Performance Analysis of Quality Measurement for Biomedical Images

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Abstract. With the rise used of biomedical images for diagnosis of diseases of a patient at various hospitals, the quality measurement of images is necessary for better diagnosis. The need for biomedical images quality measurement due to the transmission of images from one place to another place within hospitals or remote health centers. The lots of distortions may affect the quality of biomedical images during transmission. So, in this paper, the various image quality assessment parameters discussed for biomedical images. The paper gives information on various full reference-based objective assessment (OA) image quality measurement (FR-IQM) standards. The paper also gives performance analysis of FR-IQM standards for biomedical images.

1. Introduction
In medical science, biomedical images have an important role in the diagnosis of diseases. The various types of biomedical images such as X-ray, MRI, CT, US, PET, and retina are used for this purpose. Hence, the quality measurement of these images is required for biomedical image processing-based applications. The various biomedical image-based applications such as acquisition, processing, transmission and biomedical image analysis where the quality of images is required. Hence, it is important to deal with the measurement of distortion in biomedical images and their corresponding quality. In the last twenty years, many image quality measurement standards were developed by various researchers [1] [2]. These standards are divided into two types of assessment such as objective and subjective. The subjective assessment standards involve person which are particular measure perceptually quality of biomedical images. While objective assessment (OA) standards calculate approximate quality using automatic mathematic theories. These standards divided into three types such as full reference (FR-OA-IQM), no reference (NR-OA-IQM) and reduced reference (RR-OA-IQM) [1 – 3]. The basic information of these standards as per below:

1.1. Full Reference based OA-IQM
These standards measure statistical values between modified or degraded biomedical image and an original version of the biomedical image. These standards are very simple, easy to implement and understand. These standards are mainly used for quality measurements of the distorted biomedical image during transmission. Figure 1 shows the FR based OA-IQM standards. The information of various FR based OA-IQM standards is given in section 2.
1.2. No Reference (NR) based OA-IQM
These standards predicate quality of the degraded biomedical image without information of the original biomedical image. These standards are hard to implement, more complicate to understand and very rarely used in the quality measurement of biomedical images. Figure 2 shows the NR-based OA-IQM standards.

![Figure 2. NR based OA-IQM Standard](image)

The various types of NR based OA-IQM standards such as a codebook, learning, distortion specific and natural scene statistics are available in the literature [3 – 8]. These standards are mainly used for quality measurement of distorted biomedical images which are distorted by compression, noise addition, and blurring.

1.3. Reduced Reference (RNR) based OA-IQM
These standards measure image quality using a few extracted features of the original biomedical image while comparing related features of the distorted biomedical image. These standards are easy to understand compared to NR based OA-IQM standards and mainly used for a finding of distortion in the biomedical image [3]. Figure 3 shows the RR based OA-IQM standard. The limitation of these standards is that it requires a training set of distorted regions of reference biomedical image.

![Figure 3. RR based OA-IQM Standard](image)

This paper is summarized such that section 2 gives information on full reference based objective measurement IQM for biomedical images. In section 3, performance analysis of FR based OA-IQM standards for different types of biomedical images is given. Finally, the conclusion of this paper is
given.

2. FA based OA – IQM Standards
In this section, various FR based OA – IQM standards for quality measurement of the distorted medical image. The standards like mean square error (MSE) [9], root MSE (RMSE), peak signal to noise ratio (PSNR) and its various types, structural similarity index measure (SSIM) [1] [3] [10], multi-scale SSIM (MS-SSIM) [3] [11] and feature similarity index measure (FSIM) [12] are given in next subsections.

2.1. Mean Square Error (MSE) and Root MSE (RMSE)
These standards are basic measurement parameters for quality measurement of any distorted biomedical image with an original biomedical image. These standards are calculated using the below equations:

\[
\text{MSE} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} (I(x, y) - I'(x, y))^2
\]

\[
\text{RMSE} = \sqrt{\text{MSE}}
\]

Where \(I\) is an original biomedical image, \(I'\) is a distorted biomedical image, \(M\) is a row of the image and \(N\) is a column of the image.

The main characteristics of these standards [9] are like that it is easy to compute, simple to understand and main find the energy of distorted image. It measures in real values. These two standards main used in applications like medical image compression, transmission, and storage.

