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Research Article

Application of Support Vector Machine-Based Semiactive Control for Seismic Protection of Structures with Magnetorheological Dampers

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Based on recent research by Li and Liu in 2011, this paper proposes the application of support vector machine- (SVM-) based semiactive control methodology for seismic protection of structures with magnetorheological (MR) dampers. An important and challenging task of designing the MR dampers is to develop an effective semiactive control strategy that can fully exploit the capabilities of MR dampers. However, amplification of the local acceleration response of structures exists in the widely used semiactive control strategies, namely "Switch" control strategies. Then the SVM-based semiactive control strategy has been employed to design MR dampers. Firstly, the LQR controller for the numerical model of a multistory structure formulated using the dynamic dense method is constructed by using the classic LQR control theory. Secondly, an SVM model which comprises the observers and controllers in the control system is designed and trained to emulate the performance of the LQR controller. Finally, an online autofeedback semiactive control strategy is developed by resorting to SVM and then used for designing MR dampers. Simulation results show that the MR dampers utilizing the SVM-based semiactive control algorithm, which eliminates the local acceleration amplification phenomenon, can remarkably reduce the displacement, velocity, and acceleration responses of the structure.

1. Introduction

Reducing structural seismic responses, without doubt, can remarkably enhance the buildings' security. Researches are attaching much more importance on resisting the disasters due to earthquakes, after several latest big earthquakes in the world, especially the Wen-chuan great earthquake in China. The application of protective systems to mitigate the effects of seismic loads on civil engineering structures offers a promising alternative to traditional earthquake resistant design approaches. Various types of passive, active, and semiactive devices have been studied extensively by many researchers.

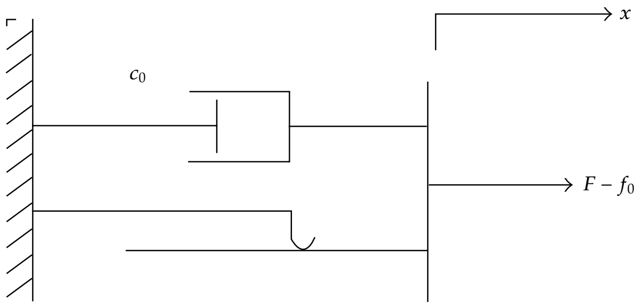

Figure 1: Bingham model of MR damper.

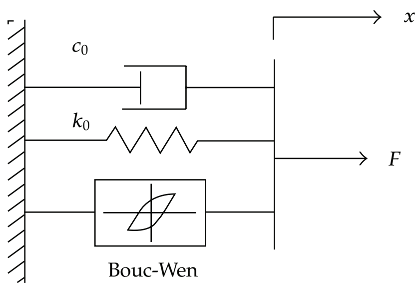

Figure 2: Bouc-Wen model of MR damper.

Passive supplemental damping strategies, including base isolation systems, viscoelastic dampers, and tuned mass dampers, are well understood and widely accepted by the engineering community as a means for mitigating the effects of dynamic loading on structures. But, these passive devices are unable to adapt to structural changes and to varying usage patterns and loading conditions [1]. It is well known that active control has the advantage of being adaptable to real-time external excitations. Nevertheless, there exist a number of serious challenges before active control can gain general acceptance by both the engineering and construction professions. If the active control system is taken into account, then a large control force must be created and the power limitation of actuator prevents this system from being implemented in actual buildings. Naturally, at current stage of structural vibration control, the semiactive control with both low power and low cost seems to be the most promising schemes for seismic protection of structures [2, 3]. Studies have shown that appropriately implemented semiactive damping systems significantly perform better than passive devices and have the potential to achieve, or even surpass, the performance of fully active systems, thus allowing for the possibility of effective response reduction during both moderate and strong seismic activity.

Among all the semiactive control devices, the magnetorheological (MR) damper is a kind of intelligent and effective semiactive control device for its attractive characteristics in applications of civil engineering, including high strength, insensitivity to contamination, and small power requirement, and can be viewed as fail-safe in that it becomes a passive damper in the case of control hardware malfunction. This device overcomes many of the expenses and technical difficulties associated with semiactive devices previously considered. Another important and challenging task of the semiactive control system design is to develop a semiactive control strategy that is implementable and can fully utilize the capability of the

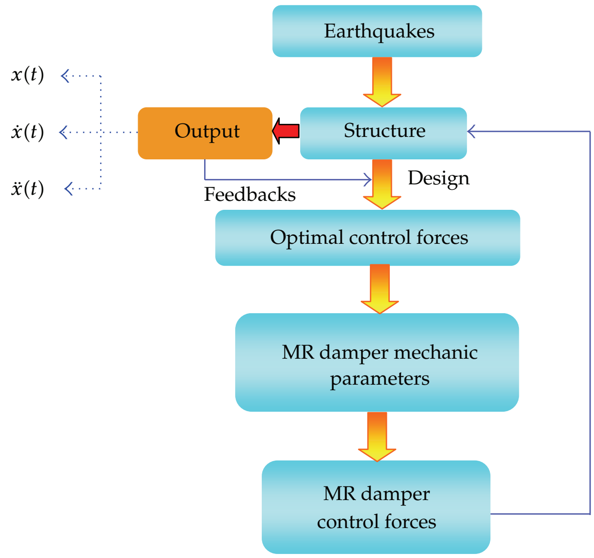

Figure 3: Flow diagram of semiactive control for structures with the MR dampers.

