



# Correlation Matching Approach for Through-Wall Corner Detection

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# **Outline**

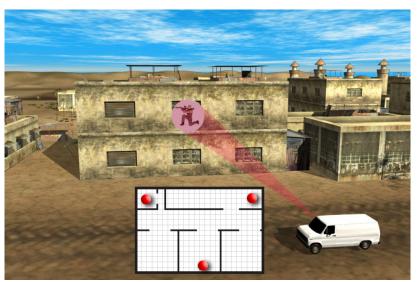
- Motivations
- Objectives
- CS-based Layout Detection for Through-the-Wall Radar Imaging
- Simulation Results
- Conclusions





# Through-the-Wall Radar Imaging

- Emerging technology
- Provides "vision" into optically obscured areas for situational awareness
- Radio Frequency is the modality of choice
- Propagation differences compared to typical radar operational scenarios provide unique challenges
- These challenges must be addressed to make through-the-wall sensors operationally viable.

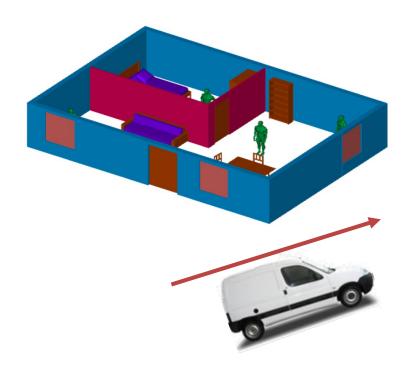


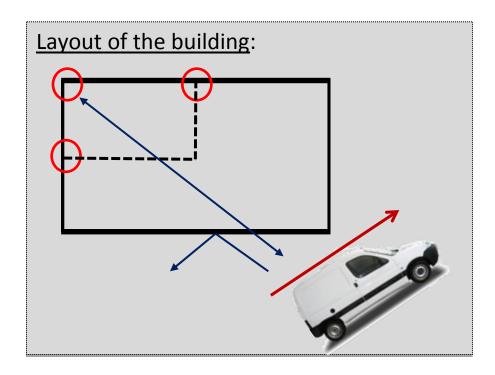




# Objective

We consider the problem of detecting building interior structures using compressive sampling with applications to through-the-wall radar and urban sensing.

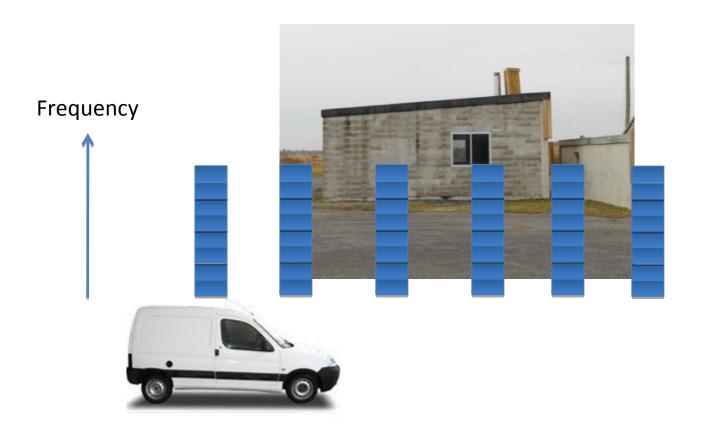








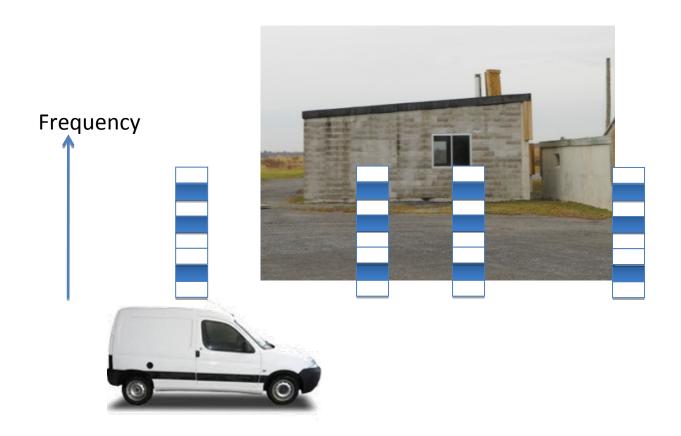
# Conventional Sensing in Stepped Frequency TWR







