INTEGRATED NAVIGATION USING GIS-BASED INFORMATION

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For many intelligent vehicles needs, GNSS alone is not sufficient and needs the help of other sensors. Geographical information can be used for navigation in two different ways: i) roads can be used as constraints of localisation space and ii) geographical information can include landmark locations. These two characteristics are described through the case study of a localisation system for urban areas.

Introduction

Precise dynamic localisation with respect to a digital map is an essential task for Advanced Driver Assistance Systems (ADAS) and for intelligent vehicles. As a matter of fact, Geographical Information Systems (GIS) can contribute to the characterisation of driving conditions by providing important data like signposts, speed limits, or hazardous zones like schools, pedestrian crossings, etc.

It is well known that GNSS (Global Navigation Satellite System) suffers from satellite outages and multi-tracks which can decrease significantly the availability and the precision of the delivered positions. This is particularly crucial in urban canyons. To deal with such problems, positioning systems often rely on the integration of GNSS and dead-reckoned or inertial sensors (odometers, MEMS - Micro-Electro-Mechanical Systems, gyrometers, etc.). Nevertheless, if an outage lasts too long, the drift of the estimated pose (position and attitude) can become too large and unsuited for some applications.

On the other hand, the maps used in a GIS include information which can contribute to the localisation process itself. For instance, the description of the road-network can be used to localise a vehicle, even when the satellites signals are blocked. Another example is a cadastral map that can include the description of the roads and of the buildings. Such maps can be very detailed and their precision can be better than one metre.

Finally, there are many localisation systems that rely on the use of extra exteroceptive sensors such as cameras, ladars (laser range scanners) (Wijesoma et al, 2004) or telecommunication-based systems (UMTS, WIFI, etc.). A common key point of these systems is to use beacons, landmarks or features the location of which needs to be known. If these beacons have been localised or if they have been detected by aboard sensors, their coordinates can be managed in the GIS database. This landmark geographical information allows correcting the estimate of the pose during navigation. The GIS can also be used as a tool to update existing landmark information.

The aim of this paper is to illustrate the use a GIS for integrated navigation in the area of Intelligent Vehicles. A positioning method using differential GPS, odometry aided by a gyrometer and a road-map is described. In order to increase the precision and to correct the drift of dead-reckoning localisation, we will study the use of visual urban landmarks. We will illustrate the usefulness of a GIS to manage the different characteristics of geographical information in different layers. The paper is organised as follows. Section 2 concerns the use of pre-existing geographical information which acts as a constraint of localisation space. Section 3 deals with the management of natural landmarks in a GIS layer for a precise localisation especially in urban environments. The management of key images information is described and analysed through experiments carried out with our experimental car.

Using Charted Roads in the Localisation Process

Introduction

Usually for automotive applications, a GIS database is a set of cartographic information provided by a cartographer. This *a priori* known information is very useful for the navigation tasks like route guidance. Indeed, for this purpose, a scanty representation of the road network is sufficient: roads are described by linear lines which correspond to the centreline of the road. The localisation is forced by the lines: the position is obtained by a projection onto the lines. This is the map-matching process. In a different approach, the geographical representation of the road network can be used as positioning information with its own inaccuracy. In such a context, the localisation problem can be considered as a "Data Fusion problem" in which several different information sources need to be combined in order to provide a more precise and reliable positioning system that is able to eliminate aberrant data for integrity purposes.

Fusion of GPS and dead-reckoning sensors

Let consider the fusion of a GPS receiver, an odometer and a gyro with a road-map. If the 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.

The mobile frame is chosen with its origin M attached to the centre of the rear axle. The vehicle position is represented by (x_k, y_k), the Cartesian coordinates of M in the projection frame of the map. The bearing angle is denoted θ_k.
If the road is perfectly planar and horizontal, the evolution model can be expressed by:

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

The pose at instant k is (x_k, y_k, θ_k) and the measured inputs are Δ_k and w_k being respectively the elementary distance covered by the rear wheels and the elementary rotation of the mobile frame. The values of Δ_k and w_k are computed using the odometer measurements and a gyrometer.

The fusion of GPS and odometry is done by Kalman Filtering (Extended KF here but it could be Uncented KF (Julier 1997)) which uses the prediction/update mechanism. In the prediction step, the car evolves using (1) and the covariance of the error is estimated.

