Multi-Block PCA Method for Image Change Detection

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Abstract

Principal component analyses (PCA) has been widely used in reduction of the dimensionality of datasets, classification, feature extraction, etc. It has been combined with many other algorithms such as EM (expectation-maximization), ANN (artificial neural network), probabilistic models, statistic analyses, etc., and has its own development such as MPCA (moving PCA), MS-PCA (multi-scale PCA), etc.

PCA –and its derivatives-- has a wide range of applications, from face detection, to change analysis. Change detection from PCA shows however a main difficulty, that is, result interpretation. In this paper, a new PCA method is developed, namely MB-PCA (Multi-Block PCA), in order to overcome this problem. Experimental results demonstrate the interest of the approach as a new way to use PCA.

Keywords: Multi-Block, PCA, change detection

1. Introduction

Principal Component Analysis (PCA) is a widely used technique for data compression and information extraction[1][2][3][4]. With the linear assumption of the datasets, PCA finds linear combinations of variables that describe major trends in a data set. It has been widely used in many fields such as classification, reduction of datasets, feature extraction, etc. And one of its application fields is to be used on change detection.

Change detection is a common and challenging subject in image processing. It is frequently used in surveillance system, image series analysis, monitoring system, satellite images analysis, etc[5][6]. And generally it is combined with the problem of segmentation or classification.

Efficient techniques to analyze changes from multi-temporal satellite images is important for many applied problems such as: urban development, environmental and agricultural monitoring[7][8][9][10][11][12].

Our project is a part of flood forecasting and land-cover use in the Red River Delta region in Vietnam. We are trying to find out the changed regions from some satellite images by comparing the differences between wet seasons and dry ones. In this field there are some literatures before[13][14][15] and some researchers used PCA to analyze images. But it seems very hard to give some good and clear explanation when using PCA analysis directly to change detection. By introducing multi-block PCA method, we can have a better viewpoint and make the results clearer.

2. General overview on PCA method

2.1 PCA technique

Given a set of images, the general PCA framework is as follows:

1) *Transform each image into a vector.*

Each image I_i has an associated intensity matrix M_i, of size n x m, in which each element means the intensity of the corresponding pixel. Then each matrix M_i is reshaped into a single vector $\boldsymbol{X}_i$, of size (n x m) x 1. If we have totally 'n_{set}' images, we can have n_{set} vectors, and then combine them all into a matrix: $A = (\boldsymbol{X}_1, \ldots, \boldsymbol{X}_{nset})$, whose size is ($n$ x m) x n_{set}, the columns of which are the vectors $\mathbf{X}_i$. Then the PCA will be carried out on this matrix A.

2) *Calculating process.*

In general PCA framework we use $Z = A^t A$, whose size is n_{set} x n_{set}. Thus we can get its eigenvalues λ_i, (i ∈ [1, n_{rank}]), and eigenvectors − i.e loading vectors $\boldsymbol{v}_i$, (i ∈ [1, n_{rank}]). n_{rank} is the rank of A and $n_{set} \geq n_{rank}$ (when $n_{set} = n_{rank}$, Z is called full-rank matrix).

And then A can be written into the linear combination of $\mathbf{v}_i$s:

$$A = TV^t = \sum_{i=1}^{n_{rank}} \mathrm{t}_i v_i^t \qquad \text{(eq. 1)}$$

in which,

$\mathbf{t}_i = A\mathbf{v}_i$, (i ∈ [1, n_{rank}])

$T = AV$ ($V = [\mathbf{v}_1 \ldots \mathbf{v}_{n_{rank}}]$)

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The relations hidden are:

$$\mathbf{v}_i^{\mathbf{t}}\, \mathbf{v}_j = \delta_{ij}, \qquad \mathbf{t}_i^{\mathbf{t}}\, \mathbf{t}_j = \delta_{ij}\lambda_i, \qquad \lambda_i\, \mathbf{v}_i^{\mathbf{t}} = \mathbf{t}_i^{\mathbf{t}}\, A$$

From SVD's (Singular Values Decomposition) view, we can get:

$$A = UDV^t = \sum_{i=1}^{n_{rank}} \mathrm{d}_i u_i v_i^t = \sum_{i=1}^{n_{rank}} t_i v_i^t \qquad \text{(eq. 2)}$$

in which, U's columns are eigenvectors of AA^t, and V's columns are eigenvectors of A^tA, while D is a diagonal matrix with the diagonal elements d_i, the singular values, which are the square roots of the eigencalues λ_i of A^tA.

