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Pattern Recognition using Normalized Feature Vectors Analysis

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Abstract

Objective: To study pattern recognition and retrieval in machine vision system application. **Methods/Analysis:** Regular and irregular pattern recognition algorithm based on sorting of radii from centre of mass is used and other tools such as Matlab, Neural networks. **Findings:** The radii from centre of mass to contour of the pattern are computed and sorted in descending order. Few top radii are taken for recognition of the given pattern. As the radii are sorted in descending order, therefore, if the pattern is orientated at any angle, the top order radii are same. This enables the pattern recognition at any orientation. Further, the radii are normalized with respect to their mean radius to make them size invariant. In addition, area, perimeter and euler number are also computed for enhancing the uniqueness degree in features vector set.

Keywords: CBIR, Extraction, Normalization, NN

1. Introduction

In most of the research work related to pattern recognition, frequency domain or spatial domain has been explored. When analysed a pattern in spatial domain or frequency domain, the main problem arises when to reconstruct the pattern using the spatial domain or frequency domain feature. Radial profile of a pattern is one solution to reconstruction of the pattern to nearest to its original one. Pattern recognition enables the computer to know what it is looking at via the image acquisition device like digital camera. If image acquisition devices are the eyes of the computer, then, pattern recognition algorithm is brain of the system that enables to identify the pattern under scanner.

Pattern recognition in image processing domain is carried out in different stages: Image acquisition, enhancement, binarization and segmentation, feature extraction, feature normalization with respect to size and orientation/rotation and correlation of features with respective pattern. Statistical features are extracted from the pattern under test in the presented work. Statistical features are extracted around the centre of mass of the pattern/object. Feature vector set includes different radii, area, perimeter and variance in radii. The feature vector set is illustrated in subsequent section of the paper.

In[1] discussed Matlab neural tool box for pattern analysis. Different patterns can be generated using the simple GUI and trained using the NN training provision. The same can be tested using the test option.

In[2] proposed neural network approach for multi class pattern. The neural network training features were extracted from the pattern after few image preprocessing operations applied on the pattern. The features were extracted from the binary image resulted out of threshold operation.

In[3] suggested gradient based neural network training using the pattern feature vector set. More were the features of a pattern, higher is the resolution at the output or more classes can be resolved.

In[4], a review of pattern analysis using statistical analysis was presented. The patterns were analyzed in different domains like spatial, frequency and wavelet domain for pattern recognition accuracy determination.

In[5], statistical processing chart for pattern analysis was discussed. Patterns were represented by their normalized features. A feature vector set was generated using different radii around centre of mass.

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In[6], hand written characters were also a class of patterns and can be identified using feature vector set. The feature vector set was unique for each of the hand written or typed fonts.

In[7], a hybrid approach between genetic algorithm and neural network was suggested to classify the patterns into different class. The system consisted of pattern segmentation, feature extraction and a classifier.

In[8], Pulse Coded Neural Network (PCNN) was suggested for pattern classifier using different features when normalized with respect to pattern mean radius.

In[9,10], Bayesian MLP Neural Networks for Image Analysis was discussed in details for pattern identification and classification.

In[11,12], a content based approach to medical X-Ray image retrieval using texture features approach was proposed. The algorithm covered the gray level co-occurrence matrix using texture features.

In[13], A novel fusion approach to content-based image retrieval was proposed for CBIR system using the image and feature fusion algorithm.

In[14], a review of the work on content-based image retrieval with high level semantics was presented and compared with different techniques.

In[15–17], segmentation of patterns from the scene was done for CBIR system. A pixel neighborhood technique was used for segmentation and later on analyzed in statistical domain. Color based segmentation was also performed for colored images.

In[18,19], color and statistical features were used for pattern segmentation and later on recognition of the same. GLCM was also used for generating the feature vector and query vector set. Legendre Moments and Support Vector Machine were also made part of the query and feature vector set.

