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Effects of JPEG compression on image classification

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Abstract. With the improvement of spatial resolution, data volume has become an increasingly significant concern, as the shear volume of data is expensive and inefficient in terms of data transmission, processing and storage. As a result, many image compression methods are in use. JPEG is one of the most popular methods. Indeed JPEG has become an industrial standard and has been implemented in many remote sensing image processing systems. This paper aims to experimentally evaluate the effects of JPEG compression on image classification. A scene of SPOT multispectral images was used. The image was compressed by JPEG at various compression levels (or using compression quality factors). All the compressed images are classified using the maximum likelihood classifier (MLC) of supervised classification and ISODATA of unsupervised classification. The classified result using the original (uncompressed) image was used as the benchmark. From the results, it can be found that there could be a significant decrease in image quality when compression is over 35-fold. As a result, the accuracy of image classification is dramatically deteriorated. However, when the compression ratio is smaller than 35-fold, the deterioration of classification accuracy is linear.

1. Introduction

In this era of information technology, vast amounts of digital information are transmitted via various types of communication channels. The demand for high speed and high capacity 'information highways' is increasing. Different algorithms have been developed to reduce the memory requirement for digital documents so that these documents can be transmitted faster and take up less storage space. Image compression algorithms have been the primary focus for the last few years due to the increase in popularity of the Internet and scanning technology. In the remote sensing industry, image compression has become more important due to the availability of high-resolution and hyper-spectral satellite imagery. The image resolution of satellite images has increased by a factor of ten for the last decade (from 10 m to 1 m), which implies a 100-fold 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 50 Mb. However, for the same scene but with 1 m resolution, the data volume will be 400 times greater.

To reduce the image data volume, three methods, i.e. subsampling, averaging and

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image compression can be used. The volume of data reduction for both subsampling and averaging techniques is a function of two user-definable parameters: the size of the sample-block and the value of the coefficient. The processing time and the resultant image size of these two techniques are mainly related to the entered parameters (Sobue *et al.* 1993). However, for significant reduction of image data volumes, compression techniques need to be employed.

There are two types of image compression techniques: lossless and lossy. The former preserves the quality of the original image by removing coding redundancy. The maximum level of compression achievable for this type of compression is about 5-fold reduction. That is, the maximum compression ratio (i.e. the ratio between original image data volume and compressed image data volume) is 5. With lossy compression, on the other hand, much higher compression ratio can be achieved at the expense of image quality. Among many lossy compression techniques, JPEG, developed by Joint Photographic Experts Group (JPEG), has been regarded as an industrial standard and widely implemented in image processing systems. This paper discusses some experimental tests on the effect of JPEG compression on image quality.

Two approaches can be adopted to evaluate the quality of compressed images. One approach is to check the image pixel by pixel to see their differences and then to compute some statistical parameters. *Fidelity* and *peak signal-to-noise ratio* (PSNR) are two widely used parameters. Fidelity means the faithfulness of the reconstructed image to the original and is a measure for geometric distortion of the reconstructed image. PSNR represents, on the other hand, radiometric degradation of the reconstructed image. The other approach is to compare the image products from both original images and compressed ones. Thematic classes, digital terrain models (DTM) and linear features are typical examples. Such a comparison might be of more interest to application scientists and will be the topic of this paper. Here is described an investigation into the effect of image compression on classification results.

On this theme, although some attempts (Paola and Schowengerdt 1995, Correa *et al.* 1998) have been made to find out the impacts of image compression on the image classification process, the tolerance and optimum level of q-factor versus the classification quality have not been investigated. This paper presents the results from a number of experiments to analyse systematically the effects of compression on the quality of classification with different compression ratio by means of JPEG compression.

Following this introduction is a brief description of the JPEG compression technique. The design of the experiments is then described and the experimental testing reported. After that, results are analysed and some conclusions are made.

2. The basics of JPEG compression

JPEG is a standard image compression scheme developed by the Joint Photographic Experts Group (JPEG). The compression scheme has two approaches: baseline and progressive. The baseline approach uses one image block sized 8×8 pixel units for the transformation of an image. The image is transformed from a pixel-format to the 64-coefficient matrix through Discrete Cosine Transformation (DCT). The representation of coefficients is then quantized to an integer to maximize compression. Afterwards, Huffman coding is used to encode the quantized coefficient. The compressed image file is then generated. To decompose the file into a pixel-image format, the inverse compression process is used. More details of JPEG compression schemes can be found in Lammi and Sarjakoski (1995) and Lane (1999). Figure 1 shows the principle of JPEG baseline compression scheme.

