AN EFFICIENT APPROACH TO GPS/INS INTEGRITY MONITORING

J. Wendel*, J. Dambeck*, G. Herbold*, S. Kiesel**, O. Meister**, R. Mönikes**

*MBDA Germany
Landshuter Str. 26, 85716 Unterschleißheim
Germany

** Institute of Theory and Systems Optimization in Electrical Engineering
University of Karlsruhe, Kaiserstr. 12, 76128 Karlsruhe
Germany

OVERVIEW

Receiver autonomous integrity monitoring (RAIM) methods are widely used in GPS/INS systems in order to provide integrity for the navigation information. In order to identify and exclude a single faulty pseudorange measurement, snapshot RAIM algorithms require at least six satellites in view. While RAIM is a reasonable and proven solution for a stand-alone GPS receiver, it is obvious that in the case of a GPS/INS system, RAIM is a sub-optimal approach, as it does not use the information provided by the INS.

One possibility to use the INS information for integrity monitoring purposes is an Interacting Multiple Model (IMM) filter bank, where each elemental filter assumes the pseudorange measurements belonging to one specific satellite to be disturbed. If the pseudorange measurements from one specific satellite are disturbed, the corresponding elemental filter will achieve a high probability, while the probabilities of the other filters processing the disturbed measurement as healthy decay towards zero. The major drawback of this approach is the computational load produced by the filter bank.

In the new integrity monitoring approach proposed in this paper, the IMM filter bank is replaced by a Generalized Pseudo-Bayesian 1 (GPB1) filter bank. After the measurements processing, an IMM initializes each elemental filter for the following propagation step differently. In opposite to that, the GPB1 elemental filters are all initialized with the best estimate, which is obtained from the blending of the filter solutions taking into account their probabilities. In the special case considered here, the system models of all elemental filters are identical. Therefore due to the identical initialization, the propagation step of each elemental filter produces the same result. This allows to use one single filter in the propagation step instead of propagating state and covariance of each elemental filter separately, thereby reducing the computational load dramatically, allowing for a real-time implementation of the proposed algorithm.

Numerical simulations illustrate that the performance of this new integrity monitoring approach is similar to the IMM-based integrity monitoring. Additionally, a reliable identification of faulty pseudorange measurements is possible with only five satellites in view, where the RAIM methods can only detect, but not identify, a fault.

1. INTRODUCTION

The integrity of the navigation information provided by a GPS/INS system is of paramount importance. This is especially true if the system operates in an environment where deliberate spoofing is very likely. Therefore, integrity monitoring algorithms are commonly used in GPS/INS systems. The receiver autonomous integrity monitoring (RAIM) algorithms test the consistency of the GPS pseudorange measurements without using further information. A wide variety of RAIM methods can be found in literature. One approach is to analyze the pseudorange residuals. Hereby, all pseudorange measurements of the current epoch are used to calculate an estimate of the user position and the receiver clock error. Based on this estimate, theoretical pseudoranges are calculated and subtracted from the actual pseudorange measurements. If the length of the resulting error vector exceeds a certain threshold, a fault is detected. The disturbed pseudorange is identified by comparing the magnitudes of the error vector components. Instead of working with a snapshot solution, the pseudoranges can also be processed in an extended Kalman filter (EKF) to obtain the residuals, see e.g. [3]. Another popular integrity monitoring approach is the parity space method, which is in principle equivalent to the approach described above, see [1]. Modifications of popular RAIM schemes to handle multi-frequency receivers and the combination of GPS and Galileo satellites are described in [9] and [12], respectively. A statistical analysis of different RAIM schemes with and without pre-filtering is given in [5]. All these algorithms have in common that a single fault can be detected with five satellites in view, while the identification and exclusion of a faulty satellite requires at least six satellites in view. However, a false identification leads to the removal of a healthy satellite, thereby destroying useful information while the faulty satellite is still used. Furthermore, when the GPS receiver is integrated with an inertial navigation system (INS), these algorithms do not use the information provided by the INS for integrity monitoring purposes.

