Contours Extraction Using Line Detection and Zernike Moment

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Abstract

Most of the contour detection methods suffers from some drawbacks such as noise, occlusion of objects, shifting, scaling and rotation of objects in image which they suppress the recognition accuracy. To solve the problem, this paper utilizes Zernike Moment (ZM) and Pseudo Zernike Moment (PZM) to extract object contour features in all situations such as rotation, scaling and shifting of object inside the image. The proposed method consist of three steps: first step employs Line Detection with Contours (LDC) in order to find the object region based on the connected components objects inside the image. In the second step, PZM is applied on the detected object regions to extract feature vector. Regarding to investigate the effectiveness of classifier at the final stage, the SVM and KNN classifiers are employed to extract final object contours. Experimental results on Caltech-101 dataset shows that classification rate is improved to 96.46%. In comparison to the former contour detectors, that proves the ability of the proposed method to detect object boundary in the most of the contour's changes such as rotation or scaling.

Keywords: Contour detection, Line Detection with Contours (LDC), Straight line detection, Zernike Moment (ZM), Feature extraction.

1. Introduction

Recognition of object boundaries is the task of object localization in an image or video frames and it has been applied on wide range of problems such as visual object tracking [1], image and video segmentation [2], biomedical engineering [3-4] and content-based image and video retrieval[5]. Typically, object recognition can be performed according to the whole geometric structure of image tokens and texture which can be considered as the shape of object. Shape-based object recognition is not only appropriate solution, but also an important problem by itself because it causes to perceive the geometric arrangement of objects in the image. Note that learning of geometric structure of object in the image can be considered as a contour of an object which shows the rapid changes in several characteristics of object inside the image such as geometry, illumination. Contour is one of the best cues which is independent of lighting conditions and variations in object color and texture. Furthermore, contour is able to efficiently match along the smoothly variations of object pose, scale and boundary, and so, contour-based recognition can be done effectively. In contour detection problem, extraction of object's contour in images is relatively

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improved like the robust contour detection methods [35-36].

A typical automatic contour-based object recognition system includes following steps [6]: edge detection, contour grouping and contour detection. The first step focuses on finding the rapid changes in some typical features including geometry, illumination, and reflectivity. The second step groups edge pixels to contour parts based on edge continuation[6].Also in this stage, some irrelevant features are removed. The last step is contour detection which aims to compare the generated contour parts with the contour segments stored in a database and finally, the matched contour parts is considered as the contour of particular object. The three steps of contour recognition system are illustrated in Fig. 1.

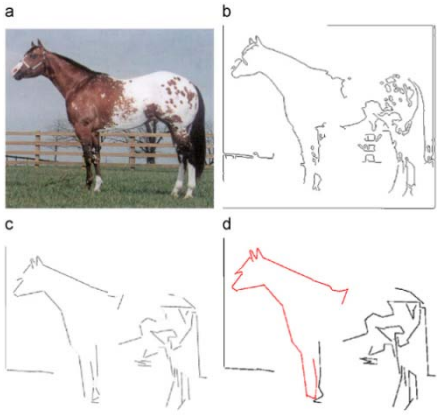

Fig. 1. (a) The original input image; (b) the edge map; (c) edge pixels group to line segments; (d) the most significant contour segment obtained by shape-based contour detection is marked in red (captured from [7]).

Along the mentioned advantages of contour recognition, it suffers from some drawbacks such as noisy boundary and background clutter. However object contour is robust to these drawbacks, but they cause poor generalization ability and so, several exemplars in hierarchical arrangement are required for recognition of deformable objects [37]. The second challenge of contour detection problem is detection of the pixels which are located around the meaningful objects and forms their contours due the small subset of pixels correspond to the object contour and appearing of the most edge pixels in the background and irrelevant texture.

