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LINEAR DISCRIMINANT ANALYSIS FOR SIGNAL PROCESSING PROBLEMS

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LINEAR DISCRIMINANT ANALYSIS FOR SIGNAL PROCESSING PROBLEMS

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ABSTRACT

Automatic classification of data is an important research area in the field of signal processing. Linear Discriminant Analysis (LDA) is commonly used for this purpose as it is able to transform the data to a new space where a linear decision region can be found. The transformation can be obtained using two different approaches: class-dependent and class-independent. The distinction between these two methods lies in the way the optimizing criterion is computed. Class-dependent LDA produces one transformation per class to discriminate that class from all other classes. Class-independent LDA produces a single transform to maximally separate all classes. To evaluate these two methods we examine the problem of determining scenic beauty ratings of forestry images. Further experiments will include classification of phonemes.

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SUMMARY

Linear Discriminant Analysis (LDA), like Principal Component Analysis (PCA), is used for data classification and dimensionality reduction. LDA maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separability. The prime difference between LDA and PCA is that PCA performs feature classification while LDA performs data classification. PCA changes both the shape and location of the data in its transformed space whereas LDA only provides more class separability by building a decision region between the classes.

The basic idea in classification involves extraction of meaningful features from the signal and using these features as data for the classification algorithm. Models are created which represent the classes of data in the feature space. The classification algorithms then process these models to obtain decision regions between the different classes of data. All classification techniques provide either a linear or nonlinear transformation of the original features to a new space wherein a more accurate classification can be performed.

Two types of data modeling approaches are applied to this problem — class-dependent LDA and class-independent LDA. The class-dependent approach involves maximizing the ratio of between class variance to within class variance to obtain adequate class separability. This approach uses two optimization criteria for transforming the data sets independently. The latter approach involves maximizing the ratio of overall variance to within class variance. These class-independent transformations use only one optimizing criterion to transform the data set. When a class-independent transformation is applied to more than two classes, a decision region is built to separate each class from all other classes. Whether LDA should be implemented with or without class dependence depends on the data set and the goals of the classification problem. If generalization is important, the class-independent transformation is preferred. However, in a static environment, better discrimination can be obtained with the class-dependent transformation.

The first application of our implementation of LDA to real data involves scenic beauty estimation of forestry images. We use 45 features comprised of red, green, and blue histogram bin values, the number of long and short lines, entropy, compression ratio, and fractal dimension. After transforming these features using LDA, the test images are classified using a euclidean distance measure into one of three classes: high, medium, or low scenic beauty. Preliminary results show PCA yields 43.3% error, while class-dependent LDA produces 35.22% error. Encouraged by this result, we plan to next apply LDA to a standard phoneme classification problem.