Two Stage SVM Classification for Hyperspectral Data

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Abstract: In this article, we present a method of enhancing the SVM classification of hyperspectral data with the use of three supporting classifiers. It is done by applying the fully trained classifiers on learning set to obtain the pattern of their behavior which then can be used for refinement of classifier construction. The second stage either is a straightforward translation of first stage, if the first stage classifiers agree on the result, or it consists of using retrained SVM classifier with only the data from learning data selected using first stage. The scheme shares some features with committee of experts fusion scheme, yet it clearly distinguishes lead classifier using the supporting ones only to refine its construction. We present the construction of two-stage scheme, then test it against the known Indian Pines HSI dataset and test it against straightforward use of SVM classifier, over which our method achieves noticeable improvement.

1 INTRODUCTION

In this article we present the two-stage classification for hyperspectral images, based on SVM classifier and refinement of learning dataset.

The presented problem of analysis of HSI data is becoming ever more present in research and practical application with the increased availability of hyperspectral imaging devices. Hyperspectral cameras present the extension of input compared to RGB cameras – they not only allow to analyze the shape and color of the objects but also the structure of reflected light, which, in turn, helps in determining the material the object consist of.

The additional information presented in hyperspectral imaging results in many applications of such data. Bhaskaran et al. in (Bhaskaran et al., 2004) describes the utilization of hyperspectral imaging in post-disaster management, Pu et al. in (Pu et al., 2015) discusses its uses in quality control in food products and Ellis, in (Ellis, 2003) focuses of hyperspectral analysis of oil-influenced soil.

Therefore it is important for the classification schemes to be able to handle such data, which lead the hyperspectral classification to be widely researched topic. And so, Xu and Li in (Xu and Li, 2014) use sparse probabilistic representation enhanced spatially by Markov Random Fields, Melgani and Bruzzone in (Melgani and Bruzzone, 2004) achieve very good results using Support Vector Machines. Chen et al. in (Chen et al., 2013) achieve class separability by projecting the samples into a high-dimensional feature space and kernelizing the sparse representation vectors of training set. Bioucas-Dias et al (in (Bioucas-Dias et al., 2012)) discuss hyperspectral unmixing methods, based on assumption that each pixel in the image in fact consists of several materials and distinguishing them leads to better classification, while, in (Fang et al., 2015) the neighborhood relations are strongly utilized by analysis of superpixels.

What we intend to do is to enhance the results of known SVM classifier which in fact achieves very good results on hyperspectral data by constructing two-stage scheme that use several specialized second-stage SVM classifiers for each initial classification.

The idea of fusing more than one classifier data is well established branch of research and includes many methods of combining the individual classification results. A broad survey of such methods can be found in (Ruta and Gabrys, 2000) by Ruta and Gabrys or in experimental comparison by Kuncheva et al. in (Kuncheva et al., 2001) followed by theoretical study by Kuncheva in (Kuncheva, 2002).

In this paper we propose two-stage scheme for refinement of SVM first stage classification. It relates to the mixture of Committee of Experts (introduced in (Perrone and Cooper, 1993)) and System Generalization method, proposed first by Wolpert in (Wolpert, 1992), yet it is not a fusion method per se, as it is in fact only the repetitive usage of the same classifier, with modified learning set.

In the first stage we use the SVM classifier as well

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as several classifiers added as the Committee of Experts. We then apply the constructed committee onto the learning set to achieve the knowledge on structure of classes for each votes combination. In the second stage, we classify the hyperspectral vector with each Committee member classifier and obtain the classification according to the similarity of votes structure to learning set. If we cannot draw conclusion we use the base SVM classifier again, but we train it only with learn vectors from classes present in the first stage votes.

In our work we will not be focusing on spatial enhancement of the classification results. We decided to not do that since while it improves the results in our test dataset, where the regions are more or less homogoenous, it not always is the case with hyperspectral data. The spatial enhancement of the result can be added for further result refinement.

