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

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ABSTRACT:

In the automobile 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 cartographic 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 for each time instant the position, orientation and velocity of the system. For this low cost GPS and MEMS sensors can be used. Comparing the dynamics of a four wheel vehicle to the dynamics of a two wheel vehicle, the latter has a higher degree of complexity, The degrees of freedom are more numerous, since the scooter can twist sideways and thus have a roll angle. Also a slight pitch angle which has to be considered because the wheel suspensions have a higher degree of movement in respect to four wheel vehicles.

In this paper an accurate real-time reconstruction of the dynamics of “Vespa” scooter is presented. A Bayesian filter provides the means for integrating the data from MEMS. With the same method the acquisition of the roll angle with the vision algorithm proposed by Frezza and Vettore (2001) will permit a control and an assessment for increasing the accuracy of vehicle position.

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1. INTRODUCTION

The survey of the position and orientation of moving vehicles is a very important problem for different reasons and in different fields. In the application which is reported in this paper we consider the problem of detecting the position and orientation of a popular Italian scooter “Vespa” for an analysis for identifying the behaviour and for proposing practical methods for corrections. The estimation of the dynamics of the parameters of interest (position in space and orientation angles) in the time domain is based on the acquisition of data from MEMS components which are controlled and integrated with data incoming from a video-camera. The paper organization is described in the following text.

Section one presents the introduction of the “Whipple model” (Whipple, 1899) of the scooter, with a diagram and a description of its different parts.

Section two deals with the application of the algorithm for the estimation of the roll angle from images coming from the video-camera using the methods presented by Frezza and Vettore (2001) and similarly in Nori and Frezza (2003).

Section three is an overview of data incoming from the MEMS components mounted on the scooter. Section four explains the use of the Bayesian filter model to integrate the MEMS sensors’ data El-Sheimy and Schwarz (1994) have .

Section five presents the final accuracy control of the results.

2. METHODS AND ALGORITHMS

2.1 The “Whipple model”

The “Whipple model” essentially consists in a inverse pendulum fixed in a frame moving along a line with ideal wheels which have no width (figure 1). The height above ground of the center of mass is defined as *h*, and δ is the angle of the heading of the front wheel and *R* is the curvature angle. The distance between the two wheels is w and b is the distance along the x axis from the rear wheel to the center of mass.

The model does not account for the movement of a driver neither of the oscillation of the scooter’s wheel suspensions. Also the possibility of the wheels sliding without turning.

From the algorithm in Frezza and Vettore (2001) it can be seen that Hough transform is used to measure the roll angle from the incoming vision data (image from from the video-camera).

The motion equations are:

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

where: x, y and z are the positions in the spatial frame, v is the directional vector, Ψ is the roll angle?? and θ is the pitch angle.

From the geometry of the system the dynamics of the roll angle ~~is~~ are defined by:

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

where R is the curvature angle and $\sigma = R^{-1}$.

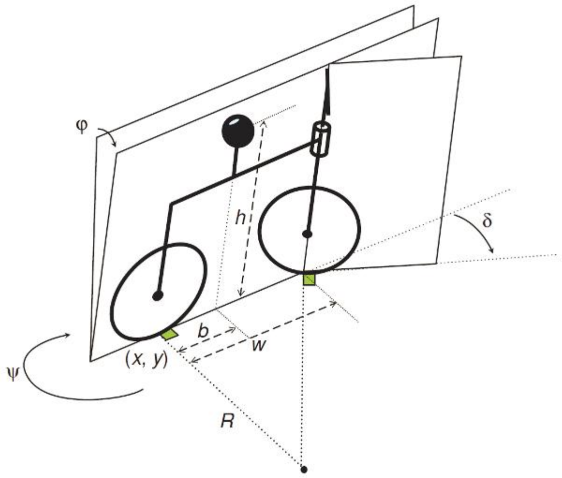

Figure 1. Schematic diagram of scooter cycle model which is represented by an inverse pendulum (courtesy of Limebeer & Sharp, 2006)

