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Adversarial Reconstruction CNN for Illumination-Robust Frontal Face Image Recovery and Recognition

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ABSTRACT

This article proposes an adversarial reconstruction convolution neural network (ARCNN) for non-uniform illumination frontal face image recovery and recognition. The proposed ARCNN includes a reconstruction network and a discriminative network. The authors employ GAN framework to learn the reconstruction network in an adversarial manner. This article integrates gradient loss and perceptual loss terms, which are able to preserve the detailed and spatial structure image information, into the overall reconstruction loss function to constraint the reconstruction procedure. Experiments are conducted on the typical illumination-sensitive dataset, extended YaleB dataset. The reconstructed results demonstrate that the proposed ARCNN approach can remove the illumination and shadow information and recover natural uniform illuminated face image from non-uniform illuminated ones. Face recognition results on the extended YaleB dataset demonstrate that the proposed ARCNN reconstruction procedure can also preserve the discriminative information of face image for classification task.

KEYWORDS

Adversarial Learning, Convolution Neural Network, Deep Learning, Face Recognition, Illumination-Robust, Image Recovery, Machine Learning, Pattern Recognition

1. INTRODUCTION

High quality images are important for improving the performance of image analysis systems and the visualization of human beings. The actual systems such as face analysis (Punnappurath, 2015; Zohra, 2017), retinal scanning (Adal, 2018; Anitha, 2010), intelligent transportation (Bulan, 2017; Xu, 2014), underwater target recognition (Hou, 2018), human-computer interaction (Zhou, 2017) all want the input images to be of high quality. However, images that captured in unconstrained conditions or using not ideal imaging devices, usually exhibit non-uniform illumination distribution and low contrast, which cause detail loss in dark and overexposure regions. This paper considers the problem of recovering the detailed information of an object under standard illumination from a non-uniform illuminated image.

Over the years, researchers present a surge of qualitative and quantitative studies on 2D and 3D non-uniform illumination processing (Gao, 2018; Xu, 2018). Since the authors only focus on

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the recovery methods of 2D non-uniform illumination images, this paper gives a brief survey of 2D illumination processing methods. Readers interested in non-uniform illumination processing of 3D objects can refer to (Xu, 2014, 2018). In 2D non-uniform illumination processing domain, removing illumination and re-mapping illumination are common traditional strategies (Gao, 2018; Shin, 2015), which are able to factorize an image into its intrinsic components, i.e. illumination, shape and reflectance components (Georgoulis, 2018). Representative approaches in this domain can roughly divide into two categories according to their diverse theoretical backgrounds, including illumination compensation/normalization methods and illumination-invariant representation methods. Illumination normalization methods attempt to redistribute the intensities of an input image in a more appropriate representation, which is less sensitive to lighting changes by applying a simple gray-scale intensity adjustment. Histogram equalization (HE), block histogram equalization and logarithmic transform are representative methods of this category (Arici, 2009). Notwithstanding their ease of implementation and the visualization improvement on lighting normalization, these methods can hardly handle shadow or highlight effects of non-uniform illumination images. In contrast, illumination-invariant representation methods try to estimate and remove unwanted illumination. Retinex-based image enhancement methods, which can recall the visual content of dark regions as well as keep the visual realism, are the mainstream methods (Gao, 2018; Shin, 2015; Chen, 2006). According to the assumption that illumination corresponds to low frequency information, Retinex-based methods estimate illumination information using low-pass Gaussian filter (Shin, 2015; Jobson, 1997) or total variation (TV) normalization model (Chen, 2006; Ng, 2011). However, due to the problems of low-pass Gaussian filter in edge preserving and TV normalization model in side effect, halo artifacts and details loss may occur in the recovered images. Recently, several optimization strategies, which globally locate important gradients of images, are proposed to estimate illumination information of images (Fu, 2015, 2016; Guo, 2017). Nevertheless, these methods may cause the damage of illumination edges and result in light source confusion and artifacts. In summary, although the state-of-the-art non-uniform illumination recovery methods have achieved great success, it still requires study to improve the recovery quality of images from non-uniform illumination condition, especially from extreme non-uniform illumination situations.

Recovering detailed information of an object from a non-uniform illuminated image is a special image-to-image transformation task. In recent years, both convolution neural networks (CNNs) and generative adversarial networks (GANs) are trained for various image-to-image transformation tasks (Wang, 2018), such as image de-noising (Zhang, 2017), image super resolution (Dong, 2016; Ledig, 2017), cross-domain image translation (Yi, 2017), etc. CNNs, which discover the optimal mapping from an input image to the transformed image by minimizing the discrepancy between the output image and ground-truth image (Dong, 2016), are very efficient for image feature representation. GANs, which estimate generate models via an adversarial training process alternating between identifying and faking (Goodfellow, 2014), are beneficial for generating realistic images. In (Wang, 2018), a perceptual adversarial network (PAN), whose adversarial architecture is composed of two CNNs, is proposed for image-to-image transformation. Experimental results show that PAN has a great capability of accomplishing image-to-image transformations. To deal with illumination recovery issue, several deep learning based approaches are proposed. In (Lore, 2017), a deep auto-encoder approach, i.e. LLNet, which is composed by three de-noising auto-encoder layers, is presented to enhance the quality of natural low-light images. Experimental results demonstrate that deep auto-encoders are effective tools to learn underlying signal characteristics and noise structures from low-light images without handcrafting. In (Li, 2018), a trainable CNN method for weakly illuminated image enhancement is proposed. This method estimate the illumination map of an input image using CNN and enhance the image based on Retinex model. In (Georgoulis, 2018), authors present a two-step deep learning approach that estimates reflectance and illumination information from a single image. CNNs are employed to estimate a reflectance map and decompose the reflectance map into reflectance parameters and an illumination map.

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