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A New Approach to Image Enhancement by Non-Linear Contrast Stretching

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***Abstract*— This paper looks at the challenge of creating new, effective ways to improve images that are intended for use in mobile applications. The purpose of this study is to improve the efficiency of enhancing images in a fully automatic mode by parameter-free image intensity transformation. This paper proposes a new approach to enhancing the image by adaptively transforming its intensity based on the analysis of brightness distribution at the boundaries of the objects of this image. To demonstrate the possibilities of this approach, new techniques of intensity transformation are proposed. The proposed techniques provide effective image enhancement without the appearance of distortion and artifacts and are focused on use in mobile applications.**

Keywords*— image enhancement, intensity transformation, contrast stretching.

I. Introduction

The major trend in virtually all areas of human activity is the ever-increasing use of mobile applications based on the real-time analysis of video information. Intensive use of technologies of image analysis requires preliminary enhancing (pre-processing) the raw images [1, 2, 3].

The need for pre-processing of source images is due to some objective reasons, the main of which are the disadvantages of the observed scenes (e.q., uneven illumination), the unfavorable conditions of shooting, the not high enough technical characteristics of the image sensor, and others [1, 2]. The effectiveness of image processing and analysis at all stages depends crucially on the quality of the initial image [2, 3, 4].

Image processing in real-time applications has several specific distinguishing features that are very important. Techniques of image pre-processing in real-time must meet the following primary requirements, namely:

- there should be a high efficiency of enhancing images for different scenes, observed objects, and any possible conditions of observation;
- pre-processing should be carried out in a fully automatic mode, without any additional interactive settings;
- computational costs should be minimal to real-time implement pre-processing in mobile gadgets with low performance.

The challenge of creating new, effective technologies to improve images through their real-time pre-processing is now particularly urgent [1, 2]. A huge amount of research has been devoted to address the task of enhancing images, but its final decision is still a very long way off [5, 6]. The most of the existing methods have significant drawbacks that limit their use to improve images in mobile applications [2, 3, 4].

This work addresses the issue of improving images in mobile applications. The purpose of this study is to improve the efficiency of enhancing images in a fully automatic mode by parameter-free image intensity transformation. To meet this challenge in this paper a new approach to enhancing the image by adaptively transforming its intensity based on the analysis of brightness distribution at the boundaries of the objects of this image is proposed.

II. Related Works

The issue of improving images has always received particular attention, and this problem is the subject of a large number of works [1, 2, 3, 5, 6]. There are now different approaches to improving images among which the most popular and widely used are ways to transform images in the spatial domain, due to the simplicity of their implementation.

The methods based on the non-inertial statistical transformations of image intensity are most often used to enhance images in real-time applications. Intensity transformation is the simplest type of conversion in a spatial domain, has low computational costs, and is very simple to implement. Intensity transformation is the simplest type of conversions in a spatial domain, highly efficient and as simple to implement, has low computational costs, and therefore is very much in demand for improving images in real-time [2, 3, 5, 6].

The most well-known and generally accepted generalized description for the technique of intensity transformation is described as [4]:

$$r = r_{\text{low}} + \left(r_{\text{upp}} - r_{\text{low}}\right) \cdot T(b), \tag{1}$$

$$0 \le r_{\text{low}} < r_{\text{upp}} \le 1, \text{ and } 0 \le b_{\min} \le b \le b_{\max} \le 1, \tag{2}$$

where b is the brightness for the current pixel in the source image B; $T(b)$ is the intensity transformation; r is the result of transforming in the current pixel; R is the transformed image; r_{low} and r_{upp} are the boundaries for the dynamic range $[r_{\text{low}}, r_{\text{upp}}]$ of possible brightness values for R.

