Map-Matching Integrity Using Multi-Hypothesis Road Tracking

Maged Jabbour, Philippe Bonnifait and Véronique Cherfaoui

Heudiasyc UMR CNRS 6599, Université de Technologie de Compiègne, France

{Maged.Jabbour, Philippe.Bonnifait, Veronique.Cherfaoui}@hds.utc.fr

***Abstract* – Efficient and reliable map-matching algorithms are essential for *Advanced Driver Assistance Systems*. While most existing solutions fail to provide trustworthy outputs when the situation is ambiguous (such as at road intersections, roundabouts or when roads are parallel), we present in this paper a new map-matching method based on multi-hypothesis road tracking that takes advantage of the geographical database road connectivity to provide a reliable road-matching solution with a confidence indicator that can be used for integrity monitoring purposes.**

Index Terms – GNSS-based Localization, Map-Matching, Multi-Hypothesis Tracking, Integrity.

I. INTRODUCTION

Map Matching (MM), using GNSS positioning and navigable maps, is a data association problem which consists in selecting the most likely road that corresponds to the current position of the mobile [19]. Unfortunately, because of large estimation errors, MM often has several solutions, i.e. several segments are declared candidates with good confidence. These segments can belong to the same road or to different roads in the case of ambiguous situations. Moreover, where there are inaccuracies in the map, or where a vehicle is being driven off-road, MM may not have a solution. Therefore, MM confidence or MM integrity is a crucial issue for many Map-Aided Advanced Driver Assistance Systems and other Intelligent Transportation Systems (ITS) applications that aim to improve road safety. In practice, any MM algorithm should be able to deliver confidence indicators. If these indicators exceed pre-defined thresholds for the particular application, the end-user should be warned that the solution provided is not reliable.

To address this integrity problem we propose in this paper a multi-hypothesis road tracking method that attempts to exploit data pertaining to road-connectivity. This approach belongs to the class of dynamic state observers. Tracking techniques [4] allow a system to observe and follow the state of a mobile target by filtering noisy observations, while detecting and excluding aberrant data. They have very efficient implementations, since they often rely on the predictor/estimator paradigm, which means that all the information can be captured in the current state estimation. Therefore, it is unnecessary to retain in memory a window of data; by using a recursive scheme, previous states can be forgotten.

For localization purposes, tracking the pose (position and attitude) of a mobile is very useful since it allows the merging of sequentially redundant data, once the initial global localization stage has been accomplished. In practice, model equations are nonlinear, and an arbitrary initialization can give rise to an erroneous convergence.

Spatial road network data can be also used to improve the performance of MM, for instance when GPS is not available, by constraining the localization space (geometry) and through anticipation (connectivity). It therefore becomes necessary to integrate navigable map information into the localization tracker. Classical map-matching methods include mainly deterministic methods [2] [24], Bayesian methods [12] and fuzzy logic methods [23] [18] [14] and set-membership methods [20].

Map matching inevitably produces situations of ambiguity, for instance at junctions or where roads are parallel, or when GPS suffers from outages. When a mono-hypothesis approach is applied there is a risk of choosing an incorrect solution. When the system detects this mistake the tracking will be reset and MM will need time to recover the correct solution. In contrast, a multi-hypothesis approach maintains all the possible solutions in situations of ambiguity; each hypothesis inhabits a private world on which the alternative hypotheses do not encroach. Hypotheses are removed when they become unlikely. Using a Bayesian framework, it is possible to quantify the probability of each hypothesis with respect to the others. So, at each step, the most probable hypothesis can be output. The main advantage of Multi-Hypothesis Map-Matching (MHMM) over a Mono-Hypothesis approach is that the true solution is tracked with a high probability: if the current solution is declared incorrect, the system can immediately output a new solution without any transient phase.

The algorithmic complexity of MHMM is usually exponential, since each hypothesis can generate new hypotheses at each sampling step. In this paper we propose using road connectivity information from the navigable map to overcome this drawback, so that new hypotheses are created only when they are really necessary. We present an MHMM based on a Gaussian mixture where each hypothesis has a corresponding Electronic Horizon (EH) that performs a Gaussian filter. The EH is a set of two roads that the hypothesis is expected to follow. A weight (sometimes known as a *score*) indicating the probability of each hypothesis with respect to the others is attributed so as to facilitate the management of the set of hypotheses. Finally, we propose a simple strategy to monitor MM integrity. Our proposal is to declare the MM worthy of confidence when there is only one credible hypothesis and when the normalized residuals of this hypothesis fall below a threshold.

The paper is organized in 5 sections: in Section II, the mathematical formulation of the use of *a priori* cartographic information about the localization space is presented. In Section III the MHMM mechanism is described. Then, in Section IV, integrity issues are discussed and a new MM integrity criterion is proposed. Finally, experimental results illustrating the performance of this approach are presented in Section V.

II. LOCALIZATION USING *A PRIORI* CARTOGRAPHIC INFORMATION ABOUT THE LOCALIZATION SPACE

Suppose that a map information source is available. This map provides *a priori* information that constrains the localization space. For example, a car is likely to be on a road, and unlikely to go through a building. The cartographic information considered here is a set of roads described by interconnected nodes. Each road comprises a start node and an end node, with several intermediate points.

In this section we formalize the problem of using *a priori* cartographic information in the localization process. We show that the map can be used as an observation (like any exteroceptive measurement) in the state observation process.

Suppose that s_k represents the mobile state vector at time k; z_k is an exteroceptive sensor observation (a GPS for example).

$$\begin{cases} s_k = f(s_{k-1}, u_k) + \alpha_k \\ z_k = h(s_k) + \beta_k \end{cases} \quad (1)$$

The localization problem consists in estimating the probability $p(s_k \mid z^k, g, u^k)$, given the set of observations $z^k = \{z_k, \ldots, z_1\}$, and the *a priori* geographical information g.

