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## QUALITY ASSESSMENT OF DYNAMIC RESPONSE MEASUREMENTS USING WIRELESS SENSOR NETWORKS: PRELIMINARY RESULTS

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### ABSTRACT

Vibration-based methods, using response measurements of civil engineering structures, are among the most popular methods for damage detection and system identification in structural health monitoring (SHM). To accurately obtain response measurements, wireless sensors networks are increasingly applied for collecting monitoring data from the observed structures. However, several types of noise usually contaminate the monitoring data leading to inaccurate or even incorrect diagnoses and prognoses of the dynamic properties of the structures. The main objective of this study is the elimination of such noise directly on the wireless sensor nodes in order to obtain high-quality monitoring data. Specifically, a wireless SHM system is designed and, for validation purposes, mounted on a tower-like laboratory test structure. The wireless sensors are provided with different embedded filters designed to improve the estimation of the system properties, which are calculated from the dynamic response measurements, i.e. from the monitoring data. In a final step, the quality of the dynamic response measurement is assessed.

**KEYWORDS :** *structural health monitoring, wireless sensors, data filtering, digital signal processing*

### INTRODUCTION

There is an increasing need for monitoring civil engineering structures that are subjected to unanticipated loading conditions such as earthquakes, wind, or snow. Structural health monitoring (SHM) has been used for many years to determine changes in the structures. Designing SHM systems includes not only the determination of optimal sensor types, number and locations, but also other significant details related to power supply, wiring, accessibility, maintenance, and the transfer and storage of monitoring data. Conventional wired monitoring systems have several constraints related to cabling, such as installation expenses and electrical disturbances of the transferred analog signals [1, 2]. To overcome these problems, wireless sensor networks have emerged as an alternative cost-efficient technology [3, 4].

As discussed in [5], the major motivation of installing wireless SHM systems are their low cost compared to wired systems, which could allow denser instrumentation to be applied on a structure for global-based damage detection. Several projects have shown the effectiveness of wireless SHM systems for damage detection of large civil engineering structures [6, 7]. Unfortunately, wireless sensors and wireless systems also have some limitations, e.g. limited computational capacity and memory of the wireless sensor nodes, possible data loss, and a lack of time synchronization [8]. Lei et al. [9] have shown solutions for the time synchronization problem of wireless sensor nodes, which has outweighed the other drawbacks of wireless monitoring systems. Elimination of the existing constraints associated

with wireless sensor systems is probably only a matter of time due to the advancement of computing and communication technologies.

The traditional design of SHM systems contains some fundamental steps: data acquisition, data communication, data processing, data storage, diagnostics, and data retrieval [10]. One of the strategies followed by the development of wireless systems is to optimize these steps in order to achieve energy efficiency and improved performance [2]. Therefore, systems have been developed, that perform specific stages of data processing already on the sensor nodes such that only the resulting information needs to be transferred to the base station [11]. The most common interest for civil engineers working in the SHM field concerning data processing would be to obtain the basic global vibration characteristics of the structures. This requires some basic data processing, for example fast Fourier transform (FFT) and peak picking on the measured signals, which has already been successfully implemented on sensor nodes [11]. However, one could think about other assessments of data processing that require filtering of the signals by embedding digital filters on the sensor nodes, particularly in wireless SHM system prior to FFT and peak picking. The goal of this paper, therefore, is to process the monitoring data on the sensor nodes by applying digital filters and then analyzing the filtered data on the sensor nodes to obtain the natural frequencies of the test structures.

Selecting the appropriate type of digital filters, specifically in SHM field, is the most crucial part in signal processing as there exist several, some of which probably having comparable applicability. A comprehensive study on digital filters and their applications is prerequisite for an appropriate signal processing. Therefore, filters selected in this preliminary study to process the data on the sensor nodes, are shortly discussed. Thereupon, the design and implementation of a prototype wireless SHM system are shown, followed by a discussion of the results and an outlook on future work.

## 1. PROTOTYPE MONITORING SYSTEM

The prototype system consists of a number of wireless sensor nodes. In this study sensor nodes of type Oracle Sun SPOTs were used. Details about these nodes can be found in [12]. The sensor nodes integrate a so called Squawk Java Virtual Machine that runs directly on the processor of the sensor nodes without an operating system. It allows integrating object-oriented algorithms into the nodes using Java programming language.

As described earlier, the sensor nodes employed are designed for collecting sensor signals, processing and analyzing the data locally and transferring the data as well as the processed results to a base station. The base station is a computer located within transmission range from the sensor nodes. There, the data is stored for further analyses.

