

TEXTURE EDGE DETECTION TECHNIQUES USING TEXTURE FEATURES AND GRADIENT-BASED EDGE DETECTORS

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Abstract

Texture edges are the locations where there is an abrupt change in image texture properties. Two novel texture edge detection techniques, which used texture feature extraction and segmentation before conventional gradient-based or zero crossing edge detection algorithms (Roberts, Sobel, Prewitt, Laplacian, Kirsch, Robinson and Canny) are proposed and tested in this paper. The most common image segmentation methods are used in experiments for texture segmentation: fuzzy c-means, gray level quantization, histogram thresholding, median cut and principal components transformation/median cut. Results from applying these texture edge detection techniques to satellite images are presented and analyzed.

1. Introduction

Spatial, spectral and texture properties have been used for many years in many remote sensing applications such as mapping and analysis of ground cover. Texture analysis methods and techniques grew in popularity during the late 1990s as the resolution of satellite images increased. Texture analysis has been studied in computer vision literature. Several definitions of texture have been formulated by researchers and one early definition is due to Haralick: "The image texture we consider is non figurative and cellular... An image texture is described by the number and types of its (tonal) primitives and the spatial organization or layout of its (tonal) primitives... A fundamental characteristic of texture: It cannot be analyzed without a frame of reference of tonal primitive being stated or implied. For any smooth gray-tone surface, there exists a scale such that when the surface is examined, it has no

texture. Then as resolution increases, it takes on a fine texture and then a coarse texture” [1].

The visual interpretation of images has relied on image spatial properties. Spectral features are also efficiently used for discrimination and identification of the objects in interpreting images besides spatial features. Remote sensing in the visible and near infrared ranges of the electromagnetic spectrum finds wide application as a method for discrimination of natural objects, their states and texture peculiarities, as well as for monitoring of ecosystems. In [2], results are presented for recognition of natural objects along a trace on the ground surface of the territory of Bulgaria using data for the solar radiation reflected from these objects. Data were collected by means of a trace multichannel spectrometer onboard the MIR spatial station.

The role of image texture and the incorporation of texture features in image classification procedures is very important with the ever-increasing spatial resolution of remotely sensed data. Augustejin [3] uses a neural network classifier for ground cover identification in satellite images based on texture measures and compares a range of texture features (co-occurrence matrices, gray-level differences, texture-tone analysis, features derived from Fourier transform, and Gabor filters). Raw pixel based classification is used to provide a baseline. The results show that the best feature set depends on the data to be classified.

Unser [4] developed local linear transforms for texture measurement. He proposed using four 2×2 Hadamard masks: the first measures the magnitude, the other three masks approximate the derivatives in horizontal, vertical and diagonal directions. After convolution with masks, the computation of the local variance using a moving window in the image is applied.

In [5], the authors introduce a novel texture description scheme. Texture representation uses a combination of edge and region statistics. The results show that edge-based representation is the best.

Feature-based texture analysis derives texture measures directly from the image by local operators, statistical attributes and examination of images in the frequency domain. The main focus of remote sensing scientists has involved the use of second-order statistics from the gray-level co-occurrence matrix. Many different methods are used to extract textural information from images: structural, statistical, model-based and transform-based. Recent research has focused on texture measures derived from moving a fixed-size, odd-numbered window through the image and calculating a variety of different pixel relationships [6]. Relatively few studies have focused on the use of lower-order statistical properties of images [7].

An edge in a nontextured image is a sequence of pixel location where there is an abrupt change in gray level (intensity) values on either side of the pixel locations. A texture edge is associated with changes in the texture characteristics. Conventional gradient-based edge detection algorithms can detect only local changes in intensity values and they are suitable only for nontextured images. When applied to textured images, gradient-based edge detection methods detect intensity edges, which are micro-edges [8].

Edge detection techniques often use a mask (2×2 , 3×3 pixels) that is convolved with the pixel in the window (Fig. 1). An edge detector can be [9]:

1. Directional which can be used to detect orientations at 90° intervals (the Roberts, Sobel and Prewitt operators).
2. Directional which can be used to detect orientation at 45° intervals (the Kirsch and Robinson operators).
3. Non-directional (the Laplacian).

