EFFICIENT EXTRACTION ALGORITHM FOR LOCAL FUZZY FEATURES OF DYNAMIC IMAGES

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ABSTRACT. Aiming at the poor extraction effect of the current extraction algorithm for local fuzzy features of dynamic images and the low extraction accuracy, a new algorithm based on FAST corner is proposed to extract the local fuzzy feature of dynamic images efficiently. Through analyzing the mode distortion existing in the local fuzzy features of dynamic images, and processing the spatial domain of dynamic images by using point processing and neighborhood processing, and processing the image frequency domain by filtering, the preprocessing of dynamic images and the effect of local fuzzy feature extraction of dynamic images are improved. On the basis of this, aiming at the shortcomings of FAST corner extraction of local fuzzy features of dynamic images, this paper puts forward the idea of algorithm optimization, and analyzes the realization process of the improved algorithm to achieve the algorithm optimization processing and complete the local fuzzy feature extraction of dynamic images. Based on the least squares method, the inaccurate local fuzzy features in the dynamic images are removed to ensure the accuracy of feature extraction. Experimental results show that the proposed algorithm can accurately extract the local fuzzy features of dynamic images, and the extraction results are better.

1. Introduction. Image feature extraction is an important research area in the field of computer vision, and it is also the basis of many current problems [21]. Since most of the dynamic images in which the target is located have the transformation like rotation, viewpoint, scale, illumination, blurring, etc., how to extract

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the stable features of the image has become a research focus in the related field [4]. In image feature extraction, the local features is the hot spot of current research [11]. The ideal image local features can express the information in the local area of image, which has the invariance to the change of the angle of view, the change of illumination, the scale scaling, the rotation, etc [12]. In recent years, with the popularization of low cost and camera-equipped mobile devices, the image local feature extraction algorithm is also developing in a more rapid and efficient direction to meet the requirements of running at the devices of low computing power and low storage power [8]. Although the traditional feature extraction algorithm has achieved some results in the feature description, most of these algorithms are computationally complex and can not meet the needs of real-time applications [5, 14]. Research on the algorithm that is simple, fast, and meets the requirements of certain application is already an urgent problem in the field [22].

Local fuzzy feature extraction of dynamic images is one of the key issues in the field of pattern recognition, data mining and machine learning. In recent years, it has been widely concerned by many researchers [7]. The local fuzzy feature extraction of dynamic images refers to the process of transforming the local fuzzy original feature space of a dynamic image into a low-dimensional projection space according to some criterion [1]. The local fuzzy feature extraction algorithm of dynamic images mainly includes linear algorithm and nonlinear algorithm [6]. Among them, the linear algorithms include principal component analysis (PCA), singular value decomposition (SVD), non-negative matrix factorization (NMF), independent component analysis (ICA) and linear discriminant analysis (LDA); and the nonlinear algorithm has multidimensional scaling (MDS), local linear embedding (LLE), guaranteed projection (LPP). In addition, there are kernel principal component analysis (KPCA), kernel linear component analysis (KLDA), Laplacian eigenmap and so on. The current mainstream local fuzzy feature extraction algorithm for dynamic images is mainly based on two ideas [9]: one is to highlight the differences between image regions based on the global features of dynamic images; the other is to use the local features of images to ensure the consistency of local structure of the samples before and after feature extraction. The biggest problem of the current research on the local fuzzy feature extraction of dynamic images is that the global and local features of the dynamic image can not be utilized at the same time, resulting in the low accuracy of the local fuzzy feature extraction and the poor extraction effect.

In order to solve the above problems, this paper proposes an efficient extraction algorithm for local fuzzy features of dynamic images based on FAST corner. The preprocessing of images is used to improve the quality of dynamic images and to ensure the effect of feature extraction. FAST corner is also used to realize the local fuzzy feature extraction of dynamic images. The least square method is used to remove the inaccurate local blurring features in the dynamic images to ensure the accuracy of feature extraction. The experimental results show that the proposed algorithm can accurately extract local fuzzy features of the dynamic images, and the extraction results are better.

