COMPRESSION OF SATELLITE IMAGES FOR REMOTE SENSING APPLICATIONS

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ABSTRACT

Remote Sensing images captured by satellites are usually stored without the use of image compression techniques, although very efficient image compression algorithms do exist, which can provide high compression rates if a small amount of distortion is allowed. In this paper it is examined the use of image compression techniques on remote sensing satellite images. The quality of images recovered from compressed data is studied from a point of view of information extraction. In particular, a Tasseled Cap Transform classification scheme is used for evaluation of measure adequateness. Four measures of quality are considered and their behavior evaluated for a set of ten coded versions of a 512 × 512 sub-scene. For each compressed set of images, the number of differently classified pixels with relation to the original sub-scene is adopted as a reference quality index. The proposed measures of quality are evaluated against this reference quality index. The original sub-scene is composed of six 512x512 LANDSAT TM images (bands 1,2,3,4,5 and 7).

KEY WORDS: Image Coding, Image Compression, Data Compression, Image Classification, Tasseled Cap

1.0 INTRODUCTION

In the last years many fast and efficient image coding algorithms have been developed, allowing significant reduction of memory requirements without significant loss of image subjective quality. Despite the high compression rates which can be obtained, the use of these algorithms with remote sensed data is not widespread. This is quite expected if one considers that the leading goal in image compression has been subjective quality, i.e. little visually perceived differences between original and compressed images.

In remote sensing applications visual fidelity is not sufficient to guarantee no loss of information, since automatic procedures are frequently used. Even in case of assisted procedures, we shall consider that the eye of a trained operator will not be as easily foolish as the eye of a casual observer.

In this work, the use of compressed images for classification is studied. Although only a particular classification scheme is considered, the results obtained should be useful to other pixel level methods.

We start by defining four quality measures for image quality evaluation. Then we describe the coders and the set of coded versions of the original sub-scene that were used for evaluation of the defined measures. In the next step we describe the method of classification been considered. Finally, the correlation between the several measures and a trustful classification distance index are determined and discussed.

1.1 QUALITY MEASURES

To define a measure of quality for a compressed image intended for classification is not a trivial task. Intuitively, one would not like to have the value of a pixel offset of its original position in such away it would look like a member of another class. In this case the allowed amount of displacement would have to be specified taking into account the class to which the pixel really belong. If we know this class, however, there is no need for additional classification! Other important relationships to be preserved are the ones that exist between pixels in a neighborhood, since many classification methods take this into account. In this work we define a few measures to be applied to each image of a scene independently of the others. The adequateness of these measures will be experimentally evaluated for a particular classification scheme.

Follows a brief description of each measure.

1.1.1 Peak Signal to Noise Ratio (PSNR)

The peak signal to noise ratio, for a 256 levels image, is defined by:

$$PSNR = 10\log_{10}\frac{255^2}{(1/L)\sum_{i=1}^{L}(X_i - \hat{X}_i)^2},$$

where L is the total number of pixels. Peak Signal to Noise Ratio is a widely used measure of image quality, even though it is not monotonically related to subjective visual quality. It is included here due to its wide usage.

1.1.2 Sigma Signal to Noise Ratio (SSNR)

This measure requires the division of the original and reconstructed images into blocks of $m = n \times n$ pixels (we chose $n = 4$). For each block the ratio between measured variance of the original block and squared error of measured standard deviation is calculated:

[1] On sabatical leave from Pontifical Catholic University of Rio de Janeiro

$$SSNR_k = 10\log_{10}\frac{\sigma_k^2}{(\sigma_k - \hat{\sigma}_k)^2}.$$

In the above equation, σ_k and $\hat{\sigma}_k$ are computed as follows:

$$\sigma_k = \sqrt{\frac{1}{m}\sum_{block\ k} X_i^2 - (\frac{1}{m}\sum_{block\ k} X_i)^2}$$

and

$$\hat{\sigma}_k = \sqrt{(1/m)\sum_{block\ k} \hat{X}_i^2 - ((1/m)\sum_{block\ k} \hat{X}_i)^2}.$$

Total SSNR is given by:

$$SSNR = \frac{1}{M}\sum_{k=1}^{M} SSNR_k,$$

where M is the number of blocks in the image.

