RESEARCH ON ITERATIVE REPAIR ALGORITHM OF HYPERCHAOTIC IMAGE BASED ON SUPPORT VECTOR MACHINE

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Abstract. The damaged area of the hyperchaotic image is prone to lack of texture information. It needs to make image restoration design to improve the information expression ability of the image. In this paper, an iterative restoration algorithm of hyperchaotic image based on support vector machine is proposed. The sample blocks in the damaged region of hyperchaotic images are divided into smooth mesh structures according to block segmentation method, and the neighborhood pixels of which points need to repair are ranked efficiently according to gradient values. According to the edge fuzzification features, the position of the important structural information of the damaged area is located. A multi-dimensional spectral peak search method is applied to construct the information feature subspace of image texture, so as to find the best matching block for restoring the damaged region of hyperchaotic image. Considering the features of structural information and texture information, the maximum likelihood algorithm is used to reconstruct the pixel elements in the image region by piecewise fitting. Through the support vector machine algorithm, the image iterative restoration is carried out. The simulation results show that the restoration method for hyperchaotic image can achieve effective restoration of image damaged area, the quality of restorationed image is better, and the computation speed is fast. The image restoration method can effectively ensure the visual effect of the reconstructed image.

1. Introduction. With the development of computer image processing technology, image processing technology is used to restore the image, and it has a good application prospect in the image protection and reconstruction [9]. Image restoration refers to use fuzzy image reconstruction and detail feature extraction method to reconstruct the edge region of the image’s details in the damaged region, so as to improve the information expression ability of the image. The lost information and the reproduction and preservation of the precious image information can be realized by image restoration. Image restoration is based on the principle of human vision, in accordance with certain criteria and algorithms, to make non-destructive

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holographic filling and display for the loss of the image and the removal information. In real life, image defects are caused by long years and improper storage and so on, so image restoration is needed. In the field of target detection, remote sensing images also need to be restored because of the lack of information and a certain angle feature [6, 27]. It can be seen that image restoration is to use the limited known prior information of the image to fill and repair the unknown area, making the image more reasonable and true in computer vision characteristics and senses, and according to the different application directions, the details of the damaged image can be reconstructed. Combined with computer graphics and virtual reality technology, image reconstruction is combined with GPU graphics processing chip to achieve image information mining and feature recovery. Image restoration technology has great application demand and value especially in the field of information recovery, such as damaged ancient calligraphy and painting. Therefore, the research of image restoration algorithm has certain frontier and practical significance [12].

Hyperchaotic images are digital images that are fuzzy imaged using chaotic imaging technology. In the process of imaging, because the Gauss random chaos, it is prone to generate noise and edge information loss, therefore, it needs for effective restoration of hyperchaotic image, to improve the ability of information expression and image quality of the image. Hyperchaotic images are widely used in the protection of archaeological relics, information perception of medical images and special effects of film and television. It is of great practical significance to study the restoration technology of hyperchaotic image [21, 31]. In traditional methods, the methods of hyperchaotic image restoration mainly use image edge fusion restoration, polarization restoration, texture segmentation and so on [28]. Three dimensional chaotic imaging and scanning technology is applied to collect the original image of the moving image, and then the edge detection and region segmentation of the collected image are carried out. Combined with the method of mesh template matching and block area matching, the hyperchaotic image restoration is realized, and the better restoration effect is achieved.

So far, a large number of literatures have been carried out in the study of image restoration. In the literature [8, 13], a feature fusion method for hyperchaotic image restoration based on wavelet domain vector quantization was proposed. The method was used to calculate the wavelet domain subvector point to line model of the hyperchaotic image restoration. By using the sparse edge pixel fusion method, the motion restoration was realized and the dynamic matching performance of the image was improved. But this method is too expensive and complicated. For the first time, Bertalnino proposed a partial differential equation based image restoration technology, which used the classical fluid mechanics method to establish the mathematical model. Chan proposed a restoration method for non textured image by using the three order PDE model. The advantage of this method is that it is effective to restoration small areas, and the drawback is that when the remaining elements in the restoration area are far away from each other, it cannot restore the single object very well [10]. Roth and Black proposed a simple image restoration algorithm based on a priori model. To enhance the effect of image restoration, texture information must be considered. Efros and Leung used the non parametric method of “growing texture” from the initial seed to imitate texture as a Markov random field (MRF). Because the method is filled in pixel level, the speed of restoration is very slow. The most influential work in this field is the example based image restoration proposed by Criminisi. The order of the method to fill is that is determined by a predefined priority function [17,18]. But the shortcoming of this method
is that the restoration effect is not ideal. So far, most of the better restoration results are based on the Partial Differential Equation (PDE) approach. In general, the PDE-based method can not restore texture information while restoring texture information. The texture restoration method is used to extract the edge contour of the image, and the hyperchaotic image is restored by combining the heat conduction model of the structure and the texture restoration. When the structure is restored, the texture information is considered, and the precision of the restoration is improved. The disadvantage of this method is that only images with fixed texture can be restored, and it is not suitable for the image with a large number of random textures [11].

