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RETINAL HAEMORRHAGE DETECTION USING SPLAT FEATURE AND HYBRID IN FUNDUS IMAGES

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Abstract - *Automated detection of diabetic retinopathy (DR), supervised approach is used and images are partitioned into non overlapping segments which covers the entire image , Each segment consist of splat which contains pixels with similar colour and spatial location ,features are extracted i.e, splat feature using filter approach followed by wrapper approach to describe its characteristics , existing consist of an approximate detection using wrapper approach , in this paper we propose a conclusion of using PSO algorithm for efficient feature selection process further KNN classifier is used for splat based annotations and classification*

Key words: *DR, Preprocessing, PSO,KNN classifier*

INTRODUCTION

In imaging science, image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.

Image processing usually refers to digital image processing, but optical and analog image processing also are possible. This article is about general techniques that apply to all of them. The acquisition of images (producing the input image in the first place) is referred to as imaging.

Closely related to image processing are computer graphics and computer vision. In computer graphics, images are manually made from physical models of objects, environments, and lighting, instead of being acquired (via imaging devices such as cameras) from natural scenes, as in most animated movies. Computer vision, on the other hand, is often considered high-level image processing out of which a machine/computer/software intends to decipher the physical contents of an image or a sequence of images (e.g., videos or 3D full-body magnetic resonance scans).

In modern sciences and technologies, images also gain much broader scopes due to the ever growing importance of scientific visualization (of often large-scale complex scientific/experimental data). Examples include microarray data in genetic research, or real-time multi-asset portfolio trading in finance.

INTRODUCTION TO THE PROJECT

Diabetic retinopathy is important for allowing timely treatment]. Because of its cost-effectiveness and patient friendliness, digital color fundus photography is a prerequisite for automated DR detection. Patients with images that are likely to contain DR are detected and referred for further management by eye care providers. The most common signs of DR are microaneurysms, small hemorrhages, exudates, drusen, and cotton wool spots. Because of the variability in appearance of these lesions, different techniques have been designed to detect each type of these lesions separately in DR detection systems.

Malarial retinopathy (MR) is characterized by retinal hemorrhages of varying sizes and shapes, often showing as Roth spots retinal whitening, papilledema, and vessel discoloration.

A method for automated detection of MR hemorrhages has been developed, studied, and validated retinal image analysis algorithms that are capable of detecting retinal lesions such as hemorrhages, exudates, microaneurysms, drusen, and cotton wool spots, as well as measure retinal arterial and venous parameters in retinal colour fundus images, with performance comparable or superior to that of ophthalmologists. A supervised pixel classification and red lesion detection method is proposed based on the analysis of features that include colour, shape, and the response of a Gaussian filter bank.To extract non-hemorrhage and malarial features, non-vessel inhibition operator using Gabor filter has been used to detect vessel feature and a multithresholds scheme based on standard hysteresis thresholding methods is applied to help separate connective elongated vessels from scattered residual edge.

It is expensive to acquire expert labeled reference standards for training and evaluation. Designing such systems requires substantial work by clinicians to define the reference standard, which is expensive and prone to error. Ideally training samples are intended to be both informative to the classification model and diverse so that information provided by individual samples overlaps as little as possible. However, often in a single training image, there can be a huge number of very similar pixel samples. Large hemorrhages /malarial symptoms or diseases occur infrequently, have non regular shape and can occur without accompanying other signs of DR, such as micro aneurysms or small hemorrhages and malarial.

They will thus be missed by systems designed to detect the regular DR lesions. Because of their low occurrence, sensitivity for detection of large hemorrhages / malarial has negligible effect . In a proposed system a set of feature is extracted from each splat and an optimal subset of splat features is selected by a filter approach which followed by a wrapper approach.

EXISTING WORK

In existing detection of retinal hemorrhages for diagnosis of diabetic retinopathy is done by supervised approach. Under this supervised approach, retinal color images are partitioned into nonoverlapping segments covering the entire image. Each segment, i.e., splat, contains pixels with similar color and spatial location. A set of features is extracted from each splat to describe its characteristics relative to its surroundings, employing responses from a variety of filter bank, interactions with neighboring splats, and shape and texture information. An optimal subset of splat features is selected by a filter approach followed by a wrapper approach. A classifier is trained with splat-based expert annotations and evaluated on the publicly available Messidor dataset.

