Material Identification Using RF Sensors and Convolutional Neural Networks

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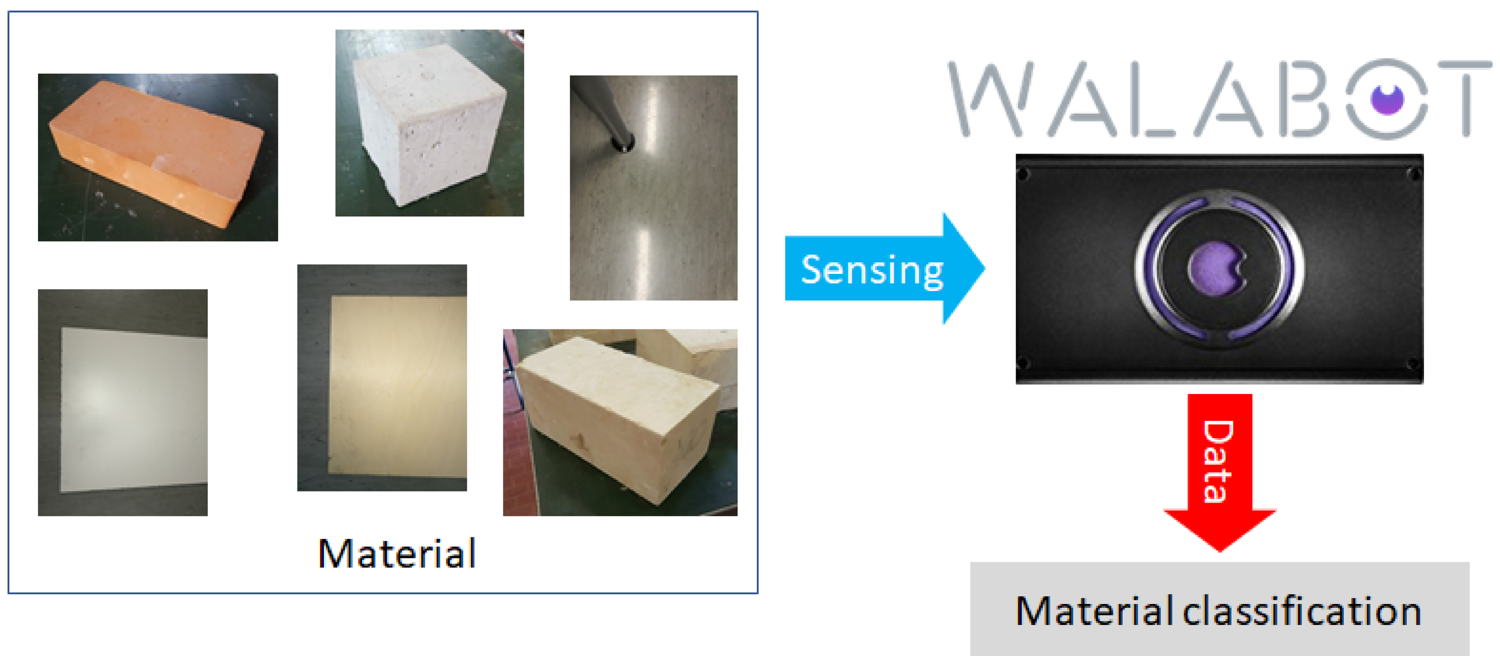
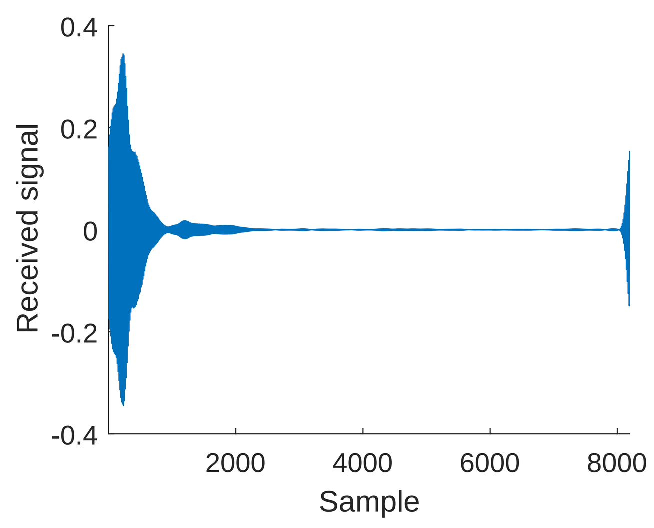
Problem Statement

