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# Road Selection using Multi-Criteria Fusion for the Road-Matching Problem

Maan E. El Najjar and Phippe Bonnifait, *Member, IEEE*

**Abstract**— This paper presents a road selection strategy for novel road-matching methods designed to support real-time navigational features within Advanced Driving-Assistance Systems. Selecting the most likely segment(s) is a crucial issue for the road-matching problem. The selection strategy merges several criteria using Belief Theory. Particular attention is given to the development of Belief functions from measurements and estimations of relative distances, headings and velocities. Experimental results, using data from ABS sensors, differential GPS receiver and accurate digital roadmap, illustrate the performances of this approach, especially in ambiguous situations.

**Index Terms**— Localization, Sensor fusion, Belief Theory, Geographical Information System, Global Positioning System.

## I. INTRODUCTION

INTELLIGENT Autonomous Vehicles currently hold the attention of many researchers because they can provide solutions in many applications related to Intelligent Transportation Systems. One example of such a system is the transport of passengers in urban environments using a CyCab [16]. For navigational needs the vehicle first needs to know its position on the road network, and then to retrieve attributes from the appropriate databases. Examples of attributes are maximum authorized speed, width of the road, presence of landmarks for precise localization, etc. Unfortunately, the precise localization on a map cannot be guaranteed because there will often be errors in the estimation of position arising from sensor imprecision and because the map represents a deformed view of the real world: roads are represented by points — nodes and shaping points— that describe the geometry of the center line.

Vehicle localization on a map has two meanings in the literature of this domain. In many works [2], [11], [13], [18], [19], **Erreur ! Source du renvoi introuvable.** it refers to the projection of the absolute position estimate onto a segment of the road network stored in the database. In this case, the vehicle is localized when the curvilinear abscissa along the segment are known from the starting node. These —arc-matching— methods therefore introduce geometric distortions, since the model of the world is a set of segments, usually with a 10-meter absolute error and a 1-meter relative error. Alternatively, vehicle localization can refer to absolute localization in the map reference frame. In this case, the localization of the vehicle does not need a projection onto the

segments representing the road in the database. Absolute localization can be very useful for the following reasons. In several kinds of databases, including those of the National French Institute of Geography (IGN), attributes, instead of being attached to the arcs representing the roads, can be stored in the database as point objects with an absolute position. Moreover, it is imprecise to suppose that the real trajectory of the vehicle can be modeled by linear arcs. The distortion introduced by such an assumption is amplified if the network database is not accurate. In reality, roads have a non-negligible width and define areas (and not lines) within which the vehicle can navigate. Furthermore, arc-matching methods are not adapted to the automatic guidance control of vehicles since lateral variation is not observable: only longitudinal control is possible using speed values attached to the arcs.

The approach presented in this paper is an absolute localization method. The global positions provided by a GPS receiver are converted into the map frame and not projected onto the segments. Therefore, the key issue is the selection of the most likely road from the database: this is what from now on we shall refer to as —road-matching—. The fusion of the selected segment with the estimated pose is not detailed in this paper. It can be performed recursively by using Kalman filtering as done in [8] when there is no ambiguity.

Generally, road selection first involves applying a 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 this stage. 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 G eoroute V2 provided by the IGN was used in this work. Its absolute precision is estimated to be several meters in detailed city format. The selection strategy proposed is based on the merging of several criteria using distance, direction and velocity measurements within the framework of Belief Theory.

In order to develop such an approach it is important to estimate continuously the pose —position and heading — of the vehicle in the frame of the map using GPS, because of its affordability and convenience. However, GPS suffers from satellite outages occurring in urban environments, under

bridges, tunnels or in forests. GPS can thus be seen as an intermittently-available positioning system that needs to be backed up by a dead-reckoning system [1]. In this work, a low-cost odometric method based on the use of encoders attached to the rear wheels is proposed. A dead-reckoned estimated pose is obtained by integrating the elementary rotations of the wheels starting from a given pose. The multisensor fusion of GPS and odometry is performed by an Extended Kalman Filter (EKF). This kind of formalism is also useful in quantifying the imprecision associated with each estimated pose. As we show in this paper, this information is of particular relevance when quantifying the selection criteria.

The outline is as follows. In section II, the EKF formalism used in performing the sensor fusion of DGPS and odometry is described. The fusion provides a continuous estimation of the heading of the vehicle and quantifies the estimation error regarding the pose: these two quantities are key parameters for the road selection problem. Next, the architecture of a usual roadmap matching algorithm is laid out. The road selection method is presented in section III. The proposed strategy fuses two criteria using Belief Theory with a fuzzy representation of sensor information. The final section is the experimental analysis of several tests carried out with our experimental car.

## II. ARCHITECTURE OF THE ROAD-MATCHING STRATEGY

At present, there would seem to be no ideal solution to the road-matching problem. All the methods which have been developed have their advantages and their drawbacks, and they were optimized for the particular application for which they were designed [22], **Erreur! Source du renvoi introuvable.** For the needs of turn-by-turn navigation systems, many of them would appear adequate. However, safety applications dedicated to Advanced Driving Assistance Systems (ADAS) require the ability to estimate the confidence in the road-matched positions. If the confidence is too low, the information retrieved from the Geographical Information System (GIS) won't be used.

Arc-matching methods consist in localizing the vehicle on the road network modeled by linear arcs. Several approaches have been proposed in the literature. Geometric approaches [2], [9], [11], [13] rely on the correlation of the estimated trajectory with the shape of the road network. Fuzzy techniques [14], [21] use models and rules to take into account map and sensor errors. These techniques are able to detect off-road situations. In the framework of Bayesian filtering, Kalman approaches [3], [15], [26] and particle filter [10] techniques have been developed. The matching relies in this case on a map pose-tracking paradigm in which the map data is treated as an observation. The ability to characterize several solutions in ambiguous situations is a new preoccupation which can be formulated with a multi-hypothesis scheme [17] or with a multi-modal density probability [10].

In this paper, we propose a new formulation to solve the problem. Given an estimated absolute localization with high availability in the frame of the map, the road-matching is

reduced to the selection of the most likely segment of the database. According to this approach, there is no projection on the segments representing the roads. If a projection is needed to retrieve the attributes attached to the segment, this projection is performed afterwards. The key issue is to have a good estimate of the pose error for the fusion process. Obviously, better is estimated the pose, less ambiguity is the selection process.

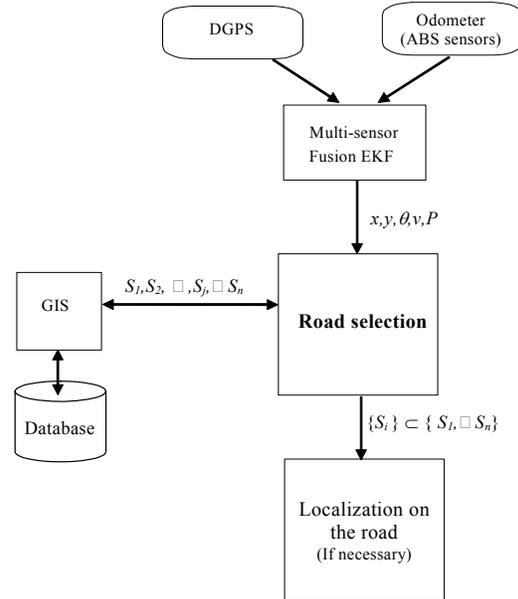


Fig. . Schematic diagram of the proposed road-matching algorithm

The road selection process can be described as in Figure 1 where  $v$  denotes the mean speed of the rear wheels. Multi-sensor fusion gives an estimation of the pose  $X=(x,y,\theta)^t$  with its associated covariance matrix  $P$ . The question is then to select the most likely segment(s) using a GIS. In order to accelerate processing (a map contains thousands of roads, each made up of several segments), an initial filter selects the  $n$  road segments  $\{S_1, \dots, S_n\}$  that are located within an interest window chosen for considerations of real-time or reliability. The center of the circle is the estimation of the current position  $(x, y)$  of the car. This initial filter can be applied at low frequency and interpreted as a cache memory as in [27]. Next, the road selection stage selects the credible segments. If necessary, the location on the segment can be done by projection. This final stage is called usually *map-matching*.

