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GABOR AND WEBER LOCAL DESCRIPTORS PERFORMANCE IN MULTISPECTRAL EARTH OBSERVATION IMAGE DATA ANALYSIS

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Abstract: *During the last decades, both the satellite sensors and remote sensing imagery are evolving so fast that the methods and techniques of processing and analyzing Earth Observation (EO) data usually are staying one step behind. In the current paper, the authors goal was to prove the usability of Gabor and Weber Local Descriptors (WLD) in multispectral image classification. The extracted Gabor and WLD features were tested with Support Vector Machines (SVM), k-Nearest Neighbors (k-NN) and k-Means classifiers.*

Keywords: *benchmarking, remote sensing, classification, Gabor filtering, Webber Local Descriptors, feature extraction*

1. INTRODUCTION

In the field of remote sensing and EO image data processing it is important to have at disposal a large variety of tools that can extract the maximum relevant information from an image [2]. The applicability of remote sensing image classification goes beyond the walls of the laboratory environment and can be used with success in crises and disaster management, in local administration and even in military applications. Also the multispectral images provide us relevant information about the land cover and land use.

Until now, there is no general rule that can be applied to create a universal information retrieval procedure regardless of the data being analyzed [3]. In most of the cases we must use specific algorithms for specific types of data.

Most of the times, the image indexing methods are based on identification and classification of image texture, image intensity or by using statistical models. The results are then grouped in a few generic classes (3-6) like crops, buildings, streets, vegetation, forest etc. [6]

In this paper, the authors are presenting a benchmark of extracted Gabor and WLD image descriptors when using SVM, k-NN and k-Means classifiers. This benchmark idea is to gather relevant results on the performance of classifiers when dealing with Gabor and WLD image descriptors in the context of multispectral image analyses. The goal is to determine the best classifier that fits best the image content given the analyzed features.

2. FEATURE SPACE AND IMAGE DESCRIPTORS

Usually, in order to proceed with image classification there are a few steps that must be taken into account. Some of these steps refer to image pre-processing, image feature extraction and image classification.

The image pre-processing step require that the analyzed image to be geometrically and radiometric correct. Also in the image pre-processing step, the multispectral data is filtered and then is cut into image patches of conveyable size. These patches are used in the image feature extraction step where the mean and standard deviation of each patch is computed. After obtaining all the statistical image descriptors for each patch we are ready for the image classification.

2.1 Gabor features. It is known that texture classification plays an important role in computer vision and its applications. Among various feature extraction methods, filter bank method such as Gabor filters has emerged as one of the most popular one. This filter bank is defined by its parameters including frequencies, orientations, frequency ratio and smooth parameters of Gaussian envelope. [5]

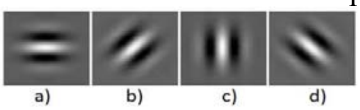

Figure 1. Gabor Filter example in spatial domain, with 4 orientations θ= 0°, 45°, 90° and 135° and scale parameters $\sigma_x = \sigma_y = 3$ pixels.

Considering the texture characteristics and other related studies, one can conclude that the human visual system responds to texture properties such as repetition, directionality and complexity [4], so the 2D Gabor filter can be expressed as in equation (1) using λ, θ, □, σ, γ parameters that represent wavelength, orientation angle (in radians), phase offset, standard deviation and filter scale. In our study we made use of Gabor filter banks with 4 orientations and 3 scales that we apply on each band of the extracted patch.

$$g_{\lambda,\theta,\varphi,\sigma,\gamma}(x,y) = e^{-(x'^2+\gamma^2 y'^2)/2\sigma^2}\cos(2\pi x'/\lambda + \varphi) \quad (1)$$

$$\frac{\sigma}{\lambda} = \frac{1}{\pi}\sqrt{\frac{\ln 2}{2}\cdot\frac{2^b+1}{2^b-1}} \quad (2)$$

$$b = \log_2 \frac{\frac{\sigma}{\lambda}\pi + \sqrt{\ln 2/2}}{\frac{\sigma}{\lambda}\pi - \sqrt{\ln 2/2}} \quad (3)$$

$$\begin{aligned} x' &= x\cdot\cos\theta + y\cdot\sin\theta \\ y' &= -x\cdot\sin\theta + y\cdot\cos\theta \end{aligned} \quad (4)$$

