# Map Matching: Comparison of Approaches using Sparse and Noisy Data

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## ABSTRACT

The process of *map matching* takes a sequence of possibly noisy GPS coordinates from a vehicle trace and estimates the actual road positions—a crucial first step needed by many GPS applications. There has been a plethora of methods for map matching published, but most of them are evaluated on low-noise datasets obtained from a planned route. And comparisons with other methods are very limited. Based on our previous unifying framework used to catalog different mathematical formulas in many published methods, we evaluate representative algorithms using the low-noise dataset from the GIS Cup 2012 and a high-noise dataset collected from Shanghai downtown. Our experiments reveal that global max-weight and global geometrical map matching methods are the most accurate, but each has its weaknesses. We therefore propose a new map matching algorithm that integrates Fréchet distance with global weight optimization, which is more accurate across all sampling intervals.

## Categories and Subject Descriptors

H.2.8 [**Database Management**]: Applications—*Spatial databases and GIS*

## General Terms

Algorithms, Experimentation, Performance

## Keywords

GPS, map matching, Fréchet distance, HMM

## 1. INTRODUCTION

Global Positioning System (GPS) receivers are integrated into navigation devices, vehicle telematics systems, and smart phones. Due to their inherent measurement error, map matching is a necessary step to pinpoint the correct location on the road network [20].


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In [16], we proposed a novel framework that encompasses most existing map matching algorithms. These algorithms determine the most probable match for a sample by calculating a weight for each candidate road location. The output route is the candidate sequence with the highest score. These algorithms differ primarily in the way they combine these factors. We call this category of methods *max-weight* methods, which can be further divided into *incremental max-weight* and *global max-weight* methods. Incremental methods determine the output for each point before advancing to the next, and global methods consider the whole trace in determining the output. The other major category consists of *global geometric* methods, which determine the best matched path solely by geometric measures such as *Fréchet distance*.

Most research work evaluates their proposed algorithm using low-noise datasets obtained from controlled experiments; algorithm comparison is typically missing or is limited to one or two cherry-picked alternatives. Using a uniform software harness, we evaluate representative algorithms in all three categories on two datasets: the low-noise dataset from the GIS Cup and a high-noise dataset we collected from Shanghai [1]. Our evaluation methodology considers both the sample-based accuracy that is used by the GIS Cup, as well as a novel path-based precision and recall. The experiments show that global methods are more accurate than incremental methods because future observations can often help determine previous locations. On the other hand, global max-weight and global geometric methods have their respective strengths and weaknesses. Global max-weight methods are accurate and robust even with long GPS sampling intervals, but they require substantial tuning and are sensitive to different data characteristics. Global geometric methods require no tuning and the matching results are easy to understand, but the performance is poor when there are alternative paths with the same optimal geometric measurements, which is often the case with long sampling intervals or high-noise data.

Based on these observations, we propose a hybrid algorithm that integrates global weight optimization into the Fréchet distance-based map matching. Our experiments show that the hybrid algorithm is more accurate than both global max-weight and global geometric algorithms across all sampling intervals. More importantly, unlike global max-weight methods, it requires very little tuning and the optimal parameters are consistent across different datasets.

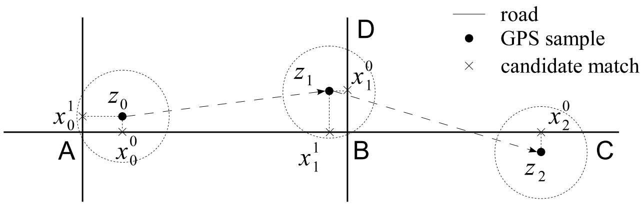



Figure 1: Max-weight map matching

Section 2 surveys representative map matching algorithms and motivates the hybrid solution. Section 3 describes the design and implementation of the hybrid algorithm. Section 4 shows experimental results, and Section 5 concludes the paper.

## 2. RELATED WORK

Most existing map matching algorithms can be classified into three categories [16]: incremental max-weight [5, 7, 8, 10, 13, 17–19], global max-weight [9, 11, 12, 14] and global geometrical methods [3, 6]. Both incremental and global max-weight methods consist of the following steps:

1. For each GPS sample $z_i$, determine a set of candidate locations $\{x_i^0, x_i^1, ...\}$, which are typically the perpendicular projections on road segments $\{y_i^0, y_i^1, ...\}$ within a radius or an error eclipse of $z_i$; see Figure 1.
2. Calculate a weight for each candidate.
3. Output the candidate sequence with the maximum weight.

