Lane-level positioning for cooperative systems using EGNOS and enhanced digital maps

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BIOGRAPHY

François Peyret, born in 1950, was graduated from the *ENSMA* in Poitiers (1974) and from *Sup'Aero* in Toulouse (1975). He is now Director of Research (equivalent of Professor), and head of the *Image processing and geopositioning* research team, at LCPC, where he is leading research activities in the field of road vehicle positioning for ADAS, especially with hybrid GNSS systems and enhanced 3D map-matching. His team is presently involved in 2 major European integrated projects in this field: CVIS and SAFESPOT from the 3^{d} eSafety call, and also in several national projects or research actions.

David Bétaille is a researcher in the Division for Metrology and Sensor Instrumentation of the LCPC, where his current activity relates to vehicles positioning by satellites systems combined with dead-reckoning and mapping. ADAS and in general road safety applications compose the research context of his lab. He received his PhD in 2004 for his investigations at University College London on phase multipath in kinematic GPS.

Jean Laneurit is a Research Engineer at the University of Technology of Compiègne, France. He received the Ph.D. degree in Vision for robotic from the University of Clermont-Ferrand, France, in 2006. His research works are about Advanced Driver Assistance Systems.

Rafael Toledo-Moreo received the M.S. degree in Automation and Electronics Engineering from the Technical University of Cartagena (UPCT), Cartagena, Spain, in 2002 and the Ph.D. degree in computer science from the University of Murcia (UMU), Murcia, Spain, in 2006. He is assistant professor of the Department of Electronics and Computer Technology, UPCT, while he also collaborates with UMU in a number of projects concerning navigation systems applied to terrestrial vehicles. Currently, he works as an invited researcher at LCPC, Nantes centre. His main fields of interest are navigation systems, satellite and inertial navigation, and data fusion in road vehicle applications.

1. INTRODUCTION

The work presented in this paper has been carried out in frame of the European CVIS project. The CVIS integrated project of the 6th framework program is aiming 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 localisation. The POMA (POsitioning and MApping) sub-project researches, develops, tests and validates 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 centre, 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/she can potentially find on his/her 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".

In this paper we present the feasibility of this concept, paying special attention to the contributions that EGNOS can provide to our purposes. The idea is not to target sub-meter accuracy in all the possible conditions, what is nowadays 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. EGNOS contributions should pass through the increase of the navigation accuracy by means of the GPS corrections sent via the geostationary satellite, and a confidence estimator of its integrity, based on the protection level parameters.

2. GENERAL DESCRIPTION OF THE SYSTEM

To achieve the aimed sub-meter positioning accuracy, a clear option would be the use of phase differential capable GPS sensors. However, the effect of its inclusion in the onboard device would result on a significant increase of the system final cost, which makes us disregard this option. The use of satellite based augmentation systems (SBAS) is feasible from the point of view of costs considerations, but its capability to provide effective sub-meter positioning accuracy for our application must be analysed. The benefits that the European Geostationary Navigation Overlay Service (EGNOS), the European SBAS, can bring to POMA are of special interest in the research presented in this paper.

A priori, the weak point of EGNOS would be its poor availability due to satellites outages. In order to provide continuous positioning the onboard equipment must be completed with other sources of information such as dead-reckoning sensors. The datum of the travelled distance is (or will shortly be) commonly available on most of modern vehicles through the CAN bus. On the other hand, low-cost gyroscopes, capable to provide the yaw angle speed, will be also accessible in the near future, as for instance those used in ESP systems. With these sensors, it is possible to mitigate short-term GPS perturbations or outages and to yield, as output of a fusion algorithm filter, an uninterrupted, more accurate and integer positioning. Nevertheless, given the poor quality of the automotive dead-reckoning 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 the absolute position in a geocentric frame such as WGS 84 cannot be the final position solution, in the cases of many applications that demand a map-matched position (absolute position projected on the digital map reference). From this point, two observations can be made: the first one is that the map-matching process is necessarily to be considered. The second one is that it should be extremely interesting for the data fusion itself to use this important a priori information contained in the digital map. From these observations, we decided to design an innovative algorithm merging the two processes of data fusion and map-matching in a unique one, the output of which would be an accurate map-matched position. This algorithm will also be presented in this paper.

