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ZRIAKHOV MYKHAILO
National Aerospace University – KhAI
https://orcid.org/0009-0008-4674-8360
e-mail: m.zriakhov@khai.edu
KRYVENKO SERGII
National Aerospace University – KhAI
https://orcid.org/0000-0001-6027-5442
e-mail: s.kryvevnko@khai.edu
LUKIN VLADIMIR
National Aerospace University – KhAI
https://orcid.org/0000-0002-1443-9685
e-mail: v.lukin@khai.edu

PECULIARITIES OF MULTISPECTRAL IMAGE LOSSY COMPRESSION

This paper concerns some aspects of lossy compression applied to six-component Landsat multispectral images where all component images have identical spatial resolution. It is shown that most component images are correlated although the cross-correlation coefficients for component images vary in rather wide limits – from 0.11 in one dataset and 0.72 in another dataset to almost unity in both cases. Compression based on discrete cosine transform is considered where 2D blocks have the size of 32×32 pixels. Embedded deblocking after decompression is applied as well. Lossy compression can be applied component-wise and in a 3D manner for spectral decorrelation of data where 6-point discrete cosine transform is applied. It is shown that, in the latter case, a significantly larger compression ratio can be achieved. The attained benefit in CR is about 30-80% compared to the component-wise compression or, alternatively, the benefit in peak signal-to-noise ratio can reach a few dB for the same compression ratio. The coders are studied for peak signal-to-noise ratio varying in the limits from about 23 dB to about 46 dB that correspond to image quality starting from annoying to practically invisible distortions. In addition, there are some image pre-processing operations that are able to further improve the compression ratio. They are image normalization and band re-ordering. All possible variants of band ordering are studied for both test images. The impact of band ordering on compressed image quality is analyzed in terms of rate/distortion curves for the 2D and 3D versions of the considered coder. It is demonstrated that, due to optimal ordering, a few % improvement of CR can be gained. However, the optimal band order for the considered multichannel images is not the same and this can cause problems in practice to be studied in the future.

Keywords: AGU coder, lossy image compression, distortion analysis, multispectral images

ЗРЯХОВ МИХАЙЛО, КРИВЕНКО СЕРГІЙ, ЛУКІН ВОЛОДИМИР
Національний аерокосмічний університет ім. М.Є. Жуковського "ХАІ"

ОСОБЛИВОСТІ СТИСНЕННЯ МУЛЬТИСПЕКТРАЛЬНИХ ЗОБРАЖЕНЬ ІЗ ВТРАТАМИ

Ця стаття стосується деяких аспектів стиснення з втратами, застосованого до шестикомпонентних мультиспектральних зображень. Показано, що компонентні зображення корельовані, хоча коефіцієнти крос-кореляції змінюються в досить широких межах. Стиснення з втратами можна застосовувати покомпонентно та в тривимірному режимі. В останньому випадку можна досягти значно більшого ступеня стиснення. Крім того, деякі операції попередньої обробки зображення можуть покращити його. Це нормалізація зображення та зміна порядку смуг. Їх вплив на якість стисненого зображення аналізується з точки зору кривих швидкість/спотворення для кодера на основі дискретного косинусного перетворення, який має 2D і 3D версії. В аналізі використовуються реальні дані Landsat.

Ключові слова: AGU кодер, стиснення зображень із втратами, аналіз спотворень, мультиспектральні зображення.

Problem overview

More and more remote sensing (RS) data are obtained nowadays. As earlier, they are acquired from satellites and aircrafts [1, 2], but the latest tendency is to obtain RS data from unmanned aerial vehicles (UAVs) and drones [3, 4].

Amount (volume) of RS data rapidly increases and this makes problems in their transfer, processing, storage, and management [5, 6]. RS data compression is a typical operation to make image transfer and storage easier [5–7]. Lossless compression allows preserving all information contained in RS data but attained compression ratio (CR) is usually unsatisfactory [8]. Due to this, lossy compression has become popular [7, 8]. In turn, lossy compression introduces inevitable distortions and it is desired to control them to avoid their too large negative impact on image quality and results of its classification, recognition, and so on [9, 10].

