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Texture Features for Segmentation of Satellite Images

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Abstract: *To be able to find different textures in an image, a simple strategy is to perform texture measurements on a moving window and assign scalar features to each of the image pixels corresponding to window centers. This operation is similar to filtering. It transforms an image into a feature image. Three novel texture features for image segmentation based on gray level texture are presented and compared. They use 3×3, 5×5 and 7×7 neighborhood masks and provide a quantitative measure of image texture using only diagonal pixels (first and second features) or all pixels of the masks (third feature). The average intensity value in the feature masks is computed. The proposed approach to compute texture features is theoretically and computationally simple: a texture feature value is a difference of the gray level value of the central pixel and the average intensity value in the feature masks. The texture feature images are used in experiments for satellite image texture segmentation. In this study, an unsupervised texture-based image segmentation algorithm is discussed. The most common image segmentation methods have been applied to the feature images: fuzzy c-means, gray level quantization, histogram thresholding, median cut and principal components transformation/median cut. Results from texture segmentation are presented and analyzed.*

Keywords: *Texture features, image segmentation, satellite images, remote sensing.*

1. Introduction

In images, texture quantifies local contrast (gray level differences) and local spatial structure. There is no precise definition of what texture is. Intuitively, texture is the local intensity “pattern”. In this paper the followed definition of texture is used: frequency of change and arrangement of tones on an image [1].

R e e d and d u B u f [2] have made a review of texture segmentation and feature extraction techniques since 1980 and claim that most development has been concentrated on feature extraction methods. The authors classified the feature extraction methods as:

1. Feature-based methods – some characteristics of texture are used to classify homogeneous regions in an image.

2. Model-based methods – the hypothesis that an underlying process governs the arrangement of pixels is used to extract the parameters of such process.

3. Structural methods – a texture can be expressed by the arrangement of some primitive element using a placement rule.

The most commonly used methods are feature-based, model-based and hybrids methods. C o c q u e r e z and P h i l i p p [3] have used a similar classification of image segmentation methods.

Various methods perform texture analysis directly upon the gray levels in an image: gray level co-occurrence matrix (GLCM) [4], autocorrelation function analysis [5], generalized co-occurrence matrices (GCM) [6], second order spatial averages [7], and two-dimensional filtering in the spatial and frequency domain [8]. We used the last approach by texture measurements on a moving window – a simple strategy to perform texture measurements on a window, assign scalar features to each of the image pixels corresponding to window centers and move the window over one unit (i.e. column or row). This operation is similar to filtering. It transforms an image into a feature image. The computing texture images has four steps:

1. Select a window size and a texture measure.

2. Center the window at each pixel (i, j) in the image.

3. Compute the texture measure.

4. Assign the computed value to the center pixel (i, j) in a new image of the same size.

Pixels close to the image border can be handled in the same manner as for filtering and convolution.

The statistics of gray-level differences have been successfully used in a number of texture analysis studies [9]. Ojala et all. [10] proposed signed gray-level differences and their multidimensional distributions for texture description. The feature Sum of differences [11] is a novel measure of texture based on edges.

$$\text{Sum of Differences} = \sum_{i}^{w_i} \sum_{j}^{w_j} \left| f(i,j) - \mu \right|, \tag{1}$$

where $f(i, j)$ is the gray level value of the root pixel of a 3×3 pixels window and μ is the mean gray level value of the entire window.

In this work easy-to-compute low-level features based on the concept of gray level differences are proposed. The main novelties of the proposed features are two: a computing scheme of the average gray level value and a texture feature determination using only the root pixel intensity and the average values. The measure Sum of differences and five texture features of the co-occurrence matrix (Angular Second Moment (ASM), Contrast, Correlation, Inverse Difference Moment (IDM) and Entropy) have been used in evaluation of the proposed texture features.

Our features have been computed by image processing and analysis program ImageJ [12]. ImageJ is a public domain Java image processing and analysis program that was developed by Wayne Rasband at the National Institutes of Helth, Bethesda, Maryland, USA. ImageJ can display, edit, analyze, process, save and print 8-bit, 16-bit and 32-bit images of various formats. It supports standard image processing functions such as contrast manipulation, filtering, edge detection and others. ImageJ was designed with an open architecture and can be extended by user-written Java plugins and macros for special acquisition, analysis and processing tacks [13]. The proposed texture features have been implemented as macros.

