A Novel LCD De-Mura Algorithm Based on Deep Learning

Yixin Xiao*, Tao He, Yu Wu, Dengxia Zhao, Bin Zhao
TCL China Star Optoelectronics Technology Co., Ltd., Shenzhen, Guangdong, China
Wei Yang*, Yangxing Liu
Wuhan TCL Group Industrial Research Institute Co., Ltd., Wuhan, Hubei, China
Co-First-Author*,Corresponding Author**

Abstract

Since its proposal in 1968, LCD has held an important position in the display field due to its mature technology and low cost advantages[1]. In order to eliminate mura defects in VA-LCD panels, the traditional Demura method requires taking multiple images of different graylevel, fitting a full graylevels brightness curve, and then calculating compensation values. The long photography time affects the production line capacity. Therefore, the paper proposes a Demura method based on deep learning, which only requires taking a single graylevel image ***as the input, using the compensation values of traditional schemes as learning labels,and using U-shaped neural network for model training, to predict the compensation values of different binding point graylevels. While greatly improving efficiency, it can achieve the effect of industry standard schemes. The experimental results show that after adopting this scheme, the number of photos taken can be reduced from 7 to 1, the Demura efficiency can be improved by 51%, the compensation data prediction error is 0.3%, and the panel uniformity is consistent with the traditional schemes;***

Author Keywords

VA-LCD; Demura; deep learning; histogram similarity

Introduction

With the development of LCD display technology, the size of displays is getting larger and the probability of mura appearing is also greatly increased; Mura refers to the uneven brightness phenomenon caused by materials, processes and other factors in monitor production, which can affect the quality of the displayed image and lead to a decrease in monitor quality. Mura can be caused by various factors, such as unstable production processes, dust in the production environment, and uneven raw materials. Therefore, Mura needs to be repaired before the panel leaves the factory, and this process is called Demura.

Demura generally consists of three steps. Firstly, the camera captures image information of the panel at different graylevels. Through preprocessing such as image geometric correction, the brightness matrix at different graylevels can be obtained; Then, based on the brightness matrix of different graylevels obtained in the previous step, fit the full graylevels brightness curve for each position. Then with the brightness at the center position as the target, adjust the input graylevel to make the brightness of all pixels consistent, and the adjusted graylevel values for each position are the corresponding compensation values; Finally, adjust the compensation data to the corresponding format according to the chip specifications, burn it to flash, and at startup, the Tcon chip reads and compensates for image data in real-time.

The focus of this paper is mainly on the compensation values calculation part in the second step mentioned above. The traditional Demura algorithm requires fitting a full graylevels brightness curve through brightness information of different graylevels, which requires taking multiple panel images of different gray levels. This greatly increases Demura's time, affects production line efficiency, and reduces production capacity. With the development of deep learning technology in recent years, it has been increasingly applied in industrial production processes. Therefore, this paper proposes a Demura method based on Unet++ Network, which reduces the number of graylevels images taken, reduce photo taking times, and thus improves production line efficiency and increases production capacity.

The main contributions of this paper are summarized as follows:

1) A deep learning compensation model for panel mura is proposed to address the problem of low efficiency caused by the need to capture 7 graylevels brightness data for traditional panel mura compensation. The model only uses the brightness data of one graylevel image to achieve mura compensation for the panel.
2) The paper proposes a mixed loss function that utilizes pixel level absolute error and image histogram similarity, greatly improving prediction accuracy.
3) Compared to traditional methods, the proposed solution reduces the number of photos taken from 7 to 1, greatly improving the Demura compensation efficiency.

Traditional Demura scheme

The traditional Demura scheme captures multiple graylevel images and calibration point image for distortion correction through a camera, and then processes them through a series of image algorithms to obtain

ISSN 0097-996X/25/5603-1582-$1.00 © 2025

compensation data. The workflow of the image processing algorithm is shown in Figure 1:

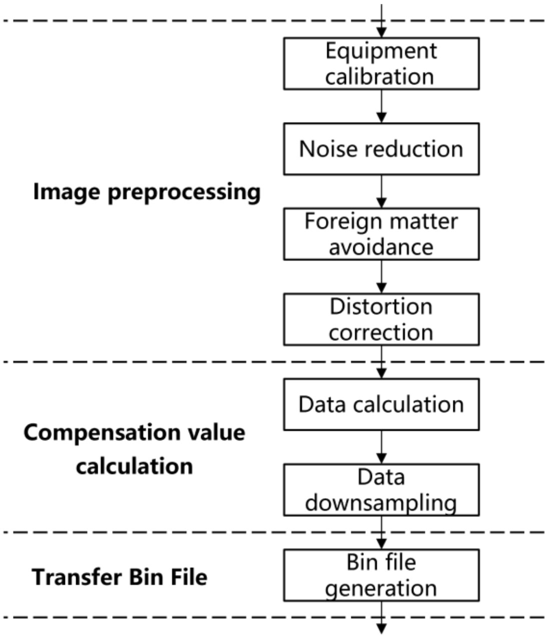


Figure 1. Image processing algorithm workflow

Step1：Due to the influence of temperature on the sensor of the camera, dark current is generated, which introduces dark noise into the imaging results. At the same time, due to the optical effect of vignetting in the camera lens itself, the illumination of the imaging surface gradually decreases from the center to the edge, as shown in Figure 2. So, in order to accurately obtain the brightness information of each position on the panel, it is necessary to first calibrate the device to eliminate dark noise and vignetting effects.

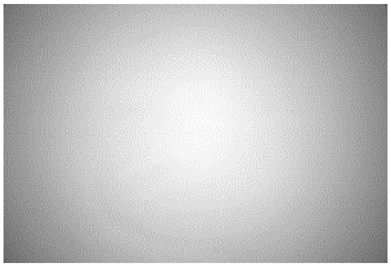


Figure. Image Vignetting effect

Step2：In addition to the inherent noise of the camera, such as dark noise, there may also be external noise, such as mechanical vibration of external electrical appliances, electromagnetic interference, and other noise generated by the working environment. Moire can also be considered as a type of aliasing interference noise. Therefore, it is necessary to perform noise reduction on the image. Usually, spatial noise reduction can be used to remove noise.

Step3：Due to the possible presence of particles, labels, POL Marks, etc. on the panel, which may affect the actual brightness acquisition, it is necessary to perform foreign object detection and repair processing on the image. The foreign object on the label is shown in Figure 3. Since the label is usually black in the 255 graylevel image, it is usually identified through threshold segmentation, and then data filling is performed using interpolation.

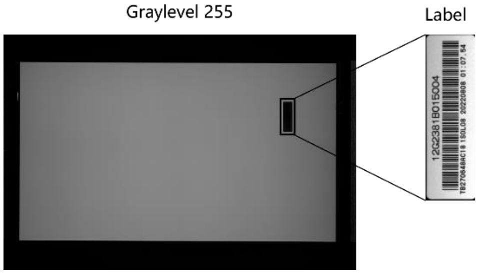


Figure 3. Label foreign object

Step4：When capturing a panel with a camera, the camera's field of view contains other information besides the panel, and ROI extraction needs to be performed first to obtain the panel area. Meanwhile, due to the inherent characteristics of optical lenses, there may be distortion during camera imaging, so distortion correction is necessary. In order to obtain the brightness information of each pixel on the panel, the corrected image size is consistent with the panel resolution, as shown in Figure 4:

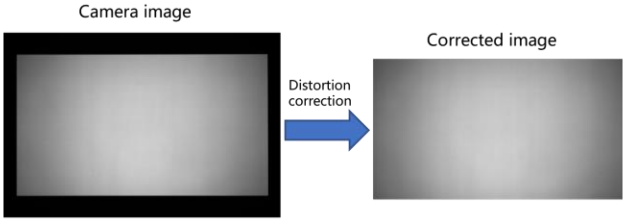


Figure 4. Distortion correction

Step5：By taking photos with a camera and undergoing the aforementioned image preprocessing, the graylevel brightness data of all pixels on the panel can be obtained. The purpose of Demura is to make the brightness displayed on the panel uniform. In order not to affect gamma correction, the target brightness is generally set to the brightness of the center point of the panel. In an ideal situation, in order to adjust the brightness of a certain position to be consistent with the center, it is necessary to know the brightness of all graylevels at that position, so it is necessary to take 256 panel images of all graylevels from 0 to 255.

