Learning of art style using AI and its evaluation based on psychological experiments

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Abstract: Generative adversarial networks (GANs) are AI technology that can achieve transformation between two image sets. Using GANs, the authors carried out a comparison among several artwork sets with four art styles: Western figurative painting set, Western abstract painting set, Chinese figurative painting set, and abstract image set created by one of the authors. The transformation from a flower photo set to each of these image sets was carried out using GAN, and four image sets, for which their original artworks and art genres were anonymised, were obtained. A psychological experiment was conducted by asking subjects to fill in questionnaires. By analysing the results, the authors found that abstract paintings and figurative paintings are judged to be different and also figurative paintings in the West and East were thought to be similar. These results show that AI can work as an analysis tool to investigate differences among artworks and art genres.

Keywords: generative adversarial networks; GANs; art genre; art history; style transfer; figurative art; abstract art.

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Ryohei Nakatsu received his BS, MS and PhD in Electronic Engineering from the Kyoto University in 1969, 1971, and 1982, respectively. After joining NTT in 1971, he mainly worked on speech recognition technology. In 1994, he became the Director of ATR Media Integration and Communications Research Laboratories. In 2002, he became a Professor at the School of Science and Technology, Kwansei Gakuin University. From March of 2008 until December 2014, he was a Professor at the National University of Singapore (NUS) and was the Director of Interactive and Digital Media Institute (IDMI) at NUS. Currently, he is serving as an Adjunct Professor of Design School at the Kyoto University.

Naoko Tosa graduated from the Department of Visual Design, Kyushu Sangyo University in 1984. She was a Lecturer at the Musashino Art University, a researcher at the ATR Media Integration and Communications Research Laboratories, an Artist Fellow at the MIT Center for Advanced Visual Studies, and a Professor at the Academic Center for Computing and Media Studies at the Kyoto University. In 2016, she was named as a Japan Cultural Envoy by the Japanese Government and exhibited her artworks in more than ten countries over the world. She is currently a Professor at the Graduate School of Advanced Integrated Studies in Human Survivability at Kyoto University. She is engaged in art production and research that express Japanese beauty by integrating art and technology.

Takashi Kusumi earned his PhD in Psychology from the Gakushuin University, Japan. He was a Lecturer at the Tsukuba University, an Associate Professor at the Tokyo Institute of Technology, and an Associate Professor at the Kyoto University. He is currently a Professor of Cognitive Psychology at the Graduate School of Education at Kyoto University, Japan. He has been working on psychological research related to thinking, language, memory, emotion, education, and computer-mediated communication. In particular, he has been researching the refinement of metaphor, synesthesia, nostalgia, déjà vu and wisdom. His research interests include human behaviour and cognitive process in virtual space.

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1 Introduction

Recently, in AI, which has mainly focused on logical processing, a method called ‘big data + deep learning’ has emerged, and it has been found that this method is highly effective in many areas. As the neural network used for deep learning resembles the structure of the human brain network, discussion on the possibility that AI simulates human intellectual ability and even exceeds it began to occur.

For Shogi (Japanese chess) and Go, AI software has recently surpassed the ability of human professional players (Silver et al., 2016, 2017). In these board games, such capabilities as judging situations, using intuition, and profoundly searching have been considered the core of human intellectual capability and deeply related to human creativity. Therefore, it is now seriously discussed whether or not AI would surpass human intellectual ability, including human creativity (Kurzweil, 2005).

Creativity and art are strongly connected. Artists create their artworks with their creativity. What kind of relationship can AI have with art? If AI has creativity, will the time come when AI becomes active even in artistic creation, and human artists are no longer needed? Such questions are becoming more and more realistic.

Recently a new technology of deep learning in AI called generative adversarial networks (GANs) has been proposed (Creswell et al., 2018). As it becomes possible to perform deep learning with fewer training samples than conventional methods, various attempts to create artworks by AI have been carried out. However, many of these methods merely let AI learn the style of a particular painter and output images with the learned style. This means that so far AI cannot create artworks. Is there a different approach to the relationship between AI and art? For example, can AI approach questions such as the difference between figurative and abstract paintings or Eastern and Western perceptions of beauty?

In this paper, as a new approach to the relationship between AI and art, the authors propose a new method of comparing various artworks or art genres by avoiding prejudice people would have toward specific artworks and art genres. Here, the role of AI is to transfer a specific art style to natural objects such as flower photos, which can anonymise the original artworks or art genres. Four types of artworks representing Eastern/Western figurative/abstract art are selected, and their art styles are transferred on flower photos using CycleGAN, one of the GANs. For the evaluation of obtained images, the methodology of psychology is adopted. The four types of obtained images with each of the four art styles, for which the original artworks or art genres are anonymised, are compared based on psychological experiments. Based on the analysis of the experiments, several results on the relationship among these four types of art styles are obtained.

2 Related works

2.1 Creation of artistic images using AI

Until the 'big data + deep learning' methodology (Kelleher, 2019) came out in the AI training process, the structure of the data feature was determined manually in advance. The great advantage of 'big data + deep learning' is that, once big data is collected, the network automatically analyses the data structure and learns it by a multilayer network without human pre-processing. With this method, collecting big data and carrying out training using it has become popular.

In attempts to use AI in the field of art, a method of collecting many artworks as big data and letting AI be trained by it has been conducted. This allows AI to learn a particular artist's artworks and output an image with the artist's art style. A typical example is 'the next Rembrandt', a project run by a university and several companies (Pickett-Groen, 2018). In this project, 346 paintings by Rembrandt were digitised and were used as data to train a multilayer network. As a result, Rembrandt's touch, colour, layout, and other characteristics are stored as information in the multilayer network. Next, when the conditions such as a white man looking at the right side, wearing black clothes with a collar and a black hat are entered, the image that looks almost like a painting by Rembrandt is obtained as an output from the multilayer network (Figure 1).

Figure 1 Rembrandt-style portrait created by 'the next Rembrandt' project (see online version for colours)

Source: Pickett-Groen (2018)

Recently, a painting produced by AI was sold at a high price of around 50,000 dollars at one art auction (Simonite, 2018). The fact that an image created by AI was sold at a high price in the art industry became a hot topic.