This article is organized as follows: in Section 2 we discuss used classification schemes, then present our two-stage approach, as well as the dataset we will use for testing. In Section 3 we present the conducted experiment and discuss its results, then we conclude our work in 4.

2 METHOD

In this section we will discuss the method of classification that we use. Firstly, we present the dataset used for experiments and the format of data. Then we proceed to short introduction to known classification algorithms we utilize. Finally we present the construction of our two-stage classification scheme.

2.1 Used Classifiers

In our experiment we will use the one main classifier (we selected well researched Support Vector Machine – SVM as defined in (Chapelle et al., 1999), as it gives very good results on the dataset, cf (Rojas et al., 2010)) and three supporting classifiers for refinement purposes. Those three will be the Bayesian Network (as in (Denoyer and Gallinari, 2004)), K-Nearest Neighbors and Decision Tree, (Friedl and Brodley, 1997) and standard KNN.

2.2 Classification Scheme

Let dataset $D = D_l \cup D_t$ where D_l be the training data and D_t be testing data. Let also $c = 1,\dots,C$ be classes of vectors in D.

Let then $Cl_i, i = 1,\dots,n$ be the partial classifiers, with Cl_1 being the main classifier (in our case it is SVM). For each $v \in D$ we denote classification of vector v using classifier Cl_i as $Cl_i(v)$ and true class of vector v as $c(v)$.

2.2.1 Building Voting Base VB

In this phase we build voting base VB to use in second stage of the scheme. The idea is to associate each voting vector with true class of the vector that resulted in that voting vector

$$VB : C^n \longrightarrow C^{<|D_l|}$$

that is each combination of votes that existed in stage one classification on D_l with true class of the data vector that resulted in such combination. Of course that means that for each combination the result is a list shorter or equal with number of data vectors in learning set $|D_l|$ and

$$\sum_{v \in C^n} |VB(v)| = |D_l|.$$

For that we obtain, for each $v \in D_l$, vote vector $\mathcal{V}(v)$ where $\mathcal{V}(v) = [Cl_1(v),\dots,Cl_n(v)]$, that is a vector of classifications of data vector v obtained by each partial classifier $Cl_i, i = 1,\dots,n$.

We construct the base VB by assigning true classes to each $\mathcal{V}(v), v \in D_l$. We of course know the true class $c(v)$, since $v \in D_l$.

VB, for each $\mathcal{V}(v)$ holds the information what were the actual classes of data vectors $v \in D_l$ when vote sequence $\mathcal{V}(v)$ occurred.

In other words for voting vector $X \in C^n$

$$VB(X) = \left\{ c(v) : v \in D_l \wedge \mathcal{V}(v) = X \right\}.$$

2.2.2 First Stage

The first stage of the scheme consists of obtaining classification of vectors $v \in D_t$ by each of $Cl_i, i = 1,\dots,n$ and obtaining $\mathcal{V}(v), v \in D_t$, the vote vectors.

The first stage, for $v \in D_t$ produces voting vector $\mathcal{V}(v)$. We can expect that the Cl_1, the main classifier, achieves significantly higher accuracy than that of the $Cl_i, j = 2,\dots,n$ (cf (Melgani and Bruzzone, 2004)). It is frequently not the case (cf Table 1, first part), yet the experiment design assumes that the main classifier will be the one with general best performance.

The result of the first stage of classification for $v \in D_t$ is therefore $\mathcal{V}(v) = [Cl_1(v),\dots,Cl_n(v)]$.

