Expert Systems With Applications 91 (2018) 223–234

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

An interpolation-based texture and pattern preserving algorithm for inpainting color images

Efsun Karaca*, M. Alper Tunga

Department of Software Engineering, Faculty of Engineering and Natural Sciences, Bahcesehir University, Istanbul, Turkey

A R T I C L E   I N F O

Article history:
Received 11 June 2017
Revised 14 August 2017
Accepted 4 September 2017
Available online 6 September 2017

Keywords:
Digital image inpainting
Texture and pattern preserving inpainting
High dimensional model representation method
Lagrange interpolation

A B S T R A C T

Image inpainting can be defined as the process of filling missing regions in a given image with appropriate intensities. Intensity values of pixels in a missing area are expected to be associated with the pixels in the surrounding area. Interpolation-based methods that can solve the problem with a high accuracy may become inefficient when the dimension of the data increases. Also, they suffer from finding the underlying texture and pattern in the missing region. In this study, we propose a texture and pattern preserving interpolation-based algorithm for inpainting missing regions in color images. First, the proposed approach produces candidate inpainting results by interpolating to the observed data at the different neighborhoods of the missing region using High Dimensional Model Representation with Lagrange interpolation. Later, a final inpainting decision is given among the candidates for each pixel in the missing region for a texture and pattern preserving inpainting. This is achieved by combining the information obtained from co-occurrence matrix and from a patch found in the image that fits best to the missing region. We evaluate the performance of the proposed approach on various color images that include different texture and pattern. We also compare the proposed approach with the state-of-the-art inpainting methods in the literature. Experimental results demonstrate the potential of the proposed approach.

© 2017 Elsevier Ltd. All rights reserved.

1. Introduction

Image inpainting techniques have been applied to many problems such as repairing damaged photos (Zhu, Wang, Jin, Wu, & Zhou, 2006), removing an object from a given image(Criminisi, Pérez, & Toyama, 2004), completing missing regions (Bertalmio, Sapiro, Caselles, & Ballester, 2000), solving red eye problems (Yoo & Park, 2009), image denoising (Eksioglu, 2014; Wang, Yang, & Fu, 2010) and image deblurring (Chan, Yip, & Park, 2005).

There are many works proposed in the literature for image inpainting. One of the pioneering image inpainting methods, Total Variation (TV), was proposed by Shen and Chan (2002). TV is a partial differential equation based inpainting method that optimizes an energy function designed for maintaining the intensity distribution of the surrounding area. Then, Zhang, Burger, Bresson, and Osher (2010) proposed a method called Non-Local Total Variation (NLTV). NLTV extends TV by adding a term to the energy function that considers nonlocal constraints for inpainting. Both TV and NLTV produces good inpainting results in only smooth regions. However, as the region to be inpainted includes complex pattern and texture, the obtained results get blurry and worsens. Exemplar-based image inpainting techniques are proposed for inpainting larger missing regions that include texture and pattern. These methods find the most probable patch within the image for inpainting the missing region. Finally, the patch is returned as an inpainting solution. These methods suffer if illumination varies in different parts of the image (Criminisi et al., 2004). Takeda, Farsiu, and Milanfar (2007) adapted and expanded kernel regression for different applications in image processing such as image denoising, upscaling, and interpolation. Although, the method produces promising inpainting results in missing regions with smooth intensities, the performance of the method in textural missing region are rather limited. Hybrid Sparse Representation (HSR) method uses the strengths of local and nonlocal sparse representations by Bayesian model averaging where the usage of local smoothness and nonlocal similarity have allowed exploitation of sparsity priors for image recovery applications (Li, 2011). Beta-Bernoulli Process Factor Analysis (BPFA) model uses several hierarchical Bayesian models to learn dictionaries for analysis of imagery with applications in inpainting (Zhou et al., 2012). The method requires a large training set for an effective learning which may not be available or expensive to obtain in many applications. Spatially Adaptive Iterative

* Corresponding author.
E-mail addresses: efsun.karaca@eng.bau.edu.tr (E. Karaca), alper.tunga@eng.bau.edu.tr (M.A. Tunga).

http://dx.doi.org/10.1016/j.eswa.2017.09.001
0957-4174/© 2017 Elsevier Ltd. All rights reserved.

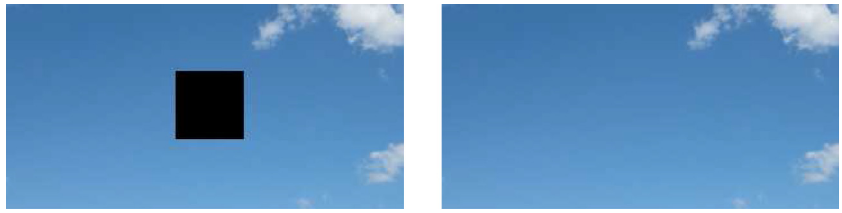

Fig. 1. An example that shows interpolation works well for inpainting smooth regions. (a) The input image with a missing region (shown with black pixels), (b) inpainting result obtained using interpolation.