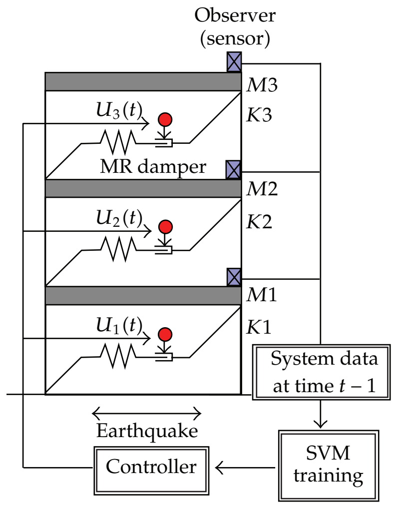

Figure 4: Structural semiactive control system with SVM control strategy.

MR damper. Nowadays, there has been growing trend toward both the application research and utilization of the MR dampers, such as Hyung et al., 2009 [4]; Bitaraf et al., 2010 [5]; K-Karamodin and H-Kazemi, 2010 [6]; Kori and Jangid, 2009 [7].

However, amplification of the local acceleration response of structures exists in the widely used semiactive control strategies, namely, "Switch" control strategies. To solve these problems, in this paper, a support vector machine (SVM) technique is introduced into the semiactive control of structure with MR dampers. SVM is a promising statistical learning theory developed by Vapnik [8]. As far as the neural network (NN) is concerned, the local minimum point, over learning, and the excessive dependence on experience in the choice of architectures and types are its inevitable limitations [9]. Whereas SVM gets rid of these

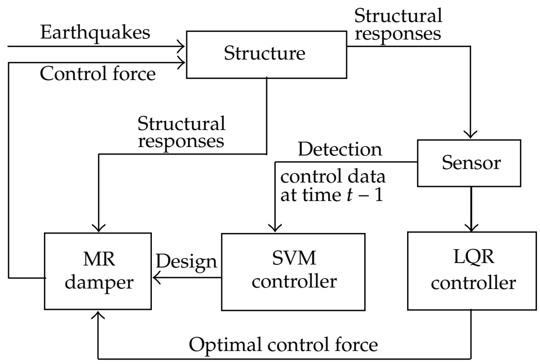

Figure 5: Implementation flow chart of structural semiactive control system with SVM control strategy for MR dampers.

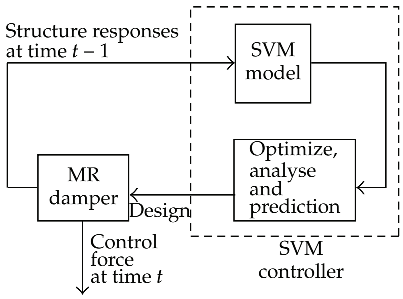

Figure 6: SVM controller.

limitations [10] and has been successfully applied to time series forecasting [11–13]. Likewise SVM provides some special advantages in the fields of small sample issues, nonlinear, and high dimensional pattern recognition. Small sample learning and global optimization are both important features. It uses nonlinear transformations to transfer practical problems into higher dimension feature space and then, constructs linear function in the higher dimension to realize the nonlinear problem in the former dimension. By doing this, SVM smartly solves the dimension problem [14, 15]. Recently, several researchers have utilized SVM to carry out the structural system identification [16, 17], nonlinear structural response prediction [18] and damage diagnosis [19]. However, it has been rarely reported that the SVM is used in the semiactive damping systems for seismic protection of structures. Attracted by the excellent performance of SVM, SVM is introduced into semiactive control algorithms, then forming a new control strategy Li and Liu [20]. Comparative numerical results demonstrate that the variable dampers using the SVM-based semiactive control algorithm is capable of providing better effectiveness in controlling the displacement and velocity of the structure, likewise vanish the acceleration amplification phenomenon. Based on recent research by Li and Liu [20], this paper proposes the application of support vector machine- (SVM-) based semiactive control methodology for seismic protection of structures with magnetorheological (MR) dampers. By resorting to the SVM, an online autofeedback semiactive control strategy for MR dampers, which eliminates the acceleration amplification phenomenon and likewise, renders better effectiveness in controlling the displacement, velocity, and acceleration responses of structures with respect to the semiactive MR dampers, is to be developed.

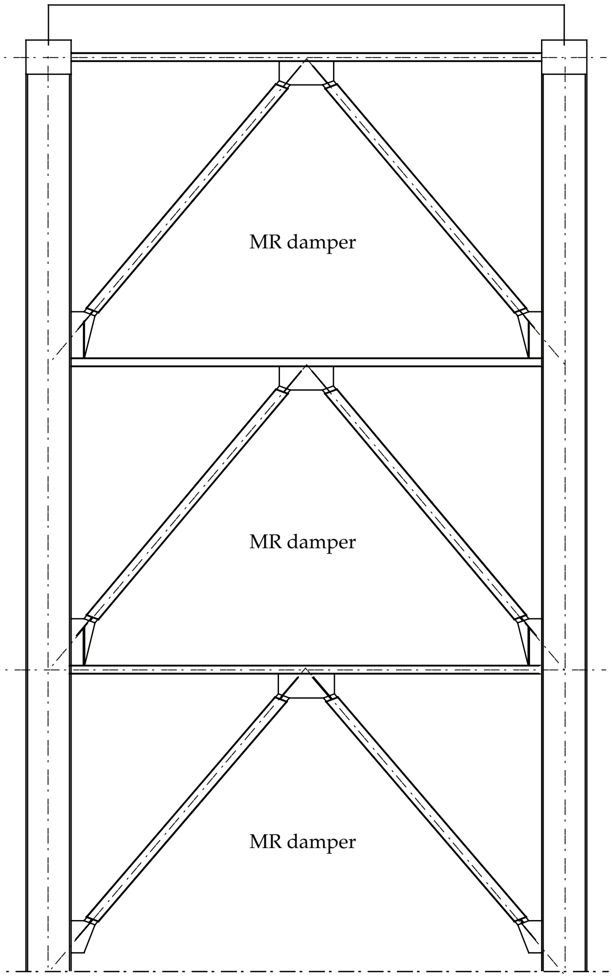

Figure 7: Analysis model of semiactive control for the structure with MR dampers.

