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External Defect classification of Citrus Fruit Images using Linear Discriminant Analysis Clustering and ANN classifiers

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Abstract: Linear Discriminant Analysis (LDA) is one technique for transforming raw data into a new feature space in which classification can be carried out more robustly. It is useful where the within-class frequencies are unequal. This method maximizes the ratio of between-class variance to the within-class variance in any particular data set and the maximal separability is guaranteed. LDA clustering models are used to classify object into different category. This study makes use of LDA for clustering the features obtained for the citrus fruit images taken in five different domains. Sub-windows of size 40x40 are cropped from the citrus fruit images having defects such as pitting, splitting and stem end rot. Features are extracted in four domains such as statistical features, fourier transform based features, discrete wavelet transform based features and stationary wavelet transform based features. The results of clustering and classification using LDA and ANN classifiers are reported

Keywords: ANN classifier, clustering, LDA

INTRODUCTION

Fruit images with varying intrinsic features such as shape, color and texture constitute highly nonlinear features in the high-dimensional observation space. Visualization and exploration of these nonlinear features, therefore, become the focus of much of the current machine learning research for grading and sorting of fruits. However, most machine vision systems using linear methods are bound to ignore subtleties of features such as concavities, texture, color and protrusions, which is a bottleneck for achieving highly accurate classification. This problem has to be solved before we can build up a high performance classification system. There are many techniques available for classification of data. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are two commonly used techniques for data classification and dimensionality reduction (Jurado *et al*., 2005; Balakrishnama and Ganapathiraju, 2010). This study aims at classification of citrus fruit images based on the external defects using LDA classifiers and ANN classifiers.

Linear discriminant analysis: Among the many available methods, the simplest and most popular approach is Linear Discriminant Analysis (LDA) (Chen and Li, 2001). Discriminant analysis aims at the classification of an object into one of *K* given classes based on information from a set of *p* predictor variables. LDA finds the optimal transformation matrix as to preserve most of the information that can be used to discriminate between the different classes (Stefan, 2004). Therefore the analysis requires the data to have appropriate class labels. It transforms raw data into a new feature space in which classification can be carried out more robustly. Linear Discriminant Analysis is useful where the within-class frequencies are unequal. This method maximizes the ratio of between-class variance to the within-class variance in any particular data set and the maximal separability is guaranteed.

The prime difference between LDA and PCA is that PCA does more of feature classification and LDA does data classification. In PCA, the shape and location of the original data sets changes when transformed to a different space whereas LDA doesn't change the location but only tries to provide more class separability and draw a decision region between the given classes. Data sets can be transformed and test vectors can be classified in the transformed space. For the images, given a set of N images {x1, x2, … xN} with each image belonging to one of c classes {X1, X2,…., Xc}, LDA finds a linear transformation matrix W in such a way that the ratio of the between-class scatter and the within-class scatter is maximized (Tae-Kyun *et al*., 2005).

One of the reasons for the popularity of LDA is that it can be used for a variety of tasks. It can be used to project high-dimensional data into a low dimension and hence produce a graphical representation. Furthermore it

can also be used for classification and to produce a discriminant function to identify areas of discrimination between classes (Gareth, 2001). Linear Discriminant Analysis (LDA)-style methods often suffer the so-called Small Sample Size (SSS) problem, when they are applied to high-dimensional pattern classification tasks such as face recognition, where the number of available training samples per subject is smaller than their dimensionality (Juwei *et al*., 2005a, b).

Linear Discriminant Analysis (LDA) is one technique for transforming raw data into a new feature space in which classification can be carried out more robustly (Michael and Jean, 2003). The within-class (1) and between-class (2) scatter matrices are defined by:

$$W = \sum_{k=1}^{K} \sum_{j=1}^{K} \left(X_{j,k} - x'_k \right)^T \left(X_{j,k} - x'_k \right) \quad (1)$$

$$B = \sum_{k=1}^{K} n_k \left(x'_k - x' \right)^T \left(x'_k - x' \right) \quad (2)$$

respectively, where m_i denotes the mean image of class X_i, m is a global mean and N_i denotes the number of images in class X_i .