Singular-value Thresholding (SAIST) is an image restoration algorithm which connects low-rank methods with simultaneous sparse coding and provides a conceptually simple interpretation from a bilateral variance estimation perspective (Dong, Shi, & Li, 2013). Both BFPA and SAIST suffer from two problems: 1) they have to solve a large-scale optimization problem with high computational complexity in dictionary learning, 2) each patch is considered independently in dictionary learning and sparse coding, which ignores the relationship among patches, resulting in inaccurate sparse coding coefficients. Group-based Sparse Representation (GSR) deals with these problems by introducing the concept of group as the basic unit of sparse representation to capture the patch relations and to reduce the computational complexity (Zhang, Zhao, & Gao, 2014). Deep learning have become very popular in many machine learning applications due to its capability of learning very complex models. There have been a limited number of deep learning-based methods used for image inpainting; they produce impressive inpainting results in various applications. Some of these methods can be found in Pathak, Krahenbuhl, Donahue, Darrell, and Efros (2016), Yeh, Chen, Lim, Hasegawa-Johnson, and Do (2016), Xie, Xu, and Chen (2012), Fawzi, Samulowitz, Turaga, and Frossard (2016) and Köhler, Schuler, Schölkopf, and Harmeling (2014). Although the powerful nature of deep learning-based methods, they require a large training set for training and an exhaustive annotation process. These shortcomings of deep learning-based methods retain the importance of developing methods that requires low or no training. Karaca and Tunga (2016a) proposes an interpolation-based image inpainting approach using Lagrange interpolation. The proposed method works well if the missing region is part of a smooth background. As in the other interpolation-based algorithms (Ballester, Bertalmio, Caselles, Sapiro, & Verdera, 2001; Karaca & Tunga, 2016b), the method proposed by Karaca and Tunga (2016a) is not able to capture and preserve underlying pattern and texture in the region to be inpainted.

In this study, we propose a texture and pattern preserving interpolation-based algorithm for inpainting missing regions in color images.

1.1. Motivation

Interpolation-based methods can produce inpainting results with high accuracy if a part of a smooth region is missing as shown in Fig. 1. However, in many cases, the underlying structure of the missing region can contain complicated texture and pattern. Such structures cannot be captured by interpolating to whole surrounding pixels of the missing region. If we have prior knowledge about the direction of texture and pattern in the missing region, interpolating to the observed neighboring pixels in only that direction can help to retain the underlying structure.

We illustrate the aforementioned difficulty of using interpolation for texture and pattern preserving inpainting in Fig. 2. Let us consider the part of a zebra body shown in Fig. 2a where a small region (shown by green) on the vertical black pattern of the zebra body is missing. If we perform Lagrange interpolation only using the pixels on the left and the right parts of the missing region, we lose the vertical black texture in zebra after inpainting (see Fig. 2b). However, if we use the pixels on the upper and the lower parts of the missing region for interpolation, the interpolation can complete the missing region quite well as shown in Fig. 2d. Inpainting results using the neighboring observed pixels on the upper-right and the lower-left, and on the upper-left and the lower-right of the missing region are also shown in Fig. 2c and e, respectively.

Performing interpolation using the observed pixels in the direction of the underlying structure is not trivial, since we do not know the direction of the texture and the pattern in advance. The problem becomes even more complex than the example in Fig. 2 when the underlying structure of the missing region consists of more complicated patterns (e.g., different textures and patterns in different directions) as in many natural images. This motivates us to exploit interpolation results obtained from different directions to develop an interpolation-based texture and pattern preserving algorithm for image inpainting.

1.2. Contributions

In this study, we propose an interpolation-based image inpainting algorithm that preserves the underlying texture and pattern in missing regions. To the best of our knowledge, this is the first texture and pattern preserving interpolation-based image inpainting algorithm which uses High Dimensional Model Representation (HMDR) method. HDMR has been used in many applications to perform an efficient interpolation (Gomez, Yücel, Hernandez-Garcia, Taylor, & Michielssen, 2015; Kasap & Tunga, 2017; Kaya, Kaya, & Bruzzone, 2017; Yücel, Bağcı, & Michielssen, 2015). The proposed approach performs interpolation by using the observed data at different directions of the missing region and generates candidate inpainting results for each direction. Then, the algorithm selects the best intensities for each pixel of the missing region among the candidate inpainting results such that the underlying texture and pattern are preserved. The inpainting result of our approach on the image in Fig. 2a is shown in Fig. 2f.

2. Proposed method

In this section, we introduce our interpolation-based texture and pattern preserving approach for inpainting color images. The overall algorithm is given in Algorithm 1. The algorithm consists of two major parts:

1) generating candidate inpainting results using HDMR with Lagrange interpolation (between lines 1–4 in Algorithm 1),

2) giving an inpainting decision among the candidates for each missing pixel by preserving the underlying texture and pattern (between lines 5–36 in Algorithm 1).

In the following two subsections, we explain these major parts of the proposed approach in details. Also, in the last subsection, we

Download English Version:

https://daneshyari.com/en/article/4942929

Download Persian Version:

https://daneshyari.com/article/4942929

Daneshyari.com