Evaluation of Sensors in Modern Smartphones for Vehicular Traffic Monitoring

Markus Forster[1], Raphael Frank[1], Thomas Engel[1]
[1]*Interdisciplinary Centre for Security, Reliability and Trust, University of Luxembourg, 1359, Luxembourg*
markus.forster@uni.lu, raphael.frank@uni.lu, thomas.engel@uni.lu

Abstract

In recent years, traffic density in the European Union has continuously increased. In the same period, the road network could not be extended to meet the growing traffic demand. A consequence is a lot of congestion on European roads, causing huge economical as well as ecological damage. These circumstances make it absolutely necessary to bring an improvement to this situation. A first step towards a much more efficient usage of the existing road network is to collect floating car data to describe the actual traffic situation in realtime. Today more and more smartphones are equipped with with all the necessary sensors (e.g. *GPS*, *Accelerometer*, *Gyroscope*). Such devices can be used to collect and distribute relevant traffic metrics that are crucial for applications such as smart vehicle guidance. This work describes how sensor data from *Microelectromechanical Systems* (MEMS) can be retrieved, corrected and fused to get an accurate picture of real world traffic phenomena.

Index Terms

Kalman Filter, Smartphones, Microelectromechanical Systems, Vehicular Traffic

I. Introduction

Over the last two decades the volume of traffic in Europe has significantly increased. On the one hand, this is caused by the increasing individual mobility. On the other hand, it is due to the fast growth of the logistic sector that adds more and more heavy traffic on our roads. In 2007, a majority of three quarters (76.4%) of the freight in the European Union was realized by road transport [1]. The problems that arise with the growing traffic affect economy as well as ecology. Traffic congestion causes many side-effects such as increased pollution, reduced mobility and road safety concerns [2]. To get these problems under control, we need a reliable system to monitor the vehicular traffic and consequently tools to allow better traffic management, e.g. traffic predictions over time and smart routing services.

A first step towards a better management of vehicular traffic is to get an overview on the actual traffic situation. Already today high end vehicles are often equipped with sensors such as GPS, acceleration sensors, odometers and gyroscopes and more recently with communication interfaces. However, it will probably require another decade until these sensors and communication devices become standard equipment. On this account it is inevitable to find a way to span this period. The approach presented in this paper is based on the idea that modern smartphones, having all the relevant sensors (e.g. GPS, Accelerometer and Gyroscope) become increasingly available. Assuming that most mobile phone users already migrated to smartphones or are going to do so in the near future, we see a chance to use those devices to collect real-time data about the traffic situation. Another advantage of the smartphone approach is that nearly all users have data flatrates and therefore are able to send the retrieved data to a remote server for further analysis.

In this paper we will introduce a technique to fusion data from different smartphone sensors in order to accurately detect real world traffic phenomena such stop and go traffic or emergency braking maneuvers. Due to the fact, that such sensors are corrupted by *noise* and some *offset errors* it is important to find a way to correct them and bring them in accordance. A suitable method to do this is to use *Kalman Filters* (KF). These kind of filters are able to filter out *measurement* as well as *system noise* and bring the measured values in accordance considering a system of linear equations that provide a physical model of real world processes.

The reminder of this paper is organized as follows. In section II we will give a brief introduction of the used hardware as well as a description of the sensor API. A consideration of *sensor offset errors* and *measurement noise* is provided in section III. Section IV gives an introduction to *Kalman Filters* (KF) and their applications. Further, we will discuss how such filters can be used to solve the problems of rotational and translational movement. Finally in section V the results from various experiments are presented and a conclusion is drawn in section VI.

II. Sensor Description

First we will give a brief introduction of the hardware and description of the different sensors used for the experiments, described in this paper. In a second step the concept of *noise* is introduced, that will play a major role in the sequel of this work.

A. Hardware

The device, used for all measurements, provided within this paper, is the LG-P990 "Optimus Speed" from LG. This smartphone is equipped with a Dual-Core processor, operating at the speed of $1GHz$ as well as an additional graphic processing unit. Moreover, the device comes with a *global positioning system* (GPS), an *accelerometer* and a *gyroscope*. A *WiFi* (802.11n) wireless network adapter, a *bluetooth* adapter as well as a 3G mobile broadband adapter operating *WCDMA*(UMTS)/GSM are included for communication purposes.

