# Towards an Estimate of Confidence in a Road-Matched Location

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*Abstract* - **This paper describes a method that provides an estimated location of an outdoor vehicle relative to a digital road map using Belief Theory and Kalman filtering. Firstly, an Extended Kalman Filter combines the DGPS and odometer measurements to produce an approximation of the vehicle's pose, which is then used to select the most likely segment from a road network database. The selection strategy merges several criteria based on distance, direction and velocity measurements using Belief Theory. In this work, a particular attention is given to the elaboration of a Localization Uncertainty Gauge which takes into account imprecision of data sources (the sensors and the map) and uncertainty of the techniques used in the fusion process. This Gauge indicates the level of confidence assigned to the selected road by the system. Real experimental results illustrate this approach.**

***Index Terms – Outdoor Localization, Sensor Fusion, Belief Theory, Extended Kalman Filtering, GIS, GPS.***

## I. INTRODUCTION

Outdoors mobile robots currently hold the attention of many researchers because they can bring solutions to many applications related to transport of passengers in urban environments. An example of such a robot is the *Cycab* [9]. The robot needs to know its position on the road network for navigation needs, but also to recover the attributes associated with these data bases. Examples of attributes are authorized maximum speed, the width of the road, the presence of landmarks for precise localization, etc. Unfortunately, the precise localization on a map cannot be guaranteed because there are always errors on the estimate of the position (GPS, proprioceptive sensors) and, because the map represents a deformed sight of the world (for example, roads are not charted). A solution to deal with this problem consists in seeking to locate the robot on the road network and, at the same time, to calculate an indicator of confidence in this positioning which is called here the "Localization Uncertainty Gauge" (*LUG*).

The quality of an absolute localization on a map depends mainly on the quality of the road-matching process which is a complicated problem when seeking to obtain reliable, precise and robust vehicle positioning on the road network [2], [5], [13].

Outdoor positioning systems often rely on GPS, because of its affordability and convenience. However, GPS suffers from satellite masks occurring in urban environments, under bridges, tunnels or in forests. GPS appears then as an intermittently-available positioning system that needs to be backed up by a dead-reckoning system [1]. In [5], the method is based on the use of encoders positioned at the rear wheel of a robot. We use these sensors to measure elementary rotations of the wheels and to estimate the displacement of the robot. Thus, a dead-reckoned estimated pose is obtained by integrating the elementary rotations of the wheels using a differential odometric model. The multisensor fusion of GPS and odometry is performed by an Extended Kalman Filter (denoted EKF in the following).

The selection of candidate roads is the first stage of the road-matching problem [12]. Generally, this involves applying a first filter which selects all the segments close to the estimated position of the vehicle. The goal is then to select the most likely segment(s) from this subset. Nowadays, since the geometry of roadmaps is more and more detailed, the number of segments representing roads is increasing. The robustness and complexity of the localization depends mainly on the road selection module. In order to be focused on this point, an accurate map Géoroute V2 provided by the French National Institute of Geography (IGN) was used in this work. Our strategy is based on the fusion of several criteria using distance, direction and velocity measurements within the framework of Belief Theory.

The pose obtained by GPS and odometry can be more accurately estimated by fusing the selected segment. The key idea is to model the fact that the true position of the vehicle is located around the centerline of the most likely road. This region depends mainly on the width of the road, which is an attribute also stored in the database. We suggest using the most likely road in order to build a new Kalman observation with its estimated associated error.

In parallel with the localization process, we propose a way to compute the *LUG* which quantifies the confidence in the road-matched location. This computation is done by taking into account the imprecision of the EKF sensor fusion stage, the uncertainty of the road selection and the topology of the charted road network around the estimated absolute position. The LUG is the novelty relatively to previously published material [5].

The outline is as follows. Section II describes the architecture of the road-matching method. The state space formulation and the observation equations are detailed. In Section III, we discuss the problem of road selection and we present the formulation of the problem in the framework of Belief Theory. The way of calculating the LUG is then presented. Finally, real data results are presented in section IV.

## II. PRINCIPLE OF THE ROAD-MATCHING METHOD: MULTI-SENSOR FUSION

The road-matching problem probably does not have an ideal solution. All developed methods have their advantages and their disadvantages and are optimized for the applications they were designed for [11], [13].

