A WIFI-BASED PASSIVE FALL DETECTION SYSTEM

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ABSTRACT

Fall detection systems based on WiFi signals are gaining popularity recently. However, most of the existing works relying on training are environment-dependent. In this paper, we propose DeFall, a novel WiFi-based environment-independent fall detection system by leveraging the features inherently associated with human falls — the patterns of speed and acceleration over time. The system consists of an offline template-generating stage and an online decision-making stage. In the offline stage, the speed of human falls is first estimated based on a statistical modeling about the Channel State Information (CSI). Dynamic Time Warping (DTW) based algorithms are applied to generate a representative template for typical human falls. Then fall event is detected in the online stage by evaluating the similarity between the patterns of realtime speed/acceleration estimates and the representative template. Extensive experiment results show that with a single pair of WiFi transceivers, the proposed system can achieve a detection rate of 96% and a false alarm rate smaller than 1.5% under both line-of-sight (LOS) and non-LOS (NLOS) scenarios.

***Index Terms*—** WiFi, Channel State Information, Fall Detection, Dynamic Time Warping

1. INTRODUCTION

The past few decades have witnessed the increase in the demand of indoor fall detection systems which aim to detect the falls for special groups of people, e.g., patients, elderly people, and pregnant women. The systems could not only help people live independently but also reduce the burden of caregivers [1]. However, most of the existing systems rely on cameras deployed in the area of interest, which is limited by the requirements of line-of-sight (LOS) condition as well as raises privacy-leakage concerns. Other conventional sensor-based fall detection systems require wearables and are thus not user-friendly.

Inspired by the fact that the radio frequency (RF) signals can be altered by the propagation environment, wireless sensing has become popular recently [2] [3]. By analyzing Channel State Information (CSI) accessible on mainstream devices nowadays, a lot of wireless sensing applications have been enabled such as indoor activity monitoring and event detection [4], motion detection [5], breathing estimation [6, 7] and non-invasive fall detection [8–12]. WiFall, a WiFi-based fall detector which extracts features from the CSI amplitude information to detect falls, is proposed in [8] [9], while Anti-Fall [10] and RT-Fall [11] further explore the efficacy of phase difference. And FallDeFi [12] exploits time-frequency analysis for fall detection. Unfortunately, they cannot be generalized well to new environments without performance degradation and re-training/calibration is needed.

In this paper, we propose DeFall, standing for "Detect Falls", a WiFi-based environment-independent fall detection system leveraging the unique patterns of the speed and acceleration during a human fall. More specifically, as a human starts to fall to the ground, his/her body will experience an extremely rapid speed increment. After the body hits the ground, the speed reduces to near zero sharply. Most of the human falls exhibit a similar pattern, rendering the feasibility of a robust fall detector by estimating the speed and acceleration of the human body. The proposed system consists of an offline template-generating stage and an online decision-making stage. In the offline stage, the speed of human falls is estimated from the WiFi CSI by applying a statistical model on the radio wave propagation in an indoor rich-scattering environment. Then band-relaxed Segmental Local Normalized Dynamic Time Warping (SLN-DTW) and DTW Barycenter Averaging (DBA) algorithms are performed to generate a representative template for a typical human fall. In the online stage, we evaluate the similarity between the patterns of the realtime speed/acceleration estimates and the representative template to detect a fall. To evaluate the performance of the proposed system, we build a prototype using commercial WiFi devices and conduct experiments under various settings. The results show that with a single pair of WiFi transceivers, the proposed system can achieve a detection rate (DR) of 96% on real falls and a false alarm rate (FAR) of 1.47% under both LOS and non-LOS (NLOS) scenarios.

The rest of the paper is organized as follows. The system design, as well as the methodology of DeFall is presented in Section 2. Experimental setup and performance evaluation are discussed in Section 3. Finally, conclusions are drawn in Section 4.

2. SYSTEM DESIGN

In this part, we present an overview about the design of the proposed WiFi-based fall detection system as Fig. 1 illustrates.

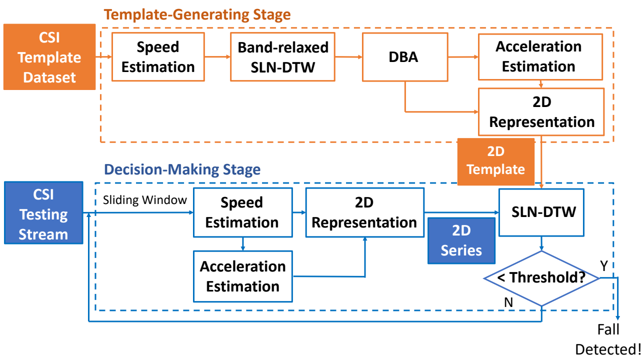


Fig. 1. Overview of system architecture.