The canny edge detection algorithm [10] is based on the zero crossing of the image function second derivative. It is known to many as the optimal edge detector.

Kazuhiro [11] proposed a method which can be applied to colour and texture edge extraction. In this method, an edge is defined not as a point where there is a large change in intensity, but as a region boundary based on the separability, which depends only on the shape of an edge. This characteristic enables easy selection of the optimum threshold value for the extraction of an edge.

Texture edge detection techniques can be used for textured object classification and object recognition. They are able to work with boundary and contour detection techniques on stages of object boundary detection or region of interest detection.

The goal of this research is to detect the macro edge separating the two or more texture regions on satellite images. The objective of this work is to develop techniques to extract texture edges in and between texture regions.

2. Texture edge detection

Edge detection is a research field within image processing and computer vision, in particular within the area of feature extraction. Edge detection consists of creating a binary image from gray scale image by finding a high intensity gradient or the second derivative zero crossings. The edges identified by edge detection are often disconnected. Discontinuities are bridged, if the distance between the two edges is within some predetermined threshold. Region boundaries and edges are closely related, since there is often sharp adjustment in intensity at the region

boundaries.

Texture edges can be micro-edges and macro-edges. Micro-edges can be detected using small-distance operators. Macro-edges need large-size edge detectors. There are many texture edge detection techniques using different texture features and different algorithms including edge detectors, image enhancement, edge models, etc. In this research, conventional edge detection techniques are used after novel proposed preprocessing scheme for texture feature extraction. Micro-edges are obtained using conventional edge detectors: the Roberts, Sobel, Prewitt, Laplacian, Kirsch, Robinson and Canny edge detection algorithms. Macro-edges are obtained using texture segmentation before edge detection. The most common segmentation algorithms are used: fuzzy c-means, gray level quantization, histogram thresholding, median cut and principal components transformation/median cut.

3. Edge detectors

Edges are used to find region boundaries. Boundaries and their parts (edges) are perpendicular to the direction of the gradient. Gradient operators can be divided into:

1. Operators approximating the first or second derivatives of the image function using differences. Operators which are rotationally invariant (Laplacian) need one convolution mask only (Fig. 1d). Operators which are able to detect edge direction (Roberts, Sobel, Prewitt, Kirsch and Robinson) are represented by a collection of masks, each corresponding to a certain direction (Fig. 1a, b, c, e, f).
2. Operators based on the zero crossings of the image function second derivative (Canny edge detector).

The Roberts operator approximates the gradient of the image function. The Sobel, Prewitt, Kirsch and Robinson operators approximate the first derivative. The Laplace operator approximates the second derivative [12].

The Canny edge detection algorithm is known as the optimal edge detector based on three criteria:

1. Detection criterion – important edges should not be missed, there should be no spurious responses.
2. Localization criterion – distance between the actual and located position of the edge should be minimal.
3. One response criterion – minimizes multiple responses to a single edge (partly covered by the first criterion).

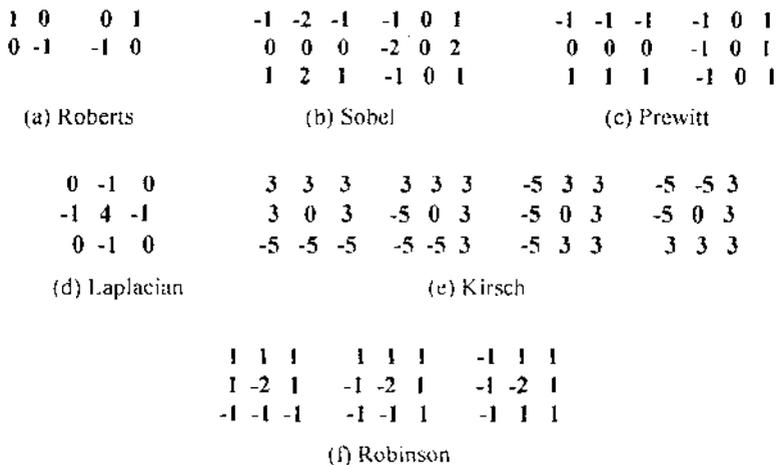


Fig. 1. Edge detectors masks

The Canny edge detector works as follows:

1. Smooths the image to eliminate noise.
2. Finds the image gradient to highlight regions with high spatial derivatives.
3. Suppresses any pixel that is not at the maximum (nonmaximal suppression).
4. Reduces the gradient array by hysteresis. It uses two thresholds. If the magnitude is below the first threshold, it is set to zero (made a nonedge). If the magnitude is above the high threshold, it is made an edge. If the magnitude is between the two thresholds, then it is set to zero.