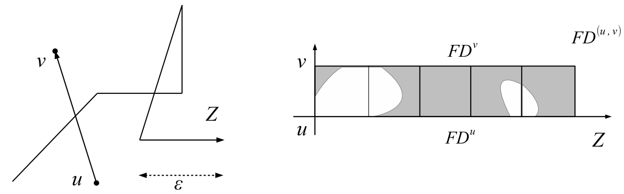
Incremental and global methods differ in the last step on how to pick the candidate sequence. Incremental methods calculate the best candidate for each sample one at a time. The calculation is based on either a range of the recent samples or a summary of all previous samples (e.g., Bayes filter). In contrast, global max-weight methods compute an aggregated weight for each candidate sequence in entirety, and they output the sequence with the maximum. Most global max-weight methods employ a Hidden Markov Model (HMM), solving with the Viterbi dynamic programming algorithm. Weight calculations for both incremental and global methods are based on a common set of features [16].

In contrast to max-weight methods, global geometric map matching finds the optimal path on the map by geometric similarity measures, e.g., Fréchet distance; these methods do not calculate a candidate set for each GPS sample [3, 6].

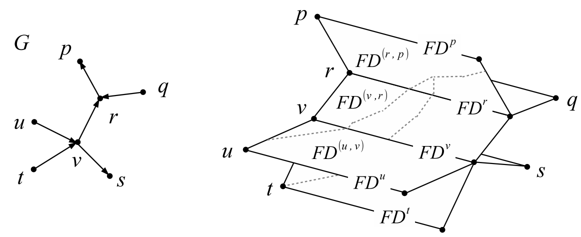
## 3. OUR HYBRID ALGORITHM

Based on the weaknesses in each category of methods, we propose to incorporate global weight optimization into map matching based on Fréchet distance. We refer readers to [3] for a more complete discussion.

We first explain the Fréchet distance calculation between two polylines. The *free space* of two curves $f, g : [0, 1] \to \mathbb{R}^2$ is defined as $F_\varepsilon(f, g) := \{(s, t) \in [0, 1]^2 \mid \|f(s) - g(t)\| \le \varepsilon\}$, where $\varepsilon$ is a given constant. Region $[0, 1]^2$ is therefore partitioned into free space and non-free space, called the *free space diagram*. It has been shown that $\delta_F(f, g) \le \varepsilon$ if and only if there exists a path within $F_\varepsilon(f, g)$ from the lower left corner $(0, 0)$ to the upper right corner $(1, 1)$, which is monotone in both coordinates [4]. This path induces functions $\alpha$ and $\beta$ in the definition of $\delta_F(f, g)$.



(a) Free space diagram $FD^{(u,v)}$ for edge $(u, v)$ and GPS trace $Z$.



(b) Free space surface consists of free space diagrams glued together according to the topology of $G$. Grey dashed paths are monotone paths in the free space, which may not be unique.

Figure 2: Free space surface illustration, based on the example in [3].

The definition of the free space between two polylines generalizes to the free space between a planar graph $G = (V, E)$ of the road network and a polyline $Z = (z_0, \dots, z_n)$ of GPS samples. With slight abuse of definition, we consider the free space diagram between a vertex $v \in V$ and $Z$. The result is a one-dimensional free space line, denoted as $FD^v$. The free space diagram between an edge $(u, v) \in E$ and $Z$ is a $1 \times n$ segment-segment diagram, denoted as $FD^{(u,v)}$; see Figure 2a for an example. Notice that the free space diagrams of all edges adjacent to a vertex $v$ share the free space line $FD^v$. We therefore construct free space diagrams $FD^{(u,v)}$ for all $(u, v) \in E$, and "glue" them together along shared free space lines, according to the topology of $G$. The resulting three-dimensional structure is called a *free space surface* of graph $G$ and polyline $Z$. Figure 2b gives an example graph $G$ and its free space surface; the trace is omitted for simplicity. There is a path in $G$ with Fréchet distance at most $\varepsilon$ to $Z$ if and only if there is a monotone path on the free space surface [3]. Finding the minimum Fréchet distance to $Z$ is achieved by parametric or binary search.

When there are multiple monotone paths on the free space surface, we apply a Viterbi-like dynamic programming algorithm to assign weights to these paths and output the one with the maximum weight. We designed a weight function that improves upon Newson09 and Lou09:

$$\arg\min\,(x_0, x_1, \dots, x_n) \sum_{i=0}^{n} t_i d_i^2 + \alpha l_i \tag{1}$$

where $t_i$ is the time interval between $z_i$ and $z_{i-1}$, $d_i$ is the great circle distance between $z_i$ and its candidate location $x_i$, and $l_i$ the shortest path from $x_i$ to $x_{i-1}$ as shown in Figure 1. The rationale of our design is the following. The summation of $l_i$ for a candidate sequence is exactly the length of the shortest path that links it, which does not change with the sampling interval.

