Synchronous Data Acquisition from Large-scale Clustered Wireless Sensor Networks

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Abstract—Wireless Sensor Networks (WSNs) have become a mainstream for observing various variables of interest for a wide variety of applications, ranging from monitoring environmental parameters to medical, military and structural health conditions. Severe resource constraints of WSNs necessitate an efficient software layer, which acts as an intermediary between the applications and hardware resources, in order to regulate the energy consumption and optimize sensor nodes’ longevity. Most of the existing software solutions lack several features, which are crucial for synchronous data acquisition tasks, including collaborative data distribution, decentralized task execution and most importantly data fusion based on the application of spatiotemporal requirements and operational modality. Therefore, WSN applications are often unable to remotely fulfill their data aggregation/mining requirements. Sensomax is an agent-based WSN middleware, which facilitates parallel data-gathering for multiple concurrent applications, in a decentralized and adaptive fashion. It autonomously disperses the applications’ data-related demands to multiple target sources (sensors), where further processing (potentially computational algorithms) applied by the subagents, and captured data from multiple sources get relayed back to the corresponding applications, either as raw data in batch or aggregated form. In this paper Sensomax’s data-gathering mechanism is applied to human-structure interaction modelling in order to capture several data streams from a single human subject, and replicate and remodel it for multiple subjects.

Keywords—WSN; SHM; Synchronous; Data-Acquisition; Concurrency; Human-Structure; Sensomax.

I. INTRODUCTION

A wireless sensor network is a collection of small and embedded devices network scattered across an environment for monitoring environmental phenomena or observing phenomena of interest. WSNs have drawn a lot of attention over the past decade; their applications include structural monitoring, military solutions, health and medical observation, fire detection, habitat monitoring to observing volcanoes and space engineering. Structural Health Monitoring (SHM) is one of the most imperative applications of WSNs, in which multiple parameters of interest need to be synchronously captured and streamed out to a central unit for further processing. Processing multiple data streams often requires multiple algorithms to be simultaneously applied upon different portions of data. This process needs to be implemented by WSNs’ middleware, which is a software layer between the applications and hardware resources. Sensomax [1,2] is a WSN middleware, which was originally designed for Sun Spot sensor devices [10], for synchronous data acquisition and is capable of concurrently applying multiple algorithms in the form of individual applications to the captured data. Here we provide a novel application of WSNs for investigating human-structure interaction.

Lateral excitation of structures caused by pedestrian traffic has been an area of focus of the engineering community since the serviceability failure of the London Millennium Footbridge (LMF) at the turn of the millennium [3, 4]. This highly prestigious structure, both due to its prominent location and historical significance (the first crossing of the river Themes in the centre of London since the opening of the Tower Bridge in 1894), suffered from large-amplitude lateral vibrations when subjected to the loading of the crowd celebrating its opening, earning an infamous nickname of the Wobbly Bridge. This highly-publicized event revealed the need for better characterization of the lateral forces exerted on structures by walking pedestrians (ground reaction forces, GRFs) with the ultimate goal of revision of the relevant structural design guidelines. In particular, the frequency content and magnitudes of frequency components of the lateral GRFs, characteristic of different walking velocities, have not been considered which could potentially have profound consequences on the amplitude of the modeled structural response. Determination of crowd imposed actions on civil engineering structures has mainly been conducted from measurements of dynamic behavior of full-scale bridges or from tests in a laboratory environment. The advantage of the former method is that it allows the entire complexity of human behavior to be captured, including inter-subject interactions, without bias due to artificiality of the environment for laboratory investigations. The disadvantage is that the behavior of individual pedestrians is unknown thus making benchmarking of theoretical models difficult. The latter method allows the behavior of an individual pedestrian to be measured in a variety of conditions to obtain results representing a behavioral continuum. The uncertainty as to the accuracy of the results from laboratory investigations pertains
to whether they are representative of real-life behavior. A considerable advancement in understanding the complicated problem of modeling human-structure interaction could be made if a method was devised allowing for simultaneous acquisition of data on behavior of individual pedestrians in a crowd and structural response. Instrumenting pedestrians and a bridge with wireless sensors capable of capturing motion data is an obvious candidate solution.

