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# Sparsity-based inverse halftoning via semi-coupled multi-dictionary learning and structural clustering

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ABSTRACT

Inverse halftoning is the restoration of a continuous-tone image from its halftone version, which is a critical process for halftone transform, digital archive management and high precision identification of halftone. In this paper, a novel inverse halftoning method based on semi-coupled multi-dictionary learning is proposed to address the cross-style image restoration from halftone images to continuous-tone images. By using semi-coupled multi-dictionary learning, multiple dictionary pairs and their corresponding mapping functions between continuous-tone image and its halftone version could be simultaneously learned. The learned multiple dictionary pairs can well represent the structure characteristics of halftone images and continuous-tone images, respectively. In addition, the mapping functions learned by semi-coupled manner can bridge the gap between the two different style images of halftone image and continuous-tone image. Unlike the existed methods, the proposed method could effectively relax the assumption of the same sparse coding coefficients in coupled dictionary learning. To obtain more accurate mapping functions, a structural clustering method for cross-style image patches is proposed by using SUSAN (smallest univalue segment assimilating nucleus) filtering and HOG (histogram of oriented gradient) features, which can capture the similar structure features from halftone images and continuous-tone images, and thus improve the classification accurate rate of halftone image patches. The experimental results demonstrate that the proposed method can restore higher quality continuous-tone images than that produced by the state-of-the-art methods, which not only reduce the screen noise in smooth regions, but also provide well fine details and clear edges.

## 1. Introduction

Binary digital halftoning (Ulichney, 1986) is a technique of converting a continuous-tone image with n-bit discrete gray levels into a 1-bit binary image. Fig. 1(b) gives a halftone image generated from Fig. 1(a), in which the enlarged area shows the distribution of black dots and white dots. Due to the low-pass filtering nature of the human visual system (HVS), halftone images can resemble original grayscale images when viewed from a distance. Now, halftoning technique has been widely used in bi-level output and display devices such as printers, fax machines, and even in plasma panels TVs (Neuhoff and Pappas, 1994). According to the methods of assigning the black and white dots in halftone images from continuous-tone images, halftoning methods can be classified into ordered dither (Ulichney, 1987; Bayer, 1973), error diffusion (Floyd, 1976; Jarvis, 1976), dot diffusion (Ulichney, 1988; Knuth, 1987; Mitsa and Parker, 1991), iterative processing (Agar and Allebach, 2005) and look-up table (LUT) (Mege and Vaidyanathan, 2000).

Inverse halftoning is an inverse process of halftoning, which can restore a continuous-tone image with 256 or more levels from its 1-bit halftone image. Since any halftoning transform can cause a considerable amount of information loses and visible distortions, the common image processing approaches, such as rotation, resizing, sharpening or feature extraction, etc., cannot directly be used in halftone images. In addition, halftone images appeared in newspapers, magazines, books, or high value documents are often copied by photographing or scanning for further applications, these copied images with screen noises and Moir artifacts need to be restored to clear and high quality continuous-tone images. Thus, how to realize inverse halftoning is a promising but challenging research area.

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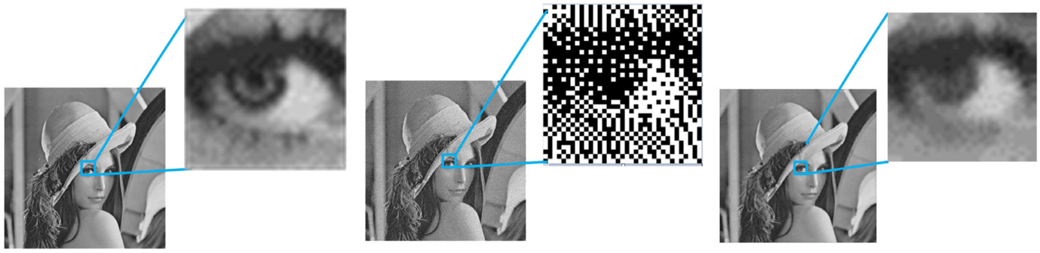

(a) (b) (c)

