







Projet Fédérateur Mobilités et Transitions Numériques [03/12/2018 – IFSTTAR Marne-la-Vallée]

ULTRA WIDE-BAND SHORT-RANGE RADAR FOR VULNERABLE ROAD USERS IDENTIFICATION

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General Problematics Overview of Technical Works

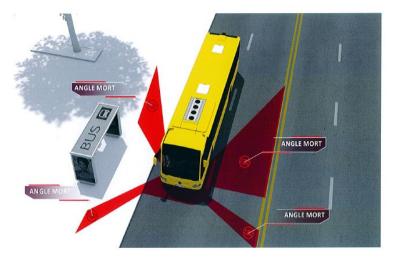
Introduction Target Detection and Identification cing Target Detection and Identification



□To deploy the system in the blind spots areas of buses and trucks

Objective:

□To develop a solution that facilitates the integration of cyclists into urban traffics and protects the pedestrians by improving their safety



General Problematics Overview of Technical Works

General Problematics

- *cyclists* and *pedestrians* are the most vulnerable road users
- around 2000 people riding bicycle are killed every year in EU countries in traffic accidents
 [ERSO, 'Traffic safety basic facts 2015: cyclists', Tech. Rep, European

Road Safety Observatory, 2015]

Fundamental causes:

- Iack of drivers visibilities (bus,truck: *blind spots*)
- Iack of attentions [cyclists, pedestrians, drivers]

Proposed Solutions and Technology

Identification of VRUs using UWB Short Range Radar

General Problematics Overview of Technical Works

Technical Issues

Target detection:

- cyclist and pedestrians have low Radar Cross Section (RCS)
- reflect a very limited amount of radar energy (low SNR)
- highly influenced by the capacity to distinguish the useful radar information and the noise or clutter.

Target Recognition:

In a real complex environment, recognizing the pedestrian and cyclist using UWB radar is required a good machine learning system

General Problematics Overview of Technical Works

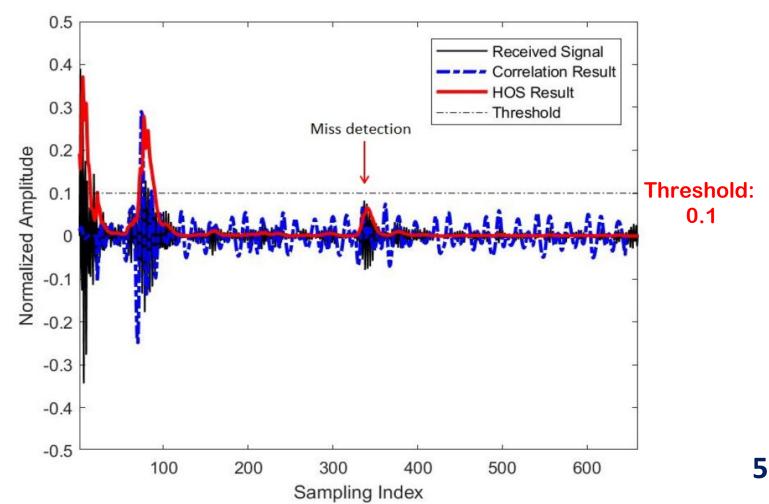
Introduction Target Detection and Identification Enhancing Target Detection and Identification Conclusion and Perspective

- Detection:
 - HOS & CA-CFAR (1-D)
 - HOS & WSD (2-D)
 - HOS : Higher Order Statistics
 - CA-CFAR detector: *Cell Averaging-Constant False Alarm Rate* detector
 - WSD : Wavelet Shrinkage Denoising
- Identification:
 - SVM: Support Vectors Machines (1-D)
 - Deep Learning Algorithm:
 - CNN (Convolution Neural Network) (2-D)



