Multi-frame Image Super-resolution Reconstruction Using Multi-grained Cascade Forest

Yaming Wang, Zhikang Luo, and Wenqing Huang

Abstract—Super-resolution image reconstruction utilizes two algorithms, where one is for single-frame image reconstruction, and the other is for multi-frame image reconstruction. Single-frame image reconstruction generally takes the first degradation and is followed by reconstruction, which essentially creates a problem of insufficient characterization. Multi-frame images provide additional information for image reconstruction relative to single frame images due to the slight differences between sequential frames. However, the existing super-resolution algorithm for multi-frame images do not take advantage of this key factor, either because of loose structure and complexity, or because the individual frames are restored poorly. This paper proposes a new SR reconstruction algorithm for images using Multi-grained Cascade Forest. Multi-frame image reconstruction is processed sequentially. Firstly, the image registration algorithm uses a convolutional neural network to register low-resolution image sequences, and then the images are reconstructed after registration by the Multi-grained Cascade Forest reconstruction algorithm. Finally, the reconstructed images are fused. The optimal algorithm is selected for each step to get the most out of the details and tightly connect the internal logic of each sequential step.This novel approach proposed in this paper, in which the depth of the cascade forest is procedurally generated for recovered images, rather than being a constant. After training each layer, the recovered image is automatically evaluated, and new layers are constructed for training until an optimal restored image is obtained. Experiments show that this method improves the quality of image reconstruction while preserving the details of the image.

Keywords—Multi-frame image SR, Image registration, SRMCF, Image fusion

I. INTRODUCTION

IMAGES obtained through photography are affected by various real-world factors, such as noise inherent to the camera imaging system, or blurring caused by the subject of the image being out of focus or in motion. These factors degrade important details, negatively impacting image quality. Super-resolution (SR) image reconstruction is specifically the technique of constructing high resolution (HR) images using single, multiple, or sequential low-resolution (LR) images in the case of degradation. It is widely used in security surveillance, medical imaging, remote sensing imaging, image

Yaming. Wang is with School of Information Science and Technology, Zhejiang Sci-Tech University, Hangzhou,China (e-mail: zgywang@126.com).

Zhikang. Luo is with Machine vision and pattern recognition laboratory,Zhejiang Sci-Tech University, Hangzhou,China (e-mail: 15990053017@163.com).

Wenqing. Huang is the correspongdence author and is with the School of Information Science and Technology, Zhejiang Sci-Tech University, Hangzhou,China (e-mail: patternrecog@163.com).

processing research and public safety. Generally, the use of sequential images for SR reconstruction provides a better reconstruction effect than that of a single image. This difference is due to the relative motion between frames in image sequences, as information observable from different angles in a single scenario is non-redundant and complementary.

In the field of digital image research,many researchers are committed to traditional image reconstruction [1]. Although the use of single-frame images for reconstruction has been extensively studied, use multi-frame images to achieve higher resolution reconstructed images than single-frame images [2]–[4]. The advantage of multi-frame reconstruction is to use not only in-frame correlation in a single frame image, but also inter-frame correlation between multiple images. In order to take advantage of multi-frame images, generally involves image registration, fusion, and other techniques to compensate for the displacement between images. There are three main methods: frequency domain method, spatial domain method, and learning method:

The benefits of the frequency domain method include it being easier to understand, as the algorithm model is based on the relationship between the image frequency domain, its calculating speed, as the computing hardware requirements are low, and its ease of application in practical engineering. Though the traditional frequency domain method is based on the sequence of image pixels [5]–[7], the relationship between displacement interpolation reconstruction [8], [9] does not account for the optical system dispersion effect on imaging quality reduction, as the registration model didn't consider factors such as spectrum aliasing effect on the sub-pixel displacement estimation.

Spatial domain methods, which include projection on convex sets [10], the maximum a posteriori method [11], the variational method [12], and neural networks are mostly based on the theory of statistical or collection. These methods have high precision, but in cases for which the research target is the spatial domain method with convex optimization, is it more complex, and the solving model contains large-scale matrix operations that require high performance computing equipment support, high power consumption, high costs. These limitations mean the method can only be practically used in scientific research. In fields that generally do not use spatial domain information, such as remote sensing observation, it is limited to apply the spatial domain method widely due to the limitations of consumer and industrial cameras.

