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Feature Extraction and Classification of Electric Power Equipment Images Based on Corner Invariant Moments

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Abstract

Feature extraction and accurate classification of electric power equipment, help to improve the automation and intelligent level of power system management. Aiming at the problems that applying Hu invariant moments to extract image feature computes large and applying corner vector to match has too dimensions, this paper presented Harris corner invariant moments algorithm. This algorithm only calculates corner coordinates other than the entire image coordinates, so can change the point feature into feature vectors, and reduce the corner matching dimensions. Combined with the SVM (Support Vector Machine) classification method, we conducted a classification for a large number of electrical equipment images, and the result shows that using Harris corner invariant moments algorithm to extract invariant moments, and classifying by these invariant moments can achieve better classification accuracy.

Keywords: *Hu invariant moments, Harris corner, feature extraction, classification*

1. Introduction

With the rapid development of intelligent electric grid construction and an increasing number of types of electric power equipment, electric power equipment management is developing from the traditional text management to multimedia and intelligent information management, thus leading to greatly increased workload and complexity of management. With the popularity of digital camera, image surveillance and other image collecting devices, the disorder problem of image information is more prominent. So it has become an urgent problem about how to organize orderly those huge number and variety of electrical power equipment in order to classify and browsing quickly [1].

The typical image classification retrieval system consists of data acquisition, preprocessing, feature extraction, classification decision and classifier [2], in which feature extraction is a key factor in the classification. Features of the image content include image color, texture, shape and other exterior features [3]. For most electric power equipment images, those color is relatively simple, and there are no obvious texture changes like wood and stone surface, so color and texture feature always are used as auxiliary features [4]. A variety of electrical power equipment is different from each other in shapes, and for the same electric power equipment, the shape feature has translation, rotation and scaling invariability. Therefore, this paper focuses mainly on shape feature of electrical power equipment as the object of research.
Domestic and foreign experts and scholars have done a lot of research work on the image shape feature extraction. Hu.M.K conducted seven shape invariant moments by using algebraic invariant moment in 1962[5]. The simple seven feature vectors can describe an image, but the calculation is relative large. Literature [6] applied Hu invariant moments to classify and retrieval electrical power equipment images, but not discussed the complexity of the algorithm.

Harris corner detection method is an effective means to greatly compress image feature [7]. In an image, corner points are the greatest changed pixels in local gray, generally accounting for only about 0.05% of the image pixels. The corner points have much information and rotation invariant features, also be able to adapt to ambient light changes [8].

This paper presents Harris corner invariant moment algorithm. First, according to Harris corner detection operator, detect image corner information, then record the corner coordinates and the gray value. Second, calculate the six Harris corner invariant moment vectors by Harris corner invariant moment algorithm. This algorithm changed point features into feature vectors,

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taking into account both the key position of the image information, but also greatly reduces the amount of computation. The experiment shows that combined with SVM classification algorithm, using the six Harris corner invariant moment vectors as feature extraction vectors to classify image is effective.

2. Harris Corner Invariant Moment Features

2.1. Hu Invariant Moments

Hu invariant moments are seven shape invariant moments that Hu.M.K conducted by using algebraic invariant moment in 1962. In x-y plane, an MxN image $f(x,y)$, the (p+q)-th order moments and central moments are defined respectively as:

$$m_{pq} = \iint_D x^p y^q f(x,y)dxdy \tag{1}$$

$$\mu_{pq} = \iint_D (x-\bar{x})^p (y-\bar{y})^q f(x,y)dxdy \tag{2}$$

Where $\bar{x} = m_{10}/m_{00}$, $\bar{y} = m_{01}/m_{00}$, these are the centroid of the image. When $f(x,y)$ is the object density, the zero-order moments m_{00} are the sum of the density, that is also the mass of the object. The central moments μ_{pq} are the metrics that measure the barycenter distribution in region R. The normalized central moments, denoted by η_{pq}, are defined as:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{(p+q+2)/2}} \tag{3}$$

Hu conducted seven invariant moments' functions by using the normalized second-order and third-order central moments. These seven functions have translation, rotation and scaling invariability.

