Style-Oriented Representative Paintings Selection

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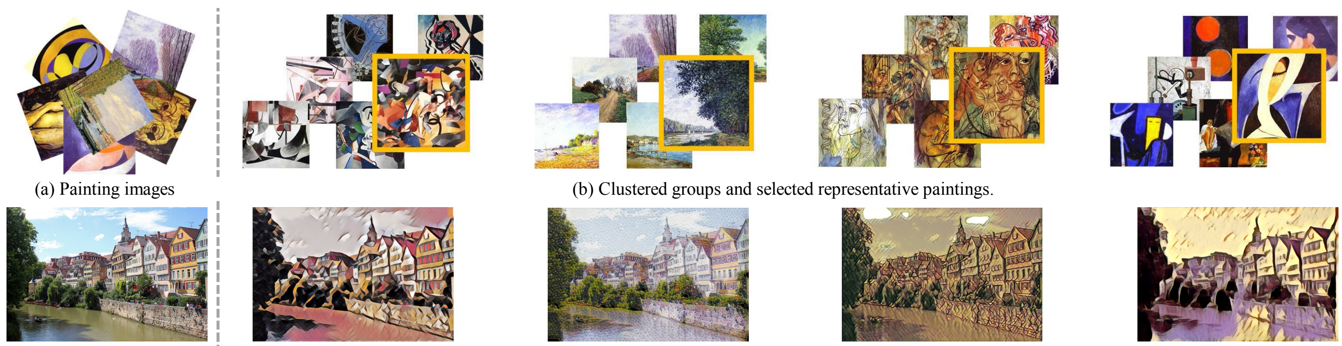

(a) Painting images (b) Clustered groups and selected representative paintings.

(c) Input photo (d) Transfer the input photo into different styles weighted by representative painting in each group.

Figure 1: Representative paintings selection by style-oriented *clustering and rejection*. For an input photo, using different groups of painting images can generate images of different styles. The painting images in (a) and (b) are by Francis Picabia.

CCS CONCEPTS

• **Computing methodologies → Computational photography**; *Image processing*;

KEYWORDS

Representative painting, rejection, style transfer

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1 INTRODUCTION

Style transfer is used as a means to render an image in the artistic style of another one. An ideal style transfer algorithm should be able to extract and represent the semantic image content from the source image and then render the content in the style of the example image. The decomposition of content and style in artistic images is bound to the coupling between the source content and the example style. Previous image style transfer works only focus on expressing the artistic style of a specific painting [Gatys et al. 2016; Liao et al. 2017]. However, the painting styles of an artist may vary throughout all his/her painting works. Usually we need to find multiple art works to represent an artist's creation characteristics, so that we can generate a series of stylized images with the artist's painting styles. In this work, we proposed a novel method to select representative paintings of an artist. Different from traditional clustering problems, we don't try to assign each image a correct label. We focus on finding the most representative ones in all the paintings. We first use K-means to preliminary cluster an artist's paintings. Clustering centres are the original representative images. Then we employ *rejection* to pick out the unrepresentative and confused samples. Finally, we update the K classes and get the new representative images.

2 ALGORITHM DETAILS

When expressing scenes of different contents, the painting styles of an artist often vary when using different strokes and colourizations. In order to categorize a series of paintings of an artist into different classes and find the representative style of each class, we need to construct a feature vector F_{cs} to describe the content and style features of a painting image.

Our algorithm starts with precomputing feature maps by a VGG-19 network which is trained on the ImageNet database for object recognition. Let $F_j(x)$ be the activations of the jth layer (convolutional layer) when processing the image x, which is a feature

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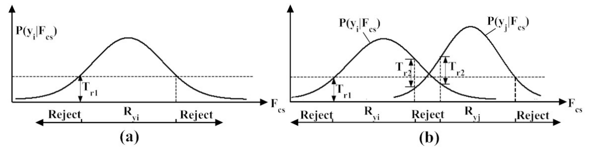

Figure 2: Rejection mechanism.

