International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Impact Factor (2012): 3.358

General Methodology for Implementation of Image Normalization Procedure Using its Wavelet Transform

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Abstract: ***Image processing is one of the fundamentals of various intelligence systems based on data analysis. In addition among the variety of different methods and approaches to image processing, image normalization methodology can be pointed out. The essence of such image processing methodology is in compensating various geometrical distortions of input image that was obtained through registering test image and forwarding it to the data mining system, in comparison with some reference (master) image. In such case, there arises a problem of time reduction for normalization procedure for some image processing systems. It is suggested that this task can be solved through the use of levels of wavelet decomposition of input image and conducting normalization procedure on separate levels. To solve this problem, this articles studies special aspects of wavelet decomposition of the image into separate levels of decomposition, functionality types of basic groups of image normalization by taking into account the use of wavelet decomposition levels of the test image, general methodology for determining transformation groups for image normalization based on wavelet decomposition. The fairness of the considered methodology is supported by the number of experiments.***

Keywords: image, normalization, functionality, wavelet transform, geometric distortions, levels of wavelet decomposition.

1. Introduction

Methodology of the preliminary and deep processing of images, representing in general separate pictures of the individual perception of the reality, is one the areas of data mining and method for extracting additional information about processes under study. This is due to the fact that over 80% of information about the world around us, people tend to perceive by means of sight. At the same time, in complex technical devices to ensure the continuity of the technological processes, or in inaccessible places or in places requiring constant visual observations for monitoring current situation, also various systems and devices are used based on the image perception of the real world and their further processing. One of the examples of such complex technical systems, based on the perception and analysis of visual images, are machine vision systems of various functional application – in particular computer vision systems, tracking systems for objects in motion, motion control systems and others.

So, for example, R. Cucchiara, M. Piccardi and P. Mello describe in their work the computer vision system that monitors public transport traffic [3]. At the same time, S. Jin, Z. Zhu and G Xu consider the video analysis system for moving objects, which allows to dynamically explore the sequence of changing scenes [10]. Such studies can be generalized in some way in the work of B. Rasolzadeh, M. Björkman, K. Huebner and D. Kragic, which studies the computer vision system for managing moving objects in the real world [19].

The work of M. J. Aitkenhead, I. A. Dalgetty, C. E. Mullins, A. J. S. McDonald and N. J. C. Strachan studies visualization system of differences between agricultural crop nursery plants and pests for subsequent chemical treatment of weeds [1]. T. Brosnan and D. W. Sun provide a review of various computer vision systems that are used for viewing and classifying different types of agricultural products and food products [2].

Compared to the works listed above, S. Kurada and C. Bradley, for example, study visual analysis system for evaluating tool wear [13].

Therefore, one can talk about the variety of various systems for data analysis based on methodology of visual objects perception. One can also talk about the variety of methods that form the basis of functioning of different computer vision system. In particular, these are methods of image preprocessing (noise reduction, contrast enhancement, localization of image separate sections) [4], [6], [9], [23], recognition methods for cognitive processing of information received [7], [18].

Nevertheless, despite the ability of using various methods processing and analysis of received visual image in different computer vision systems, one should consider both the specifics of how these images are displayed, as well as key tasks these computer vision systems fulfill.

Talking about processing and analysis methods of received visual patterns from the point of view of the specifics their presentation, then, as it is indicated in several studies [14], [20]-[22], the most promising and required methods nowadays are methods of image analysis and processing that are based on time-and-frequency signal notation and ability to transform such signal into classic video image matrix. This is due to the fact that there arises possibility of considering various aspects of images under study in the context of their presentation, as well as the ability to use different approaches to emphasize these aspects in the processing of the received visual images. In particular, as one of the most used images analysis tools that allows combining time-and-frequency signal notation and ability to transform this signal into classic video image matrix, is a wavelet transform [12].

At the same time, the main task to be solved in different computer vision systems is a task of normalization. The core task of normalization process is to compensate geometric transformations obtained in the result of deviations of input image from reference image when comparing input image with the purpose of its recognition with a number of different basic (reference) sets of possible images under study [5].

