Biologically Inspired Contrast Enhancement Using Asymmetric Gain Control

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***Abstract*—A neuro-physiologically inspired model is presented for the contrast enhancement of images. The contrast of an image is calculated using simulated on- and off-centre receptive fields whereby obtaining the corresponding two contrast maps. We propose an adaptive asymmetric gain control function that is applied to the two contrast maps which are then used to reconstruct the image resulting in its contrast enhancement. The image's mean luminance can be adjusted as desired by adjusting the asymmetricity between the gain control factors of the two maps. The model performs local contrast enhancement in the contrast domain of an image where it lends itself very naturally to such adjustments. Furthermore, the model is extended on to colour images using the concept of colour-opponent receptive fields found in the human visual system. The colour model enhances the contrast right in the colour space without extracting the luminance information from it. Being neuro-physiologically plausible, this model can be beneficial in theorising and understanding the gain control mechanisms in the primate visual system. We compare our results with the CLAHE algorithm.**

***Keywords*-Contrast enhancement; asymmetric gain control; receptive fields; image reconstruction;**

I. Introduction

Contrast is an important attribute whose subjective and quantitative impact on the image quality is enormous, determining the visibility of its details as well as its aesthetic appeal. The dynamic range of the visual stimuli in the real world is extremely large. On the contrary, image capturing and display devices are very restricted in their range, compressing the luminance levels to a very small range, thereby reducing the contrast between them significantly. Even for high dynamic range (HDR) images, displaying such an image on customary displays results in either its under- or over-exposure. This requires enhancement both to the contrast of an image as well as to its mean luminance level.

The primate visual system excels in tasks to a level so far unachievable by the best man-made systems. Among those is its amazing adaptability to a wide range of luminance levels despite having a limited dynamic range. We present a neuro-physiologically inspired model for local contrast enhancement of under- or over-exposed images using asymmetrical boosting of the on- and off-centre contrast maps. Our model gives excellent performance in enhancing the contrast of images having both uni- and multi-modal histograms. The algorithm works by computing two contrast maps of an image using the on and off-centre receptive fields of neurons, as found in the primate visual system. Contrast enhancement then becomes a straightforward operation where we rescale the contrast values in the map using a gain control function that is modelled after psychometric adaptability curves. These transformed maps are then used to reconstruct the image using the image reconstruction algorithm from [1] which results in a contrast enhanced image. Feedback is used at every iteration to modify the gain control function. A unique feature of the model is that the image's mean luminance can be controlled by asymmetrically boosting the gain control factors that are applied to the two contrast maps. While we are not aware of any neuro-physiological evidence of asymmetrical boosting, our research shows that superior results are achieved in this way as compared to symmetrical boosting on both maps. We also extend our model to colour images. For that we show three different approaches, two of which are conventional ways of dealing with colour image enhancements in which somehow the luminance component is extracted and enhanced and later added back to the unmodified colour component and the third is the biologically motivated approach using colour-opponent receptive fields where enhancement is done in the colour space itself. Our experiments show that this latter approach produces far superior results than the the other two.

II. Related Work

Much work has been done on contrast enhancement of images, only some can be mentioned here. Conventional methods use some variation of histogram equalisation [2] or tone mapping [3]. Perhaps the best known histogram equalisation method is the CLAHE algorithm [4], which performs adaptive equalisation locally. Tone mapping methods more commonly work with HDR images, mapping them onto the low dynamic range (LDR) domain or using images

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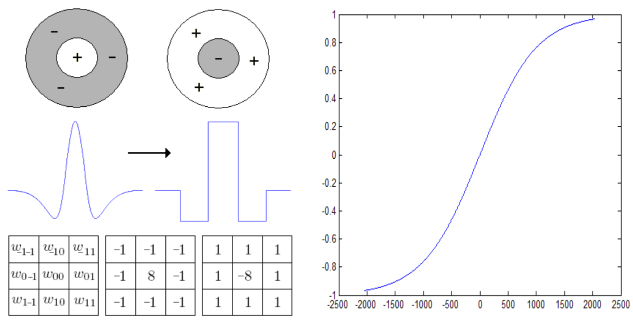

(a) (b)

Figure 1. (a) *Top:* Retinal receptive fields. On-centre (left) and off-centre (right). *Middle:* Continuous DoG (left) modelling the retinal receptive field approximated by its discretised version (right). *Bottom:* a general 3x3 mask (left) and its on-centre and off-centre weights (centre and right). (b) Tangent hyperbolic sigmoidal output function.