In addition, the techniques used to address this problem are in permanent evolution. Some problems solved today can disappear and other can appear. For example, improvements in satellite positioning systems have tended to reduce absolute positioning errors. On the other hand, making an accurate road network increases the number of points describing arcs, thus making more complicated the segment selection problem.

The road-matching method described in this section relies on Kalman filtering like in [7]. The proposed approach can be described by Figure 1. Firstly, the algorithm combines the ABS measurements with a GPS position, if it is available. Then, using this estimate, the credible roads are selected. If at least one segment is credible, a map observation is built and merged with the other data in a second Kalman filter estimation stage. We suppose that the reader is familiar with this formalism, so only the state-space representation will be detailed, i.e. the state vector, the motion model, the observation model and the covariance of the errors.

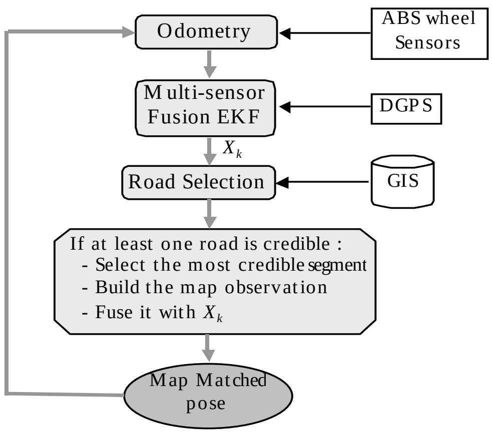



Fig. 1. Synoptic of the road-matching method.

### A. *Localization and heading estimation by combining odometry and GPS*

Let us consider a car-like vehicle with front-wheel drive. The mobile frame is chosen with its origin M attached to the center of the rear axle. The x-axis is aligned with the longitudinal axis of the car (see Fig 2).

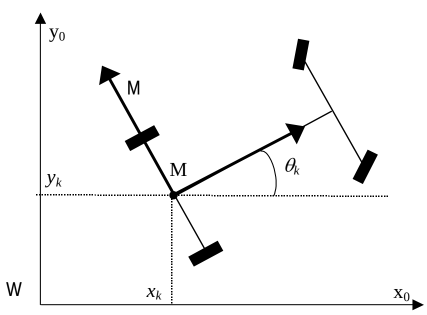



Fig. 2. The mobile frame attached to the car.

The vehicle's position is represented by the $(x_k, y_k)$ Cartesian coordinates of M in a world frame. The heading angle is denoted $\theta_k$. If the road is perfectly planar and horizontal, and if the motion is locally circular, the motion model can be expressed as [8], [3]:

$$\begin{cases} x_{k+1} = x_k + \delta_s.cos(\theta_k + \delta_\theta/2) \\ y_{k+1} = y_k + \delta_s.sin(\theta_k + \delta_\theta/2) \\ \theta_{k+1} = \theta_k + \delta_\theta \end{cases} \quad (1)$$

Where $\delta_s$ is the length of the circular arc followed by M and $\delta_\theta$ is the elementary rotation of the mobile frame. These values are computed using the ABS measurements of the rear wheels. Let denote $X_k$ the state vector containing the pose.

### B. *Observation equations: GPS and MAP*

When a GPS position is available, a correction of the odometric estimate is performed using an EKF updating stage. If the GPS satellites signal is blocked by buildings or tunnels, for example, the motion model provides an odometric estimate that can drift unboundedly.

This approximation of pose is used to select the most likely segment(s) from the database. If several segments are candidates, they constrain a sub-part of the state space (see Fig. 3).

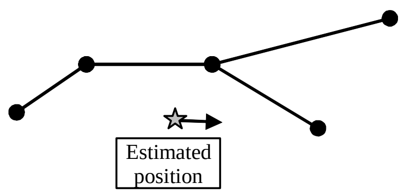



Fig. 3 Most likely segments extracted from the database.

A way to fuse these segments with the previous estimate of the pose is to use them to build "map observations" and to apply a second update Kalman stage.

The map observations can be obtained by projections onto the segments: if the orthogonal projection onto line (AB) does not make part of the segment [AB], the closer extremity is kept.

