PetGen: Design and Generation of Virtual Pets

Hongni Ye
Data Science Research Center
Duke Kunshan University
Suzhou, China
zy165@duke.edu

Ruoxin You
UCL Interaction Centre
University College London
London, United Kingdom
ruoxin.you.22@ucl.ac.uk

Kaiyuan Lou
Data Science Research Center
Duke Kunshan University
Suzhou, China
kaiyuan.lou@dukekunshan.edu.cn

Yili Wen
Data Science Research Center
Duke Kunshan University
Suzhou, China
yili.wen@dukekunshan.edu.cn

Xin Yi
Zhongguancun Laboratory
Tsinghua University
Beijing, China
yixin@tsinghua.edu.cn

Xin Tong
Data Science Research Center
Duke Kunshan University
Suzhou, China
xt43@duke.edu

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***Abstract*—Virtual pets are essential virtual characters in-game narratives and can influence players' sense of immersion. However, the design of virtual pets' appearances is often repetitive work that relies on the designers' experiences without association with the pets' potential personalities. In this work, we propose PetGen, an application that can generate varying virtual pets' appearances following the Five-Factor Model (FFM) based on AI algorithms. The 3D voxel virtual pets' appearances were initialized under four initial archetypes and then underwent recombination, dyeing, and texturing stages, where AI algorithms were applied as filters. We conducted a pilot study to learn users' perceptions of machine-generated pets. The findings revealed that participants preferred the generated pets more than those manually designed. In future work, we will explore other machine learning approaches for 3D voxel object generation, especially virtual pets with more diverse personalities and appearance traits.**

***Index Terms*—Machine learning, virtual pet, visual design, voxel generation**

I. Introduction

Researchers have extensively explored how to generate virtual content in recent years as metaverse and non-fungible token (NFT) fields have gained growing popularity and users have been the main content creators. Furthermore, researchers aim to understand users' perceptions and relationships with virtual characters to achieve specific narratives [1] as non-player characters (NPCs) can affect players' sense of immersion. Recent work applied machine learning techniques to generate 3D appearances [2]. Despite the widespread use of neural networks such as Generative Adversarial Networks (GAN) or diffusion models to replace the manual production of pictures and models in the industry, 3D model generations, more specifically, voxel virtual pets, are computationally expensive to generate and also under-explored compared to 2D images [3], [4].

Therefore, in this project, we aim to explore the personality and appearance traits of virtual pets and generate voxel virtual pets through machine learning approaches. To understand how virtual pets' appearance traits relate to their personality, we followed the Five Factor Model (FFM) guidelines [5]. Our approach involved creating multiple initial virtual pets that adhered to the specified design principles, which we then utilized as datasets to generate additional virtual pets. In addition, we performed a user study to assess the personality of the generated pets and determine how users perceived them. The findings revealed that the participants developed a stronger emotional attachment to the generated pets than those manually designed. Our research contributes to machine learning, as we incorporated Neural Cellular Automaton (NCA) into our generation process to increase the variety of generated models. This technique offers a novel means of designing game characters.

II. The Design of Virtual Pets

We begin our initial design with dogs and cats, among the most popular and common domestic pets [8]. To achieve our design objective of creating virtual pets with a broader range of appearance traits and perceived personality traits, we compiled a list of common domestic cats and dog breeds. We categorized them into clusters based on the distinctive characteristics of different body parts. In doing so, we referred to the classification systems of FCI [9] and Cat Breeds [10]. See Fig 1. A review of prior videogames, including Tamagotchi [11], Minecraft [12] and Sandbox [13] indicated that virtual pets usually had a basic silhouette and only allowed the players to customize the colors and accessories, such as toys and necklace. To expand the diversity of our generated pets, we deconstructed the pets' bodies, instead of designing based on the common traits of a specific species, into seven body parts: the head, ears, eyes, main body, limbs, and tail. The visual components of these body parts include shapes, volumes, and colors [14]. Combining the body parts with varying visual components allowed us to efficiently expand the diversity of pets' appearances within the scope of one pet species. It simplified the process for machine-generated pets.