1.1.3 Sigma to Error Ratio (SER)

The Sigma to Error Ratio also requires blocking of the images. For a single block, SER is given by:

$$SER_k = 10\log_{10}\frac{\sigma_k^2}{\frac{1}{m}\sum_{block\ k}(X_i - \hat{X}_i)^2}$$

In a block with a high SER, the mean square error is small compared to the measured block variance. This means that the pixel value displacement is small compared to the estimated variance of neighborhood pixels, presumed to belong to the same class.

1.1.4 Histogram Similarity (HS)

Histogram Similarity [1] indicates how close histograms of original and reconstructed images are. For 256 levels images it is given by:

$$HS = \frac{1}{256}\sum_{i=0}^{255}|f_o(i) - f_r(i)|,$$

where $f_o(i)$ and $f_r(i)$ are relative frequency of level i for original and reconstructed images respectively.

1.2 CODERS AND IMAGES

Three coder have been used in this work, a linear PCM, a BTC coder and the sequential mode of JPEG, a standard algorithm recently proposed by ISO (*International Standards Organization*).

The scene used in our study was acquired by LANDSAT-5 sattelite on August 1, 1988 and images the region of Tucurui in the Brazilian Amazonia. Images of TM bands 1, 2, 3, 4, 5, and 7 have been used. We considered a 512 x 512 sub-scene. The classes identified in the sub-scene and used in this work are urban zones, water, forest and pasture. All images had been radiometric corrected by INPE (Spacial Research National Institute - Brazil).

In the next sub-sections a brief description of each coder is presented. The compressed images being used are specified for each code.

1.2.1 PCM

PCM (*Pulse Code Modulation*) is the most straightforward way to digitize an analog signal. After sampling, the values are simply linearly quantized using a fixed number of levels. Our original images are PCM coded with 256 levels (8 bits per pixel). As compressed versions, we considered PCM coded images with 6, 5 and 4 bits/pixel (64, 32 and 16 levels).

1.2.2 BTC

In the BTC (*Block Truncation Coding*) technique the image is divided into $n \times n$ blocks and a two level moment-preserving adaptive quantizer is applied to the pixels of each block. In this work we used the original algorithm proposed by Delp and Mitchell in 1979 [2], which preserves mean and variance of original blocks. Note that in BTC each block is represented by an n x n bit plane together with side-information associated to mean and variance.

We considered three BTC coded versions of the original sub-scene. One of them is coded with 1.5 bits per pixel and the other two are coded with 2 bits per pixel using slightly different coders.

Moment preservation is an interesting feature when the compressed images are intended for classification.

1.2.3 JPEG

Recently a standardized image compression algorithm has been defined by CCITT and ISO's *Joint Expert Photografic Group* - JPEG (ISO/IEC JTC1/SC2/WG8 CCITT SGVIII). The refered algorithm [3] [4] provides very high compression rates through the use of transform coding followed by entropy coding. Very good compressed images, with very little visually perceived deterioration, are obtained with rates below 1 bit/pixel. JPEG is a variable rate compression algorithm. This means that compression rate varies from image to image and cannot by determined *a priori*, although it is possible to increase or decrease compression.

In this work we used four JPEG compressed versions of the original sub-scene. The mean compression rates for each set of compressed images are 0.59, 0.45, 0.32 and 0.25 bit/pixel. Due to the variable rate characteristics of JPEG, some images are more compressed than others, depending on the spectral band they represent.

1.3 TASSELED CAP TRANSFORM GREENNESS CLASSIFICATION

The Tasseled Cap transform was introduced in 1976 by Kauth and Thomas [5]. It is a linear transformation that, when applied to a set of multispectral images, results in an image which concentrates most of the information associated with agricultural cycles. This image is referred to as the Greenness image. two more images (Brightness and Wetness) are also generated, but they are not of interest for this work. The original Tasseled Cap Transform was developed for the MSS sensor. The TM version was presented by Crist and Cicone [6] in 1984.

