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Robust Face Detection Using One-Class Estimation and Real AdaBoost

SHOTARO MIWA,[1] TAKASHI HIRAI,[1] and KAZUHIKO SUMI[2]
[1]Mitsubishi Electric Corp., Japan
[2]Aoyama Gakuin University, Japan

SUMMARY

We propose a robust face detection algorithm using one-class estimation and Real AdaBoost. Inspired by the first practical face detection algorithm by Viola and Jones, many varieties of face detection algorithms have been proposed. The common feature of their algorithm is a cascaded structure of combined Haar-like features trained by a boosting algorithm. Of course this framework has achieved a successful result of high detection rate and low false positive rate in a short time and has been applied to many imaging products. But because the nonface class includes multiple subclasses and their variations are too many to be collected and covered in training data, unexpected false positives inevitably happen in the real world data. That is a problem of self-printing systems for digital cameras, because they need to handle all kinds of pictures in the real world. Furthermore, because they use detected face regions for image enhancement before printing, to suppress false positives is a big issue of self-printing systems. To solve the problem of false positives in the real world, we model a nonface class using one-class estimation of faces, and developed a new face detection algorithm combining one-class estimation and a cascaded face detection by Real AdaBoost. As a result of the experiment using pictures of digital cameras, we achieved face detection about twice as fast with eight times lower false positives than a conventional cascaded face detector, and also more precise face size detection.
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Key words: face detection; one-class estimation; AdaBoost.

1. Introduction

Viola and colleagues [1] studied various algorithms for face detection that support real-time processing on a PC. Face detection technology is now an important technology for autofocusing and exposure adjustment in digital cameras, video cameras, and other imaging devices, and for brightness correction and other image processing in digital printers and other output devices.

As objects of detection, human faces are extremely diverse in ethnic and personal features, attributes (age, sex), expression, orientation, lighting conditions, and so on, which make correct and stable detection a very difficult task. It has been even more difficult to implement face detection in real time on a PC. Thus, Viola and colleagues [1] used a binary difference filter (the so-called “Haar-like filter”) and AdaBoost to generate a precise face classifier (strong classifier) that combines multiple face classifiers (weak classifiers) based on simple thresholding of Haar-like filter outputs, and implemented a face detection algorithm that can be implemented in real time on a PC.

A number of modifications of the AdaBoost used by Viola and colleagues have been proposed, such as Real AdaBoost [4], KL Boost [5], and Float Boost [6], to achieve the same level of detection performance as the original AdaBoost with fewer classifiers. However, even with learning algorithms based on such advanced boosting, the performance of weak classifiers fell in the second half of the learning process, so that absolute improvement of detection performance was still difficult [9]. Attempts were also made to improve the weak classifiers themselves rather than the learning algorithms. For example, Lienhart and colleagues [7] proposed a method in which classifier filters were supplemented by shapes corresponding to oblique differences, and Baluja and colleagues [8] proposed configuring classifiers from filters consisting of pixel combinations. Mita and colleagues [9] focused on the number of filters that make up a weak classifier, and proposed classifiers composed of multiple filters; Chen and colleagues [10] applied Haar-like filters not only to raw images but also to their differential images. Wu and colleagues [11] focused on classifier outputs, and proposed a multivalued algorithm using an LUT (LookUp Table).

These previous face detection methods based on boosted learning consider face detection as a problem of discrimination between two classes, faces and nonfaces, and require the preparation of face and nonface data. Actually, however, in contrast to face data including a single category, nonface data include an almost number of infinite categories, and the preparation of learning data covering all possible categories is impossible. Therefore, recognition errors were inevitable in the previous methods when encountering nonface inputs not included in learning data.

Face detection technologies are now applied to various image recognition devices. Recognition errors are likely to occur because such devices process a variety of real-world images. In the case of digital cameras and digital video, the influence of recognition errors can be reduced by using multiple or continuous frames; however, recognition errors should be eliminated so as not to miss perfect shots. In the case of printers, image correction is applied to a single captured image, and hence the need to prevent misdetection is especially strong. In particular, in the self-printing terminals that have recently become popular, multiple images are corrected on the terminal side, and reduction of recognition errors is very important.

