CHANGE DETECTION USING PRINCIPAL COMPONENT ANALYSIS AND FUZZY SET THEORY

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RÉSUMÉ

Cet article présente deux nouvelles méthodes permettant de faire un meilleur usage de l'information multibande obtenue à partir de données de télédétection pour la détection des changements. Au lieu d'effectuer une analyse des composantes principales sur une combinaison d'images multibandes initiales, celle-ci a été effectuée sur des données résultant de différences d'images. Ainsi, la plupart des informations relatives aux changements ont été conservées sur les premières composantes principales. Des opérations fondées sur la théorie des ensembles flous ont été proposées en vue de combiner les informations sur les changements provenant des différents canaux en une seule image. Les zones ayant subi des changements peuvent alors être extraites de cette dernière image. Des images de Kitchener-Waterloo, en Ontario, acquises par le capteur thématique de Landsat pendant deux années successives sont utilisées pour illustrer ces méthodes. Un certain nombre de stratégies sur l'utilisation des opérations fondées sur la théorie des ensembles flous sont également présentées.

SUMMARY

In this paper two procedures that were developed to make better use of multispectral information from remotely sensed data for change detection are discussed. Instead of applying principal component analysis (PCA) to a combined data set of original multispectral images, PCA was applied to difference images. Thus, most change information was preserved in the first few principal component images. Operations based on fuzzy set theory were proposed to combine change information from different image channels into a single-image channel. Changed areas could then be extracted from this single image. Landsat Thematic Mapper (TM) images acquired in two successive years over Kitchener-Waterloo, Ontario, are used to illustrate these methods. Some strategies on the use of fuzzy set operations are discussed.

INTRODUCTION

In remote sensing, changes can be determined by comparing the spectral response differences at the same spatial location among a set of two or more multispectral images acquired at different times. These images are first spatially registered. A commonly used change detection procedure then follows in which changes are identified via thresholding a difference image that has been obtained by subtracting one band of image on one date from the same band of image on another date. However, it is usually not possible to detect changes occurring in a region using only one spectral band because different types of changes may be captured in different bands. Therefore, changes have to be enhanced and extracted from multispectral imagery.

Two types of procedures for using multispectral data in change component enhancement are commonly used. The first type involves simple image arithmetic between images of the same spectral band for two dates. For convenience, we define the two images obtained for two different dates of the same spectral band as band-pair images. Image arithmetic includes ratioing and differencing band-pair images. Images so generated are referred to as change component images. To locate and identify change automatically, change component images are thesholded or classified (Jensen, 1986; Fung and LeDrew, 1988; Pilon *et al.*, 1988; Singh, 1989). To detect changes visually, ratioed or differenced band-pair images can be analyzed based on their colour displays on a video monitor or photographic products (Howarth and Wickware, 1981; Howarth and Boassan, 1983). Although logically straightforward due to increased data redundancy and display difficulties, this type of procedure becomes inefficient to use when the image dimension (that is, the number of spectral bands) exceeds three.

To overcome these difficulties, a second type of change component enhancement procedure employs image transformation

...thods. Transformation methods include vegetation indexing (VI) (Tucker, 1979), tasseled cap analysis (KT-Transform) (Kauth and Thomas, 1976), change vector analysis (CVA) (Malila, 1980), and principal component analysis (PCA) (Lodwick, 1979; Byrne *et al.*, 1980; Ingebristen *et al.*, 1985; Fung and LeDrew, 1987). By image transformation, the change information recorded in original multispectral data can be preserved in a relatively small number of components. Rather than serving as general enhancement tools, the VI and KT-Transform methods were developed specifically for such purposes as enhancing the vegetation or the soil component. While CVA has the potential of summarizing various types of change components and their magnitudes into separate image channels, it has rarely been applied since its introduction. Among these transformation techniques, the PCA method has been most commonly used. Researchers using PCA for change detection have reported that the minor component images are likely to contain most of the change information when multispectral images that have been obtained on two dates are applied as an integrated data set. The amount of change information contained in each principal component image, however, may vary from image to image. It may not be an easy task to determine which principal component image to work with. In addition, the use of PCA in such a manner is subject to the condition that the areas of changes have to be a small proportion of the entire study area (Richards, 1984; Fung and LeDrew, 1987).

