COMBINED NEAREST MEAN CLASSIFIERS FOR MULTIPLE FEATURE CLASSIFICATION

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ABSTRACT. Pattern classification is an important stage in many image processing applications. This paper proposes a technique that is based on nearest mean classifier for classification. The proposed technique integrates three classifiers and uses colour and shape features. Experiment on small training samples has been conducted to evaluate the performance of the proposed combined nearest mean classifiers and results obtained showed that the technique was able to provide good accuracy.

Keywords: classification, multiple classifier combination, nearest mean classifier, multiple features.

INTRODUCTION

Selection of appropriate classifier is important because it can significantly affect the success of classification process (Lu & Weng, 2007). There are many classifier that has been developed for classification such as artificial neural network (Zhang, 2000), support vector machine (Vapnik, 1998), decision tree classifier (Larose, 2005), Naïve Bayes (Csurka et al., 2004) and k nearest neighbour (Hardin, 1994). Individual classifier can achieve different degrees of success for a particular application problem, but none of them are perfect (Xu et al., 1992). Individual classifier has its strengths and weaknesses. Hence combining multiple classifiers is considered as a new direction for pattern classification. Combination of multiple classifiers may outperform all individual classifier by integrating the benefits of various classifier (Du et al., 2009). Effective use of multiple features can significantly affect the success of classification (Lu & Weng, 2007).

According to Woo and Mirisae (2009) the classification of objects based on colour alone is not sufficient to identify and distinguish the objects because different objects may have the same colour. Furthermore, different objects may have the same colour and shape thus the use of colour and shape are also not adequate to identify and distinguish the objects. Therefore, multiple features are required to improve the classification accuracy.

The nearest mean classifier (NMC) was introduced by Fukunaga (1990) as a classifier which provides good performance for small sample problem (Veenman & Tax, 2005). Small sample problems are problems with number of samples smaller than the number of features (Jain & Chandrasekaran, 1982). NMC uses the similarity between patterns to determine the classification. For each class, NMC computes the class means (or centroid) of the training patterns and classifies each test patterns (or unknown objects) to the class whose class mean is closest to this test pattern. This classifier has been successfully applied to many classification problems and has shown good performances and very robust (Huang et al., 2002; Shin & Kim, 2009).

For applications with large number of features the training sample size should be large enough (Raudys & Jain, 1991). However, small sample problems were often encountered in the pattern recognition problems (Huang et al., 2002). Although NMC can provide good performance for small samples but the use of single NMC for large number of multiple features will not give good results. Generally, the use of single classifier for a large number of features is not possible to give good results because of the curse of dimensionality (Du et al., 2009). The curse of dimensionality (also known as the effect of Hughes or Hughes phenomenon) is the problem caused by the exponential increase in volume associated with adding extra dimensions to a space. Classifier combination method allows high-dimensional vector to be split into several vectors with lower dimension, thus the classifier can process the feature vector with lower dimension simultaneously (Xu et al., 1992).

PROPOSED TECHNIQUE

Object recognition and classification in the image are usually based on several features which characterize the object in the image. Features are important attributes of objects and the most common used features are colour, shape, and texture. In this study only the colour feature and shape feature are used. The proposed multiple classifiers technique consists of three phases namely image preprocessing, feature extraction and classifier combination as depicted in Figure 1.

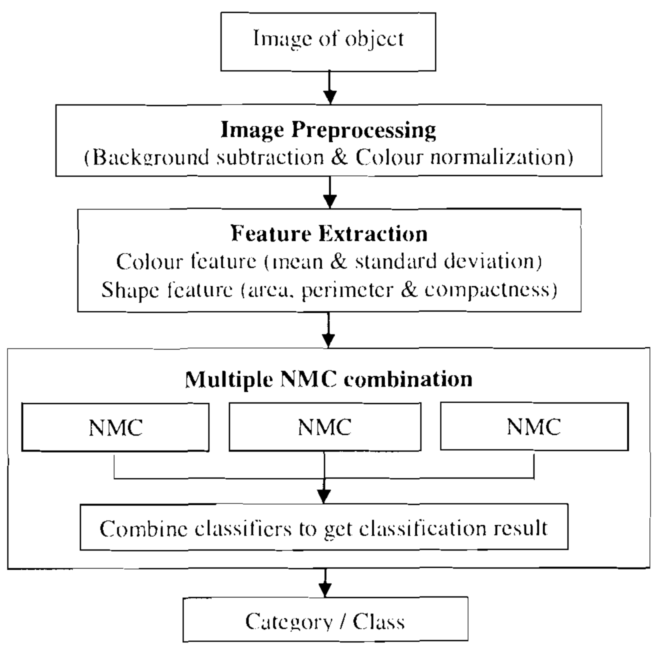

Figure 1. Multiple nearest mean combination technique

Image Preprocessing

The image will be preprocessed to obtain the feature of the object. Operations such as background subtraction and the normalization of color will be performed on the image. The background subtraction is performed with the aim to separate the object from its background. This is implemented by doing pixel subtraction (Fischer et al., 2003). Object (Q) is detected through the use of the following equation.