2. Mechanical Models for MR Dampers

MR fluids, which are suspensions of microsized magnetizable particles in an appropriate carrier liquid with some agents, belong to the class of controllable fluids. The essential characteristic of MR fluids is their ability to reversibly change from free-flowing, linear viscous liquids to semisolids having controllable yield strength in milliseconds, when exposed to a magnetic field. The feature provides simple, quiet, rapid-response interfaces between electronic controls and mechanical systems. MR dampers are semiactive control devices that utilize MR fluids to provide controllable damping forces. Dynamic constitutive relation of MR fluids is very complicated and provided damping force is intrinsically nonlinear, so there is not a consistent recognized mechanical model for MR dampers. The mechanical model for an MR damper is often established through optimization method according to experimental data. Two types of dynamic models of controllable fluid damper have been investigated by many researchers: nonparametric and parametric models. Ehrgott and Masri [21], and Gavin et al. [22] presented a nonparametric approach employing

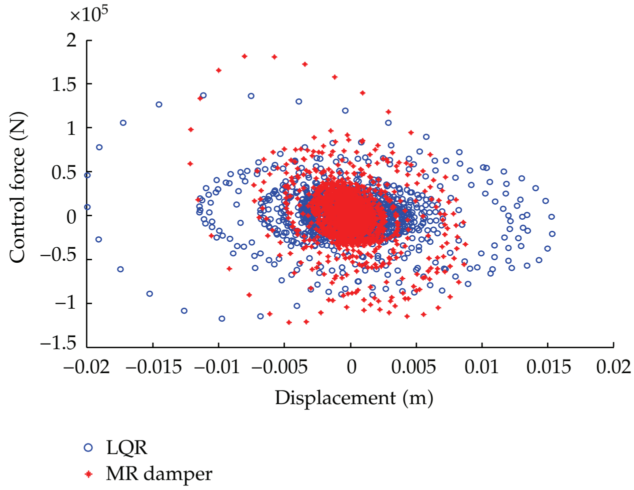

Figure 8: Control forces both in the semiactive MR dampers and the active devices in the top storey of structure subjected to El Centro wave with PGA = 0.1 g.

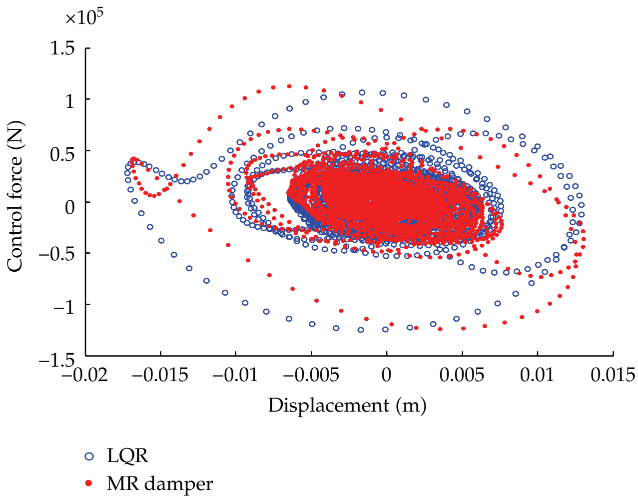

Figure 9: Control forces both in the semiactive MR dampers and the active devices in the top storey of structure subjected to Hachinohe wave with PGA = 0.1 g.

orthogonal Chebychev polynomials to estimate the damper resisting force using the damper displacement and velocity information. Chang and Roschke [23] developed a neural network model to emulate the dynamic behavior of MR dampers. However, the nonparametric damper models are quite complicated. Mechanical models for MR dampers are often established as parametric models, for example, Bingham viscoelastic-plastic model [24–26], modified Bingham viscoelastic-plastic model [27], nonlinear biviscous model [28], nonlinear hysteretic biviscous model [29], modified Dahl model [28], Bouc-Wen model [30], modified Bouc-Wen model [31], phenomenological model [30, 32], and modified phenomenological model [30]. At present, there are a variety of dynamic models for MR dampers. Some models which are simple cannot effectively simulate nonlinear dynamic characteristics of

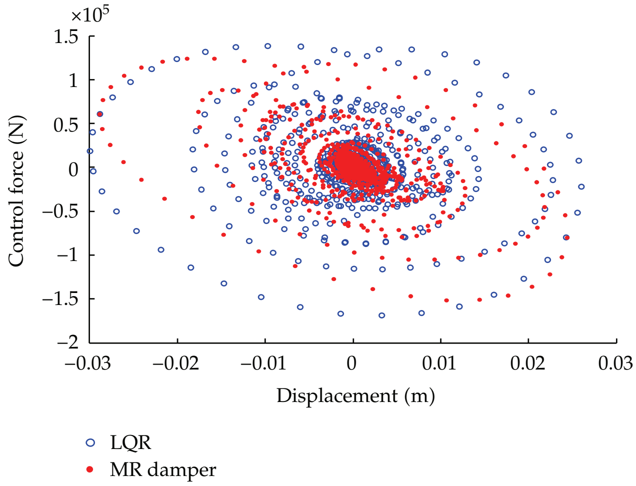

Figure 10: Control forces both in the semiactive MR dampers and the active devices in the top storey of structure subjected to Kobe wave with PGA = 0.1 g.

MR dampers. Although there are some models which can simulate nonlinear dynamic characteristics, they are established by strong nonlinear equations having a lot of parameters which result in complicated numerical calculation. In civil engineering, Bingham model and Bouc-Wen model are often used for emulating the dynamic behavior of MR dampers.

