International Journal of Scientific Research in Science and Technology
Print ISSN: 2395-6011 | Online ISSN: 2395-602X (www.ijsrst.com)
doi : https://doi.org/10.32628/IJSRST

Study and Survey Available for Removing Fences, Reflections and Raindrops from image Pattern Recognition Techniques

Arvind Singh[1], Shailesh Kumar Singh[2]
Research Scholar[1], AP[2], SHEAT COLLEGE OF ENGINEERING, VARANASI 384

Article Info
Volume 9, Issue 6
Page Number : 25-31

Publication Issue
November-December-2022

Article History
Accepted : 01 Nov 2022
Published : 04 Nov 2022

Abstract – The "de-fencing" process consists of two stages: the first is to identify the fence zones, and the second is to fill in the gaps. Numerous approaches to video-based de-fencing have been put out for more than ten years. However, there aren't many single-image-based approaches suggested. We concentrate on single-image fence removal in this study. Due to inadequate content information, conventional techniques have weak and incorrect fence detection and inpainting. We mix cutting-edge techniques based on a deep convolutional neural network (CNN) with conventional domain expertise in image processing to address these issues. We need to collect both the relevant non-fence ground truth photos and the fence images for the training phase. As a result, we create synthetic representations of natural fences using actual photographs. Additionally, the performance of the CNN for detection and inpainting is enhanced by spatial filtering processing (such as a Laplacian filter and a Gaussian filter). Without any human input, our suggested technology can automatically identify a fence and produce a clear photograph. Our technique works well for a variety of fence photos, according to experimental data.

Keywords – Deep Convolutional Neural Network, Fence Removal, Flow Estimation, Dense Optical Flow

I. INTRODUCTION

We often have to snap pictures in less-than-ideal lighting, with obstacles like windows or other objects in the way. Reflections of inside items, for instance, may ruin a photograph taken via a window of the outside. Shooting through a fence or enclosure may be necessary if we want to photograph zoo animals. Changing the camera's location or plane of focus isn't always adequate to eliminate such visual obstacles, and current computational methods still aren't compelling when removing them from photographs.

However, more advanced alternatives, like polarised lenses (to eliminate reflections), are out of reach for the average consumer. In this research, we provide a robust algorithm that enables a user to capture pictures through barriers like windows and fences while still capturing the area of interest as if the obstacles weren't there. When using our technique, users need only create slight camera motion throughout the imaging process; all other processing is handled mechanically.

Therefore, we tell the photographer to capture a series of images while gently moving the camera, much as they would do when capturing a panorama, rather than just one single shot. Our system then combines the space-time information to generate two images: one of the backdrop and one of the reflected or occluded content, based on changes in the movements of the layers caused by visual parallax. Although there are certain limitations to the scene that our arrangement imposes (for example, maintaining a relatively constant position while taking pictures), we found that frequent shooting settings are amenable to it.

Motion parallax has been used before in layer decomposition. Instead, the fundamental contribution of our study is a more stable and accurate technique for motion estimation when obstacles are present. In our method, the first step is calculating sparse motion fields on the edges of pictures after receiving an input picture sequence. This is followed by a coarse-to-fine estimation of backdrop and obstacle layers before we apply interpolation to turn the sparse edge flows into more dense motion fields.

We also demonstrate that a single framework can deal with reflections and physical occlusions. At first appearance, reflections and occlusions may seem quite different, and various approaches have been used to deal with each. While previous works have taken separate approaches to these issues, the method presented here takes a holistic view of the situation. Our system comprises mostly shared modules for these two issues, and with just minor adjustments, it outperforms prior methods that specifically addressed either subproblem. In this study, we consider both reflecting and occluding obstructions and explicitly select which kind is present in the picture to fine-tune the algorithm.

We tested our technology in various realistic and natural settings. Instead of mimicking obstacles artificially via the blending or composting of pictures (as was widely done in prior work), we conduct controlled trials to capture real situations with ground truth decompositions for quantitative assessment. Our technique is automated, compatible with most smartphone cameras, and needs just free-form camera movement from the user to scan the area. As a result of our research, we have determined that five photographs were taken along a narrow..

