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IMPLEMENTATION OF DISTRIBUTED ADAPTIVE ALGORITHAMS IN DIFFUSION WIRELESS NETWORKS

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Abstract: Adaptive filter plays an essential role within the subject of digital signal processing and wireless communication. It comprises LMS algorithm in actual time environment because of its low computational complexity and ease. The objective of this project is to study, analyze and compare on different types of adaptive filtering techniques such as Least Mean Square (LMS), Recursive Least Square (RLS) and transform domain Algorithms. Much of these chapters are concerned with a detailed mathematical analysis of algorithms. Mathematical analysis is a very important tool, since it allows many properties of the adaptive filter to be determined without expending the time or expense of computer simulation or building actual hardware. The adaptive distributed technique is situated on the incremental mode of co-operation between specific nodes, which can be distributed within the geographical subject. These nodes perform nearby computation and share the outcomes with the predefined nodes. The ensuing algorithm is allotted, co-operative and in a position to reply to the actual time trade in atmosphere.

Keywords: *Incremental, Adaptive, LMS, INC DCT-LMS, INC DFT-LMS,FTRLS and Stable-FTRLS.*

I.INTRODUCTION

A wireless sensor network (WSN) is a wireless network consisting of spatially dispersed and dedicated autonomous devices that use sensors to monitor physical or environmental conditions. A usual WSN system is formed by combining these autonomous devices, or nodes with routers and a gateway. The dispersed measurement nodes communicate wirelessly to a central gateway, which provides a connection to the wired world where you can collect, process, analyze, and present your measurement data. We can use routers to gain an additional communication link between end nodes and the gateway for extend distance and reliability in a wireless sensor network. The wireless sensor is networked and scalable, require very little power. It is also smart and software programmable, and also capable of fast data acquisition, reliable and accurate over the long term, but costs little to purchase and install, and requires nearly zero maintenance. A Wireless Sensor Network (WSN) is a wireless network consisting of spatially distributed autonomous devices using sensors to cooperatively monitor physical or environmental conditions, such as temperature, sound, vibration, pressure, motion or pollutants, at different locations. The development of wireless sensor networks was originally motivated by military applications such as battlefield surveillance. However, wireless sensor networks are now used in many civilian application areas, including environment and habitat monitoring, healthcare applications, home automation, and traffic control. In addition to one or more sensors, each node in a sensor network is typically equipped with a radio transceiver or other wireless communications device, a small microcontroller, and an energy source, usually a battery. The size of a single sensor node can vary from shoebox-sized nodes down to devices the size of grain of dust. The cost of sensor nodes is similarly variable, ranging from hundreds of dollars to a few cents, depending on the size of the sensor network and the complexity required of individual sensor nodes. Size and cost constraints on sensor nodes result in corresponding constraints on resources such as energy, memory, computational speed and bandwidth.

In computer science and telecommunications, wireless sensor networks are an active research area with numerous workshops and conferences arranged each year.WSN are used to collect data from the environment. They consist of large number of sensor nodes and one or more Base Stations. The nodes in the network are connected via Wireless communication channels. Each node has capability to sense data, process the data and send it to rest of the nodes or to Base Station. These networks are limited by the node battery lifetime.

- Wireless Sensor Network is different from traditional network.
- Wireless Sensor Network is a Single-purpose design means serving one specific application whereas traditional network general-purpose design means serving many applications.
- Energy is the main constraint in the design of all node and network components in wireless sensor network where as in traditional network typical primary design concerns are network performance and latencies, energy is not a primary concern.
- Sensor networks often operate in environments with harsh conditions where as in traditional

network devices and networks operate in controlled and mild environments.

In disbursed processing number of nodes are dispensed in a geographical discipline, it extract the information from knowledge amassed at nodes. For instance nodes disbursed in a geographical discipline collects some noisy understanding regarding a special parameter, than share it with their neighbor via some outlined network topology, the aim is to reach the required parameter of interest. The objective is to reach the certain parameter of interest and it must identical because it end result from the nodes estimation within the geographical discipline. In an evaluation allotted resolution is better than that of centralized resolution since in centralized resolution a crucial processor is required; nodes acquire noisy know-how than ship it to the vital processor for method, vital processor system the knowledge than ship again to all nodes. Accordingly for this a heavy communication between node and relevant processor required and a strong central processor additionally required, but in allotted solution, the nodes simplest will depend on their local information and an interplay with the instantaneous neighbors [2]. Allotted resolution reduces the amount of processing and communication ([1], [3]).

