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Implementation of high-gain observer on low-cost fused IR-OS sensor embedded in UAV system

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Abstract. This paper presents discrete time implementation of a high gain observer (HGO) and extended term to estimate the state velocity and acceleration from the position measured by a low-cost sensor installed on-board the unmanned aerial vehicle (UAV). Owing to the low-cost sensor, the signal produced from fused IR–OS is noisy and therefore, additional filters are used to remove the noise. This study proposes an alternative to this standard and tedious procedure using HGO. The discrete time implementation of HGO and its extended term is presented and ground tests are conducted to verify the algorithm by inducing a dynamic motion on the UAV platform embedded with the fusion IR-OS onboard. A comparison study is conducted using standard numerical differentiation and ground truth measurement by OptiTrack. The results show that EHGO can produce a velocity signal with the same quality as that of differentiated signal from fused IR-OS using Kalman filter. The novelty of HGO lies in its simplicity and its minimal tuning of parameters.

1. Introduction

Unmanned aerial vehicles (UAVs) have been perceived to have good military and civilian potentials to serve various missions such as aerial surveillance, search and rescue, and monitoring applications. In the past few years, apart from controller development for attitude stabilization, the work in design and development of UAV platform is primarily focused on enhancing the autonomy level for autonomous navigation and collision avoidance control. Providing accurate state estimation is vital for successful and reliable implementation of the controller algorithm, which consequently results in stability control of the complete UAV. Position information of UAV can be directly obtained from Global Positioning System (GPS) for outdoor applications. Meanwhile, several studies on indoor flight have been directed to the use of low-cost sensors like infrared, sonar and ultrasonic [1-3]. However, sensor measurement for the velocity and integral position is not always available and approximation is usually required.

Directly differentiating the position signal using numerical calculation is the traditional method to obtain velocity. However, this method is highly susceptible to noise and errors [4]. A Kalman filter-based velocity estimator has been developed to get smooth velocity data from position measurement using IR and sonar sensors [1]. Similar procedure using Kalman filter to estimate the smooth velocity has been presented in another study using fused data from IR and ultrasonic sensor [2]. Kalman filter is widely used for smoothing noisy data and as an estimator due to its simplicity and easy application.

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However, its effectiveness is limited only to the system that has been linearized. Other state estimation approaches reported are based on state transformation and therefore, the nonlinearities only depend on input and outputs [5], and the use of linear matrix inequality (LMI) techniques [6-7]. However, these methods involve complex gain formulas and require solving LMI or partial differential equations. The state estimation based on design of robust observers has been reported using high-gain [8] or sliding mode method [9]. The advantage of robust estimator is its capability to be directly applied to estimate rapid dynamics from complex, nonlinear system, in which linearization is not required.

This paper focuses on design of robust estimator using high-gain observer (HGO). Development of HGO over the last two decades has been reported in Ref. [8]. In an ideal differentiator, the noise in the signal will be differentiated together with the signal, thus generating large derivatives along with the differentiated signal. However, the basic concept of HGO is to simultaneously estimate derivative of a signal and quantify the noise in the signal through a few gain ratios [10]. An extended term from HGO has been proposed to estimate higher dynamics of nonlinear system, in addition to providing estimated velocity [11]. Extended high-gain observer (EHGO) has been demonstrated in an advance acquisition board with high-quality sensor of good precision. Therefore, the objective of this paper is to study the real time performance of HGO and its extended term in estimating velocity and acceleration from the position information obtained by fused measurement of low-cost infrared (IR) and ultrasonic sensor (OS).

2. Background Study

A nonlinear system is given in the normal form as shown in the following Equation 1, where$x \in R^2 = (x_1, x_2), x_1$ is the position and x_2 is velocity, y is measured output and u is control signal [12].

