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Low-cost object tracking with MEMS sensors, Kalman filtering and simplified two-filter-smoothing

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A B S T R A C T

The article focuses on using low-cost inertial navigation systems (INS) for long-term object tracking and makes use of a loose coupling integration method based on Kalman filtering in order to realize a sensor fusion between an INS and GPS. This article shows the performance of two filter smoothing to reduce the growth of errors during GPS outages. A simplification technique is applied to avoid the calculation of inverse covariance matrices for the smoothing, which reduces the possibility of numerical instabilities while increasing the computational efficiency. The research is supported with a series of experiments carried out on campus in order to verify reliability and stability of the overall system. The final solution is low-cost, miniature-size and low-weight, while having an increased accuracy compared to ordinary loosely-coupled systems and is capable of handling multiple GPS outages.

1. Introduction

In recent years, low-cost inertial navigation has been a well-known solution for indoor object tracking, navigating in densely built areas or in hybrid indoor–outdoor-environments. Since the required hardware for inertial navigation is very small, low-weight and widely available on the market, using MEMS[1] motion sensors allows for various industrial, medical or entertainment applications to be realized at very low manufacturing costs (cf. [16]). Due to the error characteristics these sensors have shown, their applicability has been limited to just simple tasks in smart phones, tablets etc. such as shaking detection, vibration measurement or bubble level applications. This research uses a sensor fusion technique to support an inertial navigation system (abbreviated as: INS) with aiding information from an external reference navigation source, in the present case: GPS. Furthermore, the work focuses on keeping the benefits of low-cost INS while obtaining long-term stability and reliability in order to accomplish shading-free object navigation. The overall goal is to provide a navigation solution for both indoor and outdoor environments within a single low-cost system. The research is supported by various experiments done with a test vehicle.

2. State of the art in object tracking and navigation

The current state of the art regarding the navigation of vehicles and dispersed and moving objects is mainly dominated by stand-alone GPS systems as well as infrastructure-dependent positioning technologies. The GPS-based tracking is always

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[1] MEMS means “Micro-electromechanical-system”.

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Nomenclature

Variable	Definition
$\_$	accent indicating a component to be a 1D-vector
$\wedge$	accent indicating a component to be estimated
$\boldsymbol{\Phi}$	15×15-dimension system transition matrix
$\boldsymbol{F}$	15×15-dimension system dynamics matrix
$\boldsymbol{G}$	15×12-dimension control matrix
$\boldsymbol{B}$	system control matrix
$\underline{\boldsymbol{z}}$	1×6-dimension measurement vector
$\boldsymbol{H}$	6×15-dimension system measurement matrix
$\boldsymbol{K}$	15×6-dimension Kalman gain matrix
$\underline{\boldsymbol{u}}_{\boldsymbol{k}}$	optional control input vector
$\underline{\boldsymbol{w}}_{\boldsymbol{k}}$	system model white noise input
$\underline{v}_{\boldsymbol{k}}$	measurement model white noise input
$\boldsymbol{Q}$	covariance matrix associated with $\underline{w}_k$
$\boldsymbol{R}$	covariance matrix associated with $\underline{v}_k$
$\underline{\boldsymbol{a}}$	3-dimension acceleration vector
$\underline{\omega}$	3-dimension angular rate vector
$\underline{\boldsymbol{p}}$	3-dimension position vector
$\underline{\boldsymbol{v}}$	3-dimension velocity vector
$\underline{\boldsymbol{b}}$	3-dimension bias vector
$\boldsymbol{C}_b^n$	3×3-dimension body to navigation frame transformation matrix
$\mathbf{n}, \mathbf{e}, \mathbf{d}$	indices indicating a component being in north, east or down direction
$\mathbf{\Omega_{ie}^n}$	skew-symmetric matrix of turn rate difference between earth rotation, transportation rate
$\underline{\boldsymbol{n}}_{ac}$	white noise input for accelerometer noise modeling
$\underline{\boldsymbol{n}}_{gy}$	white noise input for gyroscope noise modeling
$\underline{\boldsymbol{n}}_{b,ac}$	white noise input for accelerometer bias noise modeling
$\underline{\boldsymbol{n}}_{b,gy}$	white noise input for accelerometer bias noise modeling
$\underline{\tau}_{ac}$	correlation time vector for 1st order Gauss–Markov-modeled bias noise of the accelerometers
$\underline{\tau}_{by}$	correlation time vector for 1st order Gauss–Markov-modeled bias noise of the gyroscopes

