No Reference Measurement of Contrast Distortion and Optimal Contrast Enhancement

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Abstract

In this paper, a novel histogram-based model for contrast enhancement is proposed. Based on our analysis about the relationships of histogram with contrast, we establish a model which 1) achieves contrast enhancement by an optimal transform of histogram, 2) gives two metrics called contrast gain and nonlinearity of transform to measure the strength of enhancement and the seriousness of distortion caused by enhancement respectively. The ratio of the two proposed metrics not only gives a guidance for the configuration of parameter in the algorithm, but also provides a useful measurement for contrast distortion, which can be a potential solution to judge whether the contrast of an image is optimal. Experimental results show the superior performances of the proposed algorithm in image enhancement.

1. Introduction

With the development of information technology, billions of digital images are created by cameras, scanners and computers every day. During capturing, the contrast of image can be degraded by undesirable illuminant and bad weathers, so contrast enhancement is highly required for better visual perception and interpretation of the scene in many situations.

Currently, contrast enhancement algorithms can be classified into two classes from the viewpoint of methodology. The first kind of methods is based on spatial filtering. By preserving the low-frequency component with amplifying the high-frequency part, these methods achieve local contrast enhancement and make the details of image more impressive. Besides traditional bilateral filter and non-local means [2], the guided filter in [7] and the weighted least square filter in [5] also get outstanding results. In [8], the high-frequency part is directly increased by fractional differential filter.

The other class is histogram-based method. Compared with filtering-based method, histogram-based method is more widely used in global contrast enhancement and tone mapping because of the low computational complexity. The most common used method is histogram equalization (HE). Based on HE, many variant algorithms have been proposed in [4, 9, 3, 1, 11, 6].

Although so many algorithms for image enhancement have been proposed, the criterion of optimal contrast is still absent. Because of this awkward problem, most of the enhancement algorithms seem to be empirical in the configuration of parameters, which leads to the lack of adaptivity and robustness. Another problem is the difficulty of measuring contrast distortion. In
[10], an objective metric called SSIM is proposed and achieve good performance. But in practical the original ideal image is not available. Given an image, how to know whether its contrast is optimal, or how serious its contrast distortion is? Given a algorithm, how to measure its performance on contrast enhancement?

We generalize traditional HE model and propose a blind metric for contrast distortion. We propose the definitions for contrast gain and nonlinearity of transform, and use the ratio of them to measure the enhancement result. The proposed model provides a guidance for parameter selection of algorithm and image contrast measurement.

2. Extension of Traditional Equalization

Consider an image \( f \) whose available dynamic range is \([0, L]\). The histogram of \( f \) can be represented by \( H = \{h, p\} \). \( h \in R^K \) represented the total \( K \) intensity levels with the corresponding probability vector \( p \in R^K \) in the histogram. \( K \) is the number of intensity level whose probability value is non-zero. The distance between adjacent intensity levels whose probability value are non-zero is \( s_k = h_k - h_{k-1}, \ k = 2, ..., K, \ s_1 = h_1 \), which can also be expressed as a vector \( s = \nabla h \). \( \nabla \) represents derivation operator.

In [11], the expected context-free contrast of \( f \) is defined by

\[
C(H) = p^T s. \tag{1}
\]

By maximizing \( C(H) \), the strongest contrast is achieved. This is a linear programming whose solution is sparse - to the maximum probability \( p_i \), the corresponding \( s_i = L \) and other \( s_k = 0 \), which is questionable. Although (1) has obvious statistical meaning, it is not optimal as an objective function of contrast enhancement directly.

