Electronic Preprint for Journal of Information Processing Vol.27

Regular Paper

Vehicle Vibration Error Compensation on IMU-accelerometer Sensor Using Adaptive Filter and Low-pass Filter Approaches

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Received: April 10, 2018, Accepted: October 2, 2018

Abstract: In vehicle dead reckoning or vehicle positioning systems, an inertial measurement unit (IMU) sensor has an important role to provide acceleration and orientation of the vehicle. The acceleration from the IMU accelerometer is used to calculate the velocity of the vehicle, and then it estimates the vehicle's distance traveled to time. However, the accelerometer suffers from external noises such as vehicle vibrations (generated from the engine, alternator, compressor, etc) and road noises. This paper delivers deep analysis and focuses on how to handle the error from vehicle vibrations. A filter method is proposed by using a combination of adaptive least mean squares (LMS) and low-pass finite impulse response (FIR) filters. The adaptive LMS filter is used to cancel the vehicle vibration error frequencies and adapts those frequency changes in several engine rotation conditions. It is then finalized with the low-pass FIR filter which is used to filter high-frequency vibration noises. Several experiments were made and the results show that the proposed filtering method is able to give better signal to noise ratio (SNR dB) and noise attenuation ratio (ATT dB) in comparison with regular low-pass FIR filter and independent adaptive LMS filter in a particular condition.

Keywords: adaptive LMS filter, low-pass FIR filter, vehicular accelerometer, IMU sensor, on board diagnostic (OBD-II), digital signal processing

1. Introduction

The development of positioning technology, especially in a vehicle positioning system is growing rapidly nowadays. This technology arises due to the low-cost devices and the development of supporting technology such as sensor and processor technologies. Further, the development of internet technology and information distributions are making such knowledge be distributed easier and learned by people from many backgrounds. One of the technologies that are commonly adopt in positioning technology is inertial measurement unit (IMU) sensor. In some paperwork, IMU sensor is used as an inertial navigation system (INS) to support multi-sensor vehicular positioning strategy [1], [2], [3], [4]. Normally, IMU sensor is based on the microelectromechanical system (MEMS), provides the integration system of accelerometer, gyroscope, and magnetometer in one small single integrated circuit (IC). In our previous paperwork [1], the fusion algorithm of 3-internal IMU sensors was used to provide the orientation of an object particularly airport's apron vehicles. Accelerometer data were used to calculate the object acceleration and then provide velocity and traveled distance value by integrating it toward time. However, vehicle (include apron vehicles) produces internal vibration noise which effects the acceleration measurement data of the IMU sensor. Knowing the response on this vibration is very important especially in multi-frequency acceleration [5]. Overcoming this challenge, data noises analysis and filters are needed to omit the vibration error effect in the IMU sensor, especially in accelerometer sensor.

The purpose of this research is to filter the internal vibration error that occurs in the vehicle either from the engine rotation or other sources, such as alternator and air-conditioner compressor. The effect of this vibration error is quite critical. Based on our experience, this vibration error will affect the vehicular position estimation [1]. Accordingly, handling such error cannot be underestimated. This vibration error impacts the calculation/integration result from IMU-acceleration value to provide vehicle dead reckoning/positioning system (velocity and distance traveled), especially in a long period of time.

In this paper, a filtering method is proposed which combines adaptive least mean squares (LMS) filter and low-pass finite impulse response (FIR) filter to handle this error. Adaptive LMS filter is normally used to model the relationship between two signals in real time [6]. Certain research papers use this adaptive LMS filter to improve the response of accelerometer for automotive application [5], [8]. Other common applications of this digital adaptive filter are to cancel the signal error in electrocar-

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diogram (ECG) signal [9], [10] and to compensate cross-talk in acoustic signal [11]. In this paper, The LMS filter is chosen to adopt the vibration frequency error detected by the Z-axis accelerometer and then cancel the vibration error sensed in X and Y axes. The Z-axis is chosen since this axis is not influenced by the vehicle movements in other two axes (forward-backward, right-left). Further, low-pass FIR filter is then used to omit the high-frequency vibration error.

Organization of this paper is started with the initial and data noises analysis. It then continues with digital adaptive LMS and FIR filters design with several parameter set-ups. Once proper filter set-up is obtained, the designed filtering method is tested in several experiments, such as in idling and moving vehicle conditions. Next, comparative analysis between results from the proposed filtering method and the other filter methods (regular low-pass FIR filter and independent adaptive LMS filter) are carried out using the signal to noise ratio (SNR dB) and noise attenuation ratio (ATT dB) comparisons.

2. Research Overview

This section introduces briefly how to set up sensor materials and how to develop the initial analysis. Through the result from initial analysis, a filtering method is developed to compensate the vehicle vibration error. A brief explanation concerning to how the filtering method works is also given as a part of Section 2.3.

2.1 Materials

To collect data and support the initial analysis, a sensor system is developed based on 9-axis IMU sensor, OBD-II reader, and a microcontroller. The IMU sensor applied in this system is BNO055 series which includes accelerometer in 3 axes (X, Y, and Z axes) [12]. This sensor is positioned on the top-left vehicle dashboard with Y-axis toward vehicle's front and back movement, X-axis toward right and left vehicle's shift, and Z-axis toward vehicle up and down change. As mentioned previously, this sensor is used to cover vehicle movements to gain the velocity and vehicle distance traveled [1]. In fact, it also experiences vibration effects, for example engine rotation, alternator, air-conditioner, and compressor.

