EARLY DETECTION OF MACULAR EDEMA IN FUNDUS IMAGE DATASETS USING NEURAL NETWORK

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Abstract—Medical systems based on state of the art image processing and pattern recognition techniques are very common now a day. These systems are of prime interest to provide basic health care facilities to patients and support to doctors. Diabetic macular edema is one of the retinal abnormalities in which diabetic patient suffers from severe vision loss due to affected macula. It affects the central vision of the person and causes total blindness in severe cases. Dme occurs when fluid and protein deposits collect on or under the macula of the eye. These leakages cause the macula to thicken and swell, progressively distorts a persons vision. So in this article detection of exudates and its proximity towards macula determines and thereby its severity level. In this article, we propose an intelligent system for detection and grading of macular edema to assist the ophthalmologists in early and automated detection of the disease. The proposed system consists of a novel method for accurate detection of macula using a detailed feature. A two-stage methodology for the detection and classification of dme severity from color fundus images is proposed. Dme detection is carried out via a supervised learning approach using the normal fundus images. A feature extraction technique is introduced to capture the global characteristics of the fundus images and discriminate the normal from dme images.

I.INTRODUCTION

A.Macular Edema

According to the 2011 National Diabetes Fact Sheet, 8.3 % of the populations in United States have diabetes [1] and today, nearly 1.2 million people in Malaysia have been diagnosed with diabetes in which half of them are unaware that they have the disease [2]. Prolonged suffering with diabetes may lead to diabetic retinopathy which is characterized by the damage of blood vessels of the retina. Diabetic macular edema is a complication of diabetic retinopathy and is often the true cause of visual loss and blindness [3]. Diabetic macular edema is diagnosed when interstitial fluid leaks from blood vessels within the macula region. The leakage is caused by the break-down of endothelial tight junctions in microaneurysms or retinal vessels. Lipid deposits accumulated in the retina resulting from the leakage is called exudates. Clinically, the exudates appear as well-defined, yellowish white intraretinal deposits on digital fundus image. Macula contains high concentration of photoreceptors responsible for shape and colour vision and it appears as dark area as seen in Fig. 1. The centre of macula is called fovea. The important step prior to exudates extraction is to remove optic disc on the image because exudates and optic disc has similar brightness. Optic disc is the entrance of blood vessel. Original fundus image of a patient diagnosed with stage 2 diabetic macular edema. Fovea is located at the center of the macula, (dotted arrow) and optic nerve. The occlusion of optic disc will not affect the detection process as there are usually no exudates found around the optic disc. A number of techniques to extract optic disc can be found in the literature [4]. In order to extract exudates, thresholding technique is the simplest technique but any low-contrast or uneven illumination image will affect the selection of threshold value for the exudates. A new unsupervised method using mixture model based on selecting dynamic threshold for exudates is proposed in [5], obtaining a sensitivity of 90.2%. In [6], candidate exudates regions were obtained by making use of the local properties of exudates and the combined global and adaptive histogram thresholding methods. The candidate regions were then classified as exudates or non-exudates by machine learning approach using statistical classifiers. The general limitation of using classifiers includes the intensive computing power required for training and classification. Besides, training size that is sufficient enough to represent the great properties variability of exudates has to be used. Morphological approach is recently employed because it requires less computational time and less computing power. In work done in [7], morphological operators were used in combination with sets of known shapes to give optimal contrast between the exudates and the background. In [8], four brightness properties on the exudates were used as input parameters to segmentation using Fuzzy C-means clustering that later fined tune with the morphological technique. This method was tested on low-contrast images and yields a sensitivity of 87.2 % and specificity of 99.2 %. In [9], a macular grid was placed centered on the fovea to provide the ophthalmologist with the distance information between the detected exudates and the macula. An algorithm for the localization of the macular has been presented in [10] by performing a search through a correlation procedure. In this paper, we intend to take one step further by locating the fovea location to develop an automated system that classifies diabetic macular edema into different severity stages. Since we aim at the realization of an automated system to grade severity stages, we would like to use it in combination with the exudates detection

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algorithm adopted from [11] because of its simplicity and its comparable results with known research works. Fig.2 shows the flow chart of the entire system in which our proposed classification method is highlighted with dotted lines.

II. IMAGE PROCESSING

In image processing the concept of feature detection refers to methods that aim at computing abstractions of image information and making local decisions at every image point whether there is an image feature of a given type at that point or not. The resulting features will be subsets of the image domain, often in the form of isolated points, continuous curves or connected regions. Bag-of-words-based image classification approaches mostly rely on low level local shape features. However, it has been shown that combining multiple cues such as color, texture, or shape is a challenging and promising task which can improve the classification accuracy. Most of the state-of-the-art feature fusion methods usually aim to weight the cues without considering their statistical dependence in the application at hand.

