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INDIRECT INTELLIGENT SLIDING MODE CONTROL OF A SHAPE MEMORY ALLOY ACTUATED FLEXIBLE BEAM USING HYSTERETIC RECURRENT NEURAL NETWORKS

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Abstract

This paper introduces an indirect intelligent sliding mode controller (IISMC) for shape memory alloy (SMA) actuators, specifically a flexible beam deflected by a single offset SMA tendon. The controller manipulates applied voltage, which alters SMA tendon temperature to track reference bending angles. A hysteretic recurrent neural network (HRNN) captures the nonlinear, hysteretic relationship between SMA temperature and bending angle. The variable structure control strategy provides robustness to model uncertainties and parameter variations, while effectively compensating for system nonlinearities, achieving superior tracking compared to an optimized PI controller.

1. Introduction

In recent decades, a variety of medical devices (including coronary stents, catheter guide wires, eyeglass frames, etc.) have utilized the super-elastic properties of shape memory alloys (SMAs) [Morgan]. Even more recently, the actuation and self-sensing capabilities of SMAs have expanded their application to micro-scale and macro-scale robotics [Shreekumar, 2007a]. Because the power densities of SMA actuators are significantly higher than those of small electric motors, 90–100 W/kg v. 1.5–15 W/kg [Hirose], they have the potential to revolutionize the design, actuation and control of medical robotic systems (including upper-extremity prostheses [Andrianesis] and minimally-invasive surgical robots [Reynaerts, Carrozza]).

Real-time control of SMA actuated devices is complicated by the highly non-linear, hysteretic relationships between electrical input power and output stress and strain. While numerous SMA models have been developed, most are computationally intensive and are difficult to utilize for real-time control. Heuristic control algorithms (like PI or PID), occasionally augmented with a form of hysteresis compensation, are frequently utilized for SMA actuated devices. More advanced control strategies make use of nonlinear, hysteretic, or neural network SMA models [Shreekumar, 2007b]. In [Ahn], the Preisach model is used for hysteresis compensation and incorporated into a PID controller. In [Wakasa], the hysteretic recurrent neural network (HRNN) is used for hysteresis compensation combined with an auto-tuned PID controller. [Song] and [Tai] use neural networks combined with a sliding mode controller to regulate the displacement of a single SMA tendon.

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This paper introduces an indirect intelligent sliding mode controller (IISMC) for a SMA-actuated plant: a flexible beam deflected by an offset SMA tendon. Relevant applications include robotic catheters [Veeramani, 2008], active endoscopes [Montesi], and cantilever beam vibration controllers [Baz]. The sliding mode control (SMC) law manipulates SMA voltage to track reference SMA temperatures corresponding to desired bending angles.

A hysteretic recurrent neural network (HRNN) is used to map the nonlinear, hysteretic relationship between SMA temperature and bending angle. Like the well-known Preisach model [Mayergoyz], the HRNN consists of a weighted sum of operators, in this case conjoined sigmoid activation functions. However, the HRNN uses simple recurrence within each neuron to capture the directional dependence of the model. The distinct advantages of the HRNN over other hysteresis models have been established in literature [Veeramani 2009, Lien]. Veeramani et al. demonstrated the HRNN's superior generalization capabilities compared to radial basis function networks [Veeramani, 2009]. Lien et al. compared the HRNN to a rate-dependent Prandtl-Ishlinskii model for hysteretic piezoelectric actuators, and demonstrated 50% less modeling error for the HRNN [Lien].

Although hysteresis compensation in control algorithms has been explored previously, the approach presented here is unique because the HRNN maps temperature (instead of voltage or current) to bending angle, ensuring rate independence and precise mapping when reference trajectories are unknown a priori. Additionally, the temperature-based sliding mode control law ensures that the time delay between applied voltage and resulting SMA temperature is accounted for. The HRNN+SMC combination effectively addresses hysteresis and system nonlinearities, exhibits robustness to model uncertainties and parameter variations, and is computationally efficient, enabling real-time implementation. The remainder of the paper is organized as follows. Section 2 describes the controller, along with the simulation and experimental methods. The results are presented in Section 3, with concluding remarks presented in Section 4.