Further, the OBD-II reader in this system is based on ELM 327 chip processor which is also known as OBD to RS-232 interpreter. Working under the AT-command protocol, this device provides considerable parameters from the vehicle, such as velocity, engine rotation speed, and vehicle torque [13]. ELM 327 complies several OBD-II standards which are already adopted by most common vehicle worldwide. In this research, the OBD-II is used as a reader device to read and mark several engine rotation (RPM) value as a reference in vehicle vibration error analysis. All data distributed from IMU sensor and OBD-II reader are collected and managed by Arduino Due series, a 32 bit CortexM3 ARM microcontroller [14]. Several communication protocols are used to communicate with those devices as can be seen in **Fig. 1**. The data from accelerometer are collected with a sampling frequency of 200 Hz meanwhile engine rotation and velocity data from OBD-II are collected every 1 second. The data are then recorded together with time stamps for further analysis.

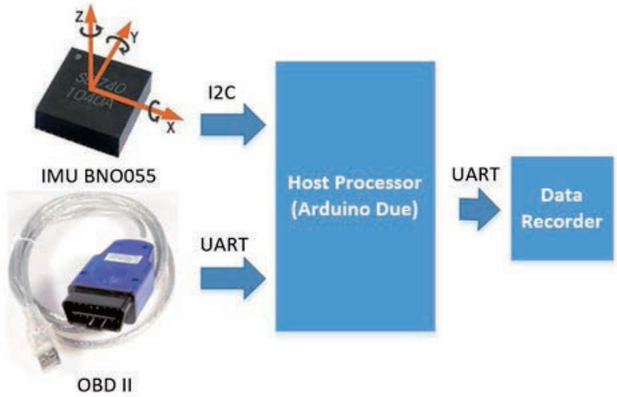

Fig. 1 Sensor system setup.

2.2 Initial Analysis

The objective of first analysis is to recognize the error frequency movement generated from the vehicle vibration. In general, the engine rotation in idle condition is varied from 600 RPM = 10 Hz (for medium to the heavy-duty truck) to 1,000 RPM = 16.67 Hz (for small passenger vehicle). On this initial analysis (preliminary experiment), first we collect acceleration data from a vehicle, Honda Kei car "That's" with 660 cc 3-cylinder engine, rotating approximately 866 RPM in the idle condition.

This vehicle is positioned in an idle condition with different engine rotation (revolution per minute, RPM) values. Those rotation values are varied from approximately 0 RPM, 866 RPM, 1,586 RPM, 2,100 RPM, 2,545 RPM, 3,015 RPM, and 3,560 RPM. From the collected acceleration data, a fast Fourier transform (FFT) technique [15] is then applied to analyze the frequency error. The results from FFT are shown in **Table 1**, **Table 2**, and **Table 3**. Table 1 represents the error frequency in X-axis, Table 2 in Y-axis, meanwhile Table 3 in Z-axis accelerometer. The first column represents the engine rotation in RPM value, the second column represents the minimum and maximum acceleration magnitudes recorded by the sensor, and the last column represents frequencies that the vibration error commonly appears for each engine rotation value. Analyzing these tables, most of the vibration error frequencies appear in the range of 10 to 80 Hz. However, in some conditions, these frequency errors are also detected at low frequencies (0 to 10 Hz) especially in the range of 2,000 to 3,000 engine RPM. Most of those error frequencies vary on every engine rotation value.

Further, **Fig. 2** shows one of the vehicle vibration spectrum frequencies at 2,100 RPM. The data from this engine rotation value is chosen because this data has a wider variation in vibration error spectrum frequency. It has a range from low to high frequency. As seen in this figure, it shows that every axis in accelerometer (X, Y, and Z axes) are sensing roughly the same vibration frequency errors. Those dominant frequencies are 1.377 Hz, 9.538 Hz, 27.22 Hz, 35.35 Hz, 47.01 Hz, 53 Hz, 64.68 Hz, and 72.82 Hz. Theoretically, the 35.34 Hz frequency is expected to be the engine vibration frequency. The expectation comes by dividing the 2,100 RPM value with 60 (minute to second). This calculation result shows that the engine frequency effect at 2,100 RPM will approximately around 35 Hz. In addition, since the vehicle

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Table 1 Error frequencies detected on acceleration in X axis for several engine rotation values.

RPM	Magnitude (m/s^2)		Error Frequency (Hz)							
	Min	Max	0–10 Hz	10–20 Hz	20–30 Hz	30–40 Hz	40–50 Hz	50–60 Hz	60–70 Hz	70–80 Hz
0	−0.041	0.039								
866	−0.3747	0.3353		14.68	22.02		44.04	55.96		
1,586	−0.89	0.889		14.03	26.56	39.91			60.12	
2,100	−0.8915	0.8585	1.377		27.22	35.35	47.01	53.01		72.82
2,545	−1.089	1.001		17.15		38.65	42.97	57.08		
3,015	−0.6246	0.5755	1.679		26.42		47.88	52.12		73.58
3,560	−0.356	0.378		14.5		33.84	40.33	59.67	66.16	

Table 2 Error frequencies detected on acceleration in Y axis for several engine rotation values.