3) About the basic matrix.

Since neither mean-centering nor rescaling was implemented (give reference to mean centering and rescaling approaches), the method upwards takes the mean size into account. Thus we use the covariance matrix A_{cov} of the input data set or the correlation matrix A_{cor} instead of using $Z= A^tA$.

A_{cov} and A_{cor} are both of size n_{set} x n_{set}, just like Z, and their elements are defined respectively by:

$\forall$ (i,j) $\in$ [1, n_{set}] x [1, n_{set}],

$$A_{\mathrm{cov}}(i,j) = Cov(X_i, X_j) = \frac{1}{nm-1}\sum_{l=1}^{nm}(X_i(l) - \overline{X}_i)(X_j(l) - \overline{X}_j) \qquad \text{(eq. 3)}$$

$$A_{cor}(i,j) = Cor(X_i, X_j) = \frac{Cov(X_i, X_j)}{\sqrt{Var(X_i)}.\sqrt{Var(X_j)}} \qquad \text{(eq. 4)}$$

In our program we use the matrix A_{cor} instead of Z to eliminate the influence of different mean values and intensity ranges.

4) Principle components.

After PCA analysis on the whole image series, we can get new images (principle components) PC_i (i$\in$ [1, n_{set}]) according to the following formula:

$$PC_i = A\mathbf{v}_i \qquad \text{(eq. 5)}$$

2.2 Experimental results on PCA

The images used for experimentation are Vegetation images. Vegetation images are 4 band multi-spectral images, with the one kilometer resolution and daily acquisition. They are dedicated to the monitoring of Earth observation at global scale. We use the ten-day synthesis (S10) products and NDVI (Normalized Difference Vegetation Index) dataset, with the resolution 1-km /pixel and the PRODUCT_ID V1KRNS10__20010101E. The chose application site is the Red River Delta, from the Hanoi Delta (Vietnam) to Yunnan province (China).

26 images were chosen from January to December, 1998. Some of them are shown in the following Figure 1. All of their sizes are 803x617, with the same region of red river flowing into the sea.

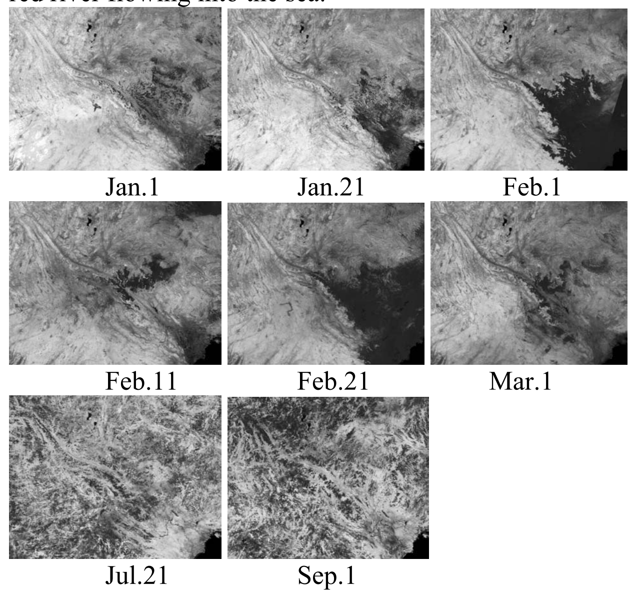


Figure 1 Input Vegetation images

The results of PCA processing following the steps from 1) to 4) are shown in Figure 2(only listed the first 6 components $PC_1 \sim PC_6$).

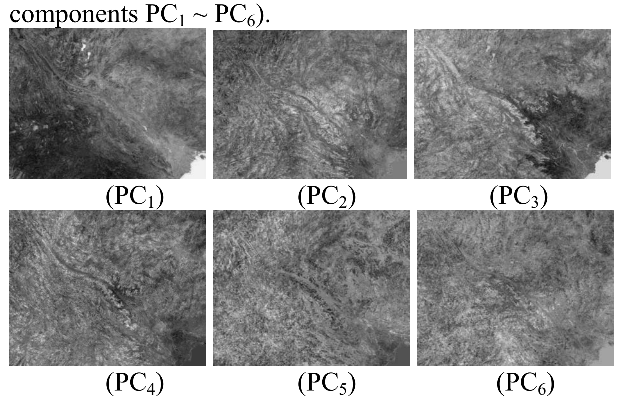


Figure 2 Output images

The corresponding eigenvalues are shown in Table 1.

