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High-precision dimensional measurement of a curtain wall cross-section using image super-resolution

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Abstract. Dimensional quality is critical to the successful installation of curtain walls, and the required dimensional tolerances are typically less than a millimeter. However, high-precision dimensional measurement of a curtain wall cross-section is practically difficult and time-consuming because the cross-sectional shapes are various and complicated, and dimensional measurement is usually performed manually in the actual field. To improve these problems, various vision-based methos are being attempted, but there have been limitations in terms of precision due to row image resolution. Therefore, this study confirmed whether image super-resolution can contribute to overcoming these limitations. To this end, an experiment on a curtain wall profile cross-section was conducted, and super-resolution generative adversarial network (SRGAN) was applied as an image super-resolution method. As a result, it was confirmed that high-precision dimensional measurement is possible from an image with enhanced resolution using SRGAN.

Introduction

A curtain wall is a structure used to cover and decorate the exterior of a building and is generally composed of aluminum profiles, glasses, and support brackets. It is widely used in modern high-rise buildings since it is light in weight, beautiful in design, and easy to install [1].

In the construction process, the curtain wall installation is considered as a risky process in terms of cost and schedule [2, 3]. The main reason is that curtain wall profiles are engineered materials which are customized in factories [4]. Unlike bulk materials [4], engineered materials take a considerable amount of time to be resupplied when dimensions are abnormal or materials are damaged. This affects the subsequent processes and the entire construction cost and period [2, 5].

To mitigate this risk, it is important to perform a thorough dimensional quality control of curtain wall components during the material production stage and warehousing stage. Dimensional quality has a great influence on the assembly performance, structural performance, and waterproof performance of a curtain wall. Typical required dimensional tolerances are less than a millimeter. However, since the cross-sectional shapes of curtain wall profiles are diverse and complex and dimensional measurement is usually performed manually in the actual field, measuring dimensions with high-precision is practically difficult and time-consuming. To improve these problems, various vision-based methos are being attempted, but there have been limitations in terms of precision due to row image resolution.

Therefore, in this study, it is attempted to confirm whether image super-resolution can contribute to overcoming these limitations. To this end, an experiment on a curtain wall profile cross-section was conducted, and super-resolution generative adversarial network (SRGAN) [6], which is a state-of-the-art deep learning-based super-resolution method, was applied. In the experiment, a VGA-resolution image of the curtain wall profile section was 16x upscaled to an 8K resolution-image using SRGAN [6], and dimensional measurement was performed.

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As a result, it was verified that dimensional measurement can be carried out with high-precision of 0.4mm of mean absolute error (MAE) and 1.1% of mean relative absolute error (MRAE) using SRGAN [6]. But this study also has limitations in that there is an assumption that input cross-sectional images are accurately photographed from the front and the measurement process is not automated. So, in this study, the process of measurement at the pixel level was performed manually. Generalization and automation of the measurement process will be left as a future study.

Methodology

In this study, dimensional measurement process for a curtain wall profile cross-section is made up of six steps. The first step is to collect the training data set consisting of 8K-resolution images taken from the cross-section of a curtain wall profile and a reference cube. Here, the reference cube is employed to convert pixel dimensions to metric dimensions, and the images of the curtain wall profile cross-section do not necessarily have to be target profile images to be inspected.

The second step is SRGAN [6] configuration and training. Compared to the original SRGAN, in this study, there are several differences in neural network architecture. First, while the original SRGAN performs 4x upscaling, in this study, 16x upscaling is performed by adding two upscale blocks to the generator of the original SRGAN. Second, since this study targets only the curtain wall profile cross-sections, the task is relatively simple. Therefore, the residual blocks of the generator were reduced from originally 16 to 4 to shorten training time and prevent overfitting. Third, unlike the original SRGAN, a loss function of Equation 1 was used when training the SRGAN generator used in this study.

$$l_{modified}^{SR} = l_{VGG}^{SR} + \left(10^{-1} \times l_{MSE}^{SR}\right) + \left(10^{-2} \times l_{Gen}^{SR}\right) \tag{1}$$

Where l_{VGG}^{SR}, l_{MSE}^{SR}, and l_{Gen}^{SR} are VGG loss, pixel-wise MSE loss, and advertising loss respectively, and the definition of each is as introduced in the original SRGAN [6].

$l_{modified}^{SR}$, modified perceptual loss in this study, differs in that it includes the VGG, MSE, and adversarial losses simultaneously compared to the original perceptual loss [6] of the original SRGAN. There is also difference in the reflection ratio of each loss. In this study, using $l_{modified}^{SR}$ (eq. 1) was more effective. Unlike the generator, the discriminator architecture and most of the other training details follow the original SRGAN [6].

