

# We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

6,900

Open access books available

186,000

International authors and editors

200M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index  
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?  
Contact [book.department@intechopen.com](mailto:book.department@intechopen.com)

Numbers displayed above are based on latest data collected.  
For more information visit [www.intechopen.com](http://www.intechopen.com)



# Target Tracking in Wireless Sensor Networks

Jianxun LI\* and Yan ZHOU\*\*,\*

\* *Department of Automation, Shanghai Jiao Tong University, Shanghai 200240, China*

\*\* *College of Information Engineering, Xiangtan University, Xiangtan 411105, China*

## 1. Introduction

Wireless sensor networks (WSNs) have gained worldwide attention in recent years, particularly with the proliferation in Micro-Electro-Mechanical Systems (MEMS) technology which has facilitated the development of smart sensors (Akyildiz et al., 2006; Akyildiz et al., 2007; Yick et al., 2008). Target tracking in WSNs is an important problem with a large spectrum of applications (Akyildiz et al., 2006; Zhao et al., 2002), such as surveillance (Valera & Velastin, 2005), natural disaster relief (Wang et al., 2003), traffic monitoring (Li et al., 2009), pursuit evasion games, etc.

### 1.1 Opportunities and challenges

A target tracking system through WSNs can have several advantages (Veeravalli & Chamberland, 2007): (i) qualitative and fidelity observations; (ii) signal processing accurately and timely; and (iii) increased system robustness and tracking accuracy. However, the use of sensor networks for target tracking presents a number of new challenges. These challenges include limited energy supply and communication bandwidth, distributed algorithms and control, and handling the fundamental performance limits of sensor nodes, especially as the size of the network becomes large. Unlike traditional networks, a WSN has its own design and resource constraints. Resource constraints include a limited amount of energy, short communication range, low bandwidth, and limited processing and storage in each node. Design constraints are application dependent and are based on the monitored environment. The environment plays a key role in determining the size of the network, the deployment scheme, and the network topology.

Power consumption is the most important design factor for WSNs (Shorey et al., 2006). Commonly, saving power during the operation of the electronic device could be achieved on more than one protocol level. Plenty of research work is dedicated to the design of power efficient schemes for target tracking which try to explore good trade-off between power consumption and tracking accuracy (see e.g. Lee et al. 2007; Xu & Lee, 2003; Walchli et al., 2007; Tsai et al., 2007, and the references therein).

Besides, the traditional target tracking methodologies make use of a centralized approach. As the number of sensors rise in the network, more messages are passed on towards the sink and will consume additional bandwidth. Thus traditional approaches are not fault tolerant as there is single point of failure and does not scale well. However, in sensor networks,

hundreds, and in the extreme, hundreds of thousands of sensors are deployed in a large geographical area. In some cases dropped from airplanes, or deployed using artillery shells. Requiring that every node must work in order for the network to operate is difficult to achieve. The network must have a high level of fault tolerance in order to be of any practical value (Hoblos et al., 2000).

In a word, target tracking algorithm considering the tradeoff between the tracking accuracy and network resources such as energy, bandwidth, and communication/computation burden is challenging.

## **1.2 Contributions and chapter organization**

In this chapter, a self-contained overview of tracking approaches through a WSN is given according the architecture of the networks. As can be seen soon, WSNs are typically classified into two main categories (Sohraby et al., 2006): hierarchical network and peer-to-peer network. For the former, naïve, tree, cluster, and hybrid network based methods are reviewed in detail. While for the latter, average consensus is usually adopted to achieve network-wide agreement on target estimate and two approaches commonly used including the dynamic consensus filter and alternating direction method. Then advantage and limitations of these approaches are compared.

Considering the stringent energy and bandwidth limitation, quantized messages based tracking method is discussed separately. Local data quantization/compression is usually adopted so as to reduce the required expenditure of resources. Then the signal processing unit, i.e. the fusion center (FC), or cluster head (CH), or any node in the network, combines the quantized messages from local sensors to produce a final estimation of the target state. In the quantized scenario, Shannon's "rate-distortion" bound that notionally is a curve of possible and impossible points on distortion (e.g. MSE versus bit-rate axes) is important and practical. In the literature, target tracking algorithms using quantized information can be categorized to mainly quantized measurement based and quantized innovation based tracking. Both categories will be overview in tail with the characteristics discussed.

The remainder of this chapter is organized as follows. Section 2 gives a taxonomy on target tracking approaches through a WSN. In Section 3, details of target tracking approaches in hierarchical network are highlighted focusing on: naïve activation based tracking, tree-based tracking methods, cluster-based tracking approaches, and hybrid tracking methods. In Section 4, target tracking in peer-to-peer sensor networks are reviewed with both embedded filter based consensus and alternating direction based consensus methods discussed. Comparison criteria are given in Section 5 and the methods aforementioned are compared. Section 6 discusses the methods based on quantized information in detail, which followed by Section 7 that gives the future research directions and concluding remarks.

## **2. A taxonomy on tracking methods**

In the literature, various algorithms and approaches for target tracking are presented but there is a deficiency of well defined classification of solutions of this well known application of WSN. This chapter presents a taxonomy of target tracking approaches as well as discussing each method under the appropriate category.

The taxonomy on the tracking techniques presented is based on the network architecture. In this chapter, we classify the WSNs into two categories (Veeravalli & Chamberland, 2007):

hierarchical (category 1 WSNs) and peer-to-peer (category 2 WSNs). For the category 1 WSNs (see Fig. 1 (a)), almost invariably mesh-based systems with multihop radio connectivity among or between wireless nodes are employed. The sensors in the vicinity of an event must be able to monitor the event of interest and report back to the sink. A sink sensor node has capability to communicate with outside world such as laptop, base station. The important characterizations of the category 1 WSNs are that (i) sensor nodes can support communications on behalf of other sensor nodes by acting as repeaters; (ii) the forwarding node can support data processing or information fusion on behalf of the sensor nodes. The category 2 WSNs (see Fig. 1 (b)), which are also referred as flat, or point-to-point network, generally are with single-hop radio connectivity to wireless nodes utilizing static routing over the wireless network. The main features of the category 2 WSNs are that (i) the forwarding node only supports static routing; (ii) each node only communicates with its neighbouring node(s) and network-wide consensus can be achieved through information exchange between neighbours.

As illustrated in Fig. 2, we taxonomize the tracking algorithms into two aspects according to the aforementioned two categories of network architecture. One is hierarchical network based tracking, the other is peer-to-peer network based tracking. The former can be further classified into four schemes, which are: Naïve activation based tracking, tree-based tracking, cluster-based tracking, and hybrid methods. In tree-based target tracking, nodes in a network may be organized in a hierarchical tree or represented as a graph in which vertices represent sensor nodes and edges are links between nodes that can directly communicate with each other.

The cluster-based methods provide scalability and better usage of bandwidth than other types of methods. If CH is formed via local network processing, extra messages are reduced and fewer messages are transmitted towards base station thus providing security as well as less usage of bandwidth (Rapaka & Madria, 2007). In the conventional cluster architecture, clusters are formed statistically at the time of network deployment and the properties of each cluster are fixed such as number of members, area covered, etc. Static clustering has several drawbacks regardless of its simplicity, for example, static membership is not robust

