Exploring Crowdsensing Potentials for Structural Health Monitoring Applications: Challenges and Opportunities

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ABSTRACT

The use of devices equipped with sensing capabilities (ranging from smartphones to smartwatches) has become commonplace in our daily lives. These devices can measure various parameters such as acceleration and position, and have the potential to be leveraged for purposes beyond their intended use. This is the main goal of crowdsensing techniques. However, if on the one hand crowdsensing is spreading for its great appeal, on the other hand sometimes the importance of key concepts related to the robustness of the measurement data collected are underestimated. This is particularly true when crowdsensing techniques target structural dynamic problems. Indeed, the accurate extraction of dynamic information beyond the resonant frequencies of the structure is still an open issue and requires tackling the problem considering metrological aspects. Including effects like different sensitivities, sampling frequencies of the devices, as well as all the other interfering inputs that might affect a structural dynamic measurement, will provide the basis for extracting enriched structural data like mode shapes and damping. This may pave the way to a paradigm shift in monitoring civil infrastructures, as fixed installations could be correlated, compensated, or even substituted by mobile solutions. To prove these potentials, this paper discusses the main challenges arising in this application field of crowdsensing, such as the need of synchronizing the devices if targeting operational deflection shapes (ODSs) reconstructions, the lower sensitivity of sensors incorporated in mobile/wearable devices (typically based on micro electro-mechanical system – MEMS – technology), etc. These issues are demonstrated and tackled by performing a three-step analysis. At first, the metrological characterization of the selected hardware is carried out. In the second step, a first experiment is conducted on a laboratory case study, to verify whether the proposed system can capture the dynamic response of the structure. The final step consists of an experimental campaign conducted on a pedestrian bridge. The results obtained clearly demonstrate the need for a multidisciplinary approach which includes metrology science when targeting crowdsensing for the assessment of the dynamic behavior of a structure.

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INTRODUCTION

As a matter of fact, there is a wide interest in exploiting low-cost devices, including smartphones, as measurement systems for structural health monitoring (SHM). Indeed, there is lot of potentials in this, as nowadays smartphones are owned by a large portion of the population and every smartphone is equipped with many sensors. This translates in large amount of potential data to be acquired and managed.

The importance of data targeted to SHM can be understood if thinking that most of the existing transport infrastructures were designed more than 50 years ago and they are aging. In Europe, it has been estimated that more than 30% of present highway bridges are structurally deficient, and this percentage increases considering all short-medium span bridges [1, 2]. The same situation on infrastructure vulnerability is a fact in the United States (US) as well [3]. As a consequence, there is a growing concern about transport infrastructure safety, maintenance and SHM systems. Only few new bridges are equipped with an integrated SHM system which continuously gives a feedback about the structure integrity. The standard procedure used to keep track on transport infrastructure integrity and to guarantee the correct safety level relies on visual inspection performed on a periodic basis [4]. The potential limitations of visual inspections are: timing and the interpretability of the condition assessment. Moreover as the infrastructure degradation worsens, a more frequent visual inspection is required leading to an increase in the maintenance cost.

The perceived cost of SHM systems typically represents a significant barrier to its widespread adoption. However, the return of investment will be significantly fast and relevant if considering that SHM systems can help identify structural deficiencies on time to enable proactive maintenance [5]. Mobile-sensor networks, particularly smartphones, can reform the way data from the infrastructure are collected by resolving this financial bottleneck. In fact these devices make possible to acquire a big amount of data which can be used to estimate the infrastructure dynamic behaviour [6] and to forecast the structure integrity. However, despite the high potentials of this approach, there still are several issues to be tackled when targeting the assessment of the dynamic behaviour of a structure. Synchronization between the different smartphones represent one of the biggest challenge, as a shared timing is mandatory to properly derive dynamic information like structural mode shapes.

Indeed, this study aims to investigate the synchronization issues that arise when employing multiple devices to estimate the modal parameters of structures, which play a pivotal role in conducting effective SHM [7]. The research focuses on scenarios where Crowdsensing techniques are utilized with numerous sensor nodes, requiring careful examination of synchronization challenges between the devices involved. The research was performed in three different phases: i) characterization of the devices to be used in the structural dynamic tests; ii) dynamic testing of a reinforced concrete beam; iii) performance of operational modal analysis of a full scale pedestrian bridge.

MATERIALS AND METHODS

To investigate the potential use of the smartphones's MEMS sensors for evaluating the dynamic behaviour of infrastructures, it is important to undertake a comprehensive characterization of these devices. The *"PhyPhox"* application was exploited for collecting accelerometer data. This app was chosen as it was developed with particular focus on the metrological performance of the embedded sensors and its ability to maintain near-constant sampling rates during data acquisition [8].