At present, the PDE algorithm has been basically mature, such as the use of the restoration of small areas such as scratches and text. Its disadvantage is that when a slightly larger damaged area is restored, it is easy to produce a staircase effect and appear false edge, causing fuzziness. In contrast, texture based image restoration algorithm can overcome these shortcomings successfully, especially the algorithm based on sample block image restoration proposed by Criminisi et al. (abbreviated as Criminisi algorithm), which is a classic algorithm based on texture image inpainting algorithm [15]. The main ideas can be summarized as follows: first, the pixels on the edge of the damaged area are selected. Then, at the center of these pixels, according to the texture features of the image, the suitable template size is selected to determine the block to be restored. Finally, the most similar matching block is selected from the undamaged area in the image, and the restoration block is replaced to complete the restoration. The experimental results show that the algorithm has a great improvement in the restoration of vison and computing time. Due to the superior performance of Criminisi algorithm, many researchers have also tried to propose some excellent performance improvement algorithms based on the existing Criminisi algorithm. On the basis of Criminisi algorithm, Wong et al [16, 29] put forward a matching algorithm based on the similarity degree between various sample blocks and blocks to be restored, to determine the best matching block algorithm for the blocks to be repaired. To a certain extent, the algorithm has achieved excellent restoration visual quality, but it takes a long time. And because the algorithm itself is too dependent on the similarity between the restored blocks and the sample blocks, the optimal matching for the restored block is not necessarily accurate [2, 3, 5, 7, 20]. Chandrasekaran et al. proposed a linear addition function to the gradient and the logarithm of gradient to determine the restoration priority algorithm for the restored block. The experimental results showed that the algorithm could obtain better restoration quality. Zhou et al analyzed the influence of structural information intensity on restoration priority in the blocks to be restored, and then proposed an improved image restoration algorithm based on structural information intensity. The algorithm can restore the structural edge image well. Xu et al. proposed an image restoration algorithm that uses the sparsity of block and block matrix (i.e. sparsity between matrices) to determine the priority of the block to be repaired and to find the best matching block [14]. Although the algorithm can effectively restore the image of the curved structure class, its sparsity is greatly calculated, which leads to low restoration efficiency. In the image restoration algorithm, finding the best matching block for a block to be repaired is computationally intensive and has significant array characteristics. In view of this, Kwok et al designed an image restoration algorithm to divide the frequency coefficient of sample block into array sorting in the GPU, which can effectively
shorten the time of image restoration [24,30]. The above research is based on the Criminisi algorithm, focusing on the restoration of texture information. Sun et al. put forward a method based on structure propagation, when using this method, the location of the important structure information in the damaged area that needs to be drawn before restoration [14,24,30]. The algorithm can guarantee the correct propagation of the structure information, but the artificial participation factor is too much to participate in. For the different restoration authors, the restoration results are not the only ones. Li and others put forward a joint restoration method based on the theory of edge region segmentation, it is to combine texture synthesis with structural information propagation, which can avoid blurring of edges and improve the speed of texture synthesis [1,4,19,22,23,25,26,32].

In this paper, an iterative restoration algorithm for hyperchaotic images based on support vector machines (SVM) is proposed. Firstly, according to the block segmentation method, the blocks in damaged region of hyperchaotic images are divided into smooth mesh structures, and the neighborhood pixels of the points needed to restore are sorted effectively according to the gradient values. According to the edge fuzzification features, the position of the important structural information of the damaged area is located. The multi-dimensional spectral peak search method is used to construct the feature subspace of the texture information of the image, so as to find the best matching block for the restoration of the damaged region of the hyperchaotic image. Considering the features of structural information and texture information, the maximum likelihood algorithm are used to reconstruct the pixel elements in the image region by piecewise fitting. Through the support vector machine algorithm, the image iterative restoration is carried out. Finally, the performance test is carried out through the simulation experiment, and the application performance of this method in improving the hyperchaotic image restoration is demonstrated.

2. Hyperchaotic block segmentation and priority decision of the block needed to restore.

2.1. Hyperchaotic image block segmentation. The sample blocks in the damaged region of the hyperchaotic image are divided into a smooth mesh structure according to the block segmentation method. The neighborhood pixels of the points needed to restore are sorted according to the gradient value. The principle diagram of block segmentation of hyperchaotic image is shown in Figure 1.
Hyperchaotic image block segmentation is divided into the following steps: the first step is to determine a priority restoration block in many of the blocks to be restored, of which the pixel of the edge is as the center; the second step is from a large number of sample blocks in intact area to find out an optimal sample block which has the highest priority (i.e. the best matching block), and the matching block is used to substitute the block to be restored; the third step is in the current restored block, the pixels which have not been set the confidence is made update operation, in order to facilitate the next image restoration operation; finally, the edge pixels are updated, then the first to third steps are repeated in turn, and the image is restored until there is no edge pixels.

In order to illustrate the basic principles of this algorithm, we have given the corresponding schematic diagram, as shown in Figure 1. Among them, Ω is the damaged area (white area), Φ is the complete area (gray area), ∂Ω is the edge line between the intact area and damaged area, p is the pixel on ∂Ω to be restored, Ψ_p represents the set of pixels in the block to be restored of which point p is the center, n_p is a orthogonal unit vector in point p and ∂Ω (i.e. |n_p| = 1), that is normal vector; ∇I_p is the gradient vector of point p, and ∇I_p^⊥ is a unit equal intensity vector (i.e. |∇I_p^⊥| = 1) perpendicular to the gradient direction of point p. Meanwhile, The size of the image to be repaired without losing the general assumption is m × n, the size of the block Ψ_p to be restored is s × s, and the average number of edge pixels which are used to calculate the priority coefficient of the block to be restored is b respectively , and b ≪ mn. Because the size of the template of the block Ψ_p to be restored is identity, the size of the search block must also meet the size of s × s, and the number t of blocks to be restored in the damaged area is basically determined.

