Image denoising: Can plain Neural Networks compete with BM3D?

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Denoising with a neural network

• E.g. an MLP with two hidden layers:
  \[ f(x) = b_3 + W_3 \tanh(b_2 + W_2 \tanh(b_1 + W_1 x)), \]
  \( x \) is the noisy patch, \( f(x) \) is the denoised patch.

• Training via stochastic gradient descent on clean/noisy patch pairs (generated on the fly).

State-of-the-art results are possible with:
1. Large variability in training data
   \( \text{(S: 200, L: 150000 images)} \)
2. Large patch sizes
   \( \text{(13x13, 17x17)} \)
3. High capacity MLPs
   \( \text{(hidden layers: 4x2047, 2x2047, 2x511)} \)
4. Long training times
   \( \text{(more than 10^8 backprops)} \)

Computationally feasible through GPUs.
No overfitting due to abundance of data.

References

Can we understand how the MLP works?

some input layer weights:

some output layer weights:

Neural networks can be trained on other types of noise

“stripe” noise: 20.23dB salicyl and pepper noise: 12.39dB JPEG quantization: 27.33dB

our result: 30.09dB our result: 34.50dB our result: 28.97dB

Limitations:

behavior at different noise levels

Average results obtained on images “Lena” and “Barbara”. 

Results 2: Comparison against other algorithms.

\[
\begin{array}{cccc}
\text{image} & \text{GSM [3]} & \text{KSVD [1]} & \text{BM3D [2]} & \text{us} \\
\hline
\text{Cameraman} & 28.66 & 28.71 & 29.40 & 29.43 \\
\text{Peppers} & 29.50 & 29.66 & 30.19 & 30.28 \\
\text{Lena} & 31.27 & 31.30 & 32.05 & 32.12 \\
\text{Boats} & 29.25 & 29.28 & 29.85 & 29.84 \\
\text{Barbara} & 27.83 & 29.50 & 30.66 & 29.21 \\
\end{array}
\]

\( \sigma = 25 \). Red is best, blue is the runner-up.