Radar-Based Human Activity Classification for Assisted Living

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Abstract

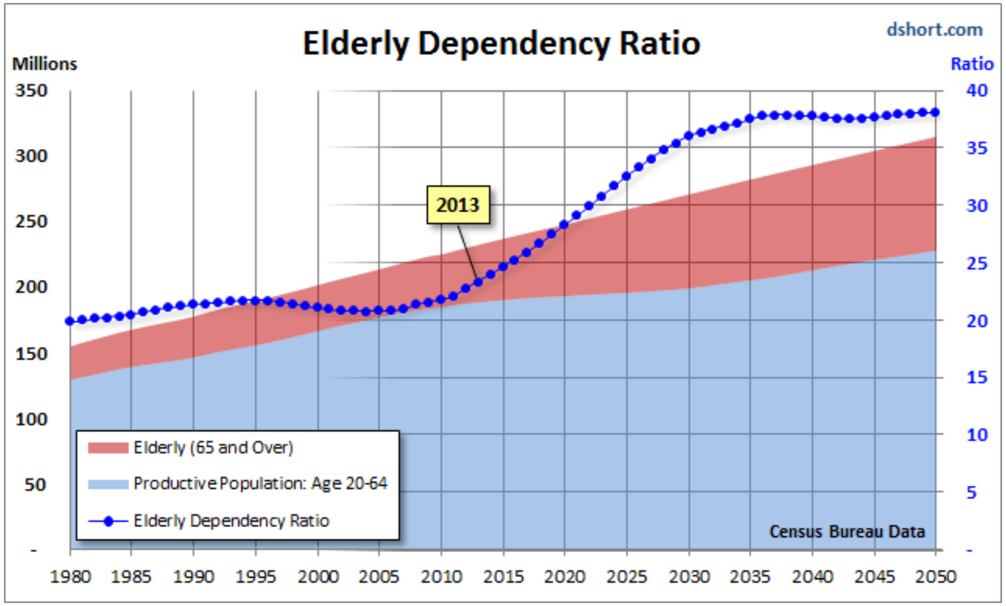
The elderly population aged 65+ years is growing and their ratio to the population aged 15-64 is expected to reach 40% by 2030. This implies that those of working age, and, subsequently, the overall economy, will face a greater burden in supporting the aging population. In addition, the demand and trend is upward for continued independent living. As such, there is a growing interest in assisted living technologies that enable self-dependent living within homes and residences for the elderly. Remote monitoring capabilities, such as detection of falls and small changes in motor functional abilities of the elderly, will address the challenges associated with self-dependent living. This talk focuses on the radar technology and discusses the time-frequency based nonstationary signal processing techniques used to provide the local signal behavior over frequency and to detail the changes in the Doppler and micro-Doppler radar signatures over time. Features that capture the intrinsic differences in the time-frequency signatures of different gross motor activities of the elderly are identified and their performance in human activity classification is demonstrated using real data measurements. Offerings of the range information, in addition to Doppler, for classifying different motion articulations with enhanced reliability are also highlighted.

Biography

Dr. Fauzia Ahmad received her Ph.D. in Electrical Engineering from the University of Pennsylvania in 1997. Currently, she is an Associate Professor in the electrical and Computer Engineering Department at Temple University, Philadelphia. Prior to joining Temple in 2016, she was a Research Professor and the Director of the Radar Imaging Laboratory at the Center for Advanced Communications, Villanova University. She is a Senior Member of the IEEE and a Fellow of SPIE. She is an Associate Editor of the IEEE Transactions on Signal Processing, IEEE Transactions on Aerospace and Electronic Systems, and IEEE Geoscience and Remote Sensing Letters, and is a member of the editorial board of the IET Radar Sonar & Navigation. Dr. Ahmad is a member of the Radar Systems Panel of the IEEE Aerospace and Electronic Systems Society, Sensor Array and Multichannel Technical Committee of the IEEE Signal Processing Society, the Electrical Cluster of the Franklin Institute Committee on Science and the Arts, and the IEEE Dennis J. Picard Medal for Radar Technologies and Applications Selection Committee. She has also been the Chair of the SPIE Compressive Sensing Conference Series since 2012. Dr. Ahmad has 220+ journal and conference publications and seven book chapters in the areas of statistical signal and array processing, radar imaging, compressive sensing, target detection, localization, and identification, direction finding, and ultrasound imaging. She has been a PI/Co-PI on various projects in the aforementioned areas with the total research awards exceeding $6.5M.

Elderly Population

- **Elderly dependency ratio** (Ratio of population aged 65+ to the population aged 20-64)



Those of working age, and, subsequently, the overall economy, will face a greater burden in supporting the aging population

Continued Independent Living

- Provision of independent living to the elderly is a growing area of interest
- Demand and trend is upward for continued independent living in the elderly
- Independence-assisting technologies that can remotely provide capabilities, such as early detection of health deterioration, fall risk assessment and fall detection, are in high demand
- Such technologies can address the challenges of self-dependent living in homes and residences for the elderly population

Falls in the Elderly Population

- Approximately 30% of people over 65 fall each year, and for those over 75, the rates are higher[1]
- 20% to 30% of those who fall suffer injuries that reduce mobility and independence and increase the risk of premature death[1]
- Falls represent the leading cause of fatal and nonfatal injuries among older adults[2]
- Direct medical costs for fall-related injuries among people aged 65+ was $34 billion in 2013 and could reach $67 billion by 2020[3]
- Prompt assistance after a fall can help reduce complications and save lives

[1]Health Evidence Network. http://www.euro.who.int/__data/assets/pdf_file/0018/74700/E82552.pdf

[2]Englander F, Hodson TJ, Terregrossa RA. Economic dimensions of slip and fall injuries. *Journal of Forensic Science.* 1996;41(5):733-746.