2.2 Weber Local Descriptors (WLD). The Weber's law (Ernst Weber) states that the change of a stimulus that will be just noticeable is a constant ratio of the original stimulus. [1] If the change is smaller than this constant ratio, it cannot be recognized. In equation (5), *ΔI* represents the barely perceptible difference of two stimulus, *I* represents the initial intensity of the stimulus and the *k* meaning is that the ratio stays constant regardless of *I* variations. This equation is known as Weber ratio. [4]

$$\frac{\Delta I}{I} = k \quad (5)$$

$$v_s^{00} = \sum_{i=0}^{p-1}(\Delta x_i) = \sum_{i=0}^{p-1}(x_i - x_c) \quad (6)$$

$$G_{ratio}(x_c) = \frac{v_s^{00}}{v_s^{01}},$$

(7)

$$\zeta(x_c) = \arctan\left(\frac{v_s^{00}}{v_s^{01}}\right) = \arctan\left(\sum_{i=0}^{p-1}\frac{(x_i - x_c)}{x_c}\right) \quad (8)$$

$$\theta(x_c) = \arctan 2\left(\frac{v_s^{11}}{v_s^{10}}\right) \quad (9)$$

$$v_s^{10} = x_5 - x_1 \quad \text{and} \quad v_s^{11} = x_7 - x_3 \quad (10)$$

The equations (8) and (9) are used when we speak about multispectral data. In the case of Synthetic Aperture Radar (SAR) data, the situation is slightly different and an adapted WLD must be used [1].

3. REMOTE SENSING IMAGE CLASSIFICATION

Remote sensing image classification is a continuous expanding domain and makes use of the multimedia image classification techniques that are modified and adapted to handle EO data. As it is well known, the procedures employed can be unsupervised (where no user effort is required), supervised (the user must prepare a training set) and object-based (based on multi resolution segmentation). In the present study we chosen a patch based approach for image content classification and we used supervised SVM and k-NN and unsupervised k-Means on Gabor and WLD image feature descriptors.

SVM represents a set of supervised learning methods used in automatic classification. The inputs of the algorithm are the training sets (stored into a database) and a test set (the computed patches). Also, the same principle is used in the k-NN classification, despite the of unsupervised k-Means case, were the user only specifies the number of classes he desire to obtain.

4. EXPERIMENTAL RESULTS

During the experimental stage, we used supervised SVM and k-NN classification and unsupervised k-Means classification along with Gabor and WLD local descriptors.

In the frame of the experimental setup we are using a WorldView2 multispectral image that illustrates the area of Bucharest, Romania (Figure 3). The scene covers almost 25 square kilometers and is characterized by 2 m spatial resolution, 8 spectral bands and 8 bits radiometric resolution representation. In our experiment, the image was resampled using nearest neighbors method in order to enhance the spatial resolution from 2 m to 1 m.

In the image classification process we used conveyable patches of 50 pixels size that covers 2.5 square kilometers. During testing we considered 5 semantic categories, as shown in Figure 2 and Figure 7. In Figure 7 is the representation of manual annotation map used in the qualitative evaluation of the study.

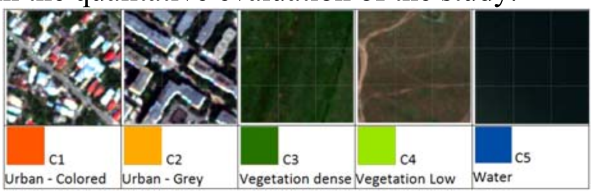

Figure 2. Land cover semantic categories and associated color representation used in classification.

In the case of supervised classification we used 20 samples per class, meaning a total of 100 samples, from the input image. The selected samples represent 0.01% from the total number of patches. In the case of the unsupervised classification no supplementary operations were needed.

Figure 3. WorldView2 image, Bucharest, Romania, 8 spectral bands, 8 bit radiometric resolution

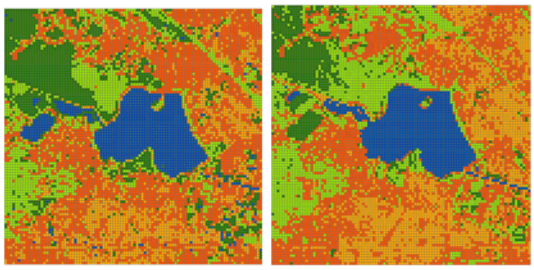

Figure 4. SVM Classification
Gabor filter (a) vs. WLD (b)

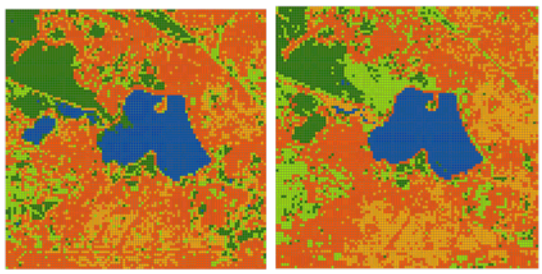

Figure 5. k-NN Classification
Gabor filter (a) vs. WLD (b)

