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Preface

Advances in micro electromechanical systems and wireless technologies have allowed for the emergence of inexpensive micro-sensors with embedded processing and communication capabilities. A wireless sensor network (WSN) is a collection of these physically distributed micro-sensors communicating with one another over wireless links. In their various shapes and forms, the WSNs have greatly facilitated and enhanced the automated, remote, and intelligent monitoring of a large variety of physical systems and have found applications in various areas, such as industrial and building automation; environmental, traffic, wildlife, and health monitoring; and military surveillance. The purpose of a WSN is to provide users access to the information of interest from data gathered by spatially distributed sensors. In most applications, users are interested in a processed data that carries useful information of a physical plant rather than a measured data contaminated by noises. Therefore, it is not surprising that signal estimation, especially the multisensor fusion estimation, has been one of the most fundamental collaborative information processing problems in WSNs. The WSN, as a typical multisensor system, has greatly extended application areas of multisensor information fusion estimation, which was originally developed for military applications, such as target tracking and navigation. Although WSNs present attractive features, challenges associated with communication constraints, such as the scarcity of bandwidth and energy, as well as the delays and packet losses, in wireless communications have to be addressed in the WSN-based information fusion estimation and have attracted increasing research interest during the past decade.

This book provides the recent advances in distributed multisensor fusion estimation methods for WSNs with communication constraints, including the energy constraint, bandwidth constraint, communication delays, and packet losses. First, a review on the latest developments in the literature is presented in Chap. 1. Then, two energy-efficient fusion estimation methods, namely, the *transmission rate* method and the *packet size reduction* method, are introduced for sensor networks with energy constraints in Chaps. 2, 3, 4 and 5. Specifically, by slowing down the sampling and estimation rates, a multi-rate fusion estimation method is presented in Chap. 2 for sensor networks, where the sampling rate and the estimation rate are allowed to be different from each other and are parameters that can be designed to meet the energy constraints. In Chap. 3, a distributed state fusion estimation method is presented for sensor networks with nonuniform estimation rates, where the estimation rates among the various local estimators are allowed to be nonuniform and different from each other, that is, each local estimator is allowed to generate local estimates independently with an adjustable rate according to its power status. In Chap. 4, a distributed H_∞ fusion estimation method is introduced for sensor networks with nonuniform sampling rates, where the sampling rate of each sensor is allowed to be nonuniform and can be adjusted according to the sensor's power status. The energy-efficient fusion estimation method based on *packet size reduction* is introduced in Chap. 5, where a dimension reduction method is presented to reduce the size of packets containing the local estimates to be transmitted to the fusion estimator. The bandwidth constraint problem is considered in Chaps. 6 and 7. Specifically, a distributed H_∞ fusion estimation method is presented for sensor networks with quantized local estimates in Chap. 6. In Chap. 7, a hierarchical structure is presented for multisensor fusion estimation systems to reduce the communication burden of the fusion center. The communication uncertainties, including the delays and packet losses, are considered in Chaps. 8 and 9. Specifically, the fusion estimation for sensor networks with communication delays is introduced in Chap. 8, while the fusion estimation with both delays and packet losses is presented in Chap. 9.

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Symbols and Acronyms

$\Re$	Field of real numbers
$\Re^n$	n-Dimensional real Euclidean space
$\Re^{m\times n}$	Space of all $m \times n$ real matrices
I	Identity matrix
$\mathbf{0}$	Zero matrix
$A > 0$	Symmetric positive definite
$A \geqslant 0$	Symmetric positive semi-definite
$A < 0$	Symmetric negative definite
$A \leqslant 0$	Symmetric negative semi-definite
A^{T}	Transpose of matrix A
A^{-1}	Inverse of matrix A
$[a_{ij}]$	A matrix composed of elements a_{ij}, $i, j \in N$
$\mathrm{col}\{x_i\}_{i\in\phi}$	A column vector composed of elements x_i, $i \in \phi$
$\mathrm{Var}(x)$	Variance of the random vector x
$\mathrm{rank}(A)$	Rank of matrix A
$\rho(A)$	Spectral radius of matrix A
$\lambda_{\max}(A)$	Maximum eigenvalue of matrix A
$\lambda_{\min}(A)$	Minimum eigenvalue of matrix A
$\mathrm{Tr}(A)$	Trace of matrix A
$x \perp y$	Orthogonal vectors x and y
$\mathrm{proj}\{\cdot\}$	Projection operator
$\mathscr{L}(x_1, x_2, \ldots)$	Linear span of the vectors $x_1, x_2, \ldots$
$\mathrm{diag}\{\cdots\}$	Block-diagonal matrix
$\|\| \cdot \|\|$	Euclidean norm of a vector and its induced norm of a matrix
sup	Supremum
inf	Infimum
$\mathscr{L}_2[0, \infty)$	Space of square integrable functions on $[0, \infty)$
$l_2[0, \infty)$	Space of square summable infinite sequence on $[0, \infty)$
$\mathrm{Prob}\{x\}$	Probability of x
$\mathbf{E}\{x\}$	Expectation of x
$\mathrm{Var}(x)$	Variance of x, i.e., $\mathrm{Var}(x) = \mathbf{E}\{xx^{\mathrm{T}}\}$

