GNSS Solutions:

MEMS and Platform Orientation & Deep Integration of GNSS/Inertial Systems

"GNSS Solutions" is a regular column featuring questions and answers about technical aspects of GNSS. Readers are invited to send their questions to the columnists, **Professor Gérard Lachapelle** and **Dr. Mark Petovello**, Department of Geomatics Engineering, University of Calgary, who will find experts to answer them. Their e-mail addresses can be found with their biographies at the conclusion of the column.

How can a GPS receiver or MEMS (micro-electro-mechanical systems) inertial sensor assembly sense a host platform's orientation? How can these sensor technologies be combined together?

Many applications need information on the orientation or attitude of the host platform, such as in the case of automatic flight control, airborne mapping or imaging, antenna pointing control, and so on. The attitude can be mathematically represented by any of the following set of parameters: a quaternion, direction cosine matrix, Gibbs vector, or Euler angles. All of these representations are mathematically equivalent and can be transformed from one to another.

Attitude determination from GPS

Two or more independent GPS receivers with L1 carrier phase output capability form the basis of an attitude determination (AD) system. However, most commercial AD products use a common reference clock to convert the received GPS RF signals into the intermediate frequency (IF). The IF signals are then fed into the tracking loops to demodulate GPS data and generate observations such as pseudorange, Doppler, and carrier phase.

One benefit of using a common clock reference is that the clock error is a common one for carrier phase measurements from all antennas, and thus it can be removed by forming single-differences between antennas. This is crucial for deriving the attitude solution from the inter-antenna single-differenced carrier phase.

GPS AD algorithms using inter-antenna single-differences can generally be divided into three functional categories: the line bias solution, integer ambiguity resolution, and the attitude solution, which will be discussed later. However, if double-difference measurements are used, the line bias solution is no longer necessary.

Line biases are mainly caused by the differences in cable lengths between antennas and receivers. They are usually treated as constant quantities and calibrated by a procedure prior to operating the GPS attitude determination receiver. They can also be treated as components of the state vector of the system, and hence estimated along with other states.

Because a GPS receiver can measure only the fractional part of the carrier phase, the integer number of wavelengths between antenna and satellite is unknown. Numerous approaches have been developed to resolve the integer ambiguity problem, including motion-based methods, search-based methods, or a combination of both.

Motion-based methods accumulate the data for a period of time until there is an obvious change in the visible GPS constellation or a rotation of the host platform. The *search-based methods*, as the name implies, search for the most likely solution from a set of the possible candidate values (often termed the "search space"). A motion-based method can be used to reduce

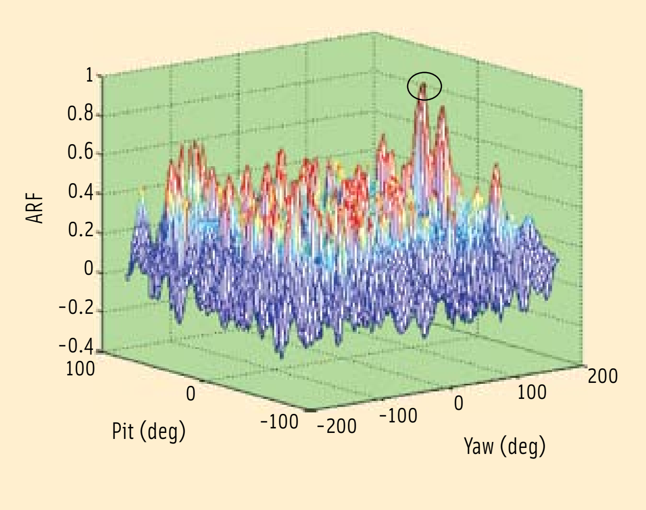

FIGURE 1 Search result using the ambiguity resolution function (ARF) in the pitch-yaw space

