SYMMETRY-BASED COMPLETION

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Keywords: Image completion, Inpainting, Symmetry detection, Structural image processing.

Abstract: Acquired images often present missing, degraded or occluded parts. Inpainting techniques try to infer lacking information, usually from valid information nearby. This work introduces a new method to complete missing parts from an image using structural information of the image. Since natural and human-made objects present several symmetries, the image structure is described in terms of axial symmetries, and extrapolating the symmetries of the valid parts completes the missing ones. In particular, this allows inferring both the edges and the textures.

1 INTRODUCTION

Acquired images are generally incomplete, either due to the degradation of the media, like old paintings, pictures or films, due to occlusion of scene parts from undesired objects or due to channel losses in digital image transmission. To overcome those issues, inpainting techniques try to complete missing regions of an image. Since the ground truth is unknown in real applications, the inferred content must be consistent with the image as a whole.

This implies two steps in the inpainting pipeline: analysis and synthesis. The analysis step determines the characteristics of the image relevant to completion. The synthesis step then uses the gathered knowledge to extend the valid region. Local methods analyze the boundary of the invalid region and the synthesis is usually performed by diffusion-like processes to propagate the boundary's color. However, the diffusion step may blur the inpainted region, harming the texture coherency. Other methods segment the image in texture-coherent regions and synthesize a new texture to fill the hole, based on the closest match with the boundary texture. Although this solves the blur problem, it may not respect the global structure of the image. In particular, completing very curved shapes or big holes remains an issue.

In this work, we propose to exploit the global structure of the image for inpainting (see Figure 7). More precisely, we estimate the image's symmetries and complete the missing part by their valid symmetric match. Since symmetry is an important coherency criterion both for natural and human-made objects, its analysis reveals much of the relevant image structure. The present paper restricts to axial symmetries of the image's edges, and may be easily extended to entail more general transformations and features. However, nice results, including textures, can already be obtained with these restrictions. This research started as a project for the course "Reconstruction Methods" at IMPA in fall 2007.

2 RELATED WORK

Since this work applies symmetry detection to inpaint missing regions of an image, we'll first review previous method of image restoration followed by works on symmetry, both from computer vision and geometric modelling.

2.1 Image Restoration

Inpainting methods can be categorized according to the extent of the region the analysis and synthesis operations work on. Early approaches use local analysis to extend the valid image from a small neighborhood around the missing region. In particular, (Bertalmio et al., 2000) propagate image lines (isophotes) into the missing part using partial differential equations, interleaving propagation steps with anisotropic diffusion (Perona and Malik, 1990). This extends the smooth regions while still respecting image edges. (Petronetto, 2004) created an inpainting algorithm inspired by heat diffusion to improve propagation. These local methods work very well for small holes

Pereira T., Paes Leme R., Velho L. and Lewiner T.
SYMMETRY-BASED COMPLETION.
DOI: 10.5220/0001655900390045
In *Proceedings of the Fourth International Conference on Computer Graphics Theory and Applications (VISIGRAPP 2009)*, page
ISBN: 978-989-8111-67-8

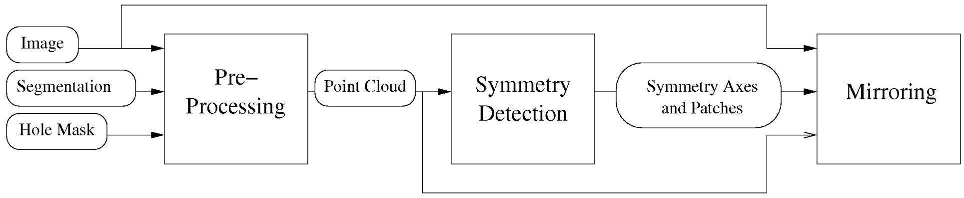


Figure 1: The input image is pre-processed to extract a sampling of the edges. The symmetry detection extracts the structure of this point cloud, and these symmetries are used for completing the missing parts by mirroring adequate valid parts.

but introduce blur when dealing with large regions, which harms the quality of results on regions with high frequencies and texture. Global analysis try to locate relevant regions in the entire image, or even in a large image database (Hays and Efros, 2007) to handle very large missing regions if similar objects are present in the database.

