

A Review on Error Correction and Object Removal for Videos Based on Inpainting with Short-Term Windows

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Abstract: ---- Video inpainting is the process of repairing missing regions (holes) in videos. Most automatic techniques are computationally intensive and unable to repair large holes. To tackle these challenges, a computationally-efficient algorithm that separately inpaint foreground objects and background is proposed. Using Dynamic Programming, foreground objects are holistically inpainted with object templates that minimize a sliding-window dissimilarity cost function. Static background are inpainted by adaptive background replacement and image inpainting. In this propose a new video inpainting method which applies to both static or free-moving camera videos. The method can be used for object removal, error concealment, and background reconstruction applications. To limit the computational time, a frame is inpainted by considering a small number of neighboring pictures which are grouped into a group of pictures (GoP). This drastically reduces the algorithm complexity and makes the approach well suited for near real-time video editing applications as well as for loss concealment applications. Experiments with several challenging video sequences show that the proposed method provides visually pleasing results for object removal, error concealment, and background reconstruction context.

Index Terms—Inpainting, registration, homography, camera motion.

I. INTRODUCTION

Image in painting, a technique to complete missing areas of a static image with information surrounding the hole has gained much popularity from the image processing community in recent years. Video inpainting started or as a natural extension of image inpainting algorithms. While still in early stages of development, it has garnered a great deal of attention due to its potential applications in video error concealment (Rane et al., 2003), multimedia editing, visualization, video stabilization (Matsushita et al., 2006) and new applications such as video modification for privacy protection (Cheung et al., 2006; Wickramasuriya et al., 2004; Zhang et al., 2005a). A straightforward extension of image in painting algorithms to video inpainting is to treat the underlying video data as a set of distinct images and apply image inpainting algorithms to them individually. This approach to video inpainting proves inadequate as it fails to take advantage of the high temporal correlation that exists in video sequences. While recent video inpainting algorithms have addressed this issue with relative success, many technical challenges still remain. The most notable ones are their algorithmic complexity and the limited hole size they can handle. In this paper, a novel video inpainting method handling the aforementioned limitations is proposed. The

proposed method is faster than state-of-the-art methods and provides visually pleasing results on the tested video sequences. While being built upon existing background estimation techniques, the proposed approach extends them by bringing the following main contributions:

- A region-based homography which limits alignment errors and reduces the computational complexity. This is a key point since misalignment is the main source of temporal incoherence in the inpainted result.
- A spatio-temporal inpainting method based on a new well-defined cost function ensuring both spatial and temporal coherence.
- An efficient spatial inpainting initialization is used for both guiding the choice of the most likely pixel value in the aligned neighboring frames and recovering static regions.
- A short-term sliding temporal window (at most 20 images) is used to perform the inpainting.

The proposed method is then drastically less complex than the most recent techniques. The paper is organized as follows. In section II related works are presented. In Section III, the main state-of-the-art video inpainting methods are presented. The proposed method is described in Section IV starting by an overview of the complete





algorithm followed by a detailed description of each step. Finally, SectionV concludes the paper.

II. RELATED WORKS

B.Pranitha Reddy, P.Sri Padma, Ch.Ganapathy Reddy: In image processing "Filling the Missing Areas (holes)" is a problem in many image processing applications [1]. Although lot of research done still it's an area of concern in many image processing applications. Image inpainting is the procedure of reconstructing lost or deteriorated parts of images. The proposed inpainting algorithm presents the novel inpainting algorithm and also the process of combining the different inpainting images. A hierarchical single image super resolution framework is used to reconstruct the high resolution details of the image, super resolution framework is implemented after the completion of combination of the low resolution inpainted images.

Marcelo Bertalmio and Guillermo Sapiro, Vicent Caselles and Coloma Ballester: Image inpainting: Inpainting, the technique of modifying an image in an undetectable form, is as ancient as art itself [24]. The goals and applications of inpainting are numerous, from the restoration of damaged paintings and photographs to the removal/replacement of selected objects. Mainly three groups of works can be found in the literature related to digital inpainting.

The first one deals with the restoration of films, the second one is related to texture synthesis, and the third one, a significantly less studied class though very influential to the work here presented, is related to disocclusion.

Miguel Granados, Kwang In Kim, James Tompkin, Jan Kautz, and Christian Theobalt proposed Background Inpainting for Videos with Dynamic Objects and a Freemoving Camera, where this approach takes as input a video, a mask marking the object to be removed, and a mask marking the dynamic objects to remain in the scene [12]. To inpaint a frame, we align other candidate frames in which parts of the missing region are visible. Among these candidates, a single source is chosen to each pixel so that the external arrangement is color-consistent. Intensity differences between sources are smoothed using gradient domain fusion.

