A NOVEL MEDICAL IMAGE DENOISING ENTITY.

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OVERVIEW

INTRODUCTION

WORK AT A GLANCE

PROBLEM FORMULATION
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SPATIAL DOMAIN APPROACHES

TRANSFORM DOMAIN APPROACHES

PROPOSED WORK

CONCLUSION

INTRODUCTION

- The incorporated noise during image acquisition degrades the human interpretation, or computer-aided analysis of the images

- For a visual analysis of medical images, the clarity of details are important.

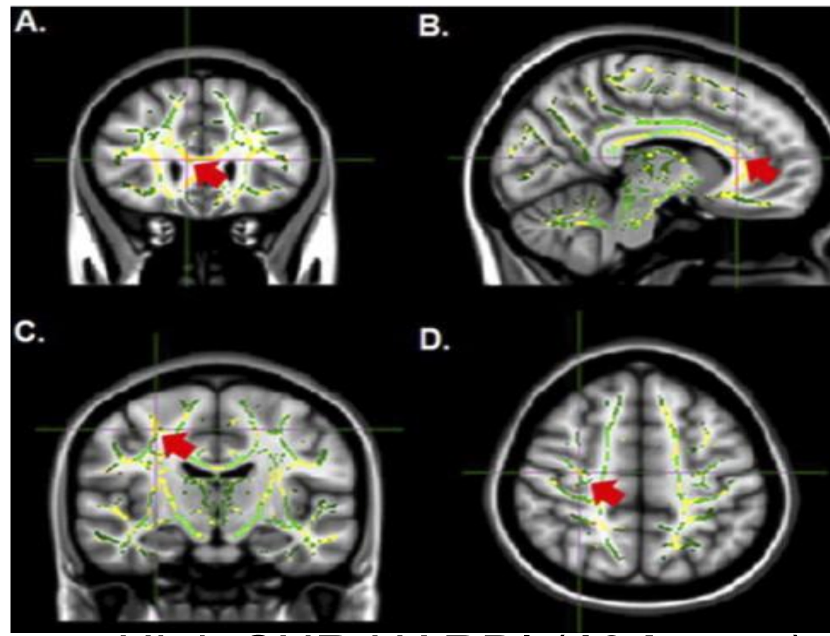
- Two approaches to reduce noise in a medical image.

SIMPLE ACQUISITION (Faster) (Low SNR)	**COMPEX ACQUISITION** (Slower) (High SNR)
1	2

MOTIVATION

- **Require long and repeated acquisition of the same subject to reduce noise and blur and to maintain a high SNR.**

High SNR DTI (**1 hour**)



High SNR HARDI (**13 hours**)

- **To recover noisy and blurry image without lengthy repeated scans, post-processing of data plays a critical role .**

THESIS AT A GLANCE

- **SPATIAL DOMAIN TECHNIQUES**
  - Bilateral filtering.
  - NLm filtering.

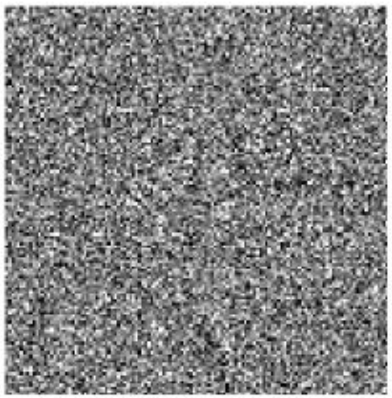
France, Bourget du Lac – February 23, 2012

- **TRANSFORM DOMAIN TECHNIQUES**
  - DWT thresholding.
  - Contourlet thresholding.

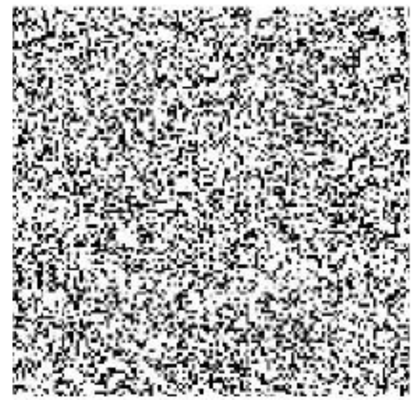
- **PROPOSE A NOVEL ENTITY FOR MEDICAL IMAGE DENOISING.**

PROBLEM FORMULATION

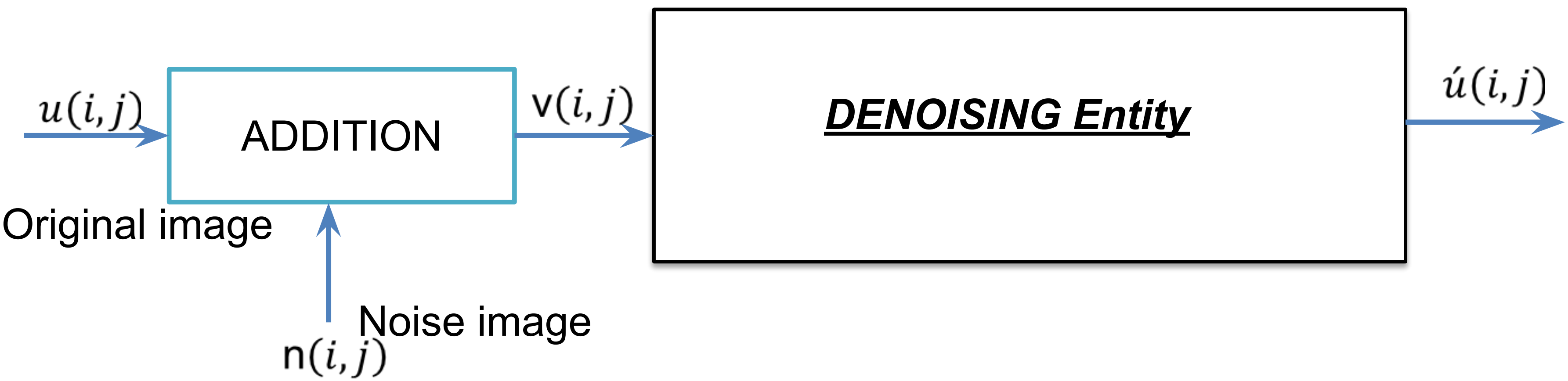
- Noise in medical images can be generalised to ***Additive White Gaussian Noise (AWGN).***



MEAN=0
VARIANCE=0.05



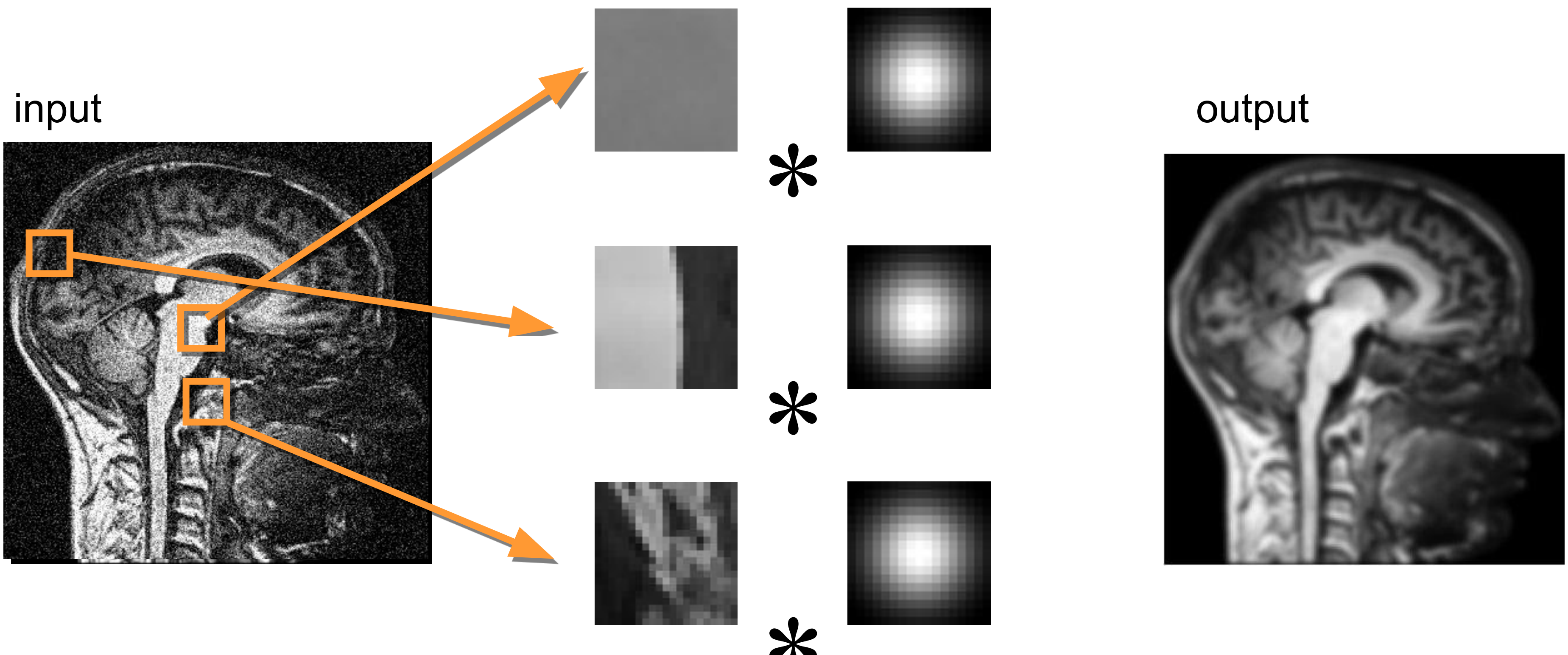
MEAN=1.5
VARIANCE=10



SPATIAL DOMAIN METHODS?

Gaussian blur → Bilateral filter → NLm filtering

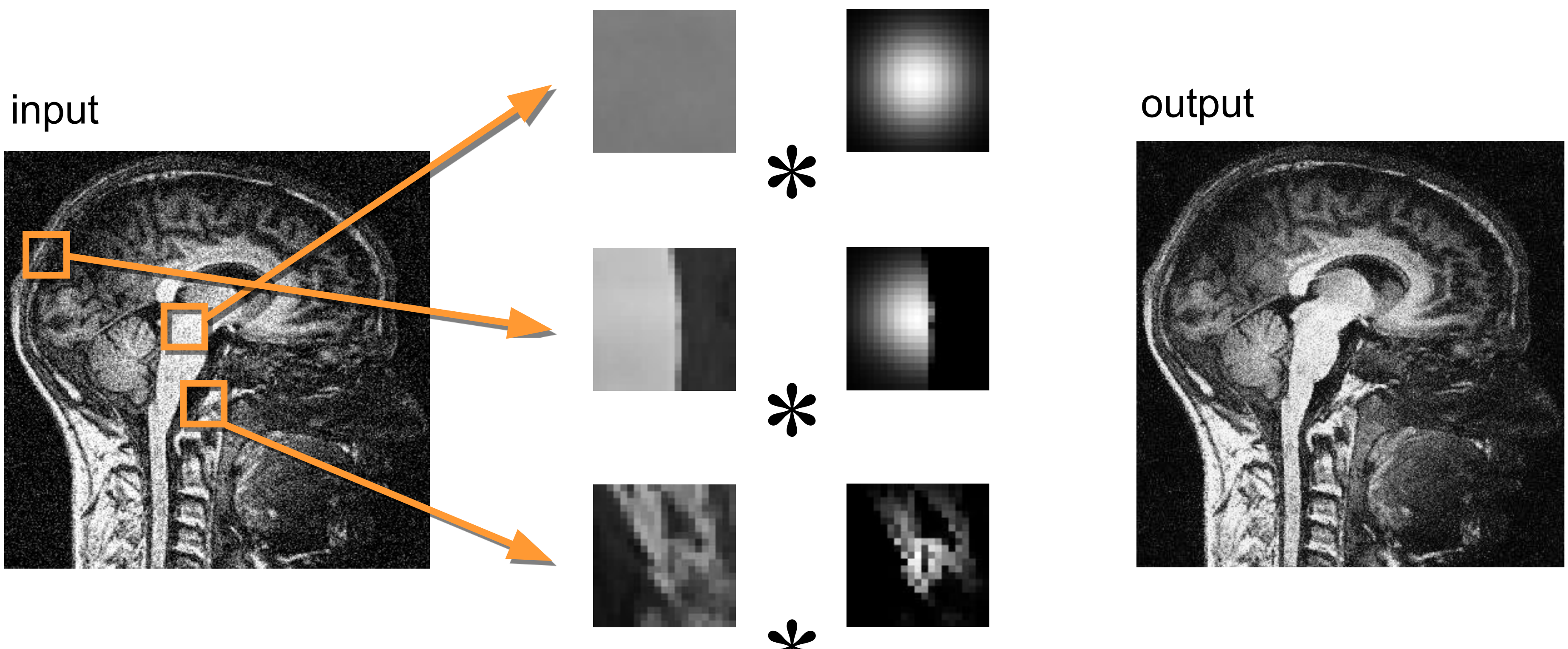
BLUR IN GAUSSIAN COMES FROM AVERAGING ACROSS EDGES



Same Gaussian kernel everywhere.

