Deep Controllable Backlight Dimming

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ABSTRACT

Dual-panel displays require local dimming algorithms in order to reproduce content with high fidelity and high dynamic range. In this work, a novel deep learning based local dimming method is proposed for rendering HDR images on dual-panel HDR displays. The method uses a Convolutional Neural Network to predict backlight values, using as input the HDR image that is to be displayed. The model is designed and trained via a controllable power parameter that allows a user to trade off between power and quality. The proposed method is evaluated against six other methods on a test set of 105 HDR images, using a variety of quantitative quality metrics. Results demonstrate improved display quality and better power consumption when using the proposed method compared to the best alternatives.

1 Introduction

High dynamic range (HDR) technology is capable of capturing, storing and displaying a much wider dynamic range of luminance compared to the traditional standard or low dynamic range (LDR) technologies. HDR imaging can significantly improve viewing experiences and has been used in photography, gaming, films, medical and industrial imaging [10] [29].

HDR is becoming one of the main features in display technology. Seetzen et al. [37] developed the first LED-based HDR display with a maximum luminance of approximately $8,500 \text{ cd/m}^2$ and a dynamic range of 50,000:1. This display is composed of two panels, a backlight panel and an LCD panel, that are used for modulating the backlight luminance and maintaining colour and details respectively. HDR displays of this kind, often termed dual-panel displays, are capable of presenting a significantly higher luminance range compared to conventional displays.

Backlight dimming (BLD) algorithms are designed for modulating the backlight of dual-panel displays according to the displayed image content. To date, many BLD algorithms have been proposed [33], mainly for LDR images. In general, BLD algorithms can be divided into two categories: global dimming and local dimming. Global dimming methods are mostly used for small size LCD devices, such as smartphones and tablets. The backlights of these devices are placed on the edges (edge-lit) because of restrictions to their thickness. Local dimming algorithms are mostly used for the devices which are directly backlit (direct-lit), such as TVs and computer monitors. Compared with global dimming algorithms, local dimming algorithms are considered to perform better in terms of image contrast and power consumption [23] [42]. Although local dimming can also be used to control edge-lit devices, a number of areas can not be controlled as effectively, unlike with directly back-lit devices.

Current methods are designed by display specialists and researchers using hand-crafted features or utilising real-time optimisation, which can be sub-optimal in the first case and may be time-consuming in the latter. Recently, data driven methods, in particular deep learning, have been used for a wide range of applications in image processing due to their strong learning and representation capabilities and efficiency. In particular, CNNs form the basis for many current state of the art models in classification, detection, image translation and synthesis [36]. Deep learning methods can bypass human expertise and heuristics by learning directly from data.

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In this paper, a novel local dimming algorithm based on a CNN architecture is proposed for displaying HDR images on dual-panel HDR monitors. The proposed CNN can efficiently predict the backlight values for each dimming area directly, providing a high fidelity reproduction of the original content. To the best of our knowledge this is the first deep learning method proposed for local dimming algorithms. Furthermore, the proposed method is conditioned via a controllable power parameter that provides a trade-off between power consumption and quality.

The primary contributions of this work are: (a) the first learning based local dimming method that uses a CNN model for rendering HDR images on a dual-panel HDR display; (b) an adaptive optimisation procedure with an input-dependent adjustable loss (c) a comprehensive objective evaluation of the proposed algorithm against existing state-of-the-art solutions.

2 Background and Related Work

A number of local dimming algorithms have been proposed to date. Furthermore, CNNs have been extensively used for addressing problems of image processing. This section introduces the basic structure of LC displays and presents an overview of existing local dimming algorithms as well as relevant CNN based methods.

2.1 Dual-Panel Display Technology

Dual-panel displays consist of a high-resolution panel that reproduces image details and colour, and a low-resolution backlight panel that controls the contrast ratio. The high resolution panel corresponds to a three-channel image $T$, while the low resolution backlight corresponds to a set of $N$ values $\{B_k \mid k \in [1, N]\}$, placed on a single-channel image, $B$. Each value corresponds to a coarse grained segment of the high resolution image, according to the placement of the individual lights on the backlight panel. For ease of notation, $B$ has the same resolution as $T$ but all the values are zero except at the $N$ locations, $S$, that correspond to each of the backlight values $B_k$.

Figure 1 shows the structure of dual panel LC displays and their three main components: the backlight panel, the diffusion panel and the LC panel. The backlight panel is the lighting source for the LC panel, while the diffusion panel is used for smoothing and dispersing the backlight in order to avoid huge luminance gaps and mismatch between neighbouring pixels. The LC panel filters the backlight to create the three channel image output at a high resolution.

