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Various Obstruction Removal Techniques from a Sequence of Images

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Abstract:-Reflection or obstruction from images is a major reason for quality degradation of images in image processing. Camera Flash is frequently used to capture a good photograph of a scene under low light conditions. However, flash images have many problems: The flash can often be blinding and too strong, leading to blown out images. This report presents separate algorithms described in the literature that attempts to remove obstructions computationally. The strengths and weaknesses of each algorithm outlined.

Keywords: flash, reflection removal, obstruction, SPBSM, SID, GPSR.

1. Introduction

As mobile imaging devices become more and more in style, users can take videos or image sequences under less controlled conditions. People are shooting a video through a transparent medium such as glass. For instance, one might take a video of a crowded street through the window of his office or home; or may take images of a glass-framed painting. In such cases, the images will contain both the scene transmitted throughout the medium and some reflection. For the purpose of image enrichment, it is frequently desirable to be able to separate the transmitted component, and the reflected one. Photographers are sometimes faced with the difficulty of taking an image of a scene with a reflective surface. This can cause many issues with reflections obstructing the desired scene and unwanted interference. There are many different ways photographers working around this by either adjusting the lighting, their positioning or adding polarizers to their camera. However, the immense majority of people does not have contact to polarizers, and it is often inconvenient to adjust one's positioning or lighting for a better picture. In the same way, to take pictures of animals in the zoo, it may need to shoot through an enclosure or a fence. Such visual obstructions are often impossible to avoid just by changing the camera position. This report explores some of the algorithms that attempt to computationally remove reflections in images.

If the image was taken through a glass window, then the picture is viewed through transparent glass so that image consists of two parts. First one is the real image of the scene beyond the glass and the second is a virtual picture of the scene reflected by the glass window. Decomposing of the single input image of the reflection is a substantial ill-posed problem. Similarly, photographs were taken under low-light provision also produce a variety of unwanted effects and artifacts. They tend to drench nearby objects while failing to light up distant ones. Since the flash intensity falls with distance from the camera, flash produces a tunnel effect, where brightness decrease promptly with depth. Furthermore, flash is widely known for producing unwanted reflections. A direct reflection of the flash itself is caused by bright objects in the scene. Because of these artifacts, it causes an error in image processing, due to the lack of additional knowledge about the scene. It becomes necessary to remove artifacts, before processing the image in the artifact removal process.

2. Overview

There are two paradigms on how to solve this issue of image reflections. There are several papers which attempt to remove, or at least diminish reflections from a single image input. These algorithms try to separate the reflection and transmission layers with different objective functions. However, this is a relatively difficult problem to solve with just a single input image. At a very high level, we can model the image using the equation, I = T + Os where I am the resulting image and T and O are the transmission and obstructed layers respectively [2]. The resulting image is simply a linear combination of the scene through the window and the reflected image. Trying to obtain two variables from just a single image is somewhat of an ill-posed problem, so different image priors are added to the objective function [3]. Recently, a more popular approach to this problem involves taking a sequence of images just by moving the camera to separate the reflection and transmission. Often, the two layers are located at different depths, so moving the camera will cause the two layers to move at different rates. This difference in motion can then be used as a robust way of separating the reflection and transmission layers [5].

3. Literature review

In this section, different approaches to reflection removal are explored: Sparse blind separation with motions superimposed image decomposition, cross projection tensor technique, gradient projection algorithm and ghosting cues detection. Each algorithm models reflection differently and utilizes different objective functions to separate the reflection and transmission layers. The goal of this paper is to evaluate each algorithm separately to determine the strengths and weaknesses of each approach.

