PCA TRANSFORM FOR IMAGE ENHANCEMENT, COMPRESSION, AND CHANGE DETECTION

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Abstract

The Principal-Components-Analysis (PCA) of KL-transform has been utilized as multi operators, (i.e. enhancement, compressor, and temporal change detector). Two images pair (*Al-Jaderiya-Baghdad-Iraq)* of 3-bands Landsat ETM+ (14.25 spatial-resolution) and Panchromatic Quick-Bird (0.6 meter) images are adopted to perform the PC analysis. Since most of the image band's information are presented in the first PCs, therefore image classification and change detection procedures are performed with little consuming time. The linear "PCA" transformation can be used to translate and rotate data into a new coordinate system that maximizes the variance of the data. It can also be implemented for enhancing the information content.

الخلاصة

في هذا البحث، تم استخدام تقنية تحويل المركبات الأساسية كعامل تحسين للصور، عامل كبس و أخيرا كعامل كشف للتغييرات الوقتية بين صورتين. استخدم لهذا الغرض زوجان من صور التحسس النائي (منطقة الجادرية-بغداد)، الأولى هي صورة المتحسس (ETM+) (بقدرة تمييز 28.5 متر)، والثانية للمتحسس Quick Bird (بقدرة تمييز 0.6 متر). أن أساس التحويل مبني على فكرة إنتاج قنوات طيفية جديدة بدون ترابط، حيث تمتاز معظم قنوات التحسس النائي بعامل ترابط عالي. ينتج عن ذلك تركز المعلومات في قناة واحدة مع الأخذ بنظر الاعتبار القيم الواحدية الناتجة، يمكن استخدام هذه القناة كصورة محسنة أو أساس لاستخراج بقية القنوات في عمليات ضغط الصور. تم كذلك دمج الصورتين أعلاه بصورة رباعية القنوات وتم كشف التغاير بين الصورتين باستخدام هذا النوع من التحويل.

Introduction

Although datasets may reflect the measurements made on one feature, they may often be correlated with other datasets. Most often, high correlation may be existed between adjacent bands, which means that these bands are not statistically independent. Principal components analysis (also referred Karhunen-Loeve analysis) is a technique that allows the production of images where the correlation between them is zero, [1]. However, increasing use of "*PCA*" technique is being made in the remote sensing sciences, especially in reducing the dimensionality of the data sets [2]. In this research, the PCA transform is applied on many datasets in order to enhance, reduce size, and detect the temporal change),[3]. The PCA enhancement processes dose not depend on the data size and the first band are always be the enhanced one. Also, in using this technique, the compression ratio is directly proportional to the No. of band.

Mathematical Description

The principal components transform can be visualized most easily in two-dimensional, shown in figure (1). Let a two-dimensional distribution of pixel values obtained in two bands, labeled simply by X_1 and X_2. A scatter plot of all the brightness values associated with each pixel in each band is shown in figure (1-a) together with the locations of their means μ_1 and μ_2. The goal is of the *PCA* to translate and / or rotate the original axes so that the original brightness values on axes X_1, X_2 are redistributed onto a new set of axes or dimensions, X_1', X_2'. For example, the simple

translation for the original data points from X_1 to X_1' and from X_2 to X_2' coordinates system might be the relationship;

$$X_1' = X_1 - \mu \quad \text{and} \quad X_2' = X_2 - \mu_2 \quad (1)$$

The origins of the new coordinates now lies at the location of both means in the original scatter of points, figure (1-b). The new coordinates system might then be rotate about its new origin (μ_1, μ_2) in the some θ degrees so that the first axis X_1' is associated with the maximum amount of variance in the scatter plot of points, figure (1-c). This new axis is called the first principal components (PC$_1$=λ_1). The second principal components (PC$_2$=λ_2), is perpendicular (orthogonal) to PC$_1$. Where λ_1, λ_2 are the transformation's Eigen values. The major and minor axes of the ellipsoid of points in bands X_1, X_2 are called the principal components.
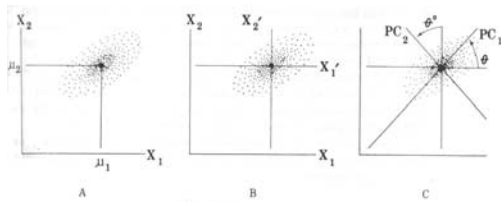

Figure (1): Two- Dimensional (PCA) Transform

To transform the original data on the X_1, X_2 axes into the PC$_1$ and PC$_2$, we must obtain cretin transformation coefficients that we can apply in a linear fashion to original pixel values. The linear transformation requires a derivation from the covariance matrix of the original data set [4].
The mathematical procedures involved the following two-dimensional "PCA" transformation, [2]. Consider a set of multi-band images f(x, y, r), each of size M3N and "r" bands.
1. Each image band should be expressed in the form of an n-dimension vector $D_{n,1}$, where n = M×N, given by, [2] :

$$D_{n,1} = \begin{bmatrix} f(1,1,1) \\ f(1,2,1) \\ . \\ . \\ . \\ f(i,j,1) \\ . \\ . \\ f(N,M,1) \end{bmatrix} \quad (2)$$