Wireless sensor network is comprised of a large number of small sensing self-powered sensor nodes distributed over a geographical area, which gather information or detect special events and communicate in a wireless fashion. Sensing, processing and communication are three key elements whose combination in one tiny device gives rise to a vast number of remote sensing applications, including environmental monitoring, precision agriculture, medical applications and battlefield surveillance. Due to their several popular applications, efficient design and implementation of wireless sensor networks have become an area of current research. Since the nodes in a network function with small and limited battery power and usually non-renewable resources, it is important to design the networks with less communication among the nodes to estimate the required parameter vector because communication and computation consumes most of the energy. However, recent advances in low power VLSI, embedded computing, communication hardware, and in general, the convergence of computing and communication are making this emerging technology a reality.

Each node in network collects noisy observations related to a certain desired parameter. In the centralized solution, every node in the network transmits its data to a central processor. This approach has the disadvantage of being non-robust to the failure of central processor and need a powerful processor. Again the central processor is lack of scalability, required a large number of communication resources. Alternatively each node in the network can estimate the parameter from the local observations and by cooperating with the neighbors. So there is a need for distributed adaptive algorithms to reduce communication overhead for low power consumptions, and low-latency system for real-time operation. Among them incremental algorithm is the majority choice.

II.PROBLEM STATEMENT

Adaptive digital filtering self-adjusts its transfer function to get an optimal model for the unknown system based on some function of error based on the output of the adaptive filter and the unknown system. To get an optimal model of the unknown system it depends on the structure, adaptive algorithm and the nature of the input signal. System Identification estimates models of dynamic systems by observing their input output response when it is difficult to obtain the mathematical model of the system.In wireless sensor network the fusion center provides a central point to estimate parametersfor optimization. Energy efficiency i.e. low power consumption, low latency, high estimation accuracy and fast convergence are important goals in estimation algorithms in sensor network. Depending on application and the resources, many algorithms are developed to solve parameter estimation problem. One approach is the centralized approach in which the most information to be present when making inference. However, the main drawback is the drainage of energy resources to transmit all observation to fusion center at every iteration. So this is wasting energy at idle time interval. Hence there was a need to find an approach that avoids the fusion center all together and allows the sensors to collaboratively make inference. This approach is called as the distributed scheme. Distributed computation of algorithms among sensors reduces energy consumption of the overall network, by tradeoff between communication cost and computational cost. In order to make the inference procedure robust to nodal failure and impulsive noise, robust estimation procedure should be used.

III.ADAPTIVE SIGNAL PROCESSING IN WSN

In practice most systems are inherently time varying and or nonlinear. The signals associated with these systems often have time-varying characteristics. Adaptive signal processing that deals with the challenging problem of estimation and tracking of time varying systems. By virtue of its applicability to time varying and or nonlinear systems, adaptive signal processing finds application in a broad range of practical fields such as telecommunications, radar and sonar signal processing, biomedical engineering and entertainment systems. In order to make the estimation and tracking task tractable, the unknown system is usually

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modeled as time-varying linear system or in some cases as a finitely parameterized nonlinear system such as the volterra filter. This simplified system modeling is guided by prior knowledge of the system characteristics. An important objective of adaptive signal processing is to learn the unknown and possibly time-varying signal statistics in conjunction with system estimation. The fundamental building block of an adaptive system is the adaptive filter. The objective of an adaptive filter is to learn an unknown system from observations of the system input or output signals utilizing any prior knowledge of the system and signal characteristics. The task of learning an unknown system is fundamental to many signal processing problems and comes in many disguises in the application of adaptive filters.

2.2 Adaptive system identification

Most adaptive filtering problems are either a special case of adaptive system identification or utilize adaptive system identification as a means of solving another signal processing problem. In this sense, adaptive system identification provides the basis for a range of signal processing applications. It is therefore, essential that we have a good understanding of the underlying principles of and assumptions relating to adaptive system identification. As depicted in Fig. 2.1, in adaptive system identification, the objective is to estimate an unknown system from its and output observations given by x(k) and d(k) , respectively. A model for the adaptive filter is chosen based on prior knowledge of the unknown system characteristics, as well as the complexity considerations.

