Signal Conditioning Algorithms on Accelerometers in an Inertial Navigation System (INS)

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***Abstract*— Localization of an unmanned vehicle, locating it in a three-dimensional space and identifying its acceleration, velocity, position and orientation accurately is a very challenging and demanding task. One of the most common systems used for localization is an Inertial Navigation System, which uses accelerometers and gyroscopes to determine position and orientation of the body in three-dimensional space. Accelerometers used in an Inertial Motion Unit (IMU) are very sensitive and susceptible to noise due to vibrations and shocks. This paper displays observations from the analysis of the various signal processing algorithms used to extract position and velocity from an accelerometer. This paper aims to enhance reliability and accuracy and overcome drawbacks of accelerometers in an inertial navigation system.**

Keywords—Accelerometer; Inertial Motion Unit; Inertial Navigation System; Localization; Weighted Moving Average; Offset Removal; Thresholding; Zero Velocity Update

I. Introduction

Inertial Navigation System (INS) is one of the systems used for localization. It has various applications which include localization for surveillance and automation of industrial tasks. It is also an integral part of devices that track physical activities,health and wellness. Inertial Motion Units (IMU) along with other sensors such as magnetometers are also used in phones to track various movements which can be used to identify the user's physical activities. IMUs are also used in shock testing to study a system's tolerance to shocks and jerks.

An IMU uses a combination of a 3-axis Accelerometer and a 3-axis Gyroscope, which measures the rate of rotation and acceleration of a body in a three-dimensional space. The accelerometer measures the acceleration taking into account all the forces acting on the sensor, along with the normal reaction of the surface below. It is used to obtain velocity and position of an unmanned vehicle by performing numerical integration on acceleration. Since the 3-axis accelerometer measures the acceleration along three Cartesian coordinate axes, it is affected by both; static forces such as gravity and dynamic forces in the form of movement of the vehicle [1]. Depending on the orientation of the sensor, a component of gravitational acceleration is observed along the axes and it is challenging to differentiate between this component and the acceleration due to the actual motion of the vehicle. Another drawback of an accelerometer is that it is very sensitive to minute vibrations which lead to stochastic errors. Moreover, due to numerical integration, these errors accumulate and cause significant velocity and positional errors [2].

Thus, it is vital to use signal conditioning algorithms which enhance the sensor's data and help to provide a reliable and accurate description of the system's position and orientation [3].

The paper is organized as follows: Section II defines the signal conditioning algorithms to be used on the accelerometer data, Section III contains the observations prior to signal conditioning and the improvements seen after implementing the algorithms described in Section II. Section IV concludes the paper and discusses the need for performing signal conditioning.

II. Signal Conditioning Algorithms

The proposed system consists of four major data processing algorithms that have been used to reduce the effect of noise on an accelerometer.

The following steps are performed on the raw acceleration data. Initially, offset removal is carried out to correct any error in orientation. Weighted moving average is applied next to smoothen the signal and to suppress the spikes. Thresholding removes any zero error in acceleration. Finally, velocity resetting is implemented to reduce the velocity and position errors.

A. Offset Removal

The acquired accelerometer data is the net acceleration resolved along the Cartesian axes and is derived from the negative of the sum of all forces acting on a body. These forces can be both static and dynamic. Since we are working in a non-inertial frame of reference, it is necessary to ensure that gravity does not affect the net force causing movement. To keep the gravitational acceleration only along the y-axis, the sensor's plane should be perfectly normal to the direction of gravity.

Practically, this is not possible as physical conditions cause the sensor's orientation to vary from ideal, and thus gravitational acceleration 'g' might have a component along the direction of movement of the sensor.

