Advances in Denoising by Multiple Copies

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Conventional image restoration algorithms use transform-domain filters, which separate noise from the sparse signal among the transform components or apply spatial smoothing filters in real space whose design relies on prior assumptions about the noise statistics. These filters also reduce the information content of the image by suppressing spatial frequencies or by recognizing only a limited set of shapes. We have previously proposed a new method called MC-MLP[1] (*m*ultiple *c*opies, *m*ultiple *l*ayer *p*erceptrons), where we have shown that denoising can be efficiently done with a nonlinear filter that operates along patch neighborhoods and multiple copies of the original image. The use of patches enables the algorithm to account for spatial correlations in the random field whereas the multiple copies are used to recognize the noise statistics. The nonlinear filter, which is implemented by a hierarchical multistage system of multilayer perceptrons (MLP), outperformed state-of-the-art denoising algorithms such as those based on collaborative filtering and total variation. Compared to conventional denoising algorithms, our method can restore images without blurring them, making it attractive for use in applications such as medical imaging where, the preservation of anatomical details is critical.

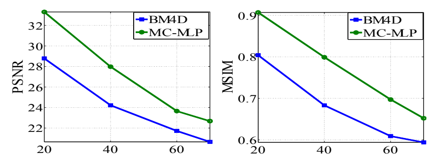

Figure 1. PSNR and MSIM comparison of MC-MLP with BM4D method for different noise levels.

While state of the art algorithms perform well as long as the images obey conditions consistent with narrow assumptions such as noise statistics, not meeting these assumptions gives rise to artifacts or losses in the image fine structure. More recent techniques based on machine learning present a new approach to image denoising that inherently encompasses several advantages. The challenge with machine learning based methods is the huge computational cost. Artificial neural networks were shown to match BM3D performance[2,3], the benchmark for additive Gaussian noise, by training a large MLP for a month on a GPU system. MC-MLP provides a platform to harness the advantages of machine learning with a fraction of the computational time. Results obtained for various noise levels and distributions indicate that it can outperform current state-of-the-art methods provided that enough training time and samples are given, under the condition of "reasonable" training time. Application to MRI images with Rician noise distribution and testing with synthetic additive Gaussian noise and arbitrary multiplicative noise has established the MC-MLP method to be a universal denoising method applicable to situations with arbitrary noise distributions which can operate under extreme noise levels. From the point of view of conventional metrics (PSNR, FSIM, MSIM), the algorithm outperforms state-of-the art methods and can handle both additive and multiplicative noises, including Gaussian and signal-dependent Rician noises[1]. Furthermore, it is computationally efficient and shows that multiple copies of the same image enable more effective noise removal with better preservation of anatomical features.

	1 Copy	Mean	MC-MLP	BM4D	TV	ORNLM	AONLM	ONLM	ODCT	PRINLM
Noise Level 1 - PSNR	17.95,	20.61,	26.13,	22.56,	25.82,	25.78,	23.07,	25.71,	23.13,	24.01,
FSIM	0.72,	0.87,	0.93,	0.92,	0.92,	0.90,	0.90,	0.90,	0.89,	0.92,
MSSIM	0.09	0.33	0.81	0.79	0.78	0.70	0.73	0.71	0.71	0.78
Noise Level 2 - PSNR	14.02,	16.46,	21.71,	19.50,	19.48,	20.77,	19.25,	21.15,	19.17,	20.30,
FSIM	0.57,	0.72,	0.85,	0.85,	0.79,	0.76,	0.76,	0.76,	0.78,	0.85,
MSSIM	0.04	0.09	0.70	0.58	0.42	0.41	0.37	0.44	0.47	0.52
Noise Level 3 - PSNR	12.95,	13.85,	19.39,	17.81,	16.73,	18.33,	16.54,	18.28,	16.54,	17.06,
FSIM	0.53,	0.58,	0.78,	0.76,	0.60,	0.76,	0.54,	0.54,	0.63,	0.78,
MSSIM	0.03	0.04	0.60	0.33	0.12	0.31	0.11	0.18	0.26	0.33

Table 1. PSNR, FSIM, AND MSSIM comparisons with other methods for MRI denoising at low to high noise levels.

