A New Gabor Filter Based Kernel for Texture Classification with SVM

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Abstract. The performance of Support Vector Machines (SVMs) is highly dependent on the choice of a kernel function suited to the problem at hand. In particular, the kernel implicitly performs a feature selection which is the most important stage in any texture classification algorithm. In this work a new Gabor filter based kernel for texture classification with SVMs is proposed. The proposed kernel function is based on a Gabor filter decomposition and exploiting linear predictive coding (LPC) in each subband, and exploiting a filter selection method to choose the best filters. The proposed texture classification method is evaluated using several texture samples, and compared with recently published methods. The comprehensive evaluation of the proposed method shows significant improvement in classification error rate.

Keywords: Texture Classification, Support Vector Machine, Linear Predictive Coding, Gabor Filters, Segmentation.

1 Introduction

Texture analysis has been an active research field due to its key role in a wide range of applications, such as industrial object recognition [1], classification of ultrasonic liver images [2] or the detection of microcalcification in digitized mammography [3].

Texture classification algorithms generally include two crucial steps: feature extraction and classification. In the feature extraction stage, a set of features are sought that can be computed efficiently and which embody as much discriminative information as possible.

The features are then used to classify the textures. A variety of classifiers have been, and we propose to use support vector machines (SVMs) which have been shown to outperform other classifiers [4]. The superiority of SVMs originates from their ability to generalize in high dimensional spaces focusing on the training examples that are most difficult to classify.

SVMs can be effective in texture classification, even without using any external features [5]. In fact, in the SVM feature extraction is implicitly performed by

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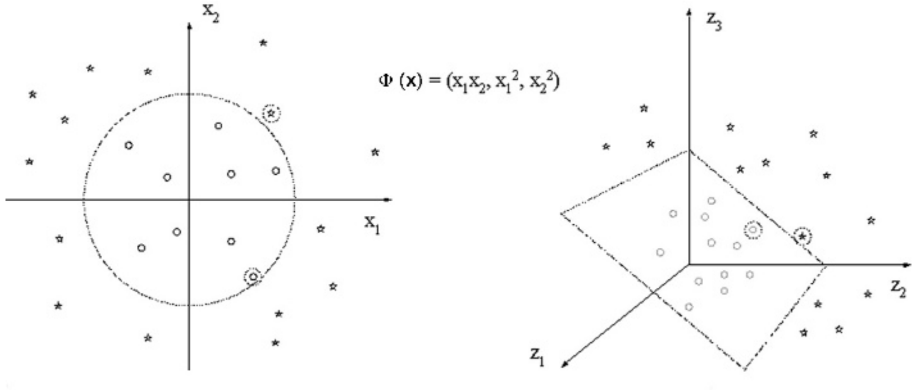


Fig. 1. A linearly nonseparable problem (Left) is converted to a linearly separable problem (Right) using a non-linear transform.

a kernel, which is defined as the dot product of two mapped patterns, and the proper selection of this kernel can significantly affect the overall performance of the algorithm.

The main focus of this paper is to propose a new kernel function and to investigate the effectiveness of external features. Specifically, we propose to use linear predictive coding (LPC) [6] in subbands of Gabor filters bank to extract efficient sets of features. While most filter bank based methods require sophisticated feature selection methods to reduce the dimensionality of the feature space, our method takes advantage of high dimensionality due to the intrinsic ability of SVMs to generalize in high dimensional spaces.

The rest of this paper is organized as follows. In Section 2 the SVMs are reviewed, in Section 3 the proposed kernel and filter selection algorithm are presented, Section 4 dedicated to experimental results.

2 SVM Review

The principle of SVMs is to construct a hyperplane as the decision surface in such a way that the margin of separation between training samples of different classes is maximized. Since a basic linear SVM scheme is not applicable to practical cases (which are not linearly separable), non-linear SVMs are widely used, in which a nonseparable pattern becomes separable with a high probability if projected into a nonlinear feature space of high dimensionality.