### A. Road selection

This problem consists in selecting the 'good' segments from the subset  $\{S_1, \dots, S_n\}$ . This problem is also called Road Reduction Filter in [8] and [23].

This stage is difficult because,

- The position is estimated with errors which can be magnified by multi-path effects. In addition, the transformation between the GPS coordinates (WGS84 system of reference) and the projection frame of the map (here the French NTF Lambert coordinates system) can induce errors.

- The coordinates of the segments are falsified by errors due to terrain measurements carried out by cartographers and also due to numerical approximation.
- The road network in the database does not always correspond to reality, i.e. it can contain old roads which no longer exist, or new roads which are not yet 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 planar view.
- The vehicle does not travel exactly on the segments representing the roads.

Section III will present a strategy using Belief Theory.

### B. GPS and ABS fusion

High availability positioning is a basic necessity in the road-matching process. As GPS is subject to satellite outages, we propose to use the ABS sensors of the rear wheels of a car to provide a continuous positioning. As most modern cars have an ABS system, it is a very cheap solution that does not require additional sensors. In this section, the fusion of GPS and odometry with an EKF is described.

Let 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).

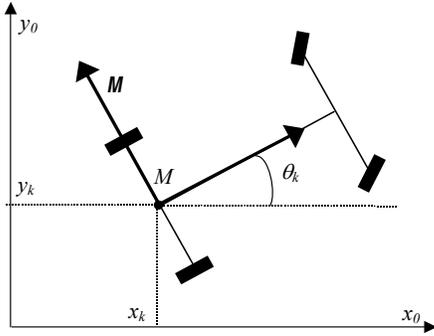


Fig. . The mobile frame attached to the car

A time index  $t_k$ , the vehicle 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 evolution model is expressed by [4]:

$$\begin{cases} x_{k+1} = x_k + \Delta_k \cdot \cos(\theta_k + \frac{\omega_k}{2}) \\ y_{k+1} = y_k + \Delta_k \cdot \sin(\theta_k + \frac{\omega_k}{2}) \\ \theta_{k+1} = \theta_k + \omega_k \end{cases} \quad (1)$$

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

In this formulation, the values of the scale factors of the ABS sensors are supposed to be precisely known after a calibration stage.

Let denote  $u_k = [\Delta_k, \omega_k]^T$  and  $X_k = [x_k, y_k, \theta_k]^T$ ,  $\alpha_k$ ,  $\gamma_k$  respectively the model noise and the ABS noise. Eq. (1) can be rewritten as:

$$X_{k+1} = f(X_k, u_k, \gamma_k) + \alpha_k \quad (2)$$

When a GPS fix is available, it is first converted from geographical co-ordinates into Cartesian co-ordinates  $Y_k$ , by a projection in the frame of the map (here French Lambert I). Then, a correction of the odometric estimate is performed using an EKF thanks to the following observation model:

$$Y_k = \begin{bmatrix} x_{gps,k} \\ y_{gps,k} \end{bmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} x_k \\ y_k \\ \theta_k \end{pmatrix} + \beta_k \quad (3)$$

$\beta_k$  denotes the GPS measurement noise. The covariance matrix  $Q_\beta$  can be estimated in real time using the NMEA sentence "GST" provided by the Trimble AgGPS132 receiver that was used in the experiments. Therefore, the noise  $\beta_k$  is not stationary. It will be noticed that a differential GPS receiver (whose precision is well adapted to the use of a precise roadmap) was used.

This architecture can be seen as a loosely-coupled fusion system. The heading  $\theta$  is not directly measured since the GPS is used as a position sensor. Let us study its observability.

From Eq. (1), we have:

$$x_{k+1} = x_k + \Delta_k \cdot \cos(\theta_k + \frac{\omega_k}{2}) \text{ and } \theta_{k+1} = \theta_k + \omega_k \quad (4)$$

Then,

$$\theta_k = \theta_{k+1} - \omega_k \text{ and } x_{k+1} = x_k + \Delta_k \cdot \cos(\theta_{k+1} - \frac{\omega_k}{2}) \quad (5)$$

By making a change of index, the heading  $\theta_k$  can be expressed by the formula:

$$\theta_k = \arccos\left(\frac{x_k - x_{k-1}}{\Delta_{k-1}}\right) + \frac{\omega_{k-1}}{2} \quad (6)$$

Therefore, the heading is expressed as a combination of  $(x_k, x_{k-1}, \Delta_{k-1}, \omega_{k-1})$ . Since  $x$  is observable (directly measured by the GPS),  $\theta$  is observable also. Nevertheless, the mathematical expression is not defined when the speed is zero, which demonstrates that the heading is observable when the vehicle is moving. When the vehicle is motionless, the heading is not observable and does not need to be estimated.

The EKF follows a predictor/estimator paradigm at a frequency of 1 Hz using the Pulse per Second (PPS) signal. The prediction stage is computed using the ABS measurements, if there is a displacement of the vehicle. This guarantees that the EKF correctly reconstructs the heading angle, since its observable. Then, in the estimation stage, the GPS corrects the drift of the dead-reckoned pose. In order to use good GPS fixes with a good precision, the GPS receiver

has to be tuned with very selective masks (DOP, elevation and signal/noise ratio). For this reason, the GPS data is intermittent but one can give a high belief in this information when it is present.

The equations are not described here but details can be found in [8]. Hereafter, we report the results of a test performed over a 4.5 km route (see Fig 3).



Fig. . Top view of the experimental run (in black).

The behavior of the filter can be characterized by examining the  $x$  and  $y$  innovations (differences between the DGPS measurements and the predicted measurements). It can be seen from Fig. 4 that the  $x$  innovation is zero mean. This figure also shows the probability distribution of the  $x$  innovation errors, which confirms its zero-mean behavior. Moreover, the autocorrelation is close to white noise since the sampling period equals one second. This global behavior indicates that the filter is correctly tuned.

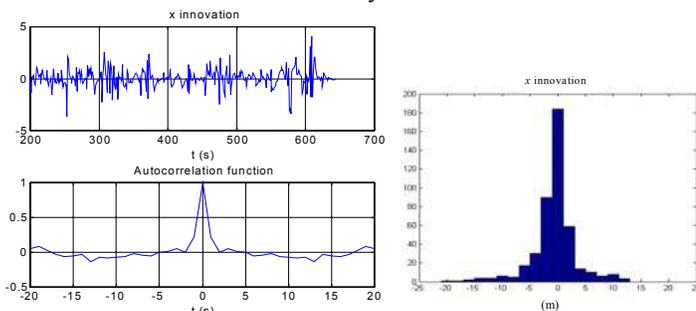


Fig. . Autocorrelation and distribution of the  $x$  innovation of the EKF

In the framework of the ARCOS French research program, this system was validated in relation to a centimeter-level accuracy PPK GPS system. The horizontal precision is in the order of 2 meters ( $1\text{-}\sigma$ ) when the GPS employs a differential pseudo-range correction [12].