Hence, it is needed to apply coders that have a proper trade-off of properties, namely, excellent rate/distortions curves (better quality of compressed images for a given CR compared to counterparts), possibility to quickly attain appropriate (desired) quality, good computational complexity, and some other ones. Currently, a lot of methods for RS image lossy compression have been designed (see [11–13] and references therein). Selection of a method for a given situation depends on several factors. They are the following: a) image properties such as the number of channels, cross-correlation of component images, noise presence and its statistical and spatial spectral characteristics; b) priority of requirements to image compression; c) main properties of coders such as computational efficiency, ability and ease of providing desired characteristics, energy compaction property of used orthogonal transforms, and so on. In this paper, we consider a particular case of multispectral data compression where it is supposed that: a) there is practically no noise in component images, at least, this noise is not visible; b) component images are already co-registered with high quality and they have approximately the same spatial resolution; c) the compression should be efficient enough in both the sense of rate/distortions and computation time although some simple operations of data pre-processing are possible (on-board).

The paper goal is to show that certain pre-processing of multispectral data and the use of their 3D lossy compression leads to considerable improvement compared to component-wise processing and some benefits compared to compression without pre-processing.

Analysis of recent sources

The need to compress multichannel signals and images appears in practice of data processing quite often. It is, in particular, typical for multichannel electrocardiogram (ECG) compression [14, 15], color image coding [16], compression of dual-polarization radar [17], multispectral [10, 18–20], and hyperspectral [11, 21] images. A common and typical property of all these types of signals and images is that data in channels (components) are quite highly correlated (at least, for most component data). In this case, a reasonable solution is to exploit this correlation for improving the data decorrelation and coder performance [15, 16, 19, 21–23]. However, there are different ways to implement this idea and, respectively, the performance of the corresponding techniques is different. So, let us start from brief analysis.

The first aspect concerns the use of 3D compression instead of component-wise. It is known that, in compression of RGB color images, a typical operation is to apply conversion from RGB to YCbCr (or other) color system to decorrelate data. This step relies on essential correlation that usually exists between RG, RB, and GB components (in fact, it varies in quite wide limits). As a result, the CR increases by about two times. Instead of RGB to YCbCr conversion, other 3-point orthogonal transforms such as Haar or discrete cosine transform (DCT) can be applied leading to similar results. It is worth recalling here that all components in RGB color images are presented as 8-bit 2D data arrays with similar dynamic ranges. However, this is not true for multispectral and hyperspectral images where dynamic ranges of component images can be considerably different [24, 25]. Different dynamic range of component images, if a 3D compression is applied to a multichannel image without proper pre-processing, might cause problems [26] where a component image with the smallest dynamic range (or several component images with small dynamic range) can be severely distorted.

To avoid this undesired effect as well as to take into account properties of the noise possibly present in (some components of) multichannel RS data, variance stabilizing transforms or certain range normalizing operations are often used in lossy compression of multichannel (in the first order, hyperspectral) images [22, 24, 26]. In lossy compression of hyperspectral images, sub-band images with similar characteristics can be grouped where the number of component images in a group is 4, 8, 16 and so on for convenience of applying decorrelation transforms [22, 24]. Note that similar signal power normalizing operations can be useful in lossy compression of multichannel ECG as data pre-processing step [15, 27]. Component images grouping and the use of 3D compression for those grouped component images produces CR improvement in lossy compression of multispectral images as well [23].

However, the following should be stressed concerning image normalizing and grouping. First, the positive effect of these operations is often considerable but limited. Even if one makes groups containing 8 or 16 component images, CR for 3D compression for them is by 2-3 times larger than for component-wise compression with the same level of distortions [24] (although it can be expected that the benefit due to more component images in a group compared to component-wise compression can be larger). Moreover, sometimes it is reasonable not to include in a group a component image that does not exhibit high correlation with other component images and compress it separately [23]. Thus, 3D compression of multispectral images needs more studies. Second, normalization of component images might introduce additional distortions into data. For example, normalization of images originally having more than 8 bits (e.g., 12 or 16 bits) to 8-bit data before compression with re-normalization to original range at decompression stage inevitably leads to errors due to rounding-off operations. However, such errors are usually considerably smaller than errors (distortions) due to lossy compression itself and, thus, can be neglected.