influenced by the dependence of a minimum number of directly visible satellites. This fact clearly limits the applicability of this technology, especially when navigating through an alternating indoor–outdoor environment and in a densely built area. Infrastructure-based systems typically have optical, acoustic or electromagnetic operating principles and are usually dependent on the installation of additional fixed equipment, networks and supporting infrastructure on pre-defined positioning-areas. Other systems use already installed signal-sources such as Wi-Fi hotspots in order to locate mobile objects in its coverage area. The basic positioning principles are across all technologies typically GPS-like triangulation principles based on the measured reception strength, time- and phase-differences or on the calculation of the received signals' entry-angles. Unlike GPS, the use is often limited to certain pre-defined application areas. The additional installation of infrastructure and the positioning dependence of external signals usually lead to high costs as well as shading and fluctuation problems. A positioning technology, which unites the advantages of a GPS with a reference-less, independent of external signals and infrastructure, inertial navigation system to an accurate, affordable and compact system, though without losing accuracy through GPS outages, would open up a broad field of applications with an unparalleled positioning and tracking flexibility.

3. Low-cost inertial navigation

The principle of an INS is based on the measurement of object motion using the inertia of a built-in proof mass in the case of its acceleration. In order to cover the degrees of freedom (DoF) a body can have in three-dimensional space, a spatial configuration of respectively three orthogonally arranged acceleration and turn rate sensors (gyroscopes) is required. Consequently, this layout allows the system to sense all forces exerted on an object in linear or angular direction.

The development of MEMS manufacturing techniques over the past 50 years make today a mass production of miniature-size inertial sensors possible. Hence, INS have become interesting for industrial, medical and consumer-market system developers. However, the full potential was rarely reached as MEMS motion sensors have bad error characteristics which get amplified through the signal processing. Signal processing consists of the integration of the acceleration signals to velocity and position information, and, the integration of the turn rate signals to orientation angles with respect to a given initial object condition.

As signals from low-cost sensors suffer from stochastic bias errors that overlap the crucial measurement information, integration results in time-growing errors in the velocity, the position and the orientation information. Thus, the navigation accuracy can only be maintained over short periods of time. According to [1], the integration of a biased signal induces an error that linearly grows over time, which is relevant to the calculation of the velocities from the acceleration signals and the orientation angles from the gyroscope signals. A second integration step, which is required for obtaining the position information from velocity, causes an error that proportionally grows with the square of calculation time. Additionally, any error in the orientation information can have an error influence with cubic time growth due to wrong compensation of the static acceleration induced by gravity.

Therefore, long-term object tracking with an acceptable accuracy via a low-cost INS is currently only reachable if the INS is combined with another navigation system. GPS is an example of a supporting system, which periodically provides the system with absolute position information, whereas the INS operates during reference signal outages. Furthermore, other supporting measurements can provide helpful information in order to enhance the navigation performance, e.g. measurement of the earth's magnetic field or the barometric altitude.

4. Kalman filtering

The Kalman filter is an optimal estimation algorithm named after Rudolf E. Kalman who presented it in 1960 (cf. [8]). With the help of a Kalman filter in conjunction with a mathematical model of the system's dynamic behavior and proper sensor measurements, it is possible to estimate future states of a system. The Kalman filter is still capable of yielding acceptable and useful results, even if the sensor data and/or the mathematical model are faulty or inaccurate. The Kalman filter algorithm is able to combine both sources of information by calculating an optimal weighting factor based on the uncertainties given for each of them.

The main idea consists in the prediction of upcoming system states by using the current states, the system model and optional system control information while the correction of the prediction is done with information gained from the measurement inputs. The usage of a standard Kalman filter algorithm requires the system to be linear, the measurements to be linear combinations of the system state components and both the errors given in the system model and the measurements to be uncorrelated and normally distributed zero-mean white noise. For systems that fulfill these requirements it can be assumed, that the Kalman filter provides optimal estimates, this means that its results are the most accurate among other estimation algorithms (cf. [3]). Moreover, the filter's working principle is recursive and hence well-suited for an implementation on a microcontroller. This fact makes it beneficial for applications that require a system to run on an embedded electronic platform.

