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Robust Global Urban Localization Based on Road Maps

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1. Introduction

This paper presents a method to perform global localization in urban environments using segment-based maps in combination with particle filters. In the proposed approach the likelihood function is generated as a grid, derived from segment-based maps. The scheme can efficiently assign weights to the particles in real time, with minimum memory requirements and without any additional pre-filtering procedure. Multi-hypothesis cases are handled transparently by the filter. A local history-based observation model is formulated as an extension to deal with 'out-of-map navigation cases. This feature is highly desirable since the map can be incomplete, or the vehicle can be actually located outside the boundaries of the provided map. The system behaves like a global localizer for urban environments, without using an actual GPS. Experimental results show the performance of the proposed method in large scale urban environments using route network description (RNDF) segment-based maps.

Accurate localization is a fundamental task in order to achieve high levels of autonomy in robot navigation and robustness in vehicle positioning. Localization systems often depend on GPS due to its affordability and convenience. However, it is well known that GPS is not fully reliable, since satellite positioning is not available anytime, anywhere. This is the case of extreme scenarios such as underwater or underground navigation, for instance. In the context of urban navigation, GPS signals are often affected by buildings ('urban canyon' effect) blocking the reception or generating undesirable jumps due to multi-path effects. Fortunately, the use of a priori maps can help in the localization process.

There are maps already available for certain environments, such as the digital maps used for road positioning. Moreover, accurate maps can be built using GIS tools for many environments, not only urban, but also off-road settings, mining areas, and others.

Usually the vehicle position is evaluated by combining absolute information such as GPS with onboard sensors such as encoders and IMUs. Since GPS information is not permanently available, significant work has been carried out in order to integrate external sensors such as laser and sonar in the localization process such as in (Leonard & Durrant-Whyte, 1991), (Guivant & Nebot, 2001).

A priori information, such as digital maps, has been used to obtain accurate global localization, usually fusing information into Bayesian filters (Fox et al., 2001). Maps of the

environment are used in (Dellaert et al., 1999) in order to differentiate between obstacles and free space, and to bias the distribution of particles. In (Oh et al., 2004) map-based priors are incorporated into the motion model, and in (Liao et al., 2003) the localization is performed using particles constrained to a Voronoi map. Segment-based maps are often used in driving assistance systems for urban vehicle navigation. In this context, maps are usually defined as graphs that represent the road network connectivity. (Najjar et al., 2005) proposes a method that uses segment-based maps and Kalman filtering to perform an accurate localization constrained to the map. The scheme relies on the selection of the appropriate candidate segment from the dataset, considering multiple criteria and the estimated location of the vehicle. A similar approach has been presented in (Taylor & Blewitt, 2000).

In this paper we present a method to perform global localization in urban environments using segment-based maps in combination with particle filters. The contributions of the proposed architecture are two. Firstly, the likelihood function is generated as a grid, based on the segment-based map. In this way the scheme can efficiently assign weights to the particles in real time, with minimum memory requirements and without any additional pre-filtering procedure. Multiple hypotheses are handled transparently by the filter. The second contribution is an extension to the observation model, called local history-based observation. Hereby, the filter is able to deal with 'out-of-map' navigation cases, a feature that is highly desirable since the map can be incomplete or the vehicle can be actually located outside the boundaries of the map.

This paper is organized as follows: Bayesian methods are briefly introduced in Section 2, with particular emphasis on localization using particle filters. Section 3 describes our proposed approach to perform vehicle localization using particle filters and route network description (RNDF) segment-based *a priori* maps. The likelihood generation scheme is shown and an extension to the observation model, the local history-based observation, is introduced. Results illustrating the performance of the system in experiments undertaken in a large urban environment are provided and detailed in Section 4. Conclusions and future work are finally discussed in Section 5.

2. Bayesian Localization

Bayesian methods (Arulampalam et al., 2002) provide a rigorous general framework for dynamic state estimation problems. Bayesian approaches aim at building the probability density function (PDF) of the state vector based on all the available information. Vehicle localization can be understood as a Bayesian estimation problem. If the robot's location at time k is expressed as the vector

$$X_k = [x_k, y_k, \phi_k]^T, \quad (1)$$

then the localization problem implies the recursive estimation of the PDF

$$p_{X_k|z^{(k)}}(X_k | z^{(k)}) \quad (2)$$

where $z^{(k)}$ is the sequence of all the available sensor measurements until time k .

In the rest of this paper we will express the probability functions without the sub indices, i.e. any expression such as $p(\xi)$ will mean $p_{\xi}(\xi)$.

If we suppose that the posterior $p(X_{k-1} | z^{(k-1)})$ at time $k-1$ is available, then the prior at time k (due to a prediction step) is:

$$p(X_k | z^{(k-1)}) = \int p(X_k | X_{k-1}) \cdot p(X_{k-1} | z^{(k-1)}) \cdot dX_{k-1} \quad (3)$$

where $p(X_k | X_{k-1})$ is the process model for the system, i.e. the motion model of the vehicle. At time k a set of measurements z_k become available allowing the synthesis of a posterior that is obtained through a Bayesian update stage as:

$$p(X_k | z^{(k)}) = C \cdot p(X_k | z^{(k-1)}) \cdot p(z_k | X_k) \quad (4)$$

where the constant C is a normalization factor, and $p(z_k | X_k)$ is the likelihood function for the related observation $z = z_k$ at state X_k , i.e. it is the observation model.

For the linear Gaussian estimation problem, the required PDF remains Gaussian on every iteration of the filter. Kalman Filter relations propagate and update the mean and covariance of the distribution. For a nonlinear non-Gaussian problem, there is in general no analytic expression for the required PDF. A particle filter can estimate parameters with non-Gaussian and potentially multimodal probability density functions. The PDF is represented as a set of random samples with associated weights, and the estimates are computed based on these samples and weights.

For a set of N particles at time k , denoted as $\{X_k^i, w_k^i\}_{i=1}^N$, the approximated posterior is:

$$p(X_k | z^{(k)}) \approx \sum_{i=1}^N w_k^i \cdot \delta(X_k^i - X_k) \quad (5)$$

where $\delta(z-a)$ is the Dirac delta function which is ∞ if $z=a$ and zero otherwise. The weights are normalized such that $\sum_{i=1}^N w_k^i = 1$ to guarantee $\int p(X_k | z^{(k)}) \cdot dX_k = 1$.

