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Deformable Models for Biomedical Data Analysis

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Introduction

The rapid development of computer and noninvasive sensor technologies is revolutionizing medicine, offering scientists and physicians powerful new investigative and diagnostic tools. Computer-based medical image analysis is an especially challenging task which has not kept pace with the ability to acquire digital images in various modalities. In response to this challenge, we have been developing several new segmentation, registration, shape reconstruction, and motion tracking techniques for multidimensional medical image analysis. Our work exploits *deformable models.*

Deformable models offer a fundamentally dynamic approach to nonrigid shape and motion analysis based on computational physics. Typically, the models are governed by the Lagrangian mechanics of elastic media, and they are coupled to various data sets (and they may be manipulated interactively) thorough force fields. Although they were originally developed in the context of computer vision [1] and computer graphics [2], deformable models are also naturally applicable to biomedical data analysis. This is because the human body is a complex, highly deformable structure.

In this summary, I will not attempt to survey the growing cavalcade of research on deformable models in medical image analysis (see, e.g., the forthcoming collection [3]). I will, however, review some of our recent work which applies deformable models to a variety of static and time varying medical data sets from scales on the macroscopic to the microscopic. The subsequent sections focus on the extraction of 3D models from serial microscopy, opthalmic image analysis, dynamic 3D cardiac image analysis, and tracking for biomechanics. The details are available in the references.

3D Models from Serial Microscopy

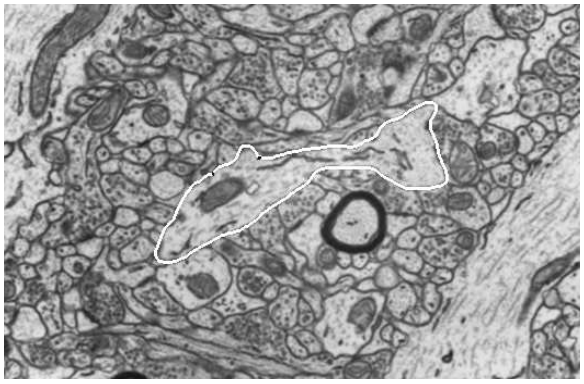
In [4, 5] we propose a new approach to the segmentation, reconstruction, and visualization of 3D models from serial microscopy. We have developed an interactive system which exploits recent computer graphics and computer vision techniques to significantly reduce the time required to build such models. The key ingredients of the system are a digital "blink comparator" for section registration, deformable contour models (the popular "snakes") for semi-automated cell segmentation, and voxel-based techniques for 3D reconstruction and visualization of complex volumes with internal structures. To date, the system has been applied to serial EM images of neuronal tissue and images of an embryo heart. Fig. 1 illustrates the nerve cell application, which reconstructs a volumetric model of the neuronal dendrite from a series of EM images of neuronal tissue sections.

Retinal Image Analysis

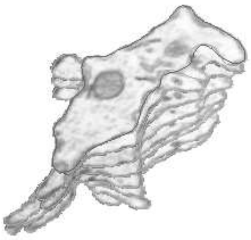
We are developing a new application of deformable models in retinal image segmentation and registration. An adaptive adjacency graph, proposed in [6], consists of a network of deformable contour models which can localize and match retinal vascular trees. The contours are connected at nodes and the adjacency relationships of regions outlined by the contours are made explicit in the graph. Fig. 2 illustrates the registration process, which is performed by placing the graph on a retinal image and allowing it to adapt to target retinal images to be registered. The adaptive adjacency graphs align with the original and target images through forces.

Cardiac Image Analysis

In [7, 8] we define a dynamic deformable balloon model—a spherical thin-plate under tension surface spline which can deform to fit multidimensional medical image data. We employ the finite element method to represent the continuous elastic surface and use quintic triangular finite elements whose nodal variables include positions as well as the first and second partial derivatives of the surface. We have developed a system, implemented on a high performance graphics workstation, which applies the model fitting technique to the segmentation of the cardiac left ventricular surface in static volume (3D) CT images. The dynamic model is also readily applicable to tracking in dynamic volume (4D) CT images in order to estimate the nonrigid LV motion over the cardiac cycle. Our system features a graphical user interface which affords interactive control over the dynamic model fitting process. Fig. 3 illustrates the reconstruction of the LV from cardiac images. The 4D dataset consists of 16 consecutive CT images of a canine heart, each $118 \times 128 \times 128\,(\times 8)$. The balloon model is attracted towards significant 3D "edges" (intensity gradients) by computing a simple 3D potential function: the Gaussian smoothed gradient of