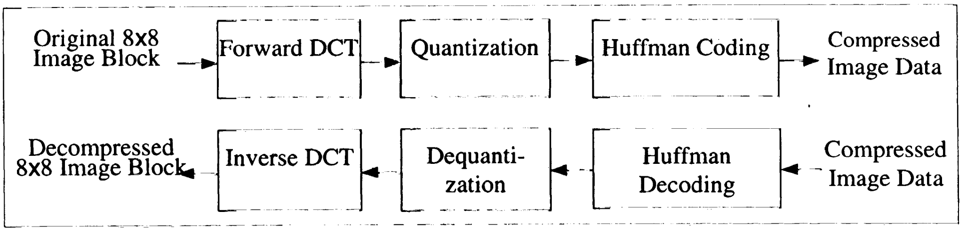

Figure 1. JPEG baseline compression scheme.

In JPEG compression, some of the information is lost during the quantization to achieve file size reduction. Hence, a permanent loss of the quality of the compressed image is unavoidably caused. To control the degree of compression, the JPEG compression algorithm allows the adjustment of an internal parameter (q-factor) to balance the compression ratio and the image's quality. This q-factor is a user-specified scaling factor, used to reduce the file size by scarifying the quality of the image. This can be achieved by scaling down the AC coefficients of DCT. DC and AC are two terms analogous to the direct and alternating electric current. DC and AC used in JPEG to represent the constant basis function and higher frequency functions, respectively. By making many AC coefficients zero, more high frequency components in the 8×8 block would be eliminated. As a result, less memory is required to encode the remaining non-zero coefficients of DCT.

As this q-factor should be selected on the basis of minimizing visual image distortion, JPEG provides some guidelines for users to select the appropriate q-factor if the JPEG programs are developed based on the free IJG JPEG software. The free IJG JPEG software uses a 0–100 scale for the q-factor. The default IJG quality setting (q-factor 75) is recommended for quality full colour images. If the original image quality is less than perfect, q-factor 50 can be used to reduce the file size without objectionable degradation. For preview or indexing purposes, a q-factor in the range of 5 to 10 can be used with very small file sizes. A higher quality cannot be achieved even with a q-factor of more than 95. It is worth mentioning that the q-factor value has a different meaning to the percentage of information to be kept in an image.

In fact, JPEG standard does not specify how quality scales should be implemented. Hence, different JPEG programs would have different quality factors. For example, Adobe Photoshop doesn't use a numeric scale but instead just three choices, 'high/medium/low,' are provided in the older version. Heleva DPW 770 uses a scale of 0–100 for the q-factor. Intergraph Match-T uses a scale of 0–300 for the q-factor instead. As quality scales are not standardized across JPEG programs, users must be very careful when passing JPEG compressed images across different programs due to the different interpretation of the q-factors.

3. Design of experimental tests

As it is reasonable that the testing results could be scene-dependent, it was decided that two test areas should be selected instead of one. In this experiment, two sub-scenes, each 512×512 pixels in size, extracted from the SPOT multispectral scene (dated 5 February 1995) were used. One sub-scene (figure 2) is the Hong Kong's Central business district (CBD), and the other (figure 3) is the Tuen Mun (TM) area, a residential area in the northwest of Hong Kong.

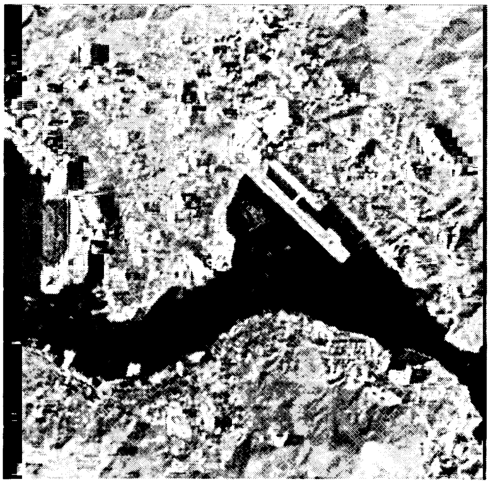

Figure 2. The CBD sub-scene.

