A Real-time Object Correction Algorithm using Cellular Neural Network for Interactive Color Image Processor

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Abstract

We present a novel model for realizing a real-time image correction of specified objects in moving pictures. A cellular neural network incorporating human visual perception functions is proposed. It enables real-time color feature detection and smoothing interpolation of the object. This model is efficiently implemented into LSI circuits by using the finite element method. Smooth and selective correction effects are obtained in the face correction.

Introduction

To expand an effective range of image reproduction, we present a novel model for luminance and color correction of specified objects in moving pictures. The conventional global correction is effective to improve the global luminance or color profile of an entire image. It can not improve the local profile of an object without affecting the background[1]. The present model incorporating the human visual functions of feature detection and smooth interpolation enables the correction even of the specific object whose the luminance histogram is inseparable from that of the other objects.

Moreover, we also demonstrate in this work that the model can be represented into a simple algorithm by a successful use of the finite-element method. As the result, the real-time image correction is realized with a single processing architecture while the conventional algorithm needs complex parallel processing architecture for the real-time correction.

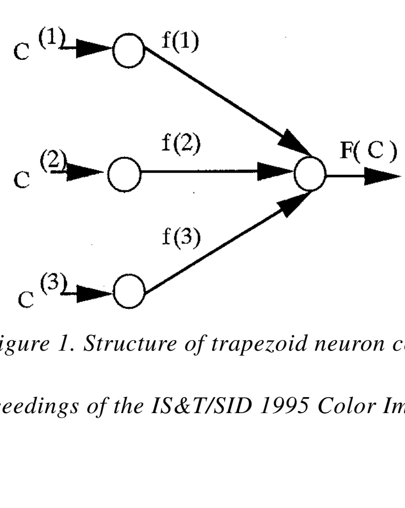

Figure 1. Structure of trapezoid neuron cell

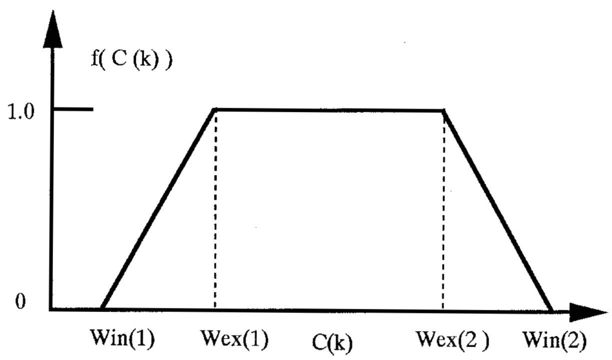

Figure 2. Trapezoid likelihood function

Local Object Correction Model

The human visual system has a function of scanning an object with a specific feature by eye-movements[2]. Image resolution obtained from eye-scanning of the object area is higher than that of the background area. We propose an object correction model to expand an effective range used for luminance and color reproduction of an object with a specific feature. In the model, we assume an object class based on the pixel color distribution and derive the pixel likelihood function L to determine the extent to which a pixel color signal belongs to the object class. A luminance or color signal is corrected in accordance with an output of the pixel likelihood function L. The pixel correction equation becomes

$$c'_{(k)}=c_{(k)} + L\bullet(G(c_{(k)})-c_{(k)}). \qquad (1)$$

(Where the G is a global correction function of a pixel luminance or color signal $c_{(k)}$.) A model of a trapezoid neuron cell is proposed to determine an object class of pixel color signals. Figures 1 and 2 show structure of a neuron cell and a trapezoid likelihood function with inclusive and exclusive parameters. A trapezoid function $f_{(k)}$ denotes the likelihood of the k-th component input $c_{(k)}$. The width parameters of each component are updated by assuming teach signals for pixel color signal inputs in an object area. For an input c_m of the object

area, a neuron to discern an object class is trained to output 1. The inclusive parameter $W_{in(i)}$ is modified to include the input c_m of the object class when the $f(c_m)$ is not equal to a teach signal.
Where i =1, 2.

$$W'_{in(i)} = W_{in(i)} + \alpha(c_m - W_{in(i)}) \text{ for } f(c_m) \neq 1. \quad (2)$$

For an input c_n of the other area, this neuron is trained to output 0. The parameter exclusive $W_{ex(i)}$ is modified to exclude the input c_n when the $f(c_n)$ is not equal to a teach signal.

$$W'_{ex(i)} = W_{ex(i)} - \alpha(c_n - W_{ex(i)}) \text{ for } f(c_n) \neq 0. \quad (3)$$

For the input ($c_{(1)}, c_{(2)}, c_{(3)}$), we assume the neuron output is given by

$$F = \left(\sum_{k=1}^{k=3} f_{(k)}(c_{(k)})\right) / 3. \quad (4)$$

The learning speed is about ten times faster than that of conventional neural networks[3]. This trapezoid neuron is suitable for a real-time feature detection of a specified object in moving pictures.