2.2. Edge detection of damaged image to be restored. Based on block segmentation, edge detection and gray feature extraction for the damaged image to be restored are carried out. The parameter u is defined as the image to be restored, Ω is the space to be restored, αΩ is the analogical boundary information of the damaged feature, p(x, t) is the unit heat transfer function of image texture subspace. To find out an optimal sample block which is matched with the block to be restored having current highest priority (i.e., the best matching block), the size of block Ψ_p to be restored is s × s. Then the low frequency coefficient vector and high frequency coefficient vector of damaged image to be restored can be calculated, to obtain the hierarchical results of promotion for the characteristic of image. The expression of Mallat wavelet coefficient is:

\[ f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*)K(x_i, x_j) + b \]  

(1)

In the formula, \( \alpha_i \) is the modulus maxima of each pixel, b represents the maximum value point of the modulo value of the damaged image to be restored in the direction of the amplitude, \( K(x_i, x_j) \) is represented as a multiple operators including the number of wavelet type unit groups, to finally generate a binary equalization coefficient of gray histogram. Where, \( \alpha_i \) and \( \alpha_i^* \) are bound by the penalty factor, in order to improve the generalization ability of Mallat wavelet learning, multi-frequency separation and improved method is used to achieve control of the punishment degree of the error sample. The control differential function is:

\[ K_{\min} = \beta K_{poly} + (1 - \beta)K_{rbf}, \quad \beta \in (0, 1) \]  

(2)
Where, $K_{poly} = [(x \cdot x_i) + 1]^2$ is the quadratic polynomial kernel function for the edge feature of the damaged image to be restored, and $K_{RBF} = \exp(-\gamma \|x - x_i\|^2)$ is the the RBF kernel function of Mallat wavelet. $\beta$ is to adjust the effect of the two kernel functions on the total mixed kernel function, that is, the weight coefficient.

The confidence and data items of the block $\Psi_p$ to be restored with the center of point $p_i$ are:

$$C(p) = \sum_{x \in (\Phi \cap \Psi_p)} I(x) / |\Psi_p|$$

$$D(p) = \frac{|\nabla I_p^{\perp}| \times |n_p| \times \cos \alpha}{M}$$

The gray image is promoted and separated, and the two value separation results of damaged breakpoint point area and non damaged area of the image to be restored are obtained.

$$\begin{cases}
V_i^d(t+1) = W \cdot V_i^d(t) + C_1 \cdot R_1 \cdot (P_i^{d\text{best}}(t) - P_i^d(t)) \\
\quad + C_2 \cdot R_2 \cdot (G_i^{d\text{best}}(t) - P_i^d(t)) \\
P_i^d(t+1) = P_i^d(t) + V_i^d(t+1)
\end{cases}$$

Among them, $V_i^d(t)$, $V_i^d(t+1)$, $P_i^d(t)$ and $P_i^d(t+1)$ are the feature strength of multi-layer Mallat wavelet lifting of damaged image to be restored, respectively. Through these methods, we can achieve two valued separation of breakpoints area and non breakpoints area of damaged images. The support vector machine iterative restoration scheme is designed to improve the global search capability of damaged image restoration. Thus, the edge detection and separation of the damaged image to be restored based on the hyperchaotic image is realized, which lays the foundation for the realization of the hyperchaotic image restoration.

### 2.3. Priority decision of restoration blocks.

The confidence degree and data item of the hyperchaotic image are important parameters for calculating the priority of the pending block to be restored. The parameters of the edge pixel point $p$ in the Figure 1 is as an example, the confidence $C(p)$ of the block to be restored represents the ratio of the sum of confidence of known pixels in block $\Psi_p$ (i.e. pixels in the intact region) and the number of all the pixels that its contained ($0 < C(p) < 1$), the greater the value is, the higher the restoration accuracy of $\Psi_p$ is, and vice versa. Obviously, the larger $C(p)$ is more conducive to repair the edge of the intact area and the damaged area of the to-be repaired block $\Psi_p$, so as to continuously guide the repair from the edge portion to the damaged area. The data item $D(p)$ of the block to be restored represents the intensity of the equal intensity line at point $p$. Its value depends on the angle $\alpha$ between the equal illumination vector $\nabla I_p^{\perp}$ and the vector $n_p$ of the point $p$. The smaller the $\alpha$ is, the greater the $D(p)$ value is, indicating that the structural information at point $p$ is stronger. But it is worth noticing that the value of $D(p)$ reflects not only the intensity of $p$’s equal illumination, but also reflects the direction of p’s equal illumination to where extending when $\Psi_p$ is restored. So, the calculation formula (6) and (7) are obtained respectively for confidence and data item of block $\Psi_p$ to be restored of which $p$ is as the center.
Among them, \( x \) represents the pixel points at the intersection point between the block \( \Psi_p \) to be restored and intact region \( \Phi \), (that is the pixels of the known information), then the confidence level of the pixel \( x \) of the initialized known information is \( I(x) = 1 \). If the point \( x \) is the pixel of the unknown information, and the corresponding confidence level is \( I(x) = 0 \). |\( \Psi_p \)| is the number of total pixels in the block \( \Psi_p \). \( M \) is a normalization coefficient, which is usually set to 255.

In the Criminisi algorithm, the formula for calculating the priority coefficient \( P(p) \) of the block \( \Psi_p \) of which point \( p \) is the center is shown as formula (8).

\[
P(p) = C(p) \times D(p)
\]

(8)

Obviously, the priority coefficient \( P(p) \) of \( \Psi_p \) is determined by the values of \( C(p) \) and \( D(p) \). If the formula (8) is directly used to determine the priority coefficient of block \( \Psi_p \), it can not effectively make priority restoration of the block with strong structural information (i.e. the value of \( D(p) \) is larger). However, the blocks to be repaired with strong structural information can not be repaired first, which often leads to a weak direction of restoration based on \( \Psi_p \), which leads to structural fracture or fuzzy structure after image restoration. Therefore, the priority coefficient \( P(p) \) of the block \( \Psi_p \) to be restored is obtained by formula (8), and the order of the block \( \Psi_p \) restoration is not truly satisfied. Thus, the priority decision of the restoration block for hyperchaotic image is realized.

