THE EFFECTS ON IMAGE CLASSIFICATION USING IMAGE COMPRESSION TECHNIQUE

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ABSTRACT

Image classification, either supervised or unsupervised approach, is an image analysis tool to categorise the unidentified pixels in an image to the designed thematic or spectral separable classes respectively in satellite-based remote sensing discipline. However, the unmanageable physical size of satellite image in somehow increases the cost of transmission, processing and storage of those image data. Using image compression techniques, such as JPEG, can no doubt reduce the physical size of image but the image quality is unavoidable to degrade. Most of these lossy compression techniques are mainly designed to exploit human vision system limitations. The degraded quality of the compressed image may not be visible or obvious when examines by human eyes. As computer-based image analysis tools are very sensitive to image quality, small changes in the image content may affect the analysed results. This paper is to evaluate the effects on the image classification using JPEG-compressed SPOT multispectral images with vary compression quality factors. All the compressed images are classified under supervised classification approach of maximum likelihood classifier (MLC) and unsupervised classification approach of ISODATA clustering (ISOCLUS). With the classified result using original (uncompressed) image as the benchmark, the integrated analysis results of the supervised and unsupervised classification indicates the tolerance of deteriorated classification performance against the compression scale. Finally, some recommendations for the optimum factor of JPEG compression for image classification are concluded.

1 INTRODUCTION

In this Information Technology Era, vast amounts of digital information are transmitting via various types of communication channels. The demands of high speed and high capacity "information highway" are increasing. On the other hand, different algorithms have been developed to reduce the memory requirement for digital documents so that these documents can be transmitted faster and taken up less storage space. Image compression algorithms have been the prime focus for the last few years due to the increase in popularity of Internet and scanning technology. As for the remote sensing industry, the issue of image compression has become more important due to the availability of high-resolution hyper-spectral satellite imagery. The image resolution of satellite image has increased by a factor of 10 times for the last decade (from 10m to 1m) which implies 100 times increase in data volume for the same area coverage. For example, for one scene of SPOT multispectral data with three channels, the storage space may be over 50Mbytes. On the contrary, for the same scene but with 1m resolution and five channels, the memory requirement will be 200 times more.

To reduce image data volume, three methods: subsampling, averaging and image compression can be used. Volume of data reduction for both subsampling and averaging techniques is a function of two user-definable parameters: size of sample-block and the value of coefficient. The processing time and the resultant image size of these two techniques are mainly related to the entered parameters (Sobue et al.,1993). Besides, the effects of decreased image size and degraded image quality are obviously by the above two methods. For the image compression techniques such as JPEG, the high-efficient process is performed.

JPEG, in somehow, is a standard image compression scheme which is written by Joint Photographic Experts Group. This compression scheme has two approaches: baseline and progressive. The baseline approach uses one image block sized 8 x 8 pixel units for the transformation of an image. The image is transformed from a pixel-format to the 64-coefficient matrix through the Discrete Cosine Transformation (DCT). The representation of coefficients is then quantized to integer to maximise compression. Afterwards, the Huffman coding is used to encode the quantized coefficient. The compressed image file is generated. To decompose the file into a pixel- image format, the inverse compression process is used. More details of the JPEG compression schemes can be found in Lammi and Sarjakoski (1995) and Lane (1999).

The JPEG compression is capable to scale down the file size of image in 10-to-1 ratio. However, the quantization effect in the compression process gives up the part of information to achieve file size reduction. Hence, the compressed image is unavoidably to loss certain degree of image's quality permanently. To control the degree of compression, JPEG compression algorithm allows the adjustment of an internal parameter (q-factor) to balance the compression ratio and image's quality. Changing the value of q-factor may result in change of file size and image quality. JPEG compression technique was designed to exploit the limitation of human vision with little or no noticeable changes of brightness and colour to human eyes. However, the change of image's quality may cause problems to machine vision.