### 1.1 Data Processing

This subsection discusses some details of digital signal processing (DSP) and filters relevant to this study. Digital filtering is often an important step of data processing within SHM systems. In general, digital filters are used in signal processing to separate combined signals and to restore distorted signals [13]. There are two sets of filters in digital signal processing: Finite Impulse Response or FIR filters (e.g. moving average filters) and Infinite Impulse Response or IIR filters (e.g. Chebyshev filters).

An FIR filter is a filter whose impulse response is of finite duration, because it settles to zero in finite time. FIR filters are applied by convolution. In DSP, convolution is the most important technique for combining two signals, namely input signals and impulse responses, to form a third signal, the output [13]. More precisely, an input signal convolved with the impulse response is equal to the output signal.

Considering an input signal,  $x(n)$ , an impulse response,  $h(m)$ , and an output signal,  $y(n)$ , the discrete convolution can be defined according to [13]: If  $x(n)$  is an  $N$  point signal running from 0

to  $N - 1$ , and  $h(m)$  is an  $M$  point signal running from 0 to  $M - 1$ , the convolution  $(*)$  of the two,  $y(n) = x(n) * h(m)$ , is an  $N + M - 1$  point signal running from 0 to  $N + M - 2$ , given by:

$$y(i) = \sum_{j=0}^{M-1} h(j) x(i - j) \quad (1)$$

The most common filter of the FIR filter family is called the Moving Average, which is popular because of its simplicity. It takes into account a number of points from the input signal and averages these points in order to produce each point in the output signal. When the averaging of the points from the input signal is one-sided, Smith [13] writes the equation as

$$y(i) = \frac{1}{M} \sum_{j=0}^{M-1} x(i + j) \quad (2)$$

where  $x(n)$  is the input signal,  $y(n)$  is the output signal, and  $M$  is the number of points in the average. This is essentially convolution with an impulse response that is a constant value with an area equal to one.

In contrast to FIR filters, Infinite Impulse Response (IIR) filters may be applied by recursion. IIR filters are therefore often called recursive filters [13]. The simplest way to express the recursion equation is

$$y(n) = a_0 x(n) + a_1 x(n - 1) + a_2 x(n - 2) + a_3 x(n - 3) + \dots \\ + b_1 y(n - 1) + b_2 y(n - 2) + b_3 y(n - 3) + \dots \quad (3)$$

where  $x(n)$  are values from an input signal, and  $y(n)$  are values from a previously calculated output signal. The values  $a$  and  $b$  are the recursion coefficients that define the filter.

One of the most commonly applied filters in signal processing from the IIR family are Chebyshev Type I filters. These filters are often applied to separate one band of frequencies from another band. The speed of Chebyshev filters is their primary advantage, which is typically more than an order of magnitude faster than any filter from the FIR filter group because of their operation by recursion rather than convolution [13]. These filters are commonly applied in decimation, which defines the process of applying an optimal low-pass filter followed by downsampling. Downsampling, as the name implies, reduces the sampling rate of a signal by an integer factor greater than one. As a result, the total data volume is significantly reduced. The application of a low-pass filter prior to downsampling is necessary to avoid aliasing [14]. To obtain more details about filtering, the interested reader is referred to [13, 14].

## 1.2 Software implementation

In DSP, the term ‘filter design’ is often used to describe the process of generating filters to be applied to a given input signal, for example to response measurements. For FIR filters, the design focuses on creating an impulse response that can then be applied to the input signal by convolution, see eq. (1). By contrast, the results of IIR filter design are the recursion coefficients that can be used in the recursion equation, as shown in eq. (3). Clearly the most basic implementation of digital filtering contains a discrete convolution or a recursion equation.

Representing the major goal of this study, figure 1 shows a flowchart of different data processing scenarios that can be implemented on the wireless sensor nodes to be executed during runtime of the wireless SHM system. The data processing scenarios are modular and can be extended if necessary. Each wireless sensor node collects the signals in time domain and is capable of both transferring the digitized data to the base station and processing the signals directly on the node before transferring the

