Autarkic and Inertial Measurements based Low-cost Reconstruction of Motorcycle Forward Speed

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***Abstract*—Although well established in the aviation community, low-cost and vehicle-independent "black-box" technology for accident analysis, adapted to mass-market ground-based vehicles, is an emerging technology with growing importance. Whilst several products suited for cars are available on the market, almost no devices adapted for motorcycles exist. Due mainly to their particular dynamics and lack of space for installing any external device, the design of a data-recorder technology for motorcycles is nontrival. This becomes even more challenging if the technology has to be independent of the motorcycle type, low-cost, easy and fast to mount, and not based on GNSS technology (for autonomy and privacy issues). Motorcycle speed is an essential information for analyzing the driver's behavior at pre-crash phase. Based on inertial data delivered from an autarkic low-cost, MEMS-based inertial measurement unit (IMU) and voltage ripple signals taken from the motorcycles battery, we reconstruct forward velocity of a motorcycle respecting 5% error bars over a wide velocity range. The off-line reconstruction is based on a strapdown navigation algorithm combined with an autonomous (i.e. *without GNSS*) aiding via an extended Kalman filter. To stabilize the growth of inertial error the filter uses as the external measurements the residual periodic voltage fluctuations of the motorcycle's generator – the residual AC ripple – together with available information on vehicle transmission and its geometry. Despite the structural simplicity of the algorithm and the relatively low performance of the IMU, we experimentally demonstrate that the proposed off-line estimator delivers accurate autarkic speed estimates for a large class of motorcycles.**

Biographies

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I. Introduction

Gaining objective insight into the actual driving behavior of vehicular traffic system users is a crucial issue for many private and governmental economic partners. One of the most important partners, the Automotive Industry, started such activities more than 40 years ago using Event Data Recorders (EDRs). Experimental EDR technologies for cars were developed with limited capacities as early as 1974. Apparent early uses of the data obtained from these technologies were for accident investigations related to research initiatives and subsequently, product performance and liability claims. However, this EDR information was and is often only accessible by hardware and software that is proprietary to the automobile manufacturer and access to this information requires the manufacturer's involvement. General Motors was the first manufacturer in 1994 to allow the general public to access and retrieve EDR information using the Vetronix Crash Data Retrieval System. Ford followed only in 2002 with pre- and post-crash recorders in their more popular models. Needless to say that these data recorders have considerable impacts to the auto-insurance industry as they can provide objective information regarding time, speed and tracking factors preceding an accident [1]. Due to the important and ongoing growth of the number of vehicles using EDR, the auto-insurance industry has and will profoundly improve claim processes and decision-making.

For powered two wheelers, no open-access EDR-technology is available which respects to both (i) the error bounds on forward speed imposed by classical accident reconstruction and (ii) the financial constraints of mass technologies. The main reason for this absence is the much more involved dynamics of single track vehicles compared to car-dynamics [2]. This gap prompted our choice of topic and the exposed results constitute a first step towards commercial development of EDR-technology for motorcycles.

The EDR technology for traffic vehicles and its use as a tool for accident reconstruction is reminiscent of the aircraft's flight data recorder. However, important differences exist. Firstly, if we downscale on a pro-rata basis the price of a data recorder for airplanes to the price of an EDR for motorcycles, we obtain production constraints on the production cost below 50 Euros – a prize the market will not allow. This makes MEMS-based low-cost solutions inevitable. A second important conceptual difference to aircraft flight data recorder concerns the sensitivity of individual car drivers and motorists to the (over-)control of their privacy. This is – besides GNSS unavailability – the main reason why EDR solutions using global positioning systems (see e.g. [3]) should be excluded. GNSS solutions are indeed able to record global information (such as where and when someone drives) which do have privacy rights. However, in order to use and transmit recorded information without special care, the EDR should gather only local data such as speed, braking activities, changes in acceleration, etc.

Accordingly, low-cost EDR-technology for motorists should be GNSS-free and MEMS-IMU based. Given these constraints, we focus hereafter on the reconstruction of motorcycle forward speed – the most significant state variable for accident reconstruction. This piece of information is computed from measurements of a commercially available, low-cost 6-axes MEMS-IMU (3 specific force and 3 angular rates sensors). A preliminary investigation with reduced accuracy constraints shows that the very same setting allows easily to reconstruct other variables such as cornering- and tracking states [4].

