



Learning the aircraft mass and thrust to improve the ground-based trajectory prediction of climbing flights



R. Alligier¹, D. Gianazza^{*}, N. Durand

ENAC, MAIAA, F-31055 Toulouse, France
Univ. de Toulouse, F-31400 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 automated tools that detect and solve conflicts between trajectories. This paper focuses on the climb phase, because predictions are much less accurate in this phase than in the cruising phase.

Trajectory prediction usually relies on a point-mass model of the forces acting on the aircraft to predict the successive points of the future trajectory. The longitudinal acceleration and climb rate are determined by an equation relating the modeled power of the forces to the kinetic and potential energy rate. Using such a model requires knowledge of the aircraft state (mass, current thrust setting, position, velocity, etc.), atmospheric conditions (wind, temperature) and aircraft intent (thrust law, speed intent). Most of this information is not available to ground-based systems.

In this paper, we improve the trajectory prediction accuracy by learning some of the unknown point-mass model parameters from past observations. These unknown parameters, mass and thrust, are adjusted by fitting the modeled specific power to the observed energy rate. The thrust law is learned from historical data, and the mass is estimated on past trajectory points. The adjusted parameters are not meant to be exact, however they are designed so as to improve the energy rate prediction. The performances of the proposed method are compared with the results of standard model-based methods relying on the Eurocontrol Base of Aircraft DATA (BADA), using two months of radar track records and weather data.

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1. Introduction

Ground-based aircraft trajectory prediction is central to most applications in Air Traffic Control and Management (ATC/ATM) and has become more so with the emergence of new operational concepts (SESAR Consortium, 2007; Swenson et al., 2006) envisioning trajectory-based operations. Moreover, trajectory prediction accuracy is essential to the new automated tools and algorithms that have emerged in the recent years. Some of these algorithms require to test a large number of alternative trajectories. As an example, in Prats et al. (2010) an iterative quasi-Newton 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

^{*} Corresponding author at: ENAC, MAIAA, F-31055 Toulouse, France. Tel.: +33 562259607.

E-mail addresses: richard.alligier@enac.fr (R. Alligier), gianazza@recherche.enac.fr (D. Gianazza).

¹ Principal corresponding author.

Nomenclature (see also Figs. 1–3)

c	thrust setting coefficient
CAS	calibrated airspeed
D	drag
ESF	energy share factor
g	gravitational acceleration
g_0	gravitational acceleration at mean sea level
h	geodetic height
H_p	geopotential pressure altitude (i.e. geopotential altitude in ISA conditions)
ISA	international standard atmosphere
L	lift
M	Mach number
m	aircraft mass
T	air temperature
Thr	thrust
V_a	true airspeed
$V_{a/x_h, y_h}$	projection of the true airspeed vector onto the local horizontal plane
V_g	ground speed (projection of the inertial speed on the local horizontal plane)
V_i	inertial velocity
W	wind, with (W_N, W_E, W_{Up}) the Northbound, Eastbound, and upward components
γ_a	air-relative flight path angle
γ_i	inertial flight path angle (i.e. angle between \vec{V}_g and \vec{V}_i)
θ_c	crab angle ($\Psi_i - \Psi_a$)
Φ	bank angle
Ψ_a	aerodynamic heading (direction of true airspeed vector)
Ψ_i	true course angle (direction of inertial velocity vector)
Ψ_w	direction of wind vector
$x_{k,i}$	vector of state variables (temperature differential, aircraft position, velocity, bank angle, etc.) for point i in trajectory k

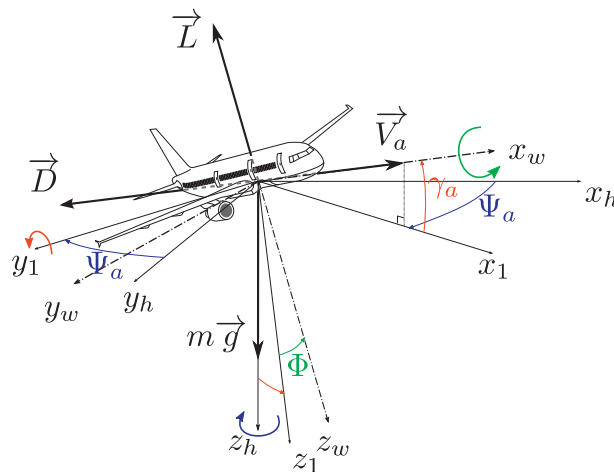


Fig. 1. Euler rotations of angles (Ψ_a, γ_a, Φ) with counter-clockwise convention, and right-handed coordinate systems.

currently being developed for ATC/ATM can detect and solve conflicts between trajectories, using Genetic Algorithms (Durand et al., 1996²), or Differential Evolution or Particle Swarm Optimization (Vanaret et al., 2012). To be efficient, these methods require a fast and accurate trajectory prediction, and the capability to test a large number of “what-if” trajectories.

² 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.

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