Approaches to Classification of Multichannel Images

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Abstract. The comparison of different approaches to classification of multichannel remote sensing images obtained by spaceborne imaging systems is presented. It is demonstrated that it is reasonable to compress original noisy images with appropriate compression ratio and then to classify the decompressed images rather than original data. Two classifiers are considered: based on radial basis function neural network and support vector machine. The latter one produces slightly better classification results.

Keywords: Multichannel image classification, image compression, remote sensing.

1 Introduction

Nowadays airborne and spaceborne remote sensing (RS) systems produce a lot of data that are valuable for such applications like ecological monitoring, forestry, agriculture, catastrophe prediction, etc [1]. Most of such systems operate in the so called multichannel mode [2]. Term “multichannel” means that for some terrain lot several component images are formed in different bands or using different polarizations of transmitted and/or received signals. Multichannel RS systems are potentially able to provide more reliable retrieval of useful information from RS data and/or more accurate estimation of sensed terrain parameters.

Multichannel data can be transferred from airborne or spaceborne carrier to an on-ground processing center without any compression, coded in a lossless manner, or lossy compressed. In case of lossless coding the provided compression ratio (CR) is commonly within the limits from 2 to 3 [3, 4] that often is inappropriate. Recently, several papers that report on possibilities of applying lossy compression to multi- and hyperspectral images have appeared (see, e.g., [5-7]). It has been demonstrated that quite good classification of multichannel RS data can be provided even if the used CR is from 20 to 50. It can be explained by the fact that the original multichannel RS

images often are noisy [8] and noise suppression using image compression techniques leads to increasing the reliability of correct classification simultaneously decreasing the data size [8-10]. The only important item is that CR should be adjusted in correspondence with noise variance for providing a proper trade-off between noise suppression and distortions introduced due to lossy compression [9,10]. This allows expecting that the probability of correct classification of multichannel RS data can be of the same order for two cases: a) applying classification procedure to original (noisy) data; b) applying classification to data compressed in a lossy manner with proper selection of a compression ratio.

The aim of this paper is twofold. The first goal is to compare both aforementioned approaches and to make up the corresponding practical recommendations. The second goal is to consider two modern classifier types based on using support vector machines (SVM) and radial basis function (RBF) neural networks (NN), both trained in a supervised manner.

2 Lossy Compression of Noisy Images

First, it is worth noting that in case of lossy compression of noisy images it is reasonable to use not typical criteria of compressed image quality [9, 10]. Recall that if one deals with traditional lossy compression of still images, the compression is basically characterized by the rate-distortion curve (PSNR vs CR) [11]. $PSNR_{or}$ for decompressed image is calculated with respect to the corresponding original image. On the contrary, if a noisy image is subject to compression, it is also expedient to control similarity of decompressed and noise-free images that can be characterized by $PSNR_{nf}$ calculated with the use of MSE between decompressed and noise free images. Certainly, $PSNR_{nf}$ can be obtained by simulations with test images to which noise has been artificially added.

Fig. 1 presents the corresponding curves for the test gray-scale image Lena corrupted by additive, zero mean Gaussian noise with variance $\sigma^2=50$. Two compression methods have been considered, the standard JPEG 2000 [12] and the recently introduced AGU coder [13].

For both considered coders the dependencies of $PSNR_{or}$ behave in conventional manner, i.e., $PSNR_{or}$ becomes smaller when the compression rate increases. The behavior of the $PSNR_{nf}$ curve is more specific. As seen, for both considered coders $PSNR_{nf}$ increases when CR reduces from 2 to approximately 0.35 bpp. At $CR \approx 0.35$ bpp the maximums for both curves are observed, and further reduction of CR leads to rapid $PSNR_{nf}$ decreasing. Such a compression rate for which the maximum of $PSNR_{nf}$ is observed called optimal operation point (OOP). Intuitively, this can be favorable for image classification.

As shown in [9], for OOP determination one should know in advance or to pre-estimate the noise characteristics, and it can be done in a blind manner [15, 16]. Approaches to provide OOP in an automatic manner have been proposed in [9, 17]. Since AGU coder provides for OOP better $PSNR_{nf}$ than JPEG2000 (see [9] and particular data in Fig. 1), below we will consider the application of AGU coder for compressing multichannel images.

Fig. 1. Dependencies PSNR_{nf} and PSNR_{or} vs CR for JPEG2000 and AGU techniques for test image Lena corrupted by additive noise with $\sigma^2=50$

3 Considered Approaches to Classification of Original Noisy and Compressed Images

Classification has been applied to the three-channel test image presented in Fig. 2,a. This image has been obtained by using Landsat TM images of three bands (ftp://ftp.glc.f.umi.acs.umd.edu/glc.f/Mosaic_Landsat), for which the corresponding ground truth map is available.