Moreover, when designing the initial set of virtual pets, we adopted the Five-Factor Model (FFM) that had commonly been applied to study human and pet per-

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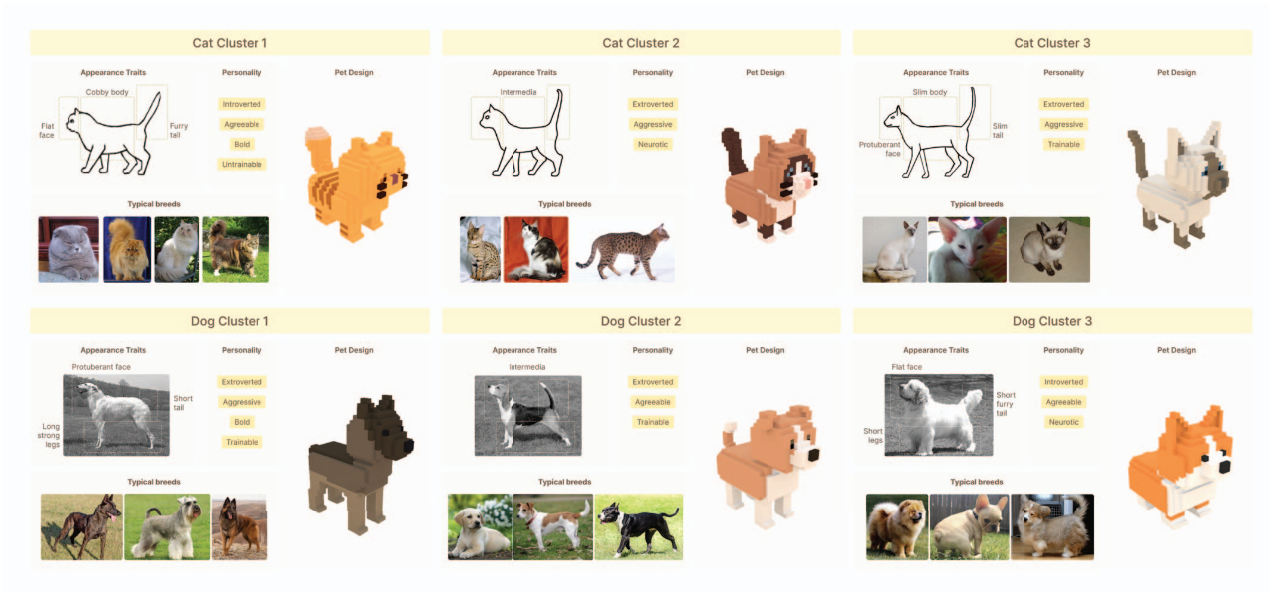

Fig. 1. Design of Cat and Dog Clusters. The pet side view pictures used for reference were obtained from [6] and [7].

sonalities [5]. The FFM [15] identified five factors by labels, typically referred to as openness to experience (inventive/curious vs. consistent/cautious), extraversion (outgoing/energetic vs. solitary/reserved), agreeableness (friendly/compassionate vs. critical/rational), neuroticism (sensitive/nervous vs. resilient/confident), impulsiveness (efficient/organized vs. extravagant/careless) [15]. For example, we identified three clusters of cats/dogs (Fig. 1) based on domestic cats' appearance traits [6] and personality traits [16]. While using machine approaches to generate virtual pets later, we also considered users' perceptions of the pets' personalities according to the pets' body (and body parts) appearances and various visual factors based on prior work [17] on animal personalities and our pilot user study. In our pilot test, we followed the FFM as the standard to measure pets' personality traits.

III. Virtual Pet Generation Method

Here in this section, we describe the machine generation approach, which consists of three major steps: combination/recombination, dying, and texturing and filters (Fig. 2).

