Automatic Generation of Traditional Patterns and Aesthetic Quality Evaluation Technology

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Abstract

As an important element for the continuation and development of modern design, traditional Chinese decorative patterns are to satisfy people's emotional dependence on nationality and tradition. At present, traditional patterns are mostly completed by professional designers. Due to the high dependence of the entire design process on labor, the design efficiency is difficult to quickly improve to meet the explosive growth of business needs. However, the large amount of material data on the Internet and the development of artificial intelligence technology provide an opportunity to solve this development bottleneck. This paper mainly studies the design and implementation of the automatic generation of traditional pattern image layout based on the generation of confrontation network and the use of aesthetic evaluation to score the quality of the generated traditional pattern image. And the scoring results are fed back to the traditional pattern layout generation network, so as to improve the quality of the generated traditional pattern layout pictures, so that the entire network structure can adapt to different scene requirements. The results show that the SSIM value of the structure similarity obtained by the image of the traditional pattern automatically generated by the model in this paper is larger and closer to 1 than the value of the SSIM obtained by other methods, indicating that the image of the traditional pattern automatically generated by the model has the highest aesthetic quality.

1. Introduction

In recent years, with the in-depth application of network technology, computer technology and multimedia technology, the traditional pattern business represented by Internet patterns has achieved rapid growth, and its market position has improved day by day, becoming the main force driving the growth of the entire industry. The emergence of new technologies makes it possible to merge a variety of traditional patterns [1-2]. Our country is a multi-ethnic country. Different regional characteristics, customs, and religious beliefs have created different ethnic cultures and art forms, which have produced unique and diverse ethnic decorative element symbols [3-4]. Chinese traditional decorative patterns are cultural symbols of a nation, and also embody the cultural connotation of a nation [5-6]. Now that there is a large amount of material data on the Internet and artificial intelligence technology has been rapidly developed, there is a new answer to the problem that the efficiency of traditional pattern design cannot meet the explosive growth of demand: the automatic generation of traditional patterns [7].

In the research based on traditional pattern automatic generation and aesthetic quality evaluation technology, many scholars have conducted research on it and achieved good results. In 2004, Microsoft Asia Research Institute and the Department of Automation of Tsinghua University jointly published the first paper on image quality evaluation, and proposed a new method to automatically distinguish between professional photographers and ordinary users' photos [8]. After that, most of the image aesthetic quality evaluation work is to design various visual features to adapt to the human evaluation of the image aesthetic quality [9]. Based on this, Abbas M S. et al. proposed a content-based image aesthetic quality evaluation [10]. On this basis, Kuznetsova I, Vovk O. and others have further extended this research idea. They proposed that images can be divided into 7 categories according to the content, and designed a way to propose the salient areas and features of the image according to the content [11]. Since 2014, the research work of image aesthetics quality evaluation has fully entered the era of deep learning. Researchers at home and abroad have improved the convolutional neural network to combine deep learning and image aesthetics quality evaluation.

This paper mainly studies the design and implementation of the automatic generation of traditional patterns based on the generation of confrontation networks and the use of aesthetic evaluation to score the quality of the generated traditional patterns, and feedback the scoring results to the layout generation network, thereby improving the quality of the generated traditional patterns , Which in turn enables the entire network structure to adapt to different scenarios [12].

2. Automatic Generation Of Traditional Patterns And Aesthetic Quality Evaluation Technology

2.1 Automatic Generation of Traditional Patterns

(1) Traditional patterns

Traditional patterns are the general term for decorative patterns on buildings or utensils. Traditional Chinese patterns are a type of traditional Chinese culture and art. They are based on natural phenomena such as characters, animals, plants, sun, moon and stars, myths and legends, folk tales, and proverbs. , Using homophonic, allegorical, symbolic, knowing, auspicious language and other different techniques to paint images to express people's beautiful hopes and visions. It has a close relationship with the cultural psychology and emotional expression of the Chinese nation. It is a combination of graphics and auspicious meaning for beautiful processing.

1) The birth of traditional patterns

The birth of patterns and patterns originated in the folks. It is the modification of utensils by using different forms of crafts or materials on the premise of satisfying practical functions. Most of the decorated patterns are derived from life and labor, and the style is simple, rough, and rustic. It caters to people's aesthetic needs, and this form of creating beauty has resonated and carried forward. Later, people turned practical products into commodities through decoration and beautification, and they were circulated and disseminated.

