INTELLIGENT VEHICLE ABSOLUTE LOCALISATION METHOD USING GIS INFORMATION A DATA FUSION APPROACH

Maan E. EL Najjar[1] **and Philippe Bonnifait**[2]
[1] *Loria – Campus Scientifique, BP.239 54506 Vandoeuvre-lès-Nancy, France*
[2] *Heudiasyc UMR CNRS 6599 Université de Technologie de Compiègne*
BP 20529, 60205 Compiègne Cedex, France.
badaoui@loria.fr philippe.bonnifait@hds.utc.fr

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 GPS and odometer measurements to produce an approximation of the vehicle 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 and a dedicated fusion operator. Thanks to this methodology, a Localization Uncertainty Gauge can be computed. This gauge indicates the level of confidence assigned to the selected road by the system. Real experimental results illustrate this approach.

Keywords: Sensor Fusion, Intelligent Vehicle, Localisation, Belief Theory, GPS, GIS.

1. INTRODUCTION

Intelligent Autonomous Vehicles 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 vehicle is a *Cycab* (Pradalier 02). The vehicle needs to initially 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 represented). 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 *Localization Uncertainty Gauge* (LUG).

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 (Abott 99). A usual method is based on the use of encoders attached to the rear wheels of the vehicle. They measure elementary rotations of the wheels. A dead-reckoned estimated pose is obtained by integrating these elementary rotations starting from a known pose. The multisensor fusion of GPS and odometry is performed by an Extended Kalman Filter (denoted EKF in the following).

This work deals with absolute localisation on a digital map. The objective is to localise the vehicle on the frame of map and not on an arc or a segment representing the road in the map database. Many methods proposed in the last five years (Bernestein 98, Joshi 02, Greenfeld 02, Kim 01, Quddus 03, Zhao 03) are *arc-matching methods*, i.e. the estimated position of the vehicle is projected on the arcs representing the roads. In this case, the model of the world is a set of segments. Arc-matching methods therefore induce geometric distortions since the most accurate digital maps present a 15 meters absolute error and a 1 meter relative error.

Absolute localization is very useful for the following reasons. In several kinds of map database like those of the French IGN (Institut Géographique National), attributes are not attached to the arcs representing the roads but stored in the database like point objects with an absolute position. In reality, roads have some width. So, it is imprecise to suppose that the trajectory of the vehicle is reduced to a linear arc. The distortion induced by such an assumption is amplified if the network database is not accurate. Moreover, arc-matching methods are not adapted to automatic guidance of vehicles since the side variation is not observable: only longitudinal control is possible using speed values attached to the arcs.

On the other hand, GIS data contains some absolute location information and it is important to capture this information. The approach presented in this paper consists firstly in the selection of the more likely road. Then, its geometry is fused with the estimated pose. This provides an absolute location.

Generally, the road selection 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 road selection module is an important stage in the vehicle localization process because the robustness of the localization depends mainly on it. The road selection stage is also important because it reduces the number of roads to be processed, which is essential for a real time implementation. In order to be focused on this point, an accurate map Géoroute V2 provided by the IGN was used in this work. The selection strategy proposed is based on the merging of several criteria using distance, direction and velocity measurements within the framework of Belief Theory.

A more accurate location of the robot can be obtained by combining the selected segment with the pose estimated jointly by GPS and odometry. The key idea is to model the fact that the true position of the vehicle is located around the centreline of the most likely road. This region depends mainly on the width of the road, which is an attribute also stored in the database. The most likely road is proposed to be used in order to build a new Kalman observation with its estimated associated error.

In parallel with the localization process, a way to compute the LUG is proposed. The LUG quantifies the confidence in the road-matched location. This computation is done by taking into account the imprecision of the EKF sensor fusion stage and the uncertainty of the road selection stage of the method detailed in (El Najjar 05).

The outline of the paper is as follows. Next section describes the architecture of the localization method. The state space formulation and the observation equations are detailed. In section III, the road selection problem is discussed and a formulation in the framework of Belief Theory is exposed. Finally, real data results illustrate the performance of such an approach.

2. SENSOR FUSION FOR THE LOCALIZATION PROCESS

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 (Tanaka 90), (Zhao 97). The performances of many navigation systems seem to be sufficient. However, safety applications or autonomous urban areas navigation need a reliable localization on the map.

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 localization method described in this section relies on Kalman filtering. 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. It's supposed 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.

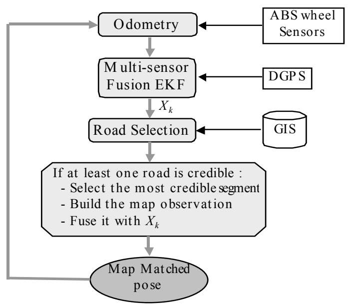


Fig. 1. Synoptic of the localization method.

2.1. *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).

The vehicle position is represented by the Cartesian co-ordinates (x_k,y_k) of M in a world frame. The heading angle is denoted θ_k. If the road is perfectly planar and horizontal, and if the motion is locally circular, the motion model can be expressed as (Tanaka 90, Bonnifait 01):

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

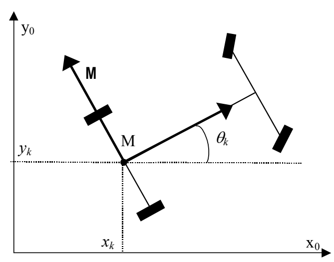


Fig. 2. The mobile frame attached to the car.

Where δs is the length of the circular arc followed by M, δθ the elementary rotation of the mobile frame. These values are computed using the ABS measurements of the rear wheels.

2.2. Observation equations: GPS and MAP

When a GPS position is available, a correction of the odometric estimation is performed using an EKF. If the GPS satellites signal is blocked by buildings or tunnels, for example, the motion model provides an odometric pose estimate.

This pose estimate is used to select the most likely segment(s) from the database. These segments are then used to build a second observation (this approach will be presented in section III). If several segments are candidates, they constrain a sub-part of the state space (see Fig. 3).

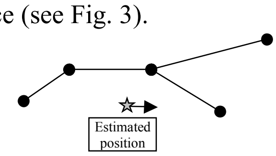


Fig. 3 Most likely segments extracted from the database.

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 (Pyo 00)
- 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 it is assumed 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.

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

Since Q_k is 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.

One way of combining the most likely segment with the other sensors is to treat it as an observation that is a function of the state vector. Much effort has been spent on modelling the map observation error in a realistic way. It has turned out that a Gaussian mixture which encloses the road works well (El Najjar 05).

3. ROAD SELECTION BY USING MULTI-CRITERIA FUSION

The road selection process can be described as on Figure 1. The multi-sensor fusion gives an estimation of the pose $X=(x,y,\theta)^t$. In order to take account of the estimation error, a Gaussian ellipse is built using the co-variance matrix P of the state vector X (El Najjar 05). The speed V is the mean speed of the rear wheels.

The question is now to select the most likely segment(s) using a Geographical Information System (GIS). In order to speed up the treatments (a map contains thousands of roads, each one having several segments), a first filter selects the n road segments $\{S_1,\ldots,S_n\}$ that are located within a radius of 100 meters, for example. The centre of the circle is the estimation of the current position (x, y) of the car.

The problem is to select the 'good' segments from the subset {S1,…, Sn}: this is the road selection problem, also called Road Reduction Filter (Taylor 01).

This stage is difficult because, the position is estimated with errors which can be increased by multi-path effects. In addition, the transformation between the GPS co-ordinates (WGS84 global system) and the French Lambert co-ordinates of the map introduces errors (<2m),

The co-ordinates 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.

The proposed 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.

3.1. 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 (Dempster 76) and mathematically formalised by Shafer in 1976. It is a generalisation 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:

$$\begin{aligned} & m(\phi) = 0 \\ & \sum_{A \subseteq \Theta} m(A) = 1 \end{aligned} \qquad (4)$$

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

As the application considered is related to road safety, only geometrical criteria are used because they are not influenced by human errors. This means that a criterion such as the speed of the vehicle is in accordance with the speed limitation is not considered.

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

- The vehicle location is close to a segment of the neighbourhood. 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 3σ 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^{Θ}.

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

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, the inaccuracy of the various information sources (GPS, odometer and digital map) should be examined and physical observations like, for example, a car travelling 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 used frame of discernment is Θ = {*Yes*, *No*}, corresponding to the answer to the following question: *is this segment the good one*? The definition referential is then 2^{Θ} = {*Yes*, *No*, *Perhaps*}.

In this paper, two credibilist criteria are used, proximity criteria and heading and velocity criteria. This kind of road selection method is open to the integration of other criteria.

Two binary criteria have been added to the two credibilist criteria in order to consider the topological characteristics of the network and the progression of the car along this network. This can prevent the algorithm from jumping between one road to another. More generally, the integration of additional criteria in the road selection stage can improve the robustness of the algorithm.

