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# MEMS Gyroscope Raw Data Noise Reduction Using Fading Memory Filter

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Nowadays, MEMS sensors are widely used in systems such as autonomous vehicles, but they still suffer from high stochastic errors such as Angle random walk (ARW) noise, which causes failure in real-signals and produces an error in the position and attitude of mobile systems. So far, many filters are developed to reduce the amount of noise in the output of the MEMS sensors. The computational overhead, the rate of noise reduction, and the phase-delay of the filter are the most important characteristics of choosing a suitable filter. In this paper, a low pass filter based on the alpha-beta filter with a very low computational overhead is proposed to reduce the amount of noise. In order to find the optimal filter gain, the improvement in the positioning is selected as a criterion, which is a tradeoff between the amount of noise reduction and the phase delay of the filtered signal. In this work, the KITTI database is used to evaluate the proposed filter. The results show that the proposed filter reduces the sensor's noise and improves the positioning of the moving car, significantly.

**Keywords:** Angle random walk noise, Noise Reduction, Alpha-Beta Filter, Fading Memory Filter

## Introduction

In electronic industry, MEMS sensors are widely used due to their lightweight, small size, high reliability and low prices. In the fields of aviation, automation and aerospace, widespread use has been made[1,2,3]. Identifying the errors of MEMS sensors is one of the essential steps prior to using them. In general, noise at the output of inertial sensors is measured using frequency analysis techniques or time-domain analysis techniques. These techniques include Power Spectral Density (PSD), Auto Correlation (AC), and Allan Variance (AV) methods[4]. PSD and AV methods are widely used in analyzing inertial systems. One of efficient methods for improving navigational accuracy is to reduce the effect of these errors in the raw data of an inertial measurement unit (IMU). For example, in order to improve the accuracy of the integral results, the raw data of the accelerometer and the gyroscope can be filtered before the integration. Kalman filter seems to be a proper filter for this purpose because it provides a useful signal based on data from the system and the real world behavior[5]. Generally, the Kalman filter is used to estimate stochastic errors in the stationary state. In motion mode, due to changes in dynamic of system, the Kalman procedure must adapt the filter and make changes to R/Q matrices and switches between parameters[6]. In noise reduction methods, Adaptive moving average algorithms for detecting angular velocity changes are used to switch to appropriate filters in different rate[7].Inaccuracy in state parameters and noise measurement may lead to undesirable results or delay in the signal[6]. Instead of applying a conventional and adaptive Kalman filter, FIR and IIR filters are more simple filtering devices to reduce noise, whose low-pass types are widely used in airborne gravity data processing[8]. The effect of any filter technique is to reduce noise, while not affecting the actual signal. Phase-lag is proportional to the degree of filter. So, by decreasing the filter's degree, phase-lag will decrease. On the other hand, this causes that the passband of the filter to increase, and consequently, the amount of noise reduction is decreasing. Therefore, there is a tradeoff between the bandwidth of the filter and the amount of error due to the passage of noise from its pass band[9,10,11]. Fixed algorithms, such as Alpha-beta filters, usually provide good performance with little computational cost[12,13].

## Noise analysis method

Prior to noise reduction procedure of the gyroscope signal, the characteristics of the errors in the output of this sensor must be analyzed. Many methods have

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been proposed to analyze the behavior of noise components in inertial sensors[13]. Generally, the noise in the output of inertial sensors can be considered as a stochastic process and can be analyzed by using time or frequency domain techniques. Using these techniques, one can find their properties and model them[4]. As mentioned before, these techniques include PSD, AC and AV methods. The Allan Variance (AV) method is the first method used to determine the spectrum of atomic clock frequency oscillations and is known for its similarity, in its statistical properties, with a random error of the gyroscope. The calculation complexity of this method is less than other similar methods and is relatively simple to interpret. AV method can be used to describe the various types of noise terminals in sensor data by applying a specific operation to the entire of data. By performing this analysis on the output data of the gyroscope, noise error sources are divided into seven categories, which include Angle Random Walk noise, Correlated noise, and sinusoidal noise. Since the correlated noise and sinusoidal noise have minor contributions to the net-sum of the total noises, and in most cases, they only appear at long time clusters, only the first five errors will be analyzed on the testing results[13]. Using AV method, the quantitative value for each of these sources of noise are determined. It is worth to mention that one of the disadvantages of this methodology is its inability of the specification of the mentioned-errors, uniquely. However, this can be resolved using Modified Allan Variance, in conjunction with pre-whiting or pre-filtering of the raw data[4]. The KITTI dataset is used to evaluate the filter performance. This dataset includes raw data of accelerometer sensors, gyroscope, and GPS connected to a self-propelled vehicle that has been collected in various tests. In the following sections of this paper, first, we introduce noise analysis methods. In the next section, the relationships and formulas of the Alpha-beta filter and its special case, the fading memory filter is explained. Then, we show how to select the filter gain. Finally, we demonstrate the results of applying the proposed filter to the gyroscope signal, and the improvement achieved in the calculation of the angle and position of the car.

