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Adaptive displacement online control of shape memory alloys actuator based on neural networks and hybrid differential evolution algorithm

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ABSTRACT

Shape memory alloys (SMAs) are smart metallic materials, which have the ability to recover their shape when heated, even under high-applied load and large inelastic deformation. This characteristic helps SMA provide an interesting alternative to replace conventional actuator. This paper proposes an adaptive online displacement control of an SMA actuator that is created by combining an adaptive feed-forward neural networks (AFNNs) model and a PID feedback controller to increase the accuracy and to eliminate the steady state error in displacement position control process of the SMA actuator. The AFNN model, which is created by combining a multi-layers perceptron neural networks (MLPNNs) structure and an auto regressive with exogenous input (ARX) model, is used for modeling and identifying the hysteresis inverse model of the SMA actuator. Then, a new hybrid differential evolution (HDE) algorithm, which is a combination between a traditional differential evolution algorithm and a back-propagation algorithm, is used to optimally generate the best weights of the AFNN model. Due to the offline identification, the proposed adaptive online displacement control can learn the hysteresis behavior of the SMA actuator in advance and then provide online control signal efficiently. Consequently, the displacement of SMA actuator is controlled robustly and more precisely.

1. Introduction

Shape memory alloys (SMA) are smart metallic materials, which have the ability to recover their original shape when heated, even under high-applied load and large inelastic deformation. A shape memory effect that is a highly nonlinear hysteresis phenomenon, occurs due to temperature and stress in the crystal structure between two different phases called austenite and martensite. Austenite is a crystal structure change at high temperature phase and martensite is a crystal structure change at low temperature phase. This phenomenon helps SMA become a potential choice of the actuator that provides an interesting alternative to the conventional actuator. Although the shape memory alloys have been recently used in many applications such as biomedical engineering [1], aerospace applications [2,3], automotive applications [4], robotic applications [5,6] and other fields, the hysteresis behavior of SMA makes it a challenge in modeling and obtaining high control performance.

In order to model and simulate the hysteresis behavior, some mathematical models have been investigated. Some research works such as the Jiles–Atherton model of ferromagnetic hysteresis [7], Preisach operator [8–10], Krasnosel'skii–Pokrovskii (KP) operator [11], and Prandtl–Ishlinskii (PI) operator [12] used physical-based model for developing different hysteresis behavior. However, all proposed models comprised many parameters which were not constant and changed depending on the working conditions. To overcome this drawback, identification based on experimental input–output data of the hysteresis behavior is an ongoing research.

Recently, the neural networks (NN) have been considered as a promising approach for identifying the nonlinear system. Studies in [13,14] indicated that the neural networks could be used effectively in identifying and controlling the nonlinear system. Thees studies proposed static and dynamic back-propagation (BP) algorithm to optimally generate the weights of neural networks (BP-NN) and to adjust the parameters. Kardan et al. [15] introduced a proposed recursive neural network structure for modeling the hysteresis behavior of an SMA spring. The experimental input–output data that was composed of the applied voltage and spring force, was used for an estimation and validation process. Wang et al. [16] introduced the proposed Jordan-plus-Elman NARX neural network model to estimate the hysteresis behavior of an ultra-thin SMA wire. Summarily, back-propagation algorithm was a popular algorithm to solve the nonlinear system identification. However, the back-propagation algorithm easily performs local

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search around the initial values and provides local optimum in studies [17,18]. To overcome this drawback, many researchers proposed evolution algorithms (EAs) to optimize the traditional BP-NN.

Recently, the evolution algorithmsbecame popular for finding the optimal solution of complex optimization problems. These EAs provided global optimum due to their capability of exploring the global solution space without trapping at a local optimum. Like evolutionary algorithms, differential evolution (DE) algorithm was considered as a powerful stochastic global optimization technique. The DE algorithm emerged as a very competitive form of evolutionary computing when the first published article on DE appeared as a technical report of R. Storn and K. V. Price in 1995 [19]. The DE algorithm was capable of handling non-differentiable, nonlinear, and multimodal objective functions. Its simplicity and straightforwardness in implementation, excellent performance, involving fewer parameters , and low space complexity, made DE as one of the most powerful tools in the field of optimization. Vesterstrom et al. [20] evaluated the performance of DE, PSO and EAs on 34 widely used benchmark problems. Karaboga et al. [21] applied the DE algorithm to the design of digital FIR filters and compared its performance to the genetic algorithm. The results from these studies showed that the DE algorithm performed better than the other algorithms. The DE algorithm had been used to train a neural network model through optimizing real and constrained integer weights. Paper [22–28] successfully developed a DE-based trained neural network. Thus, these papers demonstrated that the DE algorithm could be effectively used for training neural network models applied in versatile applications. However, DE has some drawbacks as all other evolutionary techniques, [29–31]. Firstly, DE has a good global search ability to obtain the global optimal, but it is slow at the exploitation of the solution. Secondly, DE has a slow convergence rate for high-dimensional optimization problems. Finally, DE has a possibility of stagnation phenomenon that is a state in which the optimum seeking process stagnates before finding a globally optimal solution. Due to these drawbacks, the traditional DE algorithm has a slow convergence rate and slow precision preventing its application in many areas. To overcome these drawbacks, the hybrid differential evolution algorithm based on the advantages of differential evolution and a gradient descent method has been of interest in the research. Krzysztof et al. [32] and Lee et al. [33] proposed to train the neural networks based on combining differential evolution with the gradient descent method. At each generation, the mutation and recombination created a new individual. This new individual was adapted by the gradient descent optimization methods before implementing the next generation. The experimental results showed that the hybrid algorithm had better performance and faster convergence than the differential evolution or other gradient descent methods.