2.2 Existing Local Dimming Algorithms

Local dimming algorithms can broadly be divided into three categories, depending on their characteristics.

2.2.1 Mathematical Statistics

Statistics based local dimming algorithms obtain backlight values using straightforward mathematical operators. Funamoto et al. [15] proposed the use of maximum and average intensity of a given image segment. The maximum algorithm sets the intensity of each backlight value to the maximum pixel value of the corresponding image segment. The maximum approach is sensitive to noise, while the mean method tends to produce excessively dim backlighting and can lead to significant clipping artefacts.
2.2.2 Local Image Characteristics

BLD methods are based on assigning a backlight value that depend on each local segment, rather than taking simple maximum or average values.

Cho and Kwon [8] proposed a BLD method to improve image quality using a correction term to adjust the average pixel intensity by considering the local difference between the maximum and average luminance. In addition, a new method for reducing the clipping artefacts of LCD images was used to preserve the image quality. A similar method developed by Zhang et al. [45] who also computed a correction term as the ratio of the difference of maximum and average luminance to obtain the backlight values. Lin et al. [25] inversed the cumulative distribution function (from a global histogram) to map a weighted mean of the maximum and average pixel values of each backlight segment for the resulting backlight values. Other methods, such as that introduced by Nam [32], consider both local and global brightness in order to find a better trade-off between enhancing local contrast and preserving the overall appearance of the LCD images. A roll-off scheme was used to enhance image details in the high-level grey areas. Cho et al. [9] used an image metric to obtain the intensity of the backlight and refined these values by considering local block lighting and the lighting from neighbouring blocks. Other BLDs were developed to preserve the image quality, including Kang and Kim [20] who considered the pixel distribution of an image using multiple histograms. Hsia et al. [7] proposed a method to improve the LCD image resolution by enhancing the weak edges of each image segment.

2.2.3 Optimal Methods

In BLD methods, clipping artefacts are the most significant problem that effects the displayed image quality. To keep the balance between displayed image and backlight values, some optimal BLD algorithms have been proposed.

The BLD algorithm developed by Kim et al. [21] is based on a decision rule: searching the optimal dimming value by comparing the light-leakage measure and the clipping measure to keep the light-leakage and clipping lower. Shu et al. [38] approached the local dimming of LED backlight LC displays as an optimisation problem to obtain a higher visual quality. Zhang et al. [44] also proposed an optimal method to maintain a balance between LCD image quality and power consumption. Cha et al. [5] presented an efficient optimised BLD method for edge-lit lighting-emitting diode backlight to reduce image quality fluctuation. Another category of backlight modulation methods, such as that proposed by e.g. Albrecht et al. [1], are based on a point spread function (PSF) to exploit the knowledge of light diffusion and model how light diffuses from a source. There have been many other approaches, such as those introduced by Burini et al. [3] and Mantel et al. [26], which focus primarily on achieving a trade-off between clipping and leakage. Forchhammer and Mantel [27] extended the method proposed by Mantel et al. [26] further to multiple viewers taking into account clipping and leakage as well as reflections of the ambient light. To keep the LCD image quality, Seok-Jeong Song et al. [39] proposed a pixel compensation algorithm based on deep learning for local dimming algorithms on the quantum-dot display.

Although there have been many BLD algorithms developed for enhancing image quality, these methods mostly target LDR images. To render HDR images on dual-panel displays, Seetzen et al. [37] created a method to solve this problem by splitting HDR images into two layers using square root of the image luminance channel. To assess the impact of HDR image rendering on both subjective and objective scores, Zerman et al. [43] proposed a method for HDR image rendering for the SIM2 HDR47 display by minimising power consumption and maximising the fidelity to the target pixel values. Narwaria et al. [33] also proposed an HDR image rendering solution which used a gradient-based optimisation to minimise the difference between the theoretical backlight map and the computed light map.

Duan et al. [11] explored the relationship between LCD image quality and backlight intensity and proposed an objective evaluation method for BLD methods, and also conducted a subjective experiment to validate results. The results demonstrated a strong correlation between objective and subjective evaluation of different BLD algorithms.

2.3 CNNs for Luminance Processing

Recently, CNNs have been used for addressing a large range of problems related to luminance processing because of their excellent performance and learning capabilities for analysing image characteristics.

