

Supplementary Materials: Generation of highly realistic microstructural images of alloys from limited data with a style-based generative adversarial network

Guillaume Lambard^{1,*}, Kazuhiko Yamazaki², and Masahiko Demura¹

¹National Institute for Materials Science (NIMS), Research and Services Division of Materials Data and Integrated System (MaDIS), 305-0044, Namiki 1-1, Tsukuba, Ibaraki, Japan

²JFE Steel Corporation, Steel Research Laboratory, 210-0855, 1-1 Minamiwataridacho, Kawasaki, Kanagawa, Japan

*LAMBARD.Guillaume@nims.go.jp

Inefficiency of a Luma flip transformation

Figure 1 shows the distribution of the FID as a function of the number of real SEM images (25000 kimg maximum) shown to the discriminator during the training of a StyleGAN2¹. It can be seen that the application of a Luma flip (red, see Table 1(a,c-e) in Supplementary Materials for a visual appreciation of a color-based transformation with the Luma flip activated) highly contributes to the instability and inefficiency of the training process than without (blue). Therefore, the color-based transformation is reduced to the set {contrast, brightness} in Results. Hue rotation and saturation are two transformations that do not apply to single channelled greyscale images.

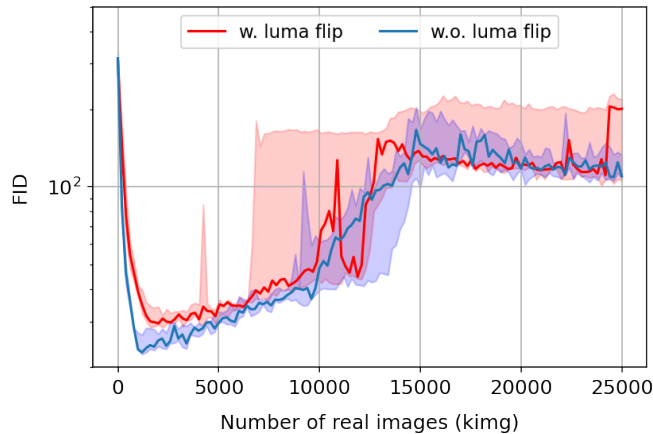


Figure 1. Fréchet inception distance (FID, lower is better) of generated to real SEM images as a function of the number of real images (per thousand images, kimg) shown to the discriminator during the training of a StyleGAN2¹ with application of a Luma flip (red) or without (blue). Solid lines and shallow areas indicate the median values as well as the minimum and maximum values, respectively, issued from three individual training runs.

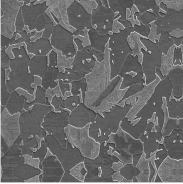
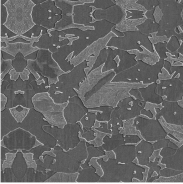
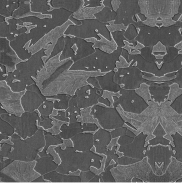
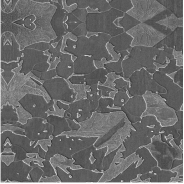
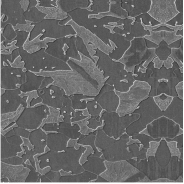
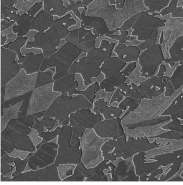
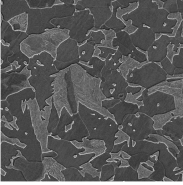
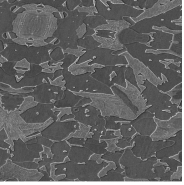
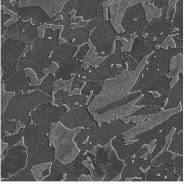
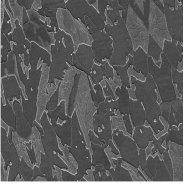
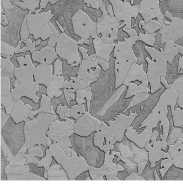
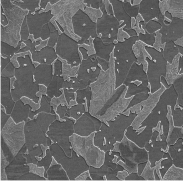
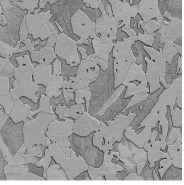
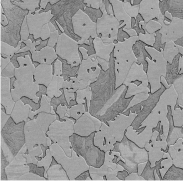
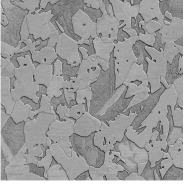
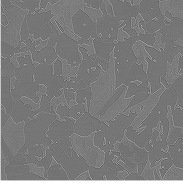
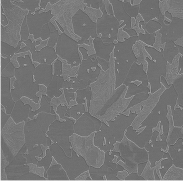
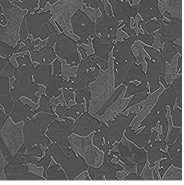
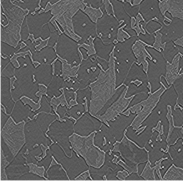
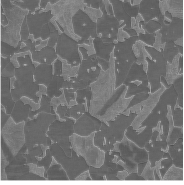
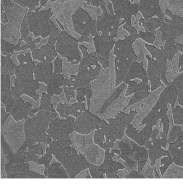
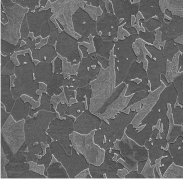
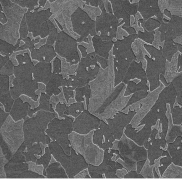
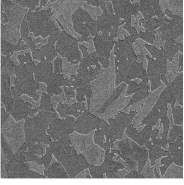
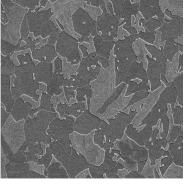
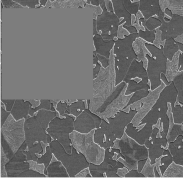
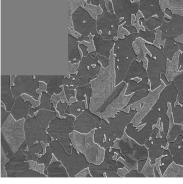
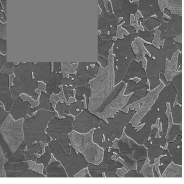
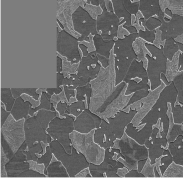
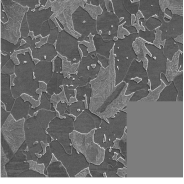
Type of transformations	a	b	c	d	e
Pixel blitting					
Geometrical					
Color					
Image-space filtering					
Additive noise					
Cutout					