However, wavelet transform as well as image normalization process are quite computationally complex procedures for visual images processing. In the end, this determines the importance of considering not only the possibility of conducting normalization with the use of wavelet transform, but also the development of the direct approach that would provide such combination of the studied procedures of image processing with general time reduction when conducting them. This determines the choice of this study subject, where the purpose of this paper can be described as the development of compensation methodology for geometric distortion of input visual images that appear when using computer vision systems, including the use of wavelet transform for processing such visual images.

2. Wavelet Transform and Image Decomposition Levels

The main idea of wavelet transform is a time-and-frequency signal notation [11]. Wavelet transform is a decomposition with the use of functions, each one of which is a shifted and scaled copy of one function – mother wavelet [8], [11].
Wavelet transform of $f(t)$ function is defined as follows:

$$W[f(t)] = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t)\,\varphi\left(\frac{t-b}{a}\right)dt\,, \qquad (1)$$

where a – is a scale;
b – is a center of time localization;
function $\varphi(t)$ is a mother wavelet and fulfills the condition:

$$\int_{-\infty}^{+\infty} \varphi(t)dt = 0\,. \qquad (2)$$

If we have some input image B, which is outlines as a matrix $B(x,y) \in L_2(R)$ (x, y - are current matrix coordinates of values of image B, displaying respectively row and column coordinates), then its wavelet transform on each decomposition level can be represented by the scheme shown on Fig.1 (index 2 ↓ is image decimation, L – low-pass filter, H – high-pass filter). Thus, in this scheme and further on we will also denote input image in view of $B(x,y)$ matrix by vv or $vv^{(i)}$, where i ($i = 1,2,...j$, $N = 2^j$, N is a linear size of the original analyzed image) – this is the level of wavelet decomposition of the reference image (image that will further be subject to wavelet transform and decomposition). Output images are denoted respectively - $v1^{(i)}$, $v2^{(i)}$, $v3^{(i)}$, $v4^{(i)}$.

For analysis of wavelet decomposition procedure by levels the reference test image has been processed (Fig.2, the size of the initial image is 256x256 pixels). The example of decomposition of test image on 3 levels is shown on Fig.3, Fig.4, and Fig.5. On Fig.3, Fig.4, and Fig.5. a) letters denote images $v1^{(i)}$, b) – $v2^{(i)}$, c) – $v3^{(i)}$, d) – $v4^{(i)}$, in accordance with scheme of Fig.1.

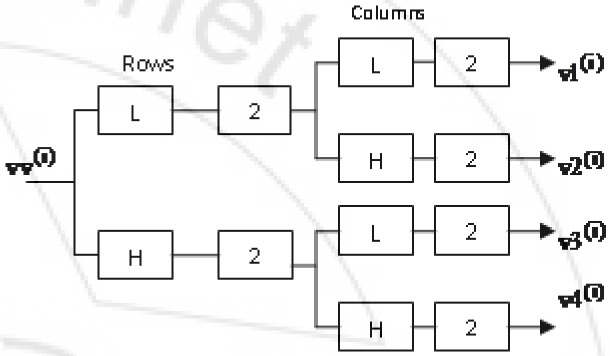

Figure 1: Two-dimensional discrete wavelet transform

Figure 2: Example of test image

As a result of decomposition, we obtain three matrixes of horizontal, vertical and diagonal components with the same resolution, that belong to each level of decomposition. At the same time, the size of image decomposition levels will equal: for the first level – 128x128 pixels, second level – 64X64 pixels and third level – 32x32 pixels. Fig. 3, Fig. 4 and Fig. 5 clearly show image structure composed of clear-cut horizontal, vertical and diagonal components that characterize the test image.

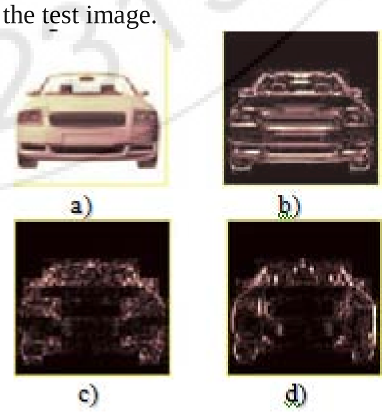

Figure 3: Result of transformation by decomposition levels 1st level

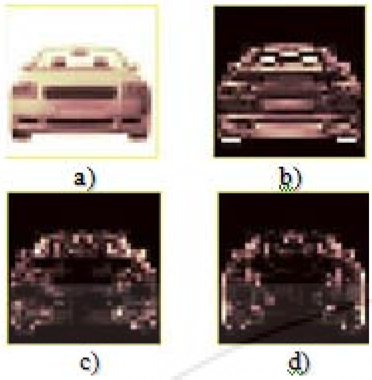

Figure 4: Result of transformation by decomposition levels 2nd level

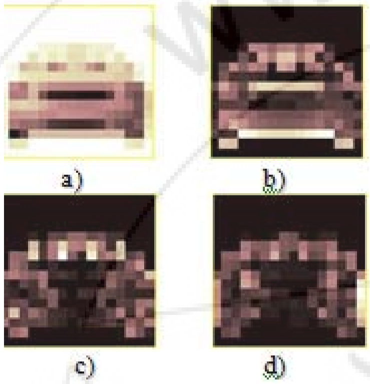

Figure 5: Result of transformation by decomposition levels 3rd level

As a result of decomposition we obtain a set of images – thumbnails of the image

$$WB^{(0)}(x,y) \supset WB^{(1)}(x,y) \supset ... \supset WB^{(i)}(x,y), \quad (3)$$

where $WB^{(0)}(x,y)$ – reference image;

$WB^{(1)}(x,y),..., WB^{(i)}(x,y)$ – thumbnails for each level of i decomposition (hereinafter Daubechies Wavelet was used). Moreover, for each of these images an extended component can be distinguished, which completes it to the images of the previous level:

$$d^{(i)} = WB^{(i+1)}(x,y) * g = WB^{(i+1)}(x,y) - WB^{(i)}(x,y), \quad (4)$$

where g – high frequency decomposition filter.

It is evident that

$$WB^{(0)}(x,y) = d^{(1)} + d^{(2)} + ... + d^{(i-1)} + WB^{(j)}(x,y). \quad (5)$$

The resulting set of images allows conducting more detailed analysis of the original image. Moreover, the transition to other decomposition levels allows to stay off the small and random details, to better identify the "internal" structure when analyzing the image. Exactly this fact can be selected as bases for selecting levels of image wavelet decomposition for image normalization.

However, as a result of wavelet decompositions, there occurs change in image size twofold on each step of wavelet transform (image is passed through filters with spectral bandwidth 0.5). It is obvious that not every level of image decomposition is suitable for normalization procedure. Therefore, it is necessary to determine the optimal level of wavelet decomposition. It is especially important for conducting procedures connected with geometric transformations – one of the forms of image normalization.

In order to determine the most optimal decomposition level, lets conduct analysis of the obtain coefficients for images $v2^{(i)}$, $v3^{(i)}$, $v4^{(i)}$. These coefficients characterize energy structure of the image on different levels of decomposition. Lets form from the obtained coefficients for images $v2^{(i)}$, $v3^{(i)}$, $v4^{(i)}$ characters $G_B^{(i)}$, $G_H^{(i)}$, $V_B^{(i)}$, $V_H^{(i)}$, $D_B^{(i)}$, $D_H^{(i)}$, that characterize horizontal, vertical and diagonal direction of reference (H) and analyzed (B) images respectively on different levels of decomposition i:

$$G_B^{(i)} = \sum_{yy=1}^{N(i)} (\max_{xx}(v2^{(i)}))^2_{yy}, \quad (6)$$

$$G_H^{(i)} = \sum_{yy=1}^{N(i)} (\max_{xx}(v2^{(i)}))^2_{yy}, \quad (7)$$

$$V_B^{(i)} = \sum_{yy=1}^{N(i)} (\max_{xx}(v3^{(i)}))^2_{yy}, \quad (8)$$

$$V_H^{(i)} = \sum_{yy=1}^{N(i)} (\max_{xx}(v3^{(i)}))^2_{yy}, \quad (9)$$

$$D_B^{(i)} = \sum_{yy=1}^{N(i)} (\max_{xx}(v4^{(i)}))^2_{yy}, \quad (10)$$

$$D_H^{(i)} = \sum_{yy=1}^{N(i)} (\max_{xx}(v4^{(i)}))^2_{yy}, \quad (11)$$

where $N(i)$ - linear dimensions of the matrix of coefficients for images $v2^{(i)}$, $v3^{(i)}$, $v4^{(i)}$, which are defined and depend on wavelet decomposition level i, summarization is conducted by all columns yy in accordance with the selected maximum for the row xx

However, as it has been mentioned above, not every level of image decomposition is suitable for normalization operation. This is due the fact, that signal undergoes significant changes once on the most scales of study, and is, therefore, characterized by the increase of wavelet coefficient for most of the detail levels, while on steady places wavelet coefficients are grouped around certain dimensioning. Selecting the decomposition level can be reduced to finding the moments of wavelet coefficients increase on the considerable amount of zoom levels.

So, the normalization should be conducted on the same decomposition level, which best preserves the structure of the image. In this case, it is possible to conduct analysis of each decomposition level and determine the optimum level of image decompositions for normalization using the following formula:

$$\frac{G_B^{(i)} + V_B^{(i)} + D_B^{(i)}}{M^{(i)}} \le \frac{G_B^{(1)} + V_B^{(1)} + D_B^{(1)}}{M^{(1)}}, \quad (12)$$

where $M^{(i)}$ – the total amount of decomposition coefficients at each level of decomposition;

$M^{(1)}$ – total number of decomposition coefficients on the first level of decomposition.
The first level that fulfills the condition (12) is the most informative.

3. Mathematical Description of Image Geometric Distortion Compensation as a set of Separate Normalization Functions

As it has already been mentioned – image normalization can involve compensation of geometric transformations, obtained as a result of deviations between input and reference images. Thus, depending on the transformation group, parameters are calculated that allow compensating geometric transformations. Such description is possible based on the use of various normalization functions that will be studied below.

Suppose we have some image B(x,y). Let this image be shifted along the Y axis. Then mathematically this kind of bias can be written as follows [15], [16]:

$$B(x,y) = B_0(x, y-m), \tag{13}$$

where B_0, B - are some reference and transformed images respectively.

m – bias parameter.

In this kind of transformation object doesn't change its geometric dimensions and orientation while shifting along Y axis.

Since the image hasn't changed its shape, but it has shifted along Y axis, then one may state that this transformation belongs to the transformation group of parallel shift along Y axis and belongs to one-parameter group – $G_{c,y}$ [5], [15], [16].

Then for group $G_{c,y}$ in formalized presentation the shift normalization (F_c) be the following [17]:

$$F_{c,y}(B) = B_0(x, y+\Phi_2), \tag{14}$$

where Φ_2 – function that defines parameters according to (13) [17]:

$$\Phi_2 = \frac{\sum_{x=1}^{N}\sum_{y=1}^{N} y \cdot vv_0(x,y)}{\sum_{x=1}^{N}\sum_{y=1}^{N} vv_0(x,y)} - \frac{\sum_{x=1}^{N}\sum_{y=1}^{N} y \cdot vv(n,m)}{\sum_{x=1}^{N}\sum_{y=1}^{N} vv(x,y)}. \tag{15}$$

In a similar way one can describe function for bias along X axis for n shift describing one-parameter group $G_{c,x}$ [17]:

$$\Phi_1 = \frac{\sum_{x=1}^{N}\sum_{y=1}^{N} x \cdot vv_0(x,y)}{\sum_{x=1}^{N}\sum_{y=1}^{N} vv_0(x,y)} - \frac{\sum_{x=1}^{N}\sum_{y=1}^{N} x \cdot vv(x,y)}{\sum_{x=1}^{N}\sum_{y=1}^{N} vv(x,y)}. \tag{16}$$

Then for the group of shifts $G_{c,x,y}$ shift parameters are determined from functions Φ_1 and Φ_2.

Thus, for shift groups, diagonal shift $G_{h,x}$, $G_{h,y}$ and $G_{h,x,y}$ representing bias [17]:

$$B(x,y) = B_0(x+hy, y), \tag{17}$$

$$B(x,y) = B_0(x, y+hx), \tag{18}$$

$$B(x,y) = B_0(x+hy, y+hx), \tag{19}$$

the corresponding functions for defining parameters of the diagonal shift are [17]:

$$\Phi_3 = \frac{\sum_{x=1}^{N}\sum_{y=1}^{N} x \cdot y \cdot vv_0(x,y)}{\sum_{x=1}^{N}\sum_{y=1}^{N} y^2 \cdot vv(x,y)}, \tag{20}$$

$$\Phi_4 = \frac{\sum_{x=1}^{N}\sum_{y=1}^{N} x \cdot y \cdot vv_0(x,y)}{\sum_{x=1}^{N}\sum_{y=1}^{N} x^2 \cdot vv(x,y)}, \tag{21}$$

or these are two functions correspondingly Φ_3 and Φ_4 for the shift group $G_{h,x,y}$.

If we have a rotating object on the image, and images B_0, B have the following functional connection [5], [15], [16]:

$$B(x,y) = B_0(x\cdot\cos\theta + y\cdot\sin\theta, -x\cdot\sin\theta + y\cdot\cos\theta), \tag{22}$$

then normalizer F_u of G_u rotation groups looks as follows [17]:

$$F_u(B) = B_0(x\cdot\cos\Phi_5 + y\cdot\sin\Phi_5, -x\cdot\sin\Phi_5 + y\cdot\cos\Phi_5),$$

where

$$\Phi_5 = \frac{1}{2}\mathrm{arctg}\frac{\sum_{x=1}^{N}\sum_{y=1}^{N}(x^3\cdot y + x\cdot y^3)\cdot 2\cdot vv_0(x,y)}{\sum_{x=1}^{N}\sum_{y=1}^{N}(x^4 + y^4)\cdot vv(x,y)}. \tag{23}$$

To consider change of scale, when we have [5], [15], [16]:

$$B(x,y) = B_0(px, py), \tag{24}$$

the corresponding function for the group of proportional change of scale G_r will look as follows [17]:

$$\Phi_6 = \frac{\sum_{x=1}^{N}\sum_{y=1}^{N} vv(x,y)}{\sum_{x=1}^{N}\sum_{y=1}^{N} vv_0(x,y)}. \tag{24}$$

If we consider a mathematical model of the prospects of the form [5], [15], [16]:

$$B(x,y) = B_0\left(\frac{x}{\lambda\cdot y+1}, \frac{y}{\lambda\cdot y+1}\right), \tag{25}$$

where λ – the parameter of homology along the axis of coordinates,
then the corresponding function for the perspective group G_s will look as follows [17]:

$$\Phi_7 = \frac{\sum_{x=1}^{N}\sum_{y=1}^{N}\frac{vv(x,y)}{x^4}}{\sum_{x=1}^{N}\sum_{y=1}^{N}\frac{vv_0(x,y)}{x^3}}. \quad (26)$$

4. Functions of basic groups of image normalization with levels of wavelet decomposition of the image under study

As a result of conducted experiments and analysis of the first level of decomposition, using calculation formula of mean difference, maximum difference and mean square error, the conclusion was made that for compensation of geometrical distortions one can use the following levels of decomposition.

The view of separate normalizers and functions is shown below:

1. For groups $G_{c,x}$, $G_{c,y}$, $G_{c,x,y}$:

General view of normalizers:

$$WF_{c,x}(B) = WB(x+\Phi w_1^{(i)}, y), \quad (27)$$

$$WF_{c,y}(B) = WB(x, y+\Phi w_2^{(i)}), \quad (28)$$

$$WF_{c,x,y}(B) = WB(x+\Phi w_1^{(i)}, y+\Phi w_2^{(i)}), \quad (29)$$

General view of functions:

$$\Phi w_1^{(i)} = \frac{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} x\cdot vv_0^{(i)}(x,y)}{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} vv_0^{(i)}(x,y)} - \frac{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} x\cdot vv^{(i)}(x,y)}{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} vv^{(i)}(x,y)}, \quad (30)$$

$$\Phi w_2^{(i)} = \frac{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} y\cdot vv_0^{(i)}(x,y)}{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} vv_0^{(i)}(x,y)} - \frac{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} y\cdot vv^{(i)}(n,m)}{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} vv^{(i)}(x,y)}. \quad (31)$$

2. For groups $G_{h,x}$, $G_{h,y}$ и $G_{h,x,y}$:

General view of normalizers:

$$WF_{h,x}(B) = WB(x+\Phi w_3^{(i)}\cdot y, y), \quad (32)$$

$$WF_{h,y}(B) = WB(x, y+\Phi w_4^{(i)}\cdot x), \quad (33)$$

$$WF_{h,x,y}(B) = WB(x+\Phi w_3^{(i)}\cdot y, y+\Phi w_4^{(i)}\cdot x), \quad (34)$$

