9

Search Algorithms and Recognition of Small Details and Fine Structures of Images in Computer Vision Systems

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1. Introduction

Search algorithms and object recognition in digital images are used in various systems of technical vision. Such systems include: vision systems of robots, the system of recognition and identification of fingerprint, authentication system for stamp on a document and many others. Description of known search algorithms and the recognition of objects in images is well represented in the literature, for example, in (Gonzalez & Woods, 2002) and (Pratt, 2001). Review of the literature shows that in most cases, problems of recognition take into account such characteristics of the object as its geometric shape and distribution of luminosity over the entire area of the object. As a criterion of recognition the standard deviation is commonly used. Spectral characteristics, the numerical moments, color characteristics, segmentation, etc. are used in addition to the basic attributes. Wavelet analysis and fractal recognition are the latest methods (Potapov et al., 2008) in image processing and pattern recognition.

Algorithms for searching small details and fine structures are used in detection and analysis of the quality of images. The accuracy of search and recognition of fine details is affected by the distortions arising during the digital compression and transmission of image signals through a noisy communication channel with interference. The peak signal-to-noise ratio (PSNR) is considered nowadays the most popular criterion of noisy images (Pratt, 2001). According to this criterion the normalized root-mean-square deviation of color coordinates is calculated and the averaging is carried out at all pixels of the image. Thus, the closer the noisy image to the original, the bigger the PSNR value and therefore the better its quality we have. However this and other similar metrics (e.g., MSE) allow for estimating only root-mean-square difference between images, therefore the best results from the metrics point of view are not always correspond to the best visual perception. For instance, the noisy image containing fine details with low contrast can have high PSNR value even when the details are not visible on the background noise.

A number of leading firms suggest hardware and software for the objective analysis of dynamic image quality. For example, Tektronix – PQA 300 analyzer, Snell & Wilcox – Mosalina software, Pixelmetrix – DVStation device (Glasman, 2004). Principles of image quality estimation in these devices are various. For example, PQA 300 analyzer measures image quality on algorithm of “Just Noticeable Difference – JND”, developed by Sarnoff

Corporation. PQA 300 analyzer carries out a series of measurements for each test sequence of images and forms common PQR estimation on the basis of JND measurements which is close to subjective estimations. To make objective analysis of image quality Snell & Wilcox firm offers a PAR method – Picture Appraisal Rating. PAR technology systems control artefacts created by compression under MPEG-2 standard. The Pixelmetrix analyzer estimates a series of images and determines definition and visibility errors of block structure and PSNR in luminosity and chromaticity signals. Works (Wang & Bovik, 2002) and (Wang et. al., 2004) propose objective methods for measuring image quality using a universal index (UQI) and on the basis of structural similarity (SSIM).
The review of objective methods of measurements shows that high contrast images are usually used in test tables, while distortions of fine details with low contrast, which are most common after a digital compression, are not taken into account. It is necessary to note that there exists a lack of practical objective methods of measurement of quality of real images: analyzers state an integrated rating of distortions as a whole and do not allow for estimating authentically distortion of local fine structures of images.
The investigation results and methods of the distortions analysis of fine details of real images after application of JPEG, JPEG-2000 and MPEG-4 compression are given in authors works (Sai, 2006) and (Sai, 2007). Results of the present work are the development in the field of objective criterions in the search systems and recognition of fine details and fine structures of the image.

2. Search algorithms

Fine details of image can be classified by the following attributes: a "dot object," a "thin line," a "texture fragment". Search algorithms of the dots and lines are simple (Gonzalez & Woods, 2002). The most common search algorithm is processing the images with a sliding mask. For example, for the mask size 3 x 3 pixels the processing is a linear combination of the mask coefficients with the luminance values of image pixels, covered with the mask. The response of each image point is defined by:

$$R = \sum_{i=1}^{9} w_i Y_i \ , \qquad (1)$$

where w_i is the mask value, Y_i is the luminance value of pixel.
Examples of masks used to identify the bright dots or the thin lines of images are presented on Fig. 1. For identifying dark dots or lines the mask coefficients should be inversed.

-1	-1	-1
-1	8	-1
-1	-1	-1

-1	-1	-1
2	2	2
-1	-1	-1

-1	2	-1
-1	2	-1
-1	2	-1

2	-1	-1
-1	2	-1
-1	-1	2

Fig. 1. Examples of mask for identifying dots and thin lines

In order to detect the dot or the line with thickness of one pixel, one should compute the response (1) for the selected mask and compare the response value with the threshold value:

$$|R| \geq T \, . \tag{2}$$

If the condition (2) is fulfilled the decision on identifying the dot or the thin line in the block size 3 x 3 is taken. The coefficients of the mask corresponding to the position of the dot or the thin line are selected in such a way that the total value of all coefficients is equal to zero. It is obvious that for blocks with a constant luminosity the value $R = 0$. The value R will be maximal for blocks containing dots or thin lines on the background elements with the same luminosity. The threshold T is chosen on the basis of a given contrast of the dot or the thin line on the background luminosity.

Consider features of the described algorithm.

1. The search algorithm is quite simple to implement. 2. The search algorithm provides good detection accuracy of fine details at the equal background luminosity and at the equal luminosity of the thin line elements or texture. 3. For real images the background luminosity values of pixels or object may change, that reduces the detection accuracy. 4. The fine details can be masked by noise and may not be detected by the criterion (2) while sending image signals through a noisy channel. 5. In the case of impulsive noise the disturbance can be detected as a dot object. 6. The algorithm takes into account only the luminosity component of the image. 7. The algorithm does not take into account the peculiarities of contrast sensitivity of vision.

The authors propose a modified algorithm for searching and detection of fine details of color digital images. The main idea of the algorithm is a transformation of primary *RGB* signals into equal color space. Such a transformation makes possible to take into account the peculiarities of visual perception of color contrast fine details during the runtime of the search algorithm.

Consider the features of the transformation of digital *RGB* signals. It is well known that the uniform color spaces, e.g. $L^*u^*v^*$, $L^*a^*b^*$ and $W^*U^*V^*$ (Novakovsky, 1988), are frequently used to evaluate the color differences between big details of the static image. In such systems the area of dispersion of color coordinates transforms from ellipsoid to sphere with the fixed radius for the whole color space. In this case the threshold size is equal to mean perceptible color difference and keeps constant value independently of the object color coordinates.

For the analyses the equal color space $W^*U^*V^*$ was selected. Color coordinates of the pixel in the $W^*U^*V^*$ (Wyszecki) system (Wyszecki, 1975) are defined as follows:

$$W^* = 25Y^{1/3} - 17 \, ;$$

$$U^* = 13W^*(u - u_0) \, ;$$

$$V^* = 13W^*(v - v_0) \, ,$$

where Y is the luminance, changed from 1 to 100, W^* - is the brightness index, U^* and V^* are the chromaticity indices, u and v are the chromaticity coordinates in Mac-Adam diagram (Mac Adam, 1974); $u_0 = 0.201$ and $v_0 = 0.307$ are the chromaticity coordinates of basic white color. The transformation from *RGB* system to the Y, u and v coordinates is done using the well-known matrix transformations (Pratt, 2001).

