

# An Analysis of Distributed Estimation Algorithms for Wireless Sensor Networks

A.Antony Viswasa Rani, E.Baburaj

## Abstract

Distributed estimation algorithms over Wireless Sensor Networks have been widely studied since the seminal work of Tsitsiklis. The goal of these algorithms is to make the network reach a consensus over the value of interest by means of local communications between the sensors. Currently there are no techniques for distributed estimation under dynamic communication constraints. Existing centralized multi sensor estimation techniques assume that the choice of which data to send from any particular sensor to the centralized node is fixed. This approach suffers serious disadvantages and is typically feasible for certain non critical static sensor situation. Future research is likely to focus on developing multi sensor estimation problem where there are time varying communication bandwidth constraints. This paper gives a brief survey of various distributed estimation algorithms applied to address the WSN issues like optimal design, node localization, data aggregation, clustering, node deployment, and target tracking.

**Index Terms**— Distributed estimation, Wireless sensor networks, Sensor design, Target tracking, Fusion, Localization, Deployment

## I. Introduction

A Wireless Sensor Network (WSN) is a network of distributed autonomous devices that can sense or monitor physical or environmental conditions cooperatively [1], each with finite battery lifetime and thus limited computing and communication capabilities. WSNs are used in numerous applications such as environmental monitoring, habitat monitoring, prediction and detection of natural calamities, medical monitoring and structural health monitoring. Major challenges in WSN are, Design and Deployment, Localization, Data Aggregation and Sensor fusion, Energy aware Routing and Clustering, Scheduling, Security and Quality of Service management.

WSNs are capable of collecting an massive amount of data over space and time. Often the ultimate aim is to derive an estimate of a parameter or function (eg. source localization, spatial distributions) from these data. The paper [12] investigates a general class of distributed algorithms for in-network data processing, eliminating the need to transmit raw data to a central point. This can provide considerable reductions in the amount of communication and energy required to obtain an precise estimate. In many realistic scenarios, the distributed algorithms are much more efficient in terms of energy and communications than centralized estimation schemes. The theory is verified through simulated applications in strong

estimation , source localization, cluster analysis and density estimation.

WSNs are often self configured networks with little or no pre-established infrastructure as well as a topology that can change dynamically. There may be physical obstacles in the network environment that can degrade considerably the wireless links among sensors. Since data are collected by sensors at geographically different locations, estimation using a WSN requires not only local information processing but also inter sensor communications. To maximize battery lifetime and reduce communication bandwidth, it is essential for each sensor to nearby compress its observed data so that only low rate inter sensor communication is required. This motivate joint design of the Compression-estimation module per sensor [2] .

The design of distributed algorithms should be coupled with the underlying WSN topology. Two popular wireless sensor network deployments characterized by the presence or absence of a Fusion Center (FC). When a fusion center is present, there is no inter sensor communication; communication is only between sensors and the FC. The FC collects locally processed data and produces a final estimate (Figure 1). In ad hoc WSNs, there is no FC, the network is itself responsible for processing the collected information and to this end, and sensors communicate with each other through the shared wireless medium.

- 
- A. Antony Viswasa rani is currently pursuing Ph.d program in information and Communication Engineering in AnnaUniversity, India, E-mail: avranicse@gmail.com
  - Dr.E.Baburaj is currently working in Sun College of Engineering and TEchnology,India, E-mail: alanchybabu@gmail.com

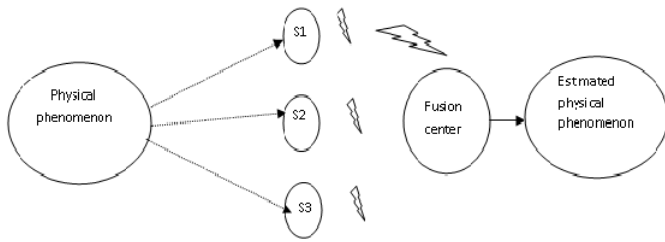


Figure 1: A WSN topology with an FC

A WSN is composed of a large number of geographically distributed sensor nodes. Though each sensor is characterized by low power constraint and limited computation and communication capabilities due to various design considerations such as small size battery, bandwidth and cost, potentially powerful networks can be constructed to accomplish various high level tasks via sensor cooperation such as Distributed Estimation, Distributed detection, and Target Localization and Tracking[6]. The objective of this paper is to give a brief idea about various distributed estimation algorithms to handle the WSN issues.