2. Methods

2.1 Plant

The plant consists of a flexible beam actuated by a single SMA tendon, Figure 1. The SMA tendon is offset from the neutral axis of the beam by a fixed distance a . As the tendon contracts, the force generated creates a moment about the beam, causing it to bend to an angle θ . A complete description of the system modeling is presented in [Veeramani, 2008].

2.2 Controller Overview

The IISMC consists of a sliding mode control law that manipulates electrical input voltage $V(t)$ to track a reference $T_r(t)$, Figure 2. This reference temperature is provided by an inverse hysteretic recurrent neural network (HRNN), while SMA temperature $T_o(t)$ is observed based on temperature measured bending angle $\theta_m(t)$.

2.3 Sliding Mode Control Law

Because the flexible beam system is inherently nonlinear and uncertain, a variable structure control strategy is employed. An augmented integral sliding surface is defined

$$s(t) = \lambda \int_0^t (T(\tau) - T_r(\tau)) d\tau + (T(t) - T_r(t)) \quad (1)$$

where $T(\cdot)$ and $T_r(\cdot)$ are the actual and reference SMA temperatures, respectively, and the integral gain λ is chosen for desired tracking performance. First-order SMA temperature dynamics are assumed

$$\dot{T}(t) = f(T(t)) + gu(t) \quad (2)$$

where $f(T(t))$ and g are estimated by models $\hat{f}(T(t))$ and $\hat{g}$ (as detailed in Section 2.4). This results in the equivalent control law

$$u_{eq}(t) = \frac{\dot{T}_r(t) - \hat{f}(T(t)) - \lambda(T(t) - T_r(t))}{\hat{g}} \quad (3)$$

Uncertainty exists between the modeled temperature dynamics $\hat{f}(T(t))$ and $\hat{g}$ and the actual temperature dynamics $f(T(t))$ and g . Additive uncertainty in $\hat{f}(T(t))$ is assumed to be bounded by $F(T)$:

$$|\hat{f}(T(t)) - f(T(t))| \leq F(T) \quad (4)$$

Because g acts to scale the input $u(t)$, multiplicative uncertainty is assumed using another known bound G

$$G^{-1} \leq \frac{\hat{g}}{g} \leq G \quad (5)$$

For robustness, a switching term is added to the equivalent control law (3)

$$u_{sw}(t) = -k \operatorname{sgn}(s(t)) \quad (6)$$

where k is chosen to guarantee stability in the presence of these model uncertainties by ensuring that the derivative of the Lyapunov function

$$\mathbf{V}(s) = \frac{1}{2} s^2 \quad (7)$$

is negative definite [Slotine], resulting in the switching gain constraint

$$k \geq \hat{g}^{-1} G(F(T) + \eta) + (G - 1) |u_{eq}(t)| \quad (8)$$

where $\eta > 0$ determines attractiveness to the sliding surface.

The switching term (6) can result in system chattering. To reduce chatter, the *sign* function in the switching term can be replaced by the *saturation* function

$$u_{sw} = -k \operatorname{sat}\left(\frac{s(t)}{\phi}\right) \quad (9)$$

where $\operatorname{sat}(\cdot)$ is defined by

$$\text{sat}(y) = \begin{cases} y, & \text{if } |y| \leq 1 \\ \text{sgn}(y), & \text{if } |y| > 1 \end{cases}$$

and the boundary layer thickness ϕ can be adjusted to address the tradeoff between tracking error and chatter.

The complete SMC law combines the equivalent control term (3) and the modified switching term (9):

$$u(t) = \frac{\dot{T}_r(t) - \widehat{f}(T(t)) - \lambda_p(T(t) - T_r(t))}{\widehat{g}} - k \text{sat} \left[\frac{\lambda_I \int_0^t (T(\tau) - T_r(\tau)) d\tau + (T(t) - T_r(t))}{\phi} \right] \quad (10)$$

where the integral gain λ in the sliding surface (1) is replaced with dual gains λ_p and λ_I that allow for the independent emphasis of proportional and integral control, respectively.