The transformation into the equal color space allows for estimating the color differences of the big image details using the minimum perceptible color difference (MPCD). These values are almost equal through the whole color space (Krivosheev & Kustarev, 1990). Here the error of the color rendering is determined by the MPCD value using the following equation:

$$\varepsilon = 3\sqrt{(\Delta W^*)^2 + (\Delta U^*)^2 + (\Delta V^*)^2}\ , \tag{3}$$

where ΔW^*, ΔU^* and ΔV^* are the difference values of color coordinates of two images. Equation (3) can be used for estimation of the color contrast of a big detail relative to the background. Threshold values on brightness and chromaticity indices depend on the size of image details, background color coordinates, time period of object presentation and noise level. Therefore the equation (3) will not be objective for the analysis of color transfer distortions of fine details.
Works (Sai, 2002) and (Sai, 2003) propose to use the normalized value of the color contrast for estimating the color transfer distortions of fine details:

$$\Delta\overline{K} = 3\sqrt{(\Delta\overline{W}^*)^2 + (\Delta\overline{U}^*)^2 + (\Delta\overline{V}^*)^2}\ , \tag{4}$$

where $\Delta\overline{W}^* = (W^*_{\max} - W^*_{\min}) / \Delta W^*_{th}$; $\Delta\overline{U}^* = (U^*_{\max} - U^*_{\min}) / \Delta U^*_{th}$ and $\Delta\overline{V}^* = (V^*_{\max} - V^*_{\min}) / \Delta V^*_{th}$ are the normalized to the thresholds contrast values of the image with fine details and ΔW^*_{th}, ΔU^*_{th} and ΔV^*_{th} are the thresholds according to brightness and chromaticity indices for fine details. These threshold values are obtained experimentally (Sai, 2003) for fine details with sizes not exceeding one pixel. From the experimental data, for fine details of the test table located on a grey background threshold values are approximately $\Delta W^*_{th} \approx 6$ MPCD and $\Delta U^*_{th} \approx \Delta V^*_{th} \approx 72$ MPCD.
Search algorithms (Sai & Sorokin, 2008) and (Sai & Sorokin, 2009) of fine details divides the image into the blocks of size 3 x 3 pixels. After this, the recognition of the image blocks using special binary masks is performed. These masks have the following attributes: a "dot object", a "thin line", a "texture fragment". This work also describes the search algorithm with sliding window size 3 x 3 pixels.
Consider the modified search algorithm.
At the first step the values $(W^*_{\max}, U^*_{\max}, V^*_{\max})$ and $(W^*_{\min}, U^*_{\min}, V^*_{\min})$ are computed along with the value of normalized color contrast (4) for a window. Next, the following condition is checked:

$$\Delta\overline{K}_{\min} < \Delta\overline{K}_n < \Delta\overline{K}_{\max}\,, \tag{5}$$

where $\Delta\overline{K}_{\min} \geq 1$ and $\Delta\overline{K}_{\max}$ are pre-defined minimal and maximal contrast values, n – number of the current block. Obviously, the maximal contrast value corresponds to the bright white detail on the black background of the image. Using Y_{max}=*100* in equation (4) we obtain $\Delta\overline{K}_{\max} \approx 19$. Note, that the definition of values $\Delta\overline{K}_{\min}$ and $\Delta\overline{K}_{\max}$ depends upon the search task. For example, if we search the fine details with low contrast the equation (5) can be defined as:

$$1 < \Delta\overline{K}_n < 4\ .$$

If the condition (5) is fulfilled the decision is made that the nth block of the image contains small details identified by an eye. If the condition (5) is not fulfilled this block is excluded from further analysis. Next, the window position is changed by one pixel (vertically or horizontally) and the first step is repeated.

At the second step the image of the block with small details is converted to the binary form. For each pixel of the block the following conditions are checked:

$$3\sqrt{\left(\frac{W_i^* - W_{\max}^*}{\Delta W_{th}^*}\right)^2 + \left(\frac{U_i^* - U_{\max}^*}{\Delta U_{th}^*}\right)^2 + \left(\frac{V_i^* - V_{\max}^*}{\Delta V_{th}^*}\right)^2} \le T_n \tag{6}$$

$$3\sqrt{\left(\frac{W_i^* - W_{\min}^*}{\Delta W_{th}^*}\right)^2 + \left(\frac{U_i^* - U_{\min}^*}{\Delta U_{th}^*}\right)^2 + \left(\frac{V_i^* - V_{\min}^*}{\Delta V_{th}^*}\right)^2} \le T_n \, , \tag{7}$$

where $i=1\ldots9$ is the pixel number in the block and T_n – threshold value. If the condition (6) is fulfilled the decision on membership of the pixel to the maximal value is taken. If the condition (7) is fulfilled the decision on membership of the pixel to the minimal value is taken. Next, the levels of one and zero are assigned to the maximal and minimal values accordingly.

The threshold value is dependent on $\Delta\overline{K}_n$ and always satisfies $T_n \le 1$. If the contrast of the block belongs to $1 < \Delta\overline{K}_n < 10$, the threshold value is equal to $T_n = 0.1 \cdot \Delta\overline{K}_n$, otherwise for $\Delta\overline{K}_n \ge 10$ we set $T_n = 1$.

At the third step the binary image of the block is compared to the binary mask from the defined set. Figures of the binary masks coincide with those defined on Fig. 1, but the value w_i is set to one for the white pixel and to zero for the dark pixel, accordingly.

The binary block of the image is compared to the binary image of the j^{th} mask with the help of a simple equation:

$$M_k = \sum_{i=1}^{9} (Ib_{n,j} - w_{k,j}) \, . \tag{8}$$

The decision is made that the given block refers to the image of the j^{th} mask in case if the computed value (8) is equal to zero. The decision about exclusion of the current block from the analysis is made if the value (8) is not equal to zero for all masks.

The same is done if the texture elements must be detected. Fig. 2 shows different examples of binary masks for the case when the number of bright pixels is equal to five.

1	0	1
0	1	0
1	0	1

0	1	1
1	0	0
0	1	1

1	1	1
0	1	0
0	1	0

0	1	1
0	0	1
1	1	0

Fig. 2. Examples of binary masks for identifying texture elements

The distinctive feature of the algorithm is that the thresholds of visual perception of fine details contrast of the image depend on the average brightness of the analyzed block. In particular, the contrast change on light blocks of the image will be more visible than on dark ones.

