



Occupant tracking using model-based data interpretation of structural vibrations

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Abstract

Sensor-based occupant tracking has potential to increase understanding of building utilization. Most occupant-localization methodologies involve costly equipment that needs regular maintenance and relies on intrusive sensing methods such as radio-frequency and optical sensor approaches. Structural-vibration-based methodologies often employ model-free techniques to triangulate the location of an occupant and thus, might lead to ambiguous interpretation in presence of obstructions in the structure. Through sparsely distributed sensors in floor slabs, incorporating finite-element simulations of various trajectories into data interpretation has the potential to provide better accuracy for occupant tracking on floors with varying rigidity. This paper presents an application of model-based data interpretation, to track an occupant within an office environment using footstep-induced vibration time histories. Error-domain model falsification, which is used to compare measured signals with simulation results, is a multiple-model approach that explicitly accommodates ambiguous data interpretation. It provides a set of candidate trajectories from an initial population of possible trajectories through incorporating various sources of uncertainties. It is shown that error-domain model falsification reduces the uncertainty of occupant tracking by falsifying wrong trajectories and this has potential to increase tracking performance for accurate occupant localization in smart building applications.

Keywords: Occupant tracking, Footstep-induced vibrations, Multiple-model data interpretation, Error-domain model falsification.

1. Introduction

Buildings incorporate increasingly sophisticated technology with the purpose of providing services that enhance occupant security and comfort. Sensing technologies are used for occupant tracking, leading the way to opportunities for new approaches. Occupant tracking might enable various enhancements in building performance such as energy management, increase information for hospital and old-age accommodation facilities, security enhancement and more informed fire rescue. Therefore, occupant tracking has much promise to improve understanding of occupant behavior and to enhance utilization of buildings.

Ongoing research have employed either radio-frequency devices (Lazik et al. 2015) or optical sensors (Erickson et al. 2013) to localize and quantify indoor occupants. Radio-frequency devices such as beacons depend on a highly instrumented infrastructure and low levels of ambient acoustic noise to accurately track occupants in buildings (Lam et al. 2016). Occupant localization using optical sensors, such as cameras and motion sensors, requires large angles of coverage and clear lines of sight (Lam et al. 2016). The use of cameras for occupant localization undermine the privacy of people and influence the behavior of occupants inside buildings.

Vibration data induced by human footsteps has been used for occupant detection and localization without infringing on the privacy of occupants (Richman et al. 2001). Footstep-impact locations have been estimated based on processing and analyzing vibration measurements using Time Difference of Arrivals (TDoAs) of recorded signals at each sensor location. These occupant localization approaches require at least three sensors covering the footstep impact location (Mirshekari et al. 2018). A large number of sensors has been required to provide accurate occupant detection and localization due to low signal-to-noise ratio of footstep-induced vibrations (Lam et al. 2016). In addition, dispersion has been observed for wave propagation through the floor leading to distorted signals and uncertain localization results due to the obstructions in the structure such as walls and beams (Mirshekari et al. 2018).

This paper contains a proposal for an alternative approach for occupant tracking based on coupling the response of vibration sensors with models of the structural behavior of buildings. This provides a way to overcome the limitations that are related to the number of required sensors and the varying rigidities of structural floors. Error-domain model-falsification (EDMF) (Goulet et al. 2013), a population-based data interpretation approach, is used to compare measurements with model simulations. EDMF accommodates multiple sources of uncertainties arising from measurements and structural simulations. EDMF has been successfully applied to more than fifteen full-scale systems including structural identification (Goulet et al. 2013) and fatigue life evaluation (Pasquier et al. 2016).

2. Model-based occupant tracking methodology

The vibration-based occupant-tracking methodology includes three steps: processing of footstep-induced vibration measurements, model simulation of predefined footstep impact locations and interpretation of footstep locations using EDMF to infer occupant trajectories.