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= f(x) + g(x)u \\ y &= x_1 \end{aligned} \tag{1}$$

In this system, only position state is measured. Given state feedback stabilizing controller, $u = \gamma(x_1, x_2)$, the velocity state x_2 has to be estimated before the controller can be implemented. The HGO algorithm is proposed in Equation 2, which is to obtain the first differentiation of position signal [13].

$$\begin{aligned} \dot{\hat{x}}_1 &= \hat{x}_2 + \frac{\alpha_1}{\varepsilon}\left(x_f - \hat{x}_f\right) \\ \dot{\hat{x}}_2 &= \hat{x}_a + \frac{\alpha_2}{\varepsilon^2}\left(x_f - \hat{x}_f\right) \end{aligned} \tag{2}$$

By adding one more integrator, the second differentiation term is estimated by Equation 3.

$$\dot{\hat{x}}_a = \frac{\alpha_3}{\varepsilon^3}(x_f - \hat{x}_f) \tag{3}$$

The complete expression of Equation 2 and Equation 3 is known as EHGO [11,14]. The term ε is the high-gain term and the value varies depending on the system. The values of α_1, α_2, α_3 are called the set of polynomials, which is chosen such that the polynomials in Equation 4 are Hurwitz and the states $\hat{x}_2$ are estimates of velocity x_v, $\hat{x}_3$ are estimates of acceleration.

$$s^3 + \alpha_1 s^2 + \alpha_2 s + \alpha_3 \tag{4}$$

The estimator algorithms in Equation 2 and Equation 3 are in continuous form. The algorithm needs to be converted into a discreet form for the real-time implementation. Inspired by the work in Ref. [4], the digital form is obtained by the following procedures. First, new observer variables $q = [q_1, q_2, q_3]$ is defined as in Equation 5, where ε is the observer gain and $\hat{x} = [\hat{x}_1, \hat{x}_1, \hat{x}_1]$ are the estimated states from Equation 2 and Equation 3.

$$q_1 = \hat{x}_1 \ , q_2 = \epsilon \hat{x}_2 \ , q_3 = \epsilon^2 \hat{\sigma}_3 \tag{5}$$

Then, the dynamics of the new variables in Equation 5 are derived by Equation 6.

$$\begin{gathered} \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix} = \begin{bmatrix} -\alpha_1/\varepsilon & 1/\varepsilon & 0 \\ -\alpha_2/\varepsilon & 0 & 1/\varepsilon \\ -\alpha_3/\varepsilon & 0 & 0 \end{bmatrix} \begin{bmatrix} q_1 \\ q_2 \\ q_3 \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_1 \\ \alpha_1 \end{bmatrix} y \\ y = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} q_1 \\ q_2 \\ q_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \end{gathered} \tag{6}$$

Equation 6 is the state–space model that will be used for discretization to digital form. The state–space is converted into digital form in MATLAB environment. Sampling rate has to be defined at this stage. Upon conversion, new A, B, C and D matrices that are produced will be coded into C# in GUI-based terminal software developed by Microsoft Visual Basic as the integrated environment. Re-conversion from digital form to continuous form is as shown in Equation 7.

$$\begin{bmatrix} \hat{x}_1 \\ \hat{x}_2 \\ \hat{x}_3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1/\varepsilon & 0 \\ 0 & 0 & 1/\varepsilon^2 \end{bmatrix} \begin{bmatrix} q_1 \\ q_2 \\ q_3 \end{bmatrix} \tag{7}$$

3. Low-Cost Collision Avoidance System

The hardware setup of motion tracking system is presented in this section. An experimental validation is performed on the low-cost collision avoidance system developed in the study presented in Ref. [2]. Data fusion from IR and OS sensors, combined with linear Kalman filter, is developed to estimate the relative position measurements between the UAV and the obstacles. The proposed collision avoidance algorithm requires the position and velocity states.

The IR–OS sensors are mounted in between quadrotor arms. The overall monitoring system shown in Figure 1 consists of quadrotor vehicle with mounted IR–OS sensors, pair of XBee wireless routers, ground PC station and OptiTrack motion tracking system based on IR cameras. The Optitrack will be the ground truth for validating the motion given by the onboard fused IR–OS sensors. Block diagram of the UAV monitoring system is illustrated in Figure 2.

