RL algorithms had better results considering the noises in the sensors.

Some future works addresses improvement of kinematic model of Robot or Agent and include additional functionality into the navigation system, for example, increase the size of scenarios and / or different setups. Finally, a comparative of the D-FCM with similar Intelligent Systems like ANFIS or Adaptive Fuzzy Systems, for example.

References


