Chapter 2
Distributed Consensus Estimation of Wireless Sensor Networks

Recently, consensus based distributed estimation has attracted considerable attention from various fields to estimate deterministic parameters and track time-varying ones. In this chapter, the state-of-the-art of distributed consensus estimation is discussed.

2.1 Consensus Based Distributed Parameter Estimation

2.1.1 Average Consensus

Average consensus develops with multi-agent systems where consensus is a vital aspect in coordination and cooperation [5]. It is a linear iteration scheme where each node updates its value as a linear weighted combination of the values received from neighbors and its own. Consensus can be guaranteed by appropriately designing the weights used in the linear schemes. However, the characteristics of WSNs introduce several challenges for average consensus as summarized below: (1) The nodes are always supplied by portable batteries whose energies are also constrained by limited physical sizes. As a result, efficiency is a vital aspect in average consensus. (2) Nodes need to exchange messages through unreliable wireless communication. The unreliability can introduce noise, dynamic topology, time delays, and other problems. How to obtain robust estimation is another issue should be concerned with. (3) The nodes are easy to be compromised and the security problem in estimation is also important.

Plenty of research work have been reported to tackle these challenges and they are classified in Table 2.1 . On the aspect of efficiency, designing protocols for reaching consensus with fast convergence rate is a choice. Matrix optimization is utilized to design the weight coefficients in [6]. The increased convergence time based on matrix optimization is limited by network connectivity. It can be slowed down even if the weights are optimized. A local prediction component is added to the update protocol in [7] and [8] which propose theoretical analysis to demonstrate the improvement of the convergence time. Lower bounds for iteration steps in average consensus and a minimum-time consensus scheme are also proposed in [9]. [10] couples the

© The Author(s) 2014
C. Chen et al., *Wireless Sensor Networks,*
SpringerBriefs in Computer Science, DOI 10.1007/978-3-319-12379-0_2

Table 2.1 Average consensus

Efficiency	
Fast convergence by designing weights	[6]
Fast convergence by a prediction component	[7, 8]
Achieving consensus with minimum iterations	[9]
Removing the computation of maximum degree	[10]
Transmitting with bounded peak power	[11]
Quantized communication data with time-varying topologies	[12]
A low complexity quantizer and refined quantization	[13]
Robustness	
Finding the weights causing least-mean-square deviation with channel noises	[14]
Convergence property under imperfect communications	[15]
Coupling consideration of channel noise and convergence rate	[16]
Convergence under Markovian random graphs	[17]
Average consensus with random topologies and noisy channels	[18]
Average consensus with asynchronous communications between sensors	[19]
Weighted average on directed graphs	[20]
Consensus over directed graphs with quantized communication	[21]
Directed networks with distributed time delays	[22]
Cyber-Security	
Analysis secure consensus through a system theoretic framework	[23, 24]
Considering two types of outlier attackers	[24]
Secure average consensus algorithms in spectrum sensing	[25, 26]
Privacy preserving consensus	[27]
Secure average consensus-based time synchronization protocol	[28]

computation of the consensus value and the estimation of Laplacian matrix that can remove the computation process of the maximum degree of the network. Notice that the main power consumption is in the communication of a node. Therefore, another way to save the energy is to use quantized communication data. A nonlinear average consensus scheme with bounded peak power is proposed in [11]. Every node proceeds a prior stage to map the data through a bounded function in order to bound the transmit power. A uniform quantizer with constant step size and a communication feedback component are introduced to deal with the sensor saturation and time-varying topologies in [12]. The correlation between the exchanged values during the consensus process is exploited in [13]. It results in a low complexity quantizer and refined quantization during the convergence process.