2. The efficient extraction algorithm for local fuzzy features of dynamic images.

2.1. Preprocessing for local fuzzy features of dynamic images. Dynamic images are generally collected by the camera for the same scene in a row, in the
dynamic images, due to various factors, the lens will move and the “movement” will
inevitably lead to fuzzy image, which is the mode distortion [15].

Assuming that \( f_1(x, y) \) and \( f_2(x, y) \) are two images represented by a two-
dimensional array, the two images have the same reference image, but due to dif-
ferences in photography angle and light, etc., the two images are different. The
relationship can be expressed as:

\[
f_2(x, y) = g[f_1(h(x, y))]
\]

Where \( h \) is the coordinate transformation which meets the two-dimensional space
representation, \((x, y)\) is the coordinates of any point on the graph, then \( g \) is the
transformation that makes the difference exist.

If the coordinate of any point on the original image is set to be \((x, y)\) and the
coordinate of the transformed image is set to be \(h(x', y')\), then there is a relational
expression between the two:

\[
\begin{bmatrix}
x' \\
y' \\
1
\end{bmatrix} =
\begin{bmatrix}
m_0 & m_1 & m_2 \\
m_3 & m_4 & m_5 \\
m_6 & m_7 & 1
\end{bmatrix}
\begin{bmatrix}
x \\
y \\
1
\end{bmatrix}
\]

The expression method of formula (2) is called homogeneous coordinate notation,
in which the matrix is a transformation matrix. The method uses \( n+1 \)-dimensional
vectors to represent \( n \)-dimensional vectors for the purpose of facilitating various
transformations. Wherein, \( m_i \) is the transform parameter, each parameter corre-
sponds to a certain meaning, \( m_2 \) means horizontal displacement, \( m_5 \) means vertical
displacement, \( m_0, m_1, m_3 \) and \( m_4 \) represent scale and rotation amount, \( m_6 \) and \( m_7 \)
represent horizontal and vertical deformation.

Each transformation can be expressed by a similar formula, from the geometric
point of view, this transformation can be atomic transformation or a complex
transformation, but all complex transformations are also the synthesis of atomic
transformation, usually includes translation, scaling, rotation, flip, wrong cut.

Rigid body transformation is a combination of translation and rotation trans-
formation. Compared with the original image, the position and orientation of the
image are changed, but the shape of image is not changed. For a straight line,
the parallelism and verticality of the rigid body before and after transformation
are the same. The homogeneous coordinate of the rigid body transformation is
expressed as:

\[
\begin{bmatrix}
x' \\
y' \\
1
\end{bmatrix} =
\begin{bmatrix}
\cos \theta & -\sin \theta & m_2 \\
\sin \theta & \cos \theta & m_5 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
x \\
y \\
1
\end{bmatrix}
\]

In the formula, the parameter \( \theta \) is a measure of the rotation transformation, and
the rotation transformation and the translation transformation are special cases of
the rigid body transformation. When \( \theta = 0 \), the above formula represents the ho-
mogeneous coordinate of the translation transformation, and when \( m_2 = m_5 = 0 \),
the above formula represents the homogeneous coordinate of the rotation transfor-
mation.

Affine transformation is a combination of linear transformation and translation
transformation. It can also be composed of translation, scaling, rotation and inver-
sion of these atomic transformations. After affine transformation, the straightness
between the original image and the transformed image is preserved. The so-called
straightness refers to a straight line or parallel lines. Compared with the rigid-body
transformation, the parallelism before and after the affine transformation is same, but the verticality no longer exists. Homogeneous coordinates of affine transformation are expressed as:

\[
\begin{bmatrix}
x' \\
y' \\
1
\end{bmatrix} = \begin{bmatrix}
m_0 & m_1 & m_2 \\
m_3 & m_4 & m_5 \\
0 & 0 & 1
\end{bmatrix} \begin{bmatrix}
x \\
y \\
1
\end{bmatrix}
\] (4)

