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Video Seamless Splicing Method Based on SURF Algorithm and Harris Corner Points Detection

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Abstract

In order to improve video image registration accuracy during splicing, a video image registration algorithm based on corner point detection and feature point integration is proposed in the article. Firstly, Harris algorithm is adopted to detect image corner points and fetch surf feature points of the image as well as integrate the corner points and feature points and eliminate the repeated points to generate feature vector; secondly, neural network is used to learn the image vector and establish image registration model, and the particle swarm algorithm is used to optimize the parameters of neural network; finally, the specific image is adopted for simulation comparison experiment. The result shows: compared with other image registration algorithms, the algorithm proposed in the article can improve image registration accuracy and efficiency and has relatively strong robustness.

Keywords: *Harris corner points; SURF feature; neutral network; image registration*

1. Introduction

As image application basis, image processing includes image segmentation, image registration, *etc.*, wherein the image registration refers to the processing procedure of establishing the corresponding relation for two or more images obtained at different time and from different angles or different sensors, and has wide application prospect in such fields as motion estimation, remote sensing, medical imaging and compute vision, so it is always the research hotspot in image processing field [1].

Image registration algorithms are divided into three types, namely space correlation registration algorithm, conversion registration algorithm and feature registration algorithm, wherein the space correlation algorithm cannot be used for the registration of the images with different resolutions and features; the conversion registration algorithm is only applicable to homogeneous image registration rather than heterogeneous image registration; the feature registration algorithm has the precondition of finding the feature points of the images before the image registration based on the feature points of two images, and compared with other registration algorithms, the feature registration algorithm is simpler and is not sensitive to image translation, revolution, illumination, *etc.*, thus becoming the present main research direction. At present, the feature extraction algorithms mainly include: Harris, Moravec, SUSAN, SIFT, SURF, *etc.*, wherein Harris, SIFT and SURF algorithms are mostly widely applied. On the basis of Moravec operator, C. Harris *et al.* proposed Harris operator, wherein Harris algorithm has such advantages as simple calculation and uniform distribution of extracted corner points, but it can be used only for the corner point detection under single scale, without scale invariance, and it can

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easily extract false corner points [2]. In 1999, Lowe, *et al.* proposed SIFT algorithm [3] with the features of rotational invariance, scale invariance, brightness invariance and good noise immunity; although this algorithm can adapt to brightness variation, it has high time complexity and long algorithm time consumption [4]. In 2006, Bay, *et al.*, proposed SURF algorithm with the performance thereof similar to that of SIFT algorithm, but due to the introduction of integral image, this algorithm was provided with the advantages of less time consumption, fast calculation speed, *etc.*; although SURF algorithm can well solve image zooming problem, the feature points extracted thereby are less stable than those extracted by Harris algorithm [5-6].

On the basis of integrating the stability of Harris corner point detection algorithm and the scale invariance, brightness invariance, noise invariance, *etc.* of SURF algorithm, an image registration algorithm based on corner point detection and feature point integration is proposed in the article, and the performance thereof is tested through simulation experiment. The simulation result shows that the algorithm proposed in the article can well solve the problems existing in single feature image registration algorithm and can obtain relatively ideal image registration result and meanwhile improve image registration speed.

2. Harris Algorithm and SURF Algorithm

2.1. Harris Algorithm

Harris algorithm employs differential operation and autocorrelation matrix to detect corner points and has the features of simple calculation, uniform and rational features of extracted corner points, quantitative extraction of feature points and stable operator. The process of carrying out Harris corner point detection for grey edge image I_g to generate corner point image I_c [7] can be expressed as follows:

Gaussian window function $W(u, v)$ is used to calculate image partial derivative, and 3*3 Gaussian window function is selected in the article and (δ_x, δ_y) is used to convert window function $W(u, v)$, namely:

$$E(\delta_x,\delta_y)=\sum_w\left[I(u+\delta_x)-I(u,v)\right]^2 \tag{1}$$

Taylor series expansion is carried out for the first item of formula (1), namely:

$$I_x(u+\delta_x,v+\delta_y)=I(u,v)+I_x(u,v)I_y(u,v)\left[\delta_x,\delta_y\right]^T \tag{2}$$

Therein, I_x and I_y respectively denote partial derivatives of x and y directions; formula (2) is put in formula (1) to obtain the following formula:

$$\begin{gathered}E(\delta_x,\delta_y)=\left[I_x(u,v)I_y(u,v)\right]\left[\delta_x,\delta_y\right]^T=\\ \left[\delta_x,\delta_y\right]M\left[\delta_x,\delta_y\right]^T\end{gathered} \tag{3}$$