One way to quickly generate a large amount of high-quality and detailed 3D models is "(re)combination" by joining one pet's head with another pet's body, we can create a new pet. When making a combination, we also change our pets' ears, eyes, and tails, increasing our model inventory exponentially. However, although we can get a large amount of "raw models" after combination, the models are not ready yet as they have inconsistent colors or shapes across the body parts. The raw models the combinator generates must first be screened and then dyed. For example, the combinator might combine a white head with a black body. Thus dyeing the pet can eliminate these unnatural appearances. We provided several color palettes for the dyeing procedure and applied a color mutation that randomly shifts the colors' RGB values; therefore, most pets will have unique colors even if applied to the same palette. Finally, in the texturing step, every machine-generated pet model will go through a texture "filter" generated by using the Neural Cellular Automaton (NCA) machine learning model [18]. The trained neural network takes points randomly distributed in space as the seed for the model's input and then outputs a 3D model, which is a 3D model with the pet's body texture used to increase the diversity of the pet's appearance. If the texture filter overlaps with the pet's voxels, those voxels' color will become darker or lighter, which leads to natural-looking spots or stripes. After these three steps, in this project, we successfully generated over 800 3D pet voxel models using machine learning to create from 3 original pet models automatically.

IV. User Study

We aimed to explore participants' perceptions and feelings about virtual pets' appearances. Therefore, we conducted a user study using online surveys to gather feedback from participants on ten virtual cats and compared their experiences with the machine-generated and manually-designed pets. All participants completed a Qualtrics form that contained four test parts. After analyzing the survey data, we contacted twenty participants whose personalities and pet-keeping experiences are diverse via email. Twelve of them agreed to take part in the interview. We conducted the interviews through Voov Meeting. We informed participants of the study's purpose and procedures and obtained their written consent before the study began. Participants received 100 RMB as compensation.

Participants. We utilized a convenience sampling approach and recruited participants in WeChat social media platform

