Map Matching Algorithm for Large-scale Datasets

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Abstract: GPS receivers embedded in cell phones and connected vehicles generate series of location measurements that can be used for various analytical purposes. A common preprocessing step of this data is the so-called map matching. The goal of map matching is to infer the trajectory that the device followed in a road network from a potentially sparse series of noisy location measurements. Although accurate and robust map matching algorithms based on probabilistic models exist, they are computationally heavy and thus impractical for processing large datasets. In this paper, we present a scalable map matching algorithm based on Dijkstra's shortest path method, that is both accurate and applicable to large datasets. Our experiments on a publicly available dataset showed that the proposed method achieves accuracy that is comparable to that of the existing map matching methods using only a fraction of computational resources. As a result, our algorithm can be used to efficiently process large datasets of noisy and potentially sparse location data that would be unexploitable using existing techniques due to their high computational requirements.

1 INTRODUCTION

With the current spread of GPS receivers, embedded into almost all cell phones and connected cars, a huge amount of GPS data from vehicular traffic is produced. The data can be used to analyze various properties of road network like traffic density, travel time, or speed, or to uncover traffic-related behavioral patterns. For all these applications, however, we need to first perform the so-called map matching, a process of mapping the GPS records to the road network to obtain the real path driven by the vehicle.

The map matching problems can be divided into two categories: *online* map matching and *offline* map matching. The online map matching is a process of determining the path of a driving vehicle, while the offline map matching computes the path after all GPS measurements have been recorded. As we study the offline map matching problem, we will use the term "map matching" to refer to the offline map matching in the remainder of this paper. While online map matching has a broader application, including the consumer market, offline map matching is a key component in traffic analysis. With the data about vehicle movement in the road network, computed by offline map matching, we can analyze traffic patterns or even estimate the speed on individual road segments (Leodolter et al., 2015).

When the location data are sparse and affected by significant measurement errors, the map matching problem becomes challenging because there are typically multiple routes in the road network that could be considered as a match for the measurements. In an urban environment, in particular, the GPS signal is often affected by multipath propagation, which, in conjunction with other effects, can result in a measurement error larger than 20 m (Merry and Bettinger, 2019). See Figure 1a for an example of measurement error in an urban environment. Furthermore, to keep energy consumption low, many devices produce data at low frequency. For example, according to Yuan et al. (2010), 66 % of the data generated by Beijing taxis were sampled with a frequency lower than one sample per minute. See also Figure 1b that illustrates the low sampling frequency problem.

To enable the processing of low-frequency high-noise GPS data, a number of map matching algorithms have been proposed (see Section 1.1). A typical map matching algorithm is based on the 2-step scheme. First, a set of candidate projections (road segments) on the road network is computed for each GPS record. Then, the most probable path is chosen

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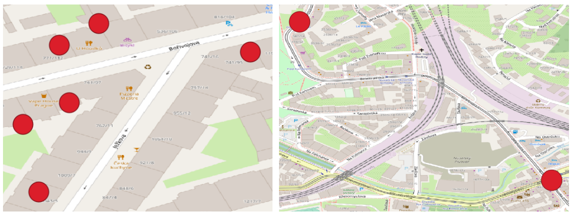

(a) (b)

Figure 1: Examples of GPS sampling problems. Each red circle represents a single GPS record. On the left, we see an example of measurement noise of GPS records. On the right, we can see the low sampling frequency problem.

so that for each record, there is one candidate projection in the final path. We refer these algorithms as *global* because they select the path that is globally optimal with respect to some model describing the map matching problem (e.g., the minimal average distance between a measurement and the corresponding candidate edge). Global map matching algorithms manage to match even very sparse GPS records with high measurement errors. These algorithms are, however, computationally heavy and thus they are impractical for the processing of large datasets, possibly containing millions of GPS traces (see, e.g., the computational time results of Tang et al. (2016)). Other methods attempt to optimize the path locally, matching the GPS measurements one by one. We refer to these approaches as *local* map matching algorithms. These methods, however, achieve unsatisfactory accuracy, especially on low-frequency high-noise datasets (see the comparison in Lou et al. (2009)).