Finally, using the odometric model, the EKF estimates continuously the  $X$  vector and the covariance matrix  $P$  of the estimated error, even when the satellite signal is blocked by

bridges, tunnels, buildings, etc. In such a situation, the pose is predicted thanks to Eq. (1) and the ABS sensors. In this case, the drift depends only on the travelled distance and not on time. It has been estimated to 10 percents of the travelled distance which is sufficient for short GPS outages. Fig. 5 illustrates the lateral drift during small GPS outages. The 3-sigma bound proves the consistency of the filter.

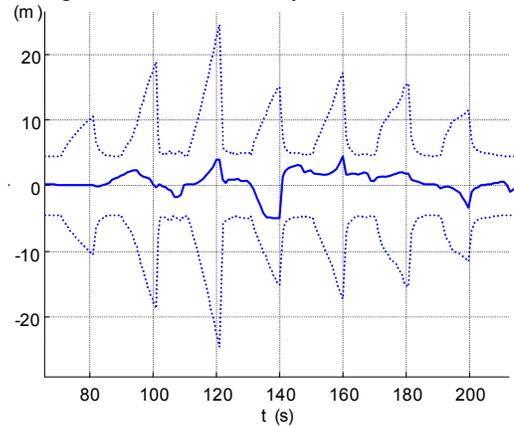


Fig. . Drift of ABS-only localization during small GPS outages.

### III. ROAD SELECTION USING MULTI-CRITERIA FUSION

Intuitively, taking many factors into consideration makes it possible to avoid matching errors that easily result from a single point of view selection. Therefore, in order to improve map-matching methods, different information sources have to be merged to provide better selection criteria for deciding the best match. For example, Quddus et al. [18] have used the  $\square$ GPS position relative to the road link $\square$  and an  $\square$ intersection relation between the GPS trace and the road links $\square$ . Syed and Cannon [21] have used the  $\square$ average distance travelled on current link $\square$  and the  $\square$ large distance traveled on current road link $\square$ . In addition, if the base road network contains detailed road attributes (speed limits, one way lanes, etc.) that potentially restrict a certain routing behavior, they can potentially be utilized to further filter inappropriate road links.

Current trends in map matching development have begun to incorporate probabilistic and fuzzy elements which are more tolerant with uncertainty (confidence in given information), imprecision (noises) and model approximations. Uncertainty typically exists in the database street map.

Several approaches can be followed to fuse multi-dimensional selection criteria. The commonly used one combines selection factors with a weighting scheme. The weighting factors are typically derived empirically from data testing or from adaptive-fuzzy-network-based training [14]. A different approach can be implemented in the framework of Belief Theory which allows partial knowledge to be taken into account. The Dempster-Shafer's rule can be used to fuse the criteria. Moreover, because of its commutativity and associativity, it is possible to incorporate any criterion and to fuse it in any order. Belief Theory also facilitates the estimation of the degree of belief in a selected road. The detection of off-road travels, for instance, is characterized by

the fact that all the segments have a low belief.

The following of this section first presents the concepts used in Belief Theory. The selection criteria will next be described, and finally the fusion of these criteria will be illustrated by a real example.

### A. Belief Theory Concepts

Belief Theory admits uncertainty into the reasoning process and suggests a way for combining uncertain data. This theory was introduced by Dempster [5] and mathematically formalized by Shafer in 1976 **Erreur ! Source du renvoi introuvable.** It is the generalization of Bayes Theory in the treatment of uncertainty. Generally, this theory is used in a multi-sensor context to fuse 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  $\Theta$ . 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 mass function  $m(\cdot)$ . It satisfies the following rules:

$$\begin{aligned} m(\phi) &= 0 \\ \sum_{A \subseteq \Theta} m(A) &= 1 \end{aligned} \quad (7)$$

A mass function is defined for each different piece of evidence. Each piece of evidence  $A$ , for which  $m(A) \neq 0$ , is called a focal element. The notion of mass is very close to the notion of probabilistic mass, except that it is not limited to a single hypothesis, but it is possible to attribute a mass for a union of hypotheses: this is the main difference with respect to Bayesian Theory.

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

$$2^\Theta = \{\emptyset, H_1, H_2, \dots, H_m, H_1 \cup H_2, \dots, H_1 \cup H_j \cup H_k \cup H_l \cup \dots \cup H_n\} \quad (8)$$

This distribution is a function of the knowledge about the source. The whole mass obtained is called  $\square$ basic mass assignment $\square$ . The sum of the component masses is equal to one. Each expert - also called source of information - defines a mass assignment according to its opinion about the situation.

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

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

Belief and plausibility bound by the following relationship:

$$Pl(A) = 1 - Bel(\bar{A}) \quad (10)$$

Where  $\bar{A}$  denotes the complement of  $A$ .

### B. Application to the Road Selection

We consider ADAS applications that are related to road safety like, for instance, Curve Warning Systems that inform the driver that he is approaching a curve with a too high speed. Therefore, 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 limit* 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 neighborhood. This criterion depends on the error ellipse.
- The segments on which the vehicle can be located are those which have an angle close to the heading of the vehicle. This criterion depends on the estimated  $3\sigma$  bound of the heading and on the speed of the car.

To build mass assignments, the inaccuracy of the various information sources (GPS, odometer and digital map) is considered and certain physical observations, for instance that a car with a speed of 40 m/s cannot be orthogonal to the direction of the segment are modeled. With this approach, information sources (i.e. criteria) are worked out from sensor data.

The problem of mass assignment for each criterion can be tackled in a global or a local way. The global strategy involves the simultaneous inspection of all the segments selected around an estimated position when affecting the 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 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  $2^\Theta = \{Yes, No, Perhaps\}$ .

#### 1) Proximity Criterion

The proximity criterion is based on the measurement of the Euclidean distance between the estimated position and each segment in the road database. In order to take into account the estimation error on the position, a Gaussian ellipse is built using the covariance matrix  $P$  of the state vector  $X$  [8]. The probability that a given state  $X_s$  is included in a 40% ellipse centered on the estimate  $X$  is expressed by the formula:

$$p(X_s) = (2\pi)^{-n/2} \cdot P^{-1/2} \cdot \exp\left(-\frac{1}{2}(X_s - X)^T P^{-1}(X_s - X)\right) \quad (11)$$

The equiprobable states  $X_s$  that characterize a  $k\%$  ellipse are given by the following equation

$$(X_s - X)^T P^{-1}(X_s - X) = k^2 \quad (12)$$

The value of  $k$  defines the % of probability. In two dimensions

$$p(Xs) = 1 - \exp\left(-\frac{k^2}{2}\right) \quad (13)$$

For example,  $k=1$  implies a 40% probability that the real position is effectively in the ellipse error. Conversely, given a chosen probability, the corresponding value of  $k$  can be computed. This value allows the semi-minor and semi-major axes of the ellipse to be determined. For the proximity criterion, the estimated error of the position is quantified by an ellipse of 99% equiprobability produced by the EKF (drawn in dark gray in Fig. 6). The estimated position  $E$  is at the center of the ellipse.