PREPROCESSING

As a preprocessing 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 color of the region within FOV. The other possibility is to mirror the FOV outside the FOV. By performing edge effect removal, preprocessing is done and feature are extracted in from all of splats, those containing pixels on the circular boundaries of FOV are excluded from further processing

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. Background regions, with gradual variations in appearance, tend to consist of fewer large splats while foreground regions consist of a larger number of smaller splats. At pixel level, the distributions of haemorrhage pixels and nonhemorrhage pixels are imbalanced, since hemorrhages usually account for a small fraction of the entire image. Instead of including only a subset of background pixels for training, as many resampling methods do, a splat-based approach maximizes the diversity of training samples by retaining all important samples.

Scale-Specific Image Over-Segmentation

To create splats which preserve desired boundaries precisely, i.e., boundaries separating hemorrhages from retinal background, perform a scale-specific image over-segmentation in two steps. Due to the variability in the appearance of hemorrhages, we firstly aggregate gradient magnitudes of the contrast enhanced dark-bright opponency image at a range of scales for localization of contrast boundaries separating blood and retinal background.

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

$$|\nabla I(x,y;s)| = \sqrt{I_x(x,y;s)^2 + I_y(x,y;s)^2}$$

$$= \sqrt{[\frac{\partial}{\partial x}(G_s * I(x,y))]^2 + [\frac{\partial}{\partial y}(G_s * I(x,y))]^2}$$

$$= \sqrt{\left[\frac{\partial G_s}{\partial x} * I(x,y)\right]^2 + \left[\frac{\partial G_s}{\partial y} * I(x,y)\right]^2} \quad \text{Where}$$

s= s1,….sn ---- (1)

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.

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.

Pixel based features

Color Channel and Opponency Images:

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

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

Characteristics of Boundaries across Neighboring Splats:

To distinguish a structure or object from its surroundings or background, it is crucial to differentiate distinct boundaries formed by neighboring 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 nonorthogonal grid, which makes extraction of regular derivative features harder. An alternative is to take advantage of the representation of Gaussian scale space. 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 .Difference of Gaussian (DoG) kernels are applied at five different smoothing scales (=1,2,4,8,16)and one baseline scale to extract such features, which is expected to span potential bandwidth of boundaries present in fundus images.

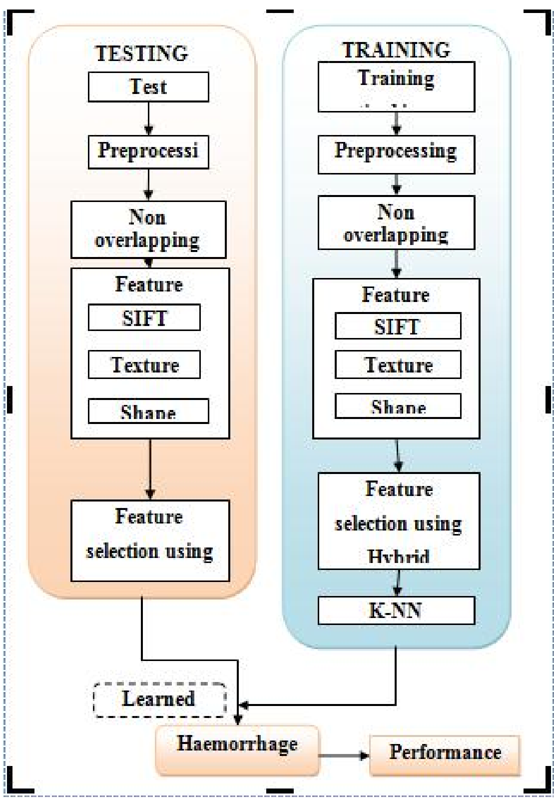
The maximum of the gradient magnitude aggregated over the scale band $|\nabla I(x,y)|$ is

$$|\nabla I(x,y)| = \max_i |\nabla I(x,y;s_i)| \text{ --- (2)}$$

In existing it require

- High computational time is required
- Detection accuracy degrades with the less features
- Overall accuracy is not improved