WSN	Wireless sensor network
KF	Kalman filter
FC	Fusion center
MSE	Mean square error
LMI	Linear matrix inequality
BRL	Bounded real lemma
LTI	Linear time-invariant

Chapter 1
Introduction

1.1 Distributed Fusion Estimation for Sensor Networks

The multisensor fusion estimation has attracted considerable research interest during the past decades and has found applications in a variety of areas, such as target tracking and localization, guidance and navigation, and fault detection [1, 2, 5, 17]. Multisensor fusion is used because of potentially improved estimation accuracy [2, 71] and enhanced reliability and robustness against sensor failures. Many useful fusion estimation methods have been presented in the literature (see, e.g., [8, 12, 14, 20, 25, 36, 41, 46, 58, 69, 70, 75, 77, 80, 86] and the references therein). Recently, the rapid developments of wireless sensor networks (WSNs) have greatly widen applications of the multisensor fusion estimation theory, which in turn, helps the WSNs monitor the environment more accurately and efficiently. Therefore, the WSN-based multisensor fusion estimation and its applications have attracted considerable research interest during the past decade [22, 39, 57, 83].

It is known that the WSN consists of a group of sensor nodes which communicate with each other via wireless networks and the sensor nodes are usually powered by batteries. Therefore, the sensor nodes are usually constrained in energy, and developing energy-efficient algorithms for WSN-based estimation to reduce energy consumption and prolong network life is of great practical significance [9, 50, 54–56, 61, 82, 97]. Consider the situation where a WSN is deployed to observe and estimate states of a dynamically changing process, but the process is not changing too rapidly. Then it is wasteful from an energy perspective for sensors to transmit every measurement to an estimator to generate estimates, and this waste is amplified by packet losses which are usually unavoidable in WSNs [34, 64, 67, 68, 74, 78, 79, 85, 92]. Therefore, it is not surprising that many research works have been denoted to the design of energy-efficient estimation methods for sensor networks with energy constraints. There are mainly two approaches in the existing results, namely, the quantization method [3, 4, 18, 22–24, 26, 30, 37–40, 47, 50, 54, 56, 63, 65, 66, 73, 82, 89, 95] and dimension-reduction method

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[10, 22, 61, 96, 97]. In the quantization method, the measurements are quantized and represented by a finite number of bits before they are transmitted to the estimator for estimation. The coarser the quantization, the smaller the size of the packet packaging the measurements, and thus one is able to save energy consumptions in the packet transmissions. In the dimension-reduction method, the dimension of the measurement to be transmitted is reduced by applying some data compression methods [97]. Consequently, the size of the packet packaging the measurement to be transmitted is reduced, and the energy consumption in the packet transmission is thus reduced. The main idea in both the quantization method and the dimension-reduction method is to reduce the packet size and ultimately reduce the energy consumption in the packet transmissions. Therefore, they may be intuitively called as the *packet size approach*. Note that in the WSNs, data packets are transmitted through wireless communication channels, which are usually constrained in bandwidth, that is, the bit rate is constrained in communication. Thus, an advantage of the *packet size* approach is that it is able to save energy and meanwhile meet the bandwidth constraint. However, the quantization usually introduces nonlinear dynamics which adds difficulty to the estimator design; moreover, the design of quantizers involves additional computations. As investigated in [97], it is usually difficult to find a data compression operator analytically when one applies the dimension-reduction method. In this book, a novel dimension-reduction method will be introduced for energy-efficient fusion estimation without involving a data compression operator. The main idea of the proposed dimension-reduction method is that only partial components of each local estimate are selected to be transmitted to the fusion center to save communication energy, and the fusion center adopts compensation strategy to compensate the components of the local estimates that are not transmitted. Detailed results will be presented in Chap. 5. Actually, in addition to the *packet size approach*, a useful and straightforward approach to save energy is to slow down the information transmission rate in the sensors, for example, the sensors may measure and transmit measurements with an interval that is several times of the sampling period. Moreover, one may purposively close the sensor nodes to save power during certain time interval and wake them up when necessary. That is to say, in many situations, it is not necessary for sensors to transmit measurements and generate estimates at every sampling instants from the energy-efficient perspective, and the sensors may work and generate estimates with two rates, namely, a fast rate and a slow rate according to their power situations. The main idea in the aforementioned approach is to slow down the measurement transmission rate and ultimately slow down the estimation rate to save energies consumed in the communication, and then one is able to make a trade-off between energy efficiency and estimation performance by appropriately designing the information transmission rates. Therefore, the approach might be intuitively called as a *transmission rate approach* and will be introduced in detail in Chaps. 2, 3 and 4. Specifically, a multi-rate scheme by which the sensors exchange measurements with neighbors and generate local estimates at a slower time scale and generate fusion estimates at a faster time scale is proposed to reduce communication costs in Chap. 2, a state fusion method with nonuniform estimate rates is introduced in Chap. 3, and an H_∞ fusion estimation method with nonuniform sampling rates is presented in Chap. 4.