The rest of the paper is organized as follows: distributed estimation and a few estimation algorithm is briefly outlined in sections II. Sections III to VII discuss applications of distributed estimation in node design and deployment, node localization, data fusion, target tracking and node coverage. Finally the concluding remarks and a future directions are given in section VIII

## II. Distributed Estimation:

Distributed Estimation of unknown deterministic parameters by a set of distributed sensor nodes and a fusion center has become an important topic in signal processing research for WSNs. Subject to a severe Bandwidth and Energy constraints, each sensor in WSNs is allowed to transmit only a quantized version of its raw measurement to the fusion center. Instead of sending the real value observations to the fusion center directly, quantization at the local sensors is essential to reduce the communication bandwidth and energy cost.

A WSN consists of a large number of sensors, where each sensor is capable of sensing, processing and transmitting environmental information. These capabilities make it possible to use WSNs in many applications. In most of these applications one need to estimate an unknown parameter using discrete time samples collected across sensors. It is not possible to send all data samples to a central location for processing. Based on WSN topology (ie. WSN with FC and Ad-hoc WSN), there are two different ways for distributed estimation. The main goal in

distributed estimation algorithm is to distribute the computations of estimation task between sensors and FC(in FC based WSN) and totally between sensors in adhoc WSNs. In FC based distributed estimation, the basic idea is to reduce the bits needed to encode the local measurements.

The *optimal distributed estimators* depend on the parametric model and the noise Probability density function (pdf). Such applications motivate universal distributed estimators that are independent of the noise or parameter distributions under either bandwidth or energy constraints. Recently distributed adaptive estimation algorithms have been proposed for distributed estimation in ad-hoc sensor networks. Diffusion implementation of distributed adaptive estimation algorithms are developed. *Diffusion based method* need more communication resources while have better performance. In [18], the scheme performs the estimation locally and recursively by the sensors measuring the parameter. Each sensor performs estimation based on its own measurement and the intermediate estimation results from its upstream sensor. The last sensor delivers the computed estimate to the destination.

In [20], the algorithm for estimating random signals using data collected by an ad-hoc WSNs based on successive refinement of local estimates. At each transmission cycle of the algorithm, information is exchanged among single hop neighbors only; the information received from these neighbors is then used to improve their local estimate.

The robustness, flexibility and reduced cost of WSNs motivate the development of new classes of estimation algorithms, which need to be designed considering the limited computational and communication capabilities of such systems. Collaboration is suitable to overcome intrinsic limitations in processing measurements from only a single sensor, which often provide data with correlated data and quantization noise. The main contribution of the paper [21] is a theoretical framework to the design of a collaborative distributed filter for tracking a time-varying signal with a WSN. The approach ensures that the filter is stable and exhibits good behavior with respect to packet losses.

The paper [22] focuses on *estimating the maximum* of the initial measures in a WSN. Two different algorithms are studied: RANDOM GOSSIP, relying on pairwise exchanges between the nodes and the BROADCAST, in which each sensor sends its value to all its neighbors. Both are asynchronous and distributed. To share the maximum value over the entire network, the standard Random pair wise Gossip approach can be used, but it does not take benefit of the broadcast nature of the wireless channel. Broadcasting causes a major issue for

averaging algorithms because the sum of measures is not conserved so the broadcast-based algorithms do not generally converge the statistical average. This is obviously not a problem while estimating the maximum value. Hence broadcasting information can be a good way to speed up convergence for the distributed estimation of the maximum in a WSN.

In [23], the authors consider the problem of *distributed adaptive estimation* in WSNs for two different observation noise conditions. In the first case, assume that there are some sensors with high observation noise variance (noisy sensors) in the network. In the second case, different variance for observation noise is assumed among the sensors which is more close to real scenario. In both cases, an initial estimate of each sensor's observation noise is obtained and then according to the extracted information, the IDLMS algorithm was modified. IDLMS, is distributed, cooperative and able to respond in real time to changes in the environment.

