Fuzzy-Based Extraction of Vascular Structures from Time-of-Flight MR Images

Nils Daniel FORKERT a,1, Dennis SÄRING a, Karolin WENZEL b, Till ILLIES b, Jens FIEHLER b, Heinz HANDELS a

a Department of Medical Informatics, University Medical Center Hamburg-Eppendorf, Germany
b Department of Diagnostic and Interventional Neuroradiology, University Medical Center Hamburg-Eppendorf, Hamburg, Germany

Abstract. In this paper an automatic fuzzy based method for the extraction of the cerebrovascular system from 3D Time-of-Flight (TOF) MRA image sequences is presented. In order to exclude non-brain tissue an automatic skull stripping method is applied in a preprocessing step. Based on the TOF images vesselness and maximum parameter images are computed first. These parameter images are then combined with the TOF sequence using a fuzzy inference. The resulting fuzzy image offers an improved enhancement of small as well as malformed vessels against the remaining brain. Finally, the fuzzy-connectedness approach is used to extract the vascular system. A first evaluation showed that the fuzzy-based method proposed performs better than a state of the art method and yields results in the range of the inter-observer variation.

Keywords. MRA, Time of Flight, cerebral vascular system, segmentation, fuzzy inference

1. Introduction

Stroke is the second most common cause of death and major cause of disability worldwide. Approximately 72% of cerebral strokes are caused by ischemia whereas approx. 20% are caused by hemorrhages due to rupture of cerebral vascular diseases like aneurysms or arteriovenous malformations (AVMs). In case of an early diagnosed cerebral vascular disease an exact knowledge of the individual anatomy is needed for optimal diagnosis, risk estimation and therapy planning.

The 3D Time-of-Flight (TOF) MRA technique is one of the most commonly used MR imaging technique for diagnosis of the cerebral system. The slice wise display of the MR images is often insufficient to obtain knowledge about the individual vascular anatomy of the brain because of its high complexity. 3D visualizations enable an improved and easier visual rating of vascular diseases. In contrast to the direct volume rendering techniques with surface-based rendering of the segmented vessels an improved and faster 3D visualization is possible. Moreover a quantification of pathological changes becomes possible based on the vessel segmentation.

1 Corresponding Author: Nils Daniel Forkert, University Medical Center Hamburg-Eppendorf, Department of Medical Informatics, Martinistr. 52 (Bldg. S14), 20246 Hamburg, Germany; E-mail: n.forkert@uke.uni-hamburg.de.
The segmentation of vascular structures is of high interest and a variety of different approaches has been developed. Hassouna et al. [1] for example used the EM-algorithm to fit a mixture of five distributions to the histogram. Then, a threshold is extracted from the mixture model, which is used during the segmentation process. Chapman et al. [2] introduced the Z-Buffer Segmentation whereas the maximum intensity projection (MIP) and the corresponding Z-Buffer are computed first and then used to extract parameters for the segmentation process. Lorigo et al. [3] presented a method for vessel reconstruction based on curve evolution, an extension of geodesic active contours based on level set methods. A more detailed overview on current vessel extraction techniques is given in [4]. The drawback of most methods is that typical vessel characteristics, like typical intensity distributions or vessel shapes are assumed, which might not occur in case of pathological changes of the vascular systems leading to problems during the segmentation.

2. Material and Methods

2.1. TOF-MRA Image Sequences and Preprocessing

The available TOF images were acquired with a 3T Trio Scanner (Siemens). Each dataset consists of 156 slices with a spatial resolution of $0.47 \times 0.47 \times 0.5$ mm$^3$.

Because of the used multi-slab technology a reduction of the amplitude can be observed in the overlapping region of the slabs (slab boundary artifact). A histogram matching technique proposed by Kholmovski et al. [5] is used to reduce these intensity inhomogeneities. Some non-cerebral tissues like bone marrow and fat are represented by an intensity distribution similar to that from vessels, leading to oversegmentations during the automatic vessel extraction. In order to overcome this problem, a skull-stripping approach especially designed for TOF images [6] is applied.

For the extraction of the cerebral vessel system the vesselness and maximum parameter images are calculated first. The vesselness filter proposed by Sato et al. [7] assigns every voxel a value based on a vesselness measure based on eigen values of the Hessian matrix. This leads to an enhanced display of the vascular structures. Since implicitly the gray value variation of healthy vessels is used in this approach, malformed vessels are not totally enhanced (Figure 1). In a second step a parameter image is computed using a maximum filter, which assigns every voxel the maximal intensity within a defined neighborhood. This is used to include information about the intensities of a voxel’s neighborhood in the fuzzy inference. The two parameter images are then combined voxel wise with the TOF image to one dataset using fuzzy inference.

![Figure 1. TOF image slice (left) and results of the vesselness filter (middle) and maximum filter (right)](image-url)
2.2. Parameter Combination Using a Fuzzy Inference System

The main benefit of fuzzy logic is the possibility of a non-linear combination and use of uncertain knowledge [8]. The first step towards the fuzzy combination is the fuzzification of the real input values. In doing so every sharp input value specifies a degree of membership of each fuzzy set. In this work three fuzzy sets (low, medium and high) described by triangular functions were used to cover each input. Figure 2a shows an example for the fuzzification of a signal from a TOF image. Here a gray value 210 of a TOF image would lead to a membership of 0 for the fuzzy set “low”, 0.8 for “medium” and 0.2 for “high”. The thresholds of the fuzzy set functions are extracted automatically from the histograms of each input dataset.