If several segments are candidates, the observation is multi-modal. Two main strategies can deal with this multimodality:

- The management of multi-hypotheses [10]
- The selection of the most likely segment from the segment set.

The management of multi-hypotheses is theoretically the ideal solution. Nevertheless, implementation is complicated because of combinatorial problems.

In this paper, the second solution is considered because of the simplicity of processing. The major drawback of this strategy is that the estimated location can be attributed to the wrong road, particularly when GPS measurements are not available. For this reason, we propose to manage an Uncertainty Gauge which indicates the ambiguousness of the location of the vehicle relative to the map.

The most likely segment is used to construct a map observation, denoted $(x_h, y_h)$, and its associated error.

Therefore, the complete observation equation becomes linear:

$$Y = \begin{bmatrix} x_{gps} \\ y_{gps} \\ x_h \\ y_h \end{bmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \cdot \begin{pmatrix} x \\ y \\ \theta \end{pmatrix} + \beta_k \qquad (2)$$

Where ($x_{gps}$, $y_{gps}$) is the GPS position measurement and ($x_h$, $y_h$) is the map observation.

The GPS measurement error can be estimated in real time using the NMEA sentence "GST" provided by the Trimble AgGPS132 receiver which has been used in the experiments. Therefore, the GPS noise is not stationary.

If we assume that the GPS position and the map observation errors are not correlated, the covariance matrix of the complete measurement Y can be separated into two parts:

- $Q_{gps}$: covariance matrix of the GPS error
- $Q_h$: covariance matrix of the map observation error.

It has turned out that a Gaussian ellipse which encloses the road works well. This ellipse has its semi-major axis very long (for example 1 sigma error about one hundred meters) and its semi-minor axis equals to the width of the road [5].

$$\boxed{Q_{gps}} \qquad Q_k = \begin{pmatrix} \sigma^2_{x,gps} & Q_{xy,gps} & 0 & 0 \\ Q_{xy,gps} & \sigma^2_{y,gps} & 0 & 0 \\ 0 & 0 & \sigma^2_{x,h} & Q_{xy,h} \\ 0 & 0 & Q_{xy,h} & \sigma^2_{y,h} \end{pmatrix}_k \qquad \boxed{Q_h} \qquad (3)$$

The covariance matrix $Q_k$ being block-diagonal, the GPS and map observations can be used in two separated Kalman filter estimation stages. This is an important issue for the real time implementation of the filter.

## III. Road Selection Using Multi-Criteria Fusion

The goal of the road selection process is to extracted the most-likely segments from the Geographical Information System (GIS) database knowing the estimate of the pose $X=(x,y,\theta)^t$, the previous matched road and extra attributes like traffic direction.

In order to take into account the error estimation, a Gaussian ellipse is built using the co-variance matrix P of the state vector $X$ [7]. On Figure 4, the speed V is the mean speed of the rear wheels.

In order to speed up the treatments (a map contains thousands of roads, each one having several segments), a first filter selects the *n closest* road segments $\{S_1,\ldots, S_n\}$ that are located within a radius of 100 meters, for example. The center of the circle is the estimation of the current position $(x, y)$ of the car. A circle has been used since it is a functionality of the GIS software *Geoconcept* that has been used in this work. For robustness considerations, the size of the circle is kept constant. Indeed, one could reduce the search area by having a radius function of the estimated covariance. This choice is not robust because, if the previous matched road was erroneous, the observer can diverge.

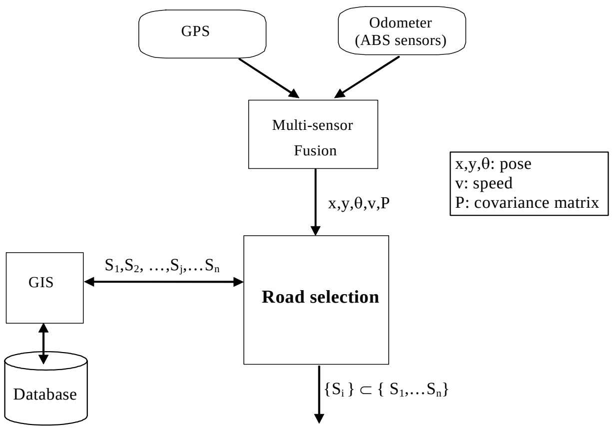



Fig. 4. Road selection strategy.