The Paper [24] deal with *linear estimation of random signals* based on reduced-dimensionality observations collected at distributed sensors and communicated to a fusion center through wireless links. Dimensionality reduction compresses sensor data to meet low power and bandwidth constraints. Canonical Correlation Analysis(CCA) is a well documented tool for data and model reduction problems encountered in various applications such as statistical data analysis, control, signal processing and econometrics. CCA provides a natural framework for estimating a random signal vector of interest based on reduced dimensionality WSN observations.

*Distributed state estimation* in WSNs has received some attention recently. It is often desirable to limit inter-sensor communications to nearby sensors. Estimation schemes and network topologies using a Fusion center may be less suited in this respect because the sensor data have to be communicated to a central location where the final processing takes place. In contrast, fully decentralized schemes without a FC use extensive in-network processing and neighbor-to-neighbor communication to achieve low energy consumption and high robustness to node failure. In [8] , an *optimal distributed Bayesian estimation* algorithm that is sequential both in time and in space ie.across sensors and requires only local communication between neighboring sensors. For the linear/Gaussian case, the algorithm reduces to a time-space sequential, distributed form of the kalman filter. This estimator algorithm can be used in Target tracking problem.

Estimation of Distribution Algorithms(EDAs)refer to a class of Evolutionary Algorithms(EAs) based on statistical modeling of the search space instead of traditional genetic operators such as crossover and mutation. In addition to sharing the robustness and global

optimization ability of Eas, the unique feature of EDAs is that they are capable of building a principled statistical model of the distribution of promising individuals and using this model to conduct highly efficient searching. Dependence chain models, Dependence tree models and Bayesian networks are some of the statistical models. For continuous optimization problems, Gaussian models are most widely employed mainly due to its computational efficiency. There are two categories for dynamic optimization. The first one is based on the idea of maintaining a memory of good individuals that the algorithm has come across during the search. The second is based on the idea of random immigrations, which means new individuals are introduced into the main population from time to time, mainly for the purpose of diversity maintenance.

*Source Direction of Arrival(DOA) estimation* is one of the challenging problem in WSN. DOA estimation is an important problem in WSN to estimate the source location which is an well known problem in the fields of Radar, Sonar, radio-astronomy, underwater Surveillance and Seismology etc. Many suboptimal techniques are available such as Multiple signal classification(MUSIC), Estimation of Signal Parameters via Rotational Invariance Technique (ESPRIT). The ML technique is used [11] here because of its superior statistical performance compared to spectral based methods. The ML method is a standard technique in Statistical estimation theory. To obtain the Exact Maximum Likelihood(EML) solutions, the DOAs must be estimated by optimizing a complicated non linear multimodal function over a high-dimensional problem space. An Adaptive PSO based solution is proposed here to compute the ML functions and explore the potential of superior performances over traditional PSO algorithms.

In the paper [15], a new iterative, distributed approach for *Linear Minimum Mean Square Error(LMMSE) estimation* in graphical models with cycles. Embedded Subgraphs Algorithm is robust to temporary communication faults such as failing links and sleeping nodes and enjoys guaranteed convergence under relatively mild conditions.

To deal with more realistic scenario, different variance for observation noise is assumed for sensors in the network. To solve the problem of different variance of observation noise, the method in paper[16] is divided into two phases: Estimating each sensor's observation noise variance and using the estimated variances to obtain the desired parameter. This algorithm is based on a diffusion Least Mean Square implementation with linear combiner model.

### III. Design

A Memetic Algorithm(MA) for the dynamic optimal design of WSNs is proposed in the paper [28]. A fixed wireless network of sensors of different operating modes was considered on a grid deployment and the MA system decided which sensors should be active, which ones should operate as Cluster Heads and whether each of the remaining active nodes should have High or Low signal range. During optimization, parameters of network connectivity, energy conservation as well as application requirements were taken into account.

