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AntShrink: Ant colony optimization for image shrinkage

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ABSTRACT

Wavelet shrinkage is an image denoising technique based on the concept of thresholding the wavelet coefficients. The key challenge of wavelet shrinkage is to find an appropriate threshold value, which is typically controlled by the signal variance. To tackle this challenge, a new image shrinkage approach, called *AntShrink*, is proposed in this paper. The proposed approach exploits the intra-scale dependency of the wavelet coefficients to estimate the signal variance *only* using the homogeneous local neighboring coefficients. This is in contrast to that *all* local neighboring coefficients are used in the conventional shrinkage approaches. Furthermore, to determine the homogeneous local neighboring coefficients, the *ant colony optimization* (ACO) technique is used in this paper to classify the wavelet coefficients. Experimental results are provided to show that the proposed approach outperforms several image denoising approaches developed in the literature.

1. Introduction

Images are often corrupted with noise during image acquisition and image transmission. Wavelet-based algorithms have been proved to be effective for tackling the image denoising problem (Donoho and Johnstone, 1995; Chang et al., 2000; Sendur and Selesnick, 2002; Luisier et al., 2007; Pizurica and Philips, 2006). Motivated by the fact that the wavelet transform packs the energy of the image into a few large coefficients, the simple shrinkage of the coefficients can offer an effective reduction in the corrupting noise. The key challenge is to estimate the signal variance, since it plays a key role to control the degree of shrinkage, consequently controls the quality of the denoised image. The signal variance value is usually estimated based on a local neighborhood of the wavelet coefficient; this local neighborhood could be all of the coefficients in its neighborhood in the same subband (Chang et al., 2000; Sendur and Selesnick, 2002), or the local neighborhood of the wavelet coefficient within the same subband (Eom and Kim, 2004; Mihcak et al., 1999; Shui, 2005).

The estimation of the signal variance from the noisy wavelet coefficients is a critical issue in image shrinkage. Most of the above-mentioned algorithms assume that the wavelet coefficients are locally independent and identically distributed; therefore, the energy distribution of the image in each subband is isotropic. In view of this, they use the isotropic (more specifically, a square-shaped) window for all subbands in each level. However, this is not true for most images, since the signal variances in the wavelet domain exhibit strong intra-scale dependency (Portilla et al., 2003).

To tackle the above challenge, a new image shrinkage approach is proposed in this paper to exploit the intra-scale dependency of the wavelet coefficients for estimating the signal variance *only* using the homogeneous local neighboring coefficients, rather than using *all* local neighboring coefficients in the conventional approaches. To determine the homogeneous local neighboring coefficients, the *ant colony optimization* (ACO) technique is considered as a promising technique to classify the wavelet coefficients in this paper. ACO is a nature-inspired optimization algorithm (Dorigo and Thomas, 2004) motivated by the natural collective behavior of real-world ant colonies. The major collective behavior is the foraging behavior that guides ants on short paths to their food sources, since ants can deposit pheromone on the ground in order to mark some favorable path that should be followed by other members of the colony. Despite that ACO has been widely applied to tackle numerous optimization problems (Dorigo et al., 2000; Cordon et al., 2002; Dorigo et al., 2002), its application in image processing is quite a few (Ouadfel and Batouche, 2003; Hegarat-Mascle et al., 2007; Ghanbarian et al., 2007; Malisia and Tizhoosh, 2006; Tian et al., 2008).

In this paper, the proposed image denoising approach, called *AntShrink*, has two stages, which are sequentially applied for all wavelet coefficients of the noisy image. The first stage of the proposed approach exploits the ACO technique to classify the wavelet coefficients. The second stage of the proposed approach shrinks the

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noisy wavelet coefficients based on the signal variance that is estimated *only* considering the homogeneous neighboring coefficients, which belong to the same category with that of the central coefficient. Since the neighborhood shape used in the proposed approach automatically adapts to the image segment, the proposed approach has fundamental difference with that the conventional fixed-form neighborhoods (i.e., all neighboring coefficients) considered in the conventional image shrinkage approaches, and the proposed approach is expected to yield superior performance.

The proposed approach yields fundamental difference with the conventional image shrinkage approaches in the following two aspects. First, the proposed approach estimates the signal variance *only* using the homogeneous local neighboring coefficients. On the contrary, the conventional approaches use *all* local neighboring coefficients. Second, to determine the homogeneous local neighboring coefficients, the ACO technique is used in this paper to classify the wavelet coefficients. This is the first time to apply the ACO to tackle the image denoising problem in the wavelet domain, despite its extensive use in various areas in the past.

The rest of this paper is organized as follows. A brief introduction to the ACO technique and the conventional image shrinkage are provided in Section 2 and Section 3, respectively. Then the proposed AnrShrink approach is presented in Section 4, which first exploits the ACO technique to perform image classification and then performs wavelet coefficients shrinkage. Extensive experimental results are provided in Section 5 to compare the proposed approach with a number of image denoising approaches. Finally, Section 6 concludes this paper.

2. Ant colony optimization

In this section, a brief introduction to ACO is proposed. ACO aims to iteratively find the optimal solution of the target problem through a guided search (i.e., the movements of a number of ants) over the solution space, by constructing the *pheromone* information. To be more specific, suppose totally K ants are applied to find the optimal solution in a space χ that consists of $M_1 \times M_2$ nodes, the procedure of ACO can be summarized as follows (Dorigo et al., 2006).

