Human Fall Detection in Indoor Environments Using Channel State Information of Wi-Fi Signals

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Abstract - Motivation

- **Aim**: Detect the fall of an individual in indoor environments.
- **How**: By monitoring Wi-Fi Channel State Information (CSI) consisting of phase and amplitude data.
- **Why it works**: Human movements alter the channel and thereby, the CSI characteristics of the received signal. Under some conditions, we can recognize this change in CSI characteristics as a signature of the activity performed and thus, identify it.
- **Why it matters:** Recognizing falls with high accuracy and as fast as possible can be critical for the health, or even survival, of elderly people leaving alone or at health risk.

Channel State Information (CSI)

- Describe how a signal propagates from the transmitter to the receiver.
- Represent combined effect of scattering, fading, and power loss with distance.
- Impulse response of a digital filter representing the channel.

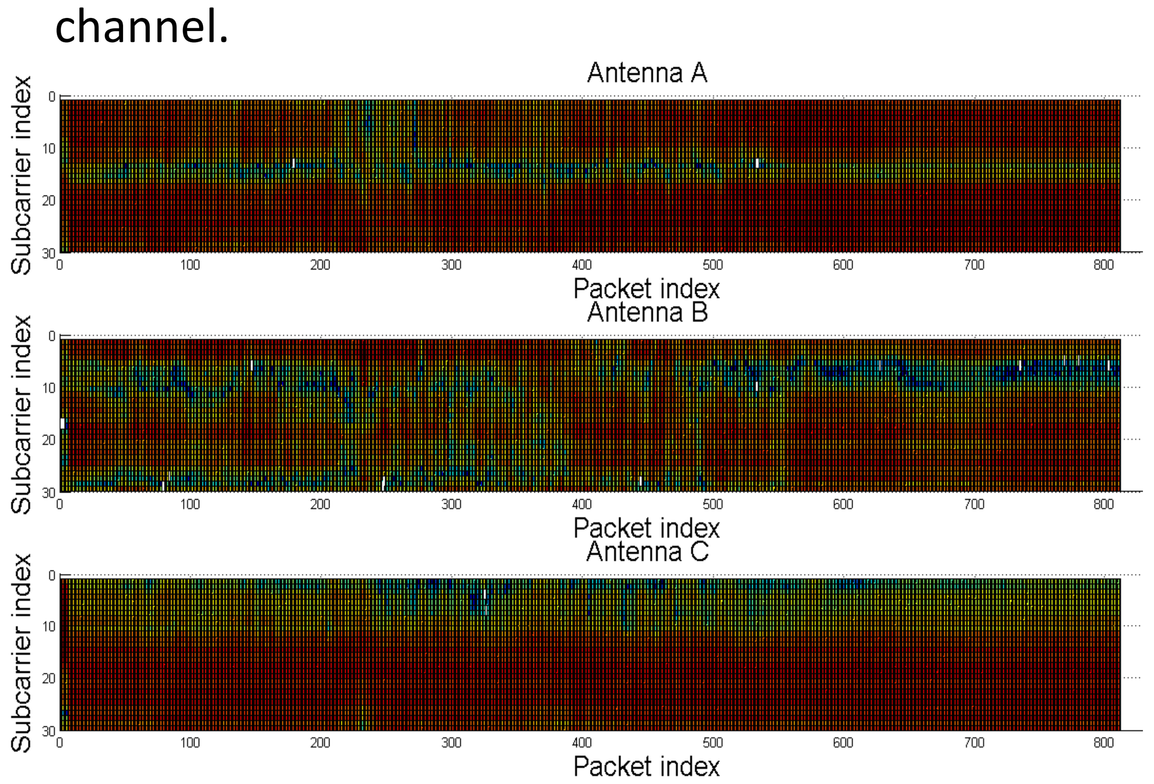


Fig. 1. Amplitude of CSI values for each Antenna Pair. Subject was walking in this test.

