Evaluation of Innovative Design of Clothing Image Elements Using Image Processing

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Excellent design of clothing image elements can enhance the attractiveness of clothing to customers. This paper used image processing technology to extract texture and color features for innovative designs of clothing image elements and used the convolutional neural network (CNN) model to evaluate some designs. The CNN model was compared with the back-propagation neural network (BPNN) model in the example analysis, and three designs were evaluated. The results showed that the image processing-based CNN model had good evaluation performance and obtained evaluation results closer to the manual evaluation results than the BPNN model. The evaluation results of the three designs also showed that all three designs achieved innovative design through effectively combining multiple image elements.

Povzetek: V članku je opisan nov način snovanja oblačil s pomočjo konvolucijske nevronske mreže.

1 Introduction

Clothing, food, housing, and transport are important parts of people's life. With the improvement of living standards, people's demand for clothing has gradually changed from covering and keeping warm to making themselves more beautiful [1]. In short, the improvement of the quality of life makes people pursue the decorative role of clothing to meet spiritual enjoyment. Therefore, in the clothing industry, the image design of clothing is also crucial, and a better image matching of clothing can attract customers to buy and increase turnover. When designing clothing, the shape follows the basic structure of the human body, so most of the clothing design is focused on the textured pattern and color matching of the clothing [2]. Excellent designs of textured patterns and colors cannot be created out of thin air. Usually, designers will collect materials from the surrounding environment or other objects according to the set theme and then combine the materials that fit the theme. In the innovative design of clothing image elements, it is necessary to evaluate the design accurately in order to make effective adjustments [3]. The intervention of intelligent algorithms makes the evaluation of designs free from the inefficiencies of manual evaluation and the bias caused by the small number of evaluators. Design evaluation by intelligent algorithms requires the use of image processing algorithms to extract the image features for identification and analysis. Ota et al. [4] used image processing techniques to automatically extract features of clothing and used a neural network for Kansei retrieval of clothing. The simulation results showed that this algorithm increased the accuracy of imitating the user's Kansei by 46.65%. Zhang et al. [5] established a collar style sample library using a clothing style map as the research object and used a round-neck Tshirt image as an example to compare and analyze the advantages and disadvantages of commonly used image

graying, sharpening, edge detection, morphological processing, and image segmentation processing methods. Zhang et al. [6] proposed a support vector machine (SVM) classifier-based objective evaluation method for seam pucker and found through experiments that the classification accuracy of the method was 96%, which was comparable to human visual performance and solved the ambiguity and subjective problems of manual evaluation. This paper used image processing technology to extract features of texture and color for innovative design of clothing image elements, used the convolutional neural network (CNN) model to evaluate some designs, compared the CNN model with the back-propagation neural network (BPNN) model in the example analysis, and evaluated three designs.

2 Evaluation of innovative design of clothing image elements based on image processing

2.1 Traditional evaluation methods for clothing design

In order to strengthen the attractiveness of clothing to customers and thus increase sales, it is necessary to make designs for clothing that can attract customers. Usually, the basic structure of clothing is unchanged, so the innovative design of clothing usually starts from the textured pattern and color matching on the clothing plane [7]. When designing the textured pattern and color matching on the clothing plane, materials are often collected from reality, and then features are extracted from the materials and combined. Reasonable and excellent designs of textured patterns and colors can significantly affect the subjective feelings of people when they look at the clothing. The innovative design of clothing needs to pay attention to the impact on human perception; however, texture and color designs are objective, and human perception is subjective. When subjective feelings assist in innovative designs, subjective perception needs to be objectively quantified to facilitate correction and perfection of designs according to the interaction between the objective attribute of design and people's subjective perception.

The traditional way of evaluating designs is mutual evaluation. In order to make the subjective perception of manual evaluation as objective as possible, on the one hand, quantitative evaluation criteria are provided to evaluators, and on the other hand, the number of evaluators is increased, and the mean value is used to measure the quality of a design [8]. This way of evaluation will make the evaluation result of a design as close as possible to the subjective perception of most people because of the use of human power. Although this evaluation method is close to an accurate subjective evaluation, it takes a long time and is difficult to select evaluators [9]. The analytic hierarchy process (AHP) method is a common manual evaluation method that applies quantitative evaluation criteria. The traditional evaluation method divides the object to be evaluated (the innovative design of clothing image elements in this paper) into several large independent aspects, then divides every aspect into small independent aspects, designs a questionnaire for every aspect, and finally collects evaluation information from the evaluators through the questionnaire. In short, it quantifies the evaluation content.

