Medical Image Edge Detection Based on Improved Differential Evolution Algorithm and Prewitt Operator

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Abstract
With the rapid development of imaging technology in medical field, medical images of different modes have different imaging principles and reflect different emphases and flaws in human physiology information. Edge detection is a key step in medical ultrasound image processing and the detection result will directly affect doctors’ diagnosis of diseases. Image edge detection can be seen as the classification problem of edge points and non-edge points. This paper comes up with a medical image edge detection method based on improved differential evolution algorithm and Prewitt operator. The threshold in traditional Prewitt edge detection algorithm is not self-adaptive and it needs to be selected by people. The value of the threshold directly affects the detection effect. To overcome this problem, this paper makes some improvements to the conventional Prewitt operator algorithm and searches the optimal threshold with differential evolution algorithm. In this way, the improved differential evolution algorithm has strong global search ability in the initial stage and it can find as many global optimal points as possible while in the post stage, it has strong local search ability to improve its accuracy and convergence speed. In the end, the simulation experiment of medical image is conducted to compare the performance of the algorithm in this paper and the traditional edge detection operator.

Key words: Medical Image Edge Detection, Differential Evolution (DE), Prewitt Operator.

1. Introduction
Medical image edge detection is not only the key foundation of medical analysis and medical diagnosis, but also the important guarantee for doctors to obtain reliable information. Edge detection is to determine and extract the objects and edges in the image and provide such image input and data support for target identification and image analysis [1]. Differential evolution (DE) algorithm is a kind of evolution algorithm based on real coding and used in optimizing the minimum of function. It is brought forth when solving the problem of chebyshev polynomial and it is the evolutionary computation method based on population difference. Similar to genetic algorithm, its overall structure also has the operations of mutation, crossover and selection [2]. Prewitt operator has excellent signal-to-noise ratio; in other words, it does not miss detecting real edges and has a low probability to detect non-edge points as edge points so as to maximize the output signal-to-noise ratio [3]. It has high accuracy in localization, namely that the edge points detected are in the center of the actual edges. Besides, Prewitt operator follows single-edge response criterion; in another word, it is less probable for single edge to have multiple responses and the false edge response is suppressed to the maximum extent. Therefore, this paper combines improved DE algorithm and Prewitt operator to enhance the effect of edge detection of medical images [4].

Prewitt edge detection method uses local extremum to detect edges. As required by edge detection, Prewitt will not miss detecting real edges and falsely detecting non-edge points, that is to say, it requires the maximum output signal-to-noise ratio. The edge points detected are very close to the actual points with regards to the location. Every practical edge point corresponds to every edge point detected [5]. DE algorithm is an intelligent
bionic algorithm by simulating the natural selection of Darwin’s biological evolutionism and the biological evolution of the mechanism of genetics and it applies to many optimization problems [6]. The idea of DE algorithm is to select an initial population from feasible region and build a fitness function for population gradually towards the optimal solution. Different from other evolutionary computations, the computation of DE preserves the global search strategy based on the population, adopts real-number coding, simple mutation operation based on differential and one-to-one competitive survival strategy and lowers the complexity of evolutionary operations. The peculiar evolutionary operations of DE computation make it have strong global convergence ability and robustness and it is very suitable to solve some optimization problems in complex environment [7].

This paper firstly, introduces the basic steps of edge detection, elaborates some common edge detection algorithms, proposes an improved edge detection algorithm based on the advantages and disadvantages of existing algorithms and improves DE algorithm. Then, it combines this improved DE algorithm with Prewitt operator and obtains the final edge image. finally, simulation experiment is conducted via the algorithm of this paper and the result shows that the improve edge detection algorithm has a more accurate detection result than Prewitt operator alone and it can well detect image edges.

2. Image Edge Detection Operator

Edge refers to the part with the most prominent changes in local image brightness and it mainly exists between targets, between target and background as well as between regions (including different colors). There is always edge between the adjacent regions with different gray value and it is the result of discontinuous gray value. Such discontinuity can always be detected by means of derivation and in general, first- and second-order derivatives are used in edge detection [8].

