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## Research Article

## The design and implementation of an accelerometer-assisted velocity observer

Yu-Sheng Lu<sup>a,\*</sup>, Sheng-Hao Liu<sup>b</sup><sup>a</sup> Department of Mechatronic Engineering, National Taiwan Normal University, 162, He-ping East Rd., Sec. 1, Taipei 106, Taiwan<sup>b</sup> Department of Mechanical Engineering, National Yunlin University of Science & Technology, Yunlin, Taiwan

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## ABSTRACT

This paper presents a dynamically compensated velocity observer (DCVO), in which acceleration measurement is employed to estimate velocity. Its sensitivity to the noise that is associated with the acceleration measurement is formulated and compared with that of a conventional state-space velocity observer (SSVO). Unlike the SSVO, the DCVO is completely insensitive to an accelerometer offset. The DCVO, the SSVO and a common ITM-based estimator are all realized in a linear motion stage, to determine their effectiveness. A sliding-mode controller is also implemented with different velocity observers, and it is shown that the DCVO enables high-frequency switching of the sliding-mode controller and also practically improves the positioning accuracy.

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## 1. Introduction

Precise linear motions are required in a variety of industrial applications, including semiconductor wafer inspection, laser-cutting machines and many numerically controlled machine tools. In these applications, motion control systems are employed, and their performance inevitably depends on the accuracy and sensitivity of the sensors for the feedback systems [1]. Position sensors, such as optical incremental encoders, are widely used to provide positional information. However, velocity sensors may not be available or suitable for certain motion control systems. For example, the velocity signals provided by tachometers are generally contaminated with noise. System cost and size are also increased when velocity sensors are incorporated into motion control systems. As a consequence, velocities are usually estimated from the positional signal using a filtering algorithm. The quality of the velocity estimation can be improved by a more advanced filtering algorithm.

Real-time velocity estimation approaches can be divided into two categories: model-based and non-model-based methods [2]. Model-based methods, such as sliding-mode observers [3,4], Generalized Proportional Integral-based observers [5], neural networks [6], dual-sampling rate observers [7], Kalman filters [8] and extended Kalman filters [9], use models of the dynamic

systems for which the velocities are to be estimated. In general, these model-based approaches require a model of a mechanical load, but the mechanical properties of the load are uncertain or difficult to ascertain. Therefore, this paper focuses on non-model-based methods, which usually use signal processing techniques.

Two of the most common non-model-based methods for velocity estimation that use positional signals from incremental encoders are the finite difference method (FDM) and the inverse-time method (ITM) [10]. The FDM is also referred to as the fixed-time (clock-driven, pulse-counting, or lines-per-period) method and evaluates the backward difference for encoder counts at fixed time intervals. This method is easily implemented in a real-time control system, since the control algorithm is also normally calculated at fixed time intervals. However, this method fails in the low-speed region, where the positional increments are relatively small for fixed time intervals, which significantly increases the effect of quantization noise and results in inferior velocity estimation. In other words, resolution by this method becomes very coarse at faster sampling rates, when the pulse counting period and thus the positional increment are small. The ITM is also referred to as the fixed-position (encoder-driven, pulse-width measuring, or reciprocal-time) method and estimates the velocity by using the time that elapses between two consecutive encoder pulses. This method gives improved resolution in the low-speed region, as the interval between two consecutive pulses is relatively long. However, this method has limitations in the high-speed regime. To detect velocities using the discrete pulse train

\* Corresponding author. Tel.: +886 2 7734 3512; fax: +886 2 2358 3074.

E-mail address: [luy@ntnu.edu.tw](mailto:luy@ntnu.edu.tw) (Y.-S. Lu).

from an incremental encoder, Ref. [11] provides an overview of existing techniques such as Taylor series expansions, backward difference expansions and least-squares fits. Ref. [12] uses the time stamping concept to improve a least-squares fit velocity estimator. Non-linear filtering techniques, including tracking differentiators [13–15], enhanced differentiators [16], high-order nonlinear differentiator [17] and differentiators using the so-called super-twisting algorithm [18], have also been developed for velocity estimation. However, they either require bounds for the acceleration or are complex in design and implementation.

Because of the advances in electromechanical microsystem (MEMS) technology, the cost of MEMS accelerometers is extremely low, when compared with that of positional sensors, such as incremental encoders. Therefore, the addition of these ubiquitous, low-cost accelerometers to positional sensors is an attractive option for high-quality velocity estimation. Ref. [19] proposes a position- and acceleration-based velocity estimation law, in which an observation time period is defined as the interval between certain past time,  $t_i$ , and the current time,  $t$ , and is chosen to be a constant multiple of the sampling period in discrete-time implementation. This law involves a double integral of acceleration over the observation time period,  $[t_i, t]$ , and can be written as:

$$\hat{v}(t) = \frac{x_m(t) - x_m(t_i)}{t - t_i} + \frac{\int_{t_i}^t \int_{\tau_i}^{\tau} a_m(\tau_a) d\tau_a d\tau}{t - t_i}, \quad (1)$$

in which  $\tau$  and  $\tau_a$  are integration variables,  $\hat{v}(t)$  is the velocity estimate and  $x_m$  and  $a_m$  respectively denote the measured position and acceleration. In practice, the measured acceleration signal usually contains an uncertain offset, which leads to a drift in the velocity estimate when the velocity estimation law (1) is used. Using the state-space approach, Refs. [1,20] present a Luenberger observer-like velocity estimator, which is referred to as state-space velocity observer (SSVO) in this paper. However, a SSVO can also be susceptible to accelerometer offset. In [21], the so-called two-channel approach is proposed for the fusion of positional and acceleration measurements. This approach uses two frequency-weighted second-order filters: one for the acceleration signal and the other for the positional signal. The velocity estimate then comprises a positional component and an acceleration component. The complementary nature of the two filters' transfer functions yields an exact all-pass characteristic, so the velocity estimate gives the true velocity in this transfer function analysis. In order to take account of the accelerometer offset, this approach uses a high-pass filter, whose pole is also one pole of the velocity observer. When this pole is close to the origin of the complex plane, the observer dynamics are limited, which produces slow transient responses. When this pole moves away from the origin, the observer dynamics are improved, but the sensitivity to high-frequency position noise, such as the position quantization error of an incremental encoder, increases.