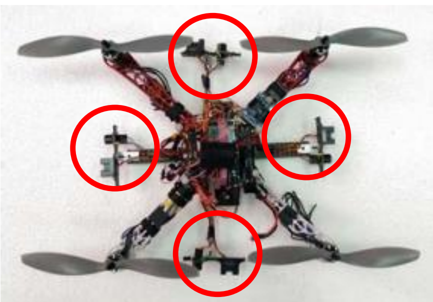

Figure 1: Four sets of fused IR-OS sensors (shown in circled)

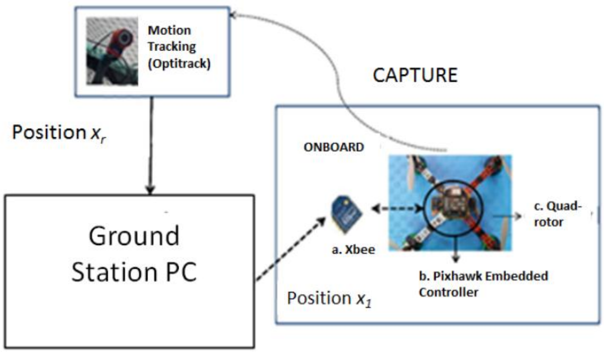

Figure 2: Low-cost UAV monitoring system

The ground station is a PC that runs on the Windows operating system using a GUI-based terminal software developed by the Microsoft Visual Studio as the integrated development environment. The quadrotor vehicle communicates with the ground station via Xbee wireless routers at a frequency of 20 Hz. The position x_1 is the signal obtained by the fused data using low-cost IR–OS sensor that has been filtered by a linear Kalman filter to obtain smooth position estimation, which is embedded onboard the quadrotor. The signal is wirelessly transmitted by Xbee to the ground PC. Meanwhile, the position x_r is the ground truth signal measured by OptiTrack indoor monitoring and transmitted to the ground PC station where the output feedback law is implemented.

In standard practice, the velocity of a vehicle is estimated from the rate of change of the position range data, and the data is filtered using linear Kalman filter to obtain smooth velocity estimation. The rate of change is based on basic numerical differentiation in Equation 8. Additionally, the acceleration based on numerical differentiation in Equation 9.

$$x_v = \frac{x_{1(n+1)} - x_{1(n)}}{t_{(n+1)} - t_{(n)}} \tag{8}$$

$$x_a = \frac{x_{v(n+1)} - x_{v(n)}}{t_{(n+1)} - t_{(n)}} \tag{9}$$

The overall structure of computing the velocity and acceleration from position x_1 by the fused IR-OS sensor using standard numerical differentiation procedure and the estimator is illustrated in Figure 3. The performance obtained from both methods is obtained.

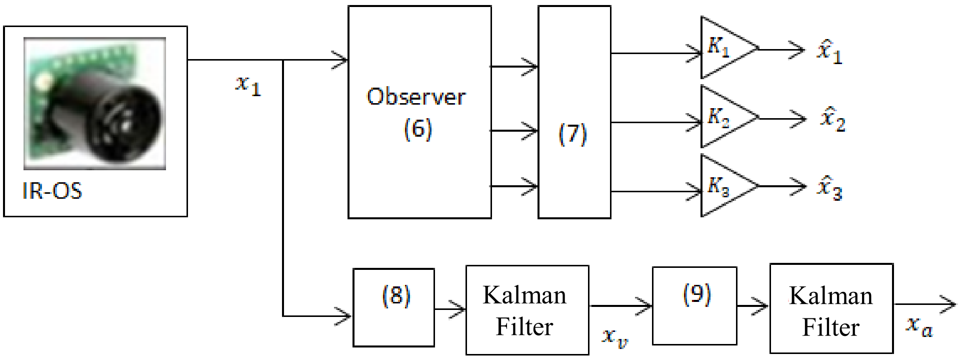

Figure 3: Structure to obtain velocity and acceleration from IR-OS position measurement

