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Fragment-aided recognition of images under poor lighting and additive impulse noises

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Abstract

On the base of the first-order integral disproportion functions, two algorithms recognizing fragments of standard images are proposed. Due to the disproportion functions techniques, the algorithms have special advantages when processing poorly lighted images, as well as with signals transmitted in the presence of additive impulse noises.

Keywords: image recognition; standard fragments; disproportion functions; poor lighting; additive impulse noise

1. Introduction

Practical image recognition often requires to recognize some standard photo/video fragments within the analyzed picture. For example, some standard objects or parts of them may be present on the terrain. Some objects may be imposed on other ones or are in fact closer to each other. In addition, they may be different scale images or to be shifted and rotated compared to the standards. Besides, they might have been distorted due to some geometric transformations.

A lot of papers/books are devoted to the problem of image recognition. In particular, a very effective tool is to normalize distorted images [1]. Pattern recognition based on fuzzy neural classifier provided the facility that is recognized correctly positioned relative coordinate axes, is proposed in [2].

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Deep neural networks-based (DNN) algorithms are also quite productive and efficient for pattern recognition [4]. Nevertheless, one of the minor points of the DNN is the necessity to accumulate databases of enormous size to make the DNN methods useful. For example, the ImageNet database is the outcome of a collaboration between Stanford University and Princeton University and has become a reference in the field of computer vision. It contains around fourteen million images originally labeled with Synsets of the WordNet lexicon tree.

However, the problem of recognizing fragments of standard images in poor light conditions is still painstaking. Basically, it is recommended to use more sensitive equipment or devices that operate in the infrared spectrum. Nevertheless, even in the daytime, lighting levels can deteriorate rapidly. In addition, one might try to obtain video images when there smoke, fog, or sediments are present. All this could weaken the intensities of the components that determine the color of the pixel in the digital image. It also may happen that these components are reduced at different degrees. As compared to the brightness of red, green and blue components of the standards, these components of the analyzed images may bleach.

In any case, the problem mainly is not in getting the right brightness components of pixels but in the necessity of recognizing correctly the fragment of the standard to which every pixel of image corresponds. Most often, one needs to recognize the fragments when the intensity of every component (color image pixel) is proportional to the intensity of the standard, but the factor of proportionality is unknown.

The value of this unknown factor cannot be determined simply by dividing the intensities of pixels that are randomly taken from the analyzed image and from a standard one. Indeed, the standard to which the pixel selected from the image corresponds is generally unknown. Thus, even under the circumstances when the analyzed image has not been distortes, shifted or pivoted with respect to the standard, it is by no means an easy task to identify the corresponding fragment of this standard.

Actually, it is required to check the proportionality relation between the color of every pixel of the image and the pixel color for each of the standards.

Another difficulty of solving the above problem may arise when, in addition to the reduced lighting, noise is superimposed on a video signal. Getting a video signal transmission usually occurs in the presence of additive noises as well as multiplicative ones. Often, additive bipolar impulse noise can appear, too.

The latter signal may have a peculiarity: the impulses often are greater than the video signal amplitude. In this case, the pixels that got the pulses of noise might become either white or black [3].

The bipolar pulse noise may arise as a result of electric welding, electrical discharges, switching processes in electrical circuits, etc. Thus, one must first fix a moment when the noise disappeared and then recognize the fragment of the standard before the noise appears again.

Often the impulse noise arises and disappears randomly; i.e., the noise is described by a random process. In practice, the statistical characteristics of this process are unknown, either. This does not allow one to implement it’s effective filtering.

In principle, recognizing a fragment of a standard image can be fulfilled in those intervals when the noise disappears, but these intervals must also be recognized.

Solving the above-described problem is quite complicated because it is usually unknown which pixel of an image corresponds to which pixel of the standard currently. Moreover, the standard itself may be non-evident, either.

In [5], this problem is considered for the case where the obstacle is described by a smooth function. However, the noise impulse frequently is non-smooth.

In contrast to the DNN techniques, our algorithm doesn’t need the preliminary learning nor accumulation of astronomic databases.

