REDUCED REFERENCE IMAGE QUALITY ASSESMENT

By

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Science (Hons.) Applied Mathematics with Computing

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DECLARATION

I hereby declare that this project report entitled “REDUCED REFERENCE IMAGE QUALITY ASSESSMENT” is my own work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

I certify that this project report entitled "**REDUCED REFERENCE IMAGE QUALITY ASSESSMENT**" was prepared by **LAI MING JIE** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Science (Hons.) Applied Mathematics With Computing at Universiti Tunku Abdul Rahman.

Approved by,

Signature : _______________________

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Date : _______________________

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REDUCED REFERENCE IMAGE
QUALITY ASSESSMENT

ABSTRACT

Image quality assessment (IQA) is an analysis on the quality of an image. It is important to ensure the quality of an image remains high after conversion through any software or transmission from sender to receiver. This is because the image quality will affect the applications of imaging technologies. There are three levels of image quality assessment based on the availability on reference image, which are full reference (FR), no reference (NR), and reduced reference (RR). This study aims to propose a new reduced reference image quality metric (IQM), by way of statistical approach, for imperfect quality reference image.

The new RR-IQM used the concept of logistic function, which demonstrates the relationship between distortion level and image quality. The logistic model is used to derive the image quality metric $R_L^2 = \frac{R_S^2}{L}$ where the carrying capacity, L is estimated by plotting graphs of sigma value, s which is the ratio of standard deviation for reference image and distorted image and R_S^2 is the coefficient of determination. The proposed R_L^2 is a RR-IQM as the perfect reference image is unnecessary. In order to assess the performance of R_L^2, PLCC and MAE are used to test their monotonicity, whereas RMSE, SRCC, and KRCC are used to assess its accuracy. A good IQM should have high PLCC, SRCC, and KRCC values and low MAE and RMSE values.

The proposed R_L^2 is then tested on a standard image database called LIVE. The results show that R_L^2 performs better than others IQMs if the reference image is degraded

by JPEG2000 and it works reasonably well under JPEG and Gaussian Blur. In addition to that, R_L^2 has good monotonicity and accuracy when reference image is of greater quality. For same distorted image, R_L^2 provides more consistent results for over a range of reference image qualities.

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CHAPTER 1

INTRODUCTION

Digital images are economical and efficient medium for communicating information. It has greatly influenced the modern lifestyle, for example telemedicine, satellite imaging, biometric surveillance, advertisement and entertainment. The quality of an image will affect the applications of imaging technologies. In such, more and more experts proposed and improved different methods of image quality assessment metric (IQM), to enrich the image processing application. IQM provides an objective indicator of the perceived quality of an image. Generally, IQM has three types of application, which are to keep tracking the quality of images for quality control systems, to standardized image processing algorithms, and to enhance the parameter settings.

An image is distorted after it is converted through any software or transmitting from sender to receiver. It has to pass through several stages before it reach the receiver. Those distortions or noises are generated and added into the image at those stages of image processing, such as image acquisition, image compression, and image reconstruction. In order to make sure that the receiver get the same quality of image as the sender, IQM acts an important role in it. According to an articles, the reporters say that the best way to assess the quality of an image is perhaps to look at it because human eyes are the ultimate receivers in most image processing environments. However, this is a very subjective opinion from different people, moreover with different visionary ability. Therefore, IQA measurements is developed to assess different images provided by different fields of users.

Mainly, the IQM algorithms can be divided into three levels, which are full reference (FR), reduced reference (RR), and no reference (NR). Full reference (FR) IQA is that an image, which is free of distortion and considered perfect in quality, is used as the reference image. Reduced reference (RR) IQA is, by using an imperfect quality image as the reference image. On the other hand, no reference image is given for no reference (NR) IQA, to carry out the assessment. Most of the IQM proposed is FR-IQM, as it is considered as the easiest way to construct the metric. However, this study is look into RR-IQM, and a new RR-IQM is proposed.

1-1 Motivation

Image quality is an important topic as it will affect the output analysis of certain aspects, especially for medical imaging. The medical imaging continues to play a stronger role in diagnosis of diseases and treatment, the importance of image quality relatively rises. A pleasing or beautiful image alone does not indicate an accurate diagnosis. Therefore, a necessity of the efforts of the image quality assessment and medical imaging professionals is required to optimize the quality and safety of health care to ensure the optimal outcome. The similar theory is applied to the satellite image. The photo grain that always appear in space photos may limit the information contents of digitized photo. A good image quality will definitely improve this limitation and give a hand in the development of topography.

On the other hand, by improving image quality will indirectly improve the quality of lives. Most of the entertainment today involve visual enjoyment, such as videos, movies, animations and photos. An obvious example is from the Korean Pop (K-pop) industry. The major selling point of K-pop is about music, which is about listening. However, another important aspect is the visual genre. Even the successful of a song or artist began to rely on television during the 1980s. Most of the music programs started to dedicate in live performances, talk shows, musical dramas, different types of show, behind-the-scenes documentaries, and music videos (MV). This has shown a great improving of quality of lives as people are upgraded from listening enjoyment to visual and audio enjoyment.

Furthermore, image quality does act an important role in business industry. People rely on imaginary to share information, learn about new knowledge, and get themselves involved on things that they are interested. Using images in business works in a same way, which help people to feel and see the products and services without relying on written messages only. A high quality images, and illustrations will definitely increase the interest and excitement of the customers. Besides, a good quality of video during video conferencing will enhance the progress of a meeting. Business partner from different places manage to call out a meeting together, just like face to face meeting if the video conferencing have a good quality. This will save time and cost of travelling, and to make sure that an important business issue is not delayed.

1-2 Objectives

In this study, a new IQM is proposed to provide an objective indicator of the perceived quality of an image. This study has the following objectives

1. To survey different image quality assessment metrics (IQM) from various articles and journals. The methods, advantages and disadvantages of those metrics is studied.
2. To develop a new reduced reference image quality measurement using logistic concept.
3. To evaluate the performance the proposed IQM in various distortion types of reference image.

4. To apply the proposed metric to certain distortion type of imperfect reference images, which are Gaussian blur, JPEG and JPEG2000 distortion. This is to ensure that the metric proposed is suitable for the targeted images.

1-3 Scope of Study

In IQA field, there are three levels of assessment available, which are full reference (FR), reduced reference (RR), and no reference (NR). In this study, only reduced reference IQA is considered. This is because RR-IQA has plenty of metrics proposed in this filed, we need to propose a more practically useful IQM to help in improving this field. We use a statistical way to construct the RR-IQM in this study.

There are quite a number of image database provided, such as Cornell-A57 database, IVC database, Toyama-MICT database, Tampere Image database, and more. By using images from different database can provide a more accurate result for IQA, as different characteristics can be found from different database. However in this study, only images in LIVE database is used in this study due to time constrain. LIVE database contains 982 images in total, where 779 of them are distorted with five different types of distortion.

In this study, only three types of distortion is included for imperfect reference image, which are Gaussian Blur, JPEG, and JEPG2000. When estimating the carrying capacity, L for each distortion types, more accurate result is found for these three distortion types. Gaussian Noise and Fast Fading distortion type do not get the accurate carrying capacity value. This may due to fewer images is included in predicting the carrying capacity value.

1-4 Definition

IQA can be divided into three levels, which are full reference (FR), reduced reference (RR), and no reference (NR). Full reference (FR) IQA is that, a reference image, which is free of distortion and considered as perfect in quality, is given. Then, a distorted image is given as well to make an assessment between them. FR-IQA is considered as the easiest way to assess an image quality, as a perfect quality of reference image is used. However, it is sometimes impractical in actual as it is difficult to obtain an original perfect quality image as the full reference.

In reduced reference (RR) IQA problem, an imperfect quality image is provided as the reference image, to carry out assessment with the distorted image given. Basically, there are three types of RR-IQA. The first one is that only some variables of reference image is available to carry out the IQA. Secondly, only certain part of the reference image is given. Lastly, only a corrupted reference image and standard deviations of both reference image and distorted image are given, where this is the type of RR-IQA studied in this study. RR-IQA is more practically used, as a reference image we can get in actual lives is mostly without perfect quality. When an RR-IQA is used, only certain information are needed based on the IQM algorithm's structure.

For no reference (NR) IQA, no reference image is given, but only the distorted image. An algorithm need to be developed to assess the quality of image provided itself without doing any referencing. NR-IQA can be considered as an ideal IQA but is the most difficult one. Up to date, there is still lack of successful NR-IQM algorithm in the field.

CHAPTER 2

LITERATURE REVIEW

Over the decade, the reduced reference (RR) image quality assessment (IQA) is mostly studied among all. Structural similarity (SSIM) index is seldom been used, as it is more suitable for full reference (FR) metric. Majority of the reduce reference IQA performed were related to logarithm function. There are three categories of metrics will be reviewed.

2-1 Statistical prior models

Statistical regression method is being used in developing image quality assessment method. Xue&Mou (2010) have proposed a new method named βW-SCM to estimate the quality of distorted image. It requires two steps before performing the new method, which are defining the SCM for redundancy reduction to present image features, and employing Weibull distribution to describe the statistics of SCM and scale parameter β is extracted as reduced reference feature. (Xue&Mou 2010)The final perceptual distortion of the tested image proposed is defined as

$$D_{\beta W-SCM} = \sum_{n=1}^{6} \sqrt{d_A^n \times d_R^n}$$

where d_A^n is the absolute deviation, d_R^n is the relative deviation, and N is the total number of scales. (Xue&Mou2010) This new method uses less reduced reference feature and has a short execution time. However, it needs to perform two steps before execute the new method proposed, which may consider lengthy steps and time consumed.

Zhang et al (2011) proposed a simple edge verification method for RR-IQA metric. Only 12 scalar features are needed as compared to other RR IQA model which need 16 scalar features. (Zhang et al 2011)The predicted objective score for one image is defined as

$$D_M = \sum_{i=1}^{4} \sum_{k=1}^{3} log_{10}[p_{c_i}(x_k) - p_{D_i}(x_k)]^2$$

where $p_{c_i}(x_k)$ and $p_{D_i}(x_k)$ is the normalized histogram comes from the statistics of the edge pattern maps C_i^p and D_i^p. (Zhang et al 2011)The proposed algorithm is simple, but the data rate is lower than other well-known IQA. (Zhang et al 2011)

D. Yang et al (2012) focus their research of RR-IQA metric based on natural image statistic in Roberts cross derivative domain. Roberts cross derivative (L.S. Davis 1975) is widely used in detecting image edges which are important geometric feature about image for visual prediction. (D. Yang et al 2012) The overall distortion between the reference and distorted image is defined as

$$Distortion = log_2(1 + \frac{D_{RAD}^X(p^X, q^X) D_{\sigma^2}^X D_k^X D_S^X + D_{RAD}^Y(p^Y, q^Y) D_{\sigma^2}^Y D_k^Y D_S^Y}{2D_0})$$

where X and Y are associated the main diagonal and the anti-diagonal of image, respectively, p^X and q^X (p^Y and q^Y) denote the probability density functions of Roberts cross derivative in the reference and distorted images, respectively, $D^Y_{KLD}(p^Y, q^Y)$ ($D^X_{KLD}(p^X, q^X)$) is the estimation of KLD between p^X and q^X (p^Y and q^Y), and $D^X_{\sigma^2}$ ($D^Y_{\sigma^2}$), $D^X_k(D^Y_k)$, D^X_S (D^Y_S) are the comparisons of variance, kurtosis and skewness, respectively. (D. Yang et al 2012) The proposed metric is less complex as compared to other RR-IQA, as only twelve parameters from the reference image is needed.(D. Yang et al 2012)Moreover, the metric can be applied for all distortion types and has a good performance as compared to other popular RR-IQA. (D. Yang et al 2012)

The coefficient of determination derived from MULFR (Multidimensional replicate linear functional relationship) model proposed by Y. F. Chang et al (2008), is used for correlation measure, denoted by R^2_F. The specialty of this measurement is where it assumes both the reference and compressed images is subjected to errors, and uses several quality attributes to calculate overall image similarity value. (Y.F. Chang et al 2008) Numerous quality attributes computed from local windows are used to calculate the overall image similarity value.

The similarity measure, ${R_F}^2$ is defined as

$$ {R_f}^2 = \frac{SS_R}{S_{yy}} = \frac{\hat{\beta} S_{xy}}{S_{yy}} $$

where $\hat{\beta} = \frac{(S_{yy} - \lambda S_{xx}) + \sqrt{(S_{yy} - \lambda S_{xx})^2 + 4\lambda S^2_{xy}}}{2S_{xy}}$, $\bar{y} = (\bar{y}_1, \bar{y}_2, \dots, \bar{y}_p)'$, $\bar{x} = (\bar{x}_1, \bar{x}_2, \dots, \bar{x}_p)'$, $S_{xx} = \sum_{i=1}^{n} x_i' x_i - n\bar{x}'\bar{x}$, $S_{yy} = \sum_{i=1}^{n} y_i' y_i - n\bar{y}'\bar{y}$ and $S_{xy} = \sum_{i=1}^{n} x_i' y_i - n\bar{x}'\bar{y}$.

The value of R^2_F shows the proportion of variation in reference image explained by the distorted image.

2-2 Structural method

The application of structural method in RR-IQA metrics is often proposed. Wang & Simoncelli (2005) have proposed a wavelet domain information measure for RR IQA. The proposed algorithm is more interested to real world users as it performs well in a wide range distortion type, easy to implement, and insensitive to small geometric distortions. (Wang &Simoncelli2005) The overall distortion between reference and distorted images as proposed is defined as

$$D = log_2(1 + \frac{1}{D_0}\sum_{k=1}^{K} |\hat{d}^k(p^k||q^k)|$$

where K is the number of subbands, p^k and q^k are the probability distributions of the k-th subband of the reference and distorted images respectively, $\hat{d}^k$ represents the KLD between p^k and q^k, and D_0 is a constant used to control scale of distortion measure. The relationship between the algorithm and subjective image quality has not been tested, and it is left over to be improved by join statistic of wavelet coefficients. (Wang &Simoncelli2005)

After that, Wang & Rehman (2012) proposed an RR-IQA algorithm, which by making use of DNT-domain image statistical properties. Their effort is to approximate the full reference (FR) SSIM with the design of SSIM approach. (Wang &Rehman2012) This shows that it may not work as effectively in RR features, because RR only provide limited amount of information about the reference image. They define a new RR distortion measure by multiplying a function into the function D that Wang & Simoncelli (2005) proposed, which is

$$D_n = g(\sigma_r, \sigma_d)\log(1 + \frac{1}{D_0}\sum_{k=1}^{K} |\hat{d}^k(p^k||q^k)|$$

The estimated SSIM value is used as a benchmark for my study. Their method will be further discuss in the methodology part.

J. Wu et al (n.d.) introduced a RR-IQA metric which use less reference data and achieve higher prediction accuracy. They suggested to represent the image structure by using the local binary pattern (LBP), which is a popular and well accepted structural descriptor, to extract structural information. (J. Wu et al n.d.)The main structural degradation proposed is defined as

$$HC\left(I_i^d, I_i^o\right) = \frac{2 \times H_i^d \cdot H_i^o}{(H_i^d)^2 + (H_i^o)^2}$$

where $i \in \{p, r\}$. The RR-IQA proposed is generally a good RR-IQA as it meet a high consistent. (J. Wu et al n.d.) However, it takes a lengthy steps to get the final result that need to perform several procedures.

2-3 Machine Learning

Machine learning method is introduced in the development of RR IQA. This method is considered a new method which a recent article is found studied about it. Mocanu et al (2015) introduced a novel stochastic RR-IQA metric, called RBMSim. It evaluates on two subjective benchmarked image databases. (Mocanu et al 2015)The RBMSim metric is defined as

$$RBMSim(DI) = \sqrt{\frac{1}{n_v}\sum_{i=1}^{n_v}(v_i^{DI} - v_i^{DI})^2}$$

where n_v is the number of visible neurons.RBMSim has a fast computational time and is therefore suitable for online applications. (Mocanu et al 2015)The author left a further discussion on to adapt RBMSim to videos by training RBMSim on all frames of video.

2-4 Metrics as comparison

Among the IQA proposed and exist for statistical prior model, SSIM, PSNR, estimated RR-SSIM, and DMOS are used as major comparison with the method proposed, R_L^2. SSIM and PSNR are used, as SSIM is a popular FR-IQA, whereas PSNR is a traditional method, which is commonly used. The estimated RR-SSIM, proposed by Z. Wang (2012) is the latest RR-IQA proposed, which has a better accuracy, consistency, and monotonicity. DMOS (Difference Mean Opinion Score) is a metric used for decades to obtain the human's user view of the quality of an image. Therefore, these four metrics are used as a comparison in this study.

2-4-1 Structural Similarity (SSIM) Index

Structural similarity (SSIM) index is a method to measure the similarity between two images. SSIM is a full reference image quality assessment metric. It is designed and proposed to improve the older metrics, such as peak signal-to-noise ratio (PSNR) and mean square error (MSE) metrics.

SSIM between two images x and y of common size is defined as

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

where μ_x is the average of x, μ_y is the average of y, σ_x^2 is the variance of x, σ_y^2 is the variance of y, σ_{xy} is the covariance of x and y, $c_1 = (k_1L)^2$ and $c_2 = (k_2L)^2$ are two variables to stabilize the division with weak denominator, with L is the dynamic range of the pixel-values, and $k_1 = 0.01,\ k_2 = 0.03$ by default.

2-4-2 Peak signal-to-noise ratio (PSNR)

The peak signal-to-noise ratio (PSNR) is the ratio between the maximum possible power of a signal and the power of distorted noise that affects its representation. PSNR is usually expressed in terms of logarithmic scale. Normally, a higher PSNR value means that image is of higher quality.

PSNR is more easily to define through the mean squared error (MSE), which is defined as

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

where $m \times n$ is the size of a grayscale image I, K is the noise approximation.

The PSNR is defined as

$$PSNR = 20\ log_{10}(MAX_I) - 10\ log_{10}(MSE)$$

where MAX_I is the maximum pixel value of the image.

2-4-3 Estimate SSIM proposed by Z. Wang (2012)

The SSIM proposed by Z. Wang (2012) is estimated by using a straight-line relationship between a newly defined reduced reference distortion measure,D_n and SSIM value. The distortion of the distorted image is evaluated by the Kullback-Leibler divergence (KLD) between the probability distribution of the original image, p(x) and the distorted image, q(x). KLD is defined as

$$d(p||q) = \int p_m(x) log \frac{p(x)}{q(x)} dx$$

where $p_m(x)$ is the model Gaussian distribution.

The new reduced reference distortion measure of the whole image is defined as

$$D_n = g(\sigma_r, \sigma_d) \log(1 + \frac{1}{D_0} \sum_{k=1}^{K} |d^k(p^k||q^k)|$$

wherep^k and q^k are the probability distributions of the k-th subband of the reference and distorted images respectively, d^k represents the KLD between p^k and q^k , and $g(\sigma_r, \sigma_d)$ is defined as

$$g(\sigma_r, \sigma_d) = \frac{||\sigma_r||^2 + ||\sigma_d||^2 + C}{2(\sigma_r \cdot \sigma_d) + C}$$

where σ_r and σ_d represent the vectors containing standard deviation σ values, K is the total number of subbands, C is a positive constant which is included to avoid instability when the dot product$\sigma_r \cdot \sigma_d$ is close to 0.

For each fixed distortion type, D_n exhibits a nearly perfect linear relationship with SSIM. This relationship reduce the SSIM estimation problem to estimate the slope factor. The straight-line relationship to estimate SSIM is defined as

$$\hat{S} = 1 - \alpha D_n$$

where α is the slope factor.

2-4-4 Difference Mean Opinion Score (DMOS)

DMOS is the most straight forward way to determine the image quality. This is conducted by asking a group of people to rate an image sequence relative to a full reference image. The range of the DMOS value is rated differently for each researcher. In this study, the range is as follow

- 0 - 20 – Very Satisfied
- 21 - 40 – Satisfied
- 41 - 60 – Some Users Satisfied
- 61 - 80 – Many Users Dissatisfied
- 81 - 100 – Most Users Dissatisfied

CHAPTER 3

METHODOLOGY

From the discussion in Chapter 2 literature review, we have seen the needs for proposing a new RR-IQA for statistical approach. The proposed metric R_L^2 is majorly based on the MULFR model, R_F^2 proposed by Chang Y. F. (2008). On the proposing of this metric, various types of distortions are included in the study as the imperfect reference image and distorted image. Those images are taken from LIVE database, which is widely used by the researchers when proposing an IQA metric. Besides, it is important to know the performance of a metric proposed to assess the quality of images. In this study, the performance of the metric proposed is examined by five evaluation methods.

3-1 Type of Distortion

There are five distortion types involved in this study, which are Gaussian blur, JPEG, JPEG2000, Fast Fading, and Gaussian Noise. Gaussian Blur, JPEG, and JPEG2000 distortions, with different bit rate are used as the imperfect reference image. For each of the different imperfect reference image, another four types of distortions are used in the distorted image to carry out this study.

Figure 3-1: Samples of Gaussian Blur Distortion with Bit Rate 0 and 11.333325.

Gaussian blur is a distortion type which having the result of blurring an image. It is typically used in reduce the image noise or to reduce the image details. In mathematics, Gaussian blur is performed by combining an image with Gaussian function.

Figure 3-2: Samples of JPEG Distortion with Bit Rate 0 and 2.7772.

JPEG is a commonly used compression designed to compress images effectively. The degree of compression can be adjusted that is the image quality factor. JPEG is the acronym for Joint Photographic Experts Group, the name for the committee who created JPEG. JPEG is generally uses a form of compression based on the discrete cosine transform (DCT).

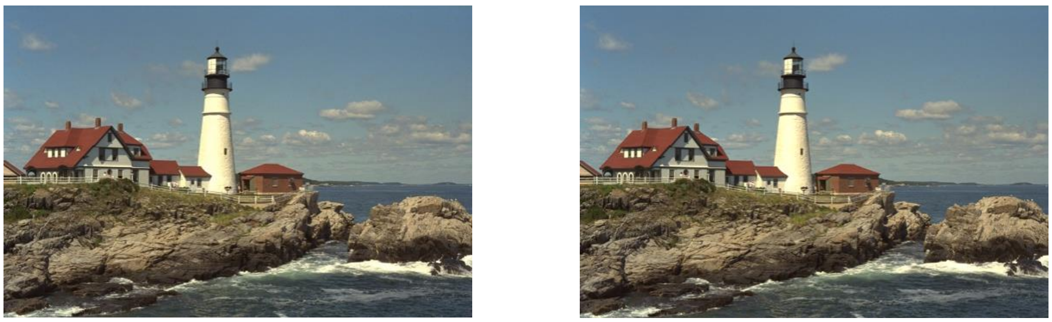


Figure 3-3: Samples of JPEG2000 Distortion with Bit Rate 0 and 2.9056.

JPEG2000 is a better image distortion or solution than JPEG. This is because it compresses images with a lesser loss of visual performance. JPEG2000 is designed in year 2000, with a wavelet-based method. However, JPEG2000 is seldom being used due to its complexity.

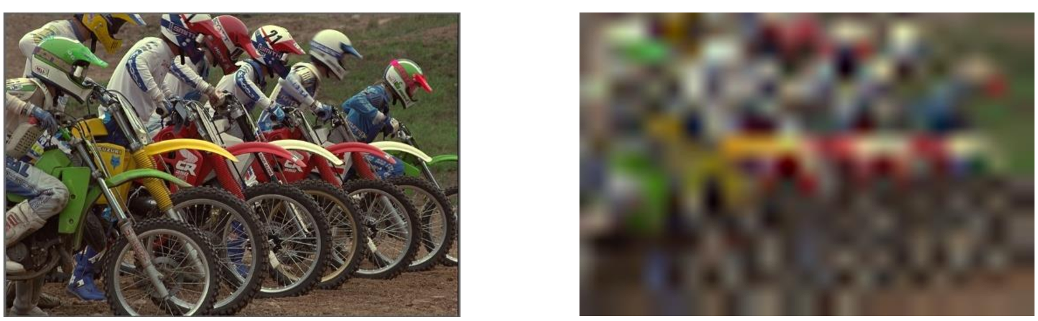


Figure 3-4: Samples of Fast Fading Distortion with Bit Rate 0 and 16.5.

Fading is the digression of a depletion affecting a media, such as images. It may changes with time or radio frequency. Fast fading is where the frequency response changes occur speedily. Practically, this type of distortion only occurs for very low data rates images.

Figure 3-5: Samples of Gaussian Noise Distortion with Bit Rate 0 and 1.0.

Noise is the departure from the ideal image and the distorted image. Gaussian noise often occur in acquisition process while sending an image. It can be caused by several reasons, such as poor illumination, high temperature, and transmission.

3-2 Test Images

In this study, three types of distortion, which are Gaussian blur, JPEG, and JPEG2000 distortion with different bit rate each, are used in the imperfect reference image. On the other hand, five types of distortion, which include Gaussian noise, fast fading, and the three types of distortion mentioned previously, with different level of bit rate each, are used as the distorted images. All of the images are from the LIVE database, which is a database that is frequently used by most of the researchers in the literature review.

Table 3-1: Information of the Test Images.

Type of Distortion	Number of Images	Number of Distortion
Gaussian Blur	29	$67 \times 29 = 1943$
Gaussian Noise	29	$56 \times 29 = 1624$
JPEG	29	$159 \times 29 = 4611$
JPEG2000	29	$149 \times 29 = 4321$
Fast Fading	29	$11 \times 29 = 319$

Figure 3-6: Example of test images used, Caps.bmp. These images have perfect quality, Gaussian blur distortion, JPEG distortion, JPEG2000 distortion, Gaussian Noise distortion, and Fast Fading distortion.

The LIVE database contains seven data sets of 982 subject-rated images, including 779 distorted images with five types of distortions at different distortion levels. The distortion types include JPEG compression, JPEG2000 compression, Gaussian blur, white noise, and fast fading channel distortion. (Wang & Simoncelli 2005)

The perfect quality image provided in LIVE database is also used as the reference image in this study. This is to compare the result with the distorted reference image.

3-3 Proposed metric, $R_L^{\,2}$

The inconsistency and inaccuracy of the FR IQM when the reference image is imperfect in quality suggests that a new IQM should be developed. Instead, a simple method is proposed, of deriving a more consistent and accurate RR-IQM from the existing FR-IQM.

Logistic regression models the relationship between a dependent and one or more independent variables. This allows us to look at the fitness of the model and the meaning of the relationships that are modelling. In many ways, it is seems to be alike with ordinary regression. However, there is a slight difference with ordinary linear regression. The ordinary regression find the best fitting line by using ordinary least squares method, while logistic regression calculate the probability of an event occur.

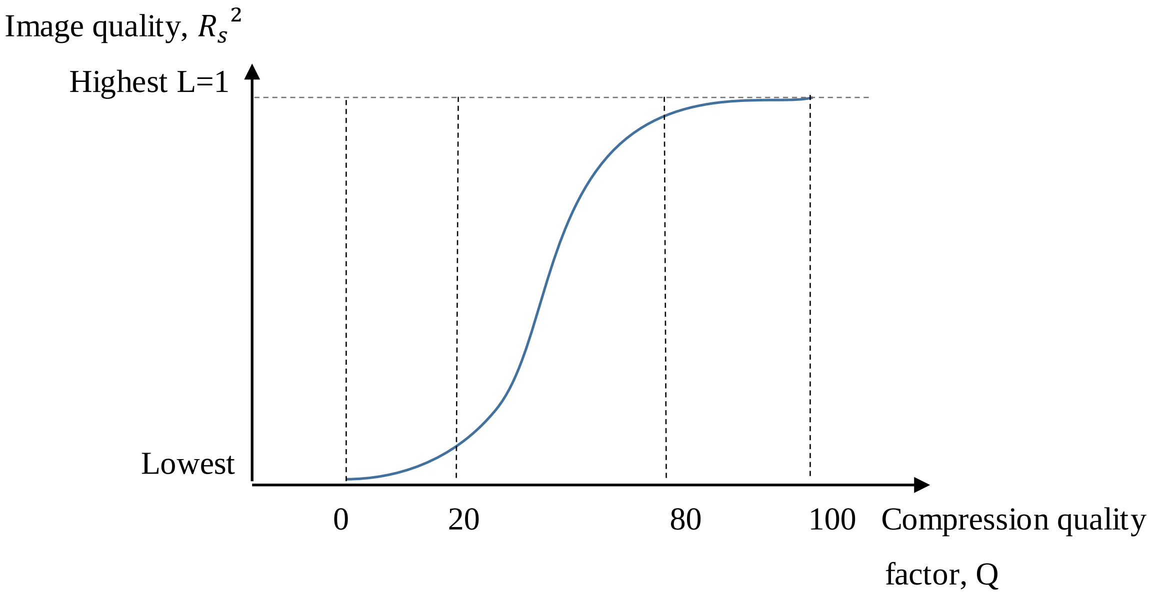


Figure 3-7: Logistic Relationship Between Compression Quality Factor and Image Quality.

