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RETINAL HEMORRHAGE DETECTION USING NEURAL NETWORK WITH SPLAT FEATURE CLASSIFICATION

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Abstract-- *A novel splat feature classification method is presented with application to retinal hemorrhage detection in fundus images. Reliable detection of retinal hemorrhages is important in the development of automated screening systems which can be translated into practice. Under 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. 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. An area under the receiver operating characteristic curve of 0.96 is achieved at the splat level and 0.87 at the image level. While we are focused on retinal hemorrhage detection, our approach has potential to be applied to other object detection tasks.* *Neural network is proposed for classification in this paper. In many image-processing applications, the attributes of shapes within images must be extracted and classified.*

Keywords—*Splat,Wrapper approach, Neural network, Fundus image*

I. INTRODUCTION

Splat is a collection of pixels with similar colour and spatial location. As haemorrhages consist of blood, they share appearance features with intravascular blood. That makes it difficult to differentiate these from retinal vessels using low level pixel features. On the contrary, by upgrading samples for classification from pixel level to splat level, information is encoded at the splat level, with fewer disturbances from pixel level noise. 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.

The most common signs of Diabetic Retinopathy (DR) are micro aneurysms, small haemorrhages, 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. Retinal haemorrhages are caused by retinal ischemia and primarily caused by abnormally fragile blood vessels in hypertension, malaria and primarily, pre-proliferative and proliferative DR. Large haemorrhages are asymptomatic except when they are located in the centre of the macula. Two examples of large retinal haemorrhages are demonstrated in Fig. 1. Compared with anatomical structures, such as optic disc, fovea and blood vessels, the shape and appearance of haemorrhages show substantial variability.

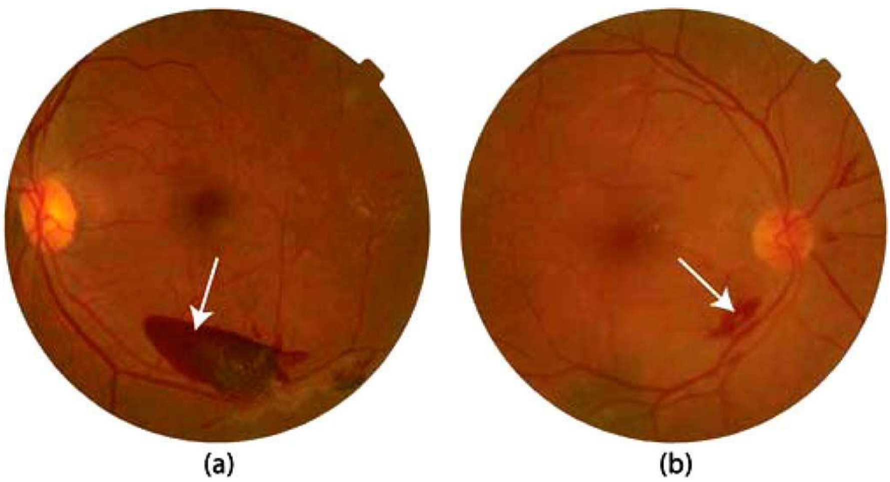

Fig.1 Examples of retinal haemorrhages with different shapes and appearances

A. Haemorrhages

A sub conjunctival haemorrhage may be brought on by a minor blow or trauma, or even by straining, sneezing, or coughing. In some cases, recurrent haemorrhages of this type may signify the onset of a blood disorder or be caused by taking aspirin or other drugs that reduce blood clotting. Vitreous or retinal haemorrhages may be the result of a complication of diabetes known as diabetic retinopathy. They may also be caused by high blood pressure or by an injury to the retina.Intraocularemmorrhage (sometimes hemophthalmos or hemophthalmia) is bleeding (hemorrhage) into the eyeball (oculus in Latin. It may be the result of physical trauma (direct injury to the eye) or medical illness. Severe hemorrhage, particularly when leading to rising pressure inside the eye, may lead to blindness. The types are Subconjunctival hemorrhage (under the conjunctiva), Hyphema (in the anterior chamber), Vitreous hemorrhage (into the vitreous), Subretinal hemorrhage (under the retina), Submacular hemorrhage (under the macula).

