Approaches to Large-Scale Urban Modeling

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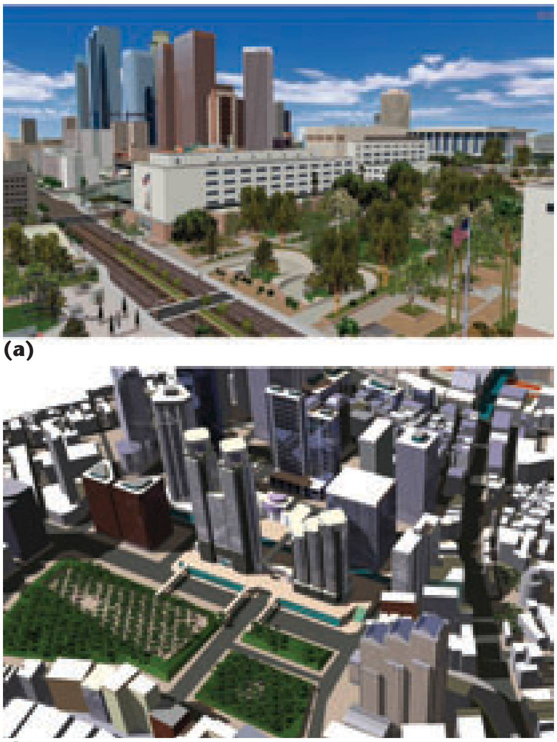
Large-scale urban modeling technologies use a variety of sensors and data acquisition techniques. The authors categorize current approaches and describe their advantages and disadvantages.

Many government agencies use urban models for development planning as well as climate, air quality, fire propagation, and public safety studies. Commercial users include phone, gas, and electric companies. Most of these users are primarily interested in models of buildings, terrain, vegetation, and traffic networks. A European Organization for Experimental Photogrammetric Research survey on city models showed that 95 percent of participants were most interested in 3D building data.[1]

Early planners created city models with wood from elaborate manual measurements. Computer technology, computer graphics, and computer-aided design (CAD) now offer powerful tools for creating and visualizing digital models of cities, as Figure 1 shows. These tools still require data to model the real-world structures, however. Manual measurement and entry are impractical; so researchers use various sensors to acquire accurate data for 3D urban landscapes. They then integrate the resulting 3D building models into spatial databases and geographic information systems (GIS) to support urban planning and analysis applications. Figure 2 shows digital models generated from GIS and other data sources.

In prior decades, model data acquisition focused mainly on imagery. Forstner[1] groups aerial image modeling techniques into automatic and semi-automatic categories. Recent advances include a wider variety of data sources. Shiode[2] and Batty et al.[3] summarize urban modeling of large cities worldwide from an application viewpoint. Batty et al. note that in 2001, 63 serious city-modeling applications existed, 38 of them developed in cities with populations of over one million, and 25 in smaller cities. The article provides Web links for the large city projects.

The complexity of application demands and technology challenges make urban modeling an intensive research area. Our survey examines current research with respect to several performance criteria including data acquisition sources, user interaction level, geometric fidelity, model completeness, and intended applications. Although modeling systems vary with respect to these criteria, data acquisition strongly influences models' characteristics and usefulness. We therefore cluster the methods into those based on photogrammetry, active sensors, and hybrid sensor systems.



1 Digital city models: (a) UCLA Urban Simulation Team's virtual Los Angeles (Courtesy of Bill Jepson UCLA Urban Simulation Laboratory, http://www.ust.ucla.edu/ustweb/ust.html) and (b) 3D Tokyo model (http://www.webscape.com/).