2.2 Clothing design evaluation model combined with image processing technology

The improvement of computer technology and the emergence of intelligent algorithms have created a new way of evaluating clothing designs. Compared with the traditional manual evaluation method, intelligent algorithms do not mix subjective feelings when evaluating designs, avoiding different evaluations of the same design by different people, and their fast calculation of designs can also improve the evaluation efficiency.



Figure 1: Basic process of evaluation model of the innovative design of clothing image elements based on image processing

Figure 1 shows the basic process of evaluating the innovative design of clothing image elements based on image processing. The process is generally divided into three parts: pre-processing of the design image [10], feature extraction of the design image, and evaluation based on the extracted features. The image pre-processing

is to remove the noise from the design image, which is beneficial to the subsequent processing. The feature extraction of the design image is realized by the image processing technology, including the extraction of both texture and color features. The evaluation of the design is to calculate and judge the design with the evaluation model according to the extracted features. This paper selects a CNN to construct the evaluation model. The CNN algorithm can directly recognize images but evaluates images from a holistic point of view. The purpose of this paper is to recognize and evaluate the image element of clothing. The evaluation is based on the angles of texture and color matching. Applying CNN on images directly may produce influence on the other factors in clothing images, so the texture and color are extracted before the use of CNN. The specific steps are as follows.

(1)The image of the clothing image element design is input and pre-processed by the Gaussian filtering method [11]. The relevant formula is:

$$\begin{cases} G(x, y) = \frac{\exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)}{\sqrt{2\pi}\sigma} \\ g(x, y) = \sum G(x+a, y+b) \otimes f(x+a, y+b), (1) \\ a \in Z\left\{-\frac{n-1}{2}, \frac{n-1}{2}\right\} \\ b \in Z\left\{-\frac{m-1}{2}, \frac{m-1}{2}\right\} \end{cases}$$

where G(x, y) is the Gaussian filter, (x, y) is the coordinates of the pixel point, σ is the standard deviation of the Gaussian function, g(x, y) is the pixel value after Gaussian filtering, *a* and *b* are the step size of pixels, both integers, $m \times n$ is the size of the filter box when filtering, and \otimes is the convolution sign.

(2) Feature extraction is performed after preprocessing, including texture and color extraction. The texture features are extracted using the canny operator. The image needs to be smoothed using the Gaussian filter first before using the Canny operator [12], which has been completed in the previous step, so the image is processed directly using the Sobel operator template in a size of $3 \times$ 3. The gradient amplitude and gradient direction angle of every pixel are calculated using the Sobel operator template, and the calculation formula is:

$$\begin{cases} G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \otimes f(x, y) \\ G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \otimes f(x, y) \\ |G| = \sqrt{G_x^2 + G_y^2} \\ \theta = \arctan\left(\frac{G_y}{G_x}\right) \end{cases}$$

where G_x and G_y are the horizontal and vertical gradients of the pixel, f(x, y) is the pre-processed image, |G| is the gradient amplitude of the pixel, and θ is the directional angle of the pixel gradient. The non-maximum suppression algorithm is used to select pixels that can be used as edge points based on their gradient amplitude and direction angle. Then, the pixels are filtered using dynamic thresholding [13] to complement and connect the edge points extracted by the non-maximal suppression algorithm to make the edges as continuous as possible.