#### IV. Target tracking

In the paper [7], the authors present a systematic analysis framework for mobile sensor networks with a flocking-based mobility control model that run a novel distributed Kalman filtering algorithm for collaborative tracking of a single target. Collaborative tracking of multiple targets(or events) in an environment arise in a variety of surveillance and security applications and intelligent transportation. Distributed estimation for static sensor networks has attracted many researchers in recent years. The existing distributed algorithms for target tracking using mobile sensor networks are extremely limited to a few instances. Information driven flocking algorithm is effectively applicable to track both a linear and a nonlinear maneuverable target.

#### V. Fusion

The paper [10], address the problem of optimizing the detection performance of sensor networks under communication constraints on the common access channel. It helps to understand tradeoffs between sensor network parameters like number of sensors, degree of quantization at each local sensor and Signal to Noise Ratio(SNR).

Distributed fusion is conceptually more complex and the required bandwidth is also higher. Decentralized Kalman Filters are often used in multisensor target tracking as such a distributed fusion architecture has several advantages compared with centralized ones[19].

In [4], each node in a WSN has complete information about the parameter being sensed. This is in contrast to the snapshot aggregation, where the sensed parameter are aggregated at the intermediate nodes till the final aggregated result reaches the root. Each node in this algorithm, instead of unicasting its sensed information to its parent, broadcasts its estimate to all its neighbors. This makes the protocol more fault tolerant and increases the information availability in the network. This is an energy efficient aggregation algorithm for WSNs that is secure and

robust against malicious insider attack by any compromised or faulty node in the network.

A sensor network optimization method is given in [25]. Long communication distances between sensors and a sink in a sensor network can greatly drain the energy of sensors and reduce the lifetime of a network. By clustering a sensor network into a number of independent clusters using a Genetic Algorithm. Transfer Energy(E) represents the energy consumed to transfer the aggregated message from the cluster to the sink. For a cluster with 'm' member nodes, cluster transfer energy is defined as,

$$E = \sum_{i=1}^m TE_{CHi} + ((m-1) \cdot TE_{CHs})$$

The first term of Equation (TE) shows the energy consumed to transmit messages from m member nodes to the cluster head. The second term ((m-1)\*ER) shows the energy consumed by the cluster head to receive m messages from the member nodes. Finally, the third term (TE) represents the energy needed to transmit from the cluster head to the sink.

#### VI. Localization

Node localization refers to creating location awareness in deployed nodes. Location information is used in geometric aware routing. Wireless sensor networks are widely adopted in many location sensitive applications including disaster management, Environmental monitoring, Military applications where the precise estimation of each node position is inevitably important when the absolute positions of a relatively small portion as anchor nodes of the underlying network were predetermined. Localization is an unconstrained optimization problem based on various distance or path measures.

Most of the existing localization methods focus on using different heuristic based or mathematical techniques to increase the precision in position estimation. However, there were recent studies showing that nature-inspired algorithms like the Ant-based or Genetic algorithms can effectively solve many complex optimization problems. In many applications, sensors have to know their geographical locations. Global Positioning System(GPS) can be used for a sensor to locate itself. In reality, it is not practical to use GPS in every sensor node because a sensor network consists of thousands of nodes and GPS becomes very costly. To solve the problem, many localization methods have been developed. Instead of requiring every node to have GPS installed, all localization methods assume only few nodes( $\geq 3$ ) are equipped with GPS hardware. These nodes are called anchor or beacon nodes and they know their positions without communicating with other nodes, other normal sensors then obtain distance information

through talking to each other and derive their positions based on the information. A good localization protocol should reduce the error in position estimation by using reasonable number of messages. Most of the existing works focus on increasing the accuracy in *position estimation* by using different mathematical techniques such as triangulation, multi lateration, multidimensional scaling, convex optimization etc. In these methods information provided by every anchor node is used without considering the position of that anchor. There is only limited research on studying the significance of anchor nodes selection, particularly for localization algorithms in anisotropic sensor networks. A network is isotropic if measurements in all directions are exhibiting the same properties; otherwise it is anisotropic.[13]

Many applications and communication protocols of the WSNs are based on the location information of sensor nodes. Therefore, how to get the location knowledge of sensor nodes based on limited resources is an important issue for WSNs. The location estimation algorithm for WSNs can be categorized as range based and range free schemes [17]. The range based scheme determines the distance between two different sensor nodes based on a variety of information such as Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA) or Received Signal Strength Indicator (RSSI). After the distance has been determined, the location can be estimated according to the distance information. The estimation of the above technologies can be affected by multipath and noise. Moreover these schemes often need to equip with additional hardware. Consequently range based schemes are impractical solutions for a resource limited WSNs.

