Asian Journal of Information Technology 6 (8): 842-846, 2007
ISSN: 1682-3915

Detection of Hard Exudates for Diabetic Retinopathy Using Contextual Clustering and Fuzzy Art Neural Network

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Abstract: The robust identification of red lesions in digital color fundus photographs is a vital pace in the development of automated screening systems for diabetic retinopathy. The retinal images are first subjected to preprocessing for color normalization and contrast enhancement. Contextual clustering algorithm is used to segment the retinal image. Before classifying the fragments, it is obligatory to locate and eliminate the optic disc. The detected candidate objects are classified as exudates or non-exudates using the features 'Convex Area' and 'Solidity' and 'Orientation'. The modular neural network is trained using a set of 25 images consisting of 5 normal images and 20 abnormal images. The trained system has been tested with 15 images and is found to acquire satisfactory results with 93.4% sensitivity and 80% specificity.

Key words: Contextual clustering, diabetic retinopathy, fuzzy art, hard exudate

INTRODUCTION

In the field of medical imaging, the accurate and automated delineation of anatomic structures from image data sequences is a perennial problem and there is a great attraction to the researching community to delve deeper in this domain. It evolves around the study of digital images with the sole objective of providing computational tools that will assist in quantification and visualization of interesting pathologies and anatomical structures. Patients with diabetes are often prone to develop eye disorders such as cataracts and glaucoma and its degree of impact on the retina may result in a loss of vision and this study is known as diabetic retinopathy, which is caused by the damage to blood vessels of the retina. Early diagnosis can certainly result in successful treatments in preventing the visual loss (Ghafour *et al*., 1983). First the fundus photographs are taken with the help of Topcon nonmydriative, a technical camera and subsequently analyzed by the ophthalmologist for the presence of abnormal features such as hard exudates, hemorrhages, cotton wool spots, drusen etc (Kanski, 1994).

The main principle behind this study is on intra retinal fatty (hard) exudates that are not only a perceptible sign of diabetic retinopathy but also an indication for the occurrence of co-existent retinal oedema and if present in the macular area, oedema and exudates are major players of visual loss in the non-proliferative forms of diabetic retinopathy (Kanski, 1994).

There are quite a number of the approaches reported in the study to detect the hard exudates. Extraction of hard exudates in grey scale images based on recursive growing technique with a sensitivity and specificity of 88.5 and 99.7%, respectively has been presented in Sinthanayothin (1999). Statistical classification for the extraction of hard exudates has been employed by Boria (1996), Young and Thomas (1974). Gardner *et al*. (1996) applied neural network to extract the lesions in a fundus image and achieved 93.1% sensitivity. Osareh *et al*. (2003) has applied the fuzzy c means for segmentation, BPA and Scaled Conjugate Gradient neural network techniques for classification and reported 93.0% sensitivity and 94.1% specificity. Osareh *et al*. (2002) has adopted various classifiers like Linear Delta Rule, K-Nearest Neighbors and Quadratic Gaussian classifier and finally concluded that neural network produces better performance than other methodologies. Osareh *et al*. (2002b) explored comparative exudates classification using Support Vector Machines and Neural Networks with 83.3% sensitivity and 95.5% specificity. A top-down and bottom-up strategy in lesion detection of background diabetic retinopathy have performed by Xiaohui and Opas (2005) using improved fuzzy c-means method. Kongbunkiat *et al*. (2006) have located the main retinal components such as optic disc, fovea and blood vessels and diabetic features such as exudates, hemorrhages and microaneurysms and reported 74.8% sensitivity and specificity 82.7%, respectively.

