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Shape Classification with Statistical Classifiers using Morphological Shape Representation Features

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Abstract - This paper compares the performance of four statistical classifiers, namely linear discriminant classifier, quadratic discriminant classifier, k-Nearest Neighborhood classifier, and parzen classifier are considered for recognition of 2D-shapes. The two features from morphological skeletons and four features from morphological shape decomposition are identified from 2D-shapes. These features are reduced using Principle Component Analysis (PCA). These reduced features are used to recognize the shapes with the above four statistical classifiers. Experimental results show that the non-parametric classifier 3-NNC gives the good recognition rate 100% among other classifiers for the combined features of morphological octagonal disk and skeletons.

Keywords - Statistical classifiers, Morphological shape Decomposition, principle component analysis, Shape Recognition.

I. INTRODUCTION

Many decision-making problems fall into the general category of pattern classification. Classification is a classical problem in many fields of science and engineering. In practical applications the number of classes for classification is greater than two. This leads to the multi-class classification problem by combining the binary classifiers in various ways.

Template matching

One of the simplest and earliest approaches to pattern recognition is based on template matching. Matching is a generic operation in pattern recognition which is used to determine the similarity between two entities (Points, curves, or shapes) of the same type. In template matching, a template (typically, a 2D shape) or a prototype of the pattern to be recognized is available. The pattern to be recognized is matched against the stored template while taking into account all allowable translation and rotation and scale changes. The similarity measure may be optimized based on the available training set. Often, the template itself is learned from the training set. Template matching is computationally demanding, but the availability of faster processor has now made this approach more feasible. Digital skeletons can be used to represent objects in a binary digital image for shape analysis and classification [5-8]. They provide an intuitive, compact representation of a shape, which make them appealing for many computer vision applications. The Shape similarity based on skeleton matching usually performs better than contour or other shape descriptors in the presence of partial occlusion and articulation of parts [9-12]. The information about the object shape and its topology is totally embedded in them and this allows the comparison of different objects by graph matching algorithms [4].

Statistical Approach

In statistical approach, each pattern is represented in terms of d features or measurements and is viewed as a point in a d-dimensional space. The goal is to choose those features that allow pattern vectors belonging different categories to occupy compact and disjoint regions in a d-dimensional space (feature set) is determined by how well patterns from different classes can be separated. Given a set of training patterns from each class, the objective is to establish decision boundaries in the feature space which separate patterns belonging to different classes. In the statistical decision theoretic approach, the decision boundaries are determined by the probability distributions of the patterns belonging to each class, which must either be specified or learned [1, 2]. Hybrid features from the shape's skeleton and boundary [16] are used to match similar shapes. Morphological shape decomposition technique [13] is used to represent shape. Features from this technique [14] are used to classify shapes using quadratic classifier. This classifier gives good classification results with shape decomposition features. The rest of this paper is organized as follows, section-2 has the brief introduction of classification methods such as LDC, QDC, kNN and Parzen classifiers. Section-3 explains the Octagonal shape features from morphological decomposition technique. Section-4 describes the results and discussions and finally section-5 has a brief conclusion.

II. CLASSIFICATION METHODS

In this section, the specific classification methods used in the comparison will be discussed. The goal is to apply each of these methods to the same datasets and report the results.

Statistical Pattern Recognition

Statistical pattern recognition has been used effectively to design a number of commercial recognition systems. In this, a pattern is represented by a set of d features, or attributes, viewed as a d-dimensional feature vector. From the well-known concepts of statistical decision theory are utilized to establish decision boundaries between pattern classes. The statistical recognition system is operated in two modes, training (learning) and testing (classification) as shown in figure 1. The role of the preprocessing module is to segment the pattern of interest from the background, remove noise, normalize the pattern, and any other operations which will contribute in defining a compact representation of the pattern. In the feature reduction module, reduce the dimensions of the multivariate data to two- or three- dimensional projection to permit a visual examination of the data. On the other hand the classification will be faster and uses less memory. The principal component analysis (PCA) [3, 17] is used for feature reduction. In the training mode, the feature extraction module finds the appropriate features for representing the input patterns and the classifier is trained to partition the feature space. In the classification mode, the trained classifier assigns the input pattern to one of the pattern classes under consideration based on the measured features.