A. Anatomical Structure of Human Eye

Fig. 1. Color fundus image with anatomical structures and lesions annotated

The human eye has been called the most complex organ in our body. It's amazing that something so small can have so many working parts.

Working of Human Eye:

In a number of ways, the human eye works much like a digital camera:

- Light is focused primarily by the cornea the clear front surface of the eye, which acts like a camera lens.
- The iris of the eye as shown in the Figure 1.1 functions like the diaphragm of a camera, controlling the amount of light reaching the back of the eye by automatically adjusting the size of the pupil.
- The eye's crystalline lens is located directly behind the pupil and further focuses light. Through a normal process called accommodation, this lens helps the eye automatically focus on near and approaching objects, like an autofocus camera lens.
- Light focused by the cornea and crystalline lens then reaches the retina the light sensitive inner lining of the back of the eye. The retina acts like an electronic image sensor of a digital camera, also converting optical images into electronic signals. The optic nerve then transmits these signals to the visual cortex the part of the brain that controls our sense of sight.
B. Purpose of Image Processing
The purpose of image processing is divided into 5 groups. They are:

1. Visualization - Observe the objects that are not visible.
2. Image sharpening and restoration - To create a better image.
3. Image retrieval - Seek for the image of interest.
5. Image Recognition – Distinguish the objects in an image.

C. Types
The two types of methods used for Image Processing are Analog and Digital Image Processing. Analog or visual techniques of image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. The image processing is not just confined to area that has to be studied but on knowledge of analyst. Association is another important tool in image processing through visual techniques. So analysts apply a combination of personal knowledge and collateral data to image processing.

D. Images And Pictures
![Sample images (green channel) and result of macula and optic disk detection. OD is indicated by a bright rectangular mask and the macula location by a circular mask. (a) Sample image A. (b) Detected macula and OD for sample image A. (c) Sample image B. (d) Detected macula and OD for sample image B.](image)

Since the severity of DME is determined based on the location of HE clusters relative to the macula, the images acquired for DME detection usually focus around the macular region. We find the best fit circle within the fundus mask with macula at the center, for a given image. The region within this circle is the desired ROI denoted as the green channel of forms the input for all subsequent processing. The center of macula is automatically detected using and restricting the search to a central region of the given image since the acquired images for DME detection are macula-centric. Since the OD shares a brightness characteristic similar to HE, it is also automatically detected and masked. The result of macula and optic disc detection can be seen in Fig. 2 where the macula is shown as a circular patch and the OD is shown as a rectangular patch.

E. Image Acquisition And Sampling
Sampling refers to the process of digitizing a continuous function. For example, suppose we take the function

\[ Y = \sin(x) + \frac{1}{3}\sin(3x) \]
and sample it at ten evenly spaced values of $x$ only. This shows an example of under sampling, where the number of points is not sufficient to reconstruct the function. Suppose we sample the function at 100 points, as shown in figure. We can clearly now reconstruct the function; all its properties can be determined from this sampling. In order to ensure that we have enough sample points, we require that the sampling period is not greater than one-half the finest detail in our function. This is known as the Nyquist criterion, and can be formulated more precisely in terms of frequencies. The Nyquist criterion can be stated as the sampling theorem, which says, in effect, that a continuous function can be reconstructed from its samples provided that the sampling frequency is at least twice the maximum frequency in the function.

Fig. 3. Graphical depiction of motion pattern generation. First pattern: a disk with one lesion (shown as a red dot). The rest are results of applying motion with decreasing rotation steps: $\pi, \pi/2, \pi/4, \pi/8$. In each case, the union of the patterns obtained after a complete cycle of rotation (0 to $2\pi$) is shown.

The creation of a motion pattern is motivated by the effect of motion on biological/computer visual system. These systems represent a scene as a set of spatially sampled (by the sensors/detectors) intensities or an image. This sampling is uniform in cameras while it is log polar in human eyes. When an object in a scene moves at a high speed, it usually leaves a smearing pattern in the captured image. Generally, the spatio-temporal changes recorded by the sensor are characteristic of the moving object. In computer vision, the estimation and removal of the smear pattern, also popularly known as motion blur in images, has been an active area of researched. We argue that there is much information about the scene in the smear pattern and propose to use it to represent an image. We do this by simulating this operation in a single image by inducing motion.