Whether these attempts are targeting art creation or simple art replication is a big question. There would be lots of future works in this area. On the other hand, what we are interested in is to apply AI for the analysis of art such as analysis of art style rather than artistic creation. In the next section, we will describe how AI can be used to extract art style and to achieve art style transfer.

2.2 Art style transfer using AI

Recently with the advance of image generation/recognition research, art style transfer, or art style migration, became popular. In art style transfer, there are two images; one is an input image, and another is an artistic image with a specific art style. The art style transfer achieves to change the input image into an image with the art style of another image. At the same time, the content of the original image is preserved. There are many studies. For example, Gatys et al. (2015) proposed a method of art style transfer using deep learning. Also, Wang et al. (2018) proposed a method based on convolutional neural network (CNN).

Deep learning uses a lot of layers that make up a neural network so that the network learns the structure of given training data without pre-processing, feature data extraction, and other processing that humans previously performed. On the other hand, there is a problem that a tremendous amount of training data is necessary for training a multilayer network.

However, recently a new learning method called GANs, which can perform deep learning with a relatively small number of training data, has been proposed (Goodfellow et al., 2014; Creswell et al., 2018). GANs are composed of two networks, a generator network, and a discriminator network, as shown in Figure 2. For example, in the case of image generation/identification, the generator network learns to generate an image that the discriminator network cannot identify. In contrast, the discriminator network learns to perform more accurate identification. Deep learning can converge even with a relatively small number of learning data by performing learning as a zero-sum game between these two networks. By modifying this basic configuration, various GANs, such as DCGAN (Radford et al., 2016), Pix2Pix (Isola et al., 2018), CycleGAN (Zhu et al., 2017), ProGAN (Karras et al., 2018), Style GAN (Karras et al., 2019), etc. have been proposed and exciting results have been obtained.

Figure 2 Basic configuration of GANs

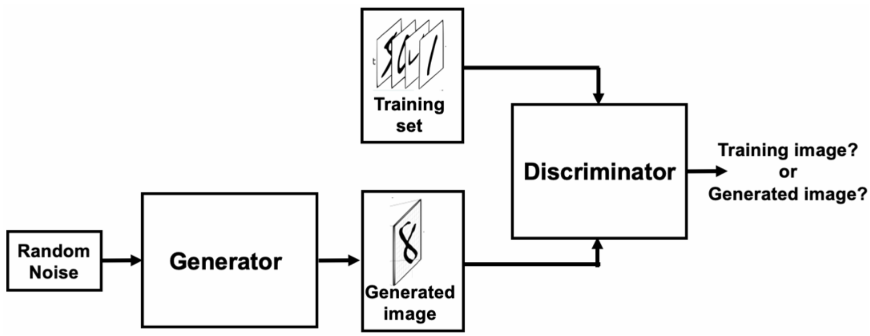
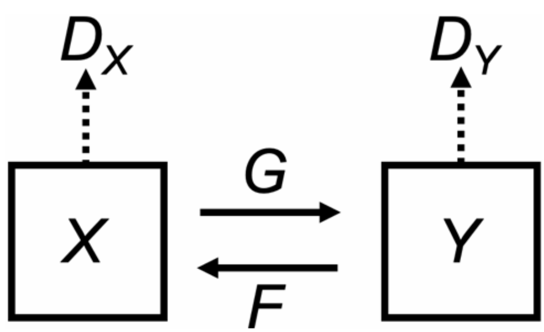


Figure 3 Basic concept of CycleGAN

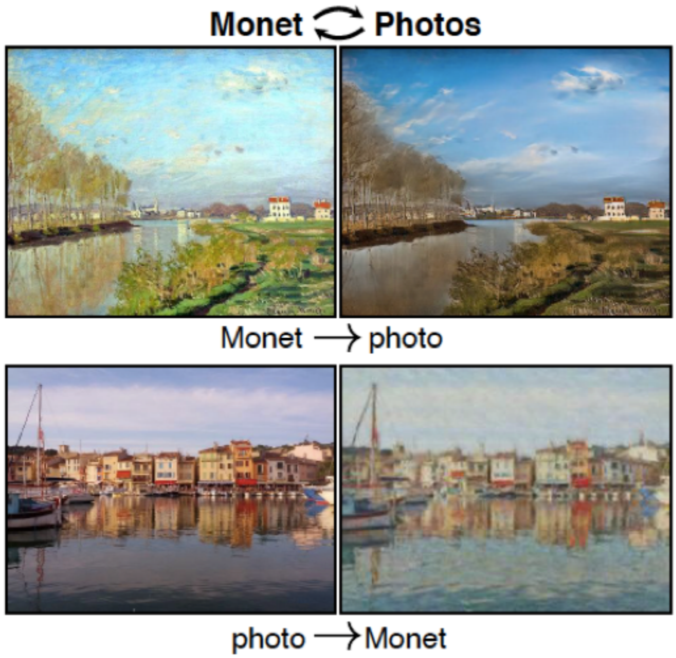


CycleGAN is a new method that enables mutual conversion between two image sets (Zhu et al., 2017). Figure 3 shows the basic concept of CycleGAN. In CycleGAN, when two image sets (X, Y) are given, a transformation function G and an inverse transformation function F between them are considered. Also, two types of errors, Dx and Dy, are considered; Dx is a difference between X and X' where X' is the transformation of X by applying G then F. Dy is an error caused by the difference between Y and Y' where Y' is obtained by applying F and G to Y. The training is carried out so that the sum of these two types of errors is minimised.

Until then, GANs required a one-to-one correspondence between images belonging to two image sets. However, in CycleGAN, even if there is no such correspondence between image sets X and Y, the transformation between them is possible. By using this feature, for example, by learning a group of landscape photographs and a group of paintings of a specific painter (for example, Monet), mutual conversion between these image sets becomes possible. Figure 4 shows how Monet's painting is converted into a photograph-like image using this feature, and a Monet-style landscape painting is created from a landscape photograph (Zhu et al., 2017).