Ambient-vibration measurements are retrieved to obtain the fundamental frequencies of the structure and baseline levels of vibration defined as three standard deviations (3σ) that are used to obtain velocity thresholds for footstep impact detection. A footstep-event signal is extracted at each sensor location when vibrations exceed detection thresholds. Each footstep-event signal is decomposed using continuous wavelet transform (CWT) to extract low-and-high frequency components. Morlet wavelet (Lin and Qu 2000) is used as the mother wavelet due to its shape similarity to the footstep impact signal. The maximum difference in velocity amplitudes (Δ_{amp}) at various frequency ranges of a footstep signal are extracted. In this study, Δ_{amp} is used as a metric to compare measurements and model simulations.

Model simulations of footstep impacts at potential locations are performed based on a physics-based model of the slab (in this case a finite-element model). All simulated footstep signals are then decomposed using CWT at similar frequency ranges used for measured footstep-event signals and Δ_{amp} is calculated. EDMF accommodates various sources of uncertainties including model imperfections, unknown model parameters as well as limited resolution and precision of sensor data and natural variability in the signal resulting from a person walking along the same trajectory multiple times. Variability is typically due to unrepeatability of walking rhythm, impact angle and load distribution.

Using a combination of on prior measurements of a walking person and engineering judgment, measurement and model uncertainties are estimated at all possible footstep locations. Thresholds for the residual between measured and simulated Δ_{amp} are calculated based on the combined uncertainties and a target reliability of identification (Goulet et al. 2013). Model

simulations that are not compatible with footstep-induced vibration measurement are rejected using EDMF. Thus, EDMF generates a candidate-location set (CLS) for each footstep event.

A sequential analysis assuming that the distance between successive footstep events cannot exceed a pre-fixed step length is subsequently performed in order to reduce ambiguity within the CLS of each footstep event. Once CLSs are obtained for all footstep event, trajectory identification is performed assuming that the person walks continuously until reaching destination without stopping or going backwards.

3. Application to full-scale office environment

Model-based occupant tracking application is applied to an office environment that includes a corridor and four offices (see Figure 1), the slab is a continuous reinforced-concrete slab (approximately area of 100m²) supported by steel beams. The slab is 20 cm thick and rests on a steel frame composed of 16 steel beams. The whole structure is supported by six steel columns. In addition, several non-structural walls made of plasterboard are underneath and above the structure. The east end of the slab is free. The slab is connected with unknown connection stiffness to a structural masonry wall at the north end and to prefabricated structural walls made of reinforced concrete at the west end.

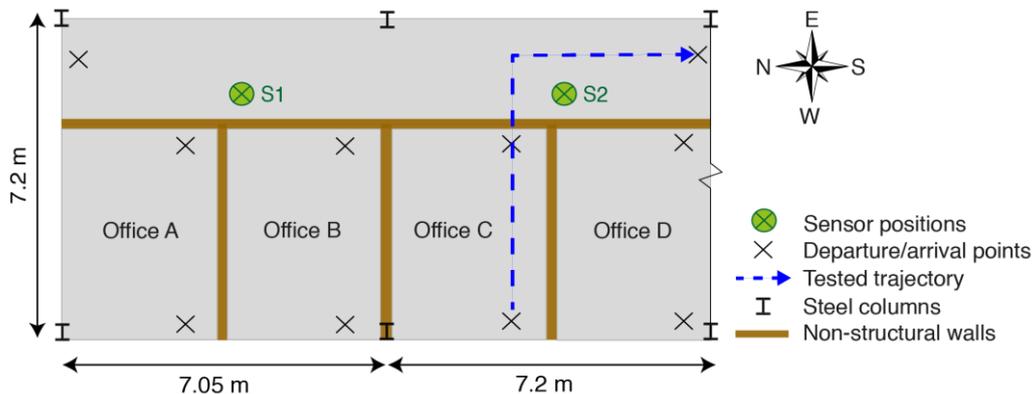


Figure 1: Drawing of the office environment composed of offices A, B, C and D as well as a corridor that used to perform occupant tracking. The tested trajectory is used for occupant tracking using model-based approaches.

Two vibration sensors (Geophones SM-24 by I/O Sensor Nederland bv) with an acquisition unit (NI PCIe-6259) are used to measure vertical velocity responses with a sampling rate of 3000 Hz. Sensors are placed on the slab with 7m spacing in the longitudinal direction. As illustrated in Figure 1, both sensors are positioned close to the office walls. Assuming that trajectories inside a same office are not considered, departure/arrival points (see Figure 1) lead to 82 possible trajectories. Model-based occupant tracking is tested on a trajectory that starts in Office C and leads to the south end of the corridor. One-person (approximately 90 kg) walks along the tested trajectory three times (walking frequency of 1.6 Hz).

