Adaptive Multi-Column Deep Neural Networks with Application to Robust Image Denoising

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Introduction

Background

Digital images are often corrupted with noise during the acquisition and transmission, disgrading performance in the later tasks such as: image recognition and medical diagnosis. But traditional denoising algorithms are carefully designed for certain type of noise or require assumptions about the statistical properties of corrupting noise.

What we do

We demonstrate the Adaptive Multi-Column sparse stacked denoising autoencoder(AMC-SSDA), a method to improve the SSDA's robustness to various noise types and provides better denoising results for both noise types presents in the training set and for noise types not seen by denoiser during training(which means we eliminate the need to determine the types of noise and let alone its statistics at test time). Additionally, strong classification performance has been achieved on corrupted MNIST digits.

Algorithms

Stacked sparse denoising autoencoders

We can define the Feedforward functions as follows:

$$\mathbf{h}(\mathbf{x}) = f(\mathbf{W}\mathbf{x} + \mathbf{b}) \tag{1}$$

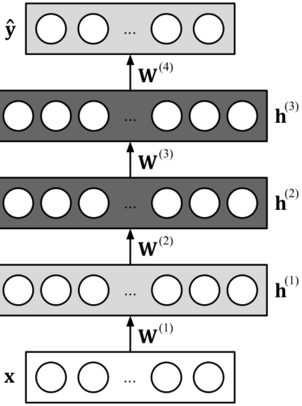
$$\hat{\mathbf{y}}(\mathbf{x}) = g\left(\mathbf{W}'\mathbf{h} + \mathbf{b}'\right) \tag{2}$$

for encoding and decoding functions:

$$\sigma(s) = \frac{1}{1 + \exp(-s)} \tag{3}$$

Algorithms

Stacked sparse denoising autoencoders



Algorithms

Stacked sparse denoising autoencoders

The DA is trained by backpropagation to minimize the sparsity reqularized reconstruction loss gived by:

$$\mathcal{L}_{\mathrm{DA}}(\mathcal{D};\Theta) = \frac{1}{N}\sum_{i=1}^{N}\|\mathbf{y}_i - \hat{\mathbf{y}}(\mathbf{x}_i)\|_2^2 + \beta\sum_{j=1}^{K}\mathrm{KL}(\rho\|\hat{\rho}_j) + \frac{\lambda}{2}\left(\|\mathbf{W}\|_{\mathrm{F}}^2 + \|\mathbf{W}'\|_{\mathrm{F}}^2\right)$$
$$\Theta = \{\mathbf{W}, \mathbf{b}, \mathbf{W}', \mathbf{b}'\} \tag{4}$$

Kullback-Leibler divergence:

$$\mathrm{KL}(\hat{\rho}_j\|\rho) = \rho\log\frac{\rho}{\hat{\rho}_j} + (1-\rho)\log\frac{(1-\rho)}{1-\hat{\rho}_j} \quad \text{where} \quad \hat{\rho}_j = \frac{1}{N}\sum_{i=1}^{N}h_j(\mathbf{x}_i) \tag{5}$$

Algorithms

Stacked sparse denoising autoencoders

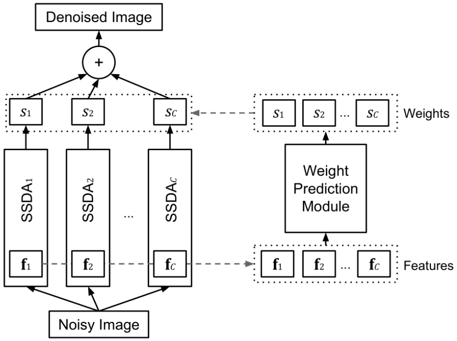
For SSDA

$$L_{\mathrm{SSDA}}(\mathcal{D};\Theta) = \frac{1}{N}\sum_{i=1}^{N}\|\mathbf{y}_i - \hat{\mathbf{y}}(\mathbf{x}_i)\|_2^2 + \frac{\lambda}{2}\sum_{l=1}^{2L}\left\|\mathbf{W}^{(l)}\right\|_{\mathrm{F}}^2 \qquad (6)$$

Algorithms

Adaptive Multi-Column SSDA

AMC-SSDA is the linear combination of serveral SSDAs, or **columns**, each trained on a single type of noise using optimized weights determined by the features of each given input image.



Algorithms

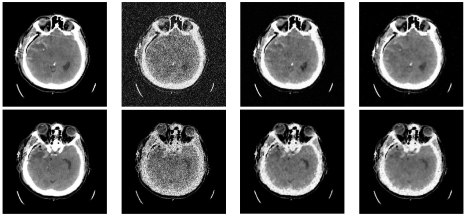
Adaptive Multi-Column SSDA

$$\begin{aligned} \text{minimize}_{\{s_c\}} \quad & \frac{1}{2}\left\|\hat{\mathbf{Y}}\mathbf{s} - \mathbf{y}\right\|^2 \\ \text{subject to} \quad & 0 \le s_c \le 1, \forall c \\ & 1 - \delta \le \sum_{c=1}^{C} s_c \le 1 + \delta \end{aligned} \tag{7}$$

Learning to predict optimal column weights via RBF Networks

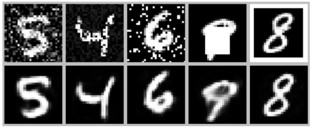
Experiments

Visualization of denoising performance



Experiments

MNIST test classification error of denoised images



Method / Noise Type	Clean	Gaussian	S & P	Speckle	Block	Border	Average
No denoising	**1.09%**	29.17%	18.63%	8.11%	25.72%	90.05%	28.80%
Gaussian SSDA	2.13%	**1.52%**	2.44%	5.10%	20.03%	8.69%	6.65%
Salt & Pepper SSDA	1.94%	1.71%	2.38%	4.78%	19.71%	2.16%	5.45%
Speckle SSDA	1.58%	5.86%	6.80%	**2.03%**	19.95%	7.36%	7.26%
Block SSDA	1.67%	5.92%	15.29%	7.64%	**5.15%**	1.81%	6.25%
Border SSDA	8.42%	19.87%	19.45%	13.89%	31.38%	**1.12%**	15.69%
AMC-SSDA	1.50%	**1.47%**	**2.22%**	**2.09%**	**5.18%**	**1.15%**	**2.27%**
Tang et al. [28]*	1.24%	-	-	-	19.09%	1.29%	-

Further

Ongoing Optimization

- Maybe analysis time limits?

References

- Forest Agostinelli Michael R. Anderson Honglak Lee. *Adaptive Multi-Column Deep Neural Networks with Application to Robust Image Denoising*