Of course, 'art style' is a complex concept and what GANs, especially CycleGAN, can extract from artworks of a specific artist or art genre is a part of the exclusive features of art style. Therefore 'art style' in this paper is limited to what the present AI can extract and transfer.

Figure 4 Conversion between landscape photos and Monet paintings using CycleGAN (see online version for colours)



Source: Zhu et al. (2017)

2.3 *Psychological evaluation of art style*

Research regarding how people evaluate the art, especially paintings, began in the late 19th century when Fechner began experimental aesthetics in an empirical procedure to quantitatively measure people's pleasant and unpleasant emotions. Since then, various psychology studies have focused on the beauty of art and the feelings derived from it. Multiple studies have been done on the art style research that the authors are interested in. For example, Okada and Inoue (1991) conducted a psychological experiment on which figurative paintings or abstract paintings were preferred and found that figurative paintings were chosen. Farkas (2002) used surrealism paintings to investigate which artworks people liked and found that famous artworks were preferred. Polzella et al. (2005) compared the case of presenting original colour paintings using landscape paintings and portraits drawn in traditional and contemporary styles with the case of presenting the paintings converted to black and white. The results showed that conventional styles were preferred, and in the case of landscape paintings, colour had a higher rating, and on the other hand, in the case of portraits, black and white had a higher rating. There are also studies examining the difference in the evaluation of paintings between art experts and amateurs. As a representative example, Winston and Cupchik (1992) investigated how experts and the amateur evaluate pure-art paintings and famous paintings and found that experts prefer pure-art painting and amateurs prefer renowned painting.

The samples used in these experiments are all original paintings or their black-and-white conversions. Therefore, it was possible to guess who created the paintings, which affected the evaluation result. As will be described in detail later, this research has the feature that such bias is avoided by using the style transfer function of AI.

3 Framework of this research

3.1 Basic concept

As described in Section 2, CycleGAN can be used to carry out transformation between two image sets, even if there is no one-to-one correspondence between images belonging to each image set. Figure 4 shows an example of conversion between a landscape photograph and a Monet landscape painting. It is observable that the mutual conversion has been successfully performed. This shows that AI can learn the feature or styles of Monet's paintings and put the styles on landscape photos to some extent (Figure 5). So far, the first CycleGAN paper (Zhu et al., 2017) merely states that landscape photographs can be converted into Monet-style paintings and vice versa. But the authors consider that CycleGAN can be applied to research investigating various issues related to art, such as comparing different art styles. Especially, the authors are very much interested in the comparison of four art styles: Eastern figurative/abstract art styles and Western figurative/abstract art styles. The purpose of this paper is to investigate this by using the power of AI art style transfer.

Figure 5 can change to Figure 6 at an abstracted level. Considering that art is an essential feature extracted from real objects or natural phenomena, one idea is to use CycleGAN to carry out conversion between real objects or natural phenomena and artworks that extract their essence.

There is a famous Aristotle's (2013) saying, 'art imitates nature'. This means that in the long history of art, the painting initially tried to imitate nature. Western realism is the extension of this trend. As the times go down, however, impressionism was born that tries to paint the light and its transitions perceived by human eyes, rather than trying to paint nature as it is. Even at this stage, the form of the objects depicted is still evident. Later, however, the history of Western painting was followed by cubism and surrealism, followed by more recent abstract paintings. When it comes to abstract paintings, it is already at an unknown level what the paintings are expressing. Nevertheless, artists try to extract essential things they felt in their hearts from the surrounding nature and make them abstract paintings.

On the other hand, the history of Eastern painting is characterised by the fact that the painted objects have been apparent since ancient times. Instead, it is characterised by minimalism that removes colour like ink painting and emphasises the characteristics of the object like Ukiyo-e in Japan and remains at the level of figurative painting compared to the West.

Figure 5 Relationship between landscape photos and landscape paintings from AI point of view

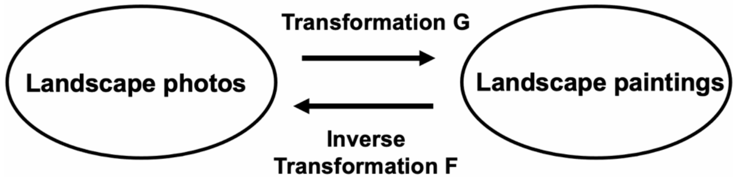
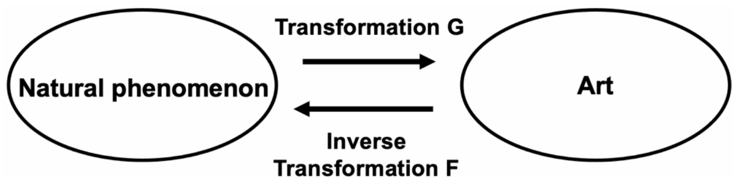


Figure 6 Relationship between art and natural phenomena from AI point of view



Under such a circumstance, it is an exciting theme to investigate the relationship among Easter/Western figurative/abstract paintings from an art style point of view with AI's help, which is the primary purpose of this research. It is relatively easy to find representative Eastern figurative art and Western figurative/abstract art. But it is not easy to find a representative Eastern abstract art. Of course, many Eastern artists have recently created abstract paintings, but most of them have been influenced by Western abstract paintings. On the other hand, Naoko Tosa, one of the authors, has been active in creating Eastern abstract art, and the authors will use her artworks as an example of Eastern abstract art. In the next section, her recent artwork based on fluid phenomena, called fluid art, will be explained.

3.2 Fluid art

Fluid behaviour is an important research subject in physics and is studied as 'fluid dynamics' (Bernard, 2015). Fluid can create stunning shapes under various conditions. As beauty is a fundamental element of art, it is natural to utilise fluid dynamics as a primary methodology of art creation. Naoko Tosa, one of the authors, has been leading a project of creating 'fluid art' by shooting the behaviour of fluid with a high-speed camera.

One good example of the fluid-based phenomenon is 'milk crown'. When a drop of milk falls on milk and is photographed with a high-speed camera, a beautiful shape like a crown is created.

