PARTIAL STYLE TRANSFER USING WEAKLY SUPERVISED SEMANTIC SEGMENTATION

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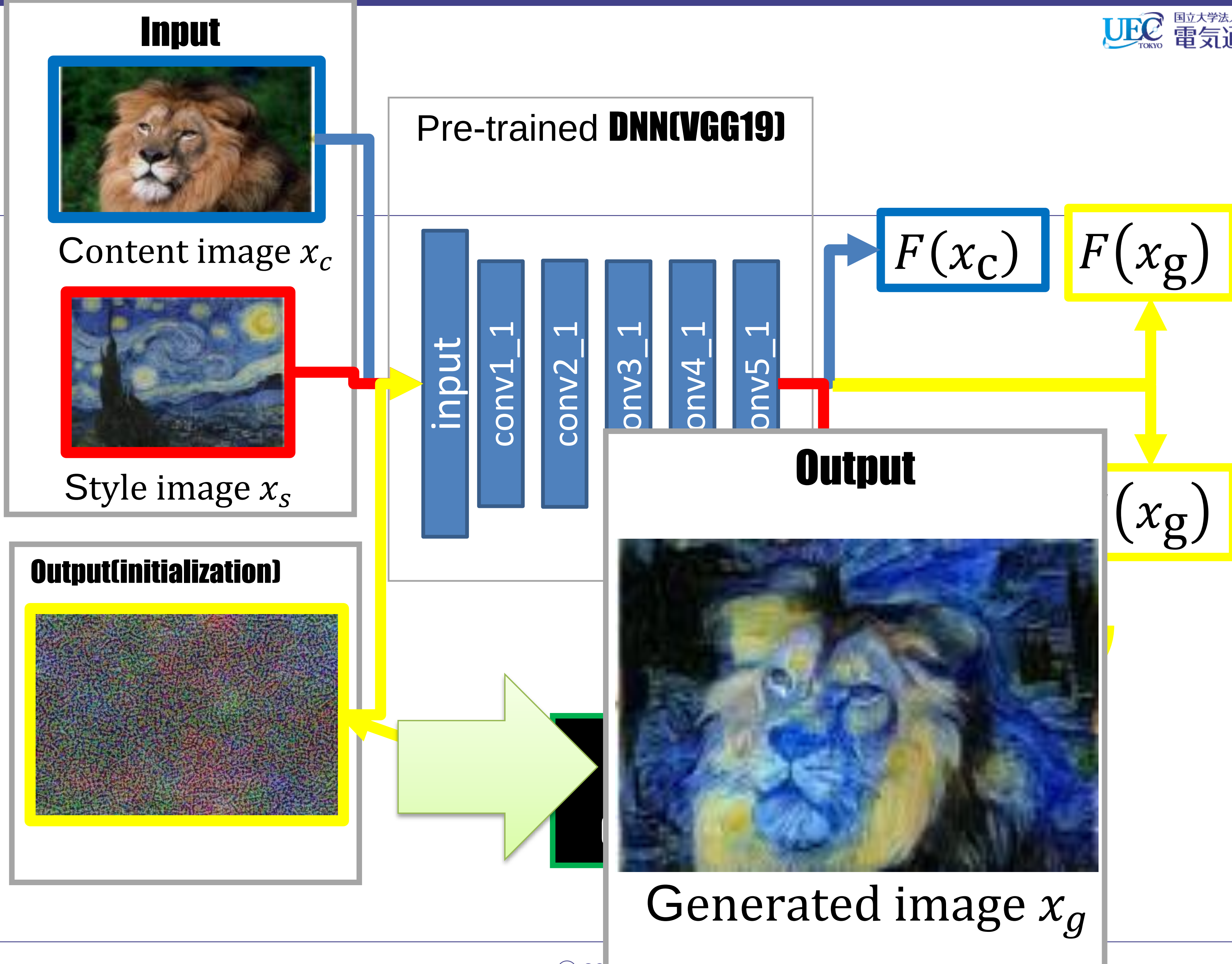
Neural style transfer

- 「A Neural Algorithm of Artistic Style」
  - Gatys et al. Year 2015, arXiv:1508.06576
  - reconstructs a new image which has the same content as a given content images and the same style as a given style image

Content image

Style image


Input
Content image x_c
Style image x_s
Output(initialization)
Pre-trained DNN(VGG19)
input
conv1_1
conv2_1
$F(x_c)$
$F(x_g)$
(x_g)
Output
Generated image x_g

