Structural Health Monitoring Using Wireless Sensor Networks with Nonsimultaneous Sampling

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Abstract. Structural health monitoring with wireless sensor networks (WSN) is an attractive alternative to traditional wired technology. The main challenges of WSNs are time synchronization, transmission of large amounts of data, and energy consumption. In this paper, autocovariance functions (ACFs) are estimated in all sensor nodes. Strict time synchronization is not necessary, because cross-correlations are not utilized. The measurement period must be long for a sufficient accuracy, but the number of samples in the transmitted ACFs is much smaller. The ACFs from all sensor nodes are transmitted to the base station for centralized data processing. Spatiotemporal correlation can be utilized, because for a stationary random process the ACFs have the same form as the free decay of the system. The covariance matrix is estimated using the training data from the undamaged structure under different environmental conditions. An extreme value statistics control chart is designed to detect damage. A numerical experiment was performed by simulating a bridge deck under stationary random excitation and variable environmental conditions. The excitation or environmental variables were not measured. Damage was a crack in a steel girder. Nonsimultaneous sampling of the WSN was simulated by selecting the starting time of the measurement randomly in each sensor node.

Keywords: Damage Detection, Wireless Sensor Network, Autocovariance Function, Spatiotemporal Correlation, Time Synchronization, Energy Efficiency, Environmental Effects.

1 Introduction

Structural health monitoring (SHM) is based on sensor data measuring vibrations in different positions of the structure. Because of long distances between sensor locations, wireless sensor networks (WSNs) have been proposed instead of traditional wired systems. The advantages of WSNs include: avoidance of cable installation and maintenance [1], self-organization, rapid deployment, flexibility, and inherent processing capability [2]. The main challenges of WSNs are: data transmission, synchronization, limited communication bandwidth, adaptability, limited energy supply, and limited memory and computational capability [1], data loss, stability, and durability [2], high sensor node density, a large number of hops, and challenges of distributed processing [3].

A common approach to SHM is based on the modal parameters of the structure (natural frequencies, mode shape vectors, and damping) that can be extracted using system identification techniques particularly developed for output-only data [4]. This approach, however, fits poorly for WSN, because long data records must be measured simultaneously in the sensor nodes and transmitted to the base station for analysis.

Time-domain methods for damage detection are an attractive alternative to feature-domain techniques. Their advantages include more reliable statistical analysis, because the data dimensionality is often low and the number of data points large. In addition, the algorithm can be fully automated, because system identification is not necessary.

If the excitation is stationary random white noise, autocovariance functions have the same form as the free decay of the system [4]. The output-only system identification is also based on covariance functions. Full covariance matrix or cross-covariance functions have also been proposed for damage detection in several studies. Cross-covariance functions require simultaneous measurements from different sensors, yielding synchronization and data transmission issues between nodes. In the present study, autocovariance functions (ACFs) are only used to detect damage. They can be estimated in the sensor node using an FFT algorithm. It was shown that the amount of energy consumed by a sensor node to compute 4096-point FFT was much less than transmitting the original time record [5].

Short ACFs replace the long measurement data in the time domain analysis. They are transmitted to the base station, where centralized damage detection is performed. Other advantages of ACFs compared to raw data are noise reduction due to averaging and spatiotemporal correlation.

For a stationary random process, asynchronous sampling is possible, with a negligible effect on the autocorrelation functions. The onset of sampling needs not be strictly at the same time, as will be seen in this paper. The sampling period must nevertheless be the same.

Liu et al. [6] proposed damage detection in a single sensor using standardized autocorrelation function (ACF) estimates. The novelty index was computed using the correlation coefficient between the current ACF and the mean of the reference ACFs. Once damage was detected, damage localization was performed by estimating cross-correlation function between sensor pairs, which required synchronization between the two sensor nodes. Li and Law [7] proposed damage detection using cross-covariance functions between sensor pairs for damage detection assuming white noise excitation. Zhang and Schmidt [8, 9] proposed damage detection based on the values of autocorrelation functions at lag zero. Avci et al. [1] proposed a decentralized damage detection method, where each sensor node monitors damage in a single joint using supervised 1D convolutional neural networks (1D CNN).

Although decentralized damage detection has been suggested, it is commonly accepted that centralized data analyses are more efficient. Therefore, a centralized procedure is proposed in this paper.