Let us see how this geographical information may be used to estimate this probability density.

$$p(s_k \mid z^k, g, u^k) = p(s_k \mid z_k, z^{k-1}, g, u^k) \quad (2)$$

Using Bayes' theorem, equation (2) can be also written as:

$$p(s_k \mid z_k, z^{k-1}, g, u^k) = \frac{p(z_k \mid s_k, z^{k-1}, g, u^k).p(s_k \mid z^{k-1}, g, u^k)}{p(z_k \mid z^{k-1}, g, u^k)} \quad (3)$$

The denominator $p(z_k \mid z^{k-1}, g, u^k)$ is independent of s_k. and can be considered as a normalization term η. (3) becomes:

$$p(s_k \mid z_k, z^{k-1}, g, u^k) = \eta . p(z_k \mid s_k, z^{k-1}, g, u^k).p(s_k \mid z^{k-1}, g, u^k) \quad (4)$$

Let us now consider each of the two expressions of this product.

Observation z_k at time k is independent of all the previous z^{k-1}, the observation noise being white. Remarking also that the exteroceptive sensor noise is independent of the map g, we have:

$$p(z_k \mid s_k, z^{k-1}, g, u^k) = p(z_k \mid s_k) \quad (5)$$

Let us now consider the second term of the product, and let us make the *a priori* density $p(s_k \mid z^{k-1}, g, u^k)$ appear using the Total Probability theorem and Bayes' theorem:

$$p(s_k \mid z^{k-1}, g, u^k) = \int p(s_k, s_{k-1} \mid z^{k-1}, g, u^k).ds_{k-1} \quad (6)$$

$$= \int p(s_k \mid s_{k-1}, z^{k-1}, g, u^k).p(s_{k-1} \mid z^{k-1}, g, u^k).ds_{k-1} \quad (7)$$

However, $p(s_k \mid s_{k-1}, z^{k-1}, g, u^k)$ represents the evolution model. It is independent of the observations z^k, and given the assumption of a 1st order Markov process, it depends only on the current entry u_k.

$$p(s_k \mid z^{k-1}, g, u^k) = \int p(s_k \mid s_{k-1}, g, u_k).p(s_{k-1} \mid z^{k-1}, g, u^{k-1}).ds_{k-1} \quad (8)$$

Substituting (5) and (8) into equation (4):

$$\underbrace{p(s_k \mid z^k, g, u^k)}_{Localization\ at\ k} = \eta . p(z_k \mid s_k). \int p(s_k \mid s_{k-1}, g, u_k). \underbrace{p(s_{k-1} \mid z^{k-1}, g, u^{k-1}) ds_{k-1}}_{Localization\ at\ k-1} \quad (9)$$

Let us now consider the term $p(s_k \mid s_{k-1}, g, u_k)$ that expresses the influence of the *a priori* information in the localization process: it can be used in the prediction step [15], [6], or considered as an observation as we proposed.

Using Bayes' theorem, we have:

$$p(s_k \mid s_{k-1}, g, u_k) = \frac{p(g \mid s_k, s_{k-1}).p(s_k \mid s_{k-1}, u_k)}{p(g \mid s_{k-1})} \quad (10)$$

Assuming that the cartographic observation does not depend on the current pose, and given that the map is a 1st order Markov process, we have:

$$p(g \mid s_{k-1}) = p(g) \quad (11)$$

$$p(g \mid s_k, s_{k-1}) = p(g \mid s_k) \quad (12)$$

To make these two assumptions valid, it is necessary that the vehicle moves relative to the map ($s_k \neq s_{k-1}$). Making substitutions in equation (10), we obtain:

$$p(s_k \mid s_{k-1}, g, u_k) = \frac{p(g \mid s_k).p(s_k \mid s_{k-1}, u_k)}{p(g)} \quad (13)$$

Equation (8) becomes:

$$p(s_k \mid z^{k-1}, g, u^k) = \int \frac{p(g \mid s_k).p(s_k \mid s_{k-1}, u_k)}{p(g)} . p(s_{k-1} \mid z^{k-1}, g, u^{k-1}).ds_{k-1} \quad (14)$$

$$= \frac{p(g \mid s_k)}{p(g)} \int p(s_k \mid s_{k-1}, u_k).p(s_{k-1} \mid z^{k-1}, g, u^{k-1}).ds_{k-1} \quad (15)$$

By introducing $\eta' = \dfrac{\eta}{p(g)}$, equation (4) can thus be written

$$p(s_k \mid z^k, u^k) = \eta'.p(z_k \mid s_k).p(g \mid s_k).$$
$$.\int p(s_k \mid s_{k-1}, u_k).p(s_{k-1} \mid z^{k-1}, g, u^{k-1}).ds_{k-1} \quad (16)$$

In this expression $p(z_k \mid s_k)$ and $p(g \mid s_k)$ represent respectively the likelihood of the exteroceptive observation and those of the map g relative to the predicted position s_k. Here the map is clearly considered as an observation.

As an example, let us consider a map of one segment representing a road on which the vehicle is traveling. This case is represented by Fig. 1, which illustrates $p(g \mid s_k)$, g being the map.

Let us consider the line Δ passing through $h(s_k)$ (where $h(s_k)$ is the projection of the state s_k in 2D map observation space) and perpendicular to the segment in question. Let us suppose that along Δ the density of probability $p(g \mid s_k)$ is Gaussian. The likelihood is obtained by calculating the innovation μ (here the deviation with the road) and by using it in the density of Gaussian probability.

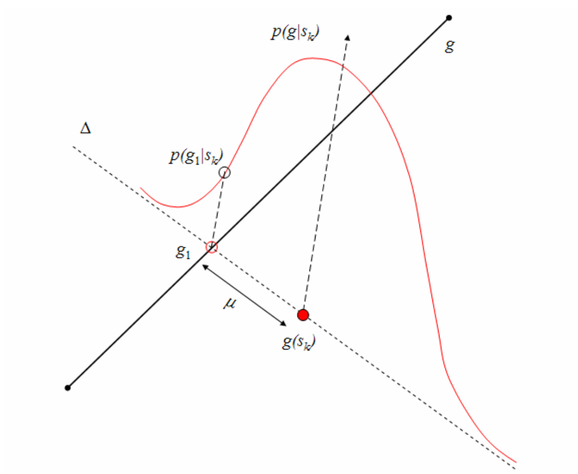

Fig. *1. Map probability expressed with as a Gaussian density function.*

It will be noticed that the probability density function can have any shape, and that it can be approximated by a mixture of Gaussians. For each Gaussian, the same approach can be applied.

