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NONLINEAR SYSTEM IDENTIFICATION USING A NOVEL IMMUNE ARTIFICIAL FISH SWARM ALGORITHM

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Abstract - This paper proposes a functional link artificial neural network(FLANN) model trained using a modified fish swarm optimization (FSO) algorithm for nonlinear system identification. The system modelling problem has been reformulated as an optimization problem. The FSO algorithm has been modified by incorporating the immunity features of the artificial immune systems. Simulation study reveals improved performance of the proposed algorithm over the conventional FSO algorithm for nonlinear system identification.

***Key words** - FLANN; Fish swarm optimization; Immune system.*

I. INTRODUCTION

Science is the study of nature to answer solutions in some problem domain and Computational algorithms and tools are all inspired by Nature to solve our real time problems in an efficient way. System identification plays an important role in many areas of research now-a-days. The linear static systems can be easily identified using traditional least mean square algorithm. However, in practice, most of the systems which we encounter are nonlinear ones. In such systems, the traditional approaches do not yield satisfactory results. Therefore, advanced nonlinear approaches have been developed for such systems. Fish swarm algorithm is basically the simulation of behaviour of school of fishes. Fish can find the area with more nutritional value through individual search or by following other fishes. This trait is emulated by fish swarm algorithm and put to use in several nonlinear identification problem.

Nonlinear System Identification is of prime importance nowadays. Its applications are manifold. It is being used in varied areas such as electrical engineering, molecular biology, interpretation of microarray data, identification of MIMO systems etc.

Nonlinear System Identification can be accomplished using various kinds of adaptive algorithms. Neural networks represent an important method in classification of patterns and approximating complex nonlinear systems.

Due to these properties, neural networks are preferred models for nonlinear systems whose mathematical models are difficult to obtain. A wide variety of neural networks models have been applied for such approximation purposes and these include models like FLANN(functionally linked artificial neural network), LeNN(Legendre neural network), PPN(polynomial perceptron network) etc.

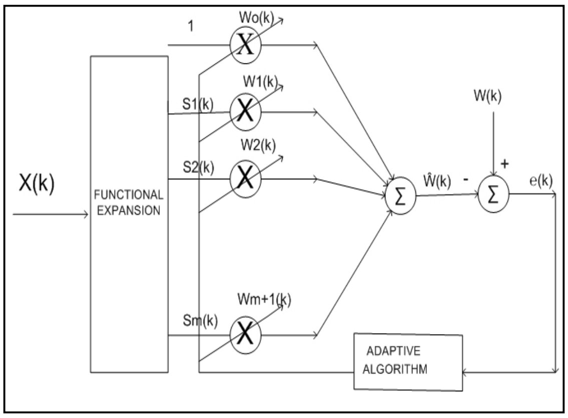

Fig. 1 : FLANN

FLANN was first proposed by Pao as a single layer ANN structure capable of forming arbitrarily wide complex Decision regions by generating non-linear decision boundaries.The use of FLANN not only increases the learning rate but also reduces the computational complexity.

The input signal X(k) is functionally expanded to a nonlinear values to an adaptive linear combiner whose weights are varied as per the iterative learning rule. Generally, LMS is used but here we have implemented Immune artificial fish swarm optimization algorithm to change the weights. In this case,we have used trigonometric based linear expansion matrix given by:

$$\emptyset i(u(k)) = \begin{Bmatrix} 1 \; for \; i = 0 \\ u(k) for \; i = 1 \\ \sin(i.pi.u(k)) \, for \; i = 2,4,\dots m \\ \cos(i.pi.u(k)) \, for \; i = 3,5,\dots.m+1 \end{Bmatrix}$$

Where i=1,2,….,m\2.As a result the total expanded values including an unity bias input becomes 2m+2.

Let the corresponding weight vector be represented as $W_i(k)$ having 2m+2 elements. The estimated output of the non-linear static part is given by-

$$F\big(u(k)\big) = \sum_{i=1}^{2m+2} Wi\emptyset i\big(u(k)\big) + \in (k)$$

Where, is approximation error.
From nature only we wanted to add one more element to our algorithm and that one was immunity.

Immunity is the ability of body to resist against diseases. The Clonal selection principle of AIS describes the activities of immune cells against the entry of pathogens or antigens and is simple and effective evolutionary computation tool to solve optimization problems.

