Neural Network Modeling Techniques for the Real-Time Rendering of the Geometry and Elasticity of 3D Objects

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Abstract – **The paper reviews measurement and neural networks modeling techniques developed by the authors for the real-time rendering of the geometry and elastic properties of 3D objects.**

I. INTRODUCTION

Haptic perception is the result of a complex investigatory dexterous manipulation act involving two distinct sensing components: (i) *cutaneous* information from touch sensors which provide data about contact force, topology, texture, and temperature of the touched object-area, and (ii) *kinesthetic* information about the positions and velocities of the kinematic structure of the hand [1].

Haptic and visual perception modalities complement each other [2], [3]. The resulting multi-sensor perception allows human operators to have a telepresence experience virtually identical with what they would have had while manipulating real physical objects.

The potential of the emergent haptic perception technologies is significant for applications requiring object telemanipulation such as: (i) robot-assisted handling of materials in industry, hazardous environments, high risk security operations, or difficult to reach environments [4]-[9], (ii) telelearning in hands-on virtual laboratory environments for science and arts [10], [11], and (iii) telemedicine and medical training simulators [12], [13].

Many interactive applications cannot rely on synthetic models, or simulations, of the manipulated objects and need models conformal to reality obtained from direct measurements of physical objects. While there are many industrial-strength techniques, using vision, laser scanners, etc., for the measurement of the 3D object shape, there are few available techniques for the acquisition of the cutaneous elastic properties of physical objects.

Multi-sensor fusion techniques are studied for the integration of the 3D geometric shape model with the measured elasticity characteristics into a *composite geometric and haptic model* which is a conformal representation of the haptic properties of a physical object.

As high rendering rates are essential for the quality of the high-fidelity virtual environments, high-speed hardware co-processors have to be developed for the efficient storage, model transformation, and real-time rendering of large numbers of composite geometric and haptic object models evolving in the virtual operation theater.

Neural Networks (NN) which are able to learn nonlinear behaviors from a limited set of measurement data can provide efficient and compact multi-media object modeling solutions. Due to their continuous, analog-like, memory behavior, NNs are able to provide instantaneously an estimation of the output value for input values that were not part of the initial training set. NNs consisting of a collection of simple neuron circuits provide the massive computational parallelism allowing for high rendering rates of complex models [14].

The paper will review geometric and elasticity measurement techniques as well as NN models developed by the authors for the real-time rendering of the geometry and elastic properties of 3D objects as part of an experimental distributed and interactive haptic virtual environment, Fig. 1, which is currently under development in the DISCOVER Lab at the University of Ottawa. An impedance-reflecting *virtual operation theatre* incorporates the *composite geometric & haptic models* of the kinematic and dynamic interaction behaviour of all manipulated objects, [8], [9]. The interactive haptic virtual environment is designed to allow any user *USER(k)* from a distributed set of users, $k=1,...NU$, to experience the haptic "hands-on feeling" while dexterously manipulating a remote physical object via a robotic telemanipulator *ROBOT(k)* ($k=1,...NR$) equipped with haptic and video sensors.

II. 3D GEOMETRIC SHAPE ACQUISITION

This section will review the structured light techniques developed at the University of Ottawa for the recovery of the 3D geometric shape of the object, [15]-[22].

Structured light is an efficient method for obtaining 3D scene information from a single 2D image by using a specially designed light source to project sheets or beams of light with a known *a priori* spatial distribution onto the scene casting lines or points on objects [23]-[25]. A camera is used to visualize, from an angle, the structured light projection on the surface. Recovery of the 3D coordinates of the points identified on the object's surface is based on the triangulation principle .

There are different patterns that can be used for structured light applications: (i) single point, (ii) single line, (iii) stripe pattern, and (iv) grid pattern.