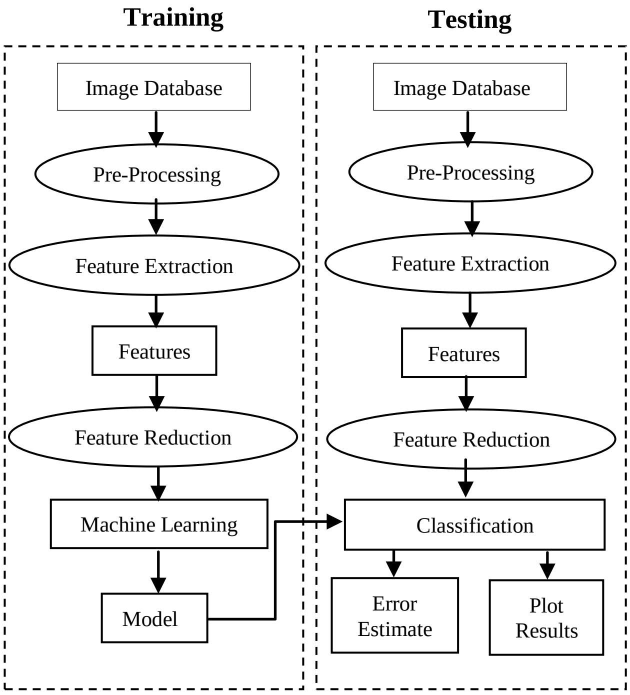

Fig 1. Model for pattern recognition system.

In the statistical pattern recognition, the decision making process can be summarized as follows: a given pattern is to be assigned to one of c categories $\omega_1, \omega_2, \ldots, \omega_c$ based on a vector of d feature values $x = (x_1, x_2, \ldots, x_d)$. The features are assumed to have a probability density or mass function conditioned on the pattern class. Thus, a pattern vector x belonging to class ω_i is viewed as an observation drawn randomly from the class-conditional probability function $p(x|\omega_i)$. A number of well-known decision rules, including the Bayes decision rule, the maximum likelihood rule, and the Neyman-Pearson rule are available to define the decision boundary. The optimal Bayes decision rule for minimizing the risk can be stated as follows: Assign input pattern x to class ω_i for which the conditional risk

$$R(\omega_i|x) = \sum_{j=1}^{c} L(\omega_i, \omega_j).P(\omega_j|x) \quad (1)$$

is minimum, where $L(\omega_i, \omega_j)$ is the loss incurred in deciding ω_i when the true class is ω_j and $P(\omega_j, x)$ is the posterior probability [3]. In the case of the 0/1 loss function, as defined in equation (2), the conditional risk becomes the conditional probability of misclassification.

$$L(\omega_i, \omega_j) = \begin{cases} 0, i = j \\ 1, i \neq j \end{cases} \quad (2)$$

For this choice of loss function, the Bayes decision rule can be simplified as follows (also called maximum a posteriori (MAP) rule): Assign input pattern x to class ω_i, if

$$P(\omega_i|x) > P(\omega_j|x) \; for \; all \; j \neq i \quad (3)$$

Various strategies are utilized to design a classifier in statistical pattern recognition, depending on the kind of information available about the class-conditional densities.

Linear Discriminant Classifier (LDC)

In a multiclass problem, a pattern x is assigned to the class for which the discriminant function is the largest. A linear discriminant function assumes that every class has equal priors $P(\omega_i)$ and each class's posterior density $p(x) \approx N(\mu_i, \sum)$, the discriminant function $g(x)$ is defined as [16].

$$g_i(x) = -\frac{1}{2}(x-\mu_i)^t \Sigma^{-1} 2(x-\mu_i) + lnP(\omega_i) \quad (4)$$
$$where \; i = 1, 2, \ldots, c$$

Each test sample is classified into the class with largest discriminant function values.

Qudratic Discriminant Classifier (QDC)

A Qudratic discriminant function assumes every class have equal priors $P(\omega_i)$ and each class's posterior density $p(x) \approx N(\mu_i, \sum_i)$, the discriminant function $g(x)$ is defined as [16].

$$g_i(x) = -\frac{1}{2}(x-\mu_i)^t\Sigma_i^{-1}(x-\mu_i) - \frac{1}{2}ln|\Sigma_i| + lnP(\omega_i) \quad \text{where } i = 1, 2, \dots, c \tag{5}$$

Each test sample is also classified into the class with largest discriminant function values.

