The Influence of the GNSS Solution on the Estimated Parameters in the Course of Sensor Integration

Roman Lesjak*, Markus Dorn*, Katrin Huber* and Manfred Wieser*
*Institute of Geodesy - Working Group Navigation, NAWI Graz, Graz University of Technology
Steyrergasse 30/II, 8010 Graz, Austria
Email: roman.lesjak@tugraz.at, Telephone: +43 316 873 6831

***Abstract*—As a result of the continuously decreasing costs of sensors, the number of applications using multiple sensors for the determination of navigation parameters increases significantly. Examples are remotely piloted aircraft systems (RPAS), pedestrian navigation using smartphones, driver assistance systems within cars, etc. All applications have in common that the costs have to be minimized. Finding the optimal sensor configuration for a specific application is a challenge because of cost limitations. While most of the time sensors are replaced when specific accuracy requirements are not met, within this paper, an approach without increased costs will be investigated. The idea behind this approach is to change the GNSS processing methodology, e.g., from single point positioning to relative positioning even though, the high position accuracy is not required. This approach allows improving the system performance of all parameters without increasing the hardware costs if the receiver supports GNSS raw data output.**

I. INTRODUCTION

GNSS and INS have been popular components for sensor integration since decades. Within the last years, this combination could also be applied to low-cost applications because of the decreasing costs for GNSS receivers and inertial sensors. As a result, nowadays, sensor integration is done for remotely piloted aircraft systems (RPAS), pedestrian navigation using smartphones, driver assistance systems within cars, etc. Nevertheless, for many applications, even nowadays the costs are to high. Within cars, for examples, the integration of GNSS receivers is actually performed, but 3-dimensional accelerometers or gyroscopes are not yet integrated although they are already in every smartphone.

The reason for the popularity of the combination of GNSS and INS is because of their complementary characteristics. While GNSS-based positioning has a very good medium- to long-term accuracy, it shows larger short-term uncertainties and may be obstructed by signal interference which can even lead to GNSS outages. On the other hand IMUs provide autonomous position solutions and hence, are independent of their surroundings. They have a good short-term accuracy but a weak medium- to long-term accuracy. When integrating GNSS and INS, the advantages of both sensors can be used to improve the overall accuracy. Depending on the type of GNSS processing and inertial sensor category, the mentioned defintions have to be refined. For example, integrating an RTK GNSS solution with a low-cost MEMS IMU, GNSS has a very good short to long-term accuracy under good conditions, while the short-term accuracy of the MEMS IMU is ok and the medium- to long-term accuracy is really bad.

Within literature, there are a lot of approaches how to integrate these sensors: extended Kalman filter, unscented Kalman filter, particle filter, and artificial intelligence approaches. While particle filter and artifical intelligence are good ways to deal with deviations from linearity and Gaussian distribution, they are non-parametric filters which usually do not estimate sensor errors. When there is the need for corrected inertial sensor measurements, there is no alternative than using a Kalman filter. Investigating the observability of the common parameters of a GNSS-INS extended Kalman filter (position, velocity, attitude, accelerometer and gyroscope offsets), the two main factors are the dynamics and the GNSS accuracy. The dynamics of an application define which states are observable and how good they are separable while the GNSS accuracy defines how good these states in general can be estimated. As a result, the accuracy and the precision of the GNSS solution have a big impact on the whole state vector but not only the position estimates. Within this paper, the influence of the GNSS solution on the state estimation shall be demonstrated by processing real measurements with a loosely-coupled extended Kalman filter.

This paper is structured as followed. Within section II, the different real-time GNSS techniques are shortly described, section III explains the principles of sensor integration, section IV shows exemplary results and section V concludes this paper.

II. GNSS ALGORITHMS

A. Single Point Positioning (SPP)

SPP (Single Point Positioning) is the standard method to determine the position by GNSS. It uses code measurements in combination with broadcast ephemeris and ionospheric parameters included in the navigation message of the satellites. SPP is the simplest, cheapest, and most popular method to determine a GNSS position in real-time with a limited accuracy

978-1-4673-7634-1/15/$31.00

of a few metres. The big advantage of this method is that it is implemented in every GNSS receiver and that the position determination can be done autonomously.

B. Differential GNSS (DGNSS)

Many GNSS receivers, even in the low-cost segment, support DGNSS position solutions. The most common DGNSS type is SBAS (Satellite-Based Augmentation Systems), e.g., EGNOS, WAAS, MSAS. The reason for this is because the user does not need a data link to a service provider since the geostationary satellites broadcast range corrections and range rate correction directly to the GNSS receiver. These signals provide an improvement of the SPP position accuracy but not an improvement of the precision since the same GNSS code measurements are used. The improvement in accuracy is due to the broadcasted range and range rate corrections and due to an improved ionosphere model. For instance, the company u-blox specifies the achievable accuracy of the horizontal SPP solution to be 2.5 metres, the accuracy including SBAS signals to be 2 metres (circular error probability CEP). The limitation using EGNOS in northern and central European countries is that geostationary satellites are not always visible. The visibility gets even worse for a mountainous environment like in Austria.