In WSNs, the multisensor fusion estimation could be done under the end-to-end information flow paradigm by communicating all the relevant measurements from various sensors to a central collector node, e.g., a sink node. Such a structure for fusion estimation is usually termed as a centralized one. The centralized structure is, however, a highly inefficient solution in WSNs, because it may cause long packet delay, consume large amounts of energies, and require a large bandwidth in the fusion center end and it has the potential for a critical failure point at the central collector node. An alternative solution is for the estimation to be performed *in-network* [19, 27, 33, 35], i.e., every sensor in the WSN with both sensing and computation capabilities performs not only as a sensor but also as an estimator, and it collects measurements only from its neighbors to generate estimates. Such a setup is usually called as the distributed structure and possesses several advantages, such as lower communication costs and bandwidth requirement in fusion center and higher reliability against sensor failures, as compared with the centralized structure. However, it is obvious that local estimates obtained at each sensor by the distributed structure are not optimal in the sense that not all the measurements in the WSN are used. Moreover, there exist disagreements among local estimates obtained at different sensors. In other words, local estimates at any two sensors may be different from each other. As pointed out in [51], such form of group disagreement regarding the signal estimates is highly undesirable for a peer-to-peer network of estimators. This gives rise to two issues that should be considered in designing a distributed estimation algorithm: (1) how could each sensor improve its local performance by taking full use of limited information from its neighbors? (2) how to reduce disagreements of local estimates among different sensors? Consensus strategy [4, 51, 52, 62, 84] and diffusion strategy [6, 7] have been presented in the literature to deal with the aforementioned two issues. The main idea of the consensus strategy is that all sensors should obtain the same estimate in steady state by using some consensus algorithms. In the diffusion strategy, both measurements and local estimates from neighboring sensors are used to generate estimates at each sensor. A hierarchical two-stage fusion estimation method will be introduced in Chaps. 2 and 7 for distributed fusion estimation.

Communication delays and packet losses are usually unavoidable in WSNs and are main sources deteriorating the estimation performance. Therefore, optimal estimation with delayed or missing measurements has attracted considerable research interest during the past decades. For example, the optimal estimation with delayed measurements has been investigated in [11, 16, 43, 45, 49, 53, 72, 81, 87, 90, 91, 93], and [13, 15, 21, 28, 31, 32, 42, 44, 48, 59, 60, 67, 88, 94] are devoted to the optimal estimation with missing measurements. However, most of the aforementioned results are concerned with single-sensor systems. For multisensor fusion estimation systems, the state estimation with uncertain observations was investigated in [76], while the robust minimum variance linear estimation for multiple sensors with different failure rates was presented in [29]. Based on the consensus strategy, a distributed H_∞ consensus filtering with multiple missing measurements was investigated in [64]. Subsequently, the optimal fusion estimation problems in the linear minimum variance sense have been investigated in [13] and [44] for multisensor systems with multiple packet dropouts. However, most of the existing results adopted the centralized fusion structure. For the multisensor fusion estimation with time delays, the information fusion problem was investigated in [72] and [43] for linear stochastic systems with delayed measurements, where the observation delays are assumed to be constant. Recently, based on the well-known federated filter, a practical architecture and some algorithms were discussed in [81] for the networked data fusion systems with time-varying delays, where the accurate time delay over each sampling period should be known for online computation of the estimators. Chapters 8 and 9 of this book are devoted to the design of multisensor fusion estimators for sensor networks with delays and packet losses. A novel model will be presented to describe the fusion system with delays and packet losses, and fusion estimators with matrix weights will be designed without resorting to the augmentation method as usually did in existing results. Moreover, some sufficient conditions for the boundness and convergence of the estimator will also be presented.

