Analysis of Impact of Lossy Image Compression on Image Quality: From Image Application Aspects

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Abstract
Reliable methods for evaluating image compression quality are needed to assess the effects caused by those algorithms, and such assessments require an application-driven process. This paper aims to provide a comprehensive analysis of the impacts of JPEG2000 compression on remote sensing image applications. Image classification and image matching quality assessment, which indicate the radiometric and geometric quality of the compressed images, were selected to test the compression impacts. Nine remote sensing images with different terrain types, land cover and image resolution were employed as original images for compression. The images were compressed by JPEG2000 at various compression ratios. In image classification quality assessment, the classification result from the original image was regarded as the ground truth. The results from original images and compressed images were then compared. In image matching accuracy assessment, the 'pixel distance' between the original image and the compressed image was computed to indicate the geometric distortion caused by image compression. From the experiments, the image quality would decrease with the increase in the compression ratio. As a result, the accuracy of image classification and the matching accuracy deteriorate when the image JPEG2000 compression ratio is very high. And the effect of JPEG2000 compression on the accuracy of image classification and image matching is generally linear.

1. Introduction

One of the characteristics of image data is the large volume, which has brought about considerable problems for image data transmission and storage in the realm of the internet, web browsing, multi-media, communication, medical imaging and remote sensing, etc. To overcome this problem, image compression plays an essential role in minimizing the data size and organizing it into a scalable stream (Ginesu et al., 2006 and Zhai et al., 2006). As a consequence, the quality of the compressed image will inevitably be degraded. It is important to study the degree of reduction of the compressed image and provide useful information for both the satellite remote sensors' designer and the ultimate image users. Many image compression algorithms have emerged in the last ten years, while the assessment of image quality is still an open problem and an area of active research (Ginesu et al., 2006 and Li et al., 2009). Over the years, many objective assessment metrics have been proposed to predict image compression quality. To be both consistent and effective, objective metrics must match with perceived image quality as measured by subjective testing (Gastaldo et al., 2005). Generally, objective metrics can be divided into two classes of assessment (Wang and Bovik, 2002). The first class is statistical information based metrics (pixel-by-pixel differences between the original and compressed images), such as the widely used mean squared error (MSE), root mean squared error (RMSE), peak signal to noise ratio (PSNR), structural similarity (SSIM), normalized perceptual image quality measure (NPIQM), singular value decomposition (SVD)-based metric, and visual information fidelity measure, etc. (Al-Otum, 2003, Toet and Lucassen, 2003, Wang et al., 2004, Sheikh et al., 2005, Shnayderman et al., 2006 and Sheikh and Bovik, 2006). The MSE or PSNR for objective assessment were most commonly used to measure the degradation in compressed images, but they fail in the presence of structured errors and do not correlate well with subjective quality measures

(Eskicioglu and Fisher, 1995, Eckert and Bradley, 1998, Winkler 1999 and Chen et al., 2004). SSIM has demonstrated its promise through a set of intuitive examples, as well as comparison to both subjective ratings and state-of-the-art objective methods (Wang et al., 2004). The second class is human visual system (HVS) based metrics incorporating perceptual models. Malo et al., (1997) developed a frequency and contrast dependent metric in the DCT (Discrete Cosine Transform) domain using a perception model: the Information Allocation Function (IAF) of the visual system. Lai and Kuo (2000) developed a fidelity measure by analysing and modelling several visual mechanisms of the HVS with the Haar transform. However, due to a lack of complete understanding of the HVS and its computational complexity, HVS based metrics have not been widely used (Al-Otum, 2003). It is desirable to have a more general image quality assessment system that is applicable to a wide variety of image compression distortions. However, to the best of our knowledge, no such method has been proposed and extensively tested (Wang et al., 2006). Since image quality is based on a definition of quality in terms of the degree to which something satisfies the requirements imposed on it (Janssen and Blommaert, 2000), we propose that in many applications the most meaningful way to assess or analyse image compression quality is to determine if the differences between the original and compressed images affect the task that the user is trying to perform. That is to say, if the distortions caused by lossy image compression have little or no effects on image application, we can say that the lossy image compression algorithm is acceptable to the ultimate image users. All of the above-mentioned metrics or methods provide significant results for image quality assessment. However, there are a few limitations of these metrics or methods that we would like to point out.

