CHAPTER 7
IMAGE QUALITY ASSESSMENT FOR JPEG COMPRESSION

This chapter focuses on the JPEG image quality assessment measured using R_P^2 which in turn indicates the performance of the JPEG image compression algorithm. A given test image (called reference image) is compressed and then decompressed (called JPEG codec image) such that the sub-region $l_i \in \text{reference image}$ and $m_i \in \text{codec image}$ are completely overlapping were extracted. Feature vectors $\boldsymbol{x}_i = \left[x_{1i}, x_{2i}\right]'$, involving luminance and contrast were calculated from l_i and similarly feature vectors $\boldsymbol{y}_i = \left[y_{1i}, y_{2i}\right]'$ calculated from m_i. The process was repeated for $i = 1, 2, \ldots, n$ and the vectors $\boldsymbol{x}_i$ and $\boldsymbol{y}_i$, $i = 1, 2, \ldots, n$ becomes the inputs to the MULFR model from which R_P^2 was calculated. The JPEG codec image is subjected to a Laplacian noise which follows a Laplacian distribution. While, two types of reference image were considered in this study, namely (i) perfect reference image without noise and (ii) imperfect reference image subjected to Gaussian noise.

An objective similarity measure should poses good properties, and the criteria of monotonicity, consistency and accuracy are selected in this study. Four frequently used test images and 27 original images obtained from Laboratory for Image and Video Engineering (LIVE) were used to investigate these properties for five similarity measures. Different combinations of image attributes such as luminance, contrast, entropy and range were extracted from each image and used as input to the MULFR model. A given test image, say Lena image, is compressed and decompressed sequentially with a given compression factor $\left(Q_i, i = 1, 2, \ldots, 10\right)$ (Gonzalez et al., 2004), and a feature vector, say entropy and range calculated from the codec image. With this feature vector, R_P^2 was calculated yielding the pair $\left(Q_i, R_P^2\right)$. For the same image at the same compression factor, MSSIM, RMSE, R_S^2 and R_F^2 are also calculated yielding the corresponding points $\left(Q_i, \mathrm{MSSIM}\right)$, $\left(Q_i, \mathrm{RMSE}\right)$, $\left(Q_i, R_S^2\right)$ and $\left(Q_i, R_F^2\right)$. The experiment was repeated for $Q_i = 10, 20, \ldots, 100$, which enable five plots showing the relationship between a given similarity measure and mean opinion score. This experiment showed that luminance and contrast was the best feature vector to use when comparing images. Let S_i denote any given similarity measure. Henceforth, the $\left(Q_i, S_i\right)$ plots using luminance and contrast were compared for each test image to investigate the properties of monotonicity, accuracy and consistency of similarity measure.

Another experiment was introduced to study the robustness of the proposed similarity measure when the reference image does not have perfect quality. The argument is that most end-users do not have the original reference image if they would like to know the image quality achieved. The Gaussian noise with mean zero and variance 0.001 was introduced into an original image and the resulted imperfect quality image was used as the reference image. The experiments were repeated and the $\left(Q_i, S_i\right)$ plots were reproduced using imperfect reference image.

Lastly, a physical interpretation was given to the R_F^2 and R_P^2 by relating these similarity values to the amount of information conveyed in the JPEG codec image. A simple binary image J with size 100×100 was created. Different percentages of distorted pixels were generated into image J and its relationship with R_F^2 and R_P^2 are determined. In JPEG compression application, the similarity value computed at a given compression factor is then used to provide a consistent interpretation of the percentage of distorted pixels, regardless of the image tested.

7.1 Test Images

A set of four frequently used test images in the literature review (Li & Wang, 2009; de Angelis et al., 2009) is being considered in this study. These test images are Lena, Airplane, Boat and Peppers, each may represents a group of images that contains similar image features. They are selected to display various image features such as contrast, luminance, sharpness and complexity. The information of these test images is summarized in Table 7.1. Examples of the standard test image are shown in Figure 7.1.

Another set of test images were obtained from image database created by LIVE (Sheikh et al., 2005) with permission. Twenty seven distortion-free high-resolution 24 bits/pixel RGB color images from the database were used in this study. The color image was converted to gray-scale image before a JPEG compression is applied. Note that JPEG codec images in the database were not used because there were compressed as a color image and the only information provided of the codec image is bite rate.

Henceforth, there are a total of 31 test (reference) images obtained from the literature and the LIVE database. Each reference image was compressed at compression factors $Q_i = 1, 2, \ldots, 100$ using Gonzalez's JPEG algorithms, producing a total of 3100 JPEG codec images.

Table 7.1: Information on the frequently used test image.

Image	Size	Features
Lena	256x256	Mixture of detail e.g. high contrast, flat regions, shading and texture.
Airplane	512x512	Low contrast, high luminance
Boat	512x512	Moderate contrast, moderate luminance
Peppers	512x512	High contrast, high luminance

Lena

Airplane

Boat

Peppers

Figure 7.1: Standard test images.

7.2 Type of Image Distortions

This chapter evaluates the quality of images that have been distorted by the lossy JPEG compression. The lossy JPEG compression is one of the commonly used compression techniques due to its coding efficiency. The lossy compression encoding and decoding processes discard the irrelevant information of an image and a video across space (spatial) and/or time (temporal), respectively. This process is irreversible due to the degradation in information. Consequently, the quality of the image after decoding will be dropped accordingly proportionate to the amount of degradation. Two typical lossy compression artifacts are blocking effect and blur. These degradations generated from JPEG compression are called Laplacian noise, which has a Laplace distribution. (Cheng & Cheng, 2009).

The JPEG encoding and decoding source codes are obtained from Gonzalez et al. (2004), which is using MATLAB 7.1 environment. The compression factor determines the amount of information that is lost and compression achieved. The compression factor (Q_i) is ranged from 1 to 100, where 1 denotes the worst codec image quality (highest compression ratio) and 100 denotes the best codec image quality (lowest compression ratio). Figure 7.2 shows some examples of the distorted version for the standard Lena test images (see Appendix B1 for more examples).

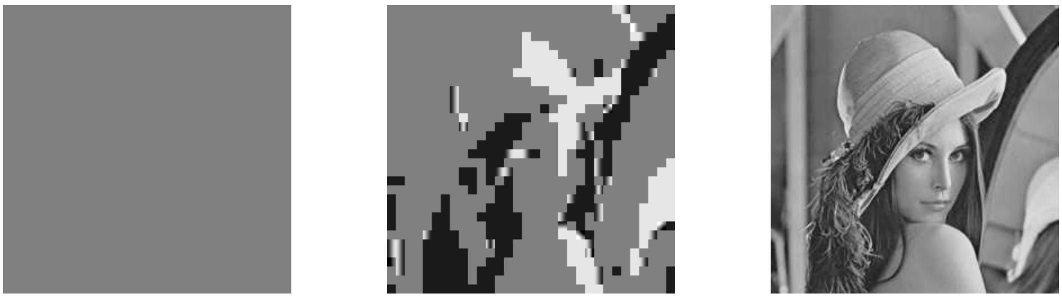


Figure 7.2: Samples of compressed images for LENA test image with increasing levels of distortion. JPEG compression with compression factors 1, 50 and 100 (from left to right).

