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Intelligent identification for Magneto-Rheological Damper

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Abstract:

In this paper, the proposed annealing robust radial basis function networks based on ν support vector regression (ν -SVR) to identify Magneto-Rheological Damper. When the radial basis function networks are used for the identification of the nonlinear dynamic system, the number of hidden nodes, the initial parameters of the kernel, and the initial weights of the network must be determined first, a ν -SVR method is proposed to solve the initial problem of radial basis function networks. That is, the SVR uses the quadratic programming optimization to determine the initial structure of the radial basis function networks. And then the proposed annealing robust radial basis function networks are trained by the annealing robust algorithm. Simulation results show the superiority of the proposed method.

Keywords: support vector regression; annealing robust learning algorithm; Magneto-Rheological Damper

1. Introduction

Magneto-rheological (MR) damper is filled with MR fluid, it is covered with coil outside piston to change magnetic field, can make MR fluid change from liquid state to semi-solid fast. With structure simplicity, low power requirement, large force capacity, and high dynamic range. MR damper attracts attentions as developed semi-active control devices for structural control applications recently. In order to describe the performance of the MR damper, Spencer et al. [1] proposed a phenomenological model based on a Bouc-Wen model.

Chang et al. [2] , Chang et al. [3] , Du et al. [4] and C. N. Ko et al. [5] developed a neural network model for the MR damper systems. Zhou and Chang [6] proposed an adaptive fuzzy control the MR damper. C. N. Ko et al. [7] proposes robust fuzzy neural networks to identify MR damper. Chen et al. [8] by annealing robust fuzzy neural networks identify of nonlinear MR damper with outliers.

Radial basis function networks with one hidden layer and rapid convergence speed is used to various applications such as system identification, time series prediction, function approximation [9-11]. But the number of hidden nodes, the initial parameters of the kernel and the initial weights of the networks not decided mathematically yet. Besides, the data we obtained sometimes contain the error measurements due to data censored. How to decide the initial structure of radial basis function networks under censored data.

Support vector regression method is a set of input and output samples used to approximate an unknown function. The ν -support vector regression is proposed by Schölkopf, Smola, Williamson and Bartlett [12], a new parameter ν is used to control the number of support vectors and training errors.

In this article, the purpose is to identify the Magneto-Rheological Damper. First, a ν support vector regression is used to determine the number of hidden nodes, the initial parameters of the kernel, and the initial weights of the radial basis function networks. Then the algorithm is applied to tune the parameters of radial basis functions and the synaptic weights. It is expected that the proposed method has fast convergence speed and the ability to identify Magneto-Rheological Damper perfectly.

2. The structure of proposed method

2.1 Radial basis function networks (RBFNs)

The structure of the RBFNs consists of an input layer, a hidden layer of radial basis functions and a linear output layer. When the radial basis functions are chosen as Gaussian functions, the RBFNs can be expressed in the form

$$\hat{y}_j(t+1) = \sum_{i=0}^{L} w_{ij} \exp\left(-\frac{\|\boldsymbol{x}-\boldsymbol{m}_i\|^2}{2\sigma_i^2}\right), \tag{1}$$

where $\hat{y}_j$ is the jth output, $\boldsymbol{x}$ is the input to the neural networks, $w_{ij}, 0 \le i \le L, 1 \le j \le p,$ are the synaptic weights, $\boldsymbol{m}_i, 0 \le i \le L,$ and $\sigma_i, 0 \le i \le L,$ are the centers and the widths of Gaussian functions respectively, and L is the number of the Gaussian functions, in which we can find that L also denotes the number of hidden nodes.