Therefore, the proposed system described in next sections is composed of:

- 1 EGNOS capable GPS sensor (Trimble Ag 132, mono-frequency, L1)
- 1 yaw rate gyroscope (E-core RD-2000 FOG gyro by KVH)
- 1 odometer (with resolution of 1pulse/26.15 cm.),
- 1 enhanced digital map, so called Emap, that describes precisely the geometry and the connections of the road elements at the lane level,
- the fusion algorithm that merges sensor and Emap data in a unique process.

In addition to these, one RTK GPS sensor of centimetre accuracy has been installed aboard the test vehicle for evaluation purposes.

3. BASIC PRINCIPLES OF EMAPS

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 sufficiently good accuracy, in the order of 10 times higher than the requested final accuracy, i.e. of about 10 cm. This requirement, unrealistic 5 or 10 years ago, is nowadays totally reasonable with the dramatic progresses achieved recently in the mobile mapping and aerial photogrammetry technologies. Moreover, these enhanced maps do not need to be established for all roads, but only for some critical areas in which the lane level accuracy is needed.

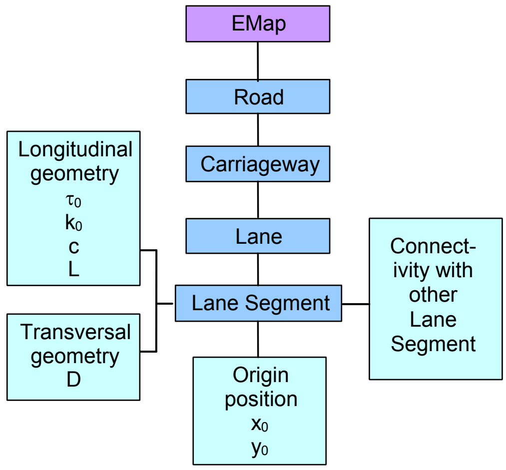
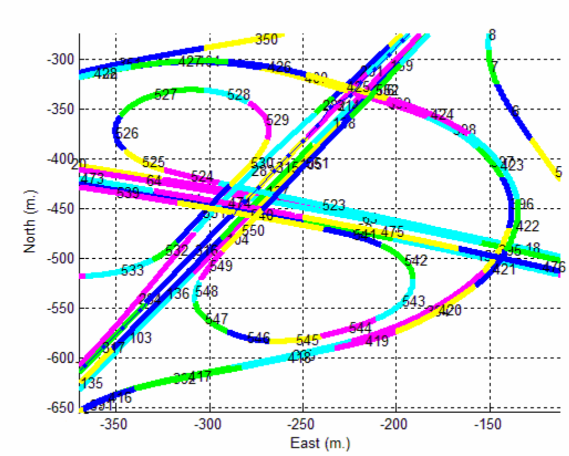
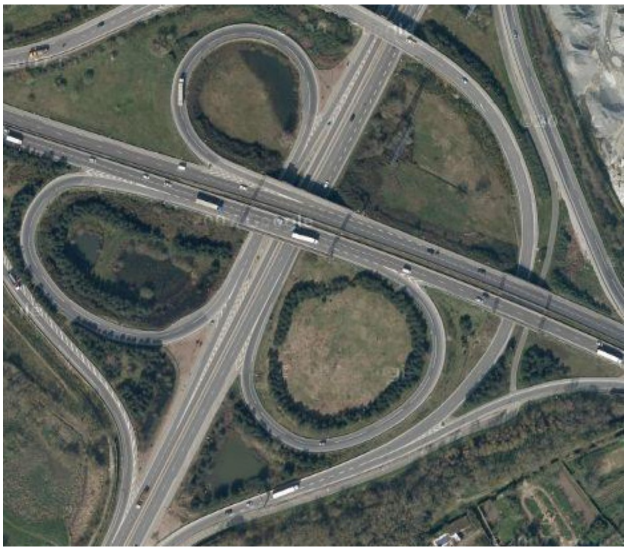