1) The test images in former image compression assessments are not sufficiently diverse, so the conclusions reached are not general. Especially, the terrain or geomorphic types of images are not differentiated in the assessment process.

2) Former studies were mainly conducted in the signal processing area and little attention has been given to effects on image applications brought about by lossy compression. All of the remote sensing images have been obtained for applications. For every specific application, the image compression assessment method should be different. In other words, an image compression assessment should be an application-driven process. For example, the geometric quality of a compressed image is the core for a mapping application, while land use and land cover applications focus on the classification quality of the compressed image.

3) The image resolution, as an important factor, has not been considered in former image compression assessment processes.

This paper focuses on providing a comprehensive analysis of lossy image compression impacts on remote sensing image applications.

2. Image Compression Techniques used in Space Missions

In current space missions, on-board image compression algorithms are widely used (Zhai 2007 and Yu et al., 2009). Table 1 gives a summary of the reviewed missions. From Table 1, we can find that lossy compression is popular among earth observation satellites and the highest compression ratio is 8:1 in order to limit the artifacts brought about by compression. Before the satellite launch, there usually will be much work to be completed by the satellite manufacturer together with the satellite user, such as the determination of the satellite remote sensors' parameters.

Table 1: Some Typical Image Compression Systems On-Board Space Missions

Satellite	Country	Launch date	Compression algorithm	Compression ratio
SPOT 5	France	May 3, 2002	DCT	2.81:1
PLEIADES	France	planning	JPEG2000	4:1
IKONOS II	USA	Sep. 24, 1999	ADPCM	4.23:1
WorldView-2	USA	Oct.8, 2009	—	2.4:1
GeoEye-1	USA	Sep. 6, 2008	ADPCM	2.6:1
Daichi (ALOS)	Japan	Jan. 24, 2006	DCT	8:1
ZIYUAN 1-02B	China	Sep. 19, 2007	SPIHT	8:1
HJ-1A/1B	China	Sep. 6, 2008	SPIHT	4:1
ZIYUAN-3	China	Jan. 9, 2012	JPEG-LS	4:1

The compression ratio is an important parameter and should be specified before the launch of the satellite. Image compression quality assessment is critical to both compression algorithm designers and image product users. In the following sections, we will analyse the lossy image compression impacts on remote sensing image quality from the image application aspects. The compression software used in this study is JASPER (version: 1.701.0) which provides JPEG2000 compression function and is freely available for academic use from the jasper project home page (http://www.ece.uvic.ca/~mdadams/jasper).

3. Methodology

Generally, there are two aspects for image quality assessment: one is the radiometric characteristics, and the other concerns the geometric characteristics. These two kinds of characteristics can easily reflect the discriminatability and measurability of the image. As to image compression quality assessment, the best way to measure the distortion brought about by compression is to evaluate the impacts after compression in terms of radiometric and geometric quality. Here we propose an objective method of image compression quality assessment. The problem for this method is seeking the means for measuring the radiometric and geometric quality changes after image compression. Thereby, two routes are selected to cover this problem and they are image classification and image matching quality assessment, namely, digital image processing and photogrammetric techniques.

3.1 The Image Classification Quality Assessment

A broad group of digital image processing techniques is directed toward image classification, the automated grouping of all or selected land cover features into summary categories. Image classification quality assessment is employed here to analyse the effects of image compression on classification accuracy. The original and compressed images adopt the same classification methods and classification system. The original image classification result was regarded as the ground truth. The results from original images and compressed images were then compared.

3.2 The Image Matching Quality Assessment

As we have discussed above, the geometric quality is also one of the important characteristics of a compressed image and it reflects the image measurability. Image matching accuracy assessment, which computes the 'pixel distance' between the original image and the compressed image, is used here. Image matching accuracy analysis shows how degradation in image quality associated with lossy compression can affect matching accuracy. First, a series of image feature points are extracted in both the original image and the compressed one; these feature points can be differentiated from their neighbouring image points. If this were not the case, it would not be possible to match them uniquely with a corresponding point in the compressed image. So far there have been a large number of algorithms for feature point extraction (Zhou and Shi 2002).

