Robust Multi-view Face Detection Using Error Correcting Output Codes

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Abstract. This paper presents a novel method to solve multi-view face detection problem by Error Correcting Output Codes (ECOC). The motivation is that face patterns can be divided into separated classes across views, and ECOC multi-class method can improve the robustness of multi-view face detection compared with the view-based methods because of its inherent error-tolerant ability. One key issue with ECOC-based multi-class classifier is how to construct effective binary classifiers. Besides applying ECOC to multi-view face detection, this paper emphasizes on designing efficient binary classifiers by learning informative features through minimizing the error rate of the ensemble ECOC multi-class classifier. Aiming at designing efficient binary classifiers, we employ spatial histograms as the representation, which provide an over-complete set of optional features that can be efficiently computed from the original images. In addition, the binary classifier is constructed as a coarse to fine procedure using fast histogram matching followed by accurate Support Vector Machine (SVM). The experimental results show that the proposed method is robust to multi-view faces, and achieves performance comparable to that of state-of-the-art approaches to multi-view face detection.

1 Introduction

Automatic detection of human faces is significant in applications, such as human-computer interaction, face recognition, expression recognition and content-based image retrieval. Face detection is a challenge due to variability in orientations, partial occlusions, and lighting conditions. A comprehensive survey on face detection can be found in [1].

Many approaches have been proposed for face detection, these approaches can be classified as two categories: global appearance-based technique and component-based technique. The first one assumes that a face can be represented as a whole unit. Several statistical learning mechanisms are explored to characterize face patterns, such as neural network [2,3], probabilistic distribution [4], support vector machines [5,6], naive Bayes classifier [7], and boosting algorithms [8,9]. The second method treats a face as a collection of components. Important facial features (eyes, nose and mouth) are first extracted, and by using their locations and relationships, the faces are detected [10].

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So far there are three ways for multi-view face detection. The first scheme is a view-based approach. In the training stage, separate face detectors are built for different views. In the testing stage, all these detectors are applied to the image and their results are merged into final detection results [4,7,9]. [11] uses a pose estimator to select a detector to find faces of the chosen view. The second scheme is described in [12] for rotated-face detection, which calculates the in-plane rotation angle of input image, and rotates the input image for a frontal face detector. The third way is to approximate smooth functions of face patterns across various views [13] or face manifold parameterized by facial pose [14].

Motivated by the idea that face patterns can be naturally divided into distinct classes according to separated facial poses, this paper proposes a novel method that detects multi-view faces using a multiclass classifier based on error correcting output codes (ECOC). With its inherent error-tolerant property, ECOC can improve the robustness to pose variation for face detection.

Dietterich and Bakiri [15,16] presented the idea of reducing multiclass problems to multiple binary problems based on ECOC. ECOC classifier design concept has been used in many applications, such as text classification [17] and face verification [18]. In ECOC related applications, one key issue is the problem how to construct optimal binary classifiers for an effective ECOC multi-class classifier. In [19], an approach is presented to learn good discriminator in linear feature space for object recognition.

In the proposed method, we emphasize on designing efficient binary classifiers by learning informative features through minimizing the error rate of the ensemble ECOC multi-class classifier. Aiming at designing efficient binary classifiers, we propose to use spatial histogram features as representation and use hierarchical classifiers that combine histogram matching and support vector machine (SVM) as binary classifiers.

Section 2 briefly describes the background of ECOC-based multi-class classification method. The overview of the proposed ECOC-based multi-view face detection approach is given in Section 3. Face representation used in the proposed method is described in Section 4. In Section 5, the method of learning an ECOC-based multi-view face detector through minimizing error rate is presented. Experimental results are provided in Section 6. Conclusions are given in Section 7.

2 Background of ECOC-Based Multi-class Classification

Let $S = \{(x_1, y_1),...,(x_m, y_m)\}$ be a set of m training samples where each instance x_i belongs to a domain X , and each label y_i takes values from a discrete set of classes $Y = \{1,...,k\}$. The task of learning a multiclass classifier is to find a function $H : X \to Y$ that maps an instance x into a class label y , $y \in Y$.