Table 1. Random selection of five examples (a, b, c, d, and e) of manipulation of an SEM image with pixel blitting (x-flip, 90° rotation, integer translation), geometrical (isotropic and anisotropic scaling, arbitrary rotation, fractional translation), color (brightness, contrast, Luma flip, Hue rotation and saturation (irrelevant to black and white images)), image-space filtering (over 4 distinct frequency bands), additive noise, or cutout transformation (see Karras *et al.*¹, pages 21-24 for details).

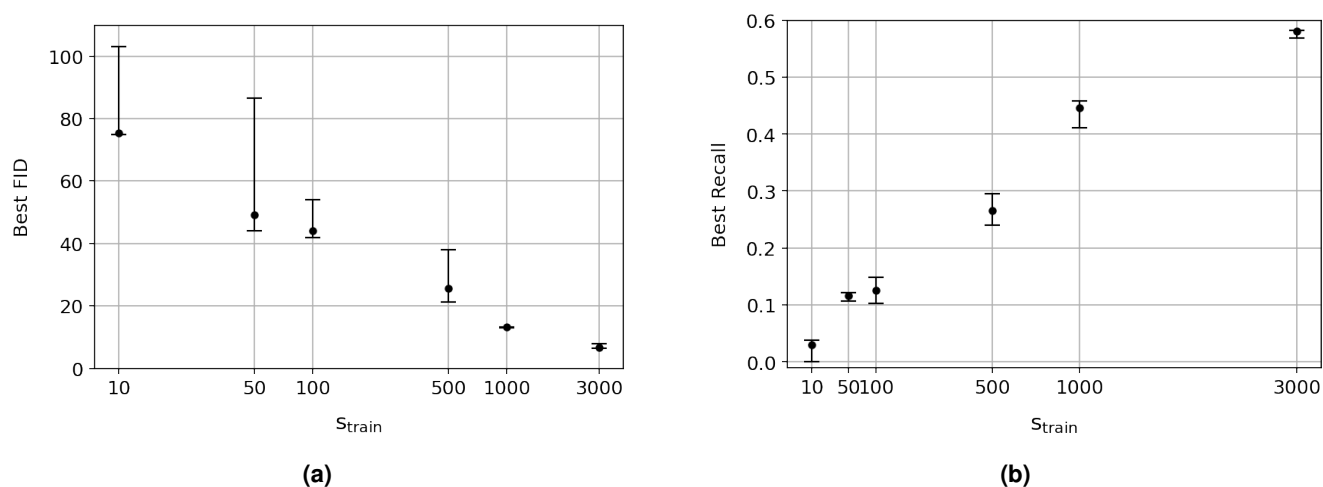


Figure 2. (a,b) Best median Fréchet inception distance² (FID, lower is better), and recall³ (higher is better) values (black dots) on generated SEM images, with their corresponding minimum and maximum values (asymmetric error bars), as a function of the training set size: 10, 50, 100, 500, 1000, and all 3000 SEM images from our dataset. Values are obtained over three consecutive runs with individual random seed of training the StyleGAN2 with ADA¹ for 25000 kimg shown to the discriminator (see Figures 3a and 3c in the main text). A logarithm and square-root based scale are here used for highlighting the dependency of the FID and recall on the training set size, respectively.