In this paper, we present a global map matching algorithm that achieves accuracy comparable to the state of the art methods using considerably less computation time. In result, this method is suitable for processing of large location datasets. Our contribution can be summarized as follows: Firstly, we created a map matching algorithm that is based on graph search, a different principle than the state-of-the-art map matching algorithms. After that, we performed a theoretical analysis of the algorithm and compared its computational complexity to two previously published map matching algorithms. Finally, we experimentally compared the accuracy and computational speed of all three algorithms on a standard map matching dataset.

We found that the proposed algorithm has lower computational complexity than the existing approaches, and the experimental evaluation has shown that our approach is able to generate the underlying route estimates with the same accuracy as existing methods, but an order of magnitude faster.

1.1 Related Work

Early map matching algorithms, developed before the advent of GPS-enabled smartphones, did not attempt to recover the complete route of the vehicle, but instead, they focused on finding the most likely road segment for each measurement (White et al., 2000). An incremental algorithm and a global optimization approach based on Fréchet distance were later proposed by Brakatsoulas et al. (2005).

Newson and Krumm (2009) formalized map matching using Hidden Markov Model (HMM). In the proposed model, the authors use the network connectivity and measurement error to characterize the emission and transition probabilities of the HMM. The HMM-based map matching proved to be robust and accurate. The matching accuracy showed to be almost perfect even for location measurements with a period of 30 seconds. A similar solution using different formalization for global optimization was presented by Lou et al. (2009), adding temporal consistency as a transition criterion. A graph search based approach that searches for a path in the road network that resembles the GPS records was presented by Wolfson (2004). The idea is similar to the approach we propose, however, the article lacks detailed description and performance evaluation against state-of-the-art methods. Other algorithms focused on high accuracy matching of sparse GPS data were presented by Rahmani and Koutsopoulos (2013). Kuijpers et al. (2016) proposed a solution that added the k-shortest path algorithm to compute the globally optimal path. The work by Tang et al. (2016) follows a similar direction, presenting a time-expanded road network graph as a formalization of the problem. In Yin et al. (2016), the authors propose a novel solution that improves the accuracy by incorporating a behavioral model in the map matching process. Moreover, they show that trajectory simplification can be used to speed up the map matching process. A map matching method based on genetic algorithms was studied by Nikolić and Jović (2017). They compared the accuracy of their approach with seven map matching methods and showed that it outperforms all of them with the exception of the HMM map matching by Newson and Krumm (2009). Finally, Zhang et al. (2021) presented a turning point based map matching method. This method that first splits the trajectory at selected turning points into smaller segments and then matches each segment separately proved to be better both in accuracy and in matching speed than five selected baseline algorithms, including works by Rahmani and Koutsopoulos (2013) and Kuijpers et al. (2016).

For a more comprehensive overview of existing map matching algorithms, we refer the reader to the existing surveys on the topic (Quddus et al., 2007; Hashemi and Karimi, 2014; Kubicka et al., 2018; Huang et al., 2021).

2 PROBLEM STATEMENT

We start by defining the necessary terms. *Road network* is a directed graph, in which the arcs represent the road segments and the nodes represent either the intersections or simply connect two following road segments. A *location measurement* contains a latitude, longitude, and the time of the measurement. Location measurements are typically obtained using a GPS receiver. A sequence of location measurements that covers a particular period of time is called a *trace*. If we connect the measurements in the trace with line segments, we get a sequence of lines, which we call a *trace linestring*. When we talk about *ground truth*, we refer to a sequence of consecutive road segments that was driven by the vehicle, while it was collecting location measurements. The ground truth is used to measure the map matching accuracy. The *match* is a sequence of consecutive road segments constructed using a map matching algorithm.

In this paper, we are interested in the map matching problem, i.e., we desire to determine the ground-truth path traversed by a vehicle in a road network from a given trace.

3 TOWARDS MAP MATCHING ALGORITHM FOR LARGE DATASETS

In this section, we briefly describe two existing map matching algorithms that we used for comparison with our algorithm and discuss their limitations. The Hidden Markov Model map matching algorithm (HMM-MM) by Newson and Krumm (2009) is a well-known example of the global map matching algorithm that is both robust and accurate, outperforming, in terms of accuracy, even recent map matching methods (Nikolić and Jović, 2017). However, it is also computationally heavy. On the other hand, the incremental algorithm from Brakatsoulas et al. (2005) is an example of a local map matching algorithm that is fast but not as accurate.

