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OBJECT RECOGNITION USING GABOR FEATURE AND CLASSIFIER

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Abstract

An optimized Gabor features and SVM based framework for object recognition is proposed in this paper. When discriminative features are extracted at optimized locations using selected Gabor wavelets, classifications are done via SVM. Compared to conventional Gabor feature based object recognition system, the system developed in this paper is both robust and efficient. The proposed method is to recognize objects from different categories of images using Gabor features. Gabor wavelets (GWs) are commonly used for extracting local features for various applications like object detection, recognition and tracking. However, extracting Gabor features is computationally intensive, so the features are Impractical for real-time applications. Wavelet transform could extract both the time (spatial) and frequency information from a given signal and the tunable kernel size allows it to perform multi-resolution analysis. Among kinds of wavelet transforms, the Gabor wavelet transform has some impressive mathematical and biological properties and has been used frequently on researches of image processing. The proposed framework has been successfully applied to two object recognition applications, i.e. face/non-face classification and face recognition. Experimental results clearly show advantages of the proposed method over other approaches.

INTRODUCTION

Feature extraction and classifier learning are essential to the performance of an object recognition system. Discriminative features and robust classifiers are always desirable to pattern recognition applications. However, discriminative features like Gabor features, either require computationally expensive feature extraction process, or have large feature dimension [1]. This paper tries to propose a framework to design efficient and robust object recognition system. Due to it's biological similarity to human vision system, Gabor features have been widely used in object recognition applications like fingerprint recognition [2] and character recognition [3]. Etc. Liu et al. [7] vectorize the Gabor responses and then apply down sampling by a factor of 64 to reduce the computation cost of the following subspace training. Their Gabor-based enhanced Fisher linear discriminate model outperforms Gabor PCA and Gabor fisher faces. A more detailed survey on Gabor wavelet based face recognition methods can be found in [1]. While subspace methods like PCA and LDA could be applied for dimension reduction [7, 8], they do not improve the efficiency of feature extraction process. Some works in the literature have tried to tackle this problem by (1) downsampling the images [9], (2) considering the Gabor responses over a reduced number of points [6], or (3) downsampling the convolution results [7, 8]. Strategies (2) and (3) have also been applied together [10]. To make SVM applicable to Gabor features, Qin and He [10] reduced the size by including only the convolution reults over 87 manually marked landmarks. Furthermore, our works [11] have also shown that facial landmarks like eyes, nose and mouth might not be the optimal locations to extract Gabor features for face recognition. In this paper, we propose a general object recognition framework based on SVM and optimized Gabor features.

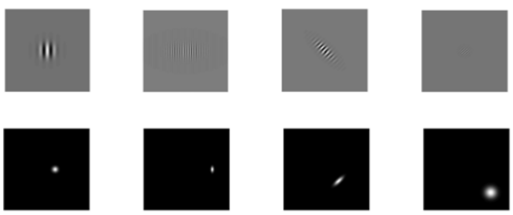
2 GABOR WAVELETS AND FEATURE EXTRACTION

In the spatial domain, the 2D Gabor wavelet is a Gaussian kernel modulated by a sinusoidal plane wave [1]:

$$g(x,y) = w(x,y)s(x,y) = e^{-(\alpha^2 x'^2 + \beta^2 y'^2)} e^{j2\pi f x'}$$
$$x' = x\cos\theta + y\sin\theta \qquad (1)$$
$$y' = -x\sin\theta + y\cos\theta$$

where f is the central frequency of the sinusoidal plane wave, θ is the anti-clockwise rotation of the Gaussian and the plane wave, α is the sharpness of the Gaussian along the major axis parallel to the wave, and β is the sharpness of the Gaussian minor axis perpendicular to the wave. To keep the ratio between frequency and sharpness constant, $\gamma = f/\alpha$ and $\eta = f/\beta$ are defined and the Gabor wavelets can now be rewritten as:

$$\varphi(x,y) = \frac{f^2}{\pi\gamma\eta} g(x,y) = \frac{f^2}{\pi\gamma\eta} e^{-(\alpha^2 x'^2 + \beta^2 y'^2)} e^{j2\pi f x'} \qquad (2)$$



(a) (b) (c) (d)

Figure 1 Gabor filters with different parameters Π(f ,θ ,γ ,η) in spatial domain (the 1st row) and frequency domain (the 2nd row)

(a) (0.1,0,1,1) a Π_a ; (b) (0.3,0,6,3) b Π_b; (c) (0.2,3π / 4,3,1) c Π_c ; (d) Π_d(0.4,3π / 4,2,2)

Once a set of Gabor wavelets have been designed, image features at different locations, frequencies and orientations can be extracted by convolving the image I (x, y) with the filters:

$$O_{\Pi(f,\theta,\gamma,\eta)}(x,y) = I * \varphi_{\Pi(f,\theta,\gamma,\eta)}(x,y) \qquad (3)$$

The number of scales and orientations may vary in different systems. We use in this paper a wavelet bank with 5 scales and 8 orientations to extract image features:

$$f_u = \frac{f_{max}}{\sqrt{2}^u}, u = 0,\ldots,4 \quad \theta_v = \frac{v}{8}\pi, v = 0,\ldots,7 \qquad (4)$$

