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Experimental evaluation of discrete sliding mode controller for piezo actuated structure with multisensor data fusion

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Abstract. This paper evaluates the closed loop performance of the reaching law based discrete sliding mode controller with multisensor data fusion (MSDF) in real time, by controlling the first two vibrating modes of a piezo actuated structure. The vibration is measured using two homogeneous piezo sensors. The states estimated from sensors output are fused. Four fusion algorithms are considered, whose output is used to control the structural vibration. The controller is designed using a model identified through linear Recursive Least Square (RLS) method, based on ARX model. Improved vibration suppression is achieved with fused data as compared to single sensor. The experimental evaluation of the closed loop performance of sliding mode controller with data fusion applied to piezo actuated structure is the contribution in this work.

Keywords: data fusion; sliding mode controller; piezoelectric; smart structure; estimation; structural vibration

1. Introduction

Developments in smart-intelligent materials technology offer great potential for active control of vibration in advanced aerospace, nuclear and automotive structural applications and have motivated many researchers to work in the field of smart structures in the last two decades. A smart structure typically consists of a host structure incorporated with sensors and actuators, and coordinated by a controller. This integrated structural system is called a smart structure, because it has the ability to perform self-diagnosis and adapt to the environmental changes. It can be seen in Chopra (2002) and Hurlebaus (2006), that the technology of smart materials and structures especially piezoelectric based smart structure has become mature over the last decade. One promising application of piezoelectric smart structure is the control and suppression of unwanted structural vibrations.

Multisensor data fusion is the process of combining output from sensors with information from other sensors, information processing blocks, databases or knowledge bases in to one representational form. It is reported in Hall (1992), that this technique is expected to

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achieve improved accuracy and more specific inferences that could be achieved by the use of single sensor alone. Data fusion will be very much useful, whenever a single sensor used for measurement does not contain all the required characteristics, for the desired range of operation. The importance and application of data fusion in robotics, control and nanopositioning are reported in Koch (2010), Garcia (2009), Besada-Portas (2009), Luo (2008), Katsura (2008) and Fleming (2008).

Continuous and discrete sliding mode control (SMC) theory is covered in Bartoszewicz (1998), Hung (1993) and Gao (1995). Application of SMC for smart structure control problem is reported in Choi (1996). The recent advancements in sliding mode theory, which is about the design of sliding mode controller via static output feedback, for a class of uncertain systems with mismatched uncertainty, design of sliding mode based discrete time reduced-order observer, design of sliding mode based output-feedback controllers for uncertain systems which are subject to time-varying state delays, design of adaptive controller for piezoelectric actuators with SMC are proposed in Zhang (2010), Mehta (2010), Han (2009) and Huang (2009) respectively. This work reveals the effectiveness and importance of data fusion in achieving improved closed loop performance, with discrete time sliding mode controller, and it is the real time implementation of the work, presented in Arunshankar (2010). This paper presents the experimental evaluation of the closed loop performance of sliding mode controller with data fusion applied to piezo actuated structure.

The paper is organized as follows: Section 2 is concerned with the experimental setup and its model used in this work. Review of Kalman and Information filter is presented in Section 3. In Section 4 review of data fusion methods namely Information fusion, State vector fusion, Simple fusion and Composite fusion methods are presented. Controller design is presented in Section 5. Results and discussion is presented in Section 6. Conclusions are drawn in Section 7.

2. Experimental setup and its model

2.1 Experimental setup

An experimental facility which is designed and developed to control the structural vibration of a clamped free aluminum beam with piezo sensing and actuation is shown in Fig 1. Two piezoceramic patches, which act as sensors are surface bonded on the bottom surface of the beam at a distance of 10 mm and 105 mm from the fixed end. Another pair of piezo patch is surface bonded on the top surface of the beam, one at a distance of 10 mm and the other at a distance of 375 mm from the fixed end, to act as control and disturbance actuators respectively. The dimensions and properties of the beam and piezoceramic patches are given in Table 1.

Piezo sensors output are conditioned by a piezo sensing system, which consists of high quality charge to voltage converters, the output of which is applied as input to the ADC of dSPACE 1104 controller board. The model identification and control algorithms are developed using Simulink software, and implemented in real time on dSPACE 1104 controller board, using MATLAB RTW and dSPACE real time interface tools. The control signal generated is converted to analog by the DAC of dSPACE 1104 controller board and is applied to the piezo actuation system, which drives the control actuator. The disturbance input is applied to the disturbance actuator using an arbitrary waveform generator (Agilent 33220A) through a piezo actuation system.

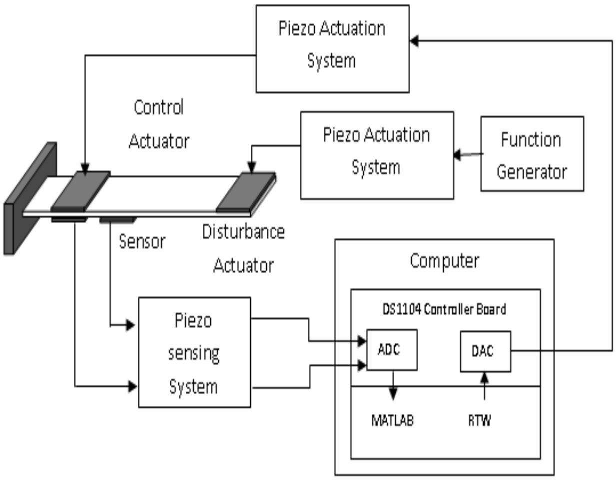


Fig. 1 Schematic of experimental set up

Table 1 Properties and dimensions of aluminum beam and piezoceramic sensor/actuator

