ASEAN Engineering Journal

Full Paper

AN ADAPTIVE KALMAN FILTERING ALGORITHM WITHOUT USING KINEMATIC MODELS

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Article history
Received
05 September 2022
Received in revised form
29 March 2023
Accepted
02 May 2023
Published online
30 November 2023

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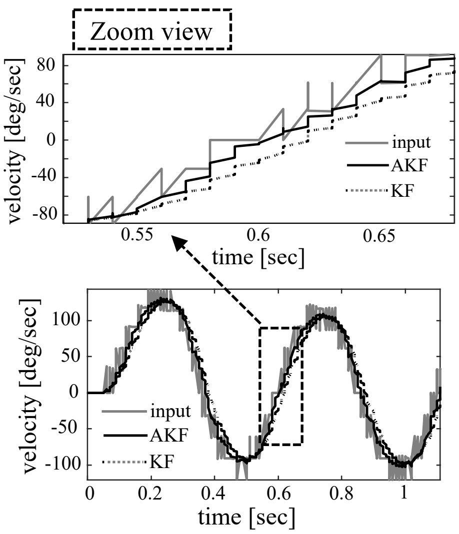
Graphical abstract



Abstract

The performance and accuracy of Kalman filter depends on its gain value related to the process noise covariance and the measurement noise variance which may vary according to experimental settings such as noise and sampling time. Thus, setting the appropriate values for the noise variances that fit for a wide range of experimental setting is a challenge for conventional Kalman filter. This paper proposes an adaptive Kalman filter with the adaptive noise variance for velocity estimation without using kinematic model. By applying only the quantized position measurement signal generated from the optical incremental encoder, an adaptive process noise variance is proposed. The experimental results show that the proposed method outperforms the conventional Kalman filter in achieving accurate and smooth velocity estimation without large time delay.

Keywords: Adaptive Kalman filter, Adaptive process noise covariance, Kalman filter, Kinematic model, Quantization error.

1.0 INTRODUCTION

In order to track a moving object on the ground or something flying in the air, the exact state of the object such as position, velocity, acceleration, jerk, snap, etc are required. The exact position from rotary motors used for moving objects can get from high-resolution sensors. The high-resolution position sensors have adequate accuracy and high resolution that can provide the accurate position. The acceleration can be estimated by differentiation of the calculated velocity that requires an accurate velocity estimation. The most common and simplest method for velocity estimation is the finite difference method that leads to poor results in low velocity [1]. Many algorithms have been proposed to increase the accuracy of velocity predictions and reduce the noises or errors. One basic approach for constructing velocity estimation is based on least squares from discrete position data [2]. Such adaptive windowing technique has been proposed to estimate velocity from quantized position data [3, 4]. Velocity estimation has been implemented from the incremental encoder in [5, 6]. Another commonly used approaches have been proposed to estimate the velocity from the position sensor [7, 8, 9, 10, 11, 12, 13], each with its own advantages with respect to others.

At present, Kalman filter (KF) is widely used in the fields of tracking and real-time prediction [14]. KF algorithm takes into account all the noises and can be applied to this problem [15]. KF needs only the current measurement signal and the estimated state of the previous time period is required [16]. The accuracy of KF is greatly affected by the noise variances. The choice of unappropriated noise variances can significantly degrade the KF's performance [17]. Kalman filter is not optimal and sometimes the filtering results are unreliable [18]. Kalman filter is state estimation algorithm, that is, it estimates the state of a system for every filtering step and update it in real time. To estimate the state of the system, the different order kinematic models can be applied depending on the considered filter issue (e.g. third order and second order kinematic model). A multidimensional form of the Kalman filter estimates many state variables simultaneously such as position, velocity, acceleration, etc. In general, KF has difficulty and large computation complexity due to its multiple state variables and estimating the covariance matrices [19].
This paper presents a new algorithm for the process noise covariance of Kalman filter regarding velocity estimation

without using kinematic model. The introduced approach has been compared to the conventional Kalman filter.