The pendulum dynamics (figure 1) is:

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

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

and because δ and φ are not concurrently exponential, hδ*sin*φ can be neglected therefore:

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

From this equation it is possible to find what φ_e angle (roll) is currently necessary to obtain an equilibrium condition of the pendulum (vehicle). Imposing φ_e as constant, dφ=0 and ddφ=0

$$\begin{aligned} 0 &= g\sin\varphi_e - \left[\sigma v^2 + b(\dot{v}\sigma + v\dot{\sigma})\right]\cos\varphi_e \\ \varphi_e &= \arctan\frac{\left[\sigma v^2 + b(\dot{v}\sigma + v\dot{\sigma})\right]}{g} \end{aligned} \tag{6}$$

and setting also dφ=0

$$\dot{\sigma}_e = \sigma\left(\frac{\dot{\delta}}{\cos\delta\sin\delta}\right) \tag{7}$$

therefore:

$$\sigma = \frac{\dot{\psi}}{v} \tag{8}$$

$$\varphi_e = \arctan\left[\dot{\psi}v + b\left(\dot{v}\frac{\dot{\psi}}{v} + \dot{\psi}\left(\frac{\dot{\delta}}{\cos\delta\sin\delta}\right)\right)\right] \tag{9}$$

In real life applications, the driver, when curving, decreases velocity by braking and then slightly accelerates, therefore d*v* is negligible, and the same applies to the front wheel angle to neglect dδ:

$$\varphi_e = \arctan\left(\frac{\delta v^2}{g}\right) = \arctan\left(\frac{\dot{\psi}v}{g}\right) \tag{10}$$

With this method, because of the simplification of the model φ_e, we do not account for all the factors which can influence it. For example the shift of the weight of the driver towards the curve center to lower the center of mass of the scooter-driver system, as can be seen in figure 2. Using this approach an equilibrium condition is obtained, where the scooter's angle towards the curve center is taken into account.

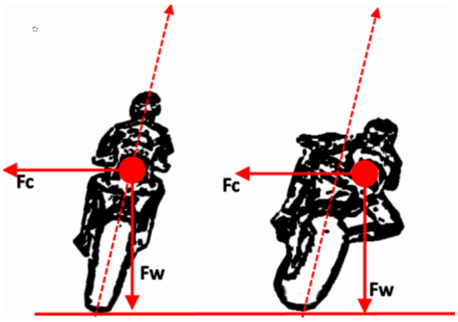

Figure 2. Schematic representation of lateral movements of scooter: Fc is centrifugal force, Fw is weight factor.

2.2 Roll angle estimation

We determine the roll (φ) and pitch (θ) angles using the Hough transformation of the video frames recorded during motion. The Hough transform detects linear features in the image (Duda and Hart, 1972) and can therefore be used to support the estimation of the roll angle. The complete trajectory reconstruction is presented in Frezza and Vettore (2001), below the incremental values of the roll (φ) and pitch (θ) angles over time (dt) are represented:

$$\begin{aligned} \Delta\hat{\varphi} &= \min\left\|\int H_t + \Delta t\left(\rho_1\alpha + \Delta\alpha\right)d\rho - \int H_t\left(\rho_1\alpha\right)d\rho\right\| \\ \Delta\hat{\theta} &= \frac{1}{\cos\varphi}\min\left\|\int H_t + \Delta t\left(\rho_1 + \Delta\rho_1\alpha\right)d\alpha - \int H_t\left(\rho_1\alpha\right)d\alpha\right\| \end{aligned} \tag{11}$$

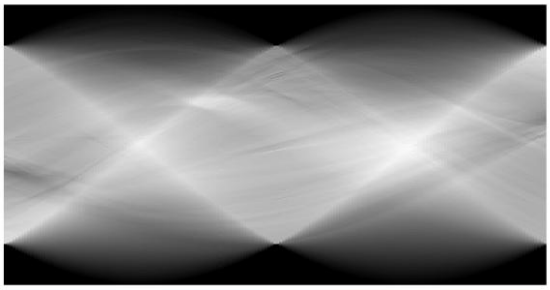

Figure 3. The Hough transform (top) of an image (bottom) taken from the frames recorded during the test drive on the track

2.3 Overview data incoming from MEMS

The system for MEMS data acquisition which is mounted on the Vespa scooter uses a Notebook PC (Acer Travelmate 6410) with 1024 Mb of RAM and a CPU processing speed of 1.66 GHz. The MEMS component is XSens MTi-28A5G35 motion tracker. This device is capable of measuring accelerations up to ±1.7g and have up to 120 Hz bandwidth.

