Efficient Identification of IIR Systems in Sensor Nodes using Diffusion Particle Swarm Optimization for Wireless Sensor Networks

Rashmi Singh
Dept. of Electronics & Communication Engineering
Bhabha Engineering Research Institute
Bhopal, India
rrsingh3013@gmail.com

Satyarth Tiwari
Dept. of Electronics & Communication Engineering
Bhabha Engineering Research Institute
Bhopal, India
sytiwari@gmail.com

Abstract—**Most distributed estimation algorithms have traditionally been designed for stable systems such as Finite Impulse Response (FIR) systems. However, recognizing that real-world systems are not always stable, this paper proposes distributed estimation for Infinite Impulse Response (IIR) systems. It focuses on diffusion-based cooperation among adaptive nodes, which is crucial for handling system instability. This approach ensures adaptability to changes in network topology, maintaining good performance even in the face of link and node failures. Simulation results demonstrate that the proposed IIR DPSO (Infinite Impulse Response diffusion particle swarm optimization) algorithm achieves comparable Mean Square Error (MSE) to the conventional IIR ILMS (Infinite Impulse Response Incremental least mean square) algorithm. Moreover, the proposed algorithm exhibits robustness to link failures, making it suitable for large-scale networks and adaptable to changing network configurations.**

Keywords— **Least Mean Square,Particle Swarm Optimzation, Mean Square Error, Infinite Impulse Response, Parameter Estimation.**

I. INTRODUCTION

In recent years, the distributed estimation of parameters has garnered significant attention among researchers, largely driven by the extensive utilization of wireless sensor networks (WSNs). These networks find application in various fields such as environmental monitoring (e.g., temperature, sound, humidity, pollution, and vibration monitoring), battlefield surveillance, health care, and home automation [1]. Sensor nodes within WSNs typically possess limited processing capabilities and rely on small batteries for power. Consequently, there is a pressing need to devise methods that consume minimal power and communication resources for processing observed data [2]. In practical scenarios, a group of nodes is deployed across a geographical area to capture raw observations and estimate specific parameters of interest amidst noisy environments. Traditional centralized parameter estimation methods entail significant communication overhead to relay data to a fusion center, consequently diminishing the overall network lifespan rapidly.

To adapt to changes in the environment, various techniques for distributed parameter estimations have been proposed [3-4]. In these approaches, each sensor independently estimates local parameters and then shares these estimates with neighboring

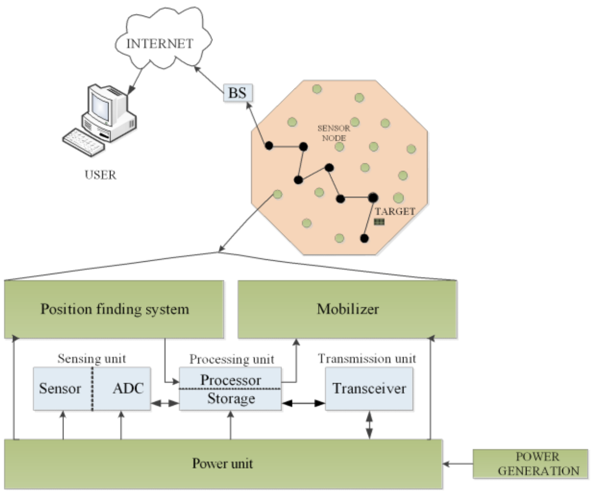


Fig.1: Architecture of Wireless Sensor Node

nodes to collectively estimate global parameters. Cooperation among nodes is facilitated through two strategies: Incremental and Diffusion [5]. In the Incremental strategy [6], nodes cyclically update their local weights based on data collected from themselves and immediate neighbors. This approach necessitates a predefined incremental path connecting all sensors in the environment, making it suitable for small networks with minimal inter-node communication. Conversely, the Diffusion strategy [7], depicted in Fig.1, involves estimating a node's weight by aggregating the estimated weights of its neighboring subset N_k, along with the data $X_k(i)$ observed by the node. This estimated value is then shared with neighboring nodes. The Diffusion mode allows each node access to a greater number of neighbors, enabling it to adapt to changes in network topology and perform more effectively in larger networks compared to the Incremental mode[8]-[9].