Before and after projective transformation, only the straight line is maintained, the parallelism and verticality do not exist. From the mathematical point of view of projective transformation, after transformation, the collinear three points are still collinear three points and collinear four point cross ratio remains same. The homogeneous coordinate of projective transformation is expressed as:

\[
\begin{bmatrix}
x' \\
y' \\
1
\end{bmatrix} = \begin{bmatrix}
m_0 & m_1 & m_2 \\
m_3 & m_4 & m_5 \\
m_6 & m_7 & 1
\end{bmatrix} \begin{bmatrix}
x \\
y \\
1
\end{bmatrix}
\] (5)

Before and after the elastic transformation, the straight line can be mapped into a curve line, and the elastic transformation can be expressed by a function, that is, \((x',y') = F(x,y)\), and \(F\) represent a mapping relationship, \((x,y)\) is a point in the original image, and \((x',y')\) is a point in the image processed with function \(F\).

Image as input information sent to the computer for processing, there is always noise caused by various reasons, thus, it is not suitable for identification of machine vision system. The image will generally be pre-processed and sent into the visual system, the pretreatment process is not a complete denoising process, its main purpose is to enhance the useful information of the image, and remove the unnecessary information as much as possible. In fact, the preprocessing of the image is to enhance useful information of the image. Image enhancement mainly carries out spatial domain processing and frequency domain processing [23].

Spatial domain processing starts from the point processing and neighborhood processing, and the frequency domain processing is mainly for filtering.

Histogram equalization belongs to one kind of point processing. The gray value distribution of most images is not uniform, and the gray value distribution is often concentrated. The uneven distribution of gray value is not good for image segmentation and image comparison. The result of histogram equalization is that the number of pixels in each gray level is basically same, so that the upper limit of the histogram obtained all shows in a horizontal state. Histogram equalization [18] can be performed as follows:

\[
P_a(n) = \frac{1}{M} \sum_{u=1}^{n} h_a(u) \] (6)

\[
b(x,y) = N \times P_a[a(x,y)] \] (7)

In the formula, \(M\) represents the number of pixels, \(N\) represents the levels of gray level, \(a(x,y)\) represents the input image, \(h_a(u)\) represents the histogram of the input image, \(b(x,y)\) is the output image processed with histogram equalization, \(n = 1,2,\ldots,N\).

Image information is inevitably entrained with noise in the process of transmission, and noise affects the recognition of the image, so in the process of image processing, it is essential to denoise. Common noise includes salt and pepper noise, impulse noise, Gaussian noise and so on. Salt and pepper noise is composed of salt
noise and pepper noise, the former is a white high-grayscale noise, the latter is a black low-grayscale noise, which are combined together to form black and white dots. Impulse noise is intermittent, and results in positive and negative random pulse, which have the greatest impact on digital data communication.

The linear filter selects the desired frequency from a number of frequencies and also removes the unwanted frequencies from many frequencies, making a significant contribution to Gaussian noise.

Mean filter is a relatively simple linear filter, which belongs to the algorithm of local space domain. The value of each pixel is replaced by the average pixel value of the surrounding points, so as to achieve the purpose of smoothing the image. The specific formula is as follows:

$$g(x, y) = \frac{1}{M} \sum_{(i,j) \in S} f(i, j) \quad (8)$$

Where $f(i, j)$ is the original image, $g(x, y)$ is the filtered image, represented by an $N \times N$-array, $S$ is a set of neighborhoods generated around $(x, y)$, and $M$ is the number of all points in neighborhood $S$. The size of $S$ determines the value of $M$, which also determines the radius of the neighborhood. The mean filter will blur the image while eliminating the noise, and the size of the radius will have a direct impact on the degree of blur of the image.

Gaussian filter is to eliminate Gaussian noise, and is a weighted average of the image process, for each pixel, the convolution and other templates are used to determine the value by getting the weighted average of the gray value within the neighborhood. Gaussian filtering can be achieved by discretizing the sliding window convolution, or by Fourier transformation. The former is more commonly used, but the latter should be taken into account when the amount of time and space is tremendously increased.