To understand the method for solving multiclass learning problems via ECOC, consider a $\{0,1\}$-valued matrix Z of size $k \times n$ where k is the number of classes and n is the length of the unique binary string assigned to each class as its *code word*. The k rows are well separated with large Hamming distance between any pair. For each column, the instances are relabeled as two *super classes* according to the binary vales (1s and 0s).

The multiclass learning method consists of two stages. (1) In the training stage, a set of n binary classifiers is constructed, where each classifier is to distinguish between the two super classes for each column. These binary classifiers are called *base classifiers*. (2) In the testing stage, each instance is tested by the base classifiers, and is represented by an output vector of length n. The distance between the output vector and the code word of each class is used to determine the class label of the instance.

3 Overview of the Proposed ECOC-Based Face Detection Method

We divide face patterns into three categories: frontal faces, left profile faces, right profile faces, according to facial pose variation out of plane. Adding non-face patterns together, we have four classes to be recognized in total. Therefore, we format multi-view face detection as a multi-class problem with four classes, and explore the problem of learning ECOC-based classifier for multi-view face detection.

Since $k = 4$, we construct a complete code of length $n = 7$, as shown in Table 1. No columns or no rows are identical or complementary in the code. For each column, one base classifier is needed to identify the super classes (refer to Section 2). In total, seven base classifiers $\{b_0, b_1, ..., b_6\}$ are to be constructed to form an ensemble classifier. According to information theory, this code has error correcting ability for any base classifier.

Table 1. ECOC codes for face detection

	b_0	b_1	b_2	b_3	b_4	b_5	b_6
Non face pattern (C_0)	0	0	0	0	0	0	0
Front face pattern (C_1)	1	1	1	1	0	0	0
Left profile face pattern (C_2)	1	1	0	0	1	1	0
Right profile face pattern (C_3)	1	0	1	0	1	0	1

We utilize an exhaustive search strategy to detect multiple faces of different sizes at different locations in an input image. The process of object detection in images is summarized in Fig. 1. It contains three steps: image sub sampling, object classification and detection results fusion.

In the Step 1, the original image is repeatedly reduced in size by a factor 1.2, resulting in a pyramid of images. A small window (image window) with a certain size 32x32 is used to scan the pyramid of images. After a sub image window is extracted from a particular location and scale of the input image pyramid, it is fed to the following procedures in the Step 2. Firstly, spatial histogram features are generated from this image window. Secondly, an ECOC-based multi-view face pattern classifier is used to identify whether the sub window contains a multi-view face. The Step 3 is a stage for detection results fusion. Overlapped face instances of different scales are merged into final detection results.

In the step 2, the input to the multi-view face detector is a vector x, which is constituted by spatial histogram features (refer to Section 4 for details) obtained on the