Active contour is an object boundary detection tool which is utilized in many object recognition techniques [8-15]. The boundary detection approaches have employed a deformable model to minimize the total of internal and external energies of model to find the object boundaries. In the internal energy, a penalty is applied on the location of incline and curvature of object boundary. In the external energy, the deformable model leads to the object boundary [16].Grouping edge pixels into contours is a salient way to find object contour and is still an open research field. For the first time, contour was utilized to recognize particular objects, matched as complete, rigid templates [38], but later for articulated objects e.g. people in [39], [40], [41], and hands in [42].In [17], the chamfer distance [18] is utilized to match fragments of contours trained from edge images. The main contribution of these methods is matching of whole contours and so, a large set of patterns is needed to find all joint object configurations. In [43], a new contour-based detection of articulated objects is proposed in which contour fragments are arranged in layered pictorial structures for detection. The main limitation of this work is preparing of tracked video sequences or manually labeled parts for training which is may be impossible for all different objects in all scenes. In [19], a network of straight lines as the contour fragments beside a sliding window search is proposed. One of the main challenges of this work is the size of sliding window in which small window searches locally and so, obtains the best recognition rates in high computational time, while the poor recognition rate with high computation speed is achieved in the case of large sliding window. In [20], an approximate solution to the hard combinatorial problem by using a voting scheme is presented where the authors introduced a relaxed context selection scheme using linear programming with shape context as the shape descriptor. To detect the contour of non-rigid object, a skeleton-based model decomposition scheme is presented [21]. Also, there are some studies that employ geometric constraints for model-based object and shape matching [22]. In [44], an object

detection method is proposed which is based on grouping the edge fragments in an image according to a contour model. This model consists of two main stages: generating object hypotheses by matching the contours composed of fragments in the part bundles to that of the edge fragments in a given image; and pick the best part-configuration by comparing of similarity between the part-configurations and the model contour. The main challenge of this work is construction of part bundles which should be cover almost all objects for recognition while it may be impossible to recognize varied object categories at multiple scales using the limited number of parts. In the other hand, collecting a large set part bundles increases the space complexity of the algorithm.

One of the best approach for object boundary detection is finding the connected components inside the input image. Connected components are the regions of objects in an image and so, can relieve the task of object boundary detection. It is important that finding the connected components is a challenge. To solve this problem, new method of Line Detection with Contours (LDC)[23] is employed to achieve the connected components of detected edges. As the mentioned before, the third step of object boundary detection is performed using the pattern recognition (matching) techniques which should be trained on the different patterns of object boundary. One of the best solutions to train the pattern recognition approach is utilization of feature vector elements extracted from the object region. Since the detection rate of pattern recognition approach highly depends on the extracted feature vector, a novel feature extractor is required for an object boundary detection system.

In order to introduce a robust object boundary detection system, this paper focuses on the combination of two first steps of edge detection and contour grouping and also improving of the last step of contour detection. To combine the two first steps, utilization of LDC is proposed to find the exact area of object. To improve the last step, a new method of geometric moment as the feature extractor is considered to extract feature vector from object regions of input image. The proposed feature extractors for object contour detection are ZM and PZM.

The rest of the paper is organized as follows. The LDC model is described in Section 2. The geometric moment, ZM and PZM, is introduced in Section 3. The proposed method is analyzed in Section 4. Evaluation of the proposed method will be presented in Section 5 and the paper is concluded in Section 6.

2. Line Detection with Contours (LDC)

LDC [24] is an algorithm to extract straight line segments from color image. It means that LDC is based on the process of line segments detection and extraction. The main procedure of LDC consists of six steps as follows: automatic normalization, Gaussian smooth, Laplacian-based edge detection to extract edge contour, thresholding, contour extraction and contour segmentation. The first six steps are common image processing functions. After the extraction of edge contours, contours of each connected component are segmented to the short regions, which are grouped by their direction into nine discrete categories (east, west, and north, south, northeast, northwest, southeast and southwest). If the same direction is repeated at least three times, then consecutive short segments show the straight lines.

Some advantages of LDC are reasonable detection rate, speed and the capability of dividing an edge into straight line segments using the actual morphology of objects [24]. In comparison to Hough Transform (HT)-based boundary detection approaches, LDC is more accurate and faster with fewer parameter setting. Also, LDC is invariance of rotation, scaling and transformation of object in the test images while HT is sensitive to above image transformations.