Prior analysis of ambient vibrations have revealed that a dominant vertical mode of the slab has a frequency of approximately 24 Hz. Based on CWT, footstep-induced vibrations are extracted for the frequency range of [20, 40] Hz to capture the response that is close to the first mode of the structure. In addition, high-frequency components of footstep-induced vibrations are extracted in the frequency range of [150, 200] Hz where the structural influence is reduced.

Model simulations are generated using a finite-element model of the slab. The dynamic response is computed based on linear modal superposition. The input load force describing the

footstep impact is a function of time applied to a single node on predefined locations. The impact-load function is conceptualized as a succession of two sine functions: heel contact (where the full weight is transmitted to the floor) and toe-off of the foot (Racic et al. 2009). The input function starts with non-zero slope and ends with zero-slope.

Model predictions are subjected to multiple sources of uncertainty. Uncertainties that arise from secondary parameters are taken into account by varying values of unknown parameters in simulations, mainly occupant weight in the interval of [50, 90] kg, footstep full-weight duration in the interval of [0.02, 0.08] s and viscous damping ratio in the interval of [1, 7] %. Model simplifications such as idealized boundary conditions and omissions of office furniture and corridor railings, are estimated to result in a uniform distribution of [-15, +25] %. Low-frequency components in model simulation are mostly affected by the applied load-function that has low frequency itself where the natural period of the structure falls within its range of values. Thus, it has been found that simulations over-estimate velocity amplitudes at low-frequency components and under-estimate amplitudes of velocity at high-frequency components. Accordingly, a uniform distribution of up to [-50, 0] % for low-frequency components and up to [0, +40] % for high-frequency components are added to the modeling uncertainty. Additional uncertainties following a uniform distribution of [-10, +10] % increases the modeling uncertainty of high-frequency components due to local structural modes that are more pronounced in high-frequency ranges.

Furthermore, model simulations contain additional uncertainties that are related to the exact values of frequency ranges while comparing footstep-impact simulations with measurements. Signal decomposition uncertainties are estimated for all possible footstep-impact locations and at each sensor position. Signal-decomposition uncertainties are estimated by taking the difference between simulated footstep signals at frequency ranges laying between 16 Hz and 48 Hz and between 126 Hz and 271 Hz for low-and-high-frequency components and the reference components at frequency ranges [20, 40] Hz and [150, 200] Hz.

As with modelling uncertainties, measurements are prone to many sources of uncertainties, including sensor resolution and precision and variation of a person walking along the same trajectory multiple times. Based on ten prior measurements on each potential footstep location, measurement uncertainties are estimated for each sensor at all possible impact locations.

Localization thresholds at each footstep location are derived from the combined uncertainties using Monte-Carlo sampling and a target reliability of identification of 99%. EDMF is then performed for all captured footstep-events. All model instances for which residuals between simulations and measurements lie outside the localization thresholds are falsified. The CLSs resulting from each footstep event are generated based on information at each sensor location for low-and-high frequency components. Assuming that the distance between successive footstep events cannot exceed a pre-fixed step length, a sequential analysis is performed in order to enhance the precision of CLSs. Figure 2 illustrates an example of several CLSs (squares) resulting from EDMF and sequential analysis of footstep events that correspond to the tested trajectory (see Figure 1). Falsified locations are circles and real footstep locations are stars.

As presented in Figure 2, all CLSs cover the real footstep locations. Thus, model-based occupant localization using EDMF and a sequential analysis provides accurate results for all footstep events. However, the precision of the CLSs are found to be generally low for footstep events that are inside offices. The lack of precision of the CLSs inside offices is due to the low

amplitudes of the measured footstep-events at sensor positions (see Figure 1). Therefore, future work on sensor layout is required in improving the precision of CLS identification.

