Wide Color-Gamut Improvement With Skin Protection Using Content-Based Analysis for Display Systems

Yeong-Kang Lai, Member, IEEE, and Shu-Ming Lee, Student Member, IEEE

Abstract—In this paper, we propose an improved color-gamut method for liquid crystal displays (LCD) with multi-phosphor white light emitting diodes (MPW LED) and a modified rich color image processing approach with skin protection. The color saturation is always used to broaden the color-gamut. By increasing the color saturation, the expanded color-gamut can be observed in the CIE 1931 color space. The human skin color is typically memorized by color information. In order to increase the color saturation, the traditional rich color method makes skin color appear unnatural, so a modified rich color method with human skin color protection is proposed. The skin color protection generates normalized chrominance and illumination features. The skin chrominance model uses the normalized color-information of the skin as a classifier in a real-time skin pixel detection system. Several geometric patterns are used to tune the skin chrominance model with the principal components in color space to give the system a better detection performance. Consequently, the skin region information is used to tune the enhancement parameter in the modified rich color image processing approach. In comparison, the proposed approach yields a better image quality than the traditional one. In mobile display systems, due to the limitation of bandwidth and memory capacity, determining how to realize the functions of a wide color-gamut improvement method with skin protection on mobile display platform is very important. Ultimately, we have implemented our proposed method in the FPGA and displayed the image on the ARM platform.

Index Terms—Color enhancement, color gamut, liquid crystal display (LCD), skin protection.

I. INTRODUCTION

In the evolution of liquid crystal displays (LCDs), there have been steady improvements in flicker elimination, high contrast, wide viewing, low power, wide color gamut, detailed graphics, response time, and brightness. These improvements have played important roles in the power consumption and image quality of LCDs. This paper develops the methodology and techniques for dynamic color enhancement with skin region detection to broaden the color gamut, making the displays more vivid. In [5]–[8], we see that there are many approaches to improve digital image quality that have been developed. However, the computational complexity is high. Some works use an approach with the same conversion ratio to enhance the image; this approach may result in the so-called color clipping effect in color images [4], [10], [11]. The color clipping effect is a common problem in conversion to broaden the color-gamut. Some colors suffer discoloration. [1], [2], [9] have proposed various approaches to define the non-movable area, in order to prevent the color from the clipping effect. The gamma curve describes the relationship between the brightness and the pixel gray scale of the display. Three independent gamma curves for R, G and B, in the color LCD sub-pixel display, are employed to increase color saturation. Recently, [1]–[9] have shown that an approach, based on the characteristic of each gamma curve to increase the color saturation, can prevent generating a clipping effect when the image is displayed on LCDs. However, the skin region of the resulting image becomes unnatural when the color saturation of the skin region has been increased, generating some quality-loss effects on the displays. For this reason, [2] proposed some approaches to protect skin regions. However, their skin chrominance model only roughly defines the skin region. Accomplishing accurate skin color detection is a challenging task when separating skin colors from non-skin colors. One important task in skin detection is color space selection, which is a more efficient approach for skin color detection. In recent years, many references have proposed comparative studies of different chrominance spaces to detect skin color, and have found that producing chrominance spaces through normalization is more efficient for skin color detection [1], [2]. Detection efficiency depends on the capability of the skin chrominance model to extract the skin-like regions to accurately detect skin pixels and non-skin pixels. What is behind skin-color detection is that, information about the skin region is used to tune the enhancement parameter in the modified rich color image processing method.

In hardware implementation, 3-D LUT uses the color-gamut mapping (CGM) method to preprocess image data to build a 3-D LUT [3], and 3-D RRLT uses the reduced 3-D color-gamut mapping method to get good implementation results [4]. In [12], Toledo et al. implemented a skin color detection method by using a Skin Probability Map (SPM) in the FPGA. However, their computational complexity is quite high. The complex algorithms and high-cost structures are not suitable for small-sized TFT LCD products, such as mobiles, PDA devices, cameras and

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Y.-K. Lai is with the Department of Electrical Engineering, National Chung Hsing University, Taichung 402, Taiwan (e-mail: yklai@dragon.nchu.edu.tw).