The rest of the paper is arranged as follows. Section 2 deals with the problem with zero noise, while Section 3 provides the extension of the algorithm to the case of any noise affecting the signal. The possibilities of extension of the general n-order derivative disproportion function (DDF) to the sequential disproportion function

(SDF) and their use for the image recognition under nonlinear noise are briefly outlined in Section 4. The paper is finished with the acknowledgments and the reference list.

2. The Problem's Statement Without Noise

First, we consider the problem when there is no noise. For a digital camera, e.g., camcorders of the images are represented as two-dimensional arrays of pixels. Each pixel has its own color value. These are transparency and intensity of red, green, and blue components. Each of them can vary from 0 to 255.

Assume that there are m reference images (standards) represented by matrices of pixels. Suppose also that after scanning we have the arrays of red $R_k = \left\{ R_k\left(q\right) \middle| 1 \le q \le N \right\}$, green $G_k = \left\{ G_k\left(q\right) \middle| 1 \le q \le N \right\}$ and blue $B_k = \left\{ B_k\left(q\right) \middle| 1 \le q \le N \right\}$ brightness values for every pixel and for every standard, where the notation is explained in the table below:

Nomenclature	
$k = 1,2, ..., m$	is the order number of the standard;
$q = i \cdot w + j$	is the pixel order number on the screen;
w	is the number of pixels in one line; $w \ge 1$;
j	is the pixel order number in a row; $1 \le j \le w$;
h	is the total number of rows in the screen;
i	is the line number; $0 \le i \le h;$
$N = \left(1+h\right) \cdot w$	is the total number of the pixels on the screen.

Similarly, the measured (output) red, green and blue components of the color pixels of the analyzed image are arranged in the arrays $r_k = \left\{ r_k\left(q\right) \middle| 1 \le q \le N \right\}$, $g_k = \left\{ g_k\left(q\right) \middle| 1 \le q \le N \right\}$, and $b_k = \left\{ b_k\left(q\right) \middle| 1 \le q \le N \right\}$, respectively ($k = 1,2,\ldots,m$).

These are obtained in poor light conditions. The analyzed image consists of fragments of the standards that must be recognized. In the case when a pixel in the image corresponds to a pixel of the k-th standard, their brightness values are proportional in (unknown) scales:

$$r_k\left(q\right) = a_k^r R_k\left(q\right),\ 1 \le q \le N; \tag{1}$$

$$g_k\left(q\right) = a_k^g G_k\left(q\right),\ 1 \le q \le N; \tag{2}$$

$$b_k\left(q\right) = a_k^b B_k\left(q\right),\ 1 \le q \le N, \tag{3}$$

where $a_k^r, a_k^g, a_k^b,\ k = 1,\ldots,m$, are the standard red, green, and blue brightness attenuation coefficients (factors), respectively.

In general, the latter factors may be different depending on the medium through which the light passes. In addition, they might accidentally change over time, for example, by passing through clouds or smoke. Thus, to solve the problem it is necessary to find for every pixel of the image the appropriate pixel of the corresponding standard. In the case of success, a proportional relationship for the brightness values of these pixels at least for one component is guaranteed.

However, the problem must be solved whenever the brightness attenuation coefficients (factors) are unknown and their values are random. Therefore, one is advised to use a method that is (in some sense) invariant to the coefficient of proportionality. Thus, the derivative disproportion funcions (DDF) proposed by the authors in their previous works [6-7] and further developed in applications to cryptosystems [8-9] will be of use to solve the considered problems.

2.1. Solving the noiseless problem by the use of the DDF

The derivative disproportion functions (DDF) are exercised in order to identify (label, tag) relevant real functions. The DDFs permit to quantitatively estimate the degree of a deviation of a numerical function from the specified functions (like, e.g., power function $y = k \cdot x^n$) for any fixed value of the argument, regardless of the associated parameters (like, for example, multiplier *k* for the power function). Here, $n \geq 1$ is an integer.