While SPP is realized in every GNSS receiver, and DGNSS is also quite often implemented, the following enhanced methods require receivers being capable of raw data output. Examples of low-cost receivers fulfilling this requirement are uBlox 6T, uBlox M8T, or NVS NV08C-CSM.

C. Real-Time Kinematics (RTK)

Many applications require very accurate positions which cannot be achieved by SPP. For this reason, the RTK (Real-Time Kinematics) algorithm was developed. RTK is based on simultaneous phase measurements of two GNSS receivers, usually a static base station with known coordinates and a kinematic rover. The position of the rover is determined relative to the known coordinates of the base station by computing differences between the measurements. As a result of this approach, many systematic errors (satellite orbit and clock errors, atmospheric delays, etc.) are cancelled or are at least reduced dramatically. Therefore, with RTK an accuracy of several centimetres can be achieved under good conditions.

The major disadvantage of RTK is the need of simultanous measurements of two receivers to the same satellites and a continuous communication link between base station and rover resulting in much bigger effort and much higher costs contrary to the SPP algorithm. RTK positioning can be done with a self-installed local base station or a regional RTK service provider. The communication can be realized as radio link (limited to a range of a few kilometers) or via GSM/GPRS.

Of course, there are companies which offer all-in-one RTK receivers, but they are usually very expensive (several thousand dollars each). One low-cost realization is the system Piksi by Swift Navigation which only costs 995$ for a set of two receivers. Nevertheless, it might be too expensive for some applications. As a result, one can use GNSS receivers with raw data output in combination with a real-time capable RTK software. There are commercial software suites as well as open source software like RTKLIB.

For applications where a continuous data link cannot be realized, the alternative technique called precise point positioning (PPP) may be suitable.

D. Precise Point Positioning (PPP)

Precise Point Positioning can be seen as an enhanced method to determine the position without the need for a base station. The idea is to use code and phase measurements on the one hand, and precise orbit and clock data as well as more precise ionospheric maps on the other hand. In addition, because PPP is no relative method, all error sources which cancel out using RTK, have to be modeled in the case of PPP. These error sources are instrumental delays, atmospheric effects, carrier phase wind-up effect, antenna phase center offset and variation and earth deformation effects.

With PPP, an accuracy of several decimeters or better can be achieved even in real-time applications. There are two ways to obtain the precise orbit and clock data in real-time, on the one hand, one can access real-time streams, or on the other hand one can download predicted precise products. Depending on the application, no continuous data link or even no data link at all is required. Comparing the real-time communication of RTK and PPP, in general, less data and less frequent data needs to be broadcasted.

For real-time PPP, there are a few processing centers worldwide which offer real-time streams for precise satellite orbit and clock data, e.g., IGS. These streams are accessed via NTRIP caster and are usually for free. There are also a lot of commercial PPP services like OmniSTAR, StarFire, and from manufacturers like Trimble, Fugro etc. The drawback of the commercial systems is that these providers usually only offer all-in-one solutions. This means that you can only use these commercial PPP services in combination with high-cost GNSS receivers from the same manufacturer.

For the PPP investigations shown within this paper, predicted precise orbit and clock files were utilized. In detail, so-called ultra-rapid PPP ephemeris in the sp3-format where used. These files are predicted four times a day and include 24 hours of predicted precise ephemeris data in 15 minutes intervals. Their accuracy decreases with the prediction time, hence, they should be downloaded directly before the start of the application to get the best possible PPP solution.

Very important for single-frequency PPP solutions is the availability of precise ionosphere information, since the ionospheric effect cannot be estimated like it is the case having multiple frequency signals (see [4]). Since the ionosphere has the biggest influence on the GNSS signals, the influence of this effect on the achieved accuracy is very big. With the broadcast information of GPS (Klobuchar parameters), the residual errors are far to big for high precision navigation. Precise ionosphere information can be obtained from, e.g., predicted VTEC (Vertical Total Electronic Content) maps in the ionex-format. These VTEC rasters are used to correct the ionospheric delays of the measured signals and are predicted for one, two, or five days in advance.

TABLE I. COMPARISON OF THE GNSS ALGORITHMS

	SPP	RTK	PPP
Real-time	Yes	Yes	Yes
Meas.	Code	Phase (+Code)	Code+Phase
Ephemeris	Broadcast	Broadcast	Precise
Add. effort	-	Base	File-download
Comm. Link	No	Yes	No
Accuracy	Metres	Centimetres	Decimetres

To account for the instrumental delays within the satellites, differential code biases (DCB) have to be applied. These biases are included, e.g., in dcb-files or in the ionex file. The DCBs describe the delays between measurements on different frequencies as well as between the code and the phase measurements. These dcb-files get updated regularly, e.g., once a month by CODE (Center for Orbit Determination in Europe).

