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Centimetric localization of a vehicle combining vision and low cost GPS

Frédéric CHAUSSE, Vincent VOISIN , Jean LANEURIT, Roland CHAPUIS *
LASMEA - UMR6602 UBP/CNRS

Abstract

Absolute localization of a vehicle in its outdoor environment is an important task for driving assistance. GPS satellite system is commonly used but the code for civil application provides only a rough metric localization. Such devices are cheap but not sufficient for navigation purposes. We show how to combine such a low cost GPS with a vision system and a numeric map to increase the accuracy of global positioning.
This system is fully operational and has been tested in real time on a 3km loop with our experimental car VELAC.

1 Introduction

Several kinds of sensors can be use to locate a vehicle in its environment. This makes it possible to classify the corresponding methods in three categories: relative localization, absolute localization, hybrid localization. The principles of each one will be first briefly discussed. Secondly our method is detailed. The last section shows the results obtained .

2 Vehicle localization

2.1 Relative localization

Relative localization relies on the determination of the position and orientation of a vehicle in a reference linked to its previous position. These kinds of technics use proprioceptive sensors giving informations about the internal state of the vehicle.

Odometer The displacement of the vehicle is obtained by the measure of the rotation of its wheels. If two wheels are equipped, the translation and the rotation of a vehicle on a planar world can be calculated. Our vehicle is equipped with a single odometer. The uncertainty on the distance, the slippage of the wheels and a non very flat ground involve a rapid derivation of the localization when the distance increases. The position has to be frequently updated by an absolute localization system.

Inertia measurement The localization is given by integrating twice the acceleration of the vehicle within a reference linked to the initial position of the vehicle. This method uses accelerometers for absolute measurement of the accelerations and gyrometers to determine angular variations. Three accelerometers grouped together with three gyrometers constitute an inertial system.
Precise inertial systems used for planes navigation are very expensive. Cheaper systems are used for robotic but have an important time derivation. They must be used with other sensors. As an example, Barshan et al. [1] include the time derivation as well as the localization parameters into a state vector updated by a Kalman filter. Vaganay [8] combines an inertial system and an odometer.

*Address: 24, av. des Landais 63177 Aubière Cedex France. E-mail: chapuis,chausse,laneurit@lasmea.univ-bpclermont.fr

Relative localization	Absolute localization
(−) Error accumulation when distance increases	(+) Error do not depends on distance
(−) Reference linked to the initial position of the vehicle	(+) Reference linked to the world
(+) No particular equipment of the environment	(−) Environment must sometime be adaptated
(+) Few calculus, so high speed	(−) Great calculation time (−) Possible loss of information

Table 1: Relative vs. Absolute localization

2.2 Absolute localization

The position is defined in some absolute reference of the world. It is based on the perception of some particular points natural or added to the environment. It uses exteroceptive sensors. It involves no time derivation but the particular points must remain in the "visual field" of the vehicle sensors. Several solutions exist:

- active or passive artificial beacons [4] [5] for example the GPS system
- use of a map [7]
- detection of particular features [3]

2.3 Hybrid localization

All the solutions described above use different kinds of sensors which all provide inaccurate information involving some uncertainty. Table 1 compares the different technics showing their advantages and drawbacks.

Most of the vehicle localization methods combine the two kinds of solution within a data fusion framework. This is mainly an algorithmic problem and the more powerful approaches use particular filtering [2] for non linear problems or Kalman filtering [5] in the linear case.

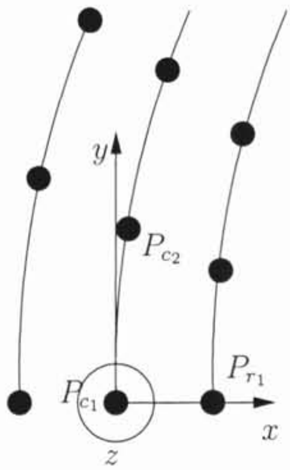

Figure 1: Reference linked to the first point of the map

3 Absolute localization combining GPS and Vision

We tend to develop an algorithm able to provide the position and the orientation of a vehicle on a road for which a numetric map is available. The solution we have designed belongs to the hybrid category. We combine three kinds of methods:

- relative localization with an odometer
- absolute localization using a low cost GPS providing the vehicle position in a global reference but with a weak precision ($\simeq 30m$)
- absolute localization obtained from a road side detection and tracking algorithm based on image analysis. Coupled with a map, it gives the vehicle position and orientation.

