

# MULTI-HYPOTHESIS MAP-MATCHING USING PARTICLE FILTERING

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## ABSTRACT

This paper describes a new Map-Matching method relying on the use of Particle Filtering. Since this method implements a multi-hypothesis road-tracking strategy, it is able to handle ambiguous situations arising at junctions or when positioning accuracy is low. In this Bayesian framework, map-matching integrity can be monitored using normalized innovation residuals. An interesting characteristic of this method is its efficient implementation since particles are constraint to the road network; the complexity is reduced to one dimension. Experimental tests carried out with real data are finally reported to illustrate the performance of the method in comparison with a ground truth. The current real-time implementation allows map-matching at 100 Hz with confidence indicators which is relevant for many map-aided ADAS applications.

## 1 INTRODUCTION

Map-Matching (MM) is an important facility for cooperative Intelligent Transportation Systems (ITS). For many applications, positioning has to be performed relatively to a digital map describing the road network, since information - like speed limit for instance - is usually attached to the poly-lines. MM is defined as a data association problem which consists in selecting the most likely roads that correspond to the current position of the mobile. Unfortunately, as a result of inaccuracies in the map or because of large position errors, MM has often several solutions, i.e. several segments be declared candidates with good confidence. These segments can belong to the same road or to different roads (ambiguous situation). To handle this issue, MM confidence indicators are crucial for many ITS applications related to safety (e.g. ADAS – Advanced Driver Assistance Systems) or road charging.

In this paper, a multi-hypothesis Bayesian “road tracking” approach that exploits road-connectedness is presented. This approach is called Multi-Hypothesis Map Matching (MHMM) and relies essentially on Kalman filtering techniques [1]. We present here a new efficient technique which consists in using a constraint particle filter. Then, thanks to the computation of Normalized Innovation Squared (NIS) signals for each hypothesis, integrity can be monitored. This will be illustrated on the experiments reported in this paper.

This paper is organized as follows. Next section presents the specifications of a project called POMA which provides positioning technologies for cooperative systems. Real-time integrity monitoring is clearly stated as a primary need. Then, section 3 presents an implementation of MHMM using a constraint particle filter. Finally, we report experimental results that have been carried out using a L1 GPS, a yaw rate gyroscope, an odometer. Databases provided by two map providers have been tested. The proposed strategy to monitor integrity is then evaluated.

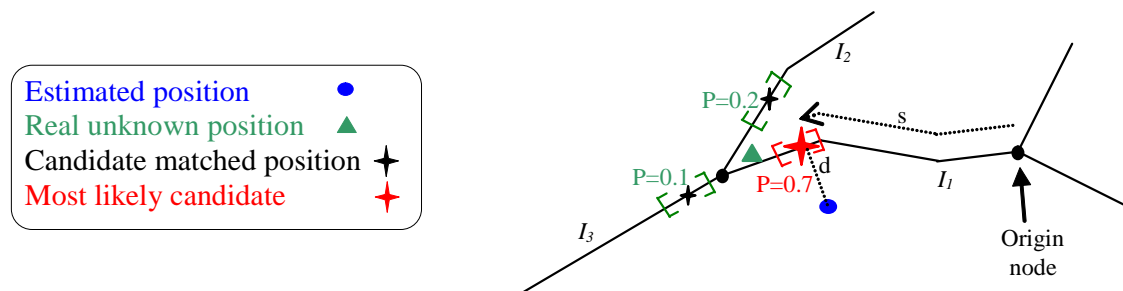
## 2 MAP-MATCHING SPECIFICATIONS INSIDE POMA

POMA (POsitioning and MApping) is a sub-project of the European project CVIS [2] that studies, develops and tests advanced positioning and mapping solutions in order to provide a set of positioning and mapping services that will run across CVIS entities.

In order to handle ambiguous situations arising from low positioning accuracy or at junctions, it has been specified that the MM module has to compute several hypotheses, one per road. Up to ten matched candidates can be outputted,. These candidates are then made accessible in OSGi Java technology to assure interoperability of applications and services based on the POMA platform. With each hypothesis, the following information has to be delivered to the client applications:

- The position of the vehicle on the poly-line is defined as the offset  $s$  (or curvilinear abscissa) since the origin node in the traveling direction,
- The lateral deviation  $d$  with respect to the poly-line (Frenet's frame sign convention),
- The identification of the road segment in the cartographic database (denoted  $I$  on Fig. 1),
- The longitudinal inaccuracy represented by a confidence location interval on the current road (squared brackets on Fig. 1),
- A confidence indicator which is the probability of the hypothesis relatively to the others,
- The norm of normalized residuals to evaluate the consistence of the data association process.