**Fig. 1.** An illustration of halftone image: (a) original image (b) halftone image (c) restored image from (b).

As the halftoning process is a many-to-one map, inverse halftoning can be considered as an inverse problem with one-to-many relationship which has no unique solution. Over the last several decades, several inverse halftoning methods have been proposed since 1990s. The presented inverse halftoning methods usually include filtering (Kite et al., 2000; Chang et al., 2001; Kim and Arce, 1994; Kim et al., 1995; Luo et al., 1998; Xiong et al., 1999; Ong et al., 2017), deconvolution (Neelamani et al., 2000b, a; Easley et al., 2009; Foi et al., 2004; Son and Choo, 2013), optimization estimation (Wong, 1995; Zheng et al., 2005; Stevenson, 1997; Liu et al., 2011),vector quantization (Ting and Riskin, 1994; Lai and Yen, 1998) and machine learning (Mese and Vaidyanathan, 2001; Pelcastre et al., 2017; Huang et al., 2008; Son and Choo, 2014; Zhang et al., 2016). In view of halftoning technique relying on the viewers inability to resolve the fine details of a binary image, low-pass filtering is a simplest inverse halftoning method to restore continuous-tone images, such as Gaussian filtering, Butterworth filtering, or median filtering, etc. The low-pass filtering is simple to implement, nevertheless seldom yields satisfactory results. In order to obtain a sharp image with a low perceived noise level, adaptive filtering (Kite et al., 2000), linear or non-linear filtering (Freitas et al., 2011; Kim and Arce, 1994; Kim et al., 1995) and transform-domain filtering (Luo et al., 1998; Xiong et al., 1999) algorithms have been introduced. Kite et al. (2000) designed a multiscale gradient estimator for the horizontal and vertical directions at each pixel, and constructed a family of FIR filters by using the gradient estimate maximum output for suppressing small-scale screening noise in smooth areas. Ong et al. (2017) proposed to use edge information to classify halftone image blocks and the LS (least squares) to further improve quality of inverse halftoned images. Inverse halftoning can be formulated as a deconvolution problem under Kite et al.'s linear approximation model (Kite et al., 1997) for error diffusion halftoning. Under the linear model, the Wavelet-based deconvolution algorithm (Neelamani et al., 2000a) was proposed for denoising the residual colored noise of halftone images. Stevenson (1997) introduced a nonlinear iteration restoration technique into inverse halftoning. The maximum a posteriori (MAP) estimate criteria using a Markov random field (MRF) model for the prior image distribution was developed to reconstruct both the smooth regions of the image and the discontinuities along image edges. Another fast and efficient inverse halftoning method was explored to restore digital halftone image based on look-up table (LUT). In this method, the LUT was created by training continuous-tone images and corresponding halftone versions, which represents the particular relation between local patterns with ordering 0 or 1 and their gray level values (Mese and Vaidyanathan, 2001). Pelcastre et al. (2017) proposed Upx atomic function and multilayer perceptron neural network to inverse halftone. Although the above inverse halftoning methods have carried out researches from filtering, halftoning image model or neural networks, and produced relatively satisfactory results, the inverse problem on converting continuous-tone images from halftoning images has not been completely resolved.

Inspired by the successful applications of sparse representation in image compression, image denoising, super-resolution image (Elad and Aharon, 2006; Yang et al., 2010; Dong et al., 2011), a novel and promising inverse halftoning method based on sparsity was firstly proposed by Son (2012). In this method, two jointed dictionaries are learned for the concatenated feature spaces of continuous-tone images and halftone images or low-pass filtered version of halftone images, tied by the same sparse representation coefficients. The experimental results showed that it was a promising method with a high restoration quality. Afterwards an upgraded version (Son and Choo, 2014) has been proposed by applying locally learned dictionary pairs via patch feature clustering, which can provide well expressed fine details and outlines. Unlike Sons method, who used coupled dictionary to restore continuous-tone images from their halftone version, the method proposed by Freitas et al. (2016) employ coupled dictionary for enhancing the visual quality of images restored using any inverse halftoning method, which can reduce the artifacts introduced by inverse methods. Since continuous-tone image and its halftone version are two different types of images describing the same scene as shown in Fig. 1, we call them cross-style images. Following this, inverse halftoning is regarded as a cross-style image restoration problem at the first time in our proposed method. Unfortunately, all the above methods are limited in sparse coding as the same sparse coding coefficients for the cross-style images, as well as limited in finding the complex mapping between the two different style images. Thus, how to find the complex mapping between the two style images, especially in case of amount of information distortion in halftone images, is a key issue for further study.

In this paper, a novel inverse halftoning method is proposed to address the cross-style image restoration from halftone image to continuous-tone image. Specifically, multiple dictionary pairs and their corresponding mapping functions are learned simultaneously. For each dictionary pair, it can represent different structural features of halftone images and continuous-tone images. Due to each dictionary pair is not fully jointed or coupled in the learning process, the mapping function from halftone images to continuous-tone images could reveal the intrinsic relationship between the two style images. To further improve the stability and accuracy of the mapping function, a cross-style image patch pair clustering method is proposed by combining the SUSAN (smallest univalue segment assimilating nucleus) filtering and HOG (histogram of oriented gradient) feature. As a consequence of the above results, multi-dictionary learning and image patch reconstruction are applied to restore a good visual preference image with low perceived screen noise, fine details and clear edges.

The remainder of this paper is organized as follows. Section 2 gives an overview of our proposed method. In Section 3, we details our proposed method of the cross-style image patch clustering and semi-coupled dictionary learning algorithm for inverse halftoning process. The effectiveness of our approach is demonstrated in Section 4 by comparing it with the state-of-the-art inverse halftoning methods. Finally, Section 5 concludes our paper with discussions and future works.

## 2. Overview of the proposed algorithm

Halftone images with only 1 or 0 value and continuous-tone images with 256 gray levels are essentially two kinds of heterogeneous styles according to their image data values, thus the continuous-tone image and halftone image should be sparsely represented by their overcomplete