

Map Matching Algorithm: Trajectory and Sequential Map Analysis on Road Network

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Abstract

The Global Positioning System (GPS) tracking data is essential for sensor data sources. It plays an important role for various systems like Traffic assessment and Prediction, routing and navigation, Fleet management etc. Trajectory data accuracy is key factor for sampling based vehicle movement using existing GPS alerting systems. GPS navigation process is not reliable because of weak signaling transmission, weather scenario, specially, tall buildings area and drass sectors in Indian scenario. Map matching finding a path between available points on the active road segment, enhance road data accuracy through minimize frechet distance for future purpose. Therefore, accurate road data, become necessary for fast map matching outcomes. This work provides to locate the frechet distance on available free space for accurate path finding. This work also contributes to measuring frechet distance, trajectory data error estimation and finding free space surface on road network with sequential map computational method.

Keywords: Weak Frechet Distance, Error Aware, Map Matching, Trajectory Data, Adaptive Clipping, Free Surface Area

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1. Introduction

Wireless sensor are very helpful for environment monitoring and communication process; researchers face challenges like computational constraints, link failure, fault tolerance for coverage network which would improve with wireless sensor coverage performance and next generation sensor technologies is necessary for mobile communication systems which will helpful on high speed mobility and tracking services [1]. Global Position System (GPS) receivers are unified into various systems like Navigation system, Vehicle telemetric system, Intelligent Transport System (ITS), Smartphone etc. GPS services are not appropriate for real time navigation on the road network especially in drass

sectors, high forestry sectors and tall building areas in Indian scenario. This era GPS users needs appropriate navigation approach without any tracking pitfalls. Map matching concept is useful for position finding on road network [2]. GPS receiver data is very necessary for position observing on digital road map. Navigation applications seriously work for accurate and reliable position sampling, analysis using sophisticated map matching algorithms, which result are not reliable due to available trajectory data quality.

This paper exploits GPS tracking trajectory data errors to pare down on the road network, presumably in the right tracking approach for high accuracy using fast map matching algorithm and adaptive clipping algorithm, which compute approximate real path between nearest road polygon's circumferences. GPS trajectory data errors are finding; and reduce by computing frechet distance, between active surfaces of polygon circumferences [3]. Existing Adaptive Clipping algorithms provide local and global map

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matching approach using Strong Frechet distance. Weak frechet distance is very important for local mapping approach; adaptive clipping approach neglect weak frechet distance for large network due to running time, storage complexity [4]. We also analysis output sensitive variant for weak frechet map using error-aware selection strategies for reliable navigation on curve polygon circumferences on road network. Trajectory Data- trajectory data is vehicle moving real time information like latitude, longitude, height, velocity, starting moment position, ending position elapsed time, etc, [5] which can easily collected using techniques such as Floating Car Data from many sources with appropriate file formats (*OSM*, *XML files*). Newson & Krumm [6] provides sophisticated map matching results based on available trajectory data, for real time position mapping on Google digital map which are not reliable for mobility time interval.

To address the challenges of map matching from noisy, low- frequency sampled trajectory data. Let we consider the large urban road network with part of different characteristic data. To compute smooth and optimized map between starting and ending moving points. The adopted approach; explore vehicle trajectories to analyzed segment and reconstruct the underline movements of network. This approach allows us to analysis input data set into groups of homogenous trajectory data and delay network.

The main contribution of this work focus on Proposed sequential map matching algorithm, Proposed vehicle location tracking algorithm, it provide optimized road network, based on original input data and threshold values, This work introduce, proximity turn sampled based algorithm for similar turns analysis on the road network and useful for create intersection nodes on available trajectory data [6]. Focus on optimized results using real data set according our research scenario to show the performance of proposed methods outperformance the current state of art.

This paper introduces, map matching issues and algorithms including optimum outcomes. Section 2 provides background details and Frechet Distance and issues are discuss in Section 3. Section 4 surmised Existing Map Matching Issues and in Section 5, we will propose Sequential Map Matching Algorithm. Section 6 Provides Results and Discussion and finally we surmised conclusion in section 7.

