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Optimal soft morphological filter for periodic noise removal using a particle swarm optimiser with passive congregation

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Abstract

Periodic noise widely appears in raw images and is often accompanied with white noise. The removal of such compound noise is a challenging problem in image processing. To avoid using the time-consuming methods such as Fourier transform, a simple and efficient spatial filter called optimal soft morphological filter (OSMF) is proposed in this paper. The filter is a combination of basic soft morphological operators and the combination parameters are optimised by an improved particle swarm optimiser with passive congregation (PSOPC) subject to the least mean square error criterion. Applying OSMF to the removal of periodic noise with different frequencies, the simulation results are analysed in comparison with spectral median filter (SMF), which show that OSMF is more effective and less time-consuming in reducing both pure periodic and compound noise meanwhile preserving the details of the original image.

Keywords: Soft morphological filter; Particle swarm optimiser; Noise removal

1. Introduction

Noise removal is a fundamental problem in image processing. In the past years, a variety of filters have been proposed aiming at the reduction of different noises. Periodic noise is a kind of noise that almost all raw images suffer from, due to electrical interference from data collecting devices, such as image scanners, capturing sensors and video cameras.

Since periodic noise has a well-defined frequency, a usual approach is to eliminate the noise in the frequency domain. In recent research, the following three frequency methods have been proposed: (a) Wiener filter [1,2], which needs a proper and precise noise model to be built and is very complicated in computation; (b) spectrum amplitude thresholding, which is suitable only for truly periodic noise with high energy in peaks [2,3]; (c) spectral median filter (SMF) [2], an effective filter with a semi-automatic detector of the peaks in the spectrum amplitude. Nonetheless, despite all their advantages, frequency filters are always computationally time-consuming and are not acceptable for time constraint applications. The inefficiency is mainly caused by the conversion between the space and frequency domains and the noise peak detecting procedure.

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This paper aims at the removal of the periodic noise using optical soft morphological filter (OSMF), a nonlinear space domain filter based on soft mathematical morphology (SMM), which requires less computational time than other traditional filters. In this paper, the design of OSMF and its application to the removal of a typical kind of periodic noise—sinusoidal noise is intensively studied and discussed.

An optimisation technique using particle swarm optimiser with passive congregation (PSOPC) is described to evolve the OSMF, because PSOPC has shown a faster convergence rate than other evolutionary algorithms such as genetic algorithms and it has very few parameters to adjust. Moreover, by introducing passive congregation, the information sharing mechanism is improved and the optimisation result is more accurate. The filtering results of OSMF are compared with those obtained by SMF [4].

The paper is arranged in the following way. Section 2 introduces some basic concepts of the problem: SMM, the optimisation algorithms PSOPC and the criteria for evaluating the performance of the filters. In Sections 3 and 4, the optimisation processes of OSMF for the removal of sinusoidal noise in both high-frequency and low-frequency conditions are expounded in detail respectively. Experimental results are also given in these sections, as well as the discussions and the analysis. The following section focuses on their capability of the reduction of compound noise. Finally, the paper is concluded in Section 6.

2. Relevant background

2.1. Soft mathematical morphology

SMM is an extension of standard mathematical morphology (MM). Instead of applying local maximum and minimum operations, SMM uses a more general weighted order statistics [5]. Besides, the structure element (SE) used in SMM is divided into two subsets: the hard centre and the soft boundary. In comparison with standard MM, SMM is more robust in noisy conditions and less sensitive to small variations in the shapes of the objects [6].

Given sets $A, B \subseteq Z^2$ and $A \subseteq B$, B is divided into two subsets: the hard centre A and the soft boundary $B - A$, where $B - A$ means the difference of the two sets. Soft dilation and soft erosion of an image f by an SE $[B, A, k]$ are defined as

$$f \oplus [B, A, k] = \max{}^{(k)}\{k \diamond (f(x - \alpha) + A(\alpha))|\alpha \in D_A\} \cup \{f(x - \beta) + B(\beta)|\beta \in D_{B-A}\},$$

$$f \ominus [B, A, k] = \min{}^{(k)}\{k \diamond (f(x + \alpha) - A(\alpha))|\alpha \in D_A\} \cup \{f(x + \beta) - B(\beta)|\beta \in D_{B-A}\},$$

respectively, where $\max^{(k)}$ and $\min^{(k)}$ denote the kth largest and smallest value in the set respectively; $\diamond$ is the repetition operator and $k \diamond f(a) = \{f(a), f(a) \cdots, f(a)\}$ (k times); D_A, D_{B-A} represent the field of definition of A and $B - A$, respectively.

Consequently, soft opening and soft closing are defined as

$$f \circ [B, A, k] = (f \ominus [B, A, k]) \oplus [B, A, k], \quad (1)$$

$$f \bullet [B, A, k] = (f \oplus [B, A, k]) \ominus [B, A, k]. \quad (2)$$

Accordingly, soft open-closing and soft close-opening are realised through cascade connection of the soft opening and closing in different orders. The two operators are defined as

$$OC(f, [B, A, k]) = (f \circ [B, A, k]) \bullet [B, A, k], \quad (3)$$

$$CO(f, [B, A, k]) = (f \bullet [B, A, k]) \circ [B, A, k]. \quad (4)$$

2.2. PSOPC

Particle swarm optimiser (PSO) is a population based algorithm developed in 1995 [7,8], inspired by social behaviour of animals such as birds flocking and fish schooling. It shares many similarities with other iteration based evolutionary computation techniques: initialise the system with a group of randomly generated population, evaluate fitness values to update the population and search for the optimal solutions by updating generations, the strategy of which is based on the previous generations.

In PSO, the population is called *swarm* and each individual in the population is called a *particle*. As stated before, after being initialised with a group of random particles, the swarm need to be updated according to certain rules. The updating algorithm of PSO is: in every iteration, each particle is updated by two best values: (a) the best solution it has achieved so far, called personal best (*pbest*); (b) the best solution achieved by any particle in the population in this iteration. If the best solution is among all the particles, it is called global best