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Precision tracking control of shape memory alloy actuators using neural networks and a sliding-mode based robust controller

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Abstract
This paper presents a new approach to controlling shape memory alloy (SMA) actuators with hysteresis compensation by using a neural network feedforward controller and a sliding-mode based robust feedback controller. SMA actuators exhibit severe hysteresis, which is often responsible for position inaccuracy in a regulation or tracking system and may even cause instability in some cases. A single SMA wire actuator is used in this research. A testing system, which includes a wire stand, a linear bearing, a bias spring, a position sensor, a programmable current amplifier and a PC-based digital data acquisition and real-time control system, is used to test the SMA wire actuator in both open- and closed-loop fashions. The proposed control includes two major parts: a feedforward neural network controller, which is used to cancel or reduce the hysteresis, and a sliding-mode based robust feedback controller, which is employed to compensate uncertainties such as the error in hysteresis cancellation and ensures the system's stability. The feedforward neural network controller is designed based on the experimental results of open-loop testing of the wire actuator. With the proposed control, tests of the SMA actuator following sinusoidal commands with different frequencies and magnitudes are conducted. The experiments show that the actual displacement of the SMA actuator with the proposed control closely followed that of the desired sinusoidal command.

(Some figures in this article are in colour only in the electronic version)

1. Introduction

Tracking control of shape memory alloy (SMA) actuators is essential in many applications such as vibration control [1, 2] and robotic applications [3]. However, due to hysteresis, an inherent nonlinear phenomenon [4] associated with SMAs [5], tracking control of SMA actuators is a challenging task. This has motivated the authors to conduct research into tracking control of SMA actuators with hysteresis compensation.

Various methods have been proposed to compensate for hysteresis. Crúz-Hernandez and Hayward [6] have discussed in their paper the use of phasers for compensation of the hysteresis by shifting the phase of the periodic signal in a piezoelectric actuator. Webb and Lagoudas [7] have presented an adaptive hysteresis model for on-line identification and closed-

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loop compensation. Song and Quinn [8] have demonstrated the use of a sliding-mode based robust controller for tracking control of an SMA wire. Elahinia and Ashrafiuon [3] applied variable structure control to an SMA actuated manipulator. Hughes and Wen [9] have implemented the Preisach model in the control of an SMA wire actuator to provide bending force to a flexible aluminum beam. Majima *et al* [10] also used the Preisach model to feedforward cancel the hysteresis in an SMA actuator in addition to a feedback controller. Ge and Jouaneh [11] have used a combination of feedforward controller and a feedback loop (proportional, integral plus derivative control) to reduce hysteresis in actuators represented by the Preisach model.

Neural networks, which possess properties of nonlinear function mapping and self-adaptation, have been used to model hysteresis [12–15] and, in some cases, to compensate for hysteresis [16, 17]. However, there are very limited studies of the use of neural networks for hysteresis compensation in SMA actuators [17]. In this research, a new approach is proposed to control SMA actuators with hysteresis compensation by using a neural network controller and a sliding-mode based robust controller. The feedforward neural network controller is used to cancel or reduce the hysteresis. Different from the approaches used in [16, 17], a sliding-mode based robust controller is used in this approach to compensate uncertainties such as the error in hysteresis cancellation and to ensure system stability. The neural network structure used in this paper is different from those in [16, 17]. Experiments have been conducted and show that the actual displacement of the actuator can closely follow that of the desired sinusoid command.

2. Basics about shape memory alloys

SMAs are smart materials which have the ability to return to a predetermined shape when heated. When an SMA is cold, or below its transformation temperature, it has a very low yield strength and can be deformed quite easily into any new shape—which it will retain. However, when the material is heated above its transformation temperature it undergoes a change in crystal structure which causes it to return to its original shape. During its phase transformation, an SMA generates an extremely large force when encountering resistances or experiences a significant change in dimensions when unrestricted.

The unique properties of SMAs make them a potentially viable choice for actuators. SMA actuators have over the years been used in a spectrum of applications. When compared with piezoelectric actuators, SMA actuators offer the salient advantage of being able to generate either larger deformations or larger forces, though at a much lower operating frequency. At present, only SMAs with a one-way shape memory effect have good mechanical properties and only this type of SMA material has been widely implemented. SMAs can be conventionally fabricated into different shapes. The most widely used are SMA wires. As illustrated in figure 1, a shape memory wire actuator is used to lift a weight. SMA wires can be precisely embedded into the face sheet of a structure of interest, such as a helicopter blade, and can actively alter the shape of the structure in a desired fashion.

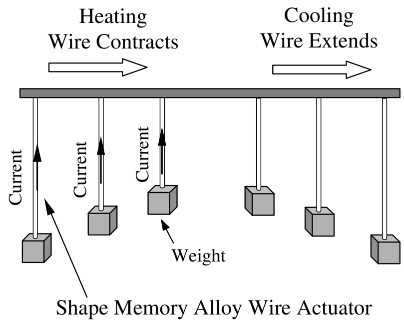

Figure 1. An SMA wire as an actuator.