The quantitative assessment of image quality is difficult, unless it is measured in terms of its application result. Image classification is one of the commonly used applications in the remote sensing industry. A study on the effects of image compression on this application is worth to analyse. Paola and Schowengerdt, (1995) reported their study results on the impacts of image compression on the image classification process. By considering four ratios of JPEG compression, the classification accuracy was still preserved in a 10-to-1 compressed image. When the highly-compressed image was classified by three different classification approaches, the accuracy of classification was degraded, as some significant spatial details in the image were lost after the compression. Alternatively, Correa et al., (1998) had issued some considerations of using JPEG in the classification. Losses of information, degrading of sensor performance and reducing of information contents are the disadvantages of image compression.

Although some attempts have been made to find out the impacts of image compression on the image classification process, limited example concerned on the tolerance and optimum level of q-factor versus the classification quality. Hence, this paper organised numbers of experiments to analyse the effects of different q-factors applied on JPEGed (JPEG compressed) images on classification quality. Two sub-scenes extracted from a SPOT multispectral image were used to conduct the experiment. Each sub-scene was compressed with various q-factors at 5-level interval in the scale of 1-100 independently. Various JPEGed images were then processed with supervised classification of maximum likelihood classifier (MLC) and unsupervised classification of ISODATA clustering (ISOCLUS). With reference to the classification results, classification accuracy and number of clusters from MLC and ISOCLUS respectively, the change of image quality is measured.

2 EXPERIMENTAL TESTING

2.1 Image Data

For the experiment, two sub-scenes, sized 512x512 pixels, extracted from the SPOT multispectral scene (dated 95/02/05) were used. One sub-scene (Figure 1) was imaged at the location of Hong Kong central business district (named CBD) and another sub-scene (Figure 2) was imaged at the location of Tuen Mun (named TM)

Figure 1. The CBD Sub-scene.

Figure 2. The TM Sub-scene.

area, a residential area in the north-west of Hong Kong SAR. Two sub-scenes have similar land coverage such as water, vegetation cover, urban area and barren lands. However, the TM image has a larger proportion of vegetation coverage and smaller proportion of urban area than that of CBD image. CBD image has similar proportion of various land coverages. The selection of different natures of image was to provide the analysis space for the compression in different spectral response from various land covers.

In this study, all the processing were carried out in using PCI ImageWorks and Xpace version 6.01.

2.2 JPEG Compression of Image Data

In the experiment, the baseline approach of JPEG compression algorithm was used. To investigate the change of classification results with respect to the q-factors, various q-factors were used for image compression. The maximum factors: 100, 99 and 95 were selected. Then after q-factor: 95, q-factors with 5 intervals were used to compress the image. The minimum q-factor valued at one was used instead of zero. Twenty-one JPEGed images were produced independently for each sub-scene. After the compression, the relationship of compression ratio (size of original image / size of JPEGed image) and the q-factor of two sub-scenes were analysed and plotted in the following graph (Figure 3).