On the other hand, the problem of nonrelevant data often arises in typical cases of object recognition. Thus researchers are investigating recognition algorithms that deal only with relevant data: so-called one-class recognition [12–16]. The concept of one-class recognition is very effective for face recognition, where all possible nonface data cannot be collected. In this investigation, we considered solving the problems of existing face detection techniques based on boosting by applying the one-class recognition approach as a means of reducing face misdetection in real-world images, especially in case of printers. We combined Real AdaBoost (an algorithm widely used due to its balance between learning time and classification performance) with one-class estimation to propose a robust face detection algorithm.

In this paper, we report on conventional cascaded face detection using Haar-like filters, a robust face detection algorithm using one-class estimation and Real AdaBoost, and the results of evaluation experiments with face image data.

2. Cascaded Face Detection Algorithm

Common features of the existing face detection methods are fast processing using Haar-like filters and integral images, the generation of classifiers using boosted learning, and the generation of fast and accurate face classifiers with cascaded structure. The conventional method considered in this investigation is the cascaded face detection algorithm developed by Viola and colleagues, with AdaBoost replaced by Real AdaBoost. Below we explain the generation of a face detector (strong classifier) using Real AdaBoost, and cascaded face detection.

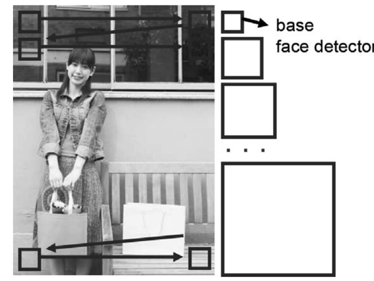


Fig. 1. Sliding window of face detector.

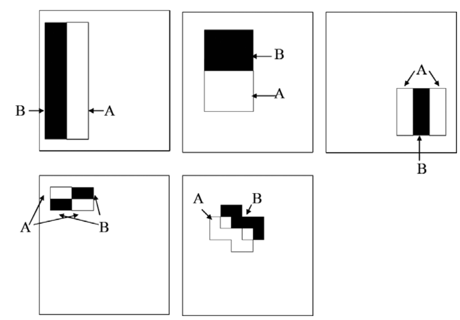


Fig. 2. Examples of Haar-like filters.

2.1 Generation of face detector using real AdaBoost

Figure 1 shows the scanning of an image by a detection window for face detection. A face detector of standard detection size is prepared, and an image is scanned while varying the size and position of the detection window. Image patches within the detection window at every scan position are classified as face and nonface, thus detecting faces with various positions and sizes.

Haar-like filters such as that shown in Fig. 2 are used to extract feature values. A Haar-like filter is applied to two local areas A and B, and outputs the difference between the total brightness values in white area A and in black area B. A Haar-like filter calculates the total of the pixel values in local areas A and B, and therefore the filter's computational complexity is proportional to the total number of pixels in A and B. However, by using an integral image $II(u, v)$, the filter's computational complexity, which initially is proportional to the total number of pixels, can be reduced so that it is proportional to the number of vertices representing the local areas, thus speeding up the processing. Here integral image $II(u, v)$ is a data structure that stores the sum of the brightness values of an area above and to the left of some

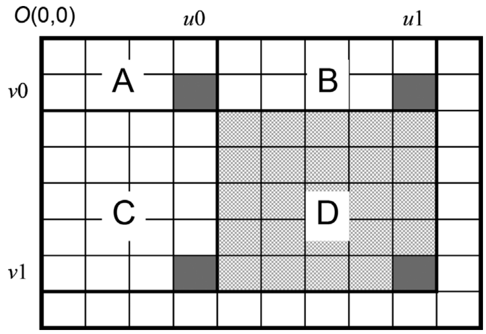


Fig. 3. Sum of pixels using integral image $II(u, v)$. (The sum of D is computed as $II(u1, v1) + II(u0, v0) - II(u0, v1) - II(u1, v0)$).

