2001

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Tarik Hammadou
Motorola Labs

Abdesselam Bouzerdoum
Edith Cowan University

10.1109/30.982811
This article was originally published as: Hammadou, T. & Bouzerdoum, A. (2001). Novel image enhancement technique using shunting inhibitory cellular neural networks. IEEE transactions on consumer electronics, 47(4), 934-940. Original article available here

NOVEL IMAGE ENHANCEMENT TECHNIQUE USING SHUNTING INHIBITORY CELLULAR NEURAL NETWORKS

Tarik Hammadou[1] and Abdessalem Bouzerdoum[2]
[1]Motorola Labs, Locked Bag 5028, Botany NSW 1455, Australia
[2]Edith Cowan University, Visual Information Processing Group, Joondalup WA, Australia

ABSTRACT

This paper describes a method for improving image quality in color CMOS image sensor. The technique simultaneously acts to compress the dynamic range, reorganize the signal to improve visibility, suppress noise, identify local features, achieve color constancy, and lightness rendition. An efficient hardware architecture and a rigorous analysis of the different modules are presented to achieve high quality CMOS digital cameras.

1. INTRODUCTION

Various types of imagers or image sensors are in use today, including Charge-Coupled Device (CCD) image sensors and complementary metal-oxide semiconductor CMOS image sensors.

CMOS image sensors typically utilize an array of active pixel image sensors and a row of register of correlated double-sampling (CDS) circuits or amplifiers to sample and hold the output of a given row of pixel image sensors of the array [1]. Each active pixel image sensor of the array of pixels typically contains a pixel amplifying device (usually a source follower).

Current CMOS image sensors, still have inferior imaging performance compared to CCD imagers, due to excessive FPN, and also due to limited dynamic range (about 72 dB) (which is reduced, in part, by excessive FPN), and low fill factor (the ratio of photodetector area to total area of the APS pixel circuitry) which results in lower sensitivity. The result, the image quality captured by CMOS image sensor is inferior to that by CCD [2]. Therefore, a digital image processor is necessary to improve the image quality of CMOS image sensors.

Several image enhancement algorithms are presented for the CCD based digital camera. However, because these algorithms are developed and optimized for CCD they will not achieve the same results for CMOS image sensors.

Further author information: Send correspondence to Tarik Hammadou Tarik: E-mail:A17088@email.mot.com

The goal of image enhancement is to process an original image in a manner such the processed image is more suitable for a desired application. In general image enhancement convert the original image into a form better suited for human and machine analysis. Image enhancement is also used to clarify image details that are blured or corrupted by noise, such removal of noise from the image is often a wrong process leading to removal of important image information along with noise.

Recently, more advanced approaches at noise removal image enhancement have been developed [3]. However image enhancement is an inexact science. A major problem in image enhancement is the characterization or prediction in an image of accurate image details and false image details. Most of the image enhancement techniques operate on the color interpolated version of the image. The color interpolation is generated from the bayer pattern. Each pixel location has the entensity level only one of three color components Red, Green or Blue. The bayer pattern image is then color interpolated such that each pixel's missing color components are approximated to give each missing color. However, such techniques often introduce error or noise specially in the case of CMOS image sensor.

Thus, enhancing an image after color interpolation may not yield very accurate results. There is a need for a general framework to perform image enhancement technique simultaneously acting to:

1. Compress the dynamic range.
2. Reorganize the signal.
3. Improve visibility.
4. Suppress noise.
5. Identify local features.
6. Achieve color constancy.
7. Lighting rendition.

Biological models based on Lateral Inhibition in biological vision systems have long been recognized as sharing both form and function with image processing algorithms. A theory of biological vision centered on the concept of

Original manuscript received June 25, 2001
Revised manuscript received October 1, 2001

Lateral Inhibittion was introduced by Bahram Nabet and Robert B. Pinter in [4]. A. Bouzerdoum and R. B. Pinter in [5] introduced a new Cellular Neural Networks (CNN's) form of a Shunting Inhibitory type namely called "Shunting Inhibitory Cellular Neural Networks". Bouzerdoum in his paper showed the derivation and biophysical interpretation, along with the stability analysis of such network.