Normalization is not the only operation that can be used to improve the compression performance. Several authors have already proposed to perform component data re-ordering for CR increasing [19, 27–30]. Concerning this approach, we can state the following. First, it can be performed on-line and off-line. For the off-line case, preliminary studies for a set of multichannel images have to be carried out to establish the “globally optimal” order according to a certain criterion. The advantage is that then the re-ordering algorithm is available in advance and no auxiliary information on the band order is needed. The drawback is that the chosen order can be not optimal for each particular image and/or each criterion of compression efficiency. For the online case, the positive effect can be larger but selection of the optimal order might need essential additional calculations. Second, most efforts have been done for hyperspectral images and/or lossless compression [28–30]. Third, the provided benefit due to band re-ordering was not large – usually it was about a few percent of CR increase. Thus, it is desired to study how large the positive effect of band re-ordering can be for lossy compression of multispectral images.

Presentation of the main material

Consider multispectral images denoted as $I(i,j,k)$ where $i=1,\ldots,I_{Im}$, $j=1,\ldots,J_{Im}$ are pixel indices and $k=1,\ldots,6$ is the sub-band index with the corresponding central wavelengths λ_k, $k=1,\ldots,6$. Examples of Landsat image fragments for images called Wyoming and Canon City are presented in Figures 1 and 2, respectively (in fact, the images from the bands 1, 2, 3, 4, 5, and 7 having the same resolution have been used). As one can see, the component images are quite similar to each other in both multispectral datasets. At least, the same structures can be easily detected. Meanwhile, the component images differ from each other and it is worth estimating cross-correlation factors for them.

This has been done and the obtained values of cross-correlation factors are given in Tables 1 and 2, respectively. As it follows from analysis of data in Table 1, cross-correlation factors are all positive and, mostly, have the values close to unity. Meanwhile, the cross-correlation factors for the fourth and other component images are quite small. The same conclusions can be drawn from analysis of data in Table 2, although the fourth component image is more correlated with other component images.