Aluminum beam		Piezoceramic sensor / actuator	
Length (m)	0.40	Length (m)	0.0765
Width (m)	0.0135	Width (m)	0.0135
Thickness (m)	0.001	Thickness (m)	0.0005
Young's modulus (Gpa)	71	Young's modulus (Gpa)	47.62
Density (kg/m^3)	2700	Density (kg/m^3)	7500
First natural frequency (Hz)	5.5	Piezoelectric strain constant (mV^{-1})	-247x10^{-12}
Second natural frequency (Hz)	30.3	Piezoelectric stress constant (VmN^{-1})	-9x10^{-3}

2.2 Model identification

The unknown parameters of smart structure dynamics are estimated using online identification method. The Recursive Least Square (RLS) method based on ARX model illustrated in Ljung (1999) is used, since it is easy to implement and has fast parameter convergence. The ARX model for the structure shown in Fig 1 is

$$\begin{aligned} &\hat{y}(k)+a_1y(k-1)+.....+a_{n_a}y(k-n_a)=b_1u(k-1)+..... \\ &+b_{n_b}u(k-n_b)+c_1r(k-1)+.....+c_{n_c}r(k-n_c)+e(k) \end{aligned} \tag{1}$$

Where $u(k)$ is input signal, $r(k)$ is excitation signal, $y(k)$ is piezo sensor output, $e(k)$ is white noise and n_a, n_b & n_c determine the model order. Since this work is focused on the design and experimental evaluation of vibration control of cantilever beam, realizing the fact that the first few vibration modes play a vital role in the structural dynamics, the model structure is selected to represent the dynamics of the first two modes of vibration. Eq. (1) is equivalently expressed as linear regression model

$$\hat{y}(k) = \varphi^T(k)\hat{\theta}(k-1) \tag{2}$$

The unknown parameter and data vector is

$$\theta = \left(a_1, a_2, ..., a_{n_a},\quad b_1, b_2, ..., b_{n_b},\quad c_1, c_2, ..., c_{n_c}\right)^T \tag{3}$$

$$\begin{aligned}\varphi(k) = (&-y(k-1), -y(k-2), ..., -y(k-n_a), u(k-1), u(k-2), ...,\\ &u(k-n_b), r(k-1), r(k-2), ..., r(k-n_c))^T\end{aligned} \tag{4}$$

For the algorithm to update the parameters at each sampling interval, it is necessary to define model prediction error, which is given as

$$\varepsilon(k) = y(k) - \hat{y}(k) \tag{5}$$

The $\varepsilon(k)$ is used to update the parameter estimate as

$$\hat{\theta}(k) = \hat{\theta}(k-1) + P(k)\varphi(k)\varepsilon(k) \tag{6}$$

where the covariance matrix $P(k)$ is updated using

$$P(k) = P(k-1)\left(1 - \frac{\varphi(k)\varphi^T(k)P(k-1)}{1 + \varphi^T(k)P(k-1)\varphi(k)}\right) \tag{7}$$

The initial values of $\hat{\theta}(k)$ and $P(k)$ are chosen to be $\hat{\theta}(0) = 0$ and $P(0) = \alpha I_Z$ with $\alpha = 10^4$. To identify the parameters, the structure is excited by a sinusoidal signal by sweeping the frequency in the range of (0-50 Hz), which includes first two natural frequencies of the beam, through disturbance actuator and a square wave signal as an input to the control actuator. The RLS algorithm is implemented by writing a C-file S-function used in MATLAB/Simulink. The sampling time is chosen to provide approximately six measurements per cycle (sampling frequency 200 Hz). Then the input-output data is collected to obtain the model. The model thus obtained is validated by observing the convergence of identified parameters, matching between actual plant and model response, using a data set that is different from the data used to calculate the model parameters. The closeness of the natural frequencies of the identified model with that of the experimentally measured is also verified. The discrete state space representation of the ARX model of the system given in Eq. (1) is

$$x(k+1) = A_d x(k) + b_d u(k) + e_d d(k);\, y(k) = C_d x(k) \tag{8}$$

where

$$A_d = \begin{bmatrix} 0.0575 & 1.0721 & -0.3505 & 0.1357 \\ -0.1423 & -0.0505 & 1.2656 & 0.3203 \\ 0.8675 & -0.1401 & 0.4852 & -0.1439 \\ -0.7012 & 0.3878 & -1.4834 & 0.7127 \end{bmatrix} b_d = \begin{bmatrix} -0.0042 \\ 0.0008 \\ -0.0014 \\ 0.0064 \end{bmatrix} e_d = \begin{bmatrix} -0.0042 \\ 0.0008 \\ -0.0014 \\ 0.0064 \end{bmatrix} C_d = [1\ 0\ 0\ 0]$$

where A_d is the system matrix, b_d the control input vector, e_d the disturbance vector, C_d the output matrix, x the state vector and y the system output. The mode frequencies obtained from the identified model are 5.5 Hz and 30.3 Hz, which are close to the experimentally measured mode frequencies. The beam is excited, by a disturbance *d(k),* initially at first mode frequency of 5.5 Hz and then at second mode frequency at 30.3 Hz, to evaluate the controller performance at resonance.

3. Estimation of states

The state variables are estimated either using Kalman filter or Information filter. The state vector fusion and simple fusion methods use Kalman filter for estimating the states. The information fusion method uses Information filter for estimating the states. The composite fusion technique uses both Kalman as well as Information filter for estimating the states. The sensors output are sampled for every 0.01 sec, which is used by the estimator algorithms for generating the states. The state estimation algorithms are developed using Simulink software and implemented in real time on dSPACE 1104 controller board using MATLAB RTW and dSPACE real time interface tools. A brief review of Kalman filter and information filter algorithms given in Mutambara (1998) is presented in this section.

