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A new method for mandala image synthesis based on WGAN-GP

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Abstract. Mandala, as an ancient image art, has been found to have many unexpected applications in recent years, including use in art therapies, meditation induction and human body state assessment. Despite the omnipresent applications of convolutional neural networks in imaging Synthesis, it can be found that there is no work on Mandala Image Synthesis yet. To fill this research gap, deep learning algorithms were considered in this study. With existing research on Generative Adversarial Network (GAN), a typical GAN network called WGAN-GP was used to produce Mandala images. The generator and discriminators in the WGAN-GP network are fully trained in this study. To prove the robustness of the employed method, this study also investigates and compares the performances of WGAN-GP and other GANs. The experimental results demonstrated the effectiveness and satisfactory performance of the employed method. In brief, our completed work can effectively help provide Mandala images for further research on it.

Keywords: mandala, image synthesis, generative adversarial network, WGAN-GP

1. Introduction

Art therapy has grown in popularity in the West. Western medical practices aimed for instance at helping individuals with anxiety usually involve pharmacological approaches [1]. However, Curry and Kasser, citing Belchamber, recommend that individuals color mandalas, which refer to “symmetrical figures that have long been used as meditative objects in spiritual traditions” [2]. Hutchinson explains that a mandala is a name that is derived from the Sanskrit word circle, and the concept denotes a Hindu and Buddhist symbol that stands for the universe and its energy [3]. Elkis-Abuhoff also makes

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the same point, but the author clarifies that the word stands for both center and circle [4]. According to Hutchinson, Hindus and Buddhists employ the symmetrical geometric designs during meditation, whereby one draws one's eye to the center of the circle, with the intricate patterns that comprise the exotic mandalas holding a special significance and providing a focal point of meditation. Fincher reports that C.G Jung is credited with introducing modern Westerners to the psychological significance of mandalas [5]. According to Fincher, Jung believed that all individuals are driven towards fulfilment of their own unique patterns, living out their potential, and experiencing wholeness. More important, at the very core of an individual's personality, which was not accessible to consciousness directly, resided the true center of a person's psyche, which Jung referred to as the self [5]. This self, as Fincher explains, operated as an individual's potential for wholeness and as their energizing force that encouraged the person to live out to their potential. Liu et al. explains that according to Jung, mandala drawing can help one to integrate one's psychological division, which consequently enhances the process of achieving psychological harmony while preserving the integrity of an individual's personality [6]. However, mandalas are also found in Native American traditions [5]. A case in point is the Zuni story of the pattern called Cloud All Alone, which emphasizes the critical role of participating in communal rituals [5]. At the same time, according to Fincher [5], the Native Americans of the Pacific Northwest are reported to have carved dishes and bowls, which they decorated with the forms of totem animals, including ravens, bears, and killer whales. Hence, mandalas, which were initially embraced by non-westerners, including Buddhists, Indians, and Native Americans, have grown in popularity in the West due to their potential to improve wellness, and there is increasing research on it today.

Generative Adversarial Networks (GANs), are a powerful class of generative models, which can be applied in series of fields, such as image synthesis. In GANs, generative modeling is just like a game between two networks: one generator network asks for some noise source to produces synthetic data, and a discriminator network distinguishes the generator's output from true data. Although GANs are competent on the producing of satisfactory sample, people usually find it hard to train GANs. Many researchers have focused on the improvement of GANs. Arjovsky analyzes the convergence properties of the value function in GANs [7], and propose the Wasserstein GAN (WGAN) [8]. In WGAN, the Wasserstein distance makes better theoretical properties of the value function than it in GANs possible, and the discriminator is asked to lie within the space of 1-Lipschitz functions, which the authors enforce through weight clipping. Then it is pointed out that critic weight clipping in WGAN can lead to undesired behavior, which will negatively impact on the implementation of promised better performance, and gradient penalty (WGAN-GP) is proposed to avoid this same problem [9]. It is proved that WGAN-GP is relatively easy to implement, more stable, and more effective than many other GANs, and that is why our group choose WGAN-GP to produce Mandala images.

