INTERNATIONAL UNIVERSITY OF APPLIED SCIENCES

10th EAI International Conference: ArtsIT, Interactivity & Game Creation (ArtsIT 2021)

ALEXANDER LEISER & TIM SCHLIPPE

AI IN ART:

SIMULATION OF THE HUMAN PAINTING PROCESS

Karlsruhe, Germany

December 3, 2021

AGENDA

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MOTIVATION: PAINTING ROBOT

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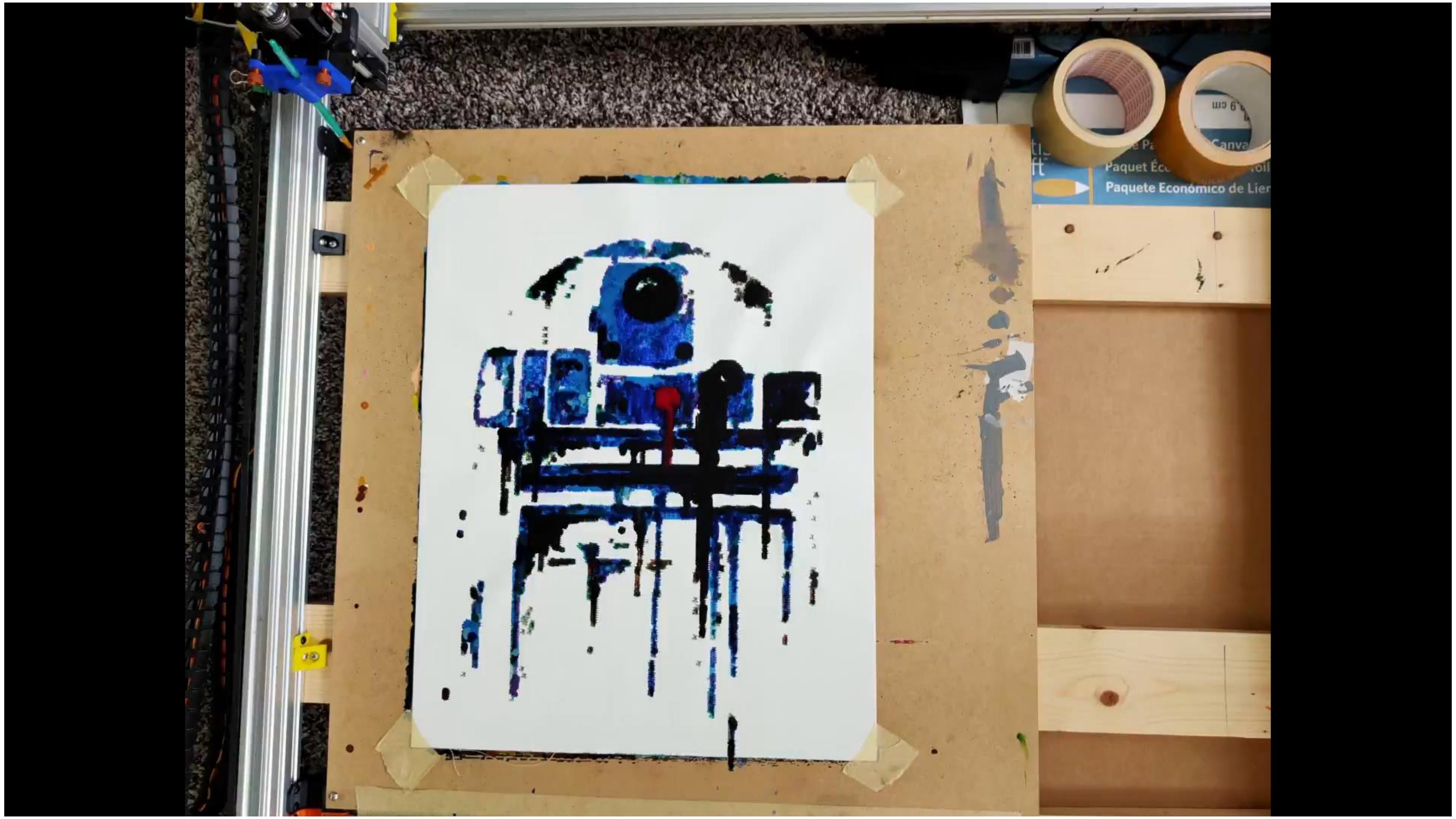

➔ **Paint acrylic pictures** on a canvas (2020) & Automatic painting including **automatic color change**

Video Source: Alexander Leiser‘s YouTube channel – vialps.com

MOTIVATION: PAINTING ROBOT

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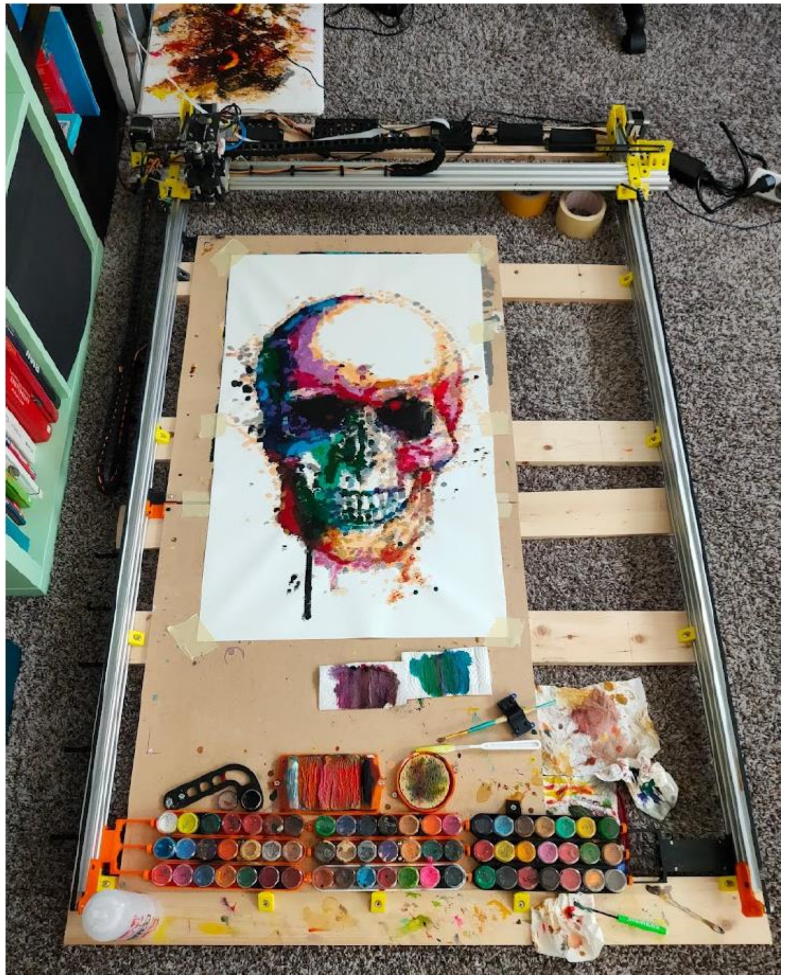

