Model-based Local Contrast Enhancement for Magnified Images

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Abstract

It has been observed that magnification of a digital image results in a decrease in perceived contrast in various imaging applications. This study is aimed to quantify the loss in our contrast perception under varied sizes of field of view first and a local contrast enhancement method is proposed to compensate for the loss by pre-emphasizing selective image frequency components. The pre-emphasis gains are determined adaptively to the size of field of view and can also be adjusted by parameters in order to accentuate the overall amount of enhancement. In consequence, improved local contrast and clarity in magnified images could be achieved and undesirable halo and random noise boost-up artifacts typically shown in conventional methods could be attenuated.

Introduction

Smart TV is thought of as an important keyword in recent television market. Basically, it can be connected through internet-protocol so various internet contents, such as down-scaled YouTube and video on demand (VOD), can be serviced; thus lower resolution images relative to broadcasting standards, e.g. Rec. 709, [1] happens to be magnified to fit the whole screen of a TV. Displaying a magnified digital image in a larger screen or viewing field causes a decrease in angular resolution and the resulting image tends to be perceptually blurred and less contrasting. [2-4] For example, when a low resolution VOD is magnified to the full screen, it appears not just blurred but also foggy or murky. (Note: the perceived contrast decrease has also been significant in developing vision correction imaging systems. [3-4]) The decrease in perceived contrast of such a magnified image might be due to a combination of image blur and of sub-sampling the larger range of contrasts in the original. [2] There is a considerable amount of efforts to quantify the image blur and restore the lost high frequency components during magnification. [5-6] However, perceived contrast decrease has not been understood very well.

This study is aimed to model the adaptive characteristics of the human visual system (HVS) by measuring contrast sensitivity under varied sizes of field of view (FOV) first. A local contrast enhancement method, which compensates for the effects of FOV on our contrast perception mechanism, is proposed. Specifically, spatial luminance contrast sensitivity function (CSF) is used as a guide for determination of the adaptive pre-emphasis gain in the proposed method. CSF can be defined in both luminance and chromatic channels but only luminance CSF is studied in the current work.

The CSF represents the amount of minimum contrast at each spatial frequency that is necessary for a visual system to distinguish a sinusoidal grating or Gabor patterns over a range of spatial frequencies from a uniform field. It is believed that CSF is in fact the envelope of the sensitivity functions for collections of neutral channels that subserve the detection and discrimination of spatial patterns. [7-8] Various computational models of luminance CSF have been published. For instance, Barten has developed two models: one that is relatively complex and physiologically inspired and the other that is simpler and empirically fitted to psychophysical data. [9] Such CSF models have been adopted in a number of works in the field of image processing in order to figure out spatial nature of the HVS and evaluate and enhance images by counteracting the effects. [10-13]

The Proposed Method

Figure 1 illustrates a schematic diagram of the proposed method based upon the pre-emphasis model [12] that intends to neutralize the change in contrast sensitivity of the HVS under varied sizes of FOV. An input image can be pre-emphasized by enhancing certain spatial frequency components before displaying the image. The pre-emphasis gains are determined adaptively to the size of FOV.

