ABSTRACT

Retinal image quality assessment is an essential task in the diagnosis of retinal diseases. Recently, there are emerging deep models to grade quality of retinal images. Current state-of-the-arts either directly transfer classification networks originally designed for natural images to quality classification of retinal image or introduce extra image quality priors via multiple CNN branches or independent CNNs. This paper proposes a dark and bright prior guided deep network for retinal image quality assessment called GuidedNet. Specifically, the dark and bright channel priors are embedded into the start layer of network to improve the discriminate ability of deep features. Experimental results on retinal image quality dataset Eye-Quality demonstrate the effectiveness of the proposed GuidedNet.

Index Terms— Retinal image quality assessment, deep network, dark channel prior, bright channel prior

1. INTRODUCTION

High-quality retinal images are required for the diagnosis of diabetic retinopathy, glaucoma and other retinal disorders [1]. They facilitates ophthalmologists make correct clinical decisions efficiently. On the contrary, low-quality images may confuse the ophthalmologists. What is worse, for computer-aided retinal image analysis systems which commonly are designed with high-quality retinal images, low quality retinal images would be a catastrophe. Thus it would be desired to assess the retinal image quality and filter low-quality images before performing downstream tasks. Clinically, retinal image quality assessment (Retinal-IQA) is performed by a trained optometrist manually, which heavily depends on operator’s experience and is time-consuming. To improve the efficiency of retinal image acquisition, automated Retinal-IQA becomes necessary.

The goal of automated image quality assessment (IQA) is to grade images in terms of quality measures. It is always formulated as an image classification problem. Current state-of-the-art Retinal-IQA methods solve it with modern CNNs as they have achieved huge successes in the field of computer vision. Some works such as [2] and [3] directly fine-tune CNNs originally designed for natural scene image classification with retinal retinal images to learn rich deep features for Retinal-IQA. To exploit more powerful representation for Retinal-IQA, complex frameworks involving multiple parallel CNN branches as shown in Fig.1(a) or multiple independent CNN networks as shown in Fig.1(b) to make use of priors about IQA are proposed. For example, Fu et al. claim that different colour spaces represent different characteristics and propose Multiple Colour-space Fusion Network (MCF-Net) [4]. MCF-Net [4] unifies three parallel CNN branches into one framework to learn complementary informative contexts from RGB, HSV and Lab colour spaces for retinal-IQA. In [5], Shen et al. claim that auxiliary tasks contribute to IQA and propose a multi-task framework for Retinal-IQA, named MFIQA. MFIQA [5] consists of a ResNet-50 network [6] for detection of region of interest (ROI), a VGG-16 network [7] for refinement of ROI location and a network consisting of two encoders to encode the global retinal images and local ROI for Retinal-IQA and three auxiliary classification tasks, i.e., artifact, clarity and field definition. It is further improved by introducing domain invariance and interpretability in [8]. Comparing to framework consisting of single networks with single branch, those complex frameworks make use of extra priors about IQA and achieve superior performances. However, the parameters to be optimised rapidly multiply. Additionally, in [5],[8], auxiliary task learning requires extra annotated data and the whole framework can not be trained end-to-end. These motivate us to develop a framework which is...
able to make priors incorporate in CNNs without increasing extra parameters and annotated data, as shown in Fig. [1]c).

![Retinal image, Dark channel, Bright channel](image)

