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Marker Selection Using Skeletonization for Very Low Training Sample Analysis of Hyperspectral Image Classification

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Abstract

This paper presents a new technique for marker selection called marker selection using skeletonization. Markers are the most reliable pixels that represent a particular class. Marker selection using skeletonization is further analysed to do classification of hyperspectral image with very low training samples, as low as one pixel per class. Both spatial and spectral information are used to improve the final classification accuracy. An Extended Morphological Profile with duality is used to extract spatial information. Furthermore, it is shown that by using the spatial and spectral information with non-parametric supervised feature extraction methods, better classification accuracy can be achieved even when very low training samples are available. The classification maps will be shown and discussed for very low training sample analysis using marker selection by skeletonization technique.

Keywords: *Classification, Feature Extraction, Hyperspectral Images, Skeletonization, Support Vector Machine*

1. Introduction

From the last two decades a lot of work has been done in hyperspectral remote sensing technology [1]. Detailed physical analysis of object structures is possible by using the advanced hyperspectral imaging sensors that are able to capture hundreds of narrow spectral channels [2].

It is now commonly accepted that using the spatial and spectral information simultaneously provides significant advantages in terms of improving the performance of classification techniques [3]. In addition, small structures are now better identified due to recent advances in spatial resolution of sensors [2]. It is well known that contextual information, i.e., the inter pixel dependency is also useful for the classification of hyperspectral images (HSIs) [4].

Apart from many other problems, one of the problems that many scientists faced in remote sensing is the limited number of training samples. A lot of work and methods have been presented to improve the classification accuracy with limited number of training samples.

In this paper very low training sample analysis (VLTSA) is performed using spatial-spectral classification scheme shown in Figure 1. Apart from the spectral information, the spatial information is extracted using Extended Morphological Profiles (EMP) with duality property (EMPD), which improves the classification accuracy better than the conventional EMP because it reduces the shape noise [5]. The original HSI is first normalized and then it is used for principal component analysis (PCA) and feature extraction (FE) analysis, this also helps to improve the classification accuracy. For FE,

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two nonparametric supervised FE techniques are used, named Decision Boundary Feature Extraction (DBFE) and

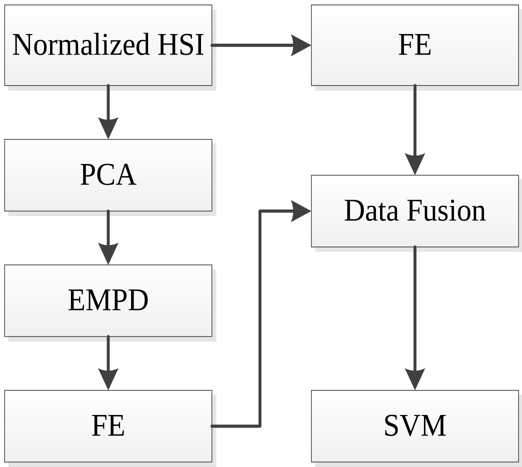


Figure 1. The Main Flow Diagram on which we have Implemented our Marker Selection Using Skeletonization Approach

Non-parametric Weighted Feature Extraction (NWFE). Support Vector Machine (SVM) for classification is used because it can handle both spatial and spectral information very efficiently. Figure 1, summaries the main flow of our work.

In supervised classification, data set is labelled based upon the available ground truth data (GTD). The training and testing samples are picked randomly. If the training samples to be picked are very limited for example only one or two, then it is very important that the picked training samples should be reliable and must represent the class for which they have been labelled for. Training samples are picked randomly, so there is a chance that they will be picked at the boundary of the class, where there is likelihood that they may not belong to the class for which they are labelled of. They may represent the neighbouring class as the classes are usually very close to each other in HSIs. So, the probability of reliability of limited training samples that have been chosen for the analysis must be increased.