There are five basic classes in the observed scene, namely, soil, grass, water surface, roads and urban areas, bushes. The percentage of pixels (more exactly, voxels) belonging to each class is rather different and it varies from 7.4% for roads and urban areas to 43.6% for grass. Two classifiers have been employed. The first one is based on Support Vector Machines (SVM) that has superior performance comparing to many standard classification techniques in various applications [18].

The SVM classifier uses a “kernel trick” method for mapping the original feature space of classified data into a higher-dimensional non-linear feature space. For

Fig. 2. The test three-channel image in RGB representation (a) and the corresponding classification map for noise-free multichannel data (b)

two-class (binary) classification problem the SVM classifier uses a hyperplane to subdivide the feature space into two regions and attributes the input feature vector to one of two classes. There are different ways for choosing a hyperplane in a feature space. One of them is a maximum margin approach that maximizes the distance from the hyperplane to the nearest training samples in a feature vector space. This approach is not applicable for training data with classification errors and data corrupted by noise, such as multichannel RS images considered in this paper. Obviously, classification errors are natural for some part of noisy data used for SVM training, and maximum margin condition can not be satisfied for all vectors of the training data set.

For training the SVM classifier we used a more practical approach. It is based on choosing a soft margin hyperplane that allows a small amount of errors in training data by introducing slack variables in the objective function. For binary classification the soft margin hyperplane is found by solving the primary optimization problem [18]

$$\min_{\mathbf{w}, b, \xi_n} \left\{ \frac{1}{2} \mathbf{w}^T \mathbf{w} + \sum_{n=1}^N C \xi_n \right\} \quad (1)$$

subject to

$$\begin{aligned} y_n (\mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}_n) + b) &\geq 1 - \xi_n, \\ \xi_n &\geq 0 \quad \text{for } i = 1, \dots, N \end{aligned} \quad (2)$$

where N is a number of training samples, $\{(\mathbf{x}_n, y_n)\}_{n=1}^N$ is the training dataset and $y_n=1$ for the first class and $y_n=-1$ for the second class of training data. ξ_n are slack variables. If $\xi_n > 0$, the slack variables indicate training data with classification errors. $C > 0$ is an error penalty parameter that determines the trade-off between the hyperplane margin and classification errors; $\mathbf{w}$ and b are the parameters of hyperplane $(\mathbf{w} \cdot \mathbf{x}_n) + b = 0$. By introducing Lagrange multipliers $\alpha_n \geq 0$, the constrained optimization problem (1) can be expressed as dual optimization problem [20]

$$\max_{\alpha_n} \left\{ \sum_{n=1}^N \alpha_n - \frac{1}{2} \sum_{m,n=1}^N \alpha_m \alpha_n y_m y_n \boldsymbol{\varphi}(\mathbf{x}_m)^T \boldsymbol{\varphi}(\mathbf{x}_n) \right\} \quad (3)$$

subject to the constraints

$$\sum_{n=1}^N \alpha_n y_n = 0, \quad \text{and } C \geq \alpha_i \geq 0 \quad \text{for } n = 1, \dots, N \quad (4)$$

where $\alpha_n \geq 0$. For Lagrange multipliers α_n not equal to zero the corresponding training vectors are named “support vectors”.

The dot product of two feature vectors in (3) is calculated indirectly by application of “kernel trick” method. A kernel function $K(\mathbf{x}, \mathbf{y})$ is expressed as

$$K(\mathbf{x}, \mathbf{y}) = \boldsymbol{\varphi}(\mathbf{x})^T \boldsymbol{\varphi}(\mathbf{y}) \quad (5)$$

where function $K(\mathbf{x}, \mathbf{y})$ is subject to Mercer's condition [18, 20]. One of the frequently used kernel functions is a radial basis function (RBF)

$$K(\mathbf{x}, \mathbf{y}) = \exp(-\gamma \|\mathbf{x} - \mathbf{y}\|^2), \quad \gamma > 0 \quad (6)$$

where γ is the function control parameter. The RBF kernel has only one parameter, it provides the same performance as linear kernel, for certain parameters it behaves like some other kernel types and is a reasonable choice for the considered classification task. Application of (5) for a hyperplane equation gives the output of SVM classifier

$$f(\mathbf{x}) = \text{sgn} \left(\sum_{n=1}^N y_n \alpha_n K(\mathbf{x}, \mathbf{x}_n) + b \right) \quad (7)$$

where $\mathbf{x}$ is the input feature vector. For the considered scenario of classifying three-channel test images, the feature vector is composed of three pixel values for RGB image components $\mathbf{x} = (x^R, x^G, x^B) \in R^3$.