The influences of environmental or operational variability on the dynamic characteristics of the structure often mask the effects of damage [10]. The normal variability must be included in the training data in order to distinguish between the environmental or operational effects and damage [11]

The paper is organized as follows. Autocovariance functions are introduced in Section 2.1. Asynchronous sampling is discussed in Section 2.2. Section 2.3 outlines damage detection in the time domain under varying environmental or operational conditions. An application of WSNs for damage detection and localization is studied with a numerical experiment of a bridge deck in Section 3. Variable excitations and environmental conditions are also considered. Finally, concluding remarks are given in Section 4.

2 Damage Detection Using Wireless Sensor Networks

2.1 Autocovariance Functions

Autocovariance functions are the damage-sensitive features proposed in this paper. The autocorrelation function (ACF) of a zero-mean sample time history record $x(t)$ is [12]:

$$R_{xx}(\tau) = \mathrm{E}[x(t)x(t+\tau)] \tag{1}$$

where E[×] is the expectation operator. ACF can be estimated with a direct method or by using FFT computations [12]. An FFT-based method is used this study, because it is much faster than the direct method when the measurement period is very long.

For a stationary random process with white noise excitation, the analytical ACF for a displacement degree-of-freedom (DOF) j can be derived, see also [4, 13, 14]:

$$R_{jj}(t) = \sum_{s=1}^{n} e^{-z_s \omega_s t}\left[A_{jjs}\cos(w_{ds}t) + B_{jjs}\sin(w_{ds}t)\right] \tag{2}$$

where n is the number of modes, and

$$A_{jjs} = \sum_{r=1}^{n} \frac{F_{rs}}{2m_r w_{dr} m_s w_{ds}} \boldsymbol{f}_{jr}\boldsymbol{f}_{js}\boldsymbol{f}_r^T \mathbf{BQB}^T \boldsymbol{f}_s \tag{3}$$

$$B_{jjs} = \sum_{r=1}^{n} \frac{G_{rs}}{2m_r w_{dr} m_s w_{ds}} \boldsymbol{f}_{jr}\boldsymbol{f}_{js}\boldsymbol{f}_r^T \mathbf{BQB}^T \boldsymbol{f}_s \tag{4}$$

$$F_{rs} = \frac{-z_r\omega_r - z_s\omega_s}{(z_r\omega_r + z_s\omega_s)^2 + (\omega_{dr}+\omega_{ds})^2} + \frac{z_r\omega_r + z_s\omega_s}{(z_r\omega_r + z_s\omega_s)^2 + (\omega_{dr}-\omega_{ds})^2} \tag{5}$$

$$G_{rs} = \frac{\omega_{dr}+\omega_{ds}}{(z_r\omega_r + z_s\omega_s)^2 + (\omega_{dr}+\omega_{ds})^2} + \frac{\omega_{dr}-\omega_{ds}}{(z_r\omega_r + z_s\omega_s)^2 + (\omega_{dr}-\omega_{ds})^2} \tag{6}$$

m_r, w_r, w_{dr}, z_r, $\boldsymbol{f}_r$, are, respectively, the modal mass, the undamped natural circular frequency, the damped natural circular frequency, damping ratio, and mode shape vector of mode r. Matrix **B** is the load distribution matrix, and **Q** is a diagonal matrix where the diagonal entries are the spectral densities of the loads. From Eq. 2, it can be seen that it has the same form as a free decay of the system. The corresponding covariance function for acceleration is the fourth derivative of $R_{jj}(t)$ with respect to t [12]. It has also the same general form as Eq. 2. This form is very advantageous, because there is a strong spatial and temporal correlation between ACFs of different DOFs [15].

2.2 Asynchronous Sampling

In wireless sensor networks, the relationship between the sensor's clock and the reference clock is [3]:

$$t_i = (1 + \alpha_i)t + \Delta t_i \tag{7}$$

where t_i is the node clock, α_i is the node clock drift rate, t is the reference clock time, and Δt_i is the initial clock offset. If the clock drift is neglected, the relationship above becomes

$$t_i = t + \Delta t_i \tag{8}$$

In this paper, the differences of initial clock offsets between sensor nodes are simulated and their effects of on damage detection are investigated. Clock offsets below 10 μs are possible using special methods [16]. Theoretically, for a stationary random process, the initial clock offset should not have an effect on the ACFs. In practice, however, the variation of the excitation characteristics may affect the ACFs. Therefore, the initial clock offset should be kept relatively small but still manageable (within one second in this paper) without a need for accurate synchronization.