[3]National Council on Aging

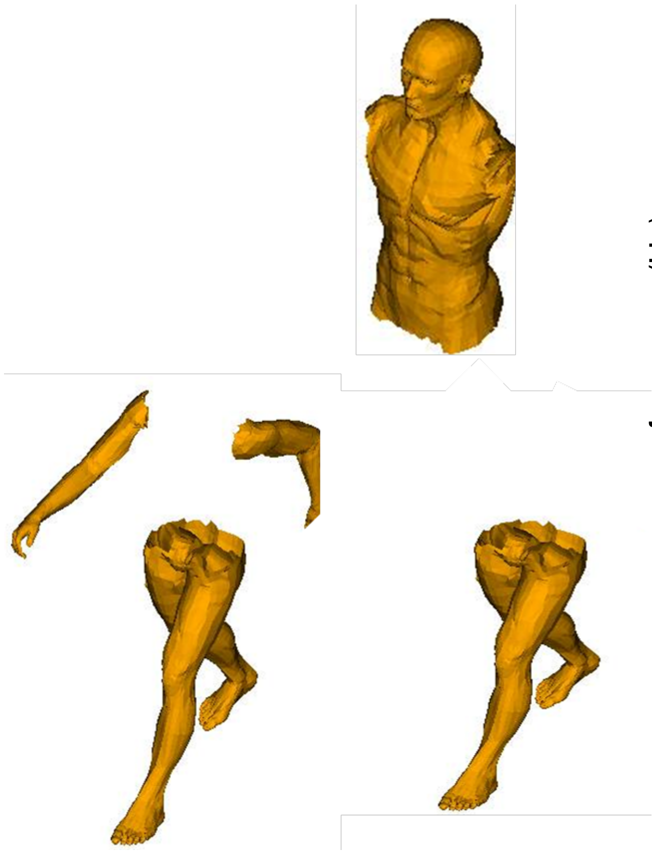
Fall Monitoring Devices

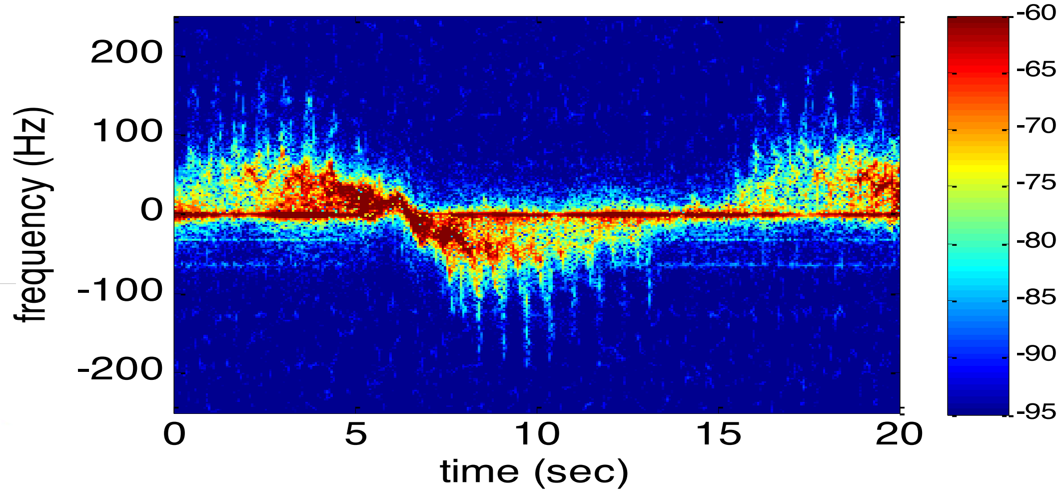
- Fall Detectors: Wearable and Non-wearable
- Wearable devices
  - “Push-button” type or Accelerometer based devices
  - Cannot be activated when loss of consciousness occurs
  - Elderly persons may forget to wear all the time
- Non-wearable devices
  - Floor vibration sensors, Microphone arrays, cameras
  - High false alarms, privacy concerns
- Radar is an alternate modality that addresses many of these concerns and has proven capability of detecting human motions

Radar-Based Motion Detection

- Doppler frequency enables estimation of radial velocity of a target
- Rotation and vibration motion of a target or its parts may produce periodic Doppler modulations of the received signal (***Micro-Doppler effect***)
- Micro-Doppler parameters may aid in target classification
  - Doppler repetition period, Doppler amplitude, and initial phase, directly indicate specific target characteristics

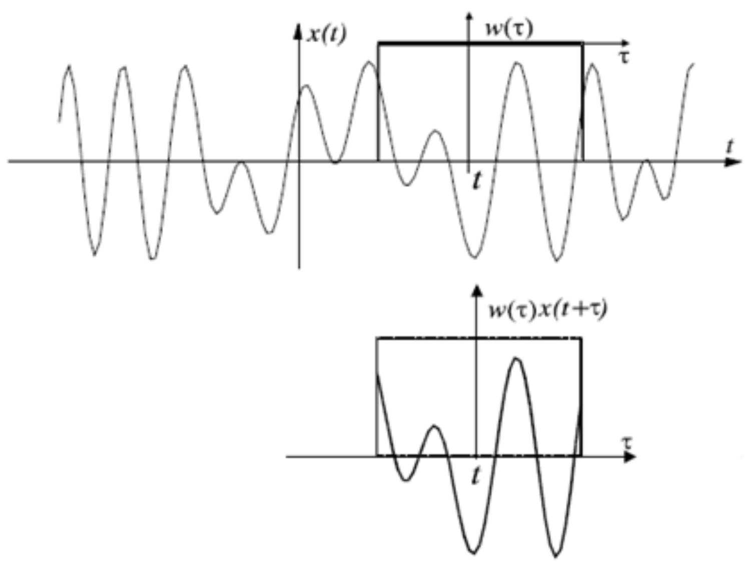
Micro-Doppler





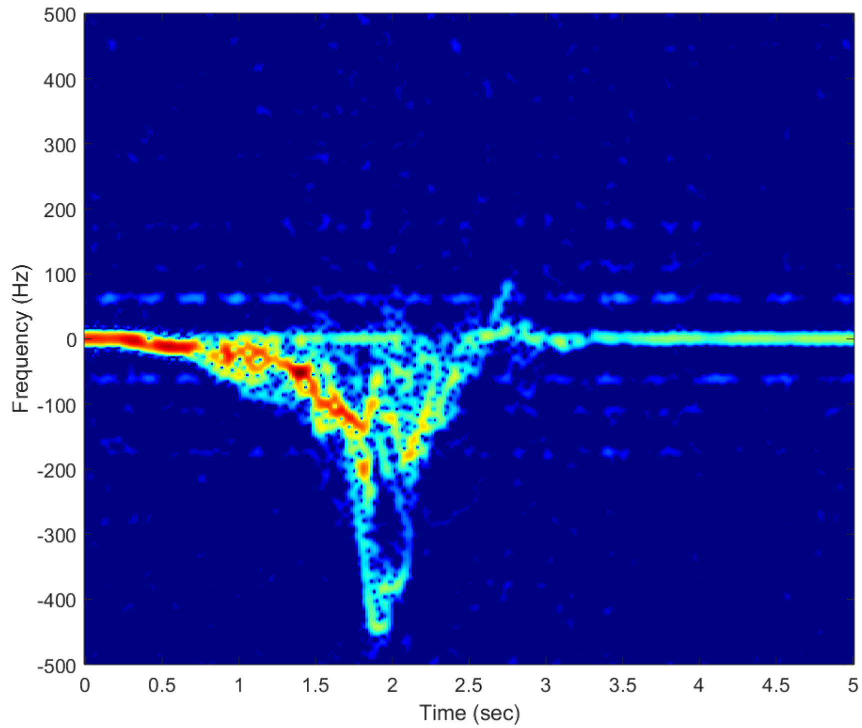
Time-Frequency Distributions

- Simplest TFD - Spectrogram

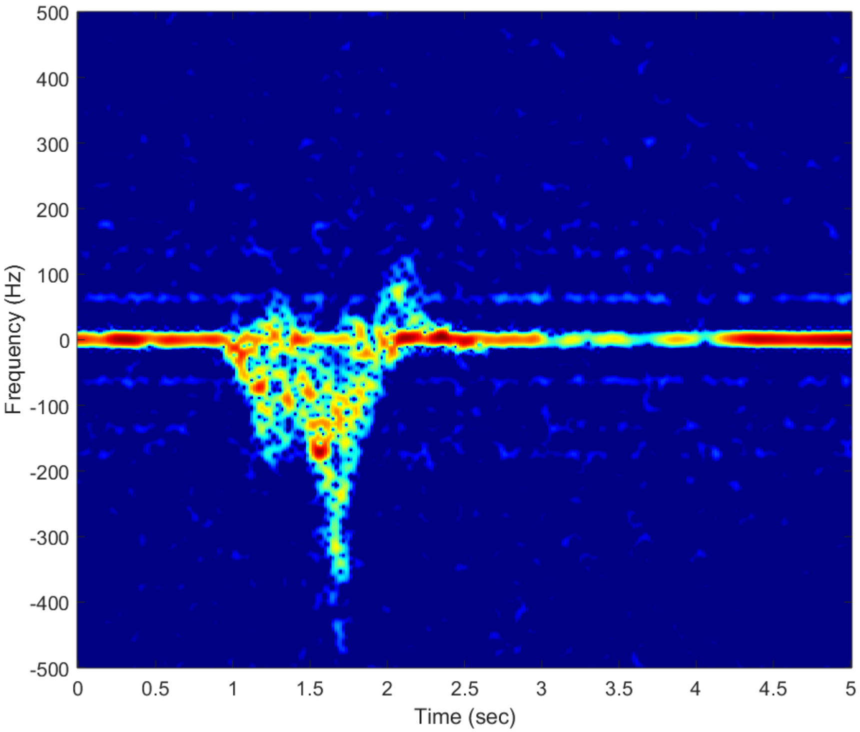


$$SPEC(n,k) = \left| \sum_{m=-N/2}^{N/2-1} x(n+m)w(m)e^{-j\frac{2\pi}{N}mk} \right|^2$$