(a)



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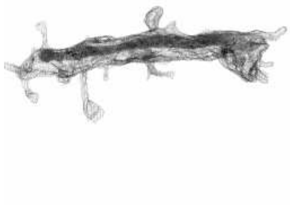

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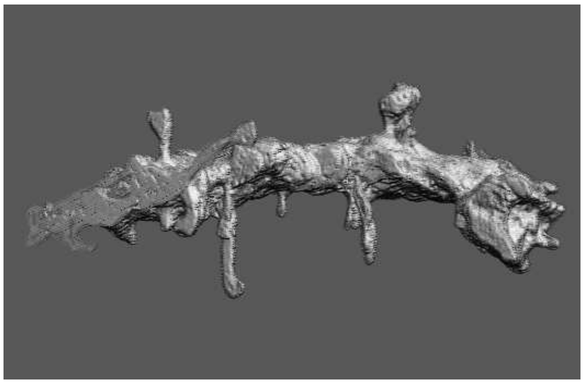
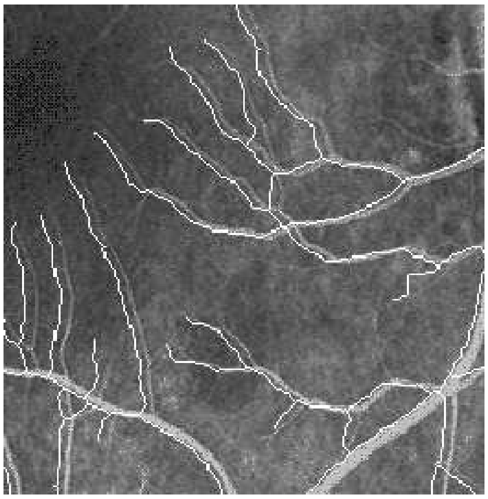
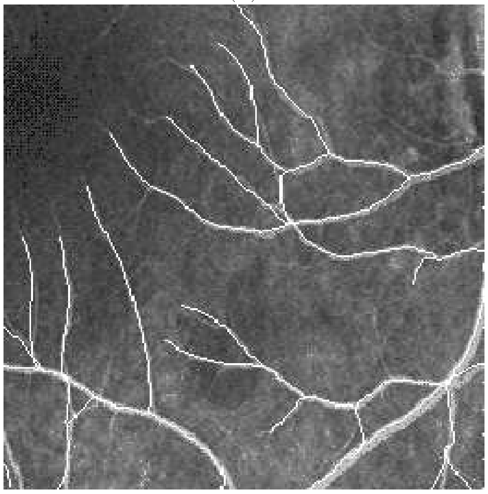


(d)

Figure 1: Segmentation, reconstruction, and visualization of neuronal dendrite.
(a) A serial tissue section image with deformable contour model (white) adhering to cell membrane. (b) Sequentially segmented cell interiors stacked in 3D. (c) Volume rendered view of translucent dendrite revealing internal structures. (d) Shaded surface of reconstructed 3D dendrite model.



(a)



(b)

Figure 2: Detection and matching of vascular tree on retinal image with adaptive adjacency graph
(a) Initial position of AAG (white). (b) Matched AAG.

the image. The final LV reconstruction is shown in Fig. 3(f). Finally, Fig. 4 illustrates the dynamic surface model tracking the LV during the cardiac cycle.

Tracking for Biomechanics

In [9] we apply continuous nonlinear Kalman filtering theory to devise new recursive shape and motion estimators. The estimators employ the Lagrange equations of deformable superquadric models as Kalman system models. To produce nonstationary shape and motion estimates from time-varying visual data, the system model continually synthesizes nonrigid motions in response to generalized forces arising from the inconsistency between the incoming observations and the estimated model state. The observation forces account formally for instantaneous uncertainties and incomplete information. A Riccati procedure updates a covariance