$$\begin{aligned}
&\varphi_1 = \eta_{20} + \eta_{02} \\
&\varphi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
&\varphi_3 = (\eta_{30} - 3\eta_{12})^2 + (\eta_{03} - 3\eta_{21})^2 \\
&\varphi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
&\varphi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] \\
&+ (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \\
&\varphi_6 = (\eta_{20} - \eta_{02})\left[(\eta_{30} + \eta_{12})^2 - (\eta_{03} + \eta_{21})^2\right] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{03} + \eta_{21}) \\
&\varphi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{03} + \eta_{21})^2\right] \\
&+ (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{03} + \eta_{21})^2\right]
\end{aligned} \tag{4}$$

2.2. Harris Corner Invariant Moment Algorithm

It's a relative effective point feature extraction algorithm by using Harris operator which only uses the first-order gray difference and Gaussian filtering. Thus it has speed calculating and strong timeliness. In addition, Harris corner points are not sensitive to image rotation, translation and gray transformation, so the Harris corner points also have the advantages of high stability, simple operation and anti-interference ability. It's considered corner points that the pixels changed greatest in local gray. Harris corner detection operator algorithm works as follows: this method uses a rectangular window or a Gaussian window to move on the image, and then we can get the derived partial 2×2 structure M from the original template window. Next, calculate the eigenvalues λ_1 and λ_2 of *M*. According to the defined corner response function *R* in formula (5), calculate the *R* value of each pixel. Finally, we select a series of corner coordinates by using local non-maxima suppression to get the appropriate threshold.

$$M=\begin{bmatrix} w_{u,v}I_x^2 & w_{u,v}I_xI_y \\ w_{u,v}I_xI_y & w_{u,v}I_y^2 \end{bmatrix}=\begin{bmatrix} A & C \\ C & B \end{bmatrix}$$
$$R=\det(M)-ktr^2(C)=AB-C^2-k(A+B)^2 \qquad (5)$$
$$tr(C)=\lambda_1+\lambda_2$$

Where I_x and I_y are zero order gray gradient.

Assume we get n corner coordinates by Harris corner detecting operator. These are recorded as series (x_1, y_1), (x_2, y_2)…(x_n, y_n), and corner coordinate gray values are denoted by *f*(*i, j*). Then according to the formula (1) and formula (2), we define the discrete corner order moments and central moments as follows:

$$m_{pq}=\sum\sum_D x^p y^q f(x,y)dxdy \qquad (6)$$

$$\mu_{pq}=\sum\sum_D (x-\bar{x})^p(y-\bar{y})^q f(x,y)dxdy \qquad (7)$$

Literature [9] did further research of Hu invariant moments method, and proved that Hu invariant moments only have translation and rotation invariability. Next, we discuss the influence of scale and contrast on the corner invariant moments. The scaling factor is denoted by ρ, and the contrast change factor is *k*. And the position is change from (*i*, *j*) to(*i'*, *j'*) , accordingly, the gradation *f*(*i*, *j*) is converted into *f*(*i'*, *j'*) from the same location. There are the following relationships:

$$\begin{bmatrix} i' \\ j' \end{bmatrix}=\rho\begin{bmatrix} i \\ j \end{bmatrix} \qquad \rho>0$$
$$f'(i',j')=kf(i,j) \qquad k>0 \qquad (8)$$

The original center moment is μ_{pq}, after the transformation is μ'_{pq}. And the coordinates of the center of gravity are respectively ($\bar{i}$, $\bar{j}$)and ($\bar{i}'$, $\bar{j}'$). Then the relationship between the transformed center moment and the original center moment is shown as formula (9):

$$\mu'_{pq}=\iint_D (i'-\bar{i}')^p(j'-\bar{j}')^q f'(i',j')=\iint_D k\rho^{p+q}(i-\bar{i})^p(j-\bar{j})^q f(i,j)=k\rho^{p+q}\mu_{pq} \qquad (9)$$

Particularly $\mu'_{00}=k\mu'_{00}$, and the normalized central moments are defined as:

$$\eta'_{pq}=\frac{\mu'_{pq}}{(\mu'_{00})^r}=\frac{k\rho^{p+q}\mu_{pq}}{(k\mu_{00})^r}=\frac{\rho^{p+q}}{k^{(p+q)/2}}\eta_{pq} \qquad (10)$$

Combined with formula (3) and (4), we can easily get the relationship of invariant moments between the original and transformed as formula (11).