When a GPS fix is available, a correction of the predicted pose is performed. In urban areas, GPS suffers from multi-tracks and bad satellite constellation that degrades the precision. So, when a GPS position is available, it is necessary to verify its coherence. For that, a Normalised 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.

$$Y_v = \begin{bmatrix} x_{GPS} \\ y_{GPS} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} . X_v + \beta_{GPS} \quad (2)$$

$$\mu_v = \begin{bmatrix} x_{GPS} - x \\ y_{GPS} - y \end{bmatrix} \quad (3)$$

$$d_m = \mu_v . (P\mu)^{-1} . \mu v^T \quad (4)$$

Where (x, y) is the predicted position and $P\mu$ is the covariance of the innovation.
If the computed distance d_m is smaller than a threshold then the GPS measurement is assumed to be correct and a correction is performed. Otherwise, the dead-reckoned pose 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 GST* sentence.

Road selection and fusion of the map information

The road selection problem consists in extracting from the GIS map the most likelihood segment using the estimated pose. There are different approaches. Usually, the distances between the estimate and the nearest segments are computed. The segment that has the smallest distance and whose driving direction corresponds to the heading of the vehicle can be considered as the good one (El Badaoui 2005, Quddus 2006).

In order to fuse the map information, a matched point is built by projecting the estimated position onto the selected segment. The matched point can be used as a map *observation* (denoted Y_{vm}):

$$Y_{vm} = \begin{bmatrix} x_{MAP} \\ y_{MAP} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} . X_v + \beta_{MAP} = C_v . X_v + \beta_{MAP} \quad (5)$$

A key point relies on the quantification of the covariance of the map β_{MAP}. An efficient way is to model the imprecision by an ellipse whose principal axle is collinear to the segment. The width of the ellipse is taken proportional to the width of the road (see Figure 1).

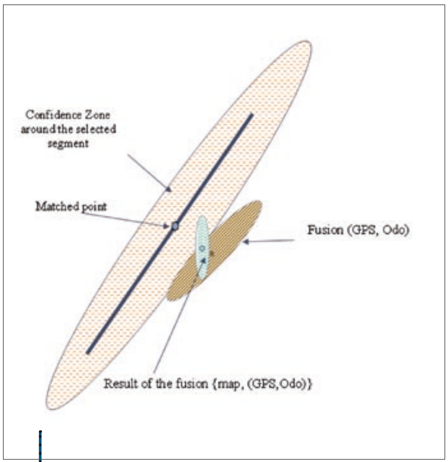

Figure 1 - Fusion of segment with previous estimated position.

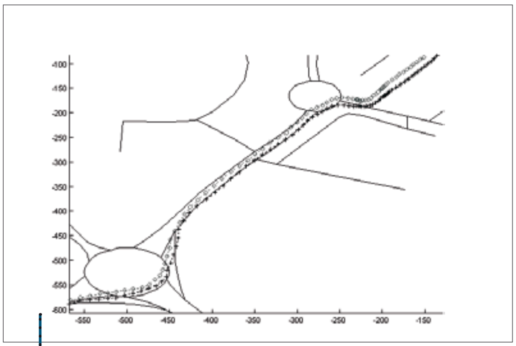

Figure 2 - DGPS positions, {DR, DGPS, map} fused positions.

A 4-km long experimental test has been performed in Compiègne with a DGPS and an IGN Géoroute V2 data-base (Figure 2). One can notice that the result of the fusion does not match exactly with the roads. This is an effect of the fusion method.

Precise Localisation using Landmarks Managed in a GIS Layer

For intelligent vehicles, there are many applications which need a high precision localisation (ie around 10/20cm). Real Time Kinematic (RTK) GPS is a very interesting candidate for this localisation purposes since it can reach few centimetres accuracy in real-time by using phase corrections. Nevertheless, this technology is not adapted to vehicles 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 "fixed" mode, the system needs to solve the phase ambiguities problem which requires typically 30s processing. A solution relies on the use of additional sensors like video cameras and ladars. 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 characterised and localised in a learning stage during which the vehicle is driven manually. Afterwards, the vehicle is able to locate itself and control its movement near to the learned trajectory. Recent works (Royer 2005) have proved the validity of such a concept.

There are different kinds of landmarks that can be classified in three categories:

1) Active landmarks. They are beacons that include 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.

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

3) Natural landmarks. Natural landmarks are features of the environment detected by aboard sensors like video cameras or ladars (Weiss 2005). They can correspond to characteristic points (edge of windows for example), road markings, roof of buildings, posts, curbs, sidewalks, etc. In cadastral maps, natural landmarks like road markings or curbs of the roads are sometimes charted by the cartographers.

A GIS is very useful to manage the landmark information in dedicated geographical information layers added to the road-map (see Figure 3) since a GIS provides a set of tools and methods that manage and handle vectorised or raster geographical information that can be enhanced geometry like cadastral information or landmarks.

In order to build a precise GIS layer including natural landmarks, a first passage is necessary.