However, to better assess the potentials of such a system, it is important to compare its performance with the ones of more standard solutions relying on high sensitivity piezoelectric accelerometers.

When dealing with systems made of different devices, each one with its own acquisition capabilities, several challenges arise.Different sampling rates, different sensitivities and different noise floor across different sensors are the main issues to be tackled. However, if on the one hand these issues are relaxed when dealing with single point measurements (i.e. each device acquiring and processing data independently from the others), on the other hand they become of uttermost importance when trying to handle mutliple-point measurements for ensemble analysis. Synchronization among the devices becomes fundamental, particularly when aiming at reconstructing the operational deflection shape (ODS) of the structure being tested, as the relative phases between the different signals play an important role.

Clock synchronization across different devices can be achieved by connecting each device to an NTP (Network Time Protocol) server or by using GPS clock synchronization. As for NTP synchronization this can be achieved by initiating an NTP requests to a server, and then calculating the time offset of each acquisition device with respect to the NTP server.

However, no matter NTP synchronization, each deveice's clock can still drift and vary differently from the others. For this reason a preliminary investigation on the variability of different clock behaviors is needed. We targeted an Android-based device and we made the device to pull a periodic connection request to the *"0.pool.ntp.org"* server. We opted for a sing-call per minute request, and we recorded the corresponding time offsets over an extensive test spanning several hours and relying on cabled and wifi connections. This process was indispensable for assessing the device clock drift, as well as

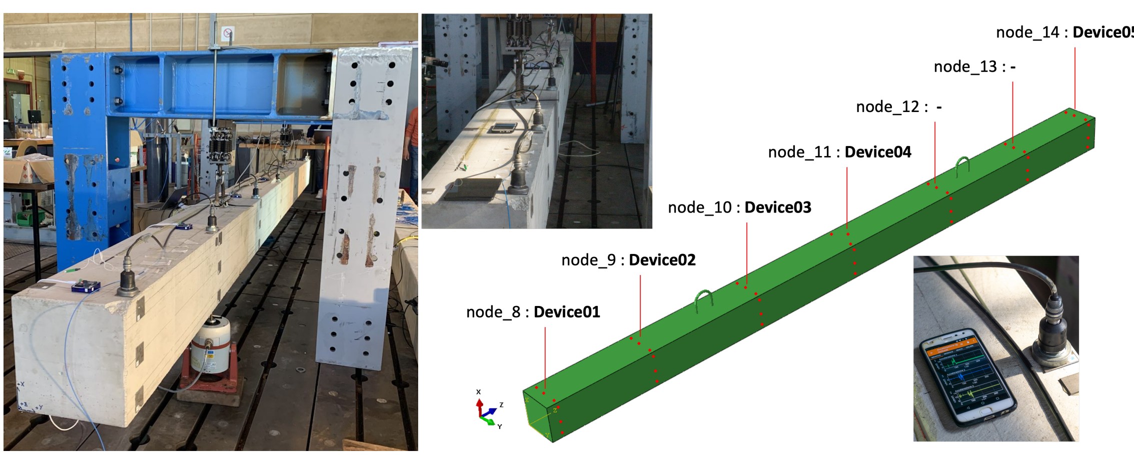

Figure 1. (left) Experimental setup: $6\ m$ suspended reinforced concrete beam excited by a random force (range: $15 - 200\ Hz$) generated using a electrodynamic shaker. (right) Schema of the beam dimensions and smartphones positions.