S.-M. Lee is with the Department of Electrical Engineering, National Chung Hsing University, Taichung 402, Taiwan, and also with Wintek Corporation, Taichung city, Taiwan.

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Fig. 1. Block diagram of proposed method.

Fig. 2. Characteristics of RGB gamma curve.

car GPS devices. For these reasons, discovering how to maintain good image quality and proper computational complexity is worth investigating.

The rest of this paper is organized as follows. The details of the proposed modified rich color image processing approach are introduced in Section II. Skin detection is described in Section III. Color space selection for skin detection and the skin regions detection method are also explained. Section IV introduces the implementation method of the proposed algorithms on an FPGA platform. Section V presents the measured experimental data. In this section, some comparison tables are shown. Finally, Section VI gives some brief conclusions.

II. ALGORITHM FOR MODIFIED RICH COLOR METHOD

In this paper, we present a method to broaden the color-gamut and to protect the skin region in an image without any color distortion, by using a non-linear stretch of color gamut on a CIE1931 diagram. The block diagram of the proposed method is shown in Fig. 1. The increase of the color-gamut is performed by using the characteristics of RGB gamma curves. The characteristics of RGB gamma curves are shown in Fig. 2. Each gamma curve has different enhancement characteristics to convert color. For a customized LCM module with an MPW LED, we first use 13 types of standard test patterns to drive the LCD panel. Optical instruments are used to measure the characteristics distribution on a CIE1976 diagram. Based on the color gamut of these standard test patterns on a CIE1976 chromaticity coordinate, the coordinate distance ratio is calculated. Then, we use the coordinate distance ratio for each color RGB to generate the color-gamut vector (F) and the Look-Up Table (LUT) of color-gamut broadening gain (S'). The color-gamut vector is used to define the non-movable area and to select the gain in color-gamut broadening gain. The color-gamut broadening gain is the enhancement value of the LCD panel which maintains the chromaticity coordinates of the image after enhancement, and it is always located inside the RGB boundary line of CIE1931 chromaticity. It can prevent the color clipping effect on the RGB boundary line. The color-gamut vector F of each color RGB is given in

\[
\text{If } MAX(R,G,B) > 240 \text{ then } F = MAX(R,G,B) - MIN(R,G,B).
\]

When an incoming pixel is calculated as the MAX (R,G,B) among the RGB color data. If \(R = MAX(R,G,B)\), we use the gain set \(S'\) of \(R\) parameters in the LUT. In order to protect the skin region, the ellipsoid on a CIE1931 diagram is used to define the human skin tone region of the image, as shown in Fig. 3. It is better than [2] which uses a strip region. Assuming the chromaticity coordinate of an incoming pixel is \((X,Y)\), we draw an ellipsoid on a CIE1931 diagram to define the human skin tone area. If the chromaticity coordinate of an incoming pixel is located inside the ellipsoid, we can determine if the pixel is human skin color. The human skin tone region is given by the ellipsoid

\[
\frac{x'^2}{a^2} + \frac{y'^2}{b^2} \leq 1
\]

\[
x' = (X - X_{center}) \times \cos(\theta) + (Y - Y_{center}) \times \sin(\theta)
\]

\[
y' = -(X - X_{center}) \times \sin(\theta) + (Y - Y_{center}) \times \cos(\theta)
\]
Fig. 4. People’s skin samples.

(S) is enhanced. We use color gamut gain $S$ to generate the enhancement matrix $E$. Incoming RGB components are converted into $R’G’B’$, as derived in

$$E = \begin{bmatrix} 1 + S & -S/2 & -S/2 \\ -S/2 & 1 + S & -S/2 \\ -S/2 & -S/2 & 1 + S \end{bmatrix}$$  \hspace{1cm} (5)

$$\begin{bmatrix} R’ \\ G’ \\ B’ \end{bmatrix} = E \begin{bmatrix} R \\ G \\ B \end{bmatrix}.$$  \hspace{1cm} (6)

The proposed modified rich color method (MRCM) algorithm is shown in Fig. 1. In Step 1, the R,G,B data is input into MCRM pixel by pixel; then two parallel processes are executed. (1) Calculate the color gamut vector $F$ and check out LUT for the color gamut gain $S’$. (2) Separate the luminance and the chrominance for skin detection. Skin detection contains three parallel components: the ellipsoid function, the one-order linear function and the luminance threshold function. In Step 2, the color-gamut gain $S$ is set by selecting color-gamut gain $S’$ or 0. The human skin tone pixel is set as a color gamut gain $S$ which is equal to 0. The new $(R’, G’, B’)$ is then calculated and output. Finally, the new data is displayed on the LCD panel. Consequently, MRCM can improve the image quality.

