AUTOMATED DETECTION OF RETINAL VENOUS PULSATIONS FROM VIDEO SEQUENCES

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Abstract: The aim of this paper is to propose a method of automated detection and parametrization of spontaneous venous pulsations, that can occur in patients with various degrees of glaucoma. The method uses uncompressed video sequences acquired from fundus video-ophthalmoscope. A parameter of pulsation is then acquired and tested for correlation with occurrence of spontaneous venous pulsations.

Keywords: Spontaneous venous pulsations, image processing, retinal video sequences

1. INTRODUCTION

The relation between heightened intraocular pressure and occurrence of glaucoma is a well-established fact. Spontaneous venous pulsations (SVP) occur when intraocular pressure exceeds retinal venous pressure. Therefore, their presence might be an indicative of developing glaucoma [1]. By capturing image sequences of a retina, the information provided by dynamic changes of retinal arteries and veins could be utilized. The spontaneous venous pulsation can be observed by an eye if present in rather larger scale. Therefore, the sequences intrinsically contain an information about the presence and magnitude of SVP. Such information could be extracted using digital image processing methods.

This paper proposes a method of SVP detection using video sequences acquired via fundus video-ophthalmoscope. Then a parameter corresponding to scale of the pulsation is extracted and compared to visual evaluation. The presence of SVP was classified into three groups based on the occurrence and scale of SVP via subjective visual examination. These groups will be compared to the resulting parameter of our approach to assess a correlation with its value.

2. DATA

The data consists of frame-by-frame video sequences gathered from 67 patients with various levels of SVP and thus glaucoma progression. The properties of the video sequences are following:

The video is encoded in raw form of motion-jpeg, resolution 640×480, 25 frames per second, coded in 8-bit grayscale, and each lasting 10 seconds. The field of view is 20°×15° and centered on the optical disk (OD).

2.1. PREPROCESSING

Image registration algorithms have been applied on these sequences to eliminate eye movements using methods described in [2]. Next, heavily blurred and distorted frames were detected using [3] to be excluded from next processing. An example of a sequence frame is illustrated in Fig. 1.

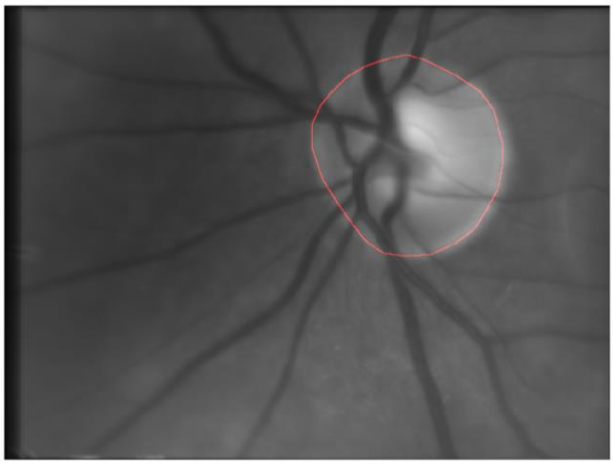


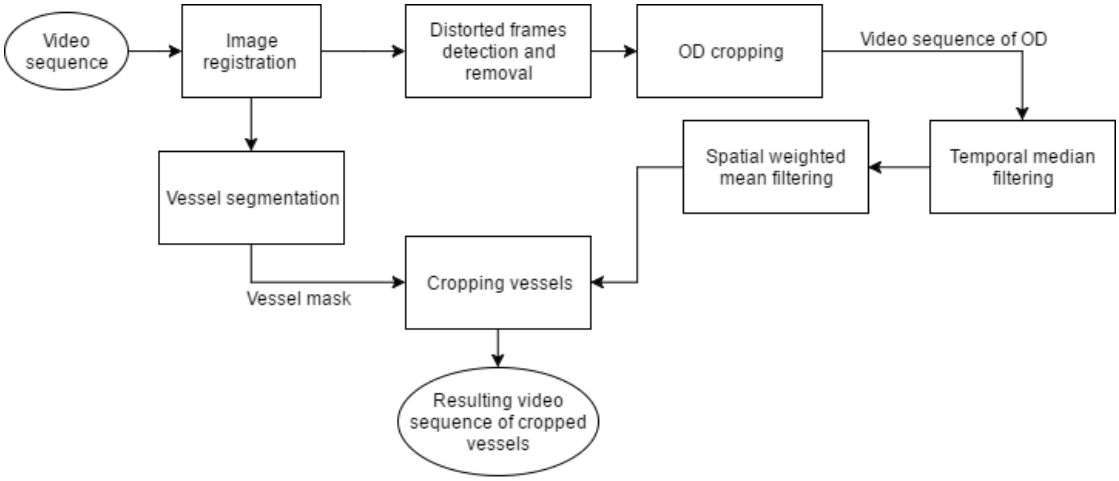
Fig. 1: A mean image from video sequence with highlighted OD