(3)Colors are extracted from the pre-processed image. This paper uses the density peak clustering algorithm [14] to extract the main color of the clothing. A large number of colors are usually used in the innovative design of clothing image elements, and the evaluation of designs also needs to consider color matching. In this paper, the density peak clustering algorithm used for color extraction does not require a prior determination of the number of clustering types and clustering centers. First, the image is converted into the color space of CIE Lab, and then the local density and relative distance of every pixel are calculated:

$$\begin{cases} \rho_{i} = \frac{\sum_{j=1}^{N} \exp\left(-\frac{1}{2} \left(\frac{d_{ij}}{d_{c}}\right)^{2}\right)}{d_{c}^{3} (2\pi)^{3/2}} \\ d_{ij} = \sqrt{(L_{i} - L_{j})^{2} + (a_{i} - a_{j})^{2} + (b_{i} - b_{j})^{2}} \\ \delta_{i} = \begin{cases} \min\left\{d_{ij}\right\} & \rho_{i} \leq \rho_{j} \\ \max\left\{d_{ij}\right\} & else \end{cases} \end{cases}$$

$$(3)$$

where ρ_i is the local density of pixel point i, N is the number of pixel points, d_{ij} is the distance between pixel points i and j, i.e., the color difference, d_c is the cut-off distance, L_i , a_i , and b_i are the parameters of pixel point i in the CIE Lab color space, and δ_i is the relative distance of pixel point i. Then, the decision diagram of the pixel points is drawn with the local density as the horizontal coordinate and the relative distance as the vertical coordinate. Every point in this decision diagram represents a pixel point, the point which is far away from the coordinate axis is taken as the center point of clustering, and the remaining pixel points are clustered.

(4)The texture and color extracted in steps (2) and (3) are input into the CNN model [15] for calculation. The basic structure of the CNN model includes the input layer, convolutional layer, pooling layer, and output layer. The convolutional and pooling layers in the middle are equivalent to the hidden layer, and their quantities are adjusted according to the demand. The basic principle of the CNN model is to perform convolution calculation on the input sample with convolution kernels in the convolution layer [16]:

$$x_j^l = f\left(\sum_{j \in M} x_i^{l-1} \cdot W_{ij}^l + b_j^l\right), (4)$$

where x_j^l is the feature map obtained by convolution kernel convolution [17], x_i^{l-1} is the feature output after the last convolution and pooling, W_{ij}^l is the weight parameter, b_j^l is the bias, M is the number of convolution kernels, and $f(\bullet)$ is the activation function. After obtaining the convolutional feature map, in order to reduce the computation of the evaluation model and improve the evaluation efficiency, the convolutional features are compressed in the pooling layer, a pooling box in a certain size slides over the convolutional features of a certain step length, and the values in the pooling box are compressed in the sliding process, either by taking the maximum value of them or by taking the average value in the box [18]. After multiple convolution and pooling operations, the feature map is calculated in the output layer to obtain the evaluation result.

If the CNN evaluation model is in the training phase, after the evaluation results are obtained in the output layer, the evaluation results need to be compared with the expected results of the sample labels to calculate the deviation between them; if the deviation is within the allowed range, the training is completed; if the deviation exceeds the allowed range, the weight parameters in the CNN evaluation model are reversely adjusted according to the deviation, and the process is repeated several times until the error converges [19].

3 Example analysis

3.1 Analyzed objects

This paper analyzed three innovative designs of clothing image elements. Figure 2 shows the works completed based on the three designs, which were No. 1 work named "*Zen*", No. 2 work named "*Spiritual Dream*", and No. 3 work named "*Spirit of Feather*".



No. 2 work "Spiritual Dream"





No. 3 work "Spirit of Feather"

Some clothing elements of No. 3 work

Figure 2: Three designs for innovative design of clothing image elements

3.2 Analysis method

This paper proposed to evaluate the clothing design with the image processing-based CNN evaluation model, and the specific steps are described above. Before evaluating the design using the CNN algorithm, the evaluation model was trained with training samples, and the training process has been described above.

The relevant parameters of the CNN model are as follows. There were two convolutional layers containing 32 convolutional kernels (2×2) , one pooling layer containing a 3×3 pooling frame, two convolutional layers containing 16 convolutional kernels (2×2) , and one pooling layer containing a 3×3 pooling frame.

The sigmoid activation function was used in the convolutional layer [15]. The pooling layer used to maxpool. The learning rate was set as 0.1. In addition, in the image processing techniques used for texture and color extraction within the evaluation model, the filter frame for Gaussian filter preprocessing was 3×3 , and d_c was set as 3 for color extraction.

