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Object Classification Techniques using Tree Based Classifiers

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Abstract:- Object recognition is presently one of the most active research areas in computer vision, pattern recognition, artificial intelligence and human activity analysis. The area of object detection and classification, attention habitually focuses on changes in the location of anobject with respect to time, since appearance information can sensibly describe the object category. In this paper, feature set obtained from the Gray Level Co-Occurrence Matrices (GLCM), representing a different stage of statistical variations of object category. The experiments are carried out using Caltech 101 dataset, considering sevenobjects viz (airplanes, camera, chair, elephant, laptop, motorbike and bonsai tree) and the extracted GLCM feature set are modeled by tree based classifier like Naive Bayes Tree and Random Forest. In the experimental results, Random Forest classifier exhibits the accuracy and effectiveness of the proposed method with an overall accuracy rate of 89.62%, which outperforms the Naive Bayes classifier.

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1. Introduction

Object recognition and classification [1] are most significant and challenging tasks in various computer vision applications such as intelligent vision [2], vehicle monitoring [3] and autonomous robot navigation [4]. The detection and recognition of visual objects are mainly considered by computer visionresearcher and the problems are viewed in two aspects: the generic case categorization and the non generic categorization case. In such cases, the task recognizes theoccurrences of a shape region, color, area, or pattern. The object recognition is the major problem of learning visual based classifications [5,6] and ensuing by real commonness of individual categories. Mainly any vision task in knowledge depends on the ability to discriminate objects, scenes, and classifications. In this paper the problem of object recognition and classification is presented. The special emphasis is on the robustness and efficiency, as these are the key properties of every recognition system aiming to be used in real-world applications [7]. In this object recognition system, the work is attempted to achieve recognition of objects under supervised classifier that directly operates over low-level statistical and texture image features.

1.1 Outline of the work

This paper deals with object recognition and classification, which aims to discriminate object category from the visual images. The proposed method is evaluated using Caltech 101 dataset [8] considered objects such as airplanes, camera, chair, elephant, laptop, motorbike and bonsai tree. Thus, theGray Level Co-Occurrence Matrices (GLCM) arecomputed and chosen as a feature set. The extractedfeature set is fed to the tree based classifiers like Naive Bayes Tree (NB Tree) and Random Forest(RF).

The rest of the paper is structured as follows. Section 2reviews related work. Section 3 provides an overview of theproposed approach. Section 4 describes the proposed featureextraction method and experimental results evaluating itsperformance on Caltech 101 dataset are presented inSection 5. Finally, Section 6 concludes the paper.

2. Related Work

Object recognition and classification is an easy task which has to be repeatedly performed on the frequent number of image processing applications. Normally, in the visual object recognition system many assorted recognition tasks are carried out, including categorization and identification. In order to obtain accurate recognition results, various feature extraction techniques are implemented and evaluated.

Most of recent works has shown that local features invariant tocommon image transformations (e.g., GLCM [9], SIFT [10]) are a dominantrepresentation for object recognition, because the featurescan be dependably detected and corresponding across instances ofthe similar object or scene under diverse viewpoints, poses,or lighting conditions. Most approaches, conversely, performrecognition with statistical feature representations using tree based and nearestneighbor [11] classifiers followedby an association step, both may beunrealistic for large training sets, since their classificationtime’s increase with the number of training examples. In [12] presents an image based representation for scene matching problem using Caltech-101 and their representationadded the idea of flexible scene correspondence to the bag-of-visual-word representations that have been usedfor image classification [13,14].Maji et al. [15] explains that one can build histogram connection kernelSVMs much competently. However, the effectiveness comesonly for pre-trained nonlinear SVMs.In factual applicationswhich involves more than thousands of training examples,linear kernel SVMs are distant more privileged as theyenjoy both greatly faster training and testing speeds,with significantlyfewer memory requirements compared to nonlinear kernels. Whereas Weber et al. [16]

ISSN: 2454-4248
271 – 276

have presented hopeful results on identifying repeatedlythree categories in a partial image database, in order to attainhuman concert one would like to see tens of thousands ofcategories recognized automatically from probably millions of images [17]. Fei-Fei et al [18] proposed a Bayesian structure toutilize priors derived from earlier learned classes in orderto speed up learning of an original class.