RPM	Magnitude (m/s^2)		Error Frequency (Hz)							
	Min	Max	0–10 Hz	10–20 Hz	20–30 Hz	30–40 Hz	40–50 Hz	50–60 Hz	60–70 Hz	70–80 Hz
0	−0.0437	0.0363								
866	−0.2135	0.1865		14.68	22.02					78
1,586	−0.268	0.301	0.765	14.03	26.58	39.91			60.12	73.44
2,100	−0.2791	0.2609	9.538		27.19	35.35	47.03	53	64.68	72.82
2,545	−0.4799	0.5301		17.1		38.64	42.83	57.07		
3,015	−0.236	0.1841			26.42		47.88	50.22		73.58
3,560	−0.2571	0.2129				33.84	40.33	59.67	66.16	

Table 3 Error frequencies detected on acceleration in Z axis for several engine rotation values.

RPM	Magnitude (m/s^2)		Error Frequency (Hz)							
	Min	Max	0–10 Hz	10–20 Hz	20–30 Hz	30–40 Hz	40–50 Hz	50–60 Hz	60–70 Hz	70–80 Hz
0	−0.1	0.11								
866	−0.6135	0.5565		14.68	22.02		44.04	55.96		
1,586	−0.930	0.791		14.03		39.91			60.1	
2,100	−1.031	1.170	1.377		27.18	35.35	47.02	52.98		72.82
2,545	−1.645	1.384		17.12			42.93	57.04		
3,015	−0.6861	0.6936			26.42		47.88	52.12		73.69
3,560	−1.01	1.02				33.84	40.32	59.66	66.14	

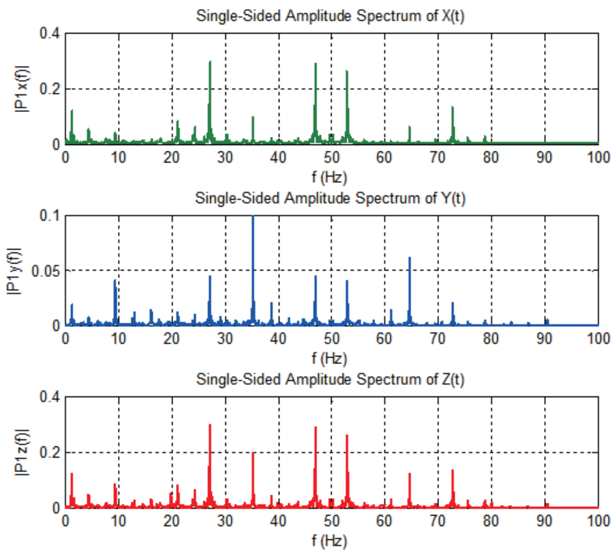

Fig. 2 Frequency spectrum of 3 axes accelerometer sensor at approximately 2,100 RPM.

used in the initial experiment has 3-cylinders engine type, 1.5 times of engine frequency will also appear as a side effect. This effect appears at approximately 52.5 Hz frequency. Other frequencies besides 35 Hz and 52.5 Hz remain undefined since they might represent the vibration from other sources, such as alternator and air-conditioner compressor. Those vibration frequencies are presented and can be also shown in Tables 1, 2, and 3.

Based on the initial frequency analysis on every engine rotation value, it can be concluded that the vehicle vibration error frequencies are changing, follows the changes of RPM values. Also, every accelerometer axis generally experiences similar vibration error frequencies. Further, those engine vibration error might appear in the low frequency region (0–10 Hz) which can not be handled by a low-pass filter. In spite of our experiment was using a typical Honda Kei car "That's", we believe that general vehicles has similar engine vibration error characteristic. Hence, analysis on other type of vehicle, particularly medium to heavy-duty vehicle, will become part of our future work.

From this preliminary result, we developed our filtering technique which will be discussed in the next section.

2.3 Proposed Method

The proposed filtering method in this research is developed based on the initial vibration error analysis. From the initial analysis results, a combination filter using adaptive LMS filter and low-pass FIR filter is proposed to lessen the vehicle vibration error effects on accelerometer sensor. The adaptive LMS filter is used to filter vibration especially in low-frequency spectrum which cannot be completed by low-pass FIR filter. The process of adaptive LMS filter is to estimate and produce an anti-error signal from a secondary source which can be used to cancel the error signal in the main signal source. As mentioned in Section 2.2, Z-axis acceleration signal practically experience similar vibration error with the other axes. However, this axis is not affected by the vehicle movements in the 2-dimensional plane (X and Y axes). Build upon these findings, the Z-axis accelerometer signal is used as a canceling-signal reference in the proposed filter. **Figure 3** shows the adaptive LMS filtering process for vehicle vibration error in X or Y axis separately with Z-axis accelerometer signal as sec-

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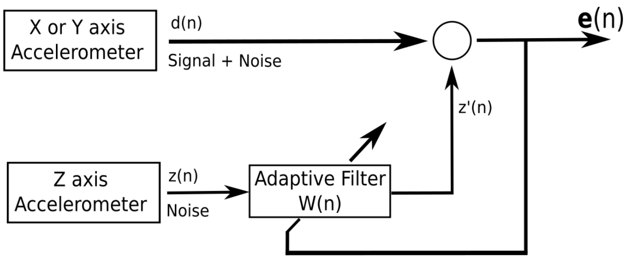

Fig. 3 Adaptive vehicle vibration noise cancellation on X or Y axis with Z axis as reference.

ondary source input to the adaptive filter.