The affinity of every cell with each other is a measure of similarity between them and is calculated by the distance between them. The antibodies present in memory has got higher preference than the one detected in primary response. During mutation, fitness as well as the affinity of antibodies gets changed.So,in each iteration antibodies with higher fitness and affinity are stored in memory and the low affinity cells are discarded.

The Clonal selection algorithm has several interesting features like adjustable search space, population size, location of multiple optima etc.

II. DEVELEOPMENT OF IAFSO

A. Artificial Fish Swarm Algorithm

As mentioned before, artificial fish swarm algorithm is the simulation of behaviour of a school of fishes, which find the zone with more nutritional value using individual search or by following other fishes. This algorithm comprises of three behaviours: preying, swarming and following behaviour. Preying behaviour is the most common behaviour for obtaining food. Fishes perceive the concentration of food through vision or sense to determine movement and then choose the tendency. Swarming behaviour is a kind of living behaviour in which the fishes assemble in groups naturally in moving processes to guarantee the existence of colony and to avoid danger. while swarming they obey three principles, which are namely Compartmentation principle, Unification principle and Cohesion principle. Compartmentation principle refers to avoiding congestion with other fellows.

Unification principle refers to moving towards average fellows' moving direction whereas the Cohesion principle refers to the movement towards the centre of the group. Also, when a fish or a group of fishes find the food, the nearby fishes approach the food by following them as quickly as possible. This is known as the following behaviour. Before constructing the artificial fish(AF) model, we will introduce some definitions first.

Xi is the position of AFi. Y=f(X) is the fitness or objective function at position S, which can represent food concentration. Xij represents the distance between AFi and AFj . Visual represents the visual scope whereas 'a' represents the crowd factor of AF. 'mf' is the number of fishes within the visual scope of one fish. 'M' step is the maximum step of the moving AF and step is a random positive number within 'M' step. S(Xijk)<‖Xi −Xj ‖ < V isual) is the set of all the AF which lie within the visual scope of Xi exploring the area at the present position. The typical behaviour of AF can be expressed as follows:

Searching behaviour :In general, the fish stroll at random. When the fish(es) discover a water area with more food, they will go quickly towards the area. Let us assume that Xi is the AF state at present, and Xj . The beahviour can be expressed as follows:
$Xj = Xi + visual.rand()$
$Xi = Xi + step.(Xi - Xj)/\|Xi - Xj\|$ if $Yj > Yi$
$Xi^{(t+1)} = Xi^{(t)} + step.rand()$ else

Swarming behaviour :In the process of swimming, the fish will swarm spontaneously in order to share the food of the swarm. Let us assume that Xi is the AF state at the present and Xc is the centre of the swarm. Then, the fish behaviour can be expressed in formula as follows:

$Xi^{(t+1)} = Xi^{(t)} + step.Rand().(Xc - Xi^{(t)})/\|Xc - Xi^{(t)}\|$

Following behaviour :When one fish of the fish swarm discovers more food, the other fish will follow it. Let us assume that Xj is the position of the fish which has discovered food and Xi is the general state of AFi. Then the behaviour can be expressed as follows:
$Xi^{(t+1)} = Xi^{(t)} + step.Rand().(Xj - Xi^{(t)})/\|Xcj - Xi^{(t)}\|$

B. Immune Artificial Fish Swarm Algorithm

The Immune Artificial Fish Swarm algorithm is an improvement over the general one. In this approach, we clone those fishes which are very near to the food source and clone them so that the population searching for better solution converges to it fastly and does not get stuck in any local solution.

Since, in Fish swarm optimization,Swarm best position is the best position in the available search space, So each fish instead of following its personal best value will now tend to follow the swarm best value to reach to food faster with added Immunity to it to prevent it from straying away from solution space .

As per clonal selection principle when an antigen or a pathogen invades the organism, numbers of antibodies are produced by the immune cells. The fittest antibody undergoes cloning operation to produce number of new cells. These are used to eliminate the invading antigens.

Employing this principle of AIS in FSO we propose thateach particle is led to the Swarm best position wherefrom the next search is started.