2) Classification of traditional patterns

There are various ways of classifying traditional patterns, but the mainstream standard is to classify them by their different applications, mainly into: architectural decorative patterns, furniture decorative patterns, ceramic decorative patterns, lacquerware patterns, clothing decorative patterns and so on. There are many types of traditional Chinese motifs, and the criteria for classifying them vary, but in this paper we have divided them into six types: animal motifs, plant motifs, character motifs, auspicious motifs, geometric motifs, and object motifs. These six types of motifs are the more common ones in life.

(2) traditional patterns used in design

Traditional patterns are rich in content and diverse in forms, and are widely used in modern designs. For example, the key patterns in geometric patterns, Fang Shengwen, F-shaped patterns and some plant patterns are often used in modern home and furniture design as decorative stitches, skirts, corners and borders.

Modern patterns have absorbed the influence of foreign culture and art forms, and there have been many types of patterns composed of dots, lines, and surfaces, and impressionist patterns. They always appear thin and pale in modern furniture and interior decoration design, and lack the rhythm of traditional Chinese patterns. And the sense of rhythm, this is the usability of form. Therefore, in modern design, the citation and insertion of traditional patterns should be based on the theme style. In today's fast-paced development, people like simplicity, so traditional patterns must be deleted and simplified, deformed and recreated to improve adaptability and consistency. Further changes in order. The methods of change include simplicity, first of all, induction, abstract transformation, and reorganization.

The first is to simplify the induction. Simplified induction is to retain the essence and charm of traditional patterns, delete repeated trivial pattern structures, highlight features, improve applicability in design, and make patterns simpler and more simplistic, more in line with the theme without losing the original patterns.

The second is abstract deformation. Abstract deformation is to deform and arrange traditional patterns according to the design requirements, that is, cut and change the shape of the pattern, use straight lines and curves, select and summarize the patterns, change the shape, and summarize them into geometric figures to meet practical requirements. Ruui patterns, fret patterns, and Octopus halo patterns are typical abstract patterns, concise and lively, which are fully reflected in the patterns of folk craft black pottery and Lu brocade.

The last is reorganization. Reorganization is to simplify and summarize when using traditional patterns, and reconstruct after abstract deformation to make it more adaptable.

(3) Automatic generation of traditional patterns

In recent years, with the development of computer technology, artificial intelligence has made great progress. For artificial intelligence, one of the visions is to develop an algorithm or technology that enables computers to synthesize human eyes to observe real-world data, such as natural language, pictures, and so on.

1) Traditional machine learning methods

Pixel RNN & Pixel CNN: The Pixel RNN and Pixel CNN proposed by Google gradually generate pixels from left to right, top to bottom, and finally generate the entire image. Their basic principle is to maximize the probability of the training data and optimize it, using the previously generated pixels as input, outputting a prediction of the statistical distribution of the value of the next pixel, and then sampling the next pixel from the distribution. However, due to the generation of pixels one by one, the obvious problem with Pixel RNN and Pixel CNN is that the speed is too slow.

AE: Auto-encoder, mainly for untagged data, and learns the low-dimensional features of the data during the generation process. Its basic principle is that the encoder learns low-dimensional features through down-sampling, and the decoder restores the image through up-sampling, and uses the L2 loss function to determine the similarity between the restored image and the original image. Because the AE discriminant network is relatively simple, the optimization goal of AE is actually just to make the generated image and the original image closer in terms of pixels. Since this optimization goal is actually relatively simple, the images generated by AE have the characteristics of blur and low quality. However, benefiting from the simple optimization goal, the AE training process is very stable, and the generated images are smoother and more uniform. This is also in the future in the research, many researchers combine it with Generative Adversarial Networks (GAN).

2) Deep learning methods

The deep generative model is the combination of the generative model and the deep neural network. All deep generative models have a common feature, that is, the neural network is used to simulate the process of data generation, that is, the neural network is used to fit complex and mysterious data generation process. There are usually two types of deep generative models: one is likelihood-based models, including Variational Auto Encoder (VAE) and its variants, flow-based models and autoregressive models, and the other is implicit Generative model, such as GAN. Nowadays, three popular models are: VAE, GAN and autoregressive model.

