Dissimilarity-Based Algorithm for Fabric Defects Detection

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***Abstract*— The paper investigates images of textures with a defect, characterized by a sufficiently prominent structure. A procedure for detecting a defect in a textured image using an intellectual procedure for assessing the similarity of different parts of the tested image scanned with a sliding window is proposed. It is assumed that an area of the image that contains a defect in whole or in part will be the least similar to the other areas considered. To assess the similarity of images in the paper, the previously proposed measures are used, built on the basis of the values of the components and the magnitude of the gradient, considered as a sample from a random variable with the Weibull distribution. The effectiveness of the proposed methods is demonstrated by experimental investigation.**

Keywords—Texture, structure, defect, anomaly, gradient, Weibull distribution, dissimilarity.

I. Introduction

When analyzing digital images, an essential characteristic is the texture, which is present in almost all images obtained and used in various fields of human intellectual activity. However, despite this, the concept of texture is not well-defined even today. As long ago R.M. Haralick wrote in [1]: «Texture is an important characteristic for the analysis of many types of images… Despite its importance and ubiquity in image data, a formal approach or precise definition of texture does not exist».

In the literature, two types of texture definitions can be distinguished. The first type is characterized by the interpretation of the texture as a repetition of the same type of basic elements (primitives) with a regular or almost regular orientation and placement in space, i.e., as a structured object. Examples in this case are textures of fabrics, brick walls, etc., which have fairly well-defined lines, edges, contours and other structural elements. Naturally, approaches based on the analysis of the structural properties of the image prevail in the methods of studying textures of this type.

In the second type, the texture is considered as a kind of rather chaotic homogeneous object that does not have pronounced edges and structural elements. For the analysis of textures of this type, probabilistic-statistical methods suggest themselves. Examples in this case are turf, bark, land viewed from a long distance, the surface of the processed products, etc. Many algorithms designed for processing textures of this type, in one way or another use the fundamental ideas outlined in [1].

One of the main tasks that often arises when analyzing both types of textures is the detection of surface defects of various materials.

As it follows from the literature, the structural methods mainly use image segmentation algorithms [2], characteristics of the edges and other components of the image [3], methods of detection and separation of the textons [4], and so on. The distinctive circumstance is that the methods mentioned above use the features of a texture and, as a rule, cannot be used in cases of the other types of textures.

Statistical and structural methods can also be used jointly, so they are also referred as combined. The main components of the combined algorithms are described in [1], besides [5] is worth mentioning as a modern application.

Spectral methods are widely used for defects detection. They are applied to determine the main direction in the cyclic texture, cycles in the spatial domain and other characteristics [6-8]. It should be noted that the use of spectral methods in automated image processing systems is impractical, since decisions made on the basis of these

methods often require professional intervention to properly explain some situations.

Thus, the analysis of the literature shows that defects detection problem is an important and urgent problem that is in the focus of attention of specialists engaged in image processing. The comprehensive analysis of the literature is not possible in the framework of this kind of paper, thus we confine ourselves to the above mentioned analysis.

In this work, we restrict ourselves to considering the situation of the first type described above, when we are dealing with texture images that have a fairly well-defined structure and types of defects that have caused an obvious violation of this structure. Examples of such situations are shown in Fig. 1.

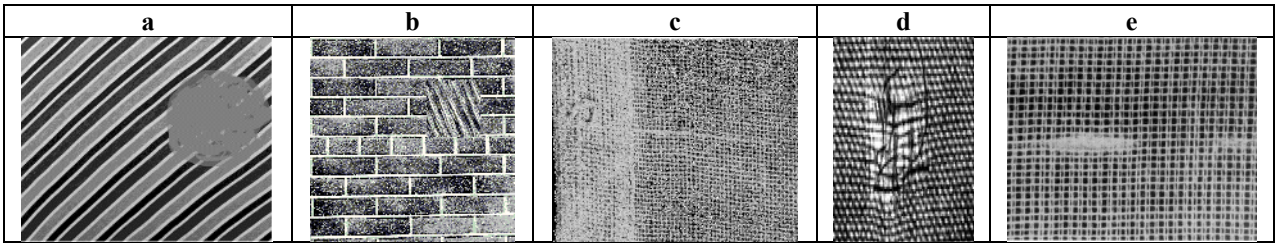


Fig. 1. Examples of samples of textures with defects that violated the structure of the image.

