International Journal of Research in Advent Technology, Vol.2, No.11, November 2014
E-ISSN: 2321-9637

Survey on Detection of Retinal Hemorrhage Disease

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Abstract-Automated detection of diabetic retinopathy (DR), as used in screening systems. A novel splat feature classification method is presented with application to retinal hemorrhage detection in fundus images. Earlier work used wrapper approach for selecting splat features for classification. However it only supports for less extracted features. To deal with this problem the present work proposes Hybrid feature selection method of Filter and Wrapper approach for selecting the extracted features. Hybrid feature selection algorithm includes particle swarm optimization method with wrapper approach for efficient feature selection process. Features such as Scale invariant feature transform (SIFT) is extracted in each splat and optimal features are selected by using proposed hybrid approach. Then classifier known as K-NN classifier is trained with splat-based expert annotations and evaluated on the publicly available dataset.

Keywords: splat, fundus image, retinal hemorrhage, KNN classifier, SIFT, Watershed segmentation.

1. INTRODUCTION

Medical image is the technique process and art of creating visual representations of the interior of a for clinical analysis and medical intervention .The retina is the part of the eye that converts light into nerve signals that are processed by the brain into visual image. Retinal hemorrhage is one of the diseases, abnormal bleeding of the blood vessels in the retina, the membrane in the back of the eye. Damage to the blood vessels in the retina, including hemorrhage is termed retinopathy. In the development of automated screening systems, detection of retinal hemorrhage is important .To detect large irregular retinal hemorrhages with high accuracy, splat feature can be used. Diabetic Retinopathy is retinopathy, which can eventually lead to blindness. It is a systemic disease, affects up to 80 percent of all patients who have had diabetes for 10 years or more. Diabetic retinopathy often has no early warning signs. There are two types of diabetic retinopathy. One type is proliferative diabetic retinopathy and another type is non-proliferative diabetic retinopathy. In the first stage which is called non-proliferative diabetic retinopathy(NPDR). The only way to detect NDPR is by fundus photography. On the second stage, as abnormal new blood vessels form at the back of the eye as a part of proliferative diabetic retinopathy(PDR).

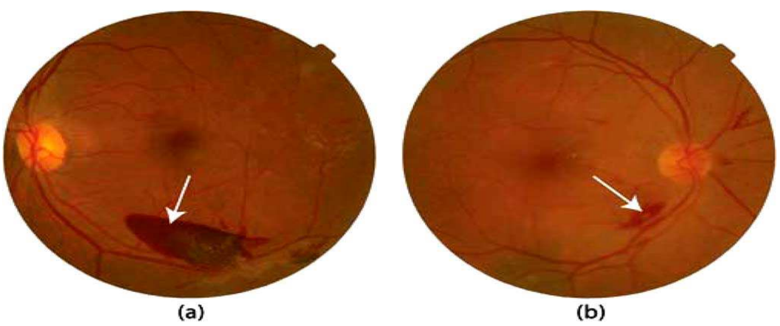

Fig. 1. Examples of retinal hemorrhages with different shapes and appearances.

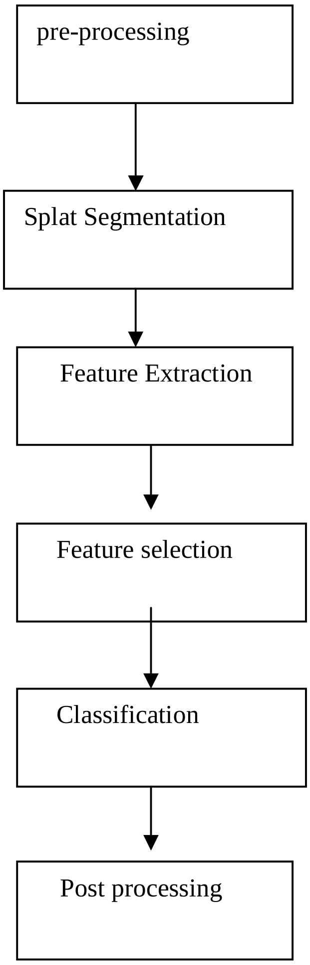

Fig 2. Flowchart for detection of retinal hemorrhage disease

2. STEPS INVOLVED IN DETECTION OF RETINAL HEMORRHAGE DISEASE

2.1 Pre-processing

As a Pre-processing step, edge effects due to limited field of view (FOV) and vignetting in fundus photographs have to be addressed to suppress irrelevant responses during feature extraction. It is conventionally performed in two ways. One is to fill the region outside FOV with the mean colour of the region within FOV. The other possibility is to mirror the FOV outside the FOV. By performing edge effect removal, pre-processing is done and feature are in from all of splats, the features are extracted and its containing pixels on the circular boundaries of FOV are excluded from further processing.

