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Retinal vessel extraction using Lattice Neural Networks with dendritic processing

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ABSTRACT

Retinal images can be used to detect and follow up several important chronic diseases. The classification of retinal images requires an experienced ophthalmologist. This has been a bottleneck to implement routine screenings performed by general physicians. It has been proposed to create automated systems that can perform such task with little intervention from humans, with partial success. In this work, we report advances in such endeavor, by using a Lattice Neural Network with Dendritic Processing (LNNDP). We report results using several metrics, and compare against well known methods such as Support Vector Machines (SVM) and Multilayer Perceptrons (MLP). Our proposal shows better performance than other approaches reported in the literature. An additional advantage is that unlike those other tools, LNNDP requires no parameters, and it automatically constructs its structure to solve a particular problem. The proposed methodology requires four steps: (1) Pre-processing, (2) Feature computation, (3) Classification and (4) Post-processing. The Hotelling T^2 control chart was used to reduce the dimensionality of the feature vector, from 7 that were used before to 5 in this work. The experiments were run on images of DRIVE and STARE databases. The results show that on average, F1-Score is better in LNNDP, compared with SVM and MLP implementations. Same improvement is observed for MCC and the accuracy.

1. Introduction

Diabetes is rapidly emerging as a global health care problem that threatens to reach pandemic levels by 2030; the number of people with diabetes worldwide is projected to increase from 171 million in 2000 to 366 million by 2030 [1]. Diabetic Retinopathy is considered as the most common diabetic eye disease that affects up to 80% of diabetics and causes blindness in many cases [2]. Arteriosclerosis is considered as the leading cause of death in people over age 45. According to [3,4], its prevalence is about 30%. High blood pressure, or hypertension is a condition present in about 26% of the total population [5]. The three above-mentioned diseases can be diagnosed and monitored via the retina observation [6]. The retina is the only place in the human body where blood vessels can be directly visualized non-invasively and *in vivo* [7].

Among the different elements of a retina image, the vascular structure is a very relevant one. The segmentation of blood vessels is a required step for further analysis that allows measuring attributes such as length, width, branching factor and tortuosity. With them, it is possible to diagnose and evaluate the evolution of several ophthalmologic and cardiovascular diseases [8,9]. Besides, the pattern of the vascular structure of the retina of an individual is unique, making it one of the best choices for biometric systems [10]. Although this segmentation process can be performed manually, it is a long and tedious work that requires experience [11].

It has been suggested that screening programs, in which retinal images are captured and analyzed, should be implemented on a regular basis. This may certainly help us to detect some of these complications earlier. However, it also implies an additional workload on specialists not only to get the image, but also to analyze it [12,13].

Nowadays, it is easier to capture retina digital images due to the development of digital ophthalmoscopes. This opens the possibility of performing automated image analysis, helping physicians to accomplish screening processes of their patients. This could also enable other applications for telemedicine. For instance, a nurse or a general doctor could capture the image of a patient in a remote place, the image can be analyzed by the intelligent system and then,

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a recommendation can be made on whether the patient needs to see an specialist or not. There are basically three kinds of retina images: color photography, red-free photography, and fluorescent angiograms. In this work, we concentrate on the first kind. Segmentation in retinal images is a challenging task because retinal images usually have low contrast and are highly noisy. This effect is caused by the safety limitations used when obtaining the image, making the boundaries of the blood vessels unclear. Also, small depth of focus in the camera as well as the motion of the eye causes different degrees of blur. On the other side, some vessels are only a few pixels in diameter and some images have substantial pathology, making it difficult to accomplish proper segmentation. Finally, there are lots of vessel crossing and branching, as well as a phenomenon called central vessel reflex which makes difficult to extract this structure [14].

This work reports the utilization of a Lattice Neural Network with Dendritic Processing (LNNDP) to automate the segmentation and extraction of the blood vessels structure from fundus images. As far as we know, this is the first time such kind of neural network is used for this purpose. This is an extended version of [15], where our first results were presented. In this new version, we extend our previous work by (a) describing the theory behind LNNDP and their different training methods, offering implementation details that were not covered in [15], (b) implementing an adaptive adjustment of parameter called margin (M) to improve the performance in the training phase, which automates a process that in [15] had to be adjusted manually, (c) presenting a comparison of our approach against other common machine learning algorithms, such as the multilayer perceptron (MLP) and the support vector machine (SVM) [16], (d) including other metrics to compare against recent approaches, and (e) we have added data from the DRIVE dataset [9] to show the robustness of LNNDP for this task.

