Image Quality Enhancement With Machine Learning Based Multi-Step Super-Resolution

Niai Yano, Hiroshi Watanabe
Graduate School of Fundamental Science and Engineering
Waseda University
Tokyo, Japan
7ncsmarvelous15@fuji.waseda.jp

***Abstract*—** Studies on Super-Resolution based on machine learning have been actively conducted as AI-used high resolution processing. In particular, Super-Resolution using Convolutional Neural Network (CNN) has become the basis of recent study on SR methods. We have proposed Multi-Step Super-Resolution (MSSR), which combines two super-resolution methods including SR using CNN, and its extended method. Further, it was shown that the subjective image quality was greatly improved. In this paper, we propose two methods that further apply MSSR. Experimental results show that the proposed method improves the image quality both visually and in reconstruction accuracy compared to the conventional method.

***Keywords*— Deep Learing, Convolutional Neural Network, Example-based Super-Resolution, Multi-Step Super-Resolution.**

I. INTRODUCTION

In recent years, the resolution of output devices has improved dramatically due to the impact of the transition to 4K (4096 × 2160) and 8K (7680 × 4320). Along with this, the opportunity to output low-resolution (LR) images on high-resolution (HR) displays has increased. On the other hand, if a low-resolution image is enlarged only by the conventional interpolation technology, there is a problem that image quality deterioration such as blurs and jaggy occurs. As a solution to this problem, a resolution expanding method called Super-Resolution (SR) technology has been actively developed. Among them, the technologies called Example-based Super-Resolution, which performs super-resolution processing using a dictionary generated by Machine Learning, is attracting attention because of their high restoration accuracy. Especially, the SR methods based on Convolutional Neural Network (CNN) have become the basis of SR methods, and many methods have been devised so far.

We have proposed novel Multi-Step Super-Resolution (MSSR) that combines two types of SR methods including SR based on CNN, with the aim of significantly improving visual resolution. MSSR is based on the hypothesis that the Example-based Super-Resolution can be regarded as an image quality enhancement filter by looking only at the super-resolution processing unit excluding the enlargement processing. In addition, we proposed an extended method that applies rotation and inversion processing and their restoration processing before and after the first super-resolution processing of MSSR, and showed that reconstruction accuracy was improved.

In this paper, we propose two SR methods (proposed method 1 and proposed method 2). In proposed method 1, super-resolution with rotation/inversion is applied to the first super-resolution processing of MSSR. In proposed method 2, super-resolution with rotation/inversion is applied to both the first and second super-resolution processing of MSSR. Experimental results show that the proposed method 2 improves the image quality both visually and in reconstruction accuracy compared to the conventional method.

II. CONVENTIONAL METHODS OF SUPER-RESOLUTION

A. Example-based Super-Resolution

Single Image Super-Resolution (SISR) is a technology that outputs one HR image from one LR image. Example-based Super-Resolution is one of SISR. Example-based Super-Resolution learns non-linear mapping from LR image to HR image during dictionary creation [1][2]. In this method, since mapping is learned in advance, high-quality images can be obtained simply by mapping during the super-resolution processing [1]. Fig. 1 shows a typical Example-based Super-Resolution block diagram. The input LR image is first enlarged by the conventional interpolation methods such as Bicubic, and this interpolated enlarged image is divided into patches.

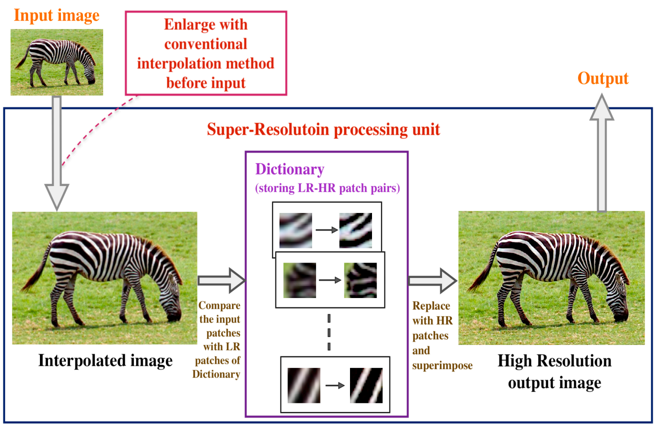

Fig. 1. Block diagram of typical Example-based Super-Resolution

The super-resolution processing unit has a dictionary that stores pre-trained LR-HR patch pairs, and each divided patch is checked against the LR patches in the dictionary. Furthermore, the divided LR patches are replaced with the corresponding HR patches and superimposed, and the missing high frequency components in the LR image are estimated.