In this study, the Mandala images were created using a standard GAN network known as WGAN-GP. the generator and discriminators in the WGAN-GP network have received enough training. This study additionally examines and contrasts the performances of WGAN-GP and other GANs to demonstrate the robustness of the utilized methodology. The experimental findings showed that the utilized approach performed effectively and satisfactorily.

2. Determination of mandala images

Not all images qualify to be mandalas. In other words, mandalas take a certain form. For instance, according to Curry and Kasser, these images feature repeating patterns and complexity, which purportedly are influential in drawing one into a state similar to meditation [1]. Citing Rhoda Kellogg, on the other hand, Smitheman-Brown and Church describe the mandala as an emergent form in creative expression after the scribble stage [10]. The image of a circle is central to the notion of a mandala, and such circularity, as Smitheman-Brown and Church explain, offers individuals channels for releasing their creative potential by nudging them towards achieving their innate maps of growth [10]. Elkis-Abuhoff reiterate this point, noting that mandalas have to carry an innate ability to provide an individual with a visual map of their journey during the course of the individual's illness and recovery [4]. Various forms of mandalas exist in art therapy.

Mandala art therapy may be employed in one of two forms. These forms include individual mandala drawing and cooperative mandala drawing [6]. The individual mandala drawing concept was also popularized by Jung. Later, Liang developed a new design based on Jung's original approach, in which a full circle was divided into different sections, resulting in an intervention the developer dubbed cooperative mandala drawing [11]. This new approach usually requires the effort of two or more people, and it is reported to enable teenagers to not only express their inner selves but also present spiritual reality of creating a mandala process with others [11]. Elsewhere, Roquet and Sas report that mandalas need to feature a sacred geometry that denotes harmony, wholeness and self [12]. These images begin from the epicenter, and they grow into concentric structures that comprise both circles and layers, which represent different aspects of the Tibetan conceptualization of the universe.

In the mandala practice, color also plays a central role. According to some researchers, one is required to paint small areas with precise and conscious movements [12]. Fincher reports that an individual's body in mandala coloring responds to color, which is the product of waves of electromagnetic energy that the individual perceives through the cells in their eyes, skin, and bones [5]. In mandala art therapy, different colors have different meanings. For instance, according to Fincher, while red is an energizing and stimulating color that relates to one's body, yellow, on the other hand, suggests rhythms of the times that are set in motion by the sun [5]. The meanings of other colors are variable, including purple for nobility and refinement, black for sinister power, orange for earthiness, and blue for eternity and infinite space [5]. Hence, color plays an important role in mandala art therapy, as it transcends mere hues, striving to communicate deeply held feelings.

3. Generation of mandala images

3.1. Generate the mandala

Generation of patterns is done automatically, and the process is as follows. In addition, the process of Mandala patterns generating can be found in Fig.1.

- The process begins with the generation of a scribble. It can be automatically generated by the computer (randomly placed circles, rectangles and lines).
- Once the scribble is formed, it is divided into sub-sections of 128×128 dimensions, each used as the beginning of the mandala pattern.
- The sub-image extracted is flipped across the diagonal axis and then flipped across the x and y axis to form a symmetric mandala with 8 cross sections.
- For the second mandala, the sub-image is flipped across the x and y axis to form a symmetric mandala with 4 cross sections.
- A circle mask is applied to both images to make the final mandala circular and symmetric.
- Once all sub-images are used, the original scribble is flipped across the x and y axis to form more unique mandalas.