## 4. EXPERIMENTS

We first discuss our evaluation methodology and then show experimental results for each dataset.

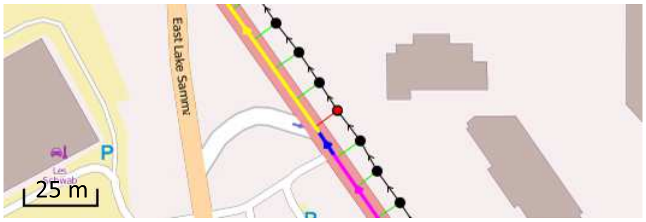



Figure 3: Sample-based evaluation can be ambiguous at road connections: The red sample is incorrectly labeled with the blue road by the ground-truth of the Seattle dataset.

## 4.1 Evaluation Methodology

We use two datasets for performance comparison, a low-noise dataset collected from planned routes in Seattle [2], and a high-noise datasets from planned routes in Shanghai. We subsample the traces to evaluate the performance at longer sampling intervals.

And we compare Yang05, Zheng11, and Griffin11 for incremental methods, and Lou09* and Newson09 for global methods [16]. For each max-weight algorithm we compare, we tune its constant parameters in the weight function to maximize its accuracy for the Seattle dataset at the one second sampling interval. Then we fix the values for the rest of experiments.

**Path evaluation.** Sample-based accuracy evaluation inevitably leads to ambiguity near road connections. Figure 3 is an example. To avoid these problems, we developed a novel path-based evaluation method, which scores the results in terms of precision and recall. We denote the set of road segments in the ground-truth path as $Truth$, and the set of segments in the matched path as $M$. We measure the precision and recall of the inferred drive path $M$ with respect to the ground truth path $Truth$ as:

$$recall = \frac{||Truth \cap M||}{||Truth||}, \quad precision = \frac{||Truth \cap M||}{||M||}$$

where $||\cdot||$ measures the total length of the road segments in the set.

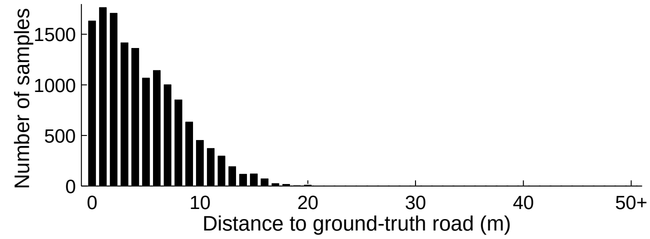
We evaluate only sample accuracy for the Seattle dataset since its ground-truth path is unknown. For our Shanghai dataset, we evaluate both sample and path accuracy.

## 4.2 Empirical Results

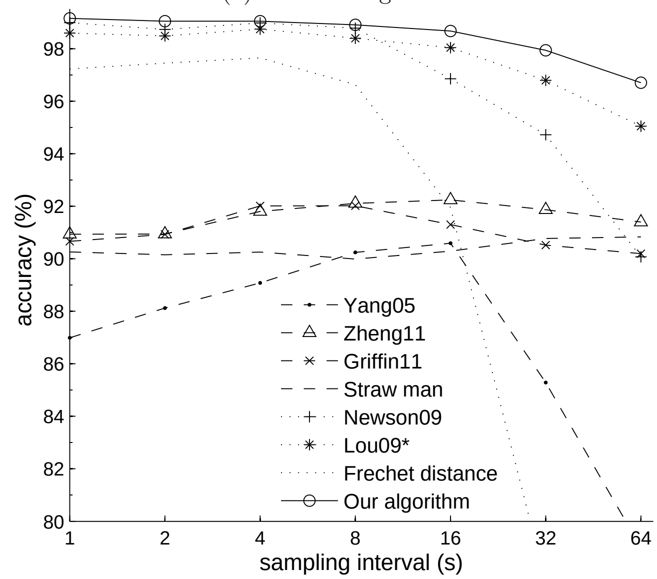
**Seattle Low-Noise Dataset** The Seattle dataset contains 14,436 samples. Each consists of a timestamp and a longitude-latitude pair. Figure 4a shows a histogram of the distance between each sample and its ground-truth road.

