

Research Article

Robust Hyperspectral Feature Extraction Method Using Edge Preserving Filters and Intrinsic Image DecompositionAli Can KARACA¹ 

¹ Kocaeli University, Electronics and Communications Engineering Department, 41001 İzmit, Kocaeli, Turkey, alicankrc@gmail.com,
http://www.orcid.org/0000-0002-6835-7634

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Abstract

Spectral-spatial feature extraction methods present an effective way for classification of hyperspectral images. However, performances of these methods may decrease depending on different data sets, classifier type, number of training samples, noise and smoothness level of data sets. In this paper, these terms are called as robustness criteria. This paper first discusses the effects of each robustness criteria for the feature extraction methods in the state-of-the-art. Secondly, a robust feature extraction method that can solve the aforementioned problems is proposed for hyperspectral image classification. The proposed method first performs dimensionality reduction and then extracts features using multiple edge preserving filters and intrinsic image decomposition method. Each robustness criteria is thoroughly examined in experiments and the results are compared with the state-of-the-art feature extraction methods. Experimental results demonstrate that the proposed method not only achieves better classification accuracies for different classifiers at lower training samples but also presents robust performance on different data sets that includes noise and smoothness effects.

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Kenar Koruyan Filtreler ve İçsel Görüntü Ayırıştırma ile Gürbüz Hiperspektral Öznelik Çıkartımı**Makale Bilgisi****Geliş:** 28 Aralık 2019**Kabul:** 31 Mayıs 2020**Yayın:** 27 Temmuz 2020

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Öz

Spektral-uzamsal öznelik çıkartımı yöntemleri, hiperspektral görüntülerin sınıflandırılması için etkin bir yol sunmaktadır. Buna rağmen, bu yöntemlerin performansları, farklı veri kümelerine, sınıflandırıcı tipine, eğitimde kullanılan örnek sayısına, veri kümesindeki gürültü ve yumuşuma seviyesine göre azalabilmektedir. Bu makalede, bahsedilen terimler gürbüzlük kriterleri olarak isimlendirilmektedir. Bu makalede öncelikle literatürdeki öznelik çıkartımı yöntemlerindeki her bir gürbüzlük teriminin etkisi tartışılmaktadır. İkinci olarak, bu problemleri çözmek için hiperspektral görüntülerin sınıflandırılması için gürbüz bir öznelik çıkartımı yöntemi önerilmektedir. Önerilen yöntem öncelikle boyut azaltımı uygulamakta ve sonrasında çoklu kenar koruyan filtreler ve içsel görüntü ayırıştırma yöntemiyle öznelikleri çıkartmaktadır. Deneylerde her bir gürbüzlük kriteri incelenmiş ve sonuçlar literatürdeki güncel öznelik yöntemleriyle karşılaştırılmıştır. Deney sonuçları, önerilen yöntem sadece az eğitim örneği sayısındaki farklı sınıflandırıcıların sınıflandırma başarımlarında daha iyi sonuç vermekle kalmayıp aynı zamanda gürültü ve yumuşama etkisine sahip farklı veri kümelerinde gürbüz bir performans sunmaktadır.

1. INTRODUCTION

Hyperspectral images (HSIs) include hundreds of spectral bands from visible to infrared regions of the spectrum and they offer high performances for land

cover classification [1]. In the literature, classification can be performed by using spectral and spectral-spatial features [1]. Spectral features are extracted by utilizing pixel-wise (PW) information such as spectral signature. However, a pixel tends to have the same classification

label with its neighbors. Therefore, in addition to spectral information, spectral-spatial features also consider spatial contextual information. For this reason, spectral-spatial features present more effective way than pixel-wise features for the classification of HSIs [2, 3].

For extraction of spectral-spatial features, several approaches have been extensively studied in recent years [3-8]. For example, Dalla Mura et al. [3] introduced extended morphological attribute profiles (EMAPs) which is an improved version of extended attribute profiles. In EMAP method, first, attribute profiles that can model spatial properties using area, moment of inertia and standard deviation are obtained. Afterwards, principal component analysis (PCA) is applied to the features of each attributes and concatenated sequentially. There are also Gabor filtering studies in the literature [4,5]. For instance, He et al. [4] presented low-rank Gabor filtering (GABOR) method which decomposes standard Gabor filter into eight sub-filters. With this discriminative model, computational efficiency of classical Gabor filter is increased and it is enabled to find high discriminative features. In another study, intrinsic image decomposition features (IIDF) is proposed to exploit reflectance and shading components of HSIs [6]. Shading component which represents useless spatial information such as image noise is successfully removed by IIDF method and only reflectance component is used in classification. Thus enables to evaluate spatial information more efficiently.

Using edge preserving filters has an upward trend in recent years [7-9]. It is possible to use edge preserving method before and after classification. For example, in edge preserving filtering (EPF), classification is carried out using only spectral features and local filtering used after classification [7]. Specifically, by means of colour guidance image, EPF is applied to probability maps of each class, then classification map is obtained by using final probability maps. In other works, edge preserving filters are used to extract features before classification step. Image fusion and recursive filtering (IFRF) method divides HSI into multiple subsets to reduce dimensionality [8]. Afterwards, an edge preserving filter called domain transform recursive filtering is applied to each feature followed by concatenation process [8]. Although IFRF achieves high classification accuracies, smoothing degree used in the method directly alters the classification results. Additionally, the differences between classes may decrease depending on smoothing process. To solve this problem, Kang et al. [9] proposed PCA-EPF features. In PCA-EPF method, features of multiple EPF filters with different parameters are combined and PCA operation is applied to resulted features. It makes a significant improvement in classification performance especially when the number of training samples is limited [9].

