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Coronary artery segmentation in X-ray angiograms using gabor filters and differential evolution

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HIGHLIGHTS

- Differential evolution is used for improving vessel detection by Gabor filters through the optimal parameter selection.
- The proposed SSG-DE method achieved a vessel detection rate of 0.9388 with a training set of 40 angiograms.
- SSG-DE achieved a coronary artery detection rate of 0.9538 with a test set of 40 angiograms.
- SSG-DE obtained a vessel segmentation accuracy of 0.9423 using the test set.
- The proposed SSG-DE method achieved the highest performance compared with six state-of-the-art vessel detection methods.

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ABSTRACT

Segmentation of coronary arteries in X-ray angiograms represents an essential task for computer-aided diagnosis, since it can help cardiologists in diagnosing and monitoring vascular abnormalities. Due to the main disadvantages of the X-ray angiograms are the nonuniform illumination, and the weak contrast between blood vessels and image background, different vessel enhancement methods have been introduced. In this paper, a novel method for blood vessel enhancement based on Gabor filters tuned using the optimization strategy of Differential evolution (DE) is proposed. Because the Gabor filters are governed by three different parameters, the optimal selection of those parameters is highly desirable in order to maximize the vessel detection rate while reducing the computational cost of the training stage. To obtain the optimal set of parameters for the Gabor filters, the area (Az) under the receiver operating characteristics curve is used as objective function. In the experimental results, the proposed method achieves an $A_z = 0.9388$ in a training set of 40 images, and for a test set of 40 images it obtains the highest performance with an $A_z = 0.9538$ compared with six state-of-the-art vessel detection methods. Finally, the proposed method achieves an accuracy of 0.9423 for vessel segmentation using the test set. In addition, the experimental results have also shown that the proposed method can be highly suitable for clinical decision support in terms of computational time and vessel segmentation performance.

1. Introduction

The coronary angiography is the current gold standard to detect and monitor coronary artery disease in clinical practice. However, this task represents a time consuming and exhaustive labor for the specialist, therefore an accurate computer system to aid the diagnosis of coronary abnormalities is highly desirable. Due to the low contrast between blood vessels and background, and the nonuniform illumination along the arteries in X-ray angiograms, the key challenge of a computer-aided system is the detection of vessel-like structures. In literature, multiple approaches have addressed this problem as the enhancement of the arteries. Some of the state-of-the-art methods for blood-vessel detection in medical images are based on mathematical morphology (Bouraoui et al., 2008; Eiho and Qian, 1997; Sun and Sang, 2008; Sun et al., 2009; Qian et al., 1998; Lara et al., 2009), Hessian matrix (Frangi et al., 1998) and Gaussian Matched Filters (GMF) (Chaudhuri et al., 1989;

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Chanwimaluang and Fan, 2003; Chanwimaluang et al., 2006; Kang et al., 2009, 2010, 2013; Al-Rawi et al., 2007; Al-Rawi and Karajeh, 2007; Cinsdikici and Aydin, 2009) which work in the spatial image domain, and Gabor Filters (Soares et al., 2006; Rangayyan et al., 2007) which work in the frequency image domain. In this work, we will focus in the use of single-scale Gabor filters.

In the literature, the most common measure of the detection performance is the area under the receiver operating characteristics (ROC) curve (Metz, 1978; Turner, 1979; McNeil and Adelstein, 1976). This analysis retrieves quantitative information about the similarity between a filter response and the corresponding ground-truth by using a sliding threshold. Moreover, the area under the ROC curve is useful to compare multiple methods based on their detection performance. The detection performance of each method depends on the parameters used to filter the input image.

For the single-scale Gabor filters, three parameters have to be tuned in order to improve the enhancement of the coronary arteries. In the literature, the exhaustive search method has been used to fit those parameters, which entails a high computational cost because of the high number of evaluations in the frequency domain, even though the optimization process is performed within a discretized search space. Commonly, one of the SSG parameters (number of oriented filters) is set to a fixed value, reducing the number of parameters to be fitted in the optimization process (Rangayyan et al., 2007). This strategy has been adopted in the present work.

On the other hand, evolutionary computation methods have been used to reduce the computational cost and time carried out by an exhaustive search in features detection (Cuevas et al., 2016; Li et al., 2010). The same idea can be extended for tuning the optimal parameters of different methods while reducing the time consumed by a full search. This approach has been explored by Cruz-Aceves et al. (2016) for the GMF method comparing four optimization methods, where the Differential Evolution algorithm proved to be the most accurate method for global optimization. More recently, a Boltzmann-based evolutionary method was used by Cervantes-Sanchez et al. (2016) in a training stage of Gabor filters, where the evolutionary method proved to reach the optimal parameters in less time than an exhaustive search.

