Improved Superpixels Generation Algorithm for Qualified Graph-Based Technique

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Abstract*: Hyperspectral Images (HSIs) represent an important source of information in the remote sensing field. Indeed, HSIs, which collect data in many spectral bands, are more simple interpretable and provide a detailed information about interest areas. However, hyperspectral imaging systems generate a huge amount of redundant data and an important level of noise. Dimensionality reduction is an important task that attempts to reduce dimensionality and remove noise so as to enhance the accuracy of remote sensing applications. The first dimensionality reduction approaches date back to 1970s, and various model-based methods have been proposed since these years. This field has known an increasing attention by the suggestion of graph based models that have yielded promising results. While graph based approaches generate considerable outputs, these models require often an important processing time to handle data. In this work, we aim to reduce the computational burden of a promising graph based method called the Modified Schroedinger Eigenmap Projections (MSEP). In this respect, we suggest an efficient superpixel algorithm, called Improved Simple Linear Iterative Clustering (Improved SLIC), to lessen the heavy computational load of the MSEP method. The proposed approach exploits the superpixels as inputs instead of pixels; and then runs the MSEP algorithm. While respecting the HSIs properties, the proposed scheme illustrates that the MSEP method can be performed with computational efficiency.*

Keywords: *Hyperspectral images, dimensionality reduction, graph, MSEP, superpixels, improved SLIC.*

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1. Introduction

Progress in remote sensing imaging has led to the emergence of a new advanced generation of satellite sensors that can produce images with very high spectral resolution, known by Hyperspectral images (HSIs). Thanks to its discrimination ability, HSIs have been widely exploited by various applications such as classification, object recognition and target detection. Despite its interesting potentialities, hyperspectral data treatment is a difficult process. Indeed, HSIs generates also an important amount of redundant data; which poses difficulties during image processing and storage. To reduce hyperspectral data, various dimensionality reduction approaches have been proposed in the last decade. The concern subject is how to reduce data dimensionality while keeping the significant properties [6, 7, 8, 14, 18, 19, 20, 22].

In this paper, we are particularly interested to the linear modified Schroedinger Eigenmap projections (MSEP) [9] approach. This latter is a recent powerful graph-based method which is based on the Modified Locality Preserving Projection (MLLP) framework [21] and the Schrodinger theory. Despite its noted classification precision, the suggested MSEP approach requires a computational effort, during the adjacency graph construction, especially when the number of the image pixels is important. To resolve the computational issue, we suggest adopting superpixels as input. In fact, generating superpixels can significantly reduce the computational load without severely affecting the classification accuracy.

Recently, several superpixel algorithms have been suggested. These algorithms can be classified into two families: graph-based techniques and gradient ascent methods [1]. The first family is derived from graph-based image models; in which superpixels are generated based on the distance between pixels and the centroid feature. In the second branch, the clusters of superpixels are generated iteratively from an initial grouping of pixels until reaching a particular convergence criterion. Since they are iterative models, gradient ascent methods yield is relatively slow. In this paper, we adopt a graph-based algorithm called Improved Simple Linear Iterative Clustering (SLIC) [13] to generate superpixels. The developed Improved SLIC is an efficient superpixel method that presents a fast implementation and powerful yield during several image clustering tasks.

This work is an attempt to lessen the computational cost of the MSEP method without impacting the significant image data properties. Section 2 presents state-of-art superpixel algorithms. We introduce the MSEP algorithm in section 3. Section 4 conducts on experimental analysis and results. Finally, section 5 outlines conclusions.

2. Graph-Based Algorithms for Superpixels Generation

2.1. State-of-the-Art Superpixel Methods

Clustering, used widely in image analysis applications, can be defined as the best grouping of an image into avariety of partitions in such way that features in the same partition are more similar to one another and features from different partitions share the maximum number of differences. Superpixels, or the partition of pixels into small clusters, can execute data more efficiently. Recently, several kinds of superpixels have been adopted for image analysis and processing. Among these methods, we can mention: the Normalized Cuts (NC) algorithm [3, 4] which is based on local texture and contours to partition a graph. It minimizes the cost function determined by the edges and texture cues. NC can provide good visually superpixels, but it is considered among the slowest methods. Felzenszwalb-Huttenlocher method [10] is another superpixel approach which segments image regions used edges concept. Although, the suggested approach exhibited a quiet computing load, it continues to produce superpixels without any control over the size or the shape proprieties. In [16, 17], the Superpixel Lattice (SL) approach was also proposed as a superpixel methodology. SL divides the image into small partitions based on optimal paths, found from graph cut algorithms. Nevertheless, the SL method doesn't take into consideration boundary maps; which can affect quality and speed outputs.

