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A Fast Spatial Patch Blending Algorithm for Artefact Reduction in Pattern-based Image Inpainting

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Abstract

We propose a fast and generic spatial patch blending technique that can be embedded within any kind of pattern-based inpainting algorithm. This extends the works of [Daisy et al. 2013] on the visual enhancement of inpainting results. We optimize this blending algorithm so that the processing time is roughly divided by a factor ten, without any loss of perceived quality. Moreover, we provide a free and simple-to-use software to make this easily reproducible.


Keywords: inpainting, spatial, patch, blending, patch-based

1 Introduction

Filling unknown or removing undesired contents from images, known as image inpainting, is a widely used tool today. Movie producers for example, use it to remove microphones or scratches from new and older movie sequences. As this kind of reconstruction tool is employed by users that want their images to look more realistic, it must obviously not damage the perceptual and visual quality of the processed images. In the state of the art, there mainly exist two kinds of inpainting methods. Geometry-based methods [Masnou and Morel 1998; Bertalmio et al. 2000; Tschumperlé and Deriche 2005] provide techniques to propagate image structures by extrapolating the local geometry. Unfortunately, these methods are often unable to synthesize non-local structures like textures. On the contrary, in pattern-based methods [Criminisi et al. 2004; Le Meur et al. 2011], user-selected image areas are reconstructed by copying patches from the known image zones, to those unknown. These methods work well to reconstruct textures. Even with some variations, like averaging several patches [Le Meur et al. 2011], they generally do not provide good result in terms of global geometry consistency. Hybrid methods also exist [Sun et al. 2005], but there are always some cases where reconstruction let some artefacts appear. Recently, [Daisy et al. 2013] introduced a spatial patch blending technique to perceptually reduce these reconstruction artefacts, without any changes in the way geometry is inpainted. Unfortunately, this method cannot be used for production work due to computational burden and memory overload.

The paper addresses these two issues and is organized as follows. First, the principle of spatial patch blending is presented through a complete summary of the method. Then, we redesign the blending algorithm and show the various improvements it implies. Finally, we illustrate the relevance of our approach by commented results and comparisons with some state-of-the-art methods.

2 Patch Blending Context and Previous Work

In [Daisy et al. 2013] was proposed a method that allows reducing artefacts produced by any patch-based inpainting algorithm [Criminisi et al. 2004; Le Meur et al. 2011] in an image $I$. A result image $J$ is produced where possible inter-patch seams and inconsistencies are cleverly hidden, rendering the image perceptually more pleasant. In this method, it is proposed to modify the process of any patch-based inpainting algorithm so that it provides additional information. The latter is used to perform the two steps of our artefact reduction technique, namely: 1) the artefact detection 2) the spatial patch blending.

• Artefact Detection. This first step of this method is empirically based on the two following hypothesis. For a reconstructed image $I$ which reconstruction patch locations are stored in a map $\mathcal{U} : p \in I \mapsto q \in I$, it is hypothesized that: 1) there are sharp color or luminosity variations where artefacts are located, and 2) patches from remote locations seem probably different. The idea is first to combine the latter to estimate a set of points $\mathcal{E}$ where the strongest artefacts are located. Then, the map $\sigma : p \in I \mapsto \sigma(p) \in \mathbb{R}$ of blending amplitudes is computed, and gives to each point $p$ inside a mask $M$ a weight depending on its distance to the nearest artefact locations and strengths (cf. Fig. 2, and (3) of [Daisy et al. 2013]).
\[\psi(q,p) = \sum_{q \in \Psi_p} w(q,p) \psi(q,p) \]

The gaussian weight function \(w(p,q) = e^{-d(p,q)^2/2\sigma^2}\) defines the way patches are blended during the process. This function strongly depends on the distance function \(d\). In [Daisy et al. 2013], they have used the minimal distance from the point \(p\) to every point in the piece of pasted patch \(\psi_q\). As shown in Fig. 3, this method provides clearly good results in terms of artefact reduction regarding a classical patch-based inpainting result. On the other hand, the memory usage for storing the map \(\hat{I}\) is too important. Then, even if it is reasonable as compared to these of the inpainting process, the computation time does not allow this method to be used easily and interactively. The main reason is that as many distance maps as reconstruction patches have to be computed. This makes the computation time to be very dependant of the mask size used for the inpainting. In addition, the size of \(\mathcal{E}\) is a little bit overestimated by the artefact detection. In this pixel per pixel process, this causes the computation to increase noticeably. The weaknesses of [Daisy et al. 2013] have brought us to redesign some parts of their algorithm to make it faster while maintaining the good perceptual quality of the results. The contributions we propose through this paper are mainly based on the enhancement of the spatial patch blending algorithm in terms of time consumption, but also memory usage.