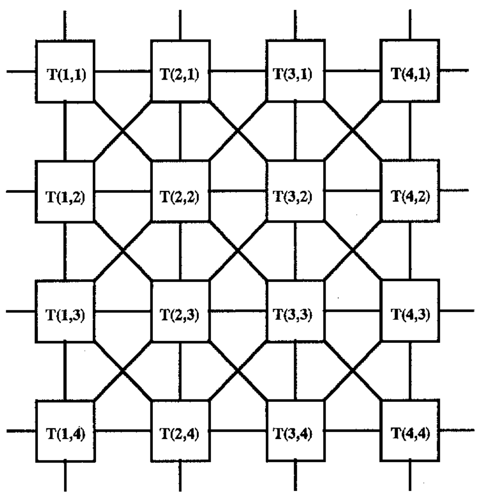

Figure 3. Cellular neural network.

The conventional object correction by using a neural network enhances discontinuous color feature points in the object area due to nonuniformity in spatial color signal distribution. We propose a model of a cellular neural network to interpolate discontinuous color feature points smoothly. Figure 3 shows a schematic diagram of a cellular neural network consisting of 16x16 trapezoid neuron cells. A neuron cell (T(u,v)) at a pixel location of (u,v) is connected to each of the cells (T(m,n)) in its r-neighborhood. We define the network output of the centroid cell T(u, v) as

$$L_{(u,v)} = \frac{1}{d^2}\left(\left(\sum_{M=u-r-1}^{m=u+r}\sum_{n=v-r-1}^{n=v+r} w_{mmuv} F(m,n)\right)\right). \quad (5)$$

(Where d=16 and r =8.) In an example of the present luminance or color correction, we assume $w_{mnij} = 1$. The resultant output L(u,v) is the likelihood averaged over 16x16 neuron cells. This object correction based on the equation (1) is effective for interpolating discontinuous pixel values smoothly.

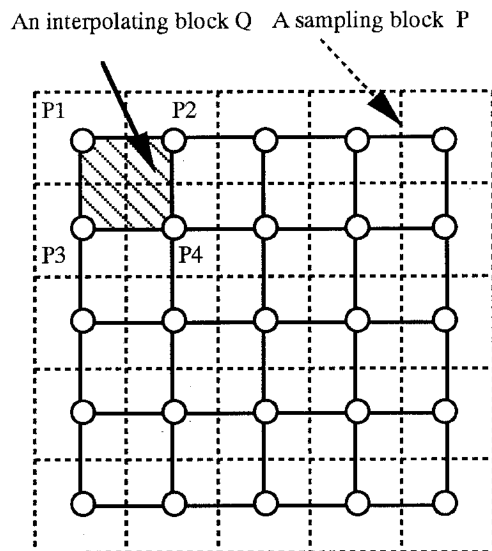

Figure 4. Block summation and interpolation ($L_{(0,0)}=L_1$, $L_{(d,0)}$-L_2, $L_{(0,d)}$-L_3 and $L_{(d,d)}=L_4$)

The network calculations of the equation of (4) consist of 768 arithmetic operations of addition and comparison and require massively parallel processors. To implement a cellular neural network into single processor architecture, we present an efficient algorithm based on the finite element method. We assume the sampling and interpolating blocks with 16x16 pixels in the figure 4. The centroids in the sampling block P_1, P_2, P_3 and P_4 are configured to correspond to the four nodal points in the hatched interpolating block Q. The calculations of the equation (4) is represented into a simple algorithm of block summation and interpolation. First, the network outputs L_1, L_2, L_3 and L_4 at the four nodal points are obtained by summing up each neuron cell output F in the sampling blocks P_1, P_2, P_3 and P_4. Second, a network output $L_{(u,v)}$ at a pixel location of (u,v) in the element is bilinearly interpolated from the nodal values. The following linear equations are assumed to obtain L_{m1} and L_{m2} at the nodes (0, v) and (d, v).

$$L_{m1} = (L_3 - L_1)*v/d + L_1. \quad (6)$$

$$Lm_2 = (L_4 - L_2)*v/d + L_4. \quad (7)$$

The nodal value at (u, v) is obtained by using

$$L(u,v) = (L_{m2} - L_{m1})/d*u + L_{m1}. \quad (8)$$

The calculations (4) of the present cellular neural network are pipelined by using the bilinear interpolation.