Taking into account all these informations, vector $X = (x, y, z, \alpha, \beta, \gamma)^T$ is estimated and updated using a Kalman filter.
x, y, z are the vehicle coordinates in a reference related to the map.
α, β, γ are the 3 angles defining the vehicle orientation regarding the axis of the reference system.

3.1 About the map

We assume a numeric map of the road is available. It is constituted of a set of points defined by their coordinates in a reference. Experimentations have been made on a two lanes road with three painted white lines outlining the lane sides. The origin of the reference is the first point P_{c_1} of the central line. The x axis is defined using the first point P_{d_1} of the right line and the y axis using the second point P_{c_2} of the central line. z axis is such as the reference is direct. Figure 1 illustrates the definition of the reference system.

3.2 Estimation of the vehicle's position

An extended Kalman filter is used to estimate the vehicle localization from the various observations mentioned above. Actually, as the evolution model of the vehicle position assumes the ground is locally flat, the vector to be estimated is $X_1 = (x, y, \gamma)^T$. The three other elements of vector X (z, α and β) are obtained from X_1 and the map.

Evolution of the vehicle's position The purpose is to set up the prediction of the future attitude $X_1(k+1/k)$ of the vehicle at time $k+1$ from its present state $X_1(k/k)$ and from the displacement Δ_s given by the odometer between times k and $k+1$, assuming a rectilinear local trajectory :

$$\begin{cases} x_{k+1} = x_k & - \quad \Delta_s cos(\gamma_k) \\ y_{k+1} = y_k & + \quad \Delta_s sin(\gamma_k) \\ \gamma_{k+1} = \gamma_k & \end{cases}$$

The error on this prediction is is represented by its covariance matrix $P_{k+1/k}$:

$$P_{k+1/k} = J_{X_k} P_{k/k} J_{X_k}^T + J_{U_k} Q_{U_k} J_{U_k}^T$$

with $Q_{U_k} = \sigma^2_{\Delta_s}$ covariance matrix of the system input $U_k = \Delta_s$.

J_{X_k} et J_{U_k} are the following jacobian matrices :

$$J_{X_k} = \frac{df}{dX}(\hat{X}_{k/k}, U_k)$$

$$J_{X_k} = \begin{pmatrix} 1 & 0 & \Delta_s \sin(\gamma_k) \\ 0 & 1 & \Delta_s \cos(\gamma_k) \\ 0 & 0 & 1 \end{pmatrix}$$

$$J_{U_k} = \frac{df}{dU}(\hat{X}_{k/k}, U_k)$$

$$J_{U_k} = \begin{pmatrix} cos(\gamma_k) \\ sin(\gamma_k) \\ 0 \end{pmatrix}$$

Estimation of z_k, α_k and β These three parameters completing the vehicle localization are calculated using X_k and the map.

- For z_k : the z value of the point of the map the closest from (x_k, y_k) is chosen for z_k.
- For α_k and β_k : γ_k defines the projection of the optical axis of the camera on the xy plane. The x and y coordinates of this vector are known. Its z coordinate is obtained using the map, the same way as for z_k. This fully defines the vector $\overrightarrow{Vy}$ supporting the optical axis. Using vector $\overrightarrow{Vz}$ normal to the road at point (x_k, y_k, z_k) obtained using once more the map, α_k and β_k are deduced.

3.3 Observations from GPS

The GPS coordinates provided by our low cost low precision system are expressed in a reference related to the center of the world. They are converted into the map system of reference.

