A Cost-effective Burn-in Compensation Method Using Deep Convolutional Networks with Detail Layer Accumulation

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ABSTRACT

In this paper, a cost-effective burn-in compensation method based on optical imaging is proposed. A deep convolutional networks using the accumulated detail layer as a reduced reference is applied to the captured images. Experimental results show that the proposed method reconstructs burn-in details effectively to be followed by multi-unit compensation.

1 Introduction

Despite advances in organic materials and manufacturing technologies, lifetime degradation still remains a technical barrier in organic light emitting diode (OLED) display application. The luminance efficiency of an OLED decreases with time of use. The non-uniform degradation recognized as a burn-in phenomenon occurs according to the amount of accumulated current density that is non-uniformly driven to each pixel of the display panel.

Data-counting methods [1] have been developed to alleviate the lifetime issue of mobile displays. The data-counting method is to predict the degree of luminance degradation from the accumulated image data based on OLED degradation model which defines relationship between the luminance degradation and elapsed time. The accuracy of the degradation model is directly related to the compensation performance. In [2], a tracing-based prediction method using different model parameters for different gray levels was proposed to accurately reflect material properties. Although data counting method can be a method of delaying the initial burn-in recognition, errors in model prediction are also accumulated due to the actual usage environment such as operating temperature and driving method and the cause of panel deviation.

After burn-in has been recognized, data counting alone cannot compensate for burn-in, even though it uses a lot of memory. The feedback information about degradation distribution, such as external sensing [3] or optical imaging, should be used to complement the open loop system. However, there are technical difficulties to acquire accurate optical imaging data without Moire under precise focusing condition. To deal with the Moire problem, a specialized equipment with high-resolution camera should be used [4]. An alternative is to apply optical blurring, but it will cause the detail loss affecting compensation performance.

In this paper, we propose a cost-effective burn-in compensation method based on optical imaging. The captured images which include degradation distribution in low resolution are processed to represent burn-in details using deep convolutional networks with the accumulated detail layer as a reduced reference. The multiunit compensation data is configured to have the sub-pixel wise compensation data for the burn-in detail region. Therefore, in order to preserve the details, accumulation is performed on the detail layer as a robust feature rather than input gray value. Experimental results show that the compensation data acquired by a low-end camera can be improved to include detail component using the proposed network with the accumulated feature. The required memory to accumulate feature is about 1/6 of sub-pixel wise accumulation with degradation model.

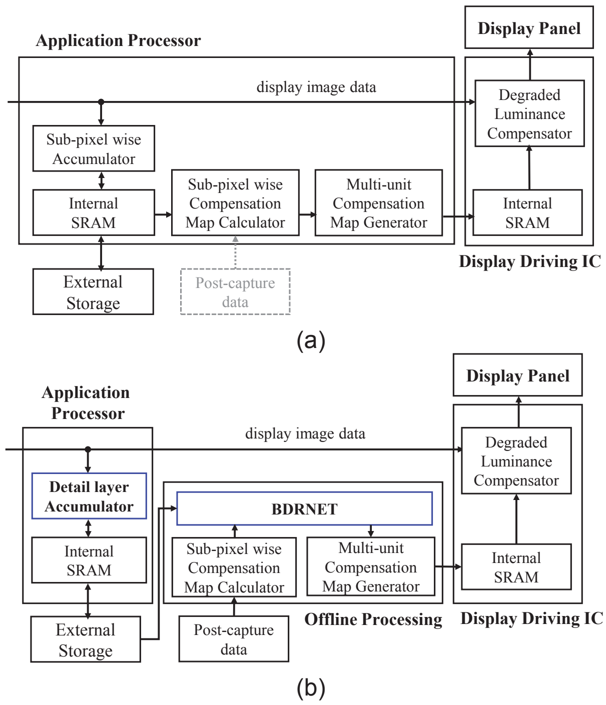
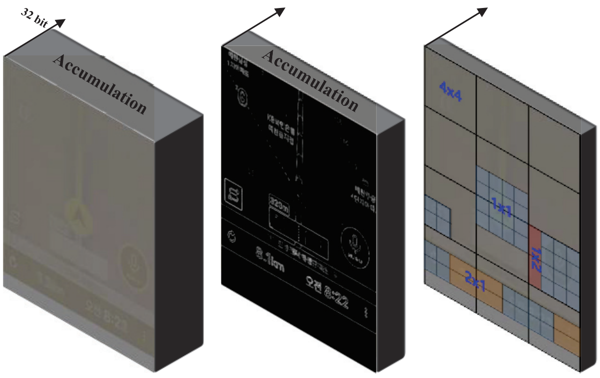