This paper is organized as follows: Section II gives an overview on Kalman filter without using kinematic model. Section III presents a new algorithm for process noise covariance of Kalman Filter and Section IV shows the filter's effectiveness through experimental evaluations. Section V makes the conclusion statements.

2.0 KALMAN FILTER WITHOUT USING KINEMATIC MODEL

In order to estimate the velocity with less complexity, one can apply KF without using kinematic model. Structure of kalman filtering algorithm without using kinematic model is as shown in figure 1, whereas the initialization step only needs to be making once, and at this initial stage two parameters are produced: initial system value $\widehat{\omega}_{0,0}$ and initial error covariance $P_{0,0}$. Measurement is performed for every filtering step, and that measurement value provides two parameters: the measured signal y_k and measurement noise variance R. The Kalman filter estimates the current velocity and the predicted velocity for every iterative step by using the following equations:

$$\widehat{\omega}_{k/k-1} = \widehat{\omega}_{k-1/k-1} \quad (1)$$

$$P_{k/k-1} = P_{k-1/k-1} + Q \quad (2)$$

$$K_k = \frac{P_{k/k-1}}{P_{k/k-1}+R} \quad (3)$$

$$\widehat{\omega}_{k/k} = \widehat{\omega}_{k/k-1} + K_k y_k \quad (4)$$

$$P_{k/k} = (1 - K_K)P_{k/k-1} \quad (5)$$

where $\widehat{\omega}_{k-1|k-1}$ and $\widehat{\omega}_{k|k}$ are the filtered velocity from KF in the period *k-1* and *k*, and $\widehat{\omega}_{k|k-1}$ is the predicted velocity in the period *k*. $P_{k-1/k-1}$, $P_{k/k}$ and $P_{k/k-1}$ are the error covariance corresponding to $\widehat{\omega}_{k-1|k-1}$, $\widehat{\omega}_{k|k}$ and $\widehat{\omega}_{k|k-1}$, respectively. K_k is the kalman gain value in the period *k* and it is related to the process noise covariance Q and the measurement noise variance R.

The accuracy and performance of KF is enhanced by adjusting its gain value according to the requirements. R and Q are important parameters that decide the estimation to close to the true value, velocity and bandwidth [20]. Usually, R is set as a constant value based on the measurement accuracy of the sensor and Q is also kept constant using a trial-and-error approach to reduce complexity. To obtain a smooth output signal from Kalman filter without delay time, R should be tuned [21]. In order to get the optimal output results with a small-time delay in a wide range of input frequency, the noise variances have to change accordingly. In that case, both Q and R are possible candidates for adaptively changing with respect to input and experimental settings. In this paper, we consider Q as the adaptive parameter as we are more interested in the process noise resulted from numerical differentiation process.

