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DCT2net: a DCT-Based Interpretable Shallow CNN
Method for Efficient and Fast Image Denoising

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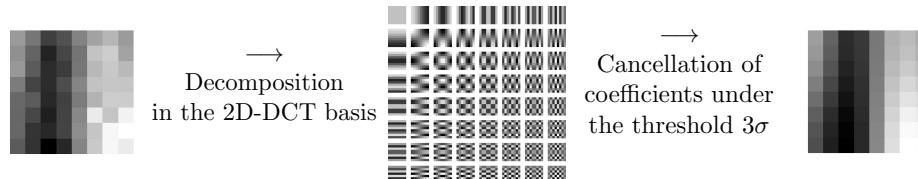
OVERVIEW

We propose an **interpretable shallow convolutional neural network** that generalizes the popular **DCT** image denoising algorithm [1]:

- ▷ We show that a DCT denoiser [1] can be seen as a shallow CNN whose weights correspond to the underlying linear transform. Fine-tuning the weights improves considerably the denoising performance.
- ▷ The resulting CNN (DCT2net) is able to handle a wide range of noise levels effectively with a single network thanks to a σ -dependent activation function.
- ▷ Displaying the learned transform gives a direct visual intuition of what the network has learned.
- ▷ To deal with remaining artifacts induced by DCT2net, an original hybrid solution between DCT and DCT2net is proposed.

DISCRETE COSINE TRANSFORM (DCT) DENOISING

A DCT denoiser [1] projects each noisy overlapping patch $y \in \mathbb{R}^n$ to the **2D-DCT basis**, and reconstructs the denoised signal with the transform coefficients higher than the threshold 3σ , in absolute value:



Formally, it amounts to estimating every overlapping patch $x \in \mathbb{R}^n$ by:

$$\hat{x} = P\varphi_\lambda(P^{-1}y) \quad \text{with} \quad \lambda = 3\sigma$$

where $\varphi_\lambda(t) = t \cdot \mathbb{1}_{\mathbb{R} \setminus [-\lambda, \lambda]}(t)$ is a hard shrinkage function and the columns of $P \in \mathbb{R}^{n \times n}$ are the basis vectors for the 2D-DCT. The n estimates of a same pixel are finally aggregated through a weighted average, with respective weight:

$$w = (1 + \|\varphi_\lambda(P^{-1}y)\|_0)^{-1}.$$

DCT2NET PRINCIPLE

All operations in DCT algorithm [1] can be interpreted in terms of convolutions with a hard shrinkage function as **σ -dependent activation function** (See Fig. 1). The weights of two first convolutions are to be found in matrices P and P^{-1} while the last ones are composed of 0 and 1 for the aggregation step.

To improve the underlying transform, we train our DCT2net on an external dataset composed of N pairs of noise-free and noisy images $(x_i, y_i)_{i \in \{1, \dots, N\}}$ corrupted with white Gaussian noise of variance σ_i^2 . Training solves:

$$P^* = \arg \min_P \sum_{i=1}^N \|F_P(y_i, \sigma_i) - x_i\|_2^2$$

where F_P denotes DCT2net.

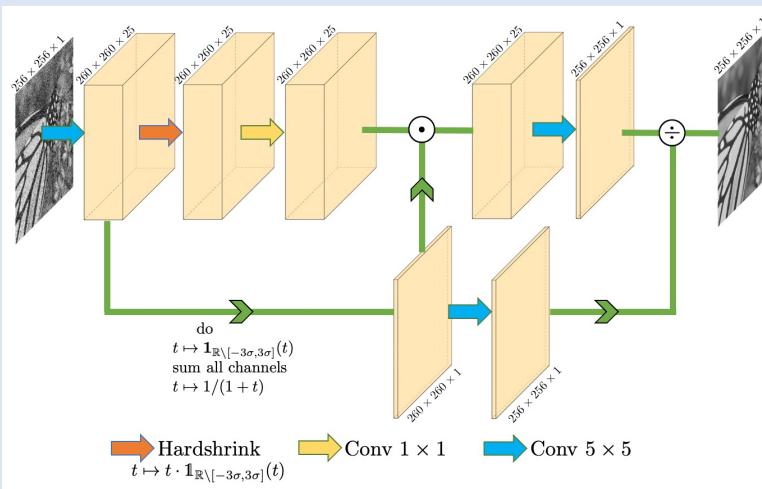


Fig. 1: Architecture of DCT2net for a patch size $n = 5 \times 5$. Note that the number of learnable parameters is equal to n^2 : the weights of the first two convolutions being linked by inverse transformation and the last convolutions being frozen with weights in $\{0, 1\}$ for the aggregation step.

