Annex E – DGPS/INS INTEGRATION

E.1 INTRODUCTION

The benefits of integrating GPS (or DGPS) with an INS are significant and diverse. Basically, each system has important shortcomings. Used in concert through some adequate algorithm, the integrated system solves the majority of these problems. All of the GPS techniques (either stand-alone or differential) suffer from some shortcomings. The most important are:

- The data rate of a GPS receiver is too low and the latency is too large to satisfy the requirements for high performance aircraft trajectory analysis, in particular with respect to the synchronisation with external events. In addition, there might be a requirement for high-rate and small latency trajectory data to provide real-time guidance information to the pilot (e.g., during fly-over-noise measurements). With the need to process radio frequency signals and the complex processing required to formulate a position or velocity solution [1], GPS data rates are usually at 1 Hz, or at best 10 Hz (an update rate of at least 20 Hz is required for real-time applications);
- High DGPS accuracy is limited by the distance between the Reference Station and the user because of the problem of ionosphere in integer ambiguity resolution on-the-fly [2];
- Selective Availability (SA) degrades differential GPS positioning accuracy over long distances;
- Influences of high accelerations on the GPS receiver clock, the code tracking loop and carrier phase loop may become significant; and
- Signal loss-of-lock and 'cycle slips' may occur very frequently due to aircraft manoeuvres or other causes.

There is little one can do to ensure the continuity of the signal propagation from the satellite to the receiver during high dynamic manoeuvres. Due to shadowing of the GPS antenna the receiver will loose track to several and in many cases to all satellites (see Chapter 8 and 9).

Stand-alone INS has its shortcomings as well. The INS is subject to an ever growing drift in position accuracy caused by various instrument error sources that cannot be eliminated in manufacturing, assembly, calibration or initial system alignment [1]. Furthermore, high quality inertial systems (i.e., platform systems) tend to be complex and expensive devices with significant risk of component failure.

The integration of (D)GPS and INS measurements might solve most of the above mentioned shortcomings: the basic update rate of an INS is 50 samples per second or higher and an INS is a totally self-contained system. The combination of INS and (D)GPS will therefore provide the required update rate, data continuity and integrity. The other advantages of an INS: low short term drift and low noise, are combined with the advantages of (D)GPS: high position accuracy and no long term drift. Therefore, in the case of DGPS/INS integration, the real-time demands on the telemetry data link are not very high because INS errors show a long term drift only and thus do not need to be updated frequently [3].

E.2 DGPS/INS INTEGRATION

Technical considerations for integration of DGPS and INS include the choice of system architecture, the integration algorithm (mostly Kalman Filter), and the characterisation and modelling of the measurements produced by the two sensors. Traditionally, GPS has been used to update the position of the INS (in other words, to control the drift behaviour of the INS). When looking to the high accuracy potential of DGPS, it is obvious to go the other way around, namely to get the positioning information primarily from GPS. Thus, the INS is now becoming the secondary sensor enabling higher interpolation in

GPS positioning updates, providing the attitude information, damping short periodic influences in GPS, and assisting in cycle slip detection and on-the-fly ambiguity resolution algorithms [4]. Clearly, both types of observations enter the Kalman filter, and only the different weighting of the data decides which sensor mainly contributes to the integrated result.

In principle, integration of DGPS with the INS can be done in levels analogously to the DGPS methods, using:

- DGPS differential pseudorange corrections [5];
- DGPS carrier phase-smoothed pseudorange corrections [5]; and
- DGPS carrier phase corrections [6].

These are also the data which can be transmitted by telemetry from the reference station to the user when following the RTCM standardised messages. For a real-time fully integrated DGPS/INS application it is clear that also the appropriate raw data, pseudoranges and carrier phases have to be transmitted, perhaps in a compressed form in order to minimise the telemetry load (e.g., in the form of pseudorange and carrier phase corrections).

Integration of INS with DGPS can be carried out in many different ways depending on the application (i.e., online/off-line evaluation, accuracy requirements). In the following paragraphs some information are given about integration algorithms for both real-time and post-processing systems.

E.3 INTEGRATION ALGORITHMS

Various options exist for the integration algorithm. In general, two main categories can be identified depending on the application: post-processing and real-time algorithms. The complexity of the algorithm is obviously related to both system accuracy requirements and computer load capacity. While for many applications a post-processing solution is acceptable, this is not useful for both navigation and online evaluation during a flight test. The state-of-the-art integration algorithm is the Kalman Filter (KF). In general terms, a KF is a recurrent, optimal estimator used in many engineering applications whenever the estimation of the state of a dynamic system is required. A KF can be used to estimate the errors which affect the solution computed in an INS or in a (D)GPS, as well as in the combination of both navigation sensors. An analytic description of Kalman filters and other integration algorithms can be found in the literature [7, 8]. In the following paragraphs some information are given about DGPS/INS Kalman filter implementations.

