A SURVEY ON OPTIC DISC DETECTION AND SEGMENTATION TECHNIQUES

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Abstract

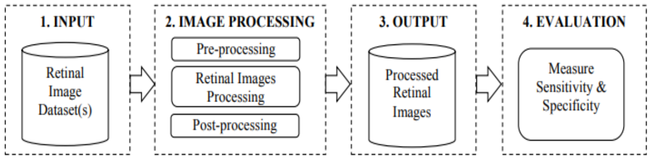
Optic disc detection and segmentation is an integral part of the automated system for screening. It is important to detect symptoms of Diabetic Retinopathy such as micro aneurysms, hard exudates, soft exudates, hemorrhages, neovascularization and macular edema. This paper examines the optic disk localization methodologies in two dimensional retinal images acquired from a fundus camera. The purpose of this article is to review and classify techniques and methods for the discovery and distribution of optical discs. The effectiveness of the partial algorithm is evaluated using a number of visual eyewear data that is publicly available through assessment evaluations that include accuracy and a real positive rating. Current and future research directions are summarized and discussed.

Keywords: Retinal Image Processing, Optic Disc(OD), Optic Disc Detection and Segmentation

1. Retinal Image Processing

The human eye is the most important organ that allows us to see the object or the place. Eyes are made of 3 layers. The inside is retina. Retina has many nerve cells. The layers of these nerve fibers are linked through synaptic. The optical disc is part of a retina called "blind spot". Macula is temporary for disk. The center is called fovea, responsible for a clear vision. Changes in the structure of the optical disc are a sign of many surgeries. The digital photography techniques are used for localization and the spectacular analysis of the optical disc. Based on the geometric relationship between the location of the optical disk and the structure of the arteries, the central macula can be placed [1]. The exact identification of optical disk refines partial distribution of exudates [2] and is used for the bottom diagnosis of hypertension [4] and diabetes [5]. Also, the Operational districts as a control point for an eye image listing, is used to calculate the equivalent of the center and artery of Retina. Sometimes it is used to detect blood vessels in the eyes. OD splits can take a lot of time to interfere with the image quality. Extensive research efforts are invoked to make automatic process for OD detection. The following section depicts the methodology of OD detection. Figure 1 provides the architecture of the image processingwith the steps to be followed, and the procedures applied.

Figure1:Retinal image processing diagram



1.Input – retinal image datasets: Contain several image shapes that make up the data entered.

2. Image processing: It has three sub steps to reorganize the retinal image and change it to a significant set of images.

i. **Preprocessing:** Primary steps generally aim to enhance the input retinal image (eg, contrast improvement, color enhancement, and removing noise).

ii. **Retinal image processing:** The main theme of retinal image processing is typically determined on segmentation of the image. This segmentation is the method of split the image into certain regions of interest. [8]. Regions of interest can contain the retinal irregularities (eg exudates, hemorrhage, aneurysms, etc.) and can also contain retinal sights (eg optical disc, macula and vascular tree).

iii. **Post-processing:** This step is considered as the final processing step projected to recognize the outer boundary or inner outline of the object that is separated into the retinal images.

3. Output – processed retinal images: The resulting data set refers to the retina image after it has been improved, processed, and then annotated. These processing images of retina are compared to basicfacts to determine the accuracy of the experimental work.

4. Evaluation: The performance of the experimental results which is given by the above steps is evaluated by metrics for positive, positive, negative, false and false negative.

2. Optic Disc Detection and Segmentation

The discovery and the localization of the main anatomy structures of optical disk, fovea, the eyes and arteries, are considered as important steps in the discovery and analysis of the lesions in the image. Consequently, the synthesis of eyes and segments can be used to create a system of mediators (neurological tests) of fundus that can be used to determine the relationship between the amount of swelling and blood relative to the optical disk and the macula. The optical disc is located on the right or left side of the background image. A first round or vertical oval shape measures approximately one sixth of the width of the image (for example, approximately 2 mm in diameter) that corresponds to approximately 80 ~ 100 pixels in the standard image of the fundus and usually appears like the light yellow or white areas, optical discs appear to be a similar area of artery blood vessels [1].

