USING THE TRANSFERABLE BELIEF MODEL TO VEHICLE NAVIGATION SYSTEM

Khalid Touil, Mourad Zribi and Mohammed Benjelloun
Université du Littoral Côte d'Opale, Maison de la recherche Blaise Pascal,
Laboratoire d'Analyse des Systèmes du Littoral, (LASL-EA 2600),
50, rue Ferdinand Buisson, B.P. 699, 62228 Calais Cedex, France.

Keywords: Global Positioning System, Dead Reckoning, a map-matching method, Transferable Belief Model.

Abstract: In general, navigation systems estimating a vehicle position is done either by using the Global Positioning System (GPS) or the Dead Reckoning (DR) systems. Other modern estimations are based on the combination of the two systems (GPS/DR). However, the position of a vehicle determined by GPS/DR is far from being perfect since it produces many errors. To solve this problem, a map-matching method is proposed in order to reduce the errors of localization caused by GPS/DR. This algorithm, which uses a digital road map, allows the detection of the correct road where a vehicle moves. In this paper, we introduce a new map-matching algorithm that employs the Transferable Belief Model (TBM). The TBM presents a general justification of belief theory and provides a flexible and adapted representation for the measured beliefs. Experimental results show the effectiveness of the utilization of the TBM to the vehicle navigation system.

1 INTRODUCTION

The car navigation systems promise to be a valuable aid for traveler's drivers of vehicles who need to reach a variety of destinations as quickly and efficiently as possible. The main role of a car navigation system is to find the car position as precisely as possible. The Global Positioning System (GPS) sensor is the most attractive one. This is because the position can be calculated on the globe if more than four satellites are detected (Parkinson, 1996). Nevertheless GPS suffers from satellite masks occurring in urban environments, such as under bridges, tunnels, etc. GPS appears then as an intermittent positioning system that demands the help of a *DR* system. This last estimates the position by integrating the displacements at every sampling time. Since this method is subject to major accumulation of errors caused by wheel slippage, surface roughness, etc.

In our work, we use the odometer sensor. We integrate GPS with odometer by employing a Kalman filter (Chui, 1991; Zhao, 2003). The estimated position by Kalman filter is proved to be optimal if the system is linear and the noise is white Gaussian (Grewal, 1993). It should be noted that as the noise of the GPS is not white Gaussian and the system is not linear, the estimated position from Kalman filter is not optimal. It leads to position errors. To reduce the error, we suggest using a map-matching approach (Bernstein, 1998; Greenfeld, 2002). It is a method of using digital map data and integrated GPS/odometer to locate the vehicle on proper road relative to digital map. Conventionally, map-matching is performed using either a geometric approach or a statistical approach. Geometric map-matching, as the name suggests, is based on pure geometric criteria identifying the road segment on which the vehicle is traveling (Lee, 1998). Statistical map-matching, is based on curve fitting onto a road network based on the history of motion (Hummel, 2005). It uses a conditional probability (Taylor, 2001). In this paper, we present a new map-matching method. This method provides an accurate position of a vehicle relatively to a digital road map using the TBM and the Kalman filter. The TBM is a model that represents quantified beliefs based on the use of belief functions, as initially proposed by Shafer (Dempster, 1967; Shafer, 1976). This map-

Touil K., Zribi M. and Benjelloun M. (2006).
USING THE TRANSFERABLE BELIEF MODEL TO VEHICLE NAVIGATION SYSTEM.
In *Proceedings of the Third International Conference on Informatics in Control, Automation and Robotics*, pages 10-17
DOI: 10.5220/0001209300100017

matching method is composed on four steps. Firstly, a Kalman filter fuses the GPS and the odometric measurements to estimate a position of the vehicle. Secondly, we use the estimated position and the variance-covariance information given by Kalman filter in order to define a zone in which Geographical Information System (GIS) will use it and we preselect the segments on which the vehicle is likely to be. Thirdly, we select among the candidate segments the most credible segment one using the TBM. Finally, we build a map observation starting from the most credible segment then to integrate it, in the formalism of Kalman as a second equation of observation. Here, we are interested in the second and the third steps of this method which represent our contribution.

