2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)
4-7 March 2018
Las Vegas, Nevada, USA

Sensing-Fi: Wi-Fi CSI and Accelerometer Fusion System for Fall Detection

Ramin Ramezani[1,2,3] Yubin Xiao [1] Arash Naeim [2,3]

***Abstract*— Falling is a major cause of death among elders. To detect falls, numerous approaches have been proposed in the past decade, including computer-vision based image processing, wearable sensors, and acoustic signal processing, etc. Though the recent advancement in infra-red LED, depth camera, MEMS (Micro-Electro-Mechanical Systems) sensors and machine learning algorithms may have enlarged the application scope, the privacy intrusion and lack of convenience still remain to be open issues which prevent these systems from large deployment. A novel Sensing-Fi system described in this paper aims to overcome such deficiencies. The system design is comprised of harnessing Wi-Fi Channel State Information (CSI) coupled with ground-mounted accelerometer to detect floor vibration, hence the system is completely passive and non-invasive, i.e., the user is not required to wear the technology contrary to wearable accelerometers. In addition, contrary to the existing standalone Wi-Fi CSI fall detection systems, it overcomes the constraint by which only one user can be present in the room. The system has shown promising results with 95% accuracy.**

***Index Terms*— Sensor Network, Fall detection, Activity Recognition, Channel State Information (CSI), WiFi, Accelerometer, Floor Vibration**

I. Introduction

A primary safety concern in older patients, both in ambulatory settings and long-term care is the risk of falls. It is estimated that 34% of patients 65 years old, 50% of non-institutionalized octogenarians, 26% of in-patients and 43% of patients in nursing homes, experience at least one fall a year[1]. Some statistics indicate that roughly 10% of falls result in serious injury, with hip fracture, brain bleeds and concussion not uncommon [2]. Numerous approaches and techniques have been developed, including Wearable sensor-based, Computer vision-based, and Ambient environment sensing-based approaches [3, 4, 5, 6]. One of the early fall detection techniques is to use *Wearable sensors* such as accelerometer, gyroscope, barometer, etc [7]. In spite of significant improvements in sensor technology, particularly in terms of size and battery, old people need to be compliant with wearing and frequently charging them. *Computer vision-based* approaches aim to detect falls by constantly recording the scenery using cameras. Although a passive technology, their privacy intrusion makes them less desirable. *Ambient environment sensing-based* approach infers a fall based upon the change of ambient information caused by falls, hence, passive and non-intrusive. The source of ambient information includes audio noise, floor vibration, infrared, wireless signals, etc. Despite resolving the privacy issue, such techniques suffer from a number of limitations such as high false-alarm rate and certain requirements for environmental settings. Systems sensing the Wi-Fi physical layer Channel State Information (CSI) have been used to detect falls since 2010 [8]. As ambient environment approach, CSI leverages the multi-path effect during the propagation of Wi-Fi signal at the fine granularity of each OFDM subcarriers. CSI is passive, low-cost and does not require any wearable body area sensor. Significant progress have been made in fall detection using CSI in Anti-Fall [9] and RT-Fall [10]. However, both systems impose a constraint that only one person can live in the room; their feasibility and scope of operation is limited.

Our Sensing-Fi system fuses Wi-Fi CSI with ground-mounted accelerometer employed to capture floor vibration caused by fall. The goal of this design is to have two fall detection models, one for Wi-Fi CSI and the other for accelerometer, to validate and assess corresponding inferences, thereby overcoming deficiencies of each system. Just to recap, Wi-Fi CSI is limited to detecting falls when only one person is present and the accelerometer model may not always distinguish the vibration caused by an object falling on the ground from a human fall

II. Related Work

Previous work exists using: a) Wi-Fi CSI and b) floor-mounted accelerometers for the basis of the a fall detection system, but there does not seem to be any literature on fusion system that integrates both techniques.