Assuming that the execution begins with the specification of the systems' initial states and the corresponding uncertainties in the form of a covariance matrix, a Kalman filter algorithm for a time-discrete linear dynamic system can be represented as (cf. [1–4,8,15]):

$$\underline{\hat{x}}_k^- = \boldsymbol{\Phi}\underline{x}_{k-1} \qquad \text{State prediction} \tag{1}$$

$$\boldsymbol{P}_k^- = \boldsymbol{\Phi}P_{k-1}\boldsymbol{\Phi}^T + \boldsymbol{Q} \qquad \text{Prediction covariance} \tag{2}$$

$$\boldsymbol{K}_k = \boldsymbol{P}_k^-\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{P}_k^-\boldsymbol{H}^T + \boldsymbol{R})^{-1} \qquad \text{Kalman gain (weighting matrix)} \tag{3}$$

$$\underline{\hat{x}}_k = \underline{\hat{x}}_k^- + \boldsymbol{K}_k(\underline{Z}_k - \boldsymbol{H}\underline{\hat{x}}_k^-) \qquad \text{Correction} \tag{4}$$

$$\boldsymbol{P}_k = (\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{H})\boldsymbol{P}_k^- \qquad \text{Correction covariance} \tag{5}$$

For the given approach, the special benefit of Kalman filtering is its applicability to the fusion of an inertial navigation system with an external aiding positioning system, which in this case shall be GPS.

4.1. System configuration and working principle

System architectures used for the fusion of GPS and INS are mainly distinguished by their functional principle being the individual subsystems operating either separately or depending on each other. The first method is known as loose coupling and it is the method used in this approach. A second common architecture is the tight coupling and it integrates the GPS calculation directly into the integration that is performed by a single Kalman filter which is then responsible for both satellite navigation and the system fusion. However, the requirement to the GPS receiver to provide raw GPS signals is not given for standard low-cost receivers. Thus, the decision for the present system falls in favor of the loose coupling method, which additionally has the benefits of a redundant hardware configuration and lower system complexity. The limitation of the GPS being dependent on free lines of sight to a minimum number of satellites shall be compensated for with the help of a post-processing algorithm as described below.The main algorithm utilized for the implementation of sensor fusion is a Kalman filter with indirect formulation. Indirect formulation means, that the estimations provided by the filter do not describe the systems' motion values themselves, but rather the errors made by the INS and the inertial sensors. The algorithm processes both the inertial sensor values in the so-called propagation step and the GPS information in the so-called measurement update step. In this approach, both the GPS position and velocity measurements are used by the Kalman filter.

Subsequent to each filter iteration, the obtained error state vector is fed back into the INS mechanization block and then reset to a zero-vector which makes the filter algorithm be in feedback configuration. The feedback configuration allows the system states to be corrected immediately after the measurements have been processed by the filter which keeps the error states small and the algorithm stable. The system overview is given in Fig. 1.

4.2. System modeling

The state vector required for the present system includes the errors of the INS-calculated position, velocity, orientation angles and the inertial sensor bias errors. It is defined by:

$$\underline{x} = \left(\Delta \mathrm{p_n}\ \Delta \mathrm{p_e}\ \Delta \mathrm{p_d}\ \Delta \mathrm{v_n}\ \Delta \mathrm{v_e}\ \Delta \mathrm{v_d}\ \Delta\alpha\ \Delta\beta\ \Delta\gamma\ \Delta \mathrm{b_{ac,x}}\ \Delta \mathrm{b_{ac,y}}\ \Delta \mathrm{b_{ac,z}}\ \Delta \mathrm{b_{gy,x}}\ \Delta \mathrm{b_{gy,y}}\ \Delta \mathrm{b_{gy,z}}\right)^T$$

With $\mathrm{b_{ac}}$ and $\mathrm{b_{gy}}$ being defined as the bias errors made by the accelerometers and the gyroscopes in each direction of the body navigation frame (cf. Fig. 3).The system dynamics equations and the relationships between the states and the measurements are non-linear for inertial navigation. Hence these equations must be linearized with the estimated states as a linearization point (cf. [4]). Firstly, the full equation for the dynamic system is given by:

$$\hat{\underline{x}}_{k+1} = \boldsymbol{\Phi}\underline{x}_k + \boldsymbol{B}\underline{u}_k + \boldsymbol{G}\underline{\omega}_k \tag{6}$$