The approach considered in this paper refers to the detection of such structural elements in textures that differ from other parts of the texture and can be considered as “defects". Therefore, the defect detection technique includes a procedure for selecting image areas with any required dimensions and a measure of the similarity of the images of these areas. In this case, the similarity measure should be weakly dependent on the size, orientation and other important parameters of the image.

II. Proposed Methodology

Images similarity measure. The problem of assessing the similarity of images is widely studied in the literature and is known as the "full reference image similarity assessment". The concept of a defect is often associated with abnormal areas of the image and is considered as unwanted formations. Therefore, both methods of similarity and dissimilarity of suspicious image areas to other areas are appropriate criterions for their detection. The images similarity measure, which is applied in this paper is based on the image structure analysis, earlier proposed in [9].

It is well known that the image edges mainly reflect the characteristics and features of the image, which help human visual system differ one image from another. Based on this provision, a set of all edges, contours and other elements available in the image is adopted as a structure of image. To determine image edges, we use gradient methods, particularly, based on the Sobel operator, which allows us to determine horizontal and vertical gradients and the magnitude of the gradient at any internal point of the image.

Let image I have the dimensions $M \times N$, intensity $I(m,n)$ of an image pixel at the coordinates (m,n).

Let $G_H(m,n)$ and $G_V(m,n)$ at a point (m,n) of an image be the horizontal and vertical gradients. Then the gradient magnitude $G(m,n)$ will be given by formula

$$G(m,n) = \sqrt{G_H^2(m,n) + G_V^2(m,n)}\,. \qquad (1)$$

We suppose that the gradient magnitude (1) is a random variable with Weibull distribution density

$$f(x;\lambda,\eta) = \frac{\eta}{\lambda}\left(\frac{x}{\lambda}\right)^{\eta-1} \exp\left[-\left(\frac{x}{\lambda}\right)^{\eta}\right], x \geq 0,$$

where $\eta > 0$ is the shape parameter, $\lambda > 0$ is the scale parameter.

Following [9], for similarity assessment of two images we use a measure based on the estimates of Weibull distribution parameters determined by formula

$$W^2 = \frac{\min(\eta_1,\eta_2)\min(\lambda_1,\lambda_2)}{\max(\eta_1,\eta_2)\max(\lambda_1,\lambda_2)},\ 0 < W^2 \leq 1\,. \qquad (2)$$

The proposed measure (2) has several important properties, which distinguish it from other similarity measures. First of all, this measure makes it possible to compare images with different sizes and orientations [10]. This is very important especially for defect detection task, because defect size and orientation, as a rule, are not known beforehand.

The gradient components G_V, G_H are used for the estimating of the dominant orientation of an image using the following procedure. By μ_H, μ_V, σ_H, σ_V denote the mean, standard deviations of the gradient components G_V, G_H, by ρ_{HV} the correlation coefficient between the components. The family of scattering ellipses is determined by formula as follows:

$$\frac{1}{1-\rho_{HV}^2}\left[\frac{(g_H-\mu_H)^2}{\sigma_H^2} - \frac{2\rho_{HV}(g_H-\mu_H)(g_V-\mu_V)}{\sigma_H\sigma_V} + \frac{(g_V-\mu_V)^2}{\sigma_V^2}\right] = C^2 \qquad (3)$$

where C is a constant.

The principal axis of the ellipse (3) coincides with the orthogonal regression line, and the slope of the principal axis is given by formula as follows:

$$tg\alpha = \frac{2*\sigma_H\sigma_V\rho_{HV}}{\sigma_H^2 - \sigma_V^2 - \sqrt{(\sigma_H^2-\sigma_V^2)^2 + 4\sigma_H^2\sigma_V^2\rho_{HV}^2}} \qquad (4)$$

We consider the formula (4) as an estimate of the "dominant orientation" or “dominant direction” of the image [10]. This formula has proved to be useful in a number of processing problems, in particular, in problems of image registration and classification [11].

It should be noted that one of the justifications for the application of these measures for this task is the similarity

between most areas of the texture image due to the definition of texture given above. This circumstance makes it possible to highlight abnormal areas in the image, which may contain information about existing defects.

Suggested defect detection scheme. Proposed defect detection scheme assumes two situations.