Consider a discrete system given by

$$x_d(k+1) = A_d x_d(k) + w(k) \tag{9}$$

where $x_d(k)$ represents the states of interest at time k, A_d the state transition matrix from time k to $k+1$, and $w(k)$ the associated process noise modelled as an uncorrelated white sequence with

$$E[w(i)w^T(j)] = \delta_{ij} Q(i) \tag{10}$$

where $Q(i)$ is the process noise covariance matrix.

The system is observed according to the linear equation

$$z(k) = Hx_d(k) + v(k) \tag{11}$$

where $z(k)$ is the vector of observations made at time k, H the observation matrix and $v(k)$ the associated observation noise modelled as an uncorrelated white sequence with

$$E[v(i)v^T(j)] = \delta_{ij} R(i) \tag{12}$$

where $R(i)$ is the measurement noise covariance matrix.

It is also assumed that

$$E[v(i)w^T(j)] = 0 \tag{13}$$

3.1 Review of Kalman estimator

Let the state estimate and covariance at time t_k be $\hat{x}(k|k)$ and $P(k|k)$

State and Covariance Prediction

$$\hat{x}(k+1|k) = A_d\hat{x}(k|k) + Bu(k) \tag{14}$$

$$P(k+1) = A_d P(k|k) A_d' + Q(k) \tag{15}$$

Measurement Prediction

$$\hat{z}(k+1|k) = H\hat{x}(k+1|k) \tag{16}$$

Calculation of Innovation Covariance

$$M(k+1) = HP(k+1|k)H' + R(k+1) \tag{17}$$

Calculation of Measurement Residual

$$e(k+1) = z(k+1) - \hat{z}(k+1|k) \tag{18}$$

Calculation of Filter Gain

$$K(k+1) = P(k+1|k)H' M(k+1)^{-1} \tag{19}$$

State and Covariance Updation

$$x(k+1|k+1) = x(k+1|k) + K(k+1)e(k+1) \tag{20}$$

$$P(k+1|k+1) = P(k+1|k) - K(k+1)H'P(k+1|k) \tag{21}$$

3.2 Review of information filter

Information filter is essentially a Kalman filter expressed in terms of the measures of information about the states of interest, rather than the direct state estimates and their associated covariances. The two key information-analytic variables are the information matrix and information state vector $\hat{f}(i \mid j)$. The information matrix F is the inverse of the covariance matrix P.

$$F(i \mid j) = P^{-1}(i \mid j) \tag{22}$$

The information state vector is the product of the inverse of the covariance matrix and the state estimate $\hat{x}(i \mid j)$.

$$\hat{f}(i \mid j) = P^{-1}(i \mid j)\hat{x}(i \mid j) \tag{23}$$

The update equation for the information state vector is

$$\hat{f}(k \mid k) = \hat{f}(k \mid k-1) + H^T R^{-1}(k)z(k) \tag{24}$$

The expression for the information matrix associated with the above estimate is

$$F(k \mid k) = F(k \mid k-1) + H^T R^{-1}(k)H \tag{25}$$

The information state contribution $i(k)$ from an observation $z(k)$, and its associated information matrix $I(k)$ are defined respectively as

$$i(k) = H^T R^{-1}(k)z(k) \tag{26}$$

$$I(k) = H^T R^{-1}(k)H \tag{27}$$

The information propagation coefficient $L(k|k-1)$, which is independent of the observation made, is

$$L(k|k-1) = F(k|k-1)A_d F^{-1}(k-1|k-1) \tag{28}$$

Prediction

$$\hat{f}(k \mid k-1) = L(k \mid k-1)\hat{f}(k-1 \mid k-1) \tag{29}$$

$$F(k \mid k-1) = \left[A_d F^{-1}(k-1 \mid k-1)A_d{}^T + Q(k)\right]^{-1} \tag{30}$$

Estimation

$$\hat{f}(k \mid k) = \hat{f}(k \mid k-1) + i(k) \tag{31}$$

$$F(k \mid k) = F(k \mid k-1) + I(k) \tag{32}$$

4. Fusion methods

A brief review of the fusion methods used in this work is presented in this section.

4.1 Information fusion

The information fusion method presented in Grime (1994) is presented here. Consider a system containing N sensors, with a composite observation model given by Eq. (33)

$$z(k) = Hx(k) + v(k) \tag{33}$$

The observation vector $z(k)$ is separated into N sub vectors of dimension N_i corresponding to the observation made by each individual sensor

$$z(k) = [z_1^T(k),.....,z_N^T(k)]^T \tag{34}$$

Also partition the observation matrix in to sub matrices corresponding to these observations

$$H = [H_1^T,.....,H_N^T]^T \tag{35}$$

The observation noise vector is also partitioned as

$$v(k) = [v_1^T(k),.....,v_N^T(k)]^T \tag{36}$$

And it is assumed that these partitions are uncorrelated

$$E[v(k)v^T(k)] = R(k) = blockdiag\{ R_1^T(k),....., R_N^T(k)\} \tag{37}$$

The sensor model now contains N equations in the form

$$z_i(k) = H_i x(k) + v_i(k) \tag{38}$$

with

$$E[v_p(i)v_q^T(j)] = \delta_{ij}\delta_{pq}R_p(i) \tag{39}$$

The information state contribution $i(k)$ from an observation $z(k)$, and its associated information matrix $I(k)$ are defined respectively as,

$$i_j(k) = H_i^T R_i^{-1}(k) z_i(k) \tag{40}$$

$$I_j(k) = H_i^T R_i^{-1}(k) H_i \tag{41}$$

Comparing Eqs. (38) and (40) implies

$$i(k) = \sum_{i=1}^{N} i_i(k) = \sum_{i=1}^{N} H_i^T R_i^{-1}(k) z_i(k) \tag{42}$$