The HMM-MM is a global map matching algorithm that leverages Hidden Markov Models to find the most probable path (sequence of road segments) from all possible paths generated by projecting location measurements to different edges in the road network. The probability of each path is computed using the emission probability (probability of visiting a node) and transition probability (probability of traveling between specific nodes). In this approach, a measurement noise model is used to determine the emission probability, while the transition probability is inferred from the difference between Euclidean and road network distance.

The incremental algorithm by Brakatsoulas et al. (2005) first finds the initial edge by choosing it from a set of candidate edges that lie within a given threshold distance from the first location measurement. Then, in each step, it tries to match the next measurement to one of the road segments that are connected to the previously matched edge. The algorithm can also utilize a look-ahead strategy: it tries to match a few location measurements ahead and propagates the score back in an attempt to avoid myopic choices that cannot be reversed later on in the process.

4 THE GRAPH SEARCH BASED MAP MATCHING

In this section, we present the proposed map matching algorithm: the Graph Search Based Map Matching (GSMM). In contrast to simple geometric algorithms (White et al., 2000), the incremental algorithm, or the HMM-MM (both described in the previous section), the proposed algorithm does not iterate over the location measurements in the trace. It searches the road network graph using a standard graph search algorithm, but instead of searching for the shortest path, it searches for the path most similar to the location measurements. In other words, the cost of each arc in the search graph encodes the likelihood of the edge being part of the ground truth path given the location measurements. We use Dijkstra's shortest path algorithm for graph search as it is simple, well studied, and does not require any heuristic. While Dijkstra's algorithm is outperformed by A* in most applications, it is hard to imagine to use it in our case, as there is no straightforward heuristic with the required properties (consistency and admissibility). However, a bidirectional variant of our algorithm can be examined in the future.

The pseudocode of the proposed algorithm is in Algorithm 1. We start by initializing the priority queue Q and by adding the start node n_s to it with priority 0. Then, we continue by a standard Dijkstra-style loop, during which we add every neighbor n of current node n_c into the queue. The algorithm ends

Algorithm 1: GSMM algorithm core.

add n_s to Q with priority 0;
while *Q is not empty* **do**
    $n_c \leftarrow$ head of Q;
    if *n_c not closed* **then**
        set n_c as closed;
        if $n_c = n_d$ **then**
            backtrack ;
        for *$n \in$ neighbors of n_c* **do**
            if *n not closed* **then**
                $c \leftarrow$ compute_cost(n);
                add n to Q with priority c;

when the destination node n_d is reached, or when the queue is empty (which cannot happen unless the road network is not a strongly connected graph). The critical part of the algorithm is the initialization discussed in Section 4.1, and the node cost computation explained in Section 4.2.

4.1 Start and end Point Determination

Determination of the start and the destination node is the essential part of the algorithm. Unlike many other algorithms, our solution can recover from a bad choice of the initial node, but a mistake in initialization can still affect the accuracy. The initial edge e_s is chosen from the set of edges E as

$$e_s = \underset{e \in E}{\operatorname{argmin}} |r_0, e| + |n^e_{to}, t|. \tag{1}$$

where r_0 is the first location measurement, n^e_{to} is the end node of the edge e and t is the trace linestring built by sequentially connecting all location measurements. Figure 2 visualizes the cost computation of a candidate initial edge. For performance reasons, we add to the set E only the edges that are closer to r_0 than a given threshold. In our experiments, we use the threshold of 100 m. When the initial edge is computed, the start node of the edge is chosen as an initial point n_s.

An analogous process is performed when determining the destination point. Instead of the first measurement, we use the last measurement, and instead of the end point of the candidate edge, we use the start point.