Table 1 Eigenvalues of PCA

PC	eigenvalue
PC_1	10.34615
PC_2	5.085591
PC_3	1.900715
PC_4	1.419621
PC_5	0.820063
PC_6	0.720243

Because our target is to detect regions of changes, it is obviously very hard to give perfect explanation based on the results upwards, though the eigenvalues of PC_1 and PC_2 as shown in Table 1 show out prominent differences with others. So we have to develop a new method to do change detection.

3. Multi-Block PCA

Because of facing many difficulties in explaining the results of the traditional PCA method when doing change detection, especially when having to give out the differences between PC_1 and PC_2, we put forward a new idea in processing PCA to try to solve such a problem both in the theory and in its application field.

In the past literatures, there does exist such a word 'multi-block' PCA[16], but its meaning is totally different from ours. It was developed under the name Consensus-PCA in process monitoring. But what we mean here is to do PCA process as following steps:

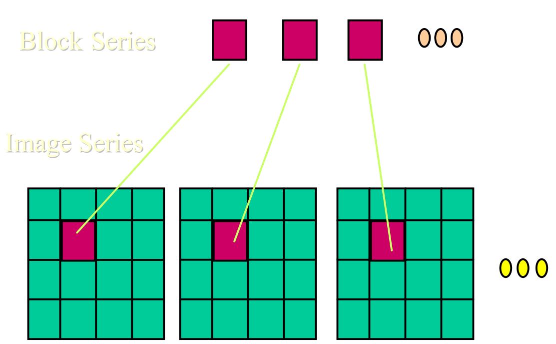
1) Partition. To divide each of the images into *m* blocks according to a defined way;
2) Group. To group the blocks at the same position in all the initial images into a block image series to make *m* series;
3) Block PCA. To analyze those block series by PCA process and get their principle components;
4) Combination. To combine those principle components with the same order of eigenvalues to form a new image.

The detail is as follows.

Partition. Beginning from a series of images $(X_1, \ldots, X_n)^t$, we divide each X_i into a group of sub-images or blocks $(B\text{-}X_{i1}, \ldots, B\text{-}X_{im})$, $i\in[1, n]$. Then all the blocks $(B\text{-}X_{ij})$, $i\in[1, n]$, $j\in[1, m]$, constitute the same matrix as $A=(X_1, \ldots, X_n)^t$, which means $A=(B\text{-}X_{ij})$.

Group. In matrix A, while fixed its row *i*, it is exactly the image X_i; while fixed its column *j*, $(B\text{-}X_{1j}, \ldots, B\text{-}X_{nj})$ can be regarded as a sub-image/block series extracted from the initial images $(X_1, \ldots, X_n)^t$, which can be seen in Figure 3. Obviously there are *m* series in total.

Figure 3 Block image series (there are *n* images in total and for each image there are *m* blocks)



Block PCA. In this step, we apply PCA analysis on those *m* block series separately. For example, in series *j*, $(B\text{-}X_{1j}, \ldots, B\text{-}X_{nj})$, $j \in [1, m]$, after PCA process we can get *n* principle components such as $(B\text{-}PC_1, B\text{-}PC_2, \ldots, B\text{-}PC_n)$, whose corresponding eigenvalues are ranked in descending orders.

Combination. After all the *m* series are processed, we obtain *m* $B\text{-}PC_1$s, which can be constructed into a new image — PC_1. Similarly, all the *m* $B\text{-}PC_2$s can be constructed into image PC_2, and so as to the other PCs. Thus we can obtain *n* new constructed images $(PC_1, PC_2, \ldots, PC_n)$. It is obvious that those images have the same size as the initial images $(X_1, \ldots, X_n)$. Inside all of the new images, PC_1 is the most important one.

Before analyzing the results upwards, we should review the general interpretation for traditional PCA. If the eigenvalue of PC_1 is much bigger than the others, PC_1 should be the background/common part of all the images $(X_1, \ldots, X_n)$, and could show the 'stable' and 'unchangeable' part of the whole image series. So it can be regarded as the 'background' of the whole image series.