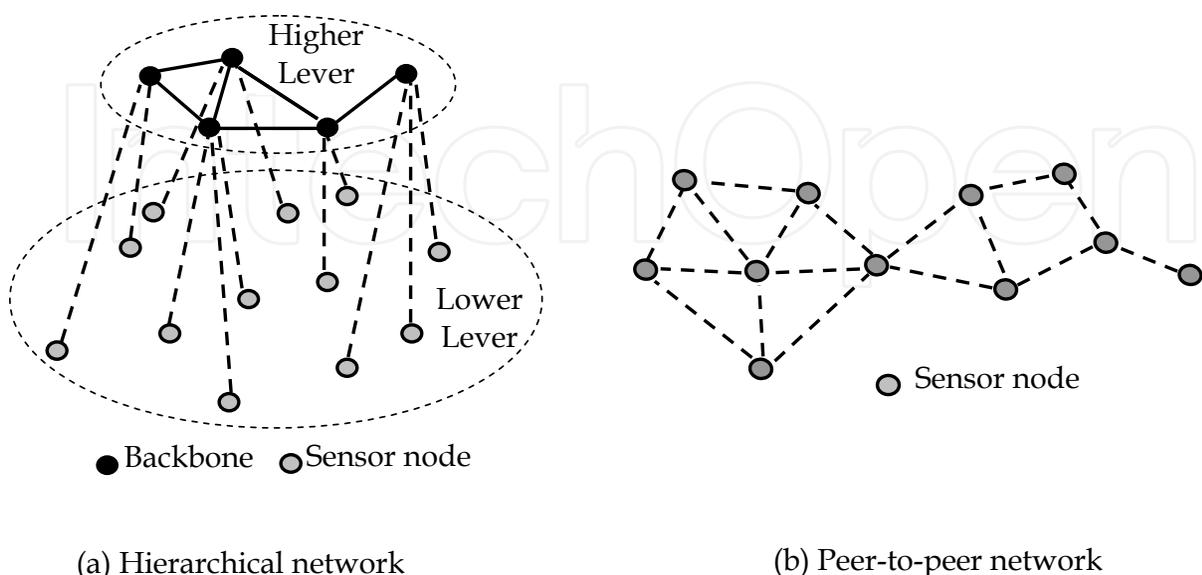


Fig. 1. Architecture of wireless sensor networks

from fault-tolerance point of view and it prevents sensor in different clusters from sharing information. In contrast, dynamic clustering offers several advantages where clusters are formed dynamically depending on occurrence of certain events, for instance, when a node with sufficient battery and computational power detects an event, it comes forward to act as a CH. To make sure only one CH remains active for target tracking, some decentralized mechanism is adapted. The CH invites nearby sensor nodes and makes them members of that cluster. Since sensors don't statistically form a cluster, they may belong to altered cluster at different timings. As only one cluster is active at a time, redundant data and interference is reduced.

According to the methods approaching consensus, the peer-to-peer networks based target tracking systems can be further classified into embedded filter based tracking and alternating-direction based tracking. Since network-wide consensus can be achieved through only information exchange between neighbours, considerable communication energy is reduced and this makes the peer-to-peer networks based tracking scalable for large-scale sensor network.

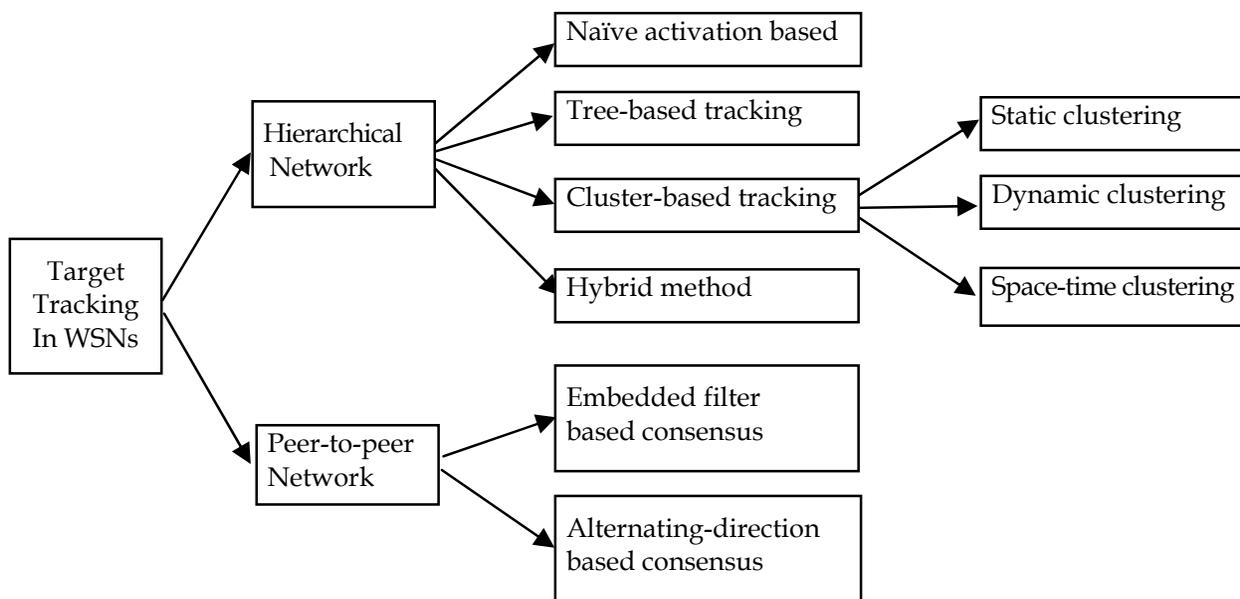


Fig. 2. Taxonomy of target tracking algorithms in WSNs.

### 3. Tracking methods for hierarchical networks

#### 3.1 Naïve activation based tracking

Naïve activation (or direct communication) based tracking scheme (Guo et al., 2003) is the simplest approach, for which all nodes are in tracking mode all the time. Each node sends the local measurement to the sink node or base station. Then the base station estimates and predicts the target state according to the received local measurements. Since it offers the best tracking results, it is a useful baseline for comparison. However, this strategy offers the worst energy efficiency and it inflicts heavy communication and computation burden on the base station or sink node. This makes the naïve approach not robust against base station failure especially for the case of link failure and channel congestion.

### 3.2 Tree-based tracking

Centralized target tracking approaches are both time and energy consuming, to avoid this limitation tree-based tracking methods are proposed, for example, Scalable Tracking Using Networked sensors (STUN) (Kung & Vlah, 2003), Dynamic Convoy Tree-Based Collaboration (DCTC) (Zhang & Cao, 2004a; Zhang & Cao, 2004b), Deviation Avoidance Tree (DAT) (Lin et al., 2004), and Dynamic Object Tracking (DOT) approach (Tsai et al., 2007).

Specifically, STUN (Kung & Vlah, 2003) is a tree-based approach in which a cost is assigned to each link calculated by Euclidean distance between the two nodes. The leaf nodes are used for tracking the moving object and then sending collected data to the sink through intermediate nodes. The intermediate nodes keep a record of detected object and whenever there is a change in that record, they send updated information to the sink. However, STUN has two drawbacks. First, drain and balance tree does not replicate physical sensor network as it is a logical tree, hence an edge may consist of multiple communication hops and may raise communication cost. Second, the construction of DAB tree does not consider query cost.

In (Zhang & Cao, 2004a; Zhang & Cao, 2004b), a spanning tree rooted at the sensor node close to a target is used for target tracking, with the target position estimated by the location of the root sensor. More statistically-oriented algorithms for mobile target identification and localization are proposed therein, which allows the designer to directly model the distributional properties of sensor signals.

A network aggregation model by organizing sensor nodes in logical tree is intended in (Lin et al., 2004). As physical topology of the network is considered, thus reducing the total communication cost. The object tracking involves two steps: update and query. In first step; location update cost is reduced by Deviation Avoidance Tree (DAT) algorithm and in second step; query cost is reduced by query cost reduction algorithm.

DOT (Tsai et al., 2007), a unique protocol reports the tracking information of moving object to moving source. First of all, the face neighbours are identified by Gabriel graph. In target discovery step, source sends request to sensor nodes and the node close to the target replies back. To detect moving target continuously, the spatial neighbours of near sensor node are waken up. In target tracking step, source send query to beacon node (node keeping track information), which reply back target's next location and the source moves towards next beacon node. The process is repeated until the source catches the target.

Lin et al. propose a CLOUD framework to track the region-based event (Lin et al., 2005). The basic idea is to dynamically form a tree-based collective structure for each event region in each time slot. However, both of their approaches in (Lin et al., 2005; Jiang et al., 2004) are limited by the dependence on the tree structure for the network topology.

