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MOTION ESTIMATION BY INTEGRATED LOW COST SYSTEM (VISION AND MEMS) FOR POSITIONING OF A SCOOTER "VESPA"

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ABSTRACT: In the automotive sector, especially in these last decade, a growing number of investigations have taken into account electronic systems to check and correct the behaviour of drivers, increasing road safety. The possibility to identify with high accuracy the vehicle position in a mapping reference frame for driving directions and best-route analysis is also another topic which attracts lot of interest from the research and development sector.
To reach the objective of accurate vehicle positioning and integrate response events, it is necessary to estimate time by time the position, orientation and velocity of the system. To this aim low cost GPS and MEMS (sensors can be used. In comparison to a four wheel vehicle, the dynamics of a two wheel vehicle (e.g. a scooter) feature a higher level of complexity. Indeed more degrees of freedom must be taken into account to describe the motion of the latter. For example a scooter can twist sideways, thus generating a roll angle. A slight pitch angle has to be considered as well, since wheel suspensions have a higher degree of motion with respect to four wheel vehicles.
In this paper we present a method for the accurate reconstruction of the trajectory of a motorcycle ("Vespa" scooter), which can be used as alternative to the "classical" approach based on the integration of GPS and INS sensors. Position and orientation of the scooter are derived from MEMS data and images acquired by on-board digital camera. A Bayesian filter provides the means for integrating the data from MEMS-based orientation sensor and the GPS receiver.

1. INTRODUCTION

Determining the position and orientation of moving vehicles in real time hase become a very important research topic in these last decade, with particular attention to the development of electronic systems for road safety purposes. Two main results of the technological progress in this field are represented by the Electronic Stability Program (ESP), an evolution of the Anti-Blocking System (ABS), and satellite positioning of vehicles. In the automotive sector, due to limited budgets and sizes, navigation sensors rely on the integration between a low cost GPS receiver and an Inertial Measurement Unit (IMU) based on MEMS(Micro-Electro-Mechanical System) technology. Such integration is commonly realized through an extended Kalman filter (Qi and Moore,), which provides optimal results for offsets, drifts and scale factors of employed sensors. However the application of this filter to motorcycle dynamics does not perform similarly. Unlike cars, motorcycles are able to rotate around its own longitudinal axis (roll), bending on the left and on the right. Therefore the yaw angular velocity is not measured by just one sensor, rather it is the result of the measurements of all three angular sensors, which contribute differently in time according to the current tilting of the motorcycle. Consequently, an error on the estimate of the roll angle at time *t* will affect the estimate of the pitch and yaw angles at next time *t+1*, as well. In this paper we consider the problem of detecting the position and orientation of a popular Italian scooter, "Vespa", using a low cost POS (Positioning and Orientation System) and images acquired by an on-board digital video camera. The estimate of the parameters (position in space and orientation angles) of the dynamic model of the scooter is achieved by integrating in a Bayesian particle filter the measurements acquired with a MEMS-based navigation sensor and a double frequency GPS receiver. In order to further improve the accuracy of orientation data, roll and pitch angles provided by the MEMS sensor are pre-filtered in a Kalman filter with those computed with the application of the cumulated Hough transform to the digital images captured by a video-camera.

The paper is organized as follows. In the next Section we present an overview of the "Whipple model" (Whipple, 1899), which constitutes the mathematical basis of the dynamic model of the motorcycle. Then in Section 3 we show how the roll angle can be estimated from the images recorded by the video-camera using the the cumulated Hough transform, as discussed in Frezza and Vettore (2001) and similarly in Nori and Frezza (2003). In Section 4 we discuss the use of a Bayesian filter model to integrate MEMS sensor data with GPS measurements, while in Section 5 we provide a short description of the system components. Finally in Section 6 we present some experimental results and draw the conclusions.