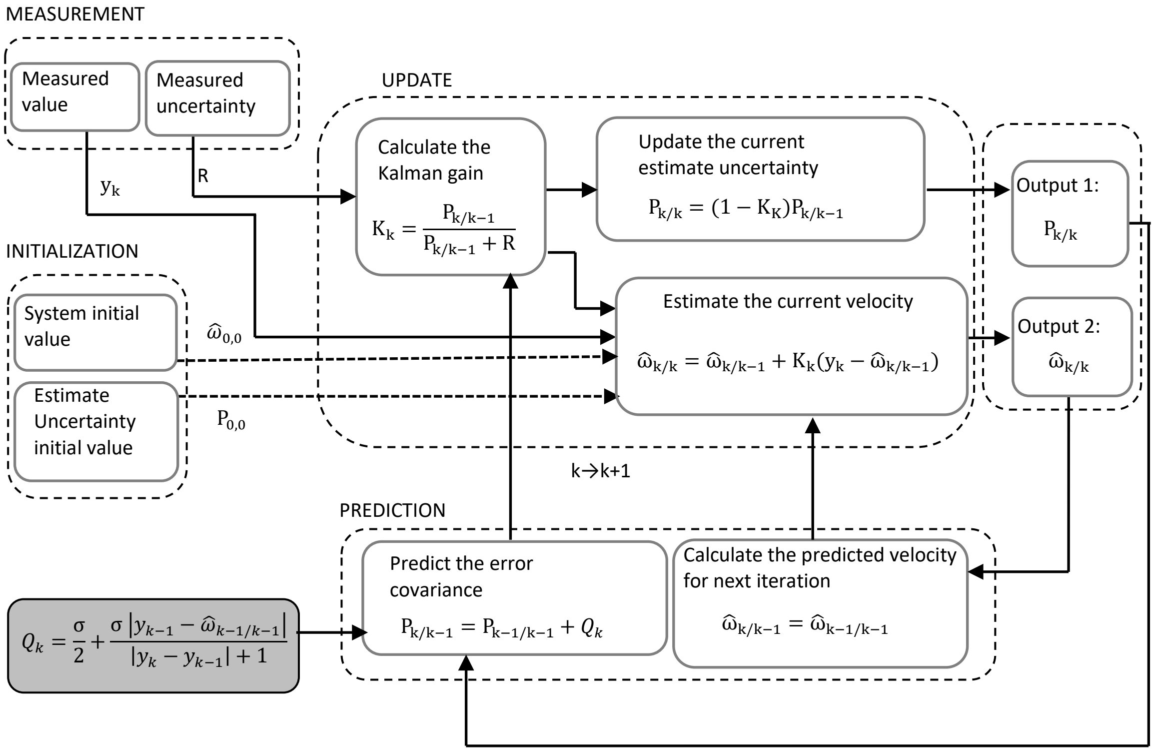


Figure 1 Implementation flowchart of the proposed adaptive Kalman filter algorithm without using kinematic model.

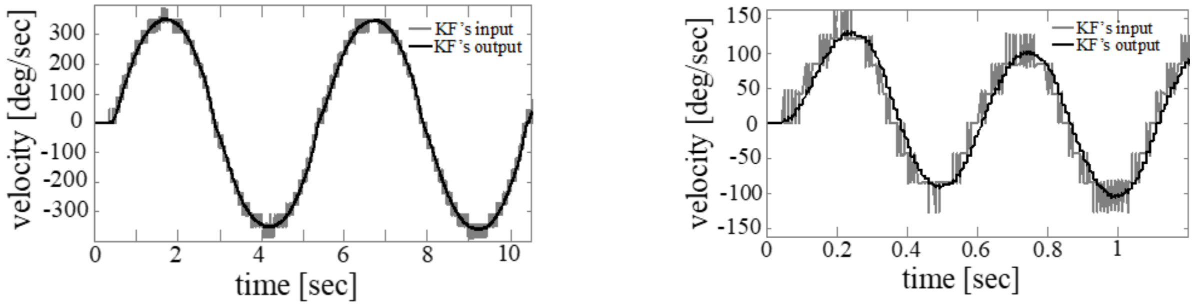


Figure 2 The performance of Kalman Filtering algorithm by using the constant process noise varicne with (a) frequency =0.2Hz and (b) frequency =2Hz. The gray and black lines represent the Kalman filter's input signal and output signal.

Figure 2 shows the output velocity estimation performances of KF filtering algorithm (by using the constant Q =10^{-7}) with the low and high frequencies f=0.2Hz and 2Hz. KF produces a smooth output signal ithout large delay at low frequency (can see black line in figure 2(a). But, the filter performance shows a considerable delay and the filter cannot follow the input signal at high frequency (see black line in figure 2(b). Three factors of the process noise covariance Q on the KF filter can be observed from figure 2 as follows:

(i) If Q is kept constant, the filter result cannot follow the input signal and has a considerable time delay at high frequency.
(ii) The filter produces the noisy output signal if Q value is set too large.
(iii) The filter's output has a significant time delay if Q is set too small value.