3. Geometric Moment

3.1. Zernike Moment (ZM)

Zernike Moment (ZM) is a statistical-based feature extraction method that efficiently extracts feature vector based on the global information in an input image. In ZM, a set of orthogonal moments is defined which are shift, rotation, and scale invariants. In pattern recognition problem, the learning method uses the invariant properties as pattern sensitive features for boundary detection [25]. ZM is based on the complex orthogonal polynomials computed as [25]

$$V_{nm}(x,y) = R_{nm}(x,y)\exp(\ jm\tan^{-1}(\frac{y}{x})) \qquad (1)$$

Where the polynomials are defined in unit circle $\left(x^2+y^2\le 1\right)$, n is order of ZM ($n\ge 0$) and m is repetition of ZM ($|m|<n$) . Radial polynomials ($R_{n,m}$) are defined as

$$R_{nm}(x,y) = \sum_{s=0}^{(n-|m|)/2} S_{n,|m|,s}(x^2+y^2)^{\frac{n-2s}{2}} \qquad (2)$$

Where

$$S_{n,|m|,s} = (-1)^S \frac{(n-s)!}{s!(\frac{n+|m|}{2}-s)!(\frac{n-|m|}{2}-s)!} \qquad (3)$$

The mapping function used in ZM is done using (2) which maps the input image into a unit circle via the transformation of Cartesian coordinates to the polar coordinates. The ZM of order n and repetition m for a grayscale image $f(x,y)$ is formulated as

$$ZM_{nm} = \frac{n+1}{\pi}\sum_x\sum_y f(x,y)V^*_{nm}(x,y) \qquad (4)$$

Where $V^*_{n,m}(x,y) = V_{n,m}(n,m)$ and ZM is computed for positive values of m. According to (4), total number of ZM for order n is equal to $\left((n+1)(n+2)\right)/2$.

3.2. Pseudo Zernike Moment (PZM)

PZM is similar to ZM except the repetition of moments (m). In the other word, term of $(n-|m|)$ in ZM should be even while in PZM, this constraint is not defined. Thus for a custom order n, number of moments in PZM is twice the number of moments in ZM. So, all equations of PZM are the same as ZM except the (2) and (3) which are changed as follows:

$$R_{nm}(x,y) = \sum_{s=0}^{(n-|m|)} S_{n,|m|,s}(x^2+y^2)^{\frac{n-s}{2}} \qquad (5)$$

$$S_{n,|m|,s} = (-1)^S \frac{(2n+1-s)!}{s!(n+|m|-s)!(n-|m|-s+1)!} \qquad (6)$$

As the same as ZM, Eq. (5) maps the input image into the unit circle in PZM.

The feature vector extracted from each input image is defined according to PZM (ZM) orders as follows:

$$FV_j = \left\{PZM_{km} \middle| k = j, j+1, \ldots, N\right\} \qquad (7)$$

where j is determined from interval [1,N−1] and so, FV_j contains all the PZM from order j to N. In Table 1, elements of feature vector are reported for j = 4, 5 and 9, and N = 10. According to Table 1, increasing of j decreases the number of elements in each feature vector (FV_j). The selection strategy of order and repetition in PZM (ZM) is performed according to [25].

4. Proposed Method (LDC-PZM)

Contrary to the previous boundary detection methods, the proposed method combines the two first stages of contour detection process by using the LDC and also the stage of feature extraction based on ZM and PZM is added to the system. As shown in Fig.2 the proposed method consists following steps: 1) object localization; 2) feature extraction; and 3) contour extraction. In the first step, the object is

localized inside the image using LDC function in which LDC tries to detect straight lines as the object contour and so, the region of all objects inside the image is found. The second step is feature extraction inside the previously localized region of object using ZM and PZM approaches. The last step of the proposed method is training and testing of pattern recognition method according to the previously extracted feature vector.

Table 1

Selecting strategy of order and repetition in PZM [25].