The sketch in Figure 3-7 demonstrates the relationship between compression quality factor and image quality. It has a logistic relationship in which a drop in quality factor at the highest level does not give a significant effect to the image quality. However, the image quality degrades dramatically at moderate compression level with obvious compression artifacts. Finally, at the lowest quality factor range, the compression level is optimum with minimum image quality value. A possible expression for this relationship is given by the logistic model

$$R_s^2(Q) = \frac{L}{1+Ae^{-kQ}} \tag{3. 1}$$

where Q is the quality factor, L is the carrying capacity, R_s^2 is the image quality value and A, k are constant values.

It is given that the compression quality factor is scaled between 0 to 100, which 0 indicates the highest compression effect while 100 represents the lowest compression effect. From the graph, compression effect between 80 to 100 has a high image quality. Compression effect between 0 to 20 has a low image quality. This indicates that a lower compression effect has a higher image quality. Besides, the compression quality between 20 to 80 shows a large gradient effect, which means error increase fast at this area. The image quality change with a fast rate which the changing effect can be obviously observed. The area with small gradient, which are the compression effect at 0 to 20 and 80 to 100, has a relatively flat variance and mean error. At these points, the changes of image quality is not obvious.

From Equation (3.1), let $R_s^2(Q)$ be the quality value of full reference metric at compression quality factor, Q. It is suggested that the quality metric, R_s^2 and quality factor, Q has a logistic relationship with ‘S’ shape

$$\frac{dR_s^2}{sQ} = kR_s^2(1 - \frac{R_s^2}{L})$$

By solving this separable differential equation, Equation (3.1) is obtained as follow

$$\int \frac{dR_s^2}{R_s^2(1 - \frac{R_s^2}{L})} = \int kdQ$$

$$\int \left(\frac{1}{R_s^2} + \frac{1}{L - R_s^2}\right) dR_s^2 = \int kdQ$$

$$ln|R_S^2| - ln|L - R_S^2| = kQ + C$$

$$\ln\left|\frac{L - R_S^2}{R_S^2}\right| = -kQ - C$$

$$\frac{L - R_S^2}{R_S^2} = Ae^{-kQ}, where\ A = \pm e^{-C}$$

$$\Longrightarrow R_S^2(Q) = \frac{L}{1 + Ae^{-kQ}} \tag{3.2}$$

where Q is the JPEG quality factor of range 1 to 100, L is the carrying capacity or upper limit of R_S^2, k is a constant value and $A = \frac{1 - R_S^2(1)}{R_S^2(1)}$.

Given a perfect full reference image, we have L=1 when the compressed image and the reference image are identical. Assuming that $R_S^2(100) = 0.99999$ and $R_S^2(1) = 0.00001$ for the highest compression quality and the lowest compression quality, respectively. We believe that even at highest compression quality, there is a little quality loss in the compressed image. Similarly, there is a little similarity between the intensity values of the two images at the lowest compression quality factor. Therefore, we have

$$A = \frac{1 - 0.0001}{0.0001} = 99999. \tag{3.3}$$

Then, Equation (3.2) becomes

$$R_S^2(Q) = \frac{1}{1 + 99999e^{-kQ}}. \tag{3.4}$$

Substitute $R_S^2(100) = 0.99999$ into Equation (3.4) yields

$$0.99999 = \frac{1}{1 + 99999e^{-100k}} \text{ or } k = \frac{1}{50} ln(99999).$$

Thus, the logistic model for R_S^2 given a perfect reference image is

$$R_S^2(Q) = \frac{1}{1+99999e^{-\frac{Q}{50}ln(99999)}}. \tag{3. 5}$$

Now, we consider a non-perfect reference image. This implies that $L < 1$. Let $\acute{R}_S^2$ be the calculated R_S^2 given a non-perfect reference image. We have

$$\acute{R}_S^2(Q) = \frac{\acute{L}}{1+99999e^{-\frac{Q}{50}ln(99999)}}. \tag{3. 6}$$

Rewrite the Equation (3.6) as

$$Q = \frac{-50}{ln\ 99999} ln[\frac{\hat{L}-\hat{R}_S^2}{99999\hat{R}_S^2}]. \tag{3. 7}$$

Therefore, the reduced reference quality measure, R_L^2 can be obtained from a non-perfect reference image by substituting Equation (3.7) into Equation (3.5), yields

$$R_S^2 = \frac{1}{1+99999e^{-\frac{1}{50}ln(99999)[\frac{-50}{ln\ 99999}ln\left(\frac{\hat{L}-\hat{R}_S^2}{99999\hat{R}_S^2}\right)]}} = \frac{\acute{R}_S^2}{\acute{L}}. \tag{3. 8}$$

The remaining task in Equation (3.8) is to estimate the value of L. Note that the value of L depends on reference image. A perfect image implies that $L = 1$, and the greater distortion of reference image, the lower value of upper limit L. One possible way of measuring the level of distortion in reference image is to consider its standard deviation. Let σ_Y^* and σ_Y be the standard deviation for the imperfect reference image and perfect reference image, respectively. We have the following properties

i. When the reference image is of perfect quality, then the ratio $\frac{\sigma_Y^*}{\sigma_Y} = 1 \Longrightarrow L = 1$.

ii. When the quality of the reference image degrades, then the ratio, s < 1 or s > 1$\Longrightarrow$ $L \rightarrow 0$.

This is further discuss in the section 3-4.

3-4 Estimate the carrying capacity, L

R_L^2 is evaluated by dividing carrying capacity, L from R_S^2. The carrying capacity, L value used is vary for different distortion type of imperfect reference image and distorted image. In this study, three distortion types of imperfect reference image are studied, which are Gaussian Blur, JPEG, and JPEG2000. Each of the reference image is tested with four other distortion types of distorted images, which included the mentioned three types of distortion, Fast Fading, and Gaussian Noise distortion.

The L value is determined by a model which is evaluated by plotting graphs of sigma value, s and R_S^2 value. The sigma value, s, is the ratio of the standard deviation for an original reference image and its distorted reference image. Initially, a graph is plotted by including all s value and R_S^2 value in one regression. However, it is found out that a better regression with higher R-squared value is obtained after separating the graph into two or more sections. R-squared value, which also known as coefficient of determination, is used to measure the fitness of the data with the regression line. With so, for this study, we proposed two or four quadratic regressions to model the data for each of the different distortion types.

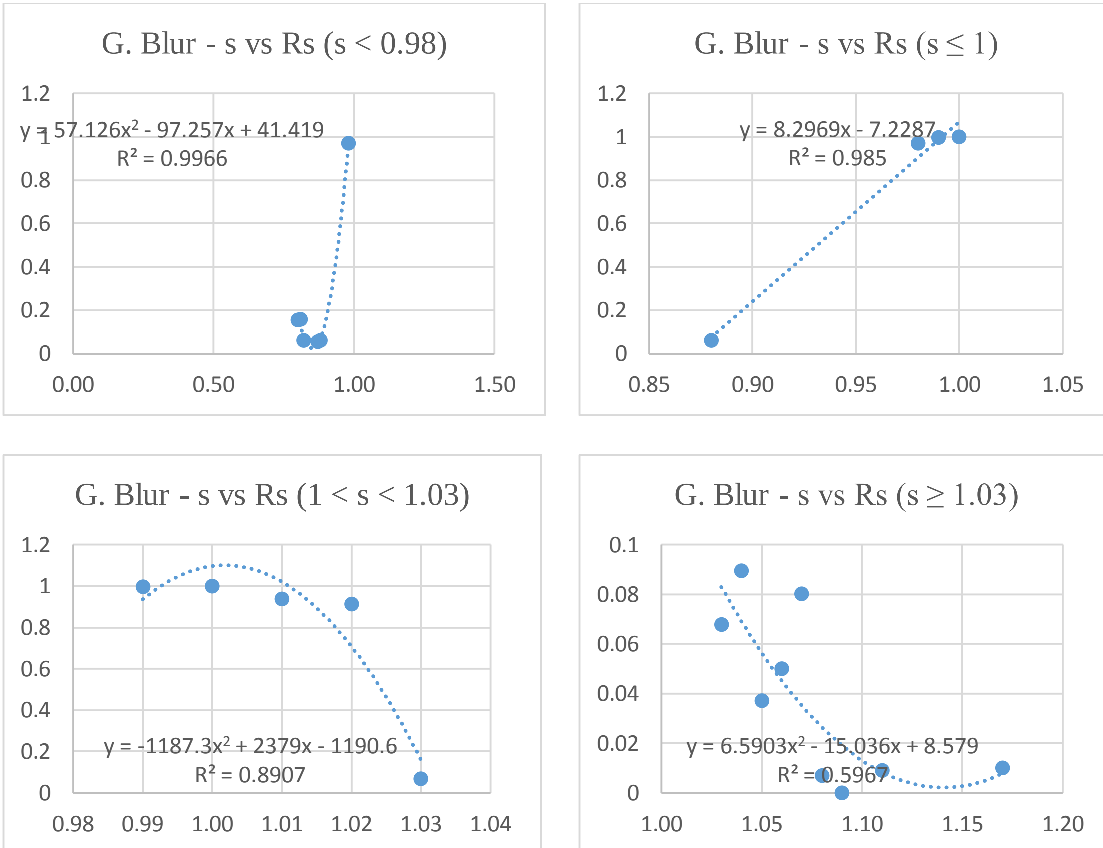
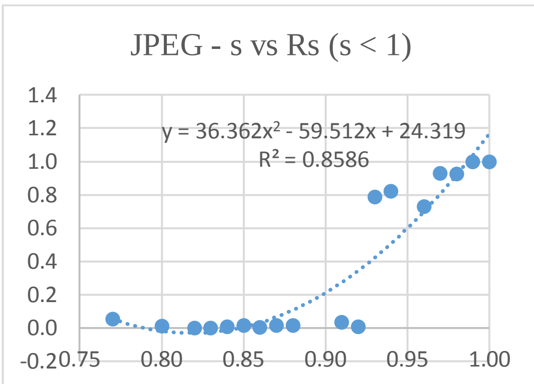


Figure 3-8: Graph plotted by s versus R_s^2 (Rs), for Gaussian Blur distortion.

The model yielded for Gaussian blur is

$$\hat{L} = \begin{cases} |57.126s^2 - 97.257s + 41.439| & if\ s < 0.98 \\ |8.2969s - 7.2487| & if\ 0.98 \leq s < 1 \\ 1 & if\ s = 1 \\ |-1187.3s^2 + 2379s - 1190.62| & if\ 1 < s < 1.03 \\ |6.5903s^2 - 15.036s + 8.599| & if\ s > 1.03 \end{cases} \tag{3. 9}$$

The regression equations of Gaussian blur stated, is obtained by plotting graphs of sigma value, s versus R_s^2 value. Figure 3-8 shows the graphs plotted for Gaussian Blur distortion, which is used to find the L value. Four sub-sections of graphs are plotted, where the first graph is plotted with *s* value less than 0.98, the second graph is plotted with *s* value less than 1 but greater than or equals to 0.98, the third graph is plotted with *s* value greater than 1 and less than 1.03, whereas the fourth graph is plotted with *s* value greater than or equals to 1.03. When *s* value equals to 1, no graph is plotted as *L* value equals to 1.



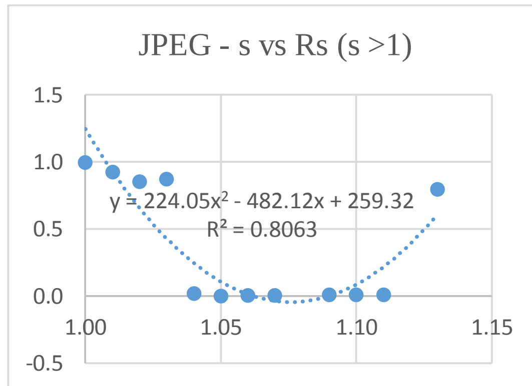


Figure 3-9: Graph plotted by *s* versus R_s^2 (Rs), for JPEG distortion.

The model yielded for JPEG is

$$\hat{L} = \begin{cases} |36.362s^2 - 59.512s + 24.349| & if\ s < 1 \\ 1 & if\ s = 1 \\ |224.05s^2 - 482.12s + 259.35| & if\ s > 1 \end{cases} \qquad (3.10)$$

The regression equations of JPEG stated, is obtained by plotting graphs of sigma value, *s* verses R_s^2 value. Figure 3-9 shows the graphs plotted for JPEG distortion, which is used to find the *L* value. Two sub-sections of graphs are plotted, where the first graph is plotted with *s* value less than 1, and the second graph is plotted with *s* value greater than 1. When *s* value equals to 1, no graph is plotted as *L* value equals to 1.

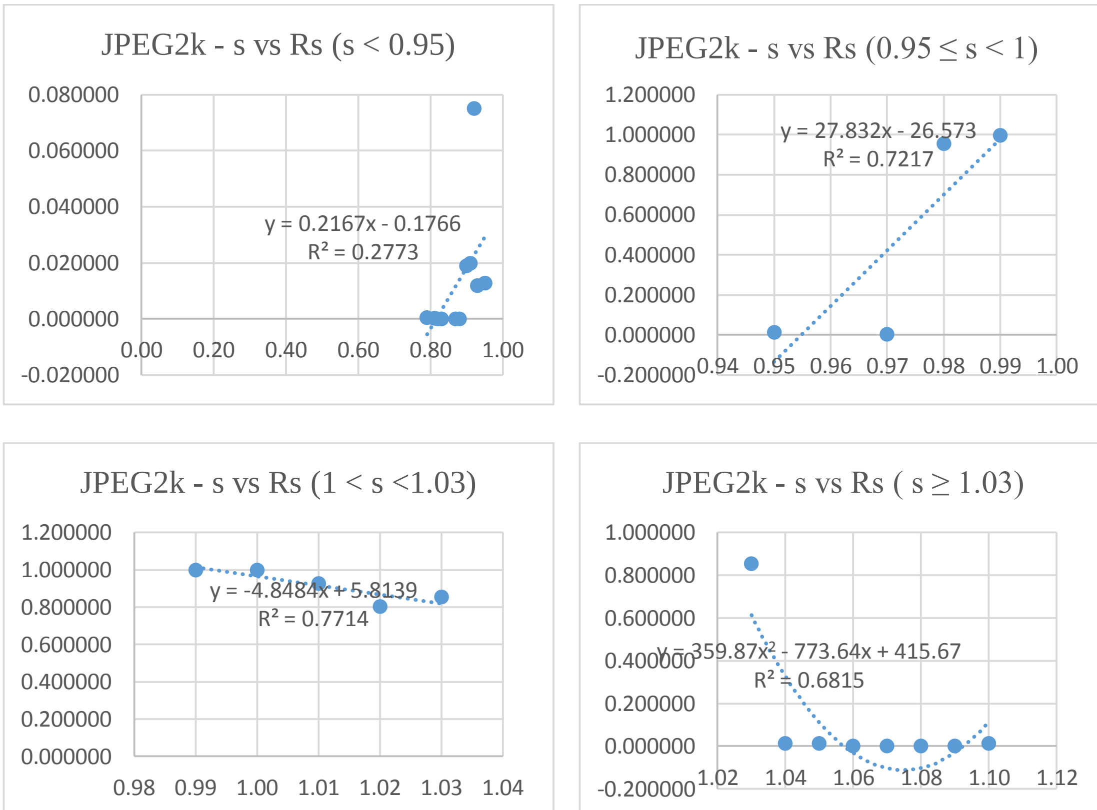


Figure 3-10: Graph plotted by s versus R_s^2 (Rs), for JPEG2000 distortion.

The model yielded for JPEG2000 is

$$\hat{L} = \begin{cases} |0.2167s - 0.2366| & if\ s < 0.95 \\ |27.832s - 26.633| & if\ 0.95 \leq s < 1 \\ 1 & if\ s = 1 \\ |-4.8484s + 5.8739| & if\ 1 < s \leq 1.03 \\ |359.87s^2 - 773.64s + 415.73| & if\ s > 1.03 \end{cases} \quad (3.11)$$

The regression equations of JPEG2000 stated, is obtained by plotting graphs of sigma value, s verses R_s^2 value. Figure 3-10 shows the graphs plotted for JPEG2000 distortion, which is used to find the *L* value. Four sub-sections of graphs are plotted, where the first graph is plotted with *s* value less than 0.95, the second graph is plotted with *s* value less than 1 but greater than or equals to 0.95, the third graph is plotted with *s* value greater than 1 and less than 1.03, whereas the fourth graph is plotted with *s* value greater than or equals to 1.03. When *s* value equals to 1, no graph is plotted as *L* value equals to 1.

3-5 Measuring the performance of IQM

A RR-IQA metrics is categorized as a good metrics when it satisfy three main properties, which are monotonicity, consistency, and accuracy. The monotonicity property can be judged by calculating the value of SRCC and KRCC. PLCC, MAE, and RMS are used to determine the accuracy of a RR-IQA metric. The consistency can be determined by observing the pattern of the graph plotted for results of different IQM. Therefore, a better IQA metric should have higher PLCC, SRCC and KRCC while lower MAE and RMS values.

3-5-1 Pearson linear correlation coefficient (PLCC)

Pearson linear correlation coefficient (PLCC), which was proposed by Karl Pearson from a related idea introduced by Francis Galton in the 1880s, is used to measure the strength of a linear relationship between two variables. The value of PLCC is always between -1 to 1. The linear relationship is strong when PLCC value is close to either -1 or 1, and is weak when close to 0. There is no linear relationship when PLCC value is 0. The positive and negative sign indicate the direction of the linear relationship. PLCC is defined as

$$PLCC = \frac{\sum_i (q_i - \bar{q}) * (o_i - \bar{o})}{\sqrt{\sum_i (q_i - \bar{q})^2 * \sum_i (o_i - \bar{o})^2}}$$

where o_i is the DMOS between reference and distorted images, and q_i is a nonlinear function.

3-5-2 Mean absolute error (MAE)

Mean absolute error (MAE) measures the average magnitude of errors in a set of estimation. The MAE is the average of absolute errors between a prediction and the true value, which in this study is between the reference image and distorted image. MAE is defined with an equation as follow

$$MAE = \frac{1}{N} \sum |q_i - o_i|$$

3-5-3 Root mean-squared (RMS) error

Root mean-squared (RMS) error is the square root of the average of the square of all error. It is often used to measure the differences between the predicted values of a model and the actually observed value. RMS can be defined as

$$RMS = \sqrt{\frac{1}{N}\sum (q_i - o_i)^2}$$

3-5-4 Spearman's rank correlation coefficient (SRCC)

The Spearman's rank correlation coefficient (SRCC) is used to measure the strength of the relationship between two sets of data. It is suitable for both discrete and continuous data. The SRCC is defined as

$$SRCC = 1 - \frac{6\sum_{i=1}^{N} d_i^2}{N(N^2 - 1)}$$

where d_i is the difference between i-th image's ranks in subjective and objective evaluations.

3-5-5 Kendall's rank correlation coefficient (KRCC)

The Kendall (1955) rank correlation coefficient is another non-parametric rank correlation metric that determine the similarity between two sets of rank given to same set of objects. The KRCC is given by

$$KRCC = \frac{N_c - N_d}{\frac{1}{2}N(N-1)}$$

where N_c and N_d are the numbers of consistent and inconsistent pairs in the data set, respectively.

3-6 Bit Rate of Distortions

In visual data and computing, the number of bits that are transmitted or processed per unit of time is called the bit rate. The bit rate is defined by calculating bits for each second. LIVE database provided each distortions with different bit rate. The higher the bit rate of distortion, the lower the quality of the image.

Different distortion has different range of bit rate value provided in LIVE database. Gaussian Blur has bit rate value between 0 and 14.9997. JPEG has bit rate value between 0 and 3.3336. The bit rate value of JPEG2000 is between 0 and 3.1539. Gaussian Noise has bit rate value between 0 and 1.9961, whereas Fast Fading has bit rate between 0 and 26.1. With different range of bit rate value given, we can say that if the bit rate value is near to 0, the distortion of distorted image is considered non-noticeable, which means that the quality of distorted image is relatively high.

CHAPTER 4

RESULTS AND DISCUSSION

Three different distortion types of imperfect reference image are used to test the image quality assessment metrics proposed. They are Gaussian Blur distortion, JPEG distortion, and JPEG2000 distortion. The sample data of Fast Fading distortion, and Gaussian Noise distortion type used as imperfect reference image are not included in this report, which is due to the inaccuracy of the L value obtained. The distorted images used are with different bit rate, which included a total of five types of distortion.

The table records the results of each pair of reference image and distorted images tested on each metrics used. Other than the RR-IQM proposed R_L^2 (RL), there are five other metrics that are involved in this study which used to make comparison. They are SSIM, PSNR, R_S^2 (Rs), estimated SSIM Ŝ (S_Dn), and DMOS value, which is given in LIVE database.

4-1 Performance of R_L^2 When Reference Image Has Gaussian Blur Distortion

Here, Gaussian Blur distorted image is used as imperfect reference image. In order to test the accuracy, consistency, and monotonicity of each of the RR-IQA applied to this distortion type of reduced reference image, different types of distorted image is tested with it. There are four types of distorted image being tested, which are JPEG, JPEG2000, Gaussian Noise, and Fast Fading distortion.

4-1-1 JPEG distorted image as compressed image

Table 4-1(a) used a perfect quality image as the reference while (b), (c), (d), (e) and (f) used a JPEG distorted image as the reference image. The bit rate of distortion increases from (b) to (f). The result value more than one is converted to one in this table. This is because the highest value qualified is one. From Table 4-1, we can see that the SSIM,R_F^2, PSNR, and R_L^2 value is decreasing gradually from (a) to (f).

SSIM is a metric designed for full reference image quality assessment. The value of SSIM decreases from (a) to (f) indicates that SSIM value is less effective when the reference image used has no perfect quality, and the bit rate of distortion increases.

The PSNR value decreases in value from (a) to (f). This is because PSNR is calculated by the mean square error of the two images involved. When the reference image is distorted, it could hardly give an accurate image quality assessment result.

Table 4-1: Results of each metrics applied on a JPEG distorted image, caps.bmp, with different level of bit rate. The imperfect reference image used is with Gaussian blur distortion. (a)Perfect quality image as reference. (b)Gaussian blur distorted image with bit rate 0.677051 as reference. (c)Gaussian blur distorted image with bit rate 1.164031 as reference. (d) Gaussian blur distorted image with bit rate 1.708303 as reference. (e) Gaussian blur distorted image with bit rate 3.083306 as reference. (f) Gaussian blur distorted image with bit rate 5.833312 as reference.

Bit Rate of G.Blur = 0

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	1	65535	0.955331	1	1	1	100
0.15312	0.75055	25.86641	0.809367	0.944352	0.91461	1	60.06954
0.1993	0.838527	29.4221	0.864707	0.975457	0.959459	1	49.85666
0.40535	0.956837	34.09477	0.930092	0.991667	1.022811	0.969551	40.20038
0.42483	0.960829	34.36081	0.930826	0.99216	1.022606	0.970228	42.87448
0.85118	0.989243	38.29867	0.900567	0.99684	1.047553	0.951589	28.3078

(a)

Bit Rate of G.Blur = 0.677051

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.98811	36.16914	0.954758	0.994885	1.049929	0.947574	100
0.15312	0.777268	26.79641	0.980614	0.95442	0.973515	0.980385	60.06954
0.1993	0.85596	30.83819	0.990581	0.982025	1.018688	0.96401	49.85666
0.40535	0.958556	34.85438	0.957608	0.992961	1.077901	0.921199	40.20038
0.42483	0.961855	34.96304	0.955887	0.993128	1.078035	0.92124	42.87448
0.85118	0.982217	35.7065	0.932128	0.994261	1.050922	0.946084	28.3078

(b)

Bit Rate of G.Blur = 1.164031

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.955954	31.70434	0.951516	0.985561	1.000461	0.985107	100
0.15312	0.79836	27.09293	0.999389	0.957153	0.998243	0.958838	60.06954
0.1993	0.857682	30.47073	0.99869	0.980376	1.043551	0.939462	49.85666
0.40535	0.93781	32.0805	0.953872	0.986649	1.050719	0.939023	40.20038
0.42483	0.940243	32.06473	0.952134	0.986584	1.051032	0.938681	42.87448
0.85118	0.953256	31.80884	0.932489	0.985841	1.002024	0.98385	28.3078

(c)

Bit Rate of G.Blur = 1.708303

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.919171	29.76012	0.920504	0.97731	1.002991	0.974396	100

0.15312	0.80847	27.00901	0.999761	0.956145	0.997198	0.958831	60.06954
0.1993	0.845062	29.52151	0.996447	0.975542	1.0425	0.935772	49.85666
0.40535	0.906951	30.18129	0.92381	0.979265	1.052305	0.93059	40.20038
0.42483	0.908739	30.15227	0.921105	0.979098	1.052611	0.930162	42.87448
0.85118	0.917651	29.87137	0.890639	0.977797	1.004531	0.973387	28.3078

(d)

Bit Rate of G.Blur = 3.083306

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.852187	27.54849	0.861114	0.96207	0.892852	1	100
0.15312	0.800037	26.26837	0.999473	0.947724	1.033336	0.91715	60.06954
0.1993	0.802469	27.67737	0.993017	0.962494	1.080058	0.891149	49.85666
0.40535	0.844566	27.86098	0.867038	0.964481	0.974968	0.989243	40.20038
0.42483	0.845674	27.84127	0.862382	0.964275	0.975538	0.988455	42.87448
0.85118	0.851185	27.63827	0.809443	0.962708	0.89523	1	28.3078

(e)

Bit Rate of G.Blur = 5.833312

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.769698	25.25396	0.786669	0.935269	1.026541	0.911088	100
0.15312	0.752876	24.70845	0.999114	0.924701	0.8933	1	60.06954
0.1993	0.734077	25.42786	0.989045	0.936735	0.938032	0.998618	49.85666
0.40535	0.764098	25.45758	0.795599	0.93787	1.001218	0.936729	40.20038
0.42483	0.764841	25.44907	0.788459	0.937682	1.001014	0.936733	42.87448
0.85118	0.768765	25.32062	0.707046	0.936031	1.025895	0.912404	28.3078

(f)

Besides, the value of R_S^2 and R_L^2 also show a decrease from Table 4-1(a) to (f). However, the decreasing of the average value is small. The distortion is non-noticeable because the bit rate of distorted image is relatively small, which indicates that the distorted image is considered high quality. Therefore, the result value is close to 1 although the bit rate is the highest here. This shows that both R_S^2 and R_L^2 are suitable for reduced reference image quality assessment. However, from (f), we can see that R_L^2 provided a better result thanR_S^2.

The Ŝ value calculated from D_n value has inconsistent changes in value, as we can see from Table 4-1 (a) to (f).The Ŝ values increase while some decrease inconsistently.

This indicates that the estimated SSIM, Ŝ is inaccurate and ineffective for reduced reference image quality assessment.

As what we can see in Table 4-1 (f), the value of each metric results is inconsistently small. This indicates that an imperfect reference image with a higher bit rate of distortion will affect the accuracy of a RR-IQA. However, the results for R_L^2 decrease in a consistent way.

Table 4-2: Results of each metrics used to judge the performance of RR-IQA metrics used.

	Bit Rate	PLCC	MAE	RMSE	SRCC	KRCC
DMOS vs SSIM	0	0.018983	53.55148	57.39575	-0.08571	-0.2
	0.677051	-0.00584	53.55148	57.39232	-0.08571	-0.2
	1.164031	-0.02299	53.55148	57.40499	-0.08571	-0.2
	1.708303	-0.02322	53.55148	57.42581	-0.08571	-0.2
	3.083306	0.013123	53.55148	57.47266	-0.08571	-0.2
	5.833312	0.100773	53.55148	57.53982	-0.02857	-0.06667
DMOS vs S_Dn	0	0.203077	53.55148	57.40849	0.085714	0.066667
	0.677051	0.213667	53.55148	57.35263	0.314286	0.2
	1.164031	0.166832	53.55148	57.35004	0.371429	0.333333
	1.708303	0.166157	53.55148	57.36977	0.371429	0.333333
	3.083306	0.165412	53.55148	57.40751	0.371429	0.333333
	5.833312	0.166106	53.55148	57.45493	0.371429	0.333333
DMOs vs Rs	0	0.001028	53.55148	57.33454	-0.08571	-0.2
	0.677051	-0.07851	53.55148	57.33329	-0.08571	-0.2
	1.164031	-0.1364	53.55148	57.33793	-0.65714	-0.46667
	1.708303	-0.16844	53.55148	57.34355	-0.65714	-0.46667
	3.083306	-0.20817	53.55148	57.35593	-0.77143	-0.6
	5.833312	-0.24557	53.55148	57.37965	-0.6	-0.46667
DMOS vs RL	0	0.74185	53.55148	57.33029	0.941124	0.894427
	0.677051	0.281114	53.55148	57.36578	0.657143	0.466667
	1.164031	0.408432	53.55148	57.35501	0.371429	0.333333
	1.708303	0.428249	53.55148	57.36144	0.371429	0.333333
	3.083306	0.021625	53.55148	57.35169	-0.23191	-0.27603
	5.833312	-0.07774	53.55148	57.36702	0.142857	0.333333

Table 4-2 shows the performance for each RR-IQA metrics on different level of distortion, which use DMOS values as a standard comparison. As mentioned in the methodology, a good RR-IQA need to have lower MAE and RMS values, while higher PLCC, SRCC and KRCC values. In Table 4-2, the lowest MAE and RMS values is highlighted with red color, while the highest PLCC, SRCC, and KRCC values is highlighted with blue color.