$$\varphi'_1=\frac{\rho^2}{k}\varphi_1,\ \varphi'_2=\frac{\rho^4}{k^2}\varphi_2,\ \varphi'_3=\frac{\rho^6}{k^3}\varphi_3,\ \varphi'_4=\frac{\rho^6}{k^3}\varphi 4,\ \varphi'_5=\frac{\rho^{12}}{k^6}\varphi_5,\ \varphi'_6=\frac{\rho^8}{k^4}\varphi_6,$$
$$\varphi'_7=\frac{\rho^{12}}{k^6}\varphi_7 \qquad (11)$$

From the formula (11), we can see that after the transformation of scale and contrast, the invariant moments are the (ρ^2/k) integer power compared with the original invariant moments, no longer remaining invariant features. We regroup the above formulas in order to eliminate the influence of scaling factor and contrast factor. So we get the six invariant moments vectors as follows:

$$\beta_1=\frac{\varphi_2}{\varphi_1^2},\quad \beta_2=\frac{\varphi_3}{\varphi_1\varphi_2},\quad \beta_3=\frac{\sqrt{\varphi_4}}{\sqrt{\varphi_3}},\quad \beta_4=\frac{\sqrt{\varphi_5}}{\varphi_4},\quad \beta_5=\frac{\varphi_6}{\varphi_1\varphi_4},\quad \beta_6=\frac{\varphi_7}{\varphi_5} \tag{12}$$

Specific algorithm steps:

(A) First, we should make the collected images size normalizing and graying. Next, filter the preprocessed images by using difference operators, and calculate I_x, I_y and I_{xy}. Then use the 5x5 Gaussian templates to smooth the image, after removing noise, we can get M.

(B) Calculate the corner response function R of the corresponding pixels according to M, where $R=AB-C^2-K(A+B)^2$. Then select a series of corner coordinates by using local non-maxima suppression to get the appropriate threshold. Record the corner coordinates as (x_1, y_1), (x_2, y_2)…(x_n, y_n), and the corresponding gray values, where corner number is n.

(C) Calculate the corner points order moments m_{pq} and center moments μ_{pq} according to the formula (6) and (7), where i=1,2,…,n.

(D) Normalize the above corner points center moments according to the formula (3), and get η_{pq}. Then calculate the seven corner points invariant moment vectors φ_1-φ_7.

(E) In actual process, since the seven invariant moment vectors vary wide, we use $\varphi^*_i=||\log|\varphi_i||$. Then we calculate the six corner point invariant moments vectors according to formula (12), which are all have translation, rotation and scaling invariability.

3. Experiment

3.1. Image Choosing Preprocessing

In this experiment, we choose five types of electric power equipment shot in the factory environment as shown in Figure 1. From left to right the five images are transformer, circuit breaker, energy meter, switch and current transformer. We use 180 images as total samples, in which 90 images are used for SVM training and the others are used for testing classification accuracy. The experimental environment is matlabR2008, combined with libsvm-3-17 software package for SVM training and testing.

Figure 1. Images used in the Experiment

Harris corner invariant moment algorithm and SVM classification are shown in Figure 2.

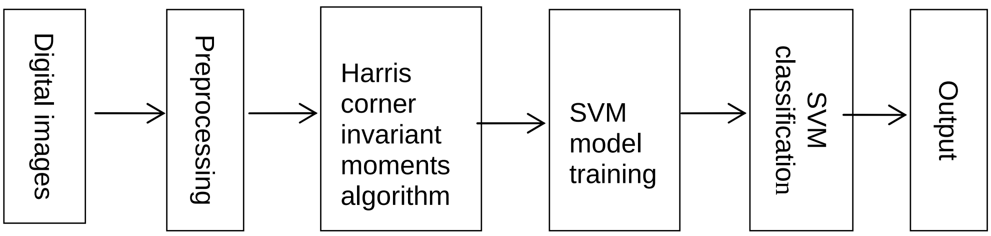

Figure 2. Experimental Procedure

Image preprocessing operations include normalizing image size, graying and enhancing image contrast with histogram equalization method. First, detect corner coordinates by Harris detecting operator. Then, calculate Harris corner invariant moment vectors β_1-β_6, and put these six vectors as extracted feature vectors. In this paper, we choose LIBSVM classifier for training and classification. According to the training samples, we train these samples, using cross-validation method to obtain the optimal parameters *g* and *c*, thus, getting the trained model. Next, input the samples to be tested to the trained SVM model, and record the misclassification number and classification accuracy.