The application of Pinter and Bouzedoum's biological vision theories has been attempted to emulate the motion detection in insect's vision, a detector array with integrated processing in analog VLSI silicon chip has been fabricated [6].

However, none of the prior art have developed an image processing technique based on Shunting Inhibition that simultaneously accomplishes dynamic range compression, contrast enhancement, reduce noise, color constancy and lightness rendition suitable for CMOS image sensors to be a good candidate for future digital cameras.

The organization of this paper is as follows. In next section we present the detailed description of the algorithm and how it is related to image processing operations. In Section 3 we describe an efficient implementation of a digital processor based on SICNN. We will describe the different preprocessing modules to achieve high quality imaging. Finally the paper ends with discussion and conclusion in Section 4.

2. DETAILED DESCRIPTION

Many image algorithms include a function to expand the dynamic range of the image. An attractive way is described in [7], a processor controls the gamma slope to extract a set of feature data from an input image. The processor calculates then the numbers of pixels of luminance values in the bright range, in the middle range and in the dark range. The gamma slope is then selected by using neural network. Another method presented in [8] makes a histogram of the luminance level in a frame and expands the dynamic range by controlling the slopes of knee compensation.

Our approach differs from that others in that we have attempted to understand the behavior of the human visual system and why lines and edges are important. In visual systems changing frequency characteristics with mean luminance is important because the nature of the noise present in the input changes significantly with mean luminance. At low values of mean luminance there is a significant proportion of high frequency noise caused by random photon events. At higher mean luminance values the signal to noise ratio improves as the proportion of random photon events decreases, making detection of high frequency component far less error prone. However biological systems adopt the strategy of changing from object detectors at low light levels to feature detectors in bright light. This is due to the change in frequency characteristics in visual cells, which act as low pass filters at low light levels and become bandpass filters as light intensity increases.

Shunting Inhibitory Cellular Neural Networks (SICNN) is a biologically inspired system of an early processing which can provide contrast and edge enhancement and dynamic range compression. The SICNN algorithm is an efficient way to achieve lightness-color constancy, we found that the proposed technique achieves a balance between enhancing the dark region and at the same time retaining the colors in the bright. The traditional point-nonlinearities are also able to enhance the dark regions but at the cost of saturating the bright regions. In Shunting Inubitory Cellular Neural Networks(SICNNs), neighbouring neurons exert mutual inhibitory interactions of the shunting type. The activity of each neuron in the feedforword SICNNs is described by a nonlinear differential equation.

$$\frac{dx_{ij}}{dt} = I_{ij}(t) - a_{ij}x_{ij} - f(\sum_{C(k,l)\in N_r} w_{ij}^{kl} I_{kl})x_{ij} \qquad (1)$$

Where x_{ij} represents the activity of the i_{th} cell, $I_{ij}(t)$, is the external input to the i_{th} neuron; $a_{ij}(>0)$ is a constant of passive decay rate of the i_{th} neuron activity; $w_{ij}(>0)$ represents the connection or coupling strength of postsynaptic activity of the j_{th} neuron transmitted to the i_{th} neuron; and the lateral inhibition function f describes the inhibitory action exhibited on the i_{th} neuron by the activity of the j_{th} neuron. The steady state solution of Eq. (1) is given by

$$x_{ij} = \frac{I_{ij}}{a_{ij} + \sum_{k,l\in N_r(C)} w_{ij} I_{kl}} \qquad (2)$$

The gain control mechanism of such system makes the network sensitive to small input values by suppressing noise while not saturating at high input values.

2.1. Dynamic Range Compression

The dynamic range DR compares the maximum signal level V_{max} with the minimum rms noise level (ΔV_{min}), in an image sensor typically obtained in the dark.

$$DR = 20\log_{10}\frac{V_{max}}{\Delta V_{min}} \qquad (3)$$

One of the major problem in digital photography due mainly to lighting conditions is the dynamic range problem. As a result most photographic and electronic cameras suffer from a comparative loss of detail and color in shadowed zones.