**Components of sensor errors**

The output of a calibrated inertial sensor can be expressed as follows:

$$y(t) = u(t) + e(t) + b(T) + N(a, \omega, T, t) \quad \ldots (1)$$

Here, y(t) is the calibrated sensor output, u(t) is the real value of the kinematic sensor (real rotation), T is temperature, b(T) is temperature dependent bias, N (a, ω, T, t) is factor dependent errors of the environment. Moreover, e(t) is stochastic errors and noises, which consists of Angle Random Walk (AWR) noise, Flickr noise, quantization error and sinusoidal error. AWR noise is a high-frequency noise, which can lead to random walk in the value of angle. The spectrum of this noise is similar to the spectrum of the white noise in the output of gyroscope. In rotation rate gyroscopes, in order to determine the overall angular variation, we should integrate the output signal of the gyroscope. Therefore, any noise in the output is also integrated and leads to a random walk in angle. Since all of the noises described above are time-independent, so the total variance of the stochastic process can be considered as the sum of the variances of all error terms. In many applications, we can ignore some of the mentioned errors, and can only consider the effect of ARW noise, in conjunction with a drift of in bias, which results to Rate Random Walk (RRW) noise. In our test, we used a variety of consumer-grade MEMS sensors. Therefore, in order to extract the true signal rate from the signal corrupted by noise, we assumed that the gyroscope output is corrupted by additive white noise, which is considered as Angle Random Walk noise.

**Alpha-Beta filter**

The alpha-beta filter is one of the techniques that is known as a cheap filter and is commonly used to track moving objects in radar applications[13]. Due to the simplicity and low computational overhead of this filter, compared to similar filters such as Kalman filters, this filter has been used in many applications, such as medical devices. To design the alpha-beta filter, we must first specify the appropriate alpha and beta coefficients. Since the alpha-beta filter can be assumed equal to the Kalman filter in steady-state mode, one of the methods of determining coefficients is the same as that used in Kalman filters. However, the investigations show that using this method does not lead to the optimal performance[14]. Another method is to use the minimum variance criterion, which minimizes the variance of the steady state error[15]. Although this criterion obtains the optimal alpha from beta, but it does not specify an optimal value for beta. In another investigation, both smoothing the noise and tracking of an accelerated target are considered. Moreover, this work has provided an optimal beta value based on target acceleration data[14]. As mentioned before, this filter is usually used to track moving targets in radar applications. The main signal used in this application is the position of a moving target. For estimating the position, the method assumes that the speed of moving object, during sampling time, is constant. For using these filters, it is required to adjust the alpha and beta coefficients properly. A simple way to adjust is presented by Zarchan which is based on experimental relationship between Alpha and Beta[15]. The filter provided by Zarchan is called a fading memory filter. In fact, the structure of the fading memory filter is very similar to the linear polynomial Kalman filter, and the only difference is that its gain is constant while in a Kalman filter the gain is changing as time goes on. The first order type of alpha beta filter has a good noise reduction capability, while it also has the highest truncation error value. Therefore, for choosing proper order of the filter, the designers must make a tradeoff between the amount of noise reduction and truncation error buildup. It is the first time that we have proposed alpha-beta filter to reduce the amount of noise in the output signal of a MEMS gyroscope. The equation 2 shows the first and equations 3 and 4 show the second order type alpha-beta filters, which are also called fading memory filters[15].

$$x_{sk} = x_{pk} + (1-\beta)(x_{ok} - x_{pk}) \quad \dots (2)$$

$$x_{sk} = x_{pk} + \alpha(x_{ok} - x_{pk}) \quad \dots (3)$$

$$v_{sk} = v_{sk-1} + \frac{\beta}{T}(v_{ok} - v_{sk-1}) \quad \dots (4)$$

$$x_{pk} = x_{sk-1} + Tv_{sk-1} \quad \dots (5)$$

Here $x_{sk}$ is the smoothed signal or the smoothed target position at kT. T is sampling time, $x_{ok}$ is the measured target position or measured signal. $x_{pk}$is the predicted target position or predicted signal. $v_{sk}$ is the smoothed target velocity or the second derivative of the measured signal, and alpha and the beta are filter gains.

