

A feature-based transfer function for liver visualization

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Abstract. This paper presents a new method for the automatic generation of patient-specific, feature-based multi-dimensional transfer functions used in the simultaneous visualization of liver blood vessels and tumors in CT datasets. The method automatically extracts the geometrical structure of the vessels and tumors with a multi-scale eigen-analysis of the image Hessian matrix. It then uses this information to optimize the transfer function based on energy minimization in a variational framework. The method overcomes key drawbacks of existing volume visualization techniques, which are limited to predefined transfer functions, require lengthy manual adjustment based on CT iso-values, and often produce suboptimal results, especially when different types of structures of interest are involved. We demonstrate the method on five clinical data sets with about 100 slices, obtained transfer functions for each in about 90 secs, and produced real-time visualizations. The visualizations were evaluated and compared to those obtained by two existing methods by an expert radiologist, who judged them superior in detail and specificity.

Keywords: CT volume visualization, liver vessels and tumors, transfer function, variational principle.

1. Introduction

Spatial visualization of key anatomical structures in clinical CT data sets has become a valuable diagnosis tool for radiologists. It helps isolate the structures of interest, better understand their spatial structure and relationship, and cope with the ever-increasing size of the data sets. However, volume visualization is still a time-consuming and challenging task, requiring technical knowledge that hinders its widespread routine clinical use. Of the two main approaches that have been proposed to date – segmentation and direct volume rendering – the latter is preferred because it does not require the explicit identification (often manual or semi-automatic) of the structure of interest. Current volume visualization methods use transfer (opacity) functions in lieu of segmentation to highlight the structures of interest. Most use CT intensity values to discriminate between the structure of interest and the background. They construct predefined multidimensional transfer functions or manually adjust them based on the intensity values. This process is time-consuming and often produces suboptimal results, especially for soft tissue structures such as liver vessels and tumors, and when simultaneously visualizing several different types of structures of interest.

The Maximum Intensity Projection (MIP) method, commonly used in angiography for vessels visualization, requires user interaction to find the discriminating iso-value between the structures of interest and the soft tissue. It often fails to eliminate the surrounding soft tissue (Fig. 1a). In addition, it cannot be extended to highlight additional structures, such as tumors. Enhancement of the original CT slice images with a Hessian before applying MIP was proposed for angiographic images [1] and for liver images [2]. However, these techniques enhance the centerlines of the vessels and not their surfaces as required in the visualization. Also, [2] requires manual segmentation of

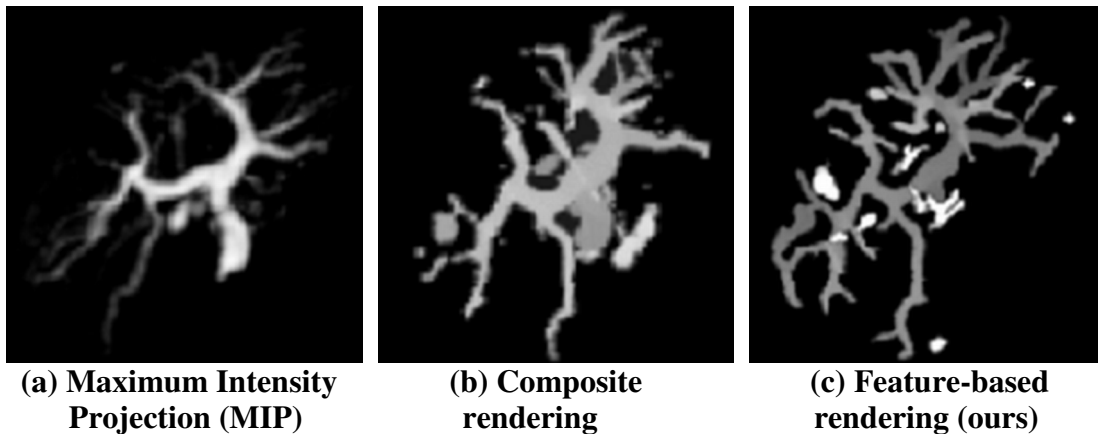


Fig. 1. Visualization images obtained by applying three volume rendering methods on the same liver CT dataset. The first two images only show the vessels since the tumors cannot be differentiated from liver tissue based on their intensity values. The third image, produced with our method, shows both the vessels (dark) and the tumors (bright).

the vessels prior to visualization. Composite rendering uses a transfer function that weights the sum of voxel intensity values along a viewing direction based on predefined iso-value weights. The difficulty is in assigning the weights, which can vary within a dataset and from one dataset to another. Due to the variability of the intensity values of different structures in the liver, this method often produces images with regions of unwanted tissue (Fig. 1b), or omits parts of the vessels. Fattal et al [3] describe one of the first attempts to automatically generate the transfer function for the visualization of fetuses in 3D ultrasound datasets. Their method generates a three-dimensional function consisting of intensity values, gradient directions, and gradient magnitudes within a variational framework by minimizing energy functional between the transfer function describing the surface of interest and the original surface. Since intensity values do vary between patients, some manual adjustment is still necessary.

2. Method

We present a new method for the automatic generation of feature-based multi-dimensional transfer functions used in the simultaneous visualization of liver vessels and tumors in CT datasets. This function is generated automatically for each patient, and optimizes the visualization for each dataset. We focus on liver visualization because many liver diagnostic and surgical procedures require 3D visualization, which, in our clinical experience, is difficult and time-consuming to obtain with existing software.

