

# A Low Grayscale Uniformity Improvement Scheme for OLED Based on Auto Demura

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## Abstract

The semiconductor display industry is accelerating its development, with Demura technology mainly applied to OLED Mini/Micro LED. New display devices such as printing display improve image quality through technical adjustments, making the display effect more uniform and clear. The visual effect of OLED can be characterized by objective indicators such as chromaticity uniformity and luminance uniformity, and requires a lot of manual subjective confirmation to ensure the final compensation effect. In order to reduce human resource costs and automate the Demura algorithm, this paper adopts a U-shaped network model to recognize and classify mura by objectifying the visual features of mura. Based on the result of classifying mura, different compensation values are used to improve the first pass rate of Demura process for display panels.

## Author Keywords

OLED; Auto Demura; U-shaped network model; Mura; Luminance non-uniformity; Image compensation

## 1. Introduction

AMOLED panels are widely used in high-end electronic products such as smartphones, televisions, and wearable devices due to a series of outstanding features. From the perspective of technological structure, OLED will account for 36.8% of global display sales in 2023, and this proportion is expected to increase to 40.4% by 2024, indicating that OLED technology's position in the global display market is gradually improving and its market share is constantly expanding. In the long run, by 2030, global display sales are expected to grow to \$153 billion, and OLED technology is expected to account for 44.5% of the global display market, becoming one of the dominant technologies. This also indicates that OLED technology will have broad market prospects and huge development potential in the future development of the global display industry, and is expected to lead the global display industry into a new stage of development.

The yield control of OLED in large-scale production process is also an important issue. Due to the complexity of the process, even a slight carelessness may lead to product defects, reduce yield, and further increase production costs.

Due to the limitations of semiconductor technology, TFTs have non-uniformity in electrical parameters such as threshold voltage and mobility, which can lead to differences in current and luminance of display devices, resulting in Mura phenomenon. OLED Demura technology, currently led by Samsung and LG, is very complex and cannot be considered mature and perfect. Various domestic manufacturers are actively developing their own Demura technology, hoping to improve yield. Therefore, this article proposes the Auto Demura scheme to make the display compensation technology of single OLED products more accurate and efficient, and to improve the first pass rate of the Demura process for display panels.

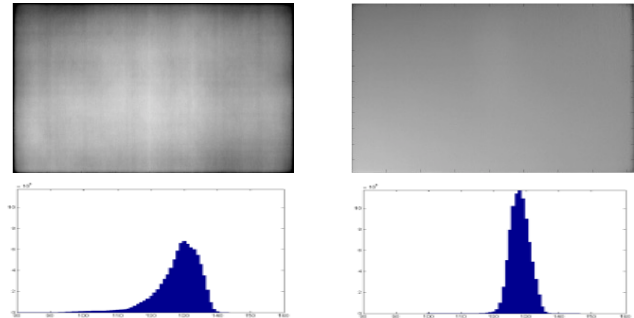


Figure 1. Comparison of Demura before and after.

## 2. Principle analysis

This 7T1C pixel circuit has three stages of operation, including reset, compensation, and light emission. Therefore, it has certain requirements for the driving capability of the circuit and the load on the panel. Its general working idea is to store the threshold voltage  $V_{th}$  of the TFT in its gate source voltage  $V_{gs}$  during the compensation stage. When emitting light at the end,  $V_{gs}$   $V_{th}$  is converted into current because  $V_{gs}$  already contains  $V_{th}$ . When converted into current, the influence of  $V_{th}$  is cancelled out, thus achieving current consistency. However, in reality, due to parasitic parameters and driving speed,  $V_{th}$  cannot completely cancel out. Namely, when  $V_{th}$  deviation exceeds a certain range (usually  $\Delta V_{th} \geq 0.5V$ ), the consistency of current cannot be guaranteed. Therefore, the compensation range of  $V_{th}$  is limited and Demura compensation is needed, and it is necessary to implement Demura compensation.

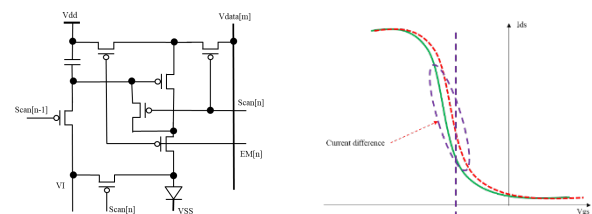


Figure 2. 7T1C pixel circuit and current curve.

Any phenomenon of color unevenness and luminance inconsistencies is called Mura. Employ algorithms to mitigate color unevenness and luminance inconsistencies is called Demura. The Demura principle is that the camera obtains mura pixel information based on monochrome R/G/B, and obtains CSV data containing the relative luminance values of each pixel. And then, fit the gamma curve of each pixel based on the CSV data of the relative luminance value of the captured grayscale image, and calculate the compensation value offset for each grayscale image by referring to the gamma curve of the central area. The Demura principle can be represented by formula(1) The demura principle is usually integrated into displays in the form of Demura IP.

$$Gray_{out} = Gray_{in} + offset * gain \tag{1}$$

Gray \ DBV	Low (2nit)	→				High (500nit)
Low(5)	d1	d6	d11	d16	d21	
↓	d2	d7	d12	d17	d22	
	d3	d8	d13	d18	d23 Reference value	
	d4	d9	d14	d19	d24	
High(128)	d5	d10	d15	d20	d25	

Figure 3. 2D lookup table setting for gain value of Demura IP.

