AUTOMATIC SELECTION OF THE TRAINING SET FOR SEMI-SUPERVISED LAND CLASSIFICATION AND SEGMENTATION OF SATELLITE IMAGES

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Abstract: Different scenarios can be found in land classification and segmentation of satellite images. First, when prior knowledge is available, the training data is generally selected by randomly picking samples within classes. When no prior knowledge is available the system can pick samples at random among all unlabeled data, which is highly unreliable, and ask the expert to label them or it can rely on the expert collaboration to improve progressively the training data applying an active learning function. We suggest a scheme to tackle the lack of prior knowledge without actively involving the expert, whose collaboration may be expensive. The proposed scheme uses a clustering technique to analyze the feature space and find the most representative samples for being labeled. In this case the expert is just involved in labeling once a reliable training data set for being representative of the features space. Once the training set is labeled by the expert, different classifiers may be built to process the rest of samples. Three different approaches are presented in this paper: the result of the clustering process, a distance based classifier, and support vector machines (SVM).

1 INTRODUCTION

The classification and segmentation of land usage in satellite images generally requires an expert who provides the corresponding labels for the different areas in the images. Some authors work with prior knowledge in a supervised scenario and training data is selected within each class (Y.Tarabalka et al., 2010)(A.Plaza and et al., 2009). Lately the research interest in active learning techniques, which move to a semi-supervised scenario, is raising. In new real databases, the expert labeling involves whether prior knowledge or checking at the land place itself, which could be highly expensive. The expert collaboration may be needed an unknown number of steps to improve the classification by helping in the training selection until the convergence condition is achieved (Tuia et al., 2009)(Li et al., 2010). Hence, the expert collaboration can be highly expensive and picking at random among the unlabeled pool is not convenient because classes are often very unbalanced and the probabilities of getting an efficient representative training data is inverse to the amount of labeled samples. Consequently, decreasing the size of labeled data is a problem. To tackle this, the most interesting samples should be provided to the expert from the beginning (Comaniciu and Meer, 2002).

In unsupervised scenarios, data analysis techniques have proved being good at providing relevant data when no prior knowledge is available. Among them, clustering techniques allow us to divide data in groups of similar samples. Specially when samples represent pixels from an image, clustering algorithms have successfully been applied to image segmentation in various fields and applications (Arbelaez et al., 2011). We aim to segment and classify hyper-spectral satellite images. Fully unsupervised procedures often have insufficient accurate classification results. For such a reason, a hybrid scenario between supervised and unsupervised techniques is our target where the methods applied could take into account some labels to build a classifier. We suggest to use a clustering analysis to find samples of interest, ask an expert for their labels and classify using that labeled set obtained. This scheme was presented in (Rajadell et al., 2011) where a $KNN1$ classifier was used. Here we suggest to assign labels to unlabeled samples according to the result given by the cluster itself and the labels provided by the expert for the modes of clusters. We also adapt and extend the method in order to be used with SVM. These new segmentation approaches provide interesting results. For

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all cases, the suggested scheme is compared with the supervised state of the art classification, resulting in outperforming previous works.

A review of the sample selection scheme with its spatial improvement is presented in Section 2. Several classification alternatives are presented in Section 3. Results will be shown and analyzed in Section 5. Finally, Section 6 presents some conclusions.

2 PRELIMINARIES

Nowadays, due to the improvement in the sensors, databases used for segmentation and classification of hyper-spectral satellite images are highly reliable in terms of spectral and spatial resolution. Therefore, we can consider that our feature space representation of the data is also highly reliable. On the other hand, in segmentation and classification of this kind of images the training data used has not been a concerned so far, without worrying about providing the most reliable information (Comaniciu and Meer, 2002). The scheme suggested in (Rajadell et al., 2011) was a first attempt in this sense. It was proposed an unsupervised selection of the training samples based on the analysis of the feature space to provide a representative set of labeled data. It proceeds as follows:

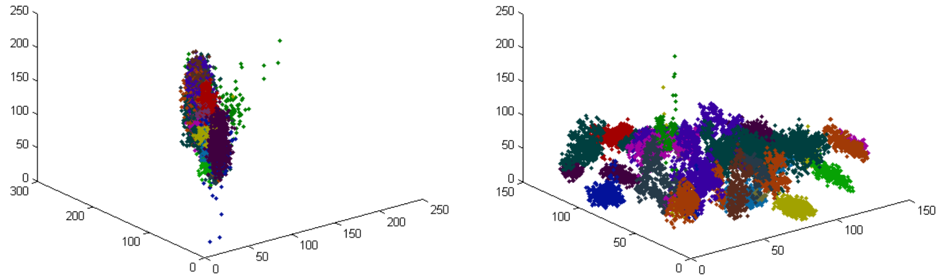
1. In order to reduce the dimensionality of the problem, a set of spectral bands, given a desired number, is selected by using a band selection method. The WaLuMi band selection method (Martínez-Usó et al., 2007) was used in this case, although any other similar method could be used.
2. A clustering process is used to select the most representative samples in the image. In this case, we have used the Mode Seek clustering procedure which is applied over the reduced feature space. An improvement in the clustering process is included by adding the spatial coordinates of each pixel in the image as additional features. Since the clustering is based on distances, spatial coordinates should also be taken into account assuming the class connection principle.
3. The modes (centers of the clusters) resulting of the previous step define the training set for the next step. The expert is involved at this point, only once, by providing the corresponding labels of the selected samples.
4. The classification of the rest of non-selected samples is performed, using the training set defined above to build the classifier. Three different classification experiments have been performed here: a *KNN* classifier with $k = 1$, a direct classification with the results of the clustering process, and an extension will be presented for the use of SVM.

2.1 Mode Seek Clustering

Given a hyper-spectral image, all pixels can be considered as samples which are characterized by their corresponding feature vectors (spectral curve). The set of features defined is called the feature space and samples (pixels) are represented as points in that multi-dimensional space. A clustering method groups similar objects (samples) in sets that are called clusters. The similarity measure between samples is defined by the cluster algorithm used. A crucial problem lies in finding a good distance measure between the objects represented by these feature vectors. Many clustering algorithms are well known. A *KNN* mode seeking method will be used in this paper (Cheng, 1995). It selects a number of modes which is controlled by the neighborhood parameter (s). For each class object x_j , the method seeks the dissimilarity to its s^{th} neighbors. Then, for the s neighbors of x_j , the dissimilarities to their s^{th} neighbors are also computed. If the dissimilarity of x_j to its s^{th} neighbor is minimum compared to those of its s neighbors, it is selected as prototype. Note that the parameter s only influences the scheme in a way that the bigger it is the less clusters the method will get since more samples will be grouped in the same cluster, that is, less modes will be selected as a result. For further information about the mode seek clustering method see (Cheng, 1995) and (Comaniciu and Meer, 2002)

2.2 Spatial Improvement

The clustering algorithm searches for local density maxima where the density function has been calculated using the distances for each sample in its s neighborhood using a dissimilarity measure as the distance between pairs of samples. In that difference, all features (dimensions) are considered. When features do not include any spatial information the class connection principle is missed (pixels that lie near in the image are likely to belong to the same class). Therefore, we suggest to include the spatial coordinates among the feature of the samples. See Fig 1.(a) where all samples have been represented in the three first features space and in different color per class. Notice that, when no spatial data is considered and all classes are located in the same space and when no prior knowledge is available for the clustering process, finding representatives for each class would be difficult since the classes themselves may lie together. Moreover, different areas of the same class may be



a b

Figure 1: Effects of including spatial information in the feature space. Plots show the samples of the database in the feature space, colored per class according to the ground-truth. (a) no spatial information is available. (b) spatial coordinates are included.

within the same cloud. However, when spatial data is included, Fig 1.(b), the single cloud of samples is broken according to spatial distances and classes (fields) are more separable. In this sense also samples belonging to the same class but lying in different places of the image are separable.

In (Rajadell et al., 2011) it was suggested to weigh the spatial coordinates by an arbitrary number to reinforce two samples that are close spatially to have a closer distance and the way round. Such a weight should be decided in terms of the range of the features provided by the spectrometer so the coordinates are overweighed but they do not cause the rest of features be dismissed in the global measure.

3 CLASSIFICATION ALTERNATIVES

The whole dataset was first reduced to 10 bands using the band method selection named in Section 2. This method is used for minimizing the correlation between features but maximizing the amount of information provided, all that without changing the feature space. Clustering was carried out tuning the parameter *s* to get a prefixed number of selected samples. Three different classification alternatives have been used.

3.1 Straightforward Schemes

1. First a *KNN* with k=1 classification has been performed with the labeled samples as training set. This is not an arbitrary choice, because the clustering procedure used is based on densities calculated on a dissimilarity space, and therefore, the local maxima correspond to samples which minimize its dissimilarity with a high amount of samples around it. Thus, the selected samples are highly representative in distance-based classifiers.
2. Second, another classification process has been performed using the straightforward result of the clustering procedure. The expert labels the selected samples. Then, all samples belonging to the cluster that each labeled sample is representing are automatically labeled in the same class. This provides a very fast pixel classification scheme as the clustering result is already available.