In the field of remote sensing of the Earth the extraction of texture features from satellite imagery provides a complementary source of data for those application in which the spectral information is not sufficient for identification, classification or segmentation of spectrally heterogeneous landscape units. Spectral reflectance characteristics of laboratory data, field data and images are traditionally used for discrimination, classification and segmentation of rock types and all land covers [14, 15]. Multispectral classification techniques provide suitable results when the classes represent structural and spectral homogeneous units, provided that the spectral response of each class is sufficiently specific. The texture of an image is related to the spatial distribution of the intensity values in the image. Texture analysis methods and techniques offer interesting possibilities to characterize the structural heterogeneity of classes in the cases of urban areas and mountain regions. In this research an image of a mountain region is segmented – Landsat 7 image of the Himalayan mountains.

The principal objective of the research is to develop and test novel texture features for image texture analysis and to implement these features for texture segmentation in satellite images of the Earth.
The research has three goals:

1. To develop novel texture features based on gray-scale information in 3×3, 5×5 and 7×7 neighborhood masks.

2. To implement these features in the image processing and analysis software ImageJ.

3. To test these features on a satellite image for texture segmentation tacks using feature-based segmentation methods and techniques.

2. Texture segmentation

2.1. Image segmentation

Image segmentation is dividing into regions of homogeneous characteristics. There are two fundamental approaches to image segmentation: region based and contour based approaches [16]. Region based approaches work as grouping together pixels with similar properties and combining proximity and similarity. Contour based approaches consist of edge detection and linking processes. We used region based image segmentation techniques.

2.2. Texture segmentation

Texture segmentation can be performed in two ways: as gray level segmentation or as feature segmentation [17]. We used the feature segmentation technique. Texture is always defined in relation to some local window. In this paper the feature segmentation technique is addressed on a 3×3, 5×5 and 7×7 neighborhood masks.

2.3. An algorithm for unsupervised texture-based image segmentation

If the number of segments is known beforehand, then the process of segmentation is termed supervised segmentation. In another case segmentation is termed unsupervised. Unsupervised segmentation methods and approaches are more suitable for the purpose of remote sensing than supervised ones.

We used a segmentation algorithm as follows:

1. Compute texture feature images of the satellite image and of its sub-images with 2, 3, 4, and 5 different textures.

2. For a given texture feature image, apply a segmentation procedure as segmentation of gray scale image.

3. Evaluate empirically the segmentation result.

2.4. Segmentation methods

Segmentation of texture feature images has been done by five image segmentation algorithms in CVIPtools [18]: fuzzy c-means, gray level quantization, histogram thresholding, median cut and principal components transformation/median cut.

1. Fuzzy C-Means (FCM) is a method of clustering. Clustering is a grouping of data with similar characteristics. This method allows one piece of data to belong to two or more clusters. The fuzzy c-means algorithm follows three steps:

- Choose a number of clusters.
- Assign randomly to each point coefficients for being in the clusters.
- Repeat until the algorithm has converged: compute the centroid for each cluster and compute (for each points) the coefficients of being in the clusters.

Apply a method of clustering over the texture feature images, the grouping of pixels with similar texture are received.

2. Gray level quantization can be regarded as global image segmentation. Image gray-level quantization deals with the digitization of the amplitude of an image function and is done by sampling the gray-level probability distribution of the image.

While a grayscale image is a texture feature image (i. e. the gray levels are the values of the texture feature), the result of gray level quantization is image segmentation based on the values of the texture feature.

3. Histogram thresholding is an image processing technique for converting a grayscale or colour image to a binary image based upon a threshold value. If a pixel has an intensity value less than the threshold value, the corresponding pixel in the resultant image is set to black. If the pixel intensity value is greather than or equal to the threshold value, the resulting pixel is set to white.

While a grayscale image is a texture feature image (i. e. the gray levels are the values of the texture feature), the result of histogram thresholding is a binary image based upon a threshold value of the texture feature.

4. The median cut algorithm is a popular algorithm for colour quantization, but can be applied to any point clustering problem. Let *B* be a set of boxes containing points, initially containing only a single box containing all points. While the number of boxes in *B* is less than desired number of clusters, the algorithm works as follows:

- Find the largest side length of any side of any box.
- Cut that box into two boxes along its largest side in such a way that half the contained points fall into each new box.
- Shrink the two new boxes so that they are just large enough to contain their points.

The results of the median cut algorithm applying over the texture feature images are the images segmented by pixel clustering. The pixel values are the texture feature values.

