Privacy preserving indoor location and fall detection system

Aleksandar Tošić
aleksandar.tosic@upr.si
University of Primorska, UP FAMNIT
Koper, Slovenia
InnoRenew CoE
Izola, Slovenia

Jernej Vičič
jernej.vicic@upr.si
University of Primorska, UP FAMNIT
Koper, Slovenia
ZRC-SAZU
Koper, Slovenia

Michael David Burnard
mike.burnard@innorenew.eu
InnoRenew CoE
Izola, Slovenia
University of Primorska, UP IAM
Koper, Slovenia

ABSTRACT

In this paper we present a prototype implementation of location aware floor tiling system. The prototype is based on cost effective and readily available sensors and controllers. They were designed to be easy to install and modular. A dynamic range adjustment algorithm was developed to make the system more flexible and more material agnostic. This allows the sensors to be integrated under virtually any flooring. The system was designed for passive and privacy preserving location detection but can be applied in various fields. In this paper we focus on the application of the technology for fall detection, studying behaviour patterns of buildings occupants, and other telemetry related to health.

CCS CONCEPTS

• **Computer systems organization** → **Embedded and cyber-physical systems**; • **Human-centered computing** → *Human computer interaction (HCI)*; • **Software and its engineering** → Software notations and tools.

KEYWORDS

Privacy preservation, Sensor Network, Location Detection, Smart Buildings

1 INTRODUCTION

Smart buildings have gained a lot of attention from both research and industry. Collecting information about the state of the building and its occupants can be very beneficial to many fields ranging from structural health monitoring, studying behavioral patterns that aid in designing buildings, and monitoring the health of a building's occupants. Most software and hardware combinations require knowledge about the position of occupants within the building at any given time. The existing approaches to on-site location data collection suffer from both usability issues and technological obstacles. Typical implementations include but are not limited to wearable devices (i.e., location aware bracelets) that can be discarded by unaware users, or require frequent battery charging, on-site support, and maintenance. Sensor networks that do not rely on wearable devices usually include cameras and microphones coupled with automatic face detection software that have a psychological impact on occupants and raise privacy concerns. To overcome these issues, the inventors designed a network of force resistor sensors deployed under the finishing layer of a floor. A high enough density of sensors allows for very accurate location detection, as well as detection of other forced-based phenomena such as falls. Additionally, walking patterns can be detected and analyzed to not only locate buildings occupants but plot a historical path. Moreover, the data can be used to create a heat-map and study behavioural patterns in of certain locations within the building. The Internet of Things (IoT) is experiencing widespread adoption across industry sectors ranging from supply chain management to smart cities, buildings, and health monitoring. However, most architectural patterns for IoT deployment rely on centralized cloud computing infrastructures [10] for providing storage and computing power. Cloud providers have high cost-based incentives to organize their infrastructure into clusters. Concerns about data protection and privacy have been growing in recent years due the frequency and severity of big data breaches becoming public [13]. As IoT adoption grows, more privacy preserving solutions and architectures must be developed to protect sensitive user data and at the same time allow harnessing the true potential of large scale sensor networks. The overall fall detection system market was valued at USD 358.6 million in 2016 and is expected to reach USD 497.3 million by 2022, at a CAGR of 5.58 % between 2017 and 2022 [12]. The growth of the fall detection market is largely driven by the growing population of older adults that can benefit from better accessibility to assistance in case of falls, improved health outcomes for those that fall, reduced medical expenses. In turn, these factors have driven increased demand for smartphone and wearable technology-based fall detection systems, and increased demand for multimodal technology. However, the low practicality and acceptability of the technology among older adults, and the use of data from simulated conditions for designing fall detection system algorithms acts as a restraining factor for the market. The technology proposed here addresses exactly these restraints. Multimodal sensors include accelerometers and gyroscopes; magnetometers; and audio, images, and video clips via speech recognition and on-demand video techniques. The last group is avoided by our system as it clashes with personal data concerns. The popularity of machine learning methods is the primary reason behind the growth of the market for multimodal sensors in the fall detection system market. Machine learning algorithms needs an array of data sources (e.g., sensor data) to carry out a real-time analysis of numbers and differentiate a fall from other activities of daily living [4]. Along with this, multimodal sensors also use artificial intelligence (AI) to detect falls.