Likelihood-based models usually optimize a negative log-likelihood function on the training set. This objective function can compare the models and measure the generalization ability on unseen data. In addition, because the model allocates the maximum probability to all samples on the training set, theoretically a likelihood-based model can cover all patterns of the data, but it is difficult to directly maximize the likelihood of the pixel space. First, the negative log likelihood in the pixel space is not necessarily a good way to evaluate the quality of the generated samples; second, for these models, they do not necessarily pay attention to the global structure of the image, so the generation effect is not very good.

The core concept of VAE is to generate the encoder and decoder framework designed by the probabilistic image model, and learn the parameters by maximizing the lower limit of the log likelihood of the data in the process. For AE, VAE has a major improvement: it can make the generated features conform to a specified distribution as much as possible, and then sample from this distribution to generate a more effective image, while AE can only ensure that the generated image is restored to The maximum point is similar to the original image.

VAE uses the mean and variance to transform the image into statistically distributed parameters. In essence, the input image is assumed to be generated through a statistical process and has randomness during encoding and decoding. VAE uses the mean and variance parameters to randomly sample an element of the distribution, and then decodes the element back to the original input. Due to the randomness in the process, the overall robustness is improved, and the coding anywhere in the latent space is meaningful, which results in every point sampled from the latent space can be decoded into an effective output.

2.2 Aesthetic Quality Evaluation Technology

(1) Evaluation method of image quality

1) Absolute evaluation

Absolute evaluation means that selected observers judge the quality of the image according to their own standards. Generally speaking, the absolute evaluation of image quality mainly adopts the Double Stimulus Continuous Scale (DSCQS) method, which provides an intuitive quality score for the image to be evaluated compared to the original image. The specific method is to put the image to be evaluated and its corresponding original image on a canvas, and then randomly play it in front of the observer. After playing for a period of time, let the observer think and choose, and then score. Finally, the scores obtained are calculated and averaged to obtain the final numerical score. Internationally, the scale for absolute evaluation only needs to be divided into 1-5, 5 scores, so it is called the 5-point system "full excellent scale".

2) Relative evaluation

The biggest difference between relative evaluation and absolute evaluation is that its evaluation method is not to compare with the original image, but to put the images that need to be evaluated together and compare them to obtain the evaluation score. Similar to absolute evaluation, relative evaluation also has its own evaluation method, usually the Single Stimulus Continuous Quality Evaluation (SSCQE). The specific method is to put all the images to be evaluated together and play them in random order to the observers. Unlike subjective evaluation, the observers need to give corresponding scores while watching. In fact, there is a set of criteria similar to subjective evaluation for relative evaluation in the world.

(2) Evaluation index of image quality

There are many evaluation indicators for image quality, common ones are Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM)

1) PSNR: Before introducing PSNR, mean square error (MSE) should be introduced. For MSE, suppose there is such a clean image I, its size is assumed to be m×n, and there is a piece of noise Image K, then the formula of MSE is described as follows:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,\ j) - K(i,\ j)]^2 \qquad (1)$$

Then PSNR is $PSNR(dB) = 10 \times \log_{10}(\frac{MAX_I^2}{MSE})^2$, where MAX_I^2 is the maximum possible pixel value of the image. In the world, B-bit binary is generally used to represent the pixel value, so MAX_I^2 is $2^B - 1$.

2) SSIM: SSIM mainly considers the comparison of three factors between two samples: brightness, contrast and structure.

$$SSIM(x,\ y) = l(x,\ y)^{\alpha} \cdot c(x,\ y)^{\beta} \cdot s(x,\ y)^{\gamma} \qquad (2)$$

2.3 Model design for automatic generation of traditional patterns based on the generation of confrontation networks

In order to generate high-quality traditional pattern layouts, it is desirable to have a model with high learning ability to represent complex layout changes. Based on this, the model of this article is proposed. The model in this paper learns the conditional distribution of a given visual layout and design attributes (traditional pattern style, suitable crowd, etc.), then samples, and finally synthesizes multiple different layouts according to the input content.