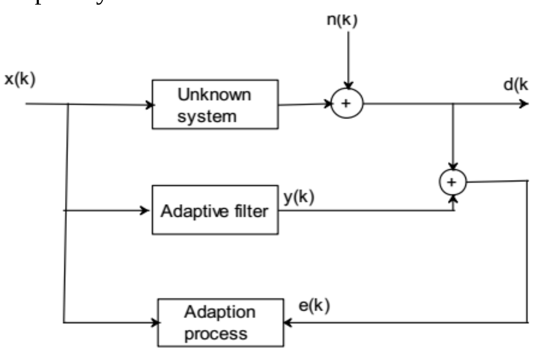

Fig..1 Adaptive system identification

In this and most preferred form, the adaptive filter is a finite impulse response filter of length N with the adjustable impulse response coefficients.

$w(k) = [w_1(k), w_2(k) \ldots \ldots w_N(k)]^T$ …………(2.1)

Here T denotes the transpose operator. Equation (1) is perhaps the most widely used Adaptation filter model mainly because of its applicability to a wide range of practical problems. In a system identification context, the adaptive filter attempt to learn the unknown system. By using a model of the unknown system represented by w(k). The difference between the noisy response of the unknown system (the desired response d(k)) and the response of the adaptive filter y(k)is called the error signal e(k).

$e(k) = d(k) - y(k)$ ………………….. (2.2)

At each iteration k the adaptive filter updates coefficients in order to minimize the appropriate norm of the error signal $e(k)$. When the error norm is minimized in a statistical sense, the corresponding $w(k)$gives an estimate of the unknown system parameters. If the unknown system is time varying, i.e. its parameters change with time, the adaptive filter can track these changes by updating its coefficients in accordance with error signal. It can take several iterations for the adoption process to converge. The time taken by the adaption process to converge provides the indication of the convergence rate.

There are two main tasks performed by the adaptive filter; viz. adaption process and filtering process. In Fig.2.1 these processes are identified by the adoption process and adaptive filter block. For linear adaptive filters given by equation (2.1), the filtering process involves convolution. If the number of filter coefficients is large, the convolution operation may prove to be computationally expensive. Reduced complexity convolution techniques based on fast Fourier transform (FFT), such as overlap-add and overlap-save may use to ease computational demand. The adoption process has also become computationally expensive for long adaptive algorithms due to the arithmetic operations required to update the adaptive filter coefficients. The computational complexity of the adoption process depends on the adoption algorithm employed. Prediction of the random signals and noise cancellation are two special cases of adaptive system identification. Fig.2.2(a) shows a one-step predictor which estimates the present value of the random signal $x(k)$based on the past values $x(k-1, \ldots. x(k-N)$. If xk is a stable autoregressive process of order N:

$x(k) = a_1 x(k-1) + a_2 x(k-2) + \ldots + a_N x(k-N) + v(k)$ (2.3)

Where $v(k)$ is white noise, the adaptive filter $w(k)$in figure 1.2(a) estimate the auto regressor coefficients $[a_1, a_2, a_3 \ldots \ldots \ldots \ldots \ldots \ldots \ldots . a_N]^T$. After convergence the prediction error $e(k)$ is equal to $v(k)$, which implies whitening of the colored noise signal $x(k)$. Referring to Fig.2.1, we observe that the adaptive system identification setup can be converted to a one step predictor by replacing the unknown system with a direct connection (short-circuiting the unknown system), setting $n(k)$ = 0 and inserting a one-sample delay z^{-1} at the input of the adaptive filter. Swapping $x(k)$and $n(k)$in the Fig. 2.1 and referring to $x(k)$ as the signal of interest and $n(k)$ as the interfering noise changes the system identification problem to a noise cancellation problem with $e(k)$ giving the cleaned signal

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(see in the Fig. 2.3). The noise signal $n(k)$is the reference signal and the unknown system represents any filtering that $n(k)$may undergo before interfering with the signal of interest $x(k)$. The sum of $x(k)$and filtered $n(k)$is the primary signal. The unknown is identified by an adaptive filter. Subtracting the adaptive filter output from the reference signal give the error signal. Minimization of the error norm implies a minimization of the difference between the adaptive filter output and the filtered reference signal.