Classification performances of feature extraction (FE) methods also depend on classifier type [2]. He et al. [2] demonstrated that utilizing Support Vector Machines (SVMs) [10] and LORSAL [11] methods give significantly different performances for the same feature extraction method.

In general, performances of FE methods can be affected depending on data sets, the number of training samples, noise level, and classification method. For example, Indian Pines and Pavia University are two popular HSIs that are widely used in the literature. Because of using different sensor systems, they have different intrinsic characteristics, signal-to-noise ratio, and spatial resolution parameters. Therefore, some FE methods may give poor performances for different data sets. Moreover, data compression is inevitable nowadays in satellite communication systems. After compression of HSIs, the data sets may have more smooth shapes and it may decrease the classification accuracy. A FE method that always gives successful results in different conditions are typically called as a robust FE method. For this reason, all these criteria are important and it is desired to give the best performance in different cases. In this paper, the criteria that can affect the classification performances are called as *robustness criteria*.

The main motivation of this paper is to develop a feature extraction method that provides more robust classification performances than the-state-of-the-art FE methods for different data sets, classifier types, number of training samples, noise and smoothness level of data sets. Major contributions of this paper are described follows.

- First of all, to the best of our knowledge, it is the first paper that defines and discusses all these *robustness criteria* together. Each robustness criteria is thoroughly examined for different FE methods and compared the performances in detail. For this purpose, first, the analysis are performed for different data sets, namely, Indian Pines, Pavia University and Salinas. Second, two well-known classifier types, SVM and LORSAL, are evaluated for different FE methods. Also, the performances in different number of training samples are measured in the experiments. Moreover, different noise and smoothness conditions are queried and robust FE methods that are not affected from these conditions are reported.
- Secondly, a robust FE method is developed that can handle aforementioned robustness criteria in this paper. In the proposed method, first, spectral dimensionality is reduced to decrease computational complexity and features of edge preserving filters and intrinsic image decomposition methods is extracted. The key idea of the proposed method is to fuse these features and obtain different kind of information from data resulting

valuable performance improvement in various conditions.

2. DATA DESCRIPTION

In order to evaluate the robustness for different data sets, three commonly used HSIs, namely, Indian Pines, Pavia University, and Salinas are used in the experiments. Indian Pines and Salinas data sets are collected by the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) sensor system over Indian and Salinas Valley in USA, respectively. The first data set, Indian Pines, consists of 145×145 pixels including 220 spectral bands. The third data set, Salinas, has a spatial coverage of 512×217 with 224 spectral bands. Ground truths of these data sets include 16 different labeled classes. Here, noisy bands of these two data sets are removed similar to [9] and corrected versions of the data sets are used in the experiments. The other data set, Pavia University, is captured by Reflective optics Imaging Spectrometer System (ROSIS) sensor system over University of Pavia Campus, Italy. This data set composed of 610×340 samples with 103 spectral channels and it is labeled with 9 classes. Spatial resolution of the datasets are 20, 1.3 and 3.7 meter/pixel for Indian Pines, Pavia University, and Salinas, respectively. Therefore, all data sets have different parameters including spatial resolution, image resolution, the number of spectral bands, and scene location. More information can be found here, [http://www.ehu.es/ccwintco/index.php/Hyperspectral Remote Sensing Scenes](http://www.ehu.es/ccwintco/index.php/Hyperspectral_Remote_Sensing_Scenes).

3. METHODOLOGY

As described in Introduction section, feature extraction methods generally utilize different types of filtering theory to exploit both spatial and spectral information. Here, edge preserving filtering has a wide usage in classification of HSIs. It smooths the homogeneous regions while preserving the edge details. This enables to reduce the noise level and reach higher accuracies. Another problem in image classification is giving unstable performances under different light conditions. In order to solve this problem, intrinsic image decomposition is recommended in the literature. The method separates the data into two components: the useful reflectance and the useless shading component, then it uses the reflectance component for hyperspectral image classification. In this paper, a new method is proposed that benefits these two powerful techniques.

Block diagram of the proposed method is given in Figure 1. First of all, hyperspectral image is divided into K different sub-band groups. Due to having similar information in sequential bands, adjacent band images

inside each sub-bands are averaged and spectral band number of HSI is reduced to K .

Let a hyperspectral image represented as **HSI** and **HSI_n** denotes n th band image of hyperspectral image. Dimension reduction is applied as

$$\mathbf{HSI}_i^R = \frac{K}{NB} \times \sum_{n=1+(i-1)\left(\frac{NB}{K}\right)}^{i\left(\frac{NB}{K}\right)} \mathbf{HSI}_n \quad i = 1, 2, \dots, K \quad (1)$$

where **HSI^R** and NB represent the reduced HSI and total number of bands in HSI, respectively. In the second step, intrinsic image decomposition (IID) is applied to the reduced HSI. IID method decomposes band images into shading and reflectance components. Here, only reflectance components are considered as IID features. Parallel to this operation, edge preserving filters are applied to smooth band images while preserving edges and details. In this method, multiple EPFs are applied with three different smoothness parameters to evaluate various spatial structures individually. In order to fuse and reduce the total number of EPF features, PCA is applied to stacked EPF features and first C PCs of EPFs are used. In the final step, IID and EPF features are concatenated sequentially and stacked feature set are used in classification.