Signal aggregation at sensor locations in human eyes and camera, gives rise to the smearing effect. In order to simulate this effect, we induce motion in a given image to generate a sequence of images. These are combined by applying a function to coalesce the intensities at each sensor location to give rise to a motion pattern. Let the given ROI be denoted as $I$. A motion pattern for is derived as follows:

$$I_{MP}(\vec{r}) = f(G_N(I(\vec{r})))$$

where $\vec{r}$ denotes a pixel location, is a transformation representing the induced motion which is assumed to be rigid. Practically speaking, generates transformed images which are combined using to coalesce the sampled intensities at each pixel location (1). Here, $G_N(I)$ is expressed as follows:

$$G_N(I) = \{R_{\theta_n}(I)\}$$

Where $R$ is a rotation matrix. The rotation angle $\theta_n = n\theta_0$ with $n = 0,1,...,N$; $\theta_0$ denotes the rotation step. When $n = 0$, we have no rotation and hence $R_0(I) = I$. Thus $G_N$ is a set of rotated versions of the given $I$ and the total number of rotated images $N = (2\pi)/(\theta_0)$.

The sampling rate $\theta_0$ of the detector determines the number of images generated in the set. In the problem at hand, since HE appear as bright localized lesions against the retinal background, they should form a bright smear pattern in whereas the textured background will be smoothed out. This representation can thus spatially enhance the characteristics of HE and help improve their detectability. At the same time, this should also serve to minimize the effect of the variability observed across images by smoothing them out. Since, the severity of the disease is directly related to the radial distance of HE in the circular ROI, rotational motion is induced to generate the desired . The transformation function is applied to to generate a sequence of images which are rotated versions of $I$. The spatial extent of smearing of intensities depends on the maximum rotation whereas the sampling rate at each location is directly related to the size of each rotation step. The generation of motion patterns is shown graphically in Fig. 3. Consider a disk with a single circle near the periphery modeling a lesion (first pattern). When rotation is applied to this pattern in steps of , a set of patterns are generated. When two patterns will be generated and their union is the second pattern in Fig. 3. The remaining patterns in this
figure are the result of the union of patterns generated with decreasing step size. It can be observed that a decrease in the step size results in several copies of the lesion in the final result. In this example, the motion pattern is obtained by using the union operation as the coalescing function. In practice, any coalescing function can be employed. The strength of the signal at will not only depend on the choice of , but also on the sampling rate.

In the problem at hand, the choice of should ideally 1) enhance the HE by increasing the extent of the smear caused by it in the motion pattern and 2) increase the homogeneity of retinal background. Accordingly, two functions namely Mean and Maximum were considered in this work. These are defined as follows:

$$P_{\text{MP}}^{\text{Mean}}(r^*) = \frac{1}{N} \sum_{n=0}^{N-1} R_{\theta_n}(I(r^*)) \quad (2)$$

$$P_{\text{MP}}^{\text{Max}}(r^*) = \max_{n=[1, \ldots, N-1]} R_{\theta_n}(I(r^*)) \quad (7)$$

While the coalescing function Mean (2) tries to achieve the averaging effect observed in motion blur, Maximum (3) tries to exploit the fact that HE usually appear brighter than any other structures in the background at the same radial distance. It can be seen that motion patterns are clearly distinct for these two classes.

F. ASPECTS OF IMAGE PROCESSING

It is convenient to subdivide different image processing algorithms into broad subclasses. There are different algorithms for different tasks and problems, and often we would like to distinguish the nature of the task at hand.

G. IMAGE ENHANCEMENT.

This refers to processing an image so that the result is more suitable for a particular application.

Example include:

- Sharpening or de-blurring an out of focus image,
- Highlighting edges,
- Improving image contrast, or brightening an image.

H. IMAGE RESTORATION.

This may be considered as reversing the damage done to an image by a known cause, for example:

- Removing of blur caused by linear motion,
- Removal of optical distortions,
- Removing periodic interference.

I. IMAGE SEGMENTATION.

This involves subdividing an image into constituent parts, or isolating certain aspects of an image:

- Ending lines, circles, or particular shapes in an image.
- In an aerial photograph, identifying cars, trees, buildings, or roads.

J. BASICS OF IMAGE DISPLAY

An image may be represented as a matrix of the grey values of its pixels. The problem here is to display that matrix on the computer screen. There are many factors which will effect the display they include:

1. Ambient lighting.
2. The monitor type and settings.

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3. The graphics card.
4. Monitor resolution.

The same image may appear very different when viewed on a dull CRT monitor or on a bright LCD monitor. The resolution can also affect the display of an image; a higher resolution may result in the image taking up less physical area on the screen, but this may be counteracted by a loss in the colour depth: the monitor may be only to display 24-bit colour at low resolutions. If the monitor is bathed in bright light (sunlight, for example), the display of the image may be compromised. Furthermore, the individual's own visual system will affect the appearance of an image: the same image, viewed by two people, may appear to have different characteristics to each person. For our purpose, we shall assume that the computer set up is as optimal as is possible, and the monitor is able to accurately reproduce the necessary grey values or colours in any image. To display the image properly, we need to add several extra commands to the image line.