The controller parameters k , ϕ , λ_p and λ_I can be chosen to satisfy the tradeoff between response time and overshoot; for this system an iterative tuning process resulted in gains $k = 24$, $\phi = 40$, $\lambda_p = 0$, and $\lambda_I = 3$.

2.4 SMA Temperature Model

The first-order SMA temperature model (2) can be derived using an energy balance

$$mc \dot{T}(t) = -h_c A_s (T(t) - T_\infty) + j(t) - \dot{x}_+(t) h_+ m - \dot{x}_-(t) h_- m \quad (11)$$

The first term of the right hand side of (11) describes convective heat loss to the environment: h_c is the convection heat transfer coefficient between the SMA tendon and its environment (temperature T_∞), and A_s is the cross-sectional area of the tendon. The second term describes heat addition through Joule heating $j(t)$, and the last two terms describe temperature change associated with SMA phase transformation, where $x_+(t)$ and $x_-(t)$ represent the martensite plus and martensite minus phase fractions, respectively, and h_+ and h_- are the corresponding latent heats of phase transformation. [Heintze] determined the magnitudes of the latent heat terms to be small in comparison to the convective cooling and Joule heating. Neglecting the latent heat terms:

$$\dot{T}(t) = -\frac{h_c A_s}{mc} (T(t) - T_\infty) + \frac{1}{mc} j(t). \quad (12)$$

Because the convective and Joule heating coefficients vary significantly with environmental conditions, and because voltage $V(t)$ is generally more convenient to control than power

$j(t) = \frac{V(t)^2}{R}$, the coefficients in (12) are lumped into parameters $h = \frac{h_c A_s}{mc}$ and $\gamma = \frac{1}{mcR}$, where R is the SMA's electrical resistance. The temperature model can thus be expressed

$$\dot{T}(t) = -h(T(t) - T_\infty) + \gamma V(t)^2 \quad (13)$$

where the heat loss coefficient h and the power coefficient γ are easier to determine experimentally (see Section 2.7). In standard form, the temperature dynamics become

$$\dot{T}(t) = \widehat{f}(T(t)) + \widehat{g}u(t) \quad (14)$$

where $\widehat{f}(T(t)) = -h(T(t) - T_\infty)$, $\widehat{g} = \gamma$, and $u(t) = V(t)^2$.

2.5 SMA Temperature Observer

Because real-time SMA temperature measurement is impractical for the flexible beam system, a Luenberger observer is used [Luenberger]. The observer dynamics, which are based on the difference between the measured and observed bending angle, are

$$\dot{T}_o(t) = -h(T_o(t) - T_\infty) + \gamma V(t)^2 + L(\theta_m(t) - \theta_o(t)) \quad (15)$$

where $T_o(t)$ is the observed SMA temperature, $\theta_m(t)$ is the measured bending angle, and $\theta_o(t)$ is the observed bending angle. The observer gain L is initialized to 2000 to ensure the observed temperature tracks the actual (unmeasured) SMA temperature during actuation.

2.6 Hysteretic Recurrent Neural Network

The sliding mode control law (10) requires a reference temperature associated with the reference bending angle. Additionally, the observer (15) requires bending angle as a function of observed tendon temperature. The correlation between tendon temperature and bending angle is highly nonlinear and hysteretic, lacking a one-to-one relation between the two. A two-phase hysteretic recurrent neural network (HRNN) is used to map this relationship. For a complete description of the HRNN and its application to SMA modeling, see [Veeramani, 2009].