Each edge detection operator has its advantages and disadvantages (Table 1). All gradient-based edge detection operators (Roberts, Sobel, Prewitt, Kirsch and Robinson) are able to detect edge direction, but they depend on the size of objects and on noise. The Roberts, Laplace and Canny edge detectors have their own advantages and disadvantages.

4. Texture features

Every pixel is described by texture feature, which must be homogenous inside a texture region. In this research, the two novel scalar texture features are used: texture feature 1 and texture feature 2 from [13]. For every pixel in the image, a 5 x 5 pixel window is considered, where $P(x,y)$ is the gray level value of pixel (x,y) . For every 5 x 5 pixel mask, the average intensity value M of pixels is calculated.

Table 1. Advantages and disadvantages of edge detection operators

Operator	Advantages	Disadvantages
The Roberts operator	The simplest and fastest operator..	It has high sensitivity to noise.
The Sobel operator	It is able to determine gradient direction.	It depends on the size of objects and has sensitivity to noise.
The Prewitt operator	It is able to determine gradient direction.	It depends on the size of objects and has sensitivity to noise.
The Laplace operator	It gives gradient magnitude only and is rotationally invariant.	It responds twice to some edges in the image.
The Kirsch operator	It is able to determine gradient direction.	It depends on the size of objects and has sensitivity to noise.
The Robinson operator	It is able to determine gradient direction.	It depends on the size of objects and has sensitivity to noise.
The Canny edge detector	The optimal edge detector based on three criteria: detection criterion, localization criterion and one response criterion. Optimal for step edges corrupted by white noise.	Smooths the shape too much and tends to create closed loops of edges.

Texture features (TF) are defined as a difference of intensity value of the central pixel and the average intensity value in the feature masks:

$$(1) \quad M_1 = (P(x+2, y-2) + P(x+2, y) + P(x+2, y+2) + P(x+1, y-1) + P(x+1, y+1) + P(x, y-2) + P(x, y) + P(x, y+2) + P(x-1, y-1) + P(x-1, y+1) + P(x-2, y-2) + P(x-2, y) + P(x-2, y+2)) / 13$$

$$(2) \quad TF_1 = P(x, y) - M_1$$

$$(3) \quad M_2 = (P(x+2, y-1) + P(x+2, y+1) + P(x+1, y-2) + P(x+1, y) + P(x+1, y+2) + P(x, y-1) + P(x, y+1) + P(x-1, y-2) + P(x-1, y) + P(x-1, y+2) + P(x-2, y-1) + P(x-2, y+1)) / 12$$

$$(4) \quad TF_2 = P(x, y) - M_2$$

These texture features are implemented in image processing and analysis software ImageJ [14] as macros. These macros display two resultant texture feature images (Figs. 3 and 4).

5. Texture edge detection techniques

Two novel edge detection techniques are proposed. The first technique is based on texture feature edge detection. The second is based on texture feature image segmentation and edge detection. Texture segmentation has been done by five image segmentation algorithms in CVIPtools [15]: fuzzy c-means, gray level quantization, histogram thresholding, median cut and principal components transformation/median cut.

The first technique works as follow:

1. Texture feature extraction by texture feature 1 and 2 [13, 14].
2. Applying conventional edge detection operators on resultant texture feature images [15].

The second technique works as follow:

1. Texture feature extraction by texture feature 1 and 2 [13, 14].
2. Resultant image segmentation by using the image segmentation algorithms in CVIPtools [15].
3. Applying conventional edge detection operators on resultant texture segmentation images [15].

