A SUPER-RESOLUTION RECONSTRUCTION METHOD FOR OF SINGLE-FRAME CHARACTER IMAGES BASED ON WAVELET NEURAL NETWORK

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ABSTRACT: The image super-resolution reconstruction technology means that a low-resolution image acquired by existing hardware devices or network conditions is reconstructed and converted into a high-resolution image using software processing. The current single-frame character image super-resolution reconstruction methods have problems of poor anti-interference performance and low resolution of reconstructed images. This paper proposes a single-frame character image super-resolution reconstruction method based on wavelet neural network. The current method extracts textures of different directions and image smoothness measures against texture characteristics of crisscrossed and diagonal directions of character images. The super-resolution reconstruction of a single frame image is achieved in the framework of maximum posterior probability. This method has low anti-interference performance, low resolution of reconstructed images. It can be seen that the image resolution obtained by the single-frame character image super-resolution reconstruction method based on wavelet neural network is higher than that based on non-negative neighborhood embedding and non-local regularization and that based on SVR.

KEYWORDS: Wavelet neural network, Single-frame character image, Super-resolution reconstruction

1 INTRODUCTION

Super-resolution reconstruction of images refers to a digital image processing technique that reconstructs a high-resolution image from one or more low-resolution images (Wu, Sun & Zhao, 2017). According to different kinds of images, the image super-resolution reconstruction mainly consists of super-resolution reconstruction of color images and super-resolution reconstruction of depth images. In the field of image processing, super resolution reconstruction techniques are generally used to increase resolution of images for the acquired low-resolution images. The current method extracts textures of different directions and image smoothness measures against texture characteristics of crisscrossed and diagonal directions of character images. The super-resolution reconstruction of a single frame image is achieved in the framework of maximum posterior probability. This method has low anti-interference performance, low resolution of reconstructed images (Wei, 2017; Li et al., 2016).

Image super-resolution reconstruction has very important application value in many fields. Therefore, the super-resolution reconstruction method for single-frame character images needs to be analyzed and studied (Fei et al., 2015). Liu Na and Li Cuihua proposed a super-resolution reconstruction method for single-frame image based on multi-level convolution neural network learning. This method constructs a PMJ model applied to super-resolution reconstruction, and performs preliminary feature extraction on the image during the sensing phase. This method cannot effectively remove the noise in the single-frame character image, and the anti-interference performance is poor (Liu & Li, 2015). Peng Yangping, Ning Beijia, Gao Xinbo reported a single-frame image super-resolution reconstruction method based on non-negative neighborhood embedding and non-local regularization, which can be well maintained; during the reconstruction phase, non-negative neighborhood embedding is used to select the number of neighbors; in the end, the non-local similarity of the image is used to construct non-local regular terms to modify the reconstruction result. The process of this method is complex, and errors are easy to occur, resulting in lower resolution of the image (Peng, Ning & Gao, 2015). Yuan Qiping, Lin Haijie, Chen Zhihong et al. came up with a single frame image super-resolution reconstruction method based on support vector regression (SVR). This method uses raster scanning to scan high and low resolution training images and extracts input vectors and label pixels from the
blocks respectively. SVR tools are utilized to regress the corresponding label pixels belonging to the super-resolution image block to complete the super-resolution reconstruction of the image. This method cannot remove the Gaussian noise in the single-frame character image, and the anti-interference performance is poor (Yuan et al., 2016). In summary, a super-resolution reconstruction method for single-frame character image based on wavelet neural network is proposed.

![Diagram](image.png)

**Fig. 1 Image degradation process**

The specific causes of motion deformation, blurring, downsampling, and additive noises in Figure 1 are as follows:

1. **Motion deformation**: there are global motion and local motion. The global motion is generated according to the motion of the camera. After the global motion, the image is deformed. After the deformation, each object in the image has the same motion characteristics and parameters, and the motion can be compensated by estimating the parameters of the two-dimensional or multi-dimensional model. The local motion is generated by the motion of each object in the scene. After local motion, the image is deformed. After the deformation, each object in the image has its own motion characteristics and parameters, which are relatively complicated to handle.

2. **Blurring**: there are mainly three types: the motion blur caused by the relative motion, the optical blur caused by the defocus of the optical imaging system and the diffraction limit and other factors, and the blurring of the low-resolution sensor. In the application of single-image super-resolution reconstruction, these blurs are usually characterized by point spread functions.