The method automatically extracts the geometrical structure of the vessels and tumors with a multi-scale eigenanalysis of the image Hessian matrix. It then uses this information to optimize the transfer function based on energy minimization in a variational framework. The novelty of the method resides in the incorporation of regions of interest, together with surface information, in the fully automatic generation of the multidimensional transfer function. The method is applicable to a wide variety of anatomical structures and allows their simultaneous visualization.

The algorithm starts by applying a Hessian based filter to identify the vessel and tumor regions in the volume. It assigns to each voxel a measure that indicates its likelihood to be a vessel or a tumor. Next, it generates a functional that describes the distance

between the desired transfer function and the original volume in terms of the structures surfaces and regions of interest. Within the variational framework, the algorithm derives from the functional a finite differences version of the Euler-Lagrange equation whose solution minimizes the functional. Finally, the equation is solved using the conjugate gradients method to obtain image voxel weights. We describe next the vessels and tumors measures, and the variational framework.

2.1 Vessel and tumor measures

To detect the regions in which liver vessels or tumors are present, we use a Hessian-based filter. This filter describes the geometric structure of vessels or tumors by analyzing the eigensystem of the 3×3 Hessian matrix H of each voxel from a 3D volumetric data. The eigenvectors of H are the directions in which the 2nd order derivatives take extremal values; the eigenvalues are the extremal values themselves.

For bright vessels on a dark background, the three eigenvalues $|\lambda_1| \leq |\lambda_2| \leq |\lambda_3|$ describe the structure of the vessel: λ_1 is the direction along the vessel, and λ_2 and λ_3 are perpendicular to it. Similarly, tumors are represented as a 3D dark blobs whose eigenvalues are approximately equal, $|\lambda_1| \approx |\lambda_2| \approx |\lambda_3|$.

We use the vesselness measurement in [1] and extend it to include blob-like shapes. The vesselness and tumor response is calculated at multiple scales in order to identify vessels and tumors with different sizes. For each voxel, the shape measures are computed from the Gaussian derivatives at multiple scales by assigning different sigma values to the Gaussians. The result is a vector with the filter response values at each scale. The final shape measure is taken to be the shape value with the highest response. The values are interpreted as a probability map in which regions with high pixel values correspond to regions of interest with high probability. Note that using the shape measure by itself as the transfer function is not sufficient, as it highlights the vessels centerlines and not their boundaries as required.

2.2 The variational framework

The variational principle is a mathematical framework for solving a class of maximum-minimum problems over function spaces. The input data is interpreted as a discretized version of continuous function $v : V \rightarrow \mathfrak{R}$, where V is a subset of \mathfrak{R}^n and n is the data dimension (three in our case). The goal is to construct another function u defined over the same domain $u : V \rightarrow \mathfrak{R}$, which identifies the features of interest (the vessels and tumors) and discards the rest (soft tissue). The search for u is formulated as an optimization problem over the space of all twice differentiable functions from V to \mathfrak{R} . Specifically, our goal is to find a function u that minimizes the integral:

$$(1) \quad E(u) = \int_V F(u, \nabla u, x) dx$$

where F is a suitably defined functional, $\nabla u = (u_x, u_y, u_z)^T$ is the gradient of u , and $u = 0$ on the boundary of V . F is a weighted linear combination of three terms:

$$(2) \quad F = \alpha F_{str} + \beta F_{tan} + \gamma F_{ind}$$

F_{str} describes the fidelity of the resulting image to the structures of interest in the original image. F_{tan} represents the difference of the tangential directions between the resulting and original images. F_{ind} requires the resulting image u to have a predefined

non-zero value u_{ind} whenever it can. In particular, it “pulls” u towards u_{ind} in areas of the image where the original image has background structures. The combination of these three terms eliminates undesired surfaces and pulls the structures of interest defined by the shape filter to fit to the surfaces in the original image. The resulting transfer function highlights the structures of interest in the liver, thus allowing their direct volume rendering without any user interaction.

3. Experimental results

We have applied our method to five clinical abdominal CT datasets of different voxel sizes. The datasets have 72-110 slices (122-150mm), with windows of length 117-193 pixels (200-300mm). First, we preprocessed the data by segmenting the liver from the CT datasets and sampled it to get isotropic volumes. For the energy functional in Eq. 1 we set $\alpha = 0.8$, $\beta = 0.05$ and $\gamma = 0.01$ as in [3]. Fig 1c shows our results on one representative dataset alongside those produced with the MIP and composite rendering methods. Note significant improvement in the information quality of the image. Fig 1a was created with the VTK library [4]; Figs 1b and 1c were created with the Volpack library [5]. The running times of the algorithm are 53-137 seconds on a Pentium 4 3GHz machine. The visualization after the computation of the transfer function is performed in real time.

4. Conclusion

We have presented a new method for the automatic generation of feature-based transfer functions. This method uses the geometrical properties of the structures of interest and a variational framework to automatically generate a smooth function. We have applied our method to the simultaneous visualization of blood vessels and tumors in liver CT datasets. We demonstrate our method on five datasets, whose visualizations were evaluated and compared to those obtained by two existing methods by an expert radiologist, who judged them superior in detail and specificity. We plan to apply our method to other soft tissue structures such as the kidney and the breast. We are also exploring alternative formulations of the structures representation and the optimization functional to generate better transfer functions. One such direction is the development of atlas based methods for the detection of structures of interest.

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