Thus, in discriminant analysis, the dependent variable (Y) is the group and the independent variables (X) are the object features that describe the group. The dependent variable is always category variable while the independent variables is any measurement scale. If we assume that the groups are linearly separable, we can use Linear Discriminant model (LDA). Linearly separable suggests that the groups can be separated by a linear combination of features that describe the objects. If only two features, the separators between objects group will become lines. If the features are three, the separator is a plane. If the number of features, which is equal to the number of independent variables, is more than 3, the separators become a hyper-plane. In discriminant analysis, object groups and several training examples of objects that have been grouped are known. The model of classification is known. The best-fit parameters of the model that can best separate the objects based on the training samples are to be found. Discriminant analysis has been successfully used for many applications. As long as we can transform the problem into a classification problem, we may apply the technique.

LDA can be viewed as a two-stage procedure. The first stage is to find the canonical variates for reducing the predictor dimension from *p* to *K* or less; the second stage is to split the canonical space linearly into K regions for class-membership prediction via the Mahalanobis distance (Chen and Li, 2001). Even though linear discriminant analysis and clustering analysis does the clustering operations they differ from each other. In clustering, the category of the object is unknown. However, we know the rule to classify which is usually based on distance and the features or the independent variables that can describe the classification are known. There is no training example to examine whether the classification is correct or not. Thus, the objects are assigned into groups merely based on the given rule. The differences between clustering and discriminant analysis are only on the training session. After the parameters are determined and we start to use the model, both models have the same usage to classify object into a number of category.

LDA for clustering: LDA is a classification technique that works in two ways:

- Reduction of the dimensionality
- Class separability

The LDA calculations are as follows:

Step 1 : Calculate the pooled Within (W) and in-Between (B) covariance matrices from Eq. (1) and (2).

$\mathbf{n_k}$: Number of objects in class k,
$\mathbf{x_{i,k}}$: Vector of object i belonging to class k.
$\mathbf{x_k}$: Centroid vector of class k.
T : Transpose (switched rows and columns).

Step 2: Maximize the ratio B/W by solving the generalized eigen values problem:

$$(B - \lambda W)\, b = 0 \quad - \quad (3)$$

where, b: Eigenvectors ; λ: Eigen values.

Step 3: Perform the transformation from the original n dimensional space into the 2 dimensional LDA space using the first two eigenvectors:

$$(X_i * b) = x_{i,\,LDA} \quad (4)$$

MATERIALS AND METHODS

Fruit samples collection: A total of 23 mandarin fruits were collected from the market, out of which 20 nos. were defective fruits and 3 nos. were good ones. Among the defective fruits 8 had pitting, 7 had stem end rot and 5 had splitting & pitting. The defects present in the fruits were identified manually based on the internet downloaded images and the images seen in the published literature. This study was carried out in Central Electronics Engineering Research Institute Lab, (CSIR Lab) Chennai

Imaging system: The imaging system consists of a color CCD camera (Pulnix TMC-6700 CL), a camera link interface compatible frame grabber card (NI-1428), an

illumination source and a personal computer system (Pentium III @ 800 MHz). Pulnix TMC-6700 CL is a progressive scan color camera with asynchronous reset capability and has camera link communication interface to the PC system through the frame grabber card. The camera has 1/2" format CCD sensor having 648 Hx484 V pixels resolution. A C-mount lens of focal length 6 mm was used. The illumination source used in the imaging system has incandescent and fluorescent lamps operating at 230V ac. (Fig 1).

Image collection and preprocessing: Images were taken for all the 23 mandarin fruits. Mandarin fruits were placed on a vertical stand, one fruit at a time in the field of view of the camera and proper illumination was ensured. About three images were captured for each of the fruit sample at different fruit positions. Using Matlab 6.1, two image-preprocessing steps were performed. As a first step, the color images were converted to gray scale images. Secondly the images were de-noised using median filtering. For feature extraction using statistical, Fourier transform, Discrete wavelet transform and Stationary wavelet domains 40x40 sub-windows were cropped from the citrus fruit images having defects such as pitting, splitting and stem end rot.