2. THE "WHIPPLE MODEL"

The "Whipple model" essentially consists in a inverse pendulum fixed in a frame moving along a line with ideal wheels which are considered to be discs with no width (figure 1). The vehicle's entire mass *m* is assumed to be concentrated at its mass center, which is located at height *h* above the ground and distance *b* from the rear wheel, along the x axis. The parameter δ denotes the steering angle, ψ the yaw angle, φ the roll angle and *w* is the distance between the two wheels. In this model the motorcycle motion is assumed to be constrained so that no lateral slip of the tires is allowed (*non-holonomic constraint*). Furthermore it doesn't take into account the movement of a driver neither the oscillation of the scooter's wheel suspensions.

The motion equations are therefore described by:

$$\begin{aligned} \dot{x} &= v\cos\psi\cos\theta \\ \dot{y} &= v\sin\psi\cos\theta \\ \dot{z} &= -v\sin\theta \end{aligned} \qquad (1)$$

where x, y and z represent the real-time vehicle positions in the spatial frame, *v* is the forward velocity, and θ is the pitch angle (not shown in figure 1).

From the geometry of the system the rate of change (i.e. first derivative) of the yaw angle is defined as follows:

$$\dot{\psi} = \frac{\tan\delta}{w\cos\varphi} v = \frac{v}{R} = \sigma v \tag{2}$$

where σ is the istantaneous curvature of the path followed by the motorcycle in the xy plane and R is the istantaneous curvature ray ($\sigma = R^{-1}$).

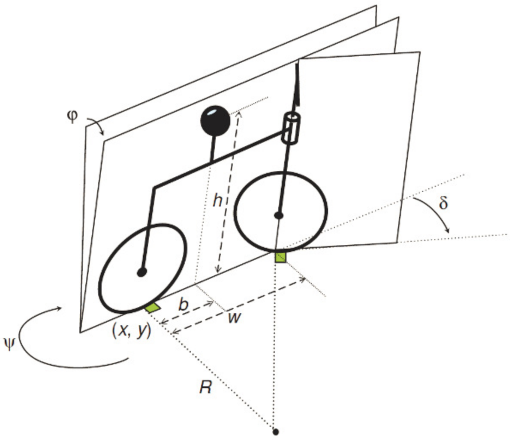


Fig. 1: The inverted pendulum motorcycle model (courtesy of Limebeer & Sharp, 2006)

According to the inverted pendulum dynamics, the roll angle satisfies the following equation:

$$h\ddot{\varphi} = g\sin\varphi - \left[(1 + h\sigma\sin\varphi)\sigma v^2 + b\ddot{\psi}\right]\cos\varphi \tag{3}$$

where g is the acceleration due to gravity. The term $h\sigma sin\varphi$ can be rewritten as a function of the steering angle δ and the roll angle φ:

$$h\sigma\sin\varphi = \frac{h}{w}\tan\delta\tan\varphi \tag{4}$$

and given that angles δ and φ do not simultaneously assume high values, the term $h\delta\ sin\varphi$ can be neglected. Therefore, taking into account also equation (2), equation (3) becomes:

$$h\ddot{\varphi} = g\sin\varphi - \left[\sigma v^2 + b(\dot{v}\sigma + v\dot{\sigma})\right]\cos\varphi \tag{5}$$

Assuming that we can measure the roll angle φ(t), the pitch angle θ□ and the velocity v(t), equation (5) could be used to estimate the curvature σ. Indeed, by integrating equation (5) we can compute the istantaneous curvature σ(t), provided that an initial condition σ(0) is given. Similarly, knowing the profile σ, if we integrate the nonholonomic kinematic model (1) from an initial position (x(0), y(0), z(0)) the path followed by the motorcycle can be fully reconstructed. In next sections we will discuss how we estimate the parameters φ, θ and v, whose knowledge represents the key point of the proposed method.

3. ESTIMATING THE ROLL & PITCH ANGLES

Assuming that the camera is strongly fixed to the motorcycle, roll and pitch angles can be estimated by detecting the position in the image (slope and distance from the image origin) of the horizon line. It can be proved that using the perspective projection camera model, the horizon line projected onto the image plane can be described in terms of roll and pitch angles as follows (see Nori and Frezza, 2003, for details):