The remainder of the paper is organized as follows: Section 2 describes current advances in retinal image processing. Section 3 introduces Lattice Neural Networks with Dendrite Processing. Section 4 presents our methodology, Section 5 describes experiments and results and finally, Section 6 presents the conclusions and future work.

2. Previous work

Although the idea of automating the analysis of eye fundus images has attracted the attention of many research groups during the last years, the problem has still not been completely solved [17,18]. In general, computed aided diagnosis via medical images is a complex task where there are usually four steps involved: preprocessing, segmentation, classification and recognition. The work reported here is focused on preprocessing and segmentation (via a classification subproblem) of retinal blood vessels.

According to [19], the developed methods for vessel detection can be roughly classified into three categories: the edge detection-based, the segmentation-based, and the probing-based. The edge detection-based algorithms use gradient masks to identify edge points between regions in a retinal image. Then, the boundary of the vessel is identified by means of intensity discontinuity. For the segmentation-based methods, a good number of options have been considered, being one of the simplest the use of a single threshold to partition a retinal image into background and vessel. Finally, the probing-based methods utilize a profile model to incrementally step forward along the inspected vessel, and identify vessel boundary during probing.

The three most important areas of active research in retinal imaging include development of cost-effective digital equipment to capture retinal images, development of techniques to study the retina function using oximetry or near-infrared analysis, and development of image processing and analysis algorithms that allow the classification of retinal images for automated diagnosis. In many cases, a set of features of the retina vascular structure can establish a probable diagnosis. Parameters such as diameter, color, curvature and opacity of blood vessels may serve as a basis for diagnosis, treatment, and monitor of the aforementioned diseases [12,20].

In [21] a system named STARE was introduced. The name stands for STructured Analysis of the REtina. The authors describe in theory what steps could be required to analyze retina images, although they did not include experimental results. In a different approach, Hoover et al. [22] define a method based on threshold probing. Such method was compared against a matched filter response (MFR), giving an improvement of 15% on the true positive detection rate.

According to [9], several other methods have been proposed to solve the problem of blood vessel segmentation. These methods can be divided into two general categories: rule based methods, and supervised learning methods. The rule based methods comprise vessel tracking, matched filter responses, grouping of edge pixels, thresholding methods, and morphology based techniques. In the case of supervised learning methods, the general approach is to use image processing techniques to enhance blood vessels, and then use of a classifier to discriminate between blood vessels and background pixels. Among the most commonly used classifiers are the multilayer perceptron (MLP), K-nearest neighbors, and support vector machines (SVM) [8,9,23].

Some of the open problems in this matter are vessel segmentation for vessels that have only a few pixels in diameter, vessel segmentation in images with substantial pathology, differentiating arteries from veins, and assessing vessel tortuosity [14].

In an effort to improve the accuracy of the currently available methods, Ramlugun et al. [24] proposed the use of Gabor filters and vessel enhancement by contrast-limited adaptive histogram equalization followed by a double sided thresholding scheme. Addressing the problem of the segmentation of small blood vessels, Li et al. [25] proposed a multi-scale vessel extraction scheme by multiplying the responses of matched filters at three scales. In a work reported by Staal et al. [9], the authors introduce the Primitive-Based Method (PBM). PBM uses image primitives extracted from image ridges that are grouped and given to a classifier. The results were interesting although the authors point out the need to improve certain aspects of the processing to decrease the computational time required. Recently, in [26] the authors use a modified matched filter, called MF-FDOG, which basically extends the original MF by using a zero-mean Gaussian and its first-order derivative. The main advantage of such a method is the competitive results it reaches, but with lower complexity.

Other authors have been interested in developing classifiers able to distinguish among arteries and veins. For example, in the work by Kondermann [27], the authors performed a comparison of two feature extraction methods and two classifiers based on support vector machines and neural networks. The best combination is able to reach 95.32% of correct classifications. Color has also been considered as an important feature for segmentation. For example in [13] and in [28]. Those approaches usually detect the dark background and remove noise, then a further step of fine segmentation is applied. The authors report up to 95.43% of correctly classified samples. Approaches based on morphological operations have also been reported [29,30]. Statistical based methods have been considered, such as linear discriminant analysis [6]. The work reported by Lau et al. [31] considers two steps. One is a segmentation of the vascular structure and the other one is a post-processing to identify true vessels based on a graph tracer. The results are very good, reaching up to 98.7% of true vessels classification.

In [32], the authors use an SVM to perform the classification of retinal images. The proposed method includes a preprocessing step to remove the optic disk edges, a normalization of the green channel and the computation of wavelets to generate a vector of

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