It would be desirable to deal with only one image channel and to extract most, if not all, change information from this channel of image. In this paper, a method is presented for transforming change information into one image channel from images of different spectral bands. The main objectives are:

- to introduce an alternative method on the use of PCA for change component enhancement with which change information is guaranteed to be preserved in the major component images regardless the proportion of changed area in a study area; and
- to demonstrate the effectiveness of fuzzy set theory in combining change information from different image channels into a single-image channel.

METHOD

The change detection procedure proposed in this study can be divided into six steps:

- spatially register images from two different dates;
- undertake a band-pair image differencing for each spectral band and reduce registration noise;
- apply PCA transformation to the multispectral difference image;
- determine change membership functions for a number of selected change component images;
- apply fuzzy operations to combine change information in different change component images into a single image;
- determine changed areas based on the image generated at step five.

At step one, two images from different dates can be registered using a geometric correction program. After the image-to-image registration, two images with the same coordinate system are obtained: $X = \{x_i | i = 1, 2, ..., n\}$ of date one and $Y = \{y_i | i = 1, 2, ..., n\}$ of date two, where $x_i' = [x_{i1}, x_{i2}, ..., x_{ip}]$ and $y_i' = [y_{i1}, y_{i2}, ..., y_{ip}]$. The parameter n denotes the number of pixels in an image and p the number of spectral bands.

At the second step, a difference image, DIF_j, for each spectral band j, can be created, where $DIF_j = \{\delta_{ij} = (x_{ij} - y_{ij}) | i = 1, 2, ..., n\}$ and $j = 1, 2, ... p$. A grey-scale mapping can then be applied to every difference image, DIF_j, $j = 1, 2, ..., p$. This further reduces registration noise in each difference image (Gong *et al.*, 1992).

In traditional change detection, one difference image of a specific spectral band is selected among these difference images. This difference image should contain more change information than the other difference images for a particular application. An image thresholding technique is then applied to detect changes using the selected difference image (Jensen, 1986; Fung and LeDrew, 1988). For example, DIF_2, the red spectral band difference image of Landsat multispectral scanner (MSS) data is usually considered to contain more information on rural to urban land-cover changes than the other three MSS bands. Thresholds T_1 and T_2 can be determined on the histogram of DIF_2 using the mean (ave) and standard deviation (std) (**Figure 1**). Deciding whether a pixel has changed is simply a matter of testing whether δ_{ij} falls outside of range $[T_1, T_2]$.

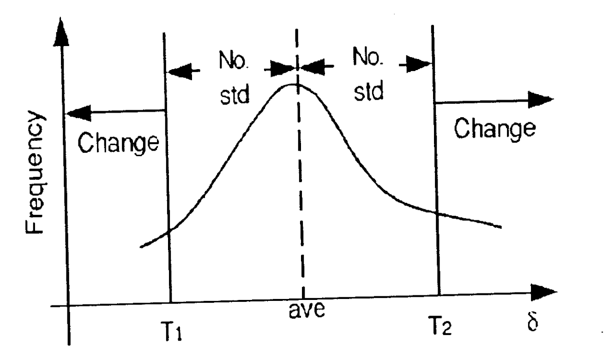

Figure 1
Change detection by thresholding a difference image. The curve shows the histogram of a difference image. Any pixel with a δ value smaller than T_1 or greater than T_2 in the difference image will be grouped into change, while a δ value between T_1 and T_2 will be grouped as unchanged. The thresholds are usually determined empirically as a number of standard deviations (No. of std) greater or smaller than the average (ave) of the difference image.

Two problems are associated with the above-mentioned traditional method, and they will be overcome by subsequent steps three to five. As mentioned in the introduction, the first problem is that different types of change information are contained in different spectral bands; thus, the use of one spectral band usually does not allow every type of changes to be detected. The second problem is that once thresholding is applied to a difference image, change information occurring at smaller magnitudes (that is, within range $[T_1, T_2]$) will be lost. Also, noise could be included as change if its magnitude falls outside range $[T_1, T_2]$.

At step three, the difference images are used to generate a variance-covariance matrix. This is used to find a new set of axes according to the eigen structure of the feature space. With the variance-covariance matrix, PCA can be applied to the difference images. The resultant principal component images are called principal component difference images, denoted by $PCD_j = \{\delta_{eij} | i = 1, 2, ..., n\}$ where $j = 1, 2, ..., p$; δ_{eij} is a pixel value for pixel i

. the jth principal component which results from a linear transformation of the difference images with the transformation coefficients determined with PCA. PCD images are obtained from a p-dimensional data set $\{x_i - y_i \mid i = 1, 2, ..., n\}$ instead of the traditional application of PCA in change detection where a combined two-date data set, $\{(x_i' \; y_i')' \mid i = 1, 2, ..., n\}$ of two p dimensions, is used. Because the variance in a difference image represents primarily change information and the purpose of PCA is to preserve most variances into the first few principal components, the application of PCA to difference images will result in most change information preserved in the first few PCD images.

At step four, the first two or three PCD images containing change information are selected. The exact number of PCDs is determined according to the eigenvalues and the correlation matrix of difference images. Each selected PCD image and its histogram are analyzed, and a fuzzy membership function of change is empirically defined based on the analysis results. From **Figure 1**, it is reasonable to assume that the more distant a pixel value δ is from the average, ave, the more likely is that pixel to fall into the change class. Based on the shape of the histogram of a PCD image, parameters of a fuzzy membership function of change can be determined. While a fuzzy membership function may take a variety of forms (Zadeh, 1978), in the case of **Figure 1** an inverse triangular-shaped function may be suitable. A more sophisticated change membership function may be determined based on the knowledge of the various types of change in the study area. For example, statistics on various change types can be estimated from selected training samples.

A fuzzy membership function of change, $\mu cj(\delta_e)$, can be defined as:

$$\mu_{cj}(\delta_e) = \begin{cases} 1 & 0 \le \delta_e < L_\delta \\ (\delta_e - \text{ave})/(L_\delta - \text{ave}) & L_\delta \le \delta_e < \text{ave} \\ (\delta_e - \text{ave})/(H_\delta - \text{ave}) & \text{ave} \le \delta_e < H_\delta \\ 1 & H_\delta \le \delta_e \le 255 \end{cases}$$

where $\mu_{cj}(\delta_e)$ represents the degree of pixel value δ_e in image PCD_j belonging to a fuzzy set of change, C. $L\delta$, ave, and $H\delta$ are the three parameters defining the inverse triangular-shaped function. $L\delta$ and $H\delta$ can be determined empirically by examining the histogram distribution of image PCD_j, and ave is the average pixel value in image PCD_j. A graphical form of $\mu_{cj}(\delta_e)$ is shown in **Figure 2**. After applying a fuzzy membership function, $\mu_{cj}(\delta_e)$, to an image, PCD_j, a change membership (CM) image, $CM_j = \{\mu_{cj}(\delta_{ei}) \mid i = 1, 2, ..., n\}$, is obtained.

At the fifth step, various change information from different CM images can be combined into one image, CCM, by applying the fuzzy set theory (Zadeh, 1965). Most operations based on the fuzzy set theory can be realized by using three basic types of fuzzy set operator: fuzzy union ($\vee$), fuzzy intersection ($\wedge$), and fuzzy complement ($\bar{\mu}$). While there are a number of definitions for fuzzy union and fuzzy intersection, the maximum and minimum rule are used in this study. Therefore, fuzzy union of μ_1 and μ_2 is equivalent to $\max(\mu_1, \mu_2)$, and their fuzzy intersection is $\min(\mu_1, \mu_2)$. A fuzzy complement of μ_1 is $1 - \mu_1$. For example, if one wishes to combine change information in three CM images in such a manner that both the subtle changes in CM_3 and changes in either CM_1 or CM_2 are included in the final resultant image, $CCM = \{\mu(\delta_i) \mid i = 1, 2, ..., n\}$, the following operation can be used:

$$\mu(\delta_i) = (1 - \mu_{c3}(\delta_i)) \wedge (\mu_{c1}(\delta_i) \vee \mu_{\chi 2}(\delta_i))$$

where $1-\mu_c3(\delta_i)$ represents the complement of $\mu_c3(\delta i)$ because subtle changes have lower degrees of change membership in image CM_3. Fuzzy set operations should be defined according to the characteristics of changes. In most cases, successful change information extraction requires that knowledge about the study area and expert knowledge on various change types be properly represented with fuzzy membership functions and fuzzy set operations.