The problem is to select the 'good' segments from the subset $\{S_1,\ldots, S_n\}$: this is the Road Selection Problem, also called Road Reduction Filter [12].

This stage is difficult because,

- The position is estimated with errors which can be increased by multi-path effects,
- The coordinates of the segments contain errors due to inaccurate terrain measurements by cartographers and because of numerical approximation,
- The road network of the database does not always correspond to reality, i.e. it can contain old roads which no longer exist, and newly-built roads might not yet be included in the database,
- The map does not contain all road network details. For example, a roundabout can be represented as a simple point,
- The vehicle is moving on a 3D surface whereas the map represents a plane sight,
- The vehicle does not run exactly on the segments representing the roads.

Our road selection method combines several criteria using Belief Theory. This approach is very flexible and allows partial knowledge to be taken into account. This section first presents the concepts of Belief Theory. The criteria for selection will then be described, and finally the combination of data will be illustrated by a simple example and some real experiments.

### A. *Criteria notion in the Belief Theory framework*

Belief Theory allows uncertainties to be incorporated into calculations and provides a way of combining uncertain data. This theory was introduced by Dempster [4] and mathematically formalized by Shafer in 1976. It is a generalization of Bayes Theory in the treatment of uncertainty. Generally, this theory is used in a multi-sensor context to merge heterogeneous information in order to obtain the best decision.

The basic entity is a set of all possible answers (also called hypotheses) to a specific question. This set is called the frame of discernment and is denoted Θ. All the hypotheses must be exclusive and exhaustive and each subset of the frame of discernment can be a possible answer to the question. The degree of belief of each hypothesis is represented by a real number in [0, 1] called the mass function m(.). It satisfies the following rules:

$$\begin{aligned} & m(\phi) = 0 \\ & \sum_{A \subseteq \Theta} m(A) = 1 \end{aligned} \tag{5}$$

A mass function is defined for all the different evidences. Each evidence $A$, for which $m(A) \neq 0$, is called a focal element.

The two criteria chosen in this article can be formulated as follows:

- The vehicle location is close to a segment of the neighborhood. This criterion depends on the error ellipse,
- The segments on which the vehicle can be located are those which have an angle approximating to the direction of the vehicle. This criterion depends on the estimated $3\sigma$ bound of the direction and on the speed of the car.

Belief Theory requires the assignment of elementary probabilistic masses defined on [0, 1]. The mass assignment is computed on the definition referential $2^{\Theta}$:

$2^{\Theta}=\{\varnothing, H_1, H_2, \dots H_n, H_1 \cup H_2, \dots, H_i \cup H_j \cup H_k \cup H_l \cup \dots H_n\}$.

This distribution is a function of the knowledge about the source. The total mass obtained is called the “basic mass assignment”. The sum of these masses is equal to one. Each expert - also called source of information - defines a mass assignment according to its opinion about the situation.

In order to build mass assignments, we shall examine the inaccuracy of the various information sources (GPS, odometer and digital map) and physical observations like, for example, a car traveling at 40 m/s cannot be orthogonal to the direction of the segment. With this approach, information sources (i.e. criteria) are worked out from sensors.

The problem of mass assignment of each criterion can be tackled in a global or local way. The global strategy involves examining simultaneously all the segments selected around an estimated position when assigning masses. The local strategy treats each segment separately with respect to the criterion under consideration. Both strategies have been studied. We have concluded that the local strategy is the more effective, especially for a real-time application.

The frame of discernment that we use is $\Theta$ = {Yes, No}, corresponding to the answer to the following question: is this segment the good one? The definition referential is then $2^{\Theta}$ = {Yes, No, Perhaps}. In this paper, we use two credibilist criteria: proximity criteria and heading and velocity criteria [5]. This kind of road selection method is an open one for the integration of other criteria. One can remark that the use of the road network topology can be fruitful.