From Table 4-2, we can see that all of the blue color is highlighted in the "DMOS vs RL" row and "DMOS vs Rs" row. PLCC judge that R_L^2 has a better performance than R_S^2, as there is more highest PLCC value in "DMOS vs RL" row. However, SRCC and KRCC show that R_S^2 has a better performance.

All the MAE values are the same, in Table 4-2. This is because MAE is the average of absolute errors between a prediction and the true value. The prediction and true value of each data set used is same, as the data are from same image, which is Caps.bmp.

RMS do not show a priority result between $R_L^2$and R_S^2, as the total number of lowest value found for each metrics is the same.

In overall, Table 4-2 shows that when a perfect quality reference image is used, R_L^2 performed the best among all. On the other hand, when the reference image has the highest distortion level, R_S^2 has the best performance.

SSIM and estimated SSIM, Ŝ have the worst results, in Table 4-2. This may due to both of the metrics are designed for a full reference image quality assessment. When they come to reduced reference image assessment, the performance will gradually decreases.

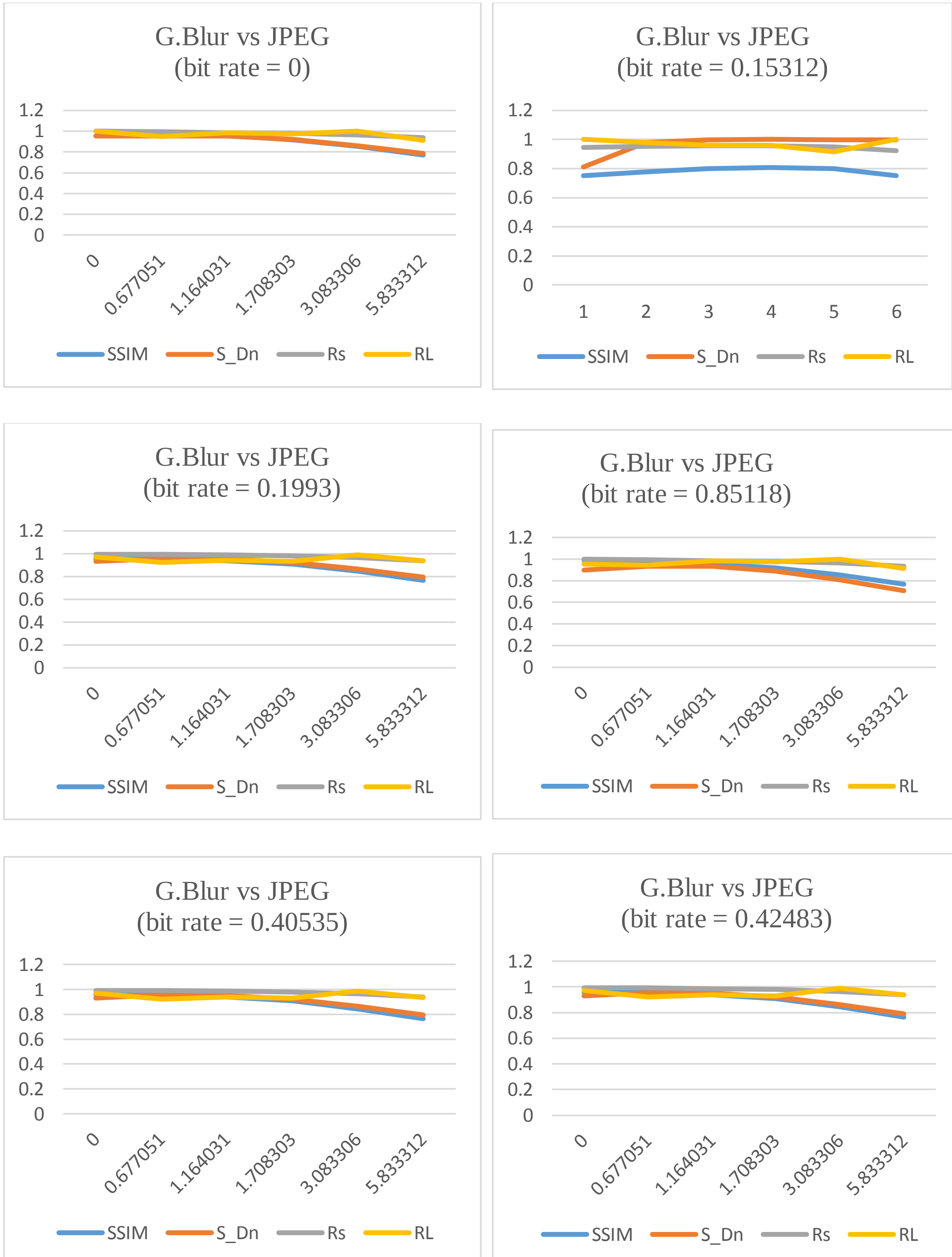


Figure 4-1: Graph plotted by IQM results versus bit rate of imperfect reference image. It is to show the relationship of each metrics, with different bit rate value of JPEG distorted value, and different level of distortion for Gaussian blur distorted reference image.

In Figure 4-1, it shows the graph plotted for each metrics with different bit rate value of distortion. The graph is used to show the performance of each metrics when the bit rate value of JPEG distorted image is increasing in each graph, and the Gaussian blur imperfect reference image has different distortion value, which is in x-axis. The flatter the pattern of the graph, indicates a better consistency of the IQM tested.

From Figure 4-1, R_L^2 has a better performance as compared to other metrics, when JPEG distorted image has a perfect quality or with bit rate 0 and 0.15312. For other JPEG distorted image, R_S^2 has an average of better consistency. Here, we can say that R_L^2 and R_S^2 provide a more consistent assessment to Gaussian blur distorted reduced reference image.

In overall, the performance of R_S^2 and R_L^2 are the best when compared to the other metrics included, when the reference image has Gaussian blur distortion is compared to JPEG distorted image.

4-1-2 JPEG2000 distorted image as compressed image

Table 4-3(a) used a perfect quality image as the reference while (b), (c), (d), (e) and (f) used a JPEG2000 distorted image as the reference image. The bit rate of distortion increases from (b) to (f). The result value more than one is converted to one in this table. This is because the highest value qualified is one. From Table 4-3, we can see that the SSIM,R_F^2, PSNR, and R_L^2 value is decreasing gradually from (a) to (f).

SSIM is a metric designed for full reference image quality assessment. The value of SSIM decreases from (a) to (f) for each of the different bit rate for Gaussian blur reference image. This indicates that SSIM value is less effective when the reference image used has no perfect quality, and the bit rate of distortion increases.

The PSNR value decreases in value from (a) to (f). This is because PSNR is calculated by the mean square error of the two images involved. When the reference image is distorted, it could hardly give an accurate image quality assessment result.

Table 4-3: Results of each metrics applied on a JPEG2000 compressed image, caps.bmp, with different level of bit rate. The imperfect reference image used is with Gaussian Blur distortion. (a)Perfect quality image as reference. (b)Gaussian Blur distorted image with bit rate 0.677051 as reference. (c)Gaussian Blur distorted image with bit rate 1.164031 as reference. (d)Gaussian Blur distorted image with bit rate 1.708303 as reference. (e)Gaussian Blur distorted image with bit rate 3.083306 as reference. (f)Gaussian Blur distorted image with bit rate 5.833312 as reference.

Bit Rate of G.Blur = 0

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	1	65535	0.968702	1	1	1	100
0.050378	0.831895	28.98727	0.845755	0.972697	0.941349	1	56.81507
0.098741	0.889199	30.8188	0.928655	0.982177	0.966907	1	53.4561
0.19944	0.929898	33.27789	0.945545	0.989921	0.990785	0.999128	46.58432
0.40137	0.964494	36.69453	0.931831	0.995423	1.031065	0.965432	34.49728
0.60354	0.977638	39.26188	0.936601	0.997469	1.043332	0.956042	26.6733

(a)

Bit Rate of G.Blur = 0.677051

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.98811	36.16914	0.962885	0.994885	1.049929	0.947574	100
0.050378	0.867478	31.23329	0.976932	0.983349	1.000447	0.982909	56.81507
0.098741	0.918368	33.20056	0.991017	0.989481	1.026189	0.964229	53.4561
0.19944	0.946333	34.63151	0.973474	0.992504	1.08101	0.918127	46.58432
0.40137	0.968186	35.52851	0.946538	0.993978	1.071281	0.927841	34.49728
0.60354	0.975993	35.71695	0.943858	0.994272	1.05704	0.94062	26.6733

(b)

Bit Rate of G.Blur = 1.164031

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.955954	31.70434	0.954946	0.985561	1.000461	0.985107	100
0.050378	0.898963	32.2477	0.995877	0.986668	1.025255	0.962364	56.81507
0.098741	0.934541	33.02777	0.991214	0.989003	1.081382	0.914574	53.4561
0.19944	0.944068	32.62334	0.966312	0.988091	1.081746	0.913422	46.58432

0.40137	0.951464	32.14243	0.941224	0.986833	1.036868	0.951744	34.49728
0.60354	0.953583	31.86576	0.937583	0.986025	1.011855	0.974472	26.6733

(c)

Bit Rate of G.Blur = 1.708303

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.919171	29.76012	0.93078	0.97731	1.002991	0.974396	100
0.050378	0.918336	32.15909	0.995143	0.986341	1.024207	0.963028	56.81507
0.098741	0.934333	31.81161	0.984653	0.98545	1.08091	0.911686	53.4561
0.19944	0.928354	30.87118	0.946939	0.98215	1.08215	0.907592	46.58432
0.40137	0.925222	30.23945	0.910937	0.979535	1.038761	0.942984	34.49728
0.60354	0.923177	29.95207	0.905541	0.978209	1.014205	0.964509	26.6733

(d)

Bit Rate of G.Blur = 3.083306

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.852187	27.54849	0.879018	0.96207	0.892852	1	100
0.050378	0.919728	30.31181	0.99142	0.979146	1.08391	0.903347	56.81507
0.098741	0.903194	29.2993	0.972439	0.974056	1.075095	0.906019	53.4561
0.19944	0.882801	28.44585	0.906914	0.96873	1.045904	0.926213	46.58432
0.40137	0.868323	27.92243	0.844752	0.964981	0.950781	1	34.49728
0.60354	0.861787	27.69965	0.835396	0.963244	0.91037	1	26.6733

(e)

Bit Rate of G.Blur = 5.833312

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.769698	25.25396	0.806571	0.935269	1.026541	0.911088	100
0.050378	0.867239	27.14056	0.98622	0.956737	0.919969	1	56.81507
0.098741	0.82954	26.35671	0.955657	0.948726	0.94546	1	53.4561
0.19944	0.807126	25.83444	0.850843	0.942673	0.969276	0.972554	46.58432
0.40137	0.789069	25.49545	0.751564	0.93842	1.009451	0.929634	34.49728
0.60354	0.780574	25.35055	0.736621	0.936494	1.021686	0.916617	26.6733

(f)

The value of R_S^2 also show a decrease from Table 4-3(a) to (f). However, the decreasing of the average value is small. This shows that R_S^2 is suitable for reduced reference image quality assessment. On the other hand, the values of R_F^2 fluctuated inconsistently from Table 4-3 (a) to (f). However, from (f), we can see that R_L^2 provided a better result thanR_S^2 in overall. The distortion is non-noticeable because the bit rate of distorted image is relatively small, which indicates that the distorted image is considered high quality. Therefore, the result value is close to 1 although the bit rate is the highest here.

The $\hat{S}$ value calculated from D_n value decreases in overall, as we can see from Table 4-3 (a) to (f). However, the $\hat{S}$ value is less than the value of R_S^2 and R_F^2 in general. This indicates that the estimated SSIM, $\hat{S}$ is less accurate and less effective for this assessment.

As what we can see in Table 4-3 (f), the value of each metric results is smaller than the previous results. This means that a Gaussian blur distorted reference image with a higher bit rate of JPEG2000 distortion will affect the accuracy of a RR-IQA. However, the results for R_L^2has the highest value among all metrics.

Table 4-4 shows the performance for each RR-IQA metrics on different level of distortion, which use DMOS values as a standard comparison. As mentioned in the methodology, a good RR-IQA need to have lower MAE and RMS values, and higher PLCC, SRCC and KRCC values. In Table 4-4, the lowest MAE and RMS values is highlighted with red color, while the highest PLCC, SRCC, and KRCC values is highlighted with blue color.

From Table 4-4, we can see that most of the blue color is highlighted in the "DMOS vs S_Dn" row and the second most is highlighted in "DMOS vs RL" row. PLCC judge that the estimated SSIM, $\hat{S}$ has a better performance, as there are more highest PLCC value in "DMOS vs RL" row. Besides, SRCC and KRCC also show that estimated SSIM, $\hat{S}$ has a better performance.

All the MAE values are the same in Table 4-4. This is because MAE is the average of absolute errors between a prediction and the true value. The prediction and true value of each data set used is same, as the data are from same image, which is Caps.bmp. RMS shows a priority result in R_S^2, as the total number of lowest value found in "DMOS vs Rs" row is the largest.

Table 4-4: Results of each metrics used to judge the performance of RR-IQA metrics used.

	Bit Rate	PLCC	MAE	RMSE	SRCC	KRCC
DMOS vs SSIM	0	0.124935	53.00435	57.10726	-0.14286	-0.33333
	0.677051	0.080613	53.00435	57.09798	-0.14286	-0.33333
	1.164031	-0.00182	53.00435	57.10328	-0.14286	-0.33333
	1.708303	-0.35411	53.00435	57.11773	-0.37143	-0.06667
	3.083306	-0.1405	53.00435	57.1579	0.142857	0.333333
	5.833312	-0.10464	53.00435	57.22557	0.142857	0.333333
DMOS vs S_Dn	0	0.220785	53.00435	57.11218	0.028571	-0.06667
	0.677051	0.340524	53.00435	57.0772	0.6	0.466667
	1.164031	0.255097	53.00435	57.07832	0.657143	0.6
	1.708303	0.249044	53.00435	57.09439	0.657143	0.6
	3.083306	0.24815	53.00435	57.12895	0.657143	0.6
	5.833312	0.248973	53.00435	57.1774	0.657143	0.6
DMOs vs Rs	0	0.077527	53.00435	57.05751	-0.14286	-0.33333
	0.677051	0.003202	53.00435	57.05617	-0.14286	-0.33333
	1.164031	-0.27829	53.00435	57.0603	-0.2	-0.06667
	1.708303	-0.11888	53.00435	57.06538	0.142857	0.333333
	3.083306	-0.06619	53.00435	57.07704	0.142857	0.333333
	5.833312	-0.04709	53.00435	57.10041	0.142857	0.333333
DMOS vs RL	0	0.688516	53.00435	57.05514	0.941124	0.894427
	0.677051	0.2879	53.00435	57.0942	0.6	0.333333
	1.164031	0.318734	53.00435	57.09006	0.257143	0.2
	1.708303	0.326821	53.00435	57.09587	0.257143	0.2
	3.083306	0.010016	53.00435	57.08835	-0.39466	-0.44721
	5.833312	-0.09579	53.00435	57.09087	0.115954	0.276026

In overall, Table 4-4 shows that when a perfect quality reference image is used, R_L^2 performed the best among all. On the other hand, when the reference image has the highest distortion level, the estimated SSIM, Ŝ has the best performance.

SSIM have the worst results, in Table 4-4. This may due to it is designed for a full reference image quality assessment. When it comes to reduced reference image quality assessment, the performance will gradually decreases.

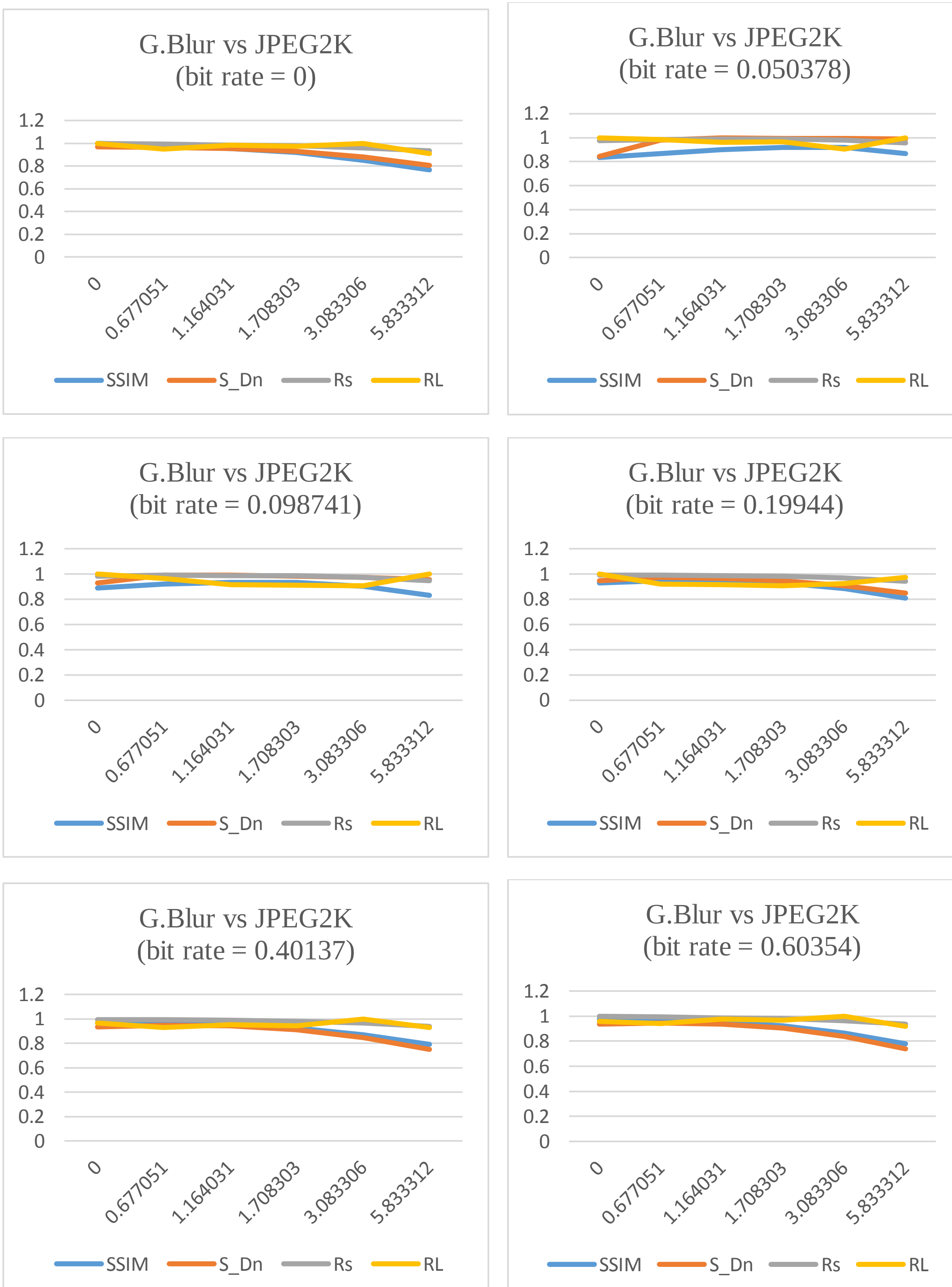


Figure 4-2: Graph plotted by IQM results versus bit rate of imperfect reference image. It is to show the relationship of each metrics, with different bit rate value of JPEG2000 distorted value, and different level of distortion for Gaussian Blur distorted reference image.

In Figure 4-2, it shows the graph plotted for each metrics with different bit rate value of distortion. The graph is used to show the performance of each metrics when the bit rate value of JPEG2000 distorted image is increasing in each graph, and the Gaussian blur distorted reference image has different distortion value, which is in x-axis of the graph. The flatter the pattern of the graph, indicates a better consistency of the IQM tested.

From Figure 4-2, R_S^2 has a better consistency as compared to other metrics, when JPEG distorted image is used as the reference image, followed by R_L^2, Here, we can say that R_S^2 provide a more accurate assessment to higher level of Gaussian blur reduced reference image.

In overall, the performance of the R_S^2 are the best as compared to the other metrics included, when the reference image has Gaussian blur distortion is compared to JPEG2000 distorted image.

4-1-3 Gaussian Noise distorted image as compressed image

Table 4-5(a) shows the use of a perfect quality image as the reference while (b), (c), (d), (e) and (f) used a Gaussian blur distorted image as the reference image. The bit rate of distortion increases from (b) to (f). The result value more than one is converted to one in this table. This is because the highest value qualified is one. From Table 4-5, we can see that the SSIM, R_F^2, PSNR, and R_L^2 value is decreasing gradually from (a) to (f).

SSIM is a metric designed for full reference image quality assessment. The value of SSIM decreases from (a) to (f) for each of the different bit rate for Gaussian blur reference image. This indicates that SSIM value is less effective when the reference image used has no perfect quality, and the bit rate of distortion increases.

The PSNR value decreases in value from (a) to (f). This is because PSNR is calculated by the mean square error of the two images involved. When the reference image is distorted, it could hardly give an accurate image quality assessment result.

Table 4-5: Results of each metrics applied on Gaussian Noise distorted image, caps.bmp. (a)Perfect quality image as reference. (b)Gaussian Blur distorted image with bit rate 0.677051 as reference. (c)Gaussian Blur distorted image with bit rate 1.164031 as reference. (d)Gaussian Blur distorted image with bit rate 1.708303 as reference. (e)Gaussian Blur distorted image with bit rate 3.083306 as reference. (f)Gaussian Blur distorted image with bit rate 5.833312 as reference.

Bit Rate of G.Blur = 0

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	1	65535	0.948758	1	1	1	100
0.015625	0.982878	39.55768	0.95635	0.997643	1.037724	0.961376	22.50337
0.03125	0.937012	33.61711	0.884508	0.990815	1.002782	0.988066	33.54177
0.0625	0.801863	27.65342	0.747118	0.964984	0.909943	1	41.3394
0.125	0.548208	21.75995	0.60953	0.87853	0.746509	1	48.03932
1	0.086885	10.31411	0.086594	0.198253	0.14375	1	67.38191

(a)

Bit Rate of G.Blur = 0.677051

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.98811	36.16914	0.825551	0.994885	1.049929	0.947574	100
0.015625	0.970982	34.56806	0.947825	0.992588	1.064204	0.932705	22.50337
0.03125	0.924787	31.74925	0.934237	0.985874	1.084049	0.909436	33.54177
0.0625	0.787781	27.10482	0.842322	0.96018	0.968815	0.991087	41.3394
0.125	0.533796	21.62159	0.686164	0.874204	0.837226	1	48.03932
1	0.084027	10.32709	0.054933	0.197344	0.176888	1	67.38191

(b)

Bit Rate of G.Blur = 1.164031

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.955954	31.70434	0.646223	0.985561	1.000461	0.985107	100
0.015625	0.938991	31.07492	0.848326	0.98332	1.023947	0.960323	22.50337
0.03125	0.893338	29.60307	0.895901	0.976737	1.074353	0.90914	33.54177
0.0625	0.757371	26.24962	0.872055	0.951309	0.993528	0.957506	41.3394
0.125	0.508428	21.37179	0.737976	0.866214	0.876948	0.987759	48.03932

1	0.080194	10.32946	0.13606	0.19558	0.192213	1	67.38191

(c)

Bit Rate of G.Blur = 1.708303

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.919171	29.76012	0.594467	0.97731	1.002991	0.974396	100
0.015625	0.902473	29.35532	0.815393	0.975121	1.026088	0.950328	22.50337
0.03125	0.857599	28.31999	0.875686	0.968631	1.075199	0.900885	33.54177
0.0625	0.723638	25.61696	0.867443	0.943476	0.992483	0.950622	41.3394
0.125	0.481207	21.16344	0.737645	0.859143	0.87525	0.981597	48.03932
1	0.07637	10.33121	0.145666	0.193957	0.191549	1	67.38191

(d)

Bit Rate of G.Blur = 3.083306

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.852187	27.54849	0.558907	0.96207	0.892852	1	100
0.015625	0.836078	27.31014	0.797405	0.959977	0.929507	1	22.50337
0.03125	0.792935	26.64351	0.863941	0.953639	1.023597	0.931655	33.54177
0.0625	0.663245	24.64884	0.857726	0.928985	1.028601	0.903154	41.3394
0.125	0.432563	20.80499	0.720564	0.84608	0.934989	0.904909	48.03932
1	0.069368	10.33642	0.090747	0.191011	0.215397	0.886787	67.38191

(e)

Bit Rate of G.Blur = 5.833312

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.769698	25.25396	0.520709	0.935269	1.026541	0.911088	100
0.015625	0.754361	25.11933	0.779552	0.933312	1.016093	0.918531	22.50337
0.03125	0.713773	24.71051	0.851599	0.927188	0.981241	0.944914	33.54177
0.0625	0.591	23.3458	0.84575	0.90342	0.888645	1	41.3394
0.125	0.375574	20.24025	0.698071	0.823054	0.715047	1	48.03932
1	0.060301	10.34148	0.016288	0.185731	0.132931	1	67.38191

(f)

The value of R_S^2 also show a decrease from Table 4-5(a) to (f). However, the decreasing of the average value is small. This shows that R_S^2 is suitable for reduced reference image quality assessment. On the other hand, the values of R_L^2 fluctuated inconsistently from Table 4-5(a) to (f). However, from (f), we can see that R_L^2 provided a better result thanR_S^2 in overall, especially for the highest value of Gaussian Noise bit rate value. The distortion is non-noticeable because the bit rate of distorted image is relatively small, which indicates that the distorted image is considered high quality. Therefore, the result value is close to 1 although the bit rate is the highest here.

The $\hat{S}$ value calculated from D_n value decreases in overall, as we can see from Table 4-5 (a) to (f). However, the $\hat{S}$ value is less than the value of R_S^2 and R_F^2 in general. This indicates that the estimated SSIM, $\hat{S}$ is less accurate and less effective for this assessment.

As what we can see in Table 4-5 (f), the value of each metric results is smaller than the previous results. This means that a Gaussian blur distorted reference image with a higher bit rate of Gaussian Noise distortion will affect the accuracy of a RR-IQA. However, the results for R_L^2 has the highest value among all metrics.

Table 4-6 shows the performance for each RR-IQA metrics on different level of distortion, which use DMOS values as a standard comparison. As mentioned in the methodology, a good RR-IQA need to have lower MAE and RMS values, and higher PLCC, SRCC and KRCC values. In Table 4-6, the lowest MAE and RMS values is highlighted with red color, while the highest PLCC, SRCC, and KRCC values is highlighted with blue color.

From Table 4-6, we can see that most of the blue color is highlighted in the "DMOS vs S_Dn" row and the second most is highlighted in "DMOS vs RL" row. PLCC judge that the estimated SSIM, $\hat{S}$ has a better performance, as there are more highest PLCC value in "DMOS vs RL" row. Besides, SRCC and KRCC also show that estimated SSIM, $\hat{S}$ has a better performance.

All the MAE values are the same in Table 4-4. This is because MAE is the average of absolute errors between a prediction and the true value. The prediction and true value of each data set used is same, as the data are from same image, which is Caps.bmp. On the other hand, RMS shows a priority result in R_L^2, as all of the lowest value found in "DMOS vs RL" row.

Table 4-6: Results of each metrics used to judge the performance of RR-IQA metrics used.