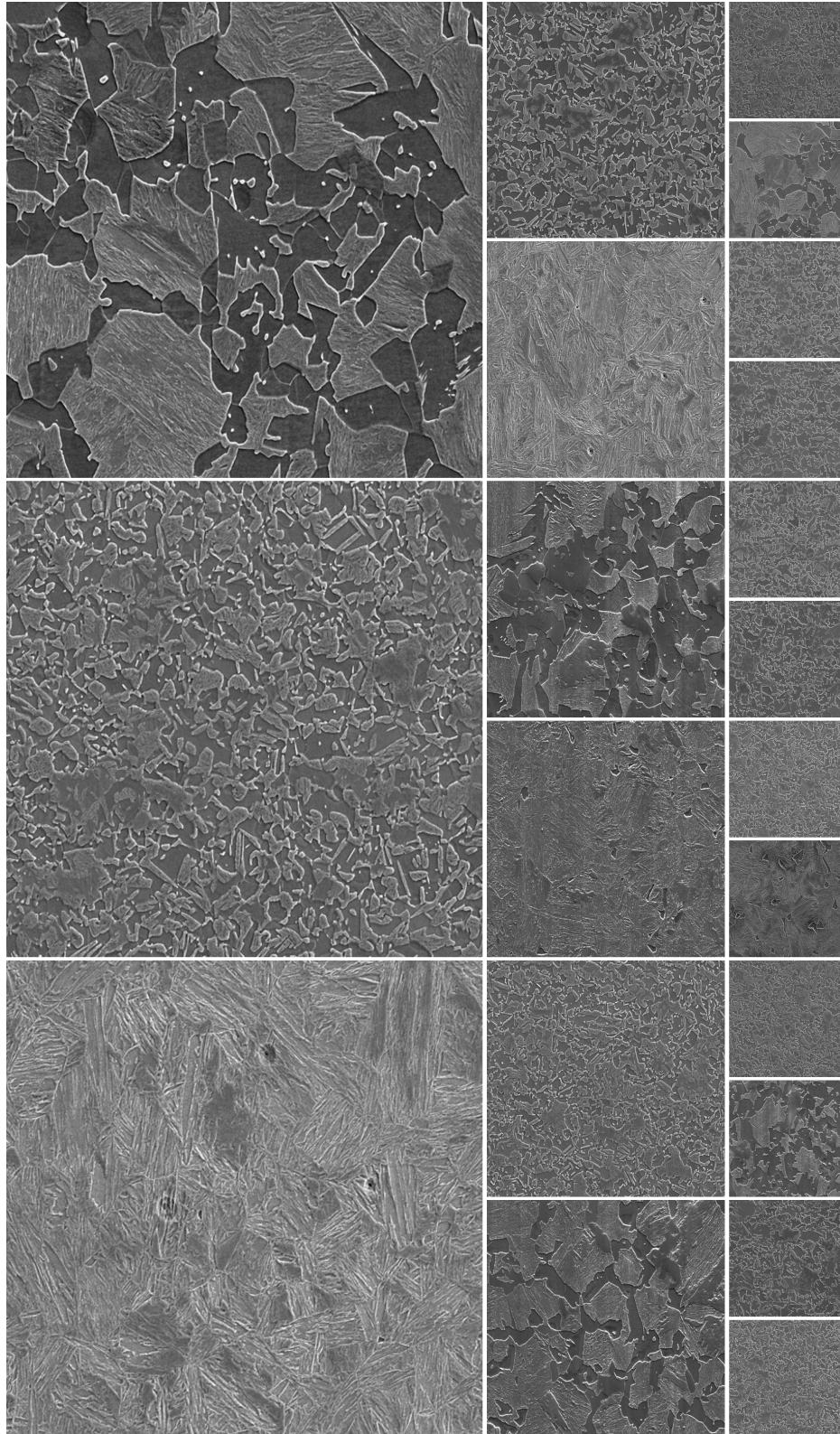


Figure 3. Random sample of 512×512 SEM images extracted from the initial dataset used in the present study. All the images are pre-processed following the pipeline detailed in Methods.