$$I(k) = \sum_{i=1}^{N} I_i(k) = \sum_{i=1}^{N} H_i^T R_i^{-1}(k) H_i \tag{43}$$

So that

$$\hat{f}(k \mid k) = \hat{f}(k \mid k-1) + \sum_{i=1}^{N} i_i(k) \tag{44}$$

$$F(k \mid k) = F(k \mid k-1) + \sum_{i=1}^{N} I_i(k) \tag{45}$$

In this method, each sensor incorporates a full state model and takes observations according to Eq. (38). They all calculate an information-state contribution from their observations in terms of $i_i(k)$ and $I_i(k)$. These are then communicated to the fusion centre and are incorporated in to the global estimate through Eqs. (44) and (45). The information state prediction is generated centrally using

$$\hat{f}(k \mid k-1) = L(k \mid k-1)\hat{f}(k-1 \mid k-1) \tag{46}$$

$$F(k \mid k-1) = \left[A_d F^{-1}(k-1 \mid k-1) A_d^T + Q(k)\right]^{-1} \tag{47}$$

The state estimate may be found at any stage from

$$\hat{x}(i \mid j) = F^{-1}(i \mid j)\hat{f}(i \mid j) \tag{48}$$

4.2 State vector fusion

The state vector fusion presented in Roecker (1998), is about combining the filtered state vectors from two sensors to form a new estimate, while taking into account the correlated process noise.

The new estimate of the state vector is given by

$$\hat{x}_{k/k} = x_{k/k}^{i} + P_{xz} P_{zz}^{-1} (x_{k/k}^{j} - x_{k/k}^{i}) \tag{49}$$

$$P_{xz} = P_{k/k}^{i} - P_{k/k}^{ij} \tag{50}$$

$$P_{zz} = P_{k/k}^{i} + P_{k/k}^{j} - P_{k/k}^{ij} - P_{k/k}^{ji} \tag{51}$$

where $x^i_{k/k}$ is the i^{th} filtered state vector, $P^i_{k/k}$ is the covariance matrix for $x^i_{k/k}$ and $P^{ij}_{k/k}$ is the cross covariance matrix between $x^i_{k/k}$ and $x^j_{k/k}$. The cross covariance matrix is given by the recursive equation

$$P^{ij}_{k/k} = (I - K^i_k H^i_k)\Phi_{k-1} P^{ij}_{k-1/k-1} \Phi^T_{k-1} (I - K^j_k H^j_k)^T + (I - K^i_k H^i_k)\Gamma_{k-1} q_{k-1} \Gamma^T_{k-1} (I - K^j_k H^j_k)^T \tag{52}$$

The covariance matrix of the fused estimate is

$$P_{k/k} = P^i_{k/k} - (P^i_{k/k} - P^{ij}_{k/k}) \times (P^i_{k/k} + P^j_{k/k} - P^{ij}_{k/k} - P^{ji}_{k/k})^{-1} (P^i_{k/k} - P^{ji}_{k/k}) \tag{53}$$

where K^i_k is the Kalman filter gain matrix for sensor *i* at time *k*.

4.3 Simple fusion

In the work by Beugnon (2000), the simple fusion method is presented. Here each and every node processes their respective measurements through optimal Kalman filter. The nodes send their estimates $x^i_{k/k}$ and $x^j_{k/k}$, and their respective error covariance matrices P^i and P^j. The global estimate at time *t*, for simple fusion is a simple complex combination as given below

$$\hat{x}(t \mid t) = P^j (P^i + P^j)^{-1} \hat{x}^i + P^i (P^i + P^j)^{-1} \hat{x}^j \tag{54}$$

where P^i and P^j are the covariance matrices.

The covariance matrix of the fused estimate is given by

$$M(t \mid t) = P^i (P^i + P^j)^{-1} P^j \tag{55}$$

4.4 Composite fusion

In composite fusion, Simple fusion algorithm is used for fusing the states, with the first sensor output estimated with a Kalman filter and the second sensor output is estimated with an information filter.

5. Sliding mode controller design

By adapting the design procedure given in Gao (1995), a discrete sliding mode controller is designed, to suppress the first two vibrating modes of the piezo actuated structure.

The reaching law for the SMC of a discrete time system is

$$s(k+1) - s(k) = -q\tau s(k) - \varepsilon\tau sgn(s(k)) \tag{56}$$

where '*s*' is the linear switching function, $\tau > 0, q > 0, 1 - q\tau > 0, \tau$ is the sampling period.

The incremental change of *s(k)* is

$$s(k+1)-s(k)=C^T x(k+1)-C^T x(k)$$
$$=C^T\Phi_\tau x(k)+C^T\Gamma_\tau u(k)-C^T x(k) \tag{57}$$

Comparing with the reaching law in Eq. (56) gives

$$s(k+1)-s(k)=-q\tau s(k)-\varepsilon\tau sgn(s(k))$$
$$=C^T\Phi_\tau x(k)+C^T\Gamma_\tau u(k)-C^T x(k) \tag{58}$$

Solving for $u(k)$ gives the control law

$$u(k)=Fx(k)+\gamma sgn(s(k)) \tag{59}$$

where

$$F=-(C^T\Gamma_\tau)^{-1}[(C^T\Phi_\tau - C^T I+q\tau C^T)]$$
$$\gamma=-(C^T\Gamma_\tau)^{-1}\varepsilon\tau$$

The switching function for the fourth order system is

$$s(k)=C^T x(k)=C_1x_1+C_2x_2+C_3x_3+C_4x_4 \tag{60}$$

where

$$C^T=\begin{bmatrix}C_1 & C_2 & C_3 & C_4\end{bmatrix}$$

C^T is determined such that eigen values of the discrete system in sliding mode lie inside the unit circle. If the system matrix is represented in controllable canonical form, then switching coefficients is determined using the method presented by Wong (1998).

$$C_1=(-1)^{n-1}\lambda_1\lambda_2........\lambda_{n-1}$$
$$......$$
$$C_n=(-1)^{n-2}(\lambda_2\lambda_3....\lambda_{n-1}+\lambda_1\lambda_3....\lambda_{n-1}+\lambda_1\lambda_2....\lambda_{n-1}) \tag{61}$$

where n is the order of difference equation and $\lambda_1, \lambda_2,.....\ \lambda_{n-1}$ are the desired eigen values.