pixel coordinates in the position of the pixel. The integral image of original image $I(u, v)$ is defined as follows:

$$II(u,\, v) = \sum_{u' \le u,\, v' \le v} I(u',\, v'). \tag{1}$$

For example, the sum $sum(D)$ of the brightness values in area D in Fig. 3 can be found using the integral image $II(u, v)$ as follows:

$$\begin{aligned} Sum(D) = {} & II(u1, v1) + II(u0, v0) \\ & - II(u0, v1) - II(u1, v0). \end{aligned} \tag{2}$$

We now explain the learning by face detector F (strong classifier) with a Haar-like filter using Real AdaBoost.

Let $x = \{x_i\}_{i=1}^{M}$ denote learning data containing M image patches, $y_i \in \{+1, -1\}$ denote the true values of the learning data (face: $+1$, nonface: -1), D_i denote the weights of learning data, and $j (1 \le j \le \mathrm{N})$ denote the learning stage. Then the weak classifier f_j is defined as follows in terms of a Haar-like filter ϕ_j, a threshold t_j, and the thresholding results α_j, β_j:

$$f_i(x_i) = \begin{cases} \alpha_j & \text{if } \phi_j(x_i) > t_j \\ \beta_j & \text{otherwise.} \end{cases} \tag{3}$$

Here the raw output $\phi_j(x_i)$ of the Haar-like filter varies with the image contrast. Thus, we use the following regularization multiplier c_j based on the variance $\sigma^2(x_i)$ of image $_{xi} = I(u, v)$:

$$c_j = \sqrt{\frac{4000.0}{\sigma^2(x_i) + 10.0}}. \tag{4}$$

In face detection, a standard detection window must be scanned over the image, and $\sigma^2(x_i)$ must be calculated every time the window size (length: m pixels, width: n pixels) or position is changed. However, $\sigma^2(x_i)$ can be calculated using the squared brightness value $I(u, v)^2$ of the pixels inside the detection window. Therefore, if preprocessing

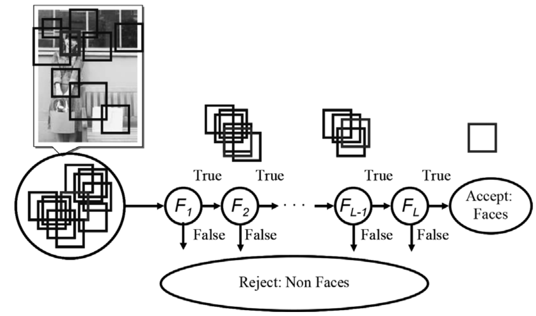


Fig. 4. Cascaded face detector.

includes the calculation of $II^2(u, v)$, in addition to integral image $II(u, v)$, then the regularization term c_j can be calculated quickly using the coordinates of the four corners of the detection window, the integral image $II(u, v)$ and $II^2(u, v)$:

$$\sigma^2(x_i) = \frac{\sum I(u,\, v)^2}{m * n} - \left(\sum \frac{I(u,\, v)}{m * n} \right)^2. \tag{5}$$

The actual parameters $\phi_j, \alpha_j, \beta_j, t_j$ of weak classifier f_j are chosen so as to minimize the following error rate e_j, while updating the learning data weights D_i in learning stage j of Real AdaBoost:

$$e_j = \min \left(\sum_{\substack{i : y_i = +1 \\ \wedge \phi(x_i) \le t}} D_i + \sum_{\substack{i : y_i = -1 \\ \wedge \phi(x_i) > t}} D_i,\ \sum_{\substack{i : y_i = +1 \\ \wedge \phi(x_i) > t}} D_i + \sum_{\substack{i : y_i = -1 \\ \wedge \phi(x_i) \le t}} D_i \right). \tag{6}$$

Finally, the strong classifier F is found as the linear sum of the weak classifiers f_j:

$$F = \sum_{j=1}^{M} f_i(x). \tag{7}$$

2.2 Cascaded face detection algorithm

The cascaded face detection algorithm is illustrated in Fig. 4.

