SWARM ROBOTICS: CONCEPTS AND IMPLEMENTATION WITH A LEADER-FOCUSED ROBOT GROUP IN AUTONOMOUS

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ABSTRACT: This paper presents a group navigation strategy based on Collective Intelligence techniques for controlling autonomous robots. The strategy uses Simplified Dynamic Cognitive Networks (s-DCN), an evolution of Fuzzy Cognitive Maps (FCM), to model and analyses complex systems. s-DCNs allow robots to make decisions in scenarios with multiple goals and interconnected variables, ideal for dynamic environments. The simulated results show that the strategy is effective in group navigation, adaptability, execution of hierarchical decision-making and agent autonomy. The paper also identifies areas for future work, aiming to further improve the efficiency and robustness of s-DCN-based systems in the context of robot navigation.
KEYWORDS: Swarm Robotics, Robotics, Leader-follower

ROBÓTICA DE ENXAME: CONCEITOS E IMPLEMENTAÇÃO COM UM GRUPO DE ROBÔS FOCADOS NO LÍDER COM NAQVEGAÇÃO AUTÔNOMA

RESUMO: Este artigo apresenta uma estratégia de navegação de grupo baseada em técnicas de Inteligência Coletiva para controlar robôs autônomos. A estratégia utiliza Redes Cognitivas Dinâmicas Simplificadas (s-DCN), uma evolução dos Mapas Cognitivos *Fuzzy* (FCM), para modelar e analisar sistemas complexos. As s-DCN permitem que os robôs tomem decisões em cenários com múltiplos objetivos e variáveis interconectadas, ideal para ambientes dinâmicos. Os resultados simulados mostram que a estratégia é eficaz na navegação em grupo, adaptabilidade, execução de tomada de decisão hierárquica e autonomia dos agentes. O artigo também identifica áreas para trabalhos futuros, visando melhorar ainda mais a eficiência e a robustez de sistemas baseados em s-DCN no contexto da navegação de robôs.
PALAVRAS-CHAVE: Robótica de Enxame, Robótica, Seguidor de líder**.**

1 I INTRODUÇÃO

Fuzzy cognitive maps (FCMs) are a modelling methodology (Kosko, 1986) that extend cognitive maps by incorporating fuzzy logic, or fuzzy numbers in some cases. This gives FCMs the semantic features of fuzzy systems and the stability properties of artificial neural networks (Stylios et al., 2008). Recently, FCMs have been conceptualized as a combination of fuzzy logic, semantic networks, artificial neural networks, and expert systems (Papageorgiou and Salmeron, 2013).

Graphically, an FCM is represented by a cyclic or acyclic graph, with causal relationships between concepts being determined, in some cases, by fuzzy numbers. The nodes (concepts) describe the characteristics of the main system behaviour and are connected to each other with a fixed weight value representing the level of cause-and-effect relationship between concepts. (In practice, the concepts may be state variables of the problem.) In this work, the concepts are sensors and actuators of a robot or mobile agent.

FCMs may not always stabilize, and may oscillate in some cases, or even exhibit chaotic behaviour. In normalized systems, the range of the weights is typically [-1, 1] (Papageorgiou, 2014).

Dynamic Cognitive Networks (DCNs) emerged as an evolution of Cognitive Maps and offer more possibilities in the management of causal structures and the modelling of systems that do not present strong linearity and accentuated temporal phenomena (Koulouriotis et al., 2005; 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 are 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, has 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. These 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 modelled by classical FCMs are only monotonic (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 around 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 proactive 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 the scope of this work to develop the architecture of the controllers. However, it will be based in behaviour (BBC – Behaviour Based Controllers), due the following characteristics: it is based by characteristics of Subsumption Architecture, purely reactive; however, the controllers go beyond that, e.g., using dynamic adaptation algorithms and complex strategy navigation. The philosophy of behaviours-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**.**

The proposed controller provides tuning and adaptation capacity, task management, and finally, the ability of interaction between the robots using an algorithm inspired by collective intelligence. Research 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 modelling 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, a Reinforcement Learning Algorithm with tuning heuristics rules is used. The s-DCN will be addressed in the 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, 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 stabilize 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 behaviour 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 (Fukuda and

Nakagawa, 1988; 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 back-ground 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 I 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.