The easiest way in a GPS/INS system to benefit from the INS for integrity monitoring purposes is to analyze the innovation that would result if the currently available pseudoranges were processed in the navigation filter. If a component of the innovation vector exceeds a certain limit, the corresponding pseudorange measurement is rejected, otherwise the pseudorange is used to update the filter state estimate. Obviously, this approach, e.g. described in [8], has a close connection to the pseudorange residual RAIM scheme. Although this approach is simple and effective, false identifications cause useful information to be destroyed while corrupt measurements are used in the solution.

Therefore, filtering approaches have been developed which try to estimate the disturbance corrupting the measurements from a specific satellite. This allows to use all information available and avoids the explicit exclusion of satellites. For jamming disturbances, an example of this strategy can be found in [2], where an IMM filter bank consisting of three filters was used, assuming three different levels of measurement noise. In [11], an integrity monitoring approach based on Multiple Model Adaptive Estimation (MMAE) filter banks is described. One MMAE filter bank is used to detect and isolate interference and jamming failures, where the filters differ by the assumed measurement noise covariance like in [2]. A second MMAE filter bank is used to handle spoofing. However, spoofing was modelled as a bias or a ramp added to all pseudorange measurements. It was already recognized in [7] that this is equivalent to a change in the receiver clock error, which can be taken into account without using a filter bank. The use of an IMM filter bank in order to estimate a spoofing disturbance was first described in [6] for a stand-alone receiver and later extended to GPS/INS systems in [7]. In this approach, a bank of filters is running in parallel, where the number of filters equals the number of visible satellites. Each elemental filter assumes a different satellite to be faulty and estimates the corresponding measurement bias. If a spoofing disturbance occurs, the elemental filter which correctly assumes the affected pseudorange to be biased will get a high probability, while the probabilities of the other filters processing the disturbed measurement as healthy decay towards zero. This approach provides an optimal state estimate in the presence of the spoofing disturbance and identifies this disturbance with five satellites in view, where RAIM methods fail to identify the fault. The drawback of this IMM-based integrity monitoring approach is the tremendous increase in computational cost caused by the bank of GPS/INS filters running in parallel.

The new integrity monitoring approach proposed in this paper is closely related to the IMM-based integrity monitoring described in [7]. However, instead of an IMM filter bank, a Generalized Pseudo-Bayesian 1 (GPB1) filter bank is used. The difference between an IMM and a GPB1 is the mixing step, which takes place after all measurements of the current epoch have been processed. While in the mixing step the IMM initializes all elemental filters differently for the following propagation step, the GPB1 initializes all elemental filters with the best estimate, i.e. identically. Now all elemental filters are GPS/INS navigation filters augmented by one state for the estimation of the spoofing disturbance. Although each filter assumes a different satellite to be faulty, the system dynamics matrices of these filters are the same. As the GPS1 initializes all filters identically, the propagation steps of all elemental filters will give identical results. Therefore it is possible to run just one filter for the propagation step, which initializes the covariance matrices and state estimates of the other filters in the filter bank after the propagation step is completed. In GPS/INS integration, by far the most computational cost is spent in the filter propagation step, while the measurement step requires significantly less computations. By running only a single filter for the propagation steps, the new integrity monitoring algorithm presented in this paper offers a dramatically reduced computational burden compared to the IMM-approach, while the advantages of IMM-based integrity monitoring – identification of single faults with only five satellites in view and no removal of healthy satellites due to false identifications – are preserved. In opposite to the IMM-based approach, the reasonable computational complexity supports a real-time implementation of the new algorithm.

The next section gives a brief description of tightly coupled GPS/INS integration, as the elemental filters forming the GPB1 filter bank are essentially tightly coupled GPS/INS navigation filters. Next, the IMM-based integrity monitoring is described, while in Section Four, the new approach using a GPB1 filter bank is presented. In Section Five, numerical simulations illustrate the impressive performance of the algorithm in two different spoofing scenarios and compare it with the IMM-based integrity monitoring and a hypothetical RAIM method. Finally, conclusions are drawn.