The SVM classifier given by equations (1)-(7) is designed for solving binary classification tasks. Several approaches have been proposed for solving multi-class problems based on direct classification of all data in one optimization formulation and combining several binary SVM classifiers [21]. The first one has to deal with all SVM parameters for the objective function optimization and it is usually more computationally expensive than the second approach that we applied for classification of the test image in Fig.2,a. It is based on one-against-one classification strategy that divides multi-class problem into $K(K-1)/2$ separate binary classification problems for all pair combinations of K classes. The binary classification problems are solved by SVM classifiers and a majority voting rule is applied to find the output class [21].

While the number of class training samples is not equal, we used different error penalty parameters C_i in the objective function (1) to provide equal contributions from every image class and achieve similar probability of correct classification. For i -th class the parameter C_i is given by

$$C_i = C^* \frac{N}{KN_i} \quad (8)$$

where C^* is a constant. N_i is a number of training samples for class i and N is a total number of samples. The error parameter C^* and the RBF control parameters are evaluated by cross-validation [19].

Another approach presumes the use of radial basis function (RBF) neural network (NN) classifier [22]. The RBF NN demonstrates high efficiency, low computational demands and simplicity of software and hardware implementation at training and classification stages [23, 24]. The RBF NN classifier we used had an input layer, single hidden layer with nonlinear neurons and an output layer with linear neurons. The number of neurons in the input layer was the same as the number of input features, and the number of output layer neurons was equal to the number of data classes. The number of neurons in the hidden layer depends on such factors, as classification complexity and feature space dimensionality. The activation function of the hidden layer neurons had the same form as the RBF kernel function (6) we considered for SVM classifier. The training of RBF NN was performed by minimizing the mean square error E of the NN output

$$E = \frac{1}{KN} \sum_{k=1}^K w_k \sum_{n=1}^N (z_{n,k} - y_{n,k})^2 \quad (9)$$

where $Z_{n,k}$ is the output of the NN output layer representing the accumulated membership of the n -th data sample to the object class k . $y_{n,k}$ is the desired output of neural network, N is the number of training samples and K is the number of classes. The error function (9) was weighted by w_k values to provide equal contributions from every image class for the different numbers of class training samples. The weight for every class is equal to the reciprocal of the number of class training samples.

A cascade-correlation algorithm that provides nearly optimal training results with the extended number of neurons in the RBF NN hidden layer was used to minimize the objective function (9). Training starts with one hidden layer neuron and the new ones are added iteratively to reduce the total residual error. The weighting coefficients of new hidden neuron are selected to provide the condition of maximum correlation between the new unit output and the trained NN output error [25]. The optimal number of hidden layer neurons is selected automatically by cross validation [19].

Classifiers have been trained in a supervised manner using small portions of images from 181 to 1610 pixels depending upon the class. In Fig. 3 the lots from which the training sets were taken are shown. After learning, the classifiers have been applied to the entire image. The pixels to which classification has been applied are depicted by black color in Fig. 3.

Learning of classifiers has been performed for each particular case of the test image. First, it was done for the original noisy image and, second, for the image compressed with optimal CR. Note that different sets of classifier parameters have been obtained for these cases. Two values of additive Gaussian noise variance have been used in simulations: 49 and 100 for byte component images. In the first case the optimal CR was about 8, and for $\sigma^2=100$ the optimal CR $\approx$ 10.7.

Fig. 3. The lots (image fragments) used for training the SVM and RBF NN classifiers

4 Experimental Result Analysis

The results obtained for SVM classifier for both variance values ($\sigma^2=49$ and $\sigma^2=100$) are presented in Table 1. For the class bare soil we have obtained 87.25% of correctly classified pixels, for grass 99.71%, for water surface – 98.38%, for roads and urban areas – 67.34%, and for bushes – 87.13% with overall accuracy $P_{\text{cor ov}} = 91.48\%$. As

seen, the lowest probability of correct classification is observed for classes for which RS data are either rather heterogeneous or appear themselves as prolonged or small size objects.

Some tendencies observed from data in Table 1 are trivial and expectable. In particular, the probabilities $P_{\text{cor } k}$ for particular classes as well as $P_{\text{cor } \text{ov}}$ for noisy images are smaller than for noise-free data irrespectively is classification applied to original images or to compressed ones. Practically for all classes increasing of σ^2 leads to decreasing of $P_{\text{cor } k}$ and, respectively, these results in reduction of $P_{\text{cor } \text{ov}}$.

