COMPARATIVE OF TWO HYBRID DYNAMIC FUZZY COGNITIVE MAPS FOR AUTONOMOUS MOBILE NAVIGATION SYSTEM

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Abstract. This work develops a knowledge-based system to autonomous navigation using Fuzzy Cognitive Maps (FCM). A new variant of FCM, named Hybrid-Dynamic Fuzzy Cognitive Maps (HD-FCM), is used to model decision tasks and/or to make inference into a mobile navigation context. Fuzzy Cognitive Maps are a tool that model qualitative structured knowledge through concepts and causal relationships. The proposed model allows representing the dynamic behavior of a mobile robot in presence of environment changes. A brief review of correlated works in the navigation area, using FCM evolutions, is presented. Some simulation results are discussed and compared with Hybrid Weighted Fuzzy System (WFS) for shows the ability of the mobile to navigate among obstacles in different scenarios (navigation environment).

Keywords: Fuzzy Cognitive Maps, Autonomous mobile navigation, Hybrid Architecture, Intelligent dynamic decision systems.

1. INTRODUCTION

The 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 and models that try to mimic or approach the capabilities of humans to solve problems (Passino and Yourkovich, 1997).

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 handled by them, especially those that endanger human health and/or the environment (Shaikh et al., 2013; Maki et al., 2010). As examples, we can cite works that describes an autonomous mobile robot for use in welding (Schroth et al., 2009), exploration environment (Salan et al., 2015), underwater (Soears et al., 2014; Briggi et al., 2008) and others. The objective this work is built controllers for Autonomous Systems. Autonomous System must have the ability to perform complex tasks with a high degree of success (at least 3 different scenarios) (Russel and Norvig, 1995).

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 the work of Mendonça et al. (2013). A Hybrid Architecture based on dynamic cognitive maps is used to model an autonomous navigation system with different goals: as example, system with avoid obstacles, exploration and reach targets in different scenarios.

A Fuzzy Cognitive Map (FCM) is a fuzzy signed directed graph with feedback that models complex systems as a collection of concepts and causal relations between concepts (Ahmadi et al., 2014). It can be found in the literature two types of FCM, cyclic and acyclic (Papageorgiou, 2014). In this work, it is used an acyclic HD-FCM, one of the FCM evolutions Through cognitive maps, beliefs or statements regarding a limited knowledge domain expressed through language words or phrases, interconnected by simple relationship of cause and effect. A dynamic FCM has its relationships dynamically adapted by a learning algorithm such as Hebb method.

There are various works in the literature that model heuristic knowledge necessary for decision-making in autonomous navigation, by means, of Classic Fuzzy and FCMs Systems (Papageorgiou, 2014; Yang and Zheng, 2007; Min et al., 2006; Pipe, 2000; Wang, 1999). In a similar way, the approach proposed in this paper is to build qualitative models to mobile navigation by means of both fuzzy systems: classical and FCM. In this case, the knowledge is structured and built as a cognitive map that represents the mobile behavior.

A Hybrid Architecture based on dynamic cognitive maps is used to model an autonomous navigation system with different goals: as example, system with avoid obstacles, exploration and reach targets in different scenarios.

This work proposes the use of Hybrid Dynamic Cognitive Maps (HD-FCM), an evolution of the Fuzzy Cognitive Maps, to build an autonomous navigation system. HD-FCM technique combines aspects from neural networks, fuzzy
logic and semantic networks, which are important AI tools. In addition, HD-FCM can acquire knowledge dynamically by using Hebb learning algorithm method.

The proposed autonomous navigation system must be able to take dynamic sequential decisions to move through the environment and sometimes it must change the trajectory due to an event. Moreover, the system must aggregate discrete and continuous knowledge about navigation. Actions such as decisions 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. This type of action easily modeled, as causal relationship in a classical FCM.

The sketch and the robot are shown in Fig 1. Measurements are in centimeters.

