Guest Editorial

Foreword to the Special Section on Meta-Level and Adversarial Tracking

A plethora of well-established tracking algorithms aim to estimate, over time, the latent *kinematic* state (e.g., position, velocity, higher order kinematics, or any other spatiotemporal characteristic) of a single or multiple targets based on the available sensory observations, including from several sources. Here, we refer to such techniques as *sensor-level* trackers.

In recent years, there has been a move toward a new paradigm in scene analysis aimed at a higher level understanding of complex scenes. The objective may be to circumvent conflict or identify opportunities, automate decision-making and optimize resources allocation as well as future actions for more effective and safer operation of sensing platform(s) or assets. This can entail determining and leveraging, as early as possible, underlying regressors (e.g., objects' intents such as destinations or future actions), social interactions (e.g., hidden group structures and hierarchies), which drive the evolution of a multitarget scene over time, and the capabilities or characteristics of competitors or adversaries. Algorithms that tackle such inference tasks and go beyond kinematic state estimation are dubbed *meta-level* and *adversarial* trackers. They belong to a higher system level compared with the sensor-level methods. In this context, adversarial tracking refers to one side estimating over-time the characteristics or strategies of its adversaries and thence calibrating its future behavior, for instance to avoid conflict.

Meta-level and adversarial tracking, therefore, present a shift away from the traditional viewpoint of a scene where objects move independently of one another in an unpremeditated manner and without regard to possible competition or group structures, toward an integrated viewpoint where intents, anomalies, group interactions, and characteristics of competitors/adversaries can be automatically learned. This also enables more accurate state estimation by capitalizing on inferred meta-level information.

Given the substantial modeling and computational challenges of formulating robust meta-level and adversarial trackers, this Special Section serves to showcase a diverse set of recent relevant technical developments and applications. It comprises of nine selected articles, drawing on recent advances in stochastic modeling, computational methods, statistical filtering, sensing systems, and others. The IEEE TRANSACTIONS ON AEROSPACE AND ELECTRONIC SYSTEMS is an ideal venue for this emerging topic, which calls for a broad high-level systems perspective that can consider decision-making and various modalities or data sources (e.g., radar, optical, RF, acoustics, social media, etc.).

The first set of three articles addresses the problem of devising suitable models that describe sophisticated behaviors exhibited by a target and capture the influence of any underlying regressor (e.g., intent, anomaly, etc.). Building on their previous work, Carravetta and White in "Embedded stochastic syntactic processes: A class of stochastic grammars equivalent by embedding to a Markov process" present a theoretical meta-level modeling framework. It is based on the concept of stochastic syntactic processes to relate general grammatical models and processes (e.g., parsing) and statistical estimation problems, most notably by embedding the syntactic process into a Markov random field. This generic formulation is relevant to a wide range of inference problems. Whereas Rezaie *et al.* propose in "Conditionally Markov modeling and optimal estimation for trajectory with waypoints and destination" a class

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of conditionally Markov sequences to model target trajectories with long range dependencies or particular patterns arising from the object starting point or origin, waypoints during the journey and final destination. Such behavior is common, for instance, in air traffic management applications. The authors examine a range of scenarios and present filters-predictors for state estimation and forecasting, particularly for the Gaussian case, with simulations to demonstrate the inference results.

A Bayesian framework for simultaneous maneuvering object tracking and intent (namely, destination) prediction, if applicable, is introduced in "Lévy state-space models for tracking and intent prediction of highly maneuverable objects" by Gan *et al*. It utilizes novel α-stable Lévy state-space models, which can effectively characterize swift target maneuvers and are expressed in this article in continuous time as Lévy processes. This is in conjunction with suitable inference routines, e.g., Rao-Blackwellised particle filtering. The efficacy of the proposed approach is demonstrated using real data from the maritime surveillance and cybernetics fields.