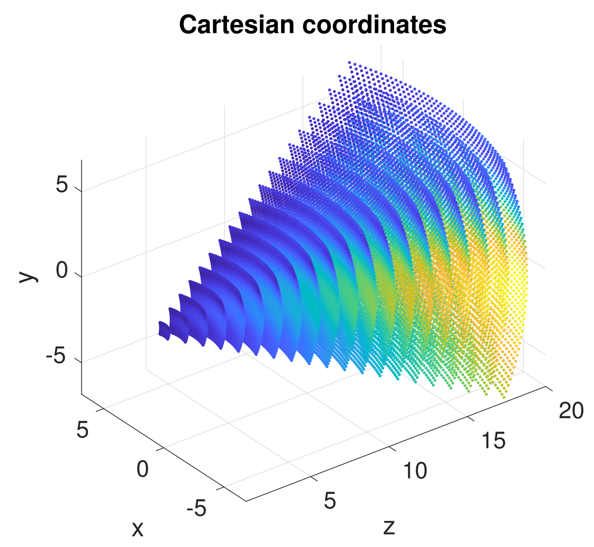
Recent years have assisted a widespreading of Radio-Frequency-based tracking and mapping algorithms for a wide range of applications, ranging from environment surveillance to human-computer interface. This work presents a material identification system based on a portable 3D imaging radar-based system, the Walabot sensor by Vayyar Technologies; the acquired three-dimensional radiance map of the analyzed object is processed by a Convolutional Neural Network in order to identify which material the object is made of. Experimental results show that processing the three-dimensional radiance volume proves to be more efficient thas processing the raw signals from antennas. Moreover, the proposed solution presents a higher accuracy with respect to some previous state-of-the-art solutions.



Walabot Acquisitions

Material classification on the Walabot output:





Raw antenna acquisition (left); scene reflectance acquisition (right)

Raw antenna acquisition $s_a(t)$:

- Signals from 40 couples of transmitting/receiving antennas

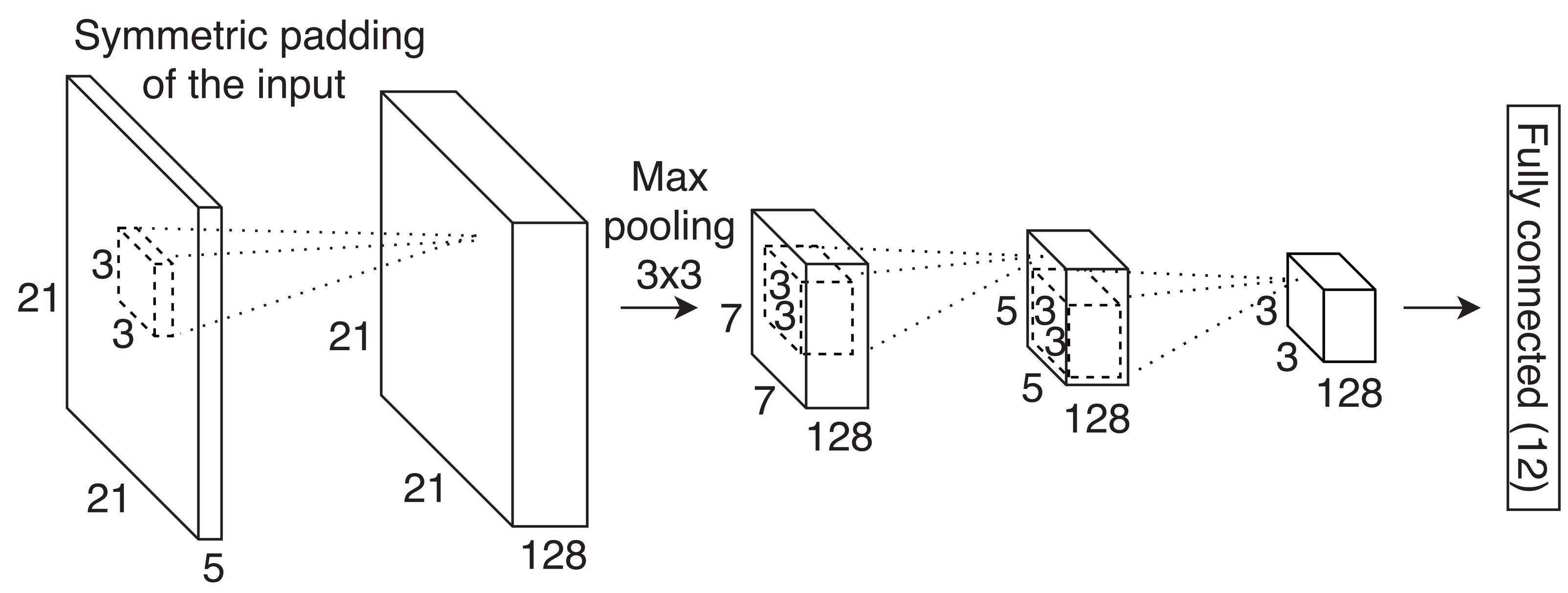
Scene reflectance $I(R,\theta,\phi)$:

- Tensor containing the ratio of received/transmitted signal power

Material Classifiers

Two classification approaches are considered:

1. **Random Forest** approach:
   It is composed by 30 trees
   The vectorized version of $s_a(t)$ or $I(R,\theta,\phi)$ are used as input
2. **CNN** approach:
   $I(R,\theta,\phi)$ is used as input
   The CNN has to extract local features from the scene reflectance



Datasets

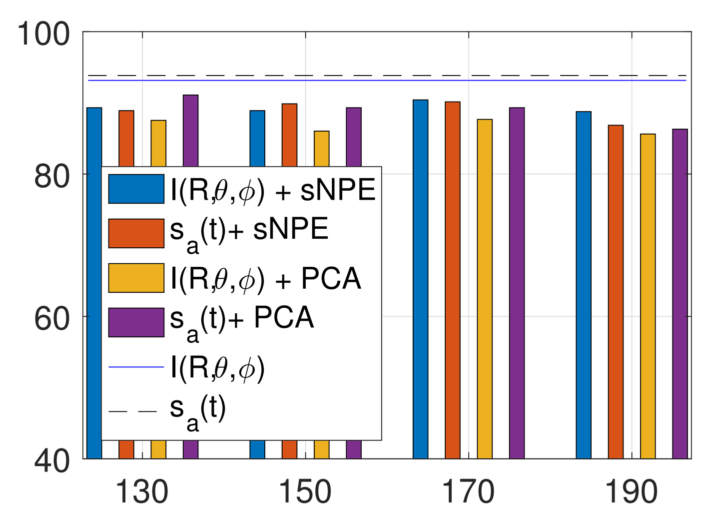
Four datasets were collected to evaluated the proposed classifiers

Materials				Datasets	
ID	material	ID	material	ID	labels
a	*polystyrene*	b	*cement blocks*	D1	h,i,j,k
c	*leccese stone*	d	*extr. solava red*	D2	*all*
e	*desk Qe*	f	*desk Ae*	D3	h,i,j,k,l
g	*stab. cement*	h	*wall*	D4	h,i,j,k,l
i	*floor*	j	*wood1*		
k	*wood2*	l	*glass*		

D1 to compare the classification performance on $s_a(t)$ and $I(R,\theta,\phi)$
D2 to campare the Random Forest approach with the CNN one
D3, **D4**, captured on different days, to evaluate the classifier robustness

Random Forest Performance

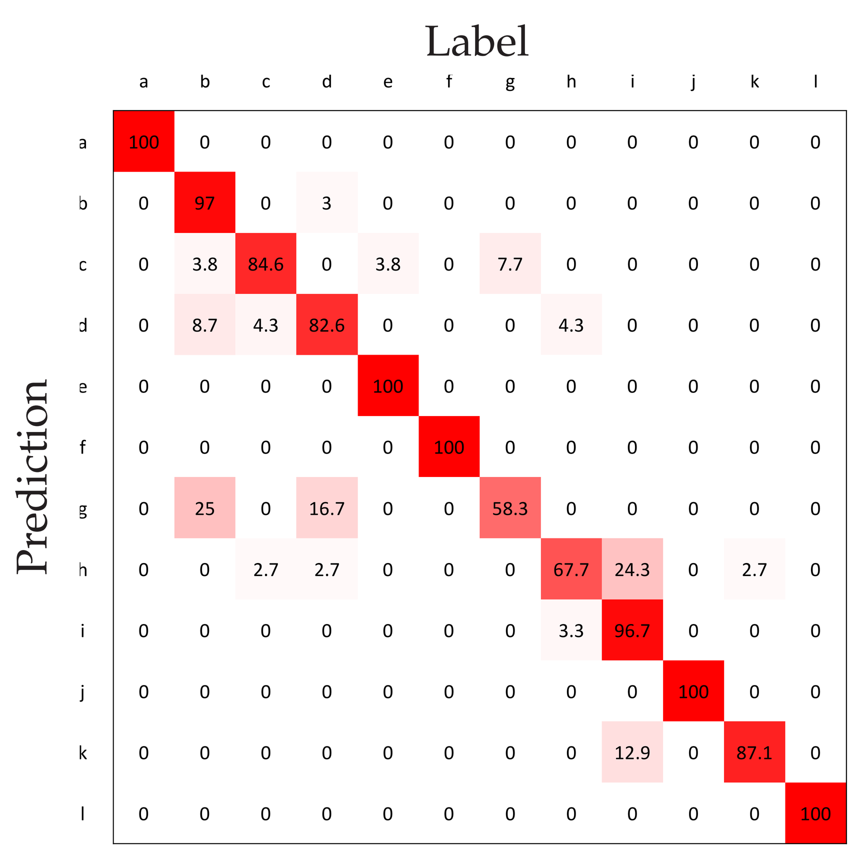
Random Forest classifier accuracy in case of $s_a(t)$ or $I(R,\theta,\phi)$ as input
PCA and sNPE are employed to compress the huge amount of input data
Evaluation on the D1 dataset