2.2 ν support vector regression

An SVR method is a set of (input, output) samples $\{(\boldsymbol{x}_i, y_i), i = 1, \cdots, N\}$ used to approximate an unknown function. Suppose that a set of basis functions $\{g(\boldsymbol{x_k})\}_{k=1}^{N}$ is given, there exists a family of functions that can be expressed as a linear expansion of the basis functions. The topic is then be changed into finding the parameters of the following basis linear expansion

$$f(\boldsymbol{x}, \boldsymbol{\theta}) = \sum_{k=1}^{N} \theta_k g(\boldsymbol{x_k}) + b\,, \tag{2}$$

where $\boldsymbol{\theta} = (\theta_1, \theta_2, \cdots, \theta_m)$ is a parameter vector to be identified and b is a constant to be found. The ν -support vector regression is proposed by Schölkopf, Smola, Williamson and Bartlett [12], which can control the number of support vectors and training errors. The problem is to find the parameters $\nu\ (0 \le \nu \le 1)$ and C to optimize the dual problem

Minimize

$$Q(\alpha,\alpha^*) = \frac{1}{2}\sum_{r,s=1}^{N}(\alpha_r^* - \alpha_r)(\alpha_s^* - \alpha_s)[\sum_{k=1}^{m} g_k(\boldsymbol{x}_r) g_k(\boldsymbol{x}_s)] - \sum_{r=1}^{N} y_r(\alpha_r - \alpha_r^*), \quad (3)$$

subject to the constraint

$$\sum_{r=1}^{N}\alpha_r^* = \sum_{r=1}^{N}\alpha_r\ , \quad (4)$$

$$0 \le \alpha_r^* \le \frac{C}{N},\ r = 1,\cdots,N\ , \quad (5)$$

$$\sum_{r=1}^{N}(\alpha_r + \alpha_r^*) \le C\cdot\nu. \quad (6)$$

It proposed by Vapnik [13] and Smola et al. [14] and the inner product of basis function $\langle g(\boldsymbol{x}_r)\cdot g(\boldsymbol{x}_s)\rangle$ is replaced via the kernel function

$$K(\boldsymbol{x}_r,\boldsymbol{x}_s) = \sum_{k=1}^{m} g_k(\boldsymbol{x}_r) g_k(\boldsymbol{x}_s). \quad (7)$$

The solution of the approach is in the form of the following linear expansion of kernel function

$$f(\boldsymbol{x},\alpha,\alpha^*) = \sum_{k=1}^{N}(\alpha_k^* - \alpha_k)K(\boldsymbol{x},\boldsymbol{x}_k) + b. \quad (8)$$

This means that the parameter θ_k in equation (2) can be represented as $\sum_{k=1}^{m}(\alpha_k^* - \alpha_k)g(\boldsymbol{x}_k)$. Note that only some of $(\alpha_k^* - \alpha_k)$'s are not zeros and the corresponding vectors $\boldsymbol{x}_k$'s are called support vectors (SVs). In this paper, the Gaussian function is used as the kernel function. hence, (8) can be rewritten as

$$f_S(\boldsymbol{x},\lambda) = \sum_{k=0}^{\#SV}\lambda_k \exp(-\frac{\|\boldsymbol{x}-\boldsymbol{x}_k\|^2}{2\sigma_k^2})\ , \quad (9)$$

where $\#SV$ is the number of SVs, $\lambda_k = (\alpha_k^* - \alpha_k) \ne 0$ and $\boldsymbol{x}_k$ are SVs.

From equation (1) and (9), $L, i, w_{ij}, \boldsymbol{m}_i$ and σ_i in (1) can be regarded as the $\#SV$, k, λ_k, $\boldsymbol{x}_k$ and σ_k in (9), respectively. From the above derivation, we can find that the number of hidden nodes L, the initial weights w_{ij}, the initial parameters $\boldsymbol{m}_i$ and σ_i, of the RBFNs are determined via the ν-SVR method.