Using the approximated posterior, the prior at time k (after a prediction stage) becomes:

$$\begin{aligned}
p(X_k | z^{(k-1)}) &= \int p(X_k | X_{k-1}) \cdot p(X_{k-1} | z^{(k-1)}) \cdot dX_{k-1} \approx \\
&\approx \int p(X_k | X_{k-1}) \cdot \sum_{i=1}^N w_{k-1}^i \cdot \delta(X_{k-1}^i - X_{k-1}) \cdot dX_{k-1} = \\
&= \sum_{i=1}^N w_{k-1}^i \cdot \int p(X_k | X_{k-1}) \cdot \delta(X_{k-1}^i - X_{k-1}) \cdot dX_{k-1} =
\end{aligned} \tag{6}$$

$$= \sum_{i=1}^N w_{k-1}^i \cdot p(X_k | X_{k-1} = X_{k-1}^i)$$

⇓

$$p(X_k | z^{(k-1)}) \approx \sum_{i=1}^N w_{k-1}^i \cdot p(X_k | X_{k-1} = X_{k-1}^i) \tag{7}$$

where $p(X_k | X_{k-1} = X_{k-1}^i)$ is the process model applied to each sample X_{k-1}^i .

This density is then used as the proposal distribution $q(X_k)$ from which samples are drawn, i.e. $X_k^i \sim q(X_k)$.

The update equation for the weights is:

$$w_k^i = w_{k-1}^i \cdot \frac{p(z_k | X_k^i) \cdot p(X_k^i | X_{k-1}^i)}{q(X_k^i)} \tag{8}$$

The posterior is again approximated as:

$$p(X_k | z^{(k)}) \approx \sum_{i=1}^N w_k^i \cdot \delta(X_k^i - X_k) \tag{9}$$

There are several details and issues before expression (8) is achieved, however those are not discussed in this paper. Several remarkable papers discuss details about the Monte Carlo approach applied to localization problems, e.g. (Dellaert et al., 1999).

3. Constrained Localization in Segment-Based Maps

The sole use of GPS can be insufficient to obtain an accurate estimation of the vehicle's location in urban navigation, as can be seen in the experiments presented in Figure 1. Figure 1a shows the trajectory reported by the GPS in an urban environment in Sydney, Australia. GPS inconsistencies such as jumps and discontinuities are shown in the close-up image in Figure 1b. In both images GPS points are shown with blue crosses, while the cyan dashed lines indicate the reported sequence and clearly show the undesirable behavior.

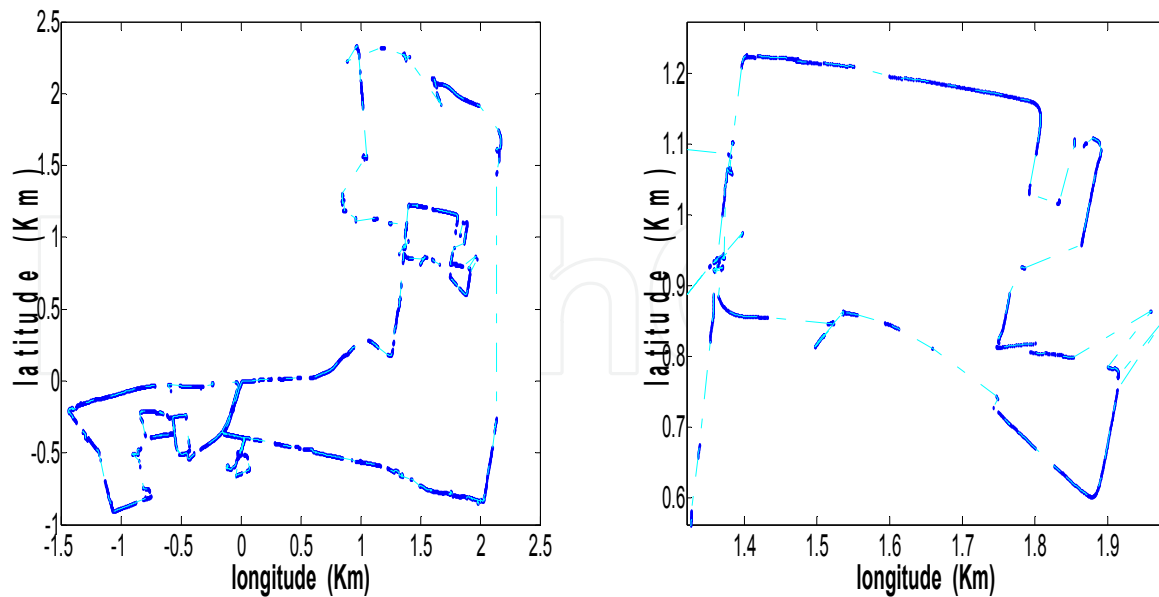


Fig. 1. GPS samples acquired during a trip in an urban context. GPS was not available in many parts of the test. The blue points show the GPS measurements and the cyan broken line indicates the sequence of measurements. Cyan segments (without superimposed blue points) mean that there was an interruption in the GPS measurements or that there was a sudden discontinuity in the measured positions.

In this section we present an approach to perform global localization in urban environments using segment-based maps in combination with particle filters. First we formulate a likelihood function using segment-based maps, such as the route network description file (RNDF). From now on we will base our formulation on a map, defined as a segment-based map. We show how the proposed scheme can be used to efficiently assign weights to the particles without any particular segment evaluation or candidate pre-selection procedure, and how multiple hypotheses can be handled automatically by the localization filter. We then introduce an extension to the observation model in order to deal with 'out-of-map' localization.

3.1. Likelihood Generation

In the context of this paper there are two definitions of likelihood functions; those are the *Base Likelihood* and the *Path Likelihood*. The Base Likelihood is intended to model the likelihood of a point, i.e. the likelihood of that point being located on a valid road. The second definition, the Path Likelihood, is the likelihood of a pose (position and heading) and some associated path to it, of being located on a valid road. Both likelihood definitions are based on the road map.

3.1.1. Road Map Definition

The road map behaves as a permanent observation model, i.e. it defines a constraint that, in combination with a dead-reckoning process, makes the pose states observable. The route network description file (RNDF) is, in the context of the Darpa Urban Challenge (Darpa, 2006), a topological map that provides *a priori* information about the urban environment. It

includes GPS coordinates for the location of road segments, waypoints, stop signs and checkpoints, as well as lane widths. Fig. 2 shows a sample of a road map.

