DECENTRALIZED CONSENSUS-BASED ESTIMATION AND TARGET TRACKING

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Contents

1 Introduction **1**
1.1 Structure of the Book 4
1.2 Notation 6

2 Theoretical Background **9**
2.1 Consensus Algorithm 9
2.1.1 Graph Theory 9
2.1.2 Matrix Theory 12
2.1.3 Consensus Protocols 14
2.1.4 Convergence Analysis 15
2.1.5 Time-Variant Information Exchange Topology 16
2.1.6 Time-Variant Information Exchange Weights 17
2.1.7 Illustrative Example 17
2.2 Data Association for Target Tracking in Clutter 21
2.2.1 Probabilistic Data Association Filter 21
2.2.2 Joint Probabilistic Data Association Filter 25
2.2.3 Linear Multi-Target Integrated PDA Filter 29

3 Consensus-Based State and Parameter Estimation **39**
3.1 Introduction 39
3.2 Consensus-Based Decentralized Overlapping State Estimator . . 41
3.2.1 Continuous-Time Case 42
3.2.2 Discrete-Time Case 54
3.3 Consensus-Based Stochastic Approximation 71
3.3.1 Problem Formulation and Algorithms 71
3.3.2 Convergence Analysis 73
3.3.3 Network Design 77
3.3.4 Illustrative Examples 80
3.3.5 Concluding Remarks 83
3.4 Decentralized Parameter Estimation 83
3.4.1 Problem Formulation and Algorithm Definition 84
3.4.2 Convergence Analysis 87

4 Consensus-Based Target Tracking 105
4.1 Adaptive Single Target Tracking in LSR Networks 105
4.1.1 Introduction 106
4.1.2 Consensus-Based Distributed Target Tracking 107
4.1.3 Adaptive Target Tracking in LSR Networks 111
4.1.4 Concluding Remarks 119
4.2 Single Target Tracking in Cluttered Environments using IPDA . 120
4.2.1 Introduction 121
4.2.2 Problem Definition; IPDA 123
4.2.3 Adaptive Consensus Filter: IPDA-ACF 126
4.2.4 Stability and Reduction of Noise Influence 132
4.2.5 Alternative IPDA-based Distributed Trackers 138
4.2.6 Illustrative Examples 140
4.2.7 Concluding Remarks 142
4.3 Single Target Tracking using Multi-step Consensus 147
4.3.1 Introduction 147
4.3.2 Distributed Target Tracking Based on Multi-step Consensus 148
4.3.3 ACF: Adaptive Multi-step Consensus Scheme 150
4.3.4 ACF: Stability and Reduction of Noise Influence 157
4.3.5 Illustrating Examples 163
4.3.6 Concluding Remarks 166
4.4 Multi-target Tracking in Cluttered Environments 167
4.4.1 Introduction 167
4.4.2 Distributed Linear Multi-target Tracking Algorithm 170
4.4.3 Track-to-Track Association and Fusion 175
4.4.4 Adaptive Consensus Scheme 177
4.4.5 Track Initiation, Confirmation, Termination. Algorithm . 180
4.4.6 Simulations 183
4.4.7 Concluding Remarks 190

Bibliography 193

List of Figures

1.1 Camera network with seven sensing nodes with limited sensing and communication ranges. . . . 4

2.1 Directed graph with five nodes. . . . 11
2.2 Nodes in a sensor network that perform measurements in order to estimate the state of an environment. . . . 18
2.3 Example of typical gates and the corresponding validation matrix. 27
2.4 Configuration of two targets and three measurements. . . . 32
2.5 Generated hypotheses for the example scenario. . . . 33

3.1 Criterion function. . . . 49
3.2 Estimation error for $k_1 = k_2 = 10$. . . . 50
3.3 Estimation error for $k_1 = k_2 = 0$. . . . 51
3.4 Average criterion as a function of N. . . . 54
3.5 Stability boundaries. . . . 62
3.6 Mean-square error for different estimators. . . . 64
3.7 Optimal consensus parameters. . . . 66
3.8 Average criterion as a function of N. . . . 70
3.9 Estimates of all nodes for algorithm AUC. . . . 81
3.10 Mean-square error for AUC with constant step-size. . . . 82
3.11 Mean-square error for AUC with tapering step-size $\varepsilon_n = 1/n$. . . . 82

4.1 Average distance between the true and the estimated positions. . 111
4.2 Variance of the estimates. . . . 112
4.3 Estimates of all the nodes of Algorithm A with and without adaptation. . . . 116
4.4 Snapshots of the estimates of the target position of all the nodes, with node positions, sensing nodes and target trajectory. . . . 117
4.5 Weighted out-degrees of the nodes. . . . 118
4.6 Target position estimates of all the nodes. . . . 118
4.7 Average distance per node between the true and the estimated positions. . . . 119
4.8 Variance of the estimates. . . . 120
4.9 Time evolution of the non-zero consensus weights. . . . 133

