



GMSD-Based Perceptually Motivated Non-local Means Filter for Image Denoising

Mohtashim Baqar[1], Sian Lun Lau[1], Mansoor Ebrahim[2]

[1]Department of Computing and Information Systems, School of Science and Technology, Sunway University, Subang Jaya, Malaysia.

[2]Faculty of Engineering, Sciences & Technology, Iqra University, Karachi, 75500, Pakistan.

Introduction

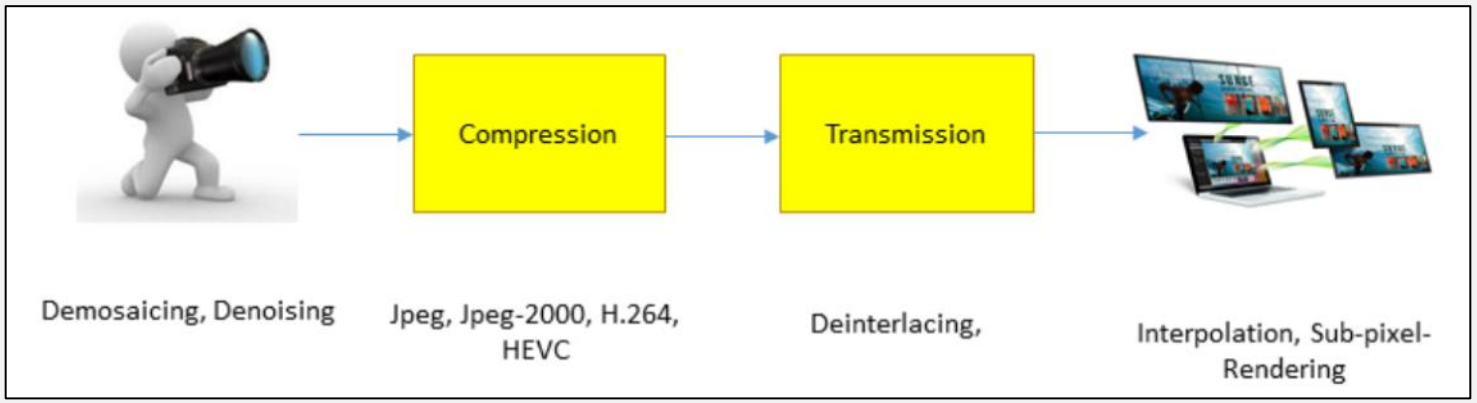
•The application and use of multimedia signals such as **image**, **video**, and **sound** have increased immensely in daily-life.

•These **visual signals** are contaminated with several varieties of **distortions** during the **acquisition**, **compression**, **transmission** and **display** of the signals on screen. So, **image reconstruction** is the most **significant elemen**t of the an image receiving system.

•Further, human vision is the ultimate receiver of these multimedia signals. Though, HVS is a complex process to model. Visual perception suggests how our human visual system perceives information.

•Thus, visual perception based Image Quality Assessment (IQA) and Just Noticeable Difference (JND) metrics have become important as they can predict the signal quality and highlight the regions of importance which are compatible with human vision.

