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An approach based on hybrid genetic algorithm applied to image denoising problem

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ABSTRACT

An approach based on hybrid genetic algorithm (HGA) is proposed for image denoising. In this problem, a digital image corrupted by a noise level must be recovered without losing important features such as edges, corners and texture. The HGA introduces a combination of genetic algorithm (GA) with image denoising methods. During the evolutionary process, this approach applies some state-of-the-art denoising methods and filtering techniques, respectively, as local search and mutation operators. A set of digital images, commonly used by the scientific community as benchmark, is contaminated by different levels of additive Gaussian noise. Another set composed of some Satellite Aperture Radar (SAR) images, corrupted with a multiplicative speckle noise, is also used during the tests. First, the computational tests evaluate several alternative designs from the proposed HGA. Next, our approach is compared against literature methods on the two mentioned sets of images. The HGA performance is competitive for the majority of the reported results, outperforming several state-of-the-art methods for images with high levels of noise.

1. Introduction

Digital images can suffer from a corruption process caused by many factors, such as limitation of the sensors to acquire the image, imperfections of the lens device, artifacts during compression and transmission processes, among others. The problem referred to as image denoising deals with such issues, aiming to reduce the amount of noise while preserving important features such as edges, corners and texture.

Image degradations can be described by Eq. (1) in the spatial domain, where $g(x, y)$ is the degraded image, $h(x, y)$ is the degradation function, $f(x, y)$ is the non-degraded image and $\eta(x, y)$ is the noise added to the image. The symbol * represents the operation of convolution [1].

$$g(x, y) = h(x, y) * f(x, y) + \eta(x, y) \quad (1)$$

However, there are situations where the only factor of degradation considered over the image is an additive noise, as shown by Eq. (2). In this case, since the function $\eta(x, y)$ is usually unknown, different probability density functions are used to estimate η and, therefore, provide basis for suppressing noise of digital images.

$$g(x, y) = f(x, y) + \eta(x, y) \quad (2)$$

Image denoising techniques have been extensively investigated in the literature [2,3] and applied to real-world problems [4] in the computer vision field. The methods have been developed based on filters [1], anisotropic and isotropic diffusion [5–7], Fourier and wavelet transforms [8,9], among other techniques. Metaheuristics have also been proposed mainly to adjust parameters for mean filter or estimate thresholds for wavelet transforms [10,11].

Although many of these methods are able to produce high quality outputs, a definitive solution for image denoising is still an open problem. This means that there is still room for improvements on existing approaches and for proposition of new ideas, so motivating the present work to introduce a hybrid genetic algorithm (HGA) with two innovative aspects. First, the genetic algorithm (GA) evolves a population of images instead of being used to set parameters for other image techniques. Second, GA can be cross-fertilized by image denoising techniques, which improves the evolutionary process as a whole. The motivation for hybridizing GAs with other techniques is to define a better search algorithms, combining the advantages of the individual pure strategies [12].

The HGA introduced in this paper combines the population based meta-heuristic with three image denoising methods: BM3D

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[8], Anisotropic Diffusion [7] and Wiener-chop [13]. The main idea is to produce high quality denoised image as outputs, so HGA must evolve within a reasonable execution time that allows for it to search for better solutions. Therefore, the strength of our evolutionary approach is applied to explore the solution space, while the denoising methods are used to improve the generated solutions. HGA is compared to other methods available in the literature using benchmark images with different levels of additive Gaussian noise, as well as the known Satellite Aperture Radar (SAR) images corrupted by a multiplicative speckle noise. The results demonstrated that the proposed HGA outperforms other methods for several images with different levels of noise.

The paper is organized as follows. Section 2 briefly reviews works related to image denoising methods. Section 3 describes the hybrid genetic algorithm developed in this work. Section 4 reports the experimental results and compares them against other approaches available in the literature. Final remarks and directions for future work are outlined in Section 5.

2. Related work

The most common techniques for performing image denoising are based on filters that smooth the images in order to suppress noise. However, these techniques in general also degrade important features of the images, such as edges, corners and texture. The filters used to suppress noise in images are classified as linear and non-linear filters. Linear filters can be expressed as a convolution of a kernel (filter) through a noise image to produce the resulting image. On the other hand, any filter that cannot be represented as a convolution operation is a non-linear filter. A linear filter that is widely used for image denoising is the Wiener filter, which works by minimizing the mean squared error between the recovered and the original images. On the other hand, a commonly used non-linear filter is the median filter, which replaces the value of each pixel by the median value of neighborhood pixels [1].

There are other techniques that aim at removing as much noise as possible, trying to preserve important features of the images. The total variation (TV) methods consider that the noisy signals in an image have high total variation and perform the denoising process by minimizing these signals [14–16]. Methods such as anisotropic and isotropic diffusion, on the other hand, use a function to identify the edges present in an image. These techniques diffuse the image continuously, smoothing it in the process, but they are able to identify when to stop the diffusion process through this edge-aware function. Therefore, they can produce an image that is smoothed and preserve its edges [5,6].

An example of anisotropic diffusion method is presented by Black et al. [7]. This method assumes that the noisy image is a piecewise-defined function that has been corrupted by a Gaussian noise with zero mean and a small variance. Moreover, it is also assumed that the difference between a pixel and its neighbors must be small and follow a normal distribution with zero mean. When the difference between a pixel and its neighbors does not fit in this pattern, it must be an edge region. Based on these assumptions and using statistical analysis, they were able to create a new edge stopping function that makes it possible to smooth the image without suppressing relevant information about edges.

Many denoising methods operate in the frequency domain, where techniques as Fourier or wavelet transforms are used, such that an image is represented by its frequencies instead of being represented by a spatial function ($f(x, y)$). The BM3D [8] is one of these methods, which uses sliding windows to run through the image and create blocks in a first step. In the second step, similar blocks are stacked together and transformed to the frequency domain. The blocks are filtered in a third step by an adapted Wiener filter and, finally, the restored image is constructed by weighing the values of the blocks that were grouped together.

Some of the most effective image denoising techniques rely on wavelet transforms. A common approach consists in searching for thresholds that limit the wavelet coefficients linked to the noisy frequencies. This process, commonly called wavelet shrinkage, is basically composed of three phases: (i) transform the image to the wavelet domain; (ii) estimate the thresholds and suppress the noise through a shrinkage rule; (iii) perform the inverse transformation and, therefore, retrieve the restored image [17,9].

A method based on the concepts of wavelet shrinkage is introduced in [9]. First, the image is divided into a set of blocks that are transformed to the wavelet domain. Next, an edge detection algorithm is applied and the thresholds for the sub-band are estimated. Then, the wavelet coefficients have their threshold limited adaptively regarding their sub-bands. After this step, a shrinkage rule is applied to identify and suppress the noisy coefficients in the image. Finally, the inverse transform is performed on the blocks and the restored image is reconstructed. A different approach to wavelet shrinkage was proposed by Ghael et al. [13]. In this technique, a wavelet shrinkage estimate is used to create a Wiener filter in the wavelet domain. Due to the fact that the filter is specially designed and takes into account the wavelet coefficients of the image, the technique becomes able to produce high quality outputs.

The approaches proposed by Orchard et al. [18] and by Wongsawat et al. [19] are based on singular-value decomposition (SVD). The first method uses a non-local mean filtering technique, where a pixel value is calculated by weighting all similar pixels in the image and not only the neighboring ones, while it still tries to eliminate discrepant pixels within a given neighborhood. On the other hand, the method proposed in [19] transforms the image to the frequency domain, separates it in blocks and decomposes them through SVD. It considers that the eigenvalues of the decomposed blocks correspond to noise and, therefore, discards them. After this, the denoised image is reconstructed by an inverse operation.

Most of the image denoising techniques consider a model where an image was corrupted by an additive white Gaussian noise. Other methods have been specially proposed to suppress non-Gaussian or non-additive noise. The work by Deledalle et al. [20] shows a non-local mean method where, instead of simply calculating an Euclidean distance to define the averages of similar pixels, it provides statistical basis to define a weighted maximum likelihood estimator. This estimator takes into account the distribution of the noise, reaching impressive results for SAR images corrupted with a multiplicative speckle noise.

Ishikawa [21] considers an image as a Markov Random Field (MRF), which is described as an undirected graph that represents a set of random variables (vertices). In this case, the pixels are the vertices and the edges in the graph are the neighborhood relationship between pixels. Each vertex of the graph can assume a range of values L, where the possibility of a vertex assuming a determined value is given by a probability function $P(X)$, with X being a state of the graph. The image denoising problem is modeled as a minimum cut problem, where it is expected that the cost of the graph cut is the same as the energy function of the MRF. Therefore, minimizing the energy function could be considered as finding the minimum cut of the graph [21].

Metaheuristic techniques have also been applied to the image denoising problem. An example of such approach is presented in [10], where particle swarm optimization (PSO) in conjunction with non-local mean filtering is applied to image denoising. The parameters of the non-local mean filter are tuned by a PSO algorithm and the obtained images are evaluated each time by a metric Q. This metric represents a measure of true image content as described in [10]. The method refines the parameters of the non-local mean filter until an optimal solution is found or the maximum number of