Augment the Spatial Resolution of Multispectral Image Using PCA Fusion Method and Classified It’s Region Using Different Techniques.

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Abstract: Image fusion is a useful technique to obtain a new image from a set of input images of the same scene that describes the scene better than any single input image date. In this research two image processing applications have been applied, first application, fuse the panchromatic and multispectral image using principle component analysis (PCA) fusion method to enhance the quality of multispectral band, where the image was capture by quick bird with spatial resolution 0.6 m and 4m for panchromatic and multi-spectral image respectively. then apply the second application, which can be achieved as classified the resultant fusing image using minimum distance, support vector machine classifier and k-mean cluster. As well as, this research shows the fidelity criteria of the fusing image and statistical distribution of the classes of the resultant fusing image.

Key words: Image fusion, PCA, minimum distance, support machine classifier, k-mean cluster.

1. Introduction

Image fusion is defined as the process of combining substantial information from several sensors using mathematical techniques in order to create a single composite image that will be more comprehensive and thus, more useful for a human operator or other computer vision tasks. The most common forms of fusion is putting various sensors together in order to detect and parametrically evaluate a sensed object, therefore as synergetic fused dataset is more useful than the original individual datasets for a specific application. As stated by several authors, data fusion is useful for several purposes such as land surface objects and phenomena detection, recognition, identification, tracking, classification, etc. These objectives maybe encountered in many fields of study like remote sensing, defense systems, robotics, medicine, space, environmental, urban, agricultural studies, etc. [1,2]. A good example of this is the fusion of multispectral satellite images of low spatial and high spectral resolution with panchromatic images of high spatial and low spectral resolution. A multispectral sensor captures light of several distinct wavelengths or bands for each spatial element or pixel. Hence, a multispectral image can be considered to consist of several layers where each layer contains the recorded intensity of light of a specified wavelength, or rather, a tight band of wavelengths. On the other hand, a panchromatic sensor captures the total intensity of light from a broad continuous range of wavelengths. Due to cost and complexity issues, the multispectral sensor has much smaller aperture than the panchromatic sensor thus reducing the spatial resolution of the sensed multispectral image [3]. Since the multispectral image contains information about light of specific and narrow bands of wavelengths, it has a high spectral resolution while the panchromatic image has low spectral resolution since it represents light of a broad spectrum of wavelengths. As well as the multispectral image has low spatial resolution while the panchromatic image has a high spatial resolution. The output is an image that has the high spectral resolution of the multispectral image and also the high spatial resolution of the panchromatic image. In this research two processing have been applied on the image. Firstly PCA fusion technique was used to fuse the panchromatic and multi-spectral band to get high spatial and spectral resolution image. Secondly supervised (minimum distance and support vector machine classifier) and k-mean unsupervised classification have been used to classify the resultant fused image to show the statistical distribution of the fused image classes. Many Image Quality Metrics such as correlation coefficient (CC), Relative Dimensionless Global Error in Synthesis (ERGAS), Relative Average Spectral Error (RASE) [4], Root Mean Squared Error (RMSE), special correlation (SC), and Spectral Information Divergence (SID) [5,6] have been used to compute the quality of resultant fused image.

2. Principal Component Analysis Method

PCA is a numerical procedure that transforms a number of correlated variables into a number of uncorrelated variables called principal components [7]. The first PC accounts for much of the variance in the data, and each succeeding component accounts for much of the remaining variance; the first PC is along the direction with the maximum variance. while the second component PC 2 is constrained to lie in the subspace perpendicular to the PC 1; within the subspace this component points to the direction of maximum variance, the third component PC 3 is taken in the maximum variance direction in the subspace perpendicular to the PC1 and PC 2 , and so on. PC basis vectors depend on
the data set. Let $X$ be a $d$-dimensional random vector with zero mean, and orthonormal projection matrix $V$ be such that $Y = VX$. The covariance of $Y$, $\text{cov}(Y)$ is a diagonal matrix. Using simple matrix algebra we get [8]

$$\text{cov}(Y) = E\{YY^T\} = E\{(V^TX)(V^TX)^T\} \quad (1)$$

$$\text{cov}(Y) = E\{(V^TX)(X^TV)\} = V^T\text{cov}(X)V \quad (2)$$

Multiply eq. (2) by $V$, the result

$$\text{cov}(Y) = VV^T\text{cov}(X)V = \text{cov}(X)V \quad (3)$$

The multispectral and panchromatic images to be fused are arranged in two column vectors. Then compute the mean value $M$ for each column, after that subtract the mean vector from each column of the data matrix $Z$, then compute the covariance matrix $C$ of $Z$ as $C = XTX$ then compute the eigenvectors $V$ and eigenvalues $D$ of $C$ and sort $V$ in decreasing order and finally; consider the first column of $V$ that corresponds to the largest Eigen value to compute the PCs NPC$_1$ and NPC$_2$ as [8].

$$\text{cov}(Y) = \begin{bmatrix} \lambda_1 & 0 & \ldots & 0 \\ 0 & \lambda_2 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \lambda_d \end{bmatrix} \quad (4)$$

$$\text{cov}(Y) = \lambda_1 V_1 \lambda_2 V_2 \lambda_3 V_3, \ldots, \lambda_d V_d \quad (5)$$

$$\lambda_i V_i = \text{cov}(X)V_i \quad I=1,2,3,\ldots,d. \quad (6)$$

The fused image is obtained by, for more information see the diagram in fig 1:

$$I_f = NPC_1 I_1 + NPC_2 I_2 \quad (7)$$

Table 1: Represents the Quality Metric of the fusing image

<table>
<thead>
<tr>
<th>criteria</th>
<th>PCA</th>
<th>Reference values</th>
</tr>
</thead>
<tbody>
<tr>
<td>CC</td>
<td>0.087531</td>
<td>0</td>
</tr>
<tr>
<td>ERGAS</td>
<td>13.4722</td>
<td>0</td>
</tr>
<tr>
<td>RASE</td>
<td>53.6048</td>
<td>0</td>
</tr>
<tr>
<td>RMSE</td>
<td>80.1904</td>
<td>0</td>
</tr>
<tr>
<td>SID</td>
<td>0.22531</td>
<td>0</td>
</tr>
<tr>
<td>SC</td>
<td>0.91943</td>
<td>1</td>
</tr>
</tbody>
</table>

The fused image using principle component analysis can be shown in fig 2 and the comparison between the original image and the fusing image can be achieved using many fidelity metric such as correlation coefficient(CC), Relative Dimensionless Global Error in Synthesis (ERGAS), Relative Average Spectral Error (RASE), Root Mean Squared Error (RMSE), special correlation( SC), and Spectral Information Divergence (SID). The result can be shown in table 1.
3. Image Classification

Digital image classification is the process of assigning pixels to classes. Usually each pixel is treated as an individual unit composed of values in several spectral bands. By comparing pixels to one another and to pixels of known identity, it is possible to assemble groups of similar pixels into classes that are associated with the informational categories of interest to users of remotely sensed data. These classes form regions on a map or an image, so that after classification the digital image is presented as a mosaic of uniform parcels, each identified by a color or symbol. These classes are, in theory, homogeneous: Pixels within classes are spectrally more similar to one another than they are to pixels in other classes. In practice, of course, each class will display some diversity, as each scene will exhibit some variability within classes [9]. In this research three classification methods have been used to perform the classification minimum distance and support machine classifier belong to supervised classification and k-mean belong to unsupervised classification, these methods can be explain as below:

3.1 Minimum Distance Classifier

It is based on the minimum distance decision rule that calculates the spectral distance between the measurement vector for the candidate pixel and the mean vector for each sample. Then it assigns the candidate pixel to the class having the minimum spectral distance. If we would use the Euclidean distance metric for instance, we would find the class L by [10]:

$$L = \text{argmin}_i \sum_{j=1}^{d} (X_i - \mu_j(L_i))^2$$

The idea behind this is that the mean should be a representative value for the class, defining usually the centre of all the sample vectors that were labeled as that class in input space. The result of applying this classifier can be shown in fig. 3.