In the formula, M is autocorrelation matrix and the calculation formula of M matrix can be obtained from formula (3), namely:

$$M=\begin{bmatrix}\sum_w(I_x(u,v))^2 & \sum_w I_x(u,v)I_y(u,v)\\ \sum_w I_x(u,v)I_y(u,v) & \sum_w(I_y(u,v))^2\end{bmatrix} \tag{4}$$

If M has two small characteristic values, then it is indicated that the present point is located at flat area; if M has one large characteristic value and one small characteristic value, then it is indicated that the present point is located at the edge. If M has two large characteristic values, then it is indicated that the present point is corner point. Harris has also provided another formula to evaluate whether this point is corner point or not.

$$R = DET(M) - K \times trace^2(M) \tag{5}$$

In the formula, *R* denotes corner point value; *k* is an adjustable sensitive parameters.

2.2. SURF Feature Extraction Algorithm

The interest point detection of SURF algorithm is based on approximate Hessian matrix, and the specific steps are as follows:

(1) Calculate the sum of image pixels and define the integral image as:

$$I_{\Sigma}(X) = \sum_{i=0}^{i \le x} \sum_{j=0}^{j \le y} I(i, j) \tag{6}$$

Therein, after image integral is well calculated, the sum of image pixels can be achieved only through 3 addition and subtraction operations, as shown in Figure 1.

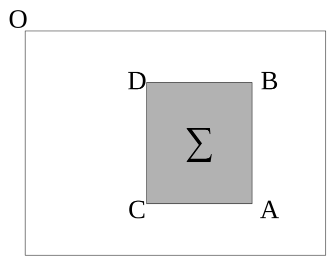


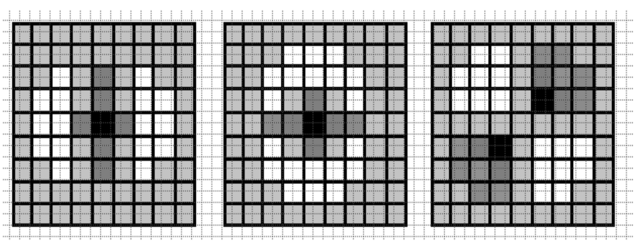
Figure 1. Sum of Pixels in Integral Image Calculation Area

(2) Calculate Hessian matrix

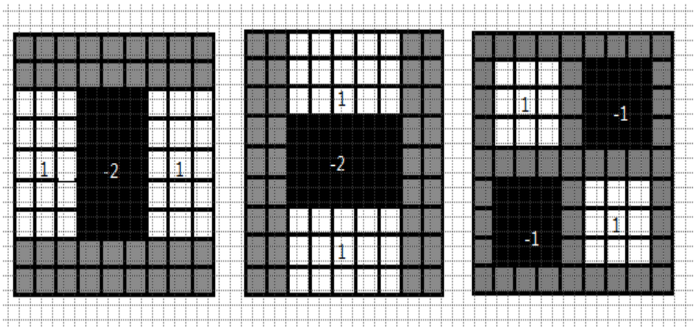
If $X = (x, y)$ is assumed as one image point, then Hessian matrix with the scale of δ at point $X = (x, y)$ is defined as:

$$H(X,\delta) = \begin{bmatrix} L_{xx}(X,\delta) & L_{xy}(X,\delta) \\ L_{xy}(X,\delta) & L_{yy}(X,\delta) \end{bmatrix} \tag{7}$$

In the formula, $L_{xx}(X,\delta)$ is the convolution of Gaussian filter second derivative and the image, and the box type filter template is as shown in Figure 2.



X Direction Y Direction X, Y Direction



X Direction Y Direction XY Direction

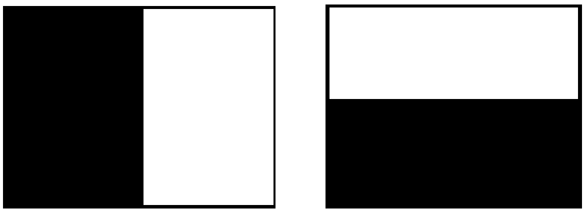
Figure 2. Box Type Filter

Calculate ΔH value of Hessian matrix at each point according to the calculation formula shown in formula (8) and then use Hessian matrix to find extremums, wherein only the extreme points which are all larger or smaller than 26 neighborhood values of previous scale and next scale and around the present scale within the three-dimensional neighborhood can be regarded as candidate feature points [8].

$$\Delta H = D_{xx}D_{yy} - (0.9D_{xy})^2 \tag{8}$$

(3) Determine main direction

Establish a sector area with feature point as the center, radius as 6δ and central angle as $\pi/3$, calculate x-y HAAR wavelet response coefficient of each point in the area, as shown in Figure 3, wherein the weight factor of the black area is -1 while that of the white area is 1. Then, turn the sector to traverse the whole circle and select the direction with longest vector as the main direction.