II. IMAGE PROCESSING

Image processing consists of a wide variety of techniques and mathematical tools to process an input image. An image is processed as soon as we start extracting data from it. The data of interest in object recognition systems are those related to the object under investigation. An image usually goes through some enhancement steps, in order to improve the extractability of interesting data and subside other data. Extensive research has been carried out in the area of image processing over the last 30 years. Image processing has a wide area of applications. Some of the important areas of application are business, medicine, military, and automation.Image processing has been defined as a wide variety of techniques that includes coding, filtering, enhancement, restoration registration, and analysis. In many applications, such as the recognition of three-dimensional objects, image processing and pattern recognition are not separate disciplines. Pattern recognition has been defined as a process of extracting features and classifying objects. In every three-dimensional (3-D) object recognition system there are units for image processing and there are others for pattern recognition.
There are two different approaches to image processing:

1.1 Analog processing This approach is very fast since the time involved in analog-to-digital (AD) and a digital-to-analog (DA) conversion is saved. But this approach is not flexible since the manipulation of images is very hard.

1.2. Digital processing This approach is slower than the analog approach but is very flexible, since manipulation is done very easily. The processing time of this approach is tremendously improved by the advent of parallel processing techniques.

III. BLOCK DIAGRAM

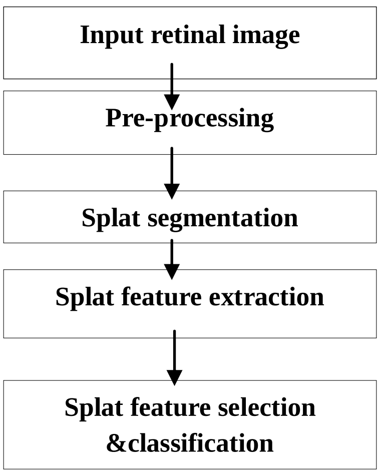

Fig.2 Block diagram of existing system

The purpose of this study is to present a supervised classification algorithm to detect large, irregular retinal hemorrhages. Reference standard hemorrhage locations were delineated by a retinal specialist (MDA) using splat-based image representation. Supervised classification predicts the likelihood of splats being hemorrhages with the optimal feature subset selected in a two-step feature selection process. From the resulting hemorrhageness map, a hemorrhage index is assigned as the image level output.

Splat segmentation Based on the assumption that pixels that are part of the same object or structure share similar color, intensity and spatial location, the image is partitioned into no overlapping splats of similar intensity covering the entire image. At pixel level, the distributions of hemorrhage pixels and non-hemorrhage pixels are imbalanced, since hemorrhages usually account for a small fraction of the entire image. Conventional image over segmentation on a regular grid generates so called "super pixels", a similar concept to "splats." But super pixels are roughly homogeneous in size and shape, resulting in a lattice pattern.

In contrast, a splat-based approach divides images into an irregular grid, depending on properties of target objects to be detected. To create splats which preserve desired boundaries precisely, i.e., boundaries separating hemorrhages from retinal background, we 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. Next, the maximum of these gradients over scale-of-interest (SOI) is taken in performing watershed segmentation. Assuming that we establish a scale-space representation of image with Gaussian kernels at SOI, the gradient magnitude is computed from its horizontal and vertical derivatives where symbol represents convolution and are the first order derivatives of Gaussian at scale along the horizontal and vertical direction. The application of gradient magnitude from a maximum pooling operation across certain scales as the topographic surface in watershed segmentation is important to obtain meaningful splats preserving hemorrhage boundaries precisely. A comparison of it with the original intensity image and gradient images outside SOI as the topographic surface for splat creation is given in Fig. 3.2. Each image in this figure contains a similar number of splats generated the same watershed algorithm. It reveals that splat distribution depends closely upon the method of acquiring a gradient image.

Splat feature extraction In this study, two categories of features are extracted for splat-based hemorrhage detection as follows: 1) splat features aggregated from pixel-based responses; 2) splat wise features.

Splat feature selection and classification 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. The dataset is partitioned into a training set and a testing set.

