MOTION-CONSISTENT VIDEO INPAINTING
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**ABSTRACT**

We propose a fast and automatic inpainting technique for high-definition videos which works under many challenging conditions such as a moving camera, a dynamic background or a long lasting occlusion. Built upon the previous work by Newson et al. [1] which optimizes a global patch-based function, our method makes a significant improvement, especially in motion preservation, by incorporating the optical flow in several stages of the algorithm. Moreover, code parallelization and a modification in the process of patches pairwise matching yield a significant reduction of computation time. Experimental results on both classical and challenging datasets show that our algorithm outperforms other state-of-the-art approaches.

**Index Terms**— Video inpainting, video restoration, patches, optical flow, video editing.

1. INTRODUCTION AND PRIOR WORKS

Video inpainting aims to fill in a missing region (an occlusion) in a video using the rest of that video to produce a “plausible” result. Video inpainting has numerous applications, ranging from restoring error concealment [2] or removing undesired objects [3] to restoring scratches or damages in vintage films [4]. While image inpainting has attracted much attention over the last two decades [5], video inpainting remains an underdeveloped and challenging field due to the difficulty of dealing with complex motions, the high sensitivity of our visual system to temporal inconsistencies, and the computational complexity. Most recent methods found in the literature address these issues using either object-based or patch-based approaches.

Under object-based approach, a preprocessing step is required to split the video into background and foreground objects, followed by an independent reconstruction of each part and the merging of the results at the end of the algorithm. Examples which fall under this category are the layered mosaic technique of Jia et al. [6], the homography-based algorithm using graph cut by Granados et al. [3] and the posture mapping scheme by Ling et al. [7]. Typically, object-based methods can provide reasonable results for reconstructing a specific object, e.g. a human. However, these techniques require some strict conditions such as periodic motion [6] or user assistance [3]. Furthermore, as the foreground and background completion procedures are performed independently, blending one with the other may cause artifacts.

In patch-based methods, patches from source regions are used to fill in the occlusion in a greedy or global fashion. Greedy methods inpaint incrementally the occlusion pixel by pixel, the reconstruction order is defined by a priority term. For example, Patwardhan et al. [8] extend to 3D space the well-known image inpainting technique in [9], whereas Daisy et al. [10] employ a tensor voting term to calculate the priority and focus on a geometry-guided blending technique to reduce space-time artifacts. In general, these greedy methods are very sensitive and, most importantly, do not have the capacity to reconstruct motion over a large occlusion and in a coherent way.

To ensure the global consistency, a global approach is needed. A natural strategy is to minimize a global patch-based function. In their seminal contribution [11], Wexler et al. pioneer the optimization of a global energy based on 3D spatio-temporal patches to preserve temporal coherency. Subsequent contributions propose various improvements. In [1], a significant step forward is made by using the 3D PatchMatch to strengthen the coherence and speed up the patch matching. In [12], Granados et al. focus on identifying a shift map in 3D space using graph-cut. Recently, Huang et al. [13] modify Wexler’s energy by adding an optical flow term to enforce the temporal coherence. These methods not only provide very impressive results but they are also compatible with many scenarios. However, they have several drawbacks such as huge computation time [12], inability to deal with motion within large occlusion [1] or unpleasant artifacts [13].

In order to fix these issues, we propose a fast video inpainting technique which builds upon [1] with three major improvements. The first and most significant advancement is the heavy use of optical flow in several stages of the algorithm. Optical flow has already been used in some previous works in video inpainting. For example, Strobel et al. [14] inpaint the optical flow field first and use the result to guide
the nearest neighbor search. Huang et al. [13] rely on optical
flow path to find the best patches and reconstruct pixel inten-
sities. As their method uses only 2D patches, optical flow is
the only part contributing to the preservation of temporal co-
herency, therefore the inaccurate synthesis of optical flow will
generate artifacts. Our method, on the other hand, maintains
the temporal consistency by using both 3D spatio-temporal
patches and an optical flow term. This term is incorporated in
several stages: it is inserted in the patch distance, controls
the patch shape, supports the nearest neighbor search, and
serves as a guide in coarse initialization. All these stages enable
us to ensure the temporal coherency and the reconstruction
of objects with complex motions occluded for long time pe-
riods. The second contribution is a significant reduction in
computation cost achieved by parallelizing the algorithm and
modifying the patch matching process. The final improve-
ment is the integration of a confidence map and a separation
map in the pixel reconstruction step to reduce artifacts. We
evaluate our method under various conditions and compare it
with some other state-of-the-art approaches using their public
datasets. The results can be found in a dedicated website.