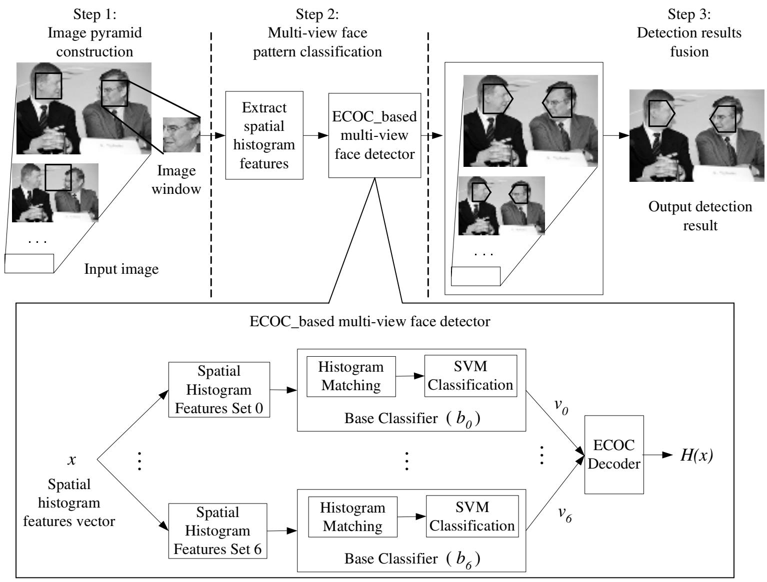

Fig. 1. The process of multi-view face detection in images

image window. For each base classifier, specific spatial histogram features are used as input. Histogram matching and SVM classification are performed hierarchically to identify which super class the vector belongs to (refer to Section 5 for details). The binary outputs by the base classifiers is transformed into an {0,1}-output vector of length $n = 7$, given as

$$V = [v_0, v_1, ..., v_6], \tag{1}$$

where v_j is the output of j th classifier, $j = 0,1,...,6$. The distance between the output vector and the code word of each class is determined by Hamming distance:

$$L_{c_i} = \sum_{j=0}^{6} | Z_{ij} - v_j |, (i = 0,...,3) . \tag{2}$$

The test instance is assigned to the class label whose code word has minimum distance, by the ECOC decode rule given by

$$H(x) = \arg\min_{c_i} \{L_{c_i} | i = 0,1,...,3\} . \tag{3}$$

4 Spatial Histogram Features for Face Representation

For each column, we refer the super class labeled by 1s as *object*, and labeled by 0s as *non-object*. Similar to our previous work [21], spatial histogram features in are used for object representation, as illustrated in Fig. 2. Spatial templates are used to encode spatial distribution of patterns. Each template is a binary rectangle mask and is denoted as $rt(x, y, w, h)$, where (x, y) is the location and (w, h) is the size of the mask respectively. We model the sub image within the masked window by histogram. This kind of histograms is called as *spatial histograms*. For a sample P, its spatial histogram associated with template $rt(x, y, w, h)$ is denoted as $SH^{rt(x,y,w,h)}(P)$.

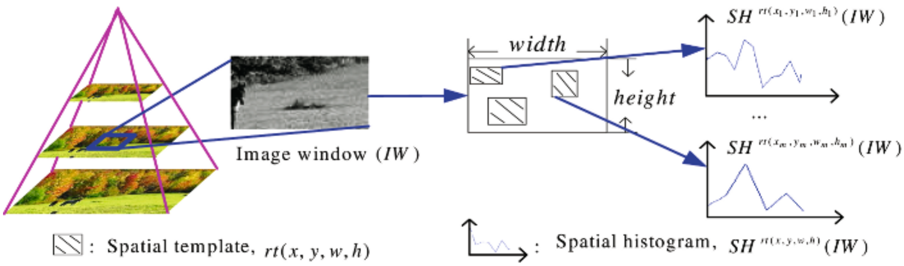

Fig. 2. Object spatial distribution is encoded by spatial histograms

Suppose a database with n object samples and a spatial template, we represent object histogram model over the spatial template by the average spatial histogram of the object training samples, defined as:

$$SH^{rt(x,y,w,h)} = \frac{1}{n}\sum_{j=1}^{n} SH^{rt(x,y,w,h)}(P_j) , \tag{4}$$

where P_j is an object training sample, and $rt(x, y, w, h)$ is the spatial template. For any sample P, we define its *spatial histogram feature* as its distance to the average object histogram, given by

$$f^{rt(x,y,w,h)}(P) = D(SH^{rt(x,y,w,h)}(P), SH^{rt(x,y,w,h)}) , \tag{5}$$

where $D(H_1, H_2)$ is the similarity of two histograms measured by intersection [20]. An object pattern is encoded by m spatial templates. Therefore, an object sample is represented by a spatial histogram feature vector in the feature space:

$$F = [f^{rt(1)},..., f^{rt(m)}] . \tag{6}$$

Feature discriminating ability: For any spatial histogram feature f_j ($1 \le j \le m$), its discriminative ability is measured by Fisher criterion

$$J(f_j) = \frac{S_b}{S_w} , \tag{7}$$

where S_b is the between-class scatter, and S_w is the total within-class scatter.