The linear dynamical equation of the system in sliding mode is given by

$$x_d(k+1)=[I-\Gamma_\tau(C^T\Gamma_\tau)^{-1}C^T]\Phi_\tau x_d(k) \tag{62}$$

Choosing the desired eigen values $\lambda_1=0.8$, $\lambda_2=0.8$ *and* $\lambda_3=0.2$ *gives*

$$C^T=\begin{bmatrix}-0.128 & 0.96 & -1.80 & 1.00\end{bmatrix}$$

The controller for this system with disturbance *d(k)* is

$$u(k) = -[C^T \Phi_\tau x(k) - 0.0634d(k) - 0.99s(k) + 0.001sgn(s(k))] \tag{63}$$

with $\varepsilon\tau = 0.001$, $q\tau = 0.01$, $\tau = 0.01$ sec and quasi-sliding mode band $\partial = 0.002$.

6. Results and discussion

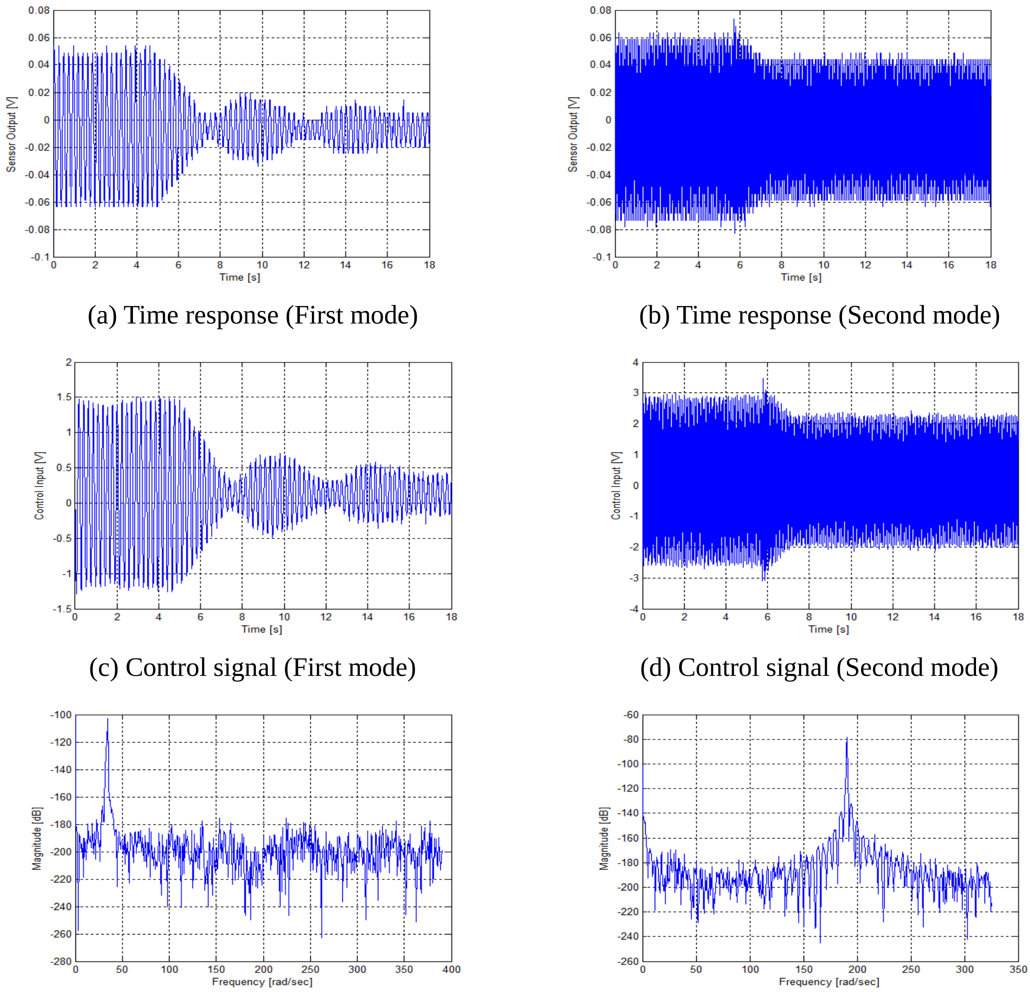
The photograph of the experimental facility is shown in Fig. 2. The controller is implemented in real time, with each sensor output sampled at 0.01 sec using the ADC of dSPACE 1104 controller board and MATLAB / Simulink. The control signal is updated for every 0.01 sec, and applied to the control actuator through the DAC of dSPACE controller board. A Simulink model is developed using MATLAB RTW for implementing the controller in real time. The fusion algorithms are developed in MATLAB, the sensor outputs are fused using each algorithm. The closed loop performance of the controller with the fused sensor output obtained from information fusion, state vector fusion, simple fusion and composite fusion algorithms is evaluated individually, by exciting the structure by a sinusoidal disturbance *d(k)* having first and second mode frequencies (5.5 Hz and 30.3 Hz) with an amplitude of 10 V_{PP} through the disturbance actuator.