Demura IP only calculates the offset of pixel level compensation for a single or a few images, and interpolates other luminance and grayscale images using gain values. At present, major manufacturers use the Demura process for each panel, but most of them adopt the common version of Gain value, which cannot be adjusted according to the actual product mura level. It is necessary to consider setting a gain value version that is compatible with more products.

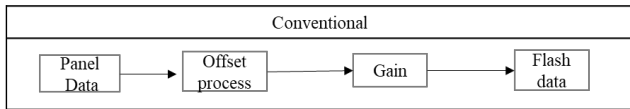


Figure 4. The process of setting the public version gain value for Demura.

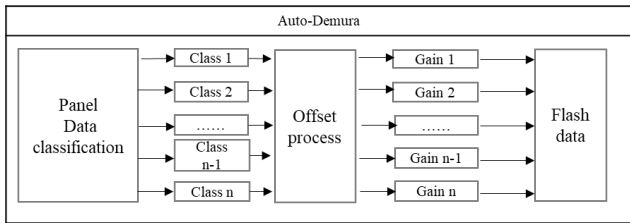


Figure 5. Auto Demura process based on relative luminance data classification.

Therefore, a recognition and classification scheme is proposed based on the current Demura process. The algorithm recognizes and classifies the relative luminance data of each pixel obtained through the Demura camera, processes and generates offset compensation data for each panel, and compensates for different versions of gain values for different categories of panels.

### 3. Results and discussion

- Mura Visual Perception Evaluation Model

The visual effect of OLED requires objective indicators such as color luminance uniformity to be calculated, as well as subjective confirmation by humans to ensure the final effect. In order to achieve algorithm automation, this article adopts a U-shaped network model of to achieve objectivity of subjective effects [1].

Mura, such as color and luminance uniformity, can be classified as pixel level effect evaluation, but Mura evaluation can be classified as feature evaluation. The network features of each layer of neural networks are the high-level features learning from the pixels, which have been maturely applied in the field of AI, especially in the field of image classification, where network features are used to replace images for image classification[2].

- Network training

In this article, a U-shaped network is used to encode the network firstly, extract visual perceptual features, and then decode the features to generate a predicted image, ensuring that the predicted image is consistent with the original image. Therefore, the extracted visual perceptual features can replace the features of the input image. In order to ensure that visual perceptual features can replace image features, the network training loss function is shown in the following formula (2).

$$loss_{train} = |y - \hat{y}| \tag{2}$$

Among them, y represents the target image, which is identical to the input.  $\hat{y}$  is the predicted image.

- Mura Visual Perception Feature Evaluation Index

This article constructs a mura visual perception evaluation index based on the ideal screen image, and calculates the difference between the test image and the ideal image. The ideal screen data construction method is as follows:

- 1) Based on the test image, select the relative luminance data of the central area of the Panel..
- 2) Calculate the average relative luminance data of 100 \* 100 pixels in the center of the image to be tested.
- 3) Generate data of the same resolution from the calculated mean to obtain ideal screen data.

In practical reasoning, extracting the network features of the test image and the ideal image, with a small difference between the two features, proves that the test image has good performance. As shown in the figure, extract 4 layers of features, as shown in loss 1, loss2,loss3,loss4, Calculate the mean as the visual perceptual feature of the image. Visual features can be represented by the following formula (3).

$$Score_{vp} = \frac{1}{4} (|loss_1 - loss_{1,gt}| + |loss_2 - loss_{2,gt}| + |loss_3 - loss_{3,gt}| + |loss_4 - loss_{4,gt}|) \tag{3}$$

Among them,  $loss_i$  represents the i-th network feature of the test image,  $loss_{i,gt}$  represents the i-th network feature of an ideal image.

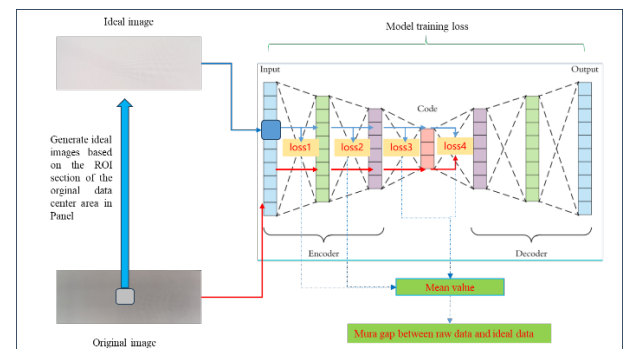


Figure 6. The U-shaped architecture.

By utilizing relative brightness data acquired by a camera, the U-Net model is applied to classify the mura. This approach is more conducive to performing demura compensation on the panel.

