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Real-time System Identification using Intelligent Algorithms

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Abstract - *This research presents an investigation into the development of real time system identification using intelligent algorithms. A simulation platform of a flexible beam vibration using finite difference (FD) method is used to demonstrate the real time capabilities of the identification algorithms. A number of approaches and algorithms for on line system identifications are explored and evaluated to demonstrate the merits of the algorithms for real time implementation. These approaches include identification using (a) traditional recursive least square (RLS) filter, (b) Genetic Algorithms (GAs) and (c) adaptive Neuro_Fuzzy (ANFIS) model. The above algorithms are used to estimate a linear discrete second order model for the flexible beam vibration. The model is implemented, tested and validated to evaluate and demonstrate the merits of the algorithms for real time system identification. Finally, a comparative performance of error convergence and real time computational complexity of the algorithms is presented and discussed through a set of experiments.*

Keywords: System identification, adaptive control, intelligent identification, recursive least squares algorithm, Genetic algorithm, ANFIS.

1 Introduction

This paper presents an investigation into the development of a discrete time model based on the observation of the input and output signals. Such models can be used for control system design, adaptive guidance or fault detection [1]. Parameter estimation, in turn system identification is a common criterion for control system, in particular for sensitive or adaptive control system design. In fact, a closed loop control system may be unstable or exhibit unacceptable transient response characteristics if the estimated parameters used in the system model for controller design do not coincide with the actual process parameters. Therefore, accurate and reliable parameters estimation technique is critical for the design and development of high-performance control systems in which the estimated parameters are often used in the field orientation, motion control, self-sensing, and other advanced algorithms. In literature, there are two basic approaches, *(i)* on-line identification methods based on state observer theory that adapt the parameters in a recursive fashion, *(ii)* off-line (batch) techniques that rely on statistical curve fitting to the measured data under specific conditions. On-line estimation schemes estimate and update parameters within the time span between successive samples. Thus it is highly desirable that the algorithm be simple and easy for real-time implementation [2], [3].

The main objective of this paper is to identify a linear discrete second order model using RLS filter, GAs and ANFIS algorithms. A simulation platform of a flexible beam system in transverse vibration using FD method [4] is considered to demonstrate the capabilities of the algorithms for real-time system identification. The proposed second order model is implemented using the RLS, GAs and ANFIS algorithms. It is then tested and validated for real-time system identification within the simulation framework of a flexible beam system. Finally, a comparative performance of the three algorithms are presented and discussed to demonstrate the capabilities of the algorithm in implementing real-time system identification.

2 Traditional RLS Algorithms

This is a traditional adaptive filter algorithm. It estimates the current parameter vector $\hat{\theta}(k)$ based on the previous estimated vector $\hat{\theta}(k-1)$, as follows [2], [3]:

$$\hat{\theta}(k) = f(\hat{\theta}(k-1), D(k), k) \qquad (1)$$

Where, $D(k)$ denotes data available at time (k), and f(.,.,.) denotes an algebraic function, the form of which determines the specific algorithm. In the case of dynamic system, data $D(k)$ normally consider the form of present and past observation of the system outputs and inputs. For multi-parameter system, this form can be represented as follows:

$$y(k) = \psi^T(k)\theta \tag{2}$$

Where,

$$\psi(k) = [-y(k-1), \cdots, -y(k-m), \\ u(k), \cdots, u(k-m)]^T \tag{3}$$

$$\theta = [a_1, \cdots, a_m, b_1, \cdots, b_{m+1}]^T \tag{4}$$

The estimation of the parameters vector θ is performed in a way such that the estimated $\hat{\theta}_r$ minimizes the cost index $J(r)$, where r denotes the number of sets of measurement,

$$J(r) = \sum_{k=1}^{r} (y(k) - \psi(k)^T \hat{\theta}(r))^2 \tag{5}$$

Equation (5) can be written in a recursive form as:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + P(k)\psi(k) \\ (y(k) - \Psi^T(k)\hat{\theta}(k-1)) \tag{6}$$

$$P(k) = \left[P(k-1) - \frac{P(k-1)u(k)\psi^T(k)P(k-1)}{1+\psi^T(k)P(k-1)\psi(k)} \right] \tag{7}$$

3 Intelligent Identification Algorithms

The conventional on-line system identification schemes are in essence local search techniques. These techniques often fail in the search for the global optimum if the search apace 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, as mentioned earlier, real-time estimation scheme requires an updated parameter within the time span between successive samples [4]. An alternative strategies using artificial intelligence algorithm could provide better solution. To achieve this goal two most commonly used algorithms are used to demonstrate the capabilities. These are described below.

