FIFTH INTERNATIONAL CONGRESS ON SOUND AND VIBRATION
DECEMBER 15-18, 1997
ADELAIDE, SOUTH AUSTRALIA

GENETIC ALGORITHMS FOR ACTIVE VIBRATION CONTROL

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ABSTRACT

This paper presents an investigation into the development of an active vibration control (AVC) system using genetic algorithms (GAs). During the last two decades, a substantial amount of research work has been carried out using GAs in various disciplines. Although GAs have gained popularity as parallel, global search techniques, their use in the area of active control is limited. This investigation attempts to develop evolutionary techniques utilising GAs for AVC applications. A flexible beam system in transverse vibration is considered in this investigation. The unwanted vibrations in the structure are assumed to be due to a single point disturbance of broadband nature. A multi-source adaptive AVC strategy is adopted for optimum cancellation of broadband vibration along the beam. This incorporates an on-line controller design and implementation strategy. Genetic algorithms are used for estimation of the adaptive controller characteristics. The AVC algorithm thus developed is implemented and simulation results verifying its performance in the suppression of broadband vibration along the beam presented and discussed.

Keywords: Active vibration control, adaptive control, genetic algorithms, recursive least squares.

1. INTRODUCTION

Active vibration control (AVC) consists of artificially generating cancelling source(s) to destructively interfere with the unwanted source and thus result in a reduction in the level of the vibration (disturbances) at desired location(s). This is realised by detecting and processing the vibration by a suitable electronic controller so that, when superimposed on the disturbances, cancellation occurs. Due to the broadband nature of the disturbances, it is required that the control mechanism in an AVC system realises suitable frequency-dependent characteristics so that cancellation over a broad range of frequencies is achieved. In practice, the spectral contents of the disturbances as well as the characteristics of system components are, in general, subject to variation, giving rise to time-varying phenomena. This implies that the control mechanism is further required to be intelligent enough to track these variations so that the desired level of performance is achieved and maintained (Tokhi and Leitch, 1991).

The evolutionary GA, imitating the collective learning paradigm of natural populations, are based upon Darwin's observations and the modern synthetic theory of evolution. The GAs were first introduced in the 1960s, embedding into the general framework of adaptation (Holland, 1975). During the last two decades, a substantial amount of research work has been carried out both in engineering and non-engineering disciplines (Chipperfield, et. al., 1994; Flockton and White, 1993; Goldberg, 1989). Although GAs have gained popularity as parallel, global search techniques, their use in the area of adaptive active control is very limited (Kristinsson and Dumont, 1992). This paper presents an investigation into the use of GAs to estimate the adaptive controller characteristics, where the controller is designed based on the plant model. This is realised by minimising the prediction error of the actual plant output and the model output. A flexible beam system in transverse vibration is considered. The unwanted vibrations in the structure are assumed to be due to a single point disturbance of broadband nature. An AVC system is designed for optimum cancellation of broadband vibration along the beam. A MATLAB GA toolbox is utilised to identify the controller parameters. The AVC algorithm is implemented and its performance assessed in the suppression of vibration along the beam.

2. ACTIVE VIBRATION CONTROL SYSTEM

2.1 The flexible beam structure

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 stationery position at the point where the force has been applied. Discretising the beam into a finite number of sections of length Δx and considering the deflection of each section at time steps Δt using the central finite difference (FD) method, a discrete approximation of the beam motion can be obtained as (Tokhi and Hossain, 1994)

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

where, $\lambda^2 = \left[(\Delta t)^2 / (\Delta x)^4\right]\mu^2$, μ is a beam constant, m is the mass of the beam, S is a penta-diagonal matrix entries of which depend on the physical properties and boundary conditions of the beam, Y_i $(i = k+1, k, k-1)$ is an $(n-1)\times 1$ matrix representing the deflection of end of sections 1 to n of the beam at time step i (beam divided into $n-1$ sections). Equation (1) is the required relation for dynamic simulation of the beam that can be implemented on a digital computer easily.

