Advanced Statistical Signal Processing for Next Generation Trajectory Prediction

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***Abstract*— Trajectory Prediction (TP) is fundamental in Air Traffic Management (ATM). This research focuses on TP for the execution phase of the flight. In contrast to exploit black-box machine learning-based solutions, we tackle TP as an estimation problem, resorting to mathematical tools arising from statistical signal processing. Our first goal is to find an optimal and robust 4D (3D space plus time) TP solution, and the real-time estimation of the aircraft's active guidance mode, observing flight data collected from Automatic Dependent Surveillance-Broadcast (ADS-B), and transponder selective mode (Mode S) transmissions. Notice that this work is at a very early stage and only preliminary results are available.**

Keywords-component; Trajectory Prediction; Statistical Signal Processing; 4D-TP; Robustness; Guidance Mode Identification; ADSB and Mode S data.

I. Introduction and Brief TP State-of-the-Art

It is a fact that the airspace is becoming denser with increasing air traffic. In this situation, airspace management faces a big challenge in maintaining the safety level. Having a precise flight planning for flights is the first step to overcome inherent system problems. The trajectory is a sequence of aircraft states during the flight. State variables such as position, airspeed and aircraft mass are considered as the main variables to describe the trajectory of the aircraft. The estimation of prediction of these states leads to more information for a better flight control. Accurate and reliable trajectory prediction (TP) is fundamental for the design of next generation air traffic services (ATS), decision support tools for traffic synchronization and separation management; as well as enhanced safety nets and collision avoidance tools; either in a (partially) automated environment, on-ground, airborne or in a distributed system. In addition, w.r.t. standard 3D TP, estimating 4D trajectories (i.e, 3D plus time) can bring more realistic results. Indeed, information on the exact position of the aircraft at a certain time can avoid conflicts.

State-of-the-art TP technology mostly relies on heuristic decision rules, using simplified dynamic models and strong assumptions when using filtering techniques. In practice, these approaches are not able to cope with system modelling inaccuracies and lead to a lack of robustness, which is known to be a key requirement for safety-critical applications such as Air Traffic Management (ATM). In this research we propose to tackle the TP problem from a probabilistic perspective, approaching it with powerful mathematical tools arising from the statistical signal processing field. Advanced robust statistical inference techniques have been shown in other contexts to provide a remarkable performance and/or robustness improvement in comparison to conventional approaches, allowing to relax stringent assumptions. We focus on accurate and robust real-time TP to provide a short-term prediction. Accurate TP in the execution phase of the flight is expected to support new or enhanced tools for advanced ATS into a Trajectory Based Operations (TBOs) environment, increasing safety, capacity, predictability, and cost-effectiveness of the future European ATM system.

The segmentation of the aircraft trajectory into distinct flight phases is a key aspect in TP problems. When considering machine learning (ML) TP algorithms the segmentation process is applicable since unpredictable behaviors are considered as outliers in real data. A methodology for automated TP analysis is introduced in [1], specifically designed for splitting the process into separated stages according to different flight phases. A Neural Network (NN) algorithm to predict the aircraft trajectories in the vertical plane was introduced in [2]. Two configurations were considered: a) strategic prediction, which is a long-term prediction, and b) tactical prediction or execution phase of the flight, which is a short-term prediction. A similar approach to infer the future air traffic flows using NNs is shown in [3]. The TP task in the case of aircraft intents in the terminal phase is investigated in [4], identifying the associated intent model and calculating the specific intent based on the such model knowledge. A 4D trajectory prediction model for both strategic and tactical TP was proposed in [5] mainly relying on historical data and real-time radar data. In the strategic TP, the method exploited the flying data history, while for the tactical or short-term prediction the predicted trajectory was updated with real-time radar data, begin able to predict the trajectory for the whole flying process. A novel approach to combine a clustering algorithm and Kalman filters (KF) for the TP problem was introduced in [6]. Hybrid estimation and intent inference algorithms are common approaches in long-term TP. In [6] a clustering algorithm was applied to process historical radar data and to derive aircraft trajectories. Subsequently, the representative trajectory set is used to feed a hybrid predictor that instantiates an Interacting Multiple Model (IMM) filter [7]. An improved trajectory prediction algorithm was proposed based on such representative trajectories.

Without relying in any ML approach, which may lead to a lack of understanding of the estimator behavior and the physical phenomena under study, a stochastic approach to track the 4D aircraft motion considering weather conditions was proposed in [8], where the optimal state sequence is computed in the maximum likelihood sense. Indeed, the method uses a Viterbi algorithm [9] to calculate the most likely sequence of states driven by a Hidden Markov Model (HMM) [10]. In [11], also resorting to a TP stochastic modelling, the flight phases are identified by a Viterbi algorithm to find the most likely sequence of hidden states. The combination of a kinematic stochastic model with a Monte Carlo method allowed to predict the possible aircraft trajectories given the initial state. A real-time aircraft active guidance mode estimation solution was proposed in [12], An IMM based on a set of Extended KF (EKF) was assessed for TP in the descent phase, which is more complicated w.r.t. the cruise phase, providing promising results for precise short-term TP. The validation was performed with Airbus Performance Engineering Program (PEP) data, which allows to obtain realistic synthetic trajectories and guidance modes, but also with real flight data collected from Automatic Dependent Surveillance-Broadcast (ADS-B) and transponder selective mode (mode S).