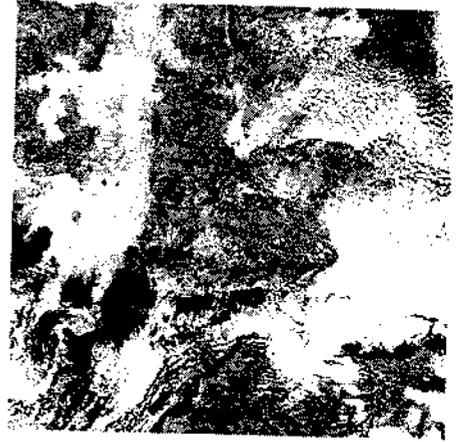
6. Experiments

The MODIS flying on NASA's Terra satellite captured the image (Fig. 2a) of floods in the border region of Western Turkey, Eastern Greece, and SouthEastern Bulgaria on November 22. The second image (Fig. 2b) shows the region on November 9, under normal conditions. Both images were made with a combination of visible and infrared light [16]. The Evros River, called the Meriç River in Turkey, flows from Bulgaria south along the border between Turkey and Greece and into the Aegean Sea. Flowing into the Evros from the east, the Ergene River is similarly flooded, as are a number of other tributaries, including the Ardas.

These satellite images are used to obtain texture feature images (Figs. 3 and 4). The implemented experiments apply the proposed texture edge detection techniques. The obtained results are presented and analyzed.

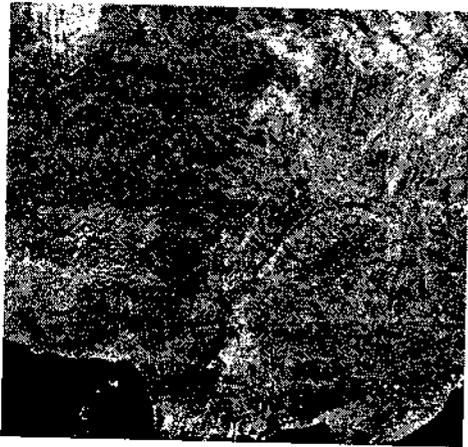


(a)

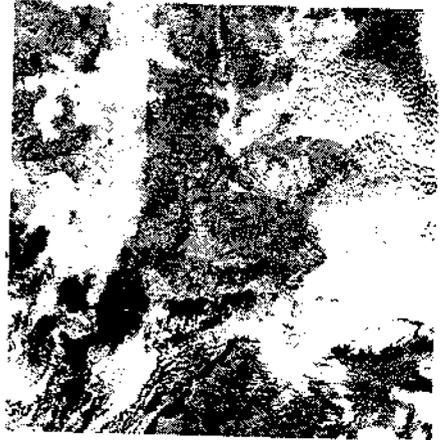


(b)

Fig. 2. The MODIS satellite images obtained on 9.11.2007 (a) and 22.11.2007 (b)

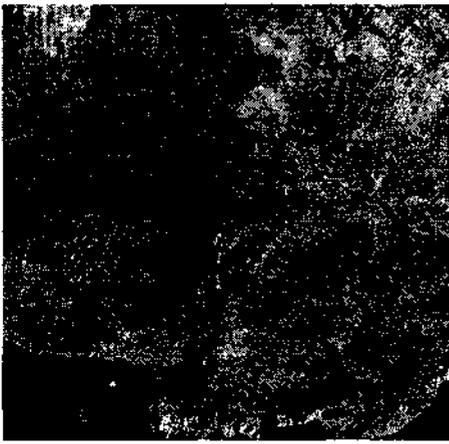


(a)



(b)

Fig. 3. The texture feature 1 images: 9.11.2007 (a) and 22.11.2007 (b)



(a)



(b)

Fig. 4. The texture feature 2 images: 9.11.2007 (a) and 22.11.2007 (b)

7. Results and discussion

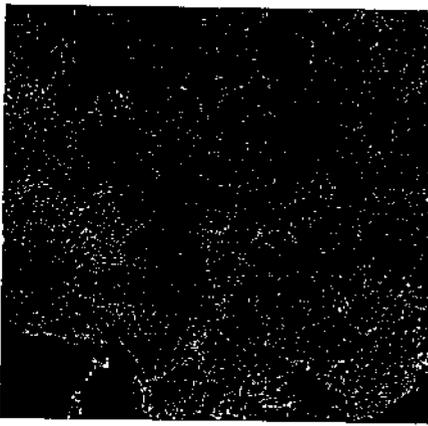
To evaluate the techniques, it is necessary to have some comparison basis for. In this research, the basis is another technique that has been widely accepted by the scientists: the Gray-Tone Difference Matrix (GTDM) and the “flat texture image” (the image minus the median filtered image).