2.2. Peak Signal to Noise Ratio (PSNR) and Weighted PSNR (WPSNR)
PSNR is mainly used for perceptual quality of the distorted biomedical image. The PSNR is calculated using the below equation. The calculation of PSNR depends on the MSE between biomedical images.

\[
\text{PSNR} = 10 \times \log_{10} \left( \frac{255^2}{\text{MSE}} \right)
\]

Where MSE is a mean square error between the distorted biomedical image and the original biomedical image. The weighted PSNR (WPSNR) is a new way of perceptual computation of biomedical images. It is computed using the below equation:

\[
\text{WPSNR} = 10 \times \log_{10} \left( \frac{255^2}{\text{NVF} \times \text{MSE}} \right)
\]

Where, NVF is a noise visibility function and lies in the interval of [0, 1]. It is computed using the below equation:

\[
\text{NVF} = \text{NORM} \left( \frac{1}{1 + \delta^2_{\text{block}}} \right)
\]

The NVF is a normalization function, and \(\delta\) is luminance variance of computed blocks. The PSNR and WPSNR are measured in decibels (dB).
2.3. Structural Similarity Index Measure (SSIM)
This standard used to measure extracted structural information from a biomedical image [2] [10]. This
standard depends on the structure of biomedical image which is an independent component of
luminance and contrast [3]. It measures the similarity between the distorted biomedical image and the
original image. SSIM computes using the below equation [3]:

\[
SSIM = \frac{(2\mu_I\mu_{I'} + C_1)(2\sigma_{I'I} + C_2)}{(\mu_I^2 + \mu_{I'}^2 + C_1)(\sigma_I^2 + \sigma_{I'}^2 + C_2)}
\]  

(6)

Where, \( I \) is the original biomedical image, \( I' \) is the distorted biomedical image, \( \mu_I \) is the average of
original biomedical image, \( \mu_{I'} \) is the average of distorted biomedical image, \( \sigma_{II} \) is the covariance of
original biomedical image and distorted biomedical image, \( C_1, C_2 \) are constants and \( N \) represents
number of windows.

Wang et al. [13] have given a special case of SSIM for the Universal Quality Index (UIQ). The SSIM
has some properties such as symmetry, boundary condition and uniqueness [2] [13]. The MATLAB
implementation of this standard is given by Z. Wang. It is mainly using for application such as
biomedical image compression and biomedical image security.

2.4. Multi-Scale Structural Similarity Index Measure (MS-SSIM)
This standard overcomes the limitation of SSIM like it is only applicable for a single scale and
stationary image. But sometime in medical science, biomedical image analysis is done for various
conditions (e.g. structural depth of image). For this purpose, researchers are introduced new quality
measures standard called MS-SSIM [11] and computed using the below equation:

\[
MS - SSIM = \frac{1}{N} \sum_{x,y} SSIM(I(x,y) - I'(x,y))
\]  

(7)

Where \( I \) is the original biomedical image and \( I' \) is the distorted biomedical image.

2.5. Feature Similarity Index Measure (FSIM)
The FSIM [12] is a computed the similarity of biomedical images using low-level characteristics such
as zero crossings and edges of the image [14 – 16]. It depends on features like gradient magnitude
(GM) and phase congruency (PC). It calculated using the below equation:

\[
S(I, I') = S_{PC}(I, I')^\alpha \cdot S_{GM}(I, I')^\beta
\]  

(8)

Where SPC is similarity measure between PC features of the distorted biomedical image and original
biomedical image; SGM is similarity measure between GM features of the distorted biomedical image and
original biomedical image; \( \alpha \) and \( \beta \) are two constant values which depend on information of the
component of the biomedical image (\( \alpha=\beta=1 \)).

3. Results and Discussion
The FR based OA-IQM standards are verified and tested by various types of biomedical images such
as retinal image [17] and mammography image [18]. The size of the test biomedical image chosen is
256x256 and shown in Figure 4.

