A Robust Eye Localization Method for Low Quality Face Images

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Abstract

Eye localization is an important part in face recognition system, because its precision closely affects the performance of face recognition. Although various methods have already achieved high precision on the face images with high quality, their precision will drop on low quality images. In this paper, we propose a robust eye localization method for low quality face images to improve the eye detection rate and localization precision. First, we propose a probabilistic cascade (P-Cascade) framework, in which we reformulate the traditional cascade classifier in a probabilistic way. The P-Cascade can give chance to each image patch contributing to the final result, regardless the patch is accepted or rejected by the cascade. Second, we propose two extensions to further improve the robustness and precision in the P-Cascade framework. There are: (1) extending feature set, and (2) stacking two classifiers in multiple scales. Extensive experiments on JAFFE, BioID, LFW and a self-collected video surveillance database show that our method is comparable to state-of-the-art methods on high quality images and can work well on low quality images. This work supplies a solid base for face recognition applications under unconstrained or surveillance environments.

1. Introduction

In most face recognition systems, face images should be aligned based on the coordinates of eyes, *e.g.* aligning two eyes to some fixed coordinates by a similarity transform. Therefore, eye localization is an important part in face recognition systems, and its precision will closely affect the performance of face recognition [12, 18]. Fig. 1 shows some face images aligned by the eye coordinates and their corresponding similarity score matrix. We can see that small disturbance of eye coordinates leads to small variation in the appearance of aligned face images, but it reduces the

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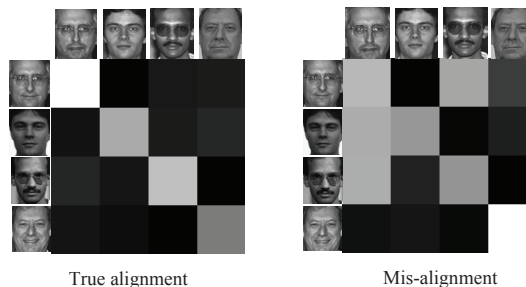*Stan Z. Li is the corresponding author.

Figure 1. The influence of mis-alignment on the similarity matrix of face matching. Left: Face matching with manually labeled eye coordinates. Right: Face matching after the eye coordinates disturbed by a small noise (subject to $[-0.1, 0.1] \times$ eye-distance uniform distribution). The similarity matrix is generated by a Gabor+LDA face recognition algorithm [10].

discriminant of the similarity score matrix. As discussed in [18, 19], this influence generally exists in almost all face recognition systems, no matter which are based on holistic or local methods.

Although, many good results [12, 21, 16, 8, 9] of eye localization were reported , they were usually obtained in some high quality face databases, such as, JAFFE, BioID and *etc.* When these methods are used under unconstrained [20] or surveillance environments, they may not work well due to the low quality of face images and large noise. Here, low quality denotes those face images affected by out-of-focus, motion, pose, illumination, expression and other factors. This paper focuses on this problem, and the objective is to propose a low quality robust eye localization method. The proposed method should have high detection rate and localization precision.

Recently, the leading methods in eye localization are almost based on Boosting classification, regression, Boosting+Cascade, Boosting+SVM, and other variants. Considering precision and computation complexity, we propose a new method for low quality images based on LBP+Boosting+Cascade [1, 23]. For two-class problem, Boosting can select the most effective subset from an overcomplete feature set. Also cascade can reject irrelevant

samples in each stage to obtain drastic speedup according to some thresholds, hence Boosting+Cascade is very appropriate for real-time detection task. However, in eye localization, the boundary between the positive and negative samples is ambiguous, especially in low quality images. Therefore, in eye localization task, the thresholds in the cascade don't have clear semantics. Those positive samples with low quality are easily rejected by the thresholds, and fail to contribute to the final result. To achieve high detection rate, we introduce a quality adaptive cascade that work in a probabilistic framework (P-Cascade). In the P-Cascade framework, each image patch can get a probability whether it's rejected or accepted by the cascade. In other words, all image patches have chance to contribute to the final result, and their contributions are determined by their corresponding probability. In this way, P-Cascade can adapt to face images with any quality.

In low quality face images, there are two main factors to affect the localization precision: noise and eye-like patterns, such as eyebrow, glasses frame, shadow and so on. To achieve high precision, we propose two extensions: (1) extending LBP feature set to improve the discriminant ability of Boosting classifier, and (2) stacking two classifiers in different scales to find a trade-off between the robustness and precision. Extensive experiments on two challenging databases show that our method can work well on low quality face images and the proposed extensions can further improve the precision.

