Diffusion Based Distributed Detection In Wireless Sensor Network

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Diffusion Based Distributed Detection In Wireless Sensor Network

Thesis submitted in partial fulfillment of the requirements for the degree of

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by

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under the guidance of

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June, 2015

dedicated to my parents...

National Institute of Technology
Rourkela

CERTIFICATE

This is to certify that the work in the thesis entitled **”Diffusion Based Distributed Detection In Wireless Sensor Network”** submitted by ***Anand Singh*** is a record of an original research work carried out by him under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of Master of Technology in Electronics and Communication Engineering (Signal and Image Processing), National Institute of Technology, Rourkela. Neither this thesis nor any part of it, to the best of my knowledge, has been submitted for any degree or academic award elsewhere.

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DECLARATION

I certify that

1. The work contained in the thesis is original and has been done by myself under the supervision of my supervisor.
2. The work has not been submitted to any other Institute for any degree or diploma.
3. I have followed the guidelines provided by the Institute in writing the thesis.
4. Whenever I have used materials (data, theoretical analysis, and text) from other sources, I have given due credit to them by citing them in the text of the thesis and giving their details in the references.
5. Whenever I have quoted written materials from other sources, I have put them under quotation marks and given due credit to the sources by citing them and giving required details in the references.

Anand Singh

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This work is one of the most important achievements of my career. Completion of my project would not have been possible without the help of many people, who have constantly helped me with their full support for which I am highly thankful to them.

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Anand Singh

Abstract

Distributed wireless sensor networks find various remote sensing purposes like battleground monitoring, target localization, environmental monitoring, accurate cultivation, mobile communication and medicinal applications. Due to a wide variety of applications of wireless data, suitable design and implementation of data detection become the modern field of study and research. The distribution of the nodes in the network provides a spatial diversity, which includes the temporal dimension for the purpose of increase the robustness of the ongoing tasks and enhance the probability of data and event detection.

In this area, we study the distributed network that contain the collection of a node connected to each other in the distributed manner. The node connected to each other is called neighbor node. In the problem of distributed detection of data, nodes have to decide based on the binary hypotheses of the measured data. In this detection problem we find the fully distributed and adaptive approach where all the node have to make own real time decision by cooperating with their immediate neighbor only and for this implementation no central processing node is required.For this distributed detection, we used diffusion based strategies Diffusion least mean square (DLMS) and Diffusion recursive least mean square(RLS) to find out distributed estimation of the parameter of interest.

Distributed detection suitable in the wireless sensor network due to their robustness to node and link failure as compare to centralized scheme,,scalability and ability to save power and communication resources.The algorithm utilized is adaptive and track the variation in the active hypotheses.After the use for detection we analyze the performance of the proposed algorithm in term of probability og detection and probability of false alarm and find out the simulation result.

We use some nonlinear techniques(huber loss , bi-square) to reduce the effect of impulsive interference on the systems. In this work, a distributed estimation and detection algorithm is developed using error saturation nonlinearity which is robust to impulsive noise or outliers.

Keywords: **adaptive network, distributed network ,global and local network,cognitive radio ,diffusion LMS ,diffusion RLS,distributed detection,distributed estimation,hypothesis testing,performance analyses**

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List of Acronyms

Acronym	Description
LMS	Least Mean Square
RLS	Rrecurssive least Mean Square
AWGN	Additive White Gaussian Noise
SNR	Signal to Noise Ratio
MSE	Mean Square Error
EM	Electro Magnetic
WSN	Wireless Sensor Network
ATC	Adapt Then Combine
CTA	Combine Then Adapt
LOS	Line Of Site
DLMS	Diffusion Least Mean Square
DRLS	Diffusion Rrecurssive Least Mean Square

Chapter 1

THESIS OVERVIEW

Thesis Objective

Motivation

TBackground and Scope of The Project

TThesis Organization

Chapter 1
THESIS OVERVIEW

1.1 Thesis Objective:

The objectives of the proposed research work are as follows

1. To detect the data based on binary hypotheses in wireless sensor network by using diffusion based distributed detection algorithm .
2. To estimate the parameter of entrust by using the diffusion based estimation in distributed wireless sensor network
3. To find out distributed robustness adaptive algorithms for estimation and detection parameters in presence of impulsive noise.
4. To find out the performence analyses of the detection algorithm in term of probability of mis detection and probability of false alarm.
5. Prform the clustrisation of network based on multi objective estimation and detection.

1.2 Motivation

The motivating behind using the distributed wireless sensor networks is the availability of devices that used in construction of transmitter an receiver like low-power micro-sensors, actuators, embedded processors, and radios etc.lots of the sensor network contain less number of sensor and wired to central processor which perform all the necessary tasks. But here in distributed wireless sensor networks sensing of signal and processing it also a distributed task and performed by the every node of the network .This type of sensing is utilized when the correct location of signal of interest os unknown over a spatial dimension. In distributed sensing We put some number of sensor closer to the phenomenon being monitored against using the one sensor. By doing it we can improve the probability of detection as the signal to noise ratio increased and and increased the chances for line of sight (LOS) communication. Thus, distributed sensing provides robustness to environmental obstacles. In the wired network it has its own advantage in the sense ease in connection ,simple design of system and simplified operation and easily accessible to renewable energy source, we use wireless because, in many existing and future aspects, the surveillance of geographical area will not infrastructure easily for communication or energy. Remote nodes must depend on local, finite, and small energy sources along with wireless communication channels.

In the centralize network the central processor used restricts the network performance due to its back and forth communication for exchanging the data that occupies more channel bandwidth and energy. Due to this we use distributed network in which every node has its memory and processing unit independently and share the data to its neighbors. Scientists and environmentalists needs to monitor soil and chemical content of air, as well as populations of animal species and plants and their density over a particular geographical area, for these type of monitoring process the primary methods are imaging and acoustics to localize, identify and track species or phenomena based on implicit signals, or explicit signals. These facilities must be deployed in remote places that lack installed energy and communications infrastructures; this is the motion for the need for low-power wireless sensor networks.

1.3 Background and Scope of The Project

The conventional distributed estimation algorithms involve significant communication overheads.In the distributed detection problem, a collection of nodes scattered over the geographical area receives measurement about the state of nature. Based on its observation of data,[15] the receiving end choose one of the possible estimates and sends it to the processing center via a predefined channel. After receiving the data, the processing center produces an estimate of the state of nature by selecting one of the possible hypotheses . It is of great advantage to reduce the communication bandwidthspectrum size and power consumptions involved inrequire for the transmission and reception of messagesdata across the resource-constrained nodes in WSNs. In the coming years, with continuingfuture, with advancesment in microelectronics, enough computing resources can be accommodated in the nodesagents of network to reduce the processing delaystime, but the communication bandwidthdelay and communication delay will pose major operational bottlenecks in the WSNs. In literature, a number of research papers have appeared and addressed the energy issues of sensor of the networks. It is of great importance and the most important thing for that is to minimize the number of communication among between the nodes by maximizing the local estimationor in each sensor node . In distributed parameter estimation problem, during each sampling instant, a typical sensor node communicates its estimate exchange its measurement either by the diffusion or incremental manner. If the nodes communicate after processing a array of data instead of communicating after each sample data, then substantial communication overhead can be reduced. It is a fact that when data is contaminated with non-Gaussian noise or outliers, the conventional algorithms which that are based on squared error minimization yield is has the Poor performance. we use some nonlinear techniques are employed to reduce the effect of impulsive interference on the systems. In this dissertation, a distributed estimation and detection algorithm is developed using error saturation nonlinearity which is robust to impulsive noise or outliers. The centralized algorithms can bBe used in WSNs for source localization. But the centralized approach in [6] [18] possesses excess communication overhead problem. A decentralized method has been proposed by dividing the large array into sub arrays for the local estimation.

1.4 Thesis Organization:

In the following chapter-1 we will know about the background and scope of this project.Chapter-2 We discuss the detail Introduction about ,Wireless Sensor network ,Adaptive Network ,Distributed Detection,Distributed Estimation Chapter-3 Deals with the mathematical formulation of the data model where we will know about the minimization techniques of mse by using the RLS and LMS, algorithm and how this diffusion process is employed in distributed sensors spread over a particular geographical area and also discuss about Naymen-Pearson Detection, MVU Estimator, Relation Between NP Detection AND MVU Estimator.In Chapter-4 we discussed about Detection with incomplete data, Diffusion Estimation Algorithm, Diffusion RLS Detection Algorithm, Diffusion LMS Detection Algorithm, Communication And Connectivity Requirement, Chapter-5 Explains about the performance analysis of these detection algorithm and calculation of the value of threshold Chapter-6 explains about the simulation results and discussion over the results we obtained and then in further chapters we will be concluding our work in addition with the future scope of this project, if any.

Chapter 2

Introduction

Chapter 2
Introduction

2.1 Introduction

Distributed processing in the network deals with the find out of information from data obtained from the different node. For example, each node in a network distributed over a geographic area could receive noisy measurement related to the different objective. The nodes would then communicate with other nodes in a particular manner, as defined by the network topology, in order to efficiently estimate the parameter. The primary objective is to find out an estimate of parameter that is exactly same as the one if every node had access to the information across the whole network.

2.2 Distributed network

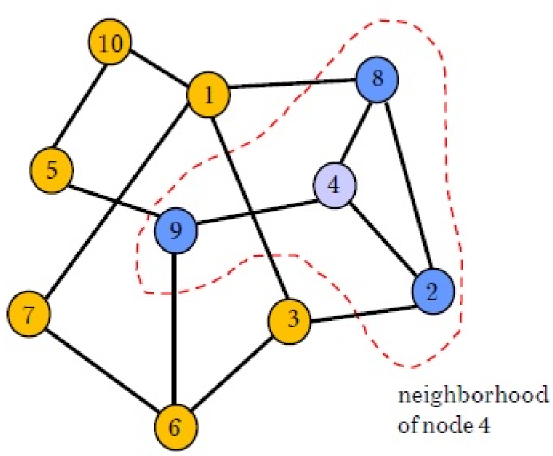

Figure 2.1: Distributed Network

In figure 2.1 A network contains the collection of nodes cooperating with each other. Nodes are connected to each other and exchanges the data. The neighborhood of any particular node consists of all nodes that are connected to it by edges (including the node itself). The figure shows that neighbors of node 4, which connected with nodes 8, 2, 4, 9.node 4 has degree 4, which is the size of its neighborhood.

In a conventional centralized solution [6], the nodes in the network receive data and send them to a fusion center for processing. After receiving the data from node central processor perform the necessary estimation tasks and distribute the estimated value to the individual nodes.For this type of operation powerful central processing is required and number of communication between the node is more.On the contrary if be consider distributed solution[12],[14],[1],[2], the nodes are depends on the local data and exchange the information with their immediate neighbors,due to this the global computational burden is distributed among the nodes, and the number of communication between the node and need of powerful processors is reduced.

Typically, the efficiency of any distributed estimation depends on the modes of cooperation[5] used in the network, as well as the processing strategies used at the node level. Regardless of the cooperative and distributed strategies used, it is an accepted fact that the processing of data at the node has to be adapt statistical variations of data and network topology changes.

At the network level, three such modes of cooperation are usually utilized: incremental [13], diffusion[2], and probabilistic diffusion. In the first, information flows in a sequential order from one node to the next node. In the incremental mode of operation network requires a cyclic form of collaboration among the nodes, and due to this it require the least amount of power and less number of communication. In a diffusion implementation, each node in the network could work as the individual adaptive filter whose aim is to estimate the parameter of interest by communicating with all its immediate neighbors as directed by the network topology. The number of communication in this case is more as compare to incremental solution. In the last mode of cooperation, the communications in the diffusion implementation can be make easy by allowing each node to interact only with a subset of its neighbors.These subset of node can be choose based on the some performance criterion.

2.3 Wireless Sensor Network

A wireless sensor network (WSN) are distributed autonomous sensors in geographical area to monitor physical or environmental conditions, such as temperature, sound, pressure, EM wave, etc..These sensors process the data and cooperatively pass it through the network to a primary location. The sensor that are connected to each other we call it node of the network. The more modern networks sensors are adaptive in nature have the ability to process the data in the adverse condition and less affected by noise. The invention of wireless sensor networks was mainly encouraged due to its military applications. Today WSN are used in many applications such as Agriculture,health monitoring, control, machine health monitoring, environmental monitoring, satellite communication, mobile communication and so on.