When photographing via reflecting surfaces or obstructing objects, it might be challenging to get clear shots since the resulting photos will include both the subjects of interest and the barriers. To enhance the quality of images acquired in such situations or to enable computers to create a proper physical interpretation of the environment.

Automatically deleting undesired reflections or occlusions from a single picture has been the subject of recent research [2, 8, 16, 17, 27, 38, 43, 45]. These techniques use ghosting signals [30] or learning-based approaches [8, 16, 38, 43, 45] to recapture the original natural visuals. While excellent results have been shown, the task of differentiating the clean backdrop from occlusions is inherently ill-posed and sometimes needs a high-level semantic comprehension of the scene to do correctly. For photos that fall beyond the norm, the effectiveness of learning-based approaches drops dramatically.

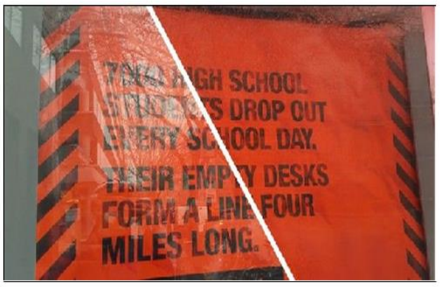
The central concept is to use the depth difference between the camera and the foreground, backdrop, and occluding items. Accordingly, the motion differences between the two layers may be seen in photos taken with a slightly moving camera [3, 9, 12, 21, 24, 34]. Several methods [1, 3, 6, 9, 12, 21, 24, 26, 31, 34] use these signals to remove reflections or fences from videos. Using a unified computational framework, Xue et al. [42] demonstrate outstanding results on several natural sequences and offer a method for removing obstructions. However, the formulation needs a computationally costly optimization procedure and is highly dependent on either the assumption of constant brightness or the accuracy of motion estimates. Current research [1] investigates model-free approaches by using a general-purpose 3D-CNN to address these concerns. Unfortunately, when applied to real-world input sequences, CNN-based approaches cannot compete with the quality of the results obtained by optimization-based algorithms.

A multi-frame obstacle removal technique that combines the best characteristics of the previous optimization- and learning-based approaches is presented in this thesis. Using an optimization-based strategy, the suggested method uses a coarse-to-fine system, alternating between dense motion estimates and background/obstruction layer reconstruction phases. The mindless motion is precisely described to bring back layer-specific information progressively. Our fusion network is readily transferrable to real-world sequences despite being trained on a lab dataset. Our results demonstrate that the proposed method beats current available algorithms on various demanding sequences and applications.

In contrast to the optimization-based formulation of [26, 42], our model is entirely data-driven and does not assume any classical properties of the scene, such as the scene's brightness being constant, the flow field's accuracy, or the surface's being flat. When these conditions are not met, it might be difficult for traditional methods to rebuild distinct layers of background and foreground. The data-driven strategies can learn from a wide variety of training data and accept erroneous results when these assumptions are not met.

(a) Reflection removal

(b) Fence removal



(c) Raindrop removal

In this work, we provide a learning-based approach for recovering clean pictures from a given brief series of photos captured by a moving camera via obstructive features such as (1) windows, (2) fences, or (3) rainfall.

II. MOTIVATION OF STUDY

A small number of studies address the issue of improving vision in adverse weather conditions; this thesis generally deals with haze or fog and rain streaks. Several strategies have been developed for raindrop detection. Using principal component analysis, Kurihara et al. [12] study the form of raindrops and then try to match an area in the test picture to the raindrops they've learned. A strategy proposed by Roser and Geiger [17] is to compare a synthetically manufactured raindrop to a spot that could have a raindrop. Initially, it is assumed that the synthetic raindrops are spherical in cross-section, and subsequently, it is supposed that they are oblate in cross-section [18]. Since raindrops may come in various forms and sizes, these assumptions could work in certain situations, but they can't be applied universally. Reflection and occlusion removal are two image processing challenges that have been studied in the past using a variety of approaches. Here, we conduct a literature review of the relevant research in these two fields. Reconstructing the backdrop and obstacle layers allows us to fine-tune optical flows to the final layer. The whole flow of our process is shown in Figure 2. Several layer decomposition issues, including reflection/obstruction/fence/rain removal, are amenable to our unified architecture. Without sacrificing generality, we present our approach through the reflection removal job. In the following sections, we discuss the three modules' specifics.