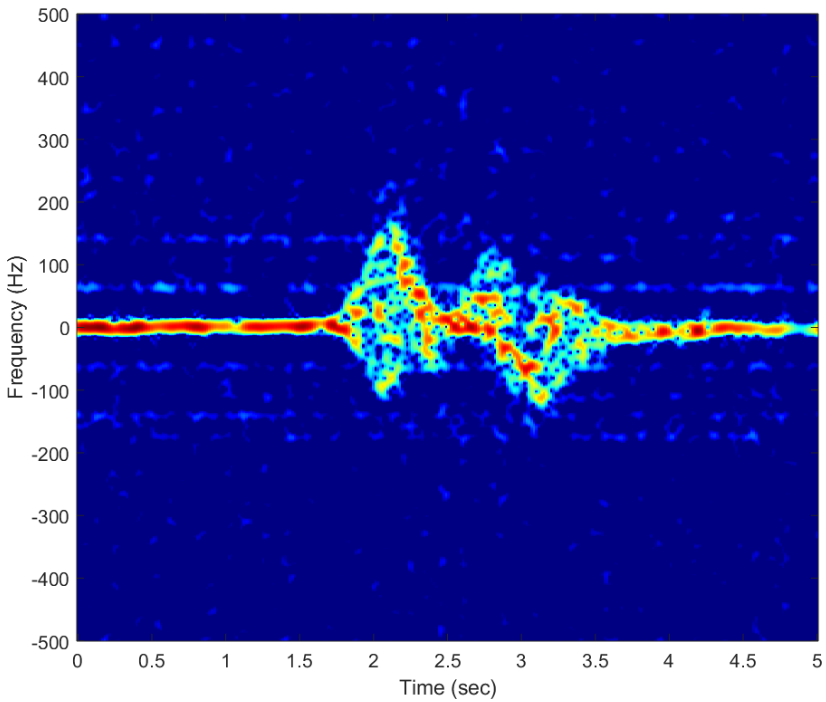
Micro-Doppler Signature - Falling



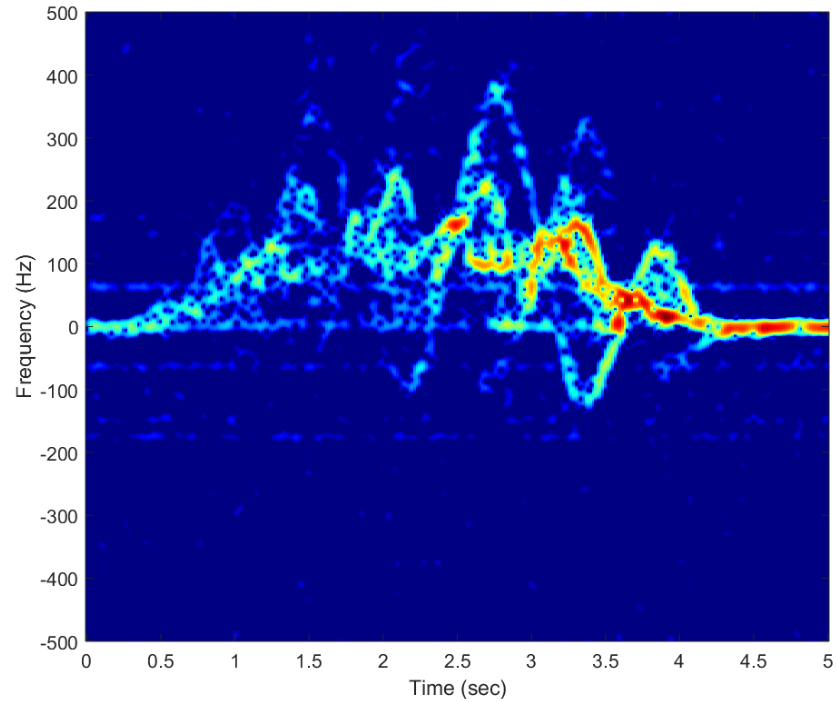
Micro-Doppler Signature - Sitting



Micro-Doppler Signatures - Other Motions



Picking up an object from the floor



Walking

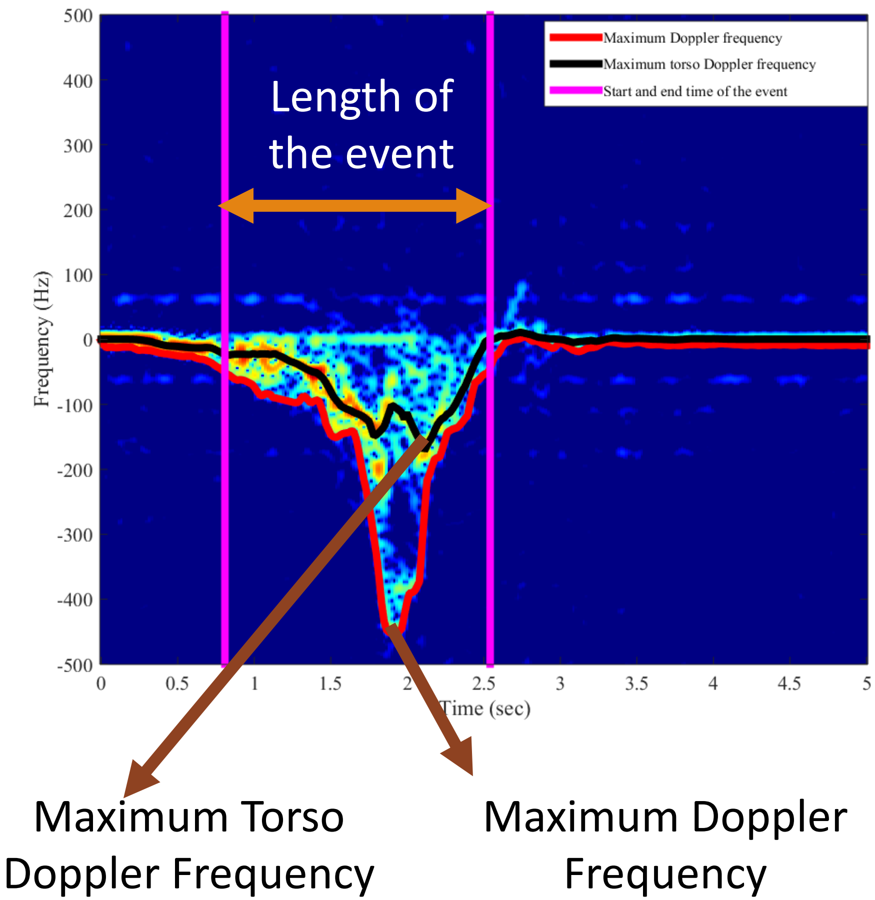
Experimental Data

- Doppler Radar with a carrier frequency of 8 GHz
- Sampling frequency of 1 kHz
- 5 different test subjects, each repeated the motions 5 times so that variations could be monitored for all the activities