The most of these methods suffer from qualitative or computational issues. In order to solve these problems, the SLIC [1, 23] was put forward. The SLIC approach is a novel version of k-means clustering; which is based on the spectral (color) and spatial distances. Since it includes spectral and spatial pixel features, the developed method presents a high computational speed in addition to its significant classification performance. Nevertheless, the conventional SLIC suffers from two main problems. Firstly, cluster centers are updated based on some misclassified pixels, produced from the first iteration. Consequently, more pixels are incorrectly classified. Secondly, small clusters are incorporated into their neighbors. Hence, generated superpixels don't cohere to the image boundary. To address these issues, an improved variant of SLIC method has been proposed by Kim *et al*. [13]. The proposed approach introduces a sigma filter to avert errors propagation. Then, it adopts luminance similarity instead of the neighbor cluster size to avoid small cluster pixels misclassification.

2.2. Improved Simple Linear Iterative Clustering (SLIC) Method

The Improved SLIC [13] superpixel method is a recent variant of the SLIC superpixel approach [1, 23]; which produces more uniform and regular superpixels with an efficient computing time. Unlike the SLIC method which produces clusters with misclassified pixels, the Improved SLIC uses a post-processing step to avoid fault pixels propagation and correct segments superpixels. The Improved SLIC algorithm can be summarized as follows:

1. Define a feature vector φ for each image pixel:

$$\varphi(x, y) = \begin{vmatrix} \delta x \\ \delta y \\ \mathrm{I}(x, y) \end{vmatrix}$$

Where x and y represent spatial positions, $\mathrm{I}(x, y)$ corresponds to the vector of each channel code values and δ is a parameter used to loadspatial and spectral features impact. δ can be phrased as the ratio of nominal size of the superpixel (S) and the superpixel regularity (R).

2. Introduce an M initial cluster centers $C_M = \varphi(x_k, y_k)$ sampled evenly. Cluster centers are, then, change to the lowest gradient location.
3. Attribute pixels to the nearest cluster center within a $2S\times2S$ neighbourhood.
4. Update cluster centers: after the first assignation, some pixels can be misclassified. Consequently, cluster centers are updated with wrong classified pixels. To avoid error propagation, the Improved SLIC adapts a sigma filter that uses only pixels which have analog luminance values with the initial centers.

$$\Omega_j = (\|Q_i - Q_j\| < \partial.\sigma_j) \cap C_j \tag{1}$$

We note that σ_j is the standard deviation of the luminance Q of the j^{th} cluster C's pixels and ∂ is a fixed constant.

5. Merge small clusters based on the luminance similarity. The luminance distance Q_D between a small cluster C and its neighbor Cf (f = 1,…,F) can be computed using (2).

$$Q_D = (\mu - \mu_f)^2 \tag{2}$$

μ and μ_f are the mean luminance values of a small cluster and its neighbour respectively.

6. Repeat until the distance between successive cluster center updates is below a predefined threshold T.

No complex mathematical models are needed for the suggested superpixel-based method, and thus, the Improved SLIC algorithm can be simply extended for HSIs processing.

3. Modified Schroedinger Eigenmaps Projections (MSEP) Algorithm

While keeping the significant HSI properties, dimensionality reduction methods tend to find the reduced subspace data points $Y=[y_1,y_2,..,y_p]$ in R^d from the original HSI ones $X=[x_1,x_2,..,x_p]$, where $X \in \mathbb{R}^n$. We note that p presents the number of HSI pixels, n is the number of spectral bands and d is the dimension of reduced subspace ($d<n$).