3.2 Extension to SVM

The scheme, as it has been presented, is not useful for classifiers that are not based on distances. However, we would like to check if providing relevant training data may be also useful for other classifiers. In this case, we extend the proposed method for SVM. For such a classifier, it is interesting to detect samples in the borders between clusters and not their centers to achieve representing the shape of the data in the feature space. Nevertheless, we do not want to increase the amount of labeled data. According to these criteria we propose selecting samples from the cluster, assuming that those samples have the same label that the cluster was given. It would be possible to take the whole cluster itself with the assumed label as training data but, depending on the database size, it would not be computationally affordable. On one hand, using the most distant samples from the cluster center would introduce an important amount of outliers in the construction of the classifier. On the other hand, using the samples around the cluster center would not help the SVM to find the shape of the cluster. Therefore, two thresholds α_1 and α_2 of the maximum distance inside each cluster has been considered. Samples between α_1 and α_2 are selected for training the SVM (see Fig 2). Although the amount of samples selected is higher than the number of modes, notice that these samples are not labeled by the expert and, consequently, the number of the labeled samples

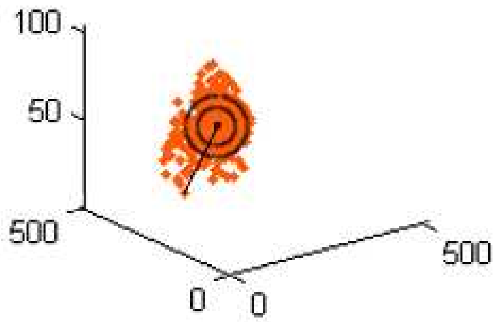


Figure 2: Training selection example for extension of the scheme to SVM necessities. The samples between α_1 and α_2 will be used to construct the SVM.

is still the same. However, the real size of the training set is larger and it should be more representative of the shape of the data. With this larger set we can train a SVM and use it to classify the whole image. The use of these samples would also be possible for the case of the *KNN* classifier. However, it is important to point out that the errors made by the clustering process in these samples are now introduced in the training set.

4 DATABASE

A well-known database has been used in the experiments (see Fig 3). Hyper-spectral image 92AV3C was provided by the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) and acquired over the Indian Pine Test Site in Northwestern Indiana in 1992. From the 220 bands that composed the image, 20 are usually ignored (the ones that cover the region of water absorption or with low SNR) (Landgrebe, 2003). The image has a spatial dimension of 145×145 pixels. Spatial resolution is 20m per pixel. Classes range from 20 to 2468 pixels in size. In it, three different growing states of soya can be found, together with other three different growing states of corn. Woods, pasture and trees are the bigger classes in terms of number of samples (pixels). Smaller classes are steel towers, hay-windrowed, alfalfa, drives, oats, grass and wheat. In total, the dataset has 16 labeled classes and unlabeled part which is known as the background. This so called background will be here considered as the 17 class for the segmentation experiments.

5 EXPERIMENTAL RESULTS

In Fig 4 the results obtained using several classification strategies are compared: *KNN* using only the center of the clusters for the training set, SVM, *KNN*

Figure 3: 92AV3C AVIRIS database. Color composition and ground-truth.

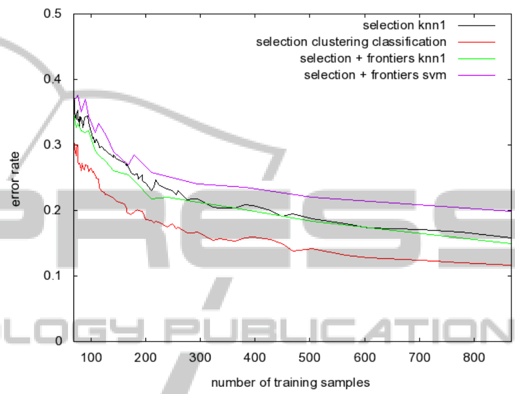


Figure 4: Learning curve in terms of error rate when increasing the size of training data in number of samples selected by the scheme suggested. Different classification methods tested using the 92AV3C database.

