INK CLASSIFICSTION IN HYPERSPECTRAL IMAGES

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***Abstract*—Hyperspectral imaging provides vital information about the objects and elements present inside the image. That's why they are very useful in satellite imagery as well as image forensics. HSI can be used for document authentication using ink analysis which can provide sufficient information about the composition and type of ink. In this project, we have implemented HSI based ink classification technique using Principle Component Analysis for dimensionality reduction and K-means clustering for ink classification. We have used this technique to classify 33 different bands of ink.**

Keywords—Hyperspectral image (HSI); k-means clustering; Principal component analysis (PCA)

I. Introduction

HSI consists of several hundreds of bands that can provide valuable information which can't be extracted from the ordinary camera images. Due to this property, Hyperspectral images are widely used in field of Satellite imagery, photogrammetry and mining. Mining companies uses HSI to detect minerals beneath the earth surface. Hyperspectral Imaging is also used for document authentication in image forensics as it provides broad spectral information for the subjected image/document. Thus HSI can be used to minimize the chances of document forgery.

In this project, we have classified 33 ink bands using PCA (Principle Component Analysis) and k means clustering. Deep learning can be used for this task, but due to only 33 bands present in the dataset, we have utilized Pattern Recognition tools to classify the ink bands. Although different clustering techniques like fuzzy c means clustering can also be used but we have used k means clustering as it is simpler and it provides the required results for simple tasks.

II. Literature review

In [1], the authors have implemented a Convolution neural network (CNN) based deep learning algorithm to detect ink mismatch for document authentication in hyperspectral Document Image (HSDI). This technique utilizes spectral features like spectral correlation and spectral context to do ink classification. Six different CNN architectures were implemented and different training vs test ratios were evaluated. Experiments were performed on different types and different ratios of ink from different manufacturers and the results were evaluated. The performance of this algorithm outperforms the previous methods. The limitation in this method is that it requires prior knowledge of ink present in the document.
In [2], local thresholding technique was applied to separate foreground pixels from background pixels and then the authors have utilized fuzzy c-means clustering for classification of different inks present in the document. Experiments were carried out using different combinations of ink and feature selection was used to get optimal results.

In [3], hyperspectral unmixing scheme is used to identify spectral signatures of the ink and their component composition. This method performed better than previous methods on the test data.

In [4], PCA is used for dimensionality reduction of HSI and k-means clustering is applied. These clusters are eventually trained by multi-class SVM. This technique was validated on three benchmark images and this scheme was compared with standard one and it gave better results than the state of the art method.

III. Methology

The complete methodology of this project is depicted in figure 1.
As depicted in the above figure, as the HSI are input to the system, the dimensions of feature space are very large, which results in overfitting. To overcome this problem, PCA is applied on these images which extracts only the useful features. After this step, k means clustering is applied for ink band classification and then each band is depicted in different color.

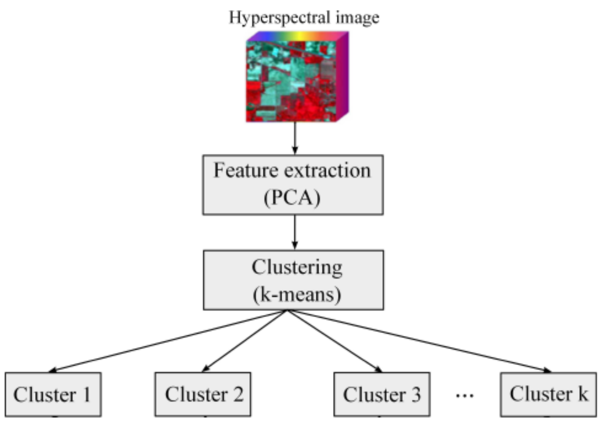


Figure 1 Methodology

A. *PCA (Principle Component Analysis):*

PCA is very useful and widely used technique for dimension reduction of the features/components.

Consider an HSI of (m * n * N) as in figure 2, the pixels (x,y) in an image can be represented by:

$$X_i = [x_1, x_2, ..., x_N]^T \quad (1)$$

N represents the no of HSI bands.

If m is the number of rows, n is the number of column in image, then M=m x n. then mean can be calculated as:

$$mean = \frac{1}{M}\sum_{i=1}^{M}[x_1, x_2, ..., x_N]_i^T \quad (2)$$

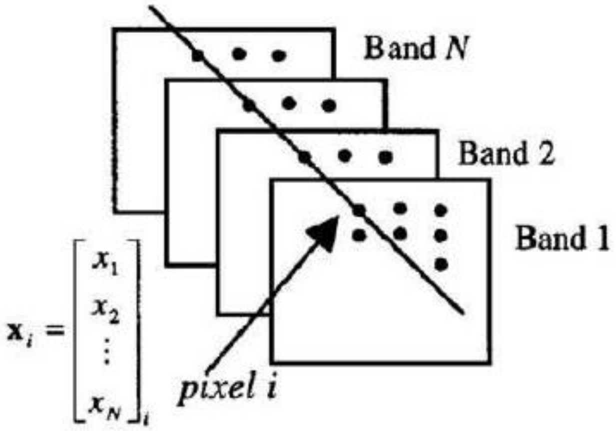


Figure 2 Pixel Vector in HSI

The covariance vector is given by:

$$C_X = \frac{1}{M}\sum_{i=1}^{M}(X_i - mean)(X_i - mean)^T \quad (3)$$

Next step is Eigen decomposition which can be found the following equation (4).

$$C_X = ADA^T \quad (4)$$

Where D is the diagonal vector consisting of eigenvalues of the covariance matrix. A is orthonormal matrix comprising of eigenvectors. The number of eigenvectors are N.

$$Y_i = A^T X_i, \ i = 1, 2, ..., M$$

Where Y is the PCA pixel vector and it represents the linear transformation. Yi contains all the PCA bands pixels. If we arrange all the eigenvalues calculated, in descending order like λ 1 >= λ 2 >= ... >= λ. N Now the first K rows of the matrix A^T form A_K^T.

$$Y_i = A_K^T X_i, \ i = 1, 2, ..., M$$

Here K represents the number of PCA having highest eigenvalue. Every pixel in HSI pixel vector can be mapped using the above transformation. Now we have M data points and each vector is of length K.