III. SKIN REGION DETECTION

Skin region detection plays an important role in broadening the color-gamut. In recent years, many references have proposed comparative studies of different chrominance spaces to detect skin color and have found that the normalized chrominance space is more efficient for skin-color detection; this reduces the dimension from a 3-D RGB color space to a chrominance space. Efficient separation of the luminance and the chrominance can reduce the influence of changes in illumination. The normalized perceptually plausible tint-saturation-luminance space (TSL) is the most suitable for skin region detection. Nevertheless, the computational complexity is high. The complex algorithms and high-cost structures are unsuitable for small-sized TFT LCD products. This is the reason why we chose two chrominance spaces (a normalized CIE1931 x-y space and a normalized r-g chrominance space) to compare for hardware implementation.

A. Detection in CIE1931x-y Space

The input RGB pixel data has been transformed into a CIE1931 x-y color space. In the color space CIE1931 x-y, we obtain the values of $x$ and $y$ by the standard formula as follows:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}.$$  \hspace{1cm} (7)

$$x = \frac{X}{(X + Y + Z)}.$$  \hspace{1cm} (8)

$$y = \frac{Y}{(X + Y + Z)}.$$  \hspace{1cm} (9)

Furthermore, the distribution of skin colors in the chromaticity coordinate is observed. In the experiment, skin samples are acquired from a limited number of people and manually segmented images. Fig. 4 shows the skin samples of these people.

In Fig. 5, the distribution of skin and non-skin regions can be observed. The left of Fig. 5 shows the coordinate distribution. By counting the number of pixels which are located within each bin in the CIE1931 space, a color histogram is obtained. The right of Fig. 5 shows 2-D cumulative histogram in a CIE1931 chrominance space; this is used to observe the probability density distribution of skin color. To detect skin pixels from an...
image, an ellipsoid window and a one-order linear equation are determined from high probability density regions. The distribution of high probability density region is shown in Fig. 6 after increasing the probability threshold.

Lips have a smaller region in the face area, and many pink/red clothes have the same chrominance as lips. The probability of lips, which belong to the non-skin class, is greater than the probability of lips which belong to the skin class. Since segmenting the skin chrominance region and lip chrominance region can decrease the error rate, the relation of lips belonging to skin probability and non-skin probability is as follows:

\[
P(\text{skin}|\text{lip}) < P(\text{nonskin}|\text{lip}).
\]

The distribution of lip regions can be observed in Fig. 7. This coordinate distribution is overlapped with the skin coordinate distribution.

### B. Detection in Normalized r-g Chrominance Space

We test RGB pixel data transformed to an r-g color space. In the color space r-g, we obtain the values of r, g by the standard formula as follows:

\[
r = \frac{R}{(R + G + B)} \quad \text{(11)}
\]

\[
g = \frac{G}{(R + G + B)}. \quad \text{(12)}
\]

The distribution of the lip chrominance region and the skin chrominance region in an r-g color space can be observed in Figs. 8 and 9. Two ellipsoid windows and a one-order linear equation are determined in the r-g color space, and used to detect skin pixels from an image. The hardware cost is double that of an ellipsoid function. Distribution of skin color in the r-g space is tighter, as seen by comparing Figs. 6 and 8. The r-g space is more effective in segmenting the skin chrominance region and lip chrominance region, as seen by comparing Figs. 8 and 9.

### C. Skin Gray Scale Histogram

A skin gray scale histogram is used to analyze the gray scale distribution of skin color. We obtain the threshold values of maximum and minimum brightness by dark skin and white skin gray scale histogram analysis. The test images are obtained in Fig. 10(a). The gray scale histogram is shown in Fig. 10(b).

