

Person Identification Using Discriminative Visual Aesthetic

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Abstract. A person's image aesthetic is defined as a set of principles that influences the person to choose favorite images over a list of options. Different persons have different visual preferences which can be used to discriminate a person from another. Recently, some research has been carried in the area of behavioral biometric and image aesthetic. Researchers prove that it is possible to identify a person from discriminative visual cues. In this paper, we develop a new and improved method for person recognition using aesthetic features. The proposed approach uses 14 perceptual and 3 content features collected from the state-of-the-art researches. To achieve significant improvement in rank 1 recognition rate, we utilize local perceptual features and Histogram Oriented Gradient (HOG) feature for the first time. However, the new feature space is 975 dimensional which increases the elapsed time of enrollment and recognition phases. To minimize it, we apply Principle Component Analysis (PCA) that reduces the dimension of the feature vector by 50% without affecting the actual recognition performance. The proposed method has been evaluated on 200 user's 40,000 images from the benchmark Flickr database. Experiment shows that the proposed method achieves 84% and 97% recognition rates in rank 1 and 5, whereas most well-performed state-of-the-art method shows 73% and 92%, respectively.

1 Introduction

Behavioral biometric is the field of study that allows identification and verification of an individual based on discriminative activity and behavioral attributes [10, 15]. Person's styles, preferences, interactions, expressions and attitudes, such as typing pattern, gait, social interaction, mouse dynamic and browsing history are the sources of behavioral traits. In contrast to physiological biometric, it has few advantages [24]. It is easily collectible through the low cost devices without the physical contact. However, as it is a highly intrinsic aspect of a person, analyzing and extracting discriminative features of behavioral traits are much more difficult. Also, it changes over time, so periodic data collection is needed depending on the type of the behavioral trait. Recently, researchers introduced visual aesthetic as a new behavioral biometric trait [14]. It is a person's set of cognitive rules that guides the person to prefer one object over others. Simply, what a person prefer can be utilized to identify that person. However, it is not a

unique trait like fingerprint. It changes over time, and can be overlapped among peoples from same social environment, family, age, group and ethnicity [11]. However, researchers experimentally prove that collection of aesthetic data from a person contains sufficient discriminative features to identify the person from others [13]. Also, researchers utilize this biometric trait to predict gender information [3, 4]. With the rapid advancement of Online Social Media (OSN), aesthetic data is becoming available to the researchers for analysis. People share their likeness, choices and preferences in the form of texts, images, videos and musics. For example, the OSN Flickr contains user's favorite set of images with few soft biometric informations, such as age and gender [9]. In 2014, a group of researchers conducted experiment on 200 Flickr user's 40,000 favorite images, and reconstructed individual's visual preference model for biometric identification and verification [14]. However, it is not feasible or practical as a biometric authentication and recognition system where high security is needed.

According to literature, forensic security is the potential application area of aesthetic biometric [13]. Forensic experts investigate a crime scene to collect physiological and behavioral traits of the suspects and victims. In many cases, absence of physiological traits pushes them to rely only on the behavioral biometric traits. Collected hand held devices can be analyzed to estimate demographic information of the suspect using aesthetic features of the images inside media directory. Moreover, various OSNs are carrying aesthetic data that can be investigated to identify list of suspects. To perform this, automated system is needed to process large image data from OSNs. As biometric identification, visual aesthetic has been rarely studied. It was first introduced by P. Lovato, in 2014, who defined it as "personal aesthetic" trait of people (that distinguishes people from each other) [14]. So far, a few state-of-the-art researches exist in this area, as well as no commercially deployed aesthetic biometric system has been found. The maximum reported recognition rates are 73% and 92% in rank 1 and 5 by the authors of [18], which is not significant enough compare to other behavioral biometric systems [24]. Motivated by this fact, we propose an improved person identification method using discriminative visual aesthetic. It shows 84% and 97% recognition rates in rank 1 and 5, respectively. The main contributions of the paper are as follows:

- Proposed an improved methodology for aesthetic based person identification that outperforms other state-of-the-art methods. It is validated based on the benchmark Flickr database [13].
- Achieved significant improvement by utilizing Histogram Oriented Gradient (HOG) and local perceptual visual features.
- Enhanced feature vector (length of 975) allowed to increase the one-vs-all learning time (as enrollment time in Biometric domain) which is mitigated using Principle Component Analysis (PCA).