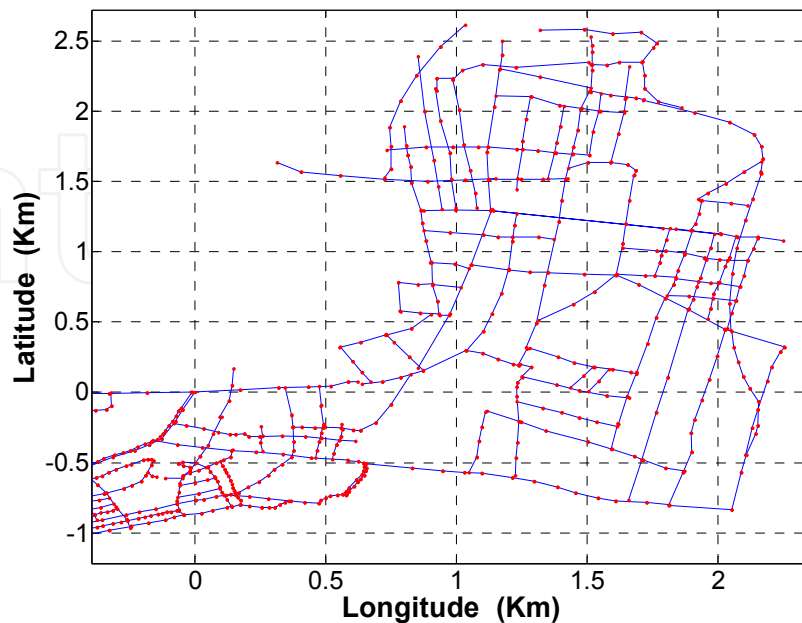


Fig. 2 Road map defined by a set of segments (continuous blue lines). The segments are defined by points expressed in a global coordinate frame (red points).

One of the key ideas in the presented approach is the synthesis of a local grid representation of the segment based map to compute the likelihood function. The advantage of this local grid-based formulation is that it can efficiently generate the likelihood function for the particles in real time and with minimal memory requirements. It can also select the possible roads (segments in the RNDF map) that can be used to perform the observation for each of the particles, without additional high-level evaluation of the potential candidate segments.

3.1.2 Base Likelihood

For a set of N particles at time k , $\{X_k^i, w_k^i\}_{i=1}^N$ we calculate the likelihood $p(z_k | X_k^i)$ based on a given segment based map as:

$$p(\text{map} | X) = \max_{j=1}^N \{f(X, S_j, C_j)\} \quad (10)$$

where $\{S_j\}_{j=1}^N$ is the set of all segments that define the road map (centers of roads) and C_j denotes the properties of segment S_j (width, lanes, lane directions etc.). The function $f(\cdot)$ is function of the distance of the position component of the state X with respect to the center of the segment S_j . Function $f(\cdot)$ is also dependent on each segment's properties such as its width and directions of its lanes. A simplified version of (10) is

$$p(\text{map} | X) = \begin{cases} 1; & \text{if } X \in L_{\text{map}}(\text{RNDF}, \Omega_k) \\ 0; & \text{if } X \notin L_{\text{map}}(\text{RNDF}, \Omega_k) \end{cases} \quad (11)$$

where the region Ω_k is just a convex hull that contains all the particles $\{X_k^j\}_{j=1}^N$.

The region $L_{\text{map}}(\text{RNDF}, \Omega_k)$ defines the roads as bands using the segment's locations and their widths provided in the RNDF. This computation is performed only in the area covered by the particles, i.e. Ω_k . Through the local computation of small windows of interest, the likelihood function can be evaluated for all of the particles in real time.

Another advantageous capability of this local grid-based formulation for the likelihood function is in terms of multi-hypothesis handling. The localization filter can deal with multi-hypothesis cases without any additional procedure in this regard. Since the selection of the local window is spanned by the area covered by the set of current particles, Ω_k , the filter can inherently perform observations for all the hypothetical vehicle locations.

3.1.3. Path Likelihood

If the observation model is directly implemented by just applying the base likelihood function on the current instances of particles, then the system will not be able to deal with *out-of-map* localization cases. The term *out-of-map* means that the vehicle is allowed to travel through unknown sections of the map (i.e. sections not included in the *a priori* road map).

Since the particles will be biased by areas of high base likelihood, the population will tend to cluster towards those regions that are assumed to be consistent with the map (e.g. existing roads on the map). This can be a desirable behavior if we assume the map is complete and the vehicle remains on it at all times. However, if we want to cope with non-existent roads, detours or other unexpected situations not considered in the RNDF representation, then this policy might lead to an inconsistent localization as the applied likelihood is not consistent with the reality.

In general the convergence of the localization filter can be improved by considering the recent history of the particles within a certain horizon of past time.

Definition of the Associated Paths

An ideal procedure would be to have particles to represent the current pose and the path of the vehicle. By matching that path with the map it would be possible to evaluate the likelihood of that hypothesis.

One way to maintain a path would be by augmenting the state vector with delayed versions of the current state. However this increase in the dimensionality of the estimated state (already a 3 DoF one) would imply a high increase in the needed number of particles.

Alternatively, there is a highly efficient way to synthesize and associate a path for each particle at time k . This path is obtained through combination of a dead-reckoning estimation (i.e. obtained from an independent estimation process) and the current value of the particle X_k^i . This associated trajectory is realistic for short horizons of time as the dead

reckoning prediction is valid just for a short term. Given a particle $X_k^i = [x_k^i \ y_k^i \ \phi_k^i]^T$ we can apply dead-reckoning estimation in reverse in order to synthesize a hypothetical

trajectory $\xi^i(t')$, $t' \in [k - \tau, k]$, where the value τ defines some horizon of time. This trajectory ends exactly at the particle instance, i.e. $\xi^i(k) = X_k^i$.

The estimated dead-reckoning trajectory is usually defined in a different coordinate system as it is the result of an independent process. The important aspect of the dead-reckoning estimate is that its path has good quality in relative terms, i.e. locally. Its shape is, after proper rotation and translation, similar to the real path of the vehicle expressed in a different coordinate frame.