5. Principal component transformation aims at transforming image areas into a set of features, the “principal components”. As much information (i. e. variance) as possible is concentrated in the first principal component, as much as possible of the rest in the second, and so on. The principal components are not correlated, in contrast to the image areas, whish are usually highly correlated.

The texture feature image areas are the areas with similar texture and this method transform its into a set of the “principal components” of texture.

2.5. Evaluation methods

Segmentation algorithms can be evaluated analytically or empirically [19]. The analytical methods examine and assess the segmentation algorithms by analyzing their principles and properties. The empirical methods evaluate the segmentation results obtained by applying the segmentation algorithms to test images and measuring the quality of results compared with a reference segmentation (empirical discrepancy methods) or by measuring some desirable properties of segmented images (empirical goodness methods). We used empirical discrepancy evaluation method, which can be both objective and quantitative. The evaluation method was applied is calculation of percentage of correctly detected number of textures. It is similar to the generalization, which is the ratio between the number of regions in the segmented image and the number of regions in the reference segmentation.

Each texture analysis method characterizes image texture in terms of the features it extracts from the image. Therefore, image texture depends on the images, the goal of research and the features that are extracted from the image. Statistical methods analyze the spatial distribution of gray values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features. Depending on the number of pixels defining the local feature, the statistical methods can be further classified into first-order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics.

We used one commonly applied and referenced statistical method: the co-occurrence method, introduced by Haralick [4]. The relative frequencies of gray level pairs of pixels separated by a distance *d* in the direction θ combined to form a relative displacement vector (d, θ), which is computed and stored in a matrix, referred to as Gray Level Co-occurrence Matrix (GLCM) P. This matrix is used to extract second-order statistical texture features. Haralick suggests 14 features describing the two dimensional probability density function *p*. In this research, we used five of the most popular features: Angular Second Moment (ASM), Contrast, Correlation, Inverse Difference Moment (IDM) and Entropy. Table 1 defines these features.

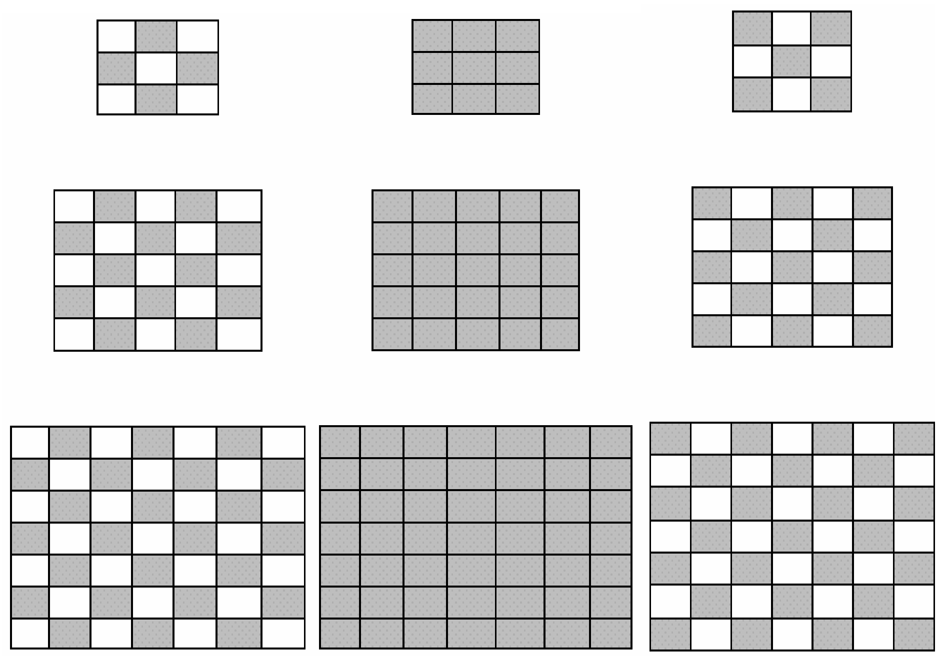
Table 1. Definitions and interpretations of the GLCM texture features used as referenced in this research

Texture feature	Definition	Interpretation
ASM	$\mathrm{ASM}=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p_{ij}^2$	Increases with regularity of the texture
Contrast	$\mathrm{Contrast}=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-j)^2\ p_{ij}$	Related to contrast of the texture. Also known as “Sum of squares variance”
Correlation	$\mathrm{Correlation}=-\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{(i-\mu_x)(j-\mu_y)}{\sqrt{\sigma_x\sigma_y}}\ p_{ij}$	A statistic of texture
IDM	$\mathrm{IDM}=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{p_{ij}}{1+(i-j)^2}$	Related to contrast of the texture. Also known as “Homogeneity”
Entropy	$\mathrm{Entropy}=-\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p_{ij}\log p_{ij}$	Increases with irregularity of the texture

3. Texture features

Before segmentation some homogeneity or similarity criterion must be defined. These criteria are specified in terms of a set of feature measures. Groups of feature measures assembled for segmentation purposes are referred to as feature vectors. The feature measures provide a quantitative measure of a certain texture characteristic.