Among the infinite number of detection windows (Fig. 1), most are nonfaces, and only very few are faces. Therefore, aiming at fast face detection, nonface detection windows must be promptly recognized and discarded. Thus, Viola and colleagues [1] considered the strong detector obtained in Eq. (7) as the following cascaded structure $F_{cascade}$, where I denotes an input image patch:

$$\begin{aligned} F_{cascade} &= \left\{ F_k(I) \right\}, \quad (1 \le k \le L), \\ F_k(I) &= \sum f_{kj}(I), \quad (1 \le j \le M_k), \\ f_{kj}(I) &= \begin{cases} \alpha_{kj} & \text{if } \phi_{kj}(I) > t_{kj} \\ \beta_{kj} & \text{otherwise} \end{cases}, \quad (1 \le j \le M_k). \end{aligned} \tag{8}$$

In the cascaded face detection algorithm, the value of the strong classifier F_k at some stage is used as a threshold. Thus, processing of many nonface detection windows is terminated, while only the few remaining face-like detection windows are transferred to the following strong classifier F_{k+1} for further recognition, which speeds up the process of face detection. Discrimination between faces and nonfaces becomes more difficult with every cascade, and therefore strong classifiers with more stages are employed at later stages.

3. Robust Face Detection Using One-Class Estimation and Real AdaBoost

A problem with face detection is that nonface data include an infinite number of classes, all of which cannot be covered by learning data. As a result, misdetection (false positives) occurs in the case of data belonging to an unknown category. We reasoned that misdetection could be eliminated by dealing only with face data, which can be collected much easier than nonface data. Later we first explain one-class estimation using nonface modeling, and then robust face detection combining one-class estimation with Real AdaBoost.

3.1 One-class estimation

Attempts have long been made to improve the performance of face detection by using the distribution of nonface data. In the method of Viola and colleagues [1], Haar-like filter scores are used as a binary threshold for weak classifiers to discriminate between face-like and other data; in contrast, Wu and colleagues [11] proposed a multivalued algorithm for this purpose. In the latter case, Haar-like filter scores in the neighborhood of a threshold are partitioned into multiple bins, and multivalued estimation of face-likeness is arranged in an LUT, which improves performance by early elimination of nonface images.

However, the filter score distribution may become uneven and unstable because of the volume of learning data, bias in the weights of individual learning samples in AdaBoost, fluctuations in the evaluation data (lighting fluctuations, noise fluctuations, and so on), and differences between the evaluation data and the learning data (face and nonface data with distributions different from the learning data). As a result, when scores around a threshold are finely partitioned in learning, the dependence on the learning data increases, and generality is lost. For this reason, Wu and colleagues [11] chose the LUT size heuristically.

However, since there are infinitely many classes of nonface data, it is impossible to cover them all in learning data. The method of Wu and colleagues [11] is helpful for early elimination of nonface data included in learning data; however, misdetections remain inevitable when an input image contains nonface data not included in the learning data.

Regarding the modeling of nonface data that are difficult to cover in learning data, in the present study we adopt one-class recognition. That is, we consider nonface classes as outliers, and eliminate them by estimation of a single class, the face class.

There are several algorithms for one-class estimation based on distribution estimation [16] or using a one-class SVM [17]. Here we share feature quantities between one-class estimation and AdaBoost: in particular, we consider the elimination of misdetections by using the high speed and robust recognition performance of Real AdaBoost, and propose a distribution estimation method using filters that constitute the weak classifiers obtained in Real AdaBoost.