For measurement of FR based OA-IQM standards, the distorted biomedical image is generated using
various types of image manipulations such as compression, noise addition, and filtering, blurring. The
distorted biomedical images are shown in Figure 5. The FR based OA-IQM standards for distorted
biomedical images tabulated in Table 1.
Figure 4. Tested Biomedical Images (a) Retinal Image (b) Mammography Image

Figure 5. Distorted Biomedical Images (a) JPEG Compression (b) Blurred (c) Sharpening (d) Median Filter (e) Mean Filter (f) Cropping (g) Speckle Noise (h) Salt & Pepper Noise (i) Gaussian Noise

Table 1. FR based OA-IQM Standards for Tested Biomedical Images

| Distortion Type       | MSE    | RMSE   | PSNR (dB) | WPSNR (dB) | SSIM   | MS-SSIM | FSIM   |
|-----------------------|--------|--------|-----------|------------|--------|---------|--------|
| (a) Retinal Image     |        |        |           |            |        |         |        |
| JPEG Compression      | 3.0937 | 1.7589 | 39.5496   | 50.9848    | 0.9668 | 0.9953  | 0.9813 |
| Blurred               | 40.5694| 6.3694 | 28.3723   | 35.3190    | 0.8610 | 0.9421  | 0.8075 |
| Sharpening            | 5.7829 | 2.4048 | 36.8329   | 56.7026    | 0.9734 | 0.9948  | 0.9696 |
| Median Filter         | 5.2468 | 2.2906 | 37.2554   | 49.2947    | 0.9790 | 0.9954  | 0.9708 |
| Mean Filter           | 9.7228 | 3.1181 | 34.5764   | 45.9862    | 0.9612 | 0.9913  | 0.9482 |
| Distortion Type   | MSE       | RMSE     | PSNR (dB) | WPSNR (dB) | SSIM   | MS-SSIM | FSIM  |
|------------------|-----------|----------|-----------|------------|--------|---------|-------|
| Cropping         | 6058.3    | 77.8350  | 6.6308    | Inf        | 0.8592 | 0.4475  | 0.9019|
| Speckle Noise    | 121.9934  | 11.0451  | 23.5910   | 42.5175    | 0.4351 | 0.8469  | 0.7538|
| Salt & Pepper Noise | 106.3979 | 10.3149  | 24.1850   | Inf        | 0.8398 | 0.9140  | 0.9157|
| Gaussian Noise   | 4110.2    | 64.1111  | 8.3157    | 39.7402    | 0.0206 | 0.2493  | 0.2315|

(b) Mammography Image

| Distortion Type   | MSE       | RMSE     | PSNR (dB) | WPSNR (dB) | SSIM   | MS-SSIM | FSIM  |
|------------------|-----------|----------|-----------|------------|--------|---------|-------|
| JPEG Compression | 8.5928    | 2.9313   | 38.2990   | 41.0857    | 0.9564 | 0.9959  | 0.9813|
| Blurred          | 171.5723  | 13.0986  | 25.2958   | 27.0820    | 0.6240 | 0.7996  | 0.7219|
| Sharpening       | 25.939    | 5.0925   | 35.5017   | 42.8007    | 0.9444 | 0.9879  | 0.9510|
| Median Filter    | 19.6365   | 4.4313   | 34.7097   | 36.5991    | 0.9444 | 0.9867  | 0.9559|
| Mean Filter      | 37.8423   | 6.1516   | 31.8606   | 33.6363    | 0.9125 | 0.9787  | 0.9353|
| Cropping         | 4974.6    | 70.5309  | 10.6728   | Inf        | 0.8463 | 0.4702  | 0.8525|
| Speckle Noise    | 262.5764  | 16.2042  | 23.4478   | 29.9293    | 0.5868 | 0.9049  | 0.7902|
| Salt & Pepper Noise | 112.8538 | 10.6233  | 27.1152   | 52.5686    | 0.8771 | 0.9514  | 0.9599|
| Gaussian Noise   | 4276.6    | 65.3957  | 11.3294   | 26.3927    | 0.0467 | 0.4122  | 0.3902|

Referring to Table 1, it is indicated that the FR based OA-IQM standards are effectively used for quality measurement of the distorted biomedical image which is distorted by blurring, sharpening, median filtering, mean filtering, speckle noise, and salt & pepper noise. There are used in various medical image processing application such as image compression, image enhancement, and image processing.

4. Conclusions

This paper gives basic information about image quality standards for biomedical images. The paper covers various objective assessment-based image quality standards such as FR based OA-IQM, NR based OA-IQM and RR based OA-IQM. The tested of FR based OA-IQM standards are successfully tested for various types of biomedical images. In the future, NR based OA-IQM and RR based OA-IQM standards will be tested for biomedical images.

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