using the same training set used for the SVM, and the classification using the plain output of the mode seek clustering. It was already shown in (Rajadell et al., 2011) that the scheme used with *KNN* clearly outperformed the random selection. Now, the classification result for the *KNN* classifier adding more samples in the clusters assuming the same label is very similar to the ones obtained with the *KNN* classifier using only the cluster centers. For SVM the thresholds used here were $\alpha_1 = 0.3$ and $\alpha_2 = 0.4$, although several combinations of values were used providing similar results in all cases. The SVM classifier provided the worst results in all experiments. This may be due to the fact that the double threshold scheme proposed assumes a spherical distribution of the samples around the cluster centers. However, this is not the case in general, and that is the reason why SVM cannot properly model the borders of the classes using these training samples. On the other hand, the mode seek clustering classification outperformed all other methods. The reason is that this sort of clustering is not based on the distance to a central sample in the cluster but to the distance to other samples in the clusters. When the distance to a central point is considered, a spheric distribution of the pixels around this point is assumed. However, the mode seek clustering provides clusters

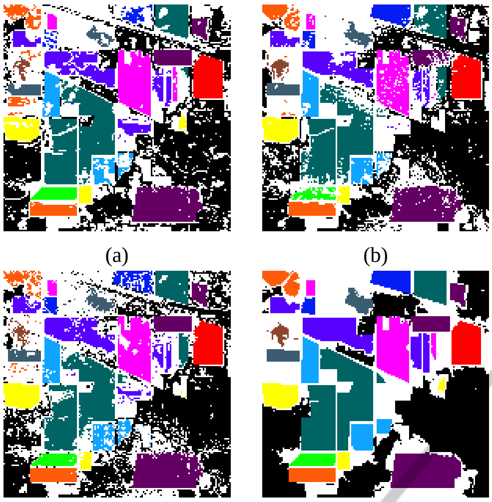


Figure 5: Segmentation-classification results using 0.33% of data for the selected training set using several classifiers. (a) *KKN* using the cluster centers. (b) SVM (c) *KNN* using the same training set as for the SVM (d) mode seek clustering.

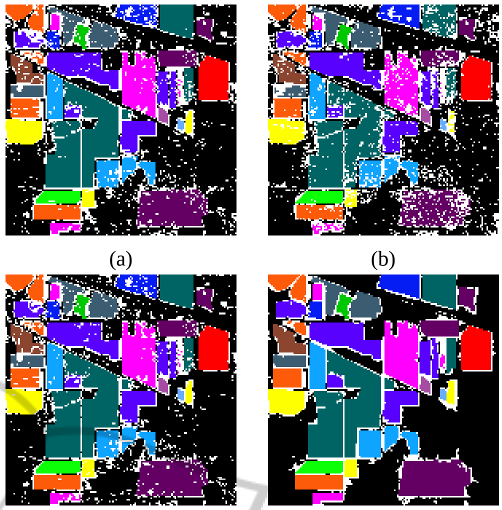
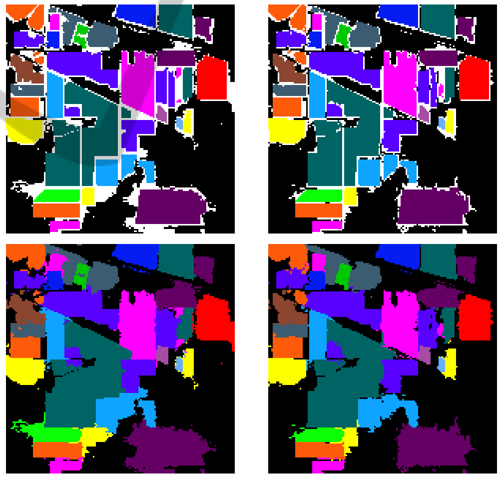


Figure 6: Segmentation-classification results using 4% of data for the selected training set using several classifiers. (a) *KKN* using the cluster centers. (b) SVM (c) *KNN* using the same training set as for the SVM (d) mode seek clustering.

that may adapt to different shapes, depending on the distribution of the samples in the feature space, and these clusters can be modeled using just one sample.

The database has 21025 samples. Fig. 5 show the classification results of several classifiers when 0.33% of the pixels in the image (69 pixels) was labeled by the expert. The classification errors are shown as white pixels. It can be noted that the clustering classifier outperformed the other classifiers not only in the percentage of classification rate but also providing smooth compact regions in the image. Similar results can be seen in Fig. 6 where 4% of the pixels in the image was labeled, where the classification errors tend to concentrate in the borders of the different regions in the image. Note that the segmentation results are quite smooth even for the background class.