A. Wi-Fi CSI Fall Detection System

In a typical indoor environment, WiFi signals propagate through the physical space via multiple paths such as ceiling, floor, wall and furniture so that the received signals in turn contain information that characterizes the environment the signals pass through [11]. Wi-Fi signal RSSI has been exploited for indoor localization, but as a MAC layer information, RSSI is coarse-grained and unstable. However, only very recently have researchers started to extract Wi-Fi CSI (phase and amplitude of each subcarrier in OFDM) from commodity Wi-Fi devices for gesture and activity recognition [12, 13]. Fall detection, in nature however, should be distinguishable from the activity recognition. Extracting falls from the countless human activities and gestures is difficult to execute autonomously in large spaces when many activities are occurring in continuum. In order to separate a Fall from other activities, RT-Fall [10] system uses the following framework: (1)CSI Stream extraction, interpolation, and filtering, (2) Segmentation, trace back time window

[1]Department of Computer Science, [2] Center for Smart Health, [3] David Geffen School of Medicine, UCLA raminr@ucla.edu, yxiao@cs.ucla.edu, anaeim@mednet.ucla.edu

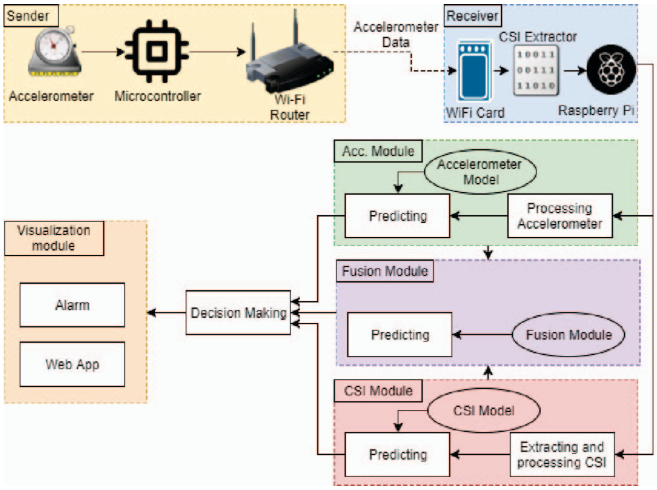

Fig. 1. High-Level System Architecture

and fall-like finish points, (3) Feature extraction and Model training, and (4) Testing and fall alarm. To make the detection more accurate, in RT-Fall, more features are extracted from not only the amplitude, but also the phase difference.

B. Floor Vibration based Fall Detection System

Activities like walking, running and falling have been observed to cause vibration on the floor that can be measured and their patterns can be distinguishable [3, 14]. During a fall, the impact of the body to the ground generates vibrations that are transmitted throughout the floor [15]. Vibration pattern differences have been observed and reported between the signature and the human fall and (a) other activities such as running or walking and (b) those generated by falling objects such as falling of a lamp or a chair [3, 14]. Researchers have been using floor-mounted accelerometer [15] and piezo transducer [16] to perform fall detection with 95% accuracy.

III. System Architecture

Our Sensing-Fi system integrates the commercial Wi-Fi router with the 3-axes accelerometer. As shown in Fig. 1, the accelerometer connects to a Micro-controller (MCU), which is responsible for processing the raw accelerometer readings. The MCU then transmits the data to the Wi-Fi router. Finally, the Wi-Fi router transmits the data wirelessly to the receiver. Meanwhile, the CSI can be extracted by the receiver from the received packets without adding other protocols to the system. There are several benefits associated with this structure: (1) the rate of the accelerometer data transmission is constant and at a relatively high frequency, (2) Wi-Fi CSI extraction takes advantage of the accelerometer data transmission without adding any overhead, (3) the system performs all transmission and computation in real-time, significantly reducing the response time and (4) the system is easier to scale since it can incorporate more accelerometer and receiver modules with ease.

After receiving the accelerometer data, the system takes advantage of the computational power of the receiver and harnesses it to execute the processing task. First the Wi-Fi CSI is extracted using a modified driver [8] as shown in figure 2, allowing the decoding of raw binary packets at the receiver end. The Wi-Fi CSI and accelerometer data are processed separately and fed into their corresponding predictive models in which the processed data of each module is used to predict falls. In addition, the combination of both data sets is used to create a "*fusion model*" which provides another prediction output. All three predictive models (CSI, Accelerometer and Fusion) in turn feed into a fall detection decision module. The following features, derived in the