Even if a plethora of solutions exist in the literature, there is still a need to overcome the lack of understanding of ML-based solutions, and to improve the robustness and precision of stochastic approaches. In this contribution we focus on the latter, review challenges and possible alternatives, in order to pave the way towards a precise TP and real-time guidance mode identification.

II. Statistical Signal Processing Approach for TP: Challenges and Alternatives

In contrast to other approaches, when considering a stochastic representation of the TP problem it is assumed that parametric models are available for the aircraft dynamics, uncertainties and performance models. The ultimate goal is to overcome the limitations of state-of-the-art stochastic approaches, and for that purpose one may seek to explore, for instance: i) nonlinear Bayesian inference techniques, ii) noise statistics estimation, iii) robust filtering methods, iv) Bayesian nonparametric solutions, v) multi-object/multi-sensor filtering if multi-aircraft TP is considered, and vi) Bayesian detection strategies for collision detection/avoidance. That is, these alternatives may provide solutions to different challenges within the TP problem for a complete probabilistic TP framework.

In general, accurate knowledge of aircraft performance data and flight-intent is available for ownship TP algorithms. However, on-board applications for intruder trajectory prediction rely on simplified aircraft performance data and have a very limited (or non-existent) knowledge of the intruder's flight-intent, for instance, to enable self-separation or conformance monitoring applications [13]. A similar limitation exists for ground-based TPs, which typically use the Airline Procedure Model (ARPM) - embedded in the Base of Aircraft Data (BADA) [14]. The ARPM, however, is generalist for most applications [15].

Precise flight-intent data is highly critical in the vertical domain since slight input inaccuracies easily lead to notable discrepancies in the vertical (and speed) trajectory profile that is finally computed by the TP. A sequence of flight phases with different parametrized guidance modes (e.g., descent at constant Mach and idle thrust) and end conditions (e.g. until reaching the target altitude) composes the aircraft vertical intent. These guidance modes describe how the throttle and elevator can operate to follow the planned trajectory and must be known by the TP to integrate the equations describing the aircraft dynamics. Additionally, flight intent is one of the main sources of uncertainty.

The TP problem can be seen from an estimation/detection point of view, and thus optimally be tackled using statistical signal processing (SSP) tools, avoiding current heuristic decision rules, being able to cope with realistic probabilistic dynamic models, and providing a principled data fusion strategy. The underlying problem is the estimation (prediction) of time-varying hidden quantities of interest (states/parameters, i.e., position and velocity of the aircraft, or its corresponding flight mode), from a set of available noisy observations. The dynamic complex system can be time-varying, nonlinear, non-Gaussian, and probably with a certain model uncertainty (i.e., model mismatch). A more complicated system model must be accounted for if the single aircraft TP case is generalized to multiple aircraft TP. Self-separation and conformance monitoring automated assistance tools, on top of the TP system outcome, must consider collision detection and resolution (CDR) strategies that can be seen as a Bayesian detection problem.

- For nonlinear/Gaussian systems, it has been shown that deterministic sampling-based strategies are a powerful filtering solution [16], then this should be the basis for state estimation if the assumptions hold. If the dynamic system is non-Gaussian, we must resort to sequential Monte Carlo methods. These techniques have already been successfully applied to ATM [17].

- All the standard filtering rely on perfect known noise statistics, then to ensure system robustness we must resort to robust filtering techniques: i) Gaussian covariance estimation, ii) exploiting hierarchically Gaussian models, or iii) use Bayesian nonparametric techniques to estimate the complete density [18].

- Taking into account the problem at hand, instead of using a single dynamic system, a better idea may be to consider a set of different dynamics. The natural solution to this problem within a filtering framework is the IMM filter. This idea has already been applied to TP for ATM purposes [12, 19-20], but several points need to be improved for real-life applicability, i.e., robustness, weather uncertainty, extension to the 4D TP problem.

- The general extension of the previous approaches to multiple aircraft TP, where the number of aircraft in the air space is unknown and may vary over time, can be formulated as a multiple target tracking (MTT) problem. Most MTT techniques developed in the past decade rely on Random Finite Sets (RFS) [21]. This provides a new statistical framework to cope with the unknown time-varying number of targets, false alarms, missed detections, clutter, and unresolved targets. This approach has not been yet applied to the specific ATM problem at hand.

To summarize, there are a plethora of different advanced SSP techniques that may be relevant to the next generation of TP for ATM applications in the execution phase of the flight.

Another important issue is the data sources available to validate the new methodologies. In order to correctly test the TP methods three families of data sources may be required: 1) Aircraft surveillance data: the main input for any TP in the execution phase of the flight. ADS-B data from FlightRadar24, OpenSky, and other similar databases may be used for this purpose. These datasets might be complemented with secondary surveillance radar tracks provided by the corresponding Air Navigation Service Provider (ANSP), in our case by spanish ENAIRE/CRIDA; 2) Weather data: from public sources such as NOAA, ECMWF or EUMETSAT (for convective weather); 3) It may be fundamental for validation purposes to have in-flight recorded data. In our case we may have access to quick access recorders (QAR) datasets provided by UPC.

