Seamless Indoor-Outdoor Transition Detection Through Door Crossing Awareness Using Deep Learning

Group 11 – KSE801 “Data Analysis based on Deep Learning”

Juho Son  
 Industrial Engineering  
 Korea Advanced Institute of Science and Technology  
 Daejeon, South Korea  
 email@email.com

Keunchul Park  
 Civil & Environmental Engineering  
 Korea Advanced Institute of Science and Technology  
 Daejeon, South Korea  
 [email@email.com](mailto:email@email.com)

Joseph Berkner  
School of Computing  
 Korea Advanced Institute of Science and Technology  
 Daejeon, South Korea  
 josephberkner@kaist.ac.kr

ABSTRACT

∗Article Title Footnote needs to be captured as Title Note

†Author Footnote to be captured as Author Note

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

*WOODSTOCK’18, June, 2018, El Paso, Texas USA*

Figure 1: Yearly trend of number of publications listed in *Google Scholar* using the keyword “Indoor Localization”

© 2018 Copyright held by the owner/author(s). 978-1-4503-0000-0/18/06...$15.00

https://doi.org/10.1145/1234567890

In indoor positioning systems, the seamless detection of environment changes (outdoor to indoor and vice versa) is a crucial part of setting up radio maps (the reference system in many such systems) and for a user-friendly experience. Nevertheless, this field is still struggling with several challenges, especially regarding the time delay between the actual transition moment and the detected one. This paper tries to address this issue by introducing deep learning approaches using heterogeneous smartphone sensor data to detect indoor-outdoor transitions. The central assumption considered here is that we define a transition moment to be associated with the usage of a door. Therefore we focus our research on detecting door crossings with said sensor data. Our results show that...

CCS CONCEPTS

• **Computing methodologies ~ Neural networks** • Information systems ~ Mobile information processing systems

KEYWORDS

Indoor-Outdoor Transition Detection, Human Activity Detection, Indoor Localization, Deep Learning

ACM Reference format:

Joseph Berkner, Keunchul Park and Juho Son. 2020. Seamless indoor-outdoor transition detection through door crossing awareness using deep learning. In *Proceedings of ACM Woodstock conference (WOODSTOCK’18). ACM, New York, NY, USA, 2 pages.* https://doi.org/10.1145/1234567890

1 Introduction

Nowadays, indoor localization receives more attention among scientists than ever before (see figure 1). This is not to any surprise, because, for one thing, people are living more than 87% of their life in indoor environments (office, home, shopping center, etc.) [1] and, for another, in recent years smartphones became an essential part of our daily life and with them the ability to directly measure the position and activity of a person. Thus, the demand and technology are ready to be explored for indoor localization, which is not a trivial task due to the absence of sufficient GPS signal coverage inside buildings. In fact, many studies and techniques exist to locate a person in indoor environments, utilizing a wide range of sensor data from mobile phones and pre-existing infrastructure [2]. Here, one of the most promising methods is a Wi-Fi signal-based approach using received signal strengths (RSS). This is mostly due to the capability of every modern smartphone to detect such signals and a pre-established constellation of WiFi access points in many publically accessible buildings, which serve as a reference system for the positioning of a person the same way satellites do in GPS. This reference system is fed with so-called fingerprints, each one of them being a vector of RSS values from different AP's corresponding to a specific position in the indoor environment. The term referred to such a set of fingerprints representing a whole indoor environment is a radio map. The construction of such radio maps was very labor-intensive in the past, as people had to visit the buildings themselves beforehand to collect fingerprint data. Hence, it was also very inflexible in its ability to adapt to changes in the environment. With the emergence of smartphones, this becomes an unpopular approach because data can be directly collected using implicit crowdsourcing [3]. Besides the increasing success of such simultaneous localization and mapping (SLAM) methods [4-7], several challenges remain up to now, one of them being seamless indoor-outdoor transition detection (IOTD). Positioning systems in general struggle with the identification of the exact moment a user enters or exits a building. However, this is crucial for SLAM-based methods to simultaneously construct an accurate radio map as well as to provide a user-friendly navigation system.

In this paper, we discuss the idea of implementing an IOTD system based on the assumption that a person uses a door of some kind to transfer between indoor and outdoor. By using human activity detection strategies with smartphone sensor data and a deep learning algorithm, we try to detect the moment a person walks through a door and, thus, the point in time of building entrance or exit.