This paper presents an accelerometer-assisted velocity observer that is completely insensitive to the accelerometer offset. Compared with the two-channel approach, the proposed approach neither limits pole locations for the observer dynamics, nor is it vulnerable to high-frequency positional noise. The two-channel approach also requires the use of two second-order filters, but the proposed approach only needs to realize a third-order model, which allows simpler implementation and a lower computational cost. In this paper, various velocity estimation methods are used practically to control the position of a screw-based linear motion stage using an accelerometer and an incremental optical linear encoder. More specifically, the so-called Integral Variable-Structure Control (IVSC), a switching control law, is used to determine the effectiveness of various velocity estimation methods.

## 2. A revisit to state-space velocity observer (SSVO)

The state-space velocity observer (SSVO) can be described by:

$$\dot{\hat{x}}(t) = \hat{v}(t) + l_1(x_m(t) - \hat{x}(t)) \quad (2)$$

$$\dot{\hat{v}}(t) = a_m(t) + l_2(x_m(t) - \hat{x}(t)), \quad (3)$$

where  $\hat{x}(t)$  denotes the positional estimate and  $l_1$  and  $l_2$  are constant observer gains. If  $x(t), v(t)$  and  $a(t)$  denote the true position, velocity and acceleration, respectively, the positional and acceleration noises are defined as  $n_x(t) = x_m(t) - x(t)$  and  $n_a(t) = a_m(t) - a(t)$ , respectively, and the positional and velocity estimation errors are defined as  $e_1(t) = x(t) - \hat{x}(t)$  and  $e_2(t) = v(t) - \hat{v}(t)$ , respectively. To analyze the observer dynamics, differentiate the positional estimation error with respect to time, which gives  $\dot{e}_1(t) = \dot{x}(t) - \dot{\hat{x}}(t) = v(t) - \hat{v}(t)$ , and substitute (2) into the equation, which yields:

$$\dot{e}_1(t) = e_2(t) - l_1(x_m(t) - \hat{x}(t)) = e_2(t) - l_1 e_1(t) - l_1 n_x(t). \quad (4)$$

Similarly, substituting (3) into the time derivative of the velocity estimation error gives:

$$\dot{e}_2(t) = a(t) - \dot{\hat{v}}(t) = -n_a(t) - l_2 e_1(t) - l_2 n_x(t). \quad (5)$$

If  $f(s)$  is defined as the Laplace transform of a time-domain signal,  $f(t)$ , that is to say, the  $s$ -domain representative of  $f(t)$ , then neglecting initial conditions, the  $s$ -domain representation of (4) and (5) is:

$$s e_1(s) = e_2(s) - l_1 e_1(s) - l_1 n_x(s) \quad (6)$$

$$s e_2(s) = -n_a(s) - l_2 e_1(s) - l_2 n_x(s). \quad (7)$$

Solving (6) and (7) for  $e_2(s)$  gives:

$$e_2(s) = -\frac{s+l_1}{s^2+l_1s+l_2} n_a(s) - \frac{l_2s}{s^2+l_1s+l_2} n_x(s). \quad (8)$$

Since  $e_2(s) = v(s) - \hat{v}(s)$ , then:

$$\hat{v}(s) = v(s) + \frac{s+l_1}{s^2+l_1s+l_2} n_a(s) + \frac{l_2s}{s^2+l_1s+l_2} n_x(s). \quad (9)$$

Therefore, the characteristic equation for the SSVO is  $s^2 + l_1s + l_2 = 0$ , from which the observer gains,  $l_1$  and  $l_2$ , can be determined. The transfer function from  $n_a(s)$  to  $\hat{v}(s)$  is  $(s+l_1)/(s^2+l_1s+l_2)$ , which demonstrates that when there is an accelerometer offset, the velocity estimate drifts. That is, the SSVO is unable to eliminate any adverse effects of an accelerometer offset.

## 3. A dynamically compensated velocity observer (DCVO)

This paper presents a dynamically compensated velocity observer (DCVO). The structure of the DCVO is presented in Fig. 1, where  $C(s)$  is a dynamic compensator that shapes the DCVO's dynamics. The discrepancy between the measured and the estimated position signals is defined as  $e = x_m - \hat{x}$  and the output of the compensator is defined as  $\mu(s) = C(s)e(s)$ . For the structure of

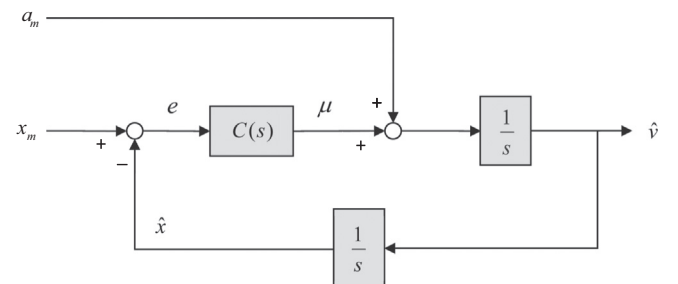


Fig. 1. Dynamically compensated velocity observer (DCVO).

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