Convolutional Neural Network based Image Segmentation Algorithm for Dual-Layer LCDs

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Abstract

Dual-layer LCDs have the advantage of high contrast ratio, but due to the physical distance between the two LC panels, parallax error may appear when viewed off-axis, affecting the display quality. In this paper, we propose a convolutional neural network-based algorithm to mitigate parallax error and improve the display quality. First, a suitable training data set is selected and the input image is processed by a convolutional neural network to output a front image and a rear image. These two images are staggered and multiplied to obtain reproduced images at different angles. The reproduced image is compared with the original image by means of a loss function, and the parameters in the convolution are continuously updated to achieve the best display quality. The algorithm proposed in this paper can effectively mitigate the parallax error phenomenon of a dual-layer LCD and improve the display quality, and the computational efficiency is also higher than the traditional algorithms.

Author Keywords

Dual-layer LCDs; Convolutional neural network; Image segmentation

1. Introduction

With the disadvantage of low contrast ratio, LCDs are greatly challenged by OLEDs. With the development of display technology, dynamic dimming technology has been widely used. However, due to the limitations of LED size and large amount of computation, dynamic dimming technology cannot achieve pixel-by-pixel local dimming. Dual-layer LCDs appear[1-3].

Dual-layer LCDs can effectively reduce light leakage and improve contrast, but due to two LCD panels, the input image must be split into two images for the front and rear panels. As the fact that there exists the physical distance between the front and rear LCD panels, parallax error can occur when viewed off-axis, affecting display quality. To address these problems, fuzzy algorithms and viewpoint compensation-based image segmentation algorithms have been proposed [4-5], but these two algorithms cannot balance image display quality and computational efficiency when mitigating parallax error. Therefore, this paper proposes a dual-layer LCD image segmentation algorithm based on convolutional neural networks, which can mitigate parallax error and improve computational efficiency as well as achieving high display quality.

2. Network Architecture and Loss Function

The purpose of the algorithm in this paper is to mitigate parallax error while improving picture quality and significantly improving computational efficiency. Existing fuzzy processing algorithms can cause serious degradation in display quality while mitigating parallax error. The dual-layer LCD image segmentation algorithm based on viewpoint compensation solves this problem by using the reference from light field algorithm but the algorithm has the defect of long computation time. The high efficiency of CNN makes it one of the best methods to solve the real-time problem.

The network architecture is rather straight-forward, as illustrated in Figure 1 The network consists of 8 2-D convolutional layers stacked in sequence. Throughout the networks, the spatial size of the tensors is constant, but only the number of channels was changed. Tensors **I** and **O** had 5 channels, each of which corresponds to a viewpoint. Tensors **L** had 2 channels, each representing a layer of the pattern. The other intermediate feature maps have 64 channels.

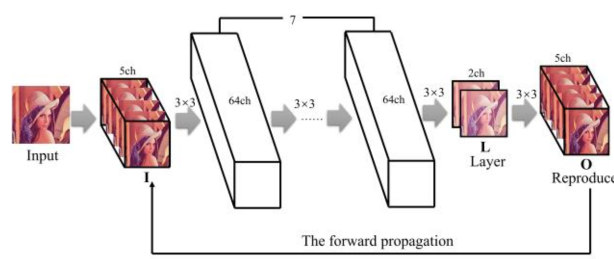

Figure 1. CNN training network structure.

After inputting the images into the network, the images of the two channels obtained represent the front LCD and the rear LCD respectively, and five images can be obtained after multiplying the front and rear images by the misalignment, which represents the real images of the human eye viewing the dual-layer LCD at five different viewing angles.

To obtain the best assigned image on the dual-layer LCD, we traine the dual-layer LCD assignment network to learn the mapping function between the original RGB images and the dual-layer assigned images. To improve the display quality of viewing the dual-layer LCD at different viewing angles, we used MSE as the loss function:

$$Loss = \frac{1}{n}\sum_{i=1}^{n}\left\| I_i^{ref} - I_i^{input} \right\|^2 \qquad (1)$$

Where I_i^{input} represents the input image, I_i^{ref} represents the reproduced image after network processing. After a lot of training, the value of the Loss function is reduced to a fairly small number and the data in the convolutional network stops updating.

When the network is trained and enters the test phase, the image enters the network after convolution to generate two images, which are output to the front panel and rear panel respectively, as shown in Figure 2.