The MSEP method is a recent contribution to graph-based dimensionality reduction algorithms; which has proven satisfactory results during HSIs classification tasks. The developed method involves the construction of an adaptive graph. The key idea is to choose conveniently the number of neighbours for each data point to build the adjacency graph. Then after, the MSEP approach incorporates spatial information with the spectral ones in order to more represent the image proprieties in the low-dimensional space. The MSEP algorithm proceeds as follows:

1. The first step deals with the adjacency graph construction that adopts the graph growing strategy [9]. Indeed, the built graph is created adaptively to the ground object's properties. Hence, Neighborhoods are formed with different sizes and the adjacency graph is constructed without any parameter.
2. The second step exploits proximity relations, extracted from the constructed graph, to compute the weighted matrix ω This latter represents the connectivity of the graph and it can be defined as follows:

$$\omega_{ij}=\begin{cases}0, \text{ if } x_i \text{ and} x_j \text{ are nearest neighbours} \\ 1 \text{ , otherwise}\end{cases} \quad (3)$$

3. While the weighted matrixω is reserved to encode spectral similarity, the cluster potential matrix V (4), defined in the third step, includes spatial elements proximity. Spatial coordinates are also extracted from the graph constructed in the first phase based on non-diagonal cluster potentials addition. The potential matrix V can be computed as bellow:

$$V=\sum_{i=1}^{k}\sum_{x_j \in N_\varepsilon^s(x_i)} V^{(i,j)}.\gamma_{ij}.e^{\frac{||x_i^s - x_j^s||^2}{\sigma_s^2}} \quad (4)$$

$N_\varepsilon^s(x_i)$ represents the set of points in X which has spatial components in the ε- neighborhood of x_i, $\gamma_{ij}= \exp(-\frac{||x_i^f - x_j^f||^2}{\sigma_f^2})$, x_i^f and x_i^s represent the pixel's spectral and spatial information, σ_f and σ_S are the spectral and spatial scale parameters and $V(^{i,j})$ is a non-diagonal matrix, incorporates spectral information, determined by:

$$V_{(k,l)}^{(i,j)} = \begin{cases}1, \text{ if } (k, l)\in \{(i, i), (j, j)\} \\ -1, \text{ if } (k, l)\in \{(i, j), (j, i)\} \\ 0, \text{ otherwise}\end{cases} \quad (5)$$

4. The last step revolves around solving the optimization problem, from which the low dimensional space data Y are produced. Maximum eigenvectors and eigenvalues can be computed from the following generalized eigendecomposition problem:

$$X Z X^T m = \lambda X D X^T m \quad (6)$$

Z is a Schroedinger matrix which being defined as a kind of incorporation between the potential coordinates V and the Laplacian matrix L, it expressed by:

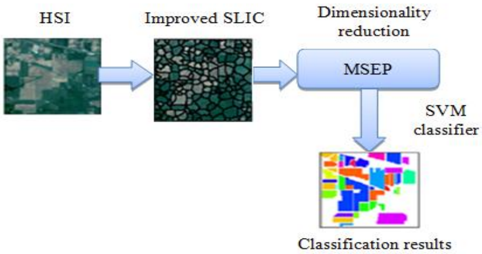


Figure 1. Architecture of the proposed approach.

$$Z = L + \alpha V \quad (7)$$

D is the diagonal weighted degree matrix, L=D-ω represents the Laplacian matrix, and α is a parameter used to load Laplacian and potential matrix participation. The resulting vectors $m_1,m_2, \ldots,m_d$ correspond to the eigenvectors of (6).

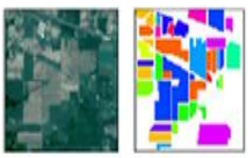
In this work, the Improved SLIC superpixel algorithm is firstly adopted, and then the algorithm MSEP is executed. The suggested approach is recapped through Figure 1.

4. Classification Experiments

After presenting the main idea and defining mathematical notions, this section is reserved for the experimental evaluation. The new suggested method, entitled Improved Schroedinger Eigenmap Projections (ImSEP), adopts the Improved SLIC superpixel pre-processing to reduce the MSEP computational burden.

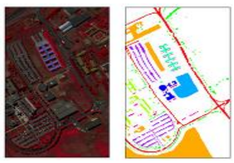
4.1. Data Sets

To evaluate the suggested methodology impact, two reference HSIs were employed, in this work, which are: Indian Pines and Pavia University data sets. The first tested image was acquired by the AVIRIS Sensor. The studied scene, taken in June of 1992, captures the northwest of Indiana United States of America (USA). It contains 200 spectral bands in the spectral range [0.4-2.5μm]. Each band contains 145×145 pixels; with a spectral resolution of



C1	C5	C9	C13
C2	C6	C10	C14
C3	C7	C11	C15
C4	C8	C12	C16

a) Indian pines.



C1	C4	C7
C2	C5	C8
C3	C6	C9

b) Pavia university.

