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Review Paper on

Quantitative Image Quality Assessment – Medical Ultrasound Images

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Abstract

Quality assessment plays a crucial role in Medical image analysis. Therefore, many research contributions are focusing on techniques which can provide quantitative assessment of image quality. This paper highlights the state-of-the-art and current progress relevant to full reference based image quality assessment of medical ultrasound images. In particular, it gives an overview of traditional methodologies and techniques employed to obtain image quality measure. Also it highlights on the new image quality measure which is based on the structural properties of image namely the Structural Similarity Index(SSIM). It also summarizes the merits and demerits of the existing image quality metric and gives a comparative results of the traditional and new (SSIM) image quality metric.

1. Introduction

Ultrasound imaging is a powerful non-invasive diagnostic tool which is often preferred in imaging modality because of its ability to provide continuous , real time images without the risk of ionization radiation and at lower cost. The final image of the Ultrasound image scanner is the basis for diagnostic decision. Hence the quality of the scanner should be of the highest quality. However like all other imaging modalities ultrasound imaging is subjected to a number of artifacts that degrade the image quality.

Quality of an image is a characteristic of an image that best measures the perceived image degradation. Digital images are subjected to wide variety of distortion during various processing, right from acquisition to the transmission to reproduction. When it comes to image quality assessment there are two types of assessment:1)Subjective Image Quality Assessment , 2) Objective Image Quality Assessment.

Subjective Image Quality Assessment is concerned with how image is perceived by a viewer and give his or her opinion on a particular image[2]. Human eyes are the ultimate Viewer of an image. However this method of assessment is time consuming, expensive, and it cannot be automated.

Objective Image Quality Assessment[1] is concerned with developing quantitative measures that can automatically predict the perceived image quality. Objective image quality metric can play important role in broad range of applications. First, it can be used dynamically to monitor and adjust the image quality. Second, it can be used to optimize algorithms in image processing systems. Third, it can be used to benchmark image processing system and algorithms. Image Quality Assessment can be done with priori information about the image or without the priori information. Hence Image quality Assessment can be divided into three categories: 1) Full reference, meaning complete image is available for reference, 2) Reduced Reference, meaning only a part of the image, in the form of extracted features are available for reference,3) No Reference, meaning no reference image is available. The image is blindly evaluated.

Assessing the clinical quality of Ultrasound images is of utmost important. Such assessment of clinical quality is generally performed subjectively because objective criteria have not yet been fully developed and accepted for evaluation of clinical image quality[3]. The different image quality measures which are usually used for objective evaluation are Mean Squared Error(MSE), Signal to Noise Ratio(SNR), Peak Signal to Noise Ratio(PSNR)[4]. They are widely used because they are simple to calculate, they have a clear physical meaning. But they do not match with the perceived image quality. In medical images , the perceived image quality is more important and accurate representation of image. Hence development of new image quality measure which can approximate the perceived image quality is required.

2. Image Quality Measure based on Error Sensitivity:

II.1. Mean Squared Error

Mean Squared Error is the most commonly used image quality measure. The goal of this measure is to compare two images by providing the quantitative score that describes the degree of similarity or the level of distortion/error between the two images.

Consider an image X_{ij} of size MXN, and another image of same size Y_{ij} { i = 1…. M}, {j = 1…. N} consisting of MXN pixels. The Mean Squared Error between the two image is given by Mean Squared Error(MSE).

$$\mathrm{MSE} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(X(i,j)-Y(i,j)\right)^2}{M\times N} \qquad (1)$$

the error image $e_{ij} = X_{ij} - Y_{ij}$ is the difference between the original image and distorted image. If one of the image is an original image of acceptable quality, and the other is a distorted image whose quality is to be evaluated , MSE gives the measure of image quality.

2.2 Peak Signal to Noise Ratio

In image processing, MSE is converted into Peak signal to noise ratio (PSNR) given by

$$\mathrm{PSNR}=10\ \log_{10}\frac{L^2}{\mathrm{MSE}} \qquad (2)$$

where L is the dynamic range of the allowable image pixel intensities. For example, for image that have allocations of 8b/pixel of gray scale, $L = 2^8 - 1 = 255$. The PSNR is useful if images having different dynamic ranges are being compared, but otherwise contains no new information.

2. 3 Advantages of Error Sensitivity Measurement

MSE, PSNR have many attractive features:

1) It is simple to calculate. It is parameter free and inexpensive to compute. It has complexity of only one multiplication and two additions per pixel.
2) It is memory less. The squared error can be evaluated at each sample, independent of other sample.
3) It has clear physical meaning. It defines the energy of the noise image. The energy is preserved even after applying linear transformation, such as Fourier Transform on the image. Hence this assures that the energy of the distortion remains same for transform domain and spatial domain.

