IMAGE QUALITY METRICS FOR BRAIN IMAGE SEGMENTATION

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Abstract : Image processing converts an image into digital form and used to perform some operations on it for getting an enhanced image or for extracting some useful information from it. The various intention of image processing is image sharpening and restoration, image retrieval, image recognition, visualization and measurement of pattern. Image processing is used in medical image analysis, remote sensing, biomedical imaging techniques, moving object tracking, intelligent transportation system etc. Image quality metrics are used to measure the quality of the processed images. Different image quality metrics are used to analyze the images. In this paper, various quality metrics for measuring brain image segmentation quality and compared through MSE,PSNR,SSIM and PSNR-B. This analysis helps to estimate the performance and to enhance the quality of segmented images.

***IndexTerms* – Segmentation, Denoised image, Quality metrics, PSNR, SSIM.**

I. INTRODUCTION

MRI images are of both panchromatic and multispectral images. The panchromatic images have higher spatial resolutions while the multispectral have relatively lower spatial resolutions but are rich in spectral information. The quality factors of an image are: Contrast, brightness, spatial resolution, noise. Objective Fidelity Criteria are based on mathematical formulations. MSE,PSNR are examples of objective fidelity criteria. Subjective Fidelity Criterias are based upon the perception of an individual rather on any mathematical formulations. HVS is such a model. The quality is rated as very poor, poor, good, very good, excellent. UQI, SSIM, FSIM (FSIMc), GSM are examples of subjective fidelity criteria.

II. IMAGE QUALITY ASSESSMENT METRICS

Image quality can be analyzed using objective or subjective methods. In the objective method, image quality assessments are performed by different algorithms that analyze the distortions and degradations in an image. Subjective image quality assessments are a method based on the way in which humans experience or perceive image quality.

2.1 Peak Signal to Noise Ratio (PSNR)

The PSNR metric is used to measure the quality of noisy and blurred image. It performs well on medical image. The value of PSNR is computed by using Mean Square Error (MSE) between pixel intensities. The high value of PSNR corresponds to better quality of image and its value depends on MSE. PSNR can be calculated by

$$\mathrm{PSNR} = 10 \times \log_{10} \frac{255^2}{\mathrm{MSE}}$$

2.2 Mean Square Error (MSE)

MSE measures the difference between predicted and expected outcome. It is used to analyze the image enhancement quality algorithm which is used for removing the noise from an image. This metric is suitable for real time images like satellite and medical images. If the MSE value increases hen the degradation increases. If it reaches zero then pixel by pixel matching of images will be perfect. MSE is given by

$$\mathrm{MSE} = \frac{1}{\mathrm{mn}} \sum_{\mathrm{i}=0}^{\mathrm{m}-1} \sum_{\mathrm{j}=0}^{\mathrm{n}-1} \left(\mathrm{I}_{\mathrm{ij}} - \mathrm{D}_{\mathrm{ij}}\right)^2$$

Where I represents original image and D represents denoised image.

2.3 Structural Content (SC)

This metric deal with spatial information of pixels in image. It is used to measure the closeness of two digital images. It can also be done by correlation function. High value of SC represents the poor quality of the image. This metric can be used in radar and steganography applications. This metric brings out the similarity between two images. It takes out the closely association of two images and implies on the fact no human eye can differentiate the two images. Higher the value of structural content specifies poor the quality of the image. When two same images are compared to each other its structural content metric value comes to 1(maximum) and the hidden data length comes to zero, hence the images are identical to each other.
The value of SC is given by

$$SC = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (y(i,j))^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j))^2}$$

2.4 Normalized Cross Correlation (NCC OR NK)

The NCC measures the similarity between two set of images. In image-processing applications, the brightness of the image can vary due to lighting and exposure conditions, the images can be first normalized. It is used in finding the incidences of a pattern or an object in an image. The application of this metric widely used in image registration areas. It can also be used to assess the quality of deconvolution algorithms. The standard values of NCC range from –1 to 1. –1 indicates perfect correlation and 1 indicates perfect anti-correlation

$$\text{NCC or NK} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} x(i,j)\, X y(i,j)}{\sum_{i=1}^{M}\sum_{j=1}^{N} (x(i,j))^2}$$

Where, M is the number of pixels in the horizontal direction, N is number of pixels in the vertical direction, x(i, j) is the filtered image at i and j co-ordinates and y(i, j) is the noisy image at i and j co-ordinates.