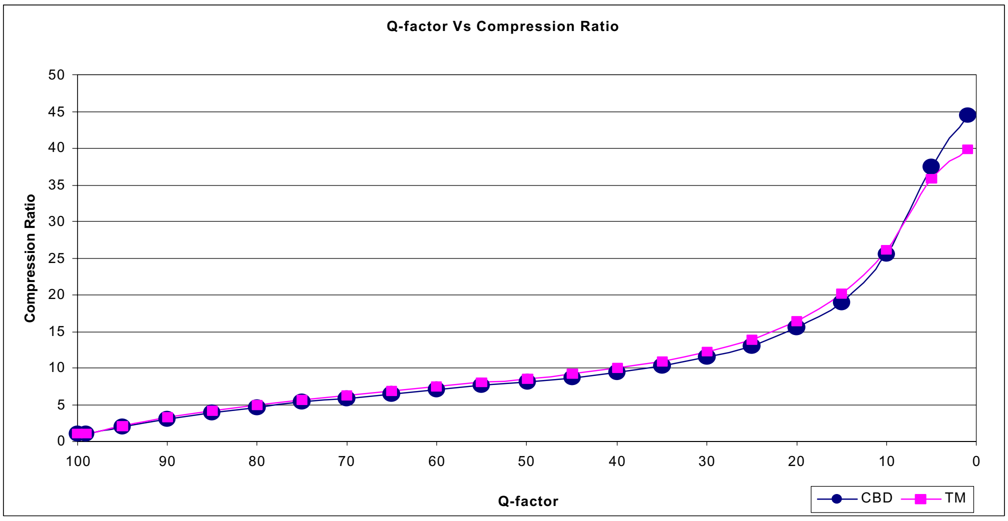

Figure 3. The relation between q-factor with compression ratio

With reference to the JPEG compression results (Figure 3), two sets of image data (from CBD and TM images) presented similar characteristics. While the q-factor was 40, JPEG was able to achieve a compression ratio of about 10 times of the original. And while the q-factor was 1, the volume of CBD and TM images was compressed about 44 and 40 times respectively. Although the use of JPEG can reduce the image's volume effectively, the degradation of JPEGed image quality is absolutely unavoidable and also visually noticeable with low q-factor value. To investigate the effect and the tolerance of compression ratio on the application of remote sensing imagery, experiment of using compressed image for land cover classification were conducted.

2.3 Classification of JPEG-Compressed Image

Image classification strategy is mainly divided into supervised and unsupervised approach. Supervised classification is to categorise the unknown pixels into different themes, based on the spectral (or statistical) characteristics of manual-defined sampled pixels. The resultant categories and the sampled area of pixels are required to define and delineate manually. Then, the spectral characteristics of those pixels are extracted and they are being used for the classification process to classify unknown pixels in the image. After the classification process, all the unknown pixels with similar spectral characteristics of the defined categories will be assigned and pixels which have their characteristics difference from the categories will be categorised as unknown. Unlike the supervised approach, unsupervised classification is processed without the manual-training process (but self-training by computer). It automatically categorises the unknown pixel into certain number of clusters based on the spectral separation. Obviously, more spectral information or larger statistical differences in an image, more numbers of clusters can be determined. The resultant clusters are natural grouping and unrelated to any themes.

In the experiment of supervised classification, five categories: water (WATER); vegetation cover (VEG); urban land use (URBAN); and barren land (BARREN) were selected. The maximum likelihood classifier (MLC) was selected for as the classification strategy. In the experiment of unsupervised classification, the ISODATA clustering (ISOCLUS) was used. Based the requirement of ISOCLUS, the estimated number of clusters was required to be per-defined (reference to PCI, 1994), but the resultant number was highly depend on the quantities of spectral information. Larger quantities of spectral information provide higher degree of spectral distinction between pixels and result in more numbers of clusters. In this experiment, the estimated numbers of resultant clusters were estimated to 256.

2.4 Analysis of Unsupervised Classification Results

The results of the unsupervised classification for the two sub-scenes (CBD and TM) against different q-factors applied for JPEG compression and the uncompressed (original) images (Uncomp) are summarised in Table 1.

Table 1. The number of resultant clusters from ISOCLUS in using uncompressed (original) and JPEGed images

JPEG	Uncomp	100	99	95	90	85	80	75
CBD	164	166	163	166	167	161	163	161
TM	153	173	173	177	174	164	169	178
JPEG	70	65	60	55	50	45	40	35
CBD	162	159	159	154	160	160	162	158
TM	170	165	187	186	187	167	180	185
JPEG	30	25	20	15	10	05	01	
CBD	158	170	162	152	152	154	10	
TM	174	174	171	174	156	139	3	

