Poster: Syncope Detection in Toilet Environments Using Wi-Fi Channel State Information

Ziqi Wang
Department of Electronic Engineering
Fudan University, China
wangzq14@fudan.edu.cn

Zhe Chen
School of Computer Science
Fudan University, China
zhechen13@fudan.edu.cn

Zhihao Gu
Department of Electronic Engineering
Fudan University, China
zhgu15@fudan.edu.cn

Yuedong Xu
Department of Electronic Engineering
Fudan University, China
ydxu@fudan.edu.cn

Junwei Yin
Department of Electronic Engineering
Fudan University, China
jwyin15@fudan.edu.cn

UbiComp/ISWC'18 Adjunct, October 8–12, 2018, Singapore, Singapore © 2018 Copyright is held by the owner/author(s).
ACM ISBN 978-1-4503-5966-5/18/10.
https://doi.org/10.1145/3267305.3267650

Abstract
Syncope and strokes in toilets can lead to severe injuries, and even pose life threats to patients. However, owing to privacy concerns, vision-based fall detection cannot be applied in such a scenario. In this poster, we propose ToiFall, a prototype for syncope detection in toilet environments. ToiFall collects Channel State Information (CSI) of commodity Wi-Fi devices. Different human movements form various textures on CSI images, and such textures can be used for feature extraction and classification. Experimental results show an accuracy of over 98% for fall detection with satisfying reliability.

Author Keywords
Channel state information; Fall detection; Action recognition

ACM Classification Keywords
[Human-centered computing]: Ubiquitous and mobile computing.

Introduction
With the 'aging tide' worldwide, the demand for mobile health monitoring systems is increasing. Disease-related falls (such as Micturition Syncope, Defecation

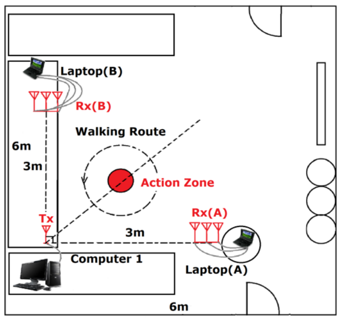

Figure 1: Test environment. Actions are performed within the action zone marked as the red dot.

Figure 2: Six movements performed by volunteers.

Movement	**Fall**	**Non-Fall**
Samples	150	200
Predicted as fall	148	3
Predicted as non-fall	2	197

Table 1: Prediction results of fall detection with SVM

Syncope, Stroke, etc.) and accidental falls happen more frequently in toilets than in other scenarios. Falls can lead to severe trauma and hemorrhage, posing life threat to patients. Moreover, medical statistics reveal that over 40% of stroke patients are unable to seek help or use emergency buttons when disease strikes [6]. Therefore, an immediate detection of such falls is crucial to the lives of patients. Vision-based fall detection techniques are relatively mature [8]. This approach, however, has its limitations. Setting up a camera in a private space may seriously violate the privacy of patients.

The state-of-the-art approaches employ ubiquitous Wi-Fi signals for fall detection. Wi-Fi Channel State Information (CSI) portrays the characteristics of the wireless channel where CSI is affected by human movements through multipath effects and thus carrying motion features. Previous works such as [1,7] leverage the Bayesian Classifier, Wavelet Analysis, or Outlier Detection techniques to process CSI data, and then apply SVM or KNN for classification of human actions. Chang et al. introduced image recognition algorithms into CSI-based motion classification [3]. Gabor filter and Bag of Word-SIFT are used for the feature extraction of CSI data. This provides deep insights for our system.

In this poster, we present ToiFall, an on-going system that passively detects syncope and stroke-related falls in toilet environments. We extract six representative movements including normal operations in toilets and falling towards all directions. The design of ToiFall follows the CSI visualization approach proposed in [3], but with specially designed experiments for falls. Experimental studies demonstrate that the fall detection accuracy is around 98% and the false alarm rate is around 1.5%.

We further proceed with the fall detection adopting deep neural networks. Our purpose is to bypass the more complicated feature extraction of CSI images, e.g. the selection of scales and orientations of Gabor filters. Our primary results show an accuracy of 99% for fall detection with residual network (ResNet)[5]. In the future, we wish to explore the interpretability of deep neural networks for fall detection, looking into their internal working mechanism in order to ensure ToiFall's reliability.

Data Acquisition

We build the system prototype using a Dell Vostro 3250 desktop with an Intel 5300 NIC as the transmitter, and two ThinkPad X200 laptops with Intel 5300 NICs as receivers. The center frequency of the Wi-Fi signals is set at 5.32 GHz. The CSITool [4] developed by Halperin et al. is loaded on all three computers for transmitting packets and collecting CSI.