The paper is organized as follows. In section 2, we recall the main concepts of Belief theory and their interpretation in the setting of TBM. In section 3, we present the adaptation of this model for the segment selection problem. Finally, experimental results will be presented in section 4.

2 THE TRANSFERABLE BELIEF MODEL

The Transferable Belief Model (TBM) provides a flexible and very powerful representation of quantified beliefs. The model was introduced by Smets (Smets, 2002) and based on the belief function theory developed by Shafer (Shafer, 1976). But, it is completely unrelated for any underlying probabilistic constraints as it is the case with the model of Dempster (Dempster, 1967) and for the hint model (Kohlas, 1995). In the TBM, two-level model for belief has been proposed: *a credal level* where belief is entertained, and a *pignistic level* where beliefs are used to make decisions.

2.1 Credal Level: Modeling of Knowledge

At the *credal level*, belief is quantified by belief functions. Let Θ be a finite set of elements called the frame of discernment. It is composed of mutually exclusive elements called hypotheses. By definition, the mapping *bel*: $\Theta \rightarrow [0,1]$ is a belief function if and only if there exists a basic belief assignment function (bba) *m*:

$$m\text{: } 2^{\Theta} \rightarrow [0,1] \tag{1}$$

such that:

$$\begin{aligned} &\forall A \subseteq \Theta \quad \sum_{A \subseteq \Theta} m(A) = 1 \\ &bel(A) = \sum_{B \subseteq A, B \neq \phi} m(B) = 1 \quad bel(\phi) = 0 \end{aligned} \tag{2}$$

The values *m(A),* are called the basic belief mass and represent the minimal (necessary) support for *A* and cannot be associated with any of the sub-propositions on the basis of available evidence (Smets, 1994). The belief (*bel(A)*) of a proposition *A* is therefore a sum of all the belief masses allocated to sub-propositions *B*. If further the piece of evidence brought by a source of information (sensor, agent, etc) shows that $B \subseteq A$ is true, then the belief mass *m(A)* initially allocated to *A is transferred to* $A \cap B$ that is where the name of TBM comes from. So far we assumed that only one of the propositions in Θ is true ("close-world" assumption) this can be generalized by letting that none of the propositions considered in Θ could be true ("open-world"). In this case, a positive basic mass can be given to an empty set ϕ. The term $m(\phi)$ represents a degree of belief that cannot be given to any of the propositions in Θ. The conjunctive rule of combination of two pieces of evidence on Θ represented by the two bba m_1 and m_2 is:

$$m_1 \oplus m_2(A) = \sum_{B \cap C = A} m_1(B) m_2(C) \ \ \forall A \subseteq \Theta \tag{3}$$

$$m_1 \oplus m_2(\phi) = \sum_{B \cap C = \phi} m_1(B) m_2(C) \tag{4}$$

The value $m_1 \oplus m_2(\phi)$ represents the incoherence between the different sources of information. It can be interpreted as a measure of the conflict between the sources.

2.2 Pignistic Level: Decision Making

At the *pignistic level*, belief is quantified by probability functions. For most applications, a decision is generally, to be taken in favor of a simple hypothesis. Within the context of the TBM, Smets defines and justifies the use of the pignistic decision rule (Shafer, 1976; Smets, 1994). Let *BetP* be the pignistic probability distribution derived from the basic belief assignment (bba) *m*. *BetP* is defined by:

$$BetP(\omega) = \sum_{\omega \in A} \frac{m(A)}{card(A)(1-m(\phi))} \quad \forall\, \omega \in \Theta \;, \tag{5}$$

where $card(A)$ is the cardinality of A.

3 SELECTION METHOD OF SEGMENT

Vehicle tracking on a given road segment is known as map-matching (Bernstein, 1998; Greenfeld, 2002). Indeed to localize oneself on a network road, it is necessary first of all to select the segment on which the vehicle is actually traveling (Zhao, 1997). In literature, there are many techniques of selection. Such as the method proposed by (El Najar, 2005) which fuses two criteria using Belief theory. Each of these criterions is characterized by belief function. In this paper, we propose a method of estimation treating these belief functions more explicitly than proposed in (El Najar, 2005). This proposition allows the reduction of both the position errors (see figure 6.d) and the conflict (by the addition of a factor of weakening or discounting see Eq. 9 and Eq. 11) computed in the Dempster-Shafer fusion rule.