Figure 1 – Emap data model

A new model of the Emap scheme is presented in Figure 1. Compared to a standard digital map used for simple navigation, generally based upon GDF standard, this new model adds Carriageway and Lane segments and their connectivity rules, not considered in GDF. As compared to previous versions of the Emap model, the distinction between lateral and longitudinal lane segment neighbourhoods has been removed, for practical reasons. Despite the fact that its inclusion is not disregarded for future developments of the algorithm, in the algorithm and the results presented in this paper no information about lateral or longitudinal directions was used to establish the lane segments connectivity.



(a)



(b)

Figure 2 – Stretch of the road topology according to the lane segment definition in Emap (a) and its real appearance (b) in GoogleMaps ®

The lane segment is the basic element that is described by its geometry and its topology, that is to say the other lane segments that are connected to the current segment. 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 equations, described by the Fresnel integrals using the parameter l as the curvilinear abscissa:

$$x(l) = x_0 + \int_0^l \cos(\tau_0 + \kappa_0 l + \frac{cl^2}{2})dl \quad 0 < l < L$$
$$y(l) = y_0 + \int_0^l \sin(\tau_0 + \kappa_0 l + \frac{cl^2}{2})dl \quad 0 < l < L \qquad (1)$$

Each segment is determined by a unique set of parameters: the coordinates of the origin (x_0, y_0), the tangent angle (τ_0) and the curvature (κ_0) at the origin and the variation rate of the curvature with respect of the curvilinear abscissa (c), which is constant for a selected clothoid. This model is also valid for straight line segments ($\kappa_0=c=0$) and for circular segments ($\kappa_0\neq0$, $c=0$). These parameters are completed with the connectivity information related to other segments.

The lane topology is described by the feasibility of a vehicle to transit from one lane segment to another, taking into account the vehicle dynamics and certain traffic rules. Currently, the lane topology includes the neighbour segments to which it is possible to make a transition from the current one. The construction of this database is based on an automated process that must be supervised to check over possible mismatches. An example of a stretch of the road and the topology created following this principle can be seen in Figure 2.

4. ENHANCED POSITIONING BASED ON EMAP

Traditionally, the positioning in navigation systems information is processed like follows:

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 two 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 bind the solution to respect the physical constraints allowing that way to eliminate automatically the outliers. Of course, the final result quality depends directly on the accuracy and precision of the measurements, 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^m_N and the orthogonal signed distance from P to the lane axis d^m_N.

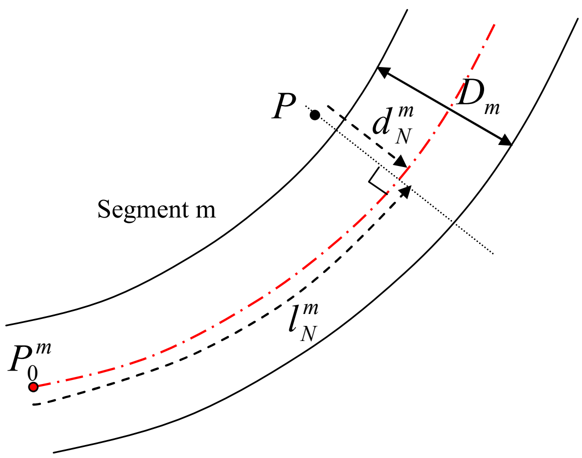


Figure 3 – Lane reference system for the map-matched position on the lane segment

4.1. MAP MATCHING WITH EMAP

In the current literature there are several approaches to the map matching issue:

1) The geometrical approach like so-called "point to point" [16] [3] [11] or "point to curve" [18] [3] [16] 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 ambiguities in the road element selection.