Experiments are set in a 6 m x 6 m square room with simple furniture. As shown in Figure 1, the two antenna pairs are placed perpendicularly to achieve maximum sensitivity. All antennas are substantially the same height (70 cm) from the ground. We recruit 17 volunteers (12 males and 5 females) of different heights and weights in experiments. Volunteers are asked to perform one of the six movements that happen frequently in toilets. These movements are listed in Figure 2: walk, stand up, sit down, fall to the left, fall to the right and fall to the front. We retrieve 250 sets of CSI data from each movement. Another 250 sets of data in absence of any movements are also

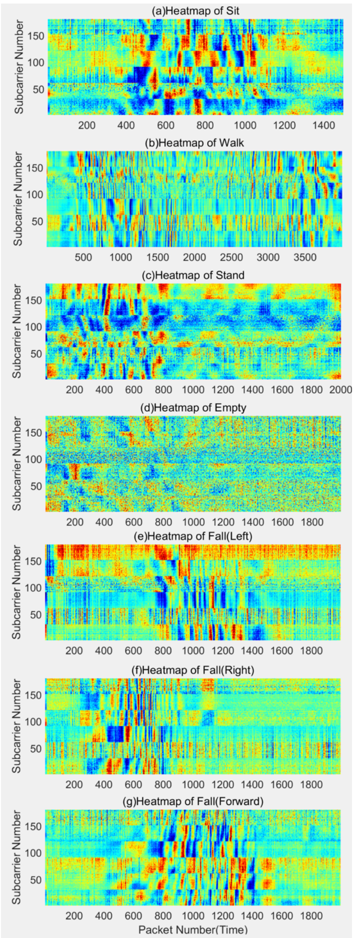

Figure 3: Heatmaps drawn with CSI matrix. (a)sit (b)walk (c)stand (d)empty (e)fall-left (f)fall-right (g)fall-forward

collected as control groups. In total, we collect CSI data of 1750 movements to form a dataset.

Methodology

Two communication links are deployed in ToiFall system, and thus we have six receiving antennas. CSITool [4] logs CSI on 30 subcarriers for each receiving antenna. We juxtapose all subcarriers and antennas to form a $180 \times time$[1] CSI matrix. In the pre-processing stage, we firstly extract amplitude of CSI data by calculating the modulus of CSI complex and then apply a 10-order Butterworth filter with cutoff frequency of 40Hz on each row to remove high-frequency noise. A centralization approach is also applied to remove static environmental components.

We observe that CSI variance is sensitive to environmental changes. After pre-processing, we propose a variance-based method for movement segmentation. ToiFall maintains a 4-second buffer and calculates the variance of the CSI amplitude within the buffer. Then ToiFall uses a dynamic threshold to detect movements. We calculate the variance of CSI at each time point, saving them into a list *var*. The first and last time points whose variance exceeds the threshold will be marked as a starting or end point of a movement. The threshold is set at:

$$threshold = min(var) + 0.4 * [max(var) - min(var)] \quad (1)$$

As shown in Figure 3, human movements are reflected as textures in the CSI matrix. From [3], we know that Gabor filters can achieve a satisfying effect in texture feature extraction. So firstly we apply a set of 15×15 Gabor filters of eight scales and six orientations [3] to the CSI matrix. For each convoluted image, we extract its mean and standard deviation. Thus we have $6 \times 8 \times 2 = 96$ features for each movement. After feature extraction, we use LIBSVM[2] library to train an SVM classifier. In the mean time, we also build another version of ToiFall using a 50-layer deep residual network (ResNet). We draw grey pictures from pre-processed CSI data, using them directly as the input of the ResNet, which can complete the tasks of feature extraction and classification simultaneously.

[1] Variable *time* refers to the number of received data packets.

Evaluation

The dataset is divided into two groups. For each movement, we randomly select 50 sets of data to form a test group, while the remaining 200 sets form a training group. The evaluation consists of two stages. Firstly, the data is divided into fall-like activities and non-fall-like activities and labeled accordingly. Then we use *precision*, *recall*, and *accuracy* to evaluate the system's ability to distinguish fall-like actions. Secondly, we further divide non-fall-like movements into four classes. Data is labeled into five categories to train a multi-class movement recognition system. We use a confusion matrix to describe the system's performance of action recognition.

Results

As shown in Table 1, ToiFall using SVM can precisely differentiate falls from non-fall activities. Table 2 reveals fall detection using deep learning. In table 1, only two falls are mislabeled as 'not fall', and there are only three false alarms among 200 non-fall actions. Table 2 reveals an even better result. We then calculate three parameters: *Accuracy*, *Precision,* and *Recall.* The results are shown in table 3.

