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Published by myself

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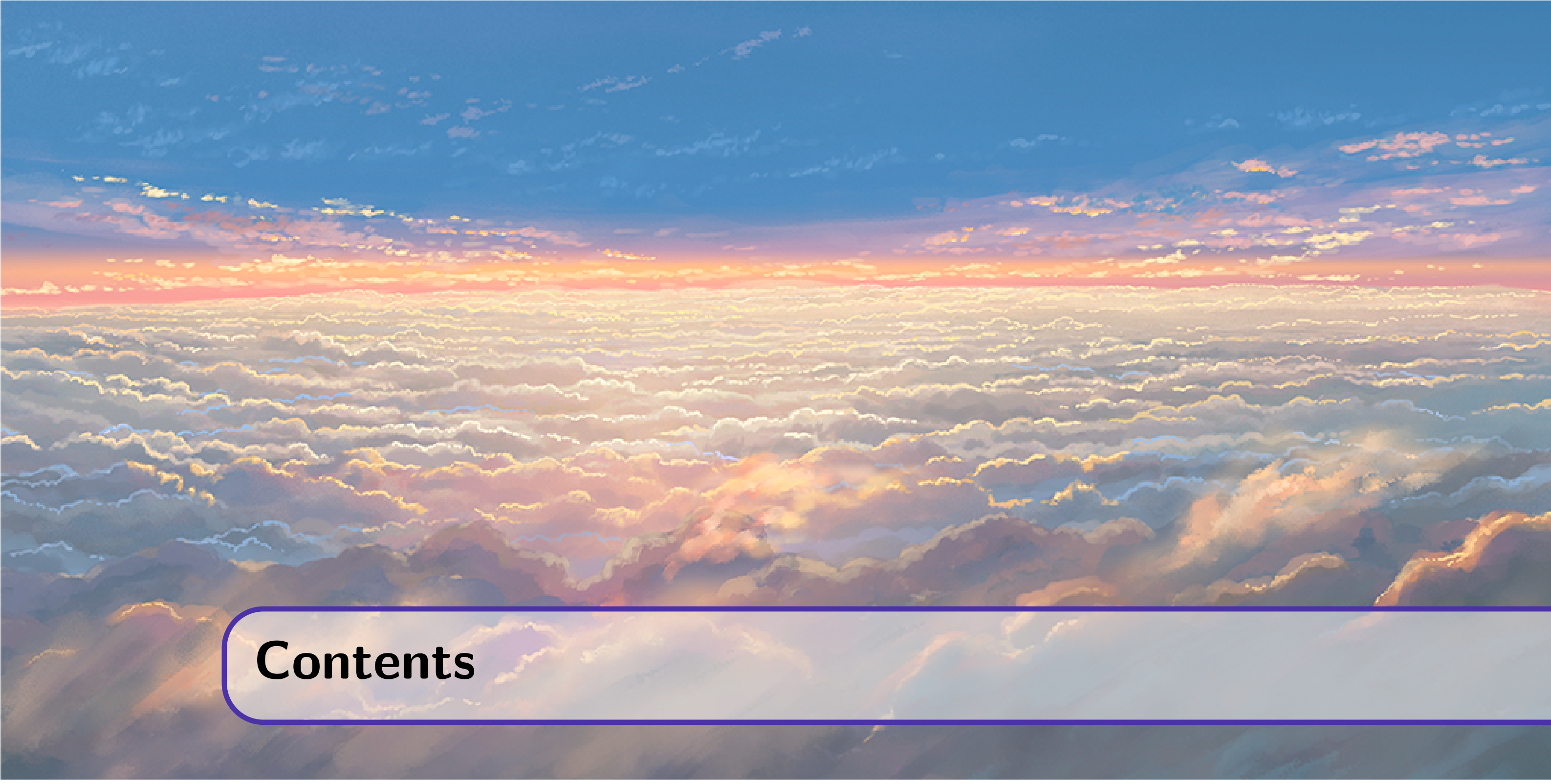


Contents

Map Matching

1. Hidden Markov Map Matching

Source: [1].

1.1 论文动机

1.1.1 原始数据

the raw input data consists of vehicle *locations* measured by GPS, Each measured point consists of a time-stamped latitude/longitude pair.

The *roads* are also represented in the conventional way, as a graph of nodes and edges. The *nodes* are at intersections, dead ends, and road name changes, and the edges represent road segments between the nodes. Some *edges* are directional to indicate one-way roads. Each node has an associated latitude/longitude to indicate its location, and each edge has a polyline（折线）of latitude/longitude pairs to represent its geometry.