2) The second kind of approach is called "multidimensional approach". To improve the geometric approach, some people propose to add other criteria for select the matched road element like the driving direction, the speed limit [16], the heading information [12] or the travelled distance on the road element [13], etc. However, confusion in the selection step is still possible when some criteria are in conflict. To solve this problem, the different criteria are generally fused to obtain a deterministic solution of the selection in using weighted schemes [8] [10] [12] or belief theory [13].
3) The last kind of map matching method is the topological approach. Sometimes, due to selection errors, the map-matched trajectory presents discontinuities which are in contradiction with vehicle behaviour. To deal with this problem, two solutions can be considered. Either the topological information is used to drive the selection step and filter out the road elements which cannot be reached with respect of previous map-matching results [16] [12] [14], 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. In these two cases, the effectiveness of the map-matching process depends strongly on the selection of the first matched road element.

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 driven by topological information using the two following selection distance criteria:

1) the signed orthogonal distance d^m_N 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^m_N 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*, that we will call "map-matched position". A relationship between these two representations exist (2) and will be used to evaluate the map matching result:

$$
\begin{aligned}
x &= x_0^m + \int_0^{l_N^m} \cos\tau^m(l_N^m)dl - d_N^m \sin\tau^m(l_N^m) \\
y &= y_0^m + \int_0^{l_N^m} \sin\tau^m(l_N^m)dl + d_N^m \cos\tau^m(l_N^m)
\end{aligned} \tag{2}
$$

$$
\text{where: } \tau^m\left(l_N^m\right) = \tau_0^m + \kappa_0^m l_N^m + \frac{c^m\left(l_N^m\right)^2}{2} \tag{3}
$$

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 fine if the position is located onto a lane segment, i.e.:

$$
p\left(P=(x,y)^T / d_N^m\right) = \begin{cases} 1 & if \quad (D^m/2 < d_N^m < D^m/2 \ldots \\ & \ldots \ \& \ \ 0 < l_N^m < L^m) \\ 0 & else \end{cases} \tag{4}
$$

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 of the positioning system. Two kinds of map-aided system can be found in the literature:

1) loosely coupled map-aided systems [5] [6] [15] where the map-matching results are only used to observe and correct the vehicle positioning and:
2) tightly coupled map-aided systems [4] [7] [14] where the map-matching results are used to observe the GPS errors.

Generally, due to 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, 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 particular filtering [6]. This multi-modal situation is even more frequent when using the Emaps since multi-lane carriageways generally offer also the possibility to drive on all the lanes, increasing consequently the matching ambiguities.

4.2. COMBINED FRENET/CARTESIAN STATE

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 (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:

$$X = ({}^{C}X, {}^{F}X)^{T} = \left([x, y, \gamma], \left[l_{N}^{m}, d_{N}^{m}, m\right]\right)^{T} \tag{5}$$

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

Finally, taking into account the particular filtering scheme, the augmented position probability density function is approximated at time k by the sample set: $\{X^{i}_{k}\ ,\ w^{i}_{k}\}_{i=1\ldots N}$, 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:

$$p\left(X_{1:k} / Y_{1:k}\right) \approx \sum X_{k}^{i} w_{k}^{i} \tag{6}$$

Our particle filter will, as a matter of fact, be composed of two different filters running in parallel: one for the evolution in time of the Cartesian sub-state ${}^{C}X = (x,y,\gamma)^{T}$ and one for evolution in time of the Frenet sub-state ${}^{F}X = (l^{m}_{n}, d^{m}_{n}, m)^{T}$, where the same vehicle position is estimated but defined in two different representations. 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.

4.3. CARTESIAN SUBSTATE EVOLUTION

The evolution of the Cartesian sub-state can be given by the following relations:

$$p\left({}^{C}X_{1:k} / {}^{C}X_{1:k-1}\right) : {}^{C}X_{k} = {}^{C}f\left({}^{C}X_{k-1}, U_{k}, W_{k}\right) \tag{7}$$

$$p\left(Y_{gps} = \left(x_{gps}, y_{gps}\right) / {}^{C}X_{1:k}\right) : Y_{gps} = H_{gps} X_{k} + V_{gps}$$

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 $v \sim N(v,\sigma^{2}_{v})$ and the rotation velocity $\omega \sim N(\omega,\sigma^{2}_{\omega})$ of the vehicle,
- W_k is the evolution model uncertainty,
- $Y_{GPS} = (x_{GPS}\ ,\ y_{GPS})$ is a GPS observation,
- H_{GPS} is the observation matrix linking GPS data to the 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 with GPS data.