II. METHODOLOGY AND CASE STUDY

In this section we describe how multiple data streams are simultaneously time-stamped and synchronized from multiple sources. We will also explain how Sensomax’s data acquisition can be applied to research on human-structure interaction. Sensomax’s architecture and operational details have been described in [1, 2]. However, in order to provide the reader with an overview of its operational paradigm and multi-clustered scheme, the architecture of Sensomax is briefly described here.

In order to run multiple applications concurrently, Sensomax abstracts the network into several groups, known as clusters, in which one node acts as the cluster-head with the rest acting as its members. Each cluster maintains an exclusive communication channel for interaction amongst its members. However, multiple applications can coexist in a single node whilst keeping their communication and execution domains isolated. Therefore multiple clusters may overlap physically without interfering with each other’s operations.

WSN applications are characterized based on their embedded requirements, which can be narrowed down into Query; Data; Time and Event conditions. Based on those, every application ultimately fits into one or a combination of the four major categories of Query-driven, Data-driven, Time-driven and Event-driven, respectively. The above-mentioned categories decide the operational paradigm in which the application needs to be executed. Sensomax extends this mechanism further by integrating the operational paradigms into the aforementioned multi-clustered execution scheme, in a way that each application, based on the number and type of embedded requirements, gets allocated to a single or multiple cluster(s), and its requirements get deployed as standalone subtasks to each of the cluster members. Such mechanism creates a centralized and collaborative execution environment where the subtasks themselves are executed independently (decentralized) and only report back their results or respond to queries.

A. Sensomax’s Data Distribution/Acquisition Model

Once the network, including all sensor nodes, gets initialized, a clock synchronization agent is deployed onto the network, in a one-hop fashion, from the gateway station. Nodes receiving this agent compare their internal clocks to the registered time in the agent and if their clock is different for more than one millisecond, they request a data stream channel to the gateway. Once data stream is granted, nodes request clock adjustment agent, which is delivered to them by the gateway. Data stream channel is to make sure agents are received in real time. The same process gets repeated for every new cluster formation, this time between the cluster-heads and their members. This process is essential since all sensed data get time-stamped with the epoch time immediately after being captured. It is worth mentioning that this process is often not required, as sensor nodes, in this case the Sun Spots, are equipped with a precise time synchronization hardware. Also nodes are synchronised to the host PC via USB port, when initially programmed with Sensomax middleware.

The next phase makes sure data are stored into the flash memory and only transmitted with an interval of at least 500ms. Based on our experiments, transmitting data over the radio with lower intervals results in significant delays in the underlying/background process and causes minor phase lags. For the purpose of the experiment mentioned throughout this paper, data get flushed out of the node every 5 seconds, in order to minimize the latencies. It is important to notice that the emphasis is on time-stamps attached to every data portion and not on the agent/packet arrival time.

Sensomax’s application execution mechanism has been modelled and examined in real-time in our previous publications [1,2]. This paper deals with time-driven applications, where measurements need to be taken at regular intervals. Time-driven application have specific requirements, which are broken down into several timers that are set up and triggered for taking measurements, data storage and transmission.

Data acquired by the cluster-heads are then bundled up and made ready for computational algorithms to be applied upon. Sensomax’s component-based architecture and the power of Java APIs, make it easy to combine multiple algorithmic modules and system resources for seamless mathematical operations. In a previous publication [8], market-based techniques were embedded into every sensor node, to regulate resource allocation for multi-paradigm applications.

B. Simultaneous Human-Structure Data Acquisition

The experiments were conducted on a custom-built instrumented treadmill located in the Earthquake Laboratory at the University of Bristol, allowing for direct measurement of the lateral GRFs. One male subject (mass of 81kg and height of 1.83m), without any locomotor impairments, participated in the experiments. After a period of habituation the data were collected from the subject walking on the treadmill for at least two minutes at each of five walking speeds set on the motor speed controller. Fourteen markers were placed at the joints of the subject body segments to obtain motion data using a motion capture system (MCS) consisting of six infrared cameras (Qualisys, Sweden).

