Enhanced Local Maps in a GIS for a Precise Localisation in Urban Areas

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***Abstract* – This paper addresses the problem of localizing a Cybercar in urban environments by using information provided by onboard sensors. For this purpose, sensors detect landmarks which have been characterized in a previous passage. As the amount of data can be significantly large, we propose a strategy to manage this information in a GIS (Geographical Information System). We illustrate our developments by using laser landmarks that are gathered in enhanced local maps that correspond to the roads of a GIS layer thanks to the use of L1 GPS data and proprioceptive sensors. Real experiments are reported to illustrate the performance of this approach.**

Key Words –Precise localization, natural landmarks, GPS, GIS.

1 Introduction

Cybercars are intelligent vehicles that can be used in urban downtown areas for the transport and mobility of the people as an alternative to the use of private cars. Several successful experiments have demonstrated that they can navigate autonomously by sensing dedicated equipment installed on the infrastructure like catadioptric beacons, magnets or wires buried in the road. A challenging issue relies on their ability to get enough autonomy to navigate in unequipped environments by using natural landmarks. An approach to reach this goal is to explicitly localize the cybercar and then to control its movement with respect to a planed trajectory.

Global Navigation Satellite-based Systems (GNSS) like GPS, Glonass or Galileo in near future are very interesting candidates for this localization purposes since Real Time Kinematic (RTK) GPS can reach few centimetres accuracy in real-time by using phase corrections broadcasted by base stations. Nevertheless, this technology is not adapted to Cybercars that evolve in urban areas since the receiver needs to see at least 5 satellites with a good configuration (small DOP). Moreover, after the loss of the RTK mode, the system needs to solve the phase ambiguities problem which requires typically 30 seconds processing. Since RTK is not adapted, one could think to use differential L1 GPS (pseudo-ranges measurements). Unfortunately, the best reachable precision is in the order of 30/50 centimetres which is not adapted to the navigation needs of a cybercar.

A solution relies on the use of additional sensors installed on board the vehicle like video cameras and laser scanners. Indeed, they are well adapted to the sensing of natural landmarks, especially those of urban areas since they are very stable like for instance the buildings or the road features. The landmarks are characterized and localized in a learning stage during which the vehicle is driven manually. Afterwards, the vehicle is able to localize itself and control its movement near to the learned trajectory. Recent works (like the experiments performed by Royer et al. [8] using computer vision for instance) have proved the validity of such a concept. A difficulty of this approach is the management and the structuring of the large amount of landmark data for on-line navigation. Indeed, how to organize the landmark information for a Cybercar that evolves in a large area containing many roads? The usual answer to this question is to gather landmarks in local maps, a local map being a set of landmarks put together because of i) memory constraints arising from the use of embedded systems, ii) the need to download or update a limited amount of data from a distant server and iii) the connections that exist between the landmarks, essential to compute a location.

On another hand, localization with respect to a digital map describing the road network is an essential task for Cybercars. Indeed, the user of the vehicle usually specifies its itinerary by indicating the address of the destination. In this case, the *geocoding* facility of a Geographical Information Systems (GIS) is very useful to convert an address like “10, King Albert road” to a global (x,y) coordinate point.

The GIS can also be used for the management of the landmarks by benefiting from the roads description stored in the map database. To achieve this goal, a GNSS receiver is needed. It is useful for the georeferencing of the landmarks characterized by the learning stage and it is useful for the extraction of the landmarks during the autonomous navigation stage. For these needs, the absolute accuracy of the GNSS positioning is not crucial since the road-map as a meter-level precision. Therefore, a L1 (single frequency) GPS receiver fused with dead-reckoned sensors in order to handle satellites outages is sufficient.

The work presented in this paper focuses on the management of natural landmarks in enhanced local maps for precise localisation by using single-frequency GPS data, dead-reckoned sensors and a road-map handled by a GIS. The case study of laser scanner landmarks is considered.