Applying Monte Carlo principles to (7), the prediction at time k of the Cartesian part of each particle will be provided by the following equations:

$$x_{k}^{i} = x_{k-1}^{i} + v^{i} \Delta_{T} \cos\left(\gamma_{k-1}^{i} + \omega^{i} \Delta_{T} / 2\right) \tag{8}$$

$$y_{k}^{i} = y_{k-1}^{i} + v^{i} \Delta_{T} \sin\left(\gamma_{k-1}^{i} + \omega^{i} \Delta_{T} / 2\right)$$

$$\gamma_{k}^{i} = \gamma_{k-1}^{i} + \omega^{i} \Delta_{T}$$

where v^{i} and ω^{i} are pure random variables drawn according to the probability densities of the speed v and the rotation velocity ω of the vehicle and Δ_T is the time elapsed between the time k and $k - 1$.

For computational reasons, we have selected a Boot-Strap configuration that takes into account the measurement equation for updating the weights of the particles. As a Gaussian hypothesis has been made on the GPS observation, the likelihood density function can be written this way:

$$p\left(Y_{GPS} / {}^{C}X_{k}^{i}\right) \approx e^{-\frac{1}{2}\left(H_{GPS}\ {}^{C}X_{i}^{k} - Y_{GPS}\right)^{T} R_{GPS}^{-1} \left(H_{GPS}\ {}^{C}X_{i}^{k} - Y_{GPS}\right)} \tag{9}$$

where the observation matrix is equal to:

$$H_{GPS} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \tag{10}$$

and the weight updating of each particle is given by:

$$w_{k}^{i} = p\left(Y_{GPS} / {}^{C}X_{1:k}^{i}\right) w_{k-1}^{i} \tag{11}$$

4.4. FRENET SUBSTATE EVOLUTION

The behaviour of the Frenet sub-state system is a little more complex since it is a composite vector made of continuous and discrete variables. Such state systems are governed by a so-called "Jump Markovian state system" [1, 2] which is, in our case, of the following form:

$$
\begin{aligned}
&m_k \sim p(m_{1:k} / X_{1:k-1}) \\
&p({}^F X_{1:k} / {}^F X_{1:k-1}) : {}^F X_k = {}^F f^m({}^F X_{k-1}, U_k, W_k) \\
&p(Y_{map}^m / {}^F X_{1:k}) : Y_{map}^m = H_{map} {}^F X_k + V_{map}^m
\end{aligned}
\tag{12}
$$

where :

- m is the mode of the Jump Markov state, in our case the mode corresponds to a description of the lane segment associated with map matching result,
- ${}^F f(.)$ 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,
- $Y^m{}_{map}$ is the map observation (or map constraint),
- $V^m{}_{map}$ is the uncertainty on the map observation.

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 (7), prediction at time k of the map-matched position of each particle is provided by the following equations:

$$
\begin{pmatrix} l_{N,k}^{m,i} \\ d_{N,k}^{m,i} \end{pmatrix} = \begin{pmatrix} l_{N,k-1}^{m,i} \\ d_{N,k-1}^{m,i} \end{pmatrix} +
$$

$$
+ \begin{pmatrix} \cos\left(\tau^m\left(d_{N,k-1}^{m,i}\right)\right) & \sin\left(\tau^m\left(d_{N,k-1}^{m,i}\right)\right) \\ -\sin\left(\tau^m\left(d_{N,k-1}^{m,i}\right)\right) & \cos\left(\tau^m\left(d_{N,k-1}^{m,i}\right)\right) \end{pmatrix} . \tag{13}
$$

$$
\cdot \begin{pmatrix} v^i \Delta_T \cos\left(\gamma_{k-1}^i + \omega^i \Delta_T\right) \\ v^i \Delta_T \sin\left(\gamma_{k-1}^i + \omega^i \Delta_T\right) \end{pmatrix}
$$

