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ACCURATE LOCALIZATION OF COMMUNICANT VEHICLES USING GPS AND VISION SYSTEM

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Abstract: The new generation of ADAS systems based on cooperation between vehicles can offer serious perspectives to the road security. The inter-vehicle cooperation is made possible thanks to the revolution in the wireless mobile ad hoc network. In this paper, we will develop a system that will minimize the imprecision of the GPS used to car tracking, based on the data given by the GPS which means the coordinates and speed in addition to the use of the vision data that will be collected from the loading system in the vehicle (camera and processor). Localization information can be exchanged between the vehicles through a wireless communication device. The creation of the system must adopt the Monte Carlo Method or what we call a particle filter for the treatment of the GPS data and vision data. An experimental study of this system is performed on our fleet of experimental communicating vehicles.

Keywords: car tracking, inter-vehicle communications, GPS, particle filter, vision.

1. INTRODUCTION

Global Navigation Satellite Systems (GNSS), such as the Global Positioning System (GPS), are so used in the urban navigation applications. However, they are not always ideal in urban areas because of the poorness of satellite coverage due to tunnels, high buildings, electronic interferences, etc also in rural areas when the signals are attenuated by foliage, mountains etc (Kap, 1996). Sometimes, the GPS signal may be also corrupted by multipath reflections. So, in order to accurate the vehicle positioning in urban areas, the GPS data must be enhanced with vision data using communication between vehicles.

This inter vehicle communication that has opened up new ideas to improve the advanced collaborative driving (in ADAS systems) with the recent quick development of wireless communications systems (Tsu, 2002). This direct collaboration by the mean of vehicle to vehicle (V2V) communications makes it possible to address certain issues of road safety. The innovation and the originality of this type of communications provide an opportunity to many research teams world-wide to investigate various aspects of wireless communications and their applications.

Our work consists on the use of GPS car tracking systems that allows locating and tracking single cars or managing fleets with GPS receivers. The position data from the vehicle are stored on board of the device or sent directly to a receiving station via communication links by using a car monitoring system. Software is used for plotting the actual position or the waypoints on maps. However, the precision to know the exact position between two cars is within 100 meters. Besides, the precision of the positioning the targets on the maps sometime is not similar to the reality specially in the real time

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tracking, for example if two roads are closed to each other or one under the other with a small spacing, the GPS makes mistakes in detecting the real position of the car and in which road is it, so for this reason, we accurate the car position given by the GPS by fusing the vision data with the GPS data. In case of GPS outage, the vision data is enough to track the vehicle position using the particle filter.

In this paper, we will detail all the systems we have used : the GPS signal and his errors using this signal to locate our vehicles, the communication systems used to transmit the coordinate of vehicles in this application, the monovision systems detecting the vehicle in the image and the particle filters used to track our vehicles.

2. THE GPS SIGNAL CHARACTERISTICS

GPS is a satellite based navigation maintained by the U.S Department Of Defense. The current constellation consists of 28 geo-stationary satellites with a period of 12 hours. The satellites transmit signals on two frequencies; L1 at 1575.42 MHz and L2 at 1227.6 MHz. These signals are bi-phase modulated by one or two PRN codes; the Coarse/Acquisition, C/A-code, and the Precise, P-code. The L1 carrier is modulated by both the C/A- and the P-codes while the L2 carrier is only modulated by the P-code. The C/A-code is transmitted at 1/10 of the fundamental GPS frequency (10.23 MHz) and is repeated every one millisecond. In contrast, the P-code is transmitted at the fundamental frequency and is only repeated every 267 days. The C/A-code is unrestricted and is used for the Standard Positioning Service (SPS) for commercial use, while the P-code is restricted for use by U.S military only. The GPS is affected by 3 types of error: Ionospheric error, Troposheric Delay, Satellite clock error, Receiver clock error, and Multi-path and noise errors. These errors can be minimized or removed by DGPS corrections; however, multipath and receiver noise cannot be compensated by using DGPS. Multipath is the corruption of the direct GPS signal by one or more signals reflected from the local surroundings. These reflections affect both pseudorange and carrier-based measurements in a GPS receiver. The reflector of electromagnetic signals could be buildings, metal surfaces, water bodies, and the ground.

All the work uses GPS data issued from the same type of receivers. Before we deal with those data we have to estimate the positioning errors and uncertainty as well as the latencies associated to those receivers. Those key elements have to be modeled due to their direct impact on the performance and the reliability of our decisional core. The GPS latencies result from the delays of the transmission, the precision of the embedded clocks and the multi-path effects. This type of errors is highly spatially correlated in that two receivers close one to the other are subject to the same errors, for further more details see (Abuhadrous, 2005).

