Feature Selection for Segmentation of Medical Images

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Segmentation attempts to divide an image into meaningful regions, and classifiers are a common segmentation method. Classifiers require multiple digital images of the same scene as input. Many types of images are available; objective selection of images to use as input to a classifier requires a systematic method to evaluate the contribution made by each image to answering the question posed.

This study addresses the development of such a method. Segmentation questions were posed by identifying pairs of tissues that must be differentiated to produce a meaningful segmented image. Each feature was assigned a figure-of-merit related to its ability to distinguish each pair, providing a basis for ranking potential input images. The figure-of-merit was the statistical distance between two populations, represented by operator-designated examples of each tissue to be distinguished.

Two different tree searches, forward selection and backward elimination, were used to rank the images. Once the images were ranked, subsets were analyzed to predict the outcome of segmentation. The split sample experiment can predict outcome, and several classifiers (maximum likelihood, interactive region mapping, and vector decomposition) were tested this way to evaluate their performance on specific classification tasks. Such experiments allow determination of which and how many of the potential input images are necessary and sufficient to address the question posed.

The method was illustrated using three practical examples. The first examined standard screening images (density-, T2-, and T1-weighted MRI) of ten normal subjects. It was found that distinguishing among different types of brain parenchyma required all three images with approximately equal importance. Grey matter, white matter, and CSF could be readily distinguished using these images; however, basal ganglia were not well distinguished from each other or from grey matter or white matter.

Among these three images, density-weighted images were most important for distinguishing blood vessels from brain parenchyma. The statistical distance predicted the performance of two classifiers, maximum likelihood and vector decomposition, as measured by the split sample experiment.

The second example applied the method to images of nineteen subjects with recurrent gliomas. Seven types of images were tested for their ability to distinguish live tumor from necrosis, edema, and normal brain; PET and contrast-enhanced T1-weighted images were ranked as the most important. Again, statistical distance predicted the performance of the maximum likelihood classifier.

The third example applied the method to images of five subjects with arteriovenous malformations. The goal was to isolate the AVM nidus from arteries, veins, and parenchyma. Density-weighted MRI and time-of-flight MRA were selected as input to segmentation by two-dimensional interactive region mapping.

It was found that success depended on the disease pattern; the nidus could be isolated by classifier alone in cases having the classic pattern of rapid flow in the feeders, moderate non-turbulent flow in the nidus, and slow flow in the drainers. However, even an image in which the classifier merely identified vessels provided useful additional information for radiosurgery planning. This example showed that although statistical distance is probability-based, it predicts the performance of a non-probabilistic classifier.