The filter's measurement model is defined as follows:

$$\underline{Z}_k = \boldsymbol{H}\underline{x}_k + \underline{v}_k \tag{7}$$

The matrix Φ is obtained through the matrix **F** which realizes the system linearization. **F** can be developed based on [4,13] and is provided as:

$$\boldsymbol{F} = \begin{array}{ccccc} & & & \mathbf{0}_{3x3} & \mathbf{0}_{3x3} \\ & \boldsymbol{F}_{INS} & & -\boldsymbol{C}_b^{\hat{n}} & \mathbf{0}_{3x3} \\ & & & \mathbf{0}_{3x3} & -\boldsymbol{C}_b^{\hat{n}} \\ \mathbf{0}_{3x3} & \mathbf{0}_{3x3} & \mathbf{0}_{3x3} & -\dfrac{1}{\underline{\tau}_{ac}} & \mathbf{0}_{3x3} \\ \mathbf{0}_{3x3} & \mathbf{0}_{3x3} & \mathbf{0}_{3x3} & \mathbf{0}_{3x3} & -\dfrac{1}{\underline{\tau}_{gy}} \end{array} \tag{8}$$

Due to its dimensions, the system model sub-matrix $\mathrm{F_{INS}}$ is given below separately (cf. Eq. (15)). In order to complete Eq. (6) the matrix ***G*** must be given:

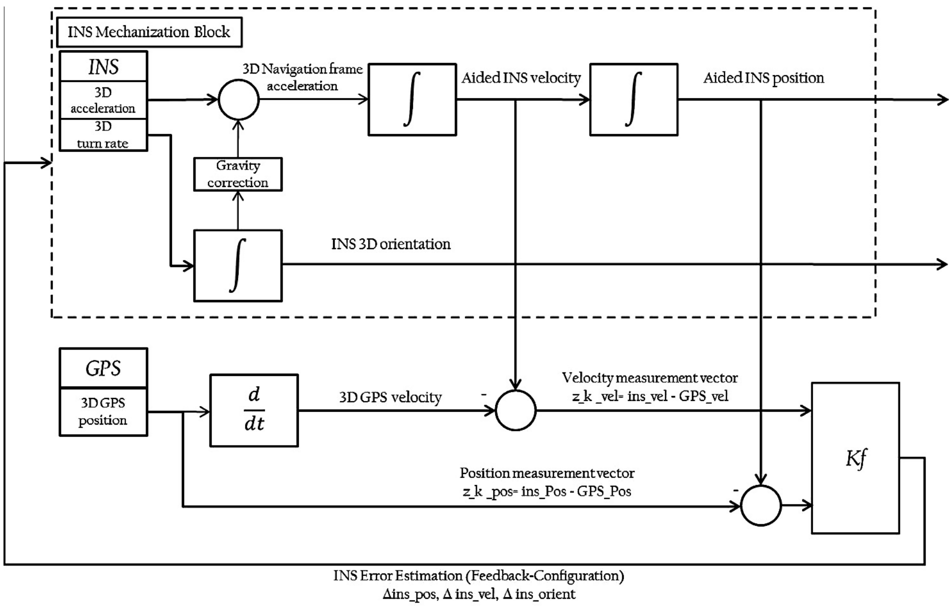

Fig. 1. GPS–INS sensor fusion system model based on Kalman filtering in feedback configuration.

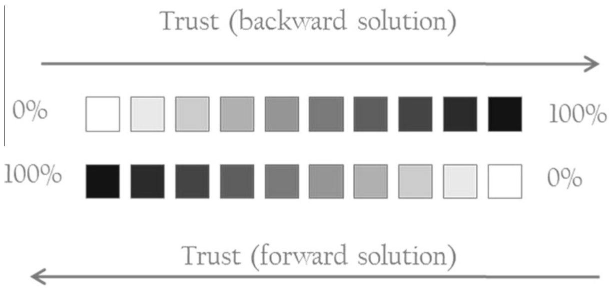

Fig. 2. Illustration of optimal weighting during reference outage time.