2.1 Concept of Gradient

Edge detection is the most fundamental operation to detect the local significant changes in image. In 1D, step edge is related to the local peak of first-order derivative of the image. Gradient is a kind of measurement of function change and an image can be deemed as the sequence of sampling points of continuous function of image intensity. Gradient is the 2D equivalent equation of first-order derivative and it is defined as a vector.

\[
G(x, y) = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} 
\]

(1)

Two important properties are related to gradient: (1) the direction of vector \(G(x, y)\) is the direction of the maximum rate of change when function \(f(x, y)\) increases; and (2) the gradient magnitude is given by the following formula:

\[
|G(x, y)| = \sqrt{G_x^2 + G_y^2}
\]

(2)

Through vector analysis, it can be seen that the direction of gradient is defined as

\[
a(x, y) = \arctan(G_y / G_x)
\]

(3)

Here, angle \(a\) is the angle relative to \(x\) axis.

For digital images, the derivative of Formula (3) can be approximated with derivation and the most simple gradient approximation equations are as follows:

\[
G_x = f[i, j + 1] - f[i, j]
\]

(4)

\[
G_y = f[i, j] - f[i + 1, j]
\]

(5)

Edge detection operators include two types: based on first-order derivatives and second-order derivatives. Among them, the former type includes Roberts operator, Sobel operation, Prewitt operator, Log operator and Canny operator etc, and the latter type includes Laplacian operator and Laplacian-Gaussian operator and so on [9].
2.2 Roberts Operator

Roberts operator is the one which uses local difference operator to search the edge.

\[
g(x, y) = \sqrt{(f(x, y) - f(x+1, y+1))^2 + (f(x, y) - f(x+1, y))^2}
\]  

(6)

Here, \( f(x, y) \) is the input image with integer pixel coordinates and square root operation makes such processing similar to the process in human visual system. Roberts operator excels in accurate edge localization, but it is sensitive to noises, so it is more suitable for the image segmentation with distinct edges and fewer noises [10].

2.3 Sobel Operator

The two convolution kernels of Sobel operators are

\[
G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad \text{and} \quad G_y = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}
\]

namely the templates of two directions, as shown in following.

(a) Sobel operator of horizontal edge  \hspace{1cm} (b) Sobel operator of vertical edge

The corresponding relationship (with 3×3 window as example) between template elements and window pixels is defined as follows:

Assume the window gray as

\[
[F] = \begin{bmatrix} F(j-1,k-1) & F(j-1,k) & F(j-1,k+1) \\ F(j,k-1) & F(j,k) & F(j,k+1) \\ F(j+1,k-1) & F(j+1,k) & F(j+1,k+1) \end{bmatrix}
\]

(7)

The convolution of template is the process of seeking the sum of products in the formula below.

\[
f_i(j, k) = \sum_{m=-1}^{1} \sum_{n=-1}^{1} F(j+m, k+n) M_{m,n}^i
\]

(8)

In this formula, \( i = 1, 2 \) represents vertical and horizontal templates respectively. \( f_i(j, k) \) is the output of edge detection by template convolution method and \( l = [L/2] \), \( L \) is the width of window. Sobel operator deals well with images with gray gradations and many noises [11].

2.4 Prewitt Operator

Prewitt operator seeks differential in one direction and average in another. So, it is not sensitive to noises; instead, it suppresses noises. Pixel averaging is equivalent to low-pass filtering of image; so, Prewitt operator cannot compete Roberts operator in edge localization, but it also handles well images with gray gradations and noises.

The convolution kernels of Prewitt operator are:

\[
G_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \quad \text{and} \quad G_y = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}
\]

(9)
Every pixel of the image uses these two kernels in convolution. Just like Sobel operator, $\infty$ norm takes the maximum value as the output and produces an image of edge magnitude [12].

2.5 Laplacian Operator

Laplacian operator is an edge detection operator of second-order derivative and it is linear and shift invariant. It is the 2D equivalent equation of second-order derivative, namely

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \tag{10}\nabla^2 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{11}$$

After second-order differential, a steep zero cross point is generated in the image edge and edge is thus judged according to this point. As Laplacian operator is a second-order derivative, it is highly sensitive to noises and for the direction where edge is not easy to detect in the double-sideband, it also has dual response to certain edges in the image[13].

2.6 Log Operator

Log (Laplacian of Gaussian) operator combines Gaussian filter and Laplacian operator for edge detection. Log operation is as follows.