Discrete sliding window convolution can be achieved with the detachable filter, and the detachable filter is the one-dimensional decomposition of multi-dimensional convolution. The two-dimensional zero-mean discrete Gaussian function is commonly used for denoise processing, and the formula can be expressed as:

$$g(x, y) = e^{-\frac{x^2 + y^2}{2\sigma^2}} \quad (9)$$

The median filter is a kind of nonlinear filter. Its core idea is to sample the gray value of odd number of points around the observed pixel and sort, and use the gray value of the middle pixel to replace the gray value of the observed pixel. The method is very suitable for removing salt and pepper noise, can better preserve the edge information, but should not be used in the smoothing of some images with more detail. Two-dimensional median filtering is expressed as:

$$g(x, y) = \text{med}\{f(x-k, y-l), (k, l \in W)\} \quad (10)$$

In the formula, $f(x, y), g(x, y)$ correspond to the original image and the filtered image, $W$ represents a $2 \times 2, 3 \times 3$ region or other shapes.

Through the above discussion, using the rigid body transformation, affine transformation, projective transformation, elastic transformation to analyze the mode distortion existing in the local fuzzy features of dynamic images. On this basis, the spatial domain of the dynamic image is processed by the point processing and the neighborhood processing. And through the filtering process to achieve the image frequency domain processing, so as to achieve dynamic image preprocessing,
improve image quality, and ensure the local fuzzy feature extraction results of dynamic images.

2.2. FAST corner based local fuzzy feature extraction algorithm of dynamic images. Through the preprocessing of image to improve the quality of the image and ensure the effect of the local fuzzy feature extraction of dynamic images. On this basis, the algorithm is improved according to the problem of FAST corner, and then the implementation process of the optimization is illustrated.

In the process of local fuzzy extraction of real dynamic images, in order to solve the scale invariance of FAST algorithm, it is especially important to construct scale space. Since Gaussian nucleus [20] is the only kernel that can achieve linear scale change, different Gaussian kernels can be used to construct scale space. Therefore, constructing Gaussian scale space and extracting FAST scale invariant features are the important processes to realize the image scale invariance.

In order to build a scale-space pyramid, the image is first smoothed by a Gaussian filter. Then, the smooth image is half-sampled both horizontally and vertically, resulting in a series of scaled images. The Gaussian pyramid [13, 19] is a characterization model of image sequence. In order to make the scale continuous, the constructed Gaussian pyramid is divided into \( O \) groups, each group has \( S \) layers. The different layers of the same group are formed by convolution of images with different Gaussian nuclei on different scales. In the Gaussian scale space, there is a scale factor \( k \) between the scales of two adjacent layers in the same group. That is, the image scale in each group corresponds in a relation \((\sigma, k\sigma, k^2\sigma, \ldots, k^{n-1}\sigma)\). For the input image of a given size \( M \times N \), the number of groups needed for a pyramid is constructed, the formula can be expressed as:

\[
O = \log_2[\min(M, N)] - 3 \tag{11}
\]

And the group number \( O \) and the layer number \( S \) of Gaussian image pyramid meet:

\[
\sigma(o, s) = \sigma_02^{o+s/S} \tag{12}
\]

Where \( \sigma_0 \) is the reference level, the value is \( 1.6 \times 2^{1/S} \), \( o \) is the group index coordinates, \( s \) is the layer index coordinates, \( S \) is the layer number of each group. Due to the 2-fold downsampling process, the Gaussian pyramid’s inner and outer dimensions meet the following criteria:

\[
\sigma(s) = \sigma_02^{s/S} \tag{13}
\]

The scale of adjacent layers is:

\[
\sigma_{s+1} = \sigma_s2^{1/S} \tag{14}
\]

The scales of adjacent groups are:

\[
\sigma_{o+1}(s) = \sigma_02^{(o+1+s)/S} \tag{15}
\]

\[
\sigma_02^{(o+S)/S} = 2\sigma_02^{s/S} \tag{16}
\]

To sum up, the scale of the same layer in two adjacent groups is 2 times, and the scales within and between groups are \( 2^{i-1}(\sigma, k\sigma, k^2\sigma, \ldots, k^{n-1}\sigma) \), \( k = 2^{1/S} \). At the same time, in order to maintain the continuity of the image scale, the first layer of each group of images are obtained by downsampling the image of final second layer of previous group. Therefore, as shown in Figure 1, the process of building a Gaussian pyramid is as follows:
1) Let the size of the input image be \(M \times N\), and is smoothed with a Gaussian kernel of 0.5.