The location of each MM candidate on a road is defined by a couple  $\{s, I\}$ . Knowing the poly-line  $I$ , it is easy to convert such a position in Cartesian or geodetic coordinates. A triplet  $\{s, I, d\}$  corresponds to an estimate of the absolute position associated with the map-matched point.

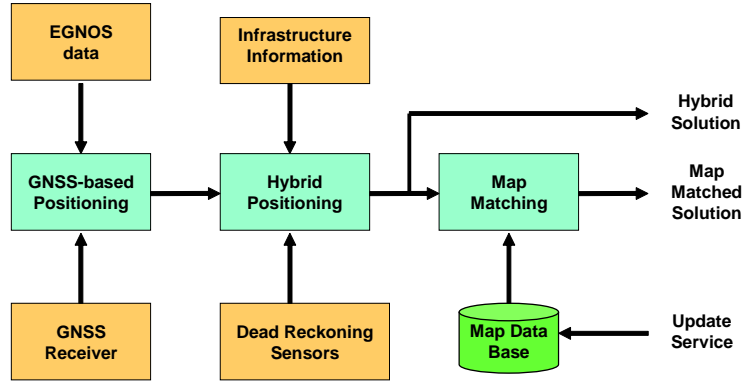


**Figure 1 - POMA Map-Matching outputs. 3 candidates are displayed.**

### 3 PARTICLE FILTERING FOR MAP-MATCHING

In this work, map-matching is performed using a loosely-coupling scheme between GPS fixes and map data. So, in order to handle GPS outages and to filter GPS errors, a first fusion stage is performed to merge GPS fixes with proprioceptive sensors (a yaw rate gyroscope and an odometer) using an Extended Kalman Filter (called hybrid positioning on Fig. 2). This fused pose is then used to do the map-matching and to compute the NIS of each hypothesis. Tightly coupled methods are also under study to use directly pseudo-range measurements instead of poses for the NIS generation [3].

Modern MM methods implement Multi-Hypothesis schemes. Indeed, MM induces unavoidable ambiguity situations for instance at junctions, in case of parallel roads, or when GPS suffers from outages or bad satellites configuration. By applying a mono-hypothesis approach, the risk is to choose a wrong solution. When the system will detect this mistake, it will need time to



**Figure 2 - Main functions of the position calculation process in POMA**

recover the good solution and the tracking will be reset. A multi-hypothesis approach maintains all the possible solutions in case of ambiguity. Hypotheses that become unlikely are removed as time and traveled distance evolve. The main drawback of this strategy is its complexity that is exponential with respect to the number of hypothesis.

The particle filter (PF) presented here implements a probabilistic road tracking method. The PF that we use has a constant number of particles which guarantees a bounded complexity. In opposition to the work presented in [4], the particles are constraint to follow the poly-lines representing the roads. This is important to have an efficient implementation since the exploration is done in only one dimension.

Let consider a map area around the estimated position which contains a set of roads (also called a “cache of road”). A map matched position is a hybrid state  $M_i = (s, I)$  where  $s$  is the curvilinear abscissa (continuous variable) and  $I$  a discrete variable corresponding to the identifier of the road in the database. The MM problem consists in estimating the probability density function (PDF)  $p((s, I)|z_{1:k})$  using particle filtering. Here,  $z_{1:k}$  represent the measurements provided by the hybrid positioning system from the first one to the current one (denoted  $k$ ):

$$z_k = [ \varphi \quad \lambda \quad \theta ]^T \quad (1)$$

At time  $k$ , this density can be approximated by  $N$  discrete particles (Dirac’s pulses) :

$$\chi_k = \{ \langle (s_k^n, I_k^n), w_k^n \rangle \}_{n=1:N} \quad (2)$$

Where  $(s_k^n, I_k^n)$  is a possible map-matched position on the road network. The weight  $w_k^n$  represents the importance of this particle. The *a posteriori* estimate is given by:

$$\hat{p}((s, I)_k | z_{1:k}) = \sum_{n=1}^N w_k^n \cdot \delta(s_k^n, I_k^n) \quad (3)$$

where  $\delta(x)$  is a Dirac having the following properties [5]:

$$\begin{cases} \delta(x - a) = 0 \text{ for all } x \neq a \\ \int \delta(x - a) dx = 1 \end{cases} \quad (4)$$