3.1 Genetic Algorithm

Genetic Algorithm (GA) simultaneously evaluates many points in the parameter space and converges towards the global solution. The genetic algorithm differs from other search techniques by the use of concepts taken from natural genetics and evolution theory. The genetic algorithm is based on the method of minimization of the prediction error [4]. 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 [3]. The GAs consider the same multi parameter system given by equation (2) then defined the following fitness function.

$$f(e) = \sum_{k=1}^{r} | y(k) - \hat{y}(k) | \tag{8}$$

where, $y(k)$ is measured output, $\hat{y}(k)$ is estimated model output, and r is the number of sets of measurement considered. Equation (8) may be written in vector form as:

$$f(e) = \sum_{k=1}^{r} \left| y(k) - \hat{\theta}_0 \hat{\psi}(k) \right| \tag{9}$$

3.2 Adaptive Neuro-Fuzzy Inference System

The basic idea behind these Neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modeling procedure 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. This learning method works similarly to that of neural networks. There is a MATLAB function in the Fuzzy Logic Toolbox that accomplishes this membership function parameter adjustment called ANFIS. This hybrid adaptive Neuro-fuzzy function ANFIS is used for system identification which is the major training routine for Sugeno-type FIS (fuzzy inference systems). The acronym ANFIS derives its name from adaptive Neuron-fuzzy inference system. ANFIS has proven to be excellent function approximation tool [5], [6].

Figure 1 shows the basic structure of the ANFIS algorithm for a first order Sugeno-style fuzzy system. It is worth noting that the Layer-1 consists of membership functions described by generalised bell function:

$$\mu(X) = (1 + ((X-c)/a)^{2b})^{-1} \tag{10}$$

where a, b and c are adaptable parameters. Layer-2 implemented the fuzzy AND operator, while Layer-3 acts to scale the firing strengths. The output of the Layer-4 is comprised of a linear combination of the inputs multiplied by the normalised firing strength w.

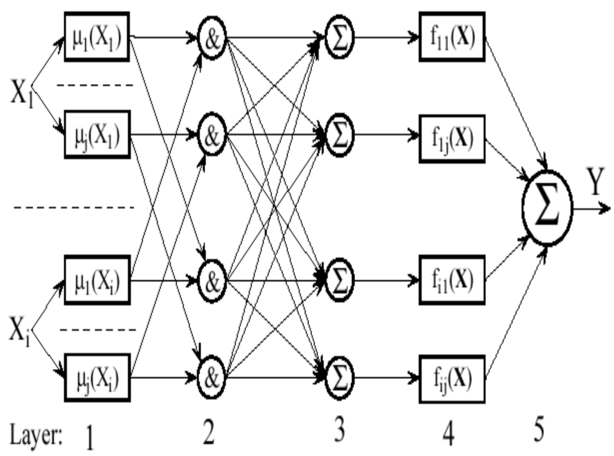

Figure 1. Basic ANFIS structure

$$Y = w(pX + r) \tag{11}$$

where p and r are adaptable parameters. Layer-5 is simple summation of the outputs of layer-4. The adjustment of modifiable parameters is a two step process. First, information is propagated forward in the network until Layer-4, where the parameters are identified by a least-squares estimator. Then the parameters in Layer-2 are modified using gradient descent. The only user specified information is the number of membership functions in the universe of discourse for each input and the input-output is considered as training information.