2. PROPOSED METHOD

2.1. Overview

Our method is based on a non-local patch-based energy, in
the spirit of [11, 1]. The energy is minimized thanks to an
iterative procedure embedded in a coarse-to-fine pyramidal
scheme. Our algorithm involves two core steps: the com-
putation of a nearest neighbor field in the occlusion which
approximates the patches best pairwise matches, and a recon-
struction step using this field to determine the values of all
occluded pixels.

Within this framework, it is essential to address many
problems such as the coherent preservation of motion, the
searching strategy to find the appropriate patches, the com-
putational complexity and the border artifacts. These prob-
lems are addressed in our method by modifying patch shapes
and patch metric, integrating a novel optical flow-driven ini-
tialization scheme, parallelizing the algorithm, speeding up
the nearest neighbor search and enhancing the reconstruction
step. These techniques will be presented in the following sec-
tions.

2.2. Energy

To handle the instability caused by camera movements, a
stabilization pre-processing is performed using the method
in [15]. After stabilization, we minimize a Wexler-like energy
$E(u, \phi)$ to find the inpainted sequence $u$ and the corre-
ponding patch correspondence (or shift map) $\phi$. Denoting $W_p(u)$
the patch centered at a pixel $p$ in the given occlusion domain
$H$, the shift $\phi(p)$ at $p$ is defined as the spatial offset $q-p$ where
$q$ is a minimizer in $H'$ of the patch distance $d(W_p^u, W_q^u)$ (see
below for the definition of $d$). The energy $E$ associated with
an image $u$ (known outside a given occlusion domain $H$) and
a shift map $\phi$ is defined as

$$ E(u, \phi) = \sum_{p \in H} d^2(W_p^u, W_{p+\phi(p)}^u) $$

Minimizing this energy ensures that each patch $W_p^u$ cen-
tered around a pixel $p$ in the occlusion domain $H$ is as close
as possible to its nearest neighbor $W_{p+\phi(p)}^u$ outside the occlu-
sion (in the sense that $p + \phi(p) \notin H$). We use a metric $d$
between patches defined by:

$$ d^2(W_p^u, W_q^u) = \frac{1}{|N_p|} \sum_{r \in N_p} \left[ \alpha \left( \|u(r) - u(r - p + q)\|^2 \right) + \beta \left( \|T(r) - T(r - p + q)\|^2 \right) + \gamma \left( \|O(r) - O(r - p + q)\|^2 \right) \right] $$

In this expression, $N_p$ indicates a spatio-temporal neigh-
borhood of $p$. It is a parallelepiped whose shape is controlled by
the optical flow vector as indicated in Figure 1. This adap-
tive shape, different from a classical rectangle cubic, en-
ables us to reduce the number of patches which contain both
background and foreground data. Following [1, 16], our dis-
tance incorporates texture features $T = (\frac{\partial u}{\partial x}, \frac{\partial u}{\partial y})$. In ad-
dition, to enhance temporal coherency, we use motion fea-
tures $O = (\|O_x\|, \|O_y\|)$, which is composed of the modulus of
the optical flow vector coordinates. Values of weights $\alpha, \beta, \gamma$
must be set according to the data (automatic setting is the pur-
pose of ongoing work).

Our energy $E$ is high dimensional and highly non-convex,
but as observed in [17] a good local minimum can be obtained
by alternate minimization w.r.t $u$ and $\phi$, coupled with a good
initialization and a coarse-to-fine multiscale scheme. Texture
and motion features in the similarity metric are key to guiding
the algorithm towards a good local minimum from the coarsest
scale. The general structure of our algorithm is as follows:

- Build multiscale pyramids for color $u$, occlusion do-
  main $H$, texture features $T$ and motion features $O$.
- Initialization at coarsest scale (see section 2.3).
- From coarsest to finest scale do:
  - Iterate until convergence:
    - $\min_{\phi}$ (nearest neighbor search, section 2.4).
    - $\min_u$ (pixels reconstruction, section 2.5).
    - features reconstruction.
  - If not finest scale: Upsample $\phi$, $u$, and features.