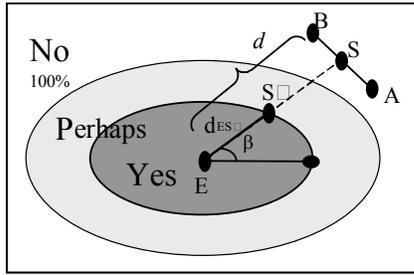


Fig. . Case of a non-credible segment

To allot a mass to a candidate segment  $[AB]$ , we proceed as follows. Let  $d$  denote the distance between the segment and point  $E$ .

Point  $S$  falls at the intersection between the segment  $[ES]$  and the ellipse. The distance  $d_{ES}$  depends on angle  $\beta$  which forms segment  $[ES]$  in the ellipse co-ordinates system. In the zone  $d < d_{ES}$  with a fuzzy modeling obtained by a probability-possibility transformation [6], [24], the degree of membership is quantified. The first curve presented in Fig. 7 assigns a mass to the *Yes* assumption.

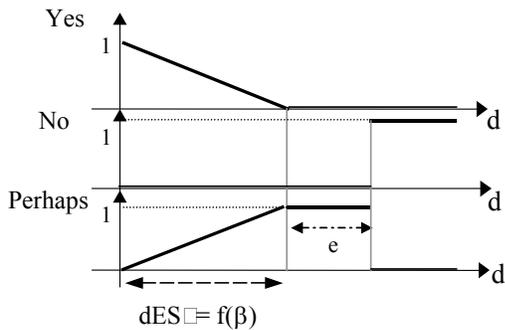


Fig. . Mass assignment of the proximity criterion

In complementing the mass of the *Yes* hypothesis, the mass to the *Perhaps* hypothesis is allotted. The mass of *Perhaps* remains constant (equals to one) for  $d_{ES} < d < d_{ES} + e$ , in order to consider the errors  $e$  on the segments coordinates of the database. Finally, the mass of the *No* assumption is a step function starting from the distance  $d = d_{ES} + e$ .

In conclusion, the mass assignment of the proximity

criterion depends on two variables:

- The distance  $d$  between the center of the ellipse and the segment,
- The angle  $\beta$  between the distance support and the major axis of the ellipse.

The problem becomes more complicated when considering the width of the road. We propose modeling the road by a rectangle centered on the segment, the length of which is equal to the length of the segment. The exact influence of the width of the road  $l$  is difficult to take into account in the computations of the criterion because  $l$  modifies the values of  $\beta$  and  $d$ . To simplify, we have chosen the following strategy:

1) If the orthogonal projection of  $E$  exists inside segment  $[AB]$ ,  $d = d_{ortho}$  (Fig. 8a).

2) If the orthogonal projection of  $E$  does not exist inside segment  $[AB]$ ,  $d = \min(d1, d2, d3)$  (Fig. 8b).

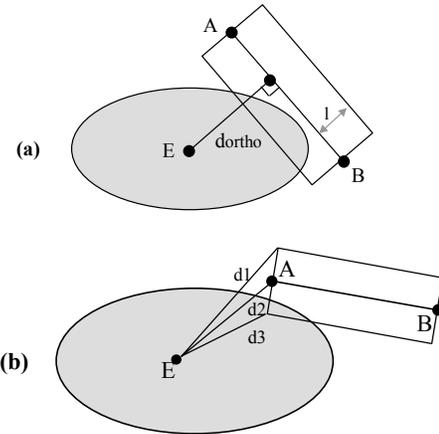


Fig. . Computation of the distance  $d$  with a rectangle rendering the road

## 2) Angular Criterion

In this section a mass-assignment function is proposed to reflect the fact that the most credible segments are those which have an angle close to the heading of the vehicle.

Figure 9 presents the fuzzy modeling of the absolute value of the difference between the heading of the vehicle (denoted  $\theta$ ) and the heading of the candidate segment (denoted  $\alpha$ ):

$$\Delta Heading = \min(|\alpha - \theta|, |\alpha - \theta + \pi|) \text{ with } \theta \in [0, \pi] \quad (14)$$

This curve is adaptive and depends on the speed of the vehicle and the standard deviation of the estimation error of the heading angle.

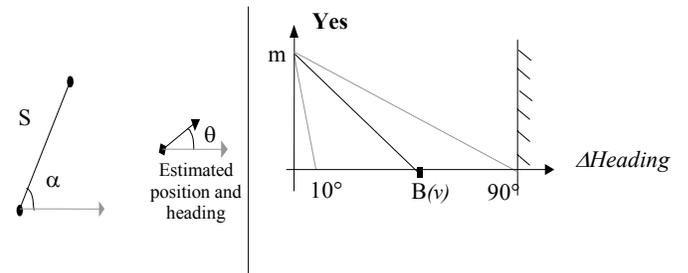


Fig. . Mass assignment of the *Yes* hypothesis for the angular criterion. On the left,  $S$  represents a candidate segment.

Let  $m$  be the maximum belief which can be assigned to the *Yes* hypothesis (see Fig. 9).  $m$  varies according to  $\sigma_\theta$  estimated by the EKF:

$$m(\sigma_\theta) = \max\left\{1 - \frac{6}{\pi}\sigma_\theta, 0\right\} \quad (15)$$

This strategy has been developed to model the fact that an uncertain heading will not induce an important mass to the *Yes* hypothesis. Let suppose that  $3\sigma_\theta = \pi/2$  represents the situation of total lack of knowledge on the estimation of the heading. In other words, the real heading is in the interval  $\left[\bar{\theta} - \frac{\pi}{2}, \bar{\theta} + \frac{\pi}{2}\right]$ .

In this case, the heading criterion must be reduced to the maximum: in Eq. (15), the mass assignment to the *Yes* hypothesis equals zero.

The scalar value  $B$  fixes the angular limit tolerated at a given velocity  $v$ :

$$B(v) = \pi/2 - \lambda \cdot v \quad (16)$$

With

- $\lambda = (90^\circ - 10^\circ) \cdot \pi / (V_{max} \cdot 180^\circ)$
- $V_{max}$  the maximum speed of the vehicle.

Eq. (16) is a heuristic model that indicates that if the speed of the vehicle is high, the difference between the heading and the segment direction should be small.

The *Perhaps* mass assignment is determined by computing the complement of the mass of *Yes*. The mass of *No* starts from the limit angle tolerated for a given speed -  $B(v)$  - and reaches one when the angle is equal to 90 degrees (Fig. 10).

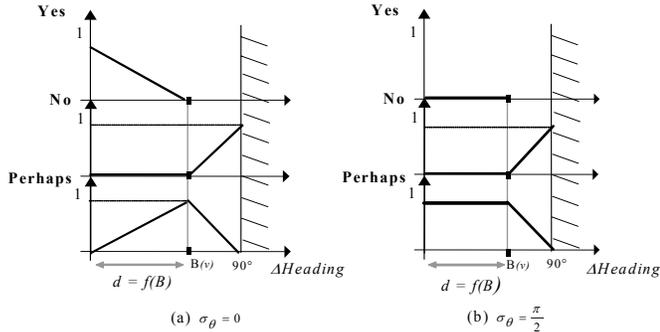


Fig. . Examples of mass assignment at a given velocity

### 3) Criteria Fusion

To improve the information obtained from two different single sources  $S_1$  and  $S_2$ , a combination of their mass assignments can be performed according to Dempster-Shafer's rule. Let  $A$ ,  $A_i$  and  $B_j$  be assumptions of the reference frame. The merging of the knowledge of  $S_1$  and  $S_2$  is given by:

$$m_\Theta(A) = \sum_{A_i \cap B_j = A} m_\Theta^{S_1}(A_i) \cdot m_\Theta^{S_2}(B_j) \quad (17)$$

If there are some conjunctions that are not focal elements, a re-normalization step is necessary to satisfy the rule  $m(\emptyset)=0$ . The coefficient of re-normalization is called  $k_\theta$  and defined as:

$$k_\theta = \sum_{A_i \cap B_j = \emptyset} m_\Theta^{S_1}(A_i) \cdot m_\Theta^{S_2}(B_j) \quad (18)$$

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

$$m_\Theta(A) = K_\theta \cdot \sum_{A_i \cap B_j = A} m_\Theta^{S_1}(A_i) \cdot m_\Theta^{S_2}(B_j) \quad (19)$$

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

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 should be used and, conversely, the maximum of belief should be used for a pessimistic decision. Many other decision rules exist in Belief Theory, especially for non-exhaustive frames of discernment. More information about them can be found in [7].

