Low-cost IMU Data Denoising using Savitzky-Golay Filters

Malek Karaim
Electrical and Computer Engineering
Queen's University
Kingston, Canada
9mk24@queensu.ca

Aboelmagd Noureldin
Electrical and Computer Engineering
Royal Military College of Canada
Kingston, Canada
noureldin-a@rmc.ca

Tashfeen B. Karamat
Electrical and Computer Engineering
Royal Military College of Canada
Kingston, Canada
tashfeen.karamat@rmc.ca

***Abstract*—MEMS sensors have been used in many applications including navigation systems. However, these sensors suffer from highly noisy measurements. If left untreated, these errors will significantly degrade the ultimate navigational solution. Hence, applying a pre-filtering technique becomes a necessity to de-noise these sensor signals to improve the overall system performance. While wavelet denoising is the most common technique for sensor data pre-filtering, it may not be suitable for real-time implementations. This paper explores another method; namely, Savitzky-Golay filters, which can provide competitive denoising performance with a less computationally demanding algorithm. The purpose of the paper is to examine the performance of the new method against wavelet de-noising with respect to both positioning and attitude accuracy and computations time. We applied the filter to denoise MEMS-based inertial sensors data in a tightly coupled integrated INS/GPS system. Our results showed that the new method outperformed the wavelet denoising approach. Moreover, the new method demands much less computations time, which makes it more suitable for embedded systems and real-time applications.**

I. Introduction

An Inertial navigation system (INS) is a self-contained navigation system that uses measurements provided by gyroscopes and accelerometers to find the position, velocity, and orientation of a moving platform relative to a known initial navigation state. During the process of inertial navigation, also known as Dead Reckoning (DR), the recursive determination of the present vehicle position and attitude information is calculated based on the previous values, and the available measurements of the direction of motion and distance travelled [1]. Ultimately, the position, velocity, and attitude information are obtained continuously. Nonetheless, inertial sensor errors such as gyroscope drifts and accelerometer biases cause a rapid degradation in the quality of this mechanization process and, in turn, in the obtained results [2]. The problem is even worse with the use of the recently emerging micro electromechanical system (MEMS) sensors. These low-cost sensors have considerable signal noise and sensor bias that cause more significant errors in the navigation solution [3]. Therefore, one vital operation in inertial navigation systems is *data denoising* [4]. Fig. 1 shows a general block diagram of the main parts of an INS. In the pre-processing data stage, a filtering technique is applied to remove most of the noise that is present in the sensor data. Applying conventional pre-filtering methods such as low-pass filters for low-cost MEMS sensors data can cause signals distortions [5]. Therefore, more advanced filters and de-noising techniques are used instead. A common denoising method in this regard is Wavelet denoising. Wavelet techniques can be applied to a signal with the aim of removing high-frequency noise to minimize the unwanted effects of sensor noise and other disturbances. Accordingly, the position errors obtained from the wavelet de-noised INS data are expected to be much smaller than those obtained from the original data [6] [7]. Towards finding an even more efficient denoising technique, this paper explores Savitzky-Golay filters.

II. Data Denoising

Wavelet is a signal transformation (or decomposition) technique that was developed to eliminate various types of noises included in images [3]. Subsequently, it has been applied in many other areas, including image processing and compression, audio signal processing, data denoising, classification, pattern recognition, and others [8]. The main advantage of this technique is its ability to denoise a given signal without causing considerable degradation of the original signal characteristics [9]. Wavelet transformation is based on analyzing a signal through windows of a range of sizes, applying wide windows (i.e., short-time intervals) to low frequencies, and narrow windows (i.e., long-time intervals) to high ones [5]. Thus, wavelet decomposition can perform local analyses of a small portion of a large signal, a feature that makes it superior to other signal processing techniques [7].

Many publications have discussed the use of wavelet for IMU data denoising. For instance, for an INS/GPS integrated system application, reference [7] showed that wavelet de-noised INS data position error results were 46%–63% better than the original INS data. It was also proved in [5] that wavelet-based decomposition performed 19.72% better than a conventional, low pass filter (LPF), prefiltering technique.

