Fine-grained occupant activity monitoring with Wi-Fi channel state information: Practical implementation of multiple receiver settings

# Hoonyong Lee; Changbum R. Ahn; Nakjung Choi

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Monitoring the long-term patterns of activities of daily life could be critical in providing remote healthcare services for living-alone elderly, as the gradual decline of ADL routine patterns is a major symptom of geriatric cognitive diseases

# Scholarcy Highlights

* As Wi-Fi networks are ubiquitous in most buildings and homes, researchers have harnessed Wi-Fi signals as a new sensing source for non-intrusive occupant monitoring systems [1]
* The Fresnel zones generated by the Access Point (AP) and Receiver 6 (R6) covered almost whole footprint of Unit B, but other two receivers were closer to the AP, which resulted in smaller Fresnel zones compared to that of R6
* The model proposed here shows a higher degree of accuracy in occupant activity classification compared to the benchmark approaches, the proposed model still has limitations for practical implementation since it classifies the occupant’s activities based on the training data of predefined activities
* The temporal-spatial features of this approach increase the overall performance of such monitoring systems
* The performance of WiSensing offers over 96% accuracy in two different indoor environments
* Monitoring the long-term patterns of activities of daily life (ADL) could be critical in providing remote healthcare services for living-alone elderly, as the gradual decline of ADL routine patterns is a major symptom of geriatric cognitive diseases [50]

# Scholarcy Summary

## Introduction

As Wi-Fi networks are ubiquitous in most buildings and homes, researchers have harnessed Wi-Fi signals as a new sensing source for non-intrusive occupant monitoring systems [1]

Such monitoring systems exploit Wi-Fi variance caused by the occupant’s movements to classify activities of daily living.

Wi-Fi-based occupant monitoring systems exploit these variations in the received Wi-Fi signals to classify occupant’s activities of daily living.

By exploiting the CSI, many studies have been performed in the fields of occupant indoor localization/tracking, identification, counting, gesture recognition, breathing/respiration/heart rate estimation, and activity classification [1]

Such monitoring systems can be utilized for smarthome healthcare systems, which detect either fall accidents or abnormal pattern of daily living for the elderly [4].

A hybrid Convolutional Neural Network (CNN)–Long Short-Term Memory (LSTM) was used as the feature extractor and activity classifier

## Conventional occupant monitoring systems

Occupants have been monitored either for building energy management or for smart-home health care by various occupancy sensor systems [4,6].

These conventional occupant monitoring systems are mainly able to detect occupant presence, count the number of occupants, and track occupant locations via video/image [23,24], motion [25,26], CO2 [27,28], temperature and humidity [29], and sound [30,31] data collected from occupancy sensors

Such monitoring systems require additional devices to collect this information, such as cameras, microphones, wearable devices, or CO2 sensors to only provide coarse-grained activity detection [32].

Such approaches are intrusive to occupants’ daily lives and raise privacy issues [6].

The RSSI-based occupancy monitoring systems could classify coarse-grained occupant activities [35]

## CSI-based occupant monitoring systems

Since the Linux CSI 802.11n tool has been published, the CSI has been used for non-intrusive occupant monitoring systems [40].

Where, i: data packet, i [1, N], N : Number of received packets, Yi : Received signal vector, Hi: CSI matrix, Xi: Transmitted signal vector, Ɲi: Noise vector For feature extracting, statistical features in the time-domain have been used for conventional machine learning algorithms, such as K.

Wi-Chase [8] provided 94% accuracy for classifying running, walking, and hand moving, exploiting the SVM with six statistical features extracted from the CSI in the time-domain: mean, standard deviation, 25th and 75th percentile, median absolute deviation, and maximum of the CSI.

The spatial information is still dismissed, as the CSI was obtained from a single receiver, which cannot monitor the entire space due to its limited coverage area

In this context, this research proposes a way to utilize multiple receivers for extracting features which contain spatial–temporal information about the occupant’s activities.

