A Novel Sensitive Color Detection Algorithm Applied to The View-Angle Compensation Technology of VA-LCD

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ABSTRACT

In this paper, we propose a novel sensitive color detection algorithm which can be applied to the view-angle compensation technology of the VA-LCD. The proposed algorithm incorporates the Gaussian probability model and the lightness suppression mechanism, and improves the image washout in the side view of panel effectively.

1. INTRODUCTION

Liquid-crystal display technology has been applied in various fields, such as intelligent housing system, electronic sports screen, commercial display screen. However, due to the optical properties of liquid crystal, the gamma curve of the VA-LCD from the side view angle is offset from the gamma curve of the positive view angle, resulting in color washout of the image from the side view. The side view angle of LCD panel is shown in Fig.1. The view-angle compensation technology has been developed to improve color washout. This technology corrects the side-looking gamma curve, in the meanwhile, the gamma value of the positive view angle is constant. Though, it is effective to improve image washout of VA-LCD, the image graininess may occur. Therefore, sensitive color detection, which is the process to adjust the sub-pixels in sensitive color area of image, is applied to view-angle compensation technology.

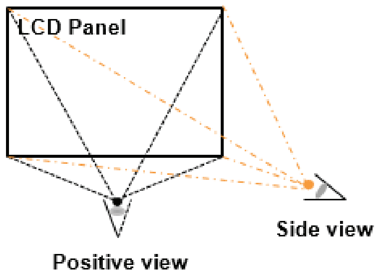


Fig.1 The positive view and the side view of LCD panel

In general, the viewing angle compensation technology improves the image color washout effectively but fail to yield high quality images with less graininess, as shown in Fig.2. Graininess appears on the baby's clothes after compensating the viewing angle. In order to overcome these drawbacks, several attempts performed skin color detection procedure.[1][2] Although the skin color detection algorithm can extract a moderate amount of skin color, and improve color washout to some extent, it may fail to provide reliable results of non-skin color area.

In this work, inspired by recent skin detection-based view-angle compensation technology, we propose a novel color detection algorithm for view angle compensation via Gaussian probability model. Firstly, according to the distribution and aggregation of sensitive color in the Ycbcr color space, we construct a Gaussian probability model that separates an input image into sensitive color and non-sensitive color regions. It can also smooth the transition between different areas. In the meantime, we propose a lightness suppression mechanism which improves the accuracy of color detection. Secondly, the guided filter is used to smooth the probability image obtained by Gaussian probability model. Finally, the proposed color detection algorithm is applied to change the sub-pixel in sensitive color area. Extensive experimental results show that the proposed color detection algorithm using in view-angle compensation technique improve the color washout and the image quality effectively.

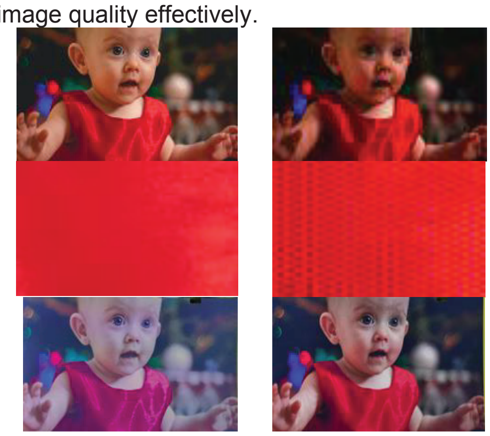


Fig2. An example of view-angle compensatoin technology. (a)the input image, (b)the improved image obtained by conventional view-angle compensation technology. The images in the second row are magnified parts of those in the first row and the images in the third row are the side view images of those in the first row.

2. THE PROPOSED ALGORITHM

2.1 Overall Framework

Fig.3 shows an overview of the proposed algorithm. Firstly, we convert the image from RGB color space to the Ycbcr color space. Secondly, we index data of the Gaussian probability model based on the distribution characteristic of sensitive color in cbcr channel. At the same time, we adopt the lightness suppression mechanism. And then we smooth the probability image by using guided filter. Finally, adopting the viewing angle technology which adjusts the sub-pixel in sensitive color area, we obtain an output image with improved color washout.