For the correction of antenna offsets and variations, the antenna calibration parameters of satellite antennas as well as high-cost antennas are included in antenna correction files (in antex-format). Since the calibration process is quite extensive, no calibration data is available for low-cost antennas. The antex file is regularly updated for new satellites or receiver antennas.

All of these files needed for PPP can be downloaded for free, e.g., from the ftp-server of CODE before the start of the application and improve the quality of the determined positions for several hours, hence, they are suitable for a huge number of applications. To obtain the best results, real-time streams should be used instead, or the files should be updated as soon as new data is available.

Again, commercial and open source software suites are available. Open source alternatives are BNC from BKG (Bundesamt fuer Kartographie und Geodaesie) or RTKLIB, so no additional costs and just little additional effort is required in comparison to the SPP solution. Nevertheless, the accuracy is considerably increased by using PPP instead of SPP.

E. Comparison of the GNSS algorithms

Table I gives a short summary of this section. It outlines that all three algorithms are appropriate for real-time applications and all techniques can be performed having a raw data capable GNSS receiver in combination with open source software like RTKLIB.

The difference of the introduced approaches lies in the differently used signals and ephemeris as well as in the different additional effort with respect to SPP and the achievable accuracy.

III. SENSOR INTEGRATION

Contemporary applications requiring navigation information not only need position or maybe velocity information, very often also the orientation is required. On the other hand, when thinking about navigation applications, the reliability or at least the integrity is very important, because people tend to trust the results given by a navigation module. Further, the spatial availability of the navigation module should also be not limited in today's application, leading to the fact that one positioning sensor is rarely sufficient. In general, the system performance improves with the number of sensors used. Nevertheless, the right choice of sensors for a specific application is very important. To give an example, for RPAS with low dynamics, the use of the magnetometer heading measurement may be essential for a good heading information. On the other hand, the use of magnetometer measurement in surroundings with strong magnetic distortions degrades the system performance since the measurements include systematic effects. As a result, for some applications, magnetometers may only be used for the initialization of the heading at the beginning of navigation.

When thinking about outdoor applications, GNSS is the first choice. Although, GNSS performs very good, a lot of the afore mentioned requirements cannot be met. This is because shadowing effects, multipath effects, jamming, etc. can tremendously decrease the quality of the GNSS position solution or even make GNSS positioning impossible. In addition, a single GNSS receiver cannot deliver attitude information.

All the afore mentioned facts lead to the need for sensor integration. GNSS is commonly integrated with inertial sensors because of their complementary characteristics. While GNSS based positioning has a very good medium- to long-term accuracy, it shows larger short-term uncertainties and may be obstructed by signal interference. Even outages of GNSS can occur because of signal obstruction. On the other hand IMUs provide autonomous position solutions and hence, are independent of their surroundings. They have a good short-term accuracy but a weak medium- to long-term accuracy. When integrating GNSS and INS, the advantages of both sensors can be used to improve the overall accuracy. In addition, a GNSS/INS system is able to estimate the 3d orientation parameters, to bridge GNSS gaps, and to further reduce the noise of the estimated position and velocity parameters.

Within literature, a lot of approaches exist for sensor integration. These are extended Kalman filter, unscented Kalman filter, particle filter, and artificial intelligence approaches. The Kalman filter solution is the most common approach for sensor integration in navigation applications. The investigations presented within this paper are a result of a loosely-coupled extend Kalman filter solution similar to literature [1], [2], or [3]. Some theoretical and practical details important for the presented investigations will be described below.

A. Extended Kalman Filter

The error state vector has a dimension of 15x1 and contains position, velocity, attitude and IMU sensor offset parameters. Because of the error state space representation, not absolut parameters, but the residual errors in the parameters are estimated. Hence, δx is the error state comprising the position errors $\delta x_n, \delta x_e, \delta x_d$ in the north-east-down (NED) frame, the velocity errors $\delta v_n, \delta v_e, \delta v_d$ in the NED frame, the attitude errors $\delta r, \delta p, \delta y$, the gyroscope biases δb_g and the accelerometer biases δb_f.

$$\begin{aligned}\delta x = \{&\delta x_n, \delta x_e, \delta x_d, \delta v_n, \delta v_e, \delta v_d, \delta r, \delta p, \delta y, ...\\ &\delta b_{g,x}, \delta b_{g,y}, \delta b_{g,z}, \delta b_{f,x}, \delta b_{f,y}, \delta b_{f,z}\}^T\end{aligned} \tag{1}$$

Most of the time, the position parameters are expressed in ellipsoidic parameters. Within this work, the position is expressed in horizontal coordinates to improve the numerical stability, since otherwise the errors in latitude and longitude, and the errors in velocity are totally different in size (difference $\approx 10^{-7}$). To change the position representation, the system dynamic equations included in the Jacobian Matrix or system matrix F have to be adapted. The system was also designed to account for a different orientation of the sensor frame and the vehicle body frame. The relative orientation is modelled as additional direction cosine matrix and has to be included into the Jacobian Matrix and in the strapdown algorithms.