One of the techniques for creating fluid art is the creation of Ikebana-like shapes when sound vibration is applied to paint or other fluids, and the phenomenon is shot with a high-speed camera. The detailed process is as follows. A speaker is placed upward, a thin rubber film is put on top of it, and a fluid such as paint is placed on it, and the speaker is vibrated with sound, then the paint jumps up, creating various shapes.

Naoko Tosa found that various fluid shapes are generated by changing the sound form, sound frequency, fluid type, fluid viscosity, etc. using this environment (Pang et al., 2015). The resulting video image was edited to match the colours of the Japanese season, producing a video art called ‘Sound of Ikebana’ (Pang et al., 2015; Tosa et al., 2019). Figure 7 shows one scene of the artwork. In April 2017, she exhibited the Sound of Ikebana using more than 60 digital signage’s at Times Square in New York. Figure 8 shows a scene of the event.

Figure 7 Scene from ‘Sound of Ikebana’ (see online version for colours)

Figure 8 ‘Sound of ikebana’ at Times Square in New York (see online version for colours)

When Naoko Tosa exhibited her video art around the world, many foreign art-related people indicated, “In Naoko Tosa’s video art, which expresses the beauty hidden in physical phenomena in abstract forms, we feel Japanese/Eastern beauty in an abstract form.” After returning to Japan, she discussed with many Japanese art critics, curators, and researchers and knew that many of them agreed with this concept. Based on this, the authors have the assumption that people feel Japanese/Eastern beauty in the Sound of Ikebana, as it is based on the extraction of hidden beauty in nature, which has been a basis of Eastern/Japanese art (Fenollosa, 1976).

The authors are very much interested in how people would evaluate this artwork, comparing it with typical Eastern/Western figurative/abstract artworks, and this is another target of this research.

3.3 Generation of four types of images with four art styles

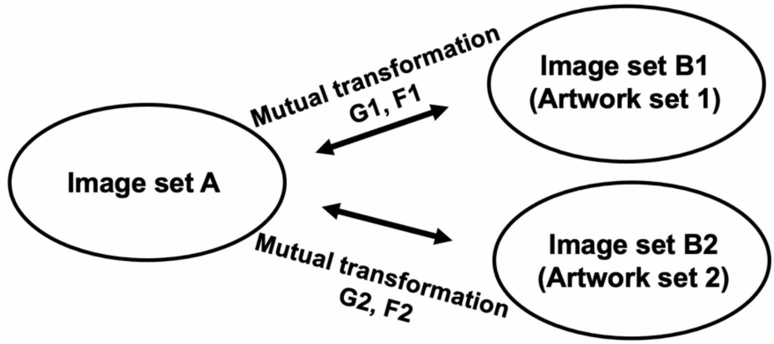
The authors are very interested in comparing different art styles, especially between Eastern and Western art styles and between figurative and abstract artworks. Also, it is interesting to investigate the positioning of the Sound of Ikebana described in the history of Eastern painting. The Sound of Ikebana does not depict landscapes or human life and looks like abstract images and videos. Nevertheless, as mentioned in Subsection 3.2, many people overseas said: "the artwork has the feeling of Japanese beauty."

In this research, these critical and exciting issues are approached based on combining style learning and style transfer with AI and psychological experiments. Specifically, the authors decided to approach as follows.

1. Two types of image sets (image set A and multiple image sets B1, B2, …) used for mutual conversion are prepared. Set A consists of photos of real or natural objects. For example, set A could be a collection of photographs of a landscape or a flower or fruit. Multiple image sets B1, B2, … are composed of art images. For example, a set of impressionism paintings or a set of cubism paintings. The images taken from artworks by Naoko Tosa described in Subsection 3.2 are also typical art images.
2. Using CycleGAN, mutual transformation (Figure 9) of an image set A and multiple images set B1, B2, … are achieved to obtain transformation functions (G1, F1), (G2, F2), … If the conversion between the two image sets is successful, it indicates that there is a close association between these image sets. In other words, the target art image is an extraction of the essential properties of the corresponding actual image. Then how to evaluate whether the conversion was successful or not? A psychological experiment is used for this.
3. A psychological experiment is performed using the image sets G1(A), G2(A), … obtained by performing the conversion G1, G2, … to the image set A. Depending on the purpose of the psychological experiment, questionnaires such as 'do you think it is beautiful?' are filled by the experiment's subjects.

Doing this would be possible to verify what kind of information is extracted as essential information from natural objects and made into artworks depending on different art styles. For example, let the image set A as photographs of a natural thing such as a flower. Let the artwork set B1 to be the Naoko Tosa's artwork described in Subsection 3.2 and the artwork set B2 to be artworks of impressionism. In Section 3, the authors assumed that Naoko Tosa's artworks extract beauty from natural phenomena. On the other hand, the artworks created by the Impressionists extract the beauty of flowers in the way of Western beauty. By asking subjects various questions about images G1(A) and G2(A), that were obtained by performing conversion using artwork set B1 and artwork set B2, it would be possible to investigate how Naoko Tosa's artwork is positioned in comparison with Western paintings and Eastern paintings.

Figure 9 Mutual conversion between two types of image sets



4 Learning of various art style and transfer of the style

4.1 Dataset

Based on the research framework described in Section 3, the authors prepared the following image sets consisting of Eastern/Western figurative/abstract paintings or images. The resolution of all images is 256 × 256.

- Image set A: 8,069 flower images (images from https://www.robots.ox.ac.uk/~vgg/data/flowers/102/).
- Image set B1: 1,072 Monet art images of flowers (images from https://people.eecs.berkeley.edu/~taesung_park/CycleGAN/datasets/).
- Image set B2: 123 Kandinsky art images (images of https://www.wikiart.org/en/wassily-kandinsky/all-works#!#filterName:Style_abstract-art,resultType:masonry).
- Image set B3: 238 Chinese hand-painted flower painting images called ‘Gongbi’ (images of Stanford University CS231N project ‘Chinese Painting Generation Using Generative Adversarial Networks’, http://cs231n.stanford.edu/reports/2017/pdfs/311.pdf).
- Image set B4: 569 images selected from ‘Sound of Ikebana’ (Tosa et al., 2019).

