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Optimal composite morphological supervised filter for image denoising using genetic programming: Application to magnetic resonance images

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ABSTRACT

Composite filters based on mathematical morphological operators (MMO) are getting considerable attraction in image denoising. Most of such approaches depend on pre-fixed combination of MMO. In this paper, we proposed a genetic programming (GP) based approach for denoising magnetic resonance images (MRI) that evolves an optimal composite morphological supervised filter (F_{OCMSF}) by combining the gray-scale MMO. The proposed method is divided into three modules: preprocessing module, GP module, and evaluation module. In preprocessing module, the required components for the development of the proposed GP based filter are prepared. In GP module, F_{OCMSF} is evolved through evaluating the fitness of several individuals over certain number of generations. Finally, the evaluation module provides the mechanism for testing and evaluating the performance of the evolved filter. The proposed method does not need any prior information about the noise variance. The improved performance of the developed filter is investigated using the standard MRI datasets and its performance is compared with previously proposed methods. Comparative analysis demonstrates the superiority of the proposed GP based scheme over the existing approaches.

1. Introduction

Magnetic resonance imaging (MRI) is widely used technique in medical diagnostic. Although it is very useful but images obtained are highly sensitive to noise. Denoising and enhancement of MR signal improve the accuracy of diagnostic system in clinical areas. This area has attracted considerable interest in the image processing research (Llado et al., 2012). MR signal is usually affected at the acquisition time by several artifacts and noise sources. One of them is thermal noise that degrades the signal to the extent to get any quantitative information (Manjon et al., 2008). Averaging of multiple acquisitions during scan can be one of the remedy to this problem. This process is not a common practice in the clinics, as increasing the acquisition time is dangerous to human health. Therefore rather than experimenting on human life the effort is being put on post processing of already obtained MR data. Several enhancement methods are applied to get reasonable data (Manjon et al., 2012).

In MRI the raw data are acquired in spatial frequency space. The acquired raw data are intrinsically complex valued and corrupted by Gaussian distributed noise. The data remain complex and Gaussian distributed after applying an inverse Fourier transform. After inverse Fourier transform the signal amplitude can be estimated directly from the complex valued data, or one can first perform a magnitude operation on this data and estimate the signal amplitude from the obtained magnitude data. The magnitude operation changes the distribution of the data from Gaussian to Rician (Macovski, 1996). Rician noise restoration is a complex task due to its variation. In low intensity regions of the signal, the Rician distribution tends to Rayleigh distribution while in high intensity regions it approaches to Gaussian distribution (Nowak, 1999). The search for efficient and effective denoising methods is still a valid challenging task.

In the literature, a variety of denoising methods have been proposed in the spatial and transform domains. One common and simple approach is to apply the Gaussian filter (Ashburner and Friston, 2000). This method is capable of reducing noise, particularly it is effective in homogeneous areas but affects high frequency signal. As a result this method blurs edges in the images. However, it is widely applied for regularization purpose (such as in voxel-based morphometry) (Ashburner and Friston, 2000) to reduce anatomical inconsistencies (Manjon et al., 2012).

In order to overcome this problem a large number of edge preserving filters are used such as anisotropic diffusion filter (ADF) (Gerig et al., 1992). This method is based on gradient information keeping the important image structures unchanged. Recently a

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new variant of ADF is proposed for Rician noise removal that has achieved good results based on a linear minimum mean squared error and partial differential equations (Krissian and Aja-Fernandez, 2009).

Transform domain based filters for denoising MR images include discrete wavelet transform (Pizurica et al., 2003), principal component analysis (Muresan and Parks, 2003), and discrete cosine transform (Yaroslavsky et al., 2001). Mostly, these methods are based on *transform-threshold-inverse transform* principle. In recent years, local transform approaches (i.e., sliding-window with or without overlapping) have obtained good results than transform domain approaches (Manjon et al., 2012).

Recently, the nonlocal means (NLM) filter introduced that is based on the natural redundancy of patterns within the images, and considered as a very simple and effective technique to reduce noise while preserving the structural information of the image (Buades et al., 2005). In the literature, multiple variants of NLM filters are used to denoise MRI (Manjon et al., 2008, 2012). In unbiased NLM the variance of noise should be known however in some applications the noise variance is unknown hence causing the technique to fail. Adaptive NLM filters have been introduced to overcome this problem by estimating noise ratio from the noisy images (Manjon et al., 2012). Most of the above discussed methods show reasonable performance only when the image model corresponds to the algorithm assumptions. Otherwise these techniques blur the edges in the image and introduce some bias in the quantification process.