$$Q(i,j) = \left|P_1(i,j) - P_2(i,j)\right| \qquad (1)$$

where P_1 is the image of object plus its background, P_2 is the background image and *i, j* are the position of the pixel on the image. In other words, Q is the absolute subtraction value of the object from its background. The threshold value of red (R), green (G) and blue (B) intensity is set to 75. This is considered ideal after several conducting experiments investigating the value.

Colour normalization operation is then performed to eliminate the influence of different lighting (Gonzalez & Woods, 1992). The equation used to normalize the colour at each pixel Q with the intensity of each colour on red component is

$$r(Q) = \frac{R(Q)}{R(Q)+G(Q)+B(Q)} \tag{2}$$

The same treatment is applied to green and blue component.

Feature Extraction

Features found in the image are extracted and placed in feature vectors. Feature vectors can be divided into three groups, i.e feature vector of mean and standard deviation on each channel of RGB and shape feature vector which consists of the area, perimeter and compactness. If the number of pixels of object image is N then the mean value (x) for each colour can be obtained as follows.

$$x = \left(r_{avg}, g_{avg}, b_{avg}\right)^T \tag{3}$$

where $r_{avg} = \frac{\sum_1^N r(Q)}{N}$, $g_{avg} = \frac{\sum_1^N g(Q)}{N}$ and $b_{avg} = \frac{\sum_1^N b(Q)}{N}$.

The feature vector of standard deviation value (y) of colour for the same number of pixels can be obtained by

$$y = \left(r_{std}, g_{std}, b_{std}\right)^T \tag{4}$$

where $r_{std} = \sqrt{\frac{\sum_1^N \left(r(Q) - r_{avg}\right)^2}{N}}$, $g_{std} = \sqrt{\frac{\sum_1^N \left(g(Q) - g_{avg}\right)^2}{N}}$ and $b_{std} = \sqrt{\frac{\sum_1^N \left(b(Q) - b_{avg}\right)^2}{N}}$

The shape-based features are measured by area, perimeter and compactness. The area of an object reflects the actual object size or weight. This can be estimated by counting the total number of pixels that are enclosed by the detected object boundary. The perimeter of an object is defined as the area that covers the boundary, i.e. the sum of the boundary points. In this study, the boundary length, i.e. perimeter is expressed using eight (8) connected chain code (Freeman, 1961). The compactness of an object is defined by

$$c = \frac{4.\pi.a}{p^2} \tag{5}$$

The feature vector of shape for any object is represented by $z = (a, p, c)^T$ where a is area, p is perimeter, and c is compactness. A circular object usually has a compactness value of 1, while objects with more complex shapes have smaller values.

The Multiple Nearest Mean Classifier Combination

The proposed method is based on the concept of different feature space by Kuncheva and Whitaker (2001). The combination model consists of three nearest mean classifiers. The input to the first and second classifiers are the colour mean and colour standard deviation feature sets respectively while the input to the third classifier is the area, perimeter and compactness feature set. Output from each classifier is the similarity value between feature of unknown object (or test pattern) and feature of samples (or training pattern). The similarity value is obtained by calculating the euclidean distance between feature vector (or pattern) of unknown object and feature vector of samples. Two vectors are close to each other will have many similarities. Feature vector of samples represented by feature vector of class mean. The class mean or centroid ($\bar{x}$) is calculated by

$$\bar{x} = \frac{1}{n_i} \sum_{j=1,n_i} x_{i,j} \tag{6}$$

where $x_{i,j}$ is the j^{th} sample feature vector from class i. If the colour mean of object is stated as x and the colour mean of centroid as $\bar{x}$, the Euclidean distance of two vectors is

$$d(x,\bar{x}) = \sqrt{\left(r_{avg} - \bar{r}_{avg}\right)^2 + \left(g_{avg} - \bar{g}_{avg}\right)^2 + \left(b_{avg} - \bar{b}_{avg}\right)^2} \tag{7}$$

The same concept is applied in calculating the Euclidean distances of colour standard deviation and shape.