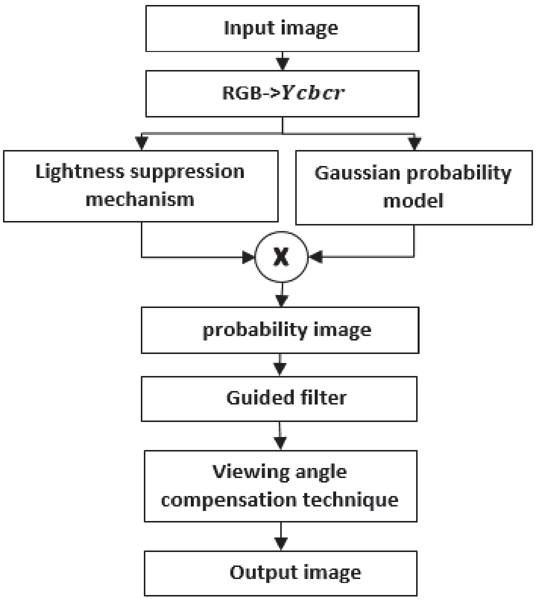


Fig. 3 The overview of proposed algorithm.

2.2 The Gaussian Probability model

In this paper, in Ycbcr color space, basing on the distribution characteristic of sensitive color data such as skin color, sky color and grass color, a Gaussian probability model was established. We fitted a Gaussian probability model by calculating two parameters of the color data set in Ycbcr color space: the central coordinates of a Gaussian model, defined as the mean of total sensitive color data set, and the covariance of Gaussian probability model, defined as dispersion of the sensitive color data set. The unitized Gaussian probability model we proposed not only detect the skin color, but also other sensitive color, as shown in Fig4. What's more, the probability transitions between sensitive color areas and non-sensitive color areas are smooth.

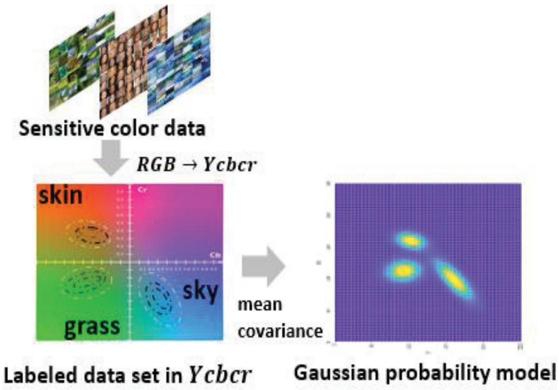


Fig.4 An example describes the fitting mechanism of Gaussian probability model based on the skin color data, sky color data and grass color data.

2.3 Obtain Probability Image Based On Sensitive Color Detection

We convert the input image from the RGB color space to the Ycbcr color space by,

$$\begin{aligned} y &= (I_R * 0.2567 + I_G * 0.5041 + I_B * 0.0979) + 16 \\ cb &= (I_R * 0.1482 + I_G * 0.2909 + I_B * 0.4391) + 128 \\ cr &= (I_R * 0.4392 + I_G * 0.3678 + I_B * 0.0714) + 128 \end{aligned} \quad (1)$$

Where I_R, I_G, I_B denote the values of the input pixels in channels R, G, and B, respectively, y is a lightness parameter, and cb and cr denote the chroma.

After converting the color space, we index the data of the Gaussian probability model. More specifically, we fit the Gaussian probability model by,

$$gauss = a * \frac{1}{(2\pi)^{\frac{d}{2}}|\Sigma|^{\frac{1}{2}}} exp[-\frac{1}{2}(X - \mu)^T \Sigma^{-1}(X - \mu)] \quad (2)$$

Where $X = [cb; cr]$ denote the multidimensional data of input image, a is an adjustable amplitude parameter, and d denotes the dimensionality of input image pixels. μ denotes the mean of the sensitive data set and is given by,

$$\mu = (\overline{cb}, \overline{cr}) \quad (3)$$

$$\overline{cb} = \frac{1}{N}\sum_{i=1}^{N} cb_i \quad (4)$$

$$\overline{cr} = \frac{1}{N}\sum_{i=1}^{N} cr_i \quad (5)$$

Where N is the number of input pixel, and Σ^{-1} and $|\Sigma|$ are the inverse and the determinant of the covariance Σ respectively, where Σ is given by,

$$\Sigma = \begin{pmatrix} \sigma_{crcr} & \sigma_{crcb} \\ \sigma_{cbcr} & \sigma_{cbcb} \end{pmatrix} \quad (6)$$

$$\sigma_{cbcr} = \frac{\sum_{i=1}^{N}(cb_i - \overline{cb})(cr_i - \overline{cr})}{N - 1} \quad (7)$$

Next, we can separate y which is obtained by (1) into multiple lightness regions by,

$$k(y)=\begin{cases} k_1*y+l_1 & y\le y_1 \\ k_2*y+l_2 & y_1<y\le y_2 \\ \cdots & \cdots \\ k_{n-1}*y+l_{n-1} & y_{n-1}<y\le y_{n-1} \\ k_n*y+l_n & y_n<y\le y_n \end{cases} \quad (8)$$

Where parameter n can be set artificially. This approach can improve the accuracy of sensitive color detection.

