

Aesthetic Evaluation of Interior Design Based on Visual Features

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ABSTRACT

In the modern context, interior design has inevitably become a part of social culture. All kinds of modeling, decoration, and furnishings in modern interior space show people's pursuit and desire for a better life. These different styles of modern interior design rely on science and technology and utilize culture and art as the connotation. Its development often reflects the cultural spirit of a nation. The aesthetic evaluation plays an important role in the modern interior design. With development of derivative digital devices, a large number of digital images have emerged. The rapid development of computer vision and artificial intelligence makes aesthetic evaluation for interior design automatic. This paper implements an intelligent aesthetic evaluation of interior design framework to help people choose the appropriate and effective interior design from collected images or mobile digital devices.

KEYWORDS

Aesthetic Evaluation, Interior Design, Machine Learning, Mobile Digital Device

1. INTRODUCTION

With the development of human society, the development of interior design is also step by step and serves people's life (Grieze & Miķelsone 2021, Hasti & Kusnia 2019). People's life and interior design promote each other with the development of society (Chen & Wang 2020, Afifi 2020). The great difference between design and art is that design pays more attention to practical functions. Different design products have different use functions, and the requirements of different interior design are also different. Because the applicable population and spatial positioning of indoor space are different, the design methods will also be different.

The interior design evaluation refers to the comparison and evaluation of the interior design (Wang & Hsiao 2018, Valiyev 2020). It should be noted that interior design evaluation belongs to a neutral attitude, which is only a scientific evaluation of interior design works. The interior design is the product of people's practical life (Tautkute 2019). In the process of interior design development, there will be cases that do not conform to the people-oriented concept, and the designed products are incompatible with the market, which is also the reason for the emergence of interior design evaluation. In order to maintain the competitiveness of the product itself, the designer must push through the old and bring forth the new. This process also needs design evaluation. In interior design, the designer himself is a design evaluator. He has been in a state of repeated modification for his own design, in which the designer plays an important role in the design process.

The interior design is a relatively large design scope, which contains many elements, such as building decoration materials (Cao 2021, Zeng & Jiang 2018), indoor furniture (Viyanon 2017, Sarkar & Bardhan 2019), and decoration style (Tong 2019, Jinkun 2017). The evaluation methods are also

DOI: 10.4018/IJMCMC.293752

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different in these different interior design elements. The interior design evaluation is used to compare and comment on design works. For a design work, the evaluation is related to its factors and consumer requirements. For the decoration materials required for interior designer, people pay more attention to its environmental protection on the premise of paying attention to its aesthetics, which is also the difference between it and other design elements. For the evaluation of decoration materials, we should take green environmental protection as the premise and focus on its functionality since the existence value of decoration materials lies in its functionality to support and form the whole indoor space.

For the evaluation method of interior design, we should not only take care the functionality and aesthetics of the furniture itself, but also put the furniture in the corresponding indoor space and watch its overall effect. Furniture has its own design style. The corresponding location in indoor space depends not only on its own style, but also on whether the design style of furniture in the whole interior design is appropriate, which is also the particularity of furniture design evaluation.

For everyone's favorite design elements, the favorite style and suitable style are different. For instance, children need bright and lively colors to suit their childlike innocence. The elder's house needs to be designed with ease, comfort and generosity, which is not suitable for a large number of complex decorations. Each design style needs special evaluation method. For the interior design evaluation, we should first start from people, adopt the people-oriented concept, and carry out scientific evaluation and theoretical analysis. However, as the object of human being is the evaluator, it is inevitable that subjective factors will appear in the interior design evaluation process, which requires our evaluators to make an objective and fair evaluation and give a rational answer to the public and society. In this paper, we adopts image aesthetics to evaluate interior design.

Image aesthetics (Ren 2017, Chen 2020) is an aesthetic way based on image and guided by art. As an important bridge for people to obtain and exchange information, the image is very specific, intuitive, easy to understand, and can greatly enrich human life and work. With the rise of computer and artificial intelligence, more and more electronic products emerge in endlessly, and a large number of digital images are emerging. It is become necessary to automatically divide the images into aesthetic grades and assist human to complete the image processing. Automatic image aesthetics evaluation (Li 2020, Peng 2021) is a research problem with great significance and wide application prospects. The potential application fields involve visual experience, such as image retrieval (Wang 2017), image editing and design (Wang 2019), human computer interaction (Dou 2019). It can be applied to many fields, especially for human-computer interaction. The image aesthetics plays an important role in all aspects related to image. Mathematical images can be applied to different fields of life and science and technology through different ways of processing.