3. Proposed Approach

The workflow of the proposed approach is shown inFig. 1. The imagesare converted from RGB to grayscale and smoothed by a Gaussian filter with akernel of size 3 × 3. It is essential to preprocessall the images to reduce noise for robust featureextraction and classification. The GLCM feature values like (*Contrast, Entropy, Sum Average, Sum Variance, Difference Variance and Difference Entropy*) are extracted from preprocessed images.The extracted features are fed tothe tree-based classifier for object recognition and classification. In this work,two tree-based classifiers such as, Naïve Bayes and Random Forest are used in order to evaluate theeffectiveness of these two classifiers on the Caltech 101 dataset.

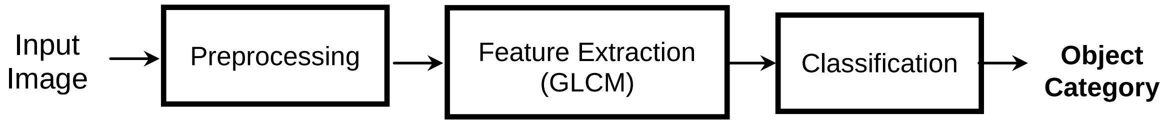

Fig. 1 Block diagram of the Proposed Approach

4.Feature Extraction

The extraction of discriminative feature is an essential problem inobject recognition, which represents the appearance information that is vital for further study. The ensuing sections present, the representation of the feature extraction method used in this work.

4.1GLCM for Object Classification

Texture analysis is a distinctive way of representing the essential characteristics of textures and represents them in simpler and distinctive form so that they can be used for robustand accurate recognition. A geometric technique of reviewing texture that deals with the spatial relationship of pixels is the gray level co-occurrence matrix. The approach and routine behind the Gray Level Co-occurrence Matrix (GLCM) method are presented in [9]. GLCM is obtained by calculating how often a pixel with grayscale intensity values *i* occurs adjacent to a pixel with the value *j*. Each element *(i, j)* in GLCM specifies the number of times that the pixel with the value *i* occurred adjacent to a pixel with value *j*. GLCM texture indicates the relationship between the reference and neighbor pixel of the gray level image at the various directions.

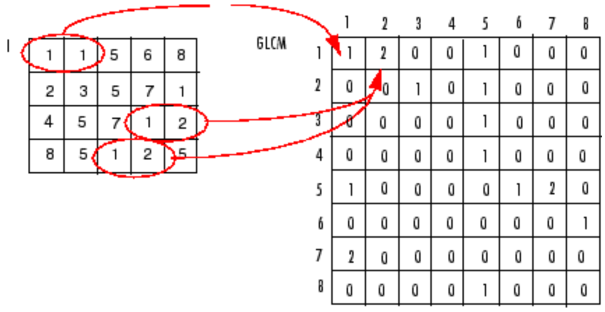

Fig. 2 GLCM Matrix for distance 1 and 0° direction.

The adjacency can be defined to take place in each of four directions 0°, 45°, 90° and 135° degrees in a two-dimensional pixel image (horizontal, vertical, left and right diagonal). GLCM matrix stores the instance occurrences between adjacent pixels. Element (1, 2) in the GLCM accommodates the value 2 because there are two occurrences of (1, 2) in the image as shown in Fig. 2. Given an Image I, of sizeN × N, the co-occurrence matrix *P* can be defined as

$$P(i,\, j) = \sum_{x=1}^{G}\sum_{y=1}^{G} \begin{cases} s1, \; if \;\; I(x,y) = i \; and \; I(x+\Delta_x, y+\Delta_y) = j; \\ 0, \qquad\qquad\qquad Otherwise \end{cases} \tag{1}$$

where the offset (Δx, Δy), specifies the ranges between the pixel of interest and its neighbor. *i, j* specifies intensity values of the image and *x, y* are the spatial location in the image *I*. In GLCM method, 7texture descriptors are used namely contrast, entropy, sum of square variance, sum of average, sum variance, difference variance and difference entropy. The texture descriptors are explained as follows:

Contrast:Measure of contrast or local intensity variation can support contributions from *p(i, j)* away from the diagonal, *i.e.* $i \neq j$

ISSN: 2454-4248
271 – 276

$$Contrast = \sum_{i,j=0}^{G-1} (i-j)^2 p(i,j) \qquad (2)$$

Entropy: This measures the randomness of the intensity distribution.

$$Entropy = \sum_{i,j=0}^{G-1} p(i,j)\ (\text{-}Inp(i,j)) \qquad (3)$$

Sum of Square Variance:

$$Variance = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} (i-\mu)^2\ p(i,j) \qquad (4)$$