The paper is organized as follows. Next section describes the GIS and the natural urban landmarks. Section 3 presents the localization and map-matching method. In section 4, the geo-referencing of the landmarks is done. In section 5, the management of landmarks during navigation stage is performed. Last section is dedicated to real experiments with our experimental vehicle.

2 GEOGRAPHICAL INFORMATION

A GIS is a set of tools and methods that manage and handle vectorized or raster geographical information. It also provides tools to extract navigation data for Cybercar like speed limits or pedestrian crossings. For an autonomous vehicle that navigates in an urban environment, the necessary functionalities consist in path planning (destination chosen by the user), map matching, attribute extraction and landmarks management for precise navigation purposes.

2.1 Road-map GIS layer

A GIS map database is usually a set of digitalized roads described by poly-lines provided by cartographers like *NavTeQ* or *TeleAtlas*. This topological information is very useful for the navigation tasks like path planning. The use of this topology is also interesting for the management of the landmarks [6] and consequently local maps. Indeed, once the location of the vehicle unambiguously map-matches with a road, the pertinent landmarks are those associated with this road. Secondly, if the vehicle is autonomous (ie driven by a regulator), it has to follow a predefined trajectory described by a set of connected roads. In this case, the pertinent landmarks are those attached with this path. Therefore, we propose in this work to map-match the landmarks with the road stored in the GIS database. Then, each road will logically define a local map.

The road layer information has been made by cartographers for route guidance purposes and has the characteristics of Table *1*.

Road-map Layer
★ Fine road connexity ★ Coarse road geometry ★ Attributes : Driving direction, Speed limit, Road ID… ★ Points Of Interest

Table 1. Road Layer Information in a GIS

2.2 Landmarks for precise localization

For precise navigation, exteroceptive landmarks are necessary. There are different kinds of landmarks that depend on the used sensors. They can be classified in the following categories:

Active landmarks. Actives landmarks are beacons that contain active components in order to transmit a signal. They mainly rely on the use of radio-frequency signals (GPS pseudolites, transponders stored in the pavement, Wifi antennas, etc.). Such landmarks are usually distinguishable from each other. In this case, sensors are receivers equipped with an antenna.

Passive landmarks. They are artificial landmarks pertinently located in the environment for localization purposes like magnets in the pavement or reflectors installed on post in curves for instance.

Natural landmarks. Natural landmarks are features of the environment detected by onboard sensors like video cameras or laser scanners [4, 9]. They can correspond to characteristic points (edge of windows for instance), road markings, roof of buildings, posts, curbs, sidewalks, etc.

Let consider visual landmarks with characteristic points (3D points [8] or 2D points [7]) for the navigation of a Cycab using a mono-camera at video rate. These landmarks are Harris points in images. With the 3D points method, one can rebuild the 3D pose of the vehicle using a sequence of images in which a significant amount of points has been detected at least in two images. These landmarks can be managed in a GIS by georeferencing the pose of the camera [5].

Another approach consists in localizing the landmarks in the same coordinate frame as the road-map. These landmarks can be complex features like image-based planes [2] or sidewalk edges.

2.3 Sidewalk edges landmarks

GPS satellites signal is often blocked in urban areas. In such a situation, a localisation system can use dead-reckoned sensors to maintain an estimate of the pose of the vehicle. It is known that the lateral drift is more important than the longitudinal one. Therefore, the laser scanner has to be used to detect as much as possible lateral landmarks. As in urban areas the sidewalks and the frontage of buildings present naturally this lateral feature, we propose to consider the use of laser scanner installed vertically (see Fig. 1). The horizontal and inclined setting proposed in [10] dedicated to road-boundary detection can be an alternative.

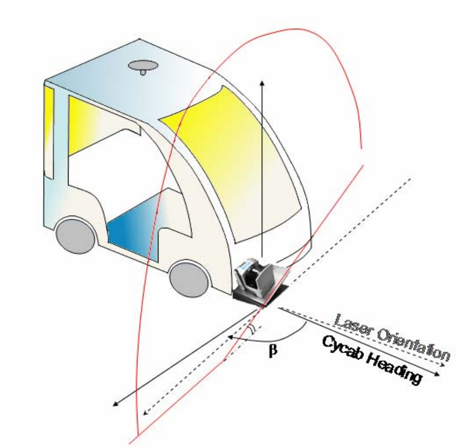

Fig. 1. A Cybercar equipped with a vertical laser scanner.