2. INTERIOR DESIGN EVALUATION THROUGH AUTOMATIC IMAGE AESTHETICS

Image aesthetics is an interdisciplinary comprehensive research topic in many fields. At the same time, it is also closely connected with the booming artificial intelligence. It has a very broad application field and development prospect. It is very meaningful to enable the computer to simulate human aesthetic perception, realize the evaluation of image aesthetics, and replace human work in dealing with massive redundancy.

With the rise of computable image aesthetic evaluation, many researchers study different methods to solve the problem of image quality evaluation. It is an urgent problem to represent the image. From a computable point of view, image aesthetic evaluation can be regarded as a process of obtaining aesthetic prediction from an image. The process can be regarded as two parts. One is feature representation. The other is model learning. For the aesthetic research of image, most of the existing literature mainly focuses on the extraction of image features, that is, to extract image features by simulating the composition mode of image or the theory of psychology and perception, so as to realize the aesthetic evaluation of image.

By comparing the research methods in different stages of image aesthetics evaluation, it can be seen that the manual feature method has more feature redundancy information and its implementation

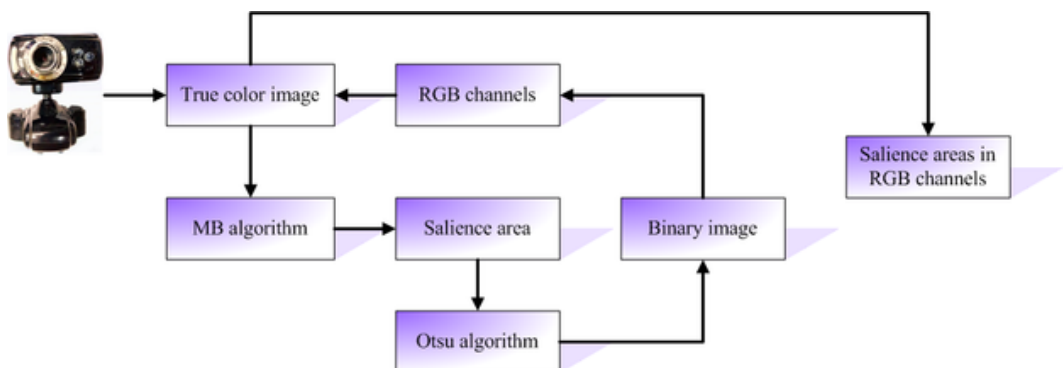
is complex. At the same time, some aesthetic related attributes are difficult to define an objective evaluation standard. Many photographic or psychological rules are descriptive, and the extracted features are only close to these rules. The general features commonly used in image classification and retrieval are applied to aesthetic evaluation directly. Although the implementation effect is better than the underlying manual features, it does not provide a better aesthetic feature descriptor for the problems related to image aesthetics. Although the features learnt by deep neural network (Fu 2018) achieve state-of-the-art results, the deep learning costs many resources to learn the feature representation model which is more complex than previous methods. Additionally, the deep learning needs massive data as training set and strong hardware equipment to support model training.

The image aesthetics evaluation considers both subjective and objective factors. It refers to people's educational background, aesthetic experience, cultural region, personal hobbies and so on. Because the categories of natural scene images are complex and rich, natural images of the same type of scene have aesthetic differences. The images from different scene types are vulnerable to semantic information, which makes the image aesthetic evaluation method vulnerable to human strong subjective factors and different forms of objective factors. Therefore, there is no unified, definite and objective evaluation standard for the evaluation of image aesthetics, which also makes researchers study image aesthetic evaluation from different perspectives.

The visual attention mechanism (Jian 2019) is an important characteristic of the human visual system. Based on this characteristic, many researchers have deeply studied the image saliency region detection algorithm which has been widely used in many fields. The existing research about saliency region detection can be summarized into the following categories: contrast characteristics based methods, spectrum characteristics based methods and information entropy theory based methods.