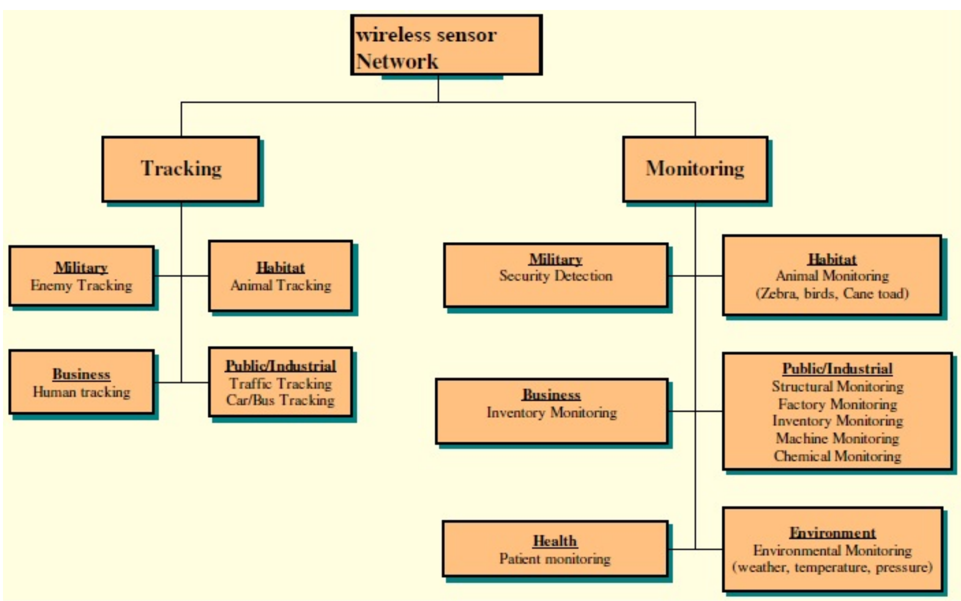

Figure 2.2: Applications of wireless sensor network

In figure 2.2 We can the wide area of application of wireless sensor network. The most significant application of wireless sensor network is in tracking and monitoring. For example, a chemical manufacturing could be observed for leakages by hundreds of sensors that automatically create a wireless interconnection network and promptly report the detection of any chemical leaks. Unlike traditional wired systems, deployment expenses would be minimal. Instead of using thousands of feet of wire routed through all the area, installers just have to put the small device,at each sensing point. The network could be expanded by just installing more sensors.In addition to reducing the installation costs, wireless sensor networks could be dynamically adapt to environment variation .

2.4 Adaptive Network

Adaptive network is define as a collection of node that has the ability to change or adapt the particular parameter of interest according to change in the environmental condition, temperature noise etc. We shall study distributed solutions in the context of adaptive networks that has the collection of agents with adaptation and learning abilities[16].The nodes are connected together through a topology and they communicate with each other through local network processing to solve inference and optimization problems in a fully distributed manner. The continuous sharing and diffusion of data across the network allows the agents to react in real time to drifts in the data and changes in the network topology. Such networks are scalable, robust to node and link failures.The networks are also have the cognitive abilities due to the sensing abilities of their nodes, their connection with their neighbors, and an inbuilt feedback mechanism for collecting and refining information as shown in In figure 2.3

Each agent is not only capable of experiencing the environment directly, but it also receives data through interactions with its neighbors and processes this information to drive its learning process.Adaptive networks are well-suited to perform decentralized information processing tasks. They are also well-suited to model several forms of complex behavior exhibited by biological and social networks. motivation. Distributed detection has been utilized before in the wireless sensor network.previously we called it decentralized detection

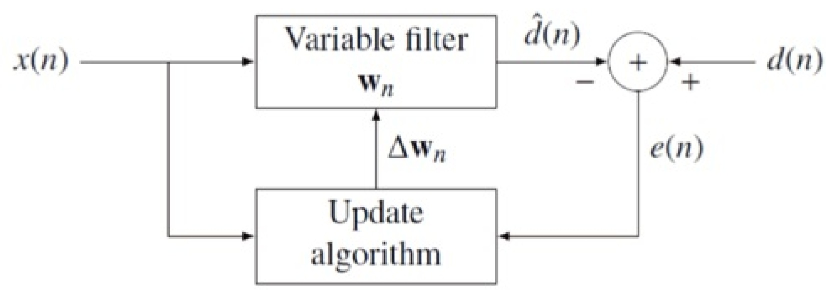

Figure 2.3: Agents of adaptive network

schemes and in this way of detection it require to share the measurements to a processing center. Detection schemes which not require any processing center, are based on average consensus [9] , [10], and every node in this detection arrangement makes an individual decision. In consensus-based schemes, nodes obtain a set of measurements of data and after that process an iterative algorithm to reach consensus. These algorithms use two-time scales: first to take the measurements and second to run the consensus iterations between measurements.Detection algorithms used in this research work based on the diffusion LMS and RLS algorithms to estimate the parameter of interest, and then utilize this estimate to perform the hypothesis test. However, other forms of diffusion methods can be used but and we focus on LMS and RLS here to perform all orations.

In the decentralized detection problem, a collection of scattered nodes receives information about the state of nature. Based on its observation of data, the node selects one of the possible estimates and sends it to the processing center via a predefined channel. After receiving the data, the processing center produces an estimate of the state of nature by selecting one of the possible hypotheses.

Apparently, a distributed network in which every node transmits a some part of its measured data to the processing center is suboptimal as compared to a controls all the observations without any loss. Although, parameter such as cost function, bandwidth, and complexity of network may explain the utilization of algorithms at the nodes of network. A general decentralized detection

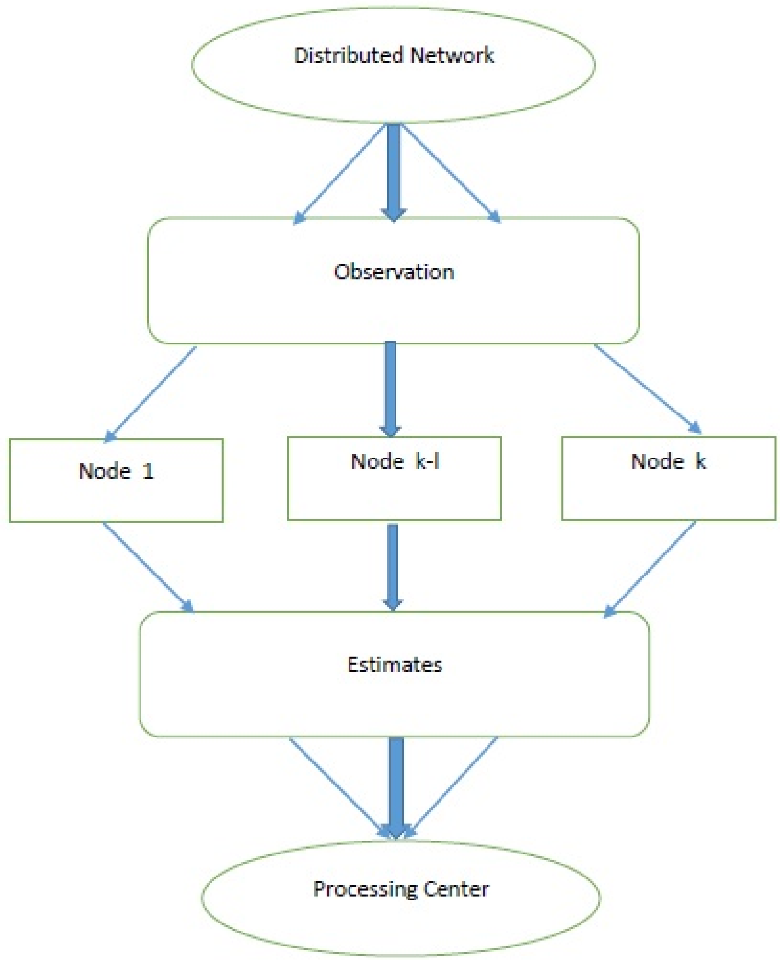

Figure 2.4: Representation of the classical decentralized detection framework.

of data in network illustrated in figure 2.4. Resource limitations in the traditional framework are obtained by fixing the number of nodes in the network and further imposing a limited alphabet constraint on the output of each sensor. This mostly bounds the quantity of information present at the processing center, as both the number of nodes and the number of possible messages per node are finite. Perfect reception of the sensor response is typically assumed at the processing center. It is necessary to acknowledge that once the structure of the data supplied by each agent is fixed, the processing center faces a conventional problem of statistical inference. As such, a likelihood-ratio test on the received information will minimize the probability of error at the processing center for a binary hypothesis testing.

2.5 Distributed Estimation

Diffusion schemes [12] have been proposed for distributed estimation, includes diffusion least mean squares (DLMS) [12], diffusion recursive least squares (DRLS)[2], and diffusion Kalman filtering[4].

Single significant difference between consensus[10] and diffusion scheme is that the consensus scheme attempts to achieve consensus among nodes of network, while latter attempts to optimize the cost functions and diffusion scheme does not need the convergence of node at the same state value. Instead of that, diffusion scheme allowed the convergence of node towards the expected solution with acceptable mean-square error value. By ignoring the need for exact consensus, diffusion schemes is more flexible in the sense of selection of combination weights and improved performance. Diffusion schemes are different in the sense that new measured data is included into the algorithm when they become available. Diffusion schemes have an advantage in the networks with tracking and learning abilities.

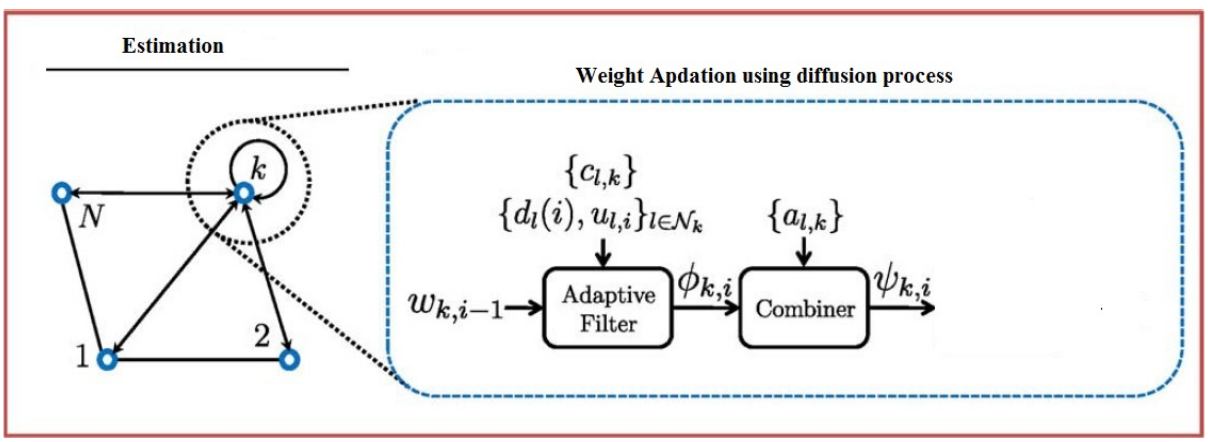

Figure 2.5: Estimation of data using diffusion strategies

In the diffusion mode of cooperation, the agents of the network share the measurements with neighbors and fuse the collected data via linear combinations. The several rule uses for combination, such as the Metropolis and relative degree rule. The calculation of combination weight is performing by using the degree of the node. Therefore, the performance rules is not stable if, for any instance, the SNR at some nodes is much less than others; because the noisy data estimated by node is diffuse into the whole network by exchanging the data among the nodes. Due to this the computation of combination factor plays the impotent role in diffusion mode of cooperation.

