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## High dynamic range imaging by sparse representation

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#### ABSTRACT

High dynamic range (HDR) imaging technology is becoming increasingly popular in various applications. A common approach to get an HDR image is the multiple exposed images fusion. However, the phenomenon of ghosting artifacts is brought in for the scene with non-static objects. This paper proposes a ghost-free HDR image synthesis algorithm that utilizes a sparse representation framework. Based on the dependency among adjacent low dynamic range (LDR) images and the sparsity of the moving object that leads to the ghost artifacts, we formulate the problem into two steps: moving object detection and ghost free HDR generation. In the moving object detection step, we formulate the problem as sparse representation due to the sparsity and instantaneous of the moving objects. In the HDR generation step, joint weighting is proposed to generate a ghost-free HDR image from the reference image. Experiments show that the proposed algorithm outperforms the state-of-the-art methods favorably on the textures and colors.

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#### 1. Introduction

High dynamic range (HDR) imaging is a technique that recovers the HDR image from several LDR images. It has become increasingly popular and attracts many researchers for x decades in various applications. Conventional digital cameras can capture a limited dynamic range which is lower than that of a natural scene to represent a pixel. A single image is difficult to preserve all the content of natural scene. As we all know, multiple pictures of the same scene are acquired using different exposure settings, and each of them will reveal different section of the natural scene dynamic range. Therefore, when taking a photograph of a scene, bright regions tend to be over-exposed while dark areas tend to be underexposed. These dark and bright regions appear saturated or lost most of the information and this kind of images are not what we want. The auto-exposure mechanism may correctly expose the region of interest, but it cannot get the whole dynamic range of image.

Many approaches have been proposed for capturing images of high dynamic ranges. A few of hardware [1,2] methods are possesses the ability to directly capturing HDR images, such as Viper Filestream, Panavision, Pixim, Spheron VR, Weiss SG. The basic principle of [2] is to simultaneously capture the exposure and spatial dimensions of the same scene irradiance. The captured

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http://dx.doi.org/10.1016/j.neucom.2017.03.083 0925-2312/© 2017 Elsevier B.V. All rights reserved. image is mapped to a high dynamic range image according to an efficient image reconstruction algorithm. The result is an imaging system that can remove ghosting artifacts. Aggarwal and Ahuja [3] describe a camera design for simultaneously sample multiple images of the same scene under different exposure settings. This is done by splitting the aperture into multiple parts and directing the light exiting from each in a different direction using an assembly of mirrors. Some method which includes additional electrodes between the photo gate and the transfer gate electrode to create charge transfer wells of different depths can capture same scene irradiance. In 2010, a control device was proposed which calculates a position and an illuminance in space where the object exists on the basis of the object luminance and the objet coordinates, calculates a camera parameter on the basis of the calculated position and illuminance and a present camera parameter, and controls the camera parameter of a video image capturing device according to the calculated camera parameter, so that the exposure amount is adjusted. Unfortunately, they are too expensive to be used widespread in many applications. Moreover, due to the limitations of digital image sensors, it is not possible to capture the full dynamic range of a scene with a single exposure. Based on those factors, exposure fusion is necessary for generate HDR image.

For the time being, the most common technique for HDR image generation is based on image synthesis which involve merging a set of conventional LDR images taken from distinct exposures. The motivation of this method is that distinct exposures capture different regional information of the scene. For instance, dark regions are captured in the longer exposures while bright regions





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has been saturated, then bright regions are captured in the shorter ones while dark regions become blackens. So, if we use different exposure time, for the same scene, we can capture different information. These together provide the possibility of getting HDR image. However, directly applying the conventional composition of LDR images methods may fail to get a high quality HDR image, since the scene in practice is often dynamic and has moving objects which will cause ghosting artifacts in HDR image.

The aim of this paper is to present a novel ghost remove approach in HDR image generation. This method is able to directly yield a HDR image where all regions appear well-exposed by composition multi-exposure images with sparse representation. Firstly, we formulate ghost region detection as a sparse representation problem which is more robust to moving object and noise. Secondly, we select a reference image which has least saturated regions among multiple exposure images. Based on the reference image, joint weighting is calculated for each exposure images. Thirdly, for dynamic scenes, the proposed approach can remove the ghosting artifacts automatically and efficiently. Experimental results show that the proposed algorithm performs favorably in generating ghost-free HDR images.