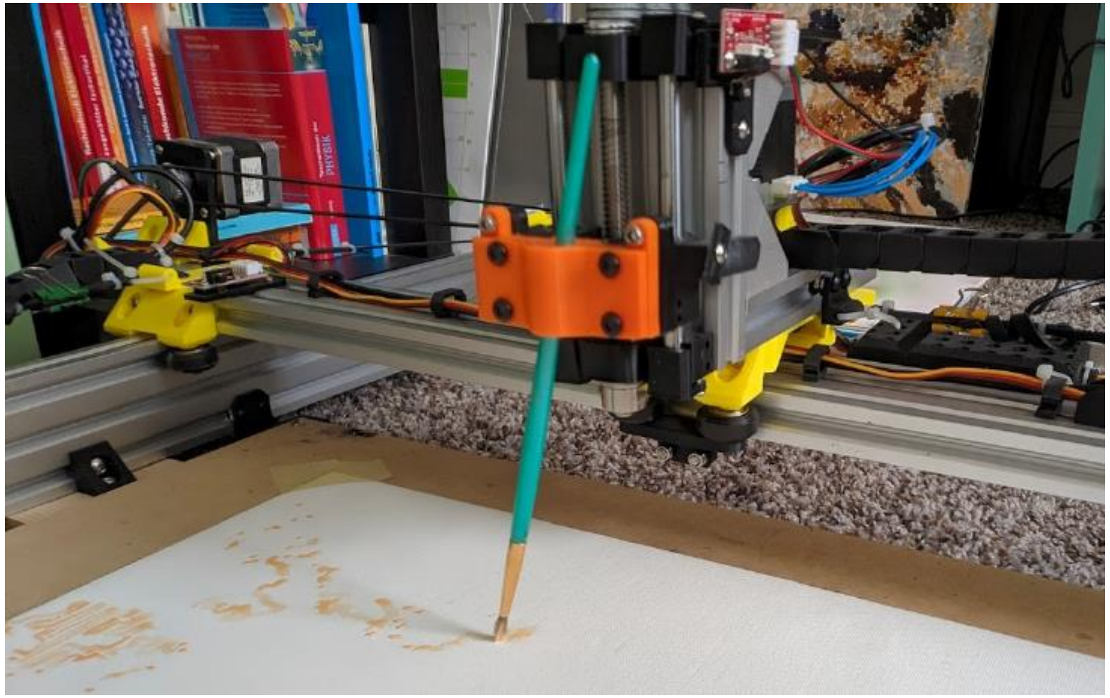

➔ However:

Robots do not paint according a human painting process.

➔ **How to simulate this painting process**

1) like humans and

2) with only the target picture?

Image Sources: Alexander Leiser's website – vialps.com

CHALLENGES:

SIMULATION OF THE HUMAN PAINTING PROCESS

CHALLENGES: HUMAN PAINTING PROCESS

Image Sources: 3KICKS fine art studio (May 2011). Sean Cheetham’s demo in advanced portraiture class painting workflow. Accessed May 24 2021. URL: http://3kicks.blogspot.com/2011/05/sean-cheethams-demo-in-advanced.html.

- ➔ Usually **from coarse to fine**
- ➔ Painting in **layers**
- ➔ **Overpaint already painted areas** sometimes multiple times

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RELATED WORK

RELATED WORK: ARTISTS

Image Sources: Arman, P. Van (2020). cloudpainter A.I. Artist Pindar Van Arman. accessed May 26 2021. URL: https://www.cloudpainter.com/process.

- ➔ Many approaches use AI to generate art
  - ➔ Cloudpainter **visualizes AI** in paintings
  - ➔ AI used for **style transfer**
  - ➔ Books like Helena Sarin's *Leaves of Manifold* or *Laila Al's Dreaming of Electric Sheep* present **randomly AI generated art**

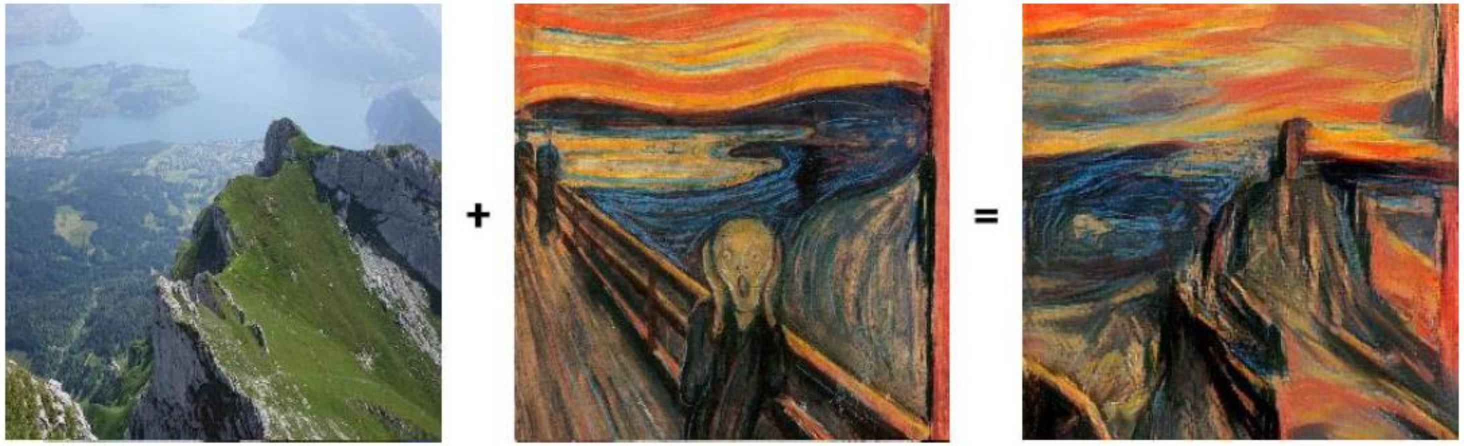
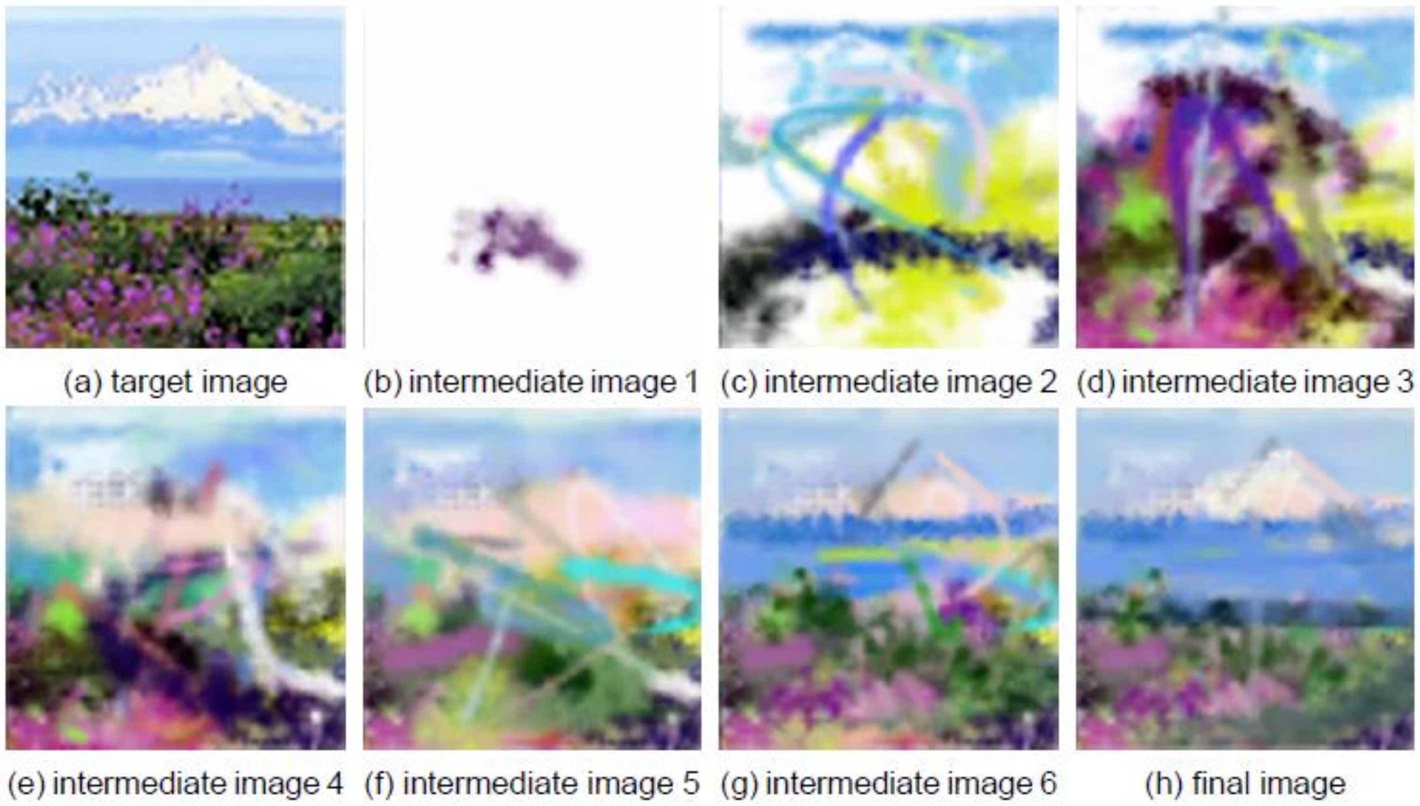