MHMM is a multimodal problem especially when the vehicle evolves in dense road network area. As this multimodality is explicit and described by the discrete variable included in each particle state, each map matched hypothesis  $h$  can be approximated by the particle sub-set:

$$\chi_{h,k} = \{ \langle (s, I)_k^n, w_k^n \rangle | I = h \}_{n=1:N} \quad (5)$$

The PF uses the topological information of the map to manage the evolution of each particle in the road network. The choice of the proposal distribution  $p((s, I)_k^n | (s, I)_{k-1}^n)$  is a crucial issue (random values are added at each prediction step in order to explore the different hypotheses). For this, the longitudinal vehicle displacement  $\underline{\Delta}$  and the topology of road network are needed. The longitudinal displacement information is given by the traveled distance estimated by the hybrid fusion and the network topology is represented for each road by a list of connected roads in the road cache.

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**Algorithm 1** Evolution of the particles set during the prediction stage

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Input : {particle set  $\chi_{k-1}$ , traveled distance  $\underline{\Delta}$ } Output : {particle set  $\chi_k$ }
For each particle  $n$  do
  Sample  $\Delta^n$ 
  Let  $d_k^n = d_{k-1}^n + \Delta^n$ 
  If ( $d_k^n > l_i$ ) Then //the particle is out of the poly-line
     $d_k^n = d_k^n - l_i$  //  $l_i$  is the length of road  $R_i$ .
    Sample  $\mathcal{I}_{k-1}^n$ 
  Else
    Let  $\mathcal{I}_k^n = \mathcal{I}_{k-1}^n$ 
  End
End
End

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In algorithm 1:

- $\Delta^n$  is a random variable sampled using a normal law  $\Delta \sim \mathcal{N}(\underline{\Delta}, \sigma_{\Delta}^2)$  where  $\underline{\Delta}$  represents the traveled distance between two sampling instants  $k$  and  $k-1$  and  $\sigma_{\Delta}$  the standard deviation of this distance.
- A new road is randomly selected using  $U(C_i) = U(0, N_c)$ , a uniform law, where  $N_c$  represents the number of connected roads with  $R_i$  (by taking into account the traveling direction).

To compute the *a posteriori* PDF and to evaluate the probability of each MM hypothesis, the weights are sequentially updated by using the likelihoods of the distance and of the heading of the current observation for every particle after the prediction stage. The heading likelihood is computed in order to implement a curve-to-curve matching strategy [6][7]. The position likelihood is applied to decrease the weight the particles that are far away from the estimated location.

$$w_k^n \propto \underbrace{e^{-\frac{1}{2} \frac{(\theta_k - \theta_k^n)^2}{\sigma_{\theta}^2 + \sigma_{\theta_{map}}^2}}}_{p(\theta_k | M_k^n)} \cdot \underbrace{e^{-\frac{1}{2} (\Delta_P^T \Sigma_P^{-1} \Delta_P)}}_{p(P_k | M_k^n)} \cdot w_{k-1}^n \quad (6)$$

where

- $p(\theta_k|M_k^n)$  is the likelihood of the particle  $n$  with respect to the heading  $\theta_k$  of the vehicle,
- $\theta_k^n$  is the orientation of the road segment where the particle  $n$  is located,
- $\sigma_{\theta_{map}}$  is the confidence in the heading given by the map,
- $p(P_k|M_k^n)$  is the likelihood of the particle  $n$  with respect to the position  $P_k$  of the vehicle,
- $M_k^n$  is the location of particle  $n$ ,
- $\sigma_{P_{map}}$  is the confidence in the map accuracy.