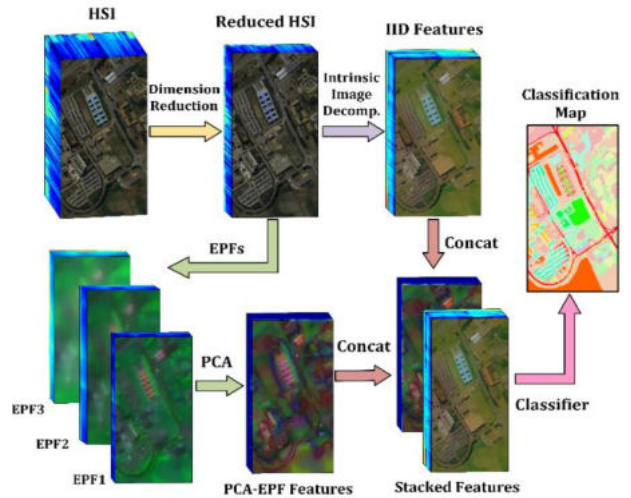


Figure 1. Block diagram of the proposed method

Intrinsic images are generally used to separate illumination and reflectance components from an image [12]. In this sense, an image can be simply obtained as

$$\mathbf{B}_p = \mathbf{R}_p \mathbf{S}_p \quad (2)$$

where **R** and **S** denote matrices of reflectance and shading components. Note that **B** denotes a spectral band image and p represents any point (x, y) in image space. However, estimation of reflectance and shading components needs optimization process. For

optimization, energy function to be minimized is shown as

$$E(\mathbf{R}, \mathbf{S}) = \sum_{p \in \mathbf{B}} \left(\mathbf{R}_p - \sum_{u \in \mathbf{N}} \beta_{p,u} \mathbf{R}_u \right)^2 + \sum_{p \in \mathbf{B}} (\mathbf{B}_p / \mathbf{S}_p - \mathbf{R}_p) \quad (3)$$

where $\beta_{p,u}$ and $\mathbf{N}$ are weight function of local window and local neighborhood window, respectively. Weight function of local window $\beta_{p,u}$ measures the similarity between pixels located at p and u points using Gaussian distance [12, 13].

In this paper, IID is applied to hyperspectral image by sub-groups. First, hyperspectral image is divided into subgroups in spectral dimension, then IID is performed to each group. For k th group, the equation can be written as follows

$$E(\mathbf{R}^k, \mathbf{S}^k) = \sum_{p \in \mathbf{B}^k} \left(\mathbf{R}_p^k - \sum_{u \in \mathbf{N}} \beta_{p,u}^k \mathbf{R}_u^k \right)^2 + \sum_{p \in \mathbf{B}^k} (\mathbf{B}_p^k / \mathbf{S}_p^k - \mathbf{R}_p^k) \quad (4)$$

where $\mathbf{R}^k$, $\mathbf{S}^k$ and $\mathbf{B}^k$ have multiple band images inside. Energy minimization is performed iteratively and after iterations are finished reflectance and shading components are obtained. More information about IID and group IID process can be found in references [5, 12].

Because of its effective performance, domain transform recursive filter (DTRF) is used as EPF. DTRF first transforms the signal to a domain using smoothness parameters σ_s and σ_r that can control smoothing effect [14]. Domain transformation can be shown as follows

$$\mathbf{DT}_p = \sum_{k=1}^p \left(1 + \frac{\sigma_s}{\sigma_r} |\mathbf{B}_I - \mathbf{B}_{I-1}| \right) \quad (5)$$

where $\mathbf{DT}_p$ denotes domain transformed value for image point p . After domain transformation, filtering can be recursively applied as follows

$$\mathbf{F}_p = (1 - a^b) \mathbf{B}_p + a^b \mathbf{F}_{p-1} \quad (6)$$

$$a = \exp(-\sqrt{2}/\sigma_s), \quad b = \mathbf{DT}_p - \mathbf{DT}_{p-1} \quad (7)$$

where $\mathbf{F}_p$, a and b denote output of filter for image point p , weight coefficient and distance between two neighboring pixels in transform domain (DT).

4. EXPERIMENTAL RESULTS

For comparative evaluation of FE methods, recent methods namely, EMAP [3], GABOR [4], IFRF [8], IIDF [6], EPF [7], and PCA-EPF [9] are used. Code implementations are realized on MATLAB[®]. So as to

evaluate the robustness of classification performances, SVM and LORSAL methods are utilized. Training samples are randomly selected for various trained data ratios (TDRs) that is defined as (#training pixels/#pixels) and experiments are repeated during 10 Monte Carlo runs for each FE method. Comparisons are made in terms of averages and standard deviations (STDs) of overall accuracies (OAs). K and C parameters of the proposed method are selected as 15 and 30, respectively. Other parameters of the methods are selected the same as reference papers. For example, multiple EPFs are extracted for three set of parameters: $(\sigma_s, \sigma_r) = \{(115, 0.6), (200, 0.9), (30, 0.9)\}$. For IID method, size of sub-groups is selected as 4. Further information for selection parameters of EPF and IIDF can be found in references [6, 7, 9].

4.1. Experiments on Original Data Sets

In the first part of the experiments, overall classification accuracies of all FE methods are obtained for each data sets with SVM and LORSAL classifiers. The results are given in Figure 2 and the width of each line represents STDs of the experiment. In addition, average OAs of different data sets at the lowest TDRs are calculated and shared in Figure 3. Here, averaging is performed over all data sets at the lowest TDR.