Image Sources: Singh, M. (Sept. 2017). Artistic Style Transfer with Convolutional Neural Network. Accessed June 4 2021. URL: https://medium.com/data-science-group-iitr/artistic-styletransfer- with-convolutional-neural-network-7ce2476039fd.

RELATED WORK: FOCUS ON TARGET IMAGE



- ➔ Others need **pre-trained neural networks** to simulate in somehow suitable time
- ➔ Example: Nakano's Neural Painters: *A learned differentiable constraint for generating brushstroke paintings* (2019)

Image Sources: Diaz-Aviles, E. (Sept. 2019). The Joy of Neural Painting. Accessed May 24 2021. URL: https://medium.com/libreai/the-joy-of-neural-painting-e4319282d51f

➔ Painting process **not realistic** & Intermediate steps **not human-like**

RELATED WORK: PAINTING PROCESS

- Method by
  Z. Huang, W. Heng & S. Zhou (2019).
  Learning to Paint with Model-based Deep Reinforcement Learning
- Needs **pre-trained neural networks** to simulate the painting process
- **Closer to human painting** process
- Blends **semi-transparent colors**

Image Source: Diaz-Aviles, E. (Sept. 2019). The Joy of Neural Painting. Accessed May 24 2021. URL: https://medium.com/libreai/the-joy-of-neural-painting-e4319282d51f

- Our **baseline** for comparison

04

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SIMULATION OF THE HUMAN PAINTING PROCESS USING FILTERS AND SEMANTIC SEGMENTATION

EXPERIMENTS

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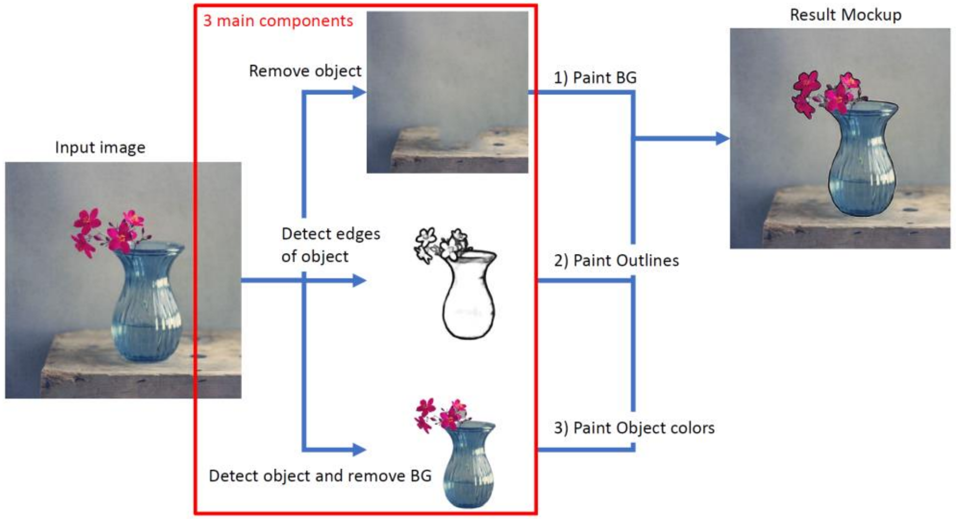
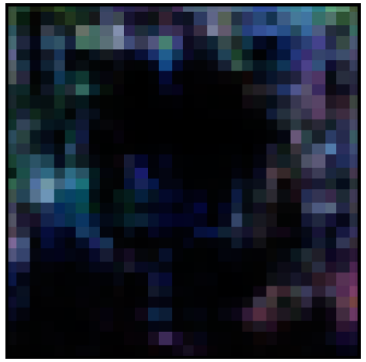
Background-edges-colors approach



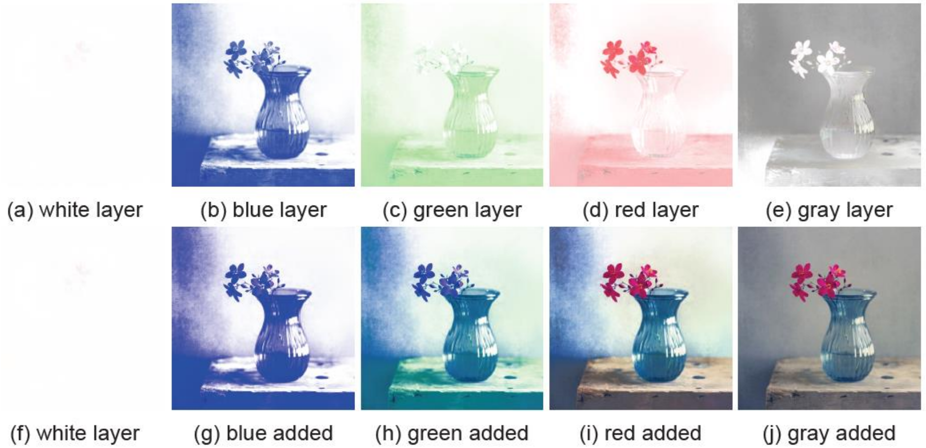
Autoencoder for iterative image generation

(a) input image

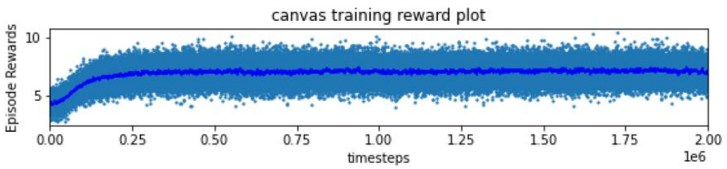


(b) reconstructed

Decompose image into colored layers



Reinforcement learning approach



Low resolution target image

Resulting image after training

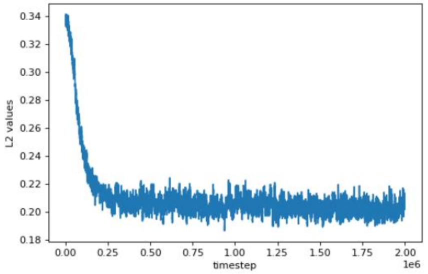


Image Sources: Custom depictions.