Issues

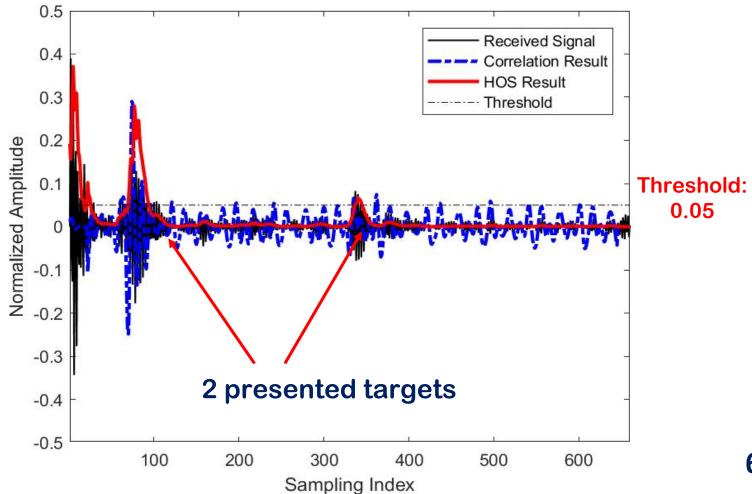
Classical Methods: 2nd Order Statistics (Auto-Correlation) - HOS





Issues

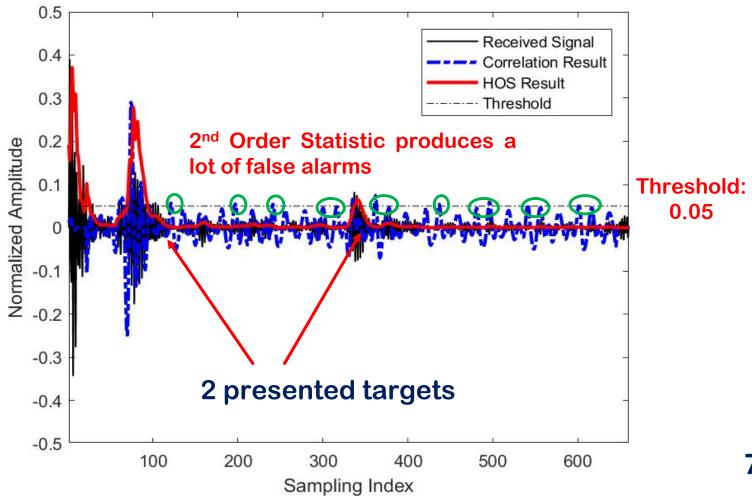
Classical Methods: 2nd Order Statistics (Auto-Correlation) - HOS



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Issues

Classical Methods: 2nd Order Statistics (Auto-Correlation) - HOS



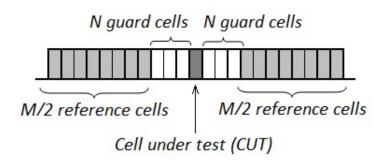
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Detection Identification

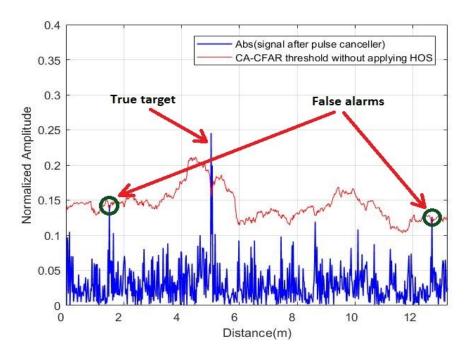
Issues

Well-Kown CA-CFAR Detector

Adaptively threshold based on local information on the background noise



Problem: Difficult to determine the number of reference cell (M)

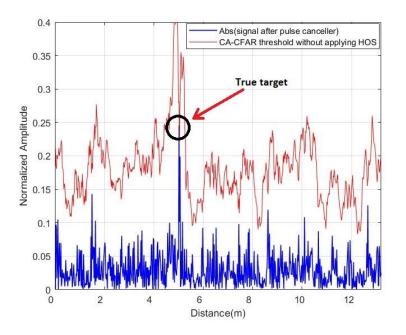


 $P_{fa} = 10^{-5}$, M = 80, and N = 2.

