RESEARCH ARTICLE

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Classification of Texture Images Based on the Histogram of Oriented Gradients Using Support Vector Machines

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ABSTRACT

Herein, using support vector machines, texture images were classified based on the histogram of oriented gradients, from which feature vectors were obtained. In addition, the success rate was examined for the feature vectors with different dimensions and the minimum length of a feature vector for performing classification was determined to be 288 elements.

Keywords: Texture classification, Support vector machines, Histogram of oriented gradients

Introduction

Texture analysis is the mostly used method in image processing. It is possible to get knowledge about segmentation and classification of spatial parameters in images by texture analysis. Texture analysis is frequently utilized in medical image processing, remote sensing, and control systems. Features of texture can be extracted with variety of methods such as statistics, geometry, model-based, and signal processing etc. [1-8]. Those features are classified by machine learning techniques such that support vector machines, artificial neural networks. Histogram of oriented gradients method has been primarily used for pedestarian detection [9]. In addition, this method has been used to solve problems about human detection, crowd detection, 3D segmentation, sign language recognition [10-13]. Support vector machines is proposed by Cortes and Vapnik for the purpose of solving two dimensional classification problem [14]. It can also be used to solve for multiclass classifying problem [15]. In addition, svm can be implemented for linear or nonlinear classification problems. In this study, hog and feature vector extraction will be discussed at first for texture images, and classification of feature vectors via support vector machine will be mentioned.

Histogram of Oriented Gradients

At first, image has been partitioned into piece of blocks and cells, and features of the image are obtained by calculating the gradient for every cell [9]. Therefore, images are represented with respect to local histograms. Vertical and horizontal gradient of the images are calculated with the help of Sobel filters. Lets assume I(x,y) is the image, f_x is horizontal gradient whose Sobel filter coefficients are [1.0,-1], and f_y represents the vertical gradient whose Sobel filter coefficients are $[1,0,-1]^T$. I(x,y) represents the intensity of the image at (x,y) point. Then gradient will be calculated as:

$$f_x(x,y) = I(x+1,y)-I(x-1,y) \quad (1)$$
$$f_y(x,y) = I(x,y+1)-I(x,y-1) \quad (2)$$

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In addition,

$$f\left(x,y\right)=\sqrt{f_x^2+f_y^2} \quad (3)$$

$$\Theta=\arctan\frac{f_y(x,y)}{f_x(x,y)} \quad (4)$$

where f(x,y) represents the magnitude and Θ stands for the phase of the gradient.

Support Vector Machines

Support vector machines classify the group of data by using optimal hyperplane [14]. It is illustrated for 2-D data in Figure 1. Problem is to calculate w and b parameters with a constraint on optimum hyperplane such that wx+b=0, and X_i can either be +1 or -1.

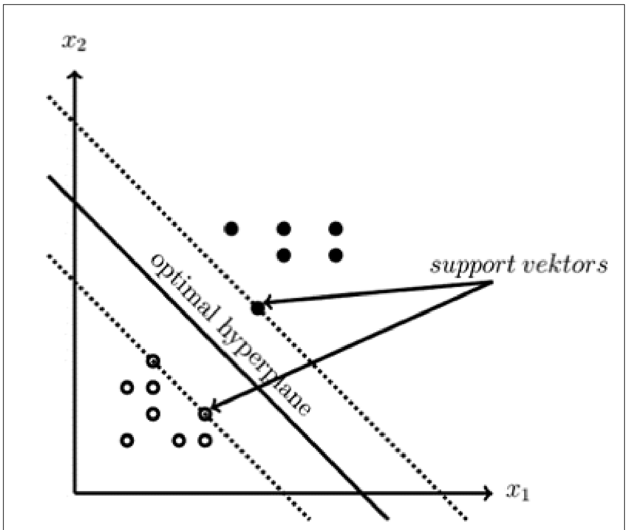

Figure 1. Support vectors and optimal hyperplane

Texture Classification via HOG

Texture data have been gathered from Salzburg Texture Image Database [16]. Size of the texture images are 512x512. Just three of the texture data: fabric, metal and tree textures are shown in Figure 2-4.

Implementation has been made by using Python programming language, and opencv machine learning library has been used. Texture images are converted into gray level images, and following methods are applied to those images.