FILTERS AND SEMANTIC SEGMENTATION

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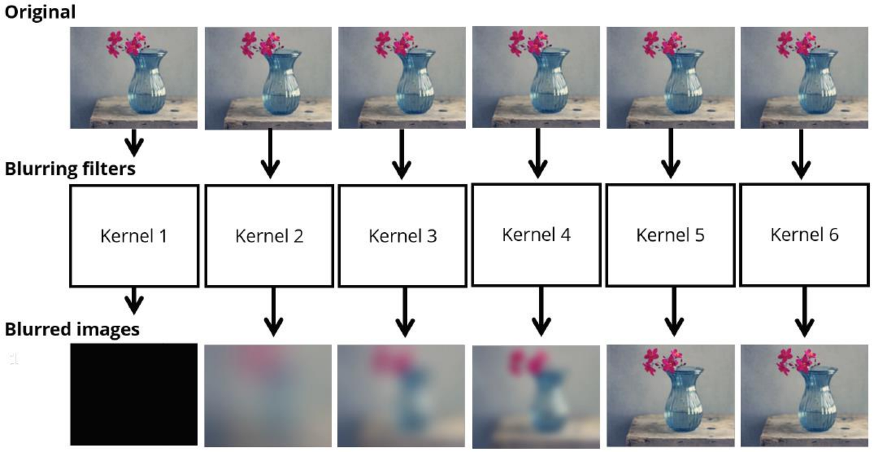
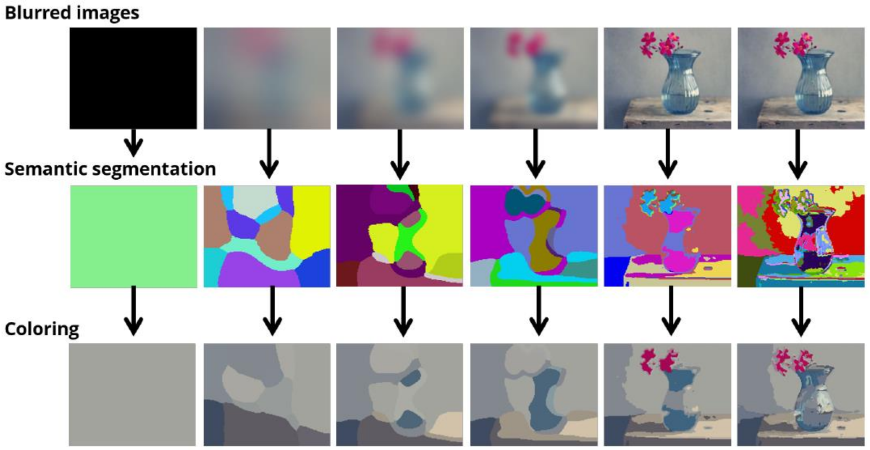


➔ General idea has 3 steps:

1. **Blurring filters**
2. **Semantic segmentation**
3. Step-wise **adding colored areas**



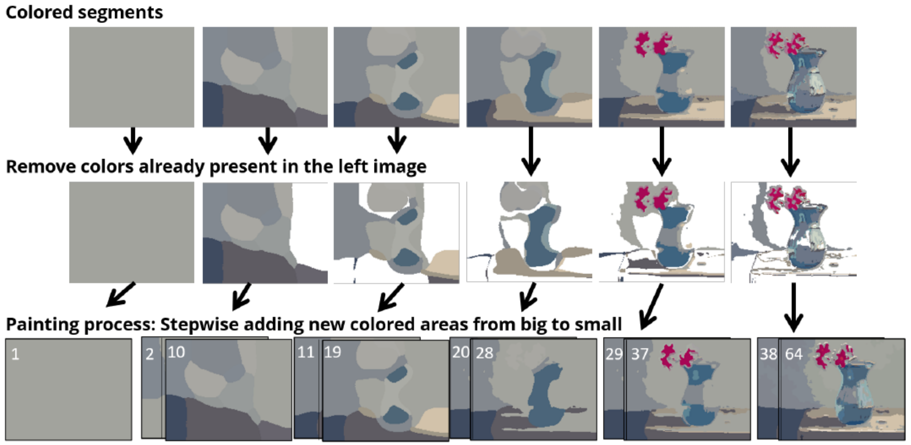
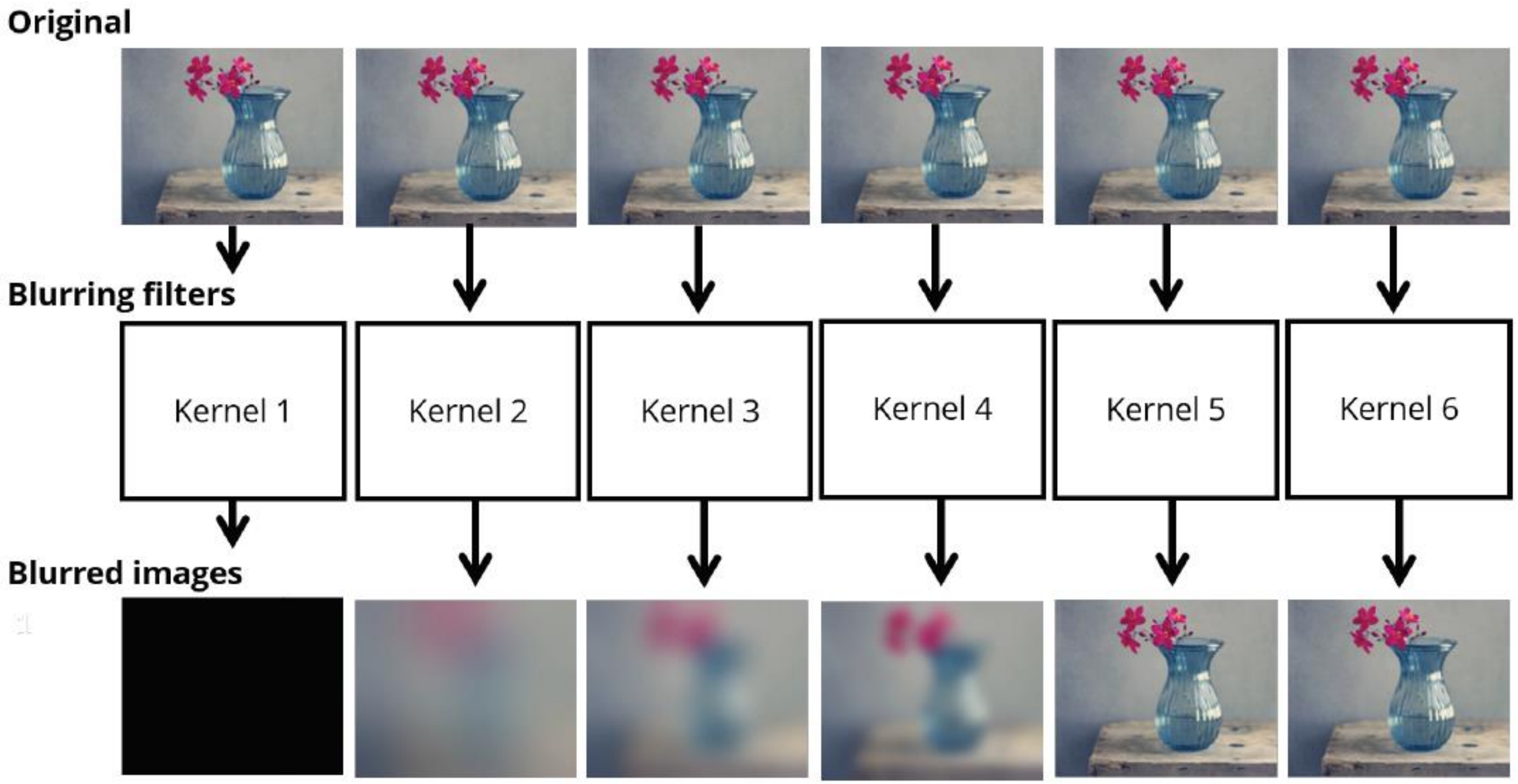


Image Sources: Custom depictions.