Chapter 3

Mathematical Formulation Of Data Modeling

Data Modeling

Naymen-Pearson Detection

MVU Estimator

Relation Between NP Detection AND MVU Estimator

Chapter 3

Mathematical Formulation Of Data Modeling

3.1 Data Modeling

consider that we have a network of N node distributed over some geographical area .We tell two node are linked to each other if they exchange the data.A node is always linked to itself. the array of node connected to node $k$is called the neighborhood of node k, and it is shown by N_k. The number of node linked to node k is celled degree od node k and denoted by n_k.If we take that at every iteration i node k take some measurement $d_k(i)$ which is related to unknown vector ω_0 of size M as fallows

$$d_k(i) = u_k(i)w^0 + v_k(i) \tag{3.1}$$

Where $u_k(i)$ of size M is known deterministic regression vector.The noise is a scaler with zero WSS Gaussian random process and uncorrelated in space and time.

$$Ev_k(i)v_k(i) = \delta_{kl}\delta_{ij}\sigma^2_{v_k} \tag{3.2}$$

Equation 3.1 is also for the case where data is real. The main aim of every node in the network to differentiate between the two hypotheses H_0 and H_1 where

$$\omega^0 = \begin{cases} 0 & under\, H_0 \\ \omega_s & unde\;\; H_1 \end{cases} \tag{3.3}$$

In order to simplify the notation, we receive the measurement for every node ***k***........N at a time . If we compute the measurement for all the node at every iteration at $j = 0...........i$ up to time i as fallows

$$d_i = col\left\{d_1(i), d_2(i), ...d_N(i)\right\} \quad (N \times 1)$$
$$U_i = col\left\{u_1(i), u_2(i), ...u_N(i)\right\} \quad (N \times M)$$
$$v_i = col\left\{v_1(i), v_2(i), ...v_N(i)\right\} \quad (N \times 1)$$
$$R_v = E v_i v_i^* = diag\left\{\sigma_{v_1}^2, \sigma_{v_2}^2 ......\sigma_{v_N}^2\right\} \quad (N \times N)$$

where diag $\{.\}$ and col$\{.\}$stack the argument diagonal and column-wise

$$D_i = col\left\{D_i, D_{i-1}, ...D_0\right\} \quad (i+1)(N \times 1)$$
$$U_i = col\left\{U_1, U_2, ...U_N\right\} \quad (i+1)(N \times M)$$
$$v_i = col\left\{v_1, v_2, ...v_0\right\} \quad (i+1)(N \times 1)$$
$$R_v = E v_i v_i^*$$
$$= diag\left\{R_v, R_v ......R_v\right\} \quad (i+1)(N \times (i-1)N)$$

The equation 4.1 can we written as

$$d_{0:i} = U_{0:i}\omega_0 + v_{0:i} \tag{3.4}$$

3.2 Naymen-Pearson Detection theorem

- In statistics,the Neyman Pearson lemma, states that when performing a hy-

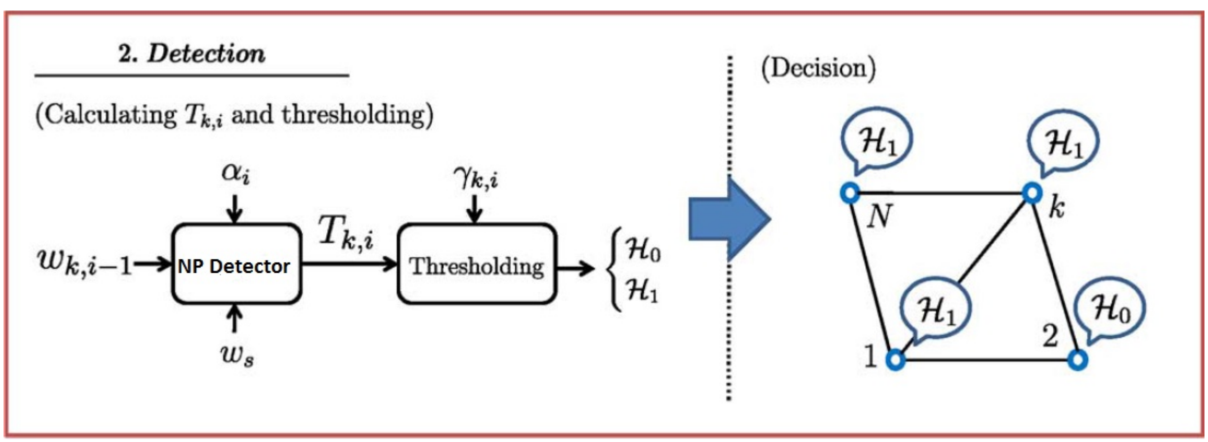

Figure 3.1: Distributed Detection based on Binary Hypotheses

pothesis test between two simple hypotheses $H_0 := 0$ and $H_1 := 1$, then the likelihood-ratio test which rejects H_0 in favour of H_1 In simple According to the NeymanPearson (NP) criterion, the detector that maximizes the probability of detection given a probability of false alarm is [[11],p.478]

$$\begin{cases} T_0\left(d_{0:i}\right) > \ \gamma_i\, under\, H_1 \\ T_0\left(d_{0:i}\right) < \ \gamma_i\ under H_0 \end{cases}$$

where the test statistics can we calculate by using

$$T_0\left(d_{0:i}\right) \triangleq \alpha_i \mathrm{Re}\left(\omega_s U_{0:i}^* R_{v,0:i}^{-1} d_{0:i}\right) \tag{3.5}$$

where α_i is positive constant and the choice of γ_i is typically depend on the choice of α_i

$$\alpha_i\left(\omega_s U_{0:i}^* R_{v,0:i}^{-1} d_{0:i}\right) \sim CN\left(\alpha_i {\omega_s}^* U_{0:i}^* R_{v,0:i}^{-1} U_{0:i}\omega_0, {\alpha_i}^2 {\omega_s}^* U_{0:i}^* R_{v,0:i}^{-1} U_{0:i}\omega_0\right)$$

$$T_0\left(d_{0:i}\right) \triangleq \begin{cases} N\left(0,\sigma^2\right) & under\, H_0 \\ N\left(\mu_i, {\sigma^2}_i\right) & under H_1 \end{cases}$$

$$\begin{aligned} &we\ have \\ &\mu_i = \alpha_i {\omega_s}^* U_{0:i}^* R_{v,0:i}^{-1} U_{0:i}\omega_0 \\ &{\sigma^2}_i = {\alpha_i}^2 {\omega_s}^* U_{0:i}^* R_{v,0:i}^{-1} U_{0:i}\omega_0 \end{aligned}$$

where S is 1 for real noise covariance and S=1/2 for complex noise varience.

The probability of detection and probability of false alarm at ith itration is given as

$$\begin{aligned} &p_f = Q\left(\tfrac{\gamma_i}{\sigma_i}\right) \\ &p_d = Q\left(\tfrac{\gamma_i-\mu_i}{\sigma_i}\right) = Q\left(Q^{-1}\left(p_f\right) - \tfrac{\mu_i}{\sigma_i}\right) \end{aligned} \tag{3.6}$$

3.3 Relation between MVU Estimator and Neyman pearson Detection

As we have assume linear model in 4.4 the measurement noise $v_{0:i}$ and regressors $U_{0:i}$ is a full rank matrix, then we have MVU estimator [5] of the parameter of interest ω_0 for the given desire data $d_{0:i}$ is given by gauss Markov theorem[7]

$$\omega_i^{mvu} = \left(U_{0:i}^* R_{0:i,v}^{-1} U_{0:i}\right)^{-1} \left(U_{0:i}^* R_{0:i,v}^{-1} d_{0:i}\right) \tag{3.7}$$

The equation (3.7) can also we consider as solution of weighted least square problem

$$\omega_{0:i}^{mvu} = \arg\min \left\|d_{0:i} - U_{0:i}\omega\right\|_{R_{v,0:i}^{-1}}^2 \tag{3.8}$$

The covareince matrix of error of MVU estimator can be given as

$$R_{\widetilde{\omega_i^{mvu}}} = E\widetilde{\omega_i^{mvu}}\widetilde{\omega_i^{mvu}}^* = \left(U_{0:i}^* R_{0:i,v}^{-1} U_{0:i}\right)^{-1}$$

$$T_i\left(d_{0:i}\right) = \alpha_i \mathrm{Re}\left(\omega_s U_{0:i} R_{0:i}^{-1} U_{0:i} \omega_{mvu}\right) \tag{3.9}$$

Now be can find out optimal test statistics by using equation (3.7) in equation (3.5)

we will use equation (3.9) in future to find out the distributed detection algorithm

Chapter 4

DISTRIBUTED DETECTION

Detection with incomplete data

Diffusion Estimation Algorithm

Diffusion RLS Detection Algorithm

Diffusion LMS Detection Algorithm

Huber loss Function

Chapter 4
DISTRIBUTED DETECTION

Previously discussed neyman pearson detection algorithm required the computation global test statistics that stylistically depend upon the desire data $d_{0:i}$ and the regressors $U_{0:i}$ across all the network agent.In the centralized network the solution of this problem is solve by the fusion center by collecting the data from the all nodes and find out optimal neyman pearson test statistics (3.5). The diffrent way to calculate the equation (3.5) is by using the equation (3.9) but the calculation of the MVU estimator is still has to access the global data.

In the network when global information is not present node have to depend on the local estimates and has to share it with the neighbors. The problem is what measurement node should share and how should they fuse the measurement coming from the neighbors node.The problem of local exchange and fusion can be view in term of distributed estimation where network agents has to estimate some unknown parameter w^0. The detection algorithm utilized here will build upon the presence of the estimate calculated in distributed manner.So some of the agent have to access to the local measurement for w^0 but not necessary equal to the minimum variance unbiased estimator. The main question is how to define the local test statistics based upon the local estimator and what will be the probability of detection and probability of false alarm by the network be. depending up on what the methods used for the parameter estimation we can use the different distribution algorithm.

4.1 Detection with incomplete data

The main problem start with equation (3.9) how can we compute the optimal test statistics T_0 from the MVU etimator . When global measurement of data is not present at the node so MVU estimator for global data can not be possible to obtain. Due to this if we replace the global estimation ω_i^{mvu} with the local estimator of ω^0 node k. we are assuming that nod k has access to the measurement and regressors from the neighbors

$$\begin{aligned} \bar{d}_{k,0:i} &= W_{k,i} d_{0:i} \, , \bar{U}_{k,0:i} = W_{k,i} U_{0:i} \\ \bar{R}_{k,0:i} &= W_{k,i} R_{v,0:i} W_{k,i}{}^{*} \end{aligned} \tag{4.1}$$

Where W_i is called weighting matrix and the value of it is 0 or 1.That is determined whether the data are available or not.

$$T_i^{loc}\left(\bar{d}_{0:i}\right) = \alpha_i \mathrm{Re}\left(\omega_s^{*} \bar{U}_{0:i} R_{0:i}^{-1} \bar{U}_{0:i} \omega_{k,i}^{loc}\right) \tag{4.2}$$

Where $\omega_{k,i}^{loc}$ is local optimal estimator of parameter for limited data.

$$\omega_{k,i}^{loc} = \left(\bar{U}_{0:i}^{*} \bar{R}_{0:i,v}^{-1} \bar{U}_{0:i}\right)^{-1} \left(\bar{U}_{0:i}^{*} \bar{R}_{0:i,v}^{-1} \bar{d}_{0:i}\right) \tag{4.3}$$

Now by using the local estimate $\omega_{k,i}^{loc}$ of the data optimal local test statistics can be calculated in distributed manner . However the performance of the local test estimator will be increased by using the diffusion estimator . since the diffusion estimator allow to diffuse the information in distributed manner across the network in real time.So we study the performance of local test statistics in term of diffusion estimation.

To solve this question, we first assume that at time i node k is able to find out the linear estimator of ω_0 in the form of

$$\omega_{k,i} = K_{k,i} d_{0:i} \tag{4.4}$$

Where $K_{k,i}$ is matrix of dimension $M \times (i-1)N$ with $M \leq N$. According to discussion it shown that the diffusion estimate $\omega_{k,i}$ is affected by data beyond the neighborhood of k. The reason for this, the diffusion process that we used shall enable these information to flow in real time without node k need to access to data beyond the neighborhood. Due to this $\omega_{k,i}$ is more useful then $\omega_{k,i}^{loc}$ of equation (4.2). The main problem is how to modify the equation (4.2) for that we use .

$$T_{k,i}\left(\omega_{k,i}\right) = \alpha_i \mathrm{Re}\left(\omega_s^* Q_{k,i}\omega_{k,i}\right) \tag{4.5}$$

Where α_i is the same positive constant and $Q_{k,i}$ is matrix we choose to meet particular performance of detection algorithm. the $T_{k,i}$ in equation (4.5) we consider test statistics of form

$$\begin{cases} T_{k,i}\left(\omega_{k,i}\right) & > & \gamma_{k,i}\ under\ H_1 \\ T_{k,i}\left(\omega_{k,i}\right) & < & \gamma_{k,i}\ under\ H_0 \end{cases} \tag{4.6}$$

Where $\gamma_{k,i}$ is the threshold value of local estimation and that will be influence the performance of detection.

Now we have to see how to select the optimum value of matrix $Q_{k,i}$ for the known $\omega_{k,i}$

Considering the previous observation model and assuming every node k of network at iteration i has access to linear estimate of w_0 given as $\omega_{k,i} = K_{k,i}d_{0:i}$. then for optimal neyman pearson test statistics $Q_{k,i}$ is .

$$Q_{k,i}^{opt} = \left(K_{k,i}U_{0:i}\right)^*\left(K_{k,i}R_{v,0:i}K_{k,i}^*\right)^{-1} \tag{4.7}$$

This equation (4.7) can be obtain by using

$$\omega_{k,i} = \left(K_{k,i}U_{0:i}\right)\omega^0 + K_{k,i}v_{0:i}$$

Now like (3.5) optimal neyman pearson detector of ω^0 is given as

$$T_{k,i}\left(\omega_{k,i}\right) = \alpha_i \mathrm{Re}\left(\omega_s^*\left(K_{k,i}U_{0:i}\right)\left(K_{k,i}R_{v,0:i}K_{k,i}^*\right)^{-1}\omega_{k,i}\right)$$
$$T_{k,i}\left(\omega_{k,i}\right) = \alpha_i \mathrm{Re}\left(\omega_s^* Q_{k,i}\omega_{k,i}\right)$$

Where $K_{k,i}$ and $Q_{k,i}^{opt}$ is given as

$$K_{k,i} = \left(U_{0:i}^* R_{0:i,v}^{-1} U_{0:i}\right)^{-1}\left(U_{0:i}^* R_{0:i,v}^{-1}\right)$$
$$Q_{k,i}^{opt} = \left(U_{0:i}^* R_{0:i,v}^{-1} U_{0:i}\right)$$

4.2 Diffusion Estimation Algorithm

In the estimation problem we first review the diffusion RLS and Diffusion LMS algorithm in the paper [14] [2]. DRLS algorithm [2] enable every agents of distributed network to estimate the parameter of interest ω_0 by using the linear observation model in (3.1) by realization of (3.8) in distributed way and local interaction.IN the reference [2] matrix C and A is combinational factor matrix with non negative entries $c_{l,k}$ and $a_{l,k}$.