The GTDM has been proposed in an attempt to define texture measures correlated with human perception of textures. In this work, five different features are used to quantitatively describe such perceptual texture properties as coarseness, contrast, busyness, complexity, and texture strength [17].

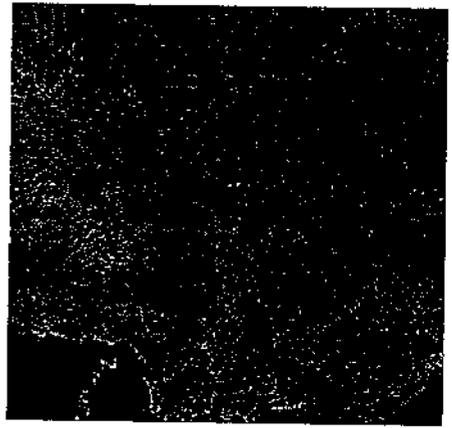
The “flat texture images” (Fig. 5) represent a texture because the operation the image minus the median filtered image removes the effect of the overall intensity level.

The edge detection operators are applied on the resultant images. The results show that proposed texture edge detection techniques have been successfully applied on satellite images with obtained rate commensurable to edge detection on these images. In the statistical approach, there is no reliable distinction between the results based on the comparison technique and the proposed techniques.

Figures 6, 7 and 8 show the complied results for the proposed technique.



(a)

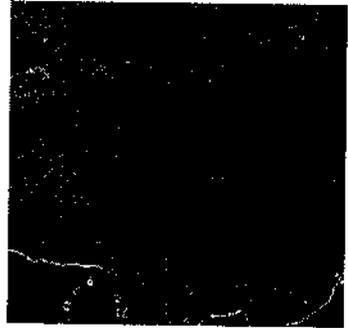


(b)

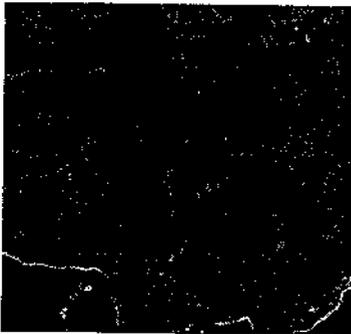
Fig. 5. The "flat texture images": 9.11.2007 (a) and 22.11.2007 (b)