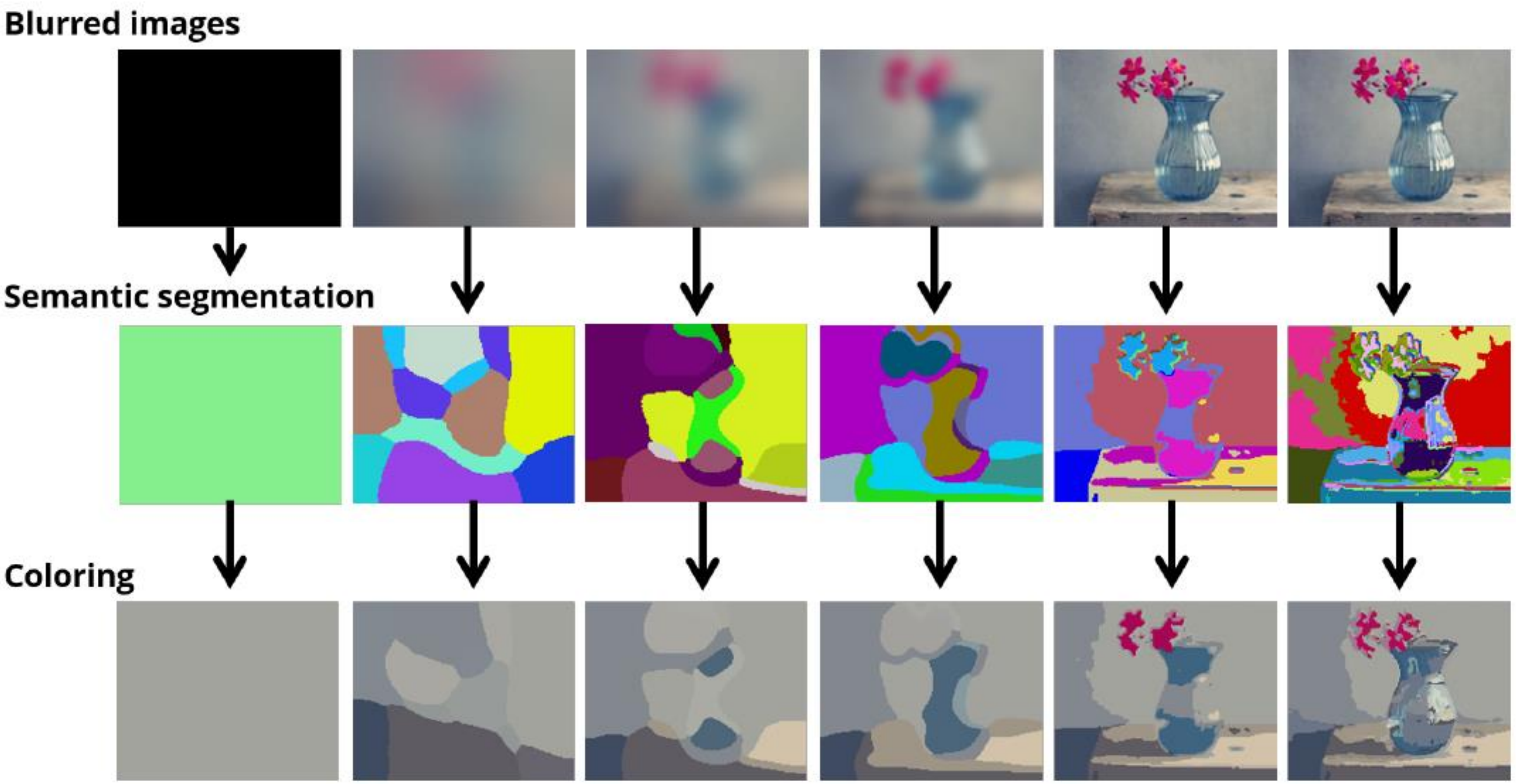
1. BLURRING FILTERS



- ➔ **Blur input image with different kernel sizes**
- ➔ Get **images with different levels of detail** as input for the next step (semantic segmentation)

Image Sources: Custom depictions.