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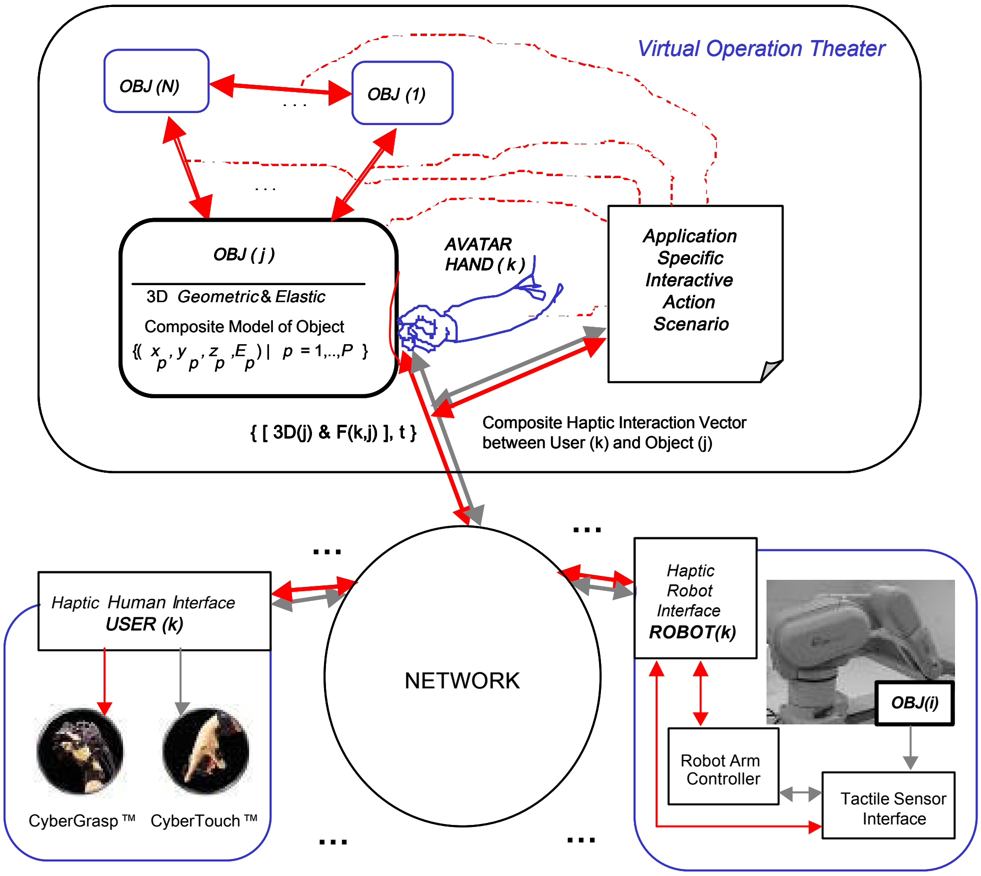

Figure 1. Distributed interactive haptic virtual environment.

We have adopted the *grid pattern* as it combines the advantages of both the simple point and the line pattern as sharp discontinuities may indicate jump boundaries at several object points. All the information needed for the reconstruction of the 3D object shape can be recovered from a single snapshot of the illuminated object surface, which has the advantage of accelerating the ranging process.

The simultaneous generation of all grid nodes or lines may introduce ambiguity in the identification of individual nodes or lines projected on object surfaces resulting in the so called *point identification problem* similar to the *correspondence problem* encountered in stereo vision.

We were using pseudo-random encoded grid patterns, which solve the point identification problem as they allow for an absolute identification of both grid coordinates, the line- and column-index, of any grid node projected on an object's surface, Fig. 2.

We use either special geometric shapes, as illustrated in Fig. 3, or colours, as illustrated in Fig. 4 - or a combination of both - to mark the distinct pseudo-random symbols used to encode the projected structured light grid.

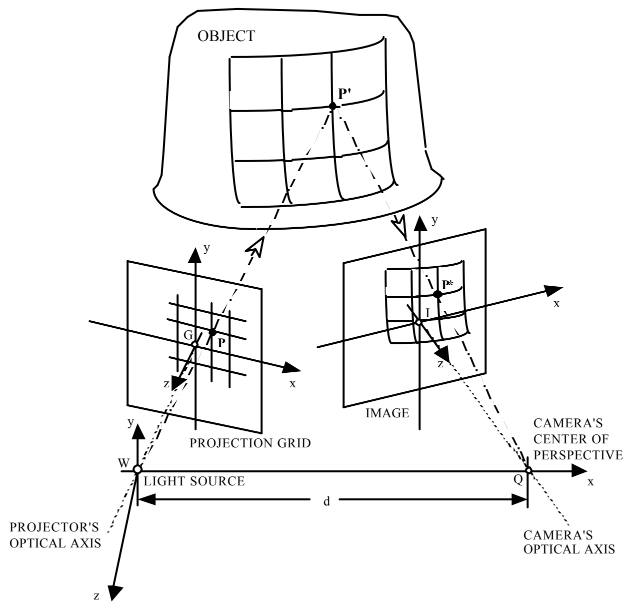

Figure 2. Point identification in grid encoded structured light.