2.1. Speed Estimation

Since the proposed system utilizes the unique pattern of the series of speed and acceleration during a human fall, it is critical to have an accurate estimate of the speed based on WiFi CSI, which is not trivial due to the complex multipath propagation indoors. Some existing approaches that utilize Doppler Frequency Shift (DFS) to estimate the speed have not considered the multipath effect and thus may not even work in NLOS conditions [13, 14].

Based on a novel statistical modeling of the electromagnetic (EM) wave propagation in a rich-scattering multipath environment [15], it has been shown that the speed of a moving object can be reliably estimated by evaluating the autocorrelation function of the physical layer CSI. It does not require training and performs equally well in both NLOS and LOS scenarios. In this paper, we adopt the methodology in [15] to estimate the speed and will use the speed estimates for fall detection.

2.2. Template-Generating Stage

In the template-generating stage of the proposed system, a template database $\mathbb{S} = \{S_1, S_2, ..., S_M\}$ is built first by including M sequences of speed estimates, each of which is calculated based on the CSI series collected during a random fall.

However, due to the time measurement error during data collection, there may exist redundant speed segments of other activities before or after the fall event. To remove the redundancy while adapting to the possible variability in event instances, we resort to band-relaxed SLN-DTW [16], which can detect low distortion local alignments between two time series by dynamic programming [17]. SLN-DTW is applied between every two speed sequences to extract their common parts. Therefore, for each sequence S_i, there are $M-1$ possible truncations with $M-1$ start indices $P_{i,s}$ and $M-1$ end indices $P_{i,e}$. And the part of S_i with index lying in $[med(P_{i,s}), med(P_{i,e})]$ is regarded as the sanitized speed sequence of the fall event in sample S_i, where $med(P_{i,s})$ and $med(P_{i,e})$ are medians of the start indices and the end indices, respectively. In this way, the template database is refined to $\hat{\mathbb{S}} = \{\hat{S}_1, \hat{S}_2, \ldots, \hat{S}_M\}$.

The speed series in database $\hat{\mathbb{S}}$ are then scaled to the same length and averaged to construct a single representative profile $\bar{S}$. Since the direct averaging of time sequences by point-to-point matching may be easily affected by shifting and misalignment, to adapt to the temporal variability, the averaging is also performed in the DTW space. The optimal average $\bar{S}$ is defined as the sequence that has the smallest summation of squared DTW distance with all series in the database. Given our template database $\hat{\mathbb{S}} = \{\hat{S}_1, \hat{S}_2, \ldots, \hat{S}_M\}$, and by denoting DTW distance as $DTW(x, y)$, which is the Euclidean distance between two time series x and y calculated along the optimal warping path, the problem to find $\bar{S}$ in the DTW space can be formulated as a convex problem:

$$\bar{S} = \arg\min_{S} \sum_{i=1}^{M} DTW^2(S, \hat{S}_i), \tag{1}$$

which can be solved by DTW Barycenter Averaging (DBA) algorithm [18]. DBA performs an iterative algorithm that refines an average sequence S on each iteration following an expectation maximization scheme with guaranteed convergence in [19]. The optimal speed time sequence, produced by DBA, is then considered as the speed template.

Besides speed, acceleration depicts the motion during a fall from another different point of view. To get a more comprehensive description of the fall events, we derive an acceleration series $\bar{S}'$ from the speed template $\bar{S}$ and combine them by point-to-point stitching to generate a 2-D template $\bar{S}_{2D}$. The efficacy of utilizing 2-D combined template $\bar{S}_{2D}$ rather than 1-D template $\bar{S}$ or $\bar{S}'$ will be discussed in Section 3.

2.3. Decision-Making Stage

After generating the template $\bar{S}_{2D}$, by comparing the speed and acceleration estimates from the incoming stream with the template, the system is able to detect a fall in real time. A sliding window first slides through the incoming CSI data stream, from which the corresponding speed and acceleration are estimated. The estimated speed and acceleration sequences are combined to form a 2-D segment T_{2D}. DeFall then compares the template $\bar{S}_{2D}$ generated in the first stage and the 2-D segment T_{2D} and evaluates their similarity. Again, since the captured segment in the sliding window may be out of sync with the template, the similarity is quantified by DTW distance.

The smaller their DTW distance is, the more similarity they have. If the DTW distance is smaller than an empirically predefined threshold γ, the system reports a fall event is detected.

Since the classic DTW is sensitive to endpoints, the idea of SLN-DTW is also applied in the decision-making stage. Simpler than the process in template-generating stage, by utilizing original SLN-DTW instead of band-relaxed SLN-DTW, only the endpoints of 2-D testing segment T_{2D} inside the sliding window are defined adaptively since the endpoints of 2-D template $\bar{S}_{2D}$ are already well-defined in the template-generating stage.