4. Results and Discussions

The observers sets of polynomial in Equation 4 are assigned as follows:α_1 = 9, α_2 = 9, α_3 = 3. In the meantime, the sampling time T_s = 0.05, which is selected based on frequency of the motion tracking system that is 20 Hz. The performance of the position state estimated using Equation 7 and Equation 6 is first compared with two different observer gains, ε = 0.05 and 0.01 as shown in Figure 3. The results of this comparison are presented in Figure 4 and also Figure 5, which show the position of the UAV as measured using the proposed estimator, ground truth position as measured by OptiTrack and also the measurement using the fused IR–OS. The plots aim to highlight the closeness of the estimated position from EHGO with the position measured by IR–US. The results show that the estimated position with observer gain ε = 0.01 is nearly indistinguishable from the position x_1 measured by the fused IR–OS sensor, as shown in Figure 5. On the other hand, Figure 4 shows that the estimated position with the position from fused IR–OS. The amplitude is larger compared to the ground truth measurement. This result concludes that the proposed estimator is workable at a high gain. The aforementioned results indicate that the gain has to be 100. When the gain is reduced, the position error between the estimated and measured position will increase. Eventually, as gain is 50, the error becomes extremely large and unacceptable because the signal amplitude is larger than the ground truth measurement.

The real-time velocity generated from the proposed estimator is compared with the result obtained from the numerical differentiation using IR–OS and the ground truth using OptiTrack, and they are as shown in Figure 6. The result obtained from HGO uses gain ε = 0.01.

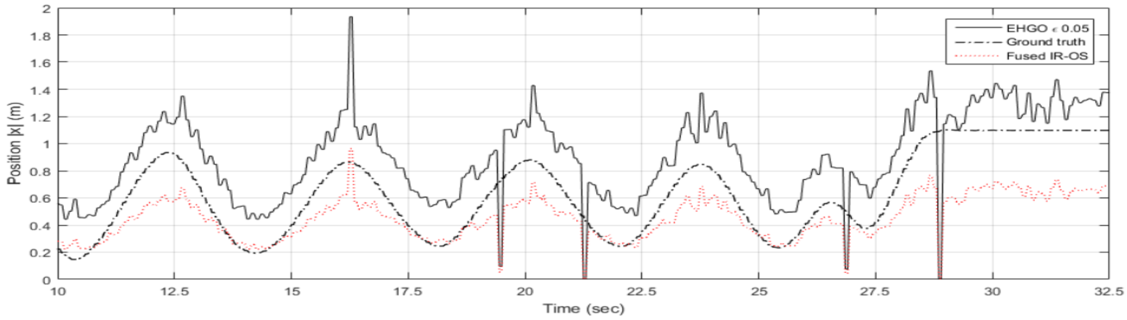

Figure 4 : Position generated by EHGO = $\hat{x}_1$ using ε = 0.05, fused IR-OS = x_1 and ground truth = x_r

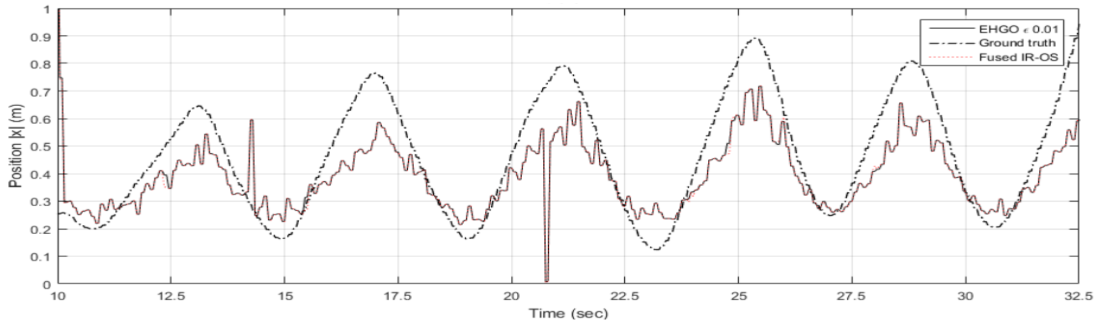

Figure 5: Position generated by EHGO = $\hat{x}_1$ using ε = 0.01, fused IR-OS = x_1 and ground truth = x_r