Our work

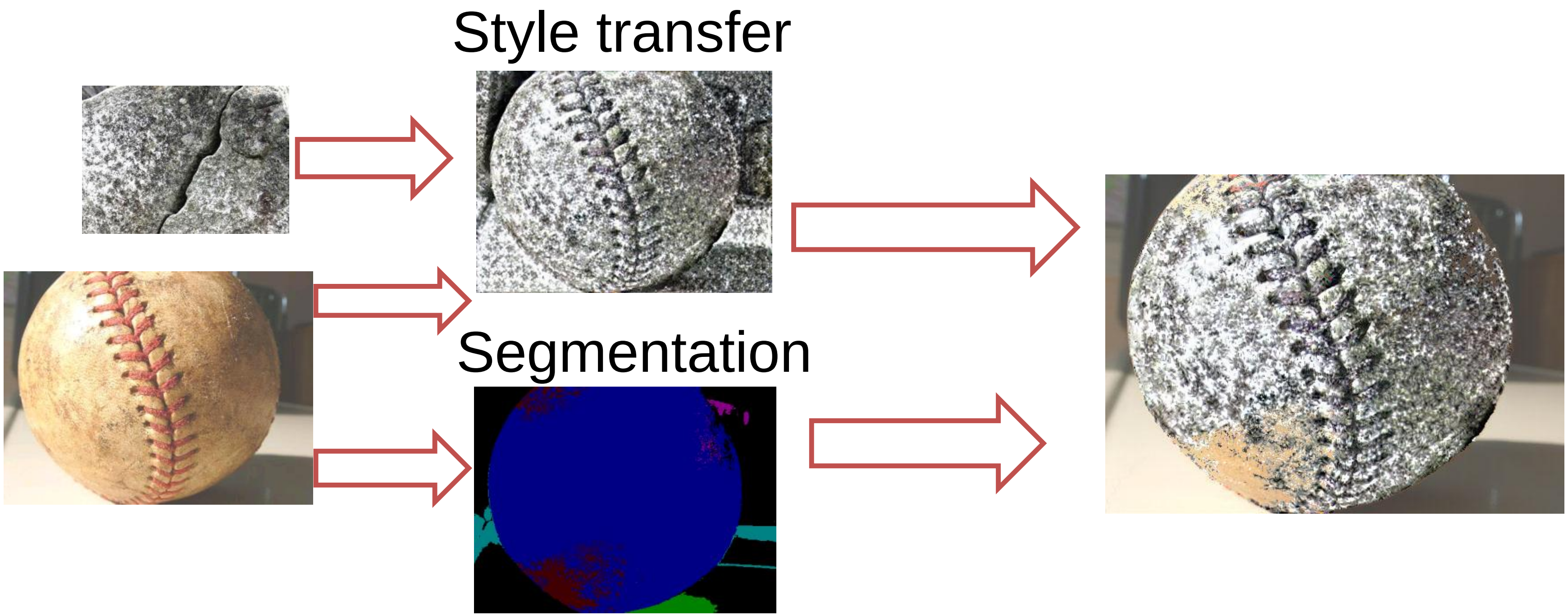
- Style transfer
  - –including the style of background even though we want to change only object regions
- Partial style transfer (Our work)
  - –segment the regions of the target materials
  - –transfer the style of the given materials to only the target regions

Changing of the material of objects

- Flickr material dataset（FMD）
  - 10 class material image（Fabric, Metal, Wood and so on）

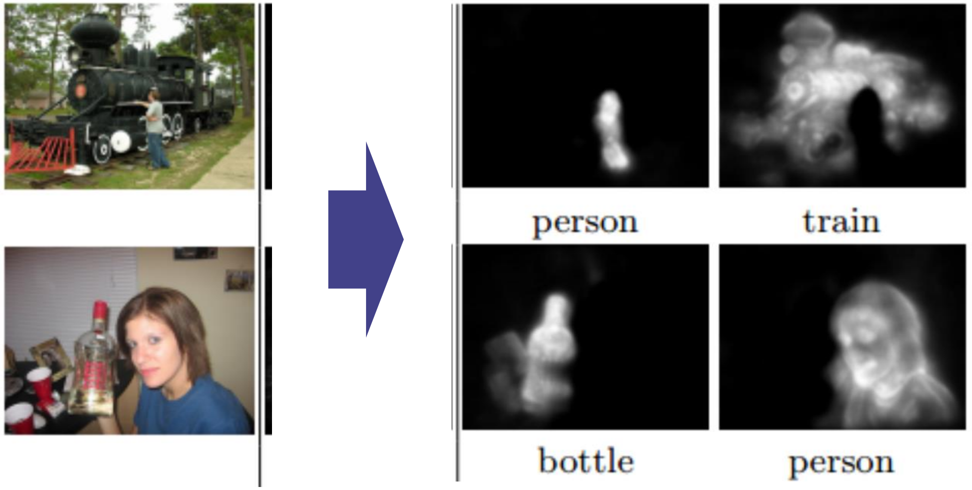
Partial style transfer

- Combining style transfer and segmentation

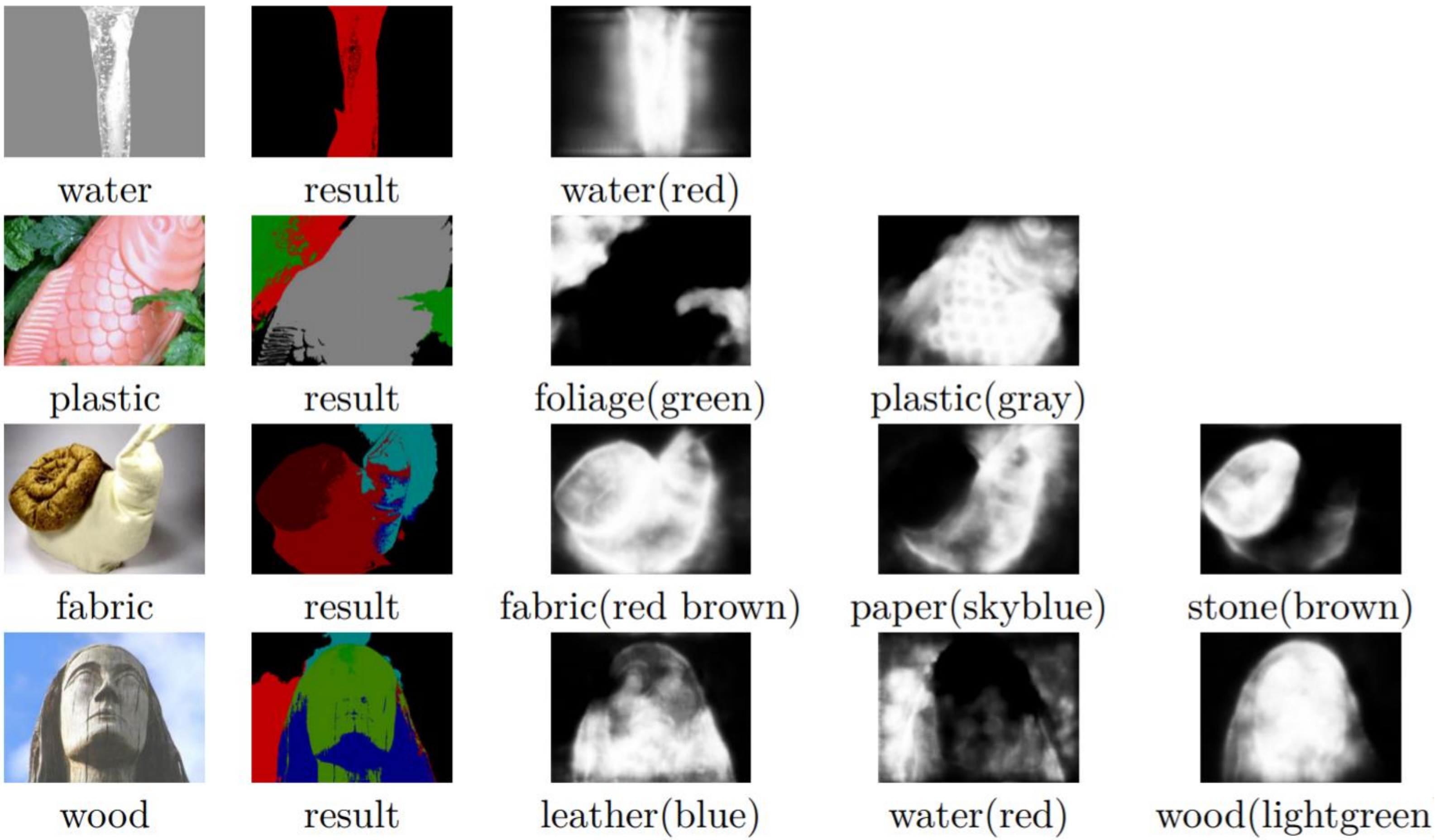


Segmentation Method

- Distict class specific saliency map
  - ECCV 2016, Shimoda et al
- Weakly supervised approach
  - Training with only class label
  - Web images (future work)



Examples of segmentation



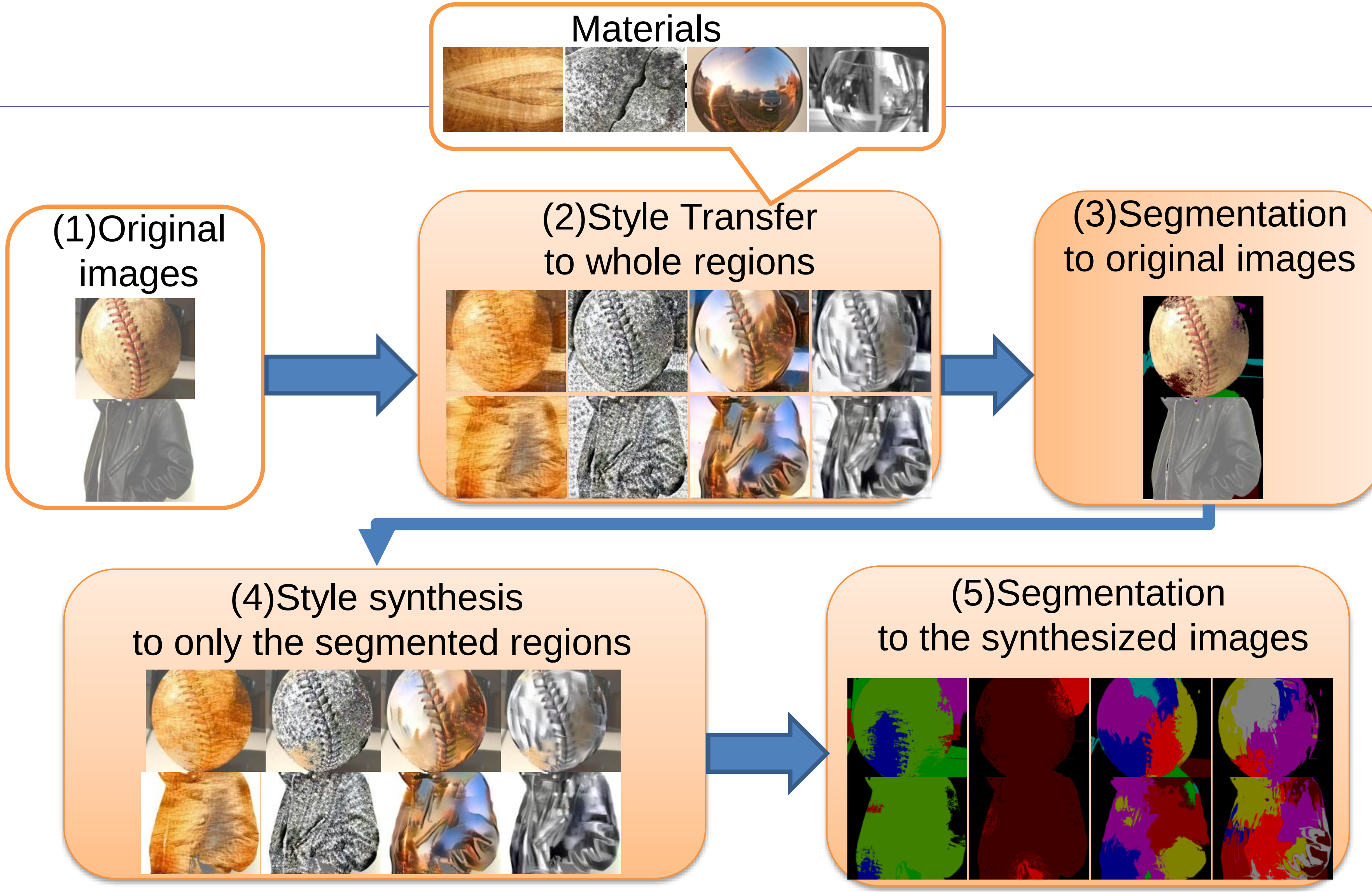
Experiments

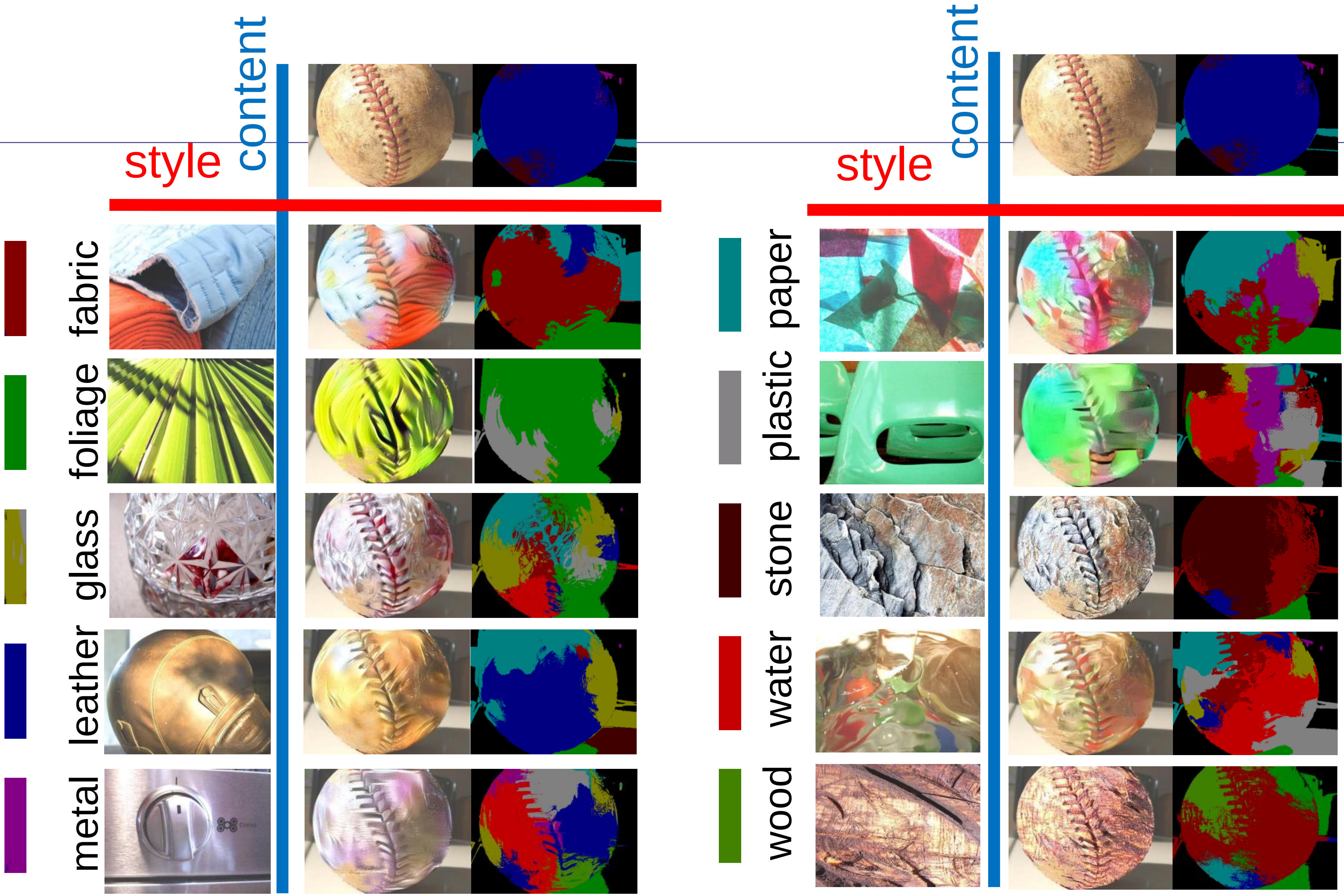
Dataset

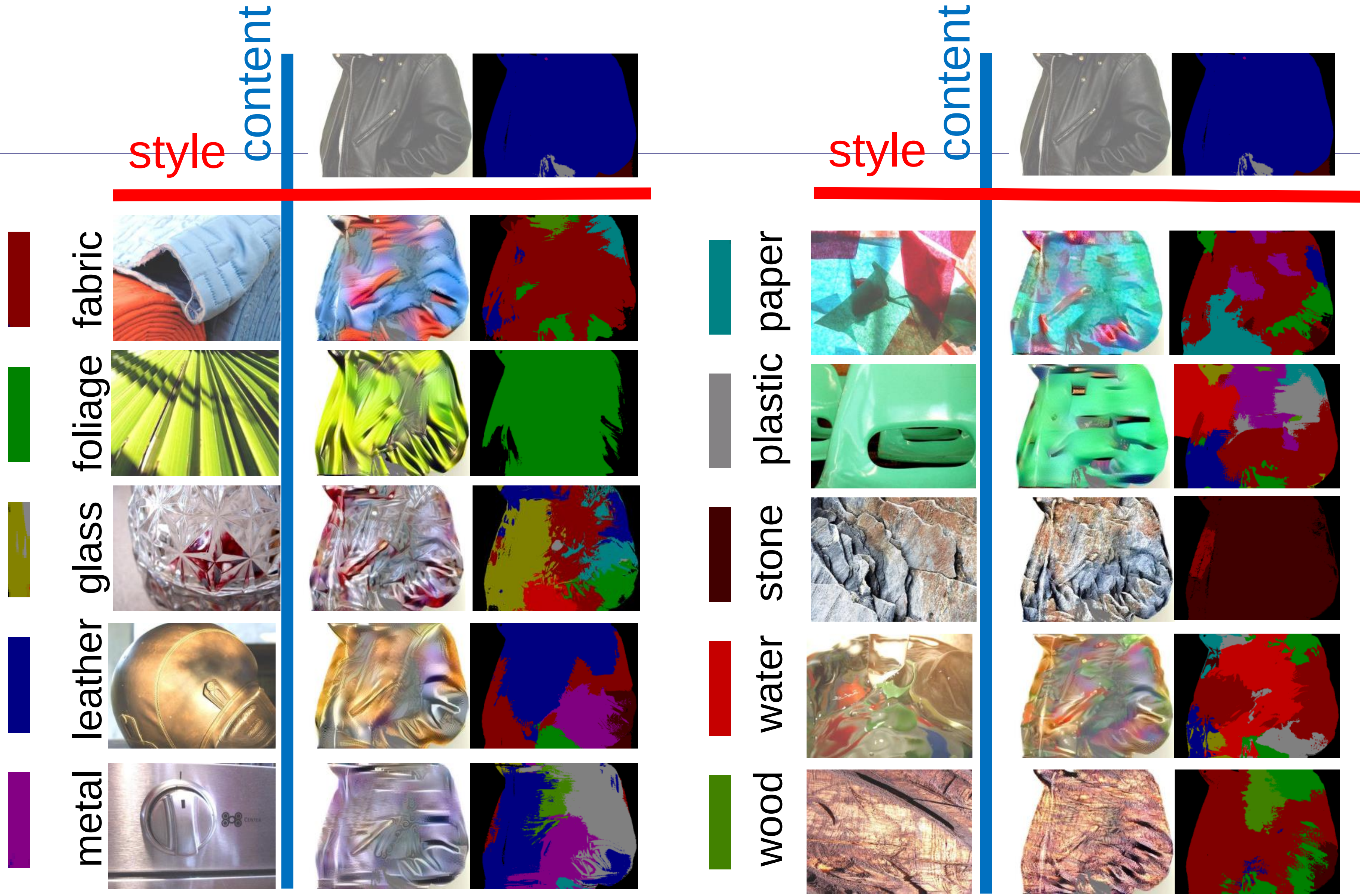
- FMD
- Two hundred style images（20 images for each class）
- Two content images (ball, jacket)

Evaluation

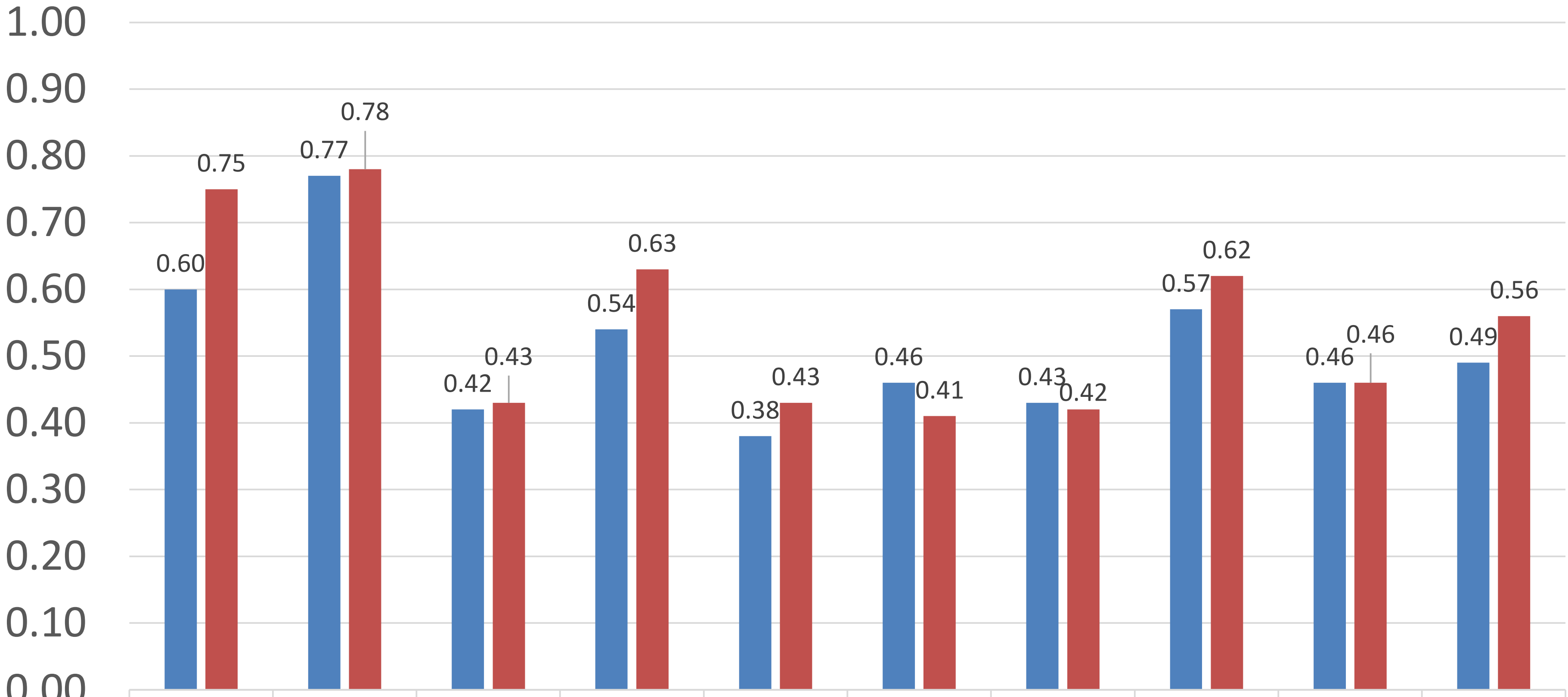
- Re-segmentation
  - Segmentation of style changed image
- Evaluation of re-segmentation result
  - Quantitative evaluation
  - Evaluation metric
    - Pixel accuracy
    - Mean IoU


Materials
(1)Original images
(2)Style Transfer to whole regions
(3)Segmentation to original images
(4)Style synthesis to only the segmented regions
(5)Segmentation to the synthesized images


content
style
fabric
foliage
glass
leather
metal
content
style
paper
plastic
stone
water
wood

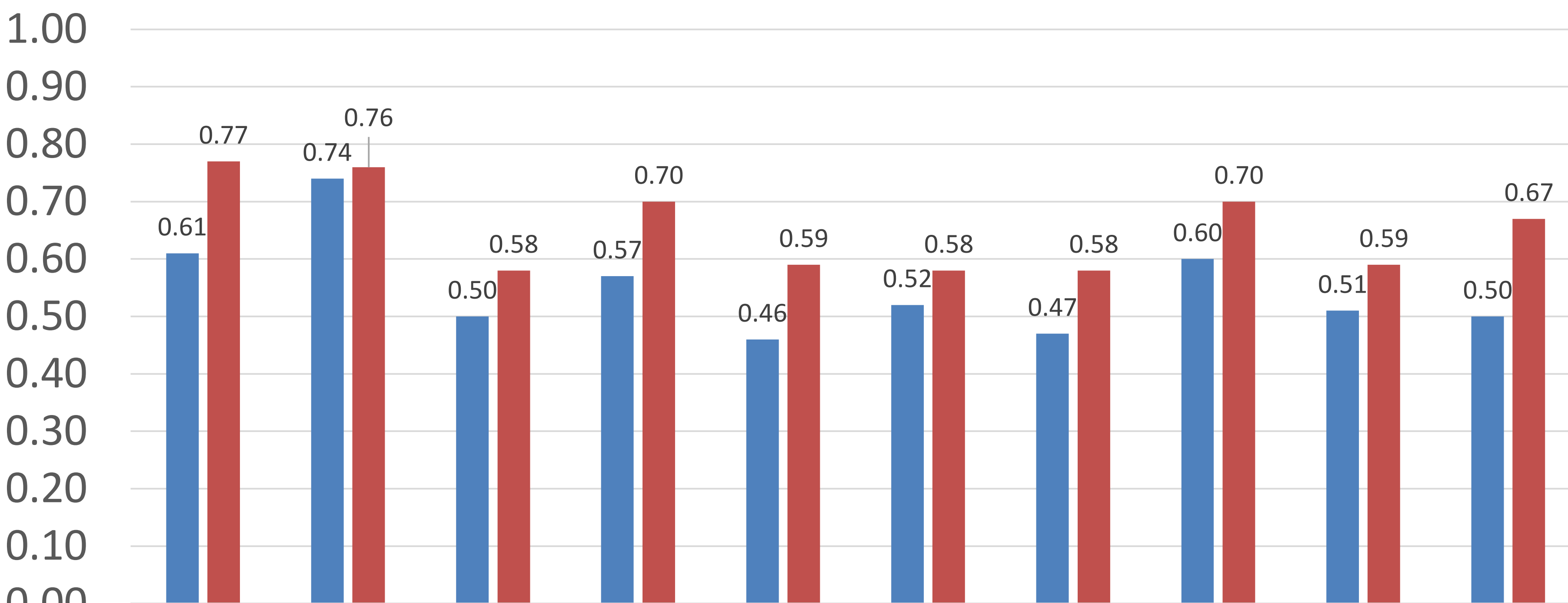

style
content
fabric
foliage
glass
leather
metal
style
content
paper
plastic
stone
water
wood

Pixel acc



	fabric	foliage	glass	leather	metal	paper	plastic	stone	water	wood
ball	0.60	0.77	0.42	0.54	0.38	0.46	0.43	0.57	0.46	0.49
jacket	0.75	0.78	0.43	0.63	0.43	0.41	0.42	0.62	0.46	0.56

Mean IoU



	fabric	foliage	glass	leather	metal	paper	plastic	stone	water	wood
ball	0.61	0.74	0.50	0.57	0.46	0.52	0.47	0.60	0.51	0.50
jacket	0.77	0.76	0.58	0.70	0.59	0.58	0.58	0.70	0.59	0.67

Analysis

- High quality results
  - foliage, fabric, stone
  - irregular and small-scale textures
  - Similar strcutuer
- Low qaulity results
  - glass, metal, plastic
  - regular textures
  - Dissimilar strcutuer

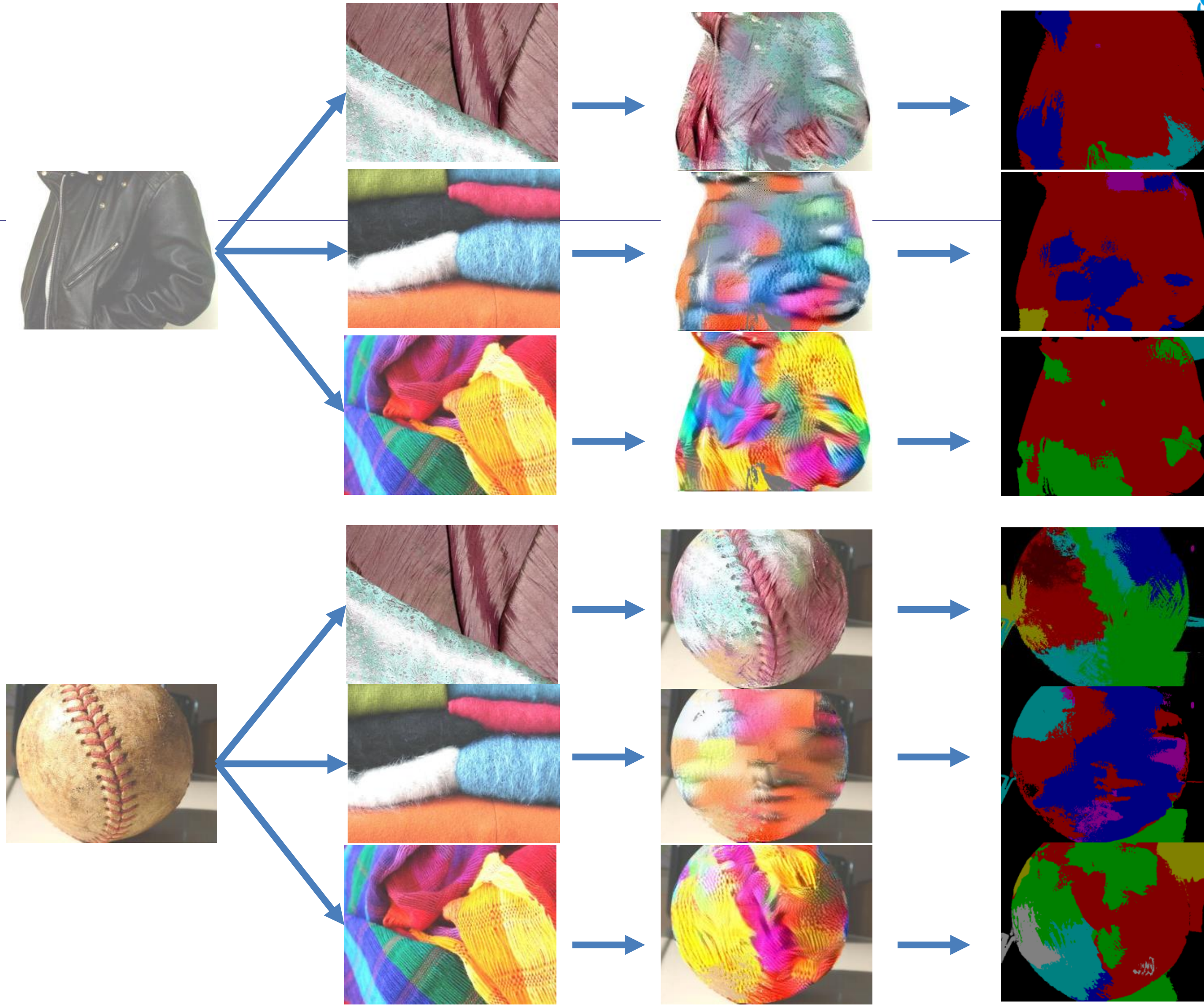
Difference on content image

In Fabric

- Content image: Ball
  - 0.61 (Mean IU)

- Content image: Jacket
  - 0.77 (Mean IU)

- Content image sturcuture is important



Content image | Style image | Generated image | Segmentation

Conclusion

- We proposed a combination of neural style transfer and semantic material image segmentation
- Neural style transfer technique could change the material of objects
- Tendency of material as image style
  - Easy:fabric, foliage and stone
  - Hard:metal, glass and plastic
- we obtained more natural results when the content of the style image is close to the content of the content image

Future work

- Select better style images or better part of style images automatically, and improve the neural style transfer method
- End-to-end network which realizes partial style transfer including both processing of segmentation and style transfer