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Noise Removal using Bi-dimensional Variational Mode Decomposition in Framework for Hyperspectral Image Segmentation

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Abstract: Hyperspectral imaging system contains stack of images collected from the sensor with different wavelengths representing the same scene on the earth. This paper presents a framework for hyperspectral image segmentation using a clustering algorithm. The framework consists of four stages in segmenting a hyperspectral data set. In the first stage, filtering is done to remove noise in image bands. Second stage consists of dimensionality reduction algorithms, in which the bands that convey less information or redundant data will be removed. In the third stage, the informative bands which are selected in the second stage are merged into a single image using hierarchical fusion technique. In the last stage, the fused image is segmented using FCM algorithm. This paper presents a new methodology of noise removal using bi-dimensional variational mode decomposition (BVMD) technique which is used in first stage of hyperspectral segmentation framework. First the noisy hyperspectral band is processed using BVMD to produce 2-D variational mode functions (VMF). Then Discrete Wavelet Transform (DWT) thresholding technique is applied to each VMF for denoising. The denoised band is reconstructed by the summation of DWT filtered VMFs. These denoised bands are used in subsequent stages in the framework, for better segmentation quality. This method is named as BVMD-DWT thresholding method and compared with BEMD-DWT thresholding method. The qualitative and quantitative analysis shows that BVMD-DWT thresholding method produces better noise removal than BEMD-DWT thresholding method and produces better segmentation results by combining all the features in hyperspectral bands.

Keywords: *Image Enhancement, Bi-dimensional Empirical Mode Decomposition, Variational Mode Decomposition, Fuzzy C-means, Remote Sensing, Image Processing.*

1. INTRODUCTION

The process of information extraction about an object on the earth using satellites is called remote sensing [1]. With the increase of spatial and spectral resolution of recently launched satellites, new methods have to be developed in analyzing the remote sensing data. In remote sensing, sensors are available that can generate hyperspectral data, involving many narrow bands in which each pixel has a continuous reflectance spectrum [2]. Unsupervised image segmentation is an important research topic in hyperspectral imaging, with the aim to develop efficient algorithms that provide high segmentation accuracy.

The hyperspectral image bands contain noise which is caused by the sensor problems or disturbance of transmission medium in the atmosphere which affects result of image segmentation. To remove noise, a new filter is designed based on Bi-dimensional Variational Mode Decomposition [BVMD] and Wavelets. The BVMD method [3] decomposes the image band into several Variational Mode Functions [VMF], with each mode has limited bandwidth in spectral domain. The wavelet based filtering is applied to all VMFs and the image band is reconstructed by combining the filtered VMFs. The same procedure is used for filtering the image bands.

After filtering, the next step is dimensionality reduction. In this paper, the dimensionality reduction is done using Spectral Correlation Mapper [SCM] based on the information present in the image bands. The dimensionality reduction step decreases many requirements for processing the hyperspectral data set such as storage space, computational load, communication bandwidth etc, thus increasing the efficiency of segmentation algorithm. After band selection, the next step is image fusion. The main goal of image fusion is to create a single image combining all the features in the selected image bands. A hierarchical image fusion technique presented in [4] is used for merging the selected image bands. In hierarchical fusion method, the images are grouped such that each group has equal number of images. This might lead to groups having images with highly varied information. In order to improve the efficiency of the algorithm, the grouping is done based on similarity between the images i.e. each group contain images with a similarity criteria. After getting a single image, the image is segmented using FCM clustering algorithm. The flow diagram of proposed framework is shown in figure 1. This method increases the segmentation accuracy both in qualitative and quantitative analysis when compared with K-means [5] and Moving k-means [6].

This paper is structured as follows: section 2 presents filtering using bi-dimensional empirical mode decomposition and wavelet filter, section 3 presents Bi-dimensional variational mode decomposition and Wavelet filtering section 4 presents dimensionality reduction method, section 5 presents hierarchical image fusion with grouping technique, section 6 presents FCM algorithm for image segmentation, section 7 shows experimental results and section 7 report conclusions.