2.3 Damage Detection

Autocovariance functions make it possible to apply damage detection in the time domain. ACFs of different sensors are correlated both spatially and temporally [15]. Therefore, spatiotemporal covariance matrix is estimated using the training data from the undamaged structure under different environmental or operational conditions. The model order must be selected by the user.

A whitening matrix is computed using the covariance matrix and all data are subjected to whitening transformation. This approach takes environmental or operational influences into account resulting in residual vectors. For damage detection, all residuals are subjected to principal component analysis (PCA), and the first principal component is only retained. The data dimensionality has now reduced to one, and an extreme value statistics (EVS) control chart is designed to detect damage. For a more detailed information about the algorithm, see [17].

Damage location is assumed to correspond to the direction of the first principal component (PC). The largest projection of the first PC on the sensor DOFs is assumed to reveal the sensor closest to damage.

3 Numerical Experiment

The monitored structure was a stiffened bridge deck with a length of 30 m and width of 11 m, and modelled with shell elements (Fig. 1). The slab was made of concrete with a Young's modulus of E = 40 GPa (at temperature T = 0°C), Poisson ratio of ν = 0.15, density of ρ = 2500 kg/m^3, and thickness of 250 mm. The stiffeners were made of steel (E = 207 GPa, ν = 0.30, ρ = 7850 kg/m^3). The longitudinal stiffeners had a web with a thickness of t = 16 mm and a height of h = 1.4 m. The bottom flange had a thickness of t = 50 mm and a width of b = 700 mm. The lateral stiffeners were 1.4 m high and 30 mm thick.

The relationship between the Young's modulus of the concrete slab and temperature was stepwise linear as shown in Fig. 2a. Temperature variation was linear along the length of the bridge between the end temperatures that varied randomly between –20°C and +40°C. Zero-mean Gaussian noise with a standard deviation of s_T = 0.2°C was added to the temperatures of each row of elements resulting in random realizations of the stiffness distributions along the bridge, some of which are plotted in Fig. 2b. It should be noted that the temperature or the Young's modulus were not measured.

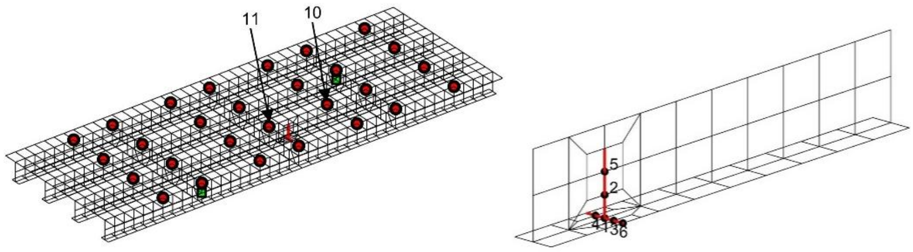
Two vertical random stationary loads in the frequency range between 0 and 20 Hz with random amplitudes and phases were applied to nodes shown with green squares in Fig. 1a. The response was computed with modal superposition using the first 30 modes. The analysis period was over 43 minutes with a sampling frequency of 100 Hz. One measurement period included 2^{18} = 262,144 samples from each sensor. Vertical accelerations were measured at 28 points shown in Fig. 1a. Measurement error was added to the responses, so that the average signal-to-noise ratio was SNR = 30 dB.

The number of measurements was 136. The first 100 measurements were acquired from the undamaged structure under random environmental conditions. Damage was an open crack in a steel girder, located between sensors 10 and 11, but slightly closer to sensor 11 (Fig. 1).

Six different crack configurations were modelled by removing the contact at 1–6 nodes. They are shown in the detailed plot in Fig. 1 indicating the order in which the nodes were separated resulting in increasing damage levels. Only the last damage scenario extended as far as the edge of the flange. Six measurements were acquired from each damage scenario. As a result, the last 36 measurements were from a damaged structure.

Fig. 3 shows the variability of the first seven natural frequencies in all 136 measurements due to environmental and damage influences. It is difficult to discern the differences between the damaged and undamaged cases separated by the vertical line in the figure.

The training data were the first 70 measurements. They were also used to design the control charts. The test data were the last 66 measurements, from which the last 36 were from the damaged structure.



a b

Fig. 1. a) Bridge deck with 28 accelerometers (red circles) and two load positions (green squares). Damage location between sensors 10 and 11 is plotted in red. b) A detail of the girder with a crack. The numbers indicate the order with which the crack propagated.