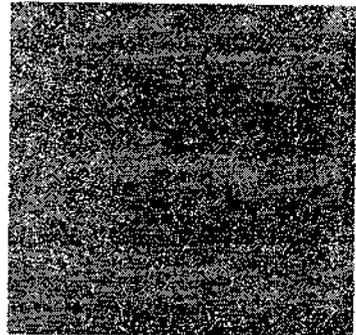
(a) *Roberts*



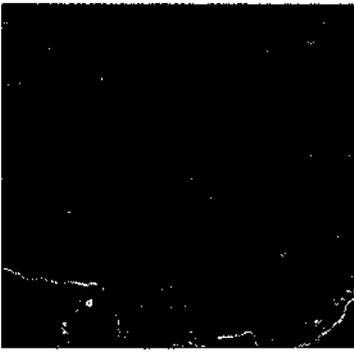
(b) *Sobel*



(c) *Prewitt*



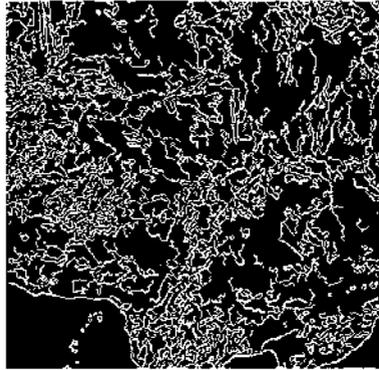
(d) *Laplacian*



(e) *Kirsch*



(f) *Robinson*



(g) *Canny*

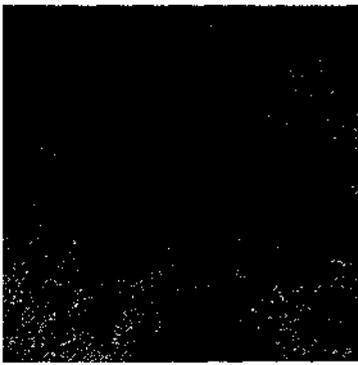
Fig. 6. The results from applying the first proposed texture edge detection technique to the satellite image obtained on 9.11.2007



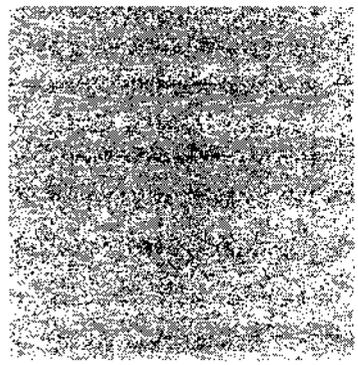
(a) *Roberts*



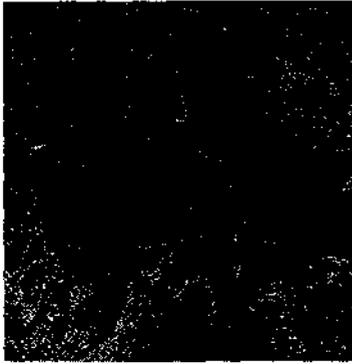
(b) *Sobel*



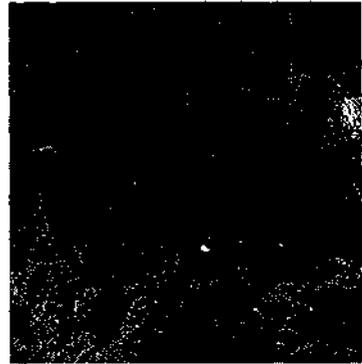
(c) *Prewitt*



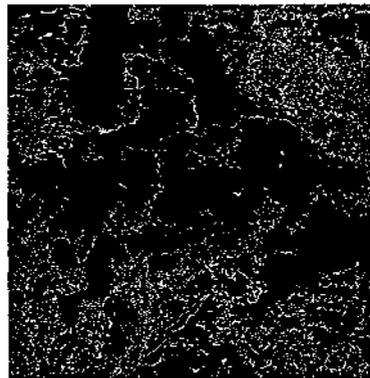
(d) *Laplacian*



(e) *Kirsch*

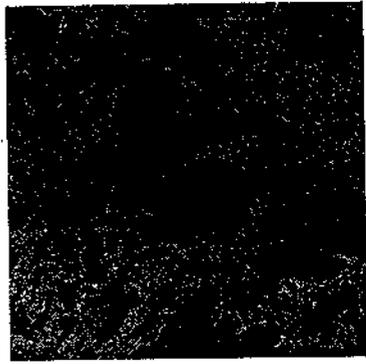
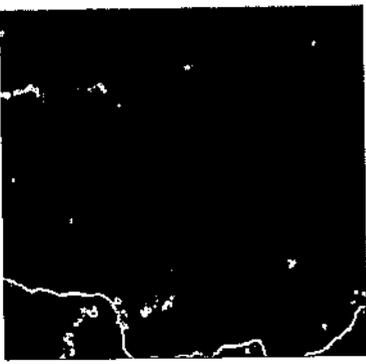


(f) *Robinson*

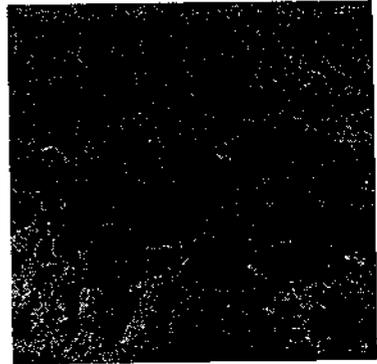
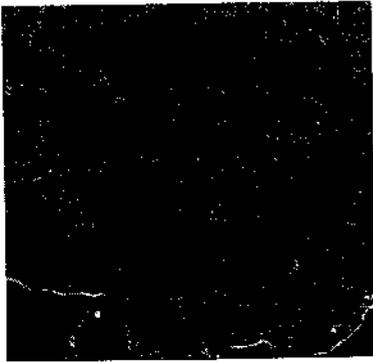