2. BI-DIMENSIONAL EMPIRICAL MODE DECOMPOSITION AND WAVELET FILTERING METHOD

Empirical Mode Decomposition [7] is a signal processing method that decomposes any non-linear and non-stationary signal into oscillatory functions called Intrinsic Mode Functions (IMF) and residue. The EMD has the property that the original signal can be reconstructed by combining IMFs and residue. The shifting process [8] to obtain IMFs on a 2-D signal (image) is summarized as follows:

1. Let $I(x, y)$ be a hyperspectral image band. Find all local maxima and local minima points in $I(x, y)$.
2. Interpolate the local maximum points- Upper envelope $Up(x, y)$

   Interpolate the local minimum points- Lower envelope $Lw(x, y)$
3. Calculate the mean of lower and upper envelopes

$$\mathrm{Mean}(x, y) = \frac{(\mathrm{Up}(x, y) + \mathrm{Lw}(x, y))}{2} \tag{1}$$

4. Subtract the mean of envelopes from original image.

$$\mathrm{Sub}(x, y) = \mathrm{I}(x, y) - \mathrm{Mean}\,(x, y) \tag{2}$$

5. If $Sub(x, y)$ is an IMF, then

$$\mathrm{IMF}_i(x, y) = \mathrm{Sub}(x, y) \tag{3}$$

6. Subtract the extracted IMF from the input signal. Now the value of I(*x*, *y*) is

$$I(x, y) = I(x, y) - IMF_i(x, y) \tag{4}$$

Repeat steps (*b*) to (*f*) for the generating next IMFs.

7. This process is repeated until I(*x*, *y*) does not have any local maxima or local minima points. Original hyperspectral image band can be reconstructed given by

$$I(x, y) = \sum_{i=1}^{n} IMF_i(x, y) + res(x, y) \tag{5}$$

2.1. Image Denoising using BEMD

The filtering of hyperspectral image band using BEMD and mean filter is given below:

1. Apply 2-D EMD for each band in the hyper spectral image to obtain IMFs.
2. The first few components are high frequency components which are suitable for de-noising using Wavelet based thresholding method. The filtered components are denoted using DIMFs.
3. The filtered image band RI is reconstructed according to the given equation:

$$RI = \sum_{i=1}^{d} DIMF + \sum_{i=d}^{k} IMF_i \tag{6}$$

The filtering mechanism is shown in figure 2.

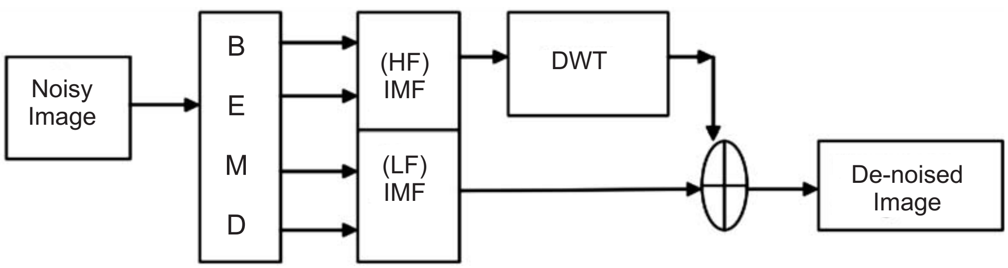

Figure 1: Filtering using BEMD + Mean filter

3. BI-DIMENSIONAL VARIATIONAL MODE DECOMPOSITION AND WAVELET FILTERING METHOD

In the Variational Mode Decomposition (VMD) framework, the signal is decomposed into *k* mode components, where each mode u_k is required to be mostly compact around a center pulsation ω_k determined along with the decomposition [3]. For a one-dimensional Signals, the algorithm to assess the bandwidth of a mode u_k is as follows:

1. Compute the analytic signal associated with u_k by means of the Hilbert transform to obtain a unilateral frequency spectrum.
2. Shift the mode's frequency spectrum to baseband by mixing with an exponential tuned to the respective estimated center frequency.
3. Estimate the bandwidth through the H1 Gaussian smoothness of the demodulated signal; for example, the squared L2-norm of the gradient.

Then, the constrained variational problem to find all the modes is defined by

$$\min_{u_k, \omega_k} = \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\| \right\}$$

Subject : $$\sum_k u_k = s \tag{7}$$

where s stands for the signal to decompose, u_k is the kth mode, ω_k is a frequency, δ is the Dirac distribution, t is a time, and * denotes convolution. Higher values of k indicate modes with lower frequency components. The same procedure will be done for 2-D VMD leading to bi-dimensional Variational Mode Decomposition [BVMD].

The mechanism of de-noising using 2-D VMD-DWT is summarized as follows

1. Apply 2-D VMD for noisy microarray to obtain VMF_i (i = 1, 2, …k). The kth VMF is called residue.
2. The VMFs are denoised with DWT Thresholding technique presented in section 2. This de-noised VMF is represented with DNVMF.
3. The denoised image is reconstructed by the summation of VMFs given by

$$\text{RI} = \sum_{i=1}^{k} \text{VMF}_i \tag{8}$$

Where RI is the reconstructed image. The flow diagram of 2-D VMD-DWT filtering is shown in figure 3

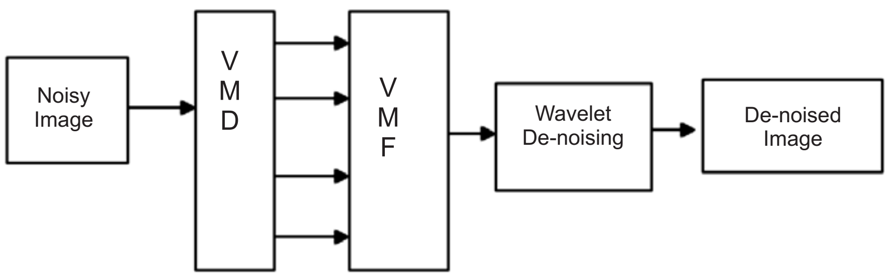

Figure 2: Flow diagram of 2-D VMD-DWT filtering method

4. BAND SELECTION METHOD

The dimensionality reduction can be done in two steps, feature extraction and band selection. The feature extraction methods retrieve the features in the original image bands to create a low dimension feature space. This feature extraction methods change the physical characteristics of the hyperspectral data set. On the other hand, the band selection methods select the best combination of image bands based on the information in the data set. The band selection methods are more suitable for dimensionality reduction of hyperspectral data sets than feature extraction methods. In literature, four band selection metrics such as Euclidean Distance [9], Spectral Angle Mapper [10], Spectral Correlation Mapper [11] and Band Correlation [11] are used to select the informative bands. In this paper, the dimensionality reduction is done using Spectral Correlation Mapper [SCM] based on the information present in the image bands. The dimensionality reduction step decreases many requirements for processing the hyperspectral data set such as storage space, computational load, communication bandwidth etc., thus increasing the efficiency of segmentation algorithm [12]. The band selection metric SCM is defined as follows [13]:

$$\mathrm{SCM}(X, Y) = \frac{\sum_{k=1}^{N_b} (X_k - \mu_X).(Y_k - \mu_Y)}{(N_b - 1).\sigma_X.\sigma_Y} \tag{9}$$

5. HIERARCHICAL IMAGE FUSION TECHNIQUE

In hierarchical image fusion technique [14], the entire data set is partitioned into P subsets of hyperspectral, where P is given by $P = \left\lceil - \right\rceil$, K number of bands in data set and M bands in each subset. First image fusion is carried out independently on these P subsets, to form P fused images. These P images are used as input for second stage fusion again by dividing into subsets. This procedure is repeated in a hierarchical manner to generate the final result of fusion in a few stages. The flow diagram of hierarchical image fusion is shown in figure 4.

The fused image F at any stage is a linear combination of input images as shown below:

$$F(x, y) = \sum_{k=1}^{M} w_k(x, y) I_k(x, y)$$

and

$$\sum_{k=1}^{M} w_i(x, y) = 1, \forall (x, y) \tag{10}$$

where $w_k (x, y)$ is the normalized weight for the pixel at location (x, y), $F(x, y)$ is the fused image.

In this paper, a small refinement to hierarchical image fusion is done. Instead of grouping the images into subsets of fixed size, in this paper the grouping is done based on the similarity metric M between the images [15]. The similarity metrics used in this paper are Average Pixel Intensity [API], Histogram Similarity [HS], Mutual Information [MI] and Correlation Similarity [CS]. The images subsets are created based on similarity metric *i.e.*, the images in a subset have same similarity. The same procedure is continued at each and every stage, until a single image is formed. In grouping the images, we use a threshold (T) for each and every group and this threshold will determine how similar the images of a group should be. If the similarity value M is less than the threshold (T), add it to the group, else add to next group and so on. According to [16], the CS based grouping technique in hierarchical fusion method produces quality fused image.

The Correlation Similarity [CS] between two images is defined as

$$CS = \frac{\sum_x \sum_y (I_{ref}(x, y) - \bar{I}_{ref})(I(x, y) - \bar{I})}{\sqrt{\sum_x \sum_y (I_{ref}(x, y) - \bar{I}_{ref})^2 (I(x, y) - \bar{I})^2}} \tag{11}$$

6. FUZZY C-MEANS (UNSUPERVISED) ALGORITHM

The FCM algorithm for segmentation of hyperspectral image is described below [17]:

1. Take randomly K initial clusters from the $m*n$ image pixels.
2. Initialize membership matrix u_{ij} with value in range 0 to 1 and value of $m = 2$.

   Assign each pixel to the cluster C_j $\{ j = 1, 2,.....K\}$ if it satisfies the following condition [D(. , .) is the Euclidean distance measure between two values].

$$\begin{aligned} u^m_{ij} D(I_i, C_j) &< u^m_{iq} D(I_i, C_q), \\ q &= 1, 2, \ldots, K \\ j &\neq q \end{aligned} \tag{12}$$

The new membership and cluster centroid values as calculated as

$$u_{ik} = \frac{1}{\sum_{j=1}^{K}\left(\frac{D(C_i, I_k)}{D(C_j, I_k)}\right)^{\frac{1}{m-1}}}, \; for\, 1 \le i \le K$$

$$\hat{C_j} = \frac{\sum \quad _{ij} \quad _{j}}{\sum \quad _{ij}} \tag{13}$$

3. Continue 2-3 until each pixel is assigned to the maximum membership cluster.

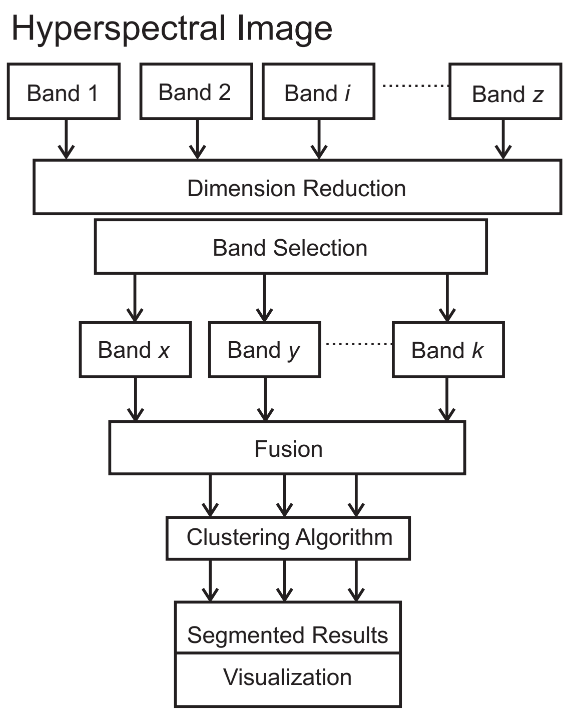

Figure 3: Framework for hyperspectral image segmentation

7. EXPERIMENTAL RESULTS

The proposed methodology is tested on Pavia University hyperspectral image data set collected from [18] containing 103 spectral bands. The dimensionality reduction is done using SCM. After dimensionality reduction, hierarchical image fusion is carried out using CS grouping technique presented in this paper. The segmentation step implemented separately by three clustering methods, K-means, Moving K-Means and Fuzzy C-means respectively. These methods are implemented in such a way that the grayscale intensity value of all the pixels in the image are grouped into nine clusters. The qualitative analysis of the proposed method on Pavia University hyperspectral data set is shown in figure 4. Quantitative analysis using Mean Square Error [19] is a numerically oriented procedure to figure out the performance of algorithms without any human error. The MSE is mathematically defined as:

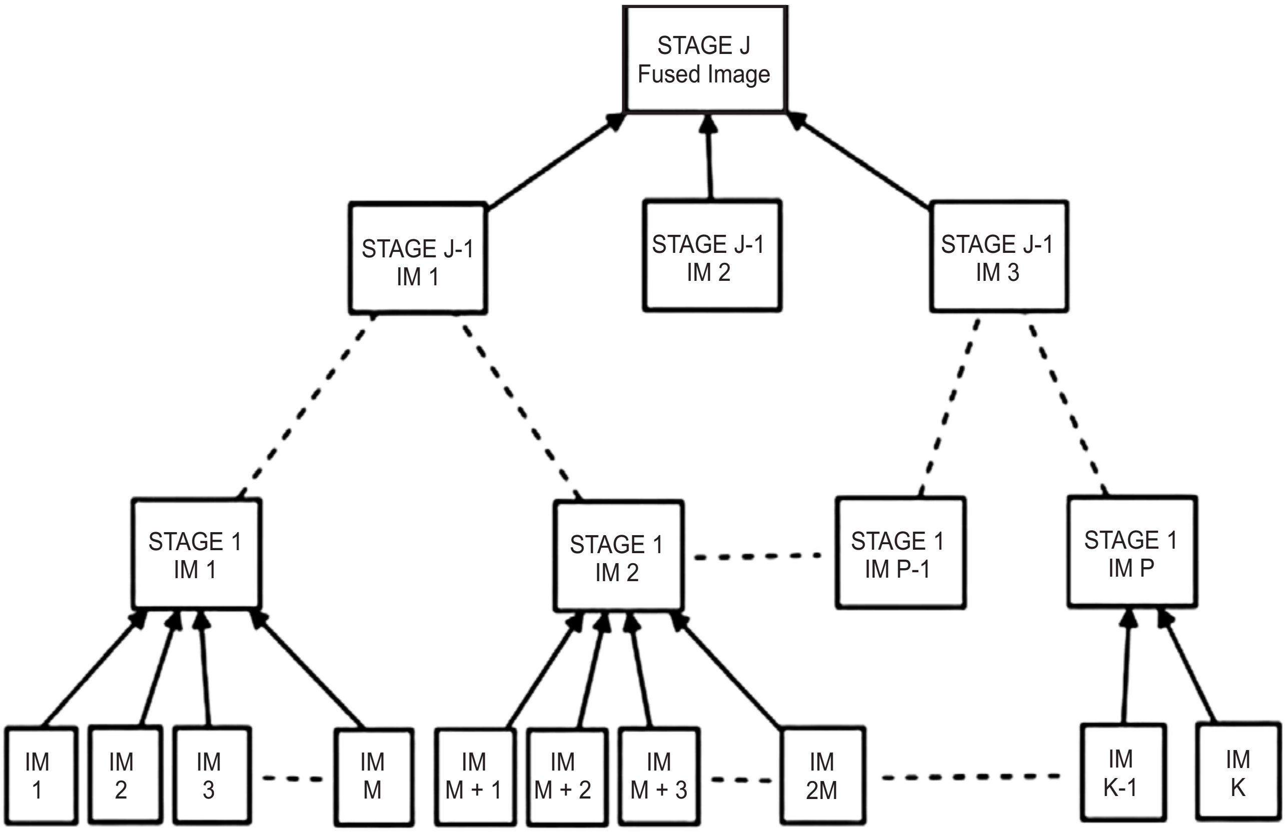

Figure 4: Hierarchical Image Fusion

$$\text{MSE} = \frac{1}{N}\sum_{j-1}^{k}\sum_{i\,e\,C_i} \| v_i - C_j \|^2 \tag{14}$$

Where N is the total number of pixels in an image and *xi* is the pixel which belongs to the jth cluster. Table 1 shows the quantitative evaluations of three clustering algorithms after segmenting the hyperspectral image with BEMD + DWT and BVMD+DWT filtering methods. The results confirm that Fuzzy C-means algorithm produces the lowest MSE value for segmenting the hyperspectral image.

Table 1
MSE values of segmented images using three clustering algorithms

Method	*MSE Values (Filtering using BEMD + Wavelet method)*	*MSE Values (Filtering using VMD + Wavelet method)*
K-means	304.1	295.6
Moving K-means	265.4	288.3
Fuzzy *c*-means	191.8	186.2