**Fig. 2.** Examples for dark and bright channel priors of different quality retinal images.

To this end, we go back to the basics and notice that, within the context of Retinal-IQA, a high-quality retinal image commonly captured under even illumination, in which salient structures such as optic disc and vessels etc. are clearly and definitely visible as shown in the first example in Fig. 2. Accordingly, we propose two novel priors. The first one is dark channel prior. It is based on the observation that, in retinal images captured with even illumination, most of local patches contain some pixels which have very low intensities in at least channels. On the contrary, in retinal images captured with uneven illumination, pixels in regions with strong illumination have high intensities in all channels. It is exactly inline with the dark channel prior which is first proposed in [9]. Fig. 2 shows the dark channels of three examples respectively graded as "Good", "Usable" and "Reject". Obviously, except for the bright structure region, i.e., optic disc region, the intensities of pixels in the dark channel map of image graded as "Good" are always low. On the contrary, the intensities of pixels in the dark channel map of images graded as "Usable" and "Reject" are uneven. Particularly, pixels in regions with strong illumination have high intensities. The second prior is bright channel prior. It is based on the observation that most bright pixels have high intensities for retinal image captured with even illumination. On the contrary, for retinal image captured with uneven illumination, intensities of the bright pixels in regions with week illumination are low. Bright channels of three examples graded as "Good", "Usable" and "Reject" shown in the third column of Fig. 2 illustrate our observation. To make priors of dark channel and bright channel incorporate in CNNs, we develop a novel framework named GuidedNet. Particularly, in GuidedNet, convolution with fixed kernels is plugged in the first layer to estimate the priors of dark channel and bright channel and guide the network to pay attention to bright regions in dark channel prior map and dark regions in bright channel prior map.

The contributions of this paper are three-fold: (1) We introduce dark channel prior and bright channel prior for Retinal-IQA and demonstrate their effectiveness; (2) We propose a novel deep network named GuidedNet for Retinal-IQA. It is able to make priors of dark channel and bright channel incorporate in CNNs without increasing extra parameters and be trained end-to-end. (3) We demonstrate the effectiveness of proposed GuidedNet on EyeQ [4] and experimental results show that our GuidedNet achieves state-of-the-art performances.

2. PROPOSED METHOD

In this section, we first present the dark and bright channel priors in retinal image. Then we detail the architecture of our proposed GuidedNet.

**Dark Channel Prior.** Dark channel prior is first proposed to haze removal in [9]. Thereafter it has been proved that the dark channel prior is a suitable image characteristic in distinguishing whether images are polluted by uneven illumination or not and widely applied to blind image deblurring [10] and dynamic scene deblurring [11]. The dark channel describes the minimum values in an image patch across all channels. Formally, according to [9], in a colour image $I$, the dark pixel at location $x$ is defined as:

$$D(I)(x) = \min_{y \in P(x)} \left( \min_{c \in \{r, g, b\}} I^c(y) \right)$$  \hspace{1cm} (1)$$

where $x$ and $y$ denote pixel locations, $P(x)$ is an image patch centred on $x$, and $I^c$ is intensity map in colour channel $c$. Fig. 2 shows the dark channel prior maps of three retinal images graded as quality levels of "Good", "Usable" and "Reject". In good quality retinal image, most dark pixels except for optic disc area have low intensities as the image is captured with even illumination, as shown in Fig. 2a2. For retinal images captured with slight uneven illumination as shown in Fig. 2b1, dark channel prior map exhibits slight uneven intensities as shown in Fig. 2b2. For image captured with serious uneven illumination as shown in Fig. 2c1, dark pixels of retinal images affected by strong illumination are brighter than those exposed with week illumination, which results in an uneven dark channel prior map, as shown in Fig. 2c2. This implies that dark channel prior map is an intuitive quality measure which indicates whether the image is captured with even illumination.

**Bright Channel Prior.** Bright channel prior describes the maximum values in an image patch across all channels. It is first explored for shadow estimation [12] and has been widely used to detect salient structures such as optic disc and vessels etc. are clearly and definitely visible as shown in the first example in Fig. 2. For retinal images captured with even illumination, most of local patches contain some pixels which have very low intensities in at least channels. On the contrary, in retinal images captured with uneven illumination, pixels in regions with strong illumination have high intensities in all channels. It is exactly inline with the dark channel prior which is first proposed in [9]. Fig. 2 shows the dark channels of three examples respectively graded as "Good", "Usable" and "Reject". Obviously, except for the bright structure region, i.e., optic disc region, the intensities of pixels in the dark channel map of image graded as "Good" are always low. On the contrary, the intensities of pixels in the dark channel map of images graded as "Usable" and "Reject" are uneven. Particularly, pixels in regions with strong illumination have high intensities. The second prior is bright channel prior. It is based on the observation that most bright pixels have high intensities for retinal image captured with even illumination. On the contrary, for retinal image captured with uneven illumination, intensities of the bright pixels in regions with week illumination are low. Bright channels of three examples graded as "Good", "Usable" and "Reject" shown in the third column of Fig. 2 illustrate our observation. To make priors of dark channel and bright channel incorporate in CNNs, we develop a novel framework named GuidedNet. Particularly, in GuidedNet, convolution with fixed kernels is plugged in the first layer to estimate the priors of dark channel and bright channel and guide the network to pay attention to bright regions in dark channel prior map and dark regions in bright channel prior map.