$T(b)$ is a monotonically non-decreasing function:

$$\forall b_1, b_2 \in [b_{\min}, b_{\max}]: \text{ if } b_1 \le b_2 \Rightarrow T(b_1) \le T(b_2), \tag{3}$$

which, as assumed, is to satisfy the following conditions:

$$0 \le T(b) \le 1 \, \forall b \in [b_{\min}, b_{\max}], \; T(b_{\min}) = 0 \wedge T(b_{\max}) = 1. \tag{4}$$

In doing so, it is most often assumed that $r_{low} = 0$ and $r_{upp} = 1$, and definition (1), respectively, takes the form:

$$r = \begin{cases} 0, & \text{if } b < b_{min}, \\ T(b), & \text{if } b_{min} \le b \le b_{max}, \\ 1, & \text{if } b_{max} < b. \end{cases} \quad (5)$$

Without loss of generality, taking into account (3), suppose that T(b) is an integral transformation that has the form:

$$T(b) = k \cdot \int_{b_{min}}^{b} t(x)\, dx\,, \quad (6)$$

where $t(b)$ is the distribution density (the increment) for $T(b)$ $(t(b) \ge 0)$; k is scaling factor, which is determined from conditions (4):

$$k = \left[\int_{b_{min}}^{b_{max}} t(x)\, dx \right]^{-1}. \quad (7)$$

The most popular intensity transformations usually belong to three best-known groups [3, 4], namely to core transformations of intensity, piecewise linear stretching techniques, and histogram matching-based techniques.

The core transformations of the image intensity are widely known [2, 3, 4], and their capabilities and features are well studied. Their effectiveness depends on the distribution of brightness and the parameters of conversion, which are typically set interactively [4].

Known techniques of linear stretching [3, 5] are based on the assumption that the increment $t(b)$ is piecewise constant function (or step function) with finitely many pieces and can be presented as a finite linear combination of indicator functions of intervals of brightness range:

$$t(b) = \sum_{i=1}^{N} \alpha_i \chi_i(b) \forall b \in [0,1], N \ge 1\,, \quad (8)$$

where α_i are constants, real numbers; N is the finite number of sub-intervals of brightness scale; $\chi_i(b)$ are indicator functions, where:

$$\chi_i(b) = \begin{cases} 1, & if\ b \in S_i \\ 0, & if\ b \notin S_i \end{cases}, \quad i = \overline{1, N} \quad (9)$$

where S_i is the i-th sub-interval (sub-range) of brightness scale ($1 \le i \le N$).

Suppose that $N = 3$ and the increment $t(b)$ has the form:

$$t(b) = \begin{cases} 0, & \text{if } b \le b_{low} \\ \dfrac{1}{b_{upp} - b_{low}}, & \text{if } b_{low} < b < b_{upp} \\ 0, & \text{if } b \ge b_{upp} \end{cases}, \quad (10)$$

where b_{low} and b_{upp} the boundaries for the interval $[b_{low}, b_{upp}]$ of dynamic range.

Based on (10), the transformation $T(b)$ (6) can be defined as:

$$r = T(b) = \begin{cases} 0, & \text{if } b \le b_{low} \\ \dfrac{b - b_{low}}{b_{upp} - b_{low}}, & \text{if } b_{low} < b < b_{upp} \\ 1, & \text{if } b \ge b_{upp} \end{cases}. \quad (11)$$

The best-known technique from this group is the min-max contrast stretching, in which $b_{low}=b_{min}$ and $b_{upp}= b_{max}$ [4].

Another well-known and popular technique is the percentile contrast stretching in which the values b_{low} and b_{upp} are determined from the conditions [3, 4]:

$$F(b_{low}) = \int_0^{b_{low}} f(x)dx = \varepsilon,$$
$$F(b_{upp}) = \int_0^{b_{upp}} f(x)dx = 1 - \varepsilon. \quad (12)$$

where $f(b)$ is probability density function (pdf); $F(b)$ is cumulative distribution function (CDF).

At known techniques of piecewise-linear stretching [4, 5], the brightness range is subdivided into a higher number of intervals ($N > 3$). In the case when $N = 4$, the increment $t(b)$ can be presented as:

$$t(b) = \begin{cases} 0, & \text{if } b < b_{low} \\ \dfrac{\alpha_2}{b_{tr} - b_{low}}, & \text{if } b_{low} \le b \le b_{tr} \\ \dfrac{1 - \alpha_2}{b_{upp} - b_{tr}}, & \text{if } b_{tr} \le b \le b_{upp} \\ 0, & \text{if } b > b_{upp} \end{cases}, \quad (13)$$

where b_{tr} is the threshold value of brightness ($b_{low} < b_{tr} < b_{upp}$); α_2 is gain factor, parameter ($0 < \alpha_2 < 1$) [6].

