Detection of Hard Exudates and Red Lesions in the Macula Using a Multiscale Approach

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***Abstract*—Diabetic retinopathy (DR) is a complication of diabetes that causes blindness to 1.8 million people in the world. The risk of vision loss from DR increases when pathologies present on the macula. In this paper, we present an automatic system to detect pathologies on the macula such as hard exudates microaneurysms, and hemorrhages. Our approach is a bottom-up implementation, which tries to capture each abnormal structure in the macula in order to detect DR lesions. This technique starts by eliminating the non-uniform illumination thereby enhancing the contrast of red lesions in the images. Possible DR lesion (hard exudates and red lesions) candidates on the macula are extracted by using amplitude-modulation frequency-modulation (AM-FM) features. AM-FM features extract texture information from different frequency scales, providing for an effective method for the detection of hard exudates and red lesions. For each lesion candidate, we also extract shape, color and other texture features that are then combined with AM-FM features. Pathologies in the macula are detected from the candidate lesions using supervised classification with Partial Least Squares.**

Diabetic Retinopathy; Amplitude-modulation Frequency-modulation (AM-FM); Partial Least Squares

I. INTRODUCTION

Located at the center of the macula, the fovea contains the highest density of photoreceptors in the retina and is responsible for the central vision. Many pathologies occurring on or near the fovea, such as clinically significant macular edema (CSME), represent a high risk for vision loss. For example, there is an association between hard exudates near the fovea and CSME [1]. However, not all the types of lesions in the macula represent a comparable risk to patients. For example, drusen, which look similar in shape and color to exudates are not immediately sight threatening; thus, must be differentiated from hard exudates, which are high risk for sight threatening disease and demand an alternate clinical pathway of patient management.

Many approaches have been proposed as a means for automatic DR screening. Most of them utilize "bottom-up" techniques in which segmentation of the lesions is required in order to detect DR. Other approaches [2, 3] are "top down" where segmentation and grading of specific lesions is not necessary to classify the image as normal or abnormal. Much of the reported work has focused either on the detection of red lesions such as microaneurysms and hemorrhages on the fundus images [4, 5, 6] or on the detection of bright lesions such as exudates and cotton wool spots [7, 8, 9]. The extraction of features on the retinal images is commonly the basis for most automatic classification systems. Morphological methods [10], Gabor filters [7], and Wavelet transforms are the most popular methods for feature extraction [5]. A number of different classifiers have been used to process the extracted features. Sopharak et al. [8] used an unsupervised method called Fuzzy C-means. The authors in [7] used Neural Networks in which each pixel is associated with a soft label indicating the probability of a pixel being bright. In a different approach to detect red lesions, Niemeijer et al. [6], used k-nearest neighbors classifier with Neural Networks.

Our approach uses an optimization approach to select the most promising Amplitude-Modulation Frequency-Modulation (AM-FM) features. Contrary to other methods, the same system is applied to detect red lesions and hard exudates.

II. DATA DESCRIPTION

The images were acquired at the University of Texas Health Science Center, San Antonio (UTHSCSA). 153 macula-centered digital fundus photographs were used to train/test our algorithm. The images were acquired using 2392x2048 pixels and 60 degrees field of view. Pixel footprint is about 9 μm. A region of 1 disc diameter (DD) centered in the fovea (1DD = 400pixels) was extracted for each image. Lesions such as hard exudates and red lesions (microaneurysms and hemorrhages) were marked by a certified ophthalmic medical technologist. N=35 images were graded as normal, and the remaining images presented two types of lesions. N=79 images presented hard exudates in the macula, and N=81 images presented red lesions. N= 42 present with both types of lesions. The normal cases also contained images with non-pathological features such as retinal sheen, foveal reflex, and low contrast. Other images presented drusen which are pathologies related to age-related macular degeneration (AMD).

III. METHODOLOGY

Fig. 1 shows the methodology used to detect the bright and dark lesions on the macula. The pre-processing block is applied only to detect red lesions. In the following

subsections, we explain the optimization procedure used to obtain the best performance of our algorithm.

