Blurred Detail Enhancement Algorithm for Motion Video Image Based on Computer Network

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Abstract. In this work, a blurred detail enhancement algorithm is proposed to improve the feature recognition ability of motion video image based on computer network. The edge contour features of motion video images are decomposed using multi-scale Retinex algorithm, and the image recognition technology based on computer network is used to simulate the human visual features to enhance and repair the overlay or blurred features contained in the images. The feature extraction and feature focusing of blurred detail of motion video image are realized by computer vision template feature matching method, respectively. On this basis, the enhancement effect of blurred detail image is achieved. The proposed method is proved to be able to can improve the output peak signal to noise ratio (PSNR) the blur detail quality, and the recognition ability of motion video images.

Keywords: Computer Network, Motion Video, Image, Enhancement, Fuzzy Recognition

1. Introduction

In sports training, it is necessary to analyze the motion video image by blurred detail feature analysis, so as to improve the recognition ability of the motion detail feature. Studying the blurred detail enhancement algorithm of motion video images is of great importance. The fast and efficient motion video image recognition is taken based on the information enhancement processing of the blurred image, and the information enhancement processing is carried out on the fuzzy pixel points of the moving video \[1\]. The key information feature points are optimized and extracted in the blurred detail feature distribution region. Robust detection and image fusion are carried out to achieve the motion video image enhancement, and the state feature information of the target is simulated by computer vision analysis method. The 3D reconstruction of the blurred detail feature of the motion video image is realized\[3\].

Traditionally, image enhancement algorithms mainly include Retinex algorithm and SIFT algorithm, which mimic the model of human visual brightness and color perception to achieve image information enhancement. On the basis of single-scale Retinex algorithm, multi-scale weighted average Retinex algorithm \[3\] with color recovery is developed, which is applied to the design of blurred detail enhancement algorithm for motion video image\[4\]. However, the traditional method
normally presents an unsatisfactory performance in identifying the blurred detail features of motion video image, with low SNR of image enhancement output being obtained. To this end, a blurred detail enhancement algorithm of motion video image based on computer network is proposed in this paper.

2. Multi-scale Retinex algorithm and feature extraction

2.1 Multi-scale Retinex algorithm
Firstly, the edge contour feature of the motion video image is decomposed using multi-scale Retinex algorithm. The gray pixel set of the initial motion video image is given as follows:

$$\min_c \left( \min_{y \in \Omega(x)} \frac{I^c(y)}{A^c} \right) = \tilde{I}(x) \min_c \left( \min_{y \in \Omega(x)} \frac{J^c(y)}{A^c} \right) + (1 - \tilde{I}(x))$$  \hspace{1cm} (1)

Based on Gamma-Gamma distribution method, the scattering physical model of blurred detail feature distribution of motion video image is constructed:

$$I(x) = J(x)t(x) + A(1 - t(x))$$  \hspace{1cm} (2)

Where $I(x)$ represents the scattering intensity of the edge feature. The edge pixel set of the blurred detail feature point distribution of video image is obtained by adaptive template matching method:

$$\tilde{I}(x) = 1 - \min_c \left( \min_{y \in \Omega(x)} \frac{J^c(y)}{A^c} \right)$$  \hspace{1cm} (3)

For a motion video blur image $J$, a multi-scale Retinex decomposition is needed in the imaging process, and the Retinex decomposition process of the motion video image is described as follows:

$$J(x) = \frac{I(x) - A}{\max(t(x), t_i)} + A$$  \hspace{1cm} (4)

$$p(\eta_s(x, y)) = \begin{cases} \frac{r}{4}, & \eta_s(x, y) = -1 \\ \frac{1 - r}{2}, & \eta_s(x, y) = 0 \\ \frac{r}{4}, & \eta_s(x, y) = 1 \end{cases}$$  \hspace{1cm} (5)

Where, $J(x)$ is the information gain coefficient, $\max(t(x), t_i)$ is the maximum density of Retinex scale decomposition, and $I(x)$ represents the blurred detail distribution coefficient. By using the geometric invariance of multi-scale Retinex decomposition \cite{5}, we can get the wavelength coefficients of edge contour as follows:

$$L = J(w, e) - \sum_{i=1}^N a_i \left[w^T \varphi(x_i) + b + c_i - y_i \right]$$  \hspace{1cm} (6)

Define

$$J^{dark}(x) = \min_c \left( \min_{y \in \Omega(x)} \frac{J^c(y)}{A^c} \right)$$  \hspace{1cm} (7)

Multi-scale Retinex decomposition is used to extract edge contour features and calibrate key information points of motion video images \cite{6}.
2.2. Edge contour feature decomposition

To enhance and repair the overlay or blur features contained in the image, assuming that \( d(x) \) is a spatial coordinate, the binary separation of the motion video image \( I(x) \) can be expressed as equation (8):

\[
I(x) = Ap(x)e^{d(x)} + A(1 - e^{d(x)}) \tag{8}
\]

For local region of \( N \times N \), the target is divided into blocks, and the weight of the information fusion block is calculated as equation (9):

\[
J(x) = \frac{I(x) - A}{\max(I(x), I_0)} + A \tag{9}
\]

The image recognition technology of computer network is used to simulate the human visual features [7]. With the eigenvalues as the weight of each principal component, the edge contour decomposition formula is obtained:

\[
a_k = (\sum_k + \varepsilon U)^{-1} \left( \frac{1}{|w|} \sum_{i \in w} I(p_i - u_k p_i) \right) \tag{10}
\]

\[
b_k = p_k - a_k^T u_k \tag{11}
\]

\[
q_i = \frac{1}{|w|} (\sum_{i \in w} (a_k l_i + b_k)) = \overline{a_k} l_i + \overline{b_k} \tag{12}
\]

According to the above block structure model, each target image is divided into equal size blocks, and the fuzzy feature segmentation and adaptive information enhancement processing of the motion video image are carried out with the template matching method [8].