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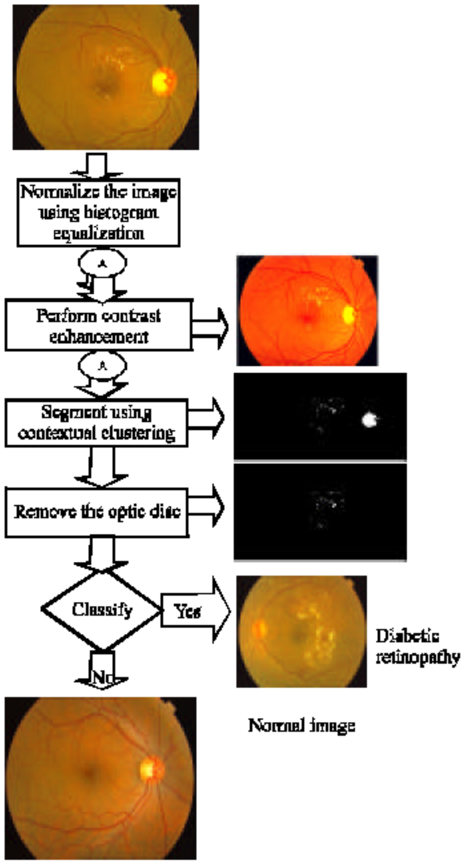


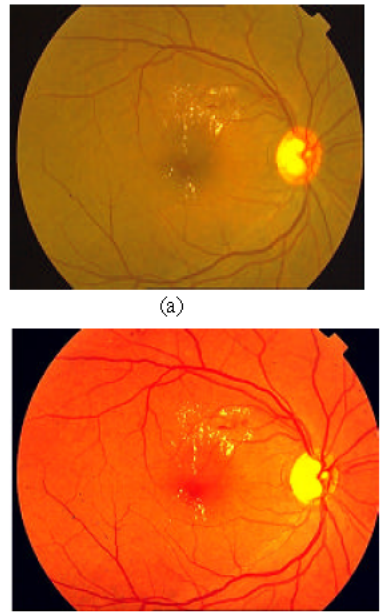
Fig. 1: Intelligent flow of the proposed system

Automatic detection of retinal anatomy to assist diabetic retinopathy screening has been developed by Fleming *et al*. (2007). In this the author has explained a robust location of the optic disc and fovea.

The deduction of diabetic hard exudates by deploying contextual clustering and subsequently the use of fuzzy art for classification are explored in this study.

The automated exudate identification system has been developed using colour retinal images provided by the Swamy Eye clinic, Chennai. According to the National Screening Committee standards all the images are obtained using a Canon CR6-45 Non-Mydriatic (CR6-45NM) retinal camera. A modified digital back unit (Sony PowerHAD 3CCD colour video camera and Canon CR-TA) is connected to the fundus camera to convert the fundus image into a digital image. The digital images are processed with an image grabber and saved on the hard drive of a Windows 2000 based Pentium -IV.

Figure 1 portrays the comprehensive view of the step-by-step process involved in the classification of diabetic retinal image.



(a)

(b)

Fig. 2: (a) Original image (b) Normalized image

MATERIALS AND METHODS

There is an extensive dissimilarity in the color of the fundus taken from different patients owing to the reasons like intrinsic attribute of lesions, decreasing color dispersion at the lesion periphery and lighting disparity, etc. This may result in color of the lesion of some images to be lighter than that of the background color. Under these conditions, there is every possibility that these lesions may erroneously be classified as background color. Hence, in the preparation of fundus images for hard exudate mining, keeping a high quality image as a reference image performs smoothing and by normalizing the colors of the other images against it will certainly enhance the quality of that image. Histogram equalization technique described in (Gonzalez and Woods, 1993) is applied independently for each RGB channel, followed by the color enhancement technique. Generally, hard exudates have the highest contrast with the background in the green color plane (Goldbaum *et al*., 1996) and hence the information from the other two planes is ignored in this study. Figure 2 represents the result of contrast enhancement.

RETINAL IMAGE SEGMENTATION

Image segmentation is a subjective and context-dependent cognitive process. It implicitly includes not only the detection and localization but also the delineation of the activated region. In medical imaging field, the precise and computerized delineation of anatomic structures from image data sequences is still an open problem. Countless methods have been developed, but as a rule, user interaction cannot be negated or the method is said to be robust only for unique kinds of images.

