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De-Noising the IMU oOutput Signals by Wavelet Transform, Autocorrelation Function and PAPR

Fatemeh Vaez

Islamic Azad University of Tiran, Tehran, Iran

Corresponding Author's E-mail: *Fatemeh.vaez@gmail.com*

Tel Number: *+98-021-66363649*

Abstract

In recent years, the advancement of inertial navigation systems (INS) with the aim of increasing road safety and underwater vehicles localization has been dramatically enhanced. One of the most important parts of these systems is the Inertial Measuring Unit (IMU), which is made up of accelerometers and gyroscope sensors. IMU output signals usually have different noises and errors. Lack of attention to these two aspects could lead to a sharp decline in the performance of a navigation system. Identifying, modeling and removing noises and errors are the most important challenges in most studies. In this paper, by modeling the accelerometers and gyroscope sensors, we make an effort to remove noises and errors from these signals. This modeling with 6 degrees-of-freedom (DOF) for 3DM-GX25 inertial setup is one of the efforts made in this paper. Due to the dramatic growth of noise reduction methods by wavelet transforms in an inertial navigation system, this method is explored in detail in this paper. Simulations show that the use of wavelet transform in 3DM-GX25 intrusion data for subsurface vehicles does not necessarily lead to improving navigation performance.

Keywords: Inertial Measurement Unit; Noise Modeling; Wavelet Transform;, Autocorrelation Function; PAPR

1. Introduction

Navigation and localization are two of the most important and decisive issues in most human activities that have always challenged researchers to achieve more and better abilities in these two categories. During the past few years, many technologies have been used for routing and positioning, each having its own inefficiencies besides their benefits. The use of Autonomous Underwater Vehicles (AUVs) has dramatically progressed in recent decades. Improving the performance of subsurface devices navigation and no need for constant attention were the main reasons for the advancement of autonomous vehicles. Collecting and measuring navigation data due to inherent and natural factors are also leading to error generation. Submarine navigation systems rely on the gyroscope sensors and the inertial navigation system (INS), but the precision of these systems, especially the INS, decreases over time. Some of the errors in the navigation system are fixed, others vary with time and frequency variations, and some are random. An error in the navigation data of a vehicle can cause difficulties in localization. In order to compensate and counteract navigation errors, it is necessary to identify and model these errors. Afterwards, they can be eliminated or compensated by means of error removal methods. Navigation data are mainly derived from gyroscope and accelerometer sensors. The flying

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navigation system errors are divided into both short-term and long-term errors. The long-terms errors could be removed by a navigation assistance systems such as GPS. One of the most important short-term errors are the noises in the output of sensors which make a great deal of mistakes in localization and speed determining of a flying device [1]. The aim of this paper is to increase the accuracy of navigation by a variety of signal processing methods that help to improve the navigation precision in many type of flying equipment. To remove short-term errors in a navigation system a bank of filters could be used.

A bank of filters consists of low-pass, band-pass and high-pass filters which use in spectral analysis, and plays an essential role in many modern signal processing applications such as voice and image processing. Transmission of signals from one point to another can be done in various ways for different purposes. One of these ways is to convert a time-based signal to a frequency-based signal which is known as Fourier transform. Another method is wavelet transform, which is a mathematical function that provides a scale-time form of a time series and their relations to analyze them. The wavelet analysis provides the use of long-range intervals for low-frequency signals and short-range intervals for high-frequency signals. It could display different aspects of different data, such as breakpoints, and discontinuities, which may not be shown by other signal analysis methods. Totally wavelet transform is so important and widely used in many applications [2] [6].