1. True size, which displays one matrix element (in this case an image pixel) for each screen pixel. More formally, we may use true size([256 256]) where the vector components give the number of screen pixels vertically and horizontally to use in the display. If the vector is not specified, it defaults to the image size.
2. Axis off which turns off the axis labelling.
3. Color map(gray(247)), which adjusts the image colour map to use shades of grey only.

Histograms

Given a greyscale image, its histogram consists of the histogram of its grey levels; that is, a graph indicating the number of times each grey level occurs in the image. We can infer a great deal about the appearance of an image from its histogram, as the following examples indicate:
- In a dark image, the grey levels (and hence the histogram) would be clustered at the lower end;
- In a uniformly bright image, the grey levels would be clustered at the upper end;
- In a well contrasted image, the grey levels would be well spread out over much of the range.

K. Linear Filtering In Matlab

The filter2 function does the job of linear filtering for us; its use is filter2(filter,image,shape) and the result is a matrix of data type double. The parameter shape is optional, it describes the method for dealing with the edges:
- Filter2(filter, image,' same') is the default; it produces a matrix of equal size to the original image matrix. It uses zero padding.

L. Edge Sharpening

Spatial filtering can be used to make edges in an image slightly sharper and crisper, which generally results in an image more pleasing to the human eye. The operation is variously called edge enhancement, edge crispening, or unsharp masking. This last term comes from the printing industry.

M. Non-Linear Filters

Linear filters, as we have seen in the previous sections, are easy to describe, and can be applied very quickly and efficiently by Matlab. A non-linear filter is obtained by a non-linear function of the grey scale values in the mask.

Simple examples are the maximum filter, which has as its output the maximum value under the mask, and the corresponding minimum filter, which has as its output the minimum value under the mask. Both the maximum and minimum filters are examples of rank-order filters. In such a filter, the elements under the mask are ordered, and a particular value returned as output. So if the values are given in increasing order, the minimum filter is a rank-order filter for which the first element is returned, and the maximum filter is a rank-order filter for which the last element is returned. For implementing a general non-linear filter in Matlab, the function to use is nlfilter, which applies a filter to an image according to a pre-defined function. If the function is not already defined, we have to create an m-file which defines it.
N. Sampling And Quantization
In order to become suitable for digital processing, an image function \( f(x,y) \) must be digitized both spatially and in amplitude. Typically, a frame grabber or digitizer is used to sample and quantize the analogue video signal. Hence in order to create an image which is digital, we need to covert continuous data into digital form. There are two steps in which it is done:

- **Sampling**
- **Quantization**

The sampling rate determines the spatial resolution of the digitized image, while the quantization level determines the number of grey levels in the digitized image. A magnitude of the sampled image is expressed as a digital value in image processing. The transition between continuous values of the image function and its digital equivalent is called quantization.

The number of quantization levels should be high enough for human perception of fine shading details in the image. The occurrence of false contours is the main problem in image which has been quantized with insufficient brightness levels.

O. Resizing Image
Image interpolation occurs when you resize or distort your image from one pixel grid to another. Image resizing is necessary when you need to increase or decrease the total number of pixels, whereas remapping can occur when you are correcting for lens distortion or rotating an image. Zooming refers to increase the quantity of pixels, so that when you zoom an image, you will see more detail.

Interpolation works by using known data to estimate values at unknown points. Image interpolation works in two directions, and tries to achieve a best approximation of a pixel's intensity based on the values at surrounding pixels. Common interpolation algorithms can be grouped into two categories: adaptive and non-adaptive. Adaptive methods change depending on what they are interpolating, whereas non-adaptive methods treat all pixels equally. Non-adaptive algorithms include: nearest neighbor, bilinear, bicubic, spline, sinc, lanczos and others. Adaptive algorithms include many proprietary algorithms in licensed software such as: Qimage, Photo Zoom Pro and Genuine Fractals.

Many compact digital cameras can perform both an optical and a digital zoom. A camera performs an optical zoom by moving the zoom lens so that it increases the magnification of light. However, a digital zoom degrades quality by simply interpolating the image. Even though the photo with digital zoom contains the same number of pixels, the detail is clearly far less than with optical zoom.

P. Aliasing And Image Enhancement
Digital sampling of any signal, whether sound, digital photographs, or other, can result in apparent signals at frequencies well below anything present in the original. Aliasing occurs when a signal is sampled at a less than twice the highest frequency present in the signal. Signals at frequencies above half the sampling rate must be filtered out to avoid the creation of signals at frequencies not present in the original sound. Thus digital sound recording equipment contains low-pass filters that remove any signals above half the sampling frequency.

Since a sampler is a linear system, then if an input is a sum of sinusoids, the output will be a sum of sampled sinusoids. This suggests that if the input contains no frequencies above the Nyquist frequency, then it will be possible to reconstruct each of the sinusoidal components from the samples. This is an intuitive statement of the Nyquist-Shannon sampling theorem.