If the process noise variance is adjusted and tuned manually for every frequency changes through the experiments, the results of KF will be smooth without large time delay. But if the noise variances are not tuned adaptively, KF will be as the other linear filters that can change the characteristics of the original signal in the process. Improper choice of Q is a challenge every frequency changes.

3.0 ADAPTIVE KALMAN FILTER (AKF) WITH AN UPDATE ADAPTIVE PROCESS NOISE COVARIANCE

To overcome this challenge, this paper proposes an adaptive Kalman filter (AKF) without using kinematic model by updating the process noise covariance Q for every filtering step. To calculate the adaptive process noise variance Q, the above-mentioned effects of Q on the conventional KF filter have been taken into the consideration. For that case, we consider two parameters: the noise in the input and the delay in the output, and they are estimated as follows. The choice of a proper process noise variance depends on the frequency. The large difference between the measured input signal and the estimated signal is considered as time delay. To get the optimal results, Q should be increased if the filter cannot quickly react to frequency changes and produces a significant delay in the estimation result. The input signal is considered noisy if the difference between the consecutive input data points are large. In order to achieve a smooth filter result, Q should be decreased without large time delay.

The proposed adaptive process noise covariance is based on only the measurement input signal and the estimated signal of the previous time period. The process noise covariance Q is adaptively calculated by;

$$Q_k = \frac{\sigma}{2} + \frac{\sigma\,|y_{k-1} - \hat{\omega}_{k-1/k-1}|}{|y_k - y_{k-1}| + 1} \qquad (6)$$

where y_k is the current input signal in the period k, y_{k-1} is the input signal in the previous period k-1 and $\hat{\omega}_{k-1/k-1}$ is the estimated signal from the filter in the period k-1, and σ is the user-defined value. The value of Q is adaptively estimated and updated for every filtering step. The measurement noise variance R is kept constant as long as the sampling time T remains unchanged. There is no accurate theory as for R value. We define a heuristic approach to calculate the measurement noise variance ($R = T^2$). The proposed AKF modifies Q_k with only one constant coefficient σ. The introduced filter is compared to the conventional Kalman filter with constant Q.

4.0 SIMULATION RESULTS

The proposed AKF and the conventional KF have been performed on sinusoidal motions with low and high frequencies freq=0.2 and 2Hz. The performed results are shown in figure 3. At low frequency, the performances of AKF and KF shows quite similar in figure 3(a). AKF performs better while KF shows a delay in high frequency (can see in figure 3(b)). In step input, the performance of the KF has a considerable time delay (can see in dotted black line of figure 4).

(a)

(b)

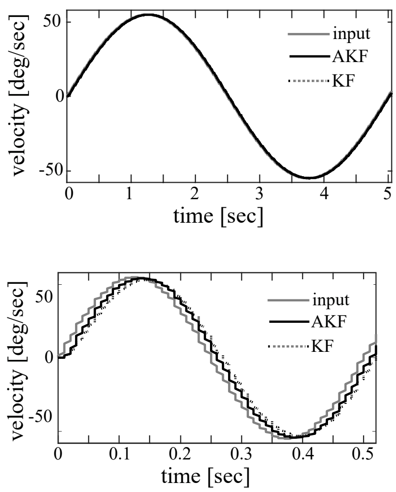


Figure 3 The proposed filter's performance evaluated on sinusoidal motions with (a) the low frequency 0.2Hz and (b) the high frequency 2Hz.

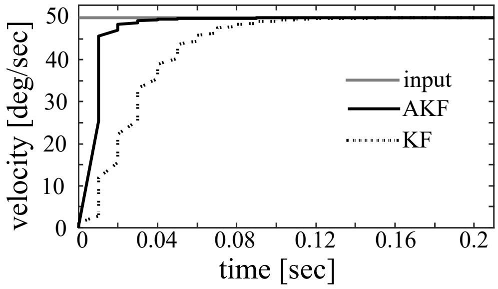


Figure 4 Filter performance evaluated on step input.