On the Greenness image all the classes mentioned in the previous section are well clustered. allowing good classification by supervised density slicing. In this work, for each set of compressed images the classification process is performed independently.

In order to obtain the three Tasseled Cap images, the six TM images are linearly combined using the coefficients shown in table 1.

Table 1. TM Tasseled Cap Coefficients

IMAGE	TM1	TM2	TM3	TM4	TM5	TM7
Brightness	0.33183	0.33121	0.55177	0.42514	0.48087	0.25252
Greenness	-0.24717	-0.16263	-0.40639	0.85468	0.05493	-0.11749
Wetness	0.13929	0.22490	0.40359	0.25178	-0.70133	-0.45732

1.4 RESULTS

The original sub-scene and all of its ten compressed versions were independently classified using the Tasseled Cap transform based method described above. The result for each compressed version was compared to the result obtained for the original scene. The number of pixels differently classified were then determined, generating a figure we called percentage of misclassified pixels. Detailed information regarding classification of all sets of images are presented in tables 2 to 12.

Table 2. Original images - supervised classification based on "greenness"

CLASS	N.PIXELS	%	LEVELS
Water	53,851	20.54	0-84
Urban Zone	27,758	10.58	85-115
Forest	130,217	49.67	116-147
Pasture	50,318	19.19	148-255

Table 3. PCM - 6 bits/pixel - supervised classification based on "greenness". Total differences: 846 (0.32%). HS: 0.20

CLASS	N.PIXELS	%	LEVELS	DIFF.
Water	53,603	20.44	0-84	-0.1%
Urban Zone	28,280	10.78	85-115	+0.2%
Forest	129,619	49.44	116-147	-0.23%
Pasture	50,642	19.31	148-255	+0.12%

Table 4. BTC1 - 2 bits/pixel - supervised classification based on "greenness". Total differences: 877 (0.33%). HS: 0.07

CLASS	N.PIXELS	%	LEVELS	DIFF.
Water	53,663	20.47	0-84	-0.07%
Urban Zone	27,545	10.50	85-115	-0.08%
Forest	129,741	49.49	116-147	-0.18%
Pasture	51,195	19.52	148-255	+0.33%

Table 5. BTC2 - 2 bits/pixel - supervised classification based on "greenness". Total differences: 940 (0.35%). HS: 0.05

CLASS	N.PIXELS	%	LEVELS	DIFF.
Water	53,642	20.46	0-84	-0.08%
Urban Zone	27,584	10.52	85-115	-0.06%
Forest	129,660	49.46	116-147	-0.21%
Pasture	51,258	19.55	148-255	+0.36%

Table 6. BTC - 1.5 bits/pixel - supervised classification based on "greenness". Total differences: 3120 (1.19%). HS: 0.38

CLASS	N.PIXELS	%	LEVELS	DIFF.
Water	56,971	21.73	0-90	+1.19%
Urban Zone	24,770	9.44	91-115	-1.14%
Forest	130,171	49.65	116-147	-0.02%
Pasture	50,232	19.16	148-255	-0.03%

Table 7. JPEG - 0.59 bits/pixel - supervised classification based on "greenness". Total differences: 3763 (1.43%). HS: 0.13

CLASS	N.PIXELS	%	LEVELS	DIFF.
Water	52,547	20.04	0-84	-0.5%
Urban Zone	28,348	10.81	85-115	+0.23%
Forest	133,390	50.88	116-147	+1.21%
Pasture	47,859	18.25	148-255	-0.94%

Table 8. JPEG - 0.45 bits/pixel - supervised classification based on "greenness". Total differences: 4130 (1.57%). HS: 0.11

CLASS	N.PIXELS	%	LEVELS	DIFF.
Water	52,500	20.02	0-84	-0.52%
Urban Zone	28,317	10.80	85-115	+0.22%
Forest	133,788	51.03	116-147	+1.36%
Pasture	47,539	18.13	148-255	-1.06%