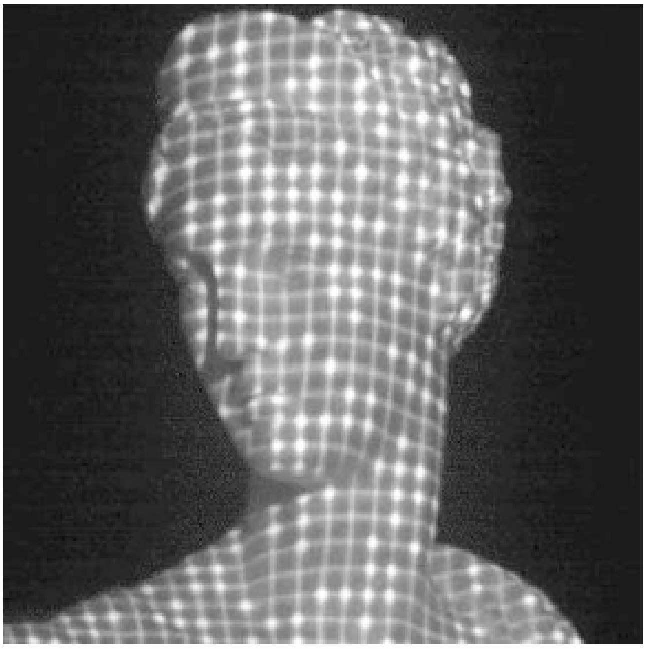

Figure 3. Image of a pseudo-random geometrically encoded grid projected on a cube, from [21].

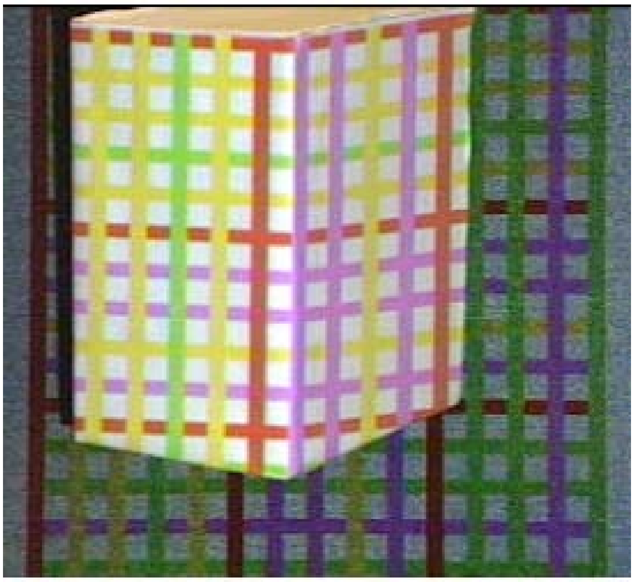

Figure 4. Image of a pseudo-random color encoded grid projected on a cube, from [19].

III. NEURAL NETWORK MODELLING OF 3D OBJECT SHAPES

This section will review the NN modeling techniques developed by Cretu et al., [26], for real time rendering and geometric transformations of the 3D object shapes.

Starting from a 3D point-cloud of the object's shape, a NN is used to provide a volumetric representation of the object. The surface of an object is described by a set of zeros in the output response of the network, while the interior or exterior of an object are mapped to a negative or positive value, respectively. The representation is continuous, compact, and accurate. This modeling technique solves the problem of large memory usage and rendering times of polygonal models, the problem of the large memory for storage of octrees, the incapability to specify a point on a surface of the implicit surfaces or the lack of representation of the object interior in the case of the *constructive solid geometry* (CSG) models, and the problems in modeling minute details of splines.

While providing a quite accurate model, with facilities to perform volumetric and implicit operations, the *multi-layer feed-forward neural network* (MLFFNN) representation implies a computationally expensive training phase and a time investment for the generation of the modeled object.