4.10 Performance of the algorithms: no clutter. 141
4.11 Snapshots of the target position estimates of all the nodes, target trajectory up to the given time instants, and the current target positions. 143
4.12 Performance of the algorithms: clutter is present. 144
4.13 Performance of the algorithms at $t = 40$ vs. network connectivity. 144
4.14 Target perceivabilities and consensus scheme parameters corresponding to these perceivabilities. 145
4.15 One realization of a sensor network together with the target trajectory. 145
4.16 Performance of the algorithms: occulted target. 146
4.17 Evolution of the target position estimates of all the nodes w.r.t the number of the consensus steps applied when a single node is receiving measurements. 157
4.18 Evolution of the target position estimates of all the nodes w.r.t the number of the consensus steps applied when two nodes are receiving measurements. 158
4.19 Sensor network of $N = 15$ cameras with their positions. 163
4.20 Average distance per node between the true and the estimated positions, and average variance of estimates, versus time. 164
4.21 Average distance per node between the true and the estimated positions, and average variance of estimates at $t = 50$, versus number of consensus steps. 165
4.22 Average distance per node between the true and the estimated positions, and average variance of estimates, versus time-different local measurement error covariances. 166
4.23 Sensor network of 15 nodes (*e.g.*, cameras), with their positions, orientations and sensing ranges 183
4.24 Average distance between the estimated and true positions and average variance of the estimates, for different algorithms. 185
4.25 Target position estimates of all nodes, together with target trajectories. 185
4.26 Average cardinality statistic for different L compared to centralized solutions (SNF-USR and CKF-GT). 186
4.27 Average OSPA values for different L compared to centralized solutions (SNF-USR and CKF-GT). 187
4.28 The a priori scatterer measurement density for two targets for all measurements. 187
4.29 Average T2T association probability corresponding to mismatches. 188

4.30 Two examples of association events in the proposed track-to-track scheme. 189
4.31 Local node variables for different observability conditions. 189
4.32 PTEs for different nodes, along with their max-consensus value and termination threshold. 190

List of Tables

3.1 Optimization results for different measurement noise levels. 48
3.2 Adaptive consensus coefficient α_1 for different values of the measurement noise variances. 64
3.3 Performance of different algorithms. 101

Preface

Fifteen years have already elapsed since we started to study *networked systems for control and signal processing.* There is a strong methodological appeal in the idea to think about numerous classical algorithms existing in control and signal processing in a new way aimed at either parallelization of globally defined functions, or at complying with the very nature of large scale and complex systems by introducing distribution of functions and trying to obtain a problem solution close to the globally optimal one. Decomposition of a given large scale and/or complex system into subsystems gives rise to a new way of thinking, leading to the so-called "multi-agent" systems, in which each agent, typically connected to one specific subsystem, should be able to solve local problems and, at the same time, to take care about the performance of the system as a whole by communicating with its neighborhood. The communication aspects play now an important, often the central role in the design of such systems, introducing new possibilities and, at the same time, new problems to be solved. One of nowadays very popular strategies for achieving a form of distributed inter-agent collaboration is based on the so-called *dynamic consensus.*

Distributed consensus based systems require completely new methodologies for both analysis and design compared to the classical approaches, opening an entire new stimulating and challenging research space, fertile for new ideas and full of interesting details. This book is devoted to one segment of this space, containing the consensus based state and parameter estimation algorithms and their applications to target tracking problems, using both radar sensors and camera networks. The book is based on original theoretically and practically verified algorithms and contains numerous practical examples. From this point of view, it can be useful for scientists and research engineers working in the domain of distributed control and signal processing. It can also be used as a textbook for graduate courses devoted to distributed multi-agent systems, distributed and intelligent control and signal processing, and target tracking. Mathematical prerequisites for following the text are at a rather high level; therefore, the book contains short presentations of some basic theoretical concepts and definitions, making reading easier.

The authors are pleased to acknowledge their debt to many colleagues for important contributions to this book. It was a pleasure and privilege to have

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1 Introduction

Recent tremendous technological advances have caused the control, communications, computing and applied mathematics research fields to fuse into a single area dealing with the, so called, *Networked Cyber-Physical Systems (NCPS)*, representing one of the greatest challenges in modern science and technology (see e.g. [1, 6, 49, 55, 73, 168]). These systems are complex systems that interact with, and are controlled by, a considerable number of distributed and networked computing elements, fulfilling time-sensitive functions while interacting and learning from the environment. Examples and applications are numerous, such as the Internet of Things (IoT), sensor networks, smart buildings, cities and power grids, formations of robots, aircraft or automobiles, intelligent transportation systems, smart manufacturing systems, space and terrestrial exploration, tele-operation, remote diagnostics and troubleshooting, medical robotics, etc.