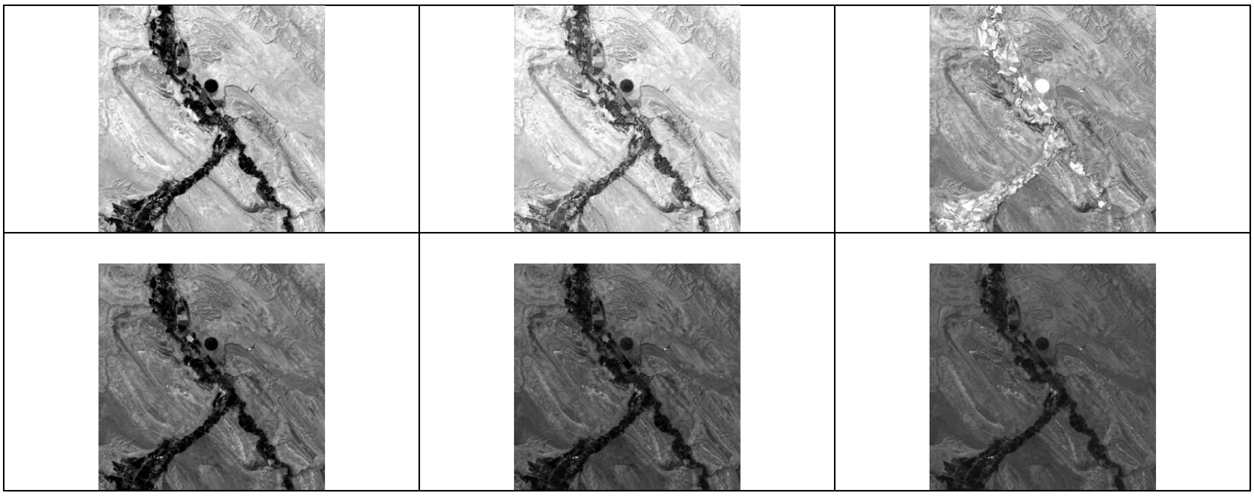

Fig. 1. Fragments for six components of the image Wyoming, 256×256 pixels

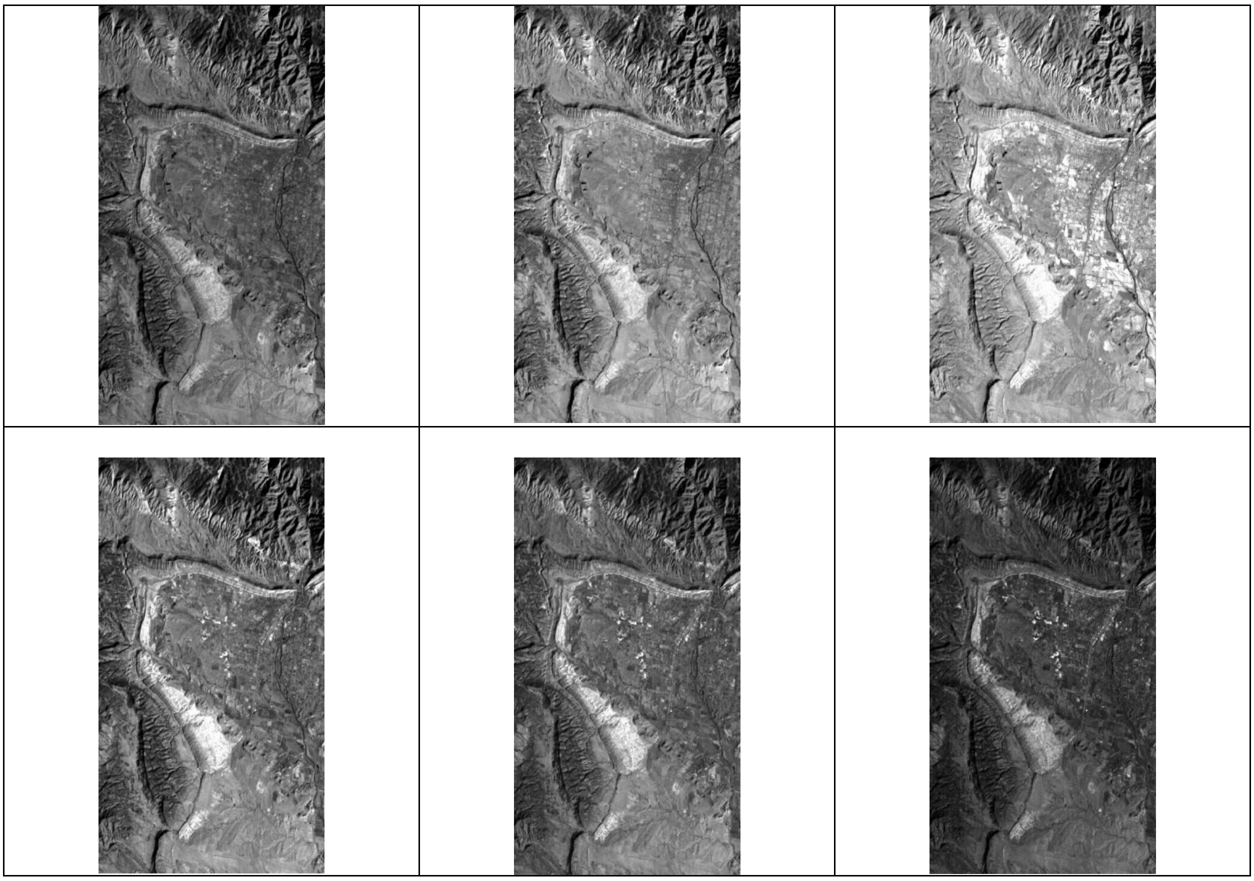

Fig. 2. Fragments for six components of the image Canon City, 256×512 pixels

Table 1

Cross-correlation factors for component images of the Wyoming dataset

Component index	1	2	3	4	5	6
1	1	0.964	0.946	0.113	0.821	0.855
2	0.964	1	0.981	0.214	0.861	0.857
3	0.946	0.981	1	0.185	0.895	0.906
4	0,113	0.214	0.185	1	0.164	0.012
5	0.821	0.861	0.895	0.164	1	0.966
6	0.855	0.857	0.906	0.012	0.966	1