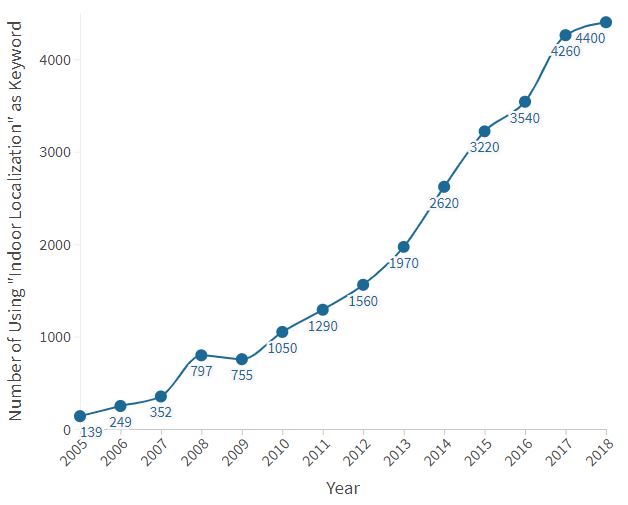


Figure 1: Yearly trend of number of publications listed in *Google Scholar* using the keyword “Indoor Localization”

2 Related Work

2.1 Indoor-Outdoor Transition Detection

IOTD is subject to extensive research in recent years. One of the earlier systems of leveraging smartphone sensor data to distinguish between outdoor and indoor environments was *IODetector* using a Hidden Markov Model (HMM) and reached a recognition accuracy of 96.2% [8]. Due to its dependence on cellular towers, it may not be a desirable approach nowadays as smartphones do not always record RSS of all neighboring towers [9]. Another multi-modal system is *SenseIO*, which used fixed detection rules from numerous sensors to reach an accuracy of over 92% [10]. However, because utilizing many sensors at the same time leads to high power consumption, other techniques exist to limit their number. Considering the fact of loss of GPS signal in indoor environments, a system may also solely use this information for IOTD [11,12]. This comes at a cost for accuracy, which may not reach the mark of 90%.

Machine learning also plays a more significant role in the field of IOTD. This includes stacking schemes [9,14] as well as semi-supervised deep learning-based methods [15].

However, only two other studies were found that did not exclusively concentrate their evaluation on the accuracy but also tried to decrease the transition time, meaning the time delay a system requires for IOTD. Sung et al. [13] proposed a sound-based IOTD system analyzing reverberation patterns of a special chirp sound probe. They achieved a detection accuracy of roughly 95%, with an average transition time of 3.81s. Zhu et al. [9] introduced a solution that accounted for all, a fast transition time (probability of switching delay within 3 s exceeding 80%) with a high detection accuracy (97.02% for new environments) for a set of environments with different levels of complexity.

2.2 Door Crossing Detection

As mentioned earlier, our approach to improving IOTD systems is to incorporate door crossing detection (DCD) as our assumption is that in most cases, a person enters/exits a building through a door. As an important note: This, however, will not account for so-called hybrid environments, in which the GPS signal is also week due to complex structures such as an open hall which do not have doors. Until now, DCD algorithms are usually vision- or infrastructure-based and mostly applied in the field of robotics. Currently, leveraging smartphone sensors for DCD has not a high demand in research yet, with only two papers addressing this strategy. Zhao et al. [16] concentrated their work on creating a lightweight solution with the primary data source coming from the magnetometer. The addition of other sensors is then based on a fusion method with a majority-voting model. The system leads to a DCD accuracy of 90% on average. However, their focus on magnetic sensor data leads to challenges in situations of noisy environments (e.g., metal doors) and due to the low quality of smartphones' magnetic sensors. Furthermore, the system was solely tested on indoor environments and thus not applied to perform IOTD. Racko et al. [17] did address this task to improve their pedestrian dead reckoning algorithm and reached an IOTD accuracy of 82.7%. However, they did not evaluate their system on transition time and mainly used accelerometer data in combination with positioning information to detect door crossing moments.  
In contrast to the above two studies, we are applying deep learning methods on heterogeneous sensor data to enhance IOTD. To the best of our knowledge, the approach of combining DCD with deep learning methods for IOTD is novel and has the potential of notably decreasing the transition time.

