Edge Detection by Pattern Matching Based on Principal Component Analysis

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Abstract

In this paper, we have proposed a new method for edge detection by pattern matching. There exist two main problems for the edge detection methods by gradient operators: (1) gradients in the templates are fixed and not related with those in real images; (2) the results are edge enhanced images and need to be transformed into binary ones by setting an appropriate threshold. In our method, the pattern templates are obtained by learning the principal components of image patches and edges are represented directly by the class of the matched templates. The effectiveness of the proposed method is demonstrated by experimental results

Keywords: boundary detection, principal component analysis, edge pattern, image patches

1 INTRODUCTION

Boundaries are important features that represent the main information in an image and can be used in later processing and analysis. Many of the boundary detection methods attempt to find the edges by pixel gradient magnitudes and/or directions. In edge detection, the images are usually transformed by a set of gradient operators. Various sets of operators have been proposed for producing images with enhanced edges [1,2,3]. All of these methods have the following characteristics: different gradient templates are convolved with the image to detect different directional edges. There exist two main problems for the edge detection by gradient operators: (1) gradients in templates are fixed and not related with the statistics in real images; (2) the results are edge enhanced images and need to be transformed into binary images by setting an appropriate threshold. Since the results depend on the pixel values, in many applications, it is hard to decide the threshold and a prior knowledge about the distribution becomes necessary.

R.D.Dony, and OJA.E. have proposed subspace classifiers for edge detection, by which a pixel is assigned to a class number determined by a vector of the neighbor pixels [4,11]. In R.D.Dony's method, the classification is applied to the vectors whose dimensions are reduced by principal component analysis, and an important property of the method is its insensitivity to illumination. This is right the point that methods by pattern matching or classifying are superior to the gradient operators. However, it is demonstrated by our experiments that the existing gradient templates can not be used as the patterns for classification.

In recent years, there is an increasing interest in the research for understanding the feature extraction ability of visual cortex by statistics analysis. Much work has been done to explain the coding principles of nature images by using the principal component analysis (PCA) [7,10] or the independent component analysis (ICA) [8,9]. All these studies are consistent with the proposal that the visual feature detectors might be the result of a redundancy reduction process [5].

In this paper, we propose an edge detection methods by pattern matching based on PCA. Different from the works until now that try to get edge filters, we use the basis functions of PCA for pattern matching. All the patterns are obtained by learning the principal components of image patches, and pixels are represented by the classes of the patterns that match the neighbor blocks best. The patterns obtained from some images can be used to others that have similar statistics. An unsupervised neural network proposed by Sanger [6] is used to extract the principal components.

The intention of this paper is trying to apply PCA to pattern matching instead of filter designing. The experimental results may help us to find new roles for PCA in feature extraction.

2 LEARNING THE PRINCIPAL COMPONENT OF IMAGES BY PCA NEURAL NETWORK

2.1 Principal component analysis

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Principal component analysis is a linear transformation that removes the correlation among the elements of a random vector. Suppose $\mathbf{x}$ is a $N\times 1$ vector with elements $x_1, x_2, \ldots x_N$ as random variables. A linear transformation defined by matrix $\mathbf{W}$ is applied to $\mathbf{x}$ and a new random vector can be produced by:

$$\mathbf{y}=\mathbf{W}(\mathbf{x}-\mathbf{m}_x)$$

where $\mathbf{m}_x$ is the mean vector of $\mathbf{x}$, and $\mathbf{W}$ is constructed in such a way that its rows are the eigenvectors of the covariance matrix of $\mathbf{x}$. Usually the eigenvectors are arranged in the order that the corresponding eigenvalues are decreased. Since $\mathbf{y}$ has a zero mean and its covariance matrix is diagonal, its elements are uncorrelated.

2.2 Neural network and learning algorithm

PCA neural network has two layers. Image patches with size $S\times S$ are arranged as the input layer nodes as shown in Fig. 1. The connection weights w_{ij} $(j=1,\ldots S^2)$ respond to the i th principal component of the sample patches. The number of the output nodes M is the number of the principal components to be used.

