Model-based interpretation of floor vibrations for indoor occupant tracking

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Abstract. Information regarding occupant flows inside buildings is beneficial for applications such as thermal-load control, market research and security enhancement. Existing methodologies for occupant tracking involve data-driven techniques that rely either on radio-frequency devices, optical sensors or vibration sensors. Such data-driven techniques suffer from ambiguous interpretations, especially in presence of obstructions and varying floor rigidities. In this contribution, an occupant-tracking strategy using footstep-induced vibrations is outlined. The goal is to incorporate information from physics-based models in the interpretation of vibration measurements. Using error-domain model falsification (EDMF) a single occupant is localized using the vibrations resulting from footstep impacts and using various shoe types. EDMF is a multiple-model approach that provides a set of candidate locations from an initial population of possible footstep locations. Model responses that contradict footstep-induced vibration measurements are rejected through incorporating several sources of uncertainty from measurements and modeling. Occupant-trajectory identification is then performed based on the candidate-location set for each detected footstep using a sequential analysis that combines information from consecutive footsteps. A full-scale case study is used to evaluate the methodology. Model-based occupant tracking that includes structural information and takes into account systematic errors and model bias has the potential to identify accurately single occupant locations in a full-scale structure.

Keywords. Occupant tracking, Footstep-induced vibrations, Physics-based model data-interpretation, Error-domain model falsification, Sequential analysis, Trajectory identification.

1. Introduction

Sensing technologies, such as embedded and portable sensors, have been increasingly used to track occupants inside buildings. Indoor-occupant tracking information has the potential to improve understanding of occupant behavior. Thus, occupant security and comfort may be enhanced. Occupant tracking information might be useful for applications such as more informed fire rescue, market research, energy management (through thermal-load prediction) and increase information regarding patient locations for hospital and old-age accommodation facilities.

Most research on occupant detection and localization strategies involve intrusive equipment such as optical sensors (Erickson, Achleitner and Cerpa, 2013) and radio-frequency devices (Lazik *et al.*, 2015) to identify indoor occupant locations. Optical sensors, such as motion sensors and cameras, require large angles of coverage and clear lines of sight to localize indoor occupants precisely (Narayana *et al.*, 2015). Radio-frequency devices, such as radio-frequency beacons and smartphones, are sensitive to changing environmental conditions that make identification of occupant locations in buildings challenging (Bekkelien, Deriaz and Marchand Maillet, 2012; Lam *et al.*, 2016). Due to the intrusive nature of these devices, they might lead to disturbing indoor occupants. Thus, unobtrusive strategies are often preferred such as vibration sensors and smart flooring systems that use thousands of floor sensors (Serra *et al.*, 2014). Such systems thus rely on costly equipment that is not compatible with large full-scale applications.

In this paper, the use of sparsely distributed vibration sensors for occupant tracking is proposed in order to preserve the privacy of indoor occupants (Richman *et al.*, 2001). Ongoing research on vibration-based occupant tracking relies on processing and analyzing floor-vibration data induced by human footsteps using Time Difference of Arrivals (TDoA) for occupant localization (Lam *et al.*, 2016). TDoA requires a large number of sensors to provide accurate occupant detection and localization due to low signal-to-noise ratio of footstep-induced floor vibrations (Lam *et al.*, 2016). The dispersive nature of structures, varying floor rigidities and the presence of obstructions such as walls lead to uncertain localization estimation (Mirshekari *et al.*, 2018). Vibration-based data interpretation for occupant tracking using a physics-based model has been applied for a single occupant walking with one type of shoe (Reuland *et al.*, 2017; Drira *et al.*, 2019). Comparing vibration measurements with physics-based models have led to accurate identification of trajectories through identifying the location of successive footstep impacts (Drira *et al.*, 2019). However, possible trajectories were limited and additional uncertainty from varying shoe types has not been assessed.