3.1 Preselection of the Road Segments

The first step is to determine which road segments are candidates for the localization of the vehicle. For this, the basic characteristic of our algorithm is the use of an elliptical confidence region around an estimated position based on error models which are associated with GPS and odometer sensors. Road segments that are within the confidence region are taken as the pseudo candidate segments. These ones represent the frame of discernment in TBM. If the confidence region does not contain any segment, then, it is assumed that the vehicle is not on a cartographic road. In such a situation, the derived positions GPS/odometer are used as the final locations of the vehicle. Many methods are available for calculating the error region around a fixed position. Variance-covariance information associated with GPS receiver outputs is often used to define an error ellipse. According to (Zhao, 1997), the error ellipse can be derived as:

$$a = k\sqrt{1/2(\sigma_x^2 + \sigma_y^2) + \sqrt{(\sigma_x^2 + \sigma_y^2)^2 + 4\sigma_{xy}^2}} \tag{6}$$

$$b = k\sqrt{1/2(\sigma_x^2 + \sigma_y^2) - \sqrt{(\sigma_x^2 - \sigma_y^2)^2 + 4\sigma_{xy}^2}} \tag{7}$$

$$\gamma = 1/2(\pi - \arctan(\frac{2\sigma_{xy}}{\sigma_x^2 - \sigma_y^2})) \tag{8}$$

where ${\sigma_x}^2$ and ${\sigma_x}^2$ are the positional error variances from the integrated GPS/odometer, σ_{xy} is the covariance, a, b are the semi-major axis and semi-minor axis of the ellipse, γ is the orientation of the ellipse relative to the North, and k is the expansion factor. The expansion factor k is a term that compensates for the errors associated with GPS, odometer and digital roadmap sensors. For simplicity, an error circle can be used instead the error ellipse. The centre of the circle is the estimate of the current position and radius R of this one is equal to the semi-major axis a (R=a). The road segments obtained, thus, form our frame of discernment $\Theta = \{Seg_1, Seg_2, ..., Seg_n\}$ or n is the total number of the pseudo candidate segments. In order to select the good road segment up on which a vehicle moves, we propose a method of selection based on the Transferable Belief Model (TBM).

3.2 The Proposed Selection Method

The proposed selection method is based on the fusion of two criteria (proximity and bearing) using the TBM. The frame of discernment is then $\Theta = \{Seg_1, ,........, Seg_n\}$. In this section, we present the proximity and the bearing criteria.

1) Proximity criterion: The proximity criterion is essentially, based on the measure of the Euclidian distance lying between the estimated position and each pseudo-candidate segment. Being given the estimated position P_j, the belief assignment function that characterizes this criterion can be obtained as follows:

$$\begin{cases} m_1(Seg_i / P_j) = \alpha_{proximity} \exp(-d_{ij} / R) \\ m_1(\Theta / P_j) = 1 - \sum_{i=1}^{n} \alpha_{proximity} \exp(-d_{ij} / R) \end{cases} \tag{9}$$

with $\alpha_{proximity}$ is the normalized factor given by:

$$\alpha_{proximity} = \beta_{proximity} / card(\Theta) \qquad (10)$$

where $card(\Theta)$ is the cardinality of Θ and $\beta_{proximity}$ ($0 \le \beta_{proximity} \le 1$) represents the confidence to the proximity criterion: it reflects our a priori knowledge on the quality of the GPS and the odometer sensors. R is the radius of the circle of preselection of the road segments and d_{ij} the distance between the estimated position P_j and the candidate segment Seg_i. The distance d_{ij} corresponds to the minimal distance among the three distances specified in Figure 1.

Let θ_j the estimate of the heading of the vehicle, and then the belief assignment function m_2 which characterizes this criterion is defined by:

$$\begin{cases} m_2(Seg_i / \theta_j) = \alpha_{bearing} \exp\left[-(a_i - \tan(\theta_j))^2\right] \\ m_2(\Theta / \theta_j) = 1 - \sum_{i=1}^{n} \alpha_{bearing} \exp\left[-(a_i - \tan(\theta_j))^2\right] \end{cases} \qquad (11)$$

where $\alpha_{bearing}$ is the normalized factor defined by:

$$\alpha_{bearing} = \beta_{bearing} / card(\Theta) \qquad (12)$$

which $\beta_{bearing}$ ($0 \le \beta_{bearing} \le 1$) represents the confidence to the bearing criterion: that value depends essentially on the speed (Figure 2); and a_i is the bearing factor of the segment Seg_i.

