Pine Crown Density Determination Using Local Binary Patterns

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***Abstract*—Competent assessment of the plantation sanitary condition allows you to plan various forest health protection measures. Automation of the tree state category assessment process could be implemented by fuzzy logic. The key role in this process plays such characteristic as the crown density degree. The paper proposes an algorithm for automatic estimating of the crown density degree using local binary patterns. Histograms of crown fragments of various densities are built on the basis of uniform patterns; the Kullback-Leibler distance is used as a measure of the difference between the two histograms. Experimental studies conducted on 1636 images of crown fragments confirm the effectiveness of applying local binary patterns to the task of the crown density degree estimation.**

Keywords*—*classification, image processinggenius, texture analysis, forest health.

I. Introduction

The sanitary condition assessment of forest plantations allows you to plan an economically and environmentally efficient action system of forest protection, which includes various sanitary actions. In the studied forest area, such an assessment is performed on the basis of individual trees status category determination. The category of tree health condition can vary from the first (healthy tree) to the sixth (old dead wood):

Categories of tree status can take values:

- healthy (without signs of weakening);
- weakened;
- severely weakened;
- drying out;
- fresh dead wood;
- old dead wood.

Currently, the tree state category is determined by a specialist during a personal examination of each tree, that requires significant human and economic resources. The quality of the tree sanitary condition estimation directly depends on the qualification of the forest health engineer. Sometimes, the different specialists estimation given can be different, because of the subjective characteristics that are used to make a decision about the state category of a particular tree. The following situation could be used as an example: the second tree state category must satisfy several requirements as sparse crown; light green needles; growth reduced, but not more than half; individual branches withered. In papers [1, 2] an approach based on fuzzy logic is proposed for automatic assessment of the tree state category that allows taking into account the subjectivity of judgments of forest health specialists. The input of the fuzzy logic controller receives such characteristics as the degree of crown density, growth, the degree of drying of branches, the fall of the bark, and the color of needles. Automatic evaluation the degree of growth, bark loss, and color of needles, because image quality can distort the true color is not always possible, making it difficult to evaluate the tree's characteristics based on color characteristics. Thereby the main characteristic of the pine state category estimation using computer vision technologies is the assessment of the degree of crown density. The degree of the crown density can take values:

- rich,
- sparse,
- openwork,
- very openwork,
- is absent.

Generally, the transition between crown density degrees determines the transition between tree state categories.

II. The Crown Density Degree Estimation Algorithm

To calculate the degree of crown density in this paper, we propose a method for assessing the texture characteristics of an image based on local binary patterns. The local binary pattern (LBP) operator, first introduced by Ojala et al. [3], is a fast, convenient, and often used texture analysis method. The LBP operator is used as an integral part of many classifiers [4–9]. Despite the great success of the LBP application in many tasks, the usual LBP operator has disadvantages, such as sensitivity to image rotation and noise, loss of local texture information, and the inability to detect large-scale texture structures [10]. In addition to these disadvantages, the LBP histograms constructed in the classical way are cumbersome, that can slow down the speed of image processing. Currently there are many variations of local binary patterns, which are devoid of these disadvantages. As a solution extended binary patterns - Extended Local Binary Patterns (ELBP) [11] could be used, due to the calculation of special binary strings (uniform patterns) and the construction of histograms based on them. Extended local binary patterns calculates according to the expression:

$$ELBP\ (P) = \sum_{n=0}^{7} s(I_n - I_c) \cdot 2^n \qquad (1)$$

where $s(x) = 1$, if $x \geq 0$, else $s(x) = 0$, I_n и I_c – brightness of the current and central pixels, representing the value of the Y component from the YUV color space. As can be seen from expression (1), the calculation of the ELBP binary code coincides with the calculation of the classical code of local binary patterns. The difference between extended binary templates and classical ones is in the way of constructing histograms from the received binary strings. Extended local binary patterns allow you to take into account such features of the image as the end of lines, edges, angles and spots, assigning a separate histogram column for each of these features. Thus, each column of the histogram describes one image feature defined by the uniform ELBP code. Extended local binary patterns are uniform when the number of transitions in a binary code from zero to one is no more than three. Examples of uniform ELBP codes are shown in Figure 1.

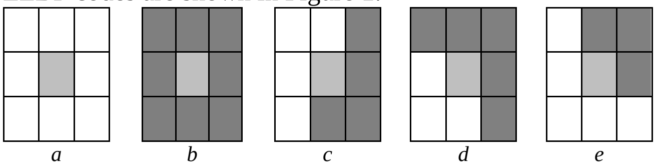

Fig. 1. Uniform patterns: (a) – a dark spot; (b) – a bright spot; (c) – edge; (d) – a light corner; (e) – a dark corner.

The total number of such codes, taking into account cyclic shifts, is fifty eight. For all non-uniform patterns, a separate column is allocated when constructing a histogram.

III. EXPERIMENTAL RESEARCH

For experimental studies, 228 images of pine of various sizes were used. All images are expertly divided into categories of sanitary conditions. The minimum image size was 396 × 452 pixels. Examples of images used are shown in Figure 2.

Fig.2. Examples of used pine images.