2 POTENTIAL USE CASES

Two key features of the proposed solution are high availability and low costs. These attributes make the technology suitable for a wide range of solutions in a variety of environments. The inventors have proposed the following use-cases:

- Specifically designed algorithms that can detect accidental falls which can be used in homes for older adults, rehabilitation centres, and other cases that support fall-prone individuals. In case a fall is detected the system alerts caregivers.
- Analyzing collected data can provide more insights into how specific areas of the building are being used. This information can help optimize the design of future buildings (and improve existing ones), improve energy efficiency, and optimize the use of active systems. These gains apply to multi-passenger vehicles such as cruise ships and airplanes, as well.
- Specific solutions where anonymous tracking of occupants is needed, such as health institutions treating patients with Alzheimer's, and buildings with high occupancy dealing with extraordinary situations (i.e., when evacuation is required before activating fire suppression systems).

The proposed solution falls into the broad category of smart building technologies. It is estimated that global IoT smart building market will approach $51.44B USD globally by 2023 and 33 % of IoT smart building market will be powered by AI technologies by then. North America will lead the IoT smart building market with 36 % share. Smart building automation systems will grow at 48.3 % CAGR from 2018 − 2023. The key solution areas are MEC, 5G, real-time IoT data analytics, and asset tracking.

3 STATE OF THE ART - RESEARCH AREA DESCRIPTION

Demographic change towards an older society has driven both interest and innovation in technological solutions for older adults. However, technology adoption by older adults is lower than in other demographic segments. Lee and Coughlin [9] cite a lack of understanding in the needs, lifestyles, and expectations from technologies designed for them by a younger demographic. This gap poses an obstacle to realizing the potential of fall-detection technologies (and other solutions). However, passive solutions that remain cost competitive should encounter fewer barriers to adoption. Fall detection systems that maintain privacy and don't require active use (i.e., don't require actively wearing a monitoring device) are likely to be considered a valuable system by more users.

While there is no clear agreement on how to classify fall detection systems [6], the simplest classification is into two broad categories: wearable, and non-wearable [2, 8]. Wearable systems are typically based on accelerometers or gyroscopes in garments or other worn items (i.e., jewelry) that detect changes in the plane of motion [2]. Non-wearable systems are typically environmental sensors that may be cameras (e.g., infrared, video), acoustic sensors like microphones, or pressure plates [2]. Other classifications of fall detection systems are divided based on data source (i.e., vision-based, ambient sensors, kinematic sensors; [5]); data availability (i.e., because falls are rare events, a taxonomy based on data sufficiency is critical [7]). Other perspectives on fall detection are based on more human-centric approaches and discuss the status of the person before and after the fall (i.e., falls from sitting and standing positions may present themselves differently to different sensors, or that differences in body shape and position may impact fall detection to different sensors) [14]. Fall detection systems based on mobile devices has recently gained interest as well (c.f., [3], [1], [11]).

In addition to the value fall detection systems provide and their cost, other major concerns are privacy and reliability. The reliability of passive wearable devices are influenced by system issues (e.g., power source, connectivity, functionality, etc.) in addition to the requirement that they be worn, which requires active measures from the user. Non-wearable passive systems have the same system reliability concerns, but do not require active engagement from the user to fulfill their purpose. However, passive systems require the system be installed where the user will spend their time. Some active systems can follow the user beyond the confines of their residence, for example those based on mobile devices connected to cellular networks.