Among the learning methods, the deep learning method shows great potential in digital image processing and receives increasingly deep study for multi-frame SR image reconstruc-

tion technology. Studies by Kappeler et al. [13] and Dong et al. [14] show that by improving motion compensation methods, such as extension of the network input, SR reconstruction of multi-frame images can be achieved by using sequential frames in video. Shi et al. [15] improved the process of low-resolution image sampling by augmenting the sub-pixel convolution layer, thereby increasing the efficiency of SR image reconstruction. Caballero et al. [16] further improved its efficiency by extending the Efficient Sub-pixel Convolutional Neural Network with spatio-temporal networks and motion compensation. Seokhwa et al. [17] proposed a hyper-resolution reconstruction algorithm based on local self-similar multi-frame images oriented locally, improving matching accuracy with less calculation.

Compared with the frequency domain and spatial domain methods, the learning-based method has made great progress and can effectively improve image quality. However, it is difficult to use in real-world applications due to its complex structure and long recovery time. As a result, making significant progress for the SR algorithm of multi-frame images is challenging.

Wang et al. proposed an SR image reconstruction algorithm based on gcForest [18]. In this paper, we build upon this method to further solve the problems of multi-frame image restoration. We propose a novel multi-frame SR image reconstruction process based on the Multi-grained Cascade Forest reconstruction algorithm (SRMCF), which is a learning method using chunking. First, a convolutional neural network is used to process image registration in advance, and then a simple deep forest model is used for recovery to fuse images and reach the final SR restoration.

II. SUPER RESOLUTION RECONSTRUCTION ALGORITHM BASED ON SRMCF

A. Image registration algorithm based on convolutional neural network

In the reconstruction of multi-frame images, due to camera shooting, lighting and other factors, a certain motion blur is generated during the imaging. In order to solve these problems, we need to register each image frame to compensate for displacement. The purpose of image registration is to solve the optimal coordinate transformation relationship between images and transform the registration image to spatially align it with the reference image [19]. There are three kinds of image registration methods: region-based image registration, transform domain-based image registration and feature-based image registration. The feature-based image registration algorithm is the most mature and most widely used method among the three types. Its primary function is the detection and extraction of feature points. Existing feature-based registration methods include SIFT, SURF, ORB, etc. Although these methods have greatly improved the processing of feature points, they cannot detect a sufficient number of feature points when the multi-frame image has appearance differences or when the detected feature points contain serious abnormal values. As a result, the registration effect is poor, and the algorithm is less robust. In order to guarantee the efficiency and effect of registration, this

paper adopts a registration algorithm based on a convolutional neural network to register LR images. Image frame feature points are extracted by convolutional neural network. By making full use of the image frame information, the effect of registration is enhanced, and the robustness of registration is improved.

Image registration algorithms based on convolutional neural network are mainly used to transform LR images to align with a reference image. First, a frame is selected from the LR image sequence as the reference frame, where the set of points detected from the reference frame is $\mathbf{X}$, and the set of points detected from the LR image is $\mathbf{Y}$. Then, the maximum expectation method (EM) is used to process $\mathbf{Y}$ to get the transformation position $\mathbf{Z}$ of $\mathbf{Y}$, denoted as Z_Y. Z_Y and $\mathbf{Z}$ are then used to solve the image conversion using thin plate spline (TPS) interpolation. The algorithms mainly consist of four parts, as follows:

- First, to detect and generate the set of feature points, a convolutional neural network is first used to extract the features of reference frames and LR images, generating corresponding point set $\mathbf{X}$ and vertex set $\mathbf{Y}$ according to the extracted features using threshold θ (where θ is a random value greater than 1) .
- Second, for the pre-matching of feature points, preliminary pre-registration is conducted by using a distance matrix of features.
- Third, accurate registration is performed using the EM algorithm to optimize the transformation parameters and calculate $\mathbf{Z}$. $\mathbf{Z}$ is then used for image registration. Set the reference frame as I_X , and other frames of LR image sequence as I_Y. Equation (1) is used to construct the generation of feature descriptors.

$$G[i,j] = exp(-\frac{\parallel x_j - y_i \parallel^2}{\beta^2}) \qquad (1)$$

where x_j and y_i represent the position points of point set $\mathbf{X}$ and point set $\mathbf{Y}$, respectively, and the gaussian variance $\beta = 2$.