Table 9. PCM - 5 bits/pixel - supervised classification based on "greenness". Total differences: 4785 (1.82%). HS: 0.57				
CLASS	**N.PIXELS**	**%**	**LEVELS**	**DIFF.**
Water	53,465	20.39	0-84	-0.15%
Urban Zone	28,432	10.84	85-115	+0.26%
Forest	134,328	51.24	116-147	+1.57%
Pasture	45,919	17.51	148-255	-1.68%

Table 10. JPEG - 0.32 bits/pixel -supervised classification based on "greenness". Total differences: 4811 (1.83%). HS: 0.21				
CLASS	**N.PIXELS**	**%**	**LEVELS**	**DIFF.**
Water	52,197	19.91	0-84	-0.63%
Urban Zone	28,386	10.82	85-115	+0.24%
Forest	134,400	51.26	116-147	+1.59%
Pasture	47,161	17.99	148-255	-1.2%

Table 11. JPEG - 0.25 bits/pixel - supervised classification based on "greenness". Total differences: 6044 (2.30%). HS: 0.19				
CLASS	**N.PIXELS**	**%**	**LEVELS**	**DIFF.**
Water	51,964	19.82	0-84	-0.72%
Urban Zone	28,574	10.90	85-115	+0.32%
Forest	135,445	51.66	116-147	+1.99%
Pasture	46,161	17.60	148-255	-1.59%

Table 12. PCM - 4 bits/pixel - supervised classification based on "greenness". Total differences: 23395 (9.41%). HS: 1.22				
CLASS	**N.PIXELS**	**%**	**LEVELS**	**DIFF.**
Water	55,111	21.02	0-86	+0.48%
Urban Zone	31,023	11.83	87-120	+1.25%
Forest	105,562	40.26	121-147	-9.41%
Pasture	70,448	26.87	148-255	+7.68%

For each compressed image, the values of PSNR, SSNR and SER were determined. In order to abstract a single figure (for each one of the measures) for each set of TM images, a linear combination of the numbers obtained for each measure, using the Tasseled Cap greenness coefficients (second row of table 1), was performed. The results are presented in table 13 ranked by percentage of misclassified pixels. In this table the histogram similarity, calculated for the Greenness image, is also presented.

1.5 CONCLUSIONS

Four measures of quality have been tested with a set of 10 compressed versions of a LANDSAT 5 TM sub-scene. Three kinds of coders were used: simple PCM's with fewer levels, three BTC coders and the JPEG algorithm, a Cosine Transform based coder.

PCM's, as expected performed poorly taking into account the low compression rates. Considering them isolated, all measures behaved in a monotonic way.

The BTC coders performed very well, providing low misclassification for medium compression rates. All measures behaved in the same non-monotonical way for this coder. However, considering the closeness of percentual misclassification this is perfectly acceptable.

The JPEG algorithm, probably due to the very high compression rates provided, presented the poorest performance, together with 4 and 5 bits PCM. For this coder, all measures but similarity behaved monotonically.

Regarding the whole set of compressed images, the measure which showed the greatest degree of coherence was SSNR, followed by SER, PSNR and similarity.

1.6 REFERENCES

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Table 13. Coded images ranked by percentage of misclassified pixels					
CODING METHOD	**% OF MISCLASSIF. PIXELS**	**SIMILARITY**	**PSNR**	**SSNR**	**SER**
PCM(6 bits)	0.32	0.20	46.45	24.03	8.33
BTC1(2 bits)	0.33	0.07	37.73	26.09	5.22
BTC2(2 bits)	0.35	0.05	37.83	46.22	21.14
BTC(1.5 bits)	1.19	0.38	34.94	16.94	-1.55
JPEG(0.59)	1.43	0.13	37.65	14.74	2.8
JPEG(0.45)	1.57	0.11	36.73	12.48	1.88
PCM(5 bits)	1.82	0.57	40.77	15.78	2.40
JPEG(0.32)	1.83	0.21	35.62	10.74	0.67
JPEG(0.25)	2.3	0.19	34.80	9.40	-0.58
PCM(4 bits)	9.41	1.22	35.11	9.02	-2.67

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