Identification of Systems With Multi-Model Error Surface by Ant Colony Optimization

[1]Shikha Tripathi , [2]Mohd Asif Ikbal
[1,2] Department of ECE, JIT ,Barabanki, India

Abstract: **The need of System identification is becoming very important as it is required in different areas like channel equalization, adaptive filtering and control, and many other applications. The basic concept behind the system identification is to determine a set of unknown model parameters based on a available noisy data. It is very helpful in the identification of full scale nonlinear structures subjected to high-intensity earthquake, Echo cancellation, for the development of Aircraft, Radar, Sonar Video and audio signal processing, Noise reduction etc. Because of these numerous application of system identification techniques it becomes very necessary to develop these techniques for the identification of system having multi-model error surfaces.**

In this work, the advantages of both gradient based algorithm and global optimizations algorithm are combined for the identification of systems with multi-model error surface. We have used Least Mean Square (LMS) which is a gradient based algorithm with Ant Colony Optimization (ACO). This optimization technique is global and by virtue of this work it has been proved that it may be very effectively applied for the said purpose. In ACO, the performance of real ant colonies to find the food source is transformed in an optimization technique to solve the optimization problems. For the validation of our approach we have implemented this algorithm using MATLAB. The simulation result confirms the validity of this approach and showed that the approach can be efficiently used for the designing and identification of systems with multi-model error surface.

Keywords— Multi-model error surface, LMS, ACO

I. INTRODUCTION

A. The Art of System Identification

As the name depicts the system identification is an approach to identify an unknown system. In the configuration shown in Fig. 1, the unknown system and an adaptive filter both in parallel and are agitated by the common input. When the output MSE (Mean square error) is minimized the filter represents the desired model. Fig. 1shows the structure used for adaptive system identification, in this diagram we find U(z), an unknown system by adaptive filter A(z). The signal x(n) excites U(z) and A(z), the desired signal u(n) is the unknown system output, minimizing the difference of output signals a(n) and u(n), the characteristics of U(z) can be determined. This approach is very helpful for the identification of the systems having uni-modal error surface. It uses gradient based algorithms for that purpose as the intrinsic stable behavior of these algorithms suffices for these systems.

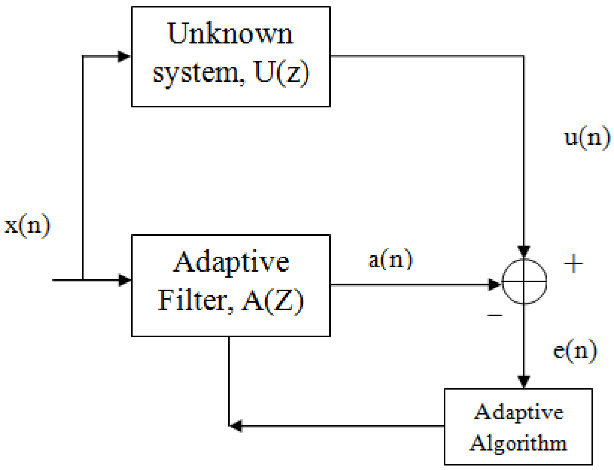

Fig. 1. Conventional modal of system identification

These algorithms are based on the process of the least-mean-square (LMS) and normalized least-mean square (NLMS) errors. On the other hand, these gradient base algorithm moves in the way of the negative gradient to find the global minimum of the error surface. The available approaches which are based on these algorithms generally lead the system with multimodal error surface to a local minimum. So as a concluding remark we would like to say that these approaches are not capable for the identification of the Systems having multi-modal error surface irrespective of the fact that these systems may provide a much better performance than the uni-modal systems having the same number of coefficients.

B. Problem Definition

As discussed above the gradient based algorithms like LMS which is used for the system identification of uni-modal error surface tries to find the global minimum of the error surface by moving in the direction of the negative gradient. During this process the optimization process may stick to a local minimum considering it as a global minimum resulting into the instability during the process of adaptation. Secondly the convergence speed of LMS algorithm is also an issue which decreases as the Eigen-value spread of the correlation matrix R, which is the ratio of the maximum to minimum Eigen value of the autocorrelation matrix, increases. Convergence rate can be increased by using NLMS (Normalized Least Squares) and RLS (Recursive Least Squares) adaptive algorithms. However, RLS algorithm demands higher storage and is also more computational intensive than LMS. Further, there is still another yet serious problem associated with LMS and NLMS algorithms, which is the choice of step-size of the search parameter that needs a trade-off between steady state miss adjustment and the speed of convergence.