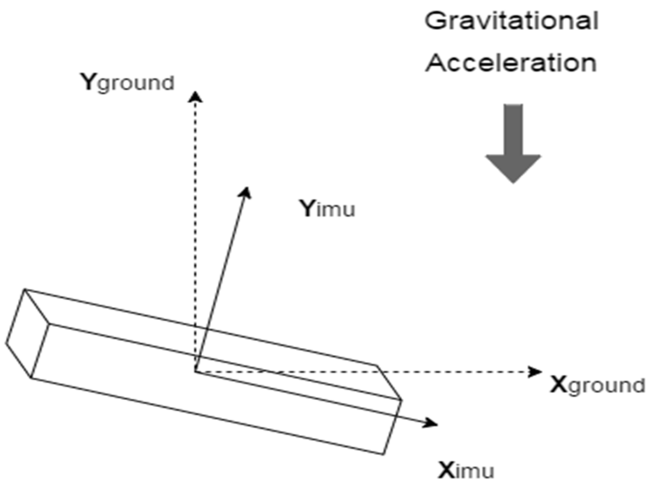

Figure 1: Orientation of sensor with respect to the ground plane

To account for this problem, the offset component of the sensor was calculated in its initial orientation. After turning the sensor on, it is kept steady for the first 500 samples. Average of these 500 samples is calculated and subtracted from subsequent values nullifying its effect on further readings.

B. Weighted Moving Average Filtering

Due to the inherent noisy nature of the accelerometer data, it is of utmost importance to carry out filtering. Although selective frequency removal is not possible due to the presence of Gaussian noise; Moving Average Filtering is used to smoothen the signal and to suppress the spikes [4].

For accurate distance calculation, it is necessary to obtain accelerometer readings that are free from noise and reflect the exact physical motion of the sensor. A moving average induces lag which increases with increase in frame length and thus it is crucial to find an optimum frame length for filtering. Following are two widely used averaging filters:

The Moving Average Filter is implemented as shown in the following equation [5]:

$$\text{avg(n)} = \frac{1}{N} * \sum_{k=0}^{N-1} x(n-k)$$

where avg(n) is the moving averaged filtered value for the nth sample, x(n) denotes the raw value of acceleration and N denotes the filter length.

The Weighted Moving Average Filter is implemented as shown in the following equation[5].

$$\text{weighted\_avg(n)} = \frac{2}{N*(N+1)} * \sum_{k=0}^{n-1} (n-k) * x(n-k)$$

where weighted_avg(n) is the weighted moving averaged filtered value for the nth sample, x(n) denotes the raw value of acceleration and N denotes the filter length.

C. Thresholding

When the IMU is kept stationary, due to the presence of stochastic errors, the accelerometer outputs non-zero acceleration that can be considered as noise. This noise causes an error in the calculation of velocity and position hence it must be reduced. The error present in the readings is 0.5-1% of the entire range and has a non-zero mean. Integration of acceleration in the presence of non-zero-mean noise results in accumulation of error.

Since this error does not exceed 0.5 - 1% we can set a suitable threshold, below which any acceleration value is set to zero. This technique increases the accuracy of the velocity and position measurements when the sensor is stationary.

Ideally, during a non-accelerated motion, the sensor should output an acceleration value of zero. However, practically, it is extremely difficult for a body to undergo perfectly non-accelerated motion and it causes the sensor to produce non-zero values of acceleration which are observed to be larger in magnitude than the stochastic errors. Thus, it is possible to select a threshold value greater than the stochastic errors but small enough to allow the detection of non-accelerated motion. Within this allowable range of threshold values, we must keep the threshold as low as possible as thresholding causes a part of the acceleration curve to be clipped when the device is accelerating or decelerating. This leads to errors in position and velocity calculations. Thus, it is very important to select an optimum threshold value.

D. Zero Velocity Updating Algorithm

In inertial navigation systems, errors in velocity and position estimation accumulate if error resetting is not performed. Zero velocity updating is a technique that minimizes the errors in velocity estimation by resetting the velocity to zero when a stationary condition is detected through proper thresholding. This technique is widely used in pedestrian navigation systems because during walking one foot always touches the ground and remains stationary (at zero velocity) for a short duration while the other foot moves [7]. The ability to efficiently differentiate between a stationary condition and a non-accelerated motion enables us to extend this technique to the vehicular motion.

