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BLOOD VESSELS SEPARATION ON ANGIOGRAMS

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A new method of classification of pixels into arteries and veins is achieved for the cerebral angiograms. A set of characteristics parameters for pixels were identified throughout the article, based on the temporal evolution of the contrast agent into the blood vessels. For simplifying the computation, only the pixels of the vessels' centerline from two test images: one belonging to the arterial phase and another one to the venous phase were selected. The Dijkstra's algorithm for the minimal path cost computation along with other filtering procedures and morphological operations are used with success for extracting the vessels centerline from the acquisition images. For identification of the clustering classes, the k-means algorithm was used. In fact, the temporal classification of the pixels is confirmed by the spatial selection made by an expert in angiograms' analysis with a score of 90,71% for artery class and 85,97% for vein class.

Keywords: classification, image processing, time series, blood vessels

1. Introduction

The vessels classification on angiograms can give some important information to physician when he has to identify vascular abnormalities. Usually, these disorders appear as a result of hemodynamic problems.

The blood vessels separation on cerebral angiograms is very useful in diagnosis of arterio-venous malformation. This disease implies an abnormal connection of arteries and veins because the capillaries, which are the joint vessels, are missing (Fig. 1.). The blood with high pressure flows directly into the less compliant vessels - the veins, and meanwhile, a nidus is formed.

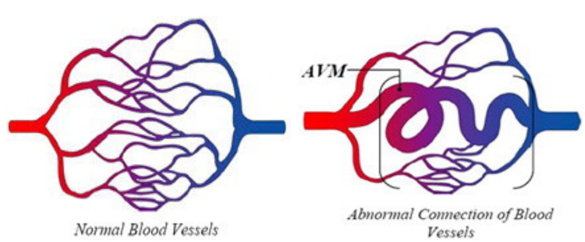

Fig. 1. Arterio-venous malformation - arteries are highlighted in red and the veins in blue [1]

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Although is an invasive and a irradiant procedure, the angiography is very used in clinical practice for detecting the blood vessels abnormalities, due to their excellent spatial and temporal resolution.

The neurosurgeon encharged with the analysis of angiograms faces the difficulty to identify the nidus into the small vessels on grayscale images (Fig. 2.).

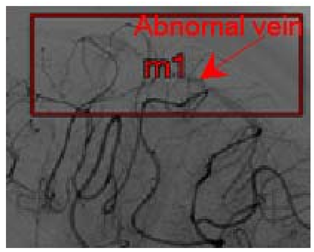

Fig. 2. The evidention of arterio-venous malformation (the appearance of an abnormal vein in the arterial phase) [12]

The purpose of the paper is to make a classification of the vessels in order to enhance the images for easily detecting the pathologies, such as arterio-venous malformation.

There are not so many references in scientific literature which address this problem, especially for cerebral case. A couple of the papers which treat the retinal vessels separation were found [2-8] but they did not treat the patient's movements in the images. In [9] a combination of k-means and hierarchical methods are used for classification of medical x-ray images. The principal component analysis is used to partition the x-ray angiograms into the cerebral circulation phases: early and late arterial, parenchymal and venous phases [10].

A couple of articles which address this topic were developed for cerebral angiograms [11-13], where different sets of parameters which characterize the data were found (the Fast Fourier transform parameters of the pixel's time intensities, the wavelet parameters of this time evolution, etc.) and were put into the clustering algorithm of k-means which generated the arteries and veins classes.

A recent patent [14] provide a solution for the blood flow evolution of the cerebral vessels' based on transit time computation. The separation of vessels can be made by the differences in the hemodynamic patterns.

From the hemodynamic laws, the blood velocity profile is a parabola, and its maximum value is found on the vessel's centerline. Therefore, in the current article, the vessels' centerline extraction was performed in order to concentrate only on the most important pixels. For them, a series of Matlab scripts were developed for finding their characteristics parameters using the time evolution of their gray level intensities and finally grouping the pixels' into arteries and veins.

The advantage of this vessels classification is the capacity to represent the geometric and the blood flow characterization of vessels.

2. Data Acquisition

X-ray angiograms are used as reference for other imagistic procedures because of their good resolutions in representing the blood vessels with the cost of invasiveness. A contrast agent is injected with the aid of a catheter into the vessel of interest. The iodine based solution gives the opacification of the blood vessels when the x-rays are emitted.