	Bit Rate	PLCC	MAE	RMSE	SRCC	KRCC
DMOS vs SSIM	0	-0.16678	52.1343	57.37961	-0.14286	-0.33333
	0.677051	-0.16462	52.1343	57.38914	-0.14286	-0.33333
	1.164031	-0.16204	52.1343	57.4112	-0.14286	-0.33333
	1.708303	-0.15938	52.1343	57.43593	-0.14286	-0.33333
	3.083306	-0.15456	52.1343	57.48069	-0.14286	-0.33333
	5.833312	-0.14884	52.1343	57.53523	-0.14286	-0.33333
DMOS vs S_Dn	0	-0.1867	52.1343	57.39904	-0.42857	-0.46667
	0.677051	-0.36244	52.1343	57.41475	-0.82857	-0.73333
	1.164031	-0.53098	52.1343	57.44983	-0.77143	-0.6
	1.708303	-0.57116	52.1343	57.46744	-0.77143	-0.6
	3.083306	-0.5773	52.1343	57.49413	-0.77143	-0.6
	5.833312	-0.57851	52.1343	57.52646	-0.77143	-0.6
DMOs vs Rs	0	-0.25166	52.1343	57.2872	-0.14286	-0.33333
	0.677051	-0.25176	52.1343	57.29079	-0.14286	-0.33333
	1.164031	-0.25186	52.1343	57.29741	-0.14286	-0.33333
	1.708303	-0.25194	52.1343	57.30327	-0.14286	-0.33333
	3.083306	-0.25208	52.1343	57.3141	-0.14286	-0.33333
	5.833312	-0.25227	52.1343	57.33319	-0.14286	-0.33333
DMOS vs RL	0	0.631012	52.1343	57.11294	0.845154	0.774597
	0.677051	0.233634	52.1343	57.13841	0.579771	0.414039
	1.164031	0.585122	52.1343	57.13149	0.657143	0.466667
	1.708303	0.561411	52.1343	57.13766	0.771429	0.6
	3.083306	0.139721	52.1343	57.16228	-0.23191	-0.27603
	5.833312	-0.13756	52.1343	57.14542	0.030359	0.149071

In overall, Table 4-6 shows that when a perfect quality reference image is used, R_L^2 performed the best among all. On the other hand, when the reference image has the highest distortion level, the estimated SSIM, Ŝ has the best performance.

SSIM have the worst results, in Table 4-6. This may due to it is designed for a full reference image quality assessment. When it comes to reduced reference image quality assessment, the performance will gradually decreases.

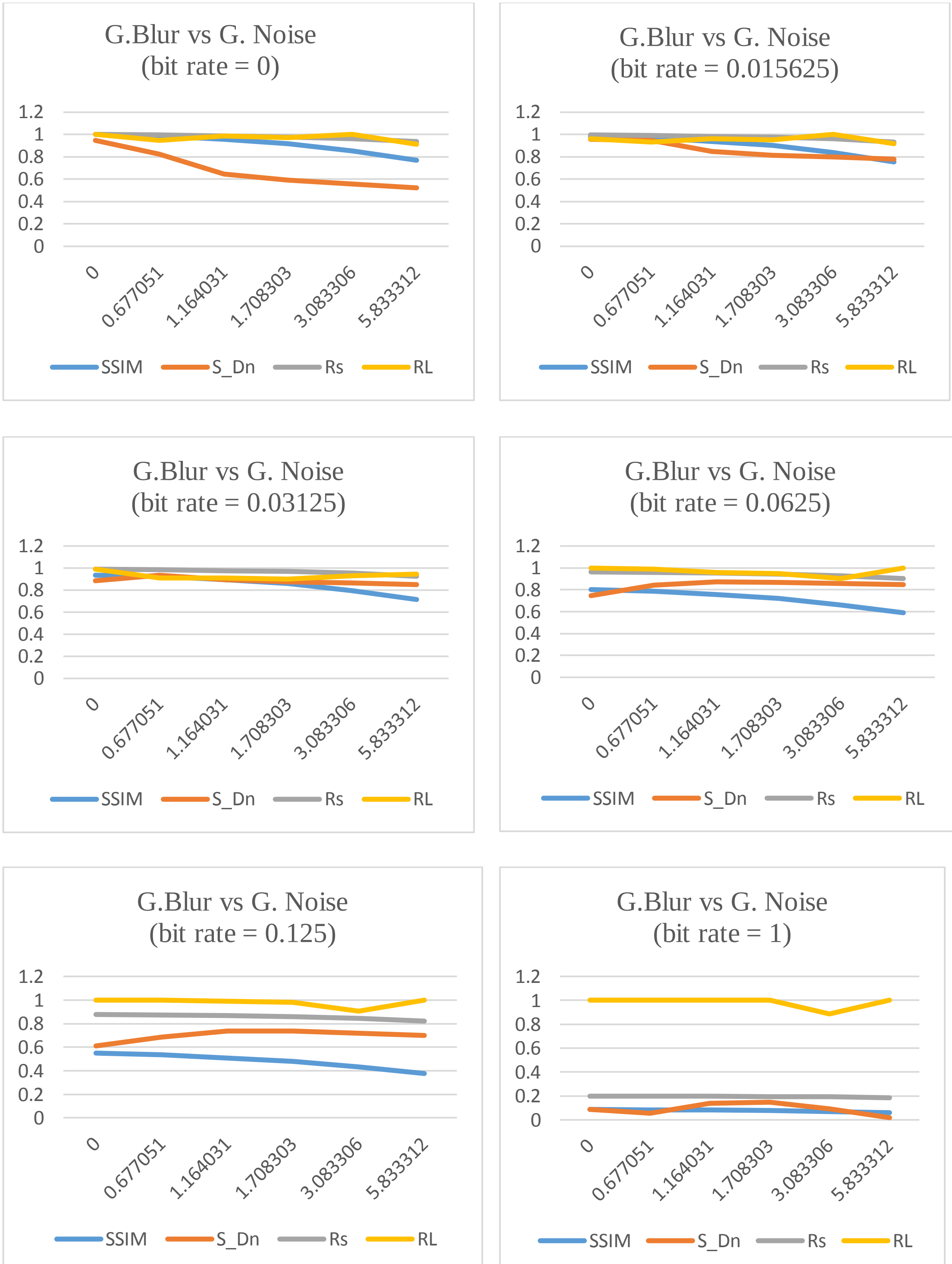


Figure 4-3: Graph plotted by IQM results versus bit rate of imperfect reference image. It is to show the relationship of each metrics, with different bit rate value of Gaussian Noise distorted value, and different level of distortion for Gaussian blur distorted reference image.

In Figure 4-3, it shows the graph plotted for each metrics with different bit rate value of distortion. The graph is used to show the performance of each metrics when the bit rate value of Gaussian Noise distorted image is increasing, and the Gaussian Blur distorted reference image has different distortion value, which is in x-axis of the graph. The flatter the pattern of the graph, indicates a better consistency of the IQM tested.

From Figure 4-3, R_L^2 has a better consistency as compared to other metrics, for the lower bit rate of Gaussian Noise distorted image. R_S^2 has better consistency when the Gaussian Noise distorted images has higher bit rate distortion. Here, we can say that R_L^2 provide a consistent assessment to Gaussian Blur reduced reference image.

In overall, the performance of the R_L^2 are the best as compared to the other metrics included, when the reference image has Gaussian Blur distortion is compared to Gaussian Boise distorted image.

4-1-4 Fast Fading distorted image as compressed image

Table 4-7(a) used a perfect quality image as the reference while (b), (c), (d), (e) and (f) used a fast fading distorted image as the reference image. The bit rate of distortion increases from (b) to (f). The result value more than one is converted to one in this table. This is because the highest value qualified is one. From Table 4-7, we can see that the SSIM, R_F^2, PSNR, and R_L^2 value is decreasing gradually from (a) to (f).

SSIM is a metric designed for full reference image quality assessment. The value of SSIM decreases from (a) to (f) for each of the different bit rate for Gaussian blur reference image. This indicates that SSIM value is less effective when the reference image used has no perfect quality, and the bit rate of distortion increases.

The PSNR value decreases in value from (a) to (f). This is because PSNR is calculated by the mean square error of the two images involved. When the reference image is distorted, it could hardly give an accurate image quality assessment result.

Table 4-7: Results of each metrics applied on a Fast Fading compressed image, caps.bmp, with different level of bit rate. The imperfect reference image used is with Gaussian blur distortion. (a)Perfect quality image as reference. (b)Gaussian Blur distorted image with bit rate 0.677051 as reference. (c)Gaussian Blur distorted image with bit rate 1.164031 as reference. (d) Gaussian Blur distorted image with bit rate 1.708303 as reference. (e)Gaussian Blur distorted image with bit rate 3.083306 as reference. (f) Gaussian Blur distorted image with bit rate 5.833312 as reference.

Bit Rate of G.Blur = 0

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	1	65535	0.954867	1	1	1	100
15.5	0.729741	25.41353	0.784455	0.936684	0.92539	1	69.00739
18.9	0.796929	26.59974	0.803897	0.952255	0.930471	1	60.05539
20.3	0.910108	29.91208	0.88453	0.97799	0.924763	1	50.70893
23.7	0.98202	36.04244	0.945002	0.994681	1.014239	0.980716	34.45273
25.1	0.96702	34.6269	0.90351	0.99263	1.01404	0.978886	42.48964

(a)

Bit Rate of G.Blur = 0.677051

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.98811	36.16914	0.912767	0.994885	1.049929	0.947574	100
15.5	0.764491	26.51579	0.948952	0.949771	0.984373	0.964848	69.00739
18.9	0.833129	28.00254	0.956637	0.964688	0.989491	0.974933	60.05539
20.3	0.944741	33.11247	0.978407	0.989227	0.983742	1	50.70893
23.7	0.984926	36.77243	0.923807	0.995468	1.08225	0.919813	34.45273
25.1	0.969061	35.03805	0.917374	0.993262	1.082321	0.917715	42.48964

(b)

Bit Rate of G.Blur = 1.164031

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.955954	31.70434	0.943989	0.985561	1.000461	0.985107	100
15.5	0.801286	27.31611	0.995716	0.957627	1.009133	0.94896	69.00739
18.9	0.86886	28.91042	0.995693	0.970987	1.014266	0.95733	60.05539

20.3	0.966993	34.86271	0.990889	0.992741	1.0085	0.984374	50.70893
23.7	0.964167	33.07663	0.945665	0.989371	1.062561	0.931119	34.45273
25.1	0.947921	32.22648	0.949438	0.987112	1.062806	0.92878	42.48964

(c)

Bit Rate of G.Blur = 1.708303

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.919171	29.76012	0.913302	0.97731	1.002991	0.974396	100
15.5	0.835779	28.0476	0.995277	0.963743	1.008087	0.956013	69.00739
18.9	0.896704	29.48205	0.99436	0.974329	1.013219	0.961617	60.05539
20.3	0.967057	34.36271	0.983923	0.991876	1.007454	0.984538	50.70893
23.7	0.931709	30.83765	0.914271	0.982145	1.06383	0.923216	34.45273
25.1	0.915085	30.29871	0.920422	0.979852	1.064067	0.920855	42.48964

(d)

Bit Rate of G.Blur = 3.083306

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.852187	27.54849	0.844948	0.96207	0.892852	1	100
15.5	0.89601	29.34151	0.991894	0.972507	1.044272	0.931278	69.00739
18.9	0.915444	29.39612	0.989957	0.973594	1.080625	0.900954	60.05539
20.3	0.920787	30.94495	0.97062	0.982215	1.043637	0.941146	50.70893
23.7	0.866126	28.23367	0.846419	0.967349	0.997522	0.969753	34.45273
25.1	0.848799	27.91118	0.85685	0.964944	0.998014	0.966864	42.48964

(e)

Bit Rate of G.Blur = 5.833312

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.769698	25.25396	0.754604	0.935269	1.026541	0.911088	100
15.5	0.941385	29.27717	0.987218	0.972207	0.904052	1	69.00739
18.9	0.857712	27.13135	0.984001	0.955507	0.90912	1	60.05539
20.3	0.83102	27.10832	0.953179	0.956745	0.903427	1	50.70893
23.7	0.782246	25.65778	0.756469	0.940572	0.992669	0.947518	34.45273
25.1	0.765456	25.4711	0.772778	0.938153	0.992471	0.94527	42.48964

(f)

The value of R_S^2 also show a decrease from Table 4-7(a) to (f). However, the decreasing of the average value is small. This shows that R_S^2 is suitable for reduced reference image quality assessment. On the other hand, the values of R_L^2decrease from

Table 4-7 (a) to (e). From Table 4-7 (f), we can see that the value of R_L^2 fluctuated inconsistently from (e). However, from (f), we can see that R_L^2 provided a better result thanR_S^2 in overall. The distortion is non-noticeable because the bit rate of distorted image is relatively small, which indicates that the distorted image is considered high quality. Therefore, the result value is close to 1 although the bit rate is the highest here.

The Ŝ value calculated from D_n value decreases in overall, as we can see from Table 4-7 (a) to (f). However, the Ŝ value is less than the value of R_S^2 and R_F^2 in general. This indicates that the estimated SSIM, Ŝ is less accurate and less effective for this assessment.

As what we can see in Table 4-7 (f), the value of each metric results is smaller than the previous results. This means that a Gaussian blur distorted reference image with a higher bit rate of fast fading distortion will affect the accuracy of a RR-IQA. However, the results for R_L^2has the highest value among all metrics.

Table 4-8 shows the performance for each RR-IQA metrics on different level of distortion, which use DMOS values as a standard comparison. As mentioned in the methodology, a good RR-IQA need to have lower MAE and RMS values, and higher PLCC, SRCC and KRCC values. In Table 4-6, the lowest MAE and RMS values is highlighted with red color, while the highest PLCC, SRCC, and KRCC values is highlighted with blue color.

From Table 4-8, we can see that most of the blue color is highlighted in the “DMOS vs RL” row and the second most is highlighted in “DMOS vs Rs” row. PLCC judge that R_L^2has a better performance, as there are more highest PLCC values in “DMOS vs RL” row. On the other hand, SRCC and KRCC show that R_S^2has a better performance.

All the MAE values are the same in Table 4-8. This is because MAE is the average of absolute errors between a prediction and the true value. The prediction and true value of each data set used is same, as the data are from same image, which is Caps.bmp. On the other hand, RMS shows a priority result in R_S^2, as most of the lowest value are found in “DMOS vs RL” row.

Table 4-8: Results of each metrics used to judge the performance of RR-IQA metrics used.

	Bit Rate	PLCC	MAE	RMSE	SRCC	KRCC
DMOS vs SSIM	0	-0.07063	59.45235	62.31471	-0.14286	-0.33333
	0.677051	-0.13318	59.45235	62.30068	-0.14286	-0.33333
	1.164031	-0.21468	59.45235	62.29807	-0.42857	-0.33333
	1.708303	-0.28928	59.45235	62.30367	-0.42857	-0.33333
	3.083306	-0.11694	59.45235	62.32691	0.085714	-0.06667
	5.833312	0.115456	59.45235	62.37843	0.314286	0.333333
DMOS vs S_Dn	0	0.001619	59.45235	62.32935	-0.14286	-0.33333
	0.677051	-0.18405	59.45235	62.2742	-0.14286	-0.2
	1.164031	-0.00618	59.45235	62.24404	0.142857	0.333333
	1.708303	0.014409	59.45235	62.25944	0.142857	0.333333
	3.083306	0.01776	59.45235	62.29383	0.142857	0.333333
	5.833312	0.019636	59.45235	62.33938	0.142857	0.333333
DMOs vs Rs	0	-0.061	59.45235	62.23934	-0.14286	-0.33333
	0.677051	-0.17178	59.45235	62.2347	-0.42857	-0.46667
	1.164031	-0.2919	59.45235	62.23551	-0.65714	-0.46667
	1.708303	-0.39052	59.45235	62.23762	-0.65714	-0.46667
	3.083306	-0.29573	59.45235	62.24445	-0.14286	-0.2
	5.833312	-0.00247	59.45235	62.26325	0.028571	0.066667
DMOS vs RL	0	0.689063	59.45235	62.22009	0.777542	0.602464
	0.677051	0.245418	59.45235	62.25663	0.371429	0.066667
	1.164031	0.6747	59.45235	62.25219	0.714286	0.466667
	1.708303	0.624327	59.45235	62.25464	0.542857	0.333333
	3.083306	0.276292	59.45235	62.25845	-0.08571	-0.2
	5.833312	-0.30718	59.45235	62.25039	-0.03036	0

In overall, Table 4-8 shows that when a perfect quality reference image is used, R_L^2 performed the best among all. This is the same to the result when the reference image has the highest distortion level.

SSIM has the worst results, in Table 4-8. This may due to it is designed for a full reference image quality assessment. When it comes to reduced reference image quality assessment, the performance will gradually decreases.

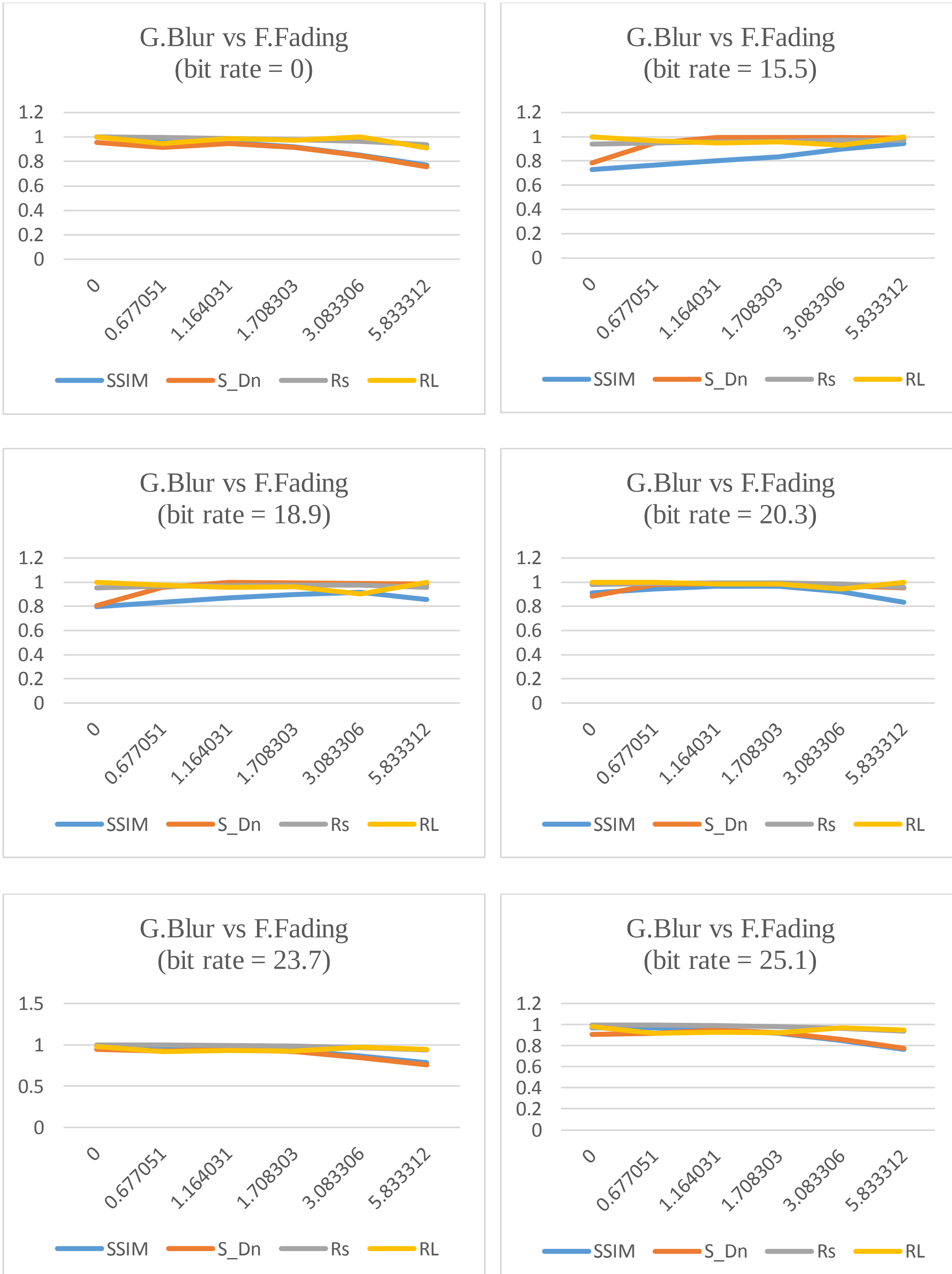


Figure 4-4: Graph plotted by IQM results versus bit rate of imperfect reference image. It is to show the relationship of each metrics, with different bit rate value of fast fading distorted value, and different level of distortion for Gaussian blur distorted reference image.

In Figure 4-4, it shows the graph plotted for each metrics with different bit rate value of distortion. The graph is used to show the performance of each metrics when the bit rate value of fast fading distorted image is increasing, and the Gaussian Blur imperfect reference image has different distortion value, which is in x-axis of the graph. The flatter the pattern of the graph, indicates a better consistency of the IQM tested.

From Figure 4-4, R_s^2 has a better consistency as compared to other metrics. R_L^2 also shows a good consistency when Fast Fading distorted image has bit rate of 15.5 and 20.3. Here, we can say that R_L^2 and R_s^2 provide a consistent assessment to Gaussian blur reduced reference image, when fast fading distorted image is compared.

In overall, the performance of the R_L^2 are the best as compared to the other metrics included, when the reference image has Gaussian blur distortion is compared to fast fading distorted image.

4-2 Performance of R_L^2 When Reference Image Has JPEG Distortion

Here, JPEG distorted image is used as the imperfect reference image. In order to test the accuracy, consistency, and monotonicity of each of the RR-IQA metrics applied to this distortion type of reduced reference image, different types of distorted image is tested with it. There are four types of distortion being tested, which are Gaussian Noise, Gaussian Blur, JPEG2000, and Fast Fading distortion.

4-2-1 Gaussian Noise distorted image as compressed image

Table 4-9(a) used a perfect quality image as the reference while (b), (c), (d), (e) and (f) used a JPEG distorted image as the reference image. The bit rate of distortion increases from (b) to (f). The result value more than one is converted to one in this table. This is because the highest value qualified is one. From Table 4-9, we can see that the SSIM,R_F^2, PSNR, and R_L^2 value is changing gradually from (a) to (f).

SSIM is a metric designed for full reference image quality assessment. The value of SSIM mostly decreases from (a) to (f) for each of the different bit rate for JPEG reference image. This indicates that SSIM value is less effective when the reference image used has no perfect quality, and the bit rate of distortion increases.

The PSNR value changes gradually in value from (a) to (f). This is because PSNR is calculated by the mean square error of the two images involved. When the reference image is distorted, it could hardly give an accurate image quality assessment result.

Table 4-9: Results of each metrics applied on a Gaussian Noise compressed image, caps.bmp, with different level of bit rate. The imperfect reference image used is with JPEG distortion. (a)Perfect quality image as reference. (b)JPEG distorted image with bit rate 0.15312 as reference. (c)JPEG distorted image with bit rate 0.1993 as reference. (d)JPEG distorted image with bit rate 0.40535 as reference. (e)JPEG distorted image with bit rate 0.42483 as reference. (f) JPEG distorted image with bit rate 0.85118 as reference.

Bit rate of JPEG = 0

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	1	65535	0.948758	1	1	1	100
0.015625	0.982878	39.55768	0.95635	0.997643	1.182376	0.843761	22.50337
0.03125	0.937012	33.61711	0.884508	0.990815	1.127765	0.878565	33.54177
0.0625	0.801863	27.65342	0.747118	0.964984	0.988936	0.97578	41.3394
0.125	0.548208	21.75995	0.60953	0.87853	0.750961	1	48.03932
1	0.086885	10.31411	0.086594	0.198253	0.201829	0.982283	67.38191

(a)

Bit rate of JPEG = 0.15312

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.75055	25.86641	0.52136	0.944352	0.783275	1	100
0.015625	0.736826	25.69911	0.779266	0.942263	0.817891	1	22.50337
0.03125	0.700132	25.22304	0.852109	0.935992	0.93869	0.997126	33.54177
0.0625	0.590008	23.6746	0.846934	0.911339	1.191458	0.764893	41.3394
0.125	0.398929	20.37069	0.697743	0.829994	0.924654	0.897627	48.03932
1	0.070903	10.28053	0.01812	0.187525	0.288998	0.648881	67.38191

(b)

Bit rate of JPEG = 0.1993

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.838527	29.4221	0.604602	0.975457	0.938386	1	100
0.015625	0.82516	29.03737	0.827638	0.973234	0.975987	0.99718	22.50337
0.03125	0.788604	28.05781	0.880518	0.966707	1.106683	0.873517	33.54177
0.0625	0.676883	25.45912	0.858074	0.941441	1.120622	0.840106	41.3394
0.125	0.470146	21.10589	0.714829	0.857496	0.863691	0.992827	48.03932
1	0.079067	10.30723	0.063732	0.193348	0.257677	0.750353	67.38191

(c)

Bit rate of JPEG = 0.40535

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.956837	34.09477	0.825124	0.991667	1.177686	0.842047	100
0.015625	0.940842	33.03038	0.944479	0.989373	1.21939	0.811368	22.50337
0.03125	0.898185	30.8782	0.924152	0.982689	1.167221	0.841905	33.54177
0.0625	0.768677	26.77462	0.830664	0.956983	1.025488	0.933198	41.3394
0.125	0.529007	21.52894	0.671057	0.871481	0.782167	1	48.03932
1	0.084655	10.31181	0.046564	0.196532	0.216996	0.905695	67.38191

(d)

Bit rate of JPEG = 0.42483

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.960829	34.36081	0.833422	0.99216	1.176875	0.843046	100
0.015625	0.944879	33.2372	0.947192	0.989865	1.218565	0.81232	22.50337
0.03125	0.901282	30.9971	0.923594	0.983155	1.167543	0.842071	33.54177
0.0625	0.771786	26.82276	0.828296	0.957458	1.025787	0.933389	41.3394
0.125	0.529767	21.54094	0.664437	0.871822	0.782422	1	48.03932
1	0.085016	10.31518	0.047764	0.196596	0.217121	0.905469	67.38191

(e)

Bit rate of JPEG = 0.85118

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS

0	0.989243	38.29867	0.90625	0.99684	1.277347	0.780399	100
0.015625	0.972578	35.90624	0.953408	0.994528	1.183399	0.8404	22.50337
0.03125	0.927503	32.37108	0.887637	0.987746	1.12876	0.875072	33.54177
0.0625	0.793575	27.30182	0.75595	0.961979	0.989857	0.971836	41.3394
0.125	0.543478	21.67105	0.609494	0.87586	0.751746	1	48.03932
1	0.086354	10.31386	0.082568	0.197676	0.202208	0.977589	67.38191

(f)

The value of R_S^2 show some changes from Table 4-9(a) to (f). However, the differences between the average values are small. This shows that R_S^2 is suitable for reduced reference image quality assessment. On the other hand, the values of R_L^2 change from Table 4-9 (a) to (f). However, from (f), we can see that R_L^2 provided a better result thanR_S^2 when the Gaussian noise distorted image has a higher bit rate of distortion. The distortion is non-noticeable because the bit rate of distorted image is relatively small, which indicates that the distorted image is considered high quality. Therefore, the result value is close to 1 although the bit rate is the highest here.

The Ŝ value calculated from D_n value changes inconsistently in overall, as we can see from Table 4-9 (a) to (f). Besides, the Ŝ value is less than the value of R_S^2 in general, and less than the value of R_F^2 when the distortion level is high. This indicates that the estimated SSIM, Ŝ is less accurate and less effective for this assessment.

As what we can see in Table 4-9 (f), the value of each metric result is much smaller than the previous results when Gaussian noise has higher distortion level. This means that a JPEG distorted reference image with a higher bit rate of Gaussian noise distortion will affect the accuracy of a RR-IQA metric. However, the results for R_L^2 has the highest value among all metrics.

Table 4-10 shows the performance for each RR-IQA metrics on different level of distortion, which use DMOS values as a standard comparison. As mentioned in the methodology, a good RR-IQA need to have lower MAE and RMS values, and higher PLCC, SRCC and KRCC values. In Table 4-10, the lowest MAE and RMS values is highlighted with red color, while the highest PLCC, SRCC, and KRCC values is highlighted with blue color.

Table 4-10: Results of each metrics used to judge the performance of RR-IQA metrics used.

