ROBOTS GROUP WITH LEADER APPLIED IN AUTONOMOUS NAVIGATION SYSTEM INSPIRED BY SWARM ROBOTICS

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Abstract— This paper presents a navigation strategy group based on Collective Intelligence techniques for the control of autonomous robots using Simplified Dynamics Cognitive Networks (s-DCN), an evolution of Fuzzy Cognitive Maps (FCM), in a multiple objective group navigation environment with a navigation strategy to avoid from obstacles and conduct an object to a target position. Constructive aspects of controllers and initial results will be presented. Finally, simulated results of the strategy`s first part in two dimensions, using a graphical environment, are presented in four different scenarios, in order to initially suggest the capability of group navigation, adaptability, hierarchical decision-making execution and autonomy of the agents.

Keywords— Swarm robotics, fuzzy cognitive maps, dynamic cognitive networks, autonomous robotic navigation.

Resumo— Este trabalho apresenta uma estratégia de navegação em grupo baseada em técnicas de Inteligência Coletiva para o controle de robôs autônomos através de Redes Cognitivas Dinâmicas Simplificadas (s-DCN), uma evolução de Mapas Cognitivos Fuzzy (FCM), em um ambiente de navegação em grupo com multiobjectivos empregando uma estratégia de navegação para desviar de obstáculos e conduzir um objetivo à uma posição alvo. Aspectos construtivos e resultados iniciais dos controladores serão apresentados. Finalmente, resultados simulados, usando um ambiente gráfico, são apresentados em quatro diferentes cenários sugerem a capacidade de navegação em grupo, adaptabilidade, tomada de decisão hierárquica e autonomia dos agentes.

Palavras-chave— Robótica de enxame, mapas cognitivos fuzzy, redes cognitivas dinâmicas, navegação robótica autônoma.

1 Introduction

Fuzzy Cognitive Maps (FCM) is a modeling methodology (Kosko, 1986) which extended the Cognitive Maps for the inclusion of Fuzzy Logic, or Fuzzy numbers in some cases, thus presenting a system with semantic features of Fuzzy systems and stability properties of Artificial Neural Network (Stylios et al., 2008). Recently the FCMs have been conceptualized as a combination of Fuzzy Logic, Semantic networks, Artificial Neural Networks, Expert Systems (Papageorgiou and Salmeron, 2013). A graphic illustration of a FCM is represented by a cyclic or acyclic graph, with it causal relationships are determined, in some cases, by Fuzzy numbers to quantify the weights between the arches among the concepts. The nodes (concepts) are used to describe the characteristic of the main system behavior and are connected to each other with a fixed weight value representing the relationship level of cause and effect between concepts (in practice the concepts may be state variables of the problem); specifically, in this work, the concepts are sensors and actuators of a robot or mobile agent. The FCM may not stabilize, and oscillate in some cases, or even present a chaotic behavior. In normalized systems, with range [-1, 1] (Papageorgiou, 2014).

The Dynamics Cognitive Networks emerged as an evolution of Cognitive Maps and offers more possibilities in the management of causal structures and the modeling of systems that does not presents strong linearity and accentuated temporal phenomena (Mendonça and Arruda, 2015; Miao et al., 2001). The values of the weights associated to the arcs can vary over time according to new types of causal relationship and concepts of the DCN, different from the Cognitive maps and Fuzzy Cognitive maps, which have their weights at fixed values; thus, allowing the construction of dynamic cognitive models that adapt naturally. There is other DCN proposals in the literature, e.g., the work of Miao et al. (2010). The s-DCN (simplified-DCN), proposal of this article, is a simplification of the original DCN in Mendonça and Arruda (2015).

The Dynamic Cognitive Networks, in which the simplified model, used in this work, was been abstracted from, add new types of relationships to FCM's classical cognitive model; in summary, it allows the treatment of occurrence of events, the time in an indirect way, and non-linearities in general. Which are two major disadvantages of the classic models, as it does not address the time due to the simultaneous occurrence of all causal relationships; and functions modeled by classical FCMs are only monotonic, major construction details of the DCN may be conferred on the doctoral thesis book of Mendonça and Arruda (2015). The cognitive model used in this research is a simplification of the original version, because only applies relationships selection that switches the operating states of the controllers and have a dynamic tuning algorithm; those are explained in the next section.