High dimensionality, uncertainty and information structure constraints are fundamental characteristics of these systems and the main motivating factors for the development of decentralized estimation, optimization and control methods. These methods treat a complex system by decomposing it into many interconnected subsystems, where each subsystem has a decision maker (intelligent agent) associated with it. The decentralized approach is imposed naturally since local agents, nowadays, can have great processing power and can locally implement optimization, estimation, control and other needed calculations. The agents usually coordinate and communicate only with a small subset of the other agents which ensures robustness and scalability, since there is no need for sending large amount of data through the network, which is usually prone to delays, losses, quantization effects, noise, etc. However, decentralized and distributed structures may suffer from lack of awareness of a global goal, possibly leading to a degradation of performance. Recent spectacular growth in the area of communication networks, including Wireless Sensor Networks (WSN), IoT and Networked Control Systems (NCS), provided a new revolutionary technological background for improving the performance of decentralized structures by exploiting possibilities of communication through networks (see e.g. [1,18,66,73,74,86,135,141–145,149,156,167,168] and references therein for more detailed treatment of these methods in various contexts not covered by this book).

One of the key factors for proper functioning of complex NCPS in numerous contexts is recursive, real-time, *decentralized and distributed estimation and tracking*[1] of a system state or parameters. Depending on the available resources, agents may have access to different measurements, different *a priori* information (such as system models and sensor characteristics), and different inter-agent communication links. Distributed estimation and tracking using sensor networks assumes that each sensor communicates and exchanges information with a subset of all the nodes (neighboring nodes) in order to estimate (and/or track) the state of the system, *without central processor (fusion center)* that collects all the information.

A general design methodology for *overlapping* decentralized estimation and tracking can been derived from the *inclusion principle*, using the *expansion/contraction* paradigm [58–60, 135, 146, 167]. Based on this principle, it is possible to decompose a large-scale system into, generally smaller, subsystems, and assign an agent to each subsystem, so that each agent can perform local (state or parameter) estimation. The possibility of the real-time information exchange among the neighboring agents/nodes, using (typically wireless) communication links/networks is exploited to implement some form of distributed dynamic *agreement* or *consensus* strategy on local state or parameter estimates. This results in a general recursive, real-time, decentralized and distributed estimation scheme allowing each agent to estimate/track the *global* system state or parameters with improved quality, by (implicitely) using the information/measurements of the other agents. In the estimation and tracking algorithms discussed in this book, the popular distributed dynamic linear consensus schemes have been used [53, 104, 119, 132, 158, 163, 164]. The scheme is implemented in an iterative fashion, requiring only minimal network-level connectedness between the agents, allowing imperfect inter-agent communication links (with limited bandwidth and possible outages and/or presence of noise). Hence, only a limited number of consensus iterations can be performed in real-time, which influences the level of disagreement between the nodes' estimates.

In this book we pay special attention to the specific problem of *distributed multi-target tracking*. Its treatment is based on the same general principles

[1] In the research community the terms distributed and decentralized are mostly used as synonyms to describe that the global state estimation task is dispersed among the elements which constitute the system. In recent years, the term distributed is more often connected to the distribution of estimation functions within the system while the term decentralized is connected to the system structure, i.e. with the absence of central unit which collects all the relevant information about the system. In all cases treated in this book, both of these semantic views are applicable.

described above, with additional utilization of several methodologies, concepts and assumptions, specific for this domain. Distributed target tracking problem can be divided into several steps: distributed information fusion, data and track association in cluttered and multi-target environment scenarios (measurement to track and track to track association), and dynamic state estimation. Data association techniques usually use or evolve around *Probabilistic Data Association* and *Joint Probabilistic Data Association* methodologies [10, 45]. One of the promising approaches in recent years has been the *Integrated Probability Data Association*, proposed in [91], using a model of target existence probability propagation in conjunction with the Probabilistic Data Association track estimation approximation. Another very appealing approach that has been built upon these results is the so-called Linear Multi-target Method [92]. It represents a computationally efficient alternative to the classical multi-target data association schemes. Dynamic state estimation part of the distributed target tracking problem typically uses local Kalman filters, designed with the corresponding data origin uncertainty having been taken into account, together with the above described consensus strategies adapted to this specific setting.

The majority of the decentralized target tracking algorithms treated in this book are discussed from the point of view of their application and adaptation to the practically very important problem of tracking in *large-scale camera networks*. The rapid improvement in quality and resolution of imaging sensors and the availability of low-cost cameras and cheap computational power, have paved the way for the creation of large scale camera networks and the corresponding applications, such as wide-area surveillance, disaster response, environmental monitoring, etc. Multiple sensors provide better area coverage, as well as views from different angles, which may lead to a robust scene understanding. The process of detecting and tracking objects of interest is one of the fundamental features of camera networks (see e.g. [87] for more details). Camera networks impose some unique and interesting challenges on the implementation of distributed estimation algorithms. These challenges arise from the fact that most cameras are directional and have limited sensing range so that at each time instant there might be a significant share of sensors that do not observe the target. This issue can be overcame by increasing the communicated information between the sensors. However, this may not be possible in practical situations where limited power, bandwidth and real-time operational requirements must be taken into account. Most standard distributed estimation algorithms perform poorly in situations characterized by limited local observability and constrained resources. Fig. 1.1 illustrates such scenario where the objective for the camera network is to collaboratively track target positions. Successful network-wide tracking assumes that each camera maintains an accurate target