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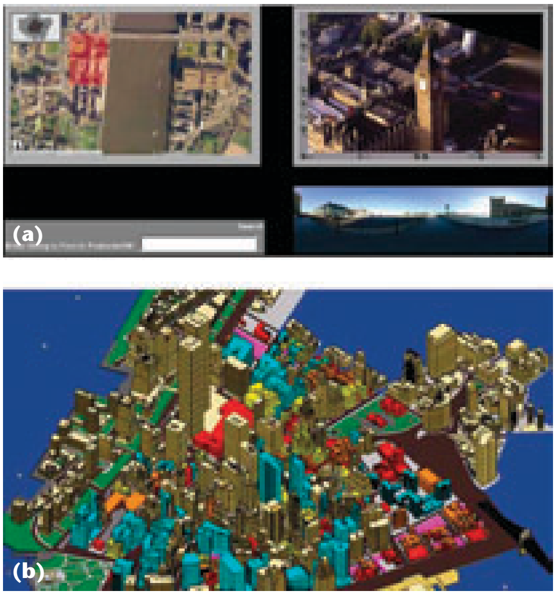
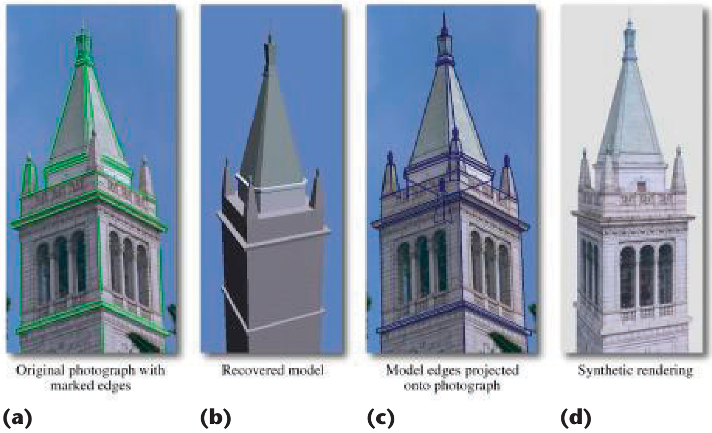


2 **Models generated from a variety of data: (a) virtual London created from a combination of CAD, GIS, and panoramic images by Batty et al.[3] (Courtesy of ESRI and Andrew Hudson-Smith.) (b) The Environmental Simulation Center's 3D model of lower Manhattan using GIS data. (Courtesy of Michael Kwartler, http://www.simcenter.org/index.html.)**



3 **Stages in the reconstruction of a 3D model of UC Berkeley's clock tower using Facade: (a) original photograph with marked edges, (b) recovered model, (c) model edges projected onto photograph, and (d) synthetic rendering. (Courtesy of Addison-Wesley and Paul E. Debevec.[4])**

4 **The MIT City Scanning Project's spherical mosaic comprising 47 source images. (Courtesy of Seth Teller, http://city.lcs.mit.edu/.)**

Photogrammetry

Modeling from images is a classic problem in computer vision and remote sensing. Photogrammetry is a cost-effective means of obtaining large-scale urban models.[1] Photogrammetric techniques use 2D images without any a priori 3D data. Different image sensors lend themselves to modeling systems developed for terrestrial, panoramic, and aerial images.

Terrestrial images

Terrestrial, or ground-level, images are the most convenient data sources. Although this data provides high-fidelity ground, vegetation, and building facade detail, it lacks building top information, and occlusion limits its range. The limited area visible in each image and the calibration needed to stitch images together makes it difficult to construct large urban areas. Terrestrial models are therefore most useful in aesthetic applications that require 3D models of only a few structures.

Devebec's Facade system is a successful terrestrial system that lets users recover basic geometric models of the photographed scenes.[4] Facade exploits user-selected edge features to build a model from 3D primitives and then verifies its accuracy by projecting the model back into the original image. The system uses view-dependent texture mapping to render photorealistic novel views. Figure 3 shows the stages in the Facade process.

Facade's appeal is its efficiency, which derives from a user interface unifying interaction with the image and geometry. It offers an effective compromise between the tedium of manual-entry CAD modeling and automatic stereo-image methods that often lack robustness.

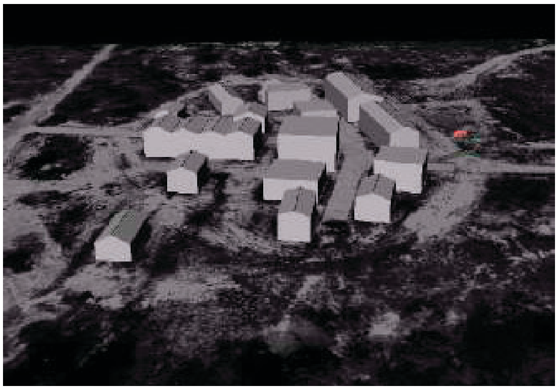
Image sequences are also useful data sources. Pollefeys proposed techniques to automatically recover 3D geometry using handheld video cameras.[5,6] Although these techniques extract useful building facade models from ground-based imagery, they don't scale well to large areas.