Image Reconstruction



Pipeline of Displaying an Image from the Stage of Acquisition

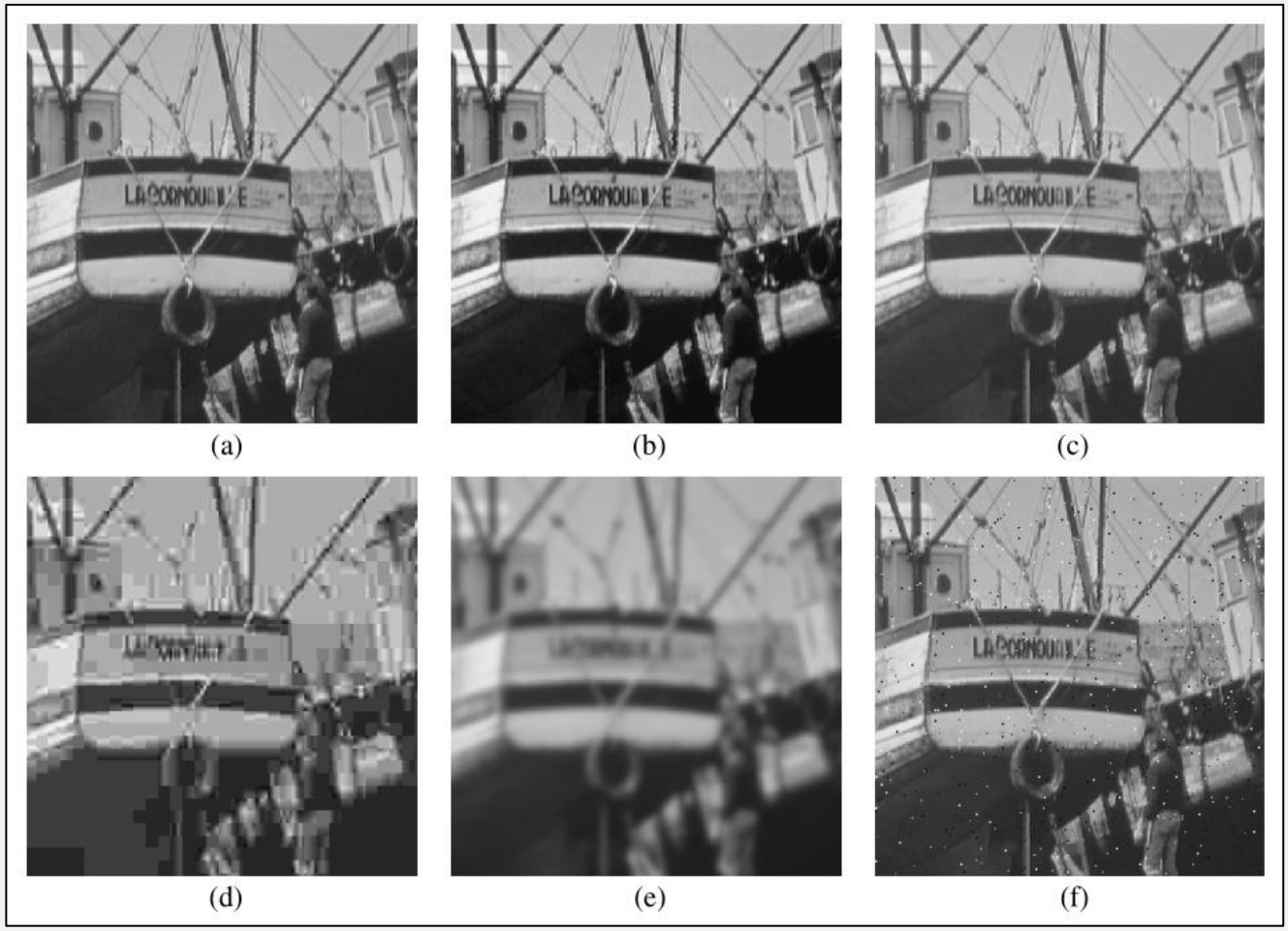
→ Image reconstruction is required either for the **estimation of missing pixels** or the **rectification of high frequency information** in the received data.

→ Most of the existing image reconstruction frameworks utilize **Mean Square Error (MSE)** for correlation and similarity calculations between/within the pixels/patches. However, literature shows that **MSE doesn't correlate well with Human Visual System** (HVS)

→ In this work, Image denoising (Gaussian Noise) problem has been taken into account as an image reconstruction problem.

→ A state-of-the-art image denoising filter, Non-local Means Filter, is modified using an image quality assessment (IQA) measure for improved visual performance.

Why (Not) MSE?



Comparison of "Boat" images with different types of distortions, all with **MSE = 210** .

(a) Original image (8 bits/pixel; cropped from **512x512** to **256x256** for visibility).

(b) Contrast-stretched image, **MSSIM = 0.9168** .

(c) Mean-shifted image, **MSSIM = 0.9900** .

(d) JPEG compressed image, **MSSIM = 0.6949** .

(e) Blurred image, **MSSIM = 0.7052**.

(f) Salt-pepper impulsive noise contaminated image, **MSSIM = 0.7748**.

Wang, Z., Bovik, A. C., Sheikh, H. R., & Simoncelli, E. P. (2004). Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing*, *13*(4), 600-612.

Has Anyone Tried This Previously?

→ Structural Similarity (SSIM*) Based Non-local Image Denoising.
→ Authors used SSIM instead of MSE to calculate similar patch(es)/pixel(s).
→ Drawbacks**: SSIM is computation very expensive and less robust in environments with high noise compared to some of the other SOTA IQA metrics i.e. GMSD.
→ As opposed to SSIM, GMSD has far better in terms accurately capturing image quality and more robust in environments with high noise intensities. Authors in **[W. Xue, 2013]** have also demonstrated the same with thorough and detailed experimental results.

***Rehman, A., & Wang, Z. (2011, September). SSIM-based non-local means image denoising. In 2011 18th IEEE International Conference on Image Processing (pp. 217-220). IEEE.**
**** Xue, W., Zhang, L., Mou, X., & Bovik, A. C. (2013). Gradient magnitude similarity deviation: A highly efficient perceptual image quality index. IEEE Transactions on Image Processing, 23(2), 684-695.**

Non-local means (NLM) filter

Averages pixels that have similar neighbourhoods

$$g(\mathbf{p}) = \frac{1}{Z} \sum_{\mathbf{q} \in I} G_\sigma(\mathcal{N}_\mathbf{p} - \mathcal{N}_\mathbf{q}) f(\mathbf{q})$$

If neighbourhood of **p** looks similar to neighbourhood of **q**, give higher weight

The weight depends on image intensities

Gaussian weighting based on difference in image intensities

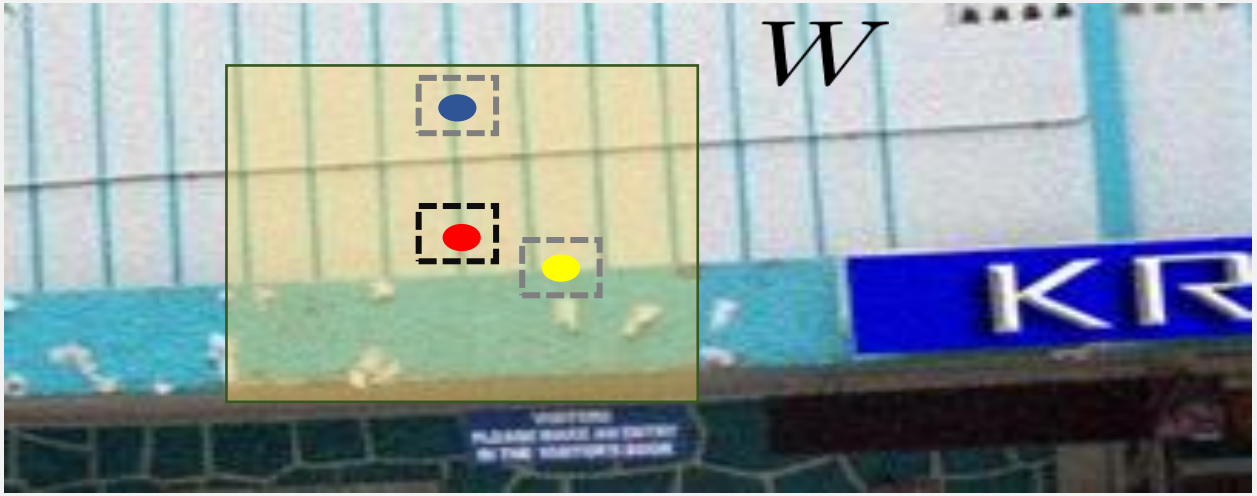
$$G_\sigma(\mathbf{x}) = e^{-\left(\frac{\sum_i x_i^2}{2\sigma^2}\right)}$$