James Hays, Brown, fall 2012 proposedSingle Image Super-resolution proposed Super-resolution Goal is to Produce a detailed, realistic output image, to be faithful to the low resolution input image [6]. Typical Super-resolution Method Build some statistical model of the visual world. Coerce an up sampled image to obey those statistics. Methods can be divided based on the statistical model – either parametric or non-parametric (data-driven). The first to use scene matches for SR, at extremely low-res Scene match statistics favored over internal statistics, Competitive results, insertion of details, texture transitions.

Barnes et al. In SIGGRAPH Patch Match proposed a randomized Correspondence Algorithm for Structural Image Editing in 2009, by using Image retargeting image can be resized to a new aspect ratio [8]. An erased region can automatically synthesized by Image completion, Image reshuffling can be used to grab portions of the image and move them around. User interaction is essential where Toolset must provide the flexibility and must be fast. Most high-level editing approaches meet only one of these criteria Flexibility by Non-parametric patch sampling.

III. EXISTING SYSTEM

Granados *et al.* have recently proposed an efficient inpainting method, yielding compelling results even for large holes and high resolution videos. A brief description is given in the following. All the frames of the input video sequence are first aligned to the target frame using the homography-based registration.

Each missing pixel is assigned to a collocated known pixel value extracted from the registered frames. To find the best one, a cost function is globally minimized. Such global minimization, which strives to find the best tradeoff between different energy terms, significantly improves the space-time consistency and the method is provide following disadvantages

- These approaches are unfortunately time consuming even for low resolution sequences.
- Another drawback concerns the minimization process which is usually steered by an initialization term also named prediction term. The initialization is obtained by a simple spatial or temporal interpolation.
- This kind of interpolation lacks accuracy to be very helpful for inpainting. For instance, the predicted term a simple weighted interpolation of collocated pixels in the aligned frames.



• This approach assumes that there is, in the stack of aligned frames, at least one unconcluded pixel for each missing pixel in the current frame.

IV. PROPOSED SYSTEM

The proposed approach performs the inpainting of the input video sequence using a sliding temporal group offrames. As illustrated in figure 1, each frame is inpaintedusing two main steps: registration (step 1) and hole filling(step 2, 3 and 4). For each target frame $It: R2 \rightarrow R3$ with a hole $\Omega_t \subset \mathbb{R}^2$, we align its neighboring frames. Each pixelin Ω_t is inpainted using the most similar collocated pixel value in the aligned neighboring frames.

Once the target frame hasbeen inpainted, the target frame is replaced in the GoP by theinpainted one. As in, two input binary mask are required to indicate the areas we want to remove and the foregroundareas.



Fig. 1. Image Inpainting

A. Image Inpainting

The image inpainting problem can be formalized using either a local or global optimization framework. In the local optimization framework, pixel values (or entire patches) are inwardly propagated from the boundaries of the missing region. A well-known algorithm of this category is the examplar-based inpainting algorithm proposed in [17]. Many variants have been proposed in the past decade (see for instance [1], [18]–[20]). Examplar-based methods are reasonably fast and give plausible results when the hole is small. However, for large holes, they suffer from a lack of global visual coherence. On the other hand, inpainting methods using a global optimization function aim at ensuring a better global image coherence.

For instance, the methods [21], [22] compute a discrete offsets field connecting unknown pixels in the hole with known pixel values in order to globally minimize an energy cost with the help of Markov Random fields (MRF) [23]–

[25]. Thanks to the global optimization constraint, MRFbased approaches often provide better inpainting quality compared to greedy examplar-based methods. This is especially true for large holes where spacetime inconsistencies are more visible. However, these methods are generally more complex than examplar-based methods.

B.Video Inpainting

There exist few video inpainting algorithms. Among them, several methods consists in extending Criminisi et al.'s algorithm [17] to video as in [6]–[8]. They introduce a similarity measure between motion vectors for seeking the best candidate patch to be copied. In 2007, Wexler *et al.* [9] presented an innovative method consisting in filling in the missing regions with the pixel values that ensure the highest spatio-temporal consistency between all overlapping patches.

The missing parts of the object are then inpainted by aligning the segmented frames and by filling in the missing pixels with aligned pixels. In the particular case of videos captured by moving cameras, neighboring frames have first to be aligned using registration methods. The performance of this kind of approaches however highly depends on the quality of both the registration and the segmentation methods, which need to be very accurate to provide reasonable inpainting results.