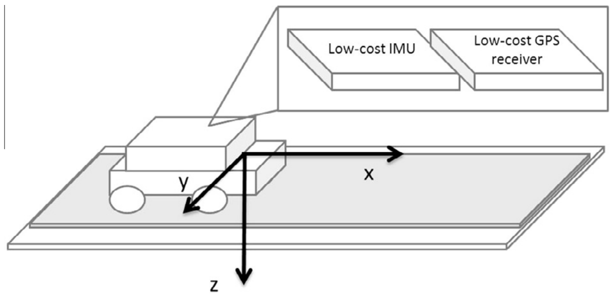

Fig. 3. Campus experiment configuration: test vehicle and body navigation frame, top right: low-cost GPS receiver, top left: miniature-size low-cost IMU with 9 DoF.

$$\boldsymbol{G} = \begin{matrix} \mathbf{0}_{3x3} & \mathbf{0}_{3x3} & \mathbf{0}_{3x3} & \mathbf{0}_{3x3} \\ -\boldsymbol{C}_b^{\hat{n}} & \mathbf{0}_{3x3} & \mathbf{0}_{3x3} & \mathbf{0}_{3x3} \\ \mathbf{0}_{3x3} & -\boldsymbol{C}_b^{\hat{n}} & \mathbf{0}_{3x3} & \mathbf{0}_{3x3} \\ \mathbf{0}_{3x3} & \mathbf{0}_{3x3} & \mathbf{I}_{3x3} & \mathbf{0}_{3x3} \\ \mathbf{0}_{3x3} & \mathbf{0}_{3x3} & \mathbf{0}_{3x3} & \mathbf{I}_{3x3} \end{matrix} \tag{9}$$

And:

$$\underline{\omega}_k = \begin{pmatrix} \underline{n}_{ac} \\ \underline{n}_{ac} \\ \underline{n}_{b,gy} \\ \underline{n}_{b,gy} \end{pmatrix} \tag{10}$$

It shall be noted, that no control inputs are used in this model.

The position estimation shall be calculated directly in dimensions of latitude and longitude radians and height meters. To prevent any calculation problems that might occur due to the differences in these values' numerical representations, the observation matrix can be used for scaling accordingly (the earth radii R_n and R_e can be obtained from [10]):

$$\boldsymbol{H_k} = \begin{pmatrix} R_n - \hat{h} \\ (R_e - \hat{h})\cos\hat{\varphi} \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \tag{11}$$

The measurement vector is chosen to handle the difference vector between the position and the velocity information provided by the GPS receiver and those estimated by the INS to provide it as an input for the Kalman filter:

$$\underline{z}_{\boldsymbol{k}} = \begin{pmatrix} \hat{\varphi} - \varphi_{GPS}(R_n - \hat{h}) \\ (\hat{\lambda} - \lambda_{GPS})(R_e - \hat{h})\cos\hat{\varphi} \\ \hat{h} - h_{GPS} \\ \hat{v}_n - v_{GPS,n} \\ \hat{v}_e - v_{GPS,e} \\ \hat{v}_d - v_{GPS,d} \end{pmatrix} \tag{12}$$

Both the velocity and position measurements provided by GPS underlie a stochastical noise $\underline{v}_k$ that analogous to the system noise $\underline{\omega}_k$ is assumed to be zero-mean and normally distributed white noise.The state transition matrix Φ needed for the propagation of the system states over time from a current discrete time step to a following one shall be given as:

$$\boldsymbol{\Phi} = e^{\boldsymbol{F}(t_{k+1} - t_k)} \tag{13}$$

Under the assumption that $t_{k+1} - t_k = \Delta t$ represents a short period of time between two INS measurements and according to [3], Eq. (13) can be approximated to:

$$\boldsymbol{\Phi} \approx \mathbf{I} + \mathbf{F}\Delta t \tag{14}$$

The purpose of the Kalman filter is the combination of information given by the INS and the GPS, with the goal of reaching a navigation performance that covers the advantages of both systems while compensating for their limitations. In the case of GPS measurements being available as a result of enough visible satellites, the measurement covariance matrix has to be chosen optimistically. In the opposite case, the navigation follows entirely the INS's performance, so the filter prediction is the part which is taken into account.