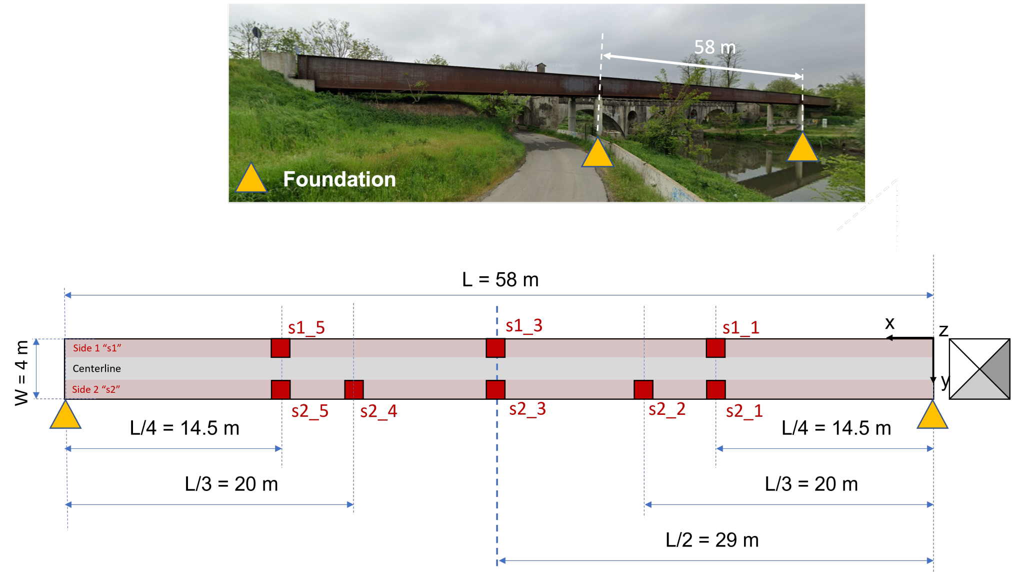

Figure 2. (top) Cerro al Lambro (MI) pedestrian bridge side view. (bottom) Schema of the sensor positions on the pedestrian bridge.

quantifying the statistical variability inherent in the offset calculated by the algorithm. Understanding the maximum error incurred during the time offset calculation prior to acquisition is a crucial consideration, as its acceptability depends on the frequencies involved in the system as will be demonstrated in this work.

Once the clock behavior was assesed, we tested the use of multi-device solution (both Android and iOS based) on a laboratory test case, i.e. 6.0 m long (0.3×0.3 m in cross-section)reinforced concrete beam. A reference measurement system involving a data acquisition board handling simultaneous sampling over the different channels and several piezoelectric accelerometers was used in parallel to the smarthphones to assess the dynamic behaviour of the beam. The structure was excited by an electrodynamic shaker. A band-limited random excitation (from $15\ Hz$ to $200\ Hz$) was used as the driving signal for the shaker. The total duration of the test was set to $15\ min$. The natural frequencies of the beam are well beyond those typically observed in civil structures (the first mode shapes occurs at $f_{1v} = 21.30\ Hz$). However, this "high-frequency" dynamic behaviour represents a challenging target for two reasons: on the one hand only the first mode shape can be addressed in the analysis, on the other hand the "high-frequency" target pushes the synchronization issues to the hardest limit. To verify this, a set of five mobile devices synchronized via NTP were positioned as shown in Figure 1 . The reference acquisition system consisted in five piezoelectric accelerometers (PCB Piezotronics 393A03) connected to two National Instrument (NI9230) boards and placed in the same locations where the five smartphones were placed.

The same smartphone network was later used for assessing the dynamic behavior of a pedestrian bridge located in Cerro al Lambro, in the province of Milan. This target structure was already extensively tested, as reported in [9] and therefore its dynamics was well knwon. The smartphones were placed along the longitudinal axis of the bridge, specifically at the locations indicated as *"side 2"* in Figure 2. The time offset between the smartphones was determined using a mobile application that leveraged the Network

Time Protocol (NTP) prior to conducting the dynamic test. Given the prior knowledge of the resonant frequencies of the bridge, the experimental procedure involved the excitation of the bridge at the frequencies corresponding to its first and second vertical modes. This was achieved by jumping, at the correct frequencies, on specific sections located at half and quarter distances along the bridge, respectively. Subsequently, the ODSs were extracted and compared to those acquired using the reference system composed by National Instrument acquisition system and five piezoelectric accelerometers (PCB Piezotronics 393B12).

DISCUSSION AND RESULTS

In a scenario involving data collection from multiple devices, each equipped with its own internal clock used for sampling data, it is feasible to model the clock time of an individual device i, denoted as t_i, as composed of a constant offset component, Δt_i and a drift component ($\alpha_i t_i$) in relation to a reference clock t (Equation 1).

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

As depicted in Figure 3, after gathering offset data at one-minute intervals over a period of approximately 16 hours, it becomes evident that the device clock exhibits a consistent time drift, resulting in an average delay of around 3 ms/h. This observed delay remains constant and reproducible across two separate trials conducted in different days. Nonetheless, when considering the possibility of periodically resynchronizing the clocks, it becomes possible to approximate the device clock time by solely considering the offset prior data acquisition (i.e., $\alpha_i = 0$ in 1), as the impact of drift can be considered negligible [10].