The given condition can be taken into account with the help of adjusting coefficients during the computation of the thresholds. For example, for the brightness threshold:

$$\Delta W_{th}^{*} = k_{W^*} \cdot \Delta W_{th}^{*}, \tag{9}$$

where $k_{W^*} \approx 1$ for the grey blocks ($70 < W^* < 90$), $k_{W^*} < 1$ for the light blocks ($W^* \geq 90$) and $k_{W^*} > 1$ for the dark blocks ($W^* \leq 70$).
Thus, the offered search algorithm allows for allocating fine details in the image for the further analysis and recognition. Compared with the classical search algorithm the developed algorithm has the following advantages. 1. The algorithm takes into account the properties of the visual perception of contrast of small details. 2. The algorithm allows for searching the color details with a given contrast. 3. Application of sliding window and binary blocks improve the accuracy of search and detection. 4. The algorithm allows for selection the texture elements from the image.
Results of experiments show that search algorithm works quite well in the processing of test images without noise. The presence of noise leads to "diffusion" of the values of pixels color coordinates in the *RGB* image signals; that reduces the accuracy of search and recognition of fine details with low contrast.
Let's consider the application of the described algorithm in the systems of search and recognition of fine details in the noisy images. The following assumptions are used in order to analyze the noise influence on the image definition reduction: 1) Interaction of signals and noise is additive. 2) Density distribution law of stationary noise probabilities is close to the normal law. 3) Noise in *RGB* signals of the decoded image is not correlative. Such assumptions are widely used in the engineering computations of noise-immune TV systems. They permit to simplify the analysis with the admissible errors.
Noise in the system results in "diffusion" of both objects color coordinates and background in the decoded image. Thus a point in *RGB* space is transformed into ellipsoid with semi axis. Their values are proportional to root-mean-square noise levels ($\sigma_R, \sigma_G, \sigma_B$). During the transformation $\{R_i G_i B_i\} \to \{W_i^* U_i^* V_i^*\}$ the values of equal color space coordinates become random variables with root-mean-square deviations ($\sigma_{W^*}, \sigma_{U^*}, \sigma_{V^*}$). Works (Sai, 2007) and (Sai, 2003) present the probability analysis of such transformation and obtain a criterion that describes when the fine detail will be recognized against the background noise. This criterion is formulated as:

$$\Delta\overline{K} \geq 3\sqrt{(\sigma_{W^*})^2 + (\sigma_{U^*})^2 + (\sigma_{V^*})^2}, \tag{10}$$

where $\Delta\overline{K}$ is normalized contrast (4) of the block with fine details; $\sigma_{W^*}, \sigma_{U^*}, \sigma_{V^*}$ - are normalized to visual perception thresholds root-mean-square deviations of noise values. Note, that this criterion uses a simple "three sigma" rule:

$$\sigma_\Sigma = \sqrt{(\sigma_{W^*})^2 + (\sigma_{U^*})^2 + (\sigma_{V^*})^2},$$

where σ_Σ is a total root-mean-square value computed for all image blocks that contain fine details.
Therefore, the low level of color contrast interval should be changed in order to take into account the influence of noise in the search algorithm. In this case the pre-defied value $\Delta\overline{K}_{\min}$ should satisfy the following condition:

$$\Delta\overline{K}_{\min} \geq 1 \text{ and } \Delta\overline{K}_{\min} \geq 3\sigma_{\Sigma} . \tag{11}$$

Thus, the search algorithm is able to detect the fine details only with high contrast if the noise level in the image is high. If $\sigma_{\Sigma} < 1/3$, then the image noise will be imperceptible or hardly noticeable for an eye during the observation of fine details with the lowest contrast. This permits to identify the fine details even with low contrast $\Delta\overline{K} \approx 1 \ldots 2$.

Proposed algorithm can be applied in automated search and object detection systems or in the computer vision systems. Consider the features of such applications.

Computer vision systems may not take into account the features of human eye perception. In this case the foto and video sensor properties should be considered: sensitivity and the dynamic signal range. Today's foto and video sensors have high sensitivity and dynamic range properties; this enables to receive digital signal with a big number of quantization levels. For example, MT9V sensors from Micron have digital *RGB* output from 10-bit ADC. Digital TV systems require 8 bit per one color channel; that corresponds to the digital interval 255/1. Along with this, threshold will be equal to one.

Therefore, during the computation of color contrast in search algorithm the transformation from *RGB* to equal color space is not necessary. The RGB space can be used directly, or it can be transformed to luminance and chromaticity system, e.g., YC_RC_B. The widely used model is defined by CCIR 601-2 (ITU-R BT.601) recommendations. The components are computed as follows:

$$\begin{aligned} Y &= 0{,}299R + 0{,}587G + 0{,}114B; \\ C_R &= 0{,}5R - 0{,}419G - 0{,}081B; \\ C_B &= -0{,}169R - 0{,}331G + 0{,}5B. \end{aligned} \tag{12}$$

Let's consider the search algorithm of fine details in the selected color space. At the first stage the contrast value in the sliding widow size 3 x 3 is computed:

$$\Delta\overline{K}_n = \sqrt{(\Delta\overline{Y})^2 + (\Delta\overline{C}_R)^2 + (\Delta\overline{C}_B)^2} , \tag{13}$$

where $\Delta\overline{Y} = (Y_{\max} - Y_{\min}) / \Delta Y$, $\Delta\overline{C}_R = (C_{R\max} - C_{R\min}) / \Delta C$ and $\Delta\overline{C}_B = (C_{B\max} - C_{B\min}) / \Delta C$ are the luminance and chromaticity contrast values of fine details, ΔY and ΔC are the luminance and chromaticity thresholds of the computer vision system. The values of thresholds of the system depend on the precision of *RGB* signals and on the noise level. If the noise level is quite low, the values of thresholds will be defined by the least significant bit of each Y, C_R and C_B signal, i.e. $\Delta Y = \Delta C = 1$.

Now let's define the upper border of the interval for the contrast values of the 8-bit Y, C_R and C_B signals. Value $Y_{\max} = 255$ is obtained by plugging the maximal values of the digital RGB signals into equation (12). Therefore, the maximal contrast value (13) is then $\Delta\overline{K}_{\max} = 255$ and the interval for the contrast is

$$\Delta\overline{K}_{\min} < \Delta\overline{K}_n < 255 . \tag{14}$$

The value of the low bound is selected using the noise level of the system like (11), where the total noise value is defined as

$$\sigma_{\Sigma} = \sqrt{(\sigma_Y)^2 + (\sigma_{C_R})^2 + (\sigma_{C_B})^2}\,,$$

$\sigma_Y, \sigma_{C_R}, \sigma_{C_B}$ - are root-mean-square deviations of noise values in the luminance and chromaticity channels. After selection of contrast interval for a block and check for the condition (5), the search of fine details is processed using equations (6)-(9).

Thus, the differences are in the selected color space and defined thresholds. In particular, during the transformation to binary form of the block instead of conditions (6) and (7) the following conditions will be applied:

$$\sqrt{(Y_i - Y_{\max})^2 + (C_{Ri} - C_{R\max})^2 + (C_{Bi} - C_{B\max})^2} \le T_n\,, \tag{15}$$

$$\sqrt{(Y_i - Y_{\min})^2 + (C_{Ri} - C_{R\min})^2 + (C_{Bi} - C_{B\min})^2} \le T_n\,, \tag{16}$$

where the constant threshold value T_n is selected greater than zero and is independent of contrast value $\Delta\overline{K}_n$. For example, during the analyses of fine details only on luminance and using $T_n = 1$ the condition (15) is changed to $|Y_i - Y_{\max}| \le 1$. This means, that the pixel has level of "one" if its luminance differs from maximal value not greater than by least significant bit. For the correct application of search algorithm in the noisy system the threshold should be selected as $T_n \ge 3\sigma_{\Sigma}$.

3. Algorithms for analyses and recognition

Previous section was devoted to the search algorithms of fine details of images using the following attributes: "dot object," "thin line," "texture fragment". The fine details detected and identified in the source image can be used for the further analyses and recognition.

The common task of search for objects and their recognition can be divided into the following steps: formation of object properties; forming the source image of the object; search for the object in the test image using the defined properties; object recognition and identification.

Small details can form a part of properties of the bigger objects while solving the recognition and identification tasks. Such bigger objects can be, e.g., stamp on the document or a fingerprint. In the task of analyzing image quality the investigation object is the distortions of fine details. These distortions arise after image compression or image transfer through the noisy channels.

Thus, one has to compare the properties of the fine details in the reference and investigated images using the defined criteria during the object recognition or distortion analyses. Such properties of the fine detail can be: attitude, form, brightness, chromaticity, contrast. For the binary images only attitude and form of the object are necessary.

Consider the well-known method (Wang at. al., 2004) of the grayscale image quality analyses – Structural Similarity Index SSIM. In this method distortions are estimated using a sliding window size 8 x 8 pixel. Suppose x and y are two nonnegative image signals, which have been aligned with each other (blocks from two images). The SSIM value is computed as:

$$SSIM(x,y) = l(x,y)\cdot c(x,y)\cdot s(x,y)\,, \tag{17}$$

where *l(x,y)* – luminance comparison function, *c(x,y)* – contrast comparison function and *s(x,y)* – structure comparison function. These functions are defined as follows:

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x{}^2 + \mu_y{}^2 + C_1},$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x{}^2 + \sigma_y{}^2 + C_2}, \tag{18}$$

$$c(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3},$$

where μ_x and μ_y are mean intensities, C_1, C_2, C_3 are constants, $\sigma_x, \sigma_y, \sigma_{xy}$ are standard deviations and correlation coefficient in the analyzed blocks of image, accordingly. The following equations define those parameters (from (Wang at. al., 2004)):

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} Y_{i(x)} \; ; \mu_y = \frac{1}{N}\sum_{i=1}^{N} Y_{i(y)} \tag{19}$$

$$\sigma_x = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(Y_{i(x)} - \mu_x)^2} \; ; \sigma_y = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(Y_{i(y)} - \mu_y)^2} \tag{20}$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(Y_{i(x)} - \mu_x)\cdot(Y_{i(y)} - \mu_y) \tag{21}$$

With the windows size 8 x 8 pixel parameter $N=64$. Constants are defined as:

$$C_1 = (K_1 L)^2 \; ; \; C_2 = (K_2 L)^2 \; ; \; C_3 = C_2 / 2, \tag{22}$$

where $L=255$ – dynamic rage of the pixels values for the grayscale image, $K_1=0.01$ and $K_2=0.03$ – defined parameters. Note, that equation (18) uses the property of human visual system (HVS): HVS is sensitive to the relative luminance change, and not the absolute luminance change.

After computing SSIM value (17) for each block, the integral value is calculated:

$$MSSIM(X,Y) = \frac{1}{M}\sum_{i=1}^{M} SSIM(x_i, y_i), \tag{23}$$

where M is a number of analyzed blocks in the image. Results presented in (Wang at. al., 2004) showed quite good correspondence between estimation (23) and subjective quality estimations for the JPEG and JPEG2000 standards. Along with this, the deviation of such estimation is much lower compared to PSNR, JND and UQI methods.

To our opinion SSIM method has the following drawbacks: 1. SSIM computations and estimation involve only the luminance of the image, this means that the distortions can not be estimated using the chromaticity component of the image. 2. SSIM computation is done

using 8 x 8 pixel block, it does not provide the estimation of distortions of fine detail with particular form. 3. SSIM method uses common properties of HVS without counting the definite thresholds of the visual perception of fine details contrast.
Consider an alternative method of distortion analyses of fine details of the image.
At the first step the position of the fine details with particular form in the reference image is located. With this purpose the search algorithm of fine details (described in section 2) on the reference image is carried out. After the execution of search algorithm the coordinates of the objects will correspond to the 3 x 3 block numbers, where those fine details were detected.
At the second step for each found j^{th} block the deviation of the maximal value of color coordinates is computed:

$$\tilde{\varepsilon}_j = \max_N \left(\sqrt{\left(\Delta\tilde{W}_i^*\right)^2 + \left(\Delta\tilde{U}_i^*\right)^2 + \left(\Delta\tilde{V}_i^*\right)^2} \right), \tag{24}$$

where $i=1\ldots N$, $N=9$ is the number of elements in the block and

$$\Delta\tilde{W}_i^* = 3(W_i^* - \tilde{W}_i^*) / \Delta W_{th}^*,$$
$$\Delta\tilde{U}_i^* = 3(U_i^* - \tilde{U}_i^*) / \Delta U_{th}^*,$$
$$\Delta\tilde{V}_i^* = 3(V_i^* - \tilde{V}_i^*) / \Delta V_{th}^*$$

are the normalized to thresholds deviations on brightness and on chromaticity for each pixel of reference ($W_i^* U_i^* V_i^*$) and corrupted ($\tilde{W}_i^* \tilde{U}_i^* \tilde{V}_i^*$) blocks.
In particular if the block is analyzed only on brightness the expression (24) will be transformed into:

$$\tilde{\varepsilon}_{j(W^*)} = \max_N \left(3\left|W_i^* - \tilde{W}_i^*\right| / \Delta W_{th}^* \right), \tag{25}$$

where $\tilde{W}_i^*$ is the value of brightness of the i^{th} pixel in the image block after the compression.
If the block is analyzed on chromaticity we obtain:

$$\tilde{\varepsilon}_{j(U^*,V^*)} = \max_N \left(\sqrt{\left(\Delta\tilde{U}_i^*\right)^2 + \left(\Delta\tilde{V}_i^*\right)^2} \right). \tag{26}$$

Equation (26) determines the maximal error of color transfer of fine details in the block.
Here it is necessary to note that in the compression standards the most complete information on fine details is contained in the brightness component. Therefore, a separate calculation of the errors on brightness and chromaticity is justified.
At the third step the average values of deviation on brightness and on chromaticity for all image blocks are calculated:

$$\bar{\varepsilon}_{W^*} = \frac{1}{M}\sum_{j=1}^{M} \tilde{\varepsilon}_{j(W^*)}; \quad \bar{\varepsilon}_{U^*,V^*} = \frac{1}{M}\sum_{j=1}^{M} \tilde{\varepsilon}_{j(U^*,V^*)}; \quad \bar{\varepsilon}_{\Sigma} = \bar{\varepsilon}_{W^*} + \bar{\varepsilon}_{U^*,V^*}, \tag{27}$$

where M is the number of blocks in the image, which contain fine details found by the search algorithm.