In this paper, a strategy for tracking a single occupant based on comparing physics-based models of the structural behavior with floor-vibration measurements is presented. This approach has the potential to overcome the limitations that are related to varying rigidities of structural floors, obstructions as well as variation of the signal related to a person walking using various shoe types. Comparisons between model simulations and measurements are carried out using error-domain model falsification (EDMF), a model-based data interpretation (Goulet and Smith, 2013). EDMF incorporates multiple sources of uncertainties arising from measurements and simulations. EDMF has been successfully applied to more than fifteen full-scale systems (Smith, 2016) including structural identification (Goulet, Michel and Smith, 2013), fatigue life evaluation (Pasquier *et al.*, 2016) and post-seismic building assessment (Reuland, Lestuzzi and Smith, 2017).

This paper starts with a description of the model-based data-interpretation methodology for occupant tracking (Section 2). Application to a full-scale system is presented in Section 3 and conclusions are discussed in Section 4.

2. Model-based occupant tracking strategy

Based on floor-vibration measurements, the identification of possible trajectories of a single occupant is achieved through five steps: processing of footstep-event signals, simulation of footstep impacts at predefined locations, localization of footstep-impacts using EDMF, reduction of footstep-impact localization ambiguities using a sequential analysis and identification of occupant trajectories based on resulting footstep-impact locations. The model-based occupant-tracking strategy is graphically summarized in Figure 1.

To start, footstep-induced floor vibrations are decomposed using continuous wavelet transform (CWT) around the dominant frequencies of the structure (derived from prior ambient-vibration measurements) in order to better discern each footstep-event signal from ambient conditions. CWT is carried out with the Morlet wavelet as mother wavelet due to shape similarity with footstep-impact signals. Baseline levels of ambient vibration (decomposed at the same frequency range using CWT) are used to set thresholds, defined as three standard deviations (3σ) of ambient noise, for occupant detection. A footstep-event signal is extracted at each sensor location when exceedance of detection thresholds is achieved. In this study, the maximum difference in amplitudes (Δ_{amp}) of non-processed footstep-event signals are used as metrics for occupant tracking (see Figure 1).

For all potential occupant locations, footstep impacts are simulated using a finite-element model and the value of Δ_{amp} for simulated footstep-impact signals is derived. Occupant localization is performed using EDMF through comparing measurements with model simulations taking into account various sources of measurement and model uncertainties. Model uncertainties that may include model imperfections and unknown model parameters are estimated base on engineering judgment (Pasquier *et al.*, 2016; Pai, Nussbaumer and Smith, 2018). Measurement uncertainties include resolution and precision of the sensors as well as variability of footstep-induced floor vibrations (due to the natural variability of walking rhythm, occupant load distribution and shoe types) are quantified using prior measurements. Localization thresholds are computed based on combined uncertainties (that define the residual between measured and simulated responses) and a target reliability of identification (Goulet, Michel and Smith, 2013). For each footstep event, simulated model responses for all locations that do not contradict measurements form the candidate location set (CLS) (see Equation 1 in Figure 1).

Subsequently, the CLS related to each detected footstep event is subjected to a sequential analysis. Based on information from the previous footstep event, it is assumed that the distance of two successive footstep impacts cannot exceed a predefined distance, such as twice the length of a step (approximately 75 cm). As walking trajectories are not defined during measurement, a candidate location (CL) of footstep event $i + 1$ is rejected when the distance with all CLs of footstep event i exceeds twice the pre-defined step length (see Equation 2 in Figure 1). Based on layout information of the full-scale case study, departure/arrival points are assumed to be pre-defined for a sake of simplicity. Starting from the first footstep event, CLs are grouped according to possible departures based on sequential analysis (see Figure 2). CLs that do not correspond to a possible departure are rejected.