For distribution (11), $T(b)$ is equal to :

$$T(b) = \begin{cases} 0, & \text{if } b < b_{low} \\ \alpha_2 \cdot \dfrac{b - b_{low}}{b_{tr} - b_{low}}, & \text{if } b_{low} \le b \le b_{tr} \\ \alpha_2 + (1 - \alpha_2) \cdot \dfrac{b - b_{tr}}{b_{upp} - b_{tr}}, & \text{if } b_{tr} \le b \le b_{upp} \\ 1, & \text{if } b > b_{upp} \end{cases}. \quad (14)$$

Most often, it is assumed that $b_{tr} = b_{mean}$ and $\alpha_2 = ½$ [6].

The critical issue in implement the piecewise linear stretching is to choosing boundaries of intervals and the values of constant α_i [1, 2].

To implement the piecewise linear stretching, we propose a new technique based on the analysis of the existing brightness values that are present in the image.

To that end, we propose to define the increment $t(b)$ as:

$$t(b) = \begin{cases} 0, & \text{if } f(b) = 0 \\ 1, & \text{if } f(b) > 0 \end{cases}. \quad (15)$$

In general, given the presence of noise in the image, the increment can be defined as:

$$t(b) = \begin{cases} 0, & \text{if } f(b) < \theta \\ 1, & \text{if } f(b) \ge \theta \end{cases}, \quad (16)$$

where θ is the threshold value.

Definitions (1), (6), and (16) are a description of the proposed technique of piecewise linear stretching.

The histogram matching (or mapping) is a statistical no-inertial transformation in which the distribution of brightness is converted into a given shape [7]. Equalization [4, 6, 7] is a particular case of the procedure of matching, in which the brightness distribution becomes uniform.

For histogram equalization we have that:

$$t(b) = f(b)\,. \tag{17}$$

In this case (17), we can define the histogram equalization as [4]:

$$r = T(b) = \int_0^b t(x)\,dx = \int_0^b f(x)\,dx = \Pr\{\,B \le b\},\tag{18}$$

where Pr { · } is probability of an event.

Histogram equalization is a high efficiency, a simplicity to implement, and has a low computational cost. However, it has several disadvantages.

The well-known and very significant drawbacks of histogram equalization based techniques are a decrease in the contrast of objects with small sizes, an excessive increase in the contrast of extended objects, and, as a consequence of this, the possible appearance of unwanted artifacts and distortions in the image.

To address these disadvantages, the equalization of the clipped histogram (clipped HE) is applied [3, 4], where:

$$t(b) = \min(f(b), \theta) = \begin{cases} f(b), & if\ f(b) \le \theta \\ \theta, & if\ f(b) > \theta \end{cases}.\tag{19}$$

Another known technique [3, 4] is the power-law intensification of the histogram (power-law HE), for which:

$$t(b) = f(b)^{\gamma} \Big/ \int_0^1 f(x)^{\gamma}\,dx\,,\tag{20}$$

where γ is the exponent, parameter.

The challenge of developing new, effective technologies to improve images through non-linear intensity transformations is now particularly urgent.

III. Proposed Technique

This paper looks at the challenge of creating new, effective ways to improve images that are intended for use in mobile applications.

The purpose of this study is to improve the efficiency of enhancing images in a fully automatic mode by parameter-free image intensity transformation. To meet this challenge in this paper proposes a new approach to enhancing the image by adaptively transforming its intensity based on the analysis of brightness distribution at the boundaries of the objects of this image.