1.2 其他论文的方法

平滑曲线匹配：create a (possibly smoothed) curve from the location measurements and attempt to find matching roads with similar geometry

■ **Example 1.1** White et al. present four algorithms, starting with the simple, nearest match scheme. Their second algorithm **adds orientation information to the nearest match approach**, comparing the measured heading to the angle of the road. Their third algorithm evolves the second algorithm to **include connectivity constraints**, and their fourth algorithm does **curve matching**.

❗ their most sophisticated algorithm, the fourth one, was outperformed by the simpler second algorithm.

■

通过拓扑结构建模：builds up a topologically feasible path through the road network. Matches are determined by a similarity measure that weights errors based on distance and orientation. The algorithm was found to perform flawlessly, even though the GPS data was collected while *Selective Availability* was turned on, leading to noisier location measurements than are available now.

模糊匹配策略：Kim and Kim look at a way to measure **how much each GPS point belongs to any given road**, taking into account its distance from the road, the shape of the road segment, and the continuity of the path. The measure is used in a **fuzzy matching scheme** with learned parameters to optimize performance.

Brakatsoulas et al. Their algorithm uses variations of the *Fréchet distance* to match the curve of the GPS trace to candidate paths in the road network.

!

One potential problem with purely geometric approaches is **their sensitivity to measurement noise and sampling rate.** Connecting the dots of a set of noisy measurements sampled at a slow rate would not match well with the road geometry, especially **direction information**.

基准方法：将 GPS 点匹配到最近邻的路上

!

result in extremely unreasonable paths involving strange U-turns, inefficient looping, and overall bizarre driving behavior.

1.3 论文贡献

- maintaining a principled approach to the problem while simultaneously making the algorithm robust to location data that is both **geometrically noisy and temporally sparse**
- a test of our map matching algorithm where we vary the levels of noise and sparseness of the sensed location data over a 50 mile urban drive

1.4 论文模型-Hidden Markov Model

The HMM models processes that involve a path through many possible states, where some state transitions are more likely than others and where the state measurements are uncertain.

1.4.1 HMM

- HMM 状态：N_r individual road segments $r_i, i = 1 \dots N_r$
- 状态的测量：每次带噪声的位置数据 Z_t
- 候选路径：有很多，可能有很曲折的
- 目标：将每个 GPS 点匹配到合适的路段上

1.4.2 已知在这个路段得到这个 GPS 点位置的概率估计

对于给定的 z_t, r_i 有 *emission probability* $x_{t,i}$

估计方法：The *great circle distance* on the surface of the earth between the measured point and the candidate match is $\|z_t - x_{t,i}\|_{great\_circle}$. For the correct match, this difference is due to GPS noise. model GPS noise as zero-mean Gaussian

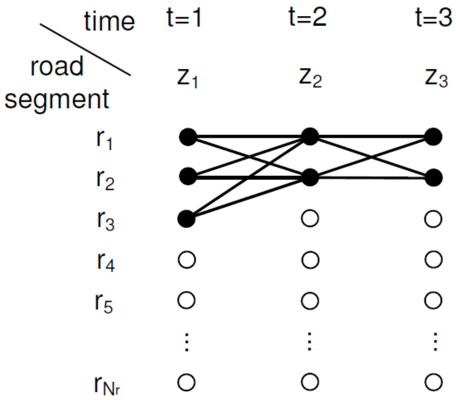


Figure 3: For each measurement z_t, the HMM considers all the road segments r_i as well as all the transitions between the road segments.