Among all NN architectures studied by Cretu et al., [26], the *neural gas network* offers both a very good modeling accuracy and a reduced computation cost. Fig. 5 shows as an example the neural gas network model of a 3D human face defined by an initial cloud of 19,080 points. This neural gas network model is remarkably compact consisting of only 1,125 points. Its generation took only 42 minutes, which is much shorter than the 3.3 hours needed for training of a MLFFNN model of the same face.

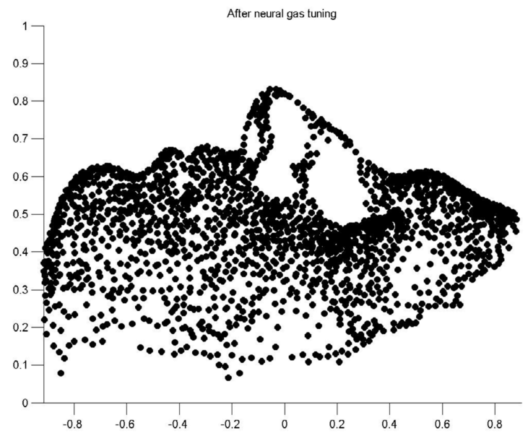

Figure 5. Neural gas network model of a 3D human face, from [26].

IV. MEASURING THE ELASTIC PROPERTIES

This section will present a measurement system developed for the recovery of the strain-stress relation at different points on the surface of a 3D object, [27].

A robot manipulator equipped with a stylus style haptic probe was used to measure the elastic properties of the object. Once the probe touches the object's surface, the 3D coordinates (x_p, y_p, z_p) of the point of contact recovered from the robot's kinematic transform function are used to index the registered elasticity characteristics.

Measuring the elastic properties of physical objects is a time consuming operation which requires moving the probe sequentially to touch one by one all the points of interest on the object surface and measuring the strain-stress relation on each point of contact.

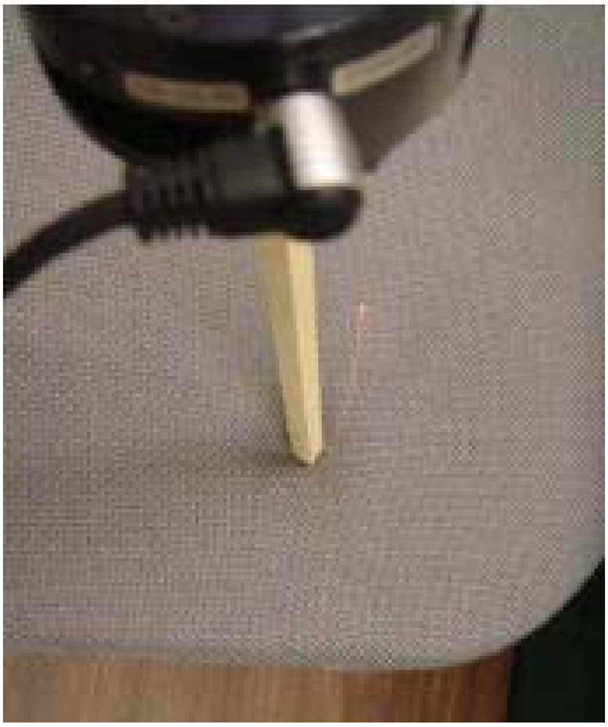

Figure 6. Force-torque sensor measuring the interaction force and torque at the point of contact between the robot manipulated probing rod and the object.

In order to minimize the number of points that have to be probed on an object surface, Cretu and al., [28], proposed a non-uniform adaptive sampling algorithm based on a self-organizing neural architecture to selectively collect data only on those points that are relevant for the characterization of the elastic behavior of a given object.

Starting from a 3D point-cloud of an *a priori* recovered geometric model of the object's shape, a neural gas network produces a compressed model of the object. During the learning procedure, the model contracts asymptotically towards the points in the input space, respecting their density and thus taking the shape of the objects encoded in the point-cloud. These modeling properties ensure that the density of the tactile probing points is higher in the regions with more pronounced variations in the geometric shape. The neural gas network architecture, its implementation and its use for adaptive sampling are described in detail in [29].

The robot applies a continuously increasing force on the haptic probe which acts on the normal direction to the object surface in each of the points deemed of interest by the adaptive sampling algorithm.