Feature-Based Approach to Fall Detection

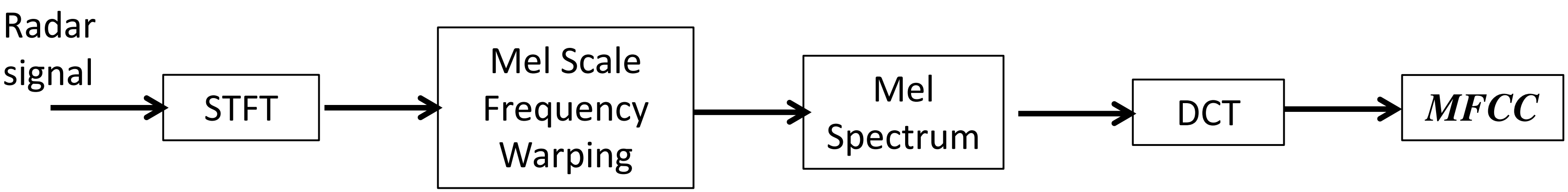
- Two classes of human activity: Fall and Non-Fall motions
- Features extracted from suitable signal representations
  - Time-frequency based features
  - Speech processing based features
  - Wavelet transform based features
  - Time-frequency based power burst curve features

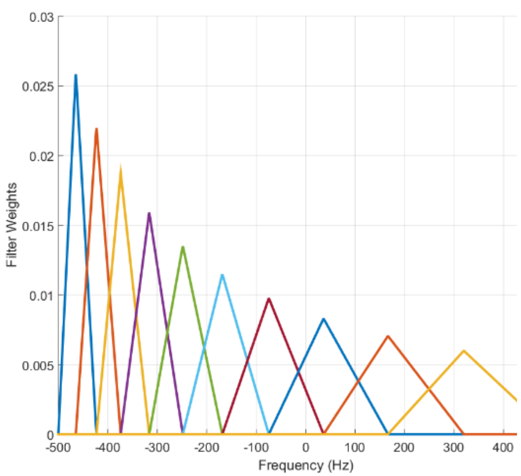
Time-Frequency Based Features



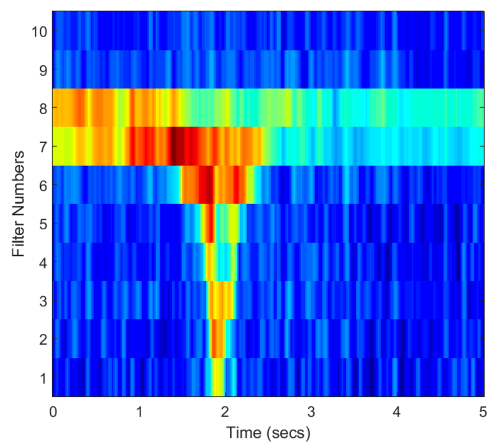
Class\Activities	Fall	Non-Fall
Fall	0.92	0.08
Non-Fall	0.06	0.94

Mel-Frequency Cepstrum Based Features





MFCC Filterbank

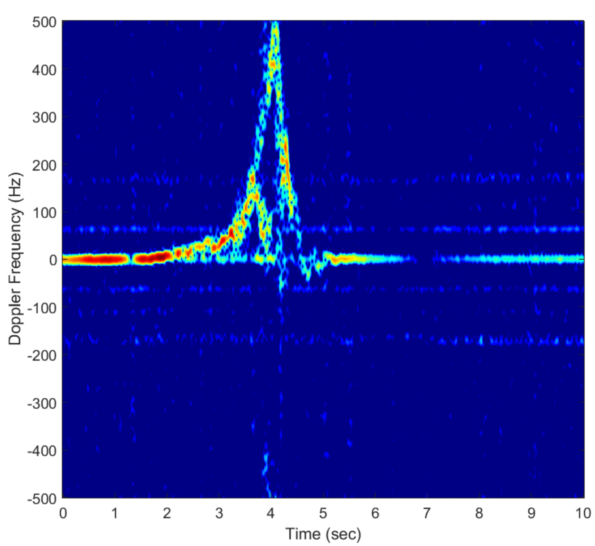


Coeffs

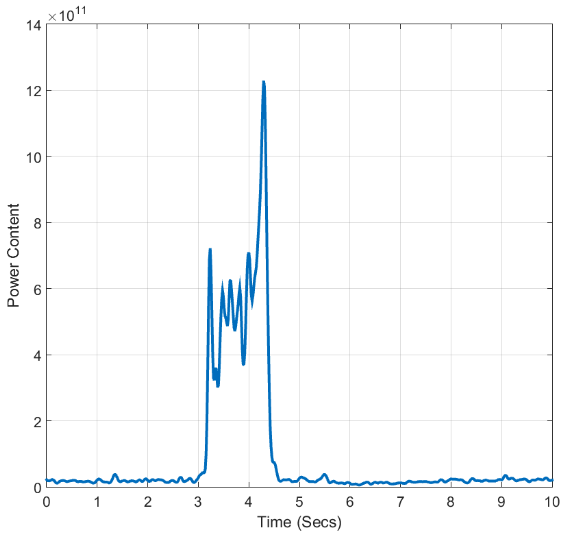
Class\Activities	Fall	Non-Fall
Fall	0.88	0.12
Non-Fall	0.09	0.91

Power Burst Curve

- Power burst curve represents the summation of signal power within a specified frequency band at a given time instant