2.1. Bingham Model

The stress-strain behavior of the Bingham model [25] is often used to describe the behavior of MR or electrorheological (ER) fluids. In this model, the plastic viscosity is defined as the slope of the measured shear stress versus shear strain rate data. Thus, for positive values of the shear rate $\dot{\gamma}$, the total stress is given by

$$\tau = \tau_y(H)\operatorname{sgn}(\dot{\gamma}) + \eta\dot{\gamma}, \tag{2.1}$$

where $\tau_y(H)$ is the yield stress induced by the magnetic or electric field and η is the viscosity.

Based on this model of the rheological behavior of ER fluids, Stanway et al. [24] proposed an idealized mechanical model, denoted by the Bingham model, for the behavior of an ER damper. The Bingham model consists of a Coulomb friction element placed in parallel with a viscous damper, as shown in Figure 1. In this model, for nonzero piston velocities $\dot{x}$, the force generated by the device is given by the fluid as follows:

$$F = f_c\operatorname{sgn}(\dot{x}) + c_0\dot{x} + f_0, \tag{2.2}$$

where c_0 is the damping coefficient; f_c is the frictional force, which is related to the fluid yield stress; f_0 denoting an offset in the force is included to account for the nonzero mean observed in the measured force due to the presence of the accumulator. Note that if at any point the velocity of the piston is zero, the force generated in the frictional element is equal to the applied force.

2.2. Bouc-Wen Model

One model that is numerically tractable and has been used extensively for modeling hysteretic systems is the Bouc-Wen model [33]. The Bouc-Wen model is extremely versatile and can exhibit a wide variety of hysteretic behavior. A schematic of this model is shown in Figure 2. The force in this system is given by

$$F = c_0\dot{x} + k_0(x - x_0) + \alpha z, \tag{2.3}$$

where the evolutionary variable z is governed by

$$\dot{z} = -\gamma|\dot{x}|z|z|^{n-1} - \beta\dot{x}|z|^n + A\dot{x}. \tag{2.4}$$

By adjusting the parameters of the model γ, β, A, and n, one can control the linearity in the unloading and the smoothness of the transition from the preyield to the postyield region. In addition, the force f_0 due to the accumulator can be directly incorporated into this model as an initial deflection x_0 of the linear spring k_0.

It is worth mentioning that the normalized Bouc-Wen model bas been presented without the overparameterization [34].

3. Semiactive Control for Seismic Structures with MR Dampers

The motion equations of the structure-semiactive control system are established as follows:

$$M\ddot{X} + C\dot{X} + KX = -ME\ddot{X}_g + B_sU, \tag{3.1}$$

where M, C, and K denote the mass, damping, and stiffness matrix of the structure, respectively; X, $\dot{X}$, and $\ddot{X}$ are the dynamic responses of the structure (displacement, velocity, and acceleration) relative to the base; U is the control force vector excited by the MR dampers; $\ddot{X}_g$ is the ground acceleration. Also, the matrices B_s and E are the location matrix for control forces and the vector of ones, respectively.

Rewriting (3.1) in state-space form gives

$$\dot{Z} = AZ + BU + D\ddot{X}_g, \tag{3.2}$$

where

$$A = \begin{bmatrix} 0 & I \\ -M^{-1}K & -M^{-1}C \end{bmatrix}, \qquad B = \begin{bmatrix} 0 \\ M^{-1}B_s \end{bmatrix},$$
$$D = -\begin{bmatrix} 0 \\ E \end{bmatrix}, \qquad Z(0) = 0. \tag{3.3}$$

In order to implement optimal control, an appropriate cost function incorporating two components, namely, both the state to be controlled and control effort, has to be constructed with the weightings on the two parts. With these considerations, the cost function over the duration $(0, t_f)$ assumes the following final form:

$$J = \frac{1}{2}\int_0^{t_f} \left[Z^T(t)QZ(t) + U^T(t)RU(t)\right] dt, \tag{3.4}$$

in which Q and R are the weighting matrices to be applied to the responses and control energy, respectively; t_f refers to the external excitation action time.

Based on the linear quadratic regulator (LQR) control theory, the optimal control forces of control devices can be calculated by

$$U = -R^{-1}B^T PZ. \tag{3.5}$$

For an infinite terminal time, the solution of matrix P to this problem can be obtained through solving the algebraic Riccati equation, which has the following form:

$$PA + A^T P - PBR^{-1}B^T P + Q = 0, \tag{3.6}$$

where

$$Q = \alpha \begin{bmatrix} K & 0 \\ 0 & M \end{bmatrix}, \qquad R = \beta\, I. \tag{3.7}$$

The present paper adopts Bingham model to simulate the property of the MR damper. Firstly, the active controllers are designed by resorting to the optimal control algorithm (LQR). Then, selecting a structure model, the optimal control forces from the active controller are obtained through analyzing the dynamic responses of the structure with the designed active controllers. Finally, through comparing the optimal active control forces with those provided by the MR dampers as semiactive control devices, the parameters of Bingham model can thus be determined. As a result, the control forces of the MR dampers at the next time step can be calculated. The flow diagram of semiactive control for structures with the MR dampers is shown in Figure 3.

4. SVM-Based Control Strategy for MR Dampers

SVM was developed to originally solve classification problems. With the introduction of Vapnik's ε-insensitive loss function, however, SVM has been extended to successfully deal with nonlinear regression estimation problem [8]. In the SVM regression, the basic idea is to map the input data x into a high-dimensional feature space by resorting to a nonlinear mapping Φ and to make linear regression in this space. The regression model can then be defined as follows:

$$y = f(x) + e, \tag{4.1}$$

where x and y represent the input and output, respectively; $f(x)$ denotes the linear regression function defined in the high-dimensional feature space; e refers to the independent random error.