Image set A was prepared to perform mutual conversion with image sets B1, B2, B3, and B4 using CycleGAN. The image set B1 consists of paintings mainly for flowers drawn by the Impressionist Monet as a representative example of Western figurative paintings. As a representative example of Western abstract paintings, Kandinsky paintings were prepared as image set B2. Image set B3 includes flower paintings of Chinese hand-painted paintings, called ‘Gongbi’ (Hua, 2018), as a representative example of Eastern figurative paintings. Image set B4 is a set of still images taken from the video art ‘Sound of Ikebana’ created by one of the authors, Naoko Tosa. As mentioned before, it is made from a physical phenomenon, and it initially does not contain ‘Japanese beauty’. But it was appreciated by people both inside and outside Japan as ‘including Japanese beauty’. In this experiment, the four art styles, Eastern/Western figurative/abstract art, are compared. The Sound of Ikebana is compared with Western and Eastern representative painting styles to clarify its standpoint.

Figure 10 shows examples from each of these artwork genres.

Figure 10 Examples from each of four genre artworks used for this research (see online version for colours)

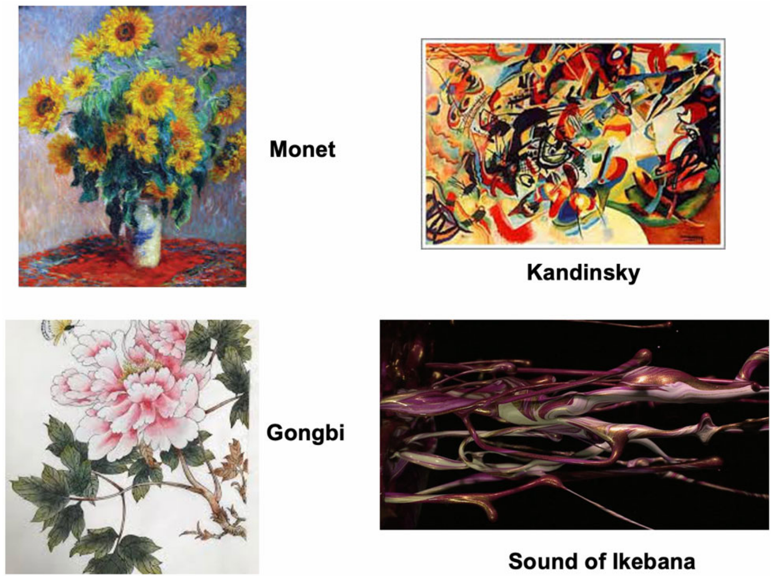
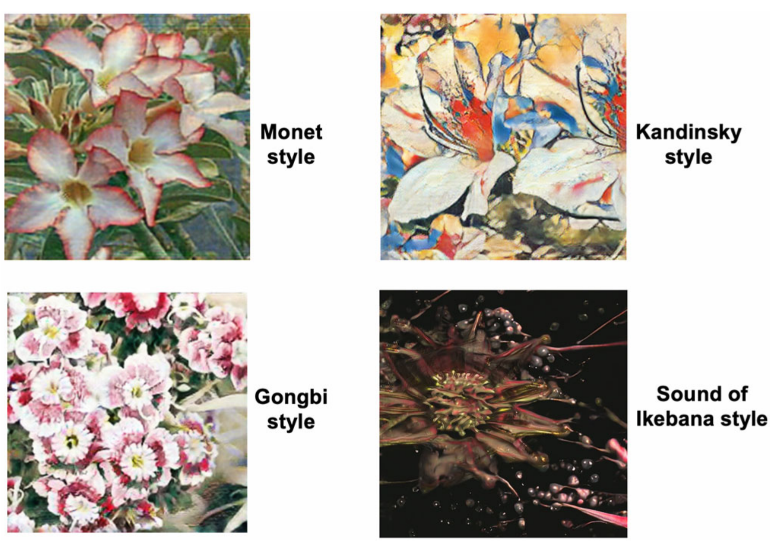


Figure 11 Example of transformation from flower photos to images with each of four art styles (see online version for colours)



The four image set G1(A), G2(A), G3(A), and G4(A) were obtained by applying the transformation functions G1, G2, G3, and G4 to the image set A. Figure 11 shows examples of the transformation from flower photos to images with each of the four art styles.

4.2 Style transfer and anonymisation

The essential question here is why it is necessary to use AI to evaluate art styles. Why Monet art, Kandinsky art, Chinese Gongbi art, and Sound of Ikebana images were not directly compared and assessed using psychological experiments? The primary purpose of using images that have been style transferred is to anonymise the original artist, artworks, and art genres.

There have been several studies that evaluated artworks through psychological experiments (Berliner, 1971; Freedman, 1988; Okada and Inoue, 1991; Winston and Cupchik, 1992; Farkas, 2002; Polzella et al., 2005). However, it is relatively easy to identify the artist for each artwork by using a copy of the original artwork. For example, knowing that a painting is Monet's art suggests that a subject has a prejudice of the artworks of Monet, a representative of the Impressionists in Western art history and that this would have a significant effect on evaluation results. One idea to avoid this effect is to use lesser-known artworks (Okada and Inoue, 1991). However, artworks of famous artists and genres can be easily identified and significantly affect evaluation experiments. On the other hand, using CycleGAN allows AI to learn an art style and apply the style of the input images to output images, thus anonymising specific artists or art genres. Therefore, such bias can be avoided in the evaluation experiment, and this is the benefit of using the AI style transfer function to evaluate artworks.

5 Evaluation of obtained results based on psychological experiment

The experiment described in Section 4 yielded results of performing various style conversions on flower images. By having people evaluate the results of applying multiple style transformations to different flower images, it may be possible to know how people perceive Japanese and Western beauty. That is the goal of this research. Since a subjective evaluation is adequate, a method used in psychological experiments, which is to present a target image to a subject, conduct a questionnaire survey, and statistically analyse the results, was used.

5.1 Psychological experiment

Four image groups, groups 1, 2, 3, and 4 are prepared by selecting four images from each of image sets G1(A), G2(A), G3(A), and G4(A), which are obtained by converting the image set A into the image sets B1, B2, B3, and B4. The resolution of each image is 256 × 256.