Figure 4b shows the accuracy of each algorithm as we increase the sampling interval between GPS samples. For reference, we include a straw man algorithm that simply matches each sample to the nearest road. The incremental methods (each shown using long-dashed lines) are not substantially better than the straw man algorithm, and they are much less accurate than global methods (upper cluster). We found they suffer from numerous freeway Y-splits. The top curve shows that our algorithm dominated in accuracy across all sampling intervals. The global algorithms all degrade at long sampling intervals. The Fréchet distance algorithm degrades due to the alternative path problem. Newson09 degrades because of its weight function design.

**Shanghai High-Noise Dataset** Our Shanghai dataset includes a total of 19,080 samples. This dataset is substantially noisier than the Seattle dataset due to the high con-




(a) Noise histogram




(b) Accuracy comparison

Figure 4: Experiments using the Seattle dataset.

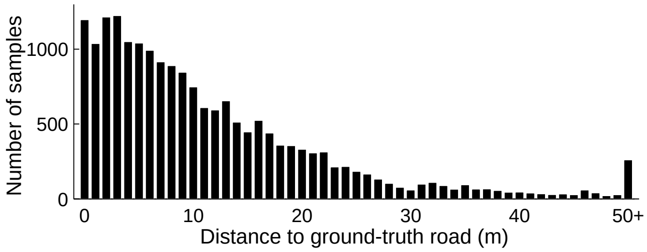
centration of high-rise buildings in Shanghai and its complex road networks [15]. Figure 5a shows the histogram of GPS noise. The maximum error is 133 m and the median is 8.97 m. We therefore set the candidate search radius to 250 m, roughly twice the maximum and five times the value for the Seattle dataset.

Under high-noise data, the performance differences among different algorithms are magnified. Incremental methods perform much worse compared with global methods. Nearest match achieves only 79% accuracy, and other incremental methods perform similarly. To simplify the presentation, we omit the results for incremental methods and show only global methods in Figure 5b. Again, our algorithm performs the best, followed by Newson09, Lou09*, and the Fréchet distance algorithm.

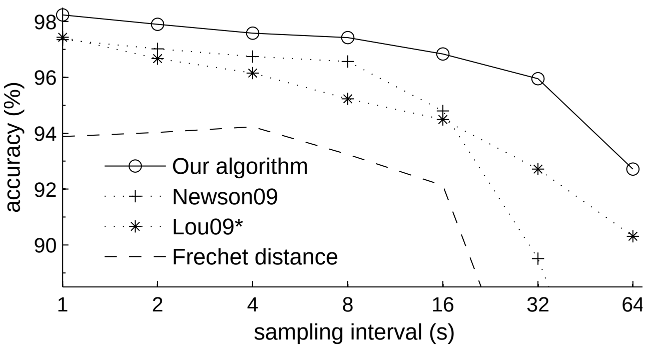
The path evaluation in Figure 5c reveals more subtle differences in their precision/recall tradeoffs as we vary the sampling interval. (Here we omit the Fréchet distance algorithm because its performance is too low—less than 50% precision because it often picks spurious paths within the maximum distance.) Interestingly, both the global max-weight methods achieve their best precision/recall tradeoff at the eight second interval, because it happens to eliminate some of the random GPS noise problems.

# 5. CONCLUSION

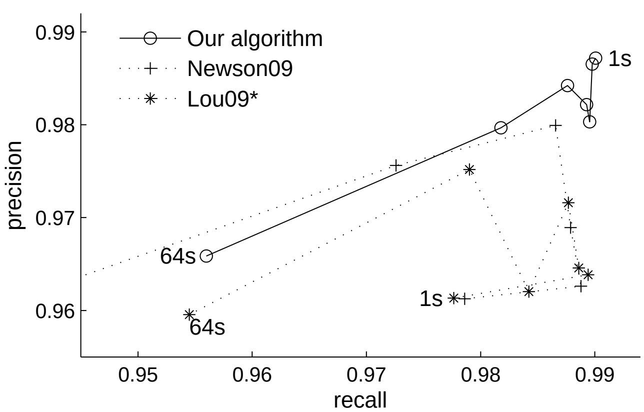
Using the framework we developed to make sense of the extensive literature on map matching, we have been able to test and compare a variety of methods empirically using three diverse test datasets. With our understanding of




(a) Sample noise histogram




(b) Sample evaluation of global methods




(c) Path evaluation using precision and recall

Figure 5: Experiments using the Shanghai dataset.

where and how different algorithms fail, we have been able to develop a new algorithm that enjoys the benefits of global max-match methods as well as global geometric methods. In testing, it dominated accuracy across the spectrum of sampling intervals—particularly under higher noise situations. This makes it the leading candidate for use on much real-world GPS data, such as volumes of fleet-management data, where the sampling interval is necessarily lower to make the data and transmission costs manageable.

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