In (Jin & Nittel, 2006), an R-tree sensor network topology is adopted for the detection and tracking of region-based targets. Two approaches: forward-all and forward-description methods are proposed for the detection of event regions. Furthermore, the authors describe three detailed algorithms: boundary detection algorithm, merging algorithm and description improvement algorithm to deal with the problems of how to detect an event boundary, how to merge the event region obtained from the child nodes in the R-tree, and how to simplify and smooth the event boundary.

### **3.3 Cluster-based tracking**

To facilitate collaborative data processing in target tracking-centric sensor networks, the cluster architecture is usually used in which sensors are organized into clusters, with each cluster consisting of a CH and several slave nodes (members). Hierarchical (clustering) techniques can aid in reducing useful energy consumption (Heinzelman et al., 2002). Clustering is particularly useful for applications that require scalability to hundreds or thousands of nodes. Scalability in this context implies the need for load balancing and efficient resource utilization. Clustering can be extremely effective in one-to-many, many-to-one, one-to-any, or one-to-all (broadcast) communication. For example, in many-to-one communication, clustering can support data fusion and reduce communication interference (Younis & Fahmy, 2004).

#### **3.3.1 Static clustering**

Conventionally, clusters are formed statically at the time of network deployment. The attributes of each cluster, such as the size of a cluster, the area it covers, and the members it possesses, are static. In spite of its simplicity, the static cluster architecture suffers from several drawbacks. First, fixed membership is not robust from the perspective of fault tolerance. If a CH dies of power depletion, all the sensors in the cluster render useless. Second, fixed membership prevents sensor nodes in different clusters from sharing information and collaborating on data processing. Finally, fixed membership cannot adapt to highly dynamic scenarios in which sensors in the region of high (low) event concentration may be instrumented to stay awake (go to sleep).

#### **3.3.2 Dynamic clustering**

Dynamic cluster architectures, on the other hand, offer several desirable features (Chen et al., 2003). Formation of a cluster is triggered by certain events of interest (e.g., detection of an approaching target with acoustic sounds). When a sensor with sufficient battery and computational power detects (with a high signal-to-noise ratio, SNR) signals of interest, it volunteers to act as a CH. No explicit leader (CH) election is required and, hence, no excessive message exchanges are incurred. As more than one “powerful” sensors may detect the signal, multiple volunteers may exist. A judicious, decentralized approach has to be applied to ensure that only one CH is active in the vicinity of a target to be tracked with high probability. Sensors in the vicinity of the active CH are “invited” to become members of the cluster and report their measurements to the CH. Compared with the static clustering approaches, dynamic clustering networked sensors do not statically belong to a cluster and may support different clusters at different times. Moreover, as only one cluster is active in the vicinity of a target with high probability, redundant data is suppressed and potential interference and contention at the MAC level is mitigated.

Examples of dynamic cluster-based tracking are information-driven sensor querying (IDSQ) (Zhao et al., 2002), DELTA (Walchli et al., 2007), and RARE (Olule et al., 2007).

Zhao et al. addressed the dynamic sensor collaboration problem in distributed tracking to determine dynamically which sensor is most appropriate to perform the sensing, what needs to be sensed, and to whom to communicate the information (Zhao et al., 2002). They developed the IDSQ approach, enabling collaboration based on resource constraints and the cost of transmitting information. Information utility functions employed include entropy,

Mahalanobis distance, and a measure on expected posterior distribution. This approach assumes that each node in the network can locally estimate the cost of sensing, processing and communicating data to another node. Although the approach is power efficient (since only few nodes are active at any given time), it is applied for tracking a single object only.

Walchli et al. present DELTA (Walchli et al., 2007), a distributive algorithm for tracking a person moving at constant speed by dynamically making a cluster and selecting CH based on light measurement. The CH is responsible to reliably monitor moving object and collaborate with sensor nodes. The limitation of DELTA algorithm is that it can only deal with constant speed, whereas, varying speed is not considered.

Energy aware probabilistic target localization algorithm for a single target using cluster-based WSN is proposed in (Zou & Chakrabarty, 2003), where a two step protocol for communication between CH and sensors in the cluster is put forward. In the first step, sensors detecting the target report to the CH by a short message. Then the CH executes localization procedure to determine the subset of sensors in the vicinity of target and query detailed target information from them.

Olule et al. investigate an energy efficient target tracking protocol based on two algorithms, ARE-Area (Reduced Area Reporting) and RARE-Node (Reduction of Active node Redundancy) via static clustering (Olule et al., 2007). RARE-Area reduces number of nodes participating in tracking by inhibiting far away nodes from taking part in tracking. RARE-node reduces redundant information by identifying overlapping sensors. Cluster is formed dynamically by prediction during target tracking (Jin et al., 2006), thus reducing number of nodes involved in tracking. Although the method consumes low energy, the missing target recovery procedure is not well defined.

Quantized measurements are usually adopted in such a network to attack the problem of limited power supply and communication bandwidth. Very recently, the problem of target tracking in a WSN that consists of randomly distributed range-only sensors is considered in (Zhou et al., 2010). The posterior Cramér-Rao lower bounds (CRLB) on the mean squared error (MSE) on target tracking with quantized range-only measurements are derived. Due to the analytical difficulties, particle filter is applied to approximate the theoretical bounds. In this paper, recursion of posterior CRLB on tracking based on both constant velocity (CV) and constant acceleration (CA) model for target dynamics and a general range-only measuring model for local sensors are obtained. More details on tracking using quantized messages can be found in Section 6.

### 3.3.3 Space-time clustering

In order to present the event processing with high accuracy, Phoha et al. propose the dynamic space-time clustering (DSTC) (Phoha et al., 2003a). In this architecture, clusters of space-time neighbouring nodes are dynamically organized to present the event around by combining the local information among nodes in the inner space-time cluster. The type and track of the target then are estimated by the CH.

Phoha et al. propose two methods by combining the DSTC and beamforming: one is DSTC beamforming controlled, the other is DSTC logic controlled beamforming (Phoha et al., 2003b). The former is composed of hundreds of low-cost DSTC nodes and a few beamforming nodes, which estimate the target position through triangulation. In the case of failure of beamforming nodes, the DSTC nodes are activated to localize the target. The latter

determine a cluster to track the target according to DSTC logic, while the member nodes run the beamforming algorithm to estimate the target state.

### **3.4 Hybrid method**

Hybrid methods are referred to the tracking algorithms that fulfill the requirements of more than one types of target tracking. Examples include distributed predictive tracking (DPT) (Yang & Sikdor, 2003), DCAT (Chen et al., 2003), and Hierarchical prediction strategy (HPS) (Wang et al., 2008).

The DPT adopts a clustering based approach for scalability and a prediction based tracking mechanism to provide a distributed and energy efficient solution (Yang & Sikdor, 2003). The protocol is proven to be robust against node or prediction failures which may result in temporary loss of the target and recovers from such scenarios quickly and with very little additional energy use.

A decentralized dynamic clustering algorithm for single target tracking (Here we referred as dynamic clustering for acoustic tracking, DCAT) is proposed in (Chen et al., 2003). Using Voronoi Diagrams, clusters are formed and only one CH becomes active when the acoustic signal strength detected by CH exceeds a pre-determined threshold. The CH then asks the sensors in its vicinity to join cluster by sending a broadcast packet. The sensor based on the probabilistic distance estimates between itself and target, decides whether it should reply to CH. Afterwards, CH executes a localization method to estimate location of target based on sensor replies and sends result to the sink.

In HPS, cluster is formed using Voronoi division and a target next location is predicted via Least Square Method but overheads are not well defined. HVE protocol uses cluster structure and prediction for estimating shape and size of forwarding zone and delivering multicast messages.

A location model determines the granularity of location information and the prediction model processes the historical data to predict next movement of mobile object. An interesting example of multiple targets tracking using prediction is given in (Chong et al., 2003).

## **4. Tracking methods for peer-to-peer networks**

For the tree- or cluster-based methods, sensing task is usually performed by several nodes at a time and inflicts heavy computation burden on the root node or the CH. This makes the tree- or cluster-based WSN tracking systems lack of robustness in case of root node or the CH failures. On the contrary, another architecture for target tracking is the peer-to-peer WSN. As it can guarantee that sensors obtain the desired estimates and rely only on single-hop communications between neighbouring nodes, the limitations mentioned above are not encountered in peer-to-peer WSN based target tracking systems.

