SELECTION OF GABOR FILTERS FOR IMPROVED TEXTURE FEATURE EXTRACTION

[1]*Weitao Li,* [2]*KeZhi Mao,* [3]*Hong Zhang, and* [1]*Tianyou Chai*

[1]Research Center of Automation, Northeastern University, Shenyang, China
[2]School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore
[3]Department of Computing Science, University of Alberta,Edmonton, Canada

ABSTRACT

Texture feature has been widely used in object recognition, image content analysis and many others. Among various approaches to texture feature extraction, Gabor filter has emerged as one of the most popular ones. Gabor filter-based feature extractor is in fact a Gabor filter bank defined by its parameters including frequencies, orientations and smooth parameters of Gaussian envelope. In the literature, different parameter settings have been suggested, and filter banks created by these parameter settings work well in general. From the perspective of pattern classification, however, filter banks thus designed may not be ideal. In the present study, we propose a new approach to Gabor filter bank design, by incorporating feature selection, i.e. filter selection, into the design process. The merits of incorporating filter selection in filter bank design are twofold. Firstly, filter selection produces a compact Gabor filter bank and hence reduces computational complexity of texture feature extraction. Secondly, Gabor filter bank thus designed produces low-dimensional feature representation with improved sample-to-feature ratio, and this in turn leads to improved performance of texture classification. Experiment results on benchmark datasets and a real application have demonstrated the effectiveness of the proposed method.

Index Terms— Texture feature, Gabor filter bank, Gabor filter selection, Fisher ratio measure

1. INTRODUCTION

As an essential characteristic of reflective images, texture feature has been widely used in object recognition, image content analysis and many others. Texture feature extraction aims to extract proper features to distinguish different textures. In the literature, numerous texture feature extraction approaches have been proposed, see for example [1, 2, 3]. In recent years, Gabor filter has received considerable attentions, and has emerged as one of the most popular approaches to texture feature extraction [4], owing to its merit of optimal localization in both spatial and frequency domains. Gabor filter-based feature extractor is in fact a Gabor filter bank consisting of filters with different frequencies and orientations. A common practice in Gabor filter design is to first define the highest frequency, the total number of frequencies n_f and the total number of orientations n_o, and then create filters based on combination of frequency and orientation parameters. In a recent study [5], it was reported that smooth parameters of Gaussian envelope play more important role than frequency and orientation parameters. If smooth parameters are also regarded as design parameters, even if a moderate number of possible values are used, the combinatorial of all the parameters creates a very large filter bank.

Gabor filter-based feature extractors can be interpreted as nonlinear functions that map images from original space to feature space, where each image is represented by its features. Although a large filter bank produces high-dimensional representations with large discriminative power, it is not expected from the perspective of pattern classification. This is because the performance of a classifier is partly determined by the relationship between the number of samples and the number of features, i.e. the sample-to-feature ratio. Practical scenarios often have limited samples, and hence low-dimensional pattern representations are preferred in order to yield high sample-to-feature ratio. We believe not all filters in the filter bank are equally important in a specific application, and some filters might produce features with neglectable discriminative power.

In this study, we propose to incorporate feature selection technique into Gabor filter design, with the goal of selecting appropriate Gabor filters to build a compact filter bank. Feature selection is a well studied issue in pattern recognition, see for example [6]. The novelty of this study is not on the feature selection algorithm itself, but on the feasibility of applying feature selection technique to assist Gabor filter design. Ideally, Gabor filters should map different textures to distinct feature space regions with large inter-class difference and small intra-class scatter. Fisher ratio, defined as the ratio of the above two measures, is therefore employed as the criterion function to evaluate and sort filters. The filters eventually selected are determined in terms of classification performance. Experimental studies show that the size of filter bank and the computations involved in feature extraction can be significantly reduced by incorporating feature selection, i.e. filter selection, into filter bank design. More importantly, improved classification performance can be achieved.

The rest of this paper is organized as follows. Gabor filter and its parameter settings are reviewed in Section 2. Filter selection algorithm based on Fisher ratio and classification performance is presented in Section 3. In Section 4, experiment results on benchmark datasets and real application are reported. Finally, conclusions are drawn in Section 5.

2. GABOR FILTER AND PARAMETER SETTINGS

Gabor filter is joint entropy minimizing frequency sensitive filter. A 2-D Gabor filter is an oriented complex sinusoidal wave modulated by a 2-D Gaussian envelope [7]. In the literature, the usual practice for texture feature extraction is to define the highest frequency f_m, the number of frequencies n_f and the number of orientations n_o [8, 9, 10]. A recent study in [5] has found that smooth parameters γ and η of Gaussian envelope play more important role than frequency and orientation parameters. If γ and η are also considered as design parameters, and assume that n_γ and n_η values are used respectively, then the total number of filters created is $n_G = n_f \times n_o \times n_\gamma \times n_\eta$. Based on the conclusions of [5], in the present study, five parameters including f_m, n_f, n_o, γ and η are used, and the setting of them is given in Table 1. The above setting generates an initial filter bank consisting of 64 filters. These filters will be evaluated and selected based on their capacity to produce large discriminative power and good classification performance as described next.