At the final step the quality rating of fine details for transfer and reproduction in the analyzed image is established using the error value (27).

The ten-point scale of quality (Sai, 2007), used in Adobe Photoshop 5.0 system, during the realization of JPEG compression algorithm is chosen. Experimental results of research of the error dependences for other test images have shown that for support of a high quality rating ($R \geq 7$) the average value of the coordinates deviation of fine details on brightness should not exceed the threshold value, i.e.,

$$\overline{\varepsilon}_{\Sigma} < 1.0 \,. \tag{28}$$

In difference to MSSIM (23) the proposed method estimates the distortions of fine details by the number of normalized visual thresholds. Thus, if the criterion (28) is fulfilled then the following decision is made: for the fine details the contrast change is imperceptible for an eye.

Experimental results showed that the objective criterion (28) is in good correlation with the subjective quality estimation not only for the JPEG standard, but also for other lossy compression algorithms applied to static images.

Let's consider the algorithm of recognition and identification of fine details in the computer vision system. The recognition properties of fine details are: attitude, contrast and form.

At the first step the search of fine details on the reference image is carried out (algorithm is described in section 2). In equation (13) of this algorithm thresholds of sensitivity for luminance and for chromaticity are used.

After the execution of search algorithm the coordinates of the objects will correspond to the 3 x 3 block numbers, where those fine details were detected. Forms of the detected details correspond to the binary masks. In particular, forms of binary masks correspond to masks depicted on Fig. 3, if the search properties are position and orientation of dark lines on the white background.

1	1	0
1	0	1
0	1	1

1	1	1
0	0	0
1	1	1

1	0	1
1	0	1
1	0	1

0	1	1
1	0	1
1	1	0

Fig. 3. Examples of binary masks for identifying thin lines

At the second step the comparison of fine details color coordinates is processed for the reference and analyzed images. For each found j^{th} block the deviation of the maximal value of color coordinates is computed (like in (24)):

$$\tilde{\varepsilon}_j = \max_N \left(\sqrt{\left(\Delta\tilde{Y}_i\right)^2 + \left(\Delta\tilde{C}_{Ri}\right)^2 + \left(\Delta\tilde{C}_{Bi}\right)^2} \right), \tag{29}$$

where

$$\Delta\tilde{Y}_i = (Y_i - \tilde{Y}_i) / \Delta Y;$$
$$\Delta\tilde{C}_{Ri} = (C_{Ri} - \tilde{C}_{Ri}) / \Delta C;$$
$$\Delta\tilde{C}_{Bi} = (C_{Bi} - \tilde{C}_{Bi}) / \Delta C$$

are the normalized to thresholds deviations on brightness and on chromaticity for each pixel of reference ($Y_i C_{Ri} C_{Bi}$) and analyzed ($\tilde{Y}_i \tilde{C}_{Ri} \tilde{C}_{Bi}$) blocks.
Next, the error value is compared to the defied threshold T:

$$\tilde{\varepsilon}_j < T \ , \tag{30}$$

where T depends on the noise level and like in (11) is selected equal to at least $3\sigma_{\Sigma}$. Obviously, bigger noise in the analyzed image corresponds to the worse recognition results.
If the criterion (30) is fulfilled then the following decision is made: the fine detail in the j^{th} block is recognized and the next block can be processed. Otherwise, the block is not recognized.
The probability of the complete object depends on the total number of blocks with fine details. For our algorithm is can be defined as:

$$P_r = N_r \ / \ N_{\Sigma} \ , \tag{31}$$

where N_r is the number of recognized blocks and N_{Σ} is the total number of blocks.
The probability value will be quite high if the deviation of color coordinates of fine details are below their thresholds. It must be noted, that the probability of recognition depends on the accuracy of matching reference and analyzed objects.
For the real images the luminance and the object contrast can significantly differ from the reference object. In this case, some blocks with fine details may not be recognized using criterion (30). The following algorithm can be applied, if the recognition properties are only attitude and form of fine details. This algorithm is based on the previously described.
At the first step the coordinates of the blocks with fine details in the reference image are obtained using the search algorithm.
At the second step the blocks in the analyzed image are processed as follows. For each selected block j size 3 x 3 pixel the transformation to binary form is carried out like in (15) and (16):

$$\sqrt{\left(\tilde{Y}_i - \tilde{Y}_{\max}\right)^2 + \left(\tilde{C}_{Ri} - \tilde{C}_{R\max}\right)^2 + \left(\tilde{C}_{Bi} - \tilde{C}_{B\max}\right)^2} <= T_n \ , \tag{32}$$

$$\sqrt{\left(\tilde{Y}_i - \tilde{Y}_{\min}\right)^2 + \left(\tilde{C}_{Ri} - \tilde{C}_{R\min}\right)^2 + \left(\tilde{C}_{Bi} - \tilde{C}_{B\min}\right)^2} <= T_n \ . \tag{33}$$

After that the j^{th} binary block of the analyzed image is compared to the binary image of the k^{th} mask:

$$M_k = \sum_{i=1}^{9} (Ib_{j,i} - w_{k,i}) \ . \tag{34}$$

The decision is made that the given j^{th} block refers to the image of the k^{th} mask in case if the computed value (34) is equal to zero. Thus, the analyzed j^{th} block has fine details identical to the j^{th} block from the reference image.

At the last step the probability of recognition is computed using equation (31).
Therefore, the proposed algorithm allows for recognition and identification of fine details using their attitude and form independent of their luminance and chromaticity.
Some examples of practical applications of algorithms are presented in the next section.

4. Examples of algorithms applications

The developed algorithms of search and recognition of fine details can be applied in different computer vision systems. For example, consider two systems: the first is a system of distortion analysis of fine details of noisy images; the second is a system of search and recognition of fine details in images of stamp.
Consider the efficiency of algorithms application in the first system.
The peak signal-to-noise ratio (PSNR) is considered nowadays the most popular criterion of noisy images (Pratt, 2001). According to this criterion the normalized root-mean-square deviation of color coordinates is calculated and the averaging is carried out at all pixels of the image. The ratio of the maximal amplitude (A) of the signal to the root-mean-square deviation in logarithmic scale defines PSNR value:

$$\mathrm{PSNR} = 20\lg \frac{A}{\sqrt{\frac{1}{N_x \cdot N_y}\sum_{i=1}^{N_x}\sum_{j=1}^{N_y}\Delta C_{i,j}}}, \tag{35}$$