Because of the drawbacks of range based schemes, many range free solutions of the positioning system are presented: based on the concept of distance vector routing, Convex Position Estimation Algorithm, Point In Triangulation (PIT) scheme. To improve centralized algorithm, a Distributed location estimation algorithm is proposed. It has a better scalability. In some applications, mobile beacon nodes are dispatched to improve the accuracy of localization. In [17], each normal node gathers the nearby beacon node's locations and then estimates its own location.

A distributed sensor positioning method based on multidimensional scaling is proposed in [30], to get the accurate position estimation and reduce error cumulation. Comparing to other positioning methods with very few anchors, it can accurately estimate the sensor's positions in network with anisotropic topology and complex terrain as well as eliminate measurement error cumulation. Also propose an on demand position estimation method based

on multidimensional scaling for one or more adjacent sensors positioning.

In [29], a short survey of the localization strategies and systems using global optimization method is presented.

## VII. Node Deployment

WSN deployment problem refers to determining positions for sensor nodes or base stations such that the desired coverage, connectivity and energy efficiency can be achieved with as few nodes as possible. In most applications a random deployment is required and sensor nodes usually scatter from an aircraft. In this deployment method sensor density is not equal in different places so some places could not be covered because of lack of sensor nodes in that place. These uncovered areas are called coverage holes which must be covered.

The coverage is one of the most important problems in Wireless Sensor networks. The design criterions for coverage techniques are, Deployment Strategy(deterministic Vs random grid based), Sensing model(Boolean, probabilistic), Sensing area(depending on sensing model), sensor mobility, Algorithm characteristics(Centralized, distributed)[26].

There are different strategies for solving coverage problem which are categorized into 3 groups based on the approaches used, namely *force based*, *grid based*, and *computational geometry based*. Force based strategies use attraction and repulsion forces to determine the optimal position of the sensors. Grid based strategies use grid points for determining the optimal position of the sensors. As for the computational geometry approach, voronoi diagram and Delaunay triangulation are commonly used in WSN coverage optimization algorithm. Coverage can be classified into three classes; Area coverage, Point coverage and Barrier(Path) coverage. Area coverage is on how to cover an area with the sensors, Point coverage deals with coverage for a set of points interest. Decreasing the probability of undetected penetration is the main issue in barrier coverage. In [14], area coverage is used, where the objective is to maximize the coverage percentage. Existence of coverage holes are very important in WSN and must be covered to increase QoS and the accuracy. Many researches exist that try to cover these holes. Most of the researches consider the network to be mobile or hybrid. Most of the nodes in hybrid network are stationary and there are few mobile nodes. The main objective of using mobile sensor nodes is to heal coverage holes after the initial network deployment, such that the area coverage can be maximized while incurring the least moving cost.

When designing a hole healing algorithm, the following issues need to be addressed. First, how to

distinguish the existence of a coverage hole and how to estimate the size of a hole. Second, what are the best target locations to relocate mobile nodes to repair coverage holes. Third, how to dispatch mobile nodes to the target locations while minimizing the moving and messaging cost.

A good coverage should minimize the overlap among the ranges of the clusters and cover all the sensors deployed within the monitored region. Minimum overlap among clusters is also desirable for energy efficiency

because it reduces the number of cluster heads in the network and improves the efficiency of algorithms such as data aggregation and routing executed at the cluster heads. A Distributed Energy Efficient Clustering with Improved Coverage (DEECIC) distributed clustering algorithm is proposed in [27], that considers both energy and topological features of sensor network.

