

Hybrid Dynamic Fuzzy Cognitive Maps for Self-Directed Mobile Direction-Finding

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Abstract: This research is an evolution of previous research in which we used a knowledge-based system to free navigation area. About 2 navigation systems are developed: one uses Fuzzy Cognitive Maps (FCM) and the other is based on a Fuzzy Logic Controller (FLC). For the first system, a variant of the traditional FCM, named Hybrid-Dynamic Fuzzy Cognitive Maps (HDFCM) is used to model decision tasks and 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 show permits speaking to the efficient conduct of a portable robot in the nearness of changes in nature. A Hierarchical Weighted Fuzzy Logic Controller (HW-FLC) creates the second route framework. Recreation results are introduced permitting a comparison of both structures and demonstrating the capacity of the portable robot to explore among impediments in various situations (course condition). At long last, beginning genuine outcomes with arduino microcontroller appear.

Key words: Fuzzy cognitive maps, autonomous navigation embedded, dynamic decision-making, intelligent dynamic decision systems, nature, HDFCM

INTRODUCTION

This research is an advancement of our past work (Mendonca *et al.*, 2015) in which we utilize a Hybrid Dynamic Fuzzy Cognitive Maps (HDFCM) to execute an independent route framework to be connected into self-sufficient portable mechanical. HD-FCMs are a development of the Fuzzy Cognitive Maps that can gain information progressively by utilizing machine learning calculations. More points of interest of this research are introduced in inspiration and goals.

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; Salan *et al.*, 2015). In another way, autonomous systems have the potential to perform complex tasks with a high degree of success without human intervention (Napoles *et al.*, 2016). There is a developing enthusiasm for the improvement of self-ruling (operators) robots and vehicles, predominantly in light of the immense differing qualities of undertakings that can be taken care of by them, particularly those that jeopardize human wellbeing or potentially the earth (Schroth *et al.*, 2009; Shaikh *et al.*, 2013). As cases, it can be referred to works that portray a versatile self-governing robot for use in welding (Spears *et al.*, 2014), condition investigation (Cliff, 2003), submerged (Mendonca *et al.*, 2013) and others.

The inspiration of this research is to propose the advancement of 2 self-ruling route frameworks that

utilizations heuristic information about the conduct of the robot/vehicle or specializes in different circumstances. The initial framework is demonstrated by Fuzzy Cognitive Maps (FCM) and temporary ones depend on Fuzzy Logic Controller (FLC). MIMO-OFDM system using different antenna configurations is designed and analyzed by Subramanian (2014). Optimal acquisition of modernized GNSS signal using a pre-compression algorithm is discussed by Taj and Kumaravel (2015).

This study investigates following research studies, design of a single input fuzzy logic controller based SVC for dynamic performance enhancement of power systems (Subramanian, 2014) uses only one data which is the signed distance and has the advantage of reduced number of rules. Survey on fuzzy petri nets for classification (Taj and Kumaravel, 2015) excellent networks which have important characteristics of combining a well-defined mathematical theory with a graphical representation of the dynamic behavior of systems. Glaucoma detection using Fuzzy C-Mean (FCM) (Surendiran *et al.*, 2016) which is a pixel of interest determined in outlined discs.

MATERIALS AND METHODS

Fuzzy cognitive MAPS background: Fuzzy cognitive maps was originally introduced by Kosko as a suitable knowledge-based methodology for modeling dynamic systems. In other words, FCM is a method for representing real-world problems regarding concepts and

causal relationships among them. The concepts used by a decision-maker are represented as nodes and the causal relationships between these concepts are represented as directed edges. And the ideas are considered as variables of the system.

The FCM structure is built from a priori knowledge of experts and afterward, it can be tuned by Heuristic methods, Genetic algorithm, swarm and other techniques. Despite the tuning step, the FCM based inference models lack robustness in the presence of dynamic modifications, not a priori modeled due to its “rigid” knowledge representation utilizing graph and matrix operation.

It goes around this issue this study builds up another sort of FCM in which its structure changes were agreeing on current model destinations for example, achieve the target and dodge snags to a route framework given FCM. Along these lines, the Hybrid-Dynamic Fuzzy Cognitive Map Model can progressively obtain and utilize the heuristic information. The HD-FCM and its application in the self-ruling route will be produced and approved in the following segments (Maki *et al.*, 2010) (Fig. 1).

Autonomous navigation systems development: The specialist controller’s design received in this research is propelled by subsumption architecture (Mataric, 2007) that permits the steady advancement of both route framework, beginning up with a straightforward model with one or just a couple of functionalities and continuously adding new goals to enhance the investigation capacity of the operator.

A Hierarchical Weighted Fuzzy Logic Controller (HWFLC) is used as a baseline for the design of the secondary navigation autonomous system (Mataric, 2007). The HW-FLC is composed of two rule bases, each one related to the mobile robot goals: reach the target and avoid obstacles.

Figure 1a, “DSx” is the lateral distance between the robot and the target (corresponding to X in Fig. 2) and “DSy” is the first distance to the target (similar to Y in Fig. 2), measured on the vertical axis. If the target is located to the left of the robot, “DSx” is negative and if it is located at the rear of the robot, “DSy” is negative. All weights (W1-3-W2-4) are the fuzzy number whose are normalized into the interval [-1, 1].