(1) Embedded network design

The embedded network learns visual and attribute features from images and attributes to guide layout generation. This paper takes images and attributes as input, and uses image and attribute encoders to generate visual and attribute feature vectors respectively. These feature vectors are combined by two fully connected layers to generate a 128-dimensional feature vector y, which can adjust the layout of the generated network.

Image coding: Given an image, this article feeds it to the pre-trained VGG16 model 3 to extract image features. The 14×14×512 output of the last convolutional layer is used as the image representation, and the spatial global average pooling is used to form a 512-dimensional vector, which is then sent to three fully connected layers to generate a 128-dimensional image vector.

Attribute coding: This article considers four design attributes: traditional pattern style, suitable people, product classification, position information of the main body of the traditional pattern, and position information of the main and auxiliary traditional pattern words in the entire traditional pattern picture. Traditional pattern style is very important to layout design, because it determines the expression form of traditional pattern. Suitable crowd refers to which type of crowd the main body of the traditional pattern is suitable for use. The commodity category is the commodity category to which the main body of the traditional pattern belongs.

(2) Layout generation network design

The layout generation network is based on GAN, which consists of a generator and a discriminator. The generator G learns to generate samples with the same distribution as the training data, while the discriminator D learns to determine whether a given sample is real or generated. In the layout generation network of this article, the generator maps the 128-dimensional potential vector to the layout. The discriminator D outputs a confidence value to indicate whether the layout x is real or generated.

(3) Realization of automatic generation model of traditional pattern layout pictures

In order to generate the layout, this article converts the output of the generator into the initial layout (60x45x3) by removing the filling elements and quantizing each value to 0 or 1. This article uses post-optimization steps to optimize element boundaries and correct small deviations between elements. In particular, this article first extracts individual elements from the initial layout by connecting component tags. In order to solve the jagged problem of the image boundary, this paper uses a series of morphological image processing operations to approach the image boundary. In order to solve the slight deviation between some elements, this article performs top/bottom/left/right alignment on them. To perform top alignment, first, if the top boundary coordinates of the element bounding box differ by less than 2 cells, the elements will be aggregated into a group. For the same group of elements, this article adjusts their top borders to align with the lowest top borders to create enough space between the elements. Similarly, this article also aligns bottom, left or right in a similar way.

The attribute information of the input image and the traditional pattern image is given, and a method of automatically generating a layout matching the input is proposed. According to the input traditional pattern style, this paper sampled 16 groups of traditional pattern themes and the relative position information of traditional pattern descriptors in the whole picture from the data set. For each set of sampled values, this article randomly generates 32 layouts. Next, according to whether the aspect ratio of the traditional pattern body in the generated layout and the aspect ratio of the input image are appropriate (greater than 1.34 or less than 0.65), if the difference is too large, it will be filtered out. Finally, in order to diversify the generated layouts, this paper uses the maximum marginal correlation criterion (MMR) to process the filtered layouts. Specifically, this paper uses the discriminator output (classification probability) as the quality score of the generated layout, and uses the L2 distance in the feature space (the average vector of the encoder in this paper is conditioned on the feature y extracted from the input content). Calculate the similarity score between the layouts. The layout with the highest quality score is ranked first and added to the ranking list L. Finally, this article returns the first three layouts as the generated layouts.

2.4 Design and Implementation of a Network Model for Evaluating Aesthetic Quality of Traditional Pattern Pictures

(1) Multi-attribute feature network design

Multi-task learning is a common method for training deep convolutional networks. Due to the diversity of aesthetic attributes, multi-task learning can realize multi-attribute evaluation of aesthetics through parameter sharing. The evaluation of aesthetic attributes is relatively independent. However, the model training process is similar. In ALD, in addition to the score for each attribute, each image has a global score. Therefore, the loss of MAFN is divided into two parts. One is the loss of each attribute (m attributes). The other is the overall loss.

General Feature Network (GFN) and Attribute Feature Network (Attribute Feature Network, AFN) use Desnet161 to extract dense feature maps. The parameters of all previous layers are shared. The output of GFN and AFN is divided into 5 parts: general characteristics and 4 aesthetic attributes. The GFN performs a fully connected operation on the output of the global aesthetic score. For the final result, perform the calculation of the mean square error (MSE) and return it to the previous layer as the model loss parameter. AFN performs a convolution operation on the attribute feature map to obtain 4 different attribute feature maps. Like GFN, the final attribute score is obtained through the fully connected layer and the mean square error loss.