Middle layer	Weig	Target layer	Weig
	ht		ht
Texture	0.5	Novelty degree	0.6
composition		Appropriate	0.4
		degree	
Color layout	0.5	Distinctive	0.3
		degree	
		Reasonable	0.2
		degree	
		Innovative	0.5
		degree	

Table 1: The hierarchical structure and weights in the manual evaluation of designs

Labels in the training samples used to train the evaluation model were manually added, which aimed to ensure that the evaluation standard, i.e., the way of thinking, was close to human evaluation as possible in the training process. This paper labeled the evaluation results using the AHP method. Table 1 shows the hierarchical structure and weights in the evaluation of designs. In the AHP method, the survey content of the questionnaire was designed according to the items in the target layer. Ten experts who have been engaged in clothing design for more than five years scored the graphic design using the 10-point system, and the average score was calculated. Then, the score of the middle layer item was calculated according to the score of every target layer and the corresponding weight. The highest layer, i.e., the final score of the design, was further calculated based on the score and weight of the middle layer items.

In the process of training and preliminary testing of the evaluation model, the samples used were selected from a variety of clothing designs on the market, and a total of 1000 sets were collected, of which 70% were used as the training set and 30% as the test set. In the training process, the results calculated by the CNN evaluation model were the score of the target layer, the middle layer, and the highest layer item. In short, the evaluation model, after getting the target layer items, did not rely on the weights in the AHP method but directly obtained the score of the middle layer and top layer items according to the mined hidden laws. The difference between the score calculated by the evaluation model and the score label of the items of different hierarchies within the sample was taken as the training error.

In order to further test the effectiveness of the CNN evaluation model, this paper also compared it with the BPNN evaluation model. The BPNN evaluation model also used image processing techniques to extract texture and color features first and then performed forward calculations on the features according to the trained parameters to obtain the results.

The evaluation model that has undergone a preliminary test evaluated the three designs provided, and the evaluation results were compared with the manual evaluation results.

3.3 Analysis results

Figure 3 shows the error comparison between the BPNN evaluation model and the CNN evaluation model. The items used for error comparison included the novelty degree, appropriate degree, distinctive degree, reasonable degree, and innovative degree of the target layer, the texture composition and color layout of the middle layer, and the design score of the top layer. As could be seen from Figure 3, the evaluation error of the CNN evaluation model was significantly smaller for either of the items. In the range of the target layer, the evaluation errors of both evaluation models for different items varied, while in the range of the middle layer and top layer, the evaluation

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errors of both evaluation models did not fluctuate much. In addition, comparing the evaluation errors of the model at different hierarchies, it was found that as the hierarchical level became higher, the evaluation error of the evaluation model in the range of that hierarchical level also increased. Overall, the CNN evaluation model was superior to the BPNN evaluation model in the evaluation performance.



Figure 3: Comparison of evaluation error between the BPNN evaluation model and the CNN evaluation model

Midd le layer	Texture composition		Color layout		
Weig ht	0.5		0.5		
Targe t layer	Nove lty degre e	Approp riate degree	Distinc tive degree	Reason able degree	Innova tive degree
Weig ht	0.6	0.4	0.3	0.2	0.5
No. 1 (man ual)	8.3	8.9	5.3	8.6	9.1
No.1 (BPN N)	7.5	8.1	4.6	8.1	8.5
No. 1 (CN N)	8.2	8.8	5.3	8.6	9.0
No. 2 (man ual)	8.5	8.6	7.8	8.7	9.2
No. 2 (BPN N)	8.0	7.9	7.1	8.1	8.3
No. 2 (CN N)	8.5	8.5	7.7	8.7	8.2
No. 3 (man ual)	7.6	8.6	6.9	8.7	9.2
No. 3 (BPN N)	7.0	7.9	5.9	7.9	8.3

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No. 3	7.6	8.6	6.9	8.6	9.2
(CN					
N)					

Table 2: Manual evaluation results and the evaluation results of the BPNN and CNN evaluation models for the three designs

The scores given by the ten experts for the three designs of clothing image elements were collected and shown in Table 2. The results of the evaluation using the BPNN and CNN evaluation models are also shown in Table 2. After calculation, the final scores of evaluation by manual, the BPNN evaluation model, and the CNN evaluation model for No. 1 work were 8.2, 7.5, and 8.1, respectively; the final scores for No. 2 work were 8.6, 7.9, and 8.3, respectively; the final scores for No. 3 work were 8.2, 7.4, and 8.2, respectively. It was found that there was not much difference in the final score between the three works. The reason for this result is that the evaluation put emphasis on whether the image elements were reasonably matched and did not involve the type of clothing. Taking the scores of manual evaluation as the standard, it was seen that all three designs were excellent. Moreover, it was seen from either the data in Table 2 or the final score obtained through a calculation that the results obtained by the CNN evaluation model were closer to the manual evaluation results.

