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Accelerated graph-based nonlinear denoising filters

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Abstract
Denoising filters, such as bilateral, guided, and total variation filters, applied to images on general graphs may require repeated application if noise is not small enough. We formulate two acceleration techniques of the resulted iterations: conjugate gradient method and Nesterov's acceleration. We numerically show efficiency of the accelerated nonlinear filters for image denoising and demonstrate 2-12 times speed-up, i.e., the acceleration techniques reduce the number of iterations required to reach a given peak signal-to-noise ratio (PSNR) by the above indicated factor of 2-12.

Keywords: Accelerated iterations, smoothing filters on graphs, image denoising

1 Introduction

Modern image denoising algorithms are edge preserving, i.e., they preserve important discontinuities in an image while attenuating noise. Many of such algorithms are based on the anisotropic diffusion idea, first formulated in [1, 2]. The idea consists in using diffusion coefficients depending on the local variance—the larger the variance the smaller the coefficient.

Popular denoising techniques, which implement the anisotropic diffusion, include the bilateral filter [3, 4, 5, 6, 7], the guided image filter [10], and the total variation denoising [11]. The fastest computer implementations of the bilateral filter are proposed in recent papers [8, 9]. The guided image filter has been included in the MATLAB Image Processing Toolbox. We also remark that the total variation denoising can be formulated in the filter form; see Section 2.3. All the three filters may be applied to images or signals on graphs; see, e.g., [12] on the graph-based methods in signal and image processing.

More recent state-of-the-art denoising methods are patch-based such as those developed in [13, 14, 15, 16, 17]. An improvement of these methods, based on a special truncation of high frequency modes, is proposed in [18, 19]. Since the patch-based algorithms use geometrically similar patches, they seem to be inconvenient for images or signals on general graphs. This

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reason might partially justify a still active research interest in the basic imaging techniques like the bilateral filter, guided image filter and total variation denoising. Moreover, the models based on the total variation enjoy very rich variational properties.

In certain situations, a single application of a smoothing filter does not produce an acceptable denoising result, and, therefore, the filter transform has to be applied repeatedly (or iteratively), say 10-1000 times, depending on the filter type and level of noise. The repetitive application procedure may be expensive even for images of moderate size. Our previous work in [22, 23] is devoted to acceleration techniques for the iterative application of smoothing filters formulated above. The results are based on the studies in [20, 21], where low-pass filters are constructed by means of projection onto the leading invariant subspaces, corresponding to the modes of lowest frequency, of a graph Laplacian matrix generated by a basic smoothing filter.

The initial publications [20, 21, 22] consider iterative application of a fixed smoothing filter, whose coefficients are defined by the input noisy image. Such a method is known under the name of power iteration. The authors of [20] propose to accelerate the power iteration by the aid of Chebyshev's polynomials. The paper [21] additionally proposes to accelerate the power iteration by the aid of the polynomials generated in the conjugate gradient method [25]. In [22], we formulate a special variant of the preconditioned conjugate method, which accelerates the power iteration for 1D and 2D signals on graphs, and demonstrate that similar acceleration can be achieved with the LOBPCG method [26].

The subsequent works [23, 24] deal with a nonlinear iterative application of filters, where a smoothing filter at each iteration is determined by the currently processed image. The resulting transform yields a nonlinear smoothing filter in contrast to the linear smoothing filter given by the power iteration with a fixed filter at each iteration. The paper [23] presents a special variant of a nonlinear preconditioned conjugate gradient method and numerically demonstrates its high efficiency for accelerated denoising of one-dimensional signals. The conference presentation [24] shows how to accelerate the nonlinear iterative filters by means of the Chebyshev polynomials.

The present note continues the work in our previous papers [22, 23] about acceleration of iterative smoothing filters and contains a number of new contributions listed below. In addition to the bilateral and guided image filters, we consider the total variation denoising and formulate it as a filter operator. In addition to the preconditioned conjugate gradient (PCG) acceleration of nonlinear iterative smoothing filters, we propose to apply Nesterov's acceleration, which is commonly used in a totally different context of iterative solution of convex minimization problems. We numerically investigate performance of the PCG acceleration of nonlinear iterative smoothing filters for two-dimensional images, which is not clear from the previous publications at all. We also numerically investigate performance of Nesterov's acceleration of nonlinear iterative smoothing filters.

2 Smoothing filters

We consider only smoothing filters, which are represented in the matrix form $x^1 = D^{-1}Wx^0$, where the vectors x^0 and x^1 of length N are the input and output signals, respectively. The entries w_{ij} of the symmetric $N \times N$ matrix W are determined by a guidance signal g, i.e. $W = W(g)$. When $g = x^0$, the filter is nonlinear and called self-guided. The diagonal matrix D has N positive diagonal entries $d_i = \sum_{j=1}^{N} w_{ij}$. The symmetric nonnegative definite matrix $L = D - W$ is commonly referred to as a graph Laplacian matrix. The spectrum of the normalized Laplacian $D^{-1/2}LD^{-1/2}$ is nonnegative real, and its largest eigenvalues correspond to the highest oscillation modes.