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 assumption is valid only for 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. $p(m^i_k \neq m^i_{k-1} / m^i_{k-1}, X^i_k)$. This probability can be computed by means of the topological information of the current lane segment m^i_k. By comparing the predicted coordinates in the Frenet references with its geometric thresholds in the current lane segments, it can be established whether the vehicle is still in the same lane segment or not. In the negative case, an algorithm based on distance criteria that estimates the most likely lane segment for the particle under consideration selects the new lane segment.

In those cases where a transition was made, the map-matched position must be recalculated taking into account the geometry of the new predicted lane segment.

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:

$$
p(Y_{map}, {}^F X_k^i) = 1 \quad if \quad (-D^{mi}/2 < d_{Nk}^{mi} < D^{mi}/2 \ldots \\
\ldots \ \& \ 0 < l_{Nk}^{mi} < L^{mi}) \\
0 \quad else
\tag{14}
$$

and the weights are updated following:

$$
w_k^i = p(Y_{map} / {}^F X_k^i) w_{k-1}^i \tag{15}
$$

According to the previous description, there are three main advantages of introducing the map matching into 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, and finally,
3) the map matching process (used only to reevaluate the map-matched position during lane change) is improved because it takes into account both topological links and vehicle behavior near these links.

5. PRELIMINARY RESULTS IN COMPLEX ENVIRONMENTS

In order to evaluate the performance of the system in real challenging environments, a number of datasets were collected to create an Emap and to perform its evaluation, following obviously different trajectories for both purposes. The area selected for these tests is located near the facilities of the LCPC Centre of Nantes. A sample of this scenario and the Emap created to represent it are shown in Figure 2.

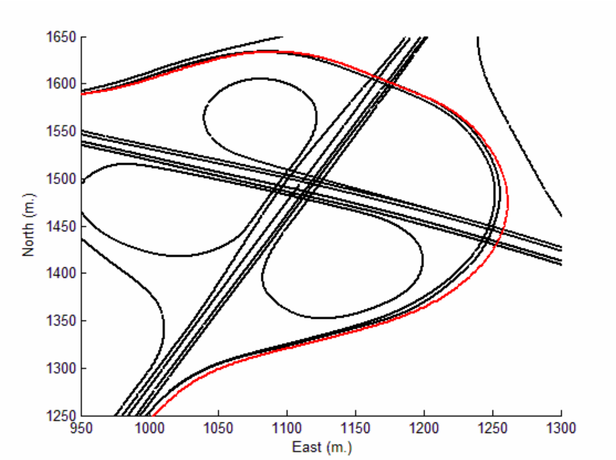


Figure 4 – Filter trajectory in absence of GPS estimated by a simple implementation of the Cartesian subsystem (solid red), superimposed to the Emap (solid black)

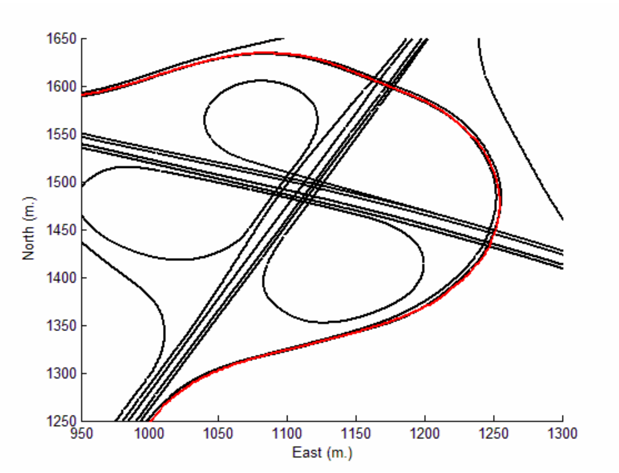


Figure 5 – Filter trajectory in absence of GPS estimated by the proposed Cartesian/Frenet subsystem (solid red), superimposed to the Emap (solid black)

The same road stretches presented in Figure 2 serve us now to show some of the results achieved in tests carried out with the proposed algorithm, firstly with only the Cartesian subsystem (Figure 4), and secondly with the combined Cartesian/Frenet implementation (Figure 5).