	Bit Rate	PLCC	MAE	RMSE	SRCC	KRCC
DMOS vs SSIM	0	-0.166775	52.1343	57.37961	-0.142857	-0.333333
	0.15312	-0.158365	52.1343	57.53796	-0.142857	-0.333333
	0.1993	-0.170178	52.1343	57.47703	-0.142857	-0.333333
	0.40535	-0.168211	52.1343	57.40533	-0.142857	-0.333333
	0.42483	-0.16784	52.1343	57.40309	-0.142857	-0.333333
	0.85118	-0.167269	52.1343	57.38598	-0.142857	-0.333333
DMOS vs S_Dn	0	-0.186698	52.1343	57.39904	-0.428571	-0.466667
	0.15312	-0.578428	52.1343	57.52579	-0.771429	-0.6
	0.1993	-0.538303	52.1343	57.48351	-0.771429	-0.6
	0.40535	-0.354531	52.1343	57.42112	-0.828571	-0.733333
	0.42483	-0.345631	52.1343	57.41957	-0.657143	-0.6
	0.85118	-0.236539	52.1343	57.4109	-0.428571	-0.466667
DMOs vs Rs	0	-0.251657	52.1343	57.2872	-0.142857	-0.333333
	0.15312	-0.251888	52.1343	57.32695	-0.142857	-0.333333
	0.1993	-0.251844	52.1343	57.30469	-0.142857	-0.333333
	0.40535	-0.251757	52.1343	57.29313	-0.142857	-0.333333
	0.42483	-0.251743	52.1343	57.2928	-0.142857	-0.333333
	0.85118	-0.251716	52.1343	57.28943	-0.142857	-0.333333
DMOS vs RL	0	0.7275816	52.1343	57.13705	0.8986451	0.8280787
	0.15312	-0.113742	52.1343	57.21957	-0.231908	-0.276026
	0.1993	0.0264684	52.1343	57.18983	0.0285714	-0.066667
	0.40535	0.0255218	52.1343	57.20806	0.4857143	0.3333333
	0.42483	0.0267729	52.1343	57.20771	0.4857143	0.3333333
	0.85118	-0.283132	52.1343	57.20242	0.0857143	0.2

From Table 4-10, we can see that most of the blue color is highlighted in the "DMOS vs S_Dn" row and the second most is highlighted in "DMOS vs RL" row. PLCC judge that the estimated SSIM, Ŝ has a better performance, as there are more highest PLCC values in "DMOS vs S_Dn" row. Besides, SRCC and KRCC also show that Ŝ has a better performance. However, RMSE shows that R_L^2 has better monotonicity. This may due to RMSE is more suitable to test the performance of R_L^2.

All the MAE values are the same in Table 4-10. This is because MAE is the average of absolute errors between a prediction and the true value. The prediction and true value of each data set used is same, as the data are from same image, which is Caps.bmp. On the other hand, RMS shows a priority result in R_L^2, as all of the lowest value are found in "DMOS vs RL" row.

In overall, Table 4-10 shows that when a perfect quality reference image is used, R_L^2 performed the best among all. However, when the reference image has the highest distortion level, R_L^2 and Ŝ have equally good performance in this assessment.

SSIM has the worst results, in Table 4-10. This may due to it is designed for a full reference image quality assessment. When it comes to reduced reference image quality assessment, the performance will gradually decreases.

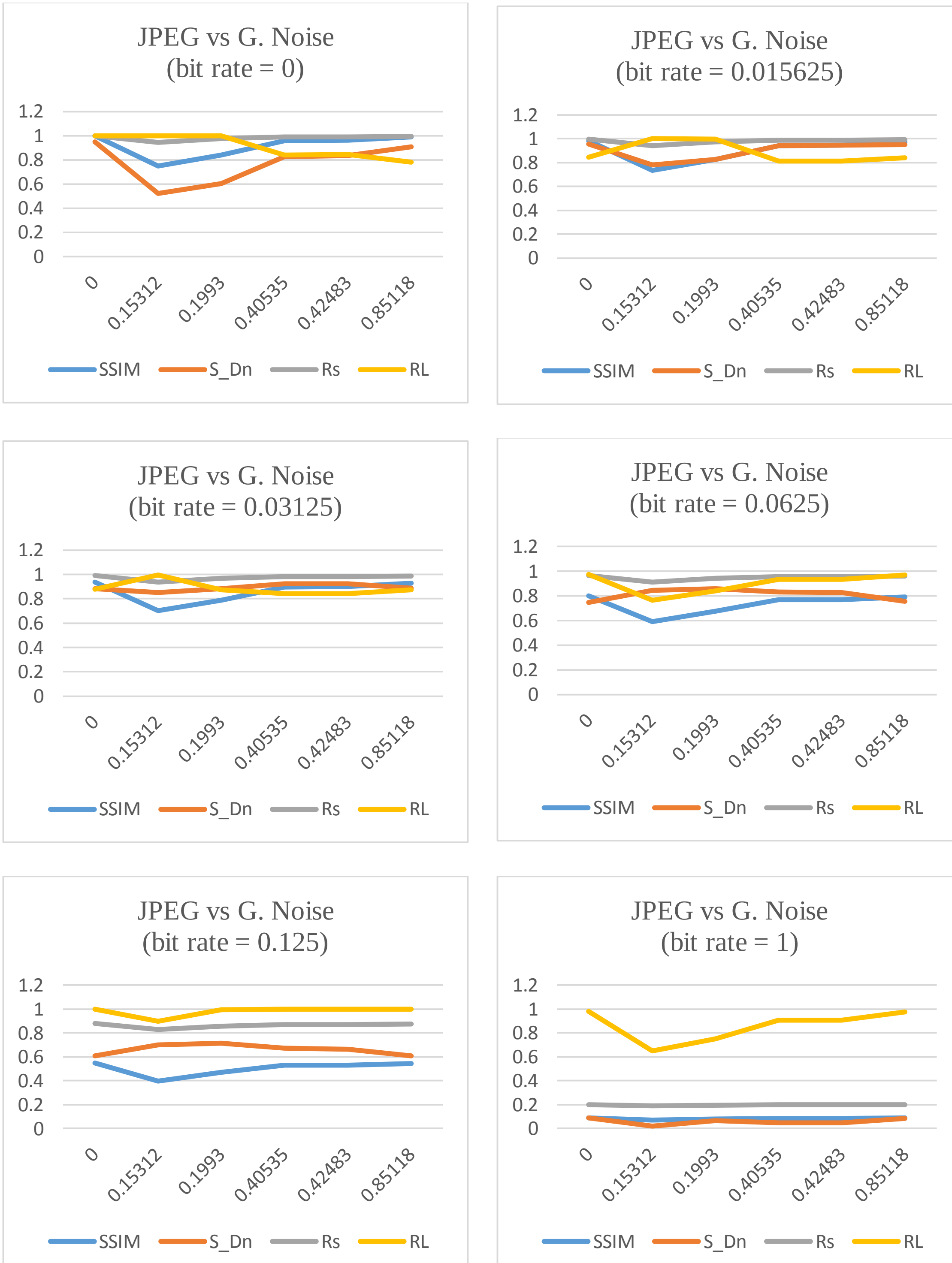


Figure 4-5: Graph plotted by IQM results versus bit rate of imperfect reference image. It is to show the relationship of each metrics, with different bit rate value of Gaussian Noise distorted value, and different level of distortion for JPEG distorted reference image.

In Figure 4-5, it shows the graph plotted for each metrics with different bit rate value of distortion. The graph is used to show the performance of each metrics when the bit rate value of Gaussian noise distorted image is increasing, and the JPEG distorted reference image has different distortion value, which is in x-axis of the graph. The flatter the pattern of the graph, indicates a better consistency of the IQM tested.

From Figure 4-5, R_S^2 shows a better consistency as compared to other metrics, for all the Gaussian noise distorted image. R_L^2 shows a bad consistency in this test, as the pattern of graph obviously fluctuated. Here, we can say that R_S^2 provide an accurate assessment to JPEG reduced reference image when Gaussian noise distorted image is tested.

In overall, the performance of the Ŝ gives a better accuracy, whereas R_S^2 shows a better consistency as compared to the other metrics included, when the reference image has JPEG distortion is compared to Gaussian noise distorted image.

4-2-2 Gaussian Blur distorted image as compressed image

Table 4-11(a) used a perfect quality image as the reference while (b), (c), (d), (e) and (f) used a JPEG distorted image as the reference image. The bit rate of distortion increases from (b) to (f). The result value more than one is converted to one in this table. This is because the highest value qualified is one. From Table 4-11, we can see that the SSIM, R_F^2, PSNR, and R_L^2 value is changing gradually from (a) to (f).

SSIM is a metric designed for full reference image quality assessment. The value of SSIM changes accordingly from (a) to (f) for each of the different bit rate for JPEG distorted reference image. This indicates that SSIM value is less effective when the reference image used has no perfect quality, and the bit rate of distortion increases.

The PSNR value changes inconsistently from (a) to (f). This is because PSNR is calculated by the mean square error of the two images involved. When the reference image is distorted, it could hardly give an accurate image quality assessment result.

Table 4-11: Results of each metrics applied on a Gaussian Blur compressed image, caps.bmp, with different level of bit rate. The imperfect reference image used is with JPEG distortion. (a)Perfect quality image as reference. (b)JPEG distorted image with bit rate 0.15312 as reference. (c)JPEG distorted image with bit rate 0.1993 as reference. (d)JPEG distorted image with bit rate 0.40535 as reference. (e)JPEG distorted image with bit rate 0.42483 as reference. (f)JPEG distorted image with bit rate 0.85118 as reference.

Bit rate of JPEG = 0

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	1	65535	0.96551	1	1	1	100
0.677051	0.98811	36.16914	0.97994	0.994885	1.106213	0.899361	24.64764
1.164031	0.955954	31.70434	0.937741	0.985561	1.068756	0.922157	40.79745
1.708303	0.919171	29.76012	0.887688	0.97731	1.070321	0.9131	54.14974
3.083306	0.852187	27.54849	0.839299	0.96207	1.017074	0.945919	60.83318
5.833312	0.769698	25.25396	0.812935	0.935269	1.192494	0.784297	69.15498

(a)

Bit rate of JPEG = 0.15312

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.75055	25.86641	0.668879	0.944352	0.783275	1	100
0.677051	0.777268	26.79641	0.79167	0.95442	0.989473	0.964574	24.64764
1.164031	0.79836	27.09293	0.911928	0.957153	1.082139	0.884501	40.79745
1.708303	0.80847	27.00901	0.965894	0.956145	1.078152	0.886836	54.14974
3.083306	0.800037	26.26837	0.978869	0.947724	1.219664	0.777036	60.83318
5.833312	0.752876	24.70845	0.97831	0.924701	0.713869	1	69.15498

(b)

Bit rate of JPEG = 0.1993

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.838527	29.4221	0.763617	0.975457	0.938386	1	100
0.677051	0.85596	30.83819	0.85715	0.982025	1.161413	0.845544	24.64764
1.164031	0.857682	30.47073	0.942994	0.980376	1.260996	0.777461	40.79745
1.708303	0.845062	29.52151	0.976586	0.975542	1.256719	0.776261	54.14974

3.083306	0.802469	27.67737	0.979394	0.962494	1.150886	0.836307	60.83318
5.833312	0.734077	25.42786	0.975356	0.936735	0.862767	1	69.15498

(c)

Bit rate of JPEG = 0.40535

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.956837	34.09477	0.835414	0.991667	1.177686	0.842047	100
0.677051	0.958556	34.85438	0.933385	0.992961	1.145227	0.867042	24.64764
1.164031	0.93781	32.0805	0.963663	0.986649	1.106994	0.891287	40.79745
1.708303	0.906951	30.18129	0.938241	0.979265	1.108592	0.883341	54.14974
3.083306	0.844566	27.86098	0.894046	0.964481	1.054226	0.914871	60.83318
5.833312	0.764098	25.45758	0.862935	0.93787	1.093527	0.857655	69.15498

(d)

Bit rate of JPEG = 0.42483

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.960829	34.36081	0.842521	0.99216	1.176875	0.843046	100
0.677051	0.961855	34.96304	0.937043	0.993128	1.145546	0.866948	24.64764
1.164031	0.940243	32.06473	0.961842	0.986584	1.107307	0.890976	40.79745
1.708303	0.908739	30.15227	0.933275	0.979098	1.108904	0.882942	54.14974
3.083306	0.845674	27.84127	0.886922	0.964275	1.054529	0.914413	60.83318
5.833312	0.764841	25.44907	0.854959	0.937682	1.092743	0.858099	69.15498

(e)

Bit rate of JPEG = 0.85118

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.989243	38.29867	0.935903	0.99684	1.277347	0.780399	100
0.677051	0.982217	35.7065	0.969127	0.994261	1.107197	0.897998	24.64764
1.164031	0.953256	31.80884	0.939184	0.985841	1.06972	0.921588	40.79745
1.708303	0.917651	29.87137	0.891438	0.977797	1.071286	0.912732	54.14974
3.083306	0.851185	27.63827	0.843948	0.962708	1.01801	0.945676	60.83318
5.833312	0.768765	25.32062	0.81569	0.936031	1.189926	0.78663	69.15498

(f)

The value of R_S^2 also show a changes from Table 4-11 (a) to (f). However, the changes between the average values are small. This shows that R_S^2 is suitable for reduced reference image quality assessment. On the other hand, the values of R_L^2 changes from Table 4-11 (a) to (f). From (f), we can see that the value of R_L^2 is smaller than the one of

R_S^2. This indicates that R_S^2 might be a better metric to assess between the JPEG distorted reference image with Gaussian blur distorted image. The distortion is non-noticeable because the bit rate of distorted image is relatively small, which indicates that the distorted image is considered high quality. Therefore, the result value is close to 1 although the bit rate is the highest here.

The Ŝ value calculated from D_n value decreases in overall, as we can see from Table 4-11 (a) to (f). However, the Ŝ value is less than the value of R_S^2 in general. This indicates that the estimated SSIM, Ŝ is less accurate and less effective as compared to R_S^2, for this assessment.

Table 4-12 shows the performance for each RR-IQA metrics on different level of distortion, which use DMOS values as a standard comparison. As mentioned in the methodology, a good RR-IQA need to have lower MAE and RMS values, and higher PLCC, SRCC and KRCC values. In Table 4-12, the lowest MAE and RMS values is highlighted with red color, while the highest PLCC, SRCC, and KRCC values is highlighted with blue color.

From Table 4-12, we can see that most of the blue color is highlighted in the "DMOS vs S_Dn" row. PLCC judge that R_L^2has a better performance, as there are more highest PLCC values in "DMOS vs RL" row. On the other hand, SRCC and KRCC show that Ŝ has a better performance.

All the MAE values are the same in Table 4-12. This is because MAE is the average of absolute errors between a prediction and the true value. The prediction and true value of each data set used is same, as the data are from same image, which is Caps.bmp. On the other hand, RMS shows a priority result in R_S^2, as most of the lowest value are found in "DMOS vs Rs" row.

Table 4-12: Results of each metrics used to judge the performance of RR-IQA metrics used.

	Bit Rate	PLCC	MAE	RMSE	SRCC	KRCC
DMOS vs SSIM	0	-0.12137	58.26383	61.98908	-0.14286	-0.33333
	0.15312	-0.56255	58.26383	62.11319	-0.48571	-0.33333
	0.1993	-0.35491	58.26383	62.07619	-0.77143	-0.6
	0.40535	-0.19274	58.26383	62.0084	-0.42857	-0.46667
	0.42483	-0.18829	58.26383	62.0063	-0.42857	-0.46667
	0.85118	-0.14441	58.26383	61.99316	-0.14286	-0.33333
DMOS vs S_Dn	0	-0.18889	58.26383	61.99937	-0.42857	-0.46667
	0.15312	-0.33277	58.26383	62.02923	0.085714	0.2
	0.1993	-0.37915	58.26383	61.99536	-0.02857	0.066667
	0.40535	-0.86945	58.26383	62.00898	-0.82857	-0.73333
	0.42483	-0.86192	58.26383	62.01037	-0.94286	-0.86667
	0.85118	-0.3289	58.26383	62.006	-0.65714	-0.6
DMOs vs Rs	0	-0.09219	58.26383	61.92903	-0.14286	-0.33333
	0.15312	-0.51869	58.26383	61.95675	-0.77143	-0.6
	0.1993	-0.34541	58.26383	61.93685	-0.82857	-0.73333
	0.40535	-0.20549	58.26383	61.93011	-0.42857	-0.46667
	0.42483	-0.1986	58.26383	61.93006	-0.42857	-0.46667
	0.85118	-0.13268	58.26383	61.92957	-0.14286	-0.33333
DMOS vs RL	0	0.284152	58.26383	61.98144	0.371429	0.333333
	0.15312	0.277661	58.26383	61.97272	0.463817	0.276026
	0.1993	0.723292	58.26383	61.99811	0.579771	0.414039
	0.40535	-0.45254	58.26383	62.02467	-0.48571	-0.33333
	0.42483	-0.44469	58.26383	62.02449	-0.48571	-0.33333
	0.85118	-0.69832	58.26383	62.03975	-0.48571	-0.33333

In overall, Table 4-12 shows that when a perfect quality reference image is used, Ŝ performed the best among all. This is the same to the result when the reference image has the highest distortion level.

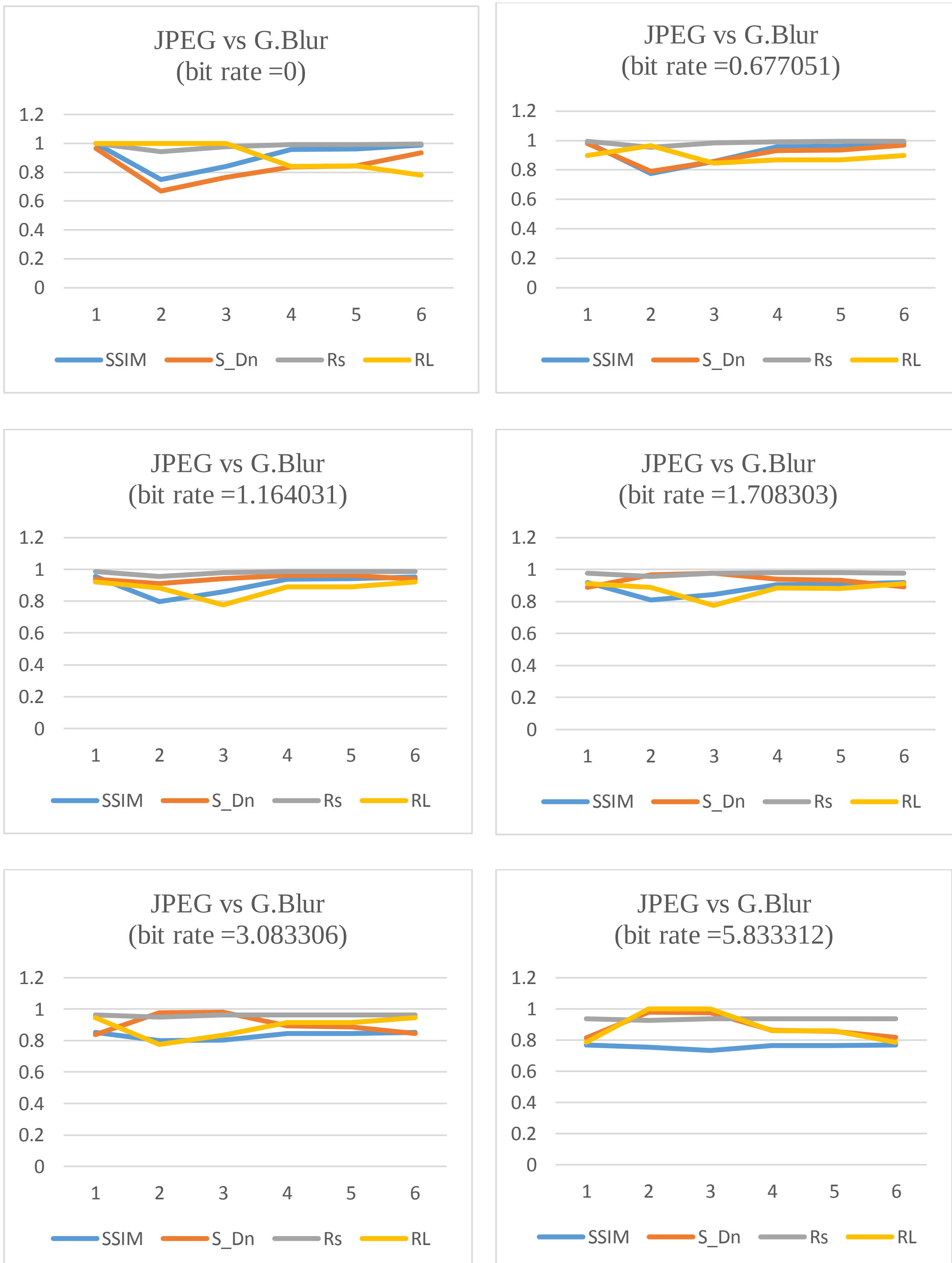


Figure 4-6: Graph plotted by IQM results versus bit rate of imperfect reference image. It is to show the relationship of each metrics, with different bit rate value of fast fading distorted value, and different level of distortion for Gaussian blur distorted reference image.

In Figure 4-6, it shows the graph plotted for each metrics with different bit rate value of distortion. The graph is used to show the performance of each metrics when the bit rate value of Gaussian blur distorted image is increasing, and the JPEG distorted reference image has different distortion value, which is in x-axis of the graph. The flatter the pattern of the graph, indicates a better consistency of the IQM tested.

From Figure 4-6, R_S^2 has a better consistency as compared to other metrics, for all the Gaussian Blur distorted image. R_L^2 do not show consistency here, as its graph pattern fluctuated a lot. Here, we can say that R_S^2 provide a consistent assessment to JPEG reduced reference image.

In overall, the performance of the Ŝ gives a better accuracy and R_S^2 gives a better consistency here, as compared to the other metrics included, when the reference image has JPEG distortion is compared to Gaussian blur distorted image.

4-2-3 JPEG2000 distorted image as compressed image

Table 4-13 (a) used a perfect quality image as the reference while (b), (c), (d), (e) and (f) used a JPEG distorted image as the reference image. The bit rate of distortion increases from (b) to (f). The result value more than one is converted to one in this table. This is because the highest value qualified is one. From Table 4-13, we can see that the SSIM, R_F^2, PSNR, and R_L^2 value is changing gradually from (a) to (f).

SSIM is a metric designed for full reference image quality assessment. The value of SSIM change randomly from (a) to (f) for each of the different bit rate for Gaussian blur reference image. This indicates that SSIM value is less effective when the reference image used has no perfect quality, and the bit rate of distortion increases.

The PSNR value changes inconsistently from (a) to (f). This is because PSNR is calculated by the mean square error of the two images involved. When the reference image is distorted, it could hardly give an accurate image quality assessment result.

Table 4-13: Results of each metrics applied on a JPEG2000 compressed image, caps.bmp, with different level of bit rate. The imperfect reference image used is with JPEG distortion. (a)Perfect quality image as reference. (b)JPEG distorted image with bit rate 0.15312 as reference. (c)JPEG distorted image with bit rate 0.1993 as reference. (d)JPEG distorted image with bit rate 0.40535 as reference. (e)JPEG distorted image with bit rate 0.42483 as reference. (f)JPEG distorted image with bit rate 0.85118 as reference.

Bit rate of JPEG = 0

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	1	65535	0.948758	1	1	1	100
0.050378	0.831895	28.98727	0.747462	0.972697	1.034881	0.939912	56.81507
0.098741	0.889199	30.8188	0.88319	0.982177	1.073039	0.915323	53.4561
0.19944	0.929898	33.27789	0.910844	0.989921	1.109314	0.892373	46.58432
0.40137	0.964494	36.69453	0.888389	0.995423	1.17187	0.849432	34.49728
0.60354	0.977638	39.26188	0.896199	0.997469	1.191261	0.837322	26.6733

(a)

Bit rate of JPEG = 0.15312

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.75055	25.86641	0.782555	0.944352	0.783275	1	100
0.050378	0.784151	26.77258	0.984179	0.953823	1.170972	0.814557	56.81507
0.098741	0.779535	26.64765	0.949621	0.952783	1.071254	0.88941	53.4561
0.19944	0.772811	26.3504	0.831634	0.949738	0.982056	0.967091	46.58432
0.40137	0.764472	26.09408	0.720993	0.946952	0.840277	1	34.49728
0.60354	0.759497	25.96464	0.703938	0.945468	0.799269	1	26.6733

(b)

Bit rate of JPEG = 0.1993

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.838527	29.4221	0.856493	0.975457	0.938386	1	100
0.050378	0.792502	29.00317	0.986329	0.97238	1.170027	0.831075	56.81507
0.098741	0.831152	29.96124	0.970226	0.977968	1.249316	0.782803	53.4561
0.19944	0.84301	30.02987	0.890879	0.978432	1.153427	0.848282	46.58432

0.40137	0.844892	29.74813	0.81218	0.977111	1.000266	0.976851	34.49728
0.60354	0.843388	29.57165	0.800987	0.976222	0.955768	1	26.6733

(c)

Bit rate of JPEG = 0.40535

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.956837	34.09477	0.926813	0.991667	1.177686	0.842047	100
0.050378	0.82605	29.35283	0.947876	0.974746	1.072409	0.908931	56.81507
0.098741	0.882259	31.1894	0.982544	0.983532	1.111366	0.884975	53.4561
0.19944	0.91915	32.89558	0.958065	0.988922	1.148391	0.861137	46.58432
0.40137	0.94521	33.85251	0.910758	0.991145	1.246271	0.795288	34.49728
0.60354	0.953084	34.08496	0.905766	0.991625	1.196976	0.828442	26.6733

(d)

Bit rate of JPEG = 0.42483

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.960829	34.36081	0.927946	0.99216	1.176875	0.843046	100
0.050378	0.827099	29.33898	0.943362	0.974623	1.072716	0.908557	56.81507
0.098741	0.88339	31.18563	0.981701	0.983492	1.111679	0.884691	53.4561
0.19944	0.920635	32.94235	0.958935	0.989025	1.14871	0.860988	46.58432
0.40137	0.947821	34.03657	0.912469	0.991505	1.245439	0.796109	34.49728
0.60354	0.956247	34.3125	0.907598	0.992047	1.196159	0.829361	26.6733

(e)

Bit rate of JPEG = 0.85118

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.989243	38.29867	0.93851	0.99684	1.277347	0.780399	100
0.050378	0.830752	29.07018	0.842197	0.973128	1.035827	0.93947	56.81507
0.098741	0.887878	30.90933	0.933187	0.982489	1.074005	0.91479	53.4561
0.19944	0.9279	33.19251	0.957251	0.989687	1.110298	0.89137	46.58432
0.40137	0.961456	35.73002	0.941572	0.994267	1.172887	0.847709	34.49728
0.60354	0.973876	37.0217	0.942446	0.995749	1.192288	0.835158	26.6733

(f)

The value of R_S^2 also show a consistent changes from Table 4-13 (a) to (f). However, the changes of the average value is small. This shows that R_S^2 is suitable for reduced reference image quality assessment. On the other hand, the values of R_L^2 changing accordingly from Table 4-13 (a) to (f). From Table 4-13 (f), we can see that R_S^2 provide a better result than R_L^2 in overall. The distortion is non-noticeable because the bit rate of distorted image is relatively small, which indicates that the distorted image is considered high quality. Therefore, the result value is close to 1 although the bit rate is the highest here.

The Ŝ value calculated from D_n value decreases in overall, as we can see from Table 4-13 (a) to (f). However, the Ŝ value is less than the value of R_s^2 in general. This indicates that the estimated SSIM, Ŝ is less accurate and less effective than R_s^2 for this assessment.

As what we can see in Table 4-13 (f), the value of each metric results is smaller than the previous results. This means that a JPEG distorted reference image with a higher bit rate of JPEG2000 distortion will affect the accuracy of a RR-IQA metrics. However, the results for R_L^2has the highest value among all metrics.

Table 4-14 shows the performance for each RR-IQA metrics on different level of distortion, which use DMOS values as a standard comparison. As mentioned in the methodology, a good RR-IQA need to have lower MAE and RMS values, and higher PLCC, SRCC and KRCC values. In Table 4-14, the lowest MAE and RMS values is highlighted with red color, while the highest PLCC, SRCC, and KRCC values is highlighted with blue color.

From Table 4-14, we can see that most of the blue color is highlighted in the "DMOS vs RL" row and the second most is highlighted in "DMOS vs S_Dn" row. PLCC judge that R_L^2 has a better performance, as there are more highest PLCC values in "DMOS vs RL" row. On the other hand, SRCC and KRCC also show that R_L^2 has a better performance among all metrics. However, RMSE shows that has better monotonicity. This may due to RMSE is more suitable to test the performance of R_s^2.

All the MAE values are the same in Table 4-14. This is because MAE is the average of absolute errors between a prediction and the true value. The prediction and true value of each data set used is same as the data are from same image, which is Caps.bmp. On the other hand, RMS shows a priority result in R_s^2, as most of the lowest value are found in "DMOS vs Rs" row.