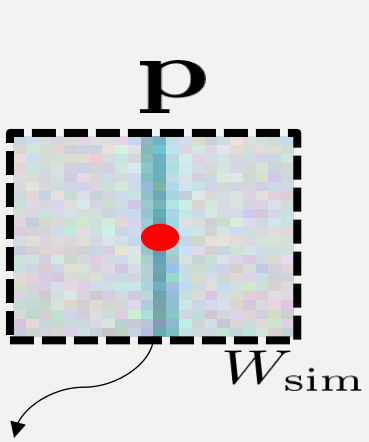
Normalization

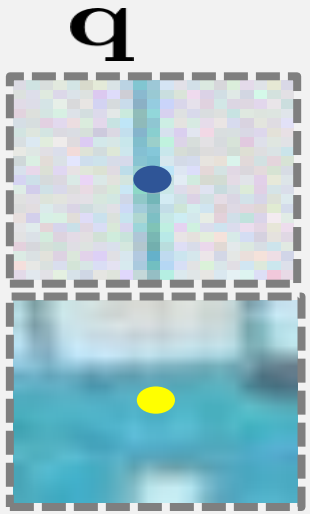
$$Z = \sum_{\mathbf{q} \in I} G_\sigma(\mathcal{N}_\mathbf{p} - \mathcal{N}_\mathbf{q})$$

Buades, A., Coll, B., & Morel, J. M. (2005, June). A non-local algorithm for image denoising. In 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) (Vol. 2, pp. 60-65). IEEE.

