IMM Estimator in Multisensor Multitarget Tracking for Air Traffic Control and Autonomous Driving

Henk A. P. Blom
Delft University of Technology
Delft, Netherlands
h.a.p.blom@tudelft.nl

Kaipei Yang
Yaakov Bar-Shalom
University of Connecticut
Storrs, Connecticut, USA
kaipei.y@gmail.com
yaakov.barshalom@uconn.edu

Many dynamical systems undergo switches in their dynamical configuration, shortly referred to as mode switching. For example, an observed aircraft or car switches from uniform motion to a maneuver mode, or switches back from a maneuver mode to uniform motion. In nonlinear filtering, the simplest model of this type is a Markov jump linear Gaussian process x_t satisfying:

$$x_t = A(\theta_t)x_{t-1} + B(\theta_t)w_t \tag{1}$$

where θ_t is a hidden Markov chain, that switches per time step with probability Π_{ij} from i to j in the set of models $\{1, \ldots, N\}$.

The problem is to estimate x_t from the noisy observation:

$$y_t = F(\theta_t)x_t + G(\theta_t)v_t \tag{2}$$

where y_t is the R^m-valued observation of the R^n-valued system state x_t. Matrices A, B, F, and G depend on θ_t, and w_t and v_t are independent white Gaussian noises.

The optimal non-linear estimator involves a number of Kalman filters that increases exponentially with time t. The interacting multiple model (IMM) estimator [1], [2] involves N Kalman filters only, one for each possible mode. To compensate for the reduction in number of filters, at the start of each estimation cycle, there is a controlled interaction/mixing between the estimates from the N Kalman filters. [1] has formally proven that these interaction/mixing equations are exact, not an approximation. At the end of each estimation cycle, the IMM estimator calculates the filter weights (mode probabilities), as well as the overall mean and covariance. Bar-Shalom et al. [3] give an in-depth explanation of the IMM estimator and its application in tracking and navigation. Kalman filters for kinematic models [3] are low-pass filters. With small noise gain B in (1) they have a low bandwidth, suitable for nearly constant velocity motion. With large B, they have a higher bandwidth and are suitable for maneuvering targets. The IMM with such models is an adaptive bandwidth estimator.

In case of no mode switching, Π is the identity matrix and IMM reduces to the well-known MM estimator. As explained by [4], the success of the IMM estimator can be attributed to its simplicity in extending the MM estimator with the exact interaction equations at the beginning of each estimation cycle, which makes IMM the natural approximation of the optimal estimator for mode-switching systems.

IMM IN AIR TRAFFIC CONTROL

In air traffic control (ATC), multisensor multitarget tracking (MTT) is a basic functionality in fusing observation data reports from various sensors into a reliable and accurate real-time air traffic situation. One of the problems to be handled by MTT is to track a sudden maneuver start and stop for aircraft. Additional problems are that sensor reports may include outlier and false measurements, both of which can be mistaken for a maneuver. Another problem is that a data report typically does not include the identity of the aircraft source or may include an erroneous identity.

In the eighties, the first author had the opportunity to investigate this problem at Netherlands Aerospace Laboratory NLR. The novel approach was to study the problem within the theory of nonlinear filtering of a jump-diffusion that evolves in a hybrid state space. This resulted in a characterization of IMM's interaction in a continuous time setting [5]. Subsequently, this interaction was developed for a discrete-time version of the IMM estimator [1]. Initially, at NLR, this research was judged to be esoteric, rather than of practical use. This view completely changed when for an IMM based track maintenance algorithm remarkably good performance was demonstrated on simulated and live data from primary radar observations of air traffic [6]. The modes of flight modelled in this research are uniform motion, speed change, right turn and left turn, while outliers, false measurements and missing identities were covered by probabilistic data association (PDA). In the follow-on phase, the research was widened to the development of a Bayesian MMT design for ATC [7].

These remarkable tracking results motivated EUROCONTROL to start the development of its multisensor multitarget tracking system ARTAS. The first ARTAS version fused data reports from multiple primary and secondary radars, and its tracking architecture was largely based on the IMM inspired design of [7]. Halfway through the nineties, ARTAS started its ATC operational use in a steadily increasing number of EUROCONTROL member states. The use of ARTAS by a steadily increasing number of ATC centres has also stimulated further development. One important development is the replacement of PDA by a joint PDA approach that avoids coalescence of neighbouring tracks [8]. Other important developments concern the fusion of data reports from new sensor types, such as Mode

S, automatic dependent surveillance (ADS), wide area multilateration (WAM), and surface movement radar (SMR) [9].

Today, ARTAS is operational for ATCs in 43 member states of EUROCONTROL, as well as in several other states, including the USA. In parallel, its further development is ongoing, such as fusing new sensor types for the tracking of an increasing number of drones.

IMM IN AUTONOMOUS DRIVING

An advanced driver assistance system (ADAS) or autonomous driving (AD) system must be capable of estimating 1) the ego vehicle's motion, orientation, behavior, and trajectory, as well as 2) the perception of surrounding objects such as other vehicles, bicycles, and pedestrians, to ensure the safety and efficiency of autonomous vehicles.

