

Obstruction Removal from an Image Sequence using Edge Flow Technique

Ashwini Gat¹, Uday Nuli²

¹Student, Computer Science & Engineering, TEI's DKTE, Ichakaranji, 416115/416115, India

²Assitant Professor, Computer Science & Engineering, TEI's DKTE, Ichakaranji, 416115/416115, India

Abstract: *Photography as a profession requires that the shooting of certain scenes take place in outdoor location as well as indoor location. The presence of a glass window grill and light source creates obstacles during indoor scenes where as presence of fence mostly obstruct the outdoor scenes. Such visual obstructions are often impossible to avoid just by changing camera position. Traditional computational approaches are still not robust enough to remove such obstructions from images without difficulty. The Proposed approach computationally removes the obstruction and occluding contents from images.*

Keywords: flash, reflection removal, obstruction.

1. Introduction

Many imaging conditions are far from best possible, forcing us to take photos through reflecting or occluding elements. As mobile imaging devices become more and more in style, user 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 busy street through the window of his office; 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. Some familiar examples include photographs of scenes taken through windows or photographs of objects which are placed within glass showcases found in retail store and museum settings. 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 and state-of-the-art computational approaches [1] are still not strong enough to remove such obstructions from images. More solutions, such as polarized lenses (for reflection removal) [2], which may progress some of those limitations, are not available to the everyday user.

A new Robust algorithm that allows a user to take photos through obstructing layers such as windows and fences, producing images of the preferred scene as if the obstructing elements are not there. Algorithm only requires the users to generate several camera motions during the imaging process, while the rest of the processing is fully automatic. The reality is that reflecting or obstructing elements are usually situated in-between the camera and the main scene, and as a result, have different depth than the main scene. Thus, instead of taking a single picture, photographer needs to take a short image sequence as slightly moving the camera. Because of differences in layers motions due to visual parallax, this algorithm then produces two images: an image of the background and an image of the reflected or occluding content.

Motion parallax is monocular depth cue in which the objects which are closer to the camera are moving faster than objects that are further away from camera and this perception is used for differentiating foreground layer and background layer. Layer decomposition is done by motion parallax by using mainly a pixel-wise flow field motion representation for each layer, and an "edge flow"[3][4] method that produces a robust initial estimation of the motion of each layer in the presence of occluding elements, as edges are less affected by the combination of the two layers[5]. Given an input image sequence, first initialize algorithm by estimating sparse motion fields on image edges[6][7], then interpolate the sparse edge flows into dense motion fields[8][9], and iteratively refine and alternate between computing the motions and determine the background and obstruction layers in a coarse-to-fine manner.

Two types of obstructions and occlusions like fences [10] can be handled by single construction. In this approach two problems solved from a single angle. This approach will work in various natural and practical scenarios, like fences, windows and other occluding elements. This approach is complete automatic and can work with any regular phone cameras, and only requires the user is to move camera in free hand manner to consider the scene.

2. Literature Review

Levin, A., Zomet, A., And Weiss, Y.[11] proposed a probabilistic model of images based on the qualitative statistics of derivative filters and corner detectors in normal scenes and used this model to find the most probable decomposition of novel image. Later Levin et al. [12] improved their algorithm using patch based priors learned from an external database. Input given as a single image and the algorithm searches for decomposition into two images that minimize the total amount of edges and corners.

Recently, Li and Brown [13] introduce strategy that extracting two layers from a single image where one layer is smoother than the other. Layer decomposition from a single-image is naturally ill-posed and solutions require extra

constraints to be imposed. This approach is applied to the intrinsic image and reflection removal problems and displays high quality layer separation and significantly faster than existing methods. Even with these priors, single image reflection removal is extremely challenging and hard to make practical for real images.

Kong et al. [14] proposed approach to separate reflection using multiple polarized images with photographs of scenes captured through glass windows. The input consists of three polarized images, each captured from the same vision but

with a different polarizer angle. The output is the high-quality separation of the reflection and background layers from each of the input images. This method performs well, but the requisite of a polarized filter and two images from equal position limits their usefulness.

