Hybrid Autonomous Navigation System Using a Dynamic Fuzzy Cognitive Maps Evolution

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***Abstract*—This work develops a knowledge based system using Fuzzy Cognitive Maps (FCM) for autonomous navigation. A new variant of FCM, named Dynamic-Fuzzy Cognitive Maps (D-FCM), is used to model decision, tasks and/or make inference in the robot/mobile navigation. Fuzzy Cognitive Maps is a tool that models qualitative structured knowledge through concepts and causal relationships. The proposed model allows representing the dynamic behavior of the mobile robot (agent) in different environments. A brief review of correlated works in navigation area using FCM and Fuzzy Systems is presented. Some simulation results are discussed highlighting the ability of the mobile to navigate among obstacles and reach targets (navigation environment).**

Keywords - Fuzzy Cognitive Maps; Autonomous Navigations; Hybrid Architecture; Intelligent dynamic decision systems.

I. INTRODUCTION

Artificial Intelligence (AI) has applications and development in various areas of knowledge, such as mathematical biology, neuroscience, computer science, swarm robotics and others. The research area of intelligent computational systems aims to develop methods that try to mimic or approach the human's capabilities to solve problems. These news methods are looking to emulate human's abilities to cope with very complex processes, based on inaccurate and/or approximated information. However, this information can be obtained from the expert's knowledge and/or operational data or behavior of an industrial system [1].

Researches in autonomous navigation are in stage of ascent. Autonomous Systems have the ability to perform complex tasks with a high degree of success [2]. In this context, the complexity involved in the task of trajectory generation is admittedly high and, in many cases, requires the autonomous system being able to learn a navigation strategy through interaction with the environment [3].

There is a growing interest in the development of autonomous (agents) robots and vehicles, mainly because of the great diversity of tasks that can be carried out by them, especially those that endanger human health and/or the environment, [4][5]. As an example, we can cite Mandow et al. [6], which describe 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. Some cases have more complexity; e.g., a Hybrid Architecture [7] is used to develop Dynamic Fuzzy Cognitive Maps-based models for autonomous navigation with different goals: avoiding obstacles, exploration, and reach targets.

This work specifically proposes the development of an autonomous navigation controller system using heuristic knowledge about the behavior of the robot/vehicle in different scenarios, modeled by Fuzzy Cognitive Maps (FCM) [8]. In this case, the robot/vehicle determines sequences of action in order to reach a given goal state from a predefined starting state.

The FCM combines aspects of Artificial Neural Networks [2], Fuzzy Logic [1], Semantics Networks [2] and others intelligent systems techniques. Through cognitive maps, beliefs or statements, regarding a limited knowledge domain, are expressed through words or phrases, interconnected by simple relationship 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 several works in the literature that model heuristic knowledge necessary for decision-making in autonomous navigation, e.g., Classic Fuzzy and FCM Systems [9]-[13]. In a similar way, the proposed approach in this paper is to build qualitative models for mobile navigation by means of fuzzy systems. However, the knowledge is structured and built as a cognitive map representing the behavior of the mobile.

Therefore, the proposed autonomous navigation system must be able to take dynamic decisions to move through the environment and change its trajectory as a result of an event. For this, the proposed FCM model must aggregate discrete

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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 in 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 types 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 as a result of decision, driven by events modeled by rules is called Dynamic-FCM. Specifically, the work of Mendonça et al. [16] presents a type of D-FCM (ED-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.

Section II presents the concept of FCM and the FCM applied in autonomous navigation. Section III illustrates the D-FCM model utilized. Section IV presents the Hybrid Architecture and a brief background. Section V shows the results, and finally, Section VI presents the conclusion and future works.

II. FUZZY COGNITIVE MAPS

Cognitive maps were initially proposed by Axelrod [16] 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. In general, these cognitive maps are "belief structure" of a person or group, allowing to infer or predict the consequences that this organization of ideas represents in the graph; in cognitive maps, a central concept is not necessary.

This mathematical model was adapted for inclusion of Fuzzy logic uncertainty. In specific, linguistics terms generating widespread fuzzy cognitive maps. Like the original, FCMs are directional graphs, 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 others through connections [8]. Each of these connections has a numerical value (weight), which represents a fuzzy variable related to the strength of its concepts.