The F matrix in general looks like

$$F = \begin{bmatrix} F_{\dot{x},x} & F_{\dot{x},v} & F_{\dot{x},\epsilon} & F_{\dot{x},b_g} & F_{\dot{x},b_f} \\ F_{\dot{v},x} & F_{\dot{v},v} & F_{\dot{v},\epsilon} & F_{\dot{v},b_g} & F_{\dot{v},b_f} \\ F_{\dot{\epsilon},x} & F_{\dot{\epsilon},v} & F_{\dot{\epsilon},\epsilon} & F_{\dot{\epsilon},b_g} & F_{\dot{\epsilon},b_f} \\ F_{\dot{b}_g,x} & F_{\dot{b}_g,v} & F_{\dot{b}_g,\epsilon} & F_{\dot{b}_g,b_g} & F_{\dot{b}_g,b_f} \\ F_{\dot{b}_f,x} & F_{\dot{b}_f,v} & F_{\dot{b}_f,\epsilon} & F_{\dot{b}_f,b_g} & F_{\dot{b}_f,b_f} \end{bmatrix} \tag{2}$$

The changes of the position representation have influence on all partial derivatives where the position is included. For example, the derivative of the position with respect to the velocity simplifies to

$$F_{\dot{x},v} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{3}$$

The additional orientation between sensor and vehicle body frame R_s^b has influence on the bias estimation. Hence $F_{\dot{v},b_f}$ and $F_{\dot{\epsilon},b_g}$ have to be extended (R_b^l ... direction cosine matrix between body and local-level frame):

$$F_{\dot{\epsilon},b_g} = -F_{\dot{v},b_f} = R_b^l \cdot R_s^b \tag{4}$$

When changing from continuous to discrete Kalman filter, the transition matrix Φ has to be computed from the system matrix. Since F is only known at discrete points in time, approximations have to be made for calculation. One common approximation is that over a short time interval τ_s, F is constant, leading to

$$\Phi_{k-1} \approx \exp(F_{k-1} \cdot \tau_s) \tag{5}$$

Φ is usually calculated by power-series expansion of F. Very often one can read in literature that the truncation after the linear term is allowed. In general, this is dependent on the magnitude of the states, the length of the propagation interval and the available error margins ([5]). The authors made the experience that for $\tau_s = 0.01s$ and RTK position accuracy, the calculation differences between truncation after the linear term and the cubic term can be in the range of the RTK noise (a few cm). Therefore it is very important to find the optimal choice depending on the individual factors.

To further reduce numerical issues within Kalman filtering, the authors also chose the Joseph form for covariance matrix propagation. This form avoids divergence problems by assuring the positive semi-definiteness of the covariance matrix (see [2]).

B. Observability

Because of the numerous publications on GNSS-INS with extended Kalman filter, a lot of people do not care about the observability of the parameters. There are a lot of assumptions that are made to get the full observability of the parameters. One assumption is that the errors are small to be allowed to make simplicifications. Another impact factor on the observability is that one has to perform several maneuvers to decorrelate specific parameters like accelerometer bias and misalignment. In addition, the quality of the observability depends on the quality of the measurements. This fact is described in [5]. If the navigation accuracy is significantly influenced by a systematic IMU error, then the error/bias will be observable. In contrast, if the error effect is much smaller than the random noise, it will not be observable. As a result, in theory, with an RTK or PPP solution rather than an SPP GNSS solution, the IMU errors should be better observable. For example, if one only has a very bad GNSS solution, the accelerometer biases cannot be estimated correctly.

In section IV, results from a test drive of a car driving on the road is shown. Looking in detail at the error equation of the heading angle, the heading error is only observable when horizontal accelerations occur. When driving along roads, accelerations mainly occur due to direction changes. When driving along straight roads, the heading error is not observable. Driving along long straight highways, this could get critical. To solve this problem, one can use GNSS heading observations. Furthermore, the error model assumes small attitude errors which especially in the heading angle cannot be guaranteed using low-cost MEMS inertial sensors. As a result, the estimation of the heading angle only with the dynamic error model does not work satisfactory. Again, the GNSS heading observations help to overcome this problem.

The intention of this paper was to improve the overall system accuracy by improving the GNSS solution. As already explained, one can expect that position and velocity errors should get smaller. In addtion, the sensor biases should become better observable, but it is hard to verify the estimation results. Attitude errors may also be better estimated. The critical fact about improving the GNSS accuracy is that it is difficult to know if the accurcy is in fact better. Let's assume, there is a sudden systematic error in the RTK solution which is not detected by outlier detection and no indication is seen from the redundancy of the GNSS solution. As a result, a much lower measurement noise of the introduced position is assumed. If now the sudden jump of let's say only 4 to 5 decimeters occurs, and the outlier detection algorithm does not find the outlier, it will have a much larger impact on the velocity and attitude estimates because of the higher weight and trust of the GNSS solution.

Within the next section, the measurement data is presented and investigations are done to show exemplary results to get an idea, how much impact better GNSS measurements have on the integrated solution. The investigations are done with a car on the road. Some of the presented results can be transferred to other applications like indoor, aviation or marine applications, others cannot.