To conclude, this paper focuses on the eye localization problem in low quality face images, and has the following contributions:

1. Discusses a challenging problem: eye localization in low quality face images, and proposes an effective method to deal with it;

2. Proposes a P-Cascade framework to weaken the influence of quality on the thresholds in traditional cascade;

3. In the P-Cascade framework, we propose a more discriminative LBP operator, and a stacked classifier in multiple scales to improve the eye localization precision;

4. Advances the standardization of eye localization testing, and publishes a low quality data set of face images captured under surveillance environment.

This paper is organized as follows. Section 2 introduces a probabilistic way to use cascade classifier, called P-Cascade. In section 3, we propose two extensions to enhance the discriminant and robustness of the P-Cascade. Section 4 conducts some experiments on high and low quality databases to illustrate the superiorities of the proposed method. Section 5 concludes the paper.

2. Eye Localization Framework

As reviewed above, Boosting+Cascade is one of the best methods among all existing eye localization methods. For high precision and low computation complexity, this section builds the P-Cascade framework based on Boosting+Cascade. Compared with the traditional Boosting+Cascade, P-Cascade has an attractive advantage: every image patch evaluated by P-Cascade has a probability belonging to positive class, and the probability will contribute to the final localization result.

2.1. Probabilistic Cascade

As we know, cascade works in an asymmetric way, which is composed of many rejecting stages. The task of each stage is to reject the most probable negative samples according to some thresholds. The asymmetric rejecting strategy can obtain a good trade-off between precision and efficiency under normal conditions, but its performance will decline in low quality images. With the variation of quality, the output scores of each stage will change. Therefore, those thresholds in cascade can not adapt all situations and would cause low detection rate in low quality images. To solve this problem, we reformulate the cascade classifier in a probabilistic way (P-Cascade), in which we give every patches chances to contribute to the localization task, including those rejected patches. Compared to the traditional cascade, the P-Cascade use more complete information of the evaluated patches and can achieve higher performance.

In P-Cascade, the thresholds of each stage work in the same way to reject irrelevant samples. The biggest difference is that, for each sample, we can get its probability belonging to the positive class (*i.e.* eye), whether it's rejected or accepted by any stage. When a sample $\mathbf{x}$ is accepted by the $(t-1)$th stage and rejected by the tth stage, the probability of $\mathbf{x}$ belonging to positive class could be evaluated by the tth stage. t is called the "rejecting stage" of the sample $\mathbf{x}$, short for r-stage. Stage classifier in the cascade can be learned by many Boosting algorithms. Here, we take Gentle-Boost [3] as an example to provide the specific form of the probability.

As discussed in [3], Gentle-Boost can be seen as logistic regression with generalized additive models, thus the relationship between the probabilities and the output of Gentle-Boost can be written as

$$p_{t(\mathbf{x})}(c = 1|\mathbf{x}) = \frac{e^{F(\mathbf{x})}}{e^{F(\mathbf{x})} + e^{-F(\mathbf{x})}}, \qquad (1)$$

where $t(\mathbf{x})$ is the r-stage of the sample $\mathbf{x}$, $F(\mathbf{x}) = \sum_i^d f_i(\mathbf{x})$ is the tth strong classifier, $f_i(\mathbf{x})$ is weak classifier. Fig. 2 shows a face image, the output values of a stage in cascade around the left eye, and their corresponding probabilities calculated by Equ.(1). From that we can see the probability map is more discriminative than the raw output of Boosting.
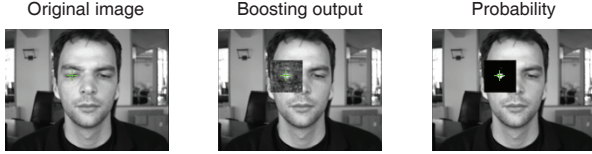
Figure 2. A face image, output scores of Boosting and their corresponding probabilities around the left eye, where the green cross is the true eye coordinate

In testing process, each sample $\mathbf{x}$ is evaluated by a trained P-Cascade and its corresponding $t(\mathbf{x})$ and $p_{t(\mathbf{x})}(c = 1|\mathbf{x})$ are recorded. However, we notice that the probabilities of those samples with different r-stage are not comparable. Because different features are evaluated in different stages, the relationship between the stages can not be built easily. Next, we will discuss how to merge these probabilities with different r-stage to get the final position of eye.

2.2. Robust Probability Estimation

Given the r-stage and probabilities of every point on a face image, the most likely position of eye is the point with maximum r-stage and probability. The max rule is good but unstable to noise and outliers.

