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# **A NOVEL SYSTEM USING ENHANCED DIGITAL MAPS AND WAAS FOR A LANE-LEVEL POSITIONING**

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Accurate real-time positioning, i.e. at the lane level, is a big challenge for a lot of advanced driver assistance systems (ADAS) under study or development. To reach the sub-meter accuracy necessary for the lane discrimination, the best from the existing technologies and state-of-the-art data fusion algorithms must be used, keeping in mind that the final commercial solution will have to be available at an acceptable price for the customer. In the frame of the European project CVIS, the LCPC is addressing this issue and this paper presents the choices that have been made: EGNOS (the European WAAS) for the main positioning technology, a new model of enhanced digital maps compliant with the lane-level objective and an innovative particle filter proposed by the LCPC team to merge sensor and map data into a unique positioning and map-matching process.

Key words: Advanced Driver Assistance Systems, lane-level real-time positioning, WAAS, enhanced digital maps, particle filtering, map-matching

## **FRAMEWORK AND OBJECTIVE OF THE RESEARCH**

The CVIS integrated project of the European Commission 6<sup>th</sup> framework program aims at creating a unified technical solution allowing all vehicles and infrastructure elements to communicate with each other in a continuous and transparent way using a variety of media and with enhanced localization. The POMA (POsitioning and MApping) sub-project will research, develop, test and validate advanced positioning and mapping solutions in order to provide a set of positioning and mapping services that will run across CVIS entities (vehicle, roadside equipment, service center, etc.). In the frame of POMA activities, a specific research action aims at developing a new system capable of locating vehicles at lane-level. This capability is valuable for a panel of ADAS, for instance *Enhanced Driver Awareness* warning the driver of any danger or obstacle that he can potentially find on his trajectory, like a wrong way driving vehicle, or new services called *Lane utilization information*, *In-vehicle variable speed limit information* or *Intelligent speed alert* with links to infrastructure.

The research that is presented below aims at demonstrating the feasibility of this concept, on given areas where the lane-level accuracy is relevant and where the general environmental situation is not too stringent, for instance on large interchanges and crossroads. The idea is not to target sub-meter accuracy always and in all conditions, which is unrealistic, but to target a system capable to tell the user application on which lane the vehicle is likely to drive and with which confidence this information is true.

## **ASSUMPTIONS AND BASIC COMPONENTS OF THE SYSTEM**

The first necessary condition to reach a sub-meter accuracy is the availability of an augmented GNSS system, such as the American WAAS or the European EGNOS, which is the unique cost-effective available technology capable of this performance. The use of phase-

differential techniques known as *RTK* is not realistic today in the context of road transportation for obvious cost and availability reasons. Today, GPS+WAAS or GPS+EGNOS systems are definitely the best candidates before the other systems such as Galileo are ready to increase the GPS-only performances.

Yet, the weak point of WAAS, i.e. its poor availability due to satellites outages, has to be improved by data fusion using other sources of information such as dead-reckoning sensors. Traveled distance is commonly available on most modern vehicles through the CAN bus and low-cost gyroscopes providing the yaw angle speed will also be accessible in a near future, for instance those used in ESP (Electric Stability Program) systems. With these sensors, it is possible to mitigate short-term GPS perturbations or outages and to yield, as output of a fusion algorithm such a Kalman filter, a more available, accurate and integer position. Nevertheless, given the poor quality of automotive sensors, this improvement is limited and it is not reasonable to expect good absolute position after a satellite outage exceeding a few tens of seconds.

Another very important point is that absolute position in a geocentric frame such as WGS 84 is finally useless since all the applications need map-matched position, i.e. absolute position projected on a digital map reference. From this point, two observations can be made: first, the map-matching process needs to be considered; second, it should be extremely interesting for the data fusion itself to use this important a priori information contained in digital maps. Hence, we decided to design an innovative algorithm merging the 2 processes of data fusion and map-matching in a unique one, the output being an accurate map-matched position.

## **THE SENSOR SET**

The experimental set-up that has been used for this paper comprises the following sensors:

- GPS/WAAS receiver: mono frequency L1, EGNOS compliant, with internal Kalman filter off.
- yaw rate gyroscope: FOG (Fiber Optic Gyro):
  - o noise (random walk):  $0.083^{\circ}/\sqrt{\text{h}}$
  - o short term bias stability (at constant temperature) (1 hour): not significant
  - o bias (over temperature range):  $< 0.4^{\circ}/\text{s}$
- odometer: encoder located in the gearbox of the test car, delivering 1 pulse for each 19.54 cm traveled by the front wheel in average.