### IV. HARDWARE IMPLEMENTATION

This paper provides a dynamic rich color method with a skin protection algorithm that is based on the image analysis and pixel-level broadening color gamut method. The algorithm is
implemented on an FPGA platform. The dynamic image processing of the FPGA-based display system is shown in Fig. 11. There are two image sources. One image source is from an MPU and the other is from a CCD camera. A multiplexer chooses one of the images to display. Because the input and output signals are different at the frequency domain, we use a memory controller and SRAM to buffer the image data. The T-con circuit generates a panel-driving signal. The modified image data is displayed on the TFT LCD in real time.

Fig. 11. Block diagram of the FPGA platform.

Fig. 12. Proposed architecture.

Fig. 13. Color-gamut selection module.

Fig. 14. Color transformation module.

Fig. 15. Image enhancement module.

Fig. 16. Implementation results of the proposed algorithm on FPGA and ARM platform: (a) test image 1 and (b) test image 2.

Fig. 12 shows our proposed architecture. We use the 13 types of standard test patterns to drive the LCD panel. Optical instruments measure the characteristics distribution on a CIE1976 diagram. Based on the color gamut of these standard test patterns on a CIE1976 chromaticity coordinate, the coordinate distance ratio is calculated. Then, we use the coordinate distance relation of each color RGB to generate the color-gamut vector (F), color-gamut broadening gain (S') and Look-Up Table (LUT). The architecture of the MRCM image engine consists of three parts: the color-gamut gain selection module, the skin detection module, and the image enhancement module.

A. Color-Gamut Gain Selection Module

The color-gamut gain selection module is shown in Fig. 13. The module transforms the pixel color from the RGB to three parameters: $MAX(R, G, B)$, $MIN(R, G, B)$, and $F$. The
module calculates the color-gamut vector $F$ and checks out the LUT for the color-gamut gain $S'$.

### B. Skin Detection Module

The skin detection module consists of four parts: color transformation, ellipsoid function, one-order linear function and brightness threshold function. The color transformation module, transforming pixel color from the RGB to Y and CIE-XYZ, is implemented by using a canonical-signed-digit (CSD) fixed-coefficient multiplier. The transformation from CIE-XYZ to CIE-xy is implemented by using a 30-bit divider. The color transformation module is shown in Fig. 14. Ellipsoid function modules are used to check the skin region. As is well known, the divider is a time-consumption component. It needs 10 clocks to calculate 10 bits. We modify the ellipsoid formula (2)–(13) as follows:

$$b^2 x'^2 + a^2 y'^2 < a^2 b^2.$$  (13)

The transformation from (2)–(13) is useful in avoiding using the divider in the ellipsoid function. We implement the ellipsoid function using a CSD fixed-coefficient multiplier. Finally, the skin detection module outputs the checking results.

### C. Image Enhancement Module

The image enhancement module is shown in Fig. 15. The selection of color-gamut gain $S$ is implemented by a 2-to-1 multiplexer. If the skin detection result is true, 0 is chosen; if the skin detection result is false, $S'$ is chosen. We may classify the $S$ into...
23 types from the LUT. If we implement the enhancement matrix by using a CSD fixed-coefficient multiplier, we must create 23 types of enhancement matrices. Gate count on FPGA is used to compare the hardware cost between 23 types of enhancement matrices and a general multiplier. A general multiplier is smaller. Consequently, we use a general multiplier to implement the enhancement matrix. In the image enhancement module, we broaden the color-gamut by the formulas as follows:

\[
R' = R(1 + S) - G\frac{S}{2} - B\frac{S}{2} \\
G' = G(1 + S) - R\frac{S}{2} - B\frac{S}{2} \\
B' = B(1 + S) - G\frac{S}{2} - R\frac{S}{2},
\]

(14) (15) (16)

The MRCM module and the dynamic image processing driving system are implemented by using hardware description language (HDL), Verilog, according to the algorithms of MRCM (Fig. 1). The block diagram of the FPGA-based platform is shown in Fig. 11; the FPGA is used to implement the image engine of the proposed MRCM. The hardware platform uses the image engine circuit to perform image processing. The gate count with the image engine is 54,373. The gate count without the image engine is 16,545. So the total gate count is 37,828 (= 54,373 − 16,545). In this study, the total equivalent gate count for the MRCM image engine is 37,828.