BILATERAL FILTER
NO AVERAGING ACROSS EDGES

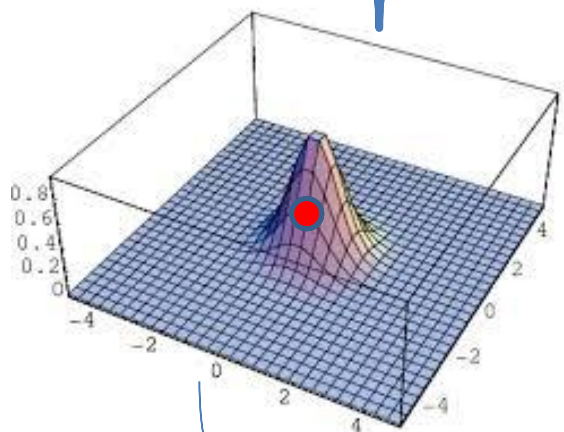
[Aurich 95, Smith 97, Tomasi 98]

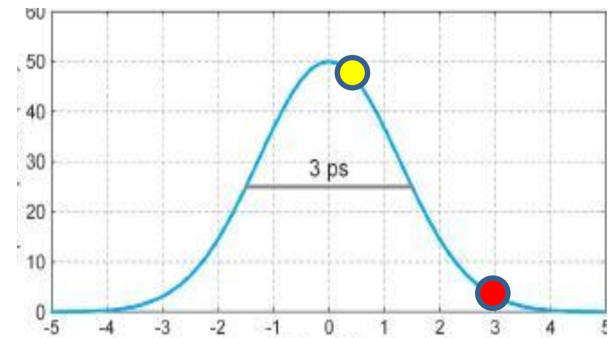


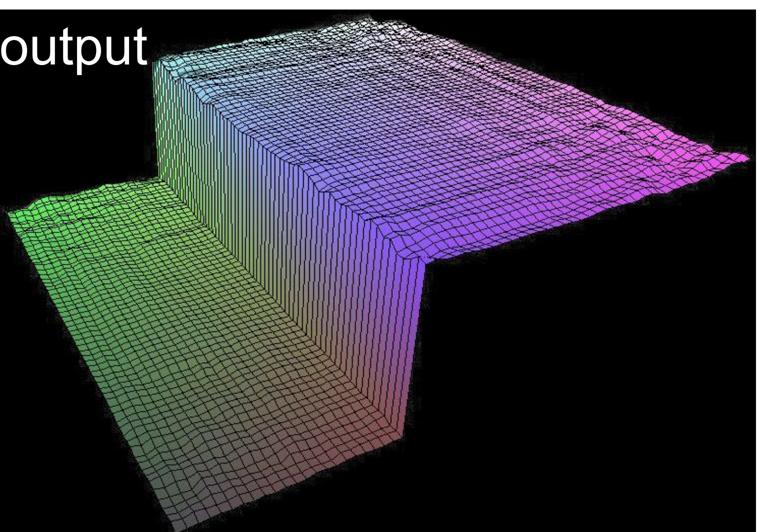
The kernel shape depends on the image content.

Bilateral Filter on a Height Field

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q}\in S} G_{\sigma_s}\left(\|\mathbf{p}-\mathbf{q}\|\right)\, G_{\sigma_r}\left(|I_{\mathbf{p}}-I_{\mathbf{q}}|\right)\, I_{\mathbf{q}}$$

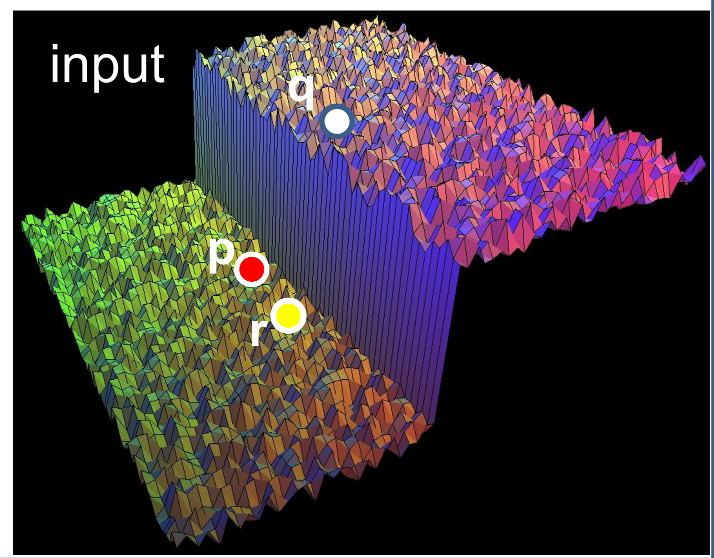




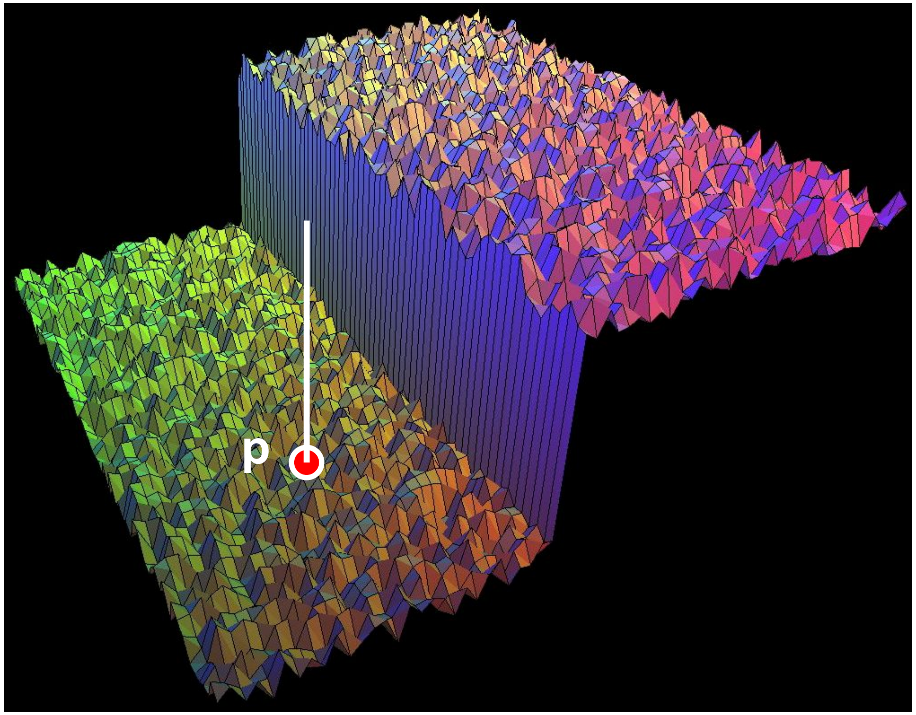


Weigh I(q)
By 2 * 0.4 = **0.8**

Weigh I(r)
By 48 * 0.4 = **19.2**



HOW TO ENHANCE PERFORMANCE OF BILATERAL FILTERING



- Bilateral very much depend on spatial intensities and thus abrupt noise values
- Need to device preprocessing technique which removes the abrupt noise value retaining <u>every edge information.</u>

NL-Means Filter (Buades 2005)

- Same goals: 'Smooth within Similar Regions'

- **KEY INSIGHT**: Generalize, extend 'Similarity'
  - **Bilateral:**
    Averages neighbors with **similar intensities**;

  - **NL-Means:**
    Averages neighbors with **similar neighborhoods!**

NL-Means Method: Buades (2005)

$$V_p = \begin{bmatrix} 0.74 \\ 0.32 \\ 0.41 \\ 0.55 \\ \cdots \\ \cdots \\ \cdots \end{bmatrix}$$

- For each and every pixel **p**:

Define a small, simple fixed size neighborhood;

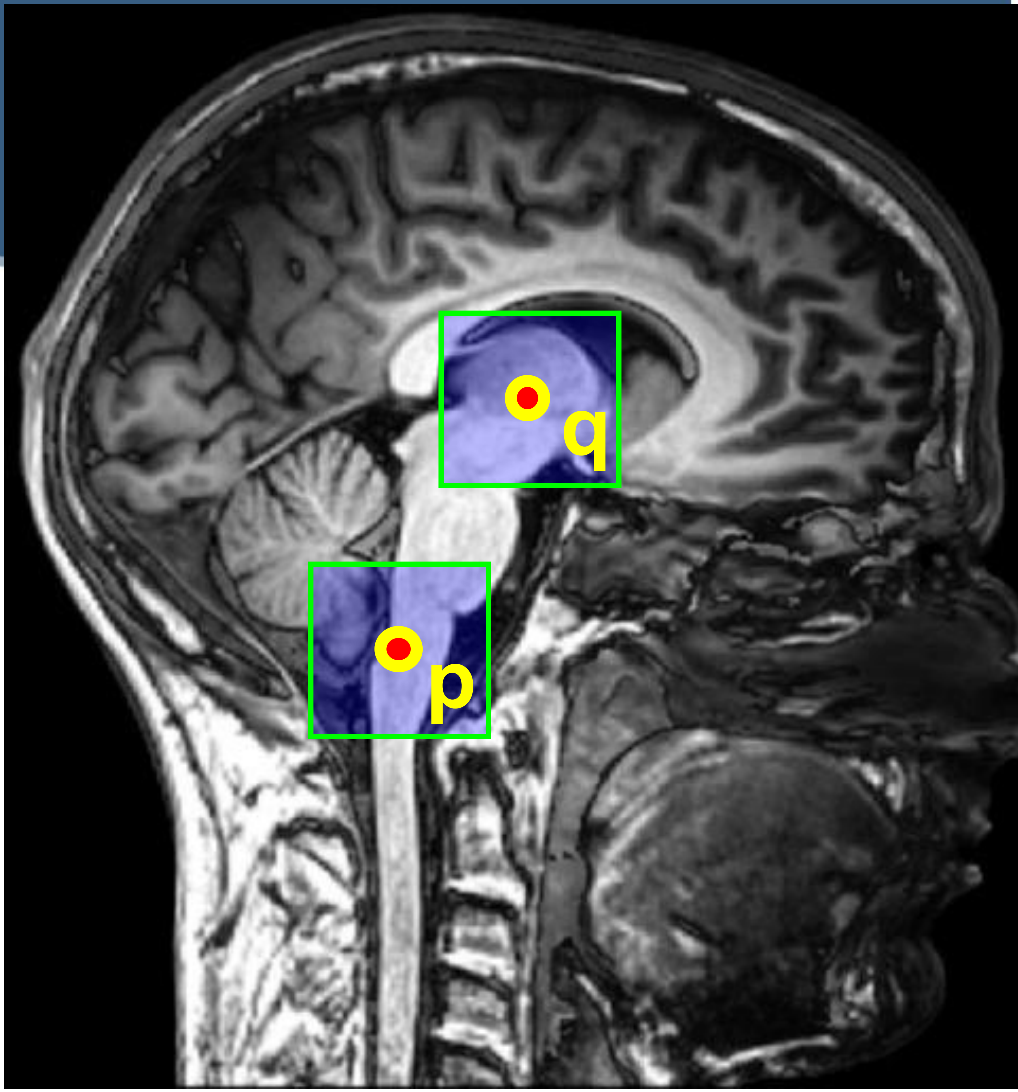
Define vector V_p: a list of neighboring pixel values.

