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Model Demising using Neural Network

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Abstract*: The search for efficient Model Demising methods is still a valid challenge at the crossing of functional analysis and statistics. In spite of the sophistication of the recently proposed methods, most algorithms have not yet attained a desirable level of applicability. All show an outstanding performance when the image model corresponds to the algorithm assumptions but fail in general and create artefacts or remove fine structures in images. The main focus of this paper is, first, to define a general mathematical and experimental methodology to compare and classify classical image denoising algorithms and, second, to propose a nonlocal means (NL-means) algorithm addressing the preservation of structure in a digital image. The mathematical analysis is based on the analysis of the "method noise," defined as the difference between a digital image and its denoised version. The NL-means algorithm is proven to be asymptotically optimal under a generic statistical image model. The denoising performance of all considered methods is compared in four ways; mathematical: asymptotic order of magnitude of the method noise under regularity assumptions; perceptual-mathematical: the algorithms artifacts and their explanation as a violation of the image model; quantitative experimental: by tables of L^2 distances of the denoised version to the original image. The fourth and perhaps most powerful evaluation method is, however, the visualization of the method noise on natural images. The more this method noise looks like a real white noise, the better the method.

***Keywords:* Multi layer perceptron, Denoising algorithms, Deconvolutional layer**

I. INTRODUCTION

Model Demising is the process of removing noise from a signal. All recording devices, both analog and digital, have traits that make them susceptible to noise. Noise can be random or white noise with no coherence, or coherent noise introduced by the device's mechanism or processing algorithms. In electronic recording devices, a major form of noise is *hiss* caused by andom electrons that, heavily influenced by heat, stray from their designated path. These stray electrons influence the voltage of the output signal and thus create detectable noise. In the case of photographic film and magnetic tape, noise (both visible and audible) is introduced due to the grain structure of the medium. In photographic film, the size of the grains in the film determines the film's sensitivity, more sensitive film having larger sized grains. In magnetic tape, the larger the grains of the magnetic particles (usually ferric oxide or magnetite), the more prone the medium is to noise.

To compensate for this, larger areas of film or magnetic tape may be used to lower the noise to an acceptable level. Model Demising is the process of removing noise from a signal. All recording devices, both analog and digital, have traits that make them susceptible to noise. Noise can be random or white noise with no coherence, or coherent noise introduced by the device's mechanism or processing algorithms. In electronic recording devices, a major form of noise is *hiss* caused by random electrons that, heavily influenced by heat, stray from their designated path. These stray electrons influence the voltage of the output signal and thus create detectable noise.

Model Demising can be described as the problem of mapping from a noisy image to a noise-free image. The best currently available denoising methods approximate this mapping with cleverly engineered algorithms. In this work we attempt to learn this mapping directly with a plain multi layer perceptron (MLP) applied to image patches. While this has been done before, we will show that by training on large image databases we are able to compete with the current state-of-the-art image denoising methods. Furthermore, our approach is easily adapted to less extensively studied types of noise (by merely exchanging the training data), for which we achieve excellent results as well.

Top = Bottom= 19mm (0.75")

Left = Right = 14.32mm (0.56")

Image denoising has always been a central problem in computer vision. At its core, de noising is an inherently illposed
problem due to the loss of information during noise addition.

I0 = D(I) + h

Here, D(I) is the degrading function with respect to original image I while h serves as additive noise. As degradation functions are not always guaranteed to be affine transformations, traditional techniques cannot fully recover noised out pixels of the clean image. Recently, applications of CNNs in solving this problem has produced increasingly promising results. Intuitively, this comes from

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the change in mindset of recovering information from the remnants to learning key features describing the noisy image and predicting the original from those traits.