According to the solutions from (2) and (8), we obtain probability image I_{pro} by,

$$I_{pro}=gauss(cb,cr)*k(y) \quad (9)$$

Fig.5 (b) shows an example of Gaussian probability model. The sensitive color can be better detected by the developed Gaussian probability model, and the probability transitions between sensitive color areas and non-sensitive areas are smooth. However, the Gaussian probability model may fail to smooth the texture in some areas of probability image. In such case, these sensitive color areas may occur blocky patches. We will discuss how to address this issue in Section2.4.

2.4 Probability Image Smoothing

As mentioned previously, the probability image obtained by the Gaussian probability model may occur blocky patches. To alleviate this problem, the guided filter[3][4] is applied to smooth the texture of probability image. The guided filter is an edge-preserving smoothing filter in which each output pixel of image is locally computed as a linear transform of the guidance image. In this work, the linear transform of guidance is expressed as,

$$I_p=a_kG_p+b_k \quad \forall p\in w_k \quad (10)$$

Where G_p and I_p denote the intensities at a pixel location k which is the center of window w_k in G and I. And G_p=I_{pro}. a_k, b_k are constant coefficients in w_k. They are given by,

$$E(a_k,b_k)=\sum_{p\in w_k}((a_kG_p+b_k-I_p)^2+\varepsilon a_k^2) \quad (11)$$

Where ε is a smoothing parameter adjusting the degree of smoothing in the filtered output, and the obtained $E(a_k,b_k)$ is the optimal solution to (1) by seeking to minimize the difference between the input and output images, which is given by,

$$a_k=\frac{(\frac{1}{|w|})\sum_{p\in w_k}G_pI_p-\bar{G}_k\bar{I}_k}{\sigma_k^2+\epsilon} \quad (12)$$

$$b_k=\bar{I}_k-a_k\bar{G}_k \quad (13)$$

Where $\bar{I}_k$ and $\bar{G}_k$ denote the mean values of I and G in window w_k respectively. |w| is the number of pixels in window w_k, and σ_k^2 is the variance of G in w_k .Theoretically, the coefficients a_k and b_k are supposed to be constant in w_k, but in practice they vary spatially. To reduce this variation, the linear transform is modified as follows,

$$I_p=(\frac{1}{|w|}\sum\nolimits_{k\in w_p}a_k)G_p+(\frac{1}{|w|}\sum\nolimits_{k\in w_p}b_k) \quad (14)$$

Guided filter is applied to the probability image. As shown in Fig.5, the blocky patches in the baby's face can be smooth better with little loss of image details.

(a) (b) (c)

Fig.5 An example describes the probability image smoothing based on guided filter. The images in the second row are the magnified parts of those in the first row. (a) the input image, (b) the probability image, (c) the output probability image after guided filter

2.5 Viewing Angle Compensation

After obtaining the smooth probability image, the probabilities are applied to adjust the sub-pixel variance in sensitive color area of image by,

$$\begin{aligned} Out_R&=I_R+gauss*(table-I_R)\\ Out_G&=I_G+gauss*(table-I_G)\\ Out_B&=I_B+gauss*(table-I_B)\end{aligned} \quad (15)$$

Where I_R, I_G, I_B and Out_R, Out_G, Out_B denote the intensities of the input pixel in channels R, G, and B respectively, table is the changed value of the sub-pixel in the viewing angle compensation technology, and gauss denote the value of probability. In this approach, the color washout is improved in sensitive color area, which can yield high quality image with less graininess to some extent.