Now let's consider the combined image PC_1 obtained from the 4 steps upwards. For each sub-block $(B\text{-}PC_1)$ of it, if its eigenvalue is much bigger than those in $(B\text{-}PC_2, \ldots, B\text{-}PC_n)$, it means it is the background/common part of all its block image series $(B\text{-}X_{1j}, \ldots, B\text{-}X_{nj})$. On the other hand, if its eigenvalue is near to some others of $(B\text{-}PC_2, \ldots, B\text{-}PC_n)$, it means it is a changed region. At last, after all the small changed regions/blocks are marked, the summary of them gives the entire changed region of the whole image series. The conclusion is based on the following rules:

1) If all the regions are similar to each other, the rank of the block series matrix will be near to 1. Then in the same block series the eigenvalue of $B\text{-}PC_1$ will be much bigger than all the other eigenvalues of $B\text{-}PC_i$. Conversely, if the calculated result of eigenvalue of $B\text{-}PC_1$ is much bigger than all the others, we can conclude there is no obvious change in this region. And across the block series, this small region keeps nearly the same.
2) If there are some changes in this small region, which means that there are more than one type in the block series but not only the pure background, the eigenvalue of $B\text{-}PC_1$ will not be so prominent compared with others. Conversely, if the eigenvalues are near to each other, it means that there exists a change in this region.

From the two rules we can conclude that the distribution of eigenvalues of block series shows if there exists a change across the image series. Those small regions with distributed eigenvalues show out all the changed regions.

4. Application of Multi-Block PCA method

In our tests the program is based on two rules:

1) For those 'backgrounds' / 'unchanged regions', most of their blocks must have very big maximal eigenvalues, which could be a main part in the whole sum of eigenvalues in their own principle component groups. On the other hand, their maximal eigenvalues should be more than at least 2 times bigger than the second eigenvalues.

2) In some principle component groups, there do exist some groups having close λ_1 and λ_2 (the maximal and second eigenvalues). And so their corresponding blocks can't be taken as the 'background' of 'common' parts of the image series but 'changeable' and 'active' region in the series.

Our tests will prove the rules right or not. From the viewpoint of calculation of eigenvalues of matrix in theory, we can also draw out similar rules.

Because conditions in reality are very complex, we try to separate them into different types and design different tests to examine the results of our method.

4.1. Man-made image series

At first we should prove the rules shown in Section 3. So we use Photoshop to make some images by ourselves based on one initial image. The series is shown in Figure 4.

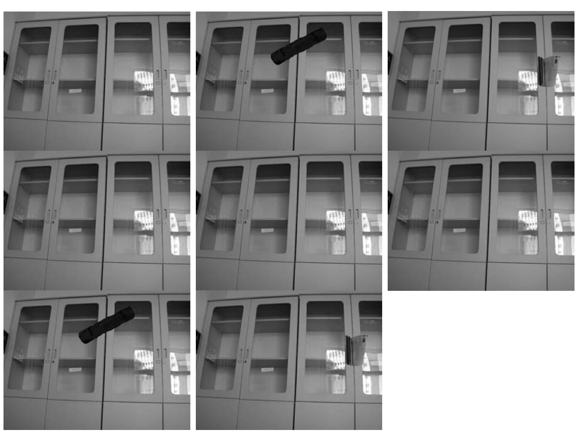


Figure 4 Image set

All the images are 640 x 480. There are two regions changed in the series. One is a long bag, the other is a journal stuffed into the gap of the shelf. The two objects are put on the initial image of shelf in Photoshop by ourselves. For the other parts of the images and other images, they are exactly identical in the intensity values.

Figure 5 shows the result of Multi-block PCA, in which a large 'pixel' representing a block. The red blocks mark out changed regions. They are near to the figures of the bag and the journal. The block's size is 20x20, which is changeable according to people's definition.

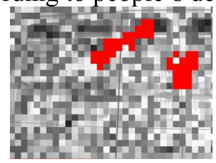


Figure 5 Result of change detection using PCA

The red regions are marked out with some differences from others as following: for the red blocks' sub-image series, the first eigenvalue of it is not too much bigger than the other eigenvalues—less than 10 times of the second eigenvalue. It means for those red block series, the eigenvalues are distributed and so there are more than one image type in the sub-image series. According to the rules in Section 3, there is a kind of change here. The threshold '10 times' is decided by experience.

