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# Combining anisotropic diffusion, transport equation and texture synthesis for inpainting textured images

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ABSTRACT

In this work we propose a new image inpainting technique that combines texture synthesis, anisotropic diffusion, transport equation and a new sampling mechanism designed to alleviate the computational burden of the inpainting process. Given an image to be inpainted, anisotropic diffusion is initially applied to generate a cartoon image. A block-based inpainting approach is then applied so that to combine the cartoon image and a measure based on transport equation that dictates the priority on which pixels are filled. A sampling region is then defined dynamically so as to hold the propagation of the edges towards image structures while avoiding unnecessary searches during the completion process. Finally, a cartoon-based metric is computed to measure likeness between target and candidate blocks. Experimental results and comparisons against existing techniques attest the good performance and flexibility of our technique when dealing with real and synthetic images.



## 1. Introduction

The problem of inpainting digital images has received great attention by the scientific community in the last decade, mainly due to the growth of important applications such as *image restoration* and *image editing*, which strongly rely on image inpainting to be effective. The basic idea of inpainting is to recover parts of an image that have been damaged or partially occluded by undesired objects. Techniques devoted to perform image inpainting can be organized in different ways. In this work we gather inpainting techniques in four main groups: *texture synthesis and exemplar-based methods*, *PDE (Partial Differential Equations) and variational modeling-based methods*, *techniques based on space transformation and sparse representation*, and *other methods and techniques that combine the previous approaches*. In the following we provide an overview of existing inpainting methods organized according to the proposed groups.

### 1.1. Texture synthesis and exemplar-based methods

*Texture synthesis algorithms* rely on the investigation of location and stationariness of texture patterns contained in the image (Efros and Leung, 1999; Efros and Freeman, 2001; Ashikhmin, 2001; Wei, 2002). The inpainting process is carried out by a pixel similarity-based copy-and-paste strategy. The core idea is to find out the group of pixels that best fits into the region to be filled and copy it to that location. This is done by measuring the similarity between group of pixels from the image and on the boundary of the region to be filled. Texture synthesis techniques are effective when the image is made up of a unique texture pattern, but they are prone to fail when multiple textures and homogeneous structures are present in the image simultaneously. The computational cost involved on texture synthesis-based algorithms is also an issue for practical applications.

Texture synthesis algorithms have been significatively improved by the so-called *exemplar/patch-based inpainting techniques*. This class of techniques applies the texture synthesis procedure to blocks of pixels, imposing a priority order for the filling process, as described in (Komodakis and Tziritas, 2007; Li and Zhao, 2011; Cao et al., 2011; Criminisi et al., 2004; Sun et al., 2005). The seminal work Criminisi et al. (2004) defines the filling order based on local image isophotes (lines of constant intensity). Given the inpainting domain $\Omega$ and the pixel $p \in \partial\Omega$ with higher priority, the algorithm performs a global search throughout the valid image extension $\Omega^c$ to select the most appropriate block of pixels (an exemplar) to fill the neighborhood of $p$. Improvements in Criminisi et al. (2004) have also been proposed such as (Cheng et al., 2005; Chen et al., 2007; Cai et al., 2008). Although techniques based on exemplar replication usually produce good results, they tend to lead to significant loss of visual congruence while still

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performing a global search that is computationally costly and prone to produce non-realistic results, as pixels far from the inpainting area are also considered in the process.

### 1.2. PDE-based inpainting methods

Unlike the approaches based on texture synthesis, *PDE-based methods* are effective when dealing with non-textured images, also presenting a less prohibitive computational cost. The use of PDE in the context of image inpainting was introduced by Bertalmío et al. (2000), proposing a third-order differential equation that simulates the manual inpainting process accomplished by professional restorators. The method transports information through image isophotes while applying an anisotropic diffusion filter to correct the evolution of the inpainting direction. In the spirit of Bertalmío et al. (2000), Shen and Chan (2002) derive a diffusive PDE using the total variation minimization principle. In order to tackle the issue related to the *Connectivity Principle* (Kanizsa, 1979) (this principle claims that broken lines tend to be connected in an unconscious way by the human mind) an improvement of Shen and Chan (2002) has been proposed in (Chan and Shen, 2001), where the authors make use of mean curvature flow to modify the conductivity coefficient of the governing PDE. Other variational/PDE-based approaches have also been proposed, as for example the method described in Tschumperlé and Deriche (2005), which produces good results when applied to small inpainting regions but that is very sensitive to the choice of parameters. Bornemann and März (2007) propose an effective and fast technique that combines a non-iterative transport equation and a fast marching algorithm, demanding however, the tuning of a large number of parameters. Burger et al. (2009) present a subgradient TV-based approach that leads to good image recovery, but its use is limited to grayscale images. Wen-Ze and Zhi-Hui (2008) present an interesting PDE that preserves quite well edges when restoring non-textured images. A common drawback of PDE-based methods is the smoothing effect introduced in the filled region. Moreover, those methods are more effective when inpainting small regions.

