A Method of Gender Classification by Integrating Facial, Hairstyle, and Clothing Images

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Abstract

This paper presents a method of gender classification by integrating facial, hairstyle, and clothing images. Initially, input images are separated into facial, hairstyle and clothing regions, and independently learned PCAs and GMMs based on thousands of sample images are applied to each region. The classification results are then integrated into a single score using some known priors based on the Bayes rule. Experimental results showed that our integration strategy significantly reduced error rate in gender classification compared with the conventional facial only approach.

1. Introduction

Classifying personal features, such as gender and age-group, of customers shopping in convenience stores or department stores using in-store cameras will enable these stores to provide the customers with personalized services. These stores will also have a marketing advantage using such customer information. Moreover, a user-friendly man-machine interface will become promising using such technique. Therefore, there are ongoing researches on the analysis of the facial images taken with the camera and the classification of gender and age-group [1][2]. However, it is difficult to acquire facial images at high resolution in the real life environment, and it is inadequate to classify gender based on facial images alone. Our goal is to improve the gender classification accuracy by using hairstyle images and clothing images in addition to facial images.

In this research, images at low resolution are used. These images capture the entire upper body of a person. An example image is shown in Figure 1. We adopt the Principal-Component-Analysis based feature extraction and Gaussian-Mixture-Model-based likelihood calculation on each classification category. As for information integration, we used multiple likelihood calculations using extracted facial, hairstyle, and clothing sections of the image.

In Section 2, we provide a method of gender classification using the facial images. In Section 3, we focus on the method using hairstyle images. In Section 4 and 5, we focus on neckties and décolletés(clothes with low-cut neckline), which are two clothing characteristics that differentiate gender. In Section 6, we describe the framework that integrates information concerning facial, hairstyle, and clothing images. Conclusion is given in Section 7, 8.

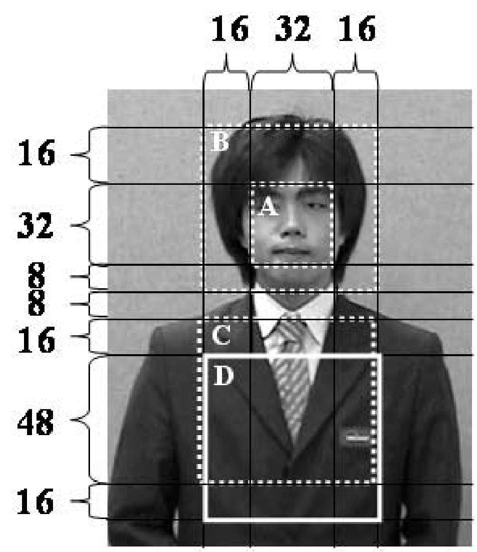

Figure 1. Example input image

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2. Gender classification using facial images

2.1. Feature extraction

In this research, images of a person's eyebrows, eyes, nose, and mouth are captured and used. This section corresponds to region A of Figure 1. This image is resized to 32X32 pixels, and is converted to 256-level grayscale. Since images will be captured at low resolution, it is difficult to extract the detailed features of a face. Thus, feature parameter is taken out from approximately 11,656 facial images including 4,389 female images and 7,267 male images by compressing dimensions using Principal Component Analysis (PCA). When cumulative proportion of PCA was set to 80%, 1,024 dimensions were compressed into 36 dimensions.

2.2. Gender classification

Some of the classification techniques available are Support Vector Machine (SVM) and Neural Networks (NN). We chose to use another technique, called Gaussian Mixture Model (GMM). We constructed female GMM using female data and male GMM from male data, and made classifications by comparing the output likelihoods from each model. The advantage of using GMM is that it can automatically express many different faces using mixture distribution, such as whether a person wears glasses or not and whether a person's mustache is heavy or not.