Before the work in [11], the most common used enhancement method is HE. Using this method, the \( i \)th the distance between adjacent intensity levels of new image, \( \hat{s}_i \), can be expressed as \( \hat{s}_i = h_i - h_{i-1} = C p_i \), \( C \) is a constant, which is equivalent to solving following optimization problem.

\[
\hat{s} = \arg \min_s \| \mathbf{P}^{-1} s \|_{\infty}, \tag{2}
\]

\[
s.t. \quad \| s \|_1 = L, \quad s_i > d.
\]

Here \( \mathbf{P}^{-1} = \text{diag}(p_1^{-1}, ..., p_K^{-1}) \). The first constraint makes sure that the output image has a suitable dynamic range and the second constraint defines the minimum distance between adjacent gray levels. However, the effect of HE is not optimal because of the unreasonable assumption that the histogram of ideal image obeys uniform distribution.

According to the analysis of (2), we find that under the same constraints, the strength of enhancement is controlled by the order of \( \mathbf{P} \). By introducing a new parameter \( q \) in the objective function, we can get a new optimization problem, as

\[
\hat{s} = \arg \min_s \| \mathbf{P}^{-q} s \|_{\infty}, \quad \text{s.t.} \quad \| s \|_1 = L, \quad s_i > d. \tag{3}
\]

Moreover, we introduce three metrics, the gain of expected context-free contrast, the nonlinearity of the histogram transform and the ratio of them, which are defined as

\[
G(q) = \frac{p^T \hat{s}}{p^T \hat{s}}, \quad \text{NL}(q) = \| \nabla (\hat{s} - \bar{s}) \|_2, \quad F(q) = \text{NL}(q) / |G(q) - 1|. \tag{4}
\]

Here \( \bar{s} \) is the original distance between adjacent intensity level, and \( c \) is a constant. These three metrics and (3) compose the proposed model. Here we assume that the transform for contrast enhancement is nonlinear so that we can exclude the transform having \( \text{NL} = 0 \).

3. Measurement of Contrast

If \( d = 0 \), the solution of (3) has closed form expression as

\[
\hat{s} = \frac{L}{\sum_{i=1}^K p_i^q [p_1^q, ..., p_K^q]^T}, \tag{6}
\]

\[
G = \frac{L}{\text{Corr}(H)} \| \mathbf{p}^q \|_1, \quad \text{NL} \approx \frac{L}{\| \nabla \mathbf{p}^q \|_2} \| \mathbf{p}^q \|_1. \tag{7}
\]

Here, \( \text{Corr}(H) \) is the expected contrast of original image. We can assume \( p_i \leq p_{i+1}, i = 1, ..., K \), without loss of generality. When \( q = 0 \), we have \( \mathbf{P}^{-q} s = s \), the \( l_\infty \) ball is centrosymmetric. In such situation, the optimal solution of (3) is reached as \( s_i = \frac{L}{K} \). When \( q > 0 \), the \( l_\infty \) balls become axial symmetric and the optimal points move from the center of the feasible domain to its boundary \( L = [0, ..., 0, L, 0, ..., 0]^T \). The label of \( L \) corresponds to the maximum of histogram \( p_{max} \). Moreover, if we denote the second maximum of histogram as \( p_{max} \), the rate of convergence to \( L \) can be expressed as

\[
Q_\infty = \lim_{q \to \infty} \| s_{q+1} - L \|_2 / \| s_q - L \|_2 = \frac{p_{max}^2}{p_{max}}. \tag{8}
\]

At the same time, the nonlinearity of transform \( \text{NL} \) and the contrast gain \( G \) also increase with \( q \).

Generally, with the increase of contrast gain, the contrast of image is enhanced. However, the nonlinearity...
Figure 2. (a,b,c) the curves of G, NL and F. (d) gives results gotten under different q values. q = 0.72 is optimal to the test image.

of transform become large at the same time, compa-
ring with the high risk of serious contrast distortion. We hope to choose an optimal value for q so that the transform has high contrast gain and low nonlinearity.

