Natural Color Representation using Ratio Learning Algorithm for Gray Level Enhancement Algorithm on Digital Color Images

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Abstract

We proposed a new framework to apply gray level image enhancement algorithm to the color domain using single layer fully connected recurrent neural networks trained using the Ratio learning algorithm. Ratio Rule learns to produce natural color rendition by representing the original pixels relationship of an image as a line of attraction in the state space. Its dynamic is then used for recalling the original color characteristics of image pixels by iteratively converging to the learned stable state after the gray level enhancement. Experiments show that the proposed framework provide natural color rendition using Ratio Rule with existing gray level enhancement algorithms.

Introduction

The human eye has a remarkable dynamic range that enables it to detect subtle contrast variations and interpret scenes under a large variety of illumination conditions [1, 2]. Conversely, image captures using camera usually lost their dynamic range since the image is digitized to a much narrower dynamic range. Physical limitations exist in the sensor arrays of image capturing devices, such as CCD and CMOS cameras. Often, the devices cannot represent scenes well that have both very bright and dark regions. The sensor cells are commonly compensated with the amount of saturation from bright regions, fading out the details in the darker regions. For instance, most images are digitized to 8 bit gray level for each red, green, and blue band [3]. Consequently, image captured in a scene in which both very bright and very dark region present result in a trade of between enhancing the dark spot at the cost of saturating the bright spot or keeping the bright spot at the cost of losing the dark spot. The well known method used for providing dynamic range compression is using Gain/offset correction, non-linear point transform, histogram equalization, and homomorphic filtering to the original image. However, these methods focused on enhancing gray level images and a direct extension of these processes into the color domain results in degraded images. Image distortion will result if the red, green, and blue components are not properly recombined after the gray level image enhancement algorithms are applied.

In this paper, we proposed a new framework to apply gray level image enhancement algorithm to the color domain using an associative memory to recall/restore the color relationship to produce images with natural color which exists in the original image. The associative memory we have used is a single layer fully connected recurrent neural network trained using the Ratio learning algorithm described in [4]. Ratio Rule learns to produce natural color rendition by representing the original pixels relationship of an image as a line of attraction in the state space. Its dynamic is then used for recalling the original color characteristics of image pixels by iteratively converging to the learned stable state after the gray level enhancement.

Color Enhancement Model

Our method of improving color images using gray level enhancement algorithm can be described as three stages: color characterization, enhancement, and color balancing. In the first stage, the relationship of the red, green, and blue components of a pixel is modeled using Ratio Rule learning algorithm [4] as:

$$w_{(\iota,\kappa)}^{(x,y)} = \frac{1}{P}\sum_{s=1}^{P}\frac{\zeta_{(\iota)\ N(s)}^{(x,y)}}{\zeta_{(\kappa)\ N(s)}^{(x,y)}} \quad \text{for} \quad 1 \le \iota,\kappa \le n \tag{1}$$

where $w_{(\iota,\kappa)}^{(x,y)}$ represents the synaptic weight from the ι^{th} neuron to the κ^{th} neuron located at (x, y) position of an image. n is 3 in this application representing *RGB* components in each pixel. The symbol $\zeta_{(\iota)\ N(s)}^{(x,y)}$ represents the ι^{th} color component (*R* or *G* or *B*) of the pixel at location (x, y) of an image. The notation *N* in the symbol $\zeta_{(\iota)\ N(s)}^{(x,y)}$ denoted the corresponding neighbors of the pixel surrounding location (x, y) with *P* pixels in the neighborhood. Eqn. (1) finds the degree of similarity between each neuron with other neurons. Ratio Rule encapsulates the relationship of the pixel by describing its *RGB* components as a line of attraction: no matter how the pixel changes its value, the proportion between *R*, *G*, and *B* is always described in this network. The activation function of each neuron can be found by considering the distance between the approximated output $w_{(\iota,\kappa)}^{(x,y)}\zeta_{(\kappa)}^{(x,y)}$ and the actual output $\zeta_{(\iota)}^{(x,y)}$. Mathematically it can be expressed as:

$$\Phi\left\{w_{(\iota,\kappa)}^{(x,y)}\zeta_{(\kappa)}^{(x,y)}\right\} = \begin{cases} \zeta_{(\iota)}^{(x,y)} & \text{if} \quad \psi_{\iota,\kappa}^{-} \le \left\{\begin{matrix}\left[w_{(\iota,\kappa)}^{(x,y)}\zeta_{(\kappa)}^{(x,y)}\right] \\ -\zeta_{(\iota)}^{(x,y)}\end{matrix}\right\} \le \psi_{\iota,\kappa}^{+} \\ w_{(\iota,\kappa)}^{(x,y)}\zeta_{(\kappa)}^{(x,y)} & \text{otherwise} \end{cases} \tag{2}$$

where

$$\psi_{\iota,\kappa}^{-} = \begin{cases} \psi_{(1,\iota,\kappa)}^{-} & \text{if} \quad 0 \le \zeta_{(\kappa)}^{(x,y)} < \dfrac{L}{\Omega} \\ \psi_{(2,\iota,\kappa)}^{-} & \text{if} \quad \dfrac{L}{\Omega} \le \zeta_{(\kappa)}^{(x,y)} < \dfrac{2L}{\Omega} \\ \quad\vdots & \\ \psi_{(\Omega,\iota,\kappa)}^{-} & \text{if} \quad \dfrac{(\Omega-1)L}{\Omega} \le \zeta_{(\kappa)}^{(x,y)} < L \end{cases} \tag{3}$$

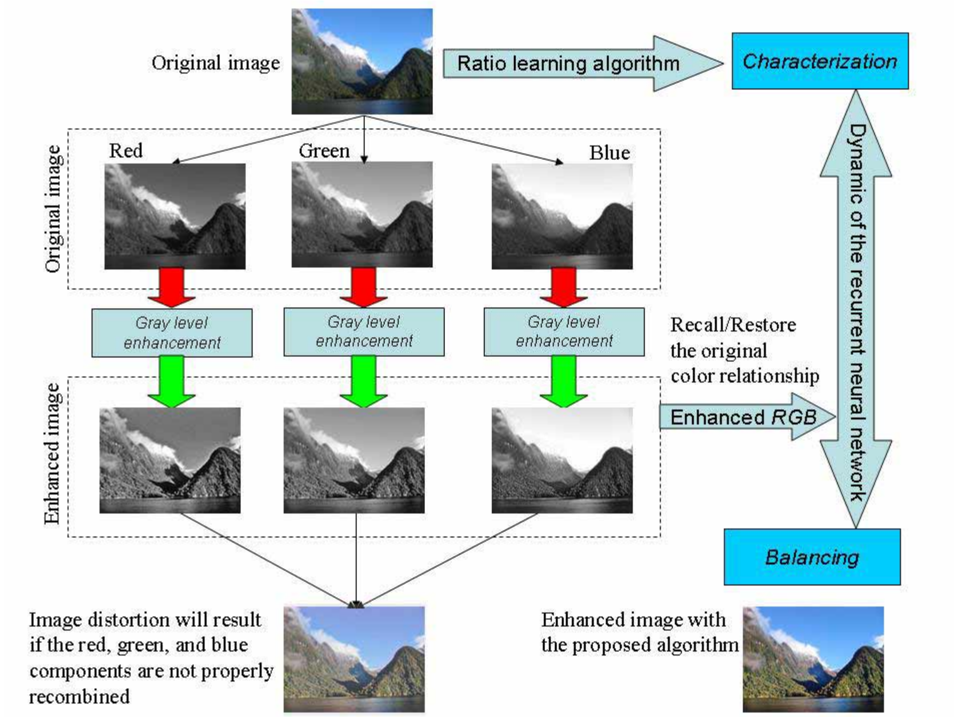

Figure 1*. Color characterization, enhancement, and color balancing system*

and

$$\psi^{+}_{\iota,\kappa} = \begin{cases} \psi^{+}_{(1,\iota,\kappa)} & \text{if} \quad 0 \le \zeta^{(x,y)}_{(\kappa)} < \dfrac{L}{\Omega} \\ \psi^{+}_{(2,\iota,\kappa)} & \text{if} \quad \dfrac{L}{\Omega} \le \zeta^{(x,y)}_{(\kappa)} < \dfrac{2L}{\Omega} \\ & \vdots \\ \psi^{+}_{(\Omega,\iota,\kappa)} & \text{if} \quad \dfrac{(\Omega-1)L}{\Omega} \le \zeta^{(x,y)}_{(\kappa)} < L \end{cases} \tag{4}$$