2. Pattern Extraction

For an efficient pattern recognition task, it is desirable to extract the pattern from the background as a binary image. The binary image should contain the Pattern Under Test (PUT) as black and background as white or vice versa. The binary image may be obtained by computing a threshold value using Otsu algorithm, adaptive thresholding or any suitable algorithm so as to extract the pattern with minimum pattern information loss.

3. Feature Extraction

Feature extraction is the prime task in an automated pattern recognition system. In earlier system, the feature vector set consists of statistical parameters (Normalized Maximum and Minimum radii in each quadrant, Normalized Intercepts on each axis, Normalized Perimeter, Normalized Area and Standard Deviation).

The feature set given above is fair enough in identifying the regular geometric patterns even at different sizes and orientations. But, when tested on irregular shapes, it shows poor recognition results on both part i.e. size and orientation.

In order to improve the limitation, all radii are taken from Centre of Mass (CoM) and are arranged in descending order. It is self understood that even if the pattern is rotated at any angle for the same size, the descending or ascending order of radii will not change.

Also, if the radii are divided by the mean radius, then the normalized radii will be same for different sizes of the same pattern. This makes the features more robust to size and orientation. Area, perimeter, standard deviations and Euler number are already rotation independent and can be normalized with respect to mean radius for size independent.

All features are computed around the centre of mass of the pattern. Centre of mass (G_x, G_y) is computed by using the first order moments of the PUT and is given by:

$$Gx = \frac{\sum_{i=1}^{N} X_i}{N}, and\ Gy = \frac{\sum_{i=1}^{N} Y_i}{N}$$

Where 'N' is the perimeter i.e. number of contour pixels or number of radii. The radius R_i of i^{th} point (X_i, Y_i) on contour of the pattern from centre of mass is given by:

$$R_i = \sqrt{(G_x - X_i)^2 + (G_y - Y_i)^2}$$

The mean radius (R_m) is given by:

$$R_m = \frac{\sum_{i=1}^{N} R_i}{N}$$

Standard Deviation (SD) is the standard deviation (σ) of radii given by:

$$\sigma = \sqrt{\sum_{i=1}^{N} \frac{(R_i - R_m)^2}{N}}$$

Where R_i, R_m and 'N' are i^{th} radius, mean radius and number of radii respectively. The area is computed by counting all the pattern pixels. The perimeter is computed by counting all the contour pixels.

Euler Number is defined as the difference of total number of objects in the image and the number of holes in those objects.

4. Feature Normalization

Radii, area and perimeter are normalized by dividing each by mean radius as follows:

$$Normalized\ Radius\ \hat{R}_i = \frac{R_i}{R_m}$$

$$Normalized\ Perimeter\ \hat{P} = \frac{P}{R_m}$$

$$Normalized\ Area\ \hat{A} = \frac{A}{R_m^2}$$

5. Results

The algorithm has been tested over number of irregular pattern. The results for two of the same are presented in Tables 1 and 2. The orientation/rotation in variancy is tested by rotating each pattern at different angle as shown in Figures 1 and 2. The top 20 radii for the patterns at different orientations shown in Figures 1 and 2 are given in Tables 1 and 2 respectively.

Figure. 1. Irregular pattern-1 at different orientation.

Figure 2. Regular pattern-2 at different orientation.

Figure 3. Irregular pattern-1of different size.