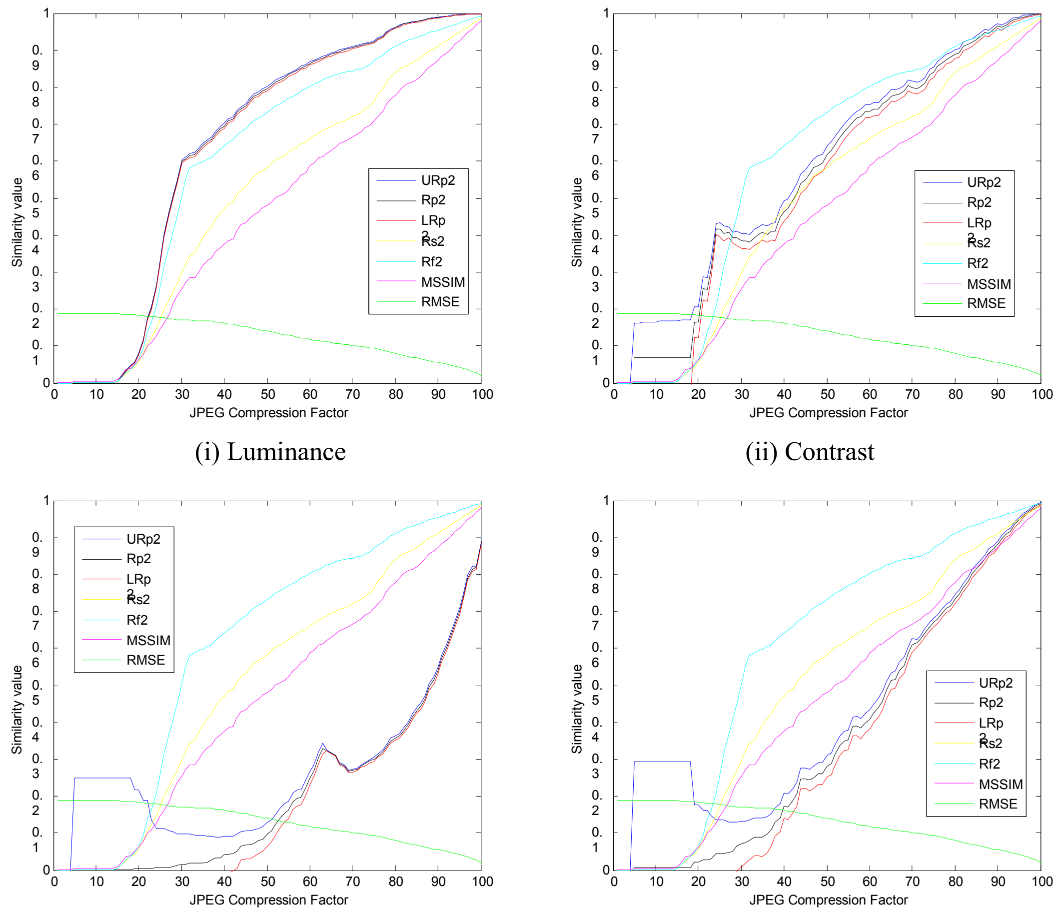
There are two types of reference images considered in this study. First, the reference image is treated as perfect test image without any noise. This is a common assumption made in full reference image quality assessment. Second, the reference images were distorted by the white Gaussian noise (or amplifier noise) with mean zero and variance 0.001. The Gaussian noise has a normal distribution. It is additive and independent at each pixel and signal intensity. This type of noise is usually embedded in an image during the image formation stage and it presents in a natural process.

7.3 Selection of Image Quality Attributes

Section 1.2.3 showed the need for considering different image attributes in assessing image quality. This section compares the effects of different combination of image attributes on the R_p^2 for JPEG compression. Four image attributes, namely image luminance, image contrast, entropy and range of brightness values are considered and their combinations are used to calculate the value of R_p^2. The selection of these image attributes does not apply to other similarity measures since their input values are pre-determined and fixed. For example, MSSIM always used luminance, contrast and correlation coefficient as its input values no matter what applications and circumstances.

Figure 7.3 shows that entropy is not a good image attribute for measuring the quality of JPEG compressed Lena image. Entropy caused a large drop in similarity values at compression factors 60 to 70 which should have a better image quality. Hence, entropy attribute will not be included in further analysis. Other attributes such as image luminance, contrast and brightness range show different effects on R_p^2. Image luminance tends to 'pull' up the value of R_p^2 at the middle level of JPEG compression factor. Meanwhile, the range of brightness seems to 'pull' down the value of R_p^2 for all compression factors. Image contrast gives R_p^2 values which are between luminance and range. However, image variance fails to produce any R_p^2 value at very low compression factors as the variances are all zero due to 'blank' compressed image (see Figure 7.2).

Combinations between image luminance, contrast and brightness range are also investigated. Even though the combination of luminance and brightness range produces the smoothest R_p^2 curve, but its R_p^2 values are relatively large at low compression factors (see Figure 7.3(vii)). Further investigation reveals that brightness range is not a dominant attribute whenever it is combined with contrast. This can be observed by comparing the combinations (contrast) and (contrast, range) where they produced similar R_p^2 curves. As such, only image luminance and contrast are selected for assessing JPEG image quality because they carry important physical meaning of an image. This observation is also agreed with MSSIM (Wang et al. (2002a) that combined the mean, variance and correlation values where the first two values represent image luminance and image contrast, respectively. The confidence interval for R_p^2 is also displayed with upper limit (blue colour) and lower limit (red colour) respectively. Note that using single attribute will generally produce unstable measure with large confidence intervals at the low compression factors (see Figures 7.3(ii)-(iv)).