Fig. 2: A mask of blood vessel already cropped into OD

Because most of the pulsations occur inside the OD, which by its higher reflectance increases contrast of the veins, the video sequences are cropped using manually selected region of interest covering OD. Algorithm for automated detection of OD is to be created separately. In order to eliminate fast saccadic movements of the eye and further stabilize the video, a temporal median filtering has been applied on each pixel of the video sequence. Next, a spatial weighted-mean filtering, where central pixel is of highest weight, was used to eliminate the general noise.

For our method, a blood vessel mask is needed. The vessels are segmented from mean image via classification-based approach [4]. Resulting mask of vessels (as well as mask of OD) is shown in Fig 2.

The preprocessing is summarized in Diag. 1:



Diag. 1: Block diagram of data preprocessing

2.2. SUBJECTIVE CATEGORIZATION

All video sequences were subjectively examined and categorized by the amount of visible pulsations into three groups:

1. Visible large pulsations
2. Visible, but small pulsations
3. No visible pulsations

These categories are used for comparison with the pulsation parameter proposed below.

3. METHODS

The proposed method uses dynamic variance of pixels' brightness of the blood vessel mask. Each frame is cropped by aforementioned blood vessel mask. Next, a histogram of each cropped and masked frame is acquired. The value of brightness equivalent to black is removed from each histogram. This value is useless, because it is caused by zero values introduced by cropping the image with the vessel mask.

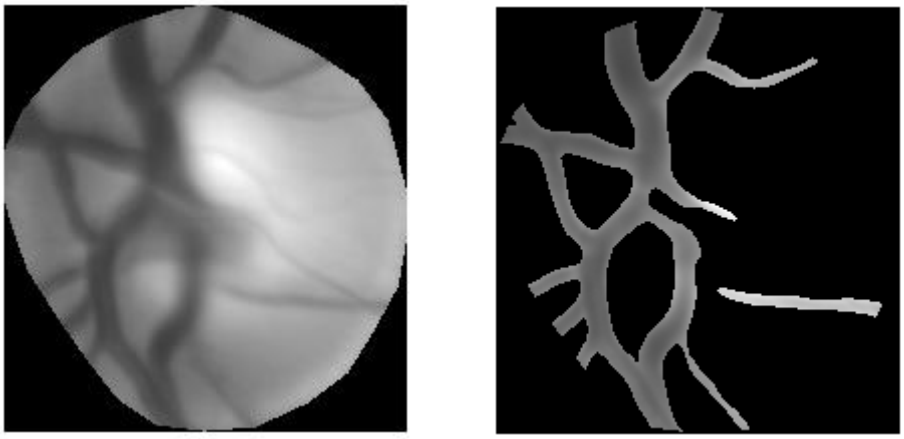


Fig. 3: A frame showing OD before and after applying the blood vessel mask

Periodic changes of the intensity distribution are expected when comparing consecutive histograms of each frame. Therefore, by stacking each of the consecutive histograms along second dimension, an image can be obtained. In this image, the first dimension (x-axis) corresponds to brightness level of the data as it does in histograms in general, second dimension (y-axis) corresponds to time and the brightness of the resulting image stands for histograms' statistical frequency. This image has an apparent rippling feature along its time dimension. This is a direct result of pulsations occurring within the blood vessel mask.