While the principles of GNSS and GNSS/inertial navigation are well understood, the challenge when working with low cost MEMS instruments and without the reception of satellite signals is to develop a robust navigation aid that can deal with the rather large instrument errors and – crucially in view of a potential commercialization – without exceeding the financial constraints. In our approach the motorcycle's battery plays a central role for the low-cost inertial navigation-aid solution. Indeed, besides mechanical support and power supply, the battery also provides – indirectly via the voltage ripple delivered from the generator after diode rectification – an external speed signal from the motor, which enables to master the poor performance of MEMS-IMUs with minimum additional cost. The extra measurements – well known in the realm of automotive speed and RPM measurements [5] – are simple to perform. Hence the associated off-line event analyzer only needs two types of parameters that depend on the motorcycle: the (dynamic) rear wheel radius r_{dyn} and the transmission rate settings of the motorcycle. The information on both parameters is freely available for a large class of motorcycles. Moreover, the whole instrumentation does not need to employ any of visible rotary- or visual-odometric measurements and can thus respond to demanding esthetic arguments of motorists.

As for the analytic approach for the inertial navigation solution, we will use expectation optimization algorithms, namely an Extended Kalman Filter (EKF) and a Hidden Markov Model (HMM) in feedback configuration. The crucial point is that, based on the EKF output and the spin signal from the motor, the HMM estimates the actual gear speed and delivers, using the known transmission ratios and the rear wheel radius of the motorcycle, a *drift free* speed signal. This quantity forms the navigation aid and re-enters the EKF – thereby considerably improving the quality of the state estimation.

Besides its low-cost nature, this HMM-based navigation aid has mainly two advantages: firstly and most importantly, it changes the nature of the speed estimation problem from a continuous state to a finite- and even low-dimensional state problem[1]. Secondly, the HMM also delivers an effective state dependent error model for the motorcycle forward speed which is crucial for the convergence – and hence the successful implementation of the EKF.

We organize the paper as follows. In Sec II, we provide an overall view on the offline data analysis concept. In Sec III we briefly describe the Inertial Navigation System (INS) and EKF equations. Sec. IV recalls the concept of HMMs and introduces the used variables. Sec. V follows with the description of the experimental setup. In Sec. VI we present measurement results before concluding in Sec. VII.

II. Off-Line Data Analysis

The inertial observations delivered by an IMU consist of specific force and angular rate signals provided by usually three orthogonally mounted accelerometers and gyroscopes, respectively. These observations enter the off-line analysis software. The software implements a strapdown inertial navigation computer which is used to derive the velocity in the vehicle's longitudinal axis x, defined as the vehicle speed at time t $v(t)$ (see Sec. III). However, due to the dead-reckoning nature of inertial navigation, the errors corrupting the inertial sensors will also be integrated, resulting in a rapidly growing error in the final navigation (velocity) solution. Therefore – and especially for low cost IMUs – the drift must be bounded by repeatedly re-calibrating the inertial-based solution with measurements provided by an external device (usually GNSS receivers). The fusion of the inertial and the external data is commonly achieved by Bayesian methods such as the EKF (see e.g. [6] for a recent account and [7] for low cost IMUs). As stated in the introduction, the (strong) economic, legal and ergonomic constraints bounded to the EDR design severely limits the choice of the external aiding (i.e. no GNSS).

[1] Estimating forward speed $v \geq 0$ is replaced by estimating gear speed $x \in \{0, ..., 6\}$.

In this research, external aiding is achieved by using motor speed estimates which are derived from voltage ripples measured at the terminal of motorcycle's battery. The motor speed n_m (measured e.g. in rounds per minute, RPM) enter, together with the vehicle speed v from the INS, the HMM as observations (see Sec. IV), from where we compute the rear wheel speed, v_w, using the mechanical transmission ratios of the motorcycle's drive train i_x (x stands for the estimated gear number) and the dynamic radius r_{dyn} of the rear wheel (both pieces of information are known from commercial available data sheets).

The architecture of the offline signal processing is depicted in Fig.(3) and further details in the following two sections.

III. The Integrated Inertial Navigation System

The IMU data (i.e. the specific forces and angular rates) are processed through the strapdown inertial mechanization algorithms (see e.g., [8]). Therefore the (3×1) gyro measurements vector $\boldsymbol{\omega}_{ib}^{b}$ – expressing angular rates of the body (b-) frame with respect to a fixed inertial (i-) frame expressed in the b-frame – are numerically integrated in order to transform the (3×1) specific force vector $\mathbf{f}^b$ from the b-frame into a local (l-) frame. The latter point is used to free the specific-force measurements $\mathbf{f}^b$ from gravity. In the reference frame we use $\vec{\mathbf{g}}^l = (0, 0, 9.81)^T$ as a simple (and position independent) gravity model and subtract it from the specific force measurements. The resulting dynamic accelerations $\vec{\mathbf{a}}^l$ are numerically integrated to velocity, from which the vehicle's longitudinal component is defined as the vehicle speed v.