3. System Design

Following is the architecture of proposed model for removing visual obstruction from images

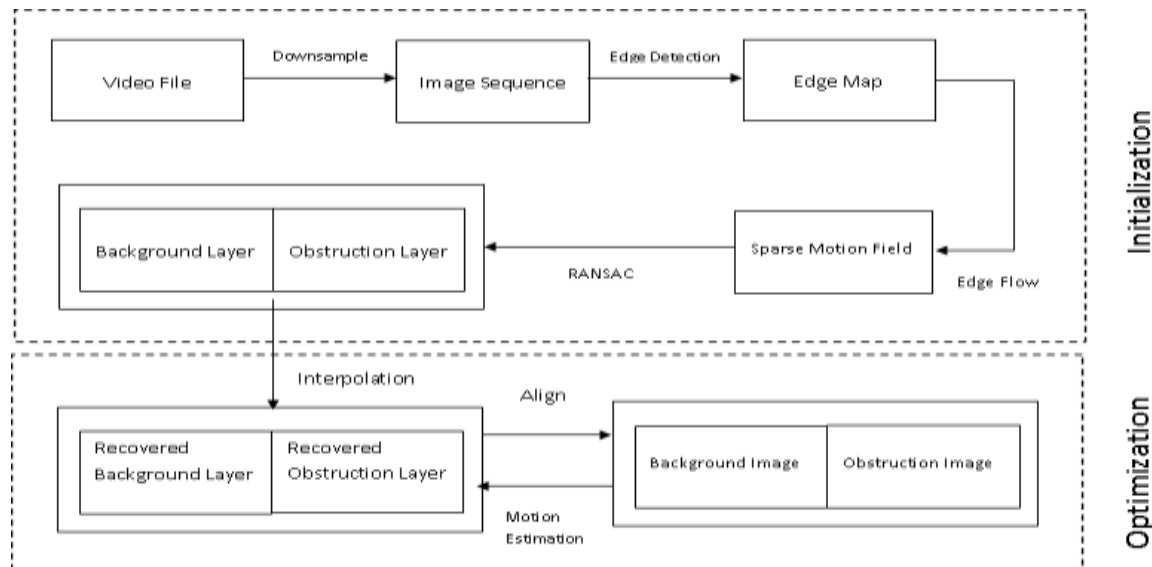


Figure 3.1: Architecture for Removing Visual Obstruction
 Proposed approach consists of two steps: Initialization and Optimization

3.1.1 Initialization

This phase contains initialization of background layer and obstruction layer. User need to take a small image sequence while slightly moving camera. Image sequence video file is downsampled into frames. By using canny edge detector; edge map of each individual frame is extracted. Later system will calculate the motion vector on extracted edge pixels from input images using edge flow technique. RANSAC [20] will assign the each edge pixel to either background layer or obstruction layer. This results in two sparse motion fields for two layers which then interpolate to produce an initial estimation of dense motion fields for each layer.

3.1.2 Optimization

In this phase background dense image is recovered by using remaining images from image sequence and foreground dense image is recovered using remaining images from image sequence. Finally system will get the recovered background image and foreground image.

3.2 Methodology

Following are the methods of implementation to overcome the problem identified.

Module I Preprocessing of video

The input to the system is a video file i.e. short image sequence while slightly moving camera. This video is downsampled into frames. The frames are subjected to canny edge algorithm to obtain extracted edge map for each frame.

Module II Edge Flow

Edge map serves as an input to calculate the motion of per-pixel detected on edges using edge flow motion estimation method. It produces sparse motion field on Image edges in the occurrence of visual obstruction.

Module III RANSAC(Random Sample Consensus)

Edge flow technique will generate the sparse motion field; it is separated into two sparse motion fields using RANSAC on the basis of foreground pixel moves a lot than background pixel. For this first fit, a perspective transformation to the sparse motion field is applied and all edge pixels that best fit this transformation is assigned to the background layer. Then the another perspective transformation to the remaining edge pixels again using RANSAC is applied, and the pixels best fitting the second transformation is assigned to the reflection layer.

Module IV Visual Surface Interpolation

Interpolation is a method of constructing a new data points within range of known data points. Compute initial per-pixel dense motion fields for Obstruction Layer and Background layer through interpolation [21]. The new pixel value is determined by calculating weighted average of sixteen closest pixels based on distance.

Module V Initial Decomposition and Optimization

Align the background in all the captured frames based on the estimated background motion. Similarly, initialize the obstruction layer. Optimization is done by first fixing the

images of each layer and solving for the motion fields, and then fixing the motion fields and solving for the images until convergence.

4. Results

This point elaborates the results of the system and evaluation on these results.

4.1 Removing Obstructions in Natural Sequences:

This system works under various scenarios, with different background entities, occluding elements. It work steadily well in all these scenarios. The above fig shows a common scenario when a person is taking a picture of an outside view, fence obstruction appears in all captured images. The system is able produce good reconstruction of background image with the occluding part removed.

5. Conclusion

This system takes sequence of images for estimating relative position of pixel. By using this difference between motion of background layer and motion obstruction layer; system will be able to separate occluded layer from image and to recover the desired background image by combining visual information from other reference images.