The most common shape memory material is an alloy of nickel and titanium called Nitinol, or NiTi, which was discovered at the Naval Ordnance Laboratory in the 1960s. This particular alloy has very good electrical and mechanical properties, long fatigue life and high corrosion resistance. As an actuator, it is capable of up to 5% strain recovery and 500 MPa restoration stress with many cycles. For example, a Nitinol wire of 0.508 mm diameter can generate as much as 70 N blocked force. Nitinol also has resistance properties which enable it to be actuated electrically by Joule heating. When an electric current is passed directly through the wire, it can generate enough heat to cause the phase transformation. In most cases, the transition temperature of the SMA is chosen such that room temperature is well below the transformation point of the material. Only with the intentional addition of heat can the SMA be actuated.

The special properties of SMAs result from a phase transformation in their crystal structure when cooled from the stronger, high-temperature cubic form (austenite) to the weaker, low-temperature parallelogram form (martensite). Figure 2 illustrates phase transformations of an SMA wire actuator. Assume that the SMA wire is initially at a low temperature and is in its martensite state (point A in figure 2). Upon heating, the SMA wire will experience a phase transformation to the cubic stronger austenite and the wire will contract in its length (point B in figure 2). Upon cooling, the SMA wire will transfer from austenite to the weaker martensite phase (point C in figure 2). At this stage, the crystal structure of the SMA is in a twinned parallelogram form. In general, its strength in terms of Young's modulus in martensite is three to six times less that in austenite. When an external tension force is applied to the wire, the wire can be easily stretched (point D in figure 2). During this process, the twinned martensite becomes detwinned martensite upon application of an external force. When the external force is removed, the wire remains in its deformed shape (point A in figure 2) until it is heated again. Figure 3 depicts the length of SMA wire versus its temperature during the phase transformation. Obviously, the transformation exhibits a hysteretic effect, in that the transformations on heating and on cooling do not overlap. This hysteretic effect adversely affects precision control of SMA actuators and may even cause the system to experience instability. Compensation of the hysteresis is a major concern during the design of control systems for SMA actuators.

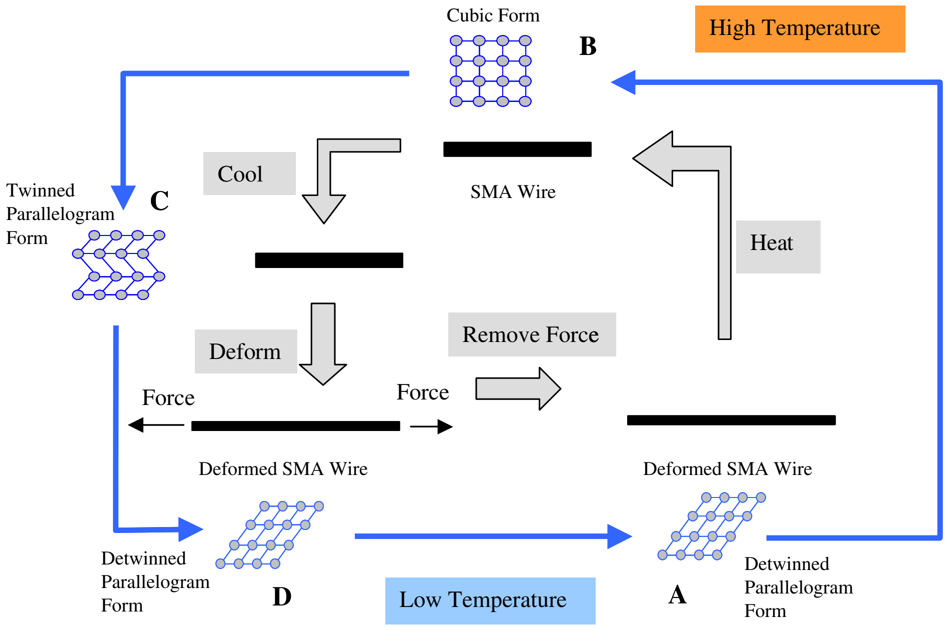

Figure 2. Phase transformation of the SMA spring (macro and micro views).

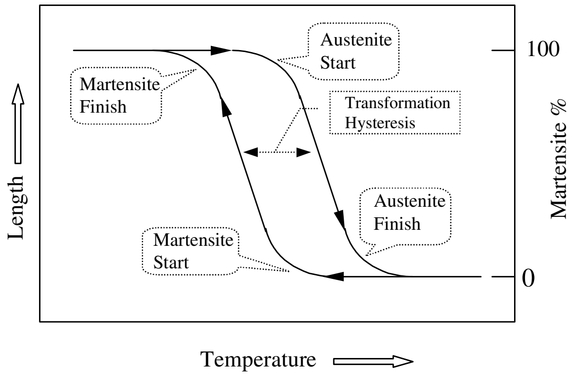

Figure 3. The hysteresis associated with SMAs.

