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Uncertainty Visualization of Stenotic Regions in Vascular Structures

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Abstract

Stenosis refers to the thinning of the inner surface (lumen) of vascular structures. Detecting stenoses and correctly estimating their degree is crucial in clinical settings for proper treatment planning. Such a planning involves a visual assessment, which in case of vascular structures is frequently based on 3D visual representations of the vessels. However, since vessel segmentation is affected by various sources of errors and noise in the imaging and image processing pipeline, it is crucial to capture and visually convey the uncertainty in a 3D visual representation. We propose a novel approach for visualizing the shape deviation of different probability levels in vascular data, where the probability levels are computed from a probabilistic segmentation approach.

1. Introduction

A main aspect of the clinical assessment of vascular structures is to detect aneurysms or stenoses, i.e., abnormal dilations or narrowings of its inner surface (lumen) [CM03]. For treatment decisions, the clinicians visually inspect the lumen extracted from 3D medical imaging data to detect and assess stenoses and their degree of severity.

Unfortunately, there are many sources of uncertainty in the medical visualization pipeline, like noise errors, imaging artifacts, and assumptions made during image processing and segmentation, which negatively affect the correct extraction of the lumen [RPHL14]. If a clinician is confronted with just one of those contour lines, the treatment decision may vary significantly depending on which one is shown. In fact, Lundström et al. [LLPY07] reported that a slight modification of the transfer function used for volume visualization may result in a significantly different shape in the vessels, which may lead to a wrong treatment. Hence, the vessel visualization shall capture and convey the uncertainty in the vessel shape.

We propose to traverse the probability space around the most likely surface and thus capture different measures that reflect the uncertainty. We then propose a non-obstructive 3D visualization for easy detection of stenotic regions and an intuitive assessment of the degree of uncertainty within the 3D setting.

In the context of medical visualization, different uncertainty visualization approaches as well as their limitations and challenges have been discussed by Ristovski et al. [RPHL14]. Slice-based visualization reduce the uncertainty visualization task to a 2D problem, which can be effectively handled using color coding or nested isolines [PRH10]. A common way to extend the 2D uncertainty visualization approaches to 3D is to use animation [LLPY07] or transparency, e.g., using semi-transparency in volume rendering or multiple nested transparent surfaces [PH10, PRW11, PRH10]. However, as animations, transparent surfaces, and volume rendering with transparency have perceptional issues [RPHL14], we try to avoid using such methods and use opaque surface renderings instead. Mapping the uncertainty using color and textures, we only alter the hue and thus, do not impede the correct surface perception.

2. 3D Visual Encoding of Uncertainty

Let D be a spatial domain and $f(p)$ describe the probability function that a point $p \in D$ belongs to a vessel structure (as computed by a probabilistic segmentation algorithm). Our goal is to visualize the probability function $f(p)$ over a volumetric domain $D \in \mathbf{R}^3$. Typically, one is interested in visualizing certain levels $L(c) := \{\mathbf{p} \in D : f(\mathbf{p}) = c\}$. For an understanding of how the levels change with varying c, one needs to look into multiple levels. Hence, one wants to understand the local change between multiple nested surfaces.

Our approach is based on rendering a single opaque surface $L(c)$ from the probability function f, which allows for good shape and depth perception. We then enhance this surface with a texture or a color (hue) that is obtained by propagating information about f to $L(c)$. More precisely, we define a margin m and map the information about interval $[L(c-m), L(c+m)]$ to $L(c)$. Assuming normal distribution, we would pick $c = 0.5$ and margin $m = 0.25$ as default values, which computes the 25% variability around the 50% probability level (in analogy to box plots).

In order to propagate from level $L(c_1)$ to level $L(c_2)$, we have to traverse probability space $S := \{\mathbf{p} \in D : f(\mathbf{p}) \in (c_1, c_2)\}$. Without loss of generality, we assume $c_1 > c_2$. Starting from a point $\mathbf{p} \in L(c_1)$, we have to find a matching point $\mathbf{q} \in L(c_2)$. Obvi-

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ously, defining $\mathbf{q}$ as being the closest point to $\mathbf{p}$ does not capture space S appropriately and can lead to undesired effects. Instead, we observe that S contains many intermediate levels $L(c_3)$ with $c_3 \in (c_1, c_2)$.Ideally, the propagation traverses $L(c_3)$ in a direction normal to the surface. If this holds true for all intermediate levels $L(c_3)$, then the curve that we traverse during propagation is generated such that its derivative is the gradient ∇ of f. Hence, starting at $c(0) = \mathbf{p}$, we iteratively step through S by computing $c(t+\Delta t) = c(t) + \Delta t \cdot \nabla(c(t))$ with sufficiently small step size Δt. The iterative process stops once we cross level $L(c_2)$, i.e., if $c(t+\Delta t) < c_2$. In this case, we compute the intersection of $L(c_2)$ with the line from $c(t)$ to $c(t+\Delta t)$ to find the actual intersection point of curve c with level $L(c_2)$, which is the sought point $\mathbf{q}$.