B. K-means clustering :

This technique is an unsupervised learning technique used to divide dataset into several clusters based upon of distance of each data point with its neighbor. Here we have used Euclidean distance. The initial centroids and number of clusters are input and based on the distances of each data point with each centroid. Each pixel is assigned to the nearest cluster. The final centroids are calculated after multiple iterations and data points are finally assigned to different clusters.

Suppose k are cluster in n samples are given such that n ∈ [1, k]. It minimizes the squared error between a cluster centroid 'c' and its members 'v' via the following criterion:

$$\underset{C}{argmin} \sum_{i=1}^{k} \sum_{j=1}^{n} \left\| \hat{v}_i - c_j \right\|^2$$

The K mean clustering algorithm is depicted in following figure:

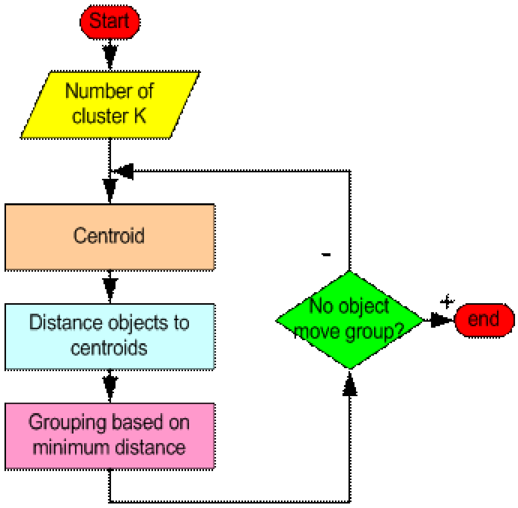


Figure 3 k-means algorithm

IV. RESULTS

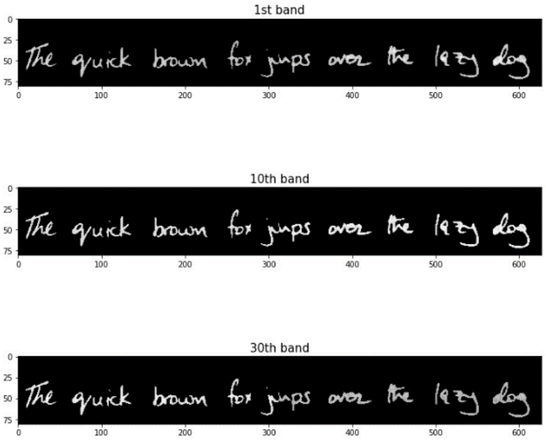
Unsupervised classification algorithm i.e. k-means divide image pixels into groups based on spectral similarity of the pixels without using any prior knowledge of the spectral classes. As a result, we get 3 clusters one for background pixels and two other clusters for two different inks as depicted in fig 6. Here we have no prior knowledge in the form of ground truth.

Performing supervised classification requires training a classifier with training data that associates samples with particular training classes. To assign class labels to pixels in an image having M rows and N columns, you must provide an MxN integer-valued ground truth array whose elements are indices for the corresponding training classes.

Many of the bands within hyperspectral images are often strongly correlated. The principal components transformation represents a linear transformation of the original image bands to a set of new, uncorrelated features. A very large percentage of the image variance can be captured in a relatively small number of principal components compared to the original number of bands.

Then we retain enough eigenvalues to capture a desired fraction of the total image variance. We then reduce the dimensionality of the image pixels by projecting them onto the remaining eigenvectors. We choose to retain a minimum of 99.9% of the total image variance as depicted by fig 7 [5].

Figure 4 1st, 10th and 30th bands of the hyperspectral image



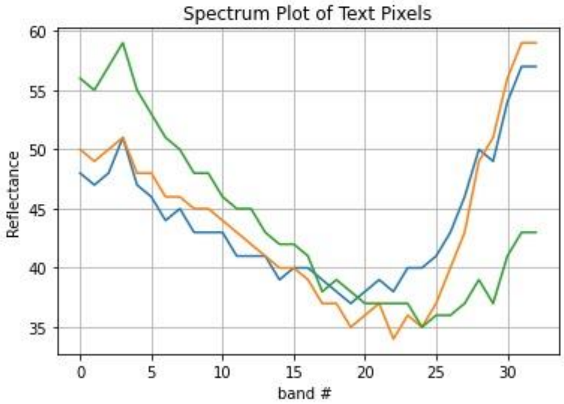


Figure 5 Plot the spectral responses of 3 random foreground pixels

Figure 6 No of inks predicted Using k means as 3 clusters are formed

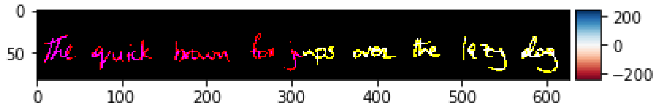


Figure 7 Use color-labeling to classify text written with different inks in the document.

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