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ベイズ統計を用いた顔性差認知モデル

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顔の性差の認知には特徴的な特定部分が使われていることはよく知られている。最近、人間の認知過程にベイズ統計が使われていることが示唆されているが、顔の性差認識にベイズ統計を使った単純な(ナイーブベイズ)モデルを応用したところ、既知の顔の性差の特徴と矛盾しない特徴認識を行うことが解った。また、女性の顔ばかり見ていると中性的な顔も男性に見えると言うよくしられた現象とも矛盾しない結果を得たので報告する。

Bayesian-based gender recognition for face images

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It is well known that gender face recognition is based upon the characteristic specific parts in face images. Recently, Bayesian statistics is supposed to be used in human recognition processes. We have applied very simple Bayesian statistics (naive Bayesian classifier) to recognize gender in face images and found that it recognizes the same parts that human beings recognize to classify face images. Although human trained for many female faces has tendency to recognize neutral faces to be male ones, this tendency is reproduced in our simple model.

1 Introduction

Face image recognition is a very important task for human beings. For example, identification of faces is performed in the distinct regions of the brain from those for recognition of other objects [1]. This is probably because face image recognition is important enough for human beings to use specific brain region. Especially, gender recognition by face images is supposed to be very important tasks for us. If we cannot recognize it correctly, we will fail in mating precess, thus will extinct. This means, we have to be trained to recognize gender quickly and correctly. In order to do this, it is better to consider some specific parts in face images. For example, almost a decade ago, Oda and Yamaguchi [2] have shown that human beings make use of specific parts in images to distinguish between male and female faces.

On the other hand, there are so many works on gender recognition of face images in computer oriented image processing study [3]. For example, Moghaddam and Yang [4] has applied support vector machines (SVM[5]) to recognize gender of face images and found that error rate can be reduced down to only 3.4 %. Thus, it is not so difficult to reconginze gender in face images by machine learning. However, there are not so many researches in which the relationship between machine learning and psychological mechanism is considered.

As such an example, Wichmann *et al* [6] has investigated both machine learning and perception in decision images for gender classification. , and concluded that PCA[7] (principal component analysis) +SVM is the closest to the human being's perception among those they investigated. However, it is not so easy to imagine that PCA+SVM is the real process that human perception employs to recognize gender in face images. It seems to be too mathematical for real living systems.

In this paper, we have tried to reproduce face gender recognition by using much more simpler machine learning systems [8], naive Bayesian classifier (see below).

2 Bayesian statistics and human perception

Recently Köding and Wolpert [9] has shown that Bayesian integration works in sensorimotor learning. In their study human brain really employs Bayesian process to minimize error in learning process. Thus, they concluded that the central nervous system employs probabilistic models during sensorimotor learning. Estimation of gender from face images is similar task, since the subjects are forced to estimate gender with uncertain information. It is sometimes not easy to do it, e.g., the error rate of human subjects is up to 16% [6]. Although there are no evidences that the visual recognition also employs Bayesian statistics, it is probable for the visual recognition to employ Bayesian statistics, too. Thus, in the following, we try to model the gender decision process from face images by Bayesian statistics.

Although Bayesian classifier with normal distribution is usually used [9], we hereafter propose much simpler model. Suppose variable g indicates gender (g=0 if the image is estimated to be female, otherwise $g = 1$) of an image. Then we assume that there is a set of variables $\theta_j (= 0, 1)$ such that

$$P(g|\{\theta_j\}) = \prod_j P(g|\theta_j),$$

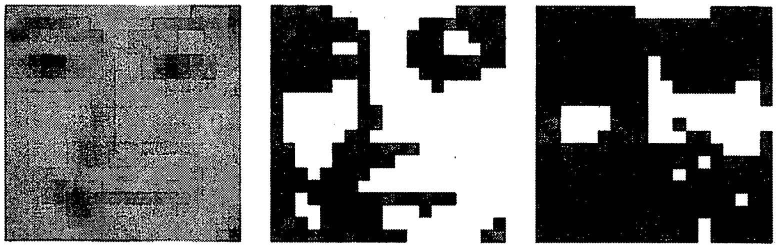
where $P(g|\cdot)$ is the conditional probability that the image has gender g. θ_j is some binary variable which is related to gender of the corresponding face image.