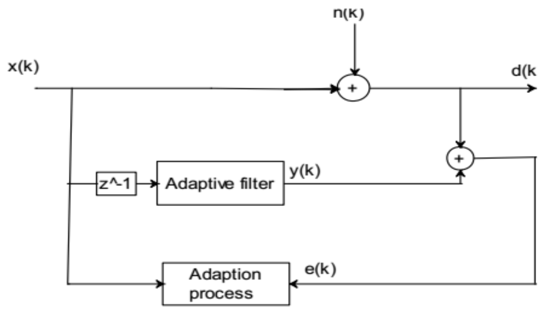

Fig.2.One step prediction of a random signal by an adaptive filter which identifies the auto regressive model of the random signal with $y(k)$ giving the prediction output and $e(k)$ the prediction error.

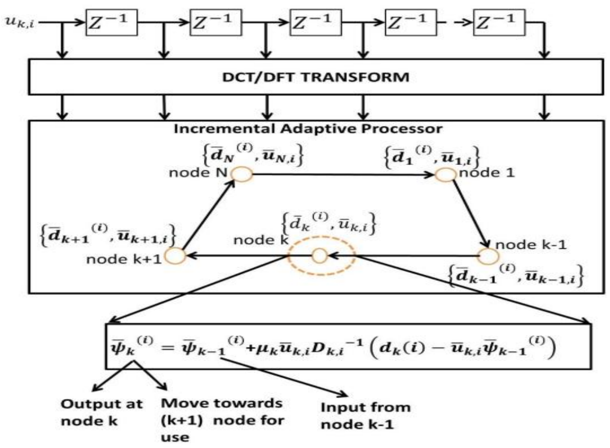

Fig..3 Block diagram of frequency domain incremental LMS algorithm

V. LMS AND RLS ALGORITHMS

In this paper we introduce the adaptive algorithm and the principles of adaptive transversal filter. Then, the derivations and properties of the famous families of the LMS and RLS algorithms are summarized. Lastly, a discussion on the limitations of the classic LMS and RLS algorithms are given.

5.1 The Least Mean Squares (LMS) Algorithm

The Least Mean Square (LMS) algorithm, introduced by Widrow and Hoff in 1960, is a linear adaptive filtering algorithm, which uses a gradient-based method of steepest decent. The LMS algorithm uses the estimates of the gradient vector from the available data and incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error.

The LMS algorithm consists of two basic processes. These are filtering process and adaptive process. A filtering process involves computing the output of a linear filter in response to an input signal and generating an estimation error by comparing this output with a desired response. An adaptive process involves the automatic adjustment of the parameters of the filter in accordance with the estimation error. The combination of these two processes working together constitutes a feedback loop.

1. Basic Idea of Gradient Search Method

$$\xi = \xi_{\min} + \lambda\left(w - w_{opt}\right)^2$$

where λ is eigenvalue equal to v_{00} in the univariable case

The first derivative, $$\frac{d\xi}{dw} = 2\lambda\left(w - w_{opt}\right) \qquad (5.1)$$

The second derivative, $$\frac{d^2\xi}{dw^2} = 2\lambda$$

Simple Gradient Search Algorithm with only *a single weight,*

$$w_{k+1} = w_k + \mu\left(-\nabla_k\right) \qquad (5.2)$$

From equation (3.1)

$$\nabla_k = \frac{d\xi}{dw}\bigg|_{w=w_k} = 2\lambda\left(w_k - w_{opt}\right)$$

Substitute in equation (3.2)

$$w_{k+1} = w_k - 2\mu\lambda\left(w_k - w_{opt}\right) \qquad (5.3)$$

Rearranging equation

$$w_{k+1} = \left(1 - 2\mu\lambda\right)w_k + 2\mu\lambda w_{opt} \qquad (5.4)$$

The equation (3.4) is a linear, first order, constant-coefficient, ordinary difference equation.