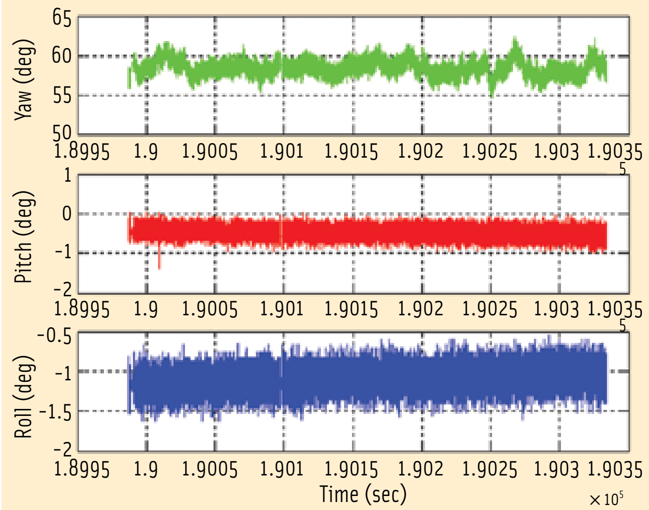

FIGURE 2 The 100Hz static attitude solution from MEMS accelerometer and magnetometer sensors for a static system

the number of ambiguity candidates to be searched and therefore improve the efficiency of the search procedure. **Figure 1** depicts a search result using the ambiguity resolution function (ARF). The correct solution lies at the highest peak (circled).

Attitude determination from MEMS inertial sensors

Micro-electro-mechanical sensors (MEMS) are experiencing rapid growth and demand in many applications because of their small size and relatively low cost, making them ideal components of a compact and affordable attitude and heading reference system (AHRS).

Today's MEMS sensors are still much less accurate than conventional fiber-optic-based or ring laser gyro inertial sensors as used for mobile mapping and precise navigation applications. Well-designed navigation filters and extra sensors can help to address these problems. However, the complex algorithms used in these approaches require powerful computational platforms to generate solutions in highly dynamic mobile applications. Therefore, a tradeoff exists between the computational speed and complexity of the data processing algorithms.

A typical MEMS sensor-based AHRS consists of micro-electro-mechanical accelerometers, magnetometers, and gyroscopes, which respectively sense the tri-axial acceleration of the host platform, the Earth's magnetic field vector, and the tri-axial angular rate.

For static applications, these measurements are combined with the known acceleration due to the gravity field and the Earth's magnetic vector in the reference coordinate system to give the orientation of the host platform. However, for a dynamic platform, gyroscope measurements must be used in order to update the attitude solution.

But a MEMS gyroscope loses accuracy very rapidly because of its bias drift characteristics. The acceleration derived from GPS can be used to calibrate the drift of the MEMS solution. **Figure 2** depicts the 100Hz Euler angles derived from accelerometer and magnetometer data for a static system.

Combination of GPS and MEMS inertial sensors

There are good reasons to combine GPS receivers and MEMS inertial sensors. For example, the inertial solution is self-contained but drifts over time, whereas the GPS solution has long-term stability but its signal is vulnerable to RF interference or blockage by buildings, etc. A combination of the two systems seems an ideal solution.

When the platform is static, the accelerometer and magnetometer data are sufficient for computing the tri-axial angular solutions. The gyroscopes can provide accurate short-term updates after compensating for their biases. The biases can be compensated by an in-house calibration, through zero-velocity updating (ZUPT), or simply averaging during a static period. In the absence of accurate bias estimation, however, the attitude accuracy would degrade over time. In a dynamic situation the GPS can be an external aid.

Two options for using the GPS involve either a GPS attitude determination system based on multiple antennas, or a standard navigation GPS receiver (with a single antenna). The multi-antenna configuration, as described earlier, can be used directly to correct the MEMS attitude solution as well as to estimate the gyroscope drift. The single-antenna solution has a simpler hardware implementation but needs additional software to support the INS, as will be discussed next.

One approach to combining single-antenna GPS with MEMS sensors is through the use of GPS-derived acceleration. This can be implemented by double-differentiating the carrier phase to obtain the range acceleration (after scaling to the proper units), which together with the GPS satellites' acceleration derived from