3 Methodology

3.1 Data Acquisition

For the data collection we used three Huawei phones

3.2 Data Preprocessing

Holding phone Huawei walking and label

5 Results

6 Discussion and Future Work

Implement model to a mobile system and test its accuracy on novel environments

7 Conclusion

Imple

 (1)

**Continuation part of Paragraph Text** The user must style this paragraph in **ParaContinue** style, which follows immediately after the **DisplayFormula** (numbered equation). The **DisplayFormula** style is applied only in case of a numbered equation. A numbered equation always has a number to its right. Insert paragraph text here. **Display Formula without Number**



The **DisplayFormulaUnnum** style is applied only in case of an unnumbered equation. An unnumbered display equation never contains an equation number to its right, and this unique property distinguishes it from a numbered equation.



Figure 1: Figure Caption and Image above the caption [In draft mode, Image will not appear on the screen]

**Theorem/Proof/Lemma.** Insert text here for the enunciation or Math statement. Insert text here for the enunciation or Math statement. Insert text here for the enunciation or Math statement. Insert text here for the enunciation or Math statement. Insert text here for the enunciation or Math statement.

....Insert text here for the Quotation or Extract, Insert text here for the Quotation or Extract, Insert text here for the Quotation or Extract, Insert text here for the Quotation or Extract, Insert text here for the Quotation or Extract, Insert text here for the Quotation or Extract.

1.1 Heading Level 2

In the below paragraph, it is explained how alt-txt value is placed in **MS Word 2010**. To add alternative text to a picture in Word 2010, follow these steps:

1. In a Word 2010 document, insert a picture.
2. Right click on the inserted picture and select the **Format Picture** option.
3. Select the **Alt Txt** option from the left-side panel options.
4. In the "Title:" and "Description:" text boxes, type the text you want to represent the picture, and then click "Close".

Below are steps to place alt-txt value in **MS Word 2013/2016**. To add alternative text to a picture in Word 2013/2016, follow these steps:

1. In a Word 2013/2016 document, insert a picture.
2. Right click on the inserted picture and select the **Format Picture** option.
3. In the settings at the right side of the window, click on the "Layout & Properties" icon (3rd option).
4. Expand **Alt Txt** option.
5. In the "Title:" and "Description:" text boxes, type the text you want to represent the picture, and then click "Close".

*1.1.1 Heading Level 3.* Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here.

*1.1.1.1 Heading Level 4.*Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here.

ACKNOWLEDGMENTS

Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here. Insert paragraph text here.

REFERENCES

[1] Neil Klepeis, William Nelson, Wayne Ott and John Robinson. 2001. The National Human Activity Pattern Survey (NHAPS): A Resource for Assessing Exposure to Environmental Pollutants. Journal of Exposure Analysis and Environmental Epidemiology 11, 3. LBNL Report #: LBNL-47713.

[2] Hui Liu, Houshang Darabi, Pat Banerjee and Jing Liu. 2007. Survey of Wireless Indoor Positioning Techniques and Systems. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 37, 6 (Nov. 2007), 1067-1080. DOI: 10.1109/TSMCC.2007.905750

[3] Baharesh Lashkari, Javad Rezazadeh, Reza Farahbakhsh and Kumbesan Sandrasegaran. 2018. Crowdsourcing and sensing for indoor localization in iot: a review. *IEEE Sensors Journal* 19, 7 (Apr. 2019), 2408-2434. DOI: 10.1109/JSEN.2018.2880180

[4] Han Zou, Ming Jin, Hao Jiang, Lihua Xie and Costas Spanos. 2017. WinIPS: wifi-based non-intrusive indoor positioning system with online radio map construction and adaptation. *IEEE Transactions on Wireless Communications* 16, 12 (Dec. 2017), 8118-8130. DOI: 10.1109/TWC.2017.2757472

[5] Suk-Hoon Jung, Byung-chul Moon and Dongsoo Han. 2015. Unsupervised learning for crowdsourced indoor localization in wireless networks. IEEE Transactions on Mobile Computing 15, 11 (Nov. 2016), 2892-2906. DOI: 10.1109/TMC.2015.2506585