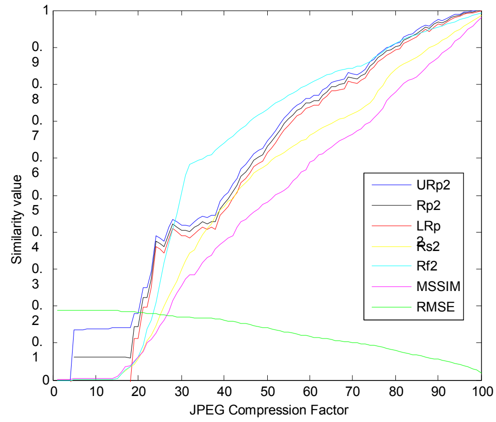


(i) Luminance

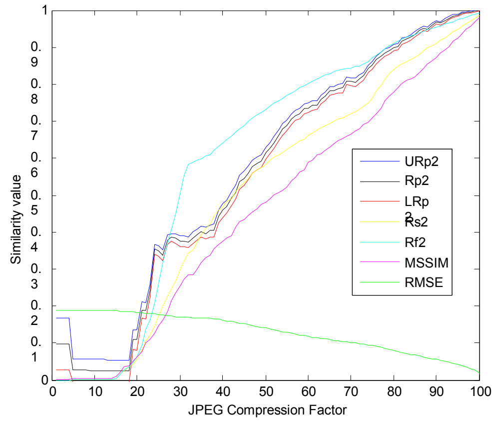
(ii) Contrast

(iii) Entropy

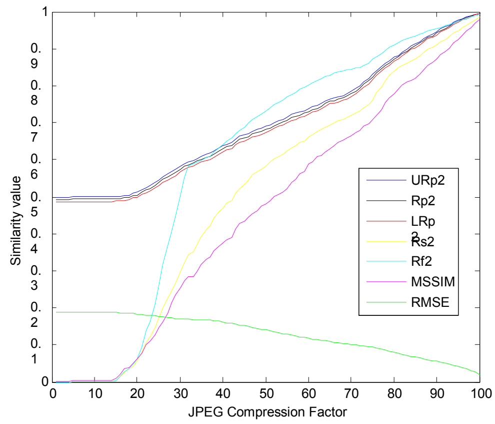
(iv) Brightness range



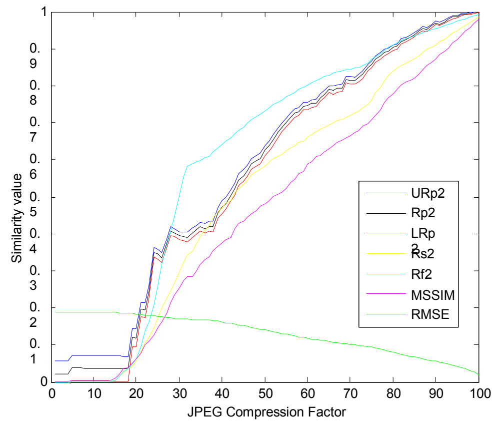
(v) Contrast and brightness range



(vi) Luminance and contrast



(vii) Luminance and brightness range



(viii) Luminance, contrast and brightness range

Figure 7.3: Plots of similarity measures (R_P^2 , R_F^2 , R_S^2 , MSSIM, RMSE) against compression factor $(Q_i = 10, 20, \ldots, 100)$ for selected feature vectors: luminance, contrast, entropy, and range. Black colour curve is R_P^2 value, red colour curve is its upper limit and blue colour curve is its lower limit.

7.4 Performance of R_F^2 and R_P^2 When Reference Image Has Perfect Quality

7.4.1 Properties for a Good Image Similarity Measure

There are several properties that a good objective ISM follows when it applied to image quality assessment. Three main properties that frequently and commonly used are monotonicity, consistency and accuracy (Winkler, 2005; Avcibas et al., 2002). These properties can be determined analytically using some statistical values or graphically from the (Q_i, S_i) plots. The definition of these properties is given as follow:

{1} Monotonicity: the similarity values should be monotonic in their relationship to the distortion levels, i.e. compression factors (Q). It is preferable that the differences of a measure's scores between two consequence distorted images should always have the same sign as the differences between the corresponding compression factors. The measure of monotonicity can be quantified by the Spearman rank-order correlation coefficient between the average similarity value across images and compression factor. Monotonicity can also be visually verified by examining the individual (Q_i, S_i) plot for each similarity measure. The monotonicity property is met if the (Q_i, S_i) plot shows monotonic trend, and the criterion is violated otherwise. Note that small fluctuations along the monotonic trend are still allowed and acceptable.

{2} Consistency: the similarity measure should provide consistent measures for all types of images, and not to fail badly for a subset of images. This study defines consistency at a given compression level as the standard deviation measured from a set of (Q_i, S_i) plots for various test images. Smaller standard deviation means higher consistency was achieved at that compression level. For visual inspection, the consistency property is determined by comparing the (Q_i, S_i) plots for various test images. The similarity measure is said to be consistent if all (Q_i, S_i) plots have similar pattern and dynamic range across test images. In other words, the similarity measure is concluded as inconsistence when (i) the (Q_i, S_i) plots have different trend, and (ii) the dynamic range of S_i vary among the test images.

{3} Accuracy: it is defined as a large and positive correlation between similarity measure and distortion level such that this correlation has minimum variation. The accurate measurement of distortion, either on algorithm performance or subjective assessment should possess a small scatter value. It can be defined as the ability of a similarity measure to reflect distortion levels with minimum average error. This can be determined by length of confidence interval of similarity measure at a given compression level. The similarity measure meets the accuracy criterion only if it produces small confidence interval.

It is worth to know that names and definitions on the above mentioned properties may vary between researchers, depend on the experiments conducted and availability of data types. For example, Winkler (2005) and Avcibas et al. (2002) compared the similarity measure with the subjective ratings using Spearman rank-order correlation coefficient, outlier ratio and Pearson correlation coefficient, respectively. In their studies, they compared the similarity value to subjective scores, instead of compression factors. Van der Weken et al. (2002) named the prediction monotonicity as reaction to noise.

Besides the above mentioned properties, Martens & Meesters (1998) and Van der Weken et al. (2002) gave some references on assessing a good objective similarity measure. Although these secondary properties are less important and not frequently referred, but it is worth to acknowledge them here:

{4} Model complexity (Martens & Meesters, 1998): the quality measure should be simple and easy to use.

{5} Symmetric (Van der Weken et al., 2002): the output of the similarity measure is expected to be independent of the order when two input images are considered.

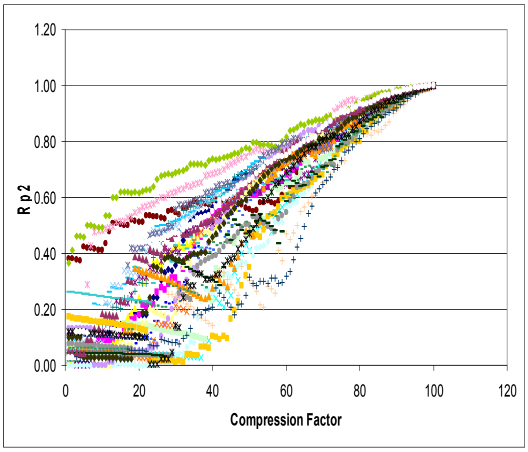
{6} Reflexivity (Van der Weken et al., 2002): the similarity measure has output one and the distance metric has output zero for two identical images.

{7} Reaction to enlightening or darkening (Van der Weken et al., 2002): the similarity measure yields a high value for enlightens or darkens on an image with a constant value. It is also expected a decreasing trend with respect to an increasing enlightening or darkening percentage.

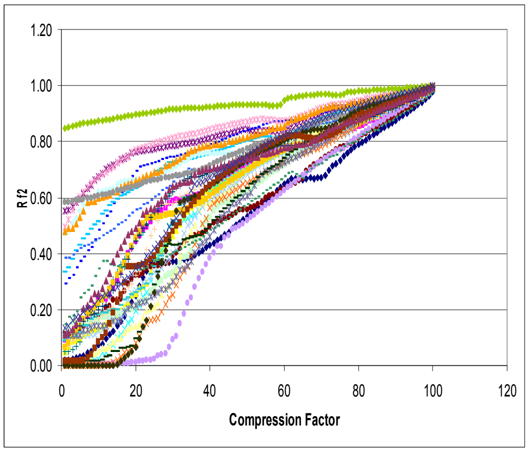
{8} Reaction to binary images (Van der Weken et al., 2002): the similarity measure produces a value between 0 and 1 for a binary image, and not only the crisp values 0 or 1.