In this research three novel scalar texture features are developed. For every pixel in the image, 3×3, 5×5 and 7×7 pixels windows are considered (Fig. 1). The features provide a quantitative measure of image texture using only diagonal pixels (first and second features) or all pixels of the masks (third feature).



(a) (b) (c)

Fig. 1. Pixels masks (3×3, 5×5 and 7×7) for texture feature 1 (a), texture feature 2 (b) and texture feature 3 (c)

For every pixels mask the average intensity value M of pixels is calculated. Texture Features (TF) are defined as a difference of intensity value of the central pixel and the average intensity value in the feature masks:

(2) $$\mathrm{TF}_i = P(x,y) - M_i,\ i = 1, 2, 3.$$

The texture feature extraction technique works in the following manner:

- For finding texture features every pixel in the image is considered as a central and followed by 3×3, 5×5 and 7×7 windows about that central pixel.
- The texture feature for that particular window is calculated.
- The intensity value of each central pixel is set to the texture feature value.
- The window then moves over one unit (i.e. column or row) and repeats the process for every pixel over the image.

4. Experiments and results

In texture segmentation experiments the pan-fused (bands 7-4-1) Landsat 7 image of the Himalayan mountains of Northern India, close to the Chinese and Nepalese borders, displayed at 1: 100000, 15 m [20] is used (Fig. 2).

Our study involves four main steps:

1. Creation of texture images using the proposed features.
2. Comparison of resultant images.
3. Segmentation of the images.
4. Evaluation of the proposed texture features.

4.1. Creation of texture images

The presented texture features are implemented in image processing and analysis software ImageJ as macros. These macros display the resultant texture feature images (Figs. 3, 4 and 5).

Fig. 2. Pan-fused (bands 7-4-1) Landsat 7 image of the Himalayan mountains of Northern India

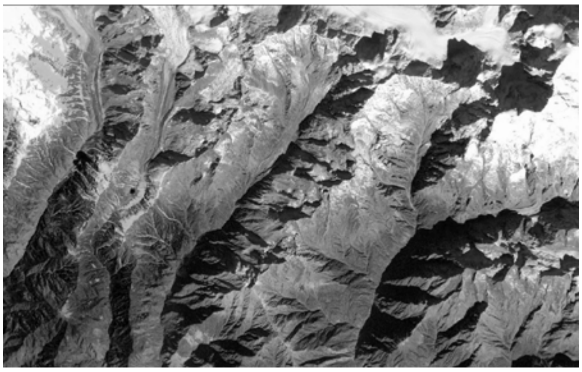


Fig. 3. The texture feature 1 image

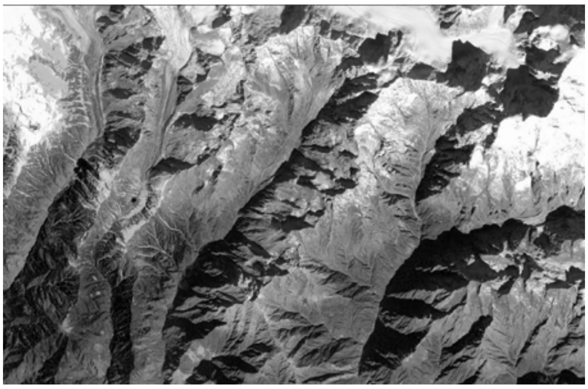


Fig. 4. The texture feature 2 image

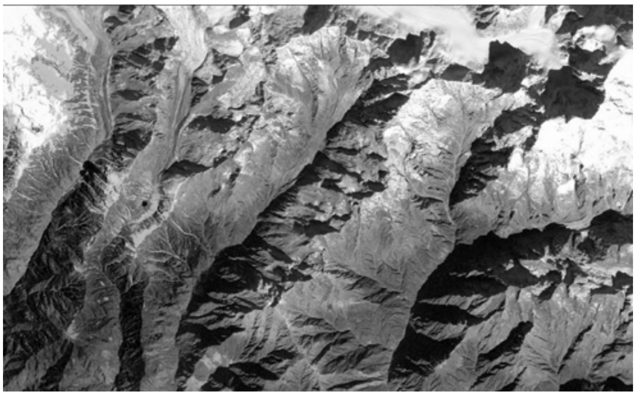


Fig. 5. The texture feature 3 image

4.2. Comparison of resultant images

The images of the texture features 1, 2 and 3 are compared. These images and the image of the feature Sum of differences are also compared. And the comparison of the resultant feature images which were calculated using masks with different sizes (3×3, 5×5 and 7×7 pixels) is made.