![Robot sketch and the robot](image)

Figure 1. Robot sketch and the robot

However, there are specific situations, such as the need to maintain a trend of motion, mainly in curves, for this HD-FCM the mobile slows down when it 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, in addition to the expected slowdown motion, the HD-FCM is structure by means of a Hebb learning method, that stabilize the mobile movements by adjusting the weights of the FCM causal relationships dynamically.

This new type of FCM has dynamic learning and is supported by a state machine that assures structural changes of FCM under different objectives. A similar FCM, named as Dynamic FCM (D-FCM) has presented by Mendonça, Arruda and Neves (2011), in which D-FCM concepts and relationships modified from decision driven by events modeled by rules. The occurrence of events and other facilities had supported the development of an autonomous robot traveling through an industrial environment.

### 2. FUZZY COGNITIVE MAPS BACKGROUND

Axelrod (1976) proposed cognitive maps (CM) to represent words, thoughts, tasks, or other items linked to a central concept and willing radially around this concept. Axelrod also developed a mathematical treatment for these maps, based in graph theory, and operations with matrices. These maps can considered as a mathematical model of “belief structure” of a person or group, allowing one 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 by Kosko (1986) generating widespread fuzzy cognitive maps. Like the original CM, FCMs are directional graph, in which the numeric values are fuzzy sets or fuzzy variables. The “graph nodes”, associated to fuzzy linguistic concepts, linked with other through fuzzy connections. Each of these connections has a numerical value (weight), which represents a fuzzy variable related to the strength of the concepts. The concepts of a (fuzzy) cognitive map 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 calculated from matrix operations, unlike much of intelligent systems whose knowledge representation based on rules if-then type.

The FCM structure is built from a priori knowledge of experts, and afterwards, heuristic methods, genetic algorithm, swarm and other techniques can tune it. Despite the tuning step, the FCM based inference models lack robustness in presence of dynamic modifications not a priori modeled due to this “rigid” knowledge representation by means of graph and matrix operation (Acampora and Loia, 2011).

To circumvent this problem, this article develops a new type of FCM in which concepts and causal relationships are dynamically into the graph from the occurrence of events. In this way, the Hybrid-Dynamic Fuzzy Cognitive Map model is able to dynamically acquire and use the heuristic knowledge. The proposed HD-FCM and its application in autonomous navigation will be developed and validated in the following sections.

Some related works, which use cognitive maps in the robotics research area, can found in the literature. Among them, we can cite the work of Min et al. (2006) that uses probabilistic FCM in the decision-making of a robot soccer team. These actions 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 (2000) uses Potential Field and a Cognitive Maps to guide an autonomous robot.
The agent architecture inspired by Braitenberg (1986), 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, this navigation system does not use a priori information about the environment (only target and initial agent pose). The FCM represents the usual navigation actions as turn right, turn left, accelerate and others. The robot does not present ability to adapt to environment changes and to take decisions in accordance with “intensity” of the sensor measurements.


3. THE HD-FCM MODEL

Figure 2 shows robot and the target inserted into an environment (scenario). It also shows the pose (angle and position) of the robot into the scenario with the latitudinal and longitudinal distances between the robot and the target. The target position is known and the agent will alternate between two FCMs (Fig. 3 and 4) in order to perform two functions: reach the targets and bypass obstacles. This is the simplest scenario where the agent goes directly toward the target.

![Figure 2. Scenario – Distances](image)

In Fig. 3, "DSx" is the lateral distance between the robot and the target (corresponding to ∆X in Fig. 1), and "DSy" is the front distance to the target (corresponding to ∆Y in Fig. 3), measured in the vertical axis. 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.

Figure 4 shows the robot (agent) for model development of the HD-FCM. The input concepts are SL (sensor-left), SR (sensor-right) and SF (sensor-front) and the output concepts are LW (left-wheel) and RW (right-wheel). The values of these concepts are the reads of the corresponding sensors. As a fuzzy number, these values are normalized into the interval [0, 1].

Figure 4 also show the concepts and relationships for avoid obstacles. In resume, weights W14 and W35 are positives; otherwise, the weights W34 and W15 are negatives. The sign and value of the causal relations depend on the intensity and influences between the respective concepts. This values are necessaries for avoid maneuvers. The weights W24 and W25 connected to frontal sensors and wheels have negative values when obstacle is near the robot decelerates. These weights tuned using Hebb learning similar FCM1.