4.2 Computing Edge Costs

For each neighbor node n, the total cost is computed as a sum of the cost of the current node and the cost of the neighbor. The cost of each neighbor is computed

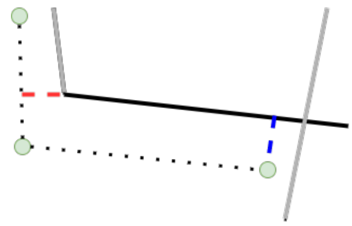

Figure 2: Initialization example. Green points represent the location measurements, gray lines are the roads, currently evaluated edge is highlighted in black. The initial edge is chosen such that it minimizes the sum of the distance between the first measurement and the edge (blue dashed line), and the distance between edge endpoint and the trace (red dashed line).

as

$$c = (c_1 + c_2)l_e/\alpha + c_3, \tag{2}$$

where the cost $c_1 = |n, t|$ is the distance of the neighbor node from the trace, and cost $c_2 = |p_{mid}, t|$ is computed as a distance between the middle point p_{mid} of the edge and the trace. These costs have to be multiplied by the length of the edge l_e to normalize them to the edge length. The constant α controls the contribution of cost c_3 that represents the difference between the length of the edge and the distance between the current and the neighbor node projections on the trace linestring:

$$c_3 = |l_e - l_{trace}|, \tag{3}$$

where

$$l_{trace} = ||p_{n_c,t}, p_{n,t}||_{trace}. \tag{4}$$

The purpose of these costs can be explained in the following series of examples. In Figure 3a, the computation of cost c_1 is illustrated. An important aspect that can be seen in this figure is that the cost for nodes n_3 and n_4 is not the Euclidean distance to the trace. The reason for this is that the algorithm always projects the nodes on the trace chronologically and consequently a neighbor node n cannot be projected before the current node n_c, that was already projected to the trace in the previous step.

The cost c_2 is computed analogously to the cost c_1, the difference being that we project the middle point of the edge, p_{mid}, instead of the neighbor node. The purpose of the cost c_2 is illustrated in Figure 3b, where we can see a situation in which relying on the cost c_1 would not suffice to determine the correct edge.

We could add more such control points as costs, but our experiments suggest that this is not effective as there were always cases for which the number of control points was insufficient. Instead, we created another cost c_3 that is designed to cover the remaining cases by comparing the length of the edge and the length along the trace between the projection of the

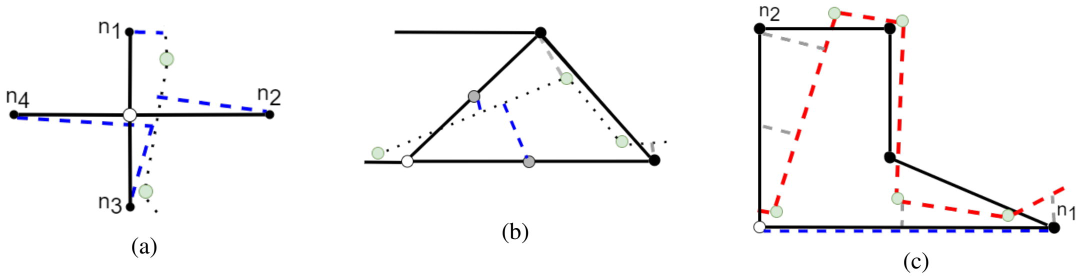

Figure 3: Illustration of computation of cost c_1 (a), c_2 (b), and c_3 (c). The costs are represented by blue dashed lines, the green points are the location measurements, the white circle is the current node, and the black circles and lines represent the road network nodes and edges, respectively. Note that in Figure a), the cost for nodes n_3 and n_4 is not the Euclidean distance to the trace because the neighbors have to be projected after the current point. On the second picture, we can see that the middle points (grey circles) can determine the correct edges even if the incorrect neighbor point has the lowest cost c_1 (gray dashed line). Finally the cost c_3 is computed for the neighbor node n_1 as the absolute value of the difference between the edge length (blue dashed line) and the length along the trace (red dotted line). We can see that both cost c_1 and cost c_2 (gray dashed lines) would mistakenly chose n_1 as the match.

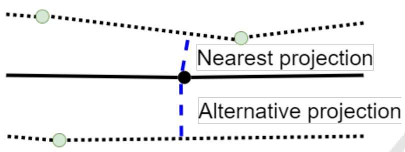

Figure 4: The example of ambiguous projection of the node. We can see the nearest projection and one alternative projection on the picture, depicted as the blue dashed line.

current node n_c on the trace (which was fixed in the previous step of the algorithm) and the projection of the neighbor node n. We can see the example where this metric is essential to correctly match the trace in Figure 3c.