On the other hand, the well-known strategy concerning estimation and tracking is decentralized Kalman filtering or nonlinear filtering scheme, e.g. extended Kalman filtering (EKF), unscented Kalman filtering (UKF), and particle filtering (PF), which involve state estimation using a set of local filters that communicate with all other nodes (see e.g. Li & Wang, 2000; Mutambara, 1998; Vercauteren & Wang, 2005, and the references therein). The information flow in the traditional decentralized Kalman filtering (see e.g. Mutambara, 1998) or unscented Kalman filtering scheme (Vercauteren & Wang, 2005) is all-to-all with

communication complexity of  $O(N^2)$  (here  $N$  is the number of sensors in the network), which is not scalable for sensor networks (Speyer et al., 2004). On the contrary, the peer-to-peer network tracking is usually based on average consensus algorithms that have proven to be effective tools for performing network-wide distributed computation task ranging from flocking to robot rendezvous as in the papers (Olfati-Saber & Murray, 2004; Tanner et al., 2007; Kar & Moura, 2009), and the references therein. Hence, we refer this kind of methods as average consensus based tracking (AC tracking).

#### 4.1 Embedded filter based consensus

Distributed estimation using peer-to-peer WSNs is based on successive refinements of local estimates maintained at individual sensors. In a nutshell, each iteration of the algorithm comprises a communication step where the sensors interchange information with their neighbours, and an update step where each sensor uses this information to refine its local estimate. In this context, estimation of deterministic parameters in linear data models, via decentralized computation of the BLUE or the sample average estimator, was considered in (Olfati-Saber & Murray, 2004; Scherber & Papadopoulos, 2005; Xiao & Boyd, 2004) using the notion of consensus averaging. Decentralized estimation of Gaussian random parameters was reported in (Delouille et al., 2004) for stationary environments, while the dynamic case was considered in (Spanos et al., 2005).

Olfati-Saber introduces a distributed Kalman filtering (DKF) algorithm that uses dynamic consensus strategy in (Olfati-Saber, 2005; Olfati-Saber, 2007). The DKF algorithm consists of a network of micro-Kalman filters each embedded with a high-gain high-pass consensus filter (or consensus protocol). The role of consensus filters is to estimate of global information contribution using only local and neighbouring information. Recently, the problem of estimating a simpler scenario with a scalar state of a dynamical system from distributed noisy measurements based on consensus strategies is considered in (Carli et al., 2006), the focuses are with the interaction between the consensus matrix, the number of messages exchanged per sampling time, and the Kalman gain for scalar systems.

Very recently, the distributed and scalable robust filtering problem using average consensus strategy in a sensor network is investigated in (Zhou & Li, 2009a). Specifically, based on the information form robust filter, every node estimates the global average information contribution using local and neighbours' information rather than using the information from whole network. Due to the adoption of iterations of robust filter, the proposed algorithm relaxes the necessity to have the prior knowledge of the noise statistics. Moreover, the proposed algorithm is applicable to large-scale sensor network since each node broadcasts message only to its neighbouring nodes.

The aforementioned embedded filter based consensus for distributed target tracking is proposed for linear systems with Gaussian or energy bounded noises, there is little result on tracking algorithm for nonlinear dynamic systems and/or nonlinear observations. In (Zhou & Li, 2009b), a distributed scalable Sigma-Point Kalman filter (DS2PKF) is proposed for distributed target tracking in a sensor network based on the dynamic consensus strategy. The main idea is to use dynamic consensus strategy to the information form sigma-point Kalman filter (ISPKF) that derived from weighted statistical linearization perspective. Each node estimates the global average information contribution by using local and neighbours' information rather than by the information from all nodes in the network. Therefore, the proposed DSPKF algorithm is completely distributed and applicable to large-scale sensor

network. A novel dynamic consensus filter is proposed, and its asymptotical convergence performance and stability are discussed.

#### **4.2 Alternating-direction based consensus**

Alternating-direction method of multipliers (Bertsekas & Tsitsiklis, 1999) is proven to be efficient in solving the distributed estimation (Schizas et al., 2008a; Schizas et al., 2008b). Recently, decentralized estimation of random signals in arbitrary nonlinear and non-Gaussian setups was considered in (Schizas & Giannakis, 2006), while distributed estimation of stationary Markov random fields was pursued in (Dogandzic & Zhang, 2006).

Adaptive algorithms based on in-network processing of distributed observations are well-motivated for online parameter estimation and tracking of (non)stationary signals using peer-to-peer WSNs. To this end, a fully distributed least mean-square (D-LMS) algorithm is developed in (Schizas et al., 2009), offering simplicity and flexibility while solely requiring single-hop communications among sensors. The resultant estimator minimizes a pertinent squared-error cost by resorting to i) the alternating-direction method of multipliers so as to gain the desired degree of parallelization and ii) a stochastic approximation iteration to cope with the time-varying statistics of the process under consideration. Information is efficiently percolated across the WSN using a subset of “bridge” sensors, which further tradeoff communication cost for robustness to sensor failures. For a linear data model and under mild assumptions aligned with those considered in the centralized LMS, stability of the novel D-LMS algorithm is established to guarantee that local sensor estimation error norms remain bounded most of the time.

Forero et al. develop a decentralized expectation-maximization (EM) algorithm to estimate the parameters of a mixture density model for use in distributed learning tasks performed with data collected at spatially deployed wireless sensors (Forero et al., 2008). The E-step in the novel iterative scheme relies on local information available to individual sensors, while during the M-step sensors exchange information only with their single hop neighbours to reach consensus and eventually percolate the global information needed to estimate the wanted parameters across the WSN.

### **5. Analysis and comparison**

All the methods mentioned above are compared in Table 1 in terms of tracking accuracy, communicational burden, scalability, computational complexity, and fault tolerance, etc. In Table 1, we rate the method into four levels, i.e. A-D, according to the performance criterions mention above. We note that criterions, such as communicational burden, tracking accuracy and fault tolerance, are proportional to energy utilization for target tracking through WSNs. If communicational burden is high for cluster formation, more energy is consumed. High tracking accuracy demand will ultimately end with additional energy usage. Similarly fault tolerance will increase overheads and energy consumption. The total energy consumption and bandwidth usage during target tracking is the key concern in the majority of the methods since the network is with strictly limited energy and bandwidth. The energy consumption of a sensor node can be divided into three main domains, radio communication, sensing and data processing.

It is also worth pointing out that all the rating levels are relative since different methods are proposed within different network scenarios. For example, the AC tracking is mainly for the

peer-to-peer network to improve the scalability. However, the cluster-based tracking such as IDSQ is mainly for the energy consumption and the lifetime.

Method	Tracking accuracy	Scalability	Computational complexity	Communicational burden	Fault tolerance
DC	A	D	B	D	A
STUN	C	C	C	C	B
DCTC	B	C	C	B	C
DAT	D	C	C	C	C
DOT	D	C	C	C	C
R-tree	B	B	D	C	C
IDSQ	C	B	A	A	B
DELTA	C	B	B	B	B
RARE	C	B	C	B	C
DSTC	B	B	B	B	B
DPT	D	C	B	C	C
DCAT	A	C	A	C	B
HPS	C	C	B	C	C
AC tracking	B	A	B	A	A

Table 1. Comparison of target tracking methods in WSNs

## 6. Quantized scenario

In the WSN tracking system, each sensor node acquires measurements which are noisy linear or nonlinear transformations of the target state. The sensors then transmit measurements to the fusion center (for the FC-based WSNs) or the neighbouring nodes (for the distributed peer-to-peer WSNs) in order to form a state estimate. If measurements were available at a common location, minimum mean-square error (MMSE) estimates could be obtained using a Kalman filter, or nonlinear estimation methods, such as UKF and PF. However, since measurements are distributed in space and there is limited communication bandwidth, the measurements have to be quantized before transmission. Thus, the original estimation problem is transformed into decentralized state estimation based on quantized measurements. The problem is further complicated by the harsh environment typical of WSNs; see e.g., Chong & Kumar, 2003, and Culler et al., 2004.