Composite filters based on mathematical morphological operators (MMO) have been used in image processing (Maragos and Schafer, 1987a, 1987b; Sinha et al., 1997; Bloch, 2011) and are getting considerable attraction in noise reduction (Sinha et al., 1997; Verd-Monedero et al., 2011; Ze-Feng et al., 2007). In the framework of MM, the set-theoretic interpretation of the morphological filters is analyzed and introduced the classical linear filters in terms of morphological correlations (Maragos and Schafer, 1987a). The theory of non-linear filters (median, order-statistic, and stack filters) has been extended by using MM, and their relation with basic morphological operations has been analyzed (Maragos and Schafer, 1987b). In MM based filters, the combinations of the basic MMO and the shape of the structuring element are important parameters. Most of the above discussed MM based approaches depend on some pre-fixed MMO combination. Therefore, in diverse nature of noise levels in MRI the performance of these approaches is limited.

Optimization techniques are incorporated in composite morphological filters to enhance the denoising capability (Sharif et al., 2010; Terebes et al., 2002). Genetic algorithm is applied to find the combination of morphological operators and morphological mask (shape and size of neighborhood) for binary image denoising (Terebes et al., 2002). Later this idea is extended for gray-scale images by using binary particle swarm optimization method (Sharif et al., 2010). Gray-scale soft morphological filters are also used in the literature for automatic image restoration (Hamid et al., 2003). While these approaches are able to enhance the denoising performance by obtaining the optimal parameters of the composite filters, they are still suffering from the same limitation i.e. the use of pre-fixed combination of different MMO. Thus, the development of an optimal composite filter that can effectively combine multiple MMO for optimal results is a challenging task.

In this paper, we address this issue and propose a genetic programming (GP) based approach to combine MMO for denoising MRI. GP approach works on the principles of natural selection and recombination to search the space for possible solutions and widely used in the applications of image processing, pattern recognition, and computer vision (Mahmood et al., 2011; Choi and Choi, 2012). In proposed scheme, an optimal composite morphological supervised

Table 1
List of frequently used symbols and notations.

Notation	Description
$f(x,y)$	Original MR magnitude image
$g(x,y)$	Noisy image degraded with Rician noise
$\hat{f}(x,y)$	Final required restored/estimated image from a noisy image $g(x,y)$
$\hat{f}_i(x,y)$	Observed image estimated by an individual i, only uses during GP evolution
V_f	Feature vector of the original image $f(x,y)$
$V_{\hat{f}_i}$	Feature vector of an observed image $\hat{f}_i(x,y)$
Pr_i	Probability of an individual i
$Fitness_i$	Fitness of an individual i
O	Set of morphological operators
S	Structuring-element/mask for morphological operations
ADF	Anisotropic diffusion filter
MF	Median filter
AWF	Adaptive Wiener filter
NLM	Nonlocal means filter
F_{OCMSF}	Optimal composite morphological supervised filter (proposed technique)
$F^{(T1)}_{OCMSF}$	Developed filter for T1-weighted dataset
$F^{(T2)}_{OCMSF}$	Developed filter for T2-weighted dataset
$F^{(PD)}_{OCMSF}$	Developed filter for PD-weighted dataset

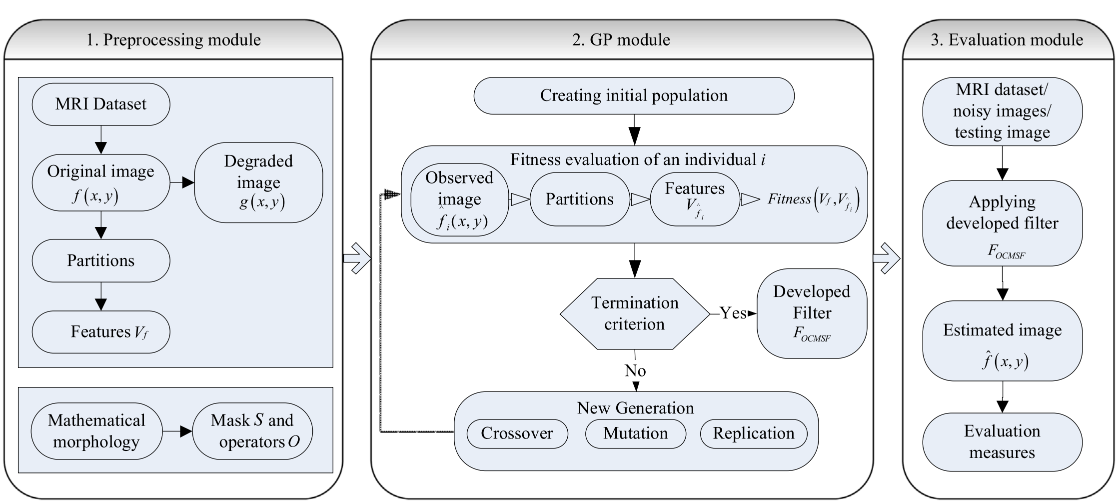

Fig. 1. Development scheme of the proposed method.