2 Literature Review

The preliminary concept of aesthetic biometric was first introduced by the authors of [13]. They created the benchmark image database consists of 40,000

favorite images from 200 Flickr users. They extracted a pool of low and high level image features, and exploited linear regression to learn the most discriminative features. Experiment showed that, if 100 images are used in the enrollment and recognition phase (from each person), then the system can recognize people with only 55% accuracy in rank 5. Although the method didn't able to show good accuracy, the literature introduced various primary aspects of aesthetic biometric and the Flickr image database. Later, the same authors improved the method by incorporating new features [14]. The previous work used 62 dimensional feature vector, whereas the new technique considered 111 feature. They kept the same linear regression method to build person specific preference models, and evaluated it on the benchmark database (shows 79% accuracy in rank 5). At the same time, another group of researchers introduced a different solution of the problem [17]. They used K-means clustering to divide the whole training space into 6 clusters. Similar thematic images were considered under same cluster. Then bagging strategy was designed to improve the stability and accuracy of the machine learning algorithm. In general, they combined the idea of clustering and bagging to create surrogate images (a different representation of the input). Then LASSO (least absolute shrinkage and selection operator) regression [21] was applied to build discriminative models. During experiment, authors considered the method [13] for comparison and normalized area under the curve (nAUC) as performance metric. The new technique was able to outperforms method [13] by 7% in nAUC. So far, the best approach is proposed by the authors of [18]. Powerful concept of counting grid [16] is applied with support vector machine (SVM) to improve the performance. It shows 92% recognition rate in rank 5 which is the highest accuracy reported in the literature. In this paper, we introduce a new approach for person identification method which is able to reach the recognition rate of 84% in rank 1 and 97% in rank 5. This significant improvement is achieved by incorporating histogram oriented gradient (HOG) feature and local feature extraction process. We apply LASSO regression with the enhanced feature vector to learn a person's preference model in one-vs-all training. The next two sections describe the proposed method and the experimental evaluation steps.

3 Proposed Methodology

3.1 Global Image Feature

The existing state-of-the-art methods [13, 14, 17, 18] use 14 perceptual and 3 content features for modeling a person's visual aesthetic. These features are heterogeneous, contain various aesthetic cues of a person [2, 7]. In our proposed method, we have considered these state-of-the-art features, as they showed promising result in person identification. Each type of feature has its own dimension. Figure 1 shows the list of features and their dimensions. Total length of the perceptual feature vector is 57, and content feature vector is 54. All these features are extracted globally from an image. So the total length of the global feature vector is 111.

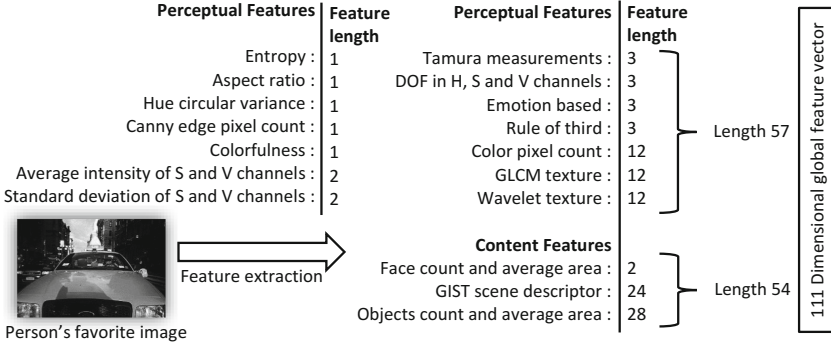


Fig. 1. List of perceptual and content features collected from [13,14,17,18].