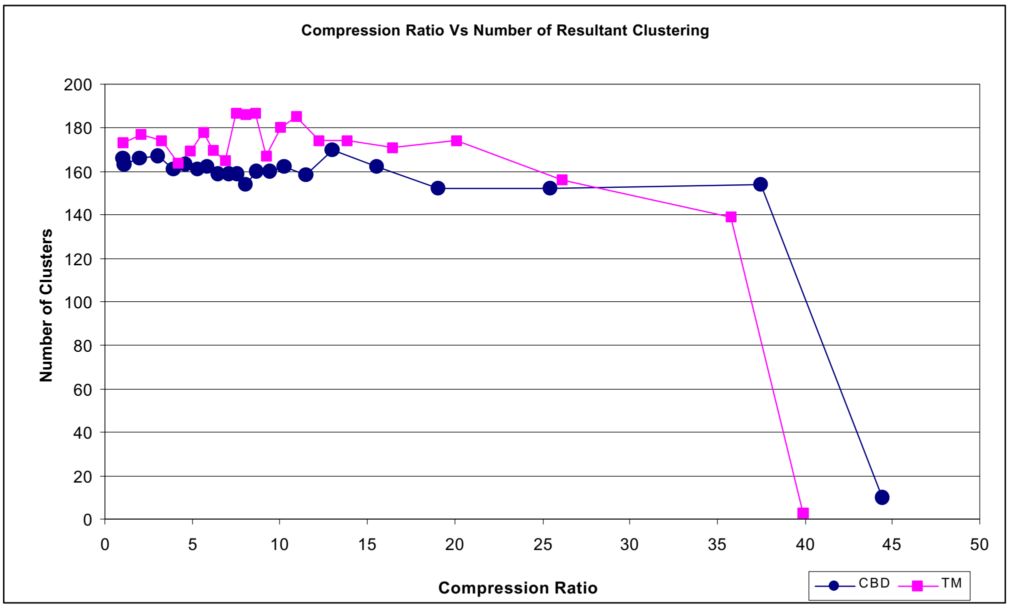

Figure 4. The relation between compression ratio with the numbers of clusters from ISODATA.

Refer to Table 1, the numbers of resultant clustering using the uncompressed images were 164 and 153 for the CBD and TM images respectively. After JPEG compression, the numbers of clusters were varied from +1.83% to -7.32% for CBD image and -7.19% to -22.22% for TM while the compression ratios were kept below 20-to-1

(Figure 4). As expected, the number of clusters reduced significantly when the compression ratio was higher than 20 to 1. That was the result of the change or distortion of the spectral characteristics, which is the side effect of image compression. In the JPEG-compression scheme, blocking effect will be generated during the 8 x 8 block transformation. This transformation distorts the digital numbers (spectral characteristics) of compressed image and might produce new digital numbers. As a result, the distorted image contents would be different from the original one and more clusters were statistically created by ISOCLUS. Using TM image as an example, the numbers of clusters for JPEGed images were more than that of the original one when the compression ratios were below 25-to-1 (q-factor >10).

However, in general, less number of clusters would be created for a compressed image because of the averaging effect created by the transformation. The 8 x 8 block transformation eliminates some of the spectral difference and resample those pixels into similar spectral contents. This effect may increase the spectral similarity among the pixels in an image and decrease the spectral discrimination during the ISOCLUS classification process. Thus, the number of clusters was decreased. This result can clearly be observed from the curves illustrated in Figure 4.

According to the findings of these experiments, applying higher compression ratio may not necessary reduce the total number of clusters identified by the unsupervised classification process. In fact, the changes are related to the distortion of the spectral values created by the block transformation. In addition, the changes may also be scene dependent as different images will have different spectral characteristics and different spectral patterns may create as a result of compression. Limited to the experiments conducted in this study, at least 9% changes of resultant clusters were detected after compression (based on the testing of CBD image).

2.5 Analysis of Supervised Classification Results

For the analysis of supervised classification results, confusion matrix (or named error matrix), an almost universally accepted image classification accuracy report, was used. It is a symmetrical array to express the number of classified pixel in the assigned category relating to the actual category from the ground truth data (Campbell, 1996; Congalton and Green, 1999). Ground truth data are an alternative set of sampled area delineated independently in an image (similar as training process). The overall accuracy of confusion matrix, which is computed by the weighting of the percentage of all corrected-classified pixels in each assigned category, is used to quantify the classification accuracy. Besides, the Kappa coefficient, which is the sum of the off-diagonal elements in the confusion matrix, was also employed in this study to calculate the actual classification agreement and the chance agreement (Shi, 1994). High value of the Kappa coefficient indicates higher reliability of the classification results. All the results in terms of these two measures were computed and summarised in Table 2.

Table 2. The MLC classification results of uncompressed (original) and JPEGed images: a) Overall Accuracy and b) Kappa Coefficient.

