Dynamic Determination of Air Traffic Flows Using Clustering

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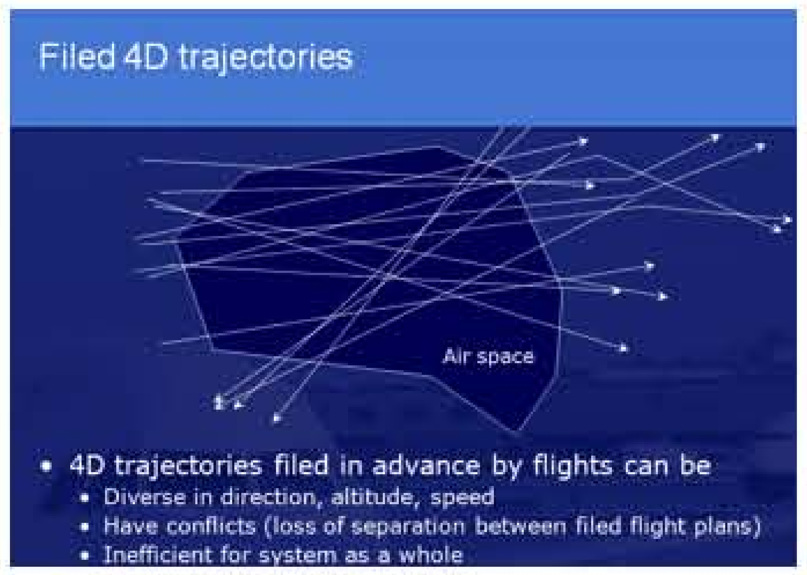
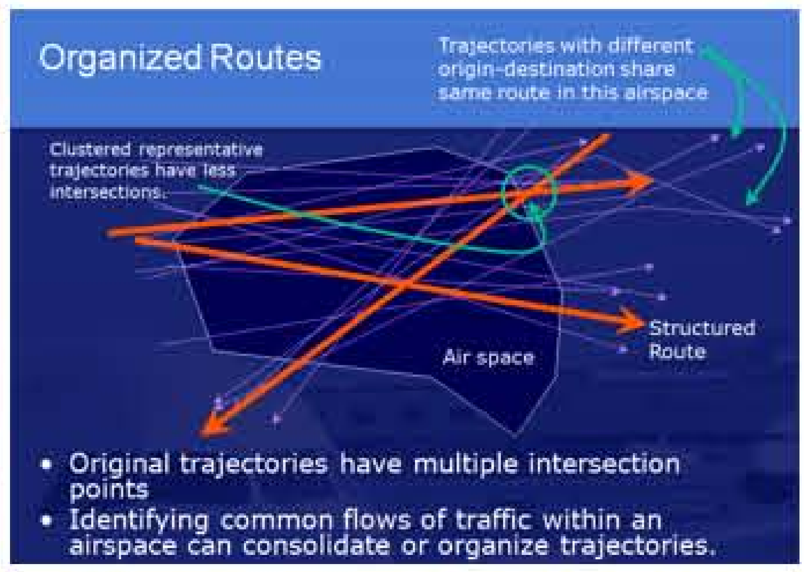
Abstract

The demand for air travel is expected to continue to increase significantly in the foreseeable future, while the delays in the system have also grown. The ability to identify where the main flows of traffic are in the National Airspace System (NAS) and to efficiently manage the flights through regions of airspace, particularly in convective weather, is crucial.

Air traffic controllers currently know the general areas of main traffic flows in the system based on experience, but as increased automation is needed to manage the growing number of flights and delays, an automated approach to identifying flows is needed. We propose a novel approach to identify the flows of air traffic using a clustering-based methodology. The trajectory is first broken into a series of great circle segments that provide for the best fit between points. An algorithm is developed that identifies turns in the trajectories using heuristics in order to identify the start and end of the segments. Then, the segments are clustered using a density-based approach that takes into account the proximity, heading, timing, and other metrics of the segments. Finally, a representative trajectory is identified for each cluster.





Objective:

•Take 4-D trajectories from flight plans and identify where the overall flows of traffic are using clustering methods.

•Dynamically and incrementally cluster based on variations in new traffic info without having to re-cluster entirely.

Motivation:

•Supports dynamic air traffic flow models, which rely on already knowing the traffic flows.

•Facilitates evaluation of weather impact at aggregate level (form of state space reduction)

•Used to reroute groups of flights in an efficient & optimal manner rather than individual flights.