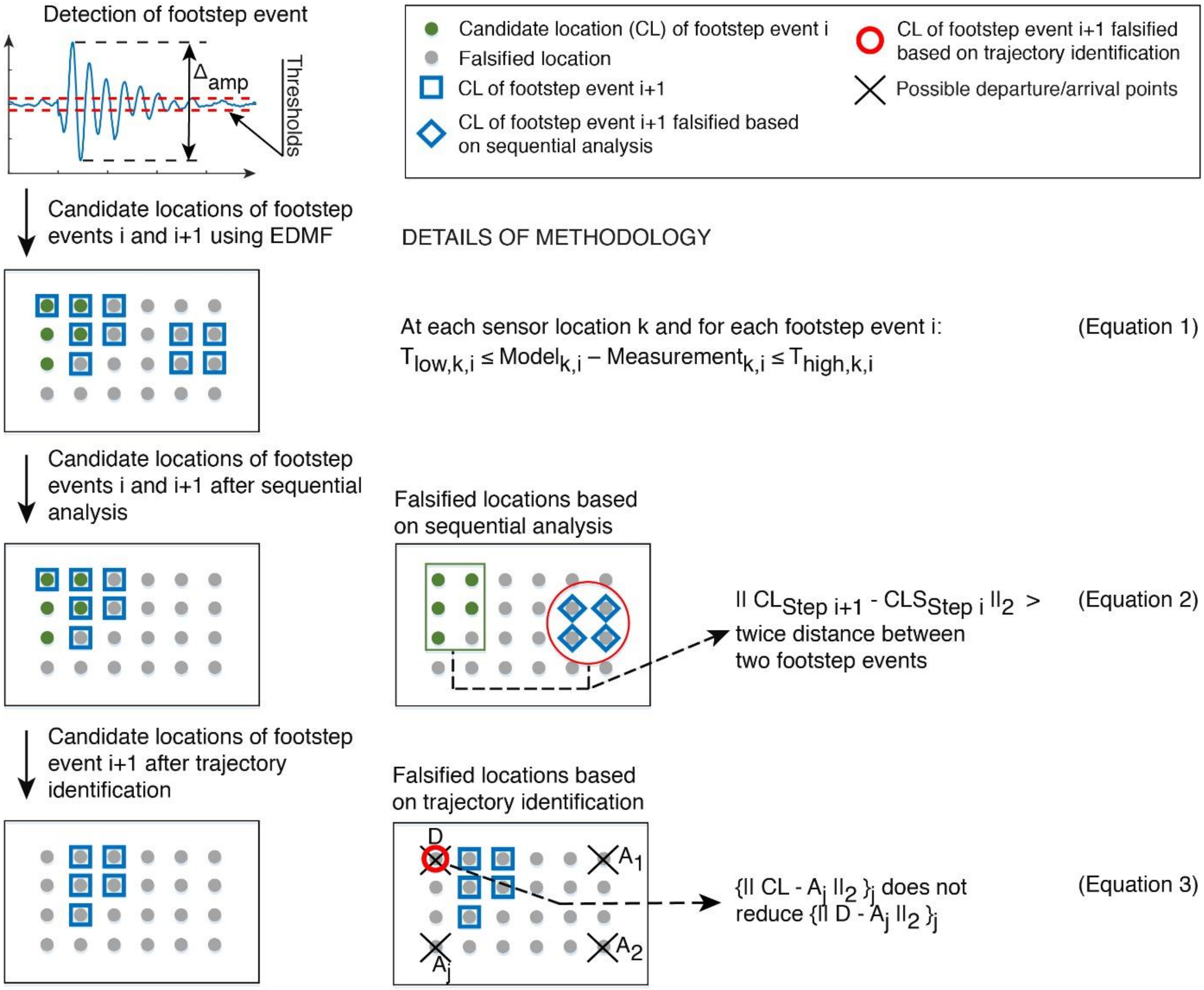


Figure 1: Measured signal of detected footstep-impact are compared with simulations. Location instances are falsified when the residual between simulations and measurements exceeds localization

thresholds ($T_{low,k}$ and $T_{high,k}$) at any sensor location. Based on information from the previous footstep event, sequential analysis reduces the population of the resulting CLS. A CL of footstep event $i+1$ ($CL_{Step\ i+1}$ in Equation 2) is falsified when its distance with all CLs of footstep event i ($CL_{Step\ i}$ in Equation 2) exceeds twice the pre-defined step length. A CL that corresponds to a possible departure (D in Equation 3) is falsified when its distances with all possible arrivals (A_j in Equation 3) do not reduce the distance of the corresponding departure with all possible arrivals, respecting CLS of previous footstep events.