Using low-cost MEMS-based inertial sensors is bound with the problem that with a loss of the GPS signal, the navigation will lose its accuracy rapidly when performing only with INS data until the reference information is recovered. This means, that the certainty of the information calculated by the Kalman filter will be high at the beginning of a GPS outage and very low at its ending. A strategy of holding the last acquired GPS position constant in order to limit the growth of errors can improve this behavior, but the principle stays the same. Smoothing algorithms are a viable and applicable solution that can improve the performance successfully.

The smoothing procedure consists of the idea, that running the fusion algorithm discussed above again, but backwards in time, can help to increase the accuracy during reference signal outages when being combined with the solution calculated forwardly in time (cf. [5–9,14]). Particularly, the so-called two-filter smoother is a common and accurate method (cf. [6]) that uses a backward Kalman filter beginning with the last and ending with the first INS and GPS measurements. The behavior of the second fusion filter during outage periods is exactly the other way round, which means that the solution is accurate at the ending and less accurate at the beginning of the outage period. The final result, ultimately, is reached with an optimal linear combination of both the first and the second fusion and has an overall accuracy that is better than both.

The computation of the regular tow-filter-smoothing algorithm and the combined solution requires variations in the system model as well as mathematically intensive inverse calculations for the covariance matrices given for the forward and the backward filter system states (cf. [6]). The simplifications made in this approach are based on the idea that changing the system model can be avoided, if the time vector is handled inversely by propagation from a current time step to a previous one and with the inversion of orientation and turn rate values as if the object moved with inverted rotation angle definitions in space with respect to the truly made motion. Furthermore, as the linear combination of both solutions always aims for the most accurate navigation value given in each data set, the classic calculation method can be replaced with a simple weighting. For this, a weighting factor shall give full trust to the forward solution at the beginning of reference outage period and full trust for the backward solution at its ending. In the middle of the period, trust is divided by half and in between, an appropriate grading is done in order to reach optimal weighting (cf. Fig. 2).

$$\boldsymbol{F_{INS}} = \left[\begin{array}{ccccccccc}
0 & 0 & \frac{v_n}{(R_n-h)^2} & \frac{1}{R_n-h} & 0 & 0 & 0 & 0 & 0 \\
\frac{v_e \sin\varphi}{(R_e-h)\cos^2\varphi} & 0 & \frac{v_e}{(R_e-h)^2\cos\varphi} & 0 & \frac{1}{(R_e-h)\cos\varphi} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
-v_e\left(2\Omega\cos\varphi - \frac{v_e}{\cos^2\varphi)(R_e-h)}\right. & 0 & \frac{v_n v_d}{(R_n-h)^2} - \frac{v_e^2\tan\varphi}{(R_e-h)^2} & \frac{v_d}{(R_n-h)} & -2\Omega\sin\varphi - \frac{2v_e\tan\varphi}{(R_e-h)} & \frac{v_n}{(R_n-h)} & & & \\
v_n\left(2\Omega\cos\varphi - \frac{v_e}{(\cos^2\varphi)(R_e-h)}\right) - 2\Omega v_d\sin\varphi & 0 & \frac{v_n v_d}{(R_e-h)^2} + \frac{v_e v_n \tan\varphi}{(R_e-h)^2} & 2\Omega\sin\varphi + \frac{v_e\tan\varphi}{(R_e-h)} & \frac{v_d}{(R_e-h)} + \frac{v_n\tan\varphi}{(R_e-h)} & 2\Omega\cos\varphi + \frac{v_e}{(R_e-h)} & & -(\mathbf{C}_b^{\hat{n}}\underline{a}_b\times) & \\
2\Omega v_e\sin\varphi & 0 & \frac{-v_e^2}{(R_e-h)^2} - \frac{v_n^2}{(R_n-h)^2} & \frac{-2v_n}{(R_n-h)} & -2\Omega\cos\varphi - \frac{2v_e}{(R_e-h)} & 0 & & & \\
\Omega\sin\varphi & 0 & -\frac{v_e}{(R_e-h)^2} & 0 & -\frac{1}{(R_e-h)} & 0 & & & \\
0 & 0 & \frac{v_n}{(R_n-h)^2} & \frac{1}{(R_n-h)} & 0 & 0 & & -\boldsymbol{\Omega}_{in}^n & \\
\Omega\cos\varphi - \frac{v_e}{(\cos^2\varphi)(R_e-h)^2} & 0 & \frac{v_e\tan\varphi}{(R_e-h)^2} & 0 & \frac{\tan\varphi}{(R_e-h)} & 0 & & &
\end{array}\right] \tag{15}$$