7.4.2 Experiments

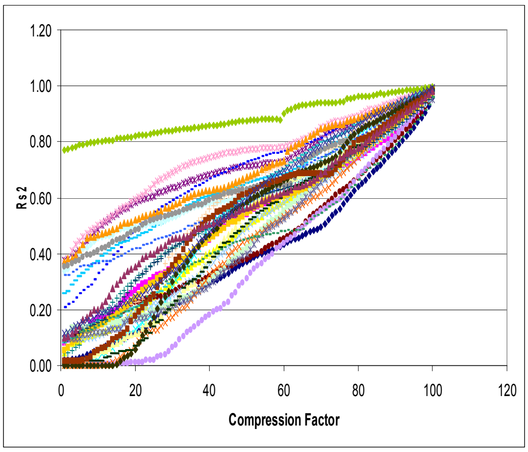
The feature vector constructed from the selected image attributes (see Section 7.3), namely luminance and contrast, is used to compute the R_P^2 for assessing the quality of JPEG codec image. For example, Figure 7.4(a) shows the biplots of $\left(Q_i, R_P^2\right)$ for 31 images using JPEG compression. The $\left(Q_i, S_i\right)$ plots for R_F^2, R_S^2, MSSIM and RMSE are also presented for comparison.



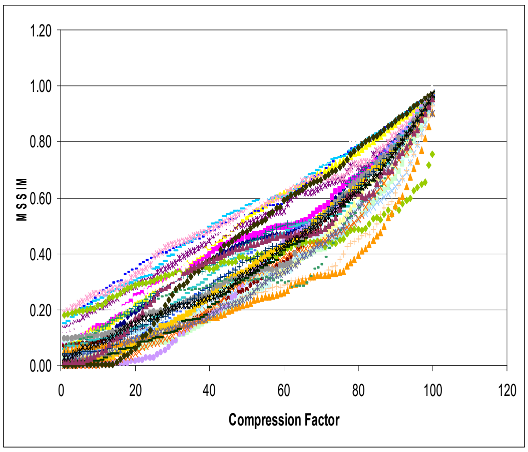
(a)



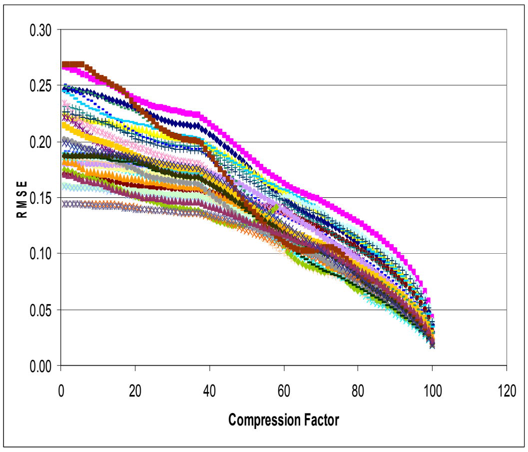
(b)



(c)



(d)



(e)

Figure 7.4: Biplots (Q_i, S_i) for R_P^2, R_F^2, R_S^2, MSSIM and RMSE at different compression factors across 31 test images.

(i) Monotonicity Property

The similarity values are calculated across 31 test images for every type of similarity measure. The average Spearman rank correlation between the similarity values and compression factors is then calculated and used as an indication of the degree of monotonicity. Table 7.2 shows that all similarity measures presented high monotonicity property.

Table 7.2: Average Spearman correlation between similarity values and compression factors.

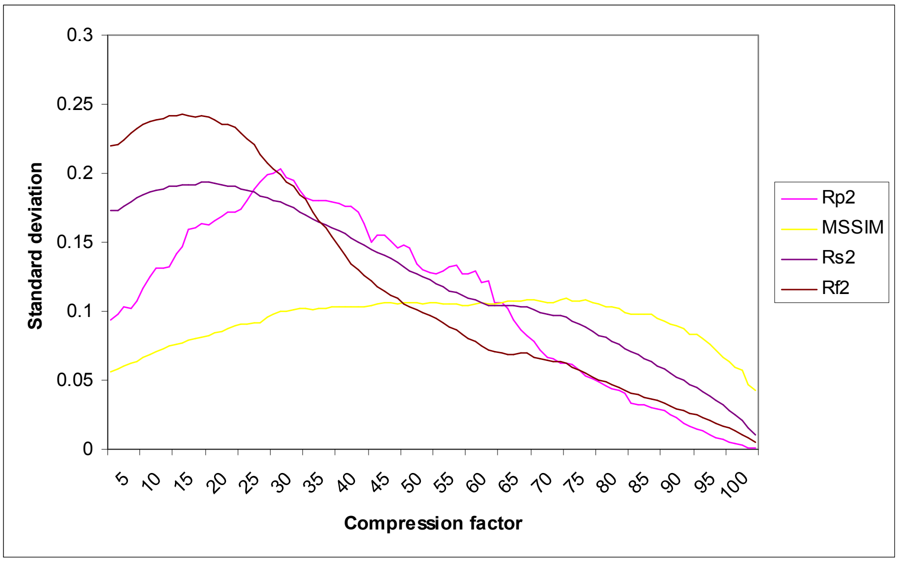
Similarity measure	R_P^2	R_F^2	R_S^2	MSSIM	RMSE
Spearman correlation coefficient	0.9756	0.9980	0.9999	0.9988	-0.9994

Similar remarks can also be obtained by examining the individual (Q_i, S_i) plot for each similarity measure in Figure 7.4 where the similarity value increases (decreases) as the level of distortion decreases with higher compression factor.

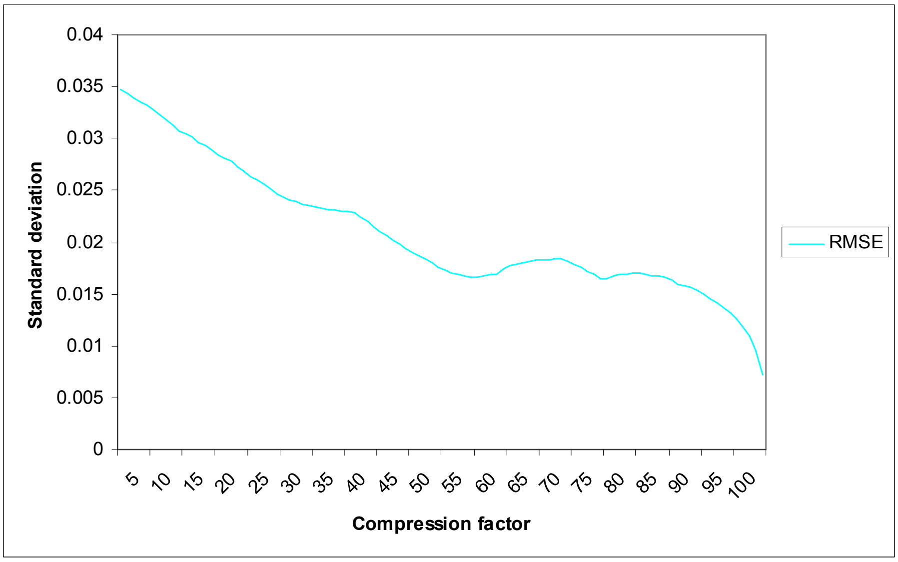
(ii) Consistency Property

Figure 7.4 shows the R_P^2 values are highly concentrated at high compression factors and larger dispersion at lower compression factors. Similar patterns were observed for R_F^2 and R_S^2. This reflects that R_P^2, R_F^2 and R_S^2 are more consistent similarity measures when the image is not badly compressed. An opposite pattern was observed for MSSIM where it values are more diverse at higher compression factors.