$$\cos\theta\cos\varphi V - \sin\varphi U = \sin\theta\cos\varphi$$

where (U,V) denote the image plane coordinates of a point P with coordinates [x,y,z] in the camera frame Σ_c.
Therefore, the pitch and roll angles θ and φ can be determined knowing the position of the horizon line in the image. Despite that the horizon cannot be easily determined due to occlusions frequently occurring in the scene, roll and pitch rates can be robustly estimated by comparing two consecutive images. Indeed, given the horizon line in the frame at time t_i , $I(t_i)$, in the next frame at time t_i+1, $I(t_i+1)$, the horizon is described by the following relationship:

$$\cos(\theta + \Delta\theta)\cos(\varphi + \Delta\varphi)V - \sin(\varphi + \Delta\varphi)U = \sin(\theta + \Delta\theta)\cos(\varphi + \Delta\varphi) \tag{6}$$

Linearizing (6) about $\theta(t)$ and $\varphi(t)$, neglecting terms of order higher than one in Δ and assuming small pitch angles ($\theta \cong 0$), we obtain

$$\sin\varphi\Delta\varphi V + \cos\varphi\Delta\varphi U = -\Delta\theta\cos\varphi \tag{7}$$

Equation (7) shows that in two successive frames, the horizon rotates by $\Delta\varphi$ and translates by $-\Delta\theta\cos\varphi$. These two quantities ($\Delta\varphi$, $\Delta\theta$) can be measured by computing the Hough transform on a region of interest centered around a neighborhood of the current estimation of the horizon line.
The Hough transform (Duda and Hart, 1972) is a feature extraction technique used in image analysis, computer vision, and digital image processing, whose purpose is to find imperfect instances of objects within a certain class of shapes by a voting procedure. This voting procedure is carried out in a parameter space, from which object candidates are obtained as local maxima in a so-called accumulator space that is explicitly constructed by the algorithm for computing the Hough transform. In this case this transform is used to determine the horizon line in the images acquired by the scooter's on.board video-camera. To this aim the parameter space is defined by the polar coordinates (ρ,α), which are related to the image coor-dinates (U,V) as follows (figure 2):

$$\rho = U\cos\alpha + V\sin\alpha \tag{8}$$

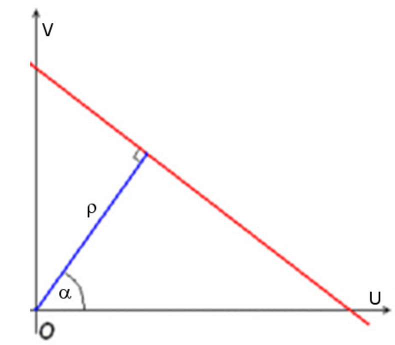


Fig. 2: The parameter space (ρ,α) of the Hough transform adopted for line detection.

Given this parametrization, points in parameter space (ρ, α) correspond to lines in the image space, while points in the image space correspond to sinusoids in parameter space, and viceversa (figure 3). The Hough transform allows therefore to determine a line (e.g. the horizon) in the image as intersection, in parameter space, of sinusoids corresponding to a set of co-linear image points. Such points can be obtained by applying an edge detection algorithm.

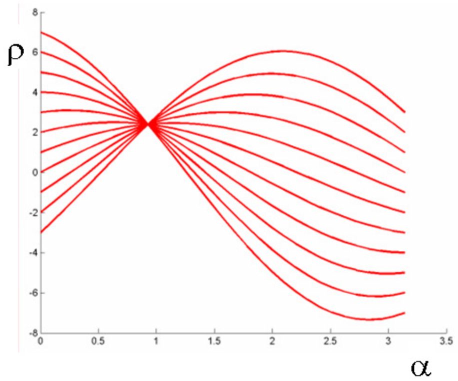


Fig. 3: Image points mapped into the parameter space.

The steps needed to compute the rates ($\Delta\varphi$, $\Delta\theta$) can be summarized as follows:

1) apply an edge detection to a predefined region of interest of the image;
2) perform a discretization the parameter space (ρ, α) by subdividing it in a set of cells (bins);
3) considering that each edge candidate is an infinitesimal line segment of polar coordinates (ρ, α), the number of edges falling in each bin is counted;
4) through this accumulation an histogram of an image in coordinates (ρ, α) is generated, whose intensity values are proportional to the number of edges falling in each bin. This histogram represents the Hough transform H(ρ, α) of the image.

5) from each histogram the corresponding cumulated Hough transform is derived. This transform is a modification of the Hough transform and is defined as follows:

$$\bar{\boldsymbol{H}}_E(\alpha) = \sum_{\rho} \boldsymbol{H}_E(\rho, \alpha) \tag{9}$$

for the roll angle ($\alpha = \varphi$), while for the pitch angle ($\alpha = \theta$) it becomes:

$$\bar{\boldsymbol{H}}_E(\rho) = \sum_{\alpha} \boldsymbol{H}_E(\rho, \alpha) \tag{10}$$

An example of the cumulated Hough transform is shown in figures 4 and 5.

6) It can be proved that if the same edges are visible at time t and t+Δt, then for the roll angle (and similarly for the pitch angle) it holds that

$$\bar{\boldsymbol{H}}_{E(t+\Delta t)}(\varphi) = \bar{\boldsymbol{H}}_{E(t)}(\varphi + \Delta\varphi(t)) \quad \forall \varphi \in [0, \pi) \tag{11}$$

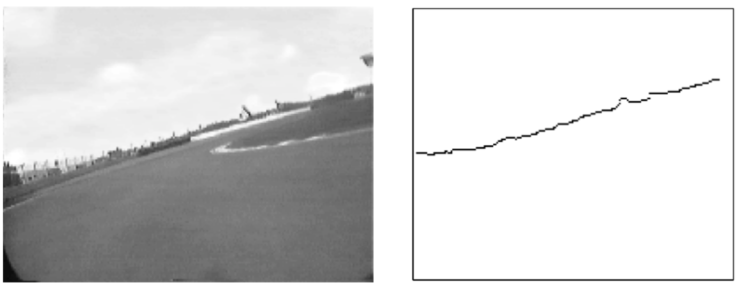
In presence of noise and considering that not all edges visible at time t remain visible at time $t+\Delta t$, a good estimation of $\Delta\varphi(\Delta t)$ can be obtained minimizing the Euclidean distance between each of the cumulated transforms at time t and $t+\Delta t$:

$$\Delta\varphi(\Delta t) = \arg\min_{\Delta\alpha} \left\| \int H_{t+\Delta t}(\rho, \alpha - \Delta\alpha) d\rho - \int H_t(\rho, \alpha) d\rho \right\| \tag{12}$$

Similarly, the estimate of the increment of the roll angle θ is computed as follows:

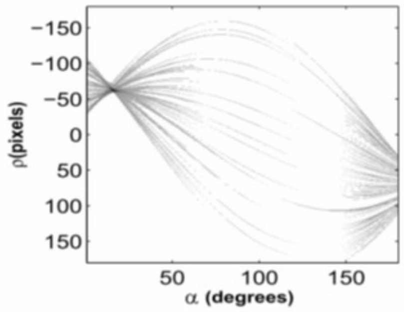
$$\Delta\theta(t) = \frac{1}{\cos\varphi} \arg\min \left\| \int H_{t+\Delta t}(\rho - \Delta\rho, \alpha) d\alpha - \int H_t(\rho, \alpha) d\alpha \right\| \tag{13}$$

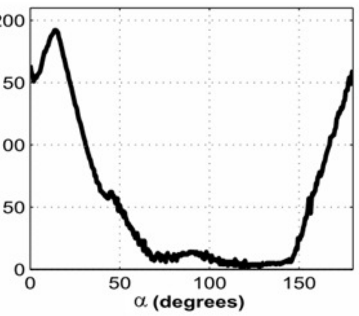
After these steps, the estimates of the roll and pitch angles are computed by time integration of the rates $\Delta\varphi$ and $\Delta\theta$.



(a) (b)

Fig. 4: Image acquired form the on-board camera (a); edge detection of the horizon line (b).





(a) (b)

Fig. 5: Hough transform obtained from the set of edges in figure 4b (a); corresponding cumulated Hough transform (b).

