Comparison of Wavelet and PCA Compression Methods for Spectral Images

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Abstract

In this paper, we study and compare wavelet and PCA compression methods for spectral images. By spectral images we mean any kind of multi-, hyper-, or ultraspectral images. In our study, we handle spectral images by channels or slices. We clarify advantages and disadvantages of wavelet based compression methods. If spectra of spectral images are smooth then wavelets can compress the spectral images quite well. We use two dimensional wavelet transforms for both spatial directions and spectrum directions. We calculate the transform using different wavelets and try several threshold values and techniques. The tests were done using 14 different natural spectral images from our spectral image database and the results were compared to each other. In judging the quality of a compression method we used three different criteria: compression time, error (measured in various ways) and compression ratio.

Introduction

Colors and spectral images are becoming more and more important in industrial applications. Also new fields of science and technology have started using spectral images. Previously, spectral images have been used in remote sensing. Precise color measurements using spectral images enable accurate display setups. E-business, some medical science applications and paper industry use spectral images in many ways. Moreover, a lot of art paintings are imaged to spectral images and there are already huge art databases available which consist of spectral images [1]. The spectral image technology has seen the same phenomenon as RGB technology. The first steps to imaging moving spectral images have been taken [2]. In the spectral videosystem data compression plays a very important role because evidently the amount of raw data is much larger than in still images: hence the need for spectral image compression is growing. Wavelets are commonly used in signal processing and image analysis applications to compress signals. If spectral image is smooth, either in spatial direction or temporal direction, then we can find some benefits of wavelets. In this research paper we concentrate on using wavelets by spatial and temporal spectral directions. We compare results to Principal Component Analysis (PCA) and three dimensional wavelet compression. In section compression methods we introduce some notations and describe the wavelet theory and the PCA. In section experiments we introduce the spectral image database which was used in our experiments and consider tentative error measurements. In section results we present our experimental results. Finally we conclude with a summary and general remarks.

Compression methods

Wavelets

Wavelets have become an important method of compression of digital images. Wavelet based compression methods are used commonly in normal images such as RGB images. In this article we study how wavelets work in spectral image compression. Kaarna has treated the compression with wavelets in his doctoral thesis [3]. He got the best results by using PCA for spectral direction and wavelets for spatial direction. After wavelet transform the coefficients contain local information about the image. This locality property of the wavelet transform is the main advantage of the waveletes compared to more traditional PCA or Fourier techniques. In wavelet analysis the signal is split to different scales which are then analysed and compressed independently. We present here only some basic facts about wavelets and refer to the following books and articles for more details [4], [5], [6].

Daubechies wavelets are probably the best-known wavelets [4]. She constructed orthonormal compactly supported wavelets with varying degrees of smoothness. Normally in image analysis and image compression the wavelet should be as smooth as possible. We used Daubechies wavelets with 2, 4, 6 and 8 nonzero coefficients. Second family of wavelets we consider is called symlets [4] which are quite similar to Daubechies wavelets. Symlets are not exactly symmetric but they are more symmetric than Daubechies wavelets. Third wavelet family is coiflets [4]. Coifman showed that in some cases it would be advantageous to have many vanishing moments for both wavelets and scaling functions. The coiflets are more symmetrical than Daubechies wavelets and symlets. The fourth wavelet family is biorthogonal [4] wavelets. The main advantage of biorthogonal wavelets is that one can achieve both symmetry and compact support.

Thresholding is an important part of wavelet compression; the wavelet transform as such does not compress anything and so the thresholding makes wavelet compression lossy. We use both hard and soft thresholding. Hard thresholding means that all values which are smaller than the threshold value are cut off:

$$x = \begin{cases} x & \text{, if } |x| > \text{T} \\ 0 & \text{, if } |x| \leq \text{T} \end{cases}$$

where T is the threshold value and x is some coefficient of the wavelet transform. In the soft thresholding [7], setting to zero the coefficients whose absolute values are lower than threshold value T and then scaling the nonzero coefficients toward zero. The soft thresholding formula is

$$x = \begin{cases} x & \text{, if } |x| \geq T_1 \\ x\frac{|x|-T_0}{T_1-T_0} & \text{, if } T_0 < |x| < T_1 \\ 0 & \text{, if } |x| \leq T_0 \end{cases}$$

where T_0 and T_1 are threshold values, x is some coefficient of the wavelet transform.