# Compressive Sensing in Stepped Frequency TWR

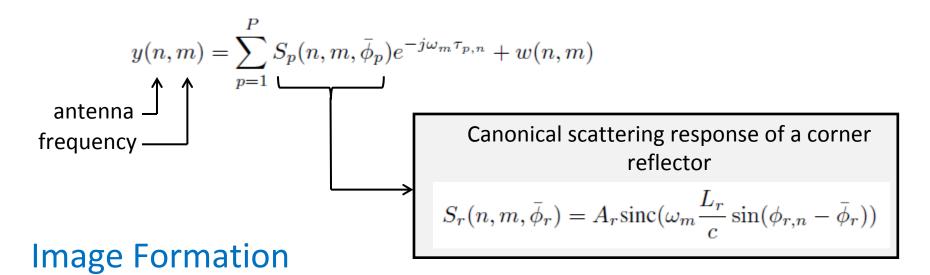






## TWRI Signal Model

The response of the scene can be modeled as the sum of responses from individual scatterers.



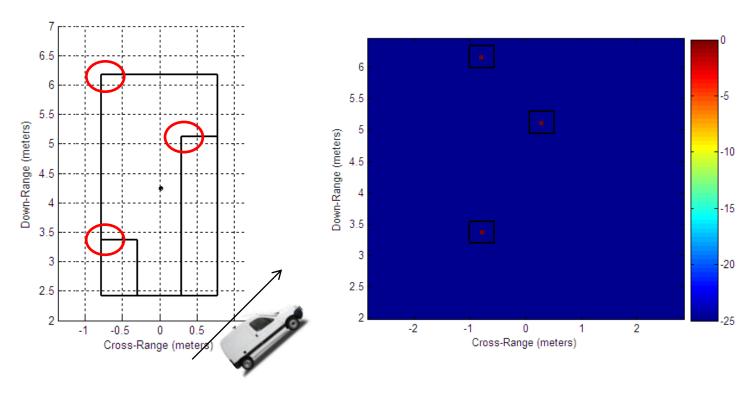
A radar image is generated as follows,

$$r(k,l) = \frac{1}{MN} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} y(m,n) e^{j\omega_m \tau_{(k,l),n}}$$





## **Building Layout Detection Problem**



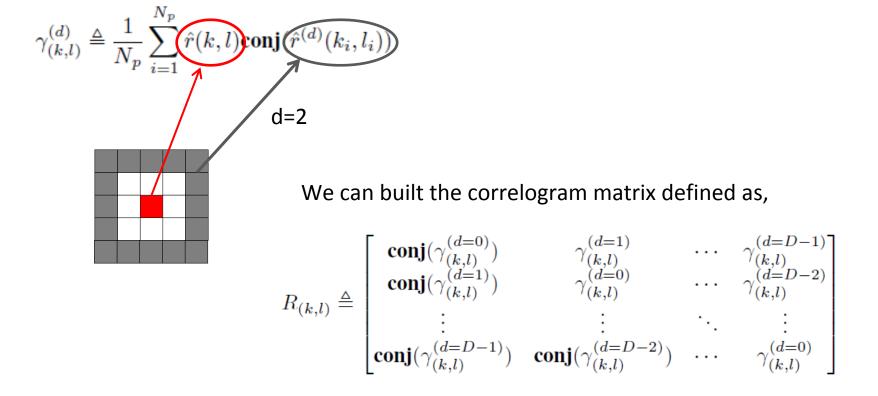
• When von tideal threastings it you describe on by parse in aig paroving the conventional point scatterer image sparsity.





### **Proposed Approach**

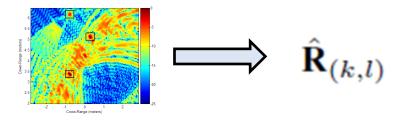
This paper uses a novel type of image descriptor: **the intensity correlogram**.