Feature sets used:

Statistical features: The images are cropped into sub windows of size 40x40. The features such as mean, variance, skewness and kurtosis are extracted from the first order histogram of the sub window. The features such as contrast, energy and entropy were calculated from the second order histogram of the sub window, which is nothing but the cooccurrence matrix.

Fourier transform features: The features are calculated from the Fast Fourier Transformed sub windows of size 40x40 such as maximum magnitude, Average magnitude, Energy of magnitude and variance of magnitude.

Stationary wavelet transform features: The mean and standard deviation of the SW transformed sub windows of size 40x40 taken up to three levels are used as features.

Discrete wavelet transform features: The mean and standard deviation of the DW transformed sub windows of size 40x40 taken up to three levels are used as features.

Linear discriminant analysis with pooled covariance: Matrix for classification: Let X be the features or independent variables of all data. Each row, denoted by k represents one object. Each column stands for one feature. Let Y be the group of the object or dependent variable of all data. Each row represents one object and it has only one column:

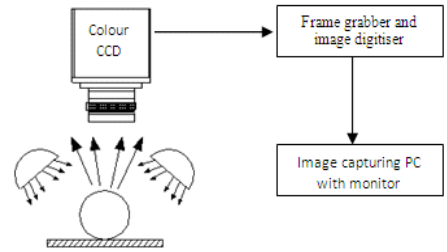


Fig. 1: Experimental set-up for imaging

X_k : Data of row k; g: Number of groups in Y
X_i : Features data for group i. Each row represents one object. Each column stands for one feature. We separate X into several groups based on the number of category in Y
m_i : Mean of features in group I which is average of X_i
m : Global mean vector that is mean of the whole data set
X_i^c : Mean corrected data, that is the features data group
I : $(X_i\text{-}m)$
C_i : $\{[X_i^c]\, X_i^c\}/n$

$$C(r,s) = \frac{1}{n}\sum_{i=1}^{g} n_i C_i(r,s)$$

where, C (r, s) is the pooled within group covariance matrix (Blackrishnama and Ganapathiraju, 2010). It is calculated for each entry (r, s) in the matrix.

C^{-1} : Inverse of the pooled covariance matrix;
P : Prior probability vector where each row represents prior probability of group i;
p_i : n_i / n

The discriminant function is given by:

$$f_i = (m_i C^{-1} X_k^T) - ½ (m_i C^{-1} m_i^T) + \ln (p_i)$$

An object k is assigned to group i that has maximum f_i:

RESULTS AND DISCUSSION

Results of clustering: Defective citrus fruit images with defects such as pitting, splitting and stem end rot were used. Windows having the defect were cropped and used for clustering. Feature sets were obtained in five domains viz. statistical features, Fourier transformation features, discrete wavelet transformation features, Stationary wavelet transformation features and Wavelet Packet transformation features. With the above stated formulae the clustering was done and the clustering results are