III. Using a Map-Matching Method Based on a Multi- Hypothesis Approach

MM is a data association problem. Data association in dynamic situations is a key issue in Multi-Target Tracking (MTT) systems [3]. The association stage consists in establishing a correlation between the predicted targets (known as tracks) and the observations detected by the sensors. Multi-Hypothesis Tracking MHT is one of the promising approaches to the multi targets tracking problem. At every stage it selects the most likely solution to the tracking problem, while retaining some other hypotheses for future assumptions. MHT supports the creation and destruction of tracks. By definition, a track is the state vector of a target, with a covariance and a score and updated with an observation, while a hypothesis is a set of compatible tracks. The likelihood of a track is determined by a score maintained as a Log-Likelihood Ratio (LLR) [21]. Different implementations of MHT algorithms are described in [4]. Because the number of tracks/hypothesis can grow exponentially, ad-hoc methods can reduce the combinatory: pruning techniques can delete tracks/hypotheses with low probabilities, and merging techniques combine similar tracks.

In this paper we assume that MHMM tracks a single vehicle position using multiple hypotheses. We are therefore describing a single target tracking case, and do not need to distinguish between *track* and *hypothesis*. To clarify this, a definition of hypothesis is given and the methods for hypothesis creation and deletion are described. The track/hypothesis score (weight) is computed and maintained as in MHT. We describe in detail the management policy for the hypotheses, where an EH comprising 2 roads is associated with each Gaussian filter.

A. Hypothesis definition

The EH associated with each hypothesis consists of two roads (each one being a poly-line): the current road and a following road connected to it. There are two main advantages. First, there is no discontinuity when approaching the end of the current road. Secondly, the MM with this EH is extremely simple since it is a poly-line without any junctions. Given the typical length of roads, it is unnecessary to retain more than two roads in memory: between two samples the distance traveled is limited to a few meters.

Hi : **Localization Hypothesis**
★ A state: a state vector $s_{i,k}$ and its associated covariance matrix $P_{i,k}$,   ★ A electronic horizon g_i that includes the road of the mother-hypothesis R_{idm} and an upcoming one R_{idf}, connected to it $g_i = \{R_{idm,i}, R_{idf,i}\}$ ★ A weight $w_{i,k}$, showing (after normalization) the relative importance of the different hypotheses   ★ An absolute confidence indicator $vr_{i,k}$ quantifying confidence in this hypothesis.

Table *1. Definition of a localization hypothesis*

A hypothesis H_i at time k is defined as being composed of the elements shown in Table 1.

B. Hypothesis Creation

One important requirement is an efficient strategy when a hypothesis reaches the end of its road. Let us assume that the location of a hypothesis is approaching the end of its EH, and that the current road is connected to two upcoming roads.

A first possibility is to replicate the current hypothesis into two others, corresponding respectively to each of the upcoming roads. The EH associated with each hypothesis includes the current road and one of the two upcoming ones. If there is no reason to favor one path over the other (such as we might, for example, in the case of a pre-computed route), then at the time of duplication the Gaussians have the same weight.

A second possibility is to clone the current hypothesis with anticipation. This is essential to take into account map and estimation errors.

More generally, let us suppose that at time k, a hypothesis i designated by $H_{i,k}$ ($s_{i,k}$, $P_{i,k}$, g_i, $w_{i,k}$, $vr_{i,k}$) arrives at a distance Δ from the end of its EH gi. The hypothesis $H_{i,k}$ is replicated into a number of new hypotheses. The information on the number of roads connected to the end of the current road n_c, is stored in the map structure: the number of created hypotheses is equal to the number of connected roads n_c. For j = 1 to n_c, each new hypothesis j gets the same weight as the mother-hypothesis i and the same state at the time of creation (i.e. state vector $s_{i,k}$ and covariance matrix $P_{i,k}$). The new EH g_j associated with each new hypothesis j contains a road from the EH $R_{idf,j}$ (roads connected to the end of the current segment) and the road $R_{idm,i}$ corresponding to the mother hypothesis (the road on which hypothesis H_i was evolving). We may express this as $R_{idm,j} = R_{idf,i}$. It should be noted that the new hypotheses do not continue to include the road $R_{idm,i}$ from their mother hypothesis, because the size of each EH g_j would then increase endlessly. Moreover, since the likelihood $vr_{l,k}$ associated with each hypothesis k is re-computed each time, it makes no sense to transmit it.

After transmitting its characteristics to the newly-created hypotheses, the mother hypothesis $H_{i,k}$ is eliminated. A normalizing step for the weights $\mathbf{w_k}$ is then carried out.

To illustrate the EH management associated with the hypotheses, consider the case of a simple intersection of three roads as shown in Fig. 2. We suppose that the hypothesis F_i, associated with the EH {ID_0, ID_1} has reached the threshold distance Δ from the end of road ID_1. Two hypotheses F_m and F_n are created from the properties of F_i. The EH associated with F_m and F_n, will be respectively composed of {ID_1 ID_2} and {ID_1 ID_3}.

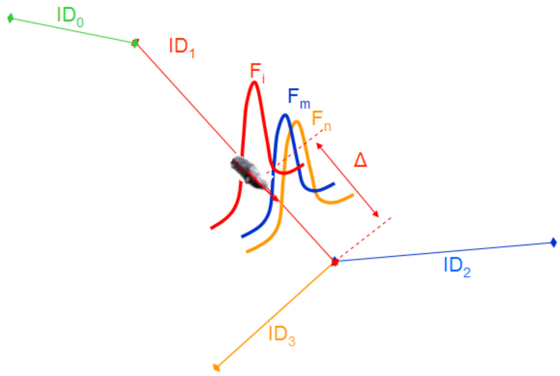

***Fig.** 2. Illustration of a 3-road intersection situation*

C. Hypothesis Deletion

As soon as a hypothesis's weight falls below a fixed deletion threshold ξ_{el}, we consider that the hypothesis is no longer credible, and it is eliminated. To avoid the elimination of a credible hypothesis H_i whose instantaneous likelihood $vr_{i,k}$ may decrease suddenly at time k, for example as a result of an inappropriate observation that causes its weight $w_{i,k}$ to fall below the deletion threshold ξ_{el}, we propose filtering the computational weight $w_{i,k}$:

$$w_{i,k} = vr_{i,k}.w_{i,k-1} + L_{mem}.w_{i,k-1} \qquad (17)$$

where L_{mem} ($0<L_{mem}<1$) is a forget factor that quantifies the part of the former w_{k-1} that is injected into w_k. Typically, L_{mem} is set to 0.1. Note that the threshold ξ_{el} is a parameter that has to be tuned respectively with the map offset.

