Method for Classification of Textures Based on Histogram and Random Events Analysis

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***Abstract*— An image histogram is a set of parameters commonly used to automatically evaluate the image during processing or recognition. When comparing or classifying different images, the histogram data can be analysed as it presents the overall colour or intensity composition of the image. This is very important in case of texture classification as the system must provide sufficient accuracy. In this paper, we present an approach and algorithm for visual analysis of images with different histograms, which can be easily implemented as a software application, improving substantially the image classification after non-destructive testing of vehicle tire's sidewall. The main contribution of this work is a software product for automated defect detection against a series of images, generated by laser shearography in a tire factory.**

Keywords-image analysis; pattern recognition; image processing.

I. Introduction

Histogram analysis [4] is often used to automatically evaluate an image during its recognition process.

Previous researches show that it is possible to use the histogram of grayscale images generated by laser shearography [6] for non-destructive testing of vehicle tires, together with Multi-Layer Perceptron neural network assisted calculations for pattern classification [3]. After further analysis, that method demonstrated some disadvantages, as some of the textures, which have obvious defects, were skipped while others, being part of the non-affected surface, were highlighted as defects. Also, another finding was that some of the images' histograms were identical due to similar samples (same model tires) in the automated shearography approach. Even if the position of a pixel or a set of pixels within the image is changed, the histogram will remain the same. That problem created the need to introduce a new flexible approach. The basic requirements led to the implementation of an algorithmic type, allowing parallel calculations and processing as well as high performance, even with limited hardware resources.

The rest of the paper is structured as follows. In Section 2, we present the algorithm step by step. An example of detected defects in images of tire carcasses is included. The conclusions and comparison with another approach for pattern recognition are presented in Section 3.

II. Description of the Method

The analyzed image color pattern is in grayscale. Initial conversion to 8 color grayscale takes place to additionally optimize the calculations. Each single pixel has a color code and is described by an elementary random event. All elementary random events $\omega_1, \omega_2, \ldots, \omega_b$ generate an event sequence with length ***b,*** where ***b*** is the number of all different color codes discovered within the given image. For example: If the different codes are $\omega_1 = 0$, $\omega_2 = 32$, s$\omega_3 = 64$, $\omega_4 = 96$, $\omega_5 = 128$, $\omega_6 = 160$, $\omega_7 = 192$, $\omega_8 = 224$, then ***b=8.***

Sequences of ***k*** simple events are introduced and each sequence allows recurrence. The relocation of two simple events will cause the production of a new sequence. A number collates to each sequence

$$\boldsymbol{\varphi(\omega_1, \ldots, \omega_k) = \sum_{i=1}^{k}(\omega_i - 1)b^{k-i} + \omega_k \rightarrow [1, b^k]} \quad \mathbf{(1)}$$

where $\omega_i = i$, $i = 1, \ldots k$.

Introduction of the unique sequence outlines the dependency between all simple random events, which can be described simultaneously by relation, regression and correlation between simple random events.

Considering the above definitions, we can present the image as a row vector of all simple random events. Following (1), starting from left to right and using a step with length 1 (single simple random event) and for pre-selected k-tuples, we calculate a number that corresponds to a class in the histogram. That is how the frequencies of the selected k-tuples are defined.

Figure 1 shows an image of a vehicle tire, the result of non-destructive control based on laser shearography, after initial conversion to 8 color grayscale. The image size is 64x64 pixels.

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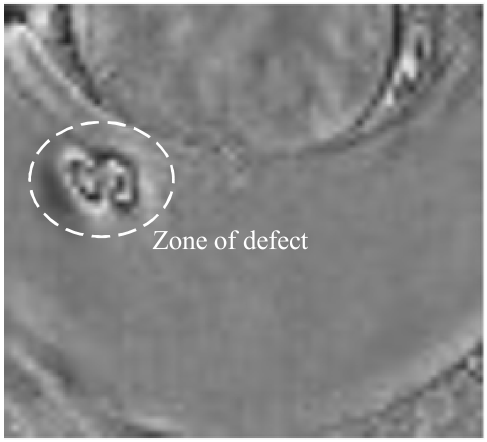

Figure 1. 64x64 pixels image, representing defect in vehicle tire carcass based on laser shearography.