On the synthesis side, several approaches consider completion as a texture synthesis problem: instead of completing at a pixel level, these methods identify small regions of the hole to be filled first and search for a best match throughout the image. The matched region is copied and blended with the surroundings. In particular, (Efros and Freeman, 2001) create new textures by putting together small patches from the current image. (Drori et al., 2003) and (Criminisi et al., 2003) complete the holes by propagating texture and contours. These methods preserve local structure of the image, but may fail to propagate global structure of the image like bending curves. In this work, we propose a technique that identifies the object structure and boundaries and incorporate this information in the completion process. We argue that structure from object symmetry can be used for inpainting in more complex examples.

2.2 Symmetry Detection

Early works in symmetry detection deal with global and exact symmetries in point sets (Wolter et al., 1985) based on pattern-matching algorithms. This restricts their applicability to image processing since most symmetries found in nature or human-made are not exact or might be slightly corrupted by noise. (Zabrodsky et al., 1995) measures the symmetry of a shape by point-wise distance to the closest perfectly symmetric shape. The level of symmetry can also be measured by matching invariant shape descriptors, such as the histogram of the gradient directions (Sun, 1995), correlation of the Gaussian images (Sun and Sherrah, 1997) or spherical functions (Kazhdan et al., 2004). Such symmetry measures work well for detecting approximate symmetry, although they are designed for global symmetry detection.

Recently, (Loy and Eklundh, 2006) used the Hough Transform to identify partial symmetries, i.e., symmetries of just one part of the object. Such partial symmetries can also be obtained by partial matching of the local geometry (Gal and Cohen-Or, 2006). In particular, (Mitra et al., 2006) accumulates evidences of larger symmetries using a spatial clustering technique in the symmetry's space. The technique used in this paper is close to (Mitra et al., 2006). However, we focus on incomplete symmetries due to occlusion in images, and thus adapted their symmetry detection for 2D shapes.

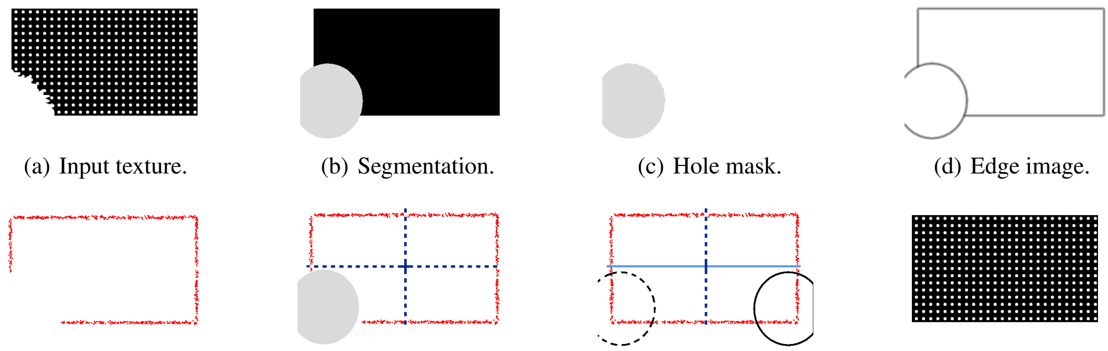
Symmetries have been used to complete shapes in different contexts. For example, (Thrun and Wegbreit, 2005) detects symmetries in 3D range image to complete based on a search in the symmetry space, and complete the whole model by a global reflection. (Zabrodsky et al., 1993) uses a symmetrization process to enhance global symmetry, even with occluded parts. (Mitra et al., 2007) achieves similar results for 3D shapes. However, these techniques do not handle partial symmetries or affect parts of a 2D image that are not missing.