2.5 Structural Similarity Index Metric (SSIM)

The Structural similarity (SSIM) metric measures quality of an image by capturing the similarity of images. Three aspects of similarity: Luminance, contrast and structure is determined and their product is measured. Luminance comparison function *l*(X,Y) for reference image X and test image Y is defined as below

$$l(X,Y) = \frac{2\mu_X\mu_Y + C1}{\mu_X^2 + \mu_Y^2 + C1}$$

Where µx and µy are the mean values of X and Y respectively and C1 is the stabilization constant. Similarly the contrast comparison function *c*(X, Y) is defined as

$$c(X,Y) = \frac{2\sigma_x\sigma_y + C2}{\sigma_x^2 + \sigma_y^2 + C2}$$

Where the standard deviation of X and Y are represented as σx and σy and C2 is the stabilization constant. The structure comparison function *s*(X, Y) is defined as

$$s(X,Y) = \frac{\sigma_{xy} + C3}{\sigma_x\sigma_y + C3}$$

The SSIM index is obtained as below

$$SSIM(X,Y) = [l(X,Y)]^{\alpha}.\,[(c(X,Y)]^{\beta}.\,[(s(X,Y)]^{\gamma}$$

2.6 PSNR Including Blocking Effect Factor

PSNR-B: PSNR-B is a new quality metric includes ordinary PSNR by blocking effect factor. PSNR-B correlates with subjective quality when compared to PSNR. Consider an image that contains integer number of blocks such that the horizontal and vertical dimensions of the image are divisible by block dimension and the blocking artifacts occur along the horizontal and vertical dimensions.

In this method, we define the mean boundary pixel squared difference and the mean nonboundary pixel squared difference for image y. Blocking artifacts will become more visible as the quantization step size increases; mean boundary pixel squared difference will increase relative to mean non boundary pixel square difference. A decoded image may contain multiple block sizes like 16×16 macro block sizes and 4×4 transform blocks, both contributing to blocking effects. The mean square error including blocking effects for reference image X and test image Y is defined. Finally the proposed PSNR-B is given as

$$PSNR - B(x,y) = 10log_{10}\frac{255^2}{MSE-B(x,y)}$$

The MSE term measures the distortion between the reference image and the test image, while the BEF term in specifically measures the amount of blocking artifacts just using the test image. These no-reference quality indices claim to be efficient for measuring the amount of blockiness, but may not be efficient for measuring image quality relative to full-reference quality assessment. We argue that the combination of MSE and BEF is an effective measurement for quality assessment considering both the distortions from the original image and the blocking effects in the test image. The PSNR-B is attractive since it is specific for assessing image quality, specifically the severity of blocking artifacts.
A new approach of PSNR-B is introduced which gives better results compared to well known blockiness specific index. In this method, a set of diagonal neighboring pixel pairs which are not lying across block boundaries are considered. Simulation results shows that the modified PSNR-B gives better results compared to well known blockiness specific indices.
Simulation Results:
Simulations are performed using Matlab software which possesses excellent graphics and matrix handling capabilities. Matlab has a separate toolbox for image processing applications, which provided simpler solutions for many of the problems encountered in

this research. In this paper image quality assessment is done by objective measurement in which evaluations are automatic and mathematical defined algorithms. A new approach of PSNR-B and well known objective evaluation algorithms for measuring image quality such as MSE, PSNR, Structural Similarity Index Metric (SSIM) and PSNR-B have used.