Performances for different data sets, classifier types and number of training samples can be discussed from robustness perspective in Figure 2. First of all, only SVM results which are given in Figure 2 (a)-(c) are analyzed. Here, it is seen that the worst case is occurred in pixelwise SVM method for all data sets. Indeed, this shows the performances when only spectral features are used. Therefore, these features do not include any spatial information. Alternatively, it is observed that PCA-EPF achieves significantly higher OAs among the state-of-the-art (SA) methods in Indian Pines data set. For example, it reaches nearly 80% accuracy at TDR=0.5% which is 8% greater than the closest method IFRF. On the other hand, IIDF obtains the best accuracies than other SA methods in Pavia and Salinas data sets. The accuracy difference between two best methods, PCA-EPF and IIDF, remains quite small about 5% in Salinas data set. However, in Pavia University data set, there are important differences between curves of PCA-EPF and IIDF methods. This shows that the best method changes concerning data sets. The proposed method provides a robust performance with respect to data set and it performs higher accuracies than the other methods. Secondly, OAs also vary depending on classification method and some methods such as EMAP and IFRF are negatively affected from this situation. For examples, in Indian Pines data set, OAs of IFRF obtained as 70% and 78% for SVM and LORSAL classifier, respectively when TDR=0.5%. Similarly, EMAP method gives

higher performances with LORSAL classifier. However, the proposed method presents similar performances for different classifiers. This allows the proposed method to give classifier-invariant results.

Third, number of training samples directly affects the classification performances. In general, differences between OAs are getting significantly bigger at low TDRs. This means some FE methods are more sensitive to number of training samples. As is seen in Figure 2 and Figure 3, the proposed method outperforms the other methods at the lowest TDRs with 87.96% and 88.12% for LORSAL and SVM, respectively. However, the performances of FE methods are generally getting closer when higher number of training samples is used.

For instance, the differences between the best method and some methods such as IIDF, PCA-EPF, GABOR and IFRF significantly decrease when TDR is equal to 10%. On the other hand, PW, EPF and EMAP methods trace poor performances with respect to number of training samples.

In summary, classification performances can directly change according to number of training samples, and different classifier type and data sets. The proposed method provides the most robust performance among the other methods. According to Figure 3, the proposed method yields nearly 88% average accuracies at the lowest TDR and it does not significantly change for LORSAL and SVM classifiers.

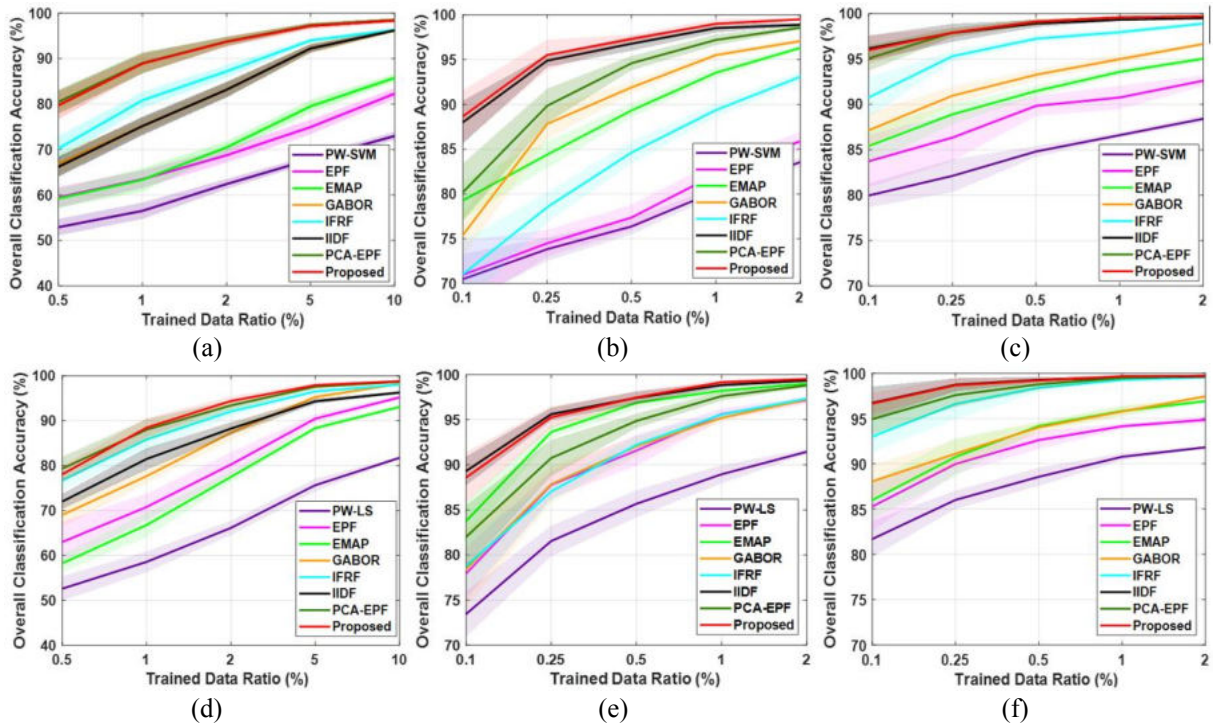


Figure 2. Overall accuracies of FE methods for SVM and LORSAL: (a), (d) SVM and LORSAL results for Indian Pines, (b), (e) SVM and LORSAL results for Pavia University, (c), (f) SVM and LORSAL results for Salinas, respectively

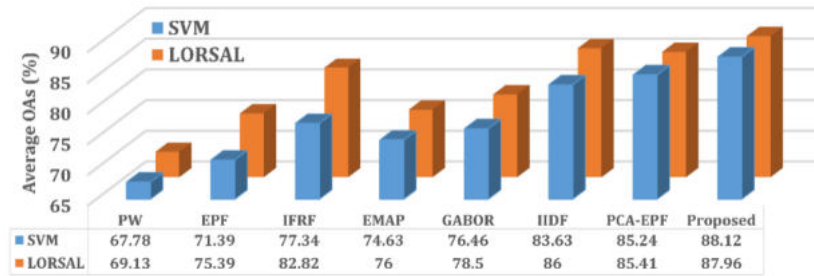


Figure 3. Average OAs of FE methods for SVM and LORSAL at the lowest TDRs

In order to visually evaluate the results, classification maps of FE methods are shared for Indian Pines, Salinas

and Pavia University data sets in Figure 4, Figure 5 and Figure 6, respectively. Number in parenthesis indicates

OAs in figure captions. Classification maps are extracted when TDRs are 1%, 0.25%, and 0.5% for Indian Pines, Pavia University, and Salinas, respectively.

Because of achieving higher OAs, LORSAL is selected to obtain classification maps. It is seen that the proposed method achieves the best performance for all data sets. In parallel to results in Figure 2, EPF and EMAP obtain the worst accurate results compared to other methods. However, the classification maps of these methods have very different characteristics. For example, EPF includes

large falsely classified regions. But, EMAP has noisy labels so it decreases classification performances. IIDF has the same effect but it obtains fewer number of noisy labels. Moreover, class labels of GABOR do not fit along the edges which shows edge preservation property of the features is weak. IFRF, PCA-EPF and the proposed method shows better edge preserving response than others. In Pavia University and Salinas data sets, IIDF method accurately assigns class labels and gets more similar maps to ground truth among the state of the art methods. It yields more sensitive predictions especially thin and sharp regions.

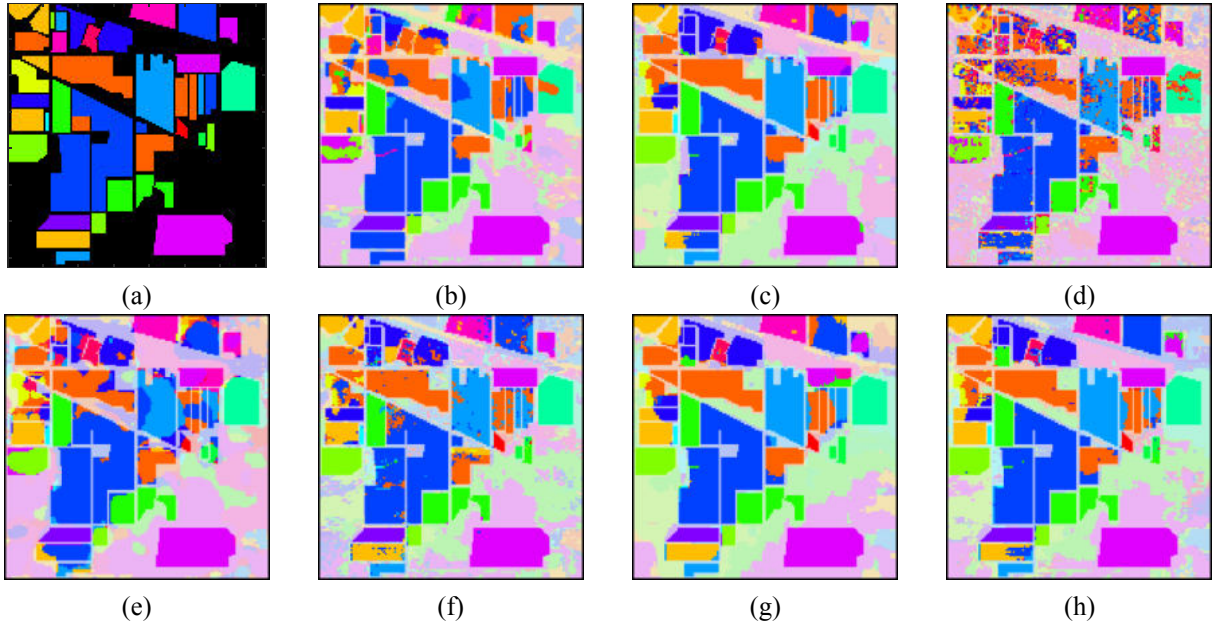


Figure 4. Ground truth of Indian Pines data set and classification maps of FE methods: (a) Ground truth, (b) EPF (73.03%), (c) IFRF (86.67%), (d) EMAP (70.42%), (e) GABOR (78.54%), (f) IIDF (84.54%), (g) PCA-EPF (88.13%), (h) Proposed (89.31%)