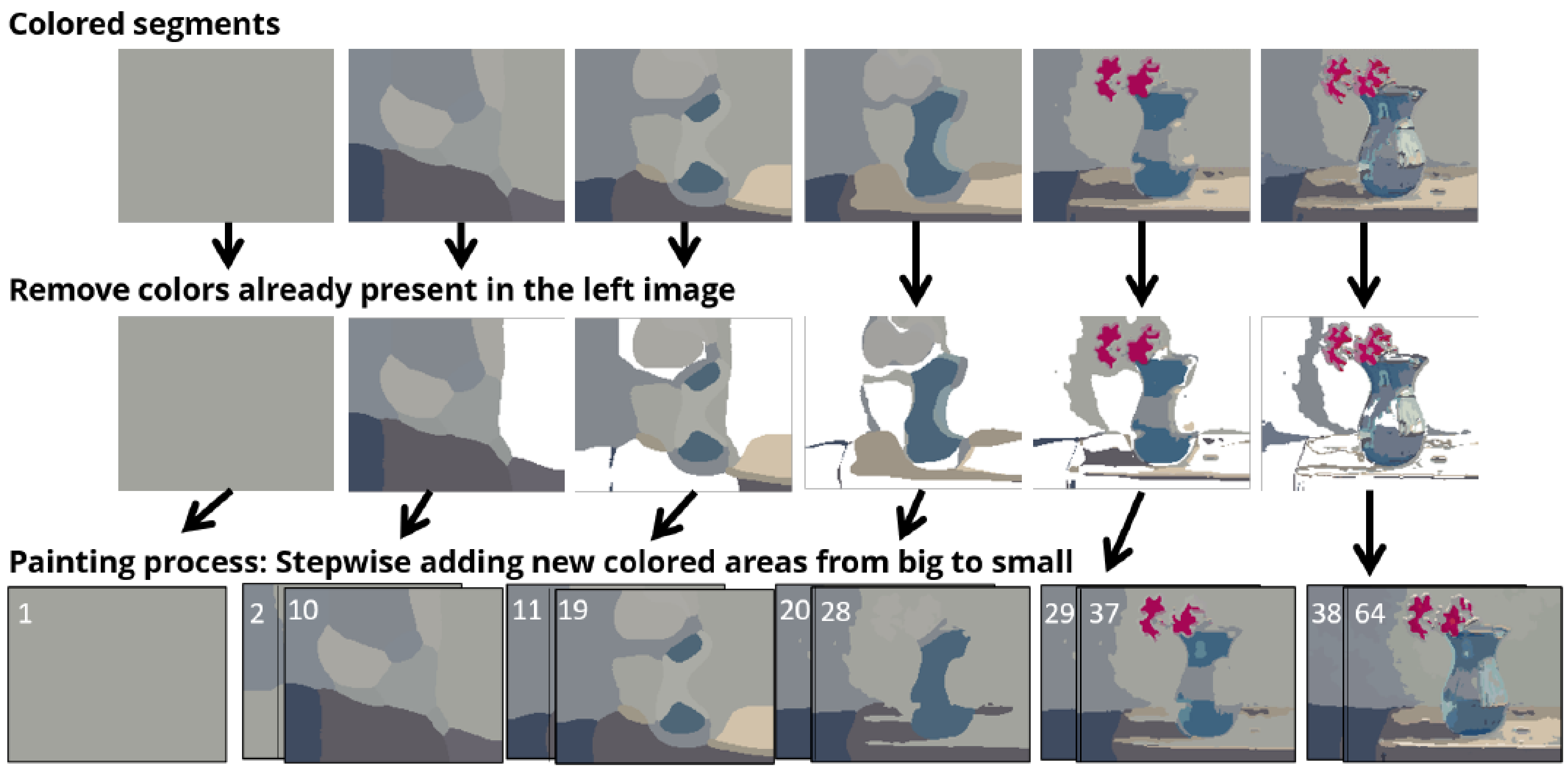
2. SEMANTIC SEGMENTATION



- Apply **semantic segmentation** to each image with different blur level
- Results in **intermediate images that contain smaller and smaller areas**
- **Recolor** each semantic segment in the color which the highest occurrence in that area

Image Sources: Custom depictions.

3. STEPWISE ADDING COLORED AREAS



- **Remove areas with** the **same color as** the image **on the left**
- Then **create individual images** from the different color areas, with each new image corresponding to a step in the painting process, and **sort** the images **with the large color areas first**

Image Sources: Custom depictions.

FILTERS AND SEMANTIC SEGMENTATION

- **Eliminates** any needed **pre-trained models** or **pre-trained neural renderer**
- **Paints in regions** to slowly fill the canvas, similar to human layering painting technique
- **Single components** like the blurring step and the semantic segmentation step **can be replaced**, **extended or changed**

Image Sources: Custom depictions.

05

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USER STUDY

SURVEY

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- 24 participants
- 19-71 years old
- painting routine varies from once a week to once a year or even never



➔ **3 different images compared**
➔ **Comparison with** Z. Huang, W. Heng & S. Zhou's **reinforcement learning** approach

Image Sources: Custom depictions.

SURVEY

LOCATION

ORDER

SHAPE

COLOR

CONTOURS

… of the areas being painted

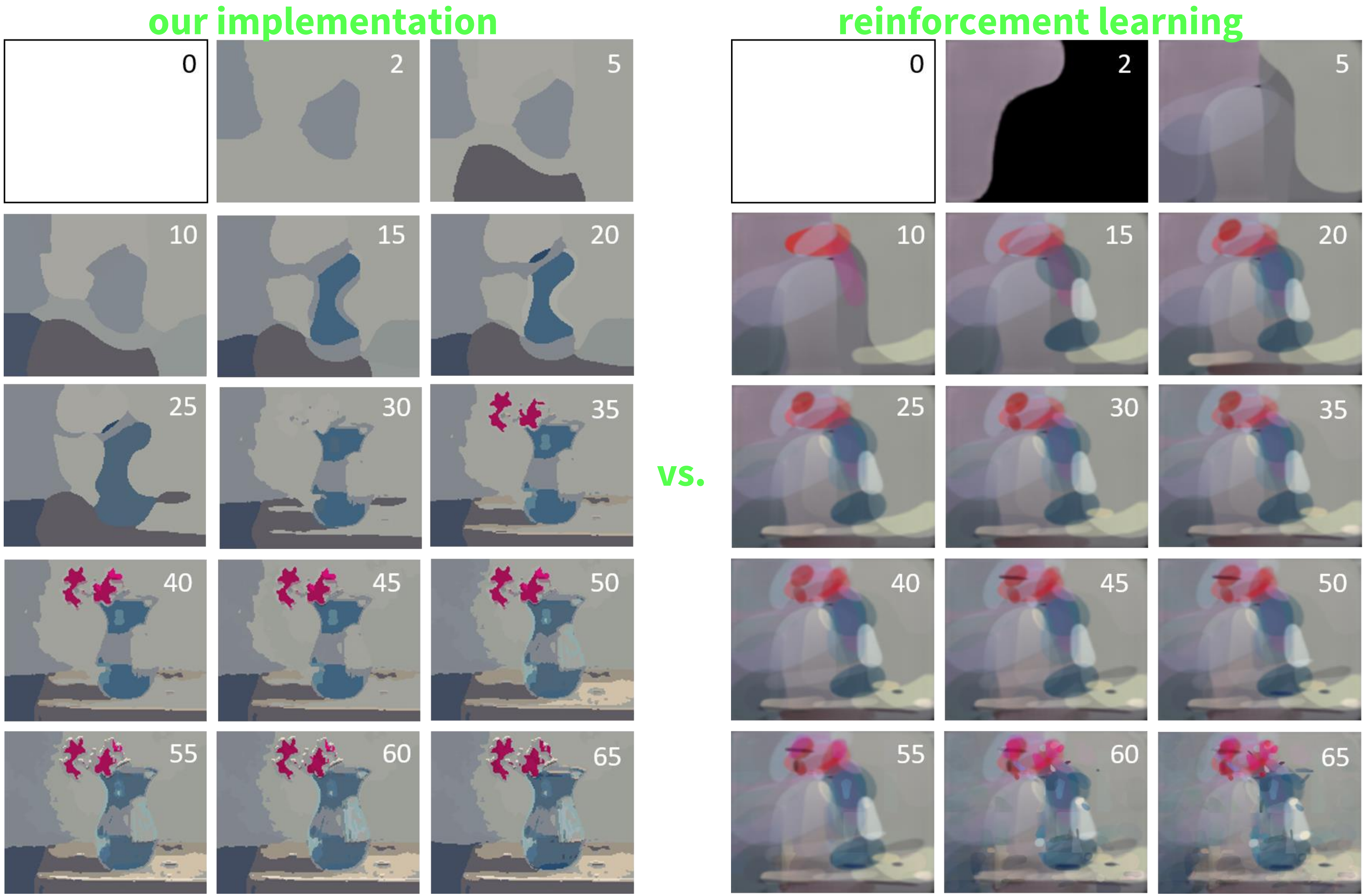


Image Sources: Custom depictions.