3. **Sampling**: the light emitted by the object is converted into an electric signal on the sensor. In order to display and store the electric signal, it needs to be sampled. The sampling process may cause signal distortion, resulting in a decrease in the sharpness of the image and output of a low-resolution image.

4. **Additive noises**: there are noises formed by mutual interference of various originals in the system, and noises in the sampling process.

Let $X$ be an ideal high-resolution image. It can be seen from Figure 1 that after $X$ undergoes motion deformation, blurring, sampling, and noises during imaging, the quality of the image obtained actually decreases, resulting in a low-resolution image. The low-resolution image may be the result of one imaging or multiple imaging.

The $k$-frame low-resolution image obtained by imaging $k$ times in the same scene is denoted as $Y_k$. The mathematical description of this process is:

$$ Y_k = DBM_k X + n_k $$  \(1) \)

Where $k = 1, 2, \ldots, K$ is the number of frames in the image sequence, $K$ is the total frame number of the image sequence in the same scene; $Y_k$ is the low-resolution image of the $k$-th frame; $X$ is the ideal high-resolution image; $D$ is the downsampling matrix; $B_k$ is the fuzzy matrix of $Y_k$; $M_k$ is the deformation matrix of $Y_k$; $n_k$ is the additive noises matrix.

After the image is imaged once, a low-resolution image is obtained, which is denoted as $Y$. This process is not impacted by a geometric transformation matrix. The mathematical description of the process is:

$$ Y = DBX + n $$ \(2) \)

For ease of description, the noise variable is removed to get a simplified expression:

$$ Y = DBX \text{ or } Y = DBX $$ \(3) \)
3 A SUPER-RESOLUTION RECONSTRUCTION METHOD FOR SINGLE-FRAME CHARACTER IMAGE

3.1 Wavelet threshold denoising

Wavelet threshold denoising can be divided into the following steps:

(1) Wavelet decomposition: appropriate wavelet basis and decomposition level are selected to decompose the image.

(2) Threshold selection and quantification: the corresponding threshold is chosen for decomposed high-frequency coefficients of each layer, and the threshold is quantified.

(3) Wavelet reconstruction: according to low frequency coefficients of the \( N \)-th layer the wavelet decomposition and the high frequency coefficients of each layer after threshold selection, the image is processed with wavelet reconstruction. In wavelet threshold denoising, the selection and quantification of thresholds are very important and directly related to the quality of denoising.

Hard threshold and soft threshold are two common methods of wavelet threshold. The hard threshold algorithm uses zero substitution when the wavelet coefficient \( W_{ij} \) is less than the threshold \( \lambda \), ie:

\[
W_{ij} = \begin{cases} 
0 & |W_{ij}| \leq \lambda \\
W_{ij} > \lambda 
\end{cases}
\]  
(4)

The soft threshold algorithm replace the wavelet coefficient \( W_{ij} \) with zero if the value is smaller than the threshold \( \lambda \), and the other is modified by subtracting the threshold \( \lambda \) from the wavelet coefficient, ie:

\[
W_{ij} = \begin{cases} 
0 & |W_{ij}| \leq \lambda \\
\text{sgn} W_{ij} \left| W_{ij} - \lambda \right| & W_{ij} > \lambda 
\end{cases}
\]  
(5)

A local adaptive threshold selection method based on wavelet decomposition layer number, local contrast and statistical characteristics of high frequency coefficients was proposed. In this method, the high-frequency coefficient matrices in each horizontal, vertical, and diagonal directions of the lifting wavelet decomposition are processed in blocks to obtain a plurality of sub-coefficient matrices. Each sub-coefficient matrix corresponds to a local information of the image. According to the number of layers, contrast, and absolute median, a threshold selection model is proposed, namely:

\[
T_{sk} = \frac{\lambda_{sk} N_{sk}}{2 - 1}
\]  
(6)

In the formula, \( k \) is 1, 2, and 3, respectively, representing the horizontal, vertical and diagonal directions; \( i \) represents the number of decomposition layers; \( y \) represents the local image in the \( i \)-th layer, the \( k \)-th direction, and the \( j \)-th sub-matrix. Contrast; \( n \) represents the absolute median of the high-frequency coefficients corresponding to the \( j \)-th sub-matrix in the layer direction. As the number of decomposition layers \( i \), local contrast \( y \), and the absolute median of high frequency coefficients in each sub-matrix are different, a more adaptive threshold is selected.