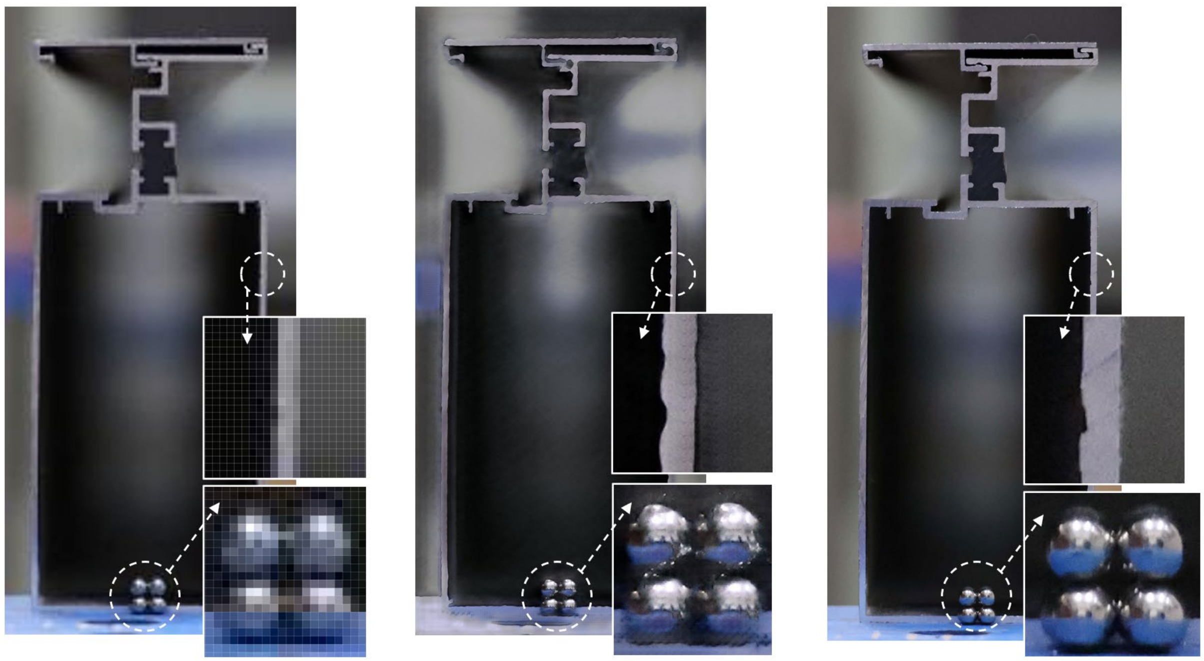
The third step is to take the image of a target profile section to be measured. This study uses a reference cube to convert measured pixel displacements to metric displacements, it is necessary to photograph the reference cube together when taking the image of a target profile cross-section (Fig. 1). As previously described, in this step, the VGA-resolution image is sufficient. However, in this study, it is assumed that the curtain wall profile cross-section and the reference cube were accurately photographed from the front, so filming should be carried out with this in mind.

The fourth step is to estimate 8K super-resolution (SR) image from the VGA low-resolution image by 16x upscaling using the trained SRGAN.

The fifth step is to measure the dimensions of the curtain-wall cross-section at the pixel level, and then, based on the reference cube, the measured pixel dimensions are converted to the metric dimensions. But, the measurement process is not automated yet in this study. So, for now, it was conducted manually. The automation of measurement process will be left for the future study.

Experiments

To confirm whether image super-resolution can contribute to high-precision dimensional measurement, an experimental dimensional measurement on a curtain wall profile cross-section was conducted. The experimental results are described step by step as follows.



(a) LR image(285×132 px) **(b) SR image** (4560×2112 px) **(c) Ground truth** (4560×2112 px)

Figure 1. Comparison of the LR, SR and ground truth images

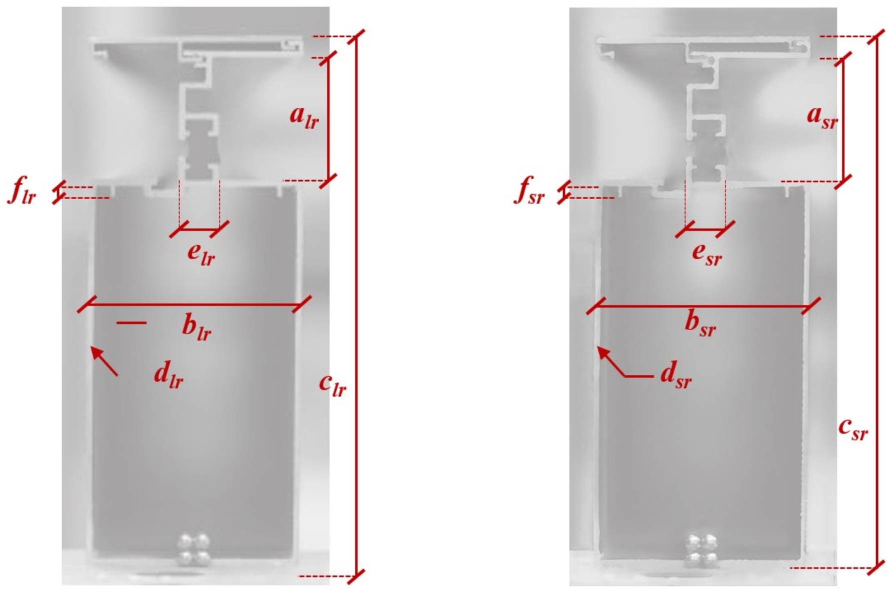
Step 1: In this experiment, two images were taken for SRGAN training. These are high-resolution cropped images of the meaningful part of 8K-resolution photo images. In this study, training of SRGAN with only two images was attempted.