where $\Delta C_{i,j} = (R_{i,j} - \tilde{R}_{i,j})^2 + (G_{i,j} - \tilde{G}_{i,j})^2 + (B_{i,j} - \tilde{B}_{i,j})^2$; R, G, B are the color signals without noise, $\tilde{R}, \tilde{G}, \tilde{B}$ are the color signals with noise and $N_x \cdot N_y$ is the number of pixels in the image.
Thus, the closer the noisy image to the original, the bigger the PSNR value (35) and therefore the better its quality we have. However this and other similar metrics allow for estimating only root-mean-square difference between images, therefore the best results from the metrics point of view are not always correspond to the best visual perception.
Filtering algorithms of noisy images are well investigated and described in literature, e.g., (Hamza et. al., 2002). They are usually specializing on suppression of a particular kind of noise. Meanwhile there are no universal filters that could detect and suppress all kinds of noise. However many kinds of noise can be rather well approximated using model of Gaussian noise. And therefore the majority of algorithms are focused on suppression of this kind of noise.
The basic problem at noise filtering is not to spoil sharpness of details borders of the image, and also not to lose the fine details that are comparable on amplitude with noise. One more complication is the rating of noise suppression quality. As a rule, the quality is estimated as follows: the artificial noise is imposed on the original image, and then the resulted image is filtered with the help of the chosen algorithm and compared to the initial image with the help of the chosen metrics. Thus, the closer the filtered image to the original, the bigger PSNR value is obtained and that is considered the quality of the filtering algorithm. As it has been pointed above, the PSNR value allows for estimating only the root-mean-square difference between images, and therefore the best results from the point of view of the metrics (also other than PSNR) do not always correspond to the best visual perception.

Let's consider the applications of the proposed algorithms for the quality estimation of fine details in the noisy images. At the beginning the search algorithm of fine details is performed using on the images without noise. The equations (3)-(8) are used, where the condition (5) is changed to:

$$\Delta \overline{K}_n > 1 . \tag{36}$$

If the normalized contrast satisfies condition (36) for blocks 3 x 3, then the decision is made that the fine details or the texture elements of big details are present in the image block.
The common criterion, when the fine details with contrast $\Delta \overline{K}_n$ will be detected by an eye on the background noise, is formulated as:

$$\Delta \overline{K} \geq 3\sqrt{(\overline{\sigma}_{W^*})^2 + (\overline{\sigma}_{U^*})^2 + (\overline{\sigma}_{V^*})^2} \ , \tag{37}$$

where $\overline{\sigma}_{W^*}, \overline{\sigma}_{U^*}, \overline{\sigma}_{V^*}$ are normalized to visual perception thresholds root-mean-square deviation values of noise.
Let's define criterion when the image noise will be imperceptible or hardly noticeable for an eye during the observation of fine details with the lowest contrast $\Delta \overline{K}_n \approx 1$:

$$\overline{\sigma}_\Sigma = \sqrt{(\overline{\sigma}_{W^*})^2 + (\overline{\sigma}_{U^*})^2 + (\overline{\sigma}_{V^*})^2} \leq 1/3 , \tag{38}$$

where $\overline{\sigma}_\Sigma$ is a total root-mean-square value computed for all image blocks that contain fine details. The root-mean-square deviation values are computed as, e.g., for brightness:

$$\overline{\sigma}_{W^*} = \max_M \left(\frac{1}{W_{th}^* \cdot N} \sum_{i=0}^{N-1} \left| W_{j,i}^* - \tilde{W}_{j,i}^* \right| \right) , \tag{39}$$

where *N=9* is a number of elements in the block, *j=1…M* and *M* is a number of blocks. Values $\overline{\sigma}_{U^*}$ and $\overline{\sigma}_{V^*}$ are computed similar to (39). Note, that in contrast to formulas (24) and (25) in (39), at first, we compute the mean value of the noise in the block and then select the maximum.
Thus, for estimating the noisiness of the fine details we should search for these details and then estimate the value $\overline{\sigma}_\Sigma$ using criterion (39). If this criterion is fulfilled the decision is made that: for the fine details the contrast change is imperceptible for an eye, and the presence of noise in the *RGB* channels does not impair the image quality.
Main differences of the new criterion (39) from the PSNR are:

1. new algorithm analyzes distortions over the part of the image: it covers only image fragments that contain the fine details;
2. root-mean-square difference between the source and noisy images is defined by the value $\overline{\sigma}_\Sigma$ which is estimated by the number of normalized thresholds of an eye.

Therefore, the proposed criterion (39) is more objective because it takes into account the features of the visual perception of the contrast distortions of fine details.
A program analyzer is implemented in order to investigate the efficiency of the quality estimation of fine details representation. As the additive noise models the fluctuation Gaussian noise and impulsive noise were selected.

Fig.4 shows examples of the test images "Lena" with different levels of the impulsive noise.

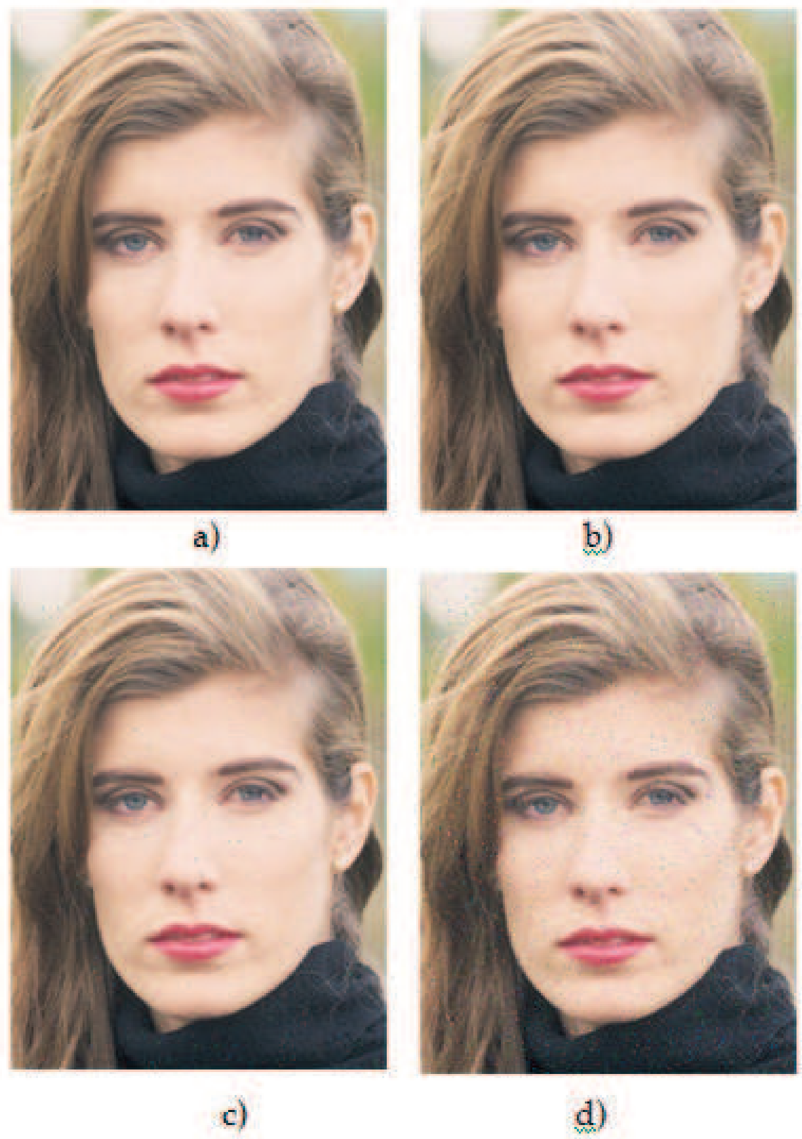

Fig. 4. Test image "Lena" with impulsive noise: a) original image; b) $P_{err} = 1 \cdot 10^{-3}$; c) $P_{err} = 1 \cdot 10^{-2}$; d) $P_{err} = 5 \cdot 10^{-2}$