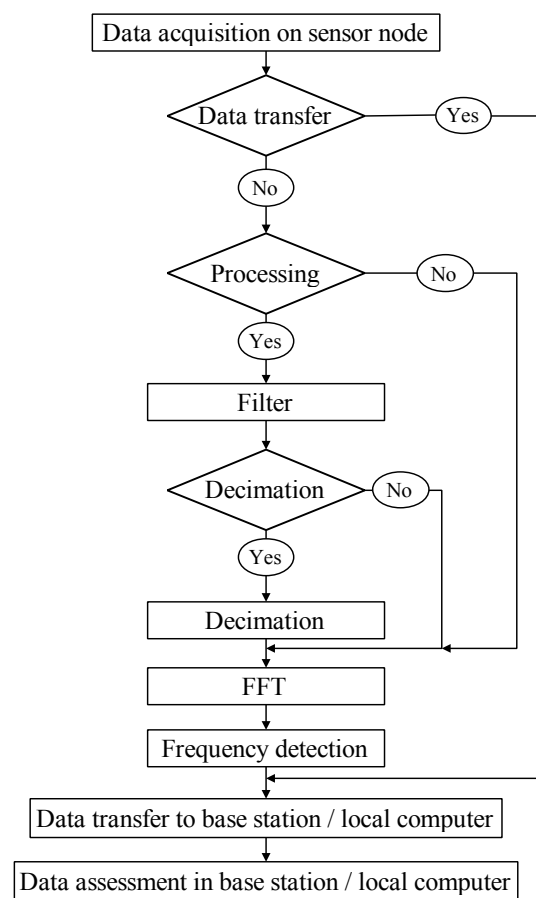


Figure 1 : Flowchart of different data processing scenarios

results. The data processing implemented in this study first applies a digital filter to the signals and then performs an FFT to extract the natural frequencies of the monitored structure by applying a peak picking method.

As mentioned earlier, the wireless SHM system is implemented based on the Java programming language. Java, as an object oriented language, uses classes to create objects on the sensor nodes and it provides initial values for state and implementations of the behaviour of the nodes. Two main classes were written to fulfill the flowchart of Fig. 1, particularly the interaction of the sensor nodes with the base station. Nearly the same classes can be used in sensor nodes. Similarly the same workflow can be applied to the data both on the sensor node and in the base station, which is useful for comparison.

The first main class, *FrequencySpectrum*, contains the methods associated with performing the FFT, generating an amplitude spectrum and performing a simple peak picking in desired frequency bands. This class also stores the spectra and the identified peaks on the nodes. The second main class, *DataFilter*, takes the raw data and produces filtered data using a pre-defined method. The methods use the appropriate classes to apply the filters. The filter classes defining convolution and recursion can be placed on the sensor node, while the classes to perform the filter design, which generate the recursion coefficients, are only operating on the base station. To apply an IIR filter, the coefficients are generated in the base station, sent to the sensor node, and then used by the recursion class. The classes related to perform the FFT, creating complex numbers, designing the IIR coefficients and applying the recursion equation were adopted from existing, well-established software packages. The organization of the *FrequencySpectrum* and *DataFilter* classes allow for the inclusion of more

spectra, frequency identification methods, other dynamic property methods such as identification of damping or mode shapes and more filters without a strict formatting or class structure. While this approach does not take advantage of inheritance from object-oriented programming, it eliminates the need to rewrite many classes that exist in public domain.

The specific implementation used for the conducted laboratory tests applies a single Chebyshev Type I filter in the decimation process. Through the `DataFilter` class, several other filters can be included in future work.

## 2. LABORATORY EXPERIMENTS

The prototype SHM system implemented in this study comprises of two wireless sensor nodes that were attached to a cantilever test structure. The cantilever had a hollow circular cross-section of PVC. The length was 3 m, it was placed in vertical direction as indicated in Fig. 2. The material properties and geometrical details of the PVC pipe are provided in Fig. 2, where  $\rho$  is the density,  $E$  is the Young's modulus and  $\nu$  is the Poisson's ratio. The PVC pipe was cast into a concrete foundation for fixation.

The main objective of the laboratory tests was to prove the functionality of the developed software embedded into the wireless sensor nodes. To validate the software, the laboratory tests aimed at obtaining the first two natural frequencies of the test structure. Each sensor node integrates a triaxial accelerometer for measuring in the directions  $X$ ,  $Y$  and  $Z$ . Details about the sensor nodes can be found in [12].

To obtain the natural frequencies from the time histories, peak picking was applied to the amplitude spectra obtained by FFT. Peak picking is simply the selection of the maximum values from the resulting amplitude spectrum in a certain frequency band. The memory capacity of the sensor nodes is 1 MB. Therefore, it was decided to limit the number of samples per channel and measurement to 2048. With a sampling rate of 100 Hz this resulted in 21 s acquisition time. Immediately after the measurement, the filtering and FFT were applied to the digitized signals on the sensor nodes.