The output of adaptive LMS filter ($\mathbf{e}(n)$) is modeled as the result between contaminated acceleration signals ($d(n)$, in X or Y axis) with the estimated error signal generated from Z-axis ($z'(n)$). As mentioned, this filtering process is done separately for X or Y axis, resulting two filter output ($\mathbf{e}(n)$) in each axis. Symbol (n) itself present the n-th number of the data. This model can be written as equation below.

$$\mathbf{e}(n) = d(n) - z'(n) \tag{1}$$

where

$\mathbf{e}(n)$: Output of the LMS adaptive filter

$d(n)$: Filter input (X or Y axis)

$z'(n)$: Filter output

$z'(n)$ is generated by processing the Z-axis accelerometer through the adaptive filter with several coefficient factors $W(n)$ as shown in equations below. Following the filter input, $W(n)$ is also generated differently for each axis.

$$z'(n) = \sum_{i=0}^{L-1}(w_i(n)z(n-i)) \tag{2}$$

$$= W(n)Z(n)^T \tag{3}$$

where the tap weights is:

$$W(n) = [w_0(n), w_1(n), \dots, w_{L-1}(n)]$$

and the input is:

$$Z(n) = [z(n), z(n-1), \dots, z(n-L+1)]$$

Tap-weight vector adaptation equation:

$$W(n+1) = W(n) + \mu\mathbf{e}(n)Z(n)^T \tag{4}$$

L in Eq. (2) represents the order of transversal adaptive filter, T in Eq. (3) represent the vector transpose function for the input signal vector $Z(n)$, and μ in Eq. (4) is the learning step value in LMS filter. Adaptive LMS filter algorithm used above follows basic LMS filter steps on its calculation process [5], [6], [7]. Once the adaptive LMS filter practiced to the X and Y acceleration values, a low-pass Humming-Window FIR filter then applied to remove remaining high-frequency errors. The low-pass FIR filter is set with 2 Hz cutoff frequency and 20th filter order.

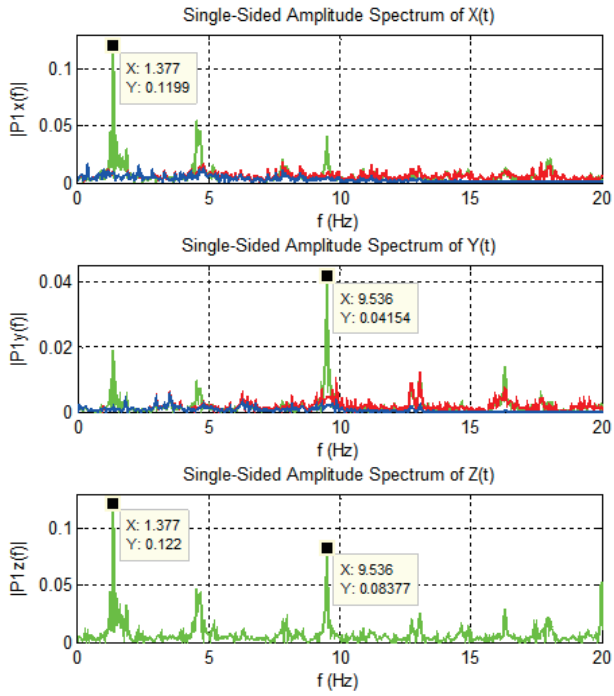

Fig. 4 Spectrum in low frequency of IMU accelerometer axes before filtering (green mark), after LMS filtering (red mark), and combined LMS and FIR filtering (blue mark) at approximately 2,100 RPM.

3. Experiment

This section discusses the experiment that was made within this research. This section covers the experimental system setup, implementation, and result analysis. As mentioned in Section 2.2, experimental setup in this section is also based on IMU sensor to collect the acceleration data, OBD-II reader to read the RPM from the vehicle, and microcontroller to process and collect those data for analysis. The system sensor is positioned in top-left vehicle dashboard, the same vehicle that we used in the initial/preliminary experiment. The experiment itself is divided into 3 experiments which are deeply explained below.

3.1 Static RPM Error Analysis

Refer to the initial analysis described in Section 2.2, data are recorded on several engine rotation values in a vehicle. Proposed filtering method is then applied to the dataset to see the performance on each RPM range. Since the vehicle is in a steady condition, the data recorded on this step are treated as pure noises. The implementation of proposed filter on those data is expected to suppress those errors into minimum value (≈ 0).