Since Bayesian theory says that

$$P(g|\theta_j) = \frac{P(g,\theta_j)}{P(\theta_j)},$$

where $P(g, \theta_j)$ is the probability that the image has gender g and θ_j, and $P(\theta_j)$ is the probability of θ_j, we can estimate $P(g|\theta_j)$ from $P(g, \theta_j)$. If we can define θ_j so as to be computed easily, it is easy to compute $P(g, \theta_j)$.

This is a so called naive Bayesian classifier. Although one may wonder if it is too simplified, it is well known that even naive Bayesian classifier can compete with more complicated methodology. Thus, hereafter we employ this naive Bayesian classifier [10].



(a) (b) (c)

Figure 1: (a) Original monochrome 256 graduation image (b) Black and white image after mean extraction. (c) Black and white image without mean extraction.

What is the simplest and the most reasonable way to define θ_j? Since visual image is sensed firstly by each visual cell as the amount of brightness (darkness), it is natural to define that θ_j represents whether visual cell detects darkness or brightness, e.g., $\theta_j = 1$ means that cell detects brightness. Since each visual cell can detect brightness or darkness of a point, it is natural to assume that θ_j represents a brightness or darkness of each pixel in face image, i.e., $\theta_j = 1$ if a pixel j is brighter than averaged brightness over pixels in the considered face image, otherwise $\theta_j = 0$. This is the most fundamental way to define θ_j for images, we believe. In the following, we employ this simplest model for gender recognition of face images. Sometimes, we have $P(\theta_j) = 1$. In this case, we simple ignore jth pixel, since it cannot be used for the classification of images.

3 Face image library

In this study, we have used face image library taken from CBCL FACE DATABASE [11]. Although it includes more than thousands of face images, we have selected 64 male and 65 female face images under the following criterion.

1. Front view.

2. Image must include all of face parts, i.e., eyebrows, eyes, nose and mouth.

3. Excluding images with something like hair and/or glasses.

4. It should not exhibit typical emotion like anger or joy.

Each image consists of 19×19 pixels. Images are translated into XPM monochrome 256 gradation figures.

As mentioned in the previous section, we have translated mean-extracted each pixel values into two values (bright ($\theta_j = 1$) or dark ($\theta_j = 0$)) for each figure. The reason of mean-extraction is because if we simply define that pixel with value greater

Sensitivity

(a) training set		
	average	SE
male	0.82	0.02
female	0.76	0.02

(b) test set		
	average	SE
male	0.66	0.03
female	0.60	0.02

Positive predictive value

(c) training set		
	average	SE
male	0.78	0.01
female	0.81	0.02

(d) test set		
	average	SE
male	0.62	0.01
female	0.66	0.02

Table 1: Sensitivity (a,b) and positive predictive values (c,d) for training and test set.

than 128 (= a half of 256) is bright, we sometimes get almost black or white image (Fig. 1) since mean brightness of each figure fluctuates from images to images.

The average error rate was estimated with 42 vs 22 data split, 42 used for training and 22 used for testing, with 10 overlapping random selections.

4 Results

In Table 1, we have shown sensitivity and positive predictive value for both training and test sets. Although one may think that it is too small to be regarded to be successful, it is not if we consider that we have dealt with very low resolution image as shown in Fig.1(b). It surely succeeds in distinguishing between male and female, although it may not be so easy also for human beings if they have to observe images as shown in Fig.1(b).

For the confirmation, we have tried to get the results for randomized set, i.e., pseudo 'male' set in the training set is set to have male and female images with equal probability. In this case, since it is impossible to learn the difference between male and female, both sensitivity and positive predictive values are typically 0.5 ± 0.03. Thus, results in Table 1 are distinct from accidental agreements.