Fig. 2 Photograph of experimental setup

Initially the beam is excited with first mode frequency (5.5 Hz), and allowed to vibrate at resonance for 5 seconds. Control is then applied. Similarly the beam is excited with second mode frequency (30.3 Hz), and allowed to vibrate at resonance for 5 seconds. Control is then applied. The closed loop response obtained for single sensor case (without fusion), in time domain, frequency domain, the control signal, for first mode and second mode are shown in Fig 3. The closed loop response obtained with information fusion, state vector fusion, simple fusion and composite fusion are shown in Figs. 4, 5, 6 and 7 respectively. It can be seen that the closed loop response shown in Fig. 3(a) is more oscillatory as compared to the response obtained by using fused data. Since the design of SMC is to follow a sliding surface, the control will not excite any near by modes and will not result in control spillover.

7. Conclusions

This paper presents the performance evaluation of reaching law based sliding mode controller in real time, for vibration suppression of a piezo actuated structure using four different data fusion methods. The closed loop responses obtained with single sensor output and fused output of sensors are investigated. The percentage of vibration suppression obtained with single sensor is 50 % for the first mode and 23.1% for the second mode, and the reduction obtained with data fusion is given in Table 2.

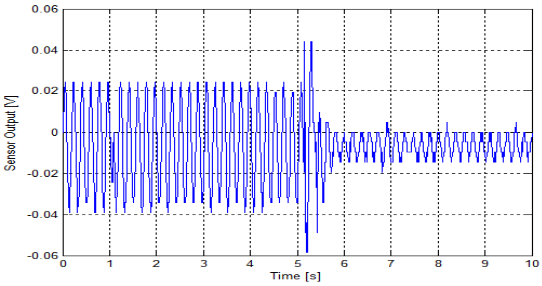


(a) Time response (First mode) (b) Time response (Second mode)

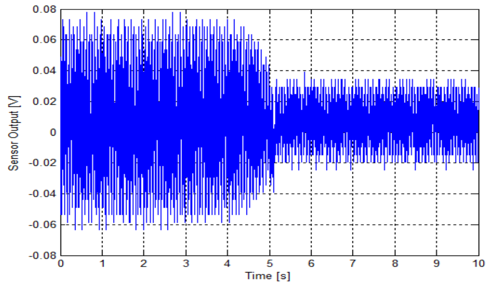
(c) Control signal (First mode) (d) Control signal (Second mode)

(e) Frequency response (First mode) (f) Frequency response (Second mode)

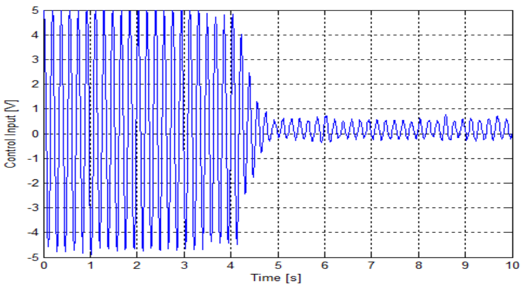
Fig. 3 Responses with single sensor (without fusion)



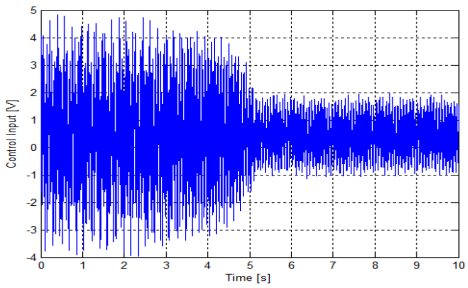
(a) Time response (First mode)



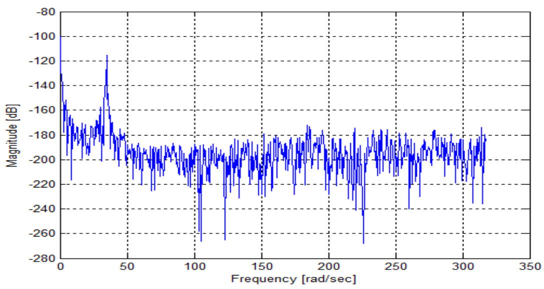
(b) Time response (Second mode)



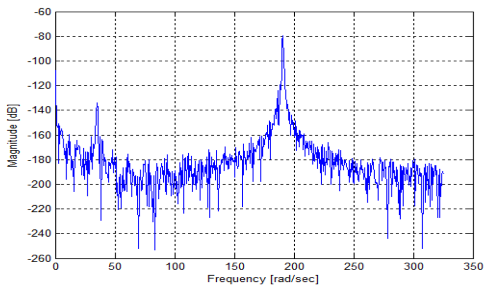
(c) Control signal (First mode)



(d) Control signal (Second mode)

