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Self-sensing SMA Actuator using Extended Kalman Filter and Artificial Neural Network

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Abstract

In this paper, self-sensing capability of Shape Memory Alloy wire actuator has been explored using Extended Kalman Filter assisted Artificial Neural Network. The change in length of a linear spring actuated using a Shape Memory Alloy wire is first estimated from the variation of its electrical resistance using Extended Kalman Filter. Though the estimation is qualitatively in agreement with the experiment, the quantitative mismatch makes it difficult to control the stretch of the spring solely based on the Extended Kalman Filter estimation. An Artificial Neural Network has been used to bridge the gap between the Extended Kalman Filter estimation and actual stretch of the spring. To evaluate the effectiveness of the Extended Kalman Filter based Artificial Neural Network model, the responses of the same are compared with that of the another Artificial Neural Network model, trained only using the experimental data. It has been observed that for the same number of neurons and same training data, Extended Kalman Filter based Artificial Neural Network model yields better result at higher frequencies.

Keywords: Shape Memory Alloy; Extended Kalman Filter; Artificial Neural Network;

1. Introduction

Shape Memory Alloy (SMA) is one of the most promising smart materials, which can memorize its low temperature shape; i.e., once deformed under external force, can regain its shape if heated above the phase transformation temperature. The low temperature phase is called Martensite (M) phase, having low yield strength, and hence can be deformed to any new shape easily. Subsequently, when heated above the critical transformation temperature, M phase

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transforms to Austenite (A) phase and it returns to its undeformed shape. While recovering its shape, it can generate up to 500 MPa of stress, while restrained from free recovery. The SMA wires exhibit large displacement capability, almost 4~5% of its initial length. These features are harnessed in SMA based actuators. It has been observed that along with the mechanical properties, the electrical properties also alter significantly, offering them as a self-sensing actuator. Recently, few researchers have explored the self-sensing capability of SMA wire actuator, using empirical relation between displacement of the spring and change in electrical resistance (ER) of the wire [1, 2, 3, 4, 5]. In this approach, one has to derive these relations provided the system parameters are changed or the extent of transformation, which depends on loading conditions, are altered. To obviate this difficulty, an Extended Kalman Filter (EKF) and Artificial Neural Network (ANN) based approach is developed and reported in this paper. Till now very few researchers reported Kalman Filter and Extended Kalman Filter to predict the state of the SMA based system to develop feedback controllers [6, 7, 8, 9]. However, EKF has not been explored for self-sensing application of SMA. Firstly, the system of interest is depicted followed by a brief introduction of EKF. Next the experimental setup is described, which is used to measure the change in ER of SMA wire actuator and the displacement of the spring. Then two ANN models are developed, one in which the EKF estimated system response is used as inputs to train the ANN model (ANN-I), whereas, the other one, denoted as ANN-II, concedes the experimentally measured data as inputs. Finally, some of the simulation results are discussed to demonstrate the capabilities of the developed ANN-I and ANN-II.

2. Description of the system

The system consists of a linear spring actuated by an SMA wire (ab), as shown in Figure 1. Here, one end of the SMA (a) is connected to spring and the other end (b) is fixed. The linear spring is used mainly to provide the restoring force to the SMA. As the SMA gets heated due to resistive heating, known as Joule’s effect, it tries to contract and resulting in an expansion of the spring by an amount δ. Because of the stiffness of the spring the SMA undergoes a partial contraction (a'b'), referred as constrained recovery. However, during cooling, in this case due to natural convection, the elastic force stretches the SMA wire back to the deformed length. The main objective of this work is to accurately determine the change in length of the spring, δ, from the measured electrical resistance of the SMA wire using EKF and ANN. In what follows the details of the ANN models are discussed.

![Fig. 1. Schematic diagram of SMA wire actuated linear spring.](image)

3. EKF Based Artificial Neural Network (ANN)

For the system of interest, an EKF has already been developed to estimate the change in length of the spring from the measured electrical resistance (ER) variation of the SMA wire. For a given applied voltage, and the corresponding change in ER, as measured using the setup discussed in section 4, the estimated displacement of the spring and the same measured experimentally are compared, as presented in Fig. 2a. One can note the quantitative discrepancy between the two. To reduce the gap, two ANN models are explored. Each ANN model consists of one hidden layer having ten neurons, three inputs and one output. The models differ from the perspective of inputs only. The first model, referred as ANN-I, intakes estimated temperature (\(T_{EKF}\)), its rate of change (\(\dot{T}_{EKF}\)) and estimated change in length of the spring (\(\delta_{EKF}\)) as obtained from the EKF. On the other hand, ANN-II model concedes the applied voltage across
SMA \( (V) \), its rate of change \( (\dot{V}) \) and the change in ER of SMA as obtained from the experiment. In both the models the output is the displacement of the spring. The whole process is explained using a flow diagram as shown in Fig. 2b. The ANN models are depicted in Figs. 2c and 2d, respectively. The rate of temperature and voltage are included as inputs to distinguish the heating and cooling part of the actuation cycles, taking care of hysteric response. The comparison of these two models is done to study the effect of the developed EKF. Both ANN-I and ANN-II are trained using the same experimental responses shown in Fig. 2a. The neural network toolbox in MATLAB©MathWorks is used for this study.