If the dead-reckoning estimate is expressed as the path $\mu^i(t') = (x_\mu(t'), y_\mu(t'), \phi_\mu(t'))$ then the process to associate it to an individual particle and to express it in the global coordinate frame is performed according to:

$$\begin{aligned} (x_\xi(t'), y_\xi(t')) &= (x_k^i, y_k^i) + R_{(\Delta_\phi(k))} \cdot (\Delta_x(t'), \Delta_y(t')) \\ \phi_\xi(t') &= \phi_k^i + \phi_\mu(t') - \phi_\mu(k) \end{aligned} \quad (12)$$

where: $(\Delta_x(t'), \Delta_y(t')) = (x_\mu(t'), y_\mu(t')) - (x_\mu(k), y_\mu(k))$, $\Delta_\phi(k) = \phi_k^i - \phi_\mu(k)$ and R_α is a rotation matrix for a yaw angle α . The angle ϕ_k^i is the heading of the particle X_k^i and $\phi_\mu(k)$ is the heading of the dead-reckoning path at time k .

Clearly, at time $t' = k$ the difference $(\Delta_x(t'), \Delta_y(t'))$ must be $(0, 0)$, and $\phi_\mu(t')|_{t'=k} - \phi_\mu(k) = 0$, consequently $\xi^i(t')|_{t'=k} = X_k^i$.

Fig. 3 (left) shows a dead-reckoning path and how it would be used to define the associated paths of two hypothetical particles. The associated paths Fig. 3 (right) are just versions of the original path adequately translated and rotated to match the particles' positions and headings.

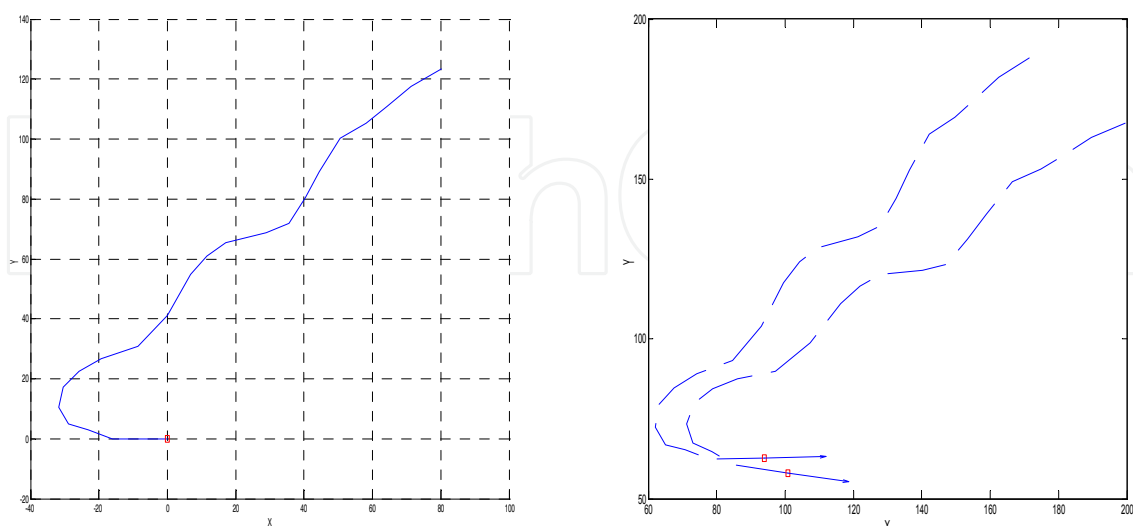


Fig. 3. The left picture shows a dead-reckoning path, expressed in a coordinate frame defined by the position and heading of the last point (red square). The right picture shows the same path associated to two arbitrary particles, expressed in a common coordinate frame

The new likelihood of a particle is now evaluated through the likelihood of its associated path with respect to the road map:

$$p^*(z_k | X_k^i) = \int_{k-\tau}^k p(z_k | \xi^i(t')) \cdot dt', \quad (13)$$

where $p(z_k | \xi)$ is the base likelihood of the point ξ , i.e. likelihood of point ξ being on the RNDF map (as defined in (11)).

In order to avoid the effect of time scale (i.e. speed) on the path likelihood, we focus the evaluation of the likelihood on the intrinsic parameter of the path, integrating over the path in space and not in time:

$$p^*(z_k | X_k^i) = \int_0^{l_s} p(z_k | \xi^i[s]) \cdot ds, \quad (14)$$

where $\xi^i[s]$ is the path expressed in function of its intrinsic parameter s and l_s is the length of integration over the path. The integration of the hypothetical path can be well approximated by a discrete summation

$$p^*(z_k | X_k^i) = \sum_{j=1}^{N_j} p(z_k | \xi^i[s_j]) \quad (15)$$

where the samples of the intrinsic parameter s_j are homogeneously spaced (although that is not strictly relevant).

Some additional refinements can be considered for the definition of (13), for instance by considering the direction of the road. This means that the base likelihood would not be just a function of the position, it would depend on the heading at the points of the path. A path's segment that crosses a road would add to the likelihood if where it invades the road it has a consistent direction (e.g. not a perpendicular one).

Fig. 4 shows an example of a base likelihood (shown as a grayscale image) and particles that represent the pose of the vehicle and their associated paths (in cyan). The particles' positions and headings are represented blue arrows. The red arrow and the red path correspond to one of most likely hypotheses.

By applying observations that consider the hypothetical past path of the particle, the out-of-map problem is mitigated (although not solved completely) for transition situations. The transition between being on the known map and going completely out of it (i.e. current pose and recent path are out of the map) can be performed safely by considering an approach based on hysteresis.

The approach is summarized as follows: If the maximum individual path likelihood (the likelihood of the particle with maximum likelihood) is higher than K_H then the process keeps all particles with likelihood $\geq K_L$. These thresholds are defined by $100\% > K_H > K_L > 0\%$. If the maximum likelihood is $< K_H$ then the process keeps all the particles and continues the processing in pure prediction mode. Usual values for these thresholds are $K_H = 70\%$, $K_L = 60\%$.