In the EM algorithm,$\mathbf{Z}$ is calculated according to Equation (2).

$$Z = Y + GW \qquad (2)$$

where $\mathbf{Y}$ represents the point set of LR image frames, $\mathbf{G}$ is the matrix generated by gaussian radical basis function (GRBF), and $\mathbf{W}$ contains the transformation parameters to be learned.

Finally, TPS interpolation is used to transform and obtain the image after registration. Fig. 1 is the effect map for registration based on the convolutional neural network. Through demonstration of the accuracy calculation of the effect map, we can conclude that proposed the algorithm can achieve improved performance, especially in the case of significantly challenging appearance differences in the image.

Fig. 1. Demonstration of the effect of convolution neural network registration

B. SRMCF-based super-resolution reconstruction algorithm for single frame imagese

Here, the SR reconstruction algorithm based on SRMCF is discussed, and then the SR algorithm based on SRMCF is constructed. The single-frame image reconstruction based on SRMCF is based on the Multi-grained Cascade Forest algorithm proposed according to Zhou [20], which simplifies the computational complexity by using its cascading forest structure, greatly reducing the time required for reconstruction. The quality of its image reconstruction is also higher than that of other reconstruction algorithms due to its first-level multiple training. The main step of this algorithm is to input a pair of HR images. If there is a corresponding LR, it will be input directly into the multi-particle scan for feature enhancement training. When the feature extraction training is completed, the model training will be carried out with the cascade forest, and then restored according to the model obtained from the training.

The SRMCF reconstruction algorithm is based on the framework of decision trees. First, a decision tree is created to initialize all the scanned feature vectors as root nodes. Then, the decision tree is trained to determine the appropriate value of the segmentation function parameter. The segmentation function allocates image block pairs to the sub-nodes of the decision tree until the stop condition is satisfied. The formula of the split function $s(x, \theta)$ is defined as Equation (3):

$$s(x, \theta) = \begin{cases} 0, & \text{if} \quad x(p) \leq x(q) + \tau \\ 1, & otherwise \end{cases} \quad (3)$$

where x represents the LR image, and θ is the parameter set of the splitting function, consisting of p, q, and . Parameters p and q represent LR image coordinates, and is the threshold of LR image block sampling.

All candidate parameters are generated using random numbers. A node stops splitting when it meets any of the following conditions: 1) The split node reaches the specified maximum tree depth, which is a pre-defined constant. 2) Splitting cannot continue according to the splitting formula. 3) The final leaf node obtained by splitting contains less than or equal to 10 categories. 4) All the split data belong to the same class.

After the tree is created, we process the split leaf non-child and leaf nodes. Each leaf node j is used to store the regression model C_j corresponding to it. The correlation coefficient between the LR image block and the HR image block is estimated by Equation (4). Each non-leaf node is used to save the update split parameters.

$$C_j = \arg \min_{C_i} \|H - LC_j\|_2^2 + \lambda \|C_j\|_2^2 \quad (4)$$

where λ is a regularization parameter used to enhance the generalization ability of C_j, H is the HR image patch, and L is the LR image patch.

After retraining the regression model, the model H^R is used to predict and reconstruct the HR image. Because there are many decision trees in the deep forest model, the input LR image blocks need to be calculated with the average of the linear regression model. Reconstruction Equation (5) is as follows:

$$H^R = \frac{1}{N} \sum_{i=1}^{N} C_j L \quad (5)$$

where N is the number of decision trees in the cascade forest, C_j is the regression model obtained in the i th decision tree, and L is the LR image patch.

The SR reconstruction algorithm based on SRMCF is fast and provides good quality. In order to improve the image reconstruction algorithm, a multi-frame image reconstruction framework based on SRMCF algorithm is constructed. The three steps that mainly comprise the algorithm are image registration for multi-frame low-resolution images, followed by SRMCF reconstruction for all images, and then the final result is obtained by fusion of the reconstructed HR images. Fig. 2 presents a flowchart of SR image reconstruction using SRMCF.
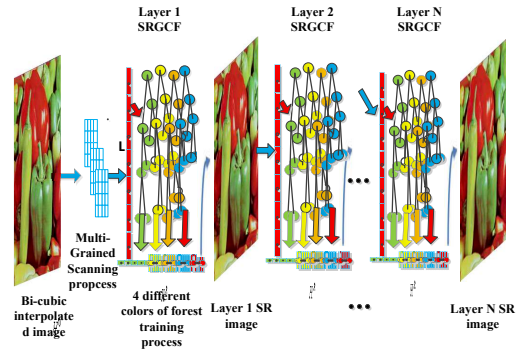

