

Digital Signal Processing and Wireless Sensor Networking

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ABSTRACT:

Adaptive filter plays an important role in the field of digital signal processing and wireless communication. It incorporates LMS algorithm in real time environment because of its low computational complexity and simplicity. The LMS algorithm encompasses RLS (recursive least square), GN (Gaussian Newton), LMF (least mean fourth) and XE-NLMF algorithms, which provides faster convergence rate and low steady state error when compared to LMS. The adaptive distributed strategy is based on the incremental mode of co-operation between different nodes, which are distributed in the geographical area. These nodes perform local computation and share the result with the predefined nodes. The resulting algorithm is distributed, co-operative and able to respond to the real time change in environment. By using incremental method, algorithms such as RLS,GN, DCT-LMS and DFT-LMS produces faster convergence and better steady state performance than that of the LMS when simulated in the presence of Gaussian noise.

Higher Order error algorithm like LMF, XE-NLMF and variable XE-NLMF algorithm produce better convergence and steady state performance under Gaussian and non-Gaussian noise. A spatial-temporal energy conservation argument is used to evaluate the steady state performance of the entire network. A topology named as CLMS (convex LMS) was presented which combined the effect of both fast and accurate filtering at the same time. Initially CLMS have parallel independent connection, the proposed topology consists of series convex connection of adaptive filters, which achieves similar result with reduced time of operation. Computer simulations corroborate the results.

Keywords:

Incremental, Adaptive, CLMS, INC DCT-LMS, QWDILMS, XENLMF, LMF, LMS.

INTRODUCTION:

Wireless Sensor Networks (WSNs) is networks composed of tiny embedded devices. Each device is capable of sensing, processing and communicating the local information. The networks can be made up of hundreds or thousands of devices that work together to communicate the information that they obtain. In distributed signal processing Number of nodes are distributed in a geographical area, it collects the information or data which is present in the node. Each node assembles some noisy information related to a certain parameter of interest and performing local estimation, then share the data to the other nodes by some defined rule. The main object behind this is to reach the parameter of interest, which really outcomes from the node after share in the network. In traditional centralized solution the nodes collect the data then send it to the central processor for processing, the central processor process the data then finally again give back the estimated data to all the node. For this a powerful central processor required and a huge amount of communication between node and central processor required.

But in case of distributed solution, the nodes only depends on their immediate neighbor. Hence in case of distributed solution the amount of processing and communication reduced. Distributed solution has large number of application including tracking of target trajectory, monitoring concentration of chemical in air or water, also having application in agriculture, environment monitoring, disaster relief management, medical etc. There are three mode of cooperation namely incremental, diffusion and probabilistic diffusion will discuss. Here we use only the incremental mode of cooperation. This chapter describes about the central distributed algorithm, non-distributed algorithm and the advantage of distributed over non distributed solution. The comparison is done on the basis of convergence rate, steady state performance and computational complexity.

There are two type of algorithm used one is incremental steepest descent solution and other is incremental adaptive solution, comparing both on the basis convergence rate and steady state performance the adaptive solution perform better than steepest descent solution. The more explanation will found each case we consider the variance of noise is small i.e. Less than one, but sometime case arises where the noise 10^{-1} variance is more than that of one, than a quality aware algorithm is used in the incremental method to maintain the steady state performance. The convergence performance of LMS (least mean square) algorithm depends on the correlation of the input data and the Eigen value spread of the covariance matrix of the regressor data. The smaller Eigen value of auto-correlation matrix results in slower convergence and larger Eigen value limit the range of the allowed step size and thereby limit the learning abilities of the filter. Best convergence result when all the Eigen value equal i.e. having unit Eigen spread, this is possible only when auto correlation matrix is constant multiplication of identity matrix. This can be achieved by pre-whiten the data by passing it through pre-whiten filter which is practically not possible.