This way of affecting the belief assignment function is known under the name of "separate sources" (Denoeux, 1997).

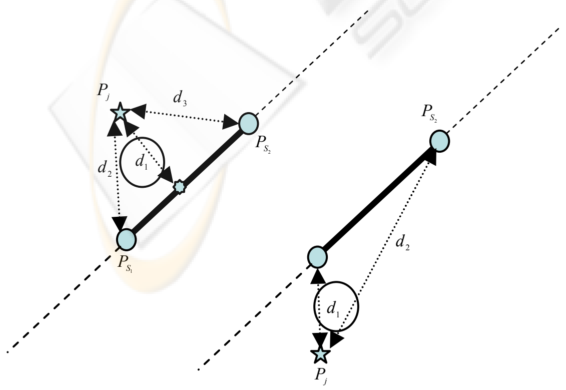

Figure 1: Distance between the point and the segment.

2) Bearing criterion: The fusion of GPS and odometer sensors by Kalman filter provides an estimate of the probable direction of a vehicle which would be relevant for the quantification of bearing criterion. The difference between the heading of a vehicle and the corresponding value from each pseudo-candidate segment is used to formulate a new belief assignment function.

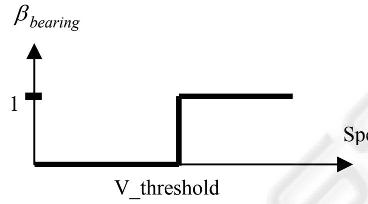

Figure 2: Confidence of the bearing criterion.

In Figure 2, V_threshold represents the threshold of the speed above of which the bearing criterion is reliable. That value is determined by the experimental tests.

3) Fusion and decision: According to the two criteria, we are in the presence of two belief assignment functions m_1 and m_2. We apply the conjunctive rule of combination (Eq. 3) in order to determine a single belief assignment function which results from the aggregation of these two assignment functions. Next, we calculate the conflict given by Eq. 4. If the conflict is lower than 0.5, we calculate the pinistic probability (Eq. 5), then we choose the segment which represents the maximum probability. If it is higher than 0.5, it is not possible to make a decision.

The choice of threshold 0.5 is obtained through the following steps: first, we have simulated many routes given in Figure 3.a, second, we have tested our algorithm with different threshold values which vary between 0.1 up to 0.9, and third, we have calculated the rate average of selection for each threshold (see Figure 3.b). According to Figure 3.b, we notice that threshold 0.5 represents a better solution in term of rate average of selection 85 %.

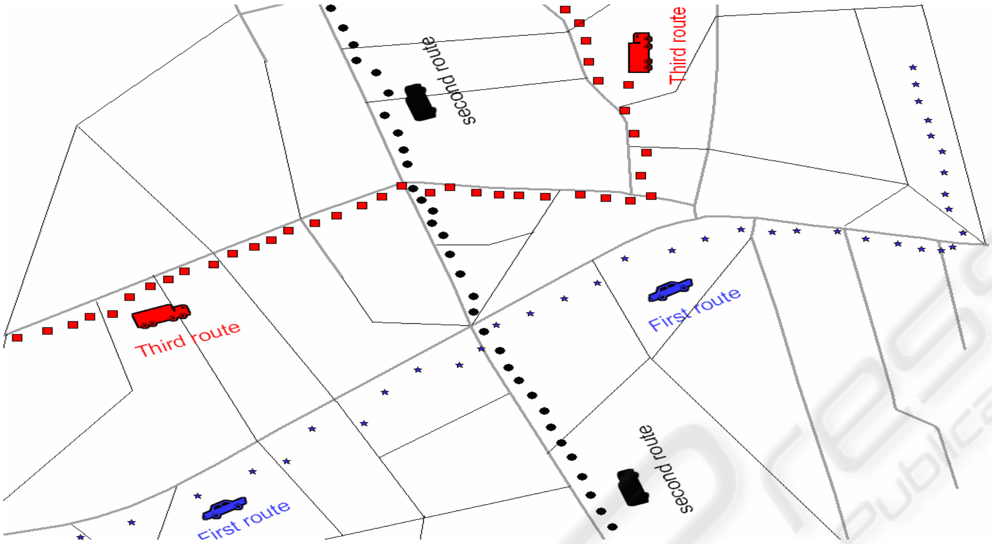

Figure 3.a: Simulation of many routes.