1.3 Problem Statement

Is there a technique of image processing which can remove undesirable reflections, Rain drop, fancy on a sean from a single digital image.

1.4 RESEARCH OBJECTIVES

To answer our issue statement, this research has the following objectives: To develop an algorithm to remove undesirable reflections, Rain drop, fancy on a sean from a single digital image.

III.LITERATURE REVIEW

A. Multi-Frame Reflection Removal

A small number of studies address the issue of improving vision in adverse weather conditions; this thesis generally deals with fog or haze and rain streaks (e.g. [2, 3, 24]). It has been suggested that many different approaches may be used to identify raindrops. Using principal component analysis (PCA), Kurihata et al. [12] study the form of raindrops and then try to match an area in the test picture with those of the learned raindrops. To avoid other areas locally identical to raindrops from being recognized as raindrops due to their transparency and diversity in form. Methods for determining whether or not a given patch contains a raindrop are proposed in [17] by Roser and Geiger.

The artificial raindrops are modeled as spheres and then oblique spheres [18]. Since raindrops may come in various forms and sizes, these assumptions could work in certain situations, but they can't be applied universally.

If the other picture does not include raindrops that obscure the same backdrop scene, it will remove the raindrops by replacing the raindrop areas with the textures of the matching image parts. Instead of stereo images, Yamashita et al. [22] suggest a similar strategy based on a series of images. You et al. [25] offer a motion-based approach to raindrop detection and a video-completion technique to delete previously recognized raindrops. Some rain can be removed using these techniques, but it's impossible to do so with a single photograph.

This network has a three-layer CNN with 512 neurons per layer. This technique is effective, especially for little droplets and debris, but it cannot cleanly process huge, thick raindrops. The final photographs also seem blurry for some reason. All of these, we believe, can be traced back to the network's low capacity and its inability to provide sufficient limits via its losses—the contrast of our findings with those obtained by other means.

Our approach uses a GAN [4], which has lately gained traction for a picture in painting and completing issue solutions, as the network's central node (e.g. [9, 13]). Similar to our approach, the discriminative network in [9] utilizes global and local evaluation. In contrast to our policy, however, the target areas are explicitly identified in the painted picture. This enables a local judgment (whether or not the local regions are sufficiently genuine). Hence, we cannot apply the current picture inpainting algorithms directly to our case. Pix2Pix [10] is another architecture with a similar goal: to convert one picture format into another. An adaptive GAN is proposed, which not only acquires the mapping from and a loss function to train the mapping from the input to the output picture. This is a generic mapping; it was not designed with raindrop removal in mind.

Existing approaches often make use of natural picture priors [10, 12, 42] and changes in patterns among the reflection layers [22]. Some of these techniques, such as dense optical flow [42], homography [12], and SIFT flow [21], describe the motion fields in different ways. Improvements in this area include learning-based layer decomposition [1] and maximizing temporal coherence [26]. To achieve better performance on real-world sequences, our technique directly simulates the dense flow fields of the obstruction layers instead of just learning a generic CNN [1].

B. Remove Reflections From Individual Images

Roser and Geiger [17] provide methods for identifying whether or not a particular patch includes a raindrop. [18] The artificial raindrops are initially designed as spheres and later as oblique spheres. Assumptions based on the fact that raindrops may occur in a broad range of shapes and sizes may work in some instances, but they cannot be applied generally. Yamashita et al. [23] used a stereo technique to identify and eliminate rain. Individual raindrops may be seen by the stereo cameras and the distance between them and the glass surface. As a result, if there are no raindrops in the other picture, it will delete them by replacing them with identical image sections with no droplets. [22] Instead of stereo pictures, Yamashita et al. advise using a sequence of photographs. You and your colleagues offer motion-based raindrop recognition and a video completion method [25]. However, even if these methods remove some rain, they can't be used in just one shot.