D. Detecting tracking divergence

Tracking divergence can occur when all hypotheses are mistaken and cease to bear any relation to the observations that update these hypotheses.

In normal conditions, if a hypothesis H_i moves away from the updating observations, its instantaneous likelihood vr_i will decrease in the update stage, and thus its weight w_i will also decrease. In the case where all available hypotheses move away from the updating observations, all their likelihoods and consequently their weights will decrease, but as a normalizing step follows, the decrease in the weights will no longer be effective.

In order, therefore, to detect system divergence, a non-normalized sum of weights should be computed, and this computation should be carried out with a time interval Δt, so as to prevent intermittent outlier observations from triggering divergence detection unnecessarily. If the non-normalized computed sum remains below a fixed threshold δ_{div} during a Δt interval, a re-initialization of the system is undertaken with the first valid GPS data based on the mechanism shown.

It should be remarked that system re-initialization occurs only rarely. It may result from significant discrepancies in digital maps in some regions, or from mismanagement of the road-map cache.

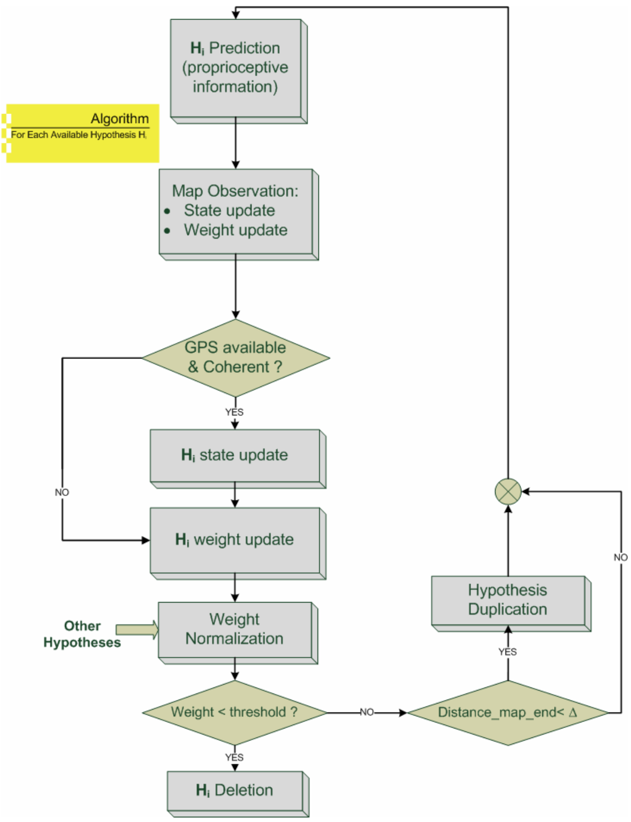

Fig. *3. Synoptic of MHMM*

E. Estimating the vehicle location from the different hypotheses

Several solutions can be proposed to achieve the estimated map matching from the different hypotheses at time *k*. We propose selecting a set of credible hypotheses as output: the normalization of the weights $w_{j,k}$ with respect to the maximum of the weights is the metric that is compared to a fixed threshold δ_{imp} to characterize the probable output hypotheses.

$$(\overline{X}_k, \overline{P}_k) = \left\{ (X_{j,k}, P_{j,k}) \mid \frac{w_{j,k}}{\max\limits_{i=1:N}(w_{i,k})} \geq \delta_{imp} \right\} \tag{18}$$

The threshold δ_{imp} must be chosen in some optimal way. If δ_{imp} is too small, a large number of hypotheses (including unlikely ones) will be proposed as outputs. In contrast, a high δ_{imp} will reduce the number of likely hypotheses to zero, one or two.

In the literature concerning particle filters [9], the notion of “effective particles” is often used to trigger a new process of particle re-sampling. Let us define the number of effective particles as:

$$N_{eff,k} = \frac{1}{\sum_{i=1}^{N} w_{i,k}^2} \tag{19}$$

In [9], the authors propose that if N_{eff} becomes less than two-thirds of the total number of particles *N*, then the particles must be re-sampled. We have adapted this strategy to the case of Gaussian particles. We have linked the threshold δ_{imp} with N_{Eff}:

$$\delta_{imp} = 1/(2.N_{eff}) \tag{20}$$

F. Practical consideration

Let us suppose that at time *k*, we have *N* hypotheses: for all the available hypotheses H_i (i=1:N), each hypothesis has its own Kalman filter. The traveled distance and heading rotation are first obtained from the dead reckoning sensors. If the vehicle is moving, the correction of the previous prediction is computed using the current GPS fix.

Suppose now that the system is operating in normal tracking mode (after the initialization stage). If we retain all the hypotheses, their number will increase without bound, given that, at the end of each road-segment, each hypothesis will be divided into at least two. We have set a maximum number of hypotheses (denoted N_{pmax}). Typically, the values of N_{pmax} range from 8 to 16 hypotheses. When the total number of hypotheses exceeds N_{pmax}, we retain N_{pmax} hypotheses according to their score w_i.