2) According to the Gaussian kernel \((\sigma, k\sigma, k^2\sigma, \ldots, k^{n-1}\sigma)\) and the smoothed image \(I(x, y)\), the convolution operation is performed according to the following relationship to generate a Gaussian image set \(L(x, y, k\sigma)\) of the first group.

\[
G(x, y, k\sigma) = \frac{1}{2\pi k^2\sigma^2} e^{-(x^2+y^2)/(2k^2\sigma^2)}
\]

\[
L(x, y, k\sigma) = G(x, y, k\sigma) \otimes I(x, y)
\]

3) Decrease the resolution of the final second layer of the first group by 2 times and use it as the input image of the second group. Then follow the procedure of step (2) to generate a second set of Gaussian images.

4) Repeat steps (2) to (3) to finally generate \(\log_2[\min(M, N)]\) - 3 sets of Gaussian pyramid images.

After the above-constructed scale space is completed, FAST feature points are extracted on each scale image of the pyramid, and the extreme point detected by FAST in the spatial and scale domains is taken as the feature point so that the FAST corner has scale invariance. FAST feature point detection can be determined by the following formula:

\[
N = \sum_{x \in \text{circle}} |I(x) - I(p)| < \varepsilon
\]

Where \(I(p)\) is the gray value of the center pixel \(p\), and \(I(x)\) is the gray value of the pixel point on the circumference. \(\varepsilon\) is the fixed threshold. By accumulating the number \(N\) of pixels satisfying the above formula, if it is greater than the set threshold, the candidate point is a corner point.

For FAST scale-invariant feature detection, firstly, FAST feature points are detected in pixels of each layer of Gaussian image at different scales in the Gaussian pyramid.
pyramid constructed above, and if the accumulated value of the point detection is greater than a given threshold, this is a candidate point. In order to eliminate pseudo-corners faster and better, we choose a threshold of 12. Secondly, the candidate feature points are non-maximized and suppressed, and some redundant feature points are removed to obtain stable feature points. Finally, after finding the stable feature points, gradient histogram is used to calculate the gradient direction and amplitude of each feature point in the area where the feature point is the center and radius is $3 \times 1.5\sigma$ ($\sigma$ is the scale value of the feature point). The formula is:

$$m(x, y) = \sqrt{(L(x + 1, y) - L(x - 1, y))^2 + (L(x, y + 1) - L(x, y - 1))^2}$$ (20)

$$\alpha(x, y) = \arctan \left[ \frac{L(x, y + 1) - L(x, y - 1)}{L(x + 1, y) - L(x - 1, y)} \right]$$ (21)

The direction corresponding to the maximum amplitude in the histogram of the gradient direction is taken as the direction of the FAST feature point. Finally, the scale invariant FAST corner feature extraction is completed, and each corner point information contains the scale, position and direction, the specific process shown in Figure 2.

Because the SIFT algorithm uses 128-dimensional feature vectors to describe the information of feature points, and the experimental and performance evaluation shows that the 128-dimension SIFT feature descriptors have good performance in different degrees of scale, affine, light and fuzzy changes. So the idea of constructing FAST feature descriptor by using SIFT algorithm can be used to construct FAST feature descriptor. The concrete realization process is:

1) In order to have rotation invariance, in the neighborhood of any FAST feature point, according to the main direction $\alpha$ of the point, the initial coordinate system is rotated by $\alpha$, and a new coordinate system is established.