The proposed approach is based on the assumption that T(b) is an integral transformation that has the form:

$$T(b) = \beta \cdot \int_{b_{\min}}^{b} \mu_t(b_{\min}, x)\cdot \mu_t(x, b_{\max})\,dx\,,\tag{21}$$

where $\mu_t(b_1, b_2)$ is the assessment of the density of increment $t(b)$ in the interval $[b_1, b_2]$ ($b_1 < b_2$):

$$\mu_t(b_1, b_2) = \begin{cases} \int_{b_1}^{b_2} t(x)\,dx \Big/ \int_{b_1}^{b_2} dx, & \text{if } b_1 < b_2\,, \\ 0, & \text{otherwise} \end{cases}\tag{22}$$

and β is the normalizing factor, which is defined as:

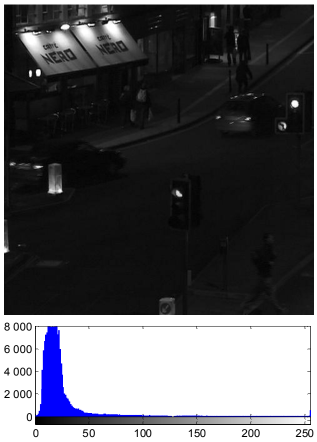
$$\beta = \left[\int_{b_{\min}}^{b_{\max}} \mu_t(b_{\min}, y)\cdot\mu_t(y, b_{\max})\,dy\right]^{-1}.\tag{23}$$

Definitions (21)-(23) describe the proposed approach to enhancing the image by adaptively transforming its intensity.

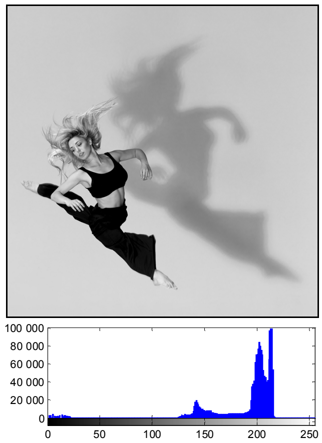
In the proposed approach (21)-(23), as the estimates of increment $t(b)$, may use the assessments (16)-(20).

IV. Research

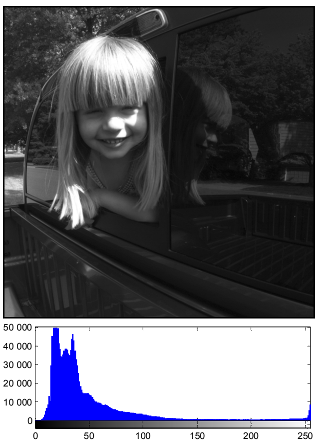
This study is based on the results of assessing contrast for four groups of images using different metrics. Each from the four groups is formed by converting the corresponding source image using selected methods of processing it. Four raw source images and their histograms are shown in Fig. 1.



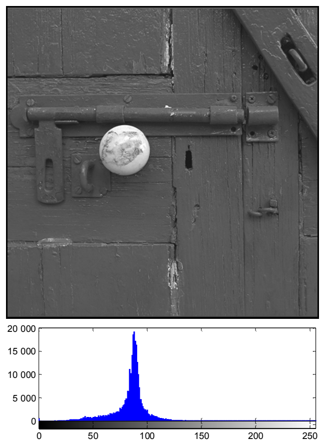
(2.0) image 1, 496×492 pixels.



(3.0) image 2, 1391×1393 pixels.



(4.0) image 3, 1312×1312 pixels.



(5.0) image 4, 512×512 pixels.

Fig. 1. The appearance of test images and their histograms.

To improve the images by converting their intensity, the known methods and proposed techniques were used:

(a) min-max stretching (11) [4, 5];
(b) percentage linear stretching (11), (12) [3, 4];

(c) proposed stretching for nonzero brightness (16);
(d) piecewise-linear stretching (14) [3, 4, 5];
(e) global histogram equalization (18) [6, 7] ;
(f) clipped histogram equalization (19) [3, 4];
(g) power-law histogram equalization (20) [3, 4];
(h) proposed technique (21)-(23) using (17);
(i) proposed technique (21)-(23) using (19);
(j) proposed technique (21)-(23) using (20).

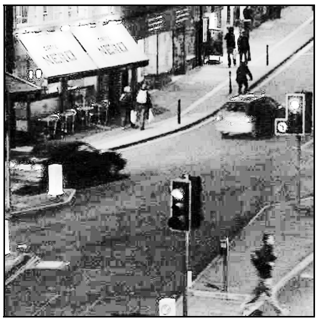
The results of processing the raw source images (Figure 1) are shown in Figures 2, 3, 4 and 5.

(2.1) min-max stretching.