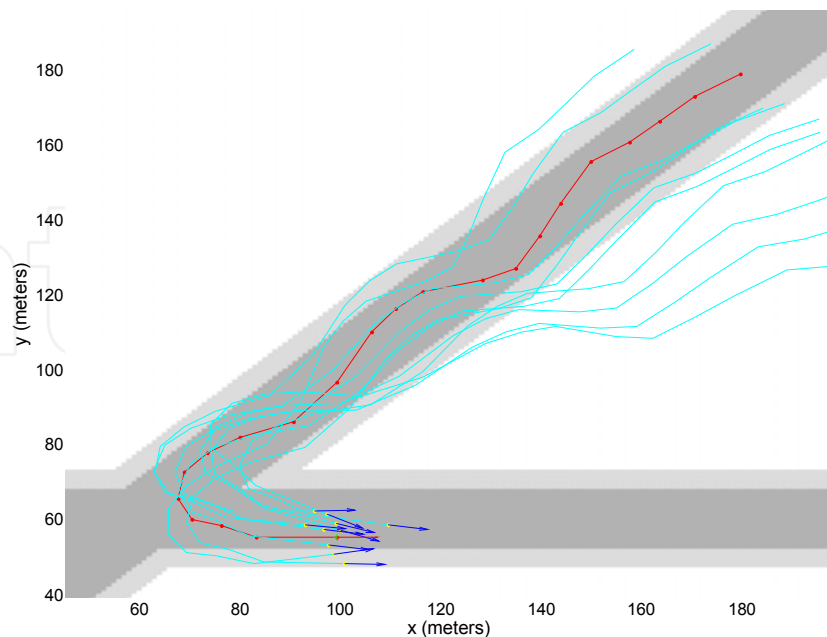


Fig. 4. A synthetic example. This region of interest (ROI) is a rectangle of 200 meters by 200 meters. A set of particles and their associated paths are superimposed to an image of base likelihood.

In the synthetic example shown in Fig. 4 the region of interest (ROI) is a rectangle of 200 meters by 200 meters. This ROI is big enough to contain the current population of particles and their associated paths.

Although all the particles are located on the road (high base likelihood); many of their associated paths abandon the zones of high base likelihood. The most likely particles are those that have a path mostly contained in the nominal zones. It can be seen the remarkable effect of a wrong heading that can rotate the associated path and make it to abandon the zones of high base likelihood (i.e. the road sections in gray).

Some particles have current values that escape the dark gray region (high base likelihood zones) however their associated paths are mostly contained in the roads. That means the real vehicle could be actually abandoning the road. This situation is repeated in Fig. 5 as well, where all the particles are located outside of the nominal road although many of them have paths that match the map constraints.

When the filter infers that the vehicle has been outside the map for sufficient time (i.e. no particles show relevant part of their paths consistent with the map), no updates are performed on the particles, i.e. the filter works in pure prediction mode.

When the vehicle enters the known map and eventually there are some particles that achieve the required path likelihood, i.e. higher than K_H , then the filter will start to apply the updates on the particles.

However this synchronization is not immediate. There could be some delay until some associated paths are consistent with the map -- the fact that a particle is well inside the road does not mean that its likelihood is high. It needs a relevant fraction of its associated path history to match the road map in order to be considered "inside the map".

This policy clearly immunizes the filter from bias when incorrect particles are temporarily on valid roads.

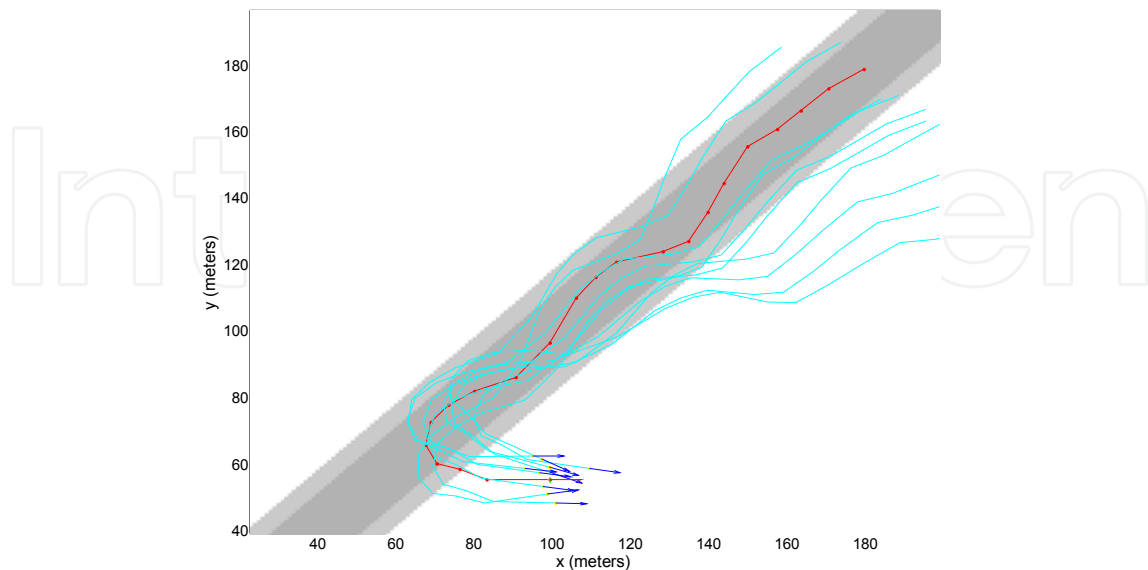


Fig. 5. This can be the situation where a vehicle temporarily abandons the road. It can be seen that although all the particles would have low base likelihood many of them have high likelihood when their associated paths are considered. Particles outside the road (low Base Likelihood) but having a correct heading would have high Path Likelihood.

4. Experimental Results

Long term experiments have been performed in urban areas of Sydney. The road maps were created by an ad-hoc Matlab tool that allowed users to define segments on top of a satellite image obtained from Google Earth. These road maps were low quality representations of the roads. This disregard for the quality of the definition of the road maps was done on purpose with the goal of exposing the approach to realistic and difficult conditions. Fig. 7 and Fig. 8 show the road map used in the estimation process. Fig. 2 shows part of the used road map as well.

The dead-reckoning process was based on the fusion of speed and heading rate measurements. The heading rate was provided by low cost three dimensional gyroscopes. A diversity of additional sensors were available in the platform (PAATV/UTE project) although those were not used in the estimation process and results presented in this paper. All the experiments and realistic simulations have validated the satisfactory performance of the approach.