Specifically, we calculate the score distribution for the outputs $\phi_j(x_i)$ of individual Haar-like filters obtained in learning, apply a normal distribution to face data, and eliminate outliers. That is, a face probability distribution model $P_{\phi j}(x_i)$ is obtained using the mean score $\mu_{\phi j}$ and standard deviation $\sigma_{\phi j}$ of the Haar-like filter outputs $\phi_j(x_i)$:

$$P_{\phi_j}(x_i) = \frac{1}{\sqrt{2\pi}\sigma_{\phi_j}} e\left(-\frac{\left(\phi_j(x_i) - \mu_{\phi_j}\right)^2}{2\sigma^2_{\sigma_j}} \right). \tag{9}$$

Then the nonface distribution model is obtained as follows:

$$\overline{P_{\phi j}(x_i)} = 1 - P_{\phi_j}(x_i). \tag{10}$$

In addition to this distribution estimation using Haar-like filters, we considered the variance $\sigma^2(x_i)$ of the brightness values obtained in the Haar-like filter calculation, and defined faces by variances exceeding the minimum variance σ^2_{min} of the learning data.

3.2 Face detection algorithm using one-class estimation and Real AdaBoost

A flowchart of the face detection algorithm using one-class estimation and Real AdaBoost is shown in Fig. 5.

For an input image patch I, the variance $\sigma^2(I)$ of the brightness value is first calculated. If the result is larger than σ^2_{min}, then the cascades $G = \{G_k\}$, $(1 \leq k \leq L)$ are applied successively. Cascade G_k consist of weak classifiers f_{kj} constituting the cascade classifier F_{cascade} in Eq. (8), Haar-like filters $\phi_{kj}(I)$, and the mean scores $\mu_{\phi kj}$ and standard deviations $\sigma_{\phi kj}$ of the $\phi_{kj}(I)$ scores:

$$G_k(I) = g\left(f_{kj}, \phi_{kj}, \mu_{\phi_{kj}}, \sigma_{\phi_{kj}}\right)(I). \tag{11}$$

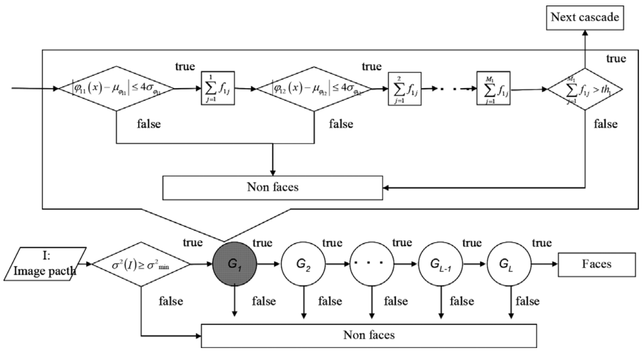


Fig. 5. Face detection combining one-class estimation and Real AdaBoost.

In detection processing, an image patch I is successively classified as true or false at every G_k, and one classified as true at the final cascade is recognized as face.

Here, recognition by one-class estimation is combined with recognition using the weak classifiers obtained by Real AdaBoost at each cascade G_k. If the variance $\sigma^2_{\phi kj}$ of the brightness values obtained in the correction calculation of the Haar-like filter $\phi_{kj}(I)$ is

$$\sigma^2_{\phi_{kj}}(I) \geq \sigma^2_{\phi_{kj}\,\mathrm{min}}, \tag{12}$$

then the patch is recognized as face-like; otherwise the patch is discarded. For a patch recognized as face-like, the Haar-like filter value is calculated and the face probability distribution model $P_{\phi j}(x_i)$ is applied. If

$$|\phi_{kj}(I) - \mu_{\phi_{kj}}| \leq 4 * \sigma_{\phi_{kj}\,\mathrm{min}}, \tag{13}$$

then the patch is recognized as face-like; otherwise the patch is discarded. For a patch recognized as face-like, the values of the weak classifiers $f_{kj}(I)$ are then calculated. This procedure is repeated until all the weak classifiers in the cascade have been processed. If

$$\sum_{j}^{M_k} f_{kj}(I) > \mathrm{it\ th}_k, \tag{14}$$

then the patch is recognized as face-like and transferred to the next cascade G_{k+1}; otherwise the patch is discarded.