The characteristics of the different MEMS sensors can be described as follows: All sensor data is given in a uniform coordinate system that is defined relatively to the screen of the device in its default orientation. Meaning, the x axis is horizontal and points to the right, the y axis is vertical and points upwards and the z axis points towards the outside of the front face of the screen. In this system, coordinates behind the screen have negative z values. For further reading please refer to [3].

B. Sensor API

The three relevant MEMS sensors, namely the *accelerometer*, the *gyroscope* and the *magnetic field sensor* are used in addition with the GPS adapter to provide a clear picture of the real world setting of the device with respect to the position, orientation, rotational velocity, translational velocity and translational acceleration.

A brief introduction of those three sensors and their functioning is given as: The *accelerometer* is a sensor measuring the accelerations along the three axes of the device by detecting forces applied to the sensor itself. For this reason, when the device is sitting on a table the accelerometer reads a magnitude of the force of gravity along the negative z-axis.

The *gyroscope* measures the angular velocity around the three axes. This means that the given values are zero if the device is in fixed orientation and give the rate of angular velocity around a certain axis if the device rotates around this axis.

The *magnetic field sensor* or *magnetometer* is measuring the strength of a magnetic field. In our application we are interested in the magnetic field of the earth which varies from $20\mu T$ at the equator to $80\mu T$ at the poles. This sensor is very sensitive to other magnetic sources such as electronic devices what makes it not very accurate.

III. Error and Noise Consideration

A. Offset Error

Due to the fact that the sensors of the microelectromechanical systems are not always positioned equal in the different smartphones or the placement is not as accurate as it should be with respect to the sensibility of the given sensors some offsets might be present. Those errors are constant over time and can be defined to be:

$$\boldsymbol{\epsilon} = |\boldsymbol{x} - \boldsymbol{x}_{\text{measure}}| \tag{1}$$

meaning the *offset error* always to be positive.

This *offset errors* can easily be found by putting the device flat on a table (neither rotational nor translational movement) and then recording the sensor values for a certain time period. Obviously, in the given configuration all measurement values except for the acceleration on the z-axis have to be zero wether a_z has to be gravity. By simply subtracting the real measurement values from the expected ones one has found the *offset errors* for the given sensors.

B. Measurement Noise

In practice, measured signals are never perfect. They are corrupted by random variations often called *noise*. The effect of random fluctuations is a characteristic of all electronic circuits. There are several sources for noise in an electronic system. Noise is regarded to be a random disturbance overlaying the useful signal and therefore has to be eliminated before or during the evaluation of the real signal.

Under the assumption that each component of a sensor is an independent and identically distributed (iid) variate $X_i, i \in \mathbb{I}$ with an arbitrary probability distribution $P(x_i)$ with mean μ_i and a finite variance σ_i^2, we conclude, by the *Central Limit Theorem* [4] that each sensor has a cumulative distribution function $\mathcal{F}_j(t), j \in \mathbb{J}$ which approaches a normal distribution $\mathcal{N}_j(\mu_j, \sigma_j^2)$. Further, we state that the measured μ_j of each sensors cumulative distribution function $\mathcal{F}_j(t)$ is the sensor's offset error value ϵ_j. Those two considerations lead us to the implication, that the cumulative distribution function $\mathcal{F}_j(t)$ is in fact a *normal distribution* $\mathcal{N}_j(0, \sigma_j^2)$. Hence, we can say that it holds true for the cumulative distribution function $\mathcal{F}_j(t), j \in \mathbb{J}$ for each sensor that:

1) The expectation value of the observed error $E[\mathcal{F}_j(t)]$ is considered to be zero and there are no dependencies between the errors of different sensors meaning that the autocorrelation function is only different from zero if we correlate the error distributions from the same sensors.

$$\begin{aligned} E[\mathcal{F}_j(t)] &= 0 \\ Cov(\mathcal{F}_m(t), \mathcal{F}_n(t)) &= \begin{cases} \sigma^2 & , m = n \\ 0 & , m \neq n \end{cases} \quad \forall m, n \in \mathbb{J} \end{aligned}$$

2) The stochastic process $\mathcal{F}_j(t), j \in \mathbb{J}$ is independent by our assumption.
3) The stochastic process $\mathcal{F}_j(t), j \in \mathbb{J}$ is a GAUSSian process by the Central Limit Theorem [4].

Finally we can conclude, that the cumulative distribution function $\mathcal{F}_j(t), j \in \mathbb{J}$ describes additive *White Gaussian noise*.