Figures 7, 8 and 9 present the position estimates as result of the estimation process. Those are shown in red (Figure 7) or in yellow (Figures 8 and 9) and are superimposed on the road map. In some parts of the test the vehicle went temporarily outside the known map. Although there was not a predefined map on those sections it was possible to infer that the estimator performed adequately. From the satellite image and the over-imposed estimated path, a human can realize that the estimated path is actually on a road not defined in the *a priori* map (Fig. 9).

It is difficult to define a true path in order to compare it with the estimated solution. This is because the estimator is intended to provide permanent global localization with a quality usually similar to a GPS. Figures 10, 11 and 12 present the estimated positions and corresponding GPS estimates although those were frequently affected by multipath and other problems.

5. Conclusions and Future Work

This paper presented a method to perform global localization in urban environments using segment-based maps together with particle filters. In the proposed approach the likelihood function is locally generated as a grid derived from segment-based maps. The scheme can efficiently assign weights to the particles in real time, with minimum memory requirements and without any additional pre-filtering procedures. Multi-hypothesis cases are handled transparently by the filter. A path-based observation model is developed as an extension to consistently deal with out-of-map navigation cases. This feature is highly desirable since the map can be incomplete, or the vehicle can be actually located outside the boundaries of the provided map.

The system behaves like a virtual GPS, providing accurate global localization without using an actual GPS.

Experimental results have shown that the proposed architecture works robustly in urban environments using segment-based road maps. These particular maps provide road network connectivity in the context of the Darpa Urban Challenge. However, the proposed architecture is general and can be used with any kind of segment-based or topological *a priori* map.

The filter is able to provide consistent localization, for extended periods of time and long traversed courses, using only rough dead-reckoning input (affected by considerably drift), and the RNDF map.

The system performs robustly in a variety of circumstances, including extreme situations such as tunnels, where a GPS-based positioning would not render any solution at all.

The continuation of this work involves different lines of research and development. One of them is the implementation of this approach as a robust and reliable module ready to be used as a localization resource by other systems. However this process should be flexible enough to allow the integration with other sources of observations such as biased compass measurements and even sporadic GPS measurements.

Other necessary and interesting lines are related to the initialization of the estimation process, particularly for cases where the robot starts at a completely unknown position. Defining a huge local area for the definition of the likelihood (and spreading a population of particles in it) is not feasible in real-time. We are investigating efficient and practical solutions for that issue.

Another area of relevance is the application of larger paths in the evaluation of the Path Likelihood. In the current implementation we consider a deterministic path, i.e. we exploit the fact that for short paths the dead-reckoning presents low uncertainty to the degree of allowing us to consider the recent path as a deterministic entity. In order to extend the path validity we need to model the path in a stochastic way, i.e. by a PDF. Although this concept is mathematically easy to define and understand it implies considerable additional computational cost.

Finally, the observability of the estimation process can be increased by considering additional sources of observation such the detection of road intersections. These additional observations would improve the observability of the process particularly when the vehicle does not perform turning maneuvers for long periods.

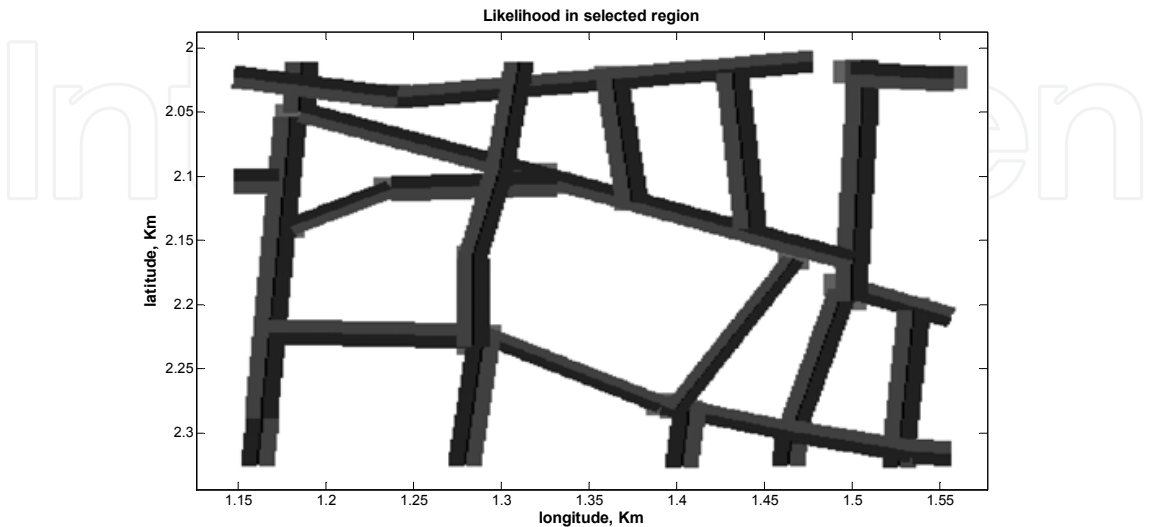


Fig. 6. A local base likelihood automatically created. This ROI is defined to be the smallest rectangle that contains the hypothetical histories of all the current particles. The different colors mean different lanes although that property was not used in the definition of the base likelihood for the experiment presented in this paper.

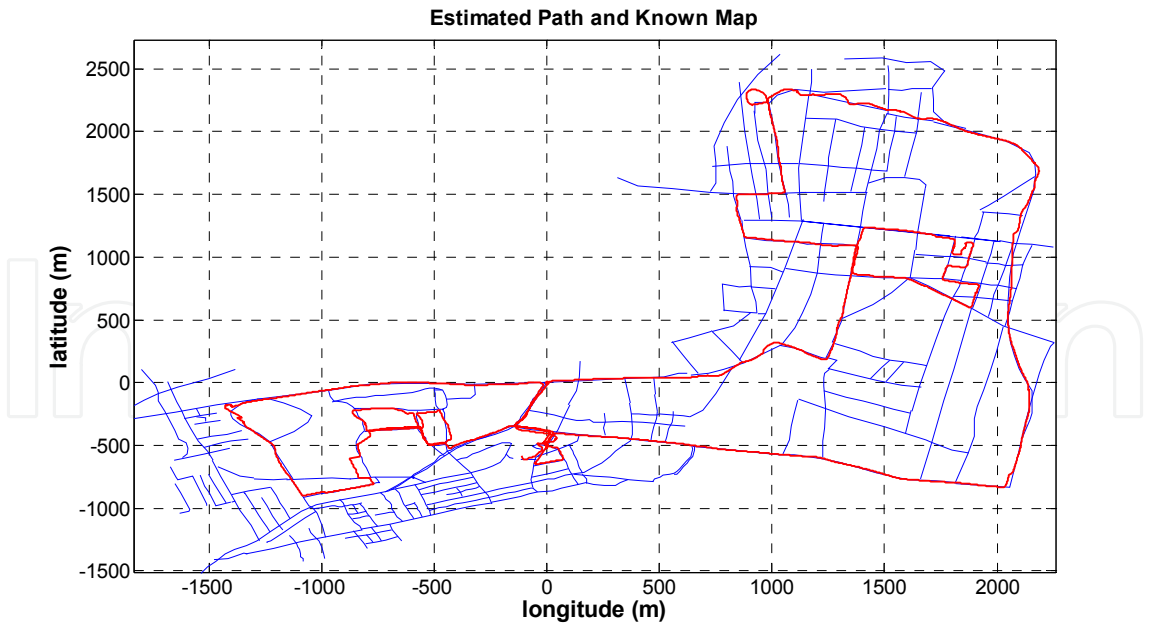


Fig. 7. Field test through Sydney. The system never gets lost. Even feeding the real-time system lower quality measurements (by playing back data corrupted with additional noise) and removing sections of roads from the a-priori map) the results are satisfactory. The red lines are the obtained solution for a long trip.



Fig. 8. Estimated path (in yellow) for one of the experiments. The known map (cyan) and a satellite image of the region are included in the picture.



Fig. 9. A section of Fig. 8 where the solution is consistent even where the map is incomplete (approximately $x=1850m$, $y=1100m$).

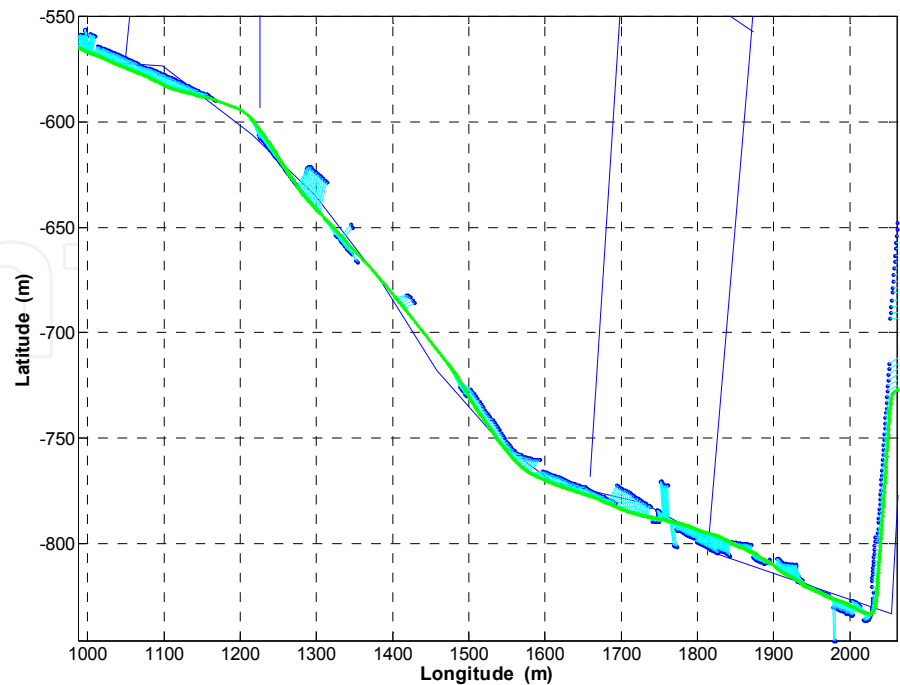


Fig. 10. A comparison between the estimated solution and the available GPS measurements. The green dots are the estimated solution and the blue ones correspond to GPS measurements. The segments in cyan connect samples of GPS and their corresponding estimated positions (i.e. exactly for the same sample time). The blue lines are the map’s segments.

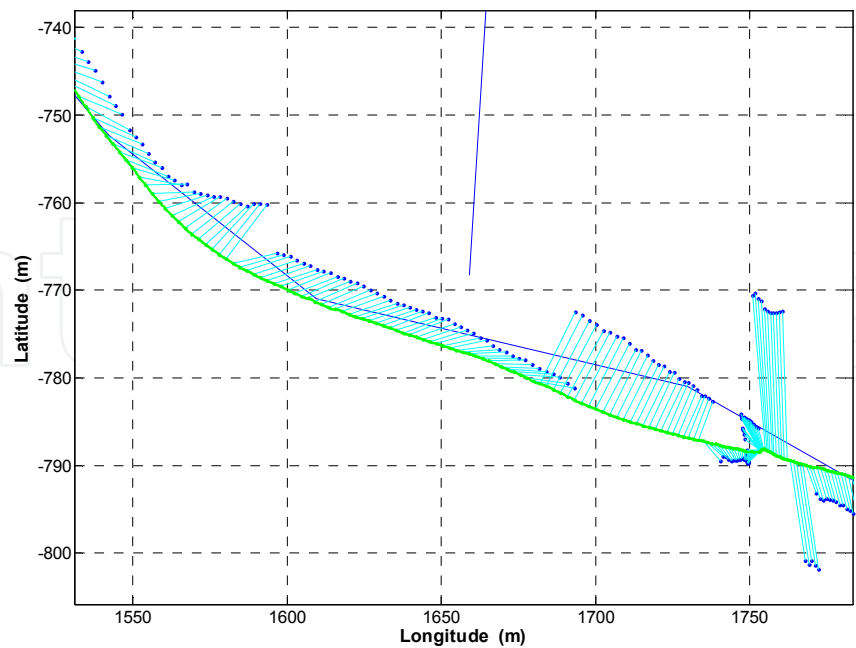


Fig. 11. A detailed view of Figure 10. It is clear that the GPS’ measurements present jumps and other inconsistencies.