SURVEY

LOCATION

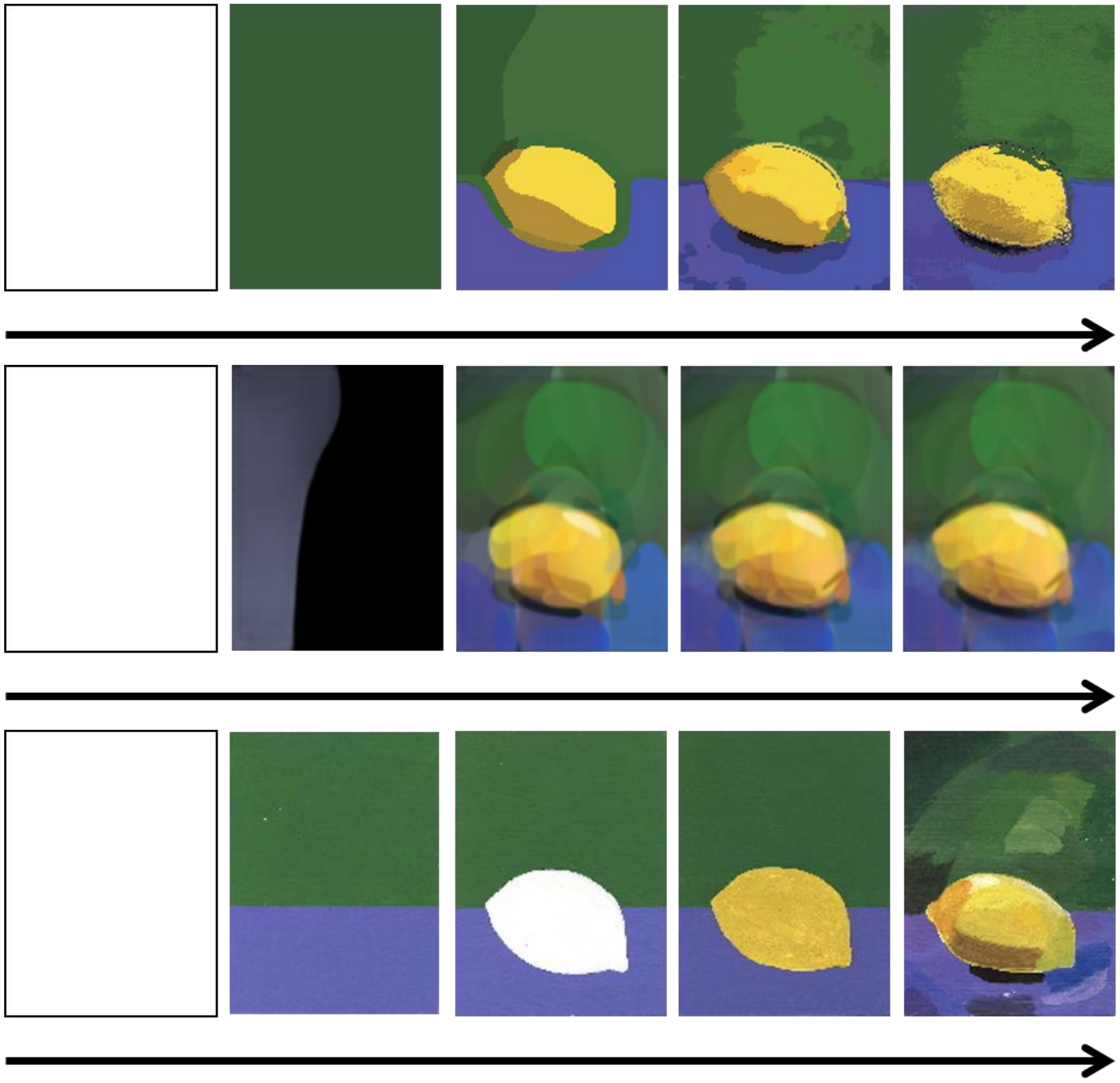
ORDER

SHAPE

COLOR

CONTOURS

... of the areas being painted



our implementation

reinforcement learning

Wizard of Oz (human)

Image Sources: Custom depictions.

SURVEY – DO YOU AGREE THAT THE PROCESS IS HUMAN-LIKE IN RELATION TO …

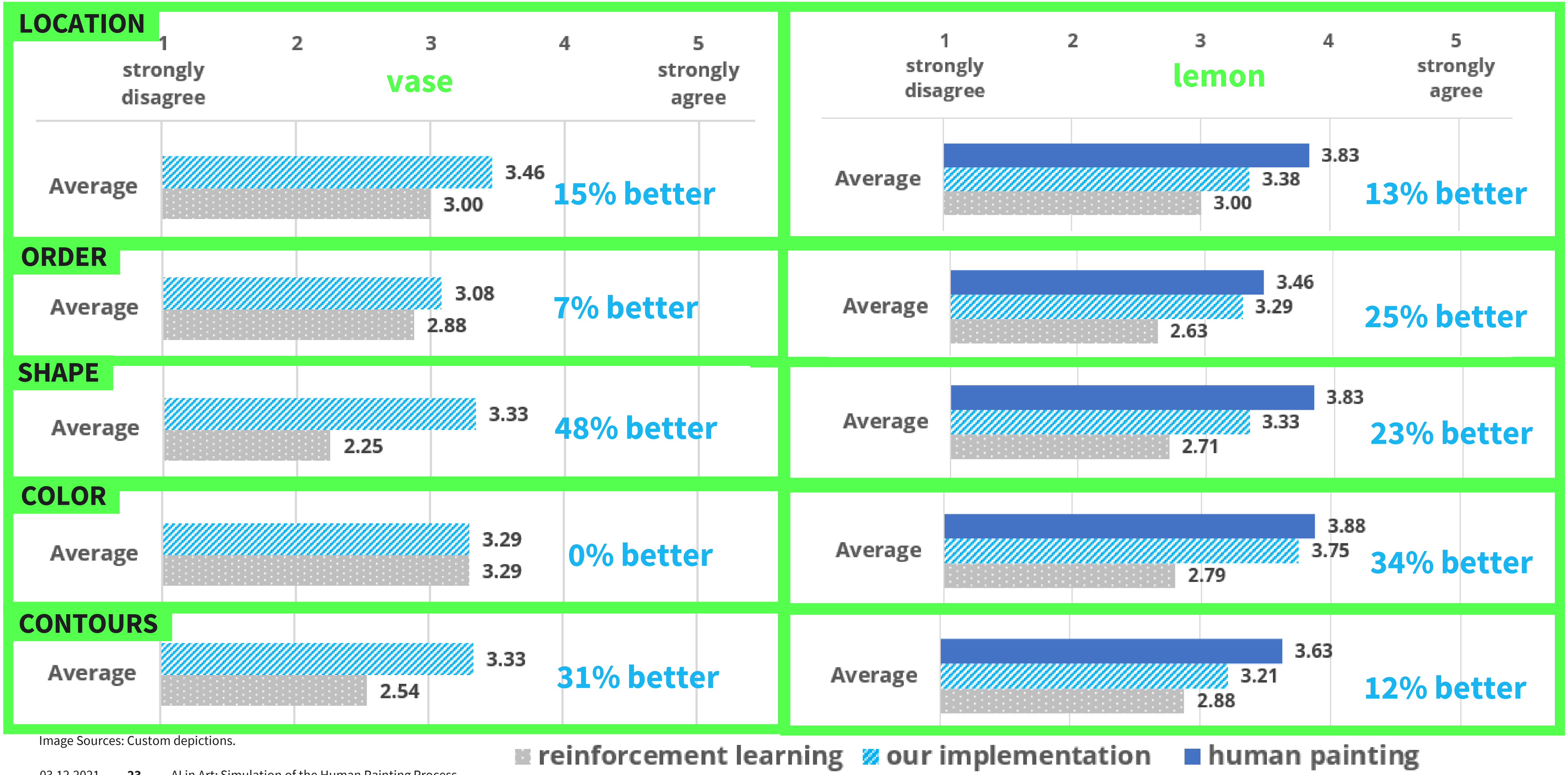


Image Sources: Custom depictions.