Figure 3. The TM sub-scene.

The two sub-scenes have similar land coverage, including water, vegetation cover, urban area and barren lands. However, the TM image has a larger proportion of vegetation cover and a smaller proportion of urban area than that of the CBD image. The CBD image has a balanced proportion of land coverage.

These two scenes were compressed at different level using various q-factors. Image classification was applied to both original image and compressed images. The results from original images and compressed images were then compared to reveal the effects of compression on the results of classification.

As stated previously, JPEG was used for testing because it has been widely implemented in many remote sensing and photogrammetric systems. The software used in this study was the PCI ImageWorks and Xpace version 6.01. The reason this system was used is its availability at the Department; there was no other reason.

4. Classification of JPEG-compressed images

In the experiment, the baseline approach of the JPEG compression algorithm was used. To investigate the change of classification results with different compression levels, various q-factors in the compression were used. The maximum factors 100, 99 and 95 were selected. After q-factor 95, q-factors at intervals of 5 were used to compress the image. A minimum level of q-factor 1 was used instead of 0. Twenty-one JPEG compressed images were produced independently for each sub-scene. After compression, the relationship between the compression and q-factors of the two sub-scenes were analysed and plotted in a graph (see figure 4). It can be seen that the two sets of image data (from the CBD and TM images) present similar characteristics. When the q-factor is 40, JPEG is able to achieve a compression ratio of about 10 times the original, and when the q-factor is 1, the volumes of the CBD and TM images were compressed about 40 times.

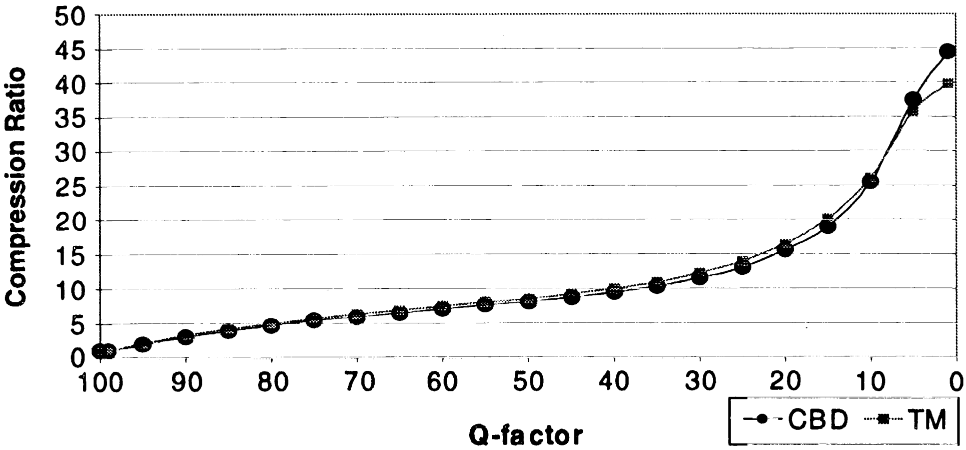

Figure 4. The relationship between q-factor and compression ratio.

Image classification was applied to both the original image and compressed images. The results from original images and compressed images were then compared. Both supervised and unsupervised classifications were tested. In the supervised classification experiment, four categories were selected: water (WATER), vegetation cover (VEG), urban land use (URBAN) and barren land (BARREN), as well as an additional unclassified class (NULL). The maximum likelihood classifier (MLC) was selected as the classification strategy. In the unsupervised classification experiment, the ISODATA clustering was used. Based on the requirement of ISODATA, it was required that the estimated number of clusters is pre-defined (PCI, 1994), but the resultant number was highly dependent on the quantities of spectral information. Larger quantities of spectral information provide higher degrees of spectral distinction between pixels and result in a greater number of clusters. In this experiment, the estimated number of resultant clusters was first given as being 256, i.e. the full grey range.

5. Analysis of unsupervised classification results

The results of the unsupervised classification for the two sub-scenes compressed at different q-factors using JPEG compression were compared with that of the uncompressed (original) images (Uncomp) and summarized in table 1. The initial setting of the parameters for the ISODATA algorithm was identical for all images.

Table 1. The number of resultant clusters from both the original and JPEG compressed images with different q-factors, using ISODATA.