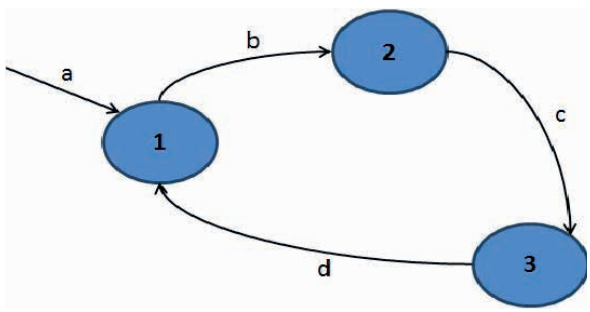

Figure 1 – Finite State Machine

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,

information, 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.

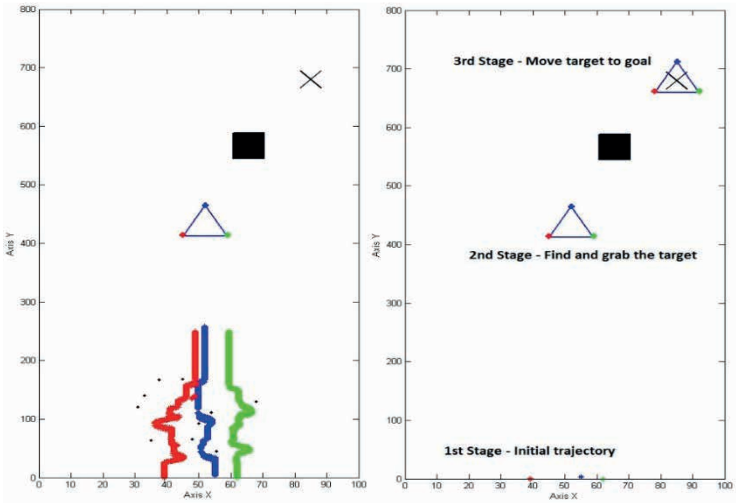

Figure 2 - Overview of the environment and the stages progression

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 information. In particular, the first step, this is simulated in this work.

As for the leader, its features are like 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).

As for the causal relationships, they are the connections between the concepts, 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 con-strictive details can be found in the work of Mendonça and Arruda (2015).

The structure of the developed s-DCN (Figure 3) 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 fol-lowers). Output concepts are T.L. (turn left), T.R. (turn right) and A.D. (acceleration/deceleration) to the actuators.

Bio-inspired algorithms will consequently im-prove 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 to the current behavior of the agents. Switching between avoid obstacles and the positions predetermined of the targets (according to navigation strategy).

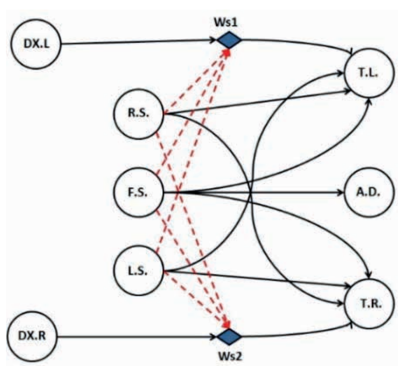

Figure 3 - Group Navigation s-DCN (controller)

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). 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 I 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 experiment's 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..

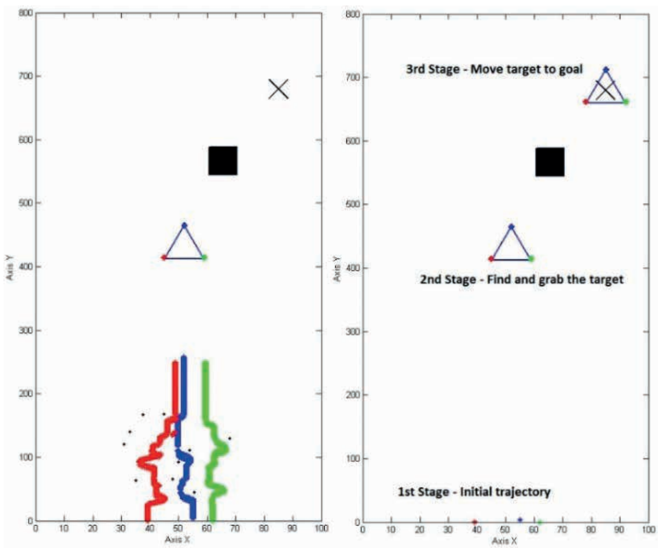

Figure 4- Overview group navigation s-DCN

An overview of the leader robot and its followers is presented in Figure 4. This shows the robots avoiding smaller obstacles, following the leader, and finally picking up their target and carrying it to the final position.

The robots can do this using a variety of sensors and algorithms. The sensors include cameras, lasers, and proximity sensors. The algorithms are used to detect obstacles, calculate the best route, and control the movements of the robots.

