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Image denoising using nonsubsampled shearlet transform and twin support vector machines

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ABSTRACT

Denoising of images is one of the most basic tasks of image processing. It is a challenging work to design a edge/texture-preserving image denoising scheme. Nonsubsampled shearlet transform (NSST) is an effective multi-scale and multi-direction analysis method, it not only can exactly compute the shearlet coefficients based on a multiresolution analysis, but also can provide nearly optimal approximation for a piecewise smooth function. Based on NSST, a new edge/texture-preserving image denoising using twin support vector machines (TSVMs) is proposed in this paper. Firstly, the noisy image is decomposed into different subbands of frequency and orientation responses using the NSST. Secondly, the feature vector for a pixel in a noisy image is formed by the spatial geometric regularity in NSST domain, and the TSVMs model is obtained by training. Then the NSST detail coefficients are divided into information-related coefficients and noise-related ones by TSVMs training model. Finally, the detail subbands of NSST coefficients are denoised by using the adaptive threshold. Extensive experimental results demonstrate that our method can obtain better performances in terms of both subjective and objective evaluations than those state-of-the-art denoising techniques. Especially, the proposed method can preserve edges and textures very well while removing noise.

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1. Introduction

NOWADAYS, images and videos have become integral parts of our lives. Applications now range from the casual documentation of events and visual communication to the more serious surveillance and medical fields. This has led to an ever-increasing demand for accurate and visually pleasing images. However, images captured by modern cameras are invariably corrupted by noise. With increasing pixel resolution but more or less the same aperture size, noise suppression has become more relevant. While advances in optics and hardware try to mitigate such undesirable effects, software-based denoising approaches are more popular as they are usually device independent and widely applicable (Chatterjee & Milanfar, 2012). The main goal of image denoising is to suppress noise from images while preserving their features, such as meaningful edges or texture details, as much as possible. In recent years, several classes of image denoising algorithms such as Nonlocal methods, Random fields, Bilateral filtering, Statistical model, and Anisotropic diffusion have all achieved much success. These algorithms are based on different theories, and all show good performance in denoising. However, the majority of those image denoising algorithms are always not able to preserve edges and texture well, causing loss of image detail information (Bhujle & Chaudhuri, 2014; Karacan, Erdem, & Erdem, 2013). The reason for this is that the existing image denoising methods usually adopt the same denoising strategy for the entire highpass subbands. But, most real-world images always contain simultaneously both many edge/texture and smooth regions, which have different properties. So, it will be more optimal if different denoising strategies can be adopted adaptively for edge/texture and smooth regions within a frequency subband.

Based on nonsubsampled shearlet transform (NSST) (Easley, Labate, & Lim, 2008) and twin support vector machines (TSVMs) (Khemchandani & Chandra, 2007), we proposed a new edge/texture-preserving image denoising algorithm in this paper, in which highpass coefficients are classified into information-related coefficients and noise-related ones, and then different denoising strategies are adopted for them. The novelty of the proposed

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algorithm includes: (1) NSST, which can yield nearly optimal approximation properties, is introduced for image denoising, (2) According to the spatial geometric regularity, NSST coefficients are classified using TSVMs with low computational complexity and good generalization, and (3) The adaptive denoising thresholds are chosen according to the local energy inside a NSST subband while considering different decomposition scales and different directions.

The rest of this paper is organized as follows. A review of previous related work is presented in Section 2. Section 3 recalls some preliminaries about TSVMs. Section 4 presents the basic theory of NSST. Section 5 describes the NSST coefficients classification using TSVMs. Section 6 introduces the new image denoising using TSVMs classification in NSST domain. Simulation results in Section 7 will be dedicated to the description of a variety of simulation experiments, which will illustrate the effectiveness of the proposed scheme. Finally, conclusions will be briefed in Section 8.

2. Related work

During the past three decades, a variety of denoising methods have been developed in the image processing and computer vision communities. Although seemingly very different, they all share the same property: to keep the meaningful edge/textures and remove less meaningful ones. The existing image denoising work can be roughly divided into *Nonlocal Methods*, *Random Fields*, *Bilateral Filtering*, *Statistical Model*, and *Anisotropic Diffusion* (Liu, Szeliski, & Kang, 2008).

Nonlocal methods: The nonlocal methods estimate every pixel intensity based on information from the whole image thereby exploiting the presence of similar patterns and features in an image. This relatively new class of denoising methods originates from the nonlocal means (NLM), introduced by Buades, Coll, and Morel (2005). Xiong and Yin (2012) proposed a detection mechanism for universal noise and a universal noise-filtering framework based on the nonlocal means. In order to make the detection results more accurate and more robust, the from-coarse-to-fine strategy and the iterative framework are used. In work (Wu, Zhang, & Ding, 2014), the curvelet transform is firstly implemented on the noisy image, and the similarity of two pixels in the noisy image is computed. Then the pixel similarity and the noisy image are utilized to obtain the final denoised result using the nonlocal means method. Wang, Xia, and Liu (2012) used Gabor-based texture features to measure the self-similarity, and proposed the Gabor feature based nonlocal means (GFNLM) filter for textured image denoising. Zhang, Feng, and Wang (2013) presented a two-directional nonlocal (TDNL) variational model for image denoising. The model consists of three components: one component is a scaled version of the original observed image and the other two components are obtained by utilizing the similarities. Other nonlocal denoising methods are moment-based (Ji, Chena, & Suna, 2009), or group similar blocks by block-matching and then apply 3D transform-domain filtering to the obtained stacks (BM3D) (Dabov, Foi, & Katkovnik, 2007).

Random fields: Random fields (RFs) are among the most common models used in low-level vision problems such as image segmentation, image classification, and image denoising. The strength of these models lies in their ability to represent both the interaction between neighboring pixels and the relationship between the observed data values and estimated labels at each pixel (Wang, Komodakis, & Paragios, 2013). RF models in statistics have existed for decades and also have a long history in image denoising. A Bayesian formulation of pixel labeling problem using a Markov random field (MRF) model decomposes the problem into a prior that enforces spatial consistency of the labels, and a likelihood function that encourages agreement between the labels and the observed data. In recent years, MRF models have been a popular choice for many low-level vision problems such as image denoising. Cao, Luo, and Yang (2011) proposed a hierarchical MRF model-based method for image denoising. The method employs a MRF model with three layers. The first layer represents the underlying texture regions, the second layer represents the noise free image, and the third layer is the observed noisy image. Zhong and Wang (2013) proposed a multiple-spectral-band conditional random fields (MSB-CRF) to simultaneously model and use the spatial and spectral dependences, and then developed two hyperspectral image denoising algorithms under the proposed MSB-CRF framework. Chen, Yu, Wang, Liu, and Shao (2013) proposed an integrated phase denoising and unwrapping algorithm based upon MRFs, in which MRF, taking a priori knowledge of interferometric phases into account, is used to model the relationship between the elements in the random variable set including both true phases and their observations. Ho and Hwang (2012) presented an approach that constructs a Bayesian network from the wavelet coefficients of a single image such that different Bayesian networks can be obtained from different input images, and utilize the maximum a posterior (MAP) estimator to derive the wavelet coefficients using MRF. Chen, Liu, and Zhang (2013) proposed a novel pixel-based algorithm, which formulates the image denoising problem as the MAP estimation problem using MRFs. Up to now, the preliminary success has been shown in the RFs based image denoising work. However, such an approach faces two challenges when applied to real-world problems. First, the RFs energy function must be computationally feasible in the sense that the minimum should be found in polynomial time. But, this does not usually happen in reality, since finding the global minimum for most energy functions associated to real-world applications is NP hard. Second, it is very hard to find energy functions that always have a global minimum exactly at the desired solution.

Bilateral filtering: A popular image denoising method is the bilateral filter (Tomasi & Manduchi, 1998), where both space and range distances are taken into account. Bilateral filter is a discretization of a particular kind of a PDE-based anisotropic diffusion. The bilateral filter takes a weighted sum of the pixels in a local neighborhood, the weights depend on both the spatial distance and the intensity distance. In this way, edge/textures are preserved well while noise is averaged out. Hu and Li (2011) presented a novel method based on the developed multiscale dual bilateral filter to fuse high spatial resolution panchromatic image and high spectral resolution multispectral image. In Jin, Xiong, and Liu (2012), a new weighting function to the bilateral filtering mechanism is firstly introduced, and then either the current pixel or the vector median is chosen as the base to take part in the bilateral filtering action. Peng, Rao, and Dianat (2014) introduced an approach for selection of the parameters of a vector bilateral filter through an optimization procedure rather than by ad hoc means. The approach is based on posing the filtering problem as one of nonlinear estimation and minimization of the Stein's unbiased risk estimate of this nonlinear estimator. In Kumar (2013), it is proposed to use the blend of Gaussian/bilateral filter and its method noise thresholding using wavelets. Zhang, Lafruit, and Lauwereins (2012) presented a constant time method for the joint bilateral filtering. First, an image data structure is proposed, coined as joint integral histograms (JIHs). Extending the classic integral images and the integral histograms, it represents the global information of two correlated images. Then, the joint bilateral filtering is transformed to computation and manipulation of histograms. Bilateral filtering has been widely adopted as a simple algorithm for image denoising. However, it cannot handle speckle noise, and it also has the tendency to oversmooth and to sharpen edge/textures.

Statistical model: Many authors have developed image denoising algorithms based on statistical model of multiscale coefficients. One means of constructing a model that is statistically homogeneous, but still able to adapt to spatially varying signal behaviors is

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