(1) Conduct smoothing filtering on image $f(x,y)$ with Gaussian filtering function $G(x,y)$. Gaussian function $G(x,y)$ is a function of circular symmetry and its smoothing is controlled by $\sigma$. $G(x,y)$ is shown as follows.

$$G(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{1}{2\sigma^2}(x^2 + y^2)\right) \tag{12}\nabla^2 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{13}$$

The smooth image $g(x,y)$ is obtained via convolution of $G(x,y)$ and $f(x,y)$, namely

$$g(x,y) = f(x,y) * G(x,y) \tag{14}$$

(2) Perform Laplacian operation on the smooth image $g(x,y)$, namely

$$h(x,y) = \nabla^2 (f(x,y) * G(x,y)) \tag{15}$$

(3) Detection: edge detection is judged based on the zero cross point (i.e. the point of $h(x,y) = 0$) of second-order derivative and it corresponds to the bigger peak of first-order derivative. The Laplacian operation on the smoothing image $G(x,y)$ is equivalent to the convolution of the Laplacian operation of $G(x,y)$ and $f(x,y)$. So, the formula above becomes

$$h(x,y) = f(x,y) * \nabla^2 G(x,y) \tag{16}$$

Laplacian function uses the approximation of 2D second-order derivative as it is a directionless operator. To avoid detecting non-significant edges, select the zero cross point with first-order derivative bigger than a certain threshold in practical applications [14].

2.7 Canny Operator

The gradient of Canny operator is calculated with the derivative of Gaussian filter and the edge detection method is to find the local maximum value of image gradient. Canny methods uses two thresholds to
respectively detect strong and weak edges and only when weak edge is connected with strong edge, the weak edge will be included in the output. Therefore, this method is not easy to be disturbed by noises and it can detect weak edges. In practical applications, the first-order derivative of Gaussian function can be selected as the suboptimal detection operator of step edges. Assume 2D Gaussian function is

\[
G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{1}{2\sigma^2}(x^2 + y^2)\right)
\]

In certain direction \(\vec{n}\), the first-order directional function of \(G(x, y)\) is

\[
G_x = \frac{\partial G}{\partial n} = \vec{n} V G
\]

In this formula,

\[
\vec{n} = \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix}, \quad V G = \begin{bmatrix} \frac{\partial G}{\partial x} \\ \frac{\partial G}{\partial y} \end{bmatrix}
\]

\(\vec{n}\) is vector direction and \(V G\) is gradient vector. We convolve image \(f(x, y)\) and \(G_x\) and change the direction of \(\vec{n}\) in the meanwhile. When \(G_x \ast f(x, y)\) gets the maximum value, \(\vec{n}\) is the direction orthogonal to edge detection at this time [15].

3. Basic Operations of Improved Differential Evolution Algorithm

Assume that population scale is \(NP\), the present evolitional generation is \(t\), the number of spatial dimensions is \(D\) and \(x_i^j (i = 1, 2, \cdots, NP; j = 1, 2, \cdots, D)\) is the \(i\)th individual in the population, perform the following three operations on every individual one by one.

(1) Mutation

The most fundamental mutation component of DE algorithm is the differential vector in the father generation and every vector corresponds to two different individuals \((x_i^1, x_i^2)\) in the population of father generation (the \(t\)th generation). The differential vector is defined as

\[
D_{i,2} = x_i^1 - x_i^2
\]

In this formula, \(r_1\) and \(r_2\) are two different individuals in the population. For every \(x_i^j\), the mutation operation is

\[
v_i^{j+1} = x_i^j + F \ast (x_i^1 - x_i^2)
\]

\(r_1, r_2, r_3 \in \{1, 2, \cdots, NP\}\) are different integers and \(F\) is scaling factor. In standard differential evolution (DE) algorithm, \(F\) is generally a fixed value and the value directly affects the convergence speed and convergence of the algorithm. In order to maintain the diversity of population in the initial stage of the search, perform global search and get several potential global optimal individuals as possible. In the post-stage of search, strengthen local search ability to improve the accuracy of algorithm. Come up with an adaptive method for scaling factor \(F\) and \(F\) reduces as the number of iterations increases, namely

\[
F = F_{\text{max}} - \frac{t(F_{\text{max}} - F_{\text{min}})}{T_{\text{max}}}
\]