Given $\mathbf{x}$ from the input space, let $\{\mathbf{\Phi}_j(\mathbf{x})\}_{j=1}^{m}$ denote the m non-linear features. Then, a linear decision surface in the non-linear space is:

$$\sum_{j=1}^{m} w_j \mathbf{\Phi}_j(\mathbf{x}) + b = 0 \tag{1}$$

given the two-class training samples $\{(\mathbf{x}_i, y_i)\}$,$y_i \in \{-1, 1\}$, the weight coefficients $\mathbf{w}$ can be found by solving an optimization problem [7]:

$$\mathbf{J}(\mathbf{w}, \alpha, \xi, b) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{N}\xi_i - \sum_{i=1}^{N}\alpha_i[y_i(\mathbf{w}^T\mathbf{\Phi}(\mathbf{x})_i + b) - 1 + \xi_i] \tag{2}$$

where C is a regularization selected by the user, and the nonnegative variables α_i are the Lagrange multipliers. In particular, Lagrange Multipliers are solved in a dual form:

$$\sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_j \mathbf{K}(\mathbf{x}_i, \mathbf{x}_j) \tag{3}$$

which leads to the non-linear SVM classifier:

$$f(x) = \sum_{i=1}^{N}\alpha_i y_i \mathbf{\Phi^T}(\mathbf{x_i})\mathbf{\Phi}(\mathbf{x}) + b = \sum_{i=1}^{N}\alpha_i y_i \mathbf{K}(\mathbf{x_i}, \mathbf{x}) + b \tag{4}$$

where the kernel function $\mathbf{K}(.,.)$ is:

$$\mathbf{K}(\mathbf{x}_1, \mathbf{x}_2) = \mathbf{\Phi^T}(\mathbf{x_1})\mathbf{\Phi}(\mathbf{x_2}) \tag{5}$$

as can be seen in (3) and (4), the nonlinear mapping $\mathbf{\Phi}(.)$ never appears explicitly in either the dual form or in the resulting decision function. Thus it is only necessary to define $\mathbf{K}(.,.)$ which implicitly defines $\mathbf{\Phi}(.)$. Our proposed kernel is presented in the next section.

3 LPC Kernel for Texture Classification

The performance of SVM classifier is strictly dependent on the choice of a SVM Kernel $\mathbf{K}(.,.)$ suited to the problem at hand. In this section we introduce a new kernel based on LPC and Gabor filters.

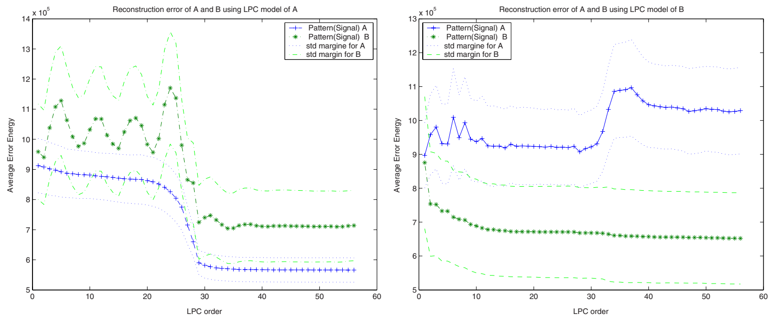
3.1 Linear Predictive Coding

Linear predictive coding (LPC) is a popular and effective technique in signal processing [6], which models a given signal $s(n)$, can be approximated as p-th order autoregressive:

$$s(n) = \sum_{i=1}^{p} a_i s(n-i) + Gu(n) \tag{6}$$

where $GU(n)$ is an hypothetical input term.

The linear prediction model indicates that a signal $s(n)$ can be estimated by an all pole system of order p with a scaled input $u(n)$. Proper selection of LPC



(a) (b)

Fig. 2. Discrimination ability of LPC for two typical textures. Dotted curves show the error margin within +/- standard deviation (std)

order leads to efficient presentation of the signal with reasonable discriminative power. Fig.2 shows discrimination ability of LPC. In this figure two typical textures A and B are considered. In Fig.2a LPC model of A is used to estimate several texture samples from A and B. In Fig.2b LPC model of texture B is used for the same experiment. Average estimation errors show strong discrimination ability for LPC model.In this paper we propose to use LPC (a_i) as features for texture samples in the subbands of Gabor filters bank.

3.2 Gabor Filter

Filter banks have the ability to decompose an image into relevant texture features for the purpose of classification. Multi-channel filtering is motivated by its ability to mimic the human visual system (HVS) [8] sensitivity to orientation and spatial-frequency. This has led to a HVS model consist of independent detectors each preceded by a relatively narrow band filter tuned to a different frequency.