5.0 EXPERIMENTAL SETUP AND RESULTS

The effectiveness of the proposed method is experimentally evaluated using a DC motor, which is connected to a gear box with a 100:1 ratio. The incremental encoder with a resolution of 64 counts/revolution is mounted on the DC motor (see the experimental setup in figure 5). The experiments are performed with sinusoidal reference signal $\boldsymbol{r(t) = A\sin(2\pi f t)}$. The sampling time period is set to $\boldsymbol{T}$ =1ms. The accuracy and performances of AKF and KF are evaluated experimentally by utilizing only the position quantized measurement signal generated from the optical incremental encoder sensor. A Savitzky–Golay filter is digital smoothing polynomial filter that is convenient to smooth a set of digital data from noisy sampled data, is applied as the velocity estimation reference signal.

In this experiments, the velocity estimated by the first order backward finite difference formulation is used as the input velocity signal. The finite difference method is based on motor shaft's position readings obtained by the optical encoder. The finite difference method applies to the discrete time position data:

$$\boldsymbol{y_k = \frac{\theta_k - \theta_{k-1}}{T}} \tag{7}$$

where θ_k and θ_{k-1} are the current and the previous measured sensor position signals, and T is the sampling time. The velocity estimation results of finite difference method contain the noises due to the measurement noises or the quantization errors from the encoder's output position signal. The proposed filter is used to reduce the noises and to increase the accuracy of the velocity estimation results. The proposed AKF doesn't use a kinematic model in order to reduce complexity. The velocity estimation results of AKF and KF have been performed experimentally on different sinusoidal motions with various frequencies are shown in figure 6.

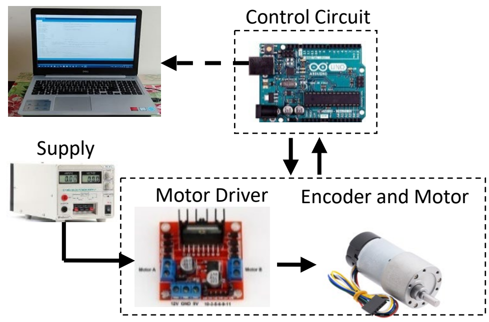


Figure 5 Experimental setup.