NL-Means Method: Buades (2005)

<u>'Similar'</u> pixels **p, q**

□ **SMALL** vector distance;

$$\| V_p - V_q \|^2$$

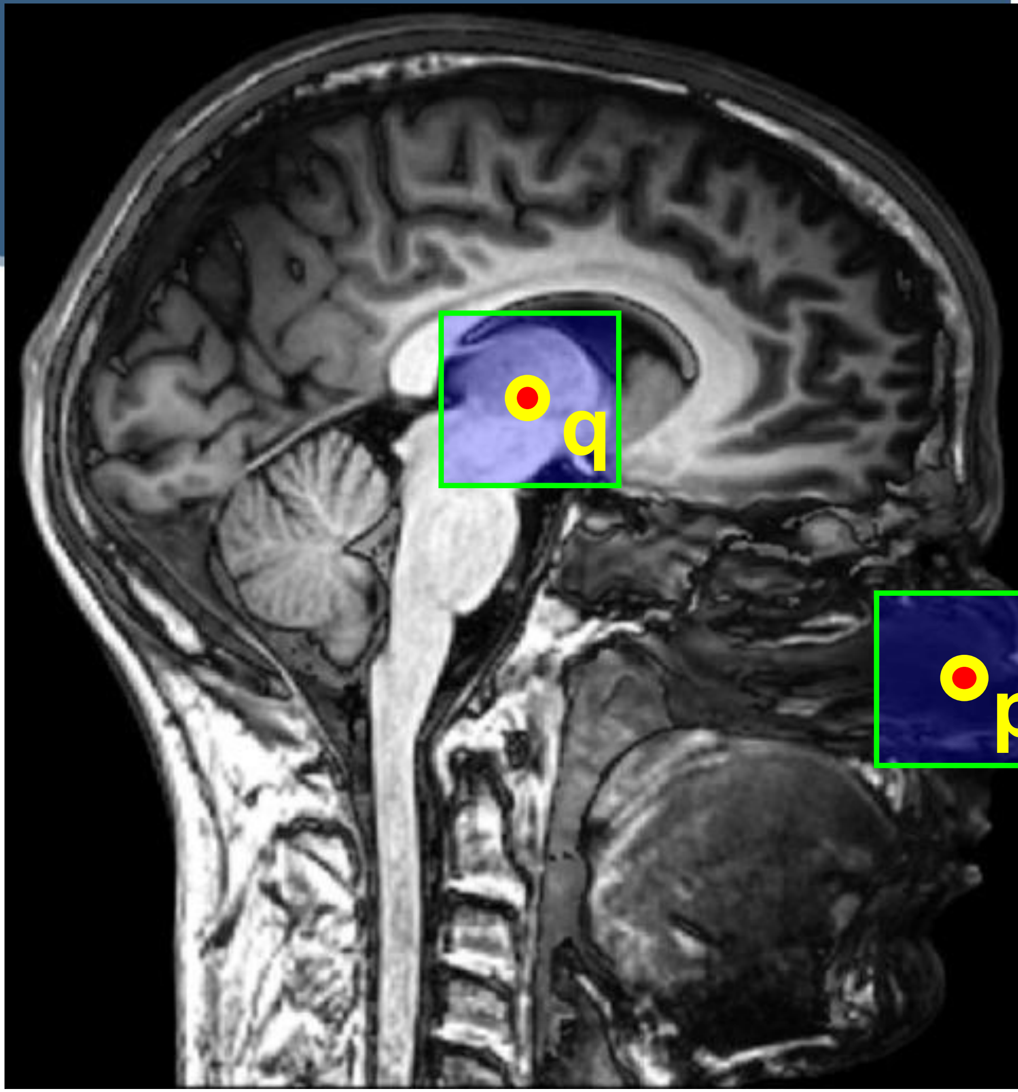


NL-Means Method: Buades (2005)

'Dissimilar' pixels **p, q**

- **LARGE** vector distance;

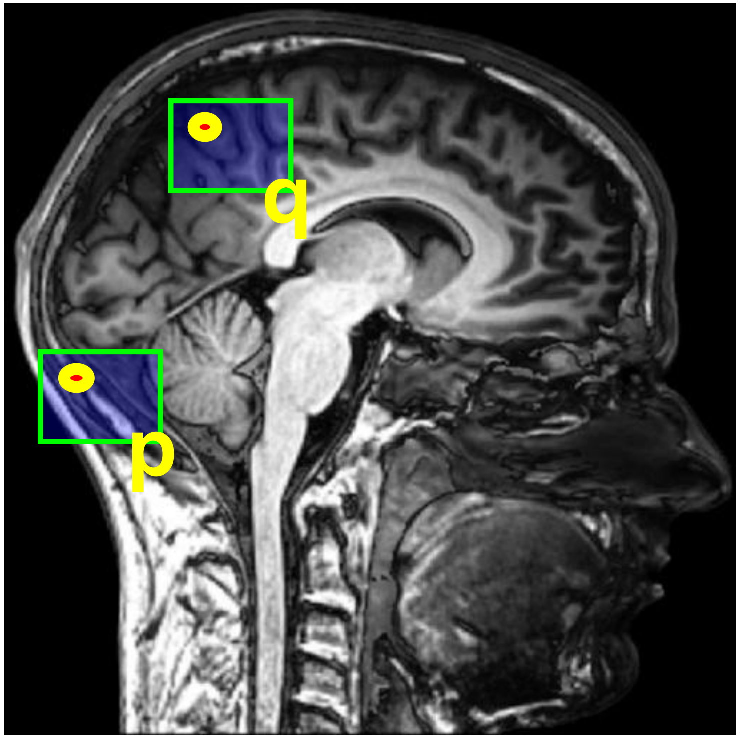
  $|| V_p - V_q ||^2$



Filter with this.

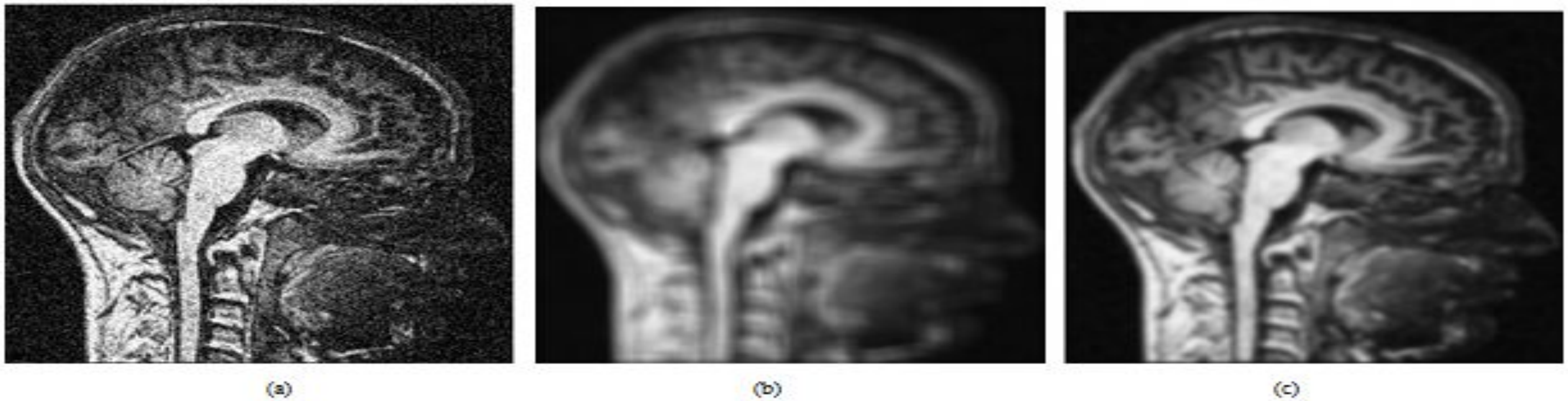
$$NLMF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_r}\left(|| \vec{V}_{\mathbf{p}} - \vec{V}_{\mathbf{q}} ||^2 \right) I_{\mathbf{q}}$$

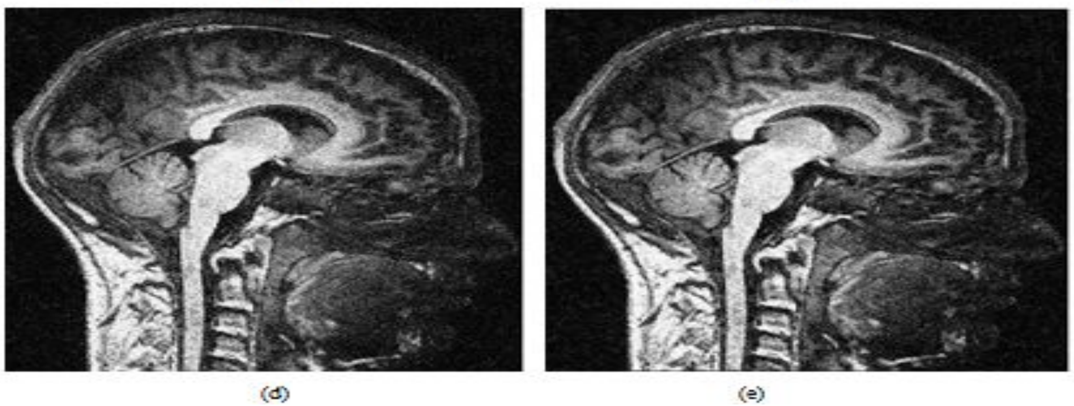
HOW TO ENHANCE PERFORMANCE OF NLM FILTERING?



- NLm peformance very much depend on spatial intensities and thus abrupt noise values
- Need to device preprocessing technique which removes the abrupt noise value retaining <u>every edge information.</u>

Result Analysis of Spatial Domain Techniques





Comparing performance
(a) Noisy image (σ = 40)
(b) Mean filtering ..
(c) Gaussian filtering
(d) Bilateral filtering
(e) NLm filtering.

Test image	Mean filtering	Gaussian filtering	Bilateral filtering	NLm filtering
		σ =29		
MRI	18.1010	21.0131	**22.5029**	**23.5457**

TRANSFORM DOMAIN METHODS?

- DISCRETE COSINE TRANSFORM(DCT)
- DISCRETE WAVELET TRANSFORM(DWT)
- CONTOURLET TRANSFORM

"IDEAL SPATIAL ADAPTATION VIA WAVELET SHRINKAGE"

D.L. Donoho, I.M. Johnstone

Biometrika, vol. 81, no. 3, pp. 425-55, 1994.

- **VisuShrink is wavelet thresholding by applying *universal threshold***

$$T_u = \sigma_n \sqrt{2\log(L)}$$

where, σ^2 is the noise variance of AWGN and *L* is the total number of pixels in an image.

- **The best empirical thresholds for universal thresholding <u>are much different from this value</u>, independent of the wavelet used.**

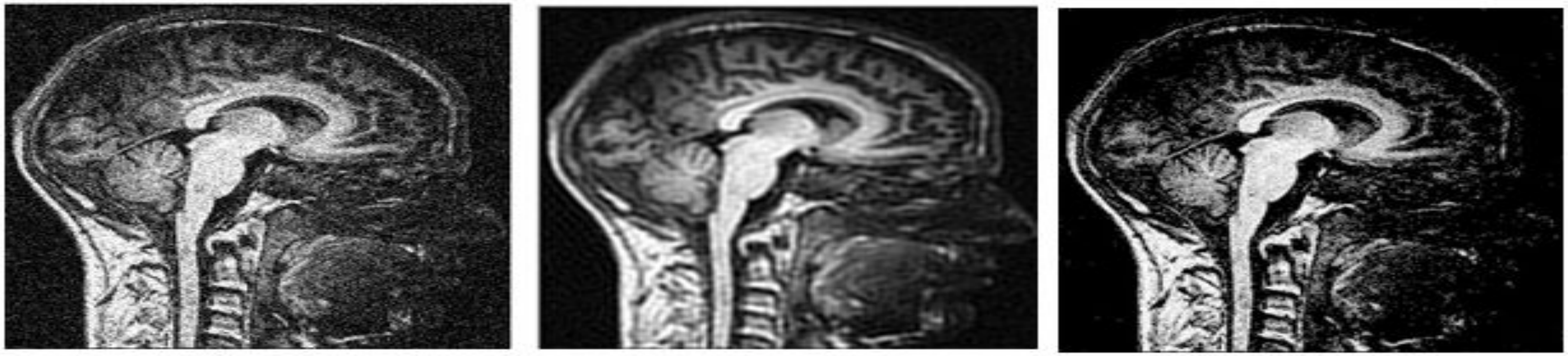
WHY CONTOURLET IS SUPERIOR?

WHAT WE WISH IN A TRANSFORM?

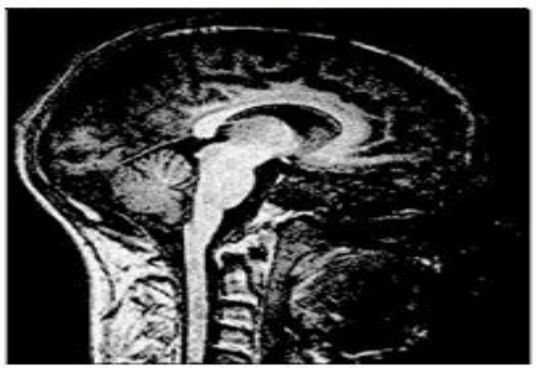
- MULTIRESOLUTION
- LOCALIZATION
- CRITICAL SAMPLING
- DIRECTIONALITY
- ANISOTROPY

- **WAVELET SATISFIES FIRST THREE WHILE CONTOURLET "ALL OF IT".**
- **BECAUSE CONTOURLET IS NOT A SEPERABLE TRANSFORM.**

Result Analysis of Frequency Domain Techniques



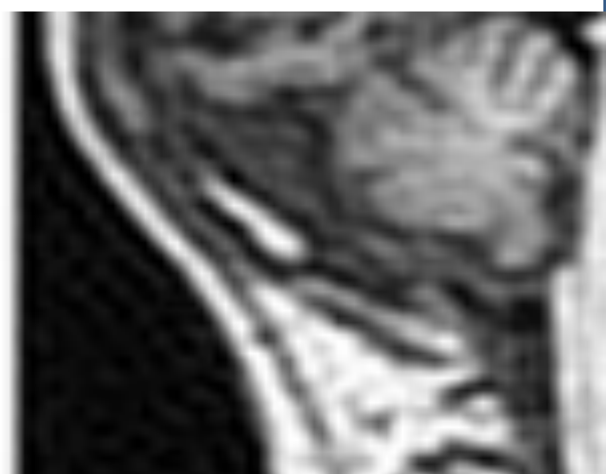
(a) (b) (c)



(d)

Comparing performance
(a) Noisy image (σ = 40)
(b) DCT based denoising
(c) DWT based denoising
(d) Contourlet based denoisng

Test image	DCT based denoising	DWT visushrink	Contourlet visushrink
MRI	21.2000	20.8224	19.4452
	Ringing effect	No ringing effect	No ringing effect



Proposed Contributions

#1 Empirically formed a scaling factor for universal threshold for Visushrink.

#2 Introduced contourlet transform for denoising and empirically formed a similar scaling factor.

#3 Introduced a new entity for medical image denoising comprised of aforementioned contourlet thresholding as a preprocessing step to non-local mean denoising.

CONTRIBUTION #1

THEORETICAL VALIDATION

- Universal threshold as derived by Donoho is hundred percent effective only when number of pixels in an image tends to infinity.

$$T = \sigma\sqrt{2\log_e N}$$

So a scaling parameter is deviced so that new threshold is $T_w = \lambda_w * T$.
Where λ_w is

$$\lambda_w = 3.944*10^{-11} S^2 - 5.5285*10^{-6} *S + 0.6022$$

and

$$S = \sigma * \sqrt{N}$$

CONTRIBUTION #2

THEORETICAL VALIDATION

For image denoising, random noise will generate significant wavelet coefficients just like true edges, but is less likely to generate significant contourlet coefficients.

$$T = \sigma\sqrt{2\log_e N}$$

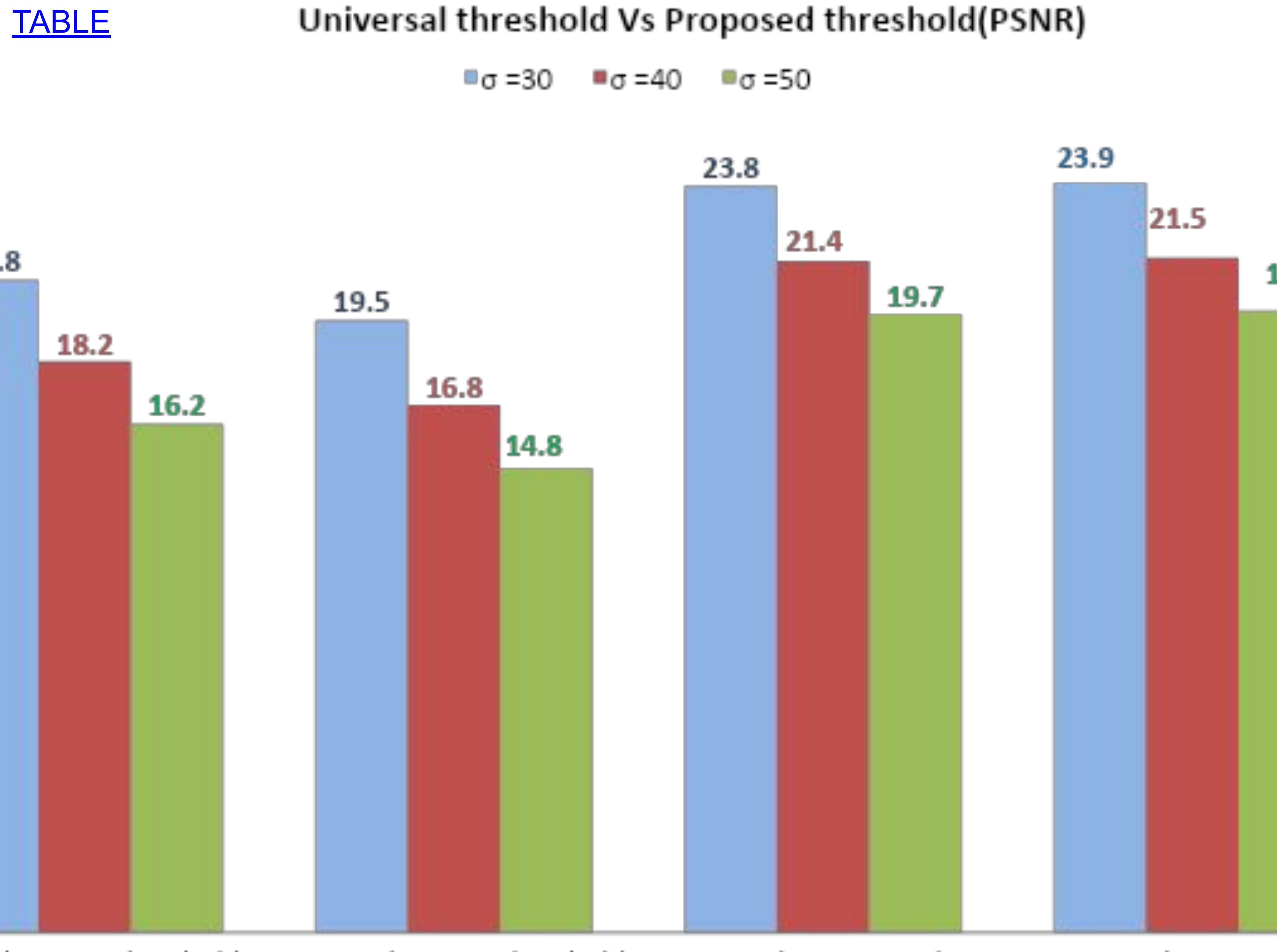
So a scaling parameter is deviced so that new threshold is $T_c = \lambda_c * T$. Where λ_c is

$$\boldsymbol{\lambda_c = 3.944*10^{-11} S^2 - 5.5285*10^{-6} *S + 0.5522}$$

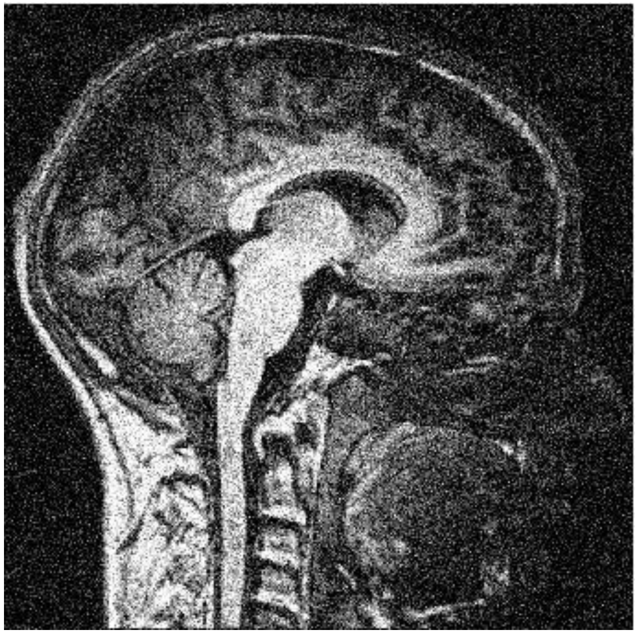
and

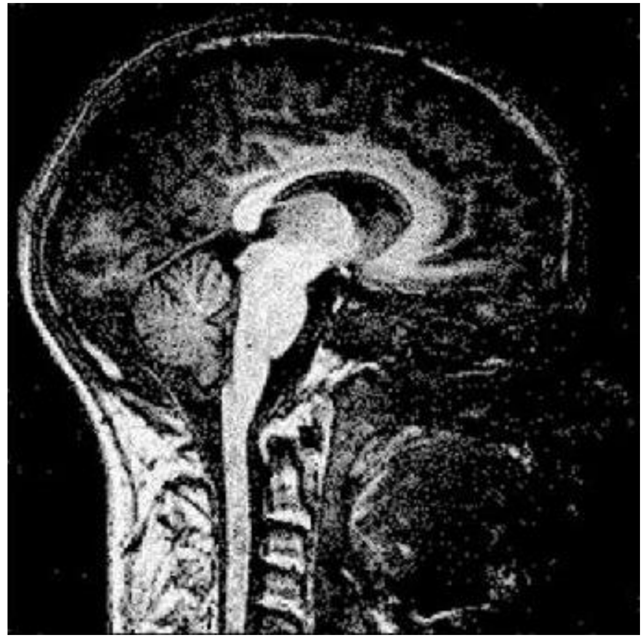
$$S = \sigma * \sqrt{N}$$

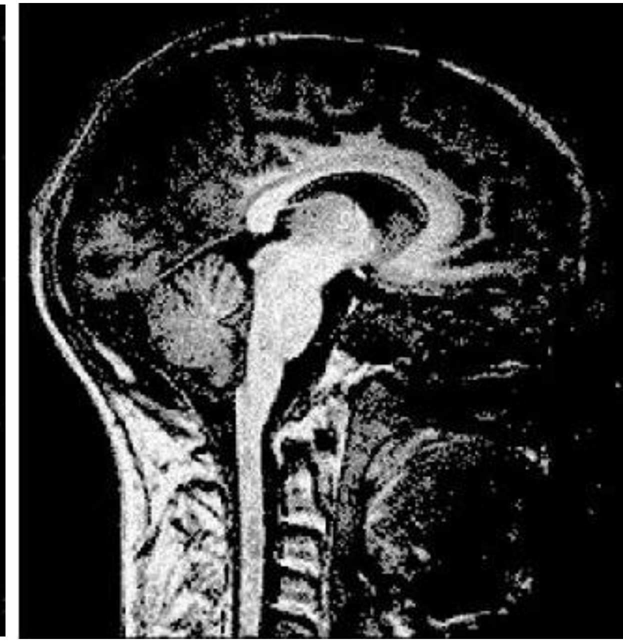
TABLE

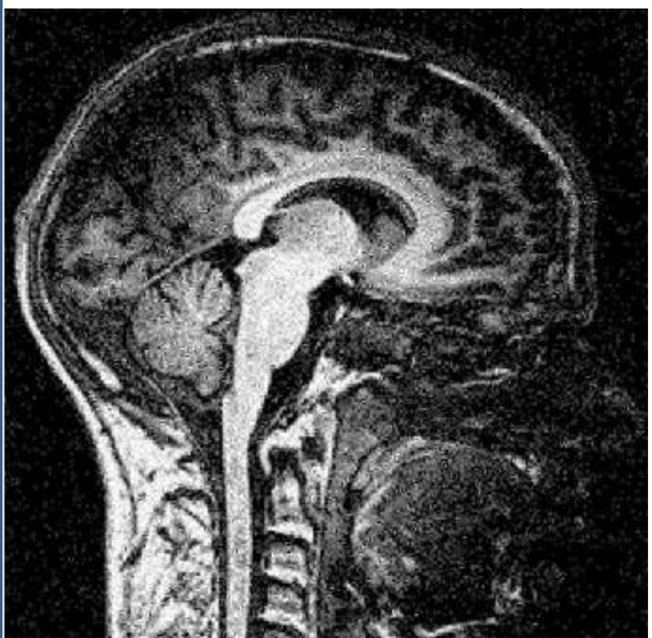

Universal threshold Vs Proposed threshold(PSNR)
σ =30
σ =40
σ =50
18.2
16.2
19.5
16.8
14.8
23.8
21.4
19.7
23.9
21.5