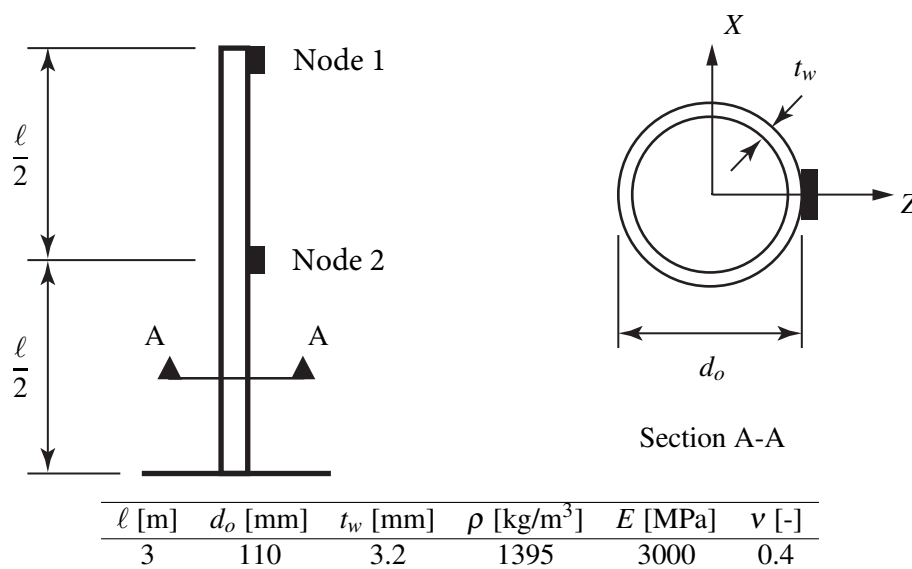


Figure 2 : Instrumentation of the laboratory test structure

Previous tests had shown that the first two natural frequencies of the test structure,  $f_1$  and  $f_2$ , were located between 1 and 20 Hz. Due to the limitation of the system processor of the nodes, only the first two natural frequencies were identified from the original and decimated signal. The documentation associated with the integrated accelerometer of the node describes the computational time required for the microcontroller to perform certain tasks. Based on this information, a maximum sampling rate of around 300 Hz is advised. The measured data is simultaneously sent from all nodes to the base station and also stored locally on the nodes in order to compare the results. The wireless transmission of measured data between sensor nodes and base station takes approximately 4 milliseconds. Therefore, the sampling rate of 100 Hz, or one sample every 10 milliseconds, was devised. At 100 Hz, the Nyquist frequency is 50 Hz, well above the second natural frequency of the test structure. During the tests, it turned out that a decimation could be applied to reduce the sampling rate to 50 Hz (i.e. Nyquist frequency of 25 Hz), since the second natural frequency was observed in previous tests below 20 Hz.

The first sensor node was mounted on the top of the structure and the second sensor node was placed in the middle of the structure. The structure was excited by impact forces with repeated excitations related to different amplitudes (impulse) and free vibration response from initially imposed displacements, see Table 1. After data acquisition, two scenarios were followed to analyze the measured data prior to apply decimation for extracting natural frequencies. The first scenario was performed on the sensor nodes directly, while the second scenario was performed on the base station. The quality of the data was assessed by observing the variation of the frequency values obtained from both scenarios.

## 2.1 Results

As a result, the frequencies of the structure identified by the wireless sensor nodes were generally consistent with those identified on the base station using the raw data and applying decimation for various excitations (Table 1). The data analyzed on the sensor nodes to obtain the frequencies are labelled 'Sensor node 1' and 'Sensor node 2' in Table 1; the data analyzed on the base station after transferring the data from the both sensor nodes to the base station is labelled 'Bs Sn 1' and 'Bs Sn 2' in Table 1 for sensor node 1 and for sensor node 2, respectively.

It should be noted that the frequency resolution ( $h_f$ ) in the discrete spectra is  $h_f \approx 0.05$  Hz, due to the short length of the time histories. The only difference appears in both identified frequencies for test 1, between sensor node 1 and the base station, which was caused by a transmission error.

Table 1 : Frequencies,  $f_1$  [Hz] and  $f_2$  [Hz], identified in the excitation (excit.) direction – Im for Impulse, ID for Initial Displacement, Bs for base station and Sn for sensor node – with the total relative difference (Rel. Diff.) [%] to the mean value,  $\bar{f}$ .