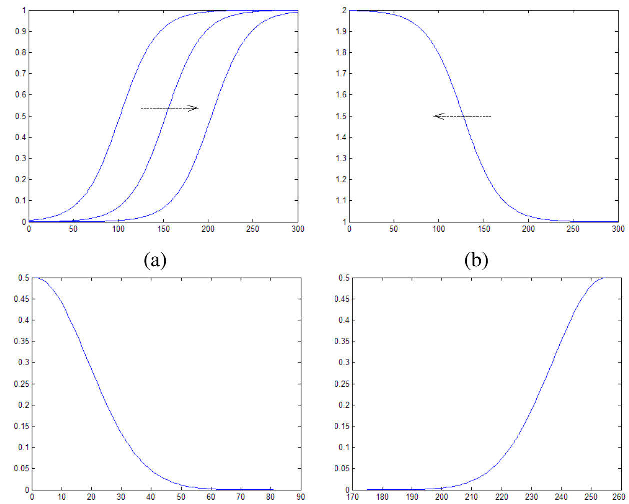

Figure 2. (a) Psychometric contrast adaptation curves. (b) Sigmoidal gain curve used by our algorithm. (c) Left-asymmetricity exponential curve for on-centre map. (d) Right-asymmetricity exponential curve for off-centre map.

captured at multiple exposures generate an output image that best captures all the detail. Among the unconventional approaches are those that use wavelets [5] and fuzzy logic [2].

Among the biological approaches [6] uses a centre-surround receptive field model for contrast enhancement. However they uses only a single receptive field type namely the on-centre off-surround. By defining a new centre-surround operator, they compare each pixel to its local average and assigns to it a new value adjusting its tone. Furthermore their algorithm only works on luminance values, so for colour images, they extract out the luminance component, contrast adjust it and regenerate the colour image. [7] uses the retinex algorithm to visualise HDR images. Some have developed methods that are based on human perception and contrast sensitivity functions [8]. Perhaps the work that comes closest to our approach is [9], which used Difference of Gaussians (DoG) to calculate contrast maps and applied some sort of gain control to it. They also use colour opponency in their algorithm. Their approach, however, is geared more towards computing spatial frequency components at different scales and applying selective gain controls to those.

In contrast to the above biological approaches, our method contains the following distinguishing traits: (a) it takes all the receptive fields in to consideration that exist in the human visual system namely the on-centre off-surround and the off-centre on-surround for luminance and colours and uses them all in cooperative manner. Specifically, we apply different gain to the on- and off-centre receptive fields and show that this is useful in controlling the mean luminance of the image (b) it takes a reconstructive approach to contrast adjustment rather than tone adjustment (c) it deals with colour images in colour domain rather than just on the luminance component, using the colour-opponent receptive fields.

III. Background

Neurons in the retina and the lateral geniculate nucleus (LGN) have an antagonistic centre-surround receptive field which is an area on the retina that may activate a particular neuron if stimulated appropriately. Because of limited bandwidth, the design of the brain separates the receptive fields into the two categories of on-centre and off-centre, each of which are half-wave rectified signals of activation. If they are combined into a composite signal, the on-centre would form the positive half, while the off-centre the negative half. Retinal cells transform an input image into a contrast image consisting of on-centre and off-centre contrast maps, which record only changes in the input, making the percept largely independent of the ambient illumination level.

In addition to the ones that detect contrast in luminance, there are cells in the primate retina that detect contrast in colours for which they are known as colour opponent cells [10]. They have a centre of one colour with a surround of a different colour. Three such cell types exist at the basic level: those having a red centre and green surround, those with a green centre and red surround and those with a blue centre and yellow (red+green) surround. Each of these types have an on-centre and off-centre version. Besides these there are more advanced variety of cells that deal with colour contrast. They are called double-opponent cells which we are not concerned with in this paper.