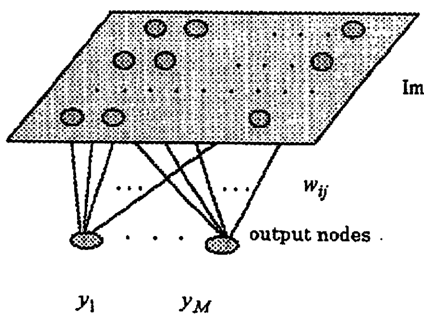

Figure 1 PCA neural network

For training patches x_{jk} $(j=1,\ldots S^2, k=1,\ldots T)$, the neural network is trained by the following algorithm:

(1) Calculate the output values as below:

$$y_{ik}=\sum_{j=1}^{S\times S} w_{ij}x_{jk} \qquad (i=1,\ldots M, k=1,\ldots T)$$

where T is the number of image patches.

(2) Update the weights by:

$$\Delta w_{ij}=\eta\left[\sum_{k=1}^{T} y_{ik}x_{jk}-\sum_{k=1}^{T}\left(\sum_{m=1}^{i} y_{ik}y_{mk}w_{mj}\right)\right]$$

$$i=1,\ldots M, j=1,\ldots S^2$$

where η is small positive learning rate.

(3) repeat 2-3 until the network converges.

2.3 Analysis of the principal components of image Patches

The 5×5 image patches used for training are randomly chosen from the original image in figure 2.

Figure 2 256×256 Original image

The rows of matrix $\mathbf{W}$ are the eigenvectors of the covariance matrix of $\mathbf{x}$ and thus orthonormal. If each row is mapped as a template with size 5×5 and the templates are arranged left-to-right, top-to-bottom, $\mathbf{W}$ can be represented as in Figure 3.

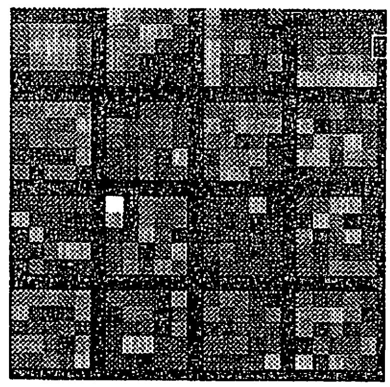

Figure 3 Normalized blocks of Matrix $\mathbf{W}$ $(M=16)$
The templates are arranged from top to down, and from left to right

The rows of $\mathbf{W}$ represent the principal components in the training patches and are arranged in order of decreasing variances. The first block in Figure 3 is similar to a Gaussian filter. The second block responds to the smoothing component and in the experiments the background is classified into this class. The third and the fourth responds to the main horizontal and vertical edges. All of the blocks except the first one can be used for edge detection.

We have found that the arrangement of the principal components is affected by the size of the image patches. In case of detectors with size 8×8, the background pixels are classified into several classes instead of a unique one because the noise within a patch increases. The detectors obtained from large size patches can extract main boundaries better than the detail edges. On the contrary, the detectors with small patch size have a better localization and are good at extracting detail features, e.g. facial features in Figure 4.

5×5 patch　　　8×8 patch

Figure 4 Edge map by different patch size

3 Edge detection by PCA neural network

Because the edge patterns extracted from the training data have been represented by the weights, the trained PCA network can be used for edge detection of images that are rather different from the training patches.

For each pixel, the surrounded $S \times S$ block is taken as the input to the PCA network. The pixel is assigned to a class number i that $y_i = \mathrm{MAX}\{y_k, k = 1,..M\}$. The block that approximately matches one of the templates will produce a large value corresponding to that template. Since all the templates are orthonormal, the block will have small values for other templates. In many edge detection methods, the maximum value over all the gradient operators is the output[1,2,3]. There are two points that we have to consider for these methods: (1) different filters may produce similar outputs for blocks with different gray scale values. (2) the result image has values in a very large range and so is difficult to be transformed into a binary image. In our method, however, the class number of the matched template instead of the maximum value is used as the output. So a pixel in the edge map is clearly represented by its pattern class and not affected by the gray scale value.