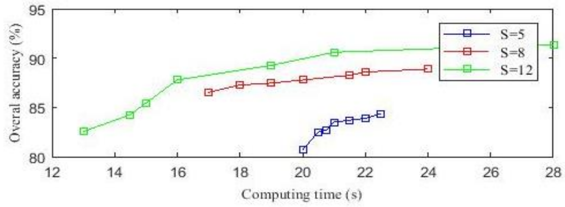
Figure 2. Color composites of the two hyperspectral data sets and their ground truth maps.

10 nm and a spatial resolution of 20 m. Indian Pines HSI includes 16 classes. The second used data set, recorded by the ROSIS sensor over Pavia University (Italy), contains 103 spectral bands with a spectral range from 0.43 to 0.86 µm and a spatial resolution of 1,3 m per pixel. Each band is composed of 640 × 340 pixels. The Pavia University image includes 9 ground truth classes. Tested HSIs and their ground truth maps, shown in Figure 2, were got from [5].

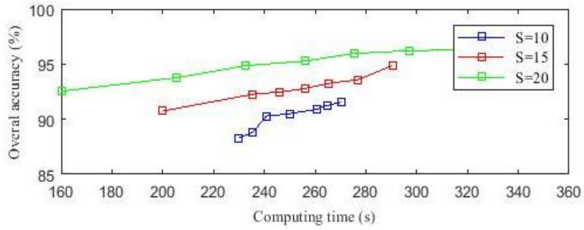
4.2. Experimental Analysis and Parameters Choice

To evaluate in an objective manner the proposed ImSEP approach, three other graph-based dimensionality reduction methods: Locality Preserving Projections (LPP) [15], Schroedinger Eigenmap Projections (SEP) [11] and modified SEP (MSEP) [9], were implemented and then they were compared to the suggested method. All tested algorithms were implemented using Matlab language. A Toshiba laptop with a 2-GHz processor and 4 GB memory was used for the experimental study.Since it can deal with high dimensional data sets, the Support Vector Machine (SVM) classifier [2] was selected to classify data classes. SVM classifier follows a supervised strategy in which, few train samples, randomly selected, are chosen from the available labeled data and used for learning. Classification result is then tested using remaining samples. Each algorithm script was repeated ten times and the average of the classification results was reported to evaluate the proposed approach yield. Confusion matrix results were used to compute classification outputs, Overall Accuracy (OA), Average Accuracy (AA) and Kappa coefficient [12]. Computing time and classification maps were also adopted to judge the proposed method efficiency.

For the Improved SLIC algorithm, two parametersshould be analyzed; which are: the nominal size of superpixel (*S*) and the superpixel regularity (*R*). Figures 3, and 4 exhibit the relationship between *S*, *R*, OA index and processing time. Figure 3 illustrates OA evolution versus computing time for the suggested ImSEP approach when the Improved SLIC superpixel methodology is implemented. Blue, Red and Green curves mark the superpixel sizes *S*=5, 8, and 12, for the Indian Pines data set and *S*=10, 15 and 20 for the Pavia University one; respectively. The Superpixel regularity *R* is altered along each curve. In Figure 4, we provided the same quantities, while switching the superpixel parameters. Blue, Red and Green curves exhibit the superpixel regularities *R*=0,01, 0,1, and 1; respectively. The superpixel size *S* is changed along each curve. From these figures, we can observe that there is a trade-off between superpixel size (*S*) and classification performance. Indeed, when *S* is wide, there are fewer superpixels. Consequently, the proposed method requires less computational charge. On the other hand, classification performance OA lowers for a wide *S*. The superpixel regularity less attracts the computational performance. In fact, the OA metric is almost stable when the regularity *R* is varied (using fixed superpixel size). To have a balance between quality and speed yields, we adopted a nominal size of superpixel *S*=8 and a superpixel regularity *R*=0,01 for the first HSI and *S*=15, *R*=0,01 for the second one. Tables 1, and 2 exhibit the details about the implemented parameters for all the tested methods.

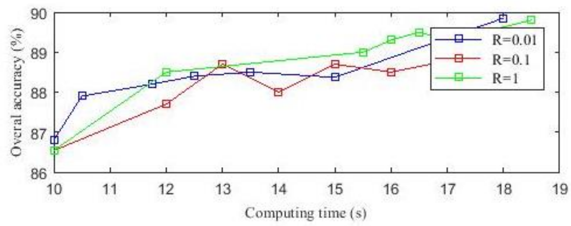


a) Indian pines.