As the contrast agent is mixing with the blood, it varies in time and along the vessel. Meanwhile, the angiograph system captures this phenomenon. The C-arm angiograph system offers the possibility to rotate the X-ray source and the image detector around the patient for obtaining more vessels' orientations and/or to magnify the vessels by adjusting the distances between the source and patient and between the source and detector. Finally, some temporal monoplane projections are taken from different view angles. The images from this study were acquired from a hospital in France and some details about the protocol and the image acquisition are provided in the Table 1.

Table 1

Protocol and image characteristics

PARAMETERS	CEREBRAL
Injection site	Carotid/vertebral
Iodine concentration	320 mgI/ml
Projection types	Antero-posterior /Lateral
No. of patients	5
No. of temporal image series	2-3
No. of images per series	~30
Spatial resolution	1024x1024
Temporal resolution	3 images/second
Contrast resolution	10 bits
Peak kilo voltage output of the x-ray generator	85
Total acquisition time	~10 seconds

The image series are affected by diverse noises, such as photons scattering, which are difficult to be quantified and eliminated [15]. The noises have a Gaussian or a Poisson distribution. For this, temporal and/or spatial processing can be undergone, as in the sections 3 and 4.

3. Spatial Analysis

The spatial processing of the image series is focused on extracting the blood vessels network. For the cerebral angiograms, the patient head is kept still and the digital subtraction angiography (section 3.1) can be applied for eliminating the background from images. After image segmentation, the skeletonization processing (section 3.2) can be applied for extracting the blood vessels' centerline.

3.1 Digital Subtraction Angiography

This is a well known technique of easily extracting the blood vessels from digital images, which implies the selection of a mask image (I_{mask}) as an image without the contrast agent and its subtraction from all the opacified images from the image series ($I_{opacified}(x,y)$):

$$I_{DSA\_lin}(x,y) = I_{mask}(x,y) - I_{\mathrm{opacified}}(x,y) \qquad (1)$$

The intensity value exponentially depends on the body thickness (n_b) and linear attenuation factor (x_b) [15]:

$$I_{mask}(x,y) = I_{ini}e^{-n_b x_b} \qquad (2)$$

$$I_{\mathrm{opacified}}(x,y) = I_{ini}e^{-(n_b x_b + n_v x_v)} \qquad (3)$$

where n_v - vessel thickness and x_v - linear attenuation factor of the vessel.

Therefore, a method to eliminate the thickness of the human body [14] would be the logarithmic digital subtraction, as following:

$$I_{DSA\_log}(x,y) = \ln\big(I_{mask}(x,y)\big) - \ln\Big(I_{\mathrm{opacified}}(x,y)\Big) = n_v x_v \qquad (4)$$

More on this topic can be found in [12].

A serious problem of digital subtraction angiography is the patient movement and the superposition of the radiographically opacified structures with the vessels. In [16] some complex methods for noise elimination from angiograms are presented. Nevertheless, the digital subtraction angiography is more often used for cerebral case, because the patient head is fixed. This method is the most simple way to segmentate the vessels from angiograms and this result is valuable for performing advanced image processing.

3.2 Vessel Centerline

The utility of vessel centerline extraction from the digital medical images has stimulated many researchers to develop different methods, such as contour pruning, fast matching or geometrical methods.

If the image series are seriously affected by patient motion and the digital subtraction angiography gives unsatisfactory results, the Frangi's vesselness enhancement filtering [17] is the solution for reducing the image noise, eliminating the background structures and finally extracting the blood vessels. Morphological operations can be applied as pre or post-processing on the output images. For this article, the skeletonization operation, followed by a pruning operation for eliminating the spurs (parasite components), were applied for obtaining a clean vessels' skeleton. On the final image a connectivity component analysis was performed for finding the graph nodes and the Dijkstra's algorithm was used for solving the problem of minimal distances between the nodes and finally finding the vessels' centerlines (Fig. 3.).

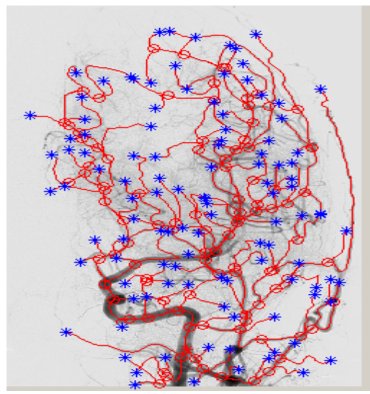

Fig. 3. The vessels' centerline detection (red line)

In the Fig. 3. the joint nodes which are the vessels' bifurcations and the terminals nodes which are the vessels' ends are marked in blue.

