RoboCoDraw: Robotic Avatar Drawing with GAN-based Style Transfer and Time-efficient Path Optimization

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Introduction

Robotic drawing as a human-robot interaction task- Robotic drawing is interactive, fascinating and entertaining to the public, with applications in a wide range of scenarios (e.g. early childhood education, psychological therapy, and social entertainment). Of these, drawing human faces is one of the most engaging tasks.

Robotic art creation – Although somewhat impressive, the generation of realistic drawings has limited level of amusement for users. To increase entertainment and engagement, we propose *RoboCoDraw*, a real-time robotic drawing system that converts input face images to cartoon avatars as a form of robotic art creation.

Main contributions:

- a two-stream CycleGAN model named AvatarGAN, that maps human faces to cartoon avatars while preserving facial features
- a modularized, interactive robotic drawing system that performs faithful style translation and time-efficient face drawing
- a path optimization formulation for the robotic drawing problem and an RKGA-based optimization algorithm with two-level local improvement heuristics





The RoboCoDraw System



Fig. 1 Pipeline of the RoboCoDraw System, consisting of two main modules: Style Transfer Module and Robot Drawing Module.

Style Transfer Module

- AvatarGAN performs photo-to-avatar translation
- Contour Generation constructs coherent contours from generated avatars with Flow-based Difference-of-Gaussian (FDoG) filtering

AvatarGAN: Two-stream CycleGAN system

- Learns mapping G_{XY} and G_{YX} between real faces (X) and cartoon-style avatars (Y)
- Align distributions of generated avatars with target domains by minimizing adversarial loss
- Preserve consistency in facial features by minimizing cycle consistency loss



Experiments and Results

Avatar Generation with AvatarGAN



Fig. 5 Left: AvatarGAN face-to-avatar translation results; Right: Results with external CUFS dataset for evaluation of generalization

Evaluation of Generated Avatars:

- Similar facial features to input face images
- More diverse features observed in output
- Creative generation of new facial features not present in training dataset

Evaluation of Generalization:

- Can generalize to CUFS Dataset
- Significantly outperforms CycleGAN on facialarea translation (Table 1)

User Study:

• Matched 10 random faces to corresponding AvatarGAN output with mean accuracy of 98%

AvatarGAN Training Datasets:

Fig. 6 Unpaired examples of (a) Chicago Face Dataset (CFD) images and (b) cartoon-style avatar images (generated from the Avataaars library) used to train AvatarGAN

Table 1 Mean cycle consistency loss of CycleGAN andAvatarGAN on the test datasets

Mathad	Mean cycle consistency loss \mathcal{L}_{cycle}				
Methou	Face	Avatar	Real facial area	Avatar facial area	
CycleGAN	0.0355	0.0167	0.2620	0.3298	
AvatarGAN	0.0367	0.0252	0.0329	0.0252	

Experiments on the Robot Drawing Module

Robot Drawing Module

- **Path Optimization** by extracting robot drawing path, then formulating drawing task as a Generalized Travelling Salesman Problem (GTSP)
- *Robot Arm Control* for interfacing with robot and execution of robotic drawing

Fig. 3 Obtaining pixel-coordinates from reference image (a). Image is (b) thinned, (c) trimmed, (d) then split at junctions.

Fig. 4 Drawing path encoded as a list of random keys. Index of

each key corresponds to a line segment (decimal part encodes

sequence, integer part encodes direction of drawing)

Extraction of Drawing Path:

• Lines are thinned and split at junctions, then traced to obtain pixel-coordinates sequences

Path Optimization GTSP Formulation:

- Encoding and decoding with random keys
- Fitness measure relates to distance traversed in air between drawing of lines

Table 2	Improven	nents in I	path	fitness	value	e of va	ario
optimiza	ation meth	nods over	⁻ the	greedy	benc	hmar	k (2
		G 1	G2	G3	G4	G5	Av

RKGA w/ 2-opt, LK	19.1	22.9	20.4	12.4	11.9	17.3
RKGA w/ 2-opt	18.0	22.5	19.8	12.2	11.3	16.8
Greedy w/ 2-opt, LK	16.9	22.5	14.7	11.0	10.3	15.1
Greedy w/ 2-opt	16.4	20.2	5.5	8.8	9.8	12.1
	GI	G2	G3	G4	GS	Avg.

Fig. 7 Pixel-coordinates extraction result. (c) is the overlay of (a) the original avatar contour and (b) a drawing simulated using extracted pixel-coordinates

• Proposed optimization algorithm (RKGA w/ 2-opt, LK) has significant average improvement in path fitness of 17.34% against the greedy search benchmark

Integrated Tests of the RoboCoDraw System

- Conducted 20 integrated trials with our *RoboCoDraw* system implemented on a UR5 robot
- Average time used for the physical drawing was 43.2 s; other computational processes (image preprocessing, AvatarGAN, contour generation, etc.) used 9.9 s

Fig. 8 (b) Avatar contours and (c) whiteboard drawings generated from (a) face image using the integrated RoboCoDraw System

Path optimization method

- RKGA with reproduction, crossover and mutation as genetic operators
- Two-level local improvement involving 2-opt, LK heuristics

Conclusions

- The proposed two-module RoboCoDraw system facilitates the efficient creation and drawing
 of personalized avatar sketches on the robotic arm, given real human face images
 - For style transfer, AvatarGAN generates more diversified cartoon avatars with much better likeness
 - For path optimization, our method has **17.34% improvement in fitness** compared with the baseline

• Great potential in public amusement and human-robot interactive entertainment applications

* This project is open-sourced. Code is available at https://github.com/Psyche-mia/Avatar-GAN