The discovery of optical discs and their properties analysis serves as an indicator of some vascular diseases such as cholesterol and glaucoma. Due to the similarities and disparities between exudates and optical discs, diabetes can be diagnosed by diagnostics and elimination of optical discs that improve diagnosis. [6].

The optical discovery process aims to set up a central optical disc, but optical edges should be set between the retina and the optical disc. The relative amount of optical cup and bone is a significant pointer for the existence of glaucoma.

3. Methodologies

The optic disk detection and segmentation is broadly categorized into the following groups.

3.1 Clustering Methods

Clustering is the process of organizing groups based on their attributes or patterns. This method describes each section by its structure and shape [7]. There are three commonly used rules algorithm like clustering k-means, fuzzy clustering rules and maximum pending algorithms. It calculates the average intensity for each class and the image segment by classifying each pixel in a class with a constant mean. Fuzzy clustering algorithms includes Fuzzy C-Means algorithm (FCM), Adaptive Fuzzy C-varieties algorithm (AFC), Fuzzy C-Shells algorithm (FCS), Fuzzy Quadric Shells algorithm (FCQS), Fuzzy C-Rectangular Shells algorithm (FCRS) and etc. The pros of the fuzzy is, it uses partial membership therefore more useful for real problems and the cons of the method is determining membership function is not easy.

3.2 Edge Based Detection Methods

Digital image can change dramatically in image light or different in intensity. These points are linked to creating a closed boundary of the object. The result of an edge-based segment is a binary image [8]. Grayscale gray and gradient are two basic methods in edge detection. Multiple operators are used by the edge detection methods, such as zero-passes, Laplacian of Guassian (LoG), and color edge tools,etc. The edge detection algorithm requires a balance between correct edge detection and low noise. Therefore, the edge detection algorithms are generally suitable for simple and noisy images. The advantages of Edge-Based Detection are: i) Secondary operators delivering reliable results. ii)It is useful when calculating the number of different objects in the image. The disadvantage of using this approach is that i) each operator is not suitable for all the different images and the computational complexity increases with the size of the operator. ii) Several times the edge is not continuous. iii) Ambiguity may cause problems.

3.3 Fuzzy Convergence Methods

This method defines the optical nerve as a focal point of the arterial network. To determine the intersection, the temporal arteries must be detected and then compaction is applied to create a hypothesis to conclude if the location found can be determined as the location of the operational district. Hoover et al. [7] established an algorithm for identifying ODs after submitting illumination. This algorithm recognizes Optic Nerve Head (ONH) by using ONH light characteristics.

3.4 Hough Transform Methods

Hough Transform is able to detect geometric shapes in the image. The optical disk has an approximate shape, so Hough's shift can be used to find the optical disc. Using radius of a fixed optical disc within the Hough parameter space, finding a circular object will be a dimensional problem. This method has a fixed radius shape at the foreground edge. To look at the end of all possible destinations for each pixel core,different edges are produced by using Sobel, Canny, Prewitt, Roberts and Log edge detection method. Maximum kernel response for each direction was saved. On this map, at the edge of the surface of the Retina, a level is used to get a binary map at the edge. Finally, the Hough Transformation technique is applied to the pixel edges in the Edge Map to collect the evidence of a fixed-circle radius in the image. The largest evidence circle has been chosen as an optical disc. [9]

3.5 Intensity Based Methods

The algorithms based on the intensity, suitable for normal images with smaller variations in intensity. These algorithms may fail when the OD is masked by blood vessels and diseases such as exudates, Cotton Wool Spot (CWS) and bright artefact. To determine the OD position from the intensity image you need to set the boot level. The brightness value is selected by setting the intensity range at 2 percentage of the image. The selected brightness is used to create binary images. Sinthanayothin et al. [1] approved a pixel of 80x80 since the OD size and variation of the approximate pixel density is used to determine the OD position. The highest pixel changes are considered as the center of the rays. Walter et al. created an OD algorithm with pixel brightness, isolated function, and color change in the color space for shadows (HueSaturatonLight)

3.6 Morphological Based Method

Welfer and. Al [10] introduces a new algorithm based on mathematical technique to identify the localization of optical discs and the edges of the optical disc. Morphological approach is applied to the gradients of the image. The gradient image can be considered as topography with boundaries between regions by Watershed transformation. Walter et al. [11] proposed method is to identify the individual regions of image with optical discs according to its properties (for example, circular areas with large regional intensities).

3.7 Machine Learning Based Methods

Artificial neural networks (ANNs) are a parallel network of process elements or nodes that simulate biological training. The image is transformed into a neural network and is trained with a set of training templates to define relationships and weight between nodes. Then, new images were divided by trained nervous networks. The division is done by using pixel distribution and edge detection [12]. ANN can also be used as a cluster method and for possible sampling. Because of the many connections that are used in the nervous system, field information can be easily incorporated into its distribution process. Although the ANNs are very consistent, their performance is usually shown on the computer by reducing the calculated properties. Some of the nervous networks that are most widely used for image use are Hopfield, Back propagation Neural Network (BPNN), Feed Forward Neural Network (FFNN), Pulse Coupled Neural Network (PCNN). The advantage of ANN's technique is that you do not need to write complex programs, but the limitations are the loss of time to train.

3.8 Pattern Recognition Methods

It recognizes the pattern that tries to break the functionality of the image using the known tag data [13]. The process of recognizing this template can be considered two tasks, such as making human-based decision-making (training) and being used to make decisions about unknown patterns. In many cases, the system is trained by the tagged "trainer" data, but other algorithms can be used to look up previously unknown templates (uncontrollable training) at when no data is tagged. The regular distributor is the nearest neighbor's classifier, where each pixel is classified in the same grade as the starting point of the training that has the nearest intensity. The nearest adjacent classifier is a summary of this approach and is considered as an unstructured administrator because it does not create a baseline conclusion for statistical data structures. The commonly used parameter determiner is the maximum probability or distribution. The advantage of this approach is to apply the division and methodology used to create a relationship between input and output. Disadvantages are complicated and limited on theme parameters

3.9 Partial Differential Equation (PDE) Methods

Image fragmentation based on PDE is usually performed by an active or serial pattern. The main idea of the snake is to change the division into a PDE framework. Some of the most popular PDE methods used for image sharing are Snake Levelling and Mumford Shah. The snake is a computerized curve that moves in the image to find the boundaries of objects under the influence of internal and external forces. The level setting method is used to represent the curve or surface area of the higher verification area. This technique not only gives the correct number change, but also makes the topological changes easy. The Mumford-Shah model uses global image information as a stop feature for image splitting, and this method benefits every image get the best picture [14]. The main advantage of this approach is the quick and appropriate approach to the timely program. The limit of this method is complex calculation

3.10 Region Based Methods

The regional section method divides images into different regions based on predetermined criteria like colors, intensity, or subject. The regional distribution method is divided into three main categories cultivation in the region, the region and the merger [15]. The technique of separating portions of the picture is a well-developed technique. Based on predefined criteria, this method extracts from the area of the image. The advantages of local methods are: i) Excellent results compared to other section methods. ii) Offers the flexibility to select interactive and automated allocation methods for images. iii) When it flows from the inner point to the outside, it is likely that there is a clear boundary for the object. The regional approach limits are: i) the establishment of stopping measures for division into a difficult task. ii) Good sequel results depend on a "correct" selection of seeds and may result in a division in the distribution of the seed if the user determines the seed. iii) Sequencing of the breed itself needs intervention by hand and is prone to error.

3.11 Template Matching Methods

The pattern matching method assumes that the optical disc is circular and has brightness based on the assumption that the model is created. Then, a work window of the size N × N is executed on the intensity of the image and for the new location of each current window, the proportion of the current window to the template is calculated. The highest contrast pixel is selected as the OD center location. Sample matching method is used by Lalonde et al. [24] to find an approximate distant. Initially, the images were normalized by applying the histogram confirmation, and then the disk area of 25 complex images was moderately calculated to obtain a gray gradient pattern. Then, the relative coefficients are used to find the perfect match between templates and all pixels in the image. Instead of creating a sample image,generate three histograms as a template, each corresponding to a color component. At the first step, they use a 6 × 6-pixel filter to reduce noise. Then, a window with a typical optical disc size (80 × 80 pixels) is used to extract the optical disc of each image of the retina. In the next step, the color components (red, green, and green) on each optical disk are separated to make the histogram of every colorparts. At last, the average histogram of each colorparts for all trial image patterns is found as a sample.

3.12 Threshold Based Methods

The survey operation converts multicast images into binary images. The appropriate T level has been chosen to separate the image pixels in several areas with the background objects. Each pixel (x, y) is considered to be a part of an object if its intensity is greater than or equal to the level. Insert image f (x, y) ≥ T otherwise pixels belong to the background [16]. Two level methods are used. When T is fixed it is called the global level. Otherwise it is called the basic level. The most commonly used storage usage is generally based on entropy, Otsu method, and more. Some basic level techniques are commonly used; low levels of simple statistical, low levels of histogram intensity, threshold based on 2-D entropy and more. The main techniques for practical applications proposed by many researchers are the P-tile method, the histogram technique, the extension of the edges. The advantages of standardized technique are: i) Quickest and most common technique used in general. ii) Easy for the hardware to be in parallel. The limitations of this technique are: i) Ignore information regarding the size of the image. ii) Highly sensitive. iii) The selection of the required value is important and often leads to excess or lower.

4. Datasets

4.1. Retinal Image Dataset

The retinal images are considered raw materials that will be consolidated, segmented and evaluated. This set of image data is usually accompanied by the fact that the base serves as a benchmark to compare and evaluate the experimental results using the actual results that are usually provided by medical professionals (i.e., eye) in a set of image data. The most extensively used data set explained in below.

4.1.1 STARE Dataset Description: STARE Structural Data [17]. There are 397 raw images captured by the Field of View (FOV). Each image in this dataset has 700 × 605 pixels with 24 bits per pixel. The images in this dataset are cut off from the top and bottom of FOV. True facts: All images in the dataset are identified with one or more negative variants of thirteen dissimilar variants that provide experimental artery distribution, including 40 images. It also has the job to find optical discs, including 81 images, along with realistic and experimental results.

4.1.2. DRIVE Dataset Description:
The DRIVE (Digital retinal Images for Vessel Extraction) database [18] has established to enable comparative studies on retinal image. The data set contains 40 images, of which 33 show no signs of diabetes, diabetes, and 7 indicate early diagnosis of dementia. Each image is captured with 8 bits in a 565 × 584-pixel color scheme with FOV of 45 degrees. For this database, the image is cropped around FOV, and each image is provided by the FOV image mask. A set of 40 images is divided into a two set of tests, both of which have 20 images for image training. The DRIVE websites provides a resulting page that shows the results of some algorithms.

4.1.3. MESSIDOR Dataset Description: MESSIDORs database (Method to Evaluate Segmentation and Indexing techniques in the field of Retinal Ophthalmology) [19] facilitates the diagnosisof Diabetes. The data set includes 1200 images in three sets. Every set is separated into four groups, each with a TIFF 100 image. The image is captured using a camera with an angle of 45 degrees using 8 bits per plane at 1440 × 960, 2240 × 1488 and 2304 × 1536 pixels. Each set is associated with a spreadsheet that includes the diagnosis of two levels, the baseline level, and the level of risk of eye swelling provided by a medical specialist for each image.

4.1.4. ONHSD Dataset Description: The data set out of the ONHSD (Optic Nerve Head Segmentation) [2] contains 99 images of fundus taken from 50 patients randomly sampled from the foot-tracking program for diabetes; Figure 96 has an Optical Fiber head (ONH). The image is obtained with a camera lens, fundus with 45-degree angles and 760 right × 570 pixels. The image has been converted to grayscale scale based on the musical component of the presentation of the HSI. There are significant differences in image quality, with many features that may affect distribution algorithms. The real reason: Centers at the hospital are notified by a doctor. After that, four doctors named the ONH edges with a roundabout (at a 15-degree angle) released from the center. The various identification of the edgesare used to show the level of subject uncertainty at the final position.