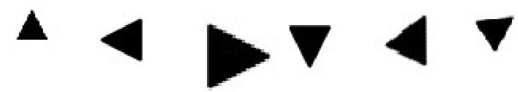

Figure 4. Regular Pattern-4 at Different Size

Table 1. Features for the Patterns shown in Figure 1

Features	Seg. No.1	Seg. No.2	Seg. No.3	Seg. No.4	Seg. No.5	Seg. No.6
R- 1	21.47	21.47	21.47	21.1	21.47	20.81
R- 2	21.47	21.1	21.1	20.81	21.47	20.62
R- 3	21.1	20.81	20.81	20.62	21.1	20.4
R- 4	20.81	20.62	20.62	20.59	20.81	20.25
R- 5	20.62	20.12	20.12	20.12	20.62	20.22
R- 6	20.12	19.92	19.92	19.92	20.12	20.12
R- 7	19.92	19.85	19.92	19.85	19.92	19.92
R- 8	19.85	19.72	19.85	19.72	19.85	19.85
R- 9	19.72	19.7	19.72	19.7	19.85	19.72
R- 10	19.7	19.7	19.7	19.7	19.72	19.72
R- 11	19.7	19.65	19.7	19.65	19.7	19.7
R- 12	19.65	19.42	19.65	19.42	19.7	19.65
R- 13	19.42	19.31	19.42	19.31	19.65	19.42
R- 14	19.31	19.24	19.31	19.24	19.42	19.31
R- 15	19.24	19.24	19.24	19.24	19.31	19.31
R- 16	19.24	19.24	19.24	19.24	19.24	19.24
R- 17	19.24	19.21	19.24	19.24	19.24	19.24
R- 18	19.21	19.1	19.21	19.21	19.24	19.21
R- 19	19.1	19.1	19.1	19.1	19.21	19.1
R- 20	19.1	19.1	19.1	19.1	19.1	19.1
Mean R	14.79	14.77	14.78	14.77	14.83	14.91
Perim.	138	138	138	138	139	138
Area	3.37	3.38	3.37	3.37	3.36	3.29
SD	0.78	0.71	0.69	0.61	0.76	0.52
Euler No	1	1	1	1	1	1

Table 2. Features for the Patterns shown in Figure 2

Features	Seg. No.1	Seg. No.2	Seg. No.3	Seg. No.4	Seg. No.5	Seg. No.6
R- 1	16.03	16.03	16.03	16.03	16.55	16.64
R- 2	16	16.03	16	16	16.16	16.4
R- 3	15.81	16	15.81	15.81	16.12	16.16
R- 4	15.26	15.81	15.26	15.26	15.26	16.16

R- 5	15.13	15.26	15.13	15.13	15.13	16.12
R- 6	15.03	15.13	15.03	15.03	15.03	16.03
R- 7	15	15.03	15	15	15.03	16
R- 8	15	15	15	15	14.87	15.81
R- 9	14.76	15	15	15	14.76	15.52
R- 10	14.42	14.76	14.76	14.76	14.42	15.23
R- 11	14.21	14.42	14.42	14.42	14.32	15.13
R- 12	14.21	14.21	14.21	14.21	14.32	15.03
R- 13	14.14	14.21	14.21	14.21	14.04	15
R- 14	14.04	14.14	14.14	14.14	13.89	14.76
R- 15	13.89	14.04	14.04	14.04	13.6	14.32
R- 16	13.45	13.89	13.89	13.89	13.6	14.32
R- 17	13.45	13.45	13.45	13.45	13.6	14.32
R- 18	13.42	13.45	13.45	13.45	13.34	14.21
R- 19	13.42	13.42	13.42	13.42	13	14.14
R- 20	13.42	13.42	13.42	13.42	13	14.04
Mean R	11.26	11.31	11.3	11.29	11.19	11.66
Perim.	77	77	77	77	74	78
Area	3.11	3.1	3.1	3.1	3.1	3.07
SD	0.88	0.9	0.85	0.85	1.03	0.86
Euler No	1	1	1	1	1	1