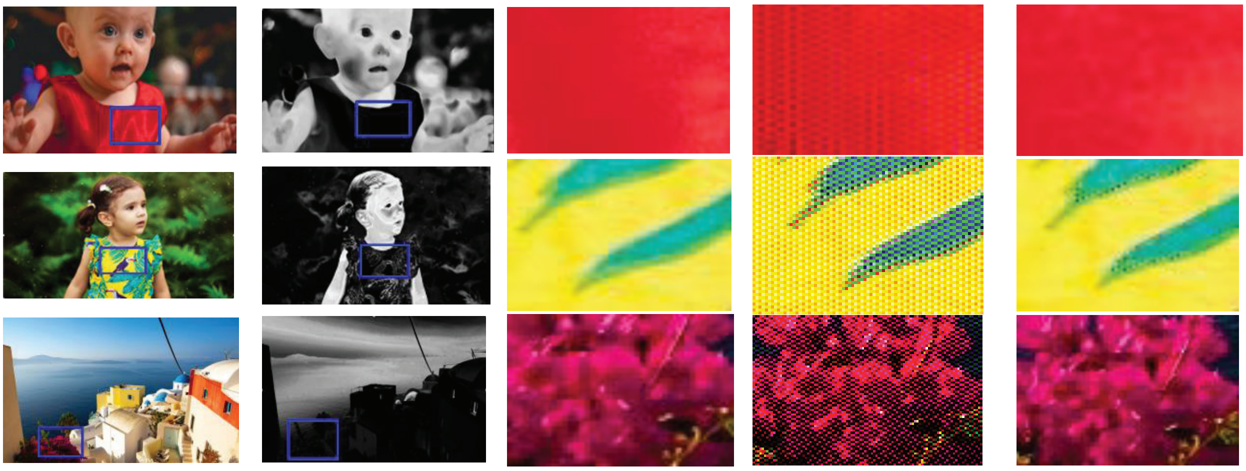
3. RESULTS

3.1 Experimental Results

We evaluate the performance of the proposed sensitive color detection algorithm for viewing angle compensation of VA-LCD on three test images both qualitatively and quantitatively. We report the results on several real-world images, and compare the performance of the proposed algorithm with the conventional viewing angle compensation technology.

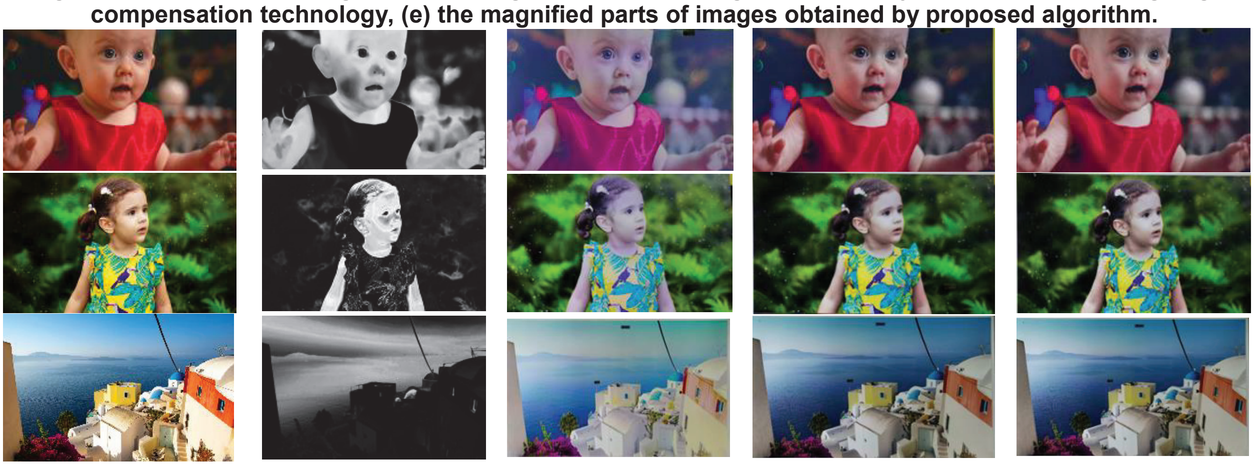
3.2 Subjective Assessment

Fig.6 and Fig.7 show the improvement results of color washout and picture graininess for the test images. Fig.6 (d) shows that the areas of the baby's clothes, the girl's dress and the flowers would occur graininess, and Fig.6 (e) shows that the proposed algorithm can reduce these graininess better. Not only that, the proposed algorithm preserves the sensitive color of images in the side view faithfully which is shown in Fig.7 (e).



(a) (b) (c) (d) (e)

Fig6. Comparison of graininess improvement results. (a) input images, (b) the probability images, (c) the magnified parts of input images, (d) the magnified parts of images obtained by conventional viewing angle compensation technology, (e) the magnified parts of images obtained by proposed algorithm.



(a) (b) (c) (d) (e)

Fig7. Comparison of color washout improvement results (a) input images (b) the probability images. (c) the input images in the side view. (d) the side-looking images obtained by conventional viewing angle compensation technology. (e) the side-looking images obtained by proposed algorithm.

4. SUMMARY

We proposed a novel sensitive color detection algorithm for viewing angle compensation of image in the side view. Experimental results on test images demonstrates that the proposed algorithm can improve the color washout and the image quality effectively. In future, research issues would include the extension of the proposed algorithm to view-angle compensation based on different scene patterns of input images in the real time.

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