Features correlation measurement: Given two spatial histogram features f_1 and f_2, we calculate the correlation between two features f_1 and f_2 as

$$Corr(f_1, f_2) = \frac{I(f_1 \mid f_2)}{H(f_1)}, \tag{8}$$

where $H(f_1)$ is entropy of f_1, $I(f_1 \mid f_2)$ is the mutual information of f_1 and f_2. Let F_s be a feature set, the correlation between F_s and a feature $f_t \notin F_s$ is given by

$$Corr(f_t, F_s) = \max\{Corr(f_t, f_k) \mid \forall f_k \in F_s\}. \tag{9}$$

5 Learning ECOC-Based Classifier for Multi-view Face Detection

We apply a hierarchical classification using cascade histogram matching and SVM as base classifier to object detection. In this section, we present the method of designing efficient binary classifiers by learning informative features through minimizing the error rate of the ensemble ECOC multi-class classifier.

5.1 Cascade Histogram Matching

Histogram matching is a direct method for object recognition. Suppose P is a sample and its spatial histogram feature with one template $rt(x, y, w, h)$ is $f^{rt(x,y,w,h)}(P)$, P is classified as object pattern if $f^{rt(x,y,w,h)}(P) \geq \theta$, otherwise P is classified as non-object pattern. θ is the threshold for classification. We select most informative spatial histogram features and combine them in a cascade form to perform histogram matching. We call this classification method as *cascade histogram matching*. If n spatial histogram features $f_1, ..., f_n$ with associated classification thresholds $\theta_1, ..., \theta_n$ are selected, the decision rule of cascade histogram matching is as follows:

$$CH(P) = \begin{cases} 1 \quad \text{object} & \text{if} \quad f_1(P) \geq \theta_1 \wedge ... \wedge f_n(P) \geq \theta_n \\ 0 \quad \text{non-object} & \text{otherwise} \end{cases} \tag{10}$$

For each column, suppose that we have (1) spatial histogram features space $F = \{f_1, ..., f_m\}$, (2) positive and negative training sets: SP and SN, (3) a positive validation set $VP = \{(x_1, y_1), ..., (x_n, y_n)\}$, and a negative validation set $VN = \{(x_1^{'}, y_1^{'}), ..., (x_k^{'}, y_k^{'})\}$, where x_i and $x_i^{'}$ are samples with m dimensional spatial histogram feature vectors, $y_i = 1$ and $y_i^{'} = 0$, (4) acceptable detection rate: D. The method for training cascade histogram matching is given in the following procedure:

1. Initialization: $F_{select} = \varnothing$, $ThreSet = \varnothing$, $t = 0$, $Acc(pre) = 0$, $Acc(cur) = 0$;
2. Compute Fisher criterion $J(f)$ using SP and SN, for each feature $f \in F$;
3. Find the spatial histogram feature f_t which has the maximal Fisher criterion value, $f_t = \arg\max_{f_j}\{J(f_j) \mid f_j \in F\}$;

4. Perform histogram matching with f_t on the validation set $V = VP \cup VN$, find a threshold θ_t such that the detection rate d on the positive validation set VP is greater than D, i.e., $d \geq D$;
5. Compute the classification accuracy on the negative validation set VN, $Acc(cur) = 1 - \frac{1}{k}\sum_{i=1}^{k} | CH(x_i^{'}) - y_i^{'} |$. $CH(x)$ is the output by histogram matching with f_t and θ_t, $CH(x) \in \{0,1\}$;
6. If the classification accuracy satisfies condition: $Acc(cur) - Acc(pre) \leq \varepsilon$ (ε is a small positive constant), the procedure exits and returns F_{select} and $ThreSet$, otherwise process following steps:
   (a) $Acc(pre) = Acc(cur)$, $SN = \varnothing$, $F_{select} = F_{select} \cup \{f_t\}$, $F = F \setminus \{f_t\}$, $ThreSet = ThreSet \cup \{\theta_t\}$, $t = t + 1$,
   (b) Perform cascade histogram matching with F_{select} and $ThreSet$ on an image set containing no target objects, put false detections into SN,
   (c) Go to step 2 and continue next iteration step.

5.2 Construction of the ECOC-Based Multi-view Face Detector

Cascade histogram matching is the coarse object detection stage. To improve detection performance, we employ SVM classification [22] as fine detection stage. By minimizing error rate, we construct an ECOC-based multi-view face detector.

Suppose that we have (1) a spatial histogram features space $F = \{f_1,..., f_m\}$, (2) a training set $s = \{(x_1, y_1),...,(x_n, y_n)\}$ and a testing set $v = \{(x_1^{'}, y_1^{'}),...,(x_k^{'}, y_k^{'})\}$, where x_i and $x_i^{'}$ are samples with m dimensional spatial histogram feature vectors, $y_i \in \{0,1,2,3\}$ and $y_i^{'} \in \{0,1,2,3\}$, (3) ECOC code matrix Z of size $k \times n$, ($k = 4$, $n = 7$) as listed in Table 1. The construction of the ECOC-based multi-view face detector is performed as the following procedure:

1. Using the method for training cascade histogram matching (see section 5.1), construct a cascade histogram matching classifier as base classifier for each column. These base classifiers $\{b_0,...,b_6\}$ constitute the ECOC multi-class classifier;
2. Set classification accuracy $Acc(pre) = 0$; for each column, find f_m^i with maximum Fisher criterion, $F_{select}^i = \{f_m^i\}$ and $F_{ori}^i = F \setminus \{f_m^i\}$, $i = 0,1,...,6$;
3. Compute each base classifier's error rate; find the base classifier b_t ($0 \leq t \leq 6$), which has maximum error rate, and update the base classifier as follows:
   (a) Compute Fisher criterion $J(f)$ and feature correlation $Corr(f, F_{select}^t)$ on the training sample set, for each feature $f \in F_{ori}^t$;

(b) Compute $Thre$ as follows:

$$\begin{cases} MinCorr = \min\{Corr(f, F^t_{select}) \mid f \in F^t_{ori}\} \\ MaxCorr = \max\{Corr(f, F^t_{select}) \mid f \in F^t_{ori}\}, \\ Thre = MinCorr * (1-\alpha) + MaxCorr * \alpha \end{cases}$$

here α is a balance weight ($0 < \alpha < 1$), we choose $\alpha = 0.2$ in experiments;

(c) Find $f' \in F^t_{ori}$ with large Fisher criterion as below:

$$f' = \arg\max_{f_j}(J(f_j) \mid Corr(f_j, F^t_{select}) \le Thre);$$

(d) Train a SVM classifier C on the training set s, using f' and F^t_{select}; update b_t with cascade histogram matching and the SVM classifier C; update the ECOC multi-class classifier with b_t;

4. Evaluate the ECOC multi-class classifier on the testing samples set v, and compute the classification accuracy:

$$Acc(cur) = 1 - \frac{1}{k}\sum_{i=1}^{k} S(C(x_i^{'}), y_i^{'}),\ S(x,y) = \begin{cases} 1 & x \ne y \\ 0 & x = y \end{cases}.$$

Here, $C(x)$ is the classification output by the classifier C, $C(x) \in \{0,1,2,3\}$;

5. If the classification accuracy satisfies condition: $Acc(cur) - Acc(pre) \ge \varepsilon$ (ε is a small positive constant), process following steps:
   (a) $Acc(pre) = Acc(cur)$, $F^t_{select} = F^t_{select} \cup \{f'\}$, $F^t_{ori} = F^t_{ori} \setminus \{f'\}$,
   (b) Go to step 3 and continue next iteration step.
6. The procedure exits and returns the ECOC multi-class classifier, which is constituted by b_i and F^i_{select} ($i = 0,1,\ldots,6$).

6 Experimental Results

We implement the proposed approach and conduct experiments to evaluate its effectiveness. Our training sample set consists of 11,400 frontal face images, 4,260 left profile face images, 4,080 right profile face images, and 17,285 non-face images, each of standard size 32x32.

The exhaustive spatial template set within 32x32 image window is 832,351, a very large amount. After reducing redundancy, 180 spatial templates are evaluated to extract spatial histogram features. For each base classifier, about 9~15 spatial templates are learned for cascade histogram matching and 20~25 are learned for SVM classification with RBF kernel function in our experiment. The multi-view face detector is composed of these base classifiers.

Experiment 1: Error-Tolerant Performance Evaluation

In order to evaluate the error-tolerant performance of the ECOC-based multi-view face detector, we collect another sample set for testing. This set contains 5,400 frontal face images, 3,011 left profile face images, 3,546 right profile face images, and 6,527 non-face images, each of standard size 32x32.

In Table 2, classification error rates of binary classifiers in the ECOC-based multi-view face detector are presented. Table 3 shows classification error rates of the ECOC-based multi-view face pattern classifier. The error rates are decreased after using ECOC to combine all the base classifiers. These results demonstrate that the system has error-tolerant ability and it is be able to recover from the errors of single base classifier.

Table 2. Classification error rates of the base classifiers

	b_0	b_1	b_2	b_3	b_4	b_5	b_6
Error rate	18.4%	18.4%	18.3%	17.9%	4.7%	25.0%	22.9%

Table 3. Classification error rates of the ECOC-based multi-view face pattern classifier

Class	Number of testing samples	Error rate
Non face pattern (C_0)	6257	4.8%
Front face pattern (C_1)	5400	1.6%
Left profile face pattern (C_2)	3011	5.5%
Right profile face pattern (C_3)	3546	4.7%
Total	18214	4.0%

Experiment 2: Testing Results on Standard Data Sets

We test our system on two standard data sets. One is MIT+CMU set [2,4], which contains 130 images with 507 frontal faces. The other is CMU-PROFILE [7], which consists of 208 images with 441 faces from full frontal view to side view. About 347 faces are in profile pose.

The ROC curves are shown in Fig. 3. In Fig. 4, some face detection examples are given. The examples demonstrate that our approach can handle multiple faces with complex backgrounds. Comparison results are shown in Table 4 and Table 5. Our system exhibits superior performance than [2,9,11,14] with higher detection rate, and achieves comparable performance compared with the system of [7,8].

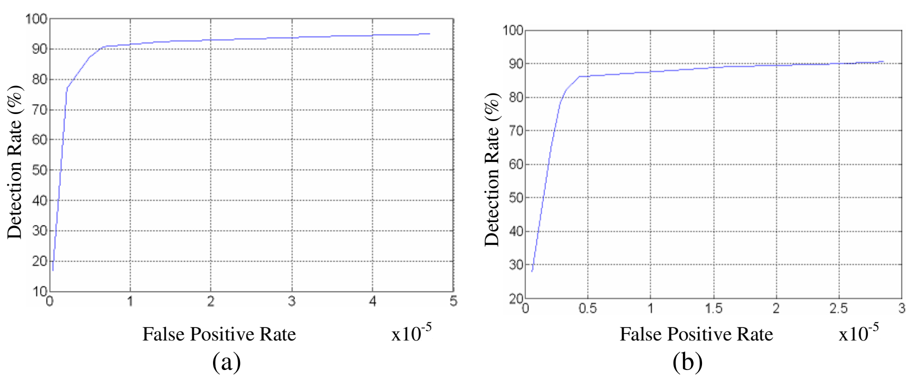

Fig. 3. ROC curves of face detection on (a) CMU+MIT test set, (b) CMU-PROFILE test set