3 METHOD

We start this section with a brief overview of the proposed method followed by the details of our process.

3.1 Overview

The proposed method is composed of two main steps: symmetry detection, corresponding to the image analysis, and mirroring for synthesis of lacking information. The interactions between these steps is schematized in Figure 1 and illustrated in Figure 2. The input image contains a user-defined mask around the invalid region. A simple pre-processing extracts from the image a structured sampling of its edges (see Figure 2(a)-(d)) from which the normal and curvature is computed. Then, the symmetry detection step identifies the many symmetry axes present in the object, as seen in 2(f). Finally, the completion step chooses the symmetry axis that best fits the missing region and mirrors the texture and edges of the valid parts into



(a) Input texture. (b) Segmentation. (c) Hole mask. (d) Edge image.

(e) Edge's points. (f) Axes and patches. (g) Mirroring. (h) Final image.

Figure 2: Illustration of the pipeline of Figure 1.

the hole (Figure 2(g)-(h)). These steps are detailed below.

3.2 Pre-processing: Object Extraction

Object identification is a well studied problem. Many algorithms have been proposed to segment images. While extremely relevant to our method, segmentation is not the focus of this work. As such, we assume receiving a segmented image as input. Symmetry extraction should ideally take into account the border as well as the interior of the image's objects. We use here only the border (edge) information for the sake of simplicity. Moreover, we represent those edges by points. Although it may lose some connectivity information, it permits a versatile representation and fits better for adapting geometric modeling techniques for symmetry detection. Therefore, we perform an edge detection on the input image through a difference of Gaussians implemented in the GIMP package (Mattis and Kimball, 2008), and remove the artificial edges generated from the user-defined hole mask. We then perform a stochastic sampling of the edges taking the gray values of the edge image as probability. This generates a point set representation of the edges. Finally, we compute the normal and the local curvature at each point of the point set.

3.3 Analysis: Symmetry Detection

We are interested in approximate and partial symmetries, since the image has incomplete information in the hidden regions and since the image content may present several inexact symmetries. Therefore, our approach is largely based on the method proposed by (Mitra et al., 2006). However, in this paper, we will restrict the space of symmetries to axial symmetries. Using the point set representation described above, valid partial symmetries should map a substantial subset of the points to another one. In its basic form, the symmetry detector stores for each pair of points their bisector as a candidate symmetry axis (see Figure 3). Then it returns the clusters of candidates with their associated matching regions. The clustering allows detecting approximate symmetries.

To improve robustness and efficiency of this basic scheme, we have enhanced this basic scheme as follows. On the one hand, we can observe that the sampling of the edges does not guarantee that a point p of the set is the exact symmetric of another sample point q. However, their normals should be mapped even with random sampling. Therefore, we define for each pair pq the candidate reflection axis T_{pq} as the line passing through the midpoint of pq and parallel to the bisector of the normals at p and q (see Figure 3). The normals are then symmetric by T_{pq}, although the points p, q may not be. On the other hand, reducing the number of candidate axes would accelerate the clustering. Notice that pairing points outputs $O(N^2)$ axes. Therefore, we only accept a pair p, q if their curvatures are similar ($0.5 < |K_1/K_2| < 2$), since the curvature is covariant with reflections. We also reject a candidate axis T_{pq} defined above if points p and the reflection of q are farther than 3.5% of the image's diagonal.

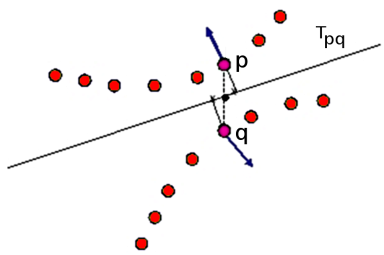
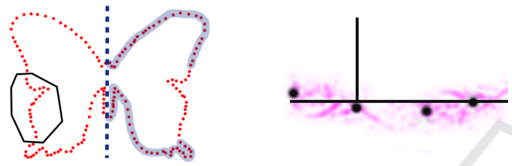


Figure 3: Symmetry axis robustly defined from normals.