One idea that comes to the mind is that the pixels at the center are more accurate to represent the class than the pixels at the boundary. Many algorithms have been proposed to choose more reliable pixels as region marker. In [6], Tarabalka *et al*. choose markers by analyzing probabilistic SVM classification results. In [7] Multiple Classification technique has been presented for marker selection in such a way that the complementary benefits of each classifier are exploited, while their weaknesses are avoided. In [8] Multiple Spectral-Spatial Classifier is presented for marker selection, which is further used for marker-controlled region growth, based on a minimum spanning forest algorithm [6]. All the above mentioned techniques for marker selections are quite complex and time consuming as well. We propose a new marker selection technique called *marker selection using skeletonization*. The best thing about this technique is that it does not depend on any classifier. The technique of marker selection using skeletonization is described as follows:

2. Marker Selection Using Skeletonization

It has been shown in [9] that the skeleton of a figure A can be expressed in terms of erosions and openings; that is,

$$S(A) = \bigcup_{k=0}^{K} S_k(A) \qquad (1)$$

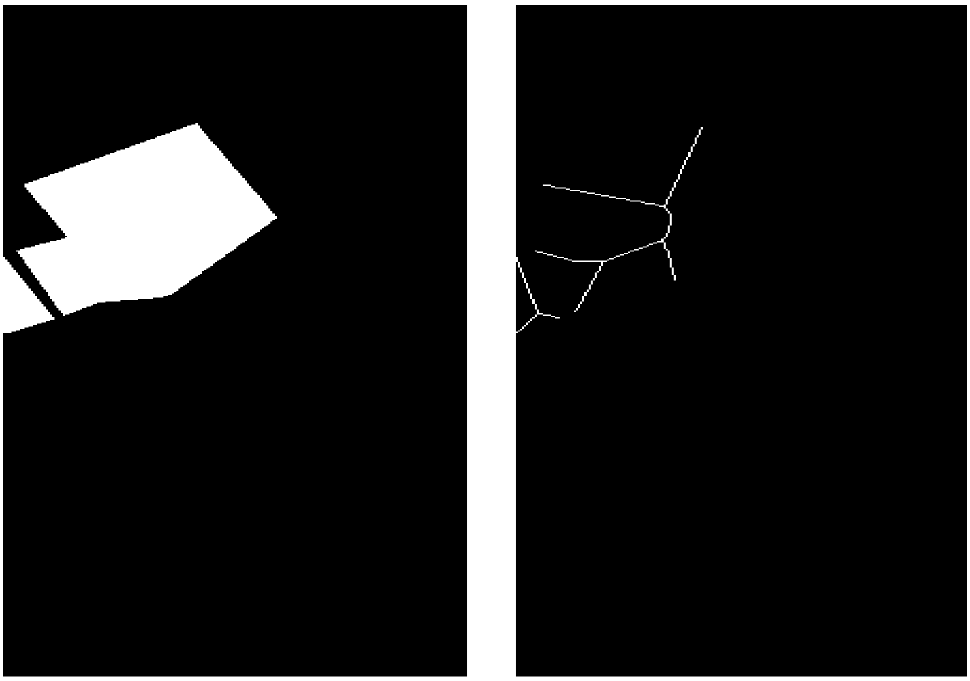
with

$$S_k(A) = (A \Theta kB) - (A \Theta kB)B \qquad (2)$$

where B is the structuring element, and $(A \Theta kB)$ indicates k successive erosions of A. K is the last iterative step before A erodes to an empty set; that is,

$$K = \max[k \mid (A \Theta kB) \neq \varnothing] \qquad (3)$$

Skeletonization with pruning of each class of the GTD of HSI is performed one by one and based on it, the very low training samples are randomly selected from the HSI data set. The skeleton of a class lies at the very core of it and the pixels (randomly selected for training samples from the skeleton) are more reliable to represent a class. In other words, the skeleton of a class represents the marker of that class. Figure 2(a) shows the class named Soil-vineyard-develop of Salinas data set and (b) shows its skeleton. The skeleton lies at the very core of the class, quite away from the boundary. On the skeleton, there is more chance that the training samples belong to a class it is representing or it has been labeled for; as the classes are very close to each other in most of the HSI data sets.