The problem of decentralized estimation based on quantized measurements has been studied in early works such as Gubner, 1993, and Lam & Reibman, 1993. Recently, universal decentralized estimation taking into account local signal-to-noise ratio (SNR) and the channel path loss in sensor network is studied (Xiao et al., 2005). When the noise probabilistic density function (PDF) is unknown, the problem of estimation based on severely quantized data has been also addressed in (Luo, 2005).

In this section, we category the tracking methods based on quantized information into quantized measurements and quantized innovations. The latter is usually with higher accuracy when using the same quantization bit rate. It is because that the range of innovations is commonly little that causes little quantization noise.

## 6.1 Quantized measurement based tracking

Quantizing measurements to estimate a parameter of interest is not the same as quantizing a signal for later reconstruction (Gray, 2006). Instead of a reconstruction algorithm, the objective is finding, e.g., MMSE optimal, estimators using quantized observations (Papadopoulos et al., 2001; Ribeiro & Giannakis, 2006). Furthermore, optimal quantizers for reconstruction are, generally, different from optimal quantizers for estimation. State estimation using quantized observations is a nonlinear estimation problem that can be solved using e.g., EKF, UKF, or PF.

From the measurement fusion perspective, the problem for target tracking using quantized information in WSNs is investigated in (Zhou & Li, 2009c) and (Zhou et al., 2009a). Due to the limited energy and bandwidth, each activated node quantizes and then transmits the local measurements by probabilistic quantization strategy. The FC estimates the target state in a dimension compression way instead of merging all the quantized messages to a vector (augmented scheme). A closed-form solution to the optimization problem for bandwidth scheduling is given, where the total energy consumption measure is minimized subject to a constraint on the mean square error (MSE) incurred by quasi-best linear unbiased estimation (Quasi-BLUE) fusion. The results are extended to the case of tracking maneuvering target and correlation noise in (Zhou & Li, 2009d) and (Zhou et al., 2009b), respectively.

Quantizing measurements is an efficient way that gives tradeoff between the bandwidth/energy constraints and tracking accuracy. However, if the values of measurements are large, quantizing measurements will bring large information loss under the limited bandwidth, which means that the variance of the quantization noise is large. In this scenario, the quantized measurements based tracking will have a low filtering accuracy. To reduce the information loss and improve the filtering accuracy, quantized innovations based tracking has been extensively investigated recently. Since the values of innovation data are smaller than those of measured data, quantizing innovations will bring smaller information loss than quantizing measurements under the same bandwidth constraint.

## 6.2 Quantized innovation based tracking

Surprisingly, for the case where quantized observations are defined as the sign of the innovation (SOI) sequence, it is possible to derive a filter with complexity and performance very close to the clairvoyant KF based on the analog-amplitude observations (Ribeiro et al., 2006). Even though promising, the approach of (Ribeiro et al., 2006) is limited to a particular 1-bit per observation quantizer. Msechu et al. introduce two novel decentralized KF estimators based on quantized measurement innovations (Msechu et al., 2008). In the first quantization approach, the region of an observation is partitioned into contiguous, non-overlapping intervals where each partition is binary encoded using a block of bits. Analysis and Monte Carlo simulations reveal that with minimal communication overhead, the mean-square error (MSE) of a novel decentralized KF tracker based on 2-3 bits comes stunningly close to that of the clairvoyant KF. In the second quantization approach, if intersensor communications can afford bits at time  $t$ , then the  $t$ th bit is iteratively formed using the sign of the difference between the observation and its estimate based on past observations (up to time  $t-1$ ) along with previous bits (up to  $t-1$ ) of the current observation.

Recently, by optimizing the filter with respect to the quantization levels, a multiple-level quantized innovation Kalman filter (MLQ-KF) for estimation of linear dynamic stochastic systems is proposed in (You et al., 2008). Furthermore, Sukhavasi and Hassibi propose a

particle filter that approximates the optimal nonlinear filter and observe that the error covariance of the particle filter follows the modified Riccati recursion (Sukhavasi, & Hassibi, 2009).

Very recently, Zhou et al. investigate the decentralized collaborative target tracking problem in a WSN from the fusion of quantized innovations perspective (Zhou et al., 2009c). A hierarchical fusion structure with feedback from the FC to each deployed sensor is proposed for tracking a target with nonlinear Gaussian dynamics. Probabilistic quantization strategy is employed in the local sensor node to quantize the innovation. After the FC received the quantized innovations, it estimates the state of the target using the Sigma-Point Kalman Filtering (SPKF). To attack the energy/power source and communication bandwidth constraints, the tradeoff between the communication energy and the global tracking accuracy is considered in (Zhou et al., 2009d). By Lagrange multiplier, a closed-form solution to the optimization problem for bandwidth scheduling is given, where the total energy consumption measure is minimized subject to a constraint on the covariance of the quantization noises. Simulation example is given to illustrate the proposed scheme obtains average percentage of communication energy saving up to 41.5% compared with the uniform quantization, while keeping tracking accuracy very closely to the clairvoyant UKF that relies on analog-amplitude measurements. In (Ozdemir et al., 2009), a new framework for target tracking in a wireless sensor network using particle filters is proposed. Under this framework, the imperfect nature of the wireless communication channels between sensors and the FC along with some physical layer design parameters of the network are incorporated in the tracking algorithm based on particle filters. It is called "channel-aware particle filtering" that derived for different wireless channel models and receiver architectures. Furthermore, the posterior CRLBs for the proposed channel-aware particle filters are also given.

## 7. Concluding remarks and open research directions

The extensively research of target tracking through WSNs inspired us to present a literature survey. In this chapter, we have explored the categories of target tracking methods, including tree-based, cluster-based, hybrid, and consensus-based tracking algorithm. Considering the stringent limitation on energy supply, the quantized messages based tracking has been discussed separately.

The emergence of WSN in the variety of application areas brought many open issues to researchers. The open research issues for target tracking in WSNs include, channel-aware tracking, mobile node aided tracking, multitarget association & tracking, cross-layer design, and fault tolerant tracking methods, etc.

First, wireless communication channels between sensors and the FC or base station are not perfect. Incorporating the statistics of the channel imperfection to the tracking algorithm is expected to improve the tracking accuracy. Second, the scenario becomes complicated in the presence of multiple targets and their tracking with mobile sensors which leads to intend more realistic solutions. Message transmission consumes more energy than local processing, thus, well organized computing and nominal transmission of messages without degradation of performance must be considered while designing a target tracking method (Rapaka & Madria, 2007). Data association is an important problem when multiple targets are present in a small region. Each node must associate its measurements of the environment with

individual targets. Combining the track association and tracking becomes more complicated, especially in circumstance of low cost sensor network with limited computation capacity and communication bandwidth (Li et al., 2010).

Another interesting issue for target tracking is the consideration of node failure. The sensor nodes are usually deployed in harsh environments so various nodes may fail, may be attacked or node energy may be depleted due to obstacles. Therefore, fault tolerant target tracking algorithms and protocols must be designed for wireless sensor networks as the fault tolerant approaches developed for traditional wired or wireless networks are not well suited for WSN because of various differences between these networks (Ding & Cheng, 2009).

The cross-layered approach in WSN is more effective and energy efficient than in traditional layered approach. While traditional layered approach endures more transfer overhead, cross-layered approach minimizes these overhead by having data shared among layers (Melodia et al., 2006; Kwon et al., 2006; Song & Hatzinakos, 2007). In the cross-layered approach, the protocol stack is treated as a system and not individual layers, independent of each other. Layers share information from the system. The development of various protocols and services in a cross-layered approach is optimized and improved as a whole.

In last decades, the problem of decentralized information fusion has been discussed extensively in the literature. However, the algorithms developed are free of energy and communication constraints, see e.g. Sun & Deng, 2004; Li & Wang, 2000; Zhou & Li, 2008a; Zhou & Li, 2008b. Novel fusion approaches include practical constraints in WSNs while keeping high fusion performance must be investigated (Ruan et al., 2008). Moreover, tracking with adaptive quantization thresholds and/or allocated bandwidth is another promising research direction since the communicational condition dependent quantization will definitely improve the estimation accuracy while using less communicational energy (Zhou et al., 2011; Xu & Li, 2010).