***j* value**	**FV_j feature elements (PZM_{km})**		**Number of feature element**
	K	**M**	
4	4	0,1,2,3,4	56
	5	0,1,2,3,4,5	
	6	0,1,2,3,4,5,6	
	7	0,1,2,3,4,5,6,7	
	8	0,1,2,3,4,5,6,7,8	
	9	0,1,2,3,4,5,6,7,8,9	
	10	0,1,2,3,4,5,6,7,8,9,10	
6	6	0,1,2,3,4,5,6	45
	7	0,1,2,3,4,5,6,7	
	8	0,1,2,3,4,5,6,7,8	
	9	0,1,2,3,4,5,6,7,8,9	
	10	0,1,2,3,4,5,6,7,8,9,10	
9	9	0,1,2,3,4,5,6,7,8,9	21
	10	0,1,2,3,4,5,6,7,8,9,10	

For instance, suppose a typical image with just a single object of "apple" inside it. To recognize the object of "apple" in the proposed system, at first, the input image is processed under the LDC function find the region of object. In the second step, the feature vector of object's region is extracted using ZM or PZM and finally, the feature vector with label of object are transferred to the learning part for training and testing of pattern recognition method.

One of the main advantages of the proposed method is independency of LDC approach to image transformations and therefore, object region is obtained even in the case of rotation or scaling of object. Also, almost feature extractors on image depend on the contour geometry and so, rotation or scaling of contour inside the image significantly decreases the accuracy of the leaning method. While on the contrary, PZM (ZM) is able to extract feature vector even in the case of rotation or scaling of contour. Since training of a pattern recognition (learning) method depends on the feature vector, extraction of informative feature vector like ZM and PZM surprisingly enhances the both of accuracy of object recognition and computation speed of leaning method. In the proposed method, two learning methods are applied on the ZM- and PZM-based feature vector for contour-based object recognition. The used learning methods are Support Vector Machine (SVM) and *k*-Nearest Neighbor (*k*-NN) which are described in details as follows.

SVM is a supervised learning method that is used for classification and regression tasks. SVM aims to construct a hyper plane with maximum margin in high-dimensional space to classify data samples. The best results of SVM are obtained when the hyper plane has the largest distance to the nearest data points from any class. If the data points are not linearly separable, the data pints are transformed to the higher-dimensional space using kernel function. In this paper, linear SVM (SVM with linear kernel) is employed for contour detection.

K-NN is a non-parametric method, which is applied on the classification and regression problems. In *k*-NN, parameter *k* is a positive number and refers to the number of neatest neighbor. In classification problem, *k*-NN classifies a data point according to majority vote of its neighbors in which the data point is classified to the most common class among its *k* nearest neighbors. In the regression problem, output of *k*-NN is a value which is averaged on the values of data point's *k* nearest neighbors.

The pseudo code of the proposed method for the task of contour-based object recognition is presented in Algorithm 1. According to Algorithm 1, the first step is creation of Zernike Basis Function (ZBF) where a sequence of polynomials orthogonal on the unit disk is constructed. Note that the polynomials orthogonal are independent of image and generated once but several times used. So, the time complexity of object recognition process is decreased. Since the proposed method is evaluated using *t*-fold cross validation, the second step of the proposed method is determining of training, validation and testing sets. Next the LDC function is applied on the input image to extract straight lines as the contour of object. After that, the produced polynomials orthogonal set (or ZBF) is employed in order to extract feature vector of object region surrounded by the detected contour. The next step is setting and training of classifier, SVM or *k*-NN (determined by the user), according to the PZM-based feature vector created in the previous step. To validate the trained classifier, the validation set of image is used to extract object contour and its label. At the final stage of training, the training error of contour detection on validation set is calculated. The final four steps of training are repeated for *t* times.