In an autonomous driving system, different sensors and sources of information provide different types of data, such as LiDAR [10], radar, cameras, GPS, inertial measurement unit, and so on. Each sensor has its strengths and weaknesses, and none of them alone can provide a complete picture of the vehicle's environment. For example, LiDAR can provide high-resolution three-dimensional point cloud data, but it can be affected by weather conditions such as rain and snow. On the other hand, radar can penetrate some weather conditions but provides lower-resolution data. By using IMM, the autonomous driving system can combine data from different sources and sensors, and rely on multiple models of the vehicle's environment to make more accurate and reliable decisions in real time. Each model is designed to capture a specific aspect of the environment, such as object detection, motion estimation (which is subject to different behavior modes), or localization. These multiple models are then used to generate a more accurate and reliable estimate of the vehicle's surroundings [11].

In a variety of autonomous driving scenarios, IMM estimation has demonstrated significant efficiency, robustness, and reliability in integrating onboard vehicle sensors in multiobject tracking (MOT) and vehicle localization. These are used for applications such as estimating road conditions and predicting drivers' turning intentions at urban intersections, i.e., can handle different behavior modes [12]. Compared to single-model-based tracking, IMM has been shown in practice to improve the accuracy of motion estimation and overall, MOT performance with less track segmentation, less object ID switching, and higher recall.

Being a model-based approach that incorporates prior knowledge, IMM fills a gap between autonomous driving and data-driven algorithms because the latter solely relies on patterns in data and may not be able to capture the full range of driving scenarios. Optimal performance of autonomous driving can be achieved by using a combination of model-based algorithms and data-driven approaches, with IMM delivering robust and reliable tracking results and machine learning and neural networks capturing more subtle patterns in the sensor data and providing additional insights. Overall, the IMM estimator will continue to be critical in the advancement of autonomous driving technology.

LOOKING AHEAD

In this short paper, IMM applications in multisensor multitarget tracking have been highlighted for air traffic and for road traffic. From these highlights it has become clear that by their objectives, these applications involve very large sets of live data streams. From this perspective, MTT has been decades ahead of the current era of large data research. This also means that the results obtained from MTT research can provide novel insight in large data research. To speak in IMM terms, this defines great opportunities for Interaction between research in Bayesian estimation and in large data.

REFERENCES

1. Blom, H. A. P. An efficient filter for abruptly changing systems. In *Proceedings 23rd IEEE Conference on Decision and Control*, Las Vegas, NV, 1984, 656–658.
2. Blom, H. A. P., and Bar-Shalom, Y. The interacting multiple model algorithm for systems with markovian switching coefficients. *IEEE Transactions on Automatic Control*, Vol. 33, 8 (1988), 780–783.
3. Bar-Shalom, Y., Li, X. R., and Kirubarajan, T. *Estimation with Applications to Tracking and Navigation*. New York, NT: Wiley, 2001.
4. Bar-Shalom, Y., Challa, S., and Blom, H. A. P. The IMM estimator as the natural approximation of the optimal estimator for hybrid systems. *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 41, 3 (2005), 986–991.
5. Blom, H. A. P. Markov jump-diffusion models and decision-making-free filtering. In *Proceedings 6th International Conference Analysis and Optimization of Systems*, Berlin, Germany, 1984, 568–580.
6. Blom, H. A. P. A sophisticated tracking algorithm for Air Traffic Control surveillance radar data. In *Proceedings 1984 International Conference on Radar*, Paris, France, 1984, 393–398.
7. Blom, H. A. P., Hogendoorn, R. A., and van Doorn, B. A. Design of a multisensor tracking system for advanced Air Traffic Control. In *Multitarget-Multisensor Tracking: Applications and Advances*, Vol. II, Y. Bar-Shalom, Ed. Boston, MA: Artech House, 1992, pp. 31–63.
8. Blom, H. A. P., and Bloem, E. A. Probabilistic data association avoiding track coalescence. *IEEE Transactions on Automatic Control*, Vol. 45, 2 (2000), 247–259.
9. EUROCONTROL. ARTAS service movement surveillance, https://www.eurocontrol.int/sites/default/files/publication/files/artas-article-paper-update-08032017.pdf, last access 10 May 2023.
10. Li, Y., and Ibanez-Guzman, J. Lidar for autonomous driving: the principles, challenges, and trends for automotive lidar and perception systems. *IEEE Signal Processing Magazine*, Vol. 37, (2020), 50–61.
11. Yuan, T., Krishnan, K., Duraisamy, B., Maile, M., and Schwarz, T. Extended object tracking using IMM approach for a real-world vehicle sensor fusion system. In *Proceedings 2017 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI)*, Daegu, South Korea, 2017, 638–643.
12. Lefkopoulos, V., Menner, M., Domahidi, A., and Zeilinger, M. N. Interaction-aware motion prediction for autonomous driving: a multiple model Kalman filtering scheme. *IEEE Robotics and Automation Letters*, Vol. 6, 1 (2021), 80–87.