The data measured in 2,100 RPM is chosen to represent the result of the filtering methods. To compare with the data of other engine rotation values (can be seen at Tables 1 and 2), vehicle vibration error frequencies detected in 2,100 RPM are more varied than others, ranged from low to high frequencies. As seen in **Fig. 4**, the result of implementing the proposed filtering method shows that the low-pass FIR filter can filter most high-frequency vibration error. Moreover, the adaptive LMS filter is able to cancel the low frequency vibration error which appears both in X and Y axes acceleration values such as frequency 1.377 Hz and 9.538 Hz. **Figure 5** shows the X and Y axes acceleration values

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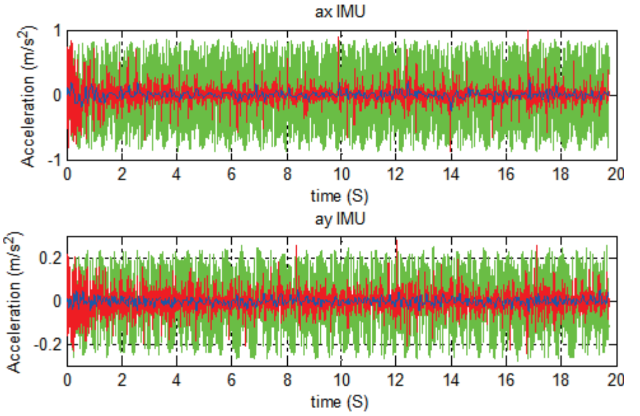

Fig. 5 Acceleration on X and Y axes before filtering (green mark), after LMS filtering (red mark), and combined LMS and FIR filtering (blue mark) at approximately 2,100 RPM.

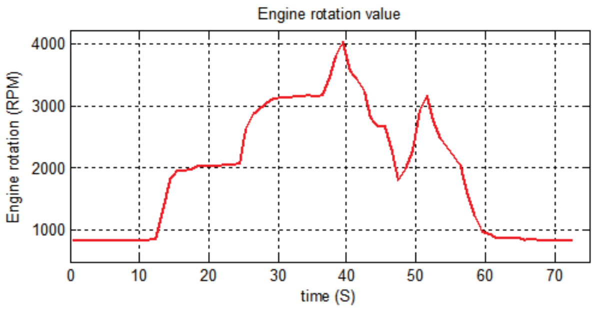

Fig. 6 Engine rotation value in random RPM error analysis.

before filtering (green mark), after adaptive filtering (red mark), and after low-pass FIR filtering (blue mark). Also referring to this figure, it can be seen that in the first 2 seconds acceleration values (red mark), adaptive LMS filter tries to adjust its coefficients. Within this period of time, adaptive LMS filter's result is gradually reduced to achieve the desired value.

3.2 Random RPM Error Analysis

The second experiment is conducted with various engine rotation values. This experiment is done to analyze the filtering performance, especially adaptive LMS filter whether it is able to adapt to the RPM changes or not. An experiment condition is set up in non-moving vehicle with engine rotation values ranged from circa 860 RPM to 4,000 RPM (**Fig. 6**). Similar to previous experiment, since it is using a vehicle in an idle condition, all data collected from all accelerometer axes are treated as noises. As results, the proposed filter approach is able to reduce the low-frequency vibration error (**Fig. 7**, red mark) and remove almost all high-frequency vibration errors detected in the vehicle IMU-accelerometer both in X and Y axes (Fig. 7, blue mark). **Figure 8** shows the accelerometer value in X and Y axes before filtering (green mark), after adaptive LMS filter (red mark), and after low-pass FIR filter (blue mark).

3.3 Moving Vehicle Error Analysis

To achieve a better analysis on the proposed filtering method performance, an experiment with moving vehicle is conducted. The experiment is set up in a straight track with road contour relatively flat. Some obstacles on road surface are spotted, such as

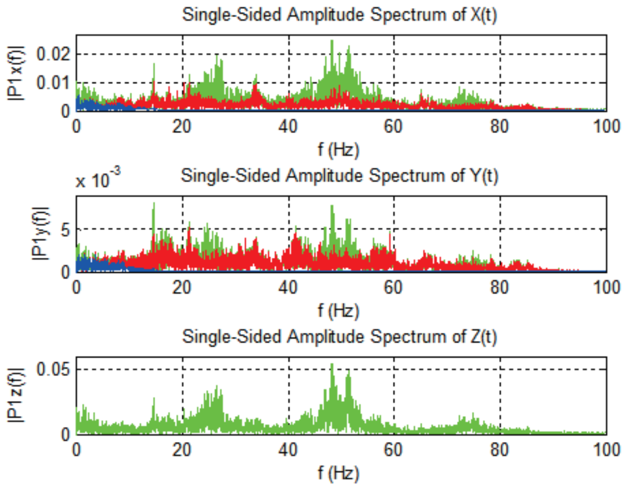

Fig. 7 Spectrum of IMU accelerometer axes before filtering (green mark), after LMS filtering (red mark), and combined LMS and FIR filtering (blue mark) at random RPM.