All these image processing except for the digital subtraction angiography were performed using the a dedicated graphical user interface developed in Matlab.

4. Temporal analysis

The temporal analysis is specific for angiography and it is its principal advantage. This analysis permits the physician to observe the blood filling and emptying of arteries and veins throughout the cardiac cycle.

The temporal resolution depends on the type of vessels, and in our case, the resolution of 3 images /second was enough to completely observe the blood flow circulation for a cardiac cycle.

A couple of important processing can be performed using the intensity values of pixels in time, such as, the maximum intensity projection for volume rendering and background removal, the time density curve, used for transit time estimation of contrast agent propagation, etc.

4.1 Time Pixel's Intensities Curve versus Time Density Curve

For a constant region volume, the pixel intensity is proportional to the amount of the contrast agent in that region, therefore is proportional to the density of the contrast agent [15].

Time pixel's intensity implies the temporal evolution of the gray levels and it is used for pixels' classification into specific classes of arteries and veins. Because this technique is very noisy, the time density curve can be used instead. The latter method uses a fixed region of interest for which the integral of the pixels is computed for every frame.

$$D(t) = \iint I(x, y, t)dxdy \tag{5}$$

where I(x,y,t) is the pixels' intensities at the acquisition time *t* and *D*(*t*) is the time density curve.

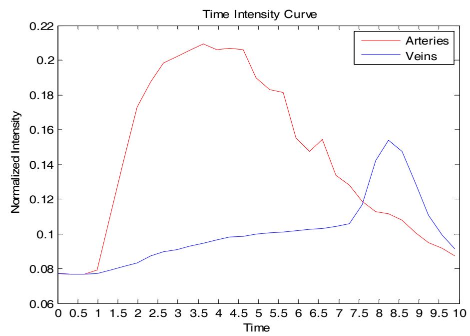

Fig. 4 The mean of time intensity curves from centerline pixels corresponding to arteries (in red) and to veins (blue)

From Fig. 4 some interesting things can be observed, the time intensity curve of arteries has significantly higher gray level intensities than that of veins and its peak value appears in the first half of acquisition time in contrast to the veins case. These observations will be exploited in the characterization of the curves (section 5.2).

In conclusion, the complexity of the x-ray angiograms generation and the images' artifacts explain the noisy pattern of the time intensity curves. Even though the time density curves which are computed for regions of image are less noisy, they are applied with more success for the blood flow estimations. Therefore, in the followings, the time intensity curves computation will be preferred, and for the hemodynamic estimation, a filtering and a fitting operations are applied with care, in order not to eliminate some important information about the pixel.

4.2 Curve fitting

The Gamma variate function [18] can be used for smoothing the time intensity curve in order to easily identify the wash-in and wash-out evolution of the contrast agent.

In [18] the slope, the peak value and other parameters which characterize the curve, were computed in order to remove the noise from data. For better results, a Savietzy – Golay filtering [20] was previously applied as in Fig. 5.

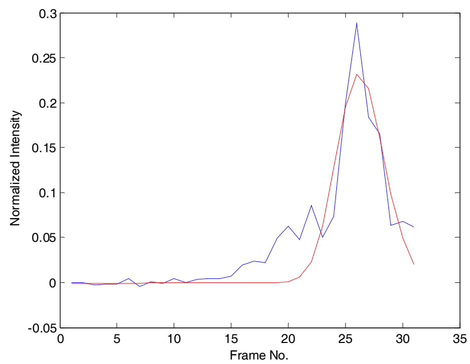

Fig 5. Filtered data (in blue) and gamma variate fitting of data (in red)

The mean root mean square error for fitting data is 0.04.

5. Data classification

The data classification comprises two main important tasks: one is finding the key parameters able to characterize the data (section 5.1.) and other one is to find a proper classification algorithm which divides the data into homogenous classes (section 5.2.).

5.1. Finding the characteristic parameters

In the current study, a couple of parameters where tested in order to better group de data into the two specific classes: arteries and veins. The background class was unnecessary because the classification was considered only for the pixels' of the vessels centerline from an image tagged in the arterial phase (only the arteries were filled with contrast agent) and other image from the venous phase (only the veins as long as the sinus were contrasted).