Fig. 2. Flowchart of SR image reconstruction using SRMCF

First, multi-grained scanning is performed on the bicubic-interpolated edge images. Then, the feature vectors obtained through scanning are used to repeatedly train the completely random forests and the ordinary random forests. As discussed above, the classification result of each layer, excepting the final layer, joins in the training of the next layer. In our method, the depth of the cascade forest is not a constant and is instead generated automatically according to the quality of the recovered image. When we finish training one layer, the recovered image is automatically evaluated. If the quality is not optimal, a new layer is constructed for training until an optimal restored image is obtained.

C. Reconstruction and Fusion

After registration of the low-resolution images, hyper-resolution reconstruction was performed for each image according to the method in subsection B. Many HR images are obtained, and the final HR image frames are obtained by fusing these images. Image fusion refers to extracting useful information from two or more images with differences, removing the redundant information, and merging them to create a high-quality image. For existing fusion methods, most use local filtering, which is designed to extract a high frequency detail activity level measurement using the comparison of different source computing definition information in advance, to design fusion rules. This task is difficult to complete, so here we adopt a new image fusion algorithm that studies direct mapping between source images and focus figures, using high quality image blocks and fuzzy version training of convolutional neural networks for map coding. This process is mainly comprised of focus detection, initial segmentation, consistency verification, and fusion.

For focus detection, two source images are first sent to the pre-training convolutional neural network model to output a score diagram, which contains the focus information of the source image. In particular, each coefficient in the score map represents the focusing characteristics of a pair of corresponding blocks from the two source images. Then, by averaging the overlapping patches, a focus map of the source image with the same size is obtained from the score map. Second, the focus diagram is divided into binary images with a threshold of 0.5. Third, we use two popular consistency verification strategies to refine the binary segmentation map (i.e., small area removal and guiding image filtering), to generate the final decision map. Finally, the pixel weighted average strategy is used to obtain the fusion image using the final decision graph. Equation (6) represents the final image fusion formula. The trained decision map $D(x, y)$ is used to fuse the two images. Additional images can be put in a series and fused sequentially as below:

$$F(x, y) = D(x, y)A(x, y) + (1 - D(x, y)B(x, y)) \quad (6)$$

where A and B are the two images to be fused, D is the decision graph, and F is the image after fusion.

In summary, the multi-frame image SR restoration algorithm based on deep forest firstly conducts the registration of LR image sequences based on a convolutional neural network, and then performs SRMCF reconstruction of each image after registration. Finally, the reconstructed image is fused based on CNN to obtain HR images. The steps of the algorithm are as follows:

- 1. Input n LR images;
- 2. Register the image sequence based on the convolution neural network.
- 3. Perform single SRMCF hyper-resolution reconstruction on n images after registration.
- 4. Performed convolutional neural network fusion on the n HR images obtained after reconstruction.
- 5. Output a fused HR image.

III. EXPERIMENTAL RESULTS AND ANALYSIS

In order to verify the effectiveness of the SR reconstruction method of multi-frame images proposed in this paper, multiple comparison experiments were conducted. The single-frame restoration and multi-frame restoration of SRMCF were compared first, which was used to prove whether the image quality restored by multi-frame images was higher than that restored by single frame images. The proposed multi-frames recovery method was compared to the nearest neighbor interpolation method (Nearst), convex sets (POCS) projection method, and piece of symmetric algorithm for the stack (PSyCo). To evaluate the performance of the algorithm, this paper uses the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) as the objective evaluation standard of quality of image reconstruction. The definition of PSNR is shown in Equation (7)):

$$PSNR = 101g \frac{255 \times 255}{MSE} \quad (7)$$

where MSE denotes the mean square deviation. As MSE decreases or $PSNR$ increases, the reconstructed image is closer to the original image.