General view of functions:

$$\Phi w_3^{i} = \frac{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} x\cdot y\cdot vv_0^{(i)}(x,y)}{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} y^2\cdot vv^{(i)}(x,y)}, \quad (35)$$

$$\Phi w_4^{(i)} = \frac{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} x\cdot y\cdot vv_0^{(i)}(x,y)}{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} x^2\cdot vv^{(i)}(x,y)}, \quad (36)$$

3. For group G_r:

General view of normalizer:

$$WF_r(B) = WB(x\cdot\Phi w_6^{(i)}, y\cdot\Phi w_6^{(i)}), \quad (37)$$

General view of function:

$$\Phi w_6^{(i)} = \frac{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} vv^{(i)}(x,y)}{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)} vv_0^{(i)}(x,y)}. \quad (38)$$

4. For group G_s:

General view of normalizer:

$$WF_s(B) = WB\left(\frac{x}{\Phi w_7^{(i)}\cdot y+1}, \frac{y}{\Phi w_7^{(i)}\cdot y+1}\right), \quad (39)$$

General view of function:

$$\Phi_7^{(i)} = \frac{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)}\frac{vv^{(i)}(x,y)}{x^4}}{\sum_{x=1}^{N(i)}\sum_{y=1}^{N(i)}\frac{vv_0^{(i)}(x,y)}{x^3}}. \quad (40)$$

So, we have defined the type and shape of different functions for normalization based on the use of various levels of wavelet decomposition of the image under study. Now, the open issue is how to define different groups of transformations for image normalization on basis of wavelet decomposition.

5. Definition of Transformation Groups for Image Normalization Based on Wavelet Decomposition

To determine transformation groups for further image normalization with the help of wavelet decomposition based on a number of experiments the following decomposition coefficients have been analyzed. It has been determined, that the obtained coefficients allow locally analyze those parts of the image that make it possible to determine to which type of geometric transformations changes occurring with the image can be referred to.

The general scheme for defining transformation groups look as follows:

1) Observing the behavior of coefficients starting from the last level of wavelet decomposition of the test image to the first one.
2) On the last level, finding the maximum coefficients and track their behavior on the following levels.

3) Calculating the energy of coefficients maximum, taking into account coefficient values of all levels of decomposition.
4) Analyzing the obtained energies in accordance with the following expressions:

If

$$W_G = \frac{\sum_{yy=1}^{N(i)} (\max_{xx}(v4_H^1))_{yy}^2}{\sum_{yy=1}^{N(i)} (\max_{xx}(v4_B^1))_{yy}^2} \approx 1, \quad (41)$$

then image transformation occur in the same plane, so it can be concluded that the image was subject to the group of shift transformations $G_{c,x}$, $G_{c,y}$, $G_{c,x,y}$ or to the group of rotation G_u. Otherwise, image can be subject to the change of scale and belongs to the groups of scale transformation G_r or was subject to projective distortions and belongs to the group of perspective G_s.

For the further determination of transformation groups belonging to the affine group of transformation, let's consider vertical and horizontal matrixes resulting from decomposition.

If

$$W_G = \begin{cases} \dfrac{\sum_{yy=1}^{N(i)} (\max_{xx}(v3_H^1))_{yy}^2}{\sum_{yy=1}^{N(i)} (\max_{xx}(v3_B^1))_{yy}^2} \approx 1 \\ \dfrac{\sum_{yy=1}^{N(i)} (\max_{xx}(v2_H^1))_{yy}^2}{\sum_{yy=1}^{N(i)} (\max_{xx}(v2_B^1))_{yy}^2} \neq 1 \end{cases}, \quad (42)$$

then there is a shift on the axis Y. Then the group of transformations corresponds to the group of parallel shifts along the axis $G_{c,y}$. Otherwise, we can say that there is a shift along axis X, and it corresponds to the group of shifts along $G_{c,x}$ axis.