2. TIGHTLY COUPLED GPS/INS INTEGRATION

In a tightly coupled GPS/INS system, GPS pseudorange measurements are used to aid the INS and to continuously calibrate the inertial measurement unit (IMU). The advantage of a tight integration is that with less than four satellites in view, an aiding of the INS is still possible. With less than four satellites, the GPS receiver cannot provide a position fix, and therefore in a loosely coupled system which processes GPS position measurements, the INS cannot be aided anymore and the information contained in the pseudorange measurements to the remaining one, two or three satellites is ignored, which is clearly sub-optimal.

The relation between a pseudorange measurement $\tilde{\rho}_i$ to satellite i and the GPS antenna position $\mathbf{x}_A$ is given by

$$(1)\quad \tilde{\rho}_i = \sqrt{\left(\mathbf{x}_{S,i} - \mathbf{x}_A\right)^T \left(\mathbf{x}_{S,i} - \mathbf{x}_A\right)} + c\Delta t \ ,$$

where $\mathbf{x}_{S,i}$ denotes the position of the i-th satellite, and $c\Delta t$ denotes the receiver clock error in meters. For some applications, the leverarm between the IMU and the GPS antenna can be neglected. In this case, the pseudorange measurement model for the navigation filter design is given by Eq. (1), otherwise Eq. (1) has to be modified appropriately. Obviously, the relationship between a pseudorange measurement and the user position is nonlinear, so an EKF has to be used. Typically, an error state space formulation is chosen, where the filter estimates the errors of the INS navigation solution, the IMU biases, and the receiver clock error. Therefore, the filter state vector comprises at least 17 components: three position, velocity and attitude errors, six inertial sensor bias errors, and two states for the receiver clock error. After the pseudorange measurements of the current epoch have been processed, the estimated errors are used to correct the total quantities, i.e. the INS navigation solution, the IMU biases and the receiver clock error. Then, the filter state vector is set to zero. For the propagation step, a system model is required which describes the dynamical behaviour of the filter state vector components. The derivation of this system model, which is used for the propagation of the filter covariance matrix only, is beyond the scope of this paper and can be found in [10]. As the estimated errors contained in the filter state vector are set to zero after the total quantities have been corrected, a propagation of the filter state is not necessary. However, the total quantities have to be propagated. Position, velocity and the attitude quaternion are propagated using a strapdown algorithm. The receiver clock error is propagated using a suitable second order model. The inertial sensor biases are usually modelled as random walk, 1st order Gauss-Markov process or random constant and propagate according to the respective model, too.

The GPS/INS navigation filter outlined briefly in this section forms the core of the elemental filters used in the IMM and GPB1 filter banks.

3. IMM-BASED INTEGRITY MONITORING

For the elemental filters used in the IMM and GPB1 filter bank, the filter state vector described in the previous section is augmented by one additional state for the estimation of a spoofing disturbance, which was modelled as a random walk. It was assumed that the spoofing disturbance is present in only one pseudorange measurement at a time, and each elemental filter assumes a different pseudorange to be corrupted. Therefore, the number of filters in the filter bank equals the number of visible satellites. The pseudoranges which are assumed to be healthy are processed as usual, while for the processing of the pseudorange which the elemental filter assumes to be corrupt, the measurement model Eq. (1) is augmented with the spoofing disturbance. It is important to recognize that in the filter system model, the spoofing disturbance is decoupled from all other states. The observability of this state is established via the measurement processing of the spoofed pseudorange only. Therefore, although each elemental filter assumes a different pseudorange to be spoofed, the system models are identical.

In the following, the IMM approach is outlined in general. Due to the nonlinearity of the system- and measurement models in GPS/INS integration, error state space Kalman filters are used. The following IMM description is easily extended to this case.

An IMM estimates the state $\mathbf{x}_k$ of a system

(2) $$\mathbf{x}_k = \mathbf{\Phi}_k(s_k)\mathbf{x}_{k-1} + \mathbf{G}_k(s_k)\mathbf{w}_k ,$$

where $\mathbf{\Phi}_k$ is the state transition matrix, $\mathbf{w}_k$ is zero-mean, white, Gaussian noise, and $\mathbf{G}_k$ is a mapping matrix. The available measurements $\tilde{\mathbf{y}}_k$ are related to the system state via