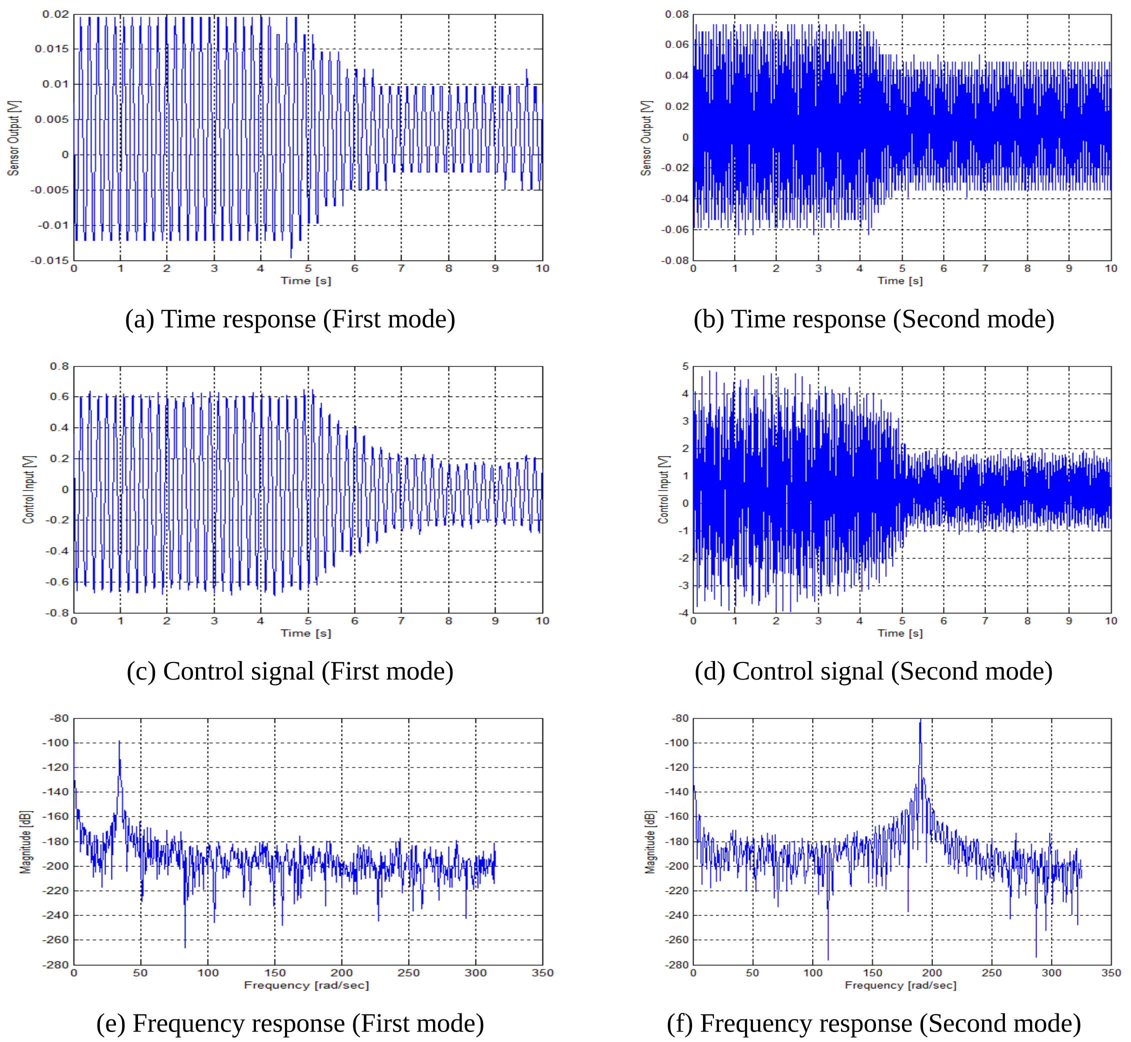


(e) Frequency response (First mode)



(f) Frequency response (Second mode)

Fig. 4 Responses with information fusion



(a) Time response (First mode)

(b) Time response (Second mode)

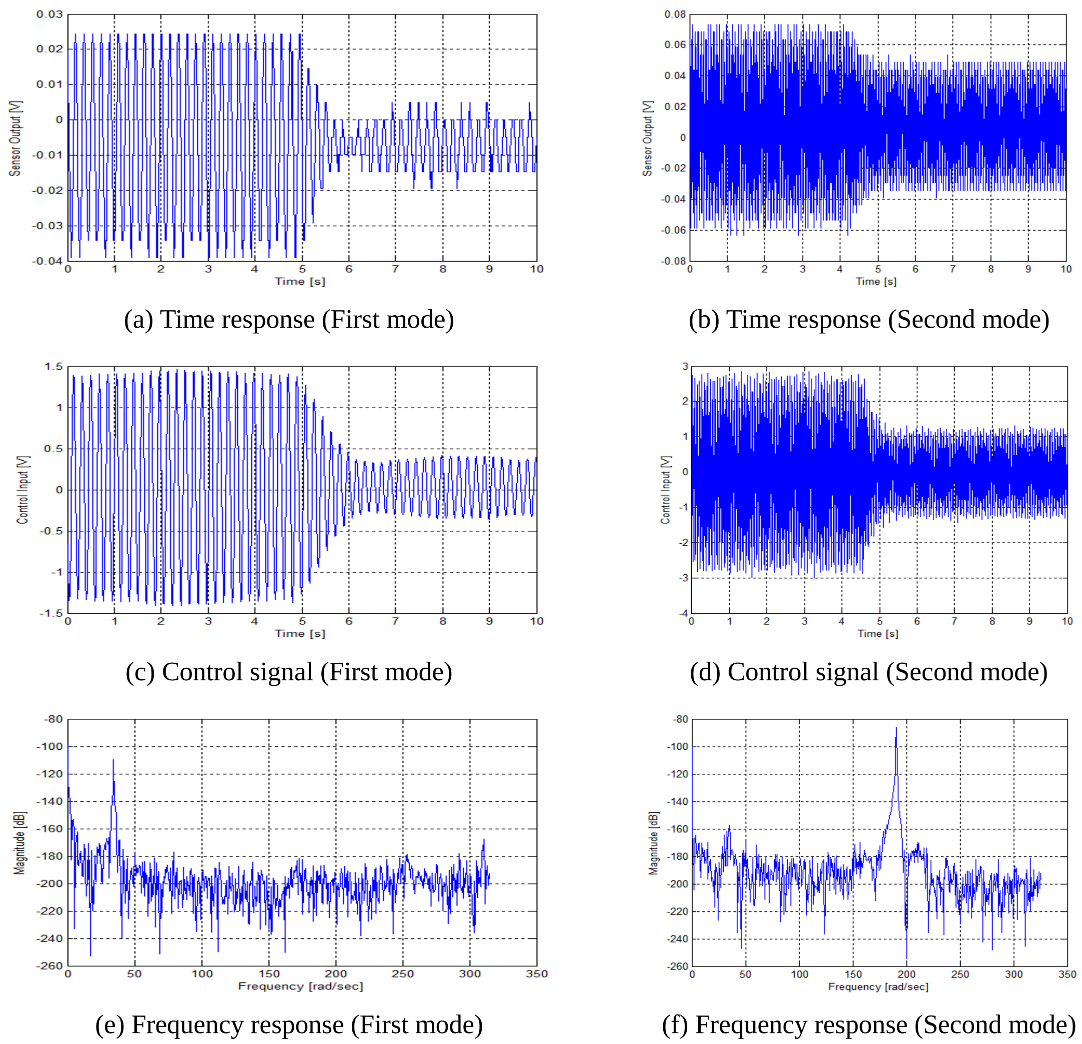
(c) Control signal (First mode)