2.4 Limitations

There are a number of reasons why MSE or PSNR may not correlate well with the human perception of quality[4][5].

1] Digital pixel values, on which the MSE is typically computed, may not exactly represent the light stimulus entering the eye.

2] Simple error summation, like the one implemented in the MSE formulation, may be markedly different from the way the HVS and the brain arrives at an assessment of the perceived distortion.

3] Two distorted image signals with the same amount of error energy may have very different structure of errors, and hence different perceptual quality

As seen from Figure 1. Although the quality MSE of all the distorted images are similar , but the appearance or distortion level of each of the distorted image is different. Hence MSE image quality metric in medical ultrasound is not desirable.

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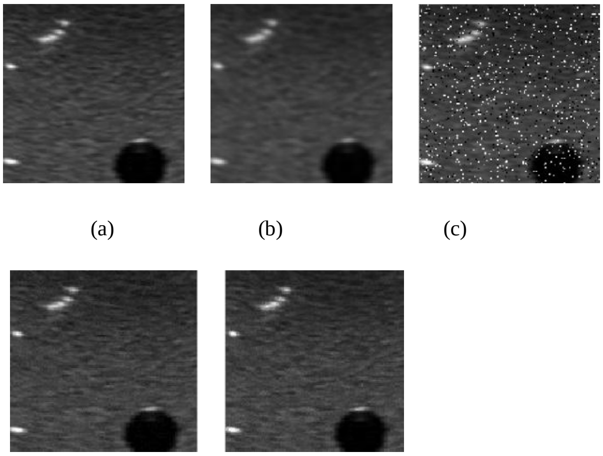


(a) (b) (c)

(d) (e)

Figure 1. Comparison of Ultrasound Images with different types of distortions all with MSE = 8. (a) Original Ultrasound Image , MSE = 0 (b) Gaussian Blurred Ultrasound Image (c) Salt-pepper impulsive contaminated image (d) Gaussian Noise contaminated Image (e) Speckle Noise contaminated Image

3. Structural Distortion based image quality measurement

Z. Wang proposed a new philosophy assuming that the human visual system (HVS) is highly adapted to extract structural information from the visual scene[5]. The new concept is very different from the previous error sensitivity philosophy,[5]which considers image degradations as perceived changes in structural information instead of perceived errors. Why human visual system is adopted for image quality assessment? Human visual system is a part of the central nervous system, which enable organisms to deal with visual details from the eyes of observer. Applying human visual system to image quality assessment is more appealing to human eyes. The luminance of an object's surface observed from human eyes is the product of the illumination and the reflectance, but the structures of an object are independent of the illumination. For the above reason,[5] defines the image structure information is independent of the average luminance and contrast calculating from the local luminance and contrast[9]. The structural similarity measurement system divides the measurement into three mutually independent components: luminance, contrast and structure shown below.