One of the main achievements of this research is the reviewing various and up-to-date references of inertial underwater navigation. Different methods have been investigated and compared. By the idea of superior techniques, we have tried to offer the best practice. In this study, we introduce and review the autocorrelation function and PAPR criteria to improve the performance of the 3DM-GX25 real-world IMU unit navigation. With the aim of reducing the complexity, noise reduction measures will be presented in the simulations. Attention to the dominant noise in the 3DM-GX25 signal is one of the advantages of the proposed method. In most researches, the dominant noise in the signal is not taken into account. This can lead to additional processing in a noise removal method. The proposed method could prevent additional calculations to eliminate Non-dominant noise by considering the dominant noise in a signal. We will show that the use of wavelet transforms to remove noise does not always lead to improved navigation system performance and ignoring the stated criteria can reduce the noise-removal efficiency in navigation recognition applications. In this paper simulation of the actual 3DM-GX25 data by using the proposed method are done. Considering theoretical investigations and simulations, we show that the proposed method could have better performance than simple wavelet transform and filtering methods.

The overall structure of the paper goes on as follows: in the next section, we will outline the inertial sensors outputs along with the error sources in these sensors. In the third section, we take the idea of the proposed method from these methods. Subsequently, by introducing Autocorrelation function and PAPR, we will analyze the noise and signal navigation errors. We also show that wavelet transform does not necessarily lead to improved navigation system performance and attention to sharp edges of the signal could help to eliminate noise and error. We simulate the real 3DM-GX25 data. Finally, in the fifth section, we summarize the results and offer suggestions for further research.

2. Denoising by Wavelet Transform

In the field of navigational sciences, the most important issue is to recover the correct signal from a noisy signal. As shown in [7] noise variation amplitude in a signal of the inertial sensors is high. Also, noise level could be different from one sensor to another. Paying attention to noise removing in the low-frequency segment of a signal can result in significant improvement in navigation performance. The basic question in using inertial sensors is how low-performance sensors can lead to precise navigation. The answer is to eliminate noise and errors. In general, noise removal methods can be performed in the frequency domain or time domain. It is also possible to use spectral analysis methods and wavelet analysis. Finally, for statistical analysis of the sensor signal, covariance, correlation, and Allan variance of a signal can be used [7].

In the most analysis in the time domain, sensor signals are assumed to follow a specific pattern associated with noise, which the noise mainly affects pattern recognition. Time domain analyzers can highlight the data segment by filtering out-band noises and deliver remain signal along with in-band noise to a navigation computing unit. This section examines the theory and method for implementing wavelet transform for inertial sensors [4]. The wavelet transform in this procedure is a pre-filter method. Using wavelet transforms improves SNR and eliminates the high noise frequency parameters. By windowing a signal, wavelet transform converts a reference signal into a time-limited signal. The possibility to change the length of the windows makes the wavelet transform suitable for local signal processing (place to place). By this, the wavelet transform can be used for high-frequency processing (narrow-window) and low-frequency processing (widescreen-windows) [4].

Considering that noise in the IMU signal, occurs in different parts of the frequency range, it seems appropriate to use a wavelet transform to counteract and eliminate such noise. Since the main signal samples are used in processing, an analysis will be done by discrete wavelet transform. In the implementation of discrete wavelet transform (DWT), the wavelet coefficients are calculated by passing through low-pass and high-pass filters. So, the signal is divided into two signals such as Figure 1 with high-frequency and low-frequency characteristics.

