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Research paper

Real-time monitoring system for local storage and data transmission by remote control

Sara Casciati [a], Michele Vece [b,*]

[a] DICAr, School of Architecture, University of Catania at Siracusa, P.za Federico di Svevia, Siracusa 96100, Italy
[b] DICAr, University of Pavia, Via Ferrata 3, Pavia 27100, Italy

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ABSTRACT

The real time estimation of the displacements of civil structures is quite sensitive to the availability of wired links between the sensors and the remote control room. Many kinds of wireless displacement sensors or indirect measurements of them have been proposed. However, most of them suffer of large time delays and accuracy issues. In this paper, the authors adopt a Kalman-filter-based data fusion to make a precise measurement of the displacements in for civil structures and infrastructures. The required accuracy can be reached exploiting the real-time satellite corrections provided by a single reference station and combining them with the acceleration signals coming from three axial accelerometers. A wireless communication transfers the information coming from the coupling of GNSS receivers and three axial accelerometers. The proposed system is validated by control mechanism and laboratory tests. The ultimate goal is a reliable scheme for a real-time structural health monitoring managed in remote control.

1. Introduction

Real-time structural health monitoring (SHM) is regarded as a hot spot in the area of civil engineering. It addresses the acquisition of structural responses and environmental factors in order to assess the structural health in view of maintenance actions. The first step is to identify the types of physical quantities to be monitored: key issues are generally accuracy, user-friendliness, and availability of the measurements. Acceleration and displacement are the most widely measured responses in SHM to determine the dynamic characteristics, the stability and the soundness of large structures.

Two kinds of techniques for measuring the displacements are currently available: (i) direct measurements, and (ii) indirect estimation approaches. The direct methods include linear variable differential transformers (LVDT), LASER-based transducers [1–2], and vision based system [3–6]. Their main drawbacks are the high costs and the synchronization issues when multiple points are required. Furthermore, the data acquisition systems have to be placed between a measurement point and a stationary reference, with challenging issues resulting from the need of wired connections.

The indirect estimation approach converts other structural responses (i.e., acceleration and strain) into displacements on the basis of their physical relationships. However, it suffers from low accuracy due to numerical errors and imperfect physical relationships [7].

Accuracy enhancements are achieved by exploiting multiple responses, via a data fusion model, to reduce the drawbacks of each single acquisition [8–10]. Indeed, the conversion of the accelerations can be improved by the simultaneous collection of displacements measured by a high precision GNSS (Global Navigation Satellite System) device. This method has been actively studied in the GPS (Global Positioning System) navigation field, but it needs to make a post-data fusion between accelerations and displacements as well [11–16].

The data acquisition is also a key issue for a successfully SHM (Structural Health Monitoring). The need of wireless connections has emerged in recent years, since the wired monitoring systems suffer for installation problems, its invasive effect, the vulnerability to mechanical damage, and the high costs for the maintenance of the wires as well. Many wireless sensor schemes have been recently proposed, but some of them suffer of large time delays and accuracy issues [16–22].

In this paper, a Kalman filter-based data fusion is adopted to make a precise measurement of the displacements induced on civil structures. The needed accuracy can be reached exploiting the real-time satellite corrections provided by a single reference station and making a combination between the resulting data and the accelerations coming from three axial accelerometers [23–25].

After that, a recent wireless communication technology is used to develop an updated solution that achieves the expected perfor-

* Corresponding author.
E-mail address: miche.vece@gmail.com (M. Vece).

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mance without additional costs and significant changes with respect to the existing analog cables. For this purpose, the ZigBee technology and the IEEE802.15.4 compliant transceiver CC2530 resulted to be the most suitable components for applications in wireless SHM systems.

Once the message has been locally acquired, the information to be sent to a remote center. In this way, it remote center operators can analyze the data and detect the effectiveness of the structure under study.

The communication is unable to use internet, when an environmental crisis interferes with the existing terrestrial network. Therefore, a VPN (Virtual Private Network) over satellite is adopted, ensuring the continuity of the monitoring operations. The features of the wireless transceivers and the tasks of a reliable satellite communication are discussed. The hardware and the software architectures are described, and an experimental validation of the connections is performed.

2. Governing relations

The European Union FP7 project named SPARTACUS (Satellite Based Asset Tracking for Supporting Emergency Management in Crisis Operations) funded the software development and the entire experimental campaign that is reported in this paper.

A reliable and efficient sensor network needs low-cost and low power to become successful in the SHM field. For this reason, the expenses for local data collection are minimized using two affordable devices assembled in a system able to produce the same performance of more expensive systems.

2.1. Specific hardware

The devices responsible for sending the acquired message are the ZigBee units. They consist of a CC2530 transceiver, equipped with a Wi-Fi antenna (dual band 2.4/5 GHz), and ended with a USB connector. Further details are provided in Section 3.

The task of running them is assigned to a PCB (Printed Circuit Board), which has the size of a credit card and allows one to collect information as an usual personal computer. The adopted electronic board is named Raspberry Pi and is prized in the range from US$20 to US$35. Secure Digital (SD) cards with different capacities may be used to store the operating system and program memory.

In the tests carried out, the authors adopted the device Ellipse-N, which is the miniature sensor produced by SBG [26]. It includes a three axial accelerometer. This system also embeds an industrial GNSS receiver, and runs an on-board Kalman filter able to make a data fusion of both measures. The limitation is that the model only supports a proprietary protocol. Indeed, the standard NMEA provides only the ultimate positioning (after the data fusion). It is worth noting that several devices that can be detached from the own manufacture protocol are available on the market, and can replace the compact SBG sensor [27–29].