Starting from the consideration that, in reality, the vessels' classification is performed based on the blood hemodynamic evolution, in the arteries, the blood circulates with a higher velocity than in the veins. Therefore it was chosen as the principal criteria of delimitation. Nevertheless, the estimation of blood flow or velocity from the angiograms is a difficult task, primarily because of the image artifacts.

The pixels' intensity can be approximated with the density of the contrast agent which circulated along the vessels (section 3.1). The maximum of the time density curve represents the maximum amount of contrast agent in that region.

This leads to the assumption that this value equals the cerebral volume [19]. Moreover, the time of contrast agent to fill that region is the difference between the time to maximum density and the time of contrast appearance in that region. This quantity is called transit time.

In Fig. 6 the wash in phase (the first slope), the wash out phase (the second negative slope) as well as the identification of the cerebral volume and the transit time from an ideal time density curve is presented.

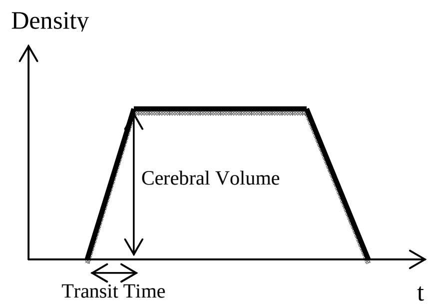

Fig 6. The time density curve approximation (addapted from [19])

With these parameters, some information about the blood flow and their corresponding vessels' pixels is provided. The more characteristics are identified, the better the pixels' classification will be.

Some additional parameters from the signal processing are also included: fast Fourier transform (used in [11-12]), the mean and the standard deviation, the minimal and the maximum gradient after the Gamma variate fitting of the time density curve, etc. The time of minimal and maximum gradient of the data were also chosen as a measure of the wash-in and wash-out slope time.

5.2. Data Clustering

For the acquired images, the most simple and efficient method for clustering the data, was the k-means algorithm. More about the data clustering can be find in [21].

Simulations with different parameters combinations were tried (section 5.1), but the best results were obtained for the following parameters:

a. The amplitude maximum, its phase and its frequency, after applying the fast Fourier transform of the pixels' time density curve
b. The deviation and the mean of the pixels' time density curve
c. The cerebral blood volume, the transit time, the time of bolus arrival, the integral, the minimum and maximum gradient from the Gamma fitted time density curve, because the most relevant results are obtained for the

denoised data. Nevertheless, some precautions are necessary with the fitting, because, in the case of small vessels, some details can be lost.

6. Results

Knowing that the algorithm must find at least 2 classes (k=2), different simulations were performed with good results for k between 2 to 6.

As we decrease the number of classes (k), the pixels from arteries tend to mixture with those of veins classes, especially the big veins from the deep venous system.

The results for k = 5 classes were found to be interesting (Fig. 7) and the pixels from each of these five classes were tagged and represented into five different colors.

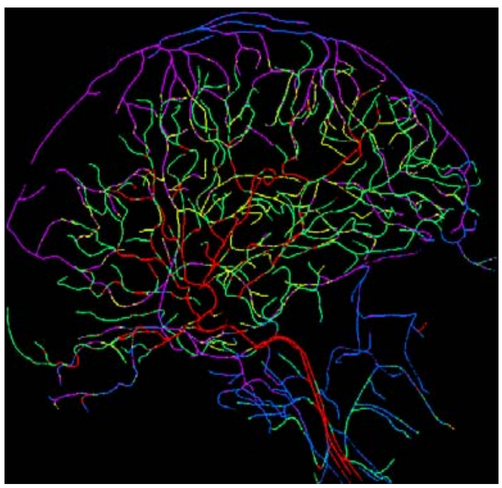

Fig. 7. Blood vessels classification with 5 classes

With the medical supervision, some classes were joined in order to finally form the two expected classes. The expert identified that the classes of pixels represented into blue and mauve are tagged into vein class and the pixels in green, yellow and red into artery class.

An expert in cerebral angiograms selected two frames from the image series: one for arteries and the other one for veins. The images did not include diseased vessels. The centerline was drawn for each image and their pixels were tagged and superimposed on the same image for constructing the ground truth as in the left image of Fig. 8. A manual classification of the pixels made by an expert for each image series was insolubly. In the right image of Fig. 8 is the result of the supervised vessels' classification after an expert tagged the five initial classes into two main classes in order to provide the possibility of visual comparison.