In this way, Gabor filters are motivated to be used due to their ability to be tuned into various orientations and spatial-frequencies. In the spatial domain a Gabor function is a Guassian modulated by exponential:

$$F(x,y) = exp(\frac{-1}{2}[\frac{x^2+y^2}{\sigma^2}]).exp(j[k_x x + k_y y]). \tag{7}$$

In this study twenty filters are constructed using five spatial radial frequencies (ω) and four orientations (θ) as recommended in [9]. where:

$$\omega = 2\pi\sqrt{k_x^2 + k_y^2}, \qquad \theta = \arctan(\frac{k_x}{k_y}) \tag{8}$$

3.3 Proposed SVM Kernel

Given an $L \times L$ image window $\mathbf{x}$ and a bank of filters $\{F^{(\alpha)}, \alpha = 1, 2, ..., K\}$,we obtain subband images $\mathbf{x}^{(\alpha)} = F^{(\alpha)} * \mathbf{x}$. LPC of $\mathbf{x}^{(\alpha)}$ are denoted as $A_{\mathbf{x}^{(\alpha)}}$ which is a $p \times 1$ vector . LPC order (p in (6)) was experimentally set to L. Motivated by the SVM kernel exploited in [10] for signal classification, we propose the following kernel:

$$\mathbf{K}(\mathbf{x}_i, \mathbf{x}_j) = exp - \frac{1}{2\eta^2}[\sum_{\alpha=1}^{q}\sum_{n=1}^{L}(\bar{A}_{x_i^\alpha}(n) - \bar{A}_{x_j^\alpha}(n))^2] \tag{9}$$

which complies with the Mercer's theorem [4].

A filter selection algorithm is used to pick q best filters among K existing filters. The notation $\bar{A}_{x_i^\alpha}$ emphasize the normalization of the LPC values:

$$\bar{A}_{x_i^\alpha}(n) = \frac{A_{x_i^\alpha}(n)}{\sum_{n=1}^{L} \mid A_{x_i^\alpha}(n) \mid} \tag{10}$$

3.4 Filter Selection

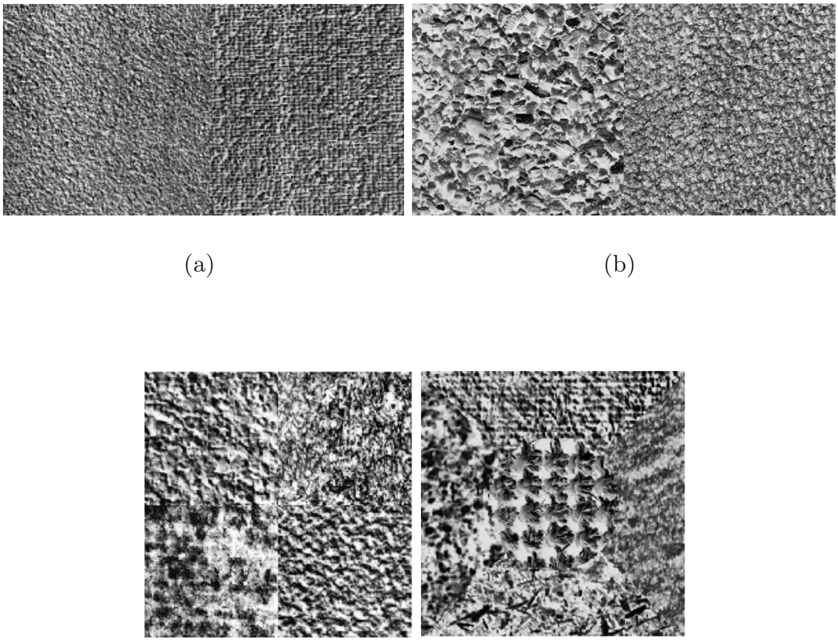
In a filter bank some filters are more effective in discriminating features of a given set of textures. To address this issue, we propose a method of filter selection to optimize classifier performance. To achieve this goal we divide training samples into two disjoint subsets, training subset (T) and validation subset (V) known as cross-validation [11]. Our filter selection algorithm is as follows:

Step0) $B = \{F^{(1)}, F^{(2)}, ..., F^{(K)}\}$ and $S = \phi$
Step1) For each filter in B train classifier over T and find classifier gain $G_{S\bigcup\{F^{(\alpha)}\}}$ over V
Step2) $\beta = \arg\max(G_{S\bigcup\{F^{(\alpha)}\}})$
Step3) $E = G_{S\bigcup\{F^{(\beta)}\}} - G_S$, $B = B - \{F^{(\beta)}\}$, $S = S\bigcup\{F^{(\beta)}\}$
Step4) repeat step 1 to 3 while $E > \varepsilon$

4 Comparison with Existing Methods

To verify the effectiveness of the proposed method(LG-SVM), experiments were performed on classification and segmentation of several test images. The test images were drawn from two different commonly used texture sources: the Brodatz album [12] and the MIT vision texture (VisTex) database [13]. All textures are gray-scale images with 256 levels. The classifiers were trained on randomly selected portions of subimages that are not included in the test images. Gray scales were linearly normalized into $[-1, 1]$ prior to training and test.