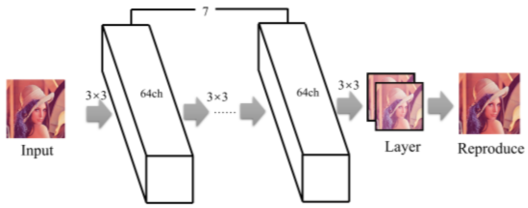

Figure 2. CNN test network structure.

3. Network Training Datasets

The application of deep learning on parallax error mitigation in a dual-layer LCD are highly dependent on the dataset, and in order to implement an end-to-end image segmentation algorithm, we constructe a suitable dataset. There are two requirements for this dataset: the first is that the dataset is required to cover as many scenes as possible; the second is that considering the reality that the viewing angle in the vertical direction is generally smaller when viewing the display, while the viewing angle in the horizontal direction is larger. As the fact the parallax error of the dual-layer LCD is especially obvious in the horizontal direction, to improve the network effect, the images with a clear texture in the vertical direction are included in the dataset.

To achieve the above goal, we collecte 2730 images, which cover a wide range of scenes. This dataset is characterized by the fact that most of the images have clear vertical textures, since vertical textures produce more obvious parallax error when viewing horizontally off-axis. Eachimage is formatted into 5 copies representing 5 view angles of the scene. In order to reduce the CNN training time, , each image in the dataset consists 10 groups and each group consists 5 above copies, as shown in Figure 3.

In order to increase the number of network training images and increase the robustness of the CNN, the dataset is processed before the network training. By adjusting the 3 colour channels of the images in the dataset and dividing them into 3 separate datasets, the number of datasets are increased to 49680 images with a ratio of 9:1 for training and validation.

We set the batch size for training to 15 and use the built-in Adam optimizer to set the number of epochs of the network to 20 for training.

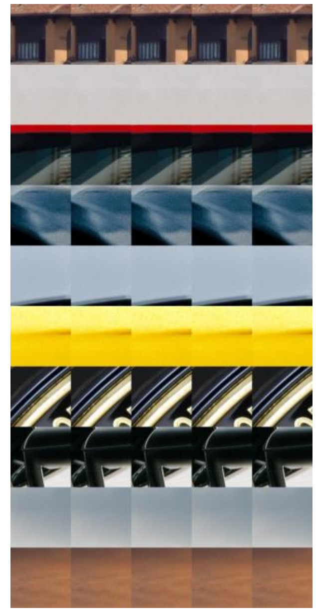

Figure 3. Schematic diagram of the training datasets.

4. Simulation Results

In order to verify the convolutional neural network-based dual-layer LCDs segmentation algorithm proposed in this paper, the fuzzy algorithm and the viewpoint compensation-based algorithm are selected for comparison.The simulation results show that the algorithm in this paper has a better performance on mitigating parallax error and improving the display quality, and also has a great improvement in computational efficiency.

In this paper, several viewpoints of 0°, 15°, 30°, 45° and 64° are selected for comparison, which represent multiple angles of the human eye in the left, middle and right of the display, etc. Figure 4 gives a comparison of the original image, fuzzy algorithm, viewpoint compensation-based algorithm and convolutional neural network-based image segmentation algorithm at the viewing angle of 64°. It can be seen that the algorithm proposed in this paper has better performance in mitigating parallax error and display quality.

In order to evaluate the reproduced images quantitatively, Peak Signal to Noise Ratio (PSNR) is introduced as an evaluation index in this paper, as shown in the following equation：

$$MSE = \frac{\sum_{i=1}^{o}\sum_{j=1}^{p}\left[I(i,j)-K(i,j)\right]^2}{o\times p} \tag{1}$$

$$PNSR = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

where I(i, j) and K(i, j) denote the grayscale values of the processed image and the original image at (i, j) pixel points, respectively, and o × p is the image resolution. In the simulation, the image dislocation method is used to simulate the viewing effect under different viewing angles.

