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Autonomous dynamic displacement estimation from data fusion of acceleration and intermittent displacement measurements

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ABSTRACT

Addressing the importance of displacement measurement of structural responses in the field of structural health monitoring, this paper presents an autonomous algorithm for dynamic displacement estimation from acceleration integration fused with displacement data intermittently measured. The presented acceleration integration algorithm of multi-rate Kalman filtering distinguishes itself from the past study in the literature by explicitly considering acceleration measurement bias. Furthermore, the algorithm is formulated by unique state definition of integration errors and error dynamics system modeling. To showcase performance of the algorithm, a series of laboratory dynamic experiments for measuring structural responses of acceleration and displacement are conducted. Improved results are demonstrated through comparison between the proposed and past study.

1. Introduction

Traditionally displacement response of structures has provided useful information to the field of structural engineering, since it can be directly converted to deformation and strain of the structures [1]. Besides the traditional preference, there are strong needs for measurement of displacement in the recent fields of health monitoring, safety/condition assessment, and system identification for civil engineering structures: for example, based on measured static and pseudo-static deflections of a bridge deck for heavy duty trucks, bridge load carrying capacity can be determined; dynamic displacement measurement are preferred over acceleration measurement in the context of system identification, since the use of displacement data as system output results in a state-space model which can be converted to physically interpretable parameters [2,3].

In practice, displacement response measurement of existing structures is fairly difficult and cumbersome. Since displacement is a relative physical quantity, it requires a reference. Thus, contact displacement sensors (e.g., LVDT and potentiometer) require stationary platforms which may increase installation cost and deteriorate accuracy of measurements. Being proposed as the alternatives, non-contact optical technology (e.g., laser scanning instruments [4]) and computer vision-based [5] and GPS-based technology [6] are popular these days. However, the relating problems still remain unsolved such as high equipment cost, low sampling rate, low resolution, just to name a few.

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There has been a strong preference of the use of measured acceleration to retrieve displacement (which is equivalent with physical quantities of position and location), since acceleration can be easily measured without a fixed reference point in the numerous fields of science and engineering (e.g., structural engineering, seismology, geodetic and navigation). Direct integration of measured acceleration yields displacement mathematically. However, the simple integration of acceleration suffers from drift issue. A plethora of strategies for remedies against case-by-case drift problems have been actively studied especially in the field of engineering seismology and are mainly categorized into two groups: baseline correction and low and high pass filtering [7]. Baseline correction is a least-square curve fitting technique in the time domain and filtering is a common noise removal technique in the frequency domain. As for displacement estimation of dynamic and pseudo-static displacements of bridge girders under passing traffic, Park et al. (2005) proposed an iterative methodology termed as the initial velocity estimation method (IVEM) by single integration of estimated velocity time histories with a zero initial value [8]. More recently, use of an analytical state-space model was proposed to correct displacement estimates of dynamic response of a bridge under vehicular load [9].

In general, it is accepted that a universal correction scheme which can be autonomously applied to pure acceleration integration is rather challenging to yield satisfactory results [10]. Thus, it seems to be inevitable to combine acceleration and intermittently measured displacement. Utilizing fusion of inherent data redundancy, high accurate displacement and velocity are estimated. The multi-rate Kalman filtering technique has been actively applied to the data fusion especially in the field of navigation and guidance [11,12]. The most significant merit of Kalman filtering is its autonomous implementation without any need of human involvement and judge unlike the aforementioned correction scheme for acceleration integration. In this context, data fusion by Kalman and its variant filtering (i.e., unscented Kalman filtering, particle filtering, etc.) has been emerged as an active research stream in the SHM community: Smyth and Wu presented a multi-rate Kalman filtering algorithm for the purpose of estimating dynamic displacement from acceleration and intermittent displacement measurements with various numerical examples [13]; Chang and Xiao applied it to an experimental example of acceleration and videogrammetric displacement sensing [14]; addressing the limit of a constant noise variance of Kalman filtering, Li and Chang proposed an adaptive time-varying noise estimation algorithm by virtue of signal subspace tracking [15].

In this study, a new algorithm of the multi-rate Kalman filtering is presented for improving accuracy of dynamic displacement estimation based on continuous acceleration and intermittent displacement measurements. The proposed estimation algorithm explicitly considers acceleration measurement bias to reflect the accelerometer inherent bias during acceleration integration. In order to consider the acceleration measurement bias, integration error evolution is modeled as system dynamics of Kalman filtering. Detailed derivation and implementation of the error dynamics-based Kalman filtering is discussed theoretically. Experimental verification is then followed using data sets of acceleration and displacement sensed by a laser optic sensor.

2. Displacement estimation from acceleration integration

2.1. Problem statement of acceleration integration

Single and double successive numerical integrations of the measured acceleration of an object in the discrete-time domain with the time interval, Δt, calculate velocity and displacement respectively as

$$\dot{x}(k+1) = \dot{x}(k) + \ddot{x}(k)\Delta t \tag{1}$$

$$x(k+1) = x(k) + \dot{x}(k)\Delta t + 0.5\ddot{x}(k)\Delta t^2 \tag{2}$$

where $\dot{x}(k)$ and $x(k)$ are the calculated velocity and displacement at the time step k, $\ddot{x}(k)$ is the measured acceleration at the time step k. Two inherent problems relating with the acceleration integration can be addressed. Seen in Eqs. (1) and (2), numerical error can be accumulated due to the zero-order hold (i.e., the values at the time step of $k+1$ are calculated from the fixed values at the time step k) and referred to as mathematical error. This is inevitable to deal with continuous-time physical phenomena in the discrete-time domain. Furthermore, there is a more fundamental problem that Eqs. (1) and (2) are based on the measured acceleration different from the true acceleration.

The measured acceleration is contaminated by measurement error and thus written in the discrete-time domain as

$$\ddot{x}(k) = \bar{\ddot{x}}(k) + \varepsilon\ddot{x}(k) \tag{3}$$

where $\bar{\ddot{x}}(k)$ is the true acceleration at the time step k, and $\varepsilon\ddot{x}(k)$ is the acceleration measurement error at the time step k. Therefore, the problem of estimating displacement and velocity from integration of the measured acceleration can be converted to that of estimating the acceleration measurement error, $\varepsilon\ddot{x}(k)$ and its contribution to integration errors. Based on the estimated error, the numerical integration can be compensated and the estimates of velocity and displacement, $\hat{\dot{x}}$ and $\hat{x}$, are calculated respectively as

$$\hat{\dot{x}}(k+1) = \hat{\dot{x}}(k) + \ddot{x}(k)\Delta t - \varepsilon\ddot{x}(k)\Delta t \tag{4}$$

$$\hat{x}(k+1) = \hat{x}(k) + \hat{\dot{x}}(k)\Delta t + 0.5\ddot{x}(k)\Delta t^2 - 0.5\varepsilon\ddot{x}(k)\Delta t^2 \tag{5}$$