Values for distances provided by the classifiers will be normalized because different features will have different scale. Normalization is done by dividing the Euclidean distance between two feature vectors and the maximum Euclidean distance between any feature vector. The Same concept is applied in normalizing of each feature sets (colour mean, colour standard deviation and shape). The combined distance $(d(Q,\bar{Q}))$, can be calculated as

$$d(Q,\bar{Q}) = \frac{d(x,\bar{x})}{\max d(x,\bar{x})} + \frac{d(y,\bar{y})}{\max d(y,\bar{y})} + \frac{d(z,\bar{z})}{\max d(z,\bar{z})} \tag{8}$$

$Q = (x, y, z)^T$ is feature vector (or pattern) of unknown object which composed by three subvectors, $\bar{Q} = (\bar{x}, \bar{y}, \bar{z})^T$ is feature vector of samples which composed by three subvectors, $\max d(x,\bar{x})$, $\max d(y,\bar{y})$ and $\max d(z,\bar{z})$ are the maximum distance between any feature vector of colour mean, colour standard deviation and shape values respectively. The classification rule is performed as follows:

If feature vector (or pattern) of unknown object is $Q = (x, y, z)^T$ and $\bar{Q}_1$, $\bar{Q}_2$ are the class mean for classes ω_1 and ω_2 respectively then Q is classified to ω_1 if and only if $d(Q,\bar{Q}_1) < d(Q,\bar{Q}_2)$ else Q is classified to ω_2 if and only if $d(Q,\bar{Q}_2) < d(Q,\bar{Q}_1)$

If the value of $d(Q,\bar{Q}) < \varepsilon$ where $\varepsilon = 0.75$ then the unknown object will be classified, otherwise the unknown object will be rejected. The threshold (ε) value of 0.75, is empirically achieved.

DATA

A sample of 84 fruits images that correspond to 12 categories have been used to form the reference values for each category. The data were divided into training set (43%) and testing set (57%), with one to three training samples were used. All images were of 640 x 480 pixels with 24-bit true colour, 256 levels of gray and RGB colour model. The types of fruits that were used are limited to variants of apples, mangoes, oranges, pears and durian. Obtained feature values are shown in Table 1.

Table 1. Reference feature values

Type of fruit	Colour mean			Colour standard deviation			Shape		
	Red	Green	Blue	Red	Green	Blue	Area	Peri meter	Compact ness
Fuji Apple	193.93	136.28	83.73	38.71	50.96	30.03	15911	438	1.04
Manalagi Apple	167.41	180.51	66.67	33.88	34.28	25.70	12581	385	1.07
Washington Apple	184.34	75.75	64.24	37.20	39.23	30.05	16455	623	0.53
Arum Manis A Mangoe	131.89	143.69	51.07	27.20	26.35	14.91	31211	1449	0.19
Arum Manis B Mangoe	112.97	132.85	47.52	17.84	20.79	16.66	17083	920	0.25
Golek Mangoe	147.24	150.16	36.51	31.02	28.58	27.73	27439	1042	0.32
Honey Mangoe	105.27	138.55	77.66	22.91	24.81	27.03	20703	1588	0.10
Podang Mangoe	203.74	143.30	48.70	34.63	34.37	30.31	16436	455	1.00
Sunkist Orange	206.37	114.51	8.17	38.68	37.96	26.97	20846	618	0.69
Siam Orange	176.46	135.07	20.09	36.46	34.53	33.22	14469	498	0.73
Peer	211.77	191.14	122.68	35.30	41.74	41.80	18324	515	0.87
Durian	117.28	123.81	50.23	19.27	20.72	25.17	72276	10769	0.01

EXPERIMENTAL RESULT

In evaluating the performance of the proposed technique, forty eight (48) new fruits images were used as the testing images. Each class has 4 new fruit images. Small number of image were used in the training process. Three categories of training images were employed. The sizes of the three categories were 12, 24 and 36 respectively. The results are shown in Table 2.

Table 2. Fruit image test result

Number of training image	Number of testing image	Classification		Success rate (%)
		True	False	
One image per class	12	12	0	100
	24	24	0	100
	36	36	0	100
	48	46	1	95.83
Two images per class	12	12	0	100
	24	24	0	100
	36	36	0	100
	48	45	2	95.83
Three images per class	12	12	0	100
	24	24	0	100
	36	36	0	100
	48	48	0	100

From the results, it can be seen that the proposed technique is able to recognize and classifying new fruit images with small training sample size. The success rate when 1 or 2 samples are used in each class is 95.83% and for the case of 3 samples, the rate reaches 100%.

CONCLUSION

Identification and classification of fruits using the proposed multiple nearest mean classifier technique has shown that the technique is capable in producing high accuracy with small sample size. Small sample size posed a problem to most classification technique as big sample size is required to produce results with acceptable accuracy. Future research could include more than two features and tested with small and big samples.

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