	CBD area	TM area	Compression ratio
Uncompressed	164	153	1:1
q-factor 100	166	173	1:1
q-factor 99	163	173	
q-factor 95	166	177	
q-factor 90	167	174	
q-factor 85	161	164	
q-factor 80	163	169	5:1
q-factor 75	161	178	
q-factor 70	162	170	
q-factor 65	159	165	
q-factor 60	159	187	
q-factor 55	154	186	
q-factor 50	160	187	
q-factor 45	160	167	
q-factor 40	162	180	
q-factor 35	158	185	10:1
q-factor 30	158	174	
q-factor 25	170	174	
q-factor 20	162	171	15:1
q-factor 15	152	174	20:1
q-factor 10	152	156	25:1
q-factor 5	154	139	35:1
q-factor 1	10	3	40:1

In table 1, the numbers of resultant clusters using parent images were 164 and 153 for the CBD and TM images, respectively. Compared with the result from parent images (see figure 4), the numbers of clusters varied from $+1.83\%$ to -7.32% and -7.19% to -22.22% for the CBD and TM images respectively, at a compression of less than 20 to 1. If no external information or data was introduced to the image contents during the compression, the changes of image and the application results were related to the change or distortion of spectral characteristics. In the JPEG compression scheme, the blocking effects are generated during the 8×8 block transformation. This transformation distorts the spectral characteristics of the compressed image and might produce new spectral values in an image. As a result, the distorted image contents are different with distinguished spectral contents from the original one, and more clusters are statistically created by ISODATA. Using the TM image as an example, the numbers of clusters for JPEG compressed images were greater than those of the original image even when the compression ratios were below 25 to 1 (q-factor >10) (see table 1).

Beside the generation of new spectral values, the distorted contents of a JPEG compressed image can also cause a decrease in the variation of spectral values, and thus reduce the number of clusters. The 8×8 block transformation eliminates some of the spectral difference and resamples those pixels into similar spectral contents. This effect may cause an increase in the spectral similarity among the pixels in a compressed image and cause a decrease in the spectral discrimination during the ISODATA clustering. Thus, the number of clusters decreases. For example, the JPEG compressed CBD images (figure 5) with the distorted spectral characteristics resulted

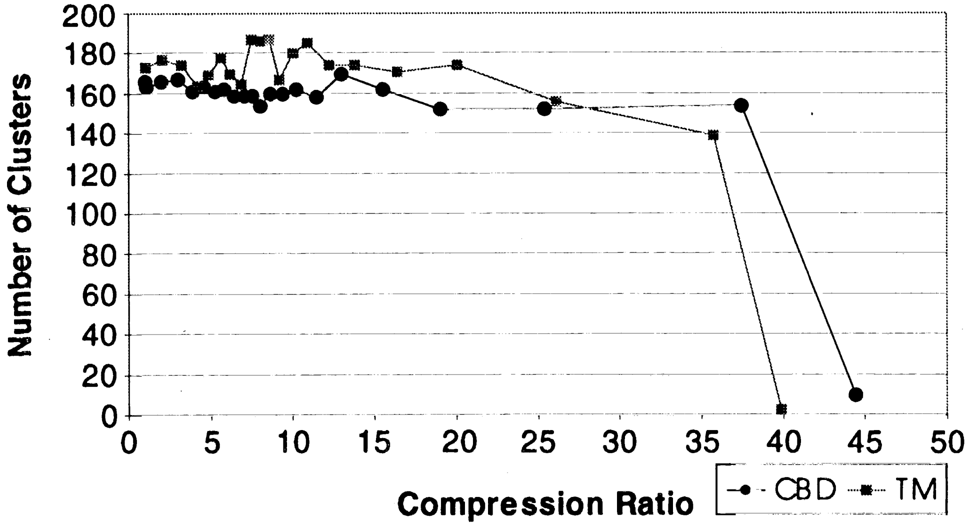

Figure 5. The relation between compression ratio and the numbers of clusters from ISODATA.

in a decrease by 7% in the number of clusters when compression was higher than 4 to 1 (q-factor <85).

Based on the findings of these experiments, it could be noted that the higher compression ratio may not necessarily cause a decrease in the number of resultant clusters. The changes in cluster numbers are also affected by the distortion of spectral values due to the blocking effects in the 8×8 block transformation (i.e. the artefacts) and vary with the characteristics of different images.