2.*2. Splat segmentation*

In this module, Splat segmentation is done on the original image. Splat-based representation is an image re-sampling strategy onto an irregular grid. Segmentation plays an important role in the detection of retinal hemorrhages .segmentation is the process of partioning a image into multiple segments.

A complete segmentation must satisfy the following criteria:

- All pixels have to be assigned to regions.

- Each pixel has to belong to a single region only.
- Each region has to be uniform with respect to a given predicate.
- Each region is a connected set of pixels.
- Any merged pair of adjacent regions has to be non-uniform.

There are different types of segmentation in image processing. They are region growing, watershed segmentation, Region growing satisfies the 3rd and 4th criteria but not the others .watershed segmentation is most popularly used in medical processing application because boundaries of the segmented regions are preserved. It is then applied to gradient magnitude image to achieve the meaningful segmented results .Assume a scale-space representation of image I(x,y;s) with Gaussian kernels G_s at SOI s$\in s_1, \dots\dots\dots\dots s_n$, the gradient magnitude $|\nabla I(x,y;s)|$ is computed from its horizontal and vertical derivatives[1]

$$\begin{aligned}|\nabla I(x,y;s)| &= \sqrt{I_x(x,y;s)^2 + I_y(x,y;s)^2} \\ &= \sqrt{\left[\frac{\partial}{\partial x}(G_s * I(x,y))\right]^2 + \left[\frac{\partial}{\partial y}(G_s * I(x,y))\right]^2} \\ &= \sqrt{\left[\frac{\partial G_s}{\partial x} * I(x,y)\right]^2 + \left[\frac{\partial G_s}{\partial y} * I(x,y)\right]^2} \\ & \qquad s = s_1, \dots, s_n\end{aligned}$$

where symbol * represents convolution and $(\partial G_s)/(\partial x)$, $(\partial G_s)/(\partial y)$ are the first order derivatives of Gaussian at scale s along the horizontal and vertical direction.

The maximum of the gradient magnitude aggregated over the scale band $|\nabla I(x,y)|$ is shown in[2]

$$|\nabla I(x,y)| = \max_i |\nabla I(x,y;s_i)|.$$

2.3. Feature Extraction

In this module three features such as SIFT, splat features aggregated from pixel-based responses and splat wise features (no aggregation is required) are extracted.

2.3.1 Pixel based features

2.3.1.1. Colour Channel and Opponency Images

Colour within each splat is extracted in RGB colour space and dark-bright (db), red-green (rg), and blue-yellow (by) opponency images[3] ,which comprise six colour components in splat feature space.

To accommodate colour variations across the dataset, normalize each image according to its dominant pixel values at three colour channels, which means most frequent pixel values present in the image are shifted to the origin of RGB colour space. No separate rescaling is performed in order to preserve the ratio between colour components.

2.3.1.2 Characteristics of Boundaries across Neighbouring Splats

To distinguish a structure or object from its surroundings or background, it is crucial to differentiate distinct boundaries formed by neighbouring splats, such as well defined sharp boundaries resulting from abrupt intensity transition, or blurred soft boundaries resulting from gradual intensity transition. Different from pixels, which are on an orthogonal grid, splats are on a non orthogonal grid, which makes extraction of regular derivative features harder. An alternative is to take advantage of the representation of Gaussian scale space[4]. Both sharp edges and soft edges are relative with respect to their underlying scale. The high intensity points and low intensity points evolve towards different directions across the scale space produced by Gaussian kernels with different σ[4].

