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Texture Based Image Enhancement Using Gamma Correction

Sekineh Asadi, Hamid Hassanpour and Ali Akbar Pouyan

Department of Computer Engineering, Shahrood University of Technology, Shahrood, Iran

Abstract: The lack of reliable model of image enhancement motivates the search for new methods to automatically enhance the quality of images. This paper presents a new automatic method based on Gamma correction for image enhancement without prior knowledge about its distortion. The system presented in this paper applies the concepts of texture mask. Experimental results demonstrate that the proposed method has a good performance on improving the quality of displayed digital images.

Key words: Image enhancement · Gamma correction · Texture mask

INTRODUCTION

One of the most important factors that directly affect the performance reliability of many computer vision systems is the luminance incident on the scene. For example in face recognition systems, the algorithms may fail to recognize faces correctly due to changes in illumination [1]. These illumination usually have a nonlinear effect on the pixel values of the images [2]. Many devices used for capturing, printing or displaying the images generally apply a transformation, called power-low [3], on each pixel of the image that has a non-linear effect on luminance:

$$s = cr^{\gamma} \tag{1}$$

In the above equation r ε [0, 1] denotes the image pixel intensity, c is a positive constant related to the device, γ is a positive constant introducing the gamma value and s is the pixel intensity output of the device.

By assuming a uniform gamma value for all regions in the image and using Eq. (1) the luminance nonlinearity can be described as a simple point-wise operation of the form [4]:

$$g(u) = u^{\gamma} \tag{2}$$

Where u ε [0, 1] denotes the image pixel intensity. By this assumption, the value of γ typically can be determined experimentally, by passing a calibration target with a full range of known luminance values through the imaging device. When the value of γ is known, inverting this process is trivial:

$$g^{-1}(u) = u^{1/\gamma} \tag{3}$$

A number of gamma correction methods are implemented in the form of real-time hardware devices. They apply calibration parameters to image pixels before saving the output of the sensor [5, 6].

But often such calibration is not available or direct access to the imaging device is not possible, for example when downloading an image from the web. In addition, most commercial digital cameras dynamically vary the amount of gamma. Hence an algorithm is needed to reduce the effects of these nonlinearities, without any knowledge about the imaging device [4].

There are a few recently published papers to determine a gamma value for offline images. In [4] a blind inverse gamma correction technique was developed exploiting the fact that gamma correction introduces specific higher-order correlations in the frequency domain. In that approach the gamma values between 0.1 and 3 are applied to image pixels in 128 × 128 windows and the best gamma value is the value that minimizing those higher order correlations. But unfortunately this method is time consuming and has limited success.

In this paper we present a technique for estimating the gamma value without any calibration information or knowledge of the imaging device. To determine the gamma value for a given image, we use texture mask. We will show that when an image is gamma corrected, its texture mask is more visible. The amount of gamma is estimated by applying a range of inverse gamma values between 0.1 and 3 in increments of 0.1 and selecting the gamma value that maximizes the sum of texture values.

Corresponding Author: Sekineh Asadi, Department of Computer Engineering, Shahrood University of Technology, Shahrood, Iran.
E-mail: asadi_amiri@yahoo.com.

