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Supervised multichannel image classification algorithm using hierarchical histogram representation

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Abstract

Multichannel image processing, in particular, supervised classification, requires designing novel time effective algorithms, because in the most of the cases slightly dimension increase leads to significant processing time growth. In this paper we describe our supervised multichannel image classification algorithm based on a hierarchical representation of multivariate histograms. The algorithm estimates the joint sample set distribution, the particular distributions of each class and the decision rule by means of specific data structure called histogram-tree. Proposed algorithm provides faster learning and classification of multidimensional input data. The experimental evaluation of the algorithm has been conducted for the hyperspectral remote sensing images. The results demonstrate that proposed algorithm is faster than the commonly used C4.5 classifier.

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Keywords: supervised classification; multichannel images; hierarchical histogram; hyperspectral remote sensing image; decision trees

1. Introduction

In image processing histogram is the common way of probability density estimation. It often appears as one of the processing steps in many algorithms such as color correction, binarization, clustering, classification and etc. In

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classification it usually plays the role of particular object feature (local histogram) or it is used as an empirical estimation of the probability density function (PDF) (global histogram).

Existing image classification algorithms exploiting histograms can be divided into several groups. The first group includes the algorithms that produce density estimation for each class separately. Many of them are supervised algorithms which receive the histogram for each class using predefined training sample. Derived probability distribution estimations allow to apply statistical classification algorithms such as Bayesian classifier or maximum likelihood classifier [1]. The second group contains classifiers based on the probability distribution mixture model [2]. This model assumes that entire input dataset probability density function can be presented as the weighted sum of the density functions for each class. This approach is usually implemented in unsupervised manner.

The histogram based image classification algorithms are significantly limited by low dimensional case (the suitable number of features varies from 2 to 4 depending on the number of bits per channel [3]). The reasons are high computational complexity and strictly memory requirements for the multivariate histogram evaluation. To avoid these limitations several algorithms based on tree data structures were developed. Some of them applied trees only for fast histogram computing and its compact storage, for example, TUBE algorithm (Tree-based Unsupervised Bin Estimator) [4], DET algorithm (Density Estimation Trees) [5], “width” and “depth” algorithms proposed in our previous article [3] and others. In this case, only the time needed for histogram estimation is optimized and further classification is performed by one of the existing statistical algorithms. The other way to employ hierarchy in classification is to store decision rules as a tree which induces the separation of the feature space into particular classes by means of a set of hypersurfaces. These surfaces are defined to optimize the quality of classification on each of the hierarchy levels. This approach is usually called decision trees [1]. Also the tree structures are useful for unsupervised classification and comprehensive dimension reduction [6].

The decision trees are an effective way to perform classification. In the supervised case they use training set to define the decision rule for each of the hierarchy levels. The main stages of such classifiers are selecting the feature component to be split, evaluating appropriate boundary to separate the feature space, checking stop growing condition. It is essential for these algorithms to stop the tree growth at the right moment. Pruning allows to avoid overtraining problem and produces more time effective learning. Since the decision rules for such algorithms separate the feature space hierarchically and statistics for classes is calculated to derive the boundary, these algorithms could be considered as implicitly estimating the distribution of the feature vectors.

In this paper we propose the algorithm which is based on the histogram-tree structure introduced in [3]. Unlike the decision trees our algorithm is oriented on native agglomeration of feature vectors in the feature space. We analyze the bit structure of each feature vector component to generate the hierarchical set of histogram cells. Binary operations make the process of tree construction relatively fast. In our case the tree has fixed maximum depth and it is not a binary tree. It also allows to estimate class histograms, entire image histogram and decision rules as the single data structure.

The detailed description of the proposed classifier is given at the rest of this paper. We also provide the experimental performance evaluation for our histogram-tree classifier and compare it with the popular decision tree algorithm C4.5 [1].

2. Image classification algorithm based on histogram-tree

2.1. Problem statement

Without loss of generality, we assume that each image pixel corresponds to the particular feature vector $x_n = (x_{n0},..., x_{nL-1})$, $n = \overline{1,..., N}$ with integer components. The symbol n refers to pixel position, symbol N denotes number of pixels in the image. The number of bits per component B determines allowable feature value range $x_{ns} \in [0, 2^B - 1]$, $s = 0,..., L-1$, where L is the dimension of feature space.

We suppose that all image pixels are related to one of the predefined classes $\Omega_i, i = 0,..., C-1$. So that the classification problem is defined as assigning of appropriate class number $\omega_n \in \{0,..., C-1\}$ to the observed feature vector x_n. We adjust our classifier in a supervised manner, i.e. the training sample with T feature vectors $y_k = (y_{k0},..., y_{kL-1})$, $k = 1,..., T$ and their class labels $\omega_k \in \{0,..., C-1\}$ are used to evaluate decision rules.