1. Defect type and parameters are fully or partially known. Particularly, possible types of defects can be given as images.

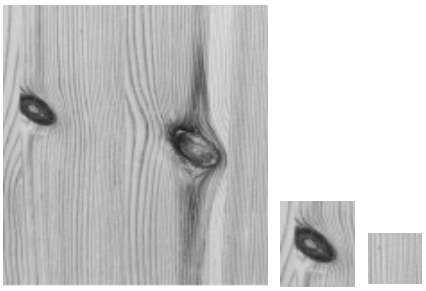
2. Type of defect is not known, but a segment of the texture without any defect is available.

In both situations the defect detection algorithm is based on using procedure "sliding window" for sequential comparing the visible segment of texture with the given template. If the similarity criterion shows significant similarity (first case) or the difference (second case), then defect is considered as detected. The sizes of window and template can differ because the using criterion is not so sensitive to these factors.

To illustrate the usage of proposed procedures, let's consider the results of various experiments described below.

III. Experimental Results

Experiment 1. Fig. 2a is an image of texture, where two different defects are clearly visible. Let's separate the picture of the two sectors, one of which does not contain a defect (Figure 2 b), while the other contains (Figure 2 c), and accept them as examples. Sliding window process must have an appropriate software system; creation of that software is one of our main goals. To show the proposed method operability, let's perform the following partial operations.



a b c

Fig. 2. Defects containing texture (a), defect segment (b) and non-defect segment (c).

1. Select on it several parts of different sizes located in different parts of the image (marked with red color in Fig. 3). They cover the defect-containing and not containing domains on the image.

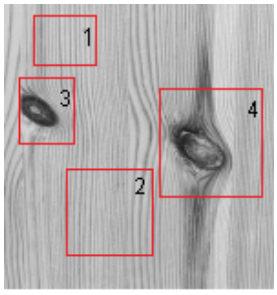


Fig. 3. Some defect containing and not containing parts of the image.

2. Compare Fig. 2b and 2c samples with Fig. 3 segments numbered 1, 2, 3 and 4, and calculate similarity criterion W^2. Calculation results (W^2 values) for appropriate images are shown in Table 1 below.

As we can see, W^2 values are large, when sliding window coincides with the part of image, which includes the compared template, and they are small otherwise. W^2 criterion allows detecting defect for both cases, regardless of its size and position location.

Table 1. Values of W^2 for images of Fig. 2 and Fig. 3.

	Fig. 3-1	Fig. 3-2	Fig. 3-3	Fig. 3-4
Fig. 2c	0.718	0.684	0.334	0.473
Fig. 2b	0.375	0.393	0.668	0.568

Models based on the Weibull distribution have been successfully applied in various applied problems. Thus, the Weibullian model for the gradient magnitude formed the basis for the texture defect detection algorithm described in [12]. The classification procedure proposed in this model is based on the use of a support vector machine in the parameter space of the Weibull distribution. However, if the number of classes is more than two, this classification procedure needs an appropriate generalization.

Another possibility of detecting a defect in a texture image is related to the construction of the similarity or dissimilarity map. By using such maps, it is possible to simultaneously detect several anomalous areas of the image and to make a general assessment of the picture of existing anomalies.

Experiment 2. Let's carry out the described procedure with respect to the images shown in Fig. 1a and Fig. 1e. The results are shown in Fig. 4c-e. At first, here an area is selected that does not contain the observed defect (shown in Fig. 4b in an enlarged format). Further, by means of sliding scanning, the similarity measure between the image of Fig. 4b and all areas of the corresponding image of Fig. 4a, obtained from a sliding scan were calculated. In this case, each pixel of the original image is associated with the above similarity measure when aligning the coordinates of the centers of the compared images. After linear contrasting, the array of the similarity measure values obtained in this way is rendered so that the larger value of the similarity measure corresponds to the larger value of the pixel intensity.

Looking at the image in Fig. 4c, one can notice that the pixels entering the area containing the defect have a darker color than the others. This means that here the similarity measure took low values. Therefore, after the usual binarization, we can see the image shown in Fig. 4d, indicating the approximate location and configuration of the desired defect on the tested image. At the same time, using the obtained array of similarity values, it is possible to separate parts of the image with high or low similarity values in order to depict a "spot" characterizing the detected defect (see Fig. 4e).