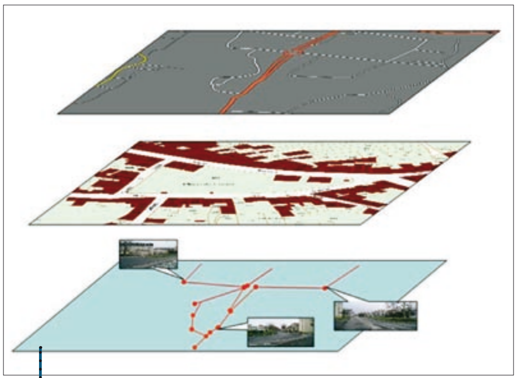

Figure 3 - Geographical Information layers: road-map layer, enhanced geometry layer, landmark layer.

A GIS is also well adapted to retrieve the landmark information each time the vehicle navigates in a known area.

A particular difficulty is the management and the structuring of a large amount of data for on-line navigation. Indeed, how to organise the landmark information for a vehicle that evolves in a large area including many roads? The usual answer to this question is to regroup 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. Local maps can be defined using the roads of the database. In such a case, the absolute accuracy of a GNSS-based positioning is not crucial since the road-map as a meter-level precision.

Case Study: Management of Visual Landmarks

Let consider visual landmarks with characteristic points 3D as used by Royer et al. for the navigation of a Cycab using a mono-camera at video rate. These landmarks are characteristic points in images called Harris points (Harris 1988). Thanks to these points, one can rebuild the 3D pose of the vehicle using a sequence of images (called *key images*) in which each feature has been detected at least in two images (Royer 2005).

In a learning stage, dated images are acquired along with other sensors. This includes dead-reckoning sensors and GPS data. Map-matched coordinates of the fused poses of the localisation algorithm shown previously are associated with the acquired images using timestamps in the same reference time coordinates. The map-matched point is the point called map observation in section 2.3. When this point is obtained, the ID (unique reference stamp in the database) of the road is retrieved.

We proposed to regroup the images in local maps to facilitate their management. For this purpose, the use of road IDs is well adapted. Indeed, a road is a set of same ID segments with eventually a junction at its beginning or/and at its end. For the management of a GIS database, two different roads have necessarily different IDs. For double direction roads, two maps are built, one for each direction: E2W (East To West) or W2E (West To East). Figure 4 shows double direction roads with images associated to each direction.

Let consider now that the vehicle navigates in a learned environment. In the navigation phase, high precision is obtained when the vehicle can use the pertinent learned landmarks regarding the observed landmarks during navigation.

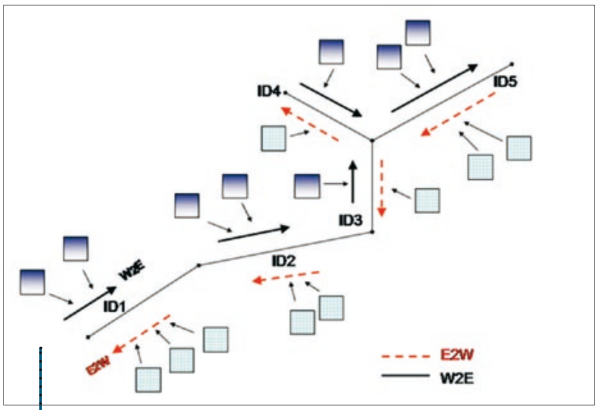

Figure 4 - Associating images to road segments.

Figure 5 - The Real time acquisition system in STRADA.

The landmarks management for navigation consists in two parallel tasks:
- Local map extraction
- Visual landmarks selection.

The goal of the local map extraction is to obtain a vehicle pose with a precision in the order of one meter and then to find the appropriate local landmarks map stored in the GIS built landmark layer. The localisation algorithm is the same one used in the learning stage: it fuses GPS, road-map information with dead reckoning sensors. A first pose is computed and a map-matching is done using the fused pose. Then the road ID is retrieved. The road ID and the driving direction permit to select the adequate local map. If the selected local map is not the current local map, the visual landmarks are then loaded in the dynamic system memory. This supervisory task is repeated during the navigation process. It guaranties the transitions between two local maps.

The local map extraction provides a local map map_j composed by a set of geo-referenced visual landmarks as previously described. To obtain a precise localisation, the navigation process needs to use the landmark l having the nearest matched position $\mathbf{X}_{mapj,l}$. This is the landmark selection. In the experiments, the landmark which is selected is the one which is the nearest and downstream.

Real experiments have been carried out with our experimental car (Figure 5) in the downtown area of Compiègne (Figure 6) using a fibre optic gyro, an odometer input and a DGPS running with a geostationary differential correction. Timestamped images were logged at the rate of 15 images per second.