# Correlation Matching (1/2)



A canonical corner in the (k,l)-th pixel



 $\mathbf{R}^{\mathrm{ref}}_{(k,l)}$ 

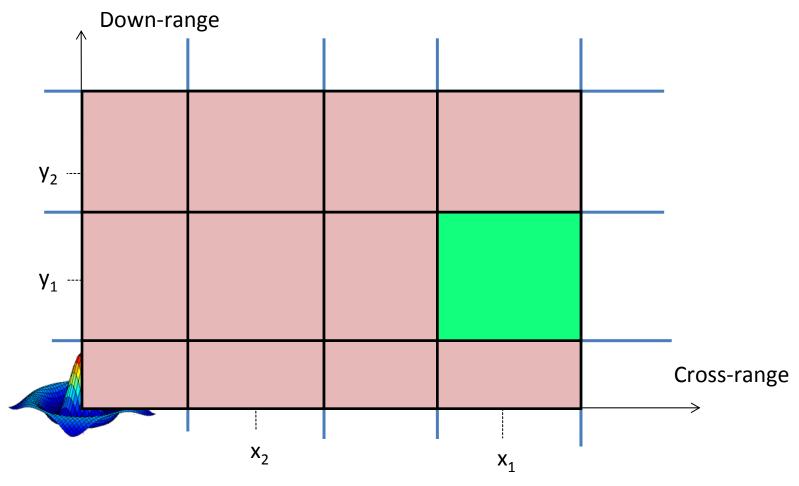
Generates a particular reference correlogram matrix.

$$\min_{\beta} \Psi \left( \hat{\mathbf{R}}_{(k,l)}, \beta(k,l) \mathbf{R}_{(k,l)}^{\text{ref}} \right)$$

- The correlation matching directly promotes sparse solution **avoiding solving the l1-norm constrained optimization problem** encountered in conventional CS.
- The feature-based nature of the proposed detector enables **corner separation from other indoor scatterers** such as furniture or humans.



# Correlation Matching (2/3)







# Correlation Matching (3/3)

#### Error Function $\Psi\left(\cdot,\cdot\right)$ ?



Corner Detector Based on the Frobenius Norm:

$$\min_{\beta(k,l)} \left| \hat{\mathbf{R}}_{(k,l)} - \beta(k,l) \mathbf{R}^{\text{ref}}_{(k,l)} \right|_{F}$$



Corner Detector Based on the Positive Semidefinite Difference between Correlogram Matrices (Eigenvalue method):

$$\begin{aligned} \max_{\beta(k,l) \geq 0} \quad & \beta(k,l) \\ \text{s.t.} \quad & \hat{\mathbf{R}}_{(k,l)} - \beta(k,l) \mathbf{R}^{\text{ref}}_{(k,l)} \succeq 0 \end{aligned}$$





# Other Corner Detection Strategies...

 $\hat{\mathbf{y}}_{(k,l)}^{\mathrm{ref}}$  Compressed reference **signal** corresponding to a canonical corner located in the (k,l)-th pixel.

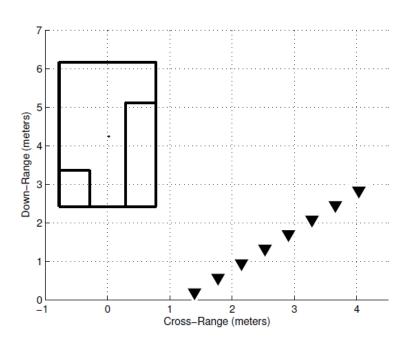
 $\hat{\mathbf{r}}_{(k,l)}^{\mathrm{ref}}$  Intensity values of the **image** corresponding to the compressive measurements of a canonical corner at position (k; l),

- **Raw data** matching:  $\min_{\sqrt{\beta(k,l)}} d^2\left(\hat{\mathbf{y}},\sqrt{\beta(k,l)}\hat{\mathbf{y}}_{(k,l)}^{\mathrm{ref}}\right)$
- Image matching:  $\min_{\sqrt{\beta}(k,l)} d^2 \left( \hat{\mathbf{r}}, \sqrt{\beta(k,l)} \hat{\mathbf{r}}_{(k,l)}^{\mathrm{ref}} \right)$