3. Optimization of blurred detail enhancement algorithm of motion video image

On the basis of the edge contour feature decomposition by multi-scale Retinex algorithm, the edge intuitionistic fuzzy set of motion video image is obtained as:

\[
p(x, t) = \lim_{\Delta t \to 0} \left[ \sigma \frac{u - (u + \Delta u)}{\Delta x} \right] = -\sigma \frac{\partial u(x, t)}{\partial x} \tag{13}
\]

Based on weighted average algorithm of region feature subspace, the gray pixel value of the image is enhanced adaptively:

\[
x_i(t) = \sum_{k=0}^{K} \sum_{t=0}^{T} \theta \left[ w_i, \ldots, w_m \right] \left[ x_i(t - k), \ldots, x_m(t - k) \right] - \sum_{k=0}^{K} \sum_{t=0}^{T} \theta \left[ w_i, \ldots, w_m \right] \tag{14}
\]

The multi-scale weighted average Retinex feature is extracted, and the blurred details of motion video images are extracted in blocks by constrained evolutionary algorithm [9]. The results are shown as follows:

\[
\begin{align*}
G_j^{mn} &\quad (j \in \{1, \ldots, p\}) \\
G_j^{mn} &= \max_{i \in \{1, \ldots, p\}} (G_j(i)) \quad (15)
\end{align*}
\]

The pre-set template matching threshold \( S \) is obtained, and the subspace of the blurred detail feature distribution is represented as:
\[
\begin{bmatrix}
x \\
y \\
\end{bmatrix} = \begin{bmatrix}
\cos \theta & -\sin \theta \\
\sin \theta & \cos \theta \\
\end{bmatrix} \begin{bmatrix}
x' \\
y' \\
\end{bmatrix}
\]

(16)

Where

\[
\theta = \arctan \left( \frac{\partial u}{\partial y} / \frac{\partial u}{\partial x} \right)
\]

(17)

The image enhancement template function is obtained by using adaptive template matching method to enhance the basic features of motion video image blur details:

\[
S_m = \frac{\text{dot}(F_m^G, F_m^P)}{\| F_m^G \| \cdot \| F_m^P \|}
\]

(18)

The region of fuzzy feature points, are enhanced by the nearest neighbor method, and then the target image is divided into \( t \) blocks with non-overlapping local blocks, which are expressed as:

\[
y_i = W_i^T M_i = [y_{i1}, y_{i2}, \ldots, y_{in}]
\]

(19)

\[
y_T = W_T^T M_T = [y_{T1}, y_{T2}, \ldots, y_{Tn}]
\]

(20)

Where, the subspace of local information of blurred detail is obtained by \( W_i \) projection of \( M_i \) and \( M_T \), and the covariance matrix is established as equation (21):

\[
C = O^T O \left[ \sum H_s(t)H_s(t)^T \sum H_s(t)H_r(t)^T \right]
\]

(21)

By using the method of region template matching, the feature transformation information of the internal information of motion video image is obtained\(^{[10]}\), and the singular value decomposition formula of blurred detail enhancement is obtained as follows:

\[
O = USV^T
\]

(22)

Based on the Radon scale transform, the feature extraction results of blur detail enhancement of motion video image can be expressed as equation (23):

\[
f_k(z) = \begin{bmatrix}
f_s(z) \\
h_r(z) \\
\end{bmatrix} = \begin{bmatrix}
h_s * f(z) \\
h_r * f(z) \\
\end{bmatrix}
\]

(23)

Where, \( f(z) \) represents the internal eigenvector of the motion video image manifold, and \( * \) presents convolution operation.

4. Simulation

Simulation is carried out to evaluate the application performance of the proposed method in the blurred detail enhancement of motion video image. A \( 10 \times 10 \) block pattern is used for the morphological segmentation of the blurred detail features of motion video images. The threshold of multi-scale Retinex decomposition is 0.25, the iterative step of extracting blurred detail feature is 1000, the size of block neighborhood is \( \omega = 7 \), and the scale of adaptive image enhancement is \( K = 50 \). The simulation of blurred detail enhancement of motion video image is carried out, and the original motion video image is obtained as shown in figure 1.
In figure 1, the key details of the image feature points are blurred. The method proposed in this paper is used to enhance the image details, results in detail enhanced image, as figure 2.

Figure 2 shows that the proposed method improves the identification ability of the feature points of blurred details and the output quality of the image.

Figure 3 shows the PSNR of different methods for image enhancement. It can be seen that the proposed method can enhance PSNR of image has by 13.7% and 12.8% compared with traditional method.

5. Conclusions
In this work, a enhancement algorithm of blurred detail of motion video image based on computer network is proposed. The multi-scale Retinex algorithm is used to decompose the edge contour
features of motion video images, and the image recognition technology based on computer network is used to simulate the human visual features to enhance and repair the overlay or blurred features contained in the images. The feature extraction and feature focusing of blurred detail of motion video image is carried out by computer vision and template feature matching method, respectively. On this basis, the enhancement effect of blurred detail image can be achieved realized. The proposed method can improve the output PSNR \( \alpha \), enhance the detail quality imaging, and improve the recognition ability of motion video images, which has a great application potential in feature extraction and recognition of motion video images.

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