This research paper is focus to the implementation of Diffusion Particle Swarm Optimization (PSO) tailored specifically for Infinite Impulse Response (IIR) systems with the objective of accurately estimating the parameters associated with each individual sensor node. Particle Swarm Optimization (PSO) is an extensively utilized metaheuristic optimization algorithm that draws inspiration from the collective behavior observed in natural phenomena such as bird flocking or fish schooling. Within the framework of PSO, a diverse population of candidate solutions, denoted as particles, navigates through the solution space in pursuit of the optimal solution. Each particle dynamically adjusts its position and velocity based not only on its individual experiences but also on the collective experiences shared among its neighboring particles. Consequently, this collaborative adaptation mechanism enables particles to converge towards solutions that approximate the global optimum, all while maintaining computational efficiency.

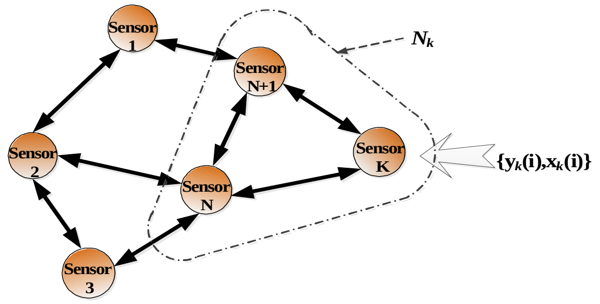


Fig.2: Diffusion Strategy for Mode of Cooperation between the nodes

However, it is noteworthy that the majority of existing optimization algorithms are primarily designed for stable systems such as Finite Impulse Response (FIR). In acknowledgment of the prevalence of real-world systems characterized by instability, we propose the development of an algorithm explicitly tailored to address the distinct challenges encountered in IIR systems. This tailored approach is anticipated to enhance the applicability and effectiveness of optimization techniques in practical scenarios characterized by the presence of unstable dynamics [10]-[13].

The structure of the work is outlined as follows. Section 2 outlines the formulation of the estimation problem utilizing a distributed strategy. Section 3 presents distributed estimation for IIR systems under incremental cooperation. Recognizing the limitations of incremental cooperation, we introduce diffusion PSO for distributed estimation of IIR systems in Section 4. In Section 5, we conduct a simulation study on two IIR systems under various noise conditions and compare the results with those obtained by IIR ILMS. Finally, Section 6 provides the conclusion of our proposed algorithm.

A. Problem Formulation

Let's consider a sensor network comprising 'K' nodes deployed across various environments. The data gathered by the kth node is denoted as k=[1,2,3……….K][15]. Each sensor's collected data is subject to noise $na_k(i)$, assumed to follow a uniformly distributed white Gaussian distribution. The input data vector, $X_k(i)$, is independent of the noise. In this context, each sensor node functions as an IIR plant, and the output of the k-th IIR plant is characterized by an equation. The input data vector, denoted as $X_k(i)$, is uncorrelated with the noise. Each sensor node is treated as an IIR plant, and the output of the *k-th* IIR plant is described by equation [11].

$$y_k(i) = \sum_{q=0}^{Q} a_q * X_k(i-q) + \sum_{p=1}^{P} b_p * y_k(i-p) + na_k(i) \qquad (1)$$

The primary aim is to determine the global parameters of interest w^0 (i.e. $[a_0 a_1 \ldots a_Q b_1 b_2 \ldots b_P]$) linked with the data captured by the sensor node[16]. These parameters can be computed using either centralized or distributed methodologies. The zeros and poles of the IIR plant are represented by $a_q(0 \le q \le Q)$ and $b_p(0 \le p \le P)$, respectively.

For the purpose of identifying distributed systems, we consider the model depicted in Figure 2. At the kth node, the output can be represented by the equation described in reference [12].

$$\hat{y}_k(i) = \left(\frac{\hat{A}(i,z)}{1 - \hat{B}(i,z)} \right) X_k(i) \qquad (2)$$

Where feed forward and feedback transfer function of K^{th} instant of $\hat{A}_k(i,z)$ and $B_k(i,z)$ *are represented by*

$$\hat{A}_k(i,z) = \sum_{q=0}^{Q} \hat{a}_{k,q}(i) * z^{-q} \qquad (3)$$

$$\hat{B}_k(i,z) = \sum_{p=1}^{P} \hat{b}_{k,p}(i) * z^{-p} \qquad (4)$$

The expression for the output of the IIR system model at the sensor node is as follows:

$$\hat{y}_k(i) = \sum_{q=0}^{Q} \hat{a}_q(i) * X_k(i-q) + \sum_{p=1}^{P} \hat{b}_p(i) * \hat{y}_k(i-p) \qquad (5)$$

The error at the k^{th} sensor node is calculated by subtracting the desired filter output $y_k(i)$ from the model filter output $\hat{y}_k(i)$ expressed as:

$$\varepsilon_k(i) = y_k(i) - y_k(i) \qquad (6)$$

The optimal weight vector, comprising both the coefficients of the forward filter path and the feedback filter path, can be estimated by minimizing the cost function [13].

$$J(w) = \arg\min \sum_{k=1}^{K} \left\| y_k(i) - X_k^T(i) w \right\| \qquad (7)$$

II. Diffusion PSO for IIR System Identification

The diffusion strategy employed for distributed estimation of parameters in an Infinite Impulse Response (IIR) system does not necessitate the establishment of any cyclic paths among sensor nodes to facilitate parameter estimation[17]-[21]. This approach operates effectively through a proposed two-step process specifically tailored for this purpose.