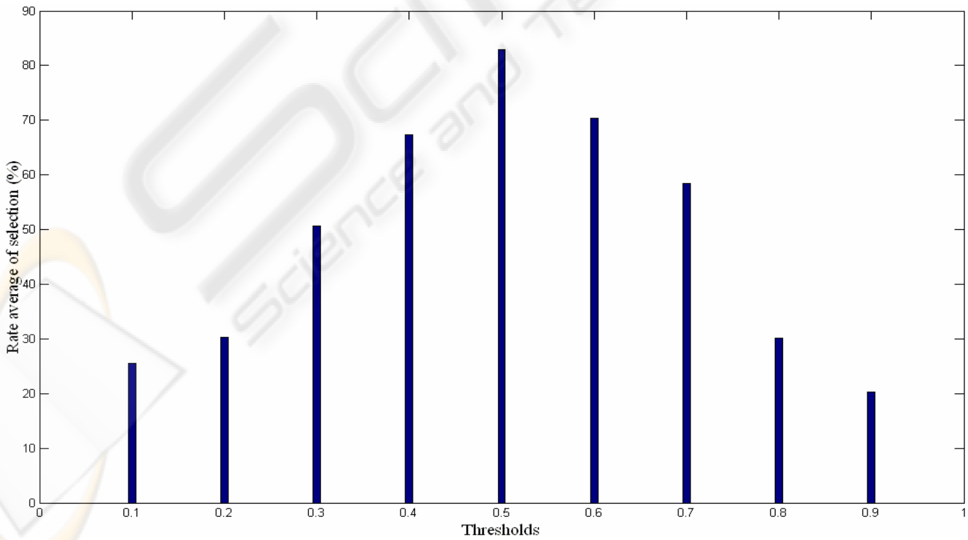

Figure 3.b: The variation of the rate average of selection according to the thresholds.

4 EXPERIMENTAL RESULTS

For the testing of the algorithm, a comprehensive field test was carried out in Calais (France). A test vehicle was equipped with a navigation platform consisting of a 12-channel single frequency GPS receiver (ProPak-G2), the interfaces require to be connected to the vehicle Speed sensor (odometer) and to the digital road map which is used as a reference that had a resolution of 3.5m. The duration of collecting data was about 1hr. As already mentioned, the purposed algorithm is developed in two steps: the first step is to seek the road segment where the vehicle moves, and the second step is to determine the vehicle location on that road segment. Figure 4 illustrates the results of the algorithm for the sample routes. The symbols + (red) and o (black) respectively represent the vehicle position before and after the application of the algorithm.

In order to evaluate the performance of our algorithm, we take the case of a problematic situation standard for example a junction of two roads (Figure 5). In this figure the circle presents the zone of preselection that contains three segments (Seg1, Seg2 and Seg3) which define our frame of discernment. The two belief assignment functions which characterize the proximity criterion and the bearing criterion are defined on this frame.

The figures (Figure 6.a, Figure 6.b, and Figure 6.c) represent a variation of belief assignment functions within this frame of discernment. The proximity criterion (Figure 5.a) shows that the Seg2 is the most credible. The bearing criterion (Figure 5.b) affirms that the segments Seg1 and Seg2 are the most credible. The combination of both criteria (Figure 5.c) confirms that Seg1 and Seg3 are the most credible. Such an ambiguous situation can be resolved if we take into account the information that Seg1 and Seg3 represent the same road.

Figure 6.d shows the variation of error sigma (northing) with time for both the integrated GPS/odometer and the proposed algorithm. The error sigma associated with the integrated GPS/odometer is much higher than that associated with the proposed algorithm. The average standard deviation before the application of the algorithm is 10 to 15m whereas it is 3 to 4m after its use.