![Figure 3. HD-FCM1 reach target](image)
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The off-line heuristic adjustment follows as after determining the causal signal, the values of the weights were initialized to +0.5 or -0.5 (depending on the causality between the concepts). After this step, observing the best dynamic behavior of mobile, is determined the final values, this final values varying around the initial values. The process is repetitive and exhaustive, because different values are added and subtracted from the initial value, to determine the final weights.

To change FCM1 to FCM2, a finite state machine used by the deliberative part of the architecture. The switching is done dynamically according to the occurrence of specific events, at first the robot will toward the target, however changes the FCM event of an obstacle at a distance of 15cm. The range of distances is 0 to 15cm.

In general, the hybrid architecture seeks to be suitable for solving complex problems, like reaching goals and others, in an optimal and efficient way, considering the dynamicity of environments that require fast response, i.e., using reactivity (Lyons and Hendriks, 1995; Policastro, Romero and Zuliani, 2007).

Thus, Hybrid Architectures in robotics seeks to combine the main features of deliberative and reactive approaches, functioning at the same time, to reduce the restriction on the scope of each of these approaches. In this work, the reactive part is represented by the FCM1 and FCM2; because the FCMs evaluate output by reading, the inputs (sensors). The deliberative part is represented by the actions planned as the hierarchical functioning of the state machine (change of FCM structure) and by Hebb method, that provides dynamic tuning of the HD-FCM in accordance the changes in the scenarios, because for each scenario there is a better model to fit it.

A two dimensional simulator was implemented in Matlab, inspired in geometry and kinematics of the real robot, to study the dynamic behavior of the mobile agent. The scale used for the simulated scenario is 1:100. Russel and Norvig (1995) suggest that in order to consider an autonomous agent, it is necessary to succeed in at least three different simulations.

The simulations compare both HD-FCM and HW-FUZZY with the same conditions (scenarios) and with the same objectives. In this context, the Hierarchical Weighted Fuzzy (HWF) controller is used as classical technique of comparison for the D-FCM proposed. The Fuzzy system is resumed in the follow. The Fuzzy I aim to determine the shortest route between the starting point and the target. This Fuzzy System consists of 48 rules in its rule base.

When the sensors detect an obstacle, the hierarchical fuzzy controller prioritizes the obstacle avoidance through the rule base (Fuzzy II). The Fuzzy II intended only to obstacle avoidance. Entries are the sensors (left, right and front, respectively) and the outputs (left and right wheel) are the pulses on wheels. This Fuzzy System II has 24 rules in the rule base (Mendonça et al., 2014). Figure 6 shows the HW-FUZZY architecture.
Thus, simulations tests with different scenarios settings suggest that both systems can be autonomous, in accordance with Russel and Norvig (1995). Firstly, Fig. 7 to 10 shows that both systems can reach targets in simple scenarios. These first simulations are simples and they show the trajectory of the agent (robot=gray trail) toward the target at a specific point between first and second quadrant and finally shows the initial and final poses of the agent.

In Fig. 7, simulation 1, using HW-FUZZY, the robot has reached the target after 655 steps with an accuracy of 1.71 cm. However, using HD-FCM the robot (agent) has reached the target after 980 steps with an accuracy of 1.97 cm.

In Fig. 8, simulation 2, the HD-FCM arrived at the target after 545 steps and 0.81 cm of precision. Using HW-FUZZY the robot achieved the target after 549 steps with accuracy around 0.82 cm.

Simulation 3 (Fig. 9) have a higher degree of difficulty to reach the target, since the obstacles distributed in the form of a spiral. Another difficulty of this problem this decision-making in series, i.e., an error in the second can influence the third and so on. It also have the addition of the item mentioned as a classic difficulty of dynamic navigation, taking conflicting decisions dynamically at the same time (avoid obstacles and reach targets).
Table 2. Results of simulation 2

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<tr>
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<th>HD-FCM</th>
<th>HW-FUZZY</th>
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<tbody>
<tr>
<td>S2-steps</td>
<td>545</td>
<td>549</td>
</tr>
<tr>
<td>S2-error</td>
<td>0.81 cm.</td>
<td>0.82 cm.</td>
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Figure 9. Simulation 3, target and obstacles, in a spiral (HD-FCM and HW-FUZZY)

Table 3. Results of simulation 3.

