COMPARATIVE PERFORMANCE OF INTELLIGENT IDENTIFICATION AND CONTROL ALGORITHMS FOR A FLEXIBLE BEAM VIBRATION

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Abstract: This research presents an investigation into the comparative performance in implementing intelligent system identification and control algorithms. Several approaches for on-line system identification and control are explored and evaluated to demonstrate the merits in implementing the algorithms for similar level of error convergence. Active vibration control (AVC) of a flexible beam system is considered as a platform for the investigation. The AVC system is designed using three different on-line identification approaches, which include (a) genetic algorithms (GAs) (b) adaptive neuro-fuzzy inference system (ANFIS) and (c) recursive least square (RLS) estimation. These algorithms are used to estimate a linear discrete model of the system. Based on these algorithms, different approaches of the AVC system are implemented, tested and validated to evaluate the relative merits of the algorithms. Finally, a comparative performance of the error convergence performance in implementing the identification and control algorithms is presented and discussed through a set of experiments.

1 INTRODUCTION

Many demanding complex identification and control algorithms cannot be satisfactorily realised in real-time due to such computational complexity. Comparative performance analysis of alternative strategies, where multiple solutions are available, could provide an opportunity to identify the best algorithm(s). Many attempts have been made in the past at devising methods of tackling the control problem using artificial intelligence (Amato et al., 2001; Hossain and Tokhi, 1997; Yamlidou et al., 1996). Many attempts have also been made for real-time control system implementation (Baxter et al., 1994; Jones, 1989; Tokhi et al., 2002). However, limited contributions have been reported on real-time performance issues in implementing intelligent identification and control algorithms (Albertos, et al.,2001;Madkour et al, 2004).

The conventional on-line system identification schemes, such as least squares, instrumental variables and maximum likelihood are in essence local search techniques. These techniques often fail in the search for the global optimum if the search space is not differentiable or linear in the parameters. On the other hand, these techniques do not iterate more than once on each datum received.

To address these issues, several approaches using artificial intelligence (AI) techniques have been reported earlier (Hossain and Tokhi, 1997). This investigation considers some of these approaches to explore comparative performance in implementing the algorithms for same error convergence.

2 ALGORITHMS

The intelligent active vibration control algorithm consists of flexible beam simulation algorithm, control algorithm and system identification using GAs, ANFIS and RLS algorithms. Therefore, three approaches of AVC algorithm are designed based on the three identification algorithms. These algorithms are briefly described below.

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2.1 Simulation and control algorithms

Consider a cantilever beam system with a force $F(x,t)$ applied at a distance x from its fixed (clamped) end at time t. This will result in a deflection $y(x,t)$ of the beam from its stationary position at the point where the force has been applied. In this manner, the governing dynamic equation of the beam is given by

$$\mu^2 \frac{\partial^4 y(x,t)}{\partial x^4} + \frac{\partial^2 y(x,t)}{\partial t^2} = \frac{1}{m} F(x,t) \quad (1)$$

where, μ is a beam constant and m is the mass of the beam. Discretising the beam into a finite number of sections (segments) of length Δx and considering the deflection of each section at time steps Δt using the central FD method, a discrete approximation to equation (1) can be obtained as (Kourmoulis, 1990)

$$Y_{k+1} = -Y_{k-1} - \lambda^2 S Y_k + \frac{(\Delta t)^2}{m} F(x,t) \quad (2)$$

where, $\lambda^2 = \mu^2 (\Delta t)^2 / (\Delta x)^4$, S is a pentadiagonal matrix, entries of which depend on the physical properties and boundary conditions of the beam, and Y_i ($i = k+1, k, k-1$) is a vector representing the deflection of end of sections 1 to n of the beam at time step i. Equation (2) is the required relation for the simulation algorithm.