## **THE ENHANCED DIGITAL MAPS**

### **Model**

Considering that lane-level accuracy is targeted, the digital maps that should be used need to describe all the lanes of the road with a sufficient accuracy, let's say 10 times better than the final accuracy requested, i.e. around 10 cm. This requirement is nowadays totally reasonable with the dramatic progresses achieved recently in the mobile mapping and aerial photogrammetry technologies. Moreover, these enhanced maps need to be established only for some critical areas in which the lane-level accuracy is needed.

The new Emap data model is presented on Figure 1. Compared to a standard digital map used for simple navigation, generally based upon GDF standard, this new model adds Carriageways and Lane segments and the description of both longitudinal and transversal geometry.

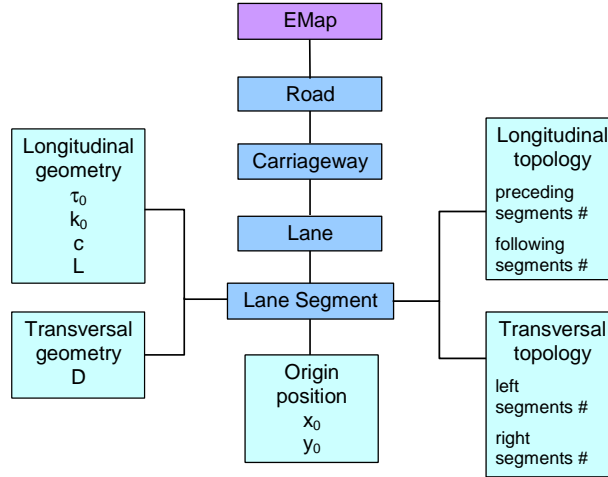


Figure 1: the Emap data model

The lane segment is the basic element described by its geometry and its topology.

The lateral geometry is limited to the width whereas the longitudinal geometry is compliant with a clothoid model of the segment central axis and described by the following Fresnel integrals using the parameter  $l$  (curvilinear abscissa):

$$\begin{aligned} x(l) &= x_0 + \int_0^l \cos\left(\tau_0 + \kappa_0 l + \frac{cl^2}{2}\right) dl & 0 < l < L \\ y(l) &= y_0 + \int_0^l \sin\left(\tau_0 + \kappa_0 l + \frac{cl^2}{2}\right) dl & 0 < l < L \end{aligned} \quad [1]$$

Each segment is determined by a unique set of parameters: the coordinates of the origin ( $x_0, y_0$ ), the tangent angle ( $\tau_0$ ) and the curvature ( $\kappa_0$ ) at the origin and the variation rate ( $c$ ) of the curvature with respect of the curvilinear abscissa ( $c$ ). This model is also valid for straight line ( $\kappa_0 = c = 0$ ) or circular segments ( $\kappa_0 \neq 0, c = 0$ ).

The longitudinal topology is described by the physically accessible segments that precede or follow the current one (we call this relation: *longitudinal connectivity*) and the lateral is described by the accessible segments at the right or the left hand side of the current one (we call this relation: *transversal connectivity*).

### Construction

Several different techniques can be used to build such enhanced digital maps, the most promising being aerial photogrammetry and land mobile mapping vehicles. We have developed a method suited to the estimation of the series of parameters ( $x_0, y_0, \tau_0, \kappa_0, c$ ) based on an Extended Kalman Filter using mobile mapping data. For this purpose, the DGPS receiver of the sensor set presented before was replaced by a kinematic receiver, which enable post-processing of phase data and achievement of centimeter level solutions (PPK: *post-processed kinematic GPS*).

The initial step in the Emap construction consists in fusing dead-reckoning and kinematic GPS solutions so that continuous positioning is available everywhere. This is done in a software module developed by the LCPC that is basically an EKF followed by a Rough linearized smoother on the complete data set time interval. Next step performs the clothoid extraction. It takes the preceding vehicle smoothed positions as observations in a filtering process, whose prediction model simply keeps parameters at instant  $k+1$  equal to those at

instant  $k$ , and observation model uses an approximation of the Fresnel integrals of the ongoing clothoïde to compute  $(x,y)$  position and the corresponding innovation with respect to local smoothed position. When this innovation exceeds a threshold (that we fixed at 5 cm), the clothoïde is ended and a new set of parameters is initialized. Last step in the Emap construction is still manual and aims at filling the connectivity relationships between all clothoïdes identified before, and store data in a database. Note that trajectories in crossroads will not be modeled.