2. Background

Map matching algorithms are use full for trajectory data process and exact location finding on appropriate time period. Adaptive Map Matching Algorithms works as Incremental and Global Map Matching Algorithm for vehicle location tracing in different road situations. Qudus, et.al [7] provides, an incremental algorithm

principle based on greedy strategy with historical mapping results, for active surface area in road network similarly Goh C. Y et.al [8] & He Z. C et.al [9] provides, incremental algorithm with sliding window and recursive principle; Sliding window divide trajectory data into the smallest points, for sequential processing when sliding window size continuously updated with segment points is large, algorithm provides optimal results.

Karagiorgou et.al [10] introduces the look ahead method for delay analysis between each segment points. Yin et.al [11] proposed, a high quality map matching method for computing nearest point's trajectory data; on active surface area of the road network which is indicates through a weighted graph, every weighted edges are decoding the distance between vehicles position for calculate shortest Path value using Dijkstra's Algorithm.

Wenk.C et. al [12] introduce, an appropriate route-finding approach using road and geometric analysis for Point to point map matching approach or line segment tracking in different whether situation on road network. Mostly route tracking research is based on GPS trajectory [13] for vehicle's variability which is more reliable than personal trajectory data collection approach Similarly, Chen. L, et.al [14] proposed, personal trajectory data collection approach which would face adequate challenges for example the diversity of trajectory data on each movement. Frechet distance is necessary parameter for accurate route finding between road networks. A global algorithm for finding all possible polygon circumferences (*circular path*) on appropriate velocity of vehicle [15].

The objective is to enhance the performance of global map matching algorithm for kinetic and precise point positioning for real time tracking.

3. Frechet Distance

Curve matrix space provide computed results between polygons in $O(p \times q \times \log_2 p \times q)$ time where p and q are curve polygon segments for example, suppose a man walking a dog in forward direction with continuous velocity where belt's minimum distance (*between man and dog*) indicate strong frechet path on active segment length and weak frechet path indicate belt's length [15]. Strong and weak path depend on belt's variant, for example suppose distance ($\epsilon > 0$) means, distance is fixed or not [27]. Alt H & Godau [16] provides a binary search method for curve circumference's radius variants at ϵ distance or $> \epsilon$ distance.

Figure.1 represent road network on right side and vehicle trajectory explicitly indicated with related path from lower left to upper right corner, indicated by a line in right side.

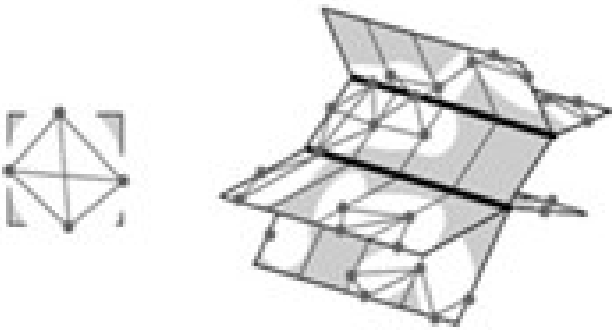


Figure 1. Road Network (left) and White surface (right)

4. Map Matching Issues with Algorithms

Map Matching is a used for continuous and smooth navigation process. Existing navigation systems are working on positional data such as longitude, latitude but, mostly systems are neglect altitude for route mapping approach on the horizontal surface; it becomes imbalance for sophisticated regions like ground road network, for example, hill station routes, rural region and tall building area. Map matching algorithms appropriate results are depend on trajectory data and digital map quality.

4.1. Problem

Let $T = (T_n | n = 1, 2, \dots, N)$ sequence of N vertices of the road network.

Every point (T_n) identify necessary parameters like Longitude, Latitude, Speed and Time stamp respectively ($T_n.Lon$), ($T_n.Lat$), ($T_n.v$), ($T_n.t$).

Procedure for computing GPS points threshold [17], let $T =$ time interval between vertices and GPS log point under a certain threshold:

$$\Delta t, T : P_1 \rightarrow P_2 \rightarrow P_3 \rightarrow \dots \rightarrow P_n \quad (1)$$

where $P_i \in L$, means contains (*latitude, longitude and time stamp*) in range $0 < p_{i+1}.t - p_i.t < (1 \leq n)$.

Segment. Let R is the mapping point on polyline (Figure 2) which indicates curve segments on the road. Number of nodes are lies on a line are indicate as (p_1, p_2, \dots, p_m) , where each node contain Longitude and Latitude where segments with

- Road width (r, w).
- Speed limit(r, v)
- Bi-direction travel [$r, d \in True, False$].