The performance of other benchmark models has increased with multiple receivers

## Methodology

The proposed model exploits one Wi-Fi transmitter and multiple receivers deployed in different fixed locations; the receivers simultaneously collect Wi-Fi signals transmitted from the AP.

The CSI data of different patterns is obtained from the multiple receivers.

The timeseries data is converted into image data using a STFT, and further integrated into one large image dataset.

The image data is fed into the CNN-LSTM model to extract features and classify the occupant’s activities.

The following section describes the three phases of the proposed model in detail: (1) data preprocessing; (2) feature extraction; (3) activity classification

## Data preprocessing

The raw CSI contains high frequency noise not related to the occupant’s activities, which themselves generate less than 10 Hz frequency in the Wi-Fi signals [4].

In this case, the transmit rate of the Wi-Fi signal was set as 100 Hz. The occupant was walking from the 1,000 to 2,000 packet number, the sections of the graphs where the CSI shows a distinct perturbation.

The occupant activity generates a unique pattern of variation in the CSI

Such patterns differ depending on the relative positions of the occupant and the receiver.

All the image data is attached side-by-side to generate integrated large image data, which preserves spatial information about the occupant’s activity

## Feature extraction

The integrated image data is fed into the CNN to extract 1,024 features which contain temporal-spatial aspects of the occupant’s activity.

In order to extract the 1,024 features, the architecture of the CNN is reconstructed from VGGNet [45].

All the convolutional layers have a 3 × 3 kernel size with zero padding, which is appropriate to the size of the input data.

A batch normalization layer is used to normalize the input data, and the max-pooling layers are used to avoid over-fitting issues.

Since the pooled features by the CNN are not appropriate to directly input into the LSTM, a flatten layer is used to convert the shape of the features into a single column

## Evaluation

The Wi-Fi signal propagation is mainly affected by the occupant’s movements, other indoor environmental factors, such as surrounding Wi-Fi signals, housing layout, or building material have an impact on the propagation, which results in performance degradation of the CSI-based activity classification models [46].

The CSI was simultaneously collected from three different receivers via the Linux CSI 802.11n tool [40]

Since the size and layout of the housing environments differed between Unit A and Unit B, all the activities were not performed identically.

The experiment was performed by one subject at a time, meaning that the received signal was affected by a single subject.

The collected CSI was independent of housing environments, subjects, and time

## Performance of the proposed model

The total number of data samples was 3,600 for Unit A and 4,320 for Unit B.

A Wi-Fi transmitter–receiver pair has a limited coverage area

It may not be possible for one receiver to detect the occupant’s activities throughout the entire indoor space, which could degrade the overall performance of.

Previous studies showed that using multiple receivers increases the performance of CSI-based occupant monitoring systems [4,22].

The data-level integration model shows that the accuracy for each subject for Unit A is a minimum of 96.11%, a maximum of 100%, an average of 98.73%, and a standard deviation of 1.39%.

For Unit B, the accuracy is a minimum of 99.53%, a maximum of 100%, an average of 99.47%, and a standard deviation of 0.79%

## Performance comparison with benchmark models

The model performance was compared with the two benchmark models. The first benchmark model was selected to be Wi-Chase [8], which exploits the SVM algorithm, the most frequently used occupant activity classifier [3].

The structure of DeepHare was fine-tuned by modifying the model architecture to be identical to the architecture of the proposed model, since the original DeepHare model shows very low accuracy for classifying CSI obtained from our experiment.

The difference between the proposed model and the modified DeepHare is in the type of image data, which exploits deep learning algorithms, the performance of the modified DeepHare is not as strong as that of the Wi-Chase model in most cases

This result shows that image data converted by STFT could preserve necessary information for accurate activity classification using the hybrid CNN-LSTM model.

The Wi-Chase model shows an degraded performance compared to other integration models because the six statistical features extracted from the data-level integration model lose activity information rather than preserving the spatial information.

The decision- or feature-level integrations, and that decision- or featurelevel integrations may not provide performances that are much better than even those obtained from a single transmitter–receiver setting

## Practical application

The proposed model is used to classify fine-grained occupant activities for building occupants, and occupant activity is closely linked to the energy consumption of buildings.

With this occupancy information, the energy management systems can control the lighting and HVAC systems to provide a comfortable indoor environment with efficient energy use.

The accumulated occupant activity information provides key clues to finding the routines of the occupant’s daily life, which results in the activity prediction.

The routine and prediction of the occupant’s activity enable us to analyze the patterns of the building energy use and predict future energy consumption

## Multiple receiver deployment

As shown in the Evaluation section, multiple receivers are essential for monitoring an occupant’s activities performed in various locations throughout an indoor space.

In the Evaluation section, when the single transceiver pair was used, Receiver 6 (R6) provided the highest accuracy for Unit B even though R6 was placed far from the AP.

The Fresnel zones generated by the AP and R6 covered almost whole footprint of Unit B, but other two receivers were closer to the AP, which resulted in smaller Fresnel zones compared to that of R6.

Since Wi-Fi signals travel via the F1 D1 - F2 path outlined, if the area of the Fresnel zones increases, the travel length increases, which results in further energy loss

In this case, the transmitter–receiver pair should be placed to generate a Fresnel zone which covers the target area.

The other two receivers generated Fresnel zones which covered areas where only certain activities were performed

## Locational dependency of receiver

The proposed Wi-Sensing could be operated by various IoT devices, which receive Wi-Fi signals and transfer the signal information to the main hub, which are connected to all the IoT devices.

The main hub could extract CSI from the transferred Wi-Fi information collected from multiple IoT devices.

As the location of the device changes, the order in which the trained large image data was made may differ from the test image data.

If the location of the device changes, the received signal will change, but this research shows the effect of the order of image generation on the performance of WiSensing.

For Unit A, the pre-trained Wi-Sensing with the image data made in the order of R1-R2-R3 shows 31.94% and 31.85% accuracies for the test image data made in the order of R2-R3-R1 and R3-R1-R2, respectively.

The retrained model by using the transfer learning algorithm shows the potential that the performance of Wi-Sensing could be retained at certain level of accuracy the locations of receivers (IoT devices) is changed over time.

An approach needs to be developed to reduce the environmental and occupant dependencies of the proposed model

## Findings

Wi-Sensing provides over 96% classification accuracy in two different indoor environments.

Wi-Chase [8] provided 94% accuracy for classifying running, walking, and hand moving, exploiting the SVM with six statistical features extracted from the CSI in the time-domain: mean, standard deviation, 25th and 75th percentile, median absolute deviation, and maximum of the CSI.

The proposed model shows 96.57% and 98.92% accuracy for the basic activity classifications for Unit A and Unit B, respectively.

For Unit B, the accuracy is a minimum of 99.53%, a maximum of 100%, an average of 99.47%, and a standard deviation of 0.79%.

The re-trained model with sample activity data shows 77.77% accuracy for the order of R2-R3-R1 and 85.18% accuracy for the order of R3-R1-R2.

The performance of WiSensing offers over 96% accuracy in two different indoor environments

## Conclusion

The model proposed here shows a higher degree of accuracy in occupant activity classification compared to the benchmark approaches, the proposed model still has limitations for practical implementation since it classifies the occupant’s activities based on the training data of predefined activities.

The proposed model is appropriate for homes where the occupant lives alone, or for individual offices in commercial buildings.

The proposed approach classifies an occupant’s activity.

This research proposed an approach to exploit multiple receivers for CSI-based occupant activity monitoring systems.

The temporal-spatial features of this approach increase the overall performance of such monitoring systems.

A hybrid CNN-LSTM model, Wi-Sensing, was proposed to classify the occupant activities.

The occupancy information—in particular fine-grained activity information—monitored by Wi-Sensing would significantly improve building automation by associating the control of HVAC, lightings, and other appliances with the occupant’s activity patterns.

Monitoring the long-term patterns of activities of daily life (ADL) could be critical in providing remote healthcare services for living-alone elderly, as the gradual decline of ADL routine patterns is a major symptom of geriatric cognitive diseases [50]