Hence same thing will achieve by unitary transformation of data, such as DFT (discrete Fourier transform), and DCT (discrete cosine transform). Adaptive algorithms based on the higher order moments of the error signal found performs better than that of LMS algorithm in some important application. The practical use of such type application is not considerable because of its lack of accuracy in the model to predict the behavior. One of such type of algorithm is LMF (least mean fourth) algorithm, which minimize the mean fourth error. It is found that the LMF algorithm outperforms than the LMS algorithm in non Gaussian noise case. We will find the family of LMF algorithm and its performance in both Gaussian and non Gaussian noise case in the chapter 4. Generally fast filter gives higher convergence rate and accurate filter gives better steady state performance. An algorithm developed named CLMS (convex LMS) algorithm which consists of two adaptive filters connected parallel. The CLMS algorithm track initially the faster convergence respond, then followed the accurate response. It has advantage that it achieve both at the same time.

It is very difficult to develop a filter which provides both at same time. Hence this algorithm has number of application in the distributed signal processing.

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. Mathematical analysis has also been extended to the transform domain adaptive filter, CLMS algorithm, XE-NLMF algorithm and variable XE-NLMF algorithm. This work has examined the convergence conditions, steady-state performance, and tracking performance. The theoretical performance is confirmed by computer simulations.

The performance is compared between the original adaptive filter algorithms and different other algorithm like incremental adaptive solution, incremental RLS, incremental GN, incremental CLMS, XE-NLMF and incremental variable XE-NLMF algorithm. Since a specific method mention previously in one adaptive filter algorithm may achieves good performance, but may not perform well in another adaptive filter algorithm, hence we will examine the number of methods in adaptive filter to find the better one. In the field of signal processing and communication Adaptive Filtering has a tremendous application such as non-linear system identification, forecasting of time-series, linear prediction, channel equalization, and noise cancellation. 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 strategy and the nature of input signal. DSP-based equalizer systems have become ubiquitous in many diverse applications including voice, data, and video communications via various transmission media.

Typical applications range from acoustic echo cancellers for full-duplex speakerphones to video deghosting systems for terrestrial television broadcasts to signal conditioners for wire line modems and wireless telephony. The effect of an equalization system is to compensate for transmission channel impairments such as frequency-dependent phase and amplitude distortion. Rather for correcting for channel frequency-response ambiguity, cancel the effects of Multipath signal and to reduce the inter-symbol interference. So, construction of Equalizer to work for the above specifications is always a challenge and an active field of research.

Incremental Adaptive Strategies over Distributed Network:

In Distributed processing number of nodes are distributed in a geographical area, it extract the information from data collected at nodes. For example nodes distributed in a geographical area collects some noisy information related to a certain parameter, than share it with their neighbor by some defined network topology, the aim is to reach the required parameter of interest. The objective is to reach the exact parameter of interest and it should same as it outcome from the nodes estimation in the geographical area. In a comparison Distributed solution is better than that of centralized solution because in centralized solution a central processor is required, nodes collect noisy information than send it to the central processor for process, central processor process the data than send back to all nodes. Hence for this a heavy communication between node and central processor required and a powerful central processor also required, but in distributed solution, the nodes only depends upon their local data and an interaction with the immediate neighbors. Distributed solution reduces the amount of processing and communication.

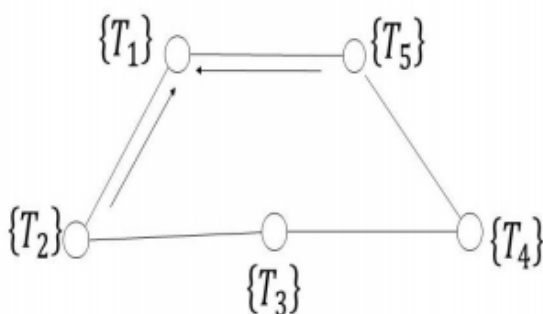


Fig. 1 Distributed network

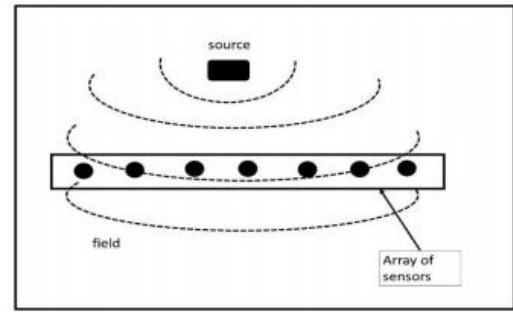


Fig. 2 monitoring a diffusion phenomenon by a network of sensors

Contribution:

When consider the forgoing issues (real time adaption with environment, low computation and communication complexity), we consider a Distributed LMS (least mean square) algorithm, since the computational complexity is less for both computation and communication. This algorithm solves the problem of new entry of data, it responds the data and also update it. The advantage of distributed algorithm than that of consensus strategy is it does not require of intermediate averaging as is done in consensus strategy. It also not required two different time scales. The distributed adaptive solution is the advance version or extension of adaptive filter, it is totally model independent i.e. it can be used without any knowledge of statistics of data. Generally adaptive filter responds to real time data and varies with statistical properties of data, distributed algorithm just extend this property to network domain.

The main purpose of this algorithm is: 1) Using distributed adaptive algorithm optimization technique to inspire the family of incremental adaptive algorithm. 2) Using incremental algorithm develop an interconnected network such that it is able to respond the real time data and also shows adaptive nature in variation with the statistical properties of the data as follow: a) Each time node receives a new information and that information is used by node to update its local estimation parameter of interest. b) After local estimation finished, the estimated parameter share with the immediate neighbors of node and repeat the same process to the other node in the network. 3) Distributed processing task is challenging, since it contain “system of systems” ,that process the data cooperatively manner both in time and space.

In distributed algorithm different nodes converge at different MSE (mean square error) levels, which reflects the statistical diversity of data and the different noise levels.

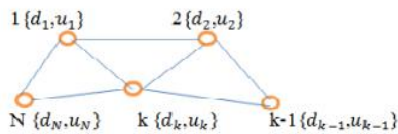


Fig. 4 Distributed network with N nodes accessing space time data

ESTIMATION PROBLEM AND ADAPTIVE DISTRIBUTED SOLUTION:

There has been lots of work we can find in the literature solving distributed optimization problem using incremental method. In distributed algorithm a cost function can be decomposed into sum of individual cost functions using incremental procedure. The procedure can be explained below in the context of MSE.

Consider a network with N nodes as shown in Fig.4. Each node has access to time realizations $\{dk(i), uk, i\}$ of zero mean spatial data $\{dk, uk\}$, $k = 1, 2, \dots, N$, where dk is a scalar and uk is a row regression vector of size $1 \times M$.

$$U \triangleq \{u_1, u_2, \dots, u_N\} (N \times M) \quad (2.5.1)$$

$$d \triangleq \{d_1, d_2, \dots, d_N\} (N \times 1) \quad (2.5.2)$$

The above quantities collect data from all N nodes. The main objective is to estimate the vector w of size $M \times 1$ that solves

$$\min_w J(w) \quad (2.5.3)$$

Where (w) represents the cost function denotes the MSE, given as follows:

$$J(w) = E \|d - Uw\|^2$$

Where E is the expectation operator. The optimal solution w_0 can be found by using the orthogonality condition given by

$$E \|d - Uw\|^2 = 0 \quad (2.5.5)$$

The solution to the above normal equation given by

$$Rdu = Ruw_0 \quad (2.5.6)$$

Where $Ru = EU^*U$ ($M \times M$), $Rdu = EU^*d = \sum_{k=1}^N Rdu_k$ ($M \times 1$)

But the solution obtained from equation (2.5.6) is not distributed in nature since for this solution we required to access the global information $\{Ru, Rdu\}$. One way to do this is process it centrally then pass the information to all the nodes, but for this we require a heavy communication between node and central

processor, also require huge amount of power. It also not adaptive in nature with respect to the environment. This is the reason why we go for the distributed solution, which reduces the communication burden and the amount of power required for communication. In this project we totally focus on the incremental mode of cooperation, where each node produces its local estimation and share it with the immediate neighbor node at a time.