- Initialize the position of each ant, as well as the pheromone matrix $\boldsymbol{\tau}^{(0)}$.
- For the construction-step index $n = 1 : N$,
  - Consecutively move each ant for L steps, according to a probabilistic transition matrix $\mathbf{p}^{(n)}$ (with a size of $M_1M_2 \times M_1M_2$).
  - Update the pheromone information matrix $\boldsymbol{\tau}^{(n)}$.
- Make the solution decision according to the final pheromone information matrix $\boldsymbol{\tau}^{(N)}$.

There are two fundamental issues in the above ACO process; that is, the establishment of the probabilistic transition matrix $\mathbf{p}^{(n)}$ and the update of the pheromone information matrix $\boldsymbol{\tau}^{(n)}$, each of which is presented in detail as follow, respectively.

First, at the nth construction step of ACO, each ant moves from the node i to the node j according to a probabilistic action rule, which is determined by Dorigo et al. (2006)

$$p_{i,j}^{(n)} = \frac{\left(\tau_{i,j}^{(n-1)}\right)^{\alpha}\left(\eta_{i,j}\right)^{\beta}}{\sum_{j\in\Omega_i}\left(\tau_{i,j}^{(n-1)}\right)^{\alpha}\left(\eta_{i,j}\right)^{\beta}}, \tag{1}$$

where $\tau_{i,j}^{(n-1)}$ is the pheromone information value of the arc linking the node i to the node j; Ω_i is the neighborhood nodes for the ant a_k given that it is on the node i; the constants α and β represent the influence of the pheromone information and the heuristic information, respectively; $\eta_{i,j}$ represents the heuristic information for going from node i to node j, which is fixed to be same for each construction step.

Second, the pheromone information matrix needs to be updated twice during the ACO procedure. The first update is performed after the movement of each ant within each construction step. More specifically, after the movement of each ant within the nth construction step, the pheromone information matrix is updated as (Dorigo et al., 2006)

$$\tau_{i,j}^{(n-1)} = \begin{cases} \tau_{i,j}^{(n-1)} + \Delta_{i,j}^{(k)}, & \text{if } (i,j) \text{ belongs to the } \textit{best tour}; \\ \tau_{i,j}^{(n-1)}, & \text{otherwise}. \end{cases} \tag{2}$$

Furthermore, the determination of *best tour* is subject to the user-defined criterion, it could be either the best tour found in the current construction step, or the best solution found since the start of the algorithm, or a combination of both of the above two (Dorigo et al., 2006). The second update is performed after the move of *all K* ants within each construction step; and the pheromone information matrix is updated as (Dorigo et al., 2006)

$$\boldsymbol{\tau}^{(n)} = (1-\psi)\cdot\boldsymbol{\tau}^{(n-1)} + \psi\cdot\boldsymbol{\tau}^{(0)}, \tag{3}$$

where ψ is the *pheromone decay coefficient*.

3. Conventional image shrinkage approach

A noisy image in wavelet domain can be mathematically modeled as (Mihcak et al., 1999)

$$\mathbf{y} = \mathbf{s} + \mathbf{n}, \tag{4}$$

where $\mathbf{y}$ is the observed noisy coefficients, $\mathbf{s}$ is the unknown original (noise-free) coefficients, and $\mathbf{n}$ is assumed to be a white Gaussian noise with a zero mean and a variance σ_n^2. The goal of image deno-

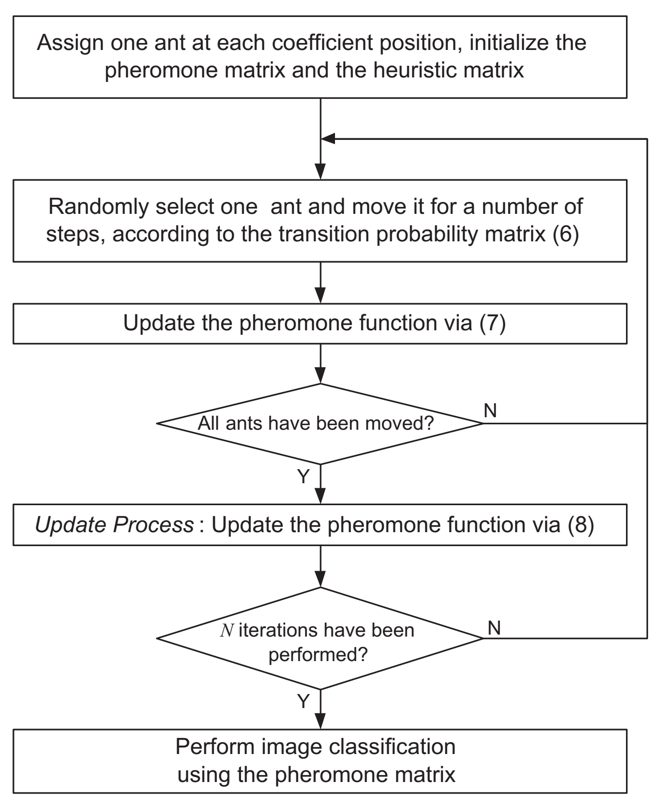

Fig. 1. A summary of the implementation of the proposed ACO-based image classification approach.