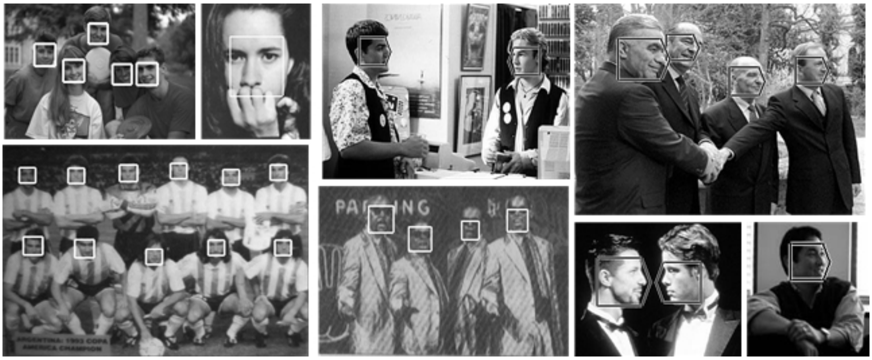

Fig. 4. Some examples of multi-view face detection

Table 4. Face detection rates on MIT+CMU set

False alarms	31	65	167
Jones and Viola [8](frontal)	85.2%	92.0%	93.9%
Rowley et.al [2]	85.0%	N/A	90.1%
Schneiderman and Kanade [7]	N/A	94.4%	N/A
Li and Zhang [9]	89.2%	N/A	N/A
Our approach	90.7%	92.3%	94.2%

Table 5. Face detection rates on CMU-PROFILE set

False alarms	91	700
Jones and Viola [11](profile)	70%	83%
Schneiderman and Kanade [7]	86%	93%
Osadchy, Miller, LeCun [14]	67%	83%
Our approach	82%	90%

Experiment 3: Performance Comparison with One-Against-Others Codes
We also conduct experiments to compare performance of ECOC codes with that of one-against-others codes. Table 6 gives the one-against-others code matrix for multi-view face detection. In each column, a binary classifier is constructed for each face

Table 6. One-against-others code for face detection

	b_0	b_1	b_2
Non face pattern (C_0)	0	0	0
Front face pattern (C_1)	1	0	0
Left profile face pattern (C_2)	0	1	0
Right profile face pattern (C_3)	0	0	1

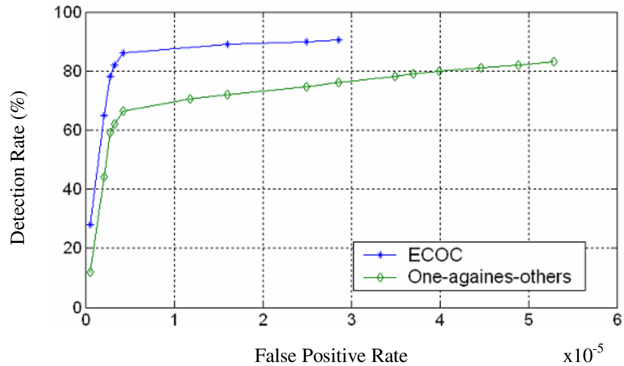

Fig. 5. Face detection performance comparison between ECOC with one-against-other: ROC on CMU-PROFILE test set

class against other face classes and non-face class. This code has no error correcting ability for base classifiers.

Fig. 5 shows the ROC comparison between the system using ECOC codes and the system using one-against-others codes. The comparison result shows that ECOC-based system achieves superior performance with higher detection rates.

7 Conclusions

In this paper, we solve multi-view face detection problem by using ECOC. The key issue is how to train effective binary classifiers for an efficient ECOC-based multi-view face detector. Our method constructs binary classifiers by learning informative features through minimizing the error rate. For purpose to obtain efficient binary classifiers, our method employs spatial histogram features as representation and hierarchical classifiers as binary classifiers. Extensive experiments show that ECOC improves the robustness to pose variation for face detection, and the proposed approach is efficient in detecting multi-view faces simultaneously. Tests on standard data sets show that the proposed method achieves performance comparable to that of state-of-the-art approaches to multi-view face detection.

The proposed approach of constructing ECOC-based multi-classifier by learning base classifiers can be viewed as a general framework of multi-classes problem based on a given code matrix. In the future work, we plan to apply this approach in multi-class objects detection with more kinds of objects.