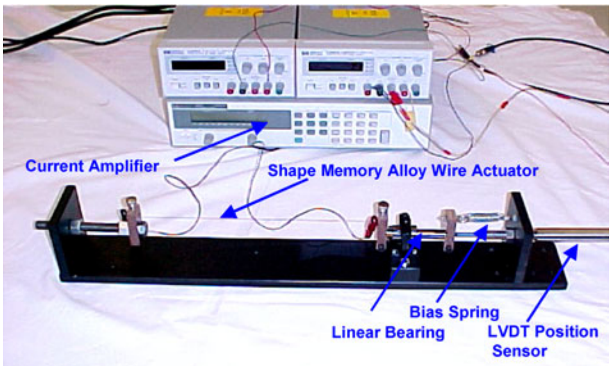

Figure 4. The single SMA wire test stand.

3. Experimental set-up

An experimental set-up (figure 4) was built to provide the capability of testing and positioning feedback control of a single SMA wire actuator under the load condition of a bias spring. Since the SMA wire only has a one-way shape memory effect, the design with a bias spring is commonly used in SMA actuators to achieve two-way control actions [18]. This design configuration is adopted in the SMA test stand. In this SMA test stand, the SMA wire is attached between two wire supports. One wire support is attached to a slider that is free to slide through a linear bearing. The slider is attached to a bias spring which pre-tensions the SMA wire. The tip of a linear variable differential transformer (LVDT) is placed against the slider to detect its position. Though a linear bearing is employed to reduce the friction effect, this bearing still exhibits nonlinear stick–slip friction to some degree.

In this experiment, a nickel–titanium (Nitinol) SMA wire (30.48 cm in length and 0.381 mm in diameter) is used. This Nitinol wire has a phase transformation temperature of 90 °C and a hysteresis width of about 20 °C. Control systems can be designed and implemented using dSPACE® data acquisition and a real-time control system with MATLAB® /Simulink. An output voltage from the real-time control system is sent to a programmable power supply. In this research, the power supply is set in constant-voltage control mode. The power supply amplifies the voltage by a factor of four and then applies the amplified voltage to the SMA wire, which results in a direct current in the shape memory wire and in turn heats the wire. The heating of the wire to a temperature above 90 °C causes a phase transformation from the weak martensite to the strong austenite, which is seen as a contraction of the wire. The contraction of the wire causes additional deformation of the spring. The LVDT sensor is used to measure the wire displacement. This displacement is then fed back to the real-time control system. Once the current is cut off and the heat is removed, the wire will eventually experience a phase transformation from austenite back to martensite as its temperature drops below 70 °C. In this weak martensite phase, the bias spring will pull the SMA wire actuator and stretch it back to its cold length. An actuation cycle is completed.

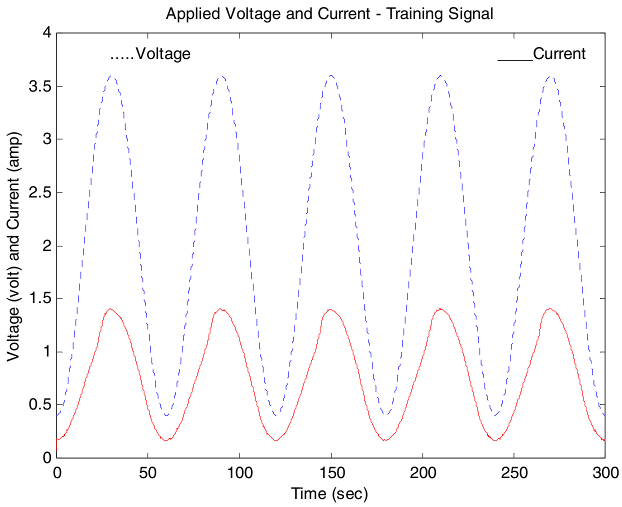

Figure 5. The applied voltage and measured current.

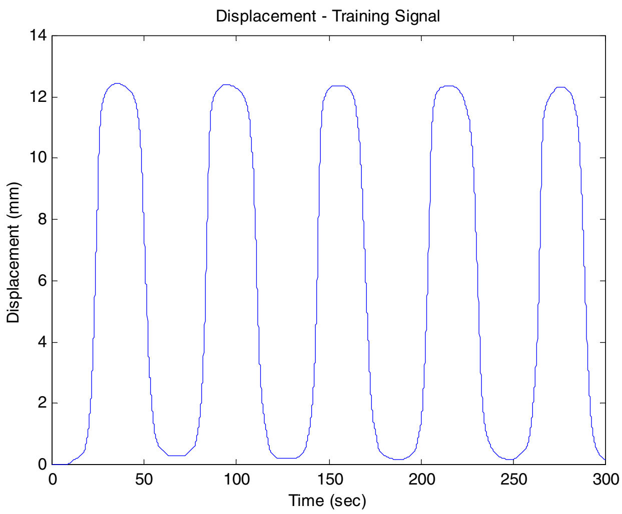

Figure 6. Displacement of the SMA wire actuator with the sinusoidal input current.