In Eq. 6:

$$\Delta_P = P_k - M_k^n \text{ and } \Sigma_P = \Sigma_{P_k} + \begin{pmatrix} \sigma_{P_{map}}^2 & 0 \\ 0 & \sigma_{P_{map}}^2 \end{pmatrix} \quad (7)$$

At the end of the correction step, the weights of the particles are normalized to one. In order to respect the specifications, particles are regrouped by roads. The score of the hypothesis corresponding to road  $a$ , i.e. its probability with respect to the others, is given by:

$$\mathbf{Pr}_{a,k} = \sum_{n=1}^{\dim(\chi_{a,k})} w_{a,k}^n \quad (8)$$

#### 4 INTEGRITY MONITORING

By definition, integrity of a localization system is a measure of the confidence that can be accorded to the exactitude of the information delivered by this system. In [8], the authors propose to monitor 3 indicators to check MM integrity: i) distance residuals, ii) heading residuals, iii) an indicator related to uncertainty of MM. Since a mono-hypothesis scheme is used, they propose to fuse the 3 indicators using fuzzy rules. Then, the integrity monitoring is done using this scalar value. Multi-hypothesis road tracking is useful for MM integrity monitoring [1]. Indeed, in case of ambiguity, the MHMM can provide several hypotheses.

While monitoring MHMM, two different risks have to be handled: ambiguity and off-road situation. This can be achieved using NIS signals that are indicators to check the consistency of each MM hypothesis. This strategy can be viewed as a validation model approach [9]. The principle consists in evaluating the similarity between the prediction of the observation  $\hat{z}_k$  and the current observation  $z_k$ . For this, an uniform random variable  $u_k = p(z_k \leq \hat{z}_k | z_{1:k-1})$  is computed, at each sample. In a PF scheme, this variable can be approximated by:

$$\bar{u}_k = \frac{1}{N} \sum_{n=1}^N p(z_k \leq \hat{z}_k^n | (s, Id)_k^n, z_{1:k-1}) \quad (9)$$

Where  $\hat{z}_k^n$  is an *a priori* observation deduced from each particle after the prediction stage. This variable can be computed for every MM hypothesis  $h$  (noted  $\bar{u}_{k,h}$ ) by taking into account the subsets in which the particles have the same identifier. Finally, the NIS value for every hypothesis can be estimated using the inverse of a Gaussian cumulative function denoted  $\Psi(\cdot)$ :

$$NIS_h \approx \Psi^{-1}(\bar{u}_{k,h}) \quad (10)$$

This method to compute the consistency of every hypothesis is very efficient in a PF framework.

Once the different hypotheses have been computed with their NIS and score values, a decision function has to be applied. This function depends mainly on the application and the risk associated. We propose to use the following strategy. First, a threshold - function of a false alarm probability - is applied to the NIS. If no hypothesis remains, the situation is declared “Don’t use”. This means that the vehicle is probably off road or the map is incomplete.

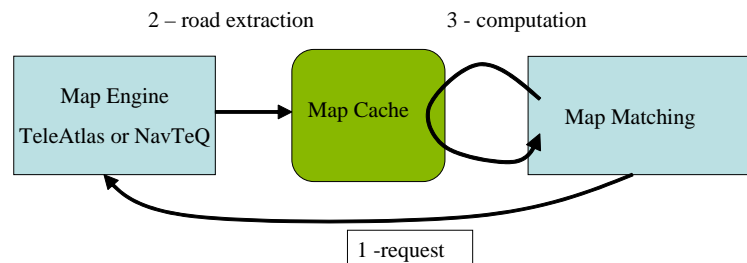
If several hypotheses have passed this test, then the ambiguity of the situation is analyzed thanks to an estimation of the remaining efficient hypotheses. The number of efficient hypotheses is computed as follows:

$$N_{eff} = \frac{1}{\sum(\mathbf{Pr}_a)^2} \quad (11)$$

- $N_{eff} < 2$  : There is no ambiguity; One hypothesis is very likely.
- $N_{eff} \geq 2$  : The situation is ambiguous.

## 5 IMPLEMENTATION AND EXPERIMENTAL RESULTS

The PF has been implemented in C++ and runs on Linux. The implementation has been realized with Boost C++ libraries and all the computations are performed in geographic coordinates since the position information and the map databases are provided in this format. The software RTMAPS has been used for rapid prototyping and debugging. A road-cache (Fig. 3) is used for two main reasons: i) The implementation is independent of the map provider, ii) Its size and structure (particularly for connectivity) has been optimized since particle filtering is processing consuming.