MAFN can extract feature maps of different attributes of an image at the same time. Therefore, the model is no longer limited to outputting a score of aesthetic characteristics. The aesthetic characteristics of an image can be evaluated from multiple attributes to better guide the comprehensive evaluation of the image. The specific results obtained by the multi-task network can also directly use knowledge transfer to extend the attribute evaluation of the ALI data set, thereby providing a wider range of aesthetic evaluation capabilities.

(2) Pay attention to network design

The attention network contains two modes, one is spatial attention after channel attention, and the other is channel attention after spatial attention. Through experiments, this article adopts the first structure as the network structure of the attention network. Given a specific (N-1) layer feature map MN-1, the channel attention weight is calculated according to the channel attention calculation. Then the weighted and (N-1) layer feature maps are linearly fused to obtain a new N layer channel-aware feature map. After that, the channel perception feature map is sent to the spatial perception attention module for calculation, and the spatial attention weight is obtained. Finally, spatial perception is performed on the channel perception feature map obtained in the previous step, that is, the features output by CNN.

(3) Language generation network design

Long-short-term memory network is a special type of RNN that learns long-term dependent information. On many issues, LSTM has achieved considerable success and has been widely used. By inputting the information of multiple attributes into the LSTM unit, the next word can be predicted based on the image characteristics and timing information.

(4) Realization of aesthetic quality evaluation network

MAFN calculates the feature matrix of different attributes through multi-task regression of 4 attribute scores. The attention network dynamically adjusts the attention weights of the channel dimensions and spatial dimensions of the obtained features. Finally, LGN generates subtitles through a long and short-term memory network. The LSTM network requires the real content of the aesthetic language evaluation in the data set and the feature mapping adjusted by the attention network.

3. Research Experiment On Automatic Generation Of Traditional Patterns And Aesthetic Quality Evaluation Technology

3.1 Research Materials and Experimental Design

In order to prove the validity of the model in this paper, the pictures of traditional patterns that are automatically generated are used for analysis, and experimental simulation and comparison are carried out. The experimental environment of the experiment in this paper is: the operating system is Windows 10, 64-bit, the compilation environment is Visual Studio 2015, and the OpenCV3.1 software library is also used at the same time. There are two ways to evaluate the pictures of automatically generated traditional patterns: one is subjective comparison, that is, subjectively observing whether the effect of the pictures of automatically generated traditional patterns meets people's visual continuity. The other is objective comparison, which uses objectively calculated data for comparison.

3.2 Analysis Method and Evaluation Content

Generally, people objectively evaluate the image effect of the automatically generated traditional patterns based on the calculated objective evaluation operator. The objective evaluation method has the advantages of uniformity, good stability, simple standard, etc. It mainly obtains quantitative data by comparing the relationship with the original image. Here are two commonly used objective evaluation formulas:

Peak Signal to Noise Ratio (PSNR): The PSNR algorithm is used to evaluate the quality of image restoration. If the value of PSNR obtained is larger, the effect of the traditional pattern image automatically generated by the model will be better.

Structural Similarity (Structural Similarity, SSIM): The value of SSIM ranges from 0 to 1 and can reach 1, indicating that the closer the SSIM value is to 1, the better the aesthetic quality of the image of the traditional pattern automatically generated by the model.

4. Research And Experiment Analysis Of Automatic Generation Of Traditional Patterns And Aesthetic Quality Evaluation Technology

4.1 PSNR Performance Comparison of Automatically Generated Traditional Pattern Pictures

In this paper, the peak signal-to-noise ratio is used as the objective evaluation formula to analyze the pictures of traditional patterns automatically generated by this model. The image removed by the target is mainly used to judge the image effect of the traditional pattern automatically generated by people's visual senses. The PSNR performance comparison data of the automatically generated traditional pattern pictures are shown in Table 1:

Table 1. PSNR performance comparison of automatically generated traditional pattern pictures