Now given n input output sampling pairs $G = \{(x_i, y_i),\ i = 1,2,\ldots,n\}$, the SVM approximation of the linear regression function $f(x)$ can be written in the following general form:

$$f(x) = \omega\Phi(x) + b, \tag{4.2}$$

where $\Phi(x)$ is the high-dimensional feature space which is nonlinearly mapped from the input space x. The coefficients ω and b are estimated by the following minimizing:

$$\begin{gathered}
R_{\text{reg}}(C) = C\frac{1}{N}\sum_{i=1}^{N} L_\varepsilon(y_i, f(x_i)) + \frac{1}{2}\|\omega\|^2 \\
L_\varepsilon(y, f(x)) = \begin{cases} |y - f(x)| - \varepsilon, & |y - f(x)| > \varepsilon, \\ 0, & |y - f(x)| \le \varepsilon. \end{cases}
\end{gathered} \tag{4.3}$$

Equation (4.3) is referred to as the regularized risk function where the first term refers to the empirical error (risk), and the second term, on the other hand, denotes the regularization term. Equation (4.3) stands for the ε-insensitive loss function which provides the advantage of enabling one to utilize sparse data points (sampling pairs) to represent the decision function given by (4.1). The parameter C represents the penalty factor. More specifically, it is the regularized constant and determines the tradeoff between the empirical risk and the regularization term. The parameter ε is the maximum allowable error which is named the tube size and equivalent to the approximation accuracy placed on the training sampling pairs.

In order to obtain the estimations of ω and b, (4.3) is transformed to the primal function by introducing the positive slack variables ξ_i and ξ_i^* as follows:

$$\text{Min}\left\{R\left(\omega, \xi^{(*)}\right) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*)\right\}, \tag{4.4}$$

subjecting to the constraints

$$\begin{gathered}
y_i - \omega\Phi(x_i) - b \le \varepsilon + \xi_i, \\
\omega\Phi(x_i) + b - y_i \le \varepsilon + \xi_i^*, \\
\xi^{(*)} \ge 0.
\end{gathered} \tag{4.5}$$

Then introduce Lagrange multipliers and exploit the optimal constraints to (4.2), then resulting in the following equation:

$$f(x, a_i, a_i^*) = \sum_{i=1}^{N} (a_i - a_i^*) K(x, x_i) + b, \tag{4.6}$$

where a_i and a_i^* are the Lagrange multipliers. They satisfy $a_i \times a_i^* = 0$, $a_i \geq 0$, $a_i^* \geq 0$, and are obtained with resorting to maximizing the dual function of (4.4) in the following form:

$$\text{Max}\left\{ R(a_i, a_i^*) = \sum_{i=1}^{N} y_i (a_i - a_i^*) - \varepsilon \sum_{i=1}^{N} (a_i + a_i^*) - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} (a_i - a_i^*) \left(a_j - a_j^*\right) K(x_i, x_j) \right\}, \tag{4.7}$$

subjecting to the constraints

$$\begin{gathered} \sum_{i=1}^{N} (a_i - a_i^*) = 0, \\ 0 \leq a_i \leq C, 0 \leq a_i^* \leq C. \end{gathered} \tag{4.8}$$

In accordance with the Karush-Kuhn-Tucker (KKT) conditions of quadratic programming, only a certain number of coefficients $(a_i - a_i^*)$ in (4.6) are to be assumed not to be equivalent to zero. The data points corresponding to them have the approximation errors equal to or larger than ε, referred to as the support vectors. These are the data points lying on or outside the ε-bound of the decision function. According to (4.6), it is apparent that the support vectors are only those elements of the data points that are used in determining the decision function while the coefficients $(a_i - a_i^*)$ of other data points are all equal to zero. Generally speaking, the larger the ε, the fewer the number of support vectors and thus the sparser the representation of the solution. However, a larger ε can also depreciate the approximation accuracy placed on the training points. In this sense, the ε is a tradeoff between the sparseness of the representation and closeness to the data [18].

In (4.7), $K(x_i, x_j)$ is defined as the Kernel function. The Kernel function can transform the problem into solving the linear regression problem in the high-dimensional feature space. The value of the kernel is equivalent to the inner product of two vectors i and j in the feature space $\Phi(x_i)$ and $\Phi(x_j)$, that is,

$$K(x_i, x_j) = \Phi(x_i) * \Phi(x_j). \tag{4.9}$$

Similarly, for $K(x, x_j)$, the Kernel function can be expressed as $K(x, x_j) = \Phi(x) * \Phi(x_j)$. The purpose of introducing the kernel function is that one can deal with feature spaces with arbitrary dimensionality while without having to compute the map $\Phi(x)$ explicitly. Any function satisfying Mercer's condition may all be used as the kernel function [8]. The parameters in these kernel functions should be carefully chosen as it implicitly defines the structure of the high-dimensional feature space and thus controls the complexity of the final solution as well as the accuracy of the result. From practical implementation point of view,

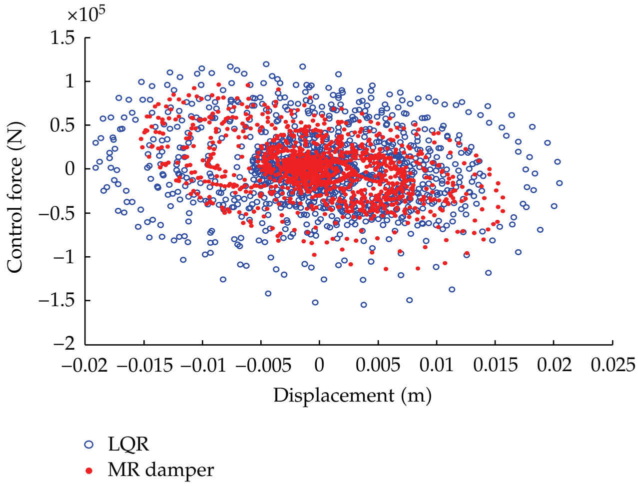

Figure 11: Control forces both in the semiactive MR dampers and the active devices in the top storey of structure subjected to Shanghai artificial wave with PGA = 0.1 g.

training SVM is identical to solving a linearly constrained quadratic programming with the number of variables being twice as that of the training data points. Once SVM is trained, it can be used for simulation and prediction purpose according to (4.6).