A first processing of the laser signal consists in detecting a pattern that corresponds to a sidewalk edge. Our algorithm is based on the detection of the slope variation of successive segments of the telemeter frame. The first value of the slope that is higher than a threshold corresponds to the edge of the sidewalk. In [10], an Extended Kalman filter is used to detect breaks in the laser signal in order to detect and compute the distance to the sidewalk edge. A prediction step is done using the last two distances of the laser beam to predict the following one, then, if the innovation between the predicted distance and the measure is higher than a threshold, the corresponding point is considered to be the sidewalk edge. In [1], the same strategy is adopted using an Unscented Kalman Filter (UKF). From the real-time implementation point of view, a compromise between low-level and high-level computations has to be found. We believe that it is better to develop effective low-level methods and to find high-level localization methods that are robust to aberrant data.

2.4 Enhanced geographical information

To store all sidewalk impacts could induce a large amount of data and consequently a huge amount of disk-space, which is unrealistic for real-time applications. In addition, during future passages, the vehicle may not detect exactly the same landmarks. Therefore, the information has to be segmented, in the same way that is done for the road-maps. A split and merge algorithm can be used (see Fig. 2).

In robotics, the management of map uncertainties is often important, especially for the approaches that follow the SLAM paradigm. Under the hypothesis of uncorrelated measurements, the imprecision on the position of the nodes of the map can be modelled by an ellipsoid.

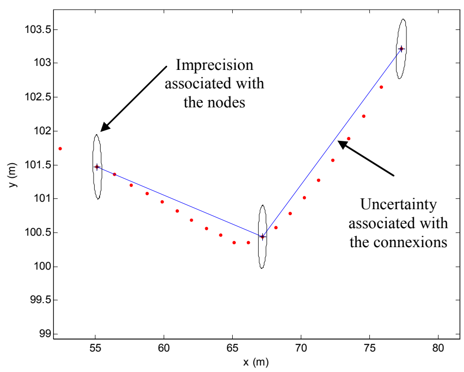

Fig. 2. Enhanced map with associated imprecision and uncertainty

The likelihood of the topological connections between the nodes needs also to be quantified since the sidewalk edge detection can be mistaken. Moreover, an urban environment is not a perfectly static environment: cars can be parked between the pavement and the Cybercar. These vehicles could later leave their car park, which will make the pavement reappear. In order to deal with these problems, a belief vector can be associated with each segment of the map. The quantification of this uncertainty can rely on heuristic considerations as long as the result belongs to the interval [0, 1]. Thanks to this formalism, regions that don't have sidewalk and those that contain parked cars are treated with the same manner: a null belief of existence is associated to them.

3 MAP-MATCHED CONTINUOUS LOCALIZATION

A way to manage natural landmarks is to have map-matched estimates of the pose of the vehicle, even if these estimates are inaccurate.

In urban areas, GPS suffers from several drawbacks such as multi-tracks and masking: GPS signal is often blocked or reflected by high-rise buildings. Because GPS alone cannot localize continuously the vehicle, it is localized by fusing an odometer, a gyrometer, GPS data and map information. If the GPS satellites signal is blocked by buildings, for example, the evolution model provides a dead-reckoned (DR) estimate, the drift of which can be corrected using the map information.

In order to simplify the matching process, we assume that the vehicle follows the pre-computed itinerary chosen by the user. Figure 4 gives an example of a pre-computed itinerary obtained thanks to a usual route calculation functionality of a GIS.

The map-matched localization is done by a pose tracking method based on Kalman filtering. The DR sensor are used in a prediction stage which is corrected by GPS, if it is available and coherent (no multi-tracks) and the map.