Movement	**Fall**	**Non-Fall**
Samples	150	200
Predicted as fall	150	3
Predicted as non-fall	0	197

Table 2: Prediction results of fall detection with ResNet

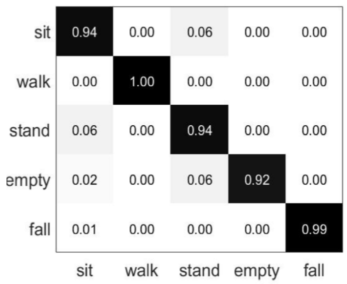

Figure 4: Confusion matrix of action recognition with SVM

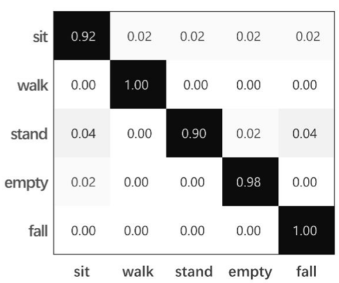

Figure 5: Confusion matrix of action recognition with ResNet

	Precision TP/(TP+FP)	Recall TP/(TP+FN)	Accuracy (TP+TN)/(TP +FP+TN+FN)
SVM	98.0%	98.7%	98.6%
ResNet	98.0%	100.0%	99.1%

Table 3: Fall detection results with two methods

Results show that the model has both good accuracy and reliability. ToiFall can acutely sense the fluctuation in CSI caused by fall-like events and provide predictions accordingly. Once the model is established, prediction only needs milliseconds, hence ToiFall can be used for real-time fall detection.

Furthermore, we subdivide the non-fall actions into four categories, building a multi-action recognition system. Figure 4 and 5 exhibit the confusion matrix of multi-class action recognition. The prediction accuracy of Sit, Walk, Stand, Empty and Fall is 94%, 100%, 94%, 92%, 99% respectively, using ToiFall with SVM. When we use ToiFall with ResNet, such accuracy reaches 92%, 100%, 90%, 98%, 100%. The overall accuracy is 96.6% with SVM and 97.1% with ResNet. As is shown in the result, our motion perception system can correctly distinguish these five types of actions.

Conclusion

This work constructs a CSI-Movement data set consisting of 1750 sets of CSI data from 17 volunteers and proposes a ToiFall system to detect syncope and stroke-related falls in toilets. This dataset is accessible on our website.[2] ToiFall system can achieve a fall detection accuracy of 98%, as well as an action recognition accuracy of over 97%. The model can precisely categorize ordinary movements inside a toilet.

[2] http://medianet.azurewebsites.net/toifall-ubicomp18/

Acknowledgements

This work is supported by Fudan's Undergraduate Research Opportunities Program (Xiyuan 17583).

References

1. Wenchang Cao, Xinhua Liu, and Fangmin Li, "Robust device-free fall detection using fine-grained Wi-Fi signatures.", Proc. of IEEE IAEAC, 2017: 1404-1408.
2. Chih-Chung Chang, and Chih-Jen Lin, "LIBSVM: a library for support vector machines.", ACM TIST, 2011, 2(3): 27.
3. Jen-Yin Chang, Kuan-Ying Lee, Yu-Lin Wei, Kate Ching-Ju Lin, Winston Hsu, "We Can 'See' You via Wi-Fi - WiFi Action Recognition via Vision-based Methods.", arXiv preprint arXiv:1608.05461 (2016).
4. Daniel Halperin, et al., "Tool release: Gathering 802.11n traces with channel state information." ACM SIGCOMM Computer Communication Review, 2011, 41(1): 53.
5. Kaiming He, Xiangyu Zhang, et al., "Deep Residual Learning for Image Recognition.", Proceedings of the IEEE CVPR, 2016: 770-778.
6. Joji Inamasu, Kazuhiro Tomiyasu and Satoru Miyatake, et al., "Clinical characteristics of stroke occurring in the toilet: Are older adults more vulnerable?.", Geriatrics & Gerontology International, 2018, 18(2): 250–255.
7. Yuxi Wang, Kaishun Wu, and Lionel M. Ni, "Wifall: Device-free fall detection by wireless networks.", IEEE Trans. on Mobile Computing, 2017, 16(2): 581-594.
8. Zhong Zhang, Christopher Conly, and Vassilis Athitsos, "A survey on vision-based fall detection.", Proc. of the 8th ACM PETRA, 2015: 46.