Many types of Example-based Super-Resolution method have been developed so far. Above all, the Example-based Super-Resolution based on CNN has become the focus of recent study due to their remarkable performance. On the other hand, methods using sparse coding have been devised in the past few years. Super-Resolution Convolutional Neural Network (SRCNN) [3] is a CNN-based method and consists of a three-layer network that can set an appropriate learning rate that guarantees convergence. A+ [4] and Sparse-coding Super-Resolution (ScSR) [5] are super-resolution methods based on sparse coding. In these methods, the input LR patch is approximated by a linear combination of multiple bases stored in the dictionary, replaced with HR patches, and superimposed to obtain a high-resolution image.

B. *Multi-Step Super-Resolution*

We have devised a method called MSSR [6] that combines A+ or ScSR and SRCNN (Fig. 2). This is a new method that obtains visually sharp images by connecting a sparse coding-based method and a CNN-based method. This method is based on the hypothesis that Example-based Super-Resolution can be regarded as a filter that improves image quality only by looking at the super-resolution processing unit, excluding the enlargement process. This hypothesis is derived from the fact that the same size conversion from LR to HR is performed in the dictionary. Based on this hypothesis, MSSR connects the super-resolution processing unit in series without using Bicubic interpolation after normal super-resolution processing. The first SR step consists of A + or ScSR, and the second SR step consists of SRCNN with bicubic interpolation removed.

As shown in Fig. 2, MSSR first upsamples the input image by a factor of 2 using bicubic interpolation. Note that a region enclosed by a dotted line is a pre-processing stage of super-resolution processing, and is added to compare the reconstruction accuracy of the final output image. Subsequently, normal super-resolution processing is performed, and finally super-resolution processing without enlargement processing is performed. Although MSSR didn't improve the reconstruction accuracy, it was shown that the image quality improved visually.

We have also proposed an expansion method (MSSR-2) that adds rotation/inversion processing and restoration processing, before and after the second super-resolution processing of MSSR (Fig. 3). This method applies our previous research results [7] to MSSR. In the method [7], super-resolution processing is performed on each of a plurality of images obtained by rotating or inverting an input image, and they are returned to the original rotation state and averaged. This reduces patch selection errors and mapping errors in the dictionary and improves reconstruction accuracy. By using this method, MSSR-2 provides better reconstruction accuracy than MSSR.

In this paper, we propose two methods that extend MSSR-2, and compare the image quality of the proposed methods with the previous method.

III. Proposed Methods

We propose two methods to apply MSSR-2 (Fig. 4 to 5). We call these methods MSSR-3 and MSSR+, respectively. Rotation/inversion processing and restoration processing are added to the first SR unit in MSSR-3 and the first and second SR units in MSSR+. In MSSR+, since multiple images are superimposed in both SR processing, higher reconstruction accuracy is expected.