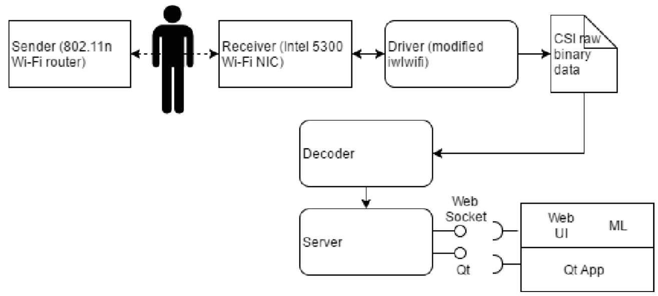

Fig. 2. CSI Extraction and Decoding

feature extraction phase, are used in both RT-Fall and Anti-Fall [9]: (1) the normalized standard deviation (STD) of CSI, (2) the median absolute deviation (MAD), (3) the offset of signal strength, (4) interquartile range (IR), (5) signal entropy, (6) the velocity of signal change, (7) the TimeLag, (8) the power decline ratio (PDR). The above features are also used in our prediction model except that both amplitude and phase of the CSI signal are used to build those features.

A. Accelerometer Model Building

The Accelerometer Model building is very similar to the CSI in (1) Preprocessing (Band-Pass Filtering), (2) Segmentation of time series, (3) Feature Extraction and (4) SVM Modeling. In our system, the accelerometer signal is shown to be clear during experimentation as the device is mounted to the floor and the Z axis exhibits the vertical vibration of the floor. The most significant Z axis features used in the proposed model are: (1) the normalized standard deviation (STD) of CSI, (2) the median absolute deviation (MAD), (3) the offset of signal strength, (4) interquartile range (IR), (5) signal entropy, (6) velocity of signal change. Our approach is similar/slightly different from Shock Response Spectrum (SRS) [8]

B. Fusion Model Building

The Fusion uses the features of both the data steams. It is important to note the different characteristics of Wi-Fi CSI and accelerometer signals in that the fall pattern does not last the same length on both signals, and based on the observations described in this paper, fall pattern is captured earlier from Wi-Fi CSI signal compared to acceleromter. The fusion module takes the features from CSI and Accelerometer signals with slightly different time stamps. This requires careful tuning so that the integration of the signals imply the correct number of falls during the analyzed period. Based on the observations of 50 falls, the overall fall period (from the beginning of the event until the subject hits the floor) does not exceed 3 seconds, hence comparison threshold is set to 3.

IV. Design Decisions and Implementation details

The system has two key blocks: sender and receiver. The sender contains Accelerometer, MCU and Wi-Fi router. The receiver can be any computer, such as Raspberry Pi, HummingBoard, laptop, etc. In the current implementation a laptop with a Wi-Fi card is used to receive the packets and to extract the CSI.

A. Sender

The sender block was implemented on Linux-based *Open-Wrt* Router Platform, and the accelerometer processing was developed on *Arduino* platform. As shown in Figure 3, these two platforms communicate with each other through Serial Bus using a protocol defined by ourselves. An MPU-

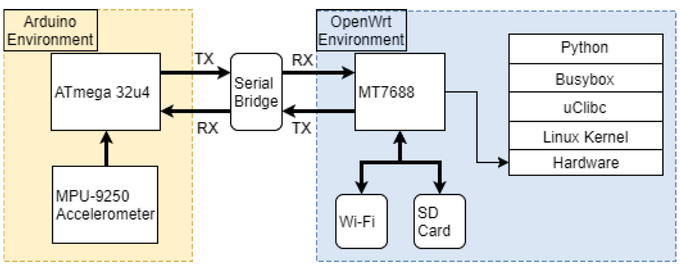

Fig. 3. Sender Architecture

9250 accelerometer was harnessed due to its high sampling frequency, low noise, and high sensitivity. In addition, ATmega32U4 was chosen as the MCU to read the sensor data and to communicate with MT7688 Wi-Fi chip. All the components are off-the-shelf commercially available and low-cost. The MCU firmware was written in C and compatible with most Arduino micro-controllers, and the sender software within router was developed in Python - a platform-independent language.