3. Algorithm for updating parameters

When utilizing the RBFNs for the identification of systems, the goal is to minimize

$$J_N(h) = \frac{1}{N}\sum_{i=1}^{N}\rho[e_k(h);\beta(h)]\ , \quad (10)$$

where

$$e_k(h) = f(k) - \hat{f}_S(\boldsymbol{x}_k), \quad (11)$$

h is the epoch number, $e_k(h)$ is the error between the kth desired output and the kth output of the RBFNs at epoch h and $\rho(\cdot)$ is a logistic loss function and defined as

$$\rho[e_k;\beta] = \frac{\beta}{2}\ln[1 + \frac{(e_k)^2}{\beta}]\ , \quad (12)$$

where $\beta(h)$ is a deterministic annealing schedule acting like the cut-off points. In this paper, the annealing robust learning algorithm is applied to train the proposed RBFNs. In this algorithm, the properties of the annealing schedule $\beta(h)$ have [15]:

(A) β_{intial}, $\beta(h)$ for the first epoch, has large values;

(B) $\beta(h) \to 0^+$ for $h \to \infty$;

(C) $\beta(h) = c/h$ for any h epoch, where c is a constant.

Based on the gradient-descent kind of learning algorithms, the synaptic weights w_{ij}, the centers $\boldsymbol{m}_i$ and the width σ_i of Gaussian function are updated as

$$\Delta w_{ij} = -\eta\frac{\partial J_N}{\partial w_{ij}} = -\eta\sum_{k=1}^{N}\varphi(e_k;\beta)\frac{\partial e_k}{\partial w_{ij}} \quad (13)$$

$$\Delta \boldsymbol{m}_i = -\eta\frac{\partial J_N}{\partial \boldsymbol{m}_i} = -\eta\sum_{k=1}^{N}\varphi(e_k;\beta)\frac{\partial e_k}{\partial \boldsymbol{m}_i} \quad (14)$$

$$\Delta \sigma_i = -\eta\frac{\partial J_N}{\partial \sigma_i} = -\eta\sum_{k=1}^{N}\varphi(e_k;\beta)\frac{\partial e_k}{\partial \sigma_i} \quad (15)$$

$$\varphi(e_k;\beta) = \frac{\partial\rho(e_k;\beta)}{\partial e_k} = \frac{e_k}{1 + (e_k)^2/\beta(h)}, \quad (16)$$

where η is a learning constant.

4. Simulation results

The phenomenological model has been proposed by Spencer et al. [1] to portray the behaviour of a prototype Magneto-Rheological damper. This phenomenological model is based on a Bouc-Wen model, the model as shown in Figure 1, and is governed by the following seven simultaneous equations:

$$F = c_1\dot{y} + k_1(x - x_0), \quad (17)$$

$$\dot{y} = \frac{1}{(c_0 + c_1)}[\alpha z + c_0\mathrm{v} + k_0(x - y)], \quad (18)$$

$$\dot{z} = -\gamma|\mathrm{v} - \dot{y}|z|z|^{n-1} - \beta(\mathrm{v} - \dot{y})|z|^n + A(\mathrm{v} - \dot{y}), \quad (19)$$

$$\alpha = \alpha_a + \alpha_b u, \quad (20)$$

$$c_1 = c_{1_a} + c_{1_b}u, \quad (21)$$

$$c_0 = c_{0_a} + c_{0_b}u, \quad (22)$$

$$\dot{u} = -\eta(u - w), \quad (23)$$

where F is the force generated by the MR damper; x is the displacement of the damper; y is an internal pseudo displacement of the MR damper; u is the output of a first order filter; v is the command voltage sent to the current driver; k_1 is the accumulator stiffness; c_0 and c_1 are the viscous damping coefficients observed at large and low velocities, respectively; k_0 is the gain to control the stiffness at large velocities; x_0 is the initial displacement of spring k_1 associated with the nominal damper force due to the accumulator; γ, β, A are hysteresis parameters for the yield element, and α is the evolutionary coefficient. In this model, there are a total of 14 model parameters $(c_{0_a}, c_{0_b}, k_0, c_{1_a}, c_{1_b}, k_1, x_0, \alpha_a, \alpha_b, \gamma, \beta, n, \eta, A)$ to characterize the MR damper. A set of parameters which is obtained by Spencer et al. [1] to characterize one MR damper using experimental data and a constrained nonlinear optimization algorithm is listed in Table 1. The output F compare with Du et al. [4] conveniently is determined on current displacement $x(t)$, velocity $\dot{x}(t)$, voltage $v(t)$, and past force $F(t-1)$, that is,