The pixels at the image boundary are used as the background image. By modeling the background image and using the minimum obstacle distance transformation method, the salient image can be extracted accurately and efficiently. The maximum variance threshold segmentation method (Wang 2018), can automatically determine the best threshold. Through the determined threshold, the image is divided into foreground image and background image, so as to realize the effective segmentation of different natural scene images. The salient region extraction structure is illustrated in Figure 1.

Figure 1. The flowchart salient region extraction



Firstly, it extracts the image salient region, and then the visual salient image is binarized based on Otsu segmentation method (the maximum variance threshold segmentation method) as the mask of the image foreground region. In order to further obtain an accurate foreground region image, firstly, the pixel of the mask plate of the foreground region is flipped as the background region image mask

plate to obtain the background region image. The foreground region image is obtained by subtracting the original image from the corresponding background region image.

For limited perceptual information, human visual attention mechanism has a certain selectivity in information processing. Through perceptual convergence processing of non-stimulus information, we can centrally perceive and process important stimulus information to achieve efficient processing of limited information. This paper uses the principle that the human eye is sensitive to the fluctuation part of the image, and obtains the prior information and fluctuation information in the gray image by using the frequency domain transformation. The procedure is summarized as follows:

Ø The frequency domain amplitude and phase angle of the image are obtained through the following equation.

$$\begin{cases} m(\mu, \gamma) = abs\left(F\left(f(x, y)\right)(\mu, \gamma)\right) \\ a(\mu, \gamma) = angle\left(F\left\{f(x, y)\right\}(\mu, \gamma)\right) \end{cases} \quad (1)$$

Ø The logarithmic spectrum of the image is computed by the following equation.

$$L(\mu, \gamma) = \log\left(m(x, y)\right) \quad (2)$$

Ø The spectral residual information of the image is obtained according to the Equation (3).

$$r(\mu, \gamma) = L(\mu, \gamma) - h_n(\mu, \gamma) * L(\mu, \gamma) \quad (3)$$

Ø The image is transformed into spatial domain based on the Equation (4) to obtain the visual saliency map.

$$sr(x, y) = g(x, y) * \left\| F^{-1} \left\{ e^{r+ja} \right\} (x, y) \right\|^2 \quad (4)$$

Here, $f(x, y)$ represents the original pixels of image, F represents the Fourier transform of the image, F^{-1} represents the inverse Fourier transform of the image, $abs(\cdot)$ represents the complex amplitude in the frequency domain, $angle(\cdot)$ represents the complex phase angle in the frequency domain, $h_n(\mu, \gamma)$ represents the mean filter with the size $n \times n$, $g(x, y)$ represents the Gaussian filter, and $*$ represents the convolution operation.

The above algorithm extracts dynamic information based on the spectral characteristics of gray image, ignores the important role of color information in salient image extraction. The HSV color space model consists of chroma, saturation and brightness components. The brightness component is obtained by calculating the maximum component in RGB three channels. It is not related to color information. At the same time, human visual perception is closely related to the hue and saturation color components. The saliency images of the above three color components respectively describe different details in the image. This paper superimposes the HSV three channel images to present the details of the saliency map from the perspectives of chromaticity, saturation and brightness. The mean filter size is set as 3, while the Gaussian filter size is set as 10.

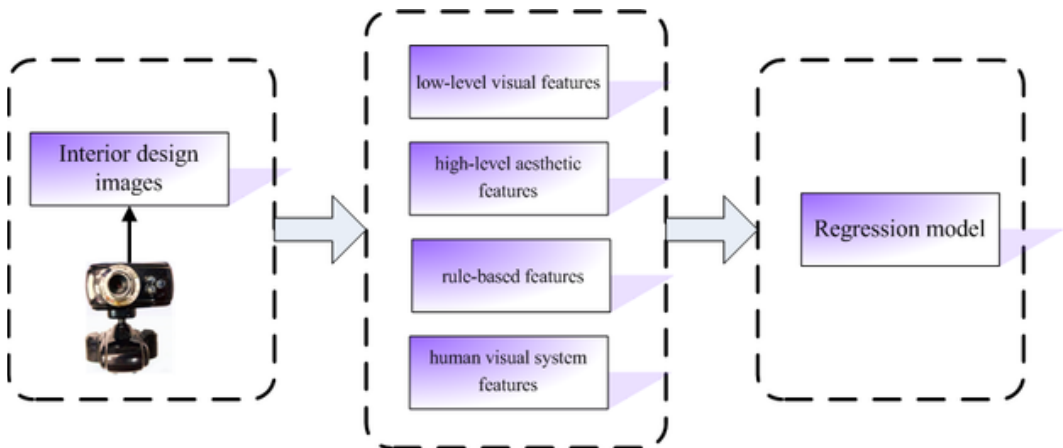
The regression evaluation method of image aesthetics is to score the aesthetics of an image. Compared with binary discrete evaluation method, regression evaluation method is a continuous