3. Improved design of image restoration algorithm.

3.1. Calculation of the best matching block for the damaged area restoration of hyperchaotic image. On the basis of the best matching block in the damaged image area of hyperchaotic image, the location of the important structural information is to draw the damaged area according to the edge fuzzy features. Multi-dimensional spectrum peak search method is used to construct the feature subspace of image texture information, to determine the priority coefficient \( P(p) \) of edge pixel point \( p \), then the restoration priority of the corresponding block \( \Psi_p \) to be restored will be determined. Then the next thing is to verify how to determine the optimal matching block of the block \( \Psi_p \) in the intact area \( \Phi \) and use to replace \( \Psi_p \) for the restoration operation. The specific needs to search in a large number of sample block \( \Psi_q (\Psi_q \subset \Phi) \), to get the best matching block which must meet the formula (8):

\[
\Psi_p' = \arg \left( \min_{\Psi_q \subset \Phi} d(\Psi_p, \Psi_q) \right)
\]

(9)

Among them, \( \Psi_q \) represents the searched sample block in the intact area, and \( d(\Psi_p, \Psi_q) \) represents the sum of variance of the known pixel points in the block \( \Psi_p \) to be restored and the corresponding pixel points in the sample block \( \Psi_q \). When all the sample blocks are traversed, the corresponding \( \Psi_q \) when the sum of variance is the minimum is the best matching block \( \Psi_p' \).

Finding the best matching block is a highly complex process. It is the core of the whole image restoration. Its complexity directly affects the speed of image restoration.
restoration process. From the vertex of the upper left corner in the image, after overwriting the image with the sample template, it searches step by step from left to right with the step of 1. After searching for a line, it immediately return to the left of the current search line, then the sample template is to move down a line of pixels, and then continue to search in the same way from left to right step by step. It repeats until all the pixels are traversed. Obviously, according to the above method, it takes \( O(mn) \) traversal times to search the best matching block once, and then the computational complexity of searching for the best matching block searched for the \( t \) blocks to be repaired is \( O(tmnm) \). Therefore, this fine point-by-point method for searching the best matching block has high computational complexity, especially when the size of damaged image is too large, the effective repair of the image will take too long, making it difficult to meet people demand. After the block \( \Psi_p \) to be restored finding the best matching block \( \Psi_p' \), \( \Psi_p' \) will be used to fill up the pixel \( y \) of unknown information \( \Psi_p \), obviously, the repaired pixel \( y \) does not assign the corresponding confidence Therefore, in order to maintain the continuity of the damaged image area which is restored, it must update the confidence level of point \( y \) after restoration, and the updated guideline is as shown in formula (10):

\[
I(y) = C(p) \quad \forall y \in \Psi_p \cap \Omega
\]  

Based on formula (10), it is known that after the block \( \Psi_p \) is restored, the confidence degree \( I(y) \) of the pixel point \( y \) of the previously unknown information is all updated to the confidence level \( C(p) \) of \( \Psi_p (0 < C(p) < 1) \). In principle, this assignment is unreasonable, for example, for the next block \( \Psi_p1 \) to be restored, the original unknown pixel information \( y \) becomes the pixels of the known information, and the assignment \( I(y) \) is less than 1. According to the fuzzy edge features, the location of the important structural information in the damaged region is to draw. The multi-dimensional spectral peak search method is used to construct the feature subspace of the texture information of the image, so as to find the best matching block for the restoration of the damaged region of the hyperchaotic image.

3.2. Design of features classification technology. In order to enhance the accuracy of diversity hyperchaotic image feature classification, machine vision recognition method is used to extract the color features of image, and the mean and standard deviation of each color component are given, to obtain the image texture features. The balance degree of the image texture distribution and the local change state of gray level are described, and the extracted image features are made grouping. The detailed steps are as follows:

It is assumed that \( N_{PW} \) is the number of pixels of color texture images after cutting, \( I_R(i,j), I_G(i,j) \) and \( I_B(i,j) \) respectively represent the R, B, G component of pixel \( (i,j) \), \( \mu_R \) is the R component in color space of the image RGB, \( \mu_G \) is the G component in color space of the image RGB and \( \mu_B \) is the B component in color space of the image RGB. Using the formula (6) calculates the standard deviation of various colors in color space of the image RGB:

\[
r_{sweert} = N_{PW} \frac{I_B(i,j) \times I_G(i,j) \times I_R(i,j)}{\{\mu_R, \mu_G, \mu_B\} \odot S_{swey}^t}
\]  

In the formula (11), \( S_{swey}^t \) represents a five dimensions feature vector composed of RGB color features.

Supposing that \( I_H(i,j), I_V(i,j) \) and \( I_S(i,j) \) represent H, V and S components of pixel \( (i,j) \) respectively, and \( \{\mu_H, \mu_V, \mu_S\} \) represent the H, V and S components
of image’s color space respectively. Then formula (12) can be used to calculate the color standard deviation of HVS color space of image.

\[ D'_{\text{swer}} = \frac{I_H(i,j) \times I_V(i,j) \times I_S(i,j)}{\{\mu_H, \mu_V, \mu_S\} \oplus P'_{\text{swer}}} \]  

(12)

In the formula (12), \( P'_{\text{swer}} \) represents a five dimensions eigenvector consisting of H, V, and S color features.

Supposing that \( m'_{\text{swer}} \) represents the measure of the mean brightness of image texture, and \( \sigma'_{\text{swer}} \) represents the measure of the mean contrast of texture. It describes the degree of evenness of the grayscale distribution of images by statistical theory. It is expressed by formula (13).

\[ \text{ASM} = \frac{\sigma'_{\text{swer}} \times m'_{\text{swer}}}{L \mp Z'_{\text{drt}}} \oplus p(z'_u) \]  

(13)

In the formula (8), \( L \) represents the total gray level, and \( Z'_{\text{drt}} \) represents the \( i-\text{th} \) gray level, and \( p(z'_u) \) represents the gray level’s distribution probability of the normalized histogram.

