Two-layer Image Contrast Enhancement in Perceptual Domain

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Abstract—Image contrast enhancement is an old but still attractive topic in image processing applications. Most operators are capable of producing visually pleasing results by interactive adjustment. However, most interactive based methods need to jointly manipulate multiple parameters to achieve a distortion-free and visually pleasing output, which require a number of trials or a certain level of knowledge/experience. In this paper, we present a new algorithm to simplify the image contrast enhancement interactivity. A contrast perception model, which unifies human contrast perception characteristics with four visual factors, is adapted in the algorithm. The four factors include physical contrast and frequency of the contrast signal, the background brightness, and a distance value that indicates how close the signal is to eye-gaze point, or visual eccentricity. The coefficients of the image enhancement are assigned based on the contrast perception model and a perceptual enhancement level parameter. Users can adjust the single perceptual enhancement value to achieve realistic image enhancement results. Experimental results demonstrated the performance of the proposed image contrast enhancement algorithm.

I. INTRODUCTION

For most image enhancement applications, the aim is to improve the interpretability or perception of information in images for human viewers. Contrast is one of the most important features to human eyes. They reflect the boundary and surface characteristics of objects, and play an important role in distinguishing one object from others. Owing to this importance, many image contrast enhancement algorithms have been developed in the last fifty years. Early image contrast enhancement algorithms can be divided into two categories: spatial methods and frequency-based methods. Spatial methods enhance image contrast in spatial domain. Among the existing methods, histogram equalization/adjustment is the most popular one. The technique adjust grayscale transform curve to stretch image contrast. Frequency-based methods generally operate on the Fourier transform of an image, and high frequency components are normally raised to improve image sharpness. However, spatial methods always cannot provide enough enhancement on image details, and frequency-based methods always bring visual artifacts, such as halo and ringing effect.

Multiscale methods draw a lot of attention in recent years. These techniques split an image into a number of channels by spatial scale, frequency and orientation, etc. Image enhancement is realized by amplifying certain channels [1], [2]. The decomposition techniques include Laplacian Pyramid, Gabor filters, Wavelet and Curvelet transforms, etc. Recently, edge-preserving and bilateral filters are developed for image decomposition [3], [4], [5]. The decomposition is based on both the gradient and scale properties of an image, and avoids having pixels from both sides of an edge. This allows the strong edge contents that essentially represents object boundary to be separated from object textures. The separation helps to improve the enhancement performance because users can apply different amplifying strategies on each decomposition channel. Using correct amplifying coefficients, it is capable of generating very clear images with minimal visual artifacts. However, the assignments of amplifying coefficients are highly image content dependent, and interactive adjustment on local coefficients is always required to achieve a visually pleasing image. The complex interactivity significantly limits the usability of these applications.

In this paper, a two-layer image contrast enhancement algorithm is developed. Using Farbman’s edge-preserving decomposition filter [5], the input image is separated into two layers: base layer and detail layer. The base layer describes the global illumination, or global tone; and the detail layer represents object textures. A further fine-tuned unified contrast perception model is used to measure the perceptual response of image contrasts. The enhancement on detail layer can be regarded as a lifting of perceptual response on the details, which represents as a local scale-up. A different enhancement strategy is applied to the base layer, which only contains strong edges. Based on the simplified contrast perceptual model, the edges are stretched to improve their sharpness. The output image is a combination of processed base and detail layer, and only one perceptual parameter is applied to control the enhancement level, the interactivity is greatly simplified.

The paper is organized as following: Section II introduces the details of the image contrast enhancement algorithm; The experimental results are presented in Section III; and the conclusions are given in Section IV.

II. IMAGE CONTRAST ENHANCEMENT ALGORITHM

In the proposed algorithm, different enhancement strategies are applied to the base layer and the detail layers. Both utilize the unified contrast perception model, as shown in figure 1.
A. Unified contrast perception model

The unified contrast perception model was previously introduced in [6], [7] for High Dynamic Range (HDR) image tone-mapping. In [6], the contrast perception model was presented in a Low Dynamic Range (LDR) display brightness index domain. The HDR tone-mapping is realized by matching the perceptual response from the input HDR and output LDR images. Plainis model [8] was adopted to estimate the HDR perceptual response. However, acceptable tone-mapped image only can be obtained by raising and compressing the results of Plainis model many times, which the authors cannot explain. In our later paper [7], which is a brief presentation, subjective viewing results are extended to HDR range and an HDR contrast perception model is built. In this paper, the unified contrast perception model is further fine-tuned into a different formula. Moreover, 8-bit image format is still widely used in current imaging industry, a display model is used to convert the contrast perception model from real-world luminance domain into 256 grayscale brightness domain. A 24-inch LCD monitor under a normal office lighting environment is used as a reference display model. It has a $\gamma = 2.2$ gamma correction curve and $1920 \times 1200$ resolution. The maximal and minimal luminance values of the monitor are 300 and 1 cd/m$^2$, respectively. And the ambient reflection is about 1 cd/m$^2$. Using the display model, the contrast perception model can expressed as following:

$$R_T = \frac{f_{RT}(C, F, B_{ind}, D)}{\alpha_1 \cdot e^{\alpha_2 C + \alpha_3 F + \alpha_4 D + \alpha_5 B_{ind} + \alpha_6}}$$

(1)

where $R_T$ denotes the reaction time of the contrast stimulus in human visual system. $\{a_i : i = 1, \cdots, 6\}$ are model parameters. $C = D_{max} - D_{min}$ represents local physical contrast, where $D_{max}$ and $D_{min}$ denote local maximal and minimal values in detail layer. $F, B_{ind}$ and $D$ denote the other three visual factors: frequency, background brightness index and the angle distance from stimulus to eye-gaze when it appears (or eccentricity), respectively. $F$ is estimated using wavelet transform, and the local dominant frequency value is selected. Moreover, we have $B_{ind} = |B - 127|$ and $B$ is the average of local base layer. It should be noted that a fixed distance $D$ is used in the operator to improve computational efficiency. In current implementation, a value suitably between foveal and peripheral vision is assigned to $D$.

It is assumed that contrast perceptual response $P_R$ has the following relationship to reaction time $R_T$:

$$P_R = -\log(R_T + C_0)$$

(2)

where $C_0 = 0$ currently.

When physical contrast $C$ is high, $P_R$ has a almost linear relationship to $C$, which can be represented as:

$$P_R \approx A \cdot C + B$$

(3)

where $A$ and $B$ are constants.

It should be noted that the only luminance contrast is used in the unified contrast perception model, the proposed algorithm should be applied to grayscale image enhancement.

B. Detail layer lifting

The details lifting is realized by increasing the $P_R$ value, or shortening the reaction time $R_T$ of the local details. Let $P_R'$ denotes the perceptual response value after lifting, then we have following lifting scheme:

$$\frac{P_R' - \beta}{P_R - \beta} = 1 - \alpha$$

(4)

where $\beta$ is a pre-defined parameter which represents a strong perceptual local detail, which is invariant to background brightness and local frequency. $0 < \alpha < 1$ is the value that indicates the perceptual enhancement level. The mapping function means the strong details should be maintained in output image and the weak details should be lifted to improve their perceivability. The weaker the detail is, the stronger it will be enhanced. For example, when the perceptual response value of an input detail is around $\beta$, no lifting is applied. On the contrary, given an input weak detail with $P_R = 0$, then we have $P_R' = \alpha \cdot \beta$, which means the perceptual response is enhanced by $e^{\alpha \cdot \beta}$ times. $\alpha = 0$ implies no enhancement is applied.

Because Equation 1 is a monotonic equations to $C$, and Equation 2 is a monotonic equations to $R_T$ too, we can estimate a $\alpha'$ from $P_R'$. As a result, a local scale factor can be obtained by:
Obviously, S is adaptive to image contents. The enhanced detail layer can be obtained by multiplying with the scale factors. Other lifting schemes, such as nonlinear lifting and equalization, can also be used. However, experiments and observations showed the linear lifting scheme always gives a better result. It is believed linear lifting maintains the relationship among the details in whole image. The strong detail in input is strong in output, and the weak is still comparatively weak in output. Keeping the relationship helps to maintain a natural look of the enhanced image.

C. Base layer stretching

As mentioned before, it is assumed that base layer represents global tone, which also should be enhanced. Considering that base layer mostly contains strong edges and halo always appear around after they are enhanced, a different scheme is developed. With a reference of Equation 3, it can be assumed that the contrasts in base layer has a linear relationship to perceptual response. They need to be stretched by the perceptual factor $\alpha$. A Unsharp Masking (USM) operator is adapted. The USM operator uses Gaussian core with a big radius value to prevent halo. The difference between the base layer and its Gaussian blurred copy is multiplied by $\alpha$, and then added to the original base layer. Using the USM operator can enhance the edges, also also avoiding stretch the base layer too much, as shown in Figure 2.

A value that is equivalent to 0.25 visual degree should be assigned to the $\sigma$ parameter of the Gaussian core. Based on the observation that viewers’ eyes generally are at a distance about 1.5× of monitor height in a normal image viewing environment. A $\sigma = 16$ pixel is used in current implementation with a reference of the above-mentioned monitor model.

III. EXPERIMENTAL RESULTS

Figure 3 shows the experimental results on “Lena” image. Figure 3(a) is the input grayscale image. Figure 3(b)-(d) are the enhanced images with $\alpha = 0.2$, $\alpha = 0.5$ and $\alpha = 0.8$, respectively. With the increase of $\alpha$ value, the image is enhanced in a perceptually stronger way. Moreover, Figure 3(e) shows the base layer, which is separated by the decomposition filter. And Figure 3(d) is the enhanced base layer. Because we didn’t consider noise in the proposed algorithm, or in that other words we treat noise as signal, the noise is enhanced accordingly by the $\alpha$ value. By observation, visual artifacts are not visible till Figure 3(d), when $\alpha = 0.8$. A suppression of high frequency details can be found around hat, which is not expected. The reason is that the decomposition filter is failed. There exist some narrow high-light strips on hat boundary, and the decomposition filter put them into detail layer as their scale is low. Due to the frequency analysis needs the grayscale values of its neighboring pixels, the high contrast signal suppresses the other details around it. However, the artifact is not strong when $\alpha \leq 0.5$. Moreover, it should be noted that the over-flow and under-flow pixel grayscale values in the enhancement is simply truncated. Therefore the enhancement in high-light and dark regions is limited.

Two more examples are shown in Figures 4 and 5, respectively. Same as Figure 3, it can be observed that the $\alpha$ value has a high correlation with enhancement level. The output images look realistic, and no obvious artifacts, such as halo, can be observed.
IV. CONCLUSION

In this paper, a new image contrast enhancement algorithm is presented. The algorithm is based on a unified contrast perception model, which unifies human contrast perceptual response with four visual factors: physical contrast and frequency of a signal, background brightness and visual eccentricity. A edge-preserving decomposition filter is adapted in the algorithm to separate input images into two layers: base layer and detail layer. Different enhancement schemes are applied to the two layers. Perceptual lifting is applied to detail layer and stretching is applied to base layer. Both are based on the contrast perception model. Experimental results confirmed the proposed image contrast enhancement algorithm can produce natural and clear image with least artifacts. Moreover, the enhancement can be controlled by single perceptual enhancement parameter, which significantly simplifies the interactivity for many image processing applications.

REFERENCES