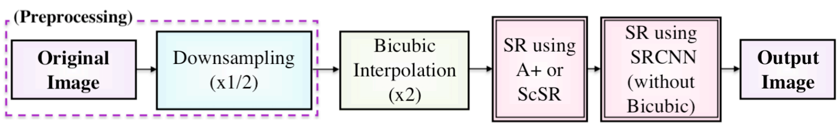

Fig. 2. Configuration diagram of MSSR

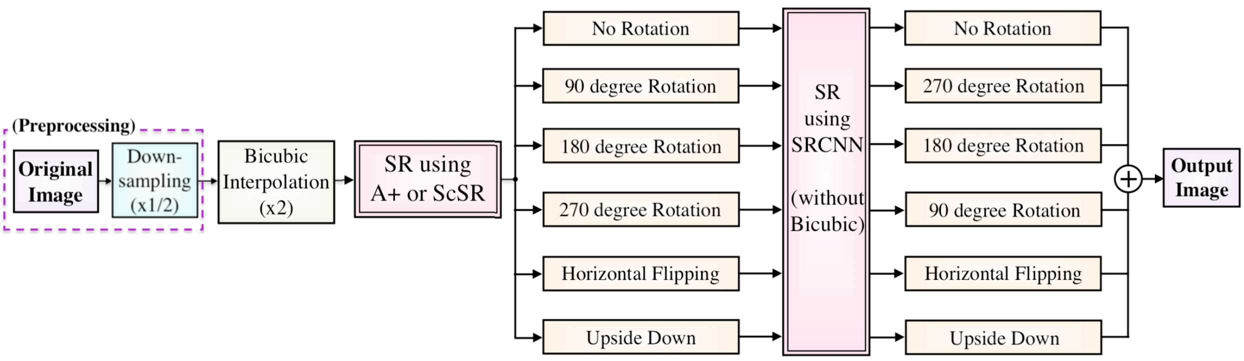

Fig. 3. Configuration diagram of MSSR-2

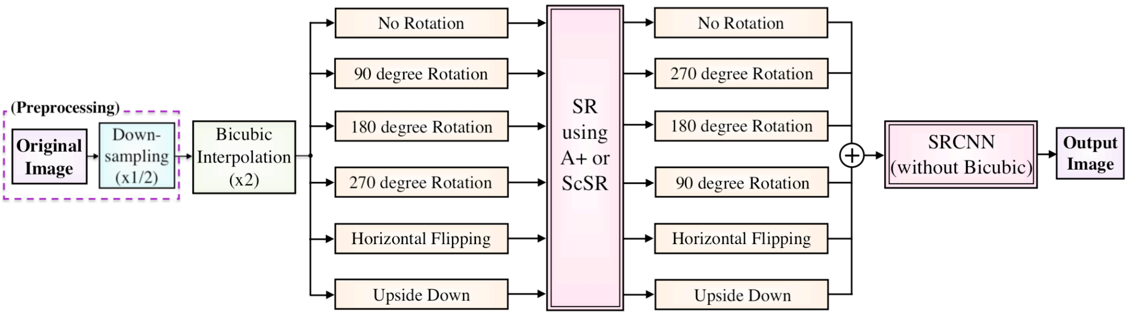

Fig. 4. Configuration diagram of Proposed Method 1 (MSSR-3)

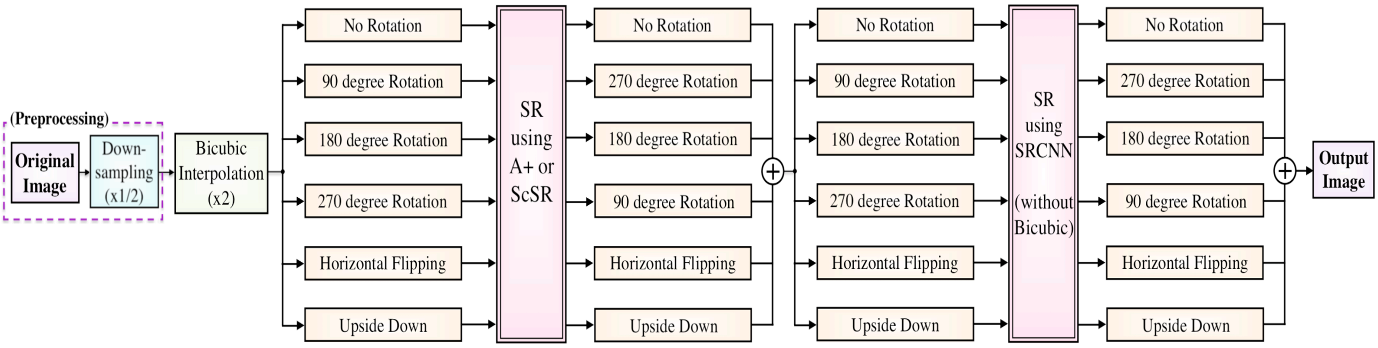

Fig. 5. Configuration diagram of Proposed Method 2 (MSSR+)

IV. EXPERIMENT

A. *Experimental method*

Standard images Set 5 and Set 14 [3] [4] were used in the experiment. The experimental results for each proposed method were compared by quantitative comparison using reconstruction accuracy and qualitative comparison by visual inspection.