Fig. 1. Trajectory in the south of Graz (©Google Earth)

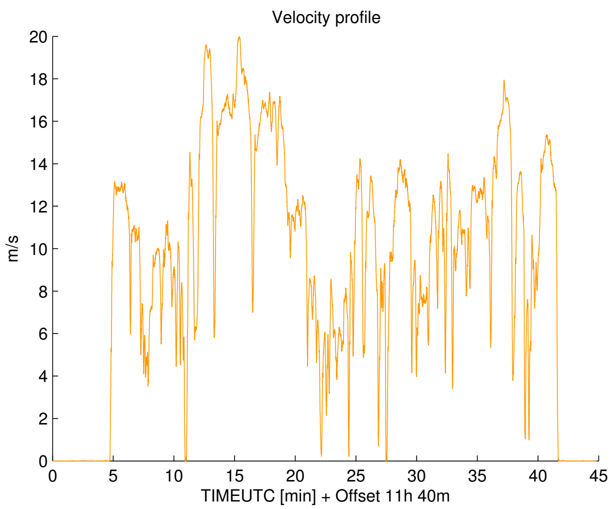

Fig. 2. Velocity profile of the trajectory

IV. Results

A. Data

The results refer to a test drive with a car in the south of Graz (see Fig.1). The velocity profile (see Fig.2) shows phases with no velocity at the beginning and the end of the trajectory (used for Zero Velocity Updates) and a maximum velocity of about 20m/s (about 70km/h). Driving with a car makes it quite easy to verify the achieved results by carrying additional high-accurate sensors. Three different types of GPS solutions were produced for this paper. First of all, a simple SPP solution, furthermore a PPP solution and an RTK solution.

In addition, a high-accurate reference solution was computed in post-processing by integrating a high-precision IMU (Inertial Measurement Unit) including ring-laser gyroscopes (iMAR iNav RQH) with a geodetic dual-frequency GPS/GLONASS receiver (Javad Sigma TRE-G3TH). A tightly-coupled integration (see [6]) was carried out with the commercial software Inertial Explorer to achieve a reference trajectory of centimetre accuracy.

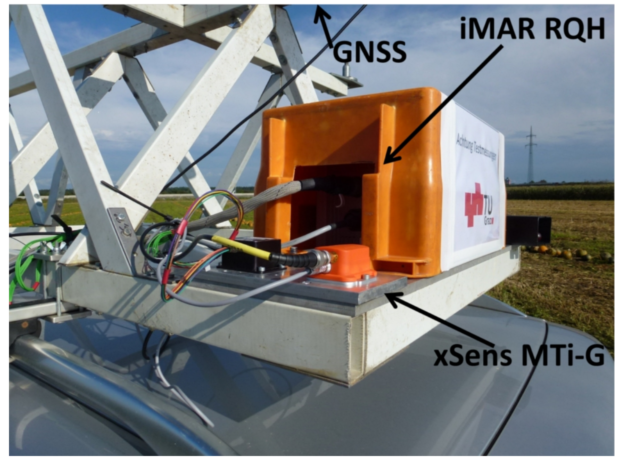

Fig. 3. Arrangement of the sensors

As input for the self-implemented sensor integration, GNSS measurements were collected from a low-cost single-frequency GPS receiver (u-blox 6T). Different types of solutions (SPP, PPP and RTK) were performed by the open source software RTKLIB ([7]) in post-processing. The GPS velocity and heading of all three types of solutions are strongly influenced by range rate measurements, hence the accuracies of these parameters are very similar. For the RTK solution, an own static base station (Novatel DLV-3, short baseline < 5 [km]) was used.

For generating an integrated solution using low-cost equipment, the raw inertial measurements of a MEMS inertial system (MTi-G by xSens) were used in addition to the mentioned GPS-only solutions (u-blox 6T). The different signals were combined within a self-implemented loosely-coupled extended Kalman filter algorithm, described in section III.

The arrangement of the different sensors on the car is shown in Fig.3, where a low-cost AeroAntenna AT575-142 antenna has collected the GPS signals for the u-blox receiver.

B. GPS Solutions

Fig.4 and 5 show the coordinate differences of the GPS-only solutions with respect to the reference solution. This is needed to understand the result presented in section IV-C. Tables II and III show the corresponding statistical values. On the one hand, the median of the deviations with respect to the reference solution is shown, on the other hand, the empirical standard deviation is shown. In this case, the median describes a systematic offset of the solution. The empirical standard deviation, otherwise, represents the noise (random errors). From the results, one can see that the GNSS conditions during the test drive were not perfect with some narrow streets with buildings next to it, especially in the south-west (see Fig.1).