The mobile frame is chosen with its origin attached to the centre of the rear axle. The x-axis is aligned with the longitudinal axle of the Cybercar. The vehicle position is represented by (x_k, y_k), the Cartesian coordinates of M in a global frame (a projection of geographic data). The bearing angle is denoted θ_k.

The evolution model of the vehicle is non-linear:

$$X_{v,k+1} = f(X_{v,k}, U_{v,k}, \gamma_k) + \alpha_{v,k} \tag{1}$$

Where $X_{v,k}$ is the vehicle state vector at the instant k, composed of (x_k, y_k, θ_k), $U_{v,k}$ the vector of the measured inputs consisting of (Δ_k, w_k), Δ_k and w_k being respectively the elementary distance covered by the rear wheels and the elementary rotation of the mobile frame. $\alpha_{v,k}$ is the process noise and γ_k represents the measurement error of the inputs. $\alpha_{v,k}$ and γ_k are assumed to be uncorrelated and zero mean noise.

If the road is perfectly planar and horizontal and if the motion is locally circular, the evolution model can be expressed by:

$$\begin{cases} x_{v,k+1} = x_{v,k} + \Delta_k.\cos\left(\theta_{v,k} + \dfrac{w_k}{2}\right) \\ y_{v,k+1} = y_{v,k} + \Delta_k.\sin\left(\theta_{v,k} + \dfrac{w_k}{2}\right) \\ \theta_{v,k+1} = \theta_{v,k} + w_k \end{cases} \tag{2}$$

The values of Δ_k and w_k are computed using the odometer measurements of the rear wheels and a fibre optic gyrometer.

The fusion of GPS, Map information and odometry is done by Kalman Filtering (EKF here but it could be UKF) which uses the prediction/update mechanism. In the prediction step, the Cybercar evolves using (2) and the covariance of the error is estimated.

When a GPS position is available, a correction of the predicted pose is performed. In urban areas, GPS suffers from multi-tracks and bad satellite constellation (urban canyoning) that degrades the position that it delivers. So, when a GPS position is available, it is necessary to verify its coherence. For that, the Normalized Innovation Squared

(NIS) with a chi-square distribution is used: a distance d_m is computed between the GPS observation and the state vector.

Let Y_v be the observation vector, μ_v the innovation vector.

$$Y_v = \begin{bmatrix} x_{GPS} \\ y_{GPS} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} . X_v + \beta_{GPS} = \mathrm{C_v} . X_v + \beta_{GPS} \quad (3)$$

$$\mu_v = \begin{bmatrix} x_{GPS} - x_v \\ y_{GPS} - y_v \end{bmatrix} \quad (4)$$

$$d_m = \mu_v . (P_{\square})^{-1} . \mu_v^T \quad (5)$$

Where (x, y) is the predicted position and $P_{\square}$ is the covariance of the innovation.

If the computed distance d_m is smaller than a threshold, for instance $\chi^2(0.05,3)$, then the GPS measurement is assumed to be correct and a correction of the predicted pose is performed. Otherwise, the dead-reckoned pose provided by the evolution model is kept. Please, note that the GPS noise is not stationary. The GPS measurement error can be estimated in real time by using the *NMEA* sentence *GST*. This information is provided by the TRIMBLE AgGPS132 GPS receiver that has been used in the experiments.

Before launching the localization system, an itinerary is computed and we assume that the vehicle follows exactly this path. Each segment in the GIS map has an Identifier (ID). This ID will be used in the following stages to perform the geo-referencing of the landmarks.

Let us consider the segment selection problem which consists in extracting from the GIS map the most likelihood segment using the estimated state vector. The distances between the estimate and the nearest segments of the itinerary are computed. The segment that has the smallest distance and whose driving direction corresponds to the heading of the vehicle is considered as the good one. As we will see in section 6, this simple matching strategy gives good results. The matched point is obtained by projecting the estimated position onto the selected segment.

