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Hybrid clustering based fuzzy structure for vibration control – Part 1: A novel algorithm for building neuro-fuzzy system

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ABSTRACT

This paper presents a new algorithm for building an adaptive neuro-fuzzy inference system (ANFIS) from a training data set called B-ANFIS. In order to increase accuracy of the model, the following issues are executed. Firstly, a data merging rule is proposed to build and perform a data-clustering strategy. Subsequently, a combination of clustering processes in the input data space and in the joint input–output data space is presented. Crucial reason of this task is to overcome problems related to initialization and contradictory fuzzy rules, which usually happen when building ANFIS. The clustering process in the input data space is accomplished based on a proposed merging-possibilistic clustering (MPC) algorithm. The effectiveness of this process is evaluated to resume a clustering process in the joint input–output data space. The optimal parameters obtained after completion of the clustering process are used to build ANFIS. Simulations based on a numerical data, 'Daily Data of Stock A', and measured data sets of a smart damper are performed to analyze and estimate accuracy. In addition, convergence and robustness of the proposed algorithm are investigated based on both theoretical and testing approaches.

1. Introduction

In design of automotive semi-active suspension, ride comfort and road handling are two crucially important factors which should be taken into account [1]. In order to accomplish this target, magneto-rheological (MR) and electro-rheological (ER) fluids, and intelligent controllers are actively researched and utilized. MR and ER fluids are smart fluids which characterize to be fast response, insensitivity to temperature fluctuation and to fluid impurity, and wide control bandwidth. It is well-known that the damping force generated by the MR/ER damper depends on the applied current/voltage, the relative velocity and gap between the piston and housing cylinder of the damper. Among these variables only the applied current/voltage can be controlled to adjust the damping force. Hence the semi-active suspension system featuring MR/ER fluid (the MR/ER suspension system) can be indirectly controlled via the input current/voltage [2]. Recently, to build intelligent controllers, fuzzy inference systems (FIS), neural networks (NN) or ANFIS have been effectively adopted. In this present work, a new approach on using ANFIS to design the controller for the semi-active MR seat suspension system is proposed. This research is separated into two parts. The first part is related to building a new ANFIS which is suitable for

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Nomenclature

$a_j^{(.)}, j=0,\ldots,n$ coefficients of the hyper-plane $A^{(.)}$
$B=[b_1, b_2, \ldots, b_M]$ center vector of data clusters
b_i center of the ith cluster
D distance square between two farthest data points in the biggest data cluster
$D_i^{(s)}$ average distance from ith data point to M hyper-planes at the sth loop
$d_{ij}^{(s)}$ distance between the ith and jth data points at the sth loop
$d_{\max}$ maximum distance between max and min vertexes in each hyperbox
E_m argument set of the merged clusters
$[E]$ accepted error
G argument set of data clusters being considered to merge
HB_t the tth hyperbox
J object function
M number of data cluster classes, or number of fuzzy-set classes
M_0 the initialization of M
n dimension number of the input data space
P data sample number of the training data set
$pHB_h^{(m)}$ the hth pure hyperbox labeled m
Q_k set of data samples belonging to the kth cluster
$R=\{R_1, R_2, \ldots, R_M\}$ density set
R_i data sample density around the ith cluster center
r^2 correlation coefficient matrix
T_t data sample set to be covered by the tth hyperbox
T_Σ training data set
$U^{(s)}$ distributive matrix $(M \times P)$ of the data space at the sth loop
$(\overline{x}_i,\ y_i)$ the ith input–output data sample of the data set
$\overline{x}_i=[x_{i1}, x_{i2}, \ldots, x_{in}]$ the ith input vector of the data set
y_i the ith output of the data set
$\hat{y}_i$ the ith output of the NF system
η adaptive coefficient
ρ merging coefficient
γ square of the distance between two farthest data points in the data set
$\mu_{B_{kh}}(\overline{x}_i)$ membership value of $\overline{x}_i$ in the hth k-labeled hyperbox, B_{kh}
$\mu_{B_k}(\overline{x}_i)$ max-membership value of $\overline{x}_i$ in the group of k-labeled hyperboxes, B_k
μ_{ij} membership value of the jth data sample in the ith cluster
$\overline{\omega}f$ max-vertex of a fusion hyperbox
$\overline{\omega}_{kh}=[\omega_{kh1}, \ldots, \omega_{khn}]$ max-vertex of the B_{kh}
$\overline{v}f$ min-vertex of a fusion hyperbox
$\overline{v}_{kh}=[v_{kh1}, \ldots, v_{khn}]$ min-vertex of the B_{kh}

the semi-active MR seat suspension system, while the second part focuses on designing the controller for the semi-active MR seat suspension system based on the built ANFIS and evaluating the semi-active suspension performance.

ANFIS, a type of artificial intelligence, can deliver effectively solutions to problems which are difficult or impossible to be performed by conventional linear methods. This mathematical model can provide crucial tools in identifying and control based on mapping completely functional relationships between independent and dependent variables [3–5]. In order to build ANFIS, the FIS can be appropriately incorporated with a NN to build an optimal fuzzy logic structure [6–8]. In other words, the fuzzy system provides a solution to deduce imprecise information from collected data set, while the NN uses the remembering capability and learning ability to enhance effectiveness of the solution. Based on a learning process, parameters of the fuzzy system such as membership functions and fuzzy rules are adaptively adjusted [6].

When designing an ANFIS from a data set, the clustering process has been acknowledged as a powerful tool to analyze data and to build the system structure [9]. The goal of the clustering process is generally to find the fuzzy sets sharing the same features or characteristics. In this process, the data set is separated to find natural groups, in which each group includes only common feature data samples [10]. To build these clusters, a clustering strategy can be performed in the input data space only [11–12], or in the joint input–output data space [7–8]. Reality shows that clustering in the joint input–output data space reflects better relationship between input data space and output data space [7,8,13,14]. Besides, accuracy of the model is also influenced by initialization [15]. To deal with this issue, Yang et al. [15] proposed an automatic merging possibilistic clustering method (AM-PCM). By this way, at the beginning time of the clustering process, all data points of the training data set are considered as initial cluster centers. After that, surrounding points around each cluster are surveyed to merge together automatically. Based on a robust strategy, a cluster-data space could be automatically established from the training data set. This method could surmount problems related to parameter-selection and initialization. However, in this method, the clustering strategy considers the input data space only. As abovementioned, the clustering in the input data space only is sometimes unsatisfactory. In practice, satisfactory data distribution in the input space may not be guaranteed for a similar distribution status in the output space. Therefore, if the separated clusters based on only the input data space is used to build fuzzy rules, deducing result of the FIS becomes unsatisfactory. The reason is that there could be contradictory rules having similar premises. This problem can be resolved (refer to Section 3 in this work).

Consequently, in this paper a new algorithm for building ANFIS named B-ANFIS is proposed, in which problems related to initialization and the contradictory fuzzy rules are considered in order to improve model accuracy. Firstly, in order to build and perform a data-clustering strategy, a data merging rule in the input data space is proposed. Subsequently, to build fuzzy sets expressing more appropriately characteristics of the data space, a hybrid clustering solution for the joint input–output data space is presented. Hence, building ANFIS based on the B-ANFIS can be separated into two phases. In the first phase,