Table 1. Setting of parameters for initial Gabor filter bank

Parameter	f_m	n_f	n_o	γ	η
Value	$\frac{\eta}{2\eta+2\sqrt{\log 2/\pi}}$	4	4	0.5,1.0	0.5,1.0

3. GABOR FILTER SELECTION FOR IMPROVED TEXTURE FEATURE EXTRACTION

Gabor filters can be interpreted as nonlinear functions that map images from the original space to feature space, where pattern classification is performed. Intuitively, if more features are used, more discriminative power is supplied to the classifier and improved pattern classification should be achieved. However, this is not necessarily true in practice. It has been observed that the performance of a classifier may degrade with an increase in the number of features when the training samples set is limited. This phenomenon is often referred to as peaking phenomenon.

The above analysis from the pattern classification perspective indicates that Gabor filter design should not be a process of simply setting and creating. Instead, feature selection, i.e. filter selection, should be an indispensible part of the filter bank design process. Feature selection is a well studied issue in pattern recognition. The basic idea of feature selection is to select a subset of features that retain major discriminative power of the full set of features available. In the present study, we introduce feature selection technique to filter design process, with the goal of selecting a compact Gabor filter bank to enhance classification performance. Please note, the novelty of this paper is not on the feature selection technique, but on the feasibility of applying feature selection technique to assist Gabor filter bank design.

Assume totally N training images from n_c classes are collected. Assume $\boldsymbol{z}_k$ denotes features extracted from filtered images by filter k. Some frequently used features are energy, mean and standard deviation of filtered images. Please note $\boldsymbol{z}_k$ could contain more than one features, and is therefore referred to as feature group k in this study. The quality of the classifier depends heavily on those selected features, hence the criterion function for the candidate features is quite important. For effective pattern classification, features should exhibit small intra-class scatter and a large inter-class separation. Fisher ratio [11], defined as the ratio of the above two measures, is therefore employed as the the criterion function to evaluate and sort features and associated Gabor filters in the present study.

Fisher ratio is related to the performance of pattern classification, but it is not the direct function of the performance. Classification accuracy is therefore used to evaluate the feature subsets generated to find the filters that should be eventually retained in the Gabor filter bank. The proposed Gabor filter selection approach is illustrated in Figure 1. Assume that

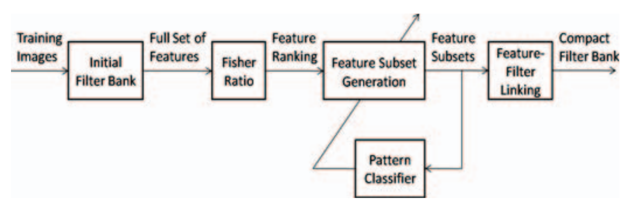

Fig. 1. Gabor filter selection based on Fisher ratio and classification performance

$\boldsymbol{m}_{i,k}, \boldsymbol{m}_{j,k}, \sigma_{i,k}$ and $\sigma_{j,k}$ denote sample mean vector and standard deviation vector of class i and j in feature space along feature group $\boldsymbol{z}_k$ respectively. The Fisher ratio class separability measure of feature group $\boldsymbol{z}_k$ between class i and j is given by:

$$J_{i,j,k} = \frac{||\boldsymbol{m}_{i,k} - \boldsymbol{m}_{j,k}||^2}{||\sigma_{i,k}||^2 + ||\sigma_{j,k}||^2} \quad (1)$$

For the case of multi-class texture classification, feature group $\boldsymbol{z}_k$ can be evaluated based on the average class separability measure given by:

$$J_k = 2 \times \frac{\sum_{i=1}^{n_c-1} \sum_{j=i+1}^{n_c-1} J_{i,j,k}}{n_c \times (n_c - 1)} \quad (2)$$

Fisher ratio provides an effective evaluation of discriminative power underlying each feature group. Gabor filters that produce features with large discriminative power should be retained and those that produce features with neglectable discriminative power should be removed from the filter bank. The feature groups produced by the n_G filters can be ranked based on their average Fisher ratio measures. Assume that $J_{k_1} \geq J_{k_2} \geq \ldots \geq J_{k_{n_G}}$, where $k_i \in 1, 2, \ldots, n_G$ denotes the index of the i_{th} ranked feature group. Based on the above ranking results, we can generate n_G candidate feature subsets corresponding to n_G candidate filter banks given as $\{z_{k_1}\}, \{z_{k_1}, z_{k_2}\}, \{z_{k_1}, z_{k_2}, z_{k_3}\}, \ldots, \{z_{k_1}, z_{k_2}, \ldots, z_{k_{n_G}}\}$. The candidate filter banks are then evaluated based on the resulted classification performance.

Generally speaking, the feature subsets generated in terms of Fisher ratio-ranked features might have redundancy and the filter bank finally selected is not the most compact. But we observed that feature groups created by the parameter setting in Table 1 are not severely correlated, a massive reduction in the number of filters could still be achieved.