4.2.1 Calculation of combination factor

As we know that from previous section matrix C and A is combinational factor matrix with non negative entries $c_{l,k}$ and $a_{l,k}$.

$$\begin{aligned} &c_{l,k} = a_{l,k} = 0 \; if \;\; l \notin N_k \\ &c_{l,k} = a_{l,k} = 1 \; if \;\; l \in N_k \\ &1^T A = 1^T \qquad 1^T C = 1^T \end{aligned} \tag{4.8}$$

That means $c_{l,k}$ and $a_{l,k}$ is 0 if node l is not linked to node k and the addition of row of matrix A and C is equal to 1.

for the calculation of combination factor different rules are available given in the table 4.1 . The combination factor A and C are not symmetric in nature.

Table 4.1: STATIC COMBINATION RULES BASED ON NETWORK TOPOLOGY

Rule	**Weight** $c_{l,k}$ **for** $l \in N_k$
Uniform	$\frac{1}{n_k}$ for all $l \in N_k$
Maximum degree	$\begin{cases} 1/N & for\, l \neq k \\ 1-(n_k-1)N & for\, l = k \end{cases}$
Metropolis	$\begin{cases} 1/max\,(n_k, n_l) & for\, l \neq k \\ 1- \sum\limits_{m \in N_k \setminus \{k\}} c_{mk} & for\, l = k \end{cases}$
Relative degree	$n_l / \sum\limits_{m \in N_k} c_{mk} \;\; for all \;\; l \in N_k$
no coopration	$\begin{cases} 0 & for\, l \neq k \\ 1 & for\, l = k \end{cases}$
r	

4.2.2 Diffusion RLS Algorithm

The diffusion RLS [2] algorithm given in (4.2.2) is calculate the estimate $\omega_{k,i}$ of ω_0 for every node k at every iteration i .And when node exchange the data [$d_k(i)$, $u_{l,i}$] with the neighbor a intermediate vector of size M is generated that is $\psi_{k,i}$. In the diffusion RLS algorithm forgetting factor is used that has the value $\lambda > 0$. Forgetting factor is useful in the sense of tracking capability and steady state performance and and its value is between $0 < \lambda \leq 1$.

Incremental update : $for\ every\ node\ k,\ repeat$

$$
\begin{aligned}
&\psi_{k,i} = \omega_{k,i-1} \\
&P_{k,i} = \lambda^{-1} P_{k,i-1} \\
&for\ all\ l \in N_k \\
&\psi_{k,i} \leftarrow \psi_{k,i} + \frac{c_{lk} P_{k,i} u^*_{l,i} \left[d_l(i) - u_{l,i} \psi_{k,i} \right]}{\sigma^2 + c_{lk} u_{k,i} P_{k,i} u^*_{l,i}} \\
&P_{k,i} \leftarrow P_{k,i} + \frac{c_{lk} P_{k,i} u^*_{l,i} u_{l,i} P_{k,i}}{\sigma^2 + c_{lk} u_{k,i} P_{k,i} u^*_{l,i}} \\
&end
\end{aligned}
$$

Diffusion update : $for\ every\ node\ k,\ repeat$

$$\omega_{k,i} = \sum_{l \in N_k} a_{l,k} \psi_{k,i} \tag{4.9}$$

For the optimization of parameter estimation we try to minimize the the Mean Square Error [MSE] . In the figure 4.1 we have ploted the [MSE] for DRLS and non cooperation RLS and the performance of DRLS is better then the non cooperation RLS on dB scale is nearly -10dB . For the given value

$$
\begin{aligned}
&\lambda = 0.95; \\
&SNR = 30dB; \\
&Number\ of\ Node\,(N) = 20; \\
&Tap\ Size\,(M)\ =\ 5;
\end{aligned}
$$

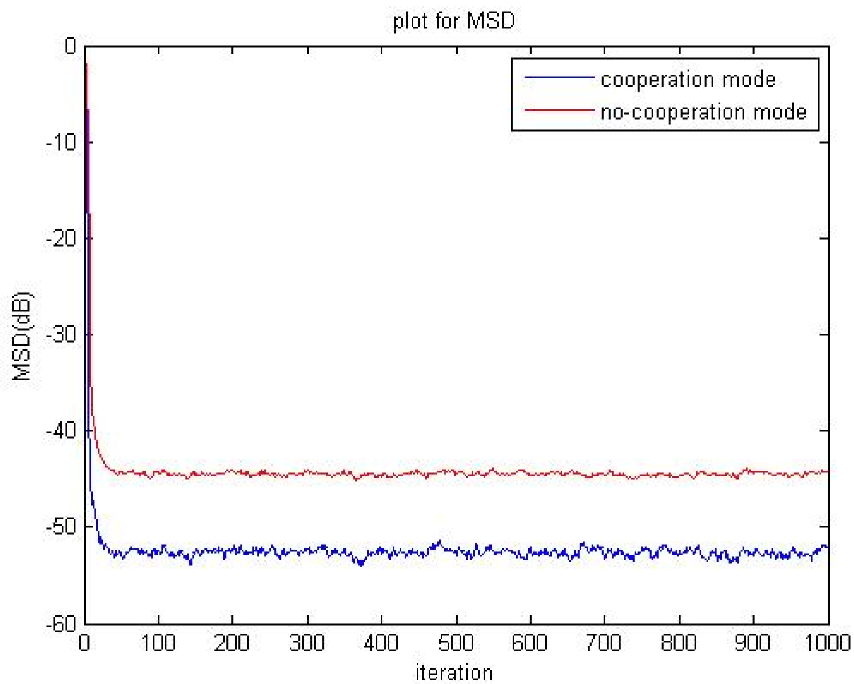

Figure 4.1: MSE plot for Diffusion RLS estimation

4.2.3 Diffusion LMS Algorithm

Diffusion LMS algorithm [12, 14] is available in two formate based on the combination and adaption of the measurement-

1. Adapt then Combine (ATC)
2. combine then Adapt (CTA)

Adapt then Combine (ATC)-In ATC as given in the figure 4.2 the first step of diffusion process is to adapt the fraction of the measurement according to the combination factor from the neighborhood . Second step is to the estimation the parameter by using the DLMS alorithe algorithm and exchange it to its neighbors.

The ATC LMS algorithm is given as-

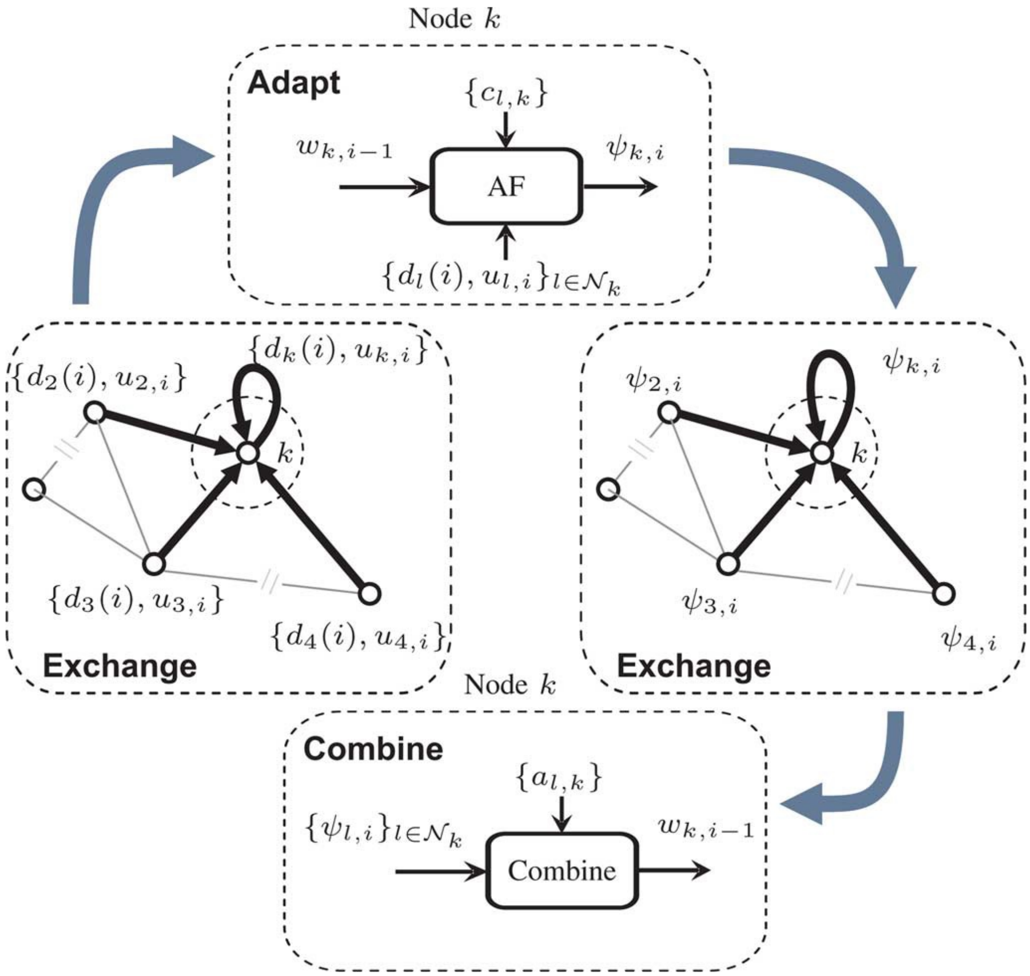

Figure 4.2: Adapt-then-Combine (ATC) diffusion strategies.

$$\begin{aligned}
&\textbf{Diffusion update} \; : \; for\; every\; node\; k,\; repeat \\
&\omega_{k,i} = \sum_{l\in N_k} a_{l,k}\psi_{k,i} \\
&\textbf{Incremental update:} \; for\; every\; node\; k,\; repeat \\
&\psi_{k,i} = \omega_{k,i-1} + \mu_k \sum_{l\in N_k} c_{l,k} u^*_{l,i}\left[d_l\left(i\right) - u_{l,i}\omega_{k,i-1}\right]
\end{aligned} \tag{4.10}$$

Combine then Adapt (CAT)-In ATC as given in the figure 4.3 the first step of diffusion process is to the estimation the parameter by using the DLMS alorithe algorithm and exchange it to its neighbors. Second step is to adapt the fraction of the measurement according to the combination factor from the neighborhood

.