To ease gradient descent during training only, $t \mapsto \mathbb{1}_{\mathbb{R} \setminus [-\lambda, \lambda]}(t)$ is replaced with the differentiable function:

$$t \mapsto \frac{t^{64}}{t^{64} + \lambda^{64}}$$

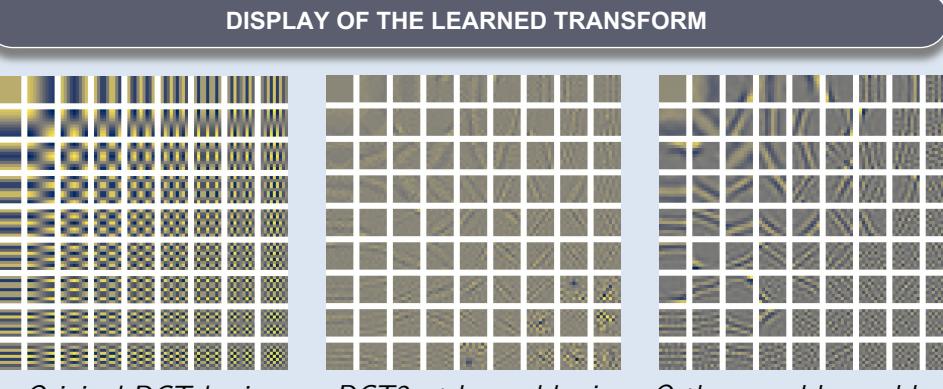


Fig. 2: Different bases of projection for patches of size $n = 9 \times 9$.

A FAST AND SHALLOW NETWORK

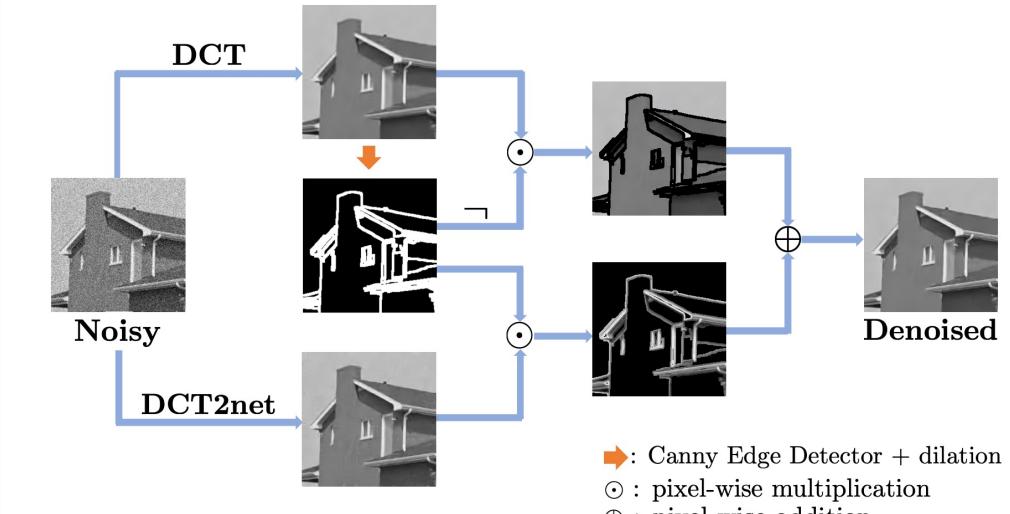
Image size	BM3D[2]	PEWA[3]	DnCNN[4]	LKSVD _{1,8,256} [5]	DCT2net
256x256	1.73	38.85	0.87 / 0.010	1.15 / 0.020	0.39 / 0.005
512x512	6.65	190.82	3.47 / 0.037	5.78 / 0.082	1.56 / 0.027
1,024x1,024	26.90	803.76	18.35 / 0.145	25.78 / 0.332	5.88 / 0.112

Table 1: Running time in seconds on CPU (left) and GPU (right) when possible.

Methods	DnCNN[4]	LKSVD _{1,8,256} [5]	DCT2net
Number of layers	17	5	2
Number of parameters	556,096	35,138	28,561

Table 2: Model complexities comparison of DCT2net with two popular networks.

DCT2NET MIXED WITH DCT TO REDUCE ARTIFACTS



RESULTS



Fig. 3: Denoising results on Castle corrupted with white Gaussian noise and $\sigma = 25$.

+0.8 dB

Methods	BM3D[2]	PEWA[3]	DnCNN[4]	LKSVD _{1,8,256} [5]	DCT[1]	DCT2net	DCT/DCT2net
$\sigma = 15$	31.07	31.04	31.72	31.33	30.32	31.09	30.97
$\sigma = 25$	28.57	28.52	29.23	28.76	27.76	28.64	28.53
$\sigma = 50$	25.62	25.53	26.23	25.68	24.86	25.68	25.59

Table 3: The average PSNR (dB) results on BSD68 corrupted with Gaussian noise.

References

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