3.2 Local Image Feature

The existing methods extract all features globally which lacks the local information of an image. On the other hand, we can extract features locally where an image is divided into number of image patches. Many researchers have argued that local image features are more robust and informative than global, which improves the recognition performance of machine learning algorithms [1,5]. Moreover, same image feature in different segments of images may create discrimination of aesthetics among persons. Hence, to improve the performance, we apply local feature extraction process. We divide an image into 9 equal size sub-regions, and apply feature extraction for each sub-region. During local processing, only the perceptual features are considered, as they are not affected by the image partition process. However, content features (such as faces, objects, image scene category, and shapes) are excluded from the local process as they are vulnerable to unaware segmentation. We also exclude the aspect ratio (a perceptual feature), as because it is same in local regions. Figure 2 shows the construction of local feature vector from an image.

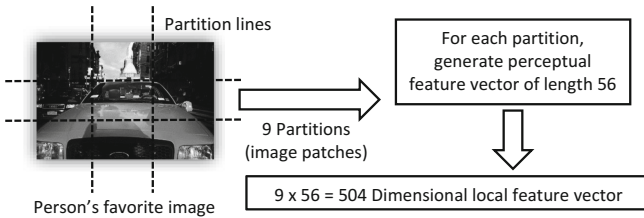


Fig. 2. Construction of local feature vector from an image.

3.3 Histogram Oriented Gradient (HOG) Feature

As content feature, state-of-art-methods use face [22], objects (14 specific items) [8] and scene descriptor [23]. In addition to these, we use HOG feature

which is a powerful shape and appearance descriptor of image contents. HOG feature was first introduced by Navneet and Bill in 2005 for the purpose of pedestrian detection [6]. Later, it was widely used by other researchers for various computer vision tasks, such as object detection [25], text extraction [20] and face recognition [19]. Motivated by this fact, we use HOG image descriptor to add more discriminative visual cues among persons. For simplicity, we use HOG descriptor with cell size of 1. Figure 3 shows the steps of generating HOG descriptor from an image. It contains 360 bins where each bin is filled up based on pixel’s gradient information. We can easily generate the gradient images (angle and magnitude) using 1st order derivative filter in both x and y directions (G_x and G_y). For each pixel location, a bin is selected based on calculated angle value on that location, and add the magnitude value with the selected bin. The HOG bins describe the local orientation information of an image and magnitude of intensity change, which is sufficient to get rough idea of an object shape and appearance. Lastly the global, local and HOG feature vectors are concatenated together to make a high dimensional vector of length 975.

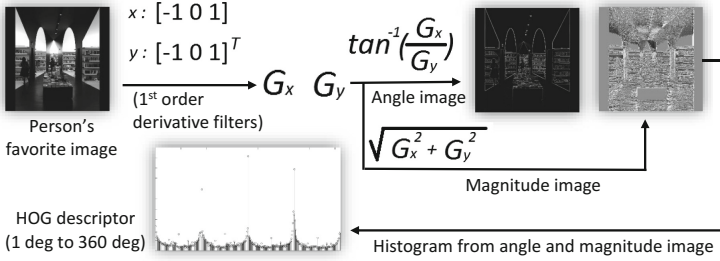


Fig. 3. Steps of generating HOG descriptor from an image.

3.4 Principle Component Analysis for Dimension Reduction

The feature vector used in the proposed model has dimension of 975 per image which increases the training time of a person’s preference model. In the proposed method, we apply LASSO regression [21] to learn preference model of a person in one-vs-all manner. To enroll and recognize 50 persons, the proposed method takes 5,334s which is significantly high. To speed up the training process, we apply Principle Component Analysis (PCA) for dimensionality reduction without having significant deviation from the actual model performance. PCA is a well known and widely used approach for data dimension reduction [12]. It is a statistical procedure that transform a set of d -dimensional observations into linearly uncorrelated variables (or principle components) using orthogonal projection. As output it gives d principle components where the first component has highest variance, and the last component has lowest variance. Top k ($k < d$) components contain most of the variances of the data. Systemically selecting top k components, and applying reverse transformation will give the k -dimensional

data having most of variances in it. In our case d is 975, and k has been assigned experimentally training time of a person is minimized without having much performance degradation.