Non-local means (NLM) filter





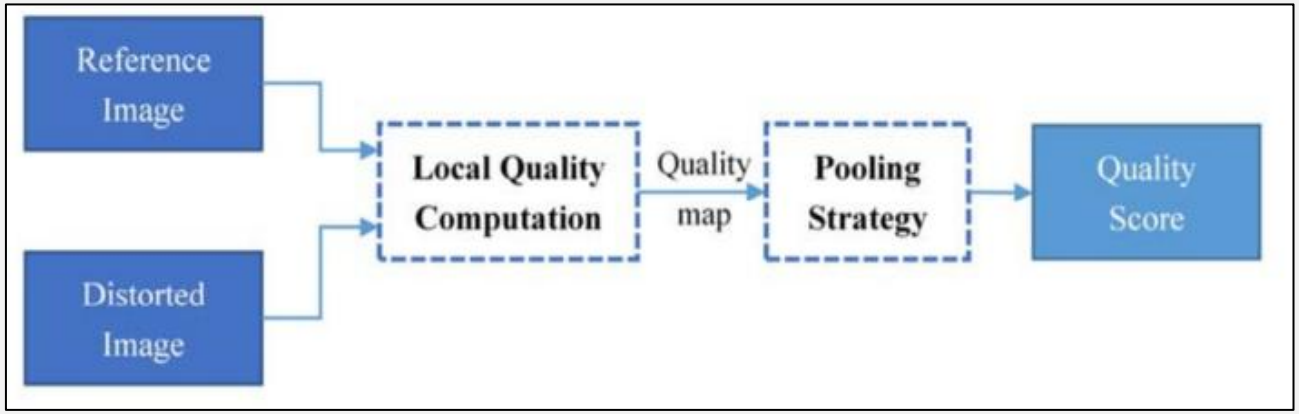


Higher weight
looks similar to **p**

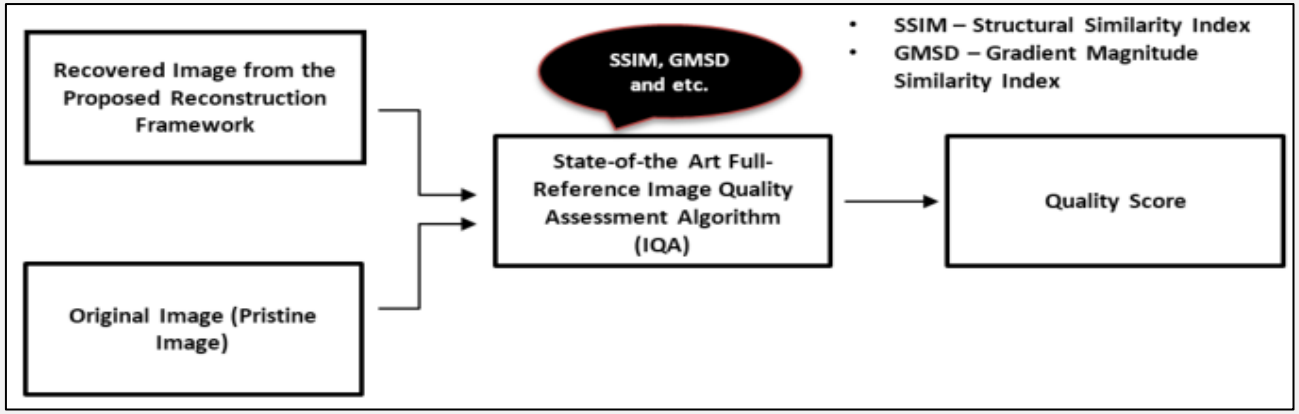
Lower weight

Validation of Proposed Method!!

Performance of the proposed method was validated using PSNR and two IQA models; Gradient Magnitude Deviation Index (GMSD) and Structural Similarity Index (SSIM). For most quality assessment algorithms, the **quality value** ranges from **0** to **1**. The basic architecture for both the models is depicted as under,



The flowchart of a class of two-step FR-IQA models



Criteria for Validation of Proposed Model

For GMSD:
Quality score of **'0'** indicates best quality and **'1'** indicates worst quality.

For SSIM:
Quality score of **'1'** indicates best quality and **'0'** indicate worst quality.

GMSD – How it works!

Gradient Magnitude Similarity Deviation, an image quality assessment metric. Answer will always be between 0 (best quality) and 1 (worst quality). The general formula is,

Local Quality Map → $$GMSD(i) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(GMS(i) - GMSM)^2}$$

Pooling Strategy → $$GMS(i) = \frac{2g(N_i)g(N_j) + c}{g(N_i)^2 + g(N_j)^2 + c}$$

where ‘c’ is a constant for numerical stability, we set c=0.0026 as suggested by the author.

Xue, W., Zhang, L., Mou, X., & Bovik, A. C. (2013). Gradient magnitude similarity deviation: A highly efficient perceptual image quality index. IEEE Transactions on Image Processing, 23(2), 684-695.

Proposed GMSD-Based Non-local means (NLM) filter

Proposed Method

$$\underset{\text{G-NLM}}{g(\mathbf{p})} = \frac{1}{Z}\sum_{\mathbf{q}\in I} G_\sigma(N_P, N_q)\, f(\mathbf{q})$$

Gaussian weighting based on difference in image intensities

$$G_\sigma(N_P, N_q) = e^{-\left(\frac{\sum_i ((N_p(i)-N_q(i))^2 . GMSD(N_P,N_q)}{2\sigma^2}\right)}$$

Normalization

$$Z = \sum_{q\epsilon I} G_\sigma(N_P, N_q)$$

Buades, A., Coll, B., & Morel, J. M. (2005, June). A non-local algorithm for image denoising. In 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) (Vol. 2, pp. 60-65). IEEE.

Environment Details and Simulation Results

Database ** :

→ **Computational and Subjective Image Quality (CSIQ) Image Quality Database :**The proposed model was validated using the CSIQ database. It is the second largest subjective database with 30 pristine references and 866 distorted images. We have tested our proposed model using the 30 available references images at different noise levels.