Finally, WSNs have the potential to enhance and change the way people interact with technology and the world (Aboelaze & Aloul, 2005). The direction of future WSNs also lies in identifying real business and industry needs. Interactions between research and development are necessary to bridge the gap between existing technology and the development of business solutions. Applying sensor technology to different applications will improve business processes as well as open up more problems for researchers.

## 8. Acknowledgements

The work was jointly supported by the National Natural Science Foundation of China (Under Grant 60874104, 60935001); 973Project (2009CB824900, 2010CB734103); Shanghai Key Basic Research Foundation (08JC1411800).

## 9. References

- Aboelaze, M. & Aloul, F. (2005). Current and future trends in sensor networks: a survey, *Proceedings of the 14th IEEE Intl. Conf. on Wireless and Optical Communication*, New York, USA, pp. 133-138
- Akyildiz, I.F.; Su, W. Sankarasubramaniam, Y. & Cayirci, E. (2002). Wireless Sensor Network: A Survey. *Computer Networks*, vol. 38, no. 4, pp. 393-422

- Akyildiz, I.F.; Melodia, T. & Chowdury, K.R. (2007). Wireless multimedia sensor networks: A survey. *IEEE Wireless Communications*, vol. 14, no. 6, pp. 32-39
- Bertsekas, D. P. & Tsitsiklis, J. N. (1999). *Parallel and Distributed Computation: Numerical Methods*, 2nd ed. Belmont, MA: Athena Scientific
- Carli, R. Chiuso, A. Schenato, L. & Zampieri, S. (2006). Distributed Kalman filtering based on consensus strategies. *IEEE J. Selected Areas in Communications*, vol. 26, no. 4, pp. 622-632
- Chen, W.P.; Hou, J.C. & Sha, L. (2003). Dynamic clustering for acoustic target tracking in wireless sensor networks, *Proceedings of 11th IEEE International Conf. Network Protocols*, Atlanta, Georgia, USA, pp. 284-294
- Chen, W.P.; Hou, J.C. & Sha, L. (2004). Dynamic clustering for acoustic target tracking in wireless sensor networks. *IEEE Transactions on Mobile Computing*, vol. 3, no. 3, pp. 258-273
- Chong, C.Y. & Kumar, S. (2003). Sensor networks: Evolution, opportunities, and challenges. *Proc. IEEE*, vol. 91, pp. 27-41
- Chong, C.Y.; Zhao, F. Mori, S. & Kumar, S. (2003). Distributed tracking in wireless Ad Hoc sensor networks, *Proceedings Sixth Intl. Conf. on Information Fusion*, Cairns, Australia, pp. 431-438
- Culler, D.; Estrin, D. & Srivastava, M. (2004). Overview of sensor networks. *Computer*, vol. 37, no. 8, pp. 41-49
- Delouille, V.; Neelamani, R. & Baraniuk, R. (2004). Robust distributed estimation in sensor networks using the embedded polygons algorithm, *Proceedings of the 3rd Int. Symp. Info. Processing Sensor Networks*, Berkeley, CA, pp. 405-413
- Ding, M. & Cheng, X. (2009). Fault tolerant target tracking in sensor networks, *Proceedings of the tenth ACM international symposium on Mobile ad hoc networking and computing*, New Orleans, LA, USA
- Dogandzic, A. & Zhang, B. (2006). Distributed estimation and detection for sensor networks using hidden Markov random field models. *IEEE Trans. Signal Process.*, vol. 54, no. 8, pp. 3200-3215
- Forero, P.A.; Cano, A. & Giannakis, G.B. (2008). Consensus-based distributed expectation-maximization algorithm for density estimation and classification using wireless sensor networks, *Proceedings of the IEEE Int'l Conf. Acoustics, Speech and Signal Processing*, pp. 1989-1992
- Gray, R. M. (2006). Quantization in task-driven sensing and distributed processing, *Proceedings Int. Conf. Acoustics, Speech, Signal Processing*, Toulouse, France, vol. 5, pp. V-1049-V-1052
- Gubner, J. (1993). Distributed estimation and quantization. *IEEE Trans. Information Theory*, vol. 39, no. 5, pp.1456-1459
- Guo, W.H.; Liu, Z.Y. & Wu, G.B. (2003). An energy-balanced transmission scheme for sensor networks, *Proceedings of the 1st Intl. Conf. Embedded Networked Sensor Systems*. Los Angeles, CA, USA, pp. 300-301
- Heinzelman, W. R.; Chandrakasan, A. & Balakrishnan, H. (2002). An application-specific protocol architecture for wireless microsensor networks. *IEEE Transactions on Wireless Communications*, vol. 1, no. 4, pp. 660-670
- Hoblos, G.; Staroswiecki, M. & Aitouche, A. (2000). Optimal design of fault tolerant sensor networks, *Proceedings of the IEEE Int'l Conf. on Control Applications*, pp. 467-472

- Jiang, C.; Dong, G. & Wang, B. (2005). Detection and tracking of region-based evolving targets in sensor networks, *Proceedings of 14th Int. Conf. on Computer Communications and Networks, ICCCN 2005*, pp:563 - 568
- Jin, G. & Nittel, S. (2006). NED: An efficient noise-tolerant event and event boundary detection algorithm in wireless sensor networks, *Proceedings of the 7th Int. Conf. on Mobile Data Management*
- Jin, G.Y.; Lu, X.Y. & Park, M.S. (2006). Dynamic clustering for object tracking in wireless sensor networks. *Ubiquitous Computing Systems*, pp.200-209
- Kar, S. & Moura, J.M.F. (2009). Distributed consensus algorithms in sensor networks with imperfect communication: link failures and channel noise. *IEEE Trans. Signal Processing*, vol. 57, no. 1, pp. 355-369
- Kung, H.T. & Vlah, D. (2003). Efficient location tracking using sensor networks, *Proceedings of the IEEE Wireless Communications and Networking Conference, New Orleans, Louisiana, USA*
- Kwon, H.; Kim, T.H. Choi, S. & Lee, B.G. (2006). A cross-layer strategy for energy-efficient reliable delivery in wireless sensor networks. *IEEE Trans. on Wireless Communications*, vol. 5, no. 12, pp. 3689-3699
- Lam, W. & Reibman, A. (1993). Quantizer design for decentralized systems with communication constrains. *IEEE Trans. Communications*, vol. 41, no. 8, pp.1602-1605
- Lee, S.M.; Cha, H. & Ha, R. (2007). Energy-aware location error handling for object tracking applications. *Wireless Sensor Networks, Computer Communication*, vol. 30, pp. 1443-1450
- Li, X.; Shu, W. Li, M. Huang, H.Y. Luo P.E. & Wu, M.Y. (2009). Performance evaluation of vehicle-based mobile sensor networks for traffic monitoring. *IEEE Trans. Vehic. Tech.*, vol. 58, no. 4, pp. 1647-1653
- Li, X. R. & Wang, J. (2000). Unified optimal linear estimation fusion – Part II: Discussions and examples, *Proceedings of the 3rd ISIF Conf. On Information Fusion, MoC2/18-MoC2/25*
- Li, X.R.; Zhu, Y. & Han, C. (2000). Unified optimal linear estimation fusion, *Proceedings of the 39th IEEE Conf. On Decision and Control, Sydney, Australia, 10-25*
- Li, Z.; Chen, S. Leung, H. & Bosse, E. (2010). Joint data association, registration, and fusion using EM-KF. *IEEE Trans. Aerospace and Electronic Systems*, Vol. 46, no. 2, pp. 496-507
- Lin, C.; King, C. & Hsiao, H. (2005). Region abstraction for event tracking in wireless Sensor networks, *Proceedings of the 8th Int. Symposium on Parallel Architectures, Algorithms, and Networks*
- Lin, C.Y.; Peng, W.C. & Tseng, Y.C. (2004). Efficient in-network moving object tracking in wireless sensor networks. Department of Computer Science and Information Engineering - National Chiao Tung University
- Luo, Z. (2005). Universal decentralized estimation in a bandwidth constrained sensor network. *IEEE Trans. Information Theory*, vol. 51, pp.2210-2219
- Melodia, T.; Vuran, M.C. & Pompili, D. (2006). The state of art in cross-layer design for wireless sensor networks. in *Network Architect. In Next Generation Internet* (M. Cesana, L. Fratta, eds.) Berlin Heidelberg: Springer-Verlag