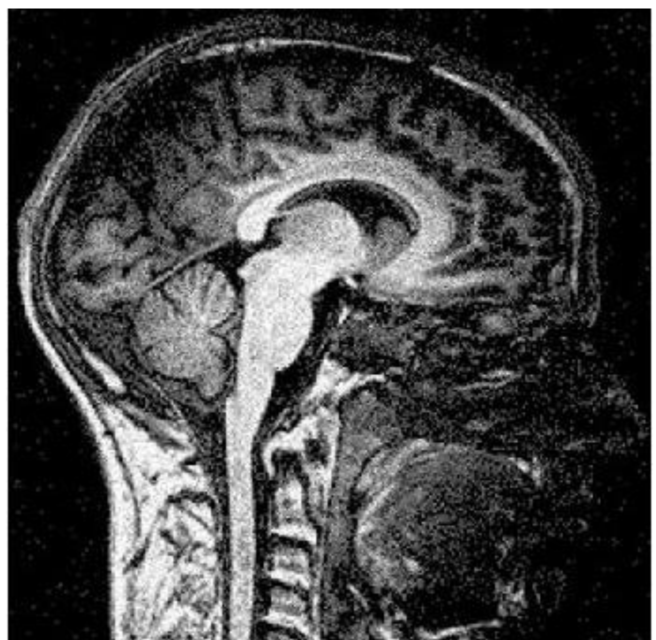
SIMULATION RESULTS #1 & #2











1 2 3
4 5

1-Noisy image(σ = 30)
2-Wavelet Univ threshold
3-Contourlet Univ threshold
4-Wavelet proposed
5-Contourlet proposed

CONTRIBUTION #3

THEORETICAL VALIDATION

Bilateral filtering –

- real homogeneous gray levels corrupted by noise is polluted significantly
- fails to efficiently remove noise in regions of homogeneous physical properties.

Contourlet denoising done before bilateral filtering,noise in homogeneous regions can be removed efficiently retaining the edge information as well as texture.

CONTRIBUTION #3

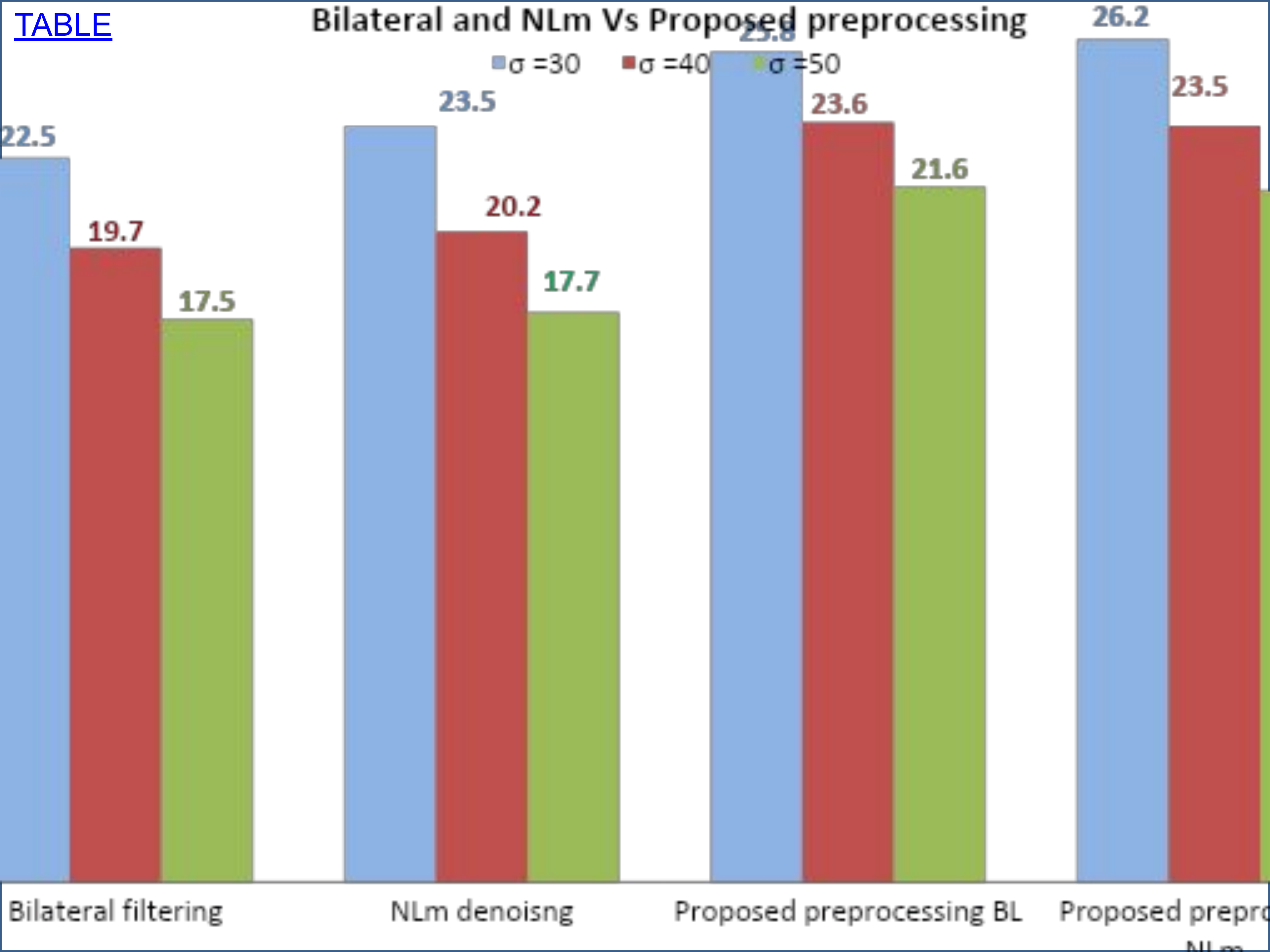
THEORETICAL VALIDATION

NLM filter –

- the calculation for similarity weights is performed in a full-space of neighborhood.
- Specifically, the accuracy of the similarity weights will be affected by noise

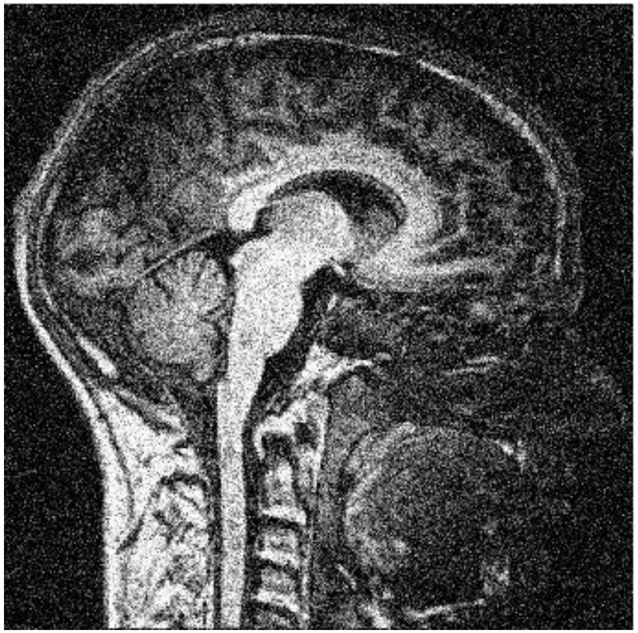
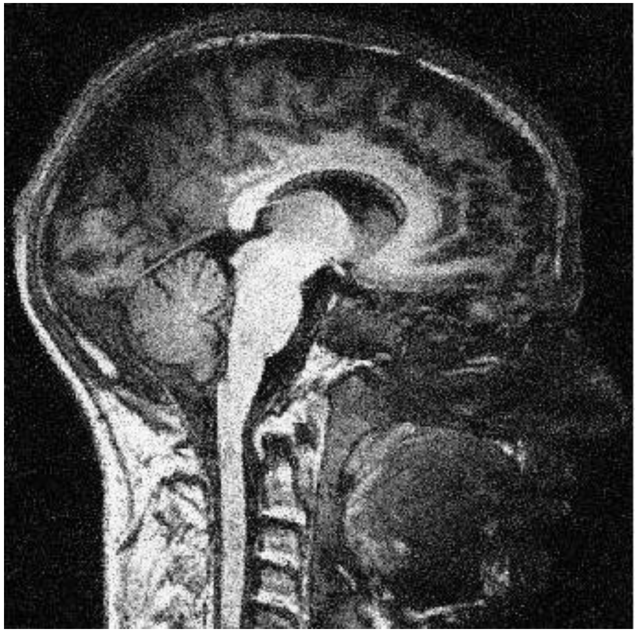
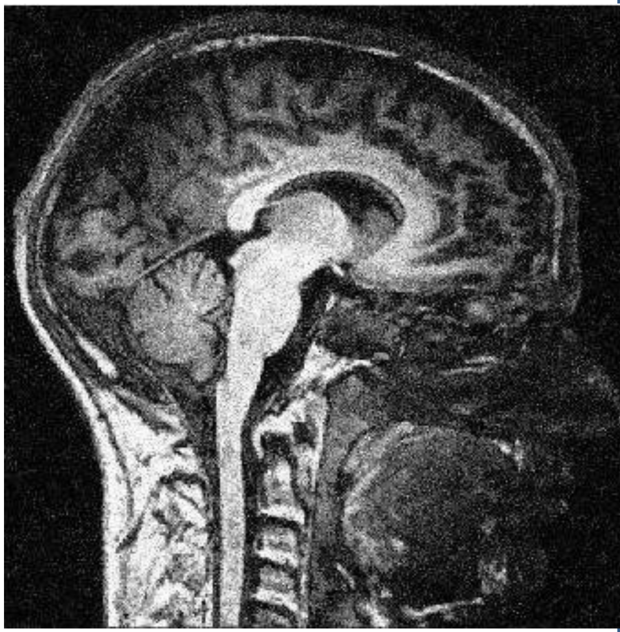
Contourlet denoising done before NLm filtering,noise in neighbourhood can be removed efficiently retaining the edge information as well as texture.