Table 4-14: Results of each metrics used to judge the performance of RR-IQA metrics used

	Bit Rate	PLCC	MAE	RMSE	SRCC	KRCC
DMOS vs SSIM	0	0.124935	53.00435	57.10726	-0.14286	-0.33333
	0.15312	-0.30372	53.00435	57.26089	0.142857	0.333333
	0.1993	-0.17555	53.00435	57.20263	-0.77143	-0.6
	0.40535	0.00363	53.00435	57.12691	-0.14286	-0.33333
	0.42483	0.011158	53.00435	57.12473	-0.14286	-0.33333
	0.85118	0.08592	53.00435	57.11161	-0.14286	-0.33333
DMOS vs S_Dn	0	0.220785	53.00435	57.15289	0.028571	-0.06667
	0.15312	0.249344	53.00435	57.19364	0.657143	0.6
	0.1993	0.258866	53.00435	57.14456	0.657143	0.6
	0.40535	0.198692	53.00435	57.10209	0.485714	0.333333
	0.42483	0.193157	53.00435	57.1022	0.485714	0.333333
	0.85118	-0.12117	53.00435	57.11785	-0.65714	-0.46667
DMOs vs Rs	0	0.077527	53.00435	57.05751	-0.14286	-0.33333
	0.15312	-0.14389	53.00435	57.09518	0.142857	0.333333
	0.1993	-0.28545	53.00435	57.07022	-0.42857	-0.2
	0.40535	-0.04603	53.00435	57.06037	-0.14286	-0.33333
	0.42483	-0.03974	53.00435	57.06017	-0.14286	-0.33333
	0.85118	0.02136	53.00435	57.05858	-0.14286	-0.33333
DMOS vs RL	0	0.967576	53.00435	57.11246	1	1
	0.15312	-0.05511	53.00435	57.09996	-0.39466	-0.44721
	0.1993	0.053146	53.00435	57.13173	-0.23191	-0.27603
	0.40535	0.263259	53.00435	57.17795	0.6	0.466667
	0.42483	0.268256	53.00435	57.17764	0.6	0.466667
	0.85118	-0.3648	53.00435	57.17655	0.142857	0.333333

In overall, Table 4-14 shows that when a perfect quality reference image is used, R_L^2 performed the best among all. However, Ŝ shows a better performance when the reference image has the highest distortion level.

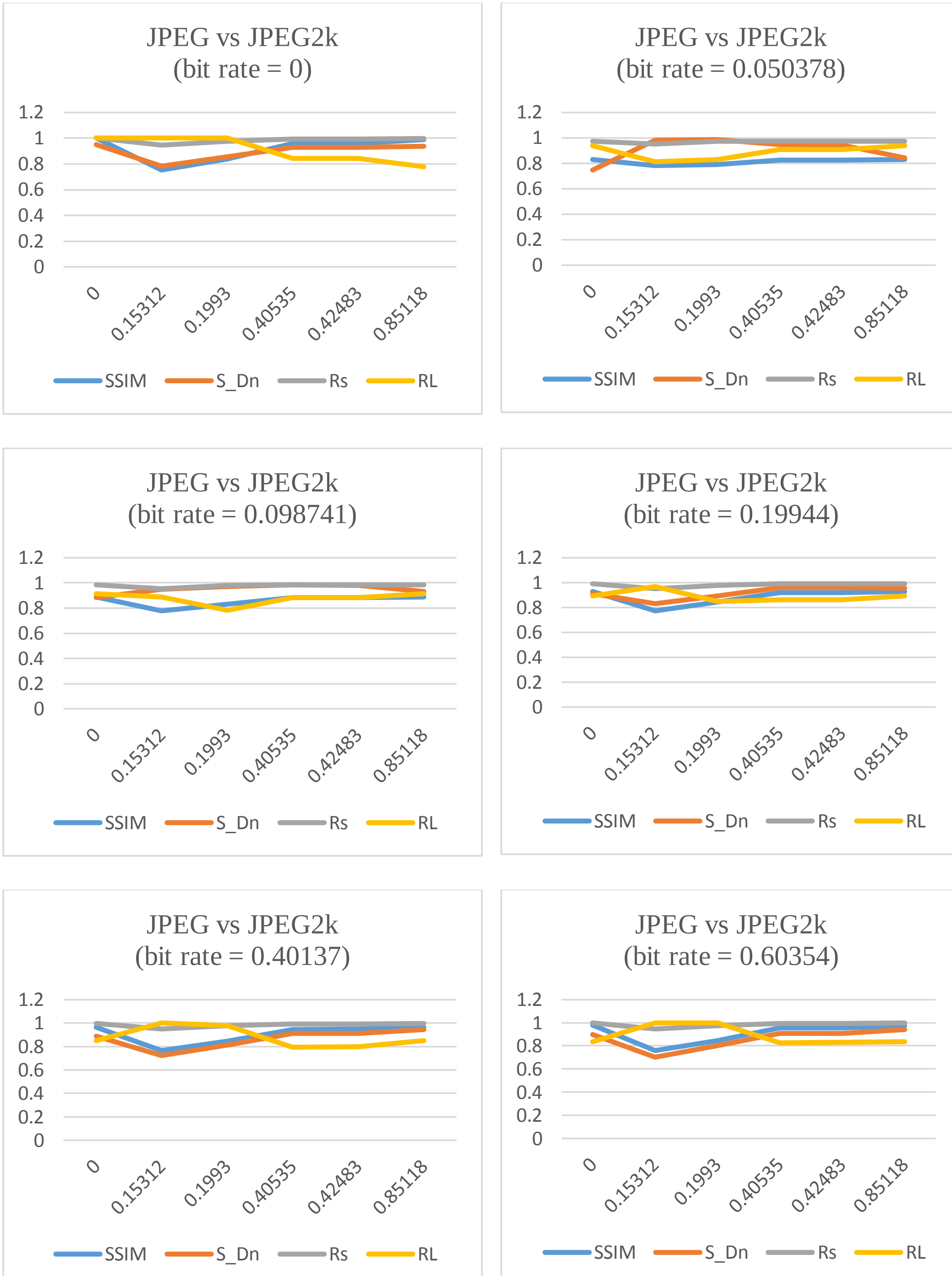


Figure 4-7: Graph plotted by IQM results versus bit rate of imperfect reference image. It is to show the relationship of each metrics, with different bit rate value of fast fading distorted value, and different level of distortion for JPEG distorted reference image.

In Figure 4-7, it shows the graph plotted for each metrics with different bit rate value of distortion. The graph is used to show the performance of each metrics when the bit rate value of JPEG2000 distorted image is increasing, and the JPEG distorted reference image has different distortion value, which is in x-axis of the graph. The flatter the pattern of the graph, indicates a better consistency of the IQM tested.

From Figure 17, R_S^2 has a better consistency as compared to other metrics, for all the JPEG2000 distorted image, in overall. R_L^2 do not show consistency here, as its graph pattern fluctuated a lot. Here, we can say that R_S^2 provide a consistent assessment to Gaussian blur reduced reference image.

In overall, the performance of R_L^2 shows a better accuracy whereas R_S^2 shows a better consistency here, as compared to the other metrics included, when the reference image has JPEG distortion is compared to JPEG2000 distorted image.

4-2-4 Fast Fading distorted image as compressed image

Table 4-15 (a) used a perfect quality image as the reference while (b), (c), (d), (e) and (f) used a JPEG distorted image as the reference image. The bit rate of distortion increases from (b) to (f). The result value more than one is converted to one in this table. This is because the highest value qualified is one. From Table 4-15, we can see that the SSIM, R_F^2, PSNR, and R_L^2 value is changing gradually from (a) to (f).

SSIM is a metric designed for full reference image quality assessment. The value of SSIM decreases from (a) to (b), and increases from (b) to (f) for each of the different bit rate for JPEG reference image. The changes is inconsistent. This indicates that SSIM value is less effective when the reference image used has no perfect quality, and the bit rate of distortion increases.

The PSNR value vary randomly from (a) to (f). This is because PSNR is calculated by the mean square error of the two images involved. When the reference image is distorted, it could hardly give an accurate image quality assessment result.

Table 4-15: Results of each metrics applied on a Fast Fading compressed image, caps.bmp, with different level of bit rate. The imperfect reference image used is with JPEG distortion. (a)Perfect quality image as reference. (b)JPEG distorted image with bit rate 0.15312 as reference. (c)JPEG distorted image with bit rate 0.1993 as reference. (d) JPEG distorted image with bit rate 0.40535 as reference. (e)JPEG distorted image with bit rate 0.42483 as reference. (f) JPEG distorted image with bit rate 0.85118 as reference.

Bit rate of JPEG = 0

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	1	65535	0.954867	1	1	1	100
15.5	0.729741	25.41353	0.784455	0.936684	1.011404	0.926123	69.00739
18.9	0.796929	26.59974	0.803897	0.952255	1.01885	0.934637	60.05539
20.3	0.910108	29.91208	0.88453	0.97799	1.010487	0.96784	50.70893
23.7	0.98202	36.04244	0.945002	0.994681	1.14553	0.868315	34.45273
25.1	0.96702	34.6269	0.90351	0.99263	1.145221	0.866758	42.48964

(a)

Bit rate of JPEG = 0.15312

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.75055	25.86641	0.722137	0.944352	0.783275	1	100
15.5	0.716703	24.91415	0.984286	0.927776	1.235467	0.750952	69.00739
18.9	0.744319	25.52031	0.980342	0.937846	1.214746	0.772051	60.05539
20.3	0.781551	26.90804	0.945962	0.955322	1.238034	0.771644	50.70893
23.7	0.759788	26.26084	0.724347	0.94884	0.898174	1	34.45273
25.1	0.7457	26.05472	0.745499	0.946497	0.898871	1	42.48964

(b)

Bit rate of JPEG = 0.1993

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.838527	29.4221	0.804389	0.975457	0.938386	1	100
15.5	0.699239	25.5967	0.983247	0.938337	1.144788	0.81966	69.00739
18.9	0.750784	26.66359	0.982879	0.952242	1.152795	0.826029	60.05539

20.3	0.830616	29.60389	0.965132	0.975988	1.143803	0.853283	50.70893
23.7	0.842929	30.04189	0.810671	0.978557	1.062932	0.92062	34.45273
25.1	0.829905	29.60889	0.826197	0.976378	1.063685	0.917921	42.48964

(c)

Bit rate of JPEG = 0.40535

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.956837	34.09477	0.84935	0.991667	1.177686	0.842047	100
15.5	0.724556	25.61992	0.895443	0.939259	1.048435	0.895868	69.00739
18.9	0.790866	26.84506	0.911851	0.954613	1.056039	0.903957	60.05539
20.3	0.897003	30.35686	0.962338	0.980006	1.047499	0.935567	50.70893
23.7	0.951717	34.1097	0.889923	0.991641	1.185349	0.836582	34.45273
25.1	0.936857	33.07751	0.873605	0.989421	1.185032	0.834932	42.48964

(d)

Bit rate of JPEG = 0.42483

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.960829	34.36081	0.850965	0.99216	1.176875	0.843046	100
15.5	0.72508	25.61132	0.885303	0.939018	1.048737	0.89538	69.00739
18.9	0.791766	26.83355	0.902731	0.954406	1.056343	0.9035	60.05539
20.3	0.898908	30.31584	0.95815	0.979778	1.047801	0.93508	50.70893
23.7	0.954865	34.25545	0.892002	0.991906	1.185674	0.836576	34.45273
25.1	0.940121	33.19536	0.87321	0.989694	1.185358	0.834933	42.48964

(e)

Bit rate of JPEG = 0.85118

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.989243	38.29867	0.913614	0.99684	1.277347	0.780399	100
15.5	0.728779	25.47895	0.784482	0.937437	1.012337	0.926013	69.00739
18.9	0.796092	26.66753	0.805391	0.952855	1.019787	0.934367	60.05539
20.3	0.908811	30.01966	0.895504	0.978457	1.01142	0.96741	50.70893
23.7	0.976055	35.34714	0.95201	0.993733	1.146534	0.866728	34.45273
25.1	0.961125	34.07193	0.909023	0.991604	1.146224	0.865105	42.48964

(f)

Besides, the value of R_S^2 also show a changes from Table 4-15 (a) to (f). However, the changes of the value is averagely small. This shows that R_S^2 is suitable for reduced reference image quality assessment. On the other hand, the values of R_L^2 changes gradually from Table 4-15 (a) to (f). However, from (f), we can see that R_S^2 provided a better result thanR_L^2 in overall. The distortion is non-noticeable because the bit rate of distorted image is relatively small, which indicates that the distorted image is considered high quality. Therefore, the result value is close to 1 although the bit rate is the highest here.

The Ŝ value calculated from D_n value changes inconsistently in overall, as we can see from Table 4-15 (a) to (f). Moreover, the Ŝ value is less than the value of R_S^2 in general. This indicates that the estimated SSIM, Ŝ is less accurate and less effective than that of R_S^2 in this assessment.

Table 4-16: Results of each metrics used to judge the performance of RR-IQA metrics used.

	Bit Rate	PLCC	MAE	RMSE	SRCC	KRCC
DMOS vs SSIM	0	-0.07063	59.45235	62.31471	-0.14286	-0.33333
	0.15312	-0.30159	59.45235	62.45317	-0.42857	-0.33333
	0.1993	-0.18396	59.45235	62.40865	-0.37143	-0.33333
	0.40535	-0.11799	59.45235	62.33586	-0.14286	-0.33333
	0.42483	-0.11493	59.45235	62.33367	-0.14286	-0.33333
	0.85118	-0.08757	59.45235	62.31923	-0.14286	-0.33333
DMOS vs S_Dn	0	0.001619	59.45235	62.32935	-0.14286	-0.33333
	0.15312	0.016342	59.45235	62.356	0.142857	0.333333
	0.1993	-0.01102	59.45235	62.31465	0.142857	0.333333
	0.40535	-0.4322	59.45235	62.3179	-0.14286	-0.2
	0.42483	-0.46876	59.45235	62.32118	-0.37143	-0.33333
	0.85118	-0.26112	59.45235	62.33734	-0.42857	-0.46667
DMOs vs Rs	0	-0.061	59.45235	62.23934	-0.14286	-0.33333
	0.15312	-0.3645	59.45235	62.27025	-0.65714	-0.46667
	0.1993	-0.23805	59.45235	62.24906	-0.82857	-0.73333
	0.40535	-0.14714	59.45235	62.24106	-0.14286	-0.33333
	0.42483	-0.14229	59.45235	62.24099	-0.14286	-0.33333
	0.85118	-0.0931	59.45235	62.24008	-0.14286	-0.33333
DMOS vs RL	0	0.820027	59.45235	62.27075	0.714286	0.466667
	0.15312	-0.03457	59.45235	62.32798	-0.33395	-0.29814
	0.1993	0.348651	59.45235	62.31222	-0.14286	-0.33333
	0.40535	-0.00176	59.45235	62.33367	0.371429	0.066667
	0.42483	0.006324	59.45235	62.33363	0.371429	0.066667
	0.85118	-0.47913	59.45235	62.32942	-0.14286	-0.2

Table 4-16 shows the performance for each RR-IQA metrics on different level of distortion, which use DMOS values as a standard comparison. As mentioned in the methodology, a good RR-IQA need to have lower MAE and RMS values, and higher PLCC, SRCC and KRCC values. In Table 4-16, the lowest MAE and RMS values is highlighted with red color, while the highest PLCC, SRCC, and KRCC values is highlighted with blue color.

From Table 4-16, we can see that most of the blue color is highlighted in the "DMOS vs RL" row and the second most is highlighted in "DMOS vs S_Dn" row, and "DMOS vs Rs" row. PLCC and SRCC judge that R_L^2has a better performance, as there are more highest PLCC and SRCC values in "DMOS vs RL" row. On the other hand, KRCC show that R_S^2has a better performance.

All the MAE values are the same in Table 4-16. This is because MAE is the average of absolute errors between a prediction and the true value. The prediction and true value of each data set used is same, as the data are from same image, which is Caps.bmp. On the other hand, RMS shows a priority result in R_S^2, as most of the lowest value are found in "DMOS vs Rs" row.

In overall, Table 4-16 shows that when a perfect quality reference image is used, R_L^2 performed the best among all. The estimated SSIM, Ŝ perform better when the reference image has the highest distortion level.

SSIM has the worst results, in Table 4-16. This may due to it is designed for a full reference image quality assessment. When it comes to reduced reference image quality assessment, the performance will gradually decreases.

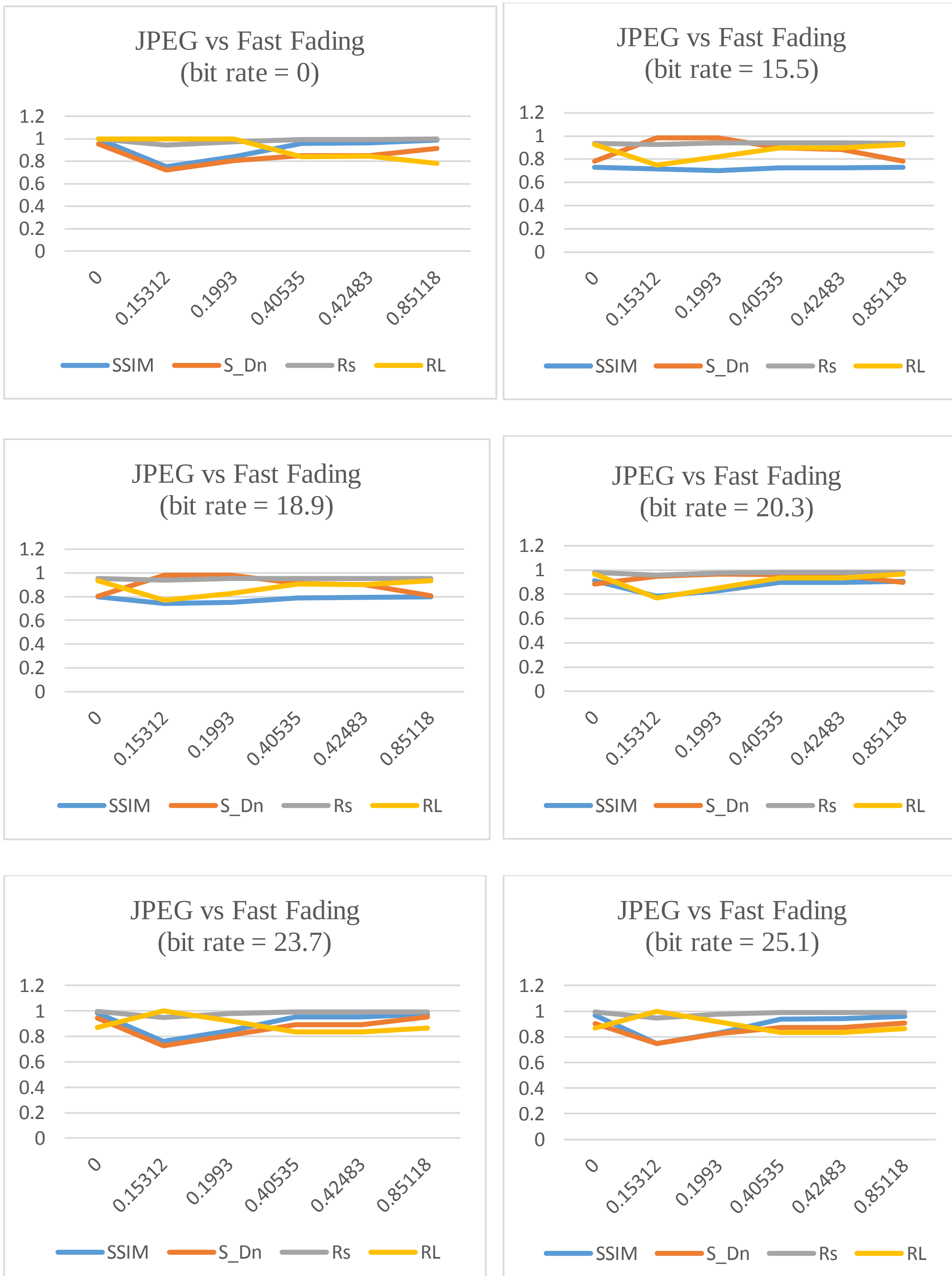


Figure 4-8: Graph plotted by IQM results versus bit rate of imperfect reference image. It is to show the relationship of each metrics, with different bit rate value of fast fading distorted value, and different level of distortion for JPEG distorted reference image.

In Figure 4-8, it shows the graph plotted for each metrics with different bit rate value of distortion. The graph is used to show the performance of each metrics when the bit rate value of fast fading distorted image is increasing, and the JPEG distorted reference image has different distortion value, which is in x-axis of the graph. The flatter the pattern of the graph, indicates a better consistency of the IQM tested.

From Figure 4-8, R_S^2 has a better consistency in overall as compared to other metrics, for all the fast fading distorted image. The pattern of graph of R_L^2 fluctuated a lot, which indicates that poor consistency is show here. Thus, we can say that R_S^2 provide a consistent assessment to JPEG reduced reference image when compared with fast fading distorted image.

In overall, R_L^2 shows a better accuracy here and R_S^2 gives a better consistency here, as compared to the other metrics included, when the reference image has JPEG distortion is compared to fast fading distorted image.

4-3 Performance of R_L^2 When Reference Image Has JPEG2000 Distortion

Here, JPEG2000 distorted image is used as a reference image. In order to test the accuracy, consistency, and monotonicity of each of the RR-IQA applied to this distortion type of reduced reference image, different types of distorted image is tested with it. There are four types of distortion being tested, which are Gaussian Noise, Fast Fading, JPEG, and Gaussian Blur distortion.

4-3-1 Gaussian Noise distorted image as compressed image

Table 4-17 (a) used a perfect quality image as the reference while (b), (c), (d), (e) and (f) used a JPEG2000 distorted image as the reference image. The bit rate of distortion increases from (b) to (f). The result value more than one is converted to one in this table. This is because the highest value qualified is one. From Table 4-17, we can see that the SSIM, R_F^2, PSNR, and R_L^2 value is changing gradually from (a) to (f).

SSIM is a metric designed for full reference image quality assessment. The value of SSIM decreases from (a) to (b) then increases from (b) to (f), for each of the different bit rate for JPEG2000 reference image. For each of SSIM value get when the bit rate of Gaussian noise is 1.0, which is the highest bit rate of distortion, is extremely small as compared to others. This indicates that SSIM value is less effective when the reference image used has no perfect quality, and the bit rate of distortion increases.

The PSNR value changes in value from (a) to (f). Besides, the PSNR value is extremely small when Gaussian Noise distortion level is high. This is because PSNR is calculated by the mean square error of the two images involved. When the reference image is distorted and the distorted image has very high distortion, it could hardly give an accurate image quality assessment result.

Table 4-17: Results of each metrics applied on a Gaussian Noise compressed image, caps.bmp, with different level of bit rate. The imperfect reference image used is with JPEG2000 distortion. (a)Perfect quality image as reference. (b)JPEG2000 distorted image with bit rate 0.050378 as reference. (c)JPEG2000 distorted image with bit rate 0.098741 as reference. (d) JPEG2000 distorted image with bit rate 0.19944 as reference. (e)JPEG2000 distorted image with bit rate 0.40137 as reference. (f) JPEG2000 distorted image with bit rate 0.60354 as reference.

Bit rate of JPEG2000 = 0

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	1	65535	0.948758	1	1	1	100
0.015625	0.982878	39.55768	0.95635	0.997643	1.163859	0.857185	22.50337
0.03125	0.937012	33.61711	0.884508	0.990815	1.046644	0.946659	33.54177
0.0625	0.801863	27.65342	0.747118	0.964984	0.735216	1	41.3394
0.125	0.548208	21.75995	0.60953	0.87853	0.145405	1	48.03932
1	0.086885	10.31411	0.086594	0.198253	0.043079	1	67.38191

(a)

Bit rate of JPEG2000 =0.050378 -

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.8318948	28.98727	0.554165	0.972697	0.962246	1	100
0.015625	0.8166617	28.64181	0.793209	0.970494	0.968447	1	22.50337
0.03125	0.7761448	27.75018	0.860548	0.964055	0.989133	0.974647	33.54177
0.0625	0.6550823	25.29597	0.853572	0.93894	1.092274	0.859619	41.3394
0.125	0.4364151	21.04515	0.717354	0.854983	0.494768	1	48.03932
1	0.0735435	10.32491	0.082769	0.19292	0.040554	1	67.38191

(b)

Bit rate of JPEG2000 =0.098741

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.8891991	30.8188	0.665464	0.982177	0.977525	1	100
0.015625	0.8734489	30.29224	0.863825	0.979918	0.983707	0.996148	22.50337
0.03125	0.8310602	29.0242	0.901455	0.97332	1.004329	0.969125	33.54177
0.0625	0.70573	25.97613	0.861153	0.948035	1.006024	0.942357	41.3394
0.125	0.4760047	21.27701	0.708887	0.863127	0.410377	1	48.03932
1	0.0788933	10.32107	0.057522	0.194814	0.041164	1	67.38191

(c)

Bit rate of JPEG2000 =0.19944

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.9298985	33.27789	0.813656	0.989921	0.991715	0.998191	100
0.015625	0.9138191	32.38334	0.936519	0.98764	0.997879	0.989739	22.50337
0.03125	0.8703455	30.46541	0.921128	0.980927	1.018441	0.963165	33.54177
0.0625	0.7414988	26.61992	0.829454	0.955359	0.925925	1	41.3394
0.125	0.5044522	21.47942	0.66839	0.869815	0.332004	1	48.03932
1	0.0825671	10.31948	0.027857	0.196383	0.04173	1	67.38191

(d)

Bit rate of JPEG2000 =0.40137

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.9644935	36.69453	0.908866	0.995423	1.015466	0.980262	100
0.015625	0.9481787	34.92294	0.951215	0.993131	1.021601	0.972132	22.50337
0.03125	0.9033235	31.90693	0.884598	0.986351	1.103925	0.893495	33.54177
0.0625	0.7711251	27.15043	0.757285	0.960597	0.791853	1	41.3394
0.125	0.5274785	21.63129	0.608444	0.874611	0.200821	1	48.03932
1	0.0848749	10.3169	0.062178	0.197439	0.042678	1	67.38191

(e)

Bit rate of JPEG2000 =0.60354

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.9776377	39.26188	0.923287	0.997469	1.022654	0.975373	100
0.015625	0.9611178	36.43961	0.946969	0.995161	1.180178	0.84323	22.50337
0.03125	0.9161968	32.60696	0.87315	0.988396	1.062893	0.92991	33.54177
0.0625	0.7829727	27.37036	0.74017	0.962581	0.751283	1	41.3394
0.125	0.5361243	21.68934	0.599675	0.876397	0.161126	1	48.03932
1	0.086065	10.31616	0.081783	0.197924	0.042965	1	67.38191

(f)

Besides, the value of R_S^2 also show a changes from Table 4-17 (a) to (f). However, the changes of the value is averagely small. This shows that R_S^2 is suitable for reduced reference image quality assessment. On the other hand, the values of R_L^2 also changes accordingly from Table 4-17 (a) to (f). However, from (f), we can see that R_L^2 provided a better result thanR_S^2 when the Gaussian noise distortion level is higher. The distortion is non-noticeable because the bit rate of distorted image is relatively small, which indicates that the distorted image is considered high quality. Therefore, the result value is close to 1 although the bit rate is the highest here.

The Ŝ value calculated from D_n value change consistently, as we can see from Table 4-17 (a) to (f). However, the Ŝ value is less than the value of R_S^2 and R_F^2 in general. This indicates that the estimated SSIM, Ŝ is less accurate and less effective for this assessment as compared to both of the metrics mentioned.

Table 4-18: Results of each metrics used to judge the performance of RR-IQA metrics used.