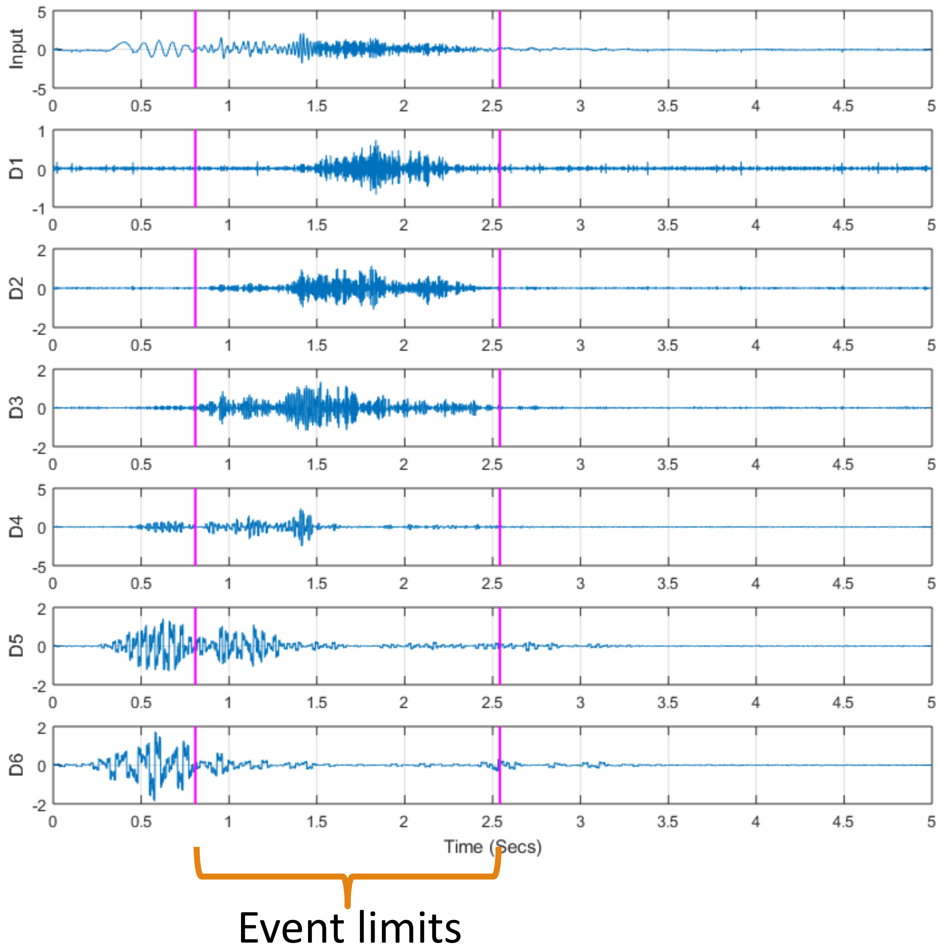
Spectrogram



PBC

Class\Activities	Fall	Non-Fall
Fall	0.90	0.10
Non-Fall	0.13	0.87

Wavelet Based Features

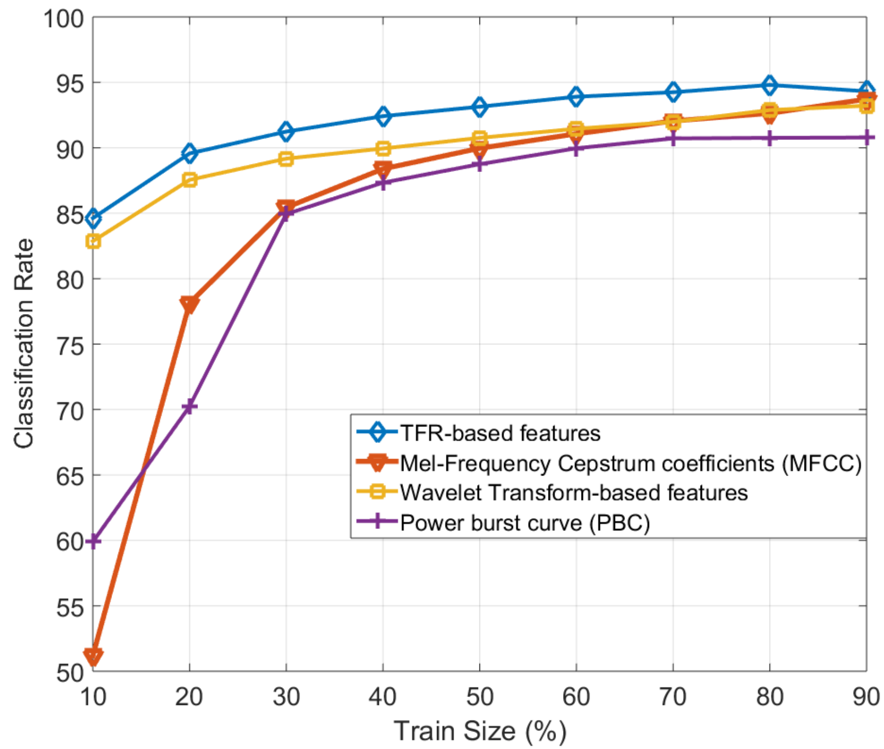


6-level Stationary Wavelet Transform
(Reverse biorthogonal wavelet 3.3)

Class\Activities	Fall	Non-Fall
Fall	0.88	0.12
Non-Fall	0.07	0.93

Classification Rate

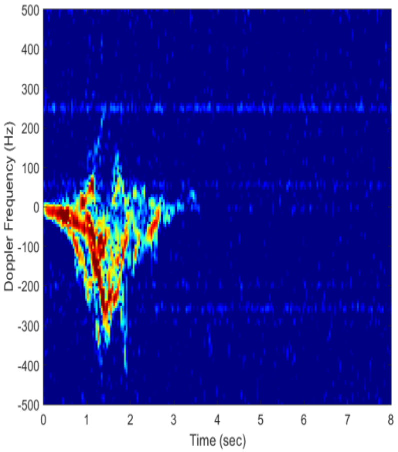
- Time-frequency based features provide the best classification results even with smaller training sizes
- Both wavelet and time-frequency features yield better results compared to other features
- MFCC and PBC methods render the classifier more computationally complex

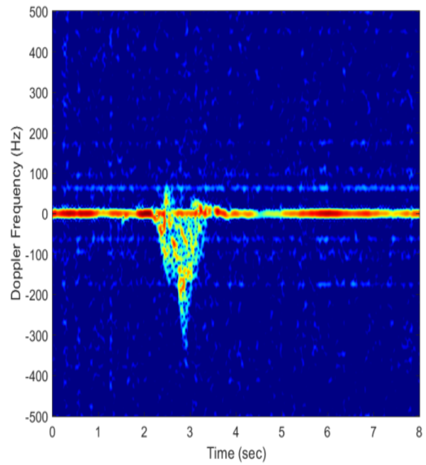


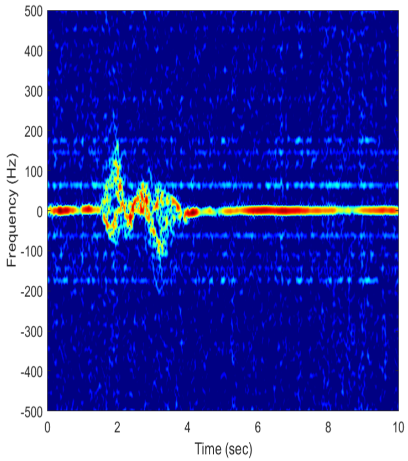
Performance

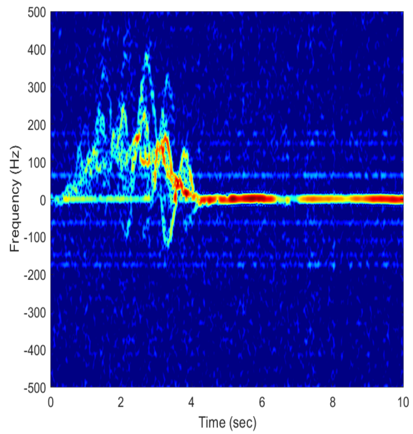
- Best classification rate is provided by the TFR-based features
- False alarms mostly originated due to confusion between falling and sitting
- Micro-Doppler signatures highly dependent on the speed of motion