Figure 4 shows the structural semiactive control system with SVM control strategy for MR dampers and the corresponding implementation flow chart is displayed in Figure 5. Also, the working mechanism of SVM controller is displayed in Figure 6. It is understood from Figure 4 that the support vector machine- (SVM-) based semiactive control strategy with a view to MR dampers for multistory structures under earthquakes embraces both the observers (sensors) and controllers and generally implements the following three steps. Firstly, the sensors acquire full-state data of the structure and the optimal control forces based on LQR control algorithm can then be obtained. Secondly, the control forces which the MR dampers need to provide can be designed through training the SVM controllers. On training, the required control forces of MR dampers at time t can be predicted by the system data at time $t-1$. Thirdly, the real-time semiactive control of MR dampers can naturally be realized.

The implementation flow chart demonstrates that the active control forces in accordance with LQR algorithm are designed by the seismic responses of the structure and then, the mechanical model of MR damper may be designed through utilizing both the active control forces and structural seismic responses. At the same time, the seismic responses of the structure equipped with the MR dampers can be obtained. After that, the seismic responses data at time $t-1$ of the structure with the MR dampers collected by the sensors can be used to predict the control forces of MR dampers at time t.

Here, it is worth pointing out that the parameters in the Kernel function, regression allowable maximum error, as well as penalty factor will determine the control effectiveness of the present control strategy. Likewise, for different earthquake waves, these parameters will vary, thus resulting in different levels of response reduction.

5. Numerical Studies

Now, consider a 3-storey shear-type frame structure with MR dampers, as shown in Figure 7. It is assumed that $m_i = 4 \times 10^5$ kg and $k_i = 1.6 \times 10^8$ N/m ($i = 1, 2, 3$). Likewise the structural damping matrix may be obtained by use of the Rayleigh damping hypothesis; that is, the damping matrix can be calculated as a linear combination of mass and stiffness matrices. In each floor is one MR damper installed. Then,

$$U = \begin{bmatrix} u_1 & u_2 & u_3 \end{bmatrix}^T,$$
$$B_s = \begin{bmatrix} 1 & -1 & 0 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix},$$
$$K = \begin{bmatrix} 3.2 & -1.6 & 0 \\ -1.6 & 3.2 & -1.6 \\ 0 & -1.6 & 1.6 \end{bmatrix} \times 10^8 (\mathrm{N/m}), \tag{5.1}$$
$$C = \begin{bmatrix} 1.2224 & -0.4800 & 0 \\ -0.4800 & 1.2224 & -0.4800 \\ 0 & -0.4800 & 0.7424 \end{bmatrix} \times 10^6 (\mathrm{N \cdot s/m}).$$

In this paper, the modified Bingham model is selected for the MR damper, that is,

$$F = f_c \operatorname{sgn}(\dot{x}) + c_0 \dot{x} + f_0, \tag{5.2}$$

where f_c, c_0, and f_0 is the controllable Coulomb force, viscous damping coefficient, and the offset damping force induced by the accumulator, respectively. F denotes the damping force of the MR damper and $\dot{x}$ refers to the sliding displacement the MR damper. The relationship between the optimal control force and the command controlling current of the MR damper as well as the size of the 50T-MR damper may refer to [35].

According to the experimental results [35] on the 50T-MR damper, the parameters of Bingham model are to be determined as $c_0 = 1500\,\mathrm{kN \cdot s/m}$, $f_0 = -504\,\mathrm{N}$. The frictional forces f_c related to the fluid yield stress are calculated via the comparison between the control forces provided by MR dampers and the active control forces obtained based on the LQR algorithm. In numerical studies, four seismic waves, namely, El Centro wave, Hachinohe wave, Kobe wave, and Shanghai artificial wave, are included into consideration, whose peak ground accelerations (PGA) are all scaled to 0.1 g.

Following the idea by Ou and Li [36, 37], the relationship of the control force and the corresponding displacement under four earthquake waves are calculated and depicted in Figures 8–11. The goal is to make appraisal and evaluation of the traceability of control forces in the semiactive MR dampers on the corresponding active control devices. Under the El Centro wave, control forces of the semiactive MR damper installed in the 1st storey of structure approach the active control forces calculated by the linear quadratic regulator (LQR) algorithm; the semiactive control forces in the 2nd storey are slightly less than the active control forces; whereas in the top storey, the semiactive control forces may be more than the active control forces at some time, as seen in Figure 8 (only the Figure of the top storey). Figure 9 display the control forces in the semiactive MR damper and the active device

