Structure Learning and Parameter Learning for Neuro-Fuzzy Model

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ABSTRACT

The typical design steps of neuro-fuzzy inference systems include structure identification and parameter estimation. Structure identification concerns with the partition methods in input and output spaces, the number of fuzzy membership functions, the number of fuzzy rules, and so on. On the other hand, parameter estimation involves determining the parameters of premises and consequents of fuzzy rules. In this thesis, we propose a multi-layered multi-input-multi-output generalized fuzzy inference system (GFIS), which combines the complementary advantages of the Mamdani and TS fuzzy models for applications of system modeling and pattern classification. The algorithms for on-line structure learning and parameter learning are developed to optimize the system performance. There are several novelties in the proposed model. (1). The input space is partitioned by cluster-oriented methods. The clustering approach results in multi-dimensional membership functions (or clusters) and the obtained membership functions are projected to each dimension to form the premise part of fuzzy rules. (2). The consequent part in each rule can represent multiple outputs. Therefore, in classification problems each rule can represent more than one class with different probabilities. The obtained fuzzy classifier can be considered as an extension of the quadratic Bayes classifier that utilizes mixture of models for esti?mating the class conditional densities. (3). The suggested on-line structure learning method can not only determine the number of rules automatically but also merge or reduce unnecessary fuzzy rules. Consequently, the GFIS can decrease computational burden, learn faster, and consume less memory in the stage of parameter estimation. To investigate the efficiency and effectiveness of the proposed model, several benchmark problems involving nonlinear dynamic system identification and pattern classification are carried out. In these applications, the GFIS shows its superiority in terms of parsimonious of rule structure, higher correct clas?sification rate, learning accuracy, fast convergence, and robustness. Furthermore, several practical examples including Synthetic Aperture Radar (SAR) image classification, TRMS control problems, and image denoising, are also illustrated. Key words : Neuro-fuzzy, Structure identification, Parameter estimation, Mamdani model, TS model, Structure and parameter learning

Keywords : Structure Learning ; Parameter Learning ; MIMO ; Twin Rotor MIMO Model ; Image Processing ; Classification

Table of Contents

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