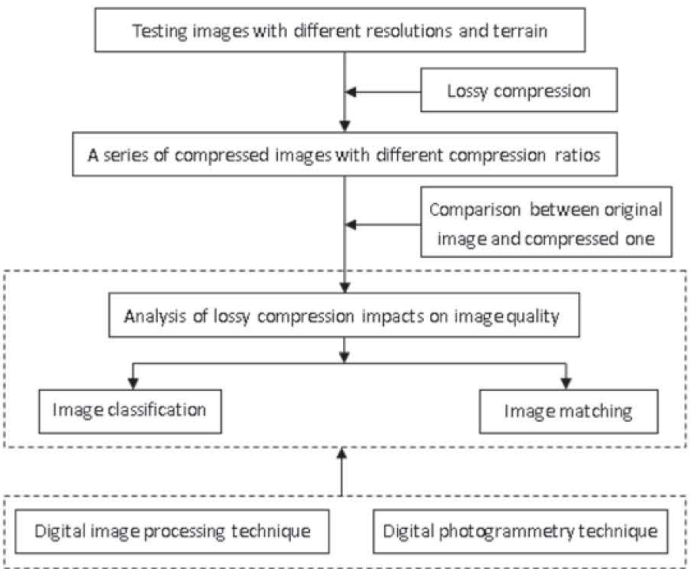

Figure 1: Workflow for the application-driven method of image compression quality assessment

In this study, the SUSAN corner detector was used. Second, feature point matching is performed to find the pixel pairs projected by the same points of a scene. Third, the 'pixel distance' between the original image and the compressed image can be computed. Let Δxy refer to image matching error, then:

$$\Delta xy=\sqrt{(x_f-x_g)^2+(y_f-y_g)^2}$$

Equation 1

(x_f, y_f) is the pixel value of original image, and (x_g, y_g) is the corresponding pixel value of the reconstructed image. Finally, the mean value for feature point's Δxy is computed.

4. Experiments

4.1 Test Images

All images used for the image compression experiment were original aerial images that had never been compressed or processed before. To ensure the number of samples is large enough for statistical analysis, a total of nine remote sensing images with different terrain types, land cover and resolution were selected as original images for compression. There were three types of image resolution, namely, 1 metre, 2 metre and 5 metre. For each image resolution, there were three test images and they are classified into one group. Here we use M1, M2 and M5 to stand for each group and the corresponding image resolutions are 1 metre, 2 metre and 5 metre. In our experiments, only panchromatic images were adopted. The test images are shown in Figure 2. In each group of these test images, images of mountainous areas have higher entropy compared to images of the plain and hilly areas, and the images of plain areas have the lowest entropy. Table 2 gives the entropy for each original image. A series of reconstructed images with compression ratios of 2:1, 4:1, 6:1, 8:1, and 10:1 were obtained.