Wavelet compression techniques

A spectral image has a three dimensional structure. The height and width of the image are spatial dimensions and the spectrum is a "temporal" dimension. When we handle spectral images by channel, we handle each spatial dimension at a time. In other words, we compress and reconstruct 61 different grayscale images per one spectral image.

When we handle spectral images by slice we use wavelets for temporal and for one spatial dimension. Again, we compress and reconstruct different grayscale images in spatial directions.

In three dimensional (3D) compression we use tensor product of three one-dimensional wavelet transform. In the other words we compress and reconstruct each dimension at a time.

PCA

The PCA is a very common method to analyze and compress discrete statistics data. There are a lot of papers on PCA, see for example [8]. PCA is based on eigenvalues and eigenvectors which are calculated from covariance matrix. The eigenvalues obtained are in fact squares of the singular values of the original matrix. Given a matrix A its singular value decomposition (SVD) is $A = U\Sigma V^T$ where U and V are orthogonal matrices, Σ is diagonal matrix with the singular values σ_i on the diagonal and T is transpose operator. The covariance matrix is in the present situation just $C = A^T A$ and hence its eigenvalues λ_i are simply $\lambda_i = \sigma_i^2$. Because C is symmetric its eigenvectors (which are right singular vectors of A, i.e the columns of V) are orthogonal. We select the largest singular values and take as an approximation to the range of A the subspace spanned by the columns of U corresponding to these singular values. Size of subspace defines how much information is selected from original image. PCA transform is optimal for keeping energy of spectrums. However, there are some disadvantages in the PCA compression method. Basefunctions have to be calculated for every spectral image and the covariance matrix should be calculated for every spectral image separately. Moreover, the PCA method is a global method for compression.

Experiments

Spectral database

Our database has a lot of different spectral images. The images were measured at the University of Joensuu, Finland, Chiba University, Japan, Saitama University, Japan, Lappeenranta University of Technology, Finland, Marine Biological Laboratory, Maryland, USA, and the University of Bristol, UK. The spectral images contain objects from many different areas such as GretagMacbeth colorchecker, printed magazine pictures, paintings, buildings and forest. We collected 14 spectral images for our experiments. We tried to select as normal images as possible. The images selected include both smooth and rough cases in the spatial and spectra dimensions. Also, we selected a few reference images to our experiments. The spatial pixel resolutions were between 149×94 and 700×608. The spectral images were filtered so that every image contained 61 spectral components from 400 nm to 700 nm, at 5 nm intervals. Figure 1 represents selected images in RGB format.

Reconstruction error measurements

We used several different error measurements. Some of the common ways to measure the error are MSE, PSNR and ΔE error measures [3]. The scale of values of spectral images influence the error measures. We used D65 standard light source for our measures. Next, we shortly describe and formulate those error measurements. I is original spectral image, $\hat{I}$ is decompressed spectral image and n is height, m is width and c is depth of spectral image I.