The MC-MLP method allows the flexibility of optimizing between two important factors: performance and computational time, where state of the art results can be achieved in a practical time. Since it was first introduced, MC-MLP has undergone new developments that further improves on its computational efficiency and extends its practicality and range of applications. While MC-MLP can be used in situations where the noise distribution is not known, where it can still learn to model it from experimental data, this requires a clean sample image for training corresponding to acquired sample noisy data. This information is not available for some applications, as is the case for noise estimation. However, similar to the specificity of typical denoising methods designed for specific types of noise statistics, existing noise estimation techniques are also designed for specific noise distributions. A noise estimation based on a variation of the MC-MLP method was developed for general noise estimation to extend the applicability of MC-MLP to applications with arbitrary noise distributions where a clean sample image cannot be provided. The MC-MLP method has been also extended to enable hybridizing of two or more denoising methods. While each denoising method usually excels in some aspects and fails in others, MC-MLP allows combining advantages of several methods in one by adding outcomes from other denoising methods to its inputs. This provides a mechanism to improve performance of any existing denoising method with reduced computational time. These developments allowed us to extend the MC-MLP method to other challenging applications such as sodium MRI, and atomic resolution electron tomography.

1. K. Youssef, et al., "Feature-Preserving Noise Removal", Trans. Image Process, 2015.
2. H. C. Burger, et. al, "Image denoising: Can plain neural networks compete with BM3D?", Proc. CVPR IEEE, 2012.
3. K. Dabov, et. al, "Image denoising by sparse 3D transform-domain collaborative filtering", IEEE Trans. Image Process, 2007.

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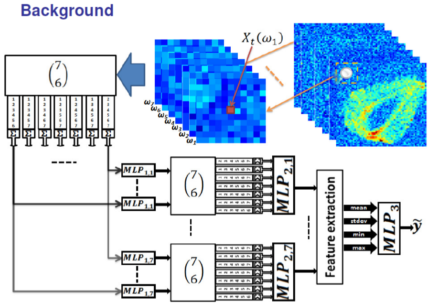
Abstract

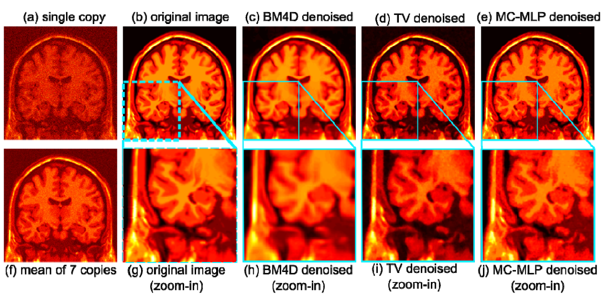
MC-MLP is a state of the art feature-preserving noise removal algorithm developed by our group that can be used under narrow assumptions for the noise statistics. It utilizes multiple copies of the same image to improve the ability to remove noise while preserving the image features rather than blurring them. A nonlinear filter is designed by machine learning. Machine learning approaches traditionally suffer from high computational cost. Our method, termed multiple copies multi-layer perceptron (MC-MLP), harnesses the advantages of machine learning with a fraction of the computational time. MC-MLP can be used in situations with arbitrary or even unknown noise distributions. Results obtained for various noise levels and distributions indicate that it can outperform current state-of-the-art methods provided that enough training time and samples are given, under the condition of "reasonable" training time. New developments reported herein include MC-MLP based noise estimation method and hybridization with existing algorithms. Here MC-MLP can learn from results obtained by other methods and outperform them in less computational time.