X Direction *Y* Direction

Figure 3. Haar Wavelet Response

2.3. Establish Descriptor

After determining the main direction of the feature point, establish a square area with the feature point as the center, side length as 20δ and direction as the main direction; then divide it into 16 subareas, respectively calculate four quantities $\sum d_x, \sum |d_x|, \sum d_y, \sum |d_y|$ for each subarea and use $V = (\sum d_x, \sum |d_x|, \sum d_y, \sum |d_y|)$ to denote each subarea; finally, connect vectors V of all 4×4 subareas to form a 64-dimensional feature vector descriptor.

3. Particle Swarm Optimized Neural Network

BP neural network is a multilayer feed-forward network, wherein the input signal is transmitted to output layer from hidden unit and the output signal is generated at the output end, and this is actually the forward transmission of the working signal. The error between the actual output and the expected output of the network is regarded as the error signal which is transmitted forwards from the output end layer by layer and continuously corrects network weights and threshold value during the backward transmission so as to make the actual output of the network closer to the target output. Additionally, the topological structure of BP neural network model includes input layer, hidden layer and output layer, as shown in Figure 4 [9].

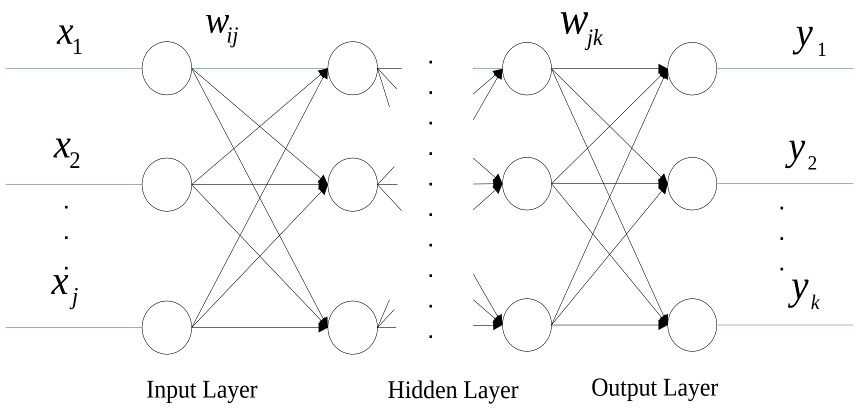


Figure 4. Basic Structure of BP Neural Network

Particle swarm algorithm is a swarm intelligence optimization algorithm with the features of easy implementation, less adjustable parameters, *etc.* Particle updating speed and position are as follows:

$$V_i = \omega V_i + c_1 \xi (p_i - x_i) + c_2 \eta (g_i - x_i) \qquad (9) \; x_i = x_i + \Delta V_i \; ; \qquad (10)$$

In the formula, V_i is speed vector; ω is inertia factor; c_1 and c_2 are acceleration factors; ξ and η are random number; p_i is optimal value of individual experience; g_i is optimal value of swarm experience; k_{max} is maximum iteration times of particle swarm; k is present iteration times of particle swarm; ω is inertia factor; and the formula mode is as follows:

$$\omega = \omega_{\max} - \left(\frac{\omega_{\max} - \omega_{\min}}{k_{\max}}\right) \times k \qquad (11)$$

In the formula, ω_{max} and ω_{min} are respectively maximum and minimum values of inertia factors [10].

Work flow chart of the parameter optimization for BP neural network through PSO algorithm is as shown in Figure 5.