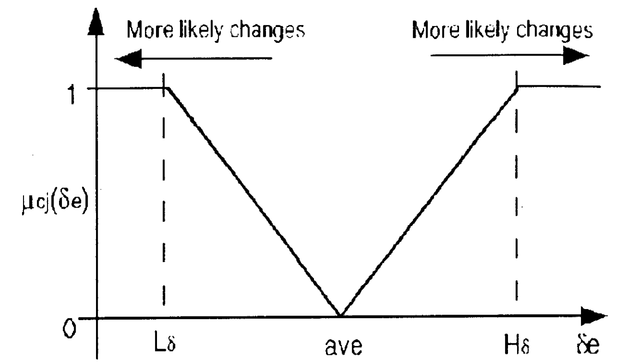

Figure 2.
An example fuzzy membership function of change. The degree of a pixel value, δ_e, belonging to change denoted by $\mu_c(\delta_e)$ ranges from 0 to 1. The further is δ_e away from ave, the higher is $\mu_c(\delta_e)$. $\mu_c(\delta_e)$ saturates as δ_e falls outside of range ($L\delta$, $H\delta$).

Once the desirable change information from different image channels has been combined into one image CCM, at the final step, the CCM itself can be stored in a database to represent change information. One can also apply the thresholding or classification technique to determine and identify areas of change and to make a change map.

TEST AND RESULTS

In this section, steps one to five on the use of PCA and fuzzy set theory in change detection in the previous section are illustrated using an example. However, no attempt was made for step six to undertake a thorough change detection of the study area. Instead, the purpose is to combine change information from different image channels into a newly created image channel.

The principal component analysis module, PCA, image arithmetic, ARI, and image display programs in the EASI/PACE image analysis software package (PCI Inc., 1991) were used in this study. Programs implementing the grey-scale mapping, the fuzzy membership functions, and the fuzzy set operations have been developed by the author as additional EASI/PACE modules.

The Study Area and Data Preparation

The study area consists of a large sector of the twin cities of Kitchener-Waterloo, Ontario, and a small part of their surrounding rural area. A number of change detection studies have been carried out for this area with both Landsat Multispectral Scanner and Thematic Mapper data (Fung and LeDrew, 1987, 1988; Fung, 1990).

TM data for this area were acquired on August 3, 1985, and July 21, 1986 (Path-Row #18-30). During this period, major changes occurred at the rural-urban fringe where agricultural land was either cleared for construction or has undergone crop rotation (Fung, 1990). Illumination difference is ignored because these two images were obtained around the same time of the year. The atmospheric difference is assumed to be horizontally homo-

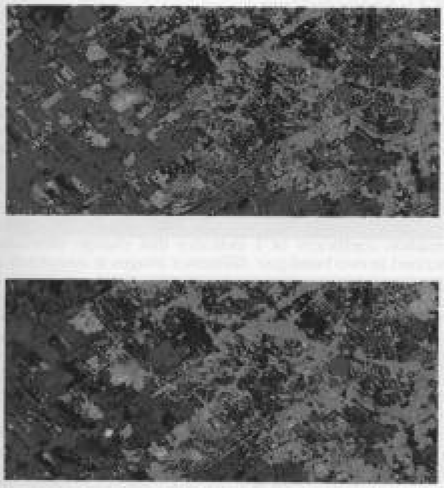

Figure 3.
The 1985 (top) and 1986 (bottom) Landsat TM images of Kitchener/Waterloo, Ontario. Both images are black-and-white versions of colour displays by assigning TM bands 2, 3, and 4 with blue, green, and red colour guns, respectively.

geneous at each image acquisition time because the size of the study area is relatively small. This assumption implies that the actual change in the difference image is not modified significantly by the atmosphere. Because TM images often manifest striping effects due to the sensor radiometric calibration problem, a destriping program has been applied to both images.