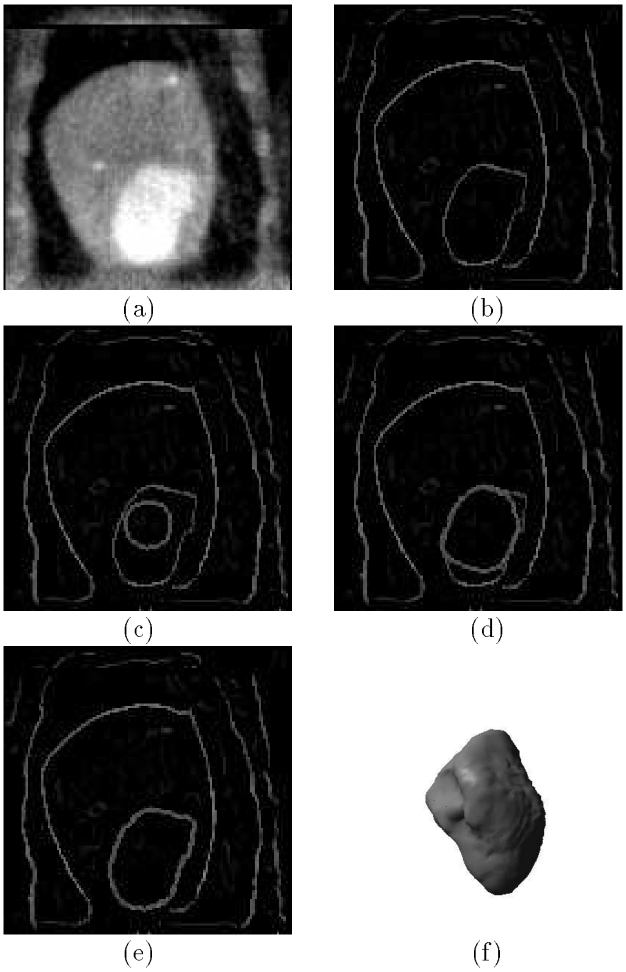


Figure 3: Intensity and processed CT slice of LV. (a) Intensity image XZ plane slice 91. (b) Edge detected image. (c) Cross section of initial model. (d)-(e) Cross section of model deforming to left ventricle. (f) 3D reconstruction of left ventricle.

matrix which transforms the forces in accordance with the system dynamics and the prior observation history. The transformed forces induce changes in the translational, rotational, and deformational state variables of the deformable superquadric system model in order to increase its consistency with the data.

The estimation technique generalizes to constrained multibody models comprising deformable superquadric parts. Fig. 5 shows shape and motion estimation of an articulated multipart upper body model composed of 5 dynamic superquadrics connected by 4 point-to-point constraints using data collected from the raising and flexing motion of the arms of a human subject. The data was collected using WATSMART, a commercial non-contact, 3D motion digitizing and analysis system. The system employs multiple optoelectric measurement cameras and infrared light emitting diode markers that may be attached to various body parts of a moving subject. The 3D coordinate data were collected using