The existing gradient templates with discrete elements can not be used as patterns. An example is given that the class of the matched template is used as the output for Harr transform. The 64 basic images obtained from Harr transform with $N = 8$ are applied to the image in Figure 2, and the result is shown in Figure 5. Different colors represent different class. Even though the horizontal and vertical edges are separated, the result is not acceptable.

Some of the simulation results are shown in Figure 6. We provide both the result of our proposed method and that of the Sobel gradient edge filter.

Figure 5 Edge map by 8×8 Harr transform mask

4 Conclusions

We have proposed a method for edge detection by analyzing the principal components of image patches. The PCA neural network is trained by using random image patches and the weights connecting to one output node can be mapped into a two dimensional pattern template. The templates represent the features in images and are arranged by decreasing variances. A set of templates has the ability to distinguish edges and edge detection can be realized as pattern matching. The template set has been applied to other images that are much different from the training image patches.

The performance of the proposed method is related with two parameters: the size of the image patch and the number of the templates. We have found in the experiment that some edges become invisible when the template number is too small, and noises increase when the number is too big. The detectors obtained from large size patches can extract main boundaries, while as the detectors with small patch size have a good localization and are good at extracting detail features.

Our approach is an edge detection method based on pattern matching. In this case, the patterns obtained from the statistics of images are much more suitable than the patterns with fixed discrete elements. The effectiveness of our method means the possible application of PCA to feature detection and representation that we plan to use in image segmentation.

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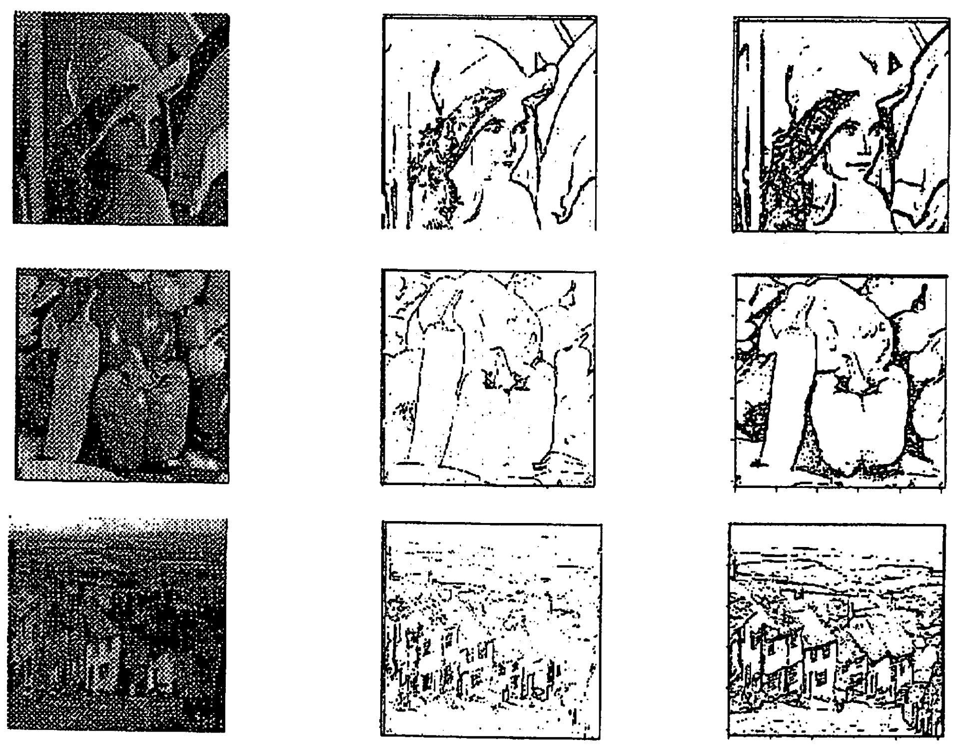

Figure 6 The edge detector is used to other images

1st column: original images; 2nd column: binary images by sobel filter;

3rd column: binary images by PCA edge detector