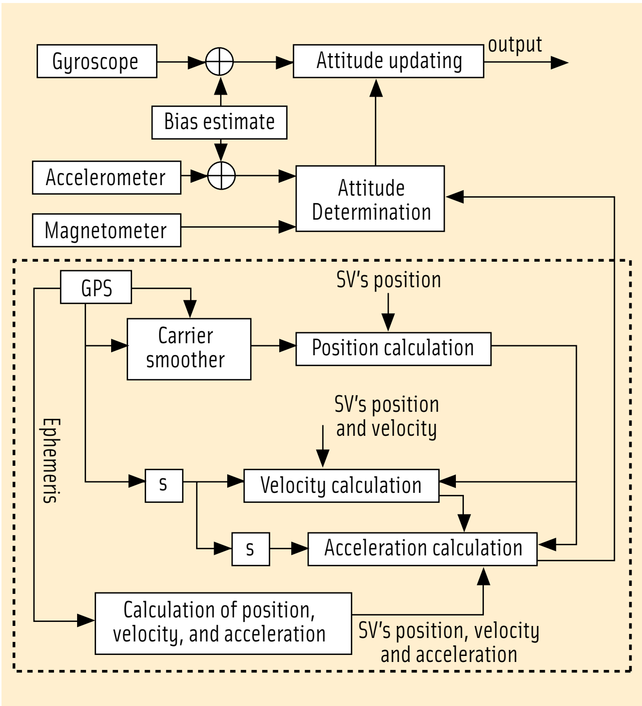

FIGURE 3 **Structure of an AHRS system based on the integration of GPS and MEMS sensors**

the broadcast ephemeris can be used to derive the receiver's acceleration. The GPS-derived acceleration provides a reference for the output of the accelerometers. In addition, combining the accelerations with the magnetometer data permits the tri-axial attitude to be determined, even on a moving platform.

The GPS solution has a relatively low update rate and, therefore, the gyroscope data can be used to interpolate the solution between two successive GPS outputs. On-line estimation of the gyroscope biases is also possible with this procedure. An example of an integrated AHRS system is shown in **Figure 3**.

Both satellite-based radio navigation and MEMS-based inertial navigation technologies are growing quickly. When the European Galileo system and the Chinese Compass are fully operational, we can expect that more satellite navigation signals in the sky will support innovations in the attitude determination technology, including the receiver technology, the integer ambiguity resolution, and robust and accurate attitude solution.

However, the major inherent disadvantage of satellite navigation systems will remain, including blocked, weakened, or interfered signals in harsh environments. The integration of MEMS inertial sensors and GNSS represents an attractive solution to achieve a tiny size, low power consumption, low cost, and full-dimensional (position, velocity, acceleration, attitude, and time) navigation system.

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What are the differences between the coherent and non-coherent versions of deep integration of combined inertial navigation and GNSS systems (INS/GNSS)?

Deep (or ultra-tightly-coupled) INS/GNSS integration differs from conventional integration architectures, such as tightly coupled ones, in that the GNSS signal tracking and INS/GNSS integration functions are combined into a single estimation algorithm. This provides improved GNSS signal-tracking performance in poor signal-to-noise environments resulting from signal attenuation, incidental interference, or deliberate jamming.

Figure 1 shows a closed-loop deep, or ultra-tightly-coupled (UTC), INS/GNSS integration architecture. The GNSS receiver performs front-end conditioning and sampling of the incoming GNSS signals and then correlates them with internally generated reference signals. The accumulated correlator outputs, known as Is and Qs, are output from the GNSS receiver to the INS/GNSS integration algorithm Kalman filter.

The GNSS receiver inputs numerically controlled oscillator (NCO) commands that control the reference signals, keeping each code phase and carrier frequency aligned with the corresponding incoming GNSS signal. The NCO commands are generated using the (corrected) inertial navigation solution, satellite constellation ephemeris parameters, satellite and receiver clock error estimates, and ionosphere and troposphere propagation delay estimates. Finally, the Kalman filter corrects the inertial navigation solution to form the integrated navigation solution.

Deep INS/GNSS integration algorithms may be divided into two categories, *coherent* and *non-coherent*. Coherent algorithms input the GNSS accumulated correlator outputs, the Is and Qs, directly to a Kalman filter as measur ements. Non-coherent algorithms first pass the Is and Qs through code and carrier discriminator functions, similar to those used in conventional GNSS signal tracking. Coherent deep integration may be further divided into centralized and federated approaches.

Figure 2 shows the data flow between the GNSS receiver and integration algorithm for coherent deep integration with a centralized Kalman filter. For the legacy GPS signals, the minimum rate at which Is and Qs may be generated is the navigation-data-message rate of 50 Hz due to the navigation message data bits. Thus, inputting the Is and Qs directly to the Kalman filter requires it to be iterated at 50 Hz or more.

For the new data-free signals (e.g., pilot components of GPS L2C and Galileo L1, etc.), or where navigation-data wipe-off is implemented, other constraints apply. The measurement vector is also large, with the number of components equal to six times the number of signals tracked (assuming three complex correlators per signal – early, prompt, and late).

To maintain carrier tracking, each reference carrier phase within the receiver may be kept aligned with that of the relevant GNSS signal by feeding back corrections from the Kalman filter after each set of I and Q measurements is processed. The round-trip communication lag can limit the bandwidth; however, a lower bandwidth may generally be used for inertially aided carrier phase tracking than for stand-alone.