4.1.5. ImageRet Dataset Description: The ImageRet database [20] is separated into two subdivisions, DIARETDB0 and DIARETDB1.These two subdivisions are used for the detection of the diabetic result. This dataset was made public in 2008, which uses a digital fundus camera, used with 50 bachelor field views, of which every dimensional image is 1152× 1152 pixels, 1500 PNG format. In DIARETDB0 the diameter contains 130 images of retina with 20 is normal and the remaining 110 images have diabetic footprints. For each background image, there is a valid match to find all truth in a particular type of image.

5. Performance Analysis

5.1 Performance Metrics

The outcome of optic disc segmentation process is based on Region Of Interest (ROI) pixels. In diagnosis, medical discs are usually classified into two groups of optics: presence or absence; in the responses provided by an observer or computer are positive or negative. Table2 [2] describes a evaluation of medical test, determined by a TruePositive (TP), FalsePositive (FP),True Negative TN (TN), and False Negative (FN)

The TP and TN indices refer to the successful response in detecting and rejecting region of interests, respectively. The true positive index (TP) indicates the positive response of a human observer or computer for the ROI that is present within the retina, while the true negative index (TN) indicates the negative response for a landmark or abnormality that is not present. On the other hand, the FP and FN indices refer to an unsuccessful rejection and detection, respectively. The false positive index (FP) indicates the positive response for the ROI that is not present, whereas the false negative index (FN) indicates the negative response for the ROI that is present [25]. Derived from the four aforementioned indices, four statistical metrics are computed in order to evaluate the detection of abnormalities, which are: sensitivity, specificity, positive predictive value, negative predictive value and accuracy. Accuracy measures the ability or quality of presentation.

Table 1: Performance metrics

Measure/Method	Present ROI	Absent ROI
Positive Response	Hit (TP)	False alarm (FP)
Negative Response	Miss (FN)	Correct rejection (TN)

Sensitivity: SENS= TP /(TP+FN)

Specificity: SPEC=TN/(TN+FP)

Accuracy= (TP+TN)/(TP+FP+TN+FN)

5.2Discussions

Table 2: Result discussion with datasets

Authors	**Approach**	**Dataset**	**No of Images**	**Performance Metric & Value**
Aquino et al. [8]	Morphological, edge detecting, and feature extraction	MESSIDOR	1200	Accuracy 0.9576
Zhang et al. [9]	Projection with vessel distribution and appearance characteristics	DRIVE	40	Success Rate 0.9506
Welfer et al. [10]	Adaptive morphological approach	DRIVE DIARETDB1	40 89	Accuracy 0.9768
Yu & Yu [15]	Iterative brightest pixels extraction	STARE	40	Sensitivity 0.9500
Cheng et al. [22]	Peripapillary atrophy elimination	STARE	650	Accuracy 0.9843
Sinha and Babu [23]	Optic disc localization using L1 minimization	DIARETDB0 DIARETDB1 DRIVE	130 89 40	Accuracy 0.9877
Zhang & Zhao [25]	Histogram-based template matching	DIARETDB0 DIARETDB1 STARE	130 89 40 40	Sensitivity 0.9877
Kumar and Sinha [26]	Maximum intensity variation	MESSIDOR DIARETDB0	40 130	Accuracy 0.9136

6. Conclusion

This paper provides a detailed overview of the algorithms used for the part of the optical drive. Also, most of the current methods have been tested for a set of set data such as DRIVE and STARE. These datasets do not offer many different images. In addition, low-quality images (between 0.4 and 0.3 megapixels) make this process more competitive. Despite the many successive approaches, improvements to segment technology have improved. This brief studyachieves an efficient OD detection performance, and because it presents excellent stability against image size change, in real application, we can resize the original retinal image into a small size in advance, and then accurate and fast OD detection will be expected.Thus optic disc can be detected with high accuracy by the methodology and dataset discussed in section 3 and 4.

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