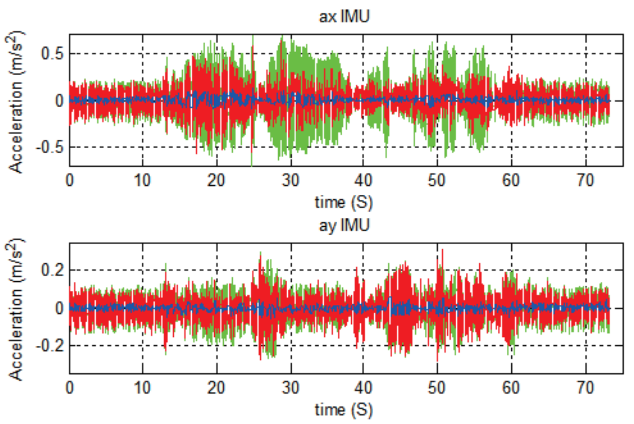

Fig. 8 Acceleration on X and Y axes before filtering (green mark), after LMS filtering (red mark), and combined LMS and FIR filtering (blue mark) at random RPM.

road patches and sewer metal-cover. The vehicle was accelerating from an idle condition up to approximately 25 km/h. It then gradually reduced the speed until the vehicle stopped. The variations of engine rotation and acceleration values collected from the OBD-II reader are shown in **Fig. 9**. This vehicle acceleration is calculated by dividing the velocity read by the OBD-II reader with its sampling time. Analyzing the spectrum frequency (**Fig. 10**), it can be seen that the implementation of the adaptive LMS filter is slightly able to cancel the magnitude of vibration error frequency. Further, the low-pass FIR filter then blocks the high frequencies and keeps the low frequency desired moving/accelerating vehicle data.

Furthermore, **Fig. 11** presents the acceleration value both in the X and Y axes of accelerometer sensor. The proposed method filter result (blue mark) shows that the proposed filter is able to reduce the vibration error in comparison with its original signal (green mark) and a single adaptive LMS filter implementation (red mark). The Y-axis graph in Fig. 11 presents the acceleration movement of the vehicle since Y-axis IMU accelerometer sensor is positioned to the vehicle toward front and reverse movements.

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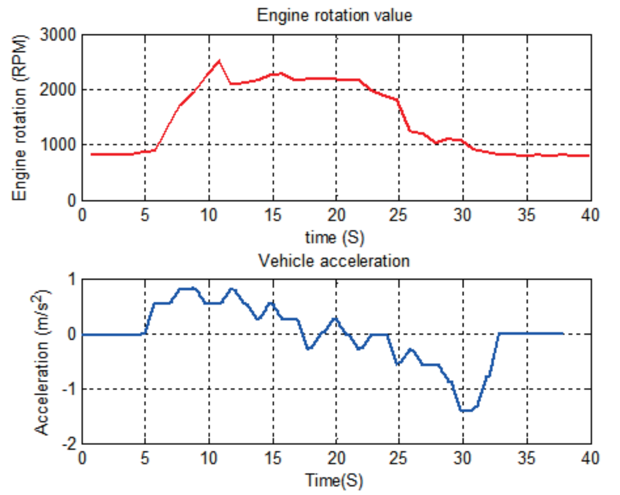

Fig. 9 Engine rotation and vehicle forward acceleration value in moving vehicle experiment read by OBD-II.

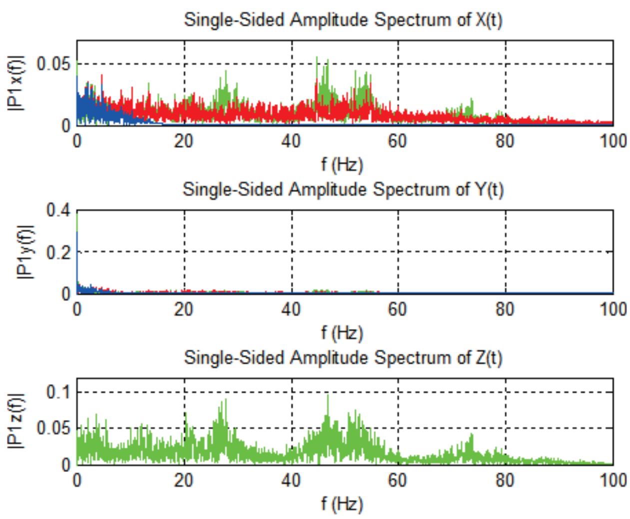

Fig. 10 Spectrum of IMU accelerometer axes before filtering (green mark), after LMS filtering (red mark), and combined LMS and FIR filtering (blue mark) in moving vehicle experiment.

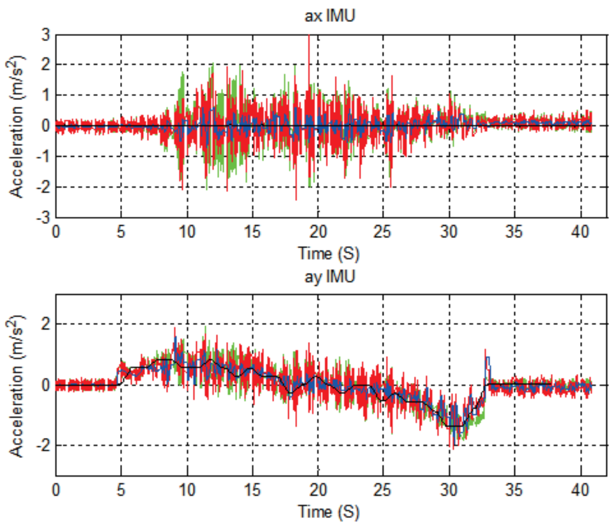

Fig. 11 Acceleration on X and Y axes before filtering (green mark), after LMS filtering (red mark), combined LMS and FIR filtering (blue mark), and vehicle acceleration reference (black mark) in moving vehicle experiment.