Background

MC-MLP operates on multiple copies of a given noisy image as compared to the conventional approach of operating on the mean value of the copies (after "signal averaging"). This allows a more accurate determination of the noise statistics which can be attenuated with averaging, especially in the case of non-Gaussian noise. Magnitude MRI images feature non-Gaussian noise. Signal averaging is typically used in MRI to improve the SNR. Attenuation from averaging can translate to loss in the fine features in the image. MC-MLP has been shown to better preserve fine features that are lost with other denoising techniques. MC-MLP uses multi-layer perceptrons as its main building blocks. We use a multi-stage architecture and training designed to achieve state of the art results in a practical time, which is usually the major limitation for learning based algorithms.

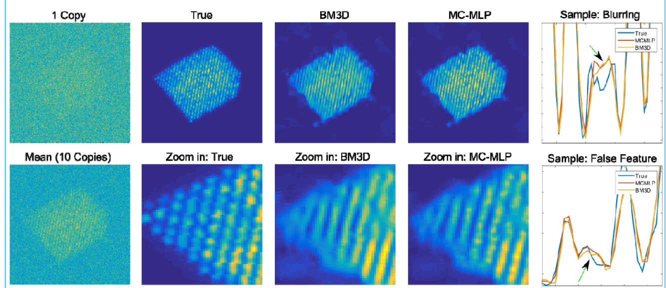


Application to [1]H (proton) MRI



A comparison of MC-MLP with Block Match 4D filtering (BM4D) and Total Variation (TV) methods for proton MRI application is shown here. The ability to operate on multiple copies allows MC-MLP to better preserve fine image features, which can be crucial for more accurate medical diagnostic. (a) Noisy image (1 copy). (b) Original (ideal) image with high SNR used as the gold standard for comparison. (c) BM4D denoising result. (d) TV denoising result. (e) MC-MLP denoising result. (f) Signal-averaged image corresponding to the mean of 7 copies. (g) Zoom in on the lower left quadrant of (b) (h) Zoom in on the lower left quadrant of (c). (i) Zoom in on the lower left quadrant of (d). (j) Zoom in on the lower left quadrant of (e).

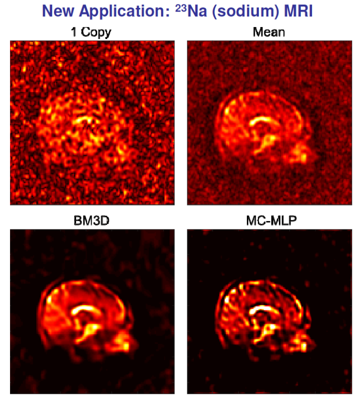
New Application: Atomic Resolution Electron Tomography



Images from an electron tomogram projection. The data in this application is contaminated by multiplicative Poisson shot noise. An adaptation of Block Match 3D filtering (BM3D) was used to denoise the data. MC-MLP yields better separation between individual atoms as shown in the zoomed-in image. BM3D on the other hand blurs some critical features of the image (atoms) to the point where it becomes impossible to distinguish individual atoms.

Projection data courtesy of Prof. Jianwei Miao (UCLA)

New Application: [23]Na (sodium) MRI



While proton MRI is the most widely used method for MRI, sodium MRI also has important potential applications. Sodium is less abundant than hydrogen, which translates to a much lower SNR. Using MC-MLP as the denoising method for this extremely noisy application demonstrates its superior performance under extreme noise conditions.

Noisy raw MRI data set courtesy of Prof. Guillaume Madelin (NYU)

Summary

MC-MLP is a high performance feature-preserving universal image denoising method. It can outperform state-of-the art methods under low to high noise levels, and can handle both additive and multiplicative noises, including Gaussian and signal-dependent Rician noises. Competing algorithms are limited to special cases where the known noise distribution meets narrow criteria. MC-MLP is general and is applicable to situations with arbitrary noise distributions and can even operate under extreme noise levels. It can also be used in situations where the noise distribution is not known. In this case, the algorithm can still learn to model the noise from experimental data.

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References

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Youssef K, Jarenwattananon NN, Bouchard LS, Feature-Preserving Noise Removal, IEEE Trans. Med. Imag. 34, 1822-1829 (2015)