•Supports dynamically reorganizing airspace (in "near" real-time) into structured routes that reduce controller workload & improve airspace utilization.

•Supports forming dynamic airspaces such as "tubes".

•From historical (as flown) perspective, can facilitate redesign of airways / routes to reduce congestion.

Parameterization of Flows

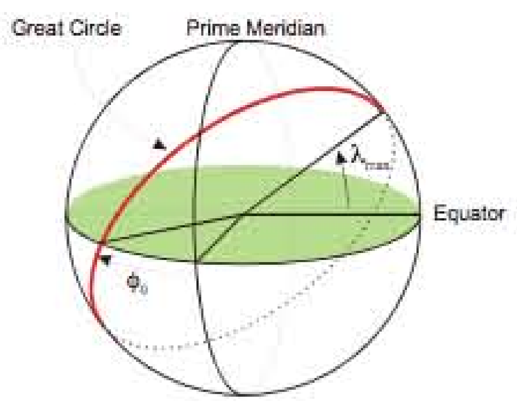
$$L = (\phi_0, \lambda_{max}, \alpha_{start}, \alpha_{end}, t_{start}, t_{end}, h)$$

- ϕ_0 longitude at which the great circle arc crosses the equator
- λ_{max} max latitude achieved by the great circle arc
- α_{start} starting angle of great circle arc
- α_{end} ending angle of great circle arc
- h altitude of flow
- t_{start} start time of flow
- t_{end} end time of flow

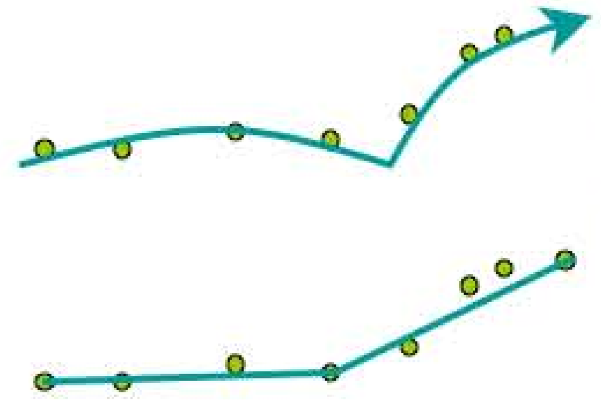
Step 1: Partition into Segments

- Trajectory is defined as series of points $J_f = p_1 p_2 p_3 \ldots p_j \ldots p_{len_f}$
- Each point is 4D $p_{fj} = \{t_{fj}, \lambda_{fj}, \phi_{fj}, h_{fj}\}$
- Partition trajectories into segments $S_f = s_{f1} s_{f2} s_{f3} \ldots s_{fk} \ldots s_{fseg_f}$

  Where each segment is a great circle (GC) arc representing a series of points in the trajectory $s_{fk} \equiv \{p_l p_{l+1} p_{l+2} \ldots p_{l+q}\} \quad 1 \le l \le len_f - q$



GC defined by a unit vector normal to the plane cutting through the spherical earth passing thru origin



Representing segments as great circles that could start & end between points can more accurately represent trajectory than lines that connect points

For each segment, find the great circle that provides the least square error fit

- Great circle normal vector

$$n_y = \beta n_z$$

$$n_x = -\frac{1}{\rho_{xx}}\left(n_y \rho_{xy} + n_z \rho_{xz}\right)$$

$$n_z = \frac{1}{\sqrt{\frac{1}{\rho_{xx}^2}(\beta\rho_{xy})^2 + 2\beta\rho_{xy}\rho_{xz} + \rho_{xz}^2 + \beta^2 + 1}}$$

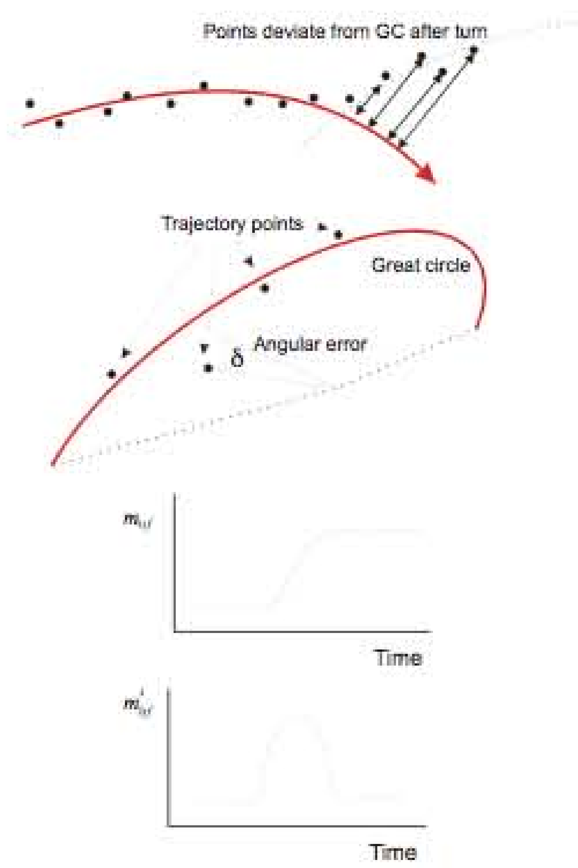
Determining transition from one segment to next