4 Discussion

With the improvement of living standards, people's pursuit of clothing is no longer limited to practical, but they began to pay more attention to the aesthetic appearance. Excellent clothing image design can attract customers' attention in the market competition, so the innovative design of clothing image elements is very important in clothing design. In the innovative design of clothing image elements, it is necessary to constantly evaluate the design plan and make corresponding adjustments. However, the evaluation of clothing designs is relatively subjective, and in order to make the evaluation as objective as possible, the evaluation of multiple people is necessary. This traditional approach is inefficient, while the emergence of intelligent algorithms provides a new way of clothing design evaluation.

This paper used image processing techniques to extract texture and color features from clothing image designs and then evaluated the designs using the CNN evaluation model based on the extracted features. The example analysis results of the CNN evaluation model are presented above. The CNN evaluation model was compared with the BPNN evaluation model through test samples. The final results showed that the CNN evaluation model outperformed the BPNN evaluation model. Finally, three designs were evaluated, and the results also showed that the results of the CNN evaluation model were closer to the manual evaluation results than the BPNN evaluation model. The three designs were analyzed based on the results of the manual evaluation and the CNN evaluation model. The image design element of No.1 work "Zen" is derived from Mahā-mayūrī-vidyā-rājñī, which presents its posture as half demon and half Buddha. The color design reflects the rich color of the peacock element through the form of multi-color dyeing. The head and body ornaments are decorated with Miao silver or old metal texture. The fabric of the dress imitates the peacock's feathers. The top is tube-style, and the skirt is flowing, reflecting its fairy atmosphere. The covered edge of the skirt is added with metal ornaments.

The image design idea of No. 2 work "Spiritual Dream" is mainly derived from the cold and reserved feeling in the movie "Frozen". The main color of the clothes is silver gray and light gray. See-through, mesh fabrics were used. It is a close-fitting fishtail skirt with a long trailing, decorated with a large number of silver rhinestones and laces. The shoes are derived from Cinderella's crystal high heels. The overall design is lightsome and reserved without losing the fairy beauty.

The image design theme of No. 3 work "Spirit of *Feather*" is a wedding dress. The designer of the work aims to express the idea that people float in the world, like feathers floating in heaven and earth, and the true essence is to pursue original nature rather than deliberately pursue. This design combines feathers, bright diamonds, and tube-bubble skirt, making the wedding dress fashionable and princess-like.

5 Conclusion

This paper extracted texture and color features from the innovative designs of clothing image elements with the image processing technology and then evaluated the designs with the CNN evaluation model. The CNN evaluation model is compared with the BPNN evaluation model through the example analysis. The results are as follows. In the test set comparison experiment, the evaluation performance of the CNN evaluation model was significantly better than that of the BPNN evaluation model. The evaluation results of the three designs further verified that the evaluation results of the CNN evaluation model for the designs were closer to the manual evaluation results. The analysis of the three designs based on the manual evaluation and the CNN evaluation model showed that all the three designs effectively combined different image elements and achieved sound innovative effects.

References

- [1] Yoxall A, Gonzalez V, Best J, Rodriguez-Falcon E M, Rowson J (2019). As you like it: Understanding the relationship between packing design and accessibility. *Packaging Technology and Science*, 32. https://doi.org/10.1002/pts.2466
- [2] Wang F (2015). Research on Design Factors and Packing Design Method of Preschool Children's Food Packing Security. Advance Journal of Food Science and Technology, 9, pp. 434-438. https://doi.org/10.19026/ajfst.9.1898
- [3] Alexa A (2015). BOOKS: GRAPHIC DISCOURSE. *Metropolis*, 34, pp. 168-168.