IV. Proposed Method

Convolving the mask with the discretised approximation of DoG in Fig. 1(a) with the image and passing the result through the hyperbolic tangent non-linearity in Fig. 1(b):

$$y(x) = \frac{1 - e^{-2x/\alpha}}{1 + e^{-2x/\alpha}} \quad (1)$$

we get the on- and off-centre contrast maps of the image, to which we then apply our asymmetric gain control function.

Psychophysical studies of contrast adaptation have shown that prolonged exposure to high-contrast patterns leads to a decrease in the perceived contrast [11]. This contrast adaptation is often indicated by a right shift of psychometric curves (Fig. 2(a)) indicating a decrease of sensitivity to low contrast. We model our gain control function by an adaptable sigmoidal function that is a reverse of the contrast adaptation function (Fig. 2(b)). The adaptation is based on the contrast values of the image at any pixel (x, y), as the image contrast is modified through iterations. Increase in image contrast at any pixel (x, y) will shift its contrast gain function to the left decreasing its gain, while those pixels whose contrast levels are still low will continue to enjoy a high gain, thus, providing local gain control for every pixel. Gain control G as a function of contrast c at any pixel (x, y) is modelled as:

$$G(c) = (g + \beta) - \frac{(g + \beta - 1)}{1 + e^{-(|c| - \gamma)/\alpha}} \quad (2)$$

where γ and α are constants that set the initial position of the curve on the contrast axis and its slope, respectively, while $(g + \beta)$ is the maximum value of the gain factor.

We call β the *asymmetricity factor*. For zero β, the same gain factor G will be applied to both the on- and off-centre contrast maps. This would give a resultant image with approximately the same mean luminance L_m as the original one. Generally, this is what we would like to have if the L_m of the input image does not fall too much to the extremes. In case the image is too dark or too bright, its L_m would also need adjustment along with its contrast. To shift L_m towards brightness, we apply a higher gain factor to the on-centre map, as compared to the off-centre one. Similarly shifting L_m towards darkness, we apply a higher gain factor to the off-centre map. This is congruent with an on-centre receptive field performing figure-ground separation of bright objects, while the off-centre one does the same for dark objects. Thus, the gain applied to the two maps differs by the value of β, if non-zero:

$$\begin{aligned} \beta_{\text{on}} &= \kappa e^{-(l_m - 255)^2/\sigma} \\ \beta_{\text{off}} &= \kappa e^{-(l_m)^2/\sigma} \end{aligned} \quad (3)$$

The curves corresponding to the on- and off-centre β are given in Fig. 2(c) and 2(d), respectively. κ sets the maximum asymmetricity applied to the maps while σ determines the region extent for which β is non-zero. l_m is the mean local luminance around any given pixel at any particular iteration. As the mean luminance of the image shifts away from the extremes, β eventually becomes zero.

These boosted contrast maps are then used to reconstruct the image using the reconstruction algorithm [1] that, given a composite contrast map of an image, is able to iteratively reconstruct the image from it. The algorithm stops when the change in image through successive iterations is below a certain threshold. Reconstruction is accomplished by a gradient descent algorithm using the difference between the original contrast map and the contrast map calculated at each iteration as the error function. The pixel update rule, as in [1], is:

$$\Delta I_A(x, y) = \eta w_{00} C_E(x, y) \quad (4)$$

where ΔI_A is the change in the actual pixel intensity at (x, y), η is the update constant and $C_E(x, y) = [C_D(x, y) - C_A(x, y)]$ is the contrast error at pixel (x, y) while w_{00} is the center weight of the DoG mask. For details of the reconstruction algorithm refer to [1].