Step 1:

$$w_k(i-1) = \sum_{l \in N_{k,i-1}} m_{kl} \phi_l(i-1) \qquad (8)$$

TABLE I. ESTIMATED PARAMETERS OBTAINED FOR EXAMPLE UNDER DIFFERENT NOISE CONDITIONS USING IIR ILMS AND IIR IPSO DURING TRAINING

True Coefficients	Estimated Parameters using IIR DPSO		Estimated Parameters Using IIR DLMS	
	20dB	10dB	20dB	10dB
0.05	0.0528	0.0528	0.0683	0.0513
-0.4	-0.4420	-0.4420	-0.3884	-0.3626
1.1314	1.090	1.090	1.1523	1.2135
-0.25	-0.2145	-0.2145	-0.2497	-0.3246

$$\phi_k(i) = w_k(i-1) - c * \nabla_k^D \tag{9}$$

In this context, N_k represents the set of neighboring nodes that are directly connected to a specific node i.e (i=1,2…N_K). step 1 involve at any given time i-1 node k has access to a set of unbiased local estimates $\{\varphi_k(i-1)\}_{k\epsilon N_k}$ from its neighborhood nodes N_k. This local estimation gathered from neighboring nodes are consolidated or merged at the node k and which gives a gross estimate weight $w_k(i$-1). m_{kl} is the merger coefficients [13] which hold the information of sensor network topology. The purpose of the merger coefficient is to determine which nodes $l \epsilon N_k$ should share their local estimates $\{\varphi_k(i-1)\}$ other nodes N_k. If nodes k and l are not connected, the value of the merger coefficient is zero; otherwise, it is one. The coefficients m_{kl} give rise to a merger matrix M=[m_{kl}].

$$m_{kl} = \frac{m_{kl}}{\sum_{r \in N_{k,j-1}} m_{kl}} \tag{10}$$

Each node in N_k will possess a distinct neighborhood within the connected sensor network. Another condition for the merger coefficient is as follows: [12]

$$\sum_l m_{kl} = 1 \tag{11}$$

$$l \in N_{k,i-1} \forall k \tag{12}$$

This help in gathering information from nodes distributed across the network [18]. Therefore, we assume that M is a stochastic matrix.

Step 2: For optimizing weights and local optimum solution, we apply Particle Swarm Optimization (PSO)[22]-[25]. The position of a particle corresponds to a candidate solution, and the velocity of the particle determines the direction and magnitude of its movement in the search space. The position of a Node N_k at iteration i is updated based on its current position and velocity, and its best-known position (personal best) and the best-known position of any particle in its neighborhood (global best).

The basic equations of PSO are as follows:

Initialization

- Initialize the position and velocity of each particle randomly within the search space.

TABLE II. COMPARISON OF SIMULATION TIME DURING TRAINING FOR EXAMPLE

Noise	Estimated Parameters	
	IIR DPSO	IIR DLMS
10dB	34.33sec	7.18sec
20dB	40.41sec	7.34sec

- Set the personal best position p_i of each particle to its initial position.
- Identify the global best position $\varphi_i(t+1)$ among all particles.

Update Equation

- Update the velocity V_i of each particle using the following equation:

$$v_i(t+1) = wv_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (\varphi_i(t-1) - x_i(t)) \tag{13}$$

Where c_1 and c_2 are acceleration coefficients and r_1 and r_2 are random values samples from an uniform distribution in the range [0,1]. W is the inertia weight controlling the impact of the previous velocity.