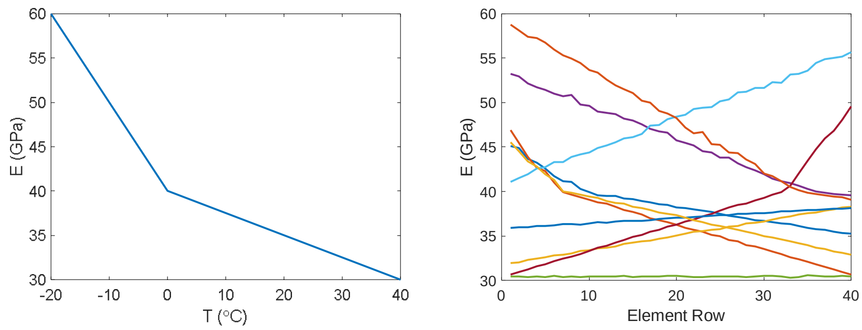


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Fig. 2. a) The effect of temperature on the Young's modulus of the concrete. b) Ten realizations of the longitudinal distributions of the Young's modulus in the concrete slab.

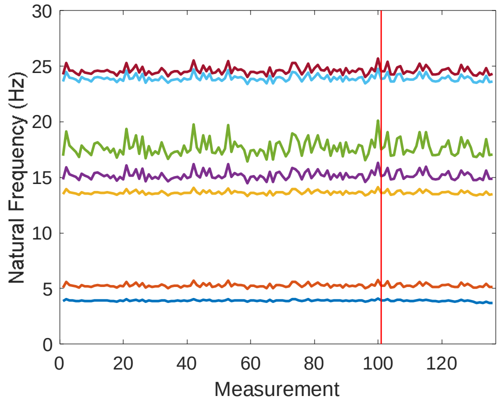


Fig. 3. Influences of the environmental variables and damage on the first seven natural frequencies. The data on the right side of the vertical line were from the damaged structure.

3.1 Initial clock offset

The influence of initial clock offset on damage detection performance was studied. The clock drift was neglected, because its effect was found insignificant in the lag range of $\tau = 0\ldots3$ s.

The sampling period of the measurement was $\Delta t = 0.01$ s. Each sensor node started sampling at a random time within one second. The measurement period was about 44 min with 2^{18} samples per measurement. Each simulation was run with a time increment $\Delta t/h$, where h was a random integer between 3 and 31. This was to assure that the sampling period was always the same by picking every hth data point from the simulated data. The first sample in each sensor node was randomly selected between 0…1 s. The value of h varied between measurements to better simulate sampling starting at random times, but was kept fixed within measurement in order to manage with a single run for each measurement.

The autocovariance functions with 300 time lags were estimated from the noisy measurements, reducing the transmitted data considerably. ACF estimates from measurement 1 are plotted in Fig. 4. All transmitted data used in damage detection are shown in Fig. 5. The effect of different excitation levels can be clearly seen.

Damage detection was performed by applying whitening to the training data and using PCA and finally designing EVS control charts shown in Fig. 6. Spatial and spatiotemporal correlation with model orders equal to 0 and 10, respectively, were used. Both models resulted in sufficient reliability for early warning with only a few false positives. Damage was correctly localized to sensor 11 in both cases (Fig. 7).

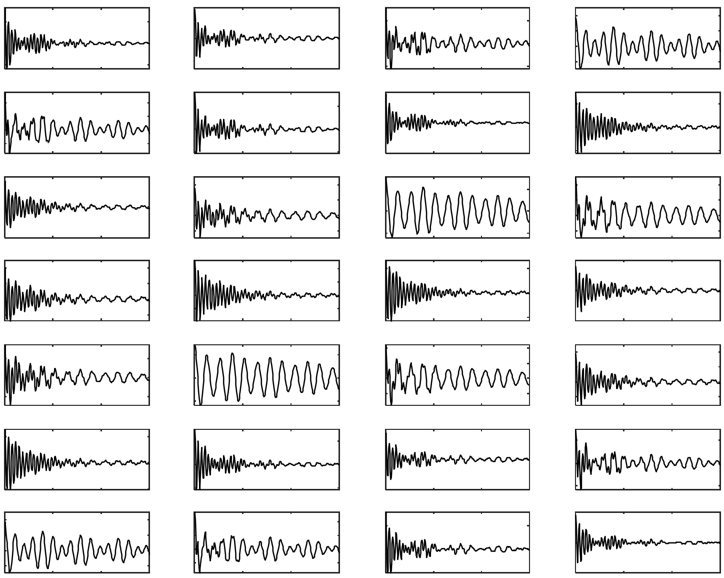


Fig. 4. ACFs of each sensor node in measurement 1.