A. Filter Equations

Let $\mathbf{r}_e^l$ be the (3×1) position vector containing the latitude ϕ, longitude λ and height h, and $\delta\mathbf{v}_e^l$ the (3×1) vector containing velocities expressed in the l-frame. The filter EKF navigation states are:

$$\mathbf{x} = \begin{bmatrix} \delta\mathbf{r}_e^l & \delta\mathbf{v}_e^l & \boldsymbol{\varepsilon}^l & \delta\mathbf{f}^b & \delta\boldsymbol{\omega}_{ib}^b \end{bmatrix}^T \quad (1)$$

where $\boldsymbol{\varepsilon}^l$ is a (3×1) vector containing misalignment errors due to the transformation errors between the b- and l-frames. The $\delta\mathbf{f}^b$ and $\delta\boldsymbol{\omega}_{ib}^b$ terms represent the accelerometer and gyroscope biases, respectively. They are usually modeled using stochastic processes (e.g. first-order Gauss-Markov process, random constant). The position error model is:

$$\delta\dot{\mathbf{r}}_e^l = -\boldsymbol{\omega}_{el}^l \times \delta\mathbf{r}_e^l + \delta\boldsymbol{\theta} \times \mathbf{v}_e^l + \delta\mathbf{v}_e^l \quad (2)$$

with $\delta\boldsymbol{\theta}$ a misalignment vector of the estimated *l*-frame (also called *computer*-frame) with respect to (true) *l*-frame as a consequence of position error:

$$\delta\boldsymbol{\theta} = \begin{bmatrix} \delta\lambda\cos\phi & -\delta\phi & -\delta\lambda\sin\phi \end{bmatrix}^T \quad (3)$$

where $\delta\phi$ and $\delta\lambda$ are errors in latitude and longitude, respectively. The velocity error model is:

$$\begin{aligned} \delta\dot{\mathbf{v}}_e^l \;=\; & -\mathbf{f}^l \times \boldsymbol{\varepsilon}^l - \left(\boldsymbol{\omega}_{ie}^l + \boldsymbol{\omega}_{il}^l\right) \times \boldsymbol{\delta}\mathbf{v}_e^l \\ & - \left(\delta\boldsymbol{\omega}_{ie}^l + \delta\boldsymbol{\omega}_{il}^l\right) \times \mathbf{v}_e^l + \mathbf{C}_b^l \delta\mathbf{f}^b + \delta\mathbf{g}^l \end{aligned} \quad (4)$$

The attitude error model (also known as the *phi-angle* error model, [10]) is:

$$\dot{\boldsymbol{\varepsilon}}^l = -\boldsymbol{\omega}_{il}^l \times \boldsymbol{\varepsilon} + \delta\boldsymbol{\omega}_{il}^l - \mathbf{C}_b^l \delta\boldsymbol{\omega}_{ib}^b \quad (5)$$

B. Extended Kalman Filter

The nonlinear discrete system and measurement relationship of the filter is [9]:

$$\begin{aligned} \mathbf{x}_k &= \mathbf{f}\left(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}\right) + \boldsymbol{\Gamma}_{k-1}\mathbf{w}_{k-1} \quad (6) \\ \mathbf{z}_k &= \mathbf{h}\left(\mathbf{x}_k\right) + \mathbf{v}_k \quad (7) \end{aligned}$$

where $\mathbf{w}_k$ and $\mathbf{v}_k$ are zero mean Gaussian white noise sequences with strength $\mathbf{Q}_k$ and $\mathbf{R}_k$, respectively. $\boldsymbol{\Gamma}_k$ represents the coupling between $\mathbf{x}_k$ and $\mathbf{w}_k$ and $\mathbf{z}_k$ is the measurement vector. At the estimation time t_k, the system is linearized around the previous state estimate. The state and conditional covariance matrix $\mathbf{P}_{k+1}^-$ are extrapolated using the transition matrix $\boldsymbol{\Phi}_k$:

$$\begin{aligned} \mathbf{x}_k^- &= \mathbf{f}\left(\mathbf{x}_{k-1}^+ \mathbf{u}_{k-1}\right) \quad (8) \\ \mathbf{P}_k^- &= \boldsymbol{\Phi}_{k-1}\mathbf{P}_{k-1}^+\boldsymbol{\Phi}_{k-1}^T + \boldsymbol{\Gamma}_{k-1}\mathbf{Q}_{k-1}\boldsymbol{\Gamma}_{k-1}^T \quad (9) \end{aligned}$$

where $\boldsymbol{\Phi}_k = \frac{\partial \mathbf{f}(\mathbf{x}_k^*, \mathbf{u}_k)}{\partial \mathbf{x}}$ with the approximate $\mathbf{x}_k^*$ usually chosen to be $\mathbf{f}\left(\mathbf{x}_{k-1}^*, \mathbf{u}_{k-1}\right)$. The Kalman gain, state and covariance update are evaluated:

$$\begin{aligned} \mathbf{K}_k &= \mathbf{P}_k^-\mathbf{H}_k^T\left(\mathbf{H}_k\mathbf{P}_k^-\mathbf{H}_k^T + \mathbf{R}_k\right)^{-1} \quad (10) \\ \mathbf{P}_k^+ &= \left(\mathbf{I} - \mathbf{K}_k\mathbf{H}_k\right)\mathbf{P}_k^- \quad (11) \\ \mathbf{x}_k^+ &= \mathbf{x}_k^- + \mathbf{K}_k\left[\mathbf{z}_k - \mathbf{h}\left(\mathbf{x}_k^-\right)\right] \quad (12) \end{aligned}$$

with $\mathbf{H}_k = \frac{\partial \mathbf{h}(\mathbf{x}_k^*)}{\partial \mathbf{x}}$.

C. Filter Initialization

Since an INS is a dead-reckoning system, the initial roll r, pitch p and yaw y angles at time t_0 are to be either known or determined. The *coarse alignment* is a procedure to estimate attitude parameters approximately [8]. The classical coarse alignment is based on the principle that the accelerometers sense only gravity $\mathbf{g}^l$, while the gyroscopes sense only the Earth rate in the b-frame, $\boldsymbol{\omega}_{ie}^b$ [8]. In low-grade (e.g. MEMS-based) gyroscopes, the noise level may typically be superior to 0.1 deg/s/$\sqrt{\text{Hz}}$ and the residual systematic errors as high as several deg/s. In such conditions, the Earth rate cannot be sensed. However, since the absolute position of the vehicle is not of interest for the given application, the determination of the initial yaw angle can be neglected and the attitude initialization problem is resumed to:

$$\begin{aligned} r &= \arcsin(\bar{f}_y/(g \cdot \cos p)) \quad (13) \\ p &= \arcsin(\bar{f}_x/g) \quad (14) \\ y &= \text{arbitrary} \quad (15) \end{aligned}$$

with $g = \|\vec{\mathbf{g}}^l\|$ and f_x, f_y the x, y components of $\mathbf{f}^b$, respectively. Although it is clear from the previous equations that the coarse self-alignment could be done at each epoch t_k, more accurate results can be obtained by averaging the data over detected non-moving period, while estimating residual systematic errors ($f_{x,y} \rightarrow \bar{f}_{x,y}$). In our implementation initial values for pitch, roll and the gyro biases are obtained by integrating a short period of static data at the start of the dataset. The initial acceleration biases are set to zero with uncertainty according to specifications provided by the manufacturer. For initial velocity estimates the external aid is used:

The initial velocity estimate $\mathbf{v}_e^l(t_0)$ is one out of seven different values – one for each gear speed x. With a given gear speed, the initial ripple measurements allow estimating forward velocity (using available transmission settings as explained in the next section). We then perform the whole velocity calculations seven times, changing the initial gear speed, and hence the initial velocity estimates. From the resulting seven forward speed calculations, we select the most probable speed trajectory. This selection uses only elementary expert knowledge such as excluding trajectories with velocity jumps, unrealistic gear speeds, negative forward speeds etc., and is further facilitated by the numerically observed fact that adjacent trajectories start to converge to each other easily.

Note that in the case of an accident, the final vehicle velocity will be null and its location is fixed. The inertial navigation filter can then be run backward in time with a perfect "initial" velocity fit. Although the absolute position of the vehicle is not of interest, the initial position $\mathbf{r}_e^l(t_0)$ needs be set at least approximatively.

IV. The HMM Approach

The a priori ignorance on both, the motorists handling actions and the actual road/traffic conditions lead us to model the motorcycle's gear speed as a Markov chain. At every (discrete) sampling point in time t_k, $k = 1, 2, ...,$ we set

$$Y_k = \text{gear speed at time } t_k$$

and suppose Y_k to be a time homogeneous Markov chain on the state space[2] $S_Y = \{0, 1, 2, ..., 6\}$ with 7×7 transition probability matrix **P**.