<table>
<thead>
<tr>
<th>Table 1. Definition of Body Segments</th>
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<tbody>
<tr>
<td><strong>Segment</strong></td>
</tr>
<tr>
<td>Upper arm*</td>
</tr>
<tr>
<td>Forearm and hand*</td>
</tr>
<tr>
<td>Thigh*</td>
</tr>
<tr>
<td>Foot and leg*</td>
</tr>
<tr>
<td>Trunk-head-neck</td>
</tr>
</tbody>
</table>

*denotes doubled segments
The definitions of nine body segments adopted in this study (four segments are doubled due to symmetry about the body midline), based on data from the markers, are presented in Table 1. Note, in order to establish motion of body segments defined in Table 1, data from some markers are employed more than once. This procedure allowed the position of the centre of mass (CoM) of the body to be determined through inverse dynamics [5] and identify the instances of heel strikes (initial contact of the leg with the ground marking the beginning of a step). The instances of heel strikes were obtained by analyzing vertical velocity signals from the markers attached to the lateral malleolus using a method similar to the one proposed by O’Connor et al. [6].

All data were sampled at 128Hz and the post-processing was done using custom written software in Matlab (MathWorks, USA). The following spatial and temporal gait parameters were established:

- **stride frequency** ($f_p$) – taken as half the pedestrian walking frequency (equal to the inverse of time between two consecutive heel strikes) and defined as the inverse of the pedestrian gait cycle period,
- **walking velocity** ($v$) – taken as the average velocity of the treadmill belt inferred from the movement of markers attached to the belt (rather than directly from the motor speed controller).

The lateral GRFs were obtained directly from force transducers supporting the treadmill. The signals were filtered with an eighth-order Butterworth low-pass anti-aliasing filter with cut-off frequency 40Hz prior to data acquisition. Time-alignment of the data from the MCS and force transducers was performed prior to data analysis. To identify the frequency content and magnitudes of frequency components of the lateral GRFs Fourier transforms were computed on the force signals. Before performing frequency analysis, to avoid leakage (undesired spread of spectral content from the actual frequencies of dominant components to other nearby frequencies), the force signal was truncated such as to contain an integer number of pedestrian gait cycles. This was achieved by taking the longest possible interval between heel strikes on the same leg. For the purpose of presentation of time histories of lateral force the signals were filtered with a two-way eighth-order Butterworth low-pass filter with cut-off frequency 6Hz. To obtain the lateral component of the GRFs with the indirect method linked-segment modeling was utilized [5]. In short, this procedure relies on division of the body into a number of segments of known position and length, using data from the MCS, and determination of their mass and centre of mass using anthropometric data. Based on these data, by modeling the body as an ensemble of interconnected segments (kinematic chain), it is possible to infer the motion of the whole body CoM. This then allows determination of the GRFs in accordance with Newton’s second law of motion.

The experimental setup and the subject during a test are presented in Figure 1. The experimental campaign was granted approval by the University of Bristol Ethics of Research Committee.

The summary of the main results is presented in Table 2. The third and the fifth harmonics of the stride frequency ($f_p$) are denoted by $f_{p,3}$ and $f_{p,5}$, respectively. Note the first value in the columns for the harmonics is the frequency of the harmonic and the second and third values, presented in brackets and separated by a slash sign, are the amplitudes of those harmonic obtained using direct (force transducers) and indirect (MCS) methods, respectively.

![Figure 1. Subject during a test on a custom-built instrumented treadmill.](image)

<table>
<thead>
<tr>
<th>Walking velocity [m/s]</th>
<th>$f_p$ [Hz][[N]/[N]]</th>
<th>$f_{p,3}$ [Hz][[N]/[N]]</th>
<th>$f_{p,5}$ [Hz][[N]/[N]]</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.77</td>
<td>(27.9/25.5)</td>
<td>(10.2/9.4)</td>
<td>(3.2/1.4)</td>
</tr>
<tr>
<td>1.16</td>
<td>0.81</td>
<td>2.45</td>
<td>4.08</td>
</tr>
<tr>
<td>1.36</td>
<td>(36.5/32.8)</td>
<td>(13.1/13.3)</td>
<td>(5.1/3.8)</td>
</tr>
<tr>
<td>1.55</td>
<td>0.87</td>
<td>2.61</td>
<td>4.34</td>
</tr>
<tr>
<td>1.75</td>
<td>(42.1/37.9)</td>
<td>(16.2/16.9)</td>
<td>(6.8/6.2)</td>
</tr>
<tr>
<td></td>
<td>0.94</td>
<td>2.82</td>
<td>4.70</td>
</tr>
<tr>
<td></td>
<td>(42.4/38.2)</td>
<td>(16.2/17.5)</td>
<td>(7.4/7.4)</td>
</tr>
<tr>
<td></td>
<td>0.98</td>
<td>2.93</td>
<td>4.88</td>
</tr>
<tr>
<td></td>
<td>(42.4/38.7)</td>
<td>(18.1/20.8)</td>
<td>(5.7/6.5)</td>
</tr>
</tbody>
</table>