The consistency property can also be determined using the standard deviation of the similarity values at a particular compression factor. The standard deviations obtained are shown in Figure 7.5(a) for R_P^2, R_F^2, R_S^2 and MSSIM and Figure 7.5(b) for RMSE. A separate figure is produced for RMSE because it generally has a smaller dynamic range less than 0.30 as compare with other similarity measures. The standard deviations for similarity values obtained at each compression factor show all similarity measures except MSSIM have a larger dispersion at lower compression factors. The MSSIM although has the highest consistency at low compression factors, but it has the lowest consistency after compression factor $Q = 61$. This indicates that the measure of image quality at low compression factors is inconsistent. The consistency performance of these similarity measures improved gradually and reaches the highest consistency at compression factor $Q = 100$.



(a)



(b)

Figure 7.5: Standard deviations of similarity values at different compression factors across 31 test images.

(iii) Accuracy Property

The length of confidence interval is used to assess the accuracy property of a similarity measure. The confidence interval of R_P^2 is calculated using Result 7, Section 4.4.6. The length of confidence interval is then defined as the upper confidence limit minus the lower confidence limit. There is no confidence interval computed for other similarity measures under the same definition of R_P^2. This is because MSSIM and RMSE are not constructed from a probability distribution. Nevertheless, Wang et al. (2004) showed that MSSIM achieves promising prediction accuracy when it is compared to subjective scores.

Figure 7.6 shows the length of confidence interval of R_P^2 at each compression factor across images. R_P^2 has lower accuracy at lower compression factors. For example, it largest length of confidence interval is 0.2668 at $Q \leq 7$ when Monarch image is used (see Figure 7.7). R_P^2 achieves better accuracy at lower levels of compression with larger compression factors.

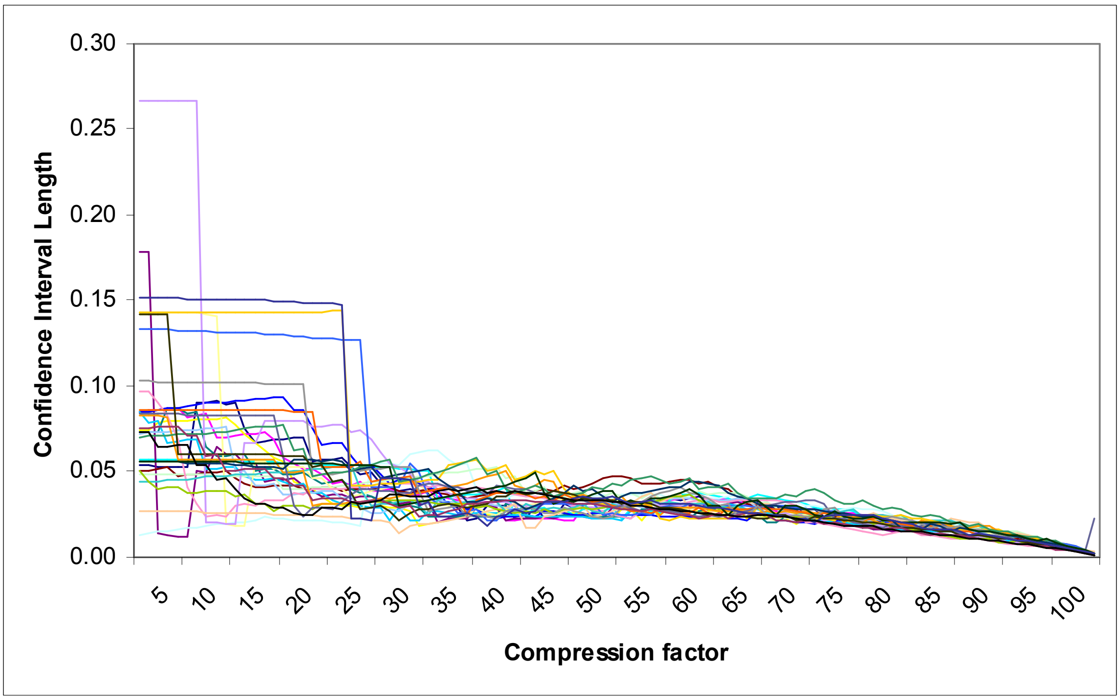


Figure 7.6: Length of confidence interval for R_P^2 at different compression factors across images.

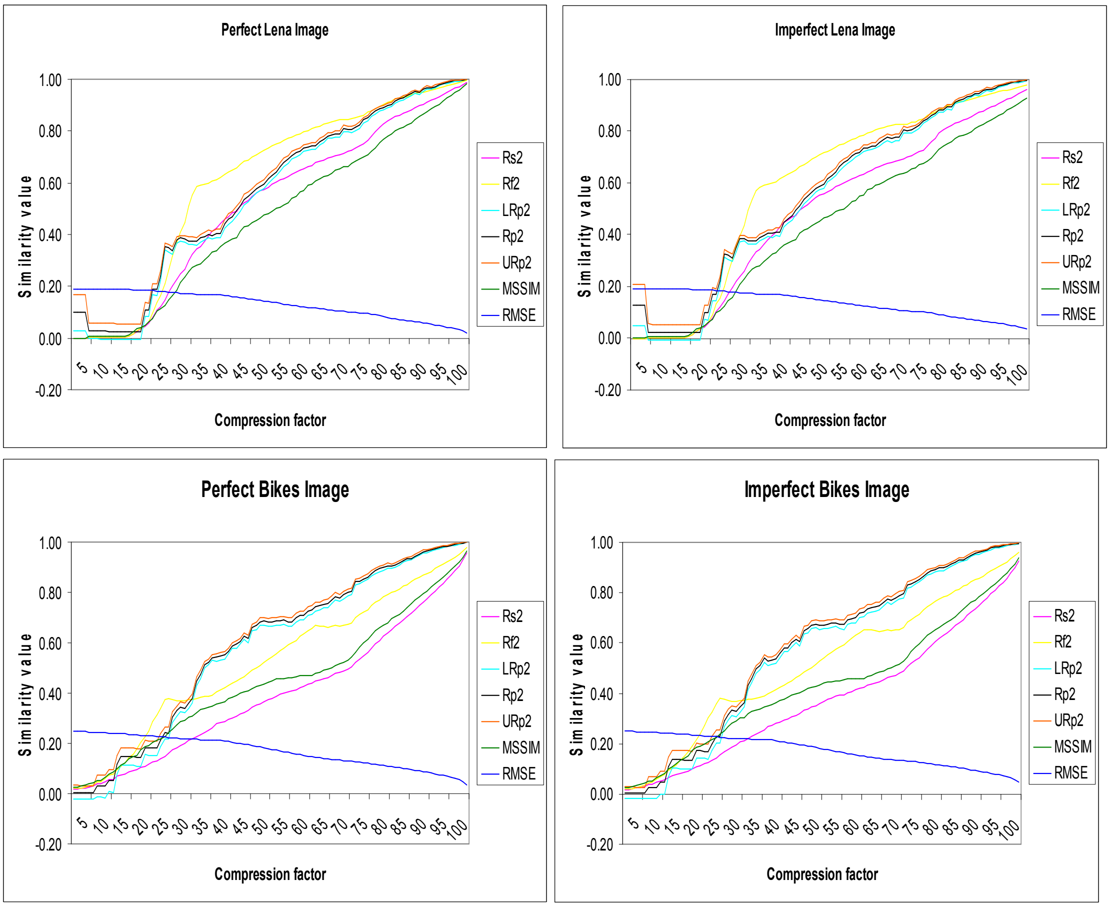
7.5 Performance of R_F^2 and R_P^2 When Reference Image Has Imperfect Quality

Most image quality measures treated the reference image as perfect quality. In practice, the reference image may also subject to noise due to various reasons. The most common type of noise appeared in an image is Gaussian white noise. Section 1.2.1 showed the existing image quality measures tend to under-estimate the image quality when the reference image is imperfect.