4. Evaluation Experiments

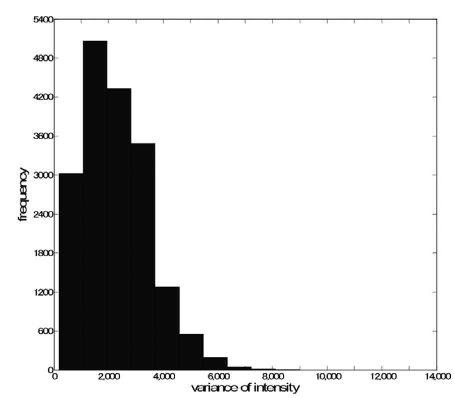
We evaluated the proposed robust face detection algorithm combining one-class estimation with Real AdaBoost, and the conventional cascaded face detection algorithm using Real AdaBoost.

4.1 Experimental results

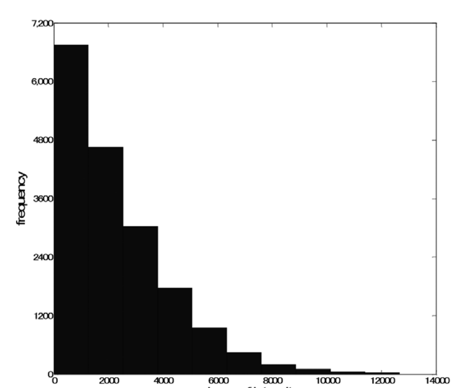
The face images used for learning were mostly full-face images of adults collected from the Internet as well as face images cut from photographs taken at the R&D center (a total of 18,000 scaled-down images). The nonface images were images of animals, vehicles, musical instruments, and other objects collected from the Internet as well as nonface fragments cut from human images (a total of 18,000 scaled-down images). Of the nonface images, the 2300 initially collected ones showed high face likeness when processed by a certain number of weak classifiers using bootstrapping [18, 19]; these were replaced by others to obtain 18,000 images. The evaluation experiments were performed using one image dataset (43 images) including individual full-face photos of adults captured by a digital camera, and two image datasets (49 images) of group photos.

The cascade created in the experiments included 38 stages and 6060 Haar-like filters.

The variance distribution of the brightness values in the learning data is shown in Fig. 6, and the score distributions of the Haar-like filters obtained in learning is shown in Fig. 7. Based on the distribution of the intensity variance in

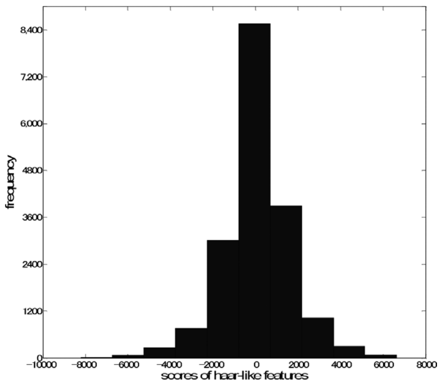


(a) face data

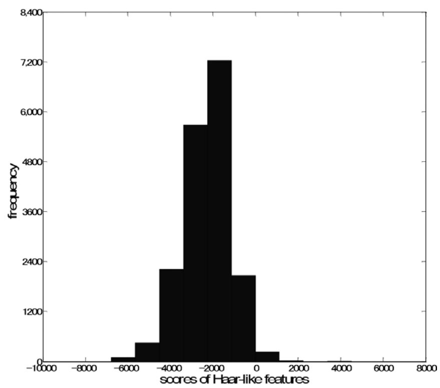


(b) non-face data

Fig. 6. Histogram of variances of intensity.



(a) face-data



(b) non-face data

Fig. 7. Histogram of scores of Haar-like features.

(a) Cascade algorithm (b) One-class + Real AdaBoost

Fig. 8. Removal of cascade algorithm's false positive .

Fig. 6, we set σ^2_{min} as 90. As indicated by Fig. 7, the Haar-like filter distributions can be approximated by a normal distribution.