2) Taking the feature point as a center, a pixel template window of size $16 \times 16$ is taken as the neighborhood of the feature descriptor, the pixel neighborhood window is divided into $16 \times 4 \times 4$ sub-regions, and then gradient histograms of 8

![Figure 2. FAST feature detection block diagram](image-url)
3) The gradient histograms of 8 directions in $4 \times 4$ sub-areas, are arranged in the order of position. Since there are $4 \times 4$ sub-areas, there are $4 \times 4 \times 8 = 128$ data in total, and finally a 128-dimensional eigenvector is formed, as shown in Figure 3.

4) Weight the eigenvectors using a standard Gaussian function with a variance of $6\sigma$, and then normalize the eigenvectors to remove the influence of illumination changes, so that the eigenvector does not change with the illumination changes to a certain extent, so as to reduce the sensitivity to changes in brightness.

5) In order to improve the discrimination of the FAST corner features, the eigenvectors are normalized once more.

Through the above discussion, the local fuzzy feature extraction algorithm of dynamic images based on FAST corner is implemented. In order to ensure the effect of local fuzzy feature extraction of dynamic images, the algorithm based on robust estimation is used to remove the inaccurate local fuzzy features.

Least square method [2,10] is an effective tool for model estimation. According to the observed data of two observables with a functional relationship, the functional relationship between them is determined. This is the problem of curve fitting in data processing.

Assuming that the two observed data are $x, y$, the functional relationship between them is expressed as:

$$y = f(x; c_1, c_2, \ldots, c_m)$$

(22)

Among them, $c_1, c_2, \ldots, c_m$ is $m$ parameters to be determined. $(x_i, y_i)(i = 1, \ldots, n)$ is $n$ observed data, corresponding to a point on the $xy$ plane. If there is no error in the data, then all $n$ data points should fall exactly on the theoretical curve. $m$ group of data are selected, and the corresponding value are input into the above formula to obtain the system of equations:

$$y_i = f(x_i; c_1, c_2, \ldots, c_m) \quad i = 1, 2, \ldots, m$$

(23)

Solving the above equation can get the value $c_1, c_2, \ldots, c_m$ to determine the functional relationship. However, when $n < m$, the value of parameter $c_1, c_2, \ldots, c_m$ can not be determined.
However, when the data is in error, the above situation is ideal, the parameter value can not be directly solved according to the above equation even \( n > m \), because the equation will be contradictive. Therefore, it can only be solved by the method of curve fitting [3, 16].

Assuming that the observed value \( y_i \) of \( y \) obeys a normal distribution, the probability density of \( y_i \) is:

\[
p(y_i) = \frac{1}{\sqrt{2\pi\sigma_i}} \exp \left\{ -\frac{[y_i - (f(x_i, C))]^2}{2\sigma_i^2} \right\}
\] (24)

Where, \( \sigma_i \) is the standard deviation of the normal distribution, \( C = (c_1, c_2, \ldots, c_m) \). Assuming that the data of each group are mutually exclusive, the likelihood function [17] of the observed value \( (y_1, y_2, \ldots, y_n) \) is:

\[
L = \frac{1}{(\sqrt{2\pi})^N \sigma_1 \cdots \sigma_N} \exp \left\{ -\frac{1}{2} \sum_{i=1}^{N} \frac{[y_i - f(x; C)]^2}{\sigma_i^2} \right\}
\] (25)

Maximizing the value of likelihood function \( L \), so the following should be taken to the minimum value.

\[
\sum_{i=1}^{N} \frac{[y_i - f(x; C)]^2}{\sigma_i^2} = \min
\] (26)

The above equation shows that using the least square method to estimate the parameters requires that the weighted sum of squares of the deviations of the observations \( y_i \) be the minimum. Because of the minimum requirements of the above formula, it should be:

\[
\frac{\partial}{\partial c_k} \sum_{i=1}^{N} \frac{[y_i - f(x; C)]^2}{\sigma_i^2} \bigg|_{c=\hat{c}} = 0
\] (27)

In the above formula, \( c_k \in C \). Thus, the system of formulas is:

\[
\sum_{i=1}^{N} \frac{[y_i - f(x; C)]^2}{\sigma_i^2} \frac{\partial f(x; C)}{\partial c_k} \bigg|_{c=\hat{c}} = 0
\] (28)

Solving for the above equation yields \( m \) estimates of the parameters \( \hat{c}_1, \hat{c}_2, \ldots, \hat{c}_m \), resulting in a fitted curve equation \( f(x; \hat{c}_1, \hat{c}_2, \ldots, \hat{c}_m) \).

