Documents Counterfeit Detection Through a Deep Learning Approach

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Context

The main topic of this work is on the detection of counterfeit documents and especially banknotes. We propose an end-to-end learning model using a deep learning approach based on Adapnet++ which manages feature extraction at multiple scale levels using several residual units. Unlike previous models based on regions of interest (ROI) and high-resolution documents, our network is feed with simple input images (i.e., a single patch) and we do not need high resolution images. Besides, discriminative regions can be visualized at different scales. Our network learns by itself which regions of interest predict the better results. Experimental results show that we are competitive compared with the state-of-the-art and our deep neural network has good ability to generalize and can be applied to other kind of documents like identity or administrative one.

Loss Functions

$$\mathcal{L}_{binary} = -\frac{1}{N}\sum_{c}^{C}\sum_{i}^{N}\tau_c \log P(y_i = c|X;\theta), \quad (1)$$

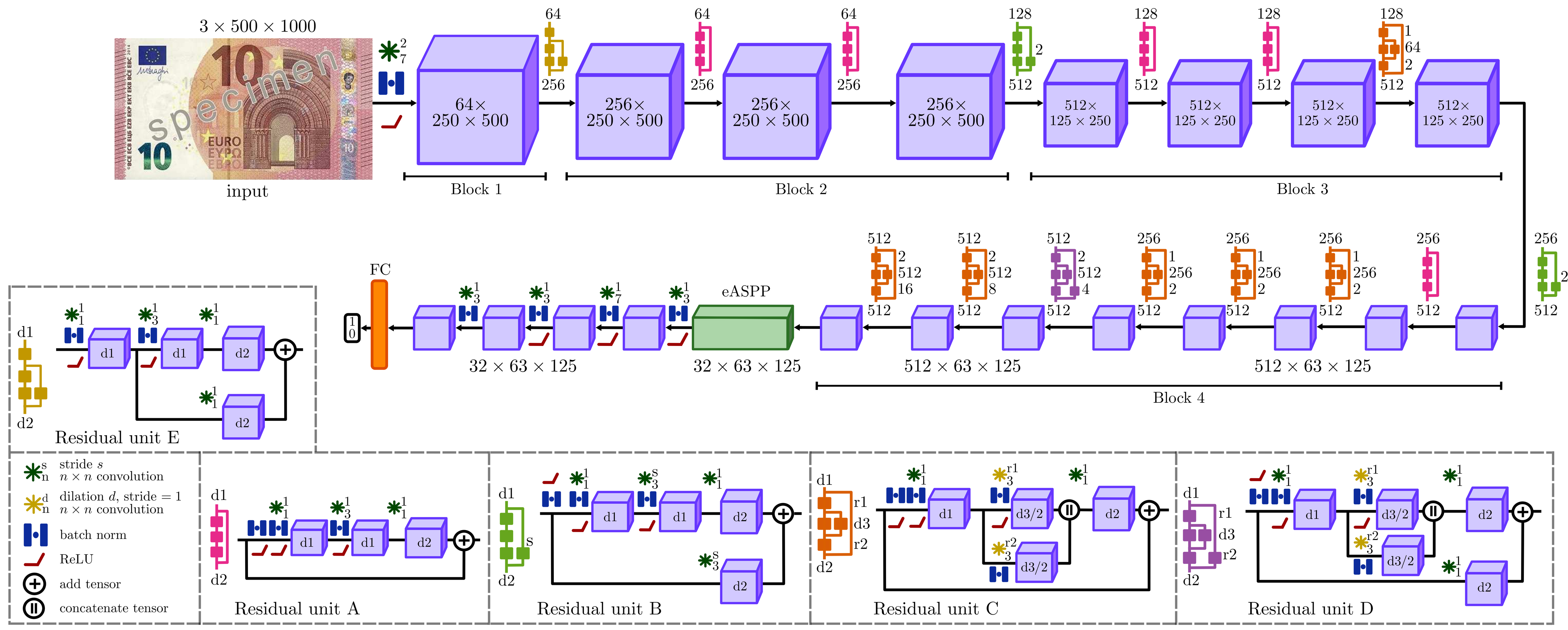
$$P\left(y_i|X;\theta\right) = \sigma(y_i) \in [0,1]. \quad (2)$$

Dataset

Table: Euro dataset (banknote photographed) taken from Berenguel. The Alias column is its short name. The * symbol denotes the combination of data types.