A. Comparison Experiment for the SRMCF Algorithm based on Single Frame and Multi-Frame Reconstruction

We compared the restoration performance of SRMCF for one frame and for multiple frames. We used a single HR image for comparison, and produced an LR image and a 4-frame LR image through different regression models. Model training and reconstruction were carried out under identical conditions. The training parameters are all $(3p) \times (3p)$ images, and the final HR image obtained after the multi-frame image registration, reconstruction, and fusion was compared with the image directly restored by the single-frame SRMCF method. The comparison results are shown in Table I below. It can be seen from Table 1 that the multi-frame image reconstruction algorithm based on SRMCF is higher in image quality than the single-frame image reconstruction algorithm based on SRMCF. Because it is necessary to carry out registration and fusion, LR images of each frame should be restored, which requires more time than the single-frame SRMCF reconstruction algorithm. In terms of the PSNR and SSIM parameters, the restored image quality is better than that of a single frame. Although the time is significantly greater in experimental parameters, in real-world applications the difference is indistinguishable to human senses.

TABLE I
COMPARISON OF THE RESTORATION EFFECTS ON SINGLE-FRAME AND MULTI-FRAME IMAGES USING THE SRMCF ALGORITHM

Parameter	Reconstruction algorithm	
	Single frame SRMCF	Multi frame SRMCF
time(s)	0.05	0.62
PSNR(dB	34.24	35.69
SSIM	0.93	0.932

(a) Low Resolution Image with T=0.01s Frame

(b) Low Resolution Image with T=0.02s Frame

(c) Low Resolution Image with T=0.03s Frame

(d) Low Resolution Image with T=0.04s Frame

Fig. 3. Four low resolution images with small continuous displacement (a), (b), (c) and (d)

Enlarged local image

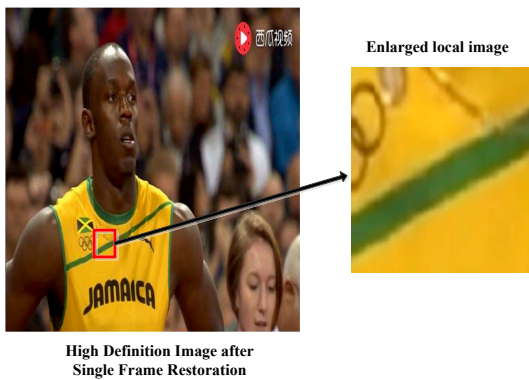**High Definition Image after Single Frame Restoration**

Fig. 4. Result and local enlargement of restored single frame image

B. Comparison Experiment for the SRMCF Algorithm based on Multiple Frames and Other Multi-Frame Restoration Algorithmsn

For the comparison of restoration performance of multi-frame images, we used the degradation model to generate 4-frame LR video images for reconstruction experiments. Nearst, POCS, and PSyCo are compared under block symmetry. The results are shown in Table II.

TABLE II
COMPARISON OF SRMCF RECONSTRUCTION WITH OTHER MULTI-FRAME IMAGE RECONSTRUCTION ALGORITHMS

Multi-frame Method	time(s)	PSNR(dB)	SSIM
Nearst	0.0491	23.29	0.89
POCS	0.55	25.68	0.87
PSyCo	0.575	27.07	0.90
SRMCF	0.62	31.69	0.932

It can be seen from Table II that the nearest neighbor interpolation algorithm has the least running time and the worst restoration quality. The other methods are slightly better, but they still require much more time than the nearest neighbor interpolation algorithm. This algorithm maintains a good reconstruction effect while also being very fast.

In order to verify whether the displacement of sequential multi-frame images has an effect on the restoration quality

of the multi-frame image reconstruction process proposed in this paper, experimental comparisons of smaller displacement and larger displacement were made. The restoration object is a sequence of low-resolution images with four consecutive frames and small displacement, as shown in Fig. 3. The single frame and multi-frame restoration algorithms proposed in this paper were validated. Comparing the effect shown in Fig. 4 and Fig. 5, it can be seen that the difference between the two restoration algorithms is not very big on the whole. However, when a local enlargement is made, it can be seen that the multi-frame restoration algorithm makes better use of the details. Fig. 6 shows a sequence of four consecutive and highly displaced low-resolution images that were used as restoration objects. Comparing the effect between Fig. 7 and Fig. 8, it can be seen that there are obvious differences on the whole. After partial enlargement, it can be seen that the information contained in the restored image after registration is greater than that restored after a single frame image, and the quality of recovery has also been relatively improved.

