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Classification of image pixels based on minimum distance and hypothesis testing

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ABSTRACT

In this article, we introduce a new method of image pixel classification. Our method is a nonparametric classification method which uses combined evidence from the multiple hypothesis testings and minimum distance to carry out the classification. Our work is motivated by the test-based classification introduced by Liao and Akritas (2007). We focus on binary and multiclass classification of image pixels taking into account both equal and unequal prior probability of classes. Experiments show that our method works better in classifying image pixels in comparison with some of the standard classification methods such as linear discriminant analysis, quadratic discriminant analysis, classification tree, the polyclass method, and the Liao and Akritas method. We apply our classifier to perform image segmentation. Experiments show that our test-based segmentation has excellent edge detection and texture preservation property for both gray scale and color images.

1. Introduction

Images can be considered as a finite collection of regions and thus can be realized by groups of pixel values representing different regions in the image. The pixels representing a particular feature or color in the image show more homogeneity in terms of distribution of pixel values. Groups of similar image pixels can be formed by comparing pixels with each other and to pixels of known identity. The groups so formed are called image pixel classes. These classes then represent different informational categories of interest and can follow any distribution.

Image pixels classification is a process of assigning pixels to different classes in the image. It is widely used in medical diagnosis and remote sensing. Some of the applications of multispectral image pixels classification in remote sensing are identification of objects in satellite images, land-use analysis, mineral exploration, and determination of earth surface composition where the knowledge of reflectance properties of various types of material is also needed for the classification. Image pixels classification has been very helpful in medical diagnosis such as chromosome karyotyping, comparison of normal and non normal blood vessels, categorization of database of X-ray images, study of anatomical structure, computer-integrated surgery, quantification of tissue volumes, treatment planning, etc. Some of the other applications of pixel classification include astronomy, face recognition, traffic control systems, agricultural imaging, computer vision etc.

Commonly used statistical methods that can be implemented for image pixels classification are linear discriminant analysis (LDA) (Hastie et al., 2009), quadratic discriminant analysis (QDA) (Hastie et al., 2009), classification tree (Breiman et al., 1998), the polyclass method (Stone et al., 1997), maximum likelihood, and Bayes classifier. Commonly used computer-based classifiers include nearest-neighbor classifier, K-nearest-neighbor, neural networks, and a support vector machine

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(Vapnik, 1982). All the aforementioned computer-based classifiers are nonparametric in that they make no assumptions on the distributions of the data to be classified. These approaches are straightforward and intuitive but barely consider the randomness of the data in each class. On the other hand, we have a mixed bag of classifiers in the given statistical classifier methods. The classification tree and the polyclass method are nonparametric whereas LDA, QDA, maximum likelihood, and Bayes classifier are parametric classifiers making assumptions about the distribution of class values. For example, LDA and QDA require that the distribution of values for all classes to be Gaussian. Similarly, maximum likelihood and Bayes classifier generally assume that the pixel intensities are independent samples from a mixture of Gaussian distributions. However in practice, image pixel values can follow any distribution. A classification method based on hypothesis testings was developed by Liao and Akritas (2007). This is a powerful nonparametric classification method which can allow the variation within a class to be taken into account through the test-statistics without making distributional assumptions. However the implementation of their method in the context of images reveals that the method can fail to correctly classify many image pixels in the given image due to small p-values. Here we introduce a minimum distance into the test-based classification and come up with a new classifier for image pixels. This new classification method eliminates the drawback of the Liao and Akritas method and works better than commonly used classification methods.

The pixels classification will be employed to perform segmentation of color images. Image segmentation is a process of dividing an image into different homogeneous regions so that the image can be represented differently making it easy to study and analyze. In fact, image segmentation can be viewed as image pixels classification based on the spatial features and color of the images. Segmentation extracts information about the structure of objects in the image and is helpful in separating and observing various parameters of interest within the image data. There are several approaches for gray scale image segmentation. Commonly used approaches include a histogram based approach (Dutta and Chaudhari, 2009), a clustering approach (Coleman and Andrews, 1979), a watersheds transformation approach (Vincent and Soille, 1991), a classifier method, a region-based approach, an edge detection-based approach, artificial neural networks etc. However there are not many literature available for color image segmentation and most of the available methods for color image are based on gray scale image segmentation approach. Readers can refer to Haralick and Shapiro (1985) and Pal and Pal (1993) for surveys on image segmentation techniques.

Classifier methods work well in image segmentation for images with quantifiable features. They can be employed in multichannel images and are efficient to employ in comparison with other approaches. In classifier-based image segmentation, training data are manually obtained to be used as references for segmentation of the entire image. As pixel values in image classes can follow any distribution, nonparametric classifiers in general are expected to produce more realistic results for a wide variety of data than the parametric classifiers. In this article, we describe how our nonparametric classifier can be used to produce accurate segmentation of color images.

The rest of the article is organized as follows. Section 2 gives details about the formation of classes, training data and test points. Section 3 describes our method for the binary classification of image pixels where we consider both equal and unequal prior probabilities of classes. In Section 4, we extend to multiclass classification for equal and unequal prior probabilities of classes. Section 5 discusses the classification of pixel values in color images. In Section 6, we provide implementation and exhibit the detailed aspects of our classification method in gray scale images. Section 7 is devoted to the comparisons of several methods of classification with our method. Section 8 discusses the segmentation of color images using our method of classifier followed by a summary.

2. Training data, classes and test points

Here, we give a description about the formation of training data, classes and test points in a given image. This will be frequently used in the implementation of different classification methods in later sections. In an image, we can define our classes of interest by selecting the regions. We use some data that is known a priori to belong to the involved classes to train the system about these classes and learn the class parameters. This data is referred to as training data. We take a rectangular part of the regions representing the class to acquire the training data of that class. We do this by randomly choosing two points in the region which will be the upper left and lower right corners of the rectangle. The rectangle so formed is simply a submatrix of the given image. Next, we put all the pixel values in the submatrix into a vector formed by adjoining each column of the submatrix below its preceding column. Then we treat this vector of pixels as training data from the corresponding class. In the classification of images, we classify a randomly selected pixel, known as test point, in the image as belonging to one of the defined classes. In the implementation of all the considered classification methods, we will randomly select equal number of test points from each of the regions representing the different classes. The misclassification error of the method on these points will help us to evaluate the performance of the proposed approach relative to other methods.

3. Binary classification

Let us consider two image pixel classes with means μ_1, μ_2 and x_0 be a randomly selected test point in the image. Denote $(x_{11}, x_{12}, x_{13}, \dots, x_{1n_1})$ and $(x_{21}, x_{22}, x_{23}, \dots, x_{1n_2})$ as the training data from class 1 and class 2 respectively. Liao and Akritas (2007) (denote as LA) suggested a classification scheme based on the following two applications of a test. The null hypothesis