The classification results are compared with original SVM [5] as well as logic operators [14], wavelet transform [15], filter banks [16], and spectral histogram [17]. The segmentation result is compared with optimal Gabor filter method [9].



(a) (b)

(c) (d)

Fig. 3. Texture images used in experiments (D# is the numbering scheme in the Brodatz album) (a)D4, D84 (b)D5, D92 (c) D4, D9, D19, and D57 (d) Fabric.0007, Fabric.0009, Leaves.0003, Misc0002, and Sand.0000 (from [13])

Images in Fig.3 are 256×256. Classifiers were trained by 1000 patterns from each texture. This corresponds to about 1.7 percent of the total available input patterns. The results are compared at different window sizes of $9 \times 9, 13 \times 13, 17 \times 17$,and 21×21. The original SVM shows the optimal classification rate at window size 17×17. In the proposed optimized SVM the classification error rate decreases by increasing window size. Classification error rates are presented in Table 1. The proposed method outperforms the original SVM specifically in larger window sizes.

In order to establish the superiority of the LG-SVM, its performance is compared with the recently published methods. In the literature, texture classification methods are evaluated both in overlapped and non-overlapped cases. In non-overlapped case, not only there is no intersection between training and test samples but also there is no overlap between them. Our proposed method is evaluated in both cases. In Logical Operators [14] and wavelet co-occurrence features method [15] overlapped samples are used. Results are listed in Table 2.

Table 1. Error Rates (percent) for two-texture and multi-texture images.

	Fig.3a		Fig.3b		Fig.3c		Fig.3d	
window size	SVM	LG-SVM	SVM	LG-SVM	SVM	LG-SVM	SVM	LG-SVM
9×9	12.7	9.6	14.6	14.2	22.3	15.2	21.8	14.5
13×13	9.4	7.6	12.1	11.2	17.3	11.9	20.0	10.3
17×17	8.6	4.1	11.9	7.3	16.1	8.7	18.5	7.2
21×21	13.0	1.2	15.6	5.0	21.8	7.1	19.7	4.3

In spectral histogram method [17] and filters bank [16] non-overlapped samples are used (Table3). In each case parameters (e.g. sample window size, number of test and train sample) are set accordingly. The results of segmentation using proposed method are shown and compared with optimized Gabor filter method [9] in Fig.4.

Table 2. Comparison of Error Rates in Logic Operators and Wavelet based method with LG-SVM

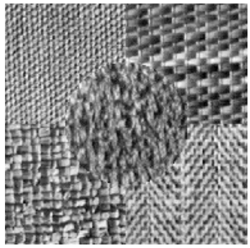
Texture	Logic Operators	LG-SVM	Texture	Wavelet	LG-SVM
D15	11	11	Bark.0006	7	11
D19	3	0	Clouds.0001	6	0
D52	19	0	Fabric.0017	2	0
D65	16	0	Grass.0001	21	4
D74	27	19	Leaves.0012	8	6
D82	14	2	Misc.0002	2	0
D84	28	5	Sand.0002	3	0

Table 3. Comparison of Error Rates with Filters Bank method and Spectral Histogram

Texture	Best Filter Bank in [16]	Spectral Histogram	LG-SVM
Fig.11h in [16]	32.3	16.9	14.7
Fig.11i in [16]	27.8	20.9	15.6

5 Conclusions

This paper described an SVM classification method based on a kernel constructed on Gabor features derived by LPC. The proposed kernel creates a



(a)

(b) (c) (d)

Fig. 4. Segmentation: (a)original image (b) LG-SVM (c) LG-SVM after smoothing (c) Optimized Gabor Filters [9]

feature space with more chance of separability at higher dimension. Excellent performance on different textures where achieved. It was shown that the proposed method outperforms recently published methods.

In this paper 1-D LPC and all pole model were used for feature extraction. Motivated by the success of this method, using 2-D LPC and zero-pole (ARMA) model are being pursued by the authors.

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