The filtered candidate axes are then represented by their distance to the origin and their angle $\phi \in [0,\pi[$ with respect to the horizontal line (see Figure 4). Clustering is performed in this two-dimensional parameter space using Mean-Shift Clustering (Comaniciu and Meer, 2002), taking into account the inversion at $\phi = \pi$. Given a candidate axis T_{pq} at the center of a cluster, we define its matching region to be the set of point pairs invariant by reflection through T_{pq}. We compute it by propagating from the initial set $S = \{p,q\}$: a neighbor r of a point $s \in S$ is added if its reflection through T_{pq} is either close to some point of the object boundary or inside the hole mask. This last condition allows detecting incomplete symmetries, which are crucial for completion.



(a) Symmetry axis. (b) Axis density.

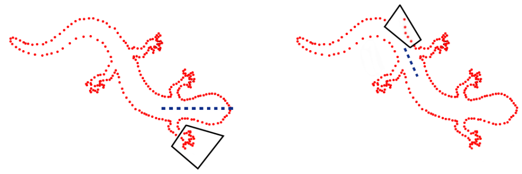
Figure 4: Clustering of candidate symmetry axis.

3.4 Synthesis: Texture Generation

The completion process first identifies from the object structure which of the detected symmetries to use, and then reflects the image's texture from visible regions into the occluded one. The ideal situation for our structural completion occurs when a single symmetry's matching region traverses the hole. In that case, the sampled points around the hole clearly define which visible region of the image is to be reflected. More precisely, the filled boundary must fit the known object boundary. In Figure 5(b) there was a discontinuity. We thus choose among all detected symmetries the one that best fits the created points with the known boundary.

However, in many real cases, in particular those with large missing parts, no mapping with a single symmetry axis would create a continuous object boundary (see Figure 5). To overcome this issue, we complete the boundary from the hole border inwards. To do so, we look for the symmetry that maps the most points while enforcing continuity in the neighborhood of the hole border (see Figure 9). This process repeats itself until either we arrive at a closed boundary or no symmetry axis satisfies the continuity requirement.

Once the axes have been defined and the valid structures have been mapped to the hole, we proceed to the image-based completion. For each pixel i of the hole, we look for the closest point p of the filled boundary. This point p has been reflected by a symmetry T which is used to find the symmetric pixel j of i. The color of j is simply copied into i. This approach is very simple and may be enhanced in future works by more advanced texture synthesis and insertion.



(a) Successful. (b) Failed.

Figure 5: A single axis achieves continuity on both sides of the hole.

4 RESULTS

In this section we first detail the implementation, followed by a description and analysis of the experiments.

4.1 Implementation Details

The method described at the previous section can be implemented with different algorithmic optimizations. During many steps of our algorithm, proximity queries were required. Therefore, we build a Delaunay triangulation at pre-processing in order to support k-nearest-neighbors queries. Among other already mentioned uses, these queries serve the normal and curvature approximations by a local second degree polynomial Monge form. In order to choose efficiently the best axis that maps a valid structure to the hole's edge, we build a proximity graph. The vertices of this graph are the valid structure points that are mirrored into the hole. A link between vertices is created when they have a common symmetry axis T and when their reflection by T are close-by. The longest path in that graph determines the best symmetry axis T.

4.2 Experiments

We experimented our technique in different contexts using images from public domains. Table 1 presents the execution times including the entire pipeline. The symmetry detection step accounts for 85% of total time. The butterfly image of Figure 7 has symmetric structures and background with the same axis. The eagle image of Figure 6 has symmetric structures for the main shape, but the background has a different symmetry. On the contrary, the turtle image of Figure

8 has a symmetric background but the animal's symmetry is artificial, although very coherent with the image. The lizard structure of Figure 5 was tested in two opposite configuration: perfect symmetric and lack of symmetry. Our method runs in quadratic time, but is very sensitive to the pruning step.