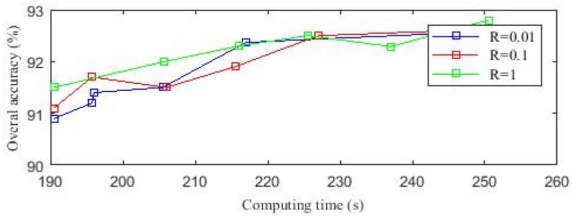


b) Pavia university data sets.

Figure 3. Classification Accuracy (OA) versus computing time with different values of *S*.



a) The indian pines.



b) The pavia data sets.

Figure 4. Classification Accuracy (OA) versus computing time with different values of *R*.

Table 1. Details about implemented parameters for the indian pines data set.

Parameters	LPP	SEP	MSEP	ImSEP
S	-	-	-	8
R	-	-	-	0,01
$\tilde{\alpha}$	-	17,78	16,11	16,11
n	20	20	20	20
σ^f	-	1	1	1
σ^s	-	1	1	1
M	-	-	-	50
T	-	-	-	200

Table 2. Details about implemented parameters for Pavia University data set.

Parameters	LPP	SEP	MSEP	ImSEP
S	-	-	-	15
R	-	-	-	0,01
$\tilde{\alpha}$	-	23,71	23,71	23,71
n	25	25	25	25
σ^f	-	1	1	1
σ^s	-	1	1	1
M	-	-	-	100
T	-	-	-	200

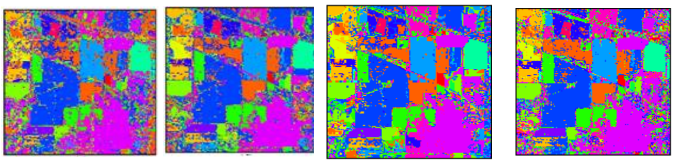
4.3. Results and Discussions

4.3.1. Indian Pines HIS

Table 3 describes the classification results for Indian Pines HSI with all tested cases. By analyzing this table, we can observe that the proposed ImSEP approach gives the highest classification accuracy: 87,80% of OA and 85,14% of Kappa. It succeeded to increase the OA index by about 11%, 9%, and 2% compared to LPP, SEP and MSEP reference methods respectively. Indeed, the correction mechanism recommended by the Improved SLIC method contributes to avoid the propagation of errors and subsequently to better adhere to image proprieties. The worst results were produced by LPP and SEP methods. In fact, the LPP gave 76,29% of OA while the SEP technique offered 78,32%. These results can be explained by the inability of the aforementioned methods to keep the dissimilarities between neighboring data points during the adjacency graph construction. With regards to AA produced results, we noticed that the ImSEP works fairly well on eight classes (C2, C3, C6, C7, C9, C12, C13 and C15) and competitively with the other ones. Note that the best AA results have been yielded by C1, C7, C8 and C9. For this image, the class C11, as the other reference techniques, still gives a low accuracy (92,55% of AA). Moreover, the integrated superpixels approach (Improved SLIC) can reduce considerably the time required to execute the MSEP algorithm. It can save about 15 seconds; which means 47,35% of computing time. We can observe also that the ImSEP dimensionality reduction method outperforms the LPP and the SEP techniques in computing efficiency. Figure 5 shows the different classification maps obtained by all the implemented algorithms, for the Indian Pines HSI. Although a certain level of inaccuracy is presented, the thematic classification maps for the SVM classifier confirm that the ImSEP dimensionality reduction approach can provide the best visualization output. Indeed, the adopted SLIC strategy succeeded to separate relatively the nearest classes. This can be seen especially in the top left area of the image. The generated maps confirm also that the proposed approach satisfied a competitive accuracy in term of visualization clarity for the large classes (C10, C11, and C12).

Table 3. Indian pines classification results for various dimensionality reduction methods.

Classes	LPP	SEP	MSEP	ImSEP
C1	99,97	**99,98**	**99,98**	99,95
C2	89,69	91,71	94,20	**95,09**
C3	93,83	94,52	96,00	**96,83**
C4	98,47	99,37	**99,57**	99,12
C5	98,94	99,00	**99,57**	99,44
C6	97,58	97,65	98,63	**98,90**
C7	99,93	99,92	99,94	**99,98**
C8	99,66	99,83	**99,92**	99,90
C9	99,82	99,70	99,82	**99,90**
C10	96,33	96,37	**97,46**	97,31
C11	89,38	88,86	**93,09**	92,55
C12	95,03	95,27	96,80	**97,71**
C13	99,15	99,48	99,71	**99,83**
C14	97,81	98,09	**98,77**	98,66
C15	97,17	96,97	97,91	**98,14**
C16	99,80	99,91	**99,92**	99,83
OA (%)	**76,29**	**78,32**	**85,65**	**87,80**
AA (%)	**97,04**	**97,29**	**98,21**	**98,32**
Kappa (%)	**72,62**	**75,02**	**83,55**	**85,14**
Time (S)	**23,62**	**27,4**	**32,63**	**17,18**



a) LPP. b) SEP. c) MSEP. d) ImSEP.