Daubechies (9/7) wavelet transform belongs to biorthogonal wavelet transform and has a linear phase. Biorhogonal wavelet transform has been widely used in image processing. The biorthogonal wavelet decomposition formula for discrete signals is:

\[
y_i = \sum_{k=1}^{\infty} h_{2k-1} y_{2k-1} + \sum_{k=1}^{\infty} g_{2k-1} y_{2k-1}
\]  
(7)

\[
z_i = \sum_{k=1}^{\infty} h_{2k} y_{2k} + \sum_{k=1}^{\infty} g_{2k} y_{2k}
\]  
(8)

In the formula, \( h \) and \( g \) represent image signals. If \( x \) is the original signal and \( y \) and \( z \) are low-frequency signals and high-frequency signals obtained after decomposition, the reconstruction formula is:

\[
X_i = \sum_{k=1}^{\infty} (\tilde{h}_{2k} y_{2k-1} + \tilde{g}_{2k} z_{2k})
\]  
(9)

3.2 Super-resolution image reconstruction based on wavelet neural network

The conversion from a low-resolution image to a super-resolution image is defined as \( F(\cdot) \), the input layer vector of the network is \( \alpha_{pq} = (P, q_{pq} W^T, \sigma(\cdot)) \) is the growth limit, and \( \Omega_{P-q} \) is the coordinate \( (p, q) \) of the point on the 2D image plane.

The 3D image constructed by the wavelet neural network reflection model can be defined as:

\[
R_{pq}(p, q) = F(w, v, a_{pq}) = \sigma(\sum_{i=0}^{N} V_i \sigma(W_i a_{pq}) + \theta)
\]  
(10)

The height of the image surface is calculated:

\[
z_{pq}(n+1) = z_{pq}(n) - \frac{E}{4} (f_{pq} + g_{pq})
\]  
(11)

In the equation, \( z_{pq} \) represents the height of the image surface, and \( f_{pq} \) and \( g_{pq} \) represent the width and length of the image surface. The expression of the reflection model based on the wavelet neural network output layer is:

\[
V = \sum_{i=0}^{N} (\phi_{pq}, \phi'_{pq})
\]  
(12)

Where \( \phi_{pq} \) is the vector of image. The hidden layer reflection model based on wavelet neural network is:

\[
w(n + 1) = w(n) + \eta w \left[ -E_{n}\frac{w_i}{w_{pq}} + E(wk) \right]
\]  
(13)

Where, \( w \) represents the space formed by the
detailed information described by the wavelet function, \( E_I \) represents the optimal nonlinearity parameter, \( E_{(wk)} \) represents the least optimized objective function, and single-frame character image super-resolution reconstruction is evaluated by the energy function \( E(\theta) \) of network. The higher \( E(\theta) \) value is, the higher the resolution of a reconstructed single-frame character image. The calculation equation of \( E(\theta) \) is:

\[
E(\theta) = \int F(W_v, r, a)^2 + \lambda
\]  

(14)

4 EXPERIMENTAL RESULTS AND ANALYSIS

In order to verify the overall validity of the single-frame character image super-resolution reconstruction method based on wavelet neural network, the single-frame character image super-resolution reconstruction method based on wavelet neural network needs to be tested. The test platform for this experiment is Matlab. The system is Windows 7.0. Single-frame character image super-resolution reconstruction method based on wavelet neural network, single-frame image super-resolution reconstruction method based on non-negative neighborhood embedding and non-local regularization, single frame image super-resolution based on SVR are tested to compare the anti-interference performance of three different methods. The test results are shown in Figure 2.

Figure 2(a) shows test results of the single frame character image super-resolution reconstruction method based on wavelet neural network. It can be seen from Figure 2(a) that when a single frame character image super-resolution reconstruction method based on wavelet neural network is used for testing, the frequency fluctuation of the signal in the image after adding the interference is small by comparing the signal frequency after adding interference and before adding the interference. The verification shows the single-frame character image super-resolution reconstruction method based on wavelet neural network has stronger anti-interference performance. Figure 2(b) shows the test results of the single-frame image super-resolution reconstruction method based on non-negative neighborhood embedding and non-local regularization. Figure 2(c) are the results of the single-frame image super-resolution reconstruction method based on SVR. Figure 2(b) and (c) show that when the single-frame image super-resolution reconstruction method based on non-negative neighborhood embedding and non-local regularization and the single-frame image super-resolution reconstruction based on support vector regression method are used, the frequency fluctuation of the signal in the image after adding the interference is large by comparing the signal frequency after adding interference and before adding the interference. It shows the single-frame character image super-resolution reconstruction method based on wavelet neural network has weaker anti-interference performance.