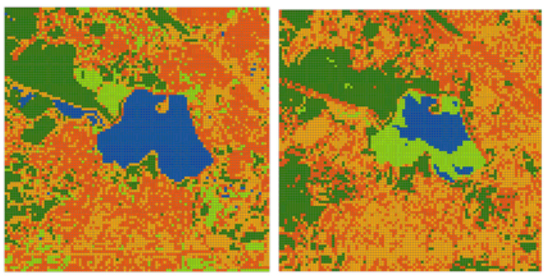

Figure 6. k-Means Classification
Gabor filter (a) vs. WLD (b)

	SVM		k-NN		k-Means	
Class	Precision	Recall	Precision	Recall	Precision	Recall
C1	80.0%	64.3%	83.6%	55.4%	69.7%	58.3%
C2	48.3%	57.8%	32.5%	40.0%	40.3%	31.5%
C3	55.7%	76.6%	49.3%	72.8%	57.4%	74.4%
C4	59.2%	51.7%	30.0%	36.8%	15.5%	27.3%
C5	87.9%	84.5%	81.3%	91.0%	90.4%	96.6%

Table 1. Confusion matrix for Gabor features classification with SVM, k-NN and k-Means

	SVM		k-NN		k-Means	
Class	Precision	Recall	Precision	Recall	Precision	Recall
C1	63.4%	54.2%	77.5%	52.3%	46.0%	45.2%
C2	50.9%	51.0%	42.9%	49.2%	54.3%	32.7%8
C3	34.6%	82.5%	37.2%	79.3%	44.8%	43.4%
C4	68.7%	43.0%	53.7%	46.1%	0.3%	0.9%
C5	93.7%	96.3%	82.1%	99.3%	36.5%	100

Table 2. Confusion matrix for WLD features classification with SVM, k-NN and k-Means

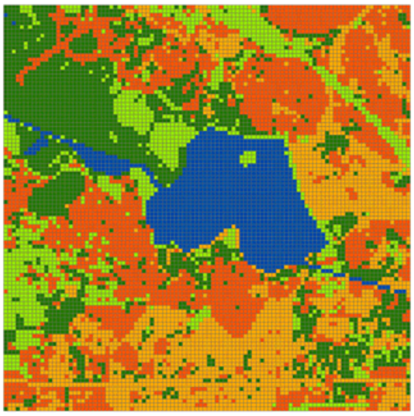

Figure 7. Reference annotation map

In Figure 4, Figure 5 and Figure 6 are shown the results of the classification benchmarking, as well in the Table 1 and Table 2 we can see the confusion matrixes resulted from the classifications.

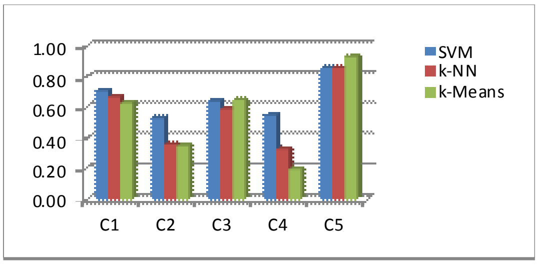

Figure 8. F-measure for Gabor features classification

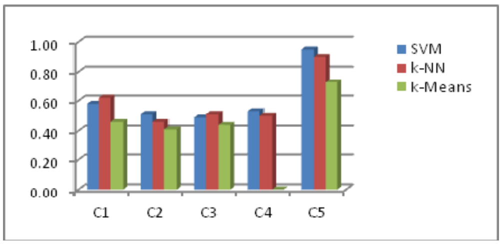

Figure 9. F-measure for WLD features classification

5. CONCLUSIONS & ACKNOWLEDGMENT

This paper has the purpose to demonstrate the usability of local descriptors in the case of multispectral EO image classification. As it can be seen from the confusion matrixes, the correct classification scores are very high in the case of classification with SVM and k-NN and not so accurate when using unsupervised k-Means. The reason we used in our tests not only supervised but also unsupervised classification methods is that we wanted a method to validate the class separation performance.

As it can be seen from the F-measure charts, Figure 8 and Figure 9, in the multispectral image classification is important not only the feature extraction method but also the classification method we use. The best results are obtained using SVM and k-NN supervised classification for Gabor and WLD also.

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