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RECOGNITION OF OBJECTS ON THE EARTH'S SURFACE THROUGH TEXTURE ANALYSIS OF SATELLITE IMAGES

Mariana Tsaneva, Doyno Petkov

STIL – Bulgarian Academy of Sciences
e-mail: mtsaneva@hotmail.com

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Abstract: *This paper considers one of the purposes of image analysis: object recognition. How texture recognition can be use for object recognition is presented. Transform methods of texture analysis, such as Gabor filter and wavelet transform, are used for detection of objects on the Earth's surface in satellite images. The importance of these methods for object recognition is demonstrated by comparison some results with results of other image analysis and texture analysis methods. Experimental results of our work illustrate some remote sensing applications of texture analysis of satellite images. The role of texture information for research and development of interpretation and classification techniques of satellite images is considered.*

Introduction

The problem of object recognition is the common task in computer vision, image processing and analysis, and remote sensing. In the computer vision literature four processing stages of object recognition are considered: image enhancement, feature extraction, image segmentation, and object recognition. On the other hand, recognition is the important phase of the classification process, which involves two phases: the learning phase and the recognition phase. Object recognition is studying and classifying an unknown object into one of a set of predefined classes [1,2]. Studying objects on the Earth's surface can used many features: spectral, texture, colour features. For texture features extraction, texture analysis methods are used. Each object can be represented in N-dimensional feature space, where N is the number of object pixels or the number of features calculated for each object. The work in this paper is closely related to texture discrimination in image processing. We consider the recognition of textures from a satellite image, containing a wide variety of natural textures of land cover objects, water and clouds. In this paper, we study texture discrimination based on two wavelet filter families, orthonormal and Gabor fractional wavelets. The purposes of this work are:

1. To develop an algorithm for texture analysis of satellite images.
2. To select the best texture features for texture recognition of objects on satellite images by wavelet decomposition of the images.

Texture recognition and object recognition

Texture can be defined as a variation of the pixel intensities in image subregions. The assumption is that the intensity variation of different objects are different [1]. We can help object recognition by characterizing texture. The texture content of the images is captured with the chosen texture analysis method. Tuceryan and Jain [3] divided texture analysis methods into four categories: statistical, geometrical, model-based and transform-based (signal processing) methods. Signal processing methods analyze the frequency content of the image. The texture content is described with the texture analysis method, which yields a set of features (texture features, which form the feature vector) for each image. These features can be scalar numbers, discrete histograms or empirical distributions. They characterize the properties of an image texture: spatial structure, contrast, roughness, orientation, etc.

The satellite images contain various objects with different textures. If the objects have periodical texture (water, deserts, urban areas), the spectral analysis methods give more information than the spatial analysis methods. If the image contains many objects with different textures or the objects with aperiodical texture (mountains), they used texture analysis methods in the spatial and spectral domain (multhichannel two-dimensional discrete filters).

A linear filter bank is normally used for the representation of texture patches by low-dimensional local descriptors. The feature vector (descriptor) formed by the outputs of N filters at a certain pixel is a rank – N linear mapping of the gray level profile within a neighborhood of that pixel. The feature vectors can be used in a recognition system. Other texture feature vectors are formed by statistical features: gray level coocurence matrix (GLCM), mean, standard deviation.

There are a number of classification algorithms: parametric statistical classifiers derived from the Bayesian decision theory, nonparametric k-nearest neighbor classifier, various neural networks, and support vector machines. Texture classification process involves the learning phase and the recognition phase. In the learning phase the target is to build a model for the texture content of each texture class present in the training data. In the recognition phase the texture content of the unknown object is first described with the same texture analysis method, then the texture features of the object are compared to those of the training images with a classification algorithm. The object is assigned to the class with the best match. If the best match is not sufficiently good according to some predefined criteria, the unknown object can be rejected instead [1, 4].

Gabor filters

One of the most popular transform based approaches for texture feature extraction has been the use of Gabor filters. In the spatial domain an image is described by its two-dimensional intensity function. The same image is described by the coefficients of sine- and cosine-basis functions at a range of frequencies and orientations (the Fourier transform). Similarly, the image can be expressed in terms of coefficients of other basis functions. Gabor used a combined representation of space and frequency to express signals in terms of Gabor functions. The traditional Gabor filter is applied to an image for extracting texture by convolving them. The procedure involves taking the Fourier transform of the image and the Gabor function, taking the convolution, and taking an inverse transform [4].