Sometimes, the vehicle completely changes its direction during a single trip. In this case, the projection of a specific edge on the trace linestring can be ambiguous, i.e., multiple points in the trace can have a similar distance to the edge, despite being very far from each other along the trace (see Figure 4). We solve such cases by providing alternative projections that are in the same and in the opposite direction of the nearest projection within a distance of 100 m. Then, we compute the total cost c for each candidate projection and choose the projection with the lowest cost.

After choosing the best projection for the candidate neighbor node, we apply another cost c_4 to the cost sum, resulting in the equation

$$c_f = c + c_4, \tag{5}$$

where c is the neighbor cost defined above and c_4 is computed as

$$c_4 = -\beta ||p_{n_c,t}, p_{n,t}||_{trace}. \tag{6}$$

In the above equation, $||p_{n_c,t}, p_{n,t}||_{trace}$ is the distance along the linestring between current and neighbor node projection and β is the forward heuristic coefficient. The weight c_4 is a heuristic that guides the search and speeds up the computation, as the edges that lead forward along the trace have a lower cost. By assigning higher values for β, we can speed up the computation significantly, but higher values can also lead to less accurate results.

5 DISCUSSION

In this section, we discuss the computational complexity, performance, advantages, and limitations of the three compared algorithms.

5.1 Complexity

The worst-case asymptotic complexity of the GSMM algorithm is identical to Dijkstra's algorithm, $O(|E| + |N| \cdot \log|N|)$, where $|E|$ is the number of road segments and $|N|$ is the number of road network nodes. The computational complexity of the HMM-based method is dominated by the Viterbi's algorithm, $O(|R| \cdot |E|^2)$, where $|R|$ is the number of location measurements in the trace. The complexity of the incremental algorithm is $O(|R|)$. In practice, however, such worst-case complexities are never reached, partly due to the structure of the input and partly due to the performance optimization tricks that would be applied in the case of practical deployment.

In HMM map matching, the complexity is reduced by considering only nodes within a fixed radius from the location measurement as candidates – this drastically reduces the number of edges $|E|$ considered by Viterbi's algorithm. In GSMM, the worst case complexity is also virtually never reached, because due to the design of the cost function, the search is focused on the vicinity of the trace.

Finally, real-world traces typically contain only tens to hundreds of location measurements. In result, the time spent on computations that depends on the dataset size $|R|$ can be easily dominated by constant-time computations. This can be easily demonstrated in the incremental algorithm, where the worst-case time complexity is exponential with respect to the lookahead depth d_l. For $d_l = 4$, as used by Brakatsoulas et al. (2005) and a conservative average branching factor $b = 4$, the complexity of evaluation of each step, which can be expressed as $O(b^{d_l})$, easily dominates the measurement count.

An important difference between the GSMM and other map matching algorithms regarding the complexity is that the complexity of the GSMM is not directly related to the number of location measurements. In the case of other algorithms, both global and local, the number of algorithm steps is linearly dependent on the number of measurements. In result, these algorithms are not suitable for dense traces, sometimes even removing a significant number of measurements from traces is proposed to speed up the algorithm (Yin et al., 2016).

5.2 Performance, Advantages, and Limitations of Our Solution

The main shortcoming of the incremental algorithm is that it can choose wrong edges for the match because the lookahead has only a constant depth and the edge cannot be changed once chosen for a projection of a location measurement. In contrast, the HMM-MM and the GSMM search for a match with a globally optimal score. Yet, the probabilities in HMM-MM and edge costs in GSMM are nothing more than a model that uses the sensor data and network topology. In addition, the optimality of the HMM map matching is affected by the fact that it only searches for measurement projection candidates below a given distance threshold.