(a) Overall Accuracy

JPEG	Uncomp	100	99	95	90	85	80	75
CBD	93.19	94.28	93.64	93.37	94.10	93.82	93.82	92.82
TM	85.24	81.39	81.17	78.24	78.02	77.27	75.37	74.93
JPEG	70	65	60	55	50	45	40	35
CBD	91.73	92.01	92.64	92.82	92.55	92.28	92.37	92.01
TM	73.47	76.23	76.72	74.72	76.40	74.12	76.99	72.82
JPEG	30	25	20	15	10	05	01	
CBD	88.83	88.83	89.37	86.92	83.20	80.84	62.86	
TM	72.49	70.05	68.20	64.62	71.62	59.25	66.30	

(b) Kappa Coefficient

JPEG	Uncomp	100	99	95	90	85	80	75
CBD	0.90	0.92	0.91	0.91	0.92	0.91	0.91	0.90
TM	0.80	0.75	0.74	0.71	0.70	0.70	0.67	0.66
JPEG	70	65	60	55	50	45	40	35
CBD	0.88	0.89	0.90	0.90	0.90	0.89	0.89	0.89
TM	0.64	0.68	0.69	0.66	0.68	0.65	0.69	0.63
JPEG	30	25	20	15	10	05	01	
CBD	0.84	0.84	0.85	0.82	0.77	0.73	0	
TM	0.63	0.60	0.57	0.52	0.61	0.45	-0.29	

Refer to the overall experimental results (Table 2), the classification results using the CBD images were accurate than that using TM image. For instance, the overall accuracy and Kappa coefficient of the original CBD image, from Table 2a, were 93.19% and 0.90 respectively; and that of TM image (Table 2b) were 85.24% and 0.80 respectively. For the classification results of JPEGed images with compression ratio lower than 20-to-1 (q-factor >= 15 in CBD and q-factor >= 20 in TM), the overall accuracy of the two scenes were decreased by 6.27% and 17.04% (Figure 5). Similarly, based on the assessment of Kappa coefficient (Figure 5), the values of JPEGed CBD and TM images were reduced by 9.31% and 28.63% respectively, while the compression was achieved to 20-to-1 ratio. The compressed image with ratio larger than 20-to-1 resulted in significantly degradation of classification accuracy as illustrated in Figure 5. For example, the overall classification accuracy of the compressed CBD and TM images were reduced by as much as 30%. Furthermore, the values of the Kappa coefficient reduced significantly with high compression ratio which indicated that the classification results was become totally unreliable.

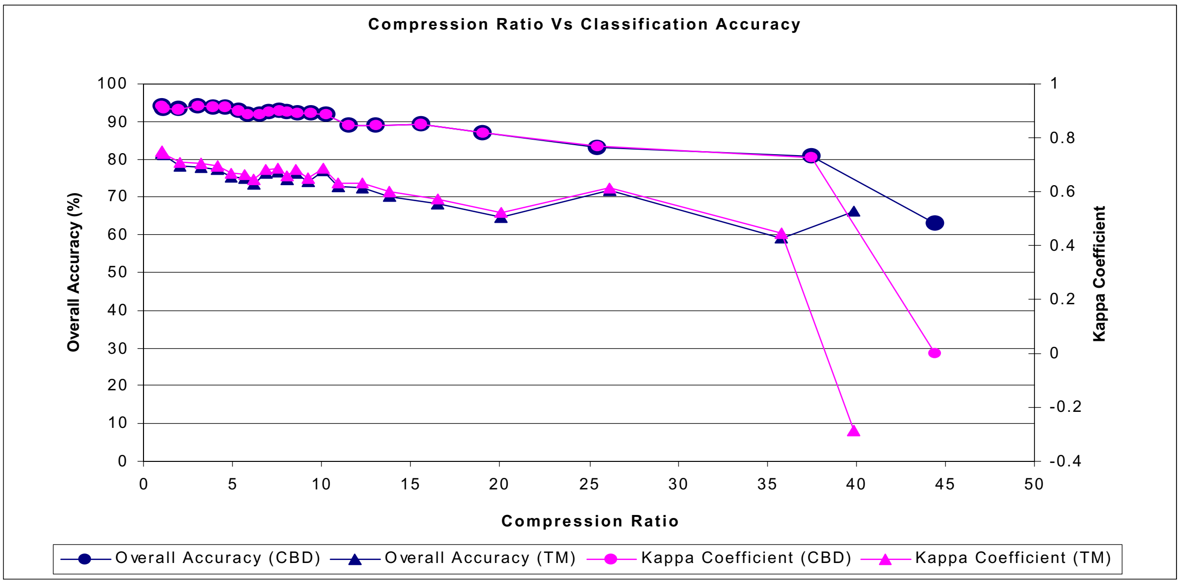

Figure 5. The relations between compression ratio and the overall accuracy and the Kappa coefficient.