SURVEY – GENERAL REALISTIC LOOK

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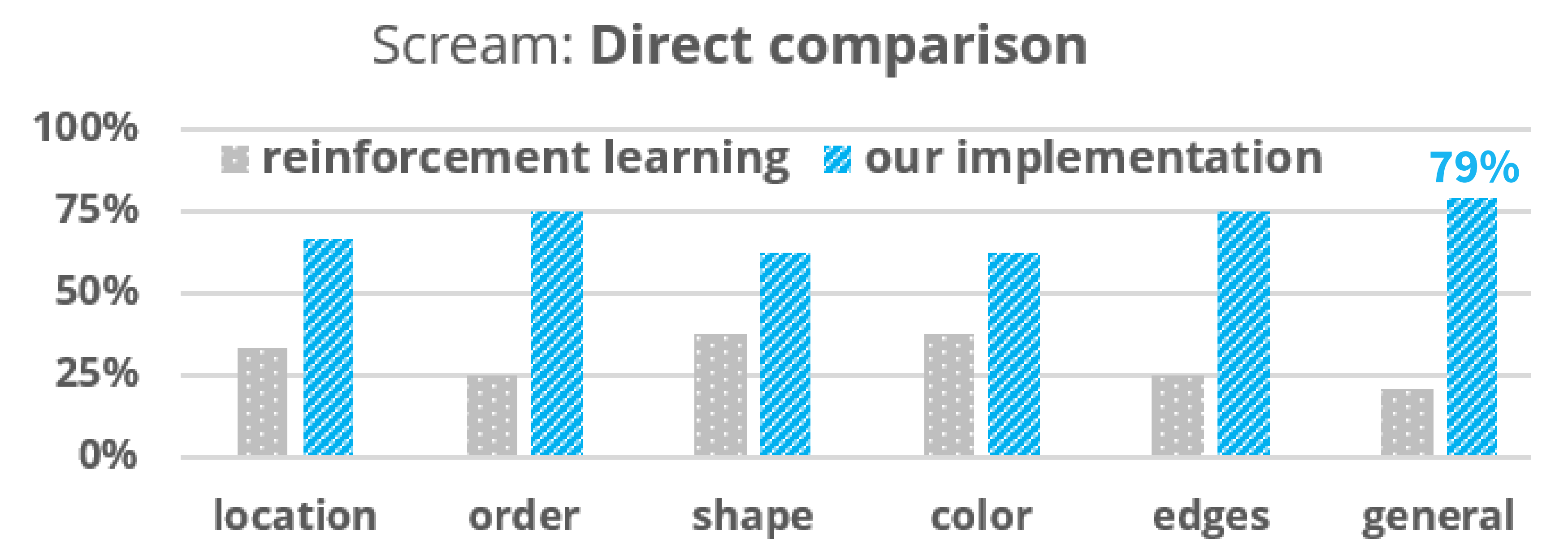
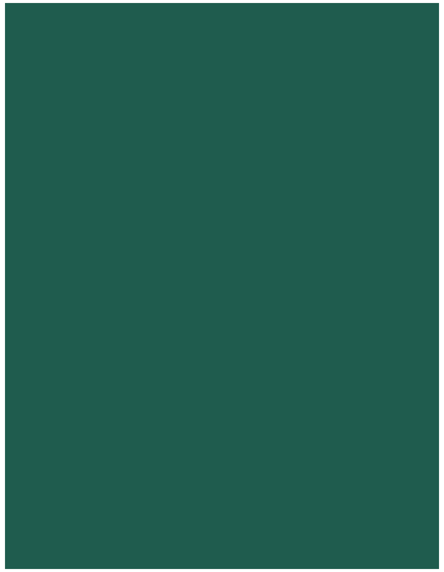
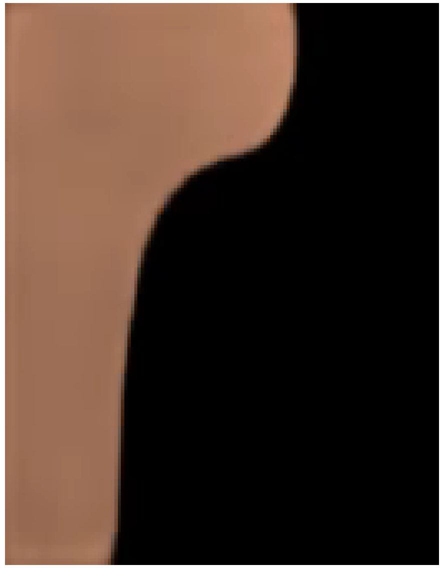
DIRECT COMPARISON



our implementation



reinforcement learning



➔ **79%** find that *our implementation* is **in general more realistic** than *reinforcement learning*

Image Sources: Custom depictions.

06

CONCLUSION AND FUTURE WORK

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Conclusion

- We evaluated and compared different approaches to simulate the human painting process
- We presented our solution for this task which is based on a combination of filters and semantic segmentation

CONCLUSION AND FUTURE WORK

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Conclusion

- We evaluated and compared different approaches to simulate the human painting process
- We presented our solution for this task which is based on a combination of filters and semantic segmentation

Future Work

- Modular approach → Try different filter combinations
- Implement edge detection to sketch outlines
- Simulate single brush-strokes within the painting areas

Future Work

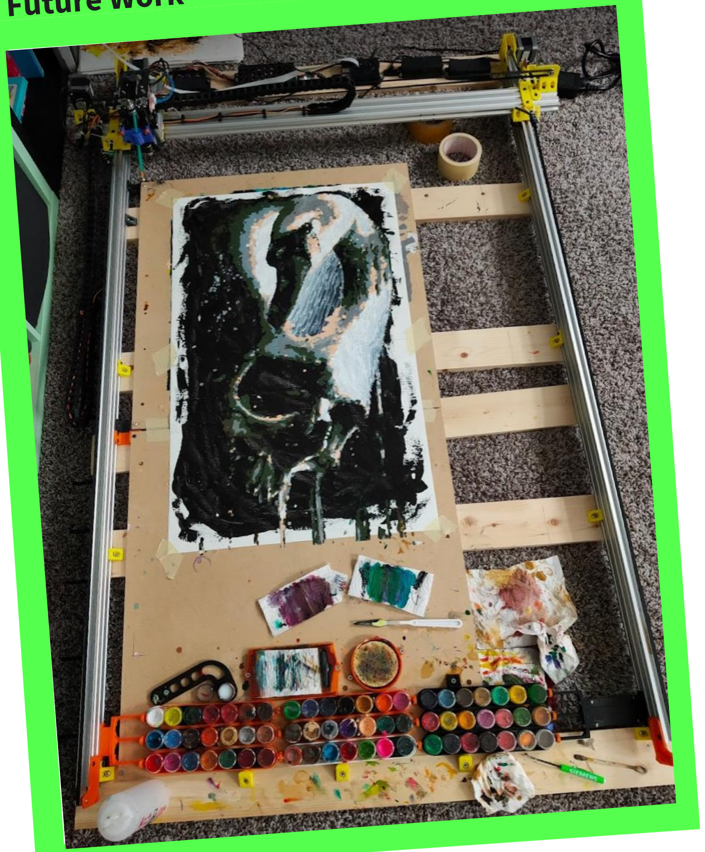

Image Source: Custom depiction.

THANK YOU

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