B. *Experimental results*

Tables I through III show a quantitative comparison of SR results when using ScSR for the first super-resolution processing. Fig. 6 compares the quantitative results when using A + for the first super-resolution process. Moreover, Fig. 7 and 8 show a visual comparison of SR results. Table I and II show a comparison of Peak Signal to Noise Ratio (PSNR) and Structural similarity (SSIM), respectively. Table III and Fig.6 show a comparison of Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE). BRISQUE is an image quality assessment (IQA) algorithm that can evaluate image quality without reference images. Higher PSNR and SSIM indicate higher image quality, and **lower** BRISQUE values indicate higher image quality.

As shown in Table I and II, MSSR+ shows the highest reconstruction accuracy among SR using MSSR although it doesn't reach the ScSR value. From Table III and Fig.6, it can be seen that MSSR-3 or MSSR+ can sometimes take lower BRISQUE value (i.e. higher quality value) than the original image. Moreover, In addition, MSSR+ reduced BRISQUE values by an average of 6.096 than Bicubic and an average of 3.186 than A+. Furthermore, MSSR-3 reduced BRISQUE values by an average of 7.335 than Bicubic, 4.425 than A+, 0.004 than MSSR, and 1.198 than MSSR-2.

TABLE I. COMPARISON OF PSNR (WHEN THE FIRST SR STEP IS SCSR)

Image Name	ScSR	MSSR	MSSR-2	MSSR-3 (Proposed)	MSSR+ (Proposed)
Baboon	**25.322**	23.823	24.126	23.859	**24.154**
Barbara	**28.536**	26.590	27.048	26.627	**27.075**
Bridge	**27.484**	25.205	25.705	25.238	**25.739**
Coastguard	**30.461**	28.609	28.864	28.680	**28.951**
Comic	**27.882**	24.905	25.419	24.939	**25.453**
Face	**35.530**	33.798	34.162	33.850	**34.206**
Flowers	**32.534**	28.812	29.370	28.858	**29.415**
Head	**35.546**	33.808	34.177	33.859	**34.218**
Man	**30.578**	28.369	28.784	28.419	**28.821**
Pepper	**34.170**	32.396	33.102	32.546	**33.150**
Ppt3	**29.471**	26.574	27.130	26.607	**27.164**

TABLE II. COMPARISON OF SSIM (WHEN THE FIRST SR STEP IS ScSR)

Image Name	ScSR	MSSR	MSSR-2	MSSR-3 (Proposed)	MSSR+ (Proposed)
Baboon	**0.829**	0.807	0.814	0.808	**0.815**
Coastguard	**0.848**	0.824	0.831	0.826	**0.833**
Face	**0.930**	0.917	0.920	0.918	**0.921**
Flowers	**0.956**	0.925	0.930	0.925	**0.931**
Foreman	**0.978**	0.957	0.962	0.958	**0.963**
Head	**0.930**	0.917	0.920	0.917	**0.921**
Lena	**0.987**	0.979	0.980	0.979	**0.981**
Monarch	**0.992**	0.978	0.980	0.978	**0.981**
Pepper	**0.984**	0.978	0.979	0.979	**0.980**

TABLE III. COMPARISON OF BRISQUE (WHEN THE FIRST SR STEP IS ScSR)

Image Name	Original	Bicubic	ScSR	MSSR	MSSR-2	MSSR-3 (Proposed)	MSSR+ (Proposed)
Baby	28.201	39.072	24.459	22.650	21.741	20.824	**20.359**
Bird	35.887	44.169	36.372	**20.488**	22.435	21.402	23.008
Face	36.604	34.738	33.256	21.684	23.320	**21.322**	22.861
Flowers	**21.833**	38.898	31.614	38.352	40.799	37.717	39.709
Foreman	30.220	40.492	29.262	4.317	5.353	**4.299**	5.578
Head	36.668	34.700	32.990	21.446	23.299	**21.141**	22.667
Lena	**16.219**	31.858	23.190	21.625	23.368	22.495	23.628
Pepper	28.093	38.132	34.062	**23.672**	26.959	24.236	26.286

Lower BRISQUE value indicates higher image quality.