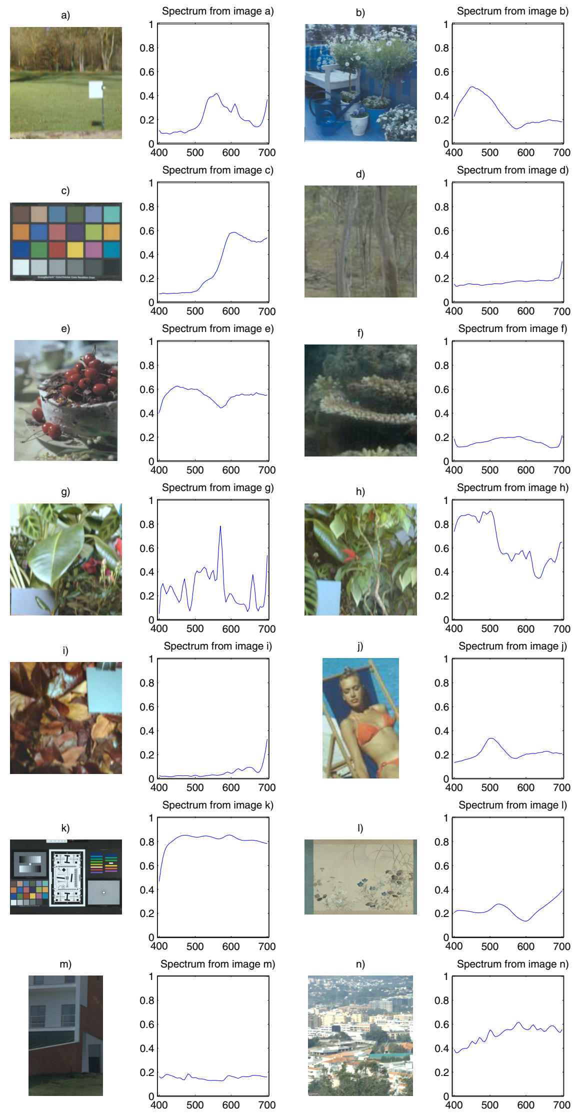

Figure 1: *Images are selected from our spectral image database.*

MSE-mean square error (scaled L^2 norm).

$$\text{MSE} = \frac{1}{n \cdot m \cdot c} \sum_{i=1}^{n \cdot m} \sum_{j=1}^{c} (I_{i,j} - \hat{I}_{i,j})^2.$$

MSE tells as squared mean value of spectrums. SNR measures noise which was caused from compression. PSNR-peak signal-to-noise ratio.

$$\text{PSNR} = 10 \log_{10} \frac{M^2}{\text{MSE}},$$

where M is theoretical maximum of image channels. PSNR also measures noise by compression; it is commonly used in image analysis. ΔE-color difference.

$$\Delta E = \sqrt{\Delta L*^2 + \Delta a*^2\ \Delta b*^2}$$

Original and reconstructed spectral images are transformed to CIELAB $L * a * b*$-images. Squared difference of each component gives an error which is based on human eye color system.

Other basic methods

After wavelet transform and thresholding we coded the spectral images with a few different methods. We found out nonzero coefficents and their three dimensional indices. Indices were coded so that spatial resolution can be 2048×2048 and spectra dimension resolution could be 1024. This means that each nonzero coefficent was coded with 32 bits. Spectral images of our database were originally in a 64 bits double format. In the wavelet transform we chopped the coefficients to 32 bits. Finally we used Linux gzip lossless compression method. There were a few different sizes of spectral images. Each image was compressed by various methods, threshold values and different wavelets. We used three methods: wavelets by channel, wavelets by slice and the PCA which we used as a reference method. All in all we tested two different methods and 16 different wavelets and five different threshold values.So the complete number of tests in one spectral image was 160. The objective image quality was evaluated by three different methods. The quality criteria were described above. We considered mostly classical MSE and PSNR reconstruction measurements. We implemented our algorithms with Matlab using Linux operating system. The computer characterics were: Intel Pentium 4 2.5 Ghz processor and 2 Gb RAM memory which is a normal PC configuration.

Results

In the figure 2, we show the results of four different spectral images. We tried to select those four images which are most representaive of our database. Selected images are c), f), g) and j). For all four images we show how ΔE and PSNR depend on compression ratio CR.

In Figure 2 the PCA is marked dashed line $--$, wavelet channel method is marked in the star $*$ and wavelet method slice is marked in the circle o. Results are scaled so that it is possible to recognize reasonable differences between different methods. For example some images for wavelet methods give a good compression ratio but they give also unreasonable ΔE or PSNR values.

Conclusion

In this paper, we studied compression methods for spectral images. The main idea of this study was to compare advantages and disadvantages of the wavelet based compression techniques and PCA. We concentrated on channel