A trajectory identification is then performed based on the CLS (obtained after sequential analysis) of each detected step event. For trajectory identification, it is assumed that the occupant walks until reaching destination without backtracking. A CL that corresponds to a possible departure is rejected when the distance is not reduced with at least one possible arrival point. This analysis is again performed sequentially, as each CLS needs to contain locations for which the distance to at least one arrival point is reduced with respect to CLS of the previous footstep event (see Equation 3 in Figure 1).

3. Application to full-scale floor-slab

The model-based occupant-tracking strategy presented in Section 2 is tested on a part of a full-scale floor slab (approximately 950 m^2). The floor is a continuous reinforced-concrete slab supported by ten concrete columns as well as several reinforced-concrete walls (see Figure 2). The slab is supported by a uni-directional reinforced-concrete beam connecting the slab with the columns (see section A-A in Figure 2). The studied surface contains several masonry walls as well as separation walls made of plasterboard as shown in Figure 2. The floor-slab contains multiple structural elements, such as columns and beams that influence vibration measurements.

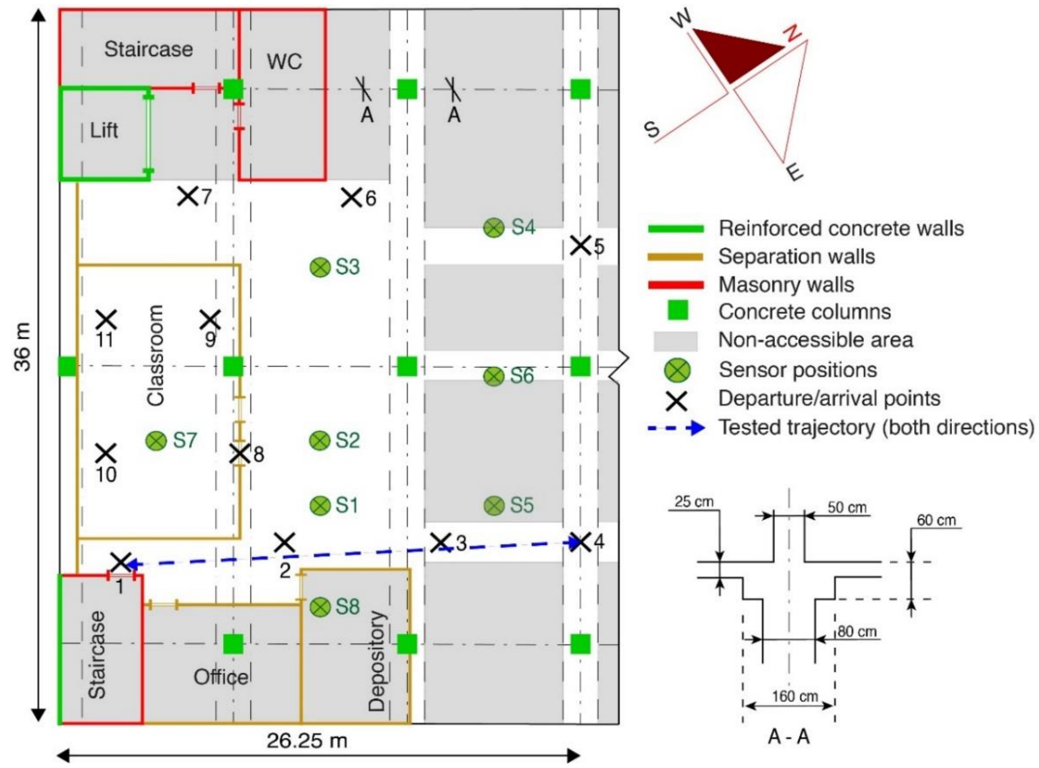


Figure 2: Occupant tracking is tested on a full-scale concrete slab. The slab contains eleven departure/arrival points for trajectories. Bi-directional trajectories of a single occupant between X1 and X4 are used for testing the presented methodology (see Figure 4).