II. RELATED WORK

Neural networks have already been used to denoise images [9]. The networks commonly used are of a special type, known as convolutional neural networks (CNNs) [10], which have been shown to be effective for various tasks such as hand-written digit and traffic sign recognition [23]. CNNs exhibit a structure (local receptive fields) specifically designed for image data. This allows for a reduction of the number of parameters compared to plain multi layer perceptrons while still providing good results. This is useful when the amount of training data is small. On the other hand, multi layer perceptrons are potentially more powerful than CNNs: MLPs can be thought of as universal function approximators [8], whereas CNNs restrict the class of possible learned functions. A different kind of neural network with a special architecture (i.e. containing a scarifying logistic) is used in [19] to denoise image patches. A small training set is used. Results are reported for strong levels of noise. It has also been attempted to denoise images by applying multi layer perceptrons on wavelet coefficients [28]. The use of wavelet bases can be seen as an attempt to incorporate prior knowledge about images. Differences to this work: Most methods we have described make assumptions about natural images. Instead we do not explicitly impose such assumptions, but rather propose a pure learning approach..

Prior to utilization of Deep Neural Nets, one of the prominent state-of-the-art metrics was the BM3D algorithm.[Dabov et al.] In it, the authors grouped similar 2D fragments and used inverse 3D transformations to achieve fine detail denoising. An alternative approach that also showed good performance was Iterative Regularization [Osher et al.], which attempted to reduce noise patterns through minimizing a standard metric like Bregman Distance. With the rise of deep learning, one of the earlier works on applying DNN to an autoencoder for feature denoising, [Bengio et al.] showed that stacking multilayered neural networks can result in very robust feature extraction under heavy noise. A later paper on semantic segmentation, [Long et al.] shows the power of Fully Connected CNNs in parsing out feature descriptors for individual entities in images. Recently, a proposed deep-CNN architecture by [Mao et al.] features a 30-layer convolutional-deconvolutional model designed for deep learning of image features. Their innovation is the inclusion of Symmetric Skip Connections (SSC) between alternating Conv- Deconv layers. The modification attempts to solve two problems with training deep CNNs. First, with increasing number of layers comes the vanishing gradient problem that prevents effective back propagation towards front layers. This is due to the structure of gradient product at each layer, where error is sequentially diminished in magnitude. In theory, alternating connections allow gradients to back propagate directly from an up sample, deconvolutional layer to the corresponding down sample, convolutional layer. Second, as details are inevitably lost during the down sampling layers, SSC can also serve as

intermediate information flow gates akin to LSTM forget gates. To prevent massive information leak through these channels, gate coefficients can be modified during training to force learning at bottleneck layers.

III. EXPERIMENTAL RESULTS

We performed all our experiments on gray-scale images. These were obtained from color images with MATLAB's rbg2gray function. Since it is unlikely that two noise samples are identical, the amount of training data is effectively infinite, no matter which dataset is used. However, the number of uncorrupted patches is restricted by the size of the dataset.

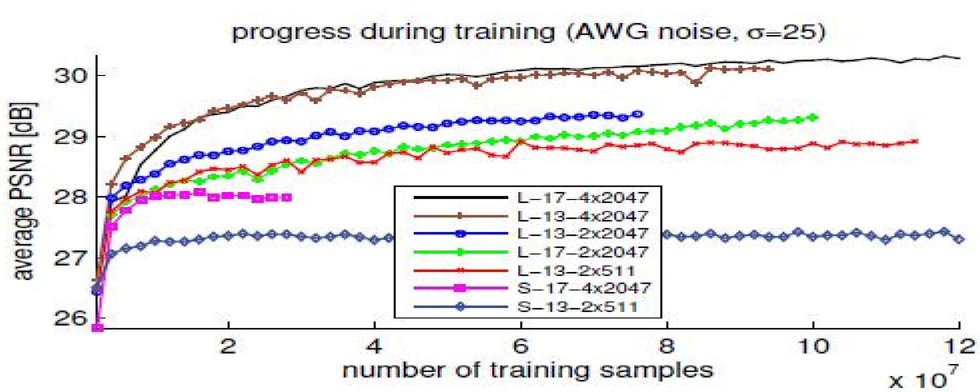

Figure 1. Improving average PSNR on the images "Barbara" and "Lena" while training.

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A. Training Data

For our experiments, we define two training sets: Small training set: The Berkeley segmentation dataset [15], containing 200 images, and Large training set: The union of the LabelMe dataset [22] (containing approximately 150; 000 images) and the Berkeley segmentation dataset. Some images in the LabelMe dataset appeared a little noisy or a little blurry, so we downscaled the images in that dataset by a factor of 2 using MATLAB's imresize function with default parameters. Test data: We define three different test sets to evaluate our approach: Standard test images: This set of 11 images contains standard images, such as "Lena" and "Barbara", that have been used to evaluate other denoising algorithms [3], Pascal VOC 2007: We randomly selected 500 images from the Pascal VOC 2007 test set [5], and McGill: We randomly selected 500 images from the McGill dataset [17].

Figure 2. Our results compared to BM3D. Our method outperforms BM3D on some images (top row). On other images however, BM3D achieves much better results than our approach. The images on which BM3D is much better than our approach usually contain some kind of regular structure, such as the stripes on Barbara's pants (bottom row).

IV. CONCLUSIONS

Neural networks can achieve state-of-art image denoising performance. For this, it is important that (i) the capacity of the network is large enough, (ii) the patch size is large enough, and (iii) the training set is large enough. These requirements can be fulfilled by implementing MLPs on GPUs that are ideally suited for the computations necessary to train and apply neural networks. Without the use of GPUs our computations could have easily taken a year of running time. However, our most competitive MLP is tailored to a single level of noise and does not generalize well to other noise levels compared to other denoising methods. This is a serious limitation which we already tried to overcome with an MLP trained on several noise levels. However, the latter does not yet achieve the same performance for · = 25 as the specialized MLP. Nonetheless, we believe that this will also be possible with a network with even higher capacity and sufficient training time.

REFERENCES

[1] M. Aharon, M. Elad, and A. Bruckstein. K-svd: An algorithm for designing overcomplete dictionaries for sparse representation. IEEE Transactions on Signal Processing, 54(11):4311–4322, 2006.
[2] A. Buades, C. Coll, and J. Morel. A review of image denoising algorithms, with a new one. Multiscale Modeling and Simulation, 4(2):490–530, 2005.
[3] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian. Image denoising by sparse 3-D transform-domain collaborative filtering. IEEE Transactions on Image Processing, 16(8):2080–2095, 2007