$$\hat{F}(t) = \hat{f}(x(t), v(t), w(t), F(t-1)). \tag{24}$$

The data is generated using a sinusoidal displacement function with an amplitude of ± 1 cm and a frequency of 3Hz and a sinusoidal voltage function with mean value of 1.6 V, an amplitude of 0.5V and a frequency of 0.5 Hz. The time duration for this validation data is 4s and the time increment is 0.002s which amounts to a total of 2000 training data sets.

The root mean square error (RMSE) of the training data is used to measure the performance of the proposed networks. The RMSE is defined as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(f_i - \hat{f}_i)^2}{N}}, \tag{25}$$

where f_i is the desired output and $\hat{f}_i$ is the output of the proposed method. The implementation of SVR is carried out using the software LIBSVM [16].

The parameters in ν-SVR are set as C=1, the Gaussian kernel function with $\nu = 0.02$, $\sigma = 1$, with the hidden nodes (i.e. the number of SVs) is obtained as 268. Based on the initial structure and the learning constant is 0.1, after 1000 epochs training, the initial and final results under the training data sets for $F(t)$ are shown in Figure 2, Figure 3, respectively, and the final RMSE is 0.0036.

In order to provide a direct estimation of the voltage that is required to produce a target control force calculated from some optimal control algorithms. The output $v(t)$ of the inverse model compare with Du et al. [4] conveniently is determined on current displacement $x(t)$, velocity $\dot{x}(t)$, force $F(t)$, and past voltage $v(t-1)$, that is,

$$\hat{v}(t) = \hat{g}(x(t), \dot{x}(t), F(t), v(t-1)). \tag{26}$$

The parameters in ν-SVR are set as C=6, the Gaussian kernel function with $\nu = 0.001$, $\sigma = 0.5$, with the hidden nodes (i.e. the number of SVs) is obtained as 182. Based on the initial structure and the learning constant is 0.05, after 2000 epochs training, the initial and final results under the training data sets for $v(t)$ are shown in Figure 4, Figure 5, respectively, and the final RMSE is 0.0035.

5. Conclusions

In this article, an initial structure of ν support vector regression based radial basis function networks is established. We utilize the ν-SVR approach to determine the number of hidden nodes, the initial parameters of the kernel and the initial weights of the proposed radial basis function networks firstly. Then the annealing robust learning algorithm is applied to tunes the parameters of the kernel and the weights of the Magneto-Rheological Damper. From the result indicated that the proposed method can be used as a feasible technique for the identification of Magneto-Rheological Damper.

6. References

[1] B. F. Spencer Jr., S. J. Dyke, M. K. Sain, and J. D. Carlson, "Phenomenological model for magnetorheological dampers," *Journal of Engineering Mechanics*, vol. 123, no. 3, pp. 230–238 (1997).

[2] C. C. Chang and P. Roschke, "Neural network modeling of a magnetorheological damper," *Journal of Intelligent Material Systems and Structures*, vol. 9, no. 9, pp. 755–764 (1998).

[3] C. C. Chang and L. Zhou, "Neural network emulation of inverse dynamics for a magnetorheological damper," *Journal of Structural Engineering*, vol. 128, no. 2, pp. 231–239 (2002).

[4] H. Du, J. Lam, and N. Zhang, "Modelling of a magneto-rheological damper by evolving radial basis function networks," *Engineering Applications of Artificial Intelligence*, vol. 19, pp. 869–881 (2006).