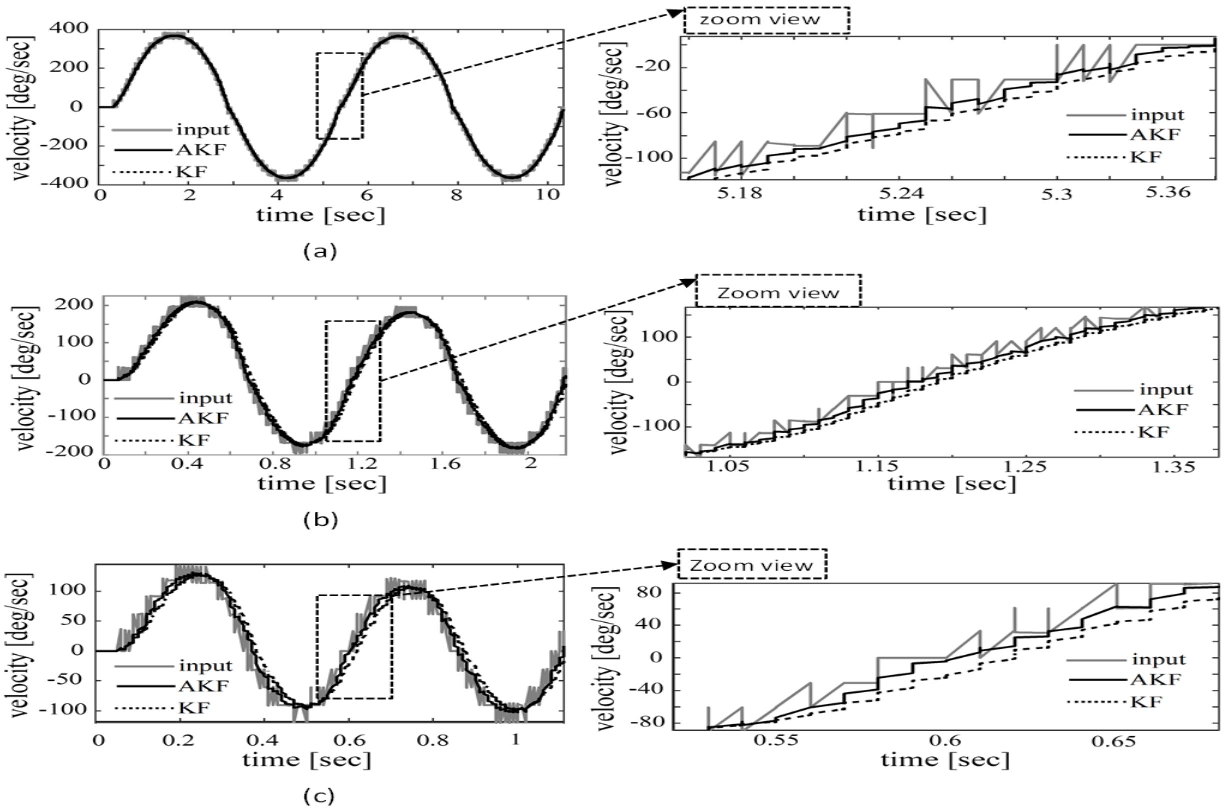


Figure 6 Velocity estimation results evaluated on sinusoidal motions with increasing frequencies (a) f=0.2Hz, (b) f= 1.0Hz and (c) f=2.0Hz recorded from experiment. The grey solid, the black solid and the dotted black lines represent the input signal, the proposed adaptive Kalman filter and the conventional Kalman filter with constant Q respectively.

According to the experimental results, AKF reduces the noises and produces a smoother filter result with a small delay. These velocity estimation results can also be visualized in the close-ups. In figure 6(a), both filter reduce noises. In figure 6(b) and 6(c), the conventional KF produces a smooth result, but, it shows a significant delay also visualized in the zoom view. Overall, the proposed AKF outperforms the KF for various frequencies. The conventional KF produces a remarkable time delay at high frequencies. Figure 7 shows the performance of AKF recorded from the experiment while the motor is supplied by constant voltage 5V. In this result, the proposed filter seems to have faster response (see in the close-ups) and KF is slow to respond. Besides the experimental tests with a variety of frequencies in sinusoidal motions, further insight into the proposed AKF's performance can be seen during the oscillatory motion (as shown in figure 8). The filter results are depicted in figure 6 and performance measures listed in Table 1. The proposed AKF reduces the velocity estimation errors compared to the KF for all indices, thus, produces a better filter result also visualized in the zoom view. The value of Q is adaptively updated for every filtering step as shown in figure 9, whereas Q is changed in each period.

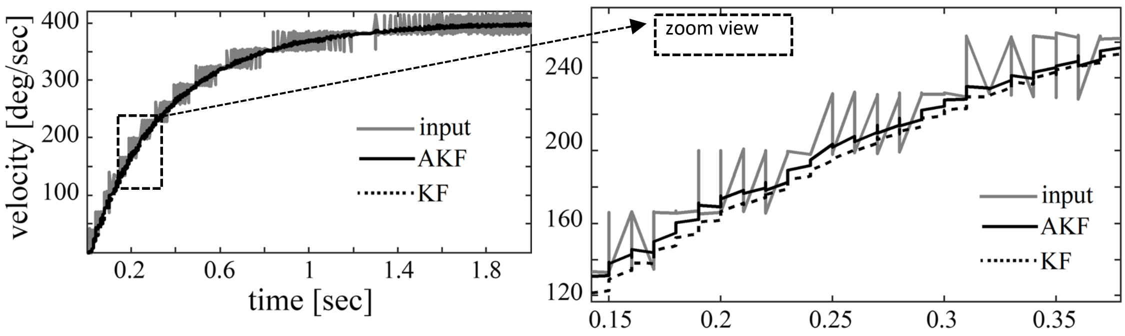


Figure 7 Filter performance recorded from the experiment while the motor is supplied by constant voltage.