The objective of this section is to study the effect of imperfect reference image to quality assessment of the JPEG codec image using R_F^2 and R_P^2. The Gaussian noise with mean zero and variance 0.001 was introduced into the original perfect reference image, yielded the imperfect reference image. Example of the perfect reference images and their corresponding imperfect reference images is given in Figure 7.7. The JPEG codec images were then compared to these reference images and their similarity values are calculated using R_F^2, R_P^2 (together with confidence interval), R_S^2, MSSIM and RMSE.

Figure 7.7: Example of perfect reference image (left) and imperfect reference image (right) with Gaussian noise $\left(\mu = 0, \sigma^2 = 0.001\right)$. These images are Bikes, Caps, House, Lighthouse2 and Monarch.

Figure 7.8 compares the (Q_i, S_i) plots obtained from perfect and imperfect reference images. Generally, all similarity measures are not affected by the imperfect reference image at low compression factors. But the impact of imperfect reference image increases gradually when compression factor increases. Figure 7.8 shows that R_P^2 is the most robust measure to the quality of reference image, in which its differences of using perfect and imperfect reference image is not noticeable. This is followed by R_F^2 that slightly under-estimate the JPEG codec image quality when imperfect reference is used. MSSIM and RMSE are greatly affected by imperfect reference image especially at high compression factors. For example, MSSIM produced similarity value 0.9445 at compression factor 100 when the perfect reference Lighthouse2 image is used. The MSSIM value dropped dramatically to 0.7278 at the same compression factor when the imperfect reference Lighthouse2 image is used.



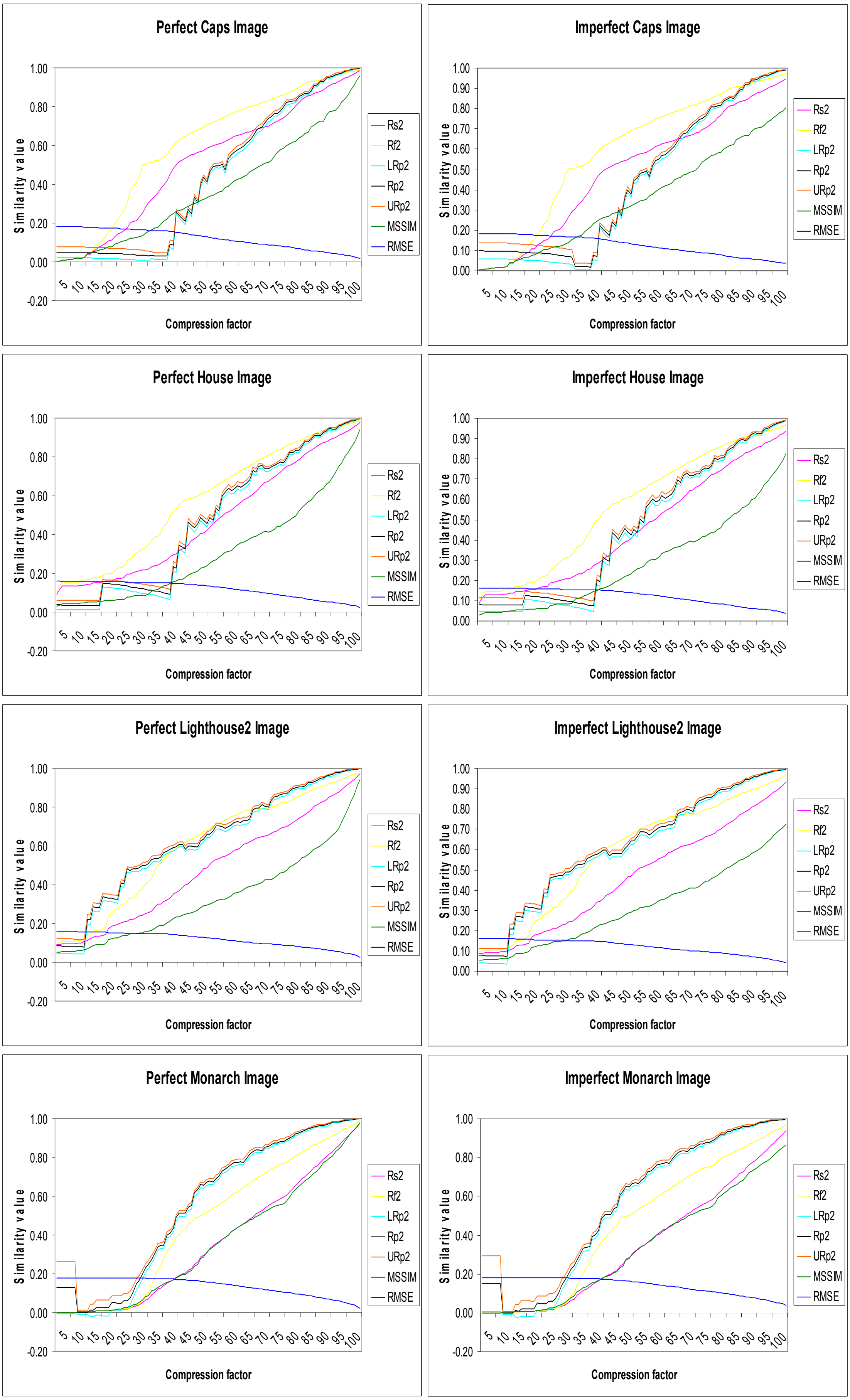


Figure 7.8: (Q_i, S_i) plots using perfect reference image (left) and imperfect reference image (right).

7.6 Estimation of Percentage of Distorted Pixels Using R_F^2 and R_P^2

It is important to realize that all existing similarity measures only indicate the similarity or dissimilarity between a distorted image and the reference image. In other words, these similarity measures only carry the information about the relative quality of the distorted image as compared to the reference image. They do not reflect the actual amount of distortion information conveyed in the JPEG codec image. For example, if a similarity measure shows the value of 0.5, it does not mean that 50% of the image is corrupted. Furthermore, it is learnt that some similarity measures provide good indication for certain type of images, but they show inconsistency in interpreting for different types of images.

Figure 7.4 and Figure 7.6 indicated that R_P^2, R_F^2, R_S^2, MSSIM and RMSE are good performance indicators for JPEG compression when perfect reference was used. Unfortunately, these plots have no practical application due to two problems: (i) JPEG compression factor is usually unknown, and (ii) The same JPEG compression factor may be resulted in different similarity values using different types of images. Figure 7.9 compares the perfect reference images with their corresponding JPEG codec images at compression factors 74 and 50, respectively. Obviously, the JPEG codec Lena image has a better visual quality as compared to JPEC codec Baboon image at a given compression factor. Instead, Lena codec image at compression factor 50 $\left(R_F^2 = 0.7320\right)$ has 'similar' image quality as Baboon codec image at compression factor 74 $\left(R_F^2 = 0.7316\right)$. This means the JPEG compression algorithm performed similarly at compression factors 50 and 70 for Lena image and Baboon image, respectively.