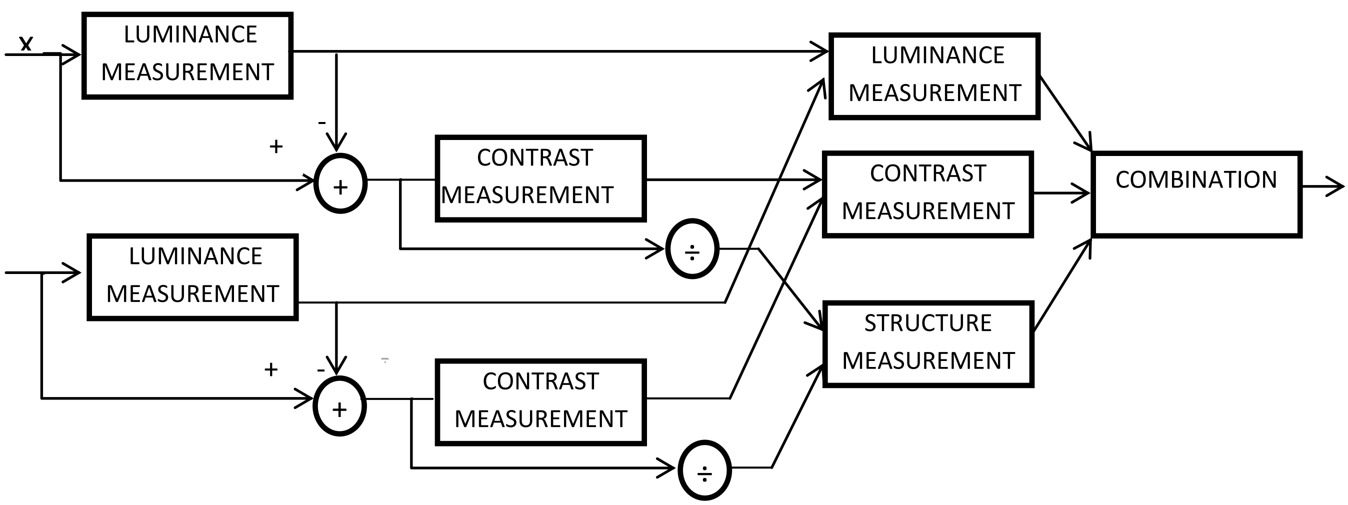


Figure 2. Block diagram of the structural similarity (SSIM) measurement

Suppose x and y are two nonnegative image signals, which have been aligned with each other (e.g., spatial patches extracted from each image). Consider one of the signals to have perfect quality, then the similarity measure can serve as a quantitative measurement of the quality of the second signal. The system separates the task of similarity measurement into three comparisons: Luminance, Contrast and Structure[6].

First, the luminance of each image is compared. This is estimated as the mean intensity, μx:

$$\mu = \sum_{i=1}^{M} \sum_{j=1}^{N} x(i,j) \tag{3}$$

The luminance comparison function l(x, y) is then a function of μx and μy.

Contrast gives the degree of brightness of an image or compares the gray value between two adjacent pixels. In structural measure mean intensity of the pixel is removed from the actual gray value. The standard deviation gives the estimate of contrast.

$$\sigma x = \left(\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) - \mu x)^2\right)^{1/2} \tag{4}$$

$$\sigma y = \left(\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (y(i,j) - \mu y)^2\right)^{1/2} \tag{5}$$

The contrast comparison c(x,y) is then comparison of σx and σy.

Finally, the structural comparison is performed between the luminance and contrast normalized signals. The images are normalized by its own standard deviation so that the two images being compared have unit standard deviation. The structure comparison s(x,y) is conducted on these two normalized images , $\frac{(x-\mu x)}{\sigma x}$, $\frac{(y-\mu y)}{\sigma y}$.

Finally the three components are combined to obtain the overall similarity measure given by S(x,y)

$$S(x,y) = f\,(l(x,y), c(x,y), s(x,y)) \tag{6}$$

where

$$l(x,y) = \frac{2\mu x \mu y + c1}{\mu x^2 + \mu y^2 + c1} \tag{7}$$

where c1 is constant included to avoid instability when μx + μy becomes zero given by

$$c1 = (K1 \times L)^2 \tag{8}$$

where L is the dynamic range of the pixel values (255 for 8-bit gray scale images), and $K1 < 1$ is a small constant. The contrast comparison function takes a similar form:

$$c(x,y) = \frac{2\sigma x \sigma y + c2}{\sigma x^2 + \sigma y^2 + c2} \tag{9}$$

where $c2 = (K2 \text{ X } L)^2$, and $K2 << 1$.

Structure comparison is conducted after luminance subtraction and contrast normalization. The correlation between $\frac{(x-\mu x)}{\sigma x}$ *and* $\frac{(y-\mu y)}{\sigma y}$ is equivalent to the correlation coefficient between x and y. Thus, the structure comparison function as follows:

$$s(x,y) = \frac{\sigma xy + c3}{\sigma x + \sigma y + c3} \tag{10}$$

As in the luminance and contrast measures, we have introduced a small constant in both denominator and numerator.In discrete form, σxy can be estimated as:

$$\sigma xy = \sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,y) - \mu x)\,(y(i,j) - \mu y) \tag{11}$$

Finally, we combine the three comparisons of Eqs. (6),(9) and (10) and name the resulting similarity measure the Structural Similarity (SSIM) index between signals x and y:

$$SSIM = [l(x,y)]^{\alpha} \times [c(x,y)]^{\beta} \times [s(x,y)]^{\Upsilon} \tag{12}$$

Where $\alpha > 0$, $\beta > 0$ and $\Upsilon > 0$ are parameters used to adjust the relative importance of the three components.

4. Implementation

For image quality assessment it is useful to apply the SSIM index locally[8], that is using a window. This is because; the image features are highly non stationary. The distortion may or may not depend on local image statistics. Localized assessment gives more information about the degradation quality of the image.

Hence a Gaussian 11X11 window can be used to find local statistics such μx, σx, σxy, μy, σy and local SSIM index. This window moves pixel by pixel over the entire image. At each step, the local statistics and SSIM index are calculated within the window.

Therefore, the estimate of local statistics is given by

$$\mu x = \sum_{i=1}^{M}\sum_{j=1}^{N} w(i,j) * x(i,j) \qquad (13)$$

$$\sigma x = \left(\sum_{i=1}^{M}\sum_{j=1}^{N} w(i,j) * (x(i,j) - \mu x)^2\right)^{1/2} \qquad (14)$$

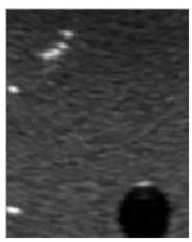
$$\sigma xy = \sum_{i=1}^{M}\sum_{j=1}^{N} wij((x(i,j) - \mu x)\,(y(i,j) - \mu y))$$
(15)

The parameters K1 = 0.01, K2= 0.03 are considered.

