Abstract

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I. What

1) Extreme learning machines (ELMs) have proven to be efficient and effective learning mechanisms for pattern classification and regression. [1]
2) Extreme learning machine (ELM), which was originally proposed for generalized single-hidden layer feedforward neural networks (SLFNs), provides efficient unified learning solutions for the applications of feature learning, clustering, regression and classification. [2]
3) Machine learning and artifi cial intelligence have seemingly never been as critical and important to real-life applications as they are in todays autonomous, big data era.[3]
4) Consequently, ELMs, which can be biologically inspired, offer signifi cant advantages such as fast learning speed, ease of implementation, and minimal human intervention.[3]
5) Modulation type is one of the most important characteristics used in signal waveform identification and classification. [4]
6) Spatial correlation is a crucial factor for practical multiple-input multiple-output (MIMO) systems. [4]

II. Contrast

1) However, the performance of IPSs suffers from noisy measurements. In this paper, two kinds of robust extreme learning machines (RELMs), corresponding to the close-to-mean constraint, and the smallresidual constraint, have been proposed to address the issue of noisy measurements in IPSs. [5]
2) However, ELMs are primarily applied to supervised learning problems. Only a few existing research papers have used ELMs to explore unlabeled data. In this paper, we extend ELMs for both semi-supervised and unsupervised tasks based on the manifold regularization, thus greatly expanding the applicability of ELMs. [1]
3) Different from the common understanding and tenet that hidden neurons of neural networks need to be iteratively adjusted during training stage, ELM theories show that hidden neurons are important but need not be iteratively tuned. [2]
4) In contrast to deep networks, MLELM doesnt require fine-tuning.[3]

III. History

1) The recently developed local learning methods provide a remedy by partitioning the feature space into a number of clusters and learning a simple local model for each cluster. [6]

IV. Our Work

1) This paper studies the general architecture of locally connected ELM, showing that: 1) ELM theories are naturally valid for local connections, thus introducing local receptive fields to the input layer; 2) each hidden node in ELM can be a combination of several hidden nodes (a subnetwork), which is also consistent with ELM theories.[2]

V. Experimental Results

1) Simulations and real-world indoor localization experiments are **extensively carried out** and the results demonstrate that the proposed algorithms can not only improve the accuracy and repeatability, but also reduce the deviation and worst case error of IPSs compared with other baseline algorithms. [5]
2) Experimental results demonstrate that the proposed method can use much less local models and time to achieve comparable or superior results to state-of-the-art SISR methods, providing a highly practical solution to real applications. [6]
3) Experimental results on the NORB dataset, a benchmark for object recognition, show that compared with conventional deep learning solutions, the proposed local receptive fields based ELM (ELM-LRF) reduces the error rate from 6.5% to 2.7% and increases the learning speed up to 200 times.[2]

REFERENCES

[1] G. Huang, S. Song, J. N. Gupta, and C. Wu, “Semi-supervised and unsupervised extreme learning machines.” *IEEE Transactions on Cybernetics*, vol. 44, no. 12, pp. 1–1, 2014. 1

[2] G. B. Huang, Z. Bai, L. L. C. Kasun, and M. V. Chi, “Local receptive fields based extreme learning machine,” *IEEE Computational Intelligence Magazine*, vol. 10, no. 2, pp. 18–29, 2015. 1

[3] L. L. C. Kasun, H. Zhou, G. B. Huang, and M. V. Chi, “Representational learning with elms for big data,” *Intelligent Systems IEEE*, vol. 28, no. 6, pp. 31–34, 2013. 1

[4] K. Hassan, I. Dayoub, W. Hamouda, C. N. Nzeza, and M. Berbineau, “Blind digital modulation identification for spatially-correlated mimo systems,” *IEEE Transactions on Wireless Communications*, vol. 11, no. 2, pp. 683–693, February 2012. 1

[5] X. Lu, H. Zou, H. Zhou, L. Xie, and G. B. Huang, “Robust extreme learning machine with its application to indoor positioning.” *IEEE Transactions on Cybernetics*, vol. 46, no. 1, pp. 1–1, 2016. 1

[6] K. Zhang, B. Wang, W. Zuo, and H. Zhang, “Joint learning of multiple regressors for single image super-resolution,” *IEEE Signal Processing Letters*, vol. 23, no. 1, pp. 102–106, 2016. 1