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Edge-preserving color image denoising through tensor voting ☆

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ABSTRACT

This paper presents a new method for edge-preserving color image denoising based on the tensor voting framework, a robust perceptual grouping technique used to extract salient information from noisy data. The tensor voting framework is adapted to encode color information through tensors in order to propagate them in a neighborhood by using a specific voting process. This voting process is specifically designed for edge-preserving color image denoising by taking into account perceptual color differences, region uniformity and edginess according to a set of intuitive perceptual criteria. Perceptual color differences are estimated by means of an optimized version of the CIEDE2000 formula, while uniformity and edginess are estimated by means of saliency maps obtained from the tensor voting process. Measurements of removed noise, edge preservation and undesirable introduced artifacts, additionally to visual inspection, show that the proposed method has a better performance than the state-of-the-art image denoising algorithms for images contaminated with CCD camera noise.

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1. Introduction

Color image denoising is an important task in computer vision and image processing, as images acquired through color image sensors are usually contaminated by noise. Color image denoising algorithms can be directly used for image restoration and other higher-level tasks as a pre-processing step. The main goal of color image denoising is to suppress noise from color images while preserving their features, such as meaningful edges or texture details, as much as possible. A color image denoising algorithm is called *edge-preserving* when it is able to accomplish this goal. Liu et al. [1] have identified the following general features that an effective, edge-preserving color image denoising algorithm must fulfill: noise must be completely removed from flat regions; edges, texture details and global contrast must be preserved; and no artifacts must appear in the result.

Designing effective, edge-preserving color image denoising algorithms is a difficult task that can be evidenced by the fact that the majority of denoising algorithms introduce undesirable blurring and/or artifacts in the filtered images. The main reason for this difficulty is that, without any other assumptions, no color image denoising algorithm can utterly comply with all the aforementioned features listed in [1]. This is mainly due to two reasons: the complete reconstruction of the original image from one contaminated by noise is not possible in general, and some of those features are nearly contradictory. For example, distinguishing between noise and texture is an open problem.

Two main approaches have been followed in color image denoising: spatial domain and transform-domain filtering. The first approach filters the input image by using the color information of every pixel and its neighbors. The major problem of these filters is their tendency to blur the images. The second approach transforms the input image to a different space, typically to the wavelet domain, filters the transformed image and applies the inverse transformation to the result. Despite its good edge preservation properties, the major criticism to transform-based denoising algorithms is the introduction of undesirable artifacts. Section 2 presents a brief review of both approaches.

In the last years, effective approaches based on perceptual grouping have been proposed in the image processing field, such as image segmentation and edge detection (e.g. [2–4]). Perceptual grouping is defined as the ability of the human visual system both to extract significant relations from input data without any previous knowledge of the content and to group these data into meaningful higher level structures, even in presence of missing or noisy data ([5,6]). Among the techniques based on perceptual grouping, the tensor voting framework (TVF) appears to be one of the most

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appropriate for edge-preserving color image denoising, since it was designed as a generic framework that can be adapted to a variety of applications well beyond the ones which it was originally applied to. The TVF was proposed more than a decade ago by Guy and Medioni ([2,7]) as a robust technique inspired in perceptual grouping for extracting salient information from noisy spatial data. Their approach is able to recover the shape of surfaces, edges and junctions present in a set of points in N-dimensional Euclidean spaces, in particular, in 2D and 3D. This method has also been found appropriate for extracting salient information in other contexts, such as for epipolar geometry estimation [8], denoising of random dot patterns [9], and video analysis (e.g., [10,11]). Recently, we have proposed an efficient scheme for reducing the complexity of tensor voting to O(1) [12].

The performance of the TVF strongly depends on two critical processes: the proper definition of the information encoding process and the voting process. On the one hand, in [7], tensors encode the most likely directions of surface normals at every given 2D or 3D point. This allows the method to solve the surface reconstruction problem, that is, to extract surfaces, edges and junctions from a set of noisy points. However, when the aim is to extract information not related to surfaces, edges or junctions, the input information must be either modeled in terms of the surface reconstruction problem or encoded into tensors through a different encoding process. This second alternative is likely to be more advantageous as the new encoding process can be specifically tailored to the problem requirements. On the other hand, the canonical voting fields proposed in [7] to propagate the encoded information were designed to estimate surface likeliness based on the hypothesis that normal vectors tend to have smooth changes on surfaces. These voting fields designed for surface reconstruction should not be directly used for other applications before assessing whether they are appropriate or not, since the assumptions on which they are based may no longer be valid in a context not related to surface reconstruction. This is the case of image denoising where, even in ideal conditions (i.e., without noise), color can change abruptly. This suggests that the use of the canonical voting fields may not be the best option in this scope.