(3) $$\tilde{\mathbf{y}}_k = \mathbf{H}_k(s_k)\mathbf{x}_k + \mathbf{C}_k(s_k)\mathbf{v}_k ,$$

where $\mathbf{H}_k$ is the measurement matrix, $\mathbf{v}_k$ is zero-mean, white, gaussian noise, and $\mathbf{C}_k$ is again a mapping matrix. The matrices occurring in these models are formulated as functions of a parameter s_k, which is a Markov chain that can take values between 1 and m. The Markov chain is described by a transition probability matrix $\mathbf{M}$, where the element M_{ij} defines the probability that the state of the Markov chain changes from $s_{i,k-1}$ to $s_{j,k}$. This Markov chain can be seen as a switch that switches between different transition matrices, measurement matrices and mapping matrices, thereby influencing the system's behaviour. An optimal estimation algorithm would yield the conditional expectation

(4) $$E[\mathbf{x}_k | \mathbf{Y}_k] = \sum_{q=1}^{m^k} E[\mathbf{x}_k | S_q, \mathbf{Y}_k] \cdot P(S_q | \mathbf{Y}_k)$$

with $\mathbf{Y}_k = \tilde{\mathbf{y}}_k, \tilde{\mathbf{y}}_{k-1}, \ldots, \tilde{\mathbf{y}}_0$. S_q denotes the q-th sequence of m^k possible sequences of Markov chain states, and $P(S_q | \mathbf{Y}_k)$ is the probability that the q-th sequence is the correct one. Obviously, the number of possible sequences grows exponentially with time, therefore it is not possible to implement a filter that considers all possible sequences for all times. The basic idea of an IMM is to approximate Eq. (4) with

(5) $$E[\mathbf{x}_k | \mathbf{Y}_k] = \sum_{j=1}^{m} E[\mathbf{x}_k | s_k = j, \mathbf{Y}_k] \cdot P(s_k = j | \mathbf{Y}_k).$$

This requires to run m elemental filters in parallel, where each elemental filter is optimal for a certain state s_k, i.e. when the system and measurement model of that filter equal the models of Eq. (2) and Eq.(3) .

The IMM equations can be easily found in the literature, e.g. [4]. A detailed derivation of the IMM equations is given in [10]. Instead of repeating these equations here, a discussion of the principle procedure is more appropriate. An IMM sequence can be divided into three parts: After the measurements have been processed in the estimation step of each elemental filter at epoch k, the filters contain the a posteriori estimates $\hat{\mathbf{x}}_{i,k}^{+}$. The estimation step is followed by the mixing, where each elemental filter

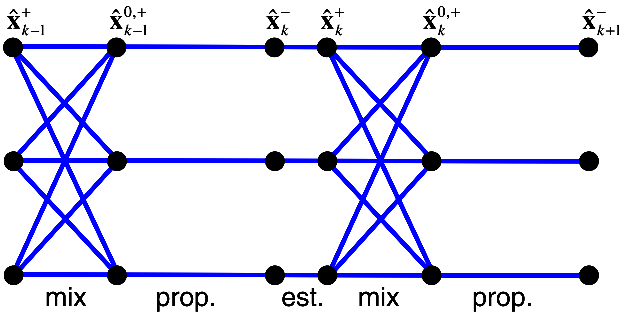

FIG 1. Propagation, estimation and mixing in an IMM containing three elemental filters.

is reinitialized with a new state estimate $\hat{\mathbf{x}}_{i,k}^{0,+}$ and a new covariance matrix $\mathbf{P}_{i,k}^{0,+}$, which are calculated from conditional model probabilities, state estimates and covariance matrices of all elemental filters. It is important to notice that in general, all filters are initialized differently. Therefore, in the following propagation step which completes the IMM sequence, each elemental filter has to be propagated separately. The IMM sequence is illustrated in Fig. 1 for the case of three elemental filters.