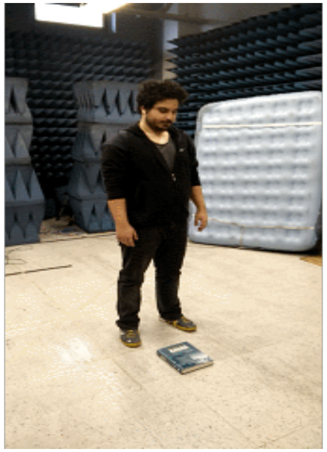
Time-Frequency Domain





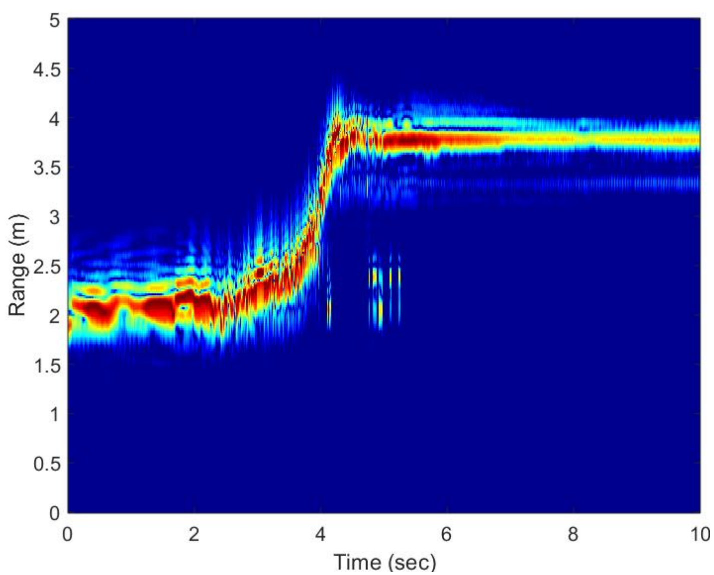




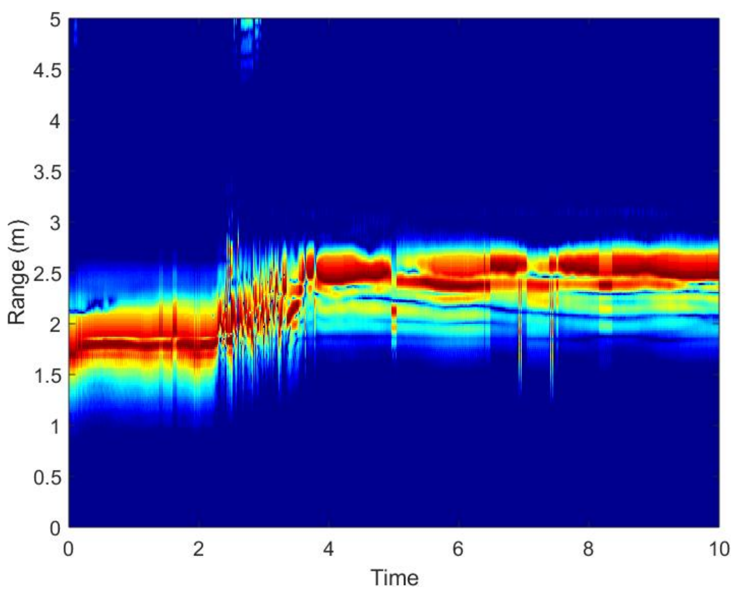


Range Information

- Micro-Doppler signatures fail to separate slow falls and fast sitting
- Range spread of the motions plays an important role to remove the ambiguity
- Requires use of a pulse-Doppler radar



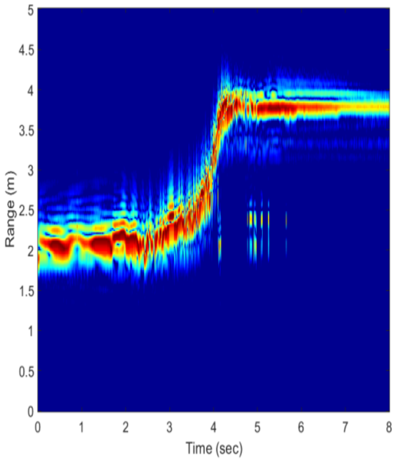
Range map of a fall

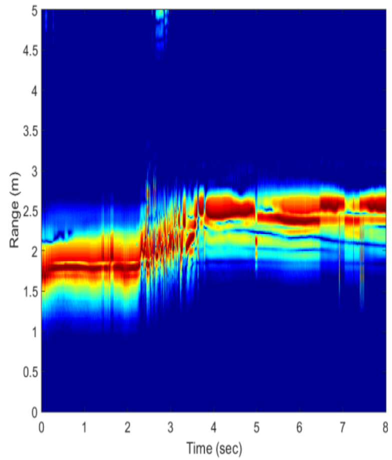


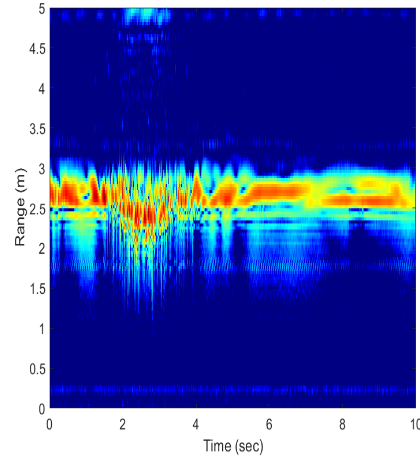
Range map of a sit

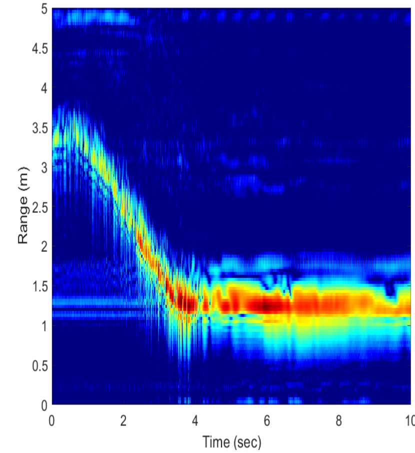
TEMPLE UNIVERSITY

Range-Time Domain





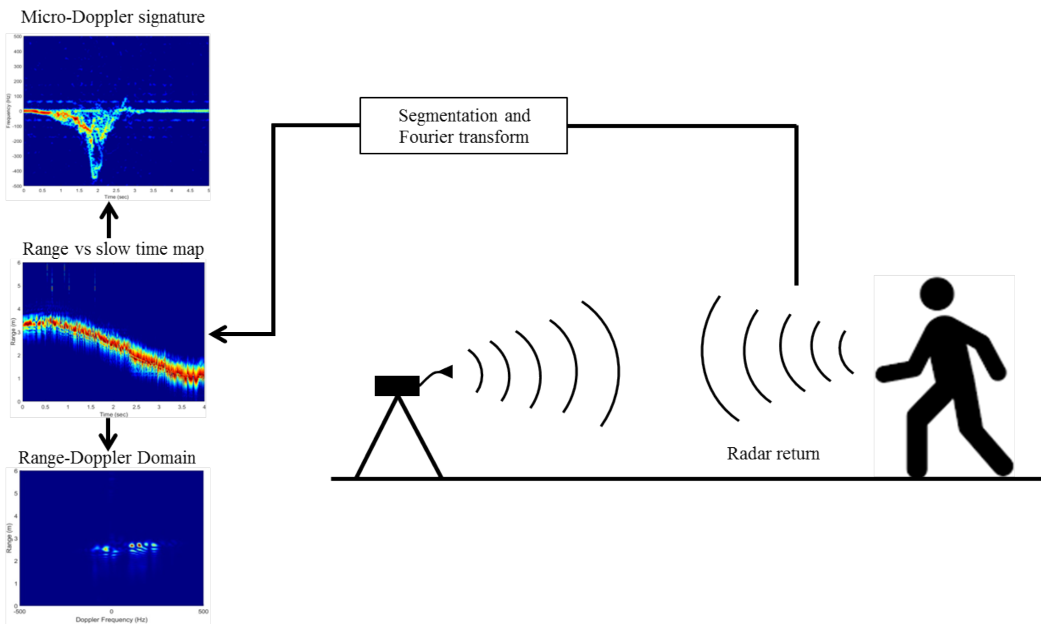




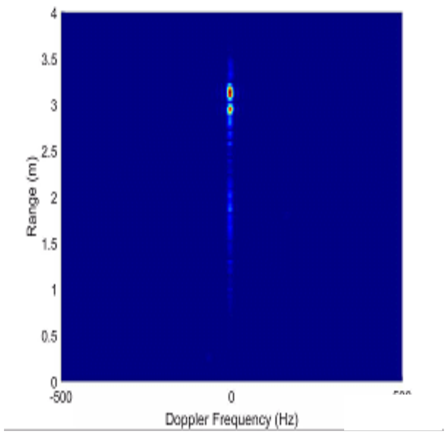
Tri-Domain Signal Representations

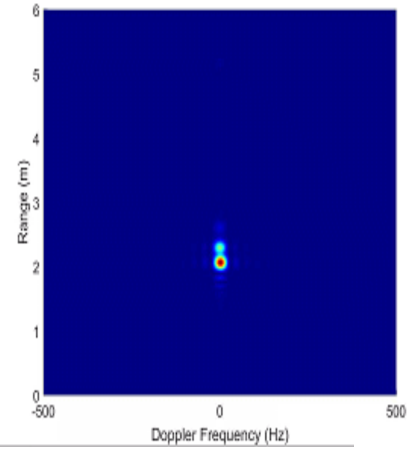
- Tri-domain signal representations
  - Time-frequency domain (Micro-Doppler signature)
  - Range-time domain
  - Range-Doppler domain