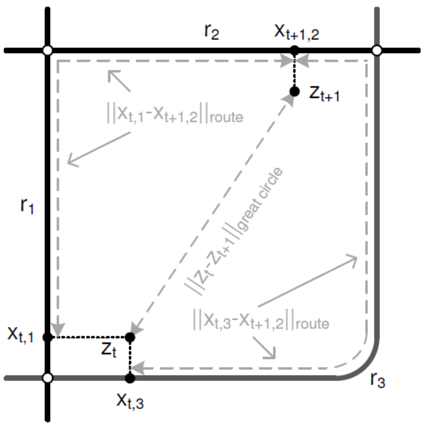
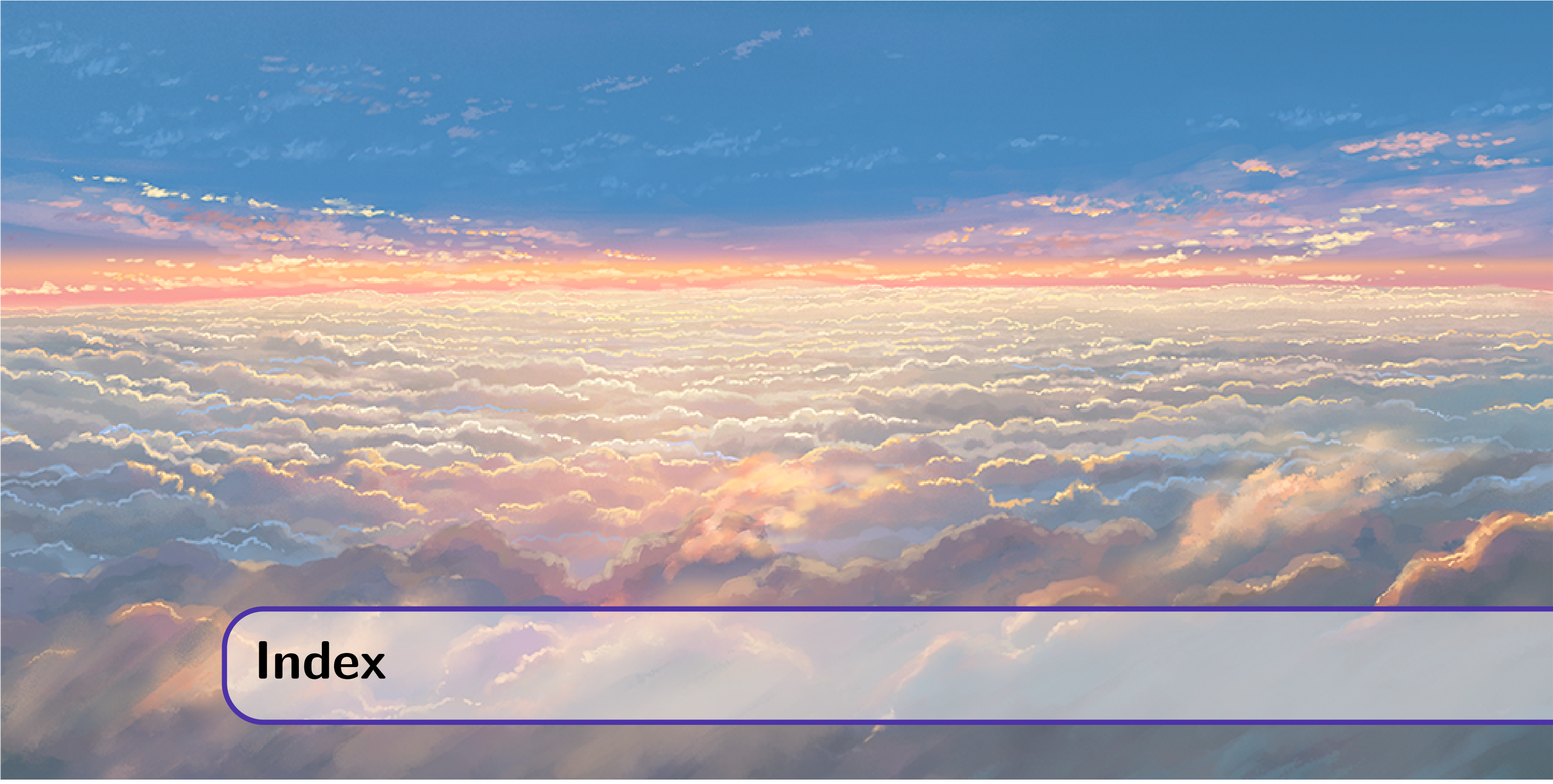


Figure 4: This shows an example of our notation. There are three road segments, r_1, r_2, and r_3, and two measured points, z_t and z_{t+1}. The first measured point, z_t, has candidate road matches at $x_{t,1}$ and $x_{t,3}$. Each match candidate results in a route to $x_{t+1,2}$, which is a match candidate for the second measured point, z_{t+1}. These two routes have their own lengths, as does the great circle path between the two measured points. Our data shows that the route distance and great circle distance are closer together for correct matches than for incorrect matches.

Bibliography

[1] Paul Newson and John Krumm. “Hidden Markov Map Matching Through Noise and Sparseness”. In: *17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM SIGSPATIAL GIS 2009), November 4-6, Seattle, WA*. 2009, pages 336–343. URL: `https://www.microsoft.com/en-us/research/publication/hidden-markov-map-matching-noise-sparseness/` (cited on page 4).



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