ADAPTIVE MESHES

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Abstract- **Here in this research paper,we have studied adaptive meshes for the non-uniform sampling and reconstruction of the visual data. Adaptive meshes are the dynamic models assembled from nodal masses connected by adjustable springs. Here open adaptive mesh and closed adaptive shell surfaces are based on triangular and rectangular elements.the advantage of this is that adaptive meshes are designed for dynamic recursive estimation of nonrigidly moving surfaces. We think that techniques should be designed for hierarchically subdividing polygonal elements in adaptive meshes and shells. A device should also b designed for discontinuity detection and preservation algorithm suitable for this device.**

Index Terms- **sampling , visual , nonrigidly , polygonal , recursive.**

I. INTRODUCTION

Visual reconstruction from noise corrupted data is a fundamental problem. Image reconstruction has occupied the image processing community for decades, and the surface reconstruction problem is presently attracting a significant amount of attention in computer vision. Most approaches to surface reconstruction begin with a variational formulation of the problem, often based on generalized spline models defined on a bounded domain in the (x; y) image plane. This is followed by a discretization of the energy functional or of the associated partial differential equations and boundary conditions on a computational grid covering the domain, leading up to a numerical solution of the resulting system of algebraic equations using iterative techniques. In conventional approaches to surface reconstruction, the continuous spline surface is represented as a single-valued function z(x; y) and the computational grid is uniform, with its nodes in predetermined fixed positions on the image plane. The nodes on the surface can move only in the verti-4Fellow, Canadian Institute for Advanced Research. cal or z direction during the iterative reconstruction procedure. We introduce a class of spatially adaptive sampling and reconstruction models whose nodes are also free to move over the (x; y) visual domain. This permits the nodes to migrate on the evolving surface during reconstruction. Enhanced representational power accrues from the adaptive placement of nodes in accordance with the complexity of the input data and the reconstructed surface. We are able to perform the simulation very efficiently using an explicit time integration procedure. Our approach is generally applicable to the adaptive sampling and reconstruction of arbitrary data sets in any number of dimensions. In addition to surface reconstruction, this paper also considers the nonuniform sampling and reconstruction of grey-level images. We propose an adaptive image sampling technique which appears to be simpler and more natural than some elaborate multistep schemes (c.f., e.g., [5, 6]).

II. DYNAMIC MESH MODELS

A dynamic mesh is a type of discrete model [12] constructed from physically-based nodes and springs.

2.1 Mesh Assembly and Boundary Conditions

It is natural to consider spring ij along with the attached nodes i and j as a uniaxial (linear) finite element. By allowing them to share nodes, uniaxial elements may be assembled into more complex composite elements, which may in turn be assembled into dynamic meshes. We utilize quadrilateral elements for image and surface reconstruction, and these elements may include cross springs to afford resistance against shearing.

III. ADAPTIVE MESHES

This section develops adaptive meshes by incorporating an adaptation process into dynamic meshes.

3.1 Adaptation Functions and Nodal Observations

The nodes of the adaptive mesh are able to make local observations about the input data. We denote a continuous input data set by d(_), where _ is a point in the coordinate system spanning the data. The formulation in this section accommodates vector-valued data in general, but the applications to image and surface reconstruction illustrate the special case of scalar data. We design the adaptation function so that larger values of Oi will indicate that, from its vantage point xi, node i is observing “interesting features” in the data, such as rapid variations in intensity or shape.

3.2 Mesh Adaptation

The adaptive mesh incorporates a feedback procedure which automatically adjusts spring parameters cij according to the observations made at the nodes to which they are attached. Generally, it makes sense to increase the stiffness of spring ij with increasing Oi and Oj , which indicates that the two associated nodes are observing interesting features in the data, and decrease the stiffness otherwise. The intended effect is for the node density to increase around interesting observations, at the expense of the density over regions in the data where interesting features are absent.

IV. ADAPTIVE IMAGE RECONSTRUCTION

Our goal in this section is to sample an image at a reduced rate and reconstruct it using an adaptive mesh. The fidelity of the reconstruction is enhanced by concentrating the nodes of the mesh where the image function is changing rapidly. We therefore adapt to the image gradient such that the node density increases in high-gradient regions. Starting with a digital image d(k; l), we compute a discrete version of (5), choosing G to be an iterated 5-point approximation to a Gaussian and H(d) = krdk, where r denotes the discrete gradient operator. We normalize the convolution to obtain a discrete adaptation function ad(k; l) whose range is [0; 1]. Projecting node positions xi into the adaptation function. Note that Oi increase with increasing curvature in the range field. Once again, we employ data forces (10). We tested the adaptive mesh on a 128 _ 128 pixel range image of a statuette , a reduced version of STAT 1 (CAT # 155) taken from the NRCC 3D image database [13]. Here, the adapted mesh is planar because data forces were turned off (_ = 0 in (10)) and the nodes of the adapted mesh are clearly denser in areas of high curvature of the statuette data.

V. CONCLUSION

We have developed a new approach to visual sampling and reconstruction motivated by concepts from numerical grid generation. We introduced adaptive mesh models that nonuniformly sample and reconstruct input intensity or range images. Adaptive meshes are dynamic models assembled from nodal masses connected by adjustable springs. Acting as mobile sampling sites, the nodes observe interesting properties of the input data, such as intensities, depths, gradients, and curvatures. The springs automatically adjust their stiffnesses based on the locally sampled information in order to concentrate nodes near rapid variations in the input data. The representational power of an adaptive mesh stems by its ability to optimally distribute the available degrees of freedom of the reconstructed model in accordance with the local complexity of the input data. We have implemented the adaptive mesh algorithm in C on a Silicon Graphics 4D-240VGX workstation. Even for fairly large meshes (upwards of 4000 nodes), the simulation runs at interactive rates on a single CPU with continuous 3D display of the mesh at every time step as it adapts to input data. The user can interactively alter the viewpoint, shading mode, and other visualization parameters as the simulation is running. We have demonstrated the adaptive sampling and reconstruction approach by applying it to intensity and range images. However, our approach is generally applicable to the adaptive sampling and reconstruction of arbitrary dimensional data sets. The nodes can sample both the evolving solution as it is being reconstructed, and they can directly sample arbitrary local properties of the input data, including positions, gradients, curvatures, etc., and in different applications, intensity, color, and texture information as well. 74

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