To find a criterion for the configuration of parameter, we select 400 images randomly from Internet and enhance them with different qs. We plot the curves of their G, NL and F respectively and find that although G and NL increase monotonously with q, F has a minimum. Figure 2 gives an example to illustrate the interesting phenomenon. The optimal value of q in our model is gotten by

\[
\hat{q} = \min_q F(q) \approx \min_q \frac{\|\nabla p\|_2^q \|p^q\|_1^{1-c} - \frac{C_{\text{opt}}}{L} \|p^q\|_1}{\|p^q\|_1}, \quad (9)
\]

which means that the nonlinearity of transform is small enough while the contrast gain is large enough. Figure 2(d) gives different enhancement results with different selections of q. Compared with other configurations, the enhancement result corresponding to \(\hat{q}\) has the best visual effect.

This feature is used to judge whether an image needs to be enhanced and how close its contrast is to the optimal one. Define contrast distortion as \(D\), which measures the bias between original contrast and the optimal one. We use following simple strategy to measure the \(D\) of image and enhance contrast optimally.

It is obvious that \(D \in [0, 1]\). The closer \(D\) is to 1, the better the contrast of original image is. Otherwise, applying our model can enhance the contrast of image and improve its visual effect greatly.

4. Experimental Results

4.1. Optimal Contrast Enhancement

For demonstrating the rationality of the proposed method, we design an experiment to test whether the enhancement result corresponding to the optimal parameter achieves the best visual effect. In the experiment, 6 images are given simultaneously in a screen, including the original image from Berkeley Segmentation Dataset(BSDS300), the result with \(\hat{q}\) and 4 results with random selected qs \(\in [0, 1]\). The images are sorted randomly. Each volunteer selects the image that he thinks has the best contrast. The experiment is stopped when the volunteer does not want to continue.

We conducted subjective test in which 50 volunteers were involved. The average number of images evaluated by each volunteer is 31.3. The probability that volunteers select the image corresponding to the optimal parameter (i.e. the exact image which has the best contrast) is 65.8%. And the error between \(\hat{q}\) and the q selected subjectively (\(\sqrt{\frac{1}{N} \sum_i^N (q_i - \hat{q}_i)^2}\)) is 0.237, which is small. Therefore, in most situations, the enhancement results of the proposed method match with our subjective test.

The proposed method can be used in the intensity channel of HSV space individually or in the RGB channels respectively. When it is used in RGB space, the experimental results in Figure 1 show that the proposed method not only achieves outstanding contrast enhancement results but also shows the power of tonal adjustment. We also give a comparison result among the proposed method and other existing methods in Figure 3. According to the experimental results, the proposed method achieves the best overall visual effect. The contrast distortions of the results of different methods are measured as well. We find that the visual effect of the results fits the measurement results, which partially proves the feasibility of the proposed method.

Initialization:
0. Give \(L = 255, d = 0.6, c = 25\) in our work.
Enhancement:
1. For input image \(f_{\text{in}}\), calculate \(C_{\text{in}}\).
2. Solve (9) to get optimal \(\hat{q}\).
3. Apply (3) with \(\hat{q}\) to get enhancement result \(f_{\text{out}}\).
4. Calculate \(C_{\text{out}}\).
Measurement:
5. \(D = \min\{\frac{C_{\text{in}}}{C_{\text{out}}}, \frac{C_{\text{out}}}{C_{\text{in}}}\}\).
4.2. Measurement of Contrast Distortion

For further demonstrating the usefulness of the proposed method, we test our metric on two image data set: the Kodak data set (http://r0k.us/graphics/kodak/). The contrast distortion of each image is listed in Table 1. We find that some Kodak’s images have little contrast distortion. While some papers about contrast enhancement algorithms [1, 11] evaluated the images of Kodak as original ones, we suggest the researchers on this area shall build an even better set than Kodak data set. It is of course our future work as well.

5. Conclusion

In this paper, we establish a contrast enhancement model which not only provides an optimal enhancement method but also gives a potential solution to the measurement of contrast distortion. This method has low computational complexity and achieves good visual effect. Currently, the psychovisual rationality of our model is not very clear. A psychovisual explanation will improve our model further.

Table 1. D of Kodak’s Images

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References