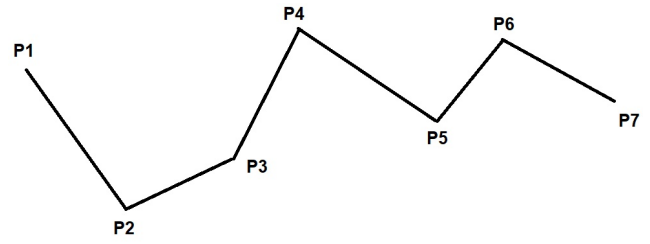


Figure 2. GPS Trajectory

Digital map. Map is a combination of many segments (k) of a road network. It provides route and location of the vehicle. Let $G = \{r_k | k = 1, 2, k\}$. The objective is to find out corresponding trajectory point (T) between segments (G).

4.2. Map matching algorithm

Map matching performance can enhance using some strategies such as graph optimization, error awareness with trajectory data, and result in the sensitive process using adaptive clipping technique.

Algorithm 1 Turn and Segment Analysis

Input: Trajectory set (T) and speed categories (C)

Output: A set of trajectory segment based on speed.

BEGIN

$T_{segm} \leftarrow \emptyset$

For $T_{segm} \in T$

For each ($L_j \in T$)

$\bar{U}(L_i) \leftarrow median(U(L_j - w)), V(T_{segm}) \in C$

$T_{segm} \leftarrow T_{segm} \cup L_g, C$

End for

End for

Return T_{segm}

END

To analyzed the tracking trajectories input data, which split into subsets with difference characteristics as per speed of moving objects. When set the input parameters of proposed algorithm for compute difference between overlapping area of the network with higher accuracy. So, that it can be merge the subsets to produce the complete network. This approach helps to construct virtual network. For analysis, the various speed for example slow, medium, and fast. The input trajectories split or filtered then an object may have to move with different speed across different subset of trajectories. A native method to achieve such condition: need to assign speed values for each line segment of trajectories. This value compute based on segment length on time interval duration between starting and ending points.

Graph Optimization algorithm. A traditional approach of curve polygon's frechet distance computation on variant frames in $\Theta(m, n)$ time duration, here m, n are curve polygon conditions where active points are search out using graph traveling technique [18]. GPS trajectory position complexity for shortest path computation between nearest active points on road segment in $O(m \times n \log(m \times m))$ time and $\Theta(m \times n)$ space complexity for every shortest path $\epsilon < \epsilon^*$, where ϵ^* indicate optimal frechet distance and ϵ represent weak frechet distance.

White surface indicate active surface area for optimal path analysis, where every pair of vertices (v) connected by an edge (e) for a path (v, e).

Sensitiveness algorithm. An optimal shortest path is important for historical data on previous tracking graph. Hash table maintain historical information on $O(1)$ time for each entity similarly output sensitive algorithm requires $O(k \times \log k)$ time, where K indicate required free space for every shortest path between start (e, p_0) and end (f, p_n) nodes, e and f are roads with p_0 and p_n position points. Sensitiveness method for shortest path finding with trajectory data refining process for upgrading map matching performance [19].

Error aware map matching. Real time tracking applications services are not reliable due to GPS signal frequency and receiver performance which is causes of tracking in GPS restricted areas, tall buildings region, narrow streets, high drass sector in our scenario. One most causes of GPS error is signal reflection when transmitted on Satellite Based Augmentation System (SBAS) due to satellite's health or weather circumstances.

The following Lemma encodes the observed trajectory properties for the road network for signal trajectory:

Lemma 1: The positive vehicle trajectory of the vertices $q_1..q_m$ in a road network that has encoded to the vertices trajectory $p_1..p_n$ including following properties

- Initial Stage: $q(1) \in A(p_i)$
- Final Stage: $q(m) \in A(p_i)$
- Intersection: $q_1..q_m$ for Intersect $A(p_i) 1 \leq 0 \leq n$
- Containment: if $q_1 \in A(p_i)$ and $q_{i+k} \in A(p_{j+1})$

Proof:

- Starting vertex q_1 is belongs to active area $A(p_1)$ in curve (*polygon*).
- Ending vertex q_m is belongs to active area $A(p_n)$

Each active vertex (n) must intersect on free space including regular moving position from start vertex p_i and end vertex p_{i+1} with measurement errors means [$q_1 \in A(p_j)$ and $q_{i+k} \in A(p_{j+1})$].