However, during actual production on the production line, in order to save T/T (Tact Time), it is not possible to capture all graylevel images, only partial graylevel images can be captured. Usually, the traditional scheme requires taking 6-8 graylevel images, fitting the full graylevel curves of each position, and then solving the function to obtain the corresponding graylevel, that is, the compensation value, when the brightness reaches the target brightness, as shown in Figure 5:

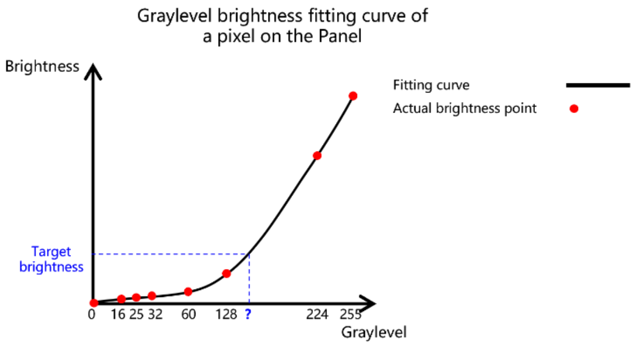
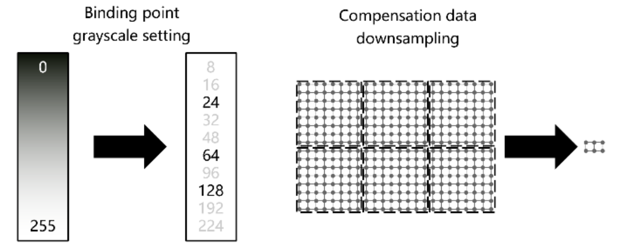


Figure 5. Graylevel brightness fitting curve

Step6：By following the above steps, the compensation values for each graylevel and position on the panel can be calculated. However, since the Demura compensation data needs to be saved in Flash on X/B, Tcon reads the compensation data from Flash for application when the panel is turned on, so the amount of data should be as small as possible. Therefore, by setting the binding point graylevel and downsampling the compensation data, the compensation data size can be reduced. For example, only 3 binding point graylevel compensation values need to be calculated, and downsample the compensation value by 8 * 8, as shown in Figure 6:



Note: Low grayscale Mura is more easily perceived by humans, hence dense sampling.

Note: The compensation data downsampling block size is usually selected as 4/8/16, with an example of 8x8

Figure 6. 3 binding points, 8 * 8 compensation

Step7：Generate the corresponding binary Bin file based on the Tcon specification using the compensation values obtained above, burn it to flash, and have the Tcon chip read and take effect when the panel is powered on, completing real-time mapping of input data and improving panel uniformity.

AI Demura scheme

The LCD AI Demura technology framework is shown in Figure 7:

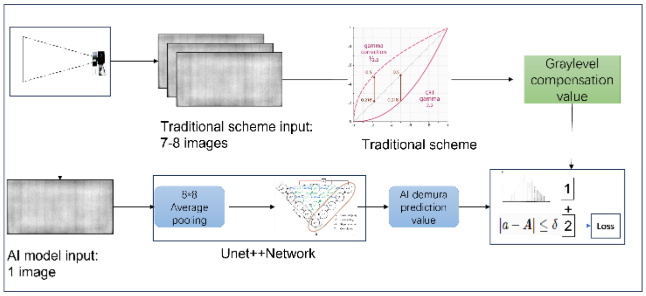


Figure 7. LCD AI Demura technology framework

1) The label for training Network: Due to the traditional Demura scheme commonly used in the industry, which can achieve a yield rate of over 99%, for a panel, a camera is used to capture 7 graylevel display data, and the compensation results of the traditional scheme commonly used in the industry are used as labels for AI network learning.
2) AI network: The AI network selects only one graylevel display data from 7 graylevel images captured by the camera as input. After passing through the AI prediction network, the output result is the predicted compensation result. Through model learning, ensure that the predicted compensation value output is consistent with the current industry standard compensation value in terms of absolute data value and brightness distribution dimensions.

Explanation of AI Model Network Architecture:

Due to the varying sizes of mura, multi-scale feature extraction is required in the network feature extraction process. Therefore, downsampling is needed to obtain feature maps of different sizes. However, in order to ensure that the output results are the same as the input size of the network, upsampling is required. The entire network structure can be regarded as a U-shaped structure. Therefore, the backbone network of this paper adopts UNET++[3] with multi-scale structure, as shown in Figure 8, which can extract mura features of different sizes and cascade the features of different sizes. The UNET++ network mainly consists of a downsampling encoder, an upsampling decoder, and a dense connection structure cascaded between layers in terms of structure. Based on the Demura compensation data prediction problem to be solved in this article, the network structure adopted in this paper can be summarized into the following four parts:

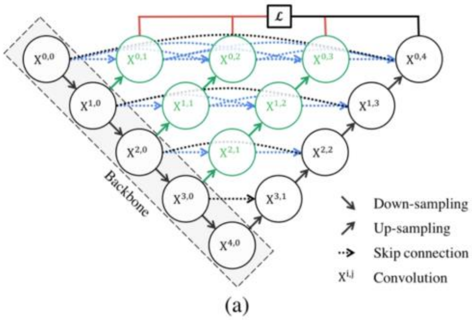


Figure 8. UNET++ Network Architecture

1. **Network header structure:** Compared to the original UNET++ network structure, this paper adds a preprocessed network header structure before the encoder, which is implemented using an 8 * 8 average pooling layer. Based on the compensation principle of IC, the same compensation value is shared for every 8 * 8 pixel block in the original image. Therefore, this paper first performs 8 * 8 average pooling on the input data to extract features from the region. The feature map size extracted from the feature map is also the output size of the entire network. This pooling operation can significantly reduce the model parameters and hardware resources required for training. After pooling, the obtained feature map is then input into the encoder module.
2. **Encoder:** After the average pooling of the network header structure, $X^{0,0}$ is obtained through two layers of convolution while keeping the size unchanged. The result is input into the UNET++ network, which implements encoding structure through 4 downsampling feature extraction modules, where $X^{0,0} \rightarrow X^{4,0}$is the downsampling feature extraction process. Among them, eachdownsampling feature extraction layer includes one downsampling layer and two convolutional layers. Between $X^{0,0}$ and $X^{1,0}$, it has undergone one downsampling and two convolution processes.

   Downsampling: The encoding process first uses a maximum pooling layer of size 2 for downsampling to reduce resolution. After each pooling operation, the size becomes 1/4 of the previous layer. As shown in Figure 8, after 4 layers of downsampling, the size of $X^{4,0}$ is reduced to $(\frac{1}{2})^4 * (\frac{1}{2})^4$.

   Convolutional feature extraction: After each layer is pooled, feature extraction is performed through 2 layers of convolution, with a kernel size of 7 and a stride of 3 to ensure that the convolution operation does not change the size.
3. **Dense connection:** Every time a downsampling feature extraction module is performed, it is connected to the previous module layer to avoid the loss of mura details caused by downsampling. Through this layer by layer connected structure, the detail information and global information of each layer are preserved, which can better extract mura features. The connection structure between adjacent layers is shown in Figure 8. If $X^{0,1}$ is a cascade operation of $X^{0,0}$ and $X^{1,0}$, since the size of $X^{1,0}$ is 1/4 of $X^{0,0}$, it is necessary to upsample $X^{1,0}$ to a size of 2 and add a convolutional layer after upsampling to train the upsampling parameters. After upsampling and convolution, concatenate $X^{0,0}$ and $X^{1,0}$ by channel to obtain $X^{0,1}$, and apply the same processing operation to other layers. In addition to performing dense connections on the downsampling feature $X^{i,0}$ to obtain $X^{i,1}$, it is also necessary to perform dense connections on $X^{i,1}$ to obtain $X^{i,2}$. For example, $X^{0,2}$ is a cascade operation of $X^{0,1}$, $X^{0,0}$, $X^{1,1}$ Other cascading operations are shown in "Skip connection" in Figure 8.
4. **Decoder:** The downsampling feature extraction of $X^{4,0}$ is further upsampled by 4 layers to increase the resolution, resulting in dense connections of $X^{0,4}$ at the same resolution, which is the output result of the model. From Figure 8, it can be seen that the entire decoding process is also achieved through multiple dense connection operations.

Loss function:

$$loss = \frac{1}{H * W}\sum_{i=1}^{H}\sum_{j=1}^{W}\left|y_{ij} - \hat{y}_{ij}\right| + (1 - cos\,(Hist(y), Hist(\hat{y})))$$

The first term in the formula is the L1 loss function, which represents the absolute error between the predicted data and the labeled data. The second term is the histogram similarity, which represents the similarity between the predicted data and the actual data histograms.

