Comparison of BRISQUE and SSIM as Image Quality Assessment (IQA) on MR optic nerve images.

Li Sze Chow[1], Raveendran Paramesran[1], and Martyn Paley[2]

[1]Electrical Engineering, University of Malaya, Kuala Lumpur, Wilayah Persekutuan, Malaysia, [2]Academic Radiology, University of Sheffield, Sheffield, South Yorkshire, United Kingdom

Introduction: The objective metrics of Image Quality Assessment (IQA) can be divided into three categories: full-reference (FR), reduced-reference (RR), no-reference (NR) [1]. The most commonly used FR-IQA method is the mean squared error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM) [2]. There were various NR-IQA methods introduced, but they still have certain limitations, ie. slow computational time due to large numbers of features or statistics. A new NR-IQA model called Blind/referenceless image spatial quality evaluator (BRISQUE) operates in the spatial domain [3]. The BRISQUE approach does not calculate the distortion-specific features, but it uses scene statistics of locally normalized luminance coefficients to quantify possible losses of "naturalness" in the image. It is statistically better than PSNR and SSIM [3]. It is highly competitive with and computationally more efficient than the other state-of-art NR-IQA. This study employed the BRISQUE and SSIM methods in comparison in assessing MR optic nerve image quality. SSIM was used because it was shown that SSIM is the most consistent in assessing medical images among other FR-IQA methods [1].

Methods:

The BRISQUE method was used to assess four types of MR optic nerve images: (i) 1.5T T1-weighted (T1W), (ii) 1.5T T2-weighted (T2W), (iii) 3.0T T1W, and (iv) 3.0T T2W images, obtained from 15 healthy volunteers. First, the locally normalized luminances are computed using local mean subtraction and divisive normalization. They are applied to a given intensity image *I(i,j)* to produce transformed luminances, known as mean subtracted contrast normalized (MSCN) coefficients [3]: $\hat{I}(i,j) = \frac{I(i,j)-\mu(i,j)}{\sigma(i,j)+C}$ where i = 1, 2,...M, j = 1, 2,...N are spatial indices, M and N are the image height and width respectively, C = 1 is a constant that prevents instabilities when the denominator tends to zero, and $\mu(i,j) = \sum_{k=-K}^{K}\sum_{l=-L}^{L} w_{k,l} I_{k,l}(i,j)$ and $\sigma(i,j) = \sqrt{\sum_{k=-K}^{K}\sum_{l=-L}^{L} w_{k,l}(I_{k,l}(i,j)-\mu(i,j))^2}$ where $w = \{w_{k,l}|k = -K,...,K,\ l = -L,...,L\}$ is a 2D circularly-symmetric Gaussian weighting function sampled out to 3 standard deviations and rescaled to unit volume. This normalization procedures greatly reduces the dependencies between neighbouring coefficients. The MSCN coefficients have characteristic statistical properties that are changed by the distortion. The statistical relationships between neighbouring pixels are also computed. An asymmetric generalized Gaussian Distribution (AGGD) model is used to provide a good fit to the empirical histograms of coefficient products from distorted images. [4]. The AGGD with zero mode is given by:

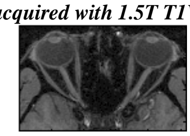
$$f(x;\nu,\sigma_l^2,\sigma_r^2) = \begin{cases} \frac{\nu}{(\beta_l+\beta_r)\Gamma(\frac{1}{\nu})}\exp\left(-\left(\frac{-x}{\beta_l}\right)^{\nu}\right) & x < 0 \\ \frac{\nu}{(\beta_l+\beta_r)\Gamma(\frac{1}{\nu})}\exp\left(-\left(\frac{x}{\beta_r}\right)^{\nu}\right) & x \geq 0 \end{cases} \quad \text{where} \quad \beta_l = \sigma_l\sqrt{\frac{\Gamma(\frac{1}{\nu})}{\Gamma(\frac{3}{\nu})}} \quad \text{and} \quad \beta_r = \sigma_r\sqrt{\frac{\Gamma(\frac{1}{\nu})}{\Gamma(\frac{3}{\nu})}}$$

The shape parameter υ decides the 'shape' of the distribution; σ_l^2 and σ_r^2 are scale parameters that determine the spread on each side of the mode, respectively. These parameters are estimated using the moment-matching based approach [4]. A regression module is required to map from the feature space to quality scores, which will give a measure of image quality.

