

# An Adaptive Selection of Gradient Magnitude Threshold in Anisotropic Diffusion of MRI

Anu S Nair, Sumesh Chandran<sup>2</sup>

Assistant Professor, Dept of Electronics & Communication Engg, College of Engg, Munnar, Idukki, Kerala<sup>1,2</sup>

**Abstract:** Anisotropic diffusion filter, being an edge preserving non-linear image restoration method, has been of wide acceptance and of intrinsic interest among the researchers in image processing domain. But judicious choice of its operational parameters is mandatory to ensure the optimum performance. Its operational parameters include number of iterations, threshold of gradient modulus etc. These operational parameters are usually selected through trial and error, through qualitative inspection of restored image. The noise retains even after the restoration and the image is likely to get blurred if the number of iterations is not wisely chosen. The selection of threshold of gradient modulus is not image driven and usually blindly chosen. Moreover, in anisotropic diffusion the diffusion coefficient is computed from the local gradient. Even the noise pixels may exhibit high local gradients in heavily corrupted images. The fine details in the image may be lost during the iterative smoothing unless the operational parameters are carefully selected. The main objective is to propose an adaptive image driven estimation of threshold of gradient magnitude, rather than setting it manually. The performance of the modified anisotropic diffusion will be compared with conventional P-M model in terms of the ability to preserve edges during restoration.

**KeyWords:** Image Quality measures include Edge Content Ratio(ECR), Pratt's Figure of Merit(PFOM) and Percentage Reduction in the Standard deviation of Noise(PRNSD).

## 1. INTRODUCTION

Restoration of medical images has been of great quest among the researchers for the last few decades. Simple spatial averaging does reduce the noise but simultaneously degrades edges also. The filtering does not respect region boundaries and the resulting images appear blurry. This undesirable effect can be reduced by the use of nonlinear filters, the most common being median filtering. Edges are retained to a certain extent in median filtering, but the filtering suppresses fine details. Another approach is adaptive filtering, which entails a trade-off between smoothing efficiency, preservation of discontinuities, and the generation of artefacts. When developing a filtering method for medical image data, image degradation by blurring or by artefacts resulting from a filtering scheme is not acceptable. The restoration scheme should ideally minimize information loss by preserving object boundaries and detailed structures, efficiently remove noise in regions of homogeneous physical properties and enhance morphological definition by sharpening discontinuities. Usually in medical images the boundary of the anomaly may be vague. Special attention has to be paid to preserve these weak edges, while performing noise restoration. Traditional Gaussian smoothing is not efficient for preserving edges since the Gaussian kernel is symmetric and orientation-insensitive, resulting in blurring artefact for edges. Hence, towards the restoration of MR/CT images, edge preserving non-linear techniques are preferable than conventional smoothing. The traditional edge-preserving smoothing approaches include Guided image filter, Kuwahara filter, anisotropic diffusion, bilateral, trilateral, Non-Local Means (NLM) and wiener

filters. Among these techniques, anisotropic diffusion, filter is of wide acceptance.

When the image contains no or a low-level noise, the high image gradient magnitudes certainly reflect the edges. However, when the image is corrupted by a high level of noise, the gradient itself turns sensitive to noise. In addition to edges, noise may also exhibit high gradients. A high gradient magnitude is generally a good indication of edges, whereas a low gradient magnitude may not always point to non-edge regions or noise. Therefore, the gradient magnitude should not be used as the sole local feature in the diffusion process. The important local features defined in a small neighbourhood of each pixel in the image may have low gradient such as blurred edges or fine details of an object, which should also be preserved during the diffusion process so that they will not mislead the post processing analysis and interpretation from the restored image. The classical P-M model considers only the gradient information of pixels for image restoration. It can thus preserve edges with large gradient strength, but inevitably smooth both noise and fine details with low gradient strength in an ill-structured image. In the P-M model, the inter-region edges will be gradually smoothed as the diffusion iteration increase, even though the edges in the original image show very high gradient contrast.

Therefore the traditional P-M model is very sensitive to the number of diffusion iterations. A careful selection of the number of iterations is required to ensure the success of the diffusion result. This is also a major drawback of the P-M model.

This article is a comprehensive review on automatic selection of operational parameters of anisotropic diffusion filter. In the forthcoming discussions, the mathematical formulation of anisotropic diffusion filter is illustrated followed by a summary of adaptive anisotropic diffusion filters.

An impressive and efficient improvement in the classical scale-space analysis was proposed by Perona and Malik in [2] where they describe the diffusion process known as Perona–Malik (PM) equation. The development of an adaptive anisotropic diffusion approach can reduce the speckle noise and at the same time preserve the edges. This article is a present regularized model of the PM diffusion equation for image segmentation. This paper present two method for automatic setting of the gradient threshold  $k$ , which is changed for each iteration of the partial differential equation (PDE) integration steps.

The method in Niftiest al. [3] provides an unsupervised machine learning process to modify the anisotropic diffusion by generating an adaptive threshold in diffusion coefficient function using statistical measures. Image histogram is employed to calculate the global grey level variance over the entire image and local grey level variance over the defined neighbourhood of each pixel of given image. The adaptive threshold in diffusion coefficient function varies in accordance with the difference between the two variances which gives a measure of intensity contrast in that neighbourhood.

Based on the intuition that the fine details in the image generally have large grey-level variance that the noisy background, the proposed diffusion model in S.M Chao and D.M Tsai[4] incorporated both local gradient and grey-level variance to preserve edges and fine details.

Current image filtering algorithms often diffuses edges of image, a directional-scale based anisotropic diffusive image filtering method was proposed by Dong ping, Zhang and Feiyuchen [5] can solve above problem. The algorithm mainly uses local directional-scale to arrest smoothing across low-gradient boundaries and around fine structures, which means it can adaptively modifies the degree of filtering at any image location depending on local object directional-scale. Pixel directional-scale allows us to accurately use a restricted homogeneity parameter for diffusive filtering in regions with fine details and in the vicinity of boundaries while a generous parameter in the interiors of homogeneous regions.

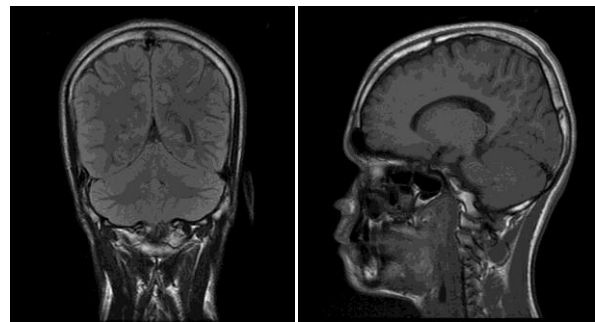
In Gilboet.al [6] the nonlinear diffusion coefficient was locally adjusted according to image features such as edges, texture, and moments. As such, it can switch the diffusion process from a forward to a backward (inverse) mode according to a given set of criteria. This results in a forward-and-backward (FAB) adaptive diffusion process that enhances features while locally denoising smoother segments of the signal or image. The FAB method was further generalized for color processing via the Beltrami flow, by adaptively modifying the structure tensor that controls the nonlinear diffusion process. The proposed structure tensor is neither positive definite nor negative, and switches between these states according to image

features. This results in a forward-and-backward diffusion flow where different regions of the image are either forward or backward diffused according to the local geometry within a neighbourhood.

Histogram Gradient-Based Anisotropic Diffusion (GHAD) was introduced in H.Y Kim [8].In GHAD, the user specifies the desired number of edge elements (edge pixels) in the filtered image. The frontier between two neighboring pixels was considered as an edge, if the modulus of their intensity difference is above a threshold. From the specified number of edge pixels, an appropriate parameter  $K$  is automatically computed in every diffusion iteration, so that the final filtered image has almost exactly specified number of edge pixels. Using this approach, the diffusion converges to a nontrivial piecewise constant image, whenever a feasible number of edges is specified

## II.PROPOSED WORK

The conventional method of analyzing geometrical, textural and intensity description of Magnetic Resonance images using Pratt's figure of merit involves huge computational complexity; which cannot be directly adopted to the present study of analysis. In this study therefore adopted Edge Content Ratio; another statistical indices for detailed analysis of given Magnetic Resonance images. In the first phase of study, Edge Content Ratio (ECR) and fractional reduction in noise standard deviation variables are compared with threshold of gradient modulus with the pre-estimated values of percentage reduction in standard deviation and Edge Content Ratio. This comparison obtained the optimum values of  $K$  and  $N$ .



segital T1 fig.1:The input MRI images for the analysis.

This analysis shows that different Magnetic Resonance image inputs gives different structured pattern of percentage reduction in standard deviation. Therefore a general conceptualization of arriving at the optimum values of  $K$  and  $N$  is not possible. For the reason Edge Content Ratio method was adopted. In the adoption of Edge Content Ratio method there obtain a results with uniform structural pattern thus the optimum values of  $K$  can be obtained. Irrespective of number of iteration the optimum value of  $K$  remains constant. On the beginning of the Edge Content Ratio curve, abrupt transitions occur, which indicate the maximum removal of noise. The Edge Content Ratio curve starts removing the noise from its beginning to the optimum value.

On reaching the maximum value of noise suppression, the further processing is truncated, otherwise the useful information of image will also be gone. This point is the optimum K value.

The binary edge map representation Magnetic Resonance image shows noise is removed in the first three iterations, there after the further iteration will remove the useful information content of the given image. More iteration leads to the over smoothed versions of image and lesser iteration result in presence of noise as exactly that of the original image. The objective function of the given analysis is the determination of maximum suppression of noise with minimum edge degradation function. Through the comparison and applications of arbitrary value of threshold, the proper value of K is obtained. In normal case the value of threshold is 0.01.

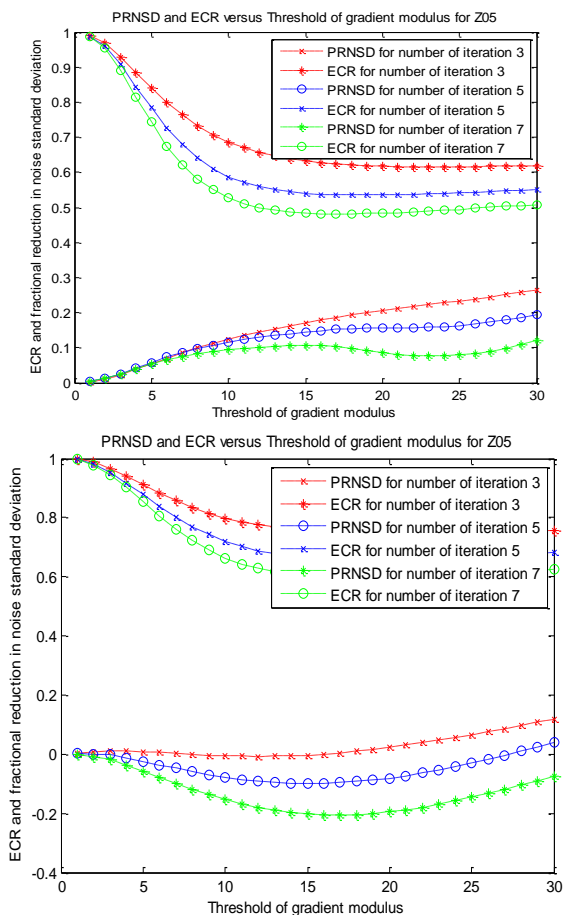


Fig.2: The Relationship between Statistical indices and K value

In the case study, 21 different Magnetic Resonance images were analyzed a uniform pattern of Edge Content Ratio curves are obtained. Through each curve 21 different optimum values of K is calculated. At the same time their equivalent standard deviation of noise are also calculated. Standard deviation of original image can be computed numerically and it cannot be computed from the graph. Now we have a 21 optimum values of K and their corresponding standard deviation of noise. There after

investigates the correlation between K a value and standard deviation of noise, using  $n^{\text{th}}$  order polynomial method. Now the objective function is the determination of the degree of polynomial. It requires a detailed mathematical regression correlation analysis.

### III CREATION OF A MATHEMATICAL MODEL

Steps for the determination of the mathematical model:

1. The correlated estimated value should be in between +1 and -1. -1 shows inverse proportional characteristic, +1 gives the direct proportional characteristics and 0 means zero correlation values between K and standard deviation of noise.
2. Establishment of the regression relation can be done using least square regression method. The main objective function is the minimum deviation from the predicted curve. It can be established through a polynomial model.
3. Draw the residual plot.
4. Find out the goodness of it. The goodness can be calculated either by using coefficient of determination of  $R^2$  value or by using adjusted  $R^2$  value. The reason behind it is simple  $R^2$  cannot be used for the higher degrees of polynomials
5. Take the regression

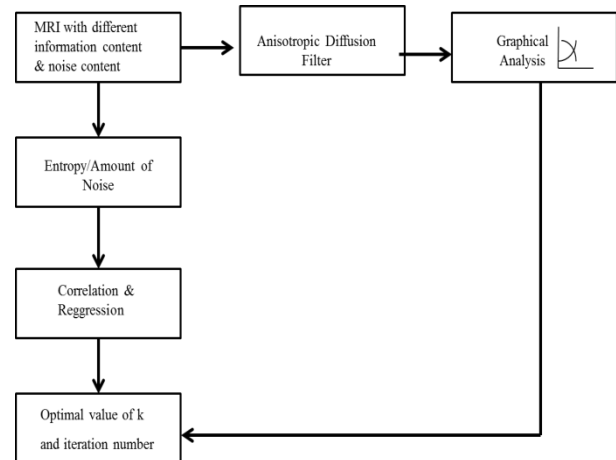


Fig.3: Block diagram of the proposed method

MRI of an image itself consist of moderate amount of noise, some of them can be predicted while others are not. The very often seen predicted noise is the blinking of eyes which may cause an abrupt change in characteristics details in the MRI. The given MRI is processed through an anisotropic diffusion filter through which maximum noise is suppressed with minimum edge degradation function.

The output of filter is graphically be analysed using one of the statistical indices called Edge Content Ratio versus the gradient of threshold value(k).At the very same time conduct a mathematical correlation regression analysis to estimate the value of the optimum threshold. Combine the mathematical formulated result and graphical result and finalise the optimum value.

IV.RESULTS AND DISCUSSIONS

Plot a graph between standard deviation of noise and optimum K value, establishing a correlation using a polynomial model. During the goodness checking of residual; if the residual have a fixed pattern, the established function account for the variability for the random variable. From the fig2, it can be seen that the residual plot have a specific pattern and do follow the actual graph. If it doesn't follow the actual graph; increase the order of polynomial. If the order increases the actual graph follows the predicted curve.

R2 means the coefficient of determination. Usually R<sup>2</sup> is expressed in percentage. 90% of R<sup>2</sup> means the function can account for 90% of variance of the predicted curve. "Polyfit" is a mathematical command to do least square regression. If the matrix is a row matrix convert it in to column format and apply "polyfit" over the matrix. The experimental result of 0.7946 indicates almost 80% correlation of predicted curve.

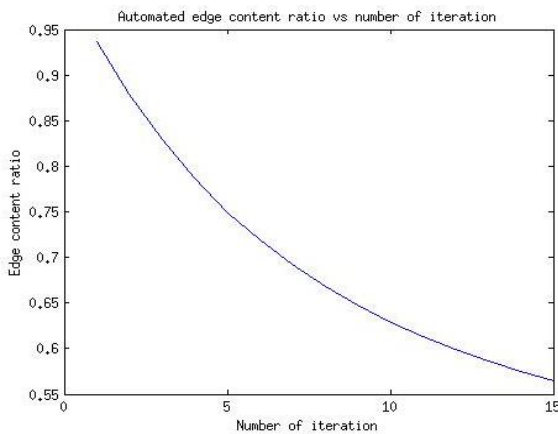
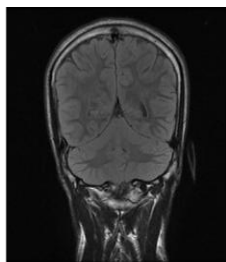
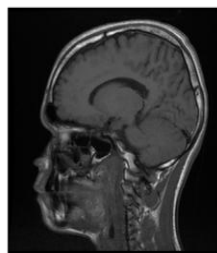


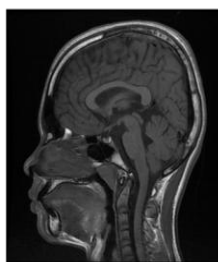
Fig.5: Relational characteristics between ECR and number of iteration



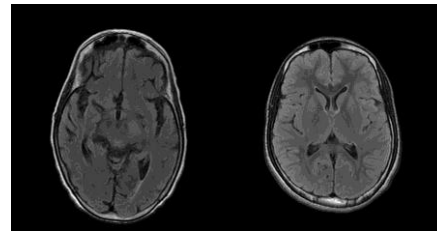
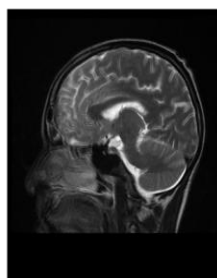
ChoronalT2 Flair\Z13



Sagital T1\Z04



SegitalT1\Z10Chorinal T2 Flair\Z10



2axial T2 flair\Z222axial T2 flair\Z18  
Fig.4: Input MRI for the Poly fit analysis

POLYNOMIAL MODEL FOR OPTIMUM VALUE OF THRESHOLD OF GRADIENT MODULUS ON NOISE STATISTICS

The experimental result shows that up to sixth order of smoothening the noise retains that is why the reason sixth order polynomial is used for the entire analysis.

The sixth order polynomial is given by  $y=a_6 x^6+a_5 x^5+a_4 x^4+a_3 x^3+a_2 x^2+a_1 x+a_0$ , where, y is the optimum value of threshold of gradient modulus and x is the standard deviation of original image. From polyfit(), we get

$$\begin{aligned}
 a_6 &= -4.1435 \\
 a_5 &= 55.0663 \\
 a_4 &= -293.9569 \\
 a_3 &= 805.0679 \\
 a_2 &= -1.1921e+03 \\
 a_1 &= 907.4342 \\
 a_0 &= -272.8776
 \end{aligned}$$

Therefore,

$$y = -4.1435x^6 + 55.0663x^5 - 293.9569x^4 + 805.0679x^3 - 1192.1x^2 + 907.4342x + 272.8776$$

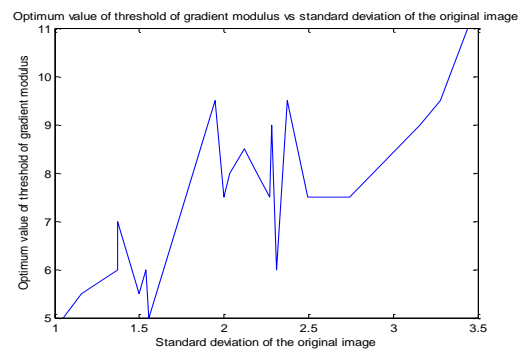


Fig.6: The linear correlation relation between the k value and the standard deviation of the deviation of the noise

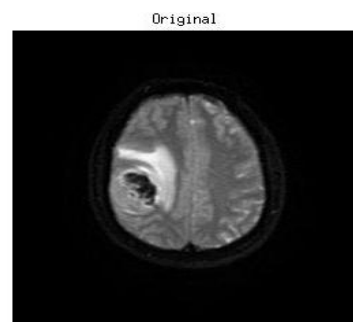
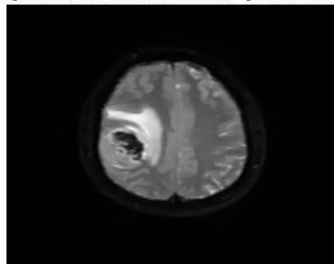


Fig.7: Input MRI for the performance analysis

Table.1: Detailed comparison of smoothened image with different statistical indices

|    | PFOM    | EPI     | SSIM    | PSNR     |
|----|---------|---------|---------|----------|
| 1  | 0.75871 | 0.89992 | 0.99957 | 51.32002 |
| 2  | 0.6521  | 0.80686 | 0.99897 | 47.52070 |
| 3  | 0.5957  | 0.72387 | 0.99832 | 45.39033 |
| 4  | 0.5603  | 0.65516 | 0.99766 | 43.95296 |
| 5  | 0.5345  | 0.59824 | 0.99700 | 42.88460 |
| 6  | 0.5141  | 0.55134 | 0.99636 | 42.04607 |
| 7  | 0.4975  | 0.51286 | 0.99573 | 41.36425 |
| 8  | 0.4841  | 0.48136 | 0.99513 | 40.79598 |
| 9  | 0.4739  | 0.45550 | 0.99455 | 40.31278 |
| 10 | 0.4654  | 0.43402 | 0.99399 | 39.89457 |

Diffused image with constant threshold of gradient modulus =6.094



Diffused image with iterated threshold of gradient modulus =6.314

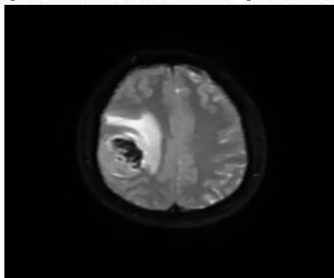


Fig.8: comparison of k value using convectional PM model and the proposed model

### V. CONCLUSION

This project proposes an adaptive image driven estimation of threshold of gradient magnitude, rather than setting it manually. The performance of the modified anisotropic diffusion will be compared with conventional P-M model in terms of the ability to preserve edges during restoration. The statistical edge preservation metric to be used in this context is Pratt's Figure of Merit (PFOM), Percentage Reduction in the Standard deviation of noise (PRNSD), Structural Similarity Index Matrix (SSIM), Edge Content Ratio (ECR), Edge Preservation Index (EPI) and Peak Signal to Noise Ratio (PSNR).

### ACKNOWLEDGMENT

This is the most satisfying, yet the most difficult part of the report to present gratifying words because most often one fail to convey the real influence, others have had on their life or work. First and the foremost, I give thanks to Almighty God who gave me the inner strength, resource and ability to complete my interim project successfully,

without which all my efforts would have been in vain. I would like to express my sincere thanks to our Principal, **Dr. M K JANA**, for his valuable support and advice. I would also like to thank Prof. **Dr. RAVI NAMBIAR**, Dean & Head of Department, Electronics & Communication for his valuable help and support. I am highly obliged to his for all the valuable suggestions and guidance he provided. I express my heartfelt gratitude to our project coordinator **Mrs. DEEPA V.T** for her help, valuable suggestions and directions. I would also like to thank my project guide **Mr. VINOD KUMAR.V** for his guidance and help throughout my project. I am indebted to all teaching and non-teaching staff of the Department of Electronics & Communication Engineering for their co-operation and support. Last but not the least I wish to express my sincere thanks to all my friends for their goodwill and constructive ideas. Above all, I am thankful to my parents for everything..

### REFERENCES

- [1] Y. Toufique, R. Cherkaoui El Moursli, Lh. Masmoudi, A. El Kharrim, M. Kaci, S. Allal. "Ultrasound Image enhancement using An Adaptive Anisotropic diffusion Filter". 2014 Middle East conference on Biomedical Engineering (MECBME) February 17-20, 2014, Hilton Hotel, Doha, Qatar.
- [2] P. Perona and Malik."Scale-space and edge detection using anisotropic diffusion".IEEE transactions on Pattern Analysis and Machine. Intelligence, 12(7), pp. 629-639, 1990.
- [3] Uddin Khan Nafis, K.V. Arya, Manisha Pattanaik, "Histogram statistics based variance controlled adaptive threshold in anisotropic diffusion for low contrast image enhancement:", Signal Processing, Volume 93, Issue 6, June 2013, Pages 1684-1693, ISSN 0165-1684, <http://dx.doi.org/10.1016/j.sigpro.2012.09.009>, (<http://www.sciencedirect.com/science/article/pii/S0165168412003295>).
- [4] Shin-Min Chao; Du-Ming Tsai; Wei-Yao Chiu; Wei-Chen Li, "Anisotropic diffusion-based detail-preserving smoothing for image restoration," Image Processing (ICIP), 2010 17th IEEE International Conference on , vol., no., pp.4145,4148, 26-29 Sept. 2010 doi: 10.1109/ICIP.2010.5653571.
- [5] Dongping Zhang, Chao Tong and Feiyu Chen "A directional-scale based anisotropic diffusive image filtering" International journal of Advancement in Computing Technology (IJACT) Volume 4, Number 9, May 2012.
- [6] G. Gilboa, N. Sochen, Y.Y. Zeevi, " Forward-and-backward diffusion processes for adaptive image enhancement and denoising", IEEE Transactions on Image Processing 11 (7) (2002) 689-703.
- [7] Hae Yong Kim " An anisotropic diffusion with meaningful scale parameter" IEEE journal 568-412 June 2010 .
- [8] C. Tsotsios, M. Petrou, "On the choice of the parameters for anisotropic diffusion in image processing", Journal Pattern Recognition archive Volume 46 Issue 5, May, 2013 Pages 1369-1381 Elsevier Science.
- [9] Sung In Cho, Suk-Ju Kang, Hi-Seok Kim, Young Kim "Dictionary-based anisotropic diffusion for noise reduction" Elsevier 46(2014)36-45.
- [10] T.Veerakumar, S.Esakkirajan and Ilavennila "Edge preserving adaptive anisotropic diffusion filter approach for the suppression of impulse noise in an image" International journal of Electronics and Communication (AEU) 68(2014) 442-452.
- [11] Luca Fabbri, Mario Greco, Messina, and Gianpaolo Pinelli "Improved Edge enhancing Diffusion filter for speckle images" IEEE Trans. vol.2 no 1 January 2014.
- [12] Xiaoshuang Ma, Huanfeng Shen, Liangpei Zhang, Hongyan Zhang "An adaptive AD method for the speckle noise filtering of PolSAR images".
- [13] Kaiming He, Jian Sun, Xiaoou Tang, " Guided Image Filtering. IEEE Transactions on Pattern Analysis and Machine Intelligence", Volume 35, Issue 6, pp. 1397-1409, June 2013.