Electronics cameras based CCD detector arrays are quite capable of acquiring image data across a wide dynamic range on the order to 2500 : 1. This range is suitable for handling most illumination variation within scenes, and lens aperture changes are usually employed to encompass scene-to-scene

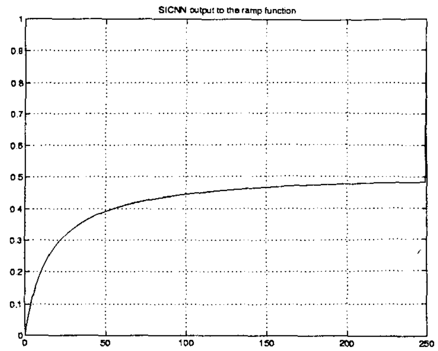

Figure 1: SICNN dynamic range compression.

illumination variations. This dynamic range is lost when the image is digitized. For example most images are digitized to 8-bits/color band and most display and print media are even more limited to 50:1 dynamic range.

Electronics camera based CMOS detector arrays suffer from excessive Fixed Pattern Noise (FPN). As a result the dynamic range is mainly limited to 72 db.

We can conclude then that Analog implementation of dynamic range compression is more suitable if the A/D converter is done at 8 bits. If the A/D is done at 10-14 bits digital implementation is more adequate specially for CMOS type imagers.

Figure 1 shows the relative gain adaptation of Shunting Inhibition, the graph was obtained by applying SICNN to the ramp function. Note that the response are logarithmic, suggesting exactly the sort of dynamic range compression observed in natural vision systems, as well as the type of signal transformation associated with homomorphic processing.

Equation (2) also demonstrate how the intensity has been coded. Each cell has a 'clue' to the total intensity without having to saturate its dynamic range by coding the intensity directly. This property is a direct result of dividing the intensity by the shunting term $(a_{ij} + \sum w_{ij} I_{kl})$ as in Eq. (2) and is due to the unique automatic gain control property of shunting inhibitory networks.

The weakness of traditional point nonlinearities such gamma correction is the amplification of noise in the dark region. Shunting Inhibition equation describes a first order low pass filter with time constant that is controlled by the shunting input and therefore is changing with mean luminance. This unique property make Shunting Inhibition capable to enhance dark region and in the same time reduce the amount of noise due to the amplification.

This type of filters in image processing are describes as combination of linear filters and nonlinear point operations

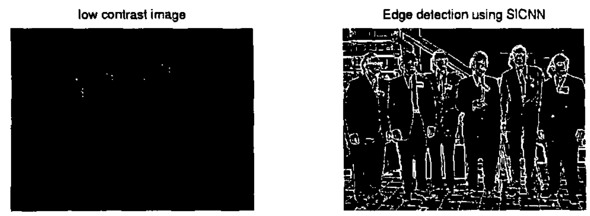

Figure 2: Edge detection from a low contrast image.

(such as division). The combination of linear filter operations with nonlinear point operations makes the whole operation nonlinear. This is well known in image processing as a very powerful instrument. Many advanced signal and image-processing techniques are of that type. This includes operators to compute local structure in images and various operations for texture analysis. Figure 2 shows the performance of the algorithm as an edge detector, we note that the input image is of very low contrast.

2.2. Color Constancy

Another problem with color images is that the images are object to color distortions when the spectral distribution of the illuminance changes. This is known as the color constancy problem. Consider the input

$$I_i = I_r I_t \tag{4}$$

Where I_r is the normalized contrast or reflectances. I_t is the total input, defined by

$$I_t = \sum_{k=1}^{n} I_k \tag{5}$$

From equation (1) and by approximating the convolution term to the input current sources, the steady state solution can be written:

$$x_i = I_r \frac{I_t}{a + \sum_{k \neq i} I_k} \tag{6}$$

Assuming that the total activity is not perturbed by the activity of one cell,

$$\sum_{k \neq i}^{n} I_k \approx \sum_{k=1}^{n} I_k = I_t \tag{7}$$

Then we can write equation (6) as

$$x_i = I_r \frac{I_t}{a + I_t} \tag{8}$$

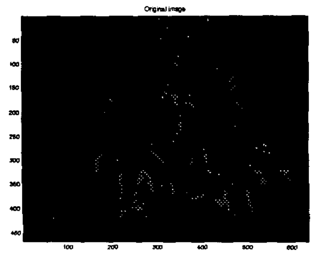

Figure 3: Input image under low luminance.