For few iterations, starting with initial guess w_0,
The first three iterations,

$$w_1 = \left(1 - 2\mu\lambda\right)w_0 + 2\mu\lambda w_{opt}$$

$$w_2 = \left(1 - 2\mu\lambda\right)^2 w_0 + 2\mu\lambda w_{opt}\left[\left(1 - 2\mu\lambda\right) + 1\right]$$

$$w_3 = \left(1 - 2\mu\lambda\right)^3 w_0 + 2\mu\lambda\ w_{opt}\left[\ \left(1 - 2\mu\lambda\right)^2 + \left(1 - 2\mu\lambda\right) + 1\ \right]$$

5.2. The Recursive Least Squares (RLS) Algorithm

The RLS algorithm as a natural extension of the method of least squares to develop and design of adaptive transversal filters such that, given the least squares estimateof the tap-weight vector of the filter at iteration

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$n-1$. Therefore, we may compute the updated estimate of the vector at iteration n upon the arrival of new data. The derivation based on a lemma in matrix algebra known as the matrix inversion lemma.

An important feature of this algorithm is that its rate of convergence is typically an order of magnitude faster than that of the simple LMS algorithm. However, this improvement of performance is achieved at the expense of an increase in computational complexity of the RLS algorithm.

Derivation of the RLS Algorithm

The Matrix Inversion Lemma

Let A and B be two positive-definite M-by-M matrices

C is positive-definite M-by-N matrix

D is positive-definite N-by-M matrix

Define $A=\left(B^{-1}+CD^{-1}C^{H}\right)$ (5.2.1)

According to matrix inversion lemma, inverse of matrix A as

$$A^{-1}=B-BC\left(D+C^{H}BC\right)^{-1}C^{H}B \qquad (5.2.2)$$

To prove the matrix inversion lemma, multiply eq (5.2.1) by eq (5.2.2)

$$AA^{-1}=\left(B^{-1}+CD^{-1}C^{H}\right)\left[\ B-BC\left(D+C^{H}BC\right)^{-1}C^{H}B\ \right]$$

$$AA^{-1}=B^{-1}B-B^{-1}BC\left(D+C^{H}BC\right)^{-1}C^{H}B+CD^{-1}C^{H}B$$
$$-CD^{-1}C^{H}\ BC\left(D+C^{H}BC\right)^{-1}C^{H}B$$

(5.2.4.)

To show that $AA^{-1}=I$.

Since Rewrite eq(5.2.4)

$$\left(D+C^{H}BC\right)\left(D+C^{H}BC\right)^{-1}=I \text{ and } B^{-1}B=I$$

$$AA^{-1}=I-C\left(D+C^{H}BC\right)^{-1}C^{H}B+CD^{-1}\left(D+C^{H}BC\right)\left(D+C^{H}BC\right)^{-1}C^{H}B$$
$$-CD^{-1}C^{H}\ BC\left(D+C^{H}BC\right)^{-1}C^{H}B$$

$$AA^{-1}=I-\left[\ C-CD^{-1}\left(D+C^{H}BC\right)+CD^{-1}C^{H}\ BC\ \right]\left(D+C^{H}BC\right)^{-1}C^{H}B$$

$$AA^{-1}=I-\left[\ C-CD^{-1}D-CD^{-1}C^{H}BC+CD^{-1}C^{H}\ BC\ \right]\left(D+C^{H}BC\right)^{-1}C^{H}B$$

$$AA^{-1}=I-\left[\ C-CD^{-1}D\ \right]\left(D+C^{H}BC\right)^{-1}C^{H}B \qquad (5.2.5)$$

Since $D^{-1}D=I$, the second term from right hand side of eq (3.37), $\left[\ C-CD^{-1}D\ \right]=0$

Therefore $AA^{-1}=I$

VI.SIMULATION RESULTS

This simulation studies the use of the LMS algorithm for adaptive equalization of a linear dispersive channel that produces distortion.