Parzen Classifier

The Parzen windows classification is a technique for nonparametric density estimation used for classification. In this approach, for estimating densities fix the size and shape of region $\mathcal{R}$. Assume that the region $\mathcal{R}$ is a d-dimentional hypercube with side length h_n and its volume V_n. Then the following is the generalized equation [16] for estimating densities.

$$p_n(x) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{V_n}\varphi\left(\frac{x-x_i}{h_n}\right) \tag{6}$$

The Parzen windows classification algorithm does not require any training phase, hence test phase quite slow. Furthermore, although asymptotical convergence guarantees on the performance of Parzen windows classifiers exist no such guarantees exist for finite sample sizes.

k-Nearest Neighborhood Classifier (kNNC)

As a nonparametric classifier, kNNC is different from Parzen classifier. The kNNC directly estimates the posteriori density instead of estimating the class conditional density for each class. It classifies a point by assigning it the label most frequently occurring among the k nearest samples. In our experiments, we choose k as 3 for all different feature spaces.

It classifies x by assigning it the label most frequently represented among the k nearest samples.

kNN class density estimates

$$\hat{p}(x|\omega_j) = \frac{k_j}{n_j Vol(x)} \tag{7}$$

Priors

$$\hat{p}(\omega_j) = \frac{n_j}{n} \tag{8}$$

Decision rule

$$\frac{k_k}{n_k Vol(x)}\frac{n_k}{n} > \frac{k_j}{n_j Vol(x)}\frac{n_j}{n} \tag{9}$$

III. Features Combined from Shape Decomposition and Skeleton

Morphological shape decomposition technique is a shape representation technique in which the shape is decomposed of several shape components. In our previous work [13, 14] shape objects are decomposed of several octagonal disk components using this technique. The sample shape and it's first four maximal octagonal disk components are as shown in figure 2. The shape features are identified and classified from these shape octagonal disk components. The four shape octagonal disk features are listed as shown below.

1. N_t is the total number of octagonal disk components.
2. S^m is the maximum octagonal disk size.
3. N_d is the total number of unique octagonal disks.
4. N_r is the number of octagonal disks to reconstruct the original shape.

The above seven shape octagonal disk features are first reduced with PCA and are used to classify shape objects. The performance of these features is tested on four statistical classifiers two from parametric (LDC, QDC) and other two from non-parametric (kNNC, Parzen) classification techniques.

The two features from morphological skeletons [16] are

1. Skeleton junction points
2. Skeleton end points

The total six features are used to classify shape objects.

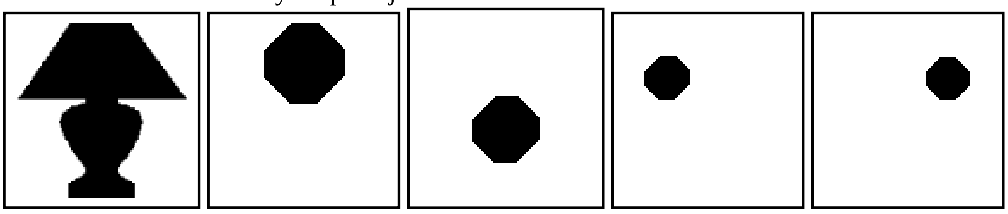

Fig. 2: Sample shape and its first four octagonal disk components.

IV. Results and Discussions

The shape models dataset consists of 21 objects and 128 views per object. Experiments are performed on 50 samples of complicated views from 128 samples of four classes of shapes as shown in figure 3.

Both parametric and non-parametric classification methods are tested to test these features. For our experiments, parametric classifiers LDC and QDC are used. For non-parametric, kNNC and Parzen are used. Here the mean and co-variances for each class are assumed to be unknown. The data is randomly divided into 70% training and 30% test. These classifiers have two phases training and testing. In the training phase the means and covariances are computed of the

training set. In the test phase, all the samples from the test data are passed to discriminant function of each class and are classified to the class that has maximum discriminant function value.
The assessment of the classifier is carried out using confusion matrix.