The HRNN, illustrated in Figure 3, consists of interconnected neurons with conjoined activation functions. At time step q , the output of each activation function is

$$f_i(\widehat{T}(q)) = \frac{1 - f_i(\widehat{T}(q-1))}{1 + \exp((T_{F,i} - \widehat{T}(q))\chi_i)} + \frac{f_i(\widehat{T}(q-1))}{1 + \exp((T_{R,i} - \widehat{T}(q))\chi_i)} \quad (16)$$

where $\widehat{T}(q)$ refers to SMA tendon temperature (either measured, observed, or reference) at the q^{th} time step. The activation functions range between 0 and 1, where 0 refers to an inactive neuron and 1 refers to an active neuron. The parameter χ_i controls how quickly the output switches between the two values, with a high value ($\chi_i \gg 1$) leading to step changes. A previously inactive neuron becomes active at the forward transition temperature $T_{F,i}$. A previously active neuron becomes inactive at the reverse transition temperature $T_{R,i}$.

The network output

$$\widehat{\theta}(q) = \sum_{i=1}^N w_i^2 f_i(\widehat{T}(q)) \quad (17)$$

is a weighted combination of these activation functions. Squaring the network weights w_i ensures a positive contribution from each neuron, and establishes a statistical distribution of SMA crystals based on their transformation temperatures:

$$\sum_{i=1}^N w_i^2 = 1 \quad (18)$$

The HRNN is trained to optimize network weights using open loop data from the physical plant. The Levenberg-Marquardt algorithm [Marquardt] is used to solve the nonlinear optimization problem governed by the cost function

$$P = \frac{1}{2} \sum_{q=1}^Q e(q)^2 \quad (19)$$

where

$$e(q) = \theta_m(q) - \hat{\theta}(q) \quad (20)$$

represents the error between an experimentally measured bending angle $\theta_m(q)$ and the HRNN-predicted angle $\hat{\theta}(q)$.

The optimization algorithm was implemented using MATLAB's *lsqnonlin* command (The MathWorks, Inc., Natick, MA) using a Jacobian defined by

$$J_{q,i} = \frac{\partial e(q)}{\partial w_i} = -2w_i f_i. \quad (21)$$

This HRNN maps observed temperature to observed bending angle; to determine reference temperature from reference bending angle requires inversion of the network. Because the analytical inverse of this network is difficult/impossible to evaluate, a bisection algorithm is used to approximate it. The bisection algorithm uses current system state information (activation states of the HRNN) and halves the SMA temperature range iteratively until a specified tolerance is achieved. The complete block diagram of the indirect intelligent sliding mode controller (IISMC) is shown in Figure 4.

2.7 Temperature Model Parameter Determination

The heat loss coefficient h of the temperature model (13) can be determined experimentally from the system's transient response, Figure 5(a). A constant voltage is applied to the flexible beam system and then switched off at time t_i . The temperature dynamics are described by

$$\dot{T}(t) = -h(T(t) - T_\infty) \quad (22)$$

which is solved analytically

$$T(t) = (T_i - T_\infty)e^{-h(t-t_i)} \quad (23)$$

where T_i is the temperature at time t_i . The heat loss coefficient is then determined by:

$$h = -\frac{1}{t-t_i} \ln \left(\frac{T-T_\infty}{T_i-T_\infty} \right) \quad (24)$$

where T is the SMA temperature at some time $t > t_i$. Because extrema in bending angle and temperature occur simultaneously, it is reasonable to assume that the bending angle decay rate is approximately equal to the temperature decay rate. Therefore, the heat loss coefficient can be approximated from

$$h \approx -\frac{1}{t-t_i} \ln \left(\frac{\theta-\theta_f}{\theta_i-\theta_f} \right) \quad (25)$$

where θ_i and θ are the measured bending angles at times t_i and $t > t_i$ respectively and θ_f is the final steady-state bending angle determined from Figure 5(a).

Once the heat loss coefficient is determined, the power coefficient is calculated from the steady-state portion of a plant step response using

$$\gamma = \frac{h(T_{ss}-T_\infty)}{V_{step}^2} \quad (26)$$

where V_{step} is the voltage step input that results in steady-state SMA temperature T_{ss} . The bending angle associated with a steady-state SMA temperature can be estimated from stress-strain data obtained at a specific SMA temperature T_{ss} , Figure 5(b). The functional relationship between stress σ and strain ϵ in the flexible beam system is calculated from