4. THE BAYESIAN PARTICLE FILTER

The key point of all navigation and tracking applications is the motion model to which bayesian recursive filters (as the particle filter) can be applied. Models which are linear in the state dynamics and non-linear in the measurements can be described as follows:

$$\begin{aligned} x_{t+1} &= Ax_t + B_u u_t + B_f f_t \\ y_t &= h(x_t) + e_t \end{aligned} \tag{14}$$

where x_t is the state vector at time *t*, u_t the input, f_t the error model, y_t the measurements and e_t the measurement error. In this model, indipendent distributions are assumed for f_t , e_t and the initial state x_0, with known probability densities p_{et} , p_{ft} and p_{x0}, respectively, but not necessarily Gaussian.

We denote the set of available observations at time *t* as

$$Y_t = \{y_0 , . . . , y_t\} \tag{15}$$

The Bayesian solution to equations (14) deals with the computing of the a prior distribution $p(x_{t+1}|Y_t)$, given past distribution $p(x_t|Y_t)$. In case noise pdfs (probability density functions) are indipendent, white and gaussian with zero mean, and $h(x_t)$ is a linear funtcion, then the optimal solution is provided by the Kalman filter. Should be this condition not satisfied, an approximation of the a prior distribution $p(x_{t+1}|Y_t)$ can be still provided using a Bayesian particle filter. This filter is an iterative process by which a collection of particles, each one representing a possible target state, approximates the a prior probability distribution, which describes the possible states of the target. Each particle is assigned a weight w_t^i, whose value will increase as closer to true value the related sample will be. When a new observation arrives, the particles are time updated to reflect the time of the observation. Then, a likelihood function is used to updated the weights of the particles based on the new information contained in the observation. Finally, resampling is performed to replace low weight particles with randomly perturbed copies of high weight particles. More details

about the Bayesian particle filter can be found in (Gustafsson et al., 2001). A block diagram of the particle filter is presented in figure 6.
Since the computational cost of a particle filter is quite high, only an adequate minimum number of variables has been included in the dynamic model of the scooter. It was therefore chosen to neglect any movement along the z axis (e.g. “bouncing” of suspensions), and to account for position variables x and y, speed v, the three angles needed for modelling the orientation (φ,θ,ψ) and the filtered version of the curvature δ. In order to further improve the accuracy of orientation data, roll and pitch angles provided by the MEMS sensor are combined and pre-filtered in a Kalman filter with those computed using the cumulated Hough transform applied to the digital images captured by a video-camera. Assuming that the system is now represented as a collection of N particles, the dynamics of the generic particle s^i (i.e. a possible system state) is described by the following model:

$$\begin{cases} x_{t+1}^i = x_t^i + v_t^i \cos(\psi_t^i)\cos(\theta_t^i)\Delta T + N(0,\Delta x_t^{i2}) \\ y_{t+1}^i = y_t^i + v_t^i \sin(\psi_t^i)\cos(\theta_t^i)\Delta T + N(0,\Delta y_t^{i2}) \\ v_{t+1}^i = v_t^i + (a_t - g\cos(\theta_t^i)\Delta T + N(0,\Delta v_t^{i2}) \\ \varphi_{t+1}^i = (1-\gamma_{r_t}^i)(\varphi_t^i + \dot{\varphi}_t^i \Delta T) + \gamma_{r_t}^i \arctan\left(\dfrac{\sigma_{f_t}^i v_t^{i2}}{g}\right) \\ \theta_{t+1}^i = \theta_t^i + \dot{\theta}_t^i \Delta T \\ \psi_{t+1}^i = \psi_t^i + \dot{\psi}_t^i \Delta T + N(0,\Delta\psi_t^{i2}) \\ \sigma_{f_{t+1}}^i = (1-\gamma_s)\sigma_{f_t}^i + \gamma_s \dfrac{\psi_t^i}{v_t^i} \\ w_{t+1}^i = \dfrac{w_t^i P_t(p_t^i)}{\sum_{j=1}^N w_t^i P_t(p_t^j)} \end{cases} \tag{16}$$