To obtain more accurate results, we use a three-step process to locate eye, which includes initialization, local search and merge. Firstly, we choose an initial point according to the face rectangle. Because the geometric relationship between eye position and face rectangle is known in the training set of face detector, the coarse positions of the left and right eyes can be predicted. For efficiency, next we only evaluate the probabilities of the points around the initial position in a $n \times n$ mesh grid. Finally, we get the location of eye by merging the first m points with largest r-stages and probabilities. The merge strategy is as follows,

$$\mathbf{e}^* = \frac{\sum_{\mathbf{e}_i \in \{\mathbf{e}_{rank-m}\}} p(c = 1|\mathbf{x}(\mathbf{e}_i))\mathbf{e}_i}{\sum_{\mathbf{e}_i \in \{\mathbf{e}_{rank-m}\}} p(c = 1|\mathbf{x}(\mathbf{e}_i))}, \quad (2)$$

where where $\mathbf{e}$ is a point in face image, $\mathbf{x}(\mathbf{e})$ is a image patch centering at $\mathbf{e}$, $\{\mathbf{e}_{rank-m}\}$ are the first m points with largest r-stages and probabilities, $p(c = 1|\mathbf{x}(\mathbf{e}_i))$ is the probability calibrated by another monolithic Boosting classifier (only containing one stage). This calibration is a key ingredient of our method, since it can remove the r-stage variable in Equ.(1) and build the connection between the points with different r-stages. Because the calibration only apply on the first m points, it nearly doesn't bring any extra computation.

The training process of P-Cascade is the same as traditional cascade, so we don't introduce it here. One can refer [22] for detail. We outline the testing process in Algorithm 1.

Algorithm 1 Eye localization using P-Cascade.

Input: A face image $I(\mathbf{e})$, the rectangle of the face Ω in the face image, a trained P-Cascade model and a monolithic Boosting model;

1. Choose an initial point based on Ω according to the known geometric relationship between the face rectangle and eye coordinates;
2. Evaluate the probabilities $p_{t(\mathbf{x})}(\mathbf{x}(\mathbf{e}_i)), i \in [1, n^2]$ on $n \times n$ mesh grid using Equ.(1) in the left-top (or right-top) quadrant of Ω;
3. Get $\{\mathbf{e}_{rank-m}\}$ by sorting all points according to probability and r-stage in descending order;
4. Calibrate the probabilities of $\{\mathbf{e}_{rank-m}\}$ by the monolithic Boosting model;

Output: The final eye coordinate is calculated by merging the points in $\{\mathbf{e}_{rank-m}\}$ using Equ.(2).
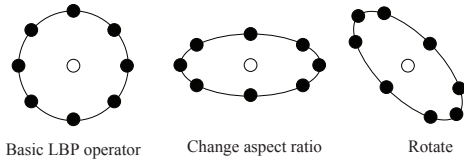

Figure 3. An LBP operator and two E-LBP operators with elliptical shape and rotation.

3. Extensions for Low Quality Images

P-Cascade is adaptive for the quality of face images, because it weaken the shortcoming of the thresholds in cascade and use the information of those rejected samples as much as possible. In this section, we propose two extensions to further improve the precision and robustness of P-Cascade from the following aspects: (1) Extending LBP feature set to enhance the discriminant of basic features; (2) Choosing the size of receptive field and stacking classifiers in multiple scales to find a trade-off between robustness and efficiency.

3.1. Extending LBP Feature Set

LBP [1] and MB-LBP have been proved more effective than Haar in face detection [23], hence we use MB-LBP as baseline in this paper for comparison. In low quality face images, classifier is easily disturbed by noise and eye-like pattern. To reject these false positives, we add two extra parameters into the original LBP operator to construct a new operator, called "Extended LBP" or E-LBP. Compared to LBP, E-LBP has two radiuses and an angle, which makes the shape of E-LBP a rotated ellipse. Their differences are shown in Fig. 3.