The matched point can be used as a map observation (denoted Y_{vm}) in order to correct the drift the DR estimate if the GPS is unavailable:

$$Y_{vm} = \begin{bmatrix} x_{MAP} \\ y_{MAP} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} . X_v + \beta_{MAP} = \mathrm{C_v} . X_v + \beta_{MAP} \quad (6)$$

Another NIS coherence test is used to verify the map observation coherence before fusing it thanks to a Kalman filter correction stage.

4 GEO-REFERENCING THE LANDMARKS

During the learning stage, urban features are detected and stored in an additional layer of the GIS, called “enhanced map layer”. Then, these features are extracted each time the vehicle navigates in the same area.

We propose to gather the detected urban landmarks in local maps to facilitate their management. For this purpose, the use of the ID of the roads defined in the GIS road-map layer is well adapted for Cybercars, since the robot uses the planned itinerary computed in the road-map layer. Moreover, a road is a set of same ID segments with eventually a junction at its beginning or/and at its end. So, while the Cybercar navigates in the same road, it uses the same set of landmarks.

Furthermore, each road can be one-way or double direction (this information is contained in the road attributes). For one-way roads, a unique local map is built. It contains all the landmarks matched to it. For double direction roads, two maps are built, one for each direction: E2W (East To West) or W2E (West To East). If the road is parallel to the y-direction, the map is called E2W if the vehicle is driving towards the North.

In the learning stage, the vehicle is driven manually. Let suppose that the Cybercar is moving in a unknown area. While moving, the laser scanner data is buffered with the corresponding road ID map-matched thanks to the method exposed in section 3. In parallel, the sidewalk detection algorithm is applied to localize the curb impact with their imprecision thanks to the estimated covariance of the state of the vehicle. The begging and the ends of the curb are identified and the potentially parked cars are detected. When a road with a different ID occurs, the buffered data is sent to the segmentation module that returns a segment or a set of connected segments with associated imprecision and accuracy (like described on Fig. 2).

Finally, Table 2 describes the information associated with each local map.

Local map : *map$_j$*
★ GIS ID ★ Direction (E2W or W2E) ★ Set of *I* landmarks made up of - Coordinates of the segmented data - Covariance Matrix of the error on the position of the nodes - Belief vector - Matched position $Xmap_{j,I}$ - Date of the acquisition

Table 2: Laser landmarks with extended attributes for their management in a GIS

5 AUTONOMOUS NAVIGATION

We consider now that the vehicle navigates in a previously learned environment. As performed in the learning stage, an itinerary is computed using the GIS road-map layer. While the vehicle follows this pre-computed itinerary, two localization processes occurs. The first one is done in the road-map layer using the map-matched method and the second one uses the landmarks for a precise localization for the control of the trajectory of the vehicle as described in [2, 7, 8].

The landmarks management for navigation consists in two parallel tasks:

- Local map extraction
- landmarks selection

Once the right landmark has been extracted, the laser scanner data can be used to correct the estimated pose.

5.1 Local map retrieval

The goal of this task is to obtain a vehicle pose with a meter-level precision and then to find the appropriate local landmarks map stored in the GIS landmark layer. The localization algorithm is the same as the one used in the learning stage: it fuses GPS, dead-reckoned sensors and road-map information corresponding to the computed itinerary. Then, the road ID is retrieved and the driving direction (E2W or W2E) is deduced from the motion. This information permits to select the adequate local map. If the selected local map does not correspond anymore to the current local map, the landmarks are loaded in the dynamic system memory.

This supervisory task is repeated during the navigation process. It guaranties correct transitions between two local maps.

5.2 Laser landmarks extraction

This part deals with the extraction and use of the segmented laser features (the sidewalk edges) within the previously selected local map map_j composed by a set of laser landmarks.

Let (x_{pred}, y_{pred}, θ_{pred}) be the predicted pose which allows to estimate the laser scanner position ($x_{T,pred}$, $y_{T,pred}$).