TABLE III. COMPARISON OF SUM OF SQUARE OF ERROR DURING TESTING FOR EXAMPLE

Noise	Estimated Parameters using IIR IPSO	
	IIR DPSO	IIR DLMS
10dB	0.0498	0.0975
20dB	0.1593	0.1816

- Update the position x_i of each particle using the updated velocity by equation (14)

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{14}$$

Update personal and Global Bests

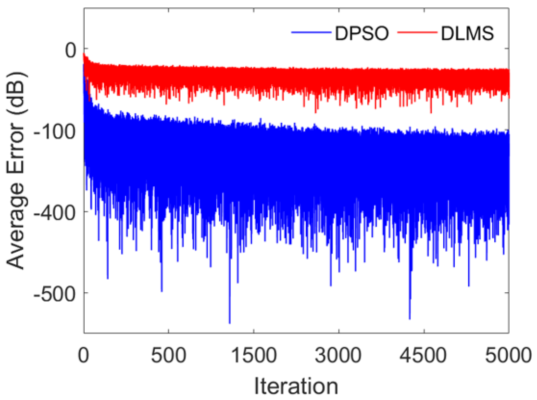
- For each particle i, update its personal best position p_i if the current position $x_i(t+1)$ is better (according to the objective function) than its previous best position.
- Update the global best position g by comparing the fitness (objective function value) of each particle's personal best position with the current global best[26]-[28].

Termination

Repeat the update process for a fixed number of iterations or until a termination condition (e.g., reaching a certain fitness threshold) is met.

III. SIMULATION RESULTS

In this section, we compare the performance of the proposed IIR DPSO algorithm with the existing IIR DLMS using two IIR systems. Each node within a sensor network contains the IIR system structure depicted in Fig. 2. The input signal is characterized as a zero-mean white random signal with a uniform distribution. The simulation is conducted under various Signal-to-Noise Ratio (SNR) conditions: 10dB and



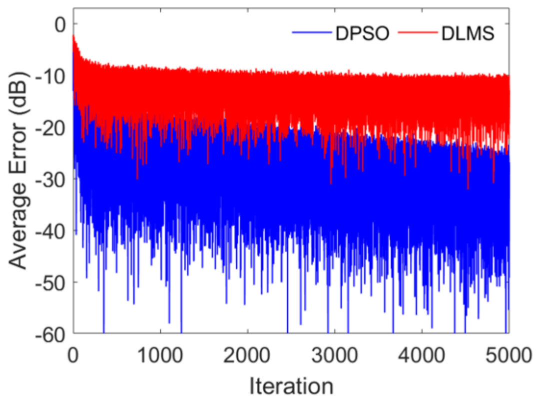


Fig.3 Comparative results of convergence achieved by IIR ILMS and IIR IPSO for example under different noise conditions (a) SNR 10dB (b) SNR 20dB.

20dB, executed on a computer equipped with an i5 processor and 8GB of RAM. The noise is additive and follows a white random process that is uncorrelated with the input signal. Key simulation parameters for the IIR DPSO include the number of sensor nodes set at 25. As the training progresses, the Mean Squared Error (MSE) at each node consistently decreases until it reaches its minimal value, signifying the conclusion of the training phase. The Sum of Squared Error (SSE) is employed as a performance metric during testing to compare the IIR DLMS and the proposed IIR DPSO algorithms.

Example 1:

The transfer function of a 2nd order IIR system [12] present at sensor node given by

$$H_p(z)=\left[\frac{0.05-0.4z^{-1}}{1-1.1314z^{-1}+0.25z^{-2}}\right] \tag{15}$$

This can be modeled using 2nd order adaptive IIR filter as

$$H_p(z)=\left[\frac{a_0+a_1z^{-1}}{1-b_1z^{-1}-b_2z^{-2}}\right] \tag{16}$$

The convergence characteristics shown in figure 3 reveals that the minimum MSEs obtained using IIR DPSO is less than IIR DLMS. The simulation time of IIR DLMS and IIR DPSO are shown in Table 2. Table 3 shows the comparison of the sum of the square of error (SSE) during testing of IIR ILMS and IIR DLMS. It is observed from Table 3 that the SSE in the case of IIR DPSO is nearly similar to IIR DLMS.

IV. CONCLUSION

The paper introduces a diffusion strategy based on the PSO algorithm for distributed parameter estimation of IIR systems deployed at each node within a sensor network. Simulation studies conducted on IIR systems demonstrate that the proposed IIR DPSO algorithm achieves lower Mean Square Error (MSE) compared to the IIR DLMS. The accuracy of filter weights in our algorithm is nearly equivalent to that of the IIR DLMS. Furthermore, it is observed that as the noise strength increases (resulting in decreased SNR values), the parameter matching value deviates, indicating a decline in effective identification quality in the presence of high noise levels. Overall, the performance evaluation of the proposed IIR DLMS algorithm highlights its suitability for parameter identification in distributed IIR systems. The algorithm proves to be effective for large sensor networks and resilient to link failures.

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