The GPS has been tuned in a 3-D only-

Figure 6 - Map around the experimental field, with the itinerary plotted in red.

mode to deliver reliable positions, by setting the DOP threshold to a low value and the SNR threshold to a high value. Such tuning induces a reliable but intermittent positioning in urban areas.

Two weeks later, we carried out navigation experiences. Figure 7 shows in bold the localisation result and in thin red the segments where visual local maps has been previously acquired. To illustrate the visual landmark management, we extracted at each sample the best key image for localisation as described before.

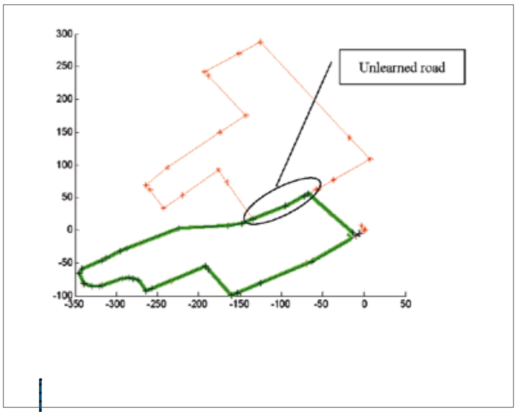

Figure 7 - Map-matched vehicle position for the key image retrieval needs.

A graphical interface allows monitoring the localisation during the navigation process. The interface displays the map and adds two positions icons: the current matched position of vehicle is drawn with an arrow and the key image selected by the algorithm is represented by a squared point. Two additional windows display the current image and the selected key-image. At each position, the interface refreshes the current position, the current image and the key-image, if it changes. Figure 8 shows this interface.

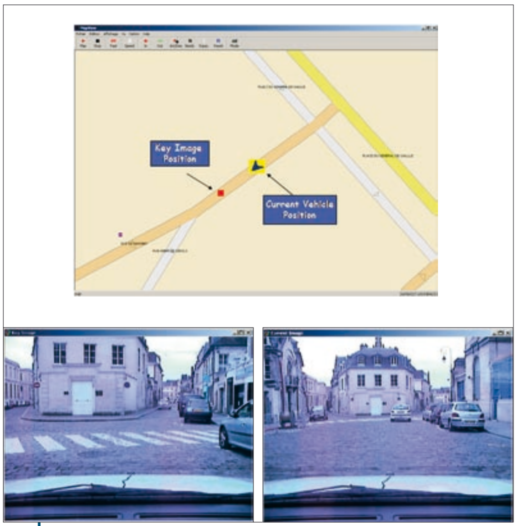

Figure 8 - Real time graphical interface(please notice that the parked vehicles are not the same). Left Key-image, right current image. .

The time stamped data was saved in order to analyse the results in post-processing and to verify that the extracted landmarks were the good ones. At each key image selection, the overlapping between key image and current image has been verified (except on the unlearned road where the system was able to detect that there was no key image). We consider that the selection is correct if the overlapping covers the half area of the images. The results give 98% overlapping when local map is available. The main errors come from the vehicle rotations at crossing road.

Conclusion

For a precise and reliable localisation, the use of an integrated navigation system is a key issue. For intelligent vehicles, the localisation system can take profit of GPS data, DR sensors and GIS data. *A priori* known GIS information can be made of networked roads or enhanced geometry maps. A data fusion method to localise the vehicle by using a road-map has been presented. It is important to notice that before using a GPS fix, its coherence is checked. This allows rejecting aberrant data arising from multi-tracks for instance. The robustness of the localisation is also improved by selecting the likeliest segment of the road-map. A map observation is then built to correct the errors. The resulting estimated position is not projected onto the likeliest road of the map, but closed to it.

The GIS can also be used to manage enhanced geometrical information and landmarks. We studied the management of visual landmarks in a dedicated layer of the GIS data. They are regrouped in local maps attached to the roads. During the navigation stage, these maps are retrieved and loaded in the memory of the localisation system and can be assimilated to a cache memory. These two applications illustrate the usefulness of a GIS for integrated navigation.

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Philippe Bonnifait (1969) graduated from the Ecole Superieure d'Electronique de l'Ouest, France, in 1992 and received the Ph.D. degree in automatic control and computer science from the Ecole Centrale de Nantes, France, in 1997. In December 2005, he obtained the *Habilitation à Diriger des Recherches* from the Université de Technologie de Compiègne (UTC). Since September 1998, he is with Heudiasyc UMR 6599, France, and he is Associate Professor at the UTC, Computer science and engineering department. His current research interests are in Intelligent Vehicles and Advanced Driving Assistance Systems, with particular emphasis on dynamic ego-localisation based on multisensor-fusion (GNSS, dead-reckoning and GIS).

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