A generative approach to Korean abstract painting Dansaekhwa

TaeJae Han, EunJeong Kang, Jinho Bae, Junghyun Park*
ModuLABS, Sogang University, ModuLABS, Samsung Electronics
hantaejae@gmail.com, eunxkang@gmail.com, silverbjin@gmail.com, ana.park@samsung.com

Abstract

This paper is expected to attract attention as it presents a unique form of Korean abstract painting known as "Dansaekhwa". In the 1970s, Korean Dansaekhwa artists recognized color and shape (e.g., triangle, rectangle, and ellipse) to be the fundamental elements of painting and sculpture. This paper presents the investigations on the ability of machine learning — how to infer emotions associated with paintings or create images based on "abstraction"? We herein preprocess various images labelled with human emotions (e.g., happy and angry) and subsequently use image-to-image translation generative adversarial networks (GANs) for training, as these models have demonstrated tremendous success in learning abstract mapping images, such as the Dansaekhwa paintings.

Keyword: Abstract Painting, Dansaekhwa, Generative Adversarial Networks (GANs)

1 Introduction

1.1 Abstract Painting

In the 1970s in Korea, Dansaekhwa became the main artistic movement involving artists such as Chung Chang-sup, Chung Sang-hwa, Ha Chong-hyun, Park Seo-Bo, and Choi Byung-so, and art works as diverse as the abstract paintings of the late artist, Kim Whan-ki. These artists were conscious of western aesthetic developments such as western minimalism, color field painting and Italian Arte Povera. Korean Dansaekhwa artists sought to attain the transcendental state in order to lose themselves to become one with their art works.

In other words, in the 1970s, they recognized that color and plain geometry (e.g., flatness and line) were the fundamental elements of painting and sculpture. Herein, we first classify emotions that humans feel, and second, we derive a constructive association of emotion-laden words with color and plain geometry.

1.2 Color/shape feature associations to emotion-laden words

Ekman and Friesen's facial action coding system (FACS) was the first widely used and empirically validated approach to classifying a person's emotional state from their facial expressions [1, 2]. According to his literatures, we use the basic emotions including happy, neutral, and angry.

In this paper, we consider the norms for emotion-laden words and their color associations. Brightness tends to be associated with positive emotional words (such as pleasure) and darkness with negative emotional words (such as arousal) [3] (see Table 1 in Appendix A). For example, the satisfied responses for the positive emotion words "Happy" were yellow(53), followed by red(17), pink(11), blue(8), and green(6) [4] (see Table 2 in Appendix B).

*corresponding author

33rd Conference on Neural Information Processing Systems (NeurIPS 2019), Vancouver, Canada.

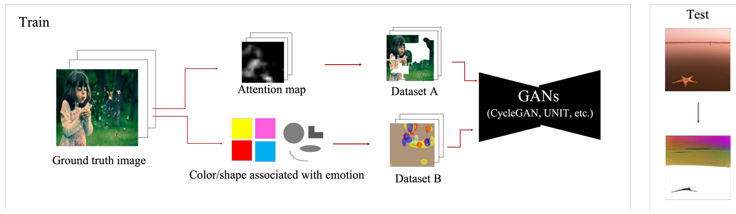


Figure 1: Abstraction painting: overview of Dansaekhwa's creation process

Previous research have investigated the manner in which shapes in natural images influence emotions in human beings: the characteristics of shapes such as roundness-angularity and simplicity-complexity have been postulated to affect emotional responses [5]. Therefore, based on the existing literature, we constructed training images for emotion-laden words and considered the color/shape feature association.

In the following section, we discuss the methodology for creating abstract objects from collections of emotion-labelled example images(https://www.imageemotion.org/).

2 Methodology

2.1 Data preprocessing

The purpose of this study is to create abstract painting images for positive and negative emotions and derive their color and shape associations. As shown in Figure 1 and Figure 2 in Appendix C, all images are preprocessed to create datasets A and B, in the following manner:

1. We use Jana Machajdik's collection of artistic photographs as the ground-truth dataset; these photographs were obtained using various categories of emotions as search terms in the art sharing site. These categories of emotions were previously determined by the artist who uploaded the photographs. The obtained datasets are labeled with emotion-laden words [4].

2. For the creation of dataset A, we first simplify and refine the image contents using class activation map. This method precisely highlights the regions of an image important for discrimination based on pretrained VGG16 model [7, 11].