Eight vibration sensors (Geophones SM-24 by I/O Sensor Nederland bv) are used to measure vertical velocity responses of the slab at a sampling rate of 1000 Hz (using an acquisition unit NI PCIe-6259). Vibration sensors are placed based on engineering judgment with the objective to cover to entire space providing clear measurements. Based on prior knowledge of the dynamical behavior of the structure sensor placement is done in order to capture higher natural modes (for example Sensors S2, S6, S7 and S8 in Figure 2) in addition to fundamental modes. In this case study, eleven departure/arrival points are assumed and define all possible trajectories (see Figure 2). The predefined departure/arrival points lead to 121 possible trajectories. Trajectories connecting points X1 and X4 are tested in both directions for model-based occupant tracking strategy. Measurements from a single occupant (approximately 90 kg) are taken using two types of shoes: hard-and-soft soled shoes. Although walking frequency is not fixed, it is naturally situated around 1.6 Hz.

Ambient-vibration measurements have revealed that vertical floor vibrations are contaminated by electrical instruments that operate at a fixed frequency of 50 Hz. Therefore, signal components at frequency range of [49-51] Hz are canceled out using a stop-band Butterworth filter to enhance signal-to-noise ratio of footstep events. Based on the ambient vibration measurements, fundamental vertical bending modes of the structure are found to be contained within the frequency range of [9-15] Hz. Using baseline levels of the ambient noise (see Section 2) and prior knowledge of walking frequency, each footstep-event signal of a walking occupant is detected and extracted successively from vibration measurements.

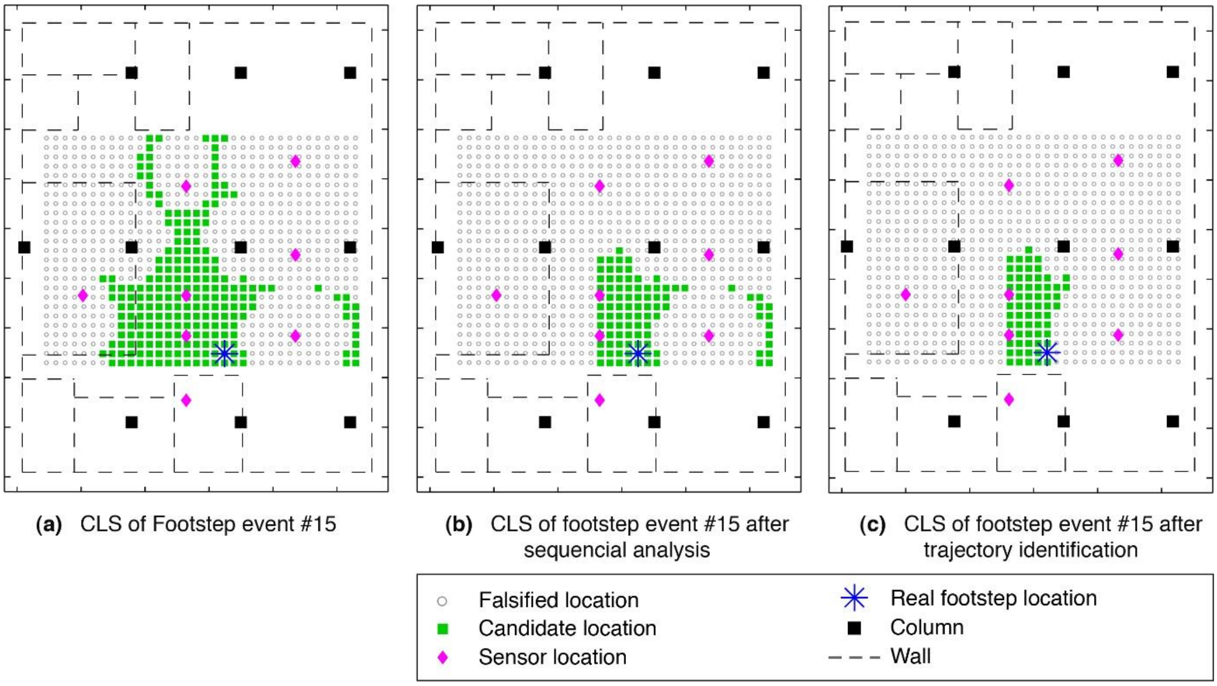
Model responses are simulated using a finite-element model of the slab. The dynamic responses of the slab generated by footstep impacts at various locations are simulated based on modal superposition. A time-history function describing the footstep-impact load is applied at all predefined locations that cover most of the accessible zones in Figure 2. Footstep-impact load function is described as a convex-shaped function that starts with non-zero slope and ends with zero slope. The input function is designed as a succession of two sine functions to illustrate events of heel contact (transmission of the full weight to the floor) and toe-off of the foot (Racic, Pavic and Brownjohn, 2009). Based on previous studies (Drira *et al.*, 2019), footstep full-weight duration (duration of the first sine function) is taken to be 0.1s and viscous damping ratio is taken to be 5% according to engineering heuristics.