Step 2: The training details of SRGAN were set as follows. Randomly cropped images of size 384 x 384 px were used from the images of the training data set, mini-batch size of 5 was applied, and data augmentation including horizontal flip and random rotation was performed. A total of 30,000 epochs of learning was conducted, and Adam [7] was used as an optimizer. The learning rate of the optimizer was applied to 10^{-4} until 15,000 epochs and 10^{-5} until 30,000 epochs. Most of the other details followed the original SRGAN [6].

Step 3: A low-resolution image taken for experimental dimensional measurement is shown in Fig. 1(a). Note that, Fig. 1(a) is different from the training data, and it is the result of cropping the meaningful part of a VGA-resolution photo image manually.

Step 4: As a result of applying the SRGAN to the experiment, a 16x upscaled SR image is shown in Fig. 1(b). It can be seen that the resolution is greatly improved compared to the LR image of Fig.1(a). Additionally, compared with Fig. 1(c), which is a ground truth high-resolution image of the actual profile, it can be confirmed that the estimation performance of SRGAN is excellent. This was an encouraging result considering that only two images were used for SRGAN training. This result means that for certain tasks and target, there is no need to invest a long time in SRGAN training.

Step 5: Using the 16x upscaled SR image, dimensions of the target profile section are measured at the pixel level, and then, based on the reference cube, these are converted to metric dimensions. In this study, this measurement process is not automated yet, it will be left for the future study. So, for now, it was conducted manually. Dimensional measurement was performed for each LR image and 16x upscaled SR image respectively. It was conducted on the target dimensions shown in Fig. 2, and the results are shown in Table 1.



(a) LR image (285×132 px) **(b) SR image** (4560×2112 px)

Figure 2. Target dimensions for experimental measurements

Table. 1 Comparison of dimensional measurement results for LR image and 16x upscaled SR image

	GT	**LR image**				**SR image**			
	Dim.	**Dimension**		**AE**	**RAE**	**Dimension**		**AE**	**RAE**
	(mm)	(pixel)	(mm)	(mm)	(%)	(pixel)	(mm)	(mm)	(%)
Ref.	**4.8**	**9**	**-**	**-**	**-**	**134**	**-**	**-**	**-**
(a)	34.8	61	32.5	2.3	6.5	969	34.7	0.1	0.3
(b)	60.2	106	56.5	3.7	6.1	1693	60.6	0.4	0.7
(c)	149.2	260	138.7	10.5	7.1	4203	150.6	1.4	0.9
(d)	1.8	4	2.1	0.3	18.5	50	1.8	0.0	0.5
(e)	11.3	20	10.7	0.6	5.6	310	11.1	0.2	1.7
(f)	3.0	5	2.7	0.3	11.1	86	3.1	0.1	2.7
Ave.	**-**	**-**	**-**	**3.0**	**9.1**	**-**	**-**	**0.4**	**1.1**

As a result of dimensional measurements using the LR image, mean absolute error (MAE) was 3.0 mm and mean relative absolute error (MRAE) was 9.1%. However, using the 16x upscaled SR image, MAE was 0.4 mm and MRAE was 1.1%. These results mean that when low-resolution images of the VGA-resolution are used for dimensional measurement, inaccurate measurement of 3mm accuracy level is performed. However, when using SRGAN, high-precision inspection of 0.4mm accuracy level is possible. This is a very significant result considering that the typical dimensional tolerances of the curtain wall profile are less than a millimeter.

Conclusion

This study confirmed whether image-resolution can contribute to high-precision dimensional measurement for a curtain wall profile cross-section. In this study, super-resolution generative adversarial network (SRGAN) [6], which is a state-of-the-art deep learning-based super-resolution method was applied to convert low-resolution images to high-resolution images for high-precision measurement.

To validate the applicability, an experimental dimensional measurement on a curtain wall profile section was conducted. Additionally, it was attempted to use only two high-resolution images for training SRGAN. As a result of the experiment, it was verified that the dimensional measurement can be carried out with high-precision of 0.4mm of mean absolute error (MAE) and 1.1% of mean relative absolute error (MRAE). Considering that the typical dimensional tolerances of the curtain wall profile are less than a millimeter, this is a very significant result. For certain tasks and target, such as dimensional quality measurement of curtain wall profile cross-section using SRGAN, it means that there is no need to invest a long time in SRGAN training.

Nevertheless, this study also has limitations in that there is an assumption that the input cross-sectional image is accurately photographed from the front and the measurement process is not automated yet. Hence, in this study, the process of measurement at the pixel level was performed manually. Generalization and automation will be left for the future study.

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