Alias	Banknote	Side	Patch	Ok	False
$B1$	10	O	6	346	256
$B2$	10	R	6	348	242
$C1$	20	O	8	392	212
$C2$	20	R	5	373	216
$D1$	50	O	8	350	309
$D2$	50	R	5	351	321
$*B3 = B1 + B2$	10	$O + R$	–	694	498
$*C3 = C1 + C2$	20	$O + R$	–	765	428
$*D3 = D1 + D2$	50	$O + R$	–	701	630
$*BCD3 =$ $B3 + C3 + D3$	$10 + 20$ $+50$	O+R	–	2160	1556

Architecture for Counterfeit



Regions Activated

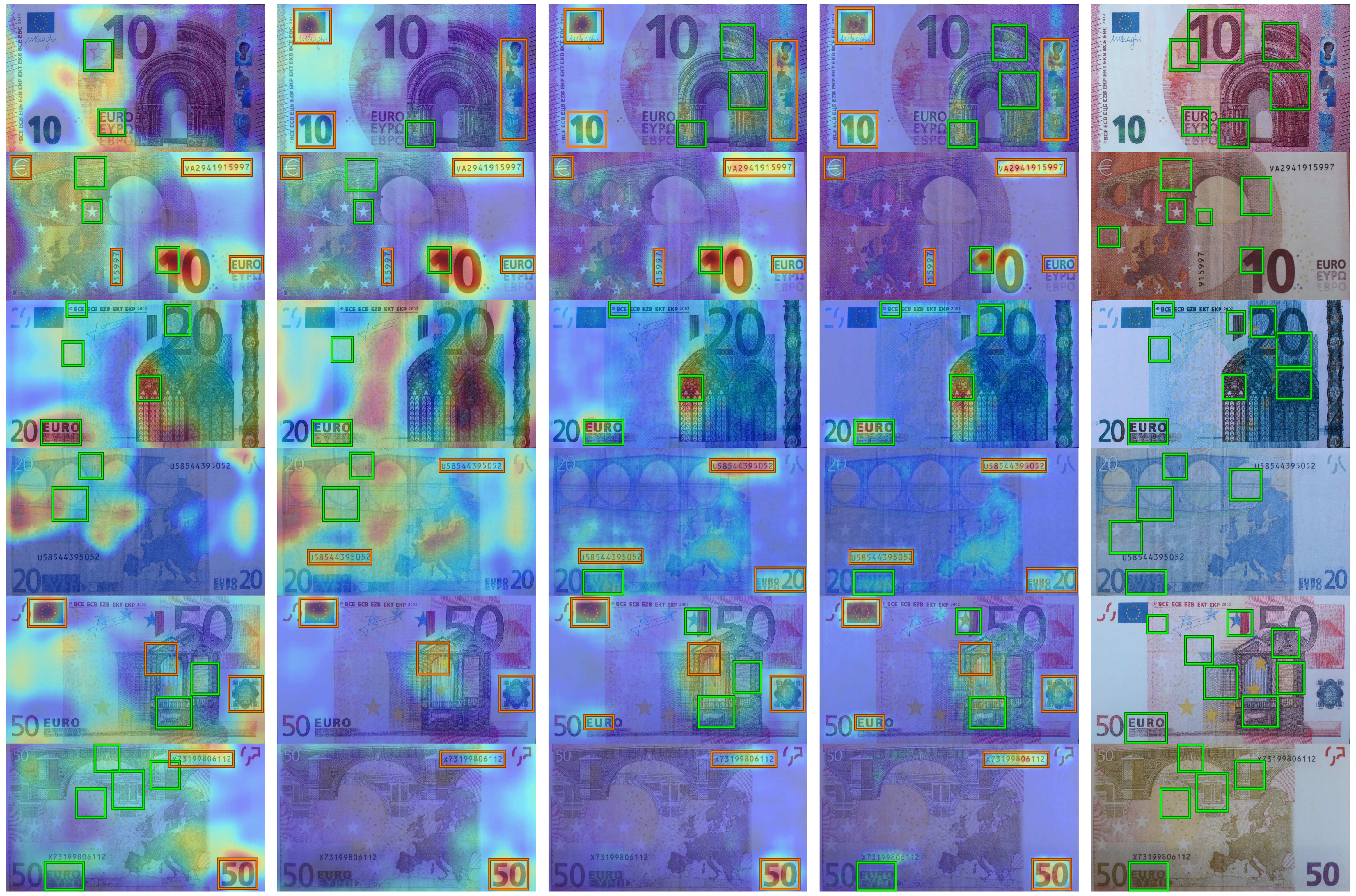


Table: Discriminative localizations at several scales, obtained by Grad-CAM, which were responsible for CNN's prediction. The columns show the regions activated to perform the prediction, on different scales from left to right (eASPP, at the end of block 4, at the beginning of block 4 and at the end of block 3). Rightmost column shows the benchmark patches used by the models.

Atrous Convolution

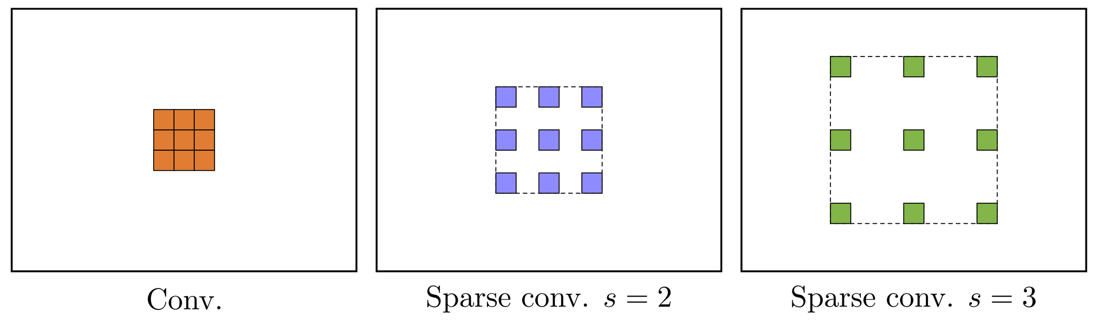


Figure: Graphics of the area visualized by a convolution operation (orange) and by sparse convolutions with different dispersion rates, s, (purple and green).