C. Frames Registration

This section is devoted to the first step of the algorithm which consists in aligning the neighboring source frames I_s with the target frame I_t . An efficient registration method is required since alignment errors can propagate and undermine the spatial and temporal coherency of the inpainted areas. In addition, the proposed registration method should be fast enough to provide a reduced complexity video inpainting algorithm. To achieve this goal, we propose a new homography-based registration to handle the alignment problem.

D. Homography

A homography is an isomorphism of projective spaces, induced by an isomorphism of the vector spaces from which the projective spaces derive.^[1] It is a bijection that maps lines to lines, and thus a collineation. In general, some collineations are not homographies, but the



fundamental theorem of projective geometry asserts that is not so in the case of real projective spaces of dimension at least two. Synonyms include projectivity, projective transformation, and projective collineation.

Historically, homographies (and projective spaces) have been introduced to study perspective and projections in Euclidean geometry, and the term *homography*, which, etymologically, roughly means "similar drawing" date from this time. At the end of 19th century, formal definitions of projective spaces were introduced, which differed from extending Euclidean or affine spaces by adding points at infinity. The term "projective transformation" originated in these abstract constructions.

These constructions divide into two classes that have been shown to be equivalent. A projective space may be constructed as the set of the lines of a vector space over a given field (the above definition is based on this version); this construction facilitates the definition of projective coordinates and allows using the tools of linear algebra for the study of homographies. The alternative approach consists in defining the projective space through a set of axioms, which do not involve explicitly any field (incidence geometry, see also synthetic geometry); in this context, collineations are easier to define than homographies, and homographies are defined as specific collineations, thus called "projective collineations".

For sake of simplicity, unless otherwise stated, the projective spaces considered in this article are supposed to be defined over a (commutative) field. Equivalently Pappus's hexagon theorem and Desargues' theorem are supposed to be true. A large part of the results remain true, or may be generalized to projective geometries for which these theorems do not hold.

E. Camera Motion

Motion estimation is the process of determining motion vectors that describe the transformation from one 2D image to another; usually from adjacent frames in a video sequence. It is an ill-posed problem as the motion is in three dimensions but the images are a projection of the 3D scene onto a 2D plane.

The motion vectors may relate to the whole image (global motion estimation) or specific parts, such as rectangular blocks, arbitrary shaped patches or even per pixel. The motion vectors may be represented by a translational model or many other models that can approximate the motion of a real video camera, such as rotation and translation in all three dimensions and zoom. More often than not, the term motion estimation and the term optical flow are used interchangeably.

V. CONCLUSION

We propose a novel video inpainting method. In a first step, neighboring frames are registered with a regionbased homography. Each plane in the scene is assimilated to a homogeneous region segmented using the mean-shift algorithm. Inpainting is then performed using a predefined energy cost which is globally minimized. A spatial inpainting is used to guide this minimization leading to improve the quality of the inpainted areas.

Existing methods are more complex. The proposed approach has a reduced complexity compared to existing methods.We have also developed a synthetic posture generation scheme that enhances the variety of postures available in the database. It becomes easier to find out the missing pixels in the picture. Missing areas are filled in by considering a sliding window of 20 frames. The constructed motion manifolds contain he entire trajectory of pixels.

Unlike Granados et al.'s ehod [13], in which three optimization steps are involved, our approach uses only two global optimization methods and uses as mentioned previously a reduced number of frames in which complexity will be reduced. Experiments show that the proposed approach provides high quality inpainting results. Future work will focus on inpainting both background and moving objects in the videos.

REFERENCES

[1] C. Guillemot and O. Le Meur, "Image inpainting: Overview and recent advances," *IEEE Signal Process. Mag.*, vol. 31, no. 1, pp. 127–144, Jan. 2014.

[2] C. Barnes, E. Shechtman, A. Finkelstein, and D. B. Goldman, "PatchMatch: A randomized correspondence algorithm for structural image editing," *ACM Trans. Graph.*, vol. 28, no. 3, pp. 24:1–24:11, Jul. 2009.

[3] D. Glasner, S. Bagon, and M. Irani, "Super-resolution from a single image," in *Proc. IEEE 12th Int. Conf. Comput. Vis.*, Sep./Oct. 2009, pp. 349–356.

[4] J. G. Apostolopoulos, W.-T. Tan, and S. J. Wee, "Video streaming: Concepts, algorithms, and systems,"



HP Lab. Palo Alto, Palo Alto, CA, USA, Tech. Rep. HPL-2002-260, 2002.