Tables 1 and 2 show the detection rates obtained for various thresholds at every stage for data sets 1 and 2, respectively. As can be seen from Tables 1(b) and 2(b), the algorithm combining one-class estimation with Real AdaBoost achieved the same level of detection rate as the conventional cascaded face detection algorithm, but the number of false positive rate was improved to about 1/8

Table 1. Evaluation of face detection (Dataset 1)

(a) Cascade detector			
Detection rat (%)	94.50	96.50	98.10
False positive rate (patches/image)	1.86	2.10	2.36
(b) One-class + Real AdaBoost			
Detection rat (%)	94.50	96.50	98.10
False positive rate (patches/image)	0.26	0.26	0.30

Table 2. Evaluation of face detection (Dataset 2)

(a) Cascade detector			
Detection rate (%)	90.90	93.60	98.34
False positive rate (patches/image)	2.20	3.11	3.48
(b) One-class + Real AdaBoost			
Detection rate (%)	80.58	88.30	91.26
False positive rate (patches/image)	0.86	1.05	1.24

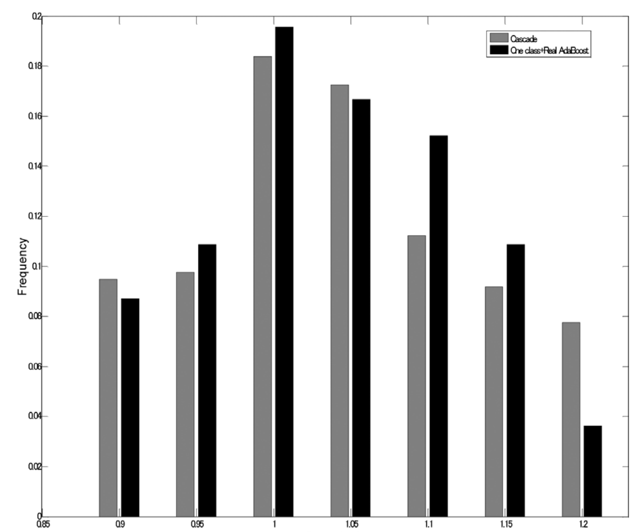


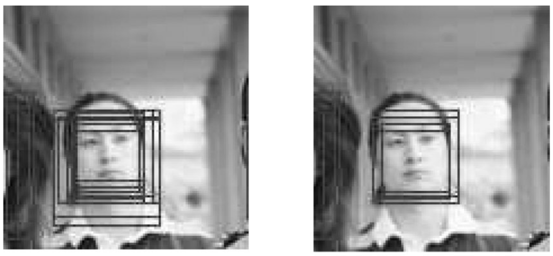
Fig. 9. Distribution of detected face scale.

for Dataset 1. On the other hand, in Dataset 2, including group photographs, the detection rate was slightly lower than with the conventional algorithm, and the false positive rate improved to about 1/3. Figure 9 shows an example of the elimination of false positives in Dataset 2. In the conventional method, there are scenes that are difficult to foresee such as background and clothes; false positive detection in such unforeseen situations is prevented by using one-class estimation.

The detection speed at the threshold offering the highest detection rate is compared in Table 3. Here the proposed method proves about 2.5 times as fast for Dataset 1, including individual portraits, and about three times as fast for Dataset 2, including group photographs.

Table 3. Detection speed comparison (VGA on Core i7 3.2 GHz)

	Cascade by RealAdaBoost (s)	One-class + Real AdaBoost (s)
Dataset 1	0.072	0.029
Dataset 2	0.082	0.028



(a) Cascade detector (b) One-class + Real AdaBoost

Fig. 10. Comparison of detected face region.

Figure 9 shows the distribution of the ratio $r = s_{\mathrm{detected}}/s_{\mathrm{true}}$ between the detected and actual face size, normalized so that the total of the faces is 1. As can be seen from the histogram, in the conventional method, there are many cases in which the extracted face size is larger than the actual size (i.e., the extracted face region is larger than necessary), for example, $r = 1.2$. In contrast, when one-class estimation is used, the distribution comes nearer to the actual size ($r = 1$) in many cases. An example of more accurate extraction is shown in Fig. 10.