The decision-making strategy adopted here is to retain the most credible segments according the law of *ideal* decision. The likelihood of a singleton assumption is characterized by its belief and its plausibility, which are calculated using the set of masses. These quantities correspond respectively to the minimum probability and the maximum probability that an assumption is 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. In our experiments, we used a threshold of 0.5.

In the following, a segment that satisfies the law of ideal decision with small conflict will be called a *credible segment*.

### C. Illustrative Example: Approaching a Junction

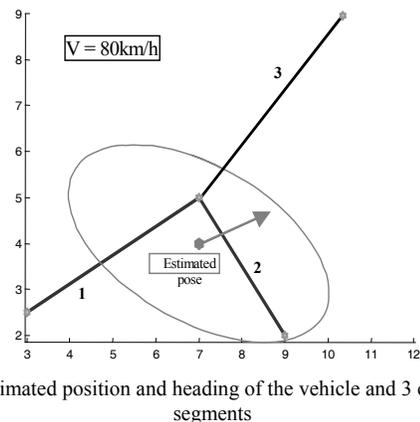


Fig. . Estimated position and heading of the vehicle and 3 candidate segments

Let us take a real case study to illustrate the method. In

Figure 11, the vehicle is traveling on the road represented by segments 1 and 3, at a speed of 80 km/h. Estimation errors and digital map errors give rise to an erroneous estimated position which is closer to segment 2 than to the others. In the following, the mass attribution, the fusion and the decision stages are described for each segment.

Figures 12, 13 and 14 show the mass assignments generated by the Belief functions. It will be noticed that for segments 1 and 3, the proximity and the heading criteria are in agreement, since both of them assign a high degree of belief to the *Yes* hypothesis, a low degree of belief to the *Perhaps* hypothesis and nothing to the *No* hypothesis. Conversely, segment 2 presents a total conflict between the two criteria.

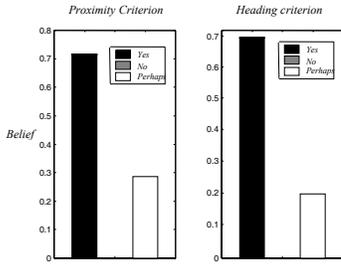


Fig. 12. Mass assignment for segment 1

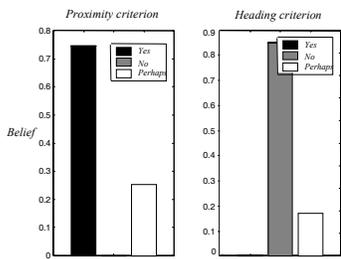


Fig.13 Mass assignment for segment 2

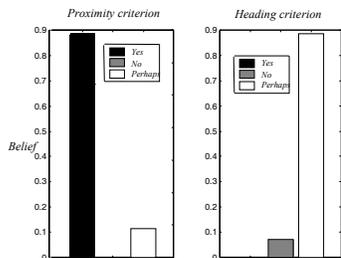


Fig. 14 Mass assignment for segment 3

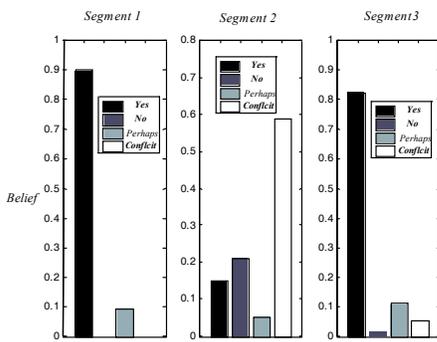


Fig. . Fusion results without normalization

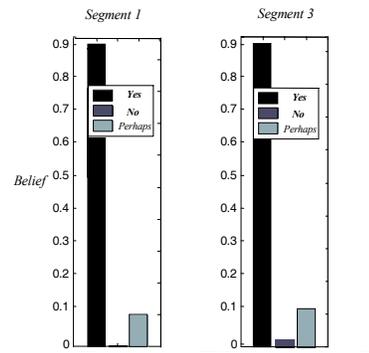


Fig. . Fusion results with normalization

Figure 15 shows the results of the fusion of the criteria with the Dempster-Shafer rule without normalization. Notice that segment 2 presents a clear conflict. The fusion of the criteria concerning segments 1 and 3, however, indicates a strong belief on the *Yes* hypothesis.

To decide if a segment is a good candidate the conflict generated by the fusion stage is first considered. As it is important for segment 2, this segment is eliminated. Next, the ideal decision law is applied after normalization of the masses. This law simply means here that if the Belief in the *Yes* hypothesis is greater than the sum of the *No* and *Perhaps* hypotheses, the segment in question is credible. Figure 16 shows that segments 1 and 3 are selected. This result corresponds to the real situation.

#### IV. EXPERIMENTAL RESULTS

The algorithm works in real-time conditions with a frequency of 1Hz<sup>1</sup>. The GPS receiver used was a Trimble AgGPS132, L1-only, working with geostationary broadcasted pseudo-range corrections (Omnistar).

Figure 17 presents an overhead view of an experimental test performed in Compiègne. The map data-base is managed and interfaced by the GeoconceptGIS software.

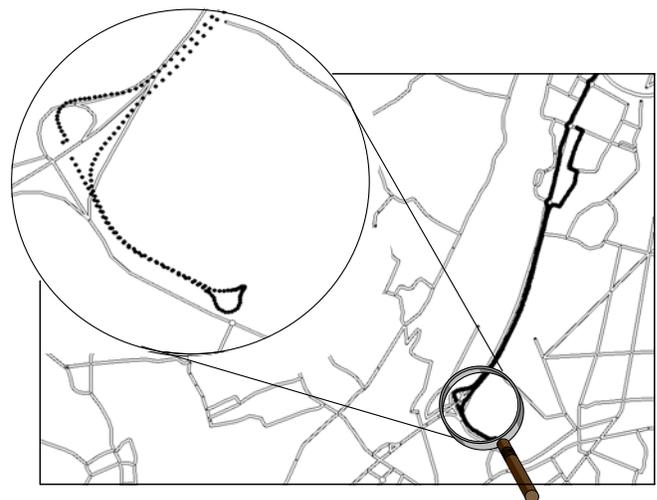


Fig . Experimental situation on the IGN GéoRouteGIS software (estimated positions are dotted)