4. Modeling SMA wire hysteresis using neural networks

Hysteresis is an inherent property of SMA actuators and it is affected by many factors such as loading condition, operating frequency and maximum applied voltage. Also nonlocal hysteretic behavior has been experimentally observed [19]. It is not the intention of this section to completely model the hysteretic effect of an SMA actuator. Instead, the hysteresis is modeled under the bias spring loading condition and the SMA actuator will operate under the maximum applied voltage. The operating frequency will not be considered during the modeling. This will simplify modeling, but at the expense of introducing modeling error. Though it is expected that the neural network model of the hysteresis can feedforwardly cancel or significantly reduce the actuator's hysteretic behavior, this modeling error will result in incomplete cancellation of the hysteresis during feedforward control when the operating frequency varies. The error associated with the incomplete cancellation of the hysteresis

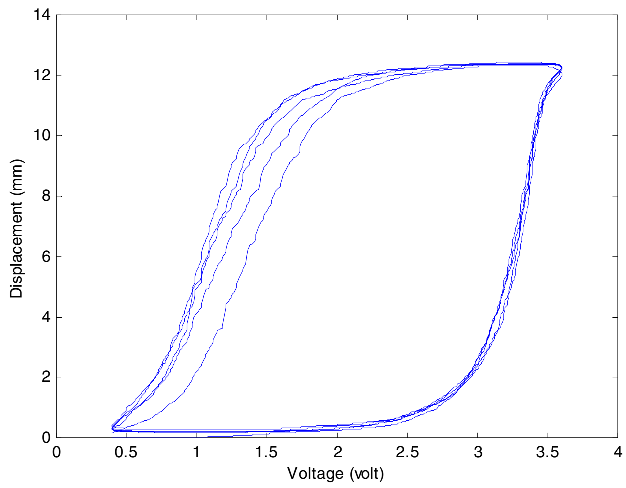

Figure 7. The hysteresis loops (displacement versus voltage).

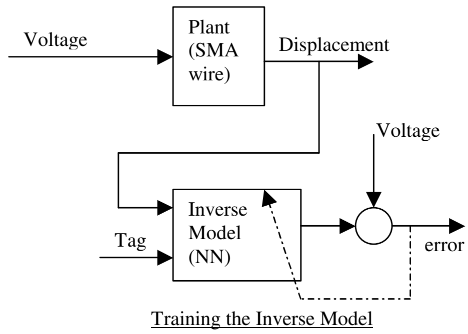

Figure 8. The neural network (NN) inverse training block diagram.

will be considered in the feedback controller design and will be compensated by a sliding-mode based robust controller.

To obtain training data, the SMA wire is excited using a sinusoidal signal with a frequency of $1/60$ Hz and a magnitude varying from 0.4 to 2.6 V. The applied voltage and the resulting current are shown in figure 5. The time history of the displacement of the SMA wire actuator is shown in figure 6. Though the applied voltage signal is sinusoidal, the displacement of the actuator is not quite sinusoidal due to the hysteresis of the SMA actuator. Figure 7 shows the relationship between the displacement of the SMA wire actuator and the applied voltage.

Figure 7 clearly demonstrates the hysteresis of the SMA wire actuator. The hysteresis loops observed have an average width of 2 V. The curves are not very smooth, and this can be attributed to the ambient conditions, which are not controlled. Another observation that can be clearly made is that the SMA wire actuator is not fully repeatable since the ambient conditions are uncontrolled. Therefore, multiple hysteresis loops are observed. However, for the purpose of modeling one representative hysteresis loop will be used. A neural network is designed as the inverse model of the plant. A multilayer feedforward neural network is trained using the same data generated from the plant that are used to train the plant model. The neural network controller is designed to model the variation of voltage as a function of displacement. For this purpose, the neural network toolbox in MATLAB® was utilized. The training methodology can be depicted schematically, as in figure 8.

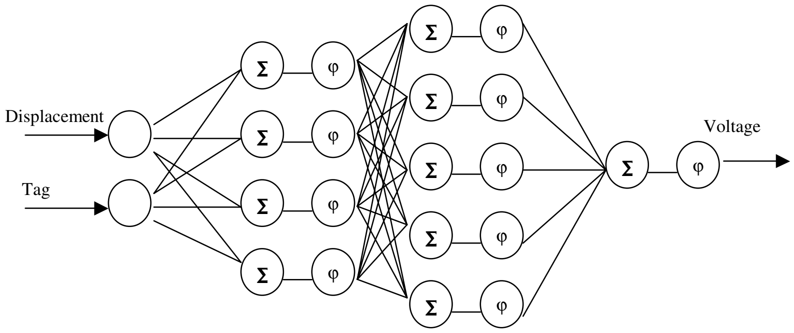

Figure 9. Schematic of the neural network inverse model.

The same data used for training the plant model are used to train the inverse model. The tagging scheme is the same, and similar tag data are used in conjunction with displacement and voltage information to generate the training signal. After tests with different combinations of number of layers and number of neurons in each layer, the neural network structure shown in figure 9 is adopted by considering factors such as modeling accuracy and training time. The adopted feedforward network has a four-layered architecture, with two hidden layers. The first hidden layer consists of four 'tansig' neurons. The second hidden layer consists of five 'tansig' neurons. The network has two inputs, the voltage and the tag, and one output, displacement. The training is done using the representative hysteresis loop. The trained neural network models the inverse behavior of the shape memory wire with a good degree of accuracy. This means that the neural network is able to model the functional hysteretic dependence of voltage on displacement. However, the neural network requires a 'tag' signal as an input, which indicates whether the position is increasing or decreasing. The inverse modeling results are shown in figure 10. The training results, as is evident from figure 10, are very good. The root mean square error of the training is 0.0332 V.