In order to visualize how this treatment captures the difference between male and female, we have defined 'mean face' as follows. A pixel has the graduation of gray scale as $x = [P(\theta_j = 1|g) \times 10]$, where $[z]$ is the largest integer which does not exceed z. Seeing mean face images in Fig. 2, we can recognize that these two (male and female mean faces) can capture essential character of male/female faces. In Fig. 3, we have colored pixels which are darker for male/female face images. Clearly, colored pixels are distinct between male and female face images.

Especially, these parts correspond to the parts by which human beings distinguish female face images from male face images [2]. Thus, in spite of simplicity

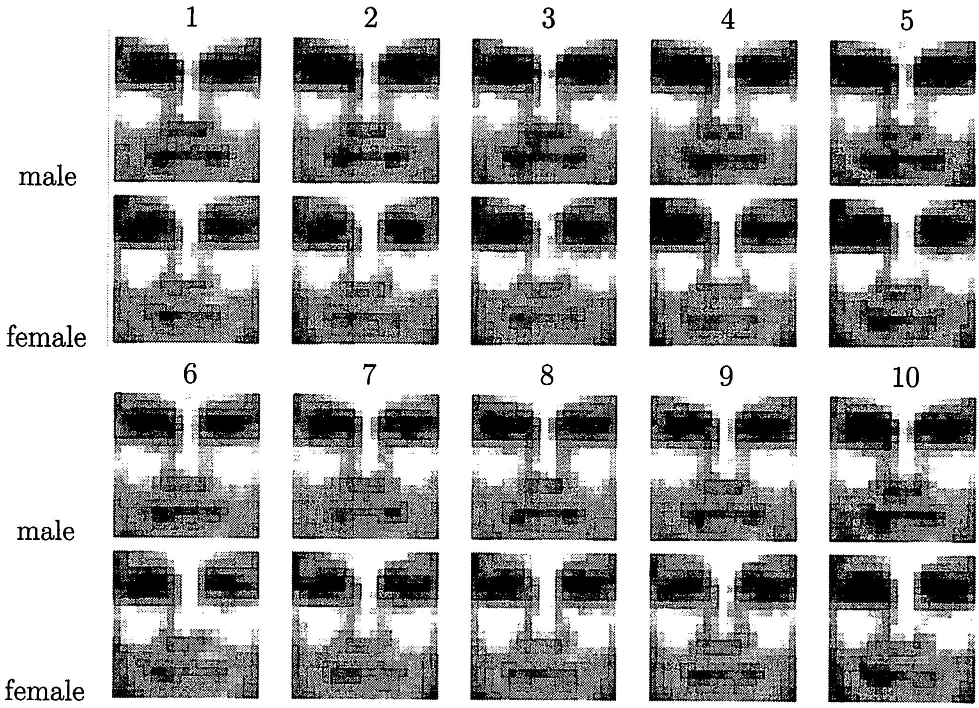


Figure 2: male/female face images for 10 training sets.

of our model to recognize gender in face images, it grasps the essential features of recognition mechanism by which we recognize gender in faces.

5 Adaptation to gender face images

It is well known that we are adaptive to face images. When there are two opposite sets of face images, after one of two sets is presented more frequently than another, we are adapted to the frequently presented set. That is, neutral images are classified to another set. When considering this effect in gender image, we feel neutral image as female-like after adaptation to male images by presenting more male images than female images. In this section, we would like to show that this effect can be reproduced in our simple model.

In order to do this, we have changed the number of female images in training set up to 52 (and the number of male images is 28). This simulates the situation of adaptation to female images. We would like to check if neutral images are judged as opposite gender, i.e., male face images. However, we do not have any neutral imaged in hand. Thus, instead, we consider how sensitivity and positive predictive value change after adaptation. In Table 2, we have shown the results. If results for training set [13] are compared with Table 1, we can notice that sensitivity for female

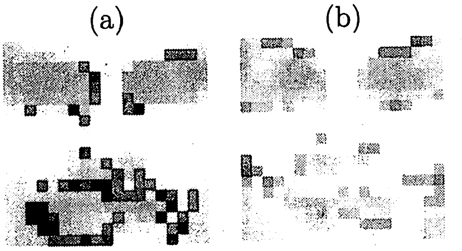


Figure 3: (a) Blue pixels are those in which male face image has tendency to be darker. (b)Red pixels are those in which female face image has tendency to be darker.

decreases while positive predictive value decreases for male. These are explained by the adaptation as follows.