where

$$\psi^{-}_{(l,\iota,\kappa)} = \min_{\forall s} \begin{bmatrix} \left\{\left[w^{(x,y)}_{(\iota,\kappa)} \zeta^{(x,y)}_{(\kappa)\ N(s)} \right] - \zeta^{(x,y)}_{(\iota)\ N(s)} \right\}, \\ \text{in the region} \\ (l-1)\dfrac{L}{\Omega} \le \zeta^{(x,y)}_{(\kappa)\ N(s)} < l\dfrac{L}{\Omega} \end{bmatrix} \quad \text{for} \quad 1 \le l \le \Omega \tag{5}$$

and

$$\psi^{+}_{(l,\iota,\kappa)} = \max_{\forall s} \begin{bmatrix} \left\{\left[w^{(x,y)}_{(\iota,\kappa)} \zeta^{(x,y)}_{(\kappa)\ N(s)} \right] - \zeta^{(x,y)}_{(\iota)\ N(s)} \right\}, \\ \text{in the region} \\ (l-1)\dfrac{L}{\Omega} \le \zeta^{(x,y)}_{(\kappa)\ N(s)} < l\dfrac{L}{\Omega} \end{bmatrix} \quad \text{for} \quad 1 \le l \le \Omega \tag{6}$$

L is the number of levels. A typical digital color image has 256 discrete intensity unit in each channel, therefore $L = 255$. Ω is the number of threshold regions around the line of attraction and $1 \le \Omega \le L$.

Stage two involves performing dynamic range compression using transforms such as Gain/offset correction, non-linear point transform, histogram equalization, and homomorphic filtering to the each *RGB* channel of the original image. The output of such filters can be described by:

$$\Upsilon_c(x,y) = T\left[I_c(x,y) \right] \tag{7}$$

where $I_c(x,y)$ is the c channel of the image I at location (x,y), $T[.]$ represents the transformation function., and Υ is the image after enhancement.

The relationships between the *RGB* channels of the image become distorted after application of filtering in stage 2. Stage 3 involves adjusting the relationship between the *RGB* components using the memory matrices obtained using eqn. (1) and activation functions obtained using eqn. (2) for associative recall. The dynamics for recalling is computed iteratively t as:

$$\zeta^{(x,y)}_{(\iota)}(t+1) = \frac{1}{n} \sum_{\kappa=1}^{n} \left[\zeta^{(x,y)}_{(\iota)}(t) + \upsilon \Delta \zeta^{(x,y)}_{(\iota,\kappa)}(t) \right] \quad \text{for} \quad 1 \le \iota \le n \tag{8}$$

where υ is the update rate ranging $0 < \upsilon \le 1$ and $\Delta\zeta^{(x,y)}_{(\iota,\kappa)}(t)$ is calculated by:

$$\Delta\zeta^{(x,y)}_{(\iota,\kappa)}(t) = \left\{ \Phi\left[w^{(x,y)}_{(\iota,\kappa)} \zeta^{(x,y)}_{(\kappa)}(t) \right] - \zeta^{(x,y)}_{(\iota)}(t) \right\} \tag{9}$$

until the network becomes stable. Figure 1 illustrates our color image enhancement process.

Comparison

We have compared the gain/offset correction, non-linear point transform, histogram equalization, and homomorphic filtering with and without our color image enhancement process: color characterization, enhancement, and color balancing.

Gain/offset Correction

The gain/offset correction is a linear transformation which transforms the scene to completely fill the dynamic range of the display medium by stretching the dynamic range of the images. Gain/offset is one of the most common methods of enhancing an image. For a display medium with the maximum dynamic range $\chi_{\max}$, the gain offset correction is describable as:

$$\Upsilon_c(x,y) = \frac{\chi_{\max}}{\tau_{\max} - \tau_{\min}} \left[I_c(x,y) - \tau_{\min} \right] \tag{10}$$

where $\tau_{\max}$ and $\tau_{\min}$ are $\max\left[I_c(x,y)\right]$ and $\min\left[I_c(x,y)\right]$ respectively.