The Cartesian method presents good results, as compared to some more common filter approaches, such as extended Kalman filters based solutions. This is especially noticeable when considering unknown initial yaw angles. Nevertheless, in cases of long GPS outages, it is a matter of time that the estimated position drifts, due to the accumulation of errors in the dead-reckoning sensors and the vehicle model.

As can be seen in Figure 5, the proposed combined Cartesian/Frenet method presents no drifts along the same stretch of the road. In the different trials performed, both methods present similar results in many situations. Since the algorithm empowered by the Frenet subsystem, updates the particles according to the road geometry, those particles that do not fulfill its requirements are eliminated, while those that follow lane segments of the road path are encouraged. Future investigations will present further details of these results.

6. EGNOS CONTRIBUTIONS

Benefits that EGNOS should bring to the proposed navigation system are:

- augmentation of the positioning accuracy, thanks to the GPS corrections broadcasted by the geostationary satellite,
- integrity in the positioning, by means of the integrity values included in the EGNOS data, that allow for example the calculation of the SBAS based HPL (Horizontal Protection Level) and VPL (Vertical Protection Level) parameters.

In this Section, we will focus on the accuracy aspects, since the study of the integrity aspects requires a very specific and detailed attention.

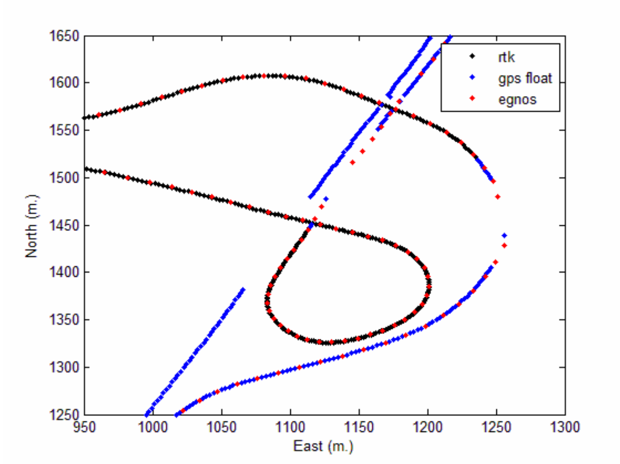


Figure 6 – RTK fix (dotted black), RTK float (dotted blue) and EGNOS (dotted red) values logged along the proposed scenario

For evaluation purposes RTK (Real Time Kinematic GPS) and EGNOS positions were logged simultaneously during the same trajectory within the bounds of the previously presented Emap. Figure 6 shows their resultant positions in the same area presented in Figures 2, 4 and 5.

As it can be seen, the availability of satellite signals affects in a similar manner EGNOS and GPS. In this image we have distinguished between RTK fixed values (in dotted black) and RTK float values (dotted blue), a priori less precise. The need of extra sensors for both map creating and navigation purposes is obvious from this Figure.

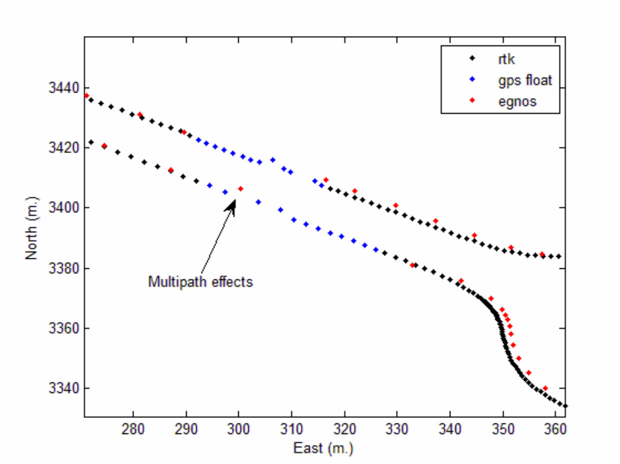


Figure 7 – Availability and multipath problems of EGNOS (dotted red), RTK fix (dotted black) and RTK float (dotted blue) in a road stretch of the test

