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Learning aircraft operational factors to improve aircraft climb prediction: A large scale multi-airport study

Richard Alligier*, David Gianazza

ENAC, Université de Toulouse, France

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ABSTRACT

Ground-based aircraft trajectory prediction is a major concern in air traffic control and management. A safe and efficient prediction is a prerequisite to the implementation of new automated tools.

In current operations, trajectory prediction is computed using a physical model. It models the forces acting on the aircraft to predict the successive points of the future trajectory. Using such a model requires knowledge of the aircraft state (mass) and aircraft intent (thrust law, speed intent). Most of this information is not available to ground-based systems.

This paper focuses on the climb phase. We improve the trajectory prediction accuracy by predicting some of the unknown point-mass model parameters. These unknown parameters are the mass and the speed intent. This study relies on ADS-B data coming from The OpenSky Network. It contains the climbing segments of the year 2017 detected by this sensor network. The 11 most frequent aircraft types are studied. The obtained data set contains millions of climbing segments from all over the world. The climbing segments are not filtered according to their altitude. Predictive models returning the missing parameters are learned from this data set, using a Machine Learning method. The trained models are tested on the two last months of the year and compared with a baseline method (BADA used with the mean parameters computed on the first ten months). Compared with this baseline, the Machine Learning approach reduce the RMSE on the altitude by 48% on average on a 10 min horizon prediction. The RMSE on the speed is reduced by 25% on average. The trajectory prediction is also improved for small climbing segments. Using only information available before the considered aircraft take-off, the Machine Learning method can predict the unknown parameters, reducing the RMSE on the altitude by 25% on average.

The data set and the Machine Learning code are publicly available.

0. Introduction

Most applications in Air Traffic Control and Management (ATC/ATM) rely on a ground-based trajectory prediction. It will be even more true with new operational concepts (SESAR Consortium, 2007; Swenson et al., 2006) envisioning trajectory-based operations. An accurate trajectory prediction is required for the new automated tools and algorithms implementing these concepts. Some of the most recent algorithms designed to solve ATM/ATC problems do require to test a large number of “what-if” alternative trajectories and it would be impractical to download them all from the aircraft. As an example, in Prats et al. (2010) an iterative quasi-Newton

* Corresponding author.
E-mail address: richard.alligier@enac.fr (R. Alligier).

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method is used to find trajectories for departing aircraft, minimizing the noise annoyance. Another example is Chaloulos et al. (2010) where Monte Carlo simulations are used to estimate the risk of conflict between trajectories, in a stochastic environment. Some of the automated tools currently being developed for ATC/ATM can detect and solve conflicts between trajectories, using Genetic Algorithms (Durand et al., 1996[1]), or Differential Evolution or Particle Swarm Optimization (Vanaret et al., 2012). In these conflict solving algorithms, each considered maneuver is associated to the trajectory predicted if such a maneuver was issued. If the trajectory prediction is bad, a large safety margin around the predicted trajectories will be taken. As a result, the only remaining conflict free maneuvers might be the one associated to a large cost. With a good trajectory prediction, the safety margin around the predicted trajectories will be smaller. The set of conflict free trajectories will be larger and might contain maneuvers of smaller cost.

Most trajectory predictors rely on a point-mass model to describe the aircraft dynamics. The aircraft is simply modeled as a point with a mass, and the second Newton's law is applied to relate the forces acting on the aircraft to the inertial acceleration of its center of mass. Such a model is formulated as a set of differential algebraic equations that must be integrated over a time interval in order to predict the successive aircraft positions, knowing the aircraft initial state (mass, current thrust setting, position, velocity, bank angle, etc.), atmospheric conditions (wind, temperature), and aircraft intent (thrust profile, speed profile, route). The Eurocontrol Base of Aircraft Data (BADA) project (Mouillet, 2017) implements such a physical model and provides default values for the models parameters.