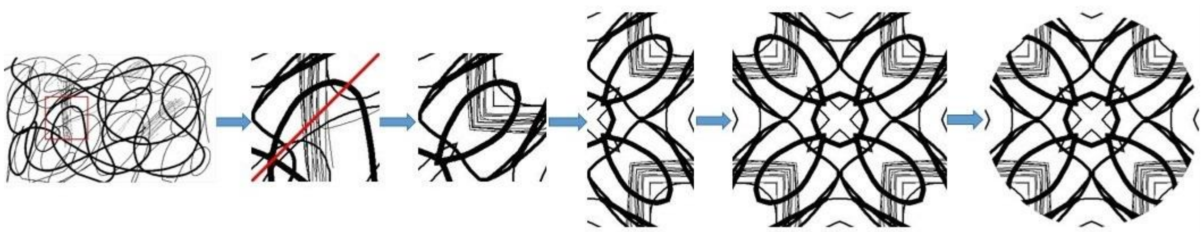

Figure 1. The process of Mandala patterns generating in this study.

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Another user-friendly custom mandala drawing tool is the section-wise drawing application, which allows the user to draw a specific section, replicated exactly, forming a mandala custom to the user's wishes. This is mainly an application to draw specific mandala patterns catering to the user's needs. The Fig. 2 below is an image generated by our code and used in the training data set. In the training session, however, we only used the lower right quarter of the image.

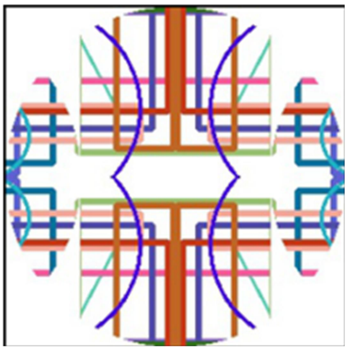
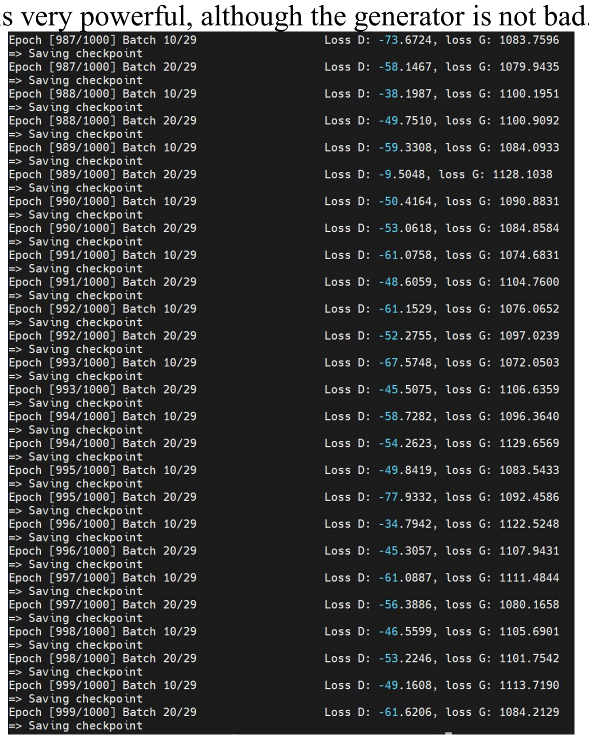


Figure 2. An image generated by our code and used in the training data set.