Model simulations are prone to multiple sources of uncertainties that arise from unknown model parameters as well as model simplifications (such as idealized boundary conditions and omissions of separation walls and furniture). Model uncertainties resulting from model simplifications and omissions are estimated as a uniform distribution of [-30, +40] %. As the applied load function operates with low-frequency component that falls within the range of natural periods of the structure, low-frequency components of model simulations are highly affected (Drira *et al.*, 2019). Thus, velocity amplitudes are over-estimated leading to additional model uncertainties of up to [-40, 0] %.

Similar to modeling uncertainties, measurements are affected by multiple sources of uncertainties: limitations of sensor resolution and precision as well as variability of footstep-induced floor vibrations. This fluctuation of floor vibrations may result from natural variability of walking rhythm and impact force as well as the type of shoes worn by the occupant. Based on prior measurements of a person walking multiple trajectories along the same predefined locations using hard-and-soft-soled shoes, measurement uncertainties are found to be bounded by the interval [-45, 45] %. A uniform uncertainty distribution is assumed due to limited number of measurements and lack of more precise information about probability distribution.

Based on combined uncertainties, using Monte-Carlo sampling, and a target reliability of identification of 95 %, thresholds for each captured footstep event are estimated for occupant localization (Pasquier *et al.*, 2016; Pai, Nussbaumer and Smith, 2018). EDMF incorporates structural behavior of the floor slab, through footstep-impact simulations at predefined locations, to identify with a binary manner an estimate of occupant localization. For each footstep event, location instances for which residuals between model simulations and floor-vibration measurements are not compatible with the falsification thresholds are falsified. Combining information from each sensor location, remaining location instances define a CLS of each footstep event (see Figure 3,a for an example). Afterward, resulting CLS of each footstep event are subjected to sequential analysis and trajectory identification to infer candidate trajectories. A representation of the improvement over the CLS (squares) for the fifth footstep event of an occupant walking with hard-soled shoes from points X4 to X1 (see Figure 2) after sequential analysis and trajectory identification is shown in Figure 3. Based on the resulting CLS of the fifth footstep event (see Figure 3), only paths from departure point X4, except for arrival point X3, are candidate trajectories.

Sequential analysis reduces the ambiguity of CLS of each footstep event by verifying that the distance between two successive footstep events does not exceed a predefined distance (twice pre-defined step length). Taking into account information from previous footstep events, sequential analysis enhances the precision of CLS of each footstep event as shown in Figure 3,b. Assuming that all departure/arrival points are predefined and that occupants walk without backtracking until reaching destination, a trajectory identification is performed to further increase the precision of the resulting CLSs. A reduction in the size of the CLS related to a possible departure point is achieved when distances with all possible arrivals do not reduce the distance between the corresponding departure and all possible arrivals (see Figure 3,c).



(a) CLS of Footstep event #15 **(b)** CLS of footstep event #15 after sequencial analysis **(c)** CLS of footstep event #15 after trajectory identification

Figure 3: Candidate location set of footstep event #15; the precision of the candidate model set is enhanced based on (b) a sequential analysis and (c) subsequent trajectory identification. Information from previous footstep events (of the same trajectory) reduces the population of candidate locations (b). Candidate locations that do not reduce the distance between a departure and all possible arrivals are falsified (c).