Figure 4. Two views of the Vespa scooter with equipment. Cameras on lateral-bottom sides and battery and sensors on the back rack.

2.4 Bayesian filter implementation

The computational cost of a filter is quite high, therefore the method presented includes a process to reduce to the minimum the number of variables to be included in the model. It was chosen to not account for any movement along the Z axis (e.g. “bouncing” of suspensions), but account for position variables X and Y, speed (*v*) and the three angles necessary for modelling the orientation: φ,θ,ψ and the filtered version of the curvature δ. The model presented below describes the dynamics of the frame. According to the definition of the Bayesian particle filter, it is necessary to add another variable, the weight, W.

$$
\begin{aligned}
x_{t+1}^{i} &= x_{t}^{i} + v_{t}^{i}\cos(\psi_{t}^{i})\cos(\theta_{t}^{i})\Delta T + N(0,\Delta x_{t}^{i2}) \\
y_{t+1}^{i} &= y_{t}^{i} + v_{t}^{i}\sin(\psi_{t}^{i})\cos(\theta_{t}^{i})\Delta T + N(0,\Delta y_{t}^{i2}) \\
v_{t+1}^{i} &= v_{t}^{i} + (a_{t}^{i} - g\cos(\theta_{t}^{i})\Delta T + N(0,\Delta v_{t}^{i2}) \\
\varphi_{t+1}^{i} &= (1-r_{t}^{i})(\varphi_{t}^{i} + \varphi_{t}^{i}\Delta T) + \gamma_{2t}^{i}\arctan\left(\frac{\sigma_{ft}^{i} v_{t}^{i2}}{g}\right) \qquad (12) \\
\theta_{t+1}^{i} &= \theta_{t}^{i} + \dot{\theta}_{t}^{i}\Delta T \\
\psi_{t+1}^{i} &= \psi_{t}^{i} + \dot{\psi}_{t}^{i}\Delta T + N(0,\Delta\psi_{t}^{i2}) \\
\sigma_{ft+1}^{i} &= (1-\gamma_{s})\sigma_{ft}^{i} + \gamma_{s}\frac{\psi_{t}^{i}}{v_{t}^{i}} \\
W &= \frac{W_{i}^{i} p_{t}(p_{t}^{i})}{\sum_{j=1}^{N} W_{t}^{i} p_{t}(p_{t}^{i})}
\end{aligned}
$$

where

$$\gamma_{2t}^{i} = \left\{ \begin{matrix} \gamma m \\ 0 \end{matrix} \right. \left(\sigma_{e} - \left|\sigma_{ft}^{i}\right|\right)\left(\dot{\varphi}_{e} - \left|\dot{\varphi}_{t}^{i}\right|\right)$$

if

$$\left|\sigma_{ft}^{i}\right| < \sigma_{e}$$

and

$$\left|\dot{\varphi}_{t}^{i}\right| < \dot{\varphi}_{e}$$

A schema of the filter is presented in figure 5.

$P_t(\cdot)$ is the function at starting point. $N(0,\Delta x^{i2}_{t})$ represents the noise factor of magnitude N modelled like a Gaussian function with a mean of zero and ,Δx^{i}_{t} standard deviation which will be defined next. The same method is used to define the other noise components, $N(0,\Delta y^{i2}_{t})$, $N(0,\Delta v^{i2}_{t})$ and $N(0,\Delta\psi^{i2}_{t})$.