Table 2

Cross-correlation factors for component images of the Canon City dataset

Component index	1	2	3	4	5	6
1	1	0.962	0.942	0.721	0.77	0.817
2	0.962	1	0.968	0.773	0.829	0.866
3	0.942	0.968	1	0.795	0.829	0.9
4	0.721	0.773	0.795	1	0.806	0.73
5	0.77	0.829	0.829	0.806	1	0.952
6	0.817	0.866	0.9	0.73	0.952	1

Let us now consider how efficient the 3D compression is. For this purpose, we have used 2D (component-wise) and 3D versions of a coder called AGU [31]. It is based on DCT in 32×32 pixel blocks, bit-plane coding of quantized DCT coefficients, and embedded deblocking after decompression. The 3D version of AGU employs spectral decorrelation using DCT with a small number of points (six in our case).

To describe the compressed image quality, we have used peak signal-to-noise ratio (PSNR) determined jointly for all six components where all component images have been presented as 8-bit data. Compression has been also characterized by bits per pixel (bpp) that varied in wide limits.

The results obtained for the considered image sets are presented in Figures 3 and 4. As it can be concluded from analysis of the curves in Fig. 3, the 3D compression offers obvious benefits: either 2-4 dB improvement of PSNR is provided for the same bpp or CR is larger by 30-80% compared to the component-wise compression. Very similar conclusions can be drawn from analysis of data in Fig. 4 (benefit in CR can be even larger, but for small PSNR when the compressed image quality is not appropriate). Thus, the 3D compression is worth applying.

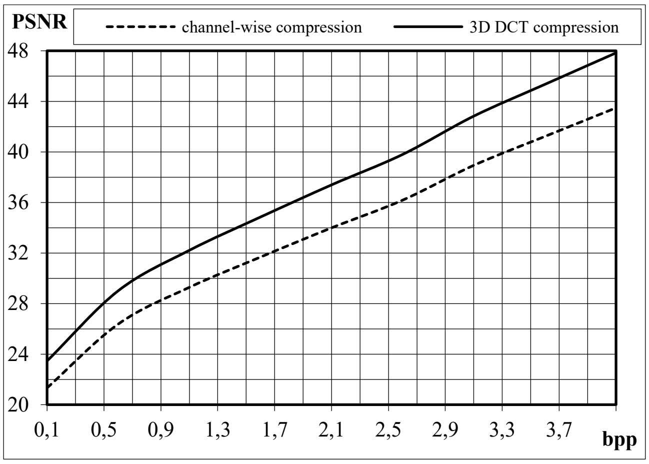

Fig. 3. PSNR vs bpp dependences for the Wyoming dataset

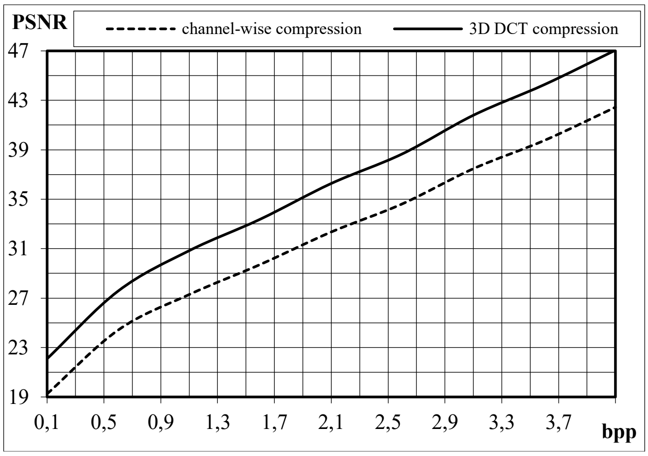

Fig. 4. PSNR vs bpp dependences for the Canon City dataset

To analyze possible benefits due to band re-ordering we have analyzed all possible variants of band order and found the best and worst variants. The obtained data have been also compared to data for the standard (initial) order. The obtained dependences are presented in Figures 5 and 6. As one can see, the benefit in PSNR due to optimal ordering is not large, it is about 0.5 dB. The benefit in CR is a few percent.