Figure:1 Original image and Segmented Image

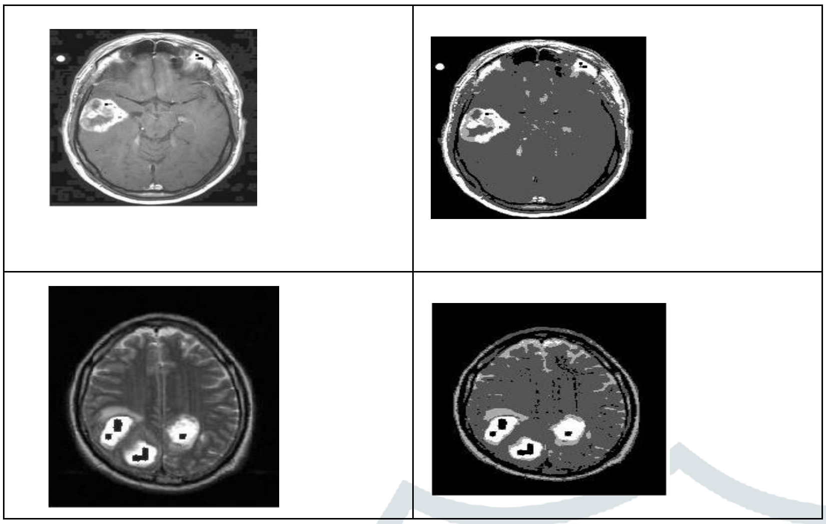

Table:1 Comparison of quality metrics

Image	SSIM	PSNR	PSNR-B (H&V Pixel pairs)	Modified PSNR-B (diagonal Pixel pairs)
Image 1	0.4017	20.56	29.55	13.99
Image 2	0.4833	14.34	30.77	36.03
Image 3	0.4234	17.45	24.44	34.26
Image 4	0.4126	16.25	25.33	32.12

Conclusion

Image quality assessment plays an important role in various image processing applications. Experimental results indicate that MSE and PSNR are very simple, easy to implement and have low computational complexities. But these methods do not show good results. MSE and PSNR are acceptable for image similarity measure only when the images differ by simply increasing distortion of a certain type. But they fail to capture image quality when they are used to measure across distortion types. SSIM is widely used method for measurement of image quality. It works accurately can measure better across distortion types as compared to MSE and PSNR, but fails in case of highly blurred image. Standard and natural images were tested by these quality metrics. Those sample images are shown in above figure. We have found that new approach of PSNR-B is the better quality metric shows better performance than the other well known quality metrics .This Analysis will brings out a new trend in the quality metrics of the image and proves to be efficient than the conventional metrics.

References

[1] Y. Yang, N. P. Galatsanos, and A. K. Katsaggelos, "Projection-based spatially adaptive reconstruction of blocktransform compressed images," *IEEE Trans. Image Process.*, vol. 4, no. 7, pp. 896–908, Jul. 1995.

[2] Y. Yang, N. P. Galatsanos, and A. K. Katsaggelos, "Regularized reconstruction to reduce blocking artifacts of block discrete cosine transform compressed images," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 3, no. 6, pp. 421– 432, Dec. 1993.

[3] H. Paek, R.-C. Kim, and S. U. Lee, "On the POCS-based post processing technique to reduce the blocking artifacts in transform coded images," *IEEE Trans.Circuits Syst. Video Technol.*, vol. 8, no. 3, pp. 358–367, 1998.

[4] S. H. Park and D. S. Kim, "Theory of projection onto narrow quantization constraint set and its applications," *IEEE Trans. Image Process.*, vol. 8, no. 10, pp. 1361–1373, Oct. 1999.

[5] A. Zakhor, "Iterative procedure for reduction of blocking effects in transform image coding," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 2, no. 1, pp. 91–95, Mar. 1992.

[6] S. Liu and A. C. Bovik, "Efficient DCT-domain blind measurement and reduction of blocking artifacts," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 12, no. 12, pp. 1139–1149, Dec. 2002.

[7] Bloch, I.: Fuzzy spatial relationships for image processing and interpretation: a review. Image Vis. Comput. 23(2), 89–110 (2005).

[8] Zhao, M.S., Fu, A.M.N., Yan, H.: A technique of three level thresholding based on probability partition and fuzzy 3-partition. IEEE Trans. Fuzzy Syst. 9(3), 469–479 (2001)

[9] Tao, W.B., Tian, J.W., Liu, J.: Image segmentation by three-level thresholding based on maximum fuzzy entropy and genetic algorithm. Pattern Recogn. Lett. 24, 3069–3078 (2003)

[10] Cao, L., Bao, P., Shi, Z.: The strongest schema learning GA and its application to multi-level thresholding. Image Vis. Comput. 26, 716–724 (2008).