Definition 1. The *derivative disproportion function (DDF) of order n* of the function $y = y(x)$ with respect to *x* ($x \neq 0$) is defined as follows:

$$@d_x^{(n)} y = \frac{y}{x^n} - \frac{1}{n!} \cdot \frac{d^n y}{dx^n}. \tag{4}$$

In the particular case of $n = 1$ (order 1), Eq. (4) of the derivative disproportion is easily reduced to:

$$@d_x^{(1)} y = \frac{y}{x} - \frac{dy}{dx}. \tag{5}$$

As one could expect, for the linear function $y = kx$, its DDF of order 1 is *zero* for any value of the coefficient *k*. The symbol @ is chosen to designate the operation of determination of disproportion. The symbol "*d*" is selected to refer to the function's derivative as the main object of disproportion calculated. Finally, the left-hand side of Eq. (5) reads "a*t d one y with respect to x*".

If a function is reported in a parametric form, the *n*-th order derivative disproportion function (DDF) defined by Eq. (4) is determined by applying the rules of calculation of $d^n y / dx^n$ under the parametric dependence of *y* on *x*. In particular, the first-order derivative disproportion of the function defined parametrically as $y = \psi(t)$ and $x = \varphi(t)$ (where *t* is the parameter and $\varphi(t) \neq 0, \varphi'(t) \neq 0$ for all *t*) has the form

$$@d_x^{(1)} y = @d_{\varphi(t)}^{(1)} \psi(t) = \frac{y}{x} - \frac{y'_t}{x'_t} = \frac{\psi(t)}{\varphi(t)} - \frac{\psi'(t)}{\varphi'(t)}. \tag{6}$$

It is clear that if $\psi(t) = k\varphi(t)$ for some constant *k*, its derivative disproportion defined by Eq. (6) equals *zero* on the (shared) domain of the functions $y = \psi(t)$ and $x = \varphi(t)$.

***Lemma 1* [6].** Each derivative disproportion function (DDF) of order *n* has the following properties*:*

1. Multiplying the function *y* by any scalar *m* results in multiplying its DDF by the same scalar.
2. The order *n* derivative disproportion function (DDF) of a sum (difference) of functions equals the sum (difference) of their DDFs.
3. For the linear function $y = kx$, its derivative disproportion of order 1 is zero for any value of the coefficient *k.*

Proof. It is readily verified by simple algebraic manipulations with the use of Definition 1.

Remark 1. In other words, the operator $@d_x^{(n)}$ defined on the space $C^n(\Omega)$ of *n* times continuously differentiable real functions is *linear* on this space.

Remark 2. Note that the brightness functions defined in Eq. (1) – (3), as well as the brightness parameters of the standards, have discrete values. That is why an "integral" (discrete difference) disproportion function of first order proposed in [10-11] is used in practice instead of disproportion functions (4) – (6).

The integral disproportion function of r_k with respect to R_k has the form:

$$I(q) = @I_{R_k}^{(1)} r_k(q) := \frac{r_k(q-1) + r_k(q)}{R_k(q-1) + R_k(q)} - \frac{r_k(q)}{R_k(q)},\ q = 2,\ldots,N. \tag{7}$$

In the framework of our recognition algorithm, it is proposed to calculate the (discrete difference) disproportion (7) for the color components of each pixel of the image with respect to the color components of each pixel for all standards.

Remark 3. As follows from Lemma 1, if proportionalities (1) – (3) hold and the color brightness functions are differentiable, then the derivative disproportionality function defined by Eq. (6) produces zero ouputs, thus confirming that the recognition has been successful. However, in practice, the arrays of pixel colors are usually discrete functions. In this case, when operating with the discrete difference disproportion function (7), we compare its outputs not with zero but with a (small) positive tolerance parameter. Whenever the disproportion function's absolute value is less or equal to the tolerance, we accept the recognition as a success. The lower the (absolute) value of the disproportion function (7), the closer is the recognized image to the desired standard fragment.

2.2. The recognition algorithm

We consider as an example the recognition of the red color output pixels as belonging to a detected standard fragment.

Algorithm 1.

Step 1. Fix a (small) positive tolerance threshold $\varepsilon > 0$. We will compare the disproportion function's (absolute) value with this parameter to accept or not the analyzed recognition.