<sup>1</sup> using a Intel Pentium III 700 MHz processor

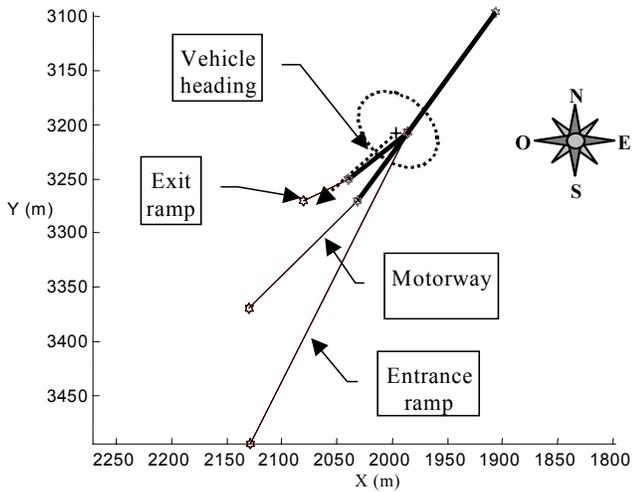


Fig. . The car exiting the motorway (local frame)

car. Moreover, they have a common point very close to the estimated position

At the beginning, three segments are selected (in bold in Fig. 18). Two of them correspond to the motorway and one to the exit ramp. As we should expect, the entrance ramp (located on the opposite side of the road) is not selected, owing to the angular criterion. Afterwards, the situation is still ambiguous (Fig. 19) until the difference between the car's heading and the angles of the motorway segments becomes significant. Then, the system is able to assert that the car is on the exit ramp (Fig. 20).

In order to provide a complete view of the evolution of beliefs with respect to the exit ramp, Figure 21 shows the evolution of belief in selected segments for about 10 positions. One can notice that the evolution of belief represents reality well. When several segments are credible, at a given moment, the road selection is ambiguous. The level of ambiguity depends if the selected segments make part of the same road. For example, segments S3 and S4 are credible, at time index 96. Obviously, this situation is less ambiguous than the one of time 91 during which three segments of two roads is credible.

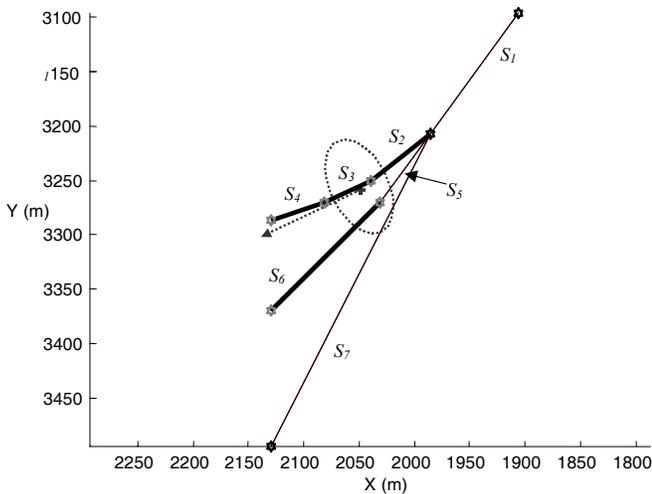


Fig. . The car on the exit ramp

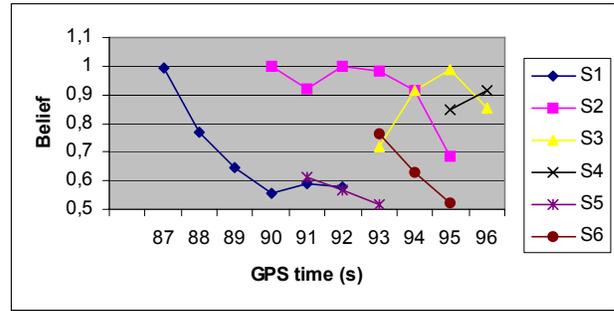


Fig. . Belief versus time.

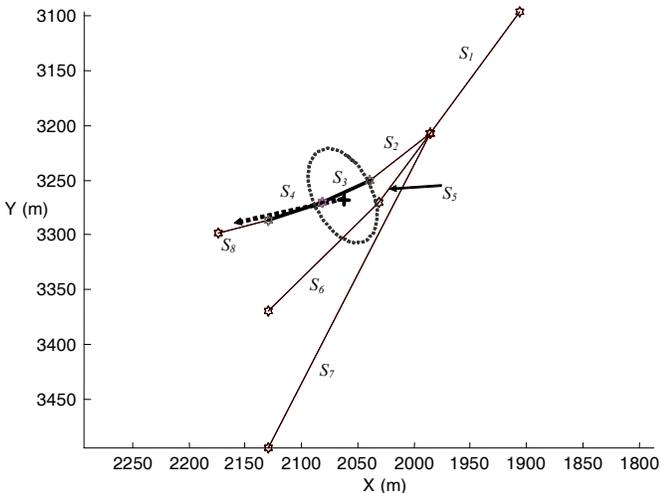


Fig. . The car on the exit ramp

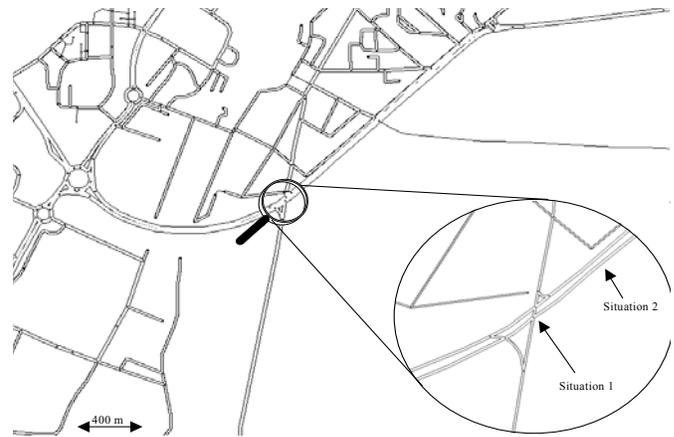


Fig. . Over had view of the test trajectory

To illustrate the road selection method, let examine how it deals with ambiguous situations. The first situation involves a motorway exit (Fig. 18). This situation is very ambiguous because the angles of three segments (the motorway, the exit ramp and the entrance ramp) are close to the heading of the

Let us analyze the behavior of the method in another potentially ambiguous situation. In Figure 22, two critical situations occur. The first one corresponds to a junction of three roads: two present the same heading, while the third road has a 45-degree angle. In the second situation, three roads have the same heading and are very close to each other (<10m). The speed of the vehicle is about 70 km/h.