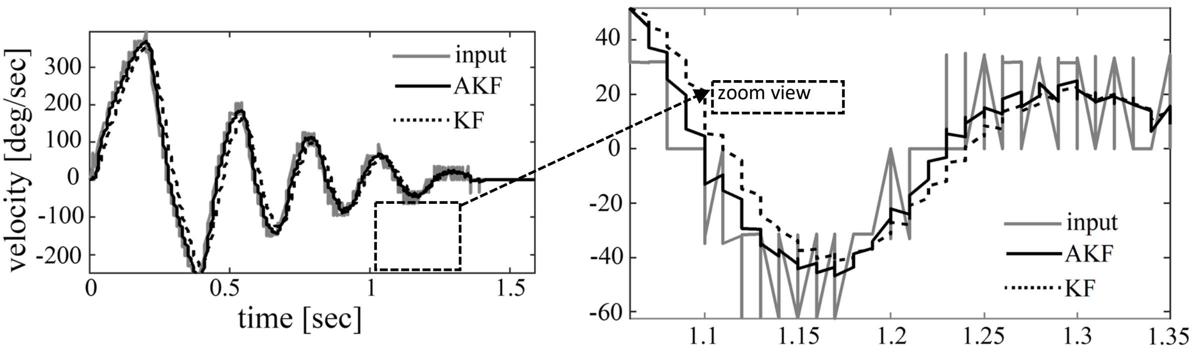


Figure 8 Velocity estimation results evaluated in oscillation motion.

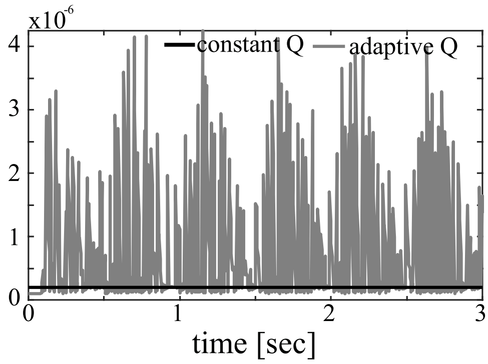


Figure 9 Updated Q for every filtering step of figure 6(b).

6.0 CONCLUSION

This paper has presented a new algorithm for the process noise covariance to overcome the limitation of Kalman filtering algorithm regarding velocity estimation. The accuracy and performance of Kalman filter is impacted by adjusting its gain value related to the process noise covariance Q and the measurement noise variance R, whereas the proposed algorithm updates only the process noise covariance Q in order to reduce complexity. The process noise variance of the Kalman filter without using kinematic model has been updated based on the filter's estimated signal of the previous time period that is convenient for use with different sensors. The presented adaptive Kalman filtering approach without using kinematic model has been compared to the conventional Kalman filter. The experimental results show that the new adaptive Kalman filter algorithm reduces noises and produces accurate velocity estimation without large time delay.

Table 1 Estimation errors of recorded sinusoidal motion according to figure 6

	Filter	RMSE	$Error_{max}$	$Error_{avg}$
f= 0.2 Hz	proposed	**5.8297**	**16.6413**	**5.0378**
	KF	8.9617	21.0291	7.7643
f= 1.0 Hz	proposed	**10.4320**	**28.2045**	**9.1402**
	KF	20.6515	37.4559	18.0974
f= 2.0 Hz	proposed	**10.7616**	**31.8643**	**9.3243**
	KF	21.8103	39.3362	19.2662

Acknowledgement

The author is very grateful to her colleagues at Mechatronic Engineering Department, Yangon Technological University, for their ongoing support, practical advice, and many discussions.

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