Defect Transfer GAN: Diverse Defect Synthesis for Data Augmentation

Ruyu Wang[1,2]; Sabrina Hoppe[1]; Eduardo Monari[1]; Macro F. Huber[2,3]

[1]Bosch Center for Artificial Intelligence

[2]Institute of Industrial Manufacturing and Management (IFF), University of Stuttgart

[3]Fraunhofer IPA

Introduction

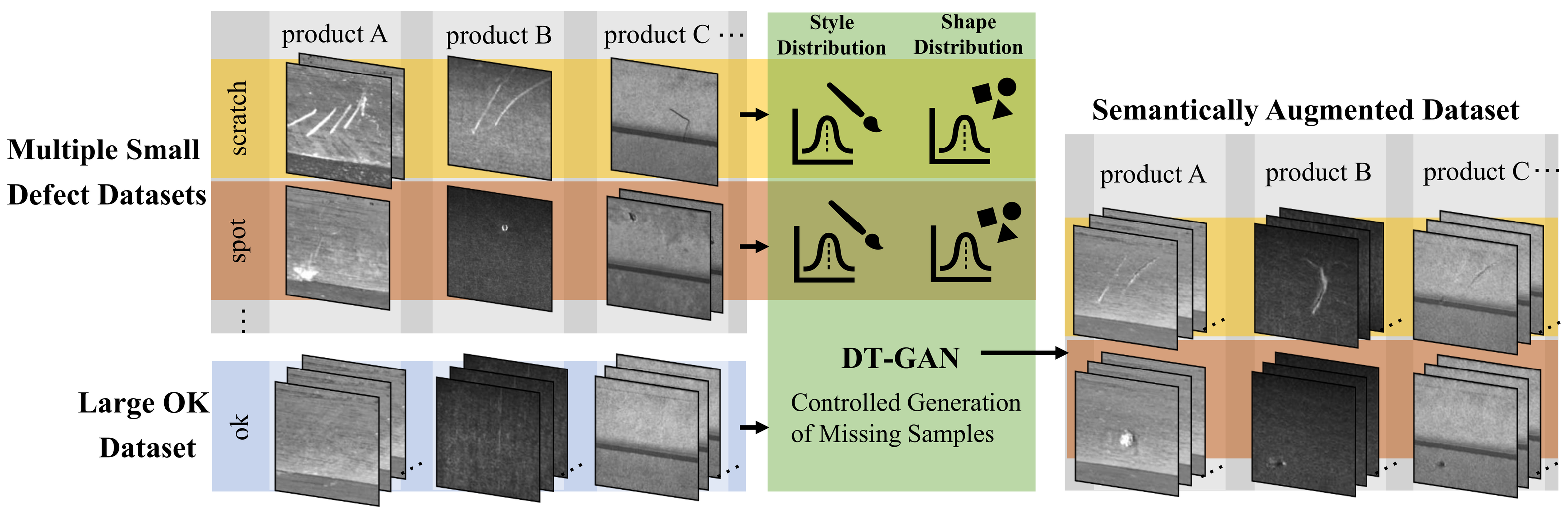
Problem: Acquisition of defective samples from production lines poses a data insufficiency / imbalance problem.

Proposal: Model the shared characteristics of defects across multiple products and produce novel defect combinations for downstream tasks