Mutation operation is also implemented to diversify the search space.The Fitness value are evaluated then for the Mutated fish as well as the Fish present in the visual scope and then the best fishes are selected for the journey of traversing.

III. IAFSO BASED LEARNING

1. Generate ‘K’ number of input-output patterns which are required to learn the network uniformly distributed.
2. Each Input pattern ‘X’ is functionally expanded.
3. Each of the desired output is compared with corresponding desired output to generate ‘k’ errors and hence mean squre error for a parameter is determined by

$$MSE(n) = \sum_{i=1}^{k} (e(i)^2)/k$$

4. Weights are varied by using AFSO based learning mechanism.
5. The MSE is plotted to obtain the learning characteristics.Learnng is stopped when minimum MSE levels are reached or maximum number of iterations are achieved.

IV. SIMULATION STUDY

In this section we carry out the simulation study of FLANN based artificial fish swarm algorithm. The block diagram of Fig.1 is simulated where the coefficients or the weights of the FLANN model are updated using LMS and AFSA. We have carried out simulation without noise as well as with noise of SNR 20dB.Simulations are carried out extensively for different sets of problems to test the functionality of new proposed algorithm using MATLAB.

The accuracy of identification of proposed model assessed by following results:

1. Comparing the response curve of Inputs and Outputs.
2. Comparing the MSE curve.

Now we have tested the workability of this novel algorithm on the following examples:

Example 1. : Linear system [0.26000.93000.2600]

Example 2. : Test function The impulse response of the plant is [0.2600, 0.9300, 0.2600] and nonlinearity associated is $yn(k) = \tanh(y(k))$ SNR 20dB.

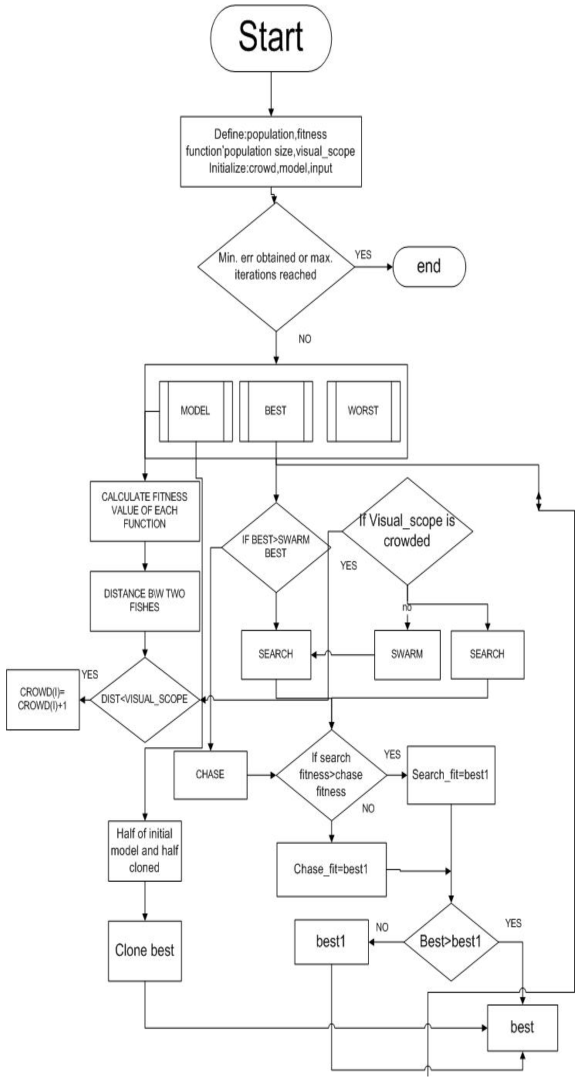

Fig. 2 : Flowchart

Example 3 : Test function Parameters of the linear system of the plant is [0.2600, 0.9300, 0.2600] and nonlinearity associated is $yn(k) = y(k) + 0.2 [y(k)]^2 - 0.1[y(k)]^3$ SNR 20dB.

Where, y(k) is the output of the linear part of the plant plant and $y_n(k)$is the output of the overall system.