3.5 LASSO Regression for Aesthetic Template Generation

To generate aesthetic template of a person, existing methods use LASSO regression [21] as binary classifier where positive class is the person, and negative class is all others. It performs automatic variable selection (through weight assignment) and regularization to improve prediction accuracy. This model has simple interpretation which can be used to find impact of heterogeneous features toward positive and negative classes [14]. Due simplicity and easy feature analysis, we also use LASSO regression for learning preference model and generating matching score for recognition. To apply LASSO regression, an image is represented as linear combination of features:

$$L = B_1F_1 + B_2F_2 + B_3F_3 + \dots + B_dF_d \quad (1)$$

where B is the person specific LASSO weights $\{B_1, B_2, B_3 \dots B_d\}$, F is the image feature vector $\{F_1, F_2, F_3 \dots F_d\}$, d is the dimension, and L is either positive (+1) or negative (-1) class label. The following error function has incorporated to find the person specific B vector using standard least square estimates.

$$Err(B) = \sum_{n=1}^N (B^T F^n - L)^2 + \alpha \sum_{i=1}^d |B_i|. \quad (2)$$

Here, N is the total number of training images, α is regularization parameter, and T is matrix transpose operator. In the error function the only parameter is α . From a range of α values, we select optimum α where minimum number of LASSO weights are zero. Finally, the solution B is the template (or preference model) for the person. In the recognition phase, matching score of a person is calculated by averaging all regression scores generated from test images and person specific weight vector B . The person with highest matching score will be the identified person.

4 Experiment and Analysis

4.1 Experimental Setup

The only publicly available database exists in this domain is the Flickr database created by Lovato [13]. It contains 40,000 color images in JPEG file format belonging to 200 randomly selected Flickr users. Each user's first 200 images under the "Favorite" tab have been considered. The process of adding favorite images is a continuous process over 23 to 441 weeks. This ensures time variance acquisition of favorite images. The database has 0.05% overlapping of images among 200 users. Samples from the database are provided in Fig. 4. For reducing



Fig. 4. Example of favorite images from one anonymous Flickr user [9].

the experimentation time, we randomly select 50 user's 10,000 images (one fourth of the database [13]) for PCA component selection, initial evaluation of the proposed method, as well as comparing 3 existing state-of-the-art methods. At the end of Sect. 4.4, we report the rank 1 and 5 recognition rates for the full database. The workstation used in the experiment has Windows 8.1 as operating system, AMD A8-7410 APU 2.2 GHz processor and 8 GB RAM. Since all the features have heterogeneous range of values, we apply z-score normalization.

4.2 PCA Component Selection

Due to large feature vector (length of 975), the training phase of the proposed method takes significant amount of time. From the point of view of biometric system, training of a person's preference model is the enrollment phase. In the proposed method, the elapsed time for enrollment and recognition of 50 persons takes 5,334 s. To reduce the training time, we apply PCA for dimensionality reduction. However, finding appropriate number of principle components is an important issue. In this experiment, we use iterative approach to select top k components (higher to lower variance of data). Starts from $k = 100$ and step size 100, we plot the recognition rate of 50 persons in rank 1 (black bars). Figure 5 shows that for $k = 500$, the recognition rate is equal to the rate of actual feature vector (without applying PCA). The elapsed time showing in the plot is the average enrollment and recognition time per person (gray bars). The time for

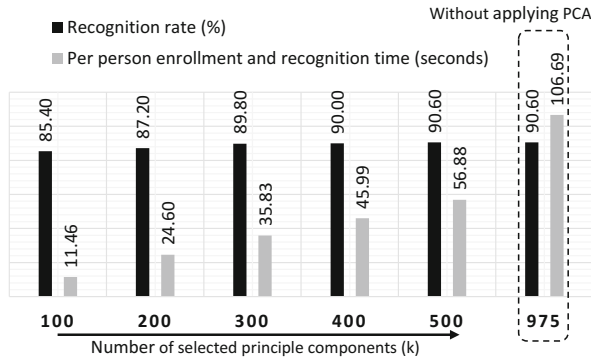


Fig. 5. Effect of number of PCA components in recognition rate and elapsed time.

feature extraction is not counted here, as it is significantly higher than the training and testing time. Experiment shows that at $k=500$, the dimension of the feature vector and elapsed time are reduced by 48.71% and 44.82%, respectively, without affecting the recognition rate.