For Figure 1, it was calculated that $\omega_1 = 0$, $\omega_2 = 32$, $\omega_3 = 64$, $\omega_4 = 96$, $\omega_5 = 128$, $\omega_6 = 160$, $\omega_7 = 192$, $\omega_8 = 224$ and $b=8$. The 2-tuples (k=2) are taken into consideration, which generates b^k classes, or 64 classes in the given example.

The histogram is calculated according to (1) and is illustrated in Figure 3.

An approach for generation of an arranged dataset based on the pixel information (symbols) is to scan the image in predefined direction (i.e. rows and columns) and to generate an array of k consecutive symbols – the so called “k-tuples”. After all k-tuples are generated, their histogram can be calculated for subsequent classification analysis. Figure 2 presents the process of generating the k-tuples; if k=3, the scan step is 1 and the directions is a row, followed by a column.

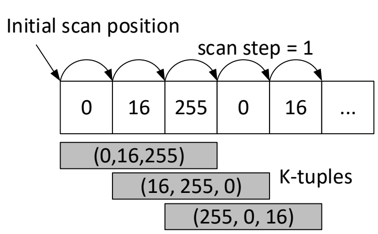

Figure 2. Example of k-tuple generation (k=3, scan step=1)

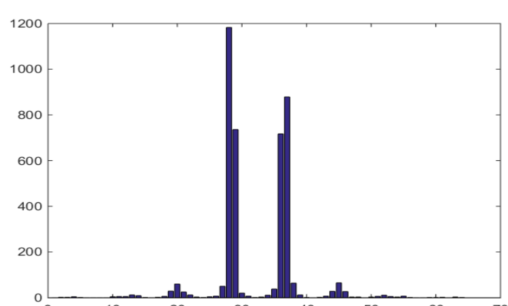

Figure 3. Histogram of 2-tuples, calculated for the image, shown in Figure 1

The same process with k=3 is shown in Figure 4.

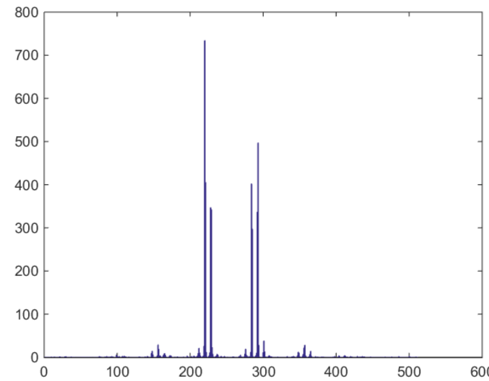

Figure 4. Histogram of 3-tuples, calculated for the image, shown in Figure 1

The histogram in Figure 3 shows the frequency of appearance of separate 2-tuples within the image and gives an opportunity for the initial image preparation to take place. It is known that the optimal selection of classes in a given histogram defines the expected frequency of a class between $N^{(2/5)} – N^{(3/5)}$, where N is the count of the simple random events (N=4096 for the current example) [1]. That is why N=147 is chosen.

All the classes from Figure 2 meeting the above requirement and having a count less than 147 are presented in Figure 5.

Figure 5. Selected pixels for N=147

Figure 5 shows the pixels of the classes with frequencies less than N.

The dependency between simple random events is defined by calculating the relation, regression and correlation between them. The definitions of relation, regression and correlation are given in [2].