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References

1. M.H. Yang, D.J. Kriegman, N. Abuja: Detecting Faces in Images: A Survey. IEEE Transactions on Pattern Analysis And Machine Intelligence, 24(1): 34-58, 2002.
2. H.A. Rowley, S. Baluja, T. Kanade: Neural Network-Based Face Detection. IEEE Transactions on Pattern Analysis And Machine Intelligence, 20(1): 29-38, 1998.
3. C. Garcia, M. Delakis: Convolutional Face Finder: A Neural Architecture for Fast and Robust Face Detection, IEEE Transactions on Pattern Analysis And Machine Intelligence, 26(11): 1408-1423, 2004.
4. K.K. Sung, T. Poggio: Example-Based Learning for View-Based Human Face Detection. IEEE Transactions on Pattern Analysis And Machine Intelligence, 20(1): 39-50,1998.
5. E.Osuna, R.Freund, F.Girosi: Training Support Vector Machines: an Application to Face Detection. Proceedings of CVPR, 130-136, 1997.
6. S.Romdhani, P.Torr, B.Scholkopf, A.Blake: Computationally efficient face detection. Proceedings of the 8th International Conference on Computer Vision, Volume 2: 695-700, 2001.
7. H. Schneiderman, T. Kanade: A Statistical Method for 3D Object Detection Applied to Faces and Cars. IEEE Conference on Computer Vision and Pattern Recognition, 2000.
8. P. Viola, M. Jones: Robust Real Time Object Detection. IEEE ICCV Workshop on Statistical and Computational Theories of Vision, 2001.
9. S.Z. Li, Z.Q. Zhang: FloatBoost Learning and Statistical Face Detection. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2004 (26): 9, 1112-1123.
10. K.C. Yow, R. Cipolla: Feature-Based Human Face Detection. CUED/F-INFENG/TR 249, 1996.
11. M. Jones, P. Viola: Fast Multi-view face detection. Technical Report TR2003-96, Mitsubishi Electric Research Laboratories, 2003.
12. H.A. Rowley, S. Baluja, T. Kanade: Rotation Invariant Neural Network-Based Face Detection. Computer Vision and Pattern Recognition, 38-44, 1998.
13. Y.M. Li, S.G. Gong, H. Liddell: Support vector regression and classification based multi-view face detection and recognition. Proceeding of Fourth IEEE International Conference on Face and Gesture Recognition, 300-305, 2000.
14. M. Osadchy, M.L. Miller, Y. LeCun: Synergistic Face Detection and Pose Estimation with Energy-Based Models. In Neural Information Processing Systems Conference, 2004.
15. T.G. Dietterich, G. Bakiri: Error-correcting output codes: A general method for improving multi-class inductive learning programs. In Proceedings of the Ninth National Conference on Artificial Intelligence (AAAI-91), AAAI Press, 1991, 572-577.
16. T.G. Dieteerich, G. Bakiri: Solving multi-class learning problems via error correcting output codes. Journal of Artificial Intelligence Research, 2,263-286, 1995.
17. R. Ghani: Using error-correcting codes for text classification. Proceedings of ICML-00, 17th International Conference on Machine Learning, 2000, pp 303-310.
18. J. Kittler, R. Ghaderi, T. Windeatt, J. Matas: Face verification via error correcting output codes. Image and Vision Computing. 21(13-14): 1163-1169, 2003).
19. S. Mahamud, M. Hebert, and J. Shi: Object recognition using boosted discriminants. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR'01), 2001.
20. M. Swain, D. Ballard: Color indexing. International Journal of Computer Vision, 7(1): 11-32, 1991.
21. H.M. Zhang, W. Gao, X.L Chen, D.B. Zhao: Learning Informative Features for Spatial Histogram-Based Object Detection. Proceedings of International Joint Conference on Neural Networks 2005, 1806-1811, 2005.
22. V. Vapnik: Statistical Learning Theory. Wiley, New York, 1998.