Apart from the availability issue, some other problems were found during the tests performed. Figure 7 shows the effects of the multipath propagation of the satellite signal. As can be easily seen, the multipath phenomenon affects both EGNOS-aided GPS (red dotted) and dual frequency RTK GPS (blue dotted) in this part of the trajectory. This confirms, as expected, that EGNOS doesn't solve multipath problems, one of the most problematic issues in GNSS positioning.

The estimated errors for EGNOS horizontal positioning along the whole test trajectory can be seen in Figure 8. For estimating the error, RTK values are assumed to provide the true trajectory. EGNOS values were collected at the frequency rate of 1 Hz, being the total test duration higher than 11 minutes. As it is confirmed in this image, multipath propagations impoverish noticeably the quality of the solution. The mean value of the horizontal position error during this test was 0.345 m, with standard deviation of 0.382 m. These values encourage the use of EGNOS in our system. However, a maximum error of 2.467 m is still too far from the aimed performance of the GNSS sensor aboard. Further improvements would be needed in the SBAS before it will be possible to completely rely on EGNOS for our purposes.

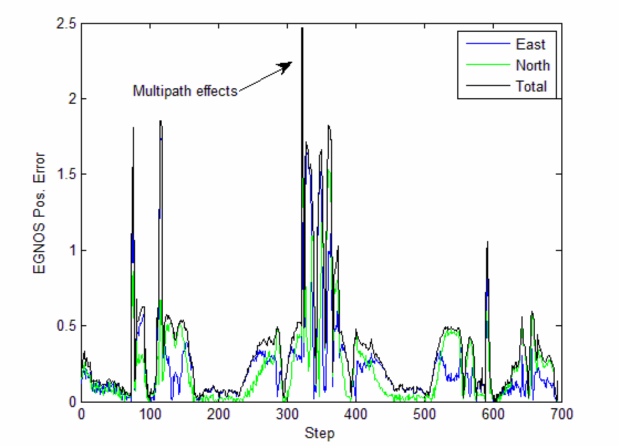


Figure 8 – Estimates of the horizontal positioning errors for East (solid blue), North (solid green) coordinates and total horizontal error (solid black) obtained by EGNOS along the test circuit

CONCLUSIONS AND FUTURE WORKS

An algorithm capable to provide enhanced positioning that avoids drifts during outages of GPS signal has been presented. To achieve success, the combination of all the different sources of information, including a priori information, must be efficiently fused.

The use of enhanced road maps (Emaps) is proposed in specific areas where precise positioning is expected. The data available in the Emap are fused with GNSS data, when available, and dead-reckoning data which could come from the vehicle sensors in the next future. The proposed filtering technique merges both localization and map-matching algorithms into a unique process, providing a directly map-matched solution consistent with the road geometry and topology.

EGNOS, the European SBAS, was originally thought as the most suitable candidate for the GNSS sensor. Its potential benefits of accuracy and integrity may serve us well for our purposes. However, its performance must be analysed with care. According to our experiments, in favourable conditions, EGNOS can supply enough accuracy to perform the aimed lane level positioning. However, it is also often affected by outages of the geostationary satellite and doesn't solve at all the GPS multipath problems, which remains the main cause of GNSS performance degradation in constrained environments.

To progress on this challenging topic of lane-level positioning for road vehicles, our further investigations will be mainly focused on the 2 following issues: integrity aspects of the hybrid EGNOS/dead-reckoning positioning and possible mitigations of the multipath effects making use as much as possible of the 3D map information.

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