Table 1. Percentage of correctly classified pixels for the trained SVM

Noise variance	Classified image	Bare soil	Grass	Water	Roads	Bushes	Overall
49	Original	82.00	94.37	96.17	67.62	71.27	85.46
49	Compressed	83.39	91.57	95.59	65.60	81.43	85.80
100	Original	74.90	91.68	94.24	59.81	67.30	81.13
100	Compressed	83.43	93.43	92.76	62.07	76.23	85.21

The most interesting fact is that for both considered values of σ^2 the probabilities $P_{\text{cor } \text{ov}}$ are larger if classification is applied to compressed RS data. For the case $\sigma^2=100$ the benefit attained due to classifying compressed data in comparison to classifying original multichannel images is considerable. This means that a positive effect due to the noise suppression taking place in case of image compression is larger than a negative effect due to the introduced distortions. Concerning particular classes, sometimes better values of $P_{\text{cor } k}$ are provided if classification is applied to the original data.

The classification maps for applying the SVM based approach to original and compressed data in the case of $\sigma^2=100$ are presented in Fig 4,a, and Fig. 4,b, respectively. Comparison of these classification maps between each other and to the more accurate classification map (Fig. 2,b) shows the following. Being applied pixel-wise to original noisy image, the classification results in quite many misclassifications represented as separate pixels surrounded by the pixels referred to another class (see Fig. 4,a). This effect appears in less degree if trained SVM classifier is applied to the compressed data.

The classification results for RBF NN are presented in Table 2. For all cases of NN training the number of hidden units was 17. The percentages of correctly classified pixels are equal to 82.42, 99.67, 97.76, 71.72, 85.14% for the classes bare soil, grass, water, roads and urban areas, and bushes, respectively; $P_{\text{cor } \text{ov}}=0.9062$. As seen, these probabilities are, in general, slightly worse than for SVM classifier.

The obtained results are quite similar to those ones presented in Table 1. The values $P_{\text{cor } \text{ov}}$ for the corresponding classifiers and noise variances differ by less than 0.01. SVM recognizes better the class “soil” while RBF NN provides better classification of water surface. Again, the overall percentage of correctly classified pixels is larger if the classifier is applied to the compressed RS data. And the difference becomes more evident if the noise variance increases (see data for $\sigma^2=100$).

Fig. 4. Classification maps for SVM applied to original (a) and compressed (b) RS data

Table 2. Percentage of correctly classified pixels for the trained RBF NN

Noise variance	Classified image	Bare soil	Grass	Water	Roads	Bushes	Overall
49	Original	75.22	95.81	99.48	66.50	75.51	85.41
49	Compressed	76.41	94.95	99.56	65.41	80.80	85.98
100	Original	73.62	91.58	99.66	67.14	65.50	81.79
100	Compressed	74.59	93.21	99.52	64.24	78.29	84.32

Fig. 5. Classification maps for RBF NN applying to original (a) and compressed (b) RS data

Examples of multichannel image classification using RBF NN for $\sigma^2=49$ are given in Fig. 5. There are some noticeable differences in the spatial structure of the classified data. In particular, there are more separate pixel misclassifications if RBF NN classifier is applied to the original noisy data (see Fig. 5,a). The most problematic class is “roads and urban areas”. Both classifiers recognize the corresponding regions with the smallest probability of correct classification. One possible reason is that we have considered pixel-by-pixel classification without taking into account any spatial features. Besides, no post-processing of the obtained primary classification maps has

been utilized. These opportunities for further classification improving can be subject of the future work.

5 Conclusions

Two approaches to classification of multichannel RS data are considered. It is shown that in case of presence of rather intensive noise in obtained images it is reasonable to perform on-board lossy compression and then to apply on-land classification of decompressed images instead of data lossless compression and using the classification of original noisy images. The CR provided for such lossy compression can be about 10 and this is considerably better than in case of lossless coding. Moreover, we considered component-wise compression of multichannel images. And if the noise level is approximately the same in all component images, the same quantization step can be used in compressing multichannel images as multidimensional data. This can lead to further improvement of CR for given performance of the coder.

The obtained results and observed tendencies are in good coincidence for two different approaches to classification, one based on SVM and the other exploiting trained RBF NN. No obvious superiority between these two classifiers has been observed.

Acknowledgements. This study was partially supported by the CONACyT as a part of research project SEMAR No.11055.

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