(a) (b)

Figure 2. (A) GTD of Class Named Soil-Vineyard-Develop of Salinas and (B) Its Skeleton in Black and White Image

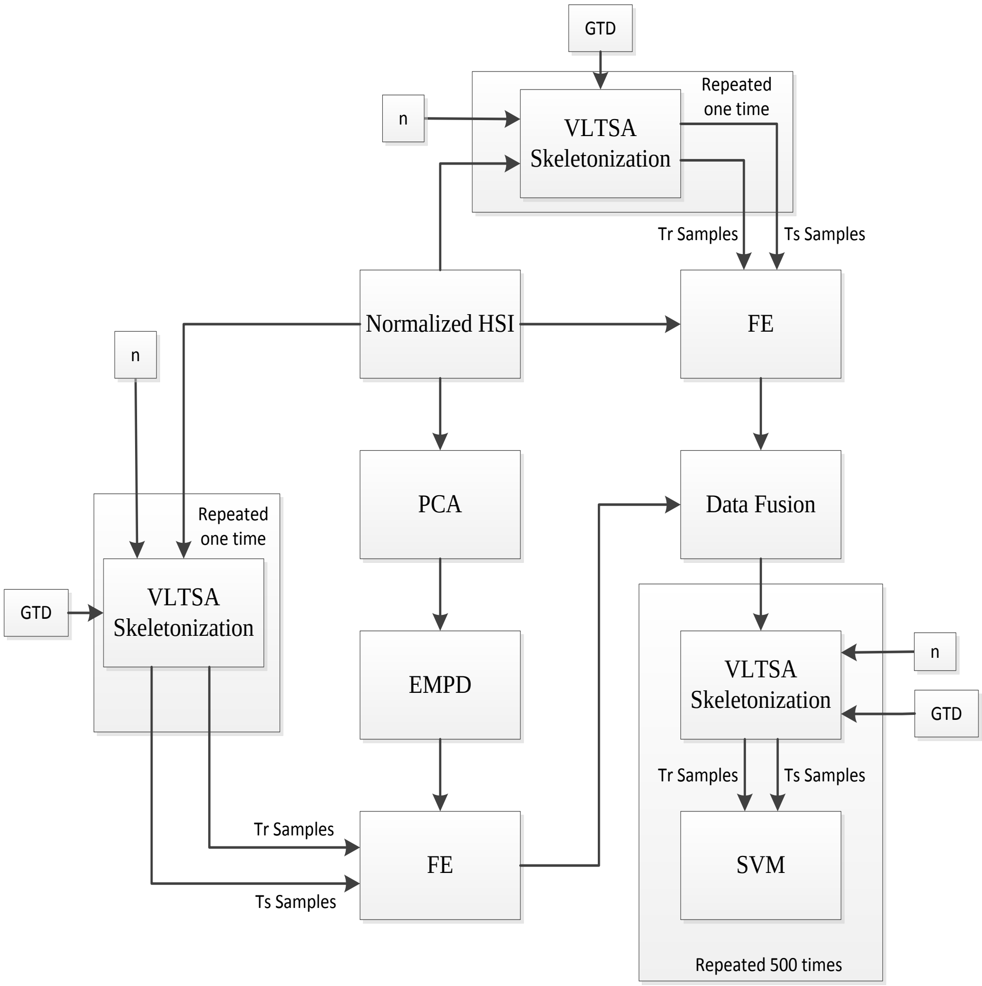


Figure 3. Proposed Marker Selection Using Skeletonization Approach; Implemented on the Figure 1

Figure 3 shows how our proposed technique is implemented on our main flow of the HSI spatial and spectral information extraction method mentioned in Figure 1. We feed in the output of our proposed technique into the FE, as non-parametric supervised feature extraction methods are used in order to remove the redundant and irrelevant information in spatial and spectral domains. The block of VLTSA Skeletonization is explained in Figure 4. Figure 4 explains our proposed approach in depth. In it each class is chosen from GTD and skeletonization is performed on it and from that skeleton training samples are selected from the HSI. The pixels in the class other than it skeleton are selected as testing samples. *n* training sample are then selected randomly from training samples selected from skeletonization technique. The process is repeated until all the classes in the GTD are finished. In the end the net *n* training samples from each class and the net testing samples from each class are send out as an output from the block of VLTSA Skeletonization. For FE our proposed approach is repeated only once. The spatial and spectral information are combined using the concatenate vector, mentioned as data fusion block in Figure 3. Our proposed