(2) Crossover

Get the individual \(u_i' = (u_i'^1, u_i'^2, \cdots, u_i'^D)\) from the mutated individual \(v_i'\) and the individual in the father generation, namely
\[ u'_i = \begin{cases} v'_j & \text{if } \text{rand}[0,1] \leq CR \text{ or } j = j_{\text{rand}} \\ x'_i & \text{if } \text{rand}[0,1] > CR \text{ and } j \neq j_{\text{rand}} \end{cases} \]  

(22)

Here, \( \text{rand}[0,1] \) is a random number in \([0,1]\), \( CR \) is a constant in the range of \([0,1]\) and it is referred to the crossover factor. The bigger \( CR \) value, the higher possibility for crossover. \( j_{\text{rand}} \) is an integer randomly selected in \([1,D]\) and it ensures that the individual \( u'_i \) needs at least one element from mutated individual \( v'_i \).

The crossover probability factor \( CR \) is

\[ CR = CR_{\min} + \frac{t(CR_{\max} - CR_{\min})}{T_{\max}} \]  

(23)

Here, \( t \) is the present number of iterations, \( T_{\max} \) is the maximum number of iterations. \( CR_{\min} = 0.1, CR_{\max} = 0.9 \). Crossover probability can well balance global and local search capacities so that the algorithm can quickly converge to the optimal solution.

(3) Selection

DE adopts the “greedy” selection strategy, in another word, select the individual with the best fitness value from the individual of father generation \( x'_i \) and the experimental individual \( u'_i \) as an individual \( x'^{+1}_i \) in the next generation and the selection operation is as follows:

\[ x'^{+1}_i = \begin{cases} x'_i & \text{if } \text{fitness}(x'_i) < \text{fitness}(u'_i) \\ u'_i & \text{otherwise} \end{cases} \]  

(24)

Here, \( \text{fitness}() \) is the fitness function and generally, the target function to be optimized is the fitness function.

4. Image Edge Detection of Prewitt Operator Based on Improved Differential Evolution Algorithm

The classical boundary extraction techniques are mostly based on differential operation. First, filter and remove noises in the image through smoothing; then, conduct first- and second-order differential operation and seek the maximum gradient value or the zero crossing point of second-order derivative and finally, select a proper threshold to extract boundary. Below are the specific steps of the algorithm in this paper.

(1) Initialize the parameters: population scale \( NP \), scaling factor \( F \), mutation factor \( CR \), the number of spatial dimensions \( D \) and the number of evolution generation \( t = 0 \). At first, according to the range of gray value of the image after the non-extremum is suppressed, determine the range of threshold and the number of encoding bits \( k \) and then randomly produce \( NP \) \( k \)-bit binary codes as the initial population. \( NP \) ranges from 30 to 120. Randomly initialize the initial population \( X(t) = \{x'_1, x'_2, \cdots, x'_{NP}\} \) and here, \( x'_i = (x'_{i1}, x'_{i2}, \cdots, x'_{iD})^T \).

(2) Evaluate the individuals and calculate the fitness of every individual.

In order to get better edges, determine the fitness function based on OTSU and the formula is as follows.

\[ \text{fitness}(t) = \sigma(t)^2 = w_1(t) * w_2(t) * (u_i(t) - u_i(t))^2 \]  

(25)

In this formula, \( t \) is the threshold; \( \text{fitness}(t) \) is the fitness function; \( w_1(t) \) is the number of pixels smaller than the threshold; \( w_2(t) \) is the number of pixels bigger than the threshold; \( u_i(t) \) is the mean gray value of all pixels smaller than the threshold and \( u_i(t) \) is the mean gray value of all pixels bigger than the threshold.

(3) Mutation: perform mutation operation on every individual according to Formula (20), obtain the mutated individual \( v'_i \) and determine the specific location of the gene to be mutated according to the mutation probability.