[5] C. N. Ko, G. Y. Liu, Y. Y. Fu, and P. Y. Chen, "Adaptive learning neural networks for system identification of a magneto-rheological damper," The Eighteenth International Symposium on Artificial Life and Robotics, Daejeon Convention Center, Daejeon, Korea, January 30-February 1 (2013).

[6] L. Zhou and C. C. Chang, "Adaptive fuzzy control for nonlinear building - magnetorheological damper system," *Journal of Structural Engineering*, vol. 129, no. 7, pp. 905–913 (2003).

[7] C. N. Ko, Y. Y. Fu and S. C. Chen, "Identification of a Magneto-Rheological Damper System Using Fuzzy Neural Networks with Time-Varying Learning Algorithm," 中華民國第二十屆模糊理論及其應用研討會. pp. 140–145, 國立中興大學. (2012).

[8] P.Y. Chen, Y.Y. Fu, K. L. Su, and J. T. Jeng, "ARFNNs under Different Types SVR for Identification of Nonlinear Magneto-Rheological Damper Systems with Outliers," *International Journal of Fuzzy Systems*, vol. 12, no. 4, pp. 311-320 (2010).

[9] Y.Y. Fu, C.J. Wu, C.N. Ko, and J.T. Jeng, "Radial

basis function networks with hybrid learning for system identification with outliers", *Applied Soft Computing*, 11, pp.3083–3092 (2011).

[10] Y.Y. Fu, C.J. Wu, C.N. Ko, J.T. Jeng, and L.C. Lai, "ARRBFNs with SVR for prediction of chaotic time series with outliers", *Artif Life Robotics*, 14, pp.29–33 (2009).

[11] Y. Y. Fu, C. J. Wu, J. T. Jeng, and C. N. Ko, "Annealing Robust Radial Basis Function Networks with Support Vector Regression for Nonlinear Inverse System Identification with Outliers", *Journal of Vibration and Control*, 16(13), pp. 1915–1940 (2010).

[12] B. Scholkopf, A. J. Smola, R. C. Williamson, and P. L. Bartlett, "New support vector algorithms," *Neural Computation*, 12, pp. 1207–1245 (2000).

[13] V. Vapnik, "The Nature of Statistical Learning Theory", *Springer*, Berlin (1995).

[14] A.J. Smola, B. Schölkopf, "From regularization operators to support vector kernels", *Neural Inf. Process System*, 10, pp.343–349 (1998).

[15] C.C. Chuang, S.F. Su, and C.C. Hsiao, "The annealing robust backpropagation (BP) learning algorithm", *IEEE Trans. Neural Networks* 11(5), pp. 1067–1077 (2000).

[16] C. C. Chang and C. J. Lin, LIBSVM: A library for support vector machines, Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm, (2007).

Table 1. Parameters for an MR damper

Parameter	Value
c_{0_a}	$21.0 Ns/cm$
c_{0_b}	$3.50 Ns/cm\ V$
k_0	$46.9 N/cm$
c_{1_a}	$283 Ns/cm$
c_{1_b}	$2.95 Ns/cm\ V$
k_1	$5.00 N/cm$
x_0	$14.3 cm$
α_a	$140 N/cm$
α_b	$695 N/cm\ V$
γ	$363\ cm^{-2}$
β	$363\ cm^{-2}$
n	2
η	$190\ s^{-1}$
A	301

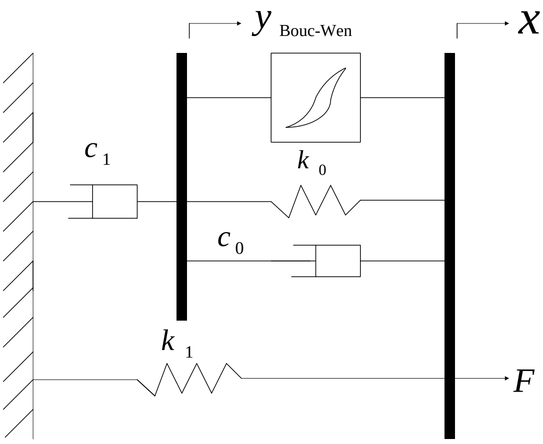

Figure 1. Phenomenological model of MR damper.