The GMM containing M components is defined as:

$$P(x;\Psi)=\sum_{m=1}^{M}\alpha_m P(x;\mu_m,\Sigma_m),$$

where x is a column vector of d components, and Ψ is a GMM parameter:

$$\Psi=(\alpha_1,\cdots,\alpha_M,\mu_1,\cdots,\mu_M,\Sigma_1,\cdots,\Sigma_M),$$

where α_m is the mixture proportion of the *m*-th component that satisfies $\sum_{m=1}^{M}\alpha_m=1$ and is a non-negative real number. The d-dimensional multivariate normal distribution density function with the mean vector μ and the variance-covariance matrix Σ is

$$P(x;\mu,\Sigma)=\frac{1}{(2\pi)^{d/2}|\Sigma|^{1/2}}\exp\left[-\frac{1}{2}(x-\mu)^t\Sigma^{-1}(x-\mu)\right],$$

where $|\Sigma|$ is the determinant of Σ, Σ^{-1} is the inverse matrix of Σ, and $(x-\mu)^t$ represents the transposed matrix of $x-\mu$. The Expectation-Maximization (EM) algorithm is used to iteratively estimate the GMM parameters [3].

We constructed female GMM using approximately 2,800 female images and male GMM using approximately 4,600 male images on a 36-dimensional space (compressed using PCA).

2.3. Classification accuracy

Accuracy of gender classification was evaluated by using 2,397 female images and 5,035 male images were used as inputs to female GMM and male GMM. The number of Gaussians is set to 10 for both males and females. The output likelihood values from both GMMs are compared for classifications. Table 1 gives the result of gender classification using the facial images. The error rate in gender classification for facial images is 10.4%.

Table 1. Gender classification results using facial images

	# samples	# miss	error rate
Female	2,397	373	15.6%
Male	5,035	400	7.9%
Total	7,432	773	10.4%

3. Gender classification using hairstyle images

3.1. Feature extraction

Hairstyle is considered to be one of the effective features in gender classification. We created hairstyle image from region B from Figure 1. The hairstyle region is extracted based on color information. This image is resized to 32X32 pixels, and is converted to 5-level grayscale. The hairstyle feature extraction method is performed by carrying out PCAs of the entire set of hairstyle images as was done on the facial images. The number of images is 11,726 including 4,433 female images and 7,293 male images. Cumulative proportion is 80%, and reduced dimension is 31.

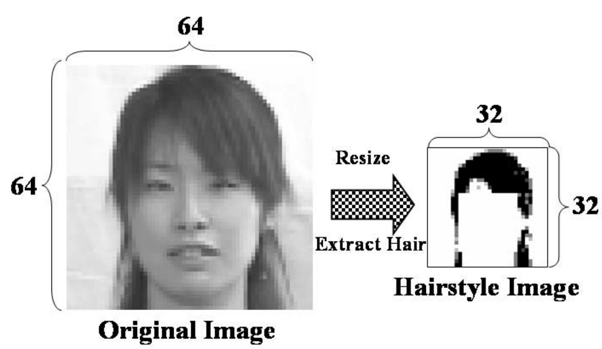

Figure 2. Example hairstyle image

3.2. Gender classification

We constructed female GMM using approximately 2,800 female images and male GMM using approximately 4,700 male images on a 31-dimensional space (compressed using PCA). We constructed female GMM and male GMM, and made classifications by comparing the output likelihoods from each model.

3.3. Classification accuracy

2,397 female images and 5,035 male images were used as inputs to female GMM and male GMM. The number of Gaussian is set to 5 for both males and females. The output likelihood values from both GMMs are compared for classifications. Table 2 gives the result of gender classification for hairstyle images.

Table 2. Gender classification result using hairstyle images

	# samples	# miss	error rate
Female	2,397	381	15.9%
Male	5,035	607	12.1%
Total	7,432	988	13.3%

4. Necktie/non-necktie classification

4.1. Feature extraction

We created necktie/non-necktie images by applying Laplacian filtering to region C from Figure 1. This image is resized to 24X24 pixels, and is converted to 256-level grayscale. We extracted features using PCA with 7,577 edge images including 1,212 necktie images and 6,365 non-necktie images. Cumulative proportion is 60%, and reduced dimension is 57.