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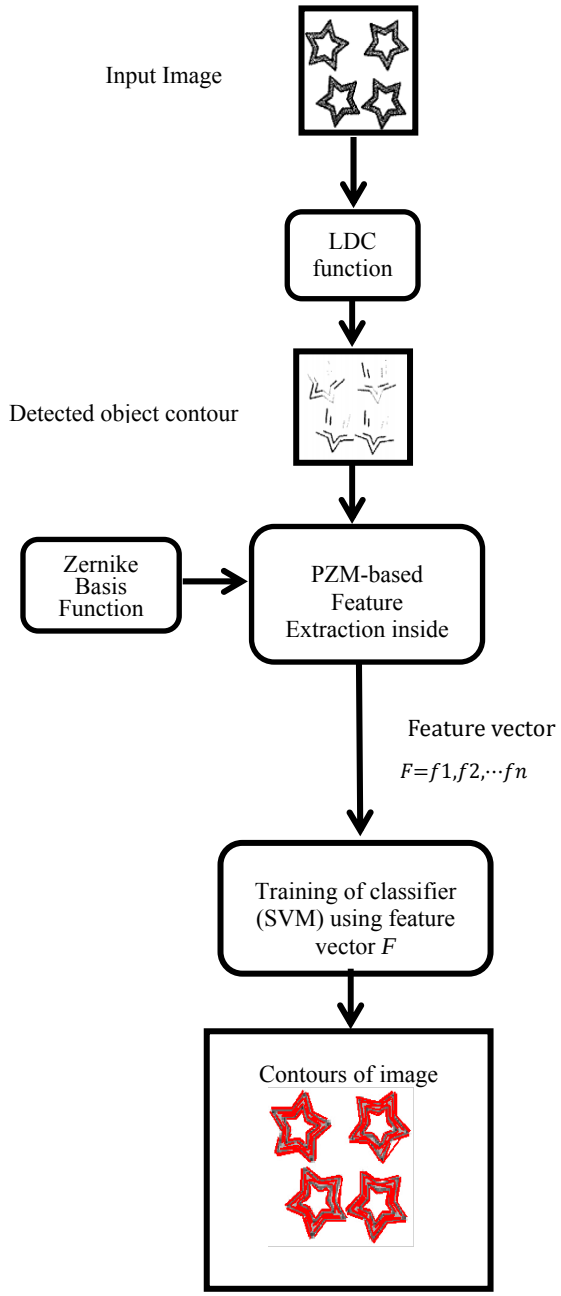

Fig. 2. Diagram of proposed method

After the training and validation of classifier, it will be tested on the test images in which LDC is applied on the j^{th} test image to extract straight lines as the contour of object. Next, the first action is feature extraction from detected contours. After that, the generated feature vector is used to extract all object contours from j^{th} test image. The stages are repeated for all test images. Finally, classification error rate will be computed.

5. Experimental Results

The goal of this paper is introduction of a new method for contour-based object recognition based on the LDC and PZM (ZM) functions. In this section, the proposed method is evaluated on Caltech-101 dataset [26] which contains 712RGBimages. Typical samples of the dataset are demonstrated in Fig. 3. It is important that the used test images are taken in different illumination conditions and on different scales. Note that the proposed method is programmed in the framework of Matlab R2010a and tested on a SONY VAIO laptop equipped with a 1.8 GHz Intel Xeon Processor with a 512 K L2 Cache.

Fig. 3. Typical examples of used dataset

As the mentioned before, effect of the combined LDC and PZM (ZM) methods as a contour detection system on two different classifiers, SVM and *k*-NN, is analyzed. In this regard, accuracyof each classifier is considered as the performance measure.To evaluate the proposed method, the dataset is divided into main parts: training and testing. In the experimental results, size of training set is 70% and the remained set of images is used for the testing phase.

Table 2 compares the results of ZM and PZM with two feature extractors of Scale-Invariant Feature Transform (SIFT)[27] and Speeded Up Robust Features (SURF) [28] on the task of contour detection. In this table, results of each feature extractor on the mentioned classifiers are reported.

Algorithm 1. Pseudo code of the proposed method for age estimation.

Input: image dataset

Outputs: recognition rate and class label of recognized object.

1. Construction of ZBF.
2. Dividing images dataset into training, validation and testing sets.
3. **For** *i*=1 to no. of cross validation
4. Object contour recognition using LDC.
5. Feature extraction on the detected contours using ZM based on ZBF.
6. Training of classifier according to the extracted feature vector.
7. Validation of trained classifier using the i^{th} validation set.
8. **End For**
9. **For***j*=1 to no. of testing image
10. Object contour recognition on test images using LDC.
11. Feature extraction from the detected contours of j^{th} testing image based on the ZBF.
12. Test the trained classifier using the extracted feature vector of previous step.
13. **End For**
14. Calculation of correct estimation rate.