A. Pre-processing for red lesion detection

For the detection of red lesions, the images are pre-processed following a three-step approach. First, we apply illumination correction using a shade correction technique [11]. Second, non-overlapping windows of 30x30 pixels are selected from the image, the bright pixels are detected and then they are replaced by the mean average value of the remaining pixels in that window. To find the optimal threshold for selecting the brightest intensity pixels, the second derivative of the histogram of the intensity pixel values is calculated. After doing so, the image is smoothed with a 9x9 average filter. Finally, the contrast is enhanced using contrast limited adaptive histogram equalization (CLAHE), as shown in Fig. 2.

B. Amplitude-Modulation Frequency-Modulation

Amplitude Modulation-Frequency Modulation (AM-FM) [12] represents an image in terms of its instantaneous amplitude and instantaneous frequency components as:

$$I(x,y) \approx \sum_{n=1}^{M} a_n(x,y)\cos\varphi_n(x,y) \quad (1)$$

where M is the number of AM-FM components, $a_n(x,y)$ denote instantaneous amplitude functions (IA) and $\varphi_n(x,y)$ denote the instantaneous phase functions. For each AM-FM component, the instantaneous frequency (IF) is defined in terms of the gradient of the phase φ_n:

$$\nabla\varphi_n(x,y) = \left(\frac{\partial\varphi_n(x,y)}{\partial x}, \frac{\partial\varphi_n(x,y)}{\partial y}\right) \quad (2)$$

In terms of textural features, for each component, three estimates of the AM-FM outputs are used: instantaneous amplitude, instantaneous frequency magnitude (IFm) and angle (IFangle). These AM-FM estimates were calculated at 5 different frequency scales which correspond to the following bands of frequencies: High (H), Medium (M), Low (L), Very Low (VL) and Ultra Low (U). Then we merged them with the low pass filter (LPF) in 13 different combinations: U-H, LPF, VL, L, M, LPF-H, U-VL, VL-L, L-M, M+H, H, U.

C. Parameter Optimization

Estimates of the IA, IF magnitude, and IF angle are calculated for the 13 different combinations of scales. Thus, a total of 39 different AM-FM feature images are obtained for each image. From them, binary maps are created by thresholding the generated AM-FM feature images. In order to find the optimal threshold value to create the binary maps, an optimization technique was used based on a subset of 53 images. Thirty different percentiles were used to test for the optimal threshold value. Here, note that lesions are characterized by low or high values of the AM-FM features images.

By using the reader-based ground-truth for hard exudates and red lesions on the macula, sensitivity and specificity were obtained and the distance to the ideal point (100%/100%) is calculated for each of the 1170 points (39 AM-FM feature images times 30 percentile values) for each image and the two types of lesions. The binary AM-FM feature images with a threshold that has the minimum distance to the ideal point (set to be less than 0.3 heuristically on training data) will be selected as an input for our system. Fig. 3 shows some examples of distances for different thresholds and different types of lesions. It can be noticed that in Fig. 3a for percentiles near 67th, the distance to the ideal point is lower than the acceptable minimum distance = 0.3 (dark blue) for most of the AM-FM feature images so many of them are useful to detect hard exudates. On the other hand, Fig 3b shows fewer cases with distances lower than 0.3 meaning that only few of them are going to be used to detect red lesions.

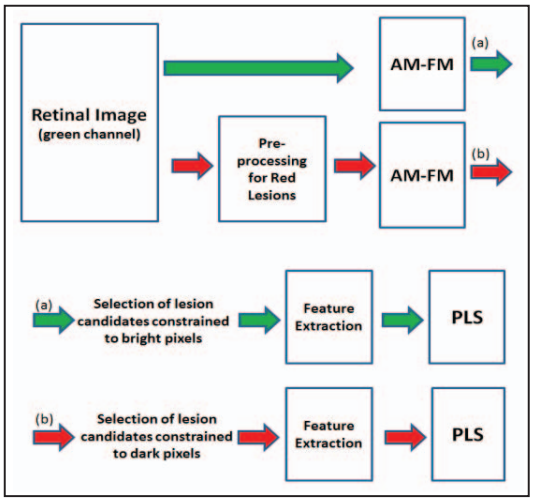

Figure 1. Block diagram of our approach to detect hard exudates and red lesions in the macula.