Fall detection systems are largely targeted towards older adults and other vulnerable groups that are likely to suffer from falls. However, the same technology can be applied in other situations as well. Pressure sensing floors may also be used to detect the presence of people in critical areas, for example to ensure an evacuation has occurred before fire suppression systems that can harm or kill people are activated. These systems operate based on sensors installed in floor systems that may replace standard floors entirely or may be mats that cover floors in critical areas.

4 THE PILOT IMPLEMENTATION

The pilot implementation is a floor system measuring 120 cm by 120 cm, with a standard laminate flooring surface over a layer of rolled foam insulating subfloor. Below this layer, a system of 9 force sensors are placed and wired to an Arduino micro-controller. When force is applied to the floor, for example by walking across, standing, or placing objects on it, voltage differential is measured to obtain estimates of amount of force applied to each sensor individually. The type of sensors used in pressure sensing tiles are force sensitive resistors that can sense force anywhere in the range of 100g-10kg.

The range can be altered by applying different resistance which was used to increase the interval to 30kg. The sensor network is dynamic, making it difficult to model. There are many factors contributing to the constant change in differential between force applied on the top of the floor tiling (i.e., walking) and measured force mostly due to unpredictable changes in the materials on all layers. Moreover, there are discrepancies between the sensing ranges of each individual sensor. Due to the varying compression resistance in the floor materials, one sensor in the network can measure higher pressure differentials than others where the material compresses less. Our solution is a dynamic range adaptive algorithm that constantly adapts the sensing range obtained from the initial calibration process. For each sensor, bounds are set as an interval $[x, y]$. The algorithm monitors the data stream and searches for new maximum and minimum values that are used to decrease the lower bound x or increase the upper bound y respectively. However, the increase is done by using the moving average with a configurable window. This is to mitigate potential outliers. To test the prototype, an application was built that can process the data stream from the controller and visualize the pressure detection in a form of a heat map. The software also includes a calibration guide for the initial setup that can be observed in Figure 2. The application also provides the an interface for data analysis. Modules can be developed to hook up to the data stream. The data stream is a snapshot of sensor data sent over a serial port (USB) every 200ms. The interface will be used to develop different modeling techniques to detect falls such as neural networks, association rules, etc.

Figure 1: Prototype solution using off-the-shelf sensors under a standard laminate floor. Arduino Mega collects all the data and a program on a notebook running all our algorithms visualizes possible fall situations.

5 DISCUSSION AND FUTURE CHALLENGES

A pilot implementation of the hardware and software solution was prepared at the beginning of 2019 and presented at the Chamber of Commerce and Industry of Slovenia at the Future Living exhibition. The setting was on display (and available for testing) for four months with no intervention. The setting comprised of an array of pressure sensing sensors integrated in a laminate floor system. The sensors were connected to a micro-controller that dynamically adjusted the sensing ranges of the array. The algorithm was capable of sensing and later ignoring placed objects. Although the technology has been tested on a small pilot implementation, the challenges presented by a specific implementation setting will bring unforeseen challenges. These challenges are amplified as most of the expected use cases involve humans and

Figure 2: Software calibration

human behaviour is hard to model. The integration of the proposed systems to the customer's environment depends also on the technologies used by the customer although the systems were developed using open interfaces. Additionally, the behaviour of the sensor grid must be tested on other materials that are less flexible and hence, decrease the sensing accuracy of the load cells. Mass production of the sensor tiles is also an aspect that still needs to be addressed. At the time of writing, a modular design based on integrated connectors in the shape of puzzle pieces is being considered. The puzzle type tiles could allow for seamless assembly with no wiring needed to create a special sensing layer underneath any type of floor.