4.3 Implementation of Existing Methods

In the area of visual aesthetic biometric, four different state-of-the-art methods were evaluated on the benchmark Flickr database. According to the articles [13,14,17,18], the authors use 5 to 20 random splitting of training and testing dataset, and report average experimental results in the literature. However, they didn't report the splitting information, used various evaluation metrics, as well as didn't compare other approaches using CMC curve. For fare comparison, we implemented existing methods, and applied same random splitting information, metrics, and CMC curve in all experiments. Method [18] is not implemented, as it is very complex and challenging, as well as lacks enough details in the original article. However, at the end of the experiment, we compare the recognition rate (in rank 1 and 5) as per the reported results [18].

In all experiments, the number of training and testing images are set to 100. For 200 users, the accuracies in rank 5 reported (using CMC curve) in the articles for the methods [13,14] are 55% and 79%, whereas our implementations show 53.4% and 78.1%. According to article [17], use of surrogate image has shown 7% improvement in recognition rate. Our implementation of method [17] with the extended feature vector from the method [14] shows 5.45% improvement of recognition rate (83.55%) over [14]. In summary, our implementations show similar results close to the source implementations.

4.4 Performance Comparison

Instead of using all 200 users from the benchmark database, we evaluate the proposed method on randomly selected 50 users (justification is provided in Sect. 4.1). Each user contributed 200 of his (or her) favorite images. We split this image set into two folds each contains 100 images using random selection without repetition. One fold is used in learning phase for enrollment purpose, and other fold is used for recognizing the person at the identification phase. In a single experiment, we apply the same selection index of images for all 50 persons. However, different experiments have different splitting. Each experiment needs to learn 50 person's preference model (in one-vs-all manner) to create aesthetic template. Then testing data from a person and all 50 templates are utilized to generate matching scores of 50 persons. Sorting matching scores in descending order gives the rank list of 50 persons. In this way, each person generates a rank list. Finally, these 50 rank lists are processed to generate average recognition rate of 50 persons from rank 1 to 10. We evaluate and compare the methods in 10 different experiments. Table 1 shows the rank 1 recognition rate for 10 experiments. It is clear that model performances are sensitive to training and testing splitting as standard deviation for methods [14,17] are 4.43 and 4.50.

Table 1. Recognition rate (in rank 1) over 10 different experiments (consider 50 users from the benchmark Flickr database).

Exp. no.	Proposed method: Rank 1 recognition rate (%)	Method [14]: Rank 1 recognition rate (%)	Method [17]: Rank 1 recognition rate (%)
1	94	74	84
2	94	78	76
3	92	70	80
4	90	70	76
5	90	64	68
6	88	68	80
7	88	72	72
8	90	68	76
9	88	78	74
10	92	72	78
Avg	90.6	71.4	76.4
Std dev	2.32	4.43	4.50

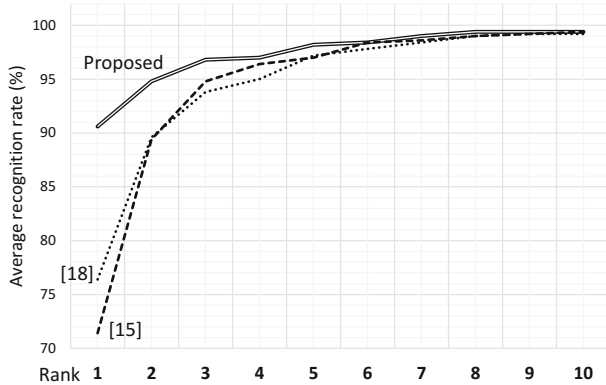


Fig. 6. Cumulative matching characteristic (CMC) curves for the proposed method, as well as existing methods [14, 17] upto rank 10. The curves have been obtained by averaging 10 different experiments with different training and testing splitting.