3. THE COMMUNICATION SYSTEMS

For our applications, we dispose of a fleet of 4 test vehicles equipped with various perception and positioning sensors as well as communication media. The four vehicles (Citroën C3 car models), are equipped with vision sensors, GPS and telecommunication devices in addition to CAN bus. We equipped two of the four vehicles with WiFi communications devices. We adopted the 802.11 standard because of its theoretical performances, its ease of use and its inner interoperability (Khaled, *et al.,* 2005). The V2V network has these characteristics: the frequency band is on the 2.4/5.8 GHz, that is emerging as the suitable band for this network. We use Dlink 802.11g+ access points with an 8 db antenna. These devices are controlled in real time by RT-MAPS through a specially designed sniffer based on the Pcap library. The role of the sniffer is to assure the communication without the use of an inadequate communication protocol. The Table I gives some results of the real capacities of the used materials. Those results (Ammoun, *et al.,* 2006) are obtained on board the vehicle.

Table 1 The real communication devices capacities.

Maximum communications range	350 m
Transmission power	32 mW
Maximum absolute speed	120 Km/h
Maximum bandwidth	7 Mb/s

4. THE VISION SYSTEM

The vision system in the prototype vehicle, used for this application is equipped with 4 digital color CCD cameras, vision-based vehicle’s rear detection system using gradient based methods and Adaboost classification, all the theories and the experiments of this vision system are detailed in the paper (Khaled, *et al.,* 05).

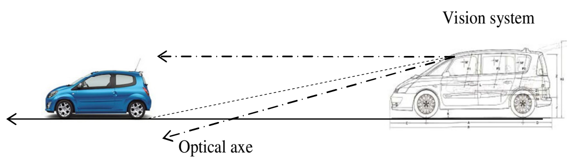

Fig.1. The vision system

In this application showed in Fig.1, we use the result of the vehicle detection to calculate the distance between the two vehicles using the pinhole camera model detailed in (Faugeras, 93). This distance is calculated as follows:

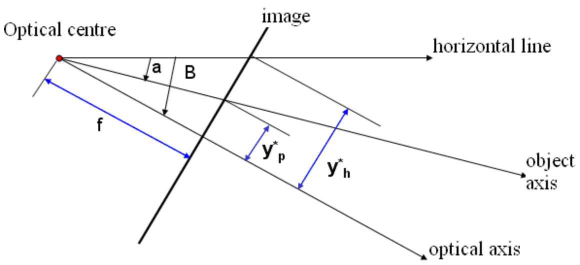

Fig.2. The intrinsic parameters of the camera.

Using the geometric relations in fig.2, we can calculate the equation (1) as following:

$$(1)\ \ Zp = \frac{H \cdot \left(f^2 + p^2 \left(\frac{N_H}{2} - y_h \right) \left(\frac{N_H}{2} - y_p \right) \right)}{f \cdot \left(y_p - y_h \right)}$$

Where z_p is the distance between the two vehicles, f is the focal length, H is the height of the camera, y_p is the distance in pixel between the position of the first mobile object detected the nearer to the vehicule and the first line of the image, y_h is the distance in pixel also between the first line of the image and the line of horizon, N_H is the number of lines, and p is the pitch.

Fig.3. The detection system on RTMaps.

The system in Fig. 3 sometimes failed to detect vehicles situated beyond 60 m, this distance is calculated from the horizontal line of the image yh. After exctracting the distance between two vehicles, the second step is to locate the vehicle in the world coordinate system, by using a transformation from image coordinate to world coordinate system, we assume that the world being a plane. Finally, we have the xy coordinate of the vehicle in the world coordinate system using the xy coordinate of the first vehicle that it detects.

5. THE SEQUENTIAL MONTE CARLO METHODS

The particle filters also known as Sequential Monte Carlo Methods are sophisticated model estimation techniques based on simulation, they are detailed in these works (Arumpalam, *et al.,* 2002), (Doucet, 1998). We will resume in this paper the Particle Filters used in our application to track the vehicle position on the road. The particle filters aim to estimate a random vector Xt called the state vector, this becomes possible only if we know the observed data referred as Yt, called the observation vector and using the estimation of the filtering density p(Xt|Y1:t) where t is the time. To perform such estimation, some information are required. These equations are:

$$(2)\ X_{t+1} = F\ (X_t, W_t);$$

$$(3)\ Y_{t+1} = H\ (X_t, V_t);$$

F and H are two non-linear functions and Wt and Vt are two general noises. As for a Kalman filter F and H should be linear and Wt and Vt should be gaussian, that is why particle filter is more powerful than Kalman filter, and the use of non-linear models and non-Gaussian noise is the main explanation for the improvement in accuracy of the particle Filters. To perform the estimation, the particle filter theory uses many results of the probabilistic theory. The first one is the Monte Carlo approximation, derived from the law of great numbers:

$$(4)\ \ \hat{p}(X_t | Y_{1:t}) = \sum_{i=1}^{N} \delta_{X_t^i}(X_t)$$

$\left(X_t^i \right)_{i:1..N}$ are N particles drawn from a law $p\left(. | Y_{1..t} \right)$, $\delta_{X_t^i}$ is the Dirac distribution centered on the particle $X_t^{(i)}$. After this, we should work on the importance sampling. Indeed it is unreasonable to think that one can sample from p at any time. To overcome this difficulty, importance sampling proposes to sample from another law q, whose support must contain the support of p. Then, the samples will have to be weighted by $\omega_t^i = \frac{p(X_t | Y_{1..t})}{q(X_t | Y_{1..t})}$. And the estimation becomes:

$$(5)\ \ p(X_t | Y_{1:t}) = \sum_{i=1}^{N} \omega_t^i \delta_{X_t^i}(X_t)$$

Under the markovian hypotheses, it can be shown that a recursive estimation of weights is possible using the formula:

$$(6)\ \ \omega_t^i \propto \omega_{t-1}^i \frac{p(Y_t | X_t^{(i)}) p(X_t^{(i)} | X_{t-1}^{(i)})}{q(X_t^{(i)} | X_{t-1}^{(i)}, Y_t)}$$

The tracking procedure is now done, but it is recommended to add one more important step : the resampling, which allows particle to be renewed, thereby avoiding the degeneracy observed in the simple particle filter procedure, the key point with re-sampling is to prevent high concentration of probability mass at a few particles. This step was added by Gordon (Gordon, *et al.*, 2002), and made the development of particle filter popular. In this work, the resampling was based on the algorithm of resampling of Campillo detailed in (Campillo, 2006).

5.1. State equation

For my application, the first step of the Particle Filters is to design a state vector matching our purpose; the state representation is characterized by the 2-D vehicle's dynamics: the position along the two world coordinates (x, y), the velocity v of the vehicle and the acceleration γ. So the Xt becomes as follows:

$$(7)\quad X_t = (x, y, v_x, v_y, \gamma_x, \gamma_y)^T$$

And the state evolution equation (2) is described by the vehicle's dynamics, we will show only along the x-component :

$$(8)\quad \begin{cases} x_{t+1} = x_t + v_t^x \Delta t + \omega_t^x \\ v_{t+1}^x = v_t^x + \gamma_t^x \Delta t + \omega_t^{v_x} \\ \gamma_{t+1}^x = \gamma_t^x + \omega_t^{\gamma_x} \end{cases}$$

Where $\omega_t^x, \omega_t^{v_x}, \omega_t^{\gamma_x}$ are additive white noises and Δt defines the sampling rate. In addition, this will be chosen as the proposal density q = $p(X_t|X_{t-1})$ called the prior density, which really simplifies the calculation of weights. It becomes : $\omega_t^{(i)} \propto \omega_{t-1}^{(i)} p(Y_t | X_t^{(i)})$.

5.2. Measurement equation

The estimator uses the vision data which combinates the GPS data of my vehicle when available in addition with the distance calculated by vision between the two vehicles in the same urban zone. Our observation vector is defined as follows; all the coordinates are in the world system:

$$(9)\quad Y_t = (x_{obs} \quad y_{obs})^T$$

And the measurement equation is taken from the pinhole model in vision:

$$(10)\quad Y_t = H(X_t) + V_t$$

Where H is the measurement function, and V_t is an additive white Gaussian noise. We can deduce from (1) that equation (10) becomes:

$$(11)\quad y_p = \frac{Zp \cdot H.\left(f^2 + p^2\left(\frac{N_H}{2} - y_h\right)N_H\right)}{f + Zp.H.p^2}$$

We calculate as $Z_p = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$, with (x_1,y_1) are the coordinates of the vehicle V_1, and (x_2,y_2) are the coordinates of the vehicle V_2.

5.3. The particle filter implementation

The algorithm that we developed to my application is the following one :

Initialization :

Generate $X_0^{(i)}$ ~ initial position given to my vehicle, for *i= 1 ,..., N* . Each sample of the state vector is referred to as a particle.

Measurement update :

Update the weights by the likelihood (more generally, any importance function, details in [Dou01])

$\omega_t^{(i)} = \omega_{t-1}^{(i)} p(Y_t | X_t^{(i)})$ with *i= 1,.., N* after we normalize the weight to $\omega_t^{(i)} = \frac{\omega_t^{(i)}}{\sum_i \omega_t^{(i)}}$. And the approximation becomes: $\hat{x}_t = \sum_{i=1}^{N} \omega_t^i x_t^i$

Resampling

- The Bayesian bootstrap :

We take *N* samples with a replacement from the set $\{X_t^{(i)}\}_{i=1:N}$ where the probability to take the sample *i* is the weight ω_t^i. We let $\omega_t^i = 1/N$ .This step is also called Sampling Importance Re-sampling (SIR).