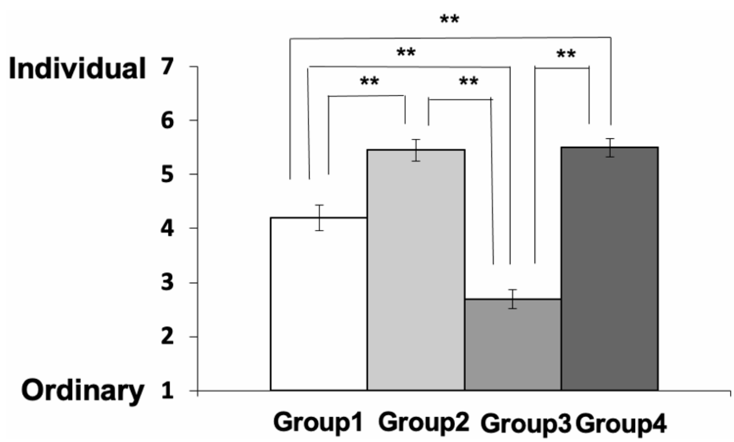
Twenty-three Kyoto University students (12 male and 11 female) joined the experiment as subjects. The gender ratio is almost half. They are mainly attendees of the class called 'art and technology' and therefore, although they are not experts of art, at least they have interests in art. And because of the interdisciplinary characteristics of this class, they belong to various faculties of Kyoto University, such as engineering, science, social science, psychology, medicine, etc. Therefore, although their ages are limited to

‘20s and early ‘30s, their preferences, interests, aptitude, etc. cover a wide range. In addition, as the lectures were carried out in English, more than half of the students are international students, coming from North America, Europe, and Southeast Asia. This means as for nationality the subjects cover a vast range.

Table 1 Adjective pairs used for evaluation

Individual-ordinary	Complex-simple
Masculine-feminine	Soft-hard
Dynamic-static	Bold-careful
Bright-dark	Lively-lonely
Warm-cold	Sharp-dull
Flashy-sober	Like-dislike
Deep-superficial	Difficult to understand-easy to understand
United-disjointed	Beautiful-ugly
Heavy-light	Artistic-non-artistic
Vivid-cloudy	Eastern-Western
Stable-unstable	

Figure 12 Subjective evaluation results for ‘individual-ordinary’



Each of the 16 images was printed out on A4 high-quality paper for samples used for the experiment. The 16 images were presented to the subject, who answered the prepared questionnaire. The order of the shown images was set randomly for each subject.

The subjects performed a seven-step subjective evaluation of the 21 items shown in Table 1. For the selection of these evaluation items, the authors referred to several studies that investigated art style in various ways (Okada and Inoue, 1991; Winston and Cupchik, 1992; Farkas, 2002; Polzella et al., 2005). As in these studies similar evaluation items were used, the 23 evaluation items used in Okada and Inoue were used in this research (Okada and Inoue, 1991). In addition, several items that have a slight significant difference in the evaluation results were excluded from the 23 adjective pairs, and one item was added that directly asks whether it looks Eastern or not, such as ‘Eastern-Western’.

5.2 Analysis

The subjective evaluations by the 23 subjects were averaged for each evaluation item, graphed, and t tested. Among the 21 items, the differences between each image group were relatively large for six items: individual-ordinary, dynamic-static, stable-unstable, bold-careful, artistic-non-artistic, and Eastern-Western. Figures 12~17 show the results of the average value and the standard error for each evaluation item. Also, the results of the t-analysis (**: significance level of 1%, *: significance level of 5%) are shown in these figures.

Figure 13 Subjective evaluation results for 'dynamic-static'

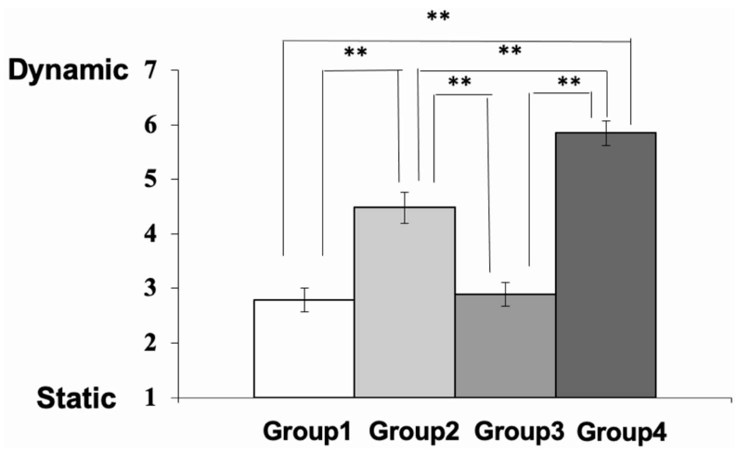


Figure 14 Subjective evaluation results for 'stable-unstable'

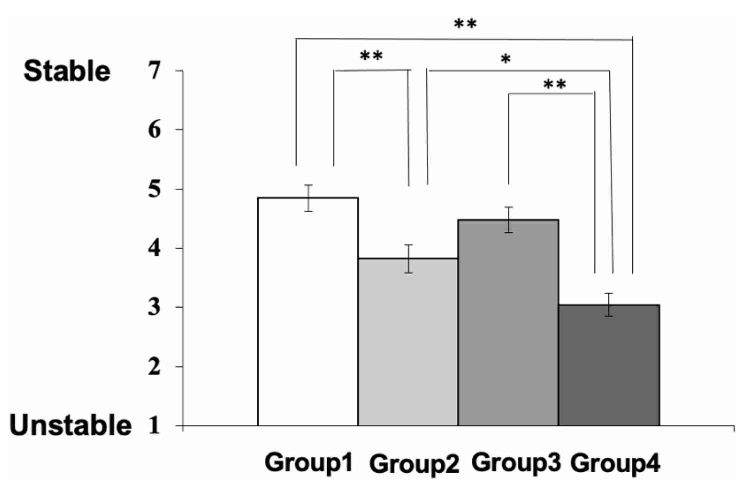


Figure 15 Subjective evaluation results for ‘bold-careful’