4. Result and discussion

4.1. Generate the mandala based on WGAN-GP

We first fed the WGAN-GP with only the data generated using Wolfram and Python. The noise dimension used in this implementation is 100 using the original setting, the total epoch is set to 1000, and the batch size is 64. The generator and discriminator models are changed slightly to fit the 128*128 size. The Fig. 3 is the final training result. We can see that, the generator loss is very high because the discriminator is very powerful, although the generator is not bad.



```
Epoch [987/1000] Batch 10/29                 Loss D: -73.6724, loss G: 1083.7596
=> Saving checkpoint
Epoch [987/1000] Batch 20/29                 Loss D: -58.1467, loss G: 1079.9435
=> Saving checkpoint
Epoch [988/1000] Batch 10/29                 Loss D: -38.1987, loss G: 1100.1951
=> Saving checkpoint
Epoch [988/1000] Batch 20/29                 Loss D: -49.7510, loss G: 1100.9092
=> Saving checkpoint
Epoch [989/1000] Batch 10/29                 Loss D: -59.3308, loss G: 1084.0933
=> Saving checkpoint
Epoch [989/1000] Batch 20/29                 Loss D: -9.5048, loss G: 1128.1038
=> Saving checkpoint
Epoch [990/1000] Batch 10/29                 Loss D: -50.4164, loss G: 1090.8831
=> Saving checkpoint
Epoch [990/1000] Batch 20/29                 Loss D: -53.0618, loss G: 1084.8584
=> Saving checkpoint
Epoch [991/1000] Batch 10/29                 Loss D: -61.0758, loss G: 1074.6831
=> Saving checkpoint
Epoch [991/1000] Batch 20/29                 Loss D: -48.6059, loss G: 1104.7600
=> Saving checkpoint
Epoch [992/1000] Batch 10/29                 Loss D: -61.1529, loss G: 1076.0652
=> Saving checkpoint
Epoch [992/1000] Batch 20/29                 Loss D: -52.2755, loss G: 1097.0239
=> Saving checkpoint
Epoch [993/1000] Batch 10/29                 Loss D: -67.5748, loss G: 1072.0503
=> Saving checkpoint
Epoch [993/1000] Batch 20/29                 Loss D: -45.5075, loss G: 1106.6359
=> Saving checkpoint
Epoch [994/1000] Batch 10/29                 Loss D: -58.7282, loss G: 1096.3640
=> Saving checkpoint
Epoch [994/1000] Batch 20/29                 Loss D: -54.2623, loss G: 1129.6569
=> Saving checkpoint
Epoch [995/1000] Batch 10/29                 Loss D: -49.8419, loss G: 1083.5433
=> Saving checkpoint
Epoch [995/1000] Batch 20/29                 Loss D: -77.9332, loss G: 1092.4586
=> Saving checkpoint
Epoch [996/1000] Batch 10/29                 Loss D: -34.7942, loss G: 1122.5248
=> Saving checkpoint
Epoch [996/1000] Batch 20/29                 Loss D: -45.3057, loss G: 1107.9431
=> Saving checkpoint
Epoch [997/1000] Batch 10/29                 Loss D: -61.0887, loss G: 1111.4844
=> Saving checkpoint
Epoch [997/1000] Batch 20/29                 Loss D: -56.3886, loss G: 1080.1658
=> Saving checkpoint
Epoch [998/1000] Batch 10/29                 Loss D: -46.5599, loss G: 1105.6901
=> Saving checkpoint
Epoch [998/1000] Batch 20/29                 Loss D: -53.2246, loss G: 1101.7542
=> Saving checkpoint
Epoch [999/1000] Batch 10/29                 Loss D: -49.1608, loss G: 1113.7190
=> Saving checkpoint
Epoch [999/1000] Batch 20/29                 Loss D: -61.6206, loss G: 1084.2129
=> Saving checkpoint
```

Figure 3. The training result when feeding the WGAN-GP with only the data generated using Wolfram and Python.

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In the Figure 4 below, there are 10 pictures showing the generator change during the training using the same batch of fixed noise, each representing training after 1k epochs. At first, the generator cannot produce good quality pics; the color is vague and monotonous, but it learned to mask the marginal places. Then, it learned to add more colors and the images are more apparent. Finally, the generator can mimic complex patterns of mandalas.