3.2. Experimental Data Acquisition

After preprocessing to the collected images and detecting Harris corner coordinates, images shown in Figure 3. In the process of selecting Harris corner coordinates, parameter *k* is 0.04. Then we calculated Harris corner invariant moment vectors β_1-β_6, a part of the training samples data shown in Table 1.

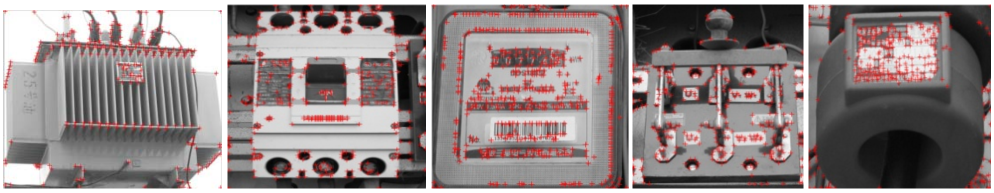

Figure 3. Images after the Corner Detection

Table 1. Part of the Training Data

Image class	β_1	β_2	β_3	β_4	β_5	β_6
Transformer	0.0940	0.0993	1.0166	0.1727	0.0670	1.0050
Breaker	0.0902	0.0975	1.0008	0.1812	0.0672	0.9942
Energy Meter	0.0931	0.0848	1.0000	0.1907	0.0715	1.0445
Switch	0.0927	0.0987	1.0147	0.1772	0.0670	0.9999
CT	0.0987	0.0949	1.0186	0.1806	0.0716	1.0252

According to SVM algorithm Vpanik proposed [10], we selected RBF(radial basis function) as kernel function, and determined the optimal parameters (*g*,*c*)=(2,0.0625) by using cross -validation algorithm in training [11], where *g* is the width parameter of RBF, *c* is the penalty factor.

3.3. Results and Analysis

Table 2. Classification Results by Harris Corner Invariant Moment Vectors

Image class	Training samples	Test samples	Misclassification number	Accuracy(%)
Transformer	19	17	3	82.35
Breaker	18	18	2	88.89
Energy Meter	20	16	2	87.50
Switch	17	19	2	89.47
CT	16	20	2	90.00

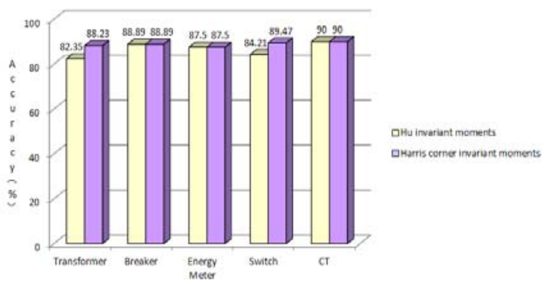

Figure 4. Comparison of Classification Accuracy

Use Harris corner invariant moment vectors β_1-β_6 to train and test. The result displayed of wrong numbers and classification accuracy, as shown in Table 2. Similarly, we also classify these five types images based on seven Hu invariant moments. In order to facilitate comparison, the classification result and comparison are shown in Figure 4.

From the above experimental results, the classification accuracy has reached a relatively satisfied status. But there also exists some misjudgment, the reasons led to these justice include that these images are mostly shot from factory environment. The equipment has different degrees of wear, consumption, and other dissipation in the environments, which also affect the image feature extraction to some extent.

First, we get the corner points detected by Harris corner operator, then according to the Harris corner invariant moment algorithm, change corner points to the six feature vectors. Formula evidence that the six feature vectors have translation, rotation and scaling invariability. Next, combined with SVM classification, use the extracted six feature vectors to classify those electric power equipment images. The experiment result shows that Harris corner invariant moment algorithm can be used as shape features to describe an image feature. Further, Harris corner invariant moments are calculated only on the corner points of the target so can greatly reduce extraction speed and data processing.

4. Conclusion

In the shooting process, electrical power equipment images are easily affected by shooting angles, distance and other factors, while the Harris corner and Hu invariant moments both have translation, rotation and scaling invariability. Therefore, we unified the corner feature and invariant moments, changing the point feature into feature vectors. This algorithm selected six Harris corner invariant moment vectors as extracted feature for the next image classification. The experiment shows it can achieve high classification accuracy. So it's fast and feasible that using Harris corner invariant moments algorithm to extract image feature, with the advantage of short time and complexity.

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