\( \text{ASM} \) is defined as a threshold to reflect the roughness of the image texture. The greater the \( \text{ASM} \) value is, the coarser the texture is. \( \text{com} \) is defined as the threshold of the local change of the image gray level, and the local change of the adjacent pixels is large, then the value of \( \text{com} \) is larger and the image visual effect is clearer. \( \text{cop} \) is defined as the extension length of a color of the image along with some direction, the longer the color extends, the greater the value of \( \text{cop} \) is, \( \text{EBT} \) is defined as a measure value of image information volume, the value can reflect the complexity or non uniformity of image texture. When the image is full of fine texture, the entropy is larger, and if the fine texture is less in the image, the entropy is smaller. \( m''_{\text{pki}} \) represents offset of image’s position. Formula (14) is used for grouping the extracted image features:

\[ A'_{\text{swer}} = \frac{m''_{\text{pki}} \oplus \text{ASM}}{\{\text{cop} \mp \text{com}\}} \oplus \frac{\text{EBT} \times r_{\text{swer}}}{x'_{\text{dery}}} \times \frac{D'_{\text{swer}}}{\text{ASM}} \oplus \frac{d'_{\text{dhjk}}}{\text{ASM}} \]  

(14)

In the upper formula, \( x'_{\text{dery}} \) represents the generation direction of the co-occurrence matrix, and \( d'_{\text{dhjk}} \) represents the average energy vector of the detail sub-graph.

To sum up, it can be explained that in the process of high efficient classification and recognition of the image characteristics of diverse forest and fruit pests, the color feature of the image is extracted firstly by the machine vision recognition method, and the mean and standard difference of each color component are given, and the texture features of the image are obtained. Firstly, the color features of the image are extracted by using machine vision recognition method, the mean and standard deviation of each color component are given, and the texture features of the image are obtained. The degree of equalization and the local change of gray level of the image’s texture distribution are described, and the extracted image features are grouped, which laid the foundation for efficient classification and identification of diverse fruit pest image features.

3.3. Efficient classification and recognition of image characteristics of insect pests based on KNN. In the efficient classification and recognition process of the image features of diverse fruit pest, the image feature \( A'_{\text{swer}} \) is as the basis after grouping obtained by section 3.3. the local binary pattern are used to give the
representative CLBP features of pests image’s feature class, to get the main mode of each image feature, and calculate the patterns which can be distinguished of every kind of pests image features, so that the fruit pest image is classified efficiently. The detailed steps are as follows:

Supposing that $\xi_{df}$ represents the average value of the whole image, and $v_{dghj}'$ represents a given pixel in the image. Based on the image feature $A_{swep}'$ after grouping obtained from the section 3.2, the formula (15) is used to give the representative CLBP characteristics of the pest image feature class based on the local binary mode.

$$A_{aqwet}' = s'_{a} v_{dghj}' \times \xi_{df}' + \left\{ \omega_{der}' \oplus x_{hjkp}' \right\}$$

In the upper formula, $\omega_{der}'$ represents the main pattern of a certain image feature, and $x_{hjkp}'$ represents the distinguishable pattern of the $s'_{sd}$-th image feature.

It is assumed that $ve_{esc}$ represents the $k$-th pattern histogram of the $o_{jko}$-th image’s feature, then the main pattern of a certain image’s feature represented by $\omega_{der}'$ is calculated by the formula (11):

$$\omega_{der}' = \frac{\left\{ x_{zcebo}' \pm c_{blp}' \right\}}{k} \times v_{esc} x_{sfg}' = \frac{ve_{esc}}{o_{jko}}$$

In the upper formula, $x_{zcebo}'$ represents the gray value of the pixel adjacent to the arbitrary pixel center $\varepsilon_{sd}'$, and $c_{blp}'$ represents the difference degree between the center $\varepsilon_{sd}'$ and its adjacent pixel.

Assuming that $p_{dghj}'$ represents the texture features based on wavelet energy, $s_{sfg}'$ represents the each color channel for pest image, $Y_{fghj}'$ represents the second layer vertical component of the $k_{sdr}'$ channels image’s wavelet decomposition, $V_{wert}'$ represents the number of all sample types of the pest image, then equation (17) can be used to calculate the distinguishable mode of the seventh image’s feature represented by $x_{hjkp}'$:

$$x_{hjkp}' = s''_{a} V_{wert}' x_{sfg}' \times p_{dghj}' + \left\{ s_{sfg}' \times p_{dghj}' \right\} \mu_{drt}'$$

In the upper formula, $\mu_{drt}'$ represents the fusion weights of multiple features.

It is assumed that $\mu_{dfr}'$ represents a training sample matrix of the $i'_{fr}$-type of pest image’s features $f$, then the image features of the variety of forest and fruit pests are classified and identified by using the formula (13).

$$h_{swever}' = A_{aqwet}' x_{hjkp}' \times \omega_{der}' \oplus f \oplus i' \times x_{pom}'$$

In the upper formula, $x_{pom}'$ represents the dimension of the training sample.

3.4. SVM- based iterative restoration. The sub-space of the noise of the hyperchaotic image is constructed, then the vector quantization decomposition is carried out, and the iterative image restoration is performed on the SVM algorithm. The quantization feature of the image is expressed as $g = \{g(i), i \in \Omega\}$. According to the density of noise distribution, pixel recombination and multidimensional scaling method are applied to the pixel fusion of hyperchaotic image restoration to obtain a full-scale hyperchaotic image. Its phase information and decay increment are denoted as $\theta(k)$, $\Delta x(k)$ and $\Delta y(k)$, respectively. Under noise interference, the
Subspace fusion SVM algorithm is used to get the output of the feature component in pixel fusion region of image, which is expressed as:

\[ I(x) = J(x)t(x) + A(1 - t(x)) \quad (19) \]