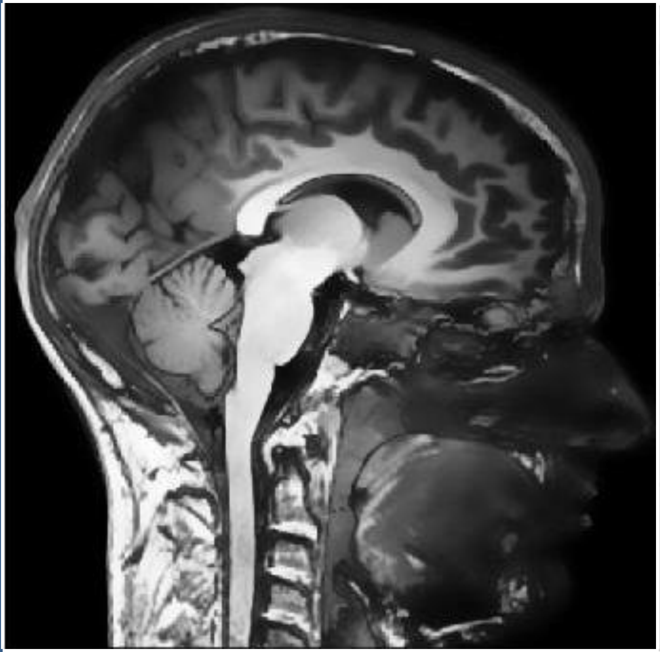
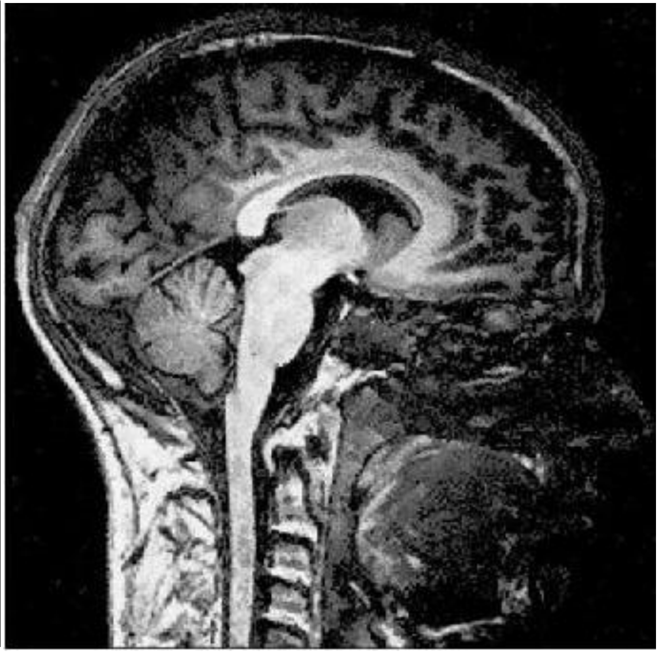
TABLE



Bilateral and NLm Vs Proposed preprocessing
σ =30
σ =40
σ =50
22.5
19.7
17.5
23.5
20.2
17.7
23.6
21.6
26.2
23.5
Bilateral filtering
NLm denoisng
Proposed preprocessing BL
Proposed prepr

SIMULATION RESULTS #3 & #4

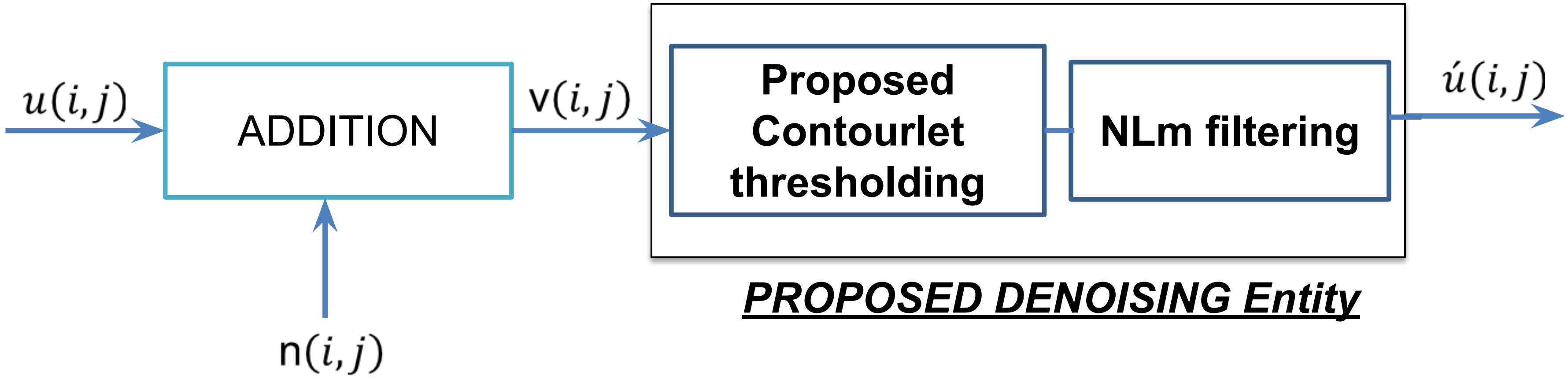




1 2 3
4 5

1-Noisy image(σ = 30)
2-Bilateral filtering
3-NLm denoising
4-Proposed scheme BL
5-Proposed scheme NLM

PROPOSED MEDICAL PROCESSING ENTITY



PROPOSED DENOISING Entity

BA

PROCESSING TIME

Maximum exceeded time from Normal process = **0.2763 second**

Test image	Bilateral filtering	NLm filtering	Proposed preprocessing prior to bilateral filtering	Proposed preprocessing prior to NLm filtering
$\sigma = 30$				
MRI	2.1578 s	2.8865 s	**2.4341 s**	**3.0889 s**
$\sigma = 40$				
MRI	2.1867 s	2.8533 s	**2.3711 s**	**3.0183 s**
$\sigma = 50$				
MRI	2.1735 s	2.8903 s	**2.3639 s**	**3.1014 s**

s/m specification-4 GB RAM,2.30 Ghz processor.

CONCLUSION

- ***Improved the performance of Wavelet based thresholding.***
- ***Introduced contourlet transform to image denoising and proved by simulation,proposed method is superior to wavelet transform.***
- ***`By introducing proposed entity for common medical image denoisng techniques,performance can be significanly increased without significantly increasing time of processing.***

REFERENCES

1. O. Christiansen, T. Lee, J. Lie, U. Sinha, and T. Chan. \Total Variation Regularization of Matrix-Valued Images." *International Journal of Biomedical Imaging*, 2007(27432):11, December 2007.
2. S.Kalaivani Narayanan, and R.S.D.Wahidabanu. A View on Despeckling in Ultrasound Imaging. International Journal of Signal Processing, Image Processing and Pattern Recognition, 2009, 2(3):85-98.
3. H. Guo, J. E. Odegard, M.Lang, A. Gopinath, J. W. Selesnick. Wavelet based Speckle Reduction with Application to SAR based ATD/R. First International Conference on Image Processing 1994:75-79.
4. Rafael C. Gonzalez, Richard E. Woods,Digital Image processing using MATLAB. Second Edition, Mc Graw hill.
5. Lu Zhang, Jiaming Chen, Yuemin Zhu, Jianhua Luo. Comparisons of Several New Denoising Methods for Medical Images. IEEE, 2009:1-4.
6. C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images. " Proc Int Conf Computer Vision, pp. 839–846, 1998.

REFERENCES

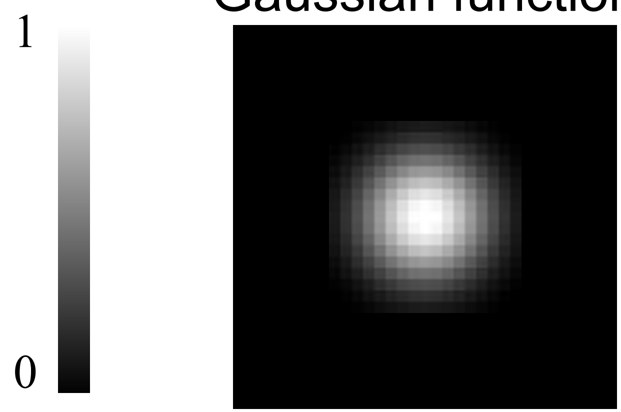
7. D. L. Donoho and I. M. Johnstone, “Ideal spatial adaptation via wavelet shrinkage,” Biometrika, 81, pp. 425–455, 1994.
8. A. Buades, B. Coll, and J. M. Morel, “A review of image denoising algorithms, with a new one,” Multiscale Modeling and Simulation (SIAM Interdisciplinary Journal), Vol. 4, No. 2, 2005, pp 490-530
9. M. N. Do and M. Vetterli, "Contourlets", in Beyond Wavelets, Academic Press, New York, 2003.Rafael C. Gonzalez, Richard E. Woods,Digital Image processing using MATLAB. Second Edition, Mc Graw hill.
10. J. B. Weaver, Y. Xu, D. M. Healy, and L. D. Cromwell, “Communications. Filtering noise from images with wavelet transforms,” Magnetic Resonance in Medicine, vol. 21, no. 2, pp. 288–295, 1991.
11. K.N. Chaudhury, D. Sage, and M. Unser, "Fast O(1) bilateral filtering using trigonometric range kernels," IEEE Trans. Image Processing, vol. 20, no. 11, 2011.

EQUATION OF GAUSSIAN FILTER

Same idea: **weighted average of pixels**.

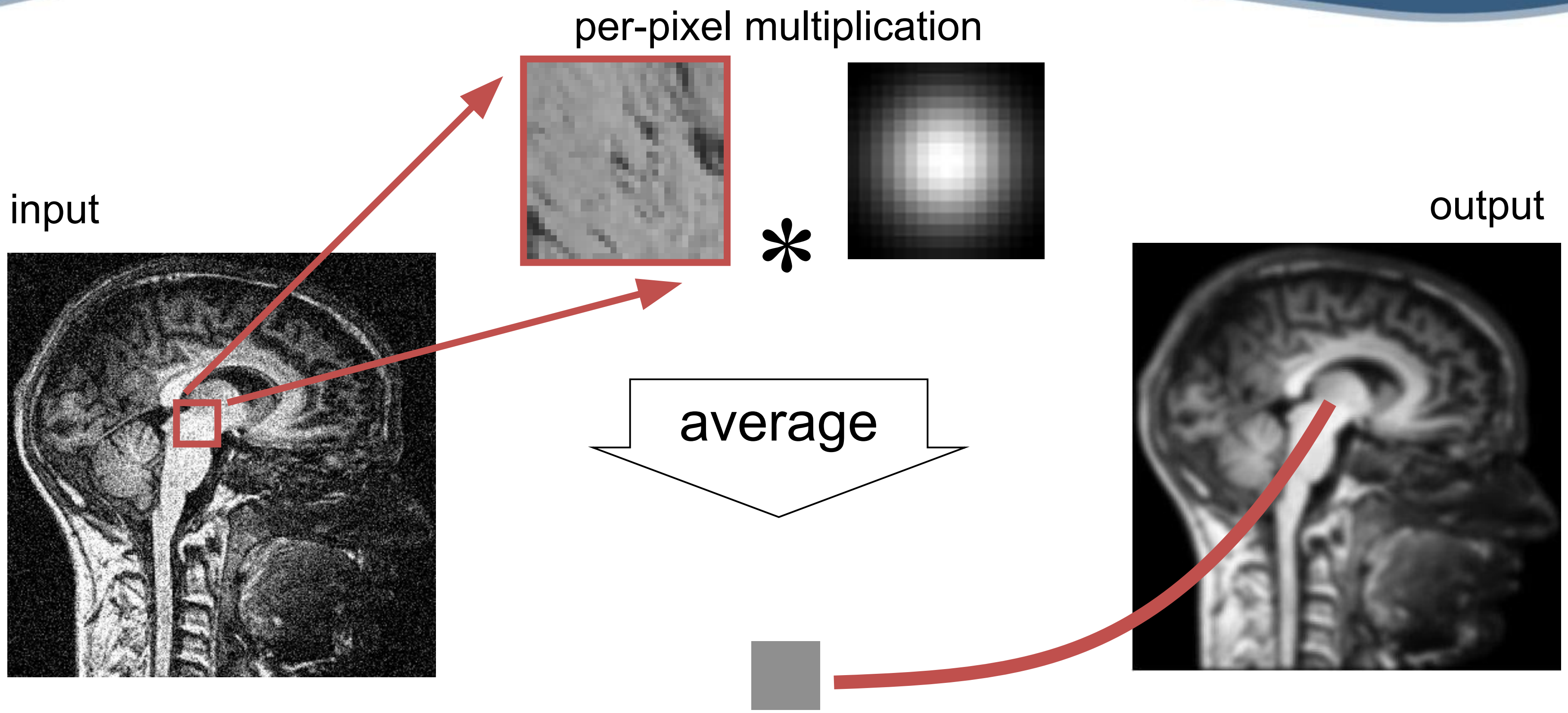
$$GB[I]_{\mathbf{p}} = \sum_{\mathbf{q} \in S} G_{\sigma}(\|\mathbf{p} - \mathbf{q}\|) I_{\mathbf{q}}$$

normalized
Gaussian function



GAUSSIAN FILTER

Gaussian blur | Bilateral filter | NLm filtering



FIXING THE GAUSSIAN BLUR": THE BILATERAL FILTER

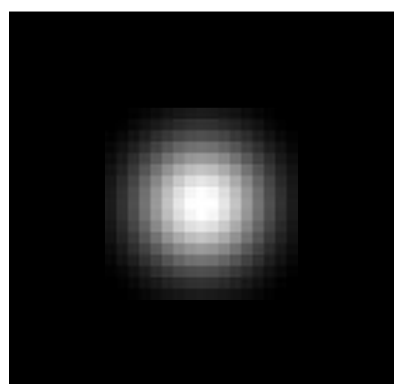
Box average → Gaussian blur → **Bilateral filter** → NLm filtering

Same idea: **weighted average of pixels**.