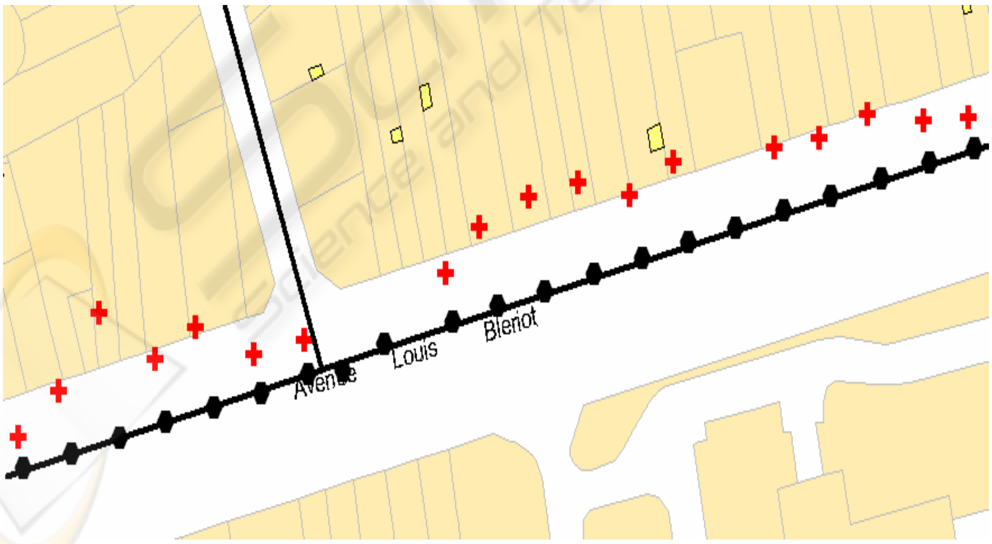

Figure 4: The results of the sample routes.

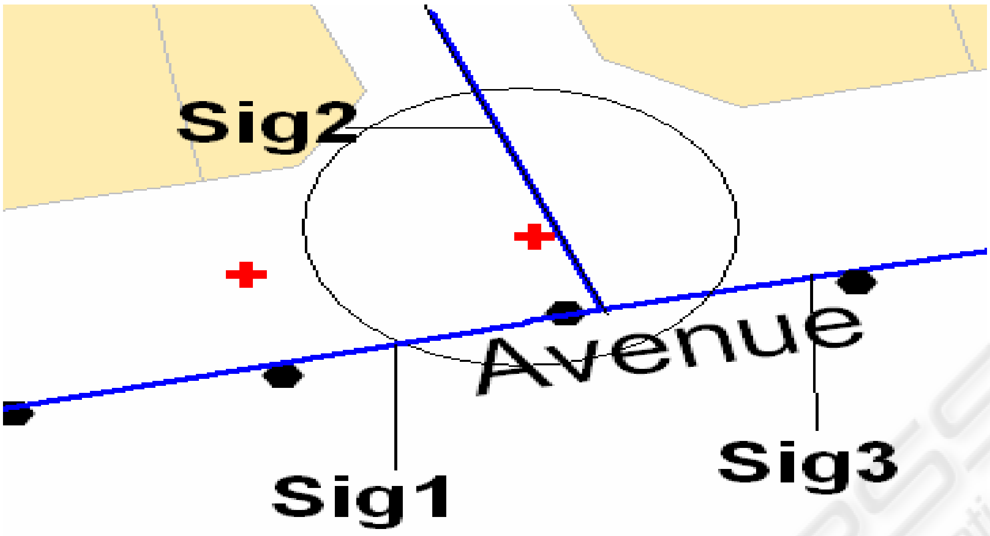

Figure 5: Candidates segments at a given moment.

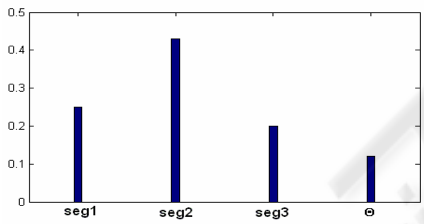

Figure 6.a: Proximity criterion.

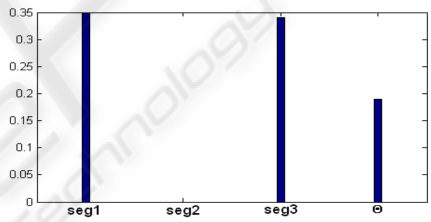

Figure 6.b: Bearing criterion.