Figure 4: SICNN Output image.

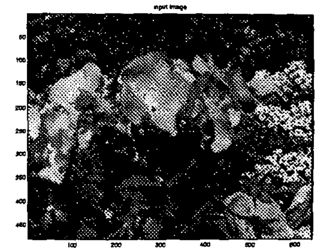

Figure 5: CMOS imager input Image.

Figure 6: SICNN Output image.

Equation (8) shows how the reflectances are modulated by mean intensity. This explain color and brightness constancy property. We can calculate the total activity of the network as

$$X_T = \sum_{i=1}^{n} x_i = \sum_{i=1}^{n} I_r \frac{I_t}{a + I_t} = \frac{I_t}{a + I_t} \tag{9}$$

Which converge to 1 as mean intensity (background) increases. This property is well known in visual psychophysics as brightness contrast. It very interesting to note that the two contradictory phenomena of brightness constancy and color constancy can be explained by the same network. Figure 3 and 4 show the result achieved under low luminance.

2.3. Color Rendition

Color rendition is a very common problem in color and non color image processing. This problem results from trying to match the processed image with what is observed. As a result,

1. lightness and color "Halo" artifacts that are especially prominent where large uniform regions of an image form a high contrast edge with "graying" in the large uniform zones.
2. Global violation of the gray world assumption which result in a global "graying out" of the image.

It is clear then that color rendition and nonlinear operations are contradictory. This conclusion motivate us to look further to the structure of our network by giving more interest to the balance between the nonlinearity of SICNN and color rendition. This balance can be achieved by an appropriate choice of the synaptic weights. Figure 5 and 6 show the result we achieved for a CMOS image sensor.

3. IMPLEMENTATION

The effectiveness of the algorithm described depend strongly on the hardware that executes it. A test system based on an FPGA has been built. The functionality of each block has been modeled and tested in VHDL. The structure of the architecture and the result of the synthesis tool are shown in figure 7 and 8. It consists of 5 modules. In the first module the bayer pattern image is color interpolated such that each pixel's missing color components are approximated to give each missing color. In the second module each pixel is color corrected then the RGB data is converted to YC matrix. The final step is to apply SICNN to the luminance component.

3.1. RGB interpolation

Most of color interpolation methods are based on the assumption of low noise environment. This is usually true for CCD sensors and high-end CMOS sensors. However,

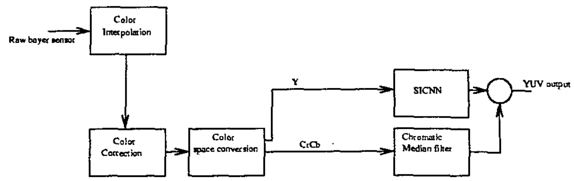

Figure 7: Structure of the digital processor.

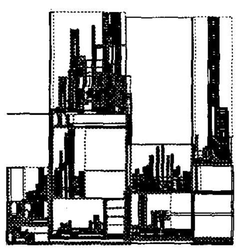

Figure 8: Generated gate level schematic.

when SNR of the captured image is low such algorithms tend to spread noise producing artificial patterns. Besides that, the algorithms usually do not take into account color influence of aliasing and fixed pattern noise. A color interpolation algorithm intended for CMOS sensors should take these problems into account.