In order to control the nonlinear hysteresis SMA actuator, the tracking control method has been investigated. In general, the tracking control can be classified into two main approaches, open-loop control without output feedback and close-loop control with output feedback. In some applications, open-loop control is used because of its simplicity and ease to design the tracking control of the SMA actuator. For this purpose, the hysteresis inverse model of the SMA actuator, which is identified for the application of the feed-forward controller, is used for providing the appropriate control input for compensating the hysteresis behavior of the SMA actuator. Song et al. [34] proposed an open-loop control based on neural network inverse model for the tracking control of the SMA wire actuator. Rosenbaum et al. [35] proposed an inverse Preisach model based feed-forward control for accurate control of an electromagnetic actuator. Gu et al. [36] proposed a modified Prandtl–Ishlinskii inverse model based on open-loop compensation control for a piezoceramic actuator. However, the performance of the feed-forward controller depends on the accuracy of the hysteresis inverse model. In addition, if the hysteresis inverse model of SMA actuator is sensitive to environmental disturbances then offline identification of hysteresis parameters results in inaccurate estimation. To improve the tracking error related to hysteresis inverse model, a combination of feed-forward and feedback controller is developed. Sayyaadi et al. [37] proposed the feed-forward feedback controller based on the generalized Prandtl–Ishlinskii inverse model and a conventional proportional–integral feedback controller for controlling the tip deflection of a large deflected flexible beam actuated by an SMA actuator wire. Song et al. [38] introduced a new approach to control the SMA actuator using a neural feed-forward controller for reducing the hysteresis and a sliding mode based feedback controller for compensating uncertainties. Asua et al. [39] proposed nonlinear control methods using the hysteresis inverse model inserted in a proportional integral with an anti-windup control loop. The hysteresis inverse model was obtained by a linear phase shift approximation and by training the neural networks.

In this paper, the proposed adaptive online displacement control of SMA actuator is created by combining an adaptive feed-forward neural networks (AFNN) model and a PID feedback controller to increase the accuracy and eliminate the steady state error in displacement position control process of the SMA actuator. The AFNN model, which is created by combining the multi-layers perceptron neural network (MLPNN) structure and auto regressive with exogenous input (ARX) model, is used for modeling and identifying the hysteresis inverse model of the SMA actuator. Hence, the proposed AFNN model possesses a powerful approximating characteristic of the MLPNN model and a strong predictive characteristic of the ARX model. Then, a new hybrid differential evolution (HDE) algorithm, which is a combination between a traditional differential evolution algorithm, and back-propagation algorithm, is used to optimally generate the best weights of the AFNN model. Due to the offline identification, the proposed

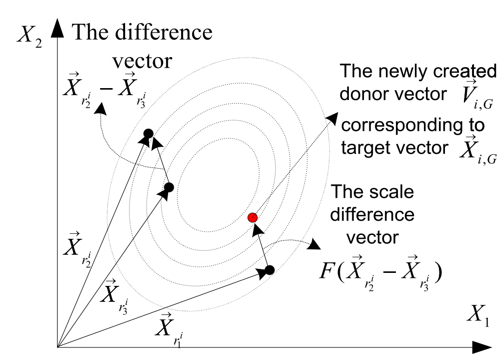

Fig. 2. DE mutation scheme in 2-D parametric space.

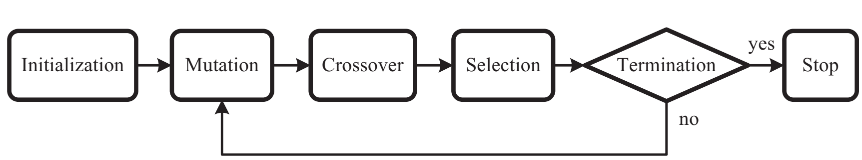

Fig. 1. The main stages of the DE algorithm.