A crown fragment samples of different densities was prepared before testing. The examples of crown fragments images are shown in Figure 3. The size of the samples is 50 × 50 pixels. At the first stage of analysis, background objects in images are deleted by the threshold processing method with a global threshold [12]. Then the image is divided into parts of 50 × 50 pixels. Each such part is compared with samples. The comparison is as follows: a histogram is constructed from the fragment and this histogram is compared with the histograms of the samples. The fragment is assigned the nearest sample density degree. As a measure of the difference between the histograms, the Kullback-Leibler distance was used, that calculated as follows:

$$D_{K,L}(f,g) = \sum_{m=1}^{P(P-1)+3} f_m \ln \frac{f_m}{g_m}, \qquad (2)$$

where f and g – histograms of a fragment and a sample of image; P – number of points in the ELBP neighborhood; m – column number. The decision on the value of crown density degree of the investigated tree is carried out by counting the number of fragments of the calculated density, taking into account their location: bottom, top or middle of the tree. To do this, each fragment is assigned a weight. Weights are reduced from the middle to the edges and from top to bottom, then the weights are grouped by degree of density and summed. The results obtained are sorted from maximum weight to minimum.

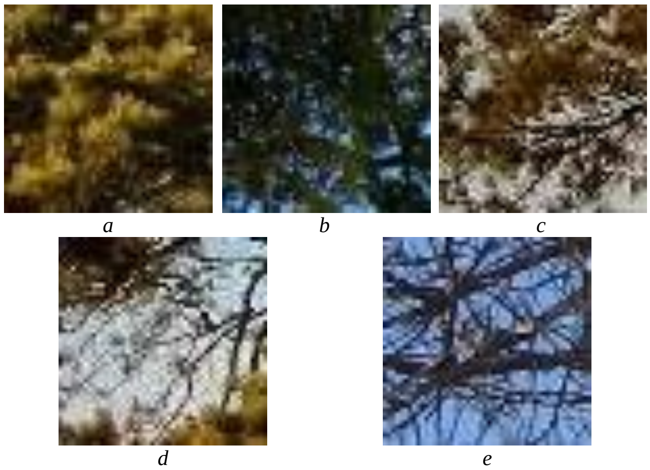

Fig.3. Pine crown fragment samples of different densities: (a) – rich; (b) – sparse; (c) – openwork; (d) – very openwork; (e) – is absent.

For a more accurate assignment of the studied image texture to a particular value of the crown density degree the scale and size occupied by the pine in the image should be taken into account. The histograms examples of various crown fragments of various densities obtained using extended local binary patterns are shown in Figure 4.

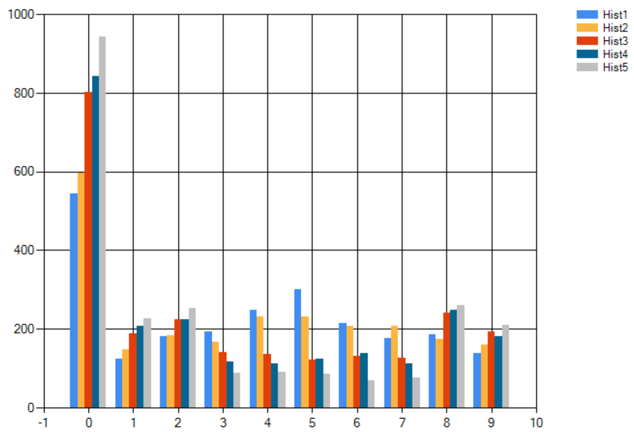

Fig. 4. ELBP-histograms for various crown fragments.

In fig. 4, the legend “Hist 1” corresponds to the crown fragment in Fig. 2-a, “Hist 2” corresponds to the crown fragment in Fig. 2-b, etc. Each column of the histogram from 1 to 9 corresponds to a rotation-invariant number of the uniform code of the extended binary template. The zero column is a collection of all non-uniform patterns for the studied image fragment. As can be seen from Figure 3, with a crown density decrease, increases a number of uniform ELBP patterns, those patterns that are responsible for reducing the number of edges in the image of the studied texture. In the work 1636 fragments of the various density crowns were used. The following indicators were used to evaluate the quality of the algorithm: a correctly classified crown sample – true recognition (TR), false negative response – false rate rejection (FRR) and false positive response – false alert rejection (FAR). The calculation results of these indicators during experimental studies are shown in table 1.

TABLE 1. THE EXPERIMENTAL STUDIES RESULTS.

Crown fragments	**LBP**			**ELBP**		
	TR	***FRR***	***FAR***	***TR***	***FRR***	***FAR***
rich	90.27	9.73	7.23	98.27	1.73	5.13
sparse	84.87	15.13	11.75	97.87	2.13	5.78
openwork	83.85	16.15	12.68	96.85	3.15	4.95
very openwork	83.45	16.55	17.74	95.45	4.55	3.99
is absent	85.34	14.66	10.25	98.34	1.66	2.78

The results of experimental studies show, that the average accuracy of assigning crown fragments using local binary patterns is 85.6%, while using extended local binary patterns, the accuracy was 97.5%. Moreover, the number of false positive and false negative responses is significantly reduced.

IV. CONCLUSION

The paper considers the application of extended local binary patterns to the problem of recognizing the pine crown density. With the help of this assessment, it is possible to determine the sanitary condition of the plantation, which will allow you to plan various measures of forest protection. The crown density degree recognizing efficiency with extended local binary patterns is increased by almost 12% to conventional local binary patterns.

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