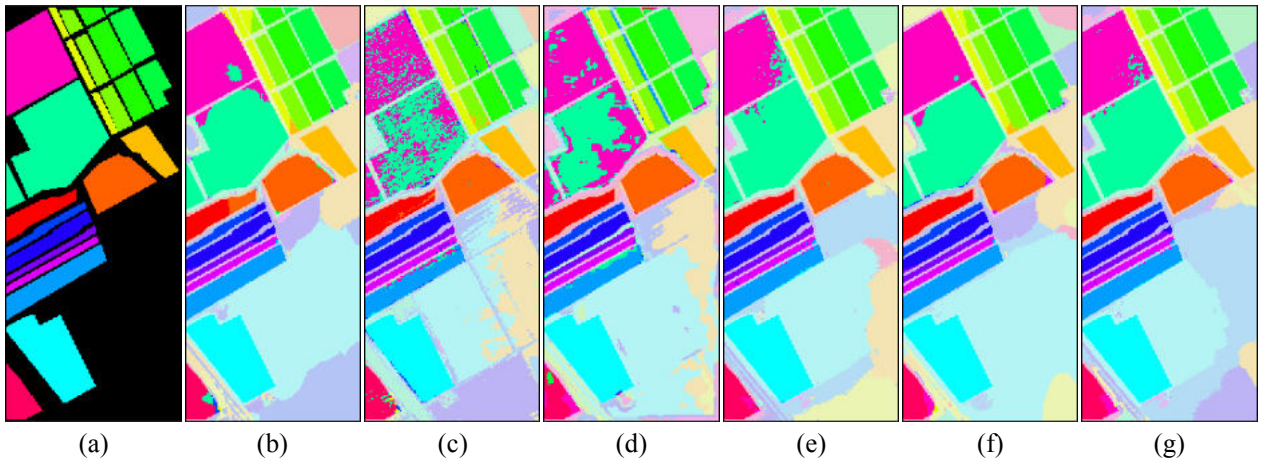


Figure 5. Ground truth of Salinas data set and classification maps of FE methods: (a) Ground truth, (b) IFRF (94.96%), (c) EMAP (87.00%), (d) GABOR (87.09%), (e) IIDF (97.26%), (f) PCA-EPF (97.14%), (g) Proposed (98.15%)

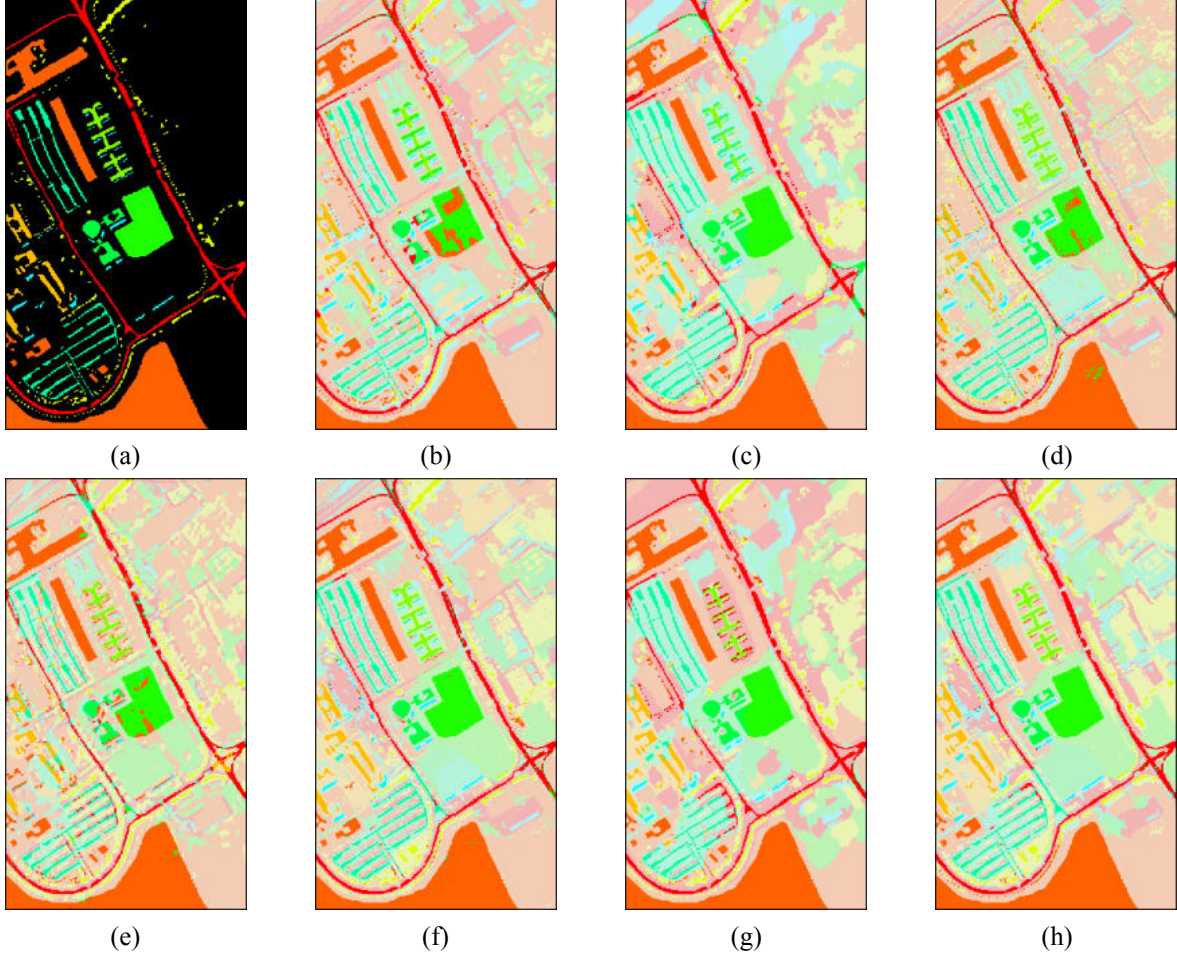


Figure 6. Ground truth of Pavia University data set and classification maps of FE methods: (a) Ground truth, (b) EPF (87.82%), (c) IFRF (88.30%), (d) EMAP (93.57%), (e) GABOR (87.25%), (f) IIDF (95.18%), (g) PCA-EPF (93.10%), (h) Proposed (95.68%)

4.2. Experiments on Noisy and Smoothed Data Sets

In the second part of the experiments, the performances of FE methods in smoothness and noise conditions are queried. For the purpose of generation smooth image, Indian Pines and Pavia University images are filtered band by band with a Gaussian kernel (STD=5). Here, it is tried to simulate the classification performances when images are compressed at low bit-rates. Similarly, noisy data sets are generated by adding normally distributed noise with (0, 75) range. Color images for different conditions of the data sets are given in Figure 7.