3.2. 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, A_i and B_i be assumptions of the definition referential 2^{Θ}. The merging of the knowledge of S1 and S2 is given by:

For all A in 2^{Θ} = {*Yes*, *No*, *Perhaps*}

$$m_{\Theta}(A)=\sum_{A_i\cap B_j=A} m_{\Theta}^{S_1}(A_i).m_{\Theta}^{S_2}(B_j) \qquad (5)$$

If conjunctions exist which are not focal elements, a re-normalisation step is necessary to satisfy the rule that $m(\phi)$=0. The coefficient of re-normalisation is called k_{θ} and is defined as:

$$k_{\theta}=\sum_{A_i\cap B_j=\phi} m_{\Theta}^{S_1}(A_i)m_{\Theta}^{S_2}(B_j) \qquad (6)$$

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

$$m_{\Theta}(A)=K_{\theta}\cdot\sum_{A_i\cap B_j=A} m_{\Theta}^{S_1}(A_i).m_{\Theta}^{S_2}(B_j) \qquad (7)$$

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

The equations of system (8) introduce a new fusion operator proposed to assign masses to assumptions in the definition referential $2^{\Theta} = \{Yes, No, Perhaps\}$. In these equations, $m_{12,i}()$ represent the assigned mass for the *i*th segment after the combination of the proximity criterion ($m_{1,i}()$) and heading criterion ($m_{2,i}()$) to assumptions *Yes*, *No* and *Perhaps* (denoted *Per* in the equations):

$$\begin{aligned}
m_{12,i}(Yes) &= m_{1,i}(Yes)m_{2,i}(Yes) \\
m_{12,i}(No) &= m_{1,i}(No)m_{2,i}(No) + m_{1,i}(No)m_{2,i}(Per) \\
&\quad + m_{1,i}(Per)m_{2,i}(No) \\
m_{12,i}(Per) &= m_{1,i}(Per)m_{2,i}(Per) + m_{1,i}(Yes)m_{2,i}(Per) \\
&\quad + m_{1,i}(Per)m_{2,i}(Yes)
\end{aligned} \tag{8}$$

This operator is pessimistic since, if one criterion says "*no*", the fusion result is "*no*" and since, if one criterion says "*perhaps*" and the other "*yes*", the result is "*perhaps*".

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

$$\begin{aligned}
Bel(A) &= \sum_{B \subseteq A} m(B) \\
Pl(A) &= \sum_{B \cap A \neq \phi} m(B)
\end{aligned} \tag{9}$$

These quantities respectively correspond respectively to the minimal and maximum probabilities of that assumption A being true.

After the combination step, several decision rules can be used to obtain the final result. It is then possible to adjust a desired behaviour. 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.

In decision-making, the strategy adopted here consists in eliminating the segments which are not credible from the point of view of the chosen criteria. A decision law to reject non credible segment without ambiguity and without conflict generation is when the belief of the assumption *No* is higher than the plausibility of other assumptions (*Yes* and *Perhaps*).

3.3. Localisation Uncertainty Gauge (LUG)

As described above, the 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, let consider all the issues that occur in this problem:

- The imprecision of the sensors measurements, the imprecision of the road network database and the imprecision of the EKF pose estimate,
- The behaviour 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 modelled 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 neighbouring 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 imprecision sources. 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.

$$\text{LUG} = Bel(S).TCCRN \tag{10}$$

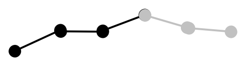
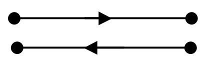
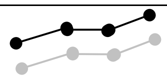
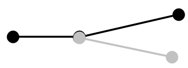
TCCRN	Ambiguousness		
	Situation	Description	Nature
1	1 segment		Non ambiguous
0.9	1 arc of several segments		Non ambiguous
0.8	2 connected arcs		Non ambiguous
0.7	2 parallel one-ways segments with opposite driving direction		Non ambiguous if direction is available
0.6	Non related parallel arcs		Ambiguous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

TABLE I Topological Coefficient of the Charted Road Network

4. EXPERIMENTAL RESULTS

A 20 minutes test has been carried out at Compiègne with the laboratory experimental car. A Tmble AgGPS132 receiver and the ABS sensors of the rear wheels of the car have been used. This section focuses on two potentially problematic situations presented on Fig. 5.

On Figures 6 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. 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.

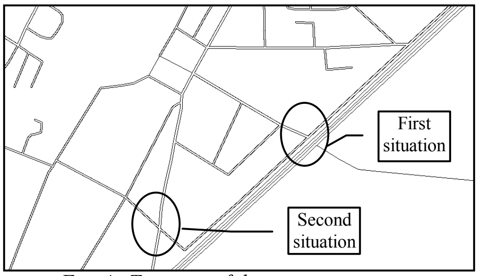


Fig. 4 . Top view of the two tests situations.

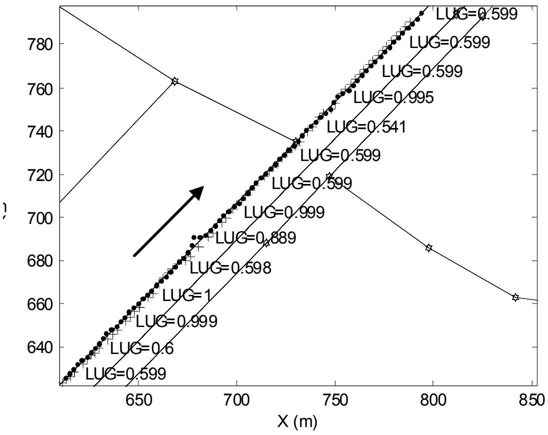


Fig. 5 . Algorithm results obtained during the first test.