As it is clear from the Section 4.2 describing the computation of the weights, GSMM tries to find the path in the road network that is most similar to the vehicle trace. This produces correct results most of the time, but in sparse traces, sometimes, the path that is more distant from the trace could be correct as it is demonstrated in Figure 5. One of the techniques that can be used to match these scenarios correctly is described by Osogami and Raymond (2013) and also by Yin et al. (2016). This technique could be incorporated in the GSMM in the form of an additional cost. Other aspects of human behavior, such

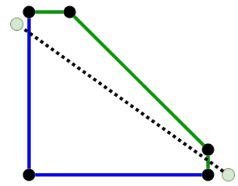

Figure 5: An example case of a problematic matching related to sparse traces. The green path is closer to the trace, but the ground-truth path is the blue path.

as temporal consistency, can be modeled as well, by simply adding the respective costs. Another advantage of the GSMM is that the edge costs are easy to compute. In contrast, in the HMM-MM, the shortest path needs to be computed to evaluate each transitional probability. The need for such frequent shortest path computation is a significant shortcoming. In fact, we observed that in our implementation, the shortest-path computations account for 98% of the runtime. Moreover, due to the ability of the GSMM to do fast matching, as demonstrated in Section 6.1, we believe that the GSMM can be used for online map matching too, simply by performing the map matching on all location measurements available so far.

The only limitation of our method are cycles in traces. Because the GSMM is based on Dijkstra algorithm, it is not able to correctly match traces containing cycles. In practice, however, we simply break self-intersecting traces in parts and match each part separately.

6 BENCHMARK

We experimentally compared the GSMM, the HMM-MM, and the incremental approach using an existing benchmark dataset[1] containing traces together with road networks and ground truths (Kubicka et al., 2018). The dataset does not contain “clean” traces, but instead, the traces contain artifacts like gaps or hives (a large number of measurements in a certain area) that are challenging for map matching algorithms. The traces in the dataset have the measurement period of one second, longer periods were created by our benchmark by subsampling the original trace. Eleven period lengths between 1 second to 5 minutes length were tested. The period of 24 seconds represents the average measurement period measured on a real dataset of almost 10 thousand taxi trips in Prague collected by a ride-hailing application Liftago. The complete histogram of the delays between points in the Prague dataset is in Figure 6. Because our al-

[1] https://zenodo.org/record/57731

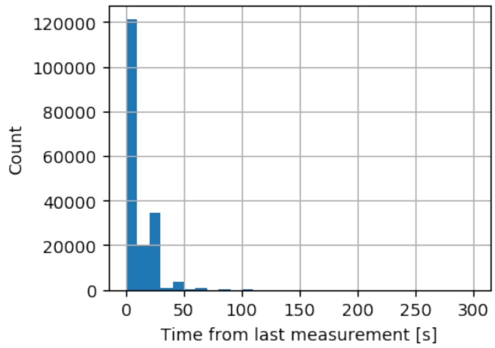

Figure 6: Histogram of delay between the traces from Prague taxi trace dataset.

gorithm cannot handle traces containing cycles, only a subset of traces without cycles was used for evaluation.

To measure the map matching accuracy, we used a metric called *Route Mismatch Fraction (RMF)* introduced by Newson and Krumm (2009). The RMF is computed as

$$RMF = \frac{l_{gt}}{l_+ + l_-}, \tag{7}$$

where l_{gt} is the ground truth length, l_+ is the length of the segments in the match that are not in the ground truth (false positive length), and l_- is the length of the segments in the ground truth not present in the match (false negative length).

All algorithms and the benchmark were implemented in Python and ran on a desktop PC with Intel Core i5 4950S CPU and 24 GB of memory. The HMM-MM algorithm was configured with parameters $\sigma = 50$ and $\beta = 2$, edges in the radius of 15 meters were considered as projection candidates. For the incremental algorithm, the parameters were configured as follows: $\mu_d = 10, n_d = 1, a = 0.17, mu_\alpha = 10, n_\alpha = 7$. The look-ahead depth was set to 4, the start area radius was set to 100 m, and max allowed skipped edges was set to 10. In the GSMM, the start area radius was set to 100 m and the forward heuristic cost weight β was set to 3.