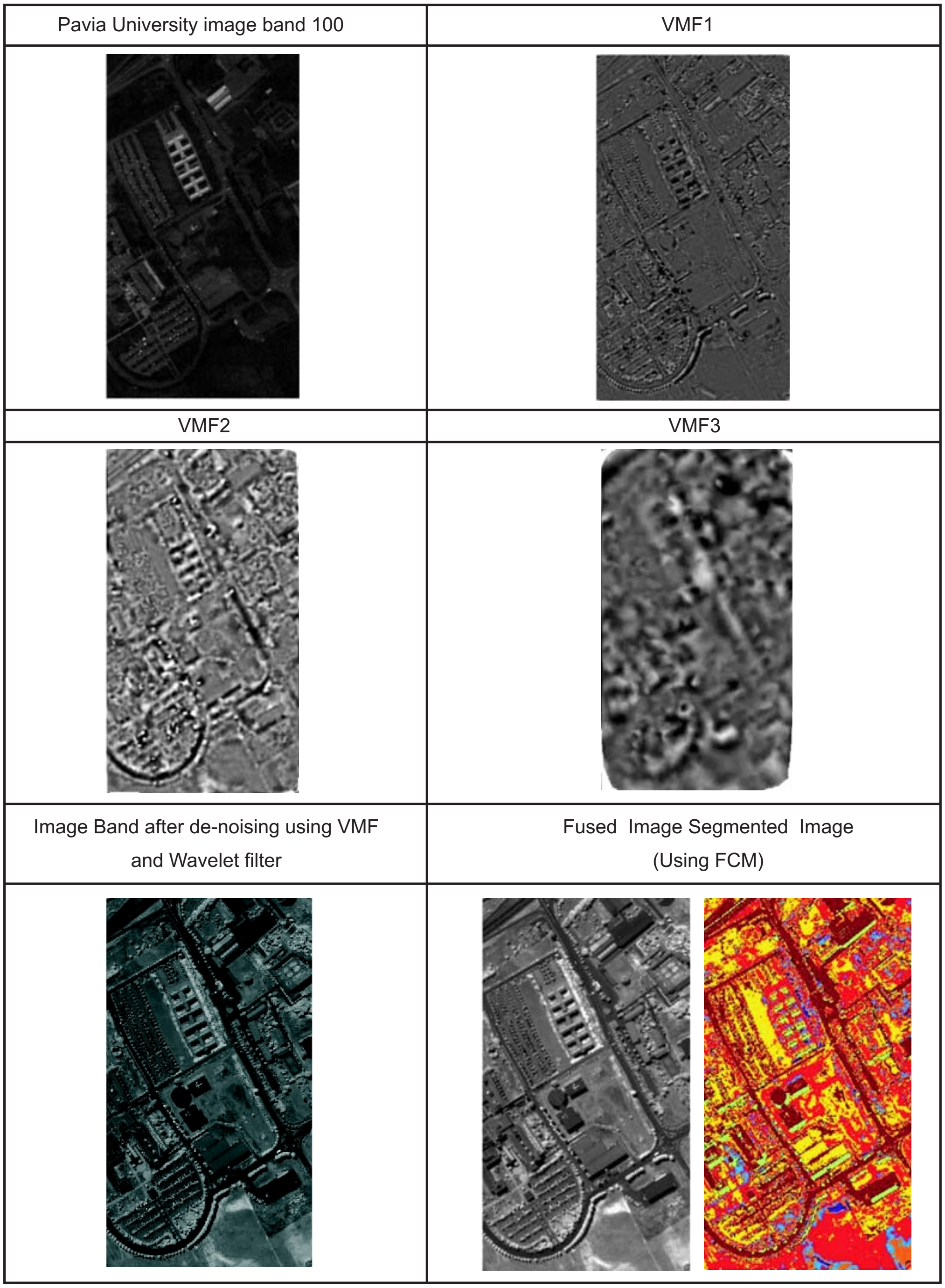

Figure 4: Hyperspectral Image segmentation

8. CONCLUSIONS

In this paper a framework for hyperspectral image segmentation is presented. The framework is carried out in four stages. First stage contains noise reduction algorithm in each image band, second stage contains dimensionality reduction using band selection methods to select informative bands leaving the bands that convey less descriptive information, third stage contains new hierarchical image fusion to generate a single informative band and in the fourth stage, segmentation using FCM algorithm. Existing methods for hyperspectral data sets is done by selecting limited number of bands normally less than seven. The accuracy of any segmentation algorithm decreases if the number of spectral bands increases. The framework presented in this paper provides a methodology for segmenting the hyperspectral data set by incorporating all the information existing in the original bands rather than selecting some spectral bands. In this paper a new methodology of noise removal is incorporated in the framework for segmentation. The framework with this noise removal algorithm segments the hyperspectral data set more accurately than other segmentation methods such as K-means and Moving *k*-means.

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