How Much Accuracy Improvement can the Cascade Denoising Algorithm Provide for a GPS/INS Integrated System?

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Background
The inertial sensor errors are composed of long term errors (low frequency components) and short term errors (high frequency components). Through the use of the INS/GPS integration process, some of these error components can be reduced or removed. Skaloud (1999).

According to Chiang et al. (2004), the long term errors are reduced by updating the integration filter with the observed error state vector estimated from GPS (position and velocity). Certain amounts of the short term errors are reduced by the smoothing that is done by the numerical integration process of the inertial data mechanization (Burton et al., 1999). However, Skaloud (1999) indicated that the benefit of the INS/GPS integration is band-limited as the lower boundary of the INS/DGPS error spectrum is mainly determined by the remaining biases in GPS observations while the upper boundary is mainly determined by short term inertial sensor errors.

Due to the consequence of sampling theory, the utilization of DGPS data to reduce the short term INS errors is not effective as the sampling rate of DGPS measurement (1-20Hz) is much lower than that of INS (50 – 200 Hz). As a result, the long term INS errors that are reduced by the integration process with GPS are usually more significant than the short term errors. For general real time land vehicular applications, as well as post-mission applications such as direct geo-referencing applications and inertial survey applications, the attitude accuracy is as critical as the positioning accuracy. For example, the roll and pitch errors are responsible for projecting the impact of gravity to the horizontal axes and cause an additional source for horizontal errors (e.g. acceleration) after integration (velocity and position errors). In addition, the heading error is the most critical factor for positional error accumulation during GPS signal blockages as it will be amplified by the vehicle’s dynamic (e.g., velocity) and introduces additional positional errors after numerical integration.

For direct geo-referencing applications such as mobile mapping systems, the accuracy of exterior orientation parameters is very critical as their impact will be amplified by the distance between the perspective centers and object point, thus causing additional positional errors in the navigation or the mapping frame. As most of the mapping grade mobile mapping applications demand centimeter level positioning accuracy, therefore they require high positioning and attitude estimation accuracy to achieve these accuracy requirements.

Motivation
In order to improve positioning as well as attitude estimation accuracies, some measures must be taken to improve the error estimation especially during GPS signal blockages. The first attempt to remove certain types of INS short term sensor errors using pre-filtering techniques was proposed by Czompo [1990]. In his research, a special frequency filtering was designed to remove the dither spike.

Burton et al., [1999] applied Wavelet-based denoising techniques to reduce the short term Inertial Navigation System (INS) sensor errors that can not be removed through Kalman filter with the additional information from Global Positioning System (GPS). The results presented in those works were very promising.

However, traditional wavelet denoising algorithms applied by those authors have been proven to have certain limitations in removing unwanted short term INS sensor errors including sensor noise and other high frequency disturbances (e.g. engine vibrations) for general land vehicular navigation applications [Chiang et al., 2004]. For land vehicular navigation application, the concern is to remove those short term errors properly and to improve the estimation accuracy without jeopardizing the true motion dynamic component of the vehicle.

This operation requires prior knowledge of the bandwidth of the land vehicle dynamics and the spectrum characteristic of the wavelet denoising algorithm. Therefore, the attitude estimation errors after applying denoised kinematic IMU measurements can be expected to be smaller than those obtained through the use of the original data if the true motion dynamic content can be well preserved and the short term errors can be removed during the denoising operation. Chiang et al., [2004] investigated the bandwidth of true motion dynamic using the kinematic IMU raw measurements sensed by several systems and suggested the bandwidth of true motion dynamic for general land vehicular applications. See Chiang et al., [2004] for more details about the spectral analysis of kinematic IMU signals.

Development of the Cascade Denoising Algorithm
Another important ingredient for applying any denoising techniques is the spectral characteristic of the wavelet decomposition. Chiang et al., [2004] investigated the relationship between the decomposition level, sampling frequencies, and the stop bands of residual frequencies corresponding to the approximate signals through the spectrum analysis of approximation signals \(A_i, i = 1, 2, 3...n\) and the detail signals \(D_i, i = 1, 2, 3...n\) generated at each wavelet decomposition level.

Through the spectrum analysis denoising algorithms and kinematics IMU signals, it is possible to determine the bandwidth of true motion dynamic that are sensed by each sensor and the stop band of wavelet-based low pass filters. As a result, an optimal decomposition level of the wavelet-based low pass filter can be determined. The signals whose frequency ranges out of the bandwidth of true motion dynamic are undesirable. Therefore, the wavelet-based low pass filter with an optimal decomposition level \(L\) for each sensor can be applied first to remove the undesirable high frequency components whose frequencies are higher than the stop bands of the low pass filters. Then the denoising algorithm is applied to remove the remaining short term errors whose frequencies are lower than
the stop bands of the low pass filters. This algorithm is called a cascade denoising algorithm and Figure 1 shows a schematic of its implementation steps.

A and D represent the “approximate” and “details” signals, respectively, generated by wavelet decomposition at each level. In addition, cA and cD represent the “approximate” and “details” coefficients at each decomposition level. The traditional denoising process can be illustrated by removing the whole block of wavelet low pass filter and decomposition level d in the bottom block.

The cascade denoising algorithm utilizes translation invariant wavelet transform, whereas, the traditional denoising algorithm uses a discrete wavelet algorithm. According to [Coifman and Donoho, 1995], the lack of translation invariance introduces artifacts when using transforms domain thresholding, which depends on the kind of transform domain being used [Coifman and Donoho, 1995]. In the neighborhood of discontinuities, wavelet denoising can exhibit pseudo-Gibbs phenomena. On the contrary, the translation invariant wavelet transform can then be applied to reduce the impact of such unwanted disturbance and improve the overall accuracy.

Through the spectral analysis of cascade denoising algorithm, the limitations of traditional denoising can be reduced by inserting a series of wavelet pass filters prior to applying regular denoising process [Chiang et al., 2004].

Figure 1. IMU signal cascade denoising.
Direct Georeferencing

Accuracy Achievement

To assess the performance of the proposed cascade denoising algorithm, a field test was conducted in a land vehicle environment using an INS/GPS integrated system consisting of a navigation grade IMU (i.e., Honeywell CIMU) and two NovAtel OEM 4 receivers. Performance of the cascade denoising algorithm was evaluated in terms of the positioning accuracy and attitude estimation accuracy during eight GPS signal outages.

There were no natural GPS signal outages in this test trajectory; thus, eight simulated GPS signal outages were introduced by removing the GPS solutions being fed into the INS Kalman filter during the simulated GPS signal outages. The reference trajectory was generated by the CIMU/DGPS integrated system without any GPS signal outages. It can be seen in Figures 2 and 3 that the utilization of a cascade denoising algorithm was able to provide visible improvements during several GPS signal outage periods. The positional errors of six GPS outage periods were successfully reduced using the denoised CIMU raw measurements.

Figure 3 illustrates the attitude estimation errors of roll, pitch, and heading, respectively. The attitude estimation accuracies were successfully improved as both the RMS errors and the maximum values of the attitude errors were reduced after applying the proposed cascade denoising algorithm. Table 1 depicts the improvement made by the proposed algorithm when a navigation grade IMU was applied. Therefore, the results presented in this article indicate the benefits of the proposed cascade denoising algorithm for GPS/INS integrated systems for real-time navigation applications and post-mission direct geo-referencing applications.

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References


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Table 1 Performance Summary

Figure 2. Estimation Accuracy in Position.

Figure 3. Estimation accuracy in attitude.