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Aircraft trajectory forecasting using local functional regression in Sobolev space

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ABSTRACT

This paper considers the problem of short to mid-term aircraft trajectory prediction, that is, the estimation of where an aircraft will be located over a 10–30 min time horizon. Such a problem is central in decision support tools, especially in conflict detection and resolution algorithms. It also appears when an air traffic controller observes traffic on the radar screen and tries to identify convergent aircraft, which may be in conflict in the near future. An innovative approach for aircraft trajectory prediction is presented in this paper. This approach is based on local linear functional regression that considers data preprocessing, localizing and solving linear regression using wavelet decomposition. This algorithm takes into account only past radar tracks, and does not use any physical or aeronautical parameters. This approach has been successfully applied to aircraft trajectories between several airports on the data set that is one year air traffic over France. The method is intrinsic and independent from airspace structure.

1. Introduction

1.1. Basics of air traffic control

Air Traffic Control (ATC) is a service provided by ground-based air traffic controllers, who manage aircraft from departure until arrival. Air Traffic Management (ATM) research and development has produced numerous Decision Support Tools (DST) aimed at providing controllers with automated conflict detection and resolution, trajectory planning, and aids for sequencing arrivals and departures at airports. At a strategic level (that is several months before flights take place), assessing controllers workload is a major concern in order to keep it within acceptable bounds and take mitigating actions if needed.

In many parts of the world, ATM induces a large amount of control workload (for example, about 8000 aircraft per day fly in the French airspace). It is not possible for a single or even a team of controllers to manage such a workload. To cope with this problem, airspace is divided into polygonal cells called sectors. A team of 2 controllers is in charge of a control sector and performs three essential tasks: monitoring (that is checking compliance of the traffic with regulatory separations), conflict resolution, and coordination (which deals with aircraft transfer from and to adjacent sectors. The first and second task heavily rely on the ability to predict where an aircraft will be located in a 10 min time window. From this observation, it is clear that controller's workload can be reduced by an accurate and automated forecast of aircraft trajectories, since the knowledge of whether conflicts are to be expected or not helps in prioritize the actions to be taken.

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Nomenclature

$\{\Omega, \mathfrak{F}, \mathbb{N}\}$	probability space
$X_\omega(t), Y_\omega(s)$	Hilbert random processes
X_n	predictor variable coming from $X_\omega(t)$
Y_n	response variable coming from $Y_\omega(s)$
$\tau_X^n,\ \tau_Y^n$	time intervals related to X_n and Y_n respectively
$W^k(\mathbb{R})$	Sobolev space of order k
λ_n	local weight
Ψ^x, Ψ^y	two different wavelet basis used for expansions
$a_{n,i}, b_{n,j}, c_{i,j}$	wavelet coefficients
$\{V\}_{j\in\mathbb{Z}}$	linear spaces generated by wavelet functions
$\beta(t,s)$	square-integrable matrix-valued function
t, s	time
i, j, k, n	waypoint

A major concern when dealing with trajectory prediction is the robustness of forecast with respect to unknown or partially known influential parameters. Many different factors have an adverse impact on the accuracy of prediction and depend on the time horizon for the forecasting. In principle, the knowledge of the flight dynamics equations for a given aircraft, the intended flight plan and exogenous parameters like temperature, wind and ATC orders will be enough to accurately model a trajectory from departure to destination. Unfortunately, many of these factors are unknown or partially known only (as an example, the take-off mass of the aircraft, or the wind during the flight can only be guessed). This is the major limitation of model based predictors, and it explains why they perform quite poorly on a real data).

Another approach is to assume that trajectories are realizations of some random process and regression techniques applied to previous trajectories. Invoking Takens theorem, it can be shown that a sufficient number of samples is enough to reconstruct a dynamics conjugate to the real one based on flight equations and thus that regression algorithms are in principle as powerful as model based predictors. Unfortunately, estimating the size of the sample to be used is a quite difficult challenge, and we cannot oversize the number of samples since having too long sequences has a detrimental effect on the numerical stability of the algorithms. The approach proposed here removes some of the limitations of classical regression by considering trajectories as functions (elements of a Sobolev space), instead of considering temporal samples of them. We also use a convenient basis for representing the so-used functions, and so limit the amount of computation.

1.2. Trajectory prediction in decision support tools

As mentioned above, the knowledge of aircraft positions along time, termed as the ‘4D trajectory’ in the context of future ATM systems, is a key ingredient for improving the capacity of the airspace and will ultimately allow the system to cope with the anticipated two to three fold increase in the number of flights by 2030.

1.2.1. Early conflict prediction

The objective of conflict prediction and resolution algorithms is to anticipate conflict situations between two or more aircraft and to propose mitigating actions to controllers (in the 2050 horizon, full automation is also an option, with the presence of humans only for monitoring purposes). Let us mention however that automated conflict resolution is a complicated task that is not yet fully solved by algorithms. The question of whether a conflict will exist with a high probability has to be answered before triggering the solver. Trajectory prediction (TP) is obviously a key ingredient for the design of efficient automated conflict solver. In such a context, the accuracy requirements stem from the need of keeping the separation in early detection.

The assessment of TP performance will be made using a composite indicator:

- Evaluation of the level of false alarms and non-detection on a test data set;
- When detection is correctly triggered, the performance is the distance in space and time between the forecast point of conflict and the real one.

The conflict prediction has the highest requirements among the two main uses of TP, and is still an open issue. The problem is worsening by the need for wind knowledge along the flight path that presently is unfortunately currently available only through weather forecast services, with a quite coarse precision and resolution both in space and time. This topic is far from being solved yet, and speaks in favor of regression based predictor since wind information can be taken into account from past trajectories observed in the vicinity (in time and space) of the area of interest.