Fig. 1 Overall block diagram of burn-in compensation on the mobile system proposed in [5] (a) and in this paper (b)

2 Proposed Method

We focus on the mobile system, of which a display driver integrated circuits (DDI) receives the multi-unit compensation map from an application processor (AP) and compensates burn-in with small internal dedicated memory. As shown in Fig. 1(a), we had proposed the mobile system with two main functional blocks, accumulator and compensator located in AP and DDI, respectively [5]. Multi-unit compensation map generator is to reduce the amount of accumulated usage data without loss of compensation performance. Fig. 2 illustrates data map configuration. Accumulated data in Fig. 2(a) can be reduced by sampling spatially and reducing temporal bit precision for compensation as shown in Fig. 2(c).



(a) (b) (c)

Fig. 2 The illustration of data map configuration. (a) accumulation map, (b) detail layer accumulation map (c) multi-unit compensation map

However, the accumulated data for all pixels is required to generate multi-unit compensation map. Although a large memory is used, it is difficult to represent actual panel state due to mismatch of empirical OLED degradation model. Therefore, we propose the mobile system in Fig. 1(b) that accumulates burn-in details necessary for multi-unit compensation while using the imaging data that reflects actual panel state as a base layer. The deep convolution networks is to reconstruct edge information using detail layer accumulation map as shown in Fig. 2(b).

2.1 Detail Layer Accumulator

The multi-unit map is generated to allocate more memories for burn-in details through localization and classification process. To detect burn-in details, the detail layer is extracted from a sub-pixel wise compensation map by decomposition using the initial 4x4 single-unit map as the base layer. The detail layer, $D_c(i,j)$ represents errors after 4x4 single-unit compensation and has higher spatial frequency components than the sampling frequency.

$$D_c(i,j) = C_{1x1}(i,j) - C_{4x4}(i,j) \qquad (1)$$

where $C_{NxN}(i,j)$ is *N*x*N* single-unit compensation map.

Since the multi-unit map is generated based on the detail layer, we focused on that the accumulation of the detail layer can be used as an edge guidance map effectively while using less memory. Since the detail layer data is a differential component, the accumulated data can be reduced. Also, edge location is a robust feature that is invariant with model accuracy. Therefore, detail layer accumulation does not require OLED degradation model to convert input gray to degradation value and accumulated degradation value to degraded luminance ratio. Detail layer accumulation is simplified using input gray data and adjusting binarization as follows.

$$D_a(i,j) = \begin{cases} 1, \ if \ I_{1x1}(i,j) - I_{4x4}(i,j) > E_{th} \\ 0, \ else \end{cases} \qquad (2)$$

where $I_{NxN}(i,j)$ is *N*x*N* averaged input data, E_{th} is a threshold value for binarization. The required memory can be reduced by about 1/6.

2.2 Burn-in Details Reconstruction Network

Burn-in Details Reconstruction Network (BDRNET) is proposed to generate a sub-pixel wise burn-in compensation data from the captured image using easily accessible devices such as smart phone. In the image, there are detail loss due to optical blur and performance deviations through camera sensors and post image signal processing. The target of BDRNET is the imaging result from a specialized optical equipment.

We are motivated by the previous work [6] which improves low-quality smartphone captured images to DLSR-quality through the deep convolutional network. In [6], a composite of perception loss and GAN network was applied to emphasize the perception quality. The discriminator CNN was used with binary cross entropy loss function for measuring texture quality. However, these are not suitable for BDRNET to acquire accurate optical information of target image in unit of pixel. Therefore, BDRNET has been modified to be suitable for burn-in details reconstruction.

Fig. 3 shows the overall architecture of the proposed BDRNET. Given a captured image which includes luminance degradation status, the target of the network is to reconstruct details in pixel unit. The network has an edge guidance image [7], accumulated detail layer, for distinguishing the burn-in characteristic and the optical characteristic as an additional input channel. The network is mainly composed of 12 CNN layers with 2 input channels and 1 output channel. We use 4 residual blocks which consist of two layers with kernels of size 3x3 and 8 channels.