- Msechu, E.J.; Roumeliotis, S.I. Ribeiro, A. & Giannakis, G.B. (2008). Decentralized quantized Kalman filtering with scalable communication cost, *IEEE Trans. Signal Process.*, vol. 56, no. 8, pp. 3727-3741
- Mutambara, A.G.O. (1998). *Decentralized estimation and control for multisensory systems*, Boca Raton, FL: CRC Press
- Olfati-Saber, R. (2005). Distributed Kalman filter with embedded consensus filters, *Proceedings of the 44<sup>th</sup> IEEE Conf. on Decision and Control, and European Control Conf.*, pp. 8179-8184
- Olfati-Saber, R. (2007). Distributed Kalman filtering for sensor networks. *46<sup>th</sup> IEEE Conf. on Decision and Control*, New Orleans, USA
- Olfati-Saber, R. & Murry, R.M. (2004). Consensus problems in network of agents with switching topology and time-delays. *IEEE Trans. Automat. Control*, vol. 49, no.9, pp. 101-115
- Olule, E.; Wang, G. Guo, M. & Dong, M. (2007). RARE: An energy efficient target tracking protocol for wireless sensor networks, *Proceedings of the Intl. Conf. on Parallel Processing*, pp. 1298-1306
- Ozdemir, O.; Niu, R. & Varshney, P.K. (2009). Tracking in wireless sensor networks using particle filtering: physical layer considerations. *IEEE Trans. Signal Processing*, vol. 57, no. 5, pp. 1987-1999
- Papadopoulos, H.; Wornell, G. & Oppenheim, A. (2001). Sequential signal encoding from noisy measurements using quantizers with dynamic bias control. *IEEE Trans. Inf. Theory*, vol. 47, no. 3, pp. 978-1002
- Phoha, S.; Jacobson, N. & Friedlander, D. (2003a). Sensor network based localization and target tracking hybridization in the operational domains of beamforming and dynamic space-time clustering. *Proceedings of the Global Telecommunications Conference*. Michigan, USA, pp. 2952- 2956
- Phoha, S.; Jacobson, N. Friedlander, D. & Brooks, R. (2003b). Sensor network based localization and tracking through hybridization in the operational domains of beamforming and dynamic space-time clustering. *Proceedings of the Conf. Global Telecommunications*. Michigan, USA, pp. 1137- 1140
- Rapaka, A. & Madria, S. (2007). Two energy efficient algorithms for tracking objects in a sensor network. *Wireless Communication Mobile Computing*, vol. 12, no. 7, pp.809-819
- Ribeiro, A. & Giannakis, G. B. (2006). Bandwidth-constrained distributed estimation for wireless sensor networks, Part II: Unknown PDF. *IEEE Trans. Signal Process.*, vol. 54, no. 3, pp. 1131-1143
- Ribeiro, A.; Giannakis, G. B. & Roumeliotis, S. I. (2006). SOI-KF: Distributed Kalman filtering with low-cost communications using the sign of innovations. *IEEE Trans. Signal Process.*, vol. 54, no. 12, pp. 4782-4795
- Ruan, Y.; Willett, P. Marrs, A. Palmieri, F. & Marano, S. (2008). Practical fusion of quantized measurements via particle filtering. *IEEE Trans. Aerosp. Electron. Syst.*, vol. 44, no. 1, pp. 15-29
- Scherber, D. & Papadopoulos, H. C. (2005). Distributed computation of averages over *ad hoc* networks. *IEEE J. Sel. Areas Commun.*, vol. 23, no. 4, pp. 776-787
- Schizas, I. D. & Giannakis, G. B. (2006). Consensus-based distributed estimation of random signals with wireless sensor networks, *Proceedings of the 40th Asilomar Conf. Signals, Systems, Computers*, Monterey, CA

- Schizas, I.D.; Mateos, G. & Giannakis, G.B. (2009). Distributed LMS for consensus-based in-network adaptive processing. *IEEE Trans. Signal Process.*, vol. 57, no. 6, pp. 2365-2382
- Shorey, R.; Ananda, A. L. Chan, M. C. & Ooi, W. T. (2006). *Mobile, Wireless, and Sensor Networks: Technology, Applications, and Future Directions*, IEEE Press, Piscataway, pp. 173-196
- Schizas, I.D.; Ribeiro, A. & Giannakis, G.B. (2008a). Consensus in Ad Hoc WSNs with noisy links – part I: distributed estimation of deterministic signals. *IEEE Trans. Signal Processing*, vol. 56, no. 1, pp. 350-364
- Schizas, I.D.; Ribeiro, A. & Giannakis, G.B. (2008b). Consensus in Ad Hoc WSNs with noisy links – part II: distributed estimation and smoothing of random signals. *IEEE Trans. Signal Processing*, vol. 56, no. 4, pp. 1650-1666
- Sohraby, K.; Minoli, D. Znati, T. (2006). *Wireless sensor networks: Technology, protocols, and applications*. Wiley-interscience, New Jersey
- Song, L. & Hatzinakos, D. (2007). A cross-layer architecture of wireless sensor networks for target tracking. *IEEE/ACM Transactions on networking*, vol. 15, no. 1, pp. 145-158
- Spanos, D. P.; Olfati-Saber, R. & Murray, R. J. (2005). Distributed sensor fusion using dynamic consensus, *Proceedings of the 16th IFAC World Congr.*, Prague, Czech Republic
- Speyer, J.L. (2004). Computation and transmission requirements for a decentralized linear-quadratic-Gaussian control problem. *IEEE Trans. Automatic Control*, vol. 49, no. 9, pp.1453-1464
- Sukhavasi, R.T. & Hassibi, B. (2009). Particle filtering for quantized innovations, *Proceedings of the IEEE Int. Conf. Acout., Speech and Signal Process.*, Taiwan, China
- Sun, S.L. & Deng, Z.L. (2004). Multi-sensor optimal information fusion Kalman filter. *Automatica*, vol. 40, no. 5, pp. 1017-1023
- Tanner, H.G.; Jadbabaie, A. & Pappas, G.J. (2007). Flocking in fixed and switching networks. *IEEE Trans. Automat. Control*, vol. 52, no. 5, pp. 863-868
- Tsai, H.W.; Chu, C.P. & Chen, T.S. (2007). Mobile object tracking in wireless sensor networks. *Computer Communications*, vol. 30, pp. 1811-1825
- Valera M. & Velastin, S.A. (2005). Intelligent distributed surveillance systems: a review. *IEE Proc. Visual Image Signal Process.*, vol. 152, no. 2, pp. 192-204
- Veeravalli V.V. & Chamberland, J.F. (2007). Detection in sensor networks. in Swami, A. Zhao, Q. Hong, Y.W. & Tong, L. Eds, *Wireless Sensor Networks: Signal Processing And Communications Perspectives*, pp. 119-148, John Wiley & Sons
- Vercauteren, T. & Wang, X. (2005). Decentralized sigma-point information filters for target tracking in collaborative sensor networks. *IEEE T. Signal Processing*, vol. 53, no. 8, pp. 2997-3009
- Walchli, M.; Skoczylas, P. Meer M. & Braun, T. (2007). Distributed event localization and tracking with wireless sensors, *Proceedings of the 5<sup>th</sup> Intl. Conf. on Wired/Wireless internet Communications*
- Wang, Q.X.; Chen, W.P. Zheng, R. Lee, K. & Sha, L. (2003). Acoustic target tracking using tiny wireless sensor devices, *Proceedings of the Int. Workshop on Information Processing in Sensor Networks*