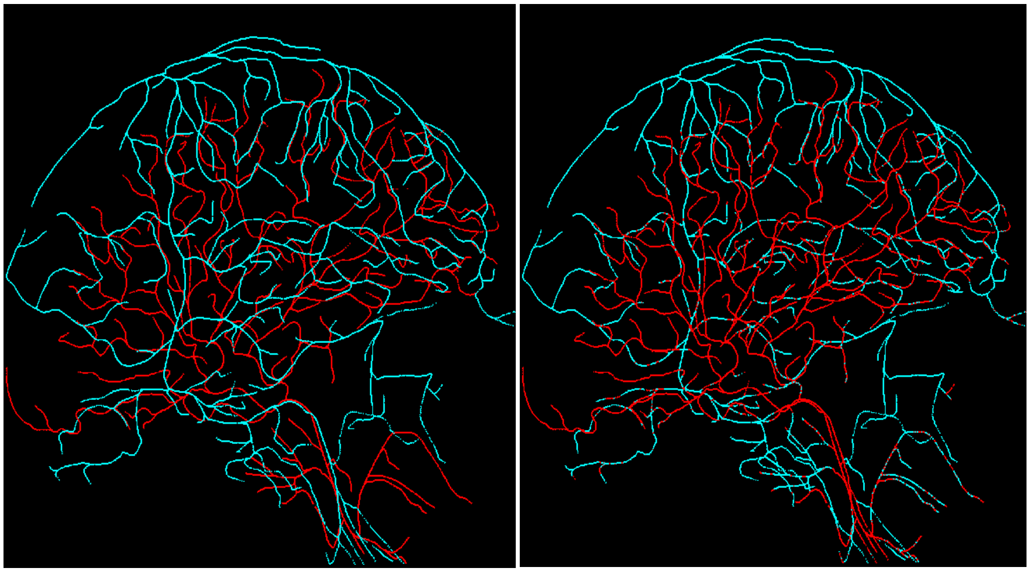

Fig. 8. In the left the blood vessels centerlines from arteries (red) and veins (blue) and in the right the results of supervised classification of pixels

The pixels resulted from the superimposing of the arteries and veins were eliminated from the study.

The validation process was made by comparing the colored pixels resulted from the supervised classification with the ground truth for each class, and the statistics of the tagged and missed pixels are provided in the Table 2.

Table 2

Classification results

Class	**Tested pixels**	**Successful identification (no. of pixels)**	**Success rate (%)**
Artery	14145	13662	90,71
Vein	16454	15062	85,97

The lower success rate in the vein classification can also be visually inspected, because the jugular vein is tagged into the artery class. An explanation could be the fact that the pixels from the jugular vein are spatially closed to those of the carotid artery, which is the main transporter of the blood into the cerebral circulation and it is opacified longer than all the other vessels in the image series.

The computational time for the parameters computation and clustering was about 33 seconds for a number of 31.516 time intensity curves.

The results can offer a perspective about the correlation between the pixels intensities and the densities of the contrast agent and the blood flow patterns which represent the criteria of delineation between the arteries and veins.

7. Conclusions

A supervised classification of pixels into arteries and veins was performed using a spatial and a temporal processing of the image series, for standard clinical angiography of the cerebral vessels.

The ground truth validation revealed a score for matched pixels of approximately 91% for artery class and 86% for the vein. This represents an improvement of the previously used methods from other scientific articles [11-13], especially for the fact of using the hemodynamic information such as the transit time and the cerebral volume as the characteristics parameters and the computational time is slower than in the case of [13], which implied the wavelet coefficients computation. Moreover, it offers a better vessels' classification, because, for example, in [12] the successful rate of identification the arteries was 78% and for veins 65%.

It must be noticed that the arteries are better tagged due to the fact that they are more contrasted than the veins and due to their superior blood flow. In opposition, the small veins are usually assimilated with the background and this burdens the vein classification and the x-ray angiograms interpretation.

The difficulty of the temporal pixels' analysis is given by the parenchymal phase. The blood from the arteries flows into the capillaries which are radiographically represented into diffused pixels' regions which will finally contribute to the time intensity curve profile as small perturbations. Also, the vessels' overlapping and the inaccuracy of the two dimensional projection imposes serious problems. For dealing this problem, a three dimensional reconstruction of the vessel is proposed as a future goal. Another future step will be the prior identification of the parenchymal phase and its elimination from the study.

Nevertheless, this research work revealed some important parameters which are able to characterize the geometric and the hemodynamic patterns of the vessels. This will provide in the end, the possibility of representing a parametric image, which will enhance the x-ray angiograms with new useful clinical information.

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