The results S are thus the convolutions of an input image I (x, y) with all of the 40 wavelets:

$$S = \{O_{u,v}(x,y) | u \in \{0,\ldots,4\}, v \in \{0,\ldots,7\}\} \qquad (5)$$

When the convolution results, $O_{u,y}$ (x,y)over each pixel of the image are concatenated to form an augmented feature vector, the size of the vector could be very large. Take an image of 24×24 for example; the convolution result will give 24×24×5×8=23,040 features. To make SVM applicable to such a large feature vector, a boosting based feature selection process is used to choose the most useful features, which are then given as input to SVM to learn an efficient and robust object recognition system.

3 THE OG-SVM CLASSIFIER

To make the SVM classifier both efficient and accurate, we propose to use optimized Gabor features for classification. As shown in Fig.2, the system starts with the Gabor feature extraction, as described in section 2. The extracted Gabor features and associated class labels for all of the training samples are then fed into the boosting algorithm to eliminate those non-discriminative features, which are not significant for classification. However, the OG-SVM classifier achieved further improvement on classification accuracy, with similar efficiency.

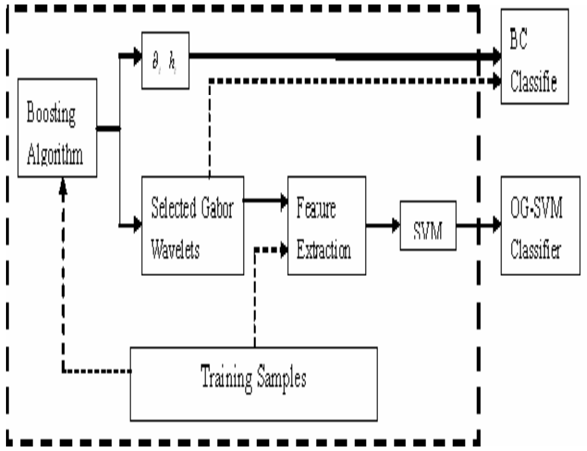


Figure 2 Learning process of the proposed OG-SVM classifier

3.1Optimized Gabor Features Identification

Boosting algorithm is adopted in this paper to select optimized Gabor features for recognition purpose. The essence of boosting algorithms is to select a number of 'weak' classifiers, which are then linearly combined into a single strong classifier. The algorithm operates as follows: for a two-class problem, m labeled training samples are given as (x_i , y_i), i = 1,2,..,m , where y_i ={−1,1} is the class label associated with sample xi € R^N. A large number of weak classifiers h :R^N→{−1,1} can be generated to form a weak classifier pool for training. Such selected Gabor features should be robust for object recognition, as intra- and extra-object space discrimination is one of the major difficulties in object recognition.Upon completion of T boosting iterations, T weak classifiers are selected to form the final strong classifier. The resulting strong classifier

$$H(x)=\text{sign}\sum_{t=1}^{T} \alpha_t h_t\ (x) \text{--------} \qquad (6)$$

called BC in this paper, is a weighted linear combination of all the selected weak classifiers, with each weak classifier using certain Gabor feature for decision. At the same time, T most significant Gabor features for object recognition can also be identified.

3.2 Support Vector Machine

Once the optimized features are selected, they can be used train SVMs. Based on an observed feature $x \in R^N$, SVM is basically a linear hyperplane classifier f (x) = (w, x) + b aimed at solving the two class problem . The classifier can separate the data from two classes very well when the data is linearly separable. Since there might be a number of such linear classifiers available, SVM chooses the one with the maximal margin, which is defined as the width that the boundary could be increased by before hitting a data point. The linear classifier f (x) with maximized margin can be found using quadratic problem (QP) optimization techniques as below:

$$F(x)=\text{sign}\sum \propto_k y_k\,(x_k, x) + b \quad \text{-----} \quad \mathbf{7}$$

where $x_k \text{€} R^N$ are the support vectors learned by SVM.

3.2 Recognition

As shown in Fig.2, once the boosting iterations and the SVM learning process are completed, two classifiers, i.e. BC and OG-SVM, are created using the T selected Gabor features. Though trained to discriminate intra-object and extra-object spaces, they could also be used for multi-class object recognition as follows: given a gallery { q_j } of m known objects and a probe p to be identified, both classifiers will first compute the Gabor feature differences $\{x_j = [d_1 \dots d_t \dots d_T]\}$ between the probe and each of the gallery images, and then calculate an intra-object confidence score using respective decision functions:

$$\delta_j = \begin{cases} \sum_{t=1}^{T} \alpha_t h_t(x_j), & \text{BC} \\ \sum_{k} a_k y_k k(x_k, x_j) + b, & \text{SVM} \end{cases} \qquad (8)$$

	BC	SVM					
		OG-SVM		G-SVM		R-SVM	
		Linear	RBF	Linear	RBF	Linear	RBF
Feature Dimension	150	150	150	23.040	23.040	576	576
Number of SVs	N/A	233	271	503	N/A	1434	1386
SVM training time	N/A	38s	75s	10h	>74h	180s	270s
FRR(%)	1.75	1.43	1.26	1.10	N/A	10.49	4.96
FAR(%)	0.61	0.36	0.30	0.18	N/A	3.78	0.97

the probe is then identified as object j that gives the maximum confidence score δ_j .