The concept of a cognitive map can be updated through the iteration with other concepts and with its own value. 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 the FCM-based inference models lack robustness in presence of dynamic modifications not a priori modeled [17]. 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 tested in the following sections.

Related work using cognitive maps in the robotics research area can be found in the literature. Among them, it can be cited the work by Min et al. [12], that employs probabilistic FCM in the decision-making of a soccer robot 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. A FCM is used by Pipe [13] to guide an autonomous robot. The FCM is designed from a priori knowledge of experts and afterwards it is refined by a genetic algorithm.

The inference process of the FCM model can be calculated by the following rule given in (1) and (2); these equations are used in several works in the literature, e.g., FCM and evolutions such as Mendonça et al. [7] and Siraj, Bridges and Vaughn [9].

$$A_i = f\left(\sum_{\substack{j=1 \\ j\neq i}}^{n} (A_j \times W_{ji}) + A_i^{old}\right) \tag{1}$$

where:

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

A review of correlated works in indoor autonomous navigation robotics can be found in [14]. The objective of this paper is to develop an autonomous explorer agent (robot) based in a low cost and open source platform with the ability to tune FCM model by interacting with the environment. The agent architecture is inspired by Braitenberg [15], who suggests the application of computational intelligence techniques, starting up with a simple model with one or only a few functionalities, and gradually adding new objectives to improve the exploration capability of the agent.

However, our navigation system does not use a priori information about the environment. The FCM represent the usual navigation actions as turn right, turn left, accelerate and others. The adaptation ability to environment changes and to take decisions in presence of random events is reached by means of a rule-based system. These rules are triggered in accordance of “intensity” of the sensor measurements. In this research, the kinematic model use sensors signal and pulses in the right and left wheels.

III. The D-FCM Model

The development of a FCM model is similar of the work of Mendonça et al.'s [16]. In this case, we identify 3 inputs related to the description of the environment (presence of obstacles) and 2 outputs describing the mobile's movements: turn left, turn right or forward (pulses in both wheels). The three inputs take values from the three sensors located at left, right and front side of the mobile.

These concepts are connected by arcs representing the actions of acceleration (positive) and braking (negative). Three decisions are originally modeled, if left sensor accuses an obstacle, 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 in smoothly vehicle deceleration. The third decision is related to a free obstacle environment; in this case, the mobile follows a straight line accelerating smoothly.

Figure 1 shows the robot (agent) for used as kinematic model development; however, it is not in the scope of this work to demonstrate the equations of the model used in the simulations, only the development and simulated results of the proposed controller. The kinematic model used have is similar physic characteristics, e.g., geometry (axes distance) and inputs and outputs development. The input concepts are LS (Left sensor), RS (Right sensor) and FS (Frontal sensor) and the output concepts are LW (Left Wheel Pulse) and RW (Right Wheel Pulse). 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].

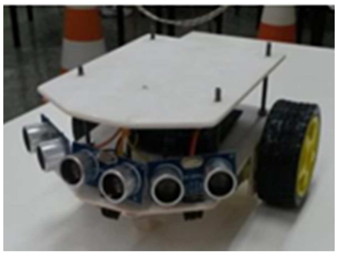

Figure 1. Structure Generic Robot using Arduino Mega

The future navigation prototype has its position estimated by the numbers of pulses given by the step motors and the obstacle avoidance is guided by the navigation system. However, the prototype is under development and the focus of this work is in its initial results obtained by the simulator. Whereas the environment is partially known, only the targets have their position known by the robot (agent). In simulation time, the robot (agent) knows its position, and the new control actions are calculated by the D-FCM, sequentially at every step.

In this work, if the target is located to the left of the robot, DSx is negative and is located at the rear of the robot, DSY is negative. The concept used is "DSx" to the lateral distance between the robot and the target (ΔX), and "DSy" to the front distance (ΔY).

Figure 2 shows the simplest case, where the agent goes directly toward the target (known point in the scenario). In this context, and two objectives were developed for the FCMs (avoid obstacles and reach the targets); the target position is known and the agent will alternate between two FCMs (using a finite state machine) to change its objectives.