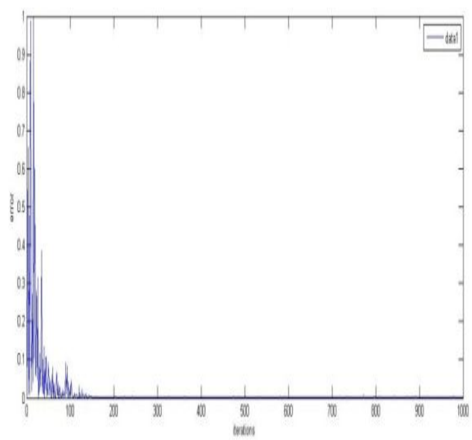

Fig. 1 : MSE curve for example 1

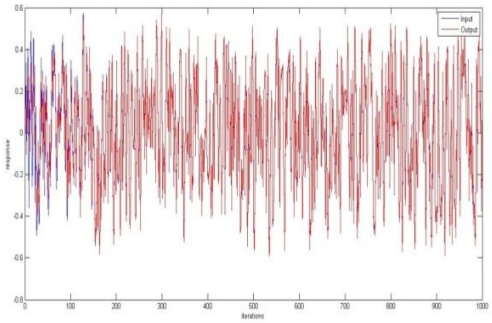

Fig. 2 : Response curve for example 1

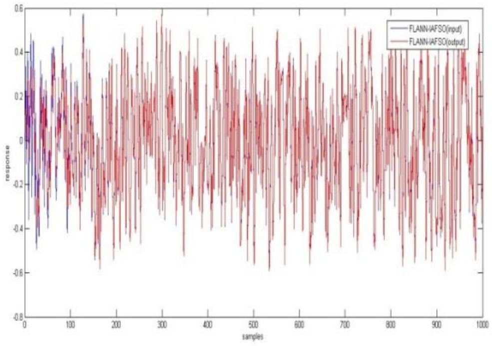

Fig. 3 : Response curve for example 2

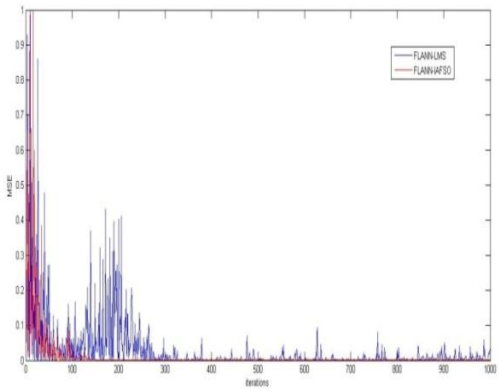

Fig. 4 : MSE curve for example 2

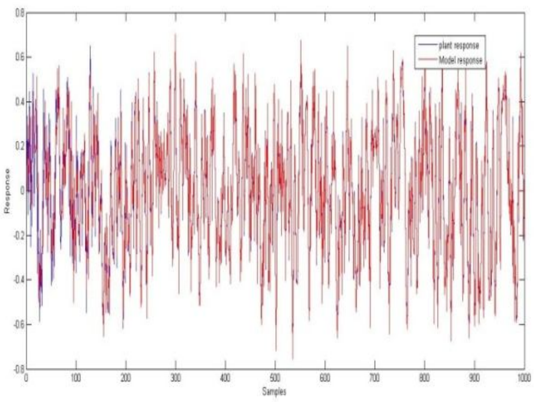

Fig. 5: response curve for example 3

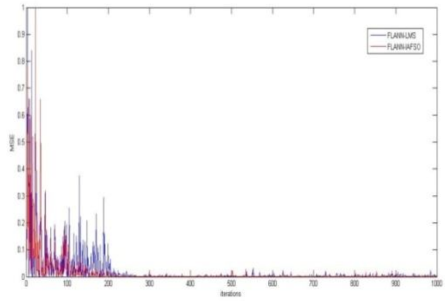

Fig. 6 : MSE curve for example 3

V. CONCLUSIONS

In this paper, we have modified the general fish swarm algorithm to convert it to immune fish swarm algorithm. We have used cloning which increases the convergence power of the solution and gives a more precise training result. In other words, we can say that the cloning of the fishes which give the best result provides immunity to the entire population. This process reduces the chance of straying of fishes from the best solution and also the chance of algorithm getting stuck in a local minimum. Thus this algorithm is both more convergent and best result giving as compared to its counterpart.

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