The whole image bands are, then, arranged into a matrix $D_{n,r}$ of n-rows and r-columns, given by, [2]:

$$D_{n,r} = \begin{bmatrix} f(1,1,1) & f(1,1,2) & \ldots\ldots & f(1,1,r) \\ f(2,1,1) & f(2,1,2) & \ldots\ldots & f(2,1,r) \\ . & . & . & . \\ . & . & . & . \\ f(i,j,1) & f(i,j,2) & \ldots\ldots & f(i,j,r) \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ f(N,M,1) & f(N,M,2) & \ldots\ldots & f(N,M,r) \end{bmatrix} \quad (3)$$

2. The mean of each column in eq.(4) should be computed by taking the arithmetic averages of each column, given by:

$$\bar{D}_{n,b} = \frac{1}{n}\sum_{i=1}^{N}\sum_{j=1}^{M} f(i,j,b), \quad \text{where b=1,2,....,r} \quad (4)$$

3. An (n-row,r-column)matrix $P_{n,r}$ is computed by subtracting the mean of each column $\bar{D}_{n,b}$ from that column values $D_{n,b}$. This matrix is called the "Mean-Corrected-Data-Matrix", its values are given by, [2]:

$$P_{j,b} = \sum_{i=1}^{n}(D_{i,b} - \bar{D}_{i,b}), \quad j=1,2,...,n \text{ and } b=1,2,....,r \quad (5)$$

4. The **covariance matrix** of the $P_{j,b}$ matrix can then be computed by:

$$C_P = E\{(D - \bar{D})(D - \bar{D})^T\} \quad (6)$$

Where E{.} is the expectation operation, "T" indicates transposition, and C_P is an r×r matrix.

5. Now, let us assume that e_i and λ_i , for i=1,2,3,……n, be the eigenvectors and corresponding eigenvalues of the matrix C_P. For convenience, we shall assume that the

eigenvalues being arranged in decreasing order, such as, $\lambda_1 \geq \lambda_2 \geq \lambda_3 \ldots \geq \lambda_n$.

6. A transform matrix " A" whose rows are the eigenvectors of C_P can should, then, be computed, given by:

$$A = \begin{bmatrix} e_{11} & e_{12} & e_{13} & \cdot & \cdot & \cdot & \cdot & \cdot & e_{1n} \\ e_{21} & e_{22} & e_{23} & \cdot & \cdot & \cdot & \cdot & \cdot & e_{2n} \\ \cdot & & & & & & & & \\ \cdot & & & & & & & & \\ \cdot & & & & & & & & \\ \cdot & & & & & & & & \\ \cdot & & & & & & & & \\ e_{n1} & e_{n2} & e_{n3} & \cdot & \cdot & \cdot & \cdot & \cdot & e_{nn} \end{bmatrix} \quad (7)$$

7. The principal components vectors can, now, be computed by utilizing the transformation:

$$Y_i = A(D_i - \overline{D_i}), \text{ for } i = 1,2,3,\ldots, r \quad (8)$$

In fact, the transformation presented in eq.(8) has several important properties, these are:

• An inverse transformation operation can be performed by, [2]:

$$D_i = A^{-1} Y_i + \overline{D_i} \quad (9)$$

Since C_P is a real, symmetric matrix, it is always possible to find a set of orthonormal eigenvectors, which yield $A^{-1} = A^T$.

• Instead of using all the eigenvectors of C_P, we can form A_K^T from only K-eigenvectors, corresponding to the largest eigenvalues λ_i.

• The Y_i vectors will then be K-dimensional and the reconstruction will no longer be exact, i.e.

$$\hat{D_i} = A_K^{-1} Y_i + \overline{D_i}, \text{ for } i = 1,2,3,\ldots, K \quad (10)$$

For the details of the computation of the eigenvectors, eigenvalues, and the corresponding principal components, using an adapted fast algorithm, see [5]. Lastly, it should be noted that we have adopted the procedures of this fast algorithm, modeled into several routines, conducted in a Visual-Basic-Program and involved in the presented work.