Recall that in a regular Markov model, it is supposed that the actual state of the process is directly visible to the observer. Therefore the transition matrix is the only parameter necessary to fix the statistics of the future states – given the present state. However, gear speeds are *not* directly accessible to us, they are hidden (see [13] for an overview of the Hidden Markov Model concept). We only get noisy measurements (observations) denoted O_k, which are related to the true state Y_k through *conditional probabilities* (see figure 1).

The complete observation set at time t_k, say $\tilde{O}_k$, includes $\boldsymbol{\omega}_{ib}^b$ and $\mathbf{f}^b$ as well as the ripple of the rectified generator's voltage U_{Batt} measured at the motorcycle's battery:

$$\tilde{O}_k = \left(\boldsymbol{\omega}_{ib}^b, \mathbf{f}_{ib}^b, U_{Batt}\right)^T \in \mathbb{R}^7.$$

[2]The set S_Y is easily adapted for motorcycles with fewer or more speeds. The state 0 corresponds to disengaged gear. A real limitation however are cycles with continuously variable transmissions.

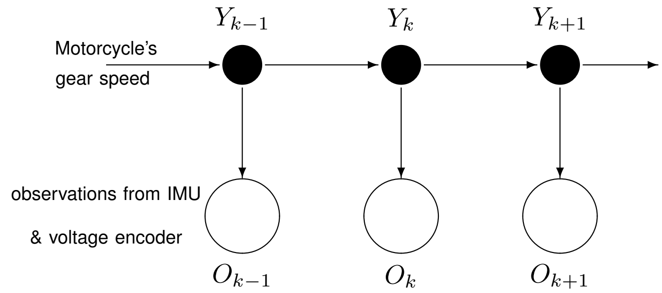

Figure 1: The hidden state at time t_k, Y_k, is indirectly observed through O_k. The arrows in the diagram denote conditional dependencies. The value of the observed variable O_k only depends on the value of the hidden variable Y_k (both at time t_k).

As exposed in Fig.(3), the inertial measurements are processed through a complete strap down navigation solution yielding estimates of forward speed $v(t)$ (measured in m/s). The rippled voltage signals from the generator undergo short time Fourier transformations and are converted into motor spin data $n_m(t)$ (measured in rounds per minutes (RPM)). At successive sampling times the forward speed $v(t_k)$ and the motor spin $n_m(t_k)$ are synchronized through a common time stamp t_k. Finally, we work for $v(t_k) > 0$ (hence only when the motorbike is moving) with the following scalar observation-variable O_k:

$$O_k := \frac{2\pi r_{dyn} n_m(t)}{60 v(t_k)} \in \mathbb{R} \tag{16}$$

that is dimensionless and relates the wheel speed with the forward speed. This relation represents a basis for estimating the motorcycle's overall transmission ratio i_{tot} at time t_k. Indeed, in steady straight run conditions, the rotative speed of the rear wheel is, in good approximation, given by n_m/i_{tot}.

The observation O_k is related to the (hidden) gear speed $Y_k = x$ through the relation:

$$O_k \sim i_{tot} = i_p i_x i_d \tag{17}$$

where i_p is the known primary transmission ratio, i_d the known chain drive transmission ratio and i_x the gear ratio for gear speed x. The strategy to infer motorcycle forward speed is now the following (compare with Fig. 3):

1) select the gear speed x corresponding to the most likely transmission ratio i_x i.e., realizing
$$Prob(Y_k = x \mid O_k) = max_{y \in S_Y}\{Prob(Y_k = y \mid O_k)\}.$$
2) compute a forward speed estimate v at time t_k through the relation $v = \frac{2\pi r_{dyn} n_m(t_k)}{60 i_p i_x i_d}$.
3) use the speed estimate v as a navigation aid measurement entering the EKF to correct the EKF propagated forward speed estimate.

The above strategy is implemented as an HMM using the freely available Matlab Toolbox “Bayes Net Toolbox” [12]. The HMM is completely given once the transition matrix **P**, the initial state probabilities, say Π, and the conditional densities $O_k \mid Y_k$ are defined.

The transition matrix is not learned, rather its components are fixed using heuristics and common sense arguments (in fact learned transition matrices did not outperform heuristic arguments). The initial state probability vector Π is uniformly distributed (all gear speeds are likely probable).

The conditional densities $O_k \mid Y_k$ are supposed to be independent normal random variables:

$$O_k \mid Y_k = x \sim N\Big(\mu(x); \sigma^2(x)\Big), x \in S_Y = \{0, 1, ..., 6\}$$

with $\mu(x) = i_p i_x i_d$ and where the variances $\sigma^2(x)$ are based on simple standard deviation computations for O_k using training data. It is noted that these data are obtained from two different test motorcycles under real (hence varying) traffic conditions and where, in addition to O_k, gear speed has been recorded. The main contributions to the variability of $\mu(x)$, however, come from cornering (see remark (2) in section VI) and acceleration/deceleration manoeuvres (see remark (3) in section VI) and not from the use of a different motorcycle.

The HMM being defined, the state analyzer then computes the most likely sequence of motorcycle state for a given sequence of observations using standard HMM-algorithms [14]:

$$\text{State at time } t_k \;= \arg\max_{y \in S_Y} \Big(P(Y_k = y \mid O_k)\Big). \qquad (18)$$

To close this section we remark that, despite the reduced observation space, all six IMU measurements and the voltage measurements have been used to compute the HMM-observations O_k. Moreover, the above strategy assumes that at each sampling step, the clutch is engaged (i.e., Y_k is in exactly one of the states defined by S_Y and no intermediate clutch states are possible).

V. Experimental Setup

Fig.(2) shows the onboard data acquisition (hardware, attached onto the motorcycle) and Fig.(3) shows the offline data processing (software).

a) On-Board Data Acquisition: Our test-motorcycle is equipped with a system for synchronized data acquisition (see Fig.(2)), including:

1) a low cost 6-axis micro electro-mechanical IMU, fixed near the center of gravity of the motorcycle.[3]

[3]For reasons of data synchronization with the reference GPS, we currently use the IMU's raw data from the Mti-G System (XSENS), whose specifications are comparable to common low cost IMUs.

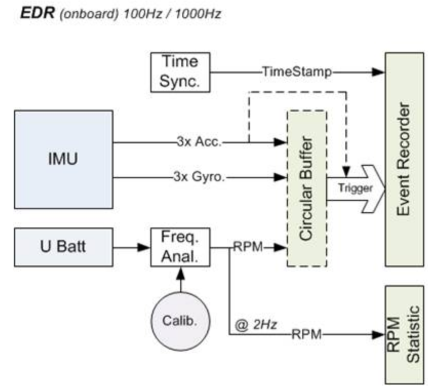

Figure 2: The schema of on-board data acquisition containing a 6-axes IMU and the voltage measurement U_{Batt}.

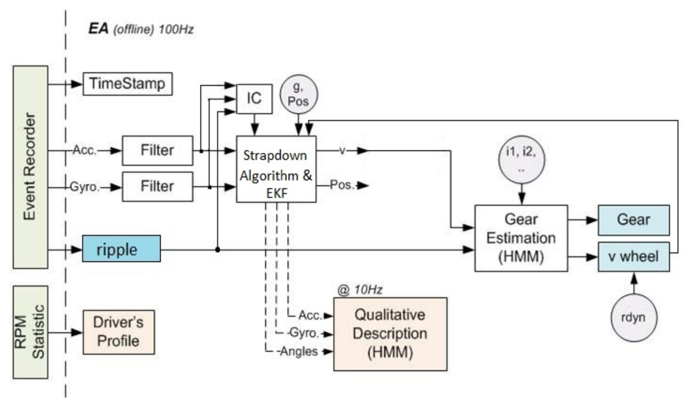

Figure 3: Inertial gyro- and acceleration inputs, together with the generators' AC ripple, are post-processed and deliver objective output sequences including vehicle speed (forward speed) and qualitative description of driver behaviors (not discussed here). The set of needed external parameters is reduced to transmission ratios i_p, i_d and the dynamic radius r_{dyn} of the rear wheel. Initial conditions IC are estimated from a short static dataset.

2) a voltage sensing device, basically a shunt over the battery terminals, to measure the voltage ripple U_{Batt} of the generator. This signal oscillates with a frequency f_g, corresponding to the generator's rotational speed. An initial calibration procedure yields the constant of proportionality c_g^m between the motor's spin frequency f_m and f_g. Finally, the motor speed is computed using the relation $n_m = (f_g \cdot c_g^m)^{-1}$.
3) a portable computer for data storing and synchronization.
4) reference measurement equipments: a GPS-system yielding the vehicle's forward speed and two Hall sensors measuring the front and the rear wheel spin.

VI. Results

We reconstructed forward speed and qualitative description of the behavior of a sport motorcycle maneuver-ing on public roadways.[4] Our test-motorcycle is a 1993 Suzuki GSX750 F, propelled by a 748ccm, 4 cylinder four-stroke engine and weights about 230kg (without rider). To observe performance of the algorithms we undertook several out of lab tests and compared the results with GPS reference data. All the state estimates are remarkably accurate if we exclude the (easily detectable) periods during which gear speed changes or undefined clutch states are present. A generic trajectory is presented and evaluated hereafter.

A. Roundabout Maneuver 180°

A complete 180^o-turn-around maneuver in the roundabout is analyzed by subdividing the actual trajectory into nine pieces, according to Fig. (4).

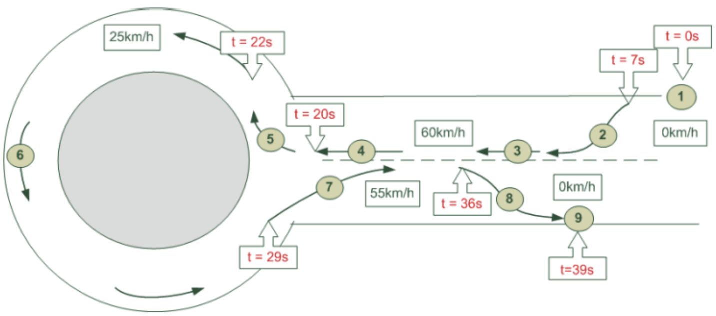

Figure 4: The 180^o roundabout maneuver is subdivided in pieces (1) to (9), with several time- and speed indications.

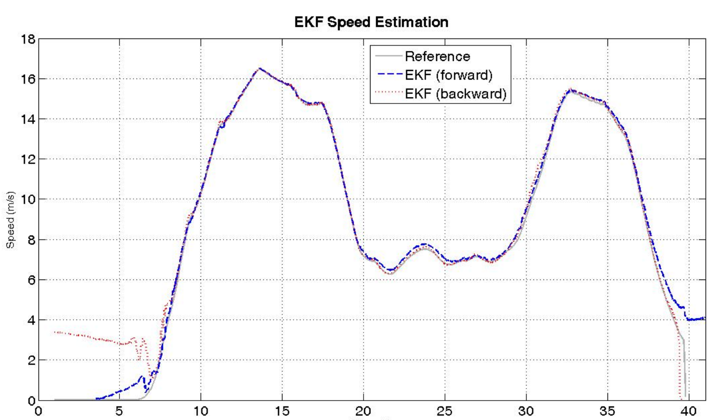

Figure 5: Vehicle Speed reconstruction for the roundabout maneuver using forward (blue) and backward (red) filtering. The reference speed (gray) is based on GPS measurements and Hall-sensor based wheel speed measurements.

Estimate of vehicle speed. Fig. (5) shows the vehicle speed v based on the proposed algorithm together with GPS reference. After phases of accelerations (2), (3) and decelerations (4), the passage of the roundabout between $20s$ and $30s$ at roughly constant speed is visible (5), (6). The acceleration towards the end of phase (6) indicates leaving the roundabout (7), followed by the deceleration (8) which indicates the end of the maneuver. With respect to GPS reference, the vehicle speed estimation $v(t)$ is excellent and stays within 5% error bounds for $v > 5m/s$.

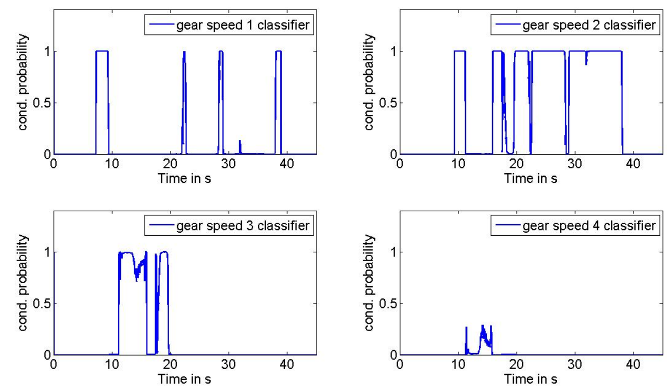

Figure 6: A partial HMM output for the roundabout maneuver. The four graphs show the conditional probabilities of observing O_t given gear speed x for $x = 1, .., 4$. The remaining probabilities for $x = 0, 5, 6$ are almost identically zero.