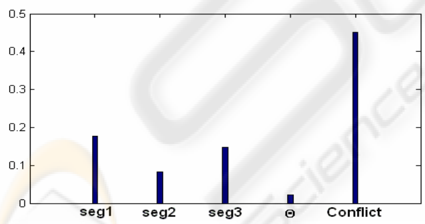

Figure 6.c: Combination of the two criteria.

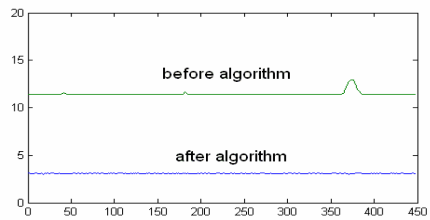

Figure 6.d: Comparison of error sigma.

5 CONCLUSION

In this paper, an algorithm based on the Transferable Belief Model (TBM) has been developed. This algorithm has proved to be very efficient, particularly in difficult operational environments such as junctions and intersections. In fact, it can be considered as an excellent tool to quantify the ambiguousness of a situation. This work has as a prospect to develop other criteria in order to treat the ambiguous situations efficiently (for example problematic situation of two 2 parallel roads).

REFERENCES

Bernstein D. and Kornhauser A., 1998. *Map matching for personal navigation assistants*, The Transportation Research Board, 77th Annual Meeting Washington.

Chui C.K. and Chen G., 1991. *Kalman filtering with real-time applications*, Springer Verlag, second edition.

Dempster A. P., 1967. *Upper and lower probabilities induced by a multivlued mapping*, Annals of Mathematical Statistics, AMS-38, pp. 325-339.

Denoeux T., 1997. *Application du modèle des croyances transférables en reconnaissance de formes*, Traitement du Signal, Vol. 14, n° 5, 443-451.

El Najjar M. and Bonnifait P., 2005. A *road-matching method for precise vehicle localization using belief theory and Kalman filtering*, Autonomous Robots 19, 173-191.

Greenfeld J. S., 2002. *Matching GPS observations to locations on a digital map*, Proceeding of the 81th Annual Meeting of the Transportation Research Board, Washington D. C.

Grewal M. S. and Andrew A. P., 1993. *Kalman Filtering: Theory and Practice*, Englewood Cliffs, NJ: Prentice-Hall.

Hummel B., Tischler K., 2005. *GPS-only Map Matching: Exploiting Vehicle Position History, Driving Restriction Information and Road Network Topology in a Statistical Framework*, In Proc. GIS Research UK (GISRUK), S. 68-77.

Kohlas J. and Monney P. A., 1995. *A Mathematical Theory of Hints: An Approach to Dempster-Shafer Theory of Evidence*, Lecture Notes in Economics and Mathematical Systems No. 425. Springer-Verlag.

Lee B. C., 1998. *A study on the correction of positioning accuracy of car navigation system and map matching algorithm,* in Proc. of 5th World Congr. Intelligent Transport Systems, Seoul, Korea.

Parkinson B. W. *and al.*, 1996. *Global Positioning System, Theory and Applications*, American Inst, Aeronautics and Astronautics.

Shafer G., 1976. *A mathematical theory of evidence*, Vol. 2702. Princeton University Press.

Smets P. and Kennes R., 1994. *The Transferable Belief Model*, Artificial Intelligence, 66, pp. 191-234.

Smets P., 2002. *Decision Making in a Context where Uncertainty is Represented by Belief Functions*, Physica-Verlag, Heidelberg, Germany, 17-61.

Smets P., 2005. *Decision making in the TBM: the Necessity of the Pignistic Transformation*, International Journal of Approximate Reasoning, pp. 133–147.

Taylor G., Blewitt G., Steup D., Corbett S., Car A., 2001. *Road reduction filtering for GPS-GIS navigation*, Proc. of 3rd AGILE Conference on Geographic Information Science, Helsinki, Finland, pp. 114-120.

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, pp. 257-275.

Zhao Y., 1997. *Intelligent Transportation Systems: Vehicle Location and Navigation Systems*, Artech House, ISBN.