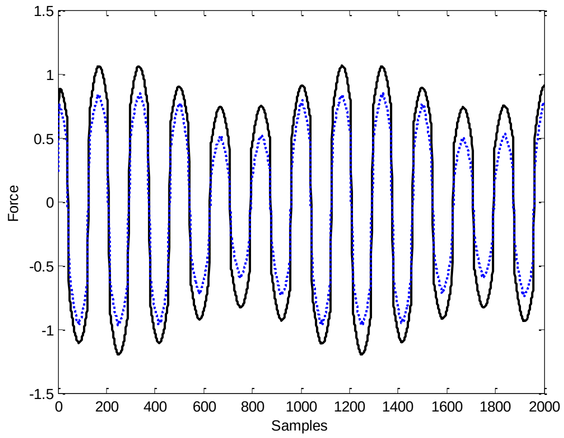

Figure 2. The initial result for force before training.

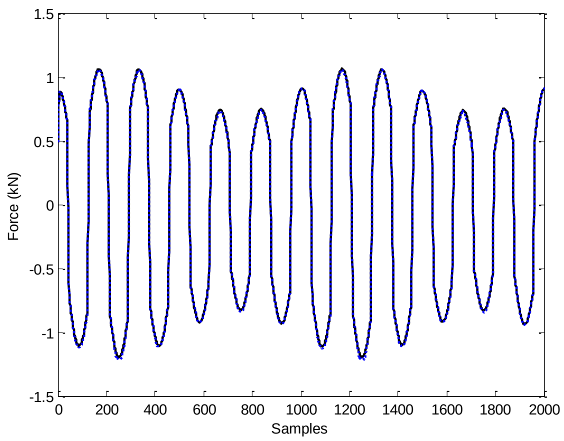

Figure 3. The final result for force after training.

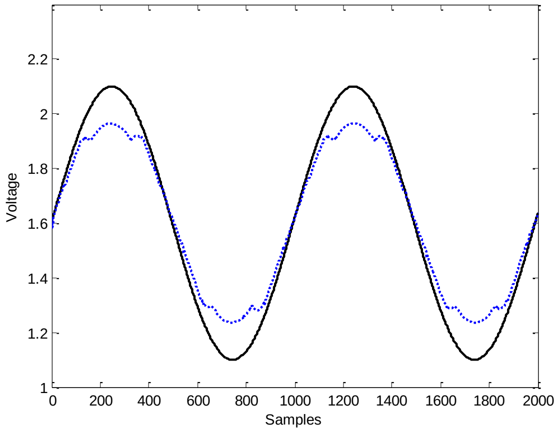

Figure 4. The initial result for voltage before training.

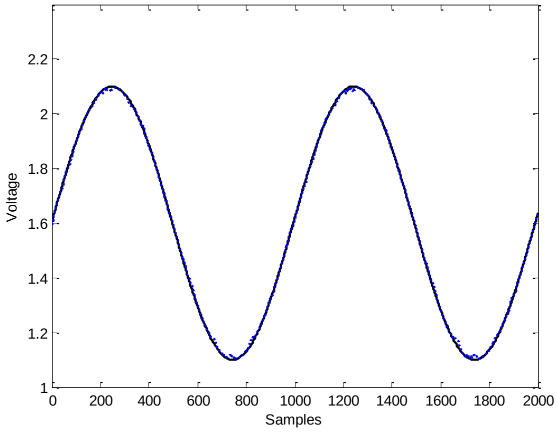

Figure 5. The final result for voltage after training.