4 EXPERIMENTAL RESULTS

4.1 Face and Non-face Classification

We first apply the proposed framework to solve a two-class object recognition task, i.e. face and non-face classification problem. A face image set is used to test performance of the proposed classifier. The face image set is provided by Carbonetto and contains 4916 images with faces and 7872 images without faces. Figure 3 shows some example face and non-face images.

Fig 3 Image from face image set

Table 1. Classification Result On Test Set

150 optimized Gabor features are selected using boosting algorithm, which are then used by BC, or SVM for classification. The performance of OG-SVM has been shown in Table 1, together with SVM trained using the whole set of Gabor features with dimension 23,040 (G-SVM), using the raw pixels with dimension 24×24=576 (R-SVM) and the BC. For R-SVM, the pixel values of each sample are concatenated to a feature vector to train SVM. A Pentium 4 1.8 GHz PC and the SVM-Light package are used in our experiments. Compared with classifiers using Gabor features, R-SVM achieves the highest FAR and FRR, which suggests that Gabor filters are good choice to extract features for classification. It also takes about 10 hours to train G-SVM with linear kernel. The results also suggest that the dimension of features shall be taken into consideration when designing practical SVM classifiers. Since SVM is specially suited for classification, OG-SVM achieves lower FAR and FRR than BC. Both methods use the same 150 Gabor features selected by

boosting algorithm. The training of OG-SVM with RBF kernel takes less than 2 minutes. Only 150 convolution operations with one variable filter are necessary to extract the selected Gabor features, which also makes OG_SVM highly memory and computational efficient.

4.2 Recognition Performance

The classifiers are then applied to the test set (200 images, 1 image per person) for face recognition and their performances are shown in Figure 4. Similarly, OG-SVM achieves higher recognition rate than BC when different number of features are used. The highest identification accuracy of 92% is achieved by OG-SVM with linear kernel when 120 Gabor features are used. The results also suggest that the difference of OG-SVM using RBF kernel and linear kernel is quite small, when the features selected by boosting algorithm are considered.

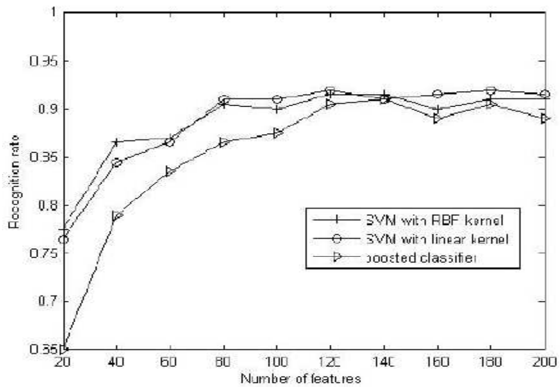


Fig 4 Identification Performance of OG-SVM and BC

To show the efficiency and accuracy of the proposed method, we also compare its performance with other Gabor feature based approaches in Table 2. The PCA and LDA methods, details of Downs maple Gabor + PCA and Down sample Gabor + LDA can be found in [8]. In the implementation, down sampling with rate 16 was used to reduce the dimension of extracted Gabor features before they are input to PCA, or LDA for further processing. The table shows that the proposed OG-SVM achieved similar accuracy with Downs maple Gabor + LDA, but with much fewer feature dimension and much less feature extraction costs. In our experiments, while it takes 100ms to train the OG-SVM classifier, the system can averagely identify 20 faces per second.

Table 2 Accuracy and efficiency of OG-SVM

Methods	Recognition Rate	No. of Convolution For Gabor Feature Extraction	Dimension of Features
PCA	60%	N/A	64*64=4096
LDA	76%	N/A	64*64=4096
Down sample Gabor + PCA	80%	64*64*40=163,840	10,240
Down sample Gabor + LDA	92%	64*64*40=163,840	10,240
BC	90%	120	120
OG-SVM	92%	120	120

5. Conclusions

We have proposed in this paper a SVM and Gabor feature based framework for object recognition. While optimized Gabor wavelets are applied at selected object landmarks for feature extraction, SVM is used for classification. A boosting based learning process has been used to reduce the feature dimension and make the Gabor feature extraction process substantially more efficient. An efficient and robust classifier, OG-SVM is then trained. The proposed object recognition framework has been successfully applied to solve two object recognition tasks,i.e. face/non-face classification and face recognition. The results clearly show the advantages of the proposed system over other approaches. When applied to face recognition, the two-class based OG-SVM has been shown to beat several multi-class based algorithms like PCA, LDA and Down sample Gabor + PCA. By combining optimized Gabor features with SVM, our method not only substantially reduces computation and memory cost of the feature extraction process, but also achieves very accurate recognition performance.

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