Although wavelet is an effective technique for low-cost INS/GPS data denoising, it is worth exploring whether there are other techniques that are more efficient. Accordingly, this paper demonstrates that Savitzky-Golay filters are a good alternative for wavelet regarding performance and much faster in execution time. While this type of filter has been widely used in many other signal processing applications [10], most notably in spectral analysis and optimization [11], owing to its ability to preserve essential characteristics of signals (e.g., height and width of a peak), it has not been investigated in-depth for use in low-cost INS/GPS data denoising.

Abraham Savitzky and Marcel J.E.Golay developed the Savitzky-Golay (S-G) filter in 1964 as a local polynomial regression method [12]. An optimized curve fitting polynomial for a given data window size (2L+1) can be obtained through a least-squares solution; therefore, the Savitzky-Golay filter can be used as a smoother [13]. Suppose that $x[n]$ is a sequence of data samples. With a group of (2L+1) samples around each data point (e.g. n=0), we form a fitting polynomial which is expressed as [10]:

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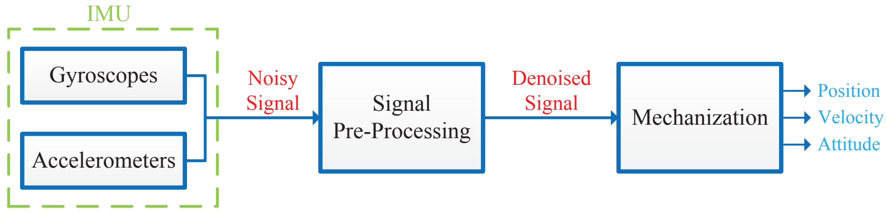

Fig. 1. The main components of an inertial navigation system.

$$p(n) = \sum_{j=0}^{N} a_j n^j \quad (1)$$

Where $a_j \left(j = 0, \ \dots, N \right)$ are the fitting coefficients and N is the polynomial order. The aim of obtaining p(n) is to minimize the error term:

$$e = \sum_{n=-L}^{L} \left(p(n) - x[n] \right)^2 \quad (2)$$

The expression of the least-squares error for this polynomial approximation is a matrix. Therefore, the least-square solution can be performed using matrix pseudoinverse; thus, the polynomial coefficients can be calculated [13]. Then, the smoothed (denoised) data samples can be obtained [14].

III. Inertial MeasurEMENt units

Every INS system has an inertial measurement unit (IMU) which is often composed of three orthogonal gyroscopes and three orthogonal accelerometers. The origin of the IMU unit is typically defined as the origin of the accelerometer triad, and the axes of the gyroscopes' triad is set parallel to the accelerometers' triad.

A. *Gyroscopes*

The role of gyroscopes inside an IMU is to observe the angular rotation of its case with respect to inertial space [15]. Based on how the system is designed, the output of a gyroscope could be an angular rate or absolute attitude information. Numerous gyroscope types are in the market now including, but not limited to, interferometric fiber-optic gyroscopes (IFOG), ring laser gyroscopes (RLG), dynamically tuned gyroscopes (DTG), and hemispherical resonant gyroscopes (HRG). The grade (quality) of gyroscopes makes a big difference in their performance and cost.

B. *Accelerometers*

An accelerometer senses the inertial reaction of a proof mass to measure its acceleration [16]. The output of an accelerometer is called *specific force* since it does not include the gravity component. Like gyroscopes, accelerometers are of various types. These include mechanical pendulous force-rebalance accelerometers, vibrating beam accelerometers (VBAs), and gravimeters.

For both gyroscopes and accelerometers, the recent trend is to use the Micro Electro Mechanical Systems (MEMS) grade sensors. These inexpensive sensors are being used for numerous low-cost navigation applications. However, these sensors have complex error characteristics, and hence their signals require filtering (signal denoising) to ensure that unwanted noise is removed before using them in an INS solution [5]. There are several denoising methods used in this regard. This paper has applied Savitzky-Golay filters to low-cost MEMS sensors data in an INS/GPS integrated navigation system and experimentally verified the improvement of the overall system performance.

IV. INS/GPS integration

High-end inertial sensors cannot be used in affordable applications mainly due to their high cost. In other cases, the size of the sensors makes it difficult to fit them to some navigation platforms. MEMS inertial sensors are inexpensive and small, making them a good candidate for many affordable navigation applications. However, they suffer from long-term drift due to their complicated errors and biases. Thus, MEMS-based navigation solutions are not reliable for long periods. On the other hand, the global positioning system (GPS) can provide navigational solutions that are highly accurate over the long-run. Still, GPS signals are susceptible to being interrupted entirely or significantly degraded due to a range of factors.

