Multi-culture Facial Attractiveness Enhancement Based on Double Knowledge Transferring

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Abstract

This paper presents a novel double knowledge transferring method to solve the multi-culture facial attractiveness enhancement problem. The existing enhancement of facial attractiveness methods just focus on one particular culture and assume the beautification model learned in one culture could be used in other cultures without adaptation. However, for the people in different cultures who do not share the same characteristics, existing models do not perform well. To address this problem, we employ the double knowledge transferring method to reduce data diversity. First, to reduce the aesthetic differences among cultures, we apply regressive manifold regularization to train a rating transferring function; second, to reduce the facial geometry feature differences, we use latent MLT (Multi-Task Learning) algorithm to find appropriate feature mappings. Treat Chinese as source culture, we apply the proposed algorithm to Malay people and demonstrate its effectiveness.

Keyword: Facial attractiveness, transfer learning, manifold regularization.

I. Introduction

In modern society, almost all the people would like their facial photographs look more attractive and feel more confident about themselves. With the increasing attention to beauty, the facial attractiveness enhancement has attracted more and more interest from research communities.

Currently, the beautification methods of the facial photograph can be divided into two types according to their contents: the texture and the shape. The texture beautification method is always used to retouch the facial image texture. As in [14], based on the assumption that homogeneous skin was generally more attractive, this method exploited a set of image filters to reduce facial imperfections, like wrinkles and moles. And in [15], it automatically beautified facial portraits, replacing the original background with a virtual one and altering the skin color of the subjects by means of color temperature estimation. Meanwhile, the shape beautification always focuses on the modification of the facial geometry. The work in [16] is an earlier study of the shape beautification, which implemented a system that could replace an individual's facial features with corresponding features of another individual. However, the facial image generated by this method may look unnatural, since perception of attractiveness is affected also by the relative positions of the facial parts. [1, 17] are methods which use machine learning to enhance the facial attractiveness. As in [1], it first trained a beautification engine based on datasets of faces with accompanying facial attractiveness ratings; then given a frontal photograph, the engine predicted a face mesh with higher attractiveness rating; finally more beautiful photograph could be obtained by morphing the original image to the target mesh. While in [17], it used KNN to obtain the target face mesh from the beautiful faces database.

A major problem of the machine learning methods is that they just focus on one culture and does not consider the impact of cultural differences. Although there are several studies indicate that the facial attractiveness is a universal notion, transcending the boundaries between different cultures, the differences obviously exist. In practice, different cultures may have significantly different aesthetic values. To illustrate this point, we empirically studied the aesthetics over different cultures. For example, the criteria for beauty differ among the Chinese and Malay populations. This will directly cause failure if we use one culture's data for training and another culture's data for testing. Since it is expensive to recollect a large amount of data for calibrating the target cultures, a more practical way might be to collect a small amount of data in the new culture, and integrate them with a large amount of data collected before in the source culture. If we can train an accurate model on the combined data, it would save much human effort. This problem is referred to as a multi-culture image attractiveness enhancement problem. The key component in our approach is how to reconstruct the training data of source culture to make it useful for the target culture.

Until now, a lot of works about transfer learning have been proposed and applied successfully in such kind of similar real world applications. In [2], the authors applied transfer learning on web document classification with the goal to classify a given web document into several predefined categories. Because the data between web sites may be different, it's not reasonable to directly apply one web page classifier learned from one web site to the other web site. The experiments showed that it was truly beneficial to transfer the classification knowledge into a new domain. In [3], the authors identified WiFi-based indoor localization problem as a transfer learning problem, since the WiFi data are highly dependent on contextual changes. By identifying several important cases of knowledge transfer, the experiments showed it could transfer localization models over time, across space and across client devices effectively.

However, for those transfer learning problems, there is an essential precondition that the label between source and target task should be the same or under the same reference system. But in our multi-culture facial attractiveness enhancement problem, because the aesthetics are different among cultures, the label which is the attractiveness rating of the facial image in one culture may be quite distinct from the other culture. This leads us not use the traditional transfer learning method directly. This paper proposes a novel double knowledge transferring method, which could accurately reconstruct the source culture data according to the calibration of the target culture data by taking advantage of the information from both the label and feature data. Specifically, our approach consists of two transferring phases, the rating transferring phase and the feature transferring phase. In the rating transferring phase, for the difference of the aesthetics among cultures, we need to transfer the facial attractiveness ratings. In the feature transferring phases, due to the difference of the geometry facial features among countries, we need to reconstruct the facial features.

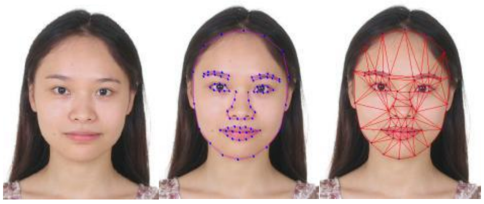
II. Data Preparation and Processing

A. *Facial Image Collection*

Our facial image dataset contains two main parts: the facial photographs of source and target culture countries, as shown in Fig.1 (a). To reduce the influence effects of age, skin color, facial expression and other irrelevant factors, the subject was confined to people in frontal view with neutral expression. Furthermore, to get a good representation of the notion of beauty, the dataset was also required to encompass both extremes of facial beauty: very attractive as well as very unattractive faces.

Dataset 1: we choose China as the source culture country and collect 100 people's photos for both female and male. They are all in frontal view with neutral expression. Face and hair comprise the entirety picture. The images all have identical lighting conditions and nearly identical orientation, in excellent resolution, with no obscuring or distracting features, such as jewelry and glasses.

Dataset 2: we choose Malay as the target culture country, and collect 25 people's photos for both female and male. This dataset meet the same criteria with the dataset 1.



(a) (b) (c)

Fig.1. (a) is samples of dataset, (b) is the 84 feature points of the ASM search, and (c) is the 234 distance edges.

B. *Feature Extraction*

For the facial images dataset, we first automatically extract a total of 84 feature points from each face, as shown in Fig.1 (b). The feature points are located on the outlines of eight different facial features: two eyebrows, two eyes, the nose, the inner and outer boundaries of the lips and the boundary of the face. Then, for these 84 feature points we could construct a Delaunay triangulation.

The triangulation consists of 234 edges, and the lengths of these edges in each face form its 234-dimensional distance vector, as shown in Fig.1 (c).

C. *Rating collection*

In this paper, we collect two parts of ratings, as shown in Fig.2. In the first part, since it's not easy for us to obtain the ratings of the target culture (Malays) and the amount of dataset2 is relatively small, then for dataset2, we gather the ratings2 from both the source and target culture to obtain the relationship of aesthetics between them; In the second part, due to the large size of dataset1, we just gather the ratings of the source culture (Chinese). For the corresponding ratings1 of the target culture, they would be computed by the rating transferring function stated in the next section.

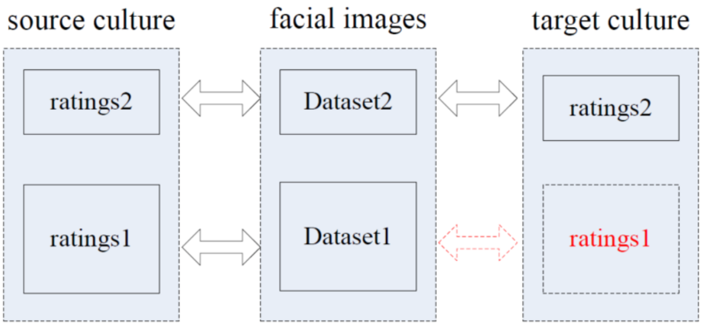


Fig.2. The ratings of datasets

The rating process is as follows: The raters were asked to first scan through the entire dataset, to obtain a general notion of the relative attractiveness of the images; then, they were instructed to use the entire attractiveness scale, and to consider only facial attractiveness in their evaluation. The images were shown in random in order to eliminate order effects; At last, a rater could look at a picture for as long as he or she liked and then score it. The raters were free to return to pictures they had already seen and adjust their ratings.

For the source culture, we invited 19 Chinese observers, 10 male and 9 female, all in their twenties; for the target culture, we respectively invited 5 male and 6 female Malay observers. Each facial image was rated on a real number scale between 1(very unattractive) and 7 (very attractive). The final attractiveness rating of a facial image was the mean of its ratings across all raters.

III. RATING transferring based on Regressive Manifold Regularization

In this paper, we take manifold regularization [12] as a semi-supervised pattern learning approach to train a rating transferring function, and further use it to predict the ratings of the target culture.

Fig.3. is the framework of the training and prediction for the rating transferring function. As stated in section II(C) rating collection, to obtain the relationship of aesthetics between the source and target culture, for the facial pictures in dataset2, we collect the ratings from both cultures. Because the ratings are based on the same facial pictures, they map to each other in the one-to-one manner. Then we take the ratings of the source and target culture for dataset2 as label data in manifold regression. For dataset1, we only have the ratings of the source culture, and then we take them as unlabeled data. The routine with the line is the training procedure, in which we take advantage of both label and unlabeled data to obtain the rating transferring function. The function contains the mapping relationship of aesthetic from the source culture to the target culture. Then, we can use this function to predict the ratings of the target culture for the unlabeled data as the red line shown in Fig 3. By this way, we transfer the source culture rating to the target culture, and put them under the same aesthetic system. That makes it possible for us to reuse the training data in the source culture. And it's also the prerequisite and guarantee for the facial feature transferring in the next step.

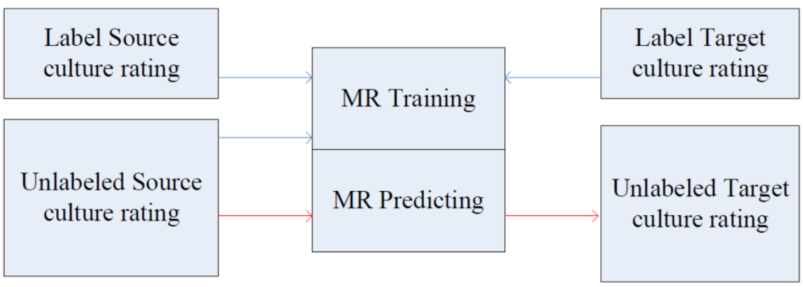


Fig. 3. The framework of rating transferring based on MR

IV. Facial feature transferring based on latent multi-task learning

In this section, we look for appropriate facial feature mappings, by which we can transfer the training data of different cultures to a well-defined low dimensional feature space. For our multi-culture beautification problem, we treat multiple cultures as multiple learning tasks. Here we obtain the feature mappings by exploiting the multi-task learning method, for our problem meets the following two assumptions. Firstly, the goal of each task is consistent, to train a beautification model for the corresponding culture. Then, they are related tasks. Secondly, since the training data are facial features, the data distributions for related tasks are similar in the high-dimensional feature space. Specially, we use latent multi-task learning proposed in [10]. It employed an alternating optimization approach to iteratively learn the feature mappings and multi-task regression models which could predict the attractiveness ratings. Then in the latent space, target culture can benefit from integrating the data collected before in the source culture to train a beatification model.

Fig.4 is the flow chat of latent multi-task learning. The inputs are training data of both the source and target culture. The outputs are the feature mappings, and the regression function in latent feature space which could predict the attractiveness ratings for target culture.

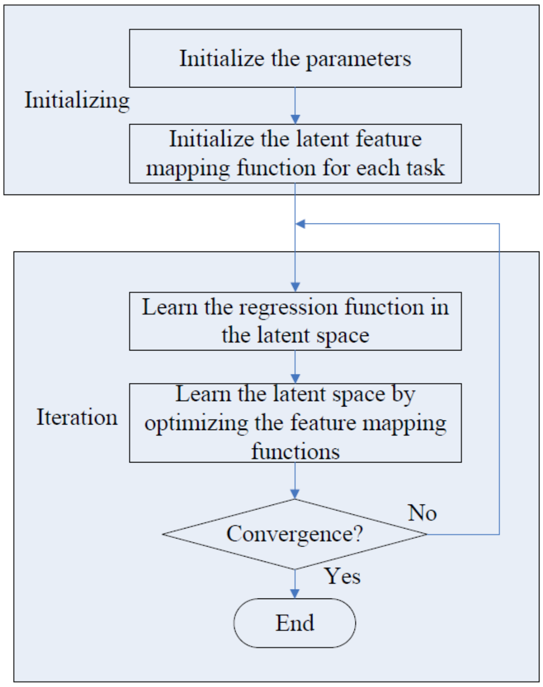


Fig. 4. The Flowchart of Latent multi-task learning

V. EXPERIMENTS

To demonstrate the technique we have implemented simple interactive application software, which was used to generate all of the examples in this paper. When loading a portrait, the software automatically detects facial features, and the user is able to examine the detected features and adjust them if necessary. Then the software computes and displays the result within a few seconds. As mentioned in section II, we treat Chinese culture as the source culture and Malay culture as the target culture, and collected 100 and 20 portraits respectively. We perform rating transferring and facial feature transferring on these two training datasets to obtain the beautification model for the target culture.

	Original portrait		SVR-beautified		Increasing percentage		
	Female	Male	Female	Male	Female	Male	All
S → S	3.57(0.52)	3.17(0.56)	4.76(0.64)	4.13(0.53)	33.46%	30.13%	31.79%
S →T	3.34(0.67)	3.26(0.63)	3.41(0.65)	3.36(0.55)	2.11%	3.22%	2.66%
T →T			3.62(0.65)	3.49(0.63)	8.39%	7.27%	7.83%
S + T → T			4.33 (0.71)	3.95(0.65)	29.64%	21.45%	25.54%

Table 1: The mean beauty scores and increasing percentage for several alternatives (the standard deviation is shown in parentheses).

First of all, we would like to confirm our motivation for considering multi-culture facial attractiveness enhancement. For source and target cultures, we randomly selected 10 male and female samples as their test data respectively. Table 1 shows the statistical results of four trials, where S represents the source culture and T represents the target culture. Row 1 corresponds to learning a beautification model on source culture’s training data, and then test the model on source culture’s test data. For the original version and beautified version of the test data, we gathered their beauty scores from 15 raters of source culture. The average ratings were increased by 31.79 percent. Row 2 corresponds to training a beautification model on source culture’s training data, and test the model on target culture’s test data. We also gathered their beauty scores for these test data’s original version and beautified version from 11 raters of target culture. The average rating was only increased by 2.66 percent. Some of the samples even had lower ratings than the original version. Compared to row 1, such a performance is far from satisfactory. This testifies our observation that there are aesthetics and geometry facial feature differences in different culture countries. Thus we need to conduct adaptation between cultures.

Second, we want to show how well our double transferring method could perform for the facial attractiveness enhancement. We use all the training data in the target culture to train a beautification model, and test it on the target culture test data. As shown in row 3, we got the average rating increase only by 7.83 percent. Note that the rate of increasing for the target culture is much smaller than the source culture as shown in row 1. This means that the quantity of training data is directly related to the performance of the beautification model. In row 4, it shows that our method is close to the result in row 1, by using all the training data of the source and target culture.

From table 1, we found our method performs better for female comparing to male. For the female, the beauty scores increase by 29.64%, while for the male by 21.45%. The possible reasons are: (1) for the reason of religion, the man with a beard is more attractive for Malays. Such non-geometric factors cannot be handled by our method; (2) the male training data did not contain any exceptionally attractive male faces; (3) the notion of male attractiveness is not as well established as that for females, so the consensus in the attractiveness ratings is less uniform for males.

VI. Conclusions and future work

In this paper, we empirically studied the aesthetic and facial geometry feature variations over different cultures, and proposed a double knowledge transferring method for the multi-culture facial attractiveness enhancement problem. The main contribution of our work is that, for facial attractiveness enhancement, we developed a novel solution for calibrating a new culture by making use of data collected before on other cultures, thus saving a great deal of data recollection and procession efforts. Taking Chinese as source culture and Malay as target culture, we applied our algorithm to the real-world multi-culture facial attractiveness enhancement problem, where our double knowledge transferring algorithm compared favorably with other baseline methods.

Currently we restrict ourselves to manipulate only the geometry of the face. However, there are also important non-geometric attributes that have a significant impact on the perceived attractiveness of a face. These factors include color and texture of hair and skin, and it would be interesting to investigate how changes in these attributes might be incorporated in our framework.

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