Table 1: Timings (seconds) on a 2.8 GHz Pentium D.

Model	#Points	#Symmetries	Timing
Butterfly	506	12	44
Eagle	765	9	83
Turtle	575	8	46
Lizard hand	271	10	87
Lizard body	294	10	122

4.3 Discussion

We achieve good results even by considering only axial symmetries and simply copying the image texture in the unknown region. When the symmetry structures traverses the holes, the completion of the foreground is neat (see Figure 7 and 8). The quality obtained in Figure 7(d) is a consequence of symmetry being present in the background also. Only in a detailed inspection, seams can be detected between the visible and the reconstructed region. These seams can only be noted in the texture, not in the background.

Our method completes images based on symmetries from the image's edges, and supposes that the object's texture is likely to follow the same transformation. However, this may not be the case. For example in Figure 6, the missing wing of the eagle was well reconstructed from the visible one, although the synthesized background differs in the tone of blue from the original one. Blending would solve this case.

Our method only works with images where symmetry is present. As most objects have symmetries, this is not a big restriction. In fact coherent results were found only when one symmetry axis dominated the hole. The completed objects above are all seen from well behaved view points. An object can be symmetric from a point of view while not being from others. One simple extension is to ask the user to mark four points defining the plane where the symmetry holds. We would then work on a transformed space where the symmetry axis is contained in the image plane. One advantage of the method is that the user knows before hand if it will work since he can usually see the symmetries himself.

5 CONCLUSIONS

In this work, we propose to incorporate global structural information of an image into inpainting techniques. In particular, we present a method for inpainting images that deals with large unknown regions by using symmetries of the picture to complete it. This scheme is fully automated requiring from user only the specification of the hole. The current technique restricts itself to the analysis of axial symmetries of the image's edges, focusing on structure rather than texture. On the one hand, the transformation space can be easily extended using the same framework, incorporating translations, rotations and eventually projective transformations at the cost of using a higher dimensional space of transformations. On the other hand, texture descriptors could be used to improve both the symmetry detection and the image synthesis (see Figure 10). Moreover, the insertion of the synthesized parts into the image can be improved by existing inpainting techniques. Another line of work, following (Hays and Efros, 2007), is to build a database of object boundaries. Completion would proceed by matching the visible part of the object with those in the database.

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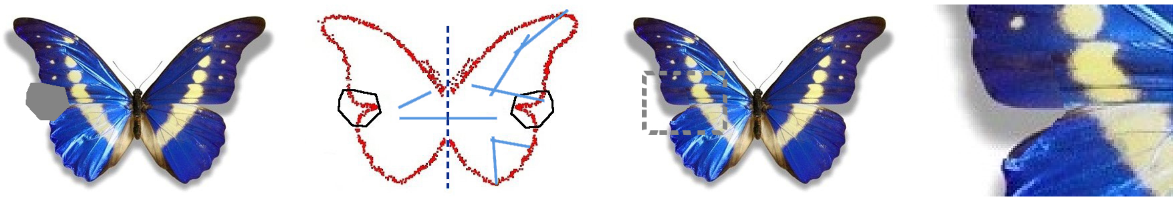
(a) Input image (b) Input image (c) Point cloud and Symmetries (d) Completed image

Figure 6: Eagle example: although the foreground is well completed, the background texture needs further or separate processing.



(a) Hole. (b) Axis. (c) Completed image. (d) Completion detail.

Figure 7: Completion of a butterfly image: the marked missing region 7(a), in gray, is identified in the global structure of the image through axial symmetries 7(b). It can be completed with texture from its symmetric part 7(c),7(d).

(a) Input image (b) Completed image (c) Ground truth

Figure 8: Turtle example: although the completion differs from the original model, it is very coherent.

(a) Input image (b) Half completed image (c) Ground truth

Figure 9: Fish example: a single axis may not ensure boundary coherency on both sides.

(a) Input image (b) Completed image (c) Ground truth

Figure 10: Flower example: texture elements are not yet considered in the analysis.