



# Multi-Style Transfer Generative Adversarial Network for Text Images

#### Honghui Yuan and Keiji Yanai

Department of Informatics, The University of Electro-Communications, Tokyo, Japan {yuan-h, yanai}@mm.inf.uec.ac.jp



国立大学法人電気通信大学



#### Introduction

- Neural style transfer have shown impressive results in deep learning.
- Recent researches have successfully completed the transition from the text font domain. to the text style domain.







Image Style Transfer Using Convolutional Neural Networks [Gatys, CVPR 2016]

Controllable Artistic Text Style Transfer via Shape-Matching GAN [Yang, CVPR2019]



#### Introduction

• However, for text style transfer, multiple style transfer often requires learning many models.

• Generating multiple styles images of texts in a single model remains an unsolved problem.





#### Introduction

• We propose a multiple style transformation network, which can generate multiple styles of text images in a single model and control the style of texts in a simple way.





# Related work 1. Style Transfer

 The existing researches (Neural image style transfer,AdaIN) related to style transformation of images have made very significant progress.







# Related work **2.Image-to-image translation**

- SPADE [7] allows users to create an actual composite image from a simple image drawn by the user.
- Proposes a new normalization layer Spatially-Adaptive Normalization.



cited from SPADE[Park et al., CVPR2019]



#### **Related work**

• SEAN [18] made improvements for SPADE [7]. Individual control of each region of a semantic segmentation image was achieved.



cited from SEAN[Zhu, CVPR 2020]

© 2021 UEC Tokyo.



## Related work 3. Text font style transfer

 Can transform text styles by learning one style image and can control different degrees of style.





cited from Shape-Matching GAN [Yang, CVPR2019]

© 2021 UEC Tokyo.



#### Shape-Matching GAN

- Base method Shape-Matching GAN.
- Stage 1:sketch module is used to change the style images into different degrees of deformation through the parameter I.

Stage I: Input Preprocessing (Backward Structure Transfer)



>from Controllable Artistic Text Style Transfer via Shape-Matching GAN [Yang, CVPR2019]



#### Shape-Matching GAN

- Base method Shape-Matching GAN.
- Stage 2: there are two main parts, structure module (GS,DS) and texture module (GT,DT).



Stage II: Forward Style (Structure and Texture) Transfer



## **Shape-Matching GAN**

• Network requires only one style image for text style transformation.

 Shape-Matching GAN works well when learning just one style, but it does not work when learning multiple styles.

multiple styles of text can not be generated
with only one model.



#### **Proposed method**

 we propose a multiple style transformation network for text style transfer based on Shape matchingGAN.

- our main idea:
  - 1.add conditions.
  - 2.optimize the network.





#### **Proposed method**

• The red line shows the network structure that we have changed for Shape-MatchingGAN.





# **Conditional input**





# **Conditional input**

• Input into the network in pairs with the style images.





## **Multi-style training**

• SPADE layer can effectively prevent the information about mask images from being washed out in the network.





#### **Multi-style training**





## **Multi-style training**

• The mask of the four kinds of the style images is used as input for SPADE ResBlk.



# Improving the quality of the generated images

Add a discriminator to make the quality of the generated images better.



# Improving the quality of the generated images

• Add a PatchGAN discriminator to our texture network.





#### Dataset

• Dataset: 129 text images, 4 style images and corresponding mask images.

Example of text image



Style image and mask image





## **Network training**

 Training process: input the style images and the corresponding mask images into the network in pairs.

 Testing stage: input the selected text image and style mask image to generate the corresponding style text image.





#### **Results of the experiments**



© 2021 UEC Tokyo.

4



#### **Results of the experiments**

![](_page_23_Picture_2.jpeg)

© 2021 UEC Tokyo.

![](_page_24_Picture_0.jpeg)

#### **Results of the ablation study**

#### Remove a part of the proposed method.

input style

![](_page_24_Picture_4.jpeg)

w/o SPADE

w/o Dpatch

![](_page_24_Picture_7.jpeg)

full model

![](_page_24_Picture_9.jpeg)

![](_page_24_Picture_10.jpeg)

![](_page_24_Picture_11.jpeg)

![](_page_24_Picture_12.jpeg)

![](_page_24_Picture_13.jpeg)

© 2021 UEC Tokyo.

![](_page_25_Picture_0.jpeg)

#### User study

#### Baseline vs Multi-style SMGAN

#### Number of votes

120

4

![](_page_25_Figure_4.jpeg)

<sup>© 2021</sup> UEC Tokyo.

![](_page_26_Picture_0.jpeg)

#### Conclusions

- In this study, we proposed a multi-style transfer network for text.
- We can also control the generation of various styles of text images in the generation stage.
- The results show that we have achieved a good effect on the generated style images based on the effective transformation of multiple text styles.

![](_page_26_Picture_5.jpeg)

![](_page_26_Picture_6.jpeg)