Towards aircraft trajectory prediction using LSTM networks

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ABSTRACT

Trajectory prediction allows for better predictability, security and efficiency in the operations of the modern Air Traffic Management. LSTM networks have been successfully applied to make short-term trajectory predictions. However, the criticality of the supervision of these operations in high density traffic zones, such as the Terminal Maneuvering Area (TMA) around the airports, require methods that provide long-term, precise predictions. In this paper, we propose a LSTM-based architecture for trajectory prediction using surveillance data (ADS-B). We conduct our experiments on the case study of flights arriving at the Madrid Barajas-Adolfo Suárez airport (Spain), using nine months worth of data. In particular, we focus on longer-term predictions than the state of the art, predicting the next 150 seconds at any point in the trajectory. This model provides an increased accuracy for 2D positioning, with mean absolute errors of 0.0238 and 0.0544 degrees for latitude and longitude, respectively, in the TMA of the destination airport.

CCS CONCEPTS

• **Information systems** → *Spatial-temporal systems*; • **Computing methodologies** → **Neural networks**.

KEYWORDS

LSTM networks, air traffic management, trajectory prediction

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1 INTRODUCTION

Intelligent Transportation Systems (ITS) have become a prominent research area in the last decades, thanks to the unprecedented growth in global mobility. The volume and complexity of these movements have enforced the development of advanced management processes, which rely on monitoring data via in-vehicle sensors and data analysis techniques. That is the case of Air Traffic Management (ATM). In particular, the area near the airports, often referred as Terminal Maneuvering Area (TMA), is a highly complex environment to manage, due to the concentration of aircraft and the safety concerns that may arise during the maneuvers required by the landing and takeoff operations. Surveillance systems provide with the necessary data to monitor the state of the aircraft throughout the flight. ADS-B (Automatic Dependent Surveillance-Broadcast) [3] has progressively replaced secondary radars for this purpose, taking advantage of the aircraft's capabilities to determine its position as well as other important flight parameters (altitude, speed, bearing, etc.)

Sensor data can be structured as *4D trajectories*, which integrate time with the 3D position (latitude, longitude and altitude), along with other relevant metadata. This paper explores how 4D trajectories can be used to improve predictions of in-flight aircraft trajectories, following a data-driven approach. Trajectory prediction enables better predictability in airspace operations, supporting the air traffic controllers to know in advance the future positions of an aircraft, and facilitating the timely detection of conflicting or potentially-risky situations [8]. However, 4D trajectories consist on long sequences (several hundreds or even thousands) of flight points, which hide long and short-term temporal dependencies within the multiple time series they comprise. Long Short-Term Memory (LSTM) networks [1] have been applied before to predict future trajectory based on past states. LSTM networks are a type of recurrent neural networks that ensure long-term memory for long sequences of data, while retaining the short-term memory capabilities of RNN to adapt to changes in the sequence data.

The rest of the paper is organized as follows. Section 2 describes the proposed architecture and its background in research. Section 3 explains our case study, and briefly discusses the main results. Finally, Section 4 presents our main conclusions, and provides an insight into our future work.

Approach	Case study	MAE_{lat}	MAE_{lon}	MAE_{alt}
LSTM [7]	MR, Partial	0.0725	0.0552	77.95
ConstLSTM [6]	SR, Complete	0.0050	0.0105	9.96
LSTM+Att [2]	Not indicated	0.0373	0.0397	2.94
BiLSTM [4]	SR, Complete	0.0206	0.0160	33.75
LSTM	MR, Complete	0.0216	0.0364	242.80
LSTM-FC	MR, Complete	0.0208	0.0373	259.20

Table 1: MAE and RMSE values for latitude and longitude (degrees), and altitude (feet) features. The approach may be *multi-route* (MR) or *single-route* (SR).

2 PROPOSAL

2.1 Previous work

LSTM networks have been extensively applied to approach sequence prediction tasks, whether alone or combined with different techniques to improve the natural capabilities of these neural networks. Shi et al. [7] used LSTM to predict all aircraft trajectories in an airspace sector using surveillance data obtained from ADS-B sources. Their approach was later improved using LSTM networks with constraints [6], which force the model to take into account different aspects of the kinematics and behaviour of an aircraft depending on the flight stage. More recently, Sahadevan et al. [4] successfully applied bidirectional LSTM to leverage both backwards and forward dependencies in the trajectories time series.

2.2 Architecture

We evaluate two LSTM-based architectures to predict the next 10 states (150 seconds of flight time) using 3D position and speed as inputs. First, a single LSTM layer with n units, and a fully connected layer of size 10 to produce the output. Second, we add two additional fully connected layers to apply a quadratic interpolation on the LSTM layer output. Our intent is to help the model to produce a smoother curve as output, more similar to the common trajectory patterns than the jagged paths that are often output by LSTM.

3 RESULTS AND DISCUSSION

3.1 Experiments

We focus on flights arriving at Madrid Barajas-Adolfo Suárez airport (ICAO: LEMD, IATA: MAD) from 40 of the busiest European airports (with a maximum of 50 trajectories per origin and month). We identify individual 4D trajectories using ADS-B data from OpenSky [5] and airports data from Eurocontrol's Network Manager[1] between January 1 and September 30, 2022. The final dataset is comprised of 7,146 trajectories, and divided into *train* (72.5%), *validation* (12.75%) and *test* (15%) subsets. The models were configured according to the optimization of two main parameters: the input window size m ($m \in [25, 65]$) and the number of units of the LSTM layer n ($n \in [10, 35]$). The optimal values were found to be 48 and 30, respectively. The models were trained for *40* epochs, and early stopping was adopted to prevent overfitting. The best model was then evaluated using the mean absolute error (MAE).

[1] https://www.eurocontrol.int/network-operations

3.2 Result analysis

Table 1 shows the main results of our experiments, and compares them with the state of the art. The LSTM and LSTM-FC models report very similar numbers for each of the considered features. LSTM-FC yields a lower MAE value for latitude, with 0.0208 degrees (2.3 kilometers), but LSTM performs better at longitude and altitude predictions (0.0364 degrees and 242 feet, respectively).

It is worth noting that none of the approaches in the state of the art is directly comparable, as they all present different case studies and focus on making single-step predictions, while our proposal aims to predict 10 timesteps into the future. However, we think this comparison is useful to position our current contributions with respect to the existing literature. Our models outperform all the considered works, in terms of MAE, in 2D positioning except [6], although this proposal focuses on a single route (flights between two airports). The situation is different when it comes to altitude, with our models performing worse than the state of the art. Our intuition is that it may be caused by the imbalance between cruise data (where altitude is generally constant) and TMA data, where aircraft perform ascending and descending manoeuvres. However, the error is still lower than acceptable from a domain point of view: MAE in altitude is 318 feet, lower than the minimum vertical separation for aircraft crossing paths standardized by ICAO (1,000 feet for aircraft flying at 29,000 feet or lower, and 2,000 feet otherwise). Further investigation of this observation is part of our future work.

4 CONCLUSIONS

In this paper, we have explored the feasibility of LSTM networks to make long-term predictions at any point in a trajectory using the flights arriving at Madrid Barajas-Adolfo Suárez airport as our case study. Our results have demonstrated to be competitive with the state of the art, which aim to make short-term predictions and focus on areas close to the airports, or specific for a particular route. Some questions remain open, such as improving the prediction of the altitude, and constitute our future work. We also aim to apply different architectures to this use case, such as the more modern Temporal Fusion Transformers, to evaluate their performance.

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