3.1 Sparse Blind Separation with Motions (SPBSM)

In SPBSM a series of shifted images taken which help to separate the reflection and transmission layers. For a sequence of images, there are m images that each contain n layers shown by the equation below [1].

$$Ii(x)=\sum_{j=1}^{n} a_{ij}\, Lj(fij(x)),\ i=1,\ldots..,m \qquad [1]$$

In this equation, x is the vector characterizing the pixel location, fij is the motion transformation of each image, Lj is the jth layer, and aij is the mixing coefficient for each layer. Each image is simply composed of a weighted sum of multiple layers that are shifted from image to image. This paper attempts to estimate each of these coefficients to separate each layer L1::: Ln. This is done by taking advantage of general properties and information of natural images. The authors examined over 130,000 images and created hypotheses on the sparsity of image gradients, the noncorrelation of the gradients of different locations in the same image, the joint behaviors of different gradients in the same image, and the independence of the gradients and pixel values of different images. These hypotheses applied to an objective function which was used to find the motion and mixing parameters of a single layer.

A similar approach is done to find the parameters and coefficients of the second layer. Finally, each layer is reconstructed using the coefficients found in the previous steps. The final objective function attempts to reconstruct layers that fit the mixing model detailed above and the extracted gradients of each layer.

3.2 Removal of Shadows and Reflections in the Images by Using Cross-Projection Tensors

In this paper cross, the projection tensor technique is used edge suppression with affine transformation on gradient fields [9]. An affine transformation is any transformation that preserves collinearity (i.e., all points lying on a line initially still lie on a line after transformation) and ratios of distances (e.g., the midpoint of a line segment remains the midpoint after transformation). Sets of parallel lines remain parallel after an affine transformation. Cross projection tensor technique removes the scene texture, edges of an image by transforming the gradient field. Flash and the ambient image are used. Cross projection tensor is obtained from the flash image and transforms the gradient field of the ambient image in it. Here no need for color calibration to handle color images.

3.3 Superimposed Image Decomposition (SID)

The superimposed image decomposition (SID) method proposed by Guo, Cao, and Ma also takes in a series of shifted photos as input but has a very different approach to solving the problem. One advantage of this algorithm is that it is more flexible regarding image translation and transformation. This is algorithm will first preprocess the images so that the shifted and rotated images are all centered on a flat plane. However, this transformation needs to be encoded into the program for each set of images. This is not done automatically, so some preprocessing of each dataset needs to occur before reflection removal can occur. The model this algorithm uses is shown in the equation below:

$$F = T + R + N \text{ -------- } \quad (2)$$

Here, F is the set of input images mapped to a matrix with the homographic transformations applied. T is the transmission matrix which contains all the transmission images of the entire set, and R and N correspond to the reflectance layer and noise respectively. To solve this problem, a single objective function is formed, and three structural priors are used: the correlation of the transmitted layer in a single set, the sparsity of the gradients, and the independence between the reflected and transmitted layers.

3.4 Gradient Projection for Sparse Reconstruction: Application to

Compressed Sensing and Other Inverse Problems

In this gradient projection algorithm for the bound constrained quadratic programming formulation is used. BCQP approach also requires the product of matrix-vector. In initialization step gradient projection is applied to a quadratic programming formulation and this will be considered as a GPSR (Gradient projection for sparse reconstruction) [10][11]. The next step of this approach is to articulate the convex unconstrained optimization problem as a quadratic program. They preferred a linear CG method to minimize the least squares cost of the inverse problem, under the limitation that the zero components of the sparse estimate produced by the GP algorithm remain at zero.

3.4 Ghosting Cues

This approach only takes in a single image as input. This method searches the image for ghosting artifacts, which are shifted, secondary reflections in an image. The image model they use is shown in the equation below.

$$I = T + R \cdot k + n \quad \text{-------(3)}$$

Here I am the input image, T and R are the transmission and reflection layers respectively, n is the noise term, and R.k is the convolution of the reflection layer with the ghosting kernel k.

4. Conclusion

In this paper separate reflection removal algorithm and compared the strengths and weaknesses of each one. SID is by far the fastest algorithm, but it performs poorly when there are only a few images in the dataset and when the scene contains lots of textured regions. SPBS-M is slower and performs well under a relatively static scene. However, when there is much association in the reflection layer, this can cause some time-aliasing artifacts to appear in both layers. The algorithm using ghosting cues was not able to cleanly separate reflections on any of the images tested. It also not works well when a scene with high textures is used. In general, algorithm which take a sequence of images seem to perform much better than algorithms that simply work on a single image.

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