Essentially, the function proposed by Gabor describes a sinusoidal wave with modulate frequencies by a Gaussian envelope. The filters ensemble is one-dimensional. It extended to the two-dimensional case by Daugman. A two-dimensional Gabor filter is sensitive to a particular frequency and orientation. They have some advantages: tunable orientation and radial frequency bandwidths, tunable center frequencies and optimally achieve joint resolution in spatial and frequency domain. A major difficulty of this method is how to determine the number of Gabor channels at the same radial frequency, and the size of the Gabor filter window [5].

Wavelet transform

Multhiresolution analysis, the so-called wavelet transform, is achieved by using a window function, whose width changes as the frequency changes [6]. If the window function is Gaussian, the obtained transform is called the Gabor transform [7]. Since low frequencies dominate virtually all real images, the two-dimensional wavelet transform has ability to decompose an image in the low-frequency channel makes it ideal for image analysis. At each level, the wavelet transform decomposes an image into four channels, which can be represented by LL (a low horizontal and low vertical frequency), LH (a low horizontal and high vertical frequency), HL, and HH (contains most of the image noise). The wavelet coefficients, the gray-level cooccurrence matrix (GLCM) texture features [8], mean and standard deviation are the most applied to get a texture information of an image.

Experiments and results

We use a true-color image of the Black Sea with a large phytoplankton bloom (Fig. 1). From the upper left corner, the countries around the Black Sea are: Ukraine to the north, Russia and Georgia to the east, Turkey to the south, and Bulgaria and Romania to the west. The Sea of Azov is the smaller body of water located just north of the Black Sea in this image. This scene was acquired by the Sea-viewing Wide Field-of-view Sensor (SeaWiFS), flying abroad the OrbView-2 satellite, on May 4, 2002.

Three kinds of experiments are implemented:

1. Experiments with subimages - forming a texture database.
2. Experiments with texture features - building a texture classification model.
3. Experiments with texture features - recognizing of unknown objects.

All these experiments are realized with subimages of satellite image of Black Sea, which are representative of texture classes.

The texture database used in our experiments consists of six different texture classes: water, phytoplankton, land, clouds, clouds + land and clouds + water. Each image of texture class is 50 x 50 pixels. These images are used in comparing the performance of different texture features: mean, standard deviation, angular second moment (ASM), contrast, correlation, inverse difference moment (IDM), entropy. The performance is measured in terms of the average retrieval rate which is defined as the average percentage number of patterns belonging to the same image as the query pattern in the top 15 matches.