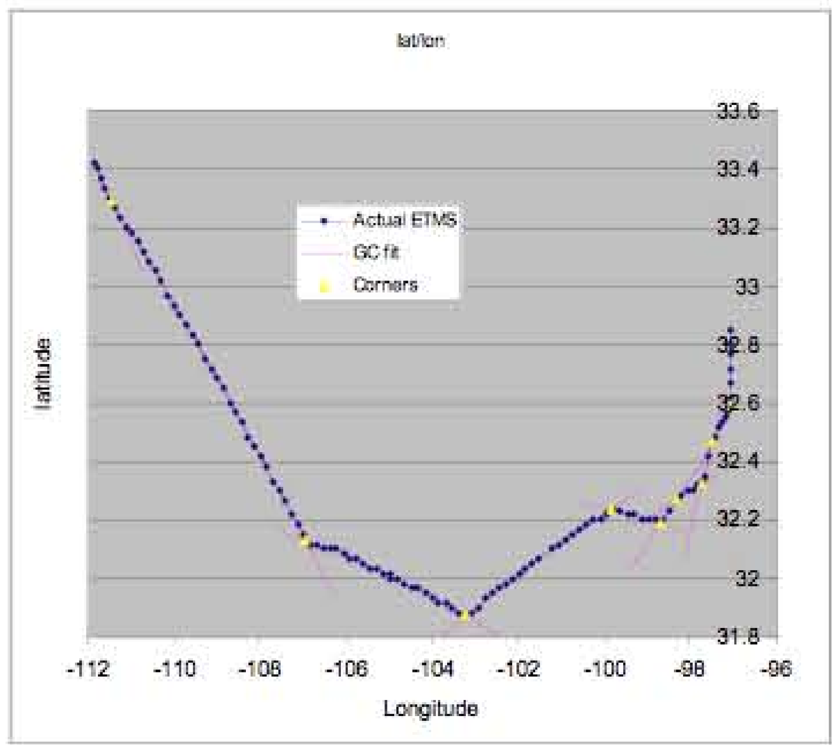
- Determine turns in trajectory and place break between one great circle segment and next.
- Determine fit of angle of deviation of points from great circle
- Examine if slope of fit deviate from current great circle according to a certain pattern.
- Parameters

  MAX_FIT_POINTS no. of points before and after the current point

  MAX_LOOKAHEAD_POINTS no. pts ahead to foresee upcoming turns

  dm_THRESHOLD_LO, dm_THRESHOLD_HI to see turn in points

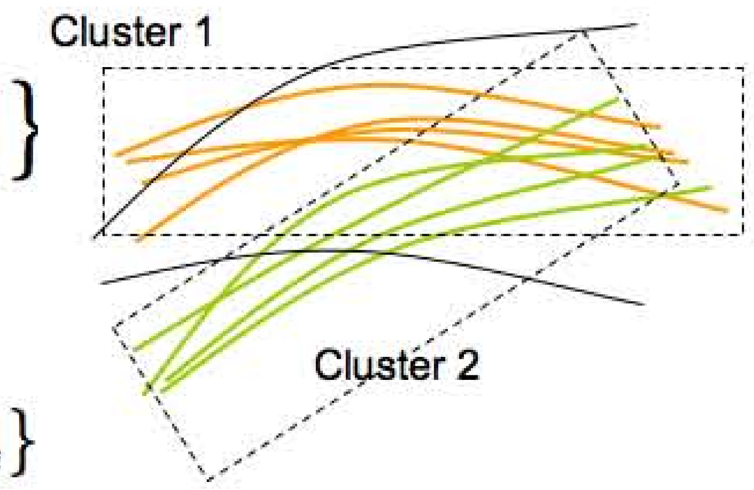




Results of algorithm to partition 4D trajectory into series of great circle segments fits reasonably well.