However, the proposed method shows significantly higher average recognition rate (90.60%), and lower standard deviation (2.32%) than other two. Figure 6 shows the CMC curve up to rank 10 for different methods. We see that the curve for the proposed method is always above the other two curves. However, all of them show similar performances after rank 5. We exclude the method [13] from the comparison as it shows significantly poor performance (41.20%) in rank 1.

In Fig. 7, we use bar charts to compare the methods. The bar chart of average recognition rate shows that the proposed method can recognize persons

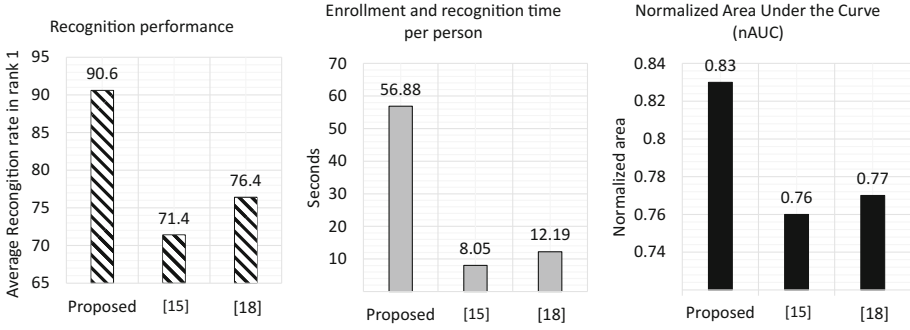


Fig. 7. Bar charts showing recognition rate, nAUC and elapsed time for the methods [14, 17] and the proposed one.

14.2% more accurately. The reason is that, use of local feature extraction and shape information add more discrimination of visual aesthetic which helps the LASSO regression to recognize people more efficiently. On the other hand, none of the existing methods use local and HOG features. Method [17] shows 5% improved performance than [14] due to imposing k-means clustering (to generate surrogate images) that minimizes noises of data through averaging. Also, it increases model stability and performance using bagging strategy. The bar chart of nAUC also depicts the superior performance of the proposed method over existing ones. nAUC is a good way to sense overall system performance in different ranks. We also provided bar chart of average elapsed time for enrollment and recognition of one person. Both methods [14, 17] use feature vector of length 111 whereas the proposed method uses PCA transformed feature vector of length 500. Method [17] shows slightly higher elapsed time than the method [14] because of applying k-means clustering and bagging process. The proposed method shows significant consumption of time which is approximately 5 times higher than the method [17]. However, we can reduce the running time by controlling number of PCA components (k) in trade of system performance. Refer to Fig. 5, we see that when $k = 100$, the elapsed time is only 11.46 s, but system performance become 85.4% (reduced by 5.2%). However, the accuracy is still 9% and 14% higher than the methods [14, 17].

We also compare the proposed method with the most well performed state-of-the-art approach [18] for all 200 user's 40,000 images. According to the literature, method [18] shows 73% and 92% of recognition rate in rank 1 and 5, whereas our proposed method gives 84% and 97%. In summary, the proposed method outperforms all existing state-of-the-art methods.

5 Conclusions

In biometric community, human aesthetic is a new concept. It is defined as a behavioral biometric trait which is sufficiently unique to differentiate a person

from. However, reconstructing a person's discriminative aesthetic preferences from favorite images is not a trivial task. Due to variability over time and similarity within same group, the area become more challenging to the researcher. However, most recently, researchers show that it possible to identify people in rank 5 with 92% accuracy using only the visual aesthetic as cue. The reported accuracy is not significant enough compare to other behavioral biometric trait. In this paper, we develop an improved method for person identification using personal aesthetic information. It achieves 84% and 97% recognition rates in rank 1 and 5 on 200 Flickr user's 40,000 favorite images. Experiment shows that the proposed method outperforms all existing state-of-the-art methods in terms of rank 1 recognition rate. As future work, we will apply more sophisticated machine learning algorithms, such as Convolutional Neural Network (CNN), Convolutional Deep Belief Network (CDBN) to improve the performance.

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