The SPP result has a large systematic error of 2.8 meters which can be seen in the median value (see Table II). This is mainly caused by the ionosphere which was proofed by

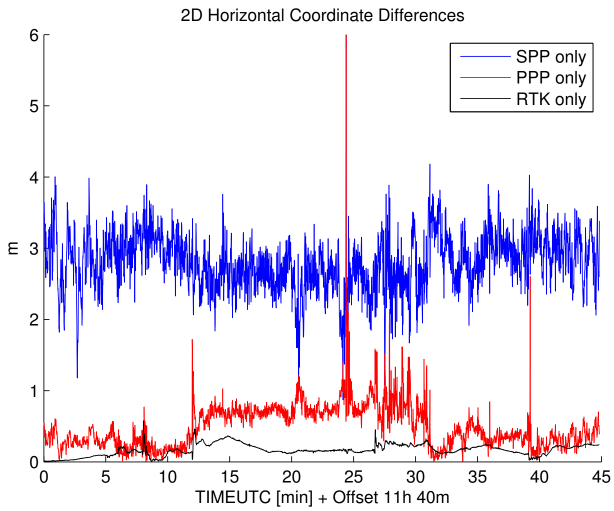

Fig. 4. Comparison of the errors in the horizontal GNSS coordinates

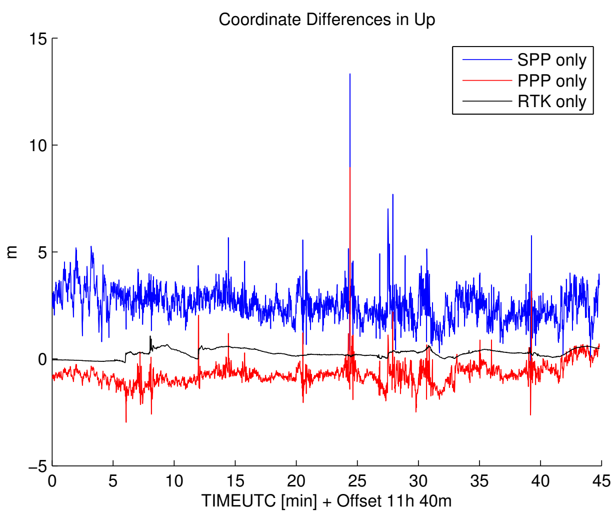

Fig. 5. Comparison of the errors in the GNSS heights

TABLE II. STATISTICAL RESULTS OF THE HORIZONTAL GNSS COORDINATES

	Median [m]	emp. Std. [m]
SPP	2.805	0.407
PPP	0.434	0.328
RTK	0.158	0.080

TABLE III. STATISTICAL RESULTS OF THE GNSS HEIGHTS

	Median [m]	emp. Std. [m]
SPP	2.522	0.782
PPP	-0.759	0.515
RTK	0.250	0.196

introducing a IONEX ionosphere model. This IONEX model was also used for the PPP solution which leads to a significant improvement of the absolute position accuracy. Looking at the empirical standard deviation (see Table II), the PPP solution brings only a slight improvement compared to SPP. This comes from the residual systematic errors in the PPP solution in the time span between minute 15 and 30 which adulterates the empirical standard deviation. Actually, the noise amplitude is at least half of the noise level of the SPP solution (see Fig.4). The reduced noise level is a result of using the more precise phase measurements. The RTK solution further improves the accuracy and precision with respect to the PPP solution. With RTK, an empirical standard deviation of about 16 centimetres for the horizontal and 24 centimetres for the vertical position could be achieved for the presented test drive (see Table II and III). For the RTK solution, a float solution was chosen, because the measurements from the low-cost equipment influenced by the reception conditions were not good enough for a continuous fixed solution. As a result, very frequent jumps between float and fixed solution occured which would later on significantly influence the integrated solution in a negative way. The improvements in height are in a similar way (see III).

C. Sensor Integration

This section analyses the influence of the quality of the different GNSS solutions on the integrated solutions. In general, if RTK processing is chosen, it is not guaranteed that the RTK accuracy is achieved over the full time span. There will be regions, where GNSS observations will be obstructed and the more sensitive GNSS phase measurements are corrupted. Hence, for both PPP and RTK, in the worst case the position solution falls back to an SPP solution and the estimation of the ambiguities has to be restarted. Depending on the satellite constellation and the number of satellites for which the ambiguities have to be reestimated, the decreased position quality will remain for a shorter or longer period of time.

Repeating the goal of this paper, the authors want to show the effect of a better estimation result of all parameters from simply improving the GNSS position accuracy and precision. As soon as the position quality is improved, also the state estimation will be improved. On the other hand, as soon as the quality gets worse, also the state estimation suffers. This fact has to be kept in mind, when analyzing the results presented later. For the state estimation, the even most critical time is the change from a good solution to a bad solution or vice versa which usually leads to a sudden jump in the position estimates. These sudden jumps lead to the estimation of wrong velocities (in the case of the error state KF, this means wrong velocity errors) which further introduces effects in the attitude estimation, etc. To avoid this effect, a GNSS RTK float solution was chosen instead of a fixed solution, because usually when an RTK fix is gained or lost, one can observe a jump in the coordinates in the size of 1-2 decimeters.