2.2 Control structure

A schematic diagram of the geometric arrangement of a single-input multi-output (SIMO) AVC structure is shown in Figure 1. A primary (disturbance) force is applied by a point source. This is detected by a detector (sensor), processed by an SIMO controller and fed to a set of k secondary sources (control actuators). The control force thus generated interferes with the disturbance force so that to achieve a reduction in the level of vibration at a set of k observation points along the beam.

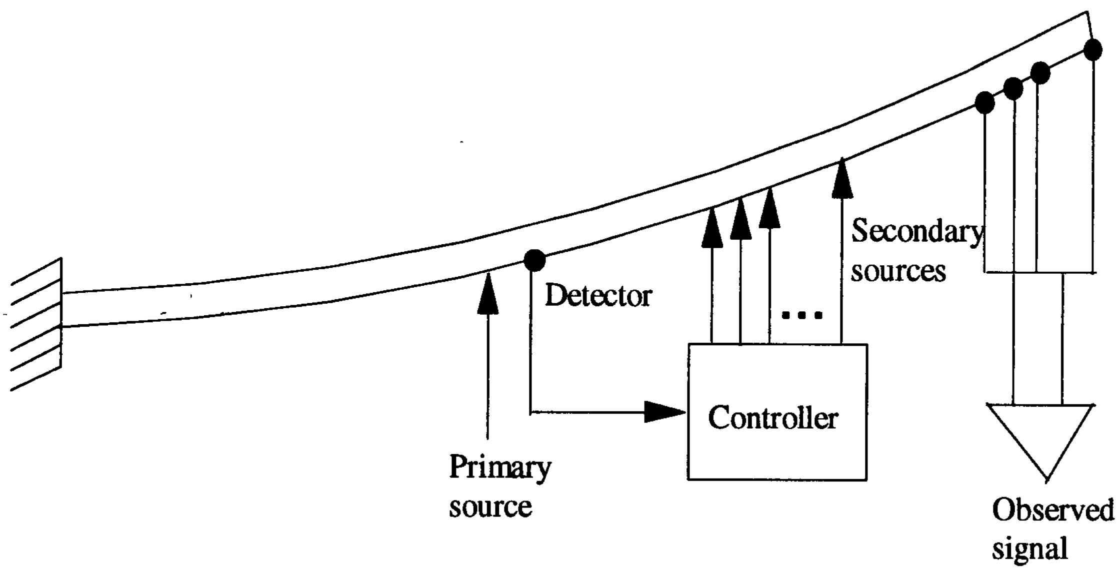


Figure 1: Schematic diagram of the AVC system.

The objective in Figure 1 is to achieve full (optimum) vibration suppression at the observation points. This is equivalent to the minimum variance design criterion in a stochastic environment. This requires the primary and secondary signals at each observation point to be equal in amplitudes and have a phase difference of 180^0 relative to one another.

To develop an on-line design and implementation mechanism for the controller, consider the system with the detected and the observed signals as the system input and output signals respectively. Thus, owing to the state of each secondary source, a model of the system between the detection point and each observation point can be obtained. This will result in a set of models with equivalent transfer functions q_{oj} $(j = 1,\ldots,k)$ when all the secondary sources are *off* and a further set of models with equivalent transfer functions q_{ij} $(i = 1,\ldots,k$; $j = 1,\ldots,k)$ when all the secondary sources are off except secondary source i. In this manner, a total of $k(k+1)$ models can be constructed. Thus, synthesising the controller within a frequency-domain representation of the system, on the basis of optimum vibration suppression at the observation points, will yield the required controller transfer function as (Tokhi and Hossain, 1994)

$$c_i = Q_i \left[\sum_{p=0}^{k} Q_p \right]^{-1} \quad ; \quad i = 1, \ldots, k \tag{2}$$

where,

$$Q_n = (-1)^n \left| \left\{ q_{pj} \right\} \right|; \quad p = 0,1,\ldots,k, \quad j = 1,\ldots.,k, \quad n = 0,1,\ldots.,j, \quad p \neq n$$

Equation (2) gives the required controller design rules in terms of the transfer characteristics q_{oj} and q_{ij} of system models. The controller can thus be designed on-line by first estimating q_{oj} and q_{ij} using a suitable system identification algorithm and then using these in equation (2). This results in a self-tuning control algorithm which can easily be implemented on a digital processor. To achieve on-line adaptation of the controller characteristics whenever a change in the system is sensed, a supervisory level control is required. The supervisor can be designed to monitor system performance and, based on a pre-specified quantitative measure of cancellation, initiate self-tuning control accordingly. In addition to monitoring system performance, the supervisory level control can be facilitated with further levels of intelligence, for example, monitoring system stability and avoiding problems due to non-minimum phase models, verifying controller characteristics on the basis of practical realisation to make sure that impractically large controller gains are not required, system behaviour in a transient period and model structure validation.