## Experimental Results

In this section, we compare the results obtained from the implementation of the navigation algorithm with filtered data and raw data of a MEMS gyroscope. We applied the proposed algorithm to the KITTI data set[16]. In order to evaluate the suggested filter, we added some white noise to the raw data collected from the output of the gyroscope. The gyro noise output with the main signal is shown in Figure 1(A). The proposed method was implemented on an AMD-Quad core FX-8800p CPU platform with a frequency of 3.4GHZ and 8Gigabyte RAM. As noted before, due to the integral nature of the navigation algorithm, the presence of noise at the output of the gyroscope sensors causes the error to occur in the angles and the

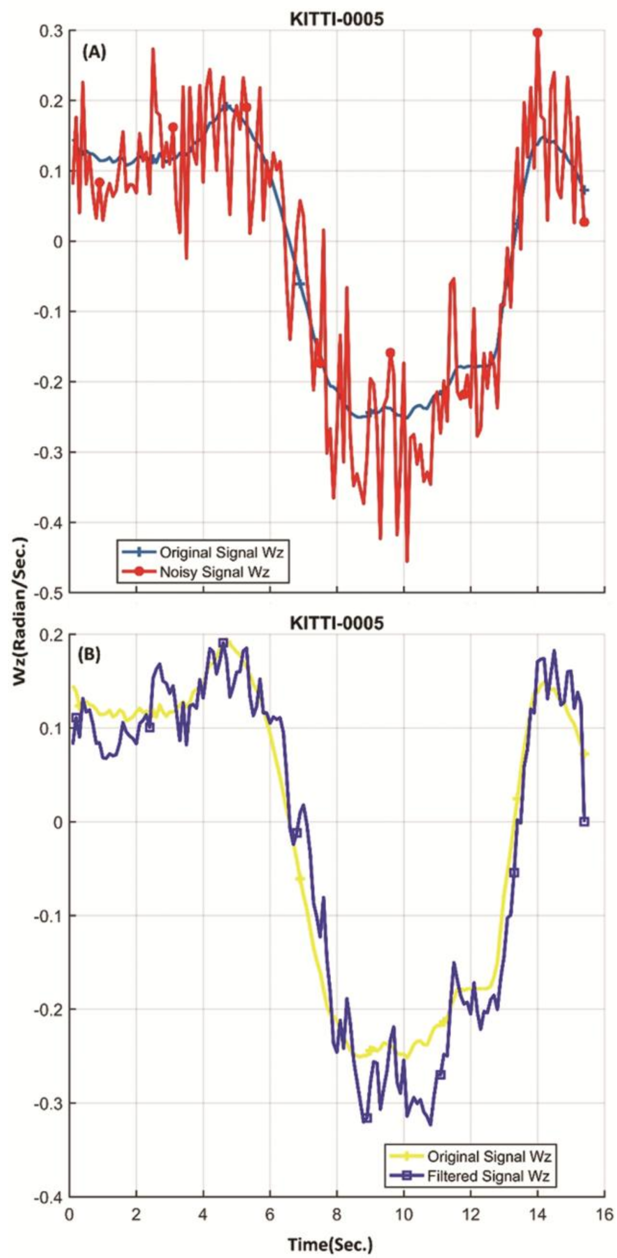


Fig. 1(a-b)—(a) Comparison of original gyroscope signal with its noisy version & (b) Comparison of original and filtered gyroscope signals (β = 0.7) position of moving car. The error in the angles causes that the physical coordinate does not match to the local navigation coordinate. The existence of such errors in accelerations will result in an error in the position of the moving object. Figure 2(A) compares the effect of ARW noise on the output signal of a gyroscope. This comparison suggests that it is necessary to reduce the effects of ARW noise by a filter in order to increase the accuracy.