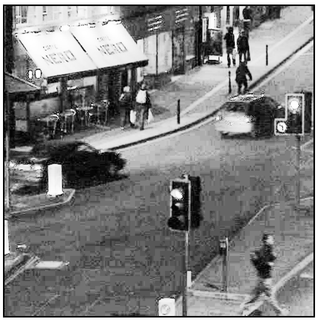
(2.2) percentile stretching.

(2.3) proposed stretching (16).

(2.4) piecewise linear stretching.

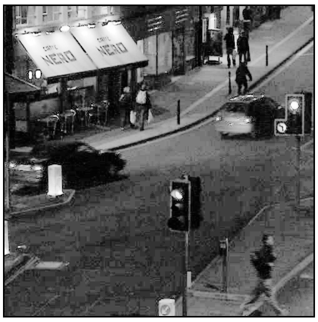


(2.5) global HE.



(2.6). clipped HE.

(2.7). power-law HE.



(2.8) proposed (21)-(23) using (17).

(2.9) proposed (21)-(23) using (19).

(2.10) proposed (21)-(23) using (20).

Fig. 2. Image processing results

(3.1) min-max stretching.

(3.2) percentile stretching.

(3.3) proposed stretching (16).

(3.4) piecewise linear stretching.

(3.5) global HE.

(3.6). clipped HE.

(3.7). power-law HE.

(3.8) proposed (21)-(23) using (17).

(3.9) proposed (21)-(23) using (19).

(3.10) proposed (21)-(23) using (20).

Fig. 3. Image processing results.

(4.1) min-max stretching.

(4.2) percentile stretching.

(4.3) proposed stretching (16).

(4.4) piecewise linear stretching.

(4.5) global HE.

(4.6). clipped HE.

(4.7). power-law HE.

(4.8) proposed (21)-(23) using (17).

(4.9) proposed (21)-(23) using (19).

(4.10) proposed (21)-(23) using (20).

Fig. 4. Image processing results.

(5.1) min-max stretching.

(5.2) percentile stretching.

(5.3) proposed stretching (16).

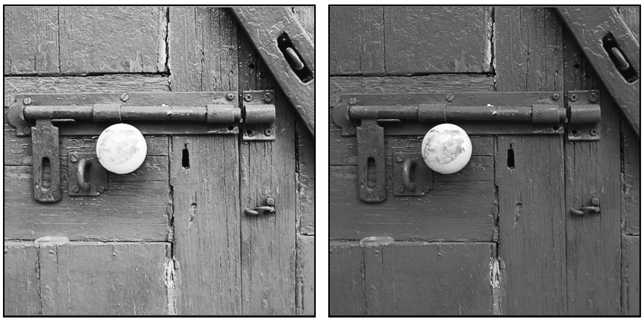
(5.4) piecewise linear stretching.

(5.5) global HE.

(5.6). clipped HE.

(5.7). power-law HE.

(5.8) proposed (21)-(23) for (17).



(5.9) proposed (21)-(23) for (19). (5.10) proposed (21)-(23) using (20).

Fig. 5. Image processing results.

To measure the global image contrast, the following metrics were used:

1) generalized contrast [8]:

$$C_{gen} = \int_0^1 \int_0^1 |x - y| f(x) f(y)\, dxdy\ , \tag{24}$$

2) incomplete integral contrast [8]:

$$C_{inc} = \int_0^1 |x - b_{mean}| f(x)\, dx\ , \tag{25}$$

3) root mean square (RSM) [4],

4) squared deviations between brightness values (DEV):

$$\mathrm{DEV} = \left[\int_0^1 \int_0^1 (x - y)^2 f(x) f(y)\, dxdy \right]^{1/2} . \tag{26}$$

The results of the studies using the above metrics of contrast are shown in Figures 6, 7, 8 and 9.

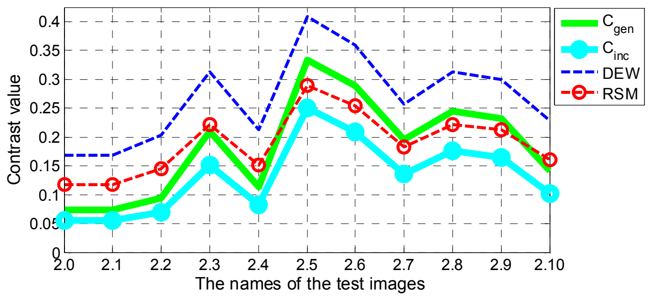


Fig. 6. Contrast of images from the first group (Figures 1 and 2).