3.4 Performance Analysis

To analyze the result performance, a signal to noise ratio in decibels (SNR dB) and a noise attenuation ratio in decibels (ATT dB) approaches are used to compare the filtering result from several filtering methods. The methods which were compared are the low-pass Humming-window FIR filter, the adaptive LMS Filter, and the proposed filter approach that combines both Adaptive LMS and low-pass FIR filters. The SNR is calculated by the formula below [9], [16].

$$SNR_{dB} = 10\log_{10}\left(\frac{d(n)}{d(n) - \mathbf{e}(n)}\right)^2 \tag{5}$$

where

$d(n)$: Desired (reference) signal, and $\mathbf{e}(n)$: Filtered signal value

As stated in Section 3.1, in the experiments which were done with a vehicle in an idle condition, all recorded acceleration data will be treated as noises. $d(n)$ is the desired signal value (reference value) which ideally ≈ 0. In fact, $d(n)$ is not absolute zero since the IMU-accelerometer has internal sensor error. This data ($d(n)$) is collected when the sensor is steady and not experience any external disturbances. However, in moving vehicle condition, $d(n)$ will be the vehicle acceleration data which were read and calculated from the OBD-II reader as can be seen in Fig. 9.

The noise attenuation ratio (ATT dB) is conducted to calculate the noise reduction value from its original signal. Attenuation itself is a general term to describe reductions in the strength of a signal [17]. This calculation can be done by calculating the ratio from the signal after filtering ($\mathbf{e}(n)$, signal output) with the signal before filtering ($d(n)$, signal output). The formula is given as follows:

$$ATT_{dB} = 10\log_{10}\left(\frac{\mathbf{e}(n)}{d(n)}\right)^2 \tag{6}$$

where

$d(n)$: Input signal value, and $\mathbf{e}(n)$: Filtered signal value

Presenting the results, **Table 4** shows the SNR dB value meanwhile **Table 5** presents ATT dB value of X and Y axes data at several vehicle experiment conditions. In these tables, the SNR and ATT results from 3 filtering methods are compared. Those are the low-pass filter (LPF), the adaptive LMS filter, and the Author's filter combination methods. As can be seen in Table 4, the RMS values are mainly negative. This indicates that the noise signals are overpowered the reference signal since the reference signal value are close to zero. The bigger the negative value means

Table 4 Signal to noise ratio of X and Y axes acceleration signal at several vehicle condition experiments.

RPM	X axis SNR (dB)			Y axis SNR (dB)		
	LPF	LMS	Proposed	LPF	LMS	Proposed
866	−7.64	−21.29	−6.53	−4.09	−16.34	−3.04
1,586	−15.4	−23.53	−14.5	−8.81	−16.7	−8.67
2,100	−21.45	−23.15	−14.27	−7.63	−13.07	−4.1
2,545	−15.15	−23.2	−13.78	−10.69	−18.01	−9.47
3,015	−16.27	−18.15	−9.34	−8.3	−12.18	−4.1
3,560	−9.54	−14.4	−5.45	−6.1	−11.37	−4.52
Rand	−13.68	−20.5	−9.1	−5.17	−14.76	−3.94
Move	−24.6	−31.57	−24.54	8.54	4.34	8.57

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Table 5 Noise attenuation ratio of X and Y axes acceleration signal at several vehicle condition experiments.

RPM	X axis SNR (dB)			Y axis SNR (dB)		
	LPF	LMS	Proposed	LPF	LMS	Proposed
866	−16.6	−6.42	−18.1	−14.4	−6.842	−16.34
1,586	−17.2	−9.73	−18.04	−13.03	−5.21	−13.41
2,100	−12.7	−13.83	−21.76	−14.15	−9.34	−19.29
2,545	−17.11	−10.48	−19.9	−16.81	−10.46	−19.32
3,015	−12.8	−13.12	−21.3	−12.79	−9.64	−19.1
3,560	−16.62	−12.58	−22.18	−15.92	−10.89	−18.79
Rand	−13.41	−5.88	−17.91	−13.58	−2.76	−15.45
Move	−7.88	−1.58	−7.96	−1.46	−0.74	−2.2

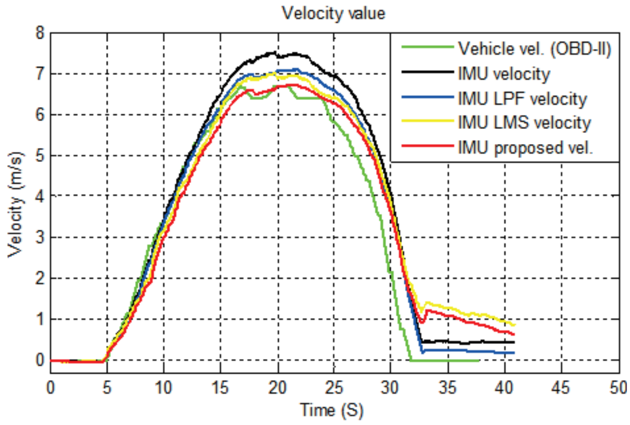

Fig. 12 Velocity comparison from vehicle acceleration and filtered IMU accelerations.

that it has more noise than others.