(g) *Canny*

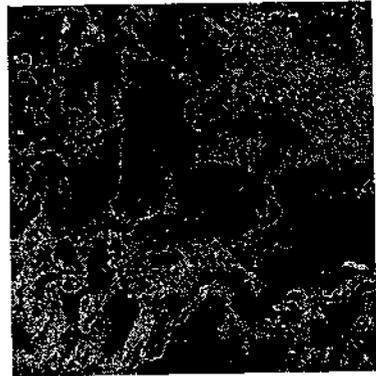
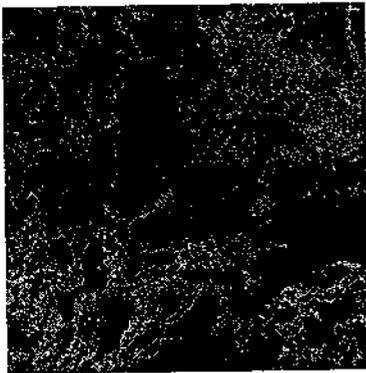
Fig. 7. The results from applying the first proposed texture edge detection technique to the satellite image obtained on 22.11.2007



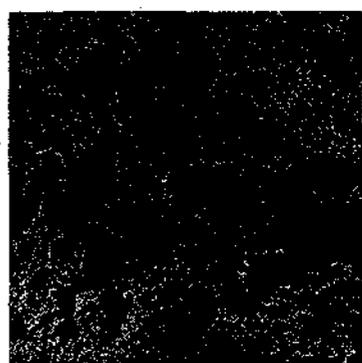
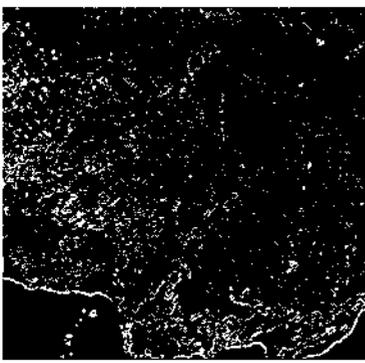
The fuzzy c-means segmentation and the Kirsch edge detection



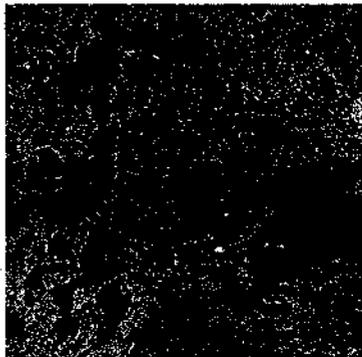
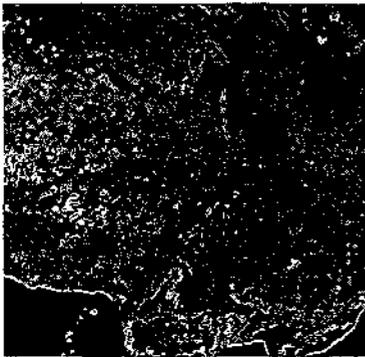
The gray level quantization segmentation and the Kirsch edge detection



The histogram thresholding segmentation and the Kirsch edge detection



The median cut segmentation and the Kirsch edge detection



The principal component transformation/median cut segmentation and the Kirsch edge detection

(a)

(b)

Fig. 8. The results from applying the second proposed texture edge detection technique on the stage of the Kirsch operator to the satellite images obtained on 9.11.2007 (a) and 22.11.2007 (b)

8. Conclusion

Two novel texture edge detection techniques are developed and tested. They have been applied to MODIS satellite images of flooded regions of Turkey, Greece and Bulgaria on 9.11.2007 (normal conditions) and 22.11.2007 (floods). The results evidence of the successful application of the proposed techniques for texture edge detection.