In current operations, the trajectory is predicted by using the reference mass $mass_{\mathrm{ref}}$ and the reference $(cas_{1\mathrm{ref}}, cas_{2\mathrm{ref}}, M_{\mathrm{ref}})$ values from BADA. The latter values describe the speed profile of a climbing aircraft. The aircraft climbs at constant CAS (Calibrated Airspeed) equals to cas_1 till 10,000 ft, then it accelerates to reach cas_2. It maintains a constant CAS at cas_2 till the transition altitude is reached, then it climbs at a constant Mach M. Although BADA associates one (cas_1, cas_2, M) value to each aircraft type, these values might be different among aircraft of the same type due to different cost-indexes for instance. Fig. 1 illustrates how these reference parameters are used to compute the trajectory.

In this paper, we apply Machine Learning methods to predict a mass m and a tuple (cas_1, cas_2, M) that will hopefully provide better trajectory prediction than the default BADA values. The four predictive models h_{mass}, h_{cas_1}, h_{cas_2} and h_M are trained on historical data containing a large number of past flights collected over the first ten of the year 2017. Once built, these models provide a specific prediction for every considered aircraft. For each aircraft, all the information available about this aircraft is embedded in a vector of features $\boldsymbol{x}$, and the predictive models compute their prediction with $\boldsymbol{x}$ as the input. Fig. 2 illustrates how the predicted trajectory is computed using the learned predictive models h_{mass}, h_{cas_1}, h_{cas_2} and h_M. These models are tested on flights collected on the last two months of 2017. All these past flights were collected on ADS-B data by The OpenSky Network. The 11 most frequent aircraft types are studied. The obtained data set contains millions of climbing segments from all over the world. They are tested on trajectory prediction problems with various starting altitude, different climbing segments duration and different prediction time horizons. We have also tested two different sets of variables for the input $\boldsymbol{x}$: one set containing only variables available before take-off and one set containing all the information available when the aircraft flies.

Previous papers (Alligier et al., 2015a,b) used a similar approach on Mode-C/Mode-S radar data concerning only two airports. In this paper we use a large ADS-B data set including 1520 airports. In addition, we consider situations that were previously untested. We also use a more rigorous methodology to determine what would be the performance of our method if it was implemented in an actual operational context. We removed all the identified possible optimistic biases of the performance evaluation.

The rest of the paper is organized as follows: Section 1 describes the context and the approach of this study. Section 2 describes some useful Machine Learning notions that help understanding the methodology applied in this study. Section 3 details the data used in this study. The application of Machine Learning techniques to our operational factors prediction problem is described in Section 4, and the results are shown and discussed in Section 5, before the conclusion.

1. Context

This section describes previous related works. In this existing context, it also describes the approach followed in this study.

1.1. Literature review

Some studies (EUROCONTROL Experimental Center, 1998; ADAPT2, 2009; Coppenbarger, 1999) detail the potential benefits that would be provided by additional or more accurate input data. In other works, the aircraft intent is formalized through the definition of an Aircraft Intent Description Language (Lopez-Leones et al., 2007; Lopes-Leonés, 2007) that could be used in air-ground data links to transmit some useful data to ground-based applications. All the necessary data required to predict aircraft trajectories might become available to ground systems someday. In the meantime different methods have been designed to obtain these input parameters from the data that is already available today.

Many recent studies (Schultz et al., 2012; Thipphavong et al., 2012; Park and Thipphavong, 2013; Alligier et al., 2014; Sun et al., 2016; Uzun and Koyuncu, 2017) used past trajectory points to estimate the aircraft mass using a total energy model such as BADA. All these methods adjust the mass to fit observed values of energy variation. Sun et al. (2017) proposes a bayesian approach to merge

[1] These algorithms are at the root of the strategic deconfliction through speed adjustments developed in the European ERASMUS project (Drogoul et al., 2009). A more recent application is the SESAR 4.7.2 (*Separation Task in En Route Trajectory-based Environment*) project, where lateral and vertical maneuvers are also used.