4.2. Photos taken by random

As shown in Figure 6, we took some photos of shelves in our own laboratory. Different from those images in last test, the images in this set are all true photos taken in different time. So their intensity values are also changing between different images. And there are obviously two changed regions which can be seen with human's eyes: one is the bag hung on the shelf, the other is a journal stuffed inside the gap of shelf. But for the other parts, it is very difficult for us to find some dissimilarity by our eyes though their intensity values are not the same owing to many reasons.

Figure 6 Initial photos taken by man

The result of Multi-block PCA is shown in Figure 7. The red crossings showed the tiny light changes in the gaps, which cannot be found out by people's eyes in initial images. Only after we made them a movie series, we can find some difference in the gaps' region. Those changes are caused by light-varying by the time. The block's size in the result is 40x40. If we use the same 20x20 block as in last test, the pattern of the image will scatter because of instability causing by too many tiny intensity changes.

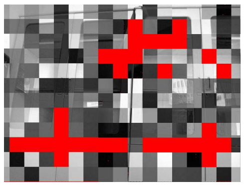


Figure 7 True images' result

The regions of the bag and the journal are not as good as in the test before. Thus it shows that the method we used is sensitive to images' tiny changes. So it should be able to help people find the dissimilarity among a series of similar images.

From this test we can see, though theoretically the multi-block PCA method sounds good, there are some problems in its realization. The most difficult one is that even if there is no any change in reality for a true scene, there will be some differences between the images taken at different time, just like the gaps' region in this test. Indeed, changes visualized in the images do not necessarily reflect a change in the true scene but can come from various factors such as meteorological conditions, changes of second order in the scene such as humidity, effect of wind, different acquisition view angles etc.

4.3. Satellite images

Using the same dataset as in Figure 1, we obtained from multi-block PCA computation the result illustrated in Figure 8.

Though it is even very difficult for specialists to give out the differences with their eyes among those images, the result shown in Figure 8 gave some possible changed regions, which will be useful for common overview. The block size here is 40x40 with the initial image size 803x617. And an explanation here is that the red lines at the bottom and at the right of the image was cause by unresolved parts because neither 803 nor 617 can be divided into integers by 40.

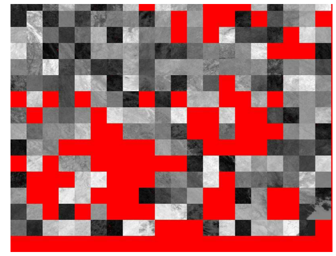


Figure 8 Result for satellite photos

Similar as the reasons explained above in last section, changes in appearance are not necessarily due to real changes. And besides of wind, humidity and view angle, there are lots of clouds in the initial dataset. So the results based on such a dataset cannot give too much meaningful information.

5. Discussion

From the tests upwards, we can find the multi-block PCA method is able to give good result of change detection for the image series taken by fixed camera and stable light condition.

And it is sensitive to camera's movement because such a movement will cause complete change of block matrix, which results in the eigenvalues' obvious change. This is useful when we want to find the difference between two similar images.

For the complex satellite images, the method is not too much helpful in finding interesting changed regions for the clouds and intensity changes in those same regions.

The advantages of the multi-block PCA compared with general PCA method on change detection are:

1) better description for the results;
2) clear physical meaning of the whole process;
3) with the block's size changed, multi-scale method can be developed;
4) with the block's shape changed, experience knowledge can be added and interesting region can be considered specially;
5) to provide a solution for PCA calculation when facing large image matrixes and there are no correlation among different parts of one single image.

The disadvantages are:

1) hard to find the clear edge of the changed regions because when the block size is getting too small, the results of PCA will be too sensitive to intensity;
2) because of the intensity difference, the combined images are not continuous in vision meaning.

A point we should mention is the computational cost. Compared with traditional PCA process, multi-block PCA hasn't increased computation time obviously.

This method is still under development. And there is some further work to do, such as the influence of the block sizes, block shapes, etc. To model an intensity transformation to eliminate the influence of light-change is also an interesting work. At the other hand, we only used one channel dataset until now, and in fact there are multi-sensorial and multi-temporal satellite images available[17][18][19][20]. How to apply Multi-block PCA method on those dataset to detect change is a good direction.

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