Figure 3 shows concepts and relationships for avoiding obstacles. In resume, weights w14 and w35 are positive, otherwise the weights w34 and w15 are negatives. These values are necessaries for avoiding maneuvers. The weights w24 and w25 are connected in the frontal sensors and wheels concepts, and have negative values because when obstacle is near, the robot should decelerate.

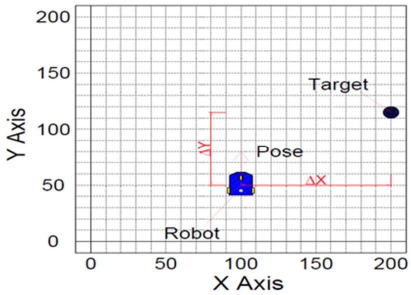

Figure 2. Scenario - Distances

If the target is located to the left of the robot, DSx is negative and is located at the rear of the robot, DSY is negative. The values are dynamically tuned by the Hebb Learning algorithm [17].

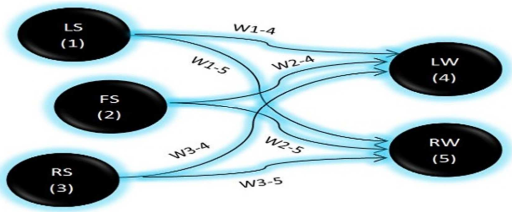

Figure 3. D-FCM avoid obstacles

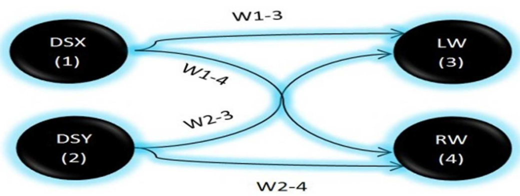

Figure 4. D-FCM reach targets.

Figure 4 shows the D-FCM_2 which its goal is to reach the one or more target using distance previously knowledge (see in Figure 2).

For changing D-FCM_1 and D-FCM_2, a finite state machine is used (Figure 5); the deliberative part of the architecture is discussed in Section IV. The switching is done dynamically according to the occurrence of events, at

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first the robot will toward the target, however, it changes D-FCM if an obstacle is at a minimum distance of 15cm.

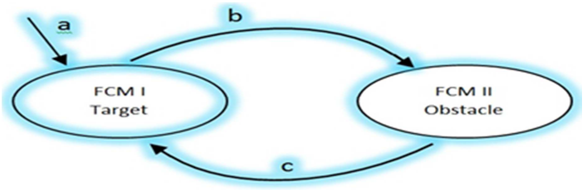

Figure 5. Finite State Machine

The language of the finite state machine is:

- a: Start Machine for reach targets;
- b: Change FCM for avoid obstacles;
- c: Return Machine for reach targets again;

Other developments in the FCM are known in the literature as E-FCM (Extended-FCM) [18], RB-FCM (Rule Based-FCM) [19] and the DCN (Dynamic Cognitive Networks) [20]. A recent survey with major variations of classic FCMs, in recent years, suggesting low computational complexity, is presented by Papageorgiou and Salmeron [21].

IV. Hybrid Architecture Background

Hybrid Architectures aims to combine the main features of deliberative and reactive approaches, trying to reduce the restriction on the scope of each of these approaches. That is, the hybrid architectures use determination to plan the actions of the robot from an internal global representation of the world knowledge, so the objectives of the robot can be achieved efficiently. Once the actions are planned, the action plan implementation is done using reactive interactions between sensors and output system, allowing quick actions towards changes in the environment. These architectures, also use deliberation to plan the actions of the robot from an internal knowledge representation of the world, so the goals of the robot can be achieved efficiently [22][23]. This D-FCM hybrid architecture is also inspired by behavior [24][25].

As shown in Figure 6, the proposed architecture is presented in a generic form to assist the D-FCM development. Each block represents a specific part of the system; the Perception System symbolizes the sensors; the Internal State System, the finite state machine; the Behavior System, the FCM´s; the Learning System, the dynamic learning algorithm; the Motor system, the system output; and at last, the Environment, the interaction with the environment (perception, planning and actions). This means that planning is not part of the perception-action cycle, interacting only when that organization have any relevant result (as an event, e.g., detecting an obstacle) of their planning.