## B. Criteria Fusion

To obtain more reliable information from two different single sources $S_1$ and $S_2$, a combination of their mass assignments can be performed using Demspter-Shafer’s rule. Let $A_i$ and $B_i$ be assumptions of the definition referential $2^{\Theta}$. The merging of the knowledge of $S_1$ and $S_2$ is given by:

For all A in $2^{\Theta}$ = {Yes, No, Perhaps}

$$m_{\Theta}(A) = \sum_{A_i \cap B_j = A} m_{\Theta}^{S_1}(A_i).m_{\Theta}^{S_2}(B_j) \tag{6}$$

If the rule $m(\phi)$=0 is not satisfied a re-normalization step is necessary. The coefficient of re-normalization is called $k_\theta$ and is defined as:

$$k_\theta = \sum_{A_i \cap B_j = \phi} m_{\Theta}^{S_1}(A_i) m_{\Theta}^{S_2}(B_j) \tag{7}$$

It represents the incoherence between the different sources. If we set $K_\theta = \frac{1}{1-k_\theta}$, the normalized expression of the combination is given by:

$$m_{\Theta}(A) = K_\theta \cdot \sum_{A_i \cap B_j = A} m_{\Theta}^{S_1}(A_i).m_{\Theta}^{S_2}(B_j) \tag{8}$$

This combination rule is independent of the order in which evidences are combined, when more than two evidences are involved.

Associated with each basic assignment, belief (*Bel*) and plausibility (*Pl*) are defined by:

$$Bel(A) = \sum_{B \subseteq A} m(B) \quad Pl(A) = \sum_{B \cap A \neq \phi} m(B) \tag{9}$$

After the combination step, several decision rules can be used to obtain the final result. It is then possible to adjust a desired behavior. If an optimistic decision is desired, the maximum of plausibility has to be used. For a pessimistic decision, one can apply the maximum of belief. Many other decision rules exist in Belief Theory, especially for non-exhaustive frames of discernment.

The decision-making strategy adopted here is to keep the most credible segments according the law of ideal decision. The likelihood of a singleton assumption is characterized by two quantities (belief and plausibility) which are calculated using the set of masses. These quantities respectively correspond to the minimal probability and the maximum probability of that assumption’s being true. Consequently, a law of decision without ambiguity is when an assumption has a belief higher than the plausibility of any other assumption.

The conflict computed in the Dempster-Shafer fusion rule is large when the two criteria are in total confusion. Therefore, we eliminate the segments which present a significant conflict. Experimentally, we have taken a threshold equals to 0.5.

## C. Making use of topology

It is important to distinguish, on the one hand, road-matching methods that use known facts about a vehicle intended route, and on the other hand methods that do not use such information. Knowing the vehicle intended route can make the road-matching more easier since the search of possible segments is more restricted. For example, matching the location of a vehicle along its pre-calculated route is a relatively easy task since the vehicle is expected to follow a fixed set of segments in a predetermined sequence. However, confining the search space to only “expected to be traveled” segments is not always a good idea since the vehicle can unintentionally deviate from this itinerary. Therefore, in our work, we avoid using route information in the Road Selection Stage.

It is also customary to distinguish road-matching methods that use only geometric information [2] from those that make use of topological information [6]. When using only geometric information, one can only make use of the "shape" of the segments and not of the way in which they are connected. Topological information makes use of the geometry of the arcs as well as the connectivity and the contiguity of the segments. This makes the topological solution much more reliable. Indeed, considering the topological characteristics of the network and the progression of the car along this network prevents the algorithm from jumping between one road and another. More generally, the integration of additional criteria in the road selection stage can improve the robustness of a road-matching algorithm.

Thus, two binary tests have been added to the two credibilist criteria:

- Test of connectivity to the segment on which the vehicle was matched at the previous stage, if this segment existed,
- Test of comparison between traffic direction, stored in the database and the estimated heading of the vehicle. This criterion is very effective for removing ambiguity in case of parallel roads.

### D. *Localization Uncertainty Gauge (LUG)*

As described above, our Road Selection method keeps only the most credible segment and, therefore, can be mistaken. The elaboration of an Uncertainty Gauge associated with the road matching results is therefore a key point. For this purpose, we propose to consider all the issues that occur in this problem:

- The imprecision of sensors measurements, the imprecision of road network database and the imprecision of the EKF pose estimate,
- The behavior of the decision strategy used in the multi-criteria fusion process,
- The geometrical and topological configuration of the roads all around the estimated pose.

Imprecision is naturally taken into account thanks to the Kalman formalism: the evolution and the observation errors of the state space representation are modeled as zero mean additive white noises. Moreover, the pose imprecision acts directly on the elaboration of the proximity and heading criteria.

The Road Selection decision method being local (the segments are treated one by one) an analysis of the neighboring road network has to be done. If an ambiguous situation occurs, the credibility of the selected road is in doubt. The resulting certainty must be decreased and propagated for the next steps. This kind of ambiguous situation is frequently met while approaching junctions or crossroads.

In case of "parallel arcs", the credibility of the selected segments must be decreased until the availability of an unambiguous map measurement. In this case, the use of the connectivity test must be cancelled.

Therefore, the belief value given by the decision law to the selected segments is at the root of the computation of the *LUG*. It naturally takes into account the different imprecisions. In order to consider in addition the ambiguousness of the topology configuration of the road network all around the estimated pose, we propose to multiply the belief value given to each selected segment by a scalar number which we call TCCRN like *Topological Coefficient of the Charted Road Network*. Its values depend on the situation and are described in table I.

$$LUG(S) = Bel(S).\ TCCRN \qquad (11)$$

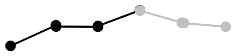
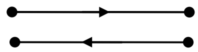
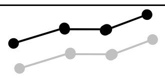
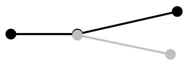
| | Ambiguousness | | |
|---|---|---|---|
| TCCRN | Situation | Description | Nature |
| 1 | 1 segment |  | Non ambiguous |
| 0.9 | 1 arc of several segments |  | Non ambiguous |
| 0.8 | 2 connected arcs |  | Non ambiguous |
| 0.7 | 2 parallel one-ways segments with opposite driving direction |  | Non ambiguous if direction is available |
| 0.6 | Non related parallel arcs |  | Ambiguous |
| 0.5 | Junction |  | Ambiguous |

TABLE I: Topological Coefficient of the Charted Road Network.

The *TTCRN* is a weighting factor the range of which has been chosen to be in the interval [1 0.5]. In this way, while approaching a junction, two segments having locally a Belief equals to one will have a LUG equals to 0.5 which indicates a totally ambiguous situation.

## IV. EXPERIMENTAL RESULTS

Three tests have been carried out at Compiègne with our experimental car (Fig. 5). We have used a differential Trimble AgGPS132 receiver and the ABS sensors of the rear wheels of the car.

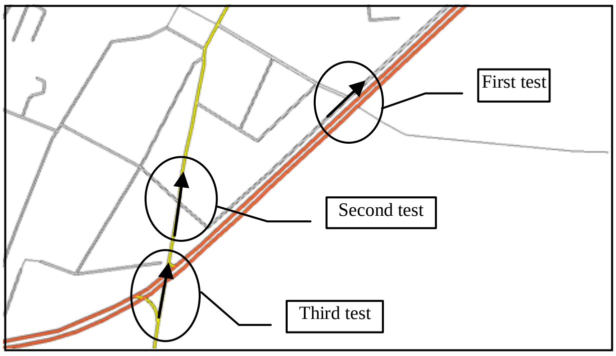



Fig. 5. Top view of the three tests.

On Figures 6, 7 and 8, the (+) sign represents the DGPS position and the (**.**) sign represents the result of the fusion of the GPS, the ABS sensors and the Map. The numerical values of the LUG are indicated for a point on 5.

Since the first situation is very complicated and ambiguous, the LUG is often low. As the matter of fact there are three parallel roads and the crossing of a crossroads. First, one can remark that the crossroads has not effect. This is due to the fact that the orthogonal roads are not credible thanks to the heading criterion.

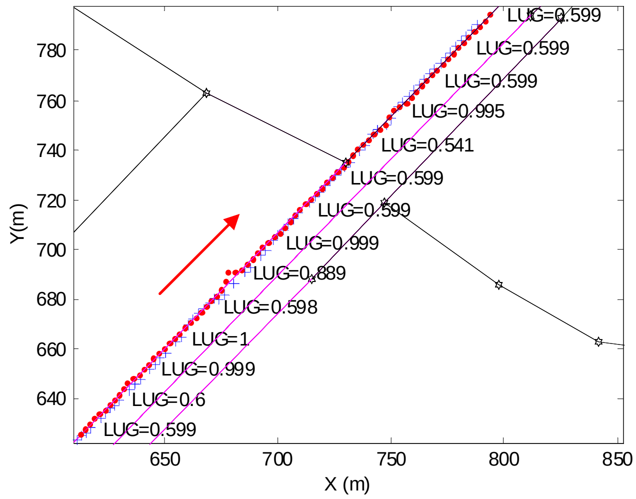



Fig. 6. Algorithm results obtained during the first test.

Moreover, we can see that the values of the LUG vary between ≈0.6 and ≈1. Indeed, the most credible segment has a very high Belief (Bel ≈1) since the estimated position is approximately on the road and, sometimes, a segment of the nearest parallel road is declared credible which induces a “Non related parallel arcs” situation (cf. Table I).

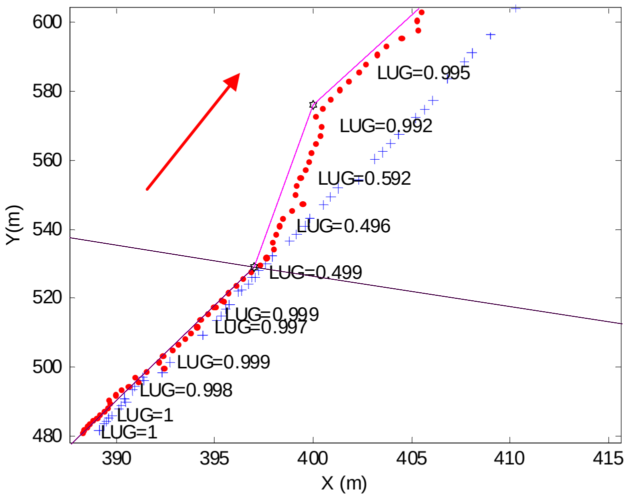



Fig. 7. Second test.

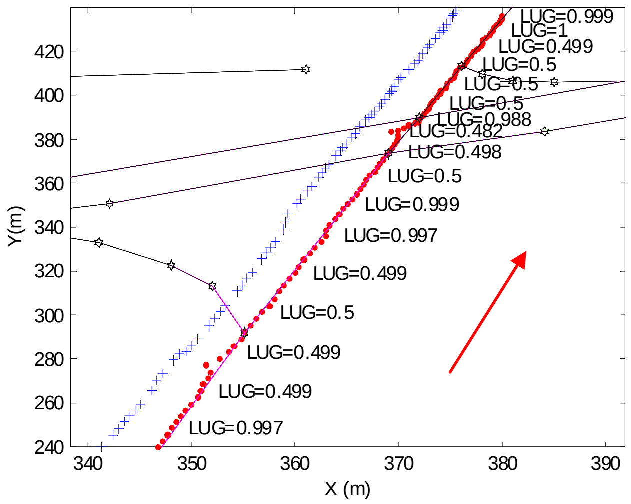



Fig. 8. Third test.

Figures 7 and 8 illustrate the approach of more ambiguous junctions because the roads are not orthogonal. In these cases, the LUG correctly represents the certainty of the locations of the map.

On Fig. 7, one can notice that the map presents an offset of several meters after the crossroads: this offset is due to cartographers’ errors. Nevertheless, the LUG converges towards 1 when the situation becomes unambiguous although the error of the chart is significant. Moreover, one can notice that the fusion of the GPS and the map data is not a simple projection on the road segment.

Finally, on Fig.8, the GPS points and the map have a constant offset which affects a little the LUG. Its numerical value logically varies between 0.5 and 1.

## V. Conclusion

This article has presented a road-matching method based on a multi-sensor fusion approach and a technique to quantify the confidence in a road-matched location which is the main contribution of this work. Our methodology relies on the use of a map observation in the Kalman filtering context and on the use of a road selection method based on multi-criteria fusion using Belief Theory.

The experimental results show the validity of the calculation of the *LUG* which can be an input to many robotics applications in which one uses an absolute positioning on maps and wants to manage the confidence on the estimated locations in order to qualify the trust in the system. This is a first step toward integrity.

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