From Fig. 3-Fig. 8, we can see that when the multi-frame image is used for reconstruction, we make full use of the information of each frame and retain the information of each frame. Therefore, when comparing Fig. 7 and Fig. 8, we can find that not only is the image resolution improved, but more details are also retained. Although the multi-frame image takes slightly longer to recover, the effect is significant.
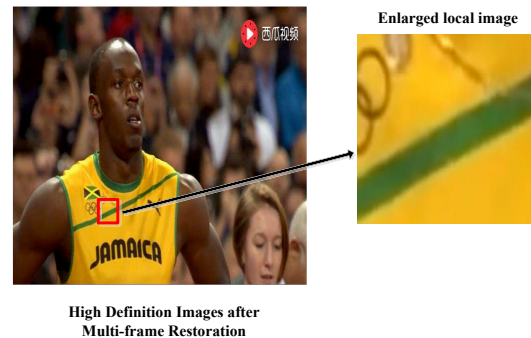

Enlarged local image

High Definition Images after Multi-frame Restoration

Fig. 5. Effect and Local Expansion of Restored Sequential Multi-frame Images with Small Displacement

(a) Low Resolution Image with T=0.01s Frame

(b) Low Resolution Image with T=0.02s Frame

(c) Low Resolution Image with T=0.03s Frame

(d) Low Resolution Image with T=0.04s Frame
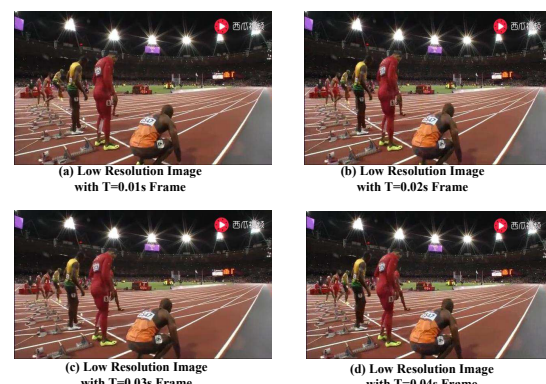
Fig. 6. Four low resolution images with large continuous displacement (a), (b), (c) and (d)

High Definition Image after Single Frame Restoration

Enlarged local image

Fig. 7. Result and local enlargement of restored single frame image

High Definition Images after Multi-frame Restoration
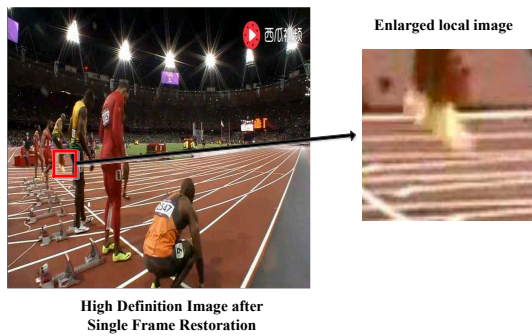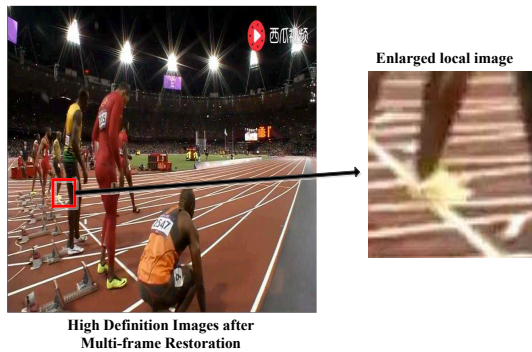
Enlarged local image

Fig. 8. Effect and Local Expansion of Restored Sequential Multi-frame Images with Small Displacement

IV. CONCLUSION

Aiming at the problem of slow reconstruction speed and general reconstruction effect of traditional multi-image SR reconstruction algorithm, a multi-image SR reconstruction algorithm based on SRMCF is proposed. Firstly, the LR image sequence is calibrated based on a convolutional neural network, and then each image is reconstructed by SRMCF. Finally, the reconstructed image is fused based on the convolutional neural network to obtain an HR image. Based on the results of experimental simulations, the reconstruction effect of the SRMCF-based multi-image SR reconstruction algorithm is greatly improved compared with that of SRMCF-based single-image SR reconstruction. Additionally, the reconstructed algorithm exhibited better reconstruction quality and faster reconstruction speed when compared with other algorithms. In the experiment, the running time of the algorithm in this paper was about 4 times that of the SRMCF-based single image reconstruction algorithm, as the algorithm performs SRMCF reconstruction for each low-resolution image. In subsequent research work, the reconstruction process can be optimized to further improve the speed of SR reconstruction, reducing the time required for reconstruction.