Sum Average:

$$Sum\ Average = \sum_{i=0}^{2G-2} i\ P_{x+y}(i) \qquad (5)$$

Sum Variance:

$$Sum\ Variance = \sum_{i=0}^{2G-2} (i-aver)^2\ P_{x+y}(i) \qquad (6)$$

Difference Variance:

$$Difference\ Variance = \sum_{i=0}^{G-1} (i-aver)^2\ P_{x+y}(i) \qquad (7)$$

Difference Entropy:

$$Difference\ Entropy = \sum_{i=0}^{G-1} p_{x+y}(i)\log(p_{x+y}(i)) \qquad (8)$$

5. Experimental Results

In this section, the proposed approach is evaluated using a Caltech 101 dataset.It contains 101 objects categories of images. It consists of 40 to 800 images per category and the size of each image is roughly 300 x 200 pixels. The sample images fromthe Caltech 101 dataset isshown in Fig. 3. The experiments are carried out using MATLAB 2013aon a computer with Pentium i3 Processor 3.42 GHz with4GB RAM. The extracted GLCM features are fed to Naïve Bayes and Random Forest classifiersusing open source machine learning tool WEKA to develop themodels, and these models are used to test the performance of the classifier.

Fig. 3Sample images from the Caltech 101 dataset.

5.1 Quantitative Evaluation

The performanceof the proposed feature extraction method on Naïve Bayes and Random Forest classifiers is testedusing 5-fold cross-validation approach. The quantitative evaluation is done withstatistical metrics like Precision, Recall (Sensitivity), Specificity, F-measureand Accuracy, The classification accuracy can be evaluated by calculating thenumber of correctly recognized object class samples (true positives), the number ofcorrectly recognized samples that do not belong to the class (true

ISSN: 2454-4248
271 – 276

negatives),and samples that either were incorrectly assigned to the class (false positives)or that were not recognized as class samples (false negatives). Sensitivity orRecall(R) gives how good an activity is identified correctly. Specificity (S) givesa measure of how good a method is identifying negative activity correctly. Precision(P) is a measure of exactness and F-measure is the harmonic mean ofPrecision and Recall. Finally, Accuracy (A) shows the overall correctness ofthe activity recognition. The statistical measures of Precision, Sensitivity (Recall), Specificity, F-measure and Accuracy is defined as

$$\text{Precision (P)} = \frac{tp}{tp + fp} \tag{9}$$

$$\text{Recall (R)} = \frac{tp}{tp + fn} \tag{10}$$

$$\text{Specificity (S)} = \frac{tn}{tn + fp} \tag{11}$$

$$\text{F-measure} = 2\frac{P \times R}{P + R} \tag{12}$$

$$\text{Accuracy (A)} = \frac{tp + tn}{tn + fp + tp + fn} \tag{13}$$

5.2 Results obtained with Naive Bayes

The confusion matrix is also called as contingency table. The confusion matrices of the Naïve Bayes classifier on Caltech 101 dataset is shown in Table 1, where diagonal of the table shows that accurate responses of object category types. The average recognition rate of Naïve Bayes is 84.92%. In Naïve Bayes, the categories like camera, laptop and bonsai tree is almost classified well with more than 85%, where as in airplane, chair, elephant and bike classesare confused with other classes. Thus, it needs further attention.

Table 1: Confusion matrix for Naïve Bayes

Class	Airplane	Camera	Chair	Elephant	Laptop	Bike	Bonsai
Airplane	**78.34**	0	16.79	0	0	0	4.87
Camera	0	**90.76**	0	1.95	7.29	0	0
Chair	0	0	**81.45**	8.43	0	0	10.12
Elephant	0	0	0	**83.56**	8.69	0	7.75
Laptop	0	0	0	6.74	**87.37**	5.89	0
Bike	0	0	2.55	3.68	5.11	**83.43**	5.23
Bonsai	0	0	0	8.87	1.57	0	**89.56**

5.2 Results obtained with Random Forest

The confusion matricesof the Random forest classifier on Caltech 101 dataset is shown in Table 2, where diagonal of the table shows that accurate responses of object category types. The average recognition rate of Random Forest is 89.62%. In Random Forest, the categories like camera, chair, elephant, laptop, bike and bonsai are almost classified well and good with more than 85%, where as airplane class is confused with chair and bonsai classes respectively.