3 DICUSSION AND CONCLUSION

As the remote sensing industry is pushing to achieve higher spatial and spectral resolutions resulted in much larger quantities of image data), using image compression techniques to reduce the image data volume has becoming mandatory instead of necessity. If image's quality is unavoidably to degrade during compression process, the optimum condition to balance the degraded image quality and compression ratio is worth to be identified. In regarding of the experiments in this study, the distortion of spectral contents caused by the blocking effect of compression is one factor to affect the numbers of clusters formed during the ISOCLUS unsupervised classification technique. The resultant number of clusters generally decreases as compression ratio becomes higher. Small percentage of increase is also observed as result of the unpredictable blocking effect. In addition, the change of cluster numbers after the compression is also scene-dependant.

For the supervised classification results of the two sub-scenes, the overall accuracy and Kappa coefficient were decreasing in a general with a linear downward trend. Refer to Figure 5, a straight line can easily be fitted onto the points with compression ratios below 20-to-1. To describe the decreasing trend, a linear regression method (more details about the method can refer to Montgomery, 1991) was employed to determine the linear trend and the slope of the line was computed. For the JPEGed CBD images, the decreasing rate of the overall accuracy was about 0.39% per one compression-ratio. For the JPEGed TM images, the decreasing rate of the overall accuracy was about 0.70% per one compression-ratio. Similar linear regression analysis can also be applied for the Kappa coefficient values for the two scenes. These decreasing rates indicate that less than one percent of accuracy will be scarified if the compression ratio is increased by one unit. It is also noted that image with higher classification accuracy will have a lower decreasing rate.

The classification accuracy of the original CBD image was above 93% but only 85% for the original TM image. Both results were considered to be acceptable (larger than 80%) during normal classification exercise when uncompressed images were used. However, when the images were being compressed and up to 20 times, the classification result for TM scene would become unacceptable very quickly but not for CBD scene. Hence, image with higher classification accuracy will have a higher tolerance for image compression. As supervised classification accuracy is a function of the accuracy of the training data, an accuracy and reliable supervised training data set becomes very important. Even though the decreasing rates for the classification accuracy of the two images were different, their trends can easily be modeled using linear regression model when the compression ratios were below 20-to-1 or with q-factor larger than 30. This observation is similar to the recommendation from various different image processing software packages which discourage the use of q-factor less than 30. On the contrary, some image processing software packages suggest to use q-factor value of higher than 70 to ensure the quality of the classification processing but the results from this experiment indicated that lower q-factor values can also be used without significant effects on the classification accuracy.

Limited to the experimental results, the tolerance of using CBD compressed images in classification was the maximum decreasing of overall accuracy less than 1.5% and less than 2.2% in the Kappa coefficient analysis, while the volume of image was compressed up to 10-to-1 of original one (q-factor = 40). But for TM image, the classification accuracy was decreased by 12.5% and 21.3% in Kappa coefficient, while the volume of compressed image was 11-to-1 of original one (q-factor = 35). As the decreasing level of classification accuracy was different, the JPEG-compression of different image contents (such as spectral homogeneity, spectral range and image characteristics) may result various distortion of image's quality. And the effects of classification using JPEGed image were highly depended on the scene's nature. For instance, the contents of CBD image (with evenly proportion of various land coverage) is more appropriated to compress than that of TM image (with more vegetation coverage). In a conclusion, the classification accuracy using highly-compressed image has potential to be degraded at minor level, if the training data set of classification was higher accurate. However, the decreasing level was still varying with different scene's characteristics. Limited to two sets of results in this study, if the compression ratio in JPEG was lower than about 5-to-1 (q-factor > 80), the decreasing level of overall classification accuracy and Kappa coefficient will be less than 10 percent and 17 percent.

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