This Special Section also has two articles on multitarget scenarios. "Sequential dynamic leadership inference using Bayesian Monte Carlo methods," by Li *et al.,* presents a probabilistic framework that not only enables the automatic learning of a group structure (namely, leadership hierarchy) from noisy data, but also facilitates more accurate (sensor-level) multitarget tracking. It employs leader–follower stochastic models and appropriate sequential Monte Carlo or Markov Chain Monte Carlo algorithms. Real animal group data are used to benchmark the various adopted inference techniques. On the computational aspects, especially when treating congested and/or large scenes, Campbell *et al.* describe in "An algorithm for large-scale multitarget tracking and parameter estimation" a method for fast, scalable, and robust multitarget tracking and parameter estimation. Simulation results for a large number of targets (e.g., a million) are shown to corroborate its efficiency. The developed approach in that paper is based on the propagation of the first two factorial cumulants of point processes, and its relevance or links to meta-level tracking are highlighted, for instance, in relation to parameter estimation.

We have two contributions on adversarial tracking. First, Krishnamurthy *et al.* in "Adversarial radar inference: Inverse tracking, identifying cognition and designing smart interference" comprehensively address three inter-related aspects of adversarial inference involving a cognitive radar treated as the "adversary". The three aspects are as follows: 1) inverse Bayesian filtering for inferring the adversary (e.g., counter-autonomous systems radar) tracker estimates of an asset (e.g., a drone), which can accordingly calibrate its future actions (e.g., to avoid detection); 2) identification of utility maximization behavior of a cognitive radar for the two key functionalities of adaptive beam allocation and waveform design by devising a constrained nonparametric set-valued estimator for the corresponding utility function; and 3) smart interference signal design informed by an estimator of the radar channels in order to confuse the adversary, for instance to mislead it to counterproductively change its transmit waveform. Second, in "A formulation of the adversarial risk for multiobject filtering," by Narykov *et al.*, the concept of adversarial risk in the context of military impact assessment is introduced with an illustrative example; it is defined as a function of multiobject state describing a group of weapons. An algorithm that estimates the risk value and captures the present uncertainty in the weapon population is developed using multiobject filters. Synthetic data are utilized to verify the developed technique and compare it to another naive method.

On revealing and modeling of anomalous behavior, the article titled "Malicious AIS spoofing and abnormal stealth deviations: A comprehensive statistical framework for maritime anomaly detection" by d'Afflisio *et al.*, tackles the problem of determining whether a vessel is maliciously hiding its true trajectory and possible deviations from prescribed nominal navigation routes by intentionally spoofing its automatic identification system messages. Two different anomaly-detection strategies are formulated within a hypothesis testing framework. They are based on the changes in the Ornstein–Uhlenbeck process long-run mean velocity parameter and supported by enlisting reliable information from monitoring systems (e.g., coastal radars and spaceborne sensor imagery). Both approaches are compared within an operational scenario with simulated data. Additionally, Rovatsos *et al.*, in "Quickest detection of anomalies of varying location and size in sensor networks," address the task of sequentially detecting moving anomalies with transient dynamics in a sensor network. The article applies the quickest detection theory in anomaly detection. It proposes an intuitive algorithm, with decision rules, and proves its asymptotic optimality under certain conditions. The introduced detection procedure, which has notable practical relevance (e.g., detecting objects that affect different sensors at different times) is evaluated by simulations. Interestingly, it can be extended to scenarios when an adversary can mask the emergence of anomalies.

It is hoped that this Special Section motivates further research into meta-level and adversarial tracking. Albeit the majority of its articles present model-based techniques, they can be combined with and/or benefit from recent advances in data-driven or machine learning inference algorithms (e.g., deep neural networks). Finally, with the ever-increasing demand for automation and optimization of resource allocation (e.g., for distributed smart and possibly cognitive sensing) in various applications, not least for robotics, surveillance, connected battlefield, and Internet of Things, the interest in meta-level and adversarial trackers is poised to grow driven by the need for more robust and holistic understanding of complex scenes.

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