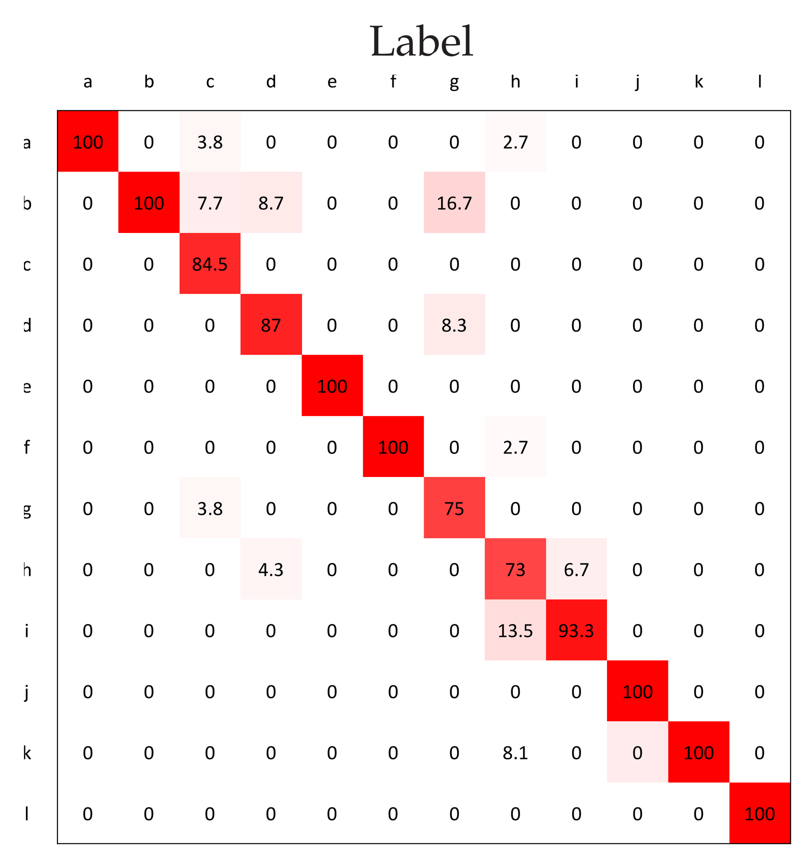
Number of extracted features

Random Forest vs CNN Performance

Performance evaluated on the D2 dataset, $I(R,\theta,\phi)$ used as input
- The random Forest classifier has 89.5% as mean accuracy
- The CNN classifier has 93.3% as mean accuracy



Random Forest



CNN

CNN Performance Repeatability

CNN trained on the training set from the D2 dataset
It is tested on the D3 and D5 dataset, captured on different days

Prediction \ Label	h	i	j	k	l
h	87.4	3.2	2.9	1.9	0
i	7.4	93.6	0	0	0
j	1	0	96.1	0	0
k	1	3.2	0	97.1	4.9
l	0	0	0	0	95.1
ω	3.2	0	1	1	0.0

D3 dataset

Prediction \ Label	h	i	j	k	l
h	74.7	4	4	2	1
i	11.1	96	0	1	0
j	1	0	96	0	0
k	2	0	0	97	0
l	1	0	0	0	99
ω	10.2	0	1	1	0.0

D4 dataset

Mean accuracy on D3 and D4 of 94% and 92.6%