We also assume that class assigned to vector $v \in D_t$ by first stage of algorithm is the classification result of main classifier,

$$Cl'(v) = Cl_1(v).$$

2.2.3 Second Stage

The second stage classification for vector $v \in D_t$, having obtained $\mathcal{V}(v)$ proceeds as follows:

i. If $\mathcal{V}(v)$ exists within voting base VB ($VB(\mathcal{V}(v))$ is a sequence of non-zero length), and there exists most frequent element of $VB(\mathcal{V}(v))$, then we consider classification result $Cl''(v)$ as that element.

$$Cl''(v) = \text{argmax}_c \gamma_{\mathcal{V}(v)}(c)$$

where

$$\gamma_{\mathcal{V}(v)}(c) = \sum_{x \in VB(\mathcal{V}(v))} \mathbf{1}_{x=c}.$$

In other words we assume $Cl''(v)$ to be the most frequent class associated with the vote vector $\mathcal{V}(v)$ in the training set.

ii. If $\mathcal{V}(v)$ exists within voting base VB, and two or more elements $c_1, c_2, \ldots, c_k, kleqC$ have equal number of instances in $VB(\mathcal{V}(v))$. Then we construct second stage classifier Cl'_1 training it with

$$\{x \in D_l : c(x) \in \{c_1, c_2, \ldots, c_k\}\}.$$

Then $Cl''(v) = Cl'_1(v)$

iii. If $\mathcal{V}(v)$ did not occur in VB, we construct second stage classifier Cl'_1 training it with

$$\{x \in D_l : c(x) \in \mathcal{V}(v)\}.$$

Then $Cl''(v) = Cl'_1(v)$

3 RESULTS

To test the presented scheme we compare the two stage classification as presented in 2.2 with the results achieved by the single stage classification using the same base classifier.

3.1 Dataset

As a dataset we use the Indian Pines hyperspectral image, a well-researched set for testing hyperspectral image analysis. The scene was gathered by AVIRIS sensor over the Indian Pines test site in North-western Indiana and consists of 145×145 pixels and 224 spectral reflectance bands in the wavelength range $0.42.5 \cdot 10^{-6}$ meters. It contains two-thirds agriculture, and one-third forest or other natural perennial vegetation. There are two major dual lane highways, a rail line, as well as some low density housing, other built structures, and smaller roads. The ground truth available is designated into sixteen classes.

3.2 Experiment

The experiment will proceed as follows:

As base classifier we use SVM with three different kernels – linear, polynomial and radial basis functions (RBF). As supporting classifiers we use Bayesian Networks, Decision Trees and K-Nearest Neighbors. The parameters for the SVM classifiers are determined by grid search as we want to get the peak performance of each kernel.

That setting gives us three classifier sets (denoted after respective kernels in SVM classifiers). For each of these three sets we perform three classifications

1. Single-stage classification using SVM classifier Cl_1.
2. Two-stage classification scheme, denoted as second stage A.
3. Two-stage classification without referring to voting base VB. In other words the two-stage scheme with the assumption that for any $v \in D_t$, $VB(\mathcal{V}(v))$ is always an empty sequence, thus applying only second stage, point *ii*.. We will denote this approach as second stage B.

For validation of the results we use 10-folds cross-validation with 10% of data used as learning dataset and remaining 90 % used as test data.

This experiment is aimed at deciding if the second stage offers actual results improvement. It also evaluates how much the two-stage scheme differs between cases with and without the using the VB (point *ii* of second stage).

The results of this part of the experiment will allow us to draw conclusions as to how representative the learning set is to the whole data set – it will determine in how many cases the training and test vectors are so similar, that they produce the same voting vector.

The main result of the experiment is presented in table 1.