Table 1 contains the experimental dependencies of $\bar{\sigma}_{\Sigma}$ and PSNR from root-mean-square noise value (σ) for the test images "Lena". Here the root-mean-square value of the Gaussian noise was set as a ratio to the maximum amplitude (A) of the signal. The following assumption was used: $\sigma \approx \sigma_R \approx \sigma_G \approx \sigma_B$.

σ	0.5	1.0	1.5	2.0	3.0
$\bar{\sigma}_{\Sigma}$	0.08	0.13	0.19	0.29	0.43
PSNR	46.67	43.96	42.27	41.03	39.32

Table 1. Dependencies of $\bar{\sigma}_{\Sigma}$ and PSNR (in dB) from σ (in %)

Table 2 presents the experimental dependencies of $\bar{\sigma}_{\Sigma}$ and PSNR from the error probability value P_{err} of the image transfer. The value P_{err} was set as a ratio of the number of error bytes to the whole number of bytes in the image when the impulsive noise was modeled.

P_{err}	$5 \cdot 10^{-4}$	$1 \cdot 10^{-3}$	$5 \cdot 10^{-3}$	$1 \cdot 10^{-2}$	$5 \cdot 10^{-2}$
$\bar{\sigma}_{\Sigma}$	0.24	0.30	0.43	0.58	0.72
PSNR	64.82	61.78	54.48	51.03	43.98

Table 2. Dependencies of $\bar{\sigma}_{\Sigma}$ and PSNR (in dB) from P_{err}

Experimental results of the quality analysis of the noisy images have shown that the PSNR estimation gives different results for fluctuation and impulsive noise. Data from Tables 1 and 2 together with the subjective estimations show that the "good" image quality is: for Gaussian noise with *PSNR>40* dB, and for impulsive noise with *PSNR>60* dB.

Therefore, the PSNR criterion is not objective for quality analysis of the images with different types of noise.

Proposed criterion (39) is more objective and gives adequate results compared to the subjective estimations independently from types of the noise. This is confirmed with the experimental results.

Consider the efficiency of developed algorithms application in the automated authentication system for stamp on a document. Two images exist in this system: a reference stamp image and a test image of a stamp on a document. For the authentication of stamp: 1) a "stamp" object should be detected and extracted from the image of a document, 2) extracted object should be aligned with the reference image, and 3) object should be identified using the defined properties.

Suppose that the initial steps of the search algorithm are already done and the "stamp" object is precisely aligned with the reference stamp image. Along with this, two stamps should be compared for the purpose of identification of the object.

In a simple case two images can be compared using the root-mean-square deviation of the pixels. This value in the YC_RC_B color space is:

$$\Delta_{\mathrm{RMS}} = \frac{1}{N_x \cdot N_y} \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} \sqrt{\left(Y_{i,j} - \tilde{Y}_{i,j}\right)^2 + \left(C_{Ri,j} - \tilde{C}_{Rj}\right)^2 + \left(C_{Bi,j} - \tilde{C}_{Bj}\right)^2}, \tag{40}$$

where YC_RC_B and $\tilde{Y}\tilde{C}_R\tilde{C}_B$ are pixel coordinates for luminosity and chromaticity of the reference and analyzed images.

Obviously, that such an integral comparison does not allow for estimating the originality of stamp for the following reasons: 1) the image of the original stamp can differ from one document to another by luminance and contrast. 2) Some parts of the stamp can be poorly printed or even be absent on the image. 3) The original document has additional dots coming from the signature or text of a document under the stamp.

Note that normally the fake stamps are of high quality level and differ from the original stamp insignificantly. Thus, the task of comparison and identification of image stamp with reference stamp is complex (Sai, 2009).

Using the developed algorithms of search and recognition of fine details we propose the following algorithm of stamp authentication.

The following properties are selected for the recognition of fine details: attitude, orientation of thin lines and texture structures. The preprocessing of reference and analyzed stamp images must be carried out:

1. Covert the images from color to grayscale system.
2. Transfer the images into the binary form.
3. Obtain the contour images using Sobel operator.
4. Filter the contour images for smoothing the edges.
5. Make contour details more definite using the Zong Sun algorithm.

Fig. 5 shows an example of reference stamp image during the preprocessing steps.