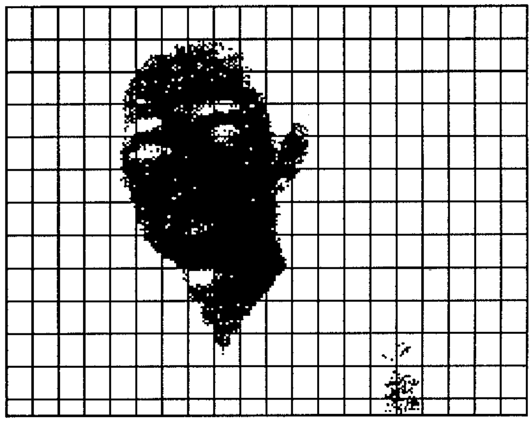

Figure 5. Extracted face area before interpolation

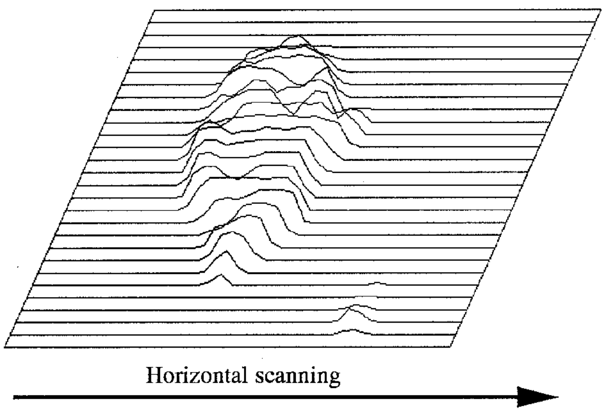

Figure 6. Smoothing interpolation of extracted face areas

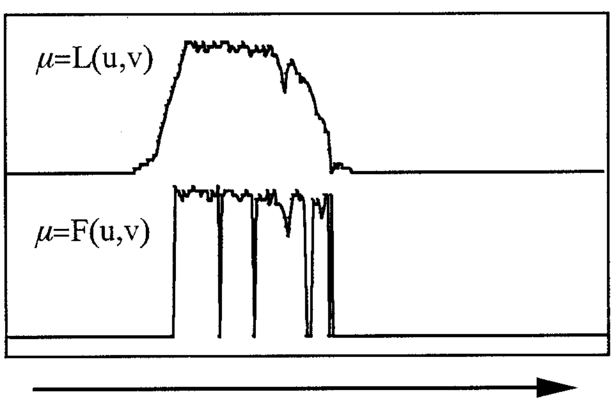

Figure 7. Horizontal profile of luminance increment $(\Delta\mu^{\circ}(G(y)-y))$

Results

We demonstrate feature detection and smooth interpolation in an example of a human face correction. Figure 5 shows the extracted face area obtained by using a neuron cell output $F_{(u,v)}$. In the face area, discontinuous feature points appear due to the nonuniformity in the color distribution. Figure 6 shows the interpolated face area obtained by using cellular network output L(u,v). The discontinuous feature points are interpolated smoothly by using a cellular neural network. Figure 7 shows the horizontal profile of the luminance increment Δy. In a case of $\mu=F_{(u,v)}$, the resultant increment Δy varies abruptly at the discontinuous points and on the boundary between the face area and the background. In a case of $\mu=L_{(u,v)}$, the discontinuous features are eliminated in the interpolated face area. The Δy gradually varies on the boundary. This result indicates that this likelihood function L(u,v) interpolates the discontinuous features fairly well.

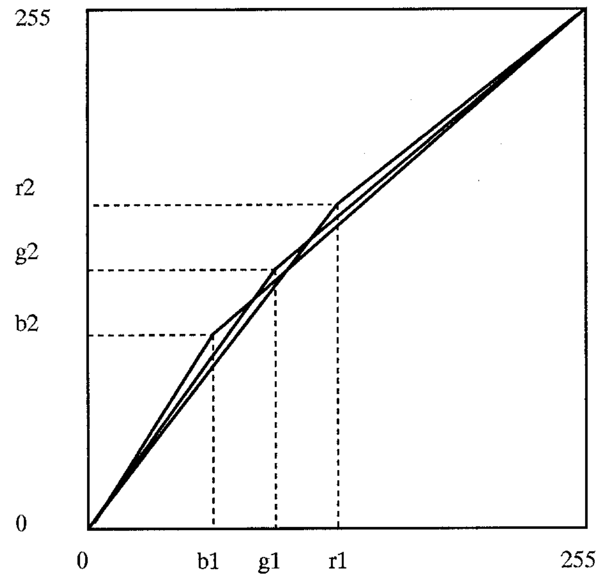

Figure 8. Global correction curve (r2,g2,b2)= (r1+Δr1,g1+Δg1,b1+Δb1)