Table 2

Comparison of ZM, SIFT and SURF on accuracy and CPU time measures

Measure	Feature extractor							
	SIFT		SURF		ZM		PZM	
	SVM	*k*-NN	SVM	*k*-NN	SVM	*k*-NN	SVM	*k*-NN
Accuracy (%)	82.99	79.88	83.71	80.62	87.62	83.41	**92.08**	87.22
CPU(S)	14	12	11	10	5	**4**	9	7

According to Table 2, all methods are evaluated on the two measures of accuracy and CPU time. Note that the proposed method is test on a SONY VAIO laptop equipped with a 1.8 GHz Intel Xeon Processor with a 512 K L2 Cache. The proposed PZM feature extractor with SVM classifier takes the first rank in accuracy measures. The second rank on accuracy measure is achieved using the ZM-based feature extractor. On the CPU time measure, the proposed ZM feature extractor is ranked as the first object contour detector and the second rank is obtained by the PZM-based feature extractor. It proves that the proposed methods, ZM and PZM, are able to detect near optimal object contour in the reduced CPU time. The reasons of this success refer to the both of LDC and PZM (or ZM) approaches. Since LDC is independent of rotation and scaling, it is able to discover straight lines in almost all forms of object contour and so, the exact (or near exact) contour of an object will be extracted. Furthermore, extraction of informative feature vector using the PZM (or ZM) method from the previously detected object region can surprisingly decrease the accuracy measure. Also, the proposed method ZM shows the minimum CPU time in Table 1 because of two reasons: 1) minimum time complexity of LDC; 2) the ZM method employs ZBF functions which are initially constructed at once and used several times. To compare the results of SVM and *k*-NN in the proposed method, the best results are obtained using the SVM and this priority is repeated in the other methods. According to Table 1, the third and last ranks achieved using the SURF and SIFT, respectively. The poor performance of both of SIFT and SURF methods is their dependency to the geometry of object contour. Fig. 4 presents visual results of the proposed PZM feature extractor on the task of object contour detection.

Fig. 4. Visual results of the proposed method on the task of boundary detection. The results are obtained using the PZM feature extractor and SVM classifier. The first row is input image, the second row shows the results of object boundary detection on the input image and the last row presents just the object boundaries.

In Table 3, the results of the proposed methods, ZM and PZM, on different sizes of training set are compared with the other contour detection methods. The different sizes of training dataset are 50%, 60%, 70% and 80%. According to Table 3, the best results of contour detection are achieved by the PZM method because of independency of scaling, shifting and rotation of object in image. The reason of poor performance of the other methods is their dependency to scaling, shifting and rotation of object in image.

Table 3

Comparison of the proposed method with the other contour detection methods on Caltech-101 dataset [26]

Contour detection methods	Training Set Size			
	50%	60%	70%	80%
Ferrari et al. [29]	40.71%	44.78%	50.17%	53.82%
Bioman et al. [30]	60.17%	63.81%	65.78%	70.81%
Zhang et al. [31]	61.55%	65.22%	68.91%	72.11%
Griffin et al. [32]	57.71%	61.91%	66.81%	71.23%
Wang et al. [33]	64.82%	65.14%	70.77%	74.33%
MST+MTP [34]	70.66%	75.01%	79.32%	84.39%
MST+MTP+SIFT [34]	74.52%	78.61%	84.21%	89.72%
Proposed method (Zernike Moment)	75.89%	81.60%	87.62%	90.52%
Proposed method (Pseudo Zernike Moment)	79.18%	84.33%	92.08%	96.46%

6. Conclusion

This paper proposed a new object contour detection which is employed the LDC, as contour detection step, and Zernike Moment (ZM) and Pseudo Zernike Moment (PZM) as the feature extractors of the system. Both of the LDC and PZM (or ZM) methods are invariance of rotation and scaling of contour inside image.LDC is a new method of straight line detection which is used as the boundary detection step. Also, both of PZM and ZM are based on a set of orthogonal moments. In the proposed method, the extracted feature elements of each object region are transformed to the SVM or *k*-NN classifier for the contour detection task. The proposed method is tested on Caltech-101 dataset. Experimental results of the proposed method on Caltech-101 dataset demonstrate that it is able to improve the contour detection rate 96.46% in reduced time complexity

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