Panoramic images

Panoramic images are another convenient and economical data source. Cameras with special lenses or mirror systems acquire the images, or an image processing software stitches them together from multiple planar-projection images. Figure 4 shows a spherical mosaic using 47 source images.

Image-based rendering techniques can create a 3D representation of an urban area from a collection of panoramic images. McMillan developed methods for generating novel views from a small set panoramic images.[7] QuickTime VR is a simple and fast method for viewing panoramic images.[8] These methods provide realistic but limited views of urban areas. Because neither approach provides explicit 3D-geometry data, integrating panoramic images with other data and scaling to large areas is difficult.

5 **Aerial image of the University of Southern California campus and surrounding area. (Image courtesy of Airborne 1, http://www.airborne1.com).**



6 **Three-dimensional models reconstructed from aerial images by the Ascender II system. (Courtesy of M. Hansen et al.[16])**

Several efforts attempt to extract 3D models from panoramic images. Shum et al., for example, use an interactive system to extract 3D models from panoramic mosaics.[9] The MIT City Scanning Project has gathered calibrated (or pose) image data sets for a portion of the MIT campus,[10] and use the calibrated spherical mosaic images to reconstruct building models with textures.[11]

Aerial images

Aerial images, such as the one in Figure 5, have several advantages over terrestrial images. For example:

- They provide accurate building footprints and roof heights.
- They can be rectified into orthoprojections, which facilitate the merger of multiple images to cover large geographic areas. Orthoprojections also facilitate fusion with 2D GIS systems, integrating the models with rich information databases.

Extensive research has examined the use of single and multiple aerial images in urban modeling. Lin et al. use monocular aerial images from a general viewpoint to detect urban buildings and construct 3D shape descriptions of them.[12] They extract buildings based on roof hypotheses formations such as flat or rectangular roofs or compositions thereof, thus allowing for L, T, and I shapes. The system selects the best hypothesis and verifies it against shadows cast by the roof and walls. It uses shadows or wall heights in oblique aerial images to estimate building height. Finally, the system generates a 3D model of the scene by combining the camera model with data for verified buildings—that is, the roof hypothesis and estimated building height.

Vanden and Frank use geometric and projective constraints to extract 3D models from a single image.[13] Because occlusion necessitates multiple images, 3D models from monocular images are usually limited to building roofs and shapes. Several researchers—for example, Baillard and Noronha et al.—use multiple aerial images and stereo algorithms to extract 3D models.[14,15] Figure 6 shows 3D models reconstructed from multiple aerial images.[16]

The complexity and quantity of data needed to represent large urban areas makes fully automatic techniques highly desirable.[17] Many barriers to fully automatic systems exist, however. For example, image noise, lighting conditions, occlusions, and scene complexity complicate *segmentation*—the identification of buildings in an image. Moreover, 3D reconstruction of complete buildings is difficult when a single building consists of complex substructures.

Aerial images often lack facade information, resulting in models with no visual realism. Integrating facade data is usually a manual process and requires additional sensor data.

At this time, semiautomatic systems are more mature and practical than automatic systems. The use of knowledge[18] and machine-learning methods,[19,20] continues to improve automatic building extraction.

Active sensors

Active sensors directly measure the depth of objects, which provide an ideal data set for urban modeling. Sensors can be further divided into two categories: ground-based and airborne-based.

Ground laser scanner

Christian et al. present a system that uses a vehicle equipped with one camera and two 2D laser scanners.[21] The camera captures images for textures, the horizontal laser scanner tracks the truck's motion, and the vertical scanner captures 3D building facade data. Similarly, Huijing and Ryosuke use a vehicle-borne sensor system with three single-row laser scanners and six line cameras.[22] A navigation system fuses data from the Global Positioning System (GPS), inertial, and odometer sensors to synchronize the laser and image data and track the system position. Such vehicle-based scanner systems capture richly detailed building facade data but lose accuracy for upper portions of tall buildings and obtain no roof or structure footprint data.