Table 3. Features for the Patterns shown in Figure 3

Features	Seg. No.1	Seg. No.2	Seg. No.3	Seg. No.4	Seg. No.5	Seg. No.6
R- 1	1.45	1.45	1.41	1.43	1.46	1.4
R- 2	1.45	1.43	1.39	1.41	1.44	1.38
R- 3	1.43	1.41	1.38	1.4	1.44	1.37
R- 4	1.41	1.4	1.36	1.39	1.4	1.36
R- 5	1.39	1.36	1.36	1.36	1.38	1.36
R- 6	1.36	1.35	1.36	1.35	1.35	1.35
R- 7	1.35	1.34	1.36	1.34	1.32	1.34
R- 8	1.34	1.34	1.34	1.34	1.32	1.33
R- 9	1.33	1.33	1.34	1.33	1.31	1.32
R- 10	1.33	1.33	1.34	1.33	1.31	1.32
R- 11	1.33	1.33	1.34	1.33	1.31	1.32
R- 12	1.33	1.31	1.33	1.31	1.3	1.32
R- 13	1.31	1.31	1.32	1.31	1.3	1.3
R- 14	1.31	1.3	1.32	1.3	1.28	1.3
R- 15	1.3	1.3	1.32	1.3	1.27	1.3
R- 16	1.3	1.3	1.31	1.3	1.27	1.29
R- 17	1.3	1.3	1.31	1.3	1.27	1.29
R- 18	1.3	1.29	1.31	1.3	1.27	1.29
R- 19	1.29	1.29	1.31	1.29	1.27	1.28
R- 20	1.29	1.29	1.31	1.29	1.26	1.28
Mean R	1	1	1	1	1	1
Perim.	0.23	0.23	0.19	0.23	0.33	0.22
Area	0.02	0.02	0.01	0.03	0.03	0.01
SD	0.05	0.05	0.03	0.04	0.06	0.03
Euler	1	1	1	1	1	1

Table 4. Features for the Patterns shown in Figure 4

Features	Seg. No.1	Seg. No.2	Seg. No.3	Seg. No.4	Seg. No.5	Seg. No.6
R- 1	1.42	1.42	1.47	1.42	1.49	1.48
R- 2	1.41	1.42	1.47	1.42	1.45	1.39
R- 3	1.39	1.41	1.47	1.4	1.45	1.39
R- 4	1.39	1.4	1.41	1.35	1.34	1.39
R- 5	1.32	1.35	1.41	1.34	1.34	1.34
R- 6	1.32	1.34	1.36	1.33	1.34	1.3
R- 7	1.32	1.33	1.36	1.33	1.34	1.3
R- 8	1.29	1.33	1.36	1.33	1.33	1.29
R- 9	1.29	1.33	1.35	1.33	1.33	1.29
R- 10	1.28	1.31	1.35	1.31	1.31	1.29
R- 11	1.28	1.28	1.35	1.28	1.3	1.29
R- 12	1.18	1.26	1.32	1.26	1.27	1.25
R- 13	1.18	1.26	1.32	1.26	1.27	1.25
R- 14	1.18	1.25	1.3	1.25	1.25	1.22
R- 15	1.16	1.24	1.3	1.24	1.25	1.22
R- 16	1.15	1.23	1.3	1.23	1.25	1.22
R- 17	1.15	1.19	1.3	1.19	1.24	1.19
R- 18	1.1	1.19	1.29	1.19	1.19	1.19
R- 19	1.09	1.19	1.29	1.19	1.19	1.18
R- 20	1.09	1.19	1.26	1.19	1.18	1.14
Mean R	1	1	1	1	1	1
Perim.	0.41	0.27	0.18	0.27	0.26	0.33
Area	3.18	3.10	3.03	3.10	3.08	3.12
SD	0.11	0.08	0.06	0.08	0.09	0.09
Euler	1	1	1	1	1	1

From the Tables 1-4, it can be observed that if the radii around centre of mass are arranged in descending order, the top order radii are almost same irrespective of the orientation of the same object and of same size. This makes the algorithm rotation independent. Further the same radii can be normalized to mean radius. This will make

the algorithm as size independent as well. The results may be seen in Tables 3 and 4.
Some more results are computed for the regular patterns in different sizes and at different orientations as shown in Figures 5 and 6. The results are compiled in Tables 5 and 6.

Figure 5. Regular pattern-3 at different orientation.

Figure 6. Regular pattern-3 in different sizes.

