Air Traffic Control: A Local Approach to the Trajectory Segmentation Issue

José Luis Guerrero, Jesús García, and José Manuel Molina

Group of Applied Artificial Intelligence (GIAA), Computer Science Department
Carlos III University of Madrid, Colmenarejo - Spain
{joseluis.guerrero, jesus.garcia, josemanuel.molina}@uc3m.es

Abstract. This paper presents a new approach for trajectory segmentation in the area of Air Traffic Control, as a basic tool for offline validation with recorded opportunity traffic data. Our approach uses local information to classify each measurement individually, constructing the final segments over these classified samples as the final solution of the process. This local classification is based on a domain transformation using motion models to identify the deviations at a local scale, as an alternative to other global approaches based on combinatorial analysis over the trajectory segmentation domain.

Keywords: Air Traffic Control, segmentation, movement model, model fitting.

1 Introduction

Air Traffic Control (ATC) is a critical area related with safety, requiring strict validation in real conditions [3]. The basic considered data are sensor plots having the following components: stereographic projections of their x and y components, covariance matrix and detection time. The coordinates may be affected by errors, containing biases and noise. These sensor plots are then divided into segments sharing the same mode of flight or MOF (this division is known as the segmentation process, not to be mistaken for the one in contexts like [8]). The difficulty of that process is to differentiate accurately the different segments, especially at their edges (where it is difficult to determine whether position variation is caused by the measuring errors or by a different MOF). To improve that accuracy, as we are handling recorded data, we may use both past and future measures for our estimations.

Even though we have presented it for the ATC domain, this problem is presented in a wide range of domains such as tracking and segmentation of an object’s trajectory in video data [2] (relating it to dimensionality issue), or the pattern recognition domain [9], (presenting segmentation as an optimization problem which trades off model fitting error versus the cost of introducing new segments, and introducing a solution based on dynamic programming).

In our current domain, some of the ideas we will be proposing in our segmentation algorithm are already found in available works, but in different contexts and applications. Machine learning techniques are applied in [5], but with very different attributes for our trajectory’s measurements (in the reference they are based on IMM filtering [10]). Also the idea of needing several basic MM’s (or movement models, a
simplification of the MOF’s) is commonly covered ([5], [12], [6]), but their use differs to the one included in our proposal (for example, as individual models on an IMM filter or in the reconstruction process). It is interesting, as well, to consider that this segmentation problem is usually presented as a first step in the larger issue of trajectory reconstruction [12], [6].

In this study we will discuss an approach to the segmentation of trajectories where the three possible MM’s are uniform, turn and accelerated movements [7]. With the presented input attributes, we will look for an algorithm that will sequentially use a different model to classify the measures belonging to each individual MM. This paper will be centered in the uniform MM.

In most cases available in the current literature on this topic, this segmentation problem and its solution are exposed as a global optimization issue [9]. Even so, all through this paper a local approach will be used. This implies that each of the trajectory’s measurements will be individually classified according to the local information around it, and segments built with the classified isolated measurements will be the last step of our solution.

The formalization for our problem will be explained in the second section of this paper. The third section will present our general approach to the solution, while the fourth will analyze some initial issues of that proposal. The fifth section will present the validation experiments for the solution presented, along with some general results using that solution. Finally we will present the conclusions obtained from the solution’s design and the overall results.

2 Problem Definition

2.1 General Problem Definition

As we presented in the introduction section, each analyzed trajectory ($T^i$) is composed by a collection of sensor reports (or measurements), which are defined by the following vector:

$$\vec{x}_j^i = (x_j^i, y_j^i, t_j^i, R_j^i), j \in \{1, ..., N^i\}$$  (1)

where the $j$ sub-index indicates the measurement number, the $i$ super-index indicates the trajectory number, $x_j^i, y_j^i$ are the stereographic projections, $t_j^i$ is the detection time, $R_j^i$ is the covariance matrix and $N^i$ is the last measurement of the analyzed trajectory.

From this problem definition our objective is to divide our trajectory into a series of segments ($B_k^i$), according to our estimated MOF. This is performed as an off-line process (meaning that we may use past and future information from our trajectory). The segmentation problem is formalized in (2)

$$T^i = \bigcup B_k^i \quad B_k^i = \{x_j^i\} \quad j \in [k_{min}, k_{max}]$$  (2)

where $k$ is the segment number and $k_{min}, k_{max}$ the given measurement boundaries for that segment. In the general definition of this problem these segments are obtained by the comparison with a test model of some windows of measurements coming from