Detection Identification

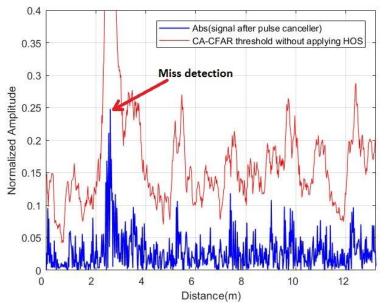
Issues

Well-Kown CA-CFAR Detector



 $P_{fa} = 10^{-5}$, M = 20, and N = 2.

If we keep this setting, the next raw data will miss the target

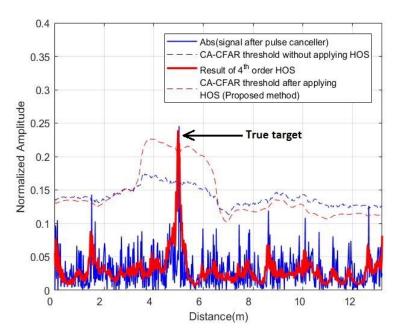


 $P_{fa} = 10^{-5}$, M = 20, and N = 2.

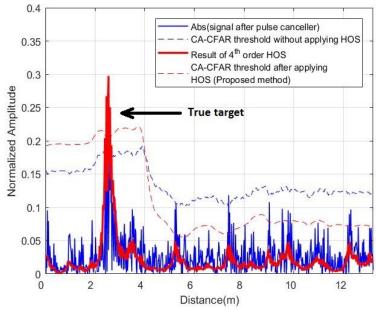
Detection Identification

Proposed Method

HOS + CA-CFAR



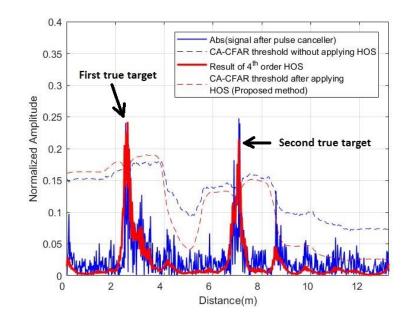
 P_{fa} = 10⁻⁵, M = 150, and N = 2. A real target presents at 5 meters away from the radar.



 P_{fa} = 10⁻⁵, M = 150, and N = 2. Two real targets present at 2.5 and 7 meters away from the radar. **10**

Detection Identification

Proposed Method

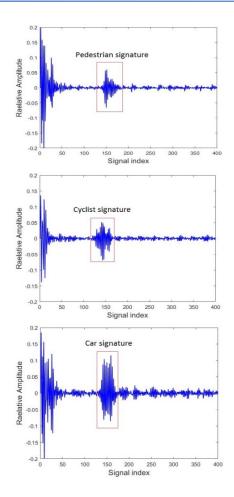


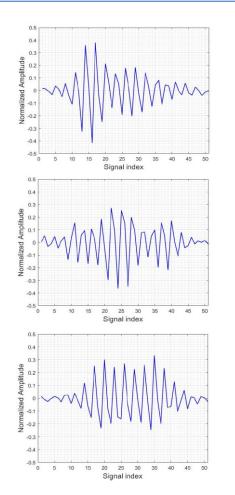
HOS + CA-CFAR

 P_{fa} = 10⁻⁵, M = 150, and N = 2. Two real targets present at 2.5 and 7 meters away from the radar.

Detection Identification

Radar Signature





Normalized Pedestrian signature

Normalized Cyclist signature

Normalized Car signature

Detection Identification

Support Vector Machine (SVM)

Result of Performance of SVM using 1-D Radar Signature

[Confusion Matrix]

	Cyclist	Pedestrian	Car		
Cyclist	96.23%	2.46%	1.31%		
Pedestrian	3.62%	95.25%	1.13%		
Car	1.60%	1.17%	97.23%		

Total Accuracy =96.24%

Total *Training* dataset= 3000, 1000 each class Total *Testing* dataset= 1200, 400 each class

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Noise Removal

Proposed Method:

Higher Order Statistics (HOS) + *Wavelet Shrinkage Decomposition* (WSD)

WSD

Advantage: preserve the signal characteristics, and regardless of its frequency contents

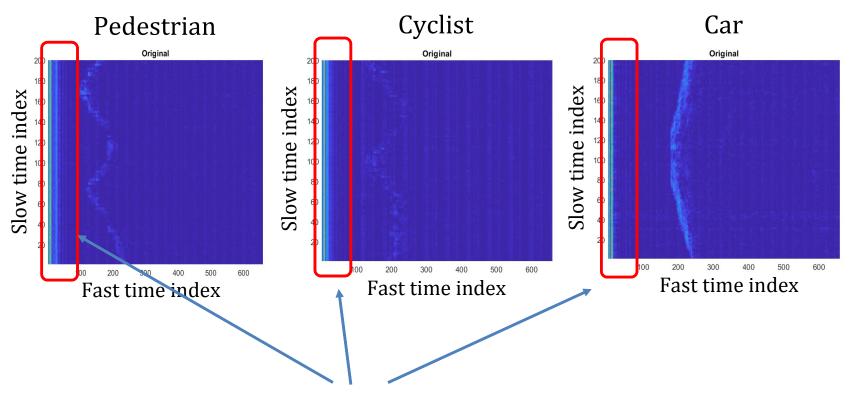
HOS

Advantage: Good in suppresing the non-gaussian noise

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Noise Removal





#1: Apply Pulse Canceller to remove direct coupling between two antennas

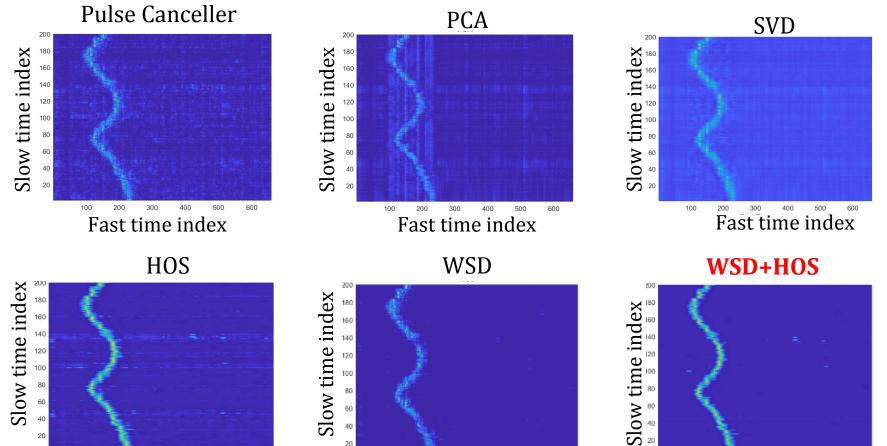
2-D Imaginary Approach

Enhancing Target Detection and Identification

Fast time index

Noise Removal





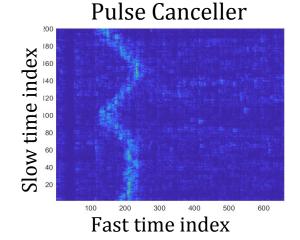
Fast time index

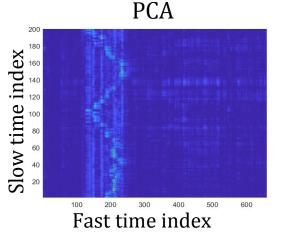
Fast time index

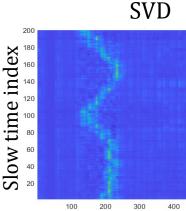
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Noise Removal