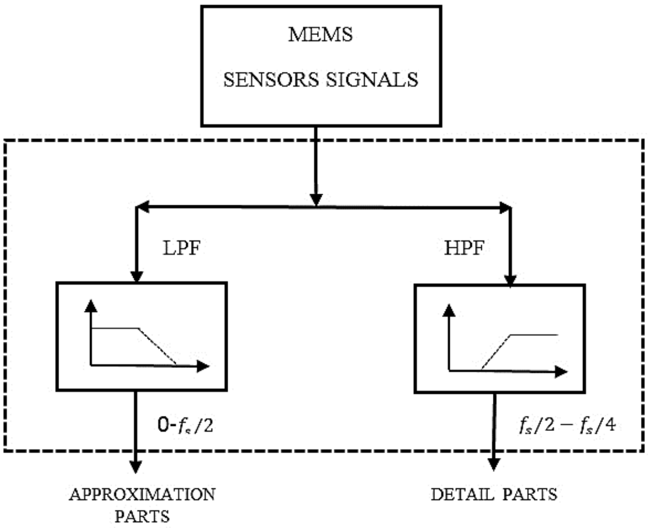

Figure 1: Signal separation by applying a discrete wavelet transform

By applying the Nyquist theorem, if a signal is sampled at f_s, then the maximum signal frequency length will not exceed $\frac{f_s}{2}$. So the cut-off frequency for both filters is $\frac{f_s}{2}$. Due to the main signal bandwidth, the filtering process can be done in several steps. This bandwidth reduction by wavelet transform is referred to as Wavelet Multiple Resolution Analysis (WMRA) [7]. It has been shown that the use of wavelet transform for noise removal compared with the use of the Butterworth low pass filter with improved SNR metrics and without deletion of details has a better performance. The level of filtering and the number of it depends on original signal bandwidth [3] [5]. The wavelet analysis theory is discussed below.

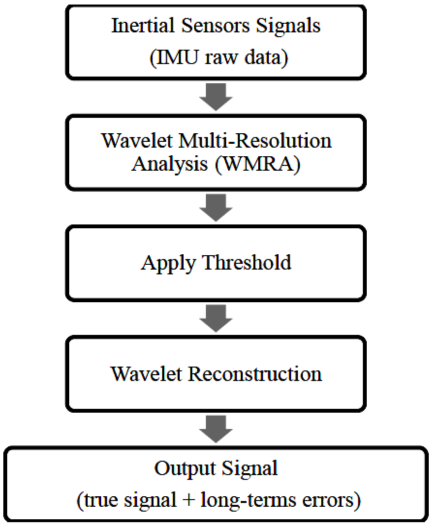

Figure 2: Block diagram the wavelet waveform analysis process with several degrees of accuracy [2]

3. REMOVING NOISE AND ERRO FROM INERTIAL SENSORS

According to the studies carried out in previous sections, in this section first, the raw data related to the IMU unit, 3DM-GX25, is examined. Then, by analyzing the wavelet, we are going to remove the noise of the IMU signals. . The focus of this section will be on 3DM-GX25 random errors and noises.

A. Autocorrelation function analysis

In the following, we show that the use of wavelet transforms does not necessarily lead to improve navigation system performance. To prove this claim, we compare the autocorrelation function of original signal the de-energized signal. As we expect solidarity from the principles of autocorrelation, the signal that has a stronger dependence between its successive data has a wider autocorrelation function and vice versa. Figure 3 to figure 5 shows the graph of the autocorrelation function of raw signals and de-energized signals in a body system. As can be seen, the autocorrelation function of the derivative signal ψ after noise removal indicates a decrease in the correlation between samples. Therefore, de-noising of signals does not necessarily lead to improved system performance.

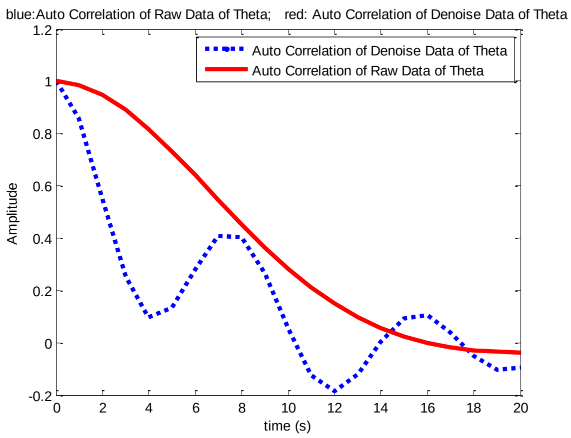

Figure 3: Autocorrelation function of the derived signal θ, 3DM-GX25 (continuous curve) and de-noise by wavelet transform and separation level L = 2 (dotted curve)