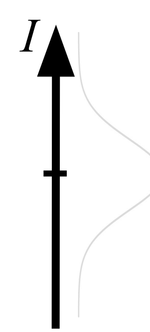
$$BF[I]_{\mathbf{p}} = \overbrace{\frac{1}{W_{\mathbf{p}}}}^{\text{new}} \sum_{\mathbf{q}\in S} \overbrace{G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)}^{\text{not new}} \, \overbrace{G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)}^{\text{new}} \, I_{\mathbf{q}}$$

normalization factor

space weight

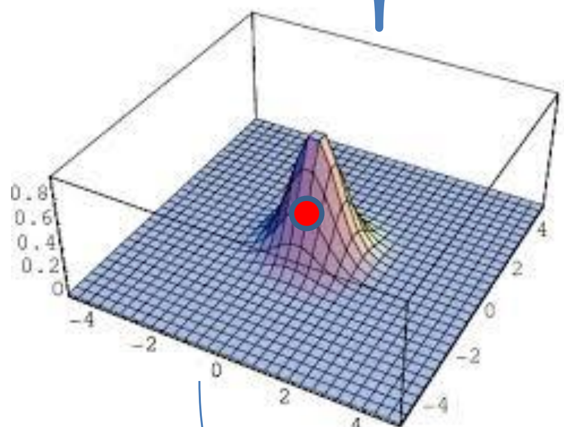


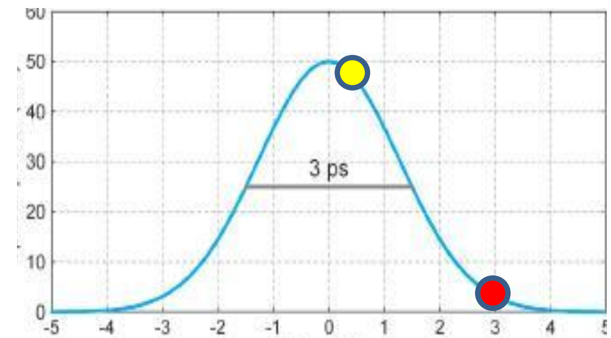
range weight

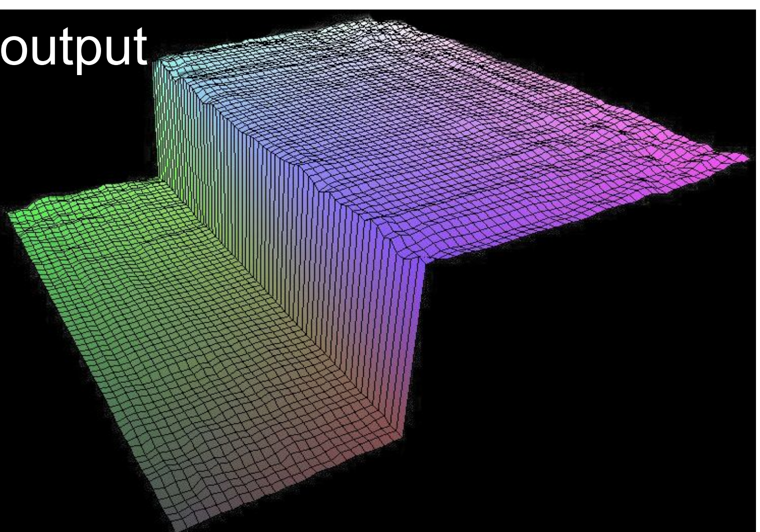


Bilateral Filter on a Height Field

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}(\| \mathbf{p} - \mathbf{q} \|) \, G_{\sigma_r}(| I_{\mathbf{p}} - I_{\mathbf{q}} |) \, I_{\mathbf{q}}$$