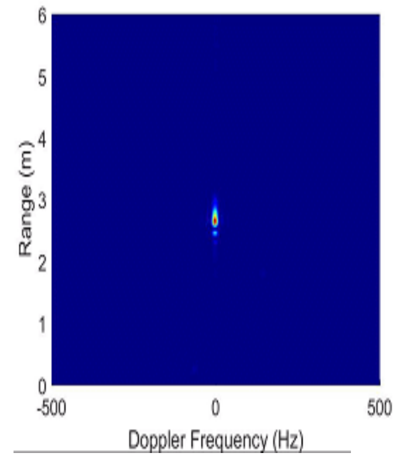
24 GHz UWB radar

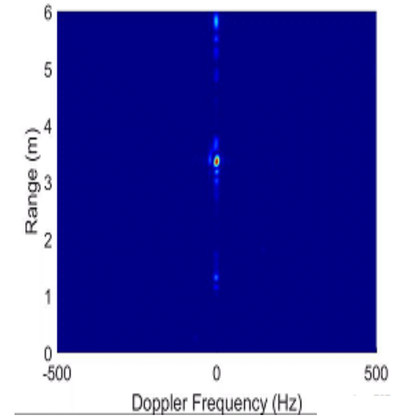


Range-Doppler Domain



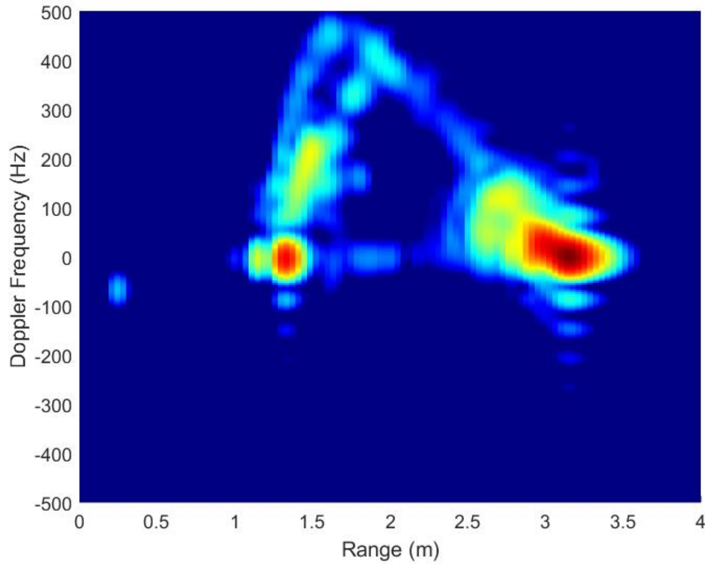




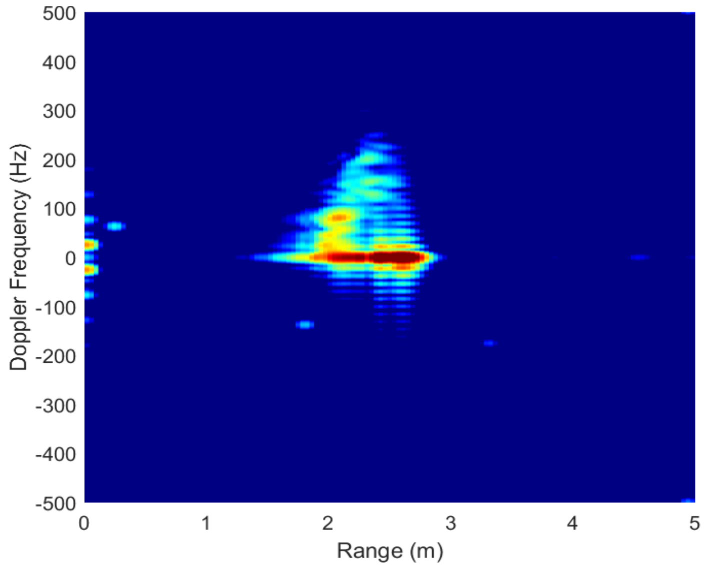


Time-Integrated Range-Doppler Domain

- Time-integrated range-Doppler domain is constituted by accumulating consecutive range-Doppler frames



Falling

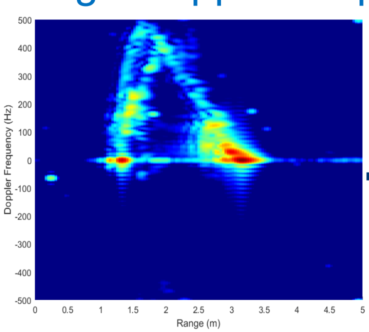


Sitting

Texture-Based Feature Extraction

- 4-step textural-based algorithm:
  i. Compute gray-level co-occurrence matrix (GLCM)
  ii. Extract 13 Haralick statistical features
  iii. Select *n* features that maximize the detection
  iv. Compute the confusion matrix

Time-integrated range-Doppler map



→ ***GLCM Computation*** → ***Statistical Feature Extraction*** → ***Feature Selection*** → ***Classification***

GLCM

- GLCM shows how often a gray-level pixel pair occurs in different directions
- Two parameters are required to construct
  - Displacement: d
  - Direction: θ

0	2	3	0
1	0	2	3
0	1	3	2
2	0	1	3

(a)