Yannick Hold-Geoffroy et al. [18] presented a CNN based technique to estimate high dynamic range outdoor illumination. A number of methods using CNNs have also been presented for Tone Mapping (HDR to LDR) and Inverse Tone Mapping (LDR to HDR) [12, 30, 24]. To the best of our knowledge, there are no local dimming methods using CNN architectures for HDR images.
Deep Controllable Backlight Dimming

3 Method

As discussed in the previous section, a variety of BLD algorithms have been proposed to date. More importantly, most methods are based on modeller expertise [15], with choices that can seem arbitrary and may not be optimal. Furthermore, non-learning-based methods can ignore abstract and high-level image features that are deemed important in many imaging applications.

The proposed deep BLD method (DBLD) addresses these issues by using a parametric model to process an input HDR image and directly predict the backlight values. The model is optimised directly from data, avoiding modeller bias and heuristics. The parametric model of choice is a CNN, trained on a dataset of HDR images and optimised to maximise the fidelity of the displayed HDR image and can be controlled via a power parameter, $p_a$, that provides a balance between power consumption and quality.

As shown in Figure 2, the procedure followed in this work is divided into two phases, a training phase and a testing phase. In the training phase, the CNN is randomly initialised and then optimised using an HDR dataset, by minimising a loss function. This is performed only once and the optimised parameters are then used in the testing phase to evaluate the method’s performance by comparing it quantitatively with other algorithms. The method also makes use of $p_a$ to control how much power the LEDs consume. This is achieved via a novel loss function formulation that takes $p_a$ into account.

3.1 Network Architecture

The proposed architecture, shown in Figure 3, is based on the UNet architecture [35], which is composed of two main parts, an encoder and a decoder, both composed of multiple convolutional layers. The encoder progressively downsamples the feature resolution until it reaches a low resolution bottleneck, which is then progressively upscaled by the decoder. At each resolution, features from the encoder are propagated directly to the decoder and concatenated, effectively combining multiple scales and speeding up convergence at optimisation.

The encoder used is a residual network architecture [17] with 18 layers. Residual networks are formed from residual blocks, where the output of the main computation of each block is added to its input, thus allowing better gradient flow and improved training of deeper networks. The implementation is taken directly from the “resnet-18” architecture in the PyTorch model library [34]. The 18-layer resnet architecture is the most lightweight of the commonly implemented residual networks. It downsamples five times and uses $3 \times 3$ convolutions, except for the first layer which is of size $7 \times 7$ and the residual-connection convolutions that are of size $1 \times 1$ and are used to match the input-output feature sizes of each block when they differ.

The decoder consists of five upsampling layers that use bilinear upsampling followed by blocks of {3 × 3 convolution - normalisation - activation - 3 × 3 convolution}, matching the feature sizes of the encoder at each resolution. The ReLU activation [31] is used both in the encoder and the decoder, along with Instance Normalisation [40], to help with convergence in the optimisation. Instance Normalisation is preferred to the more commonly used Batch Normalisation [19] for small batch sizes in gradient descent. In this work, the batch size consists of only one image at each iteration due to GPU memory constraints, since training is performed on Full-HD images. The model has a total of
Deep Controllable Backlight Dimming

13,782,031 parameters. Despite the large number of parameters, processing is quick, since most of the computation is performed on lower resolutions due to the use of the UNet architecture.

The network accepts a total of four channels of resolution $1,920 \times 1,080$, consisting of the RGB channels of the HDR image, $I$, in the $[0, 1]$ range, along with a uniform single channel that holds the power parameter, $p_a \in [0, 1]$, which adapts the power consumption of the predicted backlight values. The output of the network, $\tilde{B} \in [0, 1]$, is a single channel image containing the backlight predictions at full resolution and is the result of a logistic (sigmoid) function following the final convolution. The final backlight prediction, $B$, is formed by selecting the $N$ pixels corresponding to the $N$ LED lights in the backlight panel of the SIM2 display. These are selected as the central pixels of the corresponding areas of the image in $\tilde{B}$.

The final model for the backlight prediction, $B$, can be expressed as:

$$B(I)_{i,j} = \begin{cases} f_{CNN}(I, p_{a})_{i,j}, & \text{if } (i,j) \in S, \\ 0, & \text{otherwise} \end{cases}$$

where $S$ is the set of centres of the pixel neighbourhoods that correspond to the individual lights in the backlight panel.