TABLE 1  
 SUMMARY OF DISTRIBUTED ESTIMATION ALGORITHMS IN WSN

Task of distributed estimation	Criterion	Algorithm	Ref .	Centralized/ Distributed	Study
Scheduling of sensors to alternate between active and inactive nodes	Full coverage, Max. lifetime, min.energy consumption	Memetic Algorithm(MA)	[37]	Distributed	Simulation
Localize nodes	Min. estimation error	Micro Genetic Algorithm	[38] [13]	Distributed	Simulation
Tracking of a single target	Min. estimation error	Kalman consensus filtering(KCF)	[7]	Distributed	Simulation
Noise corrupted deterministic parameter estimation	Min.MSE	Optimal/quasi optimal rate constrained distributed estimation Algm.	[3] [6] [18]	Distributed	Simulation
Data aggregation	Reduce communication overhead	Covariance Intersection(CI) Algm.	[4]	Distributed	Simulation
Source localization	Fast convergence	APSO-EML DOA	[11]	Distributed	Simulation
Node placement	Reduce communication & computation cost	Distributed location estimation Algm.(DLE)	[17]	Distributed	Simulation
Max. value estimation	Fast convergence	RANDOM GOSSIP&BROADCAST	[22]	Distributed	Simulation
Adaptive estimation to deal with noisy sensors	Limits communication overhead	Incremental Distributed least mean square(IDLMS)	[23]	Distributed	Simulation
Sensor data compression	Reduced power and Bandwidth	Reduced dimensionality	[24]	Distributed	Simulation
Clustering	Prolong network lifetime and improve network coverage	DEECIC(Distributed Energy-Efficient Clustering with improved Coverage)	[27]	Distributed	Simulation

### VIII. Conclusions and Future direction

A Wireless Sensor Network (WSN) is a network of distributed autonomous devices that can sense or monitor physical or environmental conditions cooperatively, each

with finite battery lifetime and thus limited computing and communication capabilities. WSNs are capable of collecting an enormous amount of data over space and time. Often the ultimate objective is to derive an estimate of a parameter or function (eg.source localization, spatial

distributions) from these data. This paper gives a brief survey of various distributed estimation algorithms applied to address the WSN issues like optimal design, node localization, data aggregation, clustering, node deployment, and target tracking.

Future works include, development of robust, accurate and scalable location system is still a challenging task. Investigate localization problems for mobile sensors in wireless ad-hoc sensor networks. The investigation of the Memetic Algorithm approach and its possible use in other applications of genetic algorithms needs further research and can lead to the development of more advanced memetic algorithm. Extends the coverage algorithms in large scale networks with mobile nodes and the fault tolerant management in the WSNs to be consider. For the rate constrained distributed estimation assuming noises among different sensors are correlated and the channels from the local sensors to the fusion center are not error free. Designing an integrated approach towards development of a data aggregation model that combines several important issues such as security, processing overhead, communication overhead, energy consumption and data compression rate and also the applicability of the work to multi-sink scenarios.

WSN issues such as node deployment, localization, energy-aware clustering and data aggregation are often formulated as optimization problems. Bio inspired optimization methods are computationally efficient alternatives to analytical methods. So we can make use of this algorithm.

## References:

### References:

[1] I.Akyildiz, W.Su, Y.Sankarasubramaniam, E.Cayirci, "A survey on sensor networks", *IEEE Commun.mag.*, vol 40,no.8,pp.102-114.  
[2] Jin- Jun Xiao, Alejandro Ribeiro, Zhi-Quan Luo, and Georgios B.Giannakis, " Distributed Compression-Estimation Using Wireless Sensor Networks", *IEEE Signal Processing Magazine*, pp.27-41, July 2006.  
[3] Junlin Li and Ghassan AlRegib, "Rate Constrained Distributed Estimation in Wireless Sensor Networks", *IEEE Transactions on Signal processing*, Vol.55,No.5,May 2007,pp.1634-1643.  
[4] Jaydip Sen,"A Robust and Secure Aggregation Protocol for Wireless Sensor Networks", *Sixth IEEE International Symposium on Electronic Design, Test and Application*,pp.222- 227, 2011.  
[5] Ioannis D.Schizas, Alejandro Riberiro, and Georgios B.Giannakis " Distributed estimation with Ad Hoc Wireless sensor networks", *14th European Signal Processing Conference, EUSIPCO 2006*