Step 2. Read the (red) brightness values $R_k(q)$ of the red pixels belonging to all standards, $k = 1,\ldots,m;\ q = 1,\ldots,N$.

Step 3. Select standard $k := 1$ and read the output red pixel components as $r_1(q),\ q = 1,\ldots,N$.

Step 4. Calculate the disproportion function of r_k with respect to R_k by (7) and store its values as the array

$$D_k^R(q) := I(q),\ q = 2,\ldots,N.$$

Step 5. The recognition test. If $\left|D_k^R(q)\right| \le \varepsilon$ then we conclude that pixel *q* of the output image can be associated (identified) as the *q*-th pixel of standard (fragment) *k*. Therefore, we copy-paste the latter to pixel *q* of the analyzed image. Otherwise, i.e., if $\left|D_k^R(q)\right| > \varepsilon$ then we reject the *q*-th pixel of the *k*-th standard and leave pixel *q* of the analyzed image empty. Repeat this procedure for all *q*.

Step 6. Set $k := k+1$. If $k \le m$ the go to Step 4, else go to Step 7.

Step 7. End and show the obtained recognized image.

2.3. An illustration

Example 1. The algorithm is tested on two pictures with processing all 3 color components (red, green, and blue). Two photos shown in Fig.1 are used as the standards: One of them pictures the trees over a river, another shows a cat sleeping on the computer table.

Next, the image for recognition is presented in Fig.2. The left part of this image is the photo with the trees, whereas the right half is a fragment of the computer table of the cat. Due to a poor level of lighting, this image is almost black, with the fragments of nature and the computer table hardly visible.

Therefore, the proposed algorithm was applied. As a result, disproportions (7) have received almost zero values for the corresponding pixels of the corresponding standards. In Fig.2, both images are quite recognizable, hence the test has passed successfully.

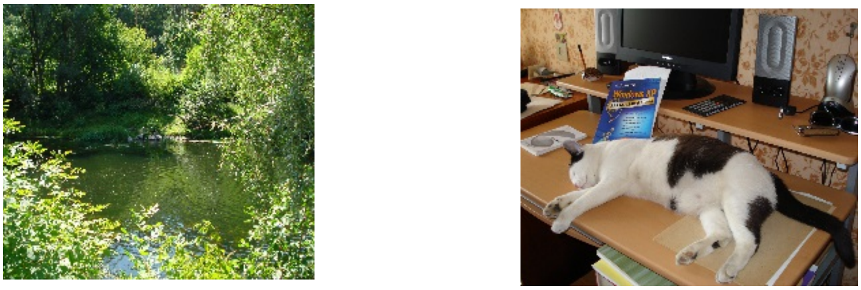

Fig. 1. The two pictures used as the standards

Fig. 2. (a) The imagees obtained before the recognition algorithm applied; (b) the final imagees after the recognition

3. The Problem's Treatment With Noise

Let us consider again the problem for only one color, for example, for the red component. If the recognition is to be realized not only under poor lighting but also in the presence of noise, then we represent the output concerning the red color component at pixel q as follows:

$$y_k(q) := r_k(q) + \eta(q),\ q = 1,\dots,N, \tag{8}$$

where $\eta = \{\eta(q) \mid q = 1,\dots,N\}$ is the array of values of signal distortures due to the transmission noise, and k denotes the number of the checked standard. Substituting expression (1) in (8) yields:

$$y_k(q) = a_k^r R_k(q) + \eta(q),\ q = 1,\dots,N. \tag{9}$$

Remember that neither the standard's number k nor the proportionality coefficient $a_k^r > 0$ is known beforehand.

Just as in the previous section, for each k = 1,2, ..., m, the disproportion function of the output $y_k = y_k(q)$

from (9) with respect to the standard (red) color intensity array $R_k = R_k(q)$ is calculated by formula (6):

$$Z_k(q) := \frac{a_k^r R_k(q) + \eta(q)}{R_k(q)} - \frac{a_k^r R'_k(q) + \eta'(q)}{R'_k(q)} = \frac{\eta(q)}{R_k(q)} - \frac{\eta'(q)}{R'_k(q)} \equiv @d_{R_k}^{(1)}\eta(q), q = 1,\ldots,N, \quad (10)$$

which coincides, by definition, with the first-order derivative disproportion of the noise function $\eta = \eta(q)$ with respect to the (red) color standard intensity distribution $R_k = R_k(q)$. The latter implies that when the noise disappears the disproportion value (10) drops to zero.