4.2 Discussion

False positives are also caused by textures, such as background or clothes. This explains why more positives occur at the same threshold in Dataset 2 that includes group portrait scenes with more background and clothes than the individual portraits in Dataset 1. In addition, such images contain more face-like regions, and the processing time increases directly in the conventional cascaded algorithm; in contrast, this effect is reduced when one-class estimation is combined with Real AdaBoost.

On the other hand, the detection performance of the proposed algorithm is slightly lower than that of the conventional algorithm in the case of Dataset 2. Analysis of the undetected faces showed that their size was near the lower detection limit. In addition, comparison of the undetected faces with detected faces of the same size showed that the former included blur, JPEG block noise, and other disturbances.

Inspection of the image data used for learning data shows that some faces are much larger than the detector size. When processing images for learning, data face regions were cut out from the original images, then scaled down to the detector size. These scaled-down face images contain low-frequency components of the original images, and as a result, blur, JPEG block noise, and other disturbances that may be present in the original image data become almost unobservable in the learning data of detector size.

When detecting faces close to the detector size (small faces near the lower detection limit), factors such as blur, JPEG block noise, and other disturbances exert a strong effect, manifested as a considerable deterioration of the detection rate. On the other hand, the face images in the learning data are free of blur, JPEG block noise, and other disturbances, and the generated face detectors are vulnerable to such disturbances.

The detection performance was also estimated for full-face images, and the group photographs included the faces of babies, which are difficult to detect by one-class estimation. This can be explained by the fact that few baby faces were included in the learning data. Oblique face images were included in the collective portraits, and the conventional cascaded algorithm was able to detect such faces. This suggests a closer relationship between the faces used as learning samples and the detected faces in the case of one-class estimation.

5. Conclusions

In conventional learning-based face detection algorithms, face detection is treated as a problem of discrimination between two classes, faces and nonfaces, and accordingly, face and nonface data are prepared. However, actually, while face data include only 1 class (faces), nonface data may include an infinite number of classes, and it is impossible to prepare nonface learning data covering all those classes. As a result, misdetections are inevitable when unclassified nonface data appear.

Addressing this problem, we introduced a one-class recognition algorithm so that nonface data are treated as outliers with respect to face data, and combined this one-class estimation with Real AdaBoost in the proposed face detection method.

Compared to the conventional method, the proposed method offered the same face detection rates for images free of blur and noise, while processing speed was increased by a factor of about 2.5 and the false positive rate was improved to about 1/8.

At the same time, we found that the detection rate dropped for faces not included in the learning data, such as blurred or noisy small-size faces, baby faces, and oblique faces.

In the future, we plan to analyze how the detection performance is affected by the attributes of the faces included in the learning data, and to improve the proposed method by increasing robustness to fluctuations of noise, age, and orientation, without sacrificing the advantages of one-class estimation.

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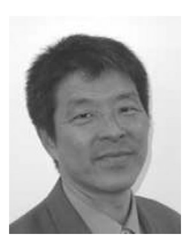
AUTHORS (from left to right)



Shotaro Miwa (nonmember) received a bachelor's degree in electrical and electronic engineering from the University of Tokyo in 1991 and joined Mitsubishi Electric Corp. and is now at the Advanced Technology R&D Center. His research interests include image recognition, learning theory and its applications (D.Eng.).

Takashi Hirai (member) completed the doctoral program in mathematical engineering at Kyoto University (Graduate School of Engineering) in 1989 and joined Mitsubishi Electric Corp. and is now at the Advanced Technology R&D Center. His research interests include security systems, equipment diagnosis systems, measurement systems (D.Eng.).

Kazuhiko Sumi (nonmember) completed the doctoral program in engineering at Kyoto University in 1984 and joined Mitsubishi Electric Corporation. He was visiting researcher at Computer Vision Laboratory, University of Maryland in 1989 and was visiting professor at Kyoto University from 2003 to 2005. He is now professor at Aoyama Gakuin University (Faculty of Science and Engineering). His research interests inlcude image processing, sensor signal processing (Doctor of Engineering).