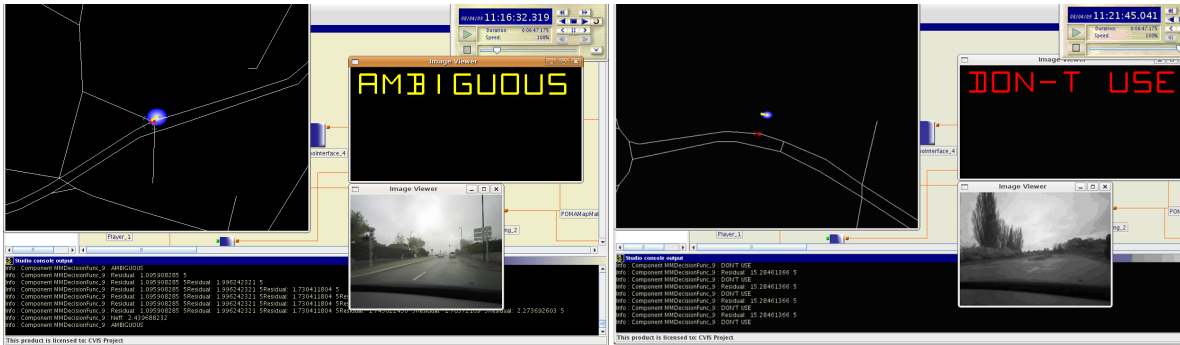


**Figure 3 - Map cache management**

Many experiments have been carried out in the framework of the project. Fig. 4 presents the screen shot of two particular situations (NIS threshold = 9). The blue ellipsoid with the yellow arrow displays the estimate given by the hybrid fusion module.

We report in the following an experiment carried out in Versailles (France) in March 2008 in the framework of the project (6.4 Km long trial, sub-urban conditions). We have used the following methodology to evaluate MHMM quality and confidence performance. A precise trajectometer (fiber optic inertial unit post-processed using PPK GPS) has been used. Its accuracy is estimated to be centimeter level. The method we propose is inspired by [8] and works as follows:

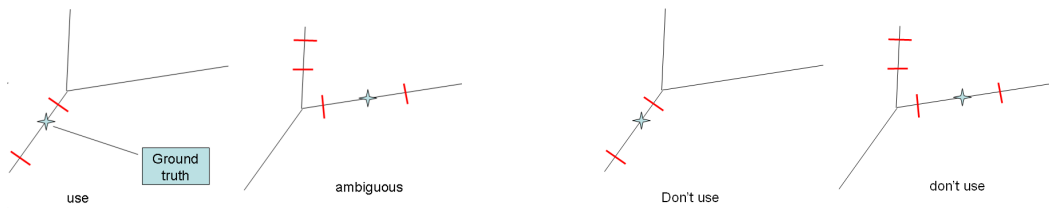
1. The traveled roads (and only them) are extracted from the map (NavTeQ or TeleAtlas). A dedicated program has been developed for this.
2. The trajectometer is map-matched on this path. Since the path presents no ambiguity, this map-matching is easy to performed. This is the ground truth for MM.



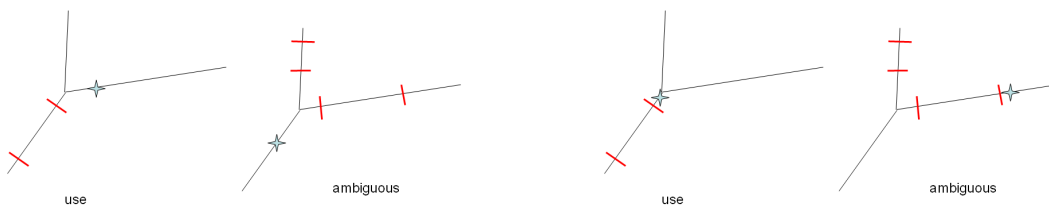
**Figure 4 - POMA display during an experiment. Left: the situation is ambiguous because of a junction. Right: the candidate is declared “don’t use” because the vehicle is located in a car park.**

3. The map-matched hypotheses outputted by the decision function in real-time with the POMA system have been recorded with their confidence indicators (5000 particles,  $\sigma_{P_{map}} = 10m$ ,  $\sigma_{\theta_{map}} = 15degrees$ ).
4. An analysis is conducted to quantify the performance of the integrity monitoring.