Many different strategies have been proposed as potential solutions to remove reflections from a single image. The presently known solutions all make use of the defocus-disparity signals from dual pixel sensors [28] and the ghosting effect [30], depth-of-field blurriness, and picture priors (either manually produced [2] or learnt from data). Despite the outcomes that were showed, removing reflections from a single image is still difficult due to the nature of this extremely poorly stated problem and the lack of motion cues. Instead, we make advantage of information about the motion of the camera to decouple the background and reflection layers of our image sequences.

C. Occlusion & Fence Removal

The goal of occlusion removal is to rid the scene of any captured impediments, such as a fence or raindrops, so that the picture or sequence may be more clearly appreciated. The existing algorithms that can identify fence patterns do so by making use of graph-cut [44], disparity maps [18], dense flow fields [42], or optical parallax [25]. One recent thesis [6] uses a CNN for fence segmentation and optical flow to retrieve the hidden pixels. Our technique trains deep CNNs for visual flow estimates and background picture reconstruction. Our recipe is not specifically tailored to eliminate fences but may be used for various similar problems.

IV. FINISHING THE VIDEO

Watermark/transcript removal video stabilization, full-frame, and Object removal are only some of the many uses for video completeness, which seek to fill plausible material in missing portions of a video [14]. To put constraints on the content synthesis [13, 40] and provide results that are consistent over time, available algorithms estimate the flow fields. The difficulty of removing obstructions is analogous to that of finishing a film. There is no need for human intervention when masking selection when eradicating fences and other visual barriers from movies.

V. DISCRETE-ELEMENT MODELING WITH LAYER-BY-LAYER DECOMPOSITION

Inverse rendering [23, 29], relighting [7], standard estimation [15], depth [15], and Intrinsic image [4, 46], all use picture layers, and layer decomposition is an old issue in computer vision. Our technique is motivated by the evolution of the methodologies for this layer decomposition.

VI. ONLINE OPTIMIZATION

Learning from the test data has proven to be an effective technique for decreasing the domain disparity between the testing and training distributions. To cite a few examples: [5, 33] self-supervised losses, [19], and [5] online template modifications that impose geometric limitations. Our unsupervised loss explicitly quantifies how well each input frame is explained by the dense flow fields and the recovered obstruction.

VII. CONCLUSIONS AND FUTURE WORK

The basic idea works with image de-fencing and filling the gaps to recover lost image details. Among the methods for detection of fence, the canny method is the best method because it gives accurate results. Among all the methods for background reconstruction, analysis shows that Exemplar based method is best. As the future work, the quality of the final result will be improved by more accurate resolution; also the work can be done on the image having the blur effect after removing the fence.

VIII. REFERENCES

[1]. Jean-Baptiste Alayrac, Joao Carreira, and Andrew Zisserman. The visual centrifuge: Model-free layered video representations. In CVPR, 2019.

[2]. Nikolaos Arvanitopoulos, Radhakrishna Achanta, and Sabine Susstrunk. Single image reflection suppression. In CVPR, 2017.

[3]. Efrat Be'Ery and Arie Yeredor. Blind separation of superimposed shifted images using parameterized