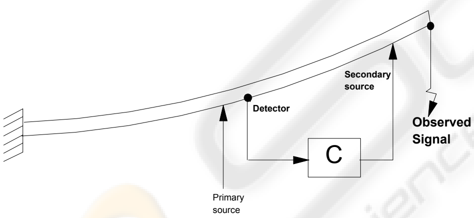

Figure 1: Active vibration control structure

A schematic diagram of an AVC structure is shown in Figure 1. A single-input single-output (SISO) AVC system is considered for vibration suppression of the beam. The unwanted (primary) disturbance is detected by a detection sensor, processed by a controller to generate a cancelling (secondary, control) signal so as to achieve cancellation at an observation point along the beam.
The objective in Figure 1 is to achieve total (optimum) vibration suppression at the observation point. This requires the primary and secondary signals at the observation point to be equal in amplitudes and to have a 180° phase difference.

ANFIS, GAs and RLS algorithms are used as system identification algorithms to estimate the AVC system cancelling signal. To identify the cancelling signal, a linear discrete second order model will be estimated using ANFIS, GA and RLS.

$$Y(z) = \frac{1 + b_1(z^{-1}) + b_2(z^{-2})}{1 + a_1(z^{-1}) + a_2(z^{-2})} U(z) \quad (3)$$

where Y is the system input and U is its output

2.2 Identification algorithms

2.2.1 Adaptive neuro-fuzzy inference system

The hybrid Adaptive Neuro-Fuzzy inference system(ANFIS) provides a method of fuzzy modelling to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input-output data. ANFIS has been proven to be an excellent function approximation tool (Jian, 1993). This function is used for system identification, which is a major training routine of Sugeno-type FIS (fuzzy inference system).

2.2.2 Genetic algorithms

A Genetic Algorithm (GA) simultaneously evaluates many points in the parameter space and converges more likely towards the global solution. This algorithm differs from other search techniques in that it uses concepts taken from natural genetics and evolution theory. The GA is used based on the method of minimization of the prediction error. The method of evolutionary computation works as follows: create a population of individuals, evaluate their fitness, generate a new population by applying genetic operators, and repeat this process for a number of times Genetic algorithms consider the same multi parameter system given by equation (3) with the following fitness function (Hossain and Tokhi, 1997):

$$J(r) = \sum_{k=1}^{r} \left| y(k) - \hat{y}(k) \right| \quad (4)$$

where, $y(k)$ is measured output, $\hat{y}(k)$ is estimated model output, and r is the number of sets of measurement considered.

2.2.3 RLS algorithm

This is a well-known traditional adaptive filter algorithm estimates the current parameter vector $\hat{\theta}(k)$ based on the previous estimated vector $\hat{\theta}(k-1)$. Estimation of the parameter vector θ is performed such that the estimate $\hat{\theta}_r$ minimizes the cost index $J(r)$, where r denotes the number of sets of measurement (Madkour et al., 2004)

3 IMPLEMENTATION AND RESULTS

A cantilever beam in transverse vibration of length $L = 0.635\,\text{m}$, mass $m = 0.037\,\text{kg}$, was considered. The beam was discretised into 19 equal-length segments. To allow dominant modes of vibration of the beam to be excited, a finite-duration step disturbance force of amplitude $0.1\,\text{N}$ was applied to the beam. The input and output samples of the plant were collected from two separate points on the beam. The sample period was selected as $\Delta t = 0.3\,\text{ms}$, which is sufficient to cover all the dominant resonance modes of vibration of the beam (Hossain, 1995).

To identify the cancelling signal, a linear discrete second order model was estimated using ANFIS, GA and RLS.

Figure 2 shows the error convergence and the real-time performances of the algorithms. It is worth mentioning that the error has been calculated based on the differences between absolute value of the original and the estimated signal. On the other hand, the execution time of the algorithms was measured for 6000 iterations with $0.3\,\text{ms}$ sampling time. Therefore, the maximum execution time of the algorithms in implementing real-time should be $1.8\,\text{s}$. It is worth noting that for the sake of better investigation on execution time, error convergences for all the algorithms were considered to be within a similar level. However, an insignificant error convergence variation is observed during implementation. With regard to the execution time in implementing the system identification algorithms, all the algorithms achieved real-time performance. It is noted that the RLS algorithm offers the best performance and ANFIS offers the worst performance among the three algorithms. It is also noted that the execution time in implementing ANFIS is double as compared to the RLS algorithm and 1.56 times as compared to the GA.