RESULTS:

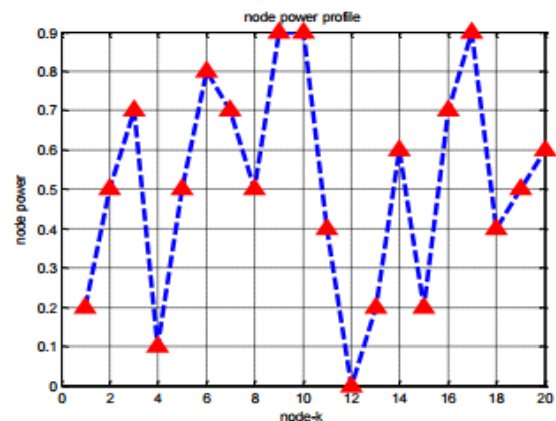


Fig. Regressor power profile

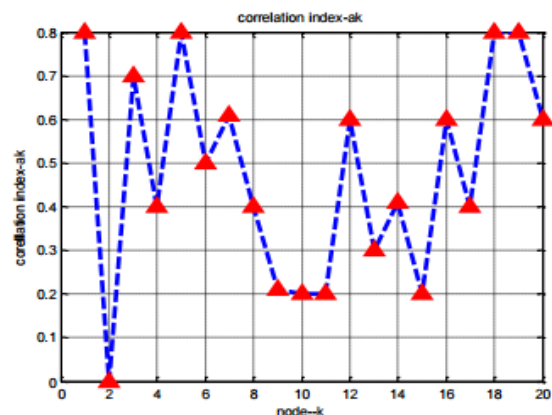


Fig. Correlation index per node

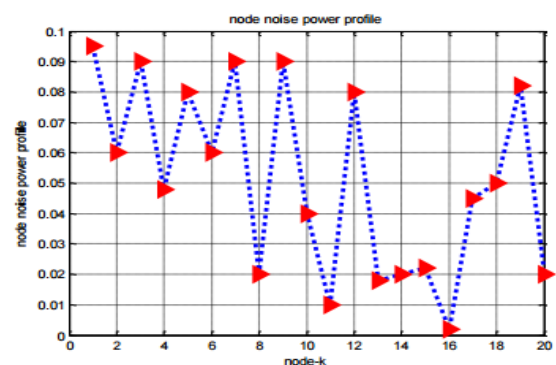


Fig. Noise power profile

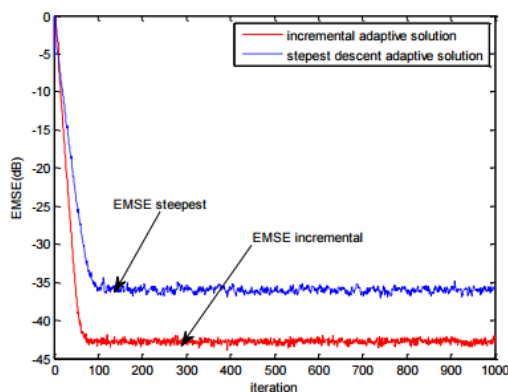


Fig. Transient MSD performance at node 1 for both incremental adaptive solution and stochastic steepest descent solution

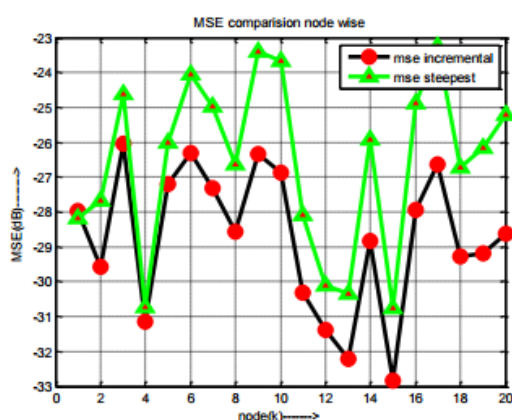


Fig. MSE performance node wise

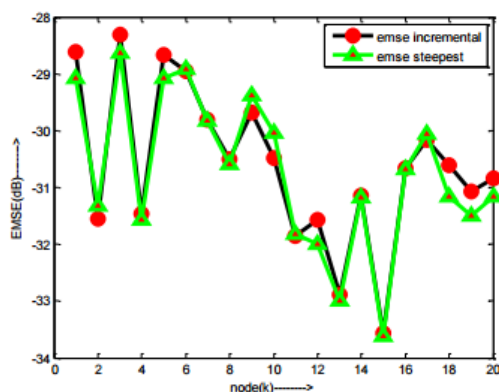


Fig. EMSE performance node wise

CONCLUSION:

Distributed signal processing has wide number of application in the field of signal processing. Day to day number of algorithms are developed to improve the convergence rate, steady state performance and to reduce the computational complexity. Here in this thesis number of algorithms like incremental steepest descent algorithm, incremental adaptive solution, INC

RLS, INC GN, INC LMF, INC XE-NLMF, INC variable XE-NLMF, INC CLMS, QWDILMS, INC DCT-LMS, INC DFT-LMS algorithms are tested to achieve the same. 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 under non Gaussian noise case like under binary noise, sinusoidal noise and uniform noise. By experiment it is found that the higher order noise algorithm like LMF algorithm, XE-NLMF and variable XE-NLMF algorithm performs better than that of LMS algorithm under non Gaussian noise case.

In all case we consider the SNR is uniform i.e. the variance of noise in all the node present in the network is less than that of one. But it not happens always practically. It is found that in number practical application the SNR of one or more node is less than that of other on that case the algorithms are fails to give better performance by using incremental adaptive strategies. To improve the performance the algorithms like QWDILMS developed which improves the steady state performance under noisy node condition by assigning special weights to each node. But the disadvantage of this algorithm is it only improves the steady state performance but not effects on the convergence rate. But by proper design the convergence rate of the QWDILMS algorithm also will improve.

REFERENCES:

- [1] N. Takahashi, I. Yamada and A. H. Sayed, "Diffusion least-mean squares with adaptive combiners," in Acoustics, Speech and Signal Processing, 2009. ICASSP 2009. IEEE International Conference on, 2009.
- [2] F. Beaufays, "Transform-domain adaptive filters: an analytical approach," Signal Processing, IEEE Transactions on, vol. 43, no. 2, pp. 422-431, 1995.

[3] J. J. Shynk and others, "Frequency-domain and multirate adaptive filtering," IEEE Signal Processing Magazine, vol. 9, no. 1, pp. 14-37, 1992.

[4] S. Narayan, A. M. Peterson and M. J. Narasimha, "Transform domain LMS algorithm," Acoustics, Speech and Signal Processing, IEEE Transactions on, vol. 31, no. 3, pp. 609-615, 1983.

[5] M. Chan, A. Zerguine and C. Cowan, "An optimised normalised LMF algorithm for sub-Gaussian noise," in Acoustics, Speech, and Signal Processing, 2003. Proceedings.(ICASSP'03). 2003 IEEE International Conference on, 2003.

[6] A. Zerguine, "Convergence behavior of the normalized least mean fourth algorithm," in Signals, Systems and Computers, 2000. Conference Record of the Thirty-Fourth Asilomar Conference on, 2000. [20] M. Chan and C. Cowan, "Using a normalised LMF algorithm for channel equalisation with cochannel interference," EUSIPCO-2002, Toulouse, France, pp. 48-51, 2002.

[7] E. Walach and B. Widrow, "The least mean fourth (LMF) adaptive algorithm and its family," Information Theory, IEEE Transactions on, vol. 30, no. 2, pp. 275-283, 1984.

[8] W. B. Lopes and C. G. Lopes, "Incremental-cooperative strategies in combination of adaptive filters.," in ICASSP, 2011.

[9] M. G. Rabbat and R. D. Nowak, "Decentralized source localization and tracking [wireless sensor networks]," in Acoustics, Speech, and Signal Processing, 2004. Proceedings.(ICASSP'04). IEEE International Conference on, 2004.

[10] C. G. Lopes and A. H. Sayed, "Distributed adaptive incremental strategies: formulation and performance analysis," in Acoustics, Speech and Signal Processing, 2006. ICASSP 2006 Proceedings.2006 IEEE International Conference on, 2006.

[11] D. P. Bertsekas, "A new class of incremental gradient methods for least squares problems," SIAM

Journal on Optimization, vol. 7, no. 4, pp. 913-926, 1997.

[12] W. M. Bazzi, A. RastegarniaR and A. Khalili, "A Quality Aware Incremental LMS Algorithm for Distributed Adaptive Estimation".

[13] T. Panigrahi and G. Panda, "Robust Distributed Learning in Wireless Sensor Network using Efficient Step Size," Procedia Technology, vol. 6, pp. 864-871, 2012.

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