ARCHITECTURE DIAGRAM



PROPOSED WORK

In proposed system automatic detection of Diabetic retinopathy is done by using Hybrid feature selection method of Filter and Wrapper approach. Hybrid mechanism includes Particle swarm optimization filter and wrapper approach for selecting optimal feature for classification. Features such as SIFT, color and Shape are extracted in splat segment of retinal images. The PSO system is initialized with a population of random solutions. This population searches for an optimal solution by updating generations. In PSO, a potential solution is called a particle. Each particle makes use of its own memory and knowledge gained by the swarm as a whole to find the best (optimal) solution in a d-dimensional search space. The particles have a positional value and velocities which direct their movement .The wrapper model approach depends on feature addition or deletion to compose subset features, and uses evaluation function with a learning algorithm to estimate the subset features. This kind of approach is similar to an optimal algorithm that searches for optimal results in a dimension space. The wrapper approach usually conducts a subset search with the optimal algorithm, and then a classification algorithm is used to evaluate the subset. Finally from the selected features, classification is performed by using K-NN classifier.

SIFT FEATURE EXTRACTION

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:

1. 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.
2. The location of the points is refined by discarding low contrasted points.
3. Based on local image features, an orientation is then assigned to each key point.
4. 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.

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.

Filter approach using PSO

In PSO based feature selection, each particle is represented by $x_i = (x_{i1}, x_{i2}, \ldots x_{id})$where d is the dimension numbers. The rate of velocity for the ith particle is represented by $v_i = (v_{i1}, v_{i2}, \ldots v_{id})$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 $pBest_i$ and represented by $p_i = (p_{i1}, p_{i2}, \ldots p_{id})$. 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

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

$$x_{id}^{new} = x_{id}^{old} + v_{id}^{new} \quad \text{--- (3)}$$

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.

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.

CLASSIFICATION USING K-NN CLASSIFIER

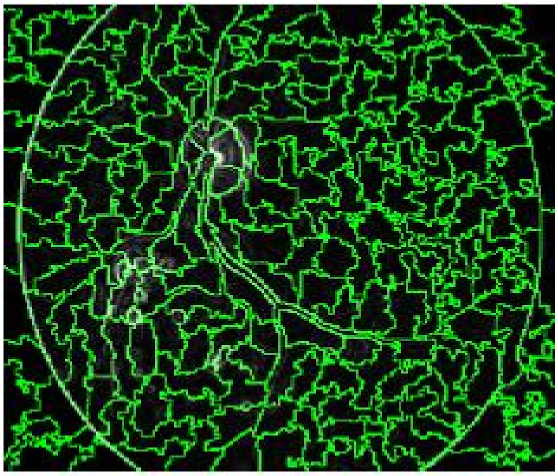
After feature selection, a trained kNN classifier is set up in a “calibrated” feature space with a set of discriminative features and a set of labeled instances. The kNN classifier assigns soft class labels to query splats based on the labels of their nearest neighbors in the feature space, i.e., those instances in the training set. When neighbors were labeled as being a haemorrhage splat, the posterior probability that the query splat comes from haemorrhage itself was determined. The distance for finding the nearest neighbors is measured with Euclidean metric in the optimized feature space. At the testing stage, the system is fully automatic.

The nearest neighbor rule attempts to estimate the a posteriori probabilities from labeled training samples. A large value of is desirable to obtain reliable estimates. But only when all of the nearest neighbors are close enough to the query sample, its a posteriori probability can be approximated by the majority labels of its neighbors. Therefore, a compromise has to be made so that the value of accounts for only a small fraction of the training samples, by using PSO, Optimal selection of features is done,Process in less time,Improved accuracy detection is obtained and Disease level is identified