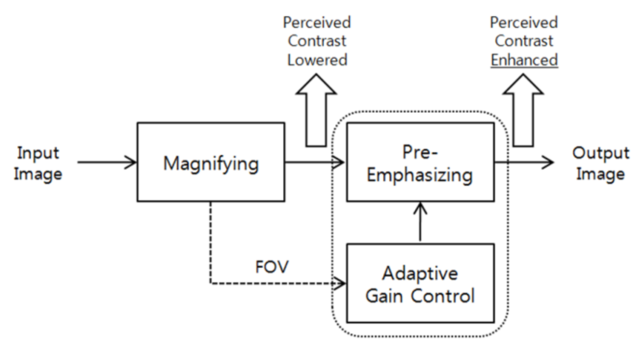


***Figure 1**. The schematic diagram based upon the pre-emphasis model [12]*

Modeling the Change in Contrast Sensitivity

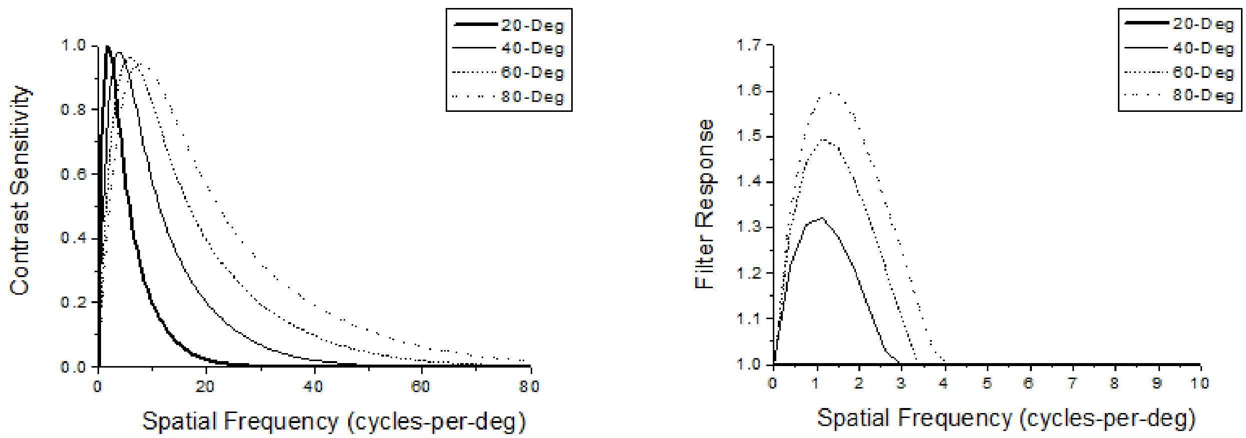
The simpler version of Barten' CSF [9] is one of the widely used CSF models which is a function of spatial frequency and mean luminance of the stimulus as shown in Equation 1. It is also dependent on the size of FOV affecting the level of maximum spatial frequency for a given imaging system.

$$CSF(u) = a \cdot u \cdot \exp(-b \cdot u)[1 + c \cdot \exp(b \cdot u)]^{0.5} \quad (1)$$

$$a = \frac{540(1 + 0.7/L)^{-0.2}}{1 + \frac{12}{w(2 + u/3)^2}}$$

$$b = 0.3(1 + 100/L)^{0.15}$$

$$c = 0.06$$



(a) *(b)*

***Figure 2**. (a) Estimated CSF with Varied FOV and (b) the adaptive pre-emphasis gains. As the size of FOV is increased, the contrast sensitivity at low and middle spatial frequencies decreases and the peak shifts towards a higher spatial frequency. However, the contrast sensitivity at high frequency increases along with the maximum resolvable spatial frequency. The pre-emphasis gain responses depend on the change in CSF and also showed band-pass shape.*

where L is adapting luminance in cd/m^2, u is spatial frequency in cycles per degree (cpd), and w is the maximum spatial frequency of a given imaging system can be determined as a function of the pixel resolution N, the FOV in degree F, and the distance between the observer and the imaging system d.

$$w = \frac{N}{4 \cdot \tan^{-1}(F/2d) \cdot 180/\pi} \quad (2)$$

As the size of FOV is increased, the width of a display should be increased and the maximum spatial frequency should be decreased; therefore the following variations can be predicted using Equation 3, as also presented in Figure 2(a). The contrast sensitivity at low and middle spatial frequencies decreases and the peak shifts towards a higher spatial frequency. However, the contrast sensitivity at high frequency increases along with the maximum resolvable spatial frequency. The shape of the function remains the same as a band-pass; exhibits a peak at a moderate spatial frequency and falls off at both lower and higher frequencies. The change in contrast sensitivity by the FOV, $\rho(u,v)$, can be modelled as

$$\rho(u) = \max(CSF_{SF}(u) - CSF_{LF}(u), 0) \quad (3)$$

where $CSF_{SF}(u)$ and $CSF_{LF}(u)$ respectively denote CSFs defined in smaller and larger sizes of FOV conditions. Equation 3 can be refined in the two-dimensional space of spatial frequency variables u and v as

$$\rho(u,v) = \max(CSF_{SF}(u,v) - CSF_{LF}(u,v), 0) \quad (4)$$

Adaptive Pre-emphasis Gain Control

The adaptive pre-emphasis gain function is given in Equation 5. Since contrast can be enhanced, when an enhancement gain greater than 1 is multiplied to the amplitude of a given image spectrum, the offset of Equation 5 should be increased up to greater than 1 and a constant value of β is added to $\rho(u,v)$. The overall amount of enhancement can also be accentuated by multiplying a constant α.