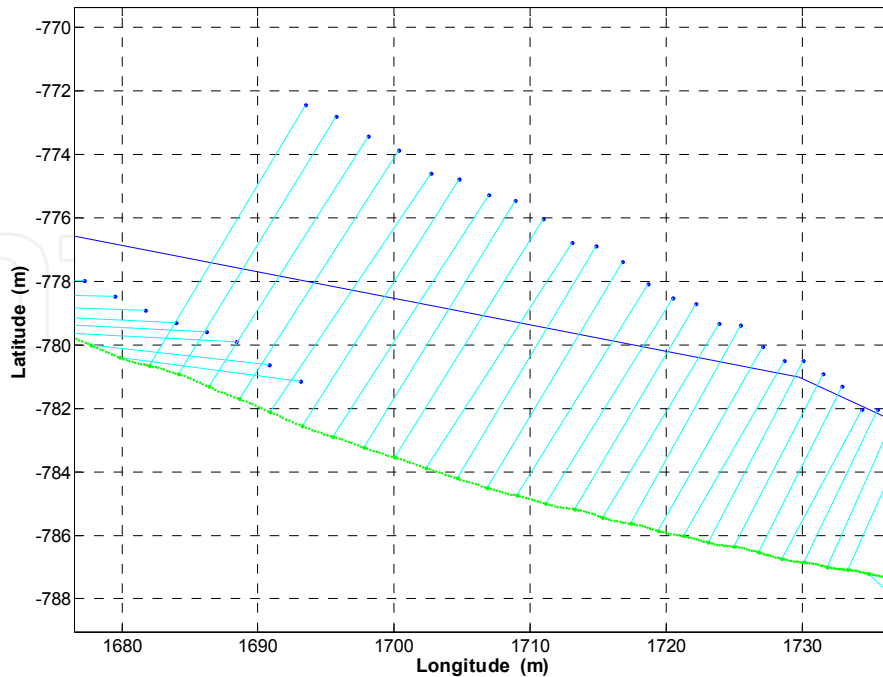


Fig. 12. A close inspection shows interesting details. The estimates are provided at frequencies higher than the GPS (5Hz). The GPS presents jumps and the road segment appears as a continuous piece-wise line (in blue), both sources of information are unreliable if used individually.

6. References

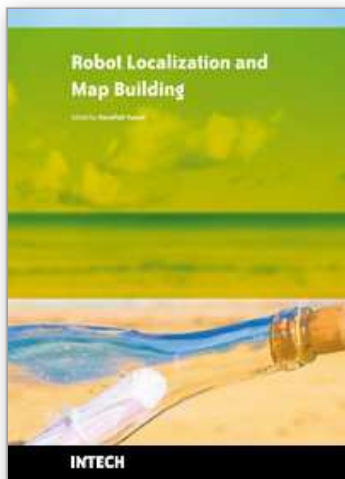
- S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A Tutorial on Particle Filters for On-line Non-linear/Non-Gaussian Bayesian Tracking," *IEEE Transactions on Signal Processing*, vol. 50, no. 2, pp. 174–188, 2002.
- F. Dellaert, D. Fox, W. Burgard, and S. Thrun, "Monte Carlo Localization for Mobile Robots," in *International Conference on Robotics and Automation*. Detroit: IEEE, 1999.
- D. Fox, S. Thrun, W. Burgard, and F. Dellaert, "Particle Filters for Mobile Robot Localization," in *Sequential Monte Carlo Methods in Practice*, A. Doucet, N. de Freitas, and Gordon, Eds. New York: Springer, 2001.
- J. E. Guivant and E. M. Nebot, "Optimization of the Simultaneous Localization and Map-building Algorithm for Real time Implementation," *IEEE Transactions on Robotics and Automation*, vol. 17, no. 3, 2001, pp. 242–257.
- J. Guivant, and R. Katz, "Global urban localization based on road maps," in *RSJ International Conference on Intelligent Robots and Systems, IROS*. San Diego, CA : IEEE, Oct. 2007, pp 1079-1084. ISBN: 978-1-4244-0912-9.
- J. J. Leonard and H. F. Durrant-Whyte, "Simultaneous Map Building and Localization for an Autonomous Mobile Robot," *IEEE/RSJ International Workshop on Intelligent Robots and Systems*. IEEE, 1991.

- L. Liao, D. Fox, J. Hightower, H. Kautz, and D. Schultz, "Voronoi Tracking: Location Estimation Using Sparse and Noisy Sensor Data," in *IEEE/RSJ International Workshop on Intelligent Robots and Systems*. Las Vegas, USA: IEEE, 2003.
- M. E. E. Najjar and P. Bonnifait, "A Road-Matching Method for Precise Vehicle Localization Using Belief Theory and Kalman Filtering," *Autonomous Robots*, vol. 19, no. 2, 2005, pp. 173–191.
- S. M. Oh, S. Tariq, B. N. Walker, and F. Dellaert, "Map based Priors for Localization," in *IEEE/RSJ International Workshop on Intelligent Robots and Systems*. Sendai, Japan: IEEE, 2004.
- G. Taylor and G. Blewitt, "Road Reduction Filtering using GPS," in *3rd AGILE Conference on Geographic Information Science*, Helsinki, Finland, 2000.
- ACFR, The University of Sydney and LCR, Universidad Nacional del Sur, "PAATV/UTE Projects," Sydney, Australia, 2006.
- Defence Advanced Research Projects Agency (DARPA), "DARPA Urban Challenge," <http://www.darpa.mil/grandchallenge/>, 2006.
- Google, "Google Earth," <http://earth.google.com/>, 2007.

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Localization and mapping are the essence of successful navigation in mobile platform technology. Localization is a fundamental task in order to achieve high levels of autonomy in robot navigation and robustness in vehicle positioning. Robot localization and mapping is commonly related to cartography, combining science, technique and computation to build a trajectory map that reality can be modelled in ways that communicate spatial information effectively. This book describes comprehensive introduction, theories and applications related to localization, positioning and map building in mobile robot and autonomous vehicle platforms. It is organized in twenty seven chapters. Each chapter is rich with different degrees of details and approaches, supported by unique and actual resources that make it possible for readers to explore and learn the up to date knowledge in robot navigation technology. Understanding the theory and principles described in this book requires a multidisciplinary background of robotics, nonlinear system, sensor network, network engineering, computer science, physics, etc.

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