4 The flexible beam system

Consider a cantilever beam as a plant model of length L, fixed at one end and free at another, with a force $U(x,t)$ applied at a distance x from its fixed (clamped) end at time t, resulting a deflection $y(x,t)$ of the beam from its stationary (fixed) position at the point where the force has been applied. The motion of the beam in transverse vibration is, thus, governed by the well known fourth-order partial differential equation (PDE) [7].

$$\mu^2 \frac{\partial^4 y(x,t)}{\partial x^4} + \frac{\partial^2 y(x,t)}{\partial t^2} = \frac{1}{m} U(x,t) \tag{12}$$

where μ is a beam constant given by $\mu^2 = \frac{EI}{\rho A}$, with ρ, A, I and E representing the mass density, cross-sectional area, moment of inertia of the beam and the Young modulus respectively, and m is the mass of the beam. The corresponding boundary conditions at the fixed and free ends of the beam are given by

$$y(0,t) = 0 \quad \text{and} \quad \frac{\partial y(0,t)}{\partial x} = 0$$
$$\frac{\partial^2 y(L,t)}{\partial x^2} = 0 \quad \text{and} \quad \frac{\partial^3 y(L,t)}{\partial x^3} = 0 \tag{13}$$

Note that the model thus utilised incorporates no damping. To construct a suitable platform for test, a method of obtaining numerical solution of the PDE in equation (12) is required. This can be achieved by using the finite difference (FD) method. This involves a discrimination of the beam into a finite number of equal-length sections (segments), each of length Δn, and considering the beam motion (deflection) for the end of each section at equally-spaced time steps of duration Δt. Thus, first-order central FD methods is used to approximate the partial derivative terms in equations (12) and (13) yields.

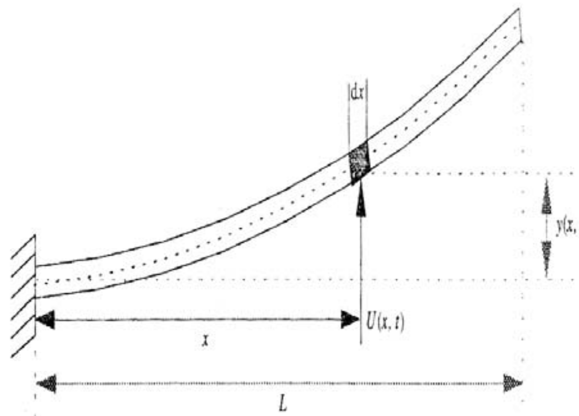

Figure 2. Schematic diagram of the cantilever beam system

$$Y_{j+1} = -Y_{j-1} - \lambda^2 S Y_j + (\Delta t)^2 U(x,t)\frac{1}{m} \tag{14}$$

where, Y_k $(k = j-1, j, j+1)$ is an $n \times 1$ matrix representing the deflection of grid-points 1 to n of the beam at time step k, S is a matrix, given in terms of characteristics of the beam and the discrimination steps Δt and Δx, and $\lambda^2 = (\Delta t)^2 (\Delta x)^{-4} \mu^2$. Equation (14) is the required relation for the simulation algorithm, characterising the behaviour of the cantilever beam system, which can be implemented on a digital computer easily. It has been shown that a necessary and sufficient condition for stability satisfying this convergence requirement is given by $0 < \lambda^2 \leq 0.25$ [8].

5 Implementation and results

A cantilever beam in transverse vibration of length L = 0.635 meter, mass m = 0.037 kg, was considered as plant for investigation. The beam was discretised into 19 small segments. To allow dominant modes of vibration of the beam to be excited, a step disturbance force (0.1N) of finite duration was applied to a suitable node of the beam. The input and output samples of the plant was collected from two suitable nodes of the beam. Moreover, sample period was selected as $\Delta t = 0.3$ ms which is sufficient to cover all the resonance modes of vibration of the beam [9].