![Fig. 2 Test results of three different methods](image_url)

In order to further verify the anti-interference ability of the single-frame character image super-resolution reconstruction method based on
wavelet neural network, the single-frame character image super-resolution reconstruction method based on wavelet neural network, non-negative neighborhood embedding and non-local regularization (method 1), SVR (method 2) are compared, and the SNR of 512×512×8 after reconstruction are compared. Equation (15) is used to calculate SNR, test results are shown in Table 1.

$$R_{\text{SNR}} = 10 \log_{10}(255^2 D)$$  \hspace{1cm} (15)

<table>
<thead>
<tr>
<th>Image number</th>
<th>Input noise intensity /dB</th>
<th>SNR /dB</th>
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<tr>
<td></td>
<td>The proposed method</td>
<td>Method 1</td>
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<tr>
<td>1</td>
<td>15</td>
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<td>2</td>
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Analysis of the data in Table 1 shows that for testing seven different images, the SNR in the image does not decrease with the increasing input noise intensity when the single-frame character image super-resolution reconstruction method based on wavelet neural network is used, which shows that the single-frame character image super-resolution reconstruction method based on wavelet neural network can effectively remove the noise in the image. When the non-local regularized single-frame image super-resolution reconstruction method and the SVR method are used, the SNR in the image decreases with the increase of the input noise intensity, which proves the non-local regularized single frame image super-resolution reconstruction method and the SVR method. Single-frame image super-resolution reconstruction method cannot remove the noise effectively when the noise intensity is high. The test results show that the SNR of single-frame character image super-resolution reconstruction method based on wavelet neural network is higher than the method based on non-negative neighbor embedding and non-local regularization, and the method under different noise intensities, which verifies that the single-frame character image super-resolution reconstruction method based on wavelet neural network are more effective.

Single-frame character image super-resolution reconstruction method based on wavelet neural network, single-frame image super-resolution reconstruction method based on non-negative
neighborhood embedding and non-local regularization, single frame image super-resolution based on SVR are tested separately, and the resolution of the images reconstructed with three methods is compared. The test results are shown in Figure 3.

Figure 3(a) is the image resolution obtained by reconstructing a single-frame character image using the single-frame character image super-resolution reconstruction method based on wavelet neural network. Figure 3(b) shows the image resolution obtained by reconstructing a single-frame character image using the single-frame image super-resolution reconstruction method based on non-negative neighborhood embedding and non-local regularization. Figure 3(c) is the image resolution obtained by reconstructing a single-frame character image using the single-frame image super-resolution reconstruction method based on SVR. Comparing Figure 3(a), (b) and (c), it can be seen that the image resolution obtained by the single-frame character image super-resolution reconstruction method based on wavelet neural network is higher than that based on non-negative neighborhood embedding and non-local regularization and that based on SVR. Because single-frame image super-resolution reconstruction based on non-negative neighborhood embedding and non-local regularization and the method based on the SVR have poor anti-interference. In the reconstruction process, the image contains too much noise, resulting in a lower resolution of the image obtained by the reconstruction.

5 CONCLUSION

The image super-resolution reconstruction technology means that a low-resolution image acquired by existing hardware devices or network conditions is reconstructed and converted into a high-resolution image using software processing. The current single-frame character image super-resolution reconstruction methods have problems of poor anti-interference performance and low resolution of reconstructed images. This paper proposes a single-frame character image super-resolution reconstruction method based on wavelet neural network. The super-resolution reconstruction of the single-frame character image is completed, and the noise in the image can be effectively removed, and a single-frame character image with higher resolution can be obtained.

Super-resolution image reconstruction is one of the hot topics in recent years. Finding a highly efficient and simple reconstruction algorithm is of great significance. There are still many problems to be solved in the study of super-resolution image reconstruction.

(1) Improvement of the super-resolution reconstruction model: The reconstruction model of the image in different research areas is different, especially in the research of super-resolution reconstruction of single-frame character images, it is necessary to combine the formation process of single-frame character images to establish a reconstruction model more suitable for single-frame character images.

(2) Evaluation of reconstructed image quality: In
practical applications, other evaluation indicators must be considered to achieve an accurate evaluation of the reconstructed image quality.

6 REFERENCES