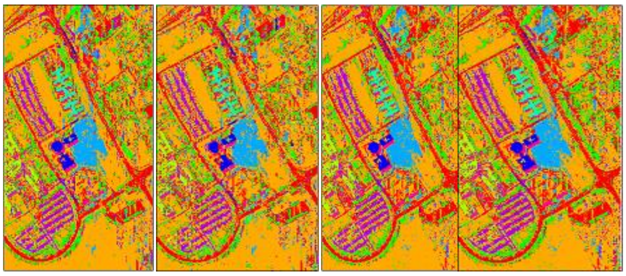
Figure 5. Indian Pines classification maps for various dimensionality reduction methods.

4.3.2. Pavia University HSI

Table 4 summarizes classification results of the second studied HSI. According to the obtained results, we can notice that the best results (92,28% of OA and 87,47% of kappa) have been achieved by the new suggested method. In fact, our approach performs better than all the tested algorithms, it improved the precision OA by about 14%, 7% and 1% compared to LPP, SEP and MSEP methods; respectively. By analyzing the AA classification results obtained by the Pavia University dataset, we can notice that the ImSEP method has the best precision compared to the other implemented methods. Indeed, the new suggested approach gave 98,06% of AA while the LPP technique maintained 93,98 %, the SEP method provided 96,78% and the original MSEP yielded 97,86%. Moreover, the quantitative classification results of the University of Pavia confirm that the novel proposed method is proficient at retaining the intrinsic hyperspectral details for the nine image classes. This can be explained by the ability of the Improved SLIC method to respect the original image properties. With respect to the processing time, it can be seen that computing time of the proposed ImSEP (234,61 s) is significantly low in comparison to the MSEP (576,21 s) and the conventional SEP (495,60 s) methods. Practically, the Improved SLIC pre-processing step can conserve about 49% of the processing time compared to the MSEP method and this can be considered as an encouraging result. Figure 6 shows the thematic classification maps for the second tested HSI with all the implemented dimensionality reduction methods. This figure confirms that the Improved SLIC pre-processing step provides a much clearer visualization than the techniques that adopt the pixels as inputs. In particular, our ImSEP approach shows a great ability to retain small image details.

Table 4. Pavia University classification results for various dimensionality reduction methods.

Classes	LPP	SEP	MSEP	ImSEP
C1	86,38	94,86	96,98	**97,27**
C2	90,15	90,86	93,69	**94,37**
C3	94,20	97,79	98,20	**98,28**
C4	93,91	96,17	97,59	**97,82**
C5	96,68	99,48	99,85	**99,86**
C6	93,95	96,61	97,72	**97,90**
C7	98,08	99,05	99,32	**99,34**
C8	94,31	96,77	97,58	**97,90**
C9	98,20	99,40	99,79	**99,82**
OA (%)	**78,75**	**85,49**	**91,36**	**92,28**
AA (%)	**93,98**	**96,78**	**97,86**	**98,06**
Kappa (%)	**72,01**	**80,20**	**86,97**	**87,47**
Time (S)	**428,76**	**495,6**	**576.21**	**234.61**



a) LPP. b) SEP. c) MSEP. d) ImSEP.

Figure 6. Pavia university classification maps for various dimensionality reduction methods.

5. Conclusions and Future Work

In this paper, a new graph-based dimensionality reduction approach, called ImSEP, was proposed for HSIs classification tasks. The suggested approach adopts a pre-processing step to lessen the computational burden of the MSEP technique. ImSEP method, tested on two real HSIs, has conducted to a satisfactory classification yield with a low computing time. Compared to the original MSEP method, the ImSEP approach has saved 47% of the processing time, for the first data set and 49% for the second one.Although obtained results are acceptable, other improvements may be made to the proposed approach input data representations, addressing more discriminating features, such as morphological features, texture features and intrinsic decomposition. This could further improve the classification performance.

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