Algorithm	Picture 1	Picture 2	Picture 3	Picture 4
CRIMINISI algorithm	27.8	31.6	31.9	25.9
FROBENIUS algorithm	30.1	32.4	31.7	25.7
CAYLEY algorithm	28.7	32.2	32.5	27.3
Experimental algorithm	31.2	33.3	32.1	30.5

It can be seen from Figure 1 that the peak signal-to-noise ratio PSNR of the image of the traditional pattern automatically generated by the model in this paper is larger than the PSNR value obtained by other methods, indicating that the image of the traditional pattern automatically generated by this method is better. The average value of the peak signal-to-noise ratio of the model in this paper is above 30dB, while the other methods are all less than 30DB.

4.2 SSIM Performance Comparison of Automatically Generated Traditional Pattern Pictures

This paper uses structural similarity as an objective evaluation formula to analyze the automatically generated pictures of traditional patterns. The structural similarity is mainly obtained by comparing images of traditional patterns that are automatically generated. The target removal image is mainly determined by people's visual senses to determine the effect of the image. The SSIM performance comparison data of the pictures of traditional patterns automatically generated under this model are shown in Table 2:

Table 2. SSIM performance comparison of automatically generated image models of traditional patterns

Algorithm	Picture 1	Picture 2	Picture 3	Picture 4
CRIMINISI algorithm	0.948	0.971	0.973	0.946
FROBENIUS algorithm	0.952	0.979	0.981	0.949
CAYLEY algorithm	0.963	0.983	0.988	0.960
Experimental algorithm	0.976	0.989	0.989	0.968

It can be seen from Figure 2 that the SSIM value of the structure similarity obtained by the image of the traditional pattern automatically generated by the model in this paper is larger and closer to 1 than the value of the SSIM obtained by other methods, indicating that the image of the traditional pattern automatically generated by the model The image has the highest aesthetic quality and is more in line with people's visual senses.

5. Conclusions

In recent years, with the in-depth application of computer technology, network technology and multimedia technology, the traditional traditional pattern industry has been greatly impacted, and an emerging traditional pattern industry has rapidly appeared and developed. This emerging traditional pattern industry is based on Internet technology and frequently delivers large quantities of traditional patterns to potential users, making the traditional traditional pattern industry have to step up and keep up with technological innovation. At the same time, with the opening up of online and offline services, the retail industry has ushered in a new round of rapid development. It not only has a rapid growth in the demand for traditional pattern design, but also has higher requirements for the timeliness of traditional pattern design.

At present, traditional pattern design is mostly done by professional designers. Due to the high dependence of the entire design process on labor, the design efficiency is difficult to quickly improve to meet the explosive growth of demand. The aesthetic attribute evaluation model of this article does not consider whether the generated pictures satisfy users. As the saying goes, customers are God, and the appearance of traditional pattern pictures is to attract customers' attention. Therefore, in the next step, user satisfaction can be added to the quality evaluation criteria to further improve the quality evaluation criteria, so that the generated traditional pattern pictures not only meet the professional aesthetic attribute evaluation, but also make users more willing to pay attention. In layman's terms, this is the generated traditional pattern pictures can be "tall" and "down-to-earth." In this way, the generated traditional pattern pictures can certainly be more in line with commercial standards.

Declarations

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Galati M, Minetola P. On the measure of the aesthetic quality of 3D printed plastic parts[J]. International Journal on Interactive Design and Manufacturing (IJIDeM), 2020, 14(4):1-12.

[2] Le W U, Jin X, Zhao G, et al. Two open-source projects for image aesthetic quality assessment[J]. Science China Information Sciences, 2019, 62(02):1-2.

[3] Pons B, Alvarez I, Thompson J. Aesthetic Quality Experiences (AQE) as a Means of Improving Reading and Writing: A Case Study[J]. Universal Journal of Educational Research, 2020, 8(11):5376-5387.

[4] Maras S. The erotic/aesthetic quality seen from the perspective of Levinas's ethical an-archaeology[J]. Filozofija i Drustvo, 2020, 31(1):98-107.

[5] Debnath S, Changder S. Computational Approaches to Aesthetic Quality Assessment of Digital Photographs: State of the Art and Future Research Directives[J]. Pattern Recognition and Image Analysis, 2020, 30(4):593-606.