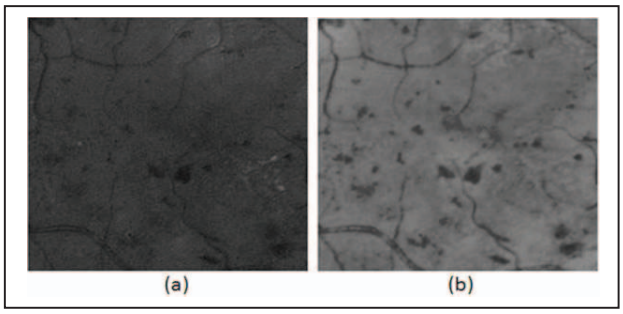

Figure 2. Pre-processing for detecting red lesions in the macula. (a) Macula from the original green channel, (b) Macula of the retinal image after apply the pre-processing block explained in section III.A.

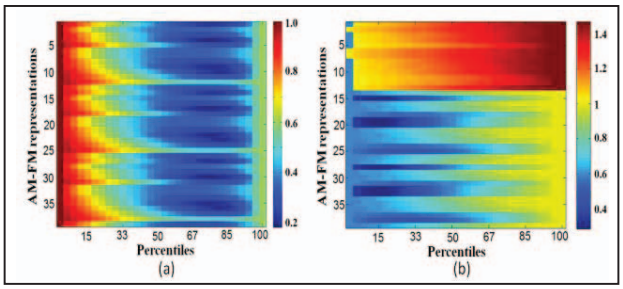

Figure 3. Map of distance values for the different thresholds. The y-axis represents the AM-FM representation for the 13 different combinations in the order specified in section A for IA(1-13), IFm (14-26), and IFangle (27-39). (a) Results of distances after applying the threshold to find lower thresholds to detect hard exudates. (b) Results of distances after applying the threshold to find upper thresholds to detect red lesions.

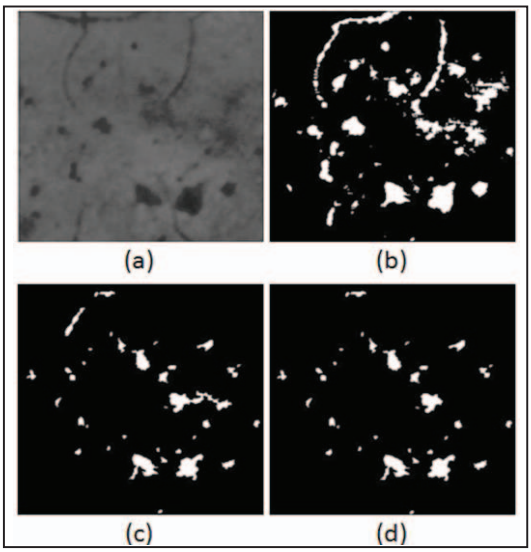

Figure 4. Extraction of lesion candidates to detect red lesions. (a) Original image, (b) Binary map obtained with the relevant scales and optimal parameters of AM-FM representation, (c) Constrained binary maps to dark pixels, (d) Candidates of red lesions after applying morphological operations

D. *Color constraint*

Color constraints are applied to the AM-FM binary output using a sliding window of 100x100 pixels. The bright pixels that are higher than the 95th percentile of the content of this window are maintained for the bright lesion detection. For red lesions detection, the threshold was set to the 7th percentile. The intensity pixels below this threshold are used to mask the AM-FM binary maps. Since there is a great amount of dark pixels in the fovea and lesions are the darkest among them, a special mask of approximately the size of the fovea is used to reduce the false positives rate detection. The pixels with intensity smaller than the 3rd percentile of the content within this window are kept to generate the dark lesions mask. Similarly, pixels that are higher than 99th percentile in the fovea are kept for the bright pixels mask. This modification was implemented after noticing that the foveal reflex, an imaging artifact, is darker than exudates when they are close to each other.

After these masks are generated, they are multiplied by the AM-FM binary maps, as it is shown in Fig 4(c). Afterwards, morphological operations to remove small objects that are considered to be noise or vessel lines are applied, as shown in Fig. 4(d).

E. *Extraction of features*

Sixty-four features are used to characterize each of the possible candidate objects in order to determine its type (non-lesion, hard exudate, red lesion). By using the pixel information of each candidate, we extracted 3 types of features: 1) Color information within the candidate and a neighborhood of pixels outside the candidate, 2) Shape (area, position, eccentricity, major and minor axis length, solidity, perimeter), and 3) Texture information using gray level concurrence matrix (contrast, energy, homogeneity, correlation). The features are normalized to have zero mean and standard deviation 1.