[6]Junlin Li and Ghassan AlRegib, "Distributed Estimation in Energy-Constrained Wireless Sensor Networks", *IEEE Transactions on Signal processing*, Vol.57,No.10,Oct. 2009,pp.3746-3758.  
[7] Reza olfati-Saber and Parisa Jalalkamali," Coupled Distributed Estimation and Control for Mobile Sensor Networks",*IEEE Transactions on Automatic Control*,Vol.57,No.9,Sep.2012.  
[8] Ondrej Hlinka and Franz Hlawatsch," Time-Space-Sequential Algorithms for Distributed Bayesian State Estimation in Serial sensor networks", in Proc.*IEEE ICASS*, 2009,pp.2057- 2060.  
[9] Bo Yuan, Maria Orlowska,Shazia Sadiq," Extending a class of continuous estimation of distribution algorithms to dynamic problems",*Springer-Verlag* 2007.  
[10] Saeed A.Aldosari, Jose M.F.Moura," Fusion in Sensor Networks with communication Constraints",*IPSN'04, April 26-27,2004,ACM*,pp 108-115.  
[11] Trilochan Panigrahi,A D Hanumantharao, Ganapati Panda, Babita Majhi and Bernard Mulgrew," Maximum Likelihood DOA Estimation in Distributed Wireless Sensor Network Using Adaptive Particle Swarm Optimization", *ICCCS 2011*: 134-137  
[12] Michael Rabbat and Robert Nowak," Distibuted Optimization in Sensor Networks", *Journal on Wireless Communications and Networking*, 2010, pp 1-12  
[13] Vincent Tam,King-Yip cheng and King-Shan Lui,"Using Micro-Genetic Algorithms to Improve Localization in Wireless Sensor Networks",*Journal of Communications*,Vol.1 No.4,July 2006.  
[14] Naeim Rahmani,Farhad Nematry,Amir Masoud rahmani and Mehdi Hosseinzadeh,"Node Placement for Maximum Coverage Based on Voronoi Diagram Using Genetic Algorithm in Wireless Sensor Networks",*Australian Journal of Basic and Applied Sciences*,5(12):3221-3232,2011.  
[15] Veronique Delouille,Ramesh "Neelsh" Neelamani and richard G.Baraniuk,"Robust Distributed Estimation Using the Embedded Subgraphs Algorithm",*IEEE Transactions on Signal processing*, Vol.54,No.8,August 2006.  
[16] Amir Rastegarnia,Mohammad Ali Tinati and Azam Khalili,"A Diffusion Least-Mean Square Algorithm for Distibuted Estimation over Wireless Sensor Networks",*World Academy of Science,Engineering and technology*, 21, 2008, pp.580-584.  
[17] Jang-Ping Sheu,Jian-Ming Li and Chih-Shun Hsu," A Distibuted Location Estimating Algorithm for Wireless Sensor Networks",Proc.of the *IEEE International Conference on Sensor Networks, Ubiquitous and Trustworthy Computing*,2006,  
[18] Amir rastegarnia, Mohammad Ali Tinati, Behzad Mozaffari,and Azam Khalili,"A Localized Recursive estimation Algorithm for vector Parameter estimation in Ad Hoc wireless Sensor Networks",*Journal of Electrical Engineering*,vol.61,No.3,2010,pp 171-176.  
[19]Markus S. Schlosser and Kristian Kroschel,"Communication Issues in Decentralized Kalman Filters", *Information Fusion* 2004.  
[20]Ioannis D.Schizas, and Georgios B.Giannakis"Consensus-Based Distributed estimation of Random Signals with Wireless sensor networks", Asilomar Conference on Signals, Systems & Computers - ASILOMAR , pp. 530-534, 2006  
[21] Alberto Speranzon,Carlo Fischione, Bjorn Johansson and Karl Henrik Johansson,"Adaptive Distibuted Estimation over Wireless Sensor Networks with Packet Losses", 46th IEEE Conference on Decision and Control, 2007, 5472 - 5477  
[22] Frank Iutzeler, Jeremie Jakubowicz,Walid hachem and Philippe Ciblat, "Distributed estimation of the maximum value over a Wireless sensor network", forty-fifth AsilomAr ConferenCe on signAls, systems & Computers, 2011