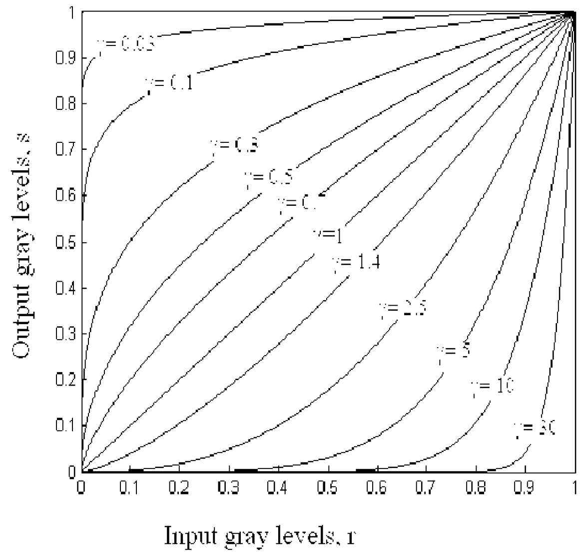
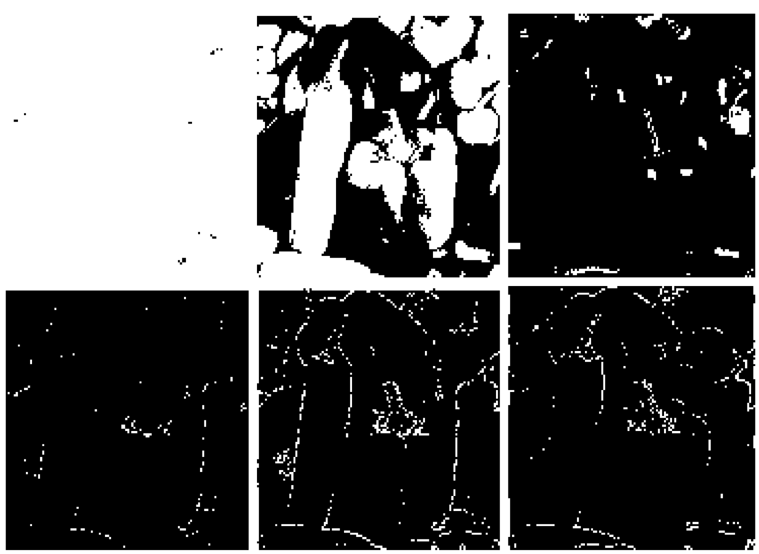


Fig. 1: Plot of the Eq.1 for various values of γ (c=1 in all cases).

a) λ=0.2 b) λ=1 (original image) c) λ=2.8

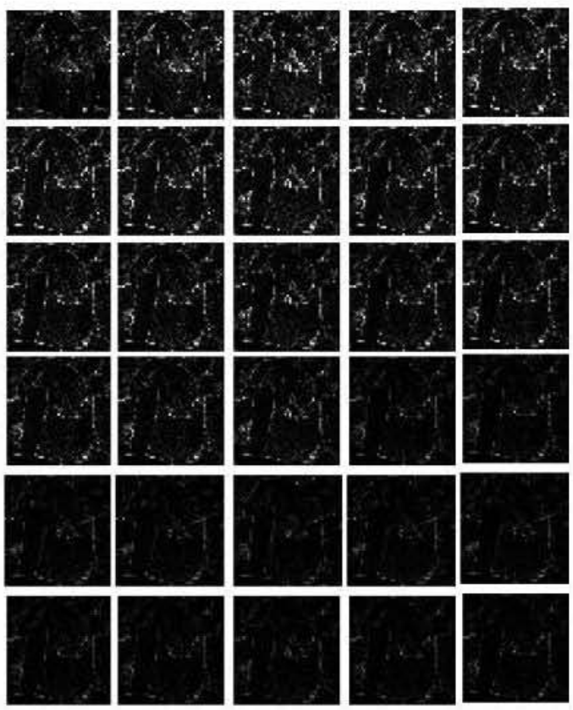
Fig. 2: Example of an image in three different gamma conditions



a) λ=0.2 b) λ=1 (original image) c) λ=2.8

Fig. 3: Texture masks of three different gamma condition images.

a) Input image



b) Thirty different gamma conditions of input image.

c) Thirty different texture masks of (b)

Fig. 4: Thirty different gamma condition images and their texture masks.

Gamma Correction and Texture Mask: Fig. 1 shows plot of s versus r for various γ values in Eq. 1. As can be conceived from the plot, when the amount of γ is less than one, the transformed image becomes lighter than the original image; see Fig. 2(a) and when the amount of γ is greater than one, the transformed image becomes darker than the original image; see Fig. 2(c). But when the gamma value is one, no change will happen; see Fig. 2(b).

As it can be seen in Fig. 2, details in original image are more obvious than the others. Hence, we need a feature to show details. We empirically find that texture mask is a good feature to show image details.

We use the texture mask that has been proposed in [7]. It uses the absolute value of the distance between each pixel and local average value within the sliding window as the mask, as shown in Eq. (4). The size of sliding window is still 3×3.