IV. KALMAN FILTER AND SENSOR FUSIONING

A. Motivation

Regarding the noisy values, it is obvious that the raw measurement data accuracy is insufficient to extract any useful information out of them. The collected data are on the one hand disturbed by some measurement noise and on the other hand it seems like they are contaminated by some constant offset. To correct the data it is necessary to perform a calibration on the device to get rid of the offset and afterwards to apply a filter, eliminating the measurement noise.

An enquiry in the corresponding literature leads to the use of *Kalman Filter* for the elimination of measurement noise. Another advantage of this filter is that it provides us a complete model for position, velocity and acceleration while having measurement data for position and acceleration. This assumption is also backed up by [5], [6], [7].

B. Kalman Filter

This section gives a brief introduction to the *Kalman Filter* (KF). Furthermore the evolution of a first order KF for rotations as well as a second order KF for the translation are given. The *Kalman Filter*, as introduced by Rudolf Emil Kalman describes a recursive solution to the Linear Fitting and Prediction Problems [8]. The filter works in the style of a *predictor-corrector estimator*, minimizing the estimated *error covariance* and therefore is optimal in that sense. For further reading, please refer to [9] [10]. The notion of *recursive* means that the KF does not require all previously measured or calculated data but has an integrated memory and therefore only relies on the last estimated and the current measured value. To obtain the variables of interest, the KF is able to process all available measurements, regardless of their precision. Prerequisites for the application of a KF are:

1) Knowledge of the system and the measurement device dynamics.
2) Statistical description of the system noise, measurement errors and uncertainty in the dynamic models.
3) Information about the initial states of the variables of interest.

General Introduction: To setup a KF it is essential to have a model description of the system one wants to describe. Such models are usually given by *differential equations*. In *state space* representation, for the *time discrete* case, which is sufficient for our purposes is given as:

$$\mathbf{x}_k = \mathbf{\Phi}_{k-1} + \mathbf{B}\mathbf{u}_k + \mathbf{w}_{k-1} \quad (2)$$

$$\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k \quad (3)$$

with

- $\mathbf{x}_k$ - the actual state vector in $\mathbb{R}^n$
- $\mathbf{\Phi}$ - the $n \times n$ state transition matrix
- $\mathbf{x}_{k-1}$ - the $\mathbb{R}^n$ vector containing the former state, including the memory
- $\mathbf{B}$ - the $n \times l$ matrix relates the optional control input to the state
- $\mathbf{u}_k$ - the $\mathbb{R}^l$ vector of control input
- $\mathbf{w}_{k-1}$ - the $\mathbb{R}^n$ vector representing the process noise
- $\mathbf{z}_k$ - the $\mathbb{R}^m$ vector of measurement values
- $\mathbf{H}$ - the $m \times n$ matri relating the state to the actual measurement
- $\mathbf{v}_k$ - the $\mathbb{R}^m$ vector representing the measurement values

The random variables $\mathbf{w}$ and $\mathbf{v}$ representing the process and measurement noise respectively are assumed to be independent, white and with multivariate normal probability distribution, meaning $p(\mathbf{w}_k) \approx \mathcal{N}(0, \mathbf{Q}_k)$ and $p(\mathbf{v}_k) \approx \mathcal{N}(0, \mathbf{R}_k)$.

The KF algorithm as given in figure 1 depicts the overall system of a time-discrete linear KF. For each run of the filter in the *time update* step an *a priori* estimate of the current state is computed by the use of the state transition matrix $\mathbf{\Phi}$ and the *a posteriori* estimate of the last filter update $\hat{\mathbf{x}}_{k-1}$. After this, an *a priori* estimate of the error covariance matrix $\mathbf{P}_k$ is derived in the sense that it only relies on the error covariance matrix from the last round of the filter and the *process noise* covariance matrix from the last round $\mathbf{Q}_{k-1}$.

The *measurement update* step is to be seen as a corrector, that brings the *a priori* estimates from the *time update* step in accord with the measured values. First a gain $\mathbf{K}_k$ is computed that minimizes the error covariance. For more detailed information please refer to [9]. In a next step the *a posteriori* estimate for the state vector is calculated by comparison between the *a priori* estimate and the weighted difference between this value and the measured one. Finally an *a posteriori* error covariance matrix is derived, that will be used in the next round of the filter.