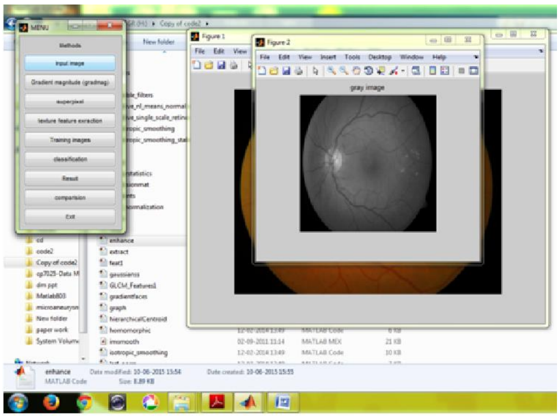
OUTPUT

1. **INPUT IMAGE**

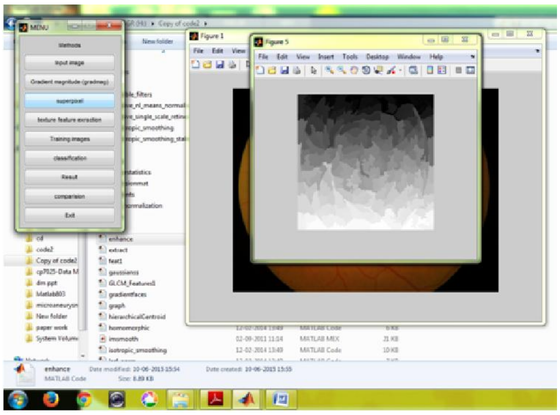
2. **SEGMENTATION**



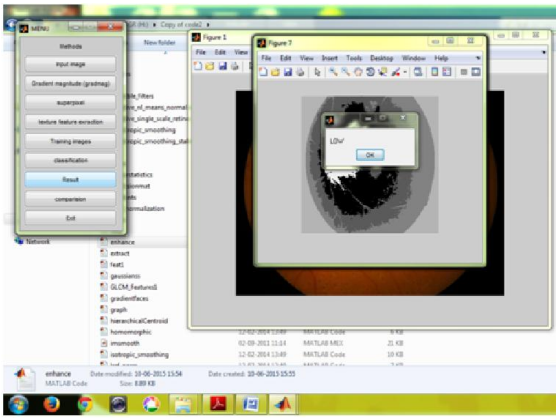
SCREEN SHOTS



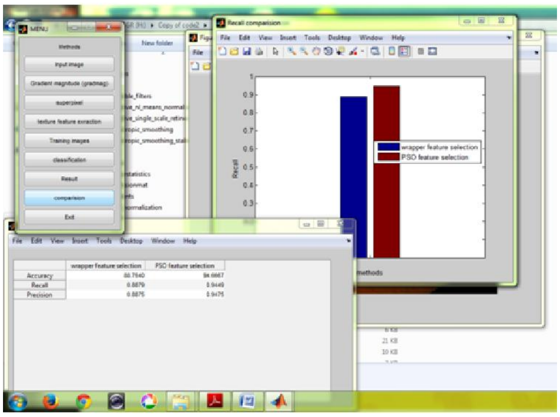
1. **INPUT IMAGE**



2.PREPROCESS



3.RESULT



4. COMPARISION GRAPH

CONCLUSION

Automated detection of diabetic retinopathy (DR), as used in screening systems, is important for allowing timely treatment, and thereby increasing accessibility to and productivity of eye care providers. Because of its cost-effectiveness and patient friendliness, digital color fundus photography is a prerequisite for automated DR detection. Patients with images that are likely to contain DR are detected and referred for further management by eye care providers. This automatic diabetic retinopathy is detected in our work by introducing a novel concepts for both feature extraction and feature classification. The hybrid PSO and wrapper approach is used in our work to extract the features effectivelyand to find out the level of disease i.e, low,moderate,high is found using PSO. The K-NN classification technique is used in our work to classify the features. The experimental results proves that our proposed work is better than the existing in terms of performance.

FUTURE WORK

Hemorrhage is obtained with high accuracy rate than the malarial and in the future the malarial accuracy rate can also be increased with other screening techniques, it will be developed methods to detect other lesions related to diabetic retinopathy and other diseases that affect the retina. Diseases like Glaucoma and Diabetic Retinopathy are in rise and Optic Disc is an important indicator of these diseases. Hence the new methodologies to detect Optic Disc and the efficient use of already existing methods arethe interest of future work.

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