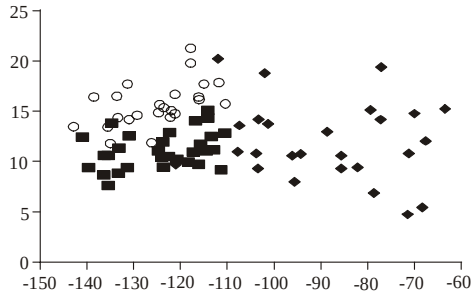


Fig. 2: LDA clustering with statistical

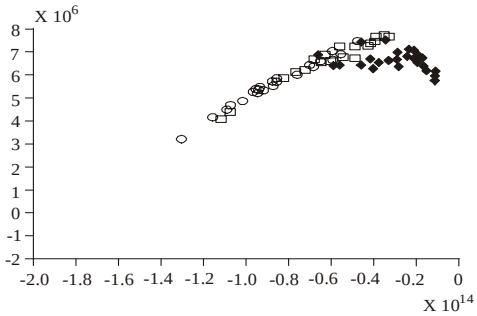


Fig. 3: LDA clustering with FT feature set

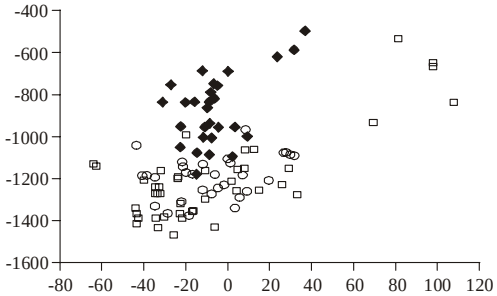


Fig. 4: LDA clustering with DWT feature set

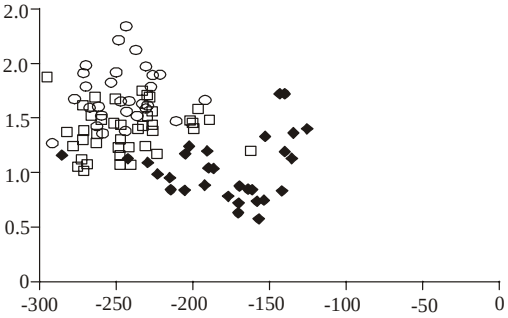


Fig. 5: LDA clustering with SWT feature set

shown below. In all the figures showing the results of LDA clustering using statistical features Fig. 2, Fourier transform features Fig. 3, Discrete wavelet transform based features Fig. 4 and Stationary wavelet transform based features Fig. 5:

- Blue colored "*" data represent the stem end rot samples
- Red colored "+" data represent splitting
- Black colored "o" data represents the pitting samples

The clustering with statistical features is shown in the above figure. Except for a few images, which had both pitting and stem end defects, the clusters are distinct indicating that the classification rate must comparatively be good.

With the Fourier feature set the cluster representing the images of the stem end rot form a distinct cluster. The other two clusters representing the citrus fruit images with pitting and splitting defects overlap each other. This is so because the images with splitting defect could not be imaged on the day of procurement. As the outer skin of the mandarin fruit is open the fruits started to develop rottenness around the place where the split had occurred. This can be clearly seen in the images of the fruit. The Fourier transform is observed to be inefficient in differentiating between the two clusters.

In the DWT feature set the cluster representing the stem end rot fruits are easily distinguishable even though the spread or scatter is more. The other two clusters are not easily separable as the between class variance is not high. DWT feature set may not classify the pitting and splitting defect as effectively as required. This may be due to the fact that the DWT results in redundant data because of the decimation. The finer information may be lost.

The clustering done with SWT feature set shows that the three classes could be formed even though few outliers are seen. The overlap of the two groups representing pitting and splitting is minimized and to a reasonable extent the clustering is efficient. This shows that the classification rate with the SWT feature set has to be higher that that obtained for FT and DWT feature set.

Results for classification using ANN classifier: The ANN classifier results are given in Table 1, 2, 3 and 4.

The Linear discriminant analysis when used as a classifier maximizes the ratio of between class variance to the within class variance. It guarantees maximum separability. The results of the LDA classification with Fourier transform features have improved compared to the distance classifier. The classification with other feature sets is not very good. This may be because of the fact that the LDA suffers from small size samples. The images were cropped into sub windows of size 80x80. So the windows with boundary of the fruit images would have been excluded from the feature extraction step resulting in lesser number of sub windows for feature extraction and

Table 1: ANN classifier for statistical features

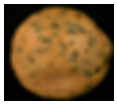
S. No	Image	LDA classification	ANNN classification	S. No	Image	LDA classification	ANNN classification
1		Stem end rot	Stem end rot	7		Stem end rot	Pitting, splitting and stem end rot
2		Pitting	Stem end rot	8		Pitting	Stem end rot
3		Pitting	Stem end rot	9		Pitting and splitting	Pitting and stem end rot
4		Pitting	Stem end rot	10		Pitting	Pitting
5		Stem end rot	Pitting	11		Pitting	Pitting and stem end rot
6		Stem end rot	Pitting	12		Pitting	Pitting

Table 2: ANN classification results for FT features

S. No	Image	LDA classification	ANNN classification	S. No	Image	LDA classification	ANNN classification
1		Stem end rot	Stem end rot	7		Pitting	Splitting
2		Stem end rot	Stem end rot	8		Pitting	Pitting