TABLE I: CONFUSION MATRIX OF LDC

True Labels	Estimated Labels: Alien	Dog	Dolphin	Eagle	Totals
Alien	**50**	0	0	0	50
Dog	0	**46**	4	0	50
Dolphin	0	3	**47**	0	50
Eagle	0	0	1	**49**	50
Totals	**50**	**49**	**52**	**49**	**200**

TABLE II: CONFUSION MATRIX FOR QDC

True Labels	Estimated Labels: Alien	Dog	Dolphin	Eagle	Totals
Alien	**50**	0	0	0	50
Dog	0	**50**	0	0	50
Dolphin	0	2	**48**	0	50
Eagle	0	0	0	**50**	50
Totals	**50**	**52**	**48**	**50**	**200**

From the above confusion matrix of LDC it is observed that, total 8 shape objects are misclassified. Four dog objects in the dog's are misclassified as dolphin objects in dolphin's class, three dolphin objects in dolphin's class are misclassified as dog objects in dog's class, and finally one eagle object from Eagle class is misclassified as dolphin object in Dolphin's class. The remaining shape objects are correctly classified and as shown in figure 4.

From the above confusion matrix of QDC it is observed that, only two shape object is misclassified. The two dolphins object from dolphin's class is misclassified as dog objects in dog's class. The other shape objects are correctly classified and as shown in figure 5.

TABLE III: CONFUSION MATRIX FOR PARZEN

True Labels	Estimated Labels: Alien	Dog	Dolphin	Eagle	Totals
Alien	**50**	0	0	0	50
Dog	0	**49**	1	0	50
Dolphin	0	1	**49**	0	50
Eagle	0	0	0	**50**	50
Totals	**50**	**50**	**50**	**50**	**200**

TABLE IV: CONFUSION MATRIX FOR KNNC

True Labels	Estimated Labels: Alien	Dog	Dolphin	Eagle	Totals
Alien	**50**	0	0	0	50
Dog	0	**50**	0	0	50
Dolphin	0	0	**50**	0	50
Eagle	0	0	0	**50**	50
Totals	**50**	**50**	**50**	**50**	**200**

From the above confusion matrix of Parzen it is observed that, total 2 shape objects are misclassified. One dolphin object from the dolphin's class are misclassified as dog objects in dog's class and one dog object from the dog's class are misclassified as dolphin objects in dolphin's class. The remaining shape objects are correctly classified and as shown in figure 6.

From the above confusion matrix of kNNC it is observed that, all shape objects are correctly classified and as shown in figure 7.

The classification parameters False Positive Rate (FPR), True Positive Rate (TPR), Error Rate (ER), and Efficiency are estimated using the confusion matrices. It is observed that the error rate is 0.5 for QDC and Parzen when compared to other classifiers LDC and 3-NNC. The efficiency is above 99% for QDC and Parzen which is shown in table V.

TABLE V: CLASSIFICATION PARAMETERS

Classifier	FPR/Sp	TPR/Sn	Error Rate	Efficiency
LDC	96.06	96	4	94.67
QDC	99.04	99	1	98.67
3-NNC	100	100	0	100
Parzen	99	99	1	98.67

V. CONCLUSION

The octagonal disk and skeleton features are tested on four statistical classifiers LDC, QDC, kNNC, and Parzen. From the experimental results it is observed that the combined features of octagonal disk and skeleton gives better classification results for both parametric and non-parametric classification approaches. In parametric classification QDC and in non-parametric classification Parzen gives good classification rate above 98%. The 3-NNC classifier gives 100% classification performance. From the results the combined features of octagonal disk and skeleton gives good shape classification.