From Fig.6, the advantages using additional sensors with a Kalman filter compared to the GNSS-only solutions can be summarized:

- It enables the estimation of 3d attitude parameters.
- It smoothes the result, which improves the precision of the velocity and position information and allows to detect outliers.

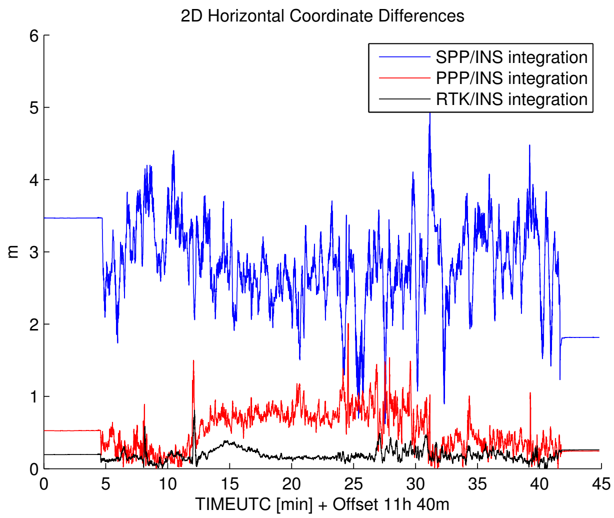

Fig. 6. Comparison of the errors in the horizontal coordinates using sensor integration

TABLE IV. STATISTICAL RESULTS OF INTEGRATED SOLUTION

	SPP/INS		PPP/INS		RTK/INS	
	Median	emp. Std.	Median	emp. Std.	Median	emp. Std.
2D-Pos [m]	2.846	0.612	0.525	0.270	0.181	0.077
Height [m]	2.599	1.066	-0.813	0.455	0.252	0.250
Vel [m/s]	0.006	0.137	0.004	0.059	0.004	0.035
Pitch [°]	-0.129	0.147	-0.046	0.105	-0.037	0.082
Heading [°]	0.116	0.340	0.017	0.267	0.008	0.271

- It usually enables a higher update rate of all parameters (because of the generally higher update rate of an IMU compared to GNSS).
- It helps to overcome data gaps during GNSS outages, which tremendously improves the reliability of the result.

The errors in the magnitude of the velocity are shown in Fig.7. The more accurate RTK solution leads to a significant improvement of the velocity estimates. This is caused by the strong correlation between position errors and velocity errors in the system dynamics matrix of the Kalman filter (see section III). In numbers, a decrease in the standard deviation of 57% for PPP and 75% for RTK could be achieved. In addition, the maximum error peaks could be significantly decreased (see Fig.7).

Fig.8 and 9 show the attitude errors of the Euler angles, pitch and heading, of the different integrated solutions with respect to the reference solution. The pitch angle cannot be calculated using a GNSS sensor exclusively, but the accuracy of pitch can be improved by reducing the errors and the noise of the GNSS solution. This is because of the correlation between the pitch angle and the forward velocity. As a result, the more accurate forward velocity when using RTK instead of SPP automatically leads to a more accurate and precise pitch angle. The accuracy of the heading cannot be improved very much, because it is mainly influenced by the GNSS course over ground which