For each condition, OAs of FE methods are obtained by SVM and LORSAL and their average classification performances are shared with their STDs ($\pm$). Table 1 and Table 2 indicate the average OA results for Indian Pines and Pavia University data sets, respectively. Note that the results are only shared lower TDRs to observe robustness to limited training samples. From Table 1 and Table 2, it is clearly seen that TDRs are extremely low.

For example, TDR=0.5% means only 61 training samples are used for Indian Pines. Similarly, 0.1% TDR corresponds to 48 training samples for Pavia University data set. Therefore, it will show the performances when the limited training samples are used.

From Table 1, it can be concluded that using both noisy and smoothed Indian Pines data set changed classification accuracies of FE methods when they are compared to original data set. In general, PCA-EPF and the proposed methods provide higher accuracies when data set is noisy. Specifically, in Indian Pines, PCA-EPF gives 76.8%, 85.6%, and 90.9% average OAs when TDRs are 0.5%, 1%, and 2%, respectively. For these TDRs, the proposed method obtains similar performances with PCA-EPF. However, other methods are negatively affected from noise situation. Especially, EMAP method obtains the lowest OAs with %49 at all. This shows that the method is very sensitive to noise.

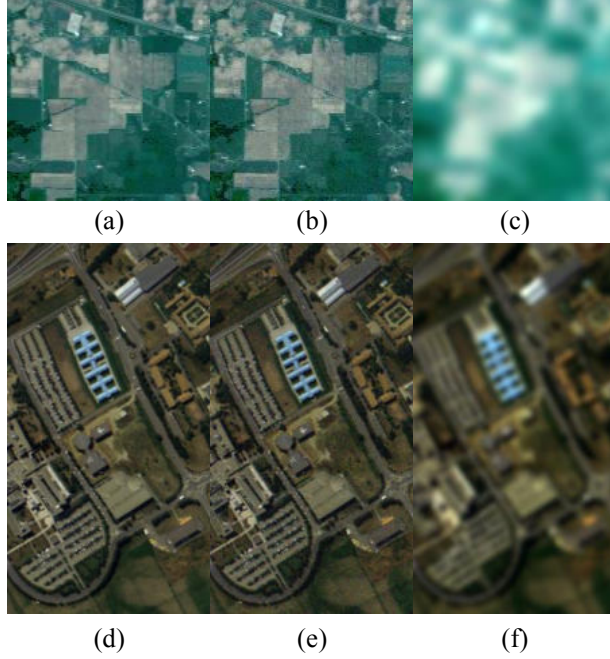


Figure 7. (a), (b), (c) Colour images of original, noisy and smoothed versions of Indian Pines and (d), (e), (f) Colour images of original, noisy and smoothed versions of Pavia University

In Indian Pines data set, smoothing process increases the overall accuracies of some FE methods such as PW and EPF methods. For instance, OAs of PW increased from 52.3% to 65.7% at the lowest TDR. Although IFRF, IIDF, PCA-EPF and the proposed method decreases the accuracies compared to original data set results, the proposed method achieves the best OAs among the other methods for all TDRs. There is obvious accuracy differences at lowest TDRs with other compared methods. Moreover, adding noise to the data set generally decreased the results of the methods while smoothing operation improved some methods such as EMAP and GABOR. Especially, GABOR provides very close accuracies to the proposed method when TDR is 2%.

Alternatively, averages of each class accuracies (AAs) are also calculated in this step. AAs of the proposed and PCA-EPF show similar behavior in parallel with OA performances. For example, AAs of the proposed method and PCA-EPF are found as 73.78% and 74.43% when TDR is 0.5% in noisy condition. In smoothed condition, the same AAs are obtained for the proposed method and PCA-EPF that are also have higher AAs than other methods.

Table 1. Average OAs (%) for noisy and smoothed versions of Indian Pines

TDR (%)	PW	EPF [7]	IFRF [8]	EMAP [3]	GABOR [4]	IIDF [6]	PCA-EPF[9]	Proposed
Noisy Indian Pines data set								
0.5	51.6±2.0	58.0±2.4	70.9±2.8	49.0±1.9	67.9±2.7	61.3±1.8	76.8±3.3	75.4±2.5
1	54.4±1.8	61.6±2.5	80.9±1.9	55.9±1.6	76.4±1.6	67.5±1.8	85.6±2.2	84.9±2.3
2	58.8±1.2	67.4±2.5	87.6±1.1	64.8±1.3	85.3±1.3	75.7±1.6	90.9±1.4	91.2±1.4
Smoothed Indian Pines data set								
0.5	65.7±2.8	67.5±2.8	69.4±3.5	70.2±2.6	73.0±2.6	70.1±2.6	75.8±2.4	76.1±2.7
1	74.8±1.4	77.0±1.5	79.1±1.6	79.0±1.6	83.3±2.5	79.5±2.2	85.1±2.0	85.2±2.2
2	83.3±1.6	85.2±1.5	85.4±1.5	87.6±1.5	90.4±1.4	86.7±1.8	90.2±1.0	90.9±1.0