Figures 5 and 6 present four relevant situations that have to be analyzed carefully. Let us define *FAR*, the false alarm rate, and *MDR*, the miss-detection rate. The Overall Correct Detection Rate is defined as  $OCDR = 1 - FAR - MDR$ . In the analysis, we suggest also to consider the case where the map-matching is good but not consistent with the longitudinal inaccuracy (cf. Fig. 6 on the right). This is called Good ID Selection (GIDS).



**Figure 5 - On the left, good match (the ground truth is located inside the bounds of the candidates) On the right, false alarms (the map-matching is good but declared incorrect by the decision function)**



**Figure 6 - On the left, miss-match - also called miss-detection - the ground truth is located outside the bounds of the candidates. On the right, miss match but good ID selection.**

The results presented in table 1 indicate that the map-matching is in general correct with both maps (GIDS are high). Furthermore, FARs are low; this is a nice property showing that the integrity monitoring process is not too pessimistic. High GIDS simultaneous with quite high MDRs indicate that the map-matching is good but not consistent with the longitudinal estimated inaccuracy (~5% of the candidates are in the situation of Fig. 6, right drawing). This phenomenon is characteristic of an offset in time somewhere in the POMA system or in the ground truth. More investigations are needed to analyze this issue.

Map	FAR (%)	MRD (%)	OCDR (%)	GIDS (%)
Map $i$	0.4	4.3	95.3	99.7
Map $j$	0.2	6.2	93.6	99.9

**Table 1** - Results obtained with the same positioning system running with NavTeQ and TeleAtlas maps

## 6 CONCLUSION

This paper has presented a MHMM algorithm. Its design has been done to provide confidence indicators in order to monitor map-matching integrity in real-time, particularly for ADAS applications. A decision function has been presented, implemented and analyzed with two different maps and the real-time POMA positioning system. The experiment shows that the method handles correctly the use of two different map technologies thanks to the unified map cache structure. Furthermore, we have noticed that the MHMM presents a good robustness, since it is the same program that has been used with the two maps with the same tuning. Finally, we have presented a method to evaluate the performance of the method using a ground truth. A method has been proposed to obtain a MM ground truth. Using this information, indicators to quantify the integrity have been computed using two different maps. The current results are encouraging.

## REFERENCES

- [1] P. Bonnifait, M. Jabbour, V. Cherfaoui, G. Dherbomez, and J. Laneurit, "Multi-hypothesis map-matching integrity for cooperative systems," in *European Navigation Conference ENC/GNSS 2008*, Toulouse, April 23-25 2008.
- [2] CVIS, "Cooperative vehicle infrastructure systems," in *Contract 6th Framework Program*, 2006-2010. [Online]. Available: <http://www.cvisproject.org/>
- [3] C. Fouque and P. Bonnifait, "Tightly coupled gis data in gnss fix computation with integrity test," *International Journal of Intelligent Information and Database Systems*, vol. 2, no. 2, pp. 167–186, 2008.
- [4] F. Gustafsson, F. Gunnarsson, N. Bergman, U. Forssell, J. Jansson, R. Karlsson, and P. J. Nordlund, "Particle filters for positioning, navigation, and tracking," *IEEE Trans on Acoustics, Speech, and Signal Processing*, vol. 50, no. 2, pp. 425–437, 2002.
- [5] B. Ristic, S. Arulampalam, and N. Gordon, *Beyond the Kalman Filter. Particle Filters for Tracking Applications*, ser. Artech House, 2004.
- [6] C. White, D. Bernstein, and A. Kornhauser, "Some map matching algorithms for personal navigation assistants," *Transportation Research Part C: Emerging Technologies*, vol. 8, pp. 91–108(18), February 2000.
- [7] R. Joshi, "Novel metrics for map-matching in in-vehicle navigation systems," in *Proceedings of the IEEE Intelligent Vehicle Symposium*, Versailles, France, June 2002.
- [8] M. A. Quddus, W. Y. Ochieng, and R. B. Noland, "Integrity of map-matching algorithms," *Transportation Research Part C*, vol. 14, pp. 283–302, 2006.
- [9] J. Vermaak, C. Andrieu, A. Doucet, and S. J. Godsill, "Particle methods for bayesian modelling and enhancement of speech signals," in *IEEE Transactions on Speech and Audio Processing*, 2002, pp. 173–185.