Difference of Gaussian (DoG) kernels are applied at five different smoothing scales (σ =1,2,4,8,16)and one baseline scale $\sigma_0 = 0.5$ to extract such features, which is expected to span potential bandwidth of boundaries present in fundus images[5].

2.3.2 SIFT Feature Extraction

2.3.2.1 Scale Invariant Feature Transform (SIFT)

Invariant features in the image can be extracted using Scale Invariant Feature Transform descriptor. The invariance is obtained in the scale and orientation of the pixels .SIFT descriptor is a local descriptor of image features which is insensitive to illuminant and other variant that is typically used as sparse feature representation. These invariant features are extracted by using following steps:

- Compute the location of potential interest points in the image by detecting the maxima and minima of filters applied at different scales all over the image.
- The location of the points is refined by discarding low contrasted points.
- Based on local image features, an orientation is then assigned to each key point.
- At last, a local feature descriptor is calculated at each key point.

In the above steps every feature is considered as a vector of 128 distinct dimensions by identifying the neighbourhood of key points.

2.4 FEATURE SELECTION USING HYBRID FEATURE SELECTION ALGORITHM

Feature selection reduces the dimensionality of feature space by identifying relevant features and ignoring those irrelevant or redundant ones, which is particularly important to a higher separability between classes. There are two major approaches for feature selection: the filter approach and the wrapper approach. The filter approach is fast, enabling their practical use on high dimensional feature spaces. It assesses individual feature separately without considering their interactions. The wrapper approach assesses different combinations of feature subsets tailored to a particular classification algorithm at the cost of longer computation time.

2.4.1 Filter approach using PSO

In PSO based feature selection, each particle is represented by $x_i = (x_{i1}, x_{i2}, \ldots\ldots x_{id})$where d is the dimension numbers. The rate of velocity for the ith particle is represented by $v_i = (v_{i1}, v_{i2}, \ldots\ldots v_{id})$and limited by V_{max} , which is determined by the user. The best previously encountered position of the ith particle (the position with the highest fitness value) is called pBesti and represented by $p_i = (p_{i1}, p_{i2}, \ldots\ldots p_{id})$. The global best value of the entire population is called gBest and represented by g=$\{g_1, g_2, \ldots . g_d\}$ .At each interaction, the particles are updated according to the following equations[1].where w is the inertia weight, c1 and c2 are acceleration (learning) factors, rand1 and rand2 are random numbers. Velocities $v_{id}^{new}$and v_{id}^{old} are those of the new and old particle, respectively, x_{id}^{old} is the current particle position (solution), and x_{id}^{new} is the updated particle position.

$$v_{id}^{new} = w \times v_{id}^{old} + c_1 \times rand_1 \times (pbest_{id} - x_i^{old})$$
$$+ c_2 \times rand_2 \times (gbest_d - x_i^{old})$$
$$x_{id}^{new} = x_{id}^{old} + v_{id}^{new}$$

2.4.2 Wrapper approach

After preliminary selection, irrelevant features are removed. By taking interactions among features into account, a wrapper approach selects optimal combinations of relevant features with their redundancy minimized. Potential combinations are evaluated depending upon certain classification algorithms.

2.5 Classification

After feature selection, a trained kNN classifier is set up in a “calibrated” feature space with a set of discriminative features and a set of labelled instances. The kNN classifier assigns soft class labels to query splats based on the labels of their nearest neighbours in the feature space, i.e., those instances in the training set. When neighbours were labelled as being a hemorrhage splat, the posterior probability that the query splat comes from hemorrhage itself was determined. The distance for finding the nearest neighbours is measured with Euclidean metric in the optimized feature space. At the testing stage, the system is fully automatic. The nearest neighbour rule attempts to estimate the a posterior probabilities from labelled training samples. A large value of is desirable to obtain reliable estimates. But only when all of the nearest neighbours are close enough to the query sample, its a posterior probability can be approximated by the majority labels of its neighbours. Therefore, a compromise has to be made so that the value of accounts for only a small fraction of the training samples.

3 .CONCLUSION

In this paper, retinal hemorrhage disease was analysis by using segmentation of fundus images and also extract the particular features like shape ,colour, SIFT. Based on those features select best feature using PSO and wrapper approach and finally classify the features.

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