evaluation method. Through the aesthetic evaluation of the image, the aesthetic grade of the image is further refined, which poses a further challenge to human simulation and learning by computer. It is an important issue of regression evaluation method to make the aesthetic evaluation of images by computer be close to the evaluation level of human beings and realize the good aesthetic prediction of natural images of different scene types.

Due to the complex influencing factors of image aesthetics, the traditional research methods of manual feature extraction are mainly feature extraction based on single aesthetic perspectives. The research methods based on single features or general features are often difficult to fully capture the different visual aesthetics of images. In order to solve this issue, this paper extracts aesthetic features from the perspective of multi factors by combining the low-level visual features, high-level aesthetic features, rule-based features and human visual system features to describe the image aesthetics features. Natural images of different scene types have their unique aesthetic feeling and the same characteristics have different aesthetic prediction performance for images of different scene types. This paper combines the high-level aesthetic features of different scene types based on the high-level aesthetic features that involve the most aesthetic factors.

The effective and stable multi perspective characteristics and the regressor are two key points in the interior design image aesthetic regression evaluation. This paper uses the combination of optimal feature combination and optimal regressors to predict the aesthetic degree of interior design images. The flowchart is illustrated in the Figure 2.

Figure 2. The architecture of interior design evaluation through digital images



In the Figure 2, the regression evaluation structure consists four parts: input data, feature extraction and selection, regressor selection and optimization, and aesthetics prediction. In the feature extraction and selection part, it considers low-level visual features, rule based features, human visual system features, and high-level aesthetic features. In the regressor selection and optimization, it learns a regressor on a training set and tunes the parameters of the regressor to obtain the best performance.

The low-level visual features include color feature, texture feature and shape feature. The most effective way to attract the observer's attention is the eye-catching and bright color and strong contrast in the image. The color information of the image is highly related to the aesthetic feeling of the image. This paper combines feature map and color moment as the low-level color feature.

When the image contain rich color texture information, the single color information cannot fully describe the aesthetic feeling of the image. At the same time, the aesthetic prediction is disturbed

by various texture information, which results in a large difference between the prediction and the human evaluation. The image texture information plays an important role in studying the image with rich detail information.

Texture can show the roughness and fineness of different regions in the image, and show the overall local detail information of the image. The detail information of the image is usually obtained through multi-scale image. This paper extracts the texture features by combining multi-scale and multi angle detail information.

In general, there is less texture information in the single subject background or blurred background image. The subject target of the image has become the main information affecting the aesthetic feeling of the image. The research on the scene of the image target area plays an important role in describing the scene information of the image. Shape information can directly reflect the scene information and subject contour information of the image, which plays an important role in capturing the spatial composition information of the image and transmitting the intuitive semantic information to the observer.

The color, texture and shape features in the underlying visual features are described from the image color information, rich texture information and target scene information. The rule-based features are different from the underlying visual feature. It describes the aesthetic degree from the aesthetic rules of the image by studying the aesthetic composition mode of the image. This paper extracts two different rule-based features, namely pattern feature and definition feature.

The low-level visual features describe the intuitive visual information in the image. The rule-based features differ from aesthetic modes of the image. The human visual system features are formed based on the human perception system to simulate human visual system. The high-level aesthetic features are extracted different aesthetic factors, including edge distribution feature, depth feature, energy feature, and regional feature.

The edge distribution information of the image reflects the overall complexity of the image. High-quality images often highlight the edge of the main area, so that the observer can intuitively understand the image information.

Professional photographers usually use the method of lowering the depth of field to blur the background area to obtain a high-definition target area, which makes the interest area of the image and the subject target more attractive. This paper adopts the HSV color components. Each component is processed by three-layer wavelet transform to obtain the wavelet coefficient images. The image is divided as 16 blocks to extract the high-frequency information of the central area and surrounding area of different color space, which is written as follows:

$$\begin{cases} w_{3,i}(x,y) = \{w_{3,i}^{lh}, w_{3,i}^{hl}, w_{3,i}^{hh}\} & (i \in h, s, v) \\ LD_i = \frac{\sum w_3(x,y)}{\sum_{i=1}^{16} \sum_{i=1}^{16} w_3(x,y)} & (i \in h, s, v) \end{cases} \quad (5)$$

In the Equation (5), $w_3(x,y)$ represents the high frequency part of wavelet transform coefficients.