	Bit Rate	PLCC	MAE	RMSE	SRCC	KRCC
DMOS vs SSIM	0	-0.16678	52.1343	57.37961	-0.14286	-0.33333
	0.050378	-0.15868	52.1343	57.48896	-0.14286	-0.33333
	0.098741	-0.16212	52.1343	57.45122	-0.14286	-0.33333
	0.19944	-0.16445	52.1343	57.4244	-0.14286	-0.33333
	0.40137	-0.16595	52.1343	57.40206	-0.14286	-0.33333
	0.60354	-0.16661	52.1343	57.39343	-0.14286	-0.33333
DMOS vs S_Dn	0	-0.1867	52.1343	57.39904	-0.42857	-0.46667
	0.050378	-0.57662	52.1343	57.49857	-0.77143	-0.6
	0.098741	-0.49346	52.1343	57.46338	-0.88571	-0.73333
	0.19944	-0.36021	52.1343	57.42937	-0.82857	-0.73333
	0.40137	-0.23286	52.1343	57.41455	-0.42857	-0.46667
	0.60354	-0.20417	52.1343	57.41115	-0.42857	-0.46667
DMOs vs Rs	0	-0.25166	52.1343	57.2872	-0.14286	-0.33333
	0.050378	-0.2519	52.1343	57.30663	-0.14286	-0.33333
	0.098741	-0.25181	52.1343	57.29988	-0.14286	-0.33333
	0.19944	-0.25175	52.1343	57.29436	-0.14286	-0.33333
	0.40137	-0.25172	52.1343	57.29043	-0.14286	-0.33333
	0.60354	-0.25172	52.1343	57.28895	-0.14286	-0.33333
DMOS vs RL	0	0.646381	52.1343	57.12344	0.845154	0.774597
	0.050378	0.253958	52.1343	57.12834	0.371868	0.258199
	0.098741	0.392748	52.1343	57.11934	0.698253	0.447214
	0.19944	0.443491	52.1343	57.11404	0.5161	0.298142
	0.40137	0.323091	52.1343	57.12696	0.5161	0.298142
	0.60354	0.547525	52.1343	57.13303	0.576818	0.447214

Table 4-18 shows the performance for each RR-IQA metrics on different level of distortion, which use DMOS values as a standard comparison. As mentioned in the methodology, a good RR-IQA need to have lower MAE and RMS values, and higher PLCC, SRCC and KRCC values. In Table 4-18, the lowest MAE and RMS values is highlighted with red color, while the highest PLCC, SRCC, and KRCC values is highlighted with blue color.

From Table 4-18, we can see that most of the blue color is highlighted in the "DMOS vs S_Dn" row and the second most is highlighted in "DMOS vs RL" row. PLCC judge that R_L^2 has a better performance, as there are more highest PLCC values in "DMOS vs RL" row. On the other hand, SRCC has equally same amount of highest value in both "DMOS vs S_Dn" and "DMOS vs RL" rows. KRCC show that $\hat{S}$ has a better performance.

All the MAE values are the same in Table 4-18. This is because MAE is the average of absolute errors between a prediction and the true value. The prediction and true value of each data set used is same, as the data are from same image, which is Caps.bmp. On the other hand, RMS shows a priority result in R_L^2, as most of the lowest value are found in "DMOS vs RL" row.

In overall, Table 4-18 shows that when a perfect quality reference image is used, R_L^2 performed the best among all. This is the same to the result when the reference image has the highest distortion level.

SSIM has the worst results, in Table 4-18. This may due to it is designed for a full reference image quality assessment. When it comes to reduced reference image quality assessment, the performance will gradually decreases.

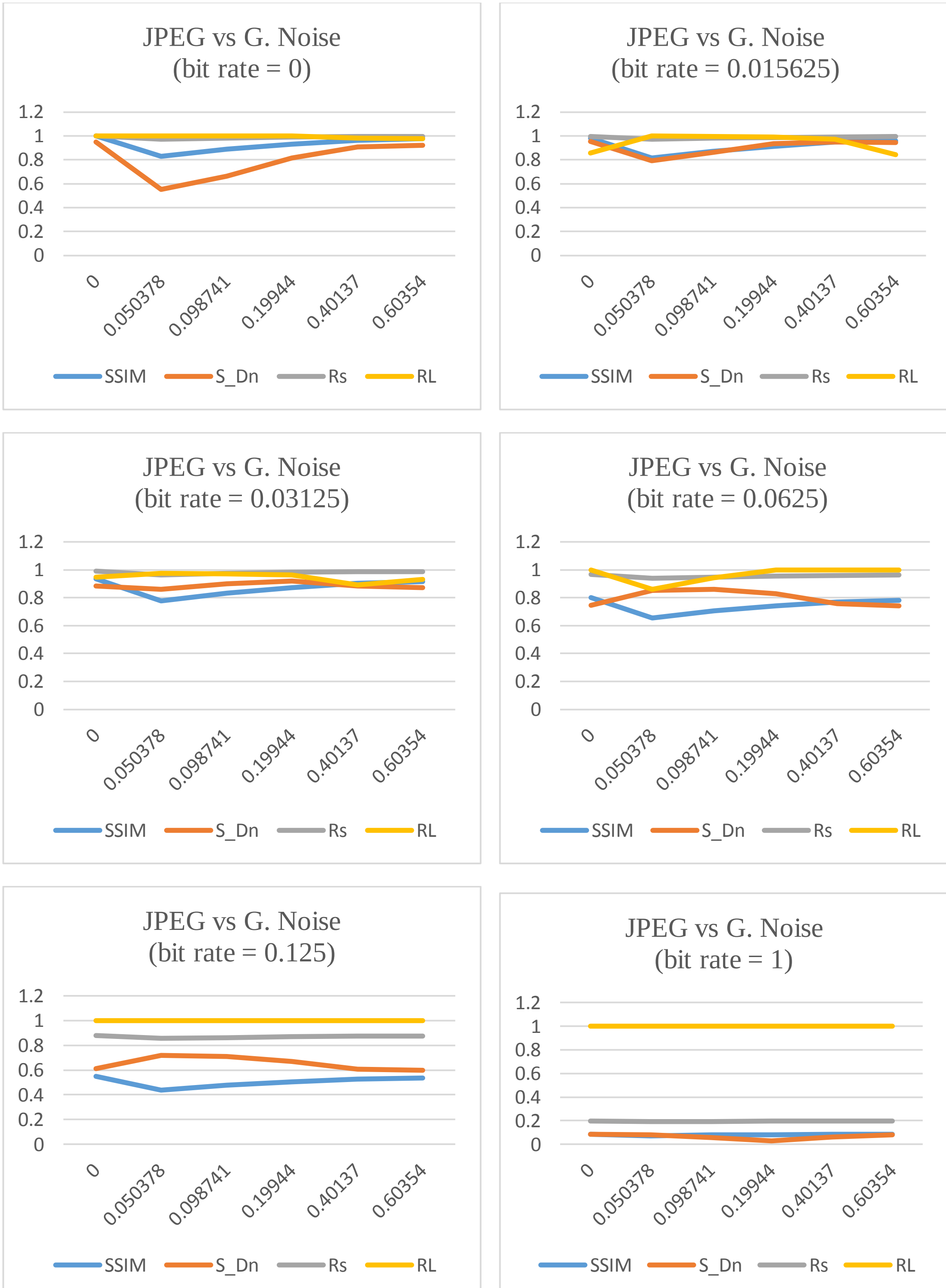


Figure 4-9: Graph plotted by IQM results versus bit rate of imperfect reference image. It is to show the relationship of each metrics, with different bit rate value of Gaussian Noise distorted value, and different level of distortion for JPEG2000 distorted reference image.

In Figure 4-9, it shows the graph plotted for each metrics with different bit rate value of distortion. The graph is used to show the performance of each metrics when the bit rate value of Gaussian noise distorted image is increasing, and the JPEG2000 distorted reference image has different distortion value, which is in x-axis of the graph. The flatter the pattern of the graph, indicates a better consistency of the IQM tested.

From Figure 4-9, R_S^2 has a better consistency as compared to other metrics, for all the Gaussian noise distorted image. R_L^2 shows a second best performance in this assessment, especially when the Gaussian noise distorted image has higher bit rate. Here, we can say that R_L^2 provide a consistent assessment to JPEG2000 reduced reference image when compared with Gaussian noise distorted image, which is in higher bit rate.

In overall, $\hat{S}$ shows a better accuracy whereas R_L^2 shows a better consistency here, as compared to the other metrics included, when the reference image has JPEG2000 distortion is compared to Gaussian Noise distorted image.

4-3-2 Fast Fading distorted image as compressed image

Table 4-19 (a) used a perfect quality image as the reference while (b), (c), (d), (e) and (f) used a JPEG2000 distorted image as the reference image. The bit rate of distortion increases from (b) to (f). The result value more than one is converted to one in this table. This is because the highest value qualified is one. From Table 4-19, we can see that the SSIM, R_F^2, PSNR, and R_L^2 value is changing gradually from (a) to (f).

SSIM is a metric designed for full reference image quality assessment. The value of SSIM changes randomly from (a) to (f) for each of the different bit rate for JPEG2000 reference image. This indicates that SSIM value is less effective when the reference image used has no perfect quality, and the bit rate of distortion increases.

The PSNR value changes inconsistently in value from (a) to (f). This is because PSNR is calculated by the mean square error of the two images involved. When the reference image is distorted, it could hardly give an accurate image quality assessment result.

Table 4-19: Results of each metrics applied on a Fast Fading compressed image, caps.bmp, with different level of bit rate. The imperfect reference image used is with JPEG2000 distortion. (a)Perfect quality image as reference. (b)JPEG2000 distorted image with bit rate 0.050378 as reference. (c)JPEG2000 distorted image with bit rate 0.098741 as reference. (d) JPEG2000 distorted image with bit rate 0.19944 as reference. (e)JPEG2000 distorted image with bit rate 0.40137 as reference. (f)JPEG2000 distorted image with bit rate 0.60354 as reference.

Bit rate of JPEG2000 =0

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	1	65535	0.954867	1	1	1	100
15.5	0.7297412	25.41353	0.784455	0.936684	0.787033	1	69.00739
18.9	0.796929	26.59974	0.803897	0.952255	0.804078	1	60.05539
20.3	0.9101077	29.91208	0.88453	0.97799	0.78493	1	50.70893
23.7	0.9820205	36.04244	0.945002	0.994681	1.085079	0.91669	34.45273
25.1	0.9670201	34.6269	0.90351	0.99263	1.084411	0.915362	42.48964

(a)

Bit rate of JPEG2000 =0.050378

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.8318948	28.98727	0.81952	0.972697	0.962246	1	100
15.5	0.8362347	27.62309	0.98968	0.960493	1.144767	0.83903	69.00739
18.9	0.8670001	28.88964	0.987747	0.970773	1.162034	0.835408	60.05539
20.3	0.8905735	32.39134	0.965517	0.987114	1.142637	0.863891	50.70893
23.7	0.8457546	29.93694	0.820673	0.977848	0.98235	0.995418	34.45273
25.1	0.8291761	29.47077	0.835784	0.975432	0.982468	0.992839	42.48964

(b)

Bit rate of JPEG2000 =0.098741

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.8891991	30.8188	0.867124	0.982177	0.977525	1	100
15.5	0.7876242	26.63278	0.981579	0.951021	1.058354	0.898585	69.00739

18.9	0.8566593	28.18228	0.983255	0.96605	1.075568	0.898177	60.05539
20.3	0.9179592	32.30432	0.979286	0.986987	1.056231	0.934443	50.70893
23.7	0.9033107	32.24996	0.874471	0.987057	0.997567	0.989465	34.45273
25.1	0.8861417	31.45271	0.882614	0.984507	0.997684	0.986792	42.48964

(c)

Bit rate of JPEG2000 =0.19944

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.9298985	33.27789	0.849209	0.989921	0.991715	0.998191	100
15.5	0.7657489	26.05069	0.903934	0.944543	0.978103	0.965689	69.00739
18.9	0.8342767	27.395	0.919891	0.959686	0.995267	0.964249	60.05539
20.3	0.9133778	31.05171	0.969349	0.982808	0.975986	1	50.70893
23.7	0.9394356	34.36608	0.893781	0.992077	1.011699	0.980606	34.45273
25.1	0.9226294	33.27805	0.881777	0.989857	1.011816	0.978298	42.48964

(d)

Bit rate of JPEG2000 =0.40137

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.9644935	36.69453	0.917166	0.995423	1.015466	0.980262	100
15.5	0.7486144	25.67798	0.790531	0.940033	0.843777	1	69.00739
18.9	0.8149839	26.92409	0.811567	0.955404	0.860858	1	60.05539
20.3	0.9148344	30.42855	0.90375	0.980319	0.84167	1	50.70893
23.7	0.9623294	35.46127	0.953522	0.993873	1.14244	0.869956	34.45273
25.1	0.9467813	34.17635	0.911751	0.991782	1.141771	0.868634	42.48964

(e)

Bit rate of JPEG2000 =0.60354

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.9776377	39.26188	0.935513	0.997469	1.022654	0.975373	100
15.5	0.7402399	25.52102	0.784784	0.938015	0.80313	1	69.00739
18.9	0.8072687	26.73348	0.804541	0.953544	0.820186	1	60.05539
20.3	0.9141381	30.12626	0.892236	0.978971	0.801027	1	50.70893
23.7	0.9716736	35.9608	0.960453	0.994556	1.101352	0.903033	34.45273
25.1	0.9564238	34.57554	0.914857	0.99252	1.100684	0.90173	42.48964

(f)

Besides, the value of R_s^2 also show a changes from Table 4-19 (a) to (f). However, the changes of the value is averagely small. This shows that R_s^2 is suitable for reduced reference image quality assessment. On the other hand, the values of R_L^2 have little changes from Table 4-19 (a) to (f). However, from (f), we can see that R_L^2 provided a better result than R_S^2 in certain level of fast fading distortion in distorted image. The distortion is non-noticeable because the bit rate of distorted image is relatively small, which indicates that the distorted image is considered high quality. Therefore, the result value is close to 1 although the bit rate is the highest here.

The Ŝ value calculated from D_n value changes randomly in overall, as we can see from Table 4-19 (a) to (f). However, the Ŝ value is less than the value of R_S^2 and R_F^2 in general. This indicates that the estimated SSIM, Ŝ is less accurate and less effective for this assessment.

Table 4-20 shows the performance for each RR-IQA metrics on different level of distortion, which use DMOS values as a standard comparison. As mentioned in the methodology, a good RR-IQA need to have lower MAE and RMS values, and higher PLCC, SRCC and KRCC values. In Table 4-6, the lowest MAE and RMS values is highlighted with red color, while the highest PLCC, SRCC, and KRCC values is highlighted with blue color.

From Table 4-20, we can see that most of the blue color is highlighted in the "DMOS vs Rs" row and the second most is highlighted in "DMOS vs RL" row. PLCC judge that R_L^2 has a better performance, as there are more highest PLCC values in "DMOS vs RL" row. On the other hand, SRCC judge that both the R_S^2 and R_L^2 has equally good performance in this assessment. KRCC show that R_S^2 has a better performance.

All the MAE values are the same in Table 4-20. This is because MAE is the average of absolute errors between a prediction and the true value. The prediction and true value of each data set used is same, as the data are from same image, which is Caps.bmp. On the other hand, RMS shows a priority result in R_S^2, as most of the lowest value are found in "DMOS vs Rs" row.

Table 4-20: Results of each metrics used to judge the performance of RR-IQA metrics used.

	Bit Rate	PLCC	MAE	RMSE	SRCC	KRCC
DMOS vs SSIM	0	-0.07063	59.45235	62.31471	-0.14286	-0.33333
	0.050378	-0.26689	59.45235	62.35888	-0.14286	-0.2
	0.098741	-0.28265	59.45235	62.33903	-0.42857	-0.33333
	0.19944	-0.19749	59.45235	62.3291	-0.42857	-0.46667
	0.40137	-0.13031	59.45235	62.32119	-0.14286	-0.33333
	0.60354	-0.11369	59.45235	62.31865	-0.14286	-0.33333
DMOS vs S_Dn	0	0.001619	59.45235	62.32935	-0.14286	-0.33333
	0.050378	0.014578	59.45235	62.30667	0.142857	0.333333
	0.098741	-0.0385	59.45235	62.28434	0.085714	0.2
	0.19944	-0.45749	59.45235	62.31293	-0.14286	-0.2
	0.40137	-0.26066	59.45235	62.33278	-0.42857	-0.46667
	0.60354	-0.16911	59.45235	62.33065	-0.42857	-0.46667
DMOs vs Rs	0	-0.061	59.45235	62.23934	-0.14286	-0.33333
	0.050378	-0.40993	59.45235	62.24151	-0.65714	-0.46667
	0.098741	-0.29844	59.45235	62.23965	-0.77143	-0.6
	0.19944	-0.19219	59.45235	62.2393	-0.42857	-0.46667
	0.40137	-0.11866	59.45235	62.2393	-0.14286	-0.33333
	0.60354	-0.09602	59.45235	62.23945	-0.14286	-0.33333
DMOS vs RL	0	0.695078	59.45235	62.23291	0.777542	0.602464
	0.050378	-0.02187	59.45235	62.29076	-0.08571	-0.2
	0.098741	0.005519	59.45235	62.26176	-0.08571	-0.2
	0.19944	0.240052	59.45235	62.23256	-0.08571	-0.06667
	0.40137	0.612963	59.45235	62.24754	0.5161	0.298142
	0.60354	0.549827	59.45235	62.24218	0.5161	0.298142

In overall, Table 4-20 shows that when a perfect quality reference image is used, R_L^2 performed the best among all. This is the same to the result when the reference image has the highest distortion level.

SSIM has the worst results, in Table 4-20. This may due to it is designed for a full reference image quality assessment. When it comes to reduced reference image quality assessment, the performance will gradually decreases.

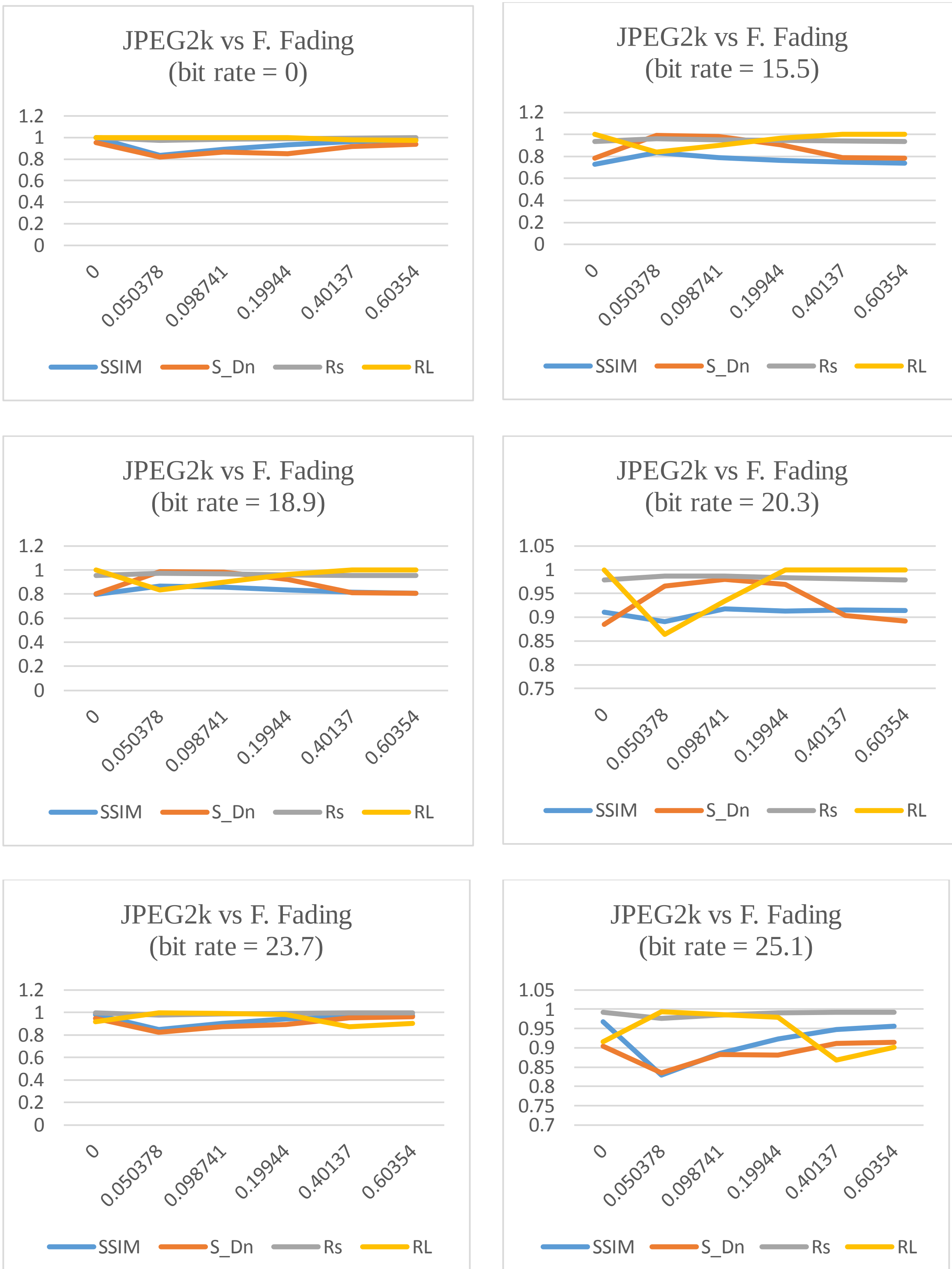


Figure 4-10: Graph plotted by IQM results versus bit rate of imperfect reference image. It is to show the relationship of each metrics, with different bit rate value of fast fading distorted value, and different level of distortion for JPEG2000 distorted reference image.

In Figure 4-10, it shows the graph plotted for each metrics with different bit rate value of distortion. The graph is used to show the performance of each metrics when the bit rate value of fast fading distorted image is increasing, and the JPEG2000 distorted reference image has different distortion value, which is in x-axis of the graph. The flatter the pattern of the graph, indicates a better consistency of the IQM tested.

From Figure 4-10, R_S^2 has a better consistency as compared to other metrics, for all the fast fading distorted image. R_L^2 only shows a better performance, when fast fading has zero level of distortion. Here, we can say that R_S^2 provide a consistent assessment to JPEG2000 reduced reference image as tested with fast fading distorted image.

In overall, the performance of the R_S^2 are the best as compared to the other metrics included, when the reference image has JPEG2000 distortion is compared to fast fading distorted image. This is because R_S^2 shows a better accuracy and consistency here.

4-3-3 JPEG distorted image as compressed image

Table 4-21 (a) used a perfect quality image as the reference while (b), (c), (d), (e) and (f) used a JPEG distorted image as the reference image. The bit rate of distortion increases from (b) to (f). The result value more than one is converted to one in this table. This is because the highest value qualified is one. From Table 4-21, we can see that the SSIM, R_F^2, PSNR, and R_L^2 value is changing gradually from (a) to (f).

SSIM is a metric designed for full reference image quality assessment. The value of SSIM changes randomly from (a) to (f) for each of the different bit rate for JPEG2000 reference image. This indicates that SSIM value is less effective when the reference image used has no perfect quality, and the bit rate of distortion increases.

The PSNR value also changes inconsistently in value from (a) to (f). This is because PSNR is calculated by the mean square error of the two images involved. When the reference image is distorted, it could hardly give an accurate image quality assessment result.

Table 4-21: Results of each metrics applied on a JPEG compressed image, caps.bmp, with different level of bit rate. The imperfect reference image used is with JPEG2000 distortion. (a)Perfect quality image as reference. (b)JPEG2000 distorted image with bit rate 0.050378 as reference. (c)JPEG2000 distorted image with bit rate 0.098741 as reference. (d) JPEG2000 distorted image with bit rate 0.19944 as reference. (e)JPEG2000 distorted image with bit rate 0.40137 as reference. (f) JPEG2000 distorted image with bit rate 0.60354 as reference.

Bit rate of JPEG2000 =0

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	1	65535	0.955331	1	1	1	100
0.15312	0.7505502	25.86641	0.809367	0.944352	0.750872	1	60.06954
0.1993	0.8385269	29.4221	0.864707	0.975457	0.901317	1	49.85666
0.40535	0.9568373	34.09477	0.930092	0.991667	1.113831	0.890321	40.20038
0.42483	0.9608291	34.36081	0.930826	0.99216	1.113143	0.891314	42.87448
0.85118	0.9892434	38.29867	0.900567	0.99684	1.196829	0.832901	28.3078

(a)

Bit rate of JPEG2000 =0.050378

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.8318948	28.98727	0.844138	0.972697	0.962246	1	100
0.15312	0.7841508	26.77258	0.999586	0.953823	1.108134	0.860747	60.06954
0.1993	0.7925018	29.00317	0.992888	0.97238	1.014779	0.958218	49.85666
0.40535	0.8260498	29.35283	0.849736	0.974746	0.977276	0.997411	40.20038
0.42483	0.8270993	29.33898	0.844382	0.974623	0.977397	0.997162	42.87448
0.85118	0.8307521	29.07018	0.78564	0.973128	0.962629	1	28.3078

(b)

Bit rate of JPEG2000 =0.098741

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.8891991	30.8188	0.89457	0.982177	0.977525	1	100
0.15312	0.7795355	26.64765	0.995163	0.952783	1.021835	0.932423	60.06954
0.1993	0.8311522	29.96124	0.997622	0.977968	1.173769	0.833186	49.85666
0.40535	0.8822586	31.1894	0.900605	0.983532	0.992509	0.990955	40.20038
0.42483	0.8833898	31.18563	0.896642	0.983492	0.992629	0.990795	42.87448

0.85118	0.8878785	30.90933	0.852637	0.982489	0.977907	1	28.3078

(c)

Bit rate of JPEG2000 =0.19944

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.9298985	33.27789	0.895235	0.989921	0.991715	0.998191	100
0.15312	0.7728114	26.3504	0.949794	0.949738	0.94169	1	60.06954
0.1993	0.8430102	30.02987	0.975741	0.978432	1.093184	0.895029	49.85666
0.40535	0.9191501	32.89558	0.918263	0.988922	1.006655	0.982384	40.20038
0.42483	0.9206346	32.94235	0.914034	0.989025	1.006776	0.982369	42.87448
0.85118	0.9278998	33.19251	0.86839	0.989687	0.992096	0.997572	28.3078

(d)

Bit rate of JPEG2000 =0.40137

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.9644935	36.69453	0.910754	0.995423	1.015466	0.980262	100
0.15312	0.7644716	26.09408	0.800669	0.946952	0.807542	1	60.06954
0.1993	0.8448925	29.74813	0.861601	0.977111	0.958298	1	49.85666
0.40535	0.9452103	33.85251	0.946376	0.991145	1.171252	0.846227	40.20038
0.42483	0.9478214	34.03657	0.945573	0.991505	1.170563	0.847033	42.87448
0.85118	0.9614563	35.73002	0.909715	0.994267	1.015846	0.978758	28.3078

(e)

Bit rate of JPEG2000 =0.60354

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.9776377	39.26188	0.929541	0.997469	1.022654	0.975373	100
0.15312	0.7594967	25.96464	0.788272	0.945468	0.766948	1	60.06954
0.1993	0.8433876	29.57165	0.847119	0.976222	0.917482	1	49.85666
0.40535	0.953084	34.08496	0.95392	0.991625	1.13012	0.877451	40.20038
0.42483	0.9562472	34.3125	0.954712	0.992047	1.129432	0.878359	42.87448
0.85118	0.973876	37.0217	0.928547	0.995749	1.023032	0.973331	28.3078

(f)

Besides, the value of R_S^2 also show a gradual changes from Table 4-21 (a) to (f). However, the changes of the value is averagely small. This shows that R_S^2 is suitable for reduced reference image quality assessment. On the other hand, the values of R_L^2 changes accordingly with the pattern of other metrics from Table 4-21 (a) to (f). From (f), we can see that R_S^2 provided a better result than R_L^2 in overall. The distortion is non-noticeable because the bit rate of distorted image is relatively small, which indicates that the distorted image is considered high quality. Therefore, the result value is close to 1 although the bit rate is the highest here.

The $\hat{S}$ value calculated from D_n value changes accordingly in overall, as we can see from Table 4-21 (a) to (f). However, the $\hat{S}$ value is less than the value of R_S^2 and R_F^2 in general. This indicates that the estimated SSIM, $\hat{S}$ is less accurate and less effective for this assessment.

Table 4-22: Results of each metrics used to judge the performance of RR-IQA metrics used.