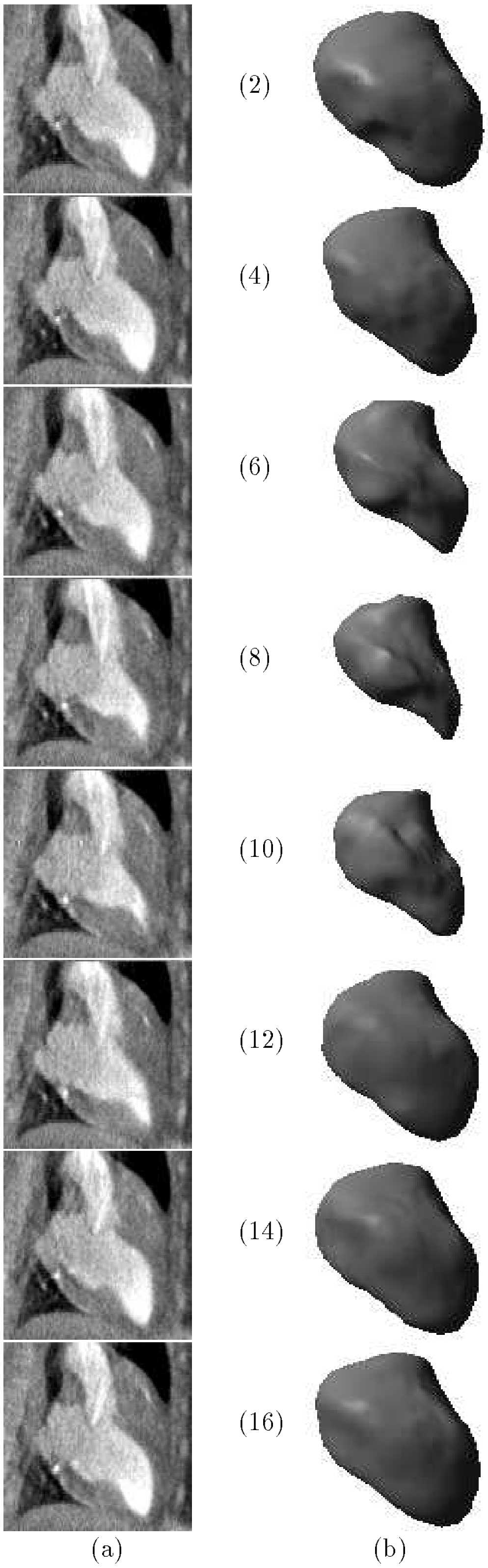
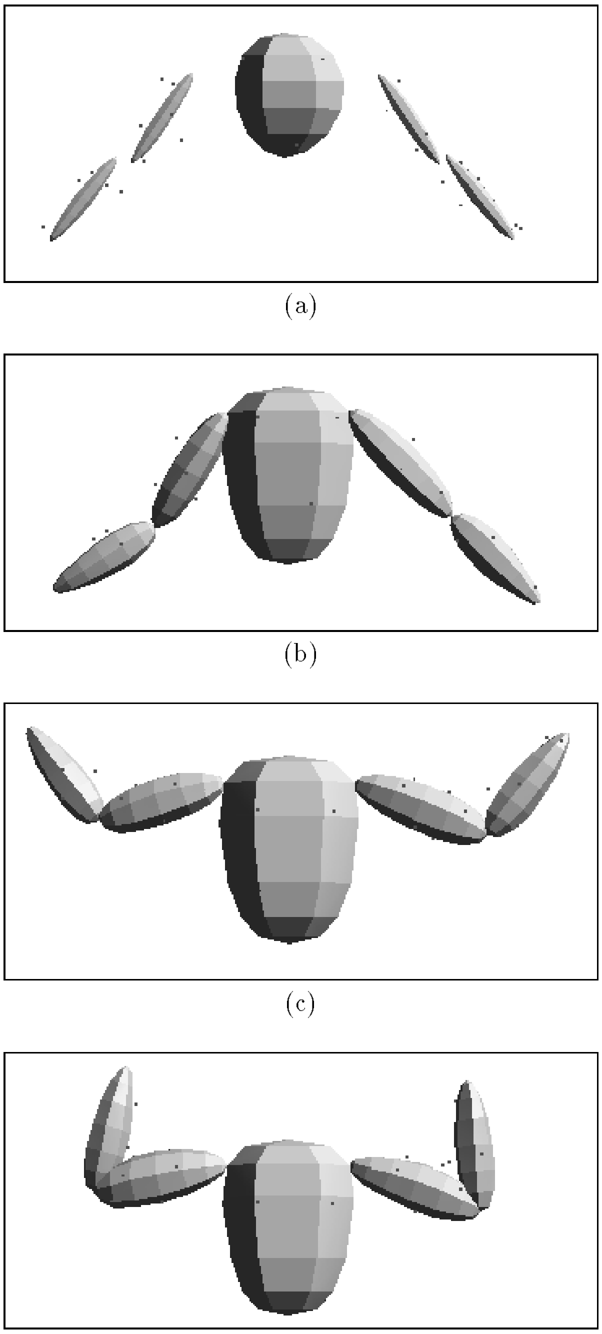


Figure 4: Tracking of LV over a cardiac cycle (a) Sagittal slice of successive CT volumes over one cardiac cycle. (b) Tracked LV surface (not to scale).



(a)

(b)

(c)

(d)

Figure 5: Tracking of articulated human arm motion. (a) Data points and initial configuration of deformable superquadric parts. (b) Reconstructed multibody model of torso and arms. (c–d) Tracking of arm motion.

4 cameras and 32 markers at a 50 Hz sampling rate, yielding 120 time frames. Fig. 5(a) shows a view of the data points and the initial part models. Figs. 5(b) show the models fitted to the data. The fitting process is driven by constraint forces and data forces from the first frame of the motion sequence. Figs. 5(c) and (d) show two frames of the multibody model tracking the articulated motion of the arms.

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