### 3.2 HDR reconstruction

As shown in the work by Duan et al. [11], the displayed HDR image can be simulated and reconstructed artificially, for objective comparisons that agree with subjective experiments. Hence, such a reconstruction can form a valid representation of the displayed image, therefore allowing for its use as part of the loss function when optimising the CNN. In theory, the resulting displayed image, $\tilde{I}$ is given by:

$$\tilde{I} = D \odot T,$$

where $T$ is the transmittance of the LC panel, $D$ is the smoothened backlight intensity from the diffusion panel. $\odot$ denotes the (pixel-wise) Hadamard product operator, broadcasted channel-wise. In general, the transmittance, $T$, is driven by the grey level of each pixel from every colour channel of the LCD image, $\tilde{C}$.

The diffusion panel output, $D$, can be estimated from the backlight values as the result of the convolution of the displayed backlight image, $B$, with the PSF [14], $g$, of the diffusion panel:

$$D = (g * B)_{i,j} = \sum_{x=1}^{W_g} \sum_{y=1}^{H_g} g_{x,y} B_{i-x,j-y},$$

where $N$ denotes the total number of backlight values and $W_g$ and $H_g$ are the width and height of the PSF filter respectively. $D$ is often referred to as the baseline luminance.
The loss function presented in Section 3.3 requires the reconstructed HDR image, \( \tilde{I} \), which in turn requires evaluation of the baseline luminance, \( D \). \( D \) is estimated by convolving the backlight prediction, \( B \), with the PSF, \( g \), following equation 3. However, the PSF for the modelled display is given as a single channel filter of size \( 1,000 \times 1,000 \). Fast differentiable convolution with large filters is not directly implemented (at the time of writing) in modern deep learning libraries [16]. Most libraries optimise small convolutions, e.g. with \( 3 \times 3 \) kernels, since almost all CNN architectures use relatively small kernels. Thus, the PSF convolution was implemented from scratch using base (differentiable) PyTorch operations [34].

In particular, the convolution is implemented using the convolution theorem, applied on \( B \) and \( g \):

\[
D = B * g = \mathcal{F}^{-1}(\mathcal{F}(B) \odot \mathcal{F}(g)),
\]

where \( \mathcal{F} \) is the Fourier Transform operator, in combination with the Discrete Fourier Transform (FFT):

\[
S_{u,v} = \mathcal{F}(T) = \frac{1}{\sqrt{HW}} \sum_{h=0}^{H-1} \sum_{w=0}^{W-1} T(h,w) e^{-2\pi i \left( \frac{h u}{H} + \frac{w v}{W} \right)},
\]

where \( T \) is the input in coordinate space and \( S \) is the representation of the input in fourier space. \( H \) and \( W \) are the height and width of the image respectively. The Fourier transform is performed using the Fast Fourier Transform (FFT) algorithm. This implementation for convolutions with large kernels is much faster and uses less memory in contrast to the default optimised convolution based on the cudnn library that would get stuck and not complete the computation on the same machine [6].

### 3.3 Loss Function

The loss function, \( L \), consists of two parts, a smooth \( L_1 \) regression loss, \( L_{\text{reg}} \), and an additional magnitude regularisation term, \( L_{\text{mag}} \), that also adapts power consumption by restricting the magnitude of the backlight predictions via the user-provided scalar power parameter, \( p_a \). The total loss is given by:

\[
L(\tilde{I}, I) = L_{\text{reg}}(\tilde{I}, I) + p_a \beta L_{\text{mag}}(B),
\]

where \( \tilde{I} \) is the HDR image reconstructed from the backlight predictions of the model using the method described in Section 3.2 and \( I \) is the target HDR image. \( \beta \) is a hyper-parameter adjusting the magnitude of the regression loss that helps with levelling the gradient contribution of the two partial losses for improved convergence. The magnitude regularisation term, \( L_{\text{mag}} \), is given by:

\[
L_{\text{mag}}(B) = \frac{1}{M_{\text{max}}} \sum_{(i,j)} B_{i,j},
\]

where \( M_{\text{max}} \) is the maximum consumption, when all backlights take their maximum value. The magnitude regularisation term restricts power consumption by penalising large backlight values. The non-learned user-provided power parameter, \( p_a \), appears directly in the loss function, changing the form of the loss during training by adjusting the contribution of the magnitude term \( L_{\text{mag}} \). Lower \( p_a \) values allow higher \( L_{\text{mag}} \) values in the loss, thus allowing higher power consumption.