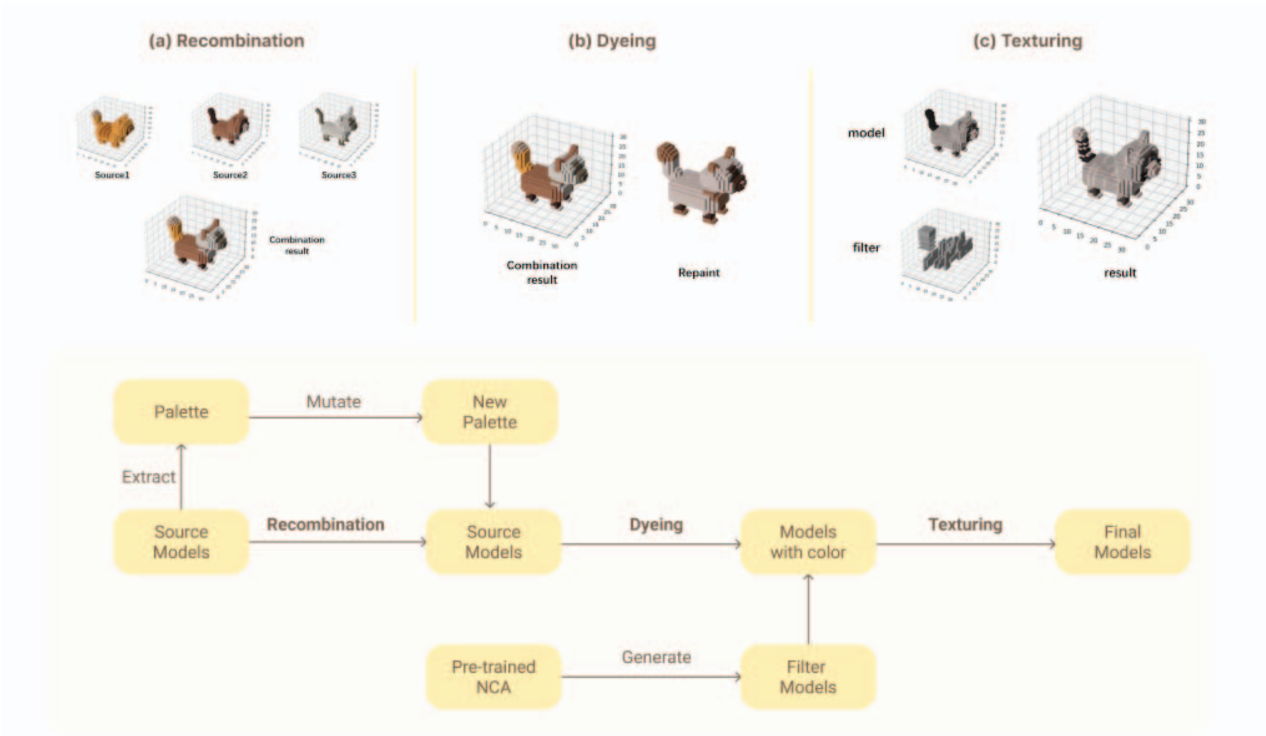

Fig. 2. Generation Procedure

Fig. 3. Generated Virtual Pets and Manual Designed Virtual Pets.

with a URL to our survey link, where participants filled it out. A total of 57 participants (19 males, 33 females, 3 non-binaries, and 2 preferred not to disclose) joined this research, 39 of which aged between 18-24 years and 18 aged between 25-34 years; 47 reported have owned real pets and 41 reported owning virtual pets.

Measurement. We gathered demographic information in the survey, including participants' gender, age, education level, and pet-raising experience. We also collected participants' self-report five-point Likert scale of their preferences for the generated pets and compared their ratings with the manually-designed ones. Participants were presented with ten images, three manually designed (M1, M2, M3) and seven machine-generated (G1 to G7) (Fig. 3).

Results. We used one-way ANOVA with the dependent variable of likability and the independent variable of pet pictures. See Fig. 3 and Table I. The ANOVA revealed a significant main effect for virtual pets ($F(9, 81) = 12.02, p < .001$). We conducted posthoc tests using the Holm correction to adjust for multiple comparisons to determine the significantly different pairs of virtual pets. The results indicated that the likability ratings for G5 (a cobby cat with a wight coat and

TABLE I
MEAN AND SD OF THE LIKABILITY OF EACH VIRTUAL PET

Virtual Pet ID	**Mean**	**SD**
M1	3.72	1.18
M2	2.82	1.30
M3	2.96	1.35
G1	2.68	1.36
G2	2.70	1.27
G3	2.46	1.38
G4	2.67	1.26
G5	3.70	1.30
G6	3.35	1.79
G7	2.53	1.27