Among them, \( A \) is the scale information of single-frame hyperchaotic image restoration, \( t(x) \) is the distribution density of noise, \( J(x)t(x) \) is the distribution distance of the edge contour point distance and the information center point. The previous frame of the image is taken as the reference frame, in the fusion region of pixel and noise, template matching is performed to obtain the template difference value of the statistical feature amount \( s(X,Y) \) of the hyperchaotic image’s edge structure, which is expressed as:

\[ N_{\text{cut}}(A,B) = \frac{\text{cut}(A,B)}{\text{assoc}(A,V)} + \frac{\text{cut}(A,B)}{\text{assoc}(B,V)} \quad (20) \]

Among them, \( \text{assoc}(A,V) \) is the gray pixel feature in the pixel subset \( A \) of the hyperchaotic image restoration, and \( \text{assoc}(B,V) \) is also a similar definition. The binary image processing is used to repair the image, and the image expression of the restored output is obtained as follows:

\[ \min_c \left( \min_{y \in \Omega(x)} \left( \frac{I^c(y)}{A^c} \right) \right) = \tilde{t}(x) \min_c \left( \min_{y \in \Omega(x)} \left( \frac{J^c(y)}{A^c} \right) \right) + (1 - \tilde{t}(x)) \quad (21) \]

Among them, \( \tilde{t}(x) \) is the sampling interval of edge pixel, \( A^c \) is the amplitude of the quantitative decomposition, \( I^c(y) \) is the delay scale. In the image damage area, through the time-frequency decomposition, image restoration and edge detection can be achieved to obtain the edge detection of the noise reduction image as follows:

\[ \tilde{t}(x) = 1 - \min_c \left( \min_{y \in \Omega(x)} \left( \frac{I^c(y)}{A^c} \right) \right) \quad (22) \]

Where \( I^c(y) \) is the initial pixel set, and \( A^c \) is the scale information of the image. Using the template matching technique, the complex discretization of hyperchaotic image restoration is performed to obtain the internal variance feature amount of the image pixel subset \( C \subseteq V \) as:

\[ r(t) = \alpha A \cos(2\pi(f_0 + f_d)(t - d)) + w(t) \quad (23) \]

The minimum cut method is used to search for the edge contour of the image, and the restored feature is obtained by iterative support vector machine iteration in vertical and horizontal bands:

\[ \text{ind}(P) = \left\{ (x,y) \in U^2 | a(x) = a(y), \forall a \in P \right\} \quad (24) \]

NCut criterion is used to evaluate the effectiveness of image restoration, which is defined as follows:

\[ N_{\text{cut}}(A,B) = \frac{\text{cut}(A,B)}{\text{assoc}(A,V)} + \frac{\text{cut}(A,B)}{\text{assoc}(B,V)} \quad (25) \]

Under the condition that the minimum value of \( N_{\text{cut}} \) is satisfied, the dynamic programming method is used to normalize the hyperchaotic image restoration to obtain the random walk entropy function of the image, which can be expressed as:

\[ H'(X) = -\sum_i \sum_j \mu_i \sum_j p_{i,j}(A) \log(p_{i,j}(A)) \quad (26) \]
Assuming that the subspace model of the image to be restored is a $N \times 1$ dimensional Gauss random vector, the difference equation is used to solve the heat conduction equation. The second order partial differential equation is obtained. The maximum likelihood estimation parameter of the texture substructure is obtained through weighted subspace fitting.

$$\eta = [\psi_0, \sigma_\psi, \sigma_s^2, \sigma_n^2]^T$$

(27)

The expression of the maximum likelihood estimation function of the holographic image restoration information is as follows:

$$L(\eta) = \ln \text{det } R_x(\eta) + \text{trace } \left( R_x^{-1}(\eta) \hat{R}_x \right)$$

(28)

Based on the mathematical morphology theory of topological theory, finite difference method discretization method is used to obtain the covariance matrices of image's holographic information restoration:

$$R_x(\eta) = R_s(\psi_0, \sigma_\psi, \sigma_s^2) + \sigma_n^2 I$$

(29)

Among them, $R_s$ is the covariance matrix of the image texture information, $R_x$ is the covariance matrix of the image structure information, $\sigma_s^2$ is the noise energy spectrum in boundary. Finally, by using the maximum likelihood algorithm and considering the features of structure information and texture information, the estimate value of shunt fitting repair of the pixel elements in the image area is as:

$$\hat{\eta} = \arg \min_{\eta} L(\eta)$$

(30)

$$\hat{R}_x = \frac{1}{K} \sum_{k=1}^{K} x_k x_k^H$$

(31)

In the formula, $x_k$ is the covariance matrix of sampling data, $K$ is the number of snapshots. Between successive snapshots is assumed to be statistically independent, and through the above processing, in fitting the restoration process, the searching for small area multidimensional holographic element is to avoid, and the holographic restoration of hyperchaotic image.

The extracted feature points are correlated with template matching according to the dynamic attributes. If the size of the image to be restored is $m \times n$, it takes $O(mn)$ ergodic times to search for an optimal match block. and the calculation of the value of $d(\Psi_p, \Psi_q)$ needs to be performed after each traversal and its comparison of operations. In order to reduce the number of traversal of the best matching block search algorithm, the iterative process of SVM-based hyperchaotic image restoration is described by the support vector machine iterative algorithm as follows:

(1) The first round of image edge contour search:

$$x(2k+1) = (x(2k) + x(2k+2)) * a + x(2k+1)$$

(32)

(2) Performing the first round of pixel update:

$$x(2k) = (x(2k-1) + x(2k+1)) * b + x(2k)$$

(33)

(3) The second round of hyperchaotic image restoration:

$$x(2k+1) = (x(2k) + x(2k+2)) * c + x(2k+1)$$

(34)

(4) The second round update:

$$x(2k) = (x(2k-1) + x(2k+1)) * d + x(2k)$$

(35)
After two rounds of prediction and update operations for hyperchaotic images, segmented fitting restoration of pixel elements in image regions is completed, and the hyperchaotic image restoration based on support vector machine iteration is completed.