$$\sigma = \frac{EI}{a^2 A_c} (\epsilon_p - \epsilon) \quad (27)$$

where EI is the bending stiffness of the beam, a is the tendon offset from the neutral axis, A_c is the cross-sectional area of the SMA tendon, and ϵ_p is the SMA pre-strain [Veeramani, 2008]. This relationship is superimposed on the constant temperature stress-strain hysteresis curve, Figure 5(b). The stress where this load line intersects the unloading curve is determined. From this stress the bending angle is calculated

$$\theta_{ss} = \frac{a A_c L}{EI} \sigma_{ss} \quad (28)$$

where L is the length of the active SMA tendon [Veeramani, 2008]. A ramp voltage input of 24.5 mV/sec is applied to the plant until this bending angle is reached; this relatively slow input rate eliminates overshoot in the bending angle response. Finally, the known temperature and voltage are used in (26) to calculate γ .

2.8 Simulation Methods

IISMC performance was simulated using the homogenized energy model (HEM) of SMAs; see [Crews] for a complete description. SMA tendon stress is determined by coupling the beam bending stress-strain relation (27) with the SMA stress-strain relation

$$\sigma(t) = \frac{\varepsilon(t) - \varepsilon_T(x_+(t) - x_-(t))}{\frac{1 - x_+(t) - x_-(t)}{E_A} + \frac{x_+(t) + x_-(t)}{E_M}} \quad (29)$$

where $x_+(t)$ and $x_-(t)$ represent the fractions of the SMA tendon in the martensite plus (tension induced) and martensite minus (compression induced) phases, respectively. These phase fractions depend on SMA tendon temperature, see [Crews] for a complete discussion of their calculation. Once stress in the tendon is known, the bending angle is calculated from

$$\theta(t) = \frac{aA_c L}{EI} \sigma(t). \quad (30)$$

For simulations, the IISMC and plant model were implemented using MATLAB's Simulink (The MathWorks, Inc., Natick, MA). Model parameters were optimized to fit open-loop experimental data obtained from the plant. HRNN training and testing data were generated by simulating plant responses to the inputs shown in Figure 6. This relatively slow, piecewise linear alternating voltage results in hysteretic temperature-bending angle data that captures the ascending and descending transition curves of the SMA. The HRNN was then trained by optimizing neuron weights, as outlined in (19)-(21). Finally, the neuron weights and transition temperatures were imported into the IISMC algorithm.

2.9 Experimental Methods

Experimental validation of the developed controller was conducted on the flexible beam system shown in Figure 7(b). The system consists of a central flexible beam (0.5 mm diameter super-elastic Nitinol) with equally-spaced collets attached to hold the SMA tendon (0.127 mm diameter Flexinol, Dynalloy, Inc. Tustin, CA) at a fixed offset from the neutral axis. The tendon was encased in PTFE tubing to minimize friction and heating in the collets.

For real-time implementation, the IISMC was programmed in Visual Studio C++ (Microsoft Corporation, Redmond, WA) and set to run at 50 Hz. During operation, commands are sent through serial communication to a microcontroller, which regulates the voltage sent from the power supply (Agilent E3620A, Agilent Technologies, Santa Clara, CA) to the SMA tendon using pulse width modulation. Assuming constant-curvature deflection [Veeramani, 2008], bending angle is calculated from 3D position sensors (trakSTAR 3D Magnetic Tracking System, Ascension Technology Corporation, Burlington, VT) which measure the location of the base and tip of the flexible beam. A complete schematic of the experimental setup is shown in Figure 7(a).

Bending angle data was acquired for HRNN training using the same plant inputs of Figure 6. SMA tendon temperature was calculated using (13). The HRNN was then trained to optimize the network weights as outlined in (19)–(21); weights were then imported into the control code.

3. Results

3.1 Temperature Model Parameters

A transient system step response, Figure 8(a), resulted in a heat loss coefficient $h = 0.637 \text{ s}^{-1}$, calculated from (25). Constant temperature stress-strain data, originally published in [Crews] and reproduced here in Figure 8(b), was obtained via tensile testing using the same SMA wire used for plant fabrication. The bending model parameters, Table 1, were measured during plant fabrication and resulted in the load line shown in Figure 8(b). Using this graph, the steady-state stress σ_{ss} and corresponding steady-state bending angle θ_{ss} were

determined. From these values, the associated input voltage was determined and the power loss coefficient $\gamma=2.47 \frac{K}{sV^2}$ was computed from (26).

3.2 Simulation Results

A HRNN with 1561 neurons was initialized with 151 normalized forward transition temperatures $T_{F,i}$ ranging from 0 to 1 at equal intervals of 0.00667. Each forward transition temperature was paired with 21 reverse transformation temperatures $T_{R,i}$ ranging from $T_{F,i} - 0.0$ to $T_{F,i} - 1.0$ at equal intervals of 0.05, where only pairs with positive reverse transformation temperatures were implemented as neurons.

The simulated training data (2660 input-output samples) and testing data (2900 input-output samples) were normalized, and the HRNN was trained to optimize network weights. Figure 9 shows the simulated training and testing data along with the optimally trained HRNN prediction. The optimal solution resulted in a training cost of 1.39×10^{-4} and a testing cost of 1.36×10^{-4} , reduced from initial values of 0.234 and 0.233, respectively, over 65 epochs. The constraint equation on network weights (18) was confirmed.

The optimized HRNN weights and transition temperatures were implemented into the IISMC and simulations were conducted to demonstrate performance without temperature model uncertainties. Figure 10 shows precise tracking of a sinusoidal bending angle reference trajectory. Figure 10(c) illustrates how effectively the observed temperature tracks the reference temperature. Additionally, the observed temperature tracks the actual SMA temperature, validating the HRNN's ability to generalize the system's hysteretic characteristics.

3.3 Experimental Results

The HRNN training process to optimize network weights was repeated using experimental training data (2660 input-output samples) and testing data (2900 input-output samples). The optimal solution resulted in a training cost of 8.79×10^{-5} and a testing cost of 2.71×10^{-4} , reduced from initial values of 0.212 and 0.200, respectively, over 27 epochs. The constraint equation (18) was satisfied to within 0.02. The resulting HRNN prediction, along with the experimentally generated training and testing data, are shown in Figure 11. The maximum error between experimental data (not used for HRNN training) and the inverse HRNN prediction was determined to be 11.3K; this error bound was utilized to establish the additive and multiplicative uncertainty bounds ($F(T)$ and G in (4) and (5), respectively) used to ensure stability robustness of the sliding mode control algorithm.

Controller performance was evaluated using a 0.05 Hz sinusoidal reference, with results shown in Figure 12. The observed temperature tracked the reference temperature, Figure 12(c), resulting in precise regulation of the reference trajectory, Figure 12(a). The control input, Figure 12(b), is composed of the equivalent control term u_{eq} , Figure 12(d), which accounted for 72% of the total input, and the switching term u_{sw} , which ensured attractiveness to the sliding surface and overcame model uncertainties.

For comparison, the gains of a proportional+integral (PI) controller were optimized using a modified version of the Ziegler-Nichols method [Chien]. The gains were then manually tuned for optimal performance, resulting in a proportional gain of $k_p = 4.5$ and an integral gain of $k_i = 10$. Figure 13 and Figure 14 compare IISMC and PI controller performance for sinusoidal and ramp bending angle reference trajectories of various frequencies. These figures demonstrate superior tracking performance for the IISMC over the PI controller. This is evident at the peaks of the reference trajectories, where the PI controller corrected based on a small error in bending angle, while the IISMC compensated for hysteresis and

corrected based on the larger error in temperature. Computing the RMS tracking error over one period, Table 2, the IISMC resulted in 33.2 ± 5.3 % less error than the PI controller for the six reference trajectories tested.

While differences in tracking error between the IISMC and the PI controller are relatively small, a primary advantage of the IISMC is evident at directional changes, where the system must overcome actuator hysteresis. In tracking situations where rapid directional changes are common, the IISMC has a clear performance benefit. Additionally, larger diameter SMA tendons often required for higher force applications have longer heating and cooling times. In those cases it is expected that the performance differences would be even more apparent, as the IISMC regulates temperature and can thus account for large delays between input voltage and resulting actuation.