[6] Anshul Rai, Krishna Chintalapudi, Venkata Padmanabhan, Rijurekha Sen. 2012. Zee: zero-effort crowdsourcing for indoor localization. In Proceedings of the 18th annual international conference on Mobile computing and networking *(Mobicom '12)*. ACM, New York, NY, USA, 293-304. DOI: https://doi.org/10.1145/2348543.2348580

[7] Min Zhang, Ling Pei and Xiaotie Deng. 2016. GraphSLAM-based crowdsourcing framework for indoor wi-fi fingerprinting. In 2016 Fourth International Conference on Ubiquitous Positioning, Indoor Navigation and Location Based Services (UPINLBS). Shanghai, 61-67. DOI: 10.1109/UPINLBS.2016.7809951

[8] Pengfei Zhou, Yuanqing Zheng, Zhenjiang Li and Guobin Shen. 2012. IODetector: A generic service for indoor outdoor detection. In *Proceedings of the 10th ACM Conference on Embedded Networked Sensor Systems (SenSys ‘12)*. ACM, New York, NY, USA, 113-126. DOI: 10.1145/2426656.2426668.

[9] Yida Zhu, Haiyong Luo, Qu Wang, Fang Zhao, Bokun Ning, Qixue Ke and Chen Zhang. 2019. A fast indoor/outdoor transition detection algorithm based on machine learning. *Sensors (Basel, Switzerland)* 19, 4 (Feb. 2019), 786. DOI: 10.3390/s19040786

[10] Mohsen Ali, Moustafa Youssef and Tamer El Batt. 2018. SenseIO: Realistic ubiquitous indoor outdoor detection system using smartphones. *IEEE Sensors Journal* 18, 9 (May 2018), 3684–3693. DOI: 10.1109/JSEN.2018.2810193

[11] Kongyang Chen and Guang Tan. 2017. SatProbe: Low-energy and fast indoor/outdoor detection based on raw GPS processing. In *Proceedings of the IEEE INFOCOM 2017—IEEE Conference on Computer Communications*. Atlanta, GA, USA, 1–9. DOI: 10.1109/INFOCOM.2017.8057095

[12] Han Gao and Paul D. Groves. 2018. Environmental context detection for adaptive navigation using gnss measurements from a smartphone. *J. Inst. Navig* 65, 99–116. DOI: 10.1002/navi.221

[13] Rakmin Sung, Suk-hoon Jung and Dongsoo Han. 2015. Sound based indoor and outdoor environment detection for seamless positioning handover. *ICT Express* 1, 3, 106–109. DOI: https://doi.org/10.1016/j.icte.2016.02.001

[14] Imran Ashraf, Soojung Hur and Yongwan Park. 2018. MagIO: Magnetic field strength based indoor- outdoor detection with a commercial smartphone. *Micromachines* 9, 10 (Oct. 2018), 534. DOI: 10.3390/mi9100534

[15] Illyyne Saffar, Marie L. A. Morel, Kamal D. Singh and Cesar Viho. 2019. Semi-supervised deep learning-based methods for indoor outdoor detection. In ICC 2019 - 2019 IEEE International Conference on Communications (ICC). Shanghai, China, 1-7. DOI: 10.1109/ICC.2019.8761297

[16] Liangyi Gong, Yiyang Zhao, Chaocan Xiang, Zhenhua Li, Chen Qian and Panlong Yang. 2019. Robust light-weight magnetic-based door event detection with smartphones. IEEE Transactions on Mobile Computing 18, 11 (Nov. 2019), 2631-2646. DOI: 10.1109/TMC.2018.2876841

[17] Jan Racko, Juraj Machaj and Peter Brida. 2018. Ubiquitous smartphone based localization with door crossing detection. *Engineering Applications of Artificial Intelligence* 75, 88-93. DOI: https://doi.org/10.1016/j.engappai.2018.08.001

Conference Name:ACM Woodstock conference

Conference Short Name:WOODSTOCK’18

Conference Location:El Paso, Texas USA

ISBN:978-1-4503-0000-0/18/06

Year:2018

Date:June

Copyright Year:2018

Copyright Statement:rightsretained

DOI:10.1145/1234567890

RRH: F. Surname et al.

Price:$15.00