Adaptive Clipping Algorithm. Adaptive Clipping algorithm working for localized map matching on weak frechet distance, for example, suppose trajectory edge between p_i and p_{i+1} is $\overline{p_i p_{i+1}}$ on velocity (v) and sampling rate (r) with every p_i in active area $A(p_i)$. On curve center p_i with radius μ or measurement error (μ) [20] and Dijkstra's Shortest Path Finding algorithm is implementing on two conditions.

Condition 1. Dijkstra on free space graph, finding the shortest path between start (p_i) to end (p_{i+1}) vertices. Free space graph vertices (p_1, e), ($v, p_1 p_2$), (p_1, \bar{e}) here,

- v is vertex;
- e is edge for ($A_{p_1 p_2}$) [*continuous changing radius of curve*] and
- \bar{e} is an edge for $A(p_2)$ [*means Active region*].

Condition 2. Dijkstra on ($n - 1$ vertices) for all available vertices (p_i, e), ($v, \overline{p_i p_{i+1}}$), (p_{i+1}, \bar{e}) on free spaces graph, here,

- v is vertex;
- e is an edge in $A(p_i p_{i+1})$ and
- e is an edge in $A(p_{i+1})[(v, \overline{p_i p_{i+1}})]$ for continuous moving position [12].

Now, we can filter GPS trajectory data (*error free*) for sensitive results on the continuous ways on the rod networks.

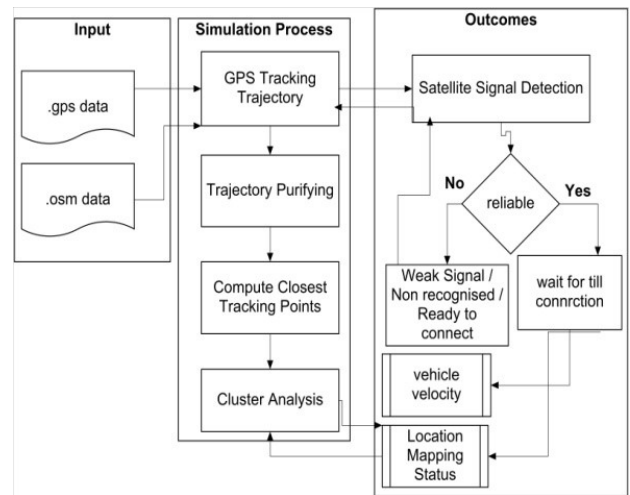


Figure 3. Methodology for GPS Signal detection Process on L_2 Frequency Data

The aim of this method, to reduce frechet distance computation time on curve circumferences radius, which also contain computed location matching status vehicle movement on the road network. Table.1 indicated the comparative analysis with different existing map matching algorithms.

Table 1. Existing Map Matching Algorithms

Sr. No	Map Matching Methods	Description	Technology	Advantage
1	Multi dimension multi scaling paradigm [26,27]	<ul style="list-style-type: none"> • Signal dissertation issue. • Spacing for noise decoding process • Road boundary 1.5m • Raw estimation filter 1.8% 	Intra direction prediction method	need to apply map encoder Error rate= < 2 m for efficient dispiriting compensation
2	Automatic change direction [29]	<ul style="list-style-type: none"> • Updating information crucial for urban application • Route planning • intelligent driving • Error ellipses derived from the GPS data. • Raw estimation filter 2.2 % 	sensor inputs, GPS trajectory, fuzzy logic road n/w,	Error rate = < 1.3 m
3	Lidar –based local trajectory [28]	<ul style="list-style-type: none"> • Traversing road segment • robust to pair measurement • raw estimation filter 2.2 % • road boundary 1.4 m 	Minimum assumption	error rate = < 1.5 m
4	Map matching method [31]	<ul style="list-style-type: none"> • Traversing road segment • robust to pair measurement • raw estimation filter 2.4 % • road boundary 1.37 m 	N-Trip protocol, PPP, real time kinetic approach	error rate = < 1 m

5. Proposed Map Matching Approach for Sequential Map

5.1. Bayes Approach

This approach provide periodic information with likelihood [32]. When we, compute time difference parameter based on filtering algorithms upon trade of between accuracy and complexity. The Kalman filter algorithm [35, 37] is adopt for simplicity implementation, tractability and robustness [33].