In addition to the previous three families of data sources, and in order to statistically characterize the estimator or TP method behavior, another key tool is a realistic simulator which allows: i) to know the true trajectory, ii) to control the system uncertainties, iii) the possibility to induce possible model mismatches, and iv) to perform representative Monte Carlo simulations.

III. Illustrative Results: Impact of Pilot Input Mismatch on Guidance Mode Tracking

In the sequel we provide some preliminary results. Notice that these results are obtained with a custom trajectory simulator which allows, as previously mentioned, to obtain a meaningful statistical characterization. It is worth mentioning that the original IMM-based guidance mode identification in [12] assume a perfect system knowledge (i.e., ideal nominal scenario without mismatch), as reproduced in the sequel.

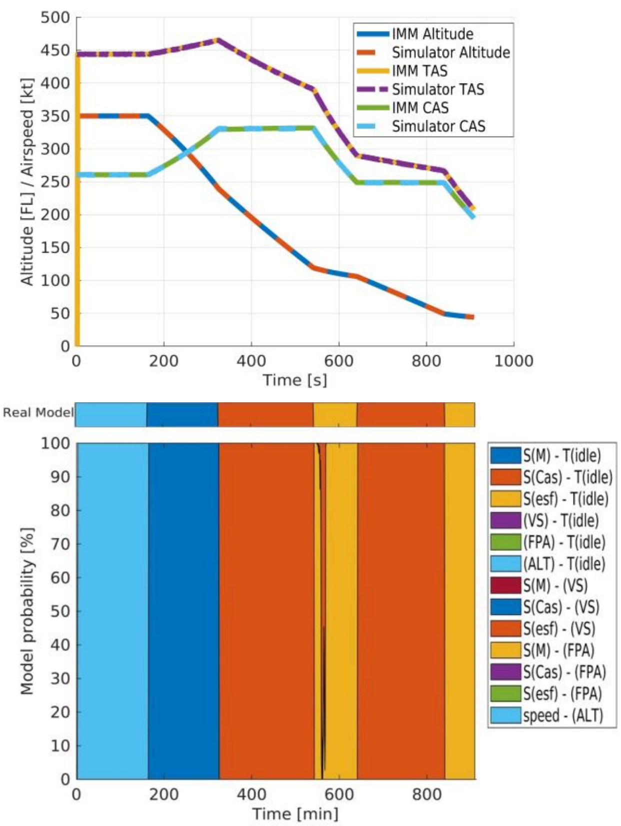

Figure 1. *Simulated and IMM estimated aircraft descent trajectory (top), real guidance mode (middle) and IMM mode probability (bottom).*

Fig. 1 (top plot) shows a particular simulated realistic aircraft descent trajectory including altitude, True AirSpeed (TAS) and Calibrated AirSpeed (CAS), together with the IMM-based estimated values. Notice that the estimates coincide with the true values, so one can state that the IMM works surprisingly well for TP. In addition, the middle and bottom plots in Fig. 1 illustrate the true guidance mode and the corresponding one identified by the IMM (i.e., model probability), which again confirms the good behavior of the filter.

But notice that the previous results were obtained with a perfect system knowledge. In real-life applications, all guidance modes are controlled by a set of pilot inputs, which may be unknown to a certain extent. Therefore, a question naturally arises: which is the impact of a possible pilot input mismatch? We illustrate the impact of a possible model mismatch for the CAS-FPA guidance mode in Fig. 2, where we provide the root mean square error (RMSE) degradation w.r.t. the optimal KF. In this case, the two pilot inputs are the energy share factor at constant CAS, and the flight path angle (FPA). The mismatch is induced in the FPA. It is obvious that the mismatched KF deviates from the optimal, which should be considered within the IMM for real-life applicability.

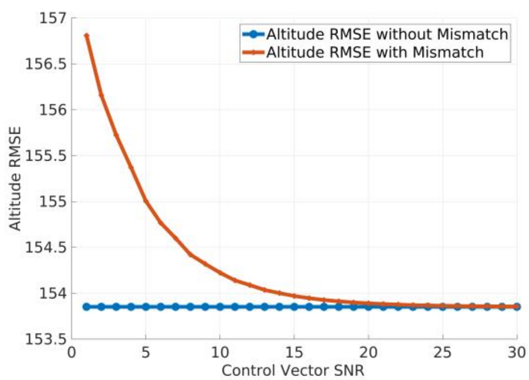

Figure 2. *Altitude prediction error in model mismatch*

IV. Conclusion

This paper presented the Trajectory Prediction (TP) problem in the execution phase of the flight. The main goal was to introduce our research path within the new concept of Trajectory Based Operations based air traffic services environment, resorting to statistical signal processing in order to increase the optimality and robustness of the solution. The preliminary results illustrated the IMM-based guidance mode identification under nominal conditions, and the impact of model mismatch, both with the proposed trajectory simulator. In future works, different statistical signal processing methods will be explored for robust TP.

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