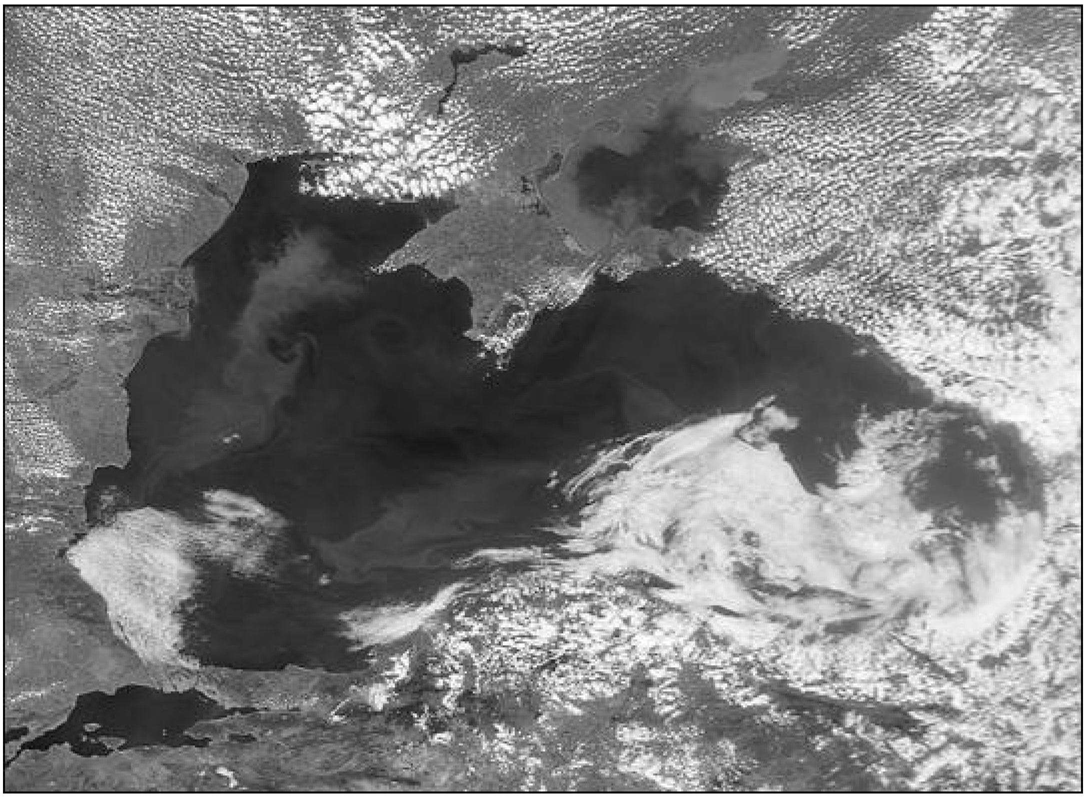

Fig. 1. *The satellite image of the Black Sea*

On the average 74.37% of the correct patterns are in the top 15 retrieved images. The training images are formed data inputs of a neural network model of texture. We use the Excel macro NNClass [9]. The neural network model is basically a set of weights between the layers of the net. The saved model containing the model inputs, our data, and the fitted model (weights) can be used as a calculator to do classification, given any new input (i. e. the feature vector of seven texture features of an unknown object in the recognition phase).

All images from the texture database and recognizing images are processed with ImageJ, the faster image processing and analysis program written in Java [10]. We also use the plugins Fraction Wavelets Transform and Module [11], and GLCM Texture.

The following algorithm for texture recognize is developed:

1. Use wavelet transformation to decompose the image into subbands (LL, LH, HL, and HH).
2. Calculate mean, standard deviation, ASM, contrast, correlation, IDM, and entropy for each image of the texture database.
3. Build a classification model by using neural networks.
4. Calculate the same texture features for an unknown object.
5. Compare the texture feature vector of the unknown object with the texture feature vectors of the texture database by neural network.

Fig. 2 shows some submages from the texture satellite images database. They are selected randomly and their feature vectors are the training input data of the classification model.

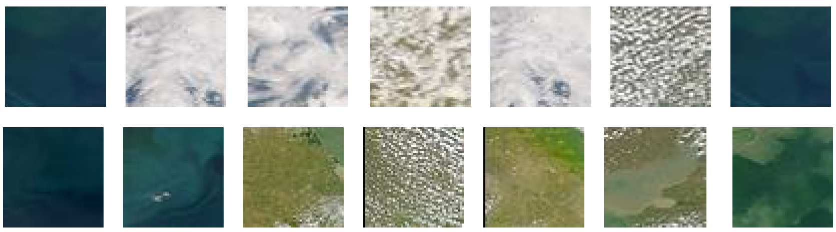

Fig. 2. *Some subimages from texture database: water, land, clouds and phytoplankton*

Table 1 and 2 show training data (texture feature vectors) of subimages of the texture database.

Table 1. *The training data of the texture features calculated after orthonormal wavelet filtering*