The system can navigate in complex environments and avoid collisions. It is also able to carry heavy objects and transport them long distances.

This system has the potential to be used in a variety of applications, including goods delivery, cleaning, and rescue. In short, the Figure 4 show overview

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 followers are 30 units. The trail of the three colors are the trajectory, or navigation memory, covered by the three agents, in which 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 the in the text are 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

In the first scenario, figure 6, 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.

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.

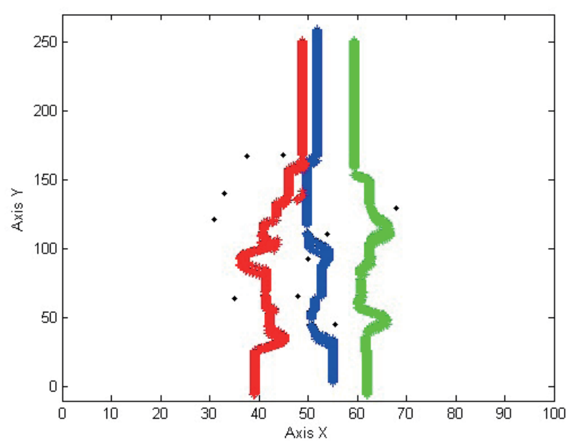

Figure 5 - s-DCN on the first scenario

3.2 Second scenario's simulation

The vehicles (agents) start far from each other, Figure 5; 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.

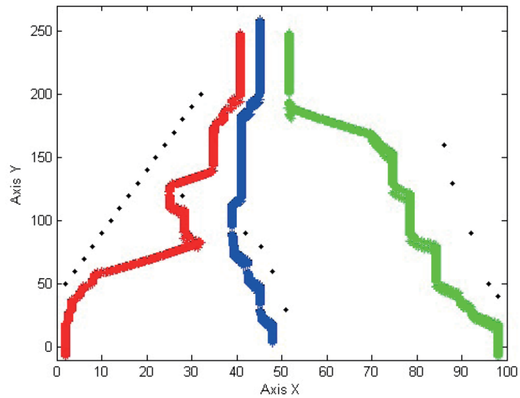

Figure 6 - s-DCN on the second scenario, showing details for path taken by the agent.

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 6 points this time, through a break in the animation. This is since if the robot's front sensor accuses an obstacle, and left sensor don´t, the robot will give preference to turn to the left.

4 I CONCLUSION AND FUTURE WORKS

The simulation results showed that the Autonomous Navigation System in group can avoid obstacles and achieving the goals set out in step 1. However, the system still needs some improvements, such as using a kinematic model with pulses on two wheels to give more realistic and accurate movements.

The results also showed that the system meets the initial objectives of a Swarm Navigation System, such as each agent interacting locally with each other and the environment, and the emergence of a coherent global standard that optimizes a problem.

The system is decentralized, but each agent or robot takes decisions according to the proposed strategy, suggesting hierarchy in the controllers.

The system is robust and adaptive to changes in the environment, and each agent using Reinforcement Learning algorithms demonstrated self-organization capability.

The system is flexible and has low computational cost, making it suitable for real-world applications such as collecting mines in war applications or pieces in industrial applications.

Future work will focus on implementing the remaining steps of the proposed strategy, comparing the proposed controllers with other similar controllers, and embedding the system in real mobile platforms.

REFERENCES

ASAMA H., FUKUDA T., AND ARAI, I. E. (1995). Distributed Autonomous Robotic Systems, Springer-Verlag.

ASO, S., YOKOTA, S., HASHIMOTO, H., OHYAMA, Y., SASAKI, A. AND KOBAYASHI, H. (2008). Control and stability for robotic swarm based on center of gravity of local swarm. In Industrial Electronics, 2008. ISIE 2008. IEEE International Symposium on, pp.1341-1346, June 30, 2008-July.

BENI, G. (2005). From Swarm Intelligence to Swarm Robotics, Swarm Robotics. SAB2004 International Workshop, Santa Monica, CA, USA, July 2004, Revised Selected Papers.

CLIFF, D. (2003). Biological inspired computing approaches to cognitive systems: a partial tour of the literature. Technical Report HPL-2003-11, Hewlett Packard Laboratories.

COSTA, E. D. S. AND GOUVEA, M. M. (2010) Autonomous navigation in dynamic environments with reinforcement learning and heuristic, Ninth International Conference on Machine Learning and Applications, pp. 37-42.