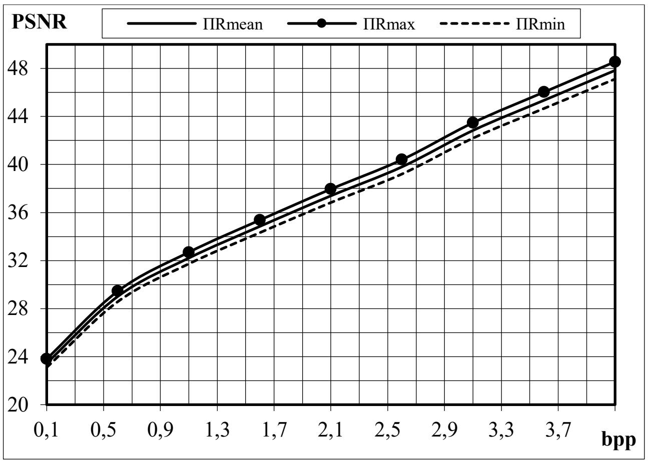

Fig. 5. PSNR vs bpp dependences for different variants of band ordering for the Wyoming dataset

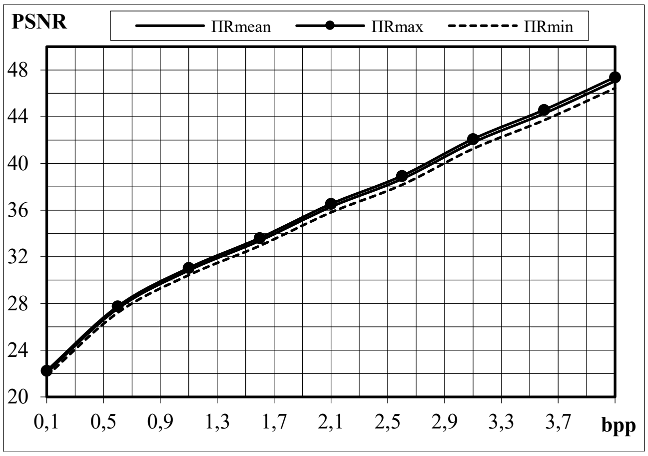

Fig. 6. PSNR vs bpp dependences for different variants of band ordering for the Canon City dataset

Then, it is interesting is the optimal order of bands the same for both datasets. The answer is "no". The optimal order is the following: 4, 2, 1, 3, 6, 5 for the Wyoming dataset and 1, 2, 3, 6, 5, 4 for the Canon City dataset. We have also calculated the indicators

$$R_{int} = \prod_{1}^{5} R(k, k+1)$$

where $R(k, k+1)$ is the cross-correlation factor for the k-th and k+1-th component images for a given variant of band ordering. It has occurred that the indicator R_{int} is the largest for the best order of bands (its values are equal to 0.17 and 0.64 for the Wyoming and Canon City datasets, respectively) and it is the smallest for the worst order of component images (its values are equal to 0.0009 and 0.30 for the Wyoming and Canon City datasets, respectively). This means that such indicator can be used to determine the best band order under condition that the matrix of cross-correlations (such as those ones in Tables 1 and 2) is calculated. But, to determine the best order, all possible R_{int} have to be calculated and the largest among them has to be found. This might require additional calculations to be carried out on-board for each obtained dataset.

Another way out seems possible. It is possible to analyze a quite larger number of datasets and to determine the optimal band order for them in statistical sense. Then, this order can be used for any acquired image. It is known in advance at transmitting and receiving sides and, thus, there is no need to code it as auxiliary data.

Conclusions

If one deals with necessity to compress multispectral images in a lossy manner, the following should be taken into account. First, the original data can be normalized to component images represented as 8-bit data. Second, it is worth applying 3D compression that allows exploiting inter-channel correlation typical for multispectral RS data in order to either improve quality of compressed images for a given CR or to increase CR for a given quality. Third, there is an opportunity to slightly increase CR due to the best band ordering. However, this option provides quite small increase of CR and might deal with additional calculations to be performed on-board.

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