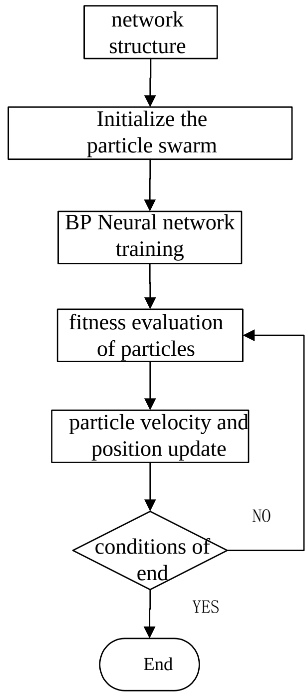


Figure 5. Flow Chart of BP Neural Network Optimization by PSO Algorithm

4. Image Registration Steps of Combination Features

(1) Adopt Harris algorithm to extract image corner points to obtain image corner points set.

(2) Adopt Hessian matrix to detect image extreme points for locating feature points and determining the positions and scales of the feature points.

(3) Combine corner points set and SURF feature points and eliminate some repeated points to form initial feature points set.

(4) Determine the main direction of the initial feature points set and generate 64-dimensional feature descriptor for each feature point.

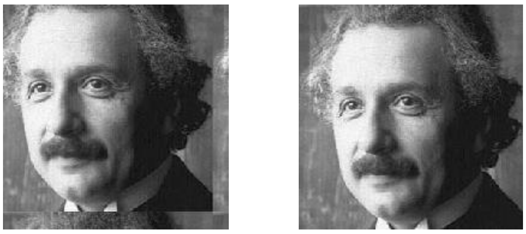
(5) Extract feature points for the reference image and the image to be registered, input these feature points into neural network for learning, and adopt particle swarm algorithm to optimize neural network parameters.

(6) According to optimal parameters, establish image registration model based on neural network and output the image registration result.

5. Simulation Experiment

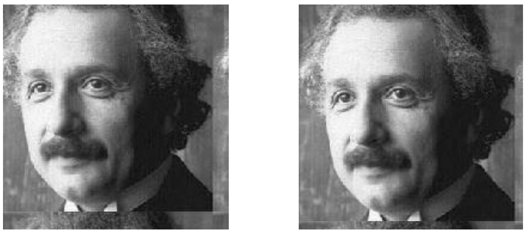
5.1. Simulation Environment

In order to verify the performance of the image registration algorithm in the article, a simulation experiment is carried out on the platform with the hardware environment as: 3.0GHzCPU, 2GB RAM, Windows XP operating system and the software environment as: MATLAB 2012 software. As the simulation object, Einstein's image is respectively moved by (9.37, 8.15), (20.45, 18.24) and (9.54, 8.65) and is added with impulse noise with the noise density of 0.1, as shown in Figure 6~8.



(a) Reference Image (a) Moved Image

Figure 6. Movement (9.37, 8.15)



(a) Reference Image (a) Moved Image

Figure 7. Movement (20.45, 18.24)

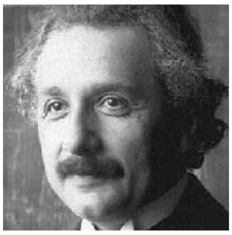
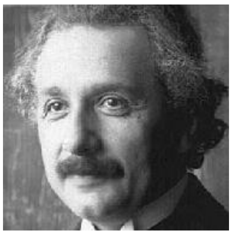
(a) Reference Image (a) Moved Image

Figure 8. Movement (9.54, 8.65) and Noise Addition (Density: 0.1)

6. Result and Analysis

6.1. Visual Effect

The result of the image registration algorithm proposed in the article is as shown in Figure 9. According to Figure 9, the algorithm proposed in the article has relatively high registration accuracy and extremely low image registration error. The experiment result shows that the algorithm proposed in the article not only has the advantages of fast speed and high efficiency owned by Harris corner point detection algorithm, but also has the advantages of scale invariance and strong noise immunity owned by SURF feature extraction algorithm, low requirement for operating environment and high calculation efficiency.

(a) Registration Result of Figure 6 (b) Registration Result of Figure 7

(c) Registration Result of Figure 8

Figure 9. Registration Result of Algorithm Proposed in the Article

6.2. Objective Performance Evaluation

During image registration process, the more the feature points, the higher the calculation complexity and the longer the registration time. The correct registration rate $r_{correct}$ is defined as follows:

$$r_{correct} = \frac{|n_1 \cap n_2|}{\min(|n_1|,|n_2|)} \times 100\% \tag{12}$$

Therein, n_1 and n_2 respectively denote the total feature points of two images; min denotes the lower one of the two.

The registration accuracy and the registration time of the algorithm mentioned in the article are as shown in Table 1. According to Table 1, the feature points extracted in the article have a small amount, and most of them can be correctly registered in a short time. The result shows that the image registration algorithm proposed in the article has high accuracy and fast speed and can ensure the timeliness of image registration.