After the adaptation to female face images (Fig. 4(b)), neutral image has less probability of femaleness than 0.5. Thus, male face image is easy to be classified to be male image while female face images becomes harder to be recognized correctly. This should increase sensitivity of male images. On the other hand, positive predictive value for male should decrease since face imaged judged as being male must include female images. These two tendencies are clearly seen in Table 2

6 Conclusion

In this study, we have demonstrated how well simple Bayesian model (naive Bayesian classifier) can recognize gender in face images. Although both sensitivity and positive predictive value are not very good, it is reasonable if we consider the simplicity of our model (we have translated pixel value into only 1 bit). In spite of that, mean face image (Fig. 2) correctly reproduce typical face for each gender which can be recognized by human beings. This may mean that gender classification is easier task than we imagine. It is reasonable since we extinct if we frequently fail in it. It must be easy, otherwise we cannot compete with other species.

Although it is general for researchers to try to increase accuracy of classification using vary complicated scheme, it may not be reasonable way to find how we human beings recognize gender from face images. Actually speaking, error rate of human subjects is reported to be up to 16 % [6], while classifier using PCA and SVM can have error rate which is as small as a few percentages [4]. This may be analogous that trying to understand how birds or insects fly by producing airplane which can fly as fast as sound.

Moreover, we have succeeded in reproducing adaptation to gender face images. From the evolutionary point of views, the adaptation is reasonable since one should select more female(male)-like faces if there are enough number of females(males), while one should accept even not so female(male)-like faces if there are not enough

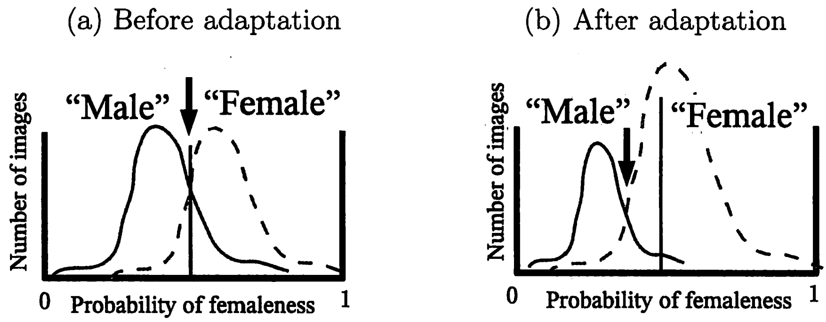


Figure 4: (a) Before adaptation, most of female face images (broken line) have larger "female probability" than 0.5 and are regarded as female faces correctly. On the other hand, most of male face images (solid line) have smaller "female probability" than 0.5 and are regarded as male faces correctly. Neutral face image (arrow) has 0.5 of "female probability". (b) After adaptation to female images, neutral image (arrow) is regarded as male, thus some of female images have smaller "female probability" than 0.5 and are wrongly regarded as male images. On the other hand, images with larger "female probability" than 0.5 include very few male images.

number of females(males). The shift of boundary toward female(male) under female(male) rich situation is coincident with this requirement. This process is important, thus should be easy to be achieved. The fact that our very simple model can reproduce this effect supports this.

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Sensitivity

(a) training set		
	average	SE
male	0.79	0.02
female	0.42	0.02

(b) test set		
	average	SE
male	0.52	0.02
female	0.50	0.03

Positive predictive value

(c) training set		
	average	SE
male	0.58	0.01
female	0.87	0.01

(b) test set		
	average	SE
male	0.80	0.01
female	0.21	0.02

Table 2: Sensitivity and positive predictive value for training and test set after adaptation to female face images.

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