Obs No.	Species_ Name	Mean	StdDev	ASM	Contrast	Correla- tion	IDM	Entropy
1	water	64.377	83.864	0.057	428.657	0.00014	0.498	4.544
2	land	97.404	48.564	0.012	435.718	0.00037	0.249	5.972
3	land	67.157	51.142	0.007	335.355	0.00036	0.219	6.34
4	clouds	88.535	60.413	0.00079	734.192	0.00025	0.066	7.626
5	clouds +land	98.615	50.667	0.00045	876.454	0.00031	0.06	7.901
6	clouds	72.413	78.879	0.005	529.996	0.00016	0.146	6.633
7	clouds +land	79.398	65.517	0.00071	655.53	0.00022	0.072	7.644
8	water	61.361	82.545	0.032	343.179	0.00015	0.403	5.012
9	phyto- plankton	77.619	44.908	0.078	165.028	0.00047	0.489	4.581
10	phyto- plankton	32.962	59.005	0.031	276.166	0.00025	0.357	5.388
11	clouds	78.927	87.08	0.032	502.01	0.00013	0.348	5.339
12	clouds	77.032	86.598	0.021	508.919	0.00013	0.28	5.553
13	clouds +water	79.602	72.126	0.027	365.428	0.00019	0.311	5.457
14	clouds +water	76.579	84.52	0.031	497.436	0.00014	0.352	5.299

Table 2. *The training data of the texture features calculated after Gabor – like wavelet transform*

Obs No.	Species_ Name	Mean	StdDev	ASM	Contrast	Correla- tion	IDM	Entropy
1	water	63.022	92.164	0.202	489.772	,00011558 121	0.684	3.484
2	land	87.891	66.453	0.075	415.895	0.00021	0.5	4.763
3	land	57.945	61.777	0.049	316.339	0.00025	0.458	5.075
4	clouds	73.38	79.855	0.005	417.477	0.00015	0.217	6.54
5	clouds +land	85.605	66.24	0.001	504.498	0.00021	0.143	7.179
6	clouds	62.627	86.268	0.033	453.558	0.00013	0.403	5.282
7	clouds +land	64.5	74.835	0.005	394.832	0.00017	0.225	6.51
8	water	58.059	88.606	0.125	389.688	0.00013	0.612	4.031
9	phyto- plankton	59.4	57.638	0.106	152.544	0.0003	0.615	3.915
10	phyto- plankton	46,936	69.26	0.172	289.174	0.00021	0.606	4.038
11	clouds	65.486	95.805	0.082	540.436	0.00011	0.559	4.151
12	clouds	65.766	93.481	0.135	522.388	0.00011	0.59	4.03
13	clouds +water	65.722	83.993	0.105	405.667	0.00014	0.558	4.32
14	clouds +water	66.347	91.251	0.117	507.92	0.00012	0.584	4.083

In Fig. 3a and 3b we can see the texture feature vectors for two of the texture classes: water and land. The figures show difference between the vectors of filtered images and vectors of the raw image.

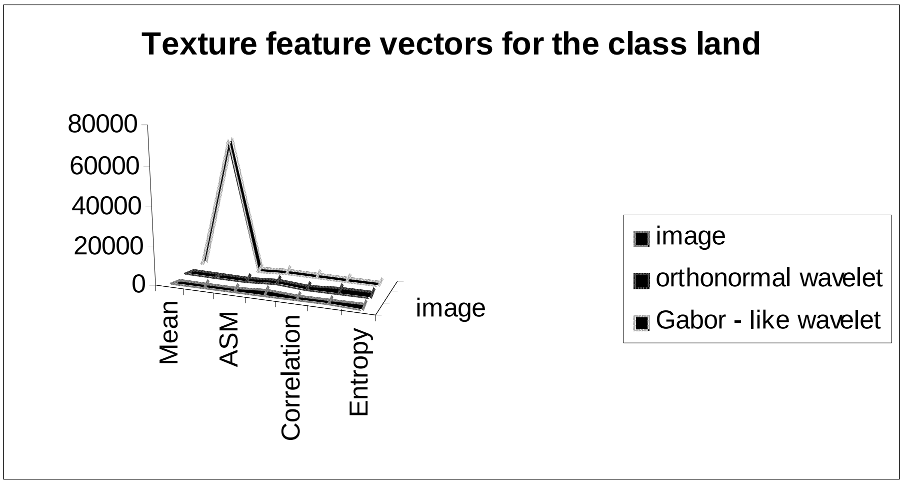

Fig 3a. *Texture feature vectors for the raw image and the filtered image of the class land*