5.2. Proposed Filter

To estimate the position of vehicle (VO) in fixed time interval, existing research work neglect the motion of vehicle [23]. Now, consider the focus on dynamic outputs, we adopt Bayesian filter for particle-tracking nodes position tracking.

$$X_0(k) = [x_0(k), y_0(k), s_0(k), h_0(k)] \quad (2)$$

Here,

- $x_0(k)$, and $y_0(k)$ is vehicle position coordinates of time k .
- $s_0(k)$ is the vehicle speed (m/sec).
- $h_0(k)$ is consider as vehicle heading (*in ration*) form the x-axis to consider the direction and measure the positive angle [40].

The state space is consider based on

$$x_0(k) = x_0(k-1) + T_{s_0}(k-1)\cos(h_0(k-1)) \quad (3)$$

$$y_0(k) = y_0(k-1) + T_{s_0}(k-1)\sin(h_0(k-1)) \quad (4)$$

$$s_0(k) = \tilde{s}_0(k) + w_k \quad (5)$$

$$h_0(k) = h_0(k-1) + \tilde{h} + w_k \quad (6)$$

Here,

- T is time interval between $k-1$ and k (in seconds).

- Δ_h is estimated heading change route during each interval (1 sec).

- s_k is estimated average speeds with in time interval when noise is define both heading and speed as Gaussian distance.

- w_k is consider as normal distribution have zero mean variations and measure equation define by $2(k)$ for composite vector of time k .

To compute individual GPS position

$$p_0(k) = p_0 - |s \propto \log \|x_a(k) - x_0(k)\| v_0(k)| \quad (7)$$

Here, v_0 is vehicle position uncertainty.

$$\tilde{x}_a^k = [\tilde{x}_a, \tilde{y}_a]^T \quad (8)$$

Gaussian distribution with mean x_a as the measure of GPS position and $[\tilde{x}_a, \tilde{y}_a]$ measure GPS position based on k derivation time interval.

5.3. Map Information

In case, road map is available [22], then compute difference between road and no road area. The proposed computation method adopt open start map (osm) where each roads are linked by a single edge line without consider the width of road. We optimized the output based on 10 m road segment as input and road directions are consider as similar or opposite. This work keeps the highest value to select road site trajectory nodes.

5.4. Lane Level Map

The road map information is considering lane level data to scaling suitability between micro scale dense points, which are more suitable or reliable for intelligent vehicles location tracking. These dense points are more accurate without long delay [27]. The Map's prototypes are utilized to cover 4 km in Ahmedabad & 2 km another network. The proposed sequential map-matching algorithm provides high quality outcomes.

Road Geometric Information. Polyline provides the geometry information of vehicle moving segment. The segment is split into various subsets of segment with segment heads.

Road Lane Marking. Each lane having Meta data with respect to markings delimiting, Geometric description provides some extra information such as solid lines for tracked segment [28].

Road Lane/ Segment Connections. No real time accurate tracking/navigation information in terms of connection b/w segment heads/links provide by existing map matching approach. Here we compute a unique path on the road network along current vehicle position.

The trajectory satisfies:

$$T(\alpha) : [0, 1] \rightarrow x_{ij} \quad (9)$$

with

$$T(0) = (0, 0)^T \quad (10)$$

and

$$T(1) = x_{location}, y_{location} \quad (11)$$

The trajectory will initially- input by curvature.

Now, need to analysis that some mapping M (Cartesian coordinates):

$$T(\alpha) \xrightarrow{M} f_t(\alpha, q_t) = \begin{bmatrix} f_x(\alpha, q_t) \\ f_y(\alpha, q_t) \end{bmatrix} \quad (12)$$

$f(\alpha, q_t)$ Indicate simulation model being t shown trisection and q are recursive parameters for process.

Consider the global reference frames, when need to re align location with the regional mapping trajectory at every time slot means

$$x_t^r = p_t^r = 0 \quad (13)$$

The simulation model can be simplified

$$x_{t+1}^r = (\Delta_n + \epsilon_n), y_{t+1} = 0 \quad (14)$$

Now, the updated local map (OSM- Open Street Map) to be consider with the vehicle location can be measured as [29] (Δ_n, Δ_ϕ) including associated uncertainty σ_Δ .