Table 2. Average OAs (%) for noisy and smoothed versions of Pavia University

TDR (%)	PW	EPF [7]	IFRF [8]	EMAP [3]	GABOR [4]	IIDF [6]	PCA-EPF[9]	Proposed
Noisy Pavia University data set								
0.10	70.2±2.3	72.4±2.7	72.8±2.7	43.6±2.2	69.9±2.7	77.4±3.3	79.8±3.0	87.1±3.4
0.25	72.8±1.4	75.3±1.5	82.1±1.5	53.4±1.1	79.0±1.5	85.5±1.7	89.3±1.7	94.2±1.2
0.50	74.0±0.8	77.7±1.0	87.5±0.9	60.9±0.5	83.9±1.2	90.1±0.8	93.8±0.8	96.9±0.6
Smoothed Pavia University data set								
0.10	72.1±3.6	72.5±3.6	74.5±2.9	75.2±2.6	77.8±2.7	82.2±1.9	80.9±2.4	83.9±2.7
0.25	81.8±1.2	82.5±1.3	79.7±1.7	84.2±1.6	88.5±1.6	88.5±1.7	86.6±1.3	89.5±1.3
0.50	85.8±1.2	86.7±1.4	85.9±1.0	88.7±1.2	92.6±0.8	92.8±1.0	91.3±0.9	93.4±1.1

Table 2 shows that the proposed method outperforms the other methods for both noisy and smoothed data sets. In noisy case, it achieves 87.1%, 94.2%, and 96.9% OAs for TDRs are 0.1%, 0.25%, and 0.5%, respectively. Also, the accuracies of the proposed method are obtained as 83.9%, 89.5%, and 93.4% for smoothing case, respectively. Among other methods, performance of PCA-EPF is higher than the other methods in noisy data set. By contrast, IIDF shows better accuracies in smoothed data set. Additionally, similar to Indian Pines results, GABOR method improves the classification performance in smoothed data. Different from Indian Pines results, the other methods obtain extremely lower OAs in noisy data set and classification performance of the proposed method is improved at least 3.1% in this case. Note that standard deviations of all methods are getting lower when TDR is increased. For noisy condition, average accuracies of IIDF, PCA-EPF and the proposed method are found as 74.5%, 79.3%, and 84.8%, respectively.

For smoothed condition, average accuracies of IIDF, PCA-EPF and the proposed method are also observed as 75.4%, 78.2%, and 79.2%, respectively. Owing to usage IIDF, and PCA-EPF, it is also seen that AAs are increased in noisy and smoothed cases for Pavia University data set. This shows the impact of the proposed method.

In general, experimental results demonstrate that the proposed method not only achieves better classification accuracies for different classifiers at extremely lower training samples but also presents robust performance on data sets that include noise and smoothness effect.

5. CONCLUSION

In this paper, robust criteria for classification of hyperspectral images are defined and discussed. It is reported that all criteria including number of training samples, noise level and selected classifier method and smoothness of data set directly affects the classification accuracies. In order to tackle these problems, a robust feature extraction method is proposed for hyperspectral images in this paper. The proposed method consists of three steps. In the first step, dimension reduction is applied to hyperspectral image with sequential averaging. Afterwards, intrinsic image decomposition and EPF features are extracted from reduced image. In the last step, final features are obtained by concatenation process. This method enables to fuse different advantages of IID and EPF methods for classification and to handle robustness criteria. In order to show effectiveness and robustness of the proposed method, classification performances are analyzed to evaluate the criteria in terms of limited training samples, classifier type, noise and smoothness effects. Classification

performance of the proposed method is compared the recent methods in literature, namely, EPF, EMAP, GABOR, IIDF, PCA-EPF. The outcomes of this paper are given as follows.

- Among the state-of-the-art methods, the best method can change depending on data sets. For example, PCA-EPF achieves significantly higher OAs among the SA methods in Indian Pines data set. On the other hand, IIDF obtains the best accuracies than other SA methods in Pavia and Salinas data sets. But, the proposed method that includes the advantages of both methods increases the average accuracies of IIDF and PCA-EPF by 3.22% and 2.72% at the lowest TDR, respectively.
- Classifier type can also affect the classification accuracies of FE method. For example, although IFRF obtains 82.82% accuracy for LORSAL classifier, the accuracy decreases to 77.34% when SVM is used. On the other hand, the proposed method yields 88.12% and 87.96% accuracies for SVM and LORSAL, respectively. This shows the performance of the proposed method is not affected from classifier type.
- Number of training samples is one of the determining factor for classification process. Most methods work unstable and give the unsuccessful results for few labeled samples. Here, the proposed method achieves the best overall performances at the lowest TDRs with 88.04% accuracy.
- Data sets may include noise and smoothing effect inside. This effects transform the classification problem into harder situation. Experiments show that the proposed method keeps the best accuracies even if the data set is noisy or smooth. Here, the proposed method yields the best accuracies with 91.2%, 90.9%, 96.9%, and 93.4% for noisy-Indian Pines, smoothed-Indian Pines, noisy-Pavia University, and smoothed-Pavia University data sets, respectively.

In the light of all the information mentioned above, it is seen that the proposed method not only obtains higher classification accuracies for different classifier types and extremely lower training samples but also it provides a robust performance on data sets that are noisy and smooth.

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VITAE

Dr. Ali Can KARACA received the B.Sc. degrees in Electrical Engineering and Electronics & Communications Engineering, and the M.Sc. degree in Electronics & Communications Engineering from Kocaeli University, Kocaeli, Turkey, in 2010, 2011, and 2014, respectively. He received Ph.D. degree in 2019 at Kocaeli University. His research interests include digital image processing, remote sensing, and hyperspectral imaging. He currently works as a research assistant in Electronics and Communications Department of Kocaeli University.