Fig. 1. Our patches are parallelepipeds with $x - y$ skew con-
trolled by the optical flow field.
2.3. Coarse initialization

Due to the non-convexity of the functionals which are typically used in global patch-based methods, having a reliable initialization is crucial for the local minimization. Nevertheless, this step is often left unspecified in the literature, with the exception of [1] where a greedy inpainting technique using onion peel priority is proposed at coarsest scale. Such method can produce a good initialization for small occlusions. However, it tends to wipe out moving objects in long lasting occlusions. To solve this issue, we propose to use the optical flow in the priority term, which somehow extends to space-time the 2D inpainting approach of Criminisi et al. [9]. More precisely, the priority term at pixel \( i \) is defined as \( Pr_i = C_i D_i \), where \( D_i \) is the average of the optical flow magnitude in the patch centered at \( i \), and \( C_i \propto \exp\left\{-d^2(i, H_{\text{coarse}})\right\} \) measures how close the pixel \( i \) is to the border of the original occlusion \( H_{\text{coarse}} \) at coarsest scale.

The coarse initialization is then obtained as follows. Following \( H' = H_{\text{coarse}} \), we repeat the following procedure until there remain only "background" pixels, defined as all pixels \( i \) such that \( D_i \leq S \), where \( S \) is an adaptive threshold obtained by Otsu’s method:

- Let \( B' = H' \setminus (H' \cap B(0,1)) \), i.e. \( B' \) is the one-pixel wide outer boundary of \( H' \). Calculate \( Pr_i \) for \( i \in B' \).
- Select patch \( P_i \) with highest priority term \( Pr_i \), and define the region to inpaint \( R_i = P_i \cap B' \).
- Inpaint \( R_i \) and get new occlusion region \( H' \rightarrow H' \setminus R_i \). Thereafter, the rest of the occlusion (i.e. background pixels) is inpainted following onion peel order.

2.4. Nearest neighbor patch search

Since its introduction by Barnes et al. [18], PatchMatch has become a classical tool for approximate nearest neighbor search in patch spaces, especially in the context of image and video inpainting, not only for computational speed but also for spatial consistency. The core part of the algorithm includes a propagation step to spread out good matches and a random search step to jump out of the local optima. These two steps are repeated in several iterations. In our video inpainting context, the spatio-temporal extension of PatchMatch by Newson et al. [1] is adopted with two important modifications to improve its efficiency:

- The first modification is a speedup of PatchMatch by parallelization, following the jump flooding technique of Barnes et al. [18]. To save even more computational cost, we use a sparse grid during the random search step. For PatchMatch searching in video, it is not necessary to perform the random search step for every occluded pixel; instead, we can apply this step only for pixels on a sparse grid, without losing the efficiency. The final improvement is to use foreground/background patch clustering to reduce the search space. Combining these factors enables our PatchMatch algorithm to run 5-7 times faster than the traditional one with the same accuracy.
- The second modification is to guide the propagation step using the optical flow. From the assumption that adjacent patches are more likely to have similar nearest neighbor offsets, PatchMatch achieves a good preservation of the spatial coherency. For temporal coherency, this assumption is only valid if the background is static or in periodic motion. Otherwise, it may not hold true. To enforce the temporal consistency, instead of propagating offsets to a fixed temporal neighbor, we propagate it following the optical flow direction. To be more formal, in the propagation step, the temporal neighbor for the patch centered at pixel \( (x,y,t) \), \( P(x,y,t) \), is \( P(x+O_x,y+O_y,t+1) \) rather than \( P(x,y,t+1) \) where \( O_x \) and \( O_y \) are the optical flow components in the \( x \) and \( y \) directions.