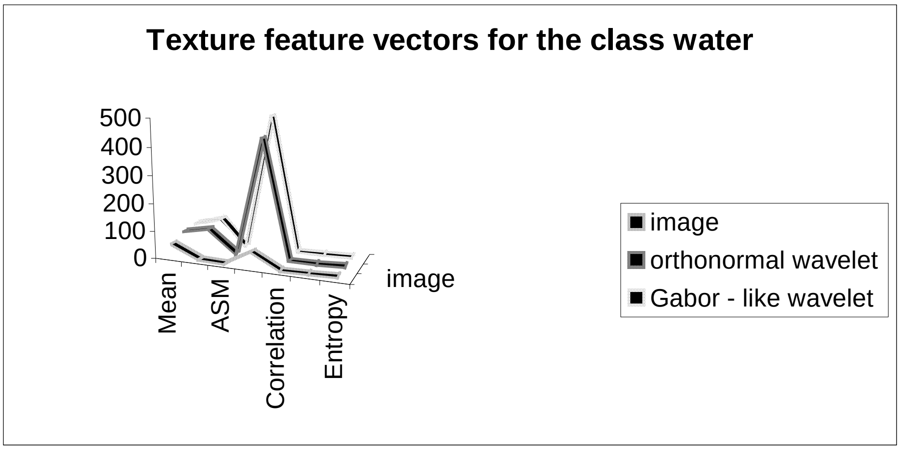

Fig. 3b. *Texture feature vectors for the raw image and the filtered image of the class water*

Discussion

The implemented experiments illustrate how texture feature vectors can be used for classification and recognition of satellite images. The developed algorithm is suitable for classify and recognize of objects with smooth components. Their texture information is concentrated in the low frequency domain. The built classification model has enough rate for the wanted object recognition correctness of 98%. In the space and frequency domains all of studying texture features have an accurate discrimination for different textures.

Other image analysis and texture analysis (we work with histogram thresholding and Gaussian filtering as a feature enhance techniques) used much more features and calculate operations for the same classification results.

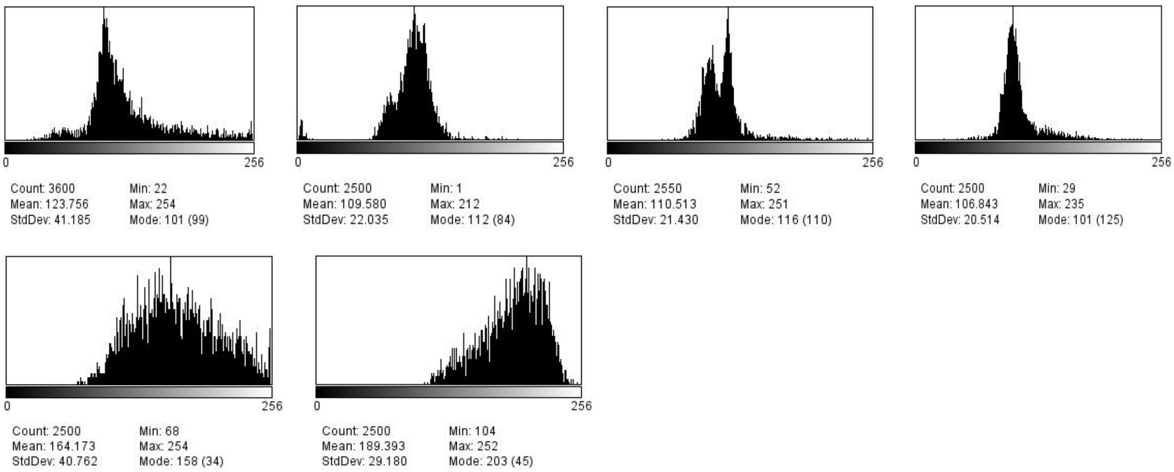

Fig. 4. *Histograms of some subimages from texture database: water, land and clouds*

The main advantages of our supervised wavelet based technique are the optimal dimension of the feature vectors and accurate discrimination of different textures.

Conclusion

This paper describes satellite image object recognition using texture features. The texture database of satellite image classes is formed and built in the texture classification model. An algorithm for texture object recognition is developed and tested by neural networks. All these image processing and analysis techniques are used texture feature information based on seventh-dimensional feature vectors. The texture features are applied to image regions of interest for recognition an unknown object.

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