3. EXPERIMENT RESULTS

3.1. Hardware Setup

We implement our scheme using off-the-shelf WiFi devices at carrier frequency 5.808GHz with a 40MHz bandwidth. To capture the fast changes of speed, we conduct extensive experiments in a typical office environment, and the sampling rate is set to 1500Hz. The detailed setup is shown in Fig. 2

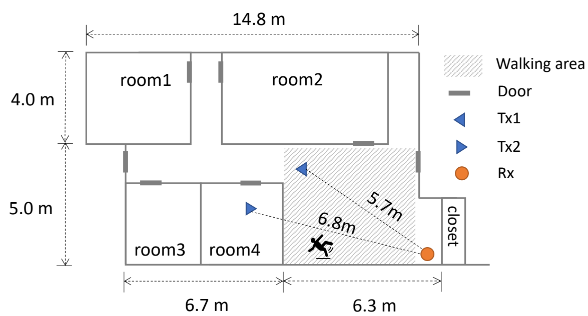
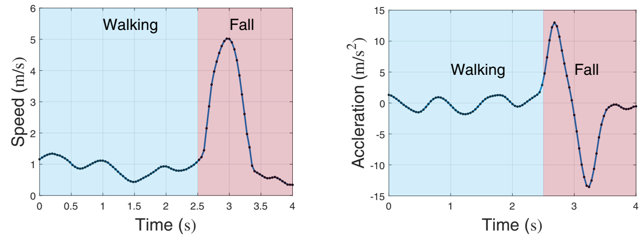


Fig. 2. Experiment setup for LOS and NLOS scenarios.

with locations of transmitter (Tx) and receiver (Rx) marked, and experiments are carried out under LOS and NLOS scenarios, respectively. Under LOS scenario, where the Tx is deployed in position Tx_1, both the Tx and Rx could "see" the subject. Under NLOS scenario, where Tx is deployed in Tx_2 and no direct path exists between the subject and the Tx.

3.2. Data Collection

The data collection is conducted in different days lasting for 3 months, during which the surrounding environment keeps changing due to the changes of the placement of furniture. To validate the feasibility of the proposed system, we first use a human-like dummy to collect both template data and testing data. After that, the CSI from real human falls are evaluated to verify the efficacy of the system. The evaluation metrics of the system performance are detection rate (DR) and false alarm rate (FAR). DR is defined as the percentage of correctly detected falls among all falls, while FAR is the percentage of non-falls that are mistaken as falls among all non-falls.



(a) Speed pattern (b) Acceleration pattern

Fig. 3. An instance of speed and acceleration patterns for "walk-then-fall".

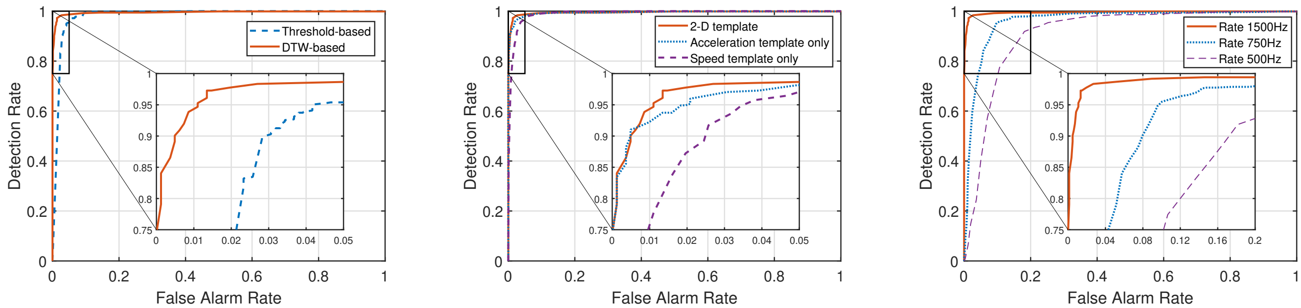
In the experiments, we consider two kinds of falls, "stand-then-fall" and "walk-then-fall". "Stand-then-fall" is performed by first making the dummy stand up supported by a stand and then letting it free fall; while "walk-then-fall" requires the experimenter to walk around the dummy and then let it fall. An instance of the speed and acceleration patterns for "walk-then-fall" is shown in Fig. 3. For non-falls, daily activities with relatively high speeds are taken into consideration including walking and sitting. As Table 1 indicates, there are a total of 846 fall samples and 814 non-fall samples.

3.3. Performance Evaluation

The generated template after sanitization and averaging is shown in Fig. 4. The tendency of the template is the same as expected with speed rising first and then dropping while the acceleration first positive and then negative.

