# Energy-aware Images: Reducing the energy consumption of OLED displays - Extended abstract

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Abstract

In the context of climate change, it is necessary to reduce as much as possible the energy consumption in the video chain. In this demonstration, we show how to reduce the consumption of displaying images on OLED screens, thanks to a shallow network specifically trained to build energy-aware images. We demonstrate qualitative and quantitative results through several metrics and real measures of energy consumption. The performances are assessed against other methods in the state-of-the-art.

**Keywords**

energy consumption, display devices, energy-aware images, attenuation map

## 1. Introduction

As the effects of climate change are more and more perceived, efforts to reduce our energy consumption should be undertaken in all domains of expertise. Information Communication Technology (ICT) accounts itself for 1.3% of global carbon emission (690MtCO2e in 2020) [1]. In particular, TVs represent up to 50% of the video chain's energy consumption. For this reason, reducing the energy needed while displaying images on screen is of high interest.

Complementing our work in [2], we propose to demonstrate an algorithm to build energy-aware images that allow for a reduction of their energy consumption while displayed. The proposed method has the advantage of reaching similar performances than other deep-based methods, while relying on a shallow, thus less energy demanding architecture. It also outperforms a simple linear scaling of the luminance. In this demonstration, qualitative and quantitative performances are shown and discussed, together with real energy measurements.

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## 2. Deep PVR

Our proposed model, called deepPVR for Deep Pixel Value Reduction, is illustrated in Figure 1. It is inpired from the R-ACE network proposed in [3], but with a revisited shallow network architecture, to reduce as much as possible the number of trainable parameters. Indeed, in accordance with our willingness to globally reduce the energy consumption, one also needs to pay a special attention to the size of the proposed networks, which directly participates to the needed training duration.

To this aim, the number of channels per layer was decreased and the CAN (Context Aggregation Network) was replaced by ATrous spatial pyramid pooling [4]. To improve the performance, and similarly to what was proposed in [5], a channel and spatial attention layers were added, however in a simplified version, by considering an adaptive 2D average pooling followed by two convolution layers, with respectively a ReLu and a sigmoid activations. The last two convolution layers output a dimming map which is simply added to the luminance of the input image to generate the energy-aware image. All convolution layers have a $3 \times 3$ kernel. A weighted average of the MAE loss, the SSIM loss, a power loss and a Total Variation (TV) loss was used as training objective. The power loss is computed as the difference between the power of the reduced image and the power of the original image reduced by a factor $1 - R$, where $R$ is the target energy reduction factor. The TV loss is computed on the dimming map as the average of the squares of its vertical and horizontal gradients.

DeepPVR architecture totals less than 5k parameters, which is an order of magnitude lower than the 41k parameters needed by R-ACE network, and far less than the 1.8 million parameters in [6].

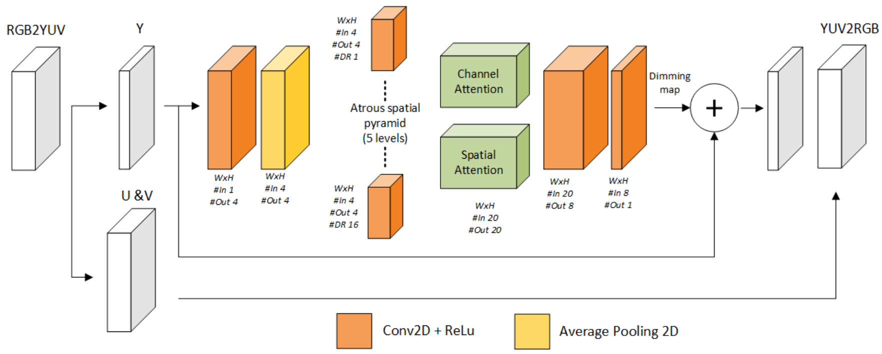


**Figure 1:** Architecture of the proposed model. #In and #Out represent the number of input and output channels, respectively. #DR stands for Dilatation Rate.

## 3. Comparison with other methods

To illustrate the performances of the proposed algorithm, we first compare with a simple linear scaling, which consists in scaling down evenly the luminance of some input image. For this purpose, we determine a scaling coefficient $k$ to reach an energy consumption target $R$, such that: $R = 1 - \frac{P_{\hat{Y}}}{P_Y}$, where $P_{\hat{Y}}$ and $P_Y$ represent the powers dissipated by the screen when

| R | ori | 10% | 20% | 40% | 60% |
|---|---|---|---|---|---|
| PSNR/SSIM | | | | | |
| deepPVR | - | 33.9/0.99 | 27.6/0.99 | 20.7/0.96 | 16.0/0.89 |
| R-ACE | - | 33.5/0.99 | 27.5/0.98 | 20.6/0.96 | 16.3/0.89 |
| LS | - | 33.5/0.99 | 27.2/0.99 | 20.6/0.96 | 16.2/0.84 |
| VIF/NIQE | | | | | |
| deepPVR | -/16.300 | 0.872/16.474 | 0.846/16.577 | 0.808/16.804 | 0.799/16.868 |
| R-ACE | -/16.300 | 0.851/16.467 | 0.789/16.322 | 0.798/16.585 | 0.788/16.643 |
| LS | -/16.300 | 0.849/17.227 | 0.773/17.164 | 0.798/17.020 | 0.789/17.041 |

**Table 1**
Results on deepPVR against state-of-the-art models (R-ACE, Linear Scaling (LS)), for different metrics (PSNR/SSIM/VIF/NIQE) on the BSDS dataset [7].

displaying the processed and the original images, respectively. Assuming that the energy model is linear, the scaling coefficient $k$ is given by: $k = (1 - R)^{1/\gamma}$, where $\gamma$ is the gamma correction of the screen.

We also compare with our own implementation of the R-ACE network [3]. In particular, we trained R-ACE network on the BSDS dataset [7] with the same loss functions used for deepPVR.

## 4. Evaluation

In the proposed demonstration, we illustrate the performances of our approach through results on images while comparing with the three methods described in section 3. An example of such results is shown in Figure 2.

A quantitative evaluation (see Table 1) is also discussed in details. Additional real measures of energy consumption are also demonstrated, together with power consumption maps.

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(a) Original (b) DeepPVR (c) R-ACE (d) Linear Scaling

**Figure 2:** Comparison between an original image, deepPVR, R-ACE and Linear Scaling for an energy reduction rate R=60%, on images from Kodak dataset [8].


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