In single sensor electronic imaging systems, scene color is acquired by sub-sampling in three-color planes to capture color image data simultaneously for red, green and blue color components. Usually this is accomplished by placing a mosaic of red, green and blue filters over a 2D single sensor array. Equation 11 shows the bayer pattern used. The signal processor has to calculate the other color components using the neighboring color pixel values.

$$\begin{bmatrix} B_{00} & G_{01} & B_{02} & G_{03} \\ G_{10} & R_{11} & G_{12} & R_{13} \\ B_{20} & G_{21} & B_{22} & G_{23} \\ G_{30} & R_{31} & G_{32} & R_{33} \end{bmatrix}. \tag{10}$$

Our objective is to use an algorithm providing a good quality images with inexpensive hardware cost. The CMOS imager has B and G color data in the even lines, and G and R color data in the odd lines. The G color pixel interpolation is different from the R and B color pixel interpolation because the G channel data have a major influence on the resolution of an image. The R and B interpolation is as follows.

$B_{11} = Average(B_{00}, B_{02}, B_{20}, B_{22})$,
$B_{12} = Average(B_{02}, B_{22})$,
$B_{21} = Average(B_{20}, B_{22}, B_{40}, B42)$,
$R_{12} = Average(R_{11}, R_{13})$,
$R_{21} = Average(R_{11}, R_{31}$
$R_{22} = Average(R_{11}, R_{13}, R_{31}, R_{33})$

There are green color pixels in every line, we interpolate the missing G pixels with three neighboring G pixel values, which require only one line memory. If we average two horizontal neighboring G pixels we may blur the edges that why we calculate the missing G value by taking the median value among the three G pixel values.

$G_{11} = Median(G_{01}, G_{10}, G12)$

3.2. Color Correction

While trying to improve color reproduction in CMOS image sensors it is obvious that the color correction methods amplifies the noise. As a result, SNR of the color-corrected image can be almost 10 dB lower. Besides that, color aliasing artifacts may become more visible. Human vision is very sensitive to noise, while can tolerate some color imperfection. In fact, the observer does not need comparing with the original scene to identify excessive noise in the displayed image. At the same time moderate errors in color reproduction cannot be recognized without comparison against the original scene. Thus, low noise is more critical than color fidelity for CMOS image sensors that have quite high noise level.

A standard color correction approach is to maximize colorimetric accuracy while assuming a noiseless environment. The color accuracy can be maximized for the entire spectrum or for some important colors. The operation is usually represented in a matrix form. This is a 3 × 3 matrix converting RGB to $R_cG_cB_c$ color corrected space. The matrix coefficients H_{ij} depend on the parameter of the sensor and need to be derived on a case-by-case manner. Based on our experiment the following matrix was obtained:

$$\begin{bmatrix} R_c \\ G_c \\ B_c \end{bmatrix} = \begin{bmatrix} 1.281 & -0.109 & -0.117 \\ -0.109 & 1.400 & -0.125 \\ -0.133 & -0.148 & 1.343 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}. \tag{11}$$

3.3. SICNN Implementation

To preserve image chromaticity while doing dynamic range compression, we must begin with calibrated input and output devices. In particular, we require a linear relationship between scene and CRT luminance of the three channels (up to a uniform multiplicative nonlinear function). This means that the CRT's gamma must be taken into account. the standard power–law method of gamma correction is only an approximation, and the best values of "gamma" varies from monitor to monitor.

There is an interesting relationship with the formulation of SICNN and gamma correction. That method uses a channel independent logarithm, which normally would have the side effect of changing the image colours. However, the operation somewhat approximates monitor gamma correction, and thus the colour shift is far less of a problem when displaying the result without gamma correction than would be expected. In fact applying gamma correction to the result of SICNN processing normally gives poor results. Specifically the images look washed out and over gamma corrected. Since SICNN can to some extent play the role of gamma correction, it is important to ensure proper gamma correction is being applied to the original image when being compared to SICNN results on a monitor.

We noticed that there is some problems with SICNN processing applied to the 3 channels one of the problems is that the image colours tend to be desaturated greyish. This is due to the manner in which grey–world–based colour constancy processing is applied to relatively small image neighbourhoods. Another problem is complement colour bleeding at certain colour edges due to the local contrast enhancement.

In this work the main idea to SICNN implementation is to separate the processing goals/effects of SICNN so that each one can be done more optimally. The RGB of the output image pixels are set so that their chromaticity is the same as in the original linear image, but their luminances are result of another preprocessing step. The SICNN processing is applied then to the luminance channel.