Experiment 3. There are types of defects, which differ from other parts of the image by dominant orientation as it can be seen in Figure 1b. The following experiment shows how such defect can be detected. The appropriate procedure based on the splitting the texture image into nearly proportionate parts and estimating the orientation angle for these parts using the formula (4). If the true sizes of the defect area are unknown, this procedure can be repeated for different sizes of parts and the distribution of the obtained values of the orientation angle can be analyzed.

This experiment was performed for the image shown in Figure 1b, which was splitted into 5x5=25 parts. In Figure 5 the splitted regions are shown by red lines. We see that the defect basically fell into parts of indices (2,4) and (3,4).

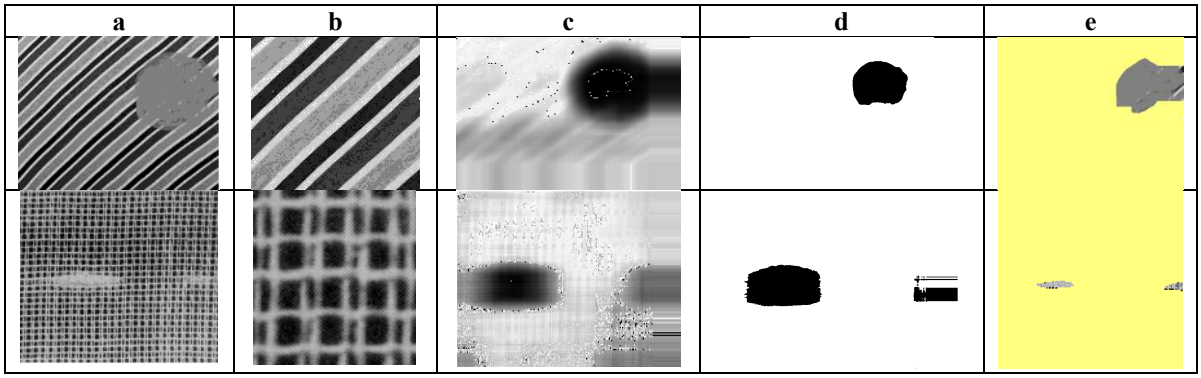


Fig. 4. Images of textures with a defect (a); A sample of the selected area of the texture that does not contain a defect (b); Visualization of an array of similarity measure values (c); Binarization results (d); Highlighted "spot" characterizing the detected defect (e).

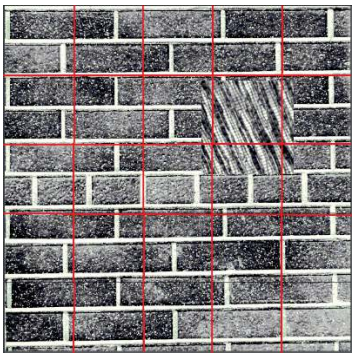


Fig. 5. Image splitted into 5x5 parts.

The values of orientation angle of degree for this situation are done in Table 2.

Table 2. Orientation angles (in degree) for splitted parts.

	1	2	3	4	5
1	-1.96	-2.76	0.17	3.16	3.05
2	-0.83	0.70	-3.02	**-65.2**	-0.3
3	2.41	5.42	1.04	**-16.4**	1.23
4	2.75	3.79	2.20	1.17	0.46
5	4.62	3.28	3.20	-0.28	0.39

We see that the elements of Table 2 of indices (2,4) and (3,4) are considerably greater than the other parts, which means that the defect is detected even if partially.

IV. CONCLUSION

The paper investigates images of textures with a defect, characterized by a sufficiently prominent structure. An attempt has been made to put into practice the search and highlighting of a defect on a textured image of considered type, using an intellectual procedure for assessing the similarity of different areas of the tested image viewed using a sliding window with appropriate dimensions. It is assumed that in the presence of a defect, an image area that contains a defect in whole or partially will be the least similar to the other areas considered. To assess the similarity of images, the previously proposed measure, constructed from the totality of the values of the components and the magnitude of the gradient, considered as a sample from a random variable with the Weibull distribution is used in this paper. The examples illustrate the usage of the proposed procedure, and the results obtained at the same time indicate its effectiveness. The conclusion is made about the usefulness of the applied approach in the tasks of automatic analysis of texture images.

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