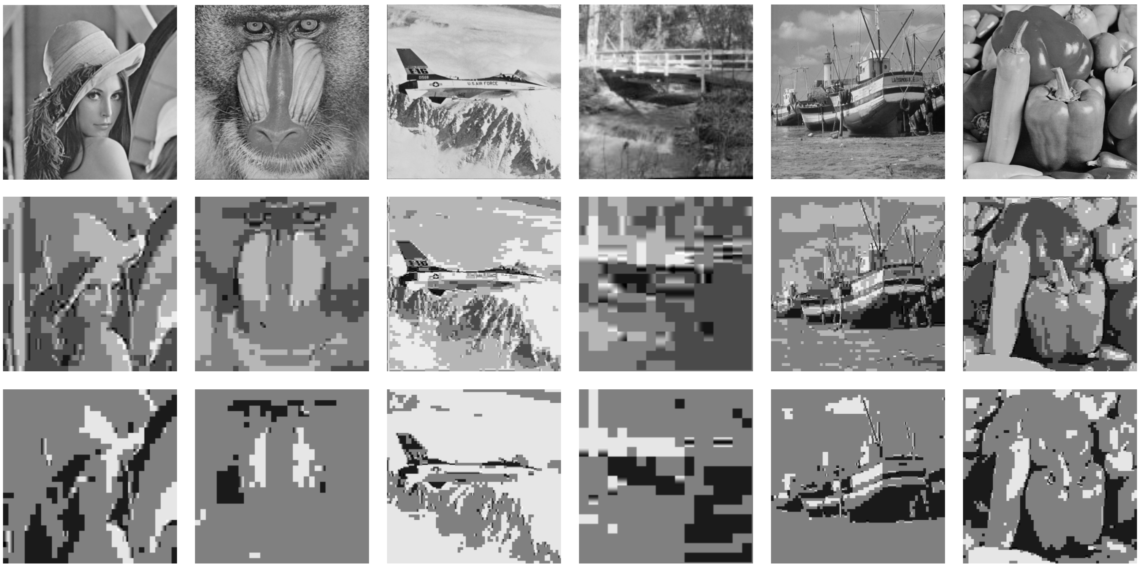


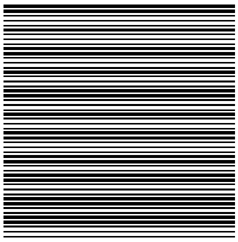
Figure 7.9: From left to right: Lena, Baboon, Airplane, Bridge, Boat and Peppers images. From top to bottom: original, decompressed image with factor 74, and decompressed image with factor 50.

This sub-section introduces a simple approach to estimate the percentage of distortion pixels conveys in the JPEG codec image. It provides a physical interpretation to the similarity measures when different types of image are used. A simple binary image *J* with size 100×100 is created, as shown in Figure 7.10. Let n_d be the number of distorted pixels randomly generated into the image *J*. For each given n_d, a set of 50 different distorted images is obtained and a mean similarity value is calculated. Image *J1*, *J2* and *J3* in Figure 7.10 are examples of the distorted image for $n_d = 100,\ 2000 \text{ and } 10000$, respectively. Figure 7.11 and Figure 7.12 show the relationship between the similarity values and the percentage of distorted pixels, η for R_P^2, R_F^2, R_S^2, MSSIM and RMSE. The fitted equations for these relationships are given as follow:

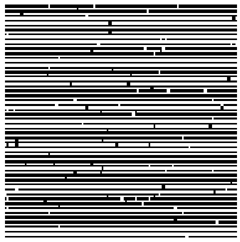
$$\begin{aligned} \text{MSSIM}(\eta) &\approx R_F^2(\eta) \\ &= \begin{cases} 1 & ,\eta \le 0.9607 \\ 1.0194\exp(-2\eta) & ,0.9607 < \eta \le 100 \end{cases} \end{aligned} \tag{7.1}$$

And $$\text{RMSE}(\eta) = -0.4\eta^2 + 0.81\eta + 0.0064 \tag{7.2}$$

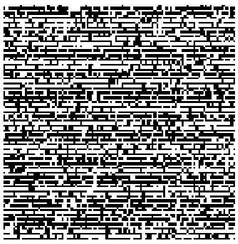
where $\eta = \dfrac{n_d}{MN} \times 100\%$, and $M \times N$ is the size of the image.



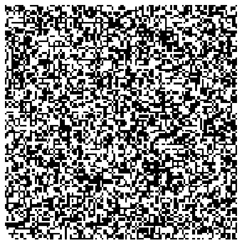
J



J1



J2



J3

Figure 7.10: Generated image and distorted images. J: simple binary image, J1: distorted image with n_d = 100, J2: distorted image with n_d = 2000, J3: distorted image with n_d = 10000.

It is showed that the fitted equations for MSSIM and R_F^2 are very close to each others and they have an inverse exponential function to the percentage of distorted pixels. RMSE is modelled by a quadratic equation. Similarly results can be obtained by using different binary image sizes.

Fitting the R_P^2 curve using exponential method does not yield a promising approximation. Hence a polynomial of order 3 is used (see Figure 7.12) and yielded the following equation.

$$R_{p=2}^2(\eta) = \begin{cases} 1 & ,\eta \le 2.80405 \\ -0.6\eta^3 + 2.165\eta^2 - 2.40237\eta + 1.0656742 & ,2.80405 > \eta > 100 \end{cases} \tag{7.3}$$

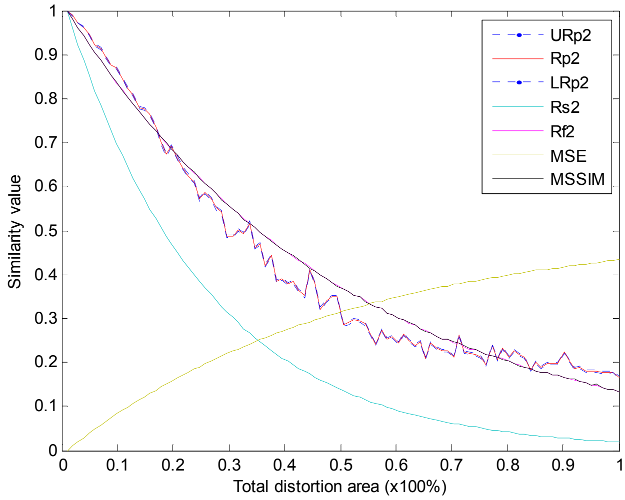


Figure 7.11: Relationship between the similarity value (mean quality index) and the percentage of distorted area. Note that Rf2= R_F^2 .

