APPLICATION OF AN INTERACTIVE FEATURE-DRIVEN SEGMENTATION

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Abstract — *We propose a method that enables anyone to quickly set up a pattern recognition system. Based on examples our system automatically estimates the problem specific constraints that are derived from features discriminating different types of objects. The constraints are used as segmentation parameters for the Constrained Region Growing technique. Good segmentation results can be achieved; the segmentation error depends on the examples presented.*

Keywords — *segmentation, constrained region growing, features, classification, interactive, feedback*

Introduction

For the recognition of patterns on digital images, usually an image processing chain (see fig. 1) is constructed. In the segmentation step an image is parted into disjoint regions, e.g. foreground and background. During feature extraction the regions' general properties are computed. Useful features are determined during the feature selection. Finally, a classification system is built that categorizes the regions according to their features.

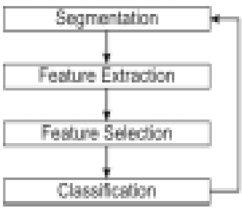

Figure 1: Image processing chain. After the segmentation, features from the regions are extracted. Important features are selected and the regions are categorized by a classifier. This chain is executed for each image.

A common problem is, that the proper algorithms for each step of the chain must be chosen manually. Mostly, explicit knowledge about the used algorithms is needed to adjust their parameters correctly, e.g. segmentation thresholds. The extracted features are often empirically chosen based on the visual perception of the patterns.

The combined algorithms are often optimized separately, but the whole chain depends on the segmentation results, e.g. the region's shape may affect the region's features.

Unfortunately segmentation is a challenging task, thus simple segmentation methods might fail on distorted images or complex scenes [1]. Many sophisticated algorithms are only suitable for a specific purpose and have to be adapted for each application.

One of the most commonly used segmentation methods is the seeded region growing (SRG) [2,3,4]. Starting from a seed pixel, regions are formed by aggregating adjacent pixels, whose gradient is below a certain threshold. The resulting regions are homogeneous in respect to their feature "gradient". Due to this fixed homogeneity criterion the region growing will fail at many cases, e.g. if a region consists of a specific texture pattern.

This can be avoided by adjusting the criterion to the segmentation problem. If it is known, which features best describe the homogeneity of a region, e.g. specific texture patterns, using these features to segment regions will improve the segmentation and the pattern recognition itself.

To use additional constraints different to the gradient, the constrained region growing (CRG) [2,4] was developed, but very few algorithms are described in literature so far:

Warfield et al. describe a CRG in [4]. Additionally to observed features they use expert knowledge from an anatomical atlas.

Pohle et al. [3] estimate the homogeneity with the gradient and simple morphological properties and adjust the segmentation parameters accordingly.

Paclík et al. [5] use spectral features for an unsupervised texture segmentation. However unsupervised clustering increases the risk of misclassifying pixels.

We however presented a more general approach in [6] where a pattern recognition system was built up from a database of manually segmented objects. This approach requires a great amount of expert work for the manual segmentations.

Therefore we propose a simplified method to create a pattern recognition process based on the feature-driven segmentation.

Feature driven segmentation

One region-of-interest (ROI) is defined for each object class, e.g. one ROI marks the class 'nucleus' and one marks the class 'non-nucleus' (see fig. 2, 1st column).

Within the ROI, features from an $n \times n$ neighbourhood of each pixel are computed, e.g. statistical properties of the histogram. The features together with the class membership are called 'observation'. Discriminating features are selected and a classifier is constructed, which can categorize pixels of different regions of the given classes. As the observations are random samples, they can only be discriminated with an estimated generalization error.

Starting from the seed pixel, the features of the local neighbourhoods of the pixels surrounding the seed are calculated. The classifier decides on the region membership of each pixel. This method creates regions that are homogeneous in respect to their pixels' class membership.

Results

The proposed method has been tested on different images: a coloured lymphocyte's nucleus on a microscopic image and a standard MRT-image of a head (figure 2). Two ROIs were defined manually. The neighbourhood size was fixed to 9×9 resp. 3×3 with a moving increment of 9 resp. 3 pixels, i.e. there was no overlap of the neighbourhoods. The seed point is automatically selected inside a ROI. Only a 4-neighbourhood is considered for the growing process as we want to avoid single-pixel diagonal region connections. To select the features we used a forward-selection [7]. For the classification we used a Quadratic Classifier based on the Mahalanobis distance [8].
Visually evaluated, the resulting segmentations are better than those of the standard region growing, which misses fine structures and fuzzy edges, while our method creates homogeneous regions according to the user's specification.

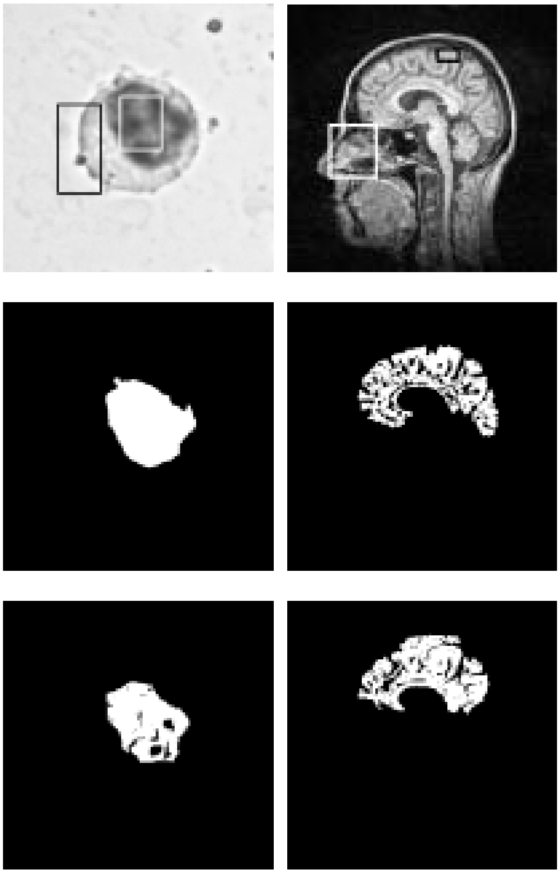

Figure 2: Segmentations. Top: Original images with user-defined ROIs per class. Middle: Interactive feature-driven segmentation. Bottom: Standard Region Growing.

Discussion

Our approach achieves satisfactory recognition and segmentation results depending on the generalization error. It requires much less user interaction, i.e. defining one ROI per desired type of region instead of manually segmenting a complex scene. Yet it relies on correct information about the classes, provided by the user. If the recognition results are poor, additional ROIs can be defined to allow our process to gather more feature values per region and build a better classifier.
The presented algorithm is a generic approach based on local pattern descriptors. A broad variety of more than 45 different feature extraction methods have been implemented so far to ensure the independence from human subjective perception.
The segmentation quality was only visually evaluated, but quantitative measures can be computed if a reference segmentation is available.
We restricted the used feature selector and classifier to a single combination, which cannot guarantee the best results. Yet our system is more flexible and can use different combinations of selectors and classifiers. We described a method to find a good combination in [9].
By increasing the number of observations per ROI, i.e. allowing an overlap for the neighbourhoods the features are extracted from, better classifiers might be derived. The computation of 45 features from approx. 5000 neighbourhoods took 20 min on a 1.6GHz Pentium IV.

Literature

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