Non-linear Transform

Non-linear transforms such as the gamma, the logarithm function, and the power-law function can be used for providing dynamic range compression to the original image. The output of such functions can be calculated as:

$$\Upsilon_c(x,y) = I_c(x,y)^{\gamma} \tag{11}$$

$$\Upsilon_c(x,y) = a\log\left[I_c(x,y)\right] \tag{12}$$

$$\Upsilon_c(x,y) = aI_c(x,y)^{\theta} \tag{13}$$

respectively. Where a is a scaling factor such that the maximum value of the enhanced image $\Upsilon_c(x,y)$ becomes *255*. The basis number, γ and θ , is used depends on the desired degree of compression of the dynamic range.

Histogram Equation

Histogram modeling techniques provide a sophisticated method for modifying the dynamic range and contrast of an image by altering that image such that its intensity histogram has a desired shape. Histogram equalization is a global technique that works well for a wide variety of images. This technique is based on the idea of remapping the histogram of the scene to a histogram that has a near-uniform distribution. Histogram equalization can be described by three simple operations:

1).Histogram formation.
2).New intensity values calculation for each intensity levels.
3).Replace the previous intensity values with the new intensity values.

This results in reassigning bright regions to darker values and dark regions to brighter values.

Homomorphic Filtering

The homomorphic system for image enhancement is based on the idea that the logarithmic operation separates $i_c(x,y)$ and $r_c(x,y)$ from the image. The homomorphic filter is an illumination-reflectance model. The model is described as:

$$I_c(x,y) = i_c(x,y)\,r_c(x,y) \tag{14}$$

where

$I_c(x,y)$ is the image intensity function

$i_c(x,y)$ is the illumination component

$r_c(x,y)$ is the reflectance component

The model assumes that $i_c(x,y)$ is the primary contributor to the dynamic range of the image and the reflectance component $r_c(x,y)$ represents the details of an object. In another word, the model described in eqn. (14) assumes that the illumination is the low frequency part of the image and the reflectance is the high frequency part of the image. With these assumptions of a slower and a faster varying component, the low pass and high pass information make it possible to treat the two components separately.

Results and Discussion

The resulting images with gain/offset correction, non-linear transform, histogram equalization and homomorphic filtering are illustrated in Figure 2. Shown on the first column is the original images, second column is the enhanced images without Ratio learning algorithm, and third column is the images with color balancing by Ratio Rule. The gain/offset correction did not contribute trivial enhancement for the type of non-uniform images where the min and max of the pixel intensities are close to 0 and 255 respectively. The image enhanced by gamma correction is shown in Figure 2b (middle) with obvious color distortion. The natural color of the image is restored after color balancing. The image with histogram equalization is shown in Figure 2c (middle) where the normal distribution of the pixel intensity results with pale appearance and overexposure of the image. However the learned relationship of the neural network restores back its natural color as illustrated in Figure 2c (right). The image boosted by homomorphic filter brings out more detail hidden in the shadows. As it can be seen in Figure 2d (middle) that the image appeared similar to the one with non-linear transform, it looks very vivid after restoring the ratio between *RGB* channels. The proposed algorithm works very well in general to retain the relationship of the color components presented in this category of distorted images.

Conclusion

A new framework to apply gray level image enhancement algorithm to the color domain is proposed. A single layer fully connected recurrent neural network trained using the Ratio learning algorithm is use as an associative memory to represent the original pixels relationship of an image as a line of attraction in the state space. Its dynamic is then used for recalling the original color characteristics to produce natural color rendition. We have described most of the common methods of enhancing an image and compared their result with and without our color image

(a) Gain/offset correction

(b) Non-linear transform

(c) Histogram equalization

(d) Homomorphic filtering

***Figure 2**. Color image enhancement (left) with (right) and without (middle) color characterization, enhancement, and color balancing*

enhancement process. We have shown that our enhancement process can provide simultaneous improvement to the dynamic range and color rendition to digital color images by simply applying gray level image enhancement algorithm in color domain.

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Author Biography

Ming-Jung Seow was born in Kuala Lumpur, Malaysia, in 1979. He received his B.S. and M.S. degrees in Computer Engineering from the Old Dominion University, Virginia, USA, in 2001 and 2002, respectively. He is currently pursuing his doctoral degree in the Department of Electrical and Computer Engineering at the Old Dominion University. His research interests are in the areas of recurrent neural network architectures and learning algorithms, and applications of neural networks and machine learning techniques in image processing, computer vision and pattern recognition.