ROC curve

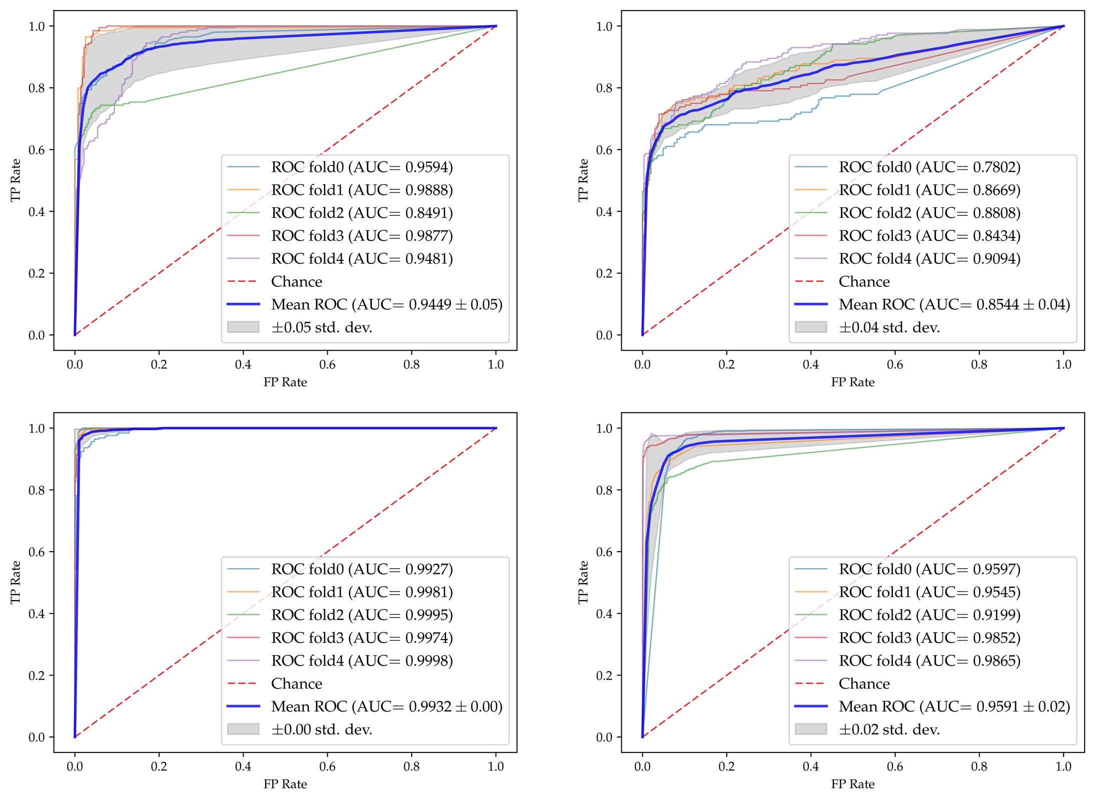


Table: Graphics of the Receiver Operating Characteristic (ROC) curves on the different types of data combined (B3, C3, D3, BCD3) to visualize the behavior (generalization) of our neural network model. Note, the y-axis represents the true positive rate (TPR), and the x-axis denotes the false positive rate (FPR).

Results

Table: Benchmark results, the $\overline{\text{AUC}}$. metric on the test set.

	SIFT-BoW	K-SVD	SCSPM	FSIM	2D-SIWPT	17Quality	Our Net
$B1$	0.9646	0.9892	0.9996	0.6718	0.7656	0.8829	0.9964
$B2$	0.9606	0.9865	0.9989	0.7766	0.7448	0.8638	0.9676
$C1$	0.9859	0.9949	1.0000	0.6664	0.7552	0.8860	0.9762
$C2$	0.9822	0.9943	1.0000	0.7105	0.7510	0.8422	0.9111
$D1$	0.9799	0.9913	0.9997	0.6399	0.6843	0.8554	0.9968
$D2$	0.9643	0.9938	1.0000	0.6477	0.6734	0.8333	0.9774
$*B3$	–	–	–	–	–	–	0.9466
$*C3$	–	–	–	–	–	–	0.8561
$*D3$	–	–	–	–	–	–	0.9975
$*BCD3$	–	–	–	–	–	–	0.9612

Table: Time comparison in seconds on the test set.

	SIFT-BoW	K-SVD	SCSPM	FSIM	2D-SIWPT	17Quality	Our Net
256×256	0.1063	1.2408	2.0997	0.2005	0.1895	0.9072	–
512×512	0.5265	3.5376	9.4853	0.2317	0.4985	3.5376	–
500×1000	–	–	–	–	–	–	0.1159