3 Enhanced Spatial Patch Blending

We propose here a spatial patch blending algorithm for pattern-based inpainting algorithms. Firstly, this method is described as it is, and then we discuss the different Enhancements in comparison with the method of [Daisy et al. 2013].

- **Spatial Patch Blending.** In classic patch-based inpainting methods, the reconstruction of an image is a kind of patchwork. Patches are iteratively extracted from the image, cut up, and the remaining pieces are pasted inside \(M\) to complete the given image. The main idea of the spatial patch blending is to point out the fact that parts of the individual patches are discarded during sequential compositing, but these parts contain valuable information that could have been used if a different insertion order had been used. In this method, the scrapped offcuts are kept and spatially blended in order to reduce seams between the pieces of patches pasted side by side. This method is defined as a pixelwise process, and for each point \(p \in M\), the set \(\Psi_p\) of patches overlapping at \(p\) is extracted. Then, a combination of all the pixels where all the patches \(\psi_q \in \Psi_p\) overlap is computed as follows:

\[J(p) = \sum_{q \in \Psi_p} w(q,p) \psi(q,p)\]

- **Spatial blending reformulation.** At first sight, the method we propose seems to be very different from [Daisy et al. 2013]. Rather than independently computing each final pixel \(J(p)\) by looking for every \(p \in M\), the set of local features that allows computing (1), we propagate each patch feature at once on the pasting neighbourhood\(s\) of \(p\). Loop on each point \(p\) is replaced by a loop on all patches \(\psi_q\) pasted in \(I\) during the inpainting. This second loop needs much less computing iterations (approximately \(n^2/2\) less where \(n \times n\) is the inpainting patch dimension). This loop factorization is theoretically possible only if the bandwidth \(\sigma(p)\) of the blending is considered as constant on the whole image. This obviously not the case. To do so, a multiscale approach is adopted. The loop on patches is repeated as many times as the number of different scales that can be considered in the values of \(\sigma\) (we have quantized these values into \(N\) scales). As \(N\) can be chosen small enough (typically about ten scales, smaller values would leads to some discontinuities in the blending), the looping repetition factor due to the multi-scale aspect of our algorithm remains much less important than the average gain of \(n^2/2\) at a specified scale. This makes the final algorithm very interesting in terms of complexity compared to the approach of [Daisy et al. 2013]. Algorithm 1 details the whole principle of our multi-scale spatial blending method.

One can notice that this method of blending acts like a post-processing of the image inpainting result, but requires to modify the considered patch-based inpainting algorithm, for the reconstruction patches locations and the reconstruction points to be stored.

- **Differences with the previous approach.** The differences of our method compared to the approach of [Daisy et al. 2013] are the following:

**Quantized spatial blending scales:** Our optimized algorithm considers a quantized version of the spatial blending amplitude map \(\sigma\). The set of the blending results \(J_s\) are computed for each scale \(\sigma_s \in [1,N] \subset \mathbb{N}\) and are then merged in a final image \(J\). This image contains pixels of \(J_1, J_2, \ldots, J_N\) depending on the local (quantized) scale defined in \(\tilde{\sigma}(p)\). The storage of all blending scales \(J_s\) can be easily avoided by transferring directly all the pixels computed at a scale \(s\) to the final image \(J\). In this case, the last loop of Algorithm 1 has to be done in the main scale loop (line 5).

**Modified weight function:** The spatial patch blending is locally performed as a linear combination of all the patches that would have overlapped with a different inpainting order. One can demonstrate that with this new algorithm, the weighting function \(w(p,q)\) of each patch (also used in (1)) depends only on the distance from a point to the neighbour reconstruction points rather than the distance from a point to a piece of pasted patch (as described in [Daisy et al. 2013]).
I pixels from to be modified by our spatial patch blending (by copying all known

formalism, one can constraint pixels from outside the mask not
take advantage of this special feature. To respect the classic inpaint-
constructed area. All the results presented in the following section
transition is created between the known colors and these of the re-

M

Mask-external spatial patch blending

that the difference between the results produced with the two weight
reformulated. From an experimental point of view, one can notice

tial blending version of the algorithm of [Daisy et al. 2013] can be

This is mainly thanks to this approximation that our optimized spa-
tial blending version of the algorithm of [Daisy et al. 2013] can be
reformulated. From an experimental point of view, one can notice
that the difference between the results produced with the two weight
functions are very difficult to see in the final blending results.