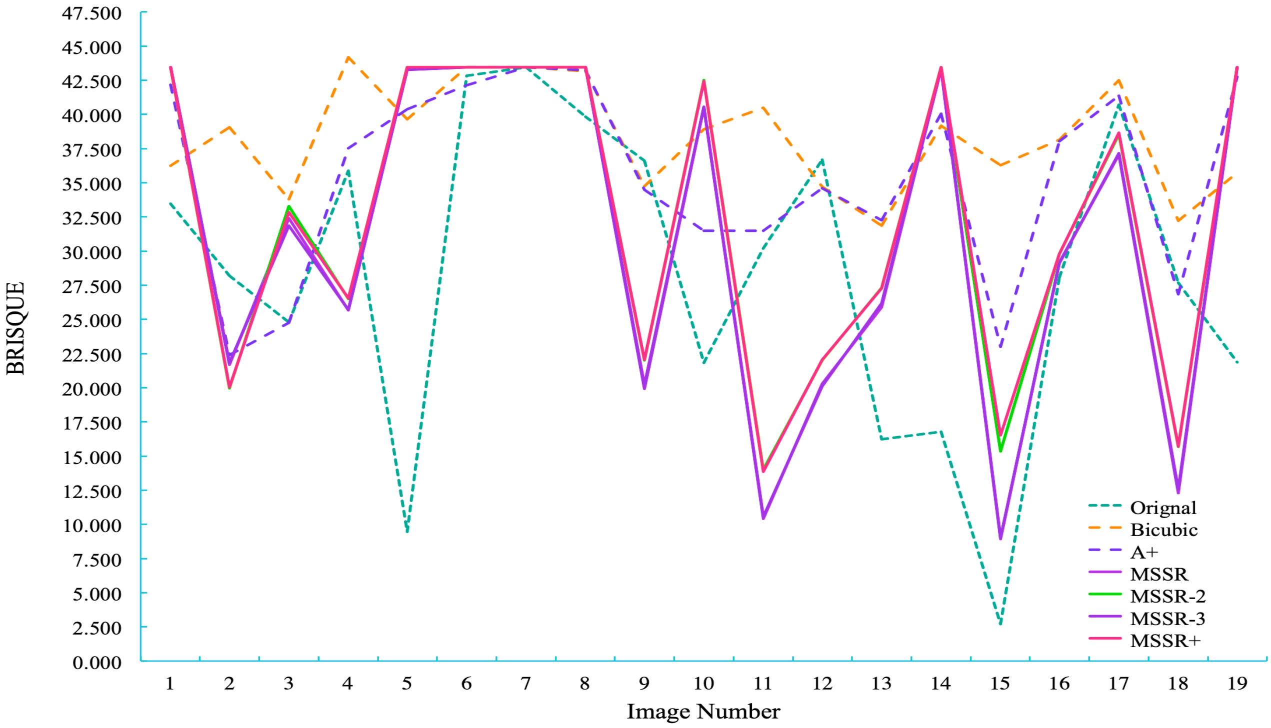

Fig. 6. The Comparison of BRISQUE

Fig. 7 shows a comparison of the super-resolution results in the standard image Comic.bmp when the first super-resolution processing is A +. Fig. 8 shows a comparison in the standard image Head.bmp when the first super-resolution processing is ScSR.

Figures show that MSSR-based super-resolution images are overwhelmingly sharper than conventional methods A + and ScSR. Especially in MSSR-3 and MSSR+, the dragon pattern at the neck in Fig. 7 became very clear. In Fig. 8, there was the least ringing around the hair in the MSSR+ super-resolution image. Furthermore, we confirmed that ringing and pseudo contours were minimized in the super-resolution image using MSSR+ than the other super-resolution images using MSSR. From the figures, images of MSSR+ appear to be the most natural visually.