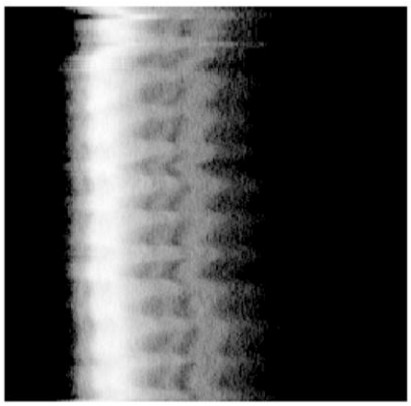


Fig. 4: Stacked consecutive histograms – a temporal histogram

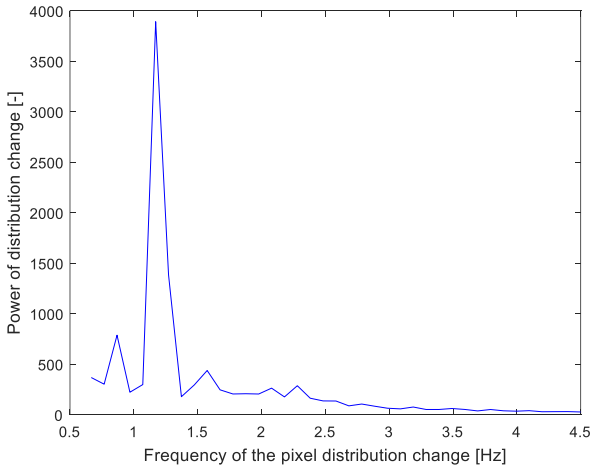


Fig. 5: A plot of power spectrum within the physiological heart rate range

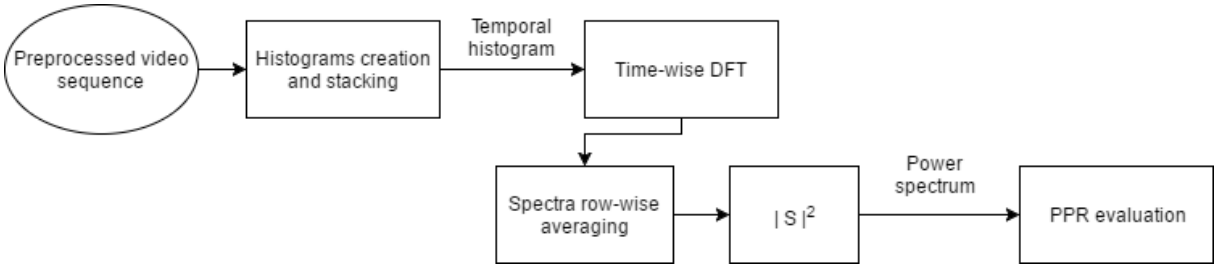
This image is the subject of next analysis. By applying Discrete Fourier transform along its time dimension (in this case a column-wise DFT) and then averaging the resulting spectra (a row-wise mean), we receive an average spectrum of changes of pixel distribution in segmented vessels. Squaring the absolute value of the spectrum yields a power spectrum. This resulting spectrum is expected to have a peak in the range of physiological heart rate values, corresponding to a power of the pulsation.

This peak is then detected and its maximum value is used for parametrization of the pulsations.

To quantify the magnitude of the pulsations a parameter *pulsation power ratio* is created. This parameter is defined by following formula:

$$PPR = \frac{S_{max}^{hr}}{\sum_{i=1}^{N} S(i)} \; [-].$$

The S represents the resulting power spectrum of intensity distribution changes, S_{max}^{hr} represents the value of maximum peak in the heart rate range, N is the number of elements of the power spectrum.



Diag. 2: Block diagram of the algorithm

4. RESULTS

The parameter *PPR* was evaluated using the proposed method on each of the video sequences. Thus, a parameter value was acquired for each video sequence. A boxplot of distribution of the parameter divided into categories based on the SVP categorization mentioned before (Section 2.2) was constructed (see Fig. 6).

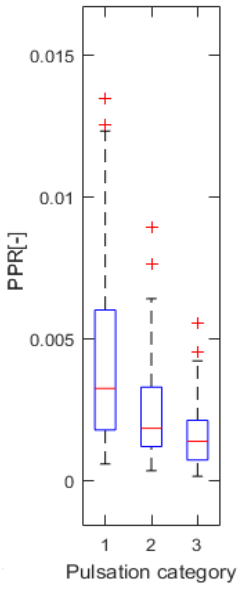


Fig. 6: Boxplots illustrating the variance of PPR in different categories

The results were then analyzed by ANOVA testing – one-way analysis of variance between each of the groups, and also between third group and first and second combined – for evaluating detection of the pulsations occurrence. The resulting p-values are shown in Table 1:

Table 1: Summary of resulting p-values

Category combination		p-value
1	2	$2.4186 \cdot 10^{-4}$
2	3	0.5659
3	1	$6.8509 \cdot 10^{-5}$
1+2	3	0.0011

5. DISCUSSION AND CONCLUSION

A method of automated detection and quantification of magnitude of spontaneous venous pulsations was proposed. A p-value lower than 0.05 indicates rejecting of the null hypothesis of no significant differences between compared groups. The resulting p-values indicate, that *PPR* could be utilized for detection of venous pulsations in the video sequences. The p-value of comparison of combined first and second group with the third indicates the possibility to use the *PPR* for binary detection of the pulsations presence (if they are present or not). Furthermore, the values of comparison between first and third group as well as first and second group imply that the value of *PPR* might correspond to magnitude of the pulsations. It should be taken into account, that the comparison precision is a directly dependent on the subjective evaluation of the expert, especially the difference between group 1 and 2 (subjective magnitude of the pulsations); this fact might be the reason for the high p-value for group 2 and 3.

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