Having computed a matching point $\mathbf{q} \in L(c_2)$ for each point $\mathbf{p} \in L(c_1)$ and the respective propagation curve $c(t), t \in [0, s]$ with $c(0) = \mathbf{p}$ and $c(s) = \mathbf{q}$, we can map the extracted information onto level $L(c_1)$. There are multiple properties of the propagation curve that can be exploited to represent the traversed probability space. The respective properties represent different aspects of the uncertainty in the shape. First, the length of the propagation curve represents the distance between the probability levels. Second, the bending of the propagation curve can be captured by the angles between surface normals of the traversed probability levels and represents shape differences of the probability levels. Third, one can also capture the deformation between probability levels, i.e., the movement in directions tangential to the probability levels or the propagation curve, respectively. Since it was a priori not obvious, which of these three properties are helpful for analyzing the shape variations, we developed three visual encodings, one for each property, which we explain as follows.

Color-coding Distance. The probability levels are close together in case of low uncertainty and far apart in case of high uncertainty. Hence, the distance between probability levels is supposingly a good indicator of the degree of uncertainty. If we are interested in a quantitative assessment of the amount of change between levels $L(c_1)$ and $L(c_2)$, we propose to use a color coding for that information. The absolute change is captured by $ch_a := \int_0^s c(t)dt$, which we estimate as $ch_a := \sum_{i=0}^{n} \|c((i+1)\Delta s) - c(i\Delta s)\|_2$, where n denotes the number of Euler steps and $c(n\Delta s) = c(d)$. Since we know the expected distance between different probability levels of the vessels wherever the vessel is healthy and the segmentation does not bring shape uncertainties (we denote it here as ch_{normal}), we can normalize the absolute change to compute the relative change by $ch_r := (ch_a - ch_{normal})/(ch_{\max} - ch_{normal})$ with $ch_r \in [0, 1]$.

Color-coding Shape Difference. When uncertainty is low, one probability level is close to an offset of another probability level, i.e., the shape of the levels is close to identical. When uncertainty is increased in an area, the shape of the levels changes, e.g., one level starts bulging out. This shape difference can be captured by investigating the change of the surface normals. We propose to estimate the difference in shape between levels $L(c_1)$ and $L(c_2)$ and color-code that estimate. Starting with surface normal $\mathbf{n}_p$, we find the normal $\mathbf{n}_{maxdiff}$ with maximal deviation from it along the projection path until we reach point q. The shape difference is then represented by $sh := \mathbf{n}_p \cdot \mathbf{n}_{maxdiff}$. Obviously, $sh \in [-1, 1]$, where $sh = 1$ if there is no shape difference.

Texture-mapping Surface Distortion. Instead of capturing the change in normal direction, one may also capture the change in tangential directions, i.e., orthogonal to the normal. This is related to showing how the surface parametrization of two levels change and can be visualized by mapping a texture to one level and displaying how the parametrized texture is distorted from one level to the other. After projecting to point q of surface level $L(c_2)$, we propagate the color from there to $L(c_1)$ (assuming the same surface parametrization). The texture propagation leads to a regular texture pattern on $L(c_1)$, if levels $L(c_1)$ and $L(c_2)$ are equidistant everywhere. Otherwise, it exhibits distortion, which conveys the level of change between levels $L(c_1)$ and $L(c_2)$.

3. Results

The result of applying this approach to an MR angiography data with synthetically added uncertain stenosis is shown in Figure 1. To encode the amount of change between $L(c-m)$ and $L(c+m)$, we execute the procedure from $L(c)$ in both directions and sum the two obtained distances, thus, showing the 25% variability around the 50% surface on a simulated uncertain stenotic region, see Figure 1. All our computations times are within a fraction of a second and allow for an embedding in an interactive system. The texture pattern (a) shows some clear distortions in the stenotic area, which indicates that the segmentation is uncertain there, but certain in the normal regions. The color-coded distance (b) shows that distances between the probability levels is highest in the most stenotic part. The color-coded shape difference (c) shows that the surface shape changes most dramatically in the transition between normal and stenotic region. In the stenotic region itself, the probability surfaces are all aligned again. This reflects correctly the ground truth.

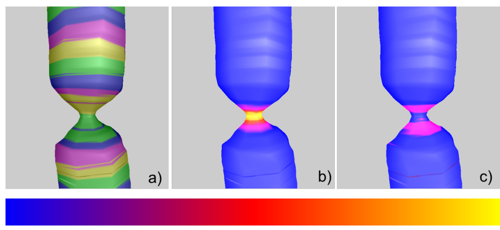

Figure 1: *(a) Texture distortion during projection. (b) Color-coding traveled distance during projection. (c) Color-coding maximum normal difference during projection. Iso-luminance color map shown below is used for not interfering with surface shading.*

4. Conclusions

We proposed a method for 3D vessel visualization where we show a single opaque (most likely) vessel surface and we convey the information from the probability field around it to the surface itself. We capture the uncertainties in terms of distance between the probability levels, the shape differences between the probability levels as well as the deformations occuring during the propagation. We visualize the first two uncertainties using color-coding, while for the last one we use textures.

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