The IMM-based integrity monitoring is realized by using the IMM formalism with the elemental filters described above, where each filter assumes one specific satellite to be disturbed. This idea could be extended to handle multiple simultaneous faults by augmenting each filter with multiple states for the estimation of the spoofing disturbances. For single faults the number of filters equals the number of visible satellites. In order to handle n simultaneous faults with m satellites in view, the number of required filters is the number of possible combinations without repetitions, which is given by the binomial coefficient

(6) $$\binom{m}{n} = \frac{m!}{n!(m-n)!}.$$

For example, detection and identification of two simultaneous faults requires fifteen filters when six satellites are in view and twenty-one filters when seven satellites are in view, which is a considerable increase in computational load compared to the single fault case.

However, even assuming only one spoofed pseudorange at a time, the computational load of the IMM-based integrity monitoring is significant.

4. GPB1-BASED INTEGRITY MONITORING

The GPB1 sequence is illustrated in Fig. 2. The only difference between an IMM filter bank and a GPB1 filter bank is the mixing step. The GPB1 initializes all elemental filters identically with the best estimate $\mathbf{x}_k^{0,+}$ and the corresponding covariance matrix $\mathbf{P}_k^{0,+}$ provided by the filter bank, which are calculated according to

(7) $$\hat{\mathbf{x}}_k^{0,+} = \sum_{i=1}^{m} \mu_k^i \hat{\mathbf{x}}_{i,k}^{+}$$

(8) $$\mathbf{P}_k^{0,+} = \sum_{i=1}^{m} \mu_k^i \left(\mathbf{P}_{i,k}^{+} + \left(\hat{\mathbf{x}}_{i,k}^{+} - \hat{\mathbf{x}}_k^{0,+} \right) \left(\hat{\mathbf{x}}_{i,k}^{+} - \hat{\mathbf{x}}_k^{0,+} \right)^T \right).$$

It has to be noted that for m elemental filters, the mixing step of the IMM requires roughly m-times the number of calculations required for the GPB1 mixing step. Nevertheless in general, the system models of the elemental filters are different, so that like for the IMM, each elemental filter has to be propagated separately. As stated in the introduction, the most computational cost produced by a GPS/INS navigation filter is spent in the propagation step. The reason for this is that the covariance matrix of the filter has to be propagated with a reasonable update rate, because the transition matrix

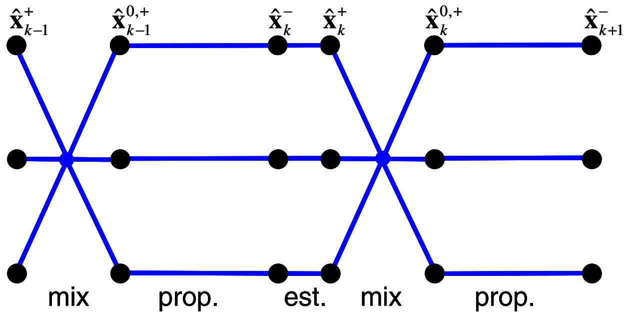

FIG 2. Propagation, estimation and mixing in a GPB1 containing three elemental filters.

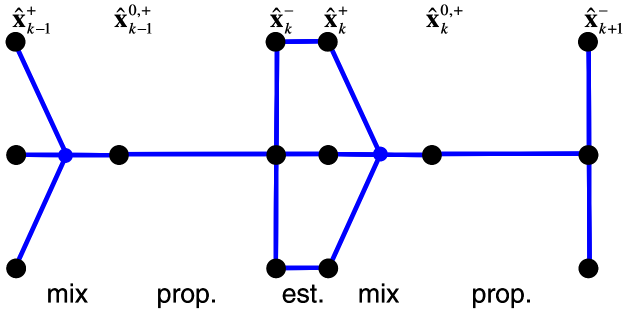

FIG 3. Propagation, estimation and mixing in a modified three filter GPB1, optimized for the case of identical system models.

contains time-varying quantities like the current acceleration and the current direction cosine matrix. This means that usually, several propagation steps are performed, e.g. every 50 or 100ms, before one measurement step takes place, e.g. every second for a typical GPS receiver.

Fortunately, the elemental GPS/INS filters of the GPB1 filter bank are based on identical system models. Therefore, the GPB1 sequence can be simplified by propagating state and covariance of just one filter, which initializes the other elemental filters when the propagation step is complete, i.e. when new measurements become available. This modified GPB1 sequence is illustrated in Fig. 3. So with m satellites in view, the additional computational cost of the modified GPB1 filter bank compared to a single GPS/INS filter is roughly $m-1$-times the computational cost of a measurement step, which should be easily tolerated. Therefore, a real-time implementation of the proposed integrity monitoring approach is absolutely feasible.

5. SIMULATION STUDY

The performance of the proposed integrity monitoring method was assessed in numerical simulations. For this purpose, a hypothetical 750s flight trajectory was generated and a satellite constellation was simulated using real almanach data. For this scenario, pseudorange measurements were simulated by calculating the distances to the satellites and adding a receiver clock error, which was generated using a clock error model given in [7]. The pseudorange measurement noise was modelled as white, Gaussian and zero-mean with a standard deviation of 3m, which was used in [7], too, and seems to be a reasonable choice for a military GPS receiver. For the generation of the IMU data, a typical tactical grade IMU was assumed with inertial sensor biases of around 1deg/h and 1mg and inertial sensor noise with a power spectral density of 2.5e-7(m/s^2)^2 and 8.4e-10 (rad/s)^2, respectively. Further IMU errors were not simulated, because the focus of this paper was to investigate the integrity monitoring performance of the different algorithms and not to make a statement concerning the achievable accuracy of the navigation information given a specific IMU.

Two different scenarios were considered with seven and five satellites in view, respectively. A time-varying spoofing disturbance was assumed according to

$$\Delta\tilde{\rho} = 100\text{m} \cdot \sin\left(\frac{2\pi}{300}t + \frac{\pi}{4}\right), \quad (9)$$

which was switched every 200s from one satellite to the next, so that during the 750s simulation time, four satellites were spoofed one after another. For each scenario 25 simulation runs were performed, which differed in the measurement noise corrupting the inertial sensor and GPS data.

Fig. 4 – Fig. 6 show the absolute position, velocity and attitude errors of the GPB1-based and the IMM-based integrity monitoring, averaged over 25 Monte Carlo runs for the 7 satellite scenario. For comparison, the performance of a single filter with a hypothetical, perfect RAIM is shown, too. The perfect RAIM was simulated simply by denying the spoofed pseudorange to the single filter, so that this filter processed only healthy pseudoranges. It can be seen that the IMM and the GPB1 show an equivalent performance. Except for short transition periods around 200s and 600s, where the spoofing disturbance is switched from one satellite to another, both integrity monitoring methods are close to the perfect RAIM. The change in the spoofed satellite is hardly visible at 400s, because the sinusoidal disturbance Eq. (9) is close to the zero crossing. In Fig. 7, the absolute errors of the estimated accelerometer and gyroscope biases are shown. All algorithms show a very similar performance, with minor advantages for the hypothetical, perfect RAIM

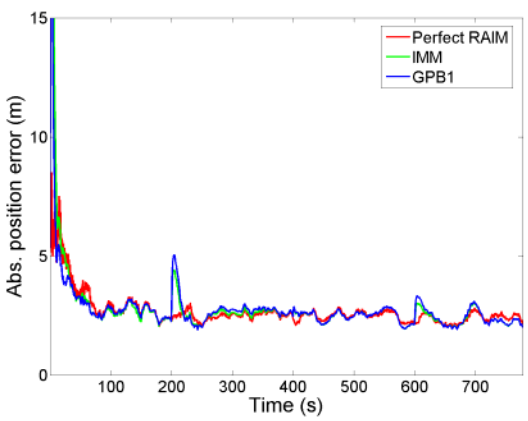

FIG 4. Absolute position error, 7 satellites in view, 25 Monte Carlo runs.

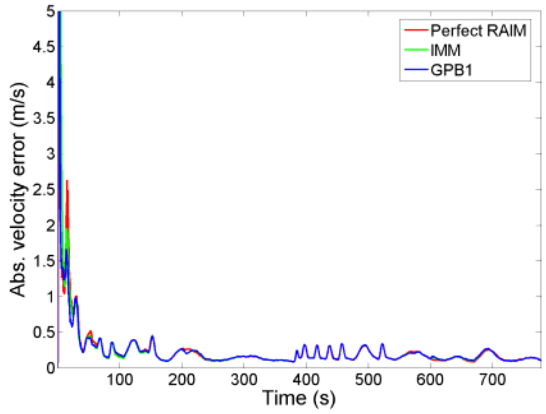

FIG 5. Absolute velocity error, 7 satellites in view, 25 Monte Carlo runs.

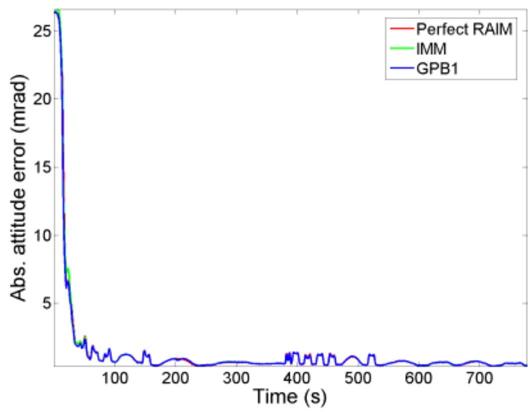

FIG 6. Absolute attitude error, 7 satellites in view, 25 Monte Carlo runs.

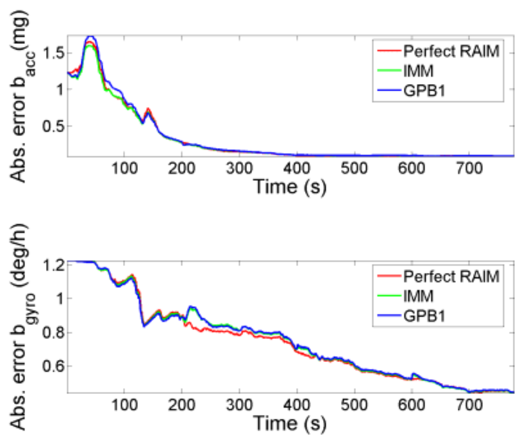

FIG 7. Abs. error of estimated accelerometer and gyroscope biases, 7 satellites in view, 25 Monte Carlo runs.

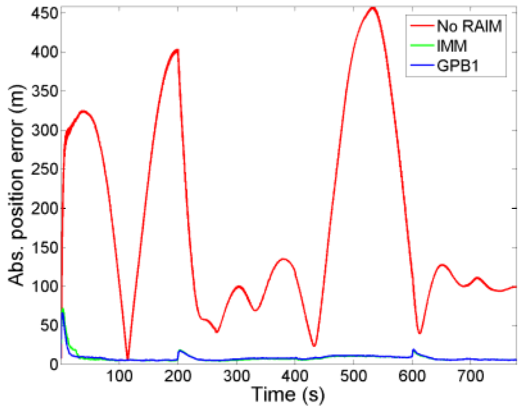

FIG 8. Absolute position error, 5 satellites in view, 25 Monte Carlo runs.

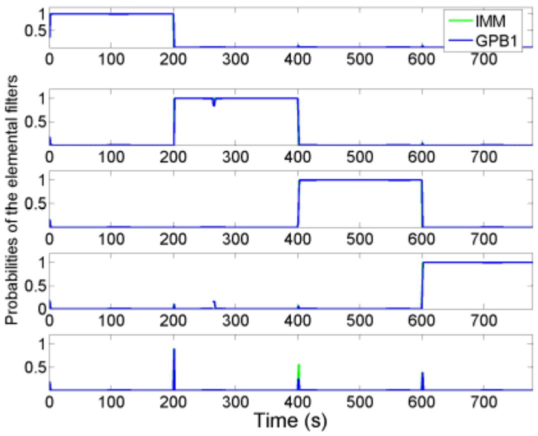

FIG 9. Model probabilities of the elemental filters during one simulation run, 5 satellites in view.

concerning the estimation of the gyroscope biases. In Fig. 8, the absolute position errors averaged over 25 simulation runs are shown for the five satellite scenario. Instead of a single filter with a perfect RAIM, the performance of a single filter with no RAIM is shown. With five satellites in view, RAIM methods can detect a fault, but the identification is not possible. This leaves two options: Either all pseudoranges are processed hoping that the disturbances is not too harmful which is similar to no RAIM, or no pseudoranges are processed, causing the navigation errors to grow with time according to the inertial navigation performance of the INS. Fig. 8 illustrates impressively, that ignoring the spoofing failure results in navigation errors that are not acceptable, while the IMM and GPB1 perform comparably well. Finally, Fig. 9 shows the model probabilities of the IMM and the GPB1 during one run. Obviously, the spoofing disturbance is detected rapidly and reliably with only five satellites in view.