In the moving vehicles SNR performance analysis, filtering result from vehicle acceleration in Y-axis accelerometer is compared with the acceleration value from OBD-II reader (Section 3.3). That is why the Y-axis moving vehicle SNR results are positive. Yet, the SNR result in X-axis moving vehicle is still using steady accelerometer value ($\approx$ 0) as a comparison since this experiment is conducted without any vehicle movement in right and left directions. It can be seen that the proposed filtering method also gives somewhat improved SNR dB value in the accelerating vehicle. Despite of the fact that our proposed method has slightly better performance than LPF filter result in moving vehicle experiment, generally Table 4 shows that the proposed method can outperform the other 2 methods with higher (better) SNR value whether in X or Y axes acceleration data.

Further, in the noise attenuation ratio calculation (ATT) results (Table 5), our proposed filtering method also surpass the LPF and the LMS filtering method, especially in the non-moving vehicle experiments. However, in the moving vehicle experiment, there is only a slight ATT improvement from our method in comparison with LPF filtering method. Nevertheless, such improvements are enough to increase the vehicle positioning performance.

As can be seen in **Fig. 12**, despite the velocity results calculated from acceleration are suffered from integral drift effect [18], velocity value which is calculated from IMU acceleration signal and filtered by our proposed method (red line) has closer value with the vehicle velocity recorded through the OBD-II reader (green line). Besides, from distance traveled calculation results which are presented in **Table 6** (calculation is based only from acceleration data), it shows that result from our filtering method distance calculation (133.15 meter) also has closer value with vehicle distance calculated from OBD-II velocity data (121.25 meter). Figure 12 and Table 6 demonstrate that although our proposed filter method is combining two type of filters, this filtering method does not lose its major vehicle movement data.

Table 6 Distance traveled calculation result comparison from original and filtered data.

Distance traveled	Methods				
	OBD-II	IMU	LPF	LMS	Proposed
Distance (Meter)	121.25	144.13	134.76	140.6	133.15

4. Related Work

The proposed filtering method in this paper is developed to compensate the vehicle vibration errors which are sensed by the IMU accelerometer sensor in vehicle positioning system. Some research showed the applications of IMU/INS sensor which is fused with other positioning sensors to provide robust vehicle position estimation [1], [2], [3], [4]. However, those paperwork are focus on how the sensor fusion strategy works, leave the importance of compensating the vehicle vibrations with proper method. The adaptive LMS filter is proved that it could cancel noises in digital signal processing. Some research shows that this filter method is able to cancel out most error in digital signal, particularly appear in ECG signal [8], [9] and acoustic signal [10].

Hernandez et al. [5], [7] introduced how to improve the accelerometer response using the LMS adaptive filter for automotive application. Nevertheless, the noise canceler which was used in this research is based on overlap-save sectioning (assuming real-valued data). Moreover, this paperwork used piezoresistive accelerometer which works only in one axis. As a comparison, we introduce a filtering method by combining the adaptive LMS filter and the low-pass FIR filter. We utilize 3 axes accelerometer, use the Z-axis signal to detect the vehicle vibrations then apply it as noise canceler in the X and Y axes acceleration values.

5. Conclusion

To conclude, our proposed filtering method which combines adaptive LMS filter and low-pass FIR filter is able to show better performance than common filtering method in accelerometer by showing higher decibels value in signal to noise ratio (SNR dB) and lower attenuation in error attenuation ratio (ATT dB) calculation. Further, the adaptive system is also able to adapt the changes in vehicle vibration frequencies appear at several engine rotation rates.

One important note is that in the moving scenario, the vehicle is also affected by external vibrations such as gravel road, road marks, bumpy road, and sewers cover. In our observation, these external disturbances are mostly effecting the IMU accelerometer in Z-axis (road disturbance generates up and down movement effects) and add external error vibrations besides the internal vehicle vibrations. As stated before, the Z-axis is used as a reference in canceling the internal vehicle vibration error and such condition worsen the filtering results. In fact, since the method initially is developed to support apron vehicle inside the airport area [1], environmental conditions such as road quality and surface contours are considered to be managed well by the airport provider. The Z-axis accelerometer is assumed to experience less external

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noises from the environment.

Furthermore, based on the fact that vehicle, in general, has similar engine rotation characteristic and the findings in our experiments, we believe that our proposed filtering method can be implemented and work, not only specific on Honda Kei car "That's", but also with other various types of vehicles. Yet, this statement needs to be proofed by doing additional experiments, especially in medium to heavy-duty vehicles as our main research object is apron airport vehicle. Some modification in filter's parameters could be needed to adjust the filter performance, for example the filter order, the filter steps, and the low-pass cut-off frequency. This activity will be part of our future research work with real apron vehicle as an object in the airport environment.

Acknowledgments This work was partially funded by the Ministry of Research, Technology, and Higher Education Republic of Indonesia, through its scholarship for Program Research and Innovation in Science Technology (RISET-Pro) World Bank Loan No.8245-ID.

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