#	0	1	2	3
0	0	3	3	1
1	3	0	0	2
2	3	0	0	3
3	1	2	3	0

#	0	1	2	3
0	1	0	1	2
1	0	0	4	0
2	1	4	0	0
3	2	0	0	1

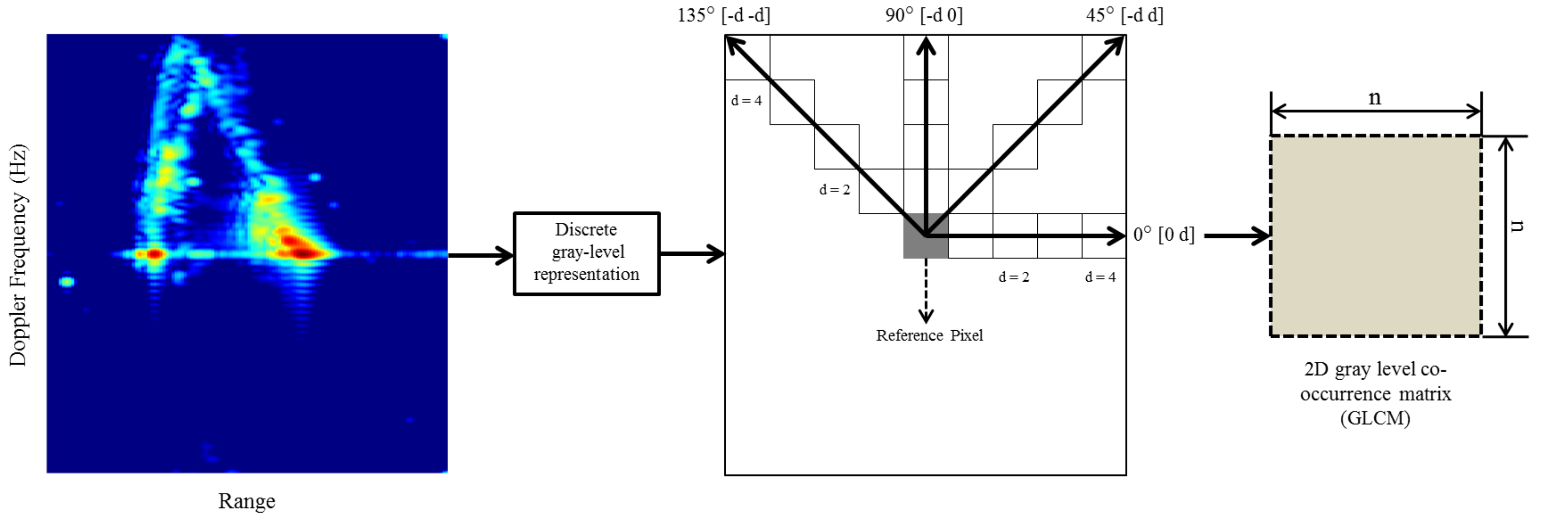
#	0	1	2	3
0	0	4	2	1
1	4	0	0	1
2	2	0	0	4
3	1	1	4	0

#	0	1	2	3
0	2	0	0	1
1	0	2	0	0
2	0	0	2	0
3	1	0	0	2

Directions 0^o, 45^o, 90^o, and 135^o with a distance d =1

GLCM

- Four directions are considered: $\theta_1: 0°, \theta_2: 45°, \theta_3: 90°, \theta_4: 135°$
- Displacement: $d_1 = 1, d_2 = 4$
- Sixteen gray levels
- 8 GLCMs, each of size 16 × 16



Statistical Features

- Haralick proposed 13 measures of textural features.
- Typical features derived from GLCM:
  - Angular second moment
  - Contrast
  - Correlation
  - Sum of squares: Variance
  - Inverse difference moment
  - Sum average
  - Sum variance
  - Sum entropy
  - Entropy
  - Difference variance
  - Difference entropy
  - Information measure of correlation 1
  - Information measure of correlation 2

R.M. Haralick, K. Shanmugam, I. Dinstein, “Textural Features for Image Classification”, IEEE Trans. Systems, Man and Cybernetics, 1973.

Feature Selection

- Do we need all statistical features to achieve good detection performance?
- Selection of the minimal set of relevant features is important for optimizing detection performance
- Different methods have been proposed
  - Mutual information
  - Entropy to rank features
  - Principal component analysis for dimension reduction
  - Sequential forward selection (SFS)

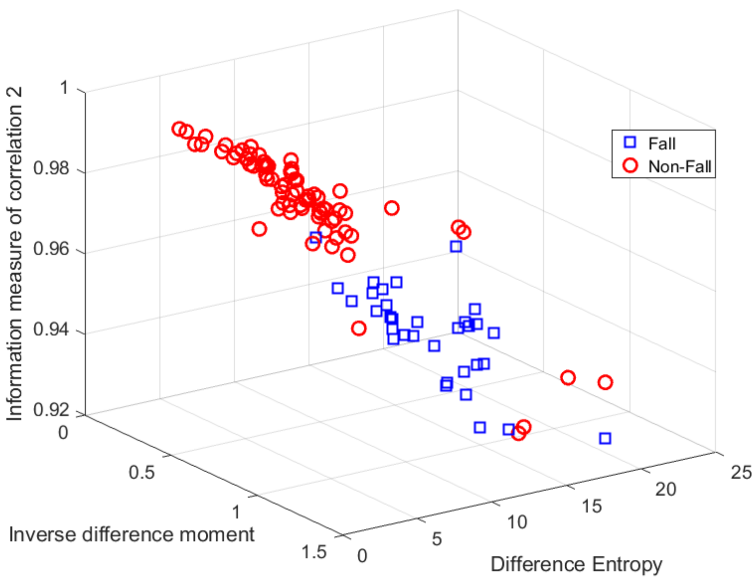
Sequential Forward Selection

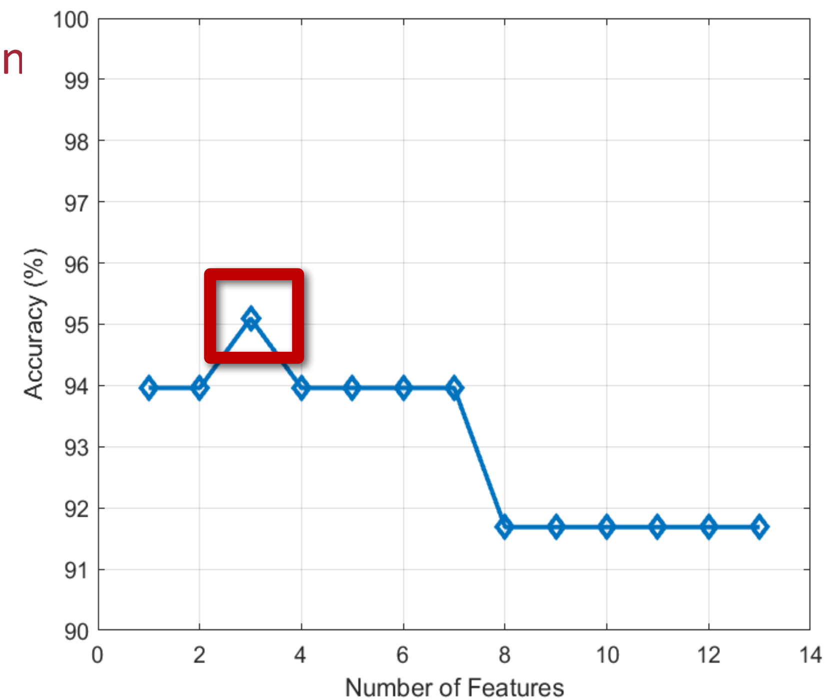
- SFS: Heuristic search method
- Selects the features yielding the highest value of a pre-defined objective function: **Classification Accuracy**
- Algorithm
  i. Start with an empty set of feature
  ii. Select the next feature, the one that yields the highest accuracy when used together with previously selected features
  iii. Update the selected feature set, and move to the next feature
  iv. Repeat steps (ii) and (iii) until total number of desired features is selected

T. Rückstieß, C. Osendorfer, P. van der Smagt, "Sequential feature selection for classification," Advances in Artificial Intelligence, Lecture Notes in Computer Science, vol. 7106, 2011

Sequential Forward Selection

- Best performance is achieved when three features are selected
  - Inverse difference moment
  - Difference entropy
  - Information measure of correlation





Classification Results

Comparison of feature sets (%)

	Accuracy	Detection Rate	False Alarm Rate	Missed
Micro-Doppler 13 statistical features	**88.54**	**88.48**	**7.40**	**15.52**
Range-Doppler 13 statistical features	**91.62**	**89.42**	**6.17**	**10.58**
Range-Doppler SFS 3 statistical features	**95.09**	**94.73**	**4.55**	**5.27**

Fall Detection

Conclusion

- Rapid early detection of elderly falls is feasible using radars signal
- Great application potential in time-critical and privacy-sensitive scenarios
- Reduction of false alarms remains the leading obstacle in final developments and marketing of this technology