2.3 Realisation with GAs

The conventional on-line system identification schemes, such as least square, instrumental variable, maximum likelihood etc., 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. In contrast, a GA simultaneously evaluates many points in the parameter space and converges toward the global solution. It does not require the search space to be differentiable or continuous and can also iterate several times on each datum received (Kargupta and Smith, 1991; Kristinsson and Dumont, 1992).

The identification process within the control mechanism presented consists of the processes of estimating the system models Q_0 and Q_1 and the controller design calculation. The GA is used here to estimate the system models Q_0 and Q_1 in the discrete-time domain in parametric form. This is based on the method of minimisation of the prediction error.

To identify the parameters of Q_0 and Q_1 using GAs, the following fitness function was adopted

$$f(e) = \sum_{n=0}^{r} \left| y(n) - \hat{y}(n) \right| \tag{3}$$

where, r represents the number of input/output samples, $y(n)$ is the desired (plant) output and $\hat{y}(n)$ is the estimated model output.

3. IMPLEMENTATIONS AND RESULTS

To investigate the performance of the self-tuning AVC algorithm the beam simulation was utilised as a test and evaluation platform. The algorithm was implemented within a single-input single-output (SISO) realisation structure and its performance was assessed with a step disturbance force as the unwanted primary disturbance.

The fitness function of equation (3) was implemented for both Q_0 and Q_1 considering each as a linear discrete second order model. Each parameter of the model was represented by a 20 bit string for 30 individuals. Figure 2 shows the convergence of the function over 300 generations. The solid and dashed lines in Figure 2 represent the convergence of prediction error for Q_0 and Q_1 respectively. Figure 3 shows the performance of the GA for the two models where the solid line and dashed line represent the desired (plant) output and estimated model output respectively.