There are also some methods to address the second challenge. Channel noise is inevitable in WSNs. Thus, many standard consensus algorithms under perfect communication may fail to converge as observed in [14]. A solution is then provided to find the best edge weights resulting in optimal estimation. In [15], authors focus on the imperfect communications and prove the convergence property under some perturbation models of exchanged data between nodes. A scheme considering both the channel noise and convergence rate is proposed in [16]. Typical WSNs also suffer from link failures, packet drops, and node failures, which results in switching topology, time delays, and other problems. [17] shows some convergence results under Markovian random graphs using the theory of Markovian jump linear systems. Average consensus with random topologies and noisy channels are investigated in [18]. Two algorithms called A-ND and A-NC are proposed to address the trade-off between bias and variance caused by link failures and noisy channels. All the average consensus algorithms require clock synchronization which is hard to achieve. Asynchronous average consensus algorithms are appropriate to tackle this problem. It is known that the necessary condition for all sensors converge to the average value is that the sum value remains the same. [19] proposes an implementation that guarantees the necessary condition in spite of asynchronous communications between nodes. Weighted average consensus takes node measurement accuracy and environmental conditions into consideration which makes the estimation more accurate and reliable. Authors in [20] modify the existing weighted average consensus algorithms to remove the requirement of bidirectional communication between neighbors. As a result, the modified algorithm can work under directed graphs. The problem of reaching consensus of a general unbalanced directed network under limited information communication is addressed in [21]. Directed networks with distributed time delays are investigated in [22]. Single and multiple time delays are investigated, respectively.

Cyber-Security is another aspect that matters in distributed average consensus. And secure average consensus algorithms have been more and more important with the wide application of distributed average consensus protocols. It aims at ensuring trustworthy computation in linear iterations in the presence of malicious inner sensors or outer intrusions. References [23, 24] model misbehavior as unknown and unmeasurable inputs and address the detection and identification problem through an unknown-input system theoretic framework. Two types of adversarial outer attacks are considered in [24]. The adversary is either able to break a number of links or add noise on the values of the nodes. Both attacks are analyzed by optimal control theory. References [25, 26] apply the secure average consensus algorithms in spectrum sensing. The secure schemes can adaptively adjust the weights of neighbors and gradually isolate the malicious nodes. The adaptive threshold is also able to mitigate the misbehaviors of inside nodes. A PPAC algorithm is proposed to guarantee the privacy of the initial values while ensure the whole network converge to the exact average in [27]. The key point is to add and subtract random noises to the iterative process. Some theoretical analyses are also given in [27]. A secure average consensus-based time synchronization protocol is proposed in [28].

Table 2.2 In-network regression consensus

Consensus-based D-LS Using ADMM	[29]
DiCE: introducing new consensus constraints to reduce exchanged message	[30]
Fast-DiCE: fast convergence by using Nesterov's optimal gradient descend method	[31]
Consensus-based D-LS with quantization and communication noise	[32]
Consensus-based D-TLS	[34]
IPI-based D-TLS: reduced computational complexity	[35]
Two stage consensus-based solution for L norm regularization	[36]
Three stage solution with low complexity and memory requirement	[37]
PSSE: iteratively exclude abnormal values	[38]
Consensus-based framework from both attacker and defender aspects	[39]