F. *Classification*

The features obtained in Section E are the inputs of a linear regression classifier based on partial least squares (PLS) [3]. The classifier is trained for each type of lesion (red lesions and hard exudates) by using the 53 images selected for training purposes.

IV. RESULTS

The optimal parameters obtained with the optimization process for the detection of hard exudates and red lesions are applied to our testing set consisting of 100 images. After the candidates for each type of lesion are extracted, the model created with the training images is applied to the images. We present results for all the candidates that we extracted for each type of lesion in Fig. 5. However, since we are interested in the detection of abnormalities in the macula per retinal image, a point of the ROC curve that has very high specificity is used to reduce the amount of false positives in the classification per image.

A. *Hard Exudates*

Fig. 5 shows the ROC curve for the detection of lesion candidates for red lesions and hard exudates. An area under the ROC curve (AUC) of 0.95 is obtained in the candidate classification. By setting the threshold to obtain a sens/spec = 66%/98%, the classifier trained to detect maculas with exudates in a testing set of 100 images (51 with exudates, 49 without exudates) achieved 100% sensitivity, with specificity of 58%.

B. *Red lesions*

An AUC of 0.90 is obtained in the candidate classification. By setting the threshold to obtain a sens/spec = 74%/90%, the detection of maculas with red

lesions in the testing set (60 with red lesions, 49 with non-red lesions) is 92%/55%.

V. Discussion

Structures captured with AM-FM features offer rich information of the analyzed lesions: hard exudates and red lesions. In addition to this, the optimization process helps us obtain high sensitivity in the detection of these lesions even in the candidate selection process prior to the classification.

Fine drusen, also a bright lesion, is a problem for the algorithm, so a post-processing to focus on the shape of these small lesions may improve its performance. As it is known, the shape of the drusen is more similar to a circle than exudates. Image enhancement may also help identify drusen first and help avoid false exudates detection.

The problem of detecting red lesions is very challenging since they present very irregular shapes and have variable texture characteristics. However, the results obtained with this optimized method are encouraging.

Vessels with branches or portions of vessels are another cause of misclassification. A more detailed analysis is going to be performed in order to eliminate those from the candidates.

VI. Conclusions

A computer-aided detection algorithm based on generalized optimization scheme of image decompositions is presented. Given the optimization process and the flexibility of the implementation, this methodology could be extended to the detection of different types of lesions. In addition, the system only requires image enhancement for red lesions since the exudates are well captured with AM-FM features. The system achieves 100% sensitivity in detecting maculas with hard exudates and 92% sensitivity in detecting maculas with red lesions. In future implementations, post-processing is going to be added in order to increase the specificity of the system.

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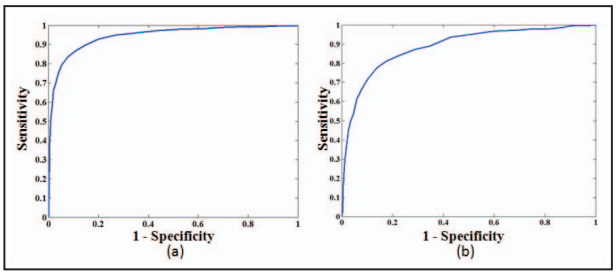

Figure 5. ROC curve of the detection of lesions of the extracted candidates. (a) Detection of exudates, (b) Detection of red lesions.

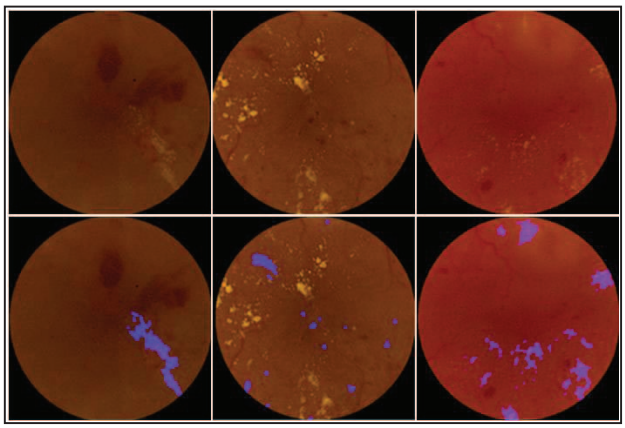

Figure 6. Results of the lesion detection in the macula algorithm for maculas with exudates (1st and 3rd columns), and for red lesions (2nd column).

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