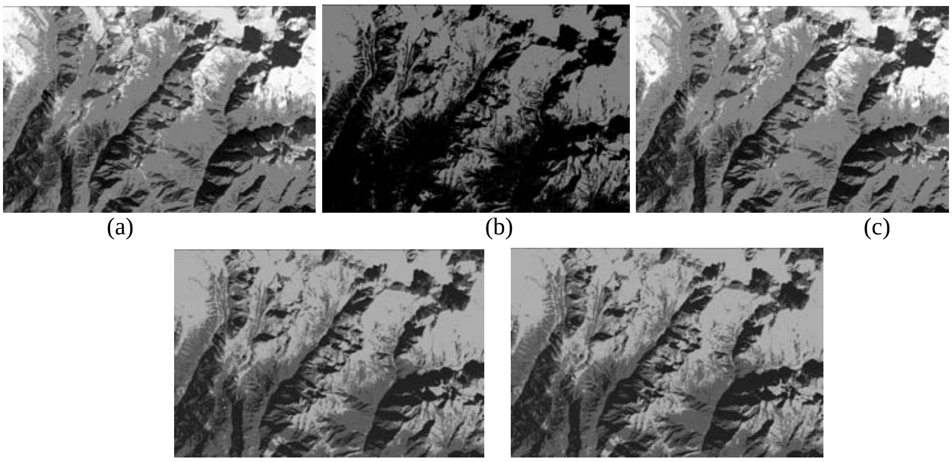
The images are compared by image calculator (by subtraction and logical operation AND), by histograms and by statistical features (mean, standard deviation, kurtosis and entropy) of sub-images with different textures. All results are the same:

1. No difference between the images of the texture feature 1, 2 and 3.
2. No difference between the images of the proposed features and the feature Sum of differences.
3. For every texture feature no difference between the images with different size of the masks: 3×3 , 5×5 and 7×7 pixels.

4.3. Segmentation of the feature images

The texture feature images are segmented by five of the CVIPtools segmentation algorithms: fuzzy c-means, gray level quantization, histogram thresholding, median cut and principal components transformation/median cut (Fig. 6). The resultant images are also the same for the texture feature 1, 2 and 3.

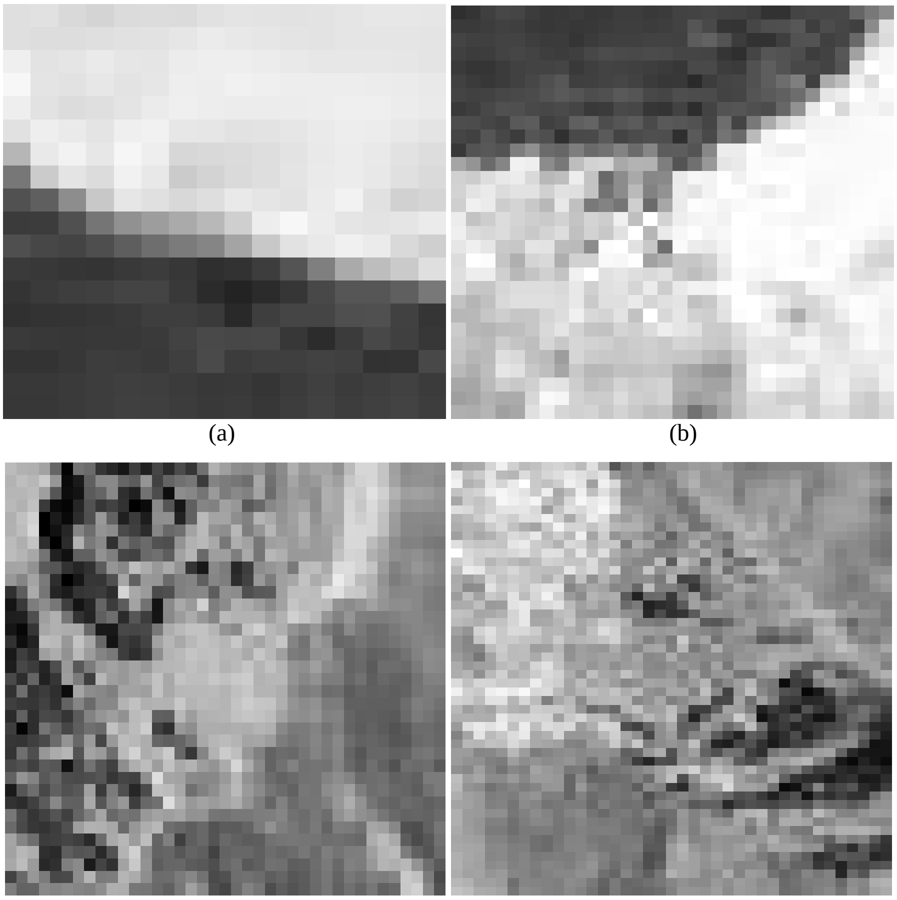
The segmentation rate of the proposed texture features is calculated as percentage of correctly detected number of textures. The experiments used by 15 sub-images of the satellite image studied with two, three, four and five different textures (Fig. 7).