6. Analysis of supervised classification results

For the analysis of supervised classification results, the confusion matrix (also known as the error matrix), an almost universally accepted image classification accuracy report, was used. It expresses the number of classified pixels in the assigned category relating to the actual category from the ground truth data (Campbell 1996; Congalton and Green 1999). The ground truth data is an alternative set of sampled area, delineated independently in an image (similar to the training process). The overall accuracy of the confusion matrix, which was computed by the weighting of the percentages of all correctly-classified pixels in each assigned category, was used to quantify the classification accuracy. In addition, the Kappa coefficient, which is a parameter scaled to a range [0,1], is also employed in this study 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 in terms of these two measures were computed and are summarized in table 2.

In the overall experimental results (table 2), the classification results using the CBD images were more accurate than those using the TM image. For instance, the overall accuracy and Kappa coefficient of the original CBD image (Uncomp) were 93.19% and 0.90 respectively; and those of the parent TM image were 85.24% and 0.80 respectively.

The results are plotted in figure 6. It is clear that with compression ratio smaller than 10:1, the effects are not that great. With compression ratios between 10:1 and

Table 2. The MLC classification results of uncompressed (original) and JPEG compressed images: overall accuracy and kappa coefficient.

	Overall accuracy		Kappa coefficient		Approximate compression ratio
	CBD area	TM area	CBD area	TM area	
Uncompressed	93.19	85.24	0.90	0.80	1:1
q-factor 100	94.28	81.39	0.92	0.75	1:1
q-factor 99	93.64	81.27	0.91	0.74	
q-factor 95	93.37	78.24	0.91	0.71	
q-factor 90	94.10	78.02	0.92	0.70	
q-factor 85	93.82	77.27	0.91	0.70	
q-factor 80	93.82	75.37	0.91	0.67	5:1
q-factor 75	92.82	74.93	0.90	0.66	
q-factor 70	91.73	73.47	0.88	0.64	
q-factor 65	92.01	76.23	0.89	0.68	
q-factor 60	92.64	76.72	0.90	0.69	
q-factor 55	92.82	74.72	0.90	0.66	
q-factor 50	92.55	76.40	0.90	0.68	
q-factor 45	92.28	74.12	0.89	0.65	
q-factor 40	92.37	76.99	0.89	0.69	
q-factor 35	92.01	72.82	0.89	0.63	10:1
q-factor 30	88.83	72.49	0.84	0.63	
q-factor 25	88.83	70.05	0.84	0.60	
q-factor 20	89.37	68.20	0.85	0.57	15:1
q-factor 15	86.92	64.62	0.82	0.52	20:1
q-factor 10	83.20	71.62	0.77	0.61	25:1
q-factor 5	80.84	59.25	0.73	0.45	35:1
q-factor 1	62.86	66.30	0.00	−0.29	40:1

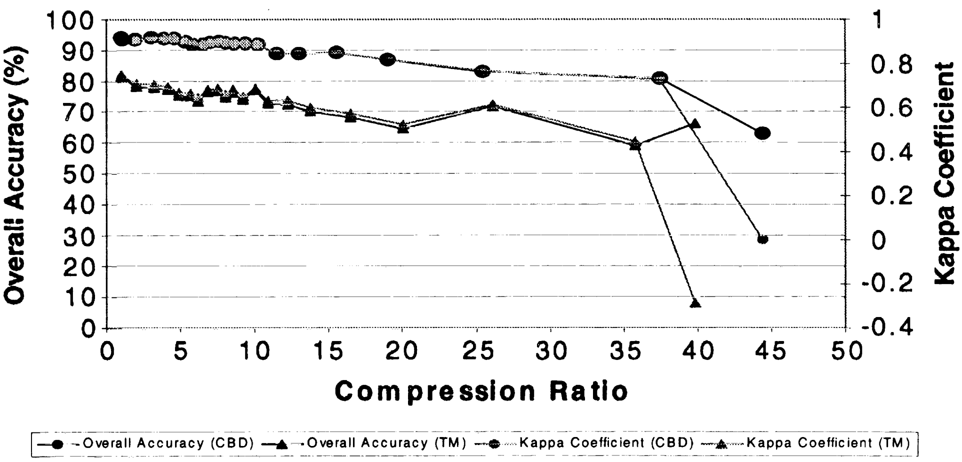

Figure 6. The relations between compression ratio, the overall accuracy and the Kappa coefficient.