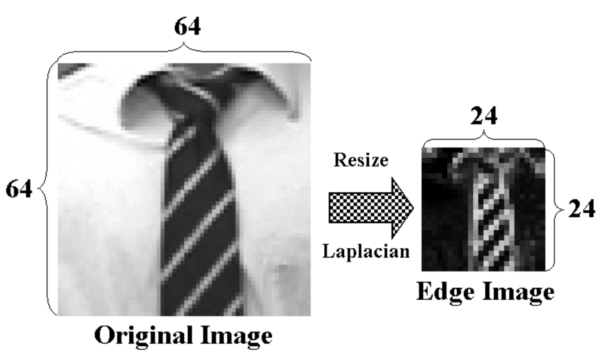

Figure 3. The example edge image for necktie/non-necktie classification

4.2. Necktie/non-necktie classification

We constructed necktie GMM using approximately 800 necktie edge images and non-necktie GMM using approximately 4,100 non-necktie edge images on a 57-dimensional space (compressed by PCA). We constructed necktie GMM and non-necktie GMM, and made classifications by comparing the output likelihoods from each model.

4.3. Classification accuracy

1,212 necktie images and 6,220 non-necktie images were used as inputs to necktie GMM and non-necktie GMM. The number of Gaussian for necktie GMM is set to 1, and 5 for non-necktie GMM. Table 3 gives the result of necktie/non-necktie classification.

Table 3. Necktie/non-necktie classification result using edge images

	# samples	# miss	error rate
Necktie	1,212	91	7.5%
Non-necktie	6,220	95	1.5%
Total	7,432	186	2.5%

5. Décolleté/non-décolleté classification

5.1. Feature extraction

We next created décolleté/non-décolleté images. What is different about this image from the necktie images is the extraction of skin region from the image. We created skin images from region D from Figure 1. This image is resized to 24X24 pixels, and is converted to 256-level grayscale. The skin region is extracted based on the person's facial skin color information. We extracted features using PCA with approximately 7,577 skin images (approximately 210 décolleté images and 7,367 non-décolleté images). Cumulative proportion is 30%, and reduced dimension is 12.

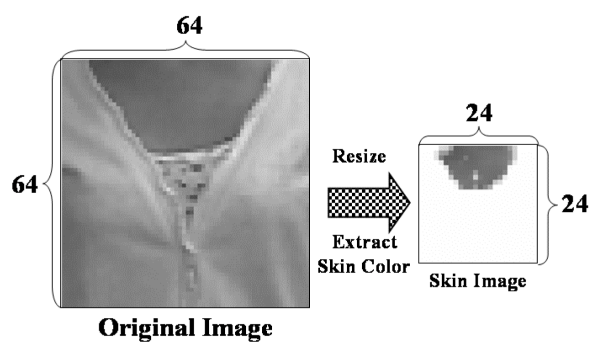

Figure 4. The example skin image for décolleté/non-décolleté classification

5.2. Décolleté/non-décolleté classification

We constructed décolleté GMM using approximately 300 décolleté skin images and non-décolleté GMM using approximately 500 non-décolleté skin images on a 12-dimensional space (compressed by PCA). Classification is done as was with other images described in the previous sections.

5.3. Classification accuracy

207 décolleté images and 7,225 non-décolleté images were used as inputs to décolleté GMM and non-décolleté GMM respectively. The number of Gaussian for décolleté GMM is set to 1, and 5 for non-décolleté GMM. Table 4 gives the result of décolleté/non-décolleté classification for skin images.