Among them, the histogram calculation method is as follows:

Divide the 0-1 interval into 10 equal parts of 0-0.1, 0.1-0.2, 0.2-0.3, etc, and calculate the proportion of predicted and actual data distribution in these 10 intervals. The final histogram can be represented by a 1 * 10 vector:

$$Hist(y) = [p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8, p_9, p_{10}].$$

Experiment and Results

In the experiment, 2000 panels were used as model training data and 400 panels were used as model testing data. Using AdamW [4] as the optimizer, with an initial learning rate of 0.01, the learning rate decreases by 10% every 5000 iterations for a total of 500 iterations, with a sample size of 8 per batch. Using the compensation value of the traditional scheme c ommonly used in the industry as a standard, analyze the absolute error between the compensation result predicted by the AI model and it. For the AI prediction model, data captured from a 25 graylevel display screen is used as input. For the industry standard scheme, display data of 8 graylevel images including 16, 25, 32, 60, 96, 128, 225, 255 were collected, and compensation data of 25, 60, 128 graylevel images were calculated using equipment on the production line as the AI prediction standard. The error test results under 12 bits are as shown in Table 1:

	25	60	128
absolute error	0.39	1.12	2.35
error ratio	0.28%	0.32%	0.29%

Table 1. Error test results

The visual comparison between the predicted compensation results and the standard compensation results is shown in Figure 9. From the visualization results, it can be seen that the predicted compensation values are basically consistent with the standard compensation values.

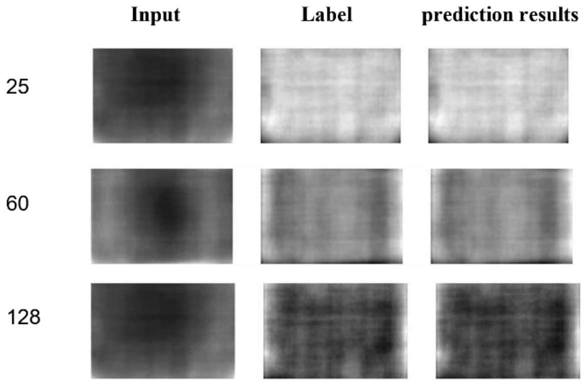


Figure 9. Visual comparison between predicted values of three binding points and standard results

Furthermore, the analysis results of the SSIM index based on structural similarity for 200 panels are as follows, where the standard range of SSIM is 0-1. From Table 2, it can be seen that the structural similarity between the predicted compensation data and the standard compensation data for the three grayscale levels exceeds 0.99, and there is basically no difference from the perspective of the human eye.

	25	60	128
SSIM	0.996	0.995	0.999

Table 2. Result of SSIM(Unit: Null)

In practical terms, the evaluation of panel Mura degree is mainly visually quantified by professionally trained personnel, using JND (Just notifiable difference) as the quantification value. The smaller the JND, the less visible the Mura [5]. This evaluation method is very accurate for evaluating local small-scale uneven brightness. For the same panel, the comparison results of traditional Demura and AI Demura compensation are shown in Table 3.

JND	traditional scheme	AI scheme
25	2.1	2.1
60	2.2	2.2
128	2.1	2.1

Tab.3 Result of JND(Unit: Null)

From Table 3, it can be seen that the AI scheme for JND value after Mura elimination is consistent with the traditional scheme, meeting the requirements of the product's mass production specifications.

Summary

This paper proposes a LCD Demura scheme based on deep learning, which uses the brightness data of a single graylevel image to predict the mura compensation values of multiple binding point graylevels. A mixed loss function based on pixel level absolute error and histogram similarity is constructed. Through experimental testing, greatly improved the mura compensation efficiency of the panel while maintaining a low prediction error, with an error of 0.3% compared to traditional solutions. After manual judgment, the uniformity of the panel compensated by deep learning is consistent with that compensated by the traditional scheme.

References

[1] JIA H P. Who will win the future of display technologies? [J]. National Science Review, 2018, 5(3): 427-431.

[2] TU Zhen-tao, FAN Rui, ZHANG Xiao-ning, et al. Influence of fitting curve between gray scale and brightness on Mura improvement of LCD panel[J]. Chinese Journal of Liquid Crystals and Displays, 2016, 31(5):442-448. (in Chinese).

[3] Zhou Z , Siddiquee M M R , Tajbakhsh N ,et al.UNet++: A Nested U-Net Architecture for Medical Image Segmentation[J]. 2018.DOI:10.1007/978-3-030-00889-5_1.

[4] Ilya Loshchilov, Frank Hutter , Decoupled Weight Decay Regularization. arXiv:1711.05101.

[5] JIN Y F, XIAO Y X, FU C L. Image preprocessing algorithm of VA-LCD Mura compensation [J]. Chinese Journal of Liquid Crystals and Displays, 2021, 36(7): 999-1005. (in Chinese)