20:1, the overall accuracy of classification and Kappa coefficient decrease steadily and linearly. With compression ratio between 20:1 and 30:1, there is some fluctuation for the TM test image. However, for the CBD test area, the linear trend is still clear. After 30-fold compression, the image quality degraded dramatically.

7. Spectral changes of images compressed at Ratio

The change in the classification result is significant at a compression ratio higher than 20 to 1 (q-factor < 20). This prompts interest in an investigation into the changes in grey values for those images compressed at high compression ration. In this study, analysis of the image difference between original and compressed at high ratio (in terms of mean and variance) was made for each image of all three channels. The percentage of the difference is listed in table 3.

In table 3, the results of CBD and TM are of a fairly similar nature. While the compression ratio increases, the change in and difference of image characteristics of channel 2 (RED) also increases. For example, when the compression ratio is higher than 25 to 1 (q-factor = 10), the mean was changed by about three per cent, compared to that of the original image. The difference in the variance in percentage is always higher than that of the other two channels (channel 1 and channel 3). In this example, the JPEG compression has higher impact on the channel 2 (RED) than on other two channels.

For the images from channels 1 and 3 (GREEN and Near-Infrared), in either CBD or TM data set, the percentage change of mean value is lower than 1 and the change of percentage mean value is lower than 19%, when the compression ratio is lower than 35 to 1 (q-factor > 5). On the other hand, when the compression ratio reaches a level of 40 to 1 (q-factor = 1), dramatic change in terms of mean and variance happens to images from these two channels.

8. Discussion and conclusions

As the remote sensing industry has a tendency to achieve higher resolution with time (i.e. a larger volume of image data), 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.

From the experiments conducted in this study, it was found that the number of clusters classified by the ISODATA algorithm is unstable. One of the reasons could be the distortion of spectral contents caused by the blocking effects in the discrete

Table 3. The spectral changes of image pixels compressed at high ratio.

		Channel 1 (GREEN)		Channel 2 (RED)		Channel 3 (Near-Infrared)	
		Mean (%)	Variance (%)	Mean (%)	Variance (%)	Mean (%)	Variance (%)
CBD	q-factor 20	−0.50	−8.57	−1.27	−11.76	0.31	0.99
	q-factor 15	0.12	−7.80	−1.33	−20.69	1.03	−4.46
	q-factor 10	−0.89	−10.06	−3.03	−14.64	0.98	−0.89
	q-factor 5	−2.02	−7.25	−3.10	−12.24	5.72	−18.79
	q-factor 1	−32.03	273.57	−1.66	181.06	12.15	238.59
TM	q-factor 20	−0.77	−9.36	−0.44	−19.14	0.67	−1.78
	q-factor 15	−0.34	−11.58	−0.60	−17.59	0.83	−5.85
	q-factor 10	−0.75	−9.14	−2.81	−8.27	0.98	−4.34
	q-factor 5	2.74	17.73	3.77	−7.34	−2.21	−1.03
	q-factor 1	−35.09	628.28	−4.43	443.34	6.42	243.07

cosine transformation. The degree of such effect on classification result is scene-dependent.

For the supervised classification of the two sub-scenes, the overall accuracy and Kappa coefficients decrease in a linear trend. To describe the decreasing rates (slope) of these two segments, a linear regression method was employed. For more details about the method, refer to Montgomery (1991). Based on this method, these segments of lines were linearized, and the slope (or change rate) of the line was then computed. As a result, for the JPEG compressed CBD images, the changing rate of the overall accuracy within that segment was about -0.39% per compression-ratio, and that of the Kappa coefficient was about -0.005 units per compression-ratio. For the JPEG compressed TM images, the changing rate of the overall accuracy within that segment was about -0.70% per compression-ratio, and that of the Kappa coefficient was about -0.009 units per compression-ratio. These decreasing rates indicate that less than one per cent of accuracy and less than 0.01 units of Kappa coefficient will be sacrificed if the compression ratio increases by one more unit.

Based on the limited testing results obtained in this study, it might be concluded that

(a) The effect of JPEG compression on accuracy of image classification is generally linear when the compression ratio is 35:1 or lower;
(b) There could be a significant decrease in image quality when compression is over 35-fold. As a result, the quality of classification results dramatically deteriorates.

However, the effect of compression on image quality is scene-dependent. Therefore, these conclusions may be only valid for those testing conditions as described in this paper.

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