"Editorial"

Fuzzy Learning and Its Applications in Neural-Engineering

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This special issue was born as a result of the successful special sessions on *Fuzzy Brain Analysis and Interfaces* that were organised within the umbrella of the 2017 and 2018 *IEEE International Conference on Fuzzy Systems (IEEE-FUZZ).* These sessions had the objective to enable an in-depth scienfic discussion of the use of computational learning frameworks to model the imprecision and vagueness that is usually found in neuro-engineering and neuroimaging contexts. Authors of best papers of these sessions were suggested to submit an article to this special issue.

Fuzzy sets and systems presents an alternative, effective and expressive framework for the processing and analysis of brain activity, thus enabling opportunities of developing direct communication pathways with the brain, in the form of brain computer/machine interfaces (BCI). Learning frameworks based in fuzzy logic can cope with high levels of uncertainty, making possible to factor in the modelling specific challenges of neuro-engineering such highly noisy environments, changing contexts or non-stationarities, or subject variabilities. This vision has been first suggested by the pioneering work on fuzzy models applied to BCI by Prof. Ching-Ten Lin et al. [1–3]; and followed later by others (Andreu-Perez et al, Prasad et al.) and further applied to brain-machine robotic control [4], identification of event related potentials (ERP) [5], estimation of brain complexity [6], inhibitory brain control [7]. In this same line, an international task force has been created to further study and develop new fuzzy approaches in neuro-engineering [8]. The impact of fuzzy approaches to the analysis of brain signals is opening new perspectives and scientific pathways in many subfields of neuro-engineering such as: brain computer/machine interfaces, computational neuroscience, cognitive neuroscience, neuroimaging, neuroinformatics, neuroergonomics, affective neuroscience, neurobiology and brain mapping.

In total three papers have been selected to make this special issue. The first paper is authored by *Cao et al.* and presents a novel multi-scale fuzzy entropy measure to measure the complexity of the brain from EEG signals. This a very novel paradigm to study and analyse brain signals in terms of their complexity using information theoretic metrics such as entropy to reflect the change in the dynamics of brain waves. In this work, the ability of this metrics are studied to be able to measure brain complexity in an experiment with steady-state visual evoke potentials (SSVEP) stimuli. *Cao et. al.* demonstrates, in a study comprising 40 participants, that this measure provides a better estimation than other non-fuzzy competing multiscale entropy methods. This work is very significant because it demonstrates that the degree of fuzziness in the brain can be quantified and used in potential clinical contexts.

Nowadays, one of the limitations of BCI applications are the number of commands they can output. Considering the limited amount of possible brain decoding classes or stimuli: Go/No-go, SSVEP, ERP detection, a way to tackle this problem is by designing efficient and novel intermediate interfaces that can make use of this rapid and reliable decoding. Alternatively, another option is to investigate the possibility of decoding multi-class mental states enabling a direct communication. In the second paper of this special issue, *Gupta et al.* presents a novel hierarchical metal-model for the decoding of brain activity into 5-classes of mental tasks. The approach is based in layered two-phase feature extraction method. The proposed approach outperforms other methods suggested in the literature. The architecture follows a tree-based structure and fuzzy models are considered for benchmarking purposes.

Data arising from large-scale neuro-engineering experiments can yield an enormous amount of data. Processing of this data is usually very compelling, as algorithms require loading all data in memory. The scalability of hardware resources is usually a costly and non-desirable solution for every problem. Software platforms such as Apache Spark [9] mitigate the processing and analysis of large data by letting the system to be able to combine and parallelise the processing of data stored in a distributed file system in a computer cluster. In the third and last paper of this special issue *Bharril et al.* presents a novel incremental fuzzy clustering algorithm for Big Data that is based in fuzzy c-means. The method has been implemented over Apache Spark and an exhaustive analysis of its time, space complexity, speedup and other big data performance metrics is performed with benchmarking datasets.

In a nutshell, the three papers of this special issue are distinct in objectives, the first proposes a novel measure of brain complexity, the second a novel method of multi-class decoding and the third a novel approach for processing big data. The three works of this special issue have in common that they provide solutions to actual challenges in neuro-engineering and a step-forwards in the use of fuzzy methods in neuro-engineering. The guest editors hope that this special issue will pave the way to further investigation and works in this research perspective.

[1] C.T. Lin, R.C. Wu, T.P. Jung, S.F. Liang, T.Y. Huang, Estimating driving performance based on EEG spectrum analysis, EURASIP J. Appl. Signal Processing. 2005 (2005) 3165–3174. doi:10.1155/ASP.2005.3165.

[2] C.T. Lin, C.H. Chuang, C.S. Huang, S.F. Tsai, S.W. Lu, Y.H. Chen, L.W. Ko, Wireless and wearable EEG system for evaluating driver vigilance, IEEE Trans. Biomed. Circuits Syst. 8 (2014) 165–176. doi:10.1109/TBCAS.2014.2316224.

[3] C.-T. Lin, Y.-C. Chen, T.-Y. Huang, T.-T. Chiu, L.-W. Ko, S.-F. Liang, H.-Y. Hsieh, S.-H. Hsu, J.-R. Duann, Development of Wireless Brain Computer Interface With Embedded Multitask Scheduling and its Application on Real-Time Driver's Drowsiness Detection and Warning, IEEE Trans. Biomed. Eng. 55 (2008) 1582–1591. doi:10.1109/TBME.2008.918566.

[4] J. Andreu-Perez, F. Cao, H. Hagras, G.-Z. Yang, A Self-Adaptive Online Brain Machine Interface of a Humanoid Robot Through a General Type-2 Fuzzy Inference System, IEEE Trans. Fuzzy Syst. 26. (2018) 101-116. doi: 10.1109/TFUZZ.2016.2637403

[5] D. Achanccaray, C. Flores, C. Fonseca, J. Andreu-Perez, A Fuzzy Genetic Algorithm for Optimal Spatial Filter Selection for P300-Based Brain Computer Interfaces, in: 2018 IEEE Int. Conf. Fuzzy Syst., IEEE, 2018: pp. 1–6. doi:10.1109/FUZZ-IEEE.2018.8491676.

[6] Z. Cao, M. Prasad, C.-T. Lin, Estimation of SSVEP-based EEG complexity using inherent fuzzy entropy, in: IEEE Int. Conf. Fuzzy Syst. (FUZZ-IEEE), 2017: pp. 1–5.

[7] J.-T. King, M. Prasad, T. Tsai, Y.-R. Ming, C.-T. Lin, Influence of Time Pressure on Inhibitory Brain Control During Emergency Driving, IEEE Trans. Syst. Man, Cybern. Syst. (2018) 1–7. doi:10.1109/TSMC.2018.2850323.

[8] Task Force on Computational Intelligence and Fuzzy Modelling in Neural Engineering. https://sites.google.com/view/fuzzy-neural-engineering/home (accessed January 25, 2019).

[9] Apache Spark™ - Unified Analytics Engine for Big Data. http://spark.apache.org/ (accessed January 26, 2019).