This holding, the challenge arises in estimating the offset at the beginning of the tests, as the responses from the server do not possess a constant value but rather fluctuate by several milliseconds due to the absence of a precise estimate of the clock offset. In addition, as can be seen from Figure 3, if the device is connected via WiFi the dispersion

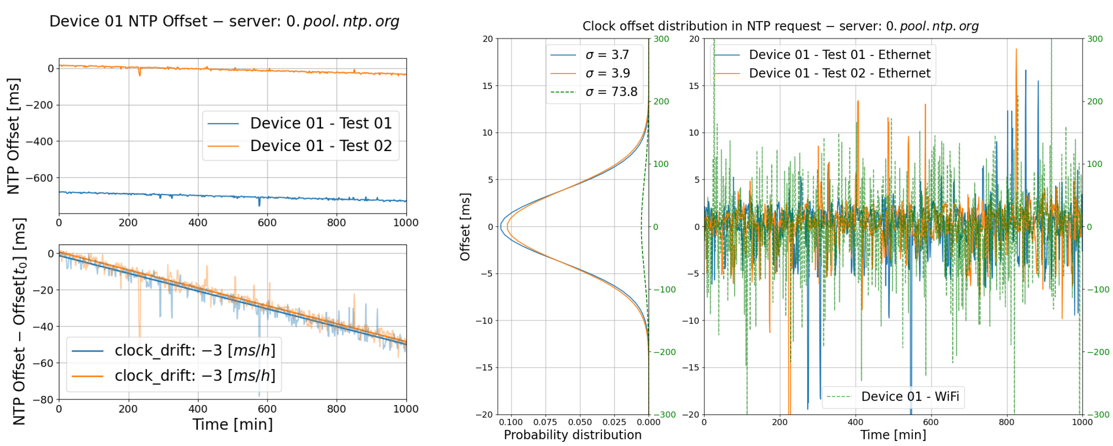

Figure 3. (left) Device clock offset and drift over 1000 min of NTP requests – server: "*0.pool.ntp.org*". (right) Distribution of the clock offset removing the device clock drift effect. The Offset label refers both to the black and green axis (colour version only).

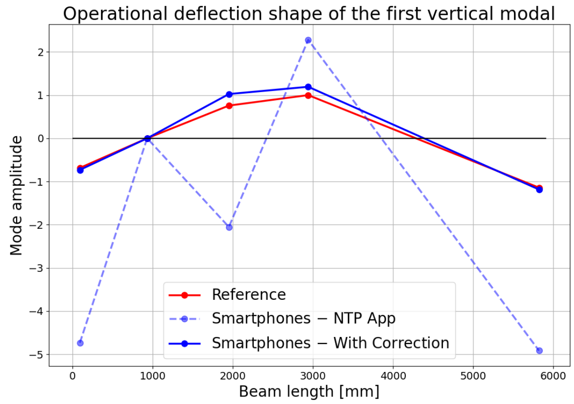

Figure 4. 1^{st} Operational deflection shape of the reinforced concrete beam before and after the clock offset correction by using a Baesyan optimization process.

TABLE I. Experimental test on the reinforced concrete beam for the identification of the 1^{st} natural frequency and relative modal shape.

Smartphone	Relative position [mm]	1^{st} natural frequency reference $[Hz]$	1^{st} natural frequency smartphone $[Hz]$	Δt_i NTP Mobile App $[ms]$	Δt_i Corrected $[ms]$
Device01	90	20.88	20.88	-20	-17
Device02	930	20.88	20.87	0	-9
Device03	1950	20.88	20.87	109	117
Device04	2940	20.88	20.87	550	559
Device05	5820	20.88	20.88	775	774

of the offset data with respect to the time clock provided by the NTP server is an order of magnitude greater than in the case of the device connected via Ethernet. Consequently, it is crucial to ascertain the maximum acceptable error when using smartphones for dynamic tests of civil structures, as the relative phases between the devices play a crucial role in the reconstruction of the ODSs of the structure.