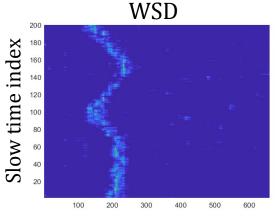


Fast time index

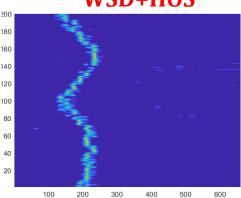
600

17





Fast time index



Slow time index

⁰⁰ 200 300 400 500 60 Fast time index

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Noise Removal

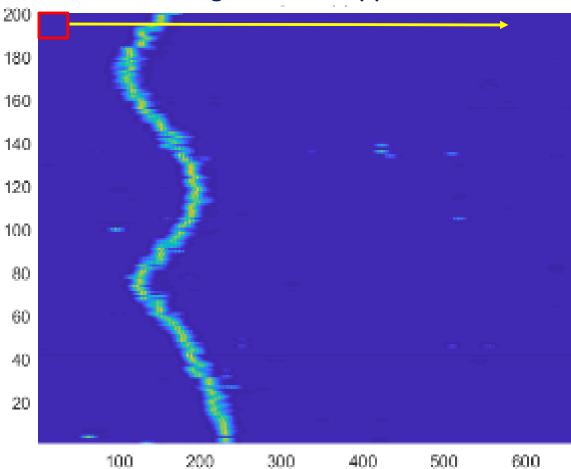
Performance of the HOS+WSD

PERFORMANCE COMPARISON SNR(dB) FOR DIFFERENT NOISE REMOVAL METHODS.

	Noise Removal Methods						
Target Types	Pulse Canceller	РСА	SVD	WSD	HOS	WSD+HOS (<i>Our Method</i>)	
Pedestrian	16.34	19.12	20.53	25.18	25.18	32.47	
Cyclist	15.68	18.26	19.48	23.22	26.02	29.13	
Car	20.82	21.44	21.91	29.30	33.99	38.61	

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Target Detection



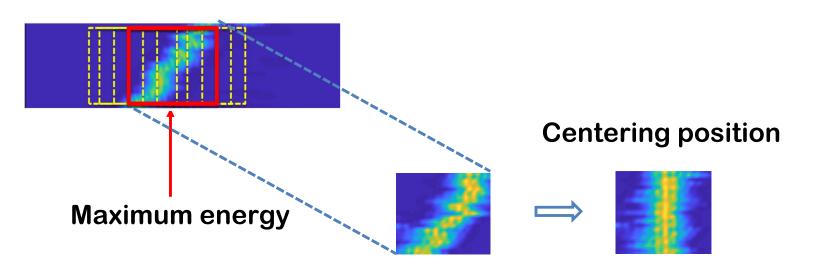
Sliding Windows Approach

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Target Detection

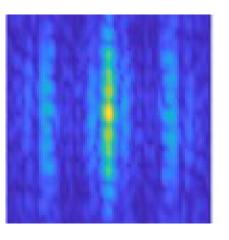
Applying Non-Maximum Suppression on the overlap windows

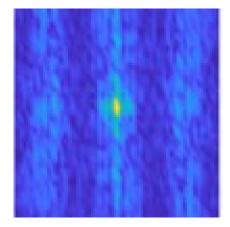


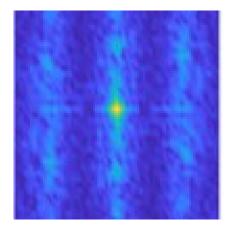
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Dataset

Transform detected region into power spectral density







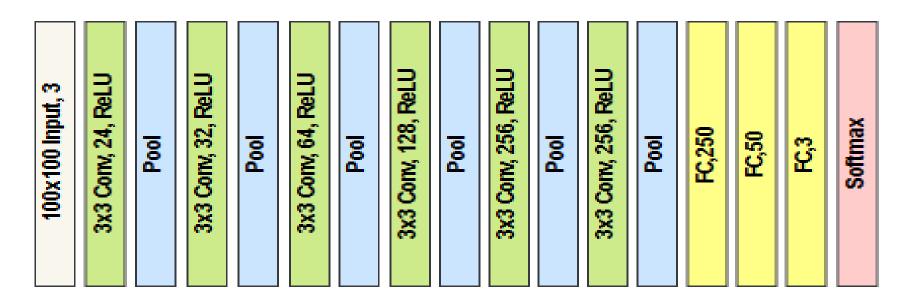




Pedestrian

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Proposed Architecture



Input Layer, 3 RGB Channels

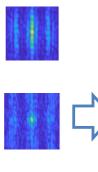
6 Convolution Layers + Max Pooling

(Filter 3x3, Channels: 24, 32, 64, 128, 256, 256)