Observation model of the GPS data The model is defined by:

$$\begin{pmatrix} x_{gps} \\ y_{gps} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x_k \\ y_k \end{pmatrix} + v$$

$$X_{GPS} = CX + v$$

This observation is blured by noise v of covariance matrix Q_{gps}. Two parameters are influencing on the precision of the position:

- The relative position of the receiver and the satellites represented by the GDOP (Geometric Dilution of Precision) value
- The precision of the estimated distance of the user from each satellite, UERE (User Equivalent Ranging Error) of about $4.2m$

These 2 parameters are included into the covariance matrix :

$$Q_{gps} = \begin{pmatrix} \sigma_{xx}^2 & 0 \\ 0 & \sigma_{yy}^2 \end{pmatrix}$$

Kalman filter also updates the covariances.

3.4 Observations from vision system

Localization can be obtained from an image analysis algorithm able to recognize the road sides in an image sequence. It estimates the distance x_0 of the vehicle from the left side of the road and the yaw angle ψ in a reference linked to the vehicle (fig. 2). It is defined by vectors:

- $V_{x_{vision}}$: normal to the road side
- $V_{y_{vision}}$: tangent to the left side
- $V_{z_{vision}}$: normal to the road

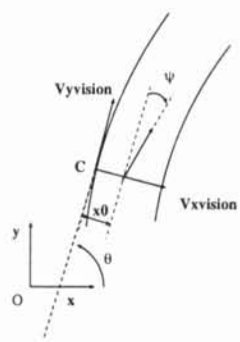

Figure 2: Parameters given by the vision algorithm in their reference

This method of our own has been widely published and more detailed explanations can be found in [6]. Then, the observation equation is given by:

$$\begin{pmatrix} x_C + x_0 cos(\theta) \\ y_C - x_0 sin(\theta) \\ \theta + \psi \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_k \\ y_k \\ \gamma_k \end{pmatrix}$$

$$X_{vision} = DX + w$$

x_C and y_C are the coordinates of the point of the left side of the road the closest from the present position $(x_k, y_k, z_k)^T$. They are deduced from the map.
θ is an angle defining the direction of vector Vy_{vision} in the map reference.
This observation is subject to perturbation w the covariance matrix of which is obtained taking into account the uncertainty on x_C, y_C and θas well as variances σ_{x0}^2 and σ_{ψ}^2 given by the vision system.

The chart diagram represented figure 3 sums up all the localization process.

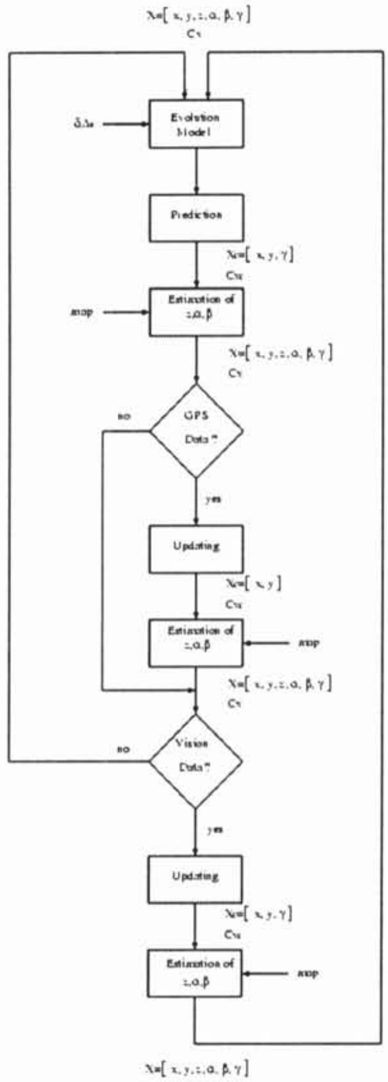

Figure 3: Chart diagram of all the localization process combining GPS and vision

4 Results

The process has been implemented in VELAC, our experimental car equipped with a single PC, a numeric camera sending images using the IEEE 1394 bus, an odometer and a low cost GPS system sending their informations to the PC via a CAN (Common Area Network) bus.

Is has been tested on a closed loop of about 2km for which a numeric map was available. The results are displayed onto the PC screen (fig. 4).