Figure 2 shows two extracted clothoïdes before a crossroad: the black crosses represent the surveyed points obtained with our mobile mapping vehicle and the red crosses the extremities of the elements. Figure 2 also illustrates the difference between longitudinal and transversal connectivity.

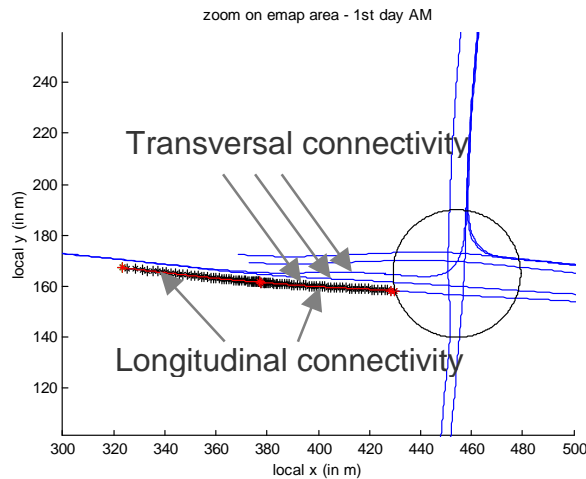


Figure 2: Longitudinally and transversally connected road elements

## THE POSITIONING/MAP-MATCHING ALGORITHM

### The hybridization principle

Traditionally, the positioning information is processed in 3 steps (for instance in navigation systems): 1) estimation of the absolute position of the vehicle in a geographical reference frame, using GPS only or through data fusion between GPS and proprioceptive sensors, 2) map-matching of the absolute position on the digital map, 3) extraction of the relevant information from the data base (attributes of map elements).

Our process hybridizes tightly the first 2 steps and estimates together the absolute position and orientation, the lane segment on which the vehicle is driving as well as the position of the vehicle in the lane segment reference system. In addition to the fact that this process is more likely to be optimum and more direct, it brings the very significant advantage to constraint the solution within the carriageway, making it possible the elimination of outliers. Of course, the quality of the final result depends directly on the measurement accuracy, like any other positioning process, as well as on the geometry of the map.

The lane reference system, also called *Frenet reference system* in which the map-matched position is expressed is illustrated in Figure 3. The coordinates of the current map-matched point  $P$  are: the id of the segment  $m$ , the curvilinear abscissa of the orthogonal projection of  $P$  onto the lane axis  $l_N^m$  and the orthogonal signed distance from  $P$  to the lane axis  $d_N^m$ .

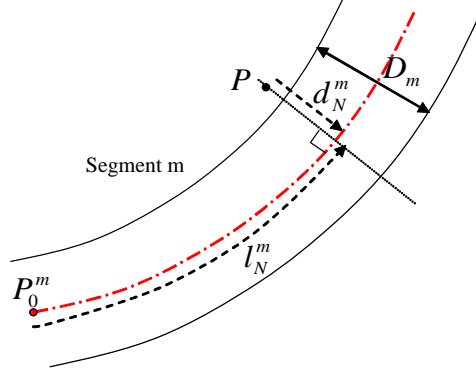


Figure 3: The lane reference system for the map-matched position on the lane segment

### Map matching with Emap

There are several approaches to the map matching issue.

1) The geometrical approach like so-called *point to point* or *point to curve* methods using only distance criteria to select the matched road element. These methods are simple to implement but are very sensitive to the map bias and/or errors and positioning errors. Moreover, the map-matching can fail when the vehicle evolves in a dense road network due to possible ambiguities in road elements selection.

2) The second kind of approach is called *multidimensional approach*. To improve the geometric approach, some people propose to add other criteria to select the matched road element like the driving direction, the speed limit, the heading information or the traveled distance on the road element, etc.

3) The last kind of map matching method is the topological approach. Either the topological information is used to drive the selection step and filter out the road elements which cannot be reached with respect to previous map-matching results, or the vehicle trajectory is compared with pieces of curve constituted by a set of connected road elements and a L2 norm criterion is used to select the best curve. This last method is so called *curve to curve* map-matching.

Within the context of enhanced maps, errors and bias on the geometry of the road network are small and the topology is perfectly known. Therefore, to achieve the map-matching included inside our process, we have decided to implement a *point to curve method* (1) (2) (3) driven by topological information using the two following selection distance criteria: 1) the signed orthogonal distance  $d_N^m$  between the positioning result  $P = (x, y)^T$  in a Cartesian reference system and the central axis of lane segment  $m$  and 2) the curvilinear abscissa  $l_N^m$  associated to this orthogonal distance (see Figure 3). These two criteria define also the vehicle position in the Frenet reference system associated with lane segment  $m$ , which we call “map-matched position”.