The straight line fitting is regarded as an example, if the fitting function is \( y = ax + b \), \( a \) and \( b \) are parameters to be estimated. The objective function using the least square method is:

\[
F(a, b) = \arg \min \sum_{k=1}^{N} [(ax_k + b) - y_k]^2
\] (29)

In order to estimate the value of \( a, b \), the minimum value of the above formula is:

\[
\begin{align*}
\frac{\partial F}{\partial a} &= \sum_{k=1}^{N} 2(ax_k + b - y_k)x_k = 0 \\
\frac{\partial F}{\partial b} &= \sum_{k=1}^{N} 2(ax_k + b - y_k) = 0
\end{align*}
\] (30)

By solving the above equation, the value of \( a \) and \( b \) can be obtained, so as to realize the inaccurate local fuzzy feature removal in dynamic images.
3. Experimental results and analysis. In order to prove the effectiveness and feasibility of the efficient extraction algorithm based on FAST corner point for local fuzzy features of dynamic images, an experiment was carried out. During the experiment, four images in the MIT database were used for image preprocessing and image feature extraction. The four images are shown in Figure 4.

In this paper, the results of image preprocessed using the proposed algorithm are analyzed. During the experiment, the four images used in the experiment are separately preprocessed, and the noise content of the four images before and after the image processing is compared. Through the experiment, the result is shown in Figure 5.

It can be seen from Figure 5 that the proposed algorithm can effectively suppress the noise in the image, improve the quality of the image and ensure the effect of the image analysis. Because the algorithm proposed in this paper analyzes the mode distortion existing in the local fuzzy features of the dynamic images by using rigid body transformation, affine transformation, projective transformation, elastic transformation during the image processing, through the spatial domain processing and the frequency domain processing to enhance the image and remove noise from the image. Therefore, the proposed algorithm improves the image preprocessing effectively and improves the quality of the image, so as to provide technical guarantee for the effect of local image feature extraction.

In the experiment, we introduce the classic algorithm of image local feature extraction based on particle swarm optimization and the local image feature extraction algorithm based on global and local manifolds, and make a detailed analysis of the
effect of features extraction. Image extraction results of different algorithms are compared, through experiments, the results are shown in Figure 6.

We can see from Figure 6 that the proposed algorithm has the largest number of feature extraction in the image. Therefore, the proposed algorithm can extract features of the image the most comprehensively. And because the algorithm proposed in this paper utilize the least square method to remove the inaccurate local fuzzy features in the process of feature extraction, to ensure the accuracy of the feature extraction. Therefore, the proposed algorithm has better extraction effect.

In summary, the algorithm proposed in this paper can preprocess the image to reduce the noise content of the image to ensure the image quality, and improve the accuracy of image feature extraction, and image feature extraction is more comprehensive.

4. Conclusion. The local fuzzy feature extraction of dynamic images is the basis of dynamic image processing. With the increase of dynamic images, more and more relevant experts and scholars have paid attention to this topic. In view of the fact that the local fuzzy feature extraction of dynamic images has low accuracy and poor extraction performance, a fast local image fuzzy feature extraction algorithm based on FAST corner is proposed to improve the quality of dynamic images by preprocessing images. To ensure the effectiveness of feature extraction, FAST corner is used to extract the local blurred features of dynamic images. Least square method
The extraction effect of the proposed algorithm is used to remove the inaccurate local blurred features in the dynamic images to ensure the accuracy of feature extraction. The experimental results show that the proposed algorithm can accurately extract the local fuzzy features of dynamic images, and the extraction results are better.

Figure 6. Comparison of image feature extraction effect of different algorithms
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