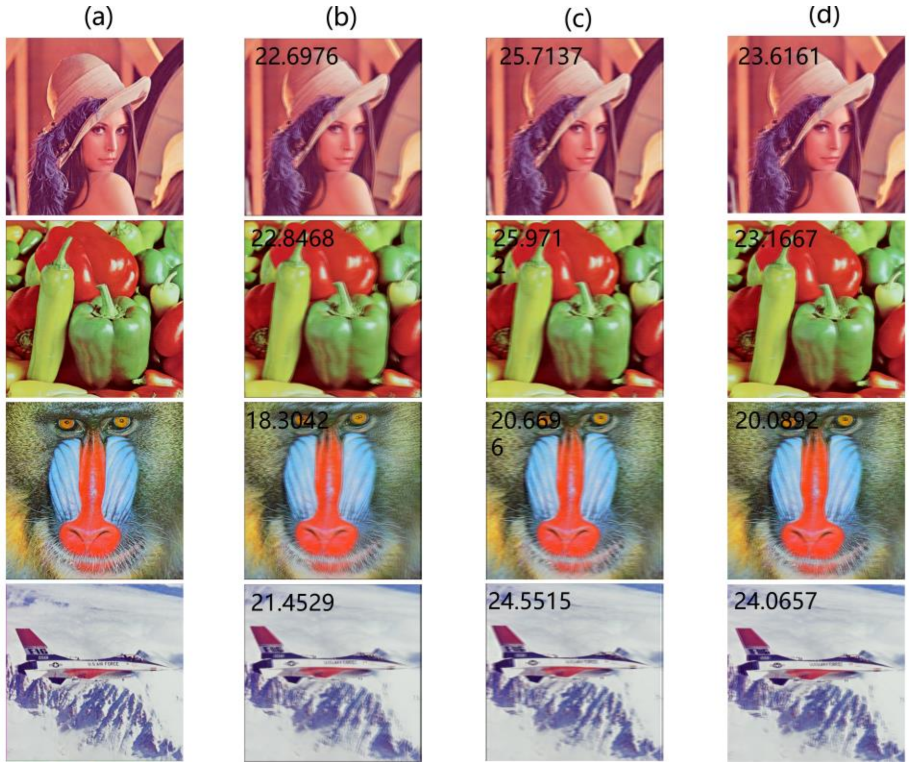

Figure 4. Simulation results. (a) original image; (b) algorithm based on fuzzy processing; (c) algorithm based on viewpoint compensation; (d) algorithm based on convolutional neural network.

The PSNRs of the images processed by the fuzzy processing-based and view compensation-based algorithms and the convolutional neural network-based image segmentation algorithms for different viewing angles of 0°, 15°, 30°, 45°, and 64° are given in Table 1.

Table **1.** PSNR values of test images processed by three algorithms at five viewing angles

	Angel	Fuzzy processing algorithm	Viewing-angle-compensation algorithm	Convolutional Neural Network algorithm
Lena	0°	26.5858	28.0479	30.3447
	15°	26.3101	27.0719	29.7971
	30°	26.4440	27.1129	28.0508
	45°	25.5154	26.2276	25.9484
	64°	22.6976	25.7137	23.6161
Baboom	0°	20.6363	22.7146	23.3749
	15°	20.4589	21.0431	23.6563
	30°	20.3416	21.0902	22.7240
	45°	19.7585	21.1871	20.9532
	64°	18.3042	20.6696	20.0892
F16	0°	25.1193	28.1999	31.5625
	15°	24.7611	27.4319	30.8406
	30°	24.5383	27.5754	28.7002
	45°	23.9565	26.1964	26.5083
	64°	21.4529	24.5515	24.0657

Peppers	0°	26.1591	29.0197	30.9051
	15°	25.8803	27.7370	30.2358
	30°	25.5345	27.7610	28.4753
	45°	24.9926	26.8573	26.3044
	64°	22.8468	25.9712	23.1667

5. Conclusion

Compared with the fuzzy algorithm and the viewpoint compensation algorithm, the algorithm in this paper has significantly improved the display quality under five viewpoints from 0° to 64°. Compared with the viewpoint compensation-based algorithm, the PSNR of the proposed algorithm is larger under the viewing angles of 0°, 15° and 30° and is comparable under the viewing angles of 45° and 64°. However, the advantage of the algorithm in this paper is that it uses convolutional neural network as a computational tool, which can significantly improve the computational efficiency. The algorithm based on viewpoint compensation takes nearly five minutes to process the image, while the algorithm proposed in this paper only takes 1183ms.

6. Acknowledgements

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7. References

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