A relationship between these two representations exists [2] + [3] and will be used to evaluate the map matching result:

$$x = x_0^m + \int_0^{l_N^m} \cos \tau^m(l_N^m) dl - d_N^m \sin \tau^m(l_N^m) \quad [2]$$

$$y = y_0^m + \int_0^{l_N^m} \sin \tau^m(l_N^m) dl + d_N^m \cos \tau^m(l_N^m)$$

$$\text{where: } \tau^m(l_N^m) = \tau_0^m + \kappa_0^m l_N^m + \frac{c^m(l_N^m)^2}{2} \quad [3]$$

Moreover, in order to limit map-matching errors when the positioning accuracy is poor, we propose to constrain the positioning results with the map by taking into account the map-matching results and the geometry of the lane segment. Therefore a positioning result can be considered as acceptable if the position is located onto a lane segment, i.e.:

$$p(P = (x, y)^T / d_N^m) = 1 \quad \text{if} \quad D^m / 2 < d_N^m < D^m / 2 \text{ \_and\_} 0 < l_N^m < L^m \quad [4]$$

0 else

where  $D^m$  and  $L^m$  are respectively the width and the length of the lane segment  $m$ .

In this case, the matching and positioning processes cannot be dissociated and must be combined in a single hybrid system so called *map-aided system*. These systems are based on Bayesian filtering schemes like Kalman filtering where the map matching result is considered as a new observation in the positioning system. Two kinds of map-aided system can be found in the literature: the *loosely coupled* map-aided systems (4) (5) where the map-matching results are only used to observe and correct the vehicle positioning and the *tightly coupled* map-aided systems (6) (7) (8) where the map-matching results are used to observe the GPS errors. Generally, due to the conventional polyline representation of roads, this new observation is considered as a Gaussian unimodal observation. However, when the vehicle evolves in complex environments such as crossroads or junctions where several road segments are probable, the fusion process fails. In these cases, the unimodal filtering is not appropriate and it is necessary to switch to a multi-hypothesis fusion scheme running several filters in parallel (9) or to use particle filter (5). This multi-modal situation is even more frequent when using Emaps since multi-lane carriageways generally offer also the possibility to drive on all the lanes, increasing consequently the matching ambiguities.

### The hybrid state system

According to the state-of-the-art and our context, we decided to use a particle filtering scheme in our positioning system, and also to use the map-matching results as a possible multi-modal observation. However, due to the complexity and the ambiguity of the relationship between position and map-matching results (see equation [2]), the map-matching results cannot be used directly as an observation. To turn around this problem, we propose to estimate the map-matched position in the fusion process together with the standard position parameters (pose). The augmented state vector of this new hybrid positioning/map matching system can be expressed as:

$$X = ({}^C X, {}^F X)^T = ([x, y, \gamma], [l_N^m, d_N^m, m])^T \quad [5]$$

The first sub-state  ${}^C X = (x, y, \gamma)^T$  is the traditional Cartesian 2D pose composed of the coordinates of the reference point of the vehicle  $P$  and the heading angle. The second sub-state, called the *Frenet sub-state*  ${}^F X = (l_N^m, d_N^m, m)^T$  represents the map-matched position of  $P$ , expressed in the lane reference system. The two sub-states are partially redundant, but this approach offers the advantage to compute in one shot all the relevant variables that are necessary for applications.

Finally, taking into account the particle filtering scheme, the augmented position probability density function is approximated at time  $k$  by the sample set:  $\{X_k^i, w_k^i\}_{i=1 \dots N}$ , where  $N$  is the number of samples or particles and  $w^i$  is the importance weight of sample  $i$  in the probability density.

The augmented position estimate is given by:

$$p(X_k / Y_{1:k}) = \sum_{i=1}^N w_k^i \delta_{X_k^i} \quad [6]$$

where  $\delta_{X_k^i}$  is the Dirac function centered on  $X_k^i$ .

### Steps of the particle filter

As a matter of fact, our particle filter will be composed of two different filters running in parallel and in a synchronized way: one for the evolution in time of the Cartesian sub-state and the other for the evolution in time of the Frenet sub-state. The main advantage of this method is the improvement of the observability of the positioning problem. Indeed, the positioning problem will be observed directly and separately by GPS data in the Cartesian representation and by the map constrains in the Frenet representation.