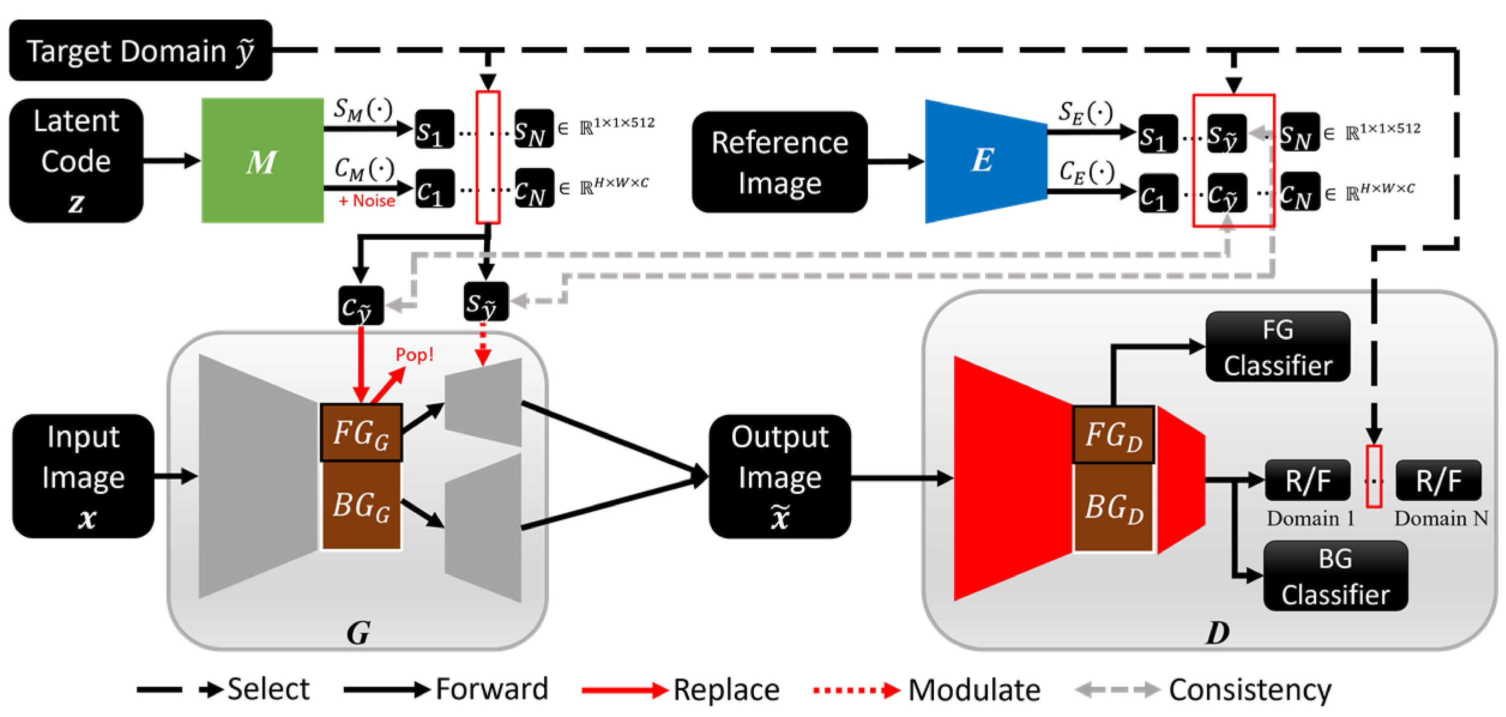
↳ **Defect Transfer GAN**

Key Contributions:

1. **An effective remedy for data insufficiency problem**
2. **A semantically meaningful data augmentation method**



Our Framework



Key Designs:

1. Style-Defect Separation
2. Foreground/Background Disentanglement
3. Multi-Task Discriminator w/ Auxiliary Classifiers
4. Anchor Domain and Noise Injection

Experimental Results

Defect Generation

1. **Quantitative Results**: **FID** as measurement for image quality and **LPIPS** for similarity.