(d) Control signal (Second mode)

(e) Frequency response (First mode)

(f) Frequency response (Second mode)

Fig. 5 Responses with state vector fusion



(a) Time response (First mode)

(b) Time response (Second mode)

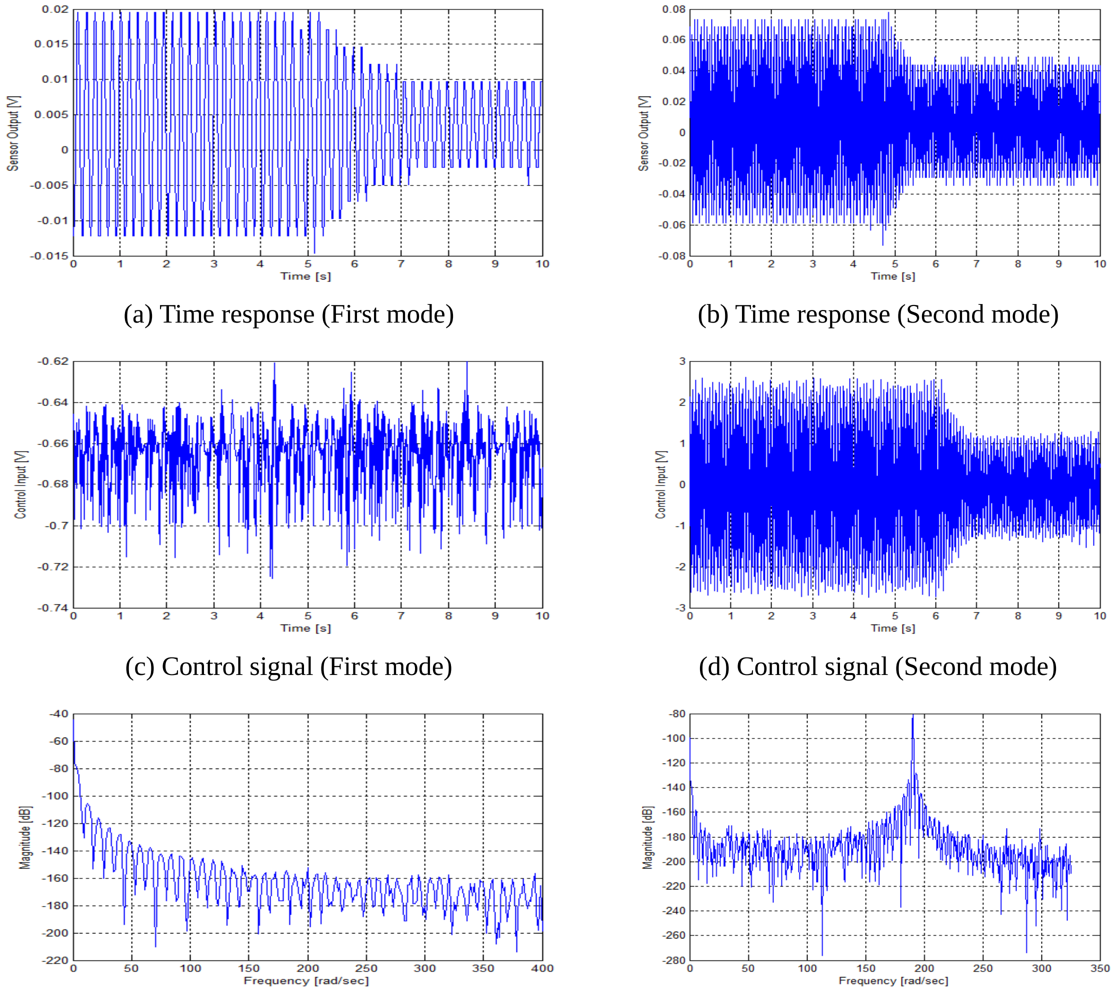
(c) Control signal (First mode)

(d) Control signal (Second mode)

(e) Frequency response (First mode)

(f) Frequency response (Second mode)

Fig. 6 Responses with simple fusion



(a) Time response (First mode)

(b) Time response (Second mode)

(c) Control signal (First mode)

(d) Control signal (Second mode)

(e) Frequency response (First mode)

(f) Frequency response (Second mode)

Fig. 7 Responses with composite fusion

Table 2 Comparison of closed loop performances with data fusion

Fusion algorithm	Percentage reduction in amplitude of vibration	
	First mode	Second mode
Information fusion	75.0 %	61.5 %
State Vector fusion	73.7 %	42.8 %
Simple fusion	73.3 %	57.1 %
Composite fusion	73.4 %	46.7 %

It can be seen from experimental results that, improved closed loop performance is achieved with fused data. This is because information contributions from sensors are collected together by the fusion process and this collective information is used by the controller for generating control input.

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