The states modeled in this study are two: get the target, located at a previously known point, and avoid obstacles, without prior knowledge of their position by the perception of sensors.

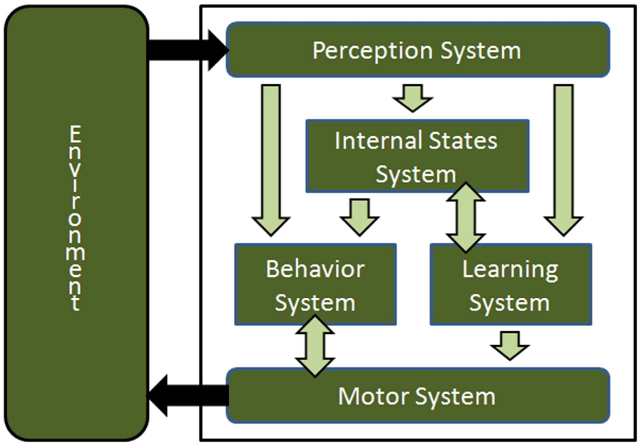

Figure 6. hybrid architecture D-FCM

The motor system is responsible for the agent movement inferences on the environment, according to its current state dynamically tuned by a Hebb learning algorithm [17], through data provided by the perception system; however, it could be also used reinforcement learning algorithms [16]. This generic Hebb equation is:

$$\Delta w_{kj}(n) = \eta y_k(n) x_j(n) \tag{3}$$

where: η is a positive constant that determines the learning rate, $\boldsymbol{x_j}$ represents the presynaptic signal $\boldsymbol{Y_k}$ represents the postsynaptic signal, $\Delta \boldsymbol{W_{kj}}$ is the synaptic weight $\boldsymbol{n}$. Each of the causal relationships of FCMs (Figures 3 and 4) uses the above equation to dynamically tune theirs weights.

The basic difference between D-FCM and classic FCM is the dynamic tuning ability of causal relationships and switching of two or more structures by state machine, according to the desired goal.

V. Results

A two dimensional simulator was implemented in Matlab to study the dynamic behavior of the mobile agent. Several studies present FCMs results, using simulation, can be found in the literature [7] [12] [13] [17] [18] [20].

The scale used for the simulated scenario is 1:100. In this context, Russel and Norvig [2] suggest that, in order to consider an autonomous agent, it is necessary to succeed in at least three different simulations. Thus, the simulations were tested with different scenarios settings to suggest autonomy. Figures 7-11 show the proposed work simulations; the first two simulations only reach targets, in different scenarios. Each simulation has a crescent level of difficulty, as proposed and specified in [15]; observe that all the scenarios are static.

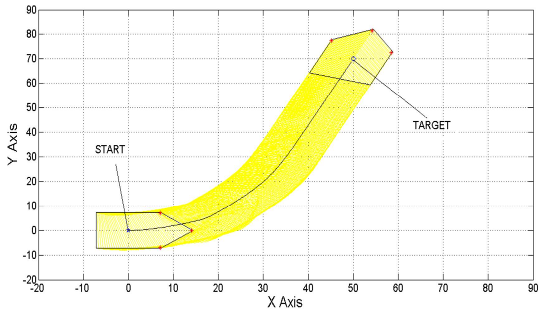

Figure 7. Simulation 1 (Target 1)

The simulation in Figure 7 is simple and shows the trajectory of the agent (robot) toward the target at a specific point, between first and second quadrant. It shows, in yellow, the trail (agent´s pose memory), and finally, it shows the initial and final pose of the agent. This explanation applies to all following figures.

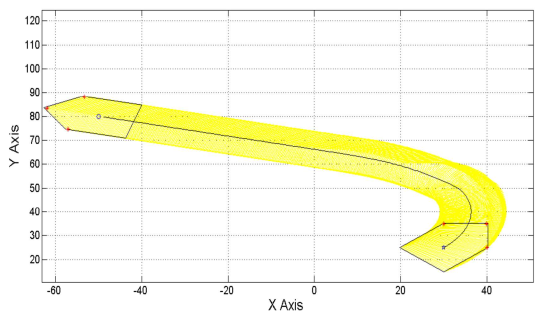

Figure 8. Simulation 2 (target 2)

The second experiment (Figure 8) is similar to the first put the show initial poses and different finals, including in different quadrants. It shows the navigation versatility of the FCM controller.