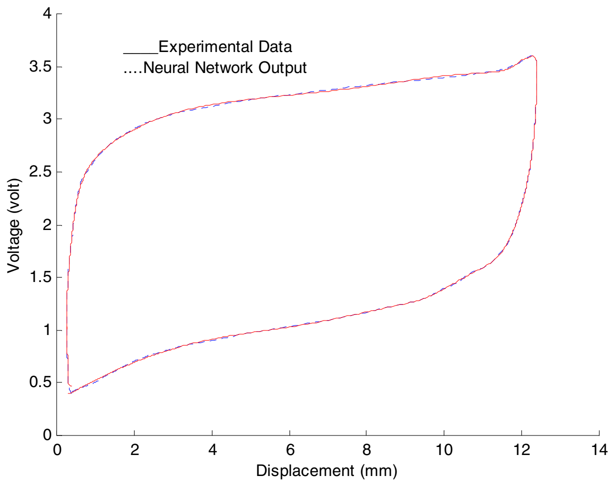

Figure 10. Results of the inverse model.

5. Control system design

The proposed controller will have both feedforward and feedback actions. The feedforward action is mainly the neural network's inverse model of the hysteresis of the SMA actuator and it is designed to cancel or significantly reduce the hysteretic effect. The feedback action involves a linear proportional plus derivative (PD) control and a nonlinear sliding-mode based robust controller. The robust controller is designed to compensate the residual hysteresis and other nonlinearities to ensure the system's stability.

To assist the feedback control design, we define the control errors as

$$e = y - y^{\mathrm{d}}, \qquad \dot{e} = \dot{y} - \dot{y}^{\mathrm{d}} \tag{1}$$

where y^{d} and $\dot{y}^{\mathrm{d}}$ are the desired position and velocity respectively. Also we define auxiliary control variables r and $\dot{r}$ by

$$r = \dot{e} + \lambda e, \qquad \dot{r} = \ddot{e} + \lambda \dot{e} \tag{2}$$

where λ is a positive constant. The surface defined by $r = 0$ represents the 'sliding surface', so that, when the dynamics are restricted to this surface, $e = 0$ and $\dot{e} = 0$ is an asymptotically stable equilibrium point with a global basin of attraction (within $r = 0$). Therefore, when the system is restricted to the sliding surface, the control errors diminish as $t \to \infty$.

Utilizing the auxiliary control variable r, the tracking controller is proposed as

$$i = i_{\mathrm{NN}} + i_f - k_D r - \rho \tanh(ar) \tag{3}$$

where k_D and a are positive constants. The functions of each control action in equation (3) are discussed as follows.

(1) The $-k_D r$ is a linear feedback action functioning as a PD control. Proportional control is used to decrease steady-state error and increase responsiveness of the actuator. The derivative control is to increase damping and to stabilize the actuator. In experiment, an appropriate value of the P gain ($-k_D\lambda$) has to be used since a large value may cause overshot and oscillations and a small value may result in larger steady state error and a slower response.
(2) The i_{NN} is the neural network inverse controller as shown in figure 5. This control action is used to feedforward cancel or significantly reduce the hysteresis of the SMA wire actuator. Since the hysteresis loops are nonrepeatable (as shown in figure 7) and other factors such as operating frequencies are not considered during modeling, this feedforward term will not exactly cancel the hysteretic effect. The residual effect will be dealt with by the sliding-mode based robust compensator. It is worthwhile

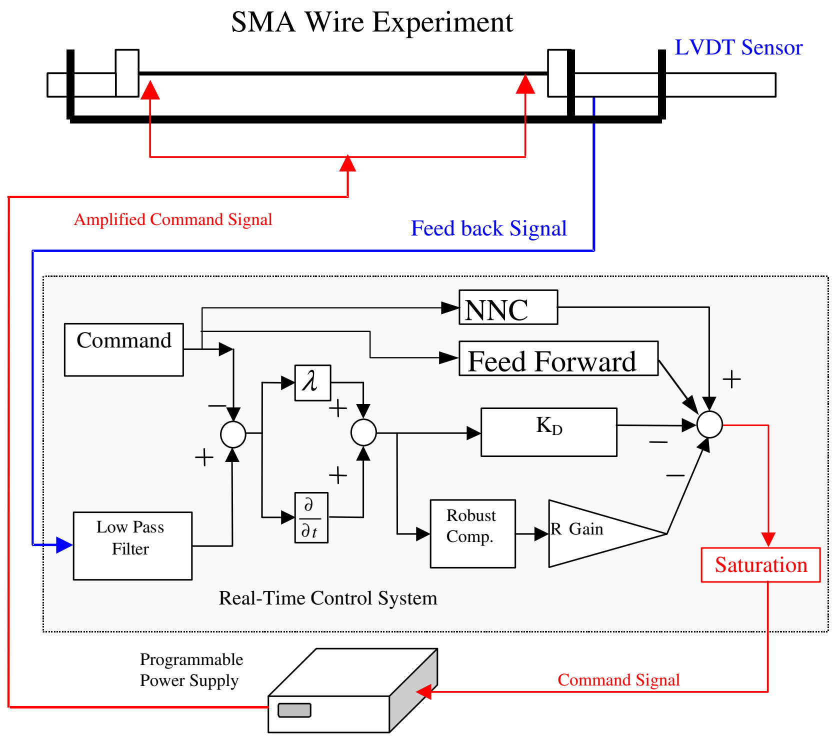

Figure 11. Block diagram of the control system design.

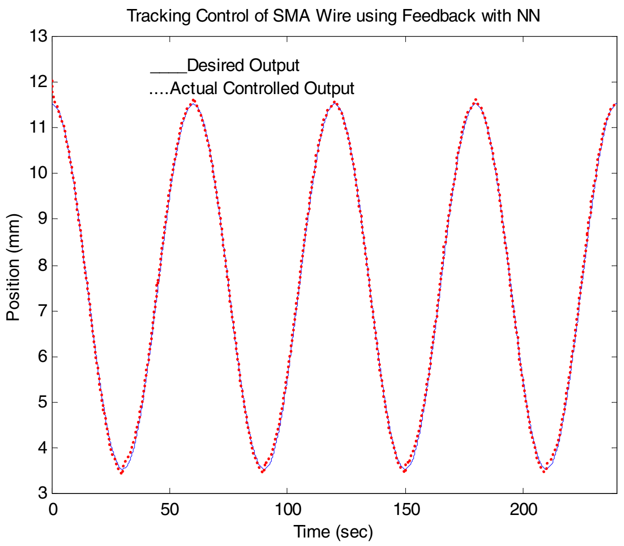

Figure 12. Tracking control results (1/60 Hz command frequency).

pointing out that the magnitude of this residual hysteresis is bounded since the neural network inverse controller is off-line trained and its magnitude is bounded. Please note that this neural network inverse controller is for the actuator under the bias spring loading condition.

(3) The i_f is a feedforward current and it is defined as

$$i_f = k_f(T\dot{y}^{\mathrm{d}} + y^{\mathrm{d}}) \tag{4}$$

where k_f is a positive constant gain and T is a positive time constant. This feedforward current is designed to provide the approximate amount of current required for the SMA actuator to follow the desired path. The actuator system with a bias spring is approximately a first-order system with a time constant T if the current is considered as the input and the displacement is considered as the output. However, this first-order model does not include the hysteretic nonlinearity. The effect of the mass of the moving parts and viscous friction in this system are neglected.

(4) The $-\rho\ \tanh(ar)$ is a sliding-mode based robust compensator and is used to compensate for the hysteresis of the actuator and to increase control accuracy and stability. The control parameter ρ is an estimated upper bound on the residual hysteresis and other nonlinearities associated with the actuator system. In this paper, ρ is also called robust (R) gain. Other nonlinearities include stick–slip friction associated with the moving parts such as the linear bearing. The constant a determines local gain near the origin when r is very small. Therefore, a larger value of a results in a smaller steady state error. However, a larger value of a also has more tendency to excite the flexible mode of the system. The value of $a$will be experimentally determined by considering the above factors.

A block diagram illustrating the control system design is shown in figure 11. As shown in figure 11, the low-pass filter with a cut-off frequency of 10 Hz is used filter out high-frequency noise in the signal from the LVDT sensor. The saturation function is used to limit the magnitude of the command signal so that the amplified voltage is less than 4 V to ensure the safe operation of the SMA wire actuator.

As pointed out earlier, in this control approach, $r = 0$ functions as the sliding surface, on which the system is

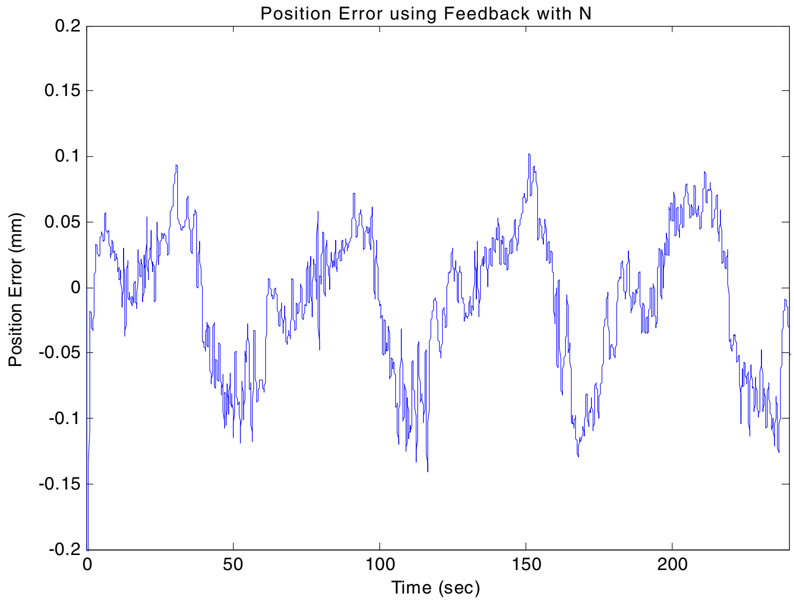

Figure 13. Position error.

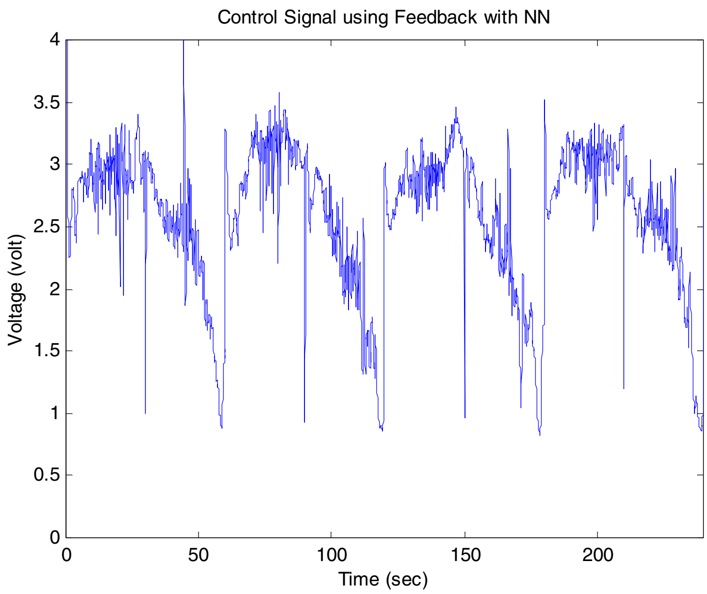

Figure 14. The applied voltage.

asymptotically stable, i.e. the control error is zero. In order to force the system onto the sliding surface, we employ the so-called smooth robust controller $-\rho\tanh(ar)$. The robust compensator is continuously differentiable with respect to the control variable r, and it generates a smooth control action. Compared with the commonly used bang–bang or saturation robust controllers, the smooth robust controller has advantages in ensuring both smooth control input and ultimately achieving uniform global stability of the closed-loop system [20].

6. Experimental results

The single SMA wire test stand (figure 4) is used for the experimental verification of the controller shown in equation (3). Though the training of the neural network feedforward term is based on the data using $1/60$ Hz actuation signal with a maximum displacement of 8 mm, commands with other frequencies and maximum displacements will be tested to examine the effectiveness and robustness of the proposed controller [21]. Five tests are conducted. During the tests, the SMA wire actuator is required to follow sinusoidal waves with frequencies of $1/15$, $1/30$, $1/60$ and $1/120$ Hz respectively. In the case of $1/30$, $1/60$ and $1/120$ Hz, the wire actuator is instructed to move with a stroke of 8 mm. A stroke of 2 mm is also required for the case of $1/60$ Hz. For the case of $1/15$ Hz, the maximum displacement is 2 mm. The controller parameters are: $\lambda = 4.0$, $K_D = 0.5$, $\rho = 0.25$, $a = 0.5$ and $k_f = 0.25$.

In the first case, the command (desired output) has a frequency of $1/60$ Hz and a displacement of 8 mm. The experimental results for the displacement of the SMA actuator are

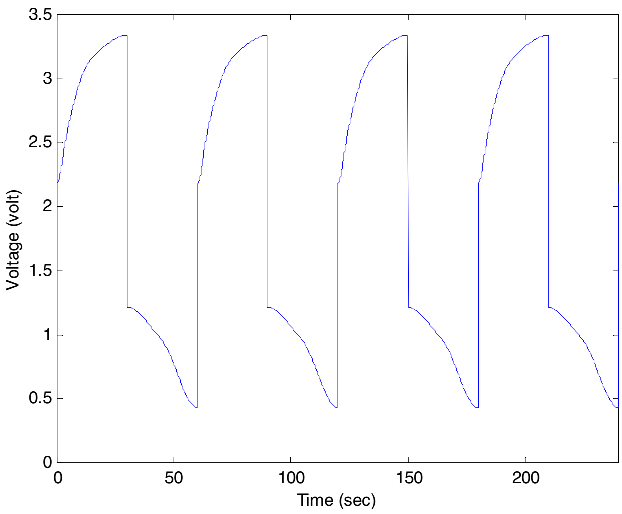

Figure 15. The neural network controller output.