2.1.2 In-Network Regression Consensus

As discussed in the previous subsection,we focus on the state of observation z or the observation matrix that is equal to the identity matrix I in average consensus. However, in many application scenarios, the state of the original target x matters. The observation matrix H often has a more general form. These problems are called linear inverse problems, and in-network regression consensus is a class of algorithms to solve them. Although in-network regression consensus is a subclass of observation-only consensus, it employs regression analysis methods like maximum likelihood and least squares estimation, which is different from average consensus. The difference leads to different research emphases. In in-network regression consensus, we always formulate the estimation of the target into a convex minimization problem which exhibits a separable structure. Using the separable characteristic of the problem, consensus-based distributed solutions are exploited. Despite of this basic formulation which directly uses the regression analysis methods, there are also algorithms considering more limitations that introduce regularization into the convex problem. Typical applications of in-network regression consensus include distributed spectrum sensing, distributed field estimation, distributed target localization and state estimation in smart grid, etc. References on in-network regression consensus are listed in Table 2.2. Reference [29] adopts the least squares (LS) technique to formulate the convex problem. By introducing the consensus constraints and following the method called alternating direction method of multiplier (ADMM), a distributed consensus algorithm is proposed. Considering new consensus constraints, a new algorithm called DiCE which can reduce the exchange messages between neighboring nodes is proposed in [30]. A Fast-DiCE that takes the advantage of Nesterov's optimal gradient descend method is then presented in [31]. However, these algorithms do not consider the communication noises and link failures which are unavoidable in WSNs. In [32], authors introduce a distributed consensus scheme for an LS problem which guarantees the convergence even in the presence of quantization or communication noise. Reference [33] investigates the performance of the algorithm when there are erroneous links between neighboring nodes. A scheme is also proposed in order to mitigate the influences and ensure satisfactory overall performance. A distributed TLS (D-TLS) is proposed in [34] to tackle the situation where the observation matrix H is also noisy. To reduce the large computational complexity caused by the process of eigenvalue decomposition in each step, a modified D-TLS called IPI-based D-TLS is proposed in [35]. Sometimes $\mathcal{L}$ norm regularization is added into the convex problem in order to improve the estimation accuracy or obtain stable solutions. This idea leads to the $\mathcal{L}$ norm recovery methods widely applied in compressed sensing, smart grid, field estimation, and other situations. Distributed consensus solutions are often chosen to solve the recovery problems. Basically, the introduction of the $\mathcal{L}$ norm regularization is dependent on the sparsity of the state to be estimated. [36] proposes a two stage algorithm to solve the $\mathcal{L}_1$ norm recovery problem. A model-robust adaptation is also adopted to control the approximation error caused by spatial quantization. An iterative thresholding and input driven consensus-based three-step method appears in [37] with low complexity and memory requirement. In order to obtain robust power state estimation, [38] proposes a distributed PSSE estimator based on ADMM to iteratively exclude the abnormal values. Sparse attack construction and state estimation are exploited in [39]. A distributed framework for both aspects are considered at the same time followed by corresponding distributed consensus algorithms.

2.1.3 Observation+Innovation Consensus

Considering the fluctuation of the deterministic parameters to be estimated and the timescales of communication and observation, the mentioned two classes of algorithms are not suitable. Observation+innovation consensus interwinds observation and estimation to tackle the problem. The estimation accuracy can be improved by introducing new observations during estimation process. And the observation matrix H also has a special form with some diagonal entries being zeros. Convergence, consensus, estimation error, and the rate of convergence rate are the important metrics to evaluate the observation+innovation consensus algorithms. They are enumerated in Table 2.3. Reference [4] provides an observation+innovation consensus algorithm for a deterministic target to remove the requirements of local observability. [40] proves the bounded estimation error of the algorithm and quantify the trade-off between connectivity, observability, and stability. Reference [41] gives a bound on the mean square of the convergence rate and studies the behavior of the algorithm with the measurements fading with time. The nonlinear observation models and noisy communication links are considered with theoretical analysis. Reference [42] addresses the problems of random link failures, stochastic communication noises, and Markovian switching topologies. Both the mean square and almost sure convergence are established. Quantization errors, successive packet dropouts, and randomly varying nonlinearities of the target are considered together in [43]. For non-Gaussian observations, there is a threshold of network degree of connectivity. If it is below

Table 2.3 Observation+innovation consensus

Removing the requirements of local observability	[4]
Quantifying the trade-off between connectivity, observability, and stability	[40]
A bound on the mean square of the convergence rate with measurement fading	[41]
Nonlinear observation models and noisy communication links	
Random link failures, stochastic communication noises, and Markovian switching topologies	[42]
Quantization errors, successive packet dropouts, and randomly varying nonlinearities	[43]
Analysing the gap between distributed algorithm and corresponding central algorithm	[3]
Applications of observation+innovation consensus	[44, 45]
Considering heterogeneous sensor networks	[46]

the threshold, a gap between distributed algorithm and its corresponding central algorithm appears. The conclusions can be found in [3]. Applications of observation+innovation consensus algorithms for economic dispatch in power systems and for wide area monitoring systems are described in [44] and [45], respectively. Notice that all the estimation models are homogeneous in the previous part, which means the nodes are identical in the network. However, heterogeneous sensor networks introduce different kinds of nodes in order to prolong the life of networks. The interesting work of applying the observation+innovation consensus in heterogeneous sensor networks is firstly addressed in [46].

