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Fundus Image Analysis Using Mathematical Morphology

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INTRODUCTION

Quantifying visible retinal pathological features enable the clinician to follow the progress of a retinal disease and may provide an important diagnostic and followup tool [Peli 1989]. In general, quantification consists of counting specific type of objects and/or area measurements. In various conditions such measures serve as a good predictor for the progression of disease. For example, the counting of microaneurysims was shown to predict the progress of diabetic retinopathy and the eventual development of subretinal neovascularization in Age Relate Maculopathy (ARM) has been attributed to an increased number of drusen, and to large drusen.

Currently, the analysis of ophthalmic images in clinical studies is performed manually by trained observers. Manual counts of small numbers of well defined objects can be accurate and reproducible, but reliability declines as the objects become less sharply defined and larger in number. The time required for manual counting also increases significantly with the number of lesions to be counted. Area measurements are less well performed manually and therefore area measurements are frequently not attempted in such studies. Many of the pathologies are of irregular shape and may have ill defined boundaries, making inter and intra observer variability more likely.

With the advent of computerized image processing for research applications, methods of measuring retinal lesions have been described. Many of the techniques proposed for detection of retinal lesions are at best semi-automated requiring user interaction at the thresholding stage [Peli 1986, Ward 1989,Gilchrist 1987]. Even with these shortcomomings computerized measurements of retinal lesions offer reasonably fast (few minutes) processing and acceptable level of reproducibility as measured by a coefficient of variation (standard deviation / mean). Results much better than the performance of trained observers that count manually lesions in images. Despite their apparent potential and the increased availability of computerized image-acquisition systems designed specifically for ophthalmic applications [Peli 1989], these digital processing methods are primarily used in the laboratories in which they were developed.

Our overall goal is to enable the progression of these tools from the laboratory environment into the clinic. To that end we need to provide the Ophthalmic community with an automated, easy to use and cost effective capability to analyze retinal images. The most critical and difficult component of such a system is the first component - object detection and segmentation. The reliability and consistency of this component determines the ability to extract meaningful diagnostic information. In this paper we describe our approach to the detection and segmentation of lesions, which is based on a non-linear image processing paradigm termed *mathematical morphology*. To demonstrate the feasibility of our technique, we focused on the detection and segmentation of macular drusen. The same approach will be used in the future for the detection and segmentation of other types of fundus lesions and features.

METHODS

Materials

Color slides of regular clinical quality obtained from patients records were digitized. Fundus photographs of 5 patients were selected for the initial stages of this project. Multiple photos of the same eye taken at the same sitting were available (minimum of three). The multiple shots were used for evaluating the reproducibility of the image-analysis technique. The set of photographs were digitized into 256x256 pixels and adjusted to include the entire macular area (within the vascular arcades inside an image of that size).

Drusen detection / segmentation

Our approach to the detection and segmentation of lesions, which is based on a non-linear image processing paradigm termed *mathematical morphology*, is quite different from current techniques as it incorporates both amplitude (intensity) and size constraints at every stage of the processing including the pre-threshold image data [Peli 1993]. The specific sequence of morphological filters enables the detection of lesions that are brighter or darker than their local background. The incorporation of size constraints at the grayscale processing level results in the rejection of significantly greater numbers of false alarms corresponding to irrelevant background as well as the increased detection performance for low contrast lesions. As illustrated in Figure 1, our analysis consists of three key computational elements; lesion cueing, coarse, and fine segmentation.

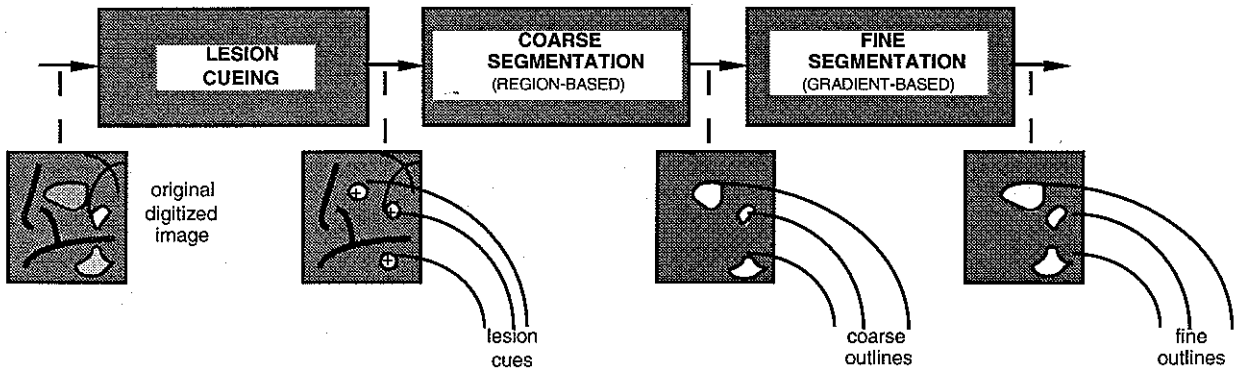

Figure 1: Multi-Stage Detection/Segmentation Process.

The cueing step locates regions in the image that are brighter than the local background and are likely to correspond to the desired lesion size (drusen). This is accomplished by first estimating the irrelevant background, subtracting the estimate from the original image (the result is termed the "residual" image) and thresholding. The estimated background is obtained by applying a sequence of morphological filters of kernel size that is proportional to the maximum expected extent of the desired lesions. Their application results in the removal of all instances of objects that are brighter than the local background and are smaller than the kernel size, while retaining all larger bright structures as well as dark objects (such as blood vessels) of all sizes.

The residual image consists of the desired lesions embedded in low level noise like background. Figure 2 illustrates a typical histogram of a "residual" image. The histogram is bimodal; mode 1 corresponds to the low level noise and mode 2 corresponds to the desired lesions. A global threshold is than set based on the estimated mean and standard deviation of the second mode corresponding to the desired lesion. The result of applying the global threshold is a set of cues that correlate with local peaks on intensity in the desired lesions.

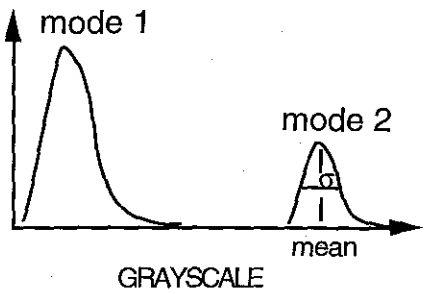

Figure 2: A Typical Bimodal Distribution of the Amplitude of the "Residual" Image. Mode 1 Corresponds to the Low Level Background and Mode 2 corresponds to the Desired Lesions.

Our segmentation approach overcomes the limitations of traditional object segmentation techniques that are either region-based or edge/gradient-based by combining both region and gradient information. We apply a two-stage segmentation process; first we estimate coarse drusen extent using a region growing technique on the "residual" image followed by boundary refinement that employs the gradient-based watershed transform [Beucher 1982].

The first stage extends the initial lesion cues that correspond to local amplitude peaks into lower amplitude levels of the residual image. The result is internal coarse boundaries. The second step extends/refines lesion boundaries to the location of gradient maxima through the application of a modified watershed transform. This process requires the marking of objects/lesions, marking of the background and estimate of the gradient image. For lesion marking we use the coarse segmentation, while the marking of the background is derived from the inversion of a dilation of object markings with a large kernel. The gradient image is estimated by the difference between the image and the image eroded with a kernel of radius 1. The watershed transform is then applied to the gradient image while imposing the constraints of both object and background marking. The resulting boundaries are located at the gradient maxima between lesion and background markings.

RESULTS

At this time we are at the first month of our six months project and therefore we currently have only initial results. Our analysis of the described process will be concluded by January 1994. At the conference we will present performance analysis of our completely automated drusen detection and segmentation technique in terms of probability of detection, false alarm rate and reproducibility of repeated photography and digitization.

Results of processing one of the digitized slides is given in Figure 3. The original digitized slide is given in Figure 3(a) and the corresponding estimated background in Figure 3(b). Notice that drusen contribution was removed while preserving large grayscale variations as well as the blood vessel across the top of the image. Figure 3(c) illustrates the output of our cueing and coarse segmentation steps. Initial cues are depicted as white regions, coarse lesion extent is marked in a gray shade and undetected areas are depicted as black regions.

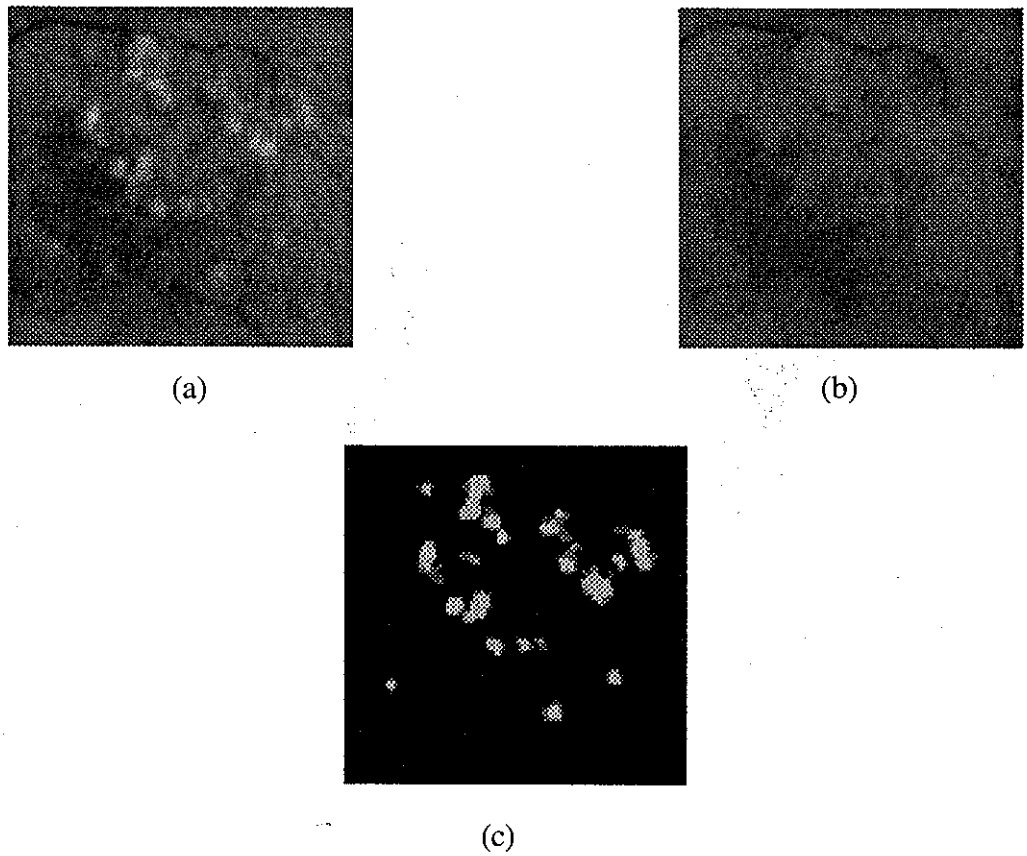

Figure 3 : Example processing of a digitized slide. (a) Original image (b) Estimated background (c) Initial cues and coarse segmentation.

ACKNOWLEDGEMENT

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