The feature work is addressed to identifying texture boundaries, which is crucial for higher-level processing of contours. Since textures consist of contours, a contour processing stage will process all the contours within the texture, which is unnecessary, as these contours do not represent boundaries. Therefore, it is beneficial to inhibit texture regions before higher-level processing, such as contour extraction occurs.

References

1. Haralick R. M. Statistical and structural approaches to texture, Proceedings of the IEEE, 1979, 786-804.
2. Krezhova D. Recognition of natural objects along a trace of the Earth's surface by spectral reflectance characteristics and photoimages, Annual of the Jubilee International Scientific Session "50 years University of Mining and Geology", 46, 2003, 375-379.
3. Augustejin M. F. Performance evaluation of texture measures for ground cover identification in satellite images by means of a neural-network classifier, IEEE Transactions on Geoscience and Remote Sensing, 33, 1995, 616-625.
4. Unser M. Local linear transforms for texture measurements, Signal Processing, 2, 1986, 61-79.
5. Kuan J. K. P., P. H. Lewis. Complex texture classification with edge information, Proceedings on Second International Conference on Visual Information System, San Diego, 1997.
6. Lillesand T. M., R. W. Kiefer. Remote Sensing and Image Interpretation, 4th edition, New York, Wiley, 2000.
7. Weszka J. S., C. R. Dyer, A. Rosenfeld. A comparative study of texture measures for terrain classification, IEEE Transaction on Systems, Man, and Cybernetics, 6, 1976, 269-285.
8. Pavan Kumar G. Edge detection in textured images, MS Theses, Department of Computer Science and Engineering, Indian Institute of Technology, Madras, August 1998, <http://speech.cs.iitm.ernet.in/Main/publications/MSTheses/PavanThesis.ps.gz>.
9. <http://www.icaen.uiowa.edu/~dip/LECTURE/PreProcessing3.html#edge>.
10. Canny J. A computational approach to edge detection, IEEE Transactions on Pattern Analysis and Machine Intelligence, 8, 1986, 679-714.
11. Kazuhiro F. Edge extraction method based on separability of image features, IEICE Transactions on Information and Systems, E78-D, No 12, 1995, 1533-1538.
12. <http://www4.gu.edu.au:8080/adt-root/uploads/approved/adt-QGU20050810.132625/public/07Chapter4.pdf>
13. Tsaneva M. Texture features for segmentation of satellite images, Cybernetics and Information Technologies, 8, No 3, 2008 (in press).
14. Rasband W. S. ImageJ, U. S. NIH, Bethesda, Maryland, USA, 1997-2007, <http://rsb.info.nih.gov/ij/>.

15. U m b a u g h S., Southern Illinois University Edwardsville. CVIPtools. <http://www.ee.siu.edu/CVIPtools>.
16. http://modis.gsfc.nasa.gov/gallery/individual.php?db_date=2007-11-30.
17. A m a d a s u n M., R. K i n g. Textural features corresponding to textural properties, IEEE Transactions on System, Man Cybernetics, 19, No 5, 1989, 1264-1274.

ТЕХНИКИ ЗА ОПРЕДЕЛЯНЕ НА ТЕКСТУРНИ ГРАНИЦИ, ИЗПОЛЗВАЩИ ТЕКСТУРНИ ПРИЗНАЦИ И ГРАДИЕНТНИ ДЕТЕКТОРИ

М. Цанева

Резюме

Текстурни граници се наричат местата в изображение, където има рязка промяна на текстурните характеристики. В работата са предложени и тествани две нови техники за определяне на текстурни граници, които използват извличане на текстурни признаци и сегментиране преди прилагането на конвенционалните градиентни алгоритми и алгоритми с пресичаща нулата втора производна за определяне на граници (на Roberts, Sobel, Prewitt, Laplacian, Kirsch, Robinson и Canny). В експериментите за текстурно сегментиране са използвани най-разпространените методи за сегментиране на изображения: fuzzy c-means, gray level quantization, histogram thresholding, median cut and principal components transformation/median cut. Представени са и са анализирани резултатите, които са получени от прилагането на тези техники за определяне на текстурни граници към спътникови изображения.