The elastic behaviour at any given point (x_p, y_p, z_p) on the object surface is described by the Hooke's law:

$$\begin{cases} \sigma_p = E_p \cdot \varepsilon_p & if\ 0 \le \varepsilon_p \le \varepsilon_{p\,\max} \\ \sigma_p = \sigma_{p\,\max} & if\ \varepsilon_{p\max} < \varepsilon_p \end{cases}$$

where E_p is the modulus of elasticity , σ_p is the stress, and ε_p is the strain on the normal direction.

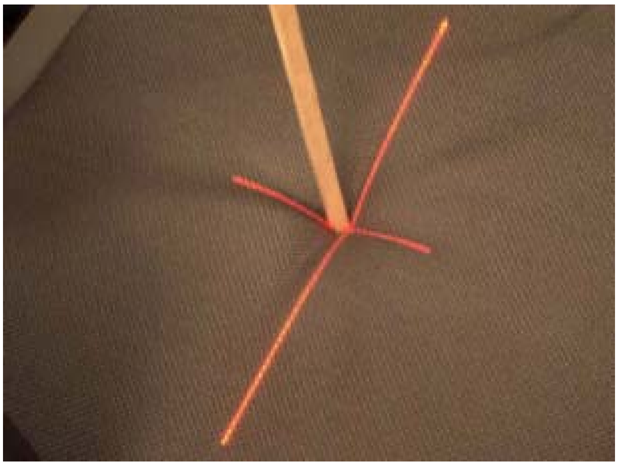

Figure 7. Laser range-finder based recovery of the geometric profiles in an area around the contact point between the probing rod and the object.

A force/torque sensor in the robot's wrist, Fig. 6, measures the force components applied on the object and a laser range finder, Fig. 7, measures the deformation of the surface of the object under the given force. The resulting mean value profiles calculated over 100 scans, consisting each of 512 samples measured along the laser sweep line on the object's surface, are then saved for each magnitude of normal force applied on the object and for each cluster of similar elasticity.

V. NEURAL NETWORK MODELLING OF 3D OBJECT ELASTICITY

A NN modeling technique, Fig. 8, has recently been proposed by Cretu et al., [27], to map elastic behavior from data collected using a joint sensing strategy, combining tactile probing and range imaging.

For each cluster of similar elasticity, a MLFFNN with two input neurons (one for the position along the scanline, *Y,* and one for the force, *F*), 25 hidden neurons and one output neuron (for the magnitude of the deformation, *Z*) is employed to learn the relation between the applied forces measured by the force-torque sensor and the corresponding geometric profiles measured by the range finder. One network is needed to model the elastic behavior of each cluster. Once trained, the NN takes as inputs the *Y* coordinate and the force *F*, and outputs the Z coordinate, as illustrated in Fig. 9 and Fig. 10.