G. Update step

Using the result demonstrated in section II, we have two separate exteroceptive observations: GPS fixes and map observations. To compute the weights efficiently, the update steps are serialized on the reasonable assumption that there is no correlation between errors. So, in the update step, the state of every hypothesis is corrected by the two observations, and thus the weights $w_{i,k}$ are also updated and normalized as many times as there are observations. We prefer to use a hybridized GPS (HGPS) instead of a standalone GPS receiver to overcome the problems of GPS jumps and, more importantly, the low availability of GPS in urban areas. If there is masking, and if navigation is using dead-reckoning prediction, HGPS continues to provide exteroceptive observation to the MHMM system and the different hypotheses continue to be updated in terms of weight and state.

It is important to remark that the map data of the EH is always coherent with its hypothesis. However, a hypothesis can rapidly become inconsistent with the HGPS (if it is an incorrect hypothesis). Thus, we have implemented a Chi-Square test with the HGPS before correcting the hypothesized pose where there is inconsistency with the HGPS. Nevertheless, the weights are always updated in order to make the confidence decrease (see Algo. 1).

The weights w_i, the likelihoods vr_i, and the filters' estimates are updated by the two exteroceptive sources. The weights of the filters are updated by the HGPS point. The weight of the incorrect hypotheses will decrease step by step. The likelihoods of the hypotheses will also be changing in the same way but more rapidly than the weights (which are cumulative normalized probabilities). The likelihoods can be interpreted as an indicator of the overall consistency of the system, like any normalized residual quantity.

Another important characteristic of the map-matching is its *spatial* nature. Many approaches rely on data fusion approaches that assume independence of the errors. If the vehicle is stationary, the same map data can be used several times, violating the independence hypothesis. For these reasons, the map-matching can be formulated by a space-triggered state space description: if the distance traveled between 2 time-steps (also known as the curvilinear abscissa) is smaller than a threshold, then the map-updating step is not done.

H. Segment selection

Each hypothesis has its own map: it is an EH composed of 2 roads. The road-matching method consists in selecting the nearest segment whose direction is compatible with the heading of the vehicle. The orthogonal projection is considered as the map-matched position and used as an exteroceptive observation by the corresponding hypothesis filter. This mechanism is used at each time step.

I. Efficient Map Update Implementation

Let us examine how the map correction stage is performed using an observation computed from the EH. We first suppose that a candidate segment has been selected. Consider the following:

- $s_{i,k} = \begin{bmatrix} x_{i,k} & y_{i,k} & \theta_{i,k} \end{bmatrix}^T$ is the pose of the hypothesis
- $Z_{i,k} = \begin{bmatrix} x_{i,k} & y_{i,k} \end{bmatrix}^T$ is a point that corresponds to the projection of the estimated position onto the most likely segment (see equation (21) and Fig. 4).

$$Z_{i,k} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \cdot s_{i,k} \qquad (21)$$

The estimate is merged with the map during the Kalman estimation stage. The covariance associated with the map observation is modeled by an ellipsoid around the selected segment, as shown in Figure 4 [7]. The center of the ellipsoid is Y_m, the orthogonal projection onto the segment of the last estimated location. In the frame associated with the segment, the longitudinal inaccuracy is far greater than the lateral inaccuracy. Theoretically, the longitudinal inaccuracy can be chosen as large as possible, even infinite for a long segment. In practice, we consider a one-sigma value in the order of the length of the segment.

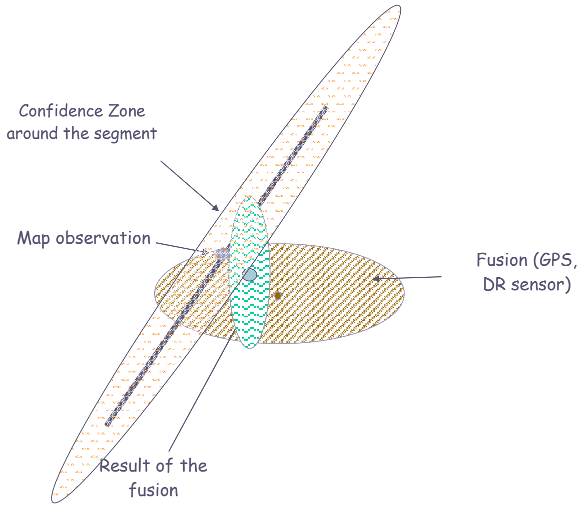

Fig. *4. Merging a hypothesis' estimate with the selected segment*

J. Complete Algorithm

1 For every hypothesis H_i at time k:

1.1. Prediction step using proprioceptive sensors

$$F_{i,s} = \left[\frac{\partial f\,(\hat{s}_{i,k-1|k-1}, u_k)}{\partial s}\right], \quad F_u = \left[\frac{\partial f\,(\hat{s}_{i,k-1|k-1}, u_k)}{\partial u}\right]$$

$$\hat{s}_{i,k|k-1} = f(\hat{s}_{i,k-1|k-1}, u_k)$$

$$P_{i,k|k-1} = F_{i,s}.P_{i,k-1|k-1}.F_{i,s}^T + F_u.Q_u.F_u^T + Q_\alpha$$

1.2. Map update step

Compute the map observation using the H_i's EH

Update the state using this observation

$$J_{i,k} = \left[\frac{\partial h\,(\hat{s}_{i,k|k-1})}{\partial s}\right]$$

$$K_{i,k} = J_{i,k}.P_{i,k|k-1}.(J_{i,k}.P_{i,k|k-1}.J_{i,k}^T + Q_\beta)^{-1}$$

$$\hat{s}_{i,k|k} = \hat{s}_{i,k|k-1} + K_{i,k}.(z_k - h(\hat{s}_{i,k|k-1}, u_k))$$

$$P_{i,k|k} = (I - K_{i,k}J_{i,k}) \cdot P_{i,k|k-1} \cdot (I - K_{i,k}J_{i,k})^T + K_{i,k} \cdot Q_\beta \cdot K_{i,k}^T$$

Update the weight using the likelihood of the map

$$w'_{i,k} = \eta.w_{i,k-1}.N(z_k; h_k(s_{i,k|k-1}), J_k.P_{i,k-1|k-1}.J_k^T + R_k)$$