[6] Lopez-Rodriguez A, Escribano-Bombin R, Hernandez-Jimenez V, et al. Perceptions of ecological and aesthetic quality by natural resource professionals and local people. A qualitative exploration in a mountainous landscape (La Rioja, Spain) [J]. Landscape research, 2019, 44(2):241-255.

[7] Biondani F G, Bissacco G, Piln L, et al. Analysis and Characterization of Machined Surfaces with Aesthetic Functionality[J]. International Journal of Automation Technology, 2019, 13(2):261-269.

[8] Liu Q, Sha D, Liu W, et al. Spatiotemporal Patterns of COVID-19 Impact on Human Activities and Environment in China Using Nighttime Light and Air Quality Data[J]. Remote Sensing, 2020, 12(10):1576.

[9] Mavrakis A, Kapsali A, Tsiros I X, et al. Air quality and meteorological patterns of an early spring heatwave event in an industrialized area of Attica, Greece[J]. Euro-Mediterranean Journal for Environmental Integration, 2021, 6(1):1-10.

[10] Abbas M S. Evaluation of Potassium Sources, Rates and Pattern on the Yield and Quality Traits of Fertigated Wheat Grown in Sandy Soil[J]. Pakistan Journal of Biological Sciences, 2020, 23(3):213-222.

[11] Kuznetsova I, Vovk O. Technology of Educational Electronic Publications' Quality Evaluation[J]. Open Journal for Information Technology, 2019, 2(1):9-20.

[12] Gonalves T, Silva W, Cardoso M J, et al. A novel approach to key point detection for the aesthetic evaluation of breast cancer surgery outcomes[J]. Health and Technology, 2020, 10(4):891-903.