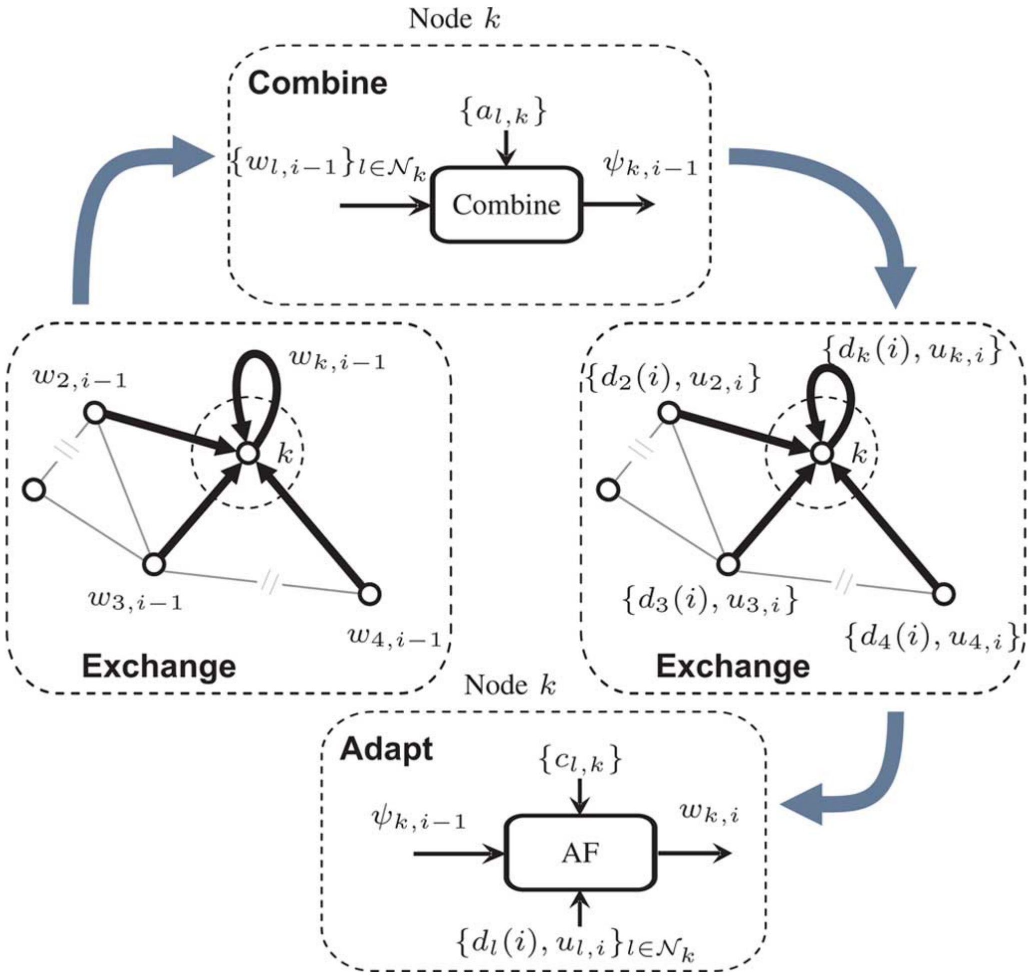

Figure 4.3: Combine-then-Adapt-then-(CTA) diffusion strategies.

$$
\begin{aligned}
&\textbf{Incremental update: } for\ every\ node\ k,\ repeat \\
&\psi_{k,i} = \omega_{k,i-1} + \mu_k \sum_{l\in N_k} c_{l,k} u_{l,i}^{*} \left[d_l(i) - u_{l,i}\omega_{k,i-1}\right] \\
&\textbf{Diffusion update } : \ for\ every\ node\ k,\ repeat \\
&\omega_{k,i} = \sum_{l\in N_k} a_{l,k}\psi_{k,i}
\end{aligned}
\tag{4.11}
$$

Here also same as DRLS for the optimization of parameter estimation we try to minimize the the Mean Square Error [MSE] . In the figure 4.4 we have ploted the [MSE] for DLMS and non cooperation LMS and the performance of DLMS is better then the non cooperation LMS on dB scale is nearly -10dB . The convergence od DLMS is also faster then non coopration LMS . For the given value

$$\mu = 0.07;$$
$$SNR = 30dB;$$
$$Number\ of\ Node\,(N) = 20;$$
$$Tap\ Size\,(M)\ =\ 5;$$

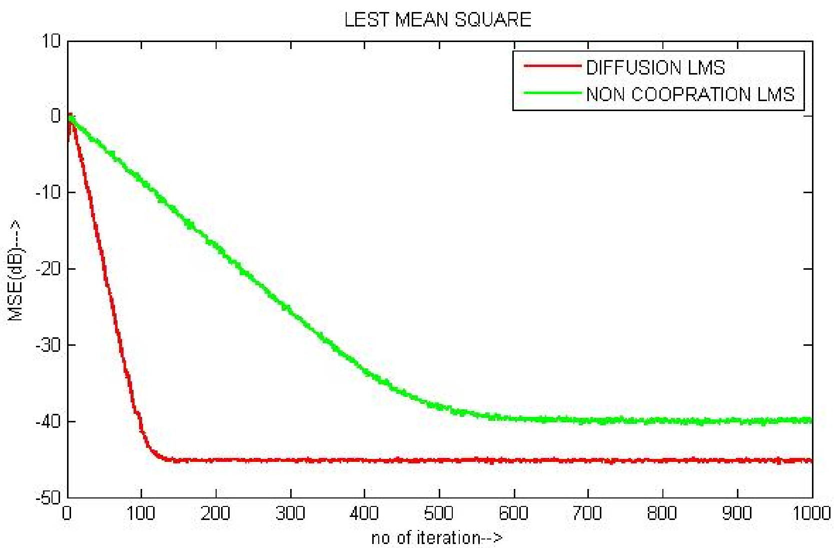

Figure 4.4: MSE plot for Diffusion RLS estimation

4.3 Diffusion RLS Detection Algorithm

For every node $k = 1....N$, compute the initial solution $\omega_{k,i-1}$ and initial matrix $P_{k,i-1}$ and$Q_{k,i-1}$ at the iteration i_0 for every iteration $i > i_0$

$$\begin{aligned}
&\textbf{Incremental update: } for\ every\ node\ k,\ repeat \\
&\psi_{k,i} = \omega_{k,i-1} \\
&Q_{k,i} = \lambda^{-1} Q_{k,i-1} \\
&P_{k,i} = \lambda^{-1} P_{k,i-1} \\
&for\ all\ l \in N_k \\
&\psi_{k,i} \leftarrow \psi_{k,i} + \tfrac{c_{lk} P_{k,i} u_{l,i}^{*} \left[d_l(i) - u_{l,i} \psi_{k,i} \right]}{\sigma^2 + c_{lk} u_{k,i} P_{k,i} u_{l,i}^{*}} \\
&P_{k,i} \leftarrow P_{k,i} + \tfrac{c_{lk} P_{k,i} u_{l,i}^{*} u_{l,i} P_{k,i}}{\sigma^2 + c_{lk} u_{k,i} P_{k,i} u_{l,i}^{*}} \\
&Q_{k,i} \leftarrow Q_{k,i} + \tfrac{c_{lk} u_{l,i} u_{l,i}^{*}}{\sigma^2} \\
&end \\
&\textbf{Diffusion update}\ :\ for\ every\ node\ k,\ repeat \\
&\omega_{k,i} = \sum_{l \in N_k} a_{l,k} \psi_{k,i} \\
&\textbf{Decision: } for\ every\ node\ k,\ repeat \\
&T_{k,i}\left(\omega_{k,i}\right) = \alpha_i \mathrm{Re}\left(\omega_s^{*} Q_{k,i} \omega_{k,i}\right) \\
&\begin{cases} T_{k,i}\left(\omega_{k,i}\right) & > & \gamma_{k,i}\ under\ H_1 \\ T_{k,i}\left(\omega_{k,i}\right) & < & \gamma_{k,i}\ under\ H_0 \end{cases}
\end{aligned} \tag{4.12}$$

In this DRLS detection algorithm (4.12) first we calculate the estimate of $\omega_{k,i}$ then utilize it to calculate the test statistics $T_{k,i}$. In this algorithm we also calculated the $Q_{k,i}$.$Q_{k,i}$ in (4.12) may be become unstable for large value of i due to this we use $\alpha_i = 1 \backslash (i+1)$

4.4 Diffusion LMS Detection Algorithm

For every node $k = 1....N$, compute the initial solution $\omega_{k,-1} = 0$ and The choice of optimum $Q_{k,i-1}$ for the better detection performance DLMS detection algorithm is $Q_{k,i-1} = 1$. at the iteration i_0 for every iteration $i > i_0$

$$\begin{aligned}
&\textbf{Incremental update: } for\ every\ node\ k,\ repeat\\
&\psi_{k,i} = \omega_{k,i-1} + \mu_k \sum_{l\in N_k} c_{l,k} u^*_{l,i}\left[d_l(i) - u_{l,i}\omega_{k,i-1}\right]\\
&\mu_{k=}\mu'_k / \sum_{l\in N_k} \frac{1}{n_k\sigma^2}\\
&\textbf{Diffusion update : } for\ every\ node\ k,\ repeat\\
&\omega_{k,i} = \sum_{l\in N_k} a_{l,k}\psi_{k,i}\\
&\textbf{Decision: } for\ every\ node\ k,\ repeat\\
&T_{k,i}\left(\omega_{k,i}\right) = \alpha_i \mathrm{Re}\left(\omega^*_s Q_{k,i}\omega_{k,i}\right)\\
&\begin{cases} T_{k,i}\left(\omega_{k,i}\right) & > & \gamma_{k,i}\ under\ H_1\\ T_{k,i}\left(\omega_{k,i}\right) & < & \gamma_{k,i}\ under\ H_0 \end{cases}
\end{aligned} \tag{4.13}$$

In this DLMS detection algorithm (4.13) first we calculate the estimate of $\omega_{k,i}$ then utilize it to calculate the test statistics $T_{k,i}$. In this algorithm we take the $Q_{k,i}$.$Q_{k,i} = 1$ in (4.13)and use $\alpha_i = 1$

4.5 Huber loss function

The Huber loss function [8] describes the penalty incurred by an estimation procedure. Huber defines the loss function piecewise by

$$L_\delta(e) = \begin{cases} \frac{1}{2}e^2 & for\ |e| \leqslant \delta\\ \delta\left(|e| - \frac{1}{2}\delta\right) & oterwise \end{cases} \tag{4.14}$$

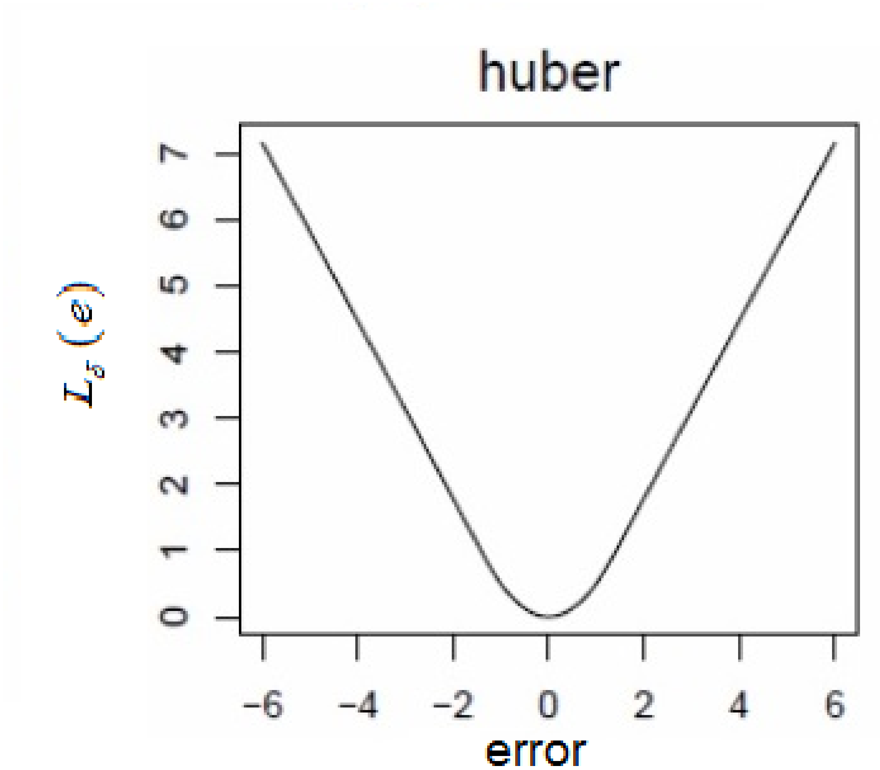

Figure 4.5: Plot of huber loss function

In this figure 4.5 function is quadratic for small values of error, and linear for large values of error, with equal values and slopes of the different sections at the two points where. The variable error often refers to the residuals, that is to the difference between the observed and predicted values.