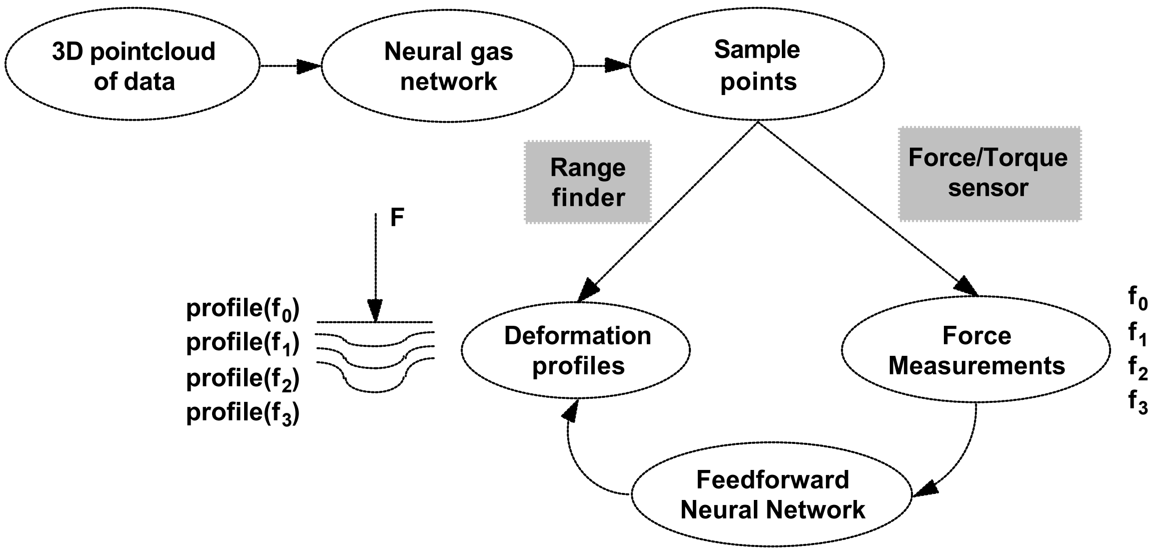

Figure 8. Neural network mapping and clustering of elastic behavior from tactile and range imaging data.

The feed-forward NNs were trained for 10000 epochs using the Levenberg-Marquardt back-propagation algorithm with a learning rate of 0.009. The whole set of measurement data had to be used for training in order to provide enough samples. For the semi-stiff material that was modelled, the mean square error reached is $3.50 x 10^{-7}$.

The resulting hapto-visual NN model allows not only to recover the elastic parameters in the sampled points but also provides an estimate on the elastic behavior on surrounding points that are not part of the selected sampling point set.

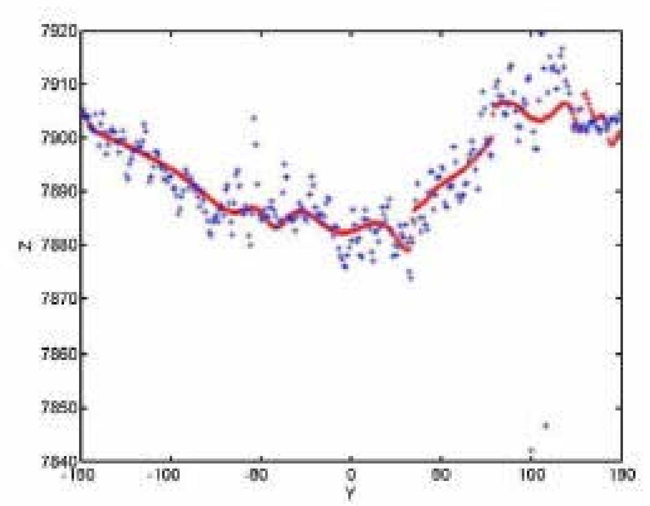

Figure 9. Real and NN modeled (Y, Z) geometric profile of a semi-stiff material (cardboard) pressed with a normal force F=0.37 N. The unit of measurement for both Y and Z axes is 0.1 mm.

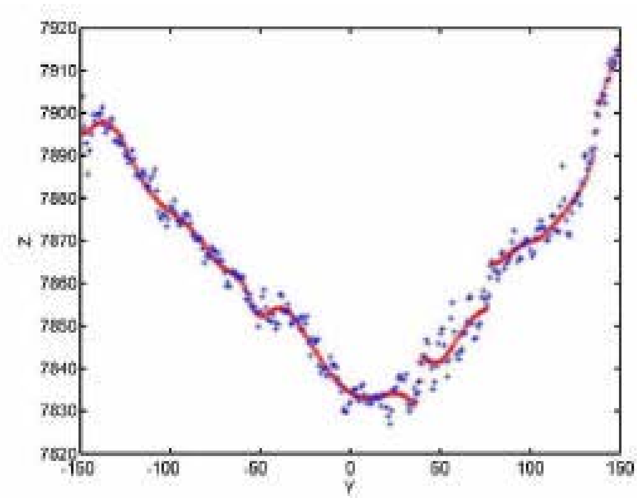

Figure 10. Real and NN modeled (Y, Z) geometric profile of a semi-stiff material (cardboard) pressed with a normal force F= 2.65 N. The unit of measurement for both Y and Z axes is 0.1 mm.

VI. CONCLUSIONS

This paper has reviewed NN modeling techniques developed by the authors for *the real-time rendering of the geometry and elastic properties of 3D objects* based on real measurement data, not on simulations.

Hardware NN architectures using stochastic data representation developed at the University of Ottawa, [30], [31], are currently used for the implementation of *haptics cards* to complement the existing *graphics cards* for real-time rendering of composite object models.

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