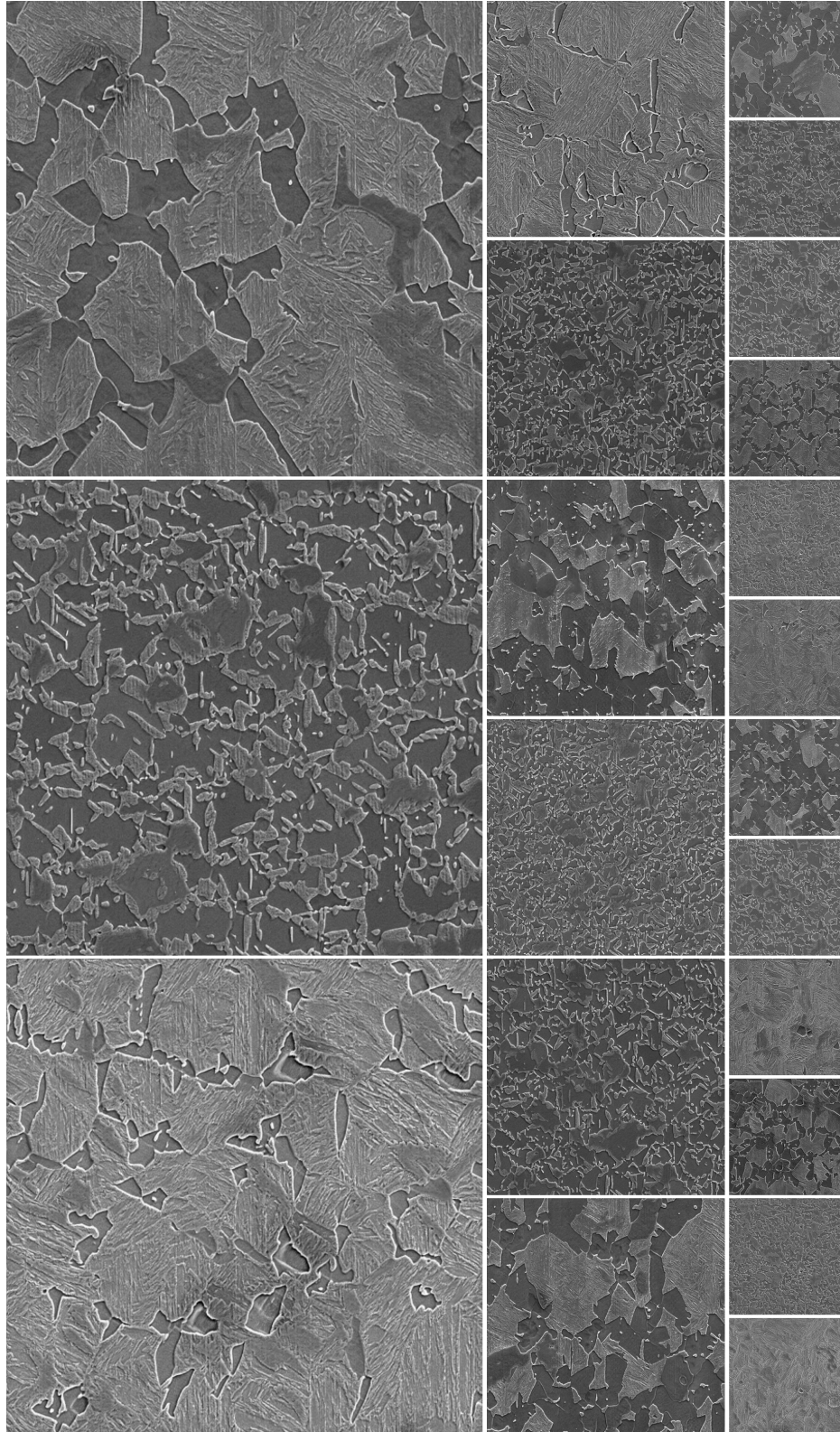


Figure 4. Random sample of non-curved 512×512 SEM images generated thanks to the StyleGAN2 with ADA¹. It is recommended to zoom in for inspecting the fine microstructural characteristics in details.

22 References

- 23 1. Karras, T. *et al.* Training generative adversarial networks with limited data. In *Proc. NeurIPS* (2020).
- 24 2. Heusel, M., Ramsauer, H., Unterthiner, T., Nessler, B. & Hochreiter, S. Gans trained by a two time-scale update rule
25 converge to a local nash equilibrium. In Guyon, I. *et al.* (eds.) *Advances in Neural Information Processing Systems*, vol. 30
26 (Curran Associates, Inc., 2017).
- 27 3. Kynkäänniemi, T., Karras, T., Laine, S., Lehtinen, J. & Aila, T. Improved precision and recall metric for assessing generative
28 models. *Adv. Neural Inf. Process. Syst.* **32** (2019).