Table 2: (Continue)

3		Pitting	Stem end rot	9		Pitting	Pitting
4		Pitting	Stem end rot	10		Pitting	Pitting
5		Pitting	Pitting	11		Pitting	Pitting
6		Pitting	Pitting	12		Pitting	Pitting

Table 3: ANN classification results for DWT features

S. No	Image	LDA classification	ANNN classification	S. No	Image	LDA classification	ANNN classification
1		Splittings splitting	Splitting	7		Pitting pitting	Pitting
2		Splitting	Splitting	8		Splitting	Pitting
3		Splitting	Stem end rot and pitting	9		Splitting	Pitting

Table 3: (Continue)

4		Splitting	Splitting	10		Splitting	Pitting
5		Splitting	Pitting and splitting	11		Splitting	Pitting and splitting
6		Splitting	Splitting, pittings and stem end rot	12		Pitting	Splitting

Table 4: ANN classification results for SWT features

S. No	Image	LDA classification	ANNN classification	S. No	Image	LDA classification	ANNN classification
1		Stem end rot	Stem end rot	7		Pitting and stem end rot	Pitting and splitting
2		Stem end rot	Stem end rot	8		Stem end rot	Pitting and splitting
3		Pitting	Pitting	9		Pitting	Pitting
4		Stem end rot	Pitting	10		Pitting and stem end rot	Pitting

Table 4: (Continue)

5	Pitting and stem end rot	Pitting and splitting	11	Pitting	Pitting
					
6	Stem end rot	Pitting and splitting	12	Pitting and stem end rot	Pitting
					

classification. WPT features were not used as only full fruit images were used for feature extraction using WPT.

CONCLUSION

Clustering the features extracted for image analysis is helpful in knowing the ability of the feature set to be classified efficiently prior to the classification stage. This study makes use of the LDA for clustering the features extracted in four domains viz. Statistical features, Fourier transformation based features, Discrete wavelet transformation based features and Stationary wavelet transformation based features.

Among the four feature sets the features obtained from the stationary wavelet transformation is found to be more discriminative and is expected to give a better classification rate compared with the other three feature sets which is also supported by the results of the classification by LDA classifier using pooled covariance matrix.

REFERENCES

Balakrishnama, S. and A. Ganapathiraju, 2010. Linear discriminant analysis-a brief tutorial. Institute for Signal and Information Processing. Retrieved from: www.music.mcgill.ca/~ich/classes/mumt611_07/.../lda_theory.pdf.

Chen, C.H. and K.C. Li, 2001. Generalizing, fisher's linear discriminant analysis via the SIR approach. J. Korean Stat Soc., 30: 193-217.

Gareth, M.J., 2001. Functional Linear Discriminant Analysis for Irregularly Sampled Curves.

Jurado, J.M., A. Alcazar, F. Pablos, M.J. Martin and A.G. Gonzalez, 2005. Classification of aniseed drinks by means of cluster, linear discriminant analysis and soft independent modelling of class analogy based on their Zn, B, Fe, Mg, Ca, Na and Si content. Talanta, 66: 1350-1354.

Juwei, L., K.N. Plataniotis, A.N. Venetsanopoulos and J. Wang, 2005a. An efficient kernel discriminant analysis method. Pattern Recogn., 38: 1788-1790.

Juwei, L., K.N. Plataniotis, A.N. Venetsanopoulos, 2005b. Regularization

studies of linear discriminant analysis in small sample size scenarios with application to face recognition. Pattern Recogn. Lett., 26(2): 181-191.

Michael, M., Goodwin and L. Jean, 2003. Audio segmentation by feature-space clustering using linear discriminant analysis and dynamic programming. IEEE Workshop on Applications of Signal Processing to Audio and Acoustics, 19-22 Oct., CA, USA, pp: 131-134.

Stefan, G., 2004. Feature Reduction with Linear Discriminant Analysis and its Performance on Phoneme Recognition.

Tae-Kyun, K., K. Hyunwoo, H. Wonjun and K. Josef, 2005. Component-based LDA face description for image retrieval and MPEG-7 standardization. Image Vis. Comput., 23: 631-642.