Signal Processing 103 (2014) 36–44

Contents lists available at ScienceDirect

Signal Processing

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

Natural image denoising using evolved local adaptive filters

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ARTICLE INFO

Article history:
Received 1 July 2013
Received in revised form
7 September 2013
Accepted 4 November 2013
Available online 23 November 2013

Keywords:
Image denoising
Bilateral filter
Genetic programming

ABSTRACT

The coefficients in previous local filters are mostly heuristically optimized, which leads to artifacts in the denoised image when the optimization is not adaptive enough to the image content. Compared to parametric filters, learning-based denoising methods are more capable of tackling the conflicting problem of noise reduction and artifact suppression. In this paper, a patch-based Evolved Local Adaptive (ELA) filter is proposed for natural image denoising. In the training process, a patch clustering is used and the genetic programming (GP) is applied afterwards for determining the optimal filter (linear or nonlinear in a tree structure) for each cluster. In the testing stage, the optimal filter trained beforehand by GP will be retrieved and employed on the input noisy patch. In addition, this adaptive scheme can be used for different noise models. Extensive experiments verify that our method can compete with and outperform the state-of-the-art local denoising methods in the presence of Gaussian or salt-and-pepper noise. Additionally, the computational efficiency has been improved significantly because of the separation of the offline training and the online testing processes.

1. Introduction

Image denoising is the process of recovering the underlying clean image from an observation that has been corrupted by various noises. Due to the fact that image quality is critical for later high-level applications (e.g., object detection), denoising is a very popular topic in the image processing field [16,26].

The existing image denoising techniques can be divided into heuristically optimized and non-parametric methods. In the first category, there are linear and nonlinear filters. Linear filters are widely applied because of their low cost. However, they tend to be ineffective in the presence of non-Gaussian noise. On the other hand, nonlinear filters are used to overcome the limitations of linear filters [5], for instance, nonlinear filters have better edge-preserving ability. However, most filters, either linear or nonlinear, are optimized through tedious tuning and testing. Since the Gaussian filter was applied to image denoising, many local filters have been proposed to improve it. The anisotropic filter [9] was designed to avoid the blurring effect of the Gaussian filter by smoothing the image only in the direction which is orthogonal to the gradient direction. The method in [15] utilizes the total variation minimization technique to smooth the homogenous regions of the image but not its edges. Similarly, the bilateral filter [23] can average pixels in the local neighborhood, which are from the same range as the central pixel, for improving the edge-preserving ability of the Gaussian filter. Nevertheless, the denoising performance of the bilateral filter depends highly on the parameter optimization.

The recent local filters which produce impressive results are mostly non-parametric. Similar to the idea of early local filters [18,9,19], a weighted averaging scheme is adopted to perform image denoising in the trained

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http://dx.doi.org/10.1016/j.sigpro.2013.11.019

filter [17] with the difference that the weights are obtained from off-line training on a large number of images. Portilla et al. [14] proposed a Gaussian scale mixture model based on a multiscale wavelet decomposition for local image statistics (BLS-GSM). Instead of fixed basis local representations, K-clustering with Singular Value Decomposition (K-SVD) [4] achieves good denoising results by adaptive learning of a dictionary from the noisy image. Each patch can be represented by a linear combination of atoms from the dictionary.

In real applications, the noise model is varied, such as impulse, uniform, Gaussian and mixed [2]. Therefore, learning-based methods are desirable because they can be adaptive based on the training data [27,25]. However, most of them can only provide a linear solution while most real degradations are not necessarily linear [4,7]. Accordingly, we address this problem by developing a local adaptive learning-based denoising method which can generate both linear and nonlinear estimations.

Genetic programming (GP) is a branch of Evolutionary Computation (EC) that stochastically transforms populations of programs into a new, better population of programs. As a random process, the results of GP can never be guaranteed, however, unexpected solutions can be generated which is beyond the human expert's consideration. GP has already been successfully used in image denoising [11,10]. Petrovic and Crnojevic [12] have developed a successful GP-based denoising method, which involves a noise detector and a noise remover for the impulse noise. Their method was not designed for other noise models, for instance, Gaussian noise.

In this paper, we propose a patch-based image denoising method that is learned from training data by genetic programming. In the training stage, a patch clustering is applied first to classify the image content before the GP process. The filter evolved by GP is more adaptive to the local image content in a linear or nonlinear form. Different from the existing GP-based denoising method [12], our function set is composed of local filters (e.g., Gaussian and bilateral filters) and arithmetic operators, which are more adaptive to various image contents. In addition, though the offline training process is very time-consuming, the online testing phase is more efficient than most of the state-of-the-art local methods. Results on additive noise reduction are comparable with the state-of-the-art. Furthermore, our proposed scheme can be extended to other noise models (e.g., salt-and-pepper noise) and other image enhancement tasks, which makes our method more versatile compared to previous similar work (e.g., [12]).

2. Related work

2.1. Bilateral filter

A bilateral filter is a nonlinear filter which removes the noise from images and preserves the edges [23]. It can be formulated by the following equation:

$$\hat{\mathbf{x}} = \frac{1}{W(\tau)} \iint_{\xi \in D} g(\xi) c(\xi,\tau) s(f(\xi), f(\tau))\, d\xi \tag{1}$$

where $\hat{\mathbf{x}}$ is the restored image, $s(f(\xi),f(\tau))$ is the similarity weight between pixel $\xi$and pixel τ. $c(\xi,\tau)$ is the weight based Euclidean distance between those two pixels. Actually, the bilateral filter is the combination of a domain filter and a range filter, which can be expressed by

$$c(\xi,\tau) = \exp^{-\|\xi-\tau\|^2/2\sigma_d^2} \tag{2}$$

$$s(g(\xi), g(\tau)) = \exp^{-\|f(\xi)-f(\tau)\|^2/2\sigma_r^2} \tag{3}$$

where σ_r and σ_d are the standard deviations of the range filter and domain filter, respectively. For the domain filter, pixels which are spatially close to the current one are given high weights. For the range filter, pixels which are similar to the reference pixel have higher weights. In this way, the weighted averaging process is done mostly along the edge and greatly reduced in the gradient direction.

2.2. A brief introduction to genetic programming

Genetic programming is an evolutionary problem-solving method which has been extensively used to evolve programs or sequences of operations [6]. The basic workflow of a genetic programming algorithm is illustrated in Fig. 1. GP can determine whether a program is good by running it and evaluate the fitness function. By comparing the fitness of different individual programs, GP can select the best program from the current population. It is also able to create new computer programs by mutation and crossover. The iteration process of selection/crossover/mutation

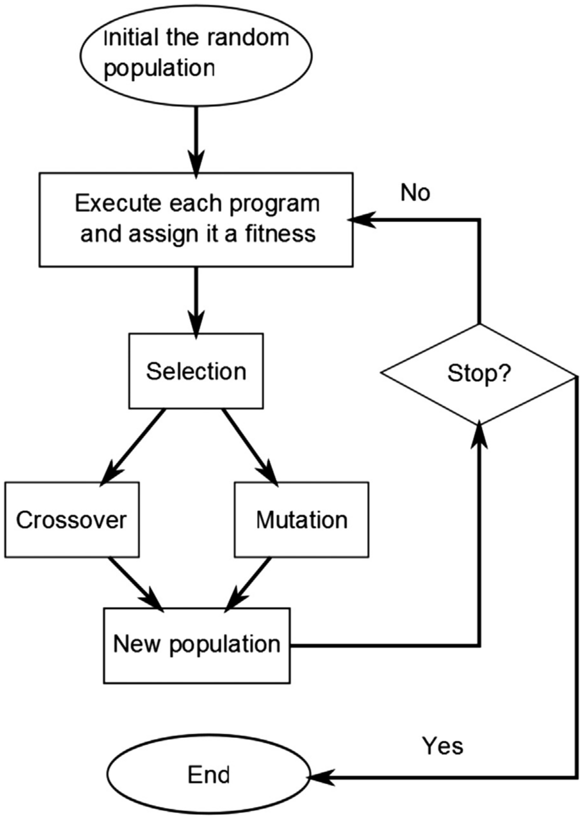

Fig. 1. The GP work flow.