6. CONCLUSIONS

The proposed integrity monitoring approach, a modified GPB1 filter bank, is comparable in performance to the IMM approach, while the computational load is reduced dramatically. This paves the path for a real-time implementation of the proposed algorithm, while this is questionable for the IMM approach. The algorithm is able to identify single faults with five satellites in view, which is not possible with RAIM methods. The GPB1 performance is close to the best performance a perfect RAIM, which of course does not exist in practice, could offer, i.e. recognizing and rejecting instantaneously a spoofed pseudorange measurement.

REFERENCES

[1] Brown, R.G., " A Baseline RAIM Scheme and a Note on the Equivalence of Three RAIM Methods", NAVIGATION, Journal of the Institute of Navigation, Vol. 39, No. 3, 1992, pp. 301-316.
[2] Chen, G., Masatoshi, H., "IMM Based Jamming Detection in a DGPS-Aided Inertial System", AIAA/NAL-NASDA-ISAS 10th Int. Space Planes and Hypersonic Systems and Technologies Conference, 24-27 April 2001, Kyoto, Japan.
[3] Jang, C.-W., Juang, J.-C., Kung, F.-C.,"Adaptive fault detection in real-time GPS positioning", IEE Proc.-Radar, Sonar and Navigation, Vol. 147, No. 5, Oct. 2000, pp. 254 – 258.
[4] Li, X.R., Jilkov, V.P., "A Survey of Maneuvering Target Tracking – Part V: Multiple Model Methods", IEEE Trans. Aerospace and Electronic Systems, Vol. 41, No. 4, Oct. 2005, pp. 1255 - 1321.
[5] Nikiforov, I., Roturier, B., "Statistical Analysis of Different RAIM Schemes", ION GPS 2002, 24-27 September 2002, Portland, OR, USA, pp. 1881 – 1892.
[6] Oshman, Y., Koifman, M., "Robust GPS Navigation in the Presence of Jamming and Spoofing", Proc. of AIAA Guidance, Navigation, and Control Conference, 11-14 August 2003, Austin, TX, USA.
[7] Oshman, Y., Koifman, M., "Robust, IMM-Based, Tightly-Coupled INS/GPS in the Presence of Spoofing", Proc. of AIAA Guidance, Navigation, and Control Confernce, 16-19 August 2004, Providence, RI, USA.
[8] Sukkarieh, S. , Nebot, E.M., Durrant-Whyte, H.F., "Achieving Integrity in an INS/GPS Navigation Loop for Autonomous Land Vehicle Applications", Proc. 1998 IEEE Int. Conference on Robotics & Automation, May 1998, Keuven, Belgium, pp. 3437 – 3442.
[9] Tsaj, Y.-H., Chang, F.-R., Yang, W.-C., Ma, C.-L., "Using Multi-Frequency for GPS Positioning and Receiver Autonomous Integrity Monitoring", Proc. 2004 IEEE Int. Conference on Control Applications, 2-4 September 2004, Taipei, Taiwan, pp. 205 – 210.
[10] Wendel, J., "Integrierte Navigationssysteme", Oldenbourg Verlag, 2007.
[11] White, N.A., Maybeck, P.S., DeVilbiss, S.L., "Detection of Interference/Jamming and Spoofing in a DGPS-Aided Inertial System", IEEE Trans. Aerospace and Electronic Systems, Vol. 34, No. 4, Oct. 1998, pp. 1208 - 1217
[12] Zink, T., Eissfeller, B., "Analyses of Integrity Monitoring Techniques for a Global Navigation Satellite System (GNSS-2)", Proc. of the IAIN World Congress / ION Annual Meeting, 26-28 June 2000, San Diego, CA, USA, pp. 117-127.