C. Formulation of problems

In this work, we have combined the benefits of both gradient based algorithm and global optimizations algorithm. For that we have allocated the same task to two different algorithms. Initially, in the global optimum valley, the LMS algorithm is tuned to provide an optimal rate of convergence without fear of encountering a local minimum. And after that to quickly focus the population on regions of interest we have used global optimization technique ACO. Which results in an optimally tuned LMS algorithm which take over and provide better results than standard LMS and most importantly it is capable for the identification of the system with multi-model error surface.

II. CONVENTIONAL LMS ALGORITHM

The Least Mean Square (LMS) algorithm uses a gradient-based method of steepest decent. It approximates the value of the gradient vector from the data available. To find the minimum mean square error value LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient according to the (1),

$$w(n+1)=w(n)+\mu e(n)x(n) \tag{1}$$

Here x (n) is the input vector of time delayed input values and is given by (2),

$$x(n)=[x(n)x(n-1) \quad \ldots\ldots\ldots\ldots x(n-N+1)]^T \tag{2}$$

The vector $w(n) = [w_0(n)\ w_1(n)\ w_2(n) .. w_{N-1}(n)]^T$ represents the coefficients of the adaptive filter tap weight vector at time n. μ is the step size parameter also known as convergence factor. The value of μ is the root for the convergence speed of the LMS algorithm. For the convergence and stability of the LMS algorithm the allowable range of λ is given in (3),

$$0 < \mu < \frac{1}{\lambda_{max}} \tag{3}$$

Here λmax is the largest Eigen value of the correlation matrix R.

III. ANT COLONY OPTIMIZATION

A. General Discription

The ant word has served as an inspiration framework for the ACO algorithm. The ACO algorithm is usually described with the help of an ant metaphor and ant-related terms in order to fully recognize the connection with the ant world.

The ACO meta-heuristic is based on a multi-agent architecture. In which ants are the agents of the system and posses dual character. On one hand, the activities which is practical in real ant colonies is that they are an idea of those behavioral traits of real ants which are about to find the shortest path and on the other hand, they have been associated with the capabilities which do not find a natural equivalent, but are generally very important for obtaining desired result when subjected for the complicated optimization jobs. In ACO a colony of independent and synchronized agents oblige in stigmergic way and work to find excellent, most optimum, solutions to the given optimization. The main concern is to transform the idea of Ant colonies to a set of agents that follows the action of real Ant to find iteratively and concomitantly numerous solutions in a comparatively simple and computationally easy way of finding the solution.

For the better understanding of this concept have a look at Fig. 2, the very first ant moves out of nest randomly in all directions in the search of food source, in our case it is either f1or f2, then it moves back to the nest (N), depositing a pheromone track. Now other may also follow any of the two path and they will also deposit the pheromone tracks. On the shortest path f1 the concentration of the pheromone tracks will be higher as it is being reinforced earlier than f2. Which will results the path f2 to become more attracting for successive ants. This process will going on and the shortest path will reinforced and the longest path will evaporate.

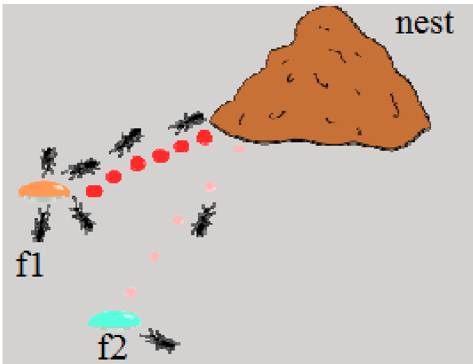

Fig. 2. Behaviour of Ants during the search of food source

Now to transform this concept in solving the computational problems we have created the following analogy.