(a) Representative images before rejection (b) Representative images after rejection

Figure 3: Rejection example. The images with red frames are representative images of each class.

map of shape $C_j \times H_j \times W_j$. We transform the feature map into a 1D vector f_c containing $C_jH_jW_j$ elements and use it as the feature vector of the image *content*. Define the Gram matrix $G_j(x)$ to be the $C_j \times C_j$ matrix whose elements are given by:

$$G_j(x)_{c,c'} = \frac{1}{C_jH_jW_j} \sum_{h=1}^{H_j} \sum_{w=1}^{W_j} F_j(x)_{h,w,c} F_j(x)_{h,w,c'}, \qquad (1)$$

where $G_j(x)$ is the inner product between the vectorized feature maps. In our algorithm, the feature space consists of the correlations between the different filter responses, where the expectation is taken over the spatial extent of the feature maps. Gram matrix calculates the correlations between these features [Gatys et al. 2016]. The elements on the diagonal of the Gram matrix reflect the numbers of times that the features appear. Thus, the Gram matrix can represent the painting style of an image. When measuring the style difference between two images, we can just compare the differences between their Gram matrices. We transform the Gram matrix into a 1D vector f_s containing C_jC_j elements and use it as the feature vector of the image *style*. Finally, we formulate the image content-style feature vector as $F_{cs} = [f_c, f_s]$.

We develop a *clustering and rejection* framework to categorize an artist's paintings and find the representative painting of each class. Firstly, K-means is conducted to cluster an artist's paintings into K classes based on the content-style feature F_{cs}. However, sometimes there may exist some images that are close to multiple clusters. This will affect the accuracy of representative painting extraction. Therefore, we integrate the concept of "rejection" to find the images which cannot be clearly classified in each class and refuse them when calculating the new representative images. We utilize Bayesian probability distribution to find the rejected images. Class-conditional-probability density is used to represent each class. Denote the image feature set of each class as $\mathcal{F} = \{F_{cs}^1, F_{cs}^2, \cdots, F_{cs}^n\}$. Assume the elements in $\mathcal{F}$ are mutually independent and obey the Gaussian distribution, then for each class y_j, we formulate the class-conditional-probability density of an image feature vector as:

$$P(F_{cs}^i|y_j) = \frac{1}{\sqrt{(2\pi)^k |\sum_j|}} e^{-\frac{1}{2}(F_{cs}^i - \mu_j)^T \sum_j^{-1} (F_{cs}^i - \mu_j)}, \qquad (2)$$

where μ_j and $\sum_j$ are computed by using maximum similarity estimation. Thus, we can get the original probability $P(y_j|F_{cs}^i)$ by $P(y_j|F_{cs}^i) = \frac{P(F_{cs}^i|y_j)P(y_j)}{P(F_{cs}^i)}$. $P(y_j|F_{cs}^i)$ indicates the probability of image F_{cs}^i belonging to class y_j. However, the original probability may be significantly affected by the paintings that are hard for style distinguishing. To boost the effectiveness of representative painting selection, we adopt *rejection* mechanism. As illustrated in Figure 2, image F_{cs}^i classified to class y_j will be rejected:

- if $P(y_j|F_{cs}^i)$ is not higher than a threshold T_{r1}, which means image F_{cs}^i is more likely to be an outlier of y_j, as shown in Figure 2(a);
- if the difference between the probability of image F_{cs}^i belonging to class y_i and class y_j is not higher than a threshold T_{r2}, which means image F_{cs}^i is easy to be confused, as shown in Figure 2(b).

In our experiments, T_{r1} and T_{r2} are respectively set as 50% and 20% of the peak value of $P(y_j|F_{cs}^i)$. Then, we update the K classes and get the new representative image with the highest $P(y_j|F_{cs}^i)$ in each class.

3 RESULTS AND CONCLUSION

In Figure 1, we show a painting clustering and representative paintings selection result by using the paintings of Francis Picabia ($K = 6$ in this experiment). We can see that our algorithm can accurately find the representative painting images of an artist based on the painting styles. Figure 3 shows the rejection examples. Apparently, by integrating rejection, the representative images can accurately present the creation characteristics of the artist. Finally, we show style transfer results by using the method of [Dumoulin et al. 2017]. For each class, we learn an N-style network on all painting images in it by using the artistic style combination scheme. We use a larger weight for the representative image during training process to make the model primarily capture the color palette and texture of the representative image. As shown in Figure 1, we can generate artistic images with different painting styles of a specific artist.

In summary, this paper presents a novel algorithm to select multiple representative painting images from the art works of an artist. In the future, we will explore a more intelligent style transfer method that can combine the artistic styles of an artist, by using the representative paintings as guidance.

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