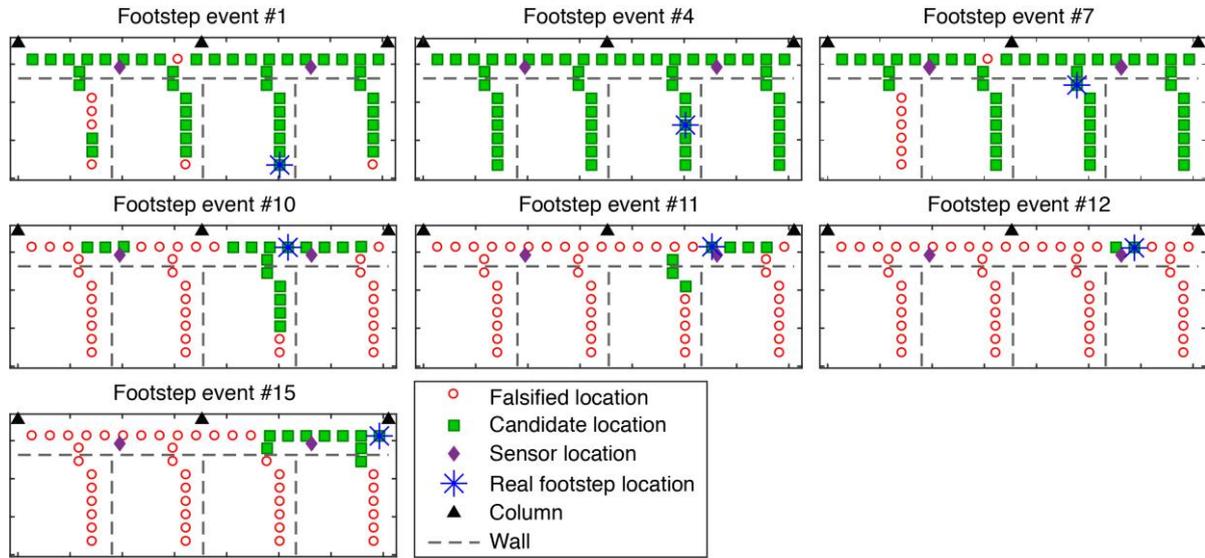


Figure 2: Candidate-location set that is obtained using EDMF and sequential analysis for each footstep event of one out of three measurements of the tested trajectory (see Figure 1).

The identification of candidate trajectories starts with considering all departure/arrival locations (see Figure 1) as possible departure points. Based on the first CLS of the captured footstep event, if a departure point is a candidate location, all corresponding trajectories to this departure spot are taken to be candidates. Further information about possible paths taken from the remaining departure are provided with CLSs of additional footstep events. In case CLS of a footstep event does not satisfy the continuity of a path, the corresponding trajectory is rejected. Once a potential trajectory is complete without exploring all the remaining footstep events, that trajectory is also rejected. The remaining paths are considered as candidate trajectories, once all CLSs of all footstep events are explored. Table 1 presents the size of the CLS from an initial location set that is composed of 52 possible locations and the remaining candidate trajectories corresponding to each footstep event shown in Figure 2 of the tested trajectory (see Figure 1).

Table 1: Size of candidate location set (52 initial locations) and the remaining candidate trajectories corresponding to each footstep event are presented for the tested trajectory (see Figures 1).

Footstep event #	Candidate locations	Candidate trajectories
1	45	58
4	52	51
7	45	33
10	17	15
11	7	4
12	2	3
15	10	1

For the tested trajectory, information provided by the footstep events #1 to #10 have led to the falsification of 67 of the 82 initial trajectories (approximately 82%). Although, precision regarding the CLSs of footstep events is low, reduction in number of candidate trajectories is high. Only the correct trajectory (see Figure 2) remains as candidate trajectory for all three measurements once all footstep-event results are explored.

4. Conclusions and outlooks

Model-based occupant tracking combine knowledge of structural behavior with measurement interpretation through accounting for systematic uncertainties and model bias. Model-based occupant tracking has the potential to reduce significantly the number of candidate occupant trajectories and provide accurate results.

The application of occupant tracking using model-based approach has been performed for one occupant only. Thus, testing several occupants walking along the same methodology is needed. In addition, general applicability of the approach is needed through tests on other full-scale structures. Finally, future work on reducing the secondary uncertainties is planned.

5. Acknowledgment

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