1.2 Book Organization

So far many important and interesting results have been presented for distributed multisensor fusion estimation for sensor networks. However, there lacks of a monograph to provide the up-to-date advances in the literature. Thus, the main purpose of this book is to fill such gap by providing some recent developments in the design of distributed fusion estimation for sensor networks with communication constraints. The materials adopted in the book are mainly based on research results of the authors.

Besides this short introduction, this book is organized as follows.

Chapter 1 provides a review on the background and latest developments of distributed fusion estimation for sensor networks with communication constraints in the literature.

Chapter 2 investigates the multi-rate distributed fusion estimation for sensor networks. A multi-rate scheme by which the sensors estimate states at a faster time scale and exchange information with neighbors at a slower time scale is proposed to reduce communication costs. The estimation is performed by taking into account the random packet losses in two stages. At the first stage, every sensor in the WSN collects measurements from its neighbors to generate a local estimate, then local estimates in the neighbors are further collected at the second stage to form a fused estimate to improve estimation performance and reduce disagreements among local estimates at different sensors. It is shown that the time scale of information exchange among sensors can be slower while still maintaining satisfactory estimation performance by using the developed estimation method.

Chapter 3 investigates the multisensor fusion estimation problem for sensor networks with nonuniform estimation rates. Firstly, each sensor generates local estimates with two rates, namely, a fast rate and a slow rate according to its power situation, where the estimation rates among the sensors are allowed to be different from each other. Secondly, a fusion rule with matrix weights is designed for each sensor to fuse available local estimates generated at different time scales. The fusion algorithm is applicable to both cases where the measurement noises are mutually correlated and are uncorrelated and is also applicable to the case where the sensors are not time synchronized. Two types of estimators are designed according to different considerations of design complexity and computation costs.

Chapter 4 is devoted to the problem of distributed sampled-data H_∞ filtering problem for sensor networks with nonuniform sampling periods. The measurements are sampled with nonuniform sampling periods, and each sensor in the network collects the sampled measurements only from its neighbors and runs a distributed H_∞ filtering algorithm to generate estimates. A sufficient existence condition for the distributed H_∞ filters is derived, and it is shown that the obtained condition critically depends on the sampling periods and the packet loss probabilities. The designed filters guarantee that the filtering system is mean square exponentially stable and all the filtering errors satisfy an average H_∞ noise attenuation level.

Chapter 5 addresses the distributed finite-horizon fusion Kalman filtering problem for a class of networked multisensor fusion systems with energy constraints. Only partial components of each local estimate are allowed to be transmitted to the fusion center over one sampling period. Then, a compensation strategy is used at the fusion center to compensate the untransmitted components of each local estimate, and a recursively distributed fusion Kalman filter is derived in the linear minimum variance sense. It is shown that the performance of the designed fusion filter is dependent on the selecting probability of each component of the local estimate; some criteria for the choice of the probabilities are derived such that the mean square errors of the fusion filter are bounded or convergent.

Chapter 6 focuses on the problem of the distributed H_∞ fusion filtering for a class of networked multisensor fusion systems with bandwidth constraints. Due to the limited bandwidth, only finite-level quantized local estimates are sent to the fusion center, and multiple finite-level logarithmic quantizers are adopted as the quantization strategy. The co-design of the fusion parameters and quantization parameters is converted into a convex optimization problem. It is shown that the performance of the fusion estimator provides better performance than each local estimator.

Chapter 7 is concerned with hierarchical fusion estimation problem for clustered sensor networks. The sensors within the same cluster are connected to a local estimator, and all the local estimators are linked with a fusion center. The fusion center and the local estimators are not required to be synchronous. A minimum variance estimation algorithm is presented for each cluster to aperiodically generate local estimates. A covariance intersection fusion strategy is presented for the fusion center to generate fused estimates by using asynchronous local estimates without knowing the cross-covariances among the local estimation errors.

Chapter 8 deals with the problem of robust fusion Kalman filtering for multisensor systems with randomly delayed measurements and parameter uncertainties. The stochastic parameter perturbations are considered, and the proposed fusion estimator is robust against the parameter uncertainties in the system model. Without resorting to the augmentation of system states and measurements, a robust optimal recursive filter for each subsystem is derived in the linear minimum variance sense by using the innovation analysis method. Based on the optimal fusion algorithm weighted by matrices, a robust distributed state fusion Kalman filter is derived, and the dimension of the designed filter is the same as the original system, which helps reduce computation costs as compared with the augmentation method.

Chapter 9 considers the problem of distributed Kalman filtering for a class of networked multisensor fusion systems with random delays and packet losses. A novel stochastic model is proposed to describe the estimation system with transmission delays and packet losses, and an optimal distributed fusion Kalman filter is designed based on the optimal fusion criterion weighted by matrices. Some sufficient conditions are derived such that the mean square error of the fusion filter is bounded or convergent.

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