In this way, one can exploit all the features of their each single component. One uses the raw data to check each kind of measures acquired by the sensors, or to run other estimation algorithms.

2.2. Data fusion based on Kalman filter

The formulation of the displacement estimation based on the Kalman filter, as provided by the Ellipse, is summarized in this section in order to clarify the sequence of steps, which have to be implemented in the software.

The aim of the proposed method is to extract the needed information to reach the best accuracy from two different measurements. The formulation to fuse acceleration and displacement is also adopted in several recent contributions [30–33].

The state-space model can be written using the definition of acceleration:

$$\begin{aligned}\dot{\boldsymbol{y}} &= \begin{bmatrix}\dot{x}_1\\ \dot{x}_2\end{bmatrix} = \begin{bmatrix}\dot{x}\\ \ddot{x}\end{bmatrix} = \begin{bmatrix}0 & 1\\ 0 & 0\end{bmatrix}\begin{bmatrix}x\\ \dot{x}\end{bmatrix} + \begin{bmatrix}0\\ 1\end{bmatrix}\ddot{x}_m + \begin{bmatrix}0\\ 1\end{bmatrix}\eta_a\\ z &= x_m = \begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix}x\\ \dot{x}\end{bmatrix} + \eta_d\end{aligned} \tag{1}$$

where $\boldsymbol{y}$ are the state variables, grouping $\ddot{x}_m$ and x_m that are the measured acceleration and displacement, η_a and η_d are the associated measurement noises of acceleration and displacement. It is assumed that η_a and η_d are white noise Gaussian processes with covariance q and r, respectively. Eq. (1) can be written in matrix form as:

$$\begin{aligned}\dot{\boldsymbol{y}} &= \boldsymbol{A}\ \boldsymbol{y} + \boldsymbol{B}\ u + \boldsymbol{w}\\ z &= \boldsymbol{H}\ \boldsymbol{y} + \upsilon\end{aligned} \tag{2}$$

where $\boldsymbol{w} \sim (0, \boldsymbol{Q})$, $\boldsymbol{Q} = [\begin{smallmatrix}0 & 0\\ 0 & q\end{smallmatrix}]$, $\upsilon \sim (0, R)$, and $R{=}r$. Moreover, let the initial state is $\boldsymbol{y}(0) \sim ([\begin{smallmatrix}0\\ 0\end{smallmatrix}], \boldsymbol{p}_0)$, and all the uncorrelatedness assumptions hold. Eq. (2) rigorously represents the relationships between the states, the measurements and the associated measurement noises.

Since all measured signals are discrete, a state-space model in the discrete time domain is desired. The discrete version of Eq. (1) is [31]:

$$\begin{aligned}\boldsymbol{y_d}(k+1) &= \begin{bmatrix}x_1(k+1)\\ x_2(k+1)\end{bmatrix} = \begin{bmatrix}1 & dt\\ 0 & 1\end{bmatrix}\begin{bmatrix}x_1(k)\\ x_2(k)\end{bmatrix}\\ &\quad + \begin{bmatrix}dt^2/2\\ dt\end{bmatrix}u(k) + \begin{bmatrix}dt^2/2\\ dt\end{bmatrix}\eta_a(k)\\ z(k) &= \begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix}x_1(k)\\ x_2(k)\end{bmatrix} + \eta_d(k)\end{aligned} \tag{3}$$

where dt is the sampling time. Eq. (43) written in compact form becomes:

$$\begin{aligned}\boldsymbol{y_d}(k+1) &= \boldsymbol{A_d}\ \boldsymbol{y_d}(k) + \boldsymbol{B_d}\ u(k) + \boldsymbol{w}(k)\\ z(k) &= \boldsymbol{H}\ \boldsymbol{y_d}(k) + \upsilon(k)\end{aligned} \tag{4}$$

where $\boldsymbol{A_d} = [\begin{smallmatrix}1 & dt\\ 0 & 1\end{smallmatrix}]$, and $\boldsymbol{B_d} = [\begin{smallmatrix}dt^2/2\\ dt\end{smallmatrix}]$. The noise processes have the covariance matrices defined as follow [31]:

$$\begin{aligned}\boldsymbol{Q_d} &= q\begin{bmatrix}dt^3/3 & dt^2/2\\ dt^2/2 & dt\end{bmatrix}\\ R_d &= r/dt\end{aligned} \tag{5}$$

The state-space model in Eq. (4) is then utilized to develop a discrete-time Kalman filter for displacement and velocity estimation. Let the initial values put to be:

$$\begin{aligned}\boldsymbol{y_d}^-(k=1) &= \begin{bmatrix}0\\ 0\end{bmatrix}\\ \boldsymbol{P}^-(k=1) &= \boldsymbol{p}_0\\ z^-(k=1) &= x_m(k=1)\end{aligned} \tag{6}$$

One computes the quantities referred to as measurements updates at k by introducing the Kalman gain $\boldsymbol{K}(k)$. Subsequently, the Kalman gain is computed by the Eq. (7):

$$\boldsymbol{K}(k) = \boldsymbol{P}^-(k)\boldsymbol{H}^T\left(\boldsymbol{H}\ \boldsymbol{P}^-(k)\boldsymbol{H}^T + R_d\right)^{-1} \tag{7}$$