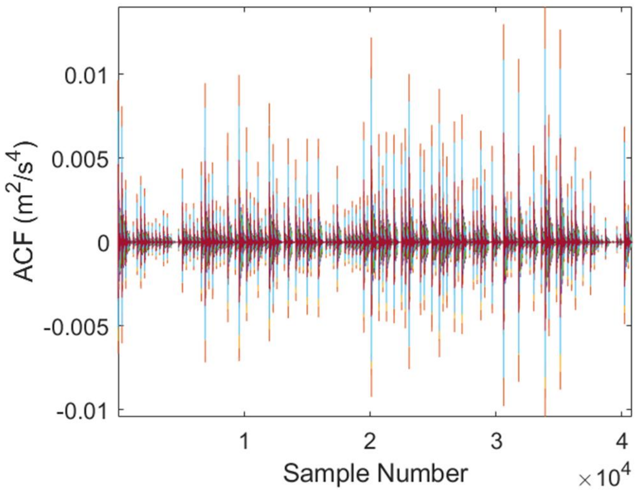
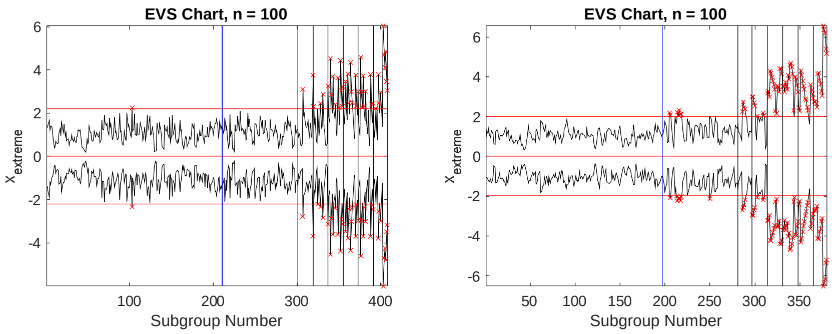
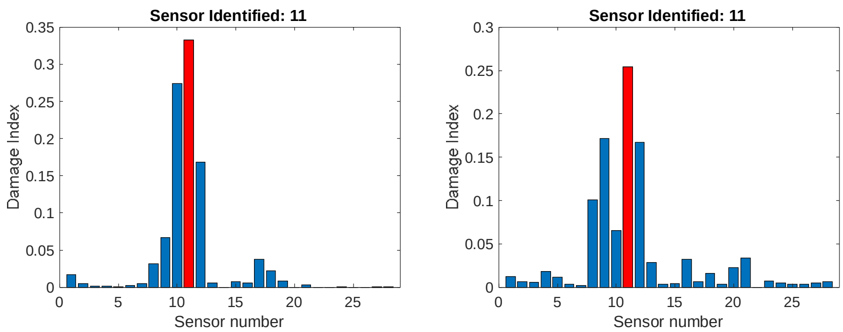


Fig. 5. ACFs of each measurement. Each ACF consisted of 300 samples.



a b

Fig. 6. EVS control charts. a) Model order = 0; b) model order = 10.



a b

Fig. 7. Damage localization. a) Model order = 0; b) model order = 10.

4 Conclusion

Three issues of wireless sensor networks in structural health monitoring were addressed: (1) synchronization, (2) transmission, and (3) energy consumption.

Introducing autocovariance functions as damage-sensitive features allows asynchronous sampling provided stationary random process is assumed. ACFs have the same form as the free decay of the system. This form makes it possible to apply spatiotemporal correlation for damage detection.

The amount of transmitted data is considerably decreased if ACFs instead of raw data are used for damage detection in the base station. Energy consumption for transmission is therefore smaller.

The remaining issue is the estimation of the ACFs in the sensor node. A long data record is needed for an accurate estimate. Therefore, limited memory could be an issue. It is also possible to estimate ACFs using spectral averages [12], which works with shorter records. Experimental research is needed to investigate the energy consumption of the proposed method.

The proposed technique can also be applied in wired systems. If strictly simultaneous sampling is not needed, more cost-efficient data acquisition systems can be used.

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