Figures 2 and 3 present a comparison between lateral components of the GRFs measured with direct (black continuous curves) and indirect (red dashed curves) methods. Figure 2 presents truncated time histories. It can be seen that the agreement between the two methods is generally good with the time of occurrence of peaks in the force obtained using the indirect method closely matching the results obtained using the direct method. Figure 3 presents the single-sided power-preserving magnitude of the FFT of the force. It can be seen that the match between the frequency components obtained using the indirect and direct methods is generally good. However, the magnitude of the first harmonic from the indirect method is underestimated relative to the results obtained using
the direct method while the magnitudes of the higher harmonics are slightly overestimated.

**Figure 2.** Exemplar truncated lateral force time histories for walking velocity of 1.55m/s

**Figure 3.** FFT diagrams corresponding to data in Figure 6.

The procedure adopted for inverse dynamics analysis allows the main components of the lateral force to be estimated with an average error of ±10%. The procedure could be refined by implementation of adaptive filtering of kinematic data to achieve even better results in reconstructing the GRFs. Therefore, it can be concluded that the kinematic data gathered using WSN could be used to evaluate crowd-induced loading on engineering structures through inverse dynamics. The first step towards achieving this goal is evaluation of WNS performance within this context.

### III. Evaluation

In this section a number of experiments are conducted to evaluate the effectiveness of Sensomax’s data acquisition system in the context of human-structure interaction.

For all experiments throughout this section, data obtained from the motion capture system, which was explained in the previous section, are fed into the SXCS simulator [7], which is an object-oriented emulator, capable of running up to 2500 virtual nodes, to firstly model the multi-cluster data-gathering scheme for a single subject, and secondly replicate the data streams for multiple subjects (here for up to 4 subjects) and repeat the data modelling.

In a previous publication [9], similar experiment was conducted for medical applications where multiple data sources (patients and elders) need to be accessed at several points (doctors and nurses). As was explained in the previous section, there are 14 points of interest (hereafter referred to as sensors) on the subject’s body, which acceleration variables, divided into X, Y and Z axis. Sensors are inclusively divided into 9 sections (hereafter referred to as clusters), according to the Sensomax clustering scheme, and each gets designated with an exclusive application, which can potentially apply computational algorithms on the captured data including the calculation of centre of mass through inverse dynamics. In total, 30000 data portions are fed into each sensor by SXCS real data generator.

**Figure 4.** Data Portions’ Synchronization Accuracy

**Figure 5.** Data Delivery Latencies to Cluster-heads

The first experiment focuses on the accuracy of data portions’ timing in each cluster, and how precise their synchronisations are when delivered to their cluster-head for further processing.

This experiment is mainly concerned with the time-stamps attached to data portions rather than their on time delivery. Figure 4 shows the average accuracy obtained from all 9
clusters on subject 1, with a variable number of data portions throughout the data capturing process. According to this figure, data portions are at least 97% synchronised, which based on the aforementioned 128Hz sampling rate, approximates to a minor phase lag of 0.23 milliseconds amongst the members of a single cluster.

Finally, since most WSNs are benchmarked based on their energy profiling, the next experiment focuses on the amount of time each subject (network) stays in low-processing state within the ~2- minute period of the experiment, with a variable number of clusters involved in the process. Figure 7 shows the total durations (in percentage) that each subject stays in the sleep mode as more clusters join the network. According to this figure there is an approximately 10% increase in the energy consumption of the network with 2 and more clusters existing in the network. Thorough study of cluster and node density has been conducted in [2,3].

IV. Conclusion

In this paper we have evaluated Sensomax’s data-acquisition capability for concurrent processing of multiple data streams within clusters. We have also validated its effectiveness for Structural Health Monitoring (SHM) applications in order to execute multiple concurrent applications via multi-paradigm context-aware clustering. In conclusion, it has been shown that the lateral component of the GRFs can be reconstructed with reasonable accuracy using the indirect method. This implies the use of wireless sensors for obtaining GRFs through inverse dynamics, for the purpose of research on human-structure interaction, may be viable.

REFERENCES