2.2 Consensus Based Distributed Tracking

Estimation and tracking of dynamic targets is one of the main objectives of WSNs. However, the previous three classes of distributed consensus algorithms are not suitable for tracking dynamic targets. Although centralized filters like Kalman filters, particle filters can track the dynamical processes, they are not implementable in distributed WSNs. To solve the estimation problem in WSNs, a lot of distributed versions have been proposed as summarized in Table 2.4. On the aspect of distributed Kalman filters, Olfati-Saber first introduces a consensus-based Kalman filter inspired by the consensus strategy in [47]. The filter consists two stages: a Kalman like measurement update and an inserted consensus term to eliminate the disagreements of sensors. A further study of the optimality and stability performance of the algorithm is then examined in [48]. An alternative consensus-based Kalman filter is proposed in [49] with the investigation of the correlation between Kalman gain and the consensus matrix. Some parameters design guides are also given in the literature in order to minimize the estimation error. However, it is far from optimal in Kalman-consensus filter (KCF) because of the correlation between local estimates. Furthermore, it is hard to exactly determine the correlation that causes the nonoptimality. An adaptive consensus-based Kalman filter is proposed in [50]. By

Table 2.4 Consensus based filters for dynamic targets

Consensus-based distributed Kalman filter	[47]
Further study of the optimality and and stability performance	[48]
Investigating correlation between Kalman gain and the consensus matrix	[49]
An adaptive consensus-based Kalman filter	[50]
Information consensus-based filter	[51, 52]
Further improving performance by designing consensus weights	[53]
Considering the network induced delays and dropouts	[54]
Robust estimator addressing uncertain channels	[55]
Quantised communications and random sensor failures	[56]
Event-driven transmission schemes	[57, 58]
Distributed optimal consensus filter for heterogeneous networks	[46]
Considering a nonlinear system model	[59]
Distributed consensus-based particle filters	[60, 61]
Distributed particle filter for nonlinear tracking	[62]

adding extra exchanged information between nodes indicating whether or not a node observes the target, the algorithm can improve the estimation accuracy compared with KCF. Other techniques resorting to information filter have been developed in [51, 52] which give insight into the influence of the correlation. Based on the information consensus-based filter, a scheme designing the consensus weights to further improve the performance is presented in [53]. In practical applications, there are often network-induced phenomena, such as delays and packets dropouts. A scheme based on local Luenberger-like observers is proposed in [54] to address the network induced delays and dropouts. Considering uncertain channels, a robust estimator with adaptive channel estimator is presented in [55]. WSNs also suffer from power constraints in practical situations which makes the energy consumption problem important. Authors in [56] adopt the probabilistic strategy to reduce the energy consumption. Alternatives such as event-driven transmission schemes are provided in [57, 58]. Each node transmits a new data only when a predefined event happens, which can significantly reduce the transmission power. Distributed optimal consensus filter appropriate for heterogeneous sensor networks can be found in [46]. [59] extends the linear consensus-based Kalman filter to a nonlinear system model. In addition to consensus-based Kalman filters, there are some other approaches designed to reach consensus. Distributed consensus-based particle filters are developed in [60] and [61]. Both of them consist of two major steps with the difference being whether average consensus or support vector machine is used at the first step. To deal with the nonlinear systems, a corresponding unscented particle filter is proposed in [62].

http://www.springer.com/978-3-319-12378-3

Wireless Sensor Networks
Distributed Consensus Estimation
Chen, C.; Zhu, S.; Guan, X.; Shen, X.S.
2014, IX, 89 p. 19 illus., Softcover
ISBN: 978-3-319-12378-3