#### Evolution of the Cartesian sub-state

The Cartesian sub-state system is in fact the state system used classically: its behavior is defined by the following relationship:

$$\left. \begin{array}{l} p({}^c X_k / {}^c X_{1:k-1}): {}^c X_k = {}^c f({}^c X_{k-1}, U_k, W_k) \\ p(Y_{gps} / {}^c X_k): Y_{gps} = H_{gps} {}^c X_k + V_{gps} \end{array} \right\} \quad [7] [8]$$

where:

- ${}^c f(.)$  is the evolution model of the vehicle in the Cartesian coordinate system, a bicycle model is used in our case,
- $U_k$  is the input vector of the evolution model, inputs are the speed  $v \sim N(v, \sigma_v^2)$  and the turn rate  $\omega \sim N(\omega, \sigma_\omega^2)$  of the vehicle,
- $W_k$  is the evolution model uncertainty,
- $Y_{gps} = (x_{gps}, y_{gps})$  is a GPS observation at instant k,
- $H_{gps}$  is the observation matrix linking GPS data to the sub-state  ${}^c X_k$ ,
- $V_{gps} \sim N(0, R_{gps})$  is the uncertainty vector on the GPS data, with  $R_{gps}$  the covariance matrix associated to GPS data.

1. Prediction. Applying Monte Carlo scheme to the dynamic equation [7], prediction at time  $k$  of the Cartesian part of each particle is provided by the following equations:

$$x_k^i = x_{k-1}^i + v^i \Delta_T \cos(\gamma_{k-1}^i + \omega^i \Delta_T / 2) \quad [9]$$

$$y_k^i = y_{k-1}^i + v^i \Delta_T \sin(\gamma_{k-1}^i + \omega^i \Delta_T / 2)$$

$$\gamma_k^i = \gamma_{k-1}^i + \omega^i \Delta_T$$

where  $v^i$  and  $\omega^i$  are pure random variables drawn according to the probability densities of the uncertainties of the speed  $v$  and the turn rate  $\omega$  of the vehicle and  $\Delta_T$  is the time elapsed between the time  $k$  and  $k-1$ .

2. Correction. The weights of the particles are updated to take into account the measurement equation. As a Gaussian hypothesis has been made on the GPS observation, the likelihood density function can be written that way:



$$p(Y_{gps}^i / X_k^i) \approx e^{-\frac{1}{2} (H_{gps}^C X_k^i - Y_{gps}^i)^T R_{gps}^{-1} (H_{gps}^C X_k^i - Y_{gps}^i)} \quad [10]$$

where observation matrix is equal to:  $H_{gps} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$  [11]

and the weight updating of each particle is given by:

$$w_k^i = p(Y_{gps}^i / X_k^i) w_{k-1}^i \quad [12]$$

### Evolution of the Frenet sub-state

The behavior of the Frenet sub-state system is more complex since it is a vector composed of continuous and discrete variables. Such state systems are governed by a so-called *Jump Markov state system* (10) (11) which is, in our case, of the following form:

$$\left. \begin{array}{l} p(X_k^F / X_{k-1}^F): X_k^F = f^m(X_{k-1}^F, U_k, W_k) \\ p(Y_{map}^m / X_k^F): Y_{map}^m = H_{map}^F X_k^F + V_{map}^m \\ m_k \sim p(m_k / m_{k-1}, X_k^F) \end{array} \right\} \quad [13] [14] [15]$$

where :

- $m$  is the mode of the Jump Markov state, in our case the mode corresponds to a description of the lane segment associated to map matching result,
- $f^m(.)$  is the evolution model of map-matched position, this model changes for each mode  $m$  and is defined by the geometry description of lane segment associated with the mode  $m$ ,
- $Y_{map}^m$  is the map observation (or map constraint),
- $V_{map}^m$  is the uncertainty on the map observation.

1. Prediction. According to Monte Carlo scheme and the geometric description of the lane segment  $m$ , and to the evolution of the vehicle position in the Cartesian reference system [9], prediction at time  $k$  of the map-matched position of each particle is provided by the following equation:

$$\begin{pmatrix} d_{N,k}^{m,i} \\ l_{N,k}^{m,i} \end{pmatrix} = \begin{pmatrix} d_{N,k-1}^{m,i} \\ l_{N,k-1}^{m,i} \end{pmatrix} + \begin{pmatrix} \cos(\tau^m(d_{N,k-1}^{m,i})) & \sin(\tau^m(d_{N,k-1}^{m,i})) \\ -\sin(\tau^m(d_{N,k-1}^{m,i})) & \cos(\tau^m(d_{N,k-1}^{m,i})) \end{pmatrix} \begin{pmatrix} v^i \Delta_T \cos(\gamma_{k-1}^i + \omega^i \Delta_T / 2) \\ v^i \Delta_T \sin(\gamma_{k-1}^i + \omega^i \Delta_T / 2) \end{pmatrix} \quad [16]$$

As a matter of fact, this equation represents the projection of the vehicle evolution in the Cartesian reference system onto the middle axis of the associated lane segment and its perpendicular. This equation assumes small displacements of the vehicle.