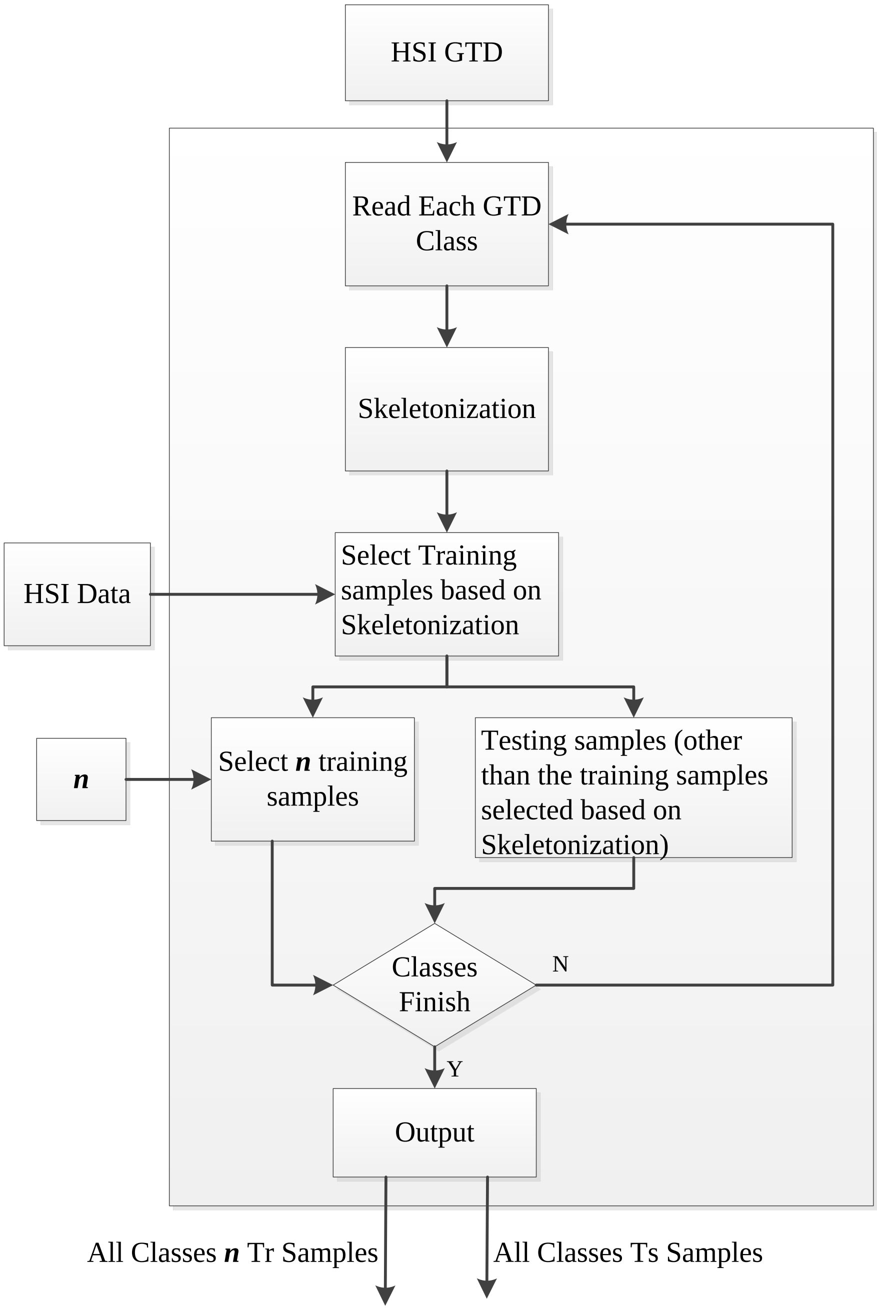


Figure 4. The VLTSA Skeletonization Block in Figure 3

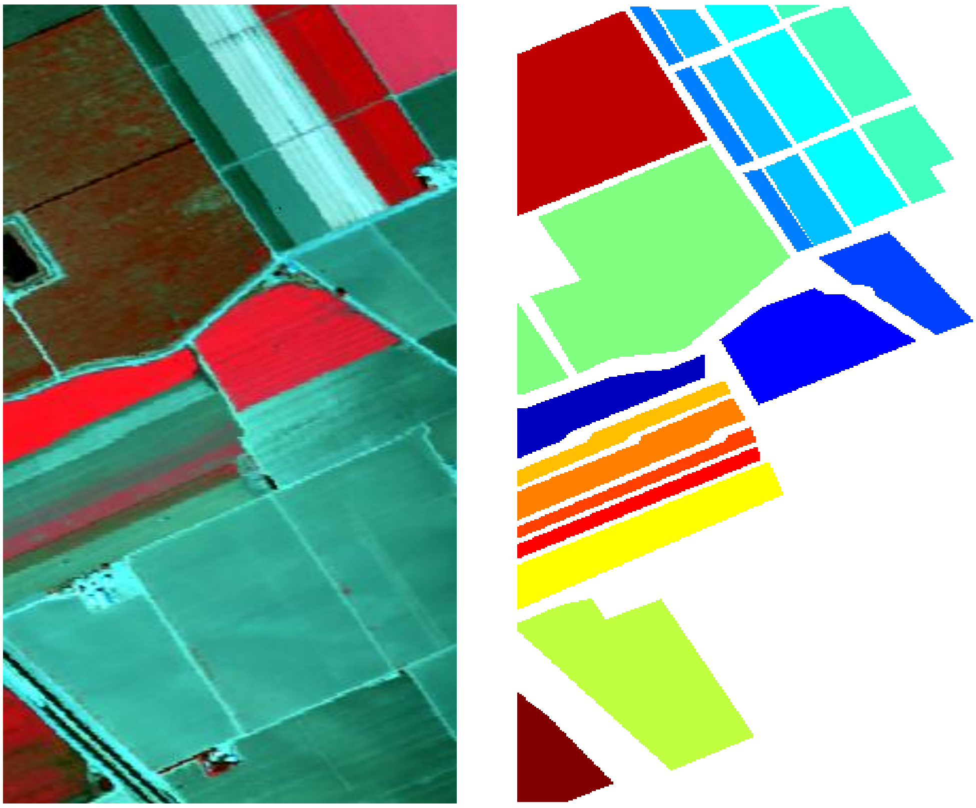
Technique of marker selection using skeletonization is implemented on the fused data. This will be fed into the classifier (SVM). At this stage the VLTSA Skeletonization technique with the SVM is repeated 500 times for the reliability of the classification results because VLTSA is performed, where the numbers of training samples are very low.

3. Non-Parametric Supervised Feature Extraction

Two supervised nonparametric FE techniques named Decision Boundary Feature Extraction (DBFE) and Nonparametric Weighted Feature Extraction (NWFE) are used to extract the spatial features in our work. Nonparametric FE is based on a nonparametric extension of the scatter matrices. There are at least two advantages of using the nonparametric scatter matrices. First, they are generally of full rank. This provides the ability to specify the number of extracted features desired and to reduce the effect of the singularity problem. It is in contrast to parametric discriminant analysis, which usually can only extract $L-1$ features [10], where L is the number of classes. Second, the nonparametric nature of scatter matrices reduces the effects of outliers and works well even for non-normal data sets and most of the hyperspectral data sets are non-normal [10].

In DBFE all features useful for discriminating the classes can be extracted from the decision boundary [11]. The decision boundary feature matrix (DBFM) [12] is formed by using the vector norm at the decision boundary. The vector norm is the normal vector to the line connecting the two pair of training samples belonging to different classes. DBFE is very much dependent of the number of training samples and can be computationally intensive.

Kuo and Landgrebe [13] proposed NWFE using the advantage of Discriminant Analysis Feature Extraction (DAFE) and DBFE and eliminating their disadvantages. The main ideas of NWFE are putting different weights on every sample to compute the weighted means and defining new nonparametric between class and within-class scatter matrices in order to obtain more than $L-1$ features [10].



