Proceedings of IMECE04
2004 ASME International Mechanical Engineering Congress
November 13–20, 2004, Anaheim, California USA

IMECE2004-62018

SURFACE RECONSTRUCTION OF *IN VIVO* GEOMETRY BASED ON MEDICAL IMAGES USING MULTILEVEL RADIAL BASIS FUNCTIONS

Yoke Kong Kuan
University of Illinois at Chicago
Chicago, Illinois

Paul F. Fischer
Argonne National Laboratory
Argonne, Illinois

Francis Loth
University of Illinois at Chicago
Chicago, Illinois

ABSTRACT

Compactly supported radial basis functions (RBFs) were used for surface reconstruction of in vivo geometry, translated from two dimensional (2D) medical images. RBFs provide a flexible approach to interpolation and approximation for problems featuring unstructured data in three-dimensional space. Point-set data are obtained from the contour of segmented 2-D slices.

Multilevel RBFs allow smoothing and fill in missing data of the original geometry while maintaining the overall structure shape.

INTRODUCTION

Computer simulations of blood flow in arteries and veins are widely used by biomedical and bioengineering researchers to study the importance of hemodynamics, the fluid dynamics of blood. Hemodynamics has been shown to be the key factor in the pathogenesis of atherosclerosis (Giddens et al 1993, Ross 1993). In particular, wall shear stress (WSS), has been investigated in the development of vessel lumen narrowing due to excessive tissue growth, intimal hyperplasia, and atherosclerosis.

An accurate representation of *in vivo* geometry is required for accurate simulation. Medical images, such as computerized tomography (CT), magnetic resonance imaging (MRI), and ultrasound (US), of a patient's blood vessels were used to obtain the data set. Regions of interest (typically the lumen) are chosen and segregated from the background.

Compactly supported RBFs was chosen because of its simplicity and fast computation procedure. On the other hand, global RBFs are useful in filling in for missing data. Therefore, multilevel RBF approach is used to integrate the best aspect of 3D scattered data fitting with locally and globally supported basis functions.

RADIAL BASIS FUNCTIONS

The generic RBF representation of a function is of the form

$$f(\vec{x}) = \sum_j \phi_j(\vec{x}) c_j \qquad (0.1)$$

where $\vec{x}$ is the position vector in region $\mathbb{R}^d$ and the sum of extends over a specified range of basis functions, j = 0, 1, …, n. The c_j are unknown coefficients to be determined. In principle, one may employ any set of basis functions $\{\phi_j\}_{j=1}^{n}$ to represent $f(x)$. As the name implies, RBFs are generally of the form

$$\phi_j(\vec{x}) = \phi\left(r_j / R \right), \qquad (0.2)$$

with

$$r_j = \left\| \vec{x} - \vec{x}_j \right\|_2 . \qquad (0.3)$$

and R is length scale that characterizes the support of the RBF. The compactly supported RBF employed here is

$$\phi\left(r / R \right) = \left[1 - \left(r / R \right)^2 \right]_+^4 \left(\frac{4r}{R} + 1 \right), \qquad (0.4)$$

which was introduced by Wendland (1995), locally supported, and leads to a sparse matrix system.

IMPLICATION OF RADIAL BASIS FUNCTIONS TO MEDICAL IMAGING

In order to illustrate the implication of RBF approach on medical images, we considered a 2D example, or single slice of the stack of images. Segmentation of images is performed by thresholding and refined manually, pixel by pixel, to achieve the operator-perceived best description of the lumen geometry

(Fig 1b). The edge detection using discretized Laplace's equation is employed to find the contour for the lumen, Fig 1C.