Part of the 1986 TM image (approximately 400 by 600 pixels) covering the study area was geometrically registered to part of the 1985 one using 12 ground control points. A first-order polynomial transformation with a nearest neighbour sampling scheme was used. The standard error of geometric registration estimated from the 12 ground control points is 0.000 and 0.198 pixels across-track and along-track, respectively. Finally, subscenes of 250 by 512 pixels of the registered images were used. A black-and-white version of the colour composite of Bands 2, 3, and 4 of this subscene is shown in **Figure 3**, with the 1985 image at the top and the 1986 one at the bottom. During the experiment, TM bands 1 to 5 and 7 from both dates have been used. They constitute a 12-channel data set.

Traditional Use of Principal Component Analysis

As described in the introduction section, in change detection, PCA has been traditionally applied to a multi-date multispectral data set. With the two-date TM images of this study, the problem associated with this procedure can be illustrated. Normally, the variance-covariance matrix obtained from the entire image (or a systematic sampling procedure is made if the image data volume is too large) is used to determine the eigenstructure (that is, the principal component axes) of the feature space. After applying PCA to the two-date TM image set, a set of 12 principal component images were obtained, and the first four principal component images are shown in **Figure 4**. It can be seen from **Figure 4** that, while PC_1 and PC_2 primarily contain information about the non-

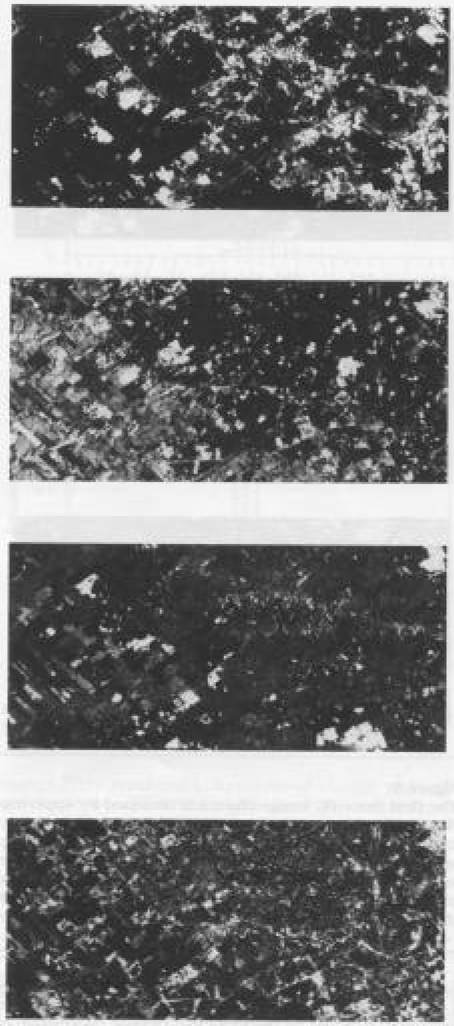

Figure 4.
The first four PC image channels obtained by applying the PCA to the two-date data set. The PCA is based on the variance-covariance matrix obtained from the entire image. PC3 mainly contains the change information.

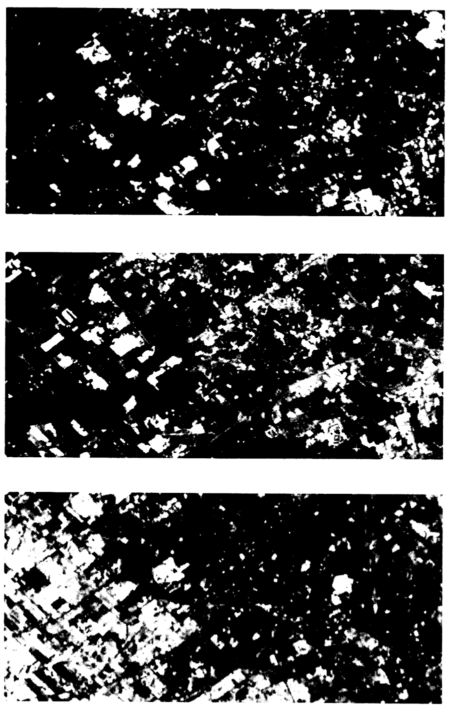

Figure 5.
The first three PC image channels obtained by applying the PCA to the two-date data set with PC_1, PC_2, and PC_3 located at the top, middle, and bottom of the figure, respectively. In this case, the PCA is based on the variance-covariance matrix obtained mainly from parts of the changed area in the image. PC_1 contains much of the change information.

changed area, change information dominates in the third principal component image, PC_3. PC_1 does not contain much change information. It would be desirable that change information can be consistently preserved in PC_3 for every change detection task. Unfortunately, this is not possible. If the proportion of the changed area changes, the PC images that contain change information will change accordingly. This can be illustrated by calculating the variance-covariance matrix mainly from some parts of the changed area. It is equivalent to calculating the variance-covariance matrix from a whole image, with a large proportion being change. With a different variance-covariance matrix, a new set of PC images has been obtained. The first three new PC images are shown in **Figure 5**. It is obvious in **Figure 5** that PC_1 contains mainly change information. The inconsistency of preserving change information in different PC images in the traditional use of PCA is a major drawback.

Principal Component Analysis of Band-Pair Difference Images, an Alternative

Difference images were derived by subtracting the 1985 image from the 1986 one. This resulted in six difference images corresponding to Landsat TM Bands 1 to 5 and 7. They were processed using the grey-scale mapping program to reduce registration noise. Each band-pair difference image usually contains specific change information. A correlation matrix constructed for all six difference images will reveal the extent of change information redundancy among these difference images. An absolute correlation coefficient of 1 indicates that change information contained in two band-pair difference images is completely redundant. On the other hand, a correlation of 0 means there is no change information duplicating between two difference images. Between the two extreme cases of 0 and 1, an absolute correlation close to 1 means that there is a high level of change information redundancy between two difference images; a low absolute correlation indicates that there is a low level of change information redundancy. It can be seen from the correlation matrix (**Table 1**) of the six difference images that change information varies from one band to another. While most of the difference images are positively correlated to a high degree, indicating they have a high level of change information redundancy, DIF_4 has very low negative correlations with the rest of the difference images. This suggests that two transformed images would result from the PCA procedure containing most of the change information.

Table 1.
Correlation coefficients of difference images.*

	DIF 1	DIF 2	DIF 3	DIF 4	DIF 5
DIF 2	0.940				
DIF 3	0.916	0.954			
DIF 4	-0.145	-0.126	-0.280		
DIF 5	0.720	0.762	0.784	-0.070	
DIF 7	0.731	0.767	0.805	-0.236	0.857

* DIF 1–5, 7 stand for difference images generated from each TM band-pair.

The PCA was applied to the processed difference images. As a result, six PCD images were obtained. The eigenvalues for all PCD image channels are listed in **Table 2**, where it can be seen that the first two PCD images contain over 90 percent of the variation of the six difference images. Because variances in difference images represent different degrees of changes, this 90 per-

Table 2.
Eigenvalues for the six principal component difference images.

PC Channel	Eigenvalue	% Variance
1	228.02	64.9
2	95.02	27.1
3	17.57	5.0
4	7.47	2.0
5	2.33	0.7
6	0.89	0.3

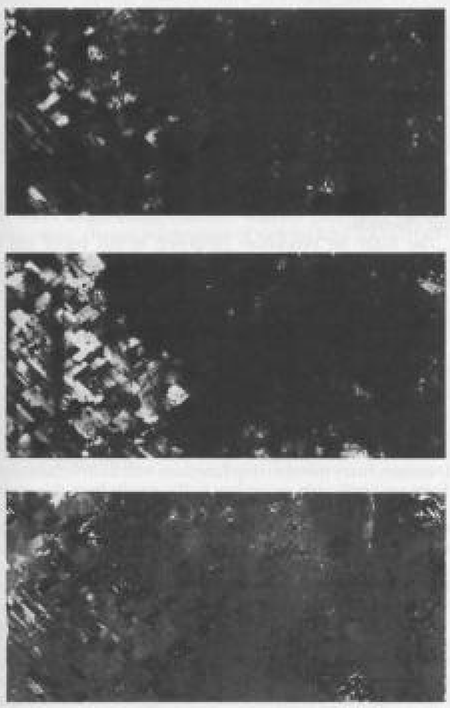

Figure 6.
The first three PCD images obtained by applying the PCA to the difference image channels with PC_1, PC_2, and PC_3 located at the top, middle, and bottom of the figure, respectively.

cent in variation indicates that most of the change information has been preserved in the first two PCD images. The first three PCD images are shown in **Figure 6**. From image PCD_3 it can be seen that the changed area contains a large portion of "pepper and salt" type of noise. For subsequent tests, only PCD_1 and PCD_2 are used.

Change Membership Images and Their Fuzzy Set Operations

The histograms for images PCD_1 and PCD_2 are shown in **Figure 7**. Because both histograms have distributions close to a normal one, fuzzy membership functions of change in a symmetrical inverse triangular form, as shown in **Figure 2**, were used. It should be noted that histogram distributions in **Figure 7** only helped to determine whether the inverse triangular function should be of symmetrical form. A histogram distribution does not offer any help for determining which type of membership function (for example, linear or non-linear) should be used. To

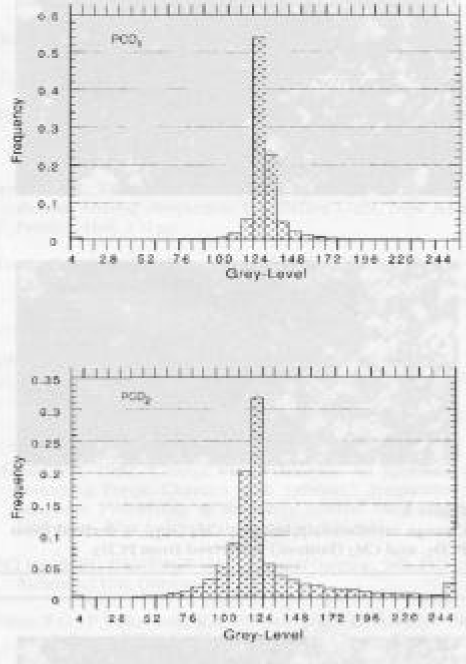

Figure 7.
The histograms of image PCD_1 and PCD_2.

construct fuzzy membership functions of change, two sets of parameter values ($L\delta$, ave, and $H\delta$) for PCD_1 and PCD_2 were determined from their histograms. They were: 97, 127, and 157; and 50, 120, and 190 for PCD_1 and PCD_2, respectively. Fuzzy membership functions were then applied to PCD_1 and PCD_2 to create CM_1 and CM_2 (**Figure 8**). Image CM_1 mainly shows land use changes from rural to urban conversion. On the other hand, it seems that crop rotation in agricultural land is primarily contained in image CM_2. Since no ground truth knowledge about changes in the study area was available, detailed change detection was not attempted. A fuzzy union was applied to image CM_1 and image CM_2 to generate image CCM (**Figure 9**). It can be seen from **Figure 9** that the change components in image CM_1 and image CM_2 have been successfully integrated into image CCM. Further change information analysis and extraction may then be done using only one image, image CCM.

DISCUSSION

Traditionally, PCA is directly applied to multi-date multispectral images. In traditional use of PCA for change component enhancement, variances and covariances are calculated not only from the changed part in multi-date original images but also from

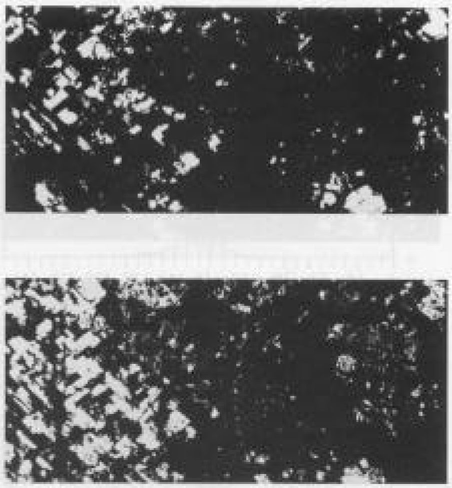

Figure 8.
Change membership images. CM_1 (top) is derived from PCD_1, and CM_2 (bottom) is derived from PCD_2.