4. CONCLUSION

The digital processor presented in the previous section has been implemented and tested on an FPGA board. The test images showed a significant improvement of CMOS sensor images quality.

Table 1: Atributes of the Digital Signal Processor.

Gate count	80,000
Memory	4kbyte
Input data width	10 bits
Output data width	7bits
Operating frequency	50 Mhz
Power consumption	800 mW
Power supply	5V, 3.3V

Shunting Inhibitory Cellular Neural Networks works quite well as a method of compressing an image's dynamic range

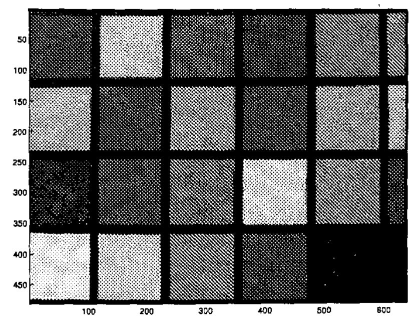

Figure 9: Test image without SICNN.

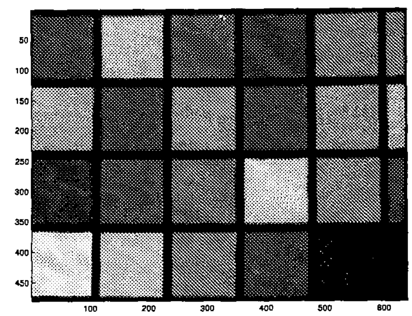

Figure 10: Test image with SICNN.

so that the image contrast looks better, in the same time SICNN technique enhances the spatial edges of the image that have been smoothed by a combination of the MTF of the optics and the color interpolation. Applying SICNN to the illuminance component helps to eliminate FPN due to the chromaticity differences.

A median filter operates on the chromiance data only. It detects a false color, this is because the optics of the system may provide a MTF significantly higher than the sensor can sample, so high frequency aliasing can be sampled into the image particularly at high illumination (glint) points. Another reason is that the color interpolation algorithm will tend to enhance single point (one color) features, creating false apparent colors at those high spatial frequency points. Figure 9 and 10 reflect the performance of the SICNN method.

We presented an optimized digital signal processor developed for CMOS image sensors, other modules like automatic gain and exposure control or automatic white balance can be added to the processor to enhance the efficiency. It is expected that such processors will close the gap between CMOS and CCD imaging quality.

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6. BIOGRAPHIES

Tarik Hammadou was born in Oran, Algeria, in 1972. He received the Dipl. Ing. degree in Electrical Engineering in 1996 from the Oran University of Technology (USTO). In 1997 he joined the Signal Processing Research Center in Queensland, Australia as scholar visitor. In 1998 he joined Edith Cowan University, Western Australia as a research assistant, working toward a master degree. Since July 2000 he is with Motorola labs Australia, engaged in CMOS image sensor research and image processing applications. His research interest include VLSI implementation of smart micro sensors, sigma delta analog to digital converters, and signal processing.

Abdessalam Bouzerdoum Dr. A. Bouzerdoum received the Masters and Ph.D. degrees, both in electrical engineering, from the University of Washington, Seattle, in 1986 and 1991, respectively. From 1991 to 1997 he was with the University of Adelaide, South Australia. In 1998 he was appointed Associate Professor at Edith Cowan University. Dr . Bouzerdoum has received several distinguished awards, amongst them the Vice Chancellor's Distinguished Researcher Award in 1998 and 1999, and the awards for Excellence in Research Leadership and Excellence in Postgraduate Supervision in 2000. In 2001 he was awarded a Visiting High-Level Researcher Fellowship from the French Ministry of Research to spend three months at the National Research Centre LASS - CNRS in Toulouse. He is currently serving as Associate Editor for the IEEE Transactions on Systems, Man and Cybernetics. His research interests include machine vision and pattern recognition, neural networks and their applications to signal and image processing problems, and VLSI implementation of smart microsensors.