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Driving Active Contours to Concave Regions

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Abstract

Broken characters restoration represents the major challenge of optical character recognition (OCR). Active contours, which have been used successfully to restore ancient documents with high degradations have drawback in restoring characters with deep concavity boundaries. Deep concavity problem represents the main obstacle, which has prevented Gradient Vector Flow active contour in converge to objects with complex concavity boundaries. In this paper, we proposed a technique to enhance (GVF) active contour using particle swarm optimization (PSO) through directing snake points (snaxels) toward correct positions into deep concavity boundaries of broken characters by comparing with genetic algorithms as an optimization method. Our experimental results showed that particle swarm optimization outperform on genetic algorithm to correct capturing the converged areas and save spent time in optimization process.

Keywords

GVF, Particle Swarm Optimizer, Deep Concavity.

Introduction

The first active contour model has been introduced by Kass et al. in 1988 and has later been developed by different researchers. Active contour or snake is a model of energy minimizing, which is affected by two factors: restrictions and image forces that attract it towards object contours. These two forces include internal forces influence the contour's smoothness during the deformation and internal forces that direct the movement of the contour towards the object's borders. The external energy computation fundamentally depends on gradient change and will accomplish on the neighborhood of every snaxel (Kass et al., 1988).

Active contours can be classified according to its representation into two sorts: parametric active contours and geometric active contours. Traditional snake algorithm has weakness in two points: first, the active contour must be initialized manually by the user near the image. Second the snake is poor convergence to boundary concavities.

Based on the active contour, these two drawbacks have been solved by a new external force for active contours. Gradient vector flow (GVF) represents the external force, which is calculated like the gradient vectors dissemination of edge map acquired from the gray image. The resulting domain will have a wide range of capture scope and forces of dynamic contours into concave areas. GVF snake algorithm was proposed by Xu and Prince to achieve better object segmentation (Xu et al., 1998).

GVF has difficulty to correct deal with object boundary with deep concavities, therefore more researches have been fulfilled to improve GVF snakes in order to enhancing the capture range and converge to deep concavity boundaries.

(B. Li et al., 2007) presented a vector field convolution (VFC) to convolve the vector field with the edge map that derived from the gray level or binary image to calculate the exterior force. VFC is like GVF except that it is formulated by framework of energy minimization while VFC snakes contracture using force balance condition.

(Xie et al., 2008) proposed the magnetostatic active contour model depended on assumed magnetic interactions between the dynamic contours and object limits in order to improve active contours capturing to complicate geometries that handle weak edges and broken limits of objects. The active contours have the ability to converge towards deep and narrow boundaries with magnetostatic force. The external force of magnetostatic is dynamic; therefore, it needs to be constantly upgraded through every time of dynamic contour deformation. So, magnetostatic is an active contour that needs high cost, which limits its applications.

(Zhao et al., 2013) proposed a way to locate the portion of dynamic contour, which has different preciseness of global force of GVF snakes.

Although the above modifications to the traditional active contour model have been work well, they have increased the computational cost. Lately, the active contour model paired with particle swarm optimization (PSO) is used to solve the complex problems.

(Tseng et al., 2009) proposed a multi-population technique to improve the ability of concavity search by quick directing the control points of active contour model into the boundary concavities.

(Cruz-Aceves et al., 2013) introduced a way in order to minimize the active contour energy to medical image segmentation using particle swarm optimization. In this way, element grouping optimization directs numerous dynamic contours through distributing the space of search into polar parts.

(R. Li et al., 2009) proposed a way using adjacent particle swarms to get the best position of control points, to improve active contour.

(Khunteta et al., 2016) proposed a way to regulate the inertia weight using fuzzy role. Inertia is a factor applied to equilibrate between global and local search.

(Zhang et al., 2020) proposed a new model of external force which takes GVF to narrow and deep concavities, which is called gradient vector flow over manifold (GVFOM). They tested it on different types of images and got better result than GVF snake.

(Rong et al., 2019) proposed a new method to train a convolutional neural network to get an external force GVF to overcome noise and false edges.

(Cheng et al., 2020) proposed a new external force called CONVEF (Convolutional Virtual Electric Field) to overcome the limitation of GVF active contours which represents the high computation cost with noisy images. The suggested external force also needs more computation although which low as compared with GVF active contours.

(Pawar et al., 2020) suggested a GVF model to detect and segment the ultrasound the kidney stone images with low contrast and assigned the stone places and remove the speckle noise.

The key goal of this research is to optimize GVF capture range using improved PSO in two steps:

1. Adding Tournament selection ways as in GA to increase the probability of better particle selection.
2. Assign divergence property as a fitness (objective) function to select a new neighboring particle with low value to converge to deep boundary.

Active Contours

Active contour model or snake is a groove under the effect of interior and exterior image forces. Exterior forces, gained by image gradient, are in charge of accomplishing the energy least points. The position of these points on this curve is denoted parametrically by:

$$v(s) = \big(x(s), y(s)\big) \tag{1}$$

The snake energy is given as:

$$E_{snake} = \int_0^1 [E_{int}\big(v(s)\big) + E_{ext}(v(s))]\, ds \tag{2}$$

Where E_{int} the interior energy of the snake and E_{ext} is the exterior energy of the image is represented as follows:

$$E_{int} = \frac{1}{2}[\alpha(s)|v_s(s)|^2 + \beta(s)|v_{ss}(s)|^2 \tag{3}$$

$$E_{ext} = -\gamma\big|\Delta I\big(v(s)\big)\big|^2 \tag{4}$$

The external energies represent the variance between GVF snake and traditional snake model. The external force $E_{external}$ in the traditional active contour is substituted by gradient vector flow for GVF snake: $V(x,y) = \big(u(x,y), v(x,y)\big)$, $V(x,y)$ is the product of decreasing the following function of energy (Xu et al., 1998):

$$E_{external} = \iint \mu\big(u_x^2 + u_y^2 + v_x^2 + v_y^2\big) + |\nabla f|^2 |V - \nabla f|^2 dxdy \tag{5}$$

Where, μ is an adapting variable and ∇f is the gradient of edge map.

The following Euler equation is to minimize the energy of Equation (5):

$$\mu\nabla^2 u - (u - f_x)\left(f_x^2 + f_y^2\right) = 0 \quad (6)$$
$$\mu\nabla^2 v - \left(v - f_y\right)\left(f_x^2 + f_y^2\right) = 0 \quad (7)$$

Where ∇^2 is the Laplacian operator.

Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is a population embraced on stochastic improvement procedure created in 1995 by Eberhart and Kennedy, Influenced by conduct of bird crowding or fish teaching. Particles represent the possible solution in PSO, which follow the present optimum solution in the problem space. In the PSO algorithm there are "n" particles and the location of every particle denotes the possible answer in D-dimensional space. The particle has two essential characteristics in the hyperspace: the memory of particles location best, which is best local (pb) and knowledge of the best global quarter is global best (gb). Position of particle is affected by velocity. Let $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ is the location of particle i in the search space at time t.The location of particle is altered through addition speed, $v_i(t)$ to the existing location (Englebritcht 2005):

$$v_i\,(t+1) = wv_i(t) + c_1r_1\big(pb(t) - x_i(t)\big) + c_2r_2\big(gb(t) - x_i(t)\big) \quad (8)$$
$$x_i\,(t+1) = x_i\,(t) + v_i\,(t+1) \quad (9)$$

x_i is the position of i_{th} particle, v_i is the velocity of i_{th} particle, c_1 , c_2 are acceleration coefficient, r_1, r_2 are random vector and w is the inertia weight to balance the local and global searches.

According to the steps mentioned above, PSO algorithm performed as the following procedure:

1. Assign the swarm size and generate random candidate solutions and velocities in order to initialize the particle.
2. Assess every particle in the pre-identified suitability function and upgrade its $p$best just in case the present suitability is better.
3. Discover the particle that has the best suitability in the entire swarm and upgrade pgbest just in case the value of suitability is better.
4. Stop in case the halting paradigm is fulfilled (e.g., dependability or cycle's number).
5. Upgrade speed and location of the considerable number of particles as indicated by (8) and (9), at that point repeat steps (2) - (5).

PSO Active Contours

PSO active contour model is applied to direct the control points into the concavity boundaries that employ the PSO to discover the best moves of points of control with a swarm of particles related to every control point (Sahoo et al., 2014).

The suggested way employs the tournament selection way and divergence property to discover the best move of control points, with a swarm of particles O_i related to every control point P_i. Every particle denotes a snaxel on the contour. In PSO personal best term denotes the best location taken by particle and suitability of the particle is affected by its neighboring position. Therefore, in this way added the tournament selection way to select the new particle position of a swarm. The divergence field was considered as the fitness used to select the new particle position. The equation below calculates Divergence as:

$$div\ F = \frac{\partial P}{\partial x} + \frac{\partial Q}{\partial y} \qquad (10)$$

Where P and Q are the horizontal and vertical axis vectors respectively, and i, j are pixel coordinates in the GVF field of the image as defined by the equation:

$$F(x, y) = P(x, y)i + Q(x, y)j \qquad (11)$$

From the divergence field, low qualities have a place with object limits, whereas great values of those regions that are far from the limits establishing the edge value θ (properly selected threshold since value of θ is restrict the depth of concavity region) to define the values of $divF$ with coordinate (i, j) revery the limit when:

$$divF(i, j) < \theta \qquad (12)$$

In every iteration $pbest$ will be upgraded. The present suitability can be compared to previous fitness calculated for particle best location. This ensures that $pbest$ term always directs the particle to deep concavity positions in the boundary object.

Materials and Methods

PSO-Active contours steps are the following:

1. Set a swarm for every control point and allocate the primary $pbest$ and $gbest$ using Triple –Tournament selection.
2. Evaluate the fitness value for every particle using Divergence field as in Eq.6

3. Minimize the local energy for every swarm to perform one-round optimization.
4. Upgrade, $gbest$, and allocate $gbest$ to be the new control point. Update $pbest$ and $gbest$ values.
5. Upgrade the speed and location for every particle.
6. Check if calculation end criteria are met (Energy is steady) otherwise circle back to stage 2.