1.3. GPS update step, if a hybrid GPS fix is available

If the fix is coherent with the current hypothesis H_i

Update the state using the hybrid GPS

$$K_{i,k} = J_{i,s}.P_{i,k|k-1}.(J_{i,s}.P_{i,k|k-1}.J_{i,s}^T + Q_\beta)^{-1}$$

$$\hat{s}_{i,k|k} = \hat{s}_{i,k|k-1} + K_{i,k}.(z_k - h(\hat{s}_{i,k|k-1}, u_k))$$

$$P_{i,k|k} = (I - K_{i,k}J_{i,k}) \cdot P_{i,k|k-1} \cdot (I - K_{i,k}J_{i,k})^T + K_{i,k} \cdot Q_\beta \cdot K_{i,k}^T$$

End If

Update the weight using the likelihood of the GPS

$$w_{i,k} = \eta.w'_{i,k}.N(z_k; h_k(s_{i,k|k-1}), J_k.P_{i,k-1|k-1}.J_k^T + R_k)$$

1.4. Hypotheses creation using connectivity

If H_i's position < Δ from the end of its EH

Replicate H_i as many times as connected roads

Delete H_i

End if

2. Normalize the weight of every hypothesis

$$w_{i,k} = \frac{w_{i,k}}{\sum_{j=1}^{N} w_{j,k}}$$

3.Hypotheses management

Sort the H_i with respect to their weight

Keep the N H_i that have the highest weight

Delete the others

4 Decision stage

Compute the number of efficient hypotheses

***Algorithm 1**. MHMM Algorithm*

$s_{i,k}$ and $P_{i,k}$ represent respectively the state vector and the covariance matrix of the hypothesis i, z_k is an observation, f and h are the evolution and observation equations, K is the filter gain, N(a,b) is a normal distribution of mean a and variance b.

IV. Integrity Issues

Nowadays, integrity is a fundamental characteristic of localization systems. For some ITS applications, integrity can be more important than precision.

By definition, the integrity of a localization system is the measure of confidence that can be accorded to the exactitude of the positioning delivered by this system.

In practice, integrity means applying successive checks to ensure that the information is valid. A good example of this concept is RAIM (Receiver Autonomous Integrity Monitoring) [1], which is a technique to verify the consistency of the current GPS navigation solution when pseudorange redundancy exists (more than 5 satellites). The principle of a snapshot RAIM is to monitor normalized residuals using a threshold computed with a Chi-Square distribution, under Gaussian assumptions and given selected False Alarm and Miss Detection probabilities.

Since snapshot methods are not adapted to dynamic sensor fusion, several results [8] indicate that integrity can be assured by checking the consistency of the innovation signal of a state observer. MM integrity can therefore be monitored using normalized innovations between candidate segments and the current estimated pose (position and heading). Unfortunately, as a result of inaccuracies in the map or because of large estimation errors, map-matching often has several solutions, i.e. several segments are declared candidates with good confidence. Applying a snapshot-like integrity test for MM is therefore time-consuming, since at each sample time several candidates can be declared safe. To tackle this problem, MHMM is very useful since it is able to make use of the road-connectivity information, so to quantify the confidence of each hypothesis with respect to the others.

Our proposal is to declare MM worthy of confidence when there is a hypothesis that is much more likely than the others, and when a test on the normalized innovations of this hypothesis is below a consistency threshold. In [17], the authors propose to monitor three indicators (distance residuals, heading residuals, and an indicator related to uncertainty of MM) to check the integrity of MM. Since a mono-hypothesis scheme is used, they propose combining the three indicators using fuzzy rules. Integrity is then monitored using this scalar value.

With MHMM, integrity monitoring has a different paradigm since there are two different criteria. First, we use the number of efficient hypotheses (termed N_{eff} in Equation 19) and a Normalized Innovation Squared (NIS) similar to a Mahalanobis distance in position and heading. This innovation information is computed between the HGPS and the predicted state of the most likely hypothesis. Algorithm 2 summarizes this simple integrity monitoring strategy. In [5], we have studied different monitoring strategies that can be used for other ITS applications (such as road charging).

Threshold$_1$= function(probability ratio between the hypotheses)
Threshold$_2$=Chi2Inv(False Alarm Probability)
Confidence=0
If N_{eff} < Threshold$_1$
    If NIS of the most likely hypothesis < threshold$_2$ Then
        Confidence=1 // MM output is confident
    End If
End If

Algorithm 2. *Integrity monitoring.*

V. RESULTS

Experiments were performed in Compiègne using a KVH fiber optic gyro, an odometer input and a Trimble AgGPS 132 (L1-only receiver). The GIS used by the map-matching module is based on a Software Development Kit (SDK) provided by BeNomad (*www.benomad.com*). The maps are size-optimized and provided in the SVS (Scalable Vector System) file format. For our prototype, we used a geographical database converted in SVS format. The SVS format is very compact since the file size for the whole town of Compiegne is only 68 KB and that for the entire Oise *département* is only 3 MB. As a source digital map, we used a NavteQ database. In this map, coordinates are expressed in the French Lambert 93 projection system.

We now report results that we obtained from a 5.7 Km test (see Fig. 5) with the car shown in Figure 6.

Fig. *5. Overview of the test site with the trajectory*

Fig. *6. Car used in the experiments*

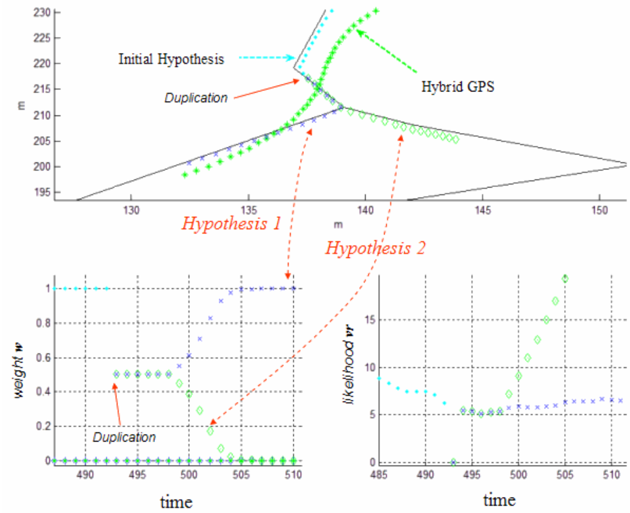

Fig. *7. Hypothesis creation at a road-intersection*

To illustrate the MHMM mechanism at intersections, Figure 7 shows a real case. An initial hypothesis (shown in dotted, light blue lines) arrives at the threshold distance Δ (here Δ=7m) from the end of the road. This road-end is connected to two different roads. The initial hypothesis is therefore divided into two new hypotheses (one is shown as 'x' and the other as '◇'). The HGPS is shown as '*'. Changes in weight w and instantaneous absolute likelihoods of the two created hypotheses vr are shown respectively in the curves on the lower left and lower right.