Table 4. Décolleté/non-décolleté classification result using skin images

	# samples	# miss	error rate
Décolleté	207	43	20.8%
Non-décolleté	7,225	417	5.8%
Total	7,432	460	6.2%

6. Multiple information integration

6.1. Likelihood-based integration

We denote the face feature extraction data as x_F, the hairstyle feature extraction data as x_H, the necktie/non-necktie data as x_T, the décolleté/non-décolleté data as x_D. Considering each data independent, the ratio of the female probability $\Pr[F \mid x_F, x_H, x_T, x_D]$ and the male probability $\Pr[M \mid x_F, x_H, x_T, x_D]$ is calculated as follows:

$$
\begin{aligned}
&\Pr[F \mid x_F, x_H, x_T, x_D] : \Pr[M \mid x_F, x_H, x_T, x_D] \\
&= \Pr[F] \times (\Pr[x_F \mid F])^{n_F} \times (\Pr[x_H \mid F])^{n_H} \\
&\quad \times (\Pr[tie \mid F] \cdot \Pr[x_T \mid tie] + \Pr[\overline{tie} \mid F] \cdot \Pr[x_T \mid \overline{tie}])^{n_T} \\
&\quad \times (\Pr[dec \mid F] \cdot \Pr[x_D \mid dec] + \Pr[\overline{dec} \mid F] \cdot \Pr[x_D \mid \overline{dec}])^{n_D} \\
&: \Pr[M] \times (\Pr[x_F \mid M])^{n_F} \times (\Pr[x_H \mid M])^{n_H} \\
&\quad \times (\Pr[tie \mid M] \cdot \Pr[x_T \mid tie] + \Pr[\overline{tie} \mid M] \cdot \Pr[x_T \mid \overline{tie}])^{n_T} \\
&\quad \times (\Pr[dec \mid M] \cdot \Pr[x_D \mid dec] + \Pr[\overline{dec} \mid M] \cdot \Pr[x_D \mid \overline{dec}])^{n_D},
\end{aligned}
$$

which is calculated using the following prior probability:

$$
\begin{aligned}
&\Pr[F] = \Pr[M] = 0.500, \\
&\Pr[tie \mid F] = 0.005, \Pr[\overline{tie} \mid F] = 0.995, \\
&\Pr[dec \mid F] = 0.050, \Pr[\overline{dec} \mid F] = 0.950, \\
&\Pr[tie \mid M] = 0.100, \Pr[\overline{tie} \mid M] = 0.900, \\
&\Pr[dec \mid M] = 0.010, \Pr[\overline{dec} \mid M] = 0.990,
\end{aligned}
$$

and n_F, n_H, n_T, n_D are weight parameters to compensate for differences between each likelihood. n_F, n_H are set to 1, and n_T, n_D are set to 5. These prior probabilities can be calculated by taking the statistics in the real life environment.

6.2. Result of integration

An integrated result is shown in Table 5. In this table, F is face, H is hairstyle, T is necktie, and D is décolleté. Facial, hairstyle, and necktie-décolleté information all seem to affect the classification result to some degree.

Table 5. Gender classification result using integrated information

	method of integration	# sample	# miss	error rate
Female	F	2397	373	15.6%
	F+H		305	12.7%
	F+H+T+D		297	12.4%
Male	F	5035	400	7.9%
	F+H		308	6.1%
	F+H+T+D		282	5.6%
Total	F	7432	773	10.4%
	F+H		613	8.2%
	F+H+T+D		579	7.8%

7. Conclusion

This paper proposed a method of gender classification by integrating information from different parts of a single image. By integrating the likelihoods of the hairstyle and clothing, we were able to reduce 25.1% of false classifications made by the conventional facial only approach. Experimental results show that classifying extracted images of the face, the hairstyle, and the clothing individually is effective in gender classification.

8. Future works

This work involved images from only the frontal view images, but we are planning to incorporate images from various angles. Moreover, by applying the integration theory mentioned in Section 6 to multi-frame integration, we plan to adapt the classification techniques to movies. Furthermore, we plan to extend the use of physical and clothing information, as well as to add more features to incorporate more classification categories such as age-group and occupation-type (such as corporate employee and student).

9. References

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