Alternatively, the reference-signal carrier phase offsets may be estimated as Kalman filter states. This enables the carrier phase to be tracked without having to keep the reference and signal phases aligned within the receiver. However, the reference and signal carrier frequencies must still be synchronized in order to maintain signal coherence within the receiver's correlators over the accumulation interval.

A distinct problem with implementing coherent deep integration using a centralized Kalman

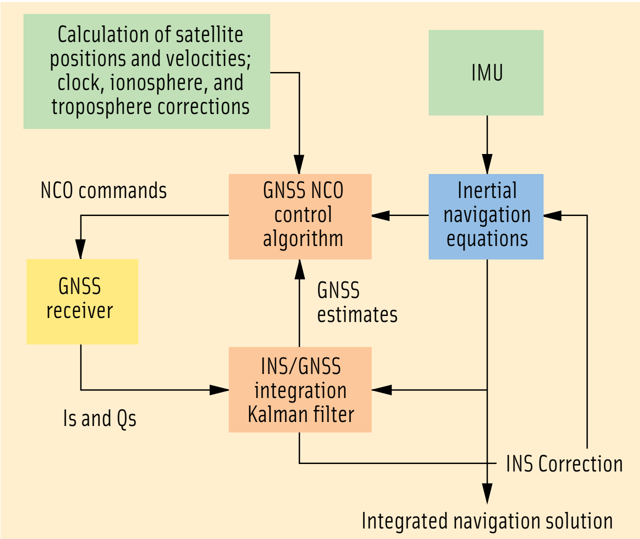

FIGURE 1 **Closed-loop dee p INS/GNSS integration architecture**

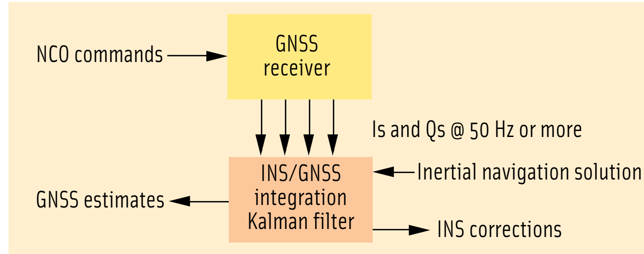

FIGURE 2 **Receiver to Kalman filter communication in centralized coherent deep INS/GNSS integration**

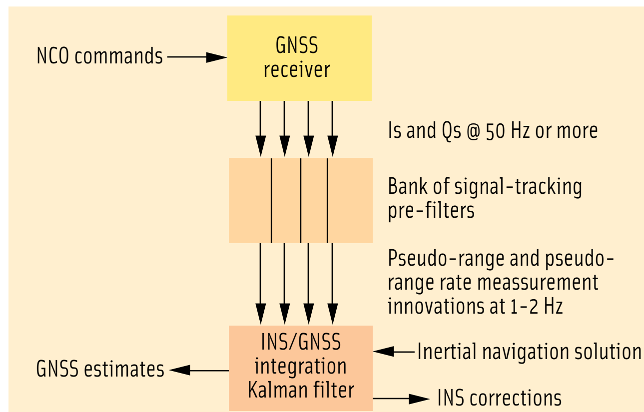

FIGURE 3 **Receiver to Kalman filter communication in federated coherent deep INS/GNSS integration**

filter is the high processor load demanded by a fast update rate and large state and measurement vectors. Therefore, in all practical implementations of coherent deep integration, a federated Kalman filter architecture is used, as shown in **Figure 3**.

A bank of tracking Kalman filters input the I and Q measurements at 50 Hz. Generally, one filter is available for each signal tracked, inputting six measurements, though dual frequency measurements from the same satellite may share a filter. Each tracking pre-filter estimates a minimum of three states: code phase tracking error, carrier frequency tracking error, and reference-signal carrier-phase offset.