Figures

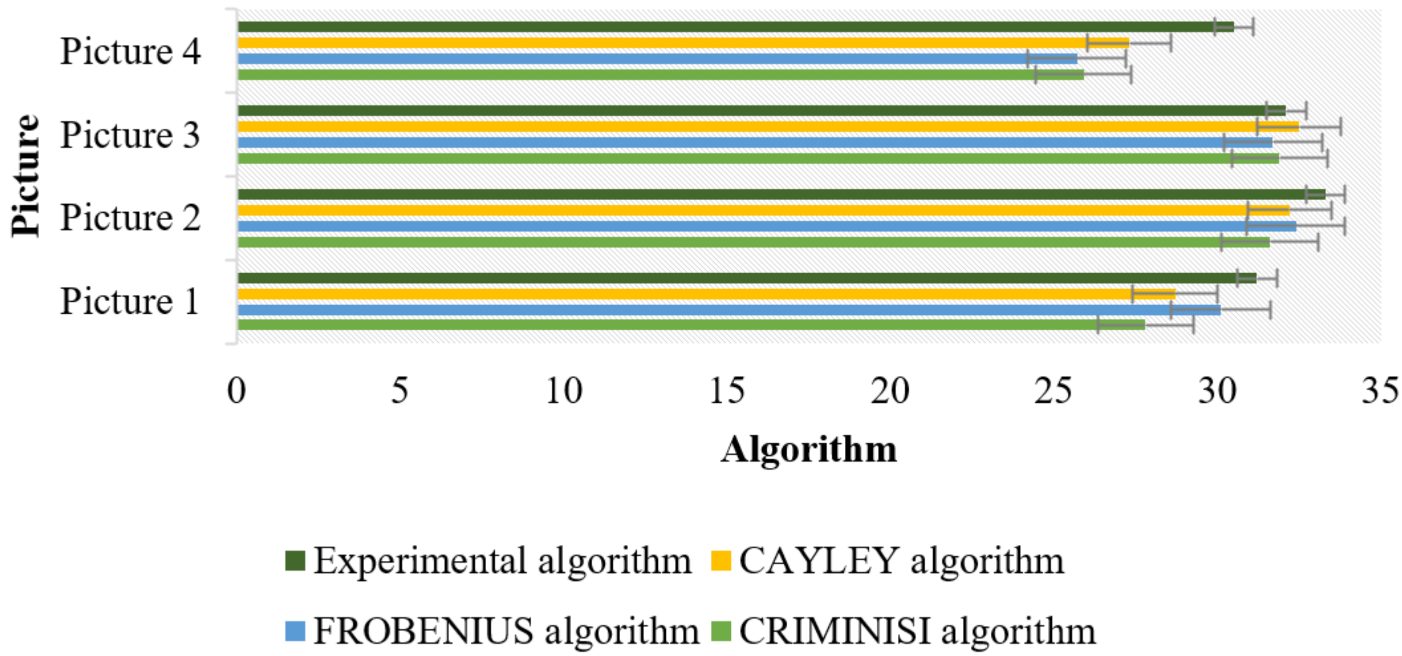

Figure 1

PSNR performance comparison of automatically generated traditional pattern pictures

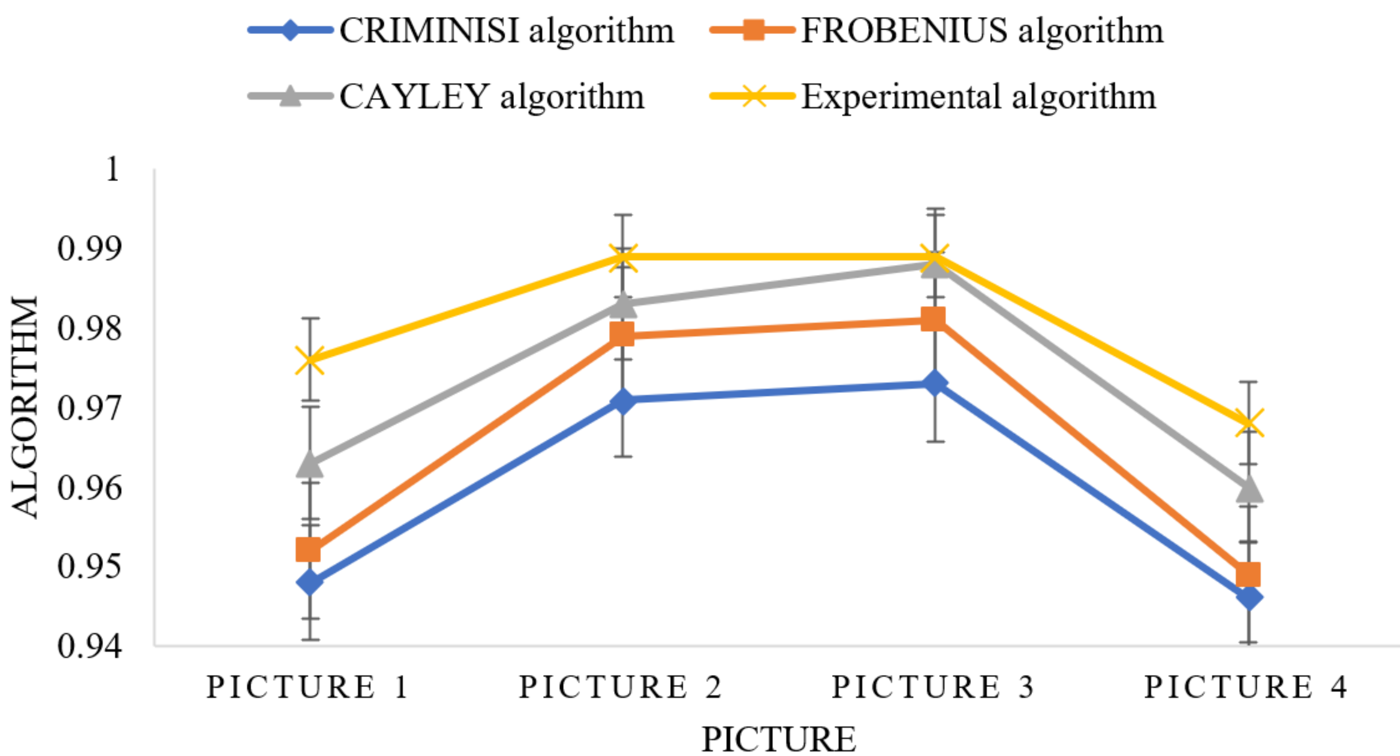

Figure 2

SSIM performance comparison of automatically generated image models of traditional patterns