### 3.4 Dataset

The training dataset consists of 958 HDR images with varying resolutions, up to 4K. None of the images contain absolute luminance values. The images are scaled keeping their aspect ratio (and zero padded if necessary) to Full-HD (1,920 \times 1,080) resolution. The intensity range is randomly selected during training, with maximum intensity chosen uniformly in the interval \([3,000, 5,000]\). This random scaling works as a form of data augmentation and to help prevent overfitting. The images are then clipped at the maximum display intensity of 4,000 nits. The additional power-adaptation scalar is randomly chosen using a uniform \( U[0, 1] \) distribution for each mini-batch. The test dataset used for evaluation is formed from 105 HDR images from the Fairchild Photographic Survey [13]. These images contain calibrated absolute luminance values and are not used during training.
3.5 Optimisation

The network was optimised until convergence of the loss for approximately 500,000 iterations, with $\beta = 20$. The Adam optimiser [22] was used, with its default learning rate $\lambda = 1e^{-3}$ and $\beta_1 = 0.9$, $\beta_2 = 0.99$. Training took 116 hours on an NVIDIA RTX 2070 Super GPU using the PyTorch library [34].

4 Results

This section presents results comparing DBLD with six other methods using quantitative analysis and qualitative visual inspection. In particular DBLD is compared against other methods: Avg and Max [15], LP [8], IMF [25], ZR [43] and DM [33].
4.1 Quantitative evaluation

DBLD is compared with the other methods using the evaluation scheme proposed by Duan et al. [11]. The authors proposed computing quantitative metrics using the reconstructed HDR images based on the model of LCD described in Section 3.2 and given by equation 2. The authors demonstrated that there is a strong correlation between objective and subjective evaluation of different BLD algorithms [11], making quantitative evaluation a viable proxy to subjective experiments. A set of 105 HDR images from the Fairchild Photographic Survey database were used to for the evaluation of the metrics. None of these 105 HDR images were not used in the training of DBLD.

The metrics used for comparison were the Perceptually Uniform (PU) [2] versions of PSNR, Multi-Scale SSIM [41], along with HDR-VDP-2.2 [28]. The power saving ratio (PSR) [4] corresponds to the percentage of power savings with respect to the maximum display power, with higher values representing further savings.

Figure 4 shows the results for the three quality metrics as a function of power saving ratio. For DBLD multiple values are computed by adjusting $p_a$ and can be seen in Figure 4 as points on the curve. While DBLD was trained using $p_a$ values $\in [0, 1]$, results are also shown for $p_a > 1$ by extrapolation, demonstrating how the method performs for very low power consumption. As can be seen, under most circumstances, other methods fall under the curve demonstrating DBLD provides better quality as a function of power usage.
Figure 5 illustrates the distribution of results across the 105 tested images for all the methods and the three quality metrics as well as the power saving ratio. As DBLD is adaptable to different outputs depending on $p_a$ we show distributions with values of $p_a$ fixed to the values of 0.5 (DBLD.50), 0.65 (DBLD.65) and 0.9 (DBLD.90). These values of $p_a$ were chosen to match the power consumption of state-of-the-art methods. DBLD outperforms all others except for ZR for PU-PSNR and HDR-VDP-2.2, while for PU-MS-SSIM it achieves the first three positions.

4.2 Visual inspection

Figure 6 shows the HDR-VDP-2.2 visibility probability maps for all the methods for a selection of images from the testing dataset. The HDR-VDP-2.2 visibility probability maps describe how likely it is for a difference to be noticed by the average observer, at each pixel, between the reconstructed HDR and the target HDR that is being displayed. Red values indicate high probability, while blue values indicate low probability of noticeable difference.

For DBLD, the same values of $p_a$ used in Section 4.1 are considered. The results show that DBLD produces higher fidelity results than the other methods and the number of perceivable artefacts reduces as $p_a$ decreases. In some methods, particularly the Avg, Max, LP and IMF methods, brighter areas appear overexposed due to the low backlight values. The ZR method can preserve more detail compared to these other methods.

4.3 Timings

DBLD takes an average of 0.061 seconds on an NVIDIA RTX 2070 Super GPU and 0.290 seconds on a (mobile) NVIDIA GTX 1050 Ti to render a Full-HD (1,920 × 1,080) image. It is worth noting that these are not optimised timings, using the model directly as implemented for training in Python. Further optimisations, for example rewriting code using a lower level language and writing specialised kernels for the computational tree of the CNN can help to further improve execution speed.

5 Conclusion and future work

In this work, a novel BLD method for HDR image rendering on HDR displays has been proposed. The method uses a CNN to predict backlight values, trained on an HDR image dataset. The method is also the first of its type to be controllable and permits adjustment of power vs. quality. Objective evaluation of the method is efficient and demonstrates improved image quality compared to other methods, including current state-of-the-art algorithms. Future work will focus on further refinement of DBLD and extend it to process HDR videos directly and in real-time.

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