The paper is organized as follows: in Section 2, we present a brief review of high dynamic range imaging methods and illustrate the problem of some methods. The sparse representation scheme is presented in Sections 3 to solve the proposed high dynamic range image optimization problem. Experimental results are presented in Section 4 to demonstrate the performance of this algorithm and final conclusions are presented in Section 5. Part of this paper was presented at the International Conference of Intelligence Science and Big Data Engineering (Iscide) in May, 2016. The main differences between this paper and the Iscide version are detailed theoretical analysis, HDR composition and more elaborate experimentation on new image data. These modifications lead to improved HDR results.

#### 2. Related work

As aforementioned in the introduction, the most common ways for generating HDR images is based on image synthesis which involve merging a set of LDR images taken from distinct exposures of the same scene. Therefore, how to fusion a sequence of differently exposed images play an important part in generate HDR images. Currently, several techniques have been proposed to deal with the problem. It is highlighted that these methods can be classified into two categories:

- (1) Fusion in irradiance domain is to synthesize all the differently exposed LDR images into an irradiance image, and then an LDR image can be captured by mapping function. Now we will explain irradiance that is the original quantities of light falling on the sensor cells.
- (2) Fusion in image pixel domain is to fuse all of the differently exposed LDR images into a single LDR image according different weight of original LDR images.

Debevec and Malik [4], Mann and Picard [5] are considered pioneer works in the field of HDR imaging, and they solve this problem by adjusting weighting function. Debevec and Malik [4] use a trigonometric function based on the assumption that the reliability of pixel values that are in the middle of the range are higher. This method is very influential in the graphics research community and gives the initial push to make HDR applications viable. In [5], they propose to use the camera response function and compose irradiance maps from different exposure images with the argument that the reliability of pixel values is related to the camera sensitivity to light. Alternatively, some other approaches solve HDR image problem. Bogoni [6] estimates motion vectors using optical flow, and used those information to map other exposure images. Kang et al. [7] also compute optical flow to find corresponding pixels among the LDR images. Recently, HDR image composition approach in {CITEHDRBIhypdeghosting2013,Robust2012 adopted the Patch-Match algorithm [10] because of its superior correspondence estimation performance. Sen et al. [9] is based on a novel patch-based energy-minimization formulation that integrates alignment and reconstruction in a joint optimization through an equation. Hu et al. [8] obtained aligned images through an optimization using the intensity and gradient information.

On the other hand, lots of algorithms employ ghost region detection to tackle the more challenging dynamic HDR task. Gallo et al. [11] detect ghost regions using a linear property of log irradiance values in a block-wise comparison. Although their approach can deal with ghost artifacts, blocking artifacts may appear near block boundaries. Jacob et al. [12] based on a weighted variance measure to detect ghost regions. Grosch [13] defined an error map to get ghost-free HDR image. While these methods still suffer a drawback that the ghost detection results sensitive to those measures. Recently, Heo et al. [14] detect ghost regions employed the joint probability density and used energy minimization to refine ghost regions. Zhang and Cham [15] used quality measures based on gradient information changes to get weighting map among different exposures image. However, we consider sparse representation approach that can remove ghost more robust.

Sparse representation intends to represent signals with as few as possible significant coefficients. This is important for many applications. For a static scene, low dynamic range images are taken from a fixed camera, however the sensor irradiance of the scene is constant [16–18]. Given the facts above, the background irradiance of low dynamic range images are consistent for the dynamic scene. Based on the theory of sparse representation, one of the background irradiance of low dynamic range image can be linear represent by other background irradiances. So we formulate the problem of ghost detection as the sparse representation due to the sparsity of moving objects.

#### 3. Proposed algorithm

Most conventional solutions require the captured LDR image to be stationary, as any movement of foreground would generate to a phenomenon called ghosting artifact in the HDR result image. In order to remove ghosting artifacts in the synthesized image, the motion foreground objects should be detected before the fusion process.

In this section, we formulate the HDR image synthesis as a sparse representation problem that detects both moving objects, under-saturated regions and over-saturated regions.

#### 3.1. Theory of sparse representation

Recently, sparse representation as a powerful tool which have been widely studied to solve the inverse problems for acquiring, representing, and reconstruction signals. Sparse representation gains widespread use due to the fact that particular characteristic of signals such as images have naturally sparseness with respect to fixed bases (i.e., Fourier, DCT, wavelet, contourlet), or dictionary. Some sparse representation methods have been used in the field of image processing [19].

Sparse representation (or sparse coding) represents a signal *x* with a over dictionary  $\Phi$  such that  $x \approx \Phi\beta$  and  $\beta$  is a sparse vector. The sparsity of  $\beta$  is the number of non-zeros elements of the sparse vector  $\beta$ , which can be indicated by  $\ell_0$ -norm. One naive

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