

# Vessel Segmentation for Angiographic Enhancement and Analysis

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**Abstract.** Angiography is a widely used method of vessel imaging for the diagnosis and treatment of pathological manifestations as well as for medical research. Vessel segmentation in angiograms is useful for analysis but also as a means to enhance the vessels. Often the vessel surface has to be quantified to evaluate the success of certain drugs treatment (e.g. aimed at angiogenesis in the case of transplanted skin) or to gain insight into different pathological manifestations (e.g. proliferative diabetic retinopathy). In this paper we describe algorithms for automatic vessel segmentation in angiograms. We first enhance likely vessel regions to obtain a vessel map which is then segmented. To remove false positives we accept in a second step only those regions showing branchings and bifurcations which are typical for a vessel tree.

## 1 Introduction

The success of a skin transplant depends on a proper revascularization of the transplanted tissue. To promote angiogenesis (vessel growth) different drugs may be administered. To evaluate the effectiveness of such a drug treatment in a research environment, we need to segment the newly grown vessels in micro-angiograms of the transplant area to quantify the surface they cover and also their length. Proliferative diabetic retinopathy is characterized by neovascularization (the growth of new blood vessels). Evaluating the vessel covered area during a retina examination is instrumental in diagnosis. Also, in computer assisted vessel surgery (e.g. PTCA for the treatment of the coronary arteries disease) vessel segmentation is needed to provide fast and easy assessment of the principal structure of the vessel tree for navigational help.

Most vessel segmentation algorithms use a two step approach. In a first step vessel specific information is identified and enhanced. In the second step the vessels are segmented. In contrasted angiograms, vessels are oriented tubular structures of a certain size with increased absorption relative to the immediate

surroundings. Many enhancement techniques are based on these observations [1, 2, 3]. The results of the enhancement step are used to segment the vessels. Vessel segmentation can be done using different methods [3]. Some of the vessel segmentation methods are fully automated while others require user interaction. Towards the above ends we seek to perform vessel segmentation based on such a two step strategy.

## 2 Methods

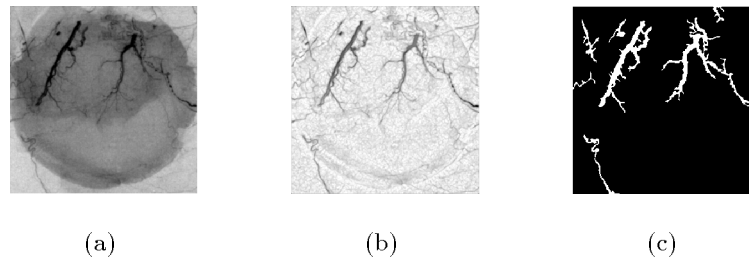
**Vessel Map.** We consider that in the analyzed images the vessels appear darker than their immediate surroundings due to their increased absorption once the contrast agent reaches them. The main purpose of the vessel map is to increase the separability between the background and vessel pixel classes facilitating thus a successful subsequent segmentation. There are two aspects which play a role in determining the separability of a certain feature space: (i) the intra-class variance which should be as small as possible and (ii) the inter-class variance which should be as large as possible. We have thus two main objectives: a homogeneous gray-level representation for both background and vessels and a large contrast.

The varying background is equalized by a morphological top-hat like operator [4]. This operator is defined as the difference between the original image and its closing. If the filter window size is chosen slightly larger than the largest vessel diameter the vessels will be suppressed after image closing, leaving only the background. Subtracting this result from the original yields then predominantly vessel information. This morphological operator successfully increases the homogeneity of the background pixels but it is not a contrast enhancer and hence it does not further increase the separability.

Conceptually, we divide the vessel pixel class into two categories. One category covers the larger vessels which contain enough contrast agent to appear with sufficient prominence in the original and tophat-filtered angiograms. The other category covers the small to mid-size vessels, which appear with less contrast, thus requiring a further enhancement step. Enhancement is carried out in the tophat images by analyzing at each scale within a multiscale approach the largest eigenvalue of the Hessian matrix. The results are combined across the scales by the maximum rule. The scales are chosen such that the larger vessels are not affected. To reduce the variance of the vessel class, the results of both tophat filtering and multiscale Hessian filtering are normalized. Finally, the normalized results are added. Larger vessels appear in the thus obtained vessel map due to their contrast in the tophat image, while mid-size and small vessels appear due to the Hessian filtering step. The vessel map computed for one of the images in our data base is shown in Fig. 1.

**Segmentation.** On the vessel map there are ideally only two classes of pixels present: vessel pixels and background pixels. Starting from an initial over-segmentation result several refinement steps are required to obtain a set of vessel candidate pixels. During these refinement steps every pixel is reclassified according to a decision rule which takes into consideration: (i) the class conditional

**Fig. 1.** Skin transplant micro-angiogram (1.5 cm in diameter) obtained as a result of laboratory experiments on rats (a), its vessel map (b), and the segmentation result (c).



pixel gray level probability and (ii) the influence of the classification results obtained for a certain set of neighboring pixels. Of particular importance in vessel segmentation is the detection of so called seed points: pixels which with a high probability belong to the vessels. To select true vessels among the vessel candidates we use seed points. Only vessel candidates connected to a seed point are considered in the final segmentation.

The over-segmentation result is obtained by thresholding the vessel map with a percentile-based threshold. As the vessel cover always (empirically) less than 50 % of the image area we choose the 50th percentile as threshold. The class conditional pixel probabilities are presumed Gaussian and parametrically estimated using the thresholding algorithm proposed by Otsu [5]. The prior information brought to bear on the class of the investigated pixel by the classification results obtained for its neighbors is modeled by means of a first-order Markov random field [6]. From this point of view the algorithm described here may also be seen as an improvement over the classical Otsu threshold.