Table 1. Image Registration Result of the Algorithm Proposed in the Article

Standard	Figure 6	Figure 7	Figure 8
Total feature points	596	762	1200
Correctly registered points	490	690	109
$r_{correct}$	90.77	87.92	85.12
Registration time (s)	2.3	2.79	3.55

6.3. Comparison with Other Methods

For algorithm test, SURF algorithm is selected as the comparison algorithm to be compared with the algorithm proposed in the article, and their correct registration rates $r_{correct}$ are as shown in Figure 10 and Figure 11. According to the contrastive analysis of Figure 10 and Figure 11, compared with SURF algorithm, the algorithm proposed in the article not only improves image registration accuracy, but also improves image registration speed and has good noise robustness.

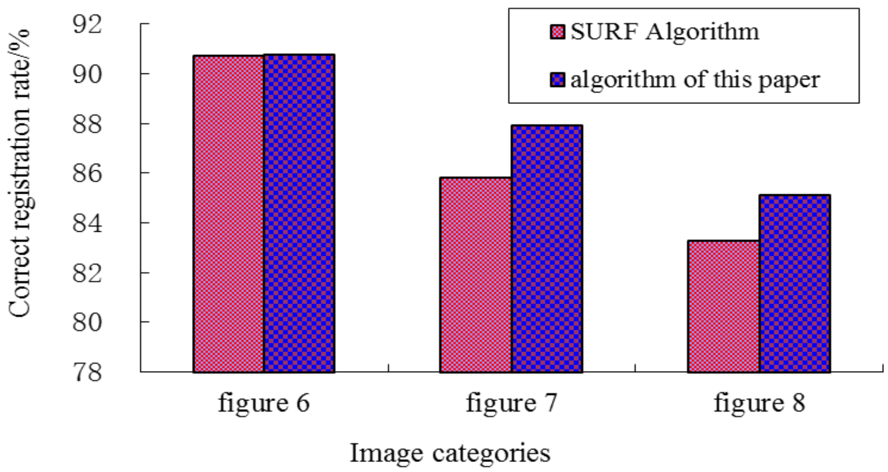


Figure 10. Comparison of Image Registration Rates of Two Algorithms

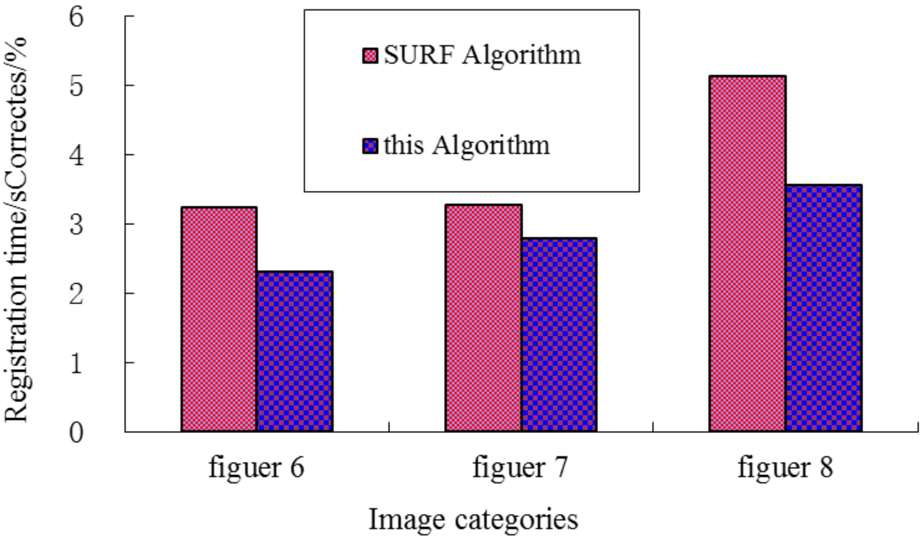


Figure 11. Comparison of Image Registration Speeds of Two Algorithms

7. Conclusion

In order to improve image registration accuracy and efficiency and solve the problems existing in single Harris corner point detection algorithm or SURF algorithm as well as take full advantages of the two algorithms, an image registration algorithm based on corner point detection and feature point integration is proposed in the article. The simulation result shows: compared with other image registration algorithms, the algorithm proposed in the article not only improves image registration accuracy and speed, but also has strong robustness, thus having wide application prospect in image analysis field.

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