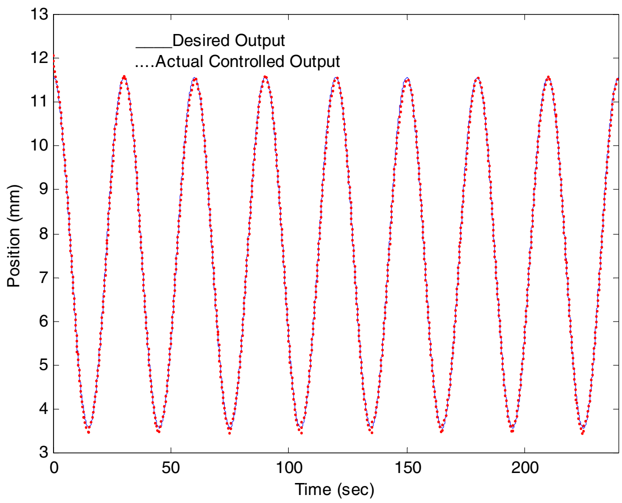

Figure 16. Tracking control results (1/30 Hz command frequency).

shown in figure 12. It is clear that the SMA actuator closely follows the command signal. The transient performance is satisfactory and there is no overshoot. To better view the tracking performance of the SMA actuator under the proposed robust control, position error is plotted separately in figure 13. The maximum error observed is less than 0.15 mm, which is less than 2% of the total stroke. The RMS error is 0.0805 mm. Considering that the system itself has a tendency to exhibit multiple hysteretic loops under the same operating condition, these results may be considered to be very good. Hence, integrating the sliding-mode feedback control with the neural network inverse hysteresis controller is found to be very effective in compensating for the hysteresis in SMA wire actuation, hence achieving more accurate tracking control for voltage actuation of the wire. The cyclically large error peaks observed are due to the response of the inverse controller near the saturation ends of the hysteresis loops, in part due to truncation errors. The applied voltage is shown in figure 14 and action of the neural network feedforward control is shown in figure 15.

In cases 2 and 3, the SMA wire actuator is required to follow sinusoidal commands with a stroke of 8 mm and with

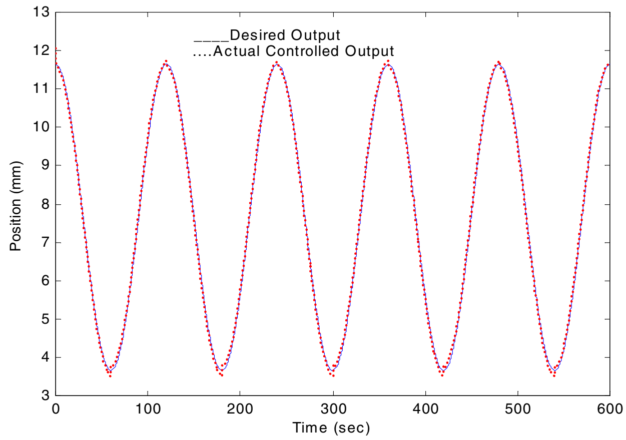

Figure 17. Tracking control results (1/120 Hz command frequency).

Table 1. Summary of experimental results [21].

Case	Frequency (Hz)	Stroke (mm)	RMS error (mm)
1	1/60	8	0.0805
2	1/30	8	0.064
3	1/120	8	0.0927
4	1/60	2	0.1018
5	1/15	4	0.1387

frequencies of 1/30 and 1/120 Hz respectively. The tracking control results are shown in figures 16 and 17 respectively. The root mean square error observed in case 2 is 0.064 mm. In fact, upon looking at the comparison plot in figure 16, the desired and actual position plots cannot be discerned. Similar satisfactory results are observed in case 3. In cases 4 and 5, the SMA actuators are required to move 2 mm at 1/60 Hz and 4 mm at 1/15 Hz respectively. Increased errors are observed at these strokes (2 and 4 mm). However, the errors are still kept at low values. The additional error associated with case 5 is introduced since 1/15 Hz is the upper limit of the bandwidth for this SMA wire actuator and there is hardly enough time for the heat to be removed from the wire during its cooling process. Table 1 summarizes RMS errors for all five cases for the purposes of comparison.

These experimental results demonstrate convincingly that the proposed method of hysteresis compensation using neural networks and a sliding-mode based controller is very effective for tracking control of SMA actuators.

7. Conclusions

In this paper, a new approach employing a neural network controller and a sliding-mode based robust controller is proposed to control SMA actuators with hysteresis compensation. The feedforward neural network controller is used to cancel or reduce the hysteresis of the SMA actuator and the sliding-mode based robust controller compensates uncertainties such as the error in hysteresis cancellation and to ensure the system's stability. A single-wire SMA actuator is used as the control object in this research. A testing system, which includes a wire stand, a linear bearing, a bias spring, a position sensor, a programmable current amplifier and a PC-based digital data acquisition and real-time control system, is used to implement the proposed controller. The experimental results show that the actual displacement of the actuator closely followed that of the desired sinusoid command with various frequencies and maximum displacements. For the case with a reference signal of a frequency of $1/60$ Hz and a maximum displacement of 8 mm, the maximum error observed was 0.15 mm, which is less than 2% of the total stroke, and the RMS error was 0.0805 mm. These results demonstrate that the proposed method of hysteresis compensation using neural networks and a sliding-mode based controller is very effective. Future work will involve training a neural network to model the inverse of multifactor-dependent hysteresis and its implementation.

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