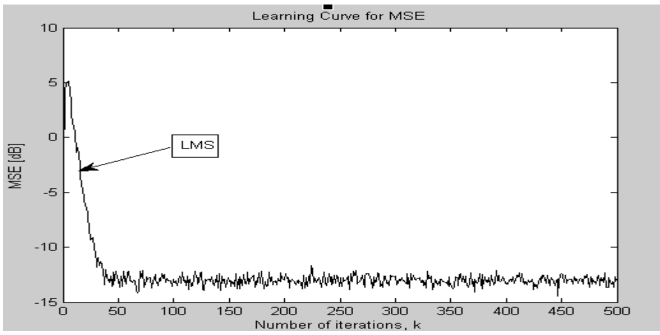

Fig.6.1 Learning Curve of LMS Algorithm

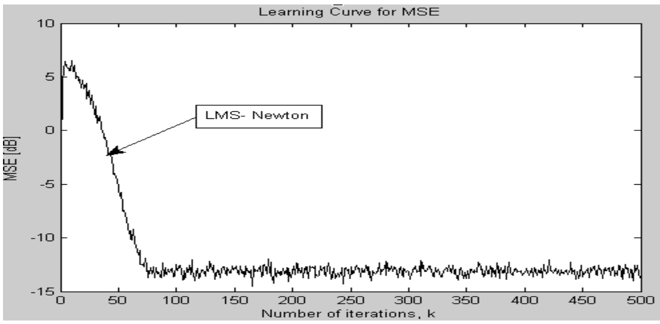

Fig.6.2. Learning Curve of LMS-Newton Algorithm

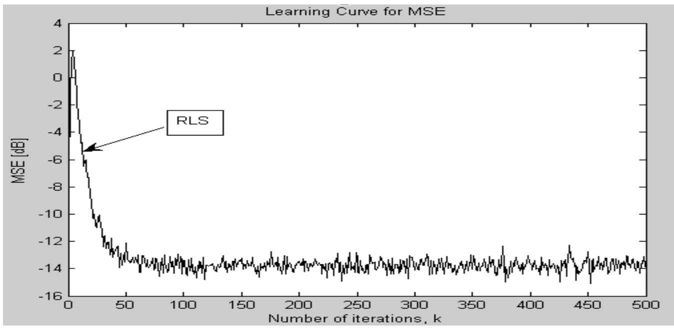

Fig 6.3. Learning Curve of RLS Algorithm

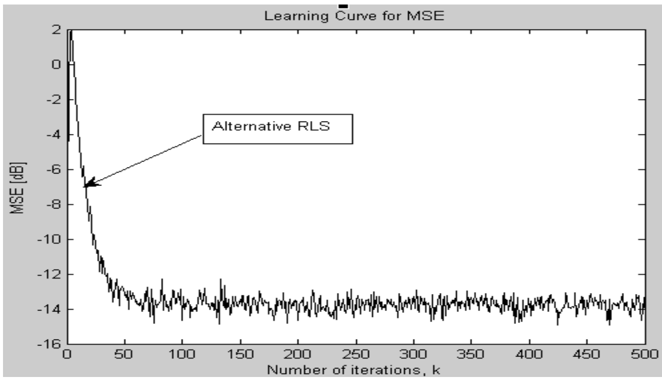

Fig 6.4. Learning Curve of Alternative-RLS Algorithm

VII.CONCLUSION

The problem of optimizing the mapping from input data into some target output has been given quite a few attentions within the literature. Countless adaptive algorithms have been created based on some criterion services like the minimal minimum mean-square error and the least-square error. Among them, the LMS algorithm and the RLS algorithm are very popular. Nevertheless, the LMS algorithm has the problems of gradual convergence and the tradeoff between the convergence and steady-state precision. The RLS algorithm has the issues of high computational complexity and numerical instability. These disorders have brought in much study effort. To improve the algorithms in terms of computational complexity, numerical robustness, rapid convergence and low estimation error, there are nonetheless rather more work remaining to be executed. Here in this thesis number of algorithms like incremental steepest descent algorithm, incremental adaptive solution, INC RLS, INC GN,INC LMF, INC, In case of INC RLS, INC-GN algorithm it achieve the goal but the computational complexity is more than that of previous. The algorithms are tested under different noise condition and at different SNR case it is found that the lower order error algorithms like INC RLS, INC GN, INC DCT-LMS, INC GN and INC DFT-LMS perform better than that of LMS algorithm under Gaussian noise case, but it fails to achieve the same undergone-Gaussian noise case like under binary noise, sinusoidal noise and uniform noise.

In distributed signal processing and wireless sensor networks one of the better developments is the Volterra filter with different algorithms such as LMS (Least Mean Square) and RLS (Recursive Least Square) and finally the FTRLS algorithm. Generally the fast filter provides better convergence rate and the accurate filter provides better steady state performance, but it is very difficult to achieve the both in a single filter. Since it is very difficult to design and also very complex, which cannot be reliable. The Stable FTRLS algorithm achieves both, by connecting the two filters in parallel or in series.

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