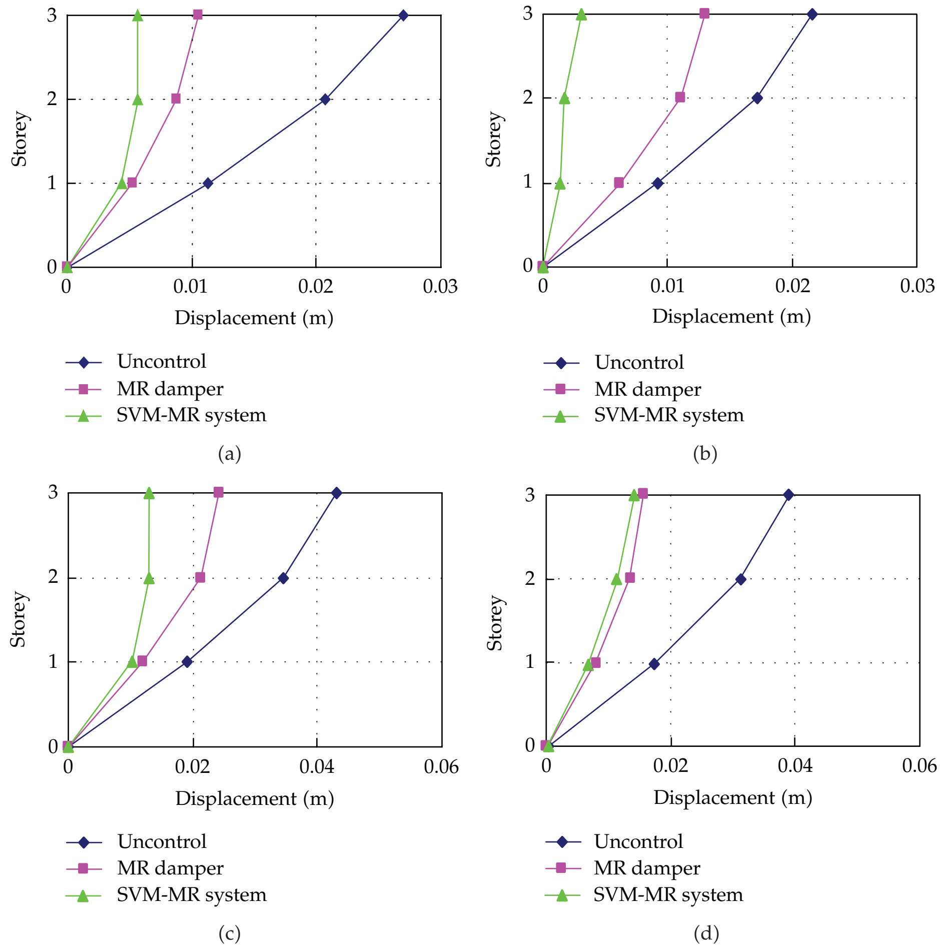

Figure 12: Displacement responses of every storey under different earthquake waves: (a) El Centro seismic wave; (b) Hachinohe seismic wave; (c) Kobe seismic wave; (d) Shanghai artificial seismic wave.

in top storey of structure subjected to Hachinohe wave with PGA = 0.1 g. The semiactive control forces closely match the active control forces, but the displacements of structure with semiactive MR dampers are slightly more than those of structure with active control devices at most time. Figure 10 show the semiactive and active control forces in top storey of structure subjected to Kobe wave with PGA = 0.1 g. At some time, the control forces supplied by MR dampers are slightly more the active control forces. Figure 11 demonstrate that the semiactive forces are close to the active control forces in top storey of structure subjected to Shanghai artificial wave with PGA = 0.1 g. It can be seen from Figures 8–11 that the control forces in the semiactive MR dampers can trace the control forces in the corresponding active devices very well.

In order to examine the seismic response reduction of the controlled structure using the present control algorithm, the peak displacement, peak velocity, and peak acceleration responses of every floor under these four seismic waves are shown, respectively, in Figures 12–14. It is seen from Figure 12 that under the action of the El-Centro wave, Kobe wave, Shanghai artificial wave, the peak displacement of the first floor is similar for the two control

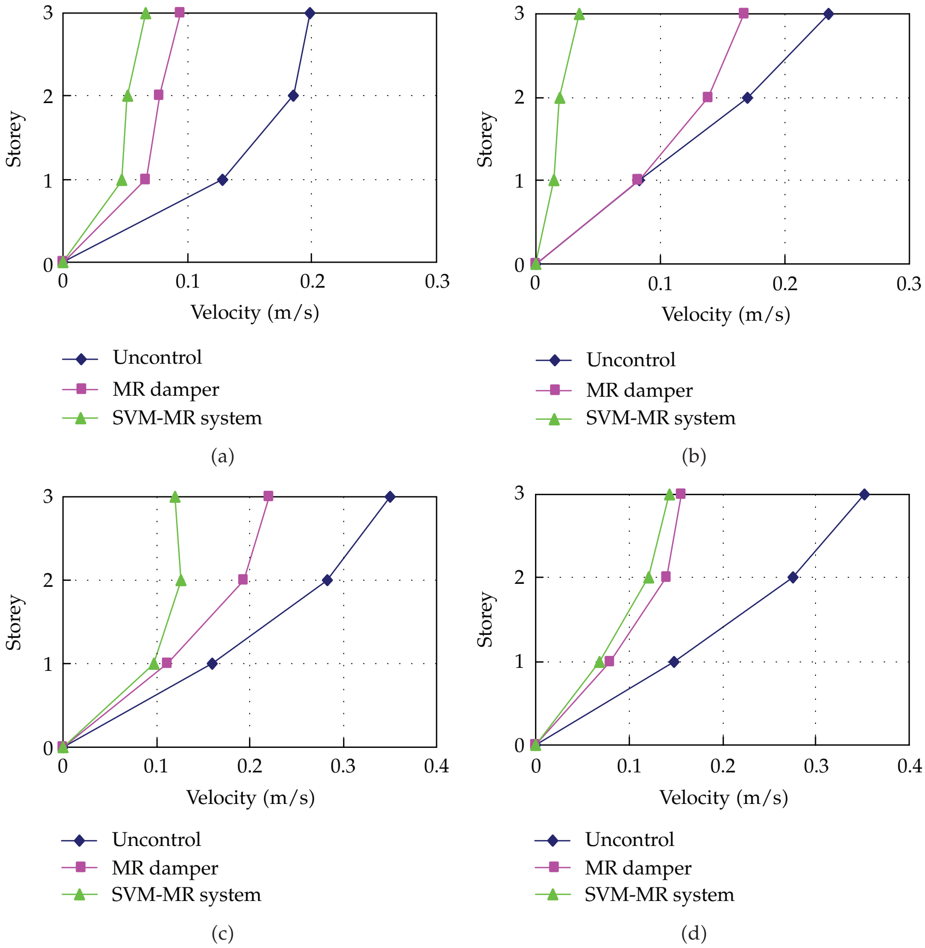

Figure 13: Velocity responses of every storey under different earthquake waves: (a) El Centro seismic wave; (b) Hachinohe seismic wave; (c) Kobe seismic wave; (d) Shanghai artificial seismic wave.