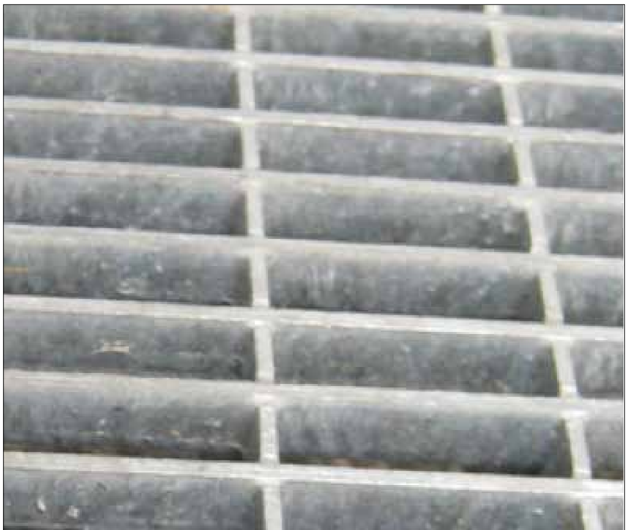

Figure 3. Texture image of metal

Figure 2. Texture image of fabric

Figure 4. Texture image of tree

Method 1
Calculate the vertical and horizontal gradient for the images of size 512x512. Calculate amplitude and angle of the gradients. Histogram of angles are calculated by dividing [0.180) degree into 9 equal pieces. For every subimage, amplitude values are accumulated for each angle in the same piece. Therefore, 9 dimensional feature vector is obtained.

Method 2
Calculate the vertical and horizontal gradient for the images of size 512x512. Calculate amplitude and angle of the gradients. Histogram of angles are calculated by dividing [-180, 180) degree into 18 equal pieces. For every subimage, amplitude values are accumulated for each angle in the same piece. Therefore, 18 dimensional feature vector is obtained.

Method 3
Texture image is divided into four piece with a size of 256x256. Calculate vertical and horizontal gradient for these subimages. Calculate amplitude and angle of the gradients. Histogram of angles are calculated by dividing [0.180) degree into 9 equal pieces. For every subimage, amplitude values are accumulated for each angle in the same piece. Therefore, 9 dimensional feature vector is obtained. Concatenate all feature vectors together, and obtain 4x9=36 dimensional feature vector.

Method 4
Texture image is divided into four piece with a size of 256x256. Calculate vertical and horizontal gradient for these subimages. Calculate amplitude and angle of the gradients. Histogram of angles are calculated by dividing [-180, 180) degree into 18 equal pieces. For every subimage, amplitude values are accumulated for each angle in the same piece. Therefore, 18 dimensional feature vector is obtained. Concatenate all feature vectors together, and obtain 4x18=72 dimensional feature vector.

Method 5
Texture image is divided into 16 piece with a size of 128x128. Calculate vertical and horizontal gradient for these subimages. Calculate amplitude and angle of the gradients. Histogram of angles are calculated by dividing [0.180) degree into 9 equal pieces. For every subimage, amplitude values are accumulated for each angle in the same piece. Therefore, 9 dimensional feature vector is obtained. Concatenate all feature vectors together, and obtain 16x9=144 dimensional feature vector.

Method 6
Texture image is divided into four piece with a size of 128x128. Calculate vertical and horizontal gradient for these subimages. Calculate amplitude and angle of the gradients. Histogram of angles are calculated by dividing [-180, 180) degree into 18 equal pieces. For every subimage, amplitude values are accumulated for each angle in the same piece. Therefore, 18 dimensional feature vector is obtained. Concatenate all feature vectors together, and obtain 16x18=288 dimensional feature vector.

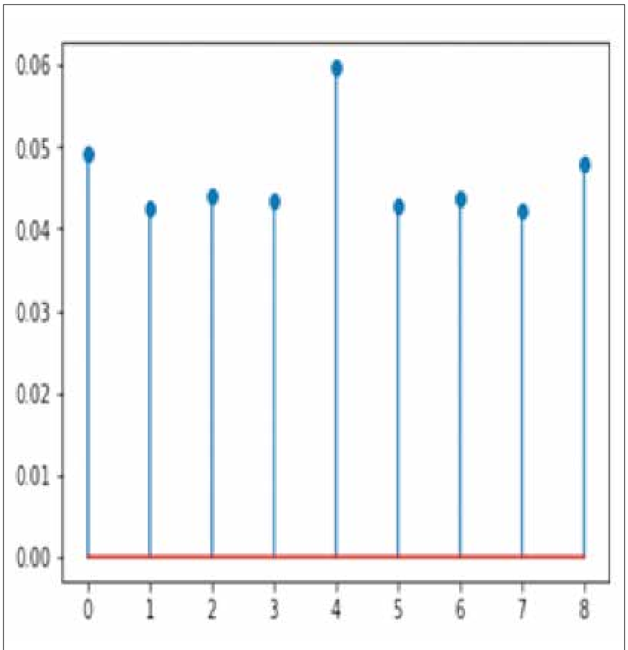

Figure 5. Feature vector calculated with Method 1.