A linear discrete second order model was estimated using the RLS, GAs and ANFIS, and their performance assessed. A comparative performance for system identification using the RLS and GAs has been reported earlier [4]. Figure 3 shows the time domain performance of the (a) RLS, (b) GA, and (c) ANFIS algorithm, where the solid signal represents actual output and doted one represents the estimated output of the model. It is observed that a significant error convergence leads almost overlapping of the two signals in each case. It is also noted that the ANFIS offers similar level of performance for error convergence as compared to the other two algorithms. Corresponding auto-power spectral density is shown in Figure 4, which further demonstrated the similarity and level of error convergence. As shown in Figure 3, the solid signal in Figure 4 represents actual output and doted one represents the estimated output of the model.

Table 1 shows the summary of the error convergence and the real-time performances of the algorithms. 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. It is noted that error convergences for all the algorithms are in similar level. It is also noted that the GAs perform better as compared to the RLS and the ANFIS offers the best performance among the three algorithms, although the overall performance variation are not very significant. However, the execution time in implementing the ANFIS is almost double as compared to the RLS algorithm and almost 1.5 times as compared to GAs.

Table 2 shows the summary of the real-time computing performance in implementing GAs based model for similar level of error convergence and fixed number of iterations (6000). It is noted that for the same number of population (32), the execution time increases 6 times for 5 times increment of the bit representation, whereas it increases 14.5 times for 10 times increment of the bit representation. In also noted that the execution time taken for the system identification is higher for larger bit representation or larger population size.