strategies. But, in reducing the peak values of the other floors displacements, the structure-SVM-MR system is superior to the structure-MR system. Likewise, in reducing the peak velocity and acceleration of every floor, the structure-SVM-MR system is also superior to the structure-MR system, as displayed in Figures 13 and 14. Under Hachinohe wave, the peak displacement and velocity responses of every floor, especially the top floor, with the SVM-MR systems is remarkably smaller than those with the semiactive MR dampers. It is verified once again that the proposed structure-SVM-MR system outperforms the structure-MR system. Summing-up conclusion is that the MR dampers utilizing the SVM-based semiactive control algorithm, which eliminates the local acceleration amplification phenomenon, can remarkably reduce the displacement, velocity, and acceleration responses of the structure.

6. Conclusions

A support vector machine (SVM) model, which is used as the control system observer and controller, is designed and trained to emulate the performance of the LQR controller. In

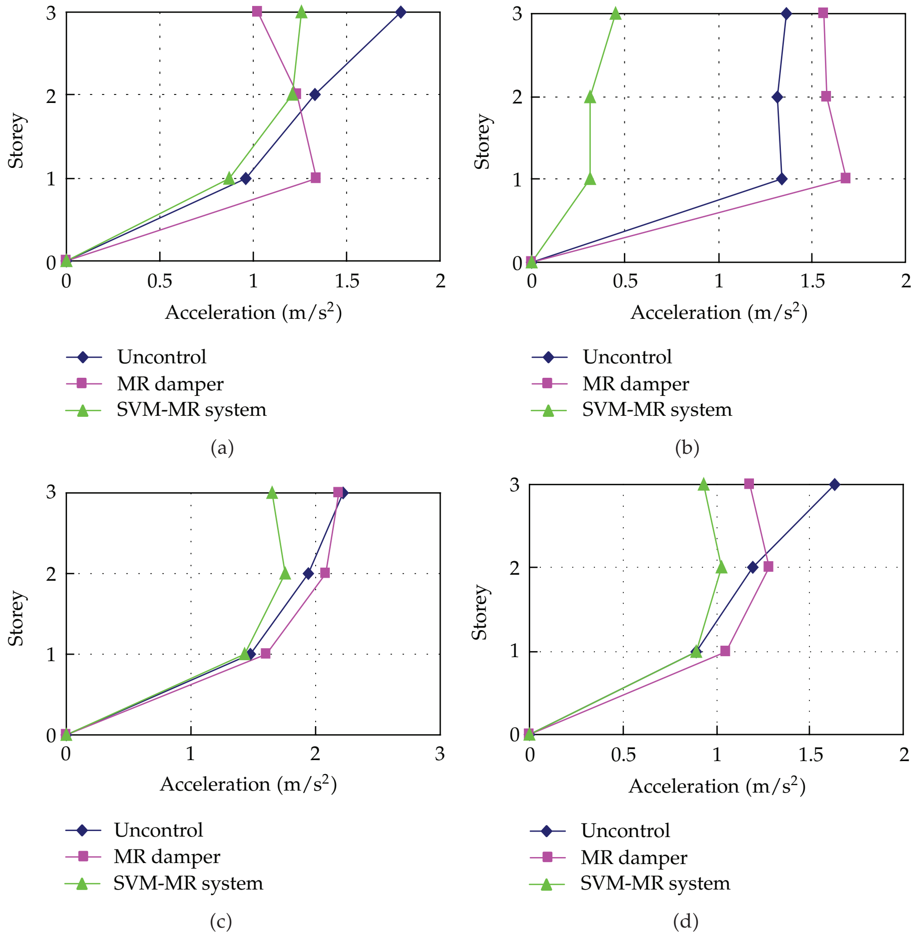

Figure 14: Acceleration responses of every storey under different earthquake waves: (a) El Centro seismic wave; (b) Hachinohe seismic wave; (c) Kobe seismic wave; (d) Shanghai artificial seismic wave.

accordance with the features of semiactive MR dampers, an online autofeedback semiactive control strategy is developed and then realized by resorting to the SVM. The controlling process is demonstrated as follows: Firstly, based on LQR algorithm, the $t-1$ time optimal control forces are calculated using the $t-1$ time seismic responses of the structure. Then, design the MR dampers in accordance with the modified Bingham model as well as both the $t-1$ time optimal control forces and seismic responses of the structure. Finally, the SVM controllers predict the t time control forces of MR dampers in terms of the $t-1$ time seismic responses of the structure—MR damper system.

In order to numerically verify the effectiveness of the present control strategy applied to the semiactive MR dampers, the time history analysis has been implemented to a 3-storey frame structure with the semiactive MR dampers designed by the SVM-based semiactive control algorithm. Comparative numerical results demonstrate that the MR dampers utilizing the SVM-based semiactive control algorithm, which eliminates the acceleration amplification phenomenon, can render better effectiveness in controlling the displacement, velocity, and acceleration responses of the structure with respect to the semiactive MR dampers. However, it is worth pointing out that the general variable dampers by use of the SVM based semiactive control algorithm is capable of providing better effectiveness in controlling the displacement and velocity of the structure with reference to the general variable dampers and vanish the acceleration amplification phenomenon.

Generally speaking, the controlling effect of SVM-MR damper is better than the controlling effect of only MR damper. This is attributed mainly to the prediction function of the SVM-MR damper system itself.

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