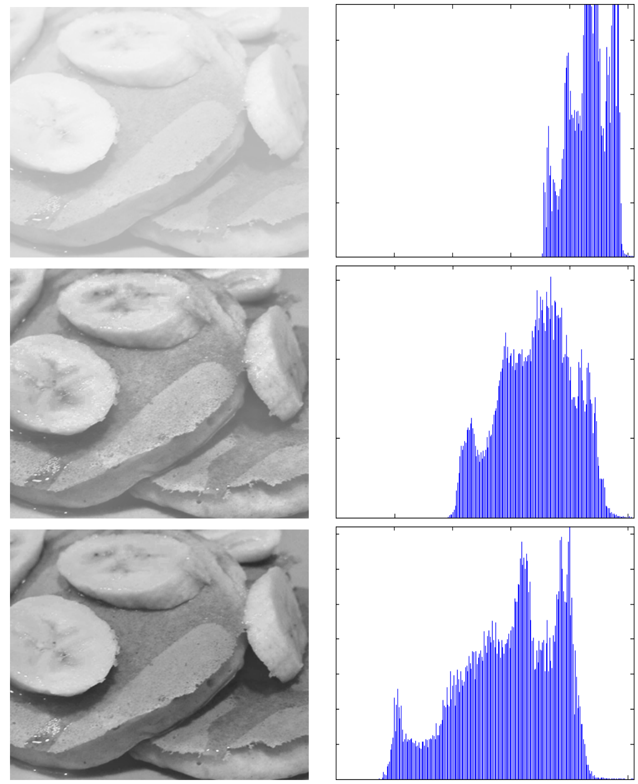

Figure 3. *(Top)*: Original image & its histogram *(Middle)*: CLAHE output *(Bottom)*: Output of our algorithm.

To validate the proposed approach experimentally, we empirically set $g = 2.0$, $\gamma = 0.5C_m$ and $\alpha = 0.08C_m$ in Eq. 2 and $\kappa = 0.5$ and $\sigma = 2.5C_m$ in Eq. 3, where C_m is the maximum possible contrast whose value depends upon the mapping performed by the tangent hyperbolic non-linearity. In our case, C_m is mapped to a value of 255. Some results are shown in Fig. 4, 5 and 3. Although image quality is a subjective and context dependent measure which is very hard to quantify, a few necessary, though not sufficient, parameters can be identified that are indicative of good image contrast, namely, the spread of the image histogram and its density. It can be seen from the histograms of our