Thus, if for some pixel number q we get $Z_k(q) = 0$ $\left[\text{or, } |Z_k(q)| \le \varepsilon \text{ for the nonlinear case}\right]$, it means there is no noise and the image pixel number q corresponds to pixel q of the k-th standard.

Otherwise, whenever if $Z_k(q) \ne 0$ for all $k = 1,\ldots,m$, it may indicate either the presence of noise or the fact that the image pixel q corresponds to no standard.

However, just was mention above, the disproportion can be calculated by (10) only when the noise is smooth enough (has the first derivative). In general, the impulsive noise is not differentiable. Again, we must remember that the brightness is presented by discrete arrays. Therefore, in this case, the first-order integral disproportion of $y_k = y_k(q)$ from (9) with respect to the standard (red) color intensity array $R_k = R_k(q)$ is computed as follows:

$$J_k = @I_{R_k}^{(1)} y_k(q) =: \frac{y_k(q-1) + y_k(q)}{R_k(q-1) + R_k(q)} - \frac{y_k(q)}{R_k(q)}, \; q = 2,\ldots,N. \quad (11)$$

Thus, in the case of additive impulse noise affecting the transmission signal, integral disproportion (11) should be used instead of (10) and compared to zero, as described in Algorithm 1. However, one must remember that in the noisy case, true recognition is possible only within the (time) interval when there is no noise.

Obviously, the algorithm requires significant computational efforts, but at the same time, it allows parallelization of computing. For example, we can check multiple standards (even all of them) simultaneously.

4. The Nonlinear Case

In practice, it happens frequently that images must be recognized which are blurred not only due to poor lighting but also because of the presence of (strong enough) nonlinear noise. Nonlinear distortions may arise owing to the transmission signal passing through equipment with nonlinear statistical parameters (e.g., such as video amplifiers).

If the nonlinear behavior of the signal can be interpreted by polynomial functions then an extension of the derivative disproportion functions (DDF), namely, the sequential disproportion function defined as follows.

Definition 2. The (*sequential*) *s-disproportion function* (SDF) *of order n* of the function $y = y(t)$ with respect to $x(t)$ ($x = x(t) \ne 0$) is found after applying formula (6) s times in a row to the n-th derivative of the parametric function $(x(t), y(t))$ with getting, as a result, the desired function $@(s)@d_{x(t)}^{(n)} y(t)$.

For instance, the first-order 3-disproportion function is obtained by the formula

$$@(3)d_{x(t)}^{(1)}y(t) := @d_{x(t)}^{(1)}\left\{@d_{x(t)}^{(1)}\left[@d_{x(t)}^{(1)}y(t)\right]\right\}. \tag{12}$$

It can be easily demonstrated that the SDF of any order drops to zero whenever the functions y and x are linked by a polynomial dependence like that:

$$y(t) = a_p x(t)^p + a_{p-1}x(t)^{p-1} + \cdots + a_1 x(t),\ \forall t \geq t_0, \tag{13}$$

for any values of the coefficients $a_i,\ i = 1,\ldots,p.$

Therefore, an algorithm similar to the above-described method for the linear case can be developed for recognition of blurred images in the presence of nonlinear noises, too.

Conclusions

The paper develops algorithms based on the first-order derivative disproportion functions (DDF) aiming at the efficient image recognition by relating the output image pixel color brightness characteristics with those of a series of standards.

The algorithms prove to be efficient and robust under the poor lighting conditions and in the presence of (any) noise when transmitting the signals. The method is recommended to employ when analyzing and recognizing the photo and video images.

In the future work, the authors are to extend the concept of DDF to the sequential disproportion functions (SDF) which will allow one take into account nonlinear noises and distortions.

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