Result Analysis

The first use of PCA was as enhancement operator. The input image was Landsat ETM+ three high correlated bands, (14.25 m-resolution Al-Jaderiya). Where, the output was three uncorrelated bands, the first band was enhanced due to new PCA transform, figures 2-a, 2-b illustrated the input and out put datasets respectively, where table 1show the statistical Eigen value for each band

2-a
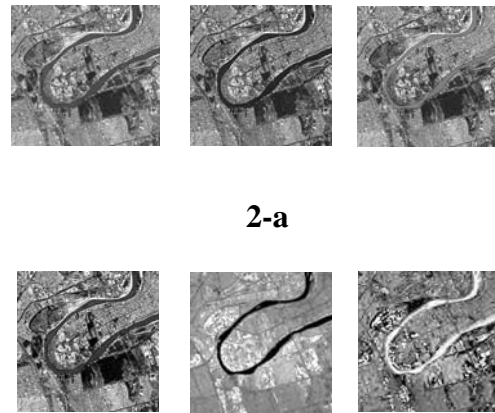
2 – b
Figure (2): Input & output Data

Table (1): Eigen Values of First PCA Result

	PC1	PC2	PC3
band	0.9552	0.0381	.00663

The second results of PCA transform was the compression process. Six bands of TM image have been compressed using this technique. The coded data consist of the first enhance band and the six Eigen values. In fact, the coding process is the forward PCA transform, when, the decoding processes the inverse PCA transform. The size of input data was 1.536 Mbytes, where, the coded data size was 304 Kbytes. The compression ratio is 5.05, this ratio is depending on the number of band, therefore, i. e., as the number of bands increase, the compression ratio will increase. Figure 3-a represented the coded data with the Eigen values as important coding parameters. Figure 3-b represented the decoded data.

band	Eigen Value
1	0.85538
2	0.08448
3	0.04753
4	0.00650
5	0.004491
6	0.001547

3-a The coding data

composite principal components. The Eigen values of this transformation are listed in table 2.
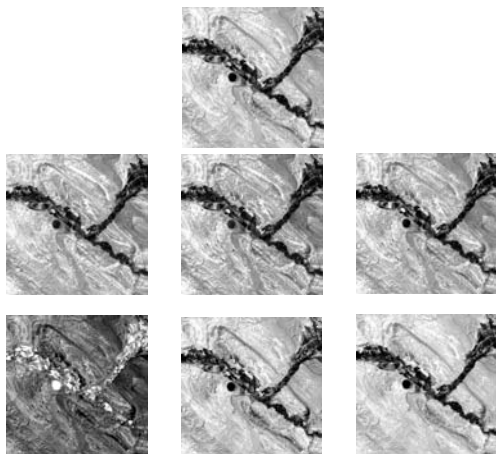
3-b The decoding data

Figure(3): The coding & Decoding data
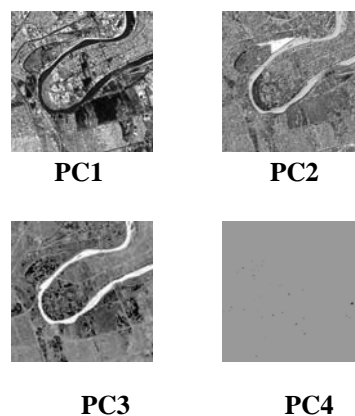
PC1   **PC2**

PC3   **PC4**

Figure (4): The Principal Component of New Composite Image

The last application of PCA was evaluated by mixed the spectral bands of the temporal match images. The first image was panchromatic resize Quick Bird sensor with new resolution of 14.25-meter exposure at 2002 for Al-Jaderiya-Baghdad zone 38 north. The second one was 3-band synthetic natural colors for the same area exposure at 2004. The synthetic natural color bands were pan sharpened 3-band images with a spatial resolution of 14.25 meters. The PCA transform is used to overcome the problems arises from the environmental variations associated with different time imagery (i.e. *As Enhancement Operator*), [6]. In this paper, the *PCA* transformation is utilized to expanding bands numbers by newly band's images. The four bands, acquired in different times, have been grouped and used to create four PC's that represent newly 4-bands. Uncorrelated principal components, in general, are presenting the changed areas. The shortcoming of this process is; the difficulties in interpreting and identifying the specific nature of the involved changes or variations [7]. However, the first PC, normally, represents the unchanged land-covers. Where, the 2nd PC's include some changed information, while the last PC's contained uncorrelated information, such as random noise or changing patches [8] & [9]. Figure (4) illustrates the results of change detection using image

Table (2): The PCA Eigen Values of Composite Image

	PC1	PC2	PC3	PC4
Band	0.6613	0.313	0.021	0.0039

Conclusions

The first application of this transformation is the enhancement operator. Always, the first PC is the enhanced band, where other bands represent the uncorrelated data. The disadvantage of this process is the limitations of use other bands.

The second usage of PCA transform indicates that as the No. of band increase the compressions ratio will increase. Also, coding by this algorithm yields complete decoded data, i.e. it is Lossless technique.

The last application of principal components analysis required new composite image. This will be yields four- components, after transform, first one indicate the no change image, where, the second showed the change in water area, figure (4 PC2) bright tone area. The other components represent uncorrelated data.

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