The contributions of this paper are three-fold: (1) We introduce dark channel prior and bright channel prior for Retinal-IQA and demonstrate their effectiveness; (2) We propose a novel deep network named GuidedNet for Retinal-IQA. It is able to make priors of dark channel and bright channel incorporate in CNNs without increasing extra parameters and be trained end-to-end. (3) We demonstrate the effectiveness of proposed GuidedNet on EyeQ [4] and experimental results show that our GuidedNet achieves state-of-the-art performances.
applied to correct under-exposed images \cite{13,14} and image deblurring \cite{10}. Here we propose to use bright channel prior to guide the CNN to pay attention to regions with week illumination. Formally, according to \cite{12}, for an image $I$, the bright pixel at location $x$ is defined as:

$$B(I)(x) = \max_{y \in P(x)} \left( \max_{c \in \{r,g,b\}} I^c(y) \right)$$ \hspace{1cm} (2)$$

where $x$ and $y$ denote pixel locations, $P(x)$ is an image patch centred on $x$, and $I^c$ is intensity map in colour channel $c$. Fig. 2 shows that most pixels are bright in a retina image with good quality, except for some vascular pixels. However, bright pixels in the low-illumination area of retinal images are darker, and the bright channels present a cloud of dark region. These imply that the bright channel prior is a property to identify abnormal dark region from retinal images.

Network Architecture. The architecture of our GuidedNet is illustrated in Fig. 3. It updates from DenseNet-121 \cite{15}, which consists of four dense blocks followed by a global average pooling (GAP) layer and a full connection (FC) layer. The FC layer maps the deep features into an image quality level. Different from DenseNet-121 \cite{15}, our GuidedNet involves a prior guided module, which replaces the first layer of DenseNet-121 \cite{15}. In practice, the dark channel prior is estimated by convolving each colour channel with a fixed Gaussian kernel followed a channel-wise minimization pooling operator. The bright channel prior can be estimated in a same way by changing the channel-wise minimisation pooling layer to channel-wise maximisation pooling layer. To implement these, we propose to use a depthwise convolutional layer \cite{16} with three fixed Gaussian kernels and stride step of 2, followed by a channel-wise MaxPool layer and MinPool layer, as shown in the blue box in Fig. 3. In this way, we obtain the bright channel prior map and dark channel prior map both size of $H/2 \times W/2$. As the second convolution layer in DenseNet-121 requires input with $K = 64$ channels, we learn the rest 62 feature maps via the standard convolution with stride step of 2. Then we concatenate the bright channel prior map, dark channel prior map and learnable feature maps as the output of our prior guided module. We note that the dark and bright channel prior maps involve the forward propagation afterwords and guide the learning of all the parameters in network via back propagation. This enforces the network pay more attention to the informative regions in dark and bright channel prior maps and make correct decisions.

3. EXPERIMENTAL RESULTS

We validate our model on a public retinal image quality assessment dataset, i.e. Eye-Quality dataset \cite{4}. The dataset contains 28792 retinal images including 12543 training and 16249 testing images. They are labelled by experts as three categories: good, usable and reject.