Table 2: Confusion matrix for Random Forest

Class	Airplane	Camera	Chair	Elephant	Laptop	Bike	Bonsai
Airplane	**80.2**	0	12.34	0	0	0	7.46
Camera	0	**94.56**	0	0	5.44	0	0
Chair	0	0	**86.69**	4.54	0	0	8.77
Elephant	0	0	0	**89.14**	4.52	0	6.34
Laptop	0	0	0	3.97	**93.28**	2.75	0
Bike	0	1.65	1.21	1.45	4.32	**89.24**	2.13
Bonsai	0	0	0	3.67	2.1	0	**94.23**

The quantitative evaluation results are tabulated in Table 3, which shows thatthe proposed approach has a higher precision, recall and F-measure for the Random Forest classifier on Caltech 101 dataset, when compared to Naïve Bayes classifiers.The overall accuracy of the proposed approach withtree based classifier on Caltech 101 dataset is shown in Fig. 4. Random forest classifier excelled inaccuracy,when compared to Naïve Bayes classification algorithm.

Table 3:Performance measure of the Caltech 101 dataset on Naïve Bayes and Random Forest

Classifier	Classes	Precision (%)	Recall (%)	Specificity (%)	F-measure (%)
Random Forest	**Airplane**	100	80.2	100	89.01
	Camera	98.29	94.56	99.73	96.39
	Chair	86.48	86.69	97.74	86.59
	Elephant	86.74	89.14	97.73	87.92
	Laptop	85.06	93.28	97.27	88.98
	Bike	97.01	89.24	99.54	92.96
	Bonsai	79.23	94.23	95.88	86.08
Naïve Bayes	**Airplane**	100	78.34	100	87.85
	Camera	100	90.76	100	95.16
	Chair	80.81	81.45	96.78	81.13
	Elephant	73.8	83.56	95.06	78.38
	Laptop	79.41	87.37	96.22	83.2
	Bike	93.41	83.43	99.02	88.14
	Bonsai	76.2	89.56	95.34	82.34

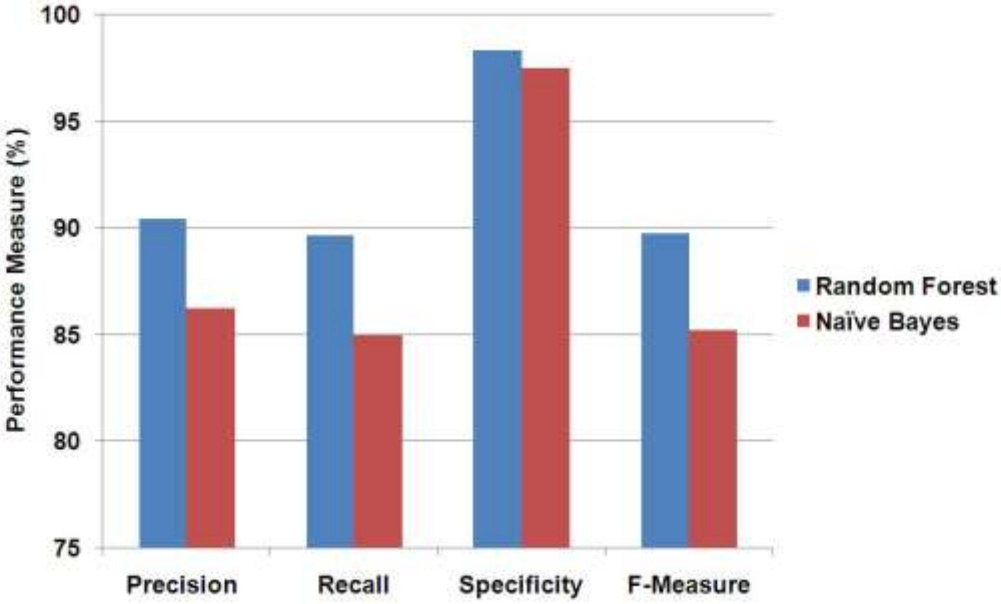

Fig. 4Performance measure of the Naïve Bayes and Random Forest classifiers

6. Conclusion and Future Work

This paper presents an efficient method of classifying object categories, using a Naïve Bayes and Random Forest. This paper presents a method called Gray Level Co-occurrence matrix (GLCM) statistical features is extracted from the Caltech 101 dataset, which signify the important texture features of object classes and gives very promising results in classifying object categories. From the experimental results, it is observed that Random Forest shows a classification accuracy of 89.62%,and demonstrated that the proposed feature method performs welland achieved good recognition results for object classification. It is observed from the experiments that the system could notdistinguish few object classes with high accuracy and is of future interest.

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