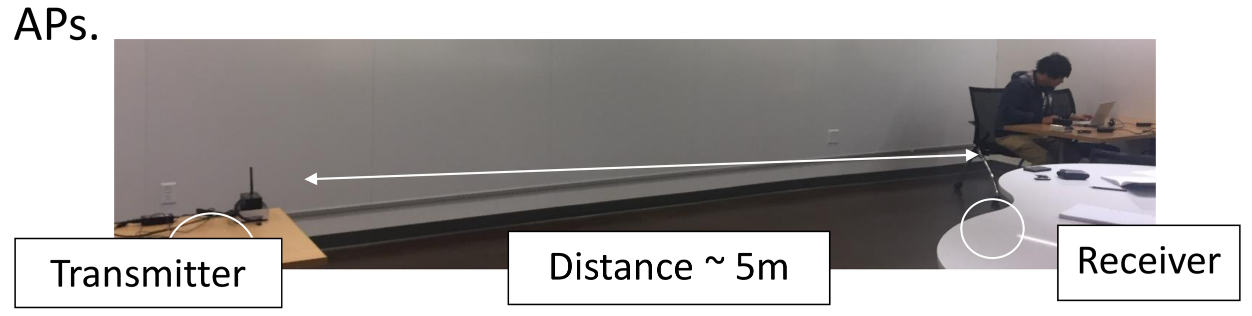
Data Collection

Equipment: Two Intel Wi-Fi Wireless Link 5300 802.11n MIMO radios.

- Transmitter: 1 antenna.
- Receiver: 3 antennas & 30 OFDM bands.
- Data: 30 complex values per sample (packet) for each antenna pair (one value per band) → 90 CSI streams.
- Transmission rate: 50 packets/second.
- Frequency: 5GHz.
- Distance between transmitter & receiver: 5 meters

Data Collection (cont'd)

2 subjects performed the activity in the space between these 2 APs.



- 10 data sets for each activity and user.
- Duration: 20 seconds.
- We used video recording to identify start and stop times of activity in the data sets.

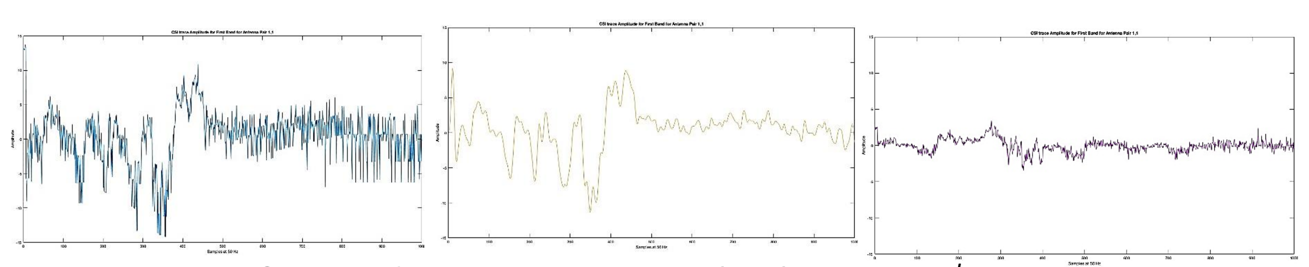
Activity	Duration	Activity	Duration
No Activity	84 sec	Sitting Down	55 sec
Walking	155 sec	Standing Up	43 sec
Running	256 sec	Lying Down	61 sec
Picking Up	55 sec	Falling	42 sec

Table summarizing duration of data sets for each activity

CSI Data Feature Extraction

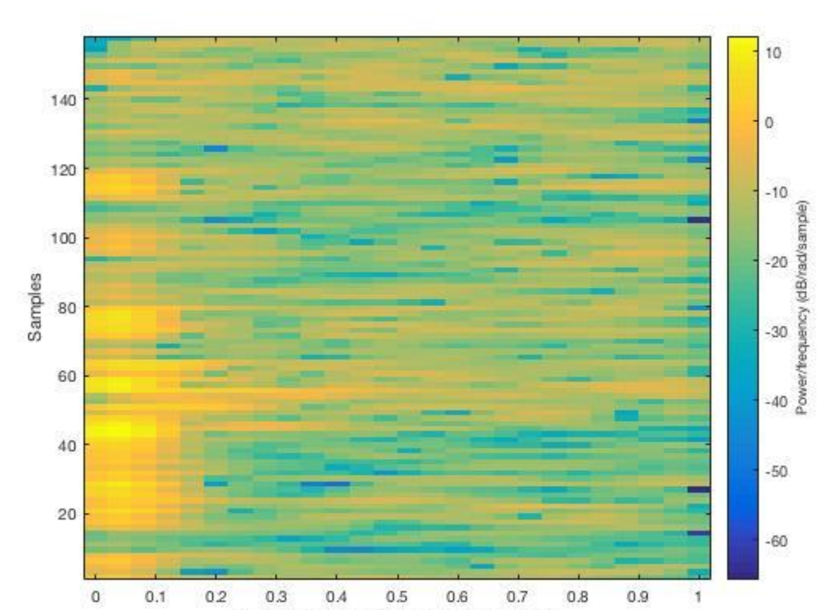
CSI data very noisy:

- Traditional filtering techniques like low pass Butterworth filter or a median filter inadequate.
- Special PCA based technique inspired by [1]
  1) Data divided in 1 second streams & PCA coefficients calculated.
  2) Eigenvectors calculated for these coefficients.
  3) Signal reconstructed from first 6 eigenvectors except for the 1st (eigenvectors 2 through 5).
- Reconstructed signal much less noisy.
- Can be used for feature extraction.



Raw Stream for Band 1 *LP Butterworth Filter* *2nd PCA Component*

- To extract features: 50 point STFT from 2nd to 6th eigenvector over 1 second window with ½ second overlap → 26 coefficients.
- Also: coefficient change (indicating changes in spectrum) → size-32 feature vector.



Spectrogram for 20 seconds of data at 25 Hz; subject on bed

Supervised Learning Results & Discussion

Training: 3 traditional ML Classifiers using labeled data: Support Vector Machines with Gaussian kernel, Decision Trees and Multinomial Logistic Regression.

- Idea: Evaluate performance for different assumptions on distribution of feature vector. SVM assumes data to be Gaussian, MLR assumes linear relationship and DTs have no prior assumption except that features are uncorrelated.
- We used 10-fold cross validation.

Model Evaluation: Multiclass problem → confusion matrices.

Discussion: Transient activities → CSI signature can last for less than a second → window size of 1 sec might be incorrect. Bias variance analysis showed: Poor performance is due to limited amount of data. Also, since DTs perform better, distribution assumptions may be incorrect.

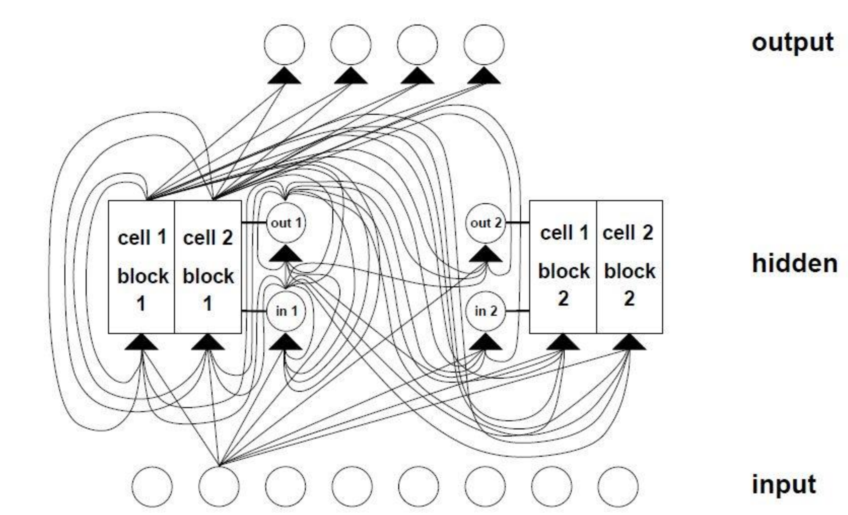
Activity	SVM	Decision Trees	Multinomial Logit Reg.
Lying Down	27%	70%	25%
Falling	0%	58%	9%
Picking up	45%	79%	36%
Running	**66%**	**88%**	**54%**
Sitting Down	30%	57%	25%
Standing Up	17%	59%	19%
Walking	**60%**	**87%**	**60%**

Table summarizing accuracy of detection for each activity for each classifier

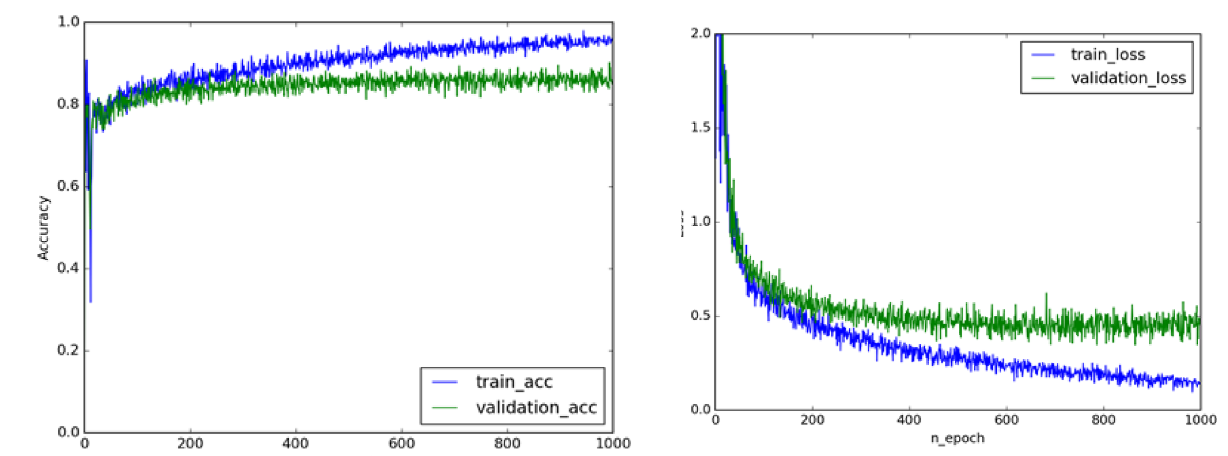
Deep Learning Results & Discussion

Training: Viewing problem as a time sequence and from discussion on traditional supervised learning, we used LSTM (Long Short Term Memory) recurrent neural network architecture for deep learning.

- 90 input units and 200 hidden units (1 hidden layer).
- Objective function: cross entropy (reason: multi-class problem).



Structure of LSTM based RNN



Model Evaluation: Training & validation set accuracy and training & validation loss to check if model is over-fitting. Test accuracy: approx. 80%

Discussion: Good accuracy on test data. Training and validation loss and accuracy curves being close to each other indicates we are not overfitting the data. We will further explore tuning the learning rate and number of hidden units.

Future Work

- Further analyze reason for poor performance of traditional classifiers by changing window size.
- Evaluate performance of state based models like HMMs to better capture transient phenomena.
- Apply Discrete Wavelet Transform to handle time and frequency information simultaneously.
- Evaluate other learning algorithms like Neural Nets to decide which traditional algorithm works the best.
- Include phase information of CSI for both traditional learning and Deep Learning.
- Collect more data for more users.

References

[1] Wei Wang, Alex X. Liu, Muhammad Shahzad, Kang Ling, and Sanglu Lu. 2015. Understanding and Modeling of WiFi Signal Based Human Activity Recognition. In *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking* (MobiCom '15)

[2] Chunmei Han, Kaishun Wu, Yuxi Wang, and Lionel M. Ni, 2014 WiFall_Device-free Fall Detection by Wireless Networks. In *IEEE Conference on Computer Communications*, (IEEE INFOCOM '14)

[3] Linux 802.11n CSI Tool. Authors: Daniel, Halperin, Wenjun Hu, Anmol Sheth, David Wetherall Maintainers: Daniel Halperin, David Ward

[4] Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." *Neural computation* 9.8 (1997): 1735-1780.