Kalman filtering provides together with the state vector, an estimation of its covaraince matrix. For each stage, it becomes possible to have an idea of the precision of the estimation. The standard deviations on the lateral position x_0 given by the vision algorithm is $0.18m$ while for the GPS alone localization, the standard deviation is $10.34m$. These are average values obtained on the loop previously described.

Combining the two kinds of informations, it appears the main error is made on the y coordinate estimation which corresponds to the road axis (figure 5).

The average standard deviation on x is $0.5m$ and $9.42m$ on y. Finally, the trajectory estimated on the whole loop is represented figure 6.

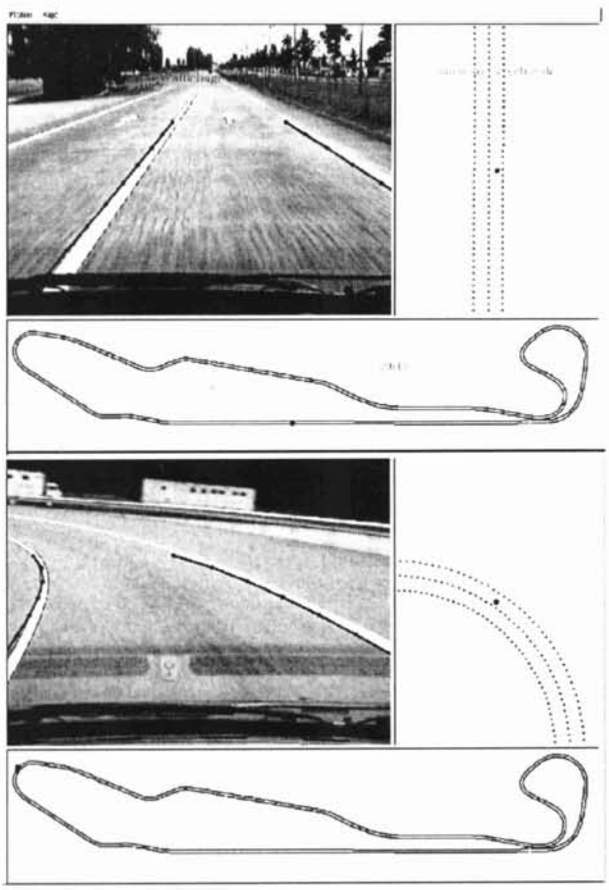

Figure 4: Two examples of the results displayed. The screen is divided in three areas: top left for the image given by the camera on which are drawn the results of lane sides detection, to right zoom of the map in the vehicle neighborhood with a point showing the vehicle, bottom for the whole map with the position of the vehicle.

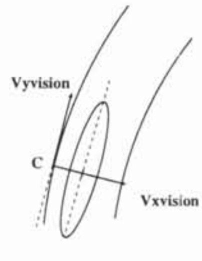

Figure 5: Uncertainty ellipsis on (x, y)

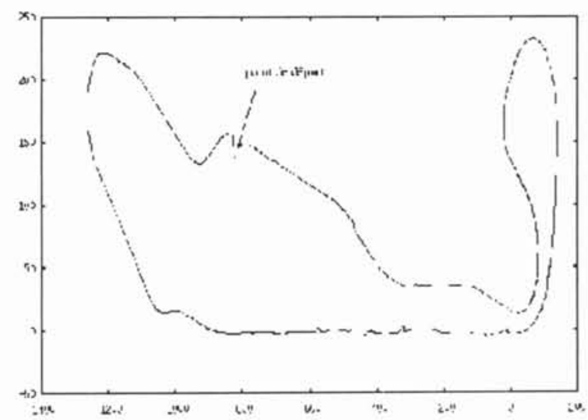

Figure 6: Estimation of the trajectory followed by the vehicle during a single loop.

5 Conclusion

The proposed method couples a vision system and a low cost low precision GPS receiver to improve global localization of a vehicle. A numeric map of the road must be available and proprioceptive data such as odometry are also used. It has been shown how such a system increases significantly the precision of the localization. The error remain high in the direction of the road axis but goes from $10m$ with the GPS alone to $0.5m$ with our system on the direction perpendicular to the road axis.

For the future, we plan to add a steer angle sensor which will make the evolution model closer to the reality.

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