Image energy describes the richness and detail information of the image from the perspective of statistics. It can provide a lot of detail information of the aesthetics of the image. The wavelet coefficients (Huang 2017) of the image can reflect the different frequency band information of the image from different transformation levels. Low frequency information contains the main information of the image, the information between high frequency and low frequency, the vertical information and horizontal information of the image. The high frequency information contains the detailed information of different directions of the image. This paper combines the low-frequency image with the high-frequency image from the perspective of main information and rich detail information of the

image to capture the energy information of the image. Based on the HSV three-channel image, the coefficient image after three-layer wavelet transform is obtained. The energy feature of each color component is extracted by the following Equation (6).

$$\begin{cases} w_{3,i}(x, y) = \{w_{3,i}^{lh}, w_{3,i}^{hl}, w_{3,i}^{hh}\} & (i \in h, s, v) \\ LD_i = \frac{\sum w_3(x, y)}{\sum_{i=1}^{16} \sum_{i=1}^{16} w_3(x, y)} & (i \in h, s, v) \end{cases} \quad (5)$$

In the Equation (5), $w_i^{hh}(x, y)$, $w_i^{hl}(x, y)$, and $w_i^{lh}(x, y)$ represent detailed sub-image of the i^{th} layer along diagonal, horizontal, and vertical direction, respectively.

The key areas in the image focus on the key information of the image, and often can intuitively express the image connotation. The observer can quickly understand the information transmitted by the photographer. At the same time, the observer is often attracted by the key areas in the image. How to obtain the key area of the image plays an important role in studying the key information of the image. Generally, the research on key areas often pays attention to the locality of the image, which is easy to make the observer fall into the local image to ignore the image related area information. For the extraction of regional features, this paper extracts regional features from the perspective of local image and global image.

For the regression evaluation method of image aesthetics, the extracted features are used to learn regression model. In this paper, we adopt support vector regression (SVR) (Drucker 1997, Zhu 2017) as the regression algorithm. Let $X \times Y = \{(x_1, y_1), \dots, (x_n, y_l)\}$ represent training set. Here, $x_i \in \mathbb{R}^n$, $y_i \in \mathbb{R}$. The aim of SVR is to find a decision function $f(x) = w^T \phi(x) + b$ by minimizing the following loss function.

$$L_\varepsilon = \begin{cases} 0, & |f(x) - y| \leq \varepsilon \\ |f(x) - y|, & otherwise \end{cases} \quad (7)$$

The objective Equation (7) is implemented by the following optimal programming

$$\begin{aligned} \min_{w, b} \quad & \frac{1}{2} \|w\|_2^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*) \\ s.t. \quad & \langle w, \varphi(x_i) \rangle - y_i \leq \varepsilon + \xi_i \\ & y_i - \langle w, \varphi(x_i) \rangle \leq \varepsilon + \xi_i^* \\ & \xi_i \geq 0, \xi_i^* \geq 0, i = 1, \dots, l. \end{aligned} \quad (8)$$

The optimal programming is convex. The solution can be obtained by solving the associated dual optimal programming which is written as follows:

$$\begin{aligned}
 \min_{\alpha, \alpha^*} \quad & \frac{1}{2} \sum_{i,j=1}^l (\alpha_i - \alpha_i^*) K(x_i, x_j) (\alpha_j - \alpha_j^*) + \varepsilon \sum_{i=1}^l (\alpha_i + \alpha_i^*) - \sum_{i=1}^l y_i (\alpha_i - \alpha_i^*) \\
 s.t. \quad & \sum_{i=1}^l (\alpha_i - \alpha_i^*) = 0 \\
 & 0 \leq \alpha_i, \alpha_i^* \leq C, i = 1, \dots, l.
 \end{aligned} \tag{9}$$

In the Equation (9), $K(x_i, x_j) = \langle \varphi(x_i), \varphi(x_j) \rangle$ in the kernel form of sample x_i and x_j in reproducing kernel Hilbert space (RKHS). The w and decision function $f(x)$ are obtained by the following equations.