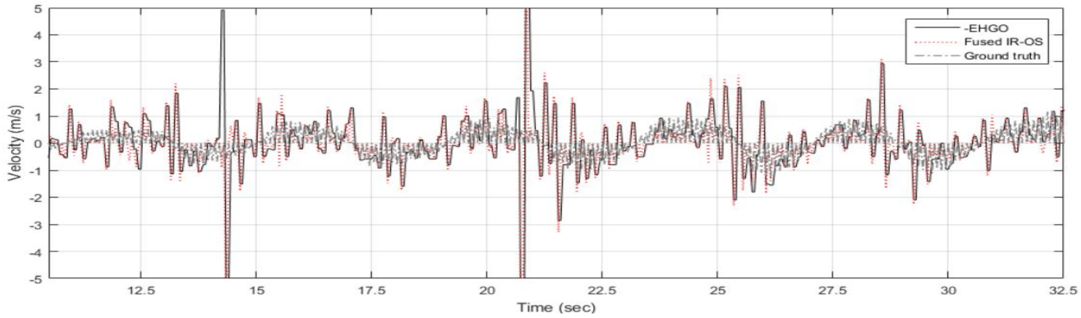

Figure 6: Velocity generated by EHGO = $\hat{x}_2$ using ε = 0.01, fused IR-OS = x_v and ground truth

Based on Figure 6, the estimated velocity by EHGO has a similar performance to the velocity from fused IR-OS. The velocity from fused IR-OS is obtained as illustrated by x_v in Figure 3. The results show that EHGO is evidently smoother in comparison to the sharp spiking observed in fused IR–OS. However, the quality of velocity signal from fused IR-OS is not as good as the quality obtained from the ground truth using OptiTrack. Although both signals are actually differentiated using the same rate of change algorithm in Equation 8, the fused IR–OS needs further filtering to obtain smoother velocity that is comparable to the ground truth.

Finally, the results in the acceleration signal generated by HGO and filtered differentiation signal are as in Figure 7. The obtained performance is similar to previously discussed velocity performance. The EHGO can estimate acceleration signal with nearly similar performance to the result in fused-IR, which is obtained by the numerical differentiation in Equation 9 and filtered noise using linear Kalman filter. The estimated signal from HGO is smooth and shows less amplitude spiking. However, similar to the velocity signal, the quality of acceleration signal obtained from the fused IR–OS is not as good as the quality generated by the ground truth. A filter is required to filter the noise of velocity signal prior the differentiation to obtain the acceleration signal.

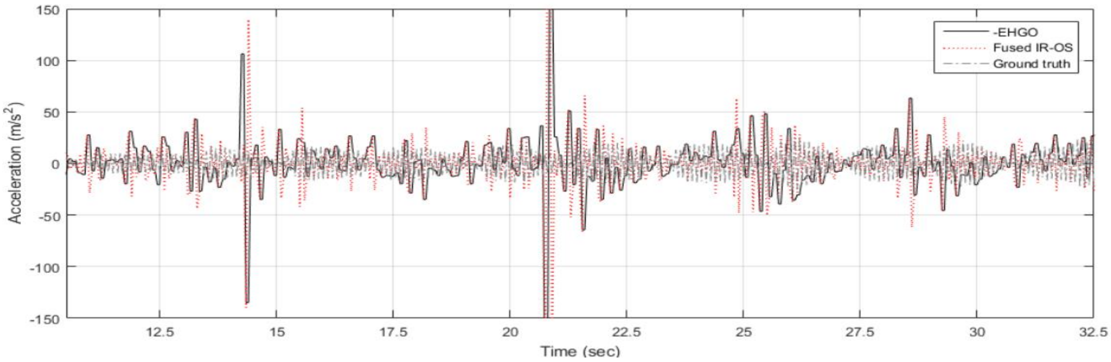

Figure 7: Acceleration generated by EHGO = $\hat{x}_3$ using ε = 0.01, fused IR-OS = x_a and ground truth

5. Conclusion

The real-time performance of EHGO has been presented to estimate velocity and acceleration states from position signal measured by on-board fused IR–OS motion tracking sensors. In standard practice, the signal needs to pass through two Kalman filters to remove the noise amplitude before and after numerical differentiation. However, by using the proposed estimator with the correct gain values, the performance quality of the velocity and acceleration signals is made slightly better. In particular, the signal obtained is smooth and has no sharp spiking. Therefore, the estimator based on HGO algorithm can be used as an alternative method to obtain the velocity and acceleration signals to replace the long computational procedure using filters. The HGO algorithm is robust such that it is able to provide smooth velocity and acceleration signals are provided without the need to use additional Kalman filter to remove noise.

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