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Poster

Facial-Expression-Aware Emotional Color Transfer

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Abstract

Emotional color transfer aims to change the evoked emotion of the source image to that of the target image by adjusting color distribution. Most of existing emotional color transfer methods ignore the facial expression features in the image. Therefore, we propose a new facial-expression-aware emotional color transfer framework. We firstly predict the emotion label of the image through the emotion classification network. Then, emotion labels are matched with pre-trained emotional models. Finally, we use the matched emotion model to transfer the color of the target image to the input image. Experiments demonstrate that our method outperforms the state-of-the-arts, which can successfully capture and transfer sophisticated emotion features.

CCS Concepts

•***Imaging and Video*** → *Image Processing;* •***Methods and Applications*** → *Artificial Intelligence; Entertainment;*

1. Introduction

Emotional color transfer is an image manipulation which changes the evoked emotion of the source image and transforms it to new emotions by adjusting color distribution. There are many traditional methods for emotional color transfer between images. Yang and Peng [YP08] first proposed an emotional color transfer algorithm. Wang et al. [WJC13] developed an automatic emotional color transfer system which can adjust the color of the image to satisfy an emotion word. Later, Ryoo [Ryo14] proposed a new method for emotional color transfer which used facial features to identify emotions of a given images. However, they do not take the facial expression features of the image into account, but simply account for the color information of the image. In recent years, convolutional neural network (CNN) has been successfully applied in image analysis [FACO17], and feature learning [XXS*15], etc. Peng et al. [PCSG15] proposed a new emotional color transfer method which selected images that represent emotion distribution of target image. However, extracting the emotion features of natural images is tedious and ambiguous.

This paper proposes a new facial-expression-aware emotional color transfer framework based on CNN, which transfers the color distribution of evoked emotion of a target image without severely interfering the high-level semantic content of the source image. Our framework categorizes the images with facial features to get the emotion label, and then transfer the emotion of the images according to the corresponding model of the label.

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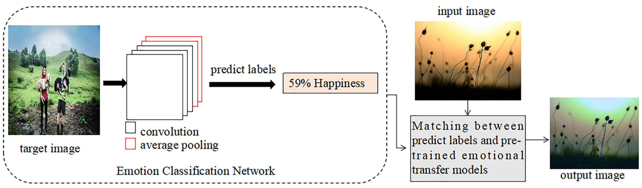

Figure 1: *The framework of the proposed facial-expression-aware emotional color transfer based on convolutional neural network.*

2. Method

We design a new facial-expression-aware emotional color transfer framework based on CNN. The flow chart of our framework is shown in Figure 1.

Emotion classification network : We design an emotion classification network including three convolutional layers, two pooling layers, four activiation layers, two dropout layers, two fully-connected layers, a flatten layer and a final classification layer. We randomly split Face-Emotion database into training set and testing set with the proportion of 8:2 and then train an emotion classifition model by using our emotion classification network. Besides, the number of output nodes is changed to 7 so that they can represent the probability of the input image being classified into each emotion category in Face-Emotion database. In the predicting phase, the probabilities of all emotion categories are normalized so that their sum is 1.

Pre – training of emotion model The pre-training network of emotion model mainly includes three components, namely a low-

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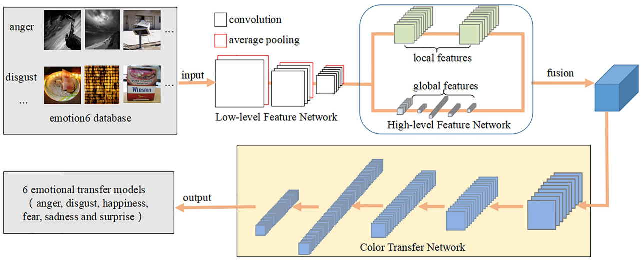

Figure 2: *The pre-training network of emotion model.*

level feature network, a high-level feature network, and a color transfer network. The framework of the pre-training network is shown in Figure 2. We use 10 convolutional layers and 3 pooling layers to obtain the low-level information of the image. The high-level features is obtained by further processing the low-level features with four convolution layers followed by three fully-connected layers. This results in a 256-dimensional vector representation of the image. In order to combine global features and local features, we introduce the fusion layer which contains a 256-dimensional vector with (intermediate level) local image features. This layer is used to incorporate global features into local features as:

$$y_{\mu,\upsilon}^{fusion} = \sigma(b + W \begin{bmatrix} y^g \\ y_{\mu,\upsilon}^l \end{bmatrix}) \tag{1}$$

where $y_{\mu,\upsilon}^{fusion}$ is the output features of the fusion layer at the coordinate (μ,υ), y^g is the global emotion classification feature, $y_{\mu,\upsilon}^l$ is the local feature at coordinate (μ,υ). W is the weight matrix and b is the bias vector. W and b are parameters that can be iteratively learned in the network. After obtaining the fusion features, we would increase the dimension of the features by convolutional layers and deconvolutional layers.

In the training phase of color transfer layer, we use the Mean Square Error (MSE) standard in color transfer layer and cross-entropy loss in high-level layer. The overall loss of our network becomes:

$$LOSS = L(y^{col}) + \eta L(y^{fus}) \tag{2}$$

where $L(y^{col})$ is the loss value of the color transfer layer, $L(y^{fus})$ is the loss value of the high-level feature network, and η is the coefficient between the color transfer layer and the high-level feature network.

3. Result

In order to verify the effectiveness of the proposed framework, we selected images from the database as input images and used our framework to change the emotions of these images. For each image, we selected the target image according to one of six categories: happiness / fear / disgust / anger / sadness / surprise. We used our framework to generate output images for each input image. Figure 3 shows the results of our framework. It can be seen from Figure 3 that the emotion distribution of our result image is similar to that of the target image.

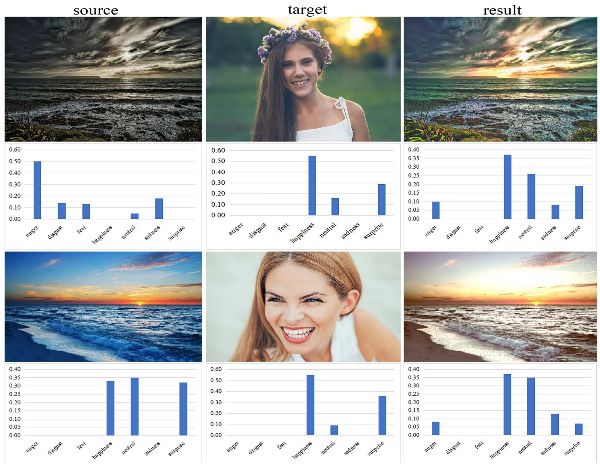

Figure 3: *Examples showing the results of emotional color transfer with different target images. In each example, the transferred image has closer evoked emotional distribution to that of the target image.*

4. Conclusion and future work

We proposed a new facial-expression-aware emotional color transfer framework based on CNN, which can change the emotion of the input image to the target. And we proposed an accurate sub-network of emotion classification network to classify the color images with facial features. In order to train the emotion model effectively, we established a new emotion database named as Face-Emotion database, in which all images are face images. Since the database is acquired manually, our training set and test set are not abundant enough. In the future work, we would expand the database so as to obtain more accurate results. We would also transfer the facial expression of the target image to the source image.

Acknowledgements

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