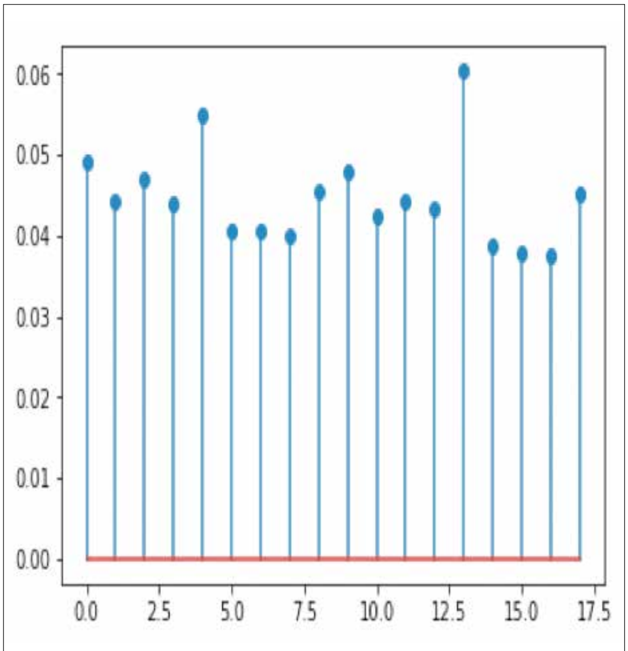

Figure 6. Feature vector calculated with Method 1.

Normalized feature vectors are calculated with all the methods before mentioned for the texture image in Figure 2. In addition, all feature vectors are shown in Figure 5-10.