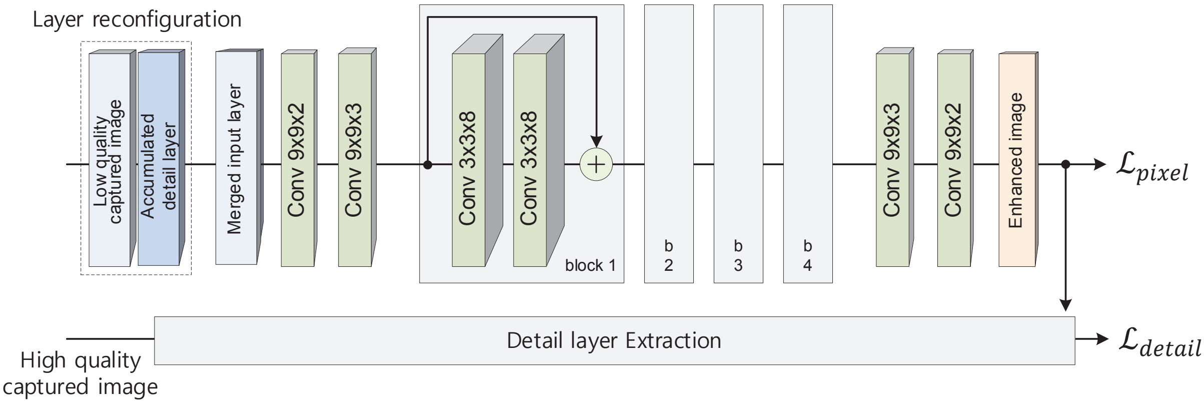


Fig. 3. The overall architecture of BDRNET

The enhanced image should be matched to the target image in terms of pixel to pixel difference. Pixel loss is defined as follows.

$$\mathcal{L}_{pixel}(X,Y) = \|X - Y\|^2 \qquad (3)$$

where X and Y are the enhanced image and the target image, respectively. However, applying the pixel loss function to every pixel negligibly reflects the significant detail loss. Burn-in detail region accounts for a small portion of the total pixel, which is the basic assumption of multi-unit compensation. To keep details, detail loss function is added along with pixel loss.

$$\mathcal{L}_{detail}(X,Y) = \|X * \varphi - Y * \varphi\|^2 \qquad (4)$$

where φ is the kernel for LoG filter.

Total loss is defined as a weighted sum of pixel loss and detail loss. The weight coefficient was determined empirically.

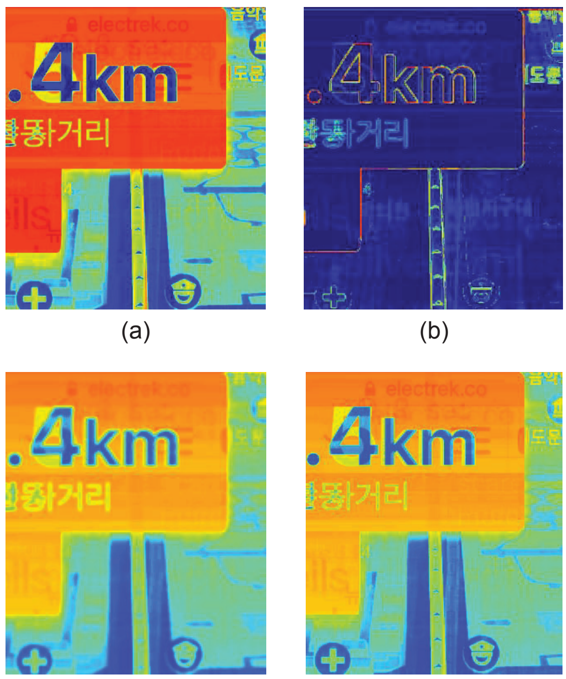
$$\mathcal{L}_{total} = \mathcal{L}_{pixel} + 2 \cdot \mathcal{L}_{detail} \qquad (5)$$

3 Experiments

BDRNET should be trained with a large database based on a data-driven approach. However, it is physically difficult to obtain different types of burn-in occurred panels through degradation in a controlled environment on different output images. To generate the data set, a degradation model-based simulator was used to generate the accumulated data and the resulting degradation map for all the video sequences.

Fig. 4 shows an example of paired data set generated through simulation, as color map images for visual convenience. The simulated degradation map and detail layer accumulated map is shown in Fig. 4(a) and Fig. 4(b), respectively. For the post-capture, optical imaging data include error of the degradation model and optical blurring due to imaging device. To contain these factors, a certain gain map assuming the error map and a low pass filter to make optical blurring is applied to the degradation map, as shown in Fig. 4(c). Given the simulated optical imaging data and the detail layer accumulated map, BDRNET is trained to produce the target image, as shown in Fig. 4(d).