Airborne Lidar

Light detection and ranging (Lidar) sensing technology evolved in the 1970s for 3D modeling. In the late 1980s, researchers began using the newly developed GPS for accurate aerial positioning. Combining the two systems increased the accuracy and lowered the cost of obtaining aerial Lidar data.

Figure 7a shows the Lidar capture system.[23] A scanned laser in an aircraft emits pulses toward the ground below and time measure equipment measures the *time of* *flight*—the time it takes for the laser to fly from the emitter to the object and reflect back to the receiver—for the depth of objects. Given accurate sensor position and orientation, the system acquires a cloud of 3D point measurements. Lidar data usually requires preprocessing. The system filters noise and differentially corrects and assembles the data into scan lines. It then performs hole filling and tessellation to create a final regular-grid digital elevation model,[24] as Figure 7b illustrates.

Airborne Lidar's accurate 3D information for structure roofs and most opaque surfaces greatly simplifies large-scale urban modeling. Much recent research examines the use of Lidar in this area.

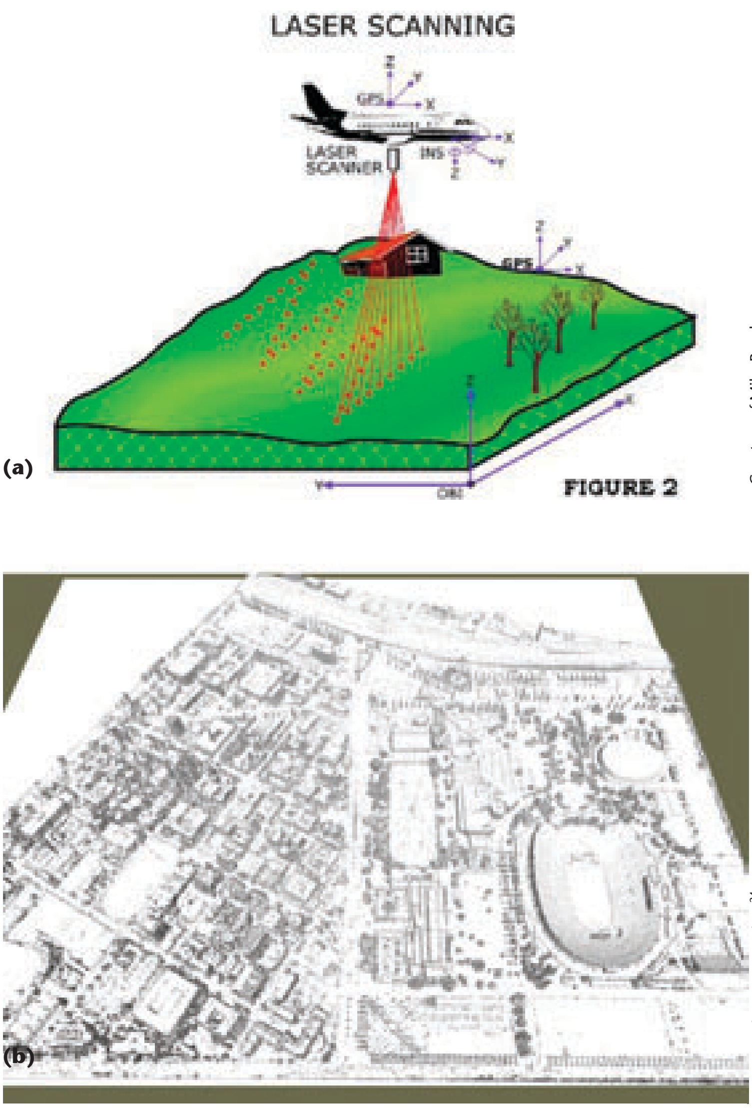
Lidar modeling systems can be manual, semiautomatic, or fully automatic.