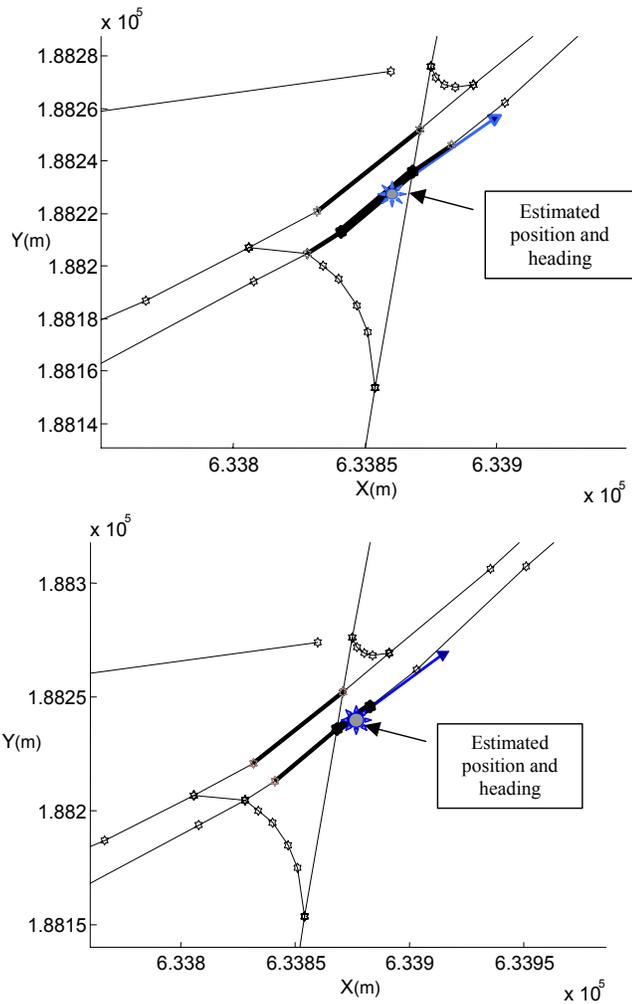


Fig. . Credibles segments are in bold and the most credible is in large bold (French Lambert coordinates)

Figure 23 shows how the system deals with the first critical situation: several credible roads are good candidates. First, it will be remarked that only the segments which represent the parallel road are selected. Moreover, as these segments belong to two different roads, the situation is ambiguous. If the application which uses the road-matching method can tolerate errors, the most credible segment can be output. In this particular case, the most credible segment corresponds to the right road, but this is purely fortuitous.

Figure 24 shows the result processing of the second critical situation. In this situation the vehicle is traveling on a wide road, represented by two arcs. A secondary road is parallel and very close to the main road. The road selection method extracts 4 segments. Once more, the situation is ambiguous because the segments belong to three different roads.

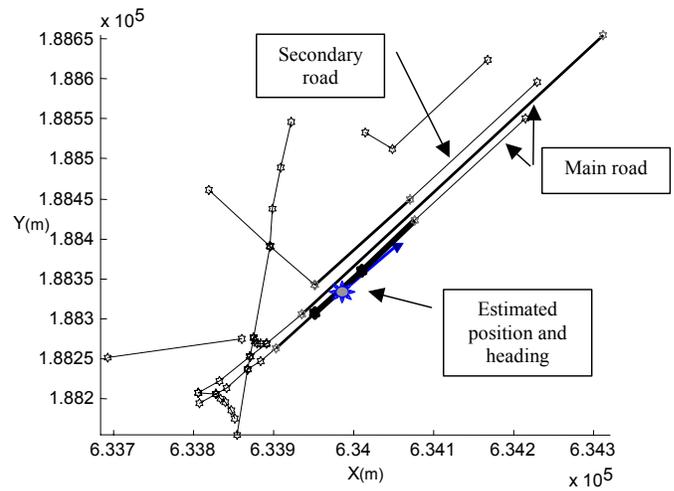


Fig. . Credibles segments are in bold and the most credible is in large bold (French Lambert coordinates)

Finally, we have tested the road-selection algorithm on the 4.5-km route presented in section II.B (see Fig 3). On Figure 25, the dotted path represents the DGPS position provided by the Trimble receiver converted into the 2D frame of the map. Each point of the second plot (plotted with  $\boxplus$ ) corresponds to the nearest point of the most credible segment to the estimated position provided by the EKF-fusion of GPS and odometry. The origin of Figure 25 has been translated in order to facilitate the readability of the scales of the axes. Even if all the credible segments are not indicated on this figure, it has been verified that the right segment was always in the list of the credible segments provided by the road selection method. One can notice that sometimes the most credible segment can be incorrect, especially in roundabouts, like the point surrounded by a circle. Since the road selection method is static (i.e. not recurrent), an incorrect selection has no effect on the next selection stage. This indicates a robustness to fault matching, if the most credible segment is considered as the matched segment. Nevertheless, we think that in case of ambiguity (i.e. the selected segments belong to different roads) a multi-hypotheses matching is preferable.

In Figure 26, the distance from the DGPS position to the most credible road is plotted. It illustrates the good performance of the road selection method since this distance is in the order of several meters. We think this is mainly due to an offset between the map and the GPS navigation solution, clearly visible on the figure. The two large values (index  $\sim 150$  and index  $\sim 300$ ) correspond to wrong selections, the second one being the one of Fig. 25. It is important to notice that the success of a map matching algorithm based uniquely on the selection of the most credible segment is contingent on the availability of accurate navigation solution and small offsets of the map.

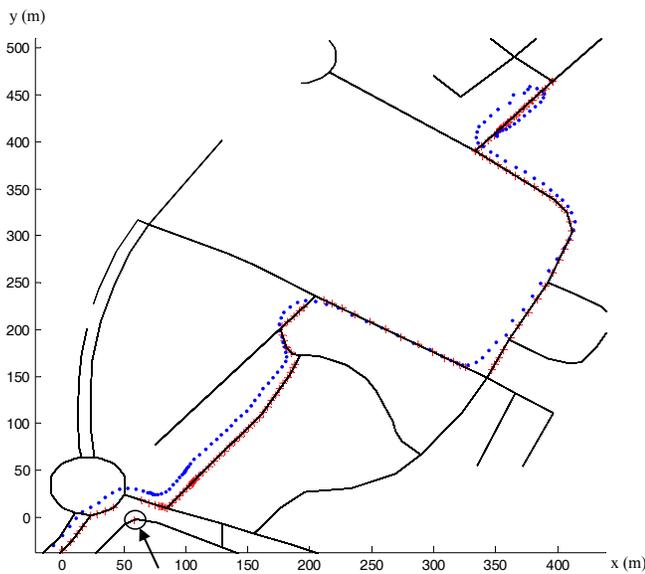


Fig. 1. GPS points (.) and nearest points of the candidate roads (+)

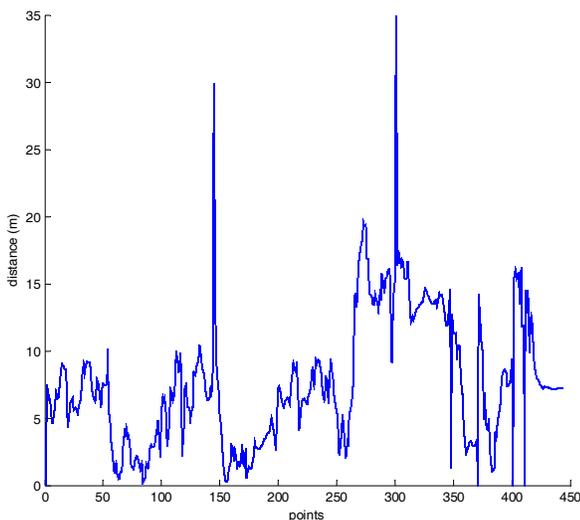


Fig. 2. Distance between DGPS path and candidate roads

## V. CONCLUSION

This article has presented a multi-criteria fusion technique for the selection of roads from a road network database, which is a key issue in road matching. The main contributions of this work are the formalization of this problem using the framework of Belief Theory, the development of assignment functions (called criteria), and an experimental validation with real data using a differential GPS and the ABS sensors. Two criteria have been proposed and developed. They use an estimated pose (position and heading) of the car obtained thanks to the fusion of GPS and ABS using an EKF. These criteria take into account the estimation error as well as geographical errors. It is interesting to note that in Belief Theory, the lack of knowledge concerning a criterion can be quantified (in this particular case, it is the *Perhaps* hypothesis)

and managed in the fusion process. Moreover, as different decision laws can be applied, different behaviors can be obtained. If a reliable behavior is desired, the ideal decision law needs to be used, as used in this work.