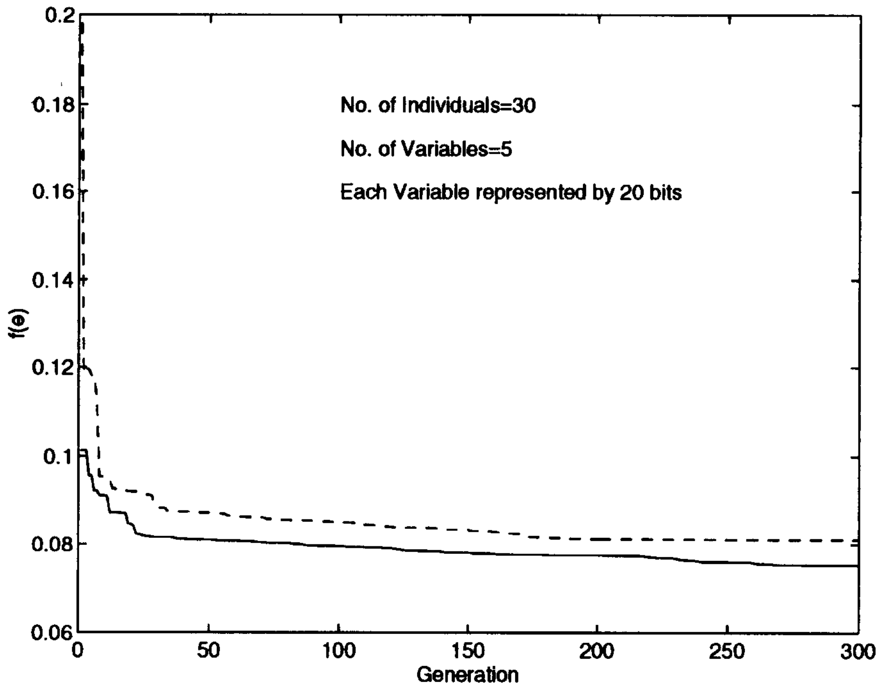
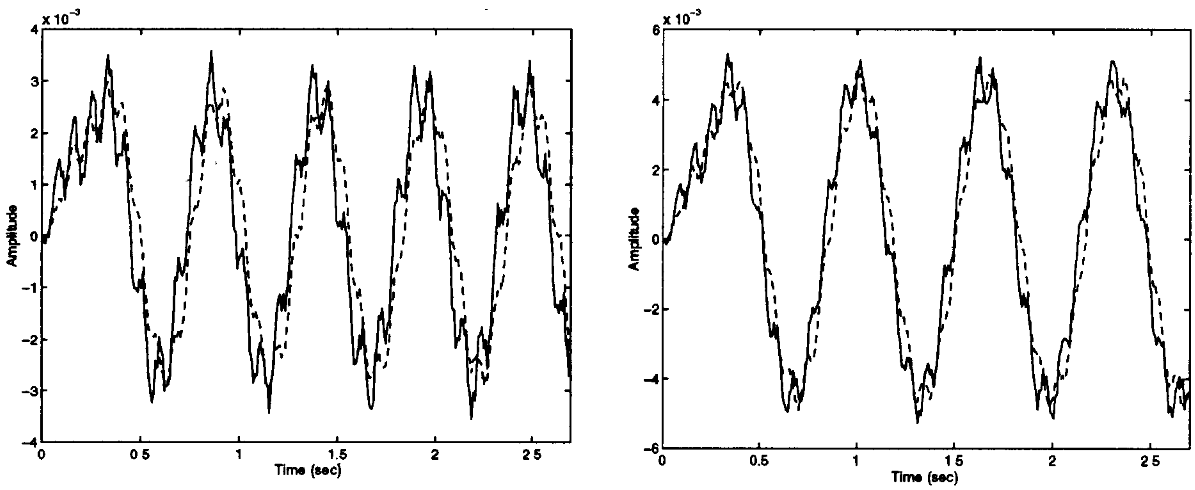


Figure 2: Convergence of fitness function.

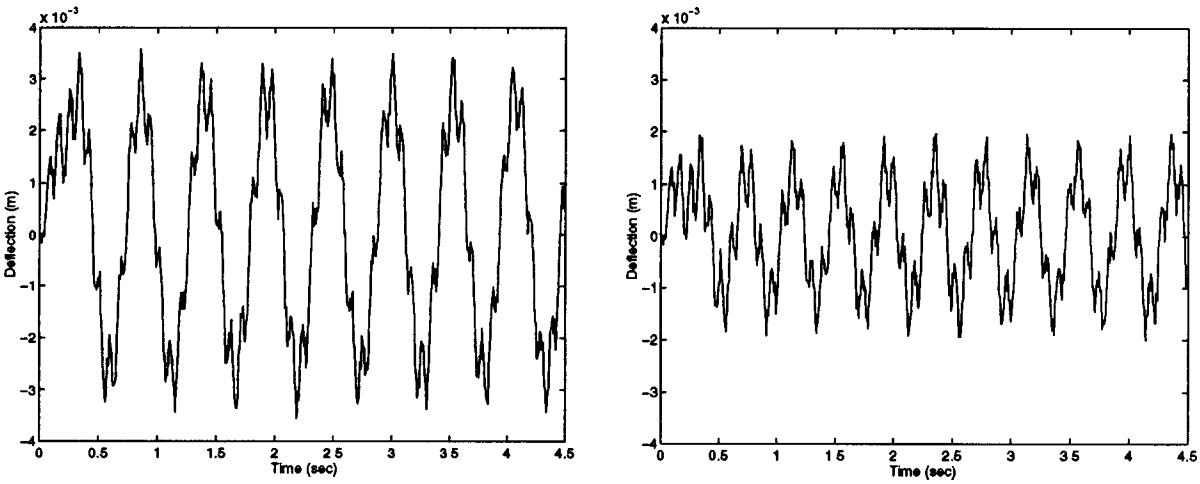
To investigate the performance of the self-tuning AVC algorithm the beam simulation was utilised as a test and evaluation platform. The algorithm was implemented within an SISO realisation structure and its performance was assessed with a ±0.1 N PRBS disturbance force as the unwanted primary disturbance applied at grid-point 12 and the control source at grid-point 20. Figure 4 shows the response of the beam before and after cancellation at the observation point (grid-point 20). Figure 5 shows the corresponding fluctuations along the length of the beam before and after cancellation. It is noted that the fluctuations along the length of the beam have been reduced significantly. It was noted through a spectral density analysis of the results in Figure 4 that, about 10 dB cancellation was achieved at the first resonance mode. The cancellation at the second resonance mode was 1dB. The vibrations at the third, fourth and fifth resonance modes were slightly reinforced. This was due to the utilisation of linear models considered in the estimation process. The system performance was also investigated with fourth-order linear models. However, this did not result in an enhancement in the performance of the system. This suggests that better cancellation may be achieved with the utilisation of non-linear system models. This together with the realisation of the system within an SIMO structure are currently under investigation. The results of these will be reported in due course.