References

- [1] LI, Y., AND BROWN, M. S, "Exploiting Reflection Change for Automatic Reflection Removal". IEEE International Conference on Computer Vision (ICCV) 2013.
- [2] GUO, X., CAO, X., AND MA, Y., "Robust Separation of Reflection from Multiple Images" IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2014.
- [3] KOPF, J., LANGGUTH, F., SCHARSTEIN, D., SZELISKI, R., GOESELE, M., AND DARMSTADT, T. U., "Image-Based Rendering in the Gradient Domain" ACM SIGGRAPH 2013.
- [4] CANNY, J., "A computational approach to edge detection". IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), 6, 679–698, 1986.
- [5] SAREL, B., AND IRANI, M., "Separating transparent layers through layer information exchange". European Conference on Computer Vision (ECCV) 2004.
- [6] FARID, H., AND ADELSON, E. H, " Separating reflections and lighting using independent components analysis". IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 1999.
- [7] GAI, K., SHI, Z., AND ZHANG, C., "Blind separation of superimposed images with unknown motions". In IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2009.
- [8] LIU, S., YUAN, L., TAN, P., AND SUN, J., "Steadyflow: Spatially smooth optical flow for video stabilization". In IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2014.
- [9] J SZELISKI, R., "Fast surface interpolation using hierarchical basis functions". IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI) 12, 6, 513–528 1990.
- [10] YAMASHITA, A., MATSUI, A., AND KANEKO, T., "Fence removal from multi-focus images". In International Conference on Pattern Recognition (ICPR)2010.
- [11] LEVIN, A., AND WEISS, Y, " User assisted separation of reflections from a single image using a sparsity prior". IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)29, 9, 1647–1654, 2007.
- [12] LI, Y., AND BROWN, M. S., "Single image layer separation using relative smoothness". In IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2014.
- [13] KONG, N., TAI, Y.-W., AND SHIN, J. S., "A physically based approach to reflection separation: from physical modeling to constrained optimization" IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI) 36, 2, 209–21, 2014.
- [14] BARNUM, P. C., NARASIMHAN, S., AND KANADE, T., "Analysis of rain and snow in frequency space". International Journal of Computer Vision (IJCV) 86, 2-3, 256–274, 2010.
- [15] PARK, M., BROCKLEHURST, K., COLLINS, R. T., AND LIU, Y, "Image de-fencing revisited". In Asian Conference on Computer Vision (ACCV) 2011.
- [16] NEWSON, A., ALMANSA, A., FRADET, M., GOUSSEAU, Y., P'EREZ, P., ET AL. "Video inpainting of complex scenes". Journal on Imaging Sciences, Society for Industrial and Applied Mathematics 2014.
- [17] Carlos cuevas, Raquel Martinez, Narciso Garcia, "Detection of Stationary Foreground Objects". In Elsevier Computer Vision and Image understanding july 2016.
- [18] N. Ohnishi, K. Kumaki, T. Yamamura, and T. Tanaka. Separating real and virtual objects from their overlapping images. In Proc. European Conference on Computer Vision (ECCV), volume 1065, pages 636–646
- [19] Crminisi, A., Perez, P., and Toyama, K. 2004. Region filling and object removal by exemplar-based image inpainting. IEEE Transaction on ImageProcessing 13, 9, 1200-1212.
- [20] Wilhelm Burger, Mark J. Burge, "Digital Image Processing: An Algorithmic Introduction Using Java". Springer transaction on Digital Image Processing 2016.
- [21] Carlos cuevas, Raquel Martinez, Narciso Garcia, "Detection of Stationary Foreground Objects". In Elsevier Computer Vision and Image understanding july 2016.
- [22] Sergei Azernikov. Sweeping solids on manifolds. In Symposium on Solid and Physical Modeling, pages 249–255, 2008.
- [23] A. Wedel, T. Pock, J. Braun, U. Franke, and D. Cremers. Duality TV-L1 flow with fundamental matrix prior. Image and Vision Computing New Zealand, November 2008.
- [24] B.K.P. Horn and B.G. Schunck. Determining optical flow. Artificial Intelligence, 17:185–203, 1981.
- [25] Bay, Herbert, Tinne Tuytelaars, and Luc Van Gool. "Surf: Speeded up robust features." Computer Vision–ECCV 2006. Springer Berlin Heidelberg, 2006. 404–417.

- [26] T. Strutz, "Data Fitting and Uncertainty", Springer Vieweg, 2nd edition, 2016.
- [27] T. Xue, M. Rubinstein, C. Liu, and W. T. Freeman, "A Computational approach for Obstruction-free Photography". ACM Transaction on Computer Graphics, 34(4):79:1–79:11, August 2015.
- [28] Matthew Hu, "Reflection Removal Algorithms". Computational Imaging and Display:EE367/CS448I, 2016.

