

Novel Fuzzy Systems for Human-Autonomous Agent Teaming

by

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Thesis submitted in fulfilment of
the requirements for the degree of

Doctor of Philosophy

under the supervision of
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February 2021

Declaration of Authorship and Originality

I, Yu-Cheng Chang, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctoral of Philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Program.

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05/02/2021

Acknowledgements

I wish to thank my esteemed supervisor – Professor Chin-Teng (CT) Lin for his invaluable supervision, support and tutelage during the whole PhD candidature period. I also thank Professor CT for offering the opportunities involving in other academic activities, which are necessary to train independent researchers.

Helps and supports from Professor Nikhil R. Pal, Dr. Yu-Kai, Wang, Dr. Ye Shi, and Dr. Zehong Cao are highly appreciated and it is also manifest from the published/revised/submitted/preparing papers enlisted as co-authors.

Furthermore, I would like to thank Dr. Jijoong Kim and Dr. Anna Dostovalova from the Defence Science and Technology Group (DSTG) for their frequent discussions about different aspects of the research. I also pay attributes to other members in the CIBCI lab for a variety of help hard to be categorized but contributing to an enjoyable and beneficial experience.

Lastly, my appreciation also goes out to my family, especially my wife PohWee Song, for their encouragement and support all through my studies.

Abstract

The Multi-agent Teaming (MAT) systems that have been widely applied in many fields provide a novel method for establishing models, conducting the analysis, implementing complex tasks and so on. The agents in an MAT system can be defined as intelligent agents, machine agents and human agents based on a particular task to exhibit flexible behaviours. This research investigates various fuzzy models to resolve the problems of designing MAT systems, such as the coordination of agents, the interpretability of actions and states, high-dimensional data and data privacy.

First, a hierarchical fuzzy logic system that is proposed to deal with the coordination of agents is applied to the simultaneous arrival of multiple mobile agents. The proposed hierarchical fuzzy logic system consists of two levels: a lower-level individual navigation control for obstacle avoidance and a higher-level coordination control to ensure the same time of arrival for all robots at their target; it enables the synchronisation of the agents' arrival times while avoiding collisions with obstacles. Apart from the hierarchical structure, a grouping and merging mechanism is developed to optimise transparent fuzzy sets and integrated into the training process to improve the fuzzy models' interpretability. Additionally, a Multi-objective hybrid GA and PSO (MGAPSO) algorithm is developed to design the hierarchical fuzzy controller efficiently. The MGAPSO leverages the exploring capability of Genetic Algorithm (GA) and the convergence capability of Particle Swarm Optimization (PSO). The simulation results demonstrate that the proposed hierarchical fuzzy controller successfully controls various numbers of robots to navigate and reach the target simultaneously safely. The optimised fuzzy sets can be interpreted by explaining the mining of fuzzy sets and the consequent components.

Moreover, this research also proposes a fuzzy Covert State Transition Diagram (FCOSTD), which provides a mechanism to automatically identify humans' external and covert states that machine agents can understand. The fuzzy-inference mechanism is used to represent the activities of the human states associated with varying behaviours. The proposed system consists of a supervised-learning-based fuzzy network featuring real-world data representing the salient features of human biosignals.

Unsupervised clustering is then conducted on the extracted feature space to determine the human’s external and covert states. A state transition diagram is introduced to investigate state change and enable the visualisation of connectivity patterns between every pair of states. We compute the transition probability between every pair of states to represent the relationships between the states. We then apply FCOSTD to real-world Electroencephalography (EEG) data collected from distracted driving experiments. FCOSTD successfully discovers the external and covert states and faithfully reveals the transition of the brain between states and the route of the state change when humans are distracted during a driving task. The experimental results demonstrate that different subjects have similar states and inter-state transition behaviour (establishing the consistency of the system) but different methods for allocating brain resources as different actions are being taken. The discovery of covert brain states offers machine agents the possibility to understand human cognitive states in a human-autonomous system.

Finally, a Distributed Fuzzy Neural Network (D-FNN) model is developed to address data privacy for multiagent decision-makers. The proposed D-FNN model considers consensus for both the antecedent and consequent layers. A novel consensus learning, which involves distributed structure learning and distributed parameter learning, is proposed to handle the D-FNN model. The proposed consensus learning algorithm is built on the well-known alternating direction method of multipliers, which does not exchange local data among agents. The simulation results on popular datasets demonstrate the superiority and effectiveness of the proposed D-FNN model and consensus learning algorithm.

The main contributions of this research are as follows. 1) For multiple-agent coordination, a hierarchical fuzzy system is proposed. This hierarchical fuzzy system consists of two levels and is applied to navigation and simultaneous arrival of mobile agents. 2) Two types of explainable fuzzy systems are proposed. One is the fuzzy system with fuzzy set transparency improvement, which optimises the number of fuzzy sets and reduces the overlap between fuzzy sets. Hence, human agents can understand the rules learned by the fuzzy controller. The second is fuzzy rule information visualisation, which considers the firing strength of fuzzy rules as useful information to extract and visualise the hidden state in the human brain. 3) Finally, the distributed fuzzy system is proposed to resolve the data privacy and high-dimensional data in designing MAT systems. A novel consensus learning is developed for the distributed fuzzy system to learn antecedent and consequent components.

Publications

Related Papers

Y. C. Chang, A. Dostovalova, C. T. Lin and J. Kim, "Intelligent Multirobot Navigation and Arrival-Time Control Using a Scalable PSO-Optimized Hierarchical Controller", *Frontiers in Artificial Intelligence*, vol. 3, 2020.

Y. C. Chang, A. Dostovalova, Z. Cao, J. Kim, D. Gibbons and C. T. Lin, "Interpretable Fuzzy Logic Control for Multi-Robot Coordination in a Cluttered Environment", submitted to *IEEE Trans. on Fuzzy Systems*.

Y. C. Chang, Y. K. Wang, N. R. Pal, C. T. Lin, "Hybrid-Learning-Based Fuzzy-Inference Covert States for Exploring the Dynamics of Brain States", submitted to *IEEE Trans. on Neural Systems and Rehabilitation Engineering*.

Y. Shi, C. Lin, **Y. C. Chang**, W. Ding, Y. Shi and X. Yao, "Consensus Learning for Distributed Fuzzy Neural Network in Big Data Environment," in *IEEE Transactions on Emerging Topics in Computational Intelligence*, June, 2020.

Other Papers

L. Zhang, Y. Shi, **Y. C. Chang** and C. T. Lin, "Hierarchical fuzzy neural networks with privacy preservation on heterogeneous big data", *IEEE Transactions on Fuzzy Systems*, pp. 1-1, 2020.

L. W. Ko, Y. C. Lu, H. Bustince, **Y. C. Chang**, et al., "Multimodal Fuzzy Fusion for Enhancing the Motor-Imagery-Based Brain Computer Interface", *IEEE Computational Intelligence Magazine*, vol. 14, no. 1, pp. 96-106, 2019.

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