This paper proposes a new solution to the problem of edge-preserving color image denoising based on an adaptation of the TVF in order to properly handle color information. First, an encoding process specifically designed to encode color, uniformity and *edginess* into tensors is presented. Second, a voting process specifically tailored to the edge-preserving color image denoising problem is also introduced. This voting process is based on the nature of the encoded information and on a set of criteria inspired by the perceptual process of image denoising.

This paper is organized as follows. Section 2 describes previous related work. Section 3 presents the criteria taken into account in the design of the algorithm proposed in this paper. Sections 4 and 5 detail the adaptation of the TVF to edge-preserving color image denoising. Section 7 shows a comparative analysis of the proposed method against some of the state-of-the-art, edge-preserving, color image denoising algorithms by using the quality metrics described in Section 6. Finally, Section 8 discusses the obtained results and makes some final remarks.

2. Previous related work

As mentioned above, two main color image denoising approaches have been followed: spatial domain filtering and transform-domain filtering. Classical filters, such as mean, median or Gaussian filters [13], bilateral filtering [14], nonlocal means [15], anisotropic diffusion [16] and Bayesian inference [17], among many others, follow the spatial domain filtering approach. Classical filters are simple, efficient and easy to implement. However, they frequently blur the filtered images and/or eliminate important details. The bilateral filter extends the concept of Gaussian filtering by adding a Gaussian weighting function that depends on the difference between pixel intensities. This filter is also efficient and easy to implement. However, it is unable to filter very noisy images. Non-local means (NLM) extends bilateral filtering by taking into account differences between pixel neighborhoods instead of pixel intensities. NLM is effective for image denoising and it is considered to belong to the state-of-the-art. However, it tends to generate undesirable quantization effects in edgeless regions. Filters based on anisotropic diffusion give more weight to neighbors located in the directions where edges are not present. Anisotropic diffusion usually models the filtering problem by means of partial differential equations (PDEs) (e.g. [16,18]), although the use of graph theory has also been proposed [19]. Anisotropic diffusion has been a successful approach, with many methods based on it belonging to the state-of-the-art (e.g., [19,18]). Techniques based on anisotropic diffusion are able to suppress noise effectively. However, they also tend to create artifacts at edges and have problems with very noisy images. Bayesian-based approaches are usually highly time consuming and face similar problems to anisotropic diffusion (e.g., [17,20]). A different successful strategy that follows the spatial domain filtering approach uses conditional random fields to detect and remove noise [1]. However, its main drawback is that it is highly time consuming. A different spatial domain approach applies evolutionary computation [21]. However, its scope of use is limited, since it requires a training stage.

The most popular technique within the transform-domain filtering approach is based on wavelets [22]. Basically, small coefficients of the wavelet transform of the input image are removed before applying the inverse transformation, since they are usually due to noise. Many adaptations of this principle have been proposed in the literature. For example, Gaussian scale mixtures [23], hidden Markov models [24] or optimal color space projection [25]. In spite of their good edge preservation properties—some of these methods are considered to belong to the state-of-the-art—the major criticism to wavelet-based denoising algorithms is the introduction of undesirable artifacts in the images. Other approaches that filter images in a transform-domain include Wiener filters [13], low pass filters using the Fast Fourier Transform [13] or methods based on *blind image separation*, which tries to separate two original signals (noise and signal in image denoising) from their addition (e.g., [26]). However, these approaches have been outperformed by other strategies. More recently, Yu et al. [27] intended to take advantage of both transform-domain and spatial domain approaches for image denoising. However, they found that their method, which is based on wavelet-based filtering and the bilateral filter, is not satisfactory to deal with real noise.

Perceptual grouping has previously been applied to color image denoising, especially in the spatial domain. For example, Ben-Shahar and Zucker [28] detect and remove color noise by using the perceptual grouping principle of good continuation [29], in taking advantage of the fact that color hue changes smoothly in most natural images. The TVF, which is also based on perceptual grouping (by using the principles of good continuation, proximity and similarity), has also been used for denoising. The application of the TVF to image processing is further discussed below in this section.

Previous studies have applied the TVF to color information mainly following two strategies. A first strategy applies the TVF to the color components directly. For example, in [30], color images are segmented by encoding the position and RGB color of every pixel into tensors of five dimensions before applying the TVF. Although this strategy uses all the color information available in the input image, it has shown limitations on noisy images. A second strategy converts color information to a simplified representation before applying the TVF. In this direction, Massad et al. [31]

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