Semiautomatic. Most complex model construction is semiautomatic, requiring a fair amount of operator intervention and resulting in painfully slow evolution of wide area models. Semiautomatic systems—including commercial software such as Cybercity, TerraScan, and I-Site—are likely to remain the most practical systems for large-scale urban modeling in the near future. However, developing automatic methods requiring little or no intervention is a clear technology trend.

You et al. developed an interactive system that models a variety of irregular building shapes.[24] The system resamples raw Lidar data into a regular grid, producing a mesh model through hole-filling and triangulation. With user guidance, the system uses a depth filter to classify mesh points as terrain or buildings. It further refines 3D building points automatically using constructive solid geometry models parametrically fit to the segmented data points. Connected sets of constructive solid geometry elements—such as the cubes, spheres, and cylinders shown in Figure 8—represent complex buildings. High-order primitives (superquadrics) model irregular shapes.

Automatic. Automatic Lidar modeling requires automatic structure segmentation and 3D reconstruction, which is complicated by occlusions between buildings or vegetation against buildings. Any 2D footprint information from imagery, GIS, or CAD data aids segmentation; however, the system must register and acquire the data a priori.

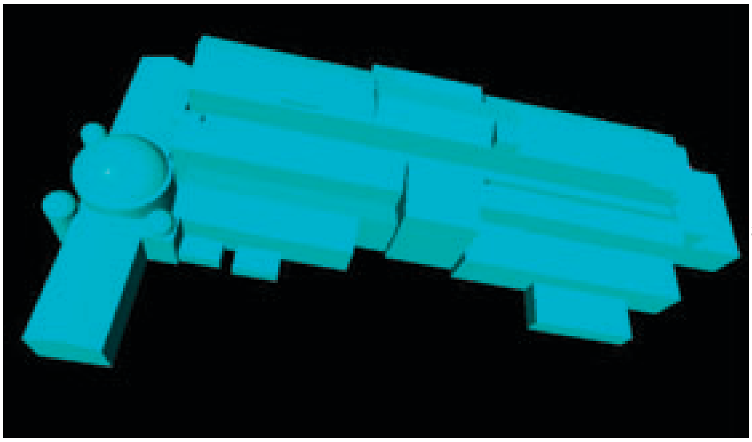
Automatic building extracting techniques proposed for Lidar differ mainly in their segmentation and reconstruction techniques. For example, Ahmed extracts simple building roofs using a 2D parameter space for plane detection,[25] as Figure 9 (next page) shows, whereas Morgan resamples the irregularly spaced Lidar data into a regular grid and then uses least-square fitting to locate roof planes.[26] Both Zhao[27] and Seresht[28] use image information and digital elevation model data to build reconstruction; Norbert uses a 2D ground plan from GIS data for segmentation and reconstruction.[29] Hans uses dense laser scanner data,[30] segmenting buildings based on height texture measures, morphological filtering, and local histogram analysis, and basing the reconstruction phase on invariant-moments analysis. George also uses high-density data for planar face reconstruction.[31]



Courtesy of Mike Renslow

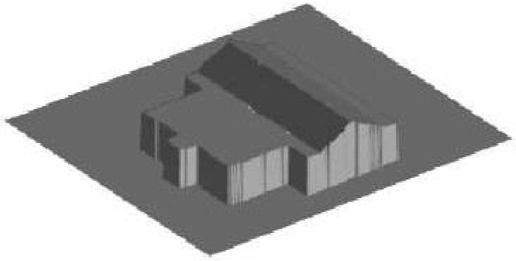
Courtesy of Springer-Verlag.[24]

7 A Lidar capture system: (a) an aircraft carrying the system flies over an area, emitting pulses and measuring their reflection. (b) A Lidar-generated digital elevation model of the USC campus and surrounding area.



Courtesy of Springer-Verlag.[24]

8 The Lidar user guides creation of a complex model using constructive solid geometry in which cubes, spheres, and cylinders represent buildings and high-order primitives represent irregular shapes.