A question is why are the $\dot{\varphi}_{t}^{i}$, $\dot{\theta}_{t}^{i}$ and $\dot{\psi}_{t}^{i}$ components different for each particle. The reason is that the measures W_x, W_y, W_z, which originate from the MEMS accelerometers area expressed in body frame coordinates and have to be converted to world frame coordinates.

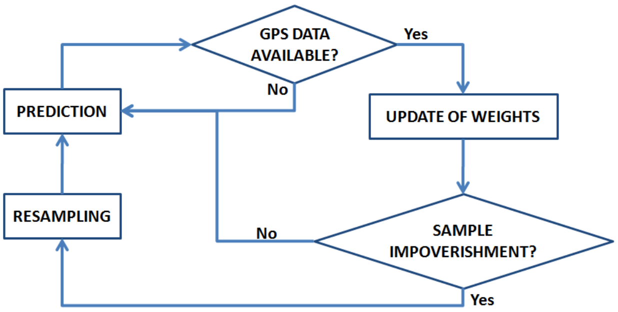

Figure 5. The Bayesian particle filter schema.

The variables which are estimated by the filter are obtained by a weighted mean using the weights W^i of all the particles s^i as reported below.

$$\begin{pmatrix} x_t \\ y_t \\ v_t \\ \varphi_t \\ \theta_t \\ \psi_t \\ \sigma_t \end{pmatrix} = \sum_{L=1}^{N} W_t^i \begin{pmatrix} x_t^i \\ y_t^i \\ v_t^i \\ \varphi_t^i \\ \theta_t^i \\ \psi_t^i \\ \sigma_t^i \end{pmatrix} \tag{13}$$

To make the filter as light as possible, the update of the weight values is not done at every step of the algorithm, but only when the GPS data is available from the receiver.

Results and conclusions

As it can be observed from figure 6 the roll angle is similar on different parts of the track tested, confirming the repeatability of the method. A little difference is noted on test number three where the speed was slower than the other tests.

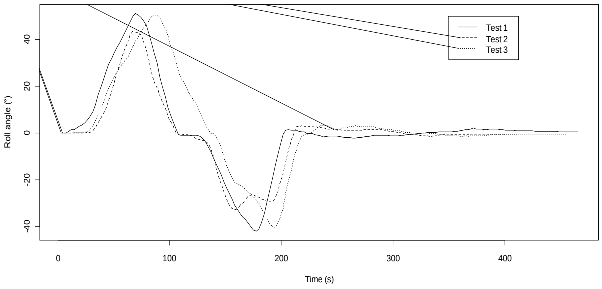

Figure 6. Comparison of roll angle on three tests over the test track.

The reconstruction from the data received during navigation in the test track and measures done in real time permitted the recording of roll and pitch angles which are coherent with each other. Utilizing measures from 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 measures 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.

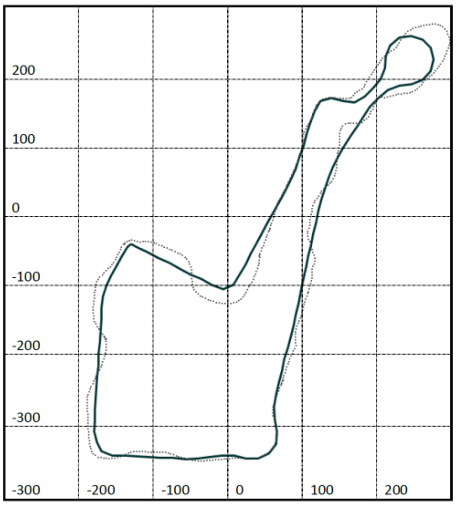

Figure 7. Estimated trajectory: solid line is GPS and dotted line is the MEMS corrected with the filter.

Future developments will be to encode the Bayesian filter inside an integrated system which can be used to equip the Vespa scooter. This can lead to future uses of traction control systems. From a theoretical point of view future developments can include the consideration of the suspensions' movement on the Z axis, and also study the influence of the front wheel angle (δ) on the estimation of the roll angle given by

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

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