6.1 Results

The comparison of the accuracy of the tested algorithms is in Figure 7. As we can see, the accuracy of the incremental algorithm is very low. Thus, we decided to remove the incremental algorithm from other comparisons, as it is clearly not able to produce reasonable matches for the benchmark dataset. The accuracy of the GSMM is comparable to HMM-MM up to the period of 30 s, which is more than the average measurement period measured on the real-world

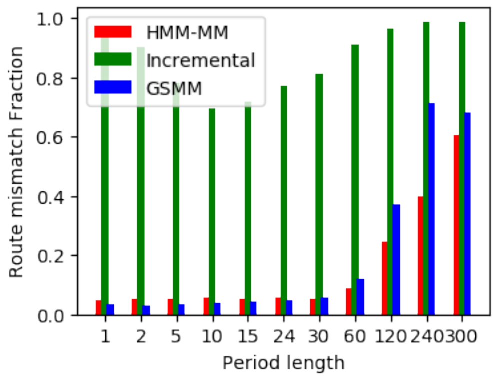

Figure 7: Comparison of the accuracy of the three evaluated algorithms on traces with different sampling frequencies.

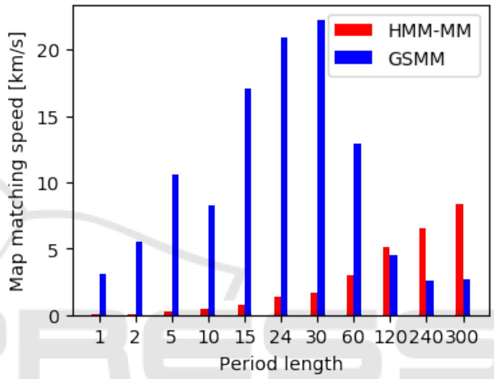

Figure 8: Comparison of speed of the GSMM and the HMM-MM on traces with different sampling frequencies.

dataset (Section 6). For periods above 30 s, the accuracy of both algorithms starts to degrade, with the GSMM declining more rapidly. Concerning the speed (Figure 8), the GSMM is faster than the HMM-MM up to the period of two minutes, under one minute period, our algorithm is more than ten times faster.

The first thing to explain is the failure of the incremental algorithm to provide reasonable matches. We investigated that the algorithm fails on the network areas with very short road segments, where a large number of road segments with similar costs can be assigned to the location measurement. We believe that authors of the algorithm measured the accuracy on a simplified road network, where these problems are rare and therefore obtained better results.

For traces with a sampling period of up to one minute, the GSMM is significantly, often an order of magnitude, faster. For longer periods, the HMM-MM dominates in speed. This is not a surprise, as for HMM-MM, the complexity depends on the number of records (see Section 5.1). The speed should, therefore, increase with a decreasing sampling frequency, which was confirmed by the results. Additionally, in global map matching algorithms, the runtime is strongly affected by the number of projection candidates. In the HMM-MM, the number of candidates is limited by the fixed radius (Newson and Krumm, 2009), which was set to 15 m in the benchmark. However, in the case of a more noisy dataset, this limit would have to be increased to obtain accurate results, decreasing the speed as a result.

7 CONCLUSION

The cell phones and connected cars produce large amounts of location data that can be used for various analytical purposes. E.g., this data can be exploited to estimate free-flow speeds or traffic densities in a road network. A common preprocessing step is map matching, where we desire to infer the path of the vehicle through the road network from sparse and noisy location measurements.

Many map matching algorithms have been proposed that excel in accuracy or robustness with respect to sparse and noisy GPS traces. Yet, with the increasing size and availability of location measurement datasets, the processing speed of map matching algorithm becomes important.

We proposed Graph Search based map matching (GSMM), a map matching algorithm based on Dijkstra's algorithm for the shortest path that is focused on reducing the computational complexity. We compared the performance of the GSMM together with a state-of-the-art global map matching algorithm (HMM-MM) and one incremental map matching algorithm on a standard, publicly available dataset.

The results show that the accuracy of the incremental algorithm is unsatisfactory. Concerning the HMM map matching, our algorithm is up to 10 x faster and it achieves higher accuracy than the HMM algorithm for records with a sampling period shorter than one minute. For lower sampling frequencies, the HMM-MM performs better, however, the real data from a taxi company shows that such low sampling frequencies are rare.

In the future, we would like to extend this method with other costs that incorporate behavioral aspects. Moreover, we plan to utilize the matched data to deliver a road speed model.

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