- The importance Sampling :

If the effective number of samples is less than a threshold N_{th} chosen as 2N/3, we resample as in the above. We should verify:

$N_{eff} = \frac{1}{\sum_i (\omega_t^{(i)})^2} < 2N/3$; for further informations on the resampling see (Campillo, 2006; Kong, *et al.,* 1994; Liu, 1996; Bergman, *et. al.,* 1999).

- Prediction :

Take Xt+1 = F (Xt,Wt), we applicate (8).

- Iteration :

Let *t:=t+1* and then iterate to item 2.

Finally, we can resume our particle filter to a component with a distance measured as an entry and the output of my particle filters is the approximation of the position of the vehicle that we track in our project.

6. EXPERIMENTS AND RESULTS

The vehicles are equipped with communication devices to exchange information among the group, they can receive the position GPS of other vehicles by communication, and use the vision system to calculate the distance between two consecutive vehicles, this distance is used to localize our vehicles and to find its position compared to other vehicles, we use a translation from the image coordinate to the 2-D world coordinate. When we have the coordinate of the vehicle in the world system, we can track them using the particle filters component. We have also the trajectory of every vehicle using the particle filters component and having as an entry the GPS data of every vehicle, when available certainly. When there is an outage of the GPS system, we use the vision system to have the distance and to locate the vehicle detected in 2-D coordinate using the 2-D coordinate of the vehicle detecting, after we can track the second vehicle using the particle filter component, it has as entry a distance, this distance is the x coordinate, or y coordinate. In the fig.4, we have the difference between the trajectory of the vehicle given by the GPS data, and the trajectory of the vehicle using the particle filters and the vision data.

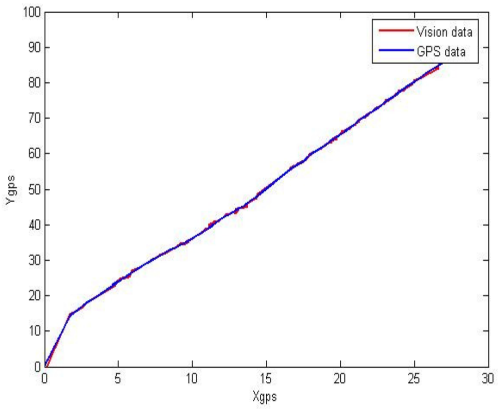

Fig.4. We have in that Figure in blue line the vehicle trajectory using the GPS data and in red line the vehicle trajectory using the vision data.

We respect these conditions of communication, the equipped vehicles can not communicate when the distance between them is higher than the maximum communication distance (350 meters), we consider that the road security is ensured in a radius sector of 350 m. The sensors and GPS data and the communication can be affected with delays or can be temporarily unavailable. Vehicle information is transmitted via a CAN bus. We also use a Navteq GIS for map matching and geo-localization of our vehicles on the road map. All sensor information is synchronized using the RTMAPS system which is a real-time framework for prototyping multi-sensor automotive applications (Nashashibi, *et al.*, 2001). This system was developed in the laboratory of ENSMP and is currently installed in the prototype vehicle. The video stream was acquired from the frontal camera mounted near the rear-view mirror with a 50° horizontal field of view and a dynamic range of 50dB. In order to evaluate the performance of our tracking system, tests were conducted under both simulation and real world conditions. Using RTMAPS, we recorded different scenarios including highway, rural and urban scenes at different times of day. We also installed the system on our host vehicle and conducted real-time tests. We were able to achieve, for a 100km/h speed, a frame rate of approximately 10 frames per second using a standard PC machine (Bi-Xeon 1 GHz and 1 GB of RAM) and without performing specific software optimisations.

7. CONCLUSION

We have presented in this paper a method for a better vehicle position estimation using the GPS, vision and the communication between vehicles, this work was on two vehicles but it can be extended to many other prototyped vehicles in a group.

The proposed solution lies on a centralized non-linear filter which fuses the available measurements. The benefits are shown on an urban transport network scenario, which proves the stability of the method and the contribution of the vision in the vehicle positioning accuracy whenever the GPS is unavailable.

This method can be applied to the accurate location of different vehicle fleets in urban areas like people transportation or (high-value) goods transportation where the positioning information must be known accurately and continuously (traveler information systems, security systems, surveillance systems, etc.)

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