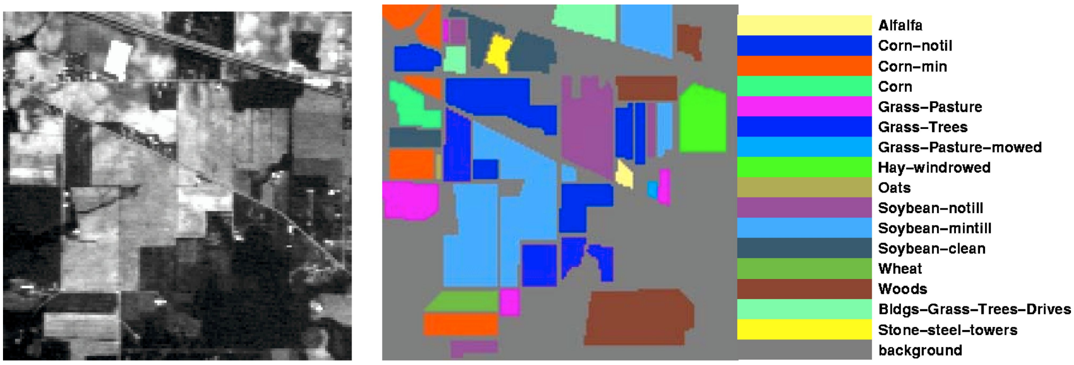
We are also able to analyze the peak possible accuracy of presented scheme. We do that by counting number of cases where $c(v) \in \mathcal{V}(v)$ - which means at least one of the $\{Cl_i\}_{i=1}^n$ classified vector v correctly.

If this does not happen, second stage cannot improve the result, as the correct class training vectors are not even considered in construction second stage classifier.

The results of this analysis is presented in Table 2.

3.3 Discussion

The results presented in table 1 show, that adding the second stage noticeably increases accuracy of SVM



(a) (b)

Figure 1: The Indian pines picture (a) and ground truth for the classification (b) From (Manian and Jimenez, 2007).

classifier, regardless the kernel. Moreover, the RBF kernel yielding best results as standalone classifier (in our experiment as well as in experiments presented in (Melgani and Bruzzone, 2004)) is the one most improved.

By comparing the classification scheme A, with VB analysis and B, only with secondary training with limited class set, we can see that the Second Stage A achieves advantage over Second Stage B, though only minimal. That suggest that the small training sample very well reflects the whole body of the data – when the voting sequence is the same, it usually means that the vector class is also the same.

There is also at least 1 correct vote in over 90 percent of cases (as seen in table 2), which means that only in 10 % of cases second stage has no chances of improving the results, since in those cases the correct $c(v)$ is not included in second-stage learning set. That suggests that a scheme for choosing the right classifier from the first stage pool could be a promising concept.

What seems to be the main downside of presented scheme is that it is time consuming – most of the second stage classifications require new SVM classifier trained with pool of vectors limited by the first stage analysis. The need of possible retraining (while it certainly lowers with greater number of train vectors) would also require to have the learning dataset available, which may be space-consuming should the dataset be really large.

4 CONCLUSION

The addition of the second stage to classification scheme, as well as several classifiers (with significantly lower accuracy rate) for refinement purposes noticeably increases the results of SVM classifier with all three analyzed kernels.

Table 1: The accuracy achieved in the experiment - in the first line we see one stage classification using SVM with three different kernels, in next three lines - the results of supporting classifiers and in the last line the accuracy by two stages classification scheme.

	Linear	Polynomial	RBF
Base SVM	0.6824	0.7701	0.7740
KNN	0.6776	0.6762	0.6845
DTree	0.6109	0.6100	0.6070
BN	0.5093	0.5041	0.4874
Sec. stage A	0.7142	0.7916	0.8136
Sec. stage B	0.7021	0.7887	0.8080

Table 2: The percentage of cases in which correct classification was present in $\mathcal{V}(v)$.

	Linear	Polynomial	RBF
$\geq$ one vote	0.8136	0.84	0.9210
$\geq$ two votes	0.8080	0.7916	0.8312

While in some cases the second stage results do not take into consideration the correct classification result (as it did not appear in any vote of the first stage), these situations constitute of less than 10 percent of cases. What can also be observed is that small learning set well reflects the whole body of hyperspectral vectors.

What is also important, that presented two stage scheme is not spatially enhanced (in the way as presented in (Xu and Li, 2014)). Thus, achieved results are not to be compared to the spatially enhanced classifiers, but only to their first stage. Further refinement of the initial classification in this manner is of course possible.

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