$$H(u,v) = \alpha \cdot \rho(u,v) + \beta \quad (5)$$

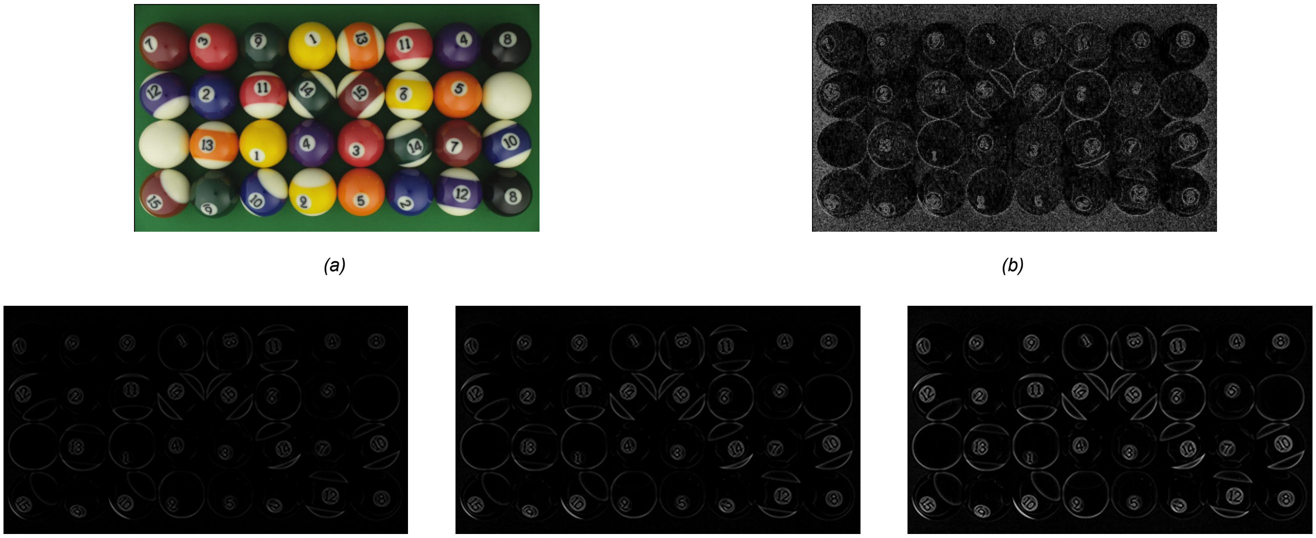
where α is normally ranged from 0.5 to 1.5 and can be varied adaptively to the FOV level as $20/F$. The offset β should be set to 1.0 in order to prevent from the halo artifacts, which is normally defined as an inverse of gradient, by preserving strong edges. In addition, noise boost-up can be attenuated in flat regions. In Figure 3, gain map examples for a test image with varied α values are illustrated with the corresponding Laplacian map. As α value increases, each pixel's gain is increased so that the overall amount of contrast enhancement can be accentuated. However, the Laplacian produces gains in strong edges and background textures and may introduce halo and random noise. When β is increased over 1.0, the obtained result tends to be blended with Figure 3(b) and sharpness of the high frequency regions can be increased; however those side effects of the conventional method can also be visible.

Figure 2(b) shows estimates of the adaptive pre-emphasis gains for the varied FOV levels (20, 40, 60, and 80-Deg) when the adapting luminance was 200 cd/m^2 and the surround was set to be dark. Since the loss in contrast sensitivity becomes larger under increased size of FOV, the gain response for 80° shows the highest. Because CSFs are known as smoothly varied band-pass filters, the pre-emphasis gain can also be smoothly changed. Therefore, Equation 5 can be used as a weighting function to determine which of parts of the image, whatever their spatial frequency, should have a higher enhancement gain.

The proposed method can be categorized into an adaptive unsharp masking [14] that a band-pass filtered, scaled version of the input signal to the signal itself as

$$O(u,v) = I(u,v) \cdot (1 + H(u,v)) \quad (6)$$

where $O(u,v)$ denotes the enhanced luminance image in CIEXYZ for the input magnified image $I(u,v)$. $H(u,v)$ is a contrast-enhancing component derived by band-pass filtering with the pre-emphasis gain weighting function in Equation 4. Note that input signals in RGB domain were converted into a device-independent color domain, i.e. CIEXYZ, using a colorimetric characterization first and its enhanced signals in CIEXYZ were reproduced in RGB with its inverse characterization. [15]



(a) (b)

(c) (d) (e)

***Figure 3**. (a) Original, (b) the Laplacian, and the proposed gain maps when (c) α = 0.75, (d) α = 1.00, and (e) α = 1.25. As α value increases, each pixel's gain is increased so that the overall amount of contrast enhancement can be accentuated. However, the Laplacian produces gains in strong edges and background textures and may introduce halo and random noise.*

Experimental

In order to verify the CSF estimation by Barten's model [9] discussed in Equation 1, a set of simple psychophysical experiments was carried out. A sinusoidal grating pattern, of which contrast modulation gradually varies (See Figure 4 for illustration), is displayed on a 55-inc. Samsung C8000 liquid crystal display. Its spatial resolution reaches up to 1920 × 1080 pixels. Along the vertical axis of the screen, contrast becomes the highest in the bottom and lowest in the top of the pattern. This sinusoidal grating pattern (**Q**) was produced by means of the product of a non-linear gradient function along the vertical axis (**M**) and a one-dimensional sinusoidal function of spatial frequency across the horizontal axis (**F**). In practice, those functions can be discretely sampled and expressed by

$$\mathbf{Q} = \mathbf{M}\mathbf{F}^{\mathrm{T}} \tag{7}$$

where $\mathbf{F}^{\mathrm{T}}$ denotes the transpose of **F**.