E.3.1 Kalman Filters

A number of implementations are possible for the (D)GPS/INS Kalman Filter. Matrix formulation methods of various types have been developed to improve numerical stability and accuracy (e.g., square root and stabilised formulations), to minimise the computational complexity by taking advantage of the diagonal characteristics of the covariance matrix (U-D factorisation formulation), and to estimate state when the state functions are non-linear (extended Kalman filter).

In general, the KF algorithm is optimal under three limiting conditions: the system model is linear, the noise is white and Gaussian with known autocorrelation function and the initial state is known. None of them are strictly verified in practice. Moreover, the computing burden grows considerably with increasing number of states modelled. Artificial Neural Networks (ANN) could be used to relax one or more of the conditions under which the KF is optimal and/or reduce the computing requirements of the KF. While the total replacement of KF with ANN filters lead to difficult design and unreliable integration functions, a hybrid network in which the ANN is used to learn the corrections to be applied to the state

prediction performed by a rule-based module, appears as the best candidate for future navigation sensor integration.

In the following paragraphs some examples are given of algorithms adopting a KF (or part of it) for integration of (D)GPS and INS measurements.

E.3.1.1 Rauch-Tung-Striebel-Algorithm

Post-processing integration of (D)GPS and INS measurements can be carried out by means of the Rauch-Tung-Striebel algorithm, which consists of a Kalman filter and a backward smoother. The forward filter can take into account previous measurements only. The smoothed estimate utilises all measurements. It is obvious that the smoothed positions are always at least as accurate as the forward filtered positions. In most cases, however, the smoothed positions are considerably more accurate than the filtered ones. It is evident that backward smoothing can only be done off-line. The filter estimates the state vector together with the error covariance matrix. The state vector contains the error components of the inertial navigation system. The smoothed trajectories and also accurate velocities are obtained by adding the state vector to the measurements delivered by the INS. The equations of the Rauch-Tung-Striebel algorithm can be found in reference [7]. With this system, an integration between (D)GPS and INS is possible and the high frequency movements of the aircraft are not smoothed out. Both positions and velocities can be obtained with a high degree of accuracy and are nearly continuously available. This is also true when the time interval between the measurements is relatively long (e.g., 1 min). There is a need to carry out a great amount of calculations and to store much data for the backward filter, but with modern computers this is not a major problem.

E.3.1.2 U-D Factorised Kalman Filter

The filtering algorithm most commonly implemented in real-time systems is the Bierman's U-D Factorised Kalman Filter. This algorithm avoids the explicit and computation of the estimation error covariance matrix P_t by propagating in terms of its factors U and D:

$$P_t = UDU^T \tag{E.1}$$

where U is a unit upper triangular matrix and D is a diagonal matrix. The U and D factors are calculated by the modified weighted Gram-Schmitt (MWGS) algorithm [9]. The *U-D* algorithm is efficient and provides significant advantages in numerical stability and precision. Specifically, the factorisation of P_t provides an effective doubling in computer word length in covariance-related calculations, and avoids filter divergence problems which can arise in more conventional filter mechanisations [7].

E.3.1.3 Artificial Neural Networks and Hybrid Networks

Although Artificial Neural Networks technology has not been fully investigated for application to integrated air navigation systems, the suitability of such technology to replace or enhance the performance of the Kalman Filter has been proven in related areas [10, 11]. However, the development of an integration algorithm completely based on neural technology (e.g., Hopfield Networks) appears impracticable at the moment. Furthermore, this solution is even more demanding than the Kalman Filter in terms of computing requirements [12]. Techniques for "On-line Training" would allow for real-time adaptation to the specific operating conditions, but further research is required in this field.

Hybrid Networks emerge as the best candidate for future applications. In an hybrid architecture an ANN is used in combination with a rule-based system (i.e., a complete Kalman Filter or part of it), in order to achieve the required adaptivity and improve the availability of the overall system. A hybrid network provides performances comparable with the Kalman Filter, but with improved adaptivity to non-linearities

and unpredicted changes in system/environment parameters. Compared with the Kalman Filter, the hybrid architecture features the high parallelism of the neural structure allowing for faster operation and higher robustness to hardware failures. The use of ANN to correct the state variables prediction operated by the rule-based module avoids computing the Kalman gain, thus considerably reducing the computing burden. Stability may be guaranteed if the output of the network is in the form of correction to a nominal gain matrix that provides a stable solution for all system parameters. The implementation of such a filter, however, would be sensitive to network topology and training strategy. An adequate testing activity would therefore be required.