TABLE I. ANALOGY BETWEEN TWO SYSTEMS

Nature	To be used for optimization
Natural territory	Nodes and Edges
Shell and Groceries	Nodes in the graph: start and destination
Ants	Agents, fake ants
Visibility	The reciprocal of distance, η
Pheromones	Fake pheromone ,τ
Oraging manners	Random walk through graph (guided by pheromones)

B. Procedure for finding the desired soultion

1) Scheme

- Construct ant solutions.
- Define attractiveness τ, based on experience from previous solutions.
- Define specific visibility function η .

2) Ant walk

- Initialize ants and nodes (states)
- Select the subsequent edge probabilistically in accordence with the attractiveness and visibility.

$$Prob(choose\ available\ edge\ e) = \frac{\tau(e)*\eta(e)}{\sum_{available\ edge\ e'} \tau(e')*\eta(e')}$$

(4)

- Every ant converse a forbidden list of impracticable transitions for that iteration
- Keep on updating the attractiveness of an edge in accordence with the number of ants that follow a perticular path.

3) Pheromone update

$$\tau(e) = \begin{cases} (1-\rho) * \tau(e), & if\ edge\ is\ not\ traversed \\ (1-\rho) * \tau(e) + new\ pheromone, & if\ edge\ is\ travered \end{cases}$$

(5)

- Parameter $0 \leq \rho \leq 1$ is known as evaporation rate.
- Pheromones can be considered as long-term memory of an ant colony.

IV. PROPOSED APPROACH

A. General Representation

So far in our discussion we have concluded that the existing algorithm can't be applied for the identification of the systems with multi-model error surface because of problems listed in I

In the available method for systems having uni-modal error surface we adjust the parameters of an adaptive filter to minimize a cost function chosen for the identification of systems using LMS adaptive algorithm. In this approach we have combine LMS algorithm with ACO. The general form of proposed algorithm is

$$W(n+1) = W(n) + \mu(n) G(e(\mathrm{X(n)}, \quad \Phi(\mathrm{n}))$$

(6)

Where G(.) is a particular vector-valued nonlinear function, μ(n) is a step size parameter as mentioned earlier, e(n) is the error signal, X(n) is the input signal vector, and Φ(n) is a vector of states that contain useful information about the characteristics of the input and error signals and it also contain the value of coefficients at earlier time instants. The reason why μ is known as step size is that it determines the level of the change or "step" that require by the algorithm in finding the useful value of coefficient vector iteratively. In this approach it is optimized by ASO.

B. The mean square error Cost Function

The form of G(.) in (6), depends on the cost function chosen for the given adaptive filtering task. For the proposed algorithm the mean-squared error (MSE) cost function is defined as

$$J_{MSE(n)} = \frac{1}{2}\int_{-\infty}^{\infty} e^2\,(n) p_n(e(n) d(e)$$
$$= \frac{1}{2} E\{e^2(n)\}$$

(7)

Where $p_n(e)$ denotes the probability density function (PDF) of the error at time n and E{.} represents the shorthand for the expectation integral which is the right hand side of the (5). This MSE cost function is important and will solve our purpose because of the following reasons.

- The minimum of $J_{MSE}(n)$ is well-defined with respect to the parameters in W(n);
- The resulting values of the coefficients which are obtained at this minima will minimize the power in the error signal e(n) and indicates that y(n) has approached d(n); and
- $J_{MSE}(n)$ is a simple function of every parameters in W(n), such that it may be differentiated with respect to any of the parameters in W(n).

C. Unknown System Model

From the Fig. 3, it is clear that we have replace the adaptive filter block by two blocks one is LMS and the other is ACO and combines the Ant Colony Optimization Algorithm with Least-Mean-Square (LMS) method, i.e. in each iteration of ACO, after the calculation of τ(e) , an LMS algorithm will be applied based on the previous τ(e) . In the proposed configuration, error signal is first send to ACO block where the appropriate step-size is being decided with comparatively less error value. Then this step-size value is directed to the LMS block, where by the virtue of LMS algorithm coefficients are updated simultaneously. The main advantage of ACO is that it does not stick with the local minima. But at the same time it is a slow process. On the other hand LMS algorithm is comparatively faster but may stick in some cases or may remain in local minima and its results are not as accurate as ACO-based procedures.