where

- ΔT is the sampling interval;
- $N(0,\Delta x^{i2}_t)$ represents the measurement noise of the X coordinate, modelled as a Gaussian function with a zero mean and standard deviation Δx^i_t. Similar assumption holds for measurement noises $N(0, \Delta y^{i2}_t)$, $N(0, \Delta v^{i2}_t)$ and $N(0,\Delta\psi^{i2}_t)$;
- $\sigma_{f_{t+1}}^i$ is the weighted combination of the curvature estimated at previous time t ($\sigma_{f_t}^i$) and the current input $\dfrac{\psi_t^i}{v_t^i}$, being γ_s the weighting term ($\gamma_s = 1/10$);
- w_t^i is weight of the i-th particle;
- $P_t(s_t^i)$ is the *importance* function, i.e. the likelihood function through which the weights are updated according to the following relationship:

$$w_{t+1}^i = w_t^i P(y^t \left| x_t^i \right.) \tag{17}$$

– $\gamma_{r_t}^i$ is a coefficient which dynamically changes in order to give more weight to minimal curvatures and roll angular velocities as denoted by:

$$\gamma_{r_t}^i = \begin{cases} \gamma_m\left(\sigma_l - \left|\sigma_{f_t}^i\right|\right)\left(\dot{\varphi}_l - \left|\dot{\varphi}_t^i\right|\right) & if \left|\sigma_{f_t}^i\right| < \sigma_l \ and \ \left|\dot{\varphi}_t^i\right| < \dot{\varphi}_l \\ 0 & otherwise \end{cases} \tag{18}$$

where σ_l and $\dot{\varphi}_l$ are the thresholds for the maximum curvature and roll angular velocity respectively. We set $\gamma_m = 1/500$, $\sigma_l = 1/100\ m^{-1}$ and $\dot{\varphi}_l = 30$ °/s.

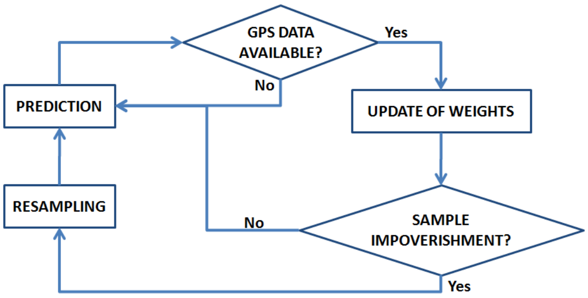


Fig. 6: Block diagram of the Bayesian particle filter.

In the model equations (16) we used different formulas for the derivatives of the orientation angles $\dot{\varphi}_t^i$, $\dot{\theta}_t^i$ and $\dot{\psi}_t^i$. This is due to the fact that the angular velocities (ω_x, ω_y, ω_z) measured by the MEMS sensor are related to the *body* frame (i.e. the coordinate system fixed with the scooter) while orientation angles (φ,θ,ψ) are determined in a *world* reference frame (e.g. the GPS coordinate system, WGS-84). A frame transformation from the *body* to the *world* frame is therefore needed, which leads to different equations for the orientation angles.

The components of the state vector at time t are then computed as weighted average of the variables estimated by the filter, using the weigths w^i of all particles s^i:

$$\begin{pmatrix} x_t \\ y_t \\ v_t \\ \varphi_t \\ \theta_t \\ \psi_t \\ \sigma_t \end{pmatrix} = \sum_{i=1}^{N} w_t^i \begin{pmatrix} x_t^i \\ y_t^i \\ v_t^i \\ \varphi_t^i \\ \theta_t^i \\ \psi_t^i \\ \sigma_{f_t}^i \end{pmatrix} \tag{19}$$

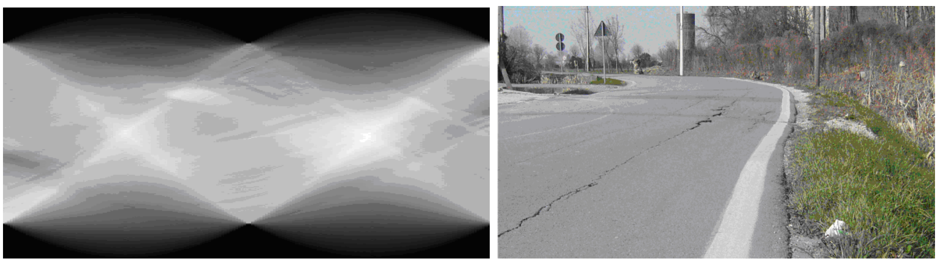
In order to limit the computational effort of the filter, the update of the particle weights w^i is not performed at every step of the algorithm, but rather when the GPS data are available from the receiver.

5. SYSTEM COMPONENTS

The method for the motion estimation of a motorcycle described in previous sections has been tested on an italian scooter, “Vespa”, which was equipped with a set of navigation sensors as shown in figure 7. The system consists of a Novatel DL-4 double frequency GPS receiver, an XSens MTi-G MEMS-based inertial sensor and a 1.3 Megapixel SONY Progressive Scan color CCD camera. Data acquisition and sensor sinchronization was handled by a Notebook PC (Acer Travelmate) provided with 1024 MB of RAM and a CPU processing speed of 1.66 GHz.

(a) (b)

Fig. 7: Side views of the Vespa scooter showing the data acquisition sensors. The digital video camera was placed on the rigth bottom side of the motorcycle (a), while battery and navigation sensors on the back rack (b).



(a) (b)

Fig. 8: The Hough transform (a) of an image acquired during a drive test (b).

6. RESULTS AND CONCLUSIONS

Three drive tests were carried out on the same track in order to evaluate the measurement repeatability, whose results for the rol angel are shwon in figure 9. A slight difference can be observed for test 3 where the speed was slower than for the other tests.

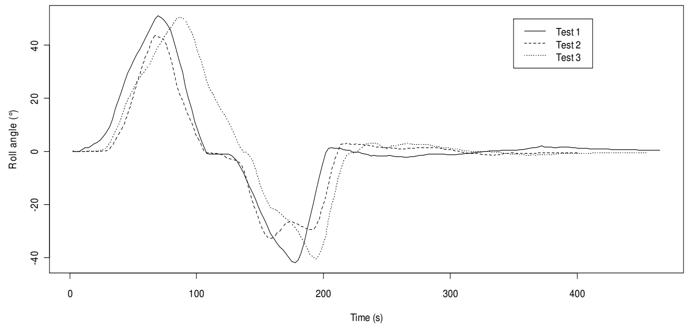


Fig. 9: Roll angle profiles computed over three tests.

The reconstruction from the data received during navigation in the test track and measures done in real time allowed the recording of roll and pitch angles which are coherent with each other. Employing the measurements generated by a simulator, optimal reconstruction can be achieved due to the absence of noise coming from vibrations, offsets and scale factors. The simulation of these error sources is not necessary as the pre-filter stage of the method will remove them and thus simulating them would not have been of interest. Other more interesting sources of error which have to be tested are wrong initial conditions and noises of the roll and pitch angles.

Of interest was the roll angle, which was brought to more than 20° to test the performance of the filter. The algorithm was able to converge, slowly, towards the real angle.

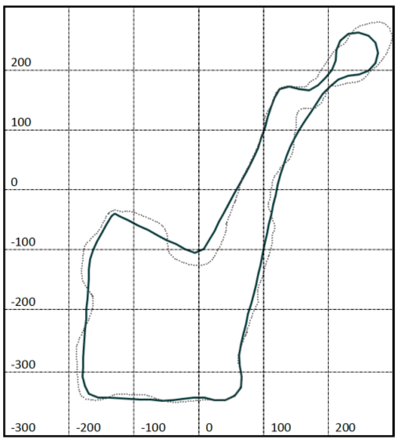


Fig. 10: Trajectory estimated with the Bayesian particle filter (dotted line) overimposed onto the differentially corrected GPS reference track (solid line).

Developments of the proposed method will deal with the encoding of the Bayesian filter inside an integrated system which can be used to equip the Vespa scooter. This can lead in the future to provide even motorcycles with traction control systems. Further developments will be the inclusion in the dynamic model of the suspensions' motion along the Z axis, and also the study of the influence of the steering angle (δ) on the estimation of the roll angle. These two parameters are indeed related by the following relationship, which can be easily derived from equation (2):

$$\varphi = arc\cos\left(\frac{\tan\delta}{W\sigma}\right) \tag{20}$$

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