As show in figure 1, character "G" represents the example of obstacle in convergence of GVF snake to deep concavity boundaries. Previously we used Triangle-step with Balloon force algorithm to improve GVF capture range and restored most of the broken characters except these characters because it has been complex and narrow concave boundaries.

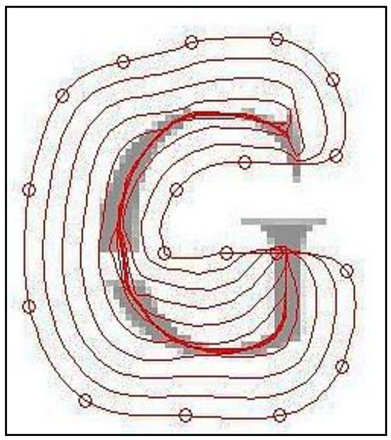

Figure 1 Snake optimization

Also, proposing an optimization of GVF snake using genetic –snake algorithm and recognized all the broken characters have deep concavity regions. In this research we applied PSO-Active contour way to optimize GVF snake and got results better than genetic-snake way, as shown in figure 1.

Performance Evaluation

In this study, we used Hausdorff Distance (HD) as a metrics to evaluate the performance of particle swarm optimization to optimize GVF snake. HD is a measurement tool that explains the degree of similarity between two sets of points or images. HD is the greatest distance between one point set to the nearest point in another point set. If$A = (a_1, a_2, .. a_n)$ and $B = (b_1, b_2, .., b_n)$ are two sets and HD was represented in the following equations:

$$H(A, B) = \max[h(A, B), h(B, A)] \qquad (13)$$

Where:

$$h(A,B) = max_{a \in A} \{min_{b \in B} \|a - b\|\} \quad (14)$$
$$h(B,A) = max_{b \in B} \{min_{b \in B} \|b - a\|\} \quad (15)$$

In case two images are fit, the HD closes to 0.

Results and Discussion

The proposed way is tested on broken character images of Latin alphabet that is taken from ISO basic Latin alphabet and images from the MNIST database. It gives a better result compared with GVF alone. All computation is done under the environment of DELL INSPIRON N5110 Computer. CPU 2.4GHz and RAM is 4 GB. The operation system is Windows7 Ultimate and the programming tool is MATLAB 7.10.0 (R2010a). Vextractor 6.42 software is used to convert raster image to vector image. The proposed way includes using Triple-Tournament selection way same as used in GA. Its standard contains in haphazard choosing a group of three particles in the swarm. These particles are then categorized based on their relative suitability and the appropriate individual is chosen for reproduction. The total procedure is recurrent n times for the whole population as shown in figure 2.

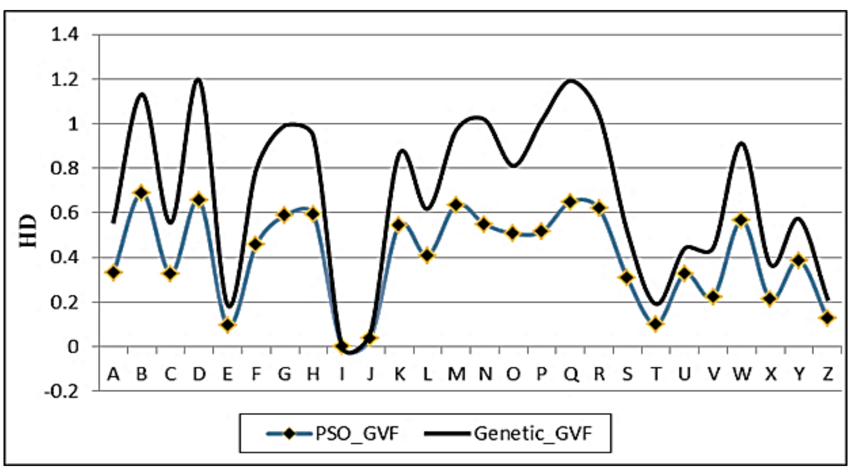

Figure 2 HD for Genetic-snake and PSO-snake

Another improvement for PSO, we used the divergence field as fitness (objective) function to select a new particle position and the particle with low divergence value only selected which is represents one of the deep concavity boundary points. These iterations continue until the energy is stable then all the snake points are converged to deep concavity boundaries with better performance from genetic-snake.

Conclusion

In this paper, we attempt to apply Particle Swarm Optimization to resolve several shortcomings of GVF snake algorithm that denotes difficult concavity problem. Using PSO supports optimization of snake points to focalize in deep concavity limits by additional Tournament selection way to select the new particle (snaxel) position and considered a divergence field as a fitness function which is based to direct the snake points towards the deep concavity regions of object boundary. The outcomes acquired from the execution of suggested algorithm on Alphabet broken characters images are good reinstated and the limited of convergence is removed.

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