Contextual Clustering (CC): Eero (2002) first developed the contextual clustering method for detecting the MR lesions. The technique uses contextual information to enhance the detection rate of weakly activated regions. Segmentation of noisy images are improved in much application by employing spatial contextual information (Eero, 2002). The main assumption behind most contextual segmentation process is that the intensity distributions of diverse classes are recognized priori or the inference can be developed from the data.

The algorithm for contextual clustering planned in this study.

Step 1: The fundus image is subdivided into 3×3 overlapping patterns (SW) and a count is taken regarding the number of movements in both directions.

Step 2: Central Value (CV) is a located from 3×3 neighbourhood and determined the number of pixel values Greater than One (GO).

Step 3: With $0<\beta<1$ and a suitable Threshold Value (TV = 162) chosen by trial and error, label the Central Pixel with the Value (CPV) using the relation with regard to its neighborhood.

$$CPV=CV+(\beta/TV)*(GO-SW/2).$$

Step 4: If CPV > TV, then the central pixel is modified as 0.1 otherwise 0.9.

Step 5: The original CPV value and the modified CPV value (0.1/0.9) along with the sum of the neighborhood values of the window are the features stored in a file.

Fuzzy art neural network: Fuzzy art is a clustering algorithm that operates on vectors with analog-valued elements (Carpenter *et al.*, 1992). A fuzzy art model generates a new category if the existing categories are not suitable for the input pattern. These algorithms have been successfully applied to numerous tasks, including speech recognition, handwritten character recognition and target recognition from radar range profiles. Such applications often require the formation of thousands of clusters in a high dimensional feature space and could benefit from parallel implementation of the algorithm for high-speed or real-time classification.

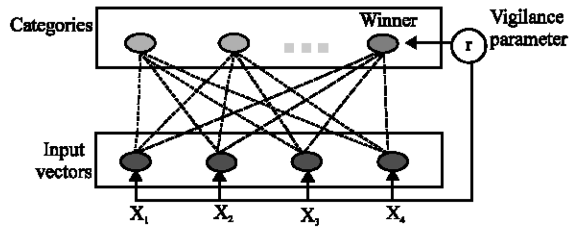


Fig. 3: Architecture of fuzzy art

Figure 3 shows the concept of Fuzzy art model. A Fuzzy art model generates a new category if the existing categories are not suitable or the input pattern. Competitive learning of Fuzzy art is done as follows (Shuta, 2000).

- Choose the winner category that has the biggest value of choice function.
- Judge the category Resonance or Reset by the match function.
  Resonance occurs if the value of match function is bigger than Vigilance parameter (r in Fig. 3).
  Then the weight of winner category is updated according to input vector.
  Otherwise, reset occurs. Then new category is generated according to input vector.
- Continue the above cycle until reset will not happen for each input vector.

HARD EXUDATES EXTRACTION

The contrast enhancement algorithm not only enhances the brightness of lesion patches that are distributed in the darker color retinal regions, but also augments the brightness of some surroundings pixels, so that these pixels would now be wrongly recognized as class lesion. Subsequently, there is a possibility for the segmented regions to contain the varying combinations of one or more retinal lesions including hard exudates, drusen, retinal light reflection most significantly the optic disc. To classify the fragmented region into exudate or non-exudates, the appropriate features of objects has to be considered to produce best class separability. The automatic optic disc localization algorithm has been carried out for location and elimination of the same. Further the segmented regions are discriminated to locate the hard exudates using features such as 'Convex Area', 'Solidity' and 'Orientation'.

Localization of optic disc: The optic disc is a component on the fundus from where optic nerves and blood vessel emerge. Localization and segmentation of an optic disc is an important step in the automated retinal image screening system. It appears comparatively brighter than the rest of the choroids due to the nonexistence of retina layer. It is found to be oval in shape with an average diameter of 1.5 to 1.7 mm and approximately 3 mm nasal to the fovea (Kheng *et al.*, 2000). Motivation for ascertainment of the optic disc is to negate it as a false positive candidate exudates region.

The image has been alienated as connected and labeled components. From this, the component with greater area has been recognized as optic disc and is eliminated, leaving only the candidate region (i.e.,) only the exudates region.

Classification: In order to classify, 10 objects are hand-labeled and their features like 'Convex Area' which represents the number of pixels in 'Convex Image', 'Solidity', the proportion of the pixels in the convex hull that are also in the region and is computed as Area/Convex Area and 'Orientation' specifies the angle (in degrees) between the x-axis and the major axis of the ellipse that has the same second-moments as the region are utilized to provide a representative dataset of two disjoint classes exudates and non-exudates. In the object classification a fuzzy art with 3 input nodes that corresponds to the features of the object were employed. Since the features produced are of analog, fuzzy art can be used to classify whether they are true candidate lesions.

RESULTS AND DISCUSSION

The various stages of results obtained are briefly described in Fig. 4. In Fig. 4 (a), the first 4 images are affected images and the last one is the normal image. Figure 4 (b) depicts the result of CC and the result of optic disc removal is shown in Fig. 4 (c).

The robustness and reliability of the algorithm was tested using twenty color fundus images of size 768 ×576. The candidate regions were located in the second plane and the images were then subjected to disc localization algorithm. The optic disc algorithm tested for all the images of training and testing and successfully identified the optic disc for 42 images with 93.33% accuracy. Lastly, the objects were classified as exudates or non-exudates in the automatic diagnosis process of exudative retinopathy for assisting the ophthalmologist to grade the retinal

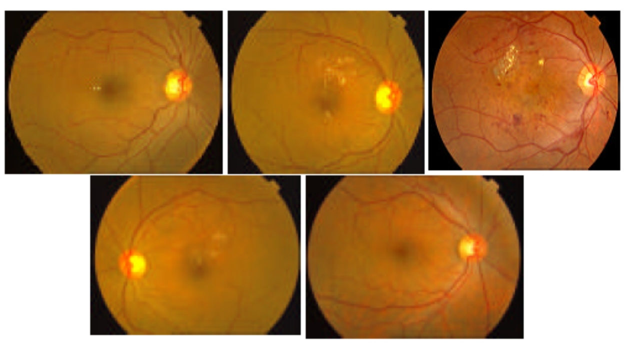


Fig. 4 a: Original images

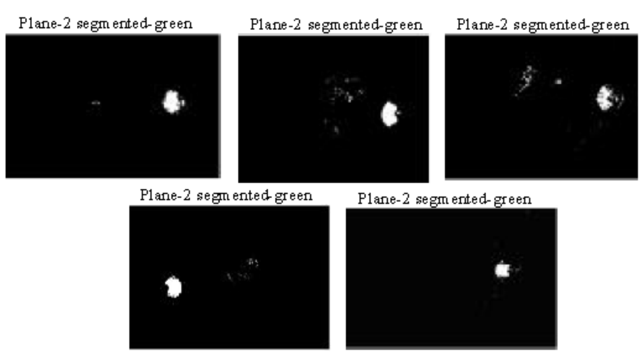


Fig. 4 b: Segmented images through CC

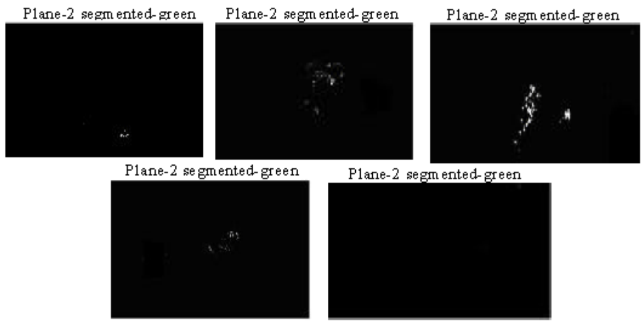


Fig. 4 (c): After elimination of optic disc

diseases. The exudates were detected in most of the cases and were found to be 93.4% sensitivity and 80% specificity. The study can be further extended to extract the other retinal pathologies like soft exudates and hemorrhages in retinal images to diagnose diabetic maculopathy.

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