Step 2: Clustering

- Set of all trajectory segments $D = \bigcup_{f \in F} \{s_{f1}, s_{f2}, \ldots, s_{fseg_f}\}$
- Each cluster consists of set of trajectory segments $C_i \subseteq D$, $C_i = \{s_{fk}\}$
- Find a set of clusters representative of flows $K = \{C_i\}$
- Find optimum clustering $P(K^*) = \min_{K \in \mathbb{C}} P(K)$



Algorithm Overview

- Arbitrarily select a trajectory segment S_i.
- Retrieve all segments density-reachable from S_i with respect to ε and MinSegs.
- If S_i is a core segment, a cluster is formed.
- If S_i is a border segment, no points are density-reachable from S_i so examine the next segment in the database.
- Continue the process until all of the segments have been processed.

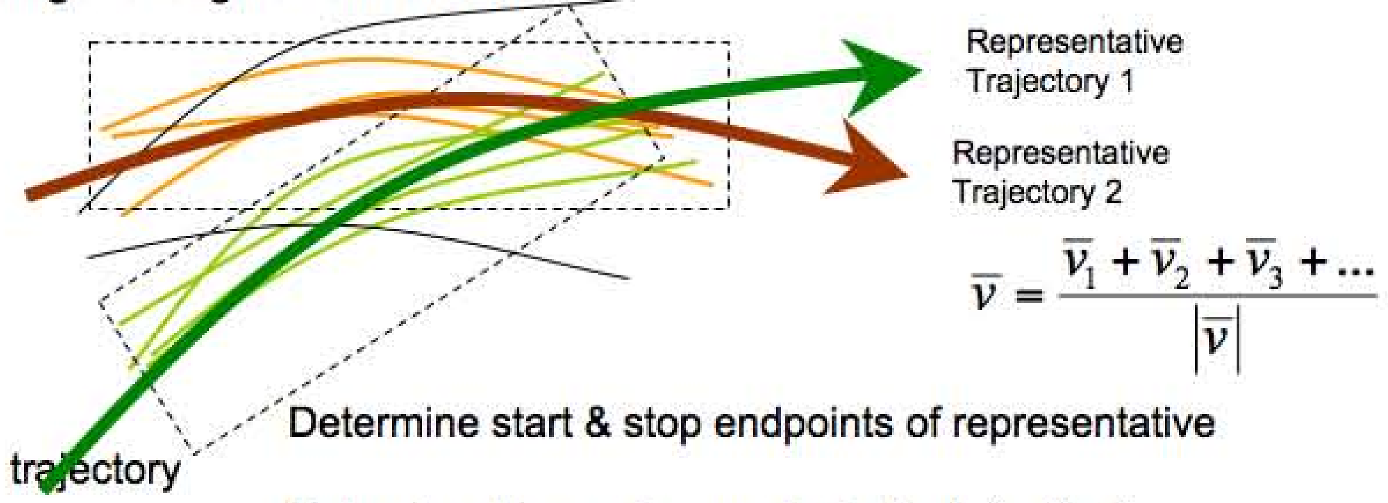
•Algorithm complexity $O(n^2)$

•Using spatial indexing method (e.g. R-tree), complexity can be reduced to $O(n \log n)$.

•Consider using RDBC (Recursive Density based Clustering) to first identify core segments, then iterate through DBSCAN using different values of ε and min segments

Step 3: Determine Representative Trajectory

Generate representative trajectory composed of great circle segments that are "average" of segments in cluster



$$\bar{v} = \frac{\bar{v}_1 + \bar{v}_2 + \bar{v}_3 + \ldots}{|\bar{v}|}$$

Determine start & stop endpoints of representative trajectory

Determine times when each cluster is "active"

Summary & Future Work

•Approach for identifying flows of air traffic in the NAS involving three steps:

- Partitioning each trajectory into segments
- Grouping the segments into clusters
- Identifying the representative trajectory for each cluster

•Method developed for partitioning aircraft 4D trajectories into a series of great circle segments with best fit

•Initial steps to define the setup of the algorithm for the clustering phase

•Future steps include

- Further development of algorithm to cluster great circle segments using attributes of proximity, heading, length of segment, and others.
- Determining representative trajectory for each cluster

•A key ability of algorithm will be to dynamically and incrementally cluster new flight segments with existing clusters without having to re-cluster the entire data set each time.

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