It is also observed that performance of the GA based system identification varies due to the bit representation and population size. Therefore, a further investigation was made to explore and demonstrate this issue. Figure 3 shows execution times in implementing the GA based system identification algorithms for 8 and 16 bits representation. It is observed that except population with 10 of 8 bit representation, none of the other situations achieved real-time performance.

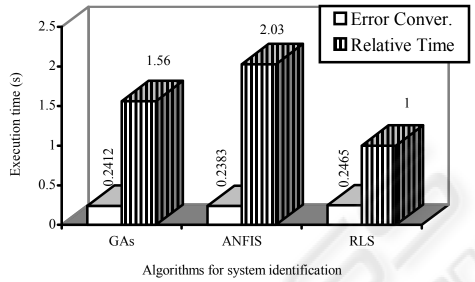

Figure 2: Relative performance in implementing the system identification algorithms

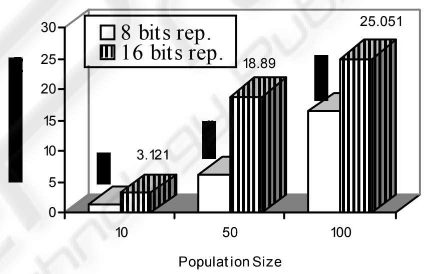

Figure 3: Performance of GA for 8 and 16 bits representation

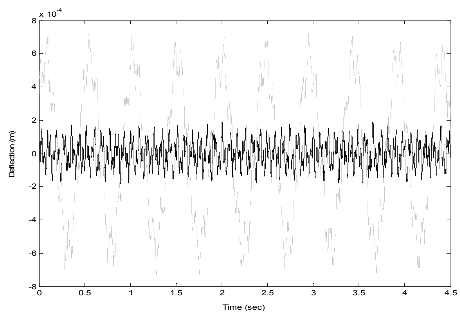

Figure 4: Performance in implementing the AVC algorithm using ANFIS

Figures 4, 5 and 6 show the time-domain performance in implementing the AVC system using, ANFIS, GA and RLS algorithms, where the dotted and solid lines represent fluctuation of the beam at the end point before and after cancellation. It is noted that ANFIS offers the best and RLS the worst performance among the three methods. It is also noted that the peak to peak end-point fluctuation after cancellation using ANFIS is 4, GA is 1.8 and RLS is 1.2 times smaller as compared to the fluctuation before cancellation.

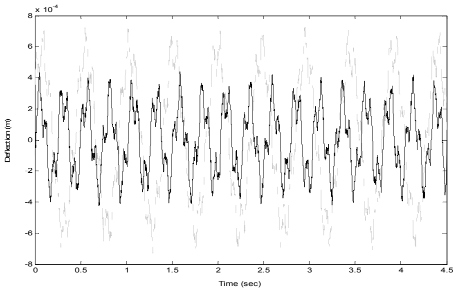

Figure 5: Performance in implementing the AVC algorithm using GA

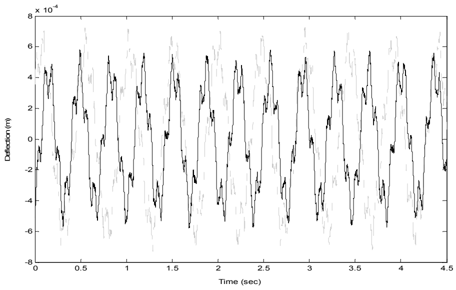

Figure 6: Performance in implementing the AVC algorithm using RLS

4 CONCLUDING REMARKS

This paper has presented the relative real-time performance and error convergence issues in implementing system identification and AVC system of a flexible beam vibration using, ANFIS, GA and RLS algorithm. A comparative performance of the algorithms has been presented and discussed through a set of experiments. For system identification, it is noted that the execution time in implementing ANFIS as compared to GA and RLS is significantly higher. However, ANFIS shows slightly better error convergence for the same number of iterations. On the other hand, real-time computing performance of GA varies based on the selection of the size of population and binary representation. It is noted that the GA with higher bit representation and larger population size for the same error convergence performs slower than ANFIS. It is also noted that the execution time for each of the three algorithms is less than the sampling time, in turn satisfying the real-time requirement. However, in case of GA, this is true only for population size 10 with 8 bit representation.

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