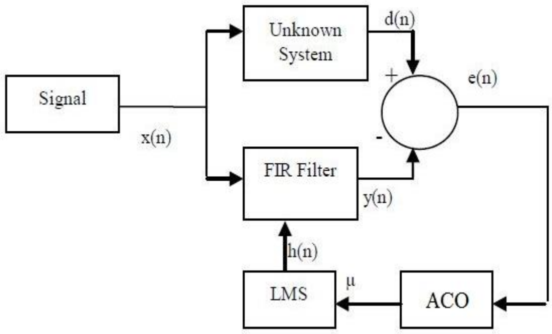

Fig. 3. Purposed model

So we have combines the advantages of both the algorithms in a way to accelerate the very slow rate of ACO and escapes from the local minima which may result from LMS.

D. Simulation Results

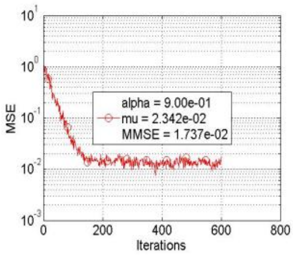

Fig. 4. (a)

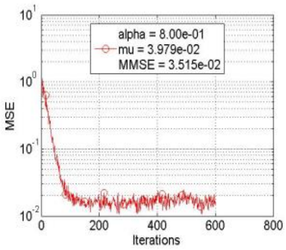

Fig. 4. (b)

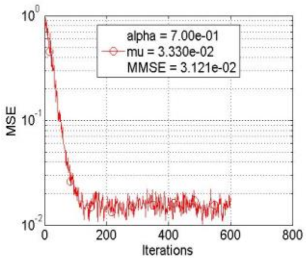

Fig. 4. (c)

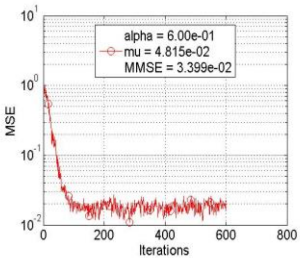

Fig. 4. (d)

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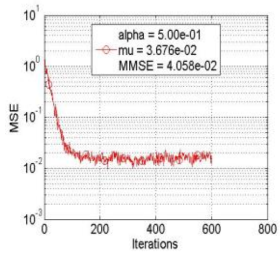

Fig. 4. (e)

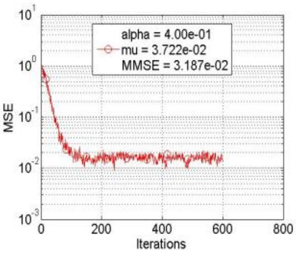

Fig. 4. (f)

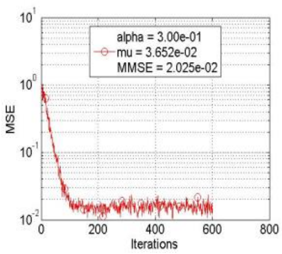

Fig. 4. (g)

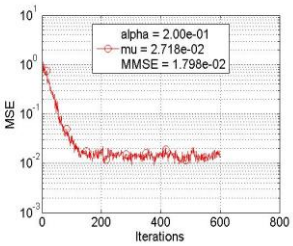

Fig. 4. (h)

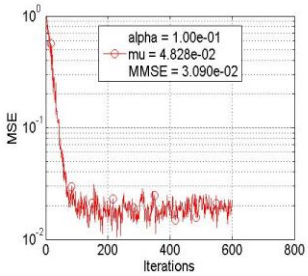

Fig. 4. (h)

Fig. 4. Simulation results based on ACO algorithm

V. CONCLUSION AND FUTURE WORK

In this work we have designed an algorithm for the identification of systems having multi-model error surface. From the simulation results it may be concluded that the cost functions have minimized up to the desired level which ensures the validity of this algorithm. It has been also observed that ACO has significantly improved the adaptive algorithms to be used for systems with multi-modal error surfaces. We can say that it is a powerful and robust algorithm as compared with the previous methods used for the identification of systems with multi-model error surface.

As a future work one may try to use this algorithm for the designing of the unknown system model and in various application of adaptive filters where multi-model error surface had been a limitations.

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