B. Receiver

A laptop equipped with Intel 5300 Wi-Fi card was used to receive the UDP accelerometer packet and CSI extraction. In order to improve real-time decoding efficiency, the CSI decoder and UDP packet decoder utilized C and bound with a Python upper-layer. The Python layer was comprised of two predictive models, built using an SVM classifier, a fusion module, a PyQt signal visualization Analysis application, and a WebSocket server to feed prediction results of both models to the Front-end Web application that can be displayed remotely.

V. Experimental Setup

Data collection was conducted in an empty laboratory room, providing a training set for the predictive modules in the proposed system. The router (sender) and the laptop

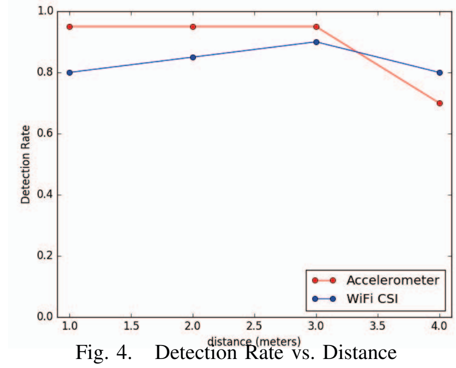

Fig. 4. Detection Rate vs. Distance

(receiver) were placed on two edges within the lab. A clear line of sight (LOS) is ideal for the best reception of WiFi CSI and placing the sender and receiver diagonally is recommended for the best result. The data sending speed was configured to 100 packets/s to allow for fine-grained temporal resolution for both CSI and accelerometer. The experimentation was designed to collect 100 instances of positive (falls) and negative events (not falls like walking and jumping) from both CSI and accelerometer modules simultaneously. To test the accuracy of the accelerometer versus distance between the sender and receiver, the sender was placed in 4 different locations of the room on the diagonal (1m, 2m, 3m, and 4m distance to receiver), Fig. 5. The hardware and software set up include: MPU-9250 accelerometer, ATmega32U4 MCU unit, LinkIt Smart 7688 (OpenWrt 15.05 OS) for Wi-Fi router, DELL Latitude E6430 with Intel WiFi 5300 receiver, Ubuntu 14.04 (Kernel 4.2) as receiver OS. The graphical user interface plotting all signals and related analysis is omitted due to page limit.

VI. Results and Discussion

Data was collected on 48 falls and 52 non-falls for testing. The predicting results of the 20 falls against different distances demonstrated highest accuracy when the distance between the sender and receiver is around 3 meters (figure 5). As a result, the distance of 3 meters was fixed in all the data collection and fusion model building. When the diagonal of the room is larger than 3 meters, more sender nodes (accelerometers) should be introduced. Different classifiers were employed, including SVM (Linear Kernel, RBF Kernel), and Adaboost classifiers. All predictive models were assessed using 5-fold cross validation. Table I shows the accuracy comparison between the Fusion, CSI and Accelerometer (Acc) models. 10 more extra falls were fed to the system to gauge the performance in real-life scenario. The system detected all 10 falls without producing any false alarm.

TABLE I
Accuracy comparison among Fusion Model, CSI Model, and Acc Model

Models	Adaboost	SVM (Linear)	SVM (RBF)
Fusion	0.90	0.90	0.95
CSI	0.88	0.90	0.87

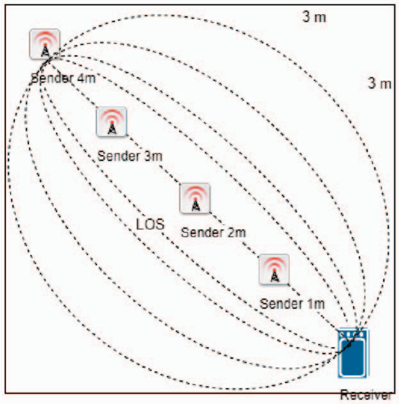

Fig. 5. Sender and receiver placement in room

A passive reliable approach to capture falls among older individuals is important for several reasons: (1) Older patients tend to provide a poor fall history, (2) there is an overlap between falls and syncope (loss of consciousness), and (3) often the risk of significant poor health outcome is tied to speed to the notification of a fall.

The introduced system was aimed to tackle some of the shortcomings of the available fall detection approaches. Although the Fusion system only performed slightly better than the state-of-the-art CSI model, the goal was primarily to investigate the possibility of incorporating accelerometer; a new system should overcome the constraint by which only one person can be present in the room for the CSI model to accurately perform. The described system is still at early stages and despite promising preliminary results, more complicated scenarios should be investigated and analyzed to improve upon the decision making module of the fusion system.

References

[1] L. Z. Rubenstein and K. R. Josephson, "The epidemiology of falls and syncope," *Clinics in geriatric medicine*, vol. 18, no. 2, pp. 141–158, 2002.

[2] M. E. Tinetti, "Preventing falls in elderly persons," *N Engl j Med*, vol. 2003, no. 348, pp. 42–49, 2003.

[3] P. J. Rajendran, "A smart and passive floor-vibration based fall detector," Ph.D. dissertation, University of Virginia, Charlottesville, VA, USA, 2007.

[4] H. Rimminen, J. Lindstrm, M. Linnavuo, and R. Sepponen, "Detection of falls among the elderly by a floor sensor using the electric near field," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 6, pp. 1475–1476, Nov 2010.

[5] Y. Li, K. C. Ho, and M. Popescu, "A microphone array system for automatic fall detection," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 5, pp. 1291–1301, May 2012.

[6] H. Foroughi, B. S. Aski, and H. Pourreza, "Intelligent video surveillance for monitoring fall detection of elderly in home environments," in *2008 11th International Conference on Computer and Information Technology*, Dec 2008, pp. 219–224.

[7] C. J. Lord and D. P. Colvin, "Falls in the elderly: Detection and assessment," in *Engineering in Medicine and Biology Society, 1991. Vol. 13: 1991., Proceedings of the Annual International Conference of the IEEE*. IEEE, pp. 1938–1939.

[8] D. Halperin, W. Hu, A. Sheth, and D. Wetherall, "Tool release: Gathering 802.11n traces with channel state information," *SIGCOMM Comput. Commun. Rev.*, vol. 41, no. 1, pp. 53–53, Jan. 2011. [Online]. Available: http://doi.acm.org/10.1145/1925861.1925870

[9] D. Zhang, H. Wang, Y. Wang, and J. Ma, "Anti-fall: A non-intrusive and real-time fall detector leveraging csi from commodity wifi devices," in *International Conference on Smart Homes and Health Telematics*. Springer, 2015, pp. 181–193.

[10] H. Wang, D. Zhang, Y. Wang, J. Ma, Y. Wang, and S. Li, "Rt-fall: A real-time and contactless fall detection system with commodity wifi devices," *IEEE Transactions on Mobile Computing*, vol. 16, no. 2, pp. 511–526, Feb 2017.

[11] K. Manasa, "Wifi for sensorless sensing: A review," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, vol. 6, June 2017.

[12] Q. Pu, S. Gupta, S. Gollakota, and S. Patel, "Whole-home gesture recognition using wireless signals," in *Proceedings of the 19th Annual International Conference on Mobile Computing & Networking*, ser. MobiCom '13. New York, NY, USA: ACM, 2013, pp. 27–38. [Online]. Available: http://doi.acm.org/10.1145/2500423.2500436

[13] P. Melgarejo, X. Zhang, P. Ramanathan, and D. Chu, "Leveraging directional antenna capabilities for fine-grained gesture recognition," in *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, ser. UbiComp '14. New York, NY, USA: ACM, 2014, pp. 541–551. [Online]. Available: http://doi.acm.org/10.1145/2632048.2632095

[14] P. Rashidi and A. Mihailidis, "A survey on ambient-assisted living tools for older adults," *IEEE journal of biomedical and health informatics*, vol. 17, no. 3, pp. 579–590, 2013.

[15] D. Litvak, Y. Zigel, and I. Gannot, "Fall detection of elderly through floor vibrations and sound," vol. 2008, pp. 4632–5, 02 2008.

[16] M. Alwan, P. Rajendran, S. Kell, D. Mack, S. Dalal, M. Wolfe, and R. Felder, "A smart and passive floor-vibration based fall detector for elderly," vol. 1, pp. 1003 – 1007, 01 2006.