$$w = \sum_{i=1}^l (\alpha_i - \alpha_i^*) \varphi(x_i) \tag{10}$$

$$f(x) = \sum_{i=1}^l (\alpha_i - \alpha_i^*) K(x_i, x) + b \tag{11}$$

3. EXPERIMENTS AND SIMULATIONS

In this section, we collect the interior design images from designers. The collected images come from 6 types of interior design. Each image is scored by 20 experts from interior design. The score ranges from 0 to 100. The final score is the average of twenty experts. The number of images from each interior design style are 2,000. The interior design images are divided into two parts equally. One part is used as training set to learn regression model. The other is used as test set to evaluate our interior design evaluation scheme. In our scheme, the interior design images are represented as the combination of low-level visual features, high-level aesthetic features, rule-based features and human visual system features.

The prediction performance of regression model is usually measured by error function. For the evaluation of interior design image aesthetics, this paper adopts root mean square error, average absolute error, correlation coefficient, and Pearson correlation coefficient.

The root mean square error (RMSE) describes the degree of divorce between the real value and the predicted value. The smaller the value is, the higher the prediction accuracy and the better performance the model has. The definition of root mean square error is shown in the following equation.

$$RMSE = \sqrt{\sum_{i=1}^l (y_i - \hat{y}_i)^2} \tag{12}$$

In the Equation (12), n represents the number of samples, y_i is the ground truth of sample x_i , and \hat{y}_i is the predicted value of sample x_i .

The average absolute error (MAE) describes the change degree of the data. The smaller the value is, the more it can reflect the actual situation of the prediction error and the better the performance of the prediction model is. The definition of average absolute error is shown in the following equation.

$$MAZ = \frac{1}{n} \sum_{i=1}^l |y_i - \hat{y}_i| \quad (13)$$

In the Equation (13), n represents the number of samples, y_i is the ground truth of sample x_i , and \hat{y}_i is the predicted value of sample x_i .

The Pearson correlation coefficient (PCC) is a measure of the linear correlation degree between two variables. It represents the similarity between the model and human evaluation. The greater value is, the stronger the correlation between variables and the better the prediction performance of the model is. The definition of Pearson correlation coefficient is shown in the following equation.

$$PCC = \frac{\text{cov}(y, \hat{y})}{\sigma_y \sigma_{\hat{y}}} = \frac{E(y\hat{y}) - E(y)E(\hat{y})}{\sqrt{E(y^2) - E^2(y)}\sqrt{E(\hat{y}^2) - E^2(\hat{y})}} \quad (14)$$

In the Equation (14), n represents the number of samples, y_i is the ground truth of sample x_i , and \hat{y}_i is the predicted value of sample x_i .

The experimental results of root mean square error (RMSE), average absolute error (MAE), and Pearson correlation coefficient (PCC) are reported in Table 1, Table 2, and Table 3, respectively.

From Table 1, the root mean square error (RMSE) of combined features archives 0.4203, 0.3526, 0.3926, 0.3515, 0.3788, and 0.4012 for style 1 to style 6, respectively, while the average RMSE reaches 0.3828. The RMSE of combined features is lower than that of only low-level visual features, high-level aesthetic features, rule-based features, or human visual system features.

Table 1. The root mean square error (RMSE) comparison of different features in interior design

	low-level visual features	high-level aesthetic features	rule-based features	human visual system features	combined features (ours)
Style 1	0.4839	0.4972	0.5013	0.4683	0.4203
Style 2	0.3886	0.4953	0.4419	0.4490	0.3526
Style 3	0.4552	0.4579	0.4977	0.4108	0.3926
Style 4	0.4752	0.4886	0.4478	0.3958	0.3515
Style 5	0.4810	0.4821	0.4918	0.3753	0.3788
Style 6	0.4465	0.4037	0.4274	0.4417	0.4012
Average	0.4551	0.4708	0.4680	0.4235	0.3828

From Table 2, the average absolute error (MAE) of combined features archives 0.2561, 0.2123, 0.2115, 0.2502, 0.2181, and 0.2289 for style 1 to style 6, respectively, while the average RMSE reaches 0.2295. The MAE of combined features is lower than that of only low-level visual features, high-level aesthetic features, rule-based features, or human visual system features.