We acquired 100 video sequences by screen recording to reflect actual smartphone usage including game, video, navigation, home screen and text. The network was trained with extracted patches that contain many details.



(a) (b)

(c) (d)

Fig. 4 Example of paired data set (a) simulated degradation map based on degradation model, (b) detail layer accumulated map, (c) simulated optical imaging data, (d) ground truth

Table 1. PSNR and SSIM result

Method			Video		Navigation		Text		Average	
Accumulation	Post-capture	Edge reconstruction	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Full reference	-	-	17.216	0.983	18.445	0.976	18.828	0.977	18.163	0.979
-	O	-	42.360	0.989	35.930	0.957	39.850	0.964	39.380	0.970
Full reference	O	Guided filter	45.937	0.996	40.423	0.991	43.916	0.987	43.426	0.991
No reference	O	**Proposed network**	46.640	0.992	43.140	0.984	45.190	0.982	44.990	0.986
Reduced reference	O		47.020	0.994	44.660	0.990	45.920	0.988	45.867	0.991
Full reference	**O**		49.420	0.999	50.590	0.999	49.680	0.998	49.897	0.998

Table 1 shows PSNR and SSIM results on test images. We compare with cases according to accumulation method, capture or not, and edge reconstruction method. The guided filter [8] can transfer the structures of the guidance image. It is shown that the guided filter can take advantage of the captured image characteristics as a base layer and the sub-pixel accumulated image characteristic as a detail layer. The proposed network can be configured to have input guidance image, such as the sub-pixel accumulated image (full reference) and the accumulated detail layer image (reduced reference), or no guidance image (no reference).

The proposed network with no reference structure shows better performance than guided filter in terms of PSNR. However, it has limitation in edge reconstruction, which results in worse performance compared to guided filter in terms of SSIM. The proposed network using accumulated detail layer as the reduced reference can enhance burn-in detail information. As more guidance information is used, the network can produce the output image more close to the target image. The proposed mobile system, including detail layer accumulation and the network, can effectively generate sub-pixel based multi-unit compensation data.

Since the proposed system aims at effective post compensation, there is a limitation in that it cannot delay initial burn-in recognition. When sub-pixel accumulation is available in AP system, the proposed network can support post compensation and accumulated data adjustment with easily accessible imaging device, such as smartphone.

4 Conclusions

In this paper, we present a cost-effective burn-in compensation method based on optical imaging. The deep convolutional network is proposed to reconstruct burn-in details in captured image to be followed by multi-unit compensation. The results show that the proposed network can be effective using detail layer accumulation without degradation model. It works as edge guidance to distinguish burn-in characteristic and the optical characteristic.

References

[1] J. Kim, J. Ko, J. Park, G. Jeong, H. Maeng, S. Park and W. Choe, “A Compensation Algorithm for Degradation in AMOLED Displays,” SID Symposium Digest of Technical Papers, pp. 445-448 (2018).

[2] S. Hong, J. Goh, J. Bae, D. Kwag, H. Kim and W. Choe, “Tracing-Based Degradation Estimation Method for Stress Profile Algorithm,” SID Symposium Digest of Technical Papers (2022).

[3] H. In and O. Kwon, “External Compensation of Nonuniform Electrical Characteristics of Thin-film Transistors and Degradation of OLED Devices in AMOLED displays,” Vol. 30, No. 4, pp. 377-379 (2009).

[4] J. Yuan, X. Feng, Z. Zheng, S. Zhang, E. Ma and H. Wu, “A High-accuracy DeMura Algorithm Based on Sub-pixel Registration,” SID Symposium Digest of Technical Papers, pp. 459-461 (2019).

[5] J. Ok, Y. Yu, J. An, S. Na, W. Jang, H. Lim and J. Lee, “A Multiunit Compensation for Organic Light-emitting Diode Burn-in in Mobile Displays,” J. SID, Vol. 29, No. 5, pp. 405-415 (2021).

[6] A. Ignatov, N. Kobyshev, R. Timofte, K. Vanhoey and L. Gool, “Dslr-quality Photos on Mobile Devices with Deep Convolutional Networks,” ICCV, pp. 3277-3285 (2017).

[7] J. Xie, R. Feris and M. Sun, “Edge-guided Single Depth Image Super Resolution,” IEEE Trans. Image Process., Vol. 25, No. 1, pp. 428-438 (2015).

[8] K. He, J. Sun and X. Tang, “Guided Image Filtering,” IEEE Trans. Pattern Anal. Mach. Intell., Vol. 35, No. 6, pp.1397-1409 (2012).