Anti-aliasing is a process which attempts to minimize the appearance of aliased diagonal edges. Anti-aliasing gives the appearance of smoother edges and higher resolution. It works by taking into account how much an ideal edge overlaps adjacent pixels.
Q. Contrast Enhancement

Image enhancement techniques have been widely used in many applications of image processing where the subjective quality of images is important for human interpretation. Contrast is an important factor in any subjective evaluation of image quality. Contrast is created by the difference in luminance reflected from two adjacent surfaces. In other words, contrast is the difference in visual properties that makes an object distinguishable from other objects and the background. In visual perception, contrast is determined by the difference in the colour and brightness of the object with other objects. Our visual system is more sensitive to contrast than absolute luminance; therefore, we can perceive the world similarly regardless of the considerable changes in illumination conditions. Many algorithms for accomplishing contrast enhancement have been developed and applied to problems in image processing. If the contrast of an image is highly concentrated on a specific range, e.g., an image is very dark, the information may be lost in those areas which are excessively and uniformly concentrated. The problem is to optimize the contrast of an image in order to represent all the information in the input image.

R. Spatial Domain Filtering

Filtering is a technique for modifying or enhancing an image. Spatial domain operation or filtering (the processed value for the current pixel processed value for the current pixel depends on both itself and surrounding pixels). Hence Filtering is a neighborhood operation, in which the value of any given pixel in the output image is determined by applying some algorithm to the values of the pixels in the neighborhood of the corresponding input pixel. A pixel's neighborhood is some set of pixels, defined by their locations relative to that pixel.

Spatial filtering is a form of finite impulse response (FIR) filtering. The filter is actually a mask of weights arranged in a rectangular pattern. The process is one of sliding the mask along the image and performing a multiply and accumulate operation on the pixels covered by the mask.

III. EXISTING SYSTEM

Diabetic macular edema is a common complication of diabetic retinopathy due to the presence of exudates in proximity with the fovea. In this paper, an automated method to classify diabetic macular edema is presented. The fovea is localized and the regions of macula are marked based on the Early Treatment Diabetic Retinopathy Studies (ETDRS) grading scale. Extraction method using marker-controlled watershed transformation is adopted and modified from the previous research. The location of the extracted exudates on the marked macular regions is computed to classify diabetic macular edema into normal, stage 1 and stage 2 diabetic macular edema. The performance of the proposed method is evaluated using 88 images of publicly available MESSIDOR.

IV. EXISTING BLOCK DIAGRAM
A. Image Database
In this work, 41 digital fundus images of normal, 14 images of stage 1 diabetic macular edema and 33 images stage 2 diabetic macular edema were selected from MESSIDOR, a publicly available database, as our test images. The images were acquired by using a colour video 3CCD camera on a Topcon TRC NW6 non-mydriatic retinograph with a 45 degree field. The images were captured using 8 bits per colour plane at 2240 x 1488. We have verified that all images are of sufficient quality and the annotations made for diagnosis have been considered as the reference standard to evaluate the results of our algorithm.

B. Exudates Detection
Prior to detecting exudates, the image has to undergo series of process to ensure adequate level of success is achieved in exudates detection. It is reliable to work on green colour component of the image because the contrast shown between the exudates, optic disc with the background is relatively higher. Contrast-limited adaptive histogram equalization (CLAHE) is done twice and contrast stretching transformation is done once to assign the exudates and optic disc with the highest intensity values. The image is then complemented to change the higher-intensity features into dark pixels. Fig.3 shows the image obtained after image is complemented. Inclusion of optic disc into the algorithm may affect the performance as the optic disc appears with almost the same contrast with exudates. Extended minima transformation is applied and the threshold parameter is set to a fixed value of 2. The output image will be a binary image whose foreground pixels mark the location of the deep regional minima. Following extended minima transformation, morphological opening and dilation are performed. In order to create a circular mask of optic disc, the optic disc centroid is identified. Prior to watershed transformation, the gradient magnitude of the optic disc eliminated image is computed by using Sobel linear filter. To control oversegmentation, an approach based on markers is used. Internal markers are obtained by using extended minima transformation on optic disc eliminated image with threshold set to 2. The external markers are obtained by using Euclidean distance transform on the internal marker image. Using the internal markers and external markers the gradient image is modified using a procedure called
minima imposition. The purpose of minima imposition is to modify the image so that regional minima occur only in marked locations. Watershed transformation image is then superimposed on the negative image and converted into a RGB image as shown in Fig. 3. A negative image. The image is then converted into binary image with threshold value of 0.93. Fig. 3 shows the extracted exudates from the original image.

C. Fovea Localization
In this paper, diabetic macular edema is defined based on the ETDRS grading scale as shown in Table I. The location of the fovea is the determinant in classifying diabetic macular edema into stages, finding the location of fovea is therefore the preliminary and crucial stage in classification. A morphological closing operator is applied on the preprocessed image (refer to Fig. 2) to discard other small features that could interfere in fovea detection. An annular mask is then created with the purpose of including fovea in the annular mask region. An annular binary mask with radius 345 to 600 pixels from the center of the optic disc is computed. The annular mask radius is defined based on experimental observations with a number of images. From the region of interest (ROI) obtained by the annular mask, the location in which pixels having minimum value in the ROI is identified as the location of the fovea because fovea appears as dark region in the fundus image. Unwanted regions of the mask are then removed once the location of fovea is identified. The images obtained following steps in fovea localization.

D. CLASSIFICATION
Disc diameter of optic disc is set to be 276 pixels based on observation on few numbers of images. The region of the macula for macular edema detection is divided into two, based on the definition given by ETDRS scale, one with a radius of 138 pixels and another with a radius of 276 pixels. If the exudates were found present in the region with radius 138 pixels, it is classified as stage 1 diabetic macular edema and if exudates were found present in region with radius 276 pixels it is classified as stage 2 diabetic macular edema. Exudates found elsewhere from these two regions are not taken into account for sign of diabetic macular edema.

VI. PROPOSED WORK
HE appear as clusters of bright, high contrast lesions and are usually well localized. The macula is a dark structure roughly at the center of the retina. In the absence of any HE (i.e., a normal retina), there is a rough rotational symmetry about the macula in the circular region of roughly twice the diameter of the optic disc. We use this observation to derive relevant features to describe the normal and abnormal cases. Given a color fundus image, a circular region of interest (ROI) is first extracted and an intermediate representation also known as the motion pattern of the ROI is created. Relevant features are then derived for to classify the given image as normal or abnormal (containing HE).
A. Region Of Interest Extraction
Since the severity of DME is determined based on the location of HE clusters relative to the macula, the images acquired for DME detection usually focus around the macular region. We find the best fit circle within the fundus mask with macula at the center, for a given image. The region within this circle is the desired ROI denoted as (see Fig. 3 for an example). The green channel of forms the input for all subsequent processing. The center of macula is automatically detected using and restricting the search to a central region of the given image shown in Fig.4, since the acquired images for DME detection are macula-centric. Since the OD shares a brightness characteristic similar to HE, it is also automatically detected and masked.

B. Generation of Motion Pattern
The creation of a motion pattern is motivated by the effect of motion on biological/computer visual system. Here motion is induced in a given image to generate a sequence of images. These are combined by applying a function to coalesce the intensities at each sensor location to give rise to a motion pattern. A motion pattern for is derived as follows, Let the given ROI be denoted as Imp.

Radon Transform based Descriptor (RTD): Given an image, its Radon transform is the projection of intensities along a line oriented at direction \( \alpha \). \( \alpha \) is the angle between the lines of projection and the x axis. We obtain a feature vector for the image IGMP by concatenating the projections for different values of angle \( \alpha \). The feature vector is normalized to address variation in the sizes of OD that occur across patients. Accentuated spatial extent of neuroretinal rim in IGMP of normal cases is reflected in the projection based feature vector. A large neuroretinal rim for normal OD will exhibit a shorter width of the intensity hill in 1-D projection in comparison to glaucomatous OD.

C. Abnormality Detection
The Mahalanobis distance is a measure of the distance between a point \( P \) and a distribution \( D \), introduced by P. C. Mahalanobis in 1936.\(^{[1]}\) It is a multi-dimensional generalization of the idea of measuring how many standard deviations away \( P \) is from the mean of \( D \). This distance is zero if \( P \) is at the mean of \( D \), and grows as \( P \) moves away from the mean: along
each principal component axis, it measures the number of standard deviations from P to the mean of D. If each of these axes is rescaled to have unit variance, then Mahalanobis distance corresponds to standard Euclidean distance in the transformed space. Mahalanobis distance is thus unitless and scale-invariant, and takes into account the correlations of the data set. Consider the problem of estimating the probability that a test point in N-dimensional Euclidean space belongs to a set, where we are given sample points that definitely belong to that set. Our first step would be to find the average or center of mass of the sample points. Intuitively, the closer the point in question is to this center of mass, the more likely it is to belong to the set.

However, we also need to know if the set is spread out over a large range or a small range, so that we can decide whether a given distance from the center is noteworthy or not. The simplistic approach is to estimate the standard deviation of the distances of the sample points from the center of mass. If the distance between the test point and the center of mass is less than one standard deviation, then we might conclude that it is highly probable that the test point belongs to the set. The further away it is, the more likely that the test point should not be classified as belonging to the set.

This intuitive approach can be made quantitative by defining the normalized distance between the test point and the set to be $\frac{d}{\sigma}$ by plugging this into the normal distribution we can derive the probability of the test point belonging to the set.