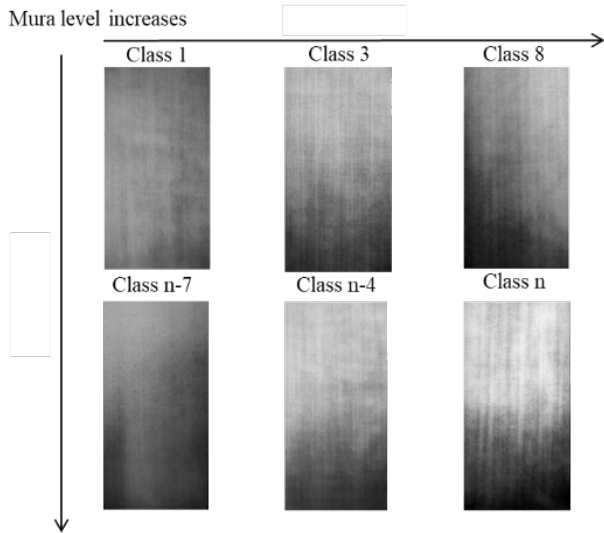


Figure 7. The U-Net model is applied to classify the mura.

Generate Panel Demura offset data based on the Demura algorithm, including identification and processing of areas with uneven chromaticity and luminance, compensation, edge processing, and other specific treatments. If different mura regions are identified and subjected to gradient transition processing, offset compensation data is more in line with the actual Panel compensation trend.

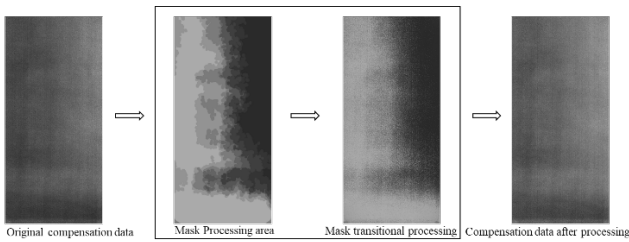


Figure 8. Gradient transition processing for recognizing different mura regions.

At the same time, the conventional solution of Demura IP cannot compensate for the display effect of the entire panel to an acceptable range by adjusting the Gain value alone. The application of Auto Demura can set different processing parameters according to different types, process local area Offset data, prevent local over-compensation or under-compensation of the panel, and achieve the best visual effect of the panel display.

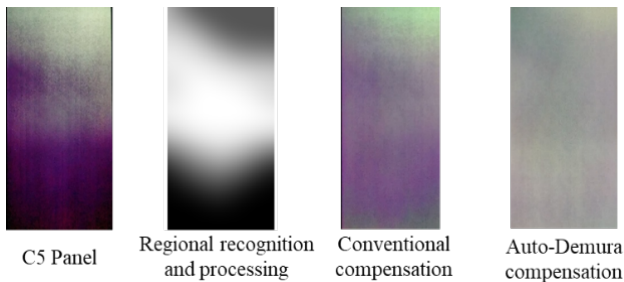


Figure 9. Comparison and display of actual compensation effects.

Using CA410 to measure and calculate the objective data of two schemes, the luminance uniformity increased from an average of 0.772 to 0.867, an increase of 12.6%. The chromaticity uniformity decreased from an average of 0.0234 to 0.0185, an increase of 20.01%.

Table 1. Comparison of uniformity between two solutions.

Panel	Conventional		Auto-Demura		Increase percentage	
	Uniform	JNCD	Uniform	JNCD	Uniform	JNCD
#1	0.735	0.0283	0.872	0.0193	18.64%	31.80%
#2	0.821	0.0202	0.866	0.0183	5.48%	9.41%
#3	0.74	0.0232	0.868	0.0196	17.30%	15.52%
#4	0.801	0.0212	0.881	0.0166	9.99%	21.70%
#5	0.692	0.0303	0.84	0.0228	21.39%	24.75%
#6	0.785	0.022	0.871	0.0158	10.96%	28.18%
#7	0.721	0.0251	0.867	0.02	20.25%	20.32%
#8	0.821	0.0202	0.866	0.0183	5.48%	9.41%
#9	0.835	0.02	0.868	0.0162	3.95%	19.00%
<b>average</b>	<b>0.772333</b>	<b>0.023389</b>	<b>0.866556</b>	<b>0.018544</b>	<b>12.60%</b>	<b>20.01%</b>

Note: The higher the luminance uniformity, the better, and the lower the chromaticity uniformity value, the better.

$$uniformity = Min(Lv)/Max(Lv) \tag{4}$$

$$JNCD = Max(\sqrt{\Delta u_i^2 + \Delta v_i^2}) \tag{5}$$

#### 4. Conclusions

This article mainly analyzes the pixel level performance evaluation of mura, using an U-shaped network to achieve mura degree classification, and creatively proposes a multi version Gain value compensation scheme. Through experimental testing, based on the Auto Demura process scheme, the visual effect of the display panel is effectively improved, and the factory's first pass rate is increased. This research result contributes to the further development of OLED technology in related fields and has positive reference value for subsequent research.

#### 5. References

1. 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.
2. Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition[J]. arXiv preprint arXiv:1409.1556, 2014.