**Selecting the order and gain of filter**

The choice of the order of filter is a trade off between the amount of noise reduction, and the amount of truncation error. So, we first apply a second-order fading memory filter to the sensor output. So far, in order to find the optimal filter gain, many methods have been proposed, which some of them are addressed earlier. Unlike many methods that only have paid attention to the output signal and reduced the amount of variance of noise, we also considered the amount of improvement resulting from the navigation algorithm and the amount of filter gain according to the improvement rate. We chose navigation that originated from the rate of reduction of noise variance and the phase-lag generated in the output of the filtered signal. In order to achieve this, we changed the beta value from 0.1 to 0.9 in step size of 0.1, and we ran the navigation algorithm once for each beta value. For each beta value, we also examined the output of the gyroscope, before and after the filtering in time and frequency domain. The analysis of the results showed that the second order fading memory filter for any values of beta between o.1 to 0.9, produces no significant improvement in the results of positioning of moving car. The reason is the presence of the derivative operation in the second-order filter relationship. Since the first-order filter is proposed to soften the signal, we applied the previous test with beta values from 0.1 to 0.9 with step size of 0.1 again for the first-order filter that is expressed in equation 3. This filter is very similar to Kalman filter and its difference is in the constant gain over time. We examined the results obtained from applying of this filter. For $\beta = 0.1$ it observed that no significant improvement is achieved at the angle and position of the moving car. This situation is clearly shown in Figure 2(A). Moreover, we saw that the frequency spectrum of the output signal in comparison to the input signal is also confirms this conclusion. By increasing the amount of filter gain, we saw that the filter was able to reduce the amount of noise, more

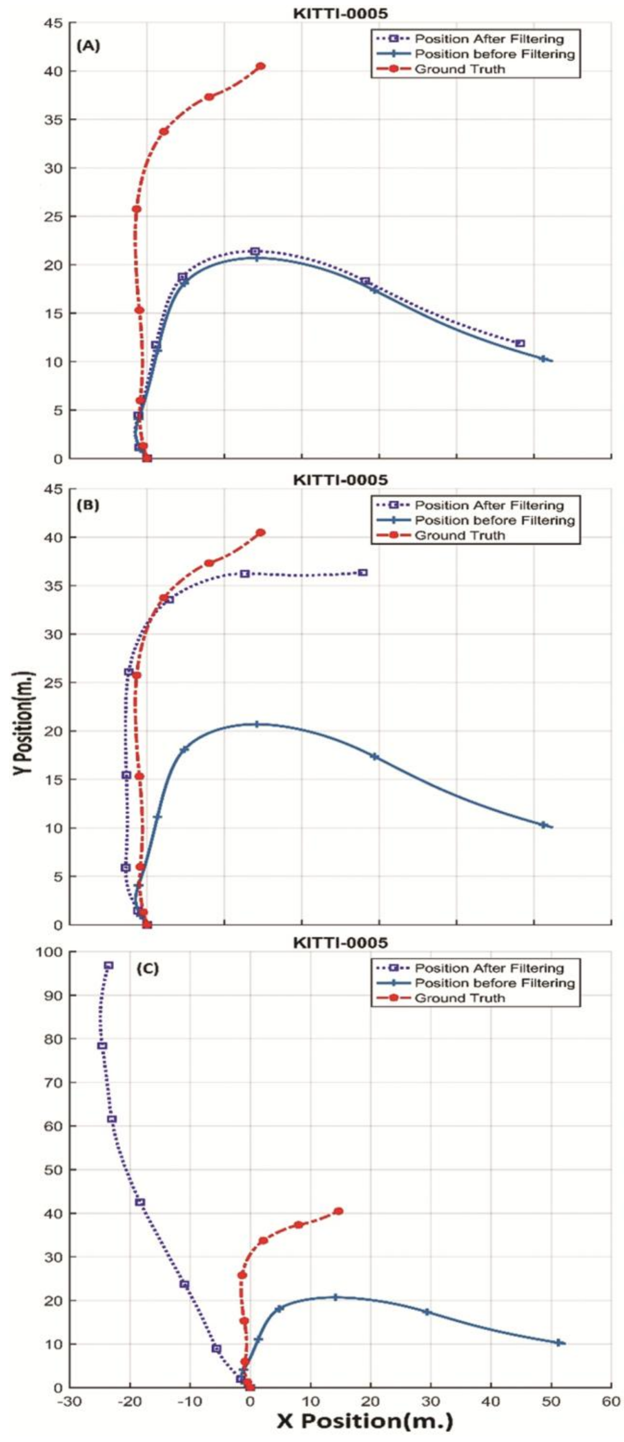


Fig. 2 (a-c)— (a) Comparison of ground truth with position, before and after filtering for $\boldsymbol{\beta = 0.1}$, (b) Comparison of ground truth with position, before and after filtering for $\boldsymbol{\beta = 0.7}$ & (c) Comparison of ground truth with position, before and after filtering for $\boldsymbol{\beta = 0.9}$