To rectify the shortcomings of using these systems individually, they have been integrated on a widescale owing to their complementary characteristics, and, accordingly, have provided a more robust navigation solution than either of the two stand-alone systems [17]. Fig. 2 depicts a general view of an INS/GPS integrated system. Furthermore, to lessen the effects of MEMS sensor errors, recent INS and INS/GPS implementations tend to use fewer sensors to obtain the same navigation solution. This approach is known as reduced inertial sensor systems (RISS) [1]. Experiments performed in this research use a RISS configuration composed of one vertically-aligned gyroscope, two accelerometers mounted to the forward and transverse directions of the vehicle frame, and a built-in vehicle speed sensor.

Based on the desired integrated navigation system characteristics, one of three known levels of integration is selected: loosely coupled INS/GPS, tightly coupled INS/GPS, or ultra-tightly coupled INS/GPS. This work presents a new signal denoising technique, using a tightly coupled INS/GPS solution environment. (As the focus of this paper is on INS signal denoising, no further details are given here about the INS/GPS integration schemes.)

V. Trajectory and Experiment Setup

The performance of the proposed denoising method was examined using real road trajectory data. A low-cost MEMS-based Crossbow IMU300CC unit was used to log the inertial sensor data at a rate of 100 Hz. Car odometry data was obtained from the vehicle's OBDII interface using the Carchip data logger. A NovAtel OEM4 GPS receiver logged the GPS data at a rate of 1 Hz. An OEM4-G2 ProPak-G2plus SPAN unit, by NovAtel, combined the OEM4 GPS receiver with a Honeywell HG1700 AG17 high-end tactical-grade IMU to provide the reference trajectory data.

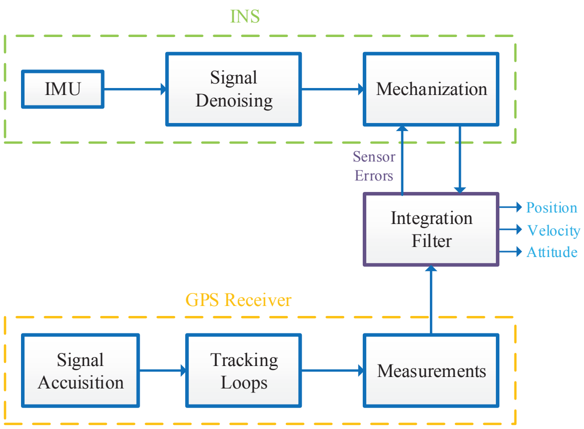

Fig. 2. General view of an INS/GPS integrated system.

Fig. 3 shows the equipment inside the van used for collecting the data from the road experiments. The trajectory was conducted in the city of Kingston, ON, Canada, and intended to incorporate a wide range of possible driving conditions, such as low and high speeds, normal and sharp turns, slopes, etc.

Fig. 3. Data logging equipment placed in a test van.

VI. RESULTS

To better verify the performance of the adopted denoising method, the integrated system was made more dependent on the INS than the GPS throughout the trajectory. Thus, ten artificial GPS signal outages were introduced at different locations of the trajectory, with outages lasting for 60 s each. During these outages, the number of visible satellites was gradually decreased to zero. For comparison, the obtained results of using Savitzky-Golay filters, are shown versus the wavelet transformation method under the same circumstances. All the work in this paper, including wavelet, Savitzky-Golay, and the INS/GPS integration algorithm, was implemented in the MATLAB environment. For the remainder of this document, Wavelet and Savitzky-Golay are shortened to WL and SG, respectively.

Fig. 4 shows the WL and SG denoised data versus raw data for the forward accelerometer. An enlarged portion of this is shown in Fig. 5 in greater detail to give the reader better insight. The original signal is shown in red, whereas the WL and SG denoised data are shown in green and blue, respectively. Similar information is indicated for the transverse accelerometer and the vertical gyroscope in Fig. 6 through Fig. 9.

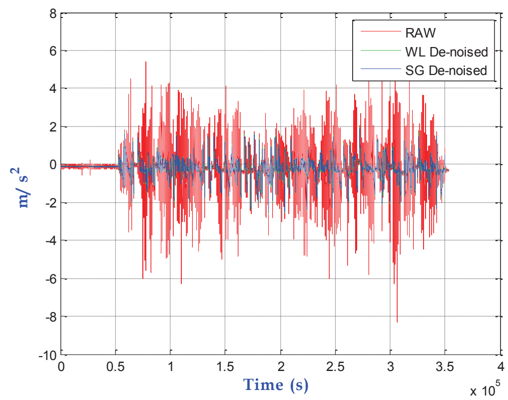

Fig. 4. Forward accelerometer data

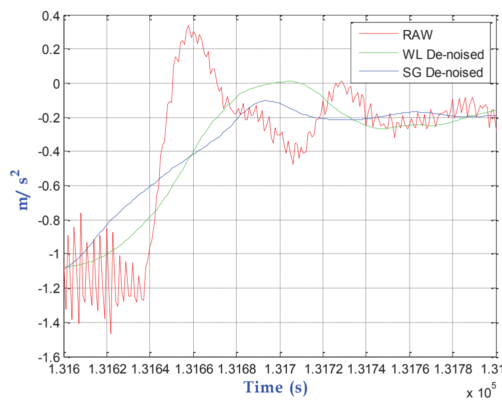

Fig. 5. An enlarged portion of forward accelerometer data.

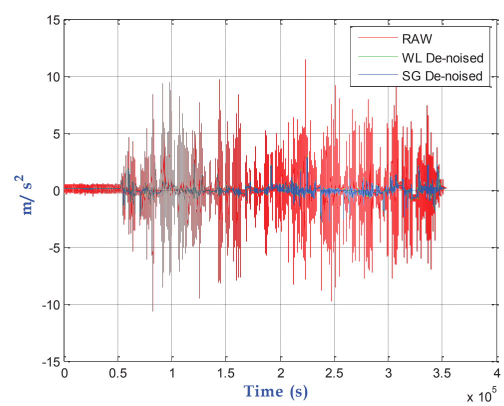

Fig. 6. Transverse accelerometer data.

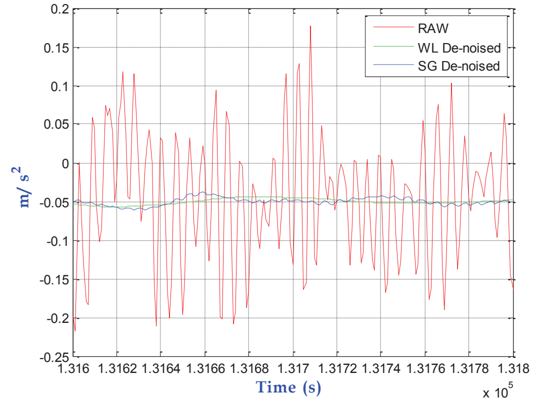

Fig. 7. An enlarged portion of transverse accelerometer data.

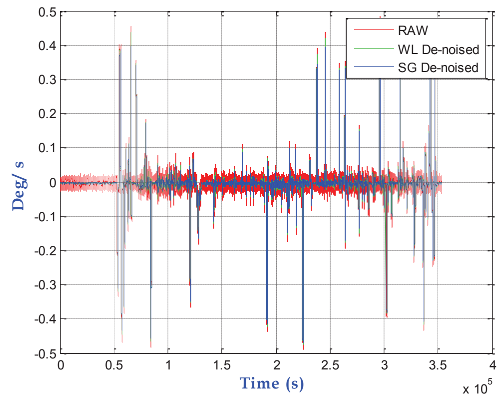

Fig. 8. Vertical gyroscope data.

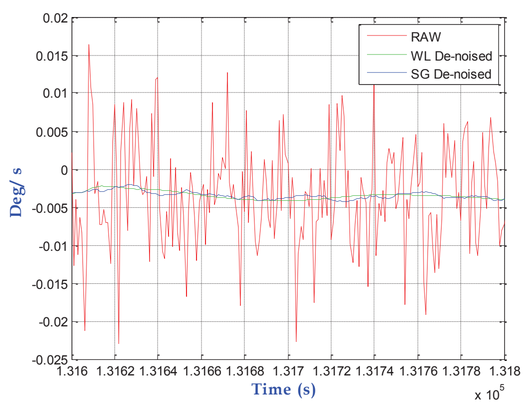

Fig. 9. An enlarged portion of vertical gyroscope data.

Overall, no significant difference is apparent between the two methods during the static portion of the trajectory (while the car was stopped). In the dynamic part, SG performed slightly better than WL in fitting the original data while removing high frequencies, strictly speaking, noise. The errors in the attitude, velocity, and position, during the artificially inserted outages, are depicted in Fig. 10, Fig. 11, and Fig. 12, respectively. Due to the very similar performance of both WL and SG denoising methods, the ultimate navigational solutions are almost identical with the slight improvement that can be noticed in the attitude solution. However, the results presented in Table 1 are even more revealing. In Table 1, root mean square (RMS) errors are given for the position solution components, with column 1 for results obtained using WL, and column 2 for SG results. The last column shows the improvement achieved using the SG method as compared to the WL method. As the bottom cell shows, the total improvement achieved across all components together is 7.6080 %. What is more, the execution time of the WL method was 3.25 times that for the SG method. This makes the SG a better candidate for embedded system implementations.

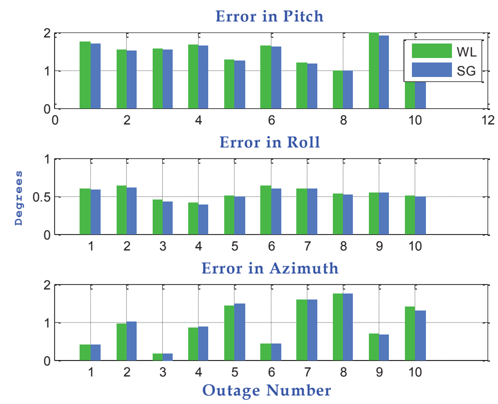

Fig. 10. Attitude solution

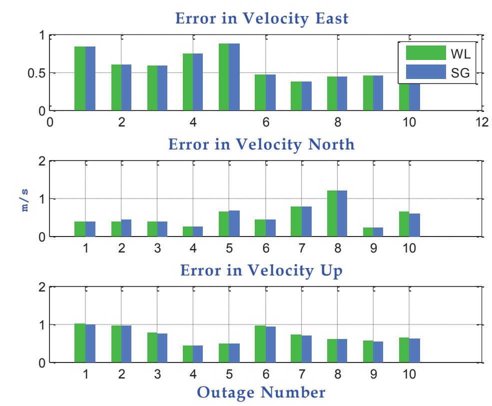

Fig. 11. Velocity solution

Fig. 12. Position solution.

Table 1. RMS errors for attitude, velocity, and position solutions.

Parameter	Denoising technique		Improvement %
	WL	SG	
Pitch (deg)	1.6293	1.5942	2.1576
Roll (deg)	0.5506	0.5342	2.9702
Azi (deg)	1.0122	1.0086	0.3551
Ve (m/s)	0.5007	0.5012	-0.0808
Vn (m/s)	0.5229	0.5236	-0.1350
Vu (m/s)	0.6534	0.6379	2.3695
East (m)	3.4687	3.4727	-0.1162
North (m)	5.3210	5.3423	-0.4000
Height (m)	12.6362	12.6362	0.0000
Total			7.1204

VII. CONCLUSIONS

MEMS-based inertial sensors suffer from complicated error characteristics such as signal noise and sensor bias. Thus, some signal pre-processing must be applied to these signals to be able to use them. Most of the research has used wavelet transformation as the technique for signal denoising. This paper suggests an effective alternative, which is Savitzky-Golay filters. These efficiently preserve essential signal characteristics, e.g., height and width of a peak, and hence, they are very common in spectral analysis and optimization. The adopted method was successfully implemented in an integrated INS/GPS environment. Experiment results showed that the Savitzky-Golay filters performed 7.6280 % better than the conventional denoising approach. More importantly, the execution time for running the WL was more than three times that for the SG. Accordingly, this exploration was considered worthwhile, and Savitzky-Golay is recommended for applications that use MEMS-based technology.

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