REFERENCES

[1] Stefano Abbate, Marco Avvenuti, Francesco Bonatesta, Guglielmo Cola, Paolo Corsini, and Alessio Vecchio. 2012. A smartphone-based fall detection system. *Pervasive Mob. Comput.* 8, 6 (dec 2012), 883–899. https://doi.org/10.1016/j.pmcj.2012.08.003

[2] Shomir Chaudhuri, Hilaire Thompson, and George Demiris. 2014. Fall Detection Devices and Their Use With Older Adults. *J. Geriatr. Phys. Ther.* 37, 4 (2014), 178–196. https://doi.org/10.1519/JPT.0b013e3182abe779 arXiv:NIHMS150003

[3] Jiangpeng Dai, Xiaole Bai, Zhimin Yang, Zhaohui Shen, and Dong Xuan. 2010. PerFallD: A pervasive fall detection system using mobile phones. *2010 8th IEEE Int. Conf. Pervasive Comput. Commun. Work. PERCOM Work. 2010* (2010), 292–297. https://doi.org/10.1109/PERCOMW.2010.5470652

[4] Céline Franco, Jacques Demongeot, Christophe Villemazet, and Nicolas Vuillerme. 2010. Behavioral telemonitoring of the elderly at home: Detection of nycthemeral rhythms drifts from location data. In *2010 IEEE 24th International Conference on Advanced Information Networking and Applications Workshops*. IEEE, 759–766.

[5] Farrukh Hijaz, Nabeel Afzal, Talal Ahmad, and Osman Hasan. 2010. Survey of fall detection and daily activity monitoring techniques. *2010 Int. Conf. Inf. Emerg. Technol. ICIET 2010* (2010), 1–6. https://doi.org/10.1109/ICIET.2010.5625702

[6] Raul Igual, Carlos Medrano, and Inmaculada Plaza. 2013. Challenges, issues and trends in fall detection systems. *Biomed. Eng. Online* 12, 1 (2013), 66. https://doi.org/10.1186/1475-925X-12-66

[7] Shehroz S. Khan and Jesse Hoey. 2017. Review of fall detection techniques: A data availability perspective. *Med. Eng. Phys.* 39 (2017), 12–22. https://doi.org/10.1016/j.medengphy.2016.10.014

[8] Matjaž Kljun, Klen Čopič Pucihar, Jason Alexander, Maheshya Weerasinghe, Cuauhtli Campos, Julie Ducasse, Barbara Kopacin, Jens Grubert, Paul Coulton, and Miha Čelar. 2019. Augmentation Not Duplication: Considerations for the Design of Digitally-Augmented Comic Books. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, Article 103, 12 pages. https://doi.org/10.1145/3290605.3300333

[9] Chaiwoo Lee and Joseph F. Coughlin. 2015. PERSPECTIVE: Older Adults' Adoption of Technology: An Integrated Approach to Identifying Determinants and Barriers. *J. Prod. Innov. Manag.* 32, 5 (sep 2015), 747–759. https://doi.org/10.1111/jpim.12176

[10] Somayya Madakam, R Ramaswamy, and Siddharth Tripathi. 2015. Internet of Things (IoT): A literature review. *Journal of Computer and Communications* 3, 05 (2015), 164.

[11] Stefan Madansingh, Timothy A. Thrasher, Charles S. Layne, and Beom Chan Lee. 2015. Smartphone based fall detection system. *ICCAS 2015 - 2015 15th Int. Conf. Control. Autom. Syst. Proc.* (2015), 370–374. https://doi.org/10.1109/ICCAS.2015.7364941

[12] Markets and markets. 2017. *Fall Detection System Market.* Technical Report. MarketsAndMarkets. 156 pages. https://www.marketsandmarkets.com/Market-Reports/fall-detection-system-market-125162303.html

[13] Wencheng Sun, Zhiping Cai, Yangyang Li, Fang Liu, Shengqun Fang, and Guoyan Wang. 2018. Security and privacy in the medical internet of things: a review. *Security and Communication Networks* 2018 (2018).

[14] X Yu. 2008. Approaches and Principles of Fall Detection. *Healthcom* 10, 1 (2008), 42–47.