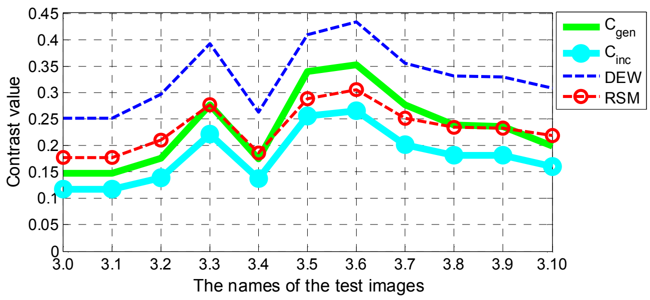


Fig. 7. Contrast of images from the second group (Fig. 1 and Fig. 3).

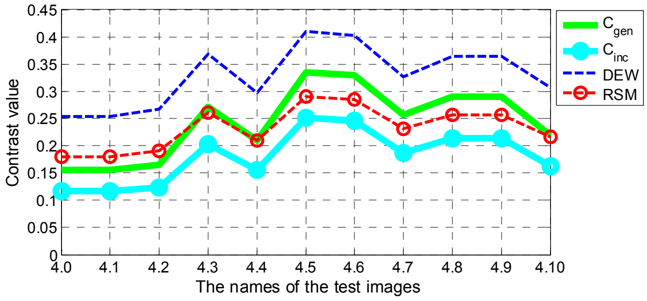


Fig. 8. Contrast of images from the third group (Fig. 1 and Fig. 4).

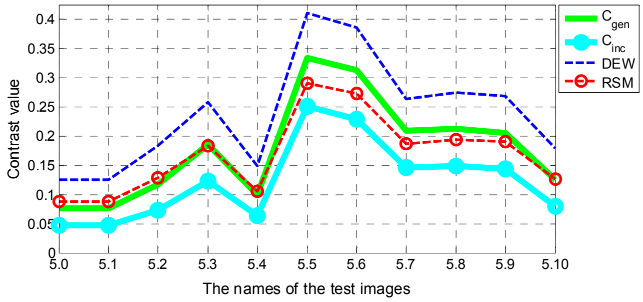


Fig. 9. Contrast of images from the fourth group (Fig. 1 and Fig. 5).

V. Discussion

The results of the studies confirm the well-known fact that methods of min-max and percentile stretching are ineffective to enhance images with a full dynamic range (Figures 2.1, 2.2, 4.1, 4.2).

The results of piecewise linear stretching (14), (16) and gamma correction are determined by the distribution of brightness and the values of the parameters of transformation (Figures 2.4, 3.3, 3.4, 5.4).

Histogram equalization based methods are most effective for increasing image contrast (Figures 2.5 - 2.7 and 4.5 - 4.7). The well-known and very significant drawbacks of these methods are a decrease in the contrast of objects with small sizes, an excessive increase in the contrast of extended objects, and, as a consequence of this, the possible appearance of unwanted artifacts and distortions in the image (Figures 3.5, 3.6, 5.5 and 5.6).

Research shows that the proposed techniques allow us to increase contrast by an average of 64-122% for all the raw images (Figures 6, 7, 8 and 9) without the appearance of unwanted artifacts and distortions (Figures 2.8, 2.9, 3.8, 3.9, 4.8, 4.9, 5.8, 5.9).

VI. Conclusions

The purpose of this study is to improve the efficiency of enhancing images in a fully automatic mode by parameter-free image intensity transformation.

In this work, a new approach to enhancing the image by adaptively transforming its intensity was proposed based on the analysis of brightness distribution at the boundaries of the objects of this image. To demonstrate the possibilities of this approach, new techniques of intensity transformation were proposed. Various approaches to assessing the increment of the function of intensity transformation had been considered.

The proposed techniques provide effective image enhancement without the appearance of distortion and artifacts and are focused on use in mobile applications.

These techniques can be considered as an alternative to traditional histogram equalization.

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