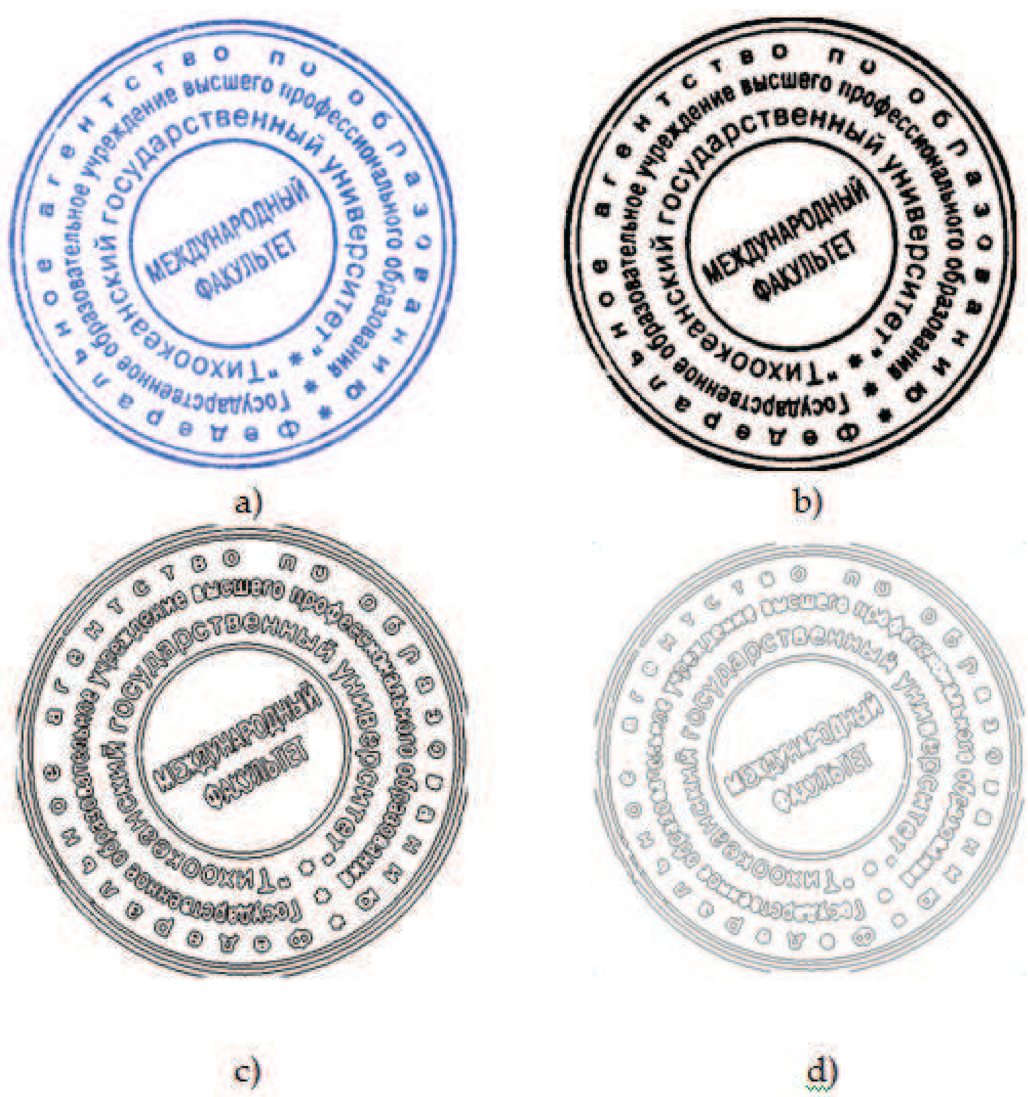

Fig. 5. Stamp image after the preprocessing: a) original image, b) binary image, c) contour image, d) image with definite contour details

Thus, the reference and analyzed stamps are obtained in a form of thin lines and texture elements after the preprocessing step. Next, the search algorithm of fine details is applied to these two images. As the images are in a binary form, obtain the blocks size 3 x 3 pixels corresponding to k^{th} mask (like in equation (8)):

$$M_k = \sum_{i=1}^{9} (Ib_{n,i} - w_{k,i}) . \qquad (41)$$

The decision is made that the given block refers to the image of the k^{th} mask in case if the computed value (41) is equal to zero. Next, check the image of the n^{th} block of analyzed image:

$$\Delta_n = \sum_{i=1}^{9} (Ib_{n,i} - \tilde{I}b_{n,i}) ; \qquad (42)$$

where $Ib_{n,i}$ and $\tilde{I}b_{n,i}$ are binary pixel values in the reference and analyzed image blocks.
The decision is made that the reference $Ib_{n,i}$ and analyzed $\tilde{I}b_{n,i}$ image blocks are identical in case if the computed value (42) is equal to zero. After this the probability of recognition is computer using (31). The system authenticates the stamp if the probability value is equal to one. Otherwise, the system outputs the numbers of blocks that are not identical for the further analyses.
Image blocks may not be identical for the following reasons:

1. Some parts of the stamp can be poorly printed or even be absent in the image.
2. The analyzed document has additional dots coming from the signature or text of a document under the stamp.
3. The superposition errors of two stamps – the reference and the analyzed one.

Coming from the research results the probability of recognition P_r will be strictly less than one due to the reduced errors. Also the probability value will be $P_r < 1$ if we would test two equal stamps and one image will be rotated for an arbitrary angle. So the described algorithm allows the selection from the analyzed stamp image only those fragments that differ from the reference image.
Taking into account the high quality of fake stamp images we could conclude that there exist no software method to identify either the given fragment belongs to the fake image or the difference has other factors. For example, the absence of some points in the analyzed block can be identified as a fake or as the absence of points due to the low quality of the stamp image. At the end stage only the human expert can make a decision.
For the effective expert work the following functions are implemented in the interactive search and identification software system:

1. Marking all non-identical blocks of analyzed stamp image with the color markers size 3 x 3 pixels. The block is marked if the value (42) is not equal to zero.
2. Selection of the marked block into the separate window using a mouse pointer. New window consists of two selected image fragments (of the reference and analyzed stamps) in tone gradation. Two images are magnified in order to increase the visual quality analyses.

3. Error value (42) is presented for the human expert to identify the conformance of the analyzed image with the reference.

Thus, the expert can visually check each "suspicious" fragment and make a decision about the genuineness of the stamp image.

Image blocks may not be identical for the following reasons: 1. some parts of the stamp can be poorly printed or even be absent on the image. 2. The analyzed document has additional dots coming from the signature or text of a document under the stamp. After recognition of the non-identical blocks they can be analyzed and corrected using interpolation and filtering methods. If the correction process does not lead to the positive result, the system decides that the stamp on a document is a fake.

5. Conclusions

The research results of the developed search and recognition algorithms have shown that these algorithms can be applied efficiently in the image quality analyses systems and different purpose computer vision systems.

Main features of the developed algorithms for search and recognition of fine details are:

1. Search algorithm uses sliding windows size 3 x 3 pixels; this allows for detecting the fine details of image.
2. The contrast thresholds of human visual perception or computer vision system are used for the computation of contrast for the block with fine details and during its transformation to binary form.
3. Distortions of fine details are estimated using the number of normalized visual thresholds in the quality estimation system. This makes possible to take objective decisions about the presence of fine details in the corrupted image or about the visibility of distortions.

Results of this work show that the high quality reproduction of fine details and fine structures of images is necessary not only for the digital TV systems but also in automated search and recognition systems.

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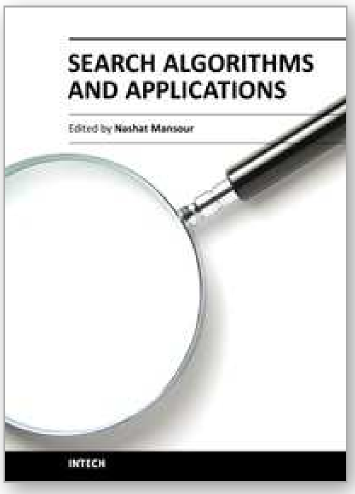

Search Algorithms and Applications

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Search algorithms aim to find solutions or objects with specified properties and constraints in a large solution search space or among a collection of objects. A solution can be a set of value assignments to variables that will satisfy the constraints or a sub-structure of a given discrete structure. In addition, there are search algorithms, mostly probabilistic, that are designed for the prospective quantum computer. This book demonstrates the wide applicability of search algorithms for the purpose of developing useful and practical solutions to problems that arise in a variety of problem domains. Although it is targeted to a wide group of readers: researchers, graduate students, and practitioners, it does not offer an exhaustive coverage of search algorithms and applications. The chapters are organized into three parts: Population-based and quantum search algorithms, Search algorithms for image and video processing, and Search algorithms for engineering applications.

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