Given a 20×20 image, the size of LBP and MB-LBP feature set are 1140 and 3969. Using E-LBP operator, we can get more numerous features, which contains 34472 features when using 4 orientations. In section 4, we will see E-LBP
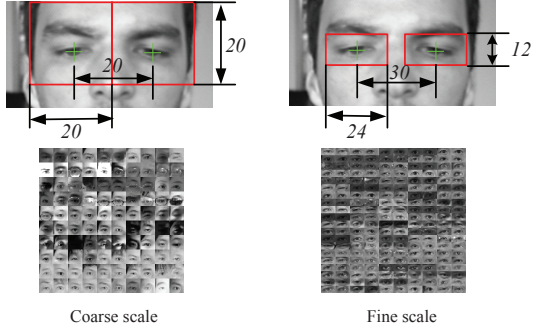
Coarse scale | Fine scale

Figure 4. The scale and geometry of training samples for two level stacked classifiers. In the first scale, the ground truth position is set at the lower part of the samples to overcome the disturbance of eyebrow. The second scale is as same as ones in most existing methods, and the ground truth position is at the center of the samples.

has better performance than MB-LBP in all experiments. The improvements are benefit from the larger feature set of E-LBP.

3.2. Stacking Classifiers

[2] discussed many aspects about the influence of the training samples on eye localization including size, geometry and the position of ground truth in the training samples. They derived a useful conclusion, that larger scale training samples would lead to more robust classifier, but smaller scale samples could have more accurate localization precision. In [12], a big receptive field containing two eyes is used for eye-pair verification, which has been proven being robust to noise and outliers.

In most existing works, the size and geometry of the eye training samples agree with the standard in [24], as shown in the right of Fig. 4. These standard eye samples only contain the eye itself but exclude the eyebrow, nose and others. In ordinary face images, this size can work well, but in poor face images, the eye is easily confused with those eye-like patterns, especially the eyebrow.

To weaken the interference of eyebrow on eye localization, we choose a geometry with bigger receptive than [24], which includes both eye and eyebrow information. The new geometry of eye training samples is shown in the left of Fig. 4. The size of receptive filed is about 1/4 of the face. Experiments on low quality databases in section 4 illustrate the superiority of this setting.

For low quality face images, robustness is the most concern, meanwhile, we don't want to loss precision yet. To this end, we propose a "coarse to fine" stacked classifiers, which includes two classifiers in multiple scales. Actually, this kind of multi-scale methods were popular in many applications, such as ASM [14]. As shown in Fig. 4, the first coarse one is trained on the samples with large receptive field described above. Using the coarse classifier, we ex-

clude those eye-like negative patterns. The second one is trained on the samples with ordinary geometry [24], which just cover the eye region. With the help of the coarse classifier, the second one can achieve high localization precision while keeping the robustness. For simplicity, we denote the coarse scale and the fine scale by S1 and S2.

When the stacked classifiers are ready, we predict the position of eyes by two steps: coarse prediction and refinement. To avoid local minima, the search region in the second step is smaller than that in the first step. The advantages of the stacked classifier will be illustrated in the following experiments.

4. Experimental Results

To illustrate the performance of the proposed method, we conduct some experiments in two scenarios, one for ordinary quality, the other for low quality. The testing process is that, given a face image and the rectangle coordinate of the face in the image, we need locate the positions of eyes in the face. The normalized error [24] is used to evaluate the error between the localized eye positions and the ground truth.

$$err = \frac{max(||l - l_g||, ||r - r_g||)}{||l_g - r_g||}, \qquad (3)$$

where, l_g and r_g are the ground truth positions (labeled by manual work) of the left and right eye respectively; l and r are the eye positions localized by an algorithm.

In experiments, the proposed method is compared with several state-of-the-art methods: MB-LBP + Boosting [23], [12], [21] , [16] and [8], among which MB-LBP is trained and tested on the same data with the proposed method, the results of the other methods are taken from the original papers directly. Due to the different experimental settings, these methods are not completely comparable, but they are still list for reference. For making the results reproducible, the training and testing set are published in our web site[1], with rectangle of faces and ground truth eye positions.

4.1. Databases

To train a general eye detector, we construct the training set from various databases including FRGC [17], CAS-PERL [4], AR [13], PF01 [6] and a private database built by our lab. The training set contains 20612 face images, thus we can get 41224 eye samples. The test sets are divided into two categories: ordinary quality and low quality. JAFFE [11] and BioID [7] are used for ordinary quality evaluation, and LFW [5] and a self-collected video surveillance (VS) database are used for low quality evaluation. The quality of these databases assessed by BIQI [15] are shown in Table 1 for reference.

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[1]http://www.cbsr.ia.ac.cn/users/dyi/eyelocalization.htm.

Table 1. The quality of JAFFE, BioID, LFW and VS assessed by BIQI (The scores are between 0 and 100, from good to bad quality).