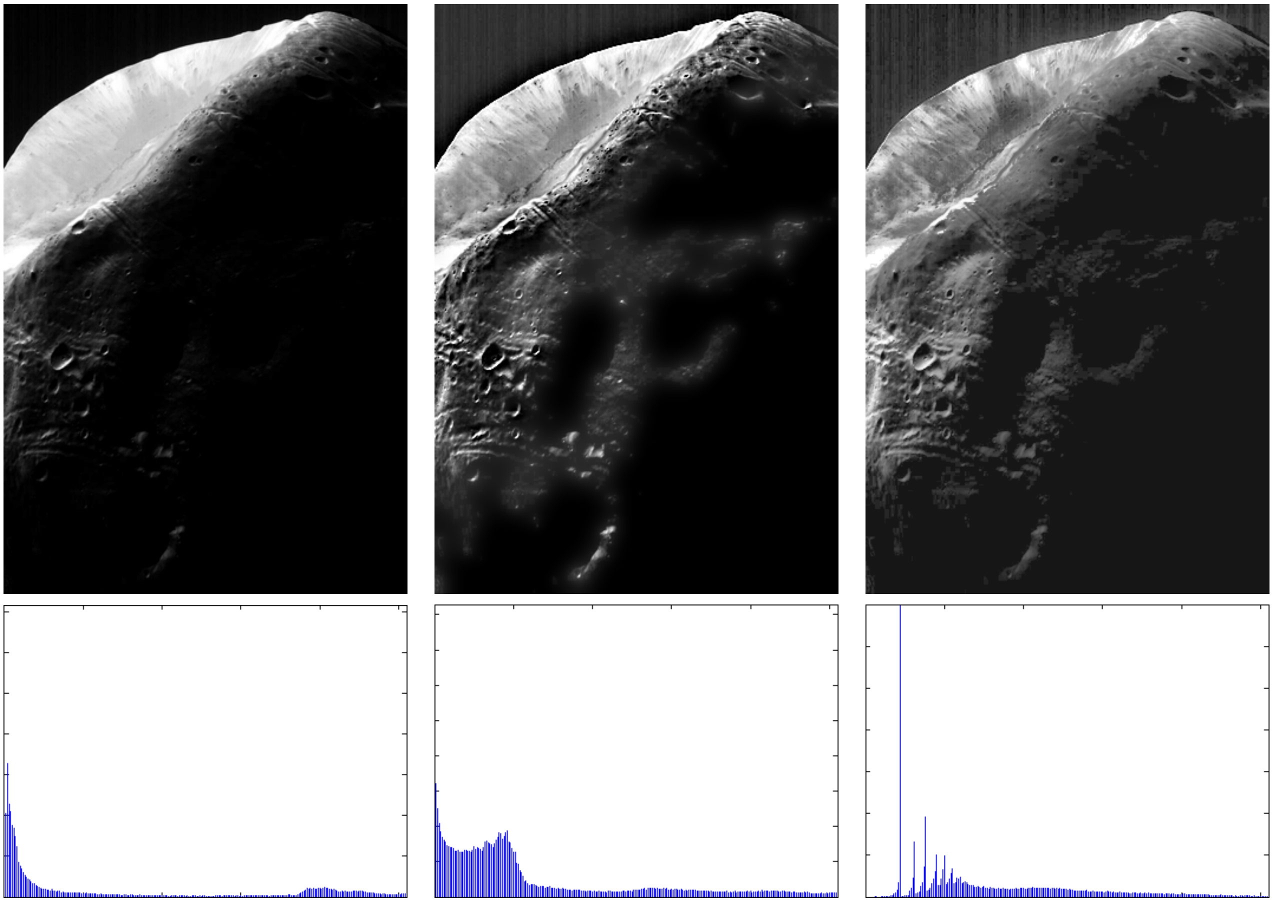

Figure 5. *(Top)*: Original image (left), output of our algorithm (mid) and CLAHE output (right) *(Bot)*: Corresponding histograms.

examples that their contrast spreading is wider than that of CLAHE and that they are quite dense with no visible gaps. Also, our algorithm is not known to produce any perceivable halo effect that some of the other contrast enhancement algorithms generate.

V. Colour Image Enhancement

We applied the same gain control model presented above to colour images. Three different colour spaces were experimented with and their results were compared.

A. *Experiments Using the RGB Space*

In the RGB space, the image is composed of three different planes corresponding to the colours red, green and blue. Each image plane was treated as an individual gray-scale image with no dependencies with any other plane. The contrast was calculated independently for all three planes resulting in six contrast maps - two for each plane (the on- and off-centre maps). Gain control was applied to each pair of contrast maps and the image of each plane was reconstructed using the reconstruction algorithm described earlier. The three reconstructed images were finally displayed as a single colour image. The results compared with the CLAHE algorithm can be seen in Fig. 6a and Fig. 7a.

B. *Experiments Using the $L^*a^*b^*$ Space*

In the $L^*a^*b^*$ space the luminance component is extracted from the image leaving its colour component untouched. This lumincance component is a gray-scale image. Contrast was calculated for this single gray-scale image giving a single pair of contrast maps (on- and off-centre). Gain control was applied to it and the image reconstructed. The gain-adjusted reconstructed image was then merged again with its original colour component to produce the final colour image. The results can be seen in Fig. 6b and Fig. 7b.

C. *Experiments Using the Colour-Opponent Receptive Fields Space*

Six contrast maps are obtained in here as well like that of the RGB space with the difference that while in the RGB space each of the pair of contrast maps were computed treating each colour independently from the other two, in here the contrast maps are computed such that each contrast map is dependent on two or more colours acting in opposition to