The left-hand side of Figure 8 shows all the hypotheses during an on-road test in Compiègne. On the right-hand side, the most likely hypothesis is shown at each point in this trial.

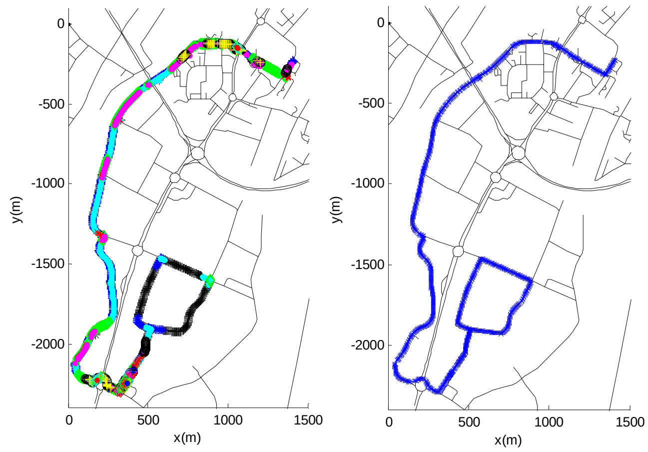

Fig. 8 *Hypotheses and the most likely one during an on-road trial.*

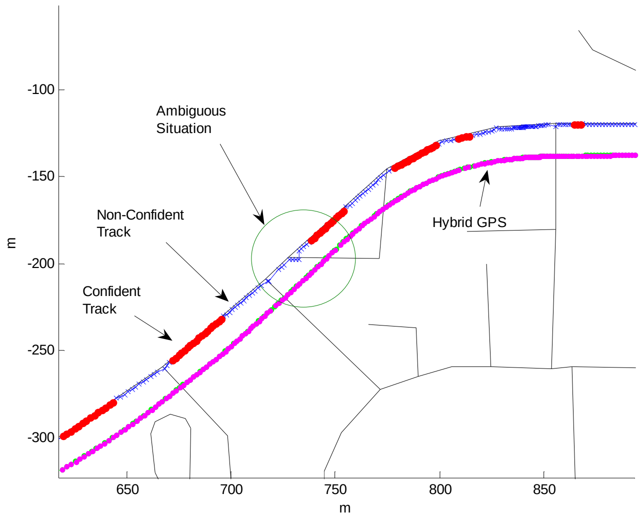

Fig. *9 Most likely hypothesis, integrity and hybrid GPS*

During on-road tests, different sensor data {GPS, wheel speed sensors, yaw rate gyro and video cameras} were acquired and saved into timestamped data files. The cameras provided different views of the vehicle's environment.

In the laboratory, we developed a "Data player" to replay and process the sensor data in similar conditions as real time. While replaying the stored localization data the player can also read images acquired by the cameras, and using this method an operator is able to know exactly, from the map and the video, which road the car is traveling on. Figure 10 gives a screenshot of a player we used.

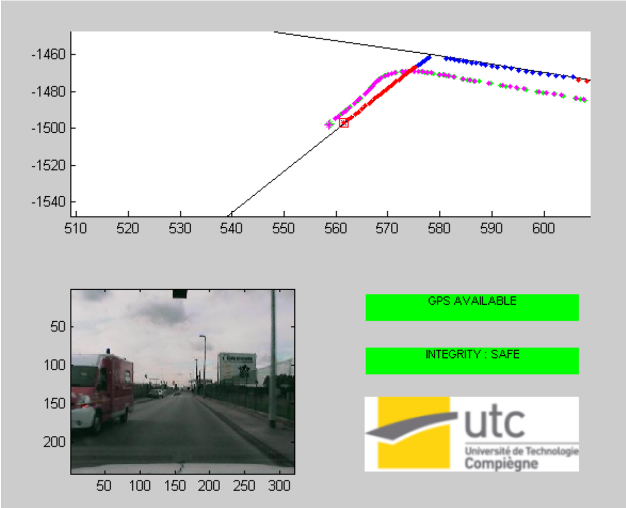

Fig. 10 - *Data player with video monitoring for the data analysis*

Figure 9 shows the integrity computation result from the most difficult part of the trial (upper part of Fig. 8). The Most Likely Hypothesis (denoted by MLH) is shown as '+', the hybrid GPS as '.', and we can clearly see that the map is offset with respect to the GPS. When the MLH is shown in bold, it means that it is considered worthy of confidence. The integrity indicator is here the bold line. We draw the reader's attention to the ambiguous situation indicated by the circle. Because of the map offset, the MLH is not the appropriate one. Nevertheless, the confidence indicator clearly indicates that the output is not likely. This correctly corresponds to the reality on the ground.