9 **Simple 3D building roof model automatically extracted from Lidar using a 2D parameter space for plane detection. (Courtesy of Ahmed Elaksher.)**

10 **An oblique view of San Francisco modeled by a hybrid system. (Courtesy of Bill Ribarsky.)**

Hybrid sensors

Large-scale urban modeling systems receive most of their data from ground and aerial image sensors, aerial active sensors, and 2D footprint data from GIS or CAD data. Each of these data sources and their corresponding modeling techniques have advantages and disadvantages.[32] For example, images provide texture and color information with high accuracy, making them necessary for texture data and appealing for extracting small model features. Lidar data samples, on the other hand, are dense 3D representations of building and terrain surfaces. Fusing these data sources can generate more accurate and automatic urban models.

Hybrid imagery and laser range sensors

Extracting features and edges from images can facilitate model feature definition and improve model accuracy.[33] High-resolution images can obtain accurate models from low resolution Lidar.[34] Semantic information such as shadows can also help in Lidar modeling.[35] A fusion of 3D points from both sensor data sets can improve the quality of model results.[36]

Cues from range data, on the other hand, can aid image segmentation and establish *correspondence* (or image matching), a classic and difficult computer vision problem. Intensity-data-based correspondence is ambiguous and nonrobust, limiting the performance of image-based modeling techniques. Matching major image features such as points or edges gives robust results, but these reconstructed points are often sparse. Lidar directly measures building height, providing dense and excellent initial estimates for image matching. As Huertas et al. show, cues from active sensors can significantly reduce computational complexity and processing time, and eliminate many false correspondences.[37]

Researchers can use image data to verify Lidar models and provide textures for visualization, which Lidar doesn't provide.[38] Without ground-truth measurements, quantitatively evaluating modeling results is difficult. Users can find errors by projecting models onto images or images as textures onto models, and then measure the errors subjectively or quantitatively.[24,39]

Fusing data from aerial sensors (aerial images and Lidar) and ground sensors (ground images and laser scanners) allows for more complete 3D building reconstruction. Aerial sensors provide accurate footprint and height data whereas ground sensors provide accurate facade data. Interactive methods combine aerial and ground images to generate complete models.[32]

A system could automatically fuse ground laser scanner data using Lidar models.[40] A horizontal laser scanner enables the automatic fusing by acquiring accurate spatial positions for registering the two model sources. Figure 10 shows a city model generated from a hybrid system.

Hybrid DSM or aerial image and 2D GIS

Two-dimensional GIS data with structure footprints are often available in modern cities. Many researchers, such as George and Norbert,[41,42] use ground plan information to aid modeling from digital surface models (DSMs) or aerial images. Ground plans provide accurate building features and boundaries that are useful for segmenting buildings from DSM. Segmentation is simplified and edges provide orientation data that is useful in model reconstruction.

While reconstructing models, researchers can use 2D building outlines from ground plans to form hypotheses for roof shapes, and height information about surfaces extracted from DSM points. Research in the fusion of ground plan and DSM data often focuses on model-based reconstruction, assuming that shape primitives can be fit to the point clouds identified by a segment of the ground plan.[43] The possible lack of extracted DSM points per segment fitting is usually performed in aggregated segments.

Assuring model accuracy

End users must be assured of a reconstructed model's credibility. Modeling approach developers should use mathematical models and theoretical analysis to quantitatively evaluate the technique and its results. A modeling technique's uncertainties depend on data sources, algorithmic strategies, scene complexity, hidden assumptions behind the data acquisition and modeling processes, and so on. Image-based techniques, for example, are sensitive to environmental lighting conditions, noise, and occlusions.

Pixel accuracy, numeric approximation, and tolerance of an image-processing algorithm (for example, feature detection) can also limit system performance. Subpixel precision image processing usually gives the best results with photogrammetry modeling techniques. When a system uses video or image sequences for modeling, each individual frame can generate errors.

Active sensors are robust, but can produce missing data (*holes*) due to the nature of the scanned materials. Very dark or highly specular surfaces are often difficult to scan with a laser range sensor, requiring an interpolation step to fill in the missing data. Such interpolations can produce erroneous 3D reconstruction if the area is large or the system uses an inappropriate interpolation strategy. In hybrid techniques, which rely on two or more sensor data sources to fuse the model, calibration errors between sensors make up a large percentage of all errors.

The lack