If

$$W_G = \begin{cases} \dfrac{\sum_{yy=1}^{N(i)} (\max_{xx}(v3_H^1))_{yy}^2}{\sum_{yy=1}^{N(i)} (\max_{xx}(v3_B^1))_{yy}^2} \approx 1 \\ \dfrac{\sum_{yy=1}^{N(i)} (\max_{xx}(v2_H^1))_{yy}^2}{\sum_{yy=1}^{N(i)} (\max_{xx}(v2_B^1))_{yy}^2} \approx 1 \end{cases}, \quad (43)$$

then there occurs shift along X and Y axis. Then the group of transformations corresponds to the group of parallel shifts along axes $G_{c,x,y}$.

At image shift the values

$$W_G = \begin{cases} \dfrac{\sum_{yy=1}^{N(i)} (\max_{xx}(v3_H^1))_{yy}^2}{\sum_{yy=1}^{N(i)} (\max_{xx}(v3_B^1))_{yy}^2} \neq 1 \\ \dfrac{\sum_{yy=1}^{N(i)} (\max_{xx}(v2_H^1))_{yy}^2}{\sum_{yy=1}^{N(i)} (\max_{xx}(v2_B^1))_{yy}^2} \neq 1 \end{cases}, \quad (44)$$

that defines the group of rotations in G_u plane.

If the number of maxima of decompositions coefficients for the reference image H does not correspond to the number of maxima of decomposition coefficients of the test image B, then it can be stated, that the image has undergone sharp distortions and corresponds to the group of perspective G_s. Defining transformation group of scale G_r follows as a consequence, based on the consideration of the previous groups.

As a confirmation of the arguments above, there are some experiments results below – the results of studying the abilities and practicability of realization of image normalization procedure based on the use of the levels of its wavelet decomposition.

6. Some experiments concerning the processing capabilities and the practicability of the realization of image normalization procedure based on the use of the levels of its wavelet decomposition

Fig. 6 shows the results of wavelet decomposition into separate levels of images decomposition using Daubechies Wavelet, which has been subjected to a group of shift transformations $G_{c,x,y}$.

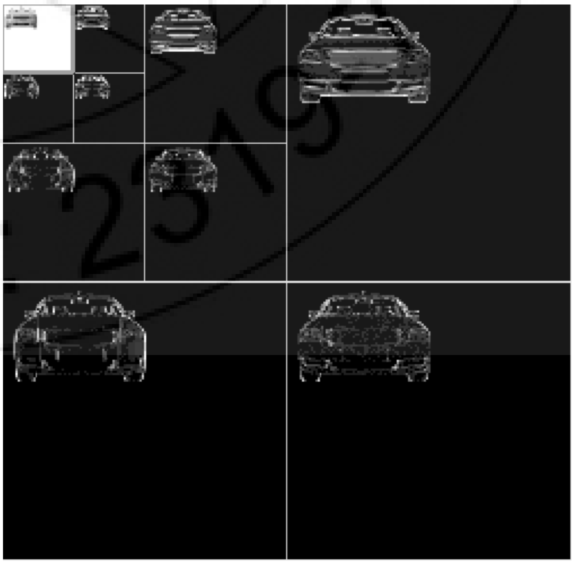

Figure 6: Wavelet decompositions of the image exposed to the group of shift transformations $G_{c,x,y}$

As seen from Fig. 6 the object under study does not change its dimensions and orientation, moves along axes X and Y. The results of the calculations showed that for W_G the conditions are performed in accordance with formula (43) -

$$W_G = \begin{cases} 0{,}92 \\ 0{,}98 \end{cases}.$$

Fig. 7 shows the results of wavelet decomposition into separate levels of image decomposition using Daubechies Wavelet, which was subjected to the group of rotation transformation G_u.

As seen from Fig. 7 the object under study does not change its dimensions and rotates on angle φ. After calculation $W_G = \begin{cases} 0{,}37 \\ 0{,}41 \end{cases}$ in accordance with formula (44), it can be stated that this transformation corresponds to a group of rotations on the plane G_u.

However, it should be noted that if the image has a fractal structure, errors in the determination of the group occur.