In this work, the single-scale Gabor filters tuned by the Differential Evolution strategy is presented in order to improve the performance of coronary arteries detection and segmentation in X-ray angiograms in an acceptable time.

2. Materials and methods

In this section, the background of single-scale Gabor filters is introduced. Also, the Differential Evolution strategy for parameters training is described below.

2.1. Database of X-ray coronary angiograms

The dataset of X-ray coronary angiograms used in this work was provided by the Mexican Institute of Social Security (IMSS), in the Medical Unit of High Specialty (UMAE) T1, in León, Guanajuato. The dataset consists of 80 grayscale images of 8 bits, each of size 300 × 300 pixels. The dataset was separated in a set of 40 images for training purposes, and a set of 40 images for testing.

2.2. Single-Scale Gabor filters (SSG)

The Gabor filter is a kernel defined as a two-dimensional Gaussian curve, modulated by a sinusoid (Gabor, 1946). The Gabor filter has been used to enhance vessel-like structures in images with low contrast (Rangayyan and Ayres, 2006; Rangayyan et al., 2007). The multiscale version of the Gabor filter was successfully applied for the coronary arteries detection (Rangayyan et al., 2008; Cruz-Aceves et al., 2015), however, it achieves high performance at the expense of a high computational cost in terms of computer memory and time consumption. Moreover, the single-scale scheme obtain good results with reasonable computational cost and time. The single-scale Gabor kernel is defined with the following expression:

Table 1
Statistical analysis of the SSG response in terms of detection rate (A_z) using the training set of images and DE as optimization strategy.

Method	Minimum	Maximum	Median	Mean	Std. dev.
Proposed SSG-DE	0.9388	**0.9388**	0.9388	0.9388	0.0000

Table 2
Statistical analysis in terms of computational time (in seconds) using the training set of angiograms.

Method	Execution time (s)	
Proposed method	minimum	**1543**
	maximum	8282
	mean	5832
	median	5603.13
	std. dev.	1569.10
SSG-BUMDA Cervantes-Sanchez et al. (2016)	mean	6755.21
Exhaustive search	mean	15,521.29

$$G(x, y) = \frac{1}{2\cdot\pi\cdot\sigma_x\cdot\sigma_y} exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right)\cdot cos(2\cdot\pi\cdot f_0\cdot x) \tag{1}$$

where the spread of the Gaussian curve in both axis is controlled by σ_x and σ_y, and the Gaussian curve is modulated in a frequency of f_0.

The single-scale Gabor filter proposed by Rangayyan et al. (2007), simplifies the kernel expression to be in function of two parameters. The first parameter defines the width of the filter (in pixels), and the second parameter l governs the length of the filter.

- $\sigma_x = \frac{\tau}{(2\cdot\sqrt{2\cdot ln(2)})}$
- $\sigma_y = \sigma_x\cdot l$
- $f_0 = 1/\tau$

A third parameter κ controls the number of orientations the kernel is rotated to create a filter bank using a rotation matrix (2), what increases the filter response (Ayres and Rangayyan, 2005, 2007).

$$R_{\theta_i} = \begin{bmatrix} \cos(\theta_i) & -\sin(\theta_i) \\ \sin(\theta_i) & \cos(\theta_i) \end{bmatrix} \tag{2}$$

where θ_i is in the range of [-π/2, π/2] evenly spaced in κ orientations. The SSG filter bank is transformed through the Discrete Fourier Transform (DFT) to the frequency domain, where each rotated kernel is convolved with the transformed image, and then transformed back to the original image space. Finally, the highest responses obtained per pixel among the κ orientations sets up the SSG response.

2.3. Differential Evolution (DE)

Differential Evolution is an optimization method for numerical problems which objective function are practically non-differentiable and their variables lay in continuous spaces (Storn and Price, 1997). Following an evolution strategy, DE is capable to find global optimal solutions. DE improves iteratively a set X^t of distinct possible solutions (3), also called individuals, through mutation, crossover and selection steps, where each individual (x_i) is composed of n features that represent the variables of the optimization problem.

$$X^t = (x_1, x_2, ..., x_N), x_i \in R^n. \tag{3}$$

The DE algorithm begins with X^0, where the features of each