5. Validation of system stability and reliability

To validate the stability and reliability of the proposed system, the decision was made in favor of real test drives and against the simulation of sensor measurement data. This was to ensure that the used inertial- and GPS-sensors where properly stressed with realistic driving conditions, especially the car's vibrations as well as realistically scaled acceleration and angular rate signals. For this purpose, eight test routes were defined on the university campus with different specifications regarding route length, travel duration, curve direction and the number and order of the curves. Among these were routes with a predominantly straight route, ones with only left- or right curves and others with alternating curve directions. The track lengths varied between 350 and 1700 m, under both low- and heavy traffic conditions, which demanded a more frequent stop and start behavior. The travel times ranged from approximately 70–350 s. Each of the defined routes were driven a total of six times under the exact same conditions with the same sensors. Then one of the routes was again driven six times with equally working but different inertial- and GPS-sensors. Within the framework of the subsequent data processing, the unaltered collected data as well as the simulated GPS signal losses of various durations, frequencies and time-of-occurrence was processed in the present algorithm and the results analyzed in terms of logic, numerical stability, and error handling, especially during the GPS signal losses. The latter lasting in different scenarios over 10, 20 and 30 s, which could also be repeatedly simulated in a measurement dataset.

The IMU[2] navigation frame was defined to follow the car's navigation frame so that their axes are identical; the *x*-axis shows to the vehicle's front and the *y*-axis to the right side. For the results given below, the GPS receiver was assumed to be shaded for a time period of 30 s starting after 40 s of acquisition. It will be shown in post-processing, that the fusion algorithm is capable of overcoming GPS signal outages without significant losses in accuracy or stability. Fig. 3 shows a sketch of the test configuration and the corresponding body navigation frame.

6. Results

Figs. 4 and 5 show two different representations of a selected track on which validation experiments were implemented. In the first figure the test track street boundaries are depicted and overlaid with independent GPS and INS measurements. The INS calculation includes signal integration and compensation of gravity. Moreover, it is assumed that the GPS data is complete, meaning that no outage was simulated. This changes in Fig. 5, which shows the results of the one-filter sensor fusion (blue curve) and a GPS signal loss assumed from 40 to 70 s (black squares). The same figure contains the smoothed solution curve including the application of an optimal combination of two Kalman filters running in opposite directions of time.

It is clear that the best results can be observed in the smoothed solution, as it provides long-term stability despite reference signal outage and low performance of the inertial navigation. The independent INS and GPS measurements divergence right from the start, ending in position errors up to 414 m after 91.5 s of measurement. This behavior could be improved with the one-filter-solution, as the growth of position errors does not occur until the GPS loses contact to the required amount of satellites. After this point, INS-only operation is available until the GPS reference signal is recovered. Ultimately, it is the smoothed solution which is capable of significantly limiting error growth during outage time. These results demonstrate

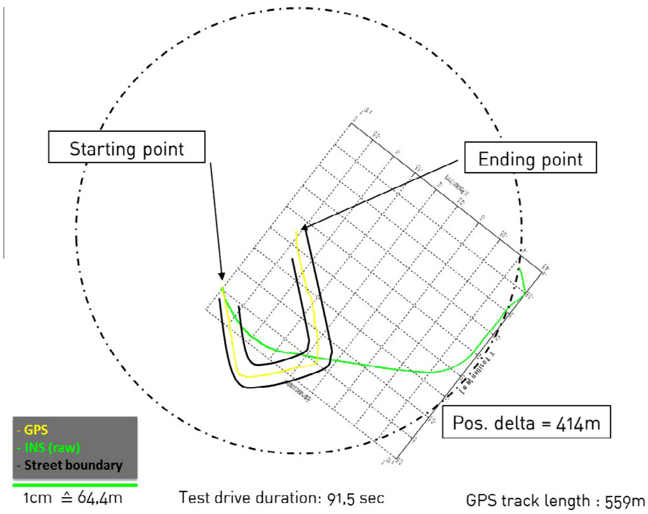

Fig. 4. Independent GPS and INS measurements sample test track, no GPS outage.