For the fuzzy inference system a base of 27 rules (3 inputs with 3 linguistic terms) were empirically defined. These rules assign each combination of linguistic terms one of five conclusions (vessel probability: very low, low, medium, high and very high) (see Figure 2b) which are also described by triangular functions using an interval from 0 to 100. The main idea defining the rule base was to weight the response of the vesselness filter stronger if the maximum filter responds a low value, whereas the TOF-input is weighted stronger otherwise. One example for a rule is “If the TOF intensity is medium and the vesselness measure high and the maximum filter response is low then the possibility that the voxel is a vessel is “high”. The fuzzy inference consists of three parts aggregation, implication and accumulation. The purpose of the aggregation is to combine the degrees of membership of the premise parts of a rule to one value for the whole premise. In this work this was implemented by a minimum operator. If for example the membership degrees for the rule stated above are 0.9 for “TOF intensity is medium”, 0.7 for “vesselness measure is high” and 0.7 for “maximum filter response is low”, then the membership degree for the whole premise would be 0.7. The purpose of the implication is to determine the membership degree of the conclusion. This was implemented by cutting the fuzzy set corresponding to the conclusion at the level of the degree of the whole premise (see Figures 2b, 2c). After all rules have been evaluated the resulting fuzzy sets are accumulated to a combined fuzzy set, which was implemented using a maximum operator (see Figure 2d). In order to extract the needed sharp value (defuzzification) the center of gravity (see Figure 2d) was calculated for every combined fuzzy set.

Figure 2. a: Histogram of the TOF image sequence (red) and calculated membership functions for the TOF-input (blue); b: triangular functions for conclusions and example for a fuzzy set; c: example of another fuzzy set; d: accumulated fuzzy set using the two fuzzy sets and the defuzzification with center of gravity
2.3. Fuzzy Connectedness Extraction of the Vascular System

The result of the fuzzy combination is an image dataset in which small vessels as well as malformed vessels are enhanced compared to the background tissues (see Figure 3a). In order to extract the vascular system from this fuzzy-parameter image a thresholding and following connected component analysis is applied. Then, the mean intensity and standard deviation are calculated in the corresponding fuzzy values of each connected component. These values are used in the fuzzy connectedness approach, proposed by Udupa et al. [9], to extract the vascular system from the fuzzy-parameter image. The voxel with the highest fuzzy value of each component is used as a seed point. The single segmentation results of every component are combined to one final result in the end using a disjunction operation.

2.4. Evaluation

In a first evaluation of the method proposed one dataset of a patient with an arteriovenous malformation (AVM) was used. Two manual segmentations of the cerebral vessel system by medical experts were generated as a gold standard. The manual segmentations were performed using a region growing approach and manual correction in the orthogonal views. Furthermore the TOF-image was segmented using the Z-buffer segmentation (ZBS) method [2].

The Dice coefficient [6] and Kappa value [10] were used for quantitative evaluation of the segmentations and the gold standard, whereas values close to 1 indicate a good consensus. The Kappa value is only calculated in a subvolume of the image and is therefore especially helpful in an area of special interest like in the AVM-nidus and its neighborhood. For this reason a manual definition of the AVM-nidus performed by a neuroradiologist was available. Based on this nidus definition a bounding box was calculated and extended by 15 voxels in every direction which then served as the subvolume for calculation of the Kappa value.

Figure 3. Slice from fuzzy parameter image (a); segmentation results for a selected area: manual extraction (b, c), ZBS-method (d), fuzzy method (e); 3D Visualization of the segmentations using surface models of the segmentations for manual extraction (f), ZBS-method (g) and fuzzy method (h)
3. Results

A Dice coefficient of 0.82 and a Kappa value of 0.84 were computed for the comparison of the two manual segmentations. The comparison of the result of the ZBS approach with the two manual segmentations yielded a Dice coefficient of 0.72 and 0.67 ($\bar{O}$ 0.695) and a Kappa coefficient of 0.76 and 0.75 ($\bar{O}$ 0.755), whereas the fuzzy approach yielded a Dice coefficient of 0.81 and 0.82 ($\bar{O}$ 0.815) and Kappa value of 0.86 and 0.84 ($\bar{O}$ 0.85). The good quantitative results were also confirmed by visual in-spection by neuroradiology experts (see Figure 3). The manual segmentation takes between 6 to 10 hours per dataset, depending on the complexity of the vascular system, whereas the ZBS-method took 5 min. and the fuzzy method 30 min. during automatic segmentation.

4. Discussion

The fuzzy-based method proposed allows a fully automatic segmentation of the cerebrovascular system in TOF MRA image sequences.

The first evaluation based on one dataset manually segmented by two medical experts showed that the procedure suggested yields good results in the range of the inter observer comparison and better results as the ZBS method. A visual inspection revealed that the ZBS algorithm suffered from an undersegmentation of small vessels, whereas using the fuzzy approach malformed as well as small and healthy vessels were well extracted. The fuzzy-based method is able to detect malformed vessels if represented by high intensities. In order to perform a more advanced evaluation more datasets and manual segmentations are needed. Furthermore it is planned to compare the results to the results of other state of the art vessel extraction techniques.

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References