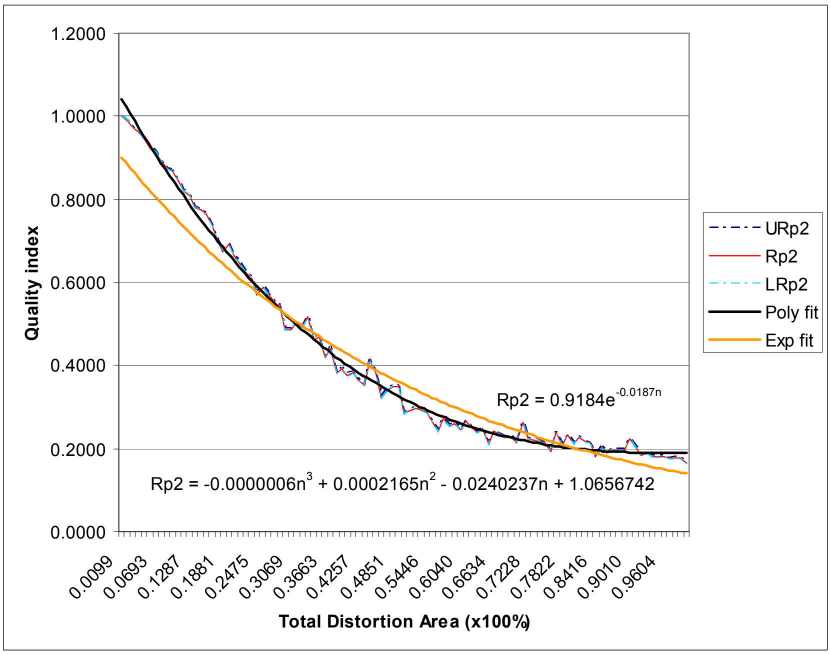


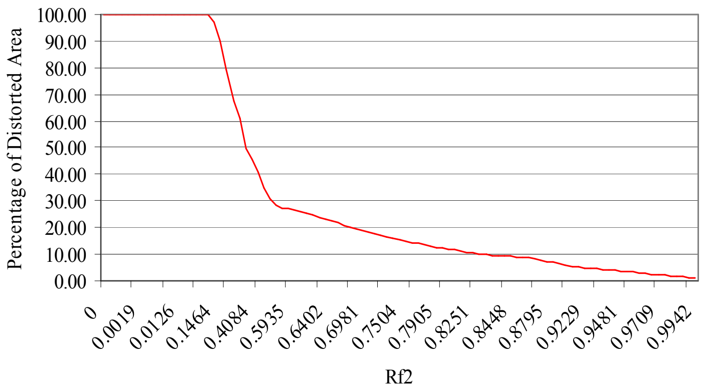
Figure 7.12: Relationship between the mean similarity/quality index and the percentage of distorted area. Note that Rp2= R_F^2 , URp2 and LRp2 are the upper and lower limits for 95% confidence interval.

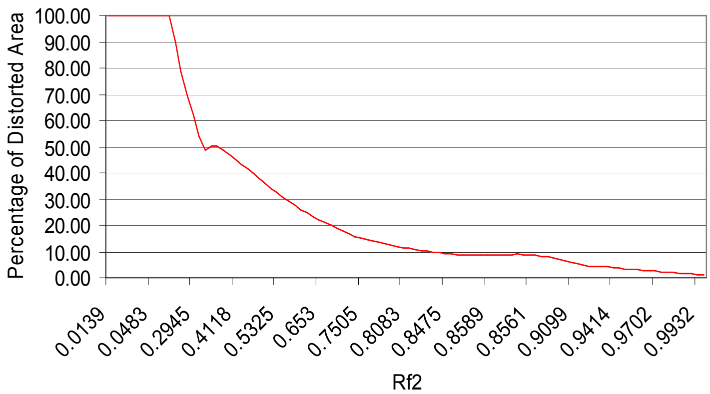
By reversing the Equations (7.1) to (7.3), the percentage of distorted pixels can be estimated from the similarity measures without knowing the actual compression factor. The reverse of Equation 7.1 for R_F^2 is given as follow.

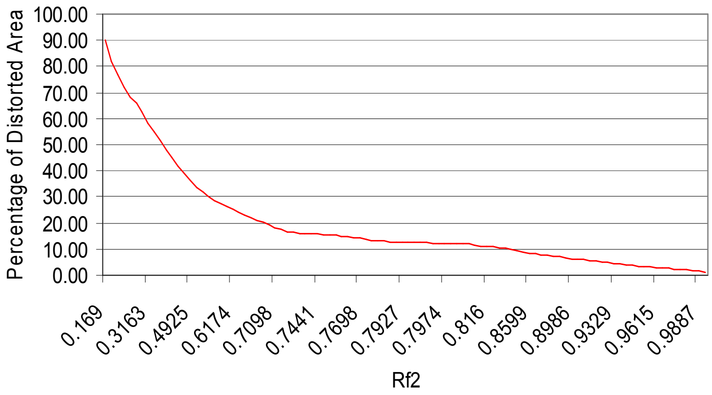
$$\eta = \begin{cases} 100 & , R_F^2 \leq 0.1379608 \\ -50\ln\left(\dfrac{R_F^2}{1.0194}\right) & , 0.1379608 < R_F^2 \leq 1 \end{cases} \tag{7.4}$$

For example, if one tries to keep the quality of an image to be less than 10% of the total number of distorted pixels (or $n_d = 1000$ distorted pixels in this case) from the reference image, then the minimum similarity value for R_F^2 value is 0.8187 calculated from Equation 7.1.

Figure 7.13 shows the estimated percentage of distorted pixels using Equation 6.4. Given a R_F^2 value, these plots show a consistent indication for the amount of distortion generated by JPEG compression, regardless of the image tested. For instance, when R_F^2 value is about 0.834, JPEG compression generated about 10% of distorted pixels on all tested images, which the results are corresponding to their image size.







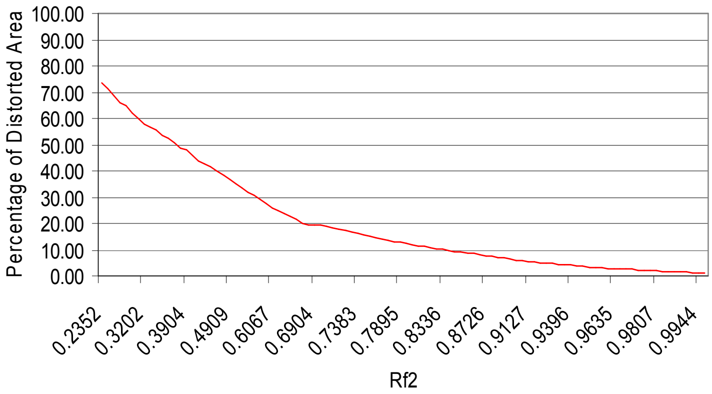


Figure 7.13: Relationship between the percentage of distorted area and R_F^2. The images used (from top to bottom) are Lena, Airplane, Boat and Peppers. Note that Rf2= R_F^2.

7.7 Summary

Both R_p^2 and R_F^2 are introduced as a quality measure for JPEG codec images. These similarity measures, together with MSSIM and RMSE performed very well when perfect reference image is used. They are generally satisfied the three properties of monotonicity, accuracy and consistency of a good objective similarity measure. R_p^2 is recommended when the image is not badly compressed while MSSIM is preferred for measuring the quality of image with high compression rate.

R_p^2 outperforms all other similarity measures when imperfect reference image is considered. This is an important advantage usage of R_p^2 as the reference image with perfect quality is usually hardly to obtain in practice.

A robust and simple interpretation of the percentage of distorted pixels generated by JPEG compression was also introduced. The percentage of distorted pixels can be estimated without information on the compression factor. It also provides consistent interpretation of a similarity measure regardless of the image used. These features strongly suggest that R_p^2 is a good performance indicator for JPEG compression algorithm.