4. Conclusion

This paper demonstrates a controller incorporating a hysteretic recurrent neural network with a sliding mode control law to regulate the bending angle of a flexible beam actuated by a single SMA tendon. The results prove controller feasibility demonstrating fast response times and precise tracking of a variety of reference trajectories. The controller effectively compensates for hysteresis in the SMA tendon and overcomes temperature model uncertainties.

Future work will focus on extending the IISMC to antagonistic SMA systems. An antagonistic pair of SMA tendons can increase actuator bandwidth, limited in the single tendon case by relatively slow tendon cooling compared to heating.

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Figure 1. SMA-actuated flexible beam system: (a) output bending angle of the deflected beam; (b) close-up showing collets used to maintain the SMA tendon at a fixed offset a .

Figure 2.
Block diagram of the IISMC showing key components and their interactions.

Figure 3.
Two-phase HRNN architecture relating SMA tendon temperature to beam bending angle.

Figure 4.

Indirect intelligent sliding mode controller (IISMC) block diagram showing the sliding mode control law (SMC), the hysteresis recurrent neural network (HRNN) and its inverse ($HRNN^{-1}$), the temperature observer, and the plant.

Figure 5.

(a) Transient step response used to estimate heat loss coefficient and (b) SMA stress-strain data at a constant temperature with superimposed load line representing the flexible beam system model (27).

Figure 6. Plant inputs for generating simulated and experimental HRNN training and testing data.

Figure 7. Experimental setup for controller validation: (a) schematic of the test setup; (b) photograph of the flexible beam system with position sensors

Figure 8.

(a) Transient plant step response used to calculate heat loss coefficient and (b) SMA tendon stress-strain data at 80 C taken from [Crews] with superimposed load line for the flexible beam system model.

Figure 9. Simulated HRNN predicted bending angle as a function of temperature compared to (a) training data and (b) testing data obtained from the flexible beam system model.

Figure 10. Simulated IISMC tracking results for a 0.05 Hz sinusoidal reference trajectory showing (a) bending angle, (b) controller generated plant input, (c) reference, observed, and actual SMA tendon temperature, and (d) contributions of the switching and equivalent control terms.

Figure 11. Experimental HRNN predicted bending angle as a function of temperature compared to (a) training data and (b) testing data obtained from the flexible beam system.

Figure 12.

Experimental IISM tracking results for a 0.05 Hz sinusoidal reference trajectory showing (a) bending angle, (b) controller generated plant input, (c) reference and observed SMA tendon temperature, and (d) contributions of the switching and equivalent control terms.

Figure 13.
Experimental IISMC and PI controller tracking performance against sinusoidal references of 0.05, 0.067, and 0.1 Hz frequencies.

Figure 14.

Experimental IISMC and PI controller tracking performance against ramp references of 0.05, 0.067, and 0.1 Hz frequencies.

Table 1

Bending model parameters

Symbol	Description	Value	Unit
EI	Beam bending stiffness	1.30×10^{-4}	Nm ²
r	SMA tendon radius	0.0635	mm
a	Tendon offset from neutral axis	1.0	mm
L	Active beam length	88.0	mm
ε_P	SMA tendon pre-strain	4.0	%

Table 2

Performance measures comparing IISMC and PI controller for sinusoidal and ramp reference trajectories of various frequencies.

Reference Trajectory	RMS Tracking Error (deg)		RMS Control (V)	
	IISMC	PI	IISMC	PI
Sinusoidal, 0.05 Hz	0.37	0.54	2.55	2.54
Sinusoidal, 0.067 Hz	0.55	0.82	2.62	2.70
Sinusoidal, 0.1 Hz	0.99	1.30	2.84	2.91
Ramp, 0.05 Hz	0.43	0.70	2.43	2.68
Ramp, 0.067 Hz	0.61	0.99	2.55	2.84
Ramp, 0.1 Hz	0.99	1.49	2.63	2.91