3.2 Support Vector Machine Classification

Support vector machine (SVM) has been used to identify the class associated with each pixel. SVM provides good classification results from complex and noisy data. SVM is a classification system derived from statistical learning theory. It separates the classes with a decision surface that maximizes the margin between the classes. The surface is often called the optimal hyperplane, and the data points closest to the hyperplane are called support vectors. The support vectors are the critical elements of the training set. The mathematical representation of each kernel is listed below. The result of applying this classifier can be shown in fig. 4.

Linear;

$$K(X_i, X_j) = X_i^T X_j$$

(11)

Polynomial;

$$K(X_i, X_j) = (\gamma X_i^T X_j + r)^d, \gamma > 0$$

(12)
RBF:

\[ K(X_i, X_j) = \exp(-\gamma \|X_i - X_j\|^2) , \gamma > 0 \] (13)

Sigmoid:

\[ K(X_i, X_j) = \tan h(\gamma X_i^T X_j + r) \] (14)

Where:

\( \gamma \) is the gamma term in the kernel function for all kernel types except linear.

\( d \) is the polynomial degree term in the kernel function for the polynomial kernel.

\( r \) is the bias term in the kernel function for the polynomial and sigmoid kernels.

\( \gamma, d, \) and \( r \) are user-controlled parameters, as their correct definition significantly increases the accuracy of the SVM solution [11].

### 3.3 K-means clustering

K-Means unsupervised classification calculates initial class means evenly distributed in the data space then iteratively clusters the pixels into the nearest class using a minimum distance technique. Each iteration recalculates class means and reclassifies pixels with respect to the new means. All pixels are classified to the nearest class unless a standard deviation or distance threshold is specified, in which case some pixels may be unclassified if they do not meet the selected criteria. This process continues until the number of pixels in each class changes by less than the selected pixel change threshold or the maximum number of iterations is reached [12]. K-means method uses \( K \) prototypes, the cancroids of clusters, to characterize the data. They are determined by minimizing the sum of squared errors, [11]. The result of applying this classifier can be shown in fig. 5.

\[
J_k = \sum_{k=1}^{K} \sum_{i \in C_k} (X_i - m_k)^2 
\] (15)

\[
m_k = \frac{\sum_{i \in C_k} X_i}{n_k} 
\] (16)

\( X \) = data matrix

\( n_k \) = is the number of points in \( C_k \)

\( C_k \) = the centroid of cluster

**Fig.3:** the result of minimum distance classifier

**Fig.4:** the result of support vector machine classifier
4. Conclusions

There are many metric as shown in table 1 have been used to analysis the results of fused images and to compare between the original and fused image. These ways include spatial and spectral quality, for spatial one it's easy to notice or to see the different between the edges of the result fusing image and multispectral. But when judging spectral quality, it seems to be more difficult to match the color of the result fusing image to the original multispectral image.

In this research PCA fusion technique has achieved on source images, these images were capture by QuickBird sensor (4m and 0.6m) resolution for multispectral and panchromatic band respectively. The second experimental part of this paper is image classification, many classification techniques have applied on the resultant fusing image. These techniques include K-mean for unsupervised, and minimum distance and support vector machine methods for supervised, no specified quality metric has been adopted to evaluate the classification method. But the statistical distribution of the classes as shown in fig.6 show that K-mean classifier give accurate classification compare with other classification technique, these belong to use three iteration when it has applied on the resultant fused image.
Fig.6: shows the statistical distribution of the image classes

5. References