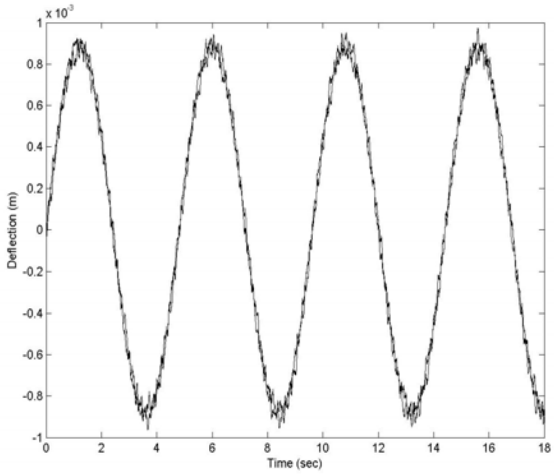

Figure 3.a. Performance of the RLS algorithm

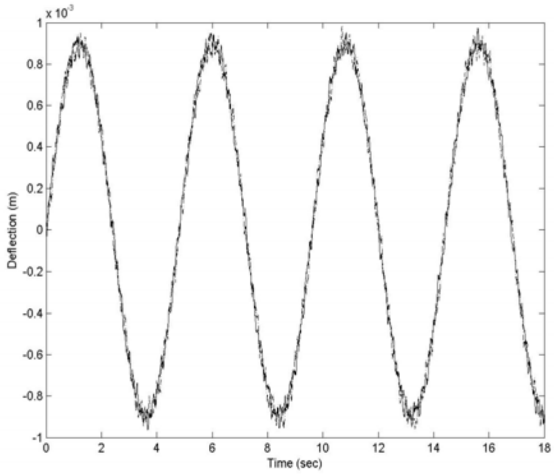

Figure 3.b. Performance of the GAs

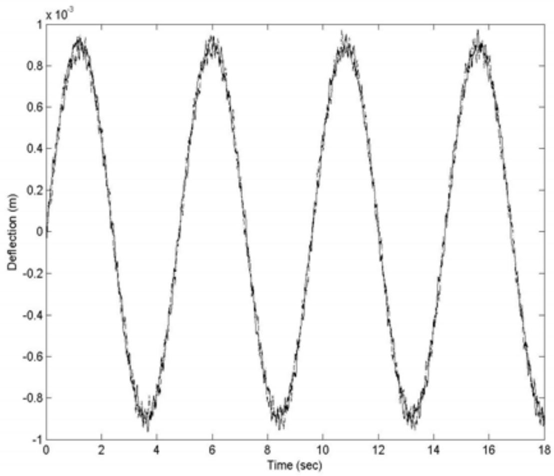

Figure 3.c. Performance of the ANFIS algorithm

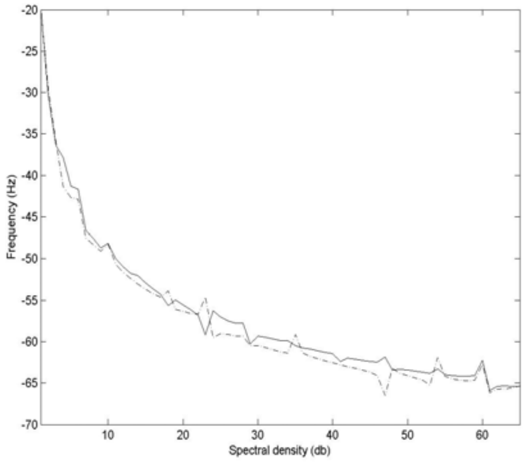

Figure 4.a. Performance of the RLS algorithm in auto-power spectral density

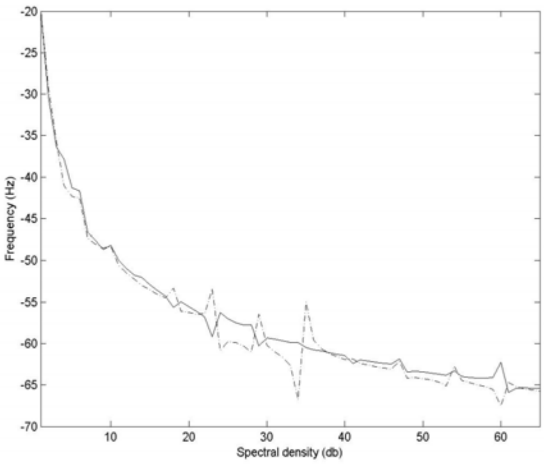

Figure 4.b. Performance of the GAs in auto-power spectral density

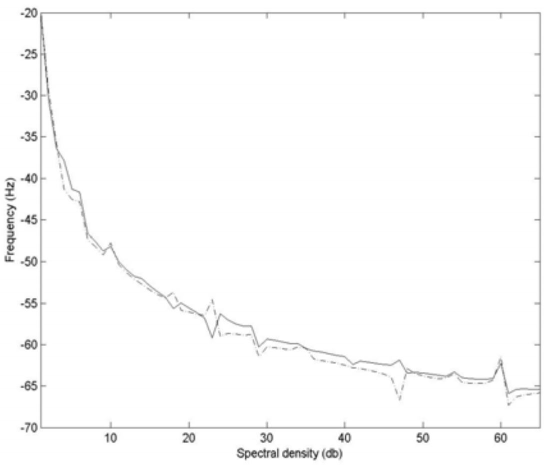

Figure 4.c. Performance of the ANFIS algorithm in auto-power spectral density

Table 1: Real-time performance in implementing the three algorithms

Algorithm	**Error**	**Time** (Sec)
RLS	0.2465	0.751
GA	0.2412	1.171
ANFIS	0.2383	1.521

Table 2: Real-time performance in implementing the GA with different size of the population and binary representation

Population	**Bit representation**	**Error Convergence**	**Time (Sec)**
8	10	0.2412	1.171
16	10	0.2375	3.121
32	10	0.2361	3.861
8	50	0.2373	6.033
16	50	0.2371	18.898
32	50	0.2365	23.6
8	100	0.2358	16.558
16	100	0.2353	25.051
32	100	0.2344	55.692

6 Conclusion

This paper has presented the real-time intelligent system identification of a flexible beam system for adaptive active vibration control. A plant model for a flexible beam system was considered to demonstrate the merits of the algorithms. A comparative performance of the algorithms has been presented and discussed through a set of experiments. It is noted that for the same number iterations, the execution time in implementing ANFIS algorithm as compared to GAs and RLS algorithms are higher. However, ANFIS shows relatively better error convergence for the same number of iterations. On the other hand, GAs real-time computing performance varies based on the selection of the size of population and binary representation. It is noted that the execution time for each of the three algorithms is less than the sampling time 0.3msec, in turn satisfied the real-time requirement. In case of GAs, this is true only for population size 8 and 10 bit representation. Finally, a comparative performance has been provided to demonstrate the capability of the algorithms for further work on real-time adaptive active control system design.

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