The drawback of the above approach was that we assumed that the sample points are distributed about the center of mass in a spherical manner. Were the distribution to be decidedly non-spherical, for instance ellipsoidal, then we would expect the probability of the test point belonging to the set to depend not only on the distance from the center of mass, but also on the direction. In those directions where the ellipsoid has a short axis the test point must be closer, while in those where the axis is long the test point can be further away from the center.

Putting this on a mathematical basis, the ellipsoid that best represents the set's probability distribution can be estimated by building the covariance matrix of the samples. The Mahalanobis distance is the distance of the test point from the center of mass divided by the width of the ellipsoid in the direction of the test point.

### VII. SYSTEM REQUIREMENT

#### A. Hardware Requirements

- Processor: Pentium -v
- Speed: 1.1 GHz
- RAM: 2 GB
- Hard Disk: 80 GB
- Key Board: Standard Keyboard
- Mouse: Two or Three Button
- Monitor: LG Color Monitor

#### B. Software Requirements

- Language: Matlab(R2013av:8.1.0)

#### C. Matlab Basic Concepts

MATLAB (matrix laboratory) is a multi-paradigm numerical computing environment and fourth-generation programming language. A proprietary programming language developed by Math Works, MATLAB allows matrix manipulations, plotting of...
functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, Fortran and Python. Although MATLAB is intended primarily for numerical computing, an optional toolbox uses the MuPAD symbolic engine, allowing access to symbolic computing capabilities. An additional package, Simulink, adds graphical multi-domain simulation and model-based design for dynamic and embedded systems In 2004, MATLAB had around one million users across industry and academia. MATLAB users come from various backgrounds of engineering, science, and economics. MATLAB is interesting in that it is dynamically compiled. In other words, when you're using it, you won't run all your code through a compiler, generate an executable, and then run the executable file to obtain a result. Instead, MATLAB simply goes line by line and performs the calculations without the need for an executable.

Partly because of this, it is possible to do calculations one line at a time at the command line using the same syntax as would be used in a file. It's even possible to write loops and branches at the command line if you want to. Of course this would often lead to a lot of wasted efforts, so doing anything beyond very simple calculations, testing to see if a certain function, syntax, etc. works, or calling a function you put into an .m file should be done within an .m file.

D. The Current Directory And Defined Path

It is necessary to declare a current directory before saving a file, loading a file, or running an M-file. By default, unless you edit the MATLAB shortcut, the current directory will be .../MATLAB/work. After you start MATLAB, change the current directory by either using the toolbar at the left-hand side of the screen, or entering the path in the bar at the top.

The current directory is the directory MATLAB will look in first for a function you try to call. Therefore if you have multiple folders and each of them has an M-file of the same name, there will not be a discrepancy if you set the current directory beforehand. The current directory is also the directory in which MATLAB will first look for a data file.

If you still want to call a function but it is not part of the current directory, you must define it using MATLAB's 'set path' utility. To access this utility, follow the path: file > set path... > add folder...

You could also go to "add folder with subfolders...", if you're adding an entire group, as you would if you were installing a toolbox. Then look for and select the folder you want. If you forget to do this and attempt to access a file that is not part of your defined path list, you will get an 'undefined function' error.

E. Saving Files

There are many ways to save to files in MATLAB.

• save - saves data to files, *.mat by default

• uisave - includes user interface

• hgsave - saves figures to files, *.fig by default

• diary [filename] - saves all the text input in the command window to a text file.

F. Loading Files

Likewise, there are many ways to load files into the workspace. One way is to use the "file" menu. To open a .m file click "open", whereas to import data from a data file select "import data..." and follow the wizard's instructions. He file must be in a recognized directory (usually your current directory, but at least one for which the path has been set). The data in the .mat file is stored with the same name as the variable originally had when it was saved. To get the name of this and all other environment variables, type "who".

To open an .m file, you can use file -> open, or type

G. File Naming Constraints

You can name files whatever you want (usually simpler is better though), with a few exceptions:
• MATLAB for Windows retains the file naming constraints set by DOS. The following characters cannot be used in filenames: (" \\ * | ? )

• You’re not allowed to use the name of a reserved word as the name of a file. For example, while.m is not a valid file name because while is one of MATLAB’s reserved words.

• When you declare an m-file function, the m-file must be the same name as the function or MATLAB will not be able to run it.

• You must save it as "factorial.m" in order to use it. MATLAB will name it for you if you save it after typing the function declaration, but if you change the name of the function you must change the name of the file manually, and vice versa.