From these results, it became clear that MSSR-3 took the lowest BRISQUE value on average. In addition, MSSR+ showed the highest reconstruction accuracy among the super-resolution using MSSR, and was able to acquire visually natural and sharp images.

V. CONCLUSION

In this paper, we proposed MSSR-3 and MSSR+, which extend the conventional method MSSR. The reconstruction accuracy of MSSR+ was the highest among super-resolution using MSSR.

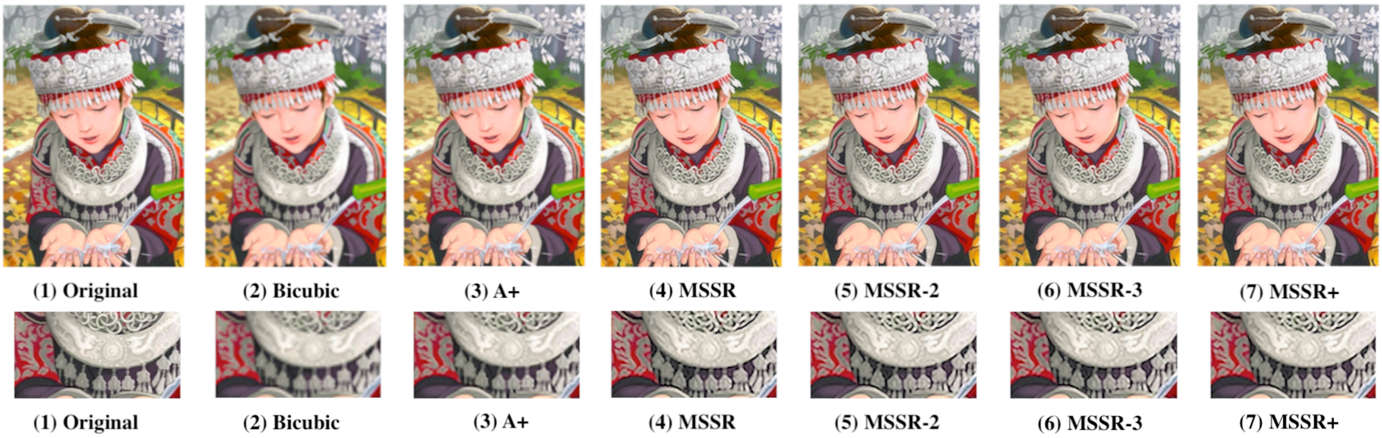

Fig. 7. The Comparison of SR results (When A+ is used for the first SR step)

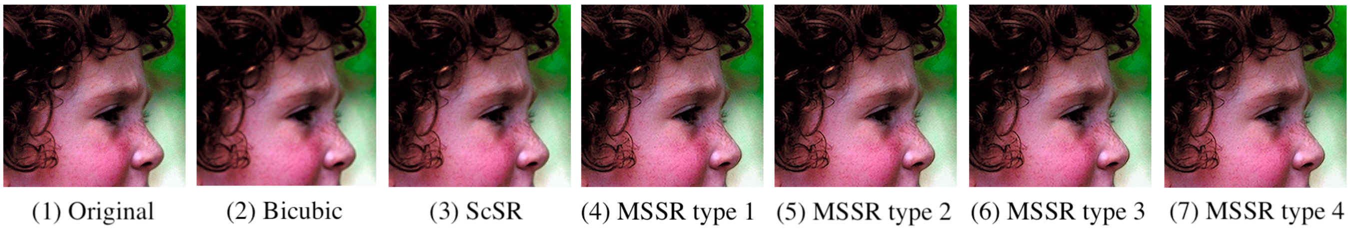

Fig. 8. The Comparison of SR results (When ScSR is used for the first SR step)

Moreover, MSSR+ minimized ringing and pseudo contours than the other super-resolution using MSSR. In addition, the BRISQUE value of MSSR-3 was the lowest (that is the best image quality).

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