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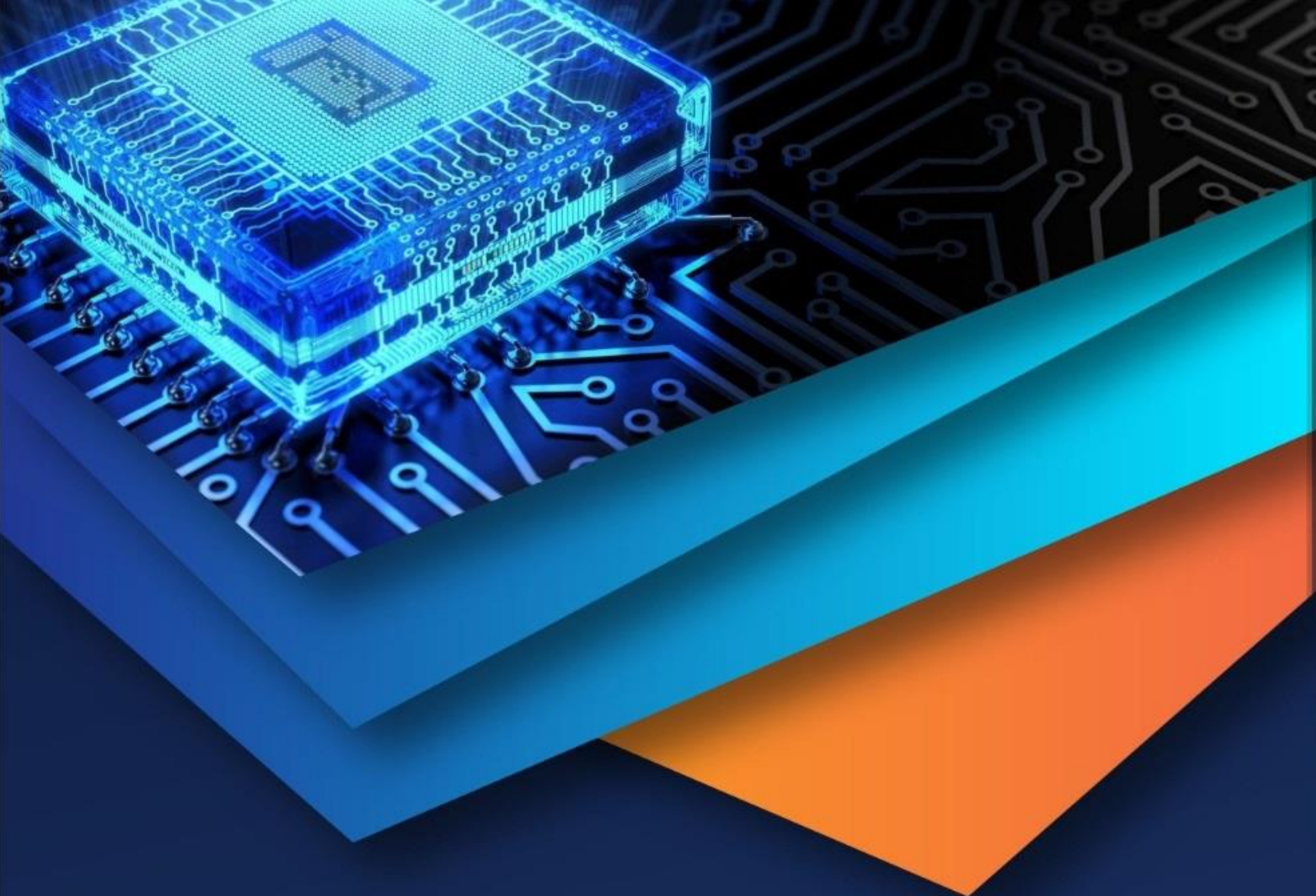
[4] M. Elad and M. Aharon. Image denoising via sparse and redundant representations over learned dictionaries. IEEE Transactions on Image Processing, 15(12):3736–3745, 2006.
[5] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman. The PASCAL Visual Object Classes Challenge 2007 (VOC2007) Results. http://www.pascalnetwork. org/challenges/VOC/voc2007/workshop/index.html
[6] A. Foi. Noise estimation and removal in mr imaging: The variance-stabilization approach. In 2011 IEEE International Symposium on Biomedical Imaging: From Nano to Macro, pages 1809–1814, 2011
[7] G. Hinton, S. Osindero, and Y. Teh. A fast learning algorithm for deep belief nets. Neural Computation, 18(7):1527–1554,2006
[8] K. Hornik, M. Stinchcombe, and H. White. Multilayer feedforward networks are universal approximators. Neural Networks,2(5):359–366, 1989
[9] V. Jain and H. Seung. Natural image denoising with convolutional networks. Advances in Neural Information ProcessingSystems (NIPS), 21:769–776, 2008.
[10] Y. LeCun, L. Bottou, Y. Bengio, and H. P. Gradient-based learning applied to document recognition. Proceedings ofthe IEEE, 86(11):2278–2324, 1998.
[11] Y. LeCun, L. Bottou, G. Orr, and K. M¨uller. Efficient backprop. Neural networks: Tricks of the trade, pages 546–546,1998.
[12] A. Levin and B. Nadler. Natural Image Denoising: Optimality and Inherent Bounds. In IEEE Conference on ComputerVision and Pattern Recognition (CVPR), 2011



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