Figure 9.
The combined change membership image CCM.

the unchanged part. The resultant principal component (PC) images will primarily contain information of either the changed part or the unchanged part of an image depending on which part of the image the variance dominates. It is often assumed that the changed part in an image is small in proportion in comparison with the unchanged part; thus change information is usually contained in minor PC images (Richards, 1984). In fact, it may be difficult to separate variances into those coming from the changed areas and those from the unchanged areas. Therefore, it is hard to determine which of those PC images contain change information. From this perspective, it is easier to use PCD images than to use PC images.

The test example presented in the previous section was designed to "shoot two birds with one stone"—that is, to illustrate the new use of the PCA procedure and to demonstrate the use of fuzzy set operations in combining change information from a number of image channels, which contain change information. The example on the two ways of using PCA clearly indicates that in traditional use of PCA, the proportion of changed area in an image determines which principal component images will contain change information. Rigorously speaking, it is the relative amount of variance between the changed area and the unchanged part in an image that determines which particular PCs contain change information. If the amount of variance from changed areas in an image dominates the total variance of the image, the first PC image will contain the change information. As the amount of variance from changed areas in an image decreases, change information will be preserved in minor PC image channels.

The fuzzy set procedure proposed in this paper can be applied to convert other types of images containing change information into change membership (CM) images. For example, instead of using PCD images, band-pair difference images and/or ratioed images can be used if one wishes to integrate different types of change information into one image channel. To do so, fuzzy membership functions have to be determined for each difference or ratio image channel. For a ratio image channel, the change information may not present a normal distribution. Therefore, different parameters or even forms of fuzzy membership functions may be used than a symmetrical inverse triangular function, as used in this research. As for difference images or the PCD images, fuzzy membership functions with an inverse triangular form are applicable, according to the results from this study.

The advantage of using CM images is that changes of various types and magnitudes are preserved. Therefore, almost no change information is lost. Subsequent fuzzy set operations can be defined according to the characteristics of specific types of changes, and these operations can be applied to CM images to extract those changes.

In the process of CM image generation, however, care has to be taken when parameter values ($L\delta$, ave, and $H\delta$) are to be determined from the difference images or PCD images. The actual data variance in each band of difference image or each channel of PCD image may be modified by scaling, which is often taken as a procedure to force the data range to fit in between 0 and 255 to produce a byte image. The scaling effect can be noted by comparing the two histograms in **Figure 7**. Contrary to the fact that PCD_1 contains more data variation than PCD_2, the effective standard deviation of PCD_2 (35) is greater than that of PCD_1 (21). In order to achieve a balanced contribution of change information from each difference image or each PCD image during the change information integration stage, the scaling effect can be compensated by adjusting $L\delta$ and $H\delta$ for each image according to the relative magnitudes of the effective standard deviations and actual standard deviations of all the image channels under consideration. For example, as indicated in **Table 2**, the actual standard deviations of PCD_1 and PCD_2, which are square roots of their corresponding eigenvalues, are 15.1 and 9.75, respectively. Due to the scaling effect, however, the effective standard deviations are 21 and 35, respectively. Therefore, a narrower range between $L\delta$ and $H\delta$ for PCD_1 than that for PCD_2 should be used. To balance the change information from PCD_1 and PCD_2 in CCM, the range ratio of [$L\delta$, $H\delta$] between PCD_1 and PCD_2 should be 0.387. The range ratio in the previous section for PCD_1 and PCD_2 is selected according to 0.387.

CONCLUSIONS

Generating difference images before undertaking the principal component analysis (PCA) for enhancing and extracting change information from multispectral images is a valuable approach. In this approach, change information is always accumulated in the first few principal component difference images, and thus makes it a trivial task for an image analyst to determine which PCA image contains change information. However, difference images tend to be noisy and noise reduction needs to be undertaken (for example, Gong *et al.*, 1992).

Operations based on the fuzzy set theory can be used to further integrate change information from different image channels into a single-image channel. With the procedure illustrated in this paper, change information of various land cover types can be eventually preserved and stored in one image channel. With this image, subsequent information extraction methods, such as thresholding, classification, and various quantitative analysis algorithms, can be applied when specific change information is to be derived from multispectral images acquired from different dates.

Further research is needed to apply the methods proposed here to practical change identification and quantitative change information extraction tasks. A training sample of a changed area should be collected as a basis for change membership function determination, while a test sample is needed for quantitative accuracy assessment.

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