HDR Imaging Using Augmented Lagrange Multipliers (ALM)

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Abstract

We consider the High Dynamic Range (HDR) imaging problem for real world scenes. We can change either the exposure time or the aperture while capturing multiple images of the scene to generate an HDR image. This paper addresses the HDR imaging problem for static and dynamic scenes when we do not have any knowledge of the camera settings. We have proposed a novel threshold for Augmented Lagrange Multipliers (ALM) framework which enables us to process the images getting rid of artifacts due to moving objects and defocus blur.

Categories and Subject Descriptors (according to ACM CCS): I.4.3 [Image Processing and Computer Vision]: Enhancement—Filtering, I.4.8 [Image Processing and Computer Vision]: Scene Analysis—Motion

1. Introduction

We address the High Dynamic Range (HDR) imaging problem in a unified sparse Robust Principal Component Analysis (RPCA) framework to obtain the desired high contrast low dynamic range (LDR) image of the scene. We show that some of the key requirements for HDR imaging such as exposure time and camera response function (CRF) can be relaxed in the proposed simple framework. HDR imaging technique suffers from problems due to dynamic objects resulting in ghosting artifacts in the final HDR image [SKY*12]. Alternatively, images with different aperture settings can be captured for HDR imaging. This approach too suffers from defocus blur as well as ghosting artifacts to some extent.

The present work makes the following contributions.

1. We introduce an approach to remove the dynamic objects from the LDR images of a dynamic scene captured with different exposure times.
2. We extend the approach to process images of a static scene captured with different aperture settings to obtain a single image free from defocus blur.

The dynamic objects can be removed by exploiting the low dimensional structure of the image by using RPCA approach proposed in [WGR*09]. In [GGC*09], this problem is addressed by detecting artifacts using log radiance value by patch-wise matching technique. For images with multi-aperture settings, a layer based restoration framework is introduced in [HK07].

The RPCA problem is solved in [LCM10] using the method of Augmented Lagrange Multipliers (ALM) using the data matrix D. The matrix A recovered using this approach from D is a low rank matrix whose columns are without any of the dynamic objects present in the observations. In related work in [OLK13], a rank-1 approach is employed to deal with artifacts and then the LDR images are combined using a function which depends on the estimated sparse error matrix E.

2. Proposed Approach

In our approach, we consider images with different exposure and aperture settings and try to recover the underlying matrix A and accounting for the dynamic objects and defocus blur in the error matrix E. Our method differs that from [OLK13] based on the objective and threshold functions. Without assuming the knowledge of CRF and exposure settings we recover the matrix A using the inexact ALM method [LCM10] with few modifications and improvements to the original iterative algorithm. Then we fuse the recovered LDR images using the technique discussed in [MKVR07].

2.1. Linearisation of intensity values

The multiple images are dependent but because of CRF suffers from non-linearity leading to poor performance of the RPCA algorithm. To perform linearisation, we model CRF as a gamma correction function as shown in equation 1.

$$I_i' = I_i^{\frac{1}{\gamma}} \tag{1}$$

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We implement the algorithm on this processed observation matrix ($\gamma = 3$) to recover the underlying low rank matrix A.

2.2. Inexact ALM and Fusion

In [WGR*09], RPCA problem is considered in which the goal is to recover a low rank matrix A from observation matrix D. The observations in D can be modelled as the sum of a low rank matrix A with some error matrix E [WGR*09]. The Lagrangian function to be minimized is given by equation 2.

$$L(A,E,Y,\mu) \doteq \|A\|_* + \lambda\|E\|_1 + \langle Y, D-A-E\rangle + \frac{\mu}{2}\|D-A-E\|_F^2 \tag{2}$$

where Y is the Lagrange multiplier and μ is the penalty parameter. This equation can be solved iteratively [LCM10]. We define a new soft thresholding operator $S_\varepsilon[x_i]$ for attenuating the singular values x_i during each iteration as shown in equation 3.

$$S_\varepsilon[x_i] = \begin{cases} x_i - \varepsilon, & x_i > \varepsilon \\ x_i, & x_i = \max(x_1, x_2, \ldots x_n) \\ x_i + \varepsilon, & x_i < -\varepsilon \\ 0, & otherwise \end{cases} \tag{3}$$

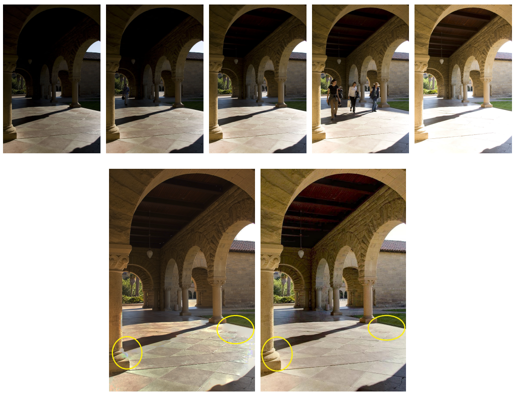
Choosing $S_\varepsilon[x_i]$ as in the above equation preserves the largest singular value and penalises the smaller singular values increasingly larger during each iteration. This doesn't affect image details and rejects only the sparse error. We apply the inverse of the gamma correction to the columns of A to obtain the LDR images and fuse them into a high quality LDR image, using exposure fusion [MKVR07].

3. Results and Discussion

Multi-exposure images with some dynamic objects are shown in Fig. 1 (Top Row). These images are processed by the proposed approach to yield better results in Fig. 1(b) compared to that of [GGC*09] in Fig. 1(a). Fig. 2 (Top Row) show three images of a scene captured with different aperture settings. We apply the proposed approach to these set of images to get the final image in Fig. 2(b). It can be observed that 2(b) is better focused image with more contrast information while Fig. 2(a) suffers from more defocus blur and artifacts at layer boundaries. Varying aperture setting is a good alternative to capture the high dynamic range of a scene and proposed framework produces satisfactory results for this approach.

4. Conclusion and Future Directions

We have developed a novel approach to address HDR imaging problem when we have multi-exposure or multi-aperture images of a scene. Assumption of sparsity on E has enabled us to address these problems using ALM method. We are able to solve the HDR imaging problem for dynamic scenes even when the CRF is not known. The proposed approach might need registration for processing multi-exposure or multi-aperture images captured using a hand-held camera.



(a) (b)

Figure 1: *Top Row: Multi-exposure images of a dynamic scene. (a) Tone mapped result of [GGC*09], and (b) LDR image obtained using our approach.*

(a) (b)

Figure 2: *Top Row: Multi aperture images of a static scene (Source: [HK07]), (a) Tone mapped result using [HK07], (b) LDR image obtained using the proposed approach.*

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