joint diagonalization. TIP, 17(3):340–353, 2008. 1
[4]. Sean Bell, Kavita Bala, and Noah Snavely. Intrinsic images in the wild. ACM TOG, 33(4):159, 2014.
[5]. Yuhua Chen, Cordelia Schmid, and Cristian Sminchisescu. Self-supervised learning with geometric constraints in the monocular video: Connecting flow, depth, and camera. In ICCV, 2019.
[6]. Chen Du, Byeongkeun Kang, Zheng Xu, Ji Dai, and Truong Nguyen. Accurate and efficient video de-fencing using convolutional neural networks and temporal information. In ICME, 2018.
[7]. Elmar Eisemann and Fre´do Durand. Flash photography enhancement via intrinsic relighting. ACM TOG, 23(3):673– 678, 2004.
[8]. Qingnan Fan, Jiaolong Yang, Gang Hua, Baoquan Chen, and David Wipf. A deep generic architecture for single image reflection removal and image smoothing. In ICCV, 2017.
[9]. Kun Gai, Zhenwei Shi, and Changshui Zhang. Blind separation of superimposed moving images using image statistics. TPAMI, 34(1):19–32, 2011.
[10]. Xiaojie Guo, Xiaochun Cao, and Yi Ma. Robust separation of reflection from multiple images. In CVPR, 2014.
[11]. Jia-Bin Huang, Sing Bing Kang, Narendra Ahuja, and Johannes Kopf. Temporally coherent completion of dynamic video. ACM TOG, 35(6):196, 2016.
[12]. Shachar Ilan and Ariel Shamir. A survey on data-driven video completion. Computer Graphics Forum, 34(6):60–85, 2015.
[13]. Meiguang Jin, Sabine Su¨sstrunk, and Paolo Favaro. Learning to see through reflections. In ICCP, 2018.
[14]. Sankaraganesh Jonna, Krishna K Nakka, and Rajiv R Sahay. Deep learning-based fence segmentation and removal from an image using a video sequence. In ECCV, 2016.
[15]. Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In ICLR, 2015.
[16]. Yu Li and Michael S Brown. Exploiting reflection change for automatic reflection removal, in ICCV, 2013.
[17]. Yu Li and Michael S Brown. Single image layer separation using relative smoothness. In CVPR, 2014.
[18]. Zhengqin Li, Mohammad Shafiei, Ravi Ramamoorthi, Kalyan Sunkavalli, and Manmohan Chandraker. Inverse rendering for complex indoor scenes: Shape, spatially-varying lighting, and svbrdf from a single image. In CVPR, 2020.
[19]. Ajay Nandoriya, Mohamed Elgharib, Changil Kim, Mohamed Hefeeda, and Wojciech Matusik. Video reflection removal through Spatio-temporal optimization. In ICCV, 2017.
[20]. Abhijith Punnappurath and Michael S Brown. Reflection removal using a dual-pixel sensor. In CVPR, 2019.
[21]. Soumyadip Sengupta, Jinwei Gu, Kihwan Kim, Guilin Liu, David W Jacobs, and Jan Kautz. Neural inverse rendering of an indoor scene from a single image. In ICCV, 2019.
[22]. YiChang Shih, Dilip Krishnan, Fredo Durand, and William T Freeman. Reflection removal using ghosting cues. In CVPR, 2015.
[23]. Deqing Sun, Xiaodong Yang, Ming-Yu Liu, and Jan Kautz. Pwc-net: Cnns for optical flow using pyramid, warping, and cost volume. In CVPR, 2018.
[24]. Yu Sun, Xiaolong Wang, Zhuang Liu, John Miller, Alexei A Efros, and Moritz Hardt. Test-time training for out-of-distribution generalization. arXiv:1909.13231, 2019.
[25]. Renjie Wan, Boxin Shi, Ling-Yu Duan, Ah-Hwee Tan, and Alex C Kot. Benchmarking single-image reflection removal algorithms. In ICCV, 2017.
[26]. Kaixuan Wei, Jiaolong Yang, Ying Fu, David Wipf, and Hua Huang. Single image reflection removal exploiting misaligned training data and network enhancements. In CVPR, 2019.
[27]. Tianfan Xue, Baian Chen, Jiajun Wu, Donglai Wei, and William T Freeman. Video enhancement with the task-oriented flow. IJCV, 127(8):1106–1125, 2019.
[28]. Jie Yang, Dong Gong, Lingqiao Liu, and Qinfeng Shi. Seeing deeply and bidirectionally: A deep learning approach for single image reflection

removal. In ECCV, 2018.
[29]. Renjiao Yi, Jue Wang, and Ping Tan. Automatic fence segmentation in videos of dynamic scenes. In CVPR, 2016.
[30]. Xuaner Zhang, Ren Ng, and Qifeng Chen. Single image reflection separation with perceptual losses. In CVPR, 2018.
[31]. Qingnan Fan, Jiaolong Yang, Gang Hua, Baoquan Chen, and David Wipf. A deep generic architecture for single image reflection removal and image smoothing. In ICCV, 2017.
[32]. Ajay Nandoriya, Mohamed Elgharib, Changil Kim, Mohamed Hefeeda, and Wojciech Matusik. Video reflection removal through Spatio-temporal optimization. In ICCV, 2017.
[33]. Xuaner Zhang, Ren Ng, and Qifeng Chen. Single image reflection separation with perceptual losses. In CVPR, 2018.