The relation between simple random events $\boldsymbol{\delta}$ is calculated by the sections $\boldsymbol{P}$ [2]:

$$\boldsymbol{\delta}(\omega_i, \omega_j) = \boldsymbol{P}(\omega_i \cap \omega_j) - \boldsymbol{P}(\omega_i)\boldsymbol{P}(\omega_j) \qquad (2)$$

where

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$$\delta(\omega_i, \omega_j) \neq \delta(\omega_j, \omega_i) \tag{3}$$

Figure 6 illustrates the relation between simple random events, as per Figure 2.

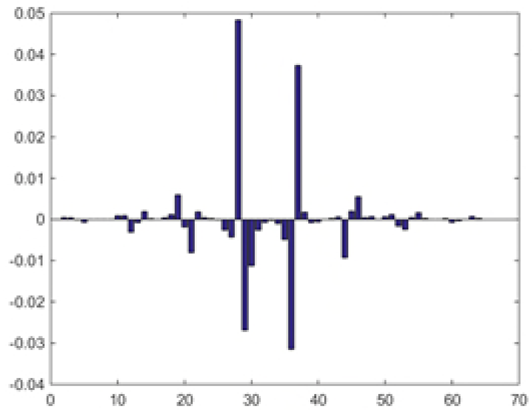

Figure 6. Relation between simple random events, calculated by (2) and (3) for the selected pixels, shown in Figure 5

A limiting constant (1/64) is selected. The constant is defined by the number of the classes – 8^2. In this way, each random event's probability is 1/64. If random events are equipropable, then the relation between them is going to be 0, according to (2). So, the classes with relation less than 1/64 are selected and the results are displayed in Figure 7.

Figure 7. Selected pixels for relation less than 1/64, based on the image, shown in Figure 1.

The coefficient of regression R of a simple random event $\boldsymbol{\omega_i}$ according to the simple random event $\boldsymbol{\omega_j}$ is defined as a difference between conditional probabilities following (4) [2].

$$R_{\omega_j}(\omega_i) = P(\omega_i|\omega_j) - P(\omega_i|\overline{\omega_j}) \tag{4}$$

Condition (3) of asymmetry defines that there are two ways to calculate R, against indexes i and j. The numeric values are shown in Figure 8.

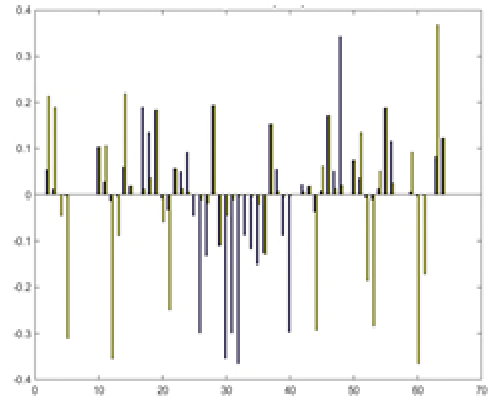

Figure 8. Coefficient of regression for (3), calculated for the relations, presented in Figure 7

A limiting constant (1/39) greater than (1/64) empirically is used for the examined set of images.

In Figure 9 are displayed the classes having regression coefficient less than (1/39).

Figure 9. Classes with limiting constant less than (1/39)

The correlation coefficient between two simple random events is given by (5) [2].

$$C(\omega_i, \omega_j) = \pm\sqrt{R_{\omega_j}(\omega_i) R_{\omega_i}(\omega_j)} \tag{5}$$

where $\boldsymbol{\omega_i}$ and $\boldsymbol{\omega_j}$ are simple random events.

For the analysis of Figure 1, C is illustrated in Figure 10.

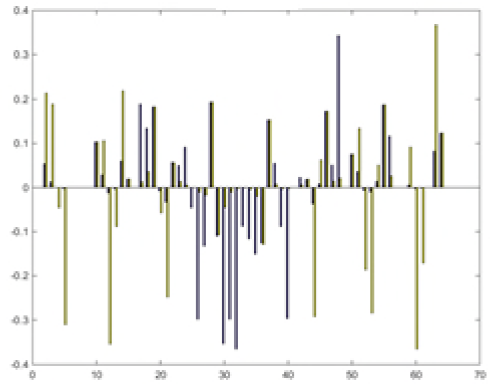

Figure 10. Coefficient of correlation calculated for the relations, given in Figure 7

The selected classes, according to the calculated value of C, are illustrated in Figure 11.