A first-order Markov random field is the extension to images (2D) of a first-order Markov random chain. A first-order Markov chain is a random process of states in which the transition probability to the next state depends solely on the previous one. For a Markov random field the dependency condition appears now in the form of a certain neighborhood which influences the state of the current pixel. The states are assimilated to classes and the over-segmentation result serves to initialize the Markov random field. Let  $Y = \{y_j\}$  denote the gray level image with a gray level  $y_j$  at each pixel  $j$ , and  $S = \{s_j\}$  the segmentation result, with a binary label  $s_j$  indicating whether pixel  $j$  belongs to background or vessels. Starting from the maximum a posteriori criterion and invoking the Bayes theorem, we seek  $S$  such that  $p(Y|S)P(S)$  is maximized. Here,  $p(Y|S)$  is the likelihood [6] linking the data  $Y$  and the segmentation result  $S$ , while  $P(S)$  denotes the a priori probability of  $S$ . Since the gray level distribution of a pixel  $j$  depends only on its class  $s_j$  [6, p.203], the  $y_j$  are *conditionally* independent, implying  $p(Y|S) = \prod_j p(y_j|s_j)$ . The conditional marginal probability  $p(y_j|s_j)$  is for each class estimated within the Otsu thresholding method described above.

The Markovian property implies that the conditional probability of  $s_j$  given all other labels depends only on the labels in a small neighborhood  $N_j$  around

the investigated pixel  $j$ , i.e.  $P(s_j|S \setminus s_j) = P(s_j|s_i, i \in N_j)$ . For a first-order cross-shaped neighborhood, we compute  $P(s_j|s_i, i \in N_j)$  as in [7, p.726] by:

$$P(s_j|s_i, i \in N_j) = \frac{e^{-s_j(\alpha+\beta \sum_{i \in N_j} s_i)}}{1 + e^{-(\alpha+\beta \sum_{i \in N_j} s_i)}} \quad (1)$$

where  $\alpha$  and  $\beta$  are parameters to be determined experimentally.

Our decision rule is then: chose the class with the largest posterior probability which we express using the Bayes rule in terms of prior probabilities and class conditional probability density functions. This decision rule is used to iteratively reclassify each pixel until the classification result remains unchanged between two consecutive iteration steps or until a certain number of iterations have passed.

After obtaining the vessel candidate pixels we use a seed points based selection mechanism to determine the real vessels. As a typical vessel tree shows multiply oriented regions (i.e. bendings, bifurcations, etc.) while the background does not, we use corner points as seeds. The corners are detected by thresholding (e.g. using the Otsu algorithm) the lower eigenvalue image of the tensor describing the orientation in a certain neighborhood [8]. The segmentation result for a skin transplant micro-angiogram is illustrated in Fig. 1.

### 3 Results and Experiments

We have tested our algorithm on skin transplant micro-angiograms obtained from laboratory experiments on rats, coronary cine-angiograms from sequences acquired in clinical routine and retinal images from a publicly available data base. All the analyzed images were reduced to a resolution of 256x256. The Tophat window size was established based on the diameter of the largest observable vessel in the respective angiograms. We have recorded the largest eigenvalue of the Hessian matrix at four different scales. For the Markov field approximation we have chosen the parameters:  $\alpha = 1$  and  $\beta = -0.65$  encouraging thus a decision in favor of the vessel pixel class. These parameters remained unchanged irrespective of the analyzed angiogram. The algorithm was allowed to iterate until the classification result remained unchanged between two consecutive iterations. We have evaluated both the quality of the vessel map using a quantitative separability measure (the  $J_1$  criterion as described in [9, p. 446]) and the segmentation results with respect to the percent of correct classifications and the percent of false positives (most false positives are encountered around vessel edges). As reference we have used hand-segmented angiograms. The results are presented in Table 1. for the vessel map and Table 2. for the segmentation. The results represent mean values obtained over all available angiograms for each angiogram type.

### 4 Conclusions

We have presented a vessel segmentation method for vessel surface quantification in angiograms. In developing this algorithm we have followed the typical

**Table 1.** Separability of different vessel maps according to the  $J_1$  criterion. The higher the result the better the separability.

Vessel map	Micro-angiogram	Coronary angiogram	Retinal images
Original image	0.1506	0.0009	0.0109
Tophat	0.6510	0.2197	0.7837
Hessian	0.5737	0.2557	0.8551
Proposed vessel map	0.7268	0.2925	0.8963

**Table 2.** Segmentation results together with the results obtained with the Otsu threshold. Legend: CC = % of correct classifications, FP = % of false positives.

Angiogram	CC	FP	CC-Otsu	FP-Otsu
Micro-angiograms	69.6869	2.7358	50.4253	1.0150
Coronary angiograms	74	2.7670	54.4590	0.9874
Retinal Images	64.8626	1.9960	36.8392	0.1576

pattern recognition paradigm: first feature extraction and then classification. In an initial step the angiograms are processed to enhance the separability between vessels and background. We obtain thus a vessel feature map which is then segmented. Starting from an over-segmentation result each pixel is reclassified using a decision rule which takes into account also the segmentation results obtained in a certain neighborhood of the investigated pixel. We have developed a new vessel map well suited for subsequent vessel segmentation which considers both the properties of the image acquisition method and the anatomical properties of vessels. The classification algorithm described here exhibits better classification results than the Otsu thresholding algorithm on which it is partially based.

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