Table 5. Features for the Patterns shown in Figure 5

Features	Seg. No.1	Seg. No.2	Seg. No.3	Seg. No.4	Seg. No.5	Seg. No.6
R- 1	1.43	1.48	1.47	1.48	1.45	1.45
R- 2	1.43	1.46	1.45	1.48	1.45	1.45
R- 3	1.43	1.46	1.44	1.47	1.42	1.43
R- 4	1.43	1.44	1.44	1.45	1.42	1.41
R- 5	1.41	1.44	1.43	1.44	1.42	1.41
R- 6	1.41	1.43	1.43	1.43	1.42	1.4
R- 7	1.4	1.43	1.43	1.43	1.4	1.4
R- 8	1.4	1.42	1.41	1.42	1.4	1.4
R- 9	1.39	1.42	1.41	1.41	1.39	1.4
R- 10	1.39	1.42	1.4	1.41	1.39	1.39
R- 11	1.39	1.41	1.4	1.4	1.38	1.39
R- 12	1.39	1.41	1.39	1.4	1.38	1.39
R- 13	1.38	1.4	1.39	1.39	1.38	1.38
R- 14	1.38	1.4	1.39	1.39	1.34	1.37
R- 15	1.37	1.4	1.39	1.39	1.34	1.36
R- 16	1.37	1.39	1.39	1.38	1.34	1.36
R- 17	1.37	1.39	1.39	1.38	1.34	1.35
R- 18	1.37	1.39	1.38	1.38	1.3	1.35
R- 19	1.36	1.39	1.38	1.38	1.3	1.34
R- 20	1.36	1.39	1.38	1.38	1.26	1.33
Mean R	1	1	1	1	1	1
Perim.	0.19	0.19	0.19	0.19	0.17	0.17
Area	0.01	0.01	0.01	0.01	0.01	0.01

SD	0.02	0.03	0.03	0.03	0.05	0.03
Euler	1	1	1	1	1	1

Table 6. Features for the Patterns shown in Figure 6

Features	Seg. No.1	Seg. No.2	Seg. No.3	Seg. No.4	Seg. No.5	Seg. No.6
R- 1	1.46	1.5	1.47	1.46	1.44	1.46
R- 2	1.44	1.46	1.45	1.45	1.44	1.44
R- 3	1.44	1.46	1.45	1.45	1.43	1.44
R- 4	1.43	1.44	1.44	1.43	1.43	1.43
R- 5	1.42	1.44	1.44	1.43	1.43	1.42
R- 6	1.42	1.42	1.43	1.41	1.43	1.42
R- 7	1.41	1.42	1.43	1.41	1.42	1.41
R- 8	1.41	1.4	1.43	1.39	1.42	1.41
R- 9	1.4	1.4	1.42	1.39	1.42	1.4
R- 10	1.4	1.4	1.42	1.38	1.41	1.4
R- 11	1.39	1.4	1.42	1.38	1.41	1.39
R- 12	1.39	1.4	1.41	1.38	1.41	1.39
R- 13	1.38	1.36	1.41	1.38	1.41	1.38
R- 14	1.38	1.31	1.41	1.37	1.41	1.38
R- 15	1.38	1.3	1.41	1.37	1.41	1.38
R- 16	1.38	1.3	1.4	1.37	1.4	1.38
R- 17	1.37	1.3	1.4	1.37	1.4	1.37
R- 18	1.37	1.26	1.39	1.35	1.39	1.37
R- 19	1.37	1.23	1.39	1.31	1.39	1.37
R- 20	1.37	1.23	1.39	1.31	1.39	1.37
Mean R	1	1	1	1	1	1
Perim.	0.19	0.34	0.11	0.26	0.09	0.19
Area	0.01	0.04	0	0.02	0	0.01
SD	0.03	0.08	0.02	0.04	0.02	0.03
Euler	1	1	1	1	1	1

6. Conclusion

The analysis of normalized radii with respect to mean radius computed around centre of mass of a pattern gives a very useful tool in identifying a given pattern. The number of radii may be increased or decreased depending upon the pattern nature. The results are computed by implementing the algorithm in Matlab version 7.0. The program may be tested for different objects as well as in different sizes. Success rate of pattern identification using the algorithm is fair enough and may be cascaded to a classifier like NN or SVM for different class generation.

The features extracted here have fair resolution capability in classifying different classes of patterns either regular or irregular.

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