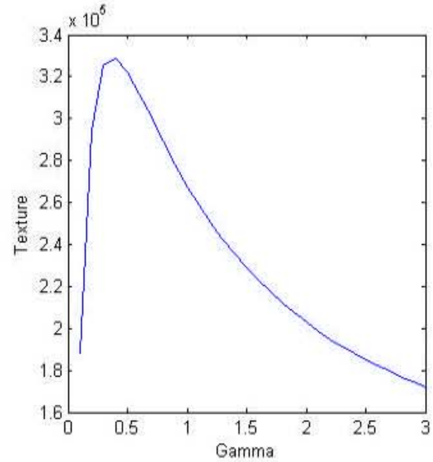
$$M_T = \left| x(i,j) - \bar{x}(i,j) \right| \tag{4}$$

$$\bar{x}(i,j) = \frac{2}{(2L+1)^2} \sum_{k=-L}^{L} \sum_{l=-L}^{L} x(i+k, j+l) \tag{5}$$

Where, x(i,j) is the pixel at the position (i,j). M_T is the texture mask; $(2L+1)^2$ represents the number of pixels in the image block.

a) Input image

c) Gamma corrected image



b) Diagram of total texture mask values for thirty different inverse gamma images. The peak point reaches a unique maximum in $\gamma^{-1} = 0.4$.

Fig. 5: An example of proposed method.

In Fig. 3, the texture mask results of three different gamma condition images are shown. As we can see the highly textured regions in the original image (Fig. 3 b) are more obvious.

Proposed Method: The goal of the present research is to predict the gamma value of an input image without any calibration information or knowledge of the imaging device. In the proposed method, first we apply a range of inverse gamma values between 0.1 and 3 in increments of 0.1 to an input image (Fig. 4 b). Hence, we have thirty images with different gamma conditions.

We compute the texture mask of each image according to Eq. (4) (Fig. 4 c) then sum up the values of each texture mask and select the gamma value that has maximum summation.

In practice this simple search strategy is effective because the function being maximized is typically well-behaved, i.e., contains a single maximum. This is illustrated in Fig. 5(b), where the texture mask values are plotted as a function of varying inverse gamma values. In Fig. 5(a), an input image has been damaged with the gamma of 0.4. First we apply thirty different inverse gamma values between 0.1 and 3 in increments of 0.1. and compute the texture mask for each image, then sum up the texture values. Note that the resulting value reaches a unique maximum in λ^{-1}=0.4 (Fig. 5 b). So according to Eq. (3) by applying this gamma value to input image, the enhanced image will be achieved (Fig. 5 c).

Experimental Results: In this paper we present a technique for estimating the gamma values without any calibration information or knowledge of the imaging device. We have shown that, the gamma value can be estimated by simply maximizing the texture mask values. Our proposed algorithm was applied on different images with different gamma conditions. Although in this paper

a) Original image b) proposed method c) method proposed in [4]

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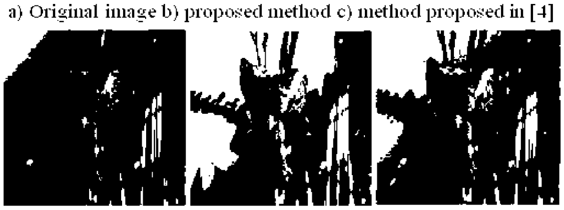

a) Original image b) proposed method c) method proposed in [4]

Fig. 6: Comparison between the proposed method and the method proposed in [4].

gray scale images were used, this technique is easily applicable for color images. For a multichannel color image, the gamma for each channel can be individually estimated as described here. First in Fig. 6, we give a comparison between the method of [4] and our proposed method for different gamma condition images.

Fig. 7 gives a comparison between the method of [4] and our proposed method for the input images with the good gamma conditions. The results show that the method of [4] may change the gamma incorrectly when the image has a good gamma condition while our method doesn't change such an image (choose the value near one for the gamma). Although our proposed method estimates the gamma value more accurately for most of the input images.

a) Original image b) proposed method c) method proposed in [4]

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Fig. 7: Comparison between the proposed method and the method proposed in [4] for good gamma condition images.

CONCLUSION

We have introduced a new gamma correction method that estimates gamma value without any calibration information or knowledge of the imaging device. In this proposed method, we assumed that the gamma correction is applied uniformly throughout the image. We will also investigate local gamma correction method that will require a more sophisticated inversion technique.

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