3. Concerning dataset B, we use the primitive algorithm that attempts to find the single most optimal shape (e.g., triangle, rectangle, and ellipse) [10]. We get parameters as predicted values that display the color/shape associated with emotion-laden words [4,5]. Those images from algorithm are randomly generated according to the image labels.

2.2 Model and Training

Using both the datasets, we trained the image translation models based on unsupervised images according to their emotions separately. We also experimented with several well-established image-to-image translation generative models (e.g. DiscoGAN [12], CycleGAN [13], and UNIT [14]).

3 Result

From the viewpoint of GANs, the final results strongly triggered the abstract concepts within the image-labeled constraints. We used triangle, rectangle, and ellipse on a virtual canvas through primitive algorithm and achieved different results for marks on a page under various conditions of emotions (see Figure 3 in Appendix D). Particularly, "Happy" was found to be the most consistent with "Dialog" by Lee Ufan in 2011, and "Neutral" was the most consistent with "Untitled", Oil on Canvas, by Yoo Youngkuk in 1956 (see Figure 4 in Appendix E).
The technique was found to be a generalized one. As a direction of future investigation, it may be interesting to discuss when these abstract visual representations do or do not match human emotions.

Acknowledgments

We would like to acknowledge our indebtedness and express our heartfelt gratitude to MOUDLABS and Yangjae Innovation Hub at Seoul, South Korea. Their friendly guidance and expert advice have been invaluable throughout all stages of the present work.

References

[1] Ekman, P., Friesen, W. V. (2003). Unmasking the face: A guide to recognizing emotions from facial clues. Ishk.

[2] Ekman, P. (1992). An argument for basic emotions. Cognition emotion, 6(3-4), 169-200.

[3] Meier, B. P., Robinson, M. D., Clore, G. L. (2004). Why good guys wear white: Automatic inferences about stimulus valence based on brightness. Psychological science, 15(2), 82-87.

[4] Sutton, T. M., Altarriba, J. (2016). Color associations to emotion and emotion-laden words: A collection of norms for stimulus construction and selection. Behavior research methods, 48(2), 686-728.

[5] Lu, X., Suryanarayan, P., Adams Jr, R. B., Li, J., Newman, M. G., Wang, J. Z. (2012, October). On shape and the computability of emotions. In Proceedings of the 20th ACM international conference on Multimedia (pp. 229-238). ACM.

[6] Machajdik, J., Hanbury, A. (2010, October). Affective image classification using features inspired by psychology and art theory. In Proceedings of the 18th ACM international conference on Multimedia (pp. 83-92). ACM.

[7] Zhou, B., Khosla, A., Lapedriza, A., Oliva, A., Torralba, A. (2016). Learning deep features for discriminative localization. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2921-2929).

[8] Lu, X., Suryanarayan, P., Adams Jr, R. B., Li, J., Newman, M. G., Wang, J. Z. (2012, October). On shape and the computability of emotions. In Proceedings of the 20th ACM international conference on Multimedia (pp. 229-238). ACM.

[9] Zhang, H., Augilius, E., Honkela, T., Laaksonen, J., Gamper, H., Alene, H. (2011, October). Analyzing emotional semantics of abstract art using low-level image features. In International Symposium on Intelligent Data Analysis (pp. 413-423). Springer, Berlin, Heidelberg.

[10] Michael Fogleman's GitHub page https://github.com/fogleman/primitive

[11] Nick Biso's GitHub page https://github.com/nickbiso/Keras-Class-Activation-Map

[12] SKTBrain's Github page https://github.com/SKTBrain/DiscoGAN

[13] Xhujoy's GitHub page https://github.com/xhujoy/CycleGAN-tensorflow

[14] Mingyuliutw's Github page https://github.com/mingyuliutw/UNIT

Appendix A

Table 1: Pleasure (valence) and arousal ratings from the Affective Norms for English Words for the emotional stimuli, on a scale of 1 (pleasant, low arousal) to 9 (unpleasant, high arousal)

Part			
Word Type	Word	Pleasure	Arousal
Positive emotion	Happy	HIGH (8.21)	HIGH (6.49)
Neutral emotion	Neutral	MEDIUM (5.00)	MEDIUM (5.00)
Negative emotion	Angry	LOW (2.85)	HIGH (7.17)