To evaluate the performance of the proposed system, different thresholds are applied in the decision-making stage and the obtained ROC curve is illustrated in Fig. 5 (a). To show the efficiency of the proposed system, we compare its ROC curve with the simple-threshold method in [15], where the simple threshold-based method detects falls based on maximum speed and maximum changes in acceleration. As Fig. 5 (a) illustrates, with the same level of FAR, the DR of the proposed system is higher than the threshold-based method and the Area Under the Curve (AUC) of the curves of DeFall is larger as well, which proves that the proposed system in this work achieves a better performance. Specifically, indicated by the magnified part in Fig. 5 (a), at the same level of the FAR lower than 1.5%, DeFall can achieve a high DR over 95% while the corresponding DR of threshold-based method drops to a value smaller than 75%.

In addition, to prove that the 2-D template $\bar{S}_{2D}$ outperforms any single template $\bar{S}$ and $\bar{S}'$, the same database is also investigated with different templates, and the corresponding ROC curves are shown in Fig. 5 (b). As shown, the 2-D combined template achieves a better performance than any single template with a more comprehensive description of activities. Meanwhile, we also find that single acceleration template $\bar{S}'$ is better than single speed template $\bar{S}$. This is because the

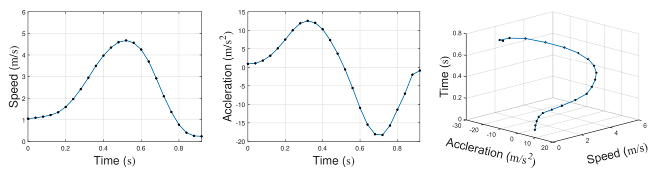


(a) ROC curves compared with threshold-based method

(b) ROC curves based on combined and single templates

(c) ROC curves with different sampling rates

Fig. 5. ROC curves.



(a) Speed template (b) Acceleration template (c) Template in 2-D feature space

Fig. 4. Generated template series.

changes of the absolute values of acceleration is larger than that of the speed values, providing higher discrimination.

Furthermore, the necessity of high sampling rate is also verified by experiments. Fig. 5 (c) shows the ROC curves with data under different sampling rates. As illustrated, the reduction of sampling rate leads to a degradation in performance of the system. The reason is that as the sampling rate decreases, the resolution and accuracy of the speed estimator degrade correspondingly.

Table 1. Experimental Results in Terms of FAR and DR

Scenario	Events		Number	DR		FAR	
LOS	Fall	Stand-then-Fall	424	97.40%	97.10%	-	-
		Walk-then-Fall	94	95.74%		-	
	non-Fall	Walking	167	-	-	0.00%	1.45%
		Sitting down	177	-		2.82%	
NLOS	Fall	Stand-then-Fall	270	98.15%	97.56%	-	-
		Walk-then-Fall	58	94.83%		-	
	non-Fall	Walking	212	-	-	0.47%	1.49%
		Sitting down	258	-		2.33%	

By selecting the threshold γ corresponding to an overall DR of 97.28% and FAR of 1.47% as decision boundary, we further tap out the performance on different activities indicated in Table 1. The reliability of the proposed system can be validated by the high accuracy with a DR higher than 97% and a FAR lower than 1.5% under either LOS or NLOS scenarios. Note that the FAR of sitting is slightly higher than walking due to the fact that sitting is more fall-like and can be easily mistaken as falls. Moreover, we have two volunteers, one male and one female to perform a total of 100 real falls. Each of them tested 25 times under NLOS and LOS scenarios, respectively. The overall DR on real falls with the selected γ is 96.00%.

3.4. Robustness Test

To study the robustness of the system against the interference from common dropping objects, we test objects with different sizes and different materials. Each object dropping from a height of $1m$ is tested 50 times and the results are indicated in Table 2, which shows that all the FARs are 0.0%, verifying the robustness of the system. This is because common objects are much smaller than a human body and therefore they have significantly less impact on wireless signal propagation.

Table 2. Robustness to Small Dropping Objects

Objects	Material	Size/Weight	FAR
Bottle	Plastic, water	$0.5kg$	0.0%
Bag	Nylon	$1kg$	0.0%
Plate	Plastic	$Radius = 12cm$	0.0%
Plate	Metal	$Radius = 10cm$	0.0%
Book	Paper	$22cm \times 18cm$	0.0%
Box	Paper	$17cm \times 17cm \times 25cm, 0.8kg$	0.0%

4. CONCLUSION

In this paper, we propose DeFall, a novel environment-independent indoor fall detection system based on commercial WiFi devices. The system utilizes a single pair of device to detect falls even through the wall. Moreover, a real prototype is built to validate the feasibility and evaluate the performance of the proposed system. According to the experimental results for detecting the falls in various environments, the proposed system can achieve a detection rate of 96.00% on real falls while maintaining a false alarm rate smaller than 1.5% under both LOS and NLOS scenarios.

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