Moreover, 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).

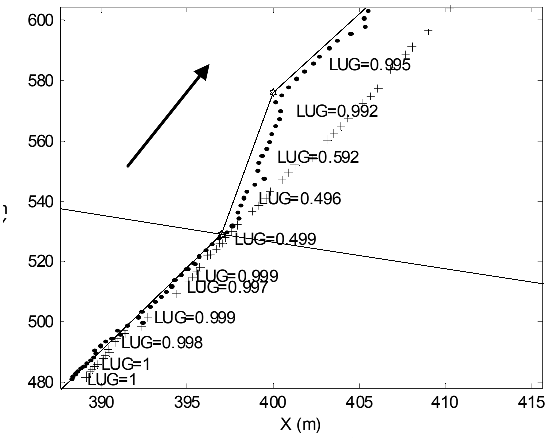


Fig. 6 . Second test.

5. CONCLUSION

This article has presented a localization method based on a multi-sensor fusion approach. The road selection stage being of crucial importance, a method based on the Belief Theory has been developed and a new fusion operator has been proposed. This methodology allows quantifying the confidence in the localization on the road network by using the belief value of the most credible segment and the geometry of the network around the estimated position. The selected segment is used afterwards to apply a new observation stage in the Kalman filtering context and to localize more precisely the vehicle on the map.

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.

6. REFERENCES

Abbott E. and Powell D. (1999). *"Land-Vehicle Navigation using GPS"*. Proc. of the IEEE, Vol. 87, No. 1.

Bernstein D and Kornhauser A. (1998). *"Map Matching for personal navigation assistants"*. 77th Annual meeting, The Trans Res. Board, Washington

Bonnifait Ph., Bouron P., Crubille P., Meizel D. (2001). *"Data Fusion of Four ABS Sensors and GPS for an Enhanced Localization of Car-like Vehicles"*. IEEE ICRA 2001 23-25, Séoul. pp. 1597-1602.

Dempster A.P. (1976). *"Upper and Lower Probabilities Induced by a Multivalued Mapping"*. Annals of Mathematical Statistics, vol.38.

El Najjar M. E. and Ph. Bonnifait. (2005) *"Road-Matching Method for Precise Vehicle Localisation using Kalman Filtering and Belief Theory"* Journal of Autonomous Robots, S.I. on Robotics Technologies for Intelligent Vehicles. Kluwer Academic Publishers.

Joshi R. (2002). *"Novel Metrics for Map-Matching in In-vehicle Navigation System"* Proc. of the IEEE Intelligent Vehicle Symposium pp.36-43.

Greenfeld J. (2002). *"Matching GPS Observations to Locations on a Digital Map"*, 81th Annual Meeting of the Transportation Research Board, January, Washington, DC.

Kim S. and Kim J.H. (2001). *"Adaptive Fuzzy-Network-Based C-measure Map-Matching Algorithm for Car Navigation System"*, IEEE Trans. On Industrial Electronics, Vol. 48, No. 2 pp. 432-441, April.

Pradalier C. and Sekhavat S (2002). *"Localization Space: a Framework for Localization and Planning, for Systems Using a Sensor/Landmarks Module"* Proc. of the IEEE Conf. on Robotics and Automation 2002.

Pyo Jong-Sun, Shin Dong-Ho Shin and Sung Tae-Kyung (2001), *"Development of a map matching method using the multiple hypothesis technique"* IEEE Intelligent Transportation Systems Conf. – Oakland (CA), USA – August 25-29.

Quddus M.A., Ochieng W.Y., Zhao L. and Noland R.B. (2003). *"A General Map Matching Algorithm for Transport Telematics Applications"*. GPS Solution 7(3), 157-167.

Tanaka J. Hirano K., itoh, T., Nobuta H. and Tsunoda S., (1990). *"Navigation System with Map-Matching Method"*. Proc of the SAE International Congress and Exposition, pp 45-50.

Taylor, G. and G. Blewitt (2000). *"Road Reduction Filtering Using GPS"*. 3th AGILE Conference on Geographic Information Science pp 114-120. Helsinki, Finland, May 25-27.

Zhao L., Ochieng W.Y., Quddus M.A. and Noland R.B. (2003). *"An Extended Kalman Filter Algorithm for Integrating GPS and Low-Cost Dead reckoning System Data for Vehicle Performance and Emissions Monitoring"* The Journal of Navigation 56, 257-275.

Zhao Y. (1997) *"Vehicle Location Navigation systems"*. Artech House, Inc.