	Bit Rate	PLCC	MAE	RMSE	SRCC	KRCC
DMOS vs SSIM	0	0.018983	53.55148	57.39575	-0.08571	-0.2
	0.050378	-0.00284	53.55148	57.48865	-0.08571	-0.2
	0.098741	-0.05578	53.55148	57.44965	-0.08571	-0.2
	0.19944	-0.0509	53.55148	57.42549	-0.08571	-0.2
	0.40137	-0.03406	53.55148	57.40777	-0.08571	-0.2
	0.60354	-0.02458	53.55148	57.40215	-0.08571	-0.2
DMOS vs S_Dn	0	0.203077	53.55148	57.40849	0.085714	0.066667
	0.050378	0.167842	53.55148	57.41847	0.371429	0.333333
	0.098741	0.164863	53.55148	57.38651	0.314286	0.2
	0.19944	0.047498	53.55148	57.39182	0.314286	0.2
	0.40137	-0.19336	53.55148	57.41887	-0.37143	-0.33333
	0.60354	-0.13983	53.55148	57.41419	-0.31429	-0.2
DMOs vs Rs	0	0.001028	53.55148	57.33454	-0.08571	-0.2
	0.050378	-0.1779	53.55148	57.34716	-0.65714	-0.46667
	0.098741	-0.14271	53.55148	57.34099	-0.65714	-0.46667
	0.19944	-0.09557	53.55148	57.33736	-0.08571	-0.2
	0.40137	-0.05117	53.55148	57.33552	-0.08571	-0.2
	0.60354	-0.0325	53.55148	57.33508	-0.08571	-0.2
DMOS vs RL	0	0.742814	53.55148	57.35841	0.941124	0.894427
	0.050378	-0.09909	53.55148	57.34986	-0.28989	-0.41404
	0.098741	0.047575	53.55148	57.35683	-0.23191	-0.27603
	0.19944	0.1556	53.55148	57.33914	0.371429	0.066667
	0.40137	0.354058	53.55148	57.36292	0.637748	0.414039
	0.60354	0.341357	53.55148	57.35736	0.637748	0.414039

Table 4-22 shows the performance for each RR-IQA metrics on different level of distortion, which use DMOS values as a standard comparison. As mentioned in the methodology, a good RR-IQA need to have lower MAE and RMS values, and higher PLCC, SRCC and KRCC values. In Table 4-22, the lowest MAE and RMS values is highlighted with red color, while the highest PLCC, SRCC, and KRCC values is highlighted with blue color.

From Table 4-22, we can see that most of the blue color is highlighted in the "DMOS vs RL" row and the second most is highlighted in "DMOS vs Rs" row. In such, PLCC, SRCC, and KRCC judge that R_L^2 has a better performance, as there are more highest PLCC, SRCC, and KRCC values in "DMOS vs RL" row.

All the MAE values are the same in Table 4-22. This is because MAE is the average of absolute errors between a prediction and the true value. The prediction and true value of each data set used is same, as the data are from same image, which is Caps.bmp. On the other hand, RMS shows a priority result in R_S^2, as all of the lowest value are found in "DMOS vs RL" row.

In overall, Table 4-22 shows that when a perfect quality reference image is used, R_L^2 performed the best among all. This is the same to the result when the reference image has the highest distortion level.

SSIM has the worst results, in Table 4-22. This may due to it is designed for a full reference image quality assessment. When it comes to reduced reference image quality assessment, the performance will gradually decreases.

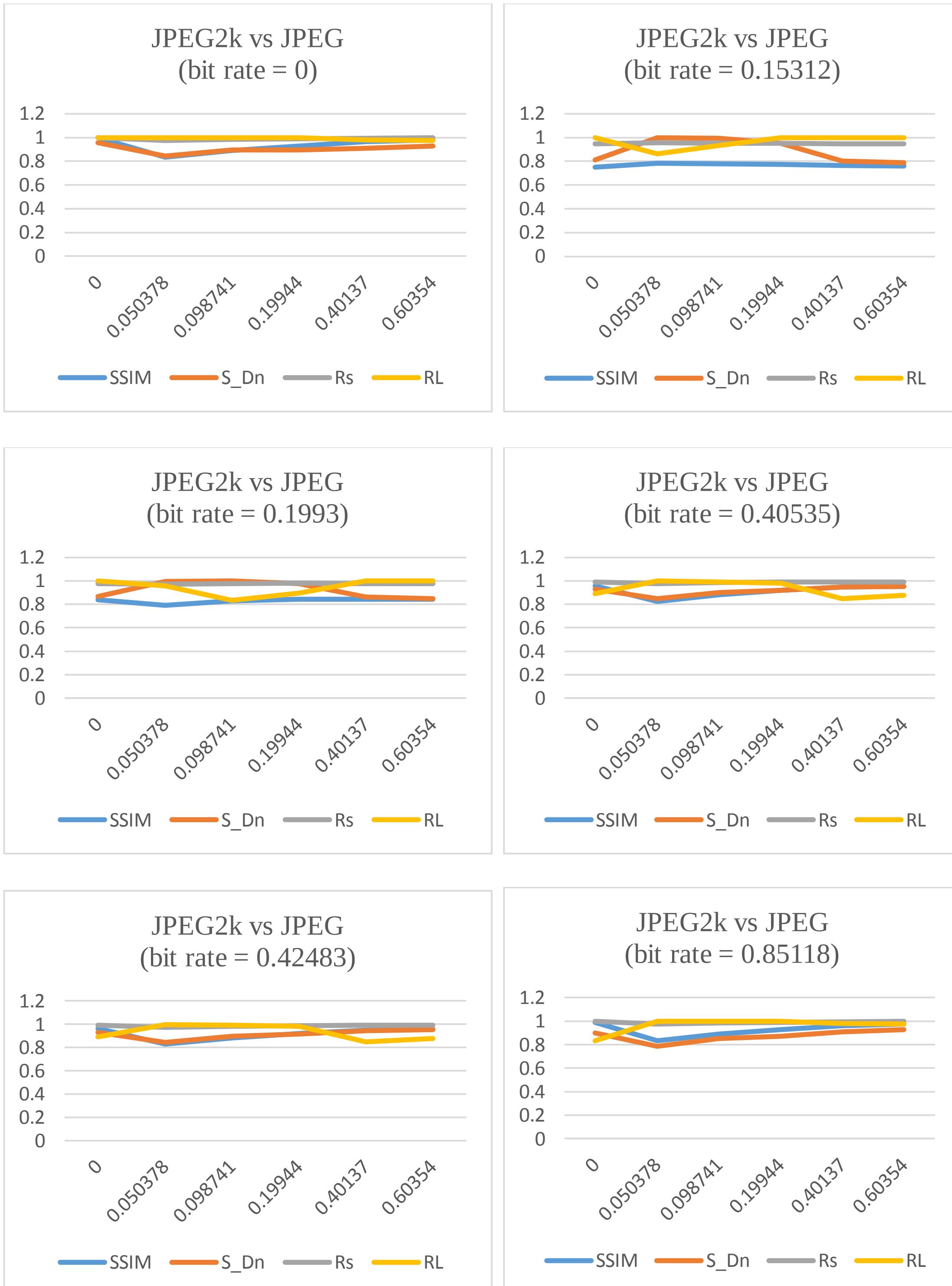


Figure 4-11: Graph plotted by IQM results versus bit rate of imperfect reference image. It is to show the relationship of each metrics, with different bit rate value of JPEG distorted value, and different level of distortion for JPEG2000 distorted reference image.

In Figure 4-11, it shows the graph plotted for each metrics with different bit rate value of distortion. The graph is used to show the performance of each metrics when the bit rate value of JPEG distorted image is increasing, and the JPEG2000 distorted reference image has different distortion value, which is in x-axis of the graph. The flatter the pattern of the graph, indicates a better consistency of the IQM tested.

From Figure 4-11, R_S^2 has a better consistency as compared to other metrics, for all distortion level of the JPEG distorted image. R_L^2 only shows a better performance when JPEG distortion level is zero. Here, we can say that R_S^2 provide a consistent assessment to JPEG2000 reduced reference image when compared with JPEG distorted image.

In overall, R_L^2 shows a better accuracy and R_S^2 gives a better consistency here, as compared to the other metrics included, when the reference image has JPEG2000 distortion is compared to JPEG distorted image.

4-3-4 Gaussian Blur distorted image as compressed image

Table 4-23 (a) used a perfect quality image as the reference while (b), (c), (d), (e) and (f) used a JPEG2000 distorted image as the reference image. The bit rate of distortion increases from (b) to (f). The result value more than one is converted to one in this table. This is because the highest value qualified is one. From Table 4-23, we can see that the SSIM, R_F^2, PSNR, and R_L^2 value changes gradually from (a) to (f).

SSIM is a metric designed for full reference image quality assessment. The value of SSIM show an inconsistent changes when Gaussian blur distorted image has higher distortion level from (a) to (f). This indicates that SSIM value is less effective when the reference image used has no perfect quality, and the bit rate of distortion increases.

The PSNR value is calculated by the mean square error of the two images involved. When the reference image is distorted, it could hardly give an accurate image quality assessment result.

Table 4-23: Results of each metrics applied on a Gaussian Blur compressed image, caps.bmp, with different level of bit rate. The imperfect reference image used is with JPEG2000 distortion. (a)Perfect quality image as reference. (b)JPEG2000 distorted image with bit rate 0.050378 as reference. (c)JPEG2000 distorted image with bit rate 0.098741 as reference. (d) JPEG2000 distorted image with bit rate 0.19944 as reference. (e)JPEG2000 distorted image with bit rate 0.40137 as reference. (f) JPEG2000 distorted image with bit rate 0.60354 as reference.

Bit rate of JPEG2000 =0

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	1	65535	0.96551	1	1	1	100
0.677051	0.9881099	36.16914	0.97994	0.994885	0.999607	0.995276	24.64764
1.164031	0.9559538	31.70434	0.937741	0.985561	0.916755	1	40.79745
1.708303	0.919171	29.76012	0.887688	0.97731	0.920245	1	54.14974
3.083306	0.852187	27.54849	0.839299	0.96207	0.800019	1	60.83318
5.833312	0.7696984	25.25396	0.812935	0.935269	1.01281	0.92344	69.15498

(a)

Bit rate of JPEG2000 =0.050378

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.8318948	28.98727	0.797729	0.972697	0.962246	1	100
0.677051	0.8674776	31.23329	0.872514	0.983349	0.997433	0.985879	24.64764
1.164031	0.8989628	32.2477	0.946429	0.986668	1.012055	0.974916	40.79745
1.708303	0.9183363	32.15909	0.979245	0.986341	1.011439	0.975186	54.14974
3.083306	0.9197284	30.31181	0.987091	0.979146	1.157923	0.845606	60.83318
5.833312	0.8672388	27.14056	0.986615	0.956737	0.94939	1	69.15498

(b)

Bit rate of JPEG2000 =0.098741

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.8891991	30.8188	0.845491	0.982177	0.977525	1	100
0.677051	0.9183678	33.20056	0.912988	0.989481	1.012603	0.977165	24.64764
1.164031	0.9345407	33.02777	0.967287	0.989003	1.18936	0.831543	40.79745
1.708303	0.9343329	31.81161	0.983425	0.98545	1.192885	0.826106	54.14974

3.083306	0.9031943	29.2993	0.979936	0.974056	1.071469	0.909085	60.83318
5.833312	0.8295402	26.35671	0.973648	0.948726	0.96471	0.983431	69.15498

(c)

Bit rate of JPEG2000 =0.19944

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.9298985	33.27789	0.846149	0.989921	0.991715	0.998191	100
0.677051	0.9463335	34.63151	0.938962	0.992504	1.192159	0.832527	24.64764
1.164031	0.9440675	32.62334	0.972405	0.988091	1.108729	0.891192	40.79745
1.708303	0.9283536	30.87118	0.95131	0.98215	1.112244	0.883035	54.14974
3.083306	0.8828013	28.44585	0.911358	0.96873	0.99118	0.97735	60.83318
5.833312	0.8071262	25.83444	0.883599	0.942673	0.978937	0.962956	69.15498

(d)

Bit rate of JPEG2000 =0.40137

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.9644935	36.69453	0.939593	0.995423	1.015466	0.980262	100
0.677051	0.9681861	35.52851	0.973787	0.993978	1.056791	0.940562	24.64764
1.164031	0.9514637	32.14243	0.947352	0.986833	0.973768	1	40.79745
1.708303	0.9252225	30.23945	0.899947	0.979535	0.977265	1	54.14974
3.083306	0.8683226	27.92243	0.853973	0.964981	0.85679	1	60.83318
5.833312	0.7890685	25.49545	0.824365	0.93842	1.00275	0.935846	69.15498

(e)

Bit rate of JPEG2000 =0.60354

Bit Rate	SSIM	PSNR	S_Dn	Rs	L	RL	DMOS
0	0.9776377	39.26188	0.952836	0.997469	1.022654	0.975373	100
0.677051	0.9759931	35.71695	0.97503	0.994272	1.015829	0.978779	24.64764
1.164031	0.9535834	31.86576	0.940036	0.986025	0.932929	1	40.79745
1.708303	0.923177	29.95207	0.892432	0.978209	0.936421	1	54.14974
3.083306	0.8617872	27.69965	0.8484	0.963244	0.816124	1	60.83318
5.833312	0.7805744	25.35055	0.821806	0.936494	1.009956	0.927262	69.15498

(f)

Besides, the value of R_S^2 also show a changes from Table 4-23(a) to (f). However, the changes of the value is averagely small. This shows that R_S^2 is suitable for reduced reference image quality assessment. On the other hand, the values of R_L^2 also changes by little difference from Table 4-23 (a) to (f). However, from (f), we can see that R_L^2 provided a better result than R_S^2 at the Gaussian blur distortion bit rate of 1.164031, 1.708303, and 3.083306. The distortion is non-noticeable because the bit rate of distorted image is relatively small, which indicates that the distorted image is considered high quality. Therefore, the result value is close to 1 although the bit rate is the highest here.

The Ŝ value calculated from D_n value changes accordingly in overall, as we can see from Table 4-23 (a) to (f). However, the Ŝ value is less than the value of R_S^2 and R_F^2 in general. This indicates that the estimated SSIM, Ŝ is less accurate and less effective for this assessment.

Table 4-24 shows the performance for each RR-IQA metrics on different level of distortion, which use DMOS values as a standard comparison. As mentioned in the methodology, a good RR-IQA need to have lower MAE and RMS values, and higher PLCC, SRCC and KRCC values. In Table 4-6, the lowest MAE and RMS values is highlighted with red color, while the highest PLCC, SRCC, and KRCC values is highlighted with blue color.

From Table 4-24, we can see that most of the blue color is highlighted in the "DMOS vs S_Dn" row and the second most is highlighted in "DMOS vs Rs" and "DMOS vs RL" rows. PLCC judge that both Ŝ and R_L^2 has a better performance, as there are more highest PLCC values in "DMOs vs S_Dn" and "DMOS vs RL" row. On the other hand, SRCC and KRCC show that Ŝ has a better performance.

All the MAE values are the same in Table 4-24. This is because MAE is the average of absolute errors between a prediction and the true value. The prediction and true value of each data set used is same, as the data are from same image, which is Caps.bmp. On the other hand, RMS shows a priority result in R_S^2 and R_L^2, as most of the lowest value are found in " DMOS vs Rs" and "DMOS vs RL" rows.

Table 4-24: Results of each metrics used to judge the performance of RR-IQA metrics used.

	Bit Rate	PLCC	MAE	RMSE	SRCC	KRCC
DMOS vs SSIM	0	-0.12137	58.26383	61.98908	-0.14286	-0.33333
	0.050378	-0.47546	58.26383	62.01897	-0.42857	-0.2
	0.098741	-0.50591	58.26383	62.00394	-0.77143	-0.6
	0.19944	-0.32503	58.26383	61.99855	-0.65714	-0.6
	0.40137	-0.2092	58.26383	61.99325	-0.42857	-0.46667
	0.60354	-0.17466	58.26383	61.99194	-0.14286	-0.33333
DMOS vs S_Dn	0	-0.18889	58.26383	61.99937	-0.42857	-0.46667
	0.050378	-0.33246	58.26383	61.98122	0.085714	0.2
	0.098741	-0.45774	58.26383	61.9666	-0.08571	-0.06667
	0.19944	-0.86176	58.26383	61.99637	-0.82857	-0.73333
	0.40137	-0.34735	58.26383	61.99941	-0.65714	-0.6
	0.60354	-0.24996	58.26383	61.99904	-0.42857	-0.46667
DMOs vs Rs	0	-0.09219	58.26383	61.92903	-0.14286	-0.33333
	0.050378	-0.55378	58.26383	61.92893	-0.77143	-0.6
	0.098741	-0.3828	58.26383	61.92818	-0.82857	-0.73333
	0.19944	-0.24197	58.26383	61.92847	-0.42857	-0.46667
	0.40137	-0.15537	58.26383	61.9288	-0.14286	-0.33333
	0.60354	-0.12384	58.26383	61.92915	-0.14286	-0.33333
DMOS vs RL	0	-0.16943	58.26383	61.92027	0.067612	0.086066
	0.050378	0.081509	58.26383	61.93795	0.463817	0.276026
	0.098741	0.399056	58.26383	61.96805	0.6	0.466667
	0.19944	0.89548	58.26383	61.95595	0.885714	0.733333
	0.40137	0.121522	58.26383	61.92674	-0.21251	-0.14907
	0.60354	-0.30357	58.26383	61.92718	-0.5161	-0.29814

In overall, Table 4-24 shows that when a perfect quality reference image is used, $\hat{S}$ performed the best among all. On the other hand, R_L^2 performed when the reference image has the highest distortion level.

SSIM has the worst results, in Table 4-24. This may due to it is designed for a full reference image quality assessment. When it comes to reduced reference image quality assessment, the performance will gradually decreases.

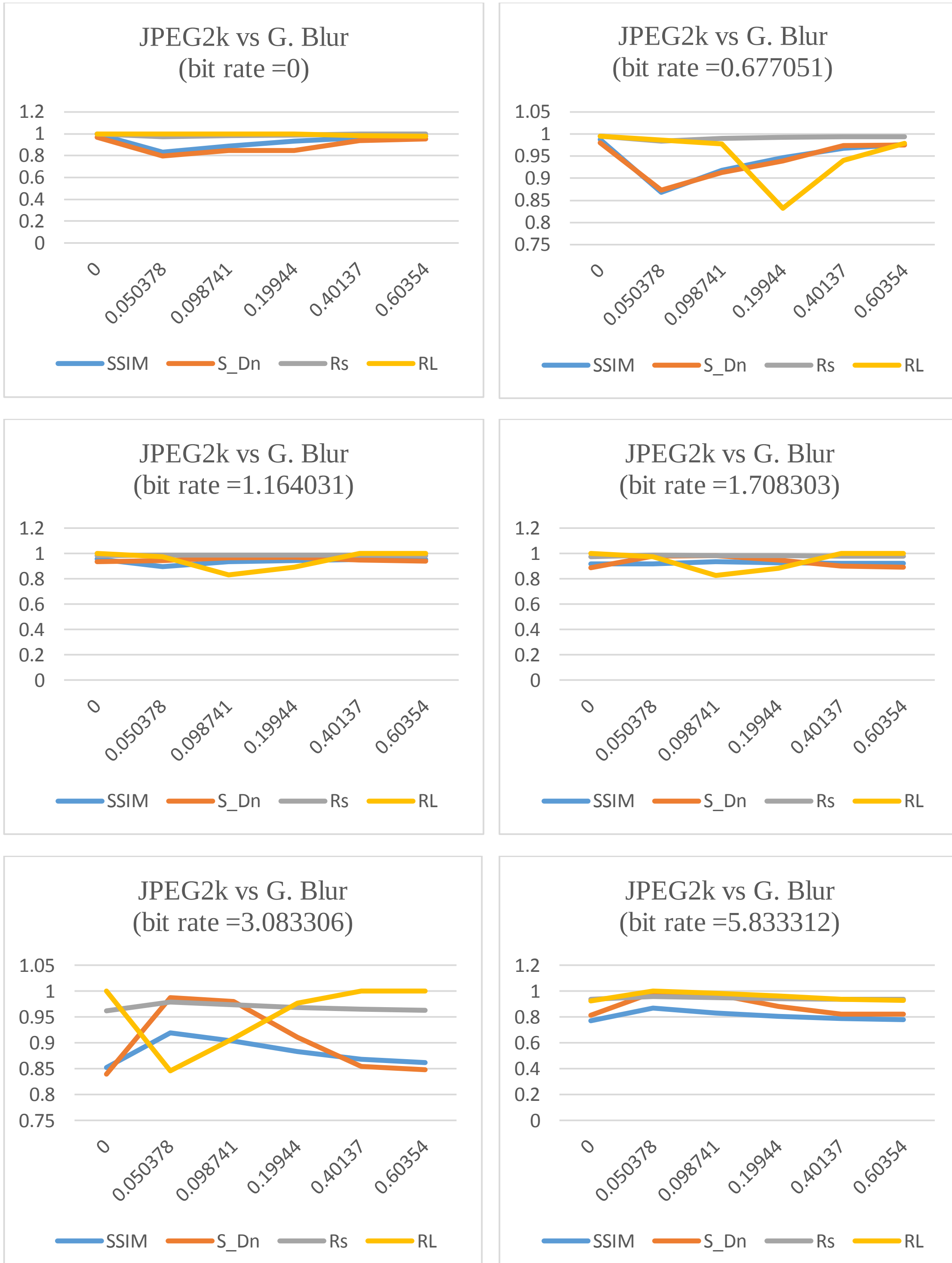


Figure 4-12: Graph plotted by IQM results versus bit rate of imperfect reference image. It is to show the relationship of each metrics, with different bit rate value of Gaussian Blur distorted value, and different level of distortion for JPEG2000 distorted reference image.

In Figure 4-12, it shows the graph plotted for each metrics with different bit rate value of distortion. The graph is used to show the performance of each metrics when the bit rate value of Fast Fading distorted image is increasing, and the Gaussian Blur distorted reference image has different distortion value, which is in x-axis of the graph. The flatter the pattern of the graph, indicates a better consistency of the IQM tested.

From Figure 4-12, R_s^2 has a better consistency as compared to other metrics, for all the Gaussian blur distorted image. R_L^2 has the second best performance when Gaussian blur distortion level is zero and the highest. Here, we can say that R_s^2 provide an accurate assessment to JPEG2000 reduced reference image as compared with Gaussian blur distorted image.

In overall, Ŝ shows a better accuracy whereas R_s^2 shows a better consistency here, as compared to the other metrics included, when the reference image has JPEG2000 distortion is compared to Gaussian blur distorted image.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

In this paper, a new statistical prior model method, R_L^2 reinforced from MULFR model which is proposed for full reference image quality assessment. The proposed R_L^2 is designed for reduced reference image quality assessment, where there is distortion applied on the imperfect reference image. This IQM is more reliable in actual applications. A major characteristic of R_L^2 is it flexibility to be used to test on different types of distortions.

To show the effectiveness of R_L^2, we tested it on a set of images with different types of distortions, which are JPEG, JPEG2000, Gaussian Noise, and Gaussian Blur, and proved that it compares positively with other IQA metrics. R_L^2 shows a good performance when JPEG2000 is used as imperfect reference image. When Gaussian Blur is used on imperfect reference image, R_s^2 and Ŝ show a good performance. For JPEG compression applied on imperfect reference image, R_s^2 shows a better consistency and monotonicity. On the other hand, R_L^2 shows a good performance when JPEG2000, JPEG, or Gaussian Blur is applied on the distorted image. R_s^2 shows an overall better performance when Fast Fading distortion is applied on distorted image. The summary of each IQM performance can be found from Table 5-1.

Table 5.1: Summary of the performance of each IQM.

G. Blur vs JPEG Monotonicity: R_L^2 Accuracy: R_s^2 Consistency: R_s^2 $\Longrightarrow$ Overall: R_s^2	**JPEG vs G. Noise** Monotonicity: Ŝ Accuracy: Ŝ Consistency: R_s^2 $\Longrightarrow$ Overall: Ŝ	**JPEG2K vs G. Noise** Monotonicity: R_L^2 Accuracy: R_L^2 Consistency: R_L^2 $\Longrightarrow$ Overall: R_L^2
G. Blur vs JPEG2K Monotonicity: Ŝ Accuracy: Ŝ Consistency: R_s^2 $\Longrightarrow$ Overall: Ŝ	**JPEG vs G. Blur** Monotonicity: R_s^2 Accuracy: R_L^2 Consistency: R_s^2 $\Longrightarrow$ Overall: R_s^2	**JPEG2K vs F. Fading** Monotonicity: R_s^2 Accuracy: R_L^2 Consistency: R_s^2 $\Longrightarrow$ Overall: R_s^2
G. Blur vs G. Noise Monotonicity: Ŝ Accuracy: Ŝ Consistency: R_L^2 $\Longrightarrow$ Overall: Ŝ	**JPEG vs JPEG2K** Monotonicity: R_L^2 Accuracy: R_L^2 Consistency: R_s^2 $\Longrightarrow$ Overall: R_L^2	**JPEG2K vs JPEG** Monotonicity: R_L^2 Accuracy: R_L^2 Consistency: R_s^2 $\Longrightarrow$ Overall: R_L^2
G. Blur vs F. Fading Monotonicity: R_L^2 Accuracy: R_s^2 Consistency: R_s^2 $\Longrightarrow$ Overall: R_s^2	**JPEG vs F. Fading** Monotonicity: R_s^2 Accuracy: R_L^2 Consistency: R_s^2 $\Longrightarrow$ Overall: R_s^2	**JPEG2K vs G. Blur** Monotonicity: R_L^2 Accuracy: R_L^2 Consistency: R_s^2 $\Longrightarrow$ Overall: R_L^2

For the perfect reference image, R_L^2, R_s^2, SSIM, and PSNR show a very good performance. They have a good accuracy, consistency, and monotonicity. SSIM is more suitable for full reference IQA. When the quality of reference image is distorted, we found that R_L^2 performs better than all other IQMs. SSIM could be seriously under measure image quality for reduced reference image, followed by PSNR, Ŝ, and R_s^2. This is a major benefit by using R_L^2 for IQA, because the perfect quality reference image is hardly obtain in actual applications, especially for the end-receiver.

There are some limitations found during conduct this study. All the images used in this study is taken from only one database, which is LIVE database. There are quite a number of image databases found in this field. By including different image database in a study, it will improve the IQM results, and make it more reliable. Different level of noise from different database can provide a more accurate results. Besides, the more accurate carrying capacity value is found for only three of the distortions, which are Gaussian Blur, JPEG, and JPEG2000. And so, only these three distortions is used in imperfect reference image. In order to include more distortion types for imperfect reference image, the carrying capacity value should be found. This can be done by including and analyzing more images from different database to get more image constraints for calculating the carrying capacity value. Besides, by doing so will also improve the existing carrying capacity value. This will provide a better performance of R_L^2.

REFERENCES

Abdul, R. and Zhou, W. (2012). *Reduced-Reference Image Quality Assessment by Structural Similarity Estimation.* [online] Available at: https://ece.uwaterloo.ca/~a5rehman/docs/RR_SSIM.pdf [Accessed 8 Jul. 2015].

Archambault, M. (2015). *JPEG 2000: The Better Alternative to JPEG That Never Made it Big*. [online] PetaPixel. Available at: http://petapixel.com/2015/09/12/jpeg-2000-the-better-alternative-to-jpeg-that-never-made-it-big/ [Accessed 20 Mar. 2016].

Developing for Developers. (2006). *How does JPEG actually work?*. [online] Available at: https://blogs.msdn.microsoft.com/devdev/2006/04/12/how-does-jpeg-actually-work/[Accessed 31 Jan. 2016].

Diwei, Y., Hongwei, L., Huiming, P., Yongluo, S. and Yuantong, S. (2015). *Reduced reference Image Quality Assessment Based on Roberts Derivative Statistic Model of Natural Image.* [online] Available at: http://www.jofcis.com/publishedpapers/2012_8_5_1837_1844.pdf [Accessed 25 Jul. 2015].

Jinjian, W., Weisi, L., Guangming, S. and Long, X. (n.d.). *Reduced-Reference Image Quality Assessment with Local Binary Structural Pattern*. [online] Available at: http://web.xidian.edu.cn/wjj/files/20140119_184936.pdf [Accessed 18 Mar. 2016].

Min, Z., Wufeng, X. and Xuanqin, M. (2013). *Reduced Reference Image Quality Assessment Based on Statistics of Edge.* [online] Available at: http://ipl.xjtu.edu.cn/ftp/wxue/RR_Min_SPIE2011.pdf [Accessed 8 Jul. 2015].

Rajiv, S. and Alan C., B. (2015). *Rred Indices: Reduced Reference Entropic DifferencingFramework For Image Quality Assessment.* [online] Available at: http://live.ece.utexas.edu/publications/2011/rs_icassp_2011.pdf [Accessed 22 Jul. 2015].

Shiqi, W., Xiang, Z., Siwei, M. and Wen, G. (2015). *Reduced Reference Image Quality Assessment Using Entropy of Primitives.* [online] Available at: http://www.jdl.ac.cn/doc/2011/20131021111321509_pid2949423.pdf [Accessed 19 Jul.2015].

Wufeng, X. and Xuanqin, M. (2010). *Reduced Reference Image Quality Assessment Based On Weibull Statistics.* [online] Available at: http://ipl.xjtu.edu.cn/download/wxue/Weibull%20RRIQA2010.pdf [Accessed 8 Jul. 2015].

Zhou, W. and Eero, P. (2005). *Reduced-Reference Image Quality Assessment Using A Wavelet-Domain Natural Image Statistic Model.* [online] Available at: https://ece.uwaterloo.ca/~z70wang/publications/ei05.pdf [Accessed 8 Jul. 2015].