DONO, T.F. AND CHUNG, T.H. (2013). Optimized transit planning and landing of aerial robotic swarms. In Robotics and Automation (ICRA), 2013 IEEE International Conference on, pp.1843-1850.

FUKUDA, T. AND NAKAGAWA S. (1988). Approach to the Dynamically Reconfigurable Robotic System. Journal of Intelligent and Robotic Systems.

GHAFFARI, A. AND ESFAHANIAN, M.R. (2013). Using swarm robots based on leader-followers method for spherical object manipulation. In Robotics and Mechatronics (ICRoM), 2013 First RSI/ISM International Conference on, pp.413-418, 13-15 Feb.

KOSKO, B. (1986). Fuzzy cognitive maps. International Journal Man-Machine Studies, vol. 24, no. 1, pp. 65-75.

KOULOURIOTIS, D. E., DIAKOULAKIS, I. E., EMIRIS, D. M. AND ZOPOUNIDIS, C. D. (2005). Development of dynamic cognitive networks as complex systems approximations: validation in financial time series. Applied Soft Computing, vo. 5, no. 2, Jan, pp. 157-179.

KUBE, C. R. AND ZHANG, H. (1997). Task Modelling in Collective Robotics. Autonomous Robots, vol.4 no.1, Kluwer Academic.

MATRIC, M. J. (2007). The Robotics Primer. MIT Press, Cambridge.

MENDONÇA, M. AND ARRUDA, L. V. R. (2015). A Contribution to the Intelligent Systems Development Using DCN. OmniScriptum GmbH & Co. KG, 2015

MIAO, Y., LIU, Z.Q., SIEW, C.K. AND MIAO, C.Y. (2001). Dynamical cognitive network — an extension of fuzzy cognitive. IEEE Trans. on Fuzzy Systems, vo. 9, no. 5, pp. 760-770.

MIAO, Y., MIAO, C., TAO, X-H., SHEN, Z. AND LIU, Z-Q. (2010). Transformation of Cognitive Maps. In Fuzzy Systems, IEEE Transactions on, vol.18, no.1, pp.114-124, Feb.

OKURA, K., YASUDA, T. AND MATSUMURA, Y. (2010). Coordinating the adaptive behavior for swarm robotic systems by using topology and weight evolving artificial neural networks. In Evolutionary Computation (CEC), 2010 IEEE Congress on, pp.1-8, 18-23 July.

Papageorgiou E.I. and Salmeron J.L. (2013). A Review of Fuzzy Cognitive Maps Research During the Last Decade. Fuzzy Systems, IEEE Transactions on, vol.21, no.1, pp.66–79,

Papageorgiou, E.I. (2014). Fuzzy Cognitive Maps for Applied Sciences and Engineering from Fundamentals to Extensions and Learning Algorithms. Springer-Verlag Berlin Heidelberg.

Parra-Gonzalez, E.F., Ramirez-Torres, J.G. and Toscano-Pulido, G. (2009). A New Object Path Planner for the Box Pushing Problem. Proceeding from Electronics, Robotics and Automotive Mechanics Conference, Cuernavaca, 2009, pp. 11 9-124, 22-25 Sept.

Russel, S. J. and Norvig, P. (1995). Artificial intelligence: a modern approach. Englewood Cliffs: Prentice Hall.

Sahin, E. (2005). Swarm Robotics: From Sources of Inspiration to Domain of Applications, Swarm Robotics. SAB2004 International Workshop, Santa Monica, CA, USA.

Sahin E. and Spears, W.M. (2005). Swarm Robotics. Springer¬Verlag, Germany, 2005.

Smithers, M. (1997). Autonomy in robots and other agents. Brains and Cognition, vol. 34, pp. 88-106.

Stylios, C. D., Georgopoulos, V. C., Malandraki, G. A. and Chouliara, S. (2008) ‘Fuzzy cognitive map architectures for medical decision support systems’, Applied Soft Computing, vo. 8, no. 3, pp. 1243-1251.

Sutton, R. and Barto, A. (1998). Reinforcement learning: an introduction. Cambridge: MIT Press.

Xiao, R., Wang, Y. and Tao, Z. (2014). Research on structure emergence based on cellular automata. Int. J. of Bio-Inspired Computation, vo. 6, no. 2, pp. 126-139.

Zhang, X., Zhang, Y., Li, Y., Zhang, Z. and Long, K. (2013). Bio-inspired adaptive routing in self-organized networks: A survey. In Communications and Networking in China (CHINACOM), 2013 8th International ICST Conference on, pp.505-510, 14-16 Aug.