- [23] Amir Rastegarnia, Mohammad Ali Tinati, and Azam Khalili, "Distributed estimation using an Improved Incremental Distributed LMS Algorithm", *World Academy of Science, Engineering and technology*, 35, 2009.
- [24] Ioannis D. Schizas, Georgios B. Giannakis and Zhi-Quan Luo, "Distributed estimation Using Reduced Dimensionality Sensor Observations", *Thirty-Ninth Asilomar Conference on Signals, Systems and Computers*, 2005, pp -1029 - 1033
- [25] Ehsan Heidari and Ali Movaghar, "An Efficient method based on Genetic Algorithms to solve Sensor network optimization problem", *International journal on applications of graph theory in Wireless adhoc networks and sensor networks (GRAPH-HOC)* Vol.3.No.1. March 2011
- [26] Parveen kumari, Yudhvir Singh, Yogesh Chaba, and Prabha Rani, "Coverage techniques and Algorithms used in Wireless Sensor network", *International journal of Computer Applications*, 2011.
- [27] Zhixin Liu, Qingchao Zheng, Liang Xue, Xinpeng Guan, "A Distributed energy-efficient clustering algorithm with improved coverage in Wireless sensor network", *Future generation Computer Systems* 28(2012) 780-790.
- [28] Konstantinos P. Ferentinos, Theodore A. Tsiligiridis, "A memetic algorithm for optimal dynamic design of wireless sensor networks", *Computer Communications* (2009);.
- [29] Ewa Niewiadomska-Szynkiewicz, Michal Marks, and Mariusa Kamola, "Localization in Wireless sensor networks using heuristic optimization techniques", *Journal of telecomm and Info.tech.* 4/2011 pp.55-64
- [30] Xiang Ji, Hongyuan Zha, "Sensor positioning in Wireless Ad-hoc Sensor Networks using Multidimensional Scaling", *IEEE INFOCOM* 2004.
- [31] David L Hall and James L. Lians, "An Introduction to Multisensor Data Fusion", *proceedings of the IEEE*, vol.85, no.1, January 1997.
- [32] Vincent Tam, King-Yip Cheng and King-Shan Lui, "Improving Localization in wireless Sensor Networks with an Evolutionary Algorithm",
- [33] Chuan-Kang Ting, Chien-Chih Liao, "A memetic algorithm for extending wireless sensor network lifetime", *Information Sciences* 180(2010) 4818-4833.
- [34] Alberto Speranzon, Carlo Fischione, and Karl Henrik Johansson, "A distributed estimation algorithm for tracking over WSNs" *Proceedings of the 45th IEEE Conference on Decision & Control*, December 13-15, 2006.
- [35] Raghavendra V. Kulkarni, Anna Forster, Ganesh Kumar Venayagamoorthy, "Computational Intelligence in Wireless Sensor Networks: A Survey", *IEEE Communications Surveys & Tutorials*, volume 13, issue 1, 2011.
- [36] Junfang, Hongbin Li, "Distributed Estimation of Gauss Markov Random fields with one bit Quantized data", *IEEE signal processing letters*, Vol.17, No.5, May 2010.
- [37] S. Faisal Alishah, Alejandro Ribeiro, G.B. Giannakis, "Bandwidth constrained MAP estimation for wireless sensor networks", *IEEE*, 2005, pp-215-219
- [38] Alejandro Ribeiro, Georgios B. Giannakis, "Bandwidth constrained Distributed estimation for wireless sensor networks part I - Gaussian Case", *IEEE TRANSACTIONS ON SIGNAL PROCESSING*, VOL. 54, NO. 3, MARCH 2006, pp-1131-1143
- [39] Yasamin Mostofi, Richard M. Murray, "Distributed Sensing and estimation under communication constraints", *45th IEEE Conference on Decision and Control*, 2006, 1013 - 1018
- [40] Jiri Ajgl, Miroslav Simandl, Jindrich Dunik, "Millman's formula in data fusion", *Proceedings of the 10th International PhD Workshop on Systems and Control*, p. 1-6, Institute of Information Theory and Automation AS CR, Hluboká nad Vltavou, 2009.