- [4] Ota S, Takenouchi H, Tokumaru M (2017). Kansei Retrieval of Clothing using Features Extracted by Deep Neural Network. *Transactions of Japan Society of Kansei Engineering*, 16. https://doi.org/10.5057/jjske.TJSKE-D-17-00003
- [5] Zhang L, Xu Z, Zhang Y (2021). Realization of clothing image contour extraction and collar segmentation. *Journal of Physics Conference Series*, 1790, pp. 012091. https://doi.org/10.1088/1742-6596/1790/1/012091
- [6] Zhang N, Pan R, Wang L, Wang S, Xiang J, Gao W (2019). Automatic seam pucker evaluation using support vector machine classifiers. *International Journal of Clothing Science & Technology*, 31, pp. 2-15. https://doi.org/10.1108/IJCST-03-2018-0046
- [7] Wang S (2020). 3D Printing clothing design based on wireless sensors and FPGA. *Microprocessors and Microsystems*, 2020, pp. 103407. https://doi.org/10.1016/j.micpro.2020.103407
- [8] Qian L, Xia Y, He X, Qian K, Wang J (2018). Electrical modeling and characterization of siliconcore coaxial through silicon vias in threedimensional integration. *IEEE Transactions on Components, Packaging, and Manufacturing Technology*, 8, pp. 1336-1343. https://doi.org/10.1109/TCPMT.2018.2854829
- [9] Lu J (2022). Innovative application of recombinant traditional visual elements in graphic design. *Informatica*, 46, pp. 101-106. https://doi.org/10.31449/inf.v46i1.3838
- [10] Liao K H (2015). The abilities of understanding spatial relations, spatial orientation, and spatial visualization affect 3D product design performance: using carton box design as an example. *International Journal of Technology & Design Education*, 27, pp. 1-17. https://doi.org/10.1007/s10798-015-9330-3
- [11] Chtioui I, Bossuyt F, de Kok M, Vanfleteren J, Bedoui M H (2016). Arbitrarily Shaped Rigid and Smart Objects Using Stretchable Interconnections. *IEEE Transactions on Components Packaging & Manufacturing Technology*, 6, pp. 533-544. https://doi.org/10.1109/TCPMT.2015.2511077
- [12] Chtioui I, Bossuyt F, de Kok M, Vanfleteren J, Bedoui M H (2016). Arbitrarily Shaped Rigid and Smart Objects Using Stretchable Interconnections. *IEEE Transactions on Components Packaging & Manufacturing Technology*, 6, pp. 533-544. https://doi.org/10.1109/TCPMT.2015.2511077
- [13] Wang S, Huang Y, Rogers J A (2015). Mechanical Designs for Inorganic Stretchable Circuits in Soft Electronics. *IEEE Transactions on Components Packaging & Manufacturing Technology*, 5, pp. 1201-1218.

https://doi.org/10.1109/TCPMT.2015.2417801

[14] Bhandari A K, Kumar A, Chaudhary S, Singh G K (2016). A novel color image multilevel thresholding based segmentation using nature inspired optimization algorithms. *Expert Systems with Applications*, 63, pp. 112-133. https://doi.org/10.1016/j.eswa.2016.06.044

- [15] Benkaddour M K (2021). CNN based features extraction for age estimation and gender classification. *Informatica*, 45, pp. 697-703. https://doi.org/10.31449/inf.v45i5.3262
- [16] Lee D, Plataniotis K N (2016). Toward a No-Reference Image Quality Assessment Using Statistics of Perceptual Color Descriptors. *IEEE Transactions on Image Processing A Publication of the IEEE Signal Processing Society*, 25, pp. 3875-3889. https://doi.org/10.1109/TIP.2016.2579308
- [17] Ni H (2020). Face recognition based on deep learning under the background of big data.

Informatica, 44, pp. 491-495. https://doi.org/10.31449/inf.v44i4.3390

- [18] Chaudhuri A (2021). Hierarchical modified fast R-CNN for object detection. *Informatica*, 45, pp. 67-81. https://doi.org/10.31449/inf.v45i7.3732
- [19] Li C, Guo J, Guo C (2017). Emerging from Water: Underwater Image Color Correction Based on Weakly Supervised Color Transfer. *IEEE Signal Processing Letters*, 25, pp. 323-327. https://doi.org/10.1109/LSP.2018.2792050