4. **Simulation experiment and performance analysis.** In order to verify this algorithm in application performance to achieve hyperchaotic image restoration, a testing platform for restoration of super chaotic image simulation is constructed. The parameters of test platform are set as follows: CPU is the Intel E8400 (dual core), GPU is the NVIDIA, GeForce GTX280 (with 240 stream processors). MATLAB programming software is used to program and simulate the key algorithm. The test object is four groups of damaged images and intact images, the resolution is 10000 × 10000, the image size is 159 × 159 pixels, and the total gray scale of image with 213 × 213 pixels is 256. The size \( s \times s \) of the sample template is 9 × 9 and 11 × 11 respectively. In order to effectively analyze the performance of SVM iterative restoration algorithm, two general sample template templates (the size \( s \times s \) is 9 × 9, 11 × 11) are used to test five image datasets. On the one hand, in order to verify the effect of rough search step in SVM algorithm on the algorithm, the 9 × 9 sample template is used to test the computation time of SVM algorithm and the SNR of the restored image when \( a = 3 \) and \( a = 4 \) (satisfy \( 2 \leq a < s/2 \)), the obtained data are in Table 1 and Table 2. On the other hand, in order to verify the influence of the size parameter \( s \) of the sample block on the SVM algorithm, the 11 × 11 template is used to test the computation time of the SVM algorithm and the SNR of the restored image when \( a = 4 \), and the data are shown in Table 3. At the same time, in order to make comparison of support vector machine algorithm and Criminisi iterative restoration algorithm for the visual effect of image restoration, in this paper, five test images are listed respectively, and by using support vector machine iterative restoration method (sample template: 9 × 9, the rough search step: \( a = 4 \)) and Criminisi algorithm (sample template: 9 × 9) the images are obtained after restoration, as shown in Figure 2 ~ 6. It can be concluded the experimental data of Table 1 ~ 3 and the visual effects comparison of Figure 3 ~ 7 that:

1) From the red marking circle of Figure 2 ~ 6, we can find that compared with support vector machine iterative restored algorithm, the image restored by Criminisi algorithm has serious structural fracture and discontinuity. While, the visual effects presented in Figures 6 and 7 show that the restored images after support vector machine iterative repair algorithm or Criminisi algorithm have good visual effects. The reason for this is that in the image restoration, restoring the block to be repaired with a stronger structure information \((D(p) \text{ is larger})\) is advantageous for determining the direction in which the block to be restored is repaired. However, in the Criminisi algorithm, the obtained priority coefficient of the to-be-repaired block fails to ensure that the block to be repaired with stronger structure information will be preferentially repaired. At the same time, calculating the confidence of unknown pixels will further affect the calculation of the priority coefficients of the next block to be repaired. On the contrary, in the SVM iterative restored algorithm, the blocks to be repaired with strong structural information can be effectively guaranteed to give priority to restore. Therefore, for the images to be repaired in Figure 2 ~ 6, the support vector machine iterative repair algorithm is more conducive to the repaired visual effects; and for the images to be repaired in Figure 6 and Figure 7, the two algorithms can effectively guarantee the visual effect of the repaired image.
Figure 2. Comparison of image “Cow” restoration effect

Figure 3. Comparison of image “Rabbit” restoration effect
(2) From the restoration time of support vector machine iterative restoration algorithm and Criminisi algorithm from Table 1, Table 2 and Table 3, it can be concluded that the restoration time needed by two algorithms increases with the size of the image to be restored (i.e., with the increase of $m \times n$). Because the computational complexity of support vector machine iterative restoration algorithm (about $O(tmn/a^2)$) and the computational complexity of Criminisi algorithm (about $O(tmn)$) increase with the size of the restored image, this test result is consistent with the related theory.

(3) From the comparison of SNR of restored images in Table 1, Table 2 and Table 3, we can see that using support vector machine iterative restoration algorithm and Criminisi algorithm, the error of SNR of restored images is smaller, keeping in 6%. This shows that the support vector machine iterative restoration algorithm is the same as the Criminisi algorithm, which can effectively ensure the quality of the restored image.

(4) Through the analysis, if the size $m \times n$ of image to be restored is greater, then the ratio of the repair efficiency of the support vector machine iterative repair algorithm to that of the Criminisi algorithm is closer to the $a^2$, so in theory, if the size of image to be restored is larger, the efficiency of support vector machine iterative restoration algorithm is the $a^2$ times than that of Criminisi algorithm. It can be seen from the restoration time ratio of the two algorithms in Table 1 (sample template size is $9 \times 9$, rough search step is $a = 3$) and Table 2 (sample template size is $9 \times 9$, rough search step is $a = 4$) that the larger the size of the restored image is,
the larger the ratio $R$ of restoration time by using support vector machine iterative restoration algorithm to that of Criminisi algorithm is, and in Table 1, the $R$ value is less than $3^2$, but as the size of the restoration image gets bigger, the value is close to $3^2$; the $R$ value in Table 2 is less than $4^2$, but as the size of the restoration image gets bigger, the value is close to $4^2$. Another thing to note is that, for the same pair of images to be restored, the $R$ value at the time of $a = 3$ is always less than the $R$ value at the time of $a = 4$. As we can know, compared with the Criminisi algorithm, when the value of rough search step length is $a$, the efficiency of the support vector machine iterative restoration algorithm is greatly influenced.

(5) The analysis of Table 2 (sample template size is $9 \times 9$, rough search step is $a = 4$) and Table 3 (sample template size is $11 \times 11$, roughly search step is $a = 4$), shows that when the size parameter $s$ of sample template changes from 9 to 11, for the same image to be restored. The restoration time of using support vector machine iterative algorithm or Criminisi algorithm will be smaller, but the ratio $R$ has little change. And all the $R$ calculated in Table 3 is also less than $4^2$. Therefore, compared with Criminisi algorithm, the value of parameter $s$ almost has no effect on the efficiency improvement of SVM iterative restoration algorithm, but what really works is the value of rough search step $a$.