# Simulation Results (1/4)



#### **SAR system**

- 8-element linear array
- Interelement spacing of 0.53m (1.77 $\lambda$  where  $\lambda$  is the wavelength at 2 GHz)

#### **Stepped-frequency signal (no-comp)**

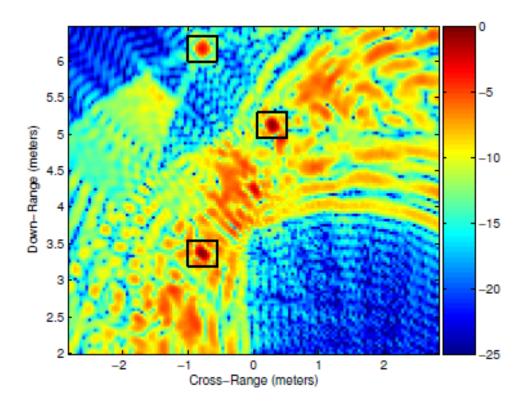
- 335 frequencies
- Covering the 1-2 GHz frequency band

#### Region to be imaged

- 128 x 128 pixels
- 5.64m (cross-range) x 4.45m (downrange) centered at (0m, 4.23m)



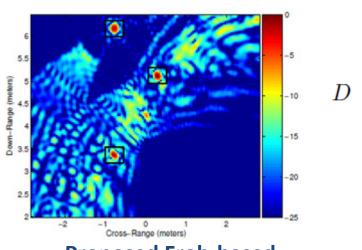
# Simulation Results (2/4)



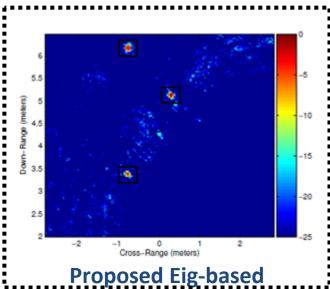




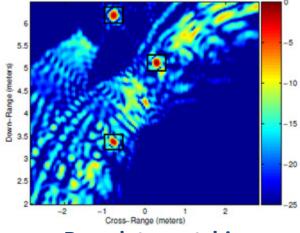
# Simulation Results (3/4) $\rho_f = \frac{34}{335} = 0.10$



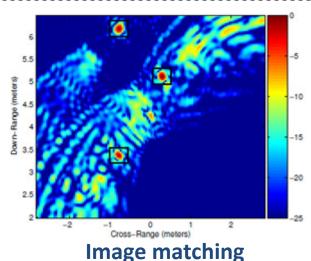
D = 30.



Proposed Frob-based



Raw data matching



16/17





# Simulation Results (4/4)

$$TCR = 20 \log_{10} \left( \frac{\max_{(k,l) \in A_t} |\beta(k,l)|}{\frac{1}{N_c} \sum_{(k,l) \in A_c} |\beta(k,l)|} \right)$$

$$\rho_f = 1$$

	D=5	D=10	D=15	D=30
Backprojection	14.45 dB			
Raw Data match.	103.53 dB			
Image match.	99.98 dB			
Frobenius norm	105.15 dB	105.49 dB	105.64 dB	105.80 dB
Eigenvalue method	265.15 dB	672.98 dB	933.64 dB	1125.03 dB

$$D = 30$$

$ ho_f$	Eigenvalue method	Frobenius norm
1	1125.03 dB	105.80 dB
0.5	1127.63 dB	106.13 dB
0.25	1125.56 dB	106.03 dB
0.10	1119.48 dB	106.75 dB





#### Conclusion

- We consider the problem of detecting building dominant scatterers using Compressive Sensing (CS) with applications to through-the-wall radar and urban sensing.
- This paper uses a novel type of image descriptor: **the intensity correlogram**. The proposed technique compares the known intensity correlogram of the scattering response of an isolated canonical corner reflector with the correlogram of the received radar signal within a correlation matching framework.
- The correlation matching procedure directly promotes sparse solution **avoiding** solving the I<sub>1</sub>-norm constrained optimization problem encountered in conventional CS; and its feature-based nature enables corner separation from other indoor scatterers.



# **Questions?**

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