Chapter 5

Performance of Algorithm

Detection performance

Computation of Threshold value

Chapter 5
Performance of Algorithm

In the previous section we discussed the detection algorithms c and (4.13) based on the diffusion LMS an diffusion RLS and computation of of matrix $Q_{k,i}$. And in this section we find out the performance of these detection algorithm (4.12) and (4.13). For that we take error quantities

$$\tilde{\omega}_{k,i} = \omega_{k,i} - \omega_0$$
$$and$$
$$\tilde{\psi}_{k,i} = \psi_{k,i} - \omega_0$$

5.1 Detection performance

Consider DRLS(4.12) and DLMS(4.13) distributed detection algorithm. For these algorithm probability of detection $P_{d,k,i}$ and probability of false alarm $P_{f,k,i}$ is given as

$$P_{d,k,i} = Q\left(\frac{\gamma_{k,i} - \alpha_i\left(\omega_s^* Q_{k,i}\omega_s\right) - \alpha_i \mathrm{Re}\left(\omega_s^* Q_{k,i}\tilde{\omega}_{k,i}\right)}{\sigma_{k,i}}\right) \tag{5.1}$$

$$P_{f,k,i} = Q\left(\frac{\gamma_{k,i} - \alpha_i \mathrm{Re}\left(\omega_s^* Q_{k,i}\tilde{\omega}_{k,i}\right)}{\sigma_{k,i}}\right) \tag{5.2}$$

$where\ \tilde{\omega}_{k,i} = \omega_{k,i} - \omega_0\ , \omega_0\ is\ the\ active\ \ hypothesys\ and$

$$\sigma_{k,i}^2 = s\alpha_i^2\left(\omega_s^* Q_{k,i} R_{\tilde{\omega}_{k,i}} Q_{k,i}\omega_s\right) \tag{5.3}$$

where $s = 1$ for real data and $s = 1/2$ for complex data $R_{\tilde{\omega}_{k,i}}$ denoted the covariance matrix of estimator and $Q_{k,i} = I$ for DLMS detection algorithm.

$$R_{\tilde{\omega}_{k,i}} = E\left[\tilde{\omega}_{k,i} - E\tilde{\omega}_{k,i}\right]\left[\tilde{\omega}_{k,i} - E\tilde{\omega}_{k,i}\right]^*$$

For the calculation of equation (5.1) and (5.2) we know that the from equation 3.1 parameter estimator is linear in $d_k(i)$ and test statistics is distributed according to

$$T_k\left(\omega_{k,i}\right) \sim N\left(\alpha_i \mathrm{Re}\left(\omega_s^* Q_{k,i} E\tilde{\omega}_{k,i}\right), \sigma_{k,i}^2\right) \tag{5.4}$$

and from circular symmetry property we know that

$$\sigma_{k,i}^2 = E\left\{\alpha_i \mathrm{Re}\left(\omega_s^* Q_{k,i}\left(\tilde{\omega}_{k,i} - E\tilde{\omega}_{k,i}\right)\right)\right\}^2$$
$$\sigma_{k,i}^2 = s\alpha_i^2\left(\omega_s^* Q_{k,i} R_{\tilde{\omega}_{k,i}} Q_{k,i}\omega_s\right)$$

And where $s = 1$ for real data and $s = 1/2$ for complex data

$$E\left(T_k\left(\omega_{k,i}\right)\right) = \alpha_i \mathrm{Re}\left(\omega_s^* Q_{k,i} E\omega_{k,i}\right)$$
$$T_k\left(\omega_{k,i}\right) = \begin{cases} \alpha_i \mathrm{Re}\left(\omega_s^* Q_{k,i} E\tilde{\omega}_{k,i}\right) & Under\ H_0 \\ \alpha_i \mathrm{Re}\left(\omega_s^* Q_{k,i} E\tilde{\omega}_{k,i}\right) + \alpha_i\left(\omega_s^* Q_{k,i} E\tilde{\omega}_{k,i}\right) & Under\ H_1 \end{cases}$$

By using the neyman pearson detection algorithm we have

$$P_{d,k,i} = Q\left(\frac{\gamma_{k,i} - E\left[T_k\left(\omega_{k,i}\right)/H_1\right]}{\sigma_{k,i}}\right)$$
$$P_{f,k,i} = Q\left(\frac{\gamma_{k,i} - E\left[T_k\left(\omega_{k,i}\right)/H_0\right]}{\sigma_{k,i}}\right)$$

By putting the value of test statistics we find out the value of equation 5.1 and5.2.

5.2 Computation of Threshold Value

In the previously discussed diffusion LMS (4.13) and diffusion RLS (4.12) detection algorithms we have used the detection threshold $\gamma_{k,i}$. For the calculation of (5.1) and (5.2) we have to first calculate the detection threshold $\gamma_{k,i}$ to make the algorithm easier we use a alternative expression for threshold calculation that can compute locally for every node.

$$\gamma_{k,i} = \sigma_{k,i} Q^{-1}\left(P_{f,i}\right) + \alpha_i\left(\omega_s^* Q_{k,i} E\tilde{\omega}_{k,i}\right) \tag{5.5}$$

We taken unbiased estimation so $E\left[\tilde{\omega}_{k,i}\right]$ is 0 . So we can ignore the second term in (5.5) To find out the value of equation (5.3) is difficult so we approximate the optimal threshold 5.5 in two step.First, we compute the optimal thresholds when for noncooperation process , and then take a correction factor in consideration for diffusion process.

$$\gamma_{k,i} = g^{-1/2}\sigma_{k,i}^{A=1}Q^{-1}\left(P_{f,i}\right) \tag{5.6}$$

Where g is the some constant corresponding to gain we get through the diffusion operation.this constant can be obtain by

$$g = \left\langle \max_{k=1...,N} \frac{\left(\sigma_{k,i}^{A=1}\right)}{\left(\sigma_{k,i}^{A\neq 1}\right)} \right\rangle$$

Where $\langle\rangle$ for the average over time

and $\sigma_{k,i}^{A=1}$ can be calculated as

$$\sigma_{k,i}^2 = s\alpha_i^2\left(\omega_s^* Q_{k,i} R_{\tilde{\omega}_{k,i}}^{A=1} Q_{k,i}\omega_s\right) \tag{5.7}$$

Where $R_{\tilde{\omega}_{k,i}}^{A=1}$ is given as

$$R_{\tilde{\omega}_{k,i}}^{A=1} = \left[I - S_{k,i}\sum_{l\in N_k}\frac{u_{l,i}^* u_{l,i}}{n_k\sigma_{vl}^2}\right] R_{\tilde{\omega}_{k,i-1}}^{A=1} \times \left[I - S_{k,i}\sum_{l\in N_k}\frac{u_{l,i}^* u_{l,i}}{n_k\sigma_{vl}^2}\right] - S_{k,i}\sum_{l\in N_k}\frac{1}{n_k\sigma_{vl}^2}u_{l,i}^* u_{l,i} S_{k,i}$$

The value of g can be computed [5] in practice by running a few iterations computing the above ratios, and averaging over different time instants.Typical values of g are 2.In order to obtain the variances, they can be computed off line given a set of measurements from all nodes, or using Monte Carlo methods to generate new measurements and computing a sample average over different realization of $T_k\left(\omega_{k,i}\right)$.

Chapter 6

Simulation Results

DLMS algorithm detection result

DRLS algorithm detection result

Comparision of DLMS and DRLS algorithm detection result

Chapter 6
Simulation Results

In this section of the theses we discuss the simulation result for the detection algorithm (4.12) and (4.13) and compare it with the local and noncooperation modal.

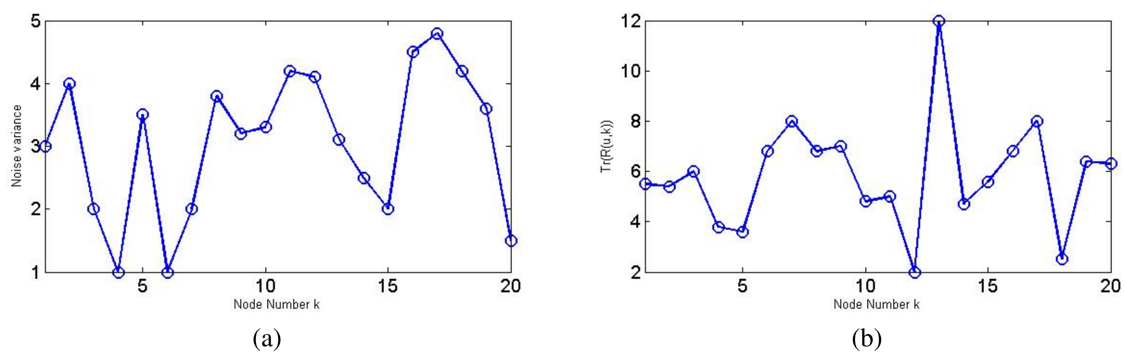

Figure 6.1: (a) Variance of Noise Added in the data (b)Trace of covariance $Tr\left(R_{u,k}\right)$ used to draw regression

We use a local distributed network that contain n= 20 node and tap size of the filter is $M = 3$. For the generation of the regressors $u_k(i)$ we use zero mean complex Gaussian distribution with variance $R_{v,k}$ for the agent k.this generated regressors is use for every experiment.the trace of convenience ,network topology used,and noise variance is use for the generation of the regressors as shown in 6.1. The probability of false alarm for every node we hahe taken is $P_{f,k,i} = 10^{-7}$ means we are assuming the one false detection of data for the 10^7 correct detection.

All the simulation result plotted here for the DLMS algorithm calculated by using the following value-

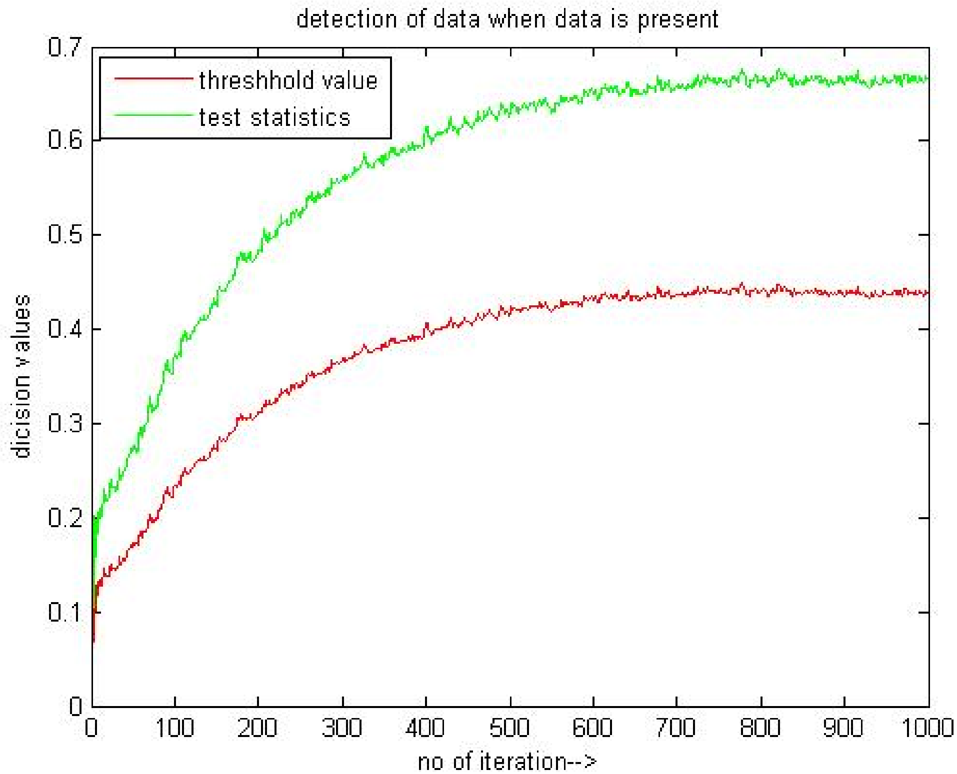

Figure 6.2: Test statistics and threshold plot for Diffusion LMS detection

$$\mu = 0.07;$$
$$SNR = 30dB;$$
$$\alpha = 1;$$
$$s = 1;$$
$$P_f = 10^{-7}$$
$$Number\ of\ Node\,(N) = 20;$$
$$Tap\ Size\,(M)\ =\ 3;$$

Figure 6.2 shown the test statistics and threshold plot for DLMS detection algorithm. In this plot when data is present then test statistics value is greater then the threshold value for correct decision when data is available at the receiving end of the node. Test statistics value is less then the threshold value for correct decision when data is not available at the receiving end of the node. In this plot after some iteration test statistics is always greater then the threshold value when data is present at the receiving end of the node.

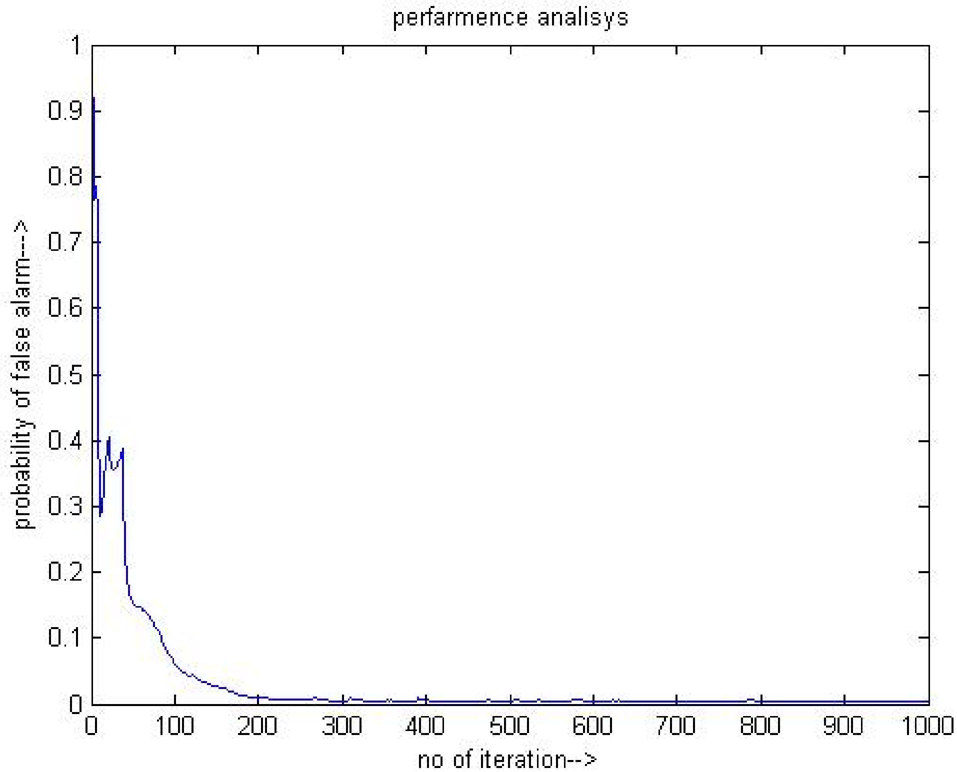

Figure 6.3: Plot of probability of false alarm for Diffusion LMS detection

Figure 6.3 shown the plot for the probability of false alarm for DLMS detection algorithm plotted for 1000 iteration and it is shown that after some iteration probability of false alarm is approaches to 10^{-7} as taken previously for the computation of threshold value in equation (5.6) .