(a) (b) (c)

(d) (e)

Fig. 6. The texture feature segmented images: (a) fuzzy c-means, (b) gray level quantization, (c) histogram thresholding, (d) median cut, (e) principal component transformation/median cut



(a) (b)

(c) (d)

Fig. 7. Sub-images with two (a), three (b), four (c) and five (d) different textures

For all 60 sub-images three main steps are followed:

1. The texture feature image is calculated for every sub-image.
2. The feature images are segmented by histogram thresholding method.
3. The number of detected textures is determined.

The results are presented in Table 2.

Table 2. Percentage of correctly detected number of textures using histogram thresholding segmentation method

Number of textures in a sub-image	Number of sub-images tested	Number of sub-images with correctly detected number of textures	Number of sub-images with wrong detection case
2	15	14	1
3	15	14	1
4	15	13	2
5	15	12	3
Total	60	53 (89%)	7 (11%)

4.4. Evaluation of the proposed texture features

The proposed texture features have been evaluated by comparison with the feature Sum of differences and with the followed GLCM texture features: ASM, Contrast, Correlation, IDM and Entropy. Two experiments were implemented:

1. Application of the Student's *t*-criterion over the set of GLCM texture features used in this study (ASM, Contrast, Correlation, IDM and Entropy) and the proposed texture features.

2. Comparison of the texture discrimination ability of the proposed features and the gray level difference texture feature Sum of differences.

By means of the Student's *t*-criterion statistically significant differences between the values of the proposed texture features and the GLCM texture features used in this study of different textures were found at $p < 0.05$ in all of the cases examined with exception of correlation (Table 3).

Table 3. The significance level p of the Student's *t*-criterion applied over the set of the texture features examined

Feature name	ASM	Contrast	Correlation	IDM	Entropy	TF 1, 2 and 3
Mean 1	0.005467	1787.887	0.0000242	0.074067	5.352933	123.0946
Mean 2	0.012933	4920.431	– 0.000022	0.146533	4.571133	186.8239
p	0.000151	0.00000000435	0.1848	0.007471	0.000000207	0.000000000242

The discrimination rate is the same for all proposed features, applied to all neighborhood masks, compared to the feature Sum of differences (over 90%).

5. Discussion

Analysis of segmented images shows that the novel texture features have been used with segmentation rate 89% received from segmentation of 60 sub-images (by 15 with two, three, four and five different textures) of the satellite image examined.

The proposed features have been compared to the feature Sum of differences, which is the prototype of the main idea of its computation. The main novelties of the proposed features are two: a computing scheme of the average gray level value and a texture feature determination using only the root pixel intensity and the average values. All results show that the proposed features and the feature Sum of differences have the same accuracy. The features have been compared to five GLCM texture features (ASM, Contrast, Correlation, IDM and Entropy). The application of the Student's t-criterion over the set of the texture features used in this study revealed that the values of features of different textures differ statistically significantly (at $p < 0.05$) with exception of the feature Correlation. The results show that the significance level p of the Student's t-criterion of the proposed texture features is the best.

6. Conclusion

Three texture features have been developed and tested in this paper. All three features have proved to be effective measures for texture segmentation. Each feature can be used instead of the other and the feature Sum of differences. The main priority of proposed features over the Sum of differences is the fast computing.

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