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Segmentation of collection of images

Gaurav S. Zarkar *, S.B. Shrote**
*(Department of E&TC, Sinhgad Institute of Technology & Science, Pune University, pune
Email: gzarkar45@gmail.com)
** (AP,Department of E&TC, Sinhgad Institute of Technology & Science, Pune University, pune
Email: sandip.shrote@gmail.com)

ABSTRACT
We present a method for semiautomatic segmentation of the vasculature in retinal images. The method produces segmentations by classifying each image pixel as vessel or nonvessel, based on the pixel's feature vector. We use a supervised technique that determines an efficient segmentation of many input images. Segmentation is depends on the user so that user can define what he wants. This is done by user can provide fully or partially labeled pixel in the image. Once tuning is done, the setup can be used to automatically segment a large collection of images that are different but share similar features.
Keywords - image segmentation, retina, vessel segmentation

I. Introduction

The term digital image refers to processing of a two dimensional picture by a digital computer. In a broader context, it implies digital processing of any two dimensional data. A digital image is an array of real or complex numbers represented by a finite number of bits. An image given in the form of a transparency, slide, photograph or an X-ray is first digitized and stored as a matrix of binary digits in computer memory. This digitized image can then be processed and/or displayed on a high-resolution television monitor. For display, the image is stored in a rapid-access buffer memory, which refreshes the monitor at a rate of 25 frames per second to produce a visually continuous display.

An automatic assessment for blood vessel anomalies of the Optic fundus initially requires the segmentation of the vessels from the background, so that suitable feature extraction and processing may be performed. Several methods have been developed for vessel segmentation, but visual inspection and evaluation by receiver operating characteristic (ROC) analysis show that there is still room for improvement: human observers are significantly more accurate than the methods, which show flaws around the optic disk and in detection of the smallest vessels[3], [4]. In addition, it is important to have segmentation algorithms that are fast and do not critically depend on configuring several parameters, so that untrained community health workers may utilize this technology. This has motivated the use of the supervised classification framework described here, which only depends on manually segmented images and can be implemented efficiently. Supervised methods for pixel classification have been shown in [2] and [5]. Feature vectors are formed by gray-scale values from a window centered on the pixel being classified.

A window of values is also used in [5], but the features used are a principal component transformation of RGB values and edge strength. In [2], ridge detection is used to form line elements and partition the image into patches belonging to each line element. Pixel features are then generated based on this representation. Many features are presented and a feature selection scheme is used to select those which provide the best class separability.

II. Materials and methods

2.1 Materials

There are different ways of obtaining ocular fundus images, Such as with color cameras, or through angiograms using fluoresce in as a tracer [6]. The drive database consists of 40 images along with manual segmentations of the vessels. The images are captured in digital form from a Canon CR5 nonmydriatic 3CCD camera at 45 field of view (FOV). The images are of size 768 584 pixels, eight bits per color channel and have a FOV of approximately 540 pixels in diameter.

The images are in compressed JPEG format, which is unfortunate for image processing but is commonly used in screening practice. The 40 images have been divided into a training and test set, each containing 20 images. The STARE database consists of 20 digitized slides captured by a TopCon TRV-50 fundus camera at 35 FOV.

2.2 General Framework

The image pixels of a fundus image are viewed as objects represented by feature vectors, so that we may apply statistical classifiers in order to segment the image. In this case, two classes are considered, vessel and nonvessel pixels.

2.3 Pixel Features

When the RGB components of the colored images are visualized separately, the green channel shows the best vessel/background contrast whereas the red and blue channels show low contrast and are very noisy [7]. Therefore, the green channel was selected to be processed by the wavelet, as well as to compose the feature vector itself, i.e., the green channel intensity of each pixel is taken as one of its features. The preprocessing algorithm starts with a region of interest (ROI) determined by the camera's aperture and iteratively grows this ROI.

2.3.1 Preprocessing

In order to reduce false detection of the border of the camera's aperture by the wavelet transform, an iterative algorithm has been developed. The preprocessing algorithm starts with a region of interest (ROI) determined by the camera's aperture and iteratively grows this ROI [8]. Each step of the algorithm consists in the following. First, the set of pixels of the exterior border of the ROI is determined, i.e., pixels that are outside the ROI and are neighbors (using four-neighborhood) to pixels inside it. Then, each pixel value of this set is replaced with the mean value of its neighbors (this time using eight-neighborhood) inside the ROI. Finally, the ROI is expanded by inclusion of this altered set of pixels.

2.3.2 Wavelet Transform Feature

Among several available analyzing wavelets, for instance, the 2-D Mexican hat and the optical wavelet, we chose the 2-D Gabor wavelet for the purposes of this work, due to its directional selectiveness capability of detecting oriented features and fine tuning to specific frequencies.

2.4 Supervised Classification for Segmentation

Supervised classification has been applied to obtain the final segmentation, with the pixel classes defined asC1=(vesselpixels)andC2=(nonvessel pixels)Several fundus images have been manually segmented [9]. Due to the computational cost of training the classifier and the large number of samples, we randomly select a subset of the available samples to actually use for training.

III. Implementation of system

3.1 K-means clustering

The K-means algorithm is an iterative technique that is used to partition an image into *K* clusters. The basic algorithm is:

1. Pick *K* cluster centers, either randomly or based on some heuristic

2. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center

3. Re-compute the cluster centers by averaging all of the pixels in the cluster

4. Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters)

In this case, distance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. *K* can be selected manually, randomly, or by a heuristic.

This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of *K*.

In statistics and machine learning, the k-means algorithm is a clustering algorithm to partition n objects into k clusters, where k < n. It is similar to the expectation-maximization algorithm for mixtures of Gaussians in that they both attempt to find the centers of natural clusters in the data. The model requires that the object attributes correspond to elements of a vector space. Since the algorithm is extremely fast, a common method is to run the algorithm several times and return the best clustering found. A drawback of the k-means algorithm is that the number of clusters k is an input parameter. An inappropriate choice of k may yield poor results. The algorithm also assumes that the variance is an appropriate measure of cluster scatter.

3.2 Semisupervised clustering

Semi-supervised clustering is introduced to cover some drawbacks of clustering (unsupervised learning) and classification (supervised learning), such as production of non-acceptable clusters or sometimes finding multiple grouping of data in the clustering process. In this situation semi-supervised clustering could be a good choice as a middle process between unsupervised learning and supervised learning. It has some applications in categorization of bioinformatics, news, images, etc.

Semi-supervised clustering uses some side-information to cover the categorization goal. This side-information could be the similar pairs from input data or information that indicates membership of the data items to specific clusters. This side-information usually has the pair-wise (must-link and cannot-link constraints) form in most studies. Must-link constraints impose data on the same cluster but cannot-link constraints impose them on different clusters.

These constraints prepare less information for algorithms than labeled data because they could extract from labels but they are more compatible for clustering. According to the process of using the side-information, semi-supervised clustering falls into two general approaches that are called search-based and similarity-based. In search-based approach, the clustering algorithm itself is modified so that user provided labels or constraints are used to bias the search for an appropriate partition. This can be done by modifying the objective function for evaluating clustering. In similarity-based approach, an existing clustering algorithm that uses a similarity metric is employed.

In this approach, first the similarity metric is trained to satisfy the labels or constraints in the supervised data and then clustering algorithms are applied on trained and untrained data.Most of the semi-supervised clustering methods have considered must-link and cannot-link constraints as side-information. Only a few methods use labeled data as side-information. The main reason for using negative and positive constraints is their accessibility in practical application. Also, the clusters number is not determined for data during clustering. In the next Sections, we have a review on clustering methods that are based on pair-wise constraints. In the former approach, the clustering algorithm changes when searching to find desired clusters that are affected by side-information and satisfaction of all constraints is noticeable during clustering.

The latter one learns distance index, before clustering then does clustering based on the learned distance index. This index attempts to reduce the distance between similar data points on the one hand and increase the distance among dissimilar data points, on the other hand.

IV. Results

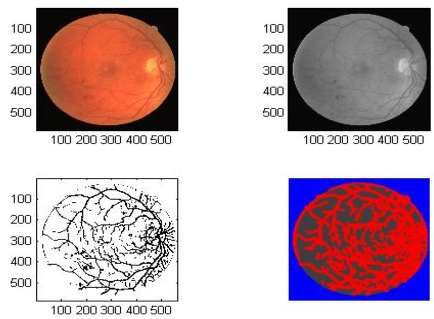

Fig.1 Retina image segmentation of first image

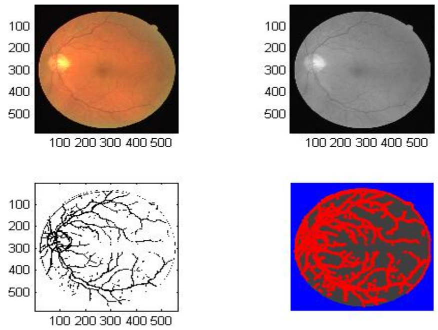

Fig.2 Retina image segmentation of second image

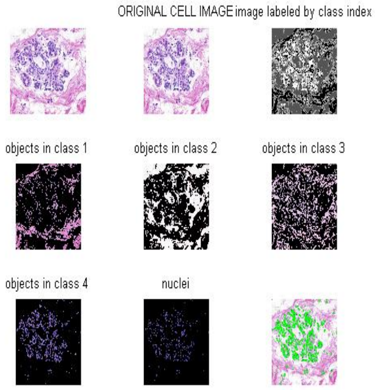

Fig.3 Cell Segmentation

V. Conclusion

In this paper, we have proposed and developed segmentation for large collection of images. The classification framework demands the use of manual labeling, but allows the methods to be trained for different types of images. While the performance difference is not large, this shows that even for the simple vessel structures there is a certain dependence of the method on the training set. We are studying the use of training sets composed of a small portion of the image to be segmented. Using this approach, a semi-automated fundus segmentation software may be developed, in which the operator only has to draw a small portion of the vessels over the input image or simply click on several pixels associated with the vessels.

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