![Fig. 2. (a) Comparison between EKF and experimental response; (b) A Schematic diagram for neural network training; (c) The structure of the neural network for ANN –I; (d) The structure of the neural network for ANN-II.](image)

4. Experimental Details

An experimental setup is developed to measure the change in length of a spring for a desired input voltage applied across the SMA wire of 125 µm diameter and 250 mm length. The overall procedure is depicted using a flow diagram in Fig. 3a. The setup comprises of a laser displacement sensor, a data acquisition system having analog input and output ports, a voltage divider circuit, an analog programmable power supply and a desktop PC, shown in Fig. 3b. Figure 3c shows the system comprising of SMA wire, connected in series, with a linear spring. The other ends of the SMA wire and spring are connected to rigid walls as presented in Fig. 1a. The displacement of the spring is measured using a laser displacement sensor, opto NCDT-1402-100 from Micro-Epsilon, Germany, with a measuring range of 100 mm and resolution of 0.6 µ; providing an analog output voltage of 0-10V. To determine the ER of the SMA wire,
a simple voltage divider circuit is designed and developed. The schematic diagram of the circuit is shown in Fig. 3d. In this circuit, the total voltage drop across the SMA wire, \( V_{ckt} \), and the same across the known resistance \( R_0 \), i.e., \( V_R \) are measured. Thus the ER of the SMA wire \( R_{SMA} \) is calculated as

\[
R_{SMA} = \left( \frac{V_{ckt} - V_R}{V_R} \right) R_0
\]

(1)

Here, \( R_0 = 5 \Omega \) is used. The voltages \( V_{ckt} \), \( V_R \) and the analog output of the laser displacement sensor are acquired using three analog input ports of DS1006, dSPACE. The chassis of DS1006 contains 20 analog input and 8 analog output ports. A simple model is developed in SIMULINK8.2©MathWorks to save the acquired data in PC and to determine the ER of the SMA wire following Eq. (1). The desired time varying voltage, to be applied to the SMA wire, is developed in SIMULINK model and is applied to SMA wire through one of the analog outputs of the DS1006. This analog signal, before being applied to SMA wire, has been amplified using the analog programmable DC power supply 6642A, Agilent. Furthermore, the stiffness of the spring is obtained experimentally. A six-axis force sensor, Gamma-9105, Schunk, is used to measure the force applied on the spring. It can measure up to 65 N in X and Y direction with a resolution of 0.0125 N and 200 N in the Z direction. It contains six analog outputs, each in the range of 1-5 V. The six analog signals need to be acquired simultaneously and once multiplied by the calibration matrix yields force and moment data. The linear spring is placed along the X-axis of the sensor. As the load is applied, the spring stretches and the deflection is measured using same laser displacement sensor mentioned above. Figure 4 shows the force-displacement diagram of the spring and its linear fit dictates the stiffness of the spring; as is found to be \( k_s \) = 0.1 N/mm.

![Fig. 3. (a) Flow chart of the experiment; (b) Actual experimental setup; (c) SMA Actuated spring; (d) Schematic of the voltage divider circuit used for resistance measurement.](image_url)
5. Results and Discussion

First, sinusoidal voltages having different frequency and amplitude are applied across the SMA wire, and the corresponding change in electrical resistance of the SMA wire and spring displacement are measured experimentally. Then EKF is used to estimate the temperature ($T_{EKF}$) and spring deflection ($\delta_{EKF}$) from the experimentally measured ER. All these are then used in the trained ANN-I, to obtain the actual displacement ($\delta_1$). Besides, the ANN-II, directly uses the experimental data and yields actual displacement ($\delta_2$). These are then compared and shown in Figs. 5 and 6. The responses, shown in Fig.5a, correspond to the sinusoidal input voltage of frequency $\omega = 0.6$ rad/s and amplitude 7 Volt. It can be observed that both the ANN models predict the displacement of the spring with reasonable accuracy. Figure 5b depicts the responses of the ANN models, in comparison to the experimental one, for a sinusoidal input voltage of same amplitude but with a frequency, $\omega = 1.25$ rad/s. It can be observed that there is a significant discrepancy in the displacement estimated by ANN-II, particularly, during cooling. This may be because ANN-II has been trained for different input frequency as shown in Fig. 2a. Though the ANN-I model has also been trained for the same input as that of ANN-II, however, the governing equations, representing SMA behavior, inculcated in the EKF helps ANN-I model in avoiding the discrepancy. The response for sinusoidal input of amplitude 4.5 Volt and frequency $\omega = 0.6$ rad/s is presented in Fig. 6a. In this case, the SMA wire undergoes partial transformation and both models have accurately captured the same. However, for sinusoidal inputs of amplitude 4.9 Volt and frequency $\omega = 1.25$ rad/s, the response as shown in Fig. 6b; clearly reveals the limitation of ANN-II. It might be possible to improve the performance of ANN-II model by increasing more hidden layers and training data; however, that requires more computational resource and training time.

![Fig. 5. Comparison between EKF and experimental response for full transformation with sinusoidal input voltage.](image-url)
6. Conclusion

In this paper, the self-sensing capability of SMA wire actuator has been harnessed using an Extended Kalman Filter based Artificial Neural Network. The effectiveness of the developed model (ANN-I) is demonstrated by comparing its response with that of another Artificial Neural Network model (ANN-II), trained based on experimental data. ANN-I concedes EKF estimated response; whereas ANN-II intakes experimentally measured inputs. Both ANN comprises same number of neurons and are trained using the same method. For the same training data, EKF based ANN model yields satisfactory performance in comparison to ANN based on experimental response, particularly at higher frequencies.

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