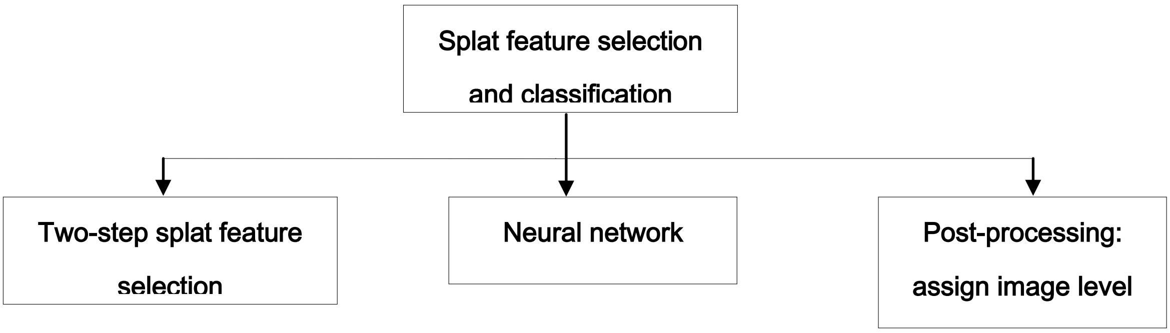

Fig.3 Splat feature selection and classification in modified method

A neural network classifier can be used here to classify the detected abnormalities stages. The k-NN stage is replaced by neural network stage. The block diagram is shown above in Fig.3 Splat-based image representation makes it easier for clinicians to annotate the boundaries of target objects, which may lower the cost of acquiring reference standard data for training. It also provides an efficient and natural way to model irregular shaped abnormalities in medical images. Aggregating features within splats improves their robustness and stability, as it is resistant to pixel level noise and intensity bias. Moreover, certain high level texture features are only meaningful when considering regions instead of pixels. Grouping of pixels into splats only depends on the attribute of neighbouring pixels instead of the number of pixels contained in each splat.

An image is digitized to convert it to a form which can be stored in a computer's memory or on some form of storage media such as a hard disk or CD-ROM. This digitization procedure can be done by a scanner, or by a video camera connected to a frame grabber board in a computer. Once the image has been digitized, it can be operated upon by various image processing operations. Image processing operations can be roughly divided into three major categories, Image Compression, Image enhancement and restoration, and Measurement extraction. Image compression is familiar to most people. It involves reducing the amount of memory needed to store a digital image. Image defects which could be caused by the digitization process or by faults in the imaging set-up (for example, bad lighting) can be corrected using Image enhancement techniques.

IV. RESULT

The first step is to apply the input image. Then a window can be obtained . From 300 training images, 233 776 splats are created and 708 of these splats are hemorrhage splats (0.30%). To alleviate the severely imbalanced data distribution between the two classes, only images containing more than five hemorrhage splats are included in the training process.

V. CONCLUSION

Neighboring pixels with similar intensity are grouped into non-overlapping splats. A set of features is extracted from each splat to describe its characteristics. These splats are taken as samples for supervised classification in a selected feature space. The algorithm is validated on the publicly available Messidor dataset with an area under the ROC curve (AUC) of 0.96 at the splat level. At the image level, an AUC of 0.87 was achieved. Sample size is decreased considerably in a splat-based framework, which is an image re-sampling method. . The speed of detecting mechanism can be increased by using neural network classifiers.The future works those can be done are adding some more abnormalities other than haemorrhages in retinal fundus images for classification, using neural network classifier to classify the detected abnormalities stages. Moreover abnormalities like Exudates, Glaucoma, Diabetic retinopathy can also be detected. The speed of detecting mechanism can be increased by using neural network classifiers.

VI. REFERENCES

[1] Li Tang, Meindert Niemeijer, Joseph M. Reinhardt, Senior Member, IEEE, Mona K. Garvin, Member, IEEE, and Michael D. Abràmoff, Senior Member, IEEE,2013, “Splat Feature Classification With Application to Retinal Hemorrhage Detection in Fundus Images”

[2] Abràmoff. M. D.,. Alward. W. L. M, Greenlee. E. C., Shuba. L, Kim. C. Y, Fingert. J. H ,and Kwon. Y. H, Apr. 2007,“Automated segmentation of the optic disc from stereo color photographs using physiologically plausible features,” Invest. Ophthalmol. Vis. Sci., vol. 48, no. 4, pp.1665–1673.

[3] Niemeijer.M, Van Ginneken. Y. H, Staal.J. Suttorp-Schulten. , M. S. A.and Abràmoff M. D., May 2005,“Automatic detection of red lesions in digital color fundus photographs,” IEEE Trans. Med. Imag., vol. 24, no. 5, pp. 584–592.

[4] Niemeijer. M.Abramoff. M. D., and. van Ginneken. B, May“Information fusion for diabetic retinopathy CAD in digital color fundus photographs,” IEEE Trans. Med. Imag., no. 5, pp.775–785.