and more. Figures 2(A) to 2(C) compare the position of the moving car, before and after filtering, with the actual position (Ground truth), for Beta of 0.1, 0.7 and

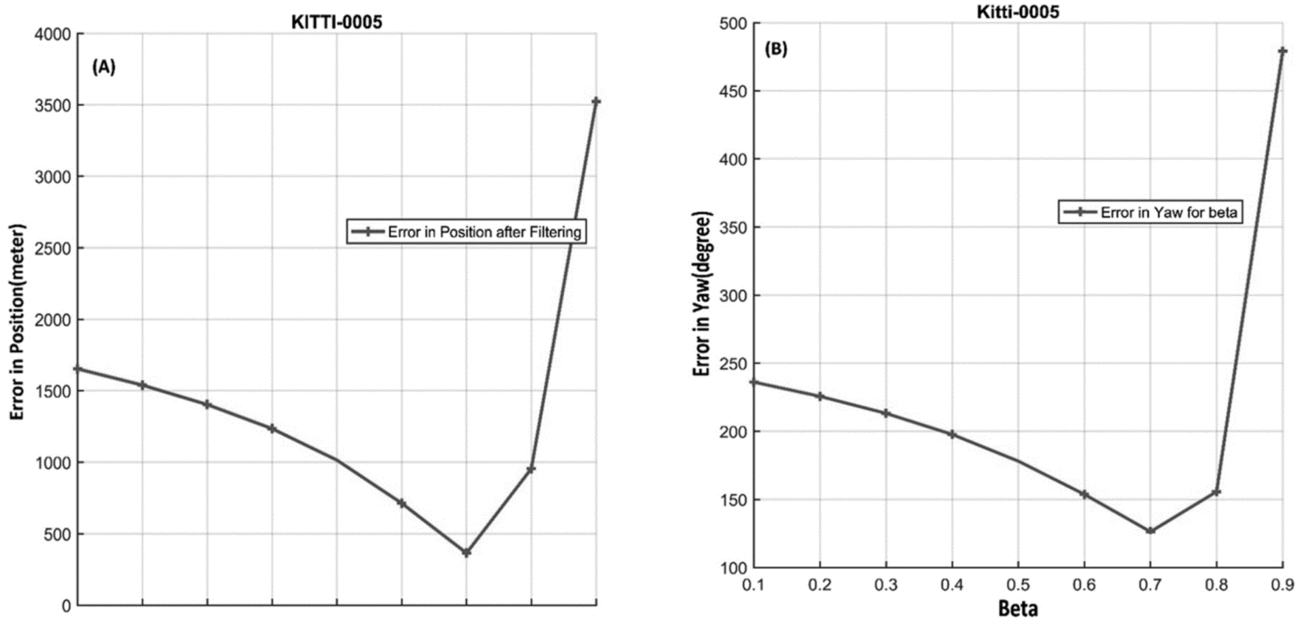


Fig. 3 (a-b)—(a) Position-error versus Beta-gain value & (b) Yaw-error versus Beta-gain value

0.9 receptively. As we see, the best match is obtained for $\beta = 0.7$. It is obvious that, while increasing the value of beta reduces noise, but it produces a phase-lag in the output of the filter. The phase-lag is so high that it has encountered a large error in the position obtained from the implementation of the navigation algorithm using this filter. Therefore, selecting the appropriate gain is a tradeoff between the rate of reduction of noise variance and the latency of the phase added to the signal due to filtering.