Simulation Platform:

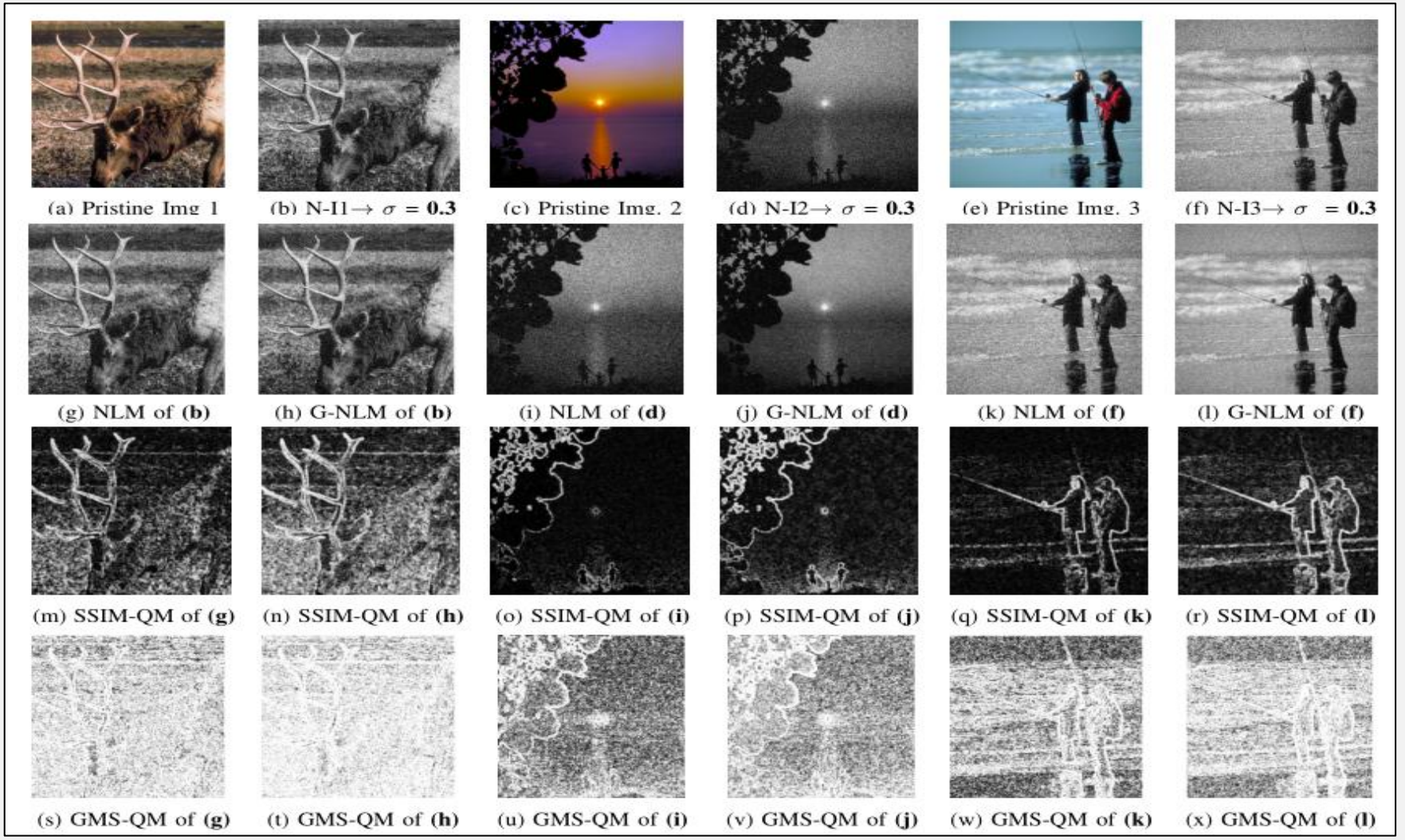
→ **MATLAB**

For Gray-Scale Images		
σ	Similarity Window (f)	Search Window (t)
0.1	3×3	21×21
0.2	5×5	21×21
0.3	5×5	21×21
0.4	7×7	35×35
0.5	9×9	35×35
0.6	9×9	35×35
0.7	9×9	35×35
0.8	11×11	35×35
0.9	11×11	35×35
1.0	11×11	35×35

Parameters for implementation of GMSD-based non-local means filter. **[From Baudes *et al*. (2005)]**

****E. C. Larson and D. M. Chandler, "Most apparent distortion: full-reference image quality assessment and the role of strategy," Journal ofElectronic Imaging, vol. 19, no. 1, p. 011006, 2010**

Comparison of NLM with G-NLM



Visual comparison of NLM and GMSD-based-NLM algorithm in terms of GMS and SSIM quality maps. Brighter map indicates better quality.