To sum up, compared with the Criminisi algorithm, support vector machine iterative restoration algorithm can not only effectively ensure the visual effect of the restored image, but also effectively save the corresponding restoration time. Therefore, the support vector machine iterative restoration algorithm is a image restoration algorithm with better performance.
Figure 6. Comparison of image “Stripes” restoration effect

Table 1. Comparison of experiment data in the first group

| Image data set | SVM iterative restoration algorithm | Criminisi algorithm | Comparison of signal-to-noise ratio: \((U - V)/V(\%)\) |
|---------------|-----------------------------------|---------------------|-----------------------------------------------|
|               | The signal to noise ratio of the restored image: | The signal to noise ratio of the restored image: | \(R = T2/T1\) |
|               | Computing time: \(T1(S)\) | Computing time: \(T2(S)\) | Restoration time | |
| Cow (512 x 384) | 209.656, 22.564 | 1545.233, 21.544 | 8.24 | ↑ 3.54 |
| Rabbit (402 x 336) | 20.53, 33.241 | 174.324, 33.232 | 8.35 | ↑ 1.56 |
| Golf (262 x 350) | 12.234, 30.665 | 85.245, 30.344 | 7.02 | ↓ 0.57 |
| Wall (190 x 186) | 6.323, 28.543 | 46.314, 30.454 | 7.34 | ↓ 5.96 |
| Stripes (176 x 155) | 2.453, 42.032 | 16.543, 43.445 | 6.64 | ↓ 3.76 |

The first set of experiments: the comparison of the restoration data is shown in Table 1.

Test parameters: the size of the sample template is \(9 \times 9\) and the rough search step is \(a = 3\).

The second experiment: comparison of restoration data, shown in Table 2.

Experimental parameters: the size of the sample template is \(9 \times 9\), and the rough search step is \(a = 4\).

The third experiment: comparison of restoration data, shown in Table 3.
Table 2. Comparison of experiment data in the second group

| Image data set | SVM iterative restoration algorithm | Criminisi algorithm | Comparison of signal-to-noise ratio: \((U - V)/V(\%)\) |
|----------------|------------------------------------|---------------------|-----------------------------------------------------|
|                | Computing the restored time image: | Computing the restored time image: | \(R = T_2/T_1\)                                      |
|                | \(T_1(S)\) \(V(dB)\)              | \(T_2(S)\) \(V(dB)\) |                                                     |
| Cow(512 × 384) | 142.354 22.545                      | 1655.221 21.444     | 11.85 \(\uparrow 1.24\)                             |
| Rabbit(402 × 336)| 15.545 32.740                     | 157.545 33.464      | 11.55 \(\downarrow 1.45\)                           |
| Golf(262 × 350) | 7.344 30.469                       | 85.565 30.443       | 11.45 \(\uparrow 0.51\)                             |
| Wall(190 × 186) | 4.455 30.908                       | 46.877 30.356       | 9.56 \(\downarrow 0.56\)                            |
| Stripes(176 × 155)| 1.666 41.876                      | 16.54 43.676        | 9.65 \(\downarrow 4.93\)                            |

Table 3. Comparison of experiment data in the third group

| Image data set | SVM iterative restoration algorithm | Criminisi algorithm | Comparison of signal-to-noise ratio: \((U - V)/V(\%)\) |
|----------------|------------------------------------|---------------------|-----------------------------------------------------|
|                | Computing the restored time image: | Computing the restored time image: | \(R = T_2/T_1\)                                      |
|                | \(T_1(S)\) \(V(dB)\)              | \(T_2(S)\) \(V(dB)\) |                                                     |
| Cow(512 × 384) | 109.464 22.454                     | 1232.243 22.976    | 11.63 \(\uparrow 1.12\)                             |
| Rabbit(402 × 336)| 13.045 31.554                  | 163.465 32.566     | 12.34 \(\downarrow 2.67\)                           |
| Golf(262 × 350) | 6.454 30.464                       | 81.354 30.654      | 13.43 \(\uparrow 0.34\)                             |
| Wall(190 × 186) | 3.833 28.578                       | 40.456 28.533      | 10.46 \(\downarrow 0.45\)                           |
| Stripes(176 × 155)| 1.354 40.665                     | 15.566 43.355      | 9.76 \(\downarrow 5.45\)                            |

Test parameters: the size of the sample template is 11 × 11 and the rough search step is \(a = 4\).

5. Conclusions. Due to the Gaussian randomness of chaos, hyperchaos images are prone to exist noise and edge information loss in the imaging process. Therefore, the hyperchaotic images need to be effectively repaired to improve the image information expression and image quality. In this paper, an iterative restoration algorithm of hyperchaotic image based on support vector machine is proposed. The sample blocks in the damaged region of hyperchaotic images are divided into smooth mesh structures according to block segmentation method, and the neighborhood pixels of which points need to repair are ranked efficiently according to gradient values. According to the edge fuzzification features, the position of the important structural information of the damaged area is located. A multi-dimensional spectral peak search method is applied to construct the information feature subspace of image texture, so as to find the best matching block for restoring the damaged region of hyperchaotic image. Considering the features of structural information and texture information, the maximum likelihood algorithm is used to reconstruct the
pixel elements in the image region by piecewise fitting. Through the support vector machine algorithm, the image iterative restoration is carried out. The research shows that the method proposed in this paper has the advantages of high quality of hyperchaotic image restoration, high time efficiency of restoration and high output signal to noise ratio, which can ensure the quality after image restoration and the required repair time is shorter. For the damage area reconstruction and restoration of hyperchaotic image, it also has a good application value.

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