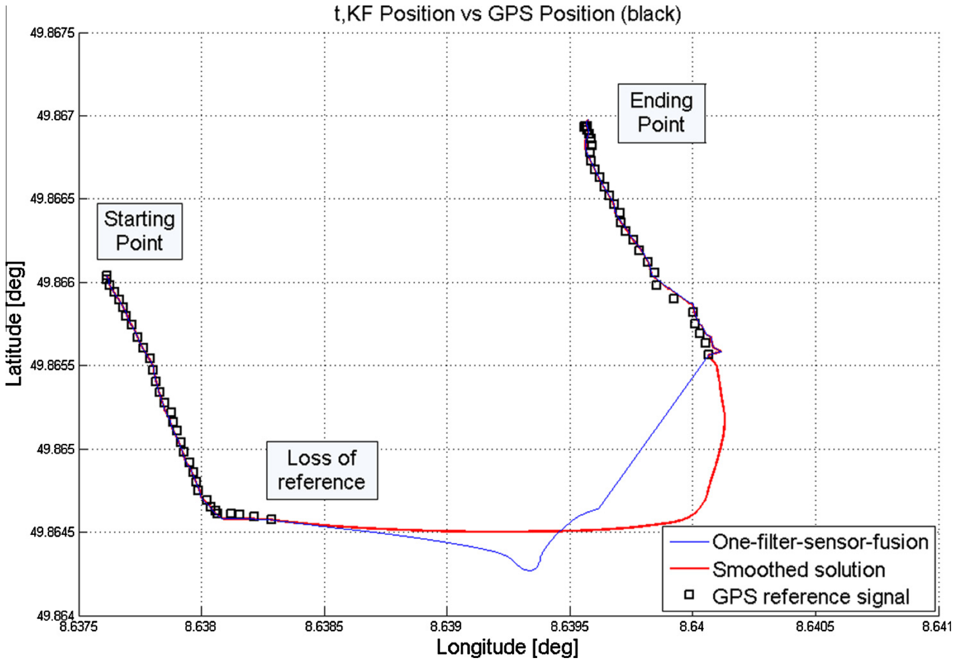

Fig. 5. One-filter GPS–INS sensor fusion (blue) and smoothed solution (red), same sample test track as in Fig. 4 and 30-s-GPS-outage. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the qualification of the present approach for the purpose of enhancing accuracy and long-term applicability of low-cost INS, despite potential loss of aiding navigation signals and low inertial sensor performance.

7. Conclusion and outlook

As discussed in the results section, the technical challenge of INS sensor drift could be overcome. The present solution is capable of handling rapidly arising errors in INS-only navigation during GPS signal outages.

Due to limitations in performance, accuracy and reliability, low-cost INS can hardly be utilized for object tracking applications which require accurate long-term behavior. In order to meet this concern, the position, velocity and orientation information provided by INS and GPS were combined through Kalman filtering and the results were smoothed by a simplified routine. As a result of these methods, different test track experiments have shown distinct reduction of the errors observed in the independent measurement phase (cf. Fig. 4) and the trajectory calculated in the one-filter-solution (cf. Fig. 5, blue curve). Furthermore, the unrestricted growth of navigation errors during the reference outage time could be resolved (cf. Fig. 5, red curve).

The present system concept is suitable for various branches of industrial and civil applications. Examples are machine monitoring, multiple-object-tracking in logistics and factory plants or operation in combined indoor-outdoor environments. As the system also provides dynamic attitude information, it can help to enhance ordinary GPS applications (cf. [11,12,17,18]). In general, applications in which a single navigation system may suffer from frequent disturbances, or systems where orientation information is crucial, the present solution will deliver the needed information and assistance.

The present work is continued by the authors aiming for improvement of forward and backward filter accuracy over longer terms of reference signal outage. This is mainly connected to the improvement of stand-alone inertial navigation performance so that simple and fast methods must be found in order to reduce the effects of sensor drift and for in-run-compensation of systematic errors with individual IMUs.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.amc.2014.03.015.

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