V. PERFORMANCE ANALYSIS

This paper provides an improved color-gamut method with skin protection based on the image analysis and pixel-level color-gamut enhancement method for Liquid Crystal Displays. Fig. 16 shows the implementation results of the test images for the proposed algorithm on FPGA and ARM platform. The skin color is retained very well. It is very close to the true color.

From the experimental results, Fig. 17 shows the original test images and color gamut without performing any algorithms. Fig. 18 shows the test images and the color gamut after performing the proposed algorithms by [1]. Fig. 19 shows the test images and the color gamut after performing our proposed MRCM. The CIE x-y is used to measure the enhancement of the color gamut. We use a skin pixel and a non-skin pixel on the color coordinate to show the different effects between the proposed MRCM and [1], shown in Figs. 20 and 21. In Fig. 20, the effect of the color gamut is improved using the proposed new method on the skin color of a human face. The skin colors have been successfully protected by our proposed method.
In Fig. 21, the non-skin color processing using the proposed new method has the same color coordinate as [1]. The new color-gamut method for LCD with MPW LED on non-skin color has the same level as [1]. We observe that our proposed method also has a good rich color image processing approach with skin protection. The computational complexity is also compared, as shown in Table I. We propose a real-time and low-cost image processing method. The image process method is implemented on a Xilinx FPGA platform. Xilinx ISE is used to synthesize the design. The critical path of the proposed algorithms is 34.153 ns. It is suitable for medium-sized and small-sized LCD panels. The hardware implementation of our proposed algorithm is faster than the software implementation of the algorithm in [1].

VI. CONCLUSION

In this paper, we proposed an improved color gamut method with skin protection for Liquid Crystal Displays. We also compared the hardware cost using a CIE x-y color space with the hardware cost using an r-g color space. The hardware cost of an ellipsoid function will double when we use the r-g color space. From the experimental results, we found that our proposed low-cost method can enhance the color gamut and protect skin tone areas.

REFERENCES


Yeong-Kang Lai (M’94) was born in Taipei, Taiwan, R.O.C., in 1966. He received the Ph.D. degree from the Institute of Electrical Engineering, National Taiwan University, Taiwan, in 1997. From 1992 to 1993, he was with the Institute of Information Science, Academia Sinica, Taiwan, where he worked on video conference system. In 1997, he was with Department of Electrical Engineering, Chang Gung University, Taoyuan, Taiwan, as an Assistant Professor. From 1998 to 2001, he was with Department of Computer Science and Information Engineering, National Dong Hwa University, Hualien, Taiwan, as an Assistant Professor. Since 2001, he has been with National Chung Hsing University, Taichung, Taiwan, where he is currently a Professor with the Department of Electrical Engineering. His research interests include 3D display, 3D video compression, DSP architecture design, video signal processor design, and VLSI signal processing.

Dr. Lai is a member of Phi Tau Phi. In 2011, he received the Outstanding Teaching Professor Award of National Chung Hsing University. In 2010, he also received the Best Paper Award of the International SoC Design Conference. Currently, he is an Associate Editor for IEEE TRANSACTIONS ON CONSUMER ELECTRONICS. He is also a member of the Technical Program Committee of IEEE International Conference on Consumer Electronics.

Shu-Ming Lee was born in Taichung, Taiwan, R.O.C., on June 03, 1973. He received the B.S. degree in Electronic Engineering from National Chin-Yi Institute of Technology in 2004, the M.S. degree in electronic engineering from National Chung-Hsing University, Taichung, Taiwan, in 2010, and is currently pursuing the Ph.D. degree in the Department of Electrical Engineering, National Chung Hsing University. He also is working at Wintek Corporation, Taichung, Taiwan. His major research interests include image and video processing, VLSI architecture design of image and video coding, and VLSI design for digital signal processing.