Test	Excit.	Sensor node 1		Sensor node 2		Bs Sn 1		Bs Sn 2		Rel. Diff. $\sum_i \Delta f_i / \bar{f}_i$
		$f_1$	$f_2$	$f_1$	$f_2$	$f_1$	$f_2$	$f_1$	$f_2$	
1	Im in Z	3.08	18.46	3.08	18.46	3.03	18.60	3.08	18.46	2.4
2	ID in Z	3.03	–	2.98	–	3.03	–	2.98	–	0.0
3	Im in Z	3.08	18.41	3.03	18.41	3.08	18.41	3.03	18.41	0.0
4	Im in Z	3.03	18.55	3.03	18.41	3.03	18.55	3.03	18.41	0.0
5	ID in X	2.98	–	2.98	–	2.98	–	2.98	–	0.0
6	Im in X	2.98	18.55	2.98	18.36	2.98	18.55	2.98	18.36	0.0
7	Im in Z	3.13	18.90	3.13	18.46	3.13	18.90	3.13	18.46	0.0
8	Im in Z	–	–	–	–	3.04	18.44	3.04	18.44	–

Fig. 3 shows an example amplitude spectrum computed both on the base station and on the sensor nodes normalized by the maximum amplitude of sensor node 1. The amplitude spectra from the unfiltered data (without applying decimation) obtained from the base station is included for comparison. It shows that the peak amplitudes of the 2<sup>nd</sup> frequency achieved from the base station before and after the decimation are not the same, which may be an effect of the filter. The values computed on the base station for a longer time history ( $2^{13}$  samples,  $h_f \approx 0.01$  Hz) are included for reference (test 8).

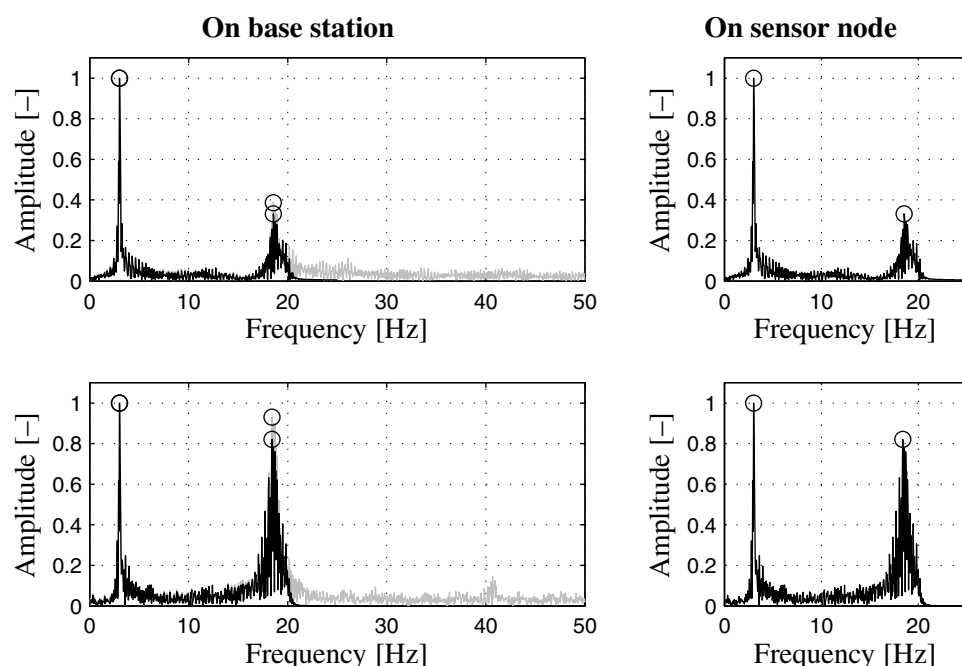


Figure 3 : Example frequency spectra before decimation (light gray, only on the base station) and after decimation (black) with identified peaks ( $\circ$ ) for sensor node 1 (top) and sensor node 2 (bottom).

## SUMMARY AND CONCLUSIONS

This paper has presented significant first steps necessary to perform quality assessments of dynamic response measurements using wireless sensor networks. The main focus has been the implementation of a general procedure for digital filtering of the measurements obtained from wireless SHM systems directly on wireless sensor nodes. As a result, a workflow has been implemented capable of improving the quality of response measurements from the monitoring data based on embedded digital filters. The relative difference between the identified frequencies obtained from both base station and sensor nodes have shown satisfactory agreements for all tests. However, it is worth mentioning that there is still no clear and consistent methodology available to quantitatively assess the quality of given monitoring data, including data processing.

This paper has also shown that the wireless sensor nodes employed are very useful for preliminary object-oriented implementation and prototyping of wireless sensor networks for SHM applications. However, strict limitations, such as system memory of the sensor nodes, show the need for more advanced wireless sensor nodes. The utilization of other wireless sensor nodes will be part of future research efforts.



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