Figure 4 illustrates examples of resulting CLSs (squares) of some footstep events that correspond to a tested trajectory of an occupant walking with soft-soled shoes from points X1 to X4 (see Figure 2). Circles correspond to falsified locations and real footstep locations (true occupant location) are represented with stars. CLS of the first captured footstep event needs to be compatible with the predefined departure points (see Figure 2), based on the same assumption than sequential analysis that verifies compatibility between subsequent step locations (see Equation 2 in Figure 1). CLs that are not compatible with a potential departure point are rejected (see footstep event #1 in Figure 4). Remaining departure points in Figure 4 are X1, X7, X9 and X11 (see Figure 2). Thus, CLs of the first footstep event are grouped based on corresponding departure points. Candidate trajectories starting from each starting point are updated with sequential analysis and trajectory identification using the information of all subsequent footstep events. CLs that verify the departure points X7, X9 and X11, illustrate the ambiguity resulting from model-based occupant localization. Measured floor vibrations are compatible with model simulations for all three departure points.

As can be seen in Figure 4, CLSs cover the true occupant locations for each footstep event. Thus, it is concluded that model-based occupant tracking provides accurate occupant localization results. However, for most footstep events precision of localization is low. Lack of precision of occupant localization may be due to the unknown parameter values of the finite-element model as well as treating the effect of shoe types as additional uncertainty source. Incorporating the existing obstructions such as separating walls and doors within trajectory identification may reduce the CLSs of footstep events and thus, will be studied in future development of the methodology.