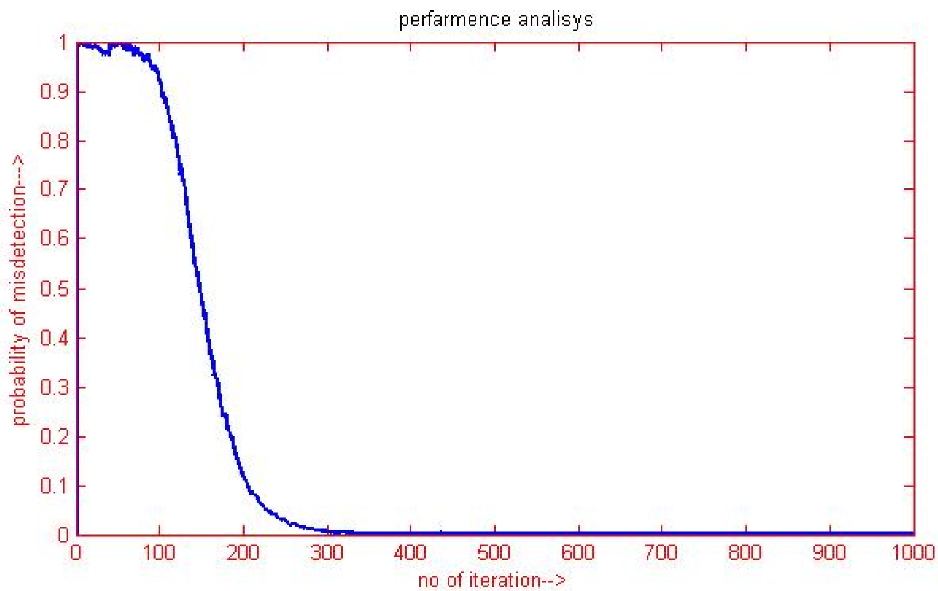

Figure 6.4: Plot of probability of mis detection for Diffusion LMS detection

Figure 6.4 shown the plot of probability of miss detection calculated for DLMS detection algorithm by using equation (4.13) for the 1000 iteration.And it is shown that after the few iteration probability of miss detection is approaches nearly to zero .

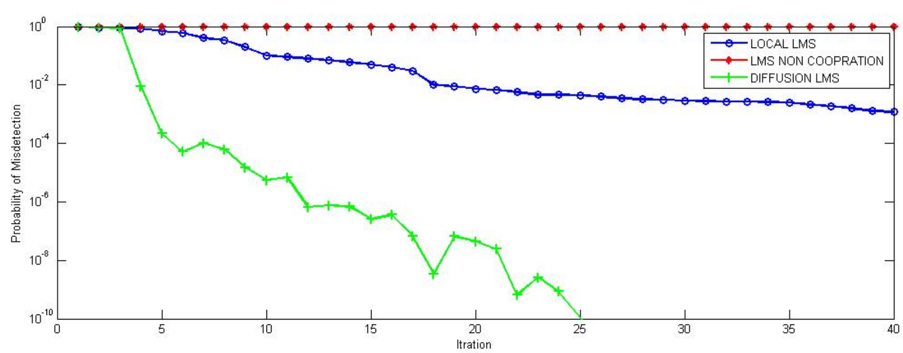

Figure 6.5: Plot of probability of mis detection for Diffusion LMS and noncooperation LMS

Figure 6.5 shown the plot of probability of miss detection calculated for DLMS ,local LMS and noncooperation detection algorithm by using equation (**??**) , reference [2] and [5] for the 40 iteration.And it is shown that after the few iteration probability of miss detection for equation (5.1) is having the much better performance for detection of data as compare to local LMS algorithm and non cooperation.

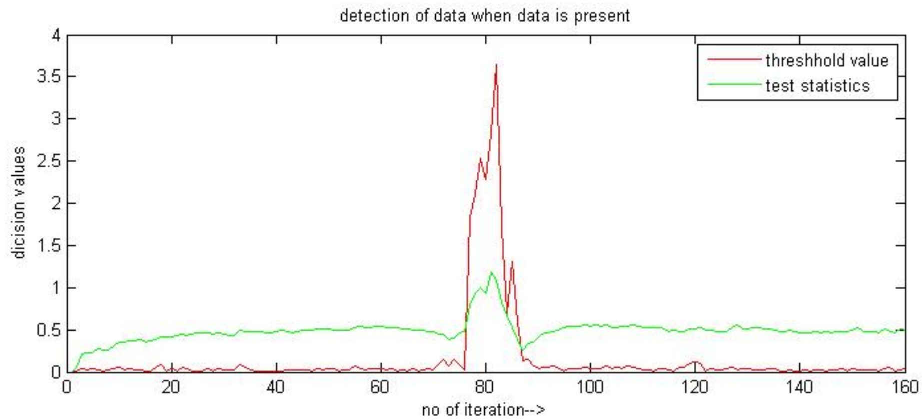

Figure 6.6: Test statistics and threshold plot for Diffusion LMS detection algorithm affected by flicker noise

In the figure 6.6 shown the effect of flicker noise entered at the iteration 70 to 90 . Due to this transition between threshold and test statistics is take place and at the presence of data the value of threshold is become larger then the test statistics due to this instead of selection of H_1 it select H_0 and miss detection of the data from 70 to 90 is sharply increased.

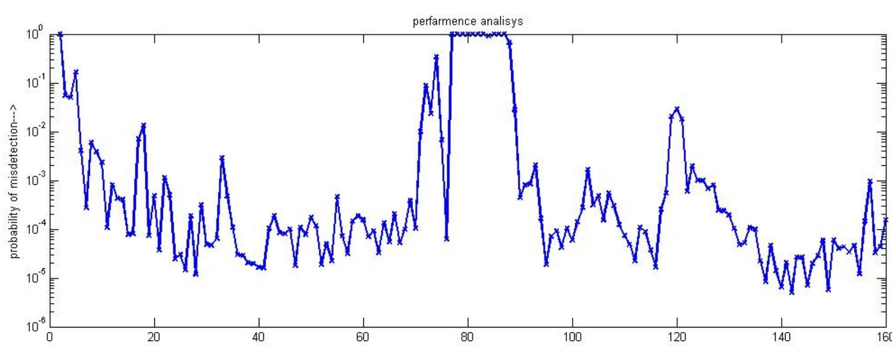

Figure 6.7: Plot of probability of mis detection for Diffusion LMS detection algorithm affected by flicker noise

In the figure 6.7 shown the effect of flicker noise entered at the iteration 70 to 90 . Due to this miss detection of the data from 70 to 90 is sharply increased.

In the figure 6.8 we used the hubber loss function to make the DLMS detec-

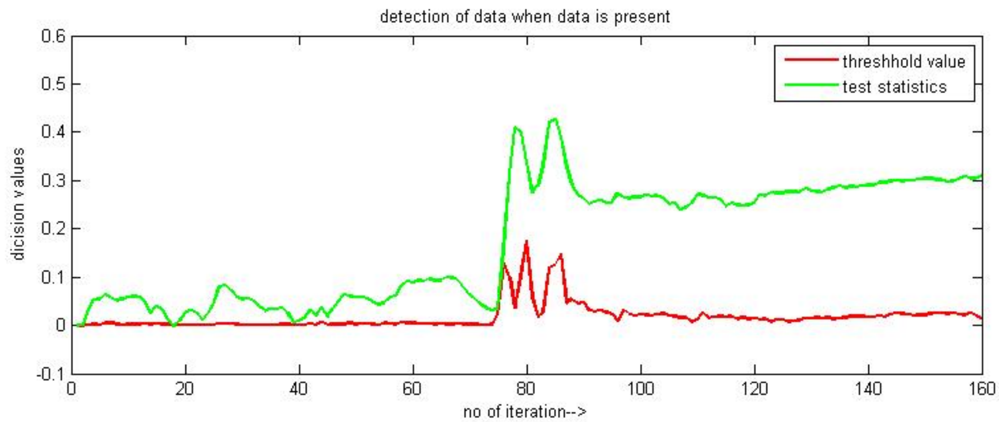

Figure 6.8: Robustness of hubber loss function in DLMS detection algorithm Plot in test statistics and threshold plot

tion algorithm robust to flicker noise. due to the use of the hubber loss function the the effect of flicker noise entered at the iteration 70 to 90 and detection of data at the iteration 70 to 90 is correctly take place. Due to this transition between threshold and test statistics that occurred previously is reduced.

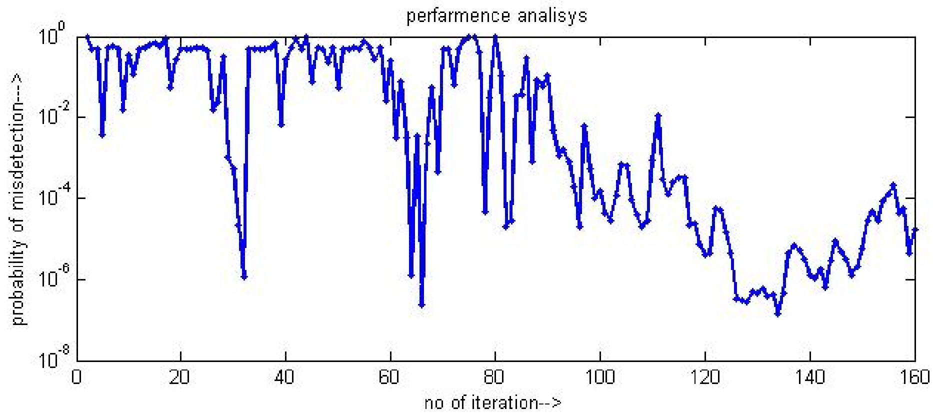

Figure 6.9: Robustness of hubber loss function in DLMS detection algorithm in probability of miss detection plot

In the figure 6.9 the effect of flicker noise entered at the iteration 70 to 90 is reduced.And due to the use of hubber loss function the probability of miss detection at the iteration from 70 to 90 is decreased.

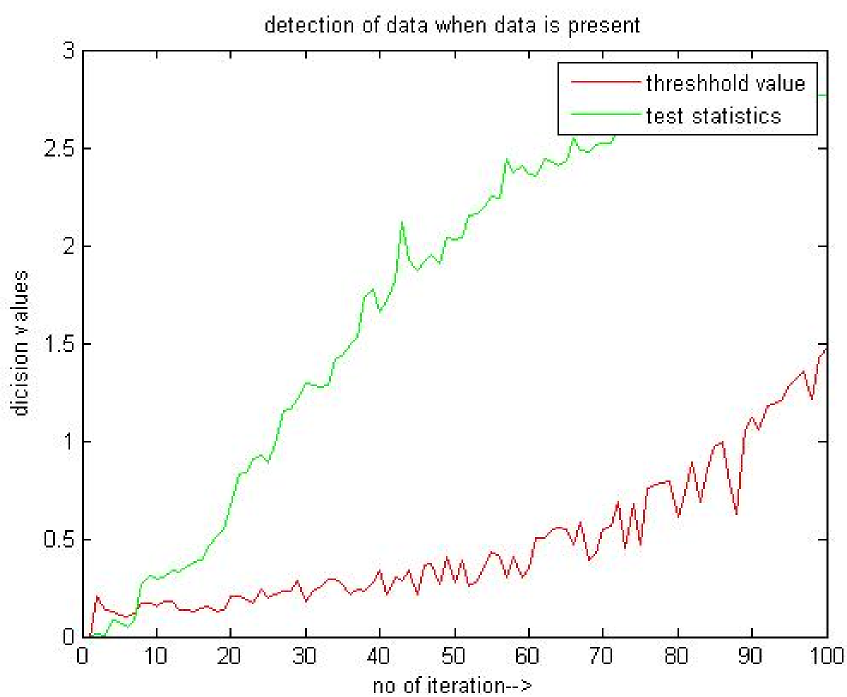

Figure 6.10: Test statistics and threshold plot for Diffusion RLS detection

In the figure 6.10 shown the test statistics and threshold plot for DRLS detection algorithm. In this plot when data is present then test statistics value is greater then the threshold value for correct decision when data is available at the receiving end of the node. Test statistics value is less then the threshold value for correct decision when data is not available at the receiving end of the node. In this plot after some iteration test statistics is always greater then the threshold value when data is present at the receiving end of the node.