Appendix B

Table 2: Color associations for the negative and positive emotion-laden words

Part		
Word Type	Color	Percentage
Happy	Yellow	53
	Red	17
	Pink	11
	Blue	8
	Green	6
	Purple	2
	White	2
	Bright red	1
Neutral	Blue	20
	Red	20
	white	20
	Black	20
	Green	20
Angry	Red	79
	Black	14
	Brown	2
	Blue	2
	Yellow	1
	Orange	1
	Dark Gray	1
	Dusty red	1

Appendix C

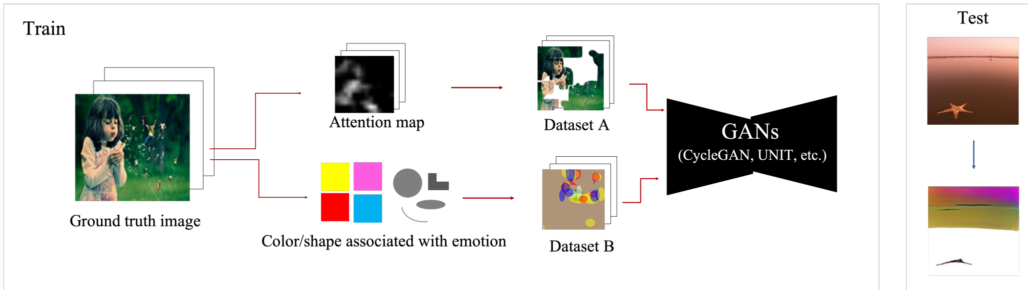


Figure 2: Abstraction painting: overview of Dansaekhwa's creation process

Appendix D

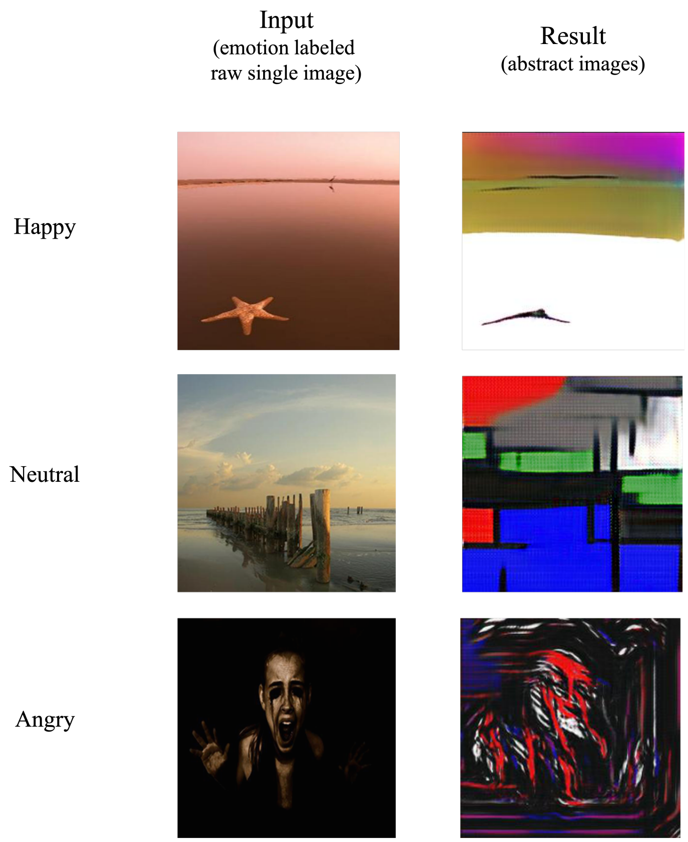
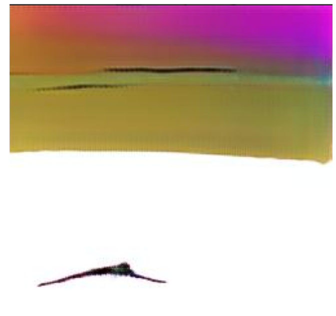
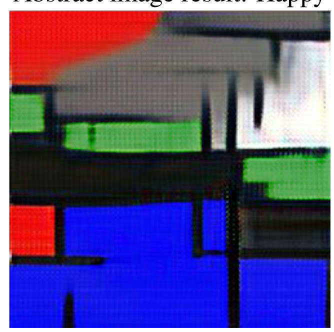


Figure 3: Collected emotion-labeled raw datasets corresponding to selected generative "Dansaekhwa"

Appendix E

(a) Lee Ufan Abstract image result: Happy

(b)Yoo Youngkuk Abstract image result: Neutral

Figure 4: Real abstract painting of Lee Jung-seob(a) and Yoo Youngkuk(b)