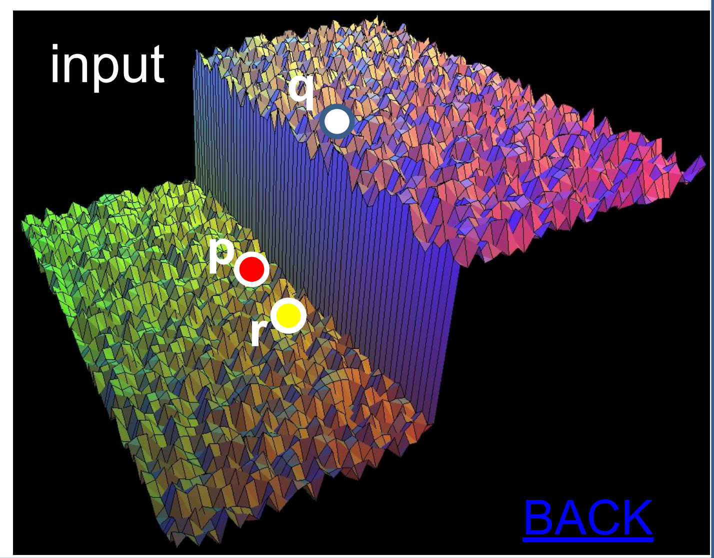






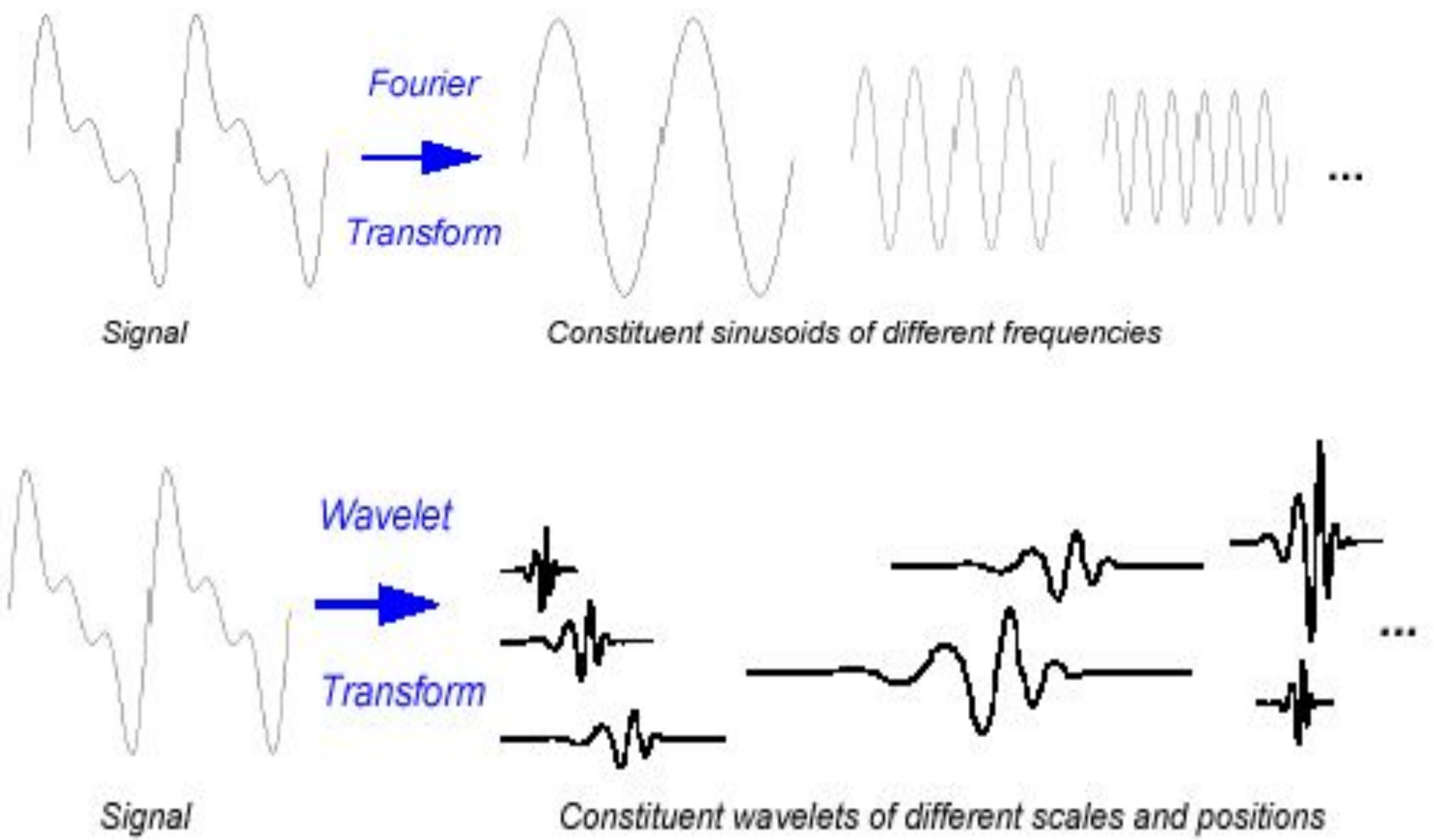
Weigh I(q)
By 2 * 0.4 = **0.8**

Weigh I(r)
By 48 * 0.4 = **19.2**

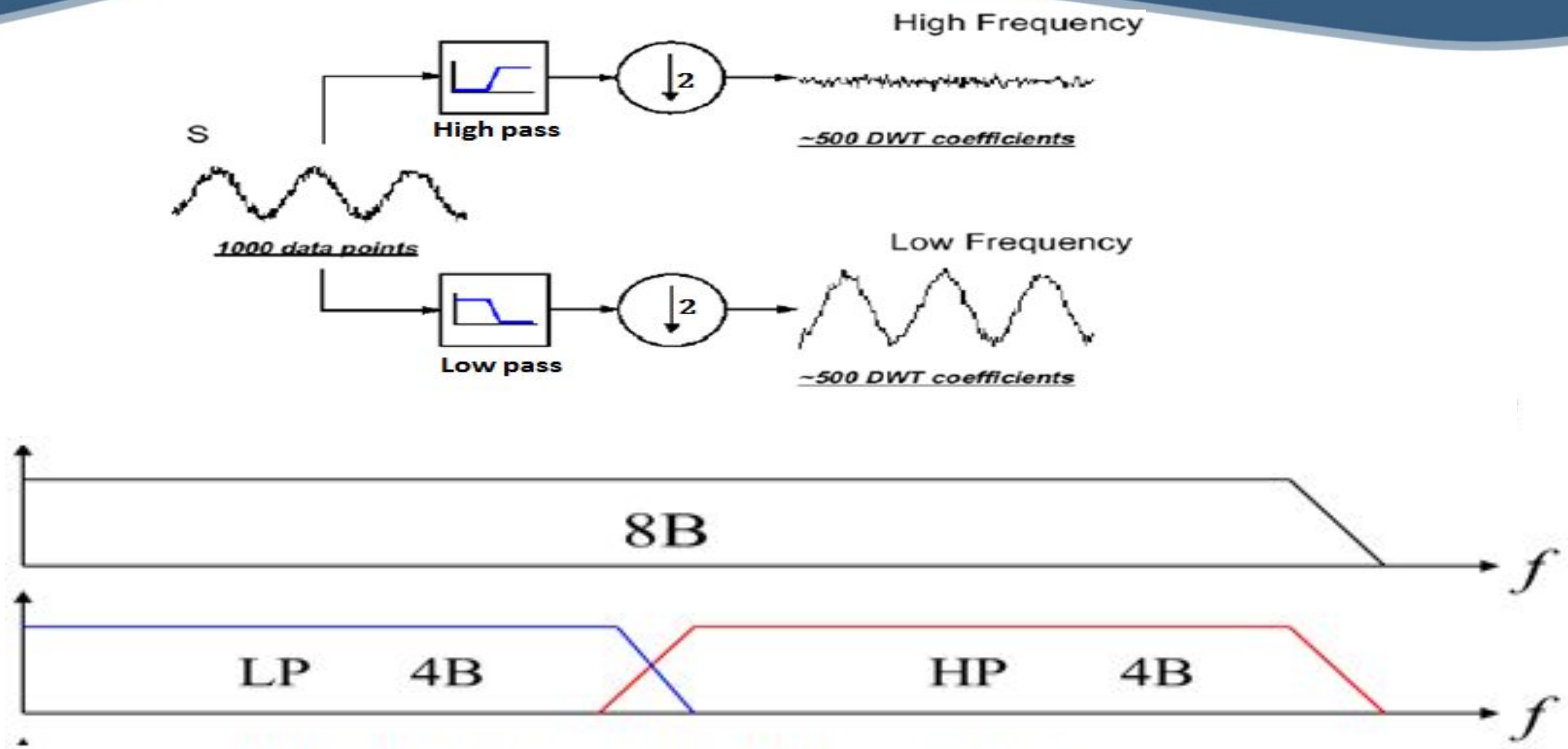


BACK

WAVELET TRANSFORM?



Discrete Wavelet Transform?

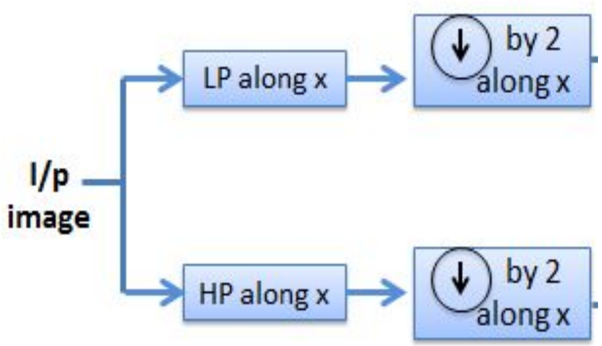


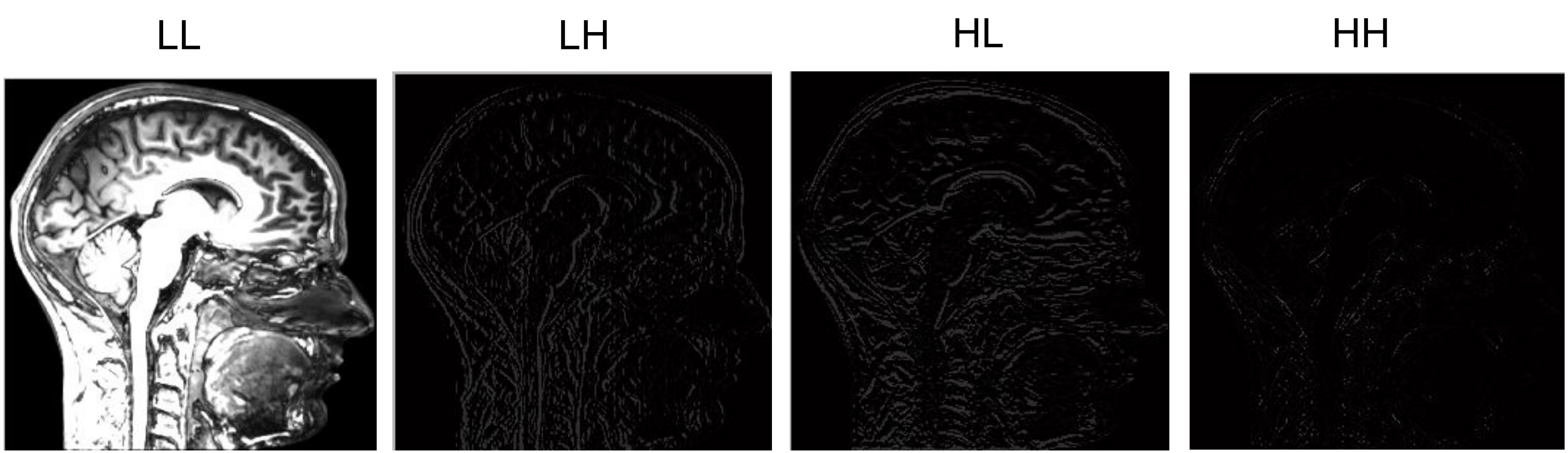
Filter domain approach of 1D wavelet transform

- **A family of wavelets is then associated with the bandpass, and a family of scaling functions with the lowpass filters.**

CONSTRUCTION OF 2D WAVELET?

- Wavelet is a seperable transform.





"IDEAL SPATIAL ADAPTATION VIA WAVELET SHRINKAGE"

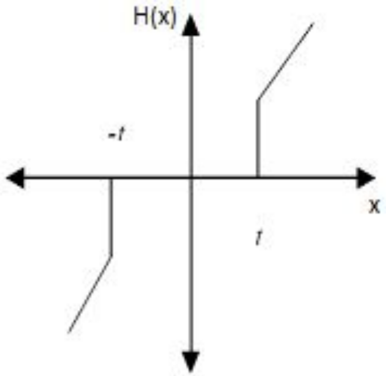
D.L. Donoho, I.M. Johnstone

Biometrika, vol. 81, no. 3, pp. 425-55, 1994.

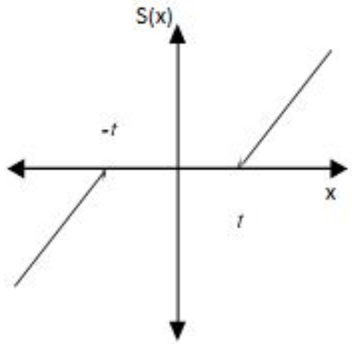
❖ **VisuShrink is wavelet thresholding by applying *universal threshold***

$$T_u = \sigma_n \sqrt{2\log(L)}$$

where, σ^2 is the noise variance of AWGN and *L* is the total number of pixels in an image.



Hard thresholding



Soft thresholding

❖ **The best empirical thresholds for both hard and soft thresholding <u>are much different from this value</u>, independent of the wavelet used.**

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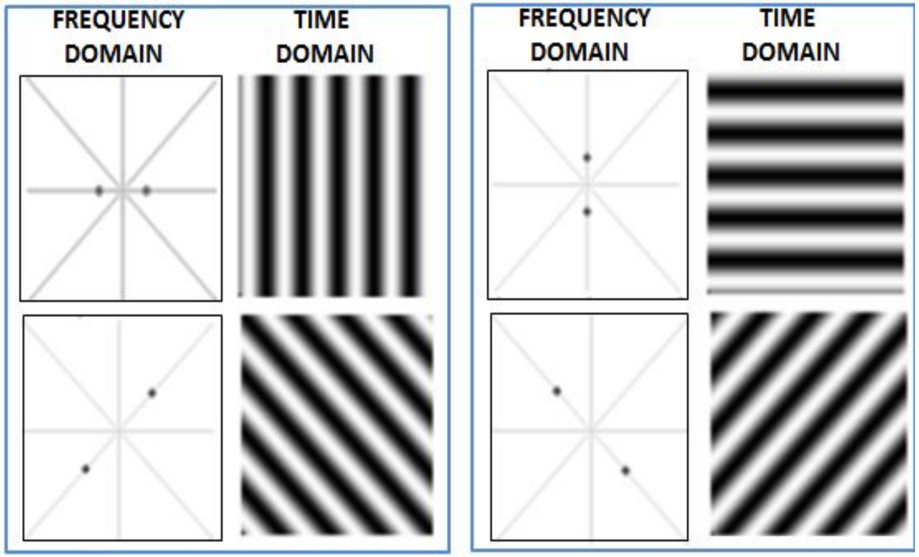
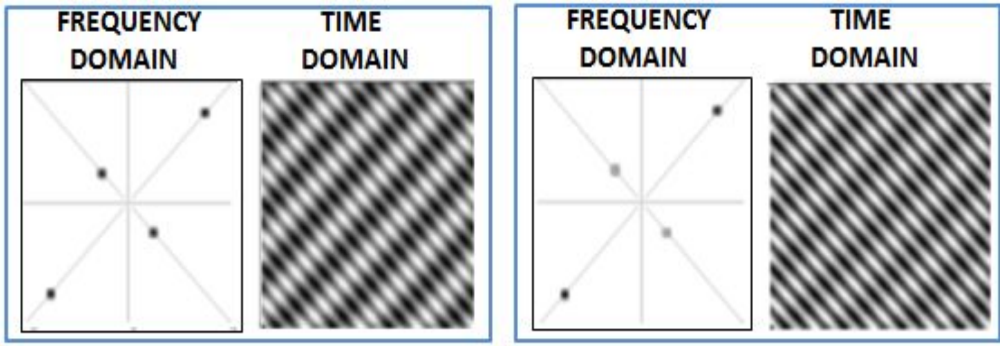
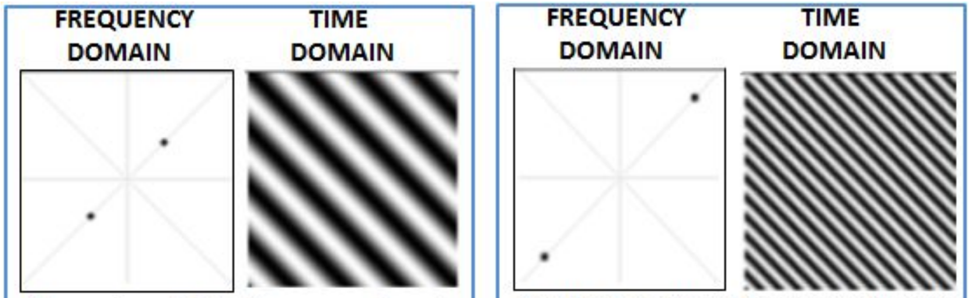
CONSTRUCTION OF CONTOURLET TRANSFORM.



Different points in frequency spectrum correspond to different directions

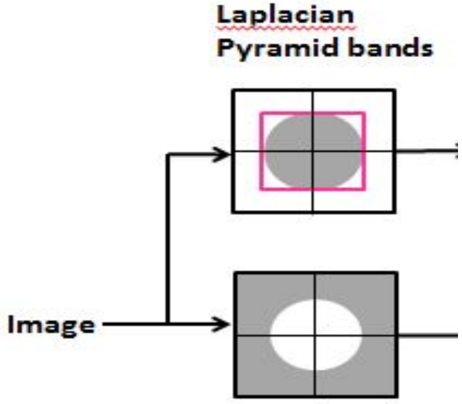


Amplitude of different points in frequency spectrum correspond to intensity of corresponding directional details.



Nearer to origin in Frequency domain, lower the frequency.

Further to origin in Frequency domain, higher the frequency.



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Proposed Entity vs Simple Bilateral and NLM Filtering

Test image	Bilateral filtering	NLm filtering	Proposed preprocessing prior to bilateral filtering	Proposed preprocessing prior to NLm filtering
$\sigma = 30$				
CT	23.8733	23.9525	**30.0319**	**30.3344**
MRI	22.5029	23.5457	**25.8689**	**26.2227**
$\sigma = 40$				
CT	20.0548	19.8352	**26.1260**	**25.1537**
MRI	19.7281	20.1621	**23.5916**	**23.5454**
$\sigma = 50$				
CT	17.3835	17.1381	**22.9191**	**22.0310**
MRI	17.4913	17.6718	**21.6140**	**21.4496**

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