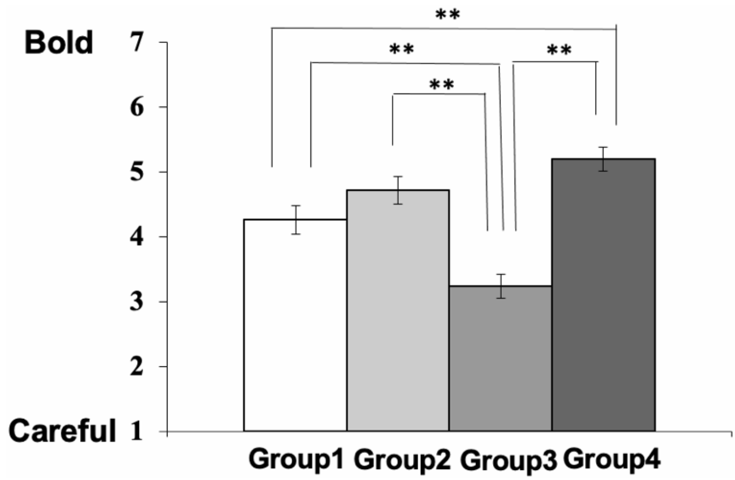


Figure 16 Subjective evaluation results for ‘artistic-non artistic’

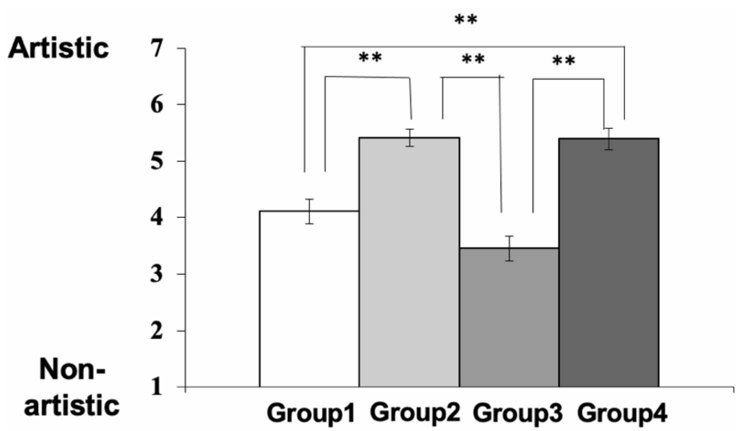
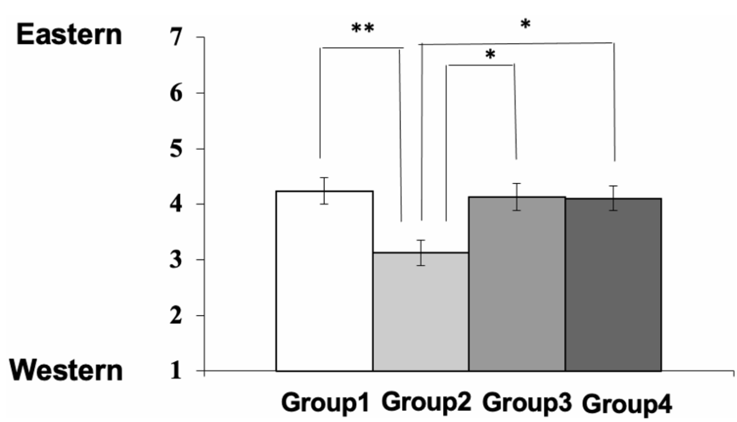


Figure 17 Subjective evaluation results for ‘Eastern-Western’



5.3 Consideration

The following is the result of the analysis based on Figures 12~17.

1 Groups 2 and 4: As can be seen from Figures 12~17, groups 2 and 4 received similar evaluations. In particular, the hypothesis that there is a significant difference between groups 2 and 4 was rejected in the items of ‘individual-ordinary’, ‘bold-careful’, and ‘artistic-non artistic’. This indicates a slightly significant difference between the style of Kandinsky and the style of Sound of Ikebana. Conversely, group 4 is evaluated as having a significant difference of 1% level from groups 1 and 3 for all items except ‘Eastern-Western’. This indicates that the Sound of Ikebana is considered abstract rather than figurative. Suppose the transition from figurative painting to abstract painting exists in the history of Western painting. In that case, the Sound of Ikebana can be positioned in the history of the transition from figurative painting to abstract painting in the East.

2 Groups 1 and 3: Similarly, as can be seen from Figures 12~17, groups 1 and 3 received similar evaluations. In particular, the hypothesis that there is a significant difference of 5% level between the ‘dynamic-static’, ‘stable-unstable’, ‘artistic-non-artistic’, and ‘Eastern-Western’ was rejected. Group 1 is an image set with the style of Western Impressionism, and group 3 is an image set with the characteristics of Eastern figurative paintings. Each original art has its features, one on the Western side and the other on the Eastern side. But in an essential part, these styles may have something in common.

3 Artistic or not: Interestingly, groups 1 and 3 are around or below the median value of 4 for ‘artistic-non-artistic’. Few people will rate Monet’s original image as non-artistic. Chinese hand-painted paintings called Gongbi have also been highly evaluated as elaborately depicting nature. However, groups 2 and 4 are evaluated as being higher artistic than groups 1 and 2. As described in Okada and Inoue (1991), figurative artworks were often evaluated higher than abstract artworks. But this psychological experiment shows a different tendency. Probably this is due in part to the young age of the subject. As the younger generation has more opportunities to watch abstract paintings and contemporary media art, they have an aesthetic sense of appreciating abstract paintings. Another cause is that instead of evaluating the original artwork itself, its style is extracted from the original image by AI, and the type is attached to photographs such as flower photos. Therefore, this is due to the characteristics of the basic procedure of this research. Using the original art image for the evaluation would be relatively easy to identify who the artist was, or even the specific artwork itself, which would significantly affect the evaluation.

4 Eastern or Western: As shown in Figure 17, the answers to the question of Eastern or Western are all around the median of 4 except for group 2. This indicates that the subject felt difficulty in answering the question of whether it was Eastern or Western and gave a response near the middle. Initially, the authors expected that the Sound of Ikebana would be evaluated as ‘Eastern’ because of the overseas evaluation that the Sound of Ikebana contains Japanese beauty, as described earlier. But so far, such a result was not obtained.