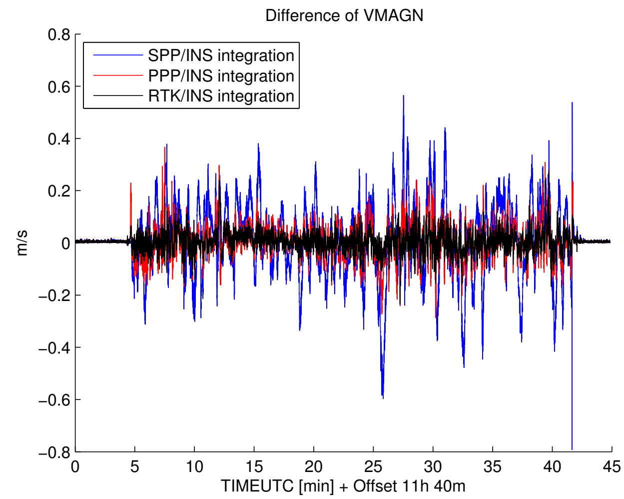

Fig. 7. Errors of the integrated velocity

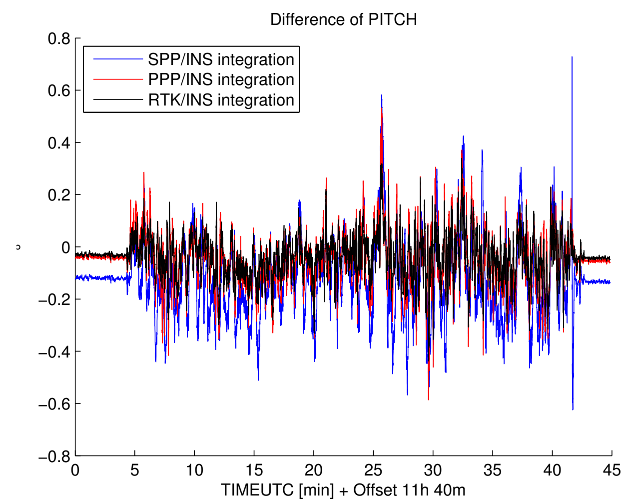

Fig. 8. Errors of the integrated pitch angle

is used to support the INS heading. The GNSS course over ground, however, is in the same order of magnitude for SPP, PPP and RTK, because it is almost exclusively calculated using range rate measurements. In numbers, an improvement of the standard deviation of 28% for pitch and 22% for the heading angle could be achieved with the PPP solution. For the RTK solution, an improvement of the standard deviation of 44% for pitch and 20% for the heading angle could be achieved. In addition, in Fig.8, the offset of the SPP solution is due to a residual sensor bias in the forward accelerometer which could not be estimated with the same quality as the PPP and RTK solution.

The improvements of the roll angle are in the same order of magnitude than the pitch angle. Even though, the roll angle is not as good determinable caused by the lower signal level in the lateral components of the car.

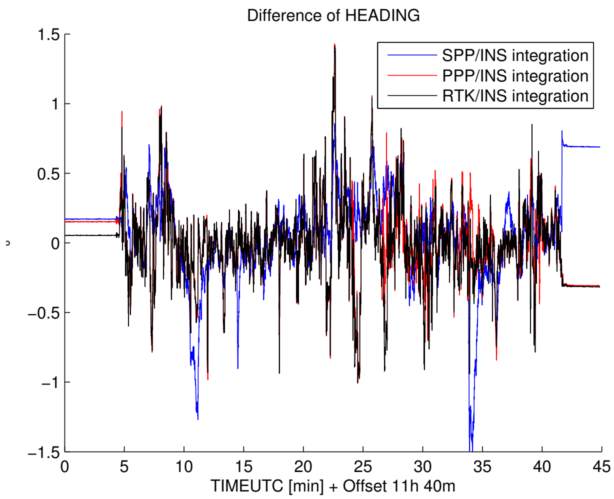

Fig. 9. Errors of the integrated heading angle

V. CONCLUSION

Within this paper, results from a loosely-coupled GNSS-INS error state Kalman filter were shown. The main focus was to investigate the influence of the position accuracy and precision on the quality of the integrated solution. The investigations were done using intentionally medium-quality measurements from a low-cost uBlox 6T GPS receiver and a MEMS IMU. Therefore, three different types of GPS solutions were calculated, namely a simple SPP solution, a PPP solution, and an RTK solution.

The results show that a PPP solution could decrease the standard deviation (std) of the velocity by 57%, the std of the pitch angle by 28%, and the std of the heading angle by 22%. The results can even further be improved by RTK leading to a decrease in the std of the velocity by 75%, the std of the pitch angle by 44%, and the std of the heading angle by 20%.

As long as the improved position quality is guaranteed, the accuracy of the parameter estimates is improved. As soon as the position quality falls back to SPP, the benefits are gone. Even more critical are undetected blunders when assuming a higher position precision because the GNSS weight is higher leading to larger estimation errors in all parameters.

ACKNOWLEDGMENT

Financial support for this project comes from the Federal Ministry for Transport, Innovation and Technology (BMVIT), represented by the Austrian Research Promotion Agency (FFG). This work was done in the scope of the project OMOSA (FFG programme TAKE OFF).

The project consortium consists of the Graz University of Technology (Institute of Geodesy, Working Group Navigation), the FH JOANNEUM (Institute of Aviation) and the companies PIDSO Propagation Ideas & Solutions GmbH and Aerodyne Systems GmbH.

REFERENCES

[1] J. Wendel, *Integrierte Navigationssysteme - Sensordatenfusion, GPS und Inertiale Navigation*, 2nd ed. München: Oldenbourg Verlag, 2011.

[2] A. Noureldin, T. B. Karamat and J. Georgy, *Fundamentals of Inertial Navigation, Satellite-based Positioning and their Integration* Berlin: Springer Verlag, 2013.

[3] E.-H. Shin, *Accuracy Improvement of Low-Cost INS/GPS for Land Applications* University of Calgary: Department of Geomatics Engineering, 2001.

[4] B. Hofmann-Wellenhof, H. Lichtenegger and E. Wasle, *GNSS - Global Navigation Satellite Systems: GPS, GLONASS, Galileo and more* Wien: Springer Verlag, 2008.

[5] P. Groves, *Principles of GNSS, Inertial, And Multisensor Integrated Navigation Systems* Boston/London: Artech House, 2008.

[6] B. Hofmann-Wellenhof, K. Legat and M. Wieser, *Navigation: Principles of Positioning and Guidance* Wien: Springer-Verlag, 2003.

[7] T. Takasu, *RTKLIB: Open Source Program Package for RTK-GPS* FOSS4G 2009 Tokyo, Japan, November 2, 2009.