From Table 3, the Pearson correlation coefficient (PCC) of combined features archives 0.3459, 0.3521, 0.3322, 0.3443, 0.3345, and 0.3514 for style 1 to style 6, respectively, while the average RMSE reaches 0.3434. The PCC of combined features is lower than that of only low-level visual features, high-level aesthetic features, rule-based features, or human visual system features. From

Table 2. The average absolute error (MAE) comparison of different features in interior design

	low-level visual features	high-level aesthetic features	rule-based features	human visual system features	combined features (ours)
Style 1	0.2712	0.2754	0.2804	0.2674	0.2561
Style 2	0.2540	0.2571	0.2293	0.2385	0.2123
Style 3	0.2258	0.2496	0.2451	0.2410	0.2115
Style 4	0.2511	0.2649	0.2595	0.2353	0.2502
Style 5	0.2605	0.2465	0.2566	0.2312	0.2181
Style 6	0.2522	0.2578	0.2670	0.2627	0.2289
Average	0.2525	0.2585	0.2563	0.2460	0.2295

Table 3. The Pearson correlation coefficient (PCC) comparison of different features in interior design

	low-level visual features	high-level aesthetic features	rule-based features	human visual system features	combined features (ours)
Style 1	0.3961	0.4077	0.3758	0.3515	0.3459
Style 2	0.3438	0.3603	0.3771	0.3975	0.3521
Style 3	0.4036	0.3957	0.3699	0.3378	0.3322
Style 4	0.3611	0.4176	0.3520	0.3398	0.3443
Style 5	0.3579	0.3779	0.3878	0.3734	0.3345
Style 6	0.3792	0.3972	0.3823	0.3673	0.3514
Average	0.3736	0.3927	0.3742	0.3612	0.3434

the results in Table 1, 2, and 3, it can be found that the combined features is much better than merely using one type of features.

4. CONCLUSION

Now, the interior design has become an essential part in modern interior space, such as personal house, department, and flat. The aesthetic evaluation plays an important role in the modern interior design. With development of derivative digital devices, a large number of digital images have been emerged. This paper utilizes machine learning and computer vision to implement an intelligent aesthetic evaluation framework for interior design evaluation. First, the interior design images are collected by using digit camera. Second, the collected interior design images are represented as the combination of associated low-level visual features, high-level aesthetic features, rule-based features and human visual system features which are extracted from the images. Third, the extracted features are used to learn a regression model, such as support vector machine. The proposed interior design evaluation scheme is verified on the collected images from designers through digital camera.