To obtain a comparative evaluation of the performance of the system, the AVC system was realised with a recursive least squares (RLS) parameter estimation algorithm. It was noted that the performance of the GA-based system was better than that of the RLS-based system. This is due to the convergence properties of the GA, as indicated earlier.



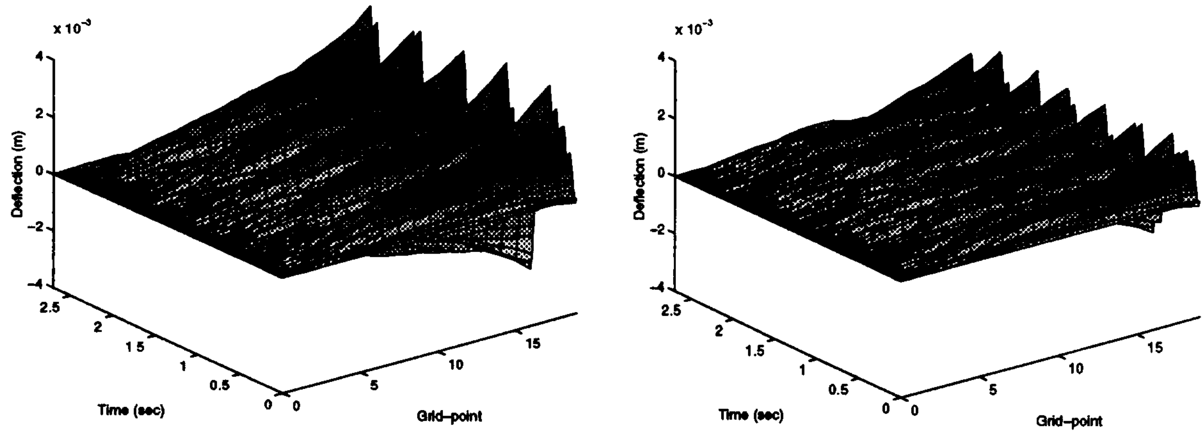
(a) Desired and model output for Q_0. (b) Desired and model output for Q_1.

Figure 3: Performance of the GA based models.



(a) Before cancellation. (b) After cancellation.

Figure 4: Response at the observation point with GA based AVC system.



(a) Before cancellation. (b) After cancellation.

Figure 5: Beam fluctuations along its length with the GA based AVC system.

4. CONCLUSION

The design and implementation of a GA based adaptive AVC algorithm for flexible beam structures has been presented, discussed, and verified through numerical simulation. A supervisory level control has been incorporated within the algorithm which allows on-line monitoring of system performance and controller adaptation. The performance of the algorithm has been verified in the suppression of broadband vibration in a flexible beam system within an SISO control structure. It has been demonstrated that significant levels of broadband cancellation can be achieved using GAs. However, GA based identification requires much more time as compared to conventional identification schemes. This implies that further work on development of efficient computing methods to allow real-time implementation of the algorithm is required. Among these, investigations into high performance computing systems, for instance parallel processing could provide suitable solutions. This work has also established future direction for investigation into non-linear system identification using GAs for active control.

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