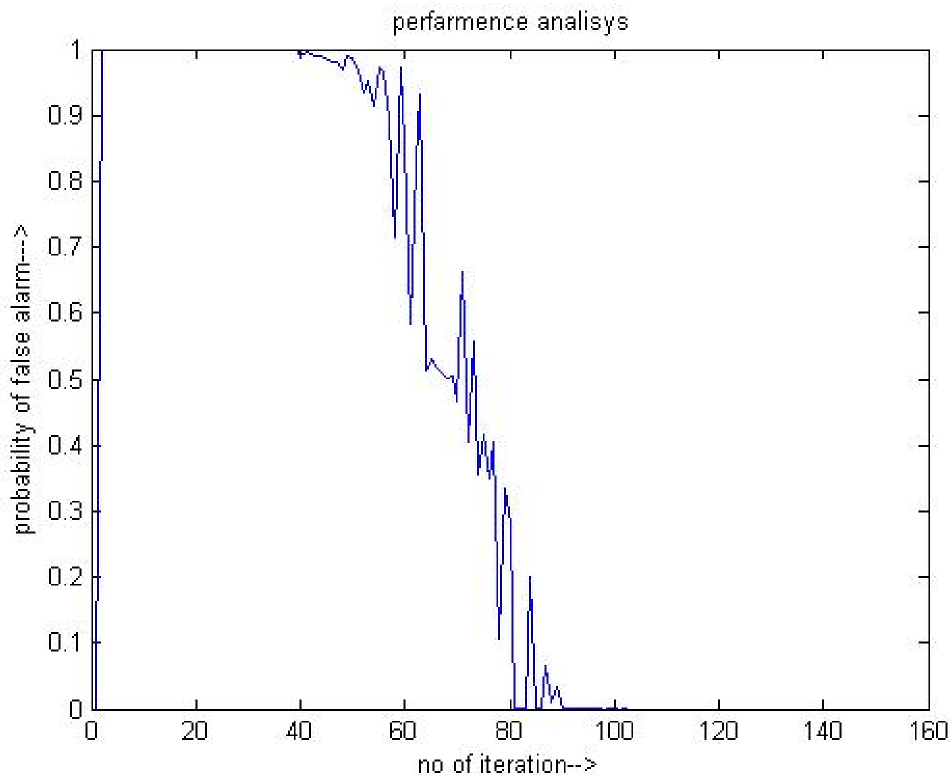

Figure 6.11: Plot of probability of false alarm for Diffusion RLS detection

Figure 6.11 shown the plot for the probability of false alarm for DLMS detection algorithm plotted for 1000 iteration and it is shown that after some iteration probability of false alarm is approaches to 10^{-7} as taken previously for the computation of threshold value in equation (5.6) .

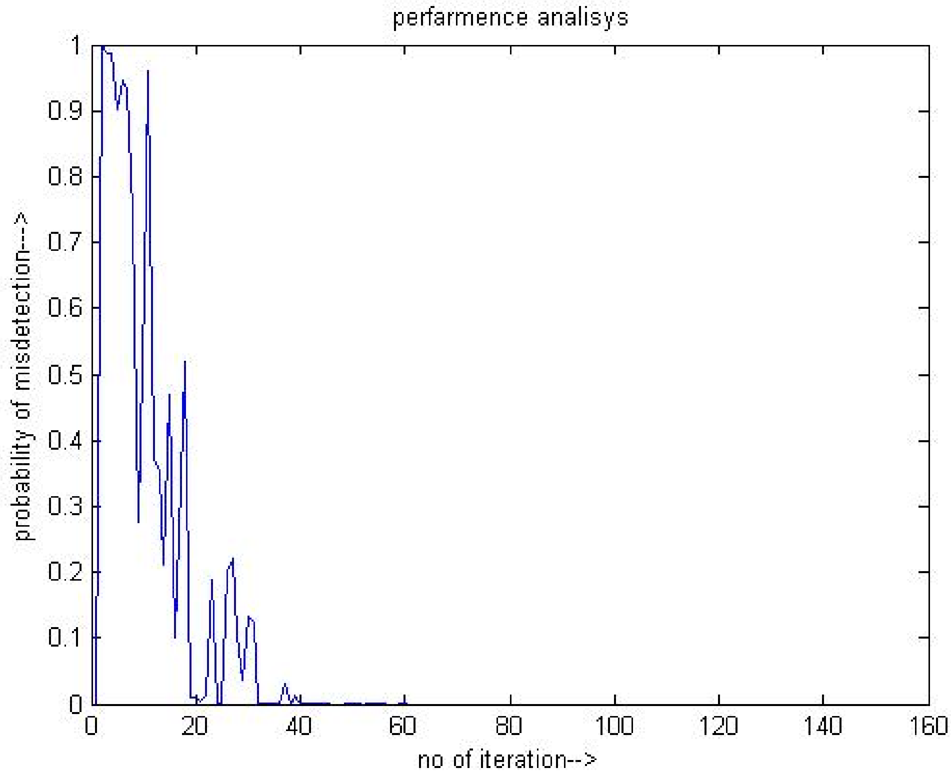

Figure 6.12: Plot of probability of mis detection for Diffusion RLS detection

Figure 6.12 shown the plot of probability of miss detection calculated for DRLS detection algorithm by using equation (4.12) for the 160 iteration.And it is shown that after the few iteration probability of miss detection is approaches nearly to zero .

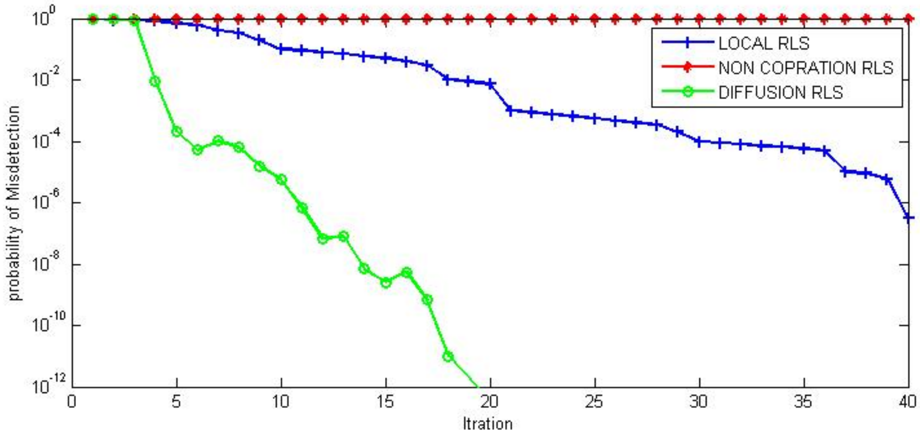

Figure 6.13: Plot of probability of mis detection for Diffusion RLS and noncooperation RLS algorithm detection

Figure 6.13 shown the plot of probability of miss detection calculated for DRLS ,local RLS and noncooperation RLS detection algorithm by using equation (5.2) , reference [2] and [5] for the 40 iteration.And it is shown that after the few iteration probability of miss detection for equation (5.1) is having the much better performance for detection of data as compare to local LMS algorithm and non cooperation.

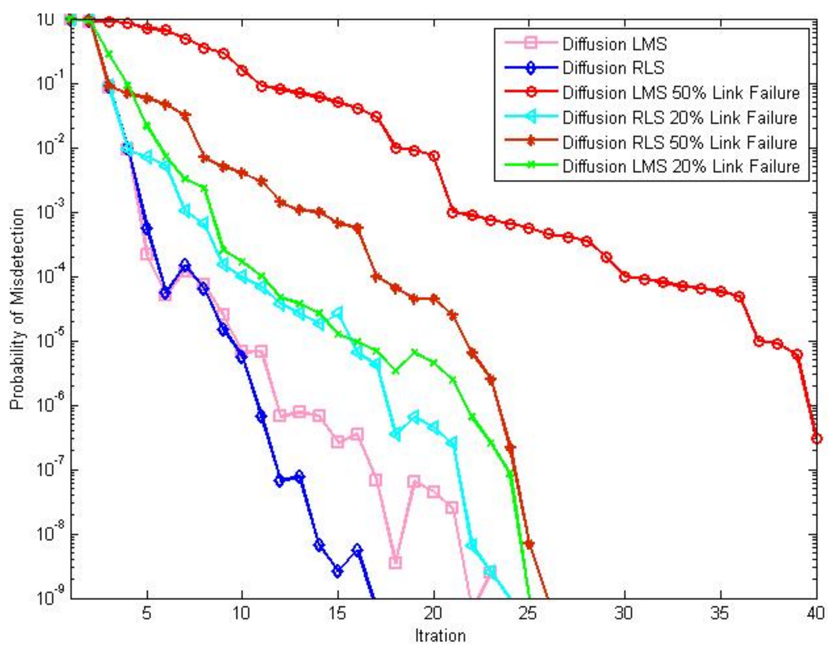

Figure 6.14: Comparison of LMS and RLS algorithm at 20 and 50 link falure condition

Figure 6.14 shown that how resistive the detection algorithm in the sense of link failure.In the figure 6.14 we find out the plot for 50% and 20% of link failure for DRLS and DLMS distributed detection algorithm. And the performance of DRLS algorithm is better then the DLMS algorithm if be compare for probability of mis detection.The worst performence of algorithm is for 50% link failure.

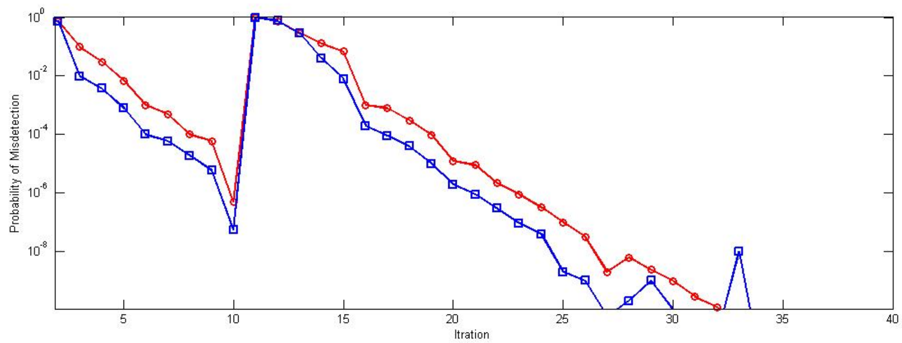

Figure 6.15: Plot of probability of mis detection for Diffusion LMS detection

Figure 6.15 shown the tracking ability of the detection algorithm when hypotheses is changed at the 10th iteration .And in the plot we shown that the tracking ability of the DLMS is better then the DRLS distributed detection algorithm.

Chapter 7

Conclusion and Future work

Conclusion

Future work

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Conclusion and Future Work

7.1 Conclusion

1. This approach proposed fully distributed detection schemes for a binary hypothesis testing problem in Gaussian noise.

2. This approach exploits the connection between detection and estimation theories and uses diffusion estimation algorithms to motivate and derive the detection algorithms.

3. We studied Detection algorithms based on diffusion RLS and diffusion LMS estimation . Finally, provide simulation results for diffusion RLS and diffusion LMS detection algorithm . And performance analysis for diffusion RLS detection and diffusion LMS algorithm.

4. In the plot of tracking ability we plotted the probability of miss detection and when the hypotheses is changed the tracking ability is DLMS is faster as compare to the DRLS.

5. We provided the plot for the link failure between the node and in this plot we have taken 20 % and 50 % link failure between the node . In this link failure the performance of DRLS detection algorithm is better then the DLMS algorithm and DRLS algorithm is able to detect the data more is the case of link failure.

6. We used the Nonlinear techniques to reduce the effect of impulsive interference on the systems. In this dissertation a distributed estimation and

detection algorithm is developed using error saturation nonlinearity which is robust to impulsive noise or outliers.

7.2 Future work

1. Clustering of the network when the different area of wireless network has the different objective or use the distributed detection algorithm for the purpose of multi objective detection in wireless sensor network.

2. Study the robustness of the diffusion algorithm to link failure of the distributed network in presence of Gaussian noise .

3. Use Nonlinear techniques are employed to reduce the effect of impulsive interference on the systems using error saturation nonlinearity which is robust to impulsive noise or outliers

4. In the future we formulate a cognitive radio problem that can be solved in a distributed manner using our proposed diffusion detection algorithms.

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