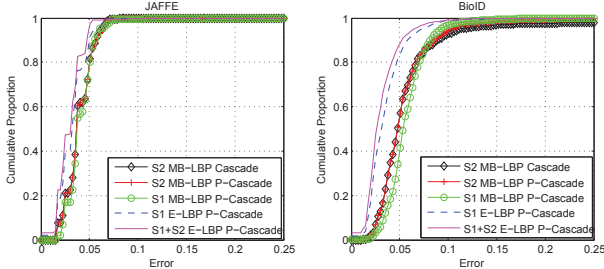|	JAFFE	BioID	LFW	VS
Mean	27.31	28.53	32.95	40.44
Deviation	2.69	6.78	7.06	7.55

Figure 5. Cumulative error curves for eye localization on JAFFE and BioID.

Table 2. Comparison of eye localization methods on JAFFE and BioID.

	JAFFE (err < 0.1)	BioID (err < 0.1)
S1+S2 E-LBP P-Cascade	**100%**	**99.01%**
[12]	98.6%	-
[21]	99.53%	91.782%
[16]	100%	93.0%
[8]	100%	96.4%

4.2. Evaluation on Ordinary Images

The cumulative error curves on JAFFE and BioID are shown in Fig. 5, in which 5 methods are compared: MB-LBP Cascade on fine scale (S2 MB-LBP Cascade), MB-LBP P-Cascade on fine scale (S2 MB-LBP P-Cascade), MB-LBP P-Cascade on coarse scale (S1 MB-LBP P-Cascade), E-LBP P-Cascade on coarse scale (S1 E-LBP P-Cascade), E-LBP stacked P-Cascade (S1+S2 E-LBP P-Cascade). Due to the good quality of JAFFE, the performances of all methods are very similar. From the results on BioID we can see two obvious phenomena : (1) E-LBP is always better than MB-LBP; (2) S2 has better precision in small error range, but poorer precision in large error range, which proves the conclusion described in section 3. The results in other papers on JAFFE and BioID are list in Table 2 for reference. Although [8] achieves very high precision, its training set and testing set are not fully independent. Therefore, the proposed method has better generalizability than [8].

4.3. Evaluation on Low Quality Images

Overall, the performances of eye localization on ordinary face images are relatively high and can satisfy the requirement of face recognition. But for face images with
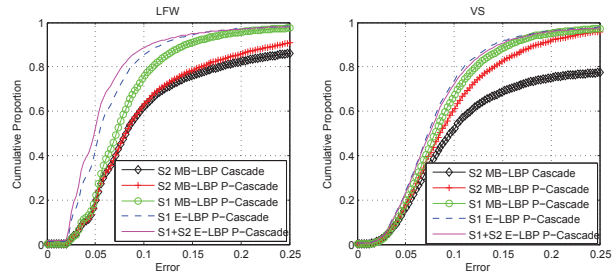

Figure 6. Cumulative error curves for eye localization on LFW and the VS.

low quality, the performance will drop drastically, and these cases often appear in unconstrained face recognition applications, *e.g.* video surveillance. To illustrate the superiority of the proposed methods under these circumstances, we test them on LFW and a self-collected video surveillance (VS) database. The 4064 face images in the VS database were captured by a practical surveillance system in one month.

Fig. 6 shows the cumulative error curves of the five methods. On LFW, "S1+S2 E-LBP P-Cascade" obtains the best precision, but on the VS database, only using S1 (coarse scale) is better than the others. This suggests that the optimal size of receptive field is closely related to the quality of face images. Generally, small receptive field suits for high quality face images, while large one suits for low quality face images. The proposed stacking strategy initially use this property, and "S1+S2 E-LBP P-Cascade" almost obtains the best performance in all cases. How to make the size of receptive field adapt to the quality of face images automatically is an interesting question. While the differences between P-Cascade and Cascade are not obvious on JAFFE and BioID, P-Cascade based methods are significantly better than traditional Cascade on these two low quality databases.

5. Conclusion

This paper focuses on the eye localization problem in low quality face images, and proposes an effective P-Cascade framework to solve it. Different from the traditional cascade classifier, all input examples in P-Cascade can get a probability whether it's accepted or rejected. In other words, all samples are treated as equal and have chance to contribute to the final result. Thanks to this property, P-Cascade can adapt to images with various quality well. In the P-Cascade framework, we propose two extensions to further improve the robustness and precision. Finally, extensive experiments are conducted to verify the superiority of the proposed methods. The results show that the proposed "S1+S2 E-LBP P-Cascade" method obtains the highest precision in terms of normalized error. As oriented to practical applications, the training and testing set are completely independent and will be published in our

web site.

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