The term "autonomy" refers not only to the capacity for action and decision of an artificial control system, but also the ability of adaptation of the decision-making mechanism (Mataric, 2007; Smithers, 1997; Russel and Norvig, 1995). A priori, one difficulty in the area of autonomous mobile robotics, is: the higher the navigation area, the variety of situations that will need decision-making, or control actions, from the agents will be proportionally higher according to the increase of the environment dimensions (Cliff, 2003).

In this context, to validate the ability of the s-DCN controller's autonomy, for the presented Group Autonomous Navigation System, four simulations of the first stage were performed using scenarios with different situations. In general terms, an agent is autonomous if it can act without direct human intervention. In this context, an agent is proactive if it only reacts to environmental stimuli, has own initiative to take actions to achieve its objectives (Mataric, 2007). This research proposes the construction of autonomous and pro-active agents, especially the leader (this agent should take initiatives to meet their targets or objectives), because the followers practically follow the leader. Section 2 will address the agents' navigation strategy for achieving the proposed goals in more details. Moreover, intelligent agents can be classified as one of the major areas of Computational Intelligent Systems.

It is not scope of this work to develop the architecture of the controllers. However, it will be based in behavior (BBC – Behavior Based Controllers), due the following characteristics: it is based by characteristics of Subsumption Architecture, purely reactive; however, the controllers go beyond that, e.g., by the use of dynamic adaptation algorithms and complex strategy navigation. The philosophy of behaviors based systems requires the information be used as non-centralized intern representation, or not manipulated in a centralized way; it is suggested in Swarm Robotics. In short, since the BBC are based in the concepts of reactive systems (but not limited to it), it also determines that behaviors should be incrementally added to the system, and that they can be executed simultaneously, in parallel, and not sequentially, one at a time. These suggestions are not "definitive solutions" (Mataric, 2007). The motivation for the development of the s-DCN controllers and for the navigation strategy is to use a future Behavior-Based Architecture. Beside the concepts cited, for the control of only one agent in complex task it is suggested the use of hybrid architectures, differently, as the case of this work, for the control of multiple robots in group. Other motivation and inspirations of this article is based by the paper of Ghaffari and Esfahanian (2013).

The objective of this work is a manipulation of the object in group, using cooperation and autonomy of agents following a leader. There are studies about object manipulation in the literature, e.g., Parra-Gonzalez et al. (2009), in which compares different algorithms for object manipulation problem but their purposes were the optimization of number of changes in direction of object along the path.

The proposed controller provides tuning and adaptation capacity, task management, and finally, ability of interaction between the robots by the use of an algorithm inspired by collective intelligence. Researches using intelligent computer systems and Swarm Robotics have been applied in the construction of autonomous navigation systems for one or group of robots, demonstrating an ability to execute complex tasks, especially in applications with little or no knowledge of the environment (Costa and Gouvea, 2010; Ghaffari and Esfahanian, 2013; Russel and Norvig, 1995; Sahin and Spears, 2005).

The modeling of the navigation system used in the robots is based on simplified-Cognitive Networks Dynamic (s-DCN). The original DCN, for being an evolved technique of Cognitive maps, consists in a portable algorithm with low computational complexity, with the possibility of being embedded in different types of microcontrollers Mendonça and Arruda (2015). Its final cognitive model has similarities with Fuzzy Cognitive Map (FCM) models, with the inclusion of other types of relationships and concepts, in which can be implemented adaptive tuning of the weights in real time, between the causal relationships of the concepts. In this work, it is used a Reinforcement Learning Algorithm with tuning heuristics rules. The s-DCN will be addressed in developing section of this article.

Specifically, the objective is to develop navigation logic to control robots in a group using the simplified-Dynamic Cognitive Networks. The environment is partially known, i.e., the position of the piece upper vertex (triangle) and the target (X) are previously known, in particular by the leader. This navigation strategy is based on following an established leader, with the leader in the superior vertex, navigating in a triangle formation. Another possible strategy is making the leader virtual and in the triangle´s center of gravity, e.g., the work of Aso et al. (2008), that uses this principle to control and stability a group of robots.

In the field of multi-robot systems consisting of many autonomous robots, the research area that deals with problems such that each robot has insufficiency to solve a given task is called Swarm Robotics (Sahin, 2005). It usually assumes that the robots or agents are homogeneous, i.e., they have the same specifications, using individual controllers. Generally, to control a robotic swarm without using a global controller, each robot needs to have sufficient capability for autonomous behavior acquisition. However, to our knowledge, there are no methods satisfying this requirement at the present stage (Ohkura et al., 2010).