The main advantage of this strategy is that it is possible to detect an ambiguous situation, where different sources of error have led to several roads becoming indistinguishable. This method can, however, detect the fact that the vehicle is not on a road stored in the database. This situation can be encountered if the roadmap is not exhaustive.

This approach is flexible and modular in the sense that it can easily integrate other criteria. The result of the fusion of two criteria can be fused with the masses assigned by a third criterion, and so on. It is therefore possible, using the same framework, to build and fuse other criteria testing, for example, the connectivity or the direction of the segments. This feature is interesting because adding other criteria is a way of increasing the robustness of the road selection.

As the segments are dealt with one by one, the size of the frame of discernment is small and, therefore, the method is well adapted to real-time conditions. For example, it takes on average 50 ms to process 10 segments with an Intel Pentium III 700MHz computer.

Finally, this method can be considered an excellent tool for improving positioning reliability, since it is possible to quantify the ambiguity of a situation and therefore the confidence in a road-match segment. This information is crucial for the development of fusion techniques that use the selected segments to improve the localization process.

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## REFERENCES

- [1] E. Abbott and D. Powell, "Land-Vehicle Navigation using GPS" in *Proc. Of the IEEE, Vol. 87, No. 1*, 1999.
- [2] D. Bernstein and A. Kornhauser, "Map Matching for personal navigation assistants" 77<sup>th</sup> Annual Meeting, The Transport Research Board, Washington D.C., USA, Januar 1993.
- [3] D. Bétaille and P. Bonnifait, "Road Maintenance Vehicles Location using DGPS, Map-Matching and Dead-Reckoning: Experimental Results of a Smoothed EKF" *IAIN World Congress in association with the USION annual meeting* San Diego. pp. 409-416, June 2000.
- [4] P. Bonnifait, P. Bouron P. Crubille and D. Meizel, "Data Fusion of Four ABS Sensors and GPS for an Enhanced Localization of Car-like Vehicles" *IEEE ICRA* Séoul. pp. 1591-1602, April 2001.
- [5] A. P. Dempster, "Upper and Lower Probabilities Induced by a Multivalued Mapping" *Annals of Mathematical Statistics*, vol. 38, 1976.
- [6] D. Dubois and H. Prade, "Fuzzy Sets and System Theory and Application" *Mathematics in science and engineering Academic Press, Inc.* vol. 144, 1993.
- [7] P. Fabiani, "Représentation Dynamique de l'Incertain et Stratégie de Prise d'Information pour un Système Autonome en Environnement Evolutif" Ph.D. dissertation, Ecole Nationale Supérieures de l'Aéronautique et de l'Espace, 1996.
- [8] M.E. El Najjar and P. Bonnifait, "A Road Matching Method for Precise Vehicle Localization using Belief Theory and Kalman Filtering" *Int. Conf. ICAR*; Coimbra, Portugal, 2004.

- [9] J. Greenfeld, □Matching GPS Observations to Locations on a Digital Map□ 81<sup>th</sup> annual Meeting of the transportation Research Board, Washington D.C., 2002.
- [10] F. Gustafsson, N. Bergman and U. Forsell, □Particles filters for positioning, Navigation and Tracking□ *IEEE Trans. on Signal Processing. Special issue on Monte Carlo methods for statistical signal processing*, vol. 50, 2002.
- [11] R. Joshi, □Novel Metrics for Map-Matching in In-vehicle Navigation System□*Proc. Of the IEEE Intelligent Vehicle Symposium*, 2002, pp. 36□43.
- [12] M. Kais, P. Bonnifait, D. Bétaille and F. Peyret, □Development of Loosely-Coupled FOG/DGPS and FOG/RTK Systems for ADAS and a Methodology to Assess their Real-Time Performance□ *Proc. Of the IEEE Intelligent Vehicle Symposium*, Las Vegas, 2005.
- [13] J. S. Kim, J. H. Lee, T. H. Kang, W. Y. Lee and Y. G. Kim, □Node based map matching algorithm for car navigation system□in *Proc. 29<sup>th</sup> ISATA Symposium*, Florence, 1996, vol. 10, pp. 121□126.
- [14] S. Kim and J.H. Kim, □Adaptive fuzzy-network-based C-measure map-matching algorithm for car navigation system□*Proc. Of the IEEE Trans. On Industrial Electronics*, vol. 48, No. 2, 2001, pp. 432□441.
- [15] E. J. Krakiwsky, C. B. Harris and R. V. C. Wong, □A Kalman Filter for Integrating Dead Reckoning, Map Matching and GPS Positioning□in *1988 Proc. IEEE Position Location and Navigation Symposium.*, pp. 39□46.
- [16] C. Pradalier and S. Sekhavat, □Localization Space: a Framework for Localization and Planning, for Systems Using a Sensor/Landmarks Module□in *2002 Proc. IEEE conf. on Robotics and Automation*.
- [17] J. S. Pyo, D. H. Shin and T. K. Sung, □Development of a map matching method using the multiple hypothesis technique□in *2001 Proc. IEEE conf. Intelligent Transportation Systems*, pp. 23□27.
- [18] M. A. Quddus W. Y. Ochieng, L. Zhao and R. B. Noland, □A General Map Matching Algorithm for Transport Telematics Applications□ *GPS Solution* 7(3), pp. 157-167, 2003.
- [19] C. A. Scott C.R. Drane, □Increased Accuracy of Motor Vehicle Position Estimation by Utilizing Map Data, Vehicle Dynamics and Other Information Sources□ in *1994 Proc. of the vehicle Navigation and Information Systems Conference*, pp. 585□590.
- [20] G. A. Shafer, *A Mathematical Theory of Evidence*, Princeton, NJ: Princeton Univ. Press, 1976
- [21] S. Syed and M. E. Cannon, □Fuzzy Logic Based-Map Matching Algorithm for Vehicle Navigation System in Urban Canyons□in *2004 Proc. of the ION National Technical Meeting*, San Diego, CA, pp. 982□993.
- [22] J. Tanaka, K. Hirano, T. Itoh, H. Nobuta and S. Tsunoda, □Navigation System with Map-Matching Method□ in *1990 Proc. of the SAE International congress and Exposition*, pp. 45□50.
- [23] G. Taylor and G. Blewitt, □Road Reduction Filtering Using GPS□ *3<sup>th</sup>. AGILE conf. on Geographic Information Science*, Helsinki, Finland, pp. 25□27. 2000.
- [24] L. A. Zadeh, □A Simple View of Dempster-Shafer Theory of Evidence and its Implication for the Rule of Combination□*The AI Magazin*. 1986
- [25] Y. Zhao, *Vehicle Location and Navigation Systems*, Norwood, MA: Artech House, 1997.
- [26] L. Zhao, W. Y. Ochieng, M. A. Quddus and R. B. Noland, □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*, vol. 56, pp. 257-275, 2003.
- [27] N. N. Zheng, S. Tang, H. Cheng, Q. Li, G. Lai and F. Y. Wang, □Toward Intelligent Driver-Assistance and Safety Warning Systems□ *IEEE Intelligent Systems*, March/April 2004. Vol. 19 N°2.



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