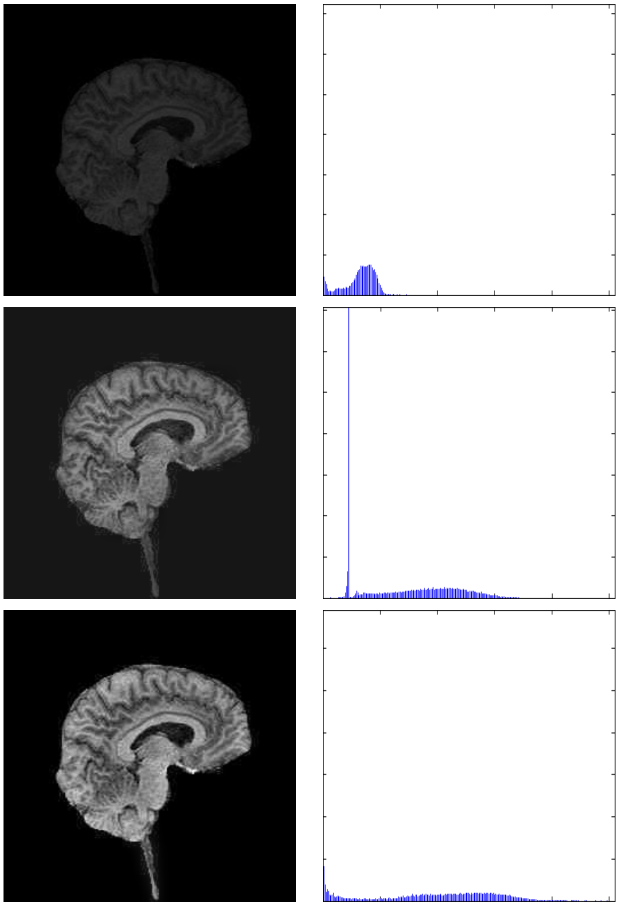

Figure 4. *(Top)*: Original image & its histogram. *(Middle)*: CLAHE output. *(Bottom)*: Output of our algorithm.

the other. Because of this opponent dependency between the colours, the result using the colour-opponent receptive fields come out to be more natural than the other two approaches. See Fig. 6c and Fig. 7c. It is believed that these colour-opponent receptive fields are the cause of colour-constancy in the primate brain [10], [12]. Here also three different images are reconstructed - one for each of the three planes of R, G, and B. The R plane image is reconstructed using the contrast maps obtained by convolving with the receptive field with a red centre. The G plane image is obtained by using the contrast maps from the green centre receptive fields and the B plane image is obtained using reconstruction from blue centre receptive field contrast maps. The difference here lies in the way the contrast maps were obtained.

VI. Conclusion

We have developed a model of contrast enhancement using our image reconstruction algorithm that is biologically inspired. A key feature of this model is the control of the mean luminance value of the image. Starting with the original image, we calculate its on- and off-centre contrast maps. We then apply local gain control to these maps, boosting the contrasts in the two maps symmetrically or asymmetrically based on the mean luminance. Symmetrical boosting keeps the mean luminance roughly the same, while enhancing the contrast, whereas asymmetrical boosting shifts the mean luminance towards the stronger weighted side. A higher gain on the off-centre map shifts the mean luminance towards the darker values, while that on the on-centre moves it towards brighter ones. We also applied the model to colour images in three different colour spaces using RGB, $L^*a^*b^*$, and the colour-opponent receptive fields. Colour-opponent receptive fields generated results that were better than those obtained by applying the gain control model to the other two colour spaces. The model is also biologically plausible since it uses only local computations and, thus, can be beneficial in gaining further understanding of the primate visual system. In the future, we plan to continue addressing the slow reconstruction phase of the algorithm, currently rendering it unsuitable for applications requiring quick enhancements.

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(a) *(left)*Original image *(centre)* Output of the proposed algorithm in the RGB space *(right)*: CLAHE output in the RGB space.

(b) *(left)* Original image *(centre)* Output of the proposed algorithm in the L*a*b* space *(right)* CLAHE output in the L*a*b* space.

(c) *(left)* Original image *(centre)* Output of the proposed algorithm using the colour-opponent receptive fields *(right)* Corresponding contrast image.

Figure 6. Images with enhancement performed in three different colour spaces and comparison with CLAHE algorithm

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(a) *(Left)*: Original image *(Centre)*: Output of the proposed algorithm in the RGB space *(Right)*: CLAHE output in the RGB space.

(b) *(Left)*: Original image *(Centre)*: Output of the proposed algorithm in the $L^*a^*b^*$ space *(Right)*: CLAHE output in the $L^*a^*b^*$ space.

(c) *(Left)*: Original image *(Centre)*: Output of the proposed algorithm using the colour-opponent receptive fields.*(Right)*: Corresponding contrast image

Figure 7. Images with enhancement performed in three different colour spaces and comparison with CLAHE algorithm