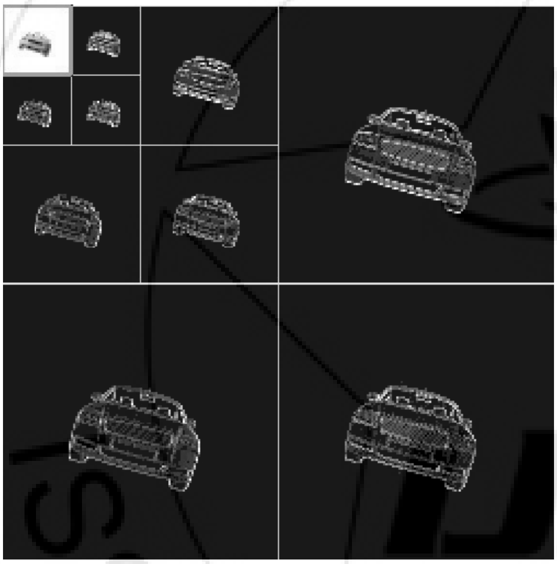

Figure 7: Wavelet decomposition of the image exposed to group of shift transformations G_u

Table 1 and Table 2 show the results of experiments that relate to the determination of transformation parameters for the normalizer describing a group of transformations of perspective G_s.

Table 1 shows the results of the determination of transformation parameters using classical procedure for description of the corresponding functions – formula (26).

Table 2 shows similar results for the search of the corresponding functions through the use of image wavelet decomposition into three levels of decomposition – formula (40). In both cases the same paramenters of the perspective change of test image were used. Measure of inaccuracy reflects the value of change of the real perspective parameters from the obtained calculated in the result of using the considered formulas for calculating functions in the classical form (table 1) and in the form of normalizers construction with the account of wavelet decomposition for test image (table 2).

Table 1: The result of determination of transformation parameters, describing the group of perspective transformations G_s by means of classical procedure of describing the corresponding functions

Transformation parameters (for different perspective distortions)	*Standard deviation Δ, %*
3,27	1,52
4,21	1,59
6,01	1,63
8,33	1,71

Table 2: The result of determination of transformation parameters, describing the group of perspective transformations G_s by means of the corresponding functions based on the use of wavelet decomposition of image into three decomposition levels

Transformation parameters	*Standard deviation Δ, %*
1st level of decomposition	
3,23	1,54
4,19	1,61
6,12	1,67
8,27	1,72
2nd level of decomposition	
3,13	2,74
4,17	2,12
5,78	2,01
8,28	1,83
3rd level of decomposition	
3,18	3,21
3,98	2,73
6,25	3,32
8,21	4,17

As is clear from table 1 and table 2, calculated parameters defining the group of perspective transformations using different computing techniques of the corresponding functions correlate between each other. This proves the correctness of the discussed above and the possibility of using the proposed methodology for realization of image normalization procedure a whole based on the use of the levels of its wavelet decomposition. In this connection, it should be underlined, that this occurs because of applying image decimation procedure on each level of its decomposition, as there occurs partial loss of information. It should also be emphasized that it occurs as a result of application of image decimation procedure on each level of its decomposition, as there occurs loss of partial information. It should also be noted that values of inaccuracy are not critical – they do not exceed 5%. Nevertheless, we should talk about the advisability to limit the level of image decomposition when considering image normalization procedure based on the use of levels of its wavelet decomposition. As such threshold limit can be taken a limitation of not more than three levels of decomposition of the test image by using appropriate normalization procedures.

7. Conclusions

As the result, the paper studies key points relating to the summary of realization methodology of image normalization procedure based on the use of its wavelet decomposition levels. Here the main point of using wavelet decomposition for realization of image normalization procedure is to establish the possibility of using image thumbnails as the result of wavelet decomposition of the analyzed image. The use of such wavelet decomposition of an image allows reducing time for normalization of input image for further recognition of the object under study.

The possibility and practicability of the realization of image normalization procedure based on the use of its wavelet decomposition levels is shown by the example of calculating different geometric distortions of the analyzed image. To confirm the suggestion there was conducted a number of experiments, the results of which are shown in this paper.

The practical implications of the obtained results are that in modern computer vision systems the type of geometric transformations should be determined. It is also shown, that the suggested methodology removes restrictions on conducting normalization in the specified group with the help of defining groups of transformations.

Disadvantages of this methodology of image normalization include insufficient study of the constructive method of controlling "false" upper limits that affect the definition of transformations groups. Though this aspect, as well as definition of the optimal level of image decomposition for its further normalization, can largely depend on the type of wavelet used. This allows defining these tasks as future directions of the research. Another aspect, which may also require addition research, is the use of adaptive wavelets in the realization methodology of image normalization procedure based on the use of its wavelet decomposition levels.

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