(4) Crossover: conduct crossover operation on every individual based on Formula (22), get the test individual \( u'_i \); select two individual according to the crossover probability; perform interchange operation on a part of the individual genes according to the random number and get two new individuals.
(5) Selection: select one from the individuals $x_t'$ of father generation and the test individuals $u_t'$ according to Formula (24) as the individuals of the next generation. Accumulate the fitness $f$ of all individuals $i$ in the present population and get the sum $\sum_{i=1}^{n} f_i$. According to the fitness value of every individual, establish the corresponding relationship in a certain region between individuals and the range $[0, \sum_{i=1}^{n} f_i]$, generate a random number in the range and select the corresponding individual to the region where the random number belongs. It can be seen that the bigger the fitness of the individuals, the higher probability to be selected. The probability for the individual to be selected is as follows:

$$p_i = \frac{f_i}{\sum_{i=1}^{n} f_i}$$

(26)

(6) Terminate the inspection: among the new generation of population $X(t+1)=\{x_1^{t+1}, x_2^{t+1}, \ldots, x_{NP}^{t+1}\}$ generated above, assume the optimal individual in $X(t+1)$ is $x_{b_{opt}}^{t+1}$, if it reaches the maximum number of evolution generations or meets the error requirements, stop the evolution and output $x_{b_{opt}}^{t+1}$ as the optimal solution; otherwise, make $t = t + 1$ and turn to Step (3). Solve the DE algorithm, get the optimal threshold and take it as the high threshold $T_h$ of Prewitt operator algorithm while the low threshold is $T_l = 0.5 * T_h$. According to these thresholds, get the final binary image.

When a pixel meets the following three conditions, it is considered as the edge point of the image.

1) The edge strength of this point is bigger than that of the two adjacent pixels along the gradient direction of this point.

2) The direction difference of two adjacent points along the direction of its gradient is smaller than $\pi/4$.

3) The maximum edge strength of the $3 \times 3$ neighborhood with this point as the center is smaller than a certain threshold.

The flowchart of improved algorithm is shown as below.

![Flowchart of the algorithm of this paper](image)

**Fig. 1** Flowchart of algorithm of this paper

5. Experiment Simulation and Analysis

The fundamental idea to detect step edge is to find the pixel points with the maximum local gradient magnitude. Image edge detection must effectively suppress noises and determine the location of edge as accurately as possible. This is a requirement of detection. So, edge detection operator must be improved in its sensitivity to both the edges and noises. We choose two medical hand images, using traditional Sobel operator, Prewitt operator and the algorithm in this paper to conduct the experiment. The test results are shown in Fig.2 and 3 below.
Fig. 2 Experiment test of Hand image 1
From the above results, we can see that the edges of the image obtained by the algorithm proposed in this paper are smooth and meticulous, the missing edges are less, the phenomenon of edge stacking is not easy to occur, and the edge location is more accurate. This algorithm shows the criteria in the form of mathematics gets the optimal edge detection template by optimizing numerical method. For 2D images, it needs to conduct convolution processing on the image with the template in several directions and select the most probable edge direction. For step edge, the shape of the optimal edge detector deduced by this paper is similar to the first-order derivative of Gaussian function as well as the symmetry and decomposability of 2D Gaussian function. In this way, we can easily compute the convolution of direction derivative and image of Gaussian function in any direction. The edges detected by this paper are local extremum points of the filtered result. As the local extremum points of first-order derivative of function correspond to the zero crossing points of second-order derivative.

6. Conclusions

Doctors need to make some image processing prior to judging patient information through ultrasound images and after the image processing, they will obtain some data and information, which are the bases for them to make a diagnosis of diseases. Edge detection in essence, adopts a certain algorithm to extract the boundary between objects and background in the image. Edge refers to the region boundary where the gray changes abruptly. The gradient of image gray distribution can reflect the changes of image gray. This paper improves differential evolution algorithm with adaptive scaling factor strategy, conducts random mutation on the individuals trapped in stagnation and balances global search ability and local search ability so as to converge the algorithm to the maximum solution. After that, it uses the combination of improved DE algorithm and Prewitt operator in the edge detection of medical images. The simulation experiment result shows that the algorithm of this paper makes some improvements in image edge detection effect compared with traditional algorithms.

Acknowledgements

This work was supported by Research Projects of Basic Scientific Research Business Expenses in Institutions of Higher Learning of Heilongjiang Province (1353MSYYB007 and 2018-KYYWFMY-0104). Science and Technology Project of Mudanjiang (Z2018s073 and Z2018g023).

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