Similar concepts have been proposed so far, such as cellular robotics (Xiao et al., 2014), collective robotics (Kube and Zhang, 1997), distributed autonomous robotic systems (Asama et al., 1995), and aerial robotic swarms (Dono and Chung, 2013). However, Beni (2005) clarifies the position of Swarm Robotics by giving importance to the emergent behavioral pattern in a swarm robotic than o other approaches. This paper is organized. Section 2 presents the background and development of the proposed strategy for group navigation and the proposed objectives. Section 3, presents and discuss the initial results; and finally; Section 4 concludes and suggest future works.

2 Background and Development of the Navigation Strategy

The task proposed in this work task is inspired by the work of Ghaffari and Esfahanian (2013). In a similar way, it is proposed a group of three robots with a triangle formation; however, with three distinct stages, as shown in the finite state machine at figure 1; of which, only the first was simulated for different scenarios, i.e., step 1.

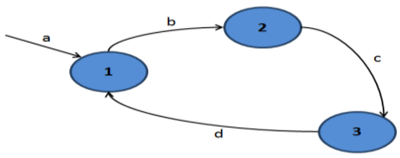

Figure 1. Finite State Machine

The Finite State Machine vocabulary is: a) Initial navigation state; b) Avoid obstacles and go towards the object (triangle); c) Pick up the object and move, in formation, to the target (X), avoiding obstacles along the way; d) Return to the initial state if there is another goal/target or if it have completed the strategy.

In short, the aim of the robot group will have three distinct states, deviate from the initial obstacles, when they reach the object the group will get in formation, because of its distributed representation of the map, each of the reference points discovered by the agents are stored in its own behavior. And finally, lead it to the goal location, avoiding an obstacle between triangle formation and the goal, "X" point, figure 2 illustrates the steps with a state machine.

The autonomous agents use decentralized control, i.e., each agent will have its own s-DCN with decision-making, with the functionality of “follow the leader” to the two followers’ robots, and move towards the object and lead it to the final position while in formation. In particular, the first step, this is simulated in this work.

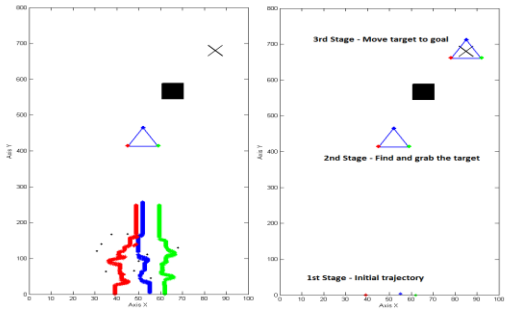

Figure 2. Overview of the environment and the stages progression

As for the leader, its features are similar to the followers, avoid obstacles, and go towards to the top corner of the object (triangle) to get in formation, for steps / states 1-2. After getting the object "triangle" in formation, the robot group has reduced its hierarchical features, to simply avoid obstacles (for both leader and followers), follow the leader (for followers) and the task of achieving the target “X” (for the leader). Figure 3 shows actions of the follower agents’ models within the hierarchical layers in states 1 and 2, similar to subsumption architecture, bottom-up (Brooks, 1986). In other words, the priorities of this architecture are: 1 - avoid obstacles; 2 - follow the leader; 3 – driving formation. As for stage 2 and 3, it’s priority is to avoid obstacle and follow the leader while in formation. The last strategy step, stage 4 would be arc “d” of state machine.

Similarly, to followers’ hierarchical layers, the leader agent’s hierarchy prioritizes the obstacle deviation, search for the object and driving formation, for states 1 and 2; and, obstacle deviation and guide object to target (X) while in formation, for states 2 and 3.

Observe that is not scope of this paper discuss the dynamics needed to perform tasks, it is restricted the necessary decision-making and behaviors, and the agents are considered as points in sequence with movements of translation and rotation.

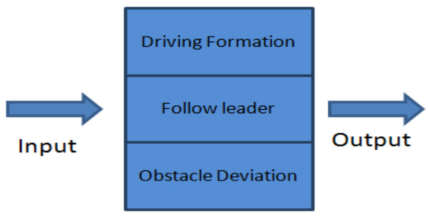

Figure 3. Features of the Followers hierarchy (states 1 and 2)

As for the causal relationships, they are the connections between the concepts, in order to identify the cause and effect between the concepts. Firstly, these cause-effect relationships must be analyzed to determine whether they have a positive or negative causality, and manually or by means of an optimization technique, setting their values and weights.

The manual mode, as used in this work, initially set the weighs of the causal relationships by observing the dynamic behavior of mobile agents. The next step, after the concepts and causal relationships are identified, is to add them to the cognitive model, the inclusion of new types of relationships and concepts that characterize a DCN, more details about the development of the DCN is presented in Mendonça and Arruda (2015). For simplicity and necessity of controlling, the model used in this work was called s-DCN (simplified-DCN), because it partially uses the available resources of its development. More constructive details can be found in the work of Mendonça and Arruda (2015).

The structure of the developed s-DCN (Figure 4) for group autonomous navigation consists of five inputs and three outputs. The input concepts are L.S. (left sensor), R.S. (right sensor), F.S. (front sensor), DX.L. (leader detection by the left side for followers) and DX.R. (leader detection by the right side for followers). Output concepts are T.L. (turn left), T.R. (turn right) and A.D. (acceleration/deceleration) to the actuators.

Bio-inspired algorithms will consequently improve the routing performance in self-organized networks (Zhang, et al, 2013). In this way, we intend to the development of the s-DCN cognitive model the following step will add the ability to adapt; essential to bio-inspired models (Ohkura et al., 2010).

The Ws1 and Ws2 selection relationship switches the inputs of the s-DCN controllers according the current behavior of the agents. Switching between avoid obstacles and the positions predetermined of the targets (according navigation strategy).

The next step is to develop a model for tuning the dynamic response controller. Thus, the controller will be able to adapt through a Reinforcement Learning algorithm based on heuristic rules and oriented by events, during navigation.

The algorithm used for the online adjustment of the causal relations weights is inspired by Sutton and Barto (1998).

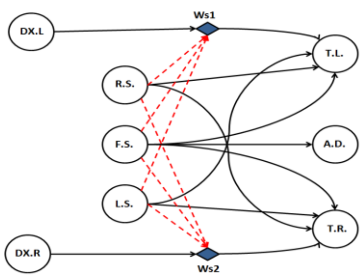

Figure 4. Group Navigation s-DCN

However, the algorithm is similar to the one used in Mendonça and Arruda (2015), which presents a more details on how to develop the RA algorithm with rules.

3 Initial Simulated Results

In the scenarios, the objective of the robots is to explore the surroundings with the leader agent (robot), according to the proposed navigation strategy; if the agents (robots) are close to each other they will prioritize the avoidance of obstacles in its path. Thus, depending on the necessary control actions in different situations, the mobile agents can ungroup from initial formation.

The simulation environment adopted for the experiments simulation of the first stage of this work, consists of a 2-D animation developed in MATLAB, represented by a XY plane. The dimensions of the X-axis are within the range of 0 to 100, while the Y-axis within the ranges of -10 to 270. The vehicles (agents) are symbolized as "*", and represented by different colors. The speed of the animation is determined by the number of iterations; the distance of the obstacle avoidance sensors are 11 units; and, the detection of the leader for the follower's are30 units. The trails of the three colors are the trajectory, or navigation memory, covered by the three agents, in whom the blue identifies the leading vehicle, and red and green are followers' vehicles. A suggested scale for real reproduction of simulation scenarios is (1: 1); and the distances measures cited in centimeters.

It is emphasized that in the simulations, the goal of mobile vehicles (agents) is to seek a formation in triangle after deviating the obstacles, distributed in the scenarios, in which are identified by the Black dots "●".

3.1 First scenario's simulation

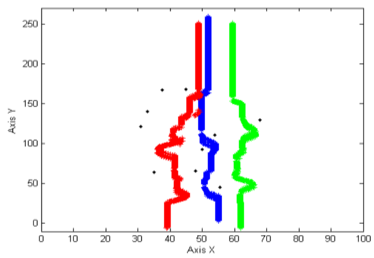

Figure 5. s-DCN on the first scenario

In the first scenario, figure 5, the three robots start next to each other. In terms of initial positions, XY coordinates, the red starts at the point [41, -3], the blue in the point [57, 5] and the green at the point [64, -3]. The robots deviate from obstacles and maintain the triangle formation at the end of the route, but it is noted that green robot is positioned in an asymmetric way with red. This is due to both positioning algorithm has a degree of randomness at the time of navigation, as the sensors for the deviation, showing very close trajectories between agents.

3.2 Second scenario's simulation

The vehicles (agents) start far from each other, Figure 6; the red in the point [4, -5], the blue in [50, 5] and the green in [100, -5]. This scenario was designed to induce that the robots find each other while navigating, thus allowing an analysis of their response for the case in which robots start distant to the leader. Figure 6a shows the obtained result of the navigation.

It is possible to visualize the dynamic behavior for prioritizing the decision-making of the red robot, the obstacle deviation, in this case, causing certain deviation of its trajectory to the leader. Figure 6b points this time, through a break in the animation. This is due to the fact that if the robot's front sensor accuses an obstacle, and left sensor don´t, the robot will give preference to turn to the left.

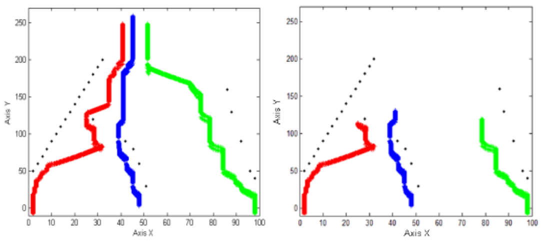

Figure 6. s-DCN on the second scenario, showing details for path taken by the agent

3.3 Third scenario's simulation

The vehicles start next to each other in third scenario, figure 7, where the red starts about at [46, -3], the blue in [52, 5] and the green in [58, -3]. In this drastic scenario, figure 8, the capability to adapt and to group of the controllers was tested with a distribution of obstacles that tends to ungroup, due necessary avoidance maneuvers.

This actions occurs due the initial positions of the robots; Blue [33, 5], leading robot or agent, and red [18, -5], follower robot or agent, that direct the navigation of two agents to the same path.

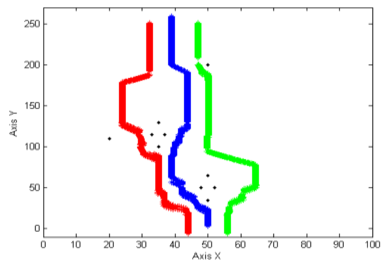

Figure 7 s-DCN on the third scenario

3.4 Fourth scenario's simulation

The performance of s-DCN controllers reached the main goal of not colliding with obstacles, or even another robot of the group, taking right decisions, as shown in figure 8. It is emphasized that: the leader (blue) begins in a position above the follower (red), and even with the interposition of the paths, there was no collision between them.

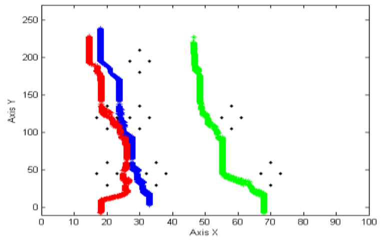

Figure 8. s-DCN on the fourth scenario (drastic scenario)

According to the results obtained from the agents, or robots, dynamic behavior (kinematic) controlled by s-DCNs navigating the four stated scenarios, it was observed that the group driving worked properly most of the time in the simulations; however, in certain times, it is observed that the movement group maneuver takes place only when there is an obstacle deviation by both the leader and the other members of the group, in addition to being in a distance of 30 units from leader (value adopted previously). This suggests future improvements or adjustments to the sensors in the simulator. In most of the scenarios, it is possible to observe the capacity of separation and regrouping (group and ungroup), relevant to Swarm Robotics (La and Sheng, 2012).

4 Conclusion and future works

With the simulation results, although early, we obtained an Autonomous Navigation System in group capable to avoid obstacles and achieve the goals set out in step 1. However, the system still needs some improvements, some due to the problems presented by the kinematic model simulation of robots used to obtain greater realism and accuracy in the movements of robots or agents. As suggestion, a kinematic model with pulses on two wheels should solve the problem, giving more realistic and accurate movements.

The results showed the initial objectives, essential to a Swarm Navigation System, for example: each agent interacts locally with each other and the environment. Emergence of coherent global standard that optimizes a problem. The system is decentralized, the actions were guided by the individual actions of the leader; however, each agent or robot take decisions according to the proposed strategy, suggesting heterarchy in the controllers.

A variety of scenarios, even if it is initial, suggest that the system response is robust and adaptive with according to changes in the environment (resilience). Finally, each agent using Reinforcement Learning algorithms demonstrated self-organization capability.

Future work aims to address the implementation of steps 2, 3 and 4 of the proposed strategy. Compare the proposed controllers with other similar controllers developed using current techniques, for example, Adaptive Fuzzy Logic. Inclusion of white noise on inputs from the sensors to evaluate the ability of controllers developed for dealing with uncertainties, and the quantification of the computational complexity of the s-DCN. And, finally after these possible advances, embed the system in real mobile platforms.

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