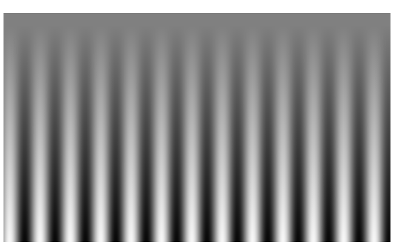


***Figure 4**. Example of sinusoidal grating pattern*

Contrast thresholds were measured at 7 spatial frequencies - 2, 3, 4, 5, 6, 7, and 8 cpd – by a 25-year old male observer with 5 repetitions. (Note: the observer is a graduate student in imaging background and authors of this paper were not included.) The observer was required to identify vertical positions of the sinusoidal pattern when the contrast became just distinguishable [16] under varied viewing distances: 1, 2, and 3 meters. Note that the surround was set to be dark. Contrast was computed using Michelson contrast, denoted as C_M (See Equation 8), and was converted into a sensitivity unit that is the reciprocal of threshold.

$$C_M = \frac{L_{Max} - L_{Min}}{L_{Max} + L_{Min}} \tag{8}$$

where L is luminance of a given pixel in an input image and maxima and minima are taken over the vertical position of the sinusoidal grating pattern.

Results and Discussion

Verifying the Estimation of FOV effects on CSF

In Figure 5, the psychophysically measured contrast sensitivity data points are depicted with the corresponding CSF model estimations. Since the data rely upon a single observer with 5 repetitions, they are not perfectly fitted as discrepancies in 8 cpd can be observed; however their central trends corresponded in general.

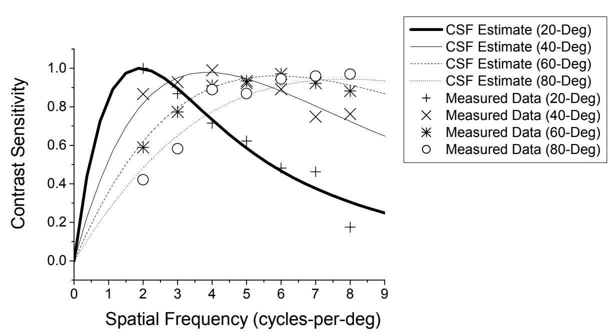


***Figure 5**. Measured contrast sensitivity vs. model estimation [9]*

(a) (b) (c)

***Figure 6**. (a) Original, (b) results of the proposed method, and (c) results of a conventional method. The local contrast and clarity of object boundaries tend to increase while the other frequency components such as strong edges and flat regions are less affected. However, halo and random noise artifacts are resulted from the conventional method.*

Performance of Local Contrast Enhancement

Figure 6 presents part of pre-emphasized results for an image simulating the increase of FOV from 20 to 70-Deg when α values are set to 1.00 along with a resultant image of the conventional unsharp masking method. By emphasizing mid-frequency component in the proposed method, local contrast and clarity of object boundaries tend to increase while the other frequency components such as strong edges and flat regions are less affected (See Figure 6(b)). However, as illustrated in Figure 6(c), it can be said that halo and random noise artifacts are resulted from the conventional unsharp masking technique. Quantitatively, a considerable increase in standard deviation across the whole image could not be achieved because only selective frequencies are enhanced in this method. However, locally measured standard deviations in smoothly varied signals including boundary of texts in the left-hand sided image and far-sight objects in the right-hand sided image in Figure 7 was increased up to 43%. Figure 7 also indicates the evaluated regions in two test images and their standard deviation value are listed in Table 1.

Table 1. Mean standard deviation for each evaluated region

Region	Input	Proposed
1	34.51	45.57
2	28.92	37.51
3	18.26	19.23
4	45.15	59.97
5	34.17	48.84
6	39.96	45.39
7	17.84	23.17

Conclusion

In this study, a local contrast enhancement method, which pre-emphasizes the loss in contrast sensitivity of the visual system, is proposed. The pre-emphasis gains are determined adaptively to the size of FOV. Experimental results could confirm the image enhancement in terms of clarity of object boundaries without any undesirable artifacts in strong edges and flat regions. For a future work, shadow and highlight tonal areas can be further enhanced by removing unwanted tone clipping cases. In addition, considering the chromatic contrast effect can be another afterthought.

***Figure 7.** Regions quantitatively evaluated*

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