E.4 INTEGRATION ARCHITECTURES

Combining (D)GPS and INS, different depths of integration can be realised. The level of integration and the particular mechanisation of the Kalman filter are dependent on:

- The task of the integration;
- The accuracy limits;
- The robustness and the stand alone capacity of each subsystem;
- The INS sensor concept (platform/strapdown); and
- The computer time capacity.

For these tasks, the basic concepts of system integration can be divided into the following topics:

- Open loop (D)GPS aided INS (OLDI);
- Closed loop (D)GPS aided INS (CLDI); and
- Fully integrated (D)GPS/INS (FIDI).

In the following paragraphs only a brief description of the various architectures is given. Further information can be found in the references [1, 13, 14].

E.4.1 Open Loop Systems

The simplest way to combine (D)GPS and INS is a reset-only mechanisation in which (D)GPS is used to periodically reset the INS solution. In this open-loop strategy the INS is not re-calibrated by (D)GPS data, so the underlying error sources in the INS still drive its navigation errors as soon as (D)GPS resets are interrupted. However, for short (D)GPS interruptions or for high quality INS, the error growth may be small enough to meet mission requirements. This is why platform inertial systems have to be used with OLDI systems operating in a high dynamic environment (e.g., military aircraft). The advantage of the open loop implementation is that, in case of inaccurate measurements, just the Kalman filter is influenced and not the inertial system calculation itself. As the sensors of a platform system are separated from the body of the aircraft by gimbals, they are operating normally at their reference point zero. The attitude angles are measured by the angles of the gimbals. The Kalman filter can run internal or external to the INS, but the errors of the inertial system have to be carefully modelled.

E.4.2 Closed Loop Systems

The main advantage of (D)GPS aiding the INS in a closed-loop mechanisation is that the INS is continuously calibrated by the Kalman Filter, using the (D)GPS data. Therefore strapdown sensors can be used in a CLDI implementation.

In contrary to platform systems, sensors of strapdown INS are not uncoupled from the aircraft body. They are operating in a dynamically more disturbed environment as there are vibrations, angular accelerations, angular oscillations which result in an additional negative influence to the system performance. In addition sensors are not operating at a reference point zero. Therefore the errors of the system will increase very rapidly and problems of numerical inaccuracy in an open loop implementation may soon increase. This is why it is advantageous to loop back the estimated sensor errors to the strapdown calculations in order to compensate for the actual system errors. Consequently, the errors of the INS will be kept low and linear error models can be used. When (D)GPS data is lost due to dynamics or satellite shadowing, the INS can continue the overall solution, but now as a highly precise unit by virtue of its recent calibration. However, this system implementation can be unstable.

E.4.3 Fully Integrated Systems

The system integration of best accuracy will be of course the full integration of both systems which requires a Kalman filter implementation at a raw/uncorrelated measurements level.

As the Kalman filter theory asks for uncorrelated measurements [7], it is optimal to use either the raw GPS measurements (i.e., the range and phase measurements to at least four satellites, the ephemeris to calculate the satellite positions and the parameters to correct for the ionospheric and troposphere errors), or (D)GPS position (and velocity) data uncorrelated between update intervals [15]. In the first case, the receiver clock errors (time offset and frequency) can be estimated as a part of the filter model.

This approach has very complex measurement equations, but requires only one Kalman Filter mechanisation. Moreover, its filtering can be most optimal since both (D)GPS errors and INS errors can be included without the instability problems typical of cascade Kalman Filters.

E.4.4 OLDI/CLDI and FIDI Comparison

The most important distinction to be made is between cascaded and non-cascaded approaches, which correspond, as mentioned before, to aided (OLDI and CLDI) or fully integrated (FIDI) architectures respectively. In the cascaded case two filters generally play the role. The first filter is a GPS filter which produces outputs (i.e., position and velocity) which are correlated between measurement times. This output is then used as input for the second filter which is the INS Kalman filter. As time correlation of this measurement input does not comply with the assumptions underlying the standard Kalman filter [7], it must be accounted for in the right way [16]. This will complicate the Kalman filter design (i.e., the potential instability of cascaded filters makes the design of the integration Kalman filter a very cautious task). However, from a hardware implementation point of view aided INS (in both OLDI and CLDI configurations) results in the simplest solution. In the non-cascaded case there is just a single Kalman filter generally based on an INS error model supplemented by a GPS error model. The GPS measurements, uncorrelated between measurement times, are differenced with the raw INS data to give measurements of the INS errors, also uncorrelated between measurements times.

E.5 REFERENCES

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