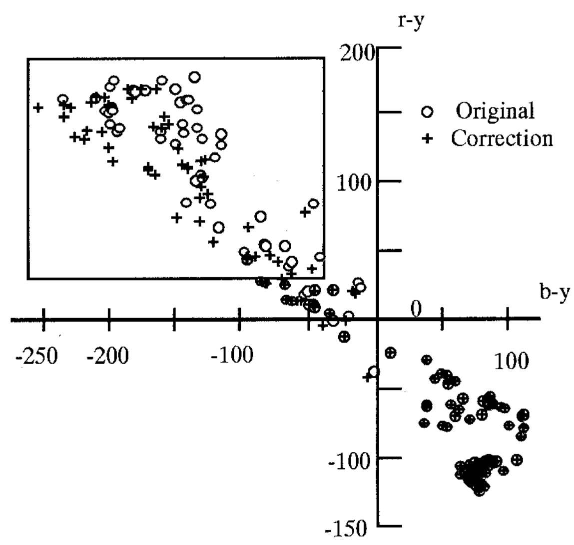

Figure 9. Variation in the color space (r-y, b-y)

To realize a preferred memory color, we present an example of facial color correction. Figure 8 shows a global correction curve, which transforms average color signal of (r1,g1,b1) into a preferred one represented by (r2, g2, b2). (Where r1=128, g1=93 and b1=56 for a picture in the figure 5.) We assume (r2, g2, b2)=(112, 90, 76) as a preferred memory color[4]. Figure 9 shows the variation in the space (r-y, b-y) induced by the object correction with μ=L(u,v). The rectangular area represents color distribution of the face class obtained by using the trapezoid neuron cell. The norm of the difference vector (Δ(r-y), Δ (b-y)) in the rectangular area is larger than that in the background. That in the background (satisfying r < y and b>y) becomes zero. The pixel values r, g and b remain unchanged since L(u,v) =0.

To expand an effective dynamic range used for a specified object, we present object correction of a luminance profile. Figure 9 shows integral luminance histogram curves of a face area and a background area. Table 1 shows luminance increment averaged over 16×16 pixels with maximal 256 scales. By a global correction, the luminance values in the curves B1 and B2 are enhanced. The average increment of the luminance in the face or background area is 36 or 16. By a local correction, only the curve A1 of the face area is enhanced. The curve A2 of the background remains unaffected. The average increment of the luminance in a face area is 28 while the increment in background remains 0. From the above results, we can conclude that this method is fairly effective to improve the tone of a face area without affecting that of the background.

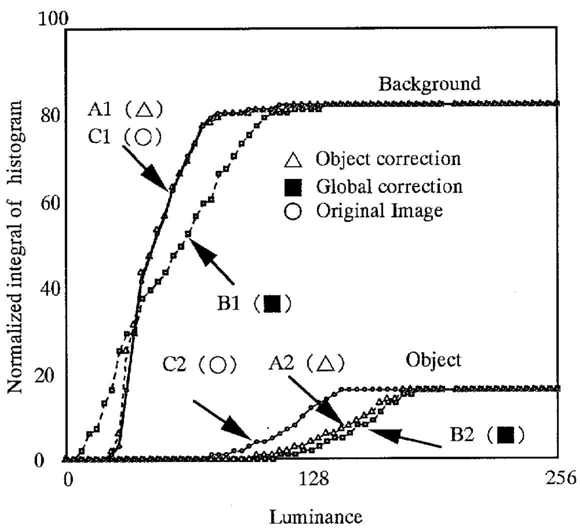

Figure 10. Correction effect on luminance profiles

Implementation

Figure 10 shows a diagram of the image correction processor board. This processor operates at 21.48MHz and corrects a NTSC moving picture within 1/60 second. The trapezoid neuron unit performs a real-time feature extraction. The block summation unit and the block interpolation unit operate simultaneously to carry out the calculations of the cellular neural network. A correction function generator generates a global correction function G (c(k)) for a nonlinear lookup-table unit LUT. The correction arithmetic unit corrects pixel values in the equation (1).

Table 1. Correction Effect on Luminance

	Face	Background
Gobal Correction	36	16
Local Correction	28	0

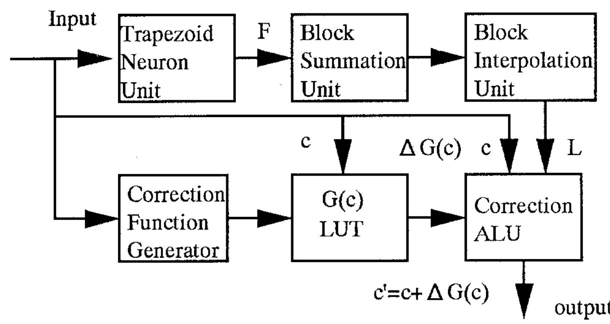

Figure 11. Image correction processor board

Summary

We propose a local object correction method based on visual perception mechanisms. A novel model of the cellular network is presented. The correction using the neural network is fairly effective to smooth discontinuous feature and to modify the tone of face area without affecting the background. The block approximation of the network calculations is suitable for VLSI-implementation. This method would realize an interactive object correction in moving picture applied for multi-media systems.

Acknowledgment

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