(a) (b)

Figure 5. (A) Three Channel Colour Composite of Salinas Data Set and (B) its Ground Truth Map

4. Experimental Results

AVIRIS Salinas data set is used for our experimentation. Salinas data set has 512 by 217 pixels with 204 bands in spectral dimension. Three channel colour (RGB) composite of its data set is shown in Figure 5(a) and it’s GTD in (b) with 16 mutually exclusive classes. This data set is chosen because it is a challenging classification problem as most of the classes have the similar spectral.

The criteria used to compare classification results involve Overall Accuracy (OA), Average Accuracy (AA) and the kappa coefficient (k). Time analysis is not done as it is obvious that lesser the feature, faster will be the processing time. *MATLAB* is used for morphological operations while *MultiSpec* software is used for feature extraction. The SVM classification is done using *LIBSVM* [14]. In our study, one-against-one strategy is used for SVM using radial basis kernel. Throughout the experiments, the normalized HSI data set is used, which is feed into *MultiSpec* software for FE, as shown in Figure. 3. The concatenate vector is used for data fusion; to combine spatial and spectral information. For PCA, DBFE and NWFE the number of features are selected based on cumulative percentage of 99%. For VLTSA, every step is performed once up-till data fusion. See Figure 3. After that, training samples are randomly selected 500 times and then averaged for the reliability of the results. Every 500 times SVM parameters C (4, 8, 16, 32, 64) and γ (1, 2, 4) are determined using five-fold cross-validation.

For DBFE leave one out covariance (LOOC) is used to estimate the covariance matrix [15], because when training samples are small the covariance matrix cannot be inverted. NWFE does not suffer from this. Note that, when NWFE is performed with only one training sample, *Multispec* software fails, as it expects matrix. So for this particular case, the FE results of NWFE when only two training samples are picked per class is used up-till data fusion. After that only one training sample is chosen per class randomly for 500 times.

Table 1 summarizes the VLTSA of Salinas data set. Comparing the first three columns of the Table 1, it can be seen that the classification accuracy increases when both spatial and spectral information is used, rather than individually. There is a clear difference in accuracies when NWFE is used as FE. Even when only one training sample is used, an OA of 75% is obtained with NWFE features, which increases to 80% when only three training samples per class are used, which is not bad. The second best result is obtained when DBFE is used as FE. Seeing the results of Table 1, it is concluded that FE is an essential step for better classification accuracy, as a lot of data in HSIs is redundant.

Table 2 shows the number of features used for classification results when DBFE and NWFE techniques are used for FE. The first digit in the bracket represents the spectral feature and the second digit represents the spatial feature and the digit outside the bracket represents the sum of spectral and spatial features. It can be seen in Table 2 that with only 19 features, when NWFE is used as FE, we get an accuracy of 75% when only one training sample per class is used.

Figure 6 shows the classification maps when only one and ten training samples per class are used by implementing VLTSA (marker selection using skeletonization). It can be seen from the classification maps that even with just one training pixel per class; still reasonable classification maps can be obtained, when NWFE is used as FE. Using our proposed technique of marker selection using skeletonization, the reliability of pixel belongs to the class for which it has been labelled for is increased. This helps us to choose more reliable pixels for VLTSA and hence results in better classification maps even with very low training samples.

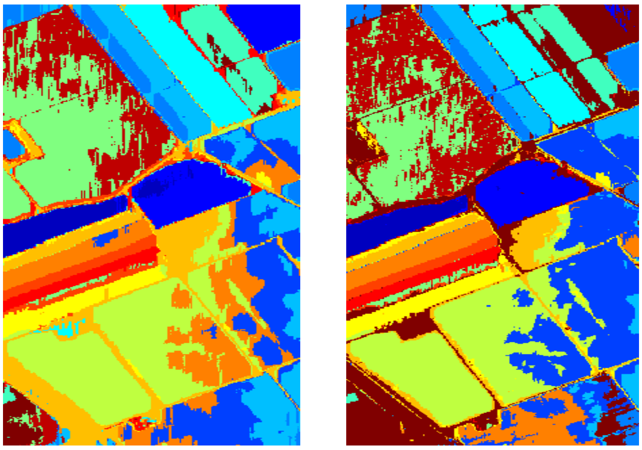
The proposed technique of marker selection using skeletonization can be used as a seed for building minimum spanning forest algorithm [6].