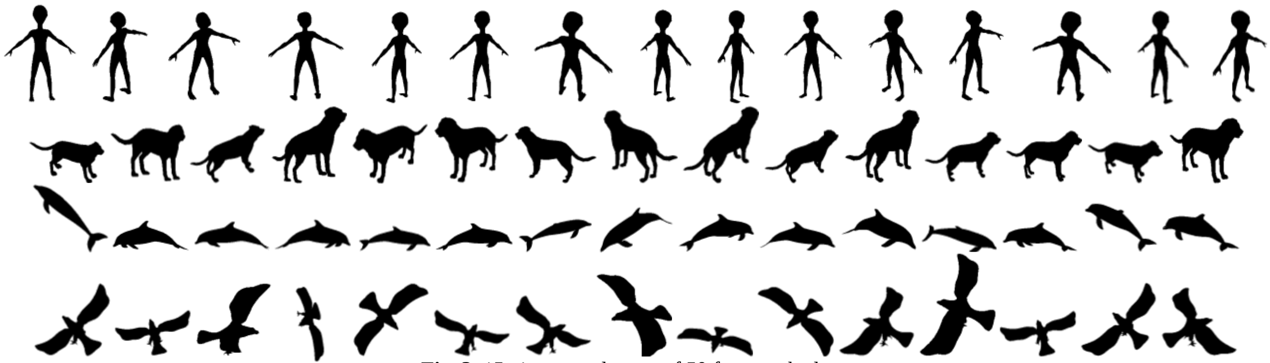

Fig. 3. 15 view samples out of 50 from each class

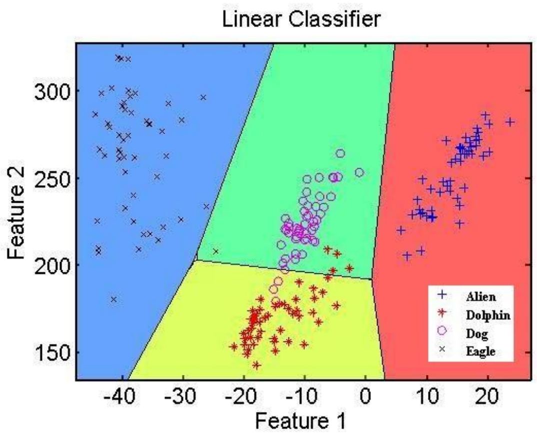

Fig. 4: Linear Disrcriminant Classifier

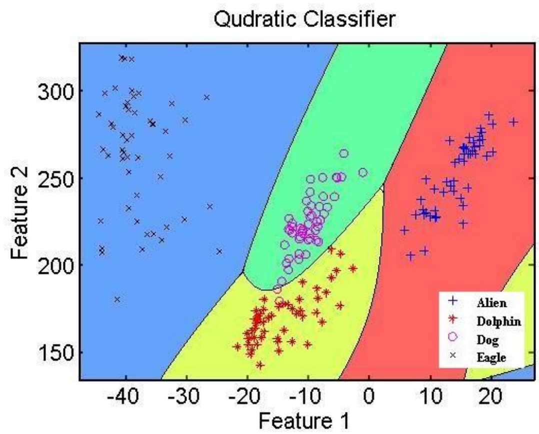

Fig. 5: Qudratic Discriminant Classifier

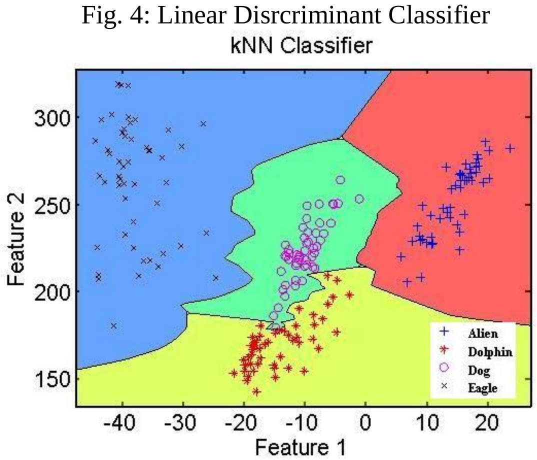

Fig. 6: k Nearest Neighbor Discriminant Classifier

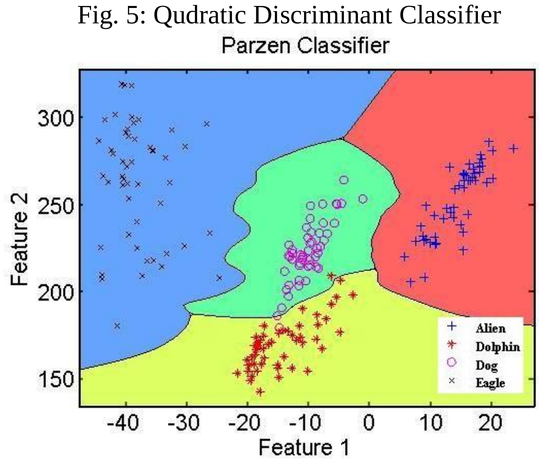

Fig. 7: Parzen Window Classifier

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