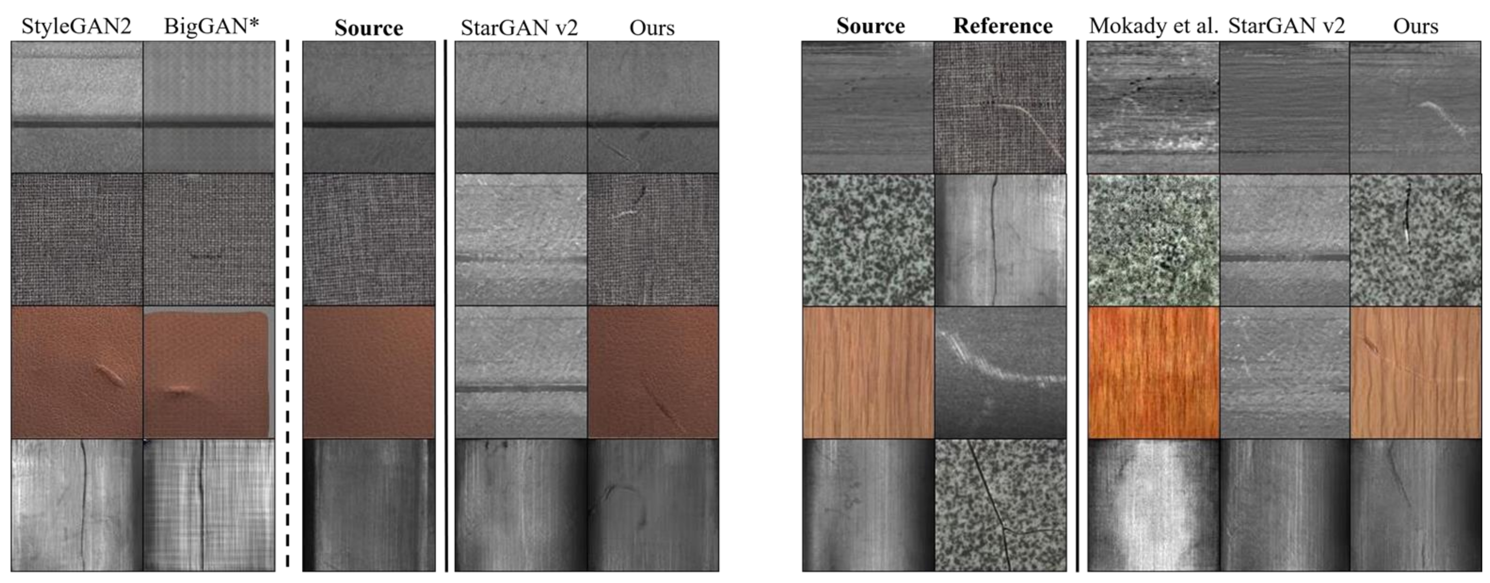
FID

Method	A	B	C	CARPET	LEATHER	TILE	WOOD	MTD	All
Mokady et al. [28]	68.69	66.9	**36.21**	41.87	60.26	275.12	81.71	68.30	**87.38**
StarGAN v2 [5]	96.85	58.28	50.95	354.31	336.63	434.77	411.37	84.49	228.46
StyleGAN2 [21]	90.1	**52.95**	138.09	51.37	**51.6**	**225.96**	140.01	**51.39**	100.18
BigGAN* [2]	218.74	134.41	270.89	34.47	101.7	391.54	113.32	67.91	166.62
Ours	**65.62**	53.62	37.94	**27.33**	78.01	352.15	**77.11**	78.41	96.27

LPIPS

Method	A	B	C	CARPET	LEATHER	TILE	WOOD	MTD
Mokady et al. [28]	0.34	0.46	0.22	0.14	0.28	0.22	0.22	0.38
StarGAN v2 [5]	0.32	0.33	0.20	0.37	0.38	0.40	0.38	0.38
StyleGAN2 [21]	0.29	0.36	0.19	0.09	0.26	0.27	0.18	0.36
BigGAN* [2]	0.30	0.29	0.19	0.08	0.22	0.21	0.18	0.37
Ours	**0.28**	**0.28**	**0.17**	**0.07**	**0.18**	**0.19**	**0.17**	**0.30**

2. **Qualitative Results**: Images from the baseline methods show clear overfitting effect and artifacts in samples while *Ours* retain high-quality and contain more pronounced defects



DT-GAN as Data Augmentation

Exemplary Task: Defect Classification

Aug. Method	Syn. Data	ResNet-50 A	ResNet-50 B	ResNet-50 C
None	None	14.91±1.52	8.2±1.49	15.24±1.51
Trad	None	13.81±2.36	6.8±1.64	16.57±3.20
Trad	Mokady et al. [28]	20.72±1.49	5.8±2.77	24.76±10.1
Trad	StarGAN v2 [5]	10.60±1.99	7.4±3.44	15.81±1.44
Trad	StyleGAN2 [21]	29.45±9.13	6.8±2.05	13.14±3.12
Trad	BigGAN* [2]	12.17±1.99	5.8±1.93	15.62±3.06
Trad	Ours	**6.72±1.65**	**4.6±0.89**	**12.76±1.97**
CutMix [42]	None	13.63±2.87	7.4±1.52	14.09±2.27
CutOut [7]	None	12.36±0.50	6.2±0.84	12.95±2.19
MixUp [44]	None	14.36±1.75	6.2±1.79	16.38±2.80
CutMix [42]	Ours	14.54±3.02	5.2±0.45	19.42±3.47
CutOut [7]	Ours	**12.18±1.99**	**4.0±1.22**	**11.42±1.50**
MixUp [44]	Ours	15.27±2.98	8.2±3.49	21.52±3.96

Outlook

Future Goal:

1. Represent defects and their styles more explicitly (e.g., localization)
2. Enhance the model transferability to unseen products

The 33rd British Machine Vision Conference 21st - 24th November 2022, London, UK