One can write the equation of line D $y = s.x + k$ passing through ($x_{T,pred}$, $y_{T,pred}$) and having $tan(\theta_{pred} + \beta)$ as slope (see Fig. 3). Let be the function

$$h(x,y) = \boldsymbol{y} - s.\boldsymbol{x} - k \tag{7}$$

The line D intersects segment [AB] only if

$$h(x_A,y_A).h(x_B,y_B) \leq 0 \tag{8}$$

To be a real sidewalk edge, the associated segment must also have a non-null belief of existence (higher than a threshold). If more than one segment satisfies these criteria, the nearest one is selected. As we will see in section 5, this simple matching strategy gives good results. Please note that the angle β (88° 24') has been determined after calibrations done on the car.

5.3 Pose Updating using the laser scanner

If a curb is detected, the laser scanner can be used to correct the pose. Let suppose here that the good segment [AB] has been selected from the enhanced map. The observation is the telemetric distance r to the sidewalk edge. r can be predicted by:

$$r_{pred} = \sqrt{(x_T - x_I)^2 + (y_T - y_I)^2} \tag{9}$$

Where (x_I, y_I) are the predicted coordinates of the intersection point of the laser beam with segment [AB] (see Fig. 3). The predicted distance r_{pred} is written as:

$$r_{pred} = \left| \frac{a.x_{pred} - y_{pred} + b}{\sqrt{a^2+1}.\cos(\theta_{pred} + \beta - \tan^{-1}(a) - \frac{\pi}{2})} \right| \tag{10}$$

Where a and b are the parameters of the segment passing by points A and B: a is the slope and b is the constant term. The distance r_{pred} is a non-linear function of the vehicle predicted pose and of the coordinates of segment [AB]. It can be used in an EKF scheme to correct the estimated pose of the Cybercar.

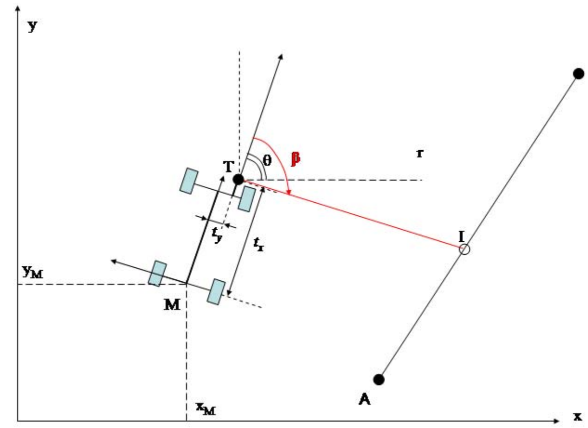

Fig. 3. Observation model using the laser scanner

When a valid laser scanner observation is available, it is important to verify its coherence. The same NIS test applied on GPS and road-map data is used here.

6 EXPERIMENTAL RESULTS

Real experiments have been carried out with our experimental car in the downtown area of Compiègne using a KVH fibre optic gyro, an odometer input and a L1 GPS receiver (Trimble AgGPS 132) running with a geostationary differential correction (Omnistar).

A SICK LMS291 Laser Range Scanner at 75Hz has been used. The laser sends sentences of 181 values, each one corresponding to a bearing angle respectively from 0 to180 degrees in the laser range scanner frame. We chose a 1° resolution and a range of 8.1m. The roll angle of the laser frame (see Fig. 1) equals 20.1° after calibration.

The GPS has been tuned in a 3-D only-mode to deliver reliable positions, by setting the threshold of DOP to a low value, and the threshold of the SNR to a high value. Such tuning induces a reliable but intermittent positioning in urban areas.

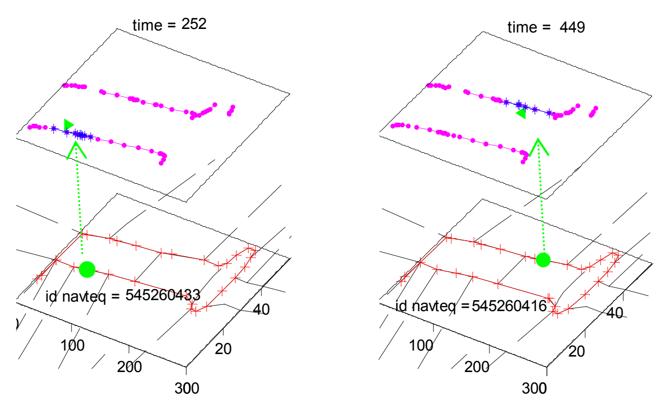

Fig. 4. Local Map extraction at two moments

The time stamped data was saved in order to analyze the results in post-processing and verify the extracted landmarks.