ACKNOWLEDGMENT

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

- Afifi, A. H. M. Y. (2020). Textile Technology And Its Complementary Design Role In Interior Architecture. *International Journal of Architectural Engineering and Urban Research*, 3(1), 26–36.
- Cao, C. (2021, February). Research on Innovative Application of Artistic Characteristics of Building Decoration Materials in Interior Design Based on Big Data. *Journal of Physics: Conference Series*, 1744(2), 022020.
- Chen, Q., Zhang, W., Zhou, N., Lei, P., Xu, Y., Zheng, Y., & Fan, J. (2020). Adaptive fractional dilated convolution network for image aesthetics assessment. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 14114-14123). IEEE.
- Chen, Z., & Wang, X. (2020). Application of AI technology in interior design. In *E3S Web of Conferences* (Vol. 179, p. 02105). E3S Web of Conferences.
- Dou, Q., Zheng, X. S., Sun, T., & Heng, P. A. (2019). Webthetics: Quantifying webpage aesthetics with deep learning. *International Journal of Human-Computer Studies*, 124, 56–66.
- Drucker, H., Burges, C. J., Kaufman, L., Smola, A., & Vapnik, V. (1997). Support vector regression machines. *Advances in Neural Information Processing Systems*, 9, 155–161.
- Fu, X., Yan, J., & Fan, C. (2018, October). Image aesthetics assessment using composite features from off-the-shelf deep models. In *2018 25th IEEE International Conference on Image Processing (ICIP)* (pp. 3528-3532). IEEE.
- Grieze, E., & Mīkelsone, E. (2021). Biomimicry element application in the interior design product development. *Economics. Ecology. Socium*, 5(2), 59–70.
- Hasti, N., & Kusnia, G. (2019, November). Role of Technology for Interior Design Sectors in Creative Economic Development. In *IOP Conference Series: Materials Science and Engineering* (Vol. 662, No. 4). IOP Publishing.
- Huang, H., He, R., Sun, Z., & Tan, T. (2017). Wavelet-srnet: A wavelet-based cnn for multi-scale face super resolution. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 1689-1697). IEEE.
- Jian, M., Zhou, Q., Cui, C., Nie, X., Luo, H., Zhao, J., & Yin, Y. (2019). Assessment of feature fusion strategies in visual attention mechanism for saliency detection. *Pattern Recognition Letters*, 127, 37–47.
- Jinkun, J., Yalan, L., & Xizhu, Y. (2017). Application of Islamic Decorative Art in Interior Design. *Furniture & Interior Design*, 1(2), 8–19.
- Li, J., Peng, H., Huosheng, H., Zhiming, L., & Tang, C. (2020). Multimodal information fusion for automatic aesthetics evaluation of robotic dance poses. *International Journal of Social Robotics*, 12(1), 5–20.
- Peng, H., Hu, J., Wang, H., Ren, H., Sun, C., Hu, H., & Li, J. (2021). Multiple Visual Feature Integration Based Automatic Aesthetics Evaluation of Robotic Dance Motions. *Information*, 12(3), 95.
- Ren, J., Shen, X., Lin, Z., Mech, R., & Foran, D. J. (2017). Personalized image aesthetics. In *Proceedings of the IEEE international conference on computer vision* (pp. 638-647). IEEE.
- Sarkar, A., & Bardhan, R. (2019, July). A simulation based framework to optimize the interior design parameters for effective Indoor Environmental Quality (IEQ) experience in affordable residential units: Cases from Mumbai, India. In *IOP Conference Series: Earth and Environmental Science* (Vol. 294, No. 1, p. 012060). IOP Publishing.
- Tautkute, I., Trzciński, T., Skorupa, A. P., Brocki, Ł., & Marasek, K. (2019). Deepstyle: Multimodal search engine for fashion and interior design. *IEEE Access: Practical Innovations, Open Solutions*, 7, 84613–84628. doi:10.1109/ACCESS.2019.2923552
- Tong, H., Wan, Q., Kaszowska, A., Panetta, K., Taylor, H. A., & Agaian, S. (2019). ARFurniture: Augmented reality interior decoration style colorization. *Electronic Imaging*, 2019(2), 175–1.
- Valiyev, A., Imamguluyev, R., & Ilkin, G. (2020, August). Application of Fuzzy Logic Model for Daylight Evaluation in Computer Aided Interior Design Areas. In *International Conference on Theory and Applications of Fuzzy Systems and Soft Computing* (pp. 715-722). Springer.

Viyanon, W., Songsuittipong, T., Piyapaisarn, P., & Sudchid, S. (2017, July). AR furniture: Integrating augmented reality technology to enhance interior design using marker and markerless tracking. *Proceedings of the 2nd International Conference on Intelligent Information Processing*, 1-7.

Wang, B., Chen, L. L., & Cheng, J. (2018). New result on maximum entropy threshold image segmentation based on P system. *Optik (Stuttgart)*, 163, 81–85.

Wang, M. F., & Hsiao, S. W. (2018, May). A Kansei-oriented method for interior design. In *2018 IEEE 22nd International Conference on Computer Supported Cooperative Work in Design (CSCWD)* (pp. 485-490). IEEE. doi:10.1109/CSCWD.2018.8465186

Wang, W., Yang, S., Zhang, W., & Zhang, J. (2019). Neural aesthetic image reviewer. *IET Computer Vision*, 13(8), 749–758.

Wang, Z., Liu, D., Chang, S., Dolcos, F., Beck, D., & Huang, T. (2017, May). Image aesthetics assessment using Deep Chatterjee's machine. In *2017 International Joint Conference on Neural Networks (IJCNN)* (pp. 941-948). IEEE.

Zeng, J., & Jiang, M. (2018, June). The Role and Application of Decorative Materials in Interior Design. *2nd International Conference on Social Sciences, Arts and Humanities (SSAH 2018)*, 9-10.

Zhu, F., Gao, J., Xu, C., Yang, J., & Tao, D. (2017). On selecting effective patterns for fast support vector regression training. *IEEE Transactions on Neural Networks and Learning Systems*, 29(8), 3610–3622.