Mask-external spatial patch blending: In Algorithm 1, the spatial
blending is naturally extended to the outside of the inpainting mask
M. In terms of visual appeal, this is very interesting since a smooth
transition is created between the known colors and these of the re-
constructed area. All the results presented in the following section
take advantage of this special feature. To respect the classic inpaint-
ing formalism, one can constraint pixels from outside the mask not
to be modified by our spatial patch blending (by copying all known
pixels from I to the final image J at the end of the process).

Performance improvement: The gain performance of our approach as compared to [Daisy et al. 2013], and the comparison with
the state-of-the-art approaches of [Criminisi et al. 2004] (inpaint-
ing without spatial patch blending) and Photoshop (very fast, based
on [Wexler et al. 2007; Barnes et al. 2009]) is illustrated Fig. 5.
In order to show the efficiency of our new method, we have made
some experimentations. Fig. 5 summarizes the results on a set of
medium-sized image ¹, and mainly gives us three interesting infor-
mations. First, the gain of time between the approach of [Daisy
et al. 2013] and our method depends on the kind of processed im-
ages (mainly depending on the size of M), but is very significant
in each case (from 6 to 30 times faster for the presented examples).

Then, there is no meaningful difference of computation time be-
tween method in [Criminisi et al. 2004] and ours. This means that
there is no additional cost to process our spatial patch blending al-
gorithm after a classic patch-based inpainting. Also, one can see
that the content-aware filling algorithm [Wexler et al. 2007; Barnes
et al. 2009] provided in Photoshop is noticeably faster than our
method, but is most likely using material accelerations like GPU
processing or multi-core programming. This is not the case of our
method, provided with standard C++ implementation with no ac-
celeration.

4 Results and Reproducibility

Some results provided by our method are illustrated Fig. 6 and com-
pared to state-of-the-art methods. Spatial patch blending is clearly
demonstrated through our examples and our way of making it faster
allows now this method to be used interactively. In addition, a soft-
ware integration of our method has been made and the source code
is now available to the community, making our fast spatial patch
blending algorithm fully reproducible:

• The source code of our technique is available as a function named
• A dedicated filter has been added to the G’MIC plugin for the
open source GIMP² software, allowing non specialist people to use
it easily thanks to an enhanced graphical user interface.

References:


Algorithm 1: Fast spatial patch blending for inpainting algorithms.

| Input: | Inpainted image I, Inpainting mask M, Number of scales N. |
| Output: | Image J with spatially blended patches. |

1. Initialize $P = \text{Ordered list of original patch center locations (p, q)}$ pasted in $M$ during the inpainting;
2. Initialize $C = \text{Ordered list of patch pasting locations (x, y)}$ of during inpainting;
3. Initialize $\sigma = \text{Estimated local blending amplitude (section 2)}$;
4. Initialize $\bar{\sigma} = \text{Uniform quantization of} \sigma \text{in} N \text{ levels} (\sigma_1, \ldots, \sigma_N)$;
5. for $s \in [1, N] \subset N$, do
6. Initialize $J_s = \text{Result color image of the blending at scale s,}$ initialized to 0 for all pixels in $M$, and $I(p)$ elsewhere;
7. Initialize $A = \text{Scalar accumulation image of the size of} I$, initialized to 0 for all pixels in $M$, and 1 elsewhere;
8. Initialize $\bar{\sigma} = \text{Image of size} m \times m$, containing a centered Gaussian of variance $\sigma$;
9. for $k \in P$ do
10. Add the patch of size $m \times m$ of $I$ located at $P(k)$ to the image $J_s$ at $C(k)$;
11. Add the image $\bar{\sigma}$ of the gaussian weights in $A$ at $C(k)$;
12. Divide $J_s$ by $A$ (normalisation of the added colors).
13. for $p \in M$, do
14. $s = \sigma(p)$;
15. $I(p) = J_s(p)$;
16. // Combine all the blending scales
17. // in a result image.

Figure 4: Illustration of the difference between weights of [Daisy et al. 2013] (a), and those used in our fast spatial patch blending algorithm (b).

Figure 5: Illustration of execution time comparison between our method, method of [Daisy et al. 2013], with state-of-the-art methods. The less, the better.

(a) Weights used in [Daisy et al. 2013]. (b) Weights use in our new method.

2013.
Figure 6: Comparison with several state-of-the-art methods (zoomed).

References