Please recall that there are two localization levels: metre-level localization in the road-map layer using fused

GPS and precise (decimetre-level) localization using the exteroceptive landmarks.

Figure 4 shows the local map extraction process at two moments of the same experiment. The pre-computed itinerary of the Cybercar is plotted in red in the bottom layer corresponding to the road-map layer. The other road segments are plotted in dashed black. The upper part represents the enhanced maps layer. The green triangle indicates the fused vehicle position in the precise map and the green circle represents the map-matched position used to extract the local feature map drawn in blue in the enhanced layer.

Each road ID can have its own local map if landmarks have been sensed. For instance, in the roundabout area (on the right part of each plot) there is no sidewalk each time there is an exit road. Moreover, the detection algorithm has missed two shorts and curved parts of the roundabout sidewalk as visible in the enhanced maps layer of Fig. 4.

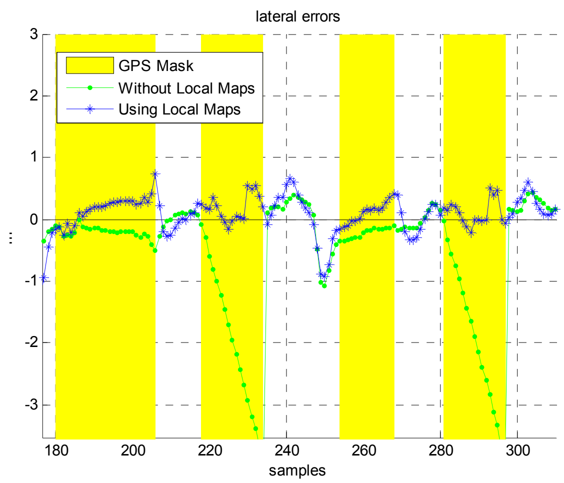

Fig. 5. Lateral localization errors with & without local maps

The geometry of the enhanced maps is more detailed and therefore the localization precision is improved. To illustrate the benefit of the enhanced maps, let consider Figure 5 which shows lateral localization results. In order to compute the estimation error, a Post Processed Kinematic (PPK) GPS receiver (a Trimble 5700 dual-frequencies L1/L2) has been used with an offline computing software (Trimble Total Control - TTC). The curve in green represents the errors (in meters) of a localization algorithm using only GPS coupled with DR sensors, the one in blue represents the localization error of the complete system which fuses GPS, DR sensors and extracted segments from local maps. The yellow bars show the GPS outages. The lateral error rarely exceeds 1 meter error, while the GPS+DR algorithm can drift significantly during GPS outages.

7 Conclusion

This article has proposed a method to manage a huge amount of landmarks data in a GIS for precise localization in urban areas. The example of laser landmarks has been considered. The method has been illustrated with real experiments carried out in the downtown area of the city of Compiègne.

Our proposition is to gather the landmarks in local enhanced maps characterized by a map-matching process performed in a road-map layer. In the work present here, a local map is a set of segments which has the same ID in the GIS database. For double direction roads, two maps can be associated with the same ID. In order to simplify the map-matching process, an itinerary obtained thanks to the route calculation of the GIS software is used. This itinerary has to be strictly followed by the vehicle during the learning and navigation stages.

Experimental results indicate that this approach is a good candidate to the management of landmarks in urban area since it allows extracting correctly landmarks stored in a previous passage. Nevertheless, the precision obtained with a laser scanner seems not efficient for autonomous navigation of a Cybercar. The use of visual landmarks obtained by computer vision is the main perspective of this research.

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