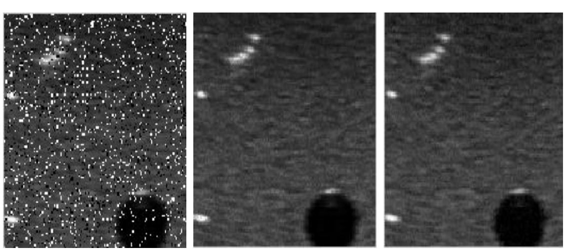
The overall single quality measure of the entire image is given by MSSIM.

$$\mathrm{MSSIM}(x,y) = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N} \mathrm{SSIM}(x(i,j), y(i,j))$$
(16)

5. Results

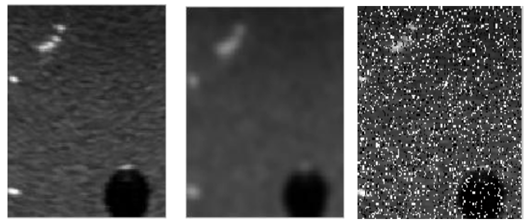


(a)

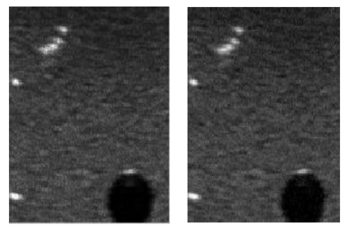


(b) (c) (d)

Figure 3. Comparison of MSSIM with MSE, Ultrasound images contaminated by Salt & pepper , multiplicative Speckle and additive Gaussian noise. (a) Original Ultrasound Image MSE =0, MSSIM = 1 (b) Salt & pepper contaminated image MSE = 15.179, MSSIM = 0.070177 (c) Speckle noise contaminated image, MSE = 15.6473, MSSIM = 0.8337(d) Gaussian noise contaminated image, MSE = 15.5706, MSSIM = 0.79425

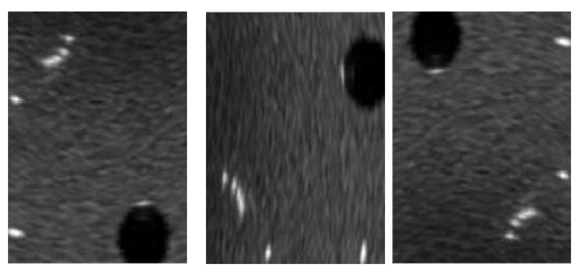


(a) (b) (c)



(d) (e)

Figure 4. Comparison of MSSIM with MSE, Ultrasound images contaminated by Gaussian Blurring , Salt and pepper noise, multiplicative Speckle and additive Gaussian noise. (a) Original Ultrasound Image MSE = 0, MSSIM = 1(b) Gaussian Blurring MSE = 25.056, MSSIM = 0.1369 (c) Salt & pepper contaminated image MSE = 24.4069 , MSSIM = 0.04367 (c) Speckle noise contaminated image , MSE = 25.65.34, MSSIM = 0.73066 (d) Gaussian noise contaminated image, MSE = 25.3399, MSSIM = 0.68078



(a) (b) (c)

Figure 5. Comparison of MSSIM of rotated images. (a) Original Ultrasound images, MSSIM =1(b) rotated 90^0 MSSIM = 0.71375, (c) rotated 180^0 MSSIM = 0.74922

6. Discussion

As seen from figure 3 and figure 4, MSSIM index performs better for Ultrasound images and wide variety of distortions. For example figure 3 shows MSSIM scores of images having near identical MSE of 8. It can be seen that MSSIM scores are much more consistent than MSE scores relative to visual perception.

However MSSIM is sensitive to relative translation, scaling, rotation of images which is undesirable as seen in figure 5. It contains a number of parameter values that have not been optimized and remain somewhat ad hoc. Also the optimization of the MSSIM index for various image processing algorithms needs to be studied and it is not an easy task since it is mathematically more cumbersome than MSE[5].

7. Conclusion

In this paper, we have summarized the traditional method of image quality assessment based on error sensitivity and its limitations in medical images. We have also discussed about the structural approaches of image quality measurement. We demonstrate the advantages of structural approach over the traditional approach. However, due to the shortcomings of the structural approaches many researchers have tried to overcome these shortcomings by develop a new image quality metric particularly for ultrasound images. There is no general-purpose metric has been agreed upon, to replace the subjective or the objective quality metrics. Hence there is still much left to be desired, and leave the door open to try and develop a new model that can improve the prediction of image quality measure accuracy in ultrasound images

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