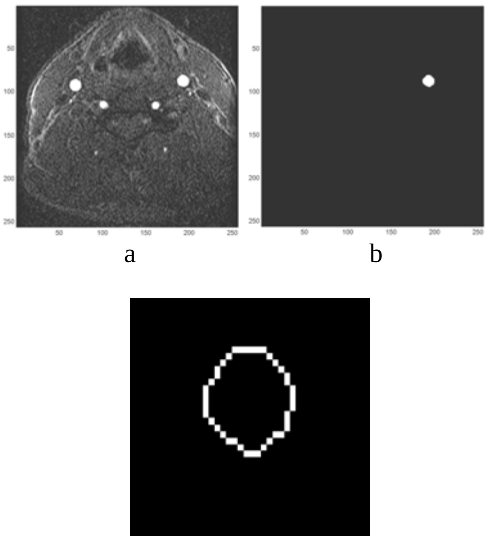

Figure 1: a) Single slices of MR images, b) Region of interest segregated from the background, c) Contour of the lumen after edge detection.

Contour points from the image are representative of the surface. To these points, we assigned the value $g = 0$. In addition, we generate two auxiliary point sets that are just interior and exterior to the surface points (Fig 2).

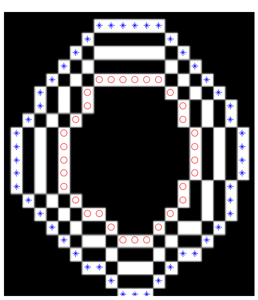

Figure 2: Points set for RBF where as surface points as white, interior (o) and exterior (*) for 2D implicit surface definition.

We assigned $g = 1$ for the interior points, and $g = -1$ for the exterior points. We solve for $\underline{c}$ and then evaluate $f(\bar{x})$ to determine the contour. The resulting contour for a 2D RBF is shown in Fig 3a.

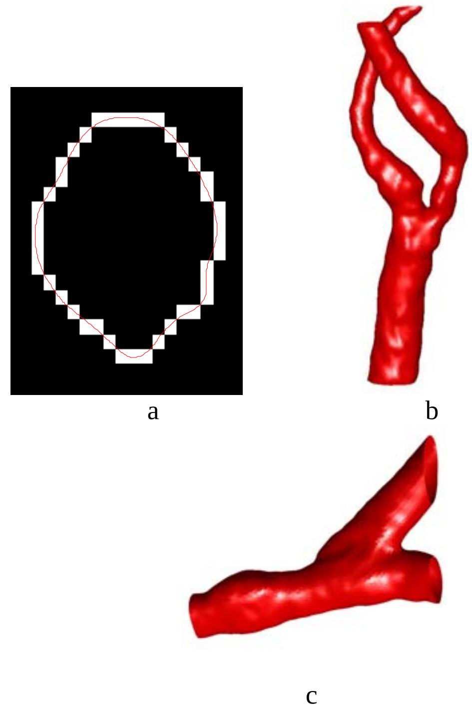

Figure 3: a) Approximation of contour of 2D image using RBF approach, b) surface reconstruction of a stenosed carotid using RBF approach, c) surface reconstruction of a pig arteriovenous graft using RBF approach.

The RBF approach remains the same for 3D surface reconstruction. In 3D space, z-level is taken into consideration. The results for 3D surface reconstruction are shown in Fig 3b-c.

CONCLUSION

This study demonstrates the application of RBFs on medical imaging to determine the lumen surface of an *in vivo* vessel geometry.

ACKNOWLEDGMENTS

This work was supported by the Whitaker Foundation (RG-01-0198), National Institutes of Health, R01 Research Project Grant (Grant No. 2RO1HL55296-04A2), R21 Research Project Grant (Grant No. 1R21EB002511-01)

REFERENCES

Giddens, D.P., Zarins, C.K., Glagov, S.: "The role of fluid mechanics in the localization and detection of atherosclerosis." *J Biomech Eng.* 115(4B):588-94, 1993.

Ross, R.: "The pathogenesis of atherosclerosis: a perspective for the 1990s." *Nature.* 362(6423): 801-9, 1993.

Wendland, H., "Error estimates for interpolation by compactly supported radial basis functions of minimal degree," *Adv. in Compute. Math 4* (1995), 389-396.