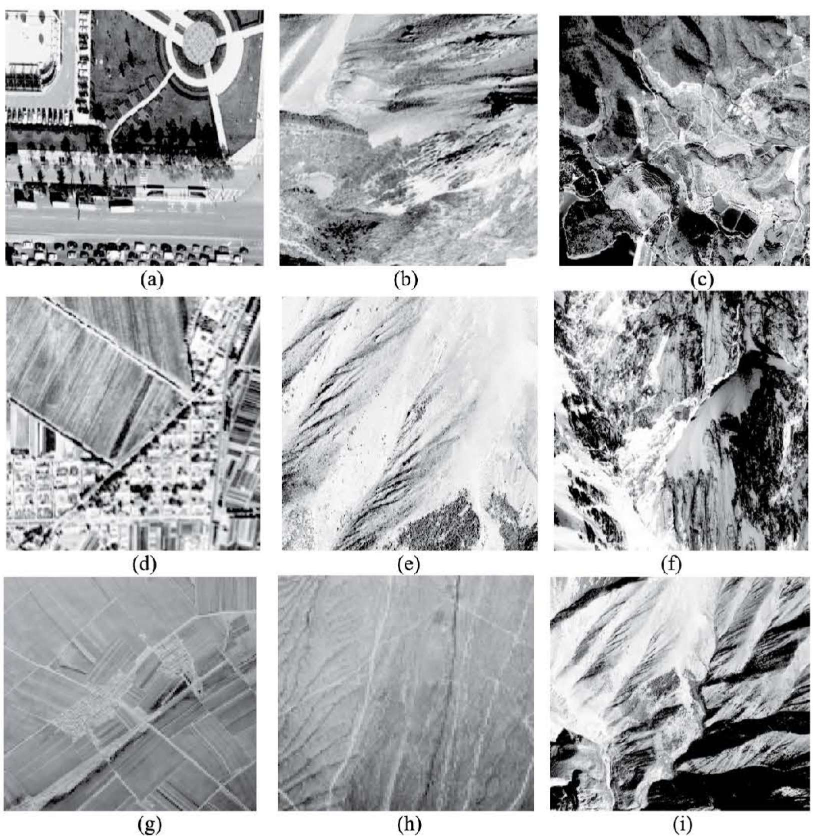

Figure 2: Examples of test images. (a)M1-Plain area, (b)M1-Hilly area, (c)M1-Mountainous area, (d)M2-Plain area, (e)M2-Hilly area. (f)M2-Mountainous area, (g)M5-Plain area, (h)M5-Hilly area, (i)M5-Mountainous area

Table 2: The entropy for each original image

Test images	Entropy
M1-Plain area	3.11
M1-Hilly area	3.12
M1-Mountainous area	3.51
M2-Plain area	3.08
M2-Hilly area	3.16
M2-Mountainous area	3.41
M5-Plain area	2.94
M5-Hilly area	3.01
M5-Mountainous area	3.42

Table 3: The isodata classification results of original and JPEG *2000* compressed images

Test images	compression ratio=2:1	compression ratio=4:1	compression ratio=6:1	compression ratio=8:1	compression ratio=10:1
M1-Plain area	0.96	0.95	0.92	0.89	0.86
M1-Hilly area	0.94	0.93	0.90	0.88	0.84
M1-Mountainous area	0.90	0.89	0.86	0.83	0.81
M2-Plain area	0.94	0.92	0.91	0.89	0.85
M2-Hilly area	0.91	0.90	0.87	0.84	0.80
M2-Mountainous area	0.89	0.86	0.84	0.83	0.78
M5-Plain area	0.92	0.90	0.88	0.85	0.83
M5-Hilly area	0.89	0.87	0.85	0.81	0.77
M5-Mountainous area	0.85	0.84	0.82	0.80	0.74

4.2 Classification of the Original Images and JPEG2000-Compressed Images

As discussed above, for each group, M1, M2 and M5, both the original image and compressed images were classified using the ISODATA method. In each group, the initial settings of the parameters for the ISODATA algorithm were identical for the original and the corresponding compressed images. We adopted the following classification system, in which five major land cover types were defined: cropland, urban, vegetation cover, water, barren land, as well as an additional unclassified class. In this study, Erdas8.7 is used as the classification software. For the analysis of classification results, the Kappa coefficient, which is a parameter scaled to a range [0, 1], was employed to calculate the actual classification agreement and the chance agreement. A higher coefficient indicates a reliable classification result. A value of 1 means perfect classification. All the results are summarized in Table 3. From Table 3, we can easily find that the accuracy of image classification deteriorates dramatically when the compression ratio is high. As to different terrain types and different image resolutions, JPEG2000 compression has different effects on them. That is, the effects of JPEG2000 on image classification are scene-dependent. For example, the mountainous area has rich texture (large entropy) and its classification accuracy is the worst in each group. With the same terrain type, the images with low resolution have lower classification accuracy. That is to say, JPEG2000 has more bad effects on texture rich areas with lower resolution than on texture sparse areas with higher resolution.

4.3 Image Matching Accuracy Assessment

For each group, the image matching process was conducted between the original and compressed images. Table 1V shows the image matching accuracy assessment results. Figure 3 depicts the relations between Δxy and the compression ratio. From Table 3, it can be found that Δxy grows with an increase in the compression ratio, but all were less than 0.21 pixel. According to Maeder (1998), JPEG has a great effect on image matching; for example, Δxy reaches 0.04 pixel when the compression ratio is 4:1. The reason is that JPEG2000 is an algorithm based on DWT, which is capable of keeping image high frequency components. As to different terrain types, steep areas have a lower Δxy than plain areas when the compression ratios are equal. This shows that the image matching process is affected greatly when the terrain is steep or complex. In steep areas, feature points become difficult to select automatically.