Figure 1b shows the robot (agent) for the HD-FCM model for deviating from obstacles. The input concepts are SL (Sensor Left), SR (Sensor-Right) and SF (Sensor-Front). The values of these concepts are the reads of the corresponding sensors and they measure how far the mobile is the obstacle. As a fuzzy number,

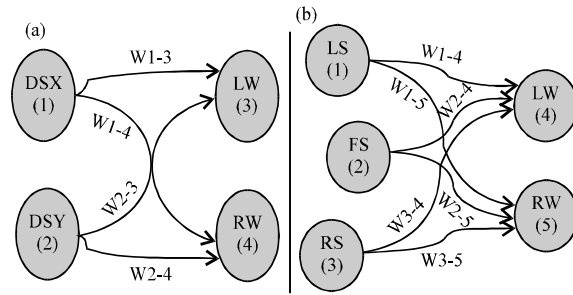


Fig. 1: HD-FCM1: a) for reach target and HD-FCM2 and b) avoid obstacles



Fig. 2: Simulation 3-FCM1 embedded in a real mobile robot

these values are normalized into the interval [0, 1]. It also shows the concepts and relationships for avoiding 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 particular concepts. These values are necessities for avoidance maneuvers. The W24 and W25 weights connected to frontal sensors and wheels have negative values when the obstacle is near the robot decelerates. These weights are tuned using Hebb learning, similar to FCM1.

RESULTS AND DISCUSSION

The autonomous navigation system has guided the robot to achieve the target as shown in sequence in Fig. 2 (reproducing the first simulation, i.e., reach the goal). Because of the exactness of wheel actuators, it was conceivable gauge the robot position and to recalculate. Another job as indicated by the geometry of the beats sent to the robot engines and the wheel boundary estimate with an accuracy of 0.75 cm (considering the actual position), utilizing 104 heartbeats in a voyaged separation of roughly 1.56 m (with 0.5% relative mistake).

CONCLUSION

The initial results obtained from the simulations and one actual experiment were convincing, since the mobile

agent accomplished its goal of reaching the targets in different configurations of simulated scenarios. In all simulations, the agent (robot) achieved the goals and avoided the obstacles. It is watched that in a good robot because of challenges for example, sensor's accuracy, phantom flag (specifically, ultrasound sensors), commotion in the estimations, it will be not conceivable to acquire comparable outcomes to reenactment for more mind boggling situations, i.e., winding condition. In any case, the underlying genuine trial (achieve target unless deterrents, just FCM) recommend that the 2 proposed various leveled structures can be utilized for self-sufficient robot's controllers.

REFERENCES

- Cliff, D., 2003. *Biologically-Inspired Computing Approaches to Cognitive Systems: A Partial Tour of the Literature*. Hewlett-Packard Company, Palo Alto, California, USA., Pages: 56.
- Maki, T., A. Kume, T. Ura, T. Sakamaki and H. Suzuki, 2010. Autonomous detection and volume determination of tubeworm colonies from underwater robotic surveys. *Proceedings of the 2010 IEEE-Sydney International Conference on OCEANS*, May 24-27, 2010, IEEE, Sydney, Australia, Australia, ISBN:978-1-4244-5221-7, pp: 1-8.
- Mataric, M.J., 2007. *The Robotics Primer*. MIT Press, Cambridge, Massachusetts, USA., Pages: 305.
- Mendonca, M., B.A. Angelico, L.V.R. Arruda and F. Neves, 2013. A Subsumption architecture to develop dynamic cognitive network-based models with autonomous navigation application. *J. Control Autom. Electr. Syst.*, 1: 117-128.
- Mendonca, M., L.V.R. Arruda, I.R. Chrun and D.E.S. Silva, 2015. Hybrid dynamic fuzzy cognitive maps evolution for autonomous navigation system. *Proceedings of the 2015 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, August 2-5, 2015, IEEE, Istanbul, Turkey, ISBN:978-1-4673-7428-6, pp: 1-7.
- Napoles, G., I. Grau, E. Papageorgiou, R. Bello and K. Vanhoof, 2016. Rough cognitive networks. *Knowledge Based Syst.*, 91: 46-61.
- Salan, S., E. Drumwright and K.I. Lin, 2015. Minimum-energy robotic exploration: A formulation and an approach. *IEEE. Trans. Syst. Man Cybern. Syst.*, 45: 175-182.
- Schroth, G., W.I.S. Genannt and K. Diepold, 2009. A cognitive system for autonomous robotic welding. *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, October 10-15, 2009, IEEE, St. Louis, Missouri, USA., ISBN:978-1-4244-3803-7, pp: 3148-3153.
- Shaikh, M.H., K. Kosuri, N.A. Ansari and M.J. Khan, 2013. The state-of-the-art intelligent navigational system for monitoring in mobile autonomous robot. *Proceedings of the 2013 International Conference on Information and Communication Technology*, March 20-22, 2013, IEEE, Bandung, Indonesia, ISBN:978-1-4673-4990-1, pp: 405-409.
- Spears, A., A.M. Howard, B. Schmidt, M. Meister and M. West *et al.*, 2014. Design and development of an under-ice autonomous underwater vehicle for use in Polar regions. *Proceedings of the 2014 International Conference on Oceans-St. John's*, September 14-19, 2014, St. John's, Newfoundland and Labrador, Canada, ISBN:978-1-4799-4918-2, pp: 1-6.
- Subramanian, D.D.P., 2014. Design of a single input fuzzy logic controller based SVC for dynamic performance enhancement of power systems. *Intl. J. Eng. Technol.*, 6: 2342-2350.
- Surendiran, J., S.V. Saravanan and C.F. Elizabeth, 2016. Glaucoma detection using Fuzzy C-Mean (FCM). *Intl. J. Pharm. Technol.*, 8: 16149-16163.
- Taj, S.M. and A. Kumaravel, 2015. Survey on fuzzy petri nets for classification. *Indian J. Sci. Technol.*, Vol. 8.