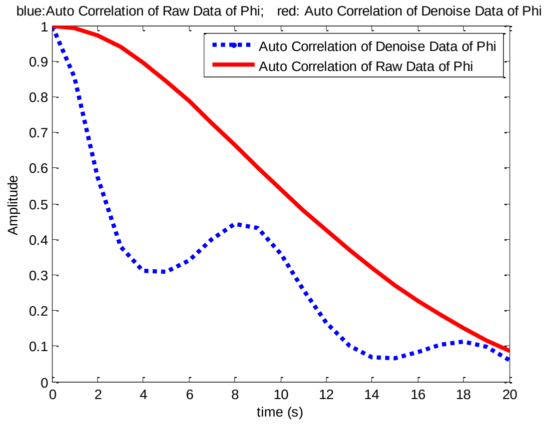

Figure 4: Autocorrelation function of the derived signal θ, 3DM-GX25 (continuous curve) and de-noise by wavelet transform and separation level L = 2 (dotted curve)

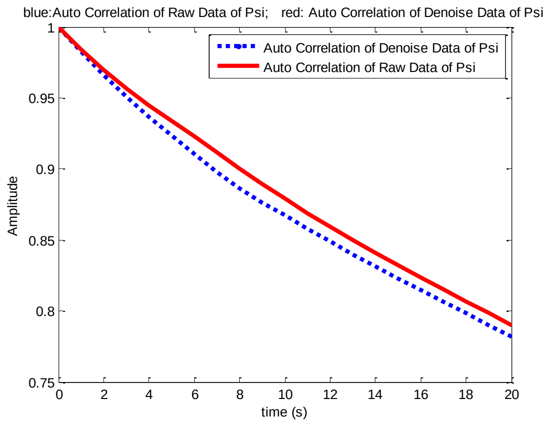

Figure 5: Autocorrelation function of the derived signal ϕ, 3DM-GX25 (continuous curve) and de-noise by wavelet transform and separation level L = 2 (dotted curve)

B. Peak to Average Power Ratio (PAPR)

The PAPR as a measure of sharp signal edges can help in designing and analyzing separation levels of noise elimination with a wavelet transform. We know that wavelet transform provides very good information about signal changes in sharp edges [8]. Knowing the number and size of sharp edges of a signal can make wavelet transform more efficient. Table 1 shows the PAPR ratio for accelerometer sensors. The mean time domain changes to maximum data size (PAPR) in accelerometer signals are much better than gyroscope signals. As can be seen, the signals that require more de-noising levels in the previous section also have a higher PAPR. Therefore, PAPR can be introduced in addition to autocorrelation function and Allan variance as a measure of de-noise reduction.

For example, consider the signal ψ, which requires a low level of noise reduction. In the PAPR benchmark analysis, the PAPR value for this signal is $PAPR_{dB} = 6.4884$, which is much lower than the rest of the body device signals. Therefore, due to the low sharp edges in this signal, noise removal is performed at lower levels. Also, consider the accelerometer signal in the z direction, in Section 3, we saw that in this signal, noise parameters dominated rapidly so need to be de-noising. By applying PAPR standard for this signal, the value $PAPR_{dB} = -3.4275$ is obtained, which represents sharp edges in this signal. Note also that these sharp edges can be clearly seen at T = 280. Therefore, the direction of de-noising with wavelet transform for the accelerometer signals in z direction requires a higher separation level.