The given matrix provides movements computation parameters

$$[\bar{x}_{t+1}, \bar{y}_{t+1}, 1]^t = T^{-1}[x_t, y_t, 1]^T \quad (15)$$

Here

$$T = \begin{bmatrix} \cos(\Delta_\phi) & -\sin(\Delta_\phi) & \Delta_n \\ \sin(\Delta_\phi) & \cos(\Delta_\phi) & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (16)$$

Suppose mapping is restrict M to be a linear function, the simulation parameters of the form

$$f(\alpha, \phi) = \theta A(\alpha) \quad (17)$$

Now, the new coordinate parameters are [30]

$$\bar{x}_{t+1} = \bar{T}_{xt} = \bar{T} f(\alpha, q_t) = \bar{T}_{qt} A(\alpha) = \bar{Q} A(\alpha) \quad (18)$$

$$\bar{Q}_{t+1} = \bar{T}_{qt} A(\alpha) \quad (19)$$

The frequency of this computation is much better than existing process shown in Table 2.

Table 2. GPS Raw Estimation information

Sr. No	Description	Raw Estimation	Filtered Estimation
1	RMS distance from center	0.85	0.95
2	No of scanned points inside road boundary	97.6	99.3
3	Proposed algorithm, -RMS distance beyond road boundary	1.39 m	0.12 m

5.5. Segment Fetching Approach

The proposed algorithm is categorized on hierarchy level, which are given below:

1. Map (.osm) data files are deploy for mapping the vehicle location according GPS sensor tracking trajectory- the velodyne H10Z-64 laser sensor used for evaluate sensor's generated pit cloud
2. The Road generating algorithm provides road boundary's information by vehicle sensor data then compute using RANSAC/ least- sequences approach for optimal trajectory point's analysis.
3. Vehicle should be implement odometer sensors- to estimate local map updated information after vehicle movements
4. The reference trajectory utilized steer the vehicle for local maps using segment traversal approach.

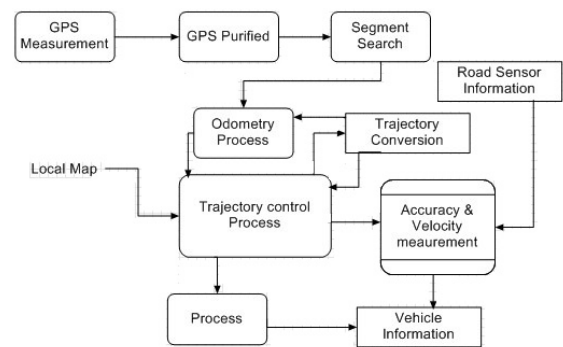


Figure 4. Working Methodology for Road Analysis and Tracking Process

Here, we compute two important possibilities that are outcomes from the fact, which we are planning on the local road network. In the algorithm 2, step 1 indicate the GPS location which may be inaccurate that navigating precisely to related coordinate in step 2.

The vertex to be attend on the graphical map may be accurate or sufficiently mismatch to GPS or Sensor's computation of reliable path from vehicle location points in all direction (forward, backward, left, right). Those issue projecting the targeted of smooth path on the free space of road network.

Algorithm 2 . Road Analysis and Tracking Process**Input:** Segment heads, road missing data, Odometer-calculated inputs.**BEGIN**

- Step 1. Check current position of vehicle on road network
 - while (current_position) \neq osm_position) do
- Step 2. Check current GPS Position on purified Trajectory of road network.
 - GPS input \neq purified trajectory input
- Step 3. Simulate trajectory input/ receiver type or single type (PPP-*Precise Point Position*/STATIC/Dynamic)
- Step 4. End of outer while
- Step 5. Compute new trajectory data based on GPS sensor input
- Step 6. Compute probabilistically force reference trajectory
- Step 7. End of outer while

END**Algorithm 3 . Map Matching Vehicle Tracking****Input:**

- Global Position Data (.GPS)
- Updated Road map data (.OSM)

Output: Estimate optimized path with tracking nodes and moving vehicle direction.**BEGIN**

- Step 1. Get initial position and uncertainty from individual data.
- Step 2. Initialized trajectory frechet distance free space randomly.
- Step 3. Measure moving object speed and continuously change segment head from initial to next.