Case 1: Empirical Study

Test Images	Image 1										Image 2									
Noise (σ)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Peak Signal-to-Noise Ratio (PSNR) dB																				
Noisy Image	15.6875	15.2310	14.2518	14.1121	14.0523	14.0133	13.5033	13.2123	12.8978	12.5687	14.9987	14.7832	14.7591	14.2583	13.9896	13.5867	13.2523	12.9985	12.7848	12.5748
NLM	17.1847	16.8457	16.5474	16.3421	15.9582	15.7741	15.2101	14.7212	14.3578	14.0341	17.5784	17.2145	16.8224	16.6101	15.9989	15.6021	14.8214	14.5648	14.1278	13.8565
GMSD-NLM	18.8999	18.2965	17.8545	17.5421	17.1864	16.8951	16.5511	16.3545	15.8678	15.6956	18.7826	18.3851	17.9878	17.5741	16.8967	16.5674	15.9978	15.8789	15.5240	15.1542
Structural Similarity Index (SSIM)																				
Noisy Image	0.7546	0.7120	0.6214	0.6012	0.5412	0.5105	0.4023	0.3024	0.2108	0.1105	0.7890	0.7512	0.6942	0.6213	0.5954	0.5302	0.4512	0.3302	0.2204	0.1890
NLM	0.7905	0.7584	0.7341	0.6589	0.6214	0.5799	0.4954	0.4214	0.3593	0.2214	0.8101	0.7765	0.7389	0.6789	0.6352	0.6012	0.5212	0.4687	0.3641	0.2987
GMSD-NLM	0.8345	0.7857	0.7421	0.6965	0.6357	0.6015	0.5845	0.5564	0.4815	0.3952	0.8897	0.8654	0.7987	0.7548	0.7021	0.6589	0.6235	0.5986	0.5021	0.4012
Gradient Magnitude Similarity Deviation (GMSD)																				
Noisy Image	0.0112	0.0393	0.0648	0.1387	0.1882	0.2345	0.2545	0.2897	0.3241	0.4052	0.0011	0.0578	0.0989	0.1478	0.1945	0.2154	0.2521	0.3012	0.3781	0.4268
NLM	0.0110	0.0212	0.0513	0.0945	0.1610	0.2001	0.2189	0.2625	0.2765	0.3312	0.0010	0.0410	0.0801	0.1199	0.1698	0.2001	0.2299	0.2765	0.3545	0.3865
GMSD-NLM	0.0009	0.0165	0.0305	0.0815	0.1387	0.1748	0.1847	0.2102	0.2414	0.2897	0.0009	0.0350	0.0721	0.1084	0.1352	0.1599	0.1845	0.2237	0.2861	0.3128

Performance comparison of NLM and GMSD-based NLM denoising algorithms while using original image patches for weight calculations.

Case 2:

Test Images	Image 1										Image 2									
Noise (σ)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Peak Signal-to-Noise Ratio (PSNR) dB																				
Noisy Image	15.6875	15.2310	14.2518	14.1121	14.0523	14.0133	13.5033	13.2123	12.8978	12.5687	14.9987	14.7832	14.7591	14.2583	13.9896	13.5867	13.2523	12.9985	12.7848	12.5748
NLM	17.0235	16.7532	16.3394	16.1385	15.8985	15.7545	15.1235	14.7135	14.3451	14.0214	17.4215	17.2105	16.8004	16.5421	15.9845	15.5325	14.7214	14.5582	14.1012	13.8565
GMSD-NLM	18.8564	18.2135	17.7135	17.2534	17.0025	16.7587	16.3575	16.0103	15.7215	15.4256	18.5512	18.2134	17.7931	17.1254	16.5354	16.1345	15.8970	15.7532	15.2341	15.0214
Structural Similarity Index (SSIM)																				
Noisy Image	0.7546	0.7120	0.6214	0.6012	0.5412	0.5105	0.4023	0.3024	0.2108	0.1105	0.7890	0.7512	0.6942	0.6213	0.5954	0.5302	0.4512	0.3302	0.2204	0.1890
NLM	0.7895	0.7562	0.7012	0.6542	0.6012	0.5782	0.4904	0.4021	0.3564	0.2142	0.8015	0.7712	0.7201	0.6648	0.6223	0.5921	0.5128	0.4578	0.3415	0.2867
GMSD-NLM	0.8125	0.7612	0.7335	0.6892	0.6314	0.6015	0.5675	0.5142	0.4412	0.3214	0.8354	0.8075	0.7745	0.7108	0.6891	0.6245	0.5872	0.5189	0.4528	0.3540
Gradient Magnitude Similarity Deviation (GMSD)																				
Noisy Image	0.0112	0.0393	0.0648	0.1387	0.1882	0.2345	0.2545	0.2897	0.3241	0.4052	0.0011	0.0578	0.0989	0.1478	0.1945	0.2154	0.2521	0.3012	0.3781	0.4268
NLM	0.0110	0.0215	0.0541	0.0962	0.1645	0.2054	0.2387	0.2745	0.2847	0.3574	0.0010	0.0478	0.0871	0.1254	0.1754	0.2012	0.2347	0.2845	0.3648	0.4010
GMSD-NLM	0.0011	0.0173	0.0354	0.0875	0.1485	0.1843	0.1987	0.2245	0.2501	0.3045	0.0010	0.0397	0.0782	0.1124	0.1432	0.1647	0.1901	0.2345	0.2901	0.3398

Performance comparison of NLM and GMSD-based NLM denoising algorithms while using noisy image patches for weight calculations

Conclusion

- In this work, a visual quality assessment metric-based image denoising algorithm has been proposed, that is, gradient magnitude similarity deviation (GMSD)-based non-local means (NLM) filter.
- **We know that MSE only deals with visible errors and does not correlate well with human visual perception, so in most cases, usually, the images processed with MSE-based mechanisms have shown poor visual quality, especially, when the noise levels (variance) are high.**
- As we understand, that each local patch in an image has diverse structural features. Once this diversity is captured, it is easier to identify patches with similar characteristics. Therefore, keeping the aforementioned in consideration, GMSD was incorporated in the conventional MSE-based non-local means filter.
- **We have demonstrated the usefulness and effectiveness of GMSD, a visual quality assessment metric, in capturing local structural variations between corresponding image patches for effective denoising.**
- Simulation results based on PNSR, SSIM and GMSD coefficients have shown that the algorithm has promise, robustness and works well even at high noise levels.

Future Work

→ Most of the application-specific algorithms utilize non-linear filters for image reconstruction and can be generalized as generic filters. However, there exist few issues and they are,

- The performance of these filters significantly drops when neighboring pixels are noisy. **Note: In these non-linear filters, the MSE between patches/pixels is used to estimate the similarity between neighboring pixels and subsequently, weights are assigned depending upon patch similarity. For such applications, where the neighborhood is noisy and, especially, the level and cause of degradation in the distorted signal is unknown. It might result in wrong edge direction estimation and/or blurred edges in the restored image.**
- The performance of these filters are highly depended upon noise density (intensity) and decaying parameters (variance of noise/ tuning parameters). **Note: Estimation of noise density is still an open research area for a lot of image processing applications.**

→ Almost, all state-of-the art image reconstruction algorithms execute pixel by pixel and considering the ever so increasing image quality i.e. image size, makes such algorithms non-viable to be used in real-time applications. So, need for computationally inexpensive or more optimized algorithms arise.

→ In addition, Due to the inability of MSE to efficiently represent the signal fidelity, a lot of Image Quality Assessment (IQA) metrics are proposed in the literature, to predict signal quality and few have tried using them in image reconstruction with good effect.

Thank You!!
Q/A(s)