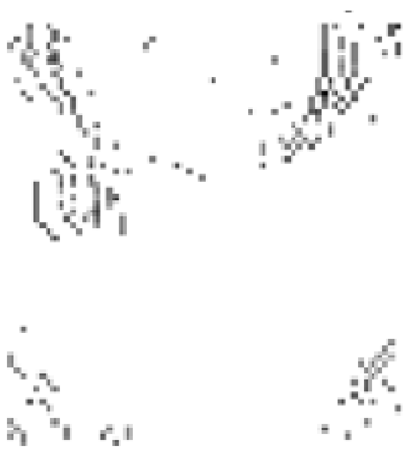

Figure 11. Selected classes according to the correlation

The value of the limiting constant is the same to compare relation, correlation and regression numeric values and their effect over the pattern classification.

Based on the proposed method, the following algorithm can be summarized:

1. Conversion of the image to 8 color greyscale
2. Definition of k-tuples
3. Calculation of the histogram
4. Calculation of the relation between simple random events
5. Calculation of the regression between simple random events
6. Calculation of the correlation between simple random events
7. Display of the detected defects

Figure 12 shows the detected defect for 20 of the test images. The analysis time for the images is 100 ms/img.

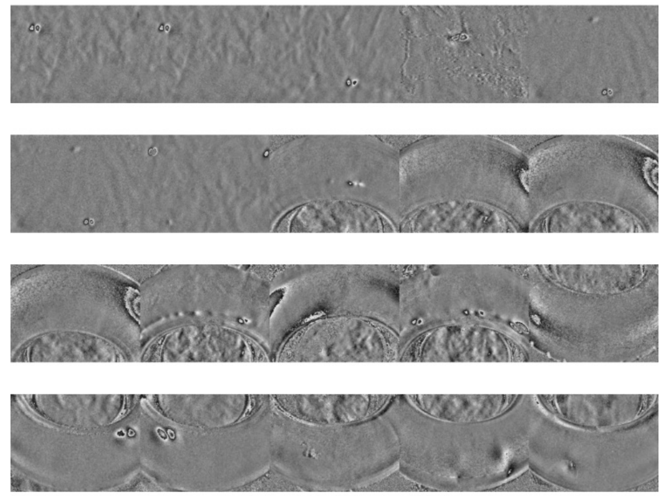

Figure 12. Detected defects in 20 images of vehicle tire carcass, based on laser shearography

III. CONCLUSIONS

The described method has been applied to over 50 grayscale images, result of shearography based, nondestructive testing in a tire factory. The number of the detected defects was 50 (100%), which proves the approach as reliable for detecting defects or abnormal differences in the texture (of the tire carcass). Compared to the X-ray based approach presented in [7], it proves its effectiveness and simple implementation, eliminating the potential endless loop if different types of defects exist in a single image. The proposed method can distinguish two or more visually different images with same histograms. Also, the required user decisions and manual interventions, that can potentially cause errors, are less than in the approach given in [7]. Due to its algorithmic structure, it was implemented easily as an experimental software and demonstrated fast processing combined with satisfactory results. It is robust against images with identical or similar histograms due to the implementation of the unique sequence logic. Potentially, the approach can be applied to all kinds of textures in grayscale images and its further development can be beneficial. As a future improvement, it could be beneficial the calculations to be executed over Graphics Processing Unit [5], to increase the parallel processes handling capabilities. The defining of the limiting constant, based on the user's expectation, is a weakness of the method and something that will be researched further. Future researches and development should include a wider overview of the most recent approaches applied to pattern classification in images, resulted of nondestructive testing.

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