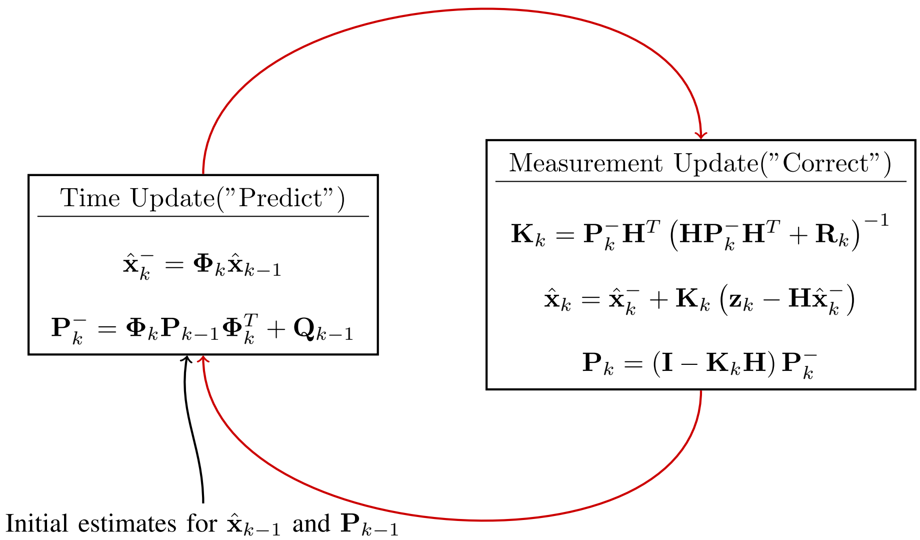


Fig. 1. *Kalman Filter* Operation in *predictor corrector* style.

C. Kalman Filter for Rotations

For every orientation measurement, the sensors provide us two distinct values, namely the angular value α, coming form the *orientation sensor* as well as the angular velocity $\dot{\alpha}$, disseminated by the *gyroscope*. These two values are sufficient to setup a *first order differential equation* modeling the rotation around a given axis. Such a model in state space representation is given by:

$$\dot{\boldsymbol{\alpha}} = \boldsymbol{F}\boldsymbol{\alpha} + \boldsymbol{w} \tag{4}$$

$$\dot{\boldsymbol{\alpha}} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \boldsymbol{\alpha} + \boldsymbol{w} \tag{5}$$

with $\boldsymbol{F}$ being the *state transition matrix*, $\boldsymbol{\alpha}$ the given state , $\dot{\boldsymbol{\alpha}}$ the state update and $\boldsymbol{w}$ being the *process noise* or *model uncertainty* for this first order differential equation system.

To transform this in a time discrete representation one has to solve the LAPLACE transform of the state transition matrix $\boldsymbol{F}$ given as:

$$\mathbf{\Phi} = \mathcal{L}^{-1} \left[(s\boldsymbol{I} - \boldsymbol{F})^{-1} \right] \tag{6}$$

$$= \mathcal{L}^{-1} \left[\left(\begin{bmatrix} s & -1 \\ 0 & s \end{bmatrix} \right)^{-1} \right] \tag{7}$$

$$= \mathcal{L}^{-1} \left[\begin{bmatrix} \frac{1}{s} & \frac{1}{s^2} \\ 0 & \frac{1}{s} \end{bmatrix} \right] \tag{8}$$

with

- $\mathbf{\Phi}(t)$ - *fundamental matrix*
- s - complex number $s = \sigma + i\omega \quad \sigma, \omega \in \mathbb{R}$
- $\boldsymbol{I}$ - identity matrix
- $\boldsymbol{F}$ - continuous state transition matrix
- $\mathcal{L}^{-1}$ - inverse LAPLACE transform

Then, from a table of inverse LAPLACE transform one can derive the fundamental matrix:

$$\mathbf{\Phi}_k = \begin{bmatrix} 1 & T_S \\ 0 & 1 \end{bmatrix} \tag{9}$$

Being aware that there is no control input $\boldsymbol{B}\boldsymbol{u}$, the time discrete model description for the angular movement turns out to be:

$$\boldsymbol{\alpha}_k = \begin{bmatrix} 1 & T_S \\ 0 & 1 \end{bmatrix} \boldsymbol{\alpha}_{k-1} + \boldsymbol{w}_{k-1} \tag{10}$$

(a) Pitch and roll angles are set to 0°.

(b) Pitch at fixed angle and roll still at 0°.

(c) Pitch and roll at fixed angles.

Fig. 2. Apparatus for angular verification.

The measurement equation for the angular values is given by:

$$\boldsymbol{\zeta}_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \boldsymbol{\alpha}_k + \boldsymbol{v}_k \tag{11}$$

due to the measurement data containing the angle ζ as well as the angular velocity $\dot{\zeta}$, only related to themselves and disturbed by some *white noise*.

D. Kalman Filter for Translation

Similar to the rotation we can collect two measurement values for the translation from the integrated sensors. Due to the fact, that these values are not position and velocity but position and acceleration, we have to use a second order state space model to describe the complete system. Analogous to the equations for rotation the model is given as:

$$\dot{\boldsymbol{x}} = \boldsymbol{F}\boldsymbol{x} + \boldsymbol{w} \tag{12}$$

$$\dot{\boldsymbol{x}} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \boldsymbol{x} + \boldsymbol{w} \tag{13}$$

with $\boldsymbol{F}$ again being the *state transition* matrix, $\boldsymbol{x}$ being the position vector $\begin{bmatrix} x & \dot{x} & \ddot{x} \end{bmatrix}^T$ and $\boldsymbol{w}$ being the process noise. Again, the time discrete representation is resolved by the use of the inverse LAPLACE transform given as:

$$\boldsymbol{\Phi}(t) = \mathcal{L}^{-1}\left[(s\boldsymbol{I} - \boldsymbol{F})^{-1}\right] \tag{14}$$

$$= \begin{bmatrix} 1 & t & \frac{t^2}{2} \\ 0 & 1 & t \\ 0 & 0 & 1 \end{bmatrix} \tag{15}$$

leading to the model equation:

$$\boldsymbol{x}_k = \begin{bmatrix} 1 & T_S & \frac{T_S^2}{2} \\ 0 & 1 & T_S \\ 0 & 0 & 1 \end{bmatrix} \boldsymbol{x}_{k-1} + w_{k-1} \tag{16}$$

and the measurement equation in the form:

$$\boldsymbol{z}_k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \boldsymbol{x}_k + \boldsymbol{v}_k \tag{17}$$

More information about *Kalman filter*, its application and the estimation of the error covariances (*process noise* and *measurement noise*) can be found in [6], [8], [10], [11], [12] and [13].

E. Fusioning

Fusioning of the available data is done in four distinct steps. First, the recent data vector

$$m = \begin{bmatrix} t^* & \\ x^*_{\text{GPS}} & \\ y^*_{\text{GPS}} & \\ \phi & \\ \theta & \\ \psi & \\ \dot{\phi} & \\ \dot{\theta} & \\ \dot{\psi} & \ddot{x} \\ \ddot{y} & \\ \ddot{z} & \\ \sigma^2_{\text{GPS}} & \end{bmatrix} \tag{18}$$

with

t^* timestamp in ms since January, 1 1970
x^*_{GPS} GPS longitude
y^*_{GPS} GPS latitude
ϕ pitch angle within the interval $]-\pi/2, \pi/2[$
θ roll angle within the interval $]-\pi, \pi[$
ψ azimuth angle within the interval $]-\pi, \pi[$
$\dot{\phi}$ angular velocity around x axis in $[rad/s]$
$\dot{\theta}$ angular velocity around y axis in $[rad/s]$
$\dot{\psi}$ angular velocity around z axis in in $[rad/s]$
$\ddot{x}$ acceleration in x direction in $[m/s^2]$
$\ddot{y}$ acceleration in y direction in $[m/s^2]$
$\ddot{z}$ acceleration in z direction in $[m/s^2]$
σ^2_{GPS} standard deviation of the actual GPS value in $[m]$

is obtained every $10ms$. Since the position data x^*_{GPS} and y^*_{GPS} are given in *GPS* coordinates, they were transformed to a metric representation by the use of the *Haversine formula* given as:

$$\begin{aligned} \Delta p &= p^*_{\text{GPS}}(k) - p^*_{\text{GPS}}(0) \quad p \in \{x, y\}, k \in \mathbb{I} \\ a_p &= \sin\left(\frac{\Delta p}{2}\right)^2 \cdot \cos(p_{\text{GPS}}(k)^*)^2 \\ c_p &= 2\text{atan2}\left(\sqrt{a_p}, \sqrt{1 - a_p}\right) \\ p(k) &= c_p \cdot 6.371 \cdot 10^6 m \quad p \in \{x, y\}, k \in \mathbb{I} \end{aligned}$$

where $p^*_{\text{GPS}}(0), p \in \{x, y\}$ denotes the initial value of the latitude or longitude respectively. For further reading we recommend [14].

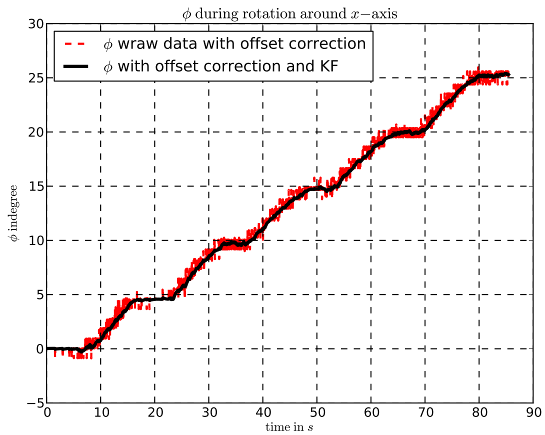
In a next step the angular values are merged and corrected by the use of the KF for rotational movement, given in section IV-C. Due to the fact, that the device's orientation relative to the vehicles is arbitrary the acceleration axes have to be transformed from device coordinate system to the global coordinate system. This rotation is performed by the use of quaternions and the *Hamilton formula* [15]. Finally, the normalized acceleration values together with the transformed position data, $(p_k, \ddot{p}_k)$ with $p \in \{x, y, y\}$ and $k \in \mathbb{I}$, now are merged by use of the KF for translations, given in section IV-D.

V. Results

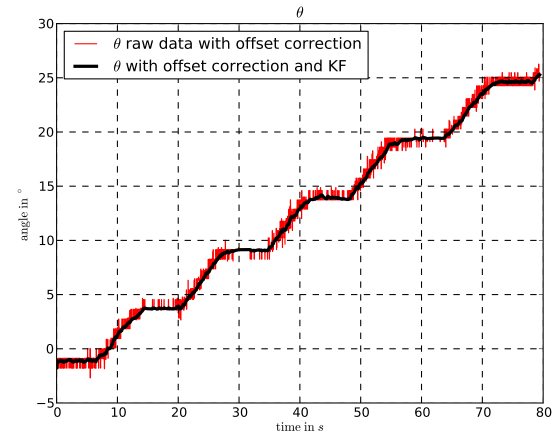
A. Testbed Setup

The validation was done by two laboratory experiments, e.g., one determining the accuracy of rotational movements and one combining rotational and translational movements. Furthermore, we accomplished three field experiments to validate the applicability of the proposed method to collect real world measurements. The three field experiments are:

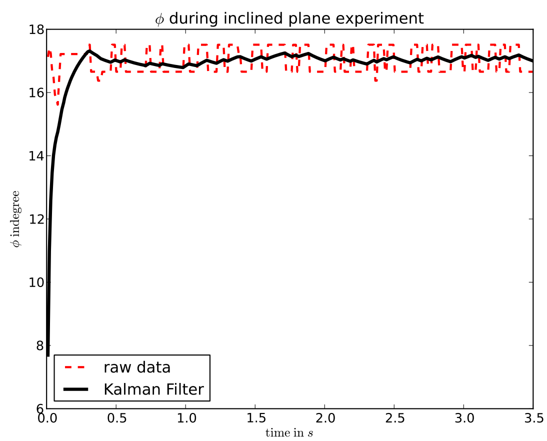
1) The first experiment comprises an acceleration with an abrupt fullbraking during a straight-line movement.
2) The second experiment shows a cyclic acceleration followed by a deceleration as one would expect in case of congestion.
3) The third experiment pictures a trajectory in an urban environment.



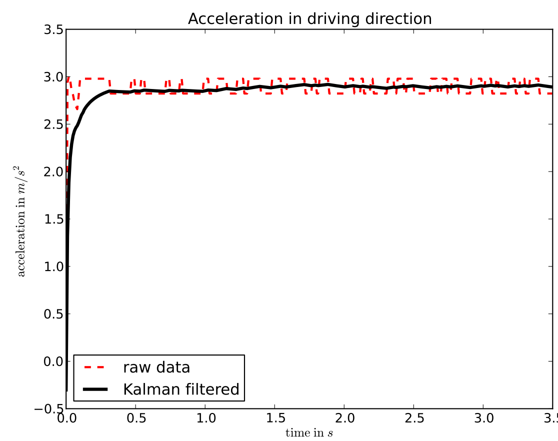
(a) Roll angle with and without *Kalman Filter*.



(b) Pitch angle with and without *Kalman Filter*.



(c) Noisy pitch angle versus filtered pitch angle.



(d) Noisy acceleration versus filtered acceleration.

Fig. 3. Validation during laboratory experiments.

B. Evaluation

Figure 3 depicts the results from the validation experiments done for the angular values and the inclined plane. For the angular experiment measurements were taken by stepwise rotations with steps of $5°$ around the pitch and roll angle in the range between $0°$ and $25°$. The red line shows the noisy signal from the raw measurement values only corrected for the offset error as mentioned before. The black line then depicts the signal after application of the proposed *Kalman Filter* for rotations.

In a second step, we extended the experiment to measure angles and translational accelerations together on an inclined plane with an angle of inclination $\alpha = 17°$. From physics, we expect an acceleration of:

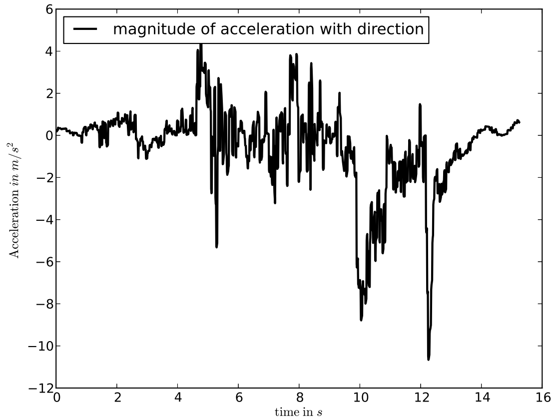
$$a = g \sin \alpha \quad (19)$$

$$\approx 9.81 \frac{m}{s^2} \sin 17° = 2.868 \frac{m}{s^2} \quad (20)$$

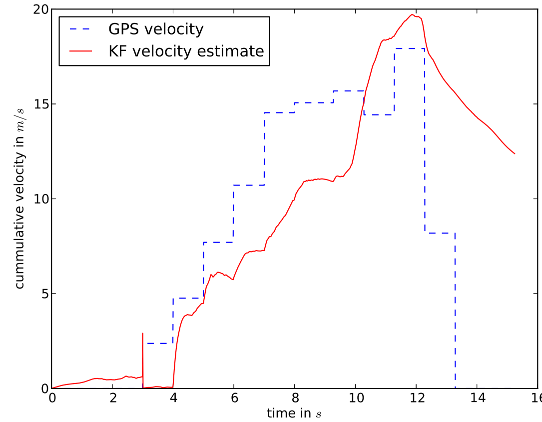
The measured inclination $\bar{\phi}$ angle and acceleration in driving direction $\bar{a}_y$ are depicted in Figures 3(c) and 3(d). The filtered inclination angle $\bar{\phi}^*$ is nearly identical with the adjusted angle $\alpha = 17°$ as shown in Figure 3(c). The filtered acceleration in driving direction $\bar{a}^*$, as demonstrated in Figure 3(d) can be evaluated as follows:

$$\bar{a}^* = \frac{1}{N} \sum_{i=1}^{N} a^*_{y_i} \quad (21)$$

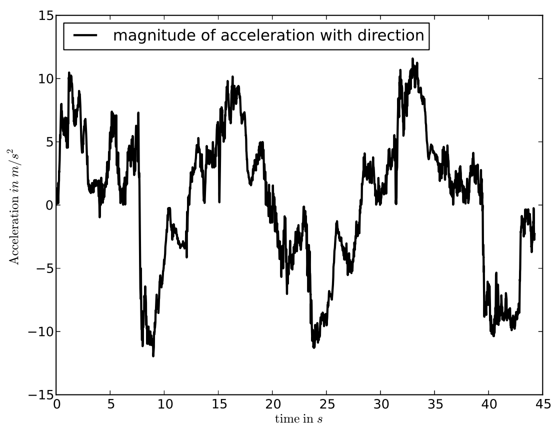
$$= 2.869 \frac{m}{s^2} \quad (22)$$



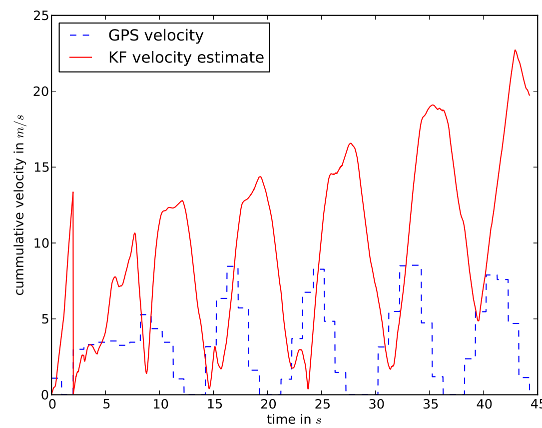
(a) Acceleration in driving direction for acceleration and sudden brake.



(b) Velocity estimate versus GPS velocity for acceleration and sudden brake.



(c) Acceleration in driving direction.



(d) Velocity estimate versus GPS velocity.

Fig. 4. Validation during field experiments.

These two experiments show clearly, that after elimination of the *offset errors* as proposed in section III-A the developed *Kalman filters* from sections IV-C and IV-D are able to filter out the *measurement noise* under laboratory conditions.

To test the proposed filters and rotation operations in a real world scenario we took several recordings when driving with different vehicles. In figure 4 the results for the first and the second experiment are depicted. In the first experiment we performed an acceleration up to $65km/h$ and then did an emergency braking with a deceleration of $a = -10m/s^2$. The results are given in figures 4(a) and 4(b). The values, depicted in figure 4(a) clearly shows the positive acceleration behavior from $t = 0 \ldots 9s$ followed by an abrupt deceleration between $t = 10 \ldots 14s$ with magnitudes between $a = -8m/s^2$ and $a = -10m/s^s$.

The second experiment is a cyclic stop and go behavior that might be typical for a traffic congestion. Figures 4(c) and 4(d) clearly reflect the cyclic movement. Even if the filter is not able to fit the real velocities in figure 4(d) the movement pattern can clearly be extracted and used for further analysis.

The noisy appearance of the acceleration values might be caused by the frequency of the engine in the vehicle which was not considered during parameter estimation for the Kalman filter. Therefore this ought to be a question for further investigations.

VI. Conclusion

In this paper we show, that the large number of consistent data in terms of position, velocity and acceleration enables us to detect important events with smartphones. One major incident could be a periodic acceleration and deceleration, pointing at a stop and go behavior. Another scenario might be a rapid deceleration as an evidence for an accident or the tail end of a traffic jam. In this work we introduce a method to use a smartphone with arbitrary orientation in a car (i.e., having the smartphone in the pocket) to monitor the traffic conditions. The residual acceleration noise mainly caused by environmental factors such as bad road conditions or engine vibrations have to be evaluated in further studies.

Since the measured orientation values are affected by offset and measurement errors it is essential, first to apply an adequate *Kalman Filter*. Due to the fact, that the orientation of the device is unknown, a rotation of the raw acceleration values with the corrected and filtered orientation angles has to be performed. This transformation is done by the use of quaternions and the *Hamilton formula* to avoid gimbal locks. The thereby produced acceleration values can this way be transformed to the global coordinate system. However, the obtained values still include offset and measurement errors that have to be corrected. After sensor fusion and correction of the rotated acceleration measurements with a *Kalman Filter* it is possible to gain a complete picture of the referential of the vehicle regarding its position, speed, acceleration and orientation. In contrast to a traffic situation acquisition system that is based solely on data obtained by a GPS and thus only provides information about the position and velocity of the vehicle, our system is more precise due to the much higher sampling frequency of the acceleration sensor.

Given that the *Kalman Filter* only relies on the last estimated value and does not process the complete data history for the estimation of the current state, it performs well on devices with limited computational power. However, the estimation of the acceleration requires a sampling rate of at least 100Hz. This has as consequence, a high power consumption of the mobile device and therefore disagrees with the users request for long battery life. A possibility to overcome the engergy constraint is to include such a system into a navigation device that is plugged to an external power supply. Since the implementation of the *Kalman Filter* algorithm as described in this paper is not optimized but rather a proof of concept, a more efficient implementation might be a step towards a final solution.

When thinking of a wide distribution of such a system, it would be possible to evaluate the data provided by other users of the community to provide a full picture of the traffic situation on a specific road or road segment. Such an approach requires further research and might be promising for a real-time incident and emergency detection.

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