### 1.3. Methods based on sparse representations

Recently, the so-called sparse representation-based methods have been introduced with great acceptance in the context of image inpainting. This group of techniques does not operate in the cartesian image domain, but in transformed domains such as those obtained by DCT (*Discrete Cosine Transform*), *wavelets* (Mallat, 2008), *curvelets* (Candes et al., 2006) and *wave atoms* (Demanet and Ying, 2007). Sparse representation-based methods rely on the assumption that it is possible to represent an image by a sparse combination of a particular set of transforms in which unfilled pixels are hierarchically ordered and predicted by handling these transforms. The seminal work by Guleryuz (2006) adaptively estimates the missing data while updating the corresponding sparse representation of the image through DCT or wavelet transform. In Elad et al. (2005) the reconstruction task is performed by employing a decomposition scheme that splits the given image in two layered-images called cartoon and texture components. The inpainting is then performed in both layers by using a sparse representation technique. Sparse representation was also used in Xu and Sun (2010) to propagate patches according to sparse linear combination of candidate patches. Inpainting based on sparsity analysis can also be achieved under the perspective of statistical Bayesian modeling. Fadili et al. (2009) accomplish the inpainting by solving a missing data estimation problem based on a Bayesian approach combined with an EM (*Expectation Maximization*) algorithm. A Bayesian model that uses simultaneously local and nonlocal sparse representations was proposed in Li (2011), where a DA (*Deterministic Annealing*) optimization scheme is employed to reduce the computational burden. From a practical point of view, although methods based on sparse decomposition produce pleasant results (specially for missing block completion), they tend to introduce blurring effects when restoring large and non-regular regions. Moreover, computational cost is also a hurdle for those methods.

### 1.4. Hybrid and other methods

Aiming at preserving relevant structures of the image, hybrid approaches intend to exploit the properties of each of the three previous inpainting methodologies. One interesting example is the association between texture replication, PDE and variational models (Komodakis and Tziritas, 2007; Cao et al., 2011; Bugeau and Bertalmío, 2009; Bertalmío et al., 2003; Grossauer, 2004; Aujol et al., 2010; Bugeau et al., 2010). In Bertalmío et al. (2003), for example, the goal is to split a given image $f$ into two components: the cartoon $u$ and texture $v$, processing each component independently. The components $u$ and $v$ hold geometric structures and texture patterns of $f$ respectively. The decomposition must, a priori, satisfy the relation

$$f = u + v, \tag{1}$$

according to the cartoon/texture theoretical decomposition model (Meyer, 2002), which was enhanced in Vese and Osher (2003, 2006) and later employed, with a numerical scheme, to ensure Eq. (1). After the decomposition, the inpainting method (Bertalmío et al., 2000) and the texture synthesis algorithm (Efros and Leung, 1999) are applied to $u$ and $v$, respectively. Both outcomes are then combined using Eq. (1) so as to generate the final result. The computational cost of processing both processings is high, mainly when the gap to be recovered is large, and satisfactory results are not always guaranteed. In Aujol et al. (2010), the authors propose a formulation based on continuous variational models in an effort to adapt exemplar-based algorithms that deal with local geometric features while still reconstructing textures.

There are also methods that exploit the inpainting problem through global energy minimization (Wexler et al., 2007; Kawai et al., 2009; Komodakis and Tziritas, 2007; Liu and Caselles, 2013). Wexler et al. (2007) formulate the reconstruction procedure as an optimization problem which employs a combination of dynamic space–time and tree structures. Kawai et al. (2009) rely on modifications of the energy functional proposed in Wexler et al. (2007) improving the spatial localization of the similarity weights and brightness invariance. Komodakis and Tziritas (2007) employ variations of the sum-product algorithm (*loopy belief propagation*) for graphs with cycles associated to "priority-based message scheduling" during the filling process. Liu and Caselles (2013) reformulate the exemplar-based model described in Demanet et al. (2003) as a global optimization problem encoding texture and structure information where the minimizer is obtained by efficiently solving a graph partitioning problem.

Other interesting inpainting methods have been successfully proposed in the literature. Hays and Efros (2007) and Li et al. (2010) have used a huge image database created from the web to find out the best set of images that approximates to the damaged image. This set is then used to perform color, texture and matching-based operations inside the inpainting domain.

### 1.5. Contributions

Encouraged by the ideas presented in (Criminisi et al., 2004; Bertalmío et al., 2000; Bertalmío et al., 2003; Calvetti et al., 2006) while simultaneously dealing with the adverse effects raised above, we propose a new inpainting method that combines: