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Blind noisy image quality evaluation using a deformable ant colony algorithm

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ABSTRACT

The objective of blind noisy image quality assessment is to evaluate the quality of the degraded noisy image without the knowledge of the ground truth image. Its performance relies on the accuracy of the noise statistics estimated from homogenous blocks. The major challenge of block-based approaches lies in the block size selection, as it affects the local noise derivation. To tackle this challenge, a *deformable ant colony optimization* (DACO) approach is proposed in this paper to adaptively adjust the ant size for image block selection. The proposed DACO approach considers that the size of the ant is adjustable during foraging. For the smooth image blocks, more pheromone is deposited, and then the size of ant is increased. Therefore, this strategy enables the ants to have dynamic food-search capability, leading to more accurate selection of homogeneous blocks. Furthermore, the regression analysis is used to obtain image quality score by exploiting the above-estimated noise statistics. Experimental results are provided to justify that the proposed approach outperforms conventional approaches to provide more accurate noise statistics estimation and achieve a consistent image quality evaluation performance for both the artificially generated and real-world noisy images.

1. Introduction

Blind image quality assessment has the capability of evaluating the quality of a given image without the availability of the original ground truth image [1]. This paper focuses on quality assessment for noisy images, since images are usually corrupted by noise in many ways, such as image acquisition and image transmission [2–4]. The evaluation of image noise aims to provide accurate noise estimates for optimizing subsequent image processing tasks, such as image denoising and segmentation.

The performance of noisy image quality evaluation relies on accurate estimation of noise statistics. Many works [5–8] have been proposed for estimation of noise variance. Generally they are classifiable into patch-based and filter-based approaches. In [5], a filter-based noise estimation method is proposed to use a Laplacian operator to suppress the image structure and utilize edge detection to exclude pixels associated with edges. This kind of approach assumes that the difference between the original image and filtered image is the ideal noise. However, this assumption is not true for images with complex structures or details. Tian and Chen [7] proposed a block-based algorithm using the *ant colony optimization* (ACO) technique, where the ACO technique is used to select smoothing image blocks for noise estimation. Liu et al. [8] proposed to select weak textured patches from a single noisy image based on the gradients of the patches, then use the principle component analysis to estimate the noise level.

Noise estimation can be used for image quality evaluation [9]. A framework for constructing an objective no-reference image quality assessment measure is described in [10], which is further enhanced to adopt visual codebooks using Gabor features extracted from local image patches [11]. It is worthy noting that the above-mentioned approaches share the same noise model: the *additive white Gaussian noise* (AWGN). However, most real-world image noises are not so simple to follow the Gaussian distribution. Therefore, the aforementioned approaches are not suitable to provide accurate noise statistics estimation, leading to unsatisfied quality evaluation for the real-world images. Moreover, these methods exploit fixed block sizes for noise estimation, where the block size is an experimentally selected parameter to heavily affect their performance.

In this paper, a new noisy image assessment approach is proposed to tackle the images corrupted by multiplicative noise. The proposed approach adaptively adjusts the ant size of the ACO technique in selecting image blocks for noise statistics estimation. More specifically, the proposed *deformable ACO* (DACO) approach

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guides the spatial movement of artificial ants with adaptive size towards homogeneous blocks in the graph, combining both global (i.e., clustering measure) properties and local (i.e., homogeneity measure) properties of blocks. Furthermore, regression analysis is used to obtain image quality score by exploiting the above-estimated noise statistics.

The rest of this paper is organized as follows. The motivation of the proposed DACO approach is presented in Section 2. Then, a new image noise estimation method is proposed in Section 3 using the proposed DACO approach. Experimental results are presented in Section 4 to evaluate the accuracy and stability performance of the proposed noise estimation approach and the consistency performance of the proposed blind image quality assessment approach. Finally, Section 5 concludes this paper.

2. Formulation of the proposed deformable ant size

In the literature, the noise statistics can be estimated from the observed noisy image using homogeneous image blocks. This is due to that the noisy image is commonly modeled by stochastic random variables added to a stationary image. Since the image consists of texture, smooth and edge regions, this complicated foreground and background make the homogeneous block difficult to be located automatically and efficiently. The ACO technique demonstrates its superior capability in automatically selecting smooth image blocks [7], where a number of artificial ants are dispatched to move on the graph for depositing pheromone on the ground. Then the following ants prefer to visit image blocks deposited with more pheromone, and finally reach the homogeneous image blocks.

The challenge of the ACO-based approach is that all ants use a fixed size for depositing pheromone. This experimentally determined size affects the accuracy performance of the estimated noise statistics and the estimated image quality. To tackle this challenge, the proposed DACO approach considers that the size of the ant is adjustable during foraging. For the smooth image blocks, more pheromone are deposited, the size of ant needs to be increased. Therefore, this strategy enables the ant to have dynamic food-search ability, leading to more accurate homogeneous block selection. Fig. 1(a) illustrates the conventional ant foraging. The ant size remains the same during the whole optimization process. In contrast, the proposed approach considers three cases of ant size during an ant foraging along the path from S_0 to S_1, S_2 and S_3, respectively, as shown in Fig. 1(b).

The ant size is modeled as a function related to the net energy as

$$\Delta\Omega = \varphi(E^+ - E^-), \tag{1}$$

where $\Delta\Omega$ is the variation of the ant size, E^+ and E^- represent the amount of absorption (i.e., food) and consumption (i.e., metabolism), respectively; $\varphi(\cdot)$ is a monotone increasing function that formulates the relationship between the size of ants and the net absorption energy. If $E^+ > E^-$, the ant size will increase gradually due to positive net energy and vice versa. According to the natural phenomenon, the larger the ant size, the greater food-search range and ability, but the more energy it needs. To summarize, the entire ant colony starts with a constant reasonable size. During the food-search procedure, the ant sizes will deform according to two factors (i.e., the individual food intake and self-energy consumption). Finally, it reaches a dynamic balance with a more suitable size, as illustrated in Fig. 2. Along the path from S_0 to S_1, the energy accumulation procedure can be formulated as

$$\Delta\Omega = \varphi\left(\int_{S_0 S_1} e^+(s)\,\mathrm{d}s - \int_{S_0 S_1} e^-(s)\,\mathrm{d}s\right), \tag{2}$$

where $e^+(\cdot)$ represents the absorption function, which promotes the ant size, and $e^-(\cdot)$ is the consumption function, which has a negative effect on the size of ant.

3. Proposed blind noisy image quality evaluation approach

3.1. Noise model

Suppose Y denotes the noisy version of the original image Z corrupted by the multiplicative noise F. The noise model can be formulated as [12]

$$Y = FZ, \tag{3}$$

where F is the normalized fading random variable in the intensity image, following a Gamma distribution with unit mean and variance $1/L$. After applying the logarithmic transformation on (3), it becomes

$$I = X + N, \tag{4}$$

where I, X, N are logarithmic version of Y, Z, F, respectively, the variance of N becomes [12]

$$\sigma^2 = \Psi(1, L), \tag{5}$$

where $\Psi(1, L)$ is known as the first-order Polygamma function of L [12]. Since the quality of the noisy image depends on the shape parameter L, we use the estimated shape parameter to evaluate the quality of image. Furthermore, as seen in (5), the shape parameter can be calculated based on the noise variance σ^2 defined in (5). The noise image quality evaluation problem boils down to the estimation of the noise variance σ^2. For that, a DACO approach will be proposed in the next section to provide the estimation of noise statistics.

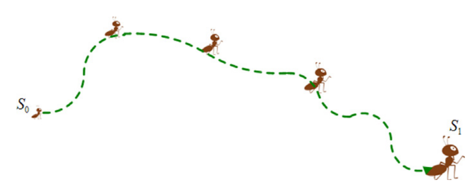

Fig. 2. The deformation of the ant size.

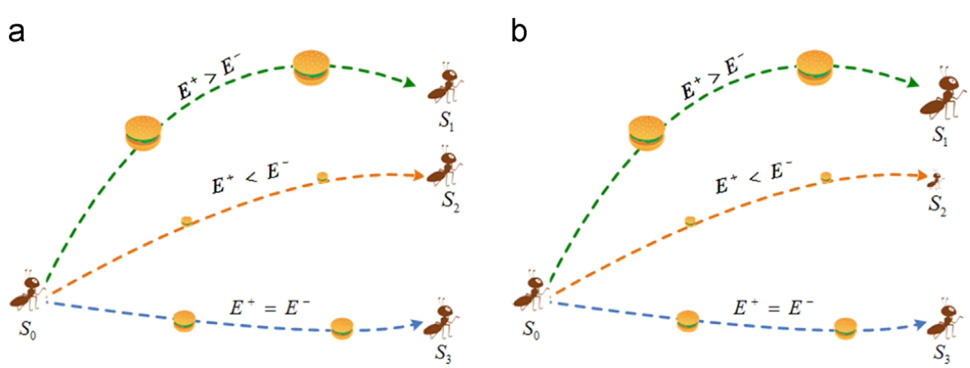

Fig. 1. The comparison of ant sizes during foraging: (a) a fixed size used in the conventional ACO approach; (b) a deformable ant size used in the proposed DACO approach.