The transition of modes depends on the probability that the vehicle evolves on a new lane segment after the evolution i.e.  $p(m_k^i \neq m_{k-1}^i / m_{k-1}^i, X_k^i)$ . This probability can be computed in taking into account the topological information (connectivity) of each segment and the new position of the vehicle on the current lane segment  $m_k^i$ .

Then four transitions of mode are possible:

- a “left” transition occurs if the segment  $m_k^i$  has a left-connex segment and  $d_{N,k}^{m,i} < -D^{m,i} / 2$ ,
- a “right” transition occurs if the segment  $m_k^i$  has a right-connex segment and  $d_{N,k}^{m,i} > D^{m,i} / 2$ ,

- a “next” transition occurs if the segment  $m_k^i$  has a next-connected segment and  $l_{N,k}^{m,i} > L^{m,i}$ ,
- a “previous” transition occurs if the segment  $m_k^i$  has a previous-connected segment and  $0 < l_{N,k}^{m,i}$ .

Notice that, if a transition of mode has occurred, the map-matched position must be reevaluated taking into account the geometry of the new lane segments. This is done by minimizing the distance between the Cartesian position and the Fresnel integrals computed iteratively using equation [1].

**2. Correction.** Finally, the weight of each particle is updated taking into account the map constraints relation.

The likelihood density of each particle with respect of the distance criteria is:

$$p(Y_{map}^m, {}^F X_k^i) = 1 \quad \text{if} \quad -D^{m,i} / 2 < d_{N,k}^{m,i} < D^{m,i} / 2 \text{ and } 0 < l_{N,k}^{m,i} < L^{m,i} \quad [17]$$

$$0 \quad \text{else}$$

and the weights are updated the following way:

$$w_k^i = p(Y_{map}^m / {}^F X_k^i) w_{k-1}^i \quad [18]$$

According to the previous description, there are three main advantages to introduce map matching result in the filtering scheme:

1. the evaluation of map matched position at each time is not needed because it is provided by the filter itself,
2. the map constraints are easy to implement,
3. the map matching process (used only to reevaluate the map-matched position during lane change) is improved because it takes into account both the topology and the vehicle behavior.

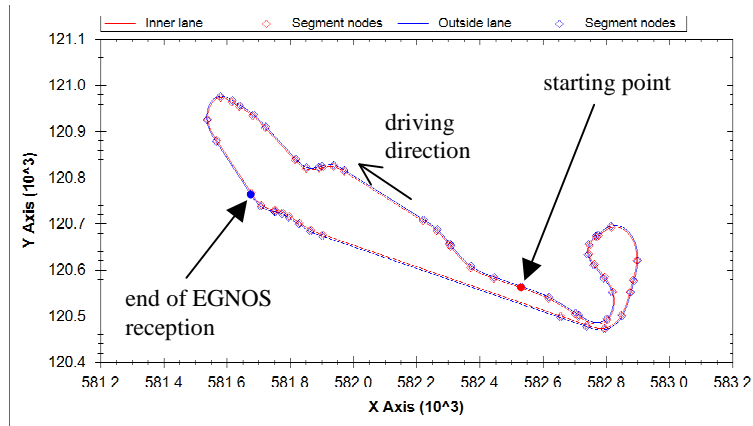
### Final hybrid positioning and map matching algorithm

- 
- **Initialization :**
    - draw  $\{ {}^C X_k^i \}_{i=1}^N$  according to the initial distribution  $p(Y_{gps}(0), {}^C X_0)$
    - evaluate  $\{ {}^F X_k^i \}_{i=1}^N$  in using map matching function
  - **Prediction :**
    - draw  $\{ {}^C X_k^i \}_{i=1}^N$  according to the proposal distribution  $p({}^C X_{1:k}, {}^C X_{1:k-1})$
    - draw  $\{ {}^F X_k^i \}_{i=1}^N$  according to the proposal distributions  $p({}^F X_{1:k}, {}^F X_{1:k-1})$  and  $p(m_{1:k} | m_{1:k-1}, {}^F X_{1:k})$
    - if  $m_{1:k} \neq m_{1:k-1}$  reevaluate  ${}^F X_{1:k}^i$  in using map matching function.
  - **Correction :**
    - evaluate importance weights:
      - \* for GPS observation :  $\tilde{w}_k^i \propto p(Y_{gps} | {}^C X_{1:k}^i)$
      - \* for map observation :  $\tilde{w}_k^i \propto p(Y_{map} | {}^F X_{1:k}^i)$
    - normalize weights:  $w_k^i = \tilde{w}_k^i / \sum_{n=1}^N \tilde{w}_k^n$
  - **Resampling :**
    - Multiply/Discard particles with respect of high/low importance weights  $w_k^i$  to obtain a new particle set  $\{ X_k^i, w_k^i \}_{i=1}^N$
    - set weight  $w_k^i = 1/N$
  - **Estimation :**
    - samples set  $\{ X_k^i, w_k^i \}_{i=1}^N$  approximate the posterior distribution:
$$p(X_{1:k} | Y_{1:k}) = \sum_{i=1}^N w_k^i \delta_{X_k^i}(dX_k)$$
-

## EXPERIMENTAL RESULTS

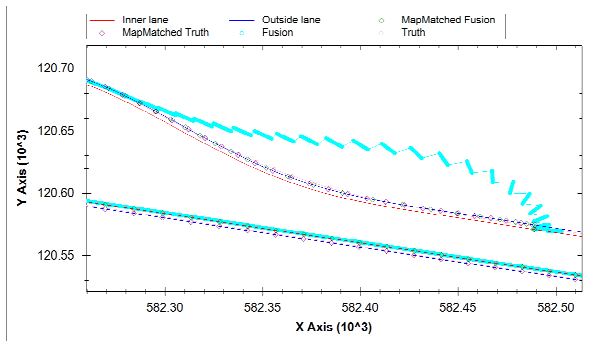
Our lane-level positioning system has been experimented using real data collected during a benchmarking campaign carried out on a closed test track located in VERSAILLES-SATORY at the end of 2005. An Emap model of the loop composed of 2 separate lanes has been established using the very accurate survey data describing the track.

Figure 4 presents a general view of the track, the Emap clothoïde elements that have been determined, the starting point and the part of the circuit where EGNOS has been available.

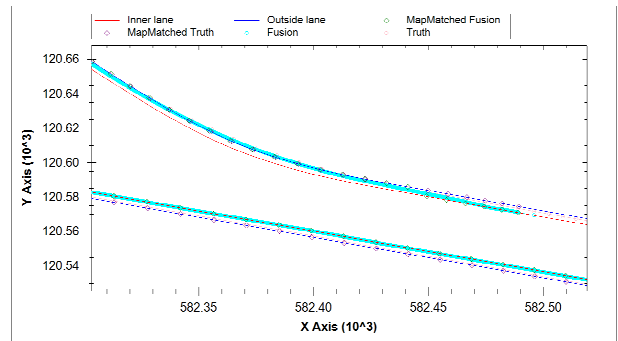


*Figure 4: General view of the test track with the Emap elements*

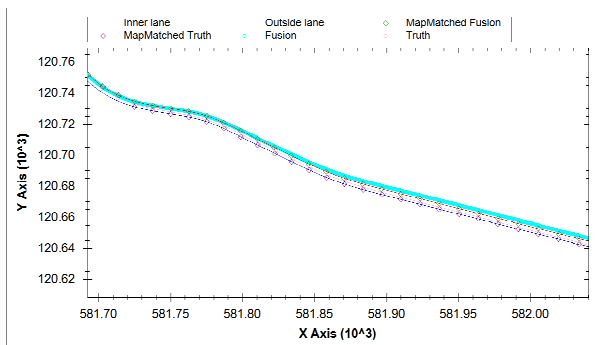
Figures 5 to 10 show some comparative results obtained on the one hand with the traditional positioning + map-matching processes (system A) and on the other hand with our novel hybridized unique process (system B). A standard Extended Kalman Filter has been used for the positioning data fusion and a distance minimization to the closest clothoïde element for the map-matching.



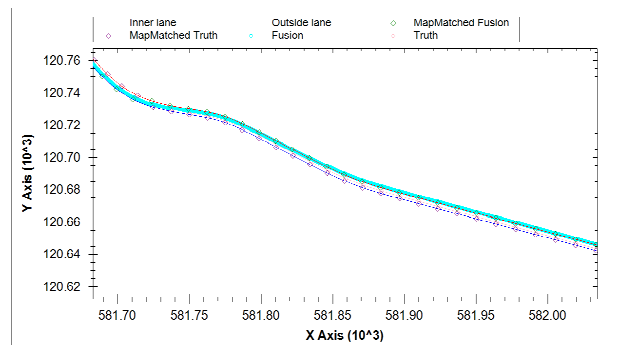
*Figure 5: Initialization area with system A*



*Figure 6: Initialization area with system B*



*Figure 7: No-EGNOS area with system A*



*Figure 8: No-EGNOS area with system B*

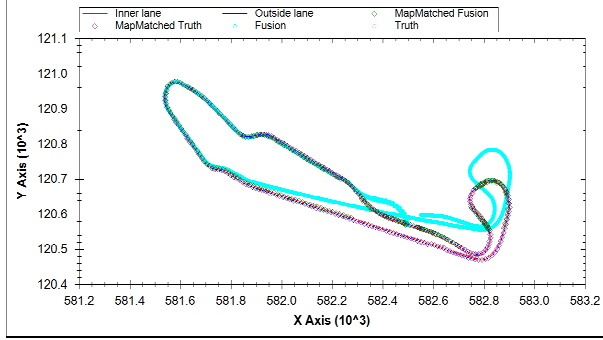


Figure 9: No-GPS simulation with system A

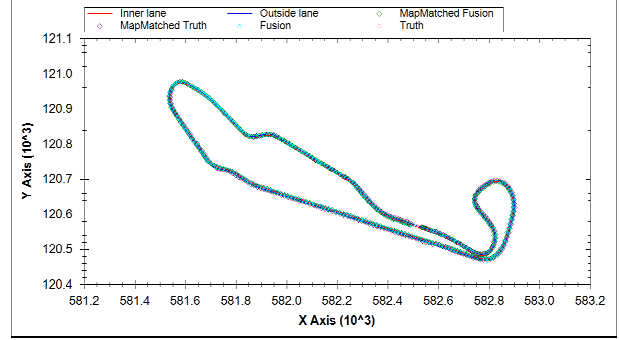


Figure 10: No-GPS simulation with system B

On all the figures, the 2 lane axes are represented, as well as the absolute position coming from the sensor data fusion (thick magenta line), true absolute position (thin pink line), estimated map-matched position (green squares) and true map-matched position (purple squares).

For system B, the estimated absolute position comes from the estimated Cartesian component of the composite state vector and the map-matched position is the projection of the current point onto the most likely lane axis, determined by the estimated element parameter  $m$ .

On Figures 5 and 6, it can be seen that the Kalman filter initialization time can be much higher than the particle filter one when the initial heading angle is not correctly initialized; Moreover, when EGNOS data are available, the global accuracy is good enough to determine the right lane.

Looking at Figures 7 and 8, it can be noticed that without EGNOS, the stand-alone accuracy of the GPS is not good enough to keep the estimation on the right lane, whatever the fusion system, but the advantage of system B is that the estimated absolute position stays closer to the lane axis, meaning that, at least for a while, the Emap constraint is efficient to correct the GPS bias.

Figures 9 and 10 have been obtained after having created a virtual total GPS outage just after the point where EGNOS is lost. It can be easily noticed that the important drift of the dead-reckoning navigation results in totally erroneous traditional map-matching whereas the map constraint prevents the position to leave the road, even if the estimated lane is not correct after a while.

## CONCLUSION AND PERSPECTIVES

This paper presents a novel combined positioning/map-matching data fusion system that merges sensor data from a GPS-WAAS receiver, dead-reckoning sensors and a precise description of the geometry and the topology of the road at lane-level called *Emap* model, developed in the frame of the European integrated project CVIS. This system has been designed to bring a solution to the lane-level positioning issue, which is necessary for a larger and larger number of new co-operative ADAS under development.

Compared to traditional methods that realize first the sensor data fusion, generally by Kalman filtering, and then the map-matching, our novel method based upon a particle filter estimating a composite state vector, offers several advantages:

1. the estimated position is constrained to stay on the road, even when large absolute positioning errors occur,

2. when a WAAS augmentation system such as EGNOS is available, the system is able to estimate the exact lane on which the vehicle is moving, with a better reliability than the standard dissociated methods,
3. the system has been designed to cope with multi-modal situations, often met on real roads.

This paper summarizes the first research investigations that we have carried out in the context of lane-level positioning using enhanced digital maps. Our future work will be mainly focused on the experimental assessment of the method in more complex environments such as crossroads or interchanges, where the ability of the algorithms to comply with multi-modal situations at junctions will be highlighted. In the meanwhile, the automatic computing of geometry, and connectivity relationships in Emaps is under development.

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