An MR image with the best quality BRISQUE index was selected from each category, and was used as a reference image in applying the SSIM method. The SSIM score was calculated using [2]: $\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)}$ where x is the reference image, y is the test image, μ_x and μ_y are the mean intensity of x and y respectively, σ_x and σ_y are the standard deviation of x and y respectively, and $\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu_x)(y_i-\mu_y)$.

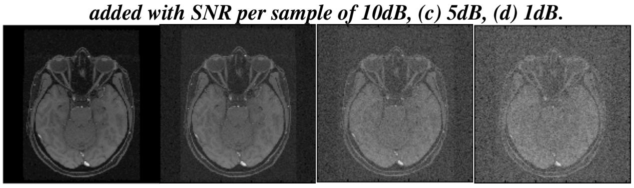
Prior to assessing all the data sets, both BRISQUE and SSIM methods were evaluated on a single image taken from 1.5T T1W sequence. Both methods were tested on the original image and modified images with white Gaussian noise added with three different values of SNR per sample as shown in Fig.1. All the analyses were performed on both a full image and cropped image (rectangle region, 110 mm x 70 mm, consisting eyeballs and optic nerves, as shown in Fig.2).

Fig.2: Cropped image acquired with 1.5T T1W.



Results:

Fig.1: (a) Original image from 1.5T T1W. (b)White Gaussian noise was added with SNR per sample of 10dB, (c) 5dB, (d) 1dB.



(a) *(b)* *(c)* *(d)*

Table 1: Evaluation of BRISQUE and SSIM indexes on original and white Gaussian noise added images.

Image		BRISQUE index		SSIM index	
		Full image	**Cropped image**	**Full image**	**Cropped image**
Original		22.46	10.82	1.00	1.00
Gaussian noise added	SNR=20dB	43.17	26.36	0.85	0.79
	SNR=10dB	66.12	64.62	0.51	0.39
	SNR=5dB	73.76	73.65	0.34	0.20

A higher quality image will produced a lower BRISQUE index or a higher SSIM index. Table 1 showed that the original image gave a better quality score by both methods. SSIM index is 1.00 on the original image because the same image was used as the reference and test images, hence verifying the algorithm. When white Gaussian noise was added, both BRISQUE and SSIM indexes show a worsening quality as the SNR decreases.

Table 2 records the mean and standard deviation values of the BRISQUE and SSIM indexes for four types of MR optic nerve images. Among the cropped images, 1.5T T1W data gave the best quality as evaluated by both methods; whereas 1.5T T2W data gave the worst quality.

Table 2: Mean BRISQUE and SSIM indexes for four types of MR optic nerve images (15 sets each)

Scanner	Image type	BRISQUE index		SSIM index	
		Full image	**Cropped image**	**Full image**	**Cropped image**
1.5T	T1W	29.25 ± 2.11	14.91 ± 2.76	0.4289 ± 0.1311	0.1072 ± 0.0226
	T2W	107.65 ± 1.36	109.95 ± 3.03	0.0403 ± 0.0721	0.0268 ± 0.0194
3.0T	T1W	29.22 ± 13.77	19.81 ± 9.32	0.1149 ± 0.1795	0.0672 ± 0.0591
	T2W	27.85 ± 3.50	24.03 ± 3.22	0.0517 ± 0.0245	0.0631 ± 0.0368

Discussion:

In Table 2, the BRISQUE index for the 1.5T T2W data (cropped image) is around 7 times larger than the 1.5T T1W data, although the images do not look 7 times worse visually. The support vector machine (SVM) library of the BRISQUE method was originally trained to evaluate natural images; hence it may not be able to evaluate the MR DICOM images accurately. The SSIM method is not suitable to assess MR images because there is no gold-standard image as reference for all scanning condition. Also, the user would not know which image could be used as reference unless he has tested the images with other types of NR-IQA. Hence, the indexes calculated in Table 2 were only used as a comparison between different sequences but they do not reflect an accurate measure of image quality. Nevertheless, SSIM can still be used as a comparative tool in rating and ordering the image quality for a pool of data.

Conclusions: It was verified that BRISQUE is more appropriate than SSIM in evaluating the quality of the MR images; however modification will be required to re-train the SVM library.

References: [1] R. Kumar et.al. Int.J Adv.Res.Comp.Sci.&Soft.Eng., 2012; 2:137-144. [2] Z. Wang et.al. IEEE Transactions of Image Proc., 2004;13(4):1-14 [3] A. Mittal et.al. IEEE Trans. Image Process, 2012;21(12):4695-4708. [4] N.E. Lasmar et.al. Proc. IEEE Int. Conf. Image Proc., 2009:2281-2284.