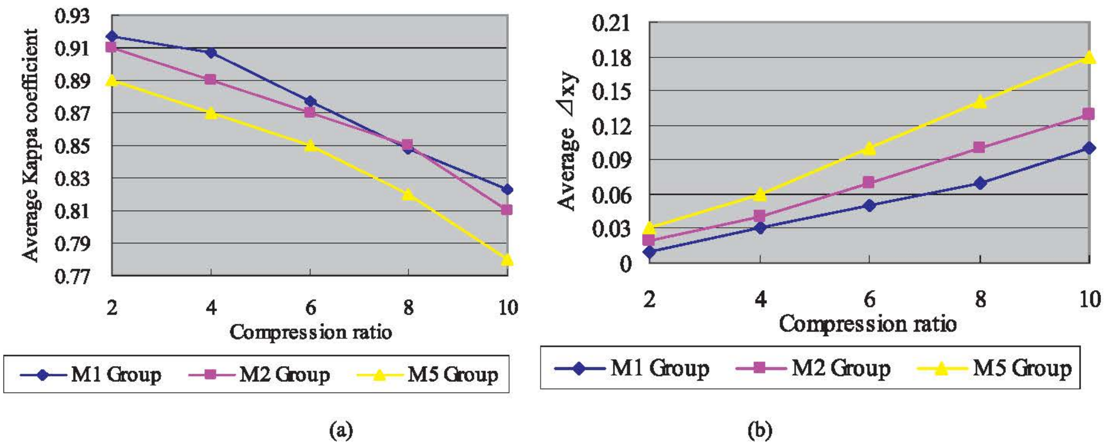

Figure 3: The relations between compression ratio and image resolution. The relations between compression ratio and average Kappa coefficient. The relations between compression ratio and average Δxy

5. Discussion and Conclusions

As the remote sensing industry has a tendency to achieve higher resolution with time, the use of compression techniques to reduce the volume of image data is necessary. As image quality is unavoidably degraded after compression, it is desirable to define an optimum compression ratio to balance the degradation in image quality with reduction in data volume (Lau et al., 2003). From the experiments conducted in this study, it was found that the compression ratio, image resolution and image terrain types have close relations with image compression quality. The higher the compression ratio, the worse is the image compression quality. This has been proved by many studies. With the same compression ratio, JPEG2000 compression has different effects on different image resolutions and terrain types. Figure 2 shows the relations between compression ratio and image resolution. The average classification accuracy and Δxy are employed here. From Figure 2, it can easily be seen that with a decrease in image resolution, the average classification accuracy decreases and the average Δxy increases. That is to say, the image compression has a greater effect on low resolution images than high resolution ones. To describe the decreasing rates of image compression quality, a linear regression method was employed. The lines in Figure 3 were linearized and the slope (or change rate) of the line was then computed. For the compressed images, the change rate of the average Kappa coefficient was about -0.013 units per compression ratio, and that of the average Δxy was about 0.014 pixel per compression ratio. These rates indicate that less than 0.02 units of Kappa coefficient and 0.02 pixels of Δxy will be sacrificed if the compression ratio increases by one more unit. Based on the limited test results obtained in this study, it might be concluded that:

1) As a result, the accuracy of image classification and the matching accuracy deteriorate when the image JPEG2000 compression ratio is very high. And the effect of JPEG2000 compression on the accuracy of image classification and image matching is generally linear.

2) As to different terrain types or texture complexity, JPEG2000 compression has different effects on them. From our experiments, it is proved that JPEG2000 has more bad effects on areas of rich texture with the same compression ratio. One of the reasons could be the distortion of textural contents caused by the smoothing effects of digital wavelet transformation.

3) By comparing JPEG2000 compression on different image resolutions, it was found that JPEG2000 has a greater effect on low resolution images than high resolution ones. So, the compression ratio for on-board image compression could be larger for high resolution satellites. In our experiments, image classification and image matching quality assessment, which indicate the radiometric and geometric quality of the compressed images, were selected to test the compression impacts. The conclusions from this study has been accepted and used in the design and implementation of Chinese ZIYUAN-3 satellite remote sensors.

For future study, the effects of compression on other image applications, such as image segmentation, target recognition and change detection, etc., could be examined in order to enrich the image quality assessment method.

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