#### Choosing the best gain

In order to obtain optimal gain, for each Beta value, we calculate the Yaw error and position error for different values of Beta. Figure 3(B) shows the error of Yaw as a function of Beta and Figure 3(A) demonstrate the position error for Beta values between 0.1 and 0.9. Based on these figures we can deduce that the lowest position-error and Yaw-error occur for the beta value of 0.7. Consequently, we can conclude that the filter is optimal for this amount of gain. Figure 1(B) compares the shape of the original signal from a moving car, without additive noise, with the output of the optimal filter. It is obvious that the phase-lag between these signals is negligible. On the other hand, in Figure 2(B) we have compared the position of the moving car, before and after filtering, with the actual position (Ground truth), for Beta of 0.7. As it is clear, there is a very good match between the filtered signal and the true position of the car.

#### Applying the filter to other data sets

The Monte Carlo test is a method for evaluating stochastic algorithms. We also applied the proposed filter to five different datasets. The results confirmed that for all of them, the lowest position and Yaw errors occur for $\beta = 0.7$. Moreover, these value of Beta delivers the minimum value of the phase-lag. Consequently, this value is optimized for these data sets.

## Conclusion

In this paper, we presented a new approach to reducing the noise of raw-data from the MEMS gyroscope using a low computing filter from the family of alpha-beta filters. We observed that for some beta values, the noise level was reduced, while the result of the navigation delay of the output signal increased, so to determine the filter gain, we should make a tradeoff between the amount of noise reduction and the phase-delay added to the signal. The results disclosed that the beta value of 0.7 leads to the best performance and brings the most improvement in determining the position of the car.

## References

1 Haniff MASM, Lee HW, Embong SS & Azid IHA, Enhancing the performance of MEMS pressure sensors using ‘v’-shaped piezoresistive-sensing elements, *J Sci Ind Res,* **73(02)** (2014) 107-111.

2 Arshad MR, Recent advancement in sensor technology for underwater applications, *Indian J Mar Sci*, **38(3)** (2009) 267-273.

3 Kal S & Das S, Development of silicon and quartz based MEMS high precision accelerometers, *Indian J Pure Appl Phys*, **45(6)** (2007) 299-303.

4 Abdel-Hamid W, *Accuracy enhancement of integrated MEMS-IMU/GPS systems for land vehicular navigation applications*, (Calgary Univ Press), 2004.

5 Kownacki C, Optimization approach to adapt Kalman filters for the real-time application of accelerometer and gyroscope signals' filtering, *Digital Signal Process*, **21(1**) (2011) 131-140.

6 Z, hang L, Xiong Z, Liu J & Lai J, Automatic switching and denoising MEMS-Gyro signal for enhanced dynamic performance. *Int J Light Electron Opt*, **127(23)** (2016) 386-394.

7 Zurbenko I, Porter P, Gui R, Rao S, Ku J & Eskridge R, Detecting discontinuities in time series of upper-air data: development and demonstration of an adaptive filter technique. *J Clim*, **9(12)** (1996) 3548-60.

8 Zhao L, Wu M, Forsberg R, Olesen AV, Zhang K & Cao J, Airborne gravity data denoising based on empirical mode decomposition, *Int J Geo-Inf*, **4(4)** (2015), 2205-2218.

9 Weisman RM, Robust longitudinal rate gyro bias estimation for reliable pitch attitude observation through utilization of a displaced accelerometer array, (Rochester Inst Technol Press), 2008.

10 Xie Gr, Pinciples of GPS and receiver design, (Publishing House Electron Ind), 2009.

11 Ban Y, Zhang Q, Niu X, Guo W, Zhang H & Liu J, How the integral operations in INS Algorithms overshadow the contributions of IMU signal denoising, *J Navig*, **66(6)** (2013) 837-858.

12 Crouse DF, A General Solution to Optimal Fixed-Gain Alpha-Beta Filters. *IEEE Signal Process Lett*. **22(7)** (2015) 901-904.

13 Chiou Y, Wang C & Yeh S, Reduced-complexity scheme using alpha–beta filtering for location tracking, *IET Commun*, **5(13)** (2011) 1806-1813.

14 Saho K, Design of Accurate α-β Tracker based on Steady-State Performance Index, *Int J Signal Process*, **1(001)** (2016) 235-242.

15 Sah,o K & Masugi M, Performance analysis of α-β-γ tracking filters using position and velocity measurements, *EURASIP J Adv Signal Process*, **1(35)** (2015) 344-350.

16 Geiger A, Lenz P, Stiller C & Urtasun R, Vision meets robotics: The KITTI dataset, *Int J Rob Res*, **14(3)** (2013) 195