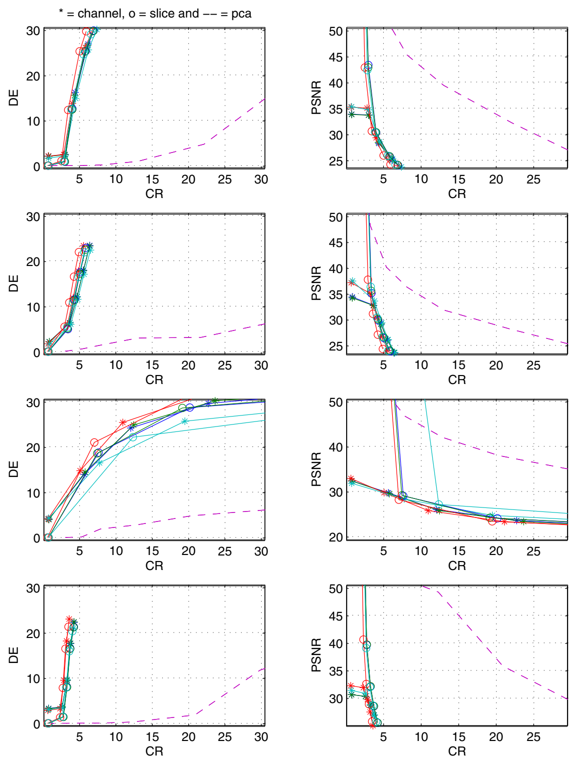

Figure 2: Results for image c) is on the top row, result for image f) is on the second row, results for image g) is on the third row and results of image j) is on the bottom row.

and slice wavelet methods and hard thresholding. For example in the channel method we used two dimensional wavelet transform for spatial dimension and for all channel images.

Basically, wavelet-based compression methods take more time than PCA. Furthermore, the slice method takes more time than channel method. Time, especially in the decompression could be very important in some applications. For example, the spectral video compression needs very fast decompression for a single spectral image. If the length of the data vector is a power of two the computations are somewhat faster. In the natural images this is hard to accomplish.

Although we studied lossy compression methods, lossless compression is also important. The role of lossless compression is much more significant for wavelet than for PCA. In fact the wavelet compression technique would have been more efficient if we had used more efficient lossless compression for wavelet coefficients. Furthermore digitaliziation of wavelet coefficients should have been more powerful.

Compression ratio is an important criterion in the lossy compression. In this study we studied compression ratios of wavelet methods and PCA. We tried to find out what kind of images should be compressed by wavelet methods and in which situations PCA yields better results. The results showed that PCA worked similarly for all spectral images, but for some spectral images wavelet based methods worked much better than PCA. Furthermore, wavelets can give bigger compression ratios than PCA. In fact there are some threshold values in the wavelet method such that compression ratio is bigger than the biggest compression ratio of PCA. PCA gave in general very similar errors for all test data for a given compression ratio. For wavelet methods the results depended quite much on the image: for some images the errors were significantly smaller than with PCA while for others PCA was slightly better. However, for some images wavelet methods gave compression ratios with acceptable errors which could not at all be achieved with PCA.

In the figure 2, we can see that ΔE value grows very fast for wavelet method when compression ratio is growing. In fact, the differences are quite huge. Wavelet methods give better compression ratios and also the channel method gives better results for ΔE than slice method. The difference is even bigger for PSNR values. It seems that only wavelet methods is not a right way to compress spectral images. PCA gives quite good CR values for reasonable ΔE and PSNR values. We would get more benefits from PCA and wavelet methods if we used mixed methods to compress spectral images. This we compress spectral direction with PCA and after that we use wavelet channel method for spatial dimension. That so called hybrid method could be powerfull for spectral images.

References

1. F. Lotti S. Porcinai S. Baronti, A. Casini, Multispectral imaging system for the mapping of pigments in works of art by use of principal-component analysis, Applied Optics, 37, 1299 (1998).
2. Takeyuki Ajito Yasuhiro Komiya Hideaki Haneishi Masahiro Yamamasaguchi Nagaaki Ohyama Kenro Ohsawa, Hiroyuki Fukuda, Six-band hdtv camera system for color reproduction based on spectral information, pp. 171–176 (2003).
3. Arto Kaarna, Multispectral image compression using the wavelet transform, Ph.D. thesis, Lappeenranta University of Technology (2000).
4. Daubechies Ingrid, Ten Lecturs on Wavelets, SIAM (1992).
5. Stephane Mallat, A Wavelet Tour of Signal Processing 2nd, Academic Press (2001).
6. Olivier Rioul and Martin Veterli, Wavelets and signal processing, IEEE, Signal Processing Magazine (1991).
7. David L. Donohono, De-noising by soft-thresholding, IEEE, Transactions on Information Theory (1995).
8. Jussi Parkinen and Timo Jaaskelainen, Color representation using statistical pattern recognition, Applied Optics, 26, 4240 (1987).