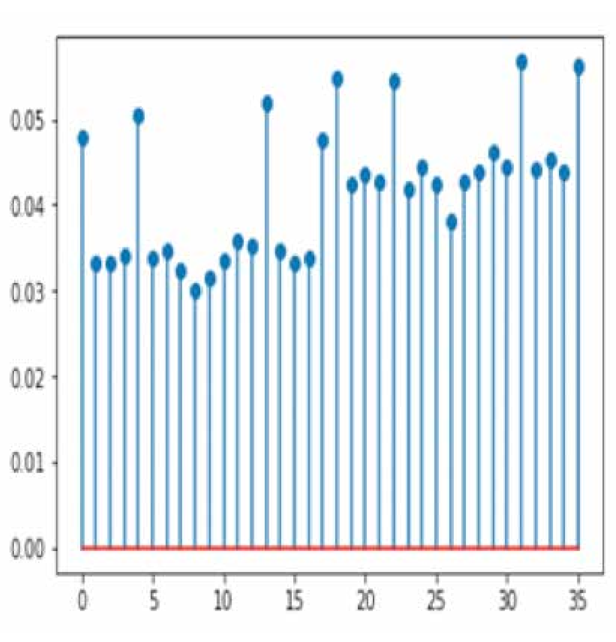

Figure 7. Feature vector calculated with Method 3

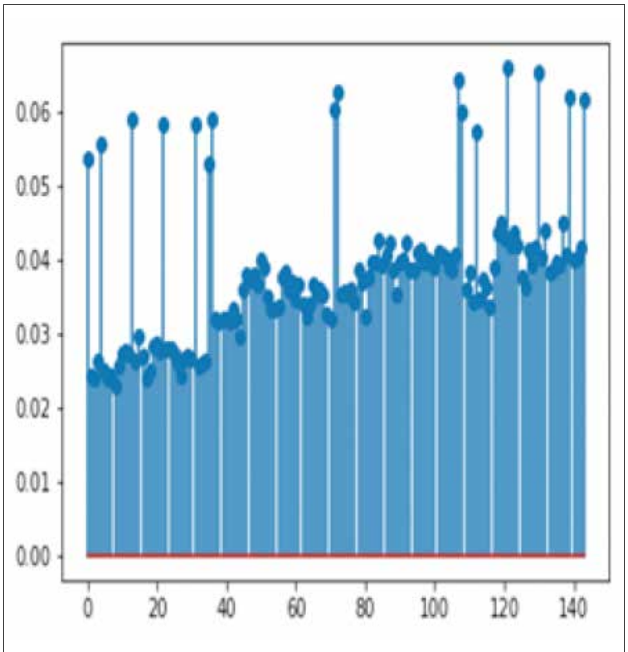

Figure 9. Feature vector calculated with Method 5

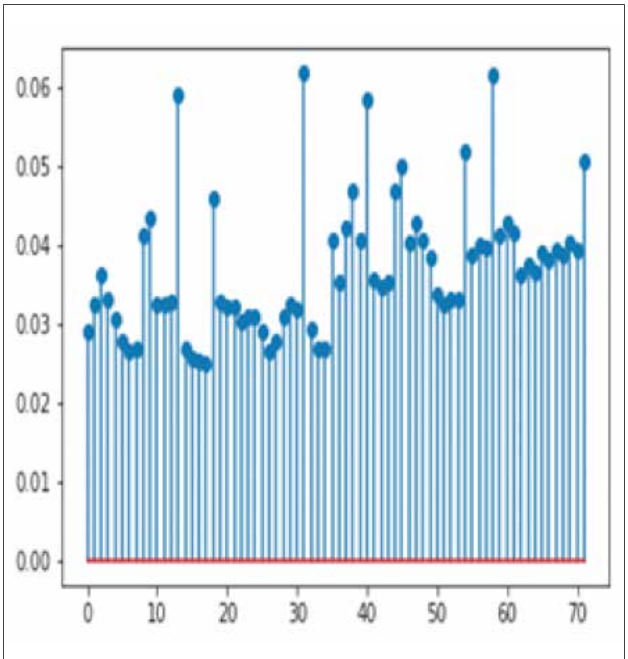

Figure 8. Feature vector calculated with Method 4

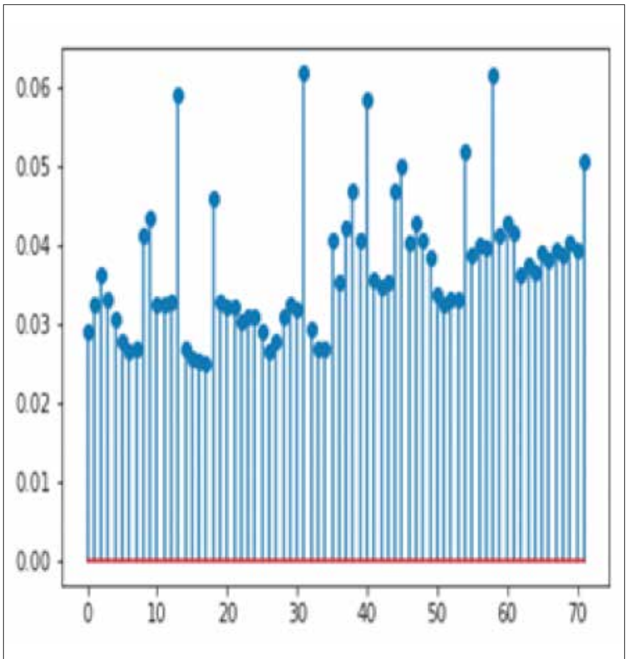

Figure 10. Feature vector calculated with Method 6

Results and Discussion

Opencv library has been used for the classification. Histogram intersection kernel is also utilized for the support vector machine. 230 of texture images which belong to 6 different class have been used as a training data, and 16 texture images have been utilized as a testing data. Success rate of classification are given in Table 1.

In the literature, size of feature vector using histogram of oriented gradients have been reported 3780 elements [18]. In the method 6, size of feature vector has obtained 288 elements.

Conclusions

Methods which are related with generating 18 piece of histograms with an angles between [-180, 180) have better perfor-

Table 1. Success rates of classification

Method	Success rate
1	43.75%
2	25%
3	50%
4	62.25%
5	31.25%
6	81.25%

mance results than other methods, i.e Method 4 and Method 6. For those methods consisting of 18 piece of histograms have better success rates when the numbers of feature vectors are increased. Method 6 is the best method when success rates are taken into account.

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