[5] Y. Matsushita, E. Ofek, W. Ge, X. Tang, and H.-Y. Shum, "Full-frame video stabilization with motion inpainting," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 7, pp. 1150–1163, Jul. 2006.

[6] K. A. Patwardhan, G. Sapiro, and M. Bertalmio, "Video inpainting under constrained camera motion," *IEEE Trans. Image Process.*, vol. 16, no. 2, pp. 545–553, Feb. 2007.

[7] T. K. Shih, N. C. Tang, and J.-N. Hwang, "Exemplarbased video inpainting without ghost shadow artifacts by maintaining temporal continuity," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 19, no. 3, pp. 347–360, Mar. 2009.

[8] T. K. Shih, N. C. Tan, J. C. Tsai, and H.-Y. Zhong, "Video falsifying by motion interpolation and inpainting," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2008, pp. 1–8.

[9] Y. Wexler, E. Shechtman, and M. Irani, "Space-time completion of video," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 3, pp. 463–476, Mar. 2007.

[10] A. Newson, A. Almansa, M. Fradet, Y. Gousseau, and P. Pérez, "Video inpainting of complex scenes," *SIAM J. Imag. Sci.*, vol. 7, no. 4, pp. 1993–2019, 2014.

[11] O. Whyte, J. Sivic, and A. Zisserman, "Get out of my picture! Internetbased inpainting," in *Proc. Brit. Mach. Vis. Conf.*, 2009, pp. 1–11.

[12] W.-Y. Lin, S. Liu, Y. Matsushita, T.-T. Ng, and L.-F. Cheong, "Smoothly varying affine stitching," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2011, pp. 345–352.

[13] M. Granados, J. Tompkin, K. I. Kim, J. Kautz, and C. Theobalt, "Background inpainting for videos with dynamic objects and a freemoving camera," in *Proc. Eur. Conf. Comput. Vis.*, 2012, pp. 682–695. [14] S. Liu, L. Yuan, P. Tan, and J. Sun, "Bundled camera paths for video stabilization," *ACM Trans. Graph.*, vol. 32, no. 4, pp. 78:1–78:10, Jul. 2013.

[15] X. Chen, Y. Shen, and Y. H. Yang, "Background estimation using graph cuts and inpainting," in *Proc. Graph. Inter.*, 2010, pp. 97–103.

[16] S. Cohen, "Background estimation as a labeling problem," in *Proc.* 10th IEEE Int. Conf. Comput. Vis., Oct. 2005, pp. 1034–1041.

[17] A. Criminisi, P. Pérez, and K. Toyama, "Region filling and object removal by exemplar-based image inpainting," *IEEE Trans. Image Process.*,vol. 13, no. 9, pp. 1200–1212, Sep. 2004. [18] P. Buyssens, M. Daisy, D. Tschumperlé, and O. Lézoray, "Exemplarbased inpainting: Technical review and new heuristics for better geometric reconstructions," *IEEE Trans. Image Process.*, vol. 24, no. 6, pp. 1809–1824, Jun. 2015. [Online]. Available: https://hal.archivesouvertes. fr/hal-01147620

[19] O. Le Meur and C. Guillemot, "Super-resolutionbased inpainting," in *Proc. Eur. Conf. Comput. Vis.*, 2012, pp. 554–567.

[20] O. Le Meur, M. Ebdelli, and C. Guillemot, "Hierarchical superresolution-based inpainting," *IEEE Trans. Image Process.*, vol. 22, no. 10, pp. 3779–3790, Oct. 2013.

[21] Y. Hu and D. Rajan, "Hybrid shift map for video retargeting," in *ProcIEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2010, pp. 577–584.

[22] Y. Pritch, E. Kav-Venaki, and S. Peleg, "Shift-map image editing," in *Proc. IEEE 12th Int. Conf. Comput. Vis.*, Sep./Oct. 2009, pp. 151–158.

[23] V. Kwatra, A. Schödl, I. Essa, G. Turk, and A. Bobick, "Graphcut textures: Image and video synthesis using graph cuts," in *Proc. ACM Trans. Graph.*, 2003, pp. 277–286.

[24] V. Kolmogorov and R. Zabin, "What energy functions can be minimized via graph cuts?" *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 26, no. 2, pp. 147–159, Feb. 2004.

[25] Y. Boykov, O. Veksler, and R. Zabih, "Fast approximate energy minimization via graph cuts," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 23, no. 11, pp. 1222–1239, Nov. 2001.



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