But this does not mean that the Sound of Ikebana is not 'Eastern'. At the same time, Monet-style images and Chinese Gongbi images were evaluated as intermediate. This indicates that the style extracted by AI has not yet reached a level to identify Western or Eastern impressions at this stage. Further research is necessary, for example, by increasing the resolution of the image and by using video images to evaluate whether the Sound of Ikebana has a Western or Eastern style.

On the other hand, it is interesting that Group 2 is evaluated as Western. Probably this is because the subject found a typical abstract painting style in the obtained image. It shows that people have a common notion of 'the abstract painting style'. In other words, this means that the appearance of abstract painting in the West has so much significance in art history.

6 Discussion

In this chapter, several issues are discussed regarding the research method for the relationship between art and AI proposed in this paper.

6.1 Relationship between AI style transfer function and art style

In this paper, using a recent AI technology called GANs, the styles of each of the two image sets AI learns A and B, and image set A is converted into an image set with the style of image set B. Then flower photographs were style-transferred into images of various art genres, and psychological experiments compared the relationships between the images in those genres. However, when applying this technique to art, the question is whether an image can be converted into another image with a particular 'art style' or not.

For this question, it is necessary to answer what art style is in the first place. Everyone agrees that each artist and art genre have its style, but it is difficult to explain what art style is. At this point, AI has the capability that the neural network can learn the characteristics of big data and output images with these characteristics by learning big data. In this research, image conversion was performed using this characteristic, and anonymisation of artworks was achieved, avoiding bias in evaluation based on the prejudice of subjects.

In similar previous studies (Okada and Inoue, 1991; Winston and Cupchik, 1992; Farkas, 2002; Polzella et al., 2005), copies of original artworks were used, and there is a possibility that in their results, such biases were involved. By utilising the capability of the AI style transfer function, the originality of this research is to propose a new methodology of art evaluation, excluding a bias caused by the prejudice of a subject. Of course, further research is needed to investigate whether art style learning and transfer in its real meaning are truly carried out or not.

6.2 Rigidity of the psychological experiment

As was described earlier, several psychological studies are investigating how people evaluate art styles of several artworks or art genres, and mainly three of them were referred in this research; Okada and Inoue (1991), Winston and Cupchik (1992) and Polzella et al. (2005). Below are the numbers of subjects (sample size) used in their psychological experiments, including this research.

- Okada and Inoue: 67
- Winston and Cupchik: 31
- Polzella et al.: 60
- this research: 23.

This means that compared with other similar studies the sample size of this research is comparable but not big enough. Also, the number of data used in the psychological experiments are 4 (for each art style) × 4 (number of art style) and is not big enough.

However, the main purpose of this research is, as was described several times, to propose a new methodology of artwork evaluation that is based on the anonymisation of a specific artwork. This research can avoid biases created by prejudice people would have for a specific artwork or art genre. The authors believe that the effectiveness of this methodology was shown by the psychological experiments using the above sample size and data size.

Of course, the rigidity of a psychological experiment is an important issue. In future studies, to make clearer the effectiveness of the proposed methodology, the authors aim to carry out more rigid psychological experiments.

6.3 Psychological experiments with students

In this research, students from Kyoto University were used as subjects. Half of them were Japanese, and the rest were students from various Western/Eastern countries. Since there is no art department at Kyoto University, these students are amateurs regarding art. The question is whether an amateur can evaluate art and why art experts such as critics and curators were not used as subjects. Indeed, art professionals have enough knowledge about art history, individual artists, individual artworks, etc. However, there is a high possibility that such knowledge would bias the psychological evaluation results. Several studies on the difference between experts and amateurs were obtained, for example, by Winston and Cupchik (1992). On the other hand, students who are not art experts are not incomprehensible to art. It is trustable how these students felt the given images based on their sensibilities and what evaluations they made based on them. At the same time, what kind of results can be obtained by conducting the same experiments using art specialists is an interesting theme, and this will be future experiments.

7 Conclusions

In this paper, a new method of handling art with AI was described. With the emergence of a new deep learning method called GANs, which can carry out deep learning using a relatively small training dataset, recently several attempts to handle art with AI have been made. However, most of these attempts are to make AI learn the artworks created by a specific artist or art genre as training data and use the learned AI to create a work similar to a specific artist or art genre. Although it has often been claimed that AI can create art by this methodology, it is incorrect. These attempts have only produced images similar to those created by a certain artist and art genre. Artists have been trying to create new methods one after another while making the most of their creativity. Such a creative process is not yet at the stage where the current AI can achieve. Rather than such an approach, there should be another approach by using GANs to investigate where the difference in art style is and the essence of the difference in an aesthetic sense between Eastern and Western beauty due to cultural differences. Such an approach would be one step closer to the essential issues related to art.

By using the method proposed in this paper, subjects were able to evaluate the styles of Western and Eastern figurative and abstract paintings without bias created by identifying specific artists and/or artworks. As a result, it was shown that the figurative paintings of the East and the West are not different. Also, it was revealed that one of the authors' artworks, 'Sound of Ikebana', has no significant difference from the abstract paintings of Kandinsky. This means that the Sound of Ikebana gives an impression similar to the Western abstract paintings.

However, at this stage, the proposed methodology is not enough to identify, using the anonymised artworks, whether they look like Western or Eastern artworks. The authors plan to conduct the following research as future work to investigate this by carrying out more rigid psychological experiments.

1 Improvement of image resolution: The resolution of the images used in this study is 256 × 256. Although the image is printed out on A4 size paper, there is no problem in obtaining the evaluation. However, their low resolution is noticeable when displaying them on a large screen. A higher resolution such as HD, Full HD, or even 4K resolution should be realised. Increasing the resolution is one direction of future research.

2 Evaluation of video art content: One of the reasons Westerners evaluate the Sound of Ikebana to be Japanese is probably because of the slow movement of the video art. To verify this, it is necessary to create a moving image with the style of the Sound of Ikebana and use it for further evaluation.

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