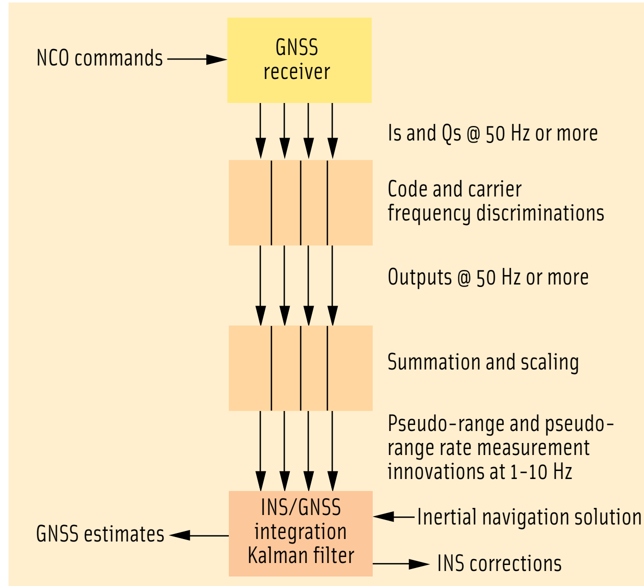

FIGURE 4 **Receiver to Kalman filter communication in non-coherent deep INS/GNSS integration**

At a slower rate, typically one or two Hertz, each tracking filter generates pseudorange and pseudorange-rate measurement innovations (i.e., errors in the locally generated signal) from its code-phase and carrier-frequency tracking error state estimates, respectively. Note that one is directly proportional to the other (assuming a first-order Doppler shift). The measurement innovations are then input to the INS/GNSS integration Kalman filter, which is identical to that used for tightly coupled integration.

To prevent cascading problems between the tracking pre-filters and the integration filter, the code phase and carrier frequency state estimates are zeroed whenever measurements are output to the integration filters. This ensures that the same information is not present in both filters simultaneously and is known as a federated zero-reset (FZR) integration architecture. This type of deep integration algorithm has been developed by the Aerospace Corporation, L3-Communications/Interstate Electronics Corporation (L3-C/IEC), Ohio University, and others.

The principal benefit of coherent deep integration is that bypassing the discriminators avoids introducing unmodeled non-linearities in the measurement inputs to the Kalman filter. This enables higher gains to be used in the Kalman filter, as the assumed measurement noise covariance does not need to overbound the discriminator non-linearities. Furthermore, coherent code tracking is less noisy than noncoherent tracking.

The main disadvantage of coherent deep integration is that the reference-signal carrier phase offset must be known in order to extract code-tracking information from the I and Q measurements. Therefore, the tracking pre-filters must be able to track carrier phase in order to track code.

Consequently, coherent deep integration is the preferred solution for applications where the precision of carrier-phase tracking is required. However, it is unsuited to applications that require operation under low signal-to-noise environments, as both code and carrier-frequency tracking can be maintained at a lower carrier power–to-noise density, C/N_0, than carrier-phase tracking. The lowest C/N_0 reported at which coherent deep integration has been maintained in hardware is 15 dB-Hz with data-bit estimation.

Figure 4 shows the data flow between the GNSS receiver and integration algorithm for non-coherent deep integration. Without navigation-data wipe-off, the Is and Qs are used to compute code and carrier-frequency discriminator functions at 50 Hz. Any standard discriminators may be used.

The code discriminator function is independent of the carrier phase; so, it can be computed regardless of whether sufficient C/N_0 exists to track carrier phase. This enables non-coherent deep integration to maintain tracking in weaker signal-to-noise environments than its coherent counterpart.

Where no significant data lag occurs, the integration algorithm's a priori estimate of the code-phase and carrier-frequency tracking errors is zero; so, normalized discriminator outputs may be converted to pseudorange and pseudorange-rate measurement innovations simply by applying a scaling factor (assuming a first-order Doppler shift).

The measurement innovations are averaged to reduce the Kalman filter update rate from 50 Hz to between 1 and 10 Hz. Averaging should always be used in preference to sub-sampling as it reduces the noise. Noncoherent deep integration algorithms have been developed by Draper Laboratories, Honeywell, L3-C/IEC, QinetiQ, Raytheon, and others.

In theory, carrier phase discriminators may be used in non-coherent deep integration. However, coherent deep integration is better for carrier-phase tracking. For applications where both high precision and low C/N_0 operation are required, mode switching should be implemented with coherent integration used as the primary mode and noncoherent as the reversionary.

Mode switching may be implemented at the pre-filtering stage, enabling a common INS/GNSS integration Kalman filter to operate in both modes (and for tightly coupled integration during initialization). Furthermore, some signals may be tracked coherently and others noncoherently at the same time. This is useful in weak-signal environments, where some signals are attenuated more than others.

Acknowledgment

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Additional Resources

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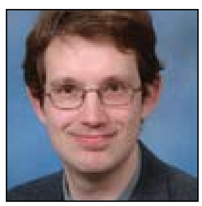

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