H. Interfacing With Other Languages
MATLAB can call functions and subroutines written in the C programming language or Fortran. A wrapper function is created allowing MATLAB data types to be passed and returned. The dynamically loadable object files created by compiling such functions are termed "MEX-files" (for MATLAB executable). Since 2014 increasing two-way interfacing with Python is being added. Libraries written in Perl, Java, ActiveX or .NET can be directly called from MATLAB, and many MATLAB libraries (for example XML or SQL support) are implemented as wrappers around Java or ActiveX libraries. Calling MATLAB from Java is more complicated, but can be done with a MATLAB toolbox which is sold separately by Math Works, or using an undocumented mechanism called JMI (Java-to-MATLAB Interface), (which should not be confused with the unrelated Java Metadata Interface that is also called JMI). As alternatives to the MuPAD based Symbolic Math Toolbox available from Math Works, MATLAB can be connected to Maple or Mathematica. Libraries also exist to import and export MathML. MATLAB is a proprietary product of MathWorks, so users are subject to vendor lock-in. Although MATLAB Builder products can deploy MATLAB functions as library files which can be used with .NET or Java application building environment, future development will still be tied to the MATLAB language. Each toolbox is purchased separately. If an evaluation license is requested, the Math Works sales department requires detailed information about the project for which MATLAB is to be evaluated. If granted (which it often is), the evaluation license is valid for two to four weeks. A student version of MATLAB is available as is a home-use license for MATLAB, SIMULINK, and a subset of Math work's Toolboxes at substantially reduced prices.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>Classification Performance of Normal and Abnormal Color Retinal Images on the DMED Dataset</th>
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</thead>
<tbody>
<tr>
<td>Method</td>
<td>Sensitivity(%)</td>
</tr>
<tr>
<td>[1]</td>
<td>100</td>
</tr>
<tr>
<td>Proposed</td>
<td>100</td>
</tr>
</tbody>
</table>

It has been reported that EU competition regulators are investigating whether Math Works refused to sell licenses to a competitor. The regulators dropped the investigation after the complainant withdrew their accusation and no evidence of wrongdoing was found.

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>Classification Performance of Normal and Abnormal Color Retinal Images on the MENI/DOCR Dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td>Sensitivity(%)</td>
</tr>
<tr>
<td>[3] (18)</td>
<td>100</td>
</tr>
<tr>
<td>Proposed (18)</td>
<td>100</td>
</tr>
<tr>
<td>Proposed (all 400 images)</td>
<td>95</td>
</tr>
</tbody>
</table>

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Simulink, developed by Math Works, is a graphical programming environment for modeling, simulating and analyzing multi domain dynamic systems. Its primary interface is a graphical block diagramming tool and a customizable set of block libraries. It offers tight integration with the rest of the MATLAB environment and can either drive MATLAB or be scripted from it. Simulink is widely used in automatic control and digital signal processing for multi domain simulation and Model-Based Design.

A. Add-On Products
Math Works and other third-party hardware and software products can be used with Simulink. For example, State flow extends Simulink with a design environment for developing state machines and flow charts.

Math Works claims that, coupled with another of their products, Simulink can automatically generate C source code for real-time implementation of systems. As the efficiency and flexibility of the code improves, this is becoming more widely adopted for production systems, in addition to being a tool for embedded system design work because of its flexibility and capacity for quick iteration. Embedded Coder creates code efficient enough for use in embedded systems.

Simulink Real-Time (formerly known as xPC Target), together with x86-based real-time systems, is an environment for simulating and testing Simulink and Stateflow models in real-time on the physical system. Another Math Works product also supports specific embedded targets. When used with other generic products, Simulink and Stateflow can automatically generate synthesizable VHDL and Verilog. Simulink Verification and Validation enables systematic verification and validation of models through modeling style checking, requirements traceability and model coverage analysis. Simulink Design Verifier uses formal methods to identify design errors like integer overflow, division by zero and dead logic, and generates test case scenarios for model checking within the Simulink environment. The result show in Fig.5. The systematic testing tool TPT is marketed as a way to perform a formal verification and validation process to stimulate Simulink models but also for use during the development phase where the developer generates inputs to test the system. By the substitution of the Constant and Signal generator blocks of Simulink, Math Works claim that the stimulation becomes reproducible.

Sim Events is used to add a library of graphical building blocks for modeling queuing systems to the Simulink environment, and to add an event-based simulation engine to the time-based simulation engine in Simulink.

**IX. CONCLUSION**

Image processing of color fundus images has the potential to play a major role in diagnosis of diabetic retinopathy. There are three different ways in which it can contribute: image enhancement, mass screening (including detection of pathologies and retinal features), and monitoring (including feature detection and registration of retinal images). Efficient algorithms for the
Detection of the optic disc and retinal exudates have been presented. Robustness and accuracy in comparison to human graders have been evaluated on a small image database. The results are encouraging and a clinical evaluation will be undertaken in order to be able to integrate the presented algorithm in a tool for diagnosis of diabetic retinopathy.

REFERENCES