The experiment in Figure 9 and 10 has an increase in its difficulty, by adding obstacles in the environment. One of the classic challenges is the problem of series decision making, i.e., an error in the second step can have influence in the third one, and so on [16].

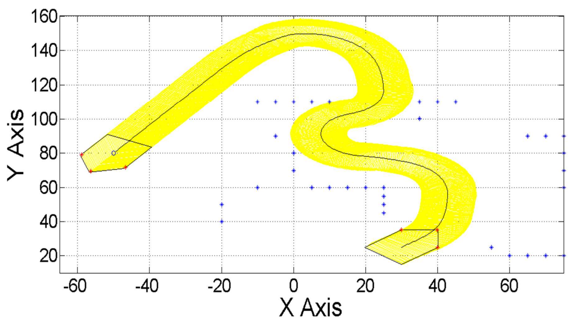

Figure 9. Simulation 3 (target and obstacles)

Figure 9 suggest autonomy due results showing positive outcomes in different scenarios, as already mentioned.

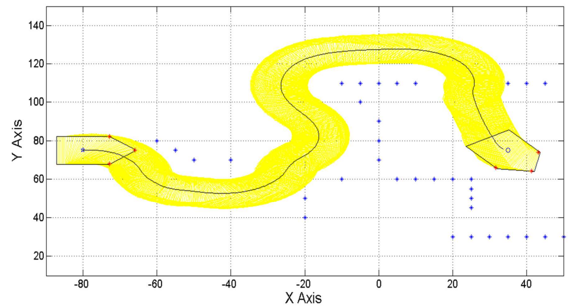

Figure 10. Simulation 4 (target and obstacles)

The simulation in Figure 11 suggests an increase in the autonomy of the controller's capacity; in particular, it shows the difficulty of reaching the target, in the center of a spiral of obstacles, successfully.

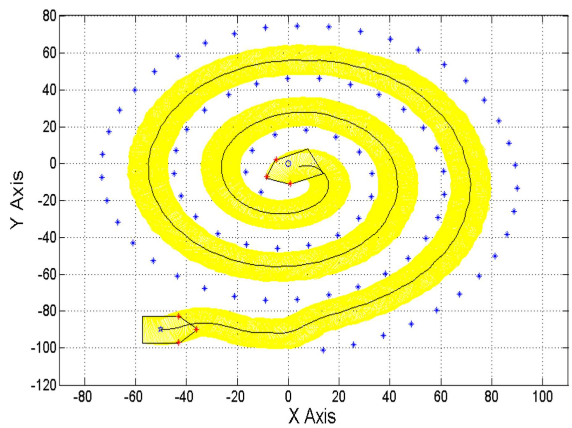

Figure 11. Simulation 5 (spiral)

VI. CONCLUSION

This paper developed a hybrid autonomous navigation architecture based on a new type of fuzzy cognitive maps, named dynamic fuzzy cognitive map, D-FCM.

The initial results obtained from the simulations were convincing, because the mobile agent accomplished the goal of reaching the target with a maximum error of few centimeters deviating from obstacles. However, in a real environment, it is difficult to reach the same precision.

Some difficulties presents in real robots, e.g., ghost signal (in particular, ultrasound sensors), noise, and others, were not considered in the simulations. However, the variations of scenarios with obstacles, highlighting the scenario with a spire of obstacles, suggest that hybrid

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architectures for autonomous robots navigation can handle achieving goals in different scenarios, with crescent degrees of difficulties.

Future work aims to compare the proposed controller with other intelligent techniques, like Classic Fuzzy or Adaptive Fuzzy and ANFIS, by comparing number of maneuvers and time required for achieving the objectives, and then, by improving the complexity of the scenarios using walls with 90 degrees.

Another target is to embed this system into a real robot using an open source development platform, such as low cost microcontroller (e.g., Arduino), due FCMs low computational complexity. Finally, a test phase is scheduled for the proposed controller in dynamic scenarios, such as in the presence of mobile and/or surprise obstacles.

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