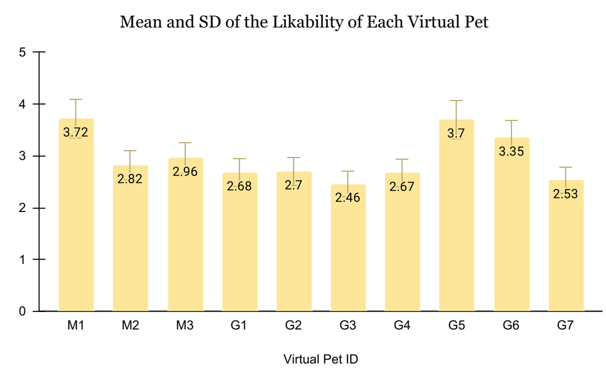

Fig. 4. Mean and SD of the Likability of Each Virtual Pet

orange coloring on its ears, breast and tails) and M1 (a cobby cat with an orange coat with brown stripes on the back) were significantly higher than those for all other virtual pets, except G6 (a cobby cat with brown markings on its face, ears, breast, and tail). Moreover, the likability rating for G6 was significantly higher than those for G3 and G7, which received the lowest mean ratings. These findings suggest that virtual pets' appearances significantly influence participants' likability ratings. Specifically, cobby cats with light-colored coats, such as G5, G6, and M1, were rated more likable than other virtual pets. Additionally, color decorations on the fur, such as the orange coloring on the ears, tail, and breast of G5 and G6 and the brown stripes on the back of M1, also appeared to impact participants' likability ratings positively. And through our interview, we found that participants could not distinguish between machine-generated pets and manually designed pets (N=4). Also, they believed that machine-generated pets basically had similar characteristics to real pets (N=4).

V. CONCLUSION

Overall, our study provides insights into the design and AI generation of virtual pets and their impact on user experiences. We created multiple initial virtual pets for the NCA machine learning model to generate virtual pets and create a diversity of the pets' appearances. Our user study revealed that the generated pets were perceived to be higher likability than those manually-designed ones. The results of our study contribute to the field of machine learning and offer a novel means of designing virtual characters. Future research could further investigate using NCA and other machine learning techniques in generating virtual pets in different generation and design stages.

REFERENCES

[1] Katja Rogers, Maria Aufheimer, Michael Weber, and Lennart E. Nacke, "Towards the visual design of non-player characters for narrative roles," *Proceedings of the 44th Graphics Interface Conference*, 2018.

[2] Hugo Cisneros, "Open-ended creation of hybrid creatures with neural cellular automata," 05 2022.

[3] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio, "Generative adversarial networks," *Communications of the ACM*, vol. 63, no. 11, pp. 139–144, 2020.

[4] Ben Poole, Ajay Jain, Jonathan T Barron, and Ben Mildenhall, "Dreamfusion: Text-to-3d using 2d diffusion," *arXiv preprint arXiv:2209.14988*, 2022.

[5] Samuel D. Gosling and Oliver P. John, "Personality dimensions in nonhuman animals," *Current Directions in Psychological Science*, vol. 8, pp. 69 – 75, 1999.

[6] Sarah Hartwell, "Conformation charts," http://messybeast.com/conformation-charts.htm.

[7] Sarah Hartwell, "What is conformation and does it matter? part 1," 2018.

[8] "Top 10 most popular pets in the world," 2021.

[9] Fédération Cynologique Internationale, "Fci breeds nomenclature," https://www.fci.be/en/Nomenclature/, Accessed: 2022-05-30.

[10] The Governing Council of the Cat Fancy, "Cat breeds," https://www.gccfcats.org/getting-a-cat/choosing/cat-breeds/, Accessed: 2023-03-28.

[11] "Tamagotchi website of tamagotch," https://tamagotchi.com/, Accessed: 2022-09-30.

[12] "Minecraft the official website of minecraft," https://www.minecraft.net/en-us, Accessed: 2022-09-30.

[13] "Sandbox the official website of tamagotch," https://www.sandbox.game/en/, Accessed: 2022-09-30.

[14] Chris Solarski, *Drawing basics and video game art: Classic to cutting-edge art techniques for winning video game design*, Watson-Guptill, 2012.

[15] Robert R McCrae and Oliver P John, "An introduction to the five-factor model and its applications," *Journal of personality*, vol. 60, no. 2, pp. 175–215, 1992.

[16] Milla Salonen, Katariina Vapalahti, Katriina Tiira, Asko Mäki-Tanila, and Hannes Lohi, "Breed differences of heritable behaviour traits in cats," vol. 9, no. 1, pp. 7949.

[17] Robert M. Yerkes, "The life history and personality of the chimpanzee," *The American Naturalist*, vol. 73, pp. 97 – 112, 1939.

[18] Alexander Mordvintsev, Ettore Randazzo, Eyvind Niklasson, and Michael Levin, "Growing neural cellular automata," *Distill*, vol. 5, pp. e23, 02 2020.