For each segment do

- Compute sample speed error;
- Compute sample heading error;
- Compute node displacement update state;

End For

- Step 4. Check map conditions
 - Minimized the node frechet distance;
 - Check the curve type;
 - Manage historical moving nodes location;

- Step 5. Analyzed the position

- Track real time GPS location (long, Lat);
- Purify the uncertainty of signals using Gaussian probability mechanism ;

- Step 6. Check threshold

- If** (Sum (weight) < zero_threshold) **then**
- Repeat Step 5;

Else

- Compute optimized weight;
- Compute optimized speed;

End If

- Step 7. To resampling threshold on the path

- If** sum(weight2)<resampling threshold **then**
- No need to lowest weight nodes;

Else

- Consider highest threshold nodes;

End If

- Step 8. Mapping Status

- Get optimized map;
- Compute tracking nodes on map;
- Measure the velocity (*speed*);

- Step 9. Exit

END

Now, we consider the corresponding speed category to each segment. The nature of vehicle movement; it preserve the high degree of fragmentation and refining the data set unusable. When start the movement, velocity (*speed*) is consider low down due to intersection or other kinds of issues but, we adopt sliding window cross the trajectory and replacing the speed value of each segment based on median computation over a series of consecutive line segment (*smooth head*) value [35]. This approach will help us to avoid excessive fragmentation of trajectory due to short change in speed. The process highlighted some objectives:

- Every line segment l_j on each trajecotry T step 1.
- The median speed is computed over a sliding window of width (w)2 in step 2.
- All segments are assign to related classes with minimum and maximum speed computation step 5 and step 6.

6. Results and Discussion

We were trying to calculate precise position within any appropriate accuracy, need to input necessary information such as longitude, latitude, height and timestamp of the base station or GPS receiver position for reliable data collection on geodetic and ellipsoidal height.

Simulation tool: RTKLIB¹ is an open source program package for standard and precise positioning with GNSS (*Global Navigation Satellite Systems*). RTKLIB consists of a portable program library and several APs (*Application programs*) utilizing the library. It supports standard and precise positioning algorithms with: GPS, GLONASS, Galileo , QZSS, BeiDou and SBAS

- It supports various positioning modes with GNSS for both real-time and post-processing: Single, DGPS/DGNSS, Kinematic, Static, Moving-Baseline, Fixed, PPP-Kinematic, PPP-Static and PPPâĀĀFixed.
- It supports many standard formats and protocols for GNSS: RINEX 2.1, 2.11, 2.12 OBS/NAV/GNAV/HNAV/LNAV/QNAV, RINEX 3.00 , 3.01, 3.02 OBS/NAV, RINEX 3.02 CLK, RTCM
- It supports several GNSS receivers' proprietary messages: NovAtel: OEM4/V/6, OEM3, OEM-Star, Superstar II, Hemisphere: Eclipse, Crescent, u-blox: LEAâĀĀ4T/5T/6T, SkyTraq: S1315F, JAVAD/ GRIL/GREIS,

¹www.rtklib.com/

- It supports external communication via: Serial, TCP/IP, NTRIP, local log file (*Record and playback*) and FTP/HTTP (*Automatic download*).
- It provides many library functions and APIs (*Application program interfaces*)

Data Set: Give data set is deploying for location tracking simulation process. Here longitude, latitude indicate location of vehicle movements within fixed time interval and moving directions are indicate by X and Y respectively left and right direction.

Table 3. Dataset information

Longitude	Latitude	Time	X (Left)	y (right)
4151.8122	08739.0505	18:28:33	221.621441	358.638214
4151.8113	08739.0497	18:28:43	221.622137	358.637185
4151.8113	08739.0497	18:28:45	221.622137	358.637185
4151.8113	08739.0497	18:28:52	221.622137	358.637185
4151.8000	08739.0539	18:28:54	221.618629	358.624158
4151.8000	08739.0518	18:28:55	221.620434	358.624173
4151.7999	08739.0517	18:28:56	221.620521	358.624058
4151.7996	08739.0515	18:28:57	221.620696	358.623714
4151.7999	08739.0511	18:28:58	221.621037	358.624062
4151.8005	08739.0508	18:28:59	221.621290	358.624754
4151.8008	08739.0506	18:29:00	221.621459	358.625101
4151.8014	08739.0501	18:29:01	221.621883	358.625794
4151.8008	08739.0504	18:29:02	221.621631	358.625102
4151.8013	08739.0501	18:29:03	221.621884	358.625679
4151.8019	08739.0498	18:29:04	221.622137	358.626372
4151.8024	08739.0495	18:29:05	221.622390	358.626949
4151.8029	08739.0491	18:29:06	221.622729	358.627527
4151.8035	08739.0488	18:29:07	221.622982	358.628219

Here, observation represents the variations on time intervals for moving direction as well as location on adopted open street map. The rapidly changes on the tracking node depend on the longitude and latitude values.