Table 1. Overall (OA) and Average (AA) Classification Accuracy in Percentage. TS Stands For Training Sample/S And Mps Stands for Measuring Parameters

TS	MPs	Spectral	EMPD	Spectral + EMPD	DBFE 99%	NWFE 99%
1	**OA**	69.409	74.633	74.259	74.771	**75.222**
	AA	74.591	79.936	79.655	80.088	**81.189**
	kappa	0.6614	0.7187	0.7147	0.7205	**0.7254**
2	**OA**	73.885	75.640	74.989	75.831	**79.525**
	AA	80.114	81.519	80.800	81.968	**85.854**
	kappa	0.7107	0.7305	0.7234	0.7326	**0.7732**
3	**OA**	76.309	79.538	79.120	79.100	**80.277**
	AA	82.741	85.504	85.300	85.150	**86.830**
	kappa	0.7374	0.7734	0.7688	0.7685	**0.7816**
4	**OA**	77.984	80.755	80.438	80.886	**81.595**
	AA	84.566	86.837	86.652	86.988	**88.017**
	kappa	0.7559	0.7868	0.7833	0.7883	**0.7961**
5	**OA**	79.081	81.837	81.608	81.499	**82.418**
	AA	85.714	87.933	87.791	87.735	**89.012**
	kappa	0.7680	0.7988	0.7963	0.7951	**0.8052**
6	**OA**	80.196	82.561	82.242	82.557	**83.977**
	AA	86.777	88.597	88.488	88.674	**90.095**
	kappa	0.7802	0.8068	0.8033	0.8068	**0.8223**
7	**OA**	81.051	83.140	82.848	82.890	**83.263**
	AA	87.515	89.191	89.018	89.078	**89.415**
	kappa	0.7896	0.8132	0.8100	0.8105	**0.8146**
8	**OA**	81.395	83.454	83.395	83.839	**85.038**
	AA	88.095	89.535	89.489	89.909	**90.953**
	kappa	0.7936	0.8167	0.8160	0.8208	**0.8341**
9	**OA**	82.100	84.039	83.964	84.063	**85.719**
	AA	88.641	89.995	89.984	89.969	**91.335**
	kappa	0.8013	0.8232	0.8223	0.8234	**0.8416**
10	**OA**	82.563	84.430	84.294	84.504	**85.591**
	AA	89.020	90.326	90.247	90.358	**91.343**
	kappa	0.8064	0.8275	0.8259	0.8282	**0.8402**

Table 2. Total Number of Features Selected During VLTSA for Salinas

No. of Training Samples	Salinas	
	DBFE 99%	NWFE 99%
1	9(4, 5)	19(13, 6)
2	12(7, 5)	19(13, 6)
3	41(20, 21)	24(16, 8)
4	38(18, 20)	24(18, 6)
5	58(34, 24)	29(21, 8)
6	61(38, 23)	27(20, 7)
7	60(36, 24)	31(23, 8)
8	59(35, 24)	34(27, 7)
9	59(32, 27)	32(25, 7)
10	60(36, 24)	33(26, 7)



(a) **(b)**

Figure 6 Salinas Classification Maps Obtained From VLTSA (A) Using NWFE As FE When Only One And (B) Ten TS Per Class Are Used. TS Stand For Training Sample/S

5. Conclusion

In this paper a new marker selection technique is proposed using skeletonization. The technique is implemented when both spatial and spectral information are extracted for hyperspectral image classification. Spatial information is extracted using Extended Morphological Profile with duality. Nonparametric feature extraction techniques are used to reduce the redundant and irrelevant information from the spatial and spectral information. VLTSA is further studied using skeletonization technique on hyperspectral image. Only one to ten training samples per class are examined and it is concluded that when NWFE is selected for FE, the better classification accuracy is obtained. It is also investigated that reasonably fine classification maps can also be obtained using VLTSA with skeletonization method.

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