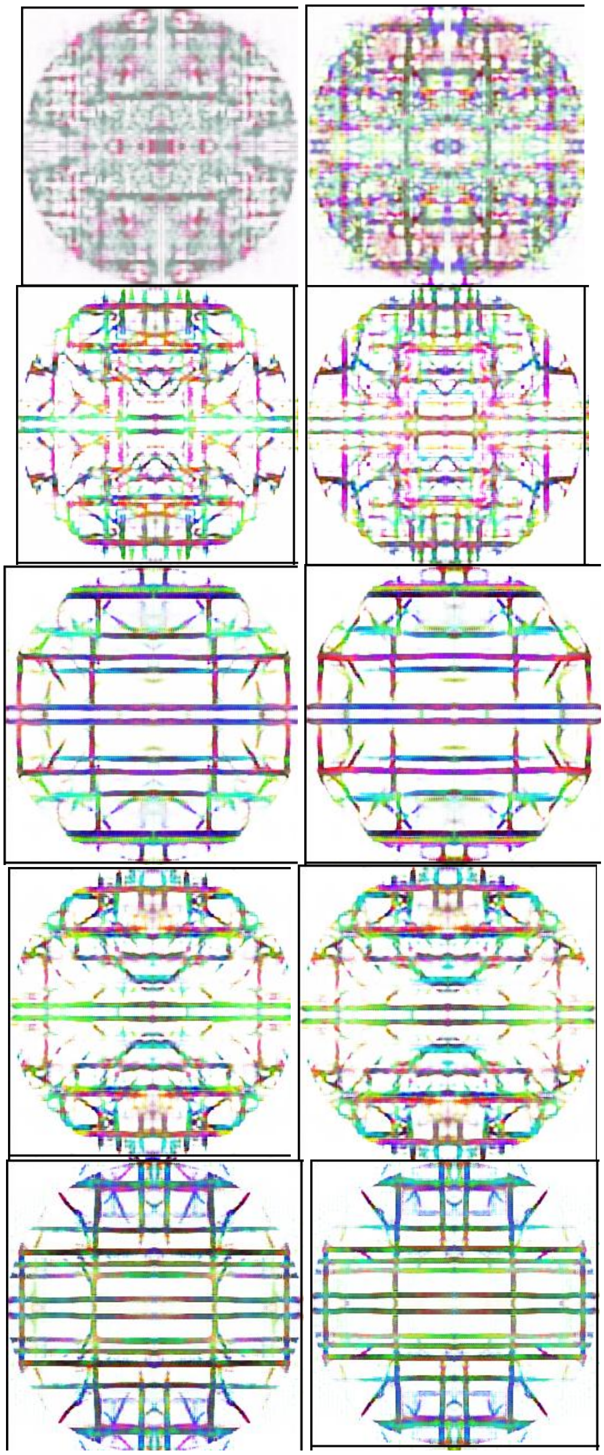

Figure 4. The 10 pictures showing the generator change during the training using the same batch of fixed noise, each representing training after 1k epochs.

4.2. Evaluation

FID is a measure of similarity between two datasets of images. It was shown to correlate well with human judgement of visual quality and is most often used to evaluate the quality of samples of Generative Adversarial Networks. FID is calculated by computing the Fréchet distance between two Gaussians fitted to feature representations of the Inception network.

We generated 640 images using generator model and calculated the FID between these images and training images, the FID is quite high about 158. It is fair to say that these images are not that well generated. In comparison, the FID between two patches of images produced by the auto-pattern.py is around 11.

The WGAN-GP we use is relatively easy to implement, more stable, and more effective than some other GANs, such as PROGAN, which cannot generate clear images after thousands of epochs as fig.5 shown below. The reason why PROGAN cannot generate clean images is self-evident; there are too many up-sample and pooling layers in PROGAN, whereas, in WGAN, these layers are replaced by transposed Conv and Conv layers.

Figure 5. A part of the output Mandala using PROGAN.

5. Conclusion

In this work, we used WGAN-GP and other GANs to generate Mandala images, and compare the output Mandala images with the original Mandala images. Based on the results and discussions presented above, our conclusions are obtained as below: 1) The WGAN-GAP is relatively easy to implement, more stable, and more effective than some other GANs, such as PROGAN, which cannot produce clear Mandala image. 2) It is shown that the outputs of WGAN-GP are not very similar to the original Mandala images. 3) Although the outputs of WGAN-GP are relatively clear, there is still a gap compared with the original Mandala images. However, the Mandalas generated by using WGAN-GP are still unsatisfactory in this study. We hope the future research on GANs will finally solve this problem, and Mandalas generated by GANs will be put into use so that people can tell whether they show the same characteristics as the origin Mandalas.

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