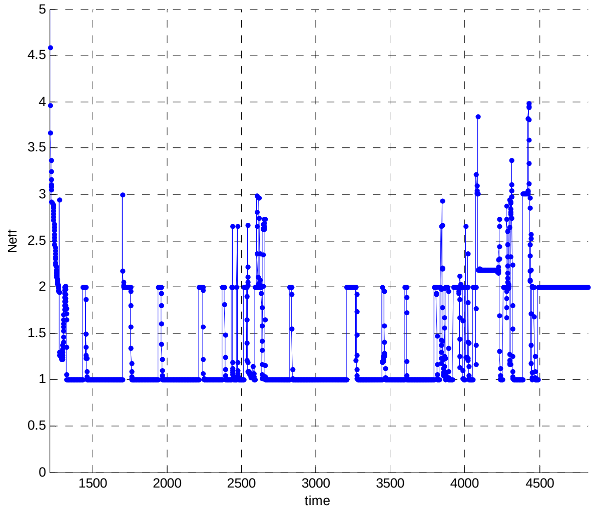

Fig. *11 Number of effective filters during the road test*

Figure 11 shows results regarding the number of efficient hypotheses N_{eff} during the test. Different values of N_{eff} were matched up with the following geographical cases: $N_{eff} \cong 1$ is often obtained for the case where the vehicle is running on segment, far from an intersection, with the associated trajectory having a fairly large weight. $N_{eff} \cong 2, 3, 4$ is generally obtained when approaching an intersection, with, respectively, 2, 3, 4 roads in the upcoming intersection.

With nominal settings, 97% good matches were obtained between the most likely hypothesis and the actual position of the vehicle. It was confirmed that the incorrect matches correspond to ambiguous situations correctly detected by the MHMM. The NIS threshold is less sensitive. In practice, we used a constant value corresponding to a $\text{Threshold}_2 = 6$ (which corresponds to a False Alarm probability of 0.05). If the errors are Gaussian, then the NIS follows a χ^2 distribution (with 2 degrees of freedom here). Usually [8], the accuracy requirement of a GNSS navigation system is specified at the 95th percentile, i.e. for any estimated position at a specific location the probability that the positioning error is within the accuracy requirement should be at least 95%.

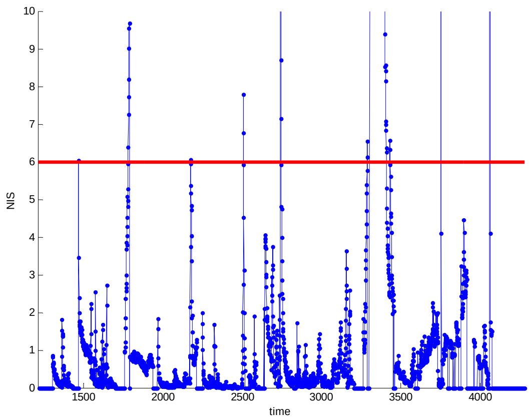

***Fig.** 12. NIS test between the Most Likely hypothesis and the HGPS*

Figure 12 shows the result of a Chi-Square test on the NIS between the most likely hypothesis and the HGPS. The bold line is the χ^2 threshold corresponding to a tail of 5%. The number of NIS points that are higher than this threshold is 4.3% of the total number of points. Thus, this result is coherent with the range of 5%. It also indicates that the Gaussian assumption regarding the noise distribution is in practice justified. The peaks in the NIS curve correspond either to false matches or to map errors (important map offsets).

Let us examine how the threshold on the number of effective hypotheses (Threshold_1) has an effect on the results of the integrity monitoring. To this end we consider the False Alarm (FA) and Missed Detections (MD) rates, as in [17]. We declare that there is a false alarm when the integrity computation asserts that the system is non-confident, while its output is correct. A missed detection is observed when the computation indicates that integrity is checked while it is not.

Let FAR denote the FA rate and MDR the MD rate. The Overall Correct Detection Rate is defined as OCDR=1-FAR-MDR [17].

Figure 13 and Table 2 show respectively the FAR and the MDR, and the FA and MD, for different N_{eff} thresholds for an on-road test composed of 3661 positions. We clearly see that if the threshold on N_{eff} is high (more permissive), the FA number decreases, but the number of MD increases. The OCDR, which is a global indicator on the good behavior of the integrity computation, increases also.

N_{eff} *Threshold*	**FA**	**MD**	OCDR
1.1	536	4	**85.25**
1.2	527	5	**85.47**
1.5	467	6	**87.08**
1.7	403	7	**88.80**
1.9	**395**	**15**	**88.80**

***Table** 2. Statistics for 3661 samples.*

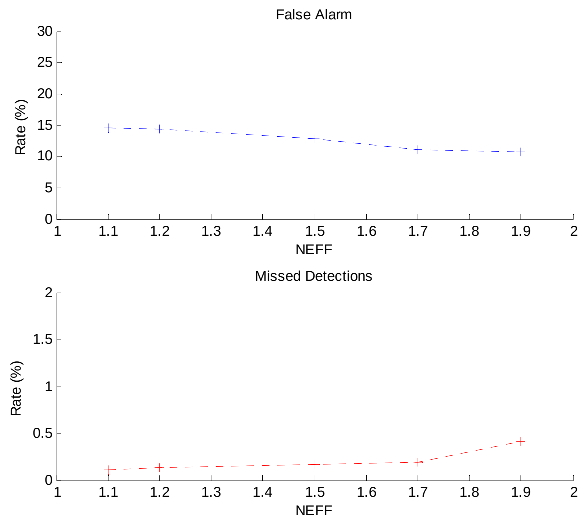

***Fig.** 13. False Alarms and Missed detections versus the number of effective hypotheses threshold.*

We observe that our integrity monitoring is cautious, since the FAR is high, entailing an availability of 85-88% for the MM. We observe also that the MDR is low (<0,5%) which is a good performance. If this criterion is crucial, the N_{eff} threshold has to be tune to a low value close to 1.

VI. Conclusion

This paper has presented a map-matching method that relies on multi-hypothesis tracking for on-road vehicles. This method combines proprioceptive sensors with GPS and map information. The main idea behind this approach is to associate a hypothesis with each newly-encountered road after an intersection or roundabout. The likelihood of each available hypothesis is evaluated by computing a recursive weight through a likelihood that updates the weight of the different hypotheses. We have proposed a simple integrity monitoring strategy that relies on two indicators. The decision rule we have proposed takes account of consistency of estimated location with the map, as well as the respective probabilities of different hypotheses to handle ambiguity zones. Real tests were carried out in real road conditions and results illustrate the performance of the method.

A direct perspective of this research is to enhance MHMM integrity computation while approaching intersections, since we have remarked that our strategy is too cautious in such cases. One idea is to merge closed hypotheses before applying the decision rule. Another perspective is to test this strategy with extensive road tests.

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