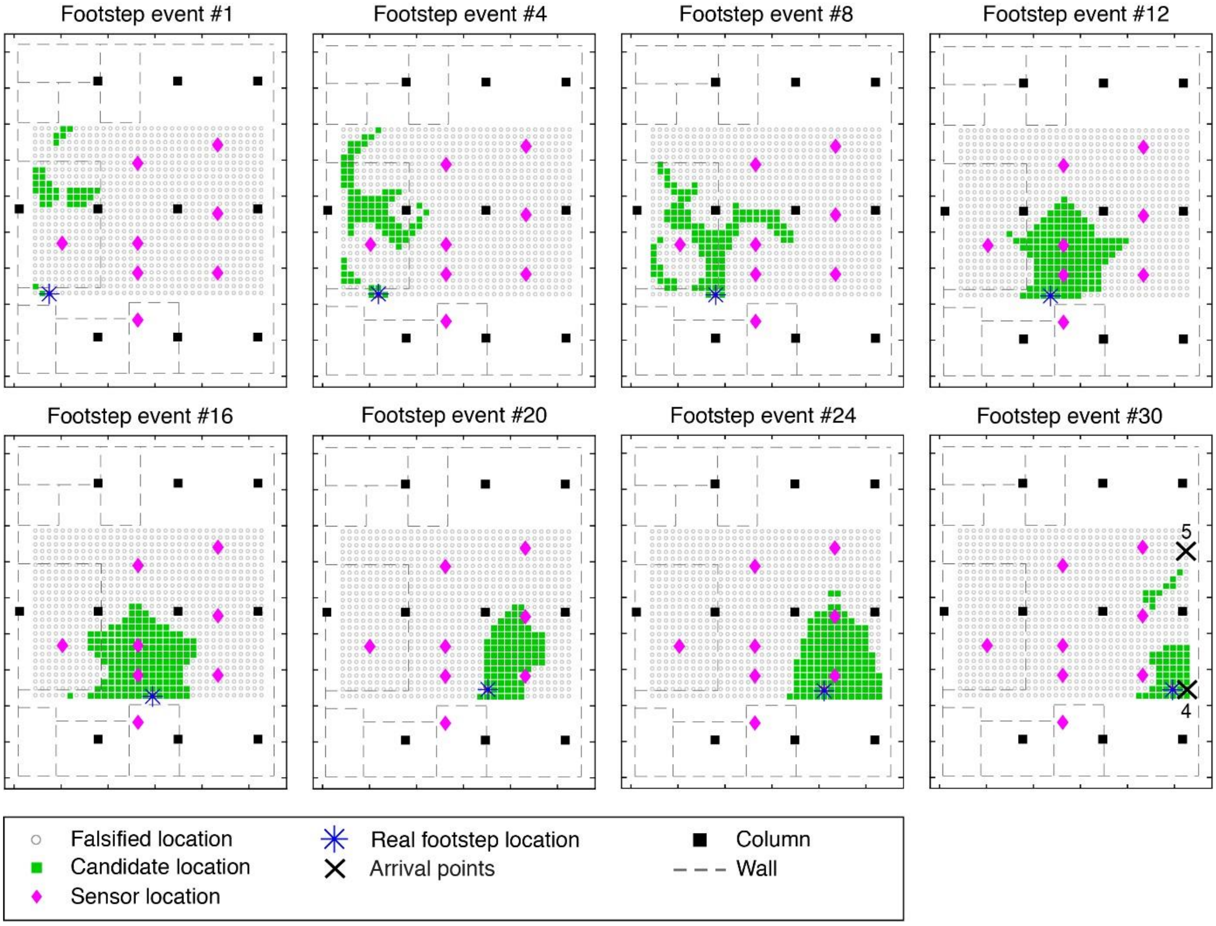


Figure 4: Candidate-location sets that are obtained using EDMF, sequential analysis and trajectory identification (see Figure 1) for an occupant walking with soft-soled shoes from X1 to X4 (see Figure 2).

Based on resulting CLSs and predefined departure/arrival points, candidate trajectories are identified and updated with information from CLS of each footstep-event. CLS of the first captured footstep event define the initial candidate trajectories. Only departure points that correspond to CLs are taken to be possible paths with the respect of all possible arrivals (see Figures 2 and 4). Exploring CLSs of remaining captured footstep events provides further information about trajectories that remain potential candidate trajectories. When a potential trajectory is achieved (reaching an arrival point) without exploring all CLS of captured footstep events, the corresponding trajectory is rejected. Once all CLSs of all captured footstep events are verified, candidate trajectories that do not end near arrival points are falsified. Based on CLS of the last captured footstep event (see footstep event #30 in Figure 4), only arrival point X4 leads to candidate trajectories. Table 1 summarizes the number of candidate trajectories at the first and the last detected footstep event of four-tested trajectories (see Figures 2 and 4).

Table 1: Number of candidate trajectories corresponding to first-and-last footstep events for four-tested trajectories (see Figure3).

Tested Trajectory	Candidate trajectories at footstep event #1	Candidate trajectories at the last footstep event
From X4 to X1; walking with hard-soled shoes (31 footstep events)	20 (out of 121)	3 (out of 121)
From X1 to X4; walking with hard-soled shoes (30 footstep events)	40	4
From X4 to X1; walking with soft-soled shoes (30 footstep events)	30	4
From X1 to X4; walking with soft-soled shoes (30 footstep events)	40	4

Starting from the first-footstep event, tested trajectories that relate points X1 and X4 of an occupant walking with hard-and-soft soled shoes (both directions) have led to a falsification of 66 % of possible initial candidate trajectories in worst cases (40 out of 121). Despite the lack of precision regarding the CLS of all footstep events, model-based occupant tracking provides a precise trajectory identification (approximately 97 %) with the correct trajectory is included in all cases.

Therefore, combining the knowledge of structural behavior with measurements and taking into account various sources of uncertainties, model-based occupant tracking has the potential to provide accurate and precise candidate trajectories of an occupant walking with different shoe types.

4. Conclusion

Model-based occupant tracking has been applied for an occupant walking with two types of shoes on a full-scale slab and leads to the following conclusions:

- Model-based occupant tracking (using error-domain model-falsification, EDMF) that includes structural information and takes into account systematic errors and model bias has the potential to identify accurately single occupant locations in a full-scale structure.

- Occupant tracking using sequential analysis and trajectory identification has the potential to provide precise occupant trajectories. For all case studies, a maximum of four candidate trajectories out of 121 have been identified.
- Model-based occupant tracking strategy can be applied to various types of shoes (sacrificing precision for accuracy) to identify accurately single occupant locations within a full-scale structure.

Future work includes studies of multiple occupants and automatic detection and correction for shoe type.

5. Acknowledgments

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