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<th>HD-FCM</th>
<th>HW-FUZZY</th>
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<tbody>
<tr>
<td>S3-steps</td>
<td>1962</td>
<td>1960</td>
</tr>
<tr>
<td>S3-error</td>
<td>9.67 cm.</td>
<td>9.67 cm.</td>
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</table>

Both architectures reach the target in simulation 3. However, the HD-FCM had a smoother trajectory. The quantitative results of both controllers were similar; i.e. the spiral environment simulation. The HD-FCM needed 1962 steps, with precision of 9.67cm, while HW-FUZZY used 1960 steps with precision of 9.67cm (same reaching target precision).

Figure 10 shows another scenario with two targets and many obstacles. The HD-FCM reached in 935 steps and accuracy around 1.68 cm. The HW-FUZZY reached in 936 steps and 1.68 cm of accuracy.

Table 4. Results for simulation 4.

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<th></th>
<th>HD-FCM</th>
<th>HW-FUZZY</th>
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<tr>
<td>S4-steps</td>
<td>935</td>
<td>936</td>
</tr>
<tr>
<td>S4-error</td>
<td>1.68 cm.</td>
<td>1.68 cm.</td>
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According to the simulated results, the number of pulses and accuracy is similar for both controllers. However, HD-FCM can be more viable to embed in real robot systems, due its low computational complexity; this observation is due to fewer mathematical operations required in the FCM [11], the practical results suggest that possibility, the initial prototype mobile robot used FCM embedded on an Arduino, i.e. FCM classic applied in an industrial controller, work of Matsumoto et al. (2013).

In real experiment (Fig. 11), a real robot with embedded FCM1 managed to achieve the target (reproduced the simulation 1). In the actual experiment, we used an estimation position as follows: the wheels are tensioned by two step motors, and due to the accuracy of such actuators was possible to recalculate a new position according to the geometry of the pulses sent to the robot motors, with a precision of 0.75 cm (with respect to target position), using 104 pulses in a traveled distance of approximately 1.56 m (approximately 0.5% error).

4. CONCLUSIONS

This paper developed an autonomous navigation system based on a new type of fuzzy cognitive maps, named Hybrid Dynamic Fuzzy Cognitive Map, HD-FCM, with hybrid architecture.

The initial results obtained from the simulations and one real experiment were convincing, because the mobile agent accomplished its goal of reaching the targets, in different configurations of simulated scenarios, there was difficulty with more complex levels (spiral example). In all simulations, the agent (robot) reach targets avoid every obstacle.

It is observed that in a real robot, because of difficulties as precision sensors, ghost signal (in particular, ultrasound sensors), noise in the measurements, it will be hardly possible to obtain similar results. However, with the variations of the scenarios with two obstacles in difficult positions, i.e. (spiral) and initial real experiment (reach target unless obstacles, only FCM), suggest that the two hybrid architectures proposed can be used for autonomous robots controllers.

The accuracy found in the real experiment was of the order of 0.5% suggests that the use of FCM embedded on a shelf "open source" low hardware feature suggests that this controller can be used in the construction of low-cost robots. Also in accordance with the real results, although initial and estimated robot position. The error finding in the order of 0.5% allows suggests that the controllers can be applied in real scenarios with small dimensions.

Future works aims to improve the complexity of the scenarios using for example, walls with 90 degrees.

Testing the proposed controller in dynamic scenarios, such as in the presence of mobile obstacles; investigate the computational complexity of the proposed tools; and finally, insert landmarks on the path to increase the precision of the robot position and check the technique of behavior in larger distances to possible industrial applications in collect pieces.

5. ACKNOWLEDGEMENTS

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6. REFERENCES