2.5. Pixel reconstruction

In this step, all pixels in the occlusion \( H \) are reconstructed using the following weighted average:

\[
u(p) = \frac{\sum_{q \in N_p} s_q^p u(p + \phi(q))}{\sum_{q \in N_p} s_q^p},\]

where the weight \( s_q^p \) is defined as:

\[
s_q^p = \exp\left(-\frac{d^2(W_q^p, W_q^p + \phi(q))}{2\sigma^2}\right)\psi_q\varphi_q^p.
\]

In this expression, the first term is the original weight of [11] based on patches similarity. We combine it with two other factors \( \psi_q \) and \( \varphi_q^p \). The first one is a confidence map inspired by Fedorov et al. [19], and given by

\[
\psi_q = \begin{cases} 
(1 - C_0) \exp\left(-\frac{d(q, H^c)}{\sigma^2}\right) + C_0 & \text{if } q \in H \\
1 & \text{otherwise}
\end{cases}
\]

where \( d(q, H^c) \) is the distance from pixel \( q \) to the occlusion border, and \( C_0, \sigma^2 \) are tuning parameters. This map is used to guide the information from the border towards the center and enables us to eliminate some border artifacts. The second term \( \varphi_q^p \) relies on a distinction between foreground and background pixels, obtained by thresholding the modulus of the optical flow. It is set to 1 if \( p \) and \( q \) are of same type (background or foreground), otherwise it is set to 0. Therefore, when we reconstruct background pixels, we use only background patches and similarly for foreground pixels. This is a simple way to avoid the common but undesirable effect of blending between background and foreground in the final result.
3. EXPERIMENTAL RESULTS

Our algorithm is implemented in Matlab with the core parts (nearest neighbor search and pixel reconstruction) in C++. For the optical flow computation, Liu’s method [20] is used. Our method is evaluated under a wide variety of conditions, including moving objects occluded by a fixed or moving domain, static or moving camera, dynamic background, large occlusions, etc. To prove the effectiveness of our method, we compare its performances with other state-of-the-art algorithms [1, 13] using their publicly available datasets. Results can be found at http://perso.enst.fr/~gousseau/vid_inp_motion/.

3.1. Comparison with Huang et al. [13]

In this experiment, we remove undesired objects in videos recorded with hand-held camera. The dataset used is the same as in Huang et al. [13], obtained from a recent benchmark dataset in object segmentation [21]. It constitutes a very challenging dataset due to the dynamic scenes, the complex camera movements, the motion blur effects and the large occlusions. The occlusion mask is constructed by dilating the ground truth using a 15x15 structuring element.

Figure 2 (a) shows some representative frames of the result. From that figure, we can see that, similar with Huang et al. [13], the spatial structure (e.g. the letters in the panel) is well-preserved with our approach. Figure 2(b) shows the result as an x-t slice of the video. It can be seen that our method has the ability to preserve temporal consistency due to the combination of 3D spatio-temporal patches and dense flow field. This is also achieved in [13]; however, because only 2D patches are used in [13], the quality of the output temporal coherency strongly depends on the accuracy of the optical flow computation. Such accuracy cannot be guaranteed in several complex sequences such as mallard, drift-chicante or breakdance. Furthermore, the incorrect synthesis of optical flow may lead to several displeasing artifacts. This is reported in [13] with the sequence loulous; meanwhile, our method provides a very plausible result with that sequence.

Another advantage of our method is its speed. While it takes Huang et al. [13] approximately 3 hours to complete one video in this dataset using 2D patches, our method takes around 50 minutes.

3.2. Comparison with Newson et al. [1]

This experiment evaluates our performance in the context of the reconstruction of moving objects. We consider several videos in which moving objects cross a fixed or a moving occlusion for a long period. Such objects can be partly or even completely occluded (sequence jumping girl) and the background can be either static or dynamic.

Representative results are illustrated in figure 3. It is clearly seen from this figure that our result outperforms that of Newson et al. [1]. Figure 3 (a) and (b) show that Newson et al.’s method [1] cannot reconstruct the foreground object (e.g. the boat) within a long occlusion. Our method, on the other hand, has the ability to fully reconstruct the background and foreground in a consummate manner even though the object is completely occluded. Moreover, by integrating the confident map in the reconstruction step, our result has less artifacts in the border than the one in [1], as can be seen in figure 3 (c).

4. CONCLUSION

This paper presents a new video inpainting technique which shows great performance in terms of both output quality and computation time thanks to a thorough use of the optical flow, a modified patch-based energy which incorporates complex informations, a modified patch searching strategy using sparse grid and patch clustering, and finally a suitable code parallelization.
5. REFERENCES