Let's consider the 2% of the samples and the cluster-based classification. See results in Fig 7.(a). Observe the top left part of the image where the selection manages to detect all of them although the classes are lying one next to each other and their size is not big. The best result is presented in Fig 7.(b), it is the classification-segmentation result for the 17-classes problem using 4% of the data. The overall error rate is 0.116 and the most relevant error is the lost of very small classes that cannot be found by the clustering. In Table 1 the results per class are presented for different sizes of the training set using cluster classification. Observe that the accuracy per class of a reduced training set is good when the class has been detected by the cluster. As long as one class is missed



$error = 0.157$ (a) $error = 0.116$ (b)

Figure 7: Segmentation-classification results using different amounts of data for the selected training set using the proposed scheme and the clustering based classification. (a) Using 2% of the data. (b) Using 4% of the data.

in the selection of the training data, this class will be entirely misclassified.

In Table 1 where the error rate per class is shown, we can see that the results obtained using 2% of the samples are already comparable in terms of per class accuracy with results obtained in supervised scenarios using 5% of the data (Y.Tarabalka et al., 2010). Notice that classes with only one spatial area are well classified with few samples needed, such as Alfalfa,

Table 1: Accuracy per class for the 17 classes classification of the AVIRIS dataset using 12 features (ten spectral features and two spatial coordinates). For a training sets of 0.33%, 2% and 4% of the data using the clustering-based classifier.

	0.33% of training data		2% of training data		4% of training data	
classes	training/total	error	training/total	error	training/total	error
Heterogenous background	22/10659	0.432	171/10659	0.262	367/10659	0.193
Stone-steel towers	0/95	1	2/95	0.139	5/95	0.033
Hay-windrowed	2/489	0.004	10/489	0.004	25/489	0.004
Corn-min till	5/834	0.214	18/834	0.076	40/834	0.045
Soybeans-no till	5/968	0.185	25/968	0.060	40/968	0.072
Alfalfa	0/54	1	1/54	0.038	3/54	0.039
Soybeans-clean till	2/614	0.488	15/614	0.066	28/614	0.056
Grass/pasture	3/497	0.105	12/497	0.064	28/497	0.042
Woods	6/1294	0.023	29/1294	0.034	58/1294	0.026
Bldg-Grass-Tree-Drives	3/380	0.021	9/380	0.011	12/380	0.011
Grass/pasture-mowed	0/26	1	1/26	0.040	1/26	0.040
Corn	1/234	0.601	6/234	0.070	10/234	0.049
Oats	0/20	1	0/20	1	0/20	1
Corn-no till	6/1434	0.278	35/1434	0.067	63/1434	0.035
Soybeans-min till	10/2468	0.069	70/2468	0.023	143/2468	0.018
Grass/trees	4/747	0.067	18/747	0.033	34/747	0.042
Wheat	1/212	0.009	7/212	0.005	11/212	0.005
Overall error		0.299		0.156		0.116

Wheat, Hay-windrowed, Grass/pasture-mowed and Corn. Some of them (as Wheat and Hay-windrowed) were already well classified when only 0.33% training data was used. The rest of the classes are divided in different spatial areas and their detection is highly dependant on the size of the area and the amount of different classes that surrounds them. Soybeans-min-till class is from the beginning well classified with only 10 samples, this is a large class whose different areas in the image are also large and well defined. The same can be concluded for other classes like Bldg-Grass-Tree-Drives or Woods. However, class Soybeans-clean till is confused with the classes around since the areas where it lies in are small despite of being a big class. The background is a special case, although it is treated here as a single class for segmentation purposes, it is composed by different areas with probably considerably different spectral signatures and, if a part of it would be missing in the training data, that part will be misclassified.

6 CONCLUSIONS

A training data selection method has been proposed in a segmentation classification scheme for scenarios in which no prior knowledge is available. This aims at improving classification and reducing the interaction with the expert who would label a very small set of points only once. This is highly interesting when expert collaboration is expensive. To get representative training data, mode seek clustering is performed. This type of clustering provides modes (representative samples) for each cluster found in the feature space and those modes are the selected samples for labeling. Thanks to a spatial improvement in the clustering, the modes provided do not contain redundant training information and can represent different spatial areas in the image that belong to the same class. The training selection has been used over several classifiers. We have experimentally proved that distance based classifiers are more adequate than SVM for such an approach. Furthermore, we have also shown that the classification obtained from the mode seek clustering outperformed the simple distance based classifiers because it better adapts to the shapes of the clusters in the feature space.

All classification strategies benefit from the selection of the labeled data to improve their performances. They provide very good results even with less labeled data than provided in other scenarios where training data was randomly selected.

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