Experimental setting. Our GuidedNet is built on the top of implementation of DenseNet-121 \cite{15} within the PyTorch framework. The weights in DenseNet-121 are initialized with the pre-trained model on ImageNet \cite{19}. Parameters are optimized by SGD on one GPU. Hyper-parameters includes: learning rate (0.01), momentum (0.9), batch size (4) and iteration epoch (20). The training images are augmented by random vertical and horizontal flipping and rotation. The original retinal images are pre-processed by method in \cite{4} for removing the surrounds dark regions, and then rescaled to uniform size of $224 \times 224$.

Comparison with the state-of-the-arts. We compare the proposed model with HVS-based algorithm \cite{17}, MR-CNN \cite{13}, DensetNet121-RGB \cite{4} and DensetNet121-MCS \cite{4}. Results of those methods are from the original paper.
Table 1. Performances of different methods on Eye-Quality

| Methods                      | Accuracy | Precision | Recall | F-measure | Parameters |
|------------------------------|----------|-----------|--------|-----------|------------|
| HVS-based algorithm [17]     | 0.8372   | 0.7404    | 0.6945 | 0.6991    | -          |
| MR-CNN [18]                  | 0.8843   | 0.8697    | 0.8700 | 0.8694    | -          |
| DenseNet121-RGB [4]          | 0.8943   | 0.8194    | 0.8114 | 0.8152    | 6.96M      |
| DenseNet121-RGB*             | 0.9045   | 0.8481    | 0.8239 | 0.8315    | 6.96M      |
| DenseNet121-MCS [4]          | 0.9175   | 0.8645    | 0.8497 | 0.8551    | 28.26M     |
| DenseNet121-MCS*             | 0.9148   | 0.8563    | 0.8482 | 0.8506    | 28.26M     |
| ours                         | 0.9255   | 0.8715    | 0.8747 | 0.8723    | 6.96M      |

We also provide our reproduced of DenseNet121-RGB* and DenseNet121-MCS*, which are marked with *. We run three times, and report the average results in Table 1. Obviously, our model achieves superior performances to the state-of-the-arts, and is much lighter than other improved deep model. In addition, the best confusion matrices of DenseNet121-RGB*, DenseNet121-MCS* and our GuidedNet are shown in Fig. 4, respectively. It validates that our method has better ability in identifying rejected retinal image.

Ablation Study. We perform ablation study on the proposed GuidedNet. Results are reported in Table 2. The first row is the baseline model adopting data augmentation of [4] in training phase, and the rest are results of models trained using augmentation strategy used in this paper. As we can see that (1) baseline results using our augmentation strategy are superior than that used in [4]. The possible reason is that random drifting in [4] may cause label noise, because distortions in retinal images are uneven. Thus, random drifting operation is not considered in this paper. (2) Our GuidedNet achieves best overall evaluation value F while incorporating dark and bright priors. (3) Embedding dark or bright prior improves the performances.

Table 2. Ablation study on the proposed model.

| Methods     | Acc  | Pre  | Rec  | F    | F-std |
|-------------|------|------|------|------|-------|
| Baseline    | 0.9045 | 0.8481 | 0.8239 | 0.8315 | 0.0085 |
| Baseline†   | 0.9217 | 0.8706 | 0.8608 | 0.8638 | 0.0026 |
| Baseline+D† | 0.9239 | 0.8706 | 0.8689 | 0.8681 | 0.0055 |
| Baseline+B† | 0.9245 | 0.8714 | 0.8682 | 0.8674 | 0.0011 |
| Baseline+DB† | **0.9255** | **0.8715** | **0.8747** | **0.8723** | **0.0035** |

4. CONCLUSION

This paper presents a simple framework for retina image quality assessment. It introduces dark and bright channel priors to predict image quality. The proposed GuidedNet builds a dark and bright priors guided layer to highlight image quality prior and does not increase much model burden. Our model does not require auxiliary landmark detection module and can be trained end-to-end. Validation on Eye-Quality dataset [4] shows the superior performances of our GuidedNet, and demonstrates the effectiveness of dark and bright channel priors in retinal image quality assessment.

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