REFERENCES

[1] R. C. Gonzalez,and R. E. Woods , "Digital image processingr",3rd ed. Upper Saddle River, NJ, USA: Prentice-Hall, 2008.

[2] M. Jung.,A. Marquina, and L. A. Vese, "Variational multiframe restoration of images degraded by noisy (stochastic) blur kernels", *J. Comput. Appl. Math* vol. 240, no. 1,pp. 45–67, 2015.

[3] Y. Fan , X. Wei, and S. Qin, "Fast and robust deblurring method with multi-frame images based on PSF estimation and total variation optimization", *Optik-Int. J. Light Electron Opt* vol. 124, no. 16,pp. 2285–2291, 2013.

[4] F. W. Wheeler, X. Liu, P. H. Peter, and R. T. Hoctor, "Multiframe image restoration for face recognition", in Proc. IEEE Workshop Signal Process. Appl. Public Secur. Forensics,pp. 16, Apr. 2007.

[5] R.Y. Tsai,and T.S. Huang, "Multipleframe image restoration and registration", Advances in computer vision and image processing. Greenwich, CT: JAI Press Inc., 1984, pp. 317-339.

[6] N.K. Bose, H.C. Kim,and H.M. Valenzuela, "Recursive implementation of total least squares algorithm for image reconstruction from noisy, undersampled multiframes", in Proc. IEEE Conf. Acoustics, Speech and Signal Processing, Minneapolis, MN, 1993, pp. 269-272.

[7] S.H. Rhee, and M.G. Kang, "Discrete cosine transform based regularized high-resolution image reconstruction algorithm", *Opt. Eng* vol. 38, no. 8,pp. 1348–1356, 1999.

[8] H. Hanchuan, W. Peikang, "Super-resolution image reconstruction based on an improvement frequency domain registration approach", *Electron Meas Technol* vol. 33, no. 5,pp. 58–61, 2010.

[9] P. Vanderwalle, Sbaiz L., J. Vanderwalle, "Super-resolution from unregistered and totally aliased signals using subspace methods", *IEEE Trans. Signal Procss* vol. 55, no. 70,pp. 3687–3703, 2007.

[10] C.C. Chen, "A multi-frame super-resolution algorithm using POCS and wavelet",Montreal: Concordia University, 2010.

[11] C. Liu, D. Q. Sun, "A bayesian approach to adaptive video super resolution", IEEE Conf. Comput. Vis Pattern Recognit, vol.42, no. 7, pp. 209-216, 2011.

[12] F. Shi, J. Cheng, L. Wang, "Low-rank total variation for image super-resolution", Proc. Conf. Med. Image Comput. and Comput-Assist Interv, vol.16, no. 1, pp. 155-162, 2013.

[13] A. Kappeler, S. Yoo, Q. Dai, "Video super-resolution with convolutional neural networks", *IEEE Trans. Comput Image* vol. 2, no. 2,pp. 1–1, 2016.

[14] C. Dong, C.L. Chen, K. He, "Image super-resolution using deep convolutianal networks, *IEEE Trans Pattern Anal Mach Intell* vol. 38, no. 2,pp. 295–307, 2016.

[15] W. Shi, J. Caballero, F. Huszar, "Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network", IEEE Conf Comput Vis Pattern Recognit pp.1874-1883, 2016.

[16] J. Caballero, C. Ledig, A. Aitken, "Real-time video super-resolution with spatio-temporal networks and motion compensation", Comput Vis Pattern Recognit, 2017, arXiv preprint arXiv:1611. 05250v2.

[17] S. Jeong, I. Yoon, J. Joonki, "Multi-frame example-based superresolution using locally directional self-similarity, *IEEE Trans. Consum. Electron* vol. 61, no. 3,pp. 353–358, 2015.

[18] Y. M. Wang , Z. K. Luo, "Image SR based on MultiGrained Cascade Forests. Multiresolution and Information Processing".

[19] X. Liu , J. Yang , J. Sun, "Image registration approach based on SIFT, *Infrared and Laser Eng* vol. 37, no. 1,pp. 156–160, 2008.

[20] Z. H. Zhou, J. Feng, "Deep forest: Towards an alternative to deep neural networks, *arXiv preprint* arXiv:1702.08835, 2017.