3 Fully Connected Layers, Channels: 250, 50 and 3 Softmax Output Layer: 3 Classes

Feature Maps Visualisation

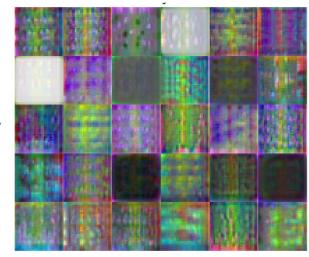
Input Images



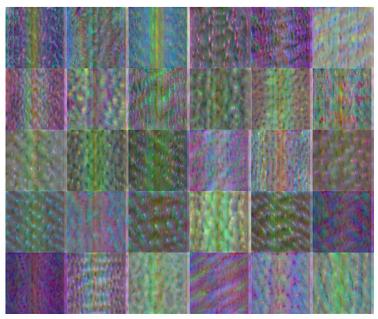


Layer Conv_3 Features

Enhancing Target Detection and Identification



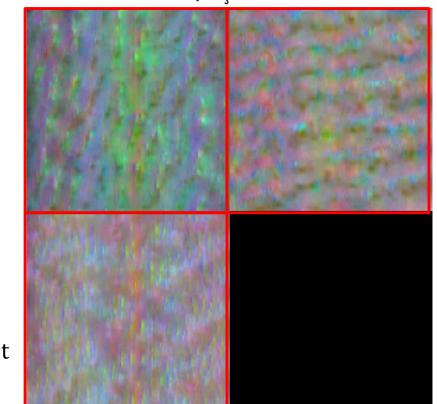
Layer Conv_5 Features



Pedestrian

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Feature Maps Visualisation



Layer fc, Features

Car

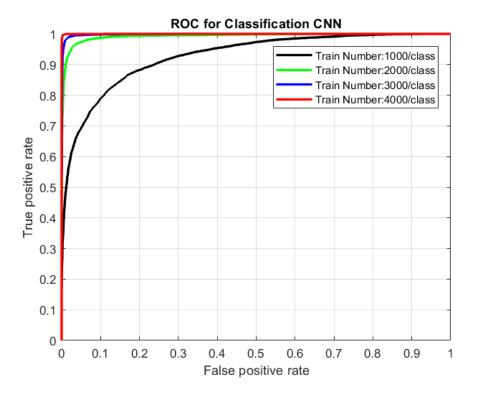
Cyclist

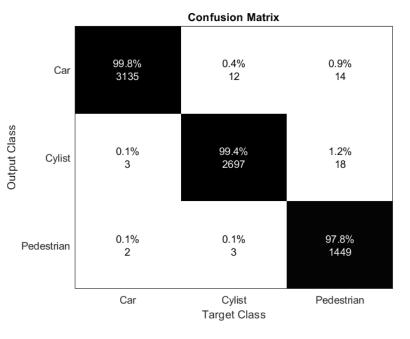
2-D Imaginary Approach Convolution Neural Network (CNN)

Performance Evaluation

Receiver Operating Characteristic (ROC)

Confusion Matrix





- The task of detecting the cyclist and pedestrian using UWB radar requires a good separation of two subspaces data (Signal and Noise)
- Combination of Higher Order Statistics (HOS) and Wavelet Srinkage Denoising (WSD) promises a better result for noise removal and provides good SNR.
- Convolution Neural Network (CNN) is very promising technology in identification of Vulnerable Road Users (cylist and pedestrian) using UWB radar
- This research's method will be applied to develop a system protection of VRUs by combining a tracking system like Extended Kalman Filter and Particle Filter



THANK YOU FOR YOUR ATTENTION