- Wang, Z.; Li, H. Shen, X. Sun, X. & Wang, Z. (2008). Tracking and predicting moving targets in hierarchical sensor networks, *Proceedings of the IEEE Intl. Conf. on Networking, Sensing and Control*, pp. 1169-1173
- Xiao, J.J.; Cui, S. Luo, Z. Q. & Goldsmith, A.J. (2006). Power scheduling of universal decentralized estimation in sensor networks. *IEEE Trans. Signal Process.*, vol. 54, no. 2, pp. 413-421
- Xiao, L. & Boyd, S. (2004). Fast linear iterations for distributed averaging. *Syst. Control Lett.*, vol. 53, pp. 65-78
- Xu, J. & Li, J. (2010). State estimation with quantized sensor information in wireless sensor networks. *IET Signal Processing*, (peer reviewed, to appear).
- Xu Y. & Lee, W.C. (2003). On localized prediction for power efficient object tracking in sensor networks, *Proceedings of the 1st Intl. Workshop on Mobile Distributed computing*, Providence RI, pp. 434-439
- Yang, H. & Sikdor, B. (2003). A protocol for tracking mobile targets using sensor network, *Proceedings of the First IEEE International Workshop on Sensor Network Protocols and Applications*, Anchorage, Alaska, pp. 71-81
- Yick, J.; Mukherjee, B. & Ghosal, D. (2008). Wireless sensor network survey. *Computer Networks*, vol. 52, no. 12, pp. 2292-2330
- You, K.; Xie, L. Sun, S. & Xiao, W. (2008). Multiple-level quantized innovation Kalman filter, *Proceedings of the 17th IFAC World Congress*, Seoul, Korea
- Younis, O. & Fahmy, S. (2004). Distributed clustering in ad-hoc sensor networks: a hybrid, energy-efficient approach, *Proceedings of the 23rd Annual Joint Conf. IEEE Computer & Communications Societies*, INFOCOM
- Zhang, W. & Cao, G. (2004a). Optimizing tree reconfiguration for mobile target tracking in sensor networks. *IEEE INFOCOM*, HongKong, China
- Zhang, W. & Cao, G. (2004b). DCTC: Dynamic convoy tree-based collaboration for target tracking in sensor networks. *IEEE Transactions on Wireless Communications*, vol. 3, no. 5, pp. 1689-1701
- Zhao, F.; Shin, J. & Reich, J. (2002). Information-driven dynamic sensor collaboration for tracking applications. *IEEE Signal Proces. Mag.*, vol.19, no. 2, pp. 61-72
- Zhou, Y. & Li, J. (2008a). Data fusion of unknown correlations using internal ellipsoidal approximation, *Proceedings 17th International Foundation Automatic Control World Congress*, Seoul, Korea
- Zhou, Y. & Li, J. (2008b). Robust decentralized data fusion based on internal ellipsoid approximation, *Proceedings of the 17th International Foundation Automatic Control World Congress*, Seoul, Korea
- Zhou, Y. & Li, J. (2009a). Average consensus based scalable robust filtering for sensor network, *Proceedings of the 5th Intl. Conf. Wireless Communications, Networking and Mobile Computing*, Beijing, China
- Zhou, Y. & Li, J. (2009b). Scalable distributed sigma-point Kalman filtering for sensor networks: dynamic consensus approach, *Proceedings of the IEEE Intl. Conf. on Systems, Man, and Cybernetics*, San Antonio, Texas, USA
- Zhou, Y. & Li, J. (2009c). Quantized measurement fusion for target tracking in wireless sensor networks, *Proceedings of the 48th IEEE Conf. on Decision and Control and 28th Chinese Control Conference*, pp. 6835-6840, Shanghai, China

- Zhou, Y. & Li, J. (2009d). Collaborative maneuvering target tracking in wireless sensor network with quantized measurements, *Proceedings of the IEEE Intl. Conf. on Systems, Man, and Cybernetics*, San Antonio, Texas, USA
- Zhou, Y. Li, J. & Wang, D. (2009a). Weighted average approach to quantized measurement fusion in wireless sensor network, *Proceedings of the 5th Intl. Conf. Wireless Communications, Networking and Mobile Computing*, Beijing, China
- Zhou, Y.; Li, J. & Wang, D. (2009b). Quantized measurement fusion in wireless sensor network with correlated sensor noises, *Proceedings of the 7th IEEE Intl. Conf. on Control & Automation*, pp. 1868-1873, Christchurch, New Zealand
- Zhou, Y.; Li, J. & Wang, D. (2009c). Collaborative Target Tracking in Wireless Sensor Networks using Quantized Innovations and Sigma-Point Kalman Filtering, *Proceedings of the IEEE Intl. Symp. Industrial Electronics*, Seoul, Korea
- Zhou, Y.; Li, J. & Wang, D. (2009d). Unscented Kalman filtering based quantized innovation fusion for target tracking in WSN with feedback, *Proceedings of the Intl. Conf. Machine Learning and Cybernetics*, Baoding, China
- Zhou, Y.; Li, J. & Wang, D. (2010). Posterior Cramér-Rao lower bounds for target tracking in sensor networks with quantized range-only measurements. *IEEE Signal Processing Letters*, vol. 17, no. 2, pp. 157-160
- Zhou, Y.; Li, J. & Wang, D. (2011). Target tracking in wireless sensor networks using adaptive measurement quantization. *Science In China - Series F: Information Sciences* (peer reviewed, to appear).
- Zou, Y. & Chakrabarty, K. (2003). Target localization based on energy considerations in distributed sensor networks, *Proceedings of the 1st IEEE Intl. Workshop on Sensor Network Protocols and Applications*, Anchorage, Alaska, pp.51-58

IntechOpen



## **Wireless Sensor Networks: Application-Centric Design**

Edited by Yen Kheng Tan

ISBN 978-953-307-321-7

Hard cover, 492 pages

**Publisher** InTech

**Published online** 14, December, 2010

**Published in print edition** December, 2010

Over the past decade, there has been a prolific increase in the research, development and commercialisation of Wireless Sensor Networks (WSNs) and their associated technologies. WSNs have found application in a vast range of different domains, scenarios and disciplines. These have included healthcare, defence and security, environmental monitoring and building/structural health monitoring. However, as a result of the broad array of pertinent applications, WSN researchers have also realised the application specificity of the domain; it is incredibly difficult, if not impossible, to find an application-independent solution to most WSN problems. Hence, research into WSNs dictates the adoption of an application-centric design process. This book is not intended to be a comprehensive review of all WSN applications and deployments to date. Instead, it is a collection of state-of-the-art research papers discussing current applications and deployment experiences, but also the communication and data processing technologies that are fundamental in further developing solutions to applications. Whilst a common foundation is retained through all chapters, this book contains a broad array of often differing interpretations, configurations and limitations of WSNs, and this highlights the diversity of this ever-changing research area. The chapters have been categorised into three distinct sections: applications and case studies, communication and networking, and information and data processing. The readership of this book is intended to be postgraduate/postdoctoral researchers and professional engineers, though some of the chapters may be of relevance to interested master's level students.

### **How to reference**

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Jianxun Li and Yan Zhou (2010). Target Tracking in Wireless Sensor Networks, *Wireless Sensor Networks: Application-Centric Design*, Yen Kheng Tan (Ed.), ISBN: 978-953-307-321-7, InTech, Available from: <http://www.intechopen.com/books/wireless-sensor-networks-application-centric-design/target-tracking-in-wireless-sensor-networks>

**INTECH**  
open science | open minds

### **InTech Europe**

University Campus STeP Ri  
Slavka Krautzeka 83/A  
51000 Rijeka, Croatia  
Phone: +385 (51) 770 447

### **InTech China**

Unit 405, Office Block, Hotel Equatorial Shanghai  
No.65, Yan An Road (West), Shanghai, 200040, China  
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元  
Phone: +86-21-62489820

[www.intechopen.com](http://www.intechopen.com)

Fax: +385 (51) 686 166  
www.intechopen.com

Fax: +86-21-62489821

IntechOpen

IntechOpen

© 2010 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the [Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License](#), which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.

IntechOpen

IntechOpen