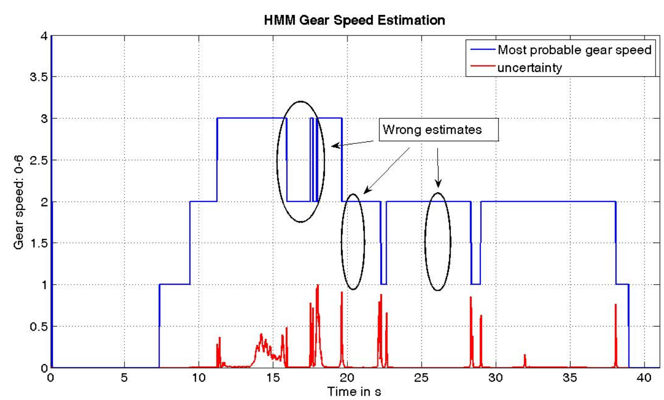

Figure 7: The gear speed classifier according to eq.(18) selects the most probable gear speed (blue). As an ad hoc measure of classifier uncertainty we us the relative distance to the second most probable gear speed (red) eq.(19). Values close to one indicate uncertainty for our gear speed estimate.

HMM output. Fig. (6) shows the conditional probabilities computed in the framework of the HMM for gear speeds $1, .., 4$. Fig. (7) shows the most probable gear speed given the observations O_t together with an ad hoc measure of

[4] An analogous analysis with a 50ccm scooter yielding results of comparable accuracy has been performed.

uncertainty U defined by:

$$U(t) = 1 - \frac{P_1(t) - P_2(t)}{P_1(t)} = \frac{P_2(t)}{P_1(t)} \tag{19}$$

where $P_1(t)$ (resp. $P_2(t)$) is the most (resp. second most) probable gear speed at time t. Clearly, U takes on values between 0 and 1 and indicates, with increasing values, increasing uncertainty whether the most probable gear speed is really the correct one.

Referring to Fig. (4) and (7) we see that, during the phases of accelerations (2), (3), the conditional probabilities give convincing evidence for gear speed state (they are either very close to 1 or close to 0). However, as indicated by U, periods of uncertain and even wrong gear speed estimations exist. For example, before entering the roundabout (17s-20s) and before leaving it (28s-29s), the gear speed is wrongly estimated ($x = 2$ would be correct). The resulting velocity jumps in the HMM output, however, are completely smoothed away by the EKF.

Remarks.

(1) Below $15km/h$, IMU drift and undefined clutch states (motor idle and clutch disengaged, or phases of engaging) influence remarkably the probabilistic estimation of the gear speed and may lead to erroneous wheel speed estimations. At the same time the accidents occurring at such low speeds have usually less serious consequences therefore the larger estimation uncertainty is permissible.

(2) During periods of important cornering, the road/wheel contact does not take place on the largest circumference of the wheel. This well known fact enhances the angular velocity of the wheel, without increasing forward speed of the motorcycle. Thanks to an analytic treatment (see [11], section 4.1.3) as well as the estimation of motorcycle inclination (r-angle) we can compensate this source of errors.

(3) Another source of differences between the rear wheel speed and the vehicle's (true) forward speed is longitudinal wheel slip. The presence of rear wheel slip will overestimate forward speed during acceleration and will underestimate forward speed during periods of rear wheel braking. For non-critical maneuvers, this error is clearly below 5%. Note that critical maneuvers (full braking, sharp cornering or combinations) are detected by the qualitative output of the HMM. Therefore the off-line analysis is able to recognize situations where the wheel speed is not a faithful piece of information for inferring forward speed.

VII. Conclusion

Despite the fact that the dynamics of single tracked vehicles are considerably more difficult to describe than dynamics of double tracked vehicles, an autarkic reconstruction of motorcycle speed is feasible with low-cost devices. Basically, a low-cost 6 axis inertial measurement unit (IMU), a shunt and a clock together with a storage device are enough to compose embedded black-box technology for motorcycles. Power-supply and the external voltage signal that provides IMU-aiding are both delivered by the motorcycles battery. With a minimum amount of expert knowledge, an initial calibration of transmission as well as a few available parameters related to a motorcycle, we can reconstruct forward speed with high accuracy. In particular, during phases without important accelerations and cornering, the forward speed estimation corresponds to the reference (GPS-derived) velocities better than 5%. During phases with important accelerations or cornering, the estimation errors may grow beyond the 5% error bounds. Such critical situations are, however, easily detectable and partially removable through ad hoc considerations.

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