TABLE I. PAPR, MEAN, AND RMS RATIO FOR 3DM-GX25 SENSOR CATEGORIES

Inertial Sensor	**Peak**	**Average**	**RMS**	**PAPR** $= \frac{(\text{Peak})^2}{(\text{RMS})^2}$	**PAPR$_{\text{dB}}$=10log**
P	0.8433	-3.9×10^{-4}	0.2041	17.0654	28.3705
Q	0.4619	7.5×10^{-4}	0.0929	24.7109	32.0724
R	0.4998	7.2×10^{-4}	0.1082	21.3414	30.6065
ψ'	3. 1250	0.0654	2. 2592	1.9133	6.4884
θ'	0.1505	-0.0218	0.0570	6.9780	19.4277
Φ'	0.3843	-0.0536	0.1343	8.1917	21.0312
Accelerometer X Axis	2.1478	2.1478	0.6555	10.7349	23.7350
Accelerometer Y Axis	5.3339	5.3339	1.4300	13.9136	26.3287
Accelerometer Z Axis	-9.9536	-9.9536	11.8143	0.7098	-3. 4275

Ccnclusion

In this paper, we investigated the effect of noise and error on the performance of an inertial navigation system. At first, we introduced inertial navigation, IMU unit, and various navigation methods. In the first section, one of the most important challenges in IMU signal processing was expressed. In the third section, we examined the methods and ideas presented in the references. In this section, noise removal methods from the IMU signal were investigated by wavelet transform. Most research has not led to the optimal de-noising signal. Also, in a few methods that have led to optimal signal de-noising, the underlying navigation principles have not been investigated. Accordingly, in the fourth section, with the de-noising approach in a system, we examined the equations for converting the body and ground coordinates.

Next, we introduced the concept of the variance of Allan as a suitable tool and a proposed method for expressing the type and extent of noise effects in a signal. Value of the Allan variance for the IMU unit was determined by 3DM-GX25 model and examined the dominant noise in the signal of this IMU. We showed that by using the proposed method, we can determine the dominant noise for any of the 3DM-GX25 accelerometer and gyroscope sensors. One of the advantages of the proposed method in this study is the attention to the dominant noise in the 3DM-GX25 signal.

In most studies, the third part does not focus on the dominant noise in the signal. This can lead to additional processing in de-nulling process trend. Proposed method in this study by providing the dominant signals in the signal can prevent additional calculations to eliminate non-dominant noise. We have shown that applying a wavelet transform to de-noise does not necessarily lead to improved navigation system performance. The proposed method by providing dominant signals in the signal can prevent additional calculations to eliminate non-lethal noise. In this study, we have shown that applying the wavelet transform to de-noise does not necessarily lead to improved navigation system performance. The proposed method in this study was simulated in terms of actual 3DM-GX25 data.

References

[1] Skoglund, Martin. "Inertial Navigation and Mapping for Autonomous Vehicles." (2014).

[2] Siouris, G., M., Missile Guidance and Control Systems, Springer-Verlag New York,Inc., pp. 521-522, 2004.

[3] W. S. Flenniken. " MODELING INERTIAL MEASUREMENT UNITS AND ANALYZING THE EFFECT OF THEIR ERRORS IN NAVIGATION APPLICATIONS." M.A. thesis, University of Auburn Alabama, December 2005.

[4] M. D. F. A. N. Bento. "*Development and Validation of an IMU/GPS/Galileo Integration Navigation System for UAV*." M.A. thesis, University of the Federal Armed Forces Munich, Germany, April 2013.

[5] V. EKÜTEKİN "*NAVIGATION AND CONTROL STUDIES ON CRUISE MISSILES*. " MIDDLE EAST TECHNICAL UNIVERSITY (2007).

[6] Hicks, S., "Advance Cruise Missile Guidance System Description", Proceedings of the IEEE Aerospace and Electronics Conference, 1993.

[7] H. Hou. "*Modeling Inertial Sensors Errors Using Allan Variance*." M.A. thesis, University of the Calgary,Alberta canada, September 2004.

[8] Zhou, Ling, et al. "*Terrain aided navigation for long-range AUVs using a new bathymetric contour matching method*." Advanced Intelligent Mechatronics (AIM), 2015 IEEE International Conference on. IEEE, 2015.