Figure 5. Solution status position on carrier phase L1

Figure 5 provide available GPS signal strength with sufficient quality for all satellite position in different

color bar where gray represents not used, orange means waiting for connection, deep green means connecting or running, light green means data active or processing, red indicate communication errors, deep pick upcoming activation status message.

After input observation, compute the position solution for GPST status or X/Y/Z means longitude, latitude and height component including ration factor of ambiguity validation in the figure because unreliable input data become causes of high level pitfalls such as position error, residual error.

In case, computing precise position on L_1 or L_2 carrier phase; results are not up to mark due to weak GPS signaling indicated in Figure.6.

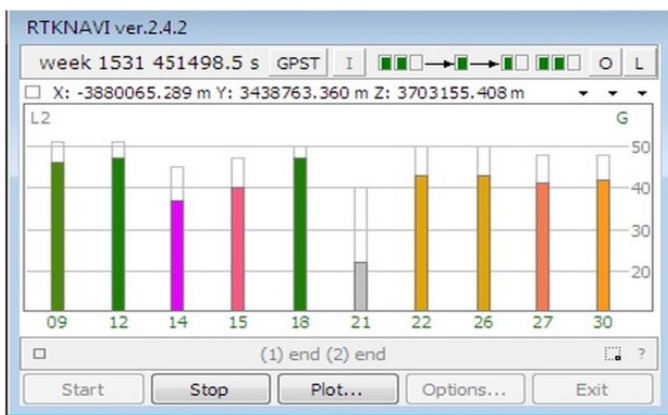


Figure 6. PPP signal status on carrier phase L_1

In addition, when computing precise position points with high frequency carrier phase L_5 , GPS signals are not recognized for other input stream L_5 represented in Figure 7.

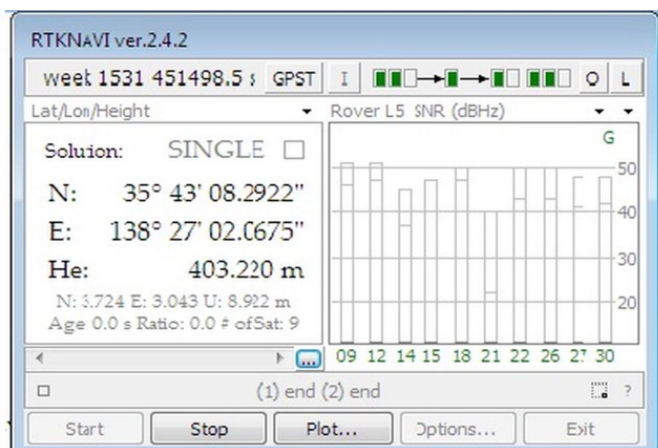


Figure 7. PPP signal status on carrier phase L_5

The road segment and traveling points are indicated in Figure 8 and technical summary is shown in Table 2.

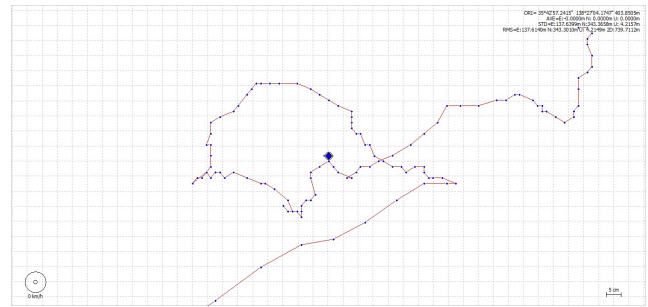


Figure 8. Vehicle location movements on L2 frequency signals

7. Conclusion and Future Work

This work introduces a fast and accurate map matching algorithm and adaptive Clipping algorithm for all possible curves navigation with minimum weak frechet distance in local frechet space. We introduce map-matching issues with solution strategies for error awareness solution and provide mathematical exposure for process analysis. The proposed method raw estimation summary is providing in the given Table 2.

In addition to the future work, we would like to compute precise position for narrow streets, hill station routes, rural region and tall building area with GPS services on L_1/L_2 carrier phase signals or high quality frequency L_5 carrier phase signals using another satellite system (IRNSS) which is helpful for precise navigation in our scenario.

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