The test on the reinforced concrete beam focused on the analysis of the first bending mode of the beam, as this is the only mode occurring within the sampling frequency ranges of the devices. As presented in Table I, the identification of the first natural frequency achieved by the different devices is accurate and highlights the precise sampling frequency achieved by using the *PhyPhox* mobile app. However, challenges arise when attempting to reconstruct the ODS of the first mode due to the poor synchronization of the different clocks of the devices. In fact, as depicted in Figure 4 (dashed line), the shape reconstructed with the devices synchronized via the mobile NTP synchronization app (Table I) significantly deviates from the shape reconstructed using the reference accelerometers. Consequently, the problem was approached by exploiting a Bayesian optimizer, which aimed to optimize the following cost function:

$$J(\mathbf{w}(\Delta\mathbf{t})) = min(|\mathbf{w}_{ref} - \mathbf{w}(\Delta\mathbf{t})|_{l1}) \quad (2)$$

where the $\mathbf{w}_{ref}$ is the vector containing the reference ODS and $\mathbf{w}(\Delta\mathbf{t})$ is the ODS calculated with the devices. The goal of this analysis is to demonstrate that the sole assessment of a time offset prior executing a dynamic test is not enough to guarantee a robust and stable synchronization among the different smartphones. The Bayesian optimizer targets the identification of the best $\Delta\mathbf{t}$ by minimizing the distance between the two ODSs in order to understand the time delay in ms from the one picked up with the mobile application. The optimization results are reported in Table I and the corrected ODS is reported in Figure 4. It is well evident that the optimized delays differ from those registered at the beginning of the test. Even though the time differences seems small, these are enough to create modification to the ODS. This is critical in a SHM application, as a modification in the

As for the Cerro al Lambro pedestrian bridge test, the frequencies of the structural dynamics involved are significantly lower than those of the lab-scale reinforced concrete beam. Such a difference suggests that eventual time offsets between the different devices due to the devices missynchronization have lower impact in the reconstruction of the bridge ODSs. In fact, when no phase correction is taken into account, the modal shape reconstruction of the first and second flexural modes ($f = 1.75\ Hz$, $f = 4.66\ Hz$) exhibits remarkable similarity to the shape calculated using the reference sensors, both in terms of relative amplitudes and phases (see Figure 5). This surely paves the way to the use of smartphones for assessing also the ODSs of the target structure.

TABLE II. Test setup and results on a full scale pedestrian Bridge.

Smartphone	Position	Δt_i NTP Mobile App $[ms]$	1^{st} natural frequency reference $[Hz]$	1^{st} natural frequency smart-phone $[Hz]$	2^{nd} natural frequency reference $[Hz]$	2^{nd} natural frequency smart-phone $[Hz]$
Device01	s2_1	7	1.75	1.75	4.66	4.66
Device02	s2_2	10	1.75	1.75	4.66	4.66
Device03	s2_3	450	1.75	1.75	4.60	4.60
Device04	s2_4	399	1.75	1.75	4.66	4.66
Device05	s2_5	-396	1.75	1.75	4.66	4.66

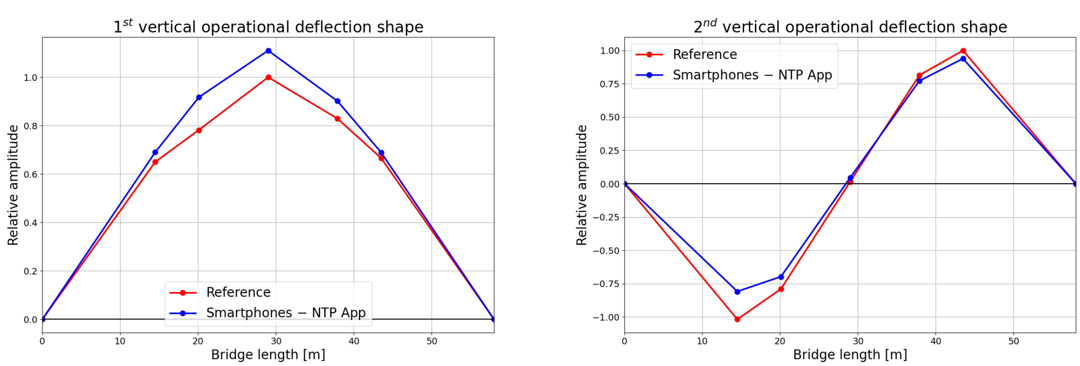

Figure 5. Bridge operational deflection shapes of the first 2 vertical modes obtained with reference system and 5 devices positioned along the pedestrian bridge.

CONCLUDING REMARKS

This study aimed at discussing the potentials and the constraints one should consider when addressing the use of multiple smartphones in structural health monitoring applications. Specifically, the investigation focused on the issue of device synchronization and its impact on the reconstruction of structural deflection shapes. It was observed that in structures whose resonant frequencies occur in the low frequency range, like those commonly found in civil structures, the synchronization error becomes less strict, while it becomes relevant in the high frequency range and cannot be disregarded if targeting an ODS reconstruction. In this case, more precise synchronization strategies are required to ensure accurate results.

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