The Fisher ratio and classification performance-based filter selection algorithm is summarized below:

(i)Input training images to the generated initial Gabor filter bank and extract features from the output images of all filters;

(ii)Calculate sample mean and standard deviation of each texture class along all the features and obtain average Fisher ratio measure for each feature group, and then rank all the feature groups based on their average Fisher ratio measures in descending order;

(iii)Perform pattern classification of the training images using the first 1 feature group to the first n_s feature groups, after which very little or no improvement is observed in the classification performance;

(iv)Link the first n_s feature groups back to the corresponding Gabor filters. Retain the n_s filters and the obtained filter bank is regarded as the final filter bank for texture feature extraction.

4. EXPERIMENTS

4.1. Experiment 1

Benchmark texture databases including Outex database and Brodatz album were used to test the effectiveness of our algorithm. The first 41 (D1-D41) and 29 (each from every category) texture images were collected from the two databases respectively, and each image is considered as one texture class. In the experiment, each image is divided into 16 non-overlapping sub-images with dimension of 32×32 to generate 16 image samples for each texture class. Experimental studies including training and testing were all performed on the sub-images.

From each filtered images by each Gabor filter, two values were extracted as features. One feature is the mean value of the image intensity, and another is the standard deviation. In addition, k-nearest neighbor pattern classifier (k=3) was used in the present study. Other features such as energy and other classifiers such as support vector machines and neural networks etc are equally applicable.

To estimate classification accuracy, bootstrapping [12] with 500 repeats was performed. For comparison purpose, Gabor filter banks without filter selection were also tested in the experiment, and the results are shown in Table 2-3. The

Table 2. Classification results on Outex dataset

Methods	Accuracy(%)	No. of filters
D.A. Clausi et al.[9]	93.58±0.92	24
S. Li et al.[8]	93.34±1.34	36
F. Bianconi et al.[5]	92.75±1.38	288
Our method	94.61±0.50	6.7±6.3

Table 3. Classification results on Brodatz dataset

Methods	Accuracy(%)	No. of filters
D.A. Clausi et al.[9]	87.68±0.96	24
S. Li et al.[8]	86.74±1.10	36
F. Bianconi et al.[5]	86.13±1.00	288
Our method	88.84±1.74	9.0±5.7

classification accuracy and the number of selected filters are presented in the format of mean value±standard deviation of 500 repeats. Tables 2-3 show that feature selection, i.e. filter selection, achieved a mass reduction in the number of filters. This not only reduces computational complexity of texture feature extraction, but also leads to improved classifications. Also, the above results coincide with peaking phenomenon, i.e. for a fixed sample size, the resulted classification performance degrades as more filters are used.

4.1.1. Experiment 2

Oil sand mining is a major industry in the Canadian province of Alberta. In transportation of oil sand using convey belt, large lump ores on convey belts could block crushers and cause productive intermission. At present, image intensity-based pattern classification technique is employed to detect large lump ore. Unfortunately, this approach is prone to seasonal changes. In winter, steam generates when newly excavated ore is exposed to cold air, and the resulted images could have similar intensity to lump ore images. This makes intensity-based methods often fail to discriminate large lump ore images from steam images. To deal with this problem, we propose to use texture features for large lump ore detection.

The data, supplied by an oil sand company, includes 196 lump ore images and 150 steam images, and two example images are shown in Figure 2. Based on experts advice, region of interests (ROI), which is located in the central part of an image, should be used in the detection of lump ore.

Following the same procedure as in Experiment 1, bootstrapping with 500 repeats was performed to estimate the accuracy of k-nearest neighbor pattern classification. For comparison purpose, the performance of Gabor filter banks without filter selection, DT-CWT [13]-based method and image intensity-based method were also tested in the experiment, and the results are summarized in Table 4.

As indicated in Table 4, feature selection, i.e. filter selection, achieves a significant reduction of the filter bank size. Table 4 also shows the peaking phenomenon. In addition,Gabor filter-based method is more effective than image intensity-based method and DT-CWT-based method.

(a) lump ore image (b) steam image

Fig. 2. Example images in Experiment 2

Table 4. Classification results of sand lump and steam images

Methods	Accuracy(%)	No. of filters
Image intensity	52. 85±6.53	-
DT-CWT[13]	90. 99±4.78	-
D.A. Clausi et al.[9]	95. 97±4.29	24
S. Li et al.[8]	95. 25±4.11	36
Our method	98. 24±0.92	8.4±5.7

5. CONCLUSIONS

In this study, we have presented a new approach to Gabor filter design by incorporating feature selection, i.e. filter selection, into filter bank design process. By filter selection, we can obtain a compact Gabor filter bank that demands reduced computations. More importantly, the compact Gabor filter bank produces low-dimensional pattern representations in the feature space with improved sample-to-feature ratio. As a direct result, improved classification performance can be achieved. Comparison studies on benchmark datasets and real application in oil sand lump detection have proved the aforementioned advantages of the proposed approach.

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