An Efficient Representation of Shape for Object Recognition and Classification using Circular Shift Method

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Abstract— Object recognition/classification is a hugely researched domain in the areas of computer vision & image processing. The most valuable feature for object recognition is its shape, which is defined for 2D space. In which, a circular shift algorithm is used for finding the exact shape of the object. Finding an appropriate set of features is an essential problem in the design of object recognition system. Before going to recognize the object, first find the shape of the object then a K-nearest neighbor classifier is used for classification. The experimental result shows that the method for classification gives impressive results of above 96% when it was tested on Flavia dataset that contains 32 kinds of plant leaves. It means that the method gives better performance compared to the original work.

Index Terms- Computer vision, object recognition and classification, shape, color, texture, K-NN classifier.

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1 INTRODUCTION

Object recognition plays a crucial role in Computer Vision applications, specifically in the semantic description of visual content whereas it is a simple task for a human observer [1], [2]. Object recognition is the task of identifying and labeling the parts of a two-dimensional (2D) image of a scene that correspond to objects in the scene [3]. It is challenging to recognize an object from visual information. Objects are very often distinguishable on the basis of their visible features, among these features; an object's shape is frequently an important key to its recognition. The representation of shape is thoroughly discussed in Refs. [4, 5] and in both, sets of criteria for the evaluation of shape are proposed. Effectively representing shape, however, still remains one of the biggest hurdles to overcome in the field of automated recognition.

Object recognition is tricky because a combination of factors must be considered to identify objects. These factors may include limitations on allowable shapes, the semantics of the scene context, and the information present in the image itself [6].Objects are likely appear at different locations in the image and they can be deformed, rotated, rescaled, differently illuminated or also occluded with respect to a reference view [7]. For effective visual object recognition, a large number of views of each object are required due to viewpoint changes and it is also necessary to recognize a large number of objects, even for relatively simple tasks [8]. Constructing appropriate object models is vital to object recognition, which is a fundamental difficulty in computer vision. Desirable characteristics of a model include good representation of objects, fast and efficient learning algorithms with minimum supervised information [9]. The most common object recognition approaches can be classified into appearance-based [10, 11, 12, 13], model-based [14, 15] and approaches based on local features [16, 17]. Many practical object recognition systems are appearance-based or model-based. To be successful they address two major interrelated problems: Object representation and object matching. The representation should be good enough to allow for reliable and efficient matching [18].

In this paper, we have investigated two vital research techniques available in the literature for the recognition of objects in digital images. The object recognition approaches based on the image processing and pattern recognition techniques: circular shift algorithm and k-Nearest Neighbors (k-NN) are chosen for investigation. The techniques elected for investigation are programmed in Mat lab and the investigation is performed with the aid of the Flavia dataset, which contains gray scale images of 20 objects; for each object 72 views are gathered, with a separation of 5o. Initially, four distinct datasets are formed from the original dataset for investigation. The formed datasets are of size 6, 12, 24 and 36 respectively, each with different views of objects for training. Afterwards, the programmed techniques are trained with the formed datasets. The results of the investigation are presented in the experimental results section.

The remainder is organized as follows: Section 1 discusses the related studies; Section 2 describes the notations of the proposed system. Section 3 describes the proposed system. Section 4 explains the geometric shape features for object recognition system. Section 5 for experimental results and finally section 6 concludes the results.

2 General Description of the Approach

In this paper a method is described which consists of three algorithms are integrally linked aspects. The first is right shift the image, second is circular shift image and the third is diagonal shift image. The present paper proposes a new method for exact shape of the object based on edges using circular shifting operations based on the right, circular and diagonal shift operations. up and bottom. The following notations are used for detection of shape using edges based on circular shifting.

1. RS   Row shift
2. CLS   Circular Left Shift
3. CRS   Circular Right Shift
4. CS   Column Shift
5. CTS   Circular Top Shift
6. CBS   Circular Bottom Shift
7. DS   Diagonal Shift

Using the above notations, the following algorithms are used for shifting different images.

Algorithm 1. Finding Right Shift Image

Step 1: Read the original image (I_1) of size m×n.
Step 2: Apply CLS operation on image I_1 produces I_2.
Step 3: Image differencing between I_1 and I_2 obtains left slope edge pixels I_3.
Step 4: Apply CRS operation on image I_1 produces I_4.
Step 5: Image differencing between I_1 and I_4 obtains right slope edge pixels I_5.
Step 6: Obtain right shift (RS) image I_6, i.e. $I_6 = I_3 + I_5$.

Algorithm 2. Finding Circular Shift Image

Step 1: Read the original image (I_1) of size m×n.
Step 2: Apply CTS operation on image I_1 produces I_2.
Step 3: Image differencing between I_1 and I_2 obtains top slope edge pixels I_3.
Step 4: Apply CBS operation on image I_1 produces I_4.
Step 5: Image differencing between I_1 and I_4 obtains bottom slope edge pixels I_5.
Step 6: Obtain circular shift (CS) image I_6, i.e. $I_6 = I_3 + I_5$.

Algorithm 3. Finding Diagonal Shift Image

Step 1: Read the original image (I_1) of size m×n.
Step 2: Apply CS operation on diagonal image I_1 produces I_2.
Step 3: Image differencing between I_1 and I_2 obtains diagonal edge (DS) pixels I_3.

3 Proposed Method for Object Shape Extraction

The most valuable feature for object recognition is its *shape*, which is defined for 2D space. The second most important feature is color which is a perception of the wavelength of light reflected from the surface of an object. Color is frequently the first characteristic used when looking for an object in the surrounding. This section presents in detail the proposed method of representing shapes in natural images based on color and shape features. The proposed method for extraction of object shape based on **Algorithms 1, 2 & 3** respectively are as shown in Fig.(1).
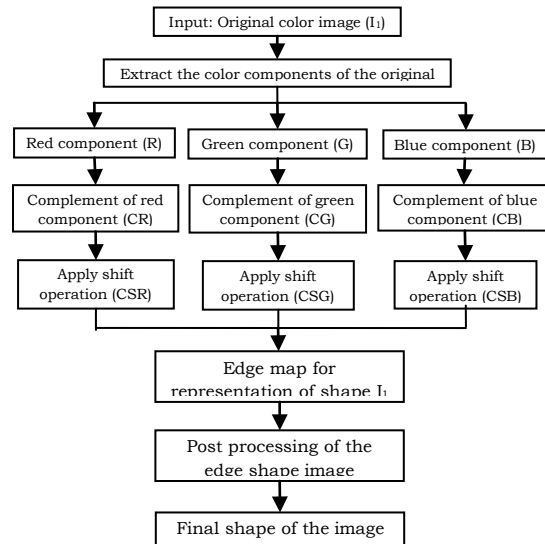

Fig.1. Flowchart for the proposed circular shift method for extraction of edge shape image.

The following steps represent the proposed method are as follows.
Step 1: Read the original image (I_1) of size m×n×p.
Step 2: Extract the individual color components (i.e. R, G, and B) of the image I_1.
Step 3: Obtain the real complement for individual components separately.
Step 4: Find RS image for individual real complement.
Step 5: Find CS image for individual real complement.
Step 6: Find DS image for individual real complement.
Step 7: For strong real connected edges for representation of shape, add the obtained results of Step 4, Step5 and Step 6.
Step 8: Post processing of the resultant edge image to get the final output of the shape image.
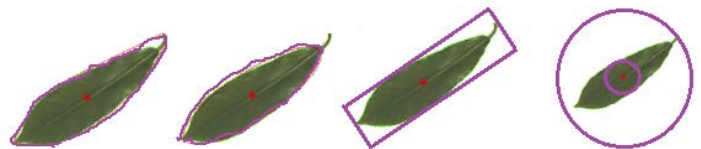
4 Geometric Features

The geometric features consist of Aspect ratio, Convexity, Sphericity, Solidity and Circularity. For object recognition system Figure 2 and Equations (1)-(5) represents the geometric shape descriptors .
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Fig .2. The Leaf ROI (a) convex hull, (b) ellipse, (c) MBR (d) Incircle and excircle.

During calculations of the shape descriptors, area of the object is defined as the net area not the filled area because the net area represents the shape better than the filled area.

1. Aspect ratio is the ratio between the maximum length L_{max} and the minimum length L_{min} of the '*Minimum Bounding Rectangle*' (MBR) around the leaf.

2. $f_1 = L_{max}/L_{min}$ Convexity is the relative amount that an image object differs from a convex object. Convexity is defined as the ratio between A_{roi} and the convex hull area (A_c): $f_2 = A_c/A_{roi}$

3. Sphericity is the ratio of the radius of the incircle of the ROI (r_i) and the radius of the excircle of the ROI (r_c). $f_3 = \frac{r_i}{r_c}$

4. Solidity measures the density of an object. A measure of solidity can be obtained as the ratio of the image object's area to the area of the object's convex hull. A value of 1 signifies a solid object, and a value less than 1 will signify an object having an irregular boundary, or containing holes (Wirth2005).

5. Circularity is defined based on the mean and variance of ROI: $f_5 = \mu_{roi}/\sigma_{roi}$

5 Experimental Results

To show the significance of the proposed novel method the present study have evaluated shape features on extracted shape image for object recognition and classification of images from Flavia dataset. The proposed method is tested on both standard and real world images are used to show the efficiency of the proposed method. The standard image dataset consists of Flavia dataset was introduced in [19] and contains 1907 images of leaves of 32 kinds of leaves with green color (50 to 77 images for each species). Each image contains exactly one leaflet: there is no compound or occluded leaves. All images have resolution 1600×1200 px. The dataset is publicly available at the following URL: http://flavia.sourceforge.net/. The following Fig.2 shows Flavia dataset of 32 leaves with original names.

To do classification, the images are randomly divided into non-overlapping windows of different sizes and the resulting windows are divided into two disjoint sets, one for training and one for testing. Each set contained leaves from 32 classes. Shape features are evaluated on each leaf of the Flavia dataset and the results are stored in the feature database. Similarity measurement between image of the query and the images in the database is done by measuring Euclidean distance metric. Euclidean distance is defines as in Equation (1)

$$d(Q,R) = \sum_{i=1}^{N}(Q_i - R_i)^2 \qquad (1)$$

Where d(Q,R) is distance between features in the query image Q and features in the reference image R. Meanwhile, N is number of shape features. From the Table 1, it is observed that the mean success rate for Flavia dataset 96.5%. It is found that the success rate is improved much by combining statistical and structural approaches.

6 CONCLUSIONS

The most valuable feature for object recognition is its shape and the second most important feature is color which is a perception of the wavelength of light reflected from the surface of an object. By considering the features of color and shape, a novel method for object recognition system is developed. Based on outline of the shape object, different shape features are used for object classification. The result gives 96.5% of accuracy, which is compared to better results than the original work. It gives the optimum accuracy of the object classification system.

TABLE 1: Mean percentage correct classification rate of Flavia Dataset

Object Image	% of correct classification rate	Object Image	% of correct classification rate
Pubescent bamboo	95	Chinese Toon	98.5
Chinese horse chestnut	94.75	Peach	97.5
Anhui Barberry	98.5	Goldenrain tree	96.6
Chinese redbud	97.5	Big-fruited Holly	97.5
True indigo	95.75	Japanese cheese wood	94.5
Japanese maple	94.6	Wintersweet	95.5
Nanmu	95.75	Camphor tree	95
Castor aralia	97	Japan Arrow wood	98.5
Chinese cinnamon	98	Sweet osmanthus	96.5
Deodar	99	Ford Wood lotus	97.5
Ginkgo	93.5	Trident maple	95.5
Crape myrtle	95.5	Beale's barberry	95.5
Oleander	98	Southern magnolia	98
Yew plum pine	95.5	Canadian poplar	95.5
Japanese Flowering Cherry	96	Chinese tulip tree	97
Glossy Privet	97	Tangerine	98.5

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Fig.2. Flavia Dataset: Pubescent bamboo, Chinese horse chestnut, Anhui Barberry, Chinese redbud, True indigo, Japanese maple, Nanmu, Castor aralia, Chinese cinnamon, Deodar, Ginkgo, Crape myrtle, Oleander, Yew plum pine, Japanese Flowering Cherry, Glossy Privet, Chinese Toon, Peach, Goldenrain tree, Big-fruited Holly, Japanese cheesewood, Wintersweet, Camphor tree, Japan Arrowwood, Sweet osmanthus, Ford Woodlotus, Trident maple, Beale's barberry, Southern magnolia, Canadian poplar, Chinese tulip tree, Tangerine.

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