In our , a stationary condition is detected only after a predefined number of consecutive sample values are observed to be zero. This ensures that the zero velocity updating algorithm does not reset the velocity unless a stationary condition is detected reliably. Velocity resetting reduces accumulation of errors in velocity and position calculation.

III. Observations and Results

For the development and testing of our algorithms, we have used the sensor MPU-6050, which is a six-axis (Gyro + Accelerometer) MEMS MotionTracking device [7]. It is a low power, low cost and high-performance device designed for use in smartphones, tablets, wearable sensors and unmanned vehicles. It contains a 3-axis accelerometer and a 3-axis gyroscope.

The onboard accelerometer has a user-programmable full scale range of +/-2g, +/-4g, +/-8g and +/-16g (g = 9.8m/s2). For implementing our algorithms, we have programmed it to work in +/-2g mode to provide maximum sensitivity. It has an integrated 16-bit ADC to enable simultaneous sampling of accelerometer without using a multiplexer. The sensor is capable of sampling the accelerometer at 1 kHz and sending the data via I2C interface.

Following are the observations and results derived after performing extensive testing on MPU-6050:

A. Offset Removal

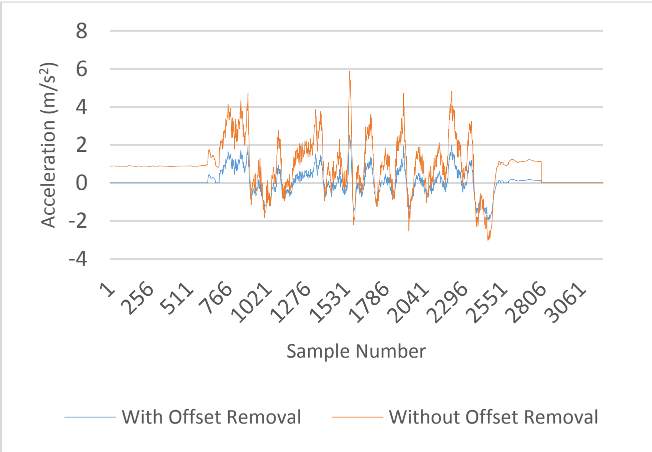

Figure 2: Effect of Offset Removal on Acceleration

As shown in the Fig.2, the device's initial orientation is not perfectly normal to the gravitational acceleration. This causes the acceleration graph to shift upward by a component of gravity (Without Offset Removal). On applying the offset removal technique, the effect of this component can be nullified.

B. Weighted Moving Average Filtering

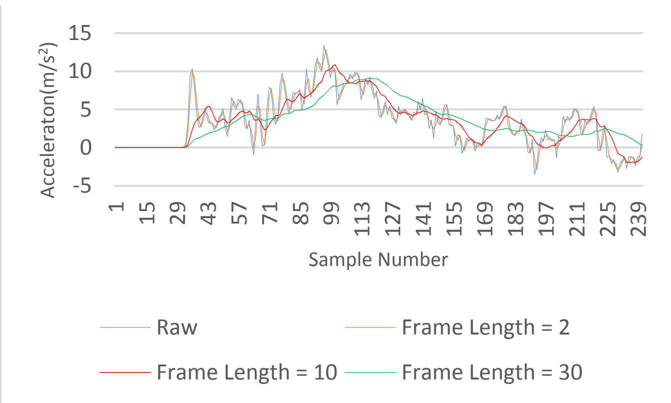

Figure 3: Effect of Frame Length of Averaging Filter on Acceleration

The Moving Average Filter was tested for various frame lengths. It can be inferred from Fig.3, that an increase in frame length decreases responsivity to the variations in raw data and increases lag. However, as seen in the above figure, a very small frame length could not remove the fluctuations in the raw data.

On considering the trade-off between filter induced lag and responsivity, empirically it was found that with a frame length of 10, the averaging filter performed best.

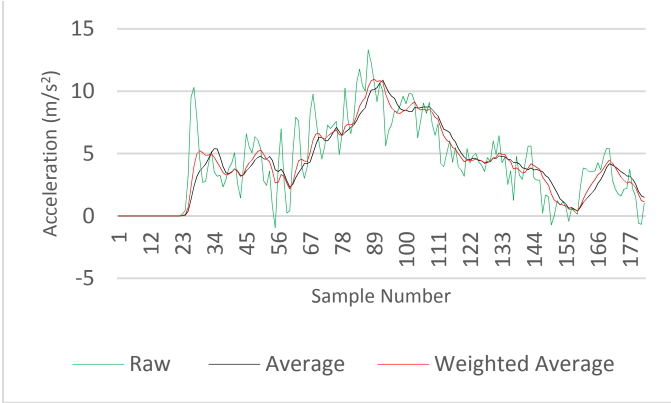

Figure 4: Comparing effects of weighted averaging with averaging filter on acceleration

As seen in Fig.4, the Weighted Moving Average filter further improved responsivity to the variations in raw data in comparison to the Moving Average Filter. From the inferences made above, the Weighted Moving Average Filter was chosen over the Moving Average Filter.

C. Thresholding

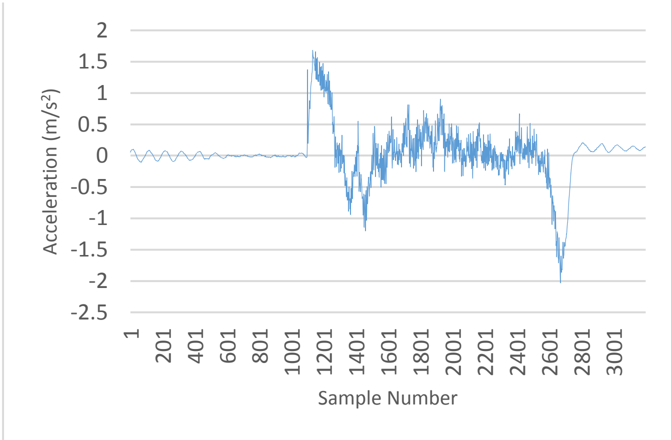

Figure 6: Effect of noise without thresholding on acceleration

As seen in Fig.6, noise is present in the data between sample numbers 1 - 601 and 2801 - 3000.

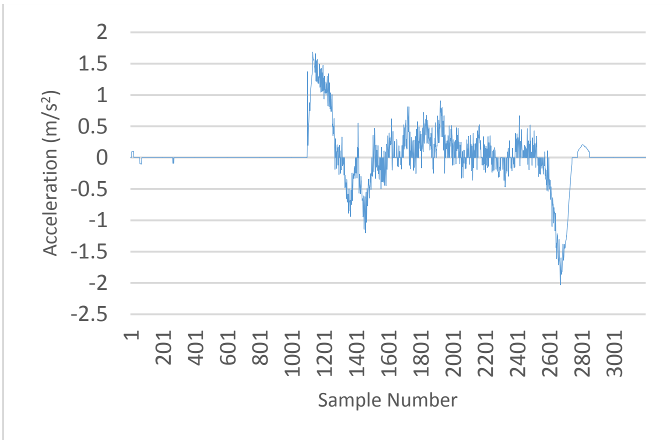

Figure 7: Effect of appropriate thresholding on acceleration

The threshold is selected such that the stochastic errors (samples 1 to 1000) are removed, but the non-accelerated motion (1500 to 2500) is still detected. After applying this appropriate threshold, a significant reduction in the noise spikes can be observed in Fig.7 as compared to Fig.6.

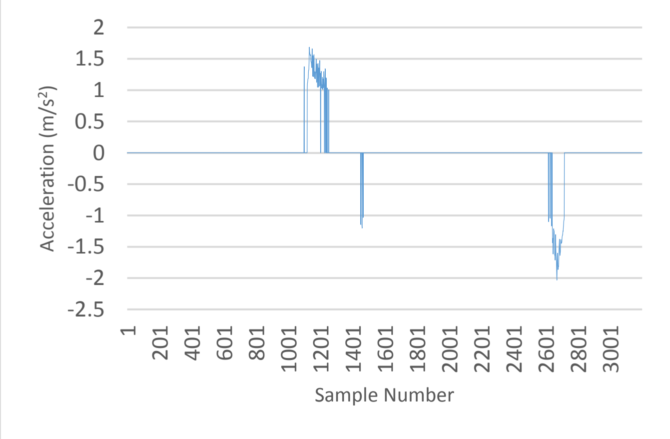

Figure 8: Effect of applying a high threshold on acceleration

It is observed in Fig.8 that a part of the acceleration spike near 1001-1201 and a part of the deceleration spike near 2601-2801 is being clipped due to the application of a high threshold. It results in the incorrect estimation of velocity and position after numerical integration.

D. Zero Velocity Updating Algorithm

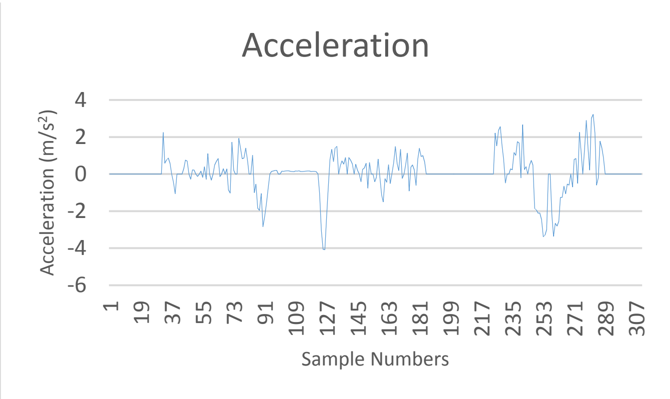

Figure 9: Acceleration data during non-accelerated motion and rest

This figure represents the motion of the sensor when it undergoes non-accelerated motion between sample numbers 37-73 and 145-181 and is kept stationary between sample numbers 181-217. It is observed that the values of acceleration during non-accelerated motion, are in the range of 2-8% of the total range of accelerations. Also, during the stationary condition, the thresholding ensures that the acceleration values are equal to zero. We took advantage of this difference between the range of acceleration values for non-accelerated motion and stationary condition and applied the zero velocity updating algorithm [8].

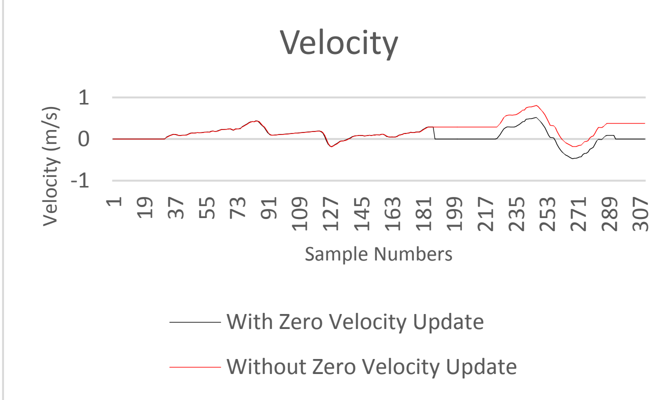

Figure 10: Effect of Zero Velocity Update Algorithm on velocity

This figure shows the velocity plot corresponding to the acceleration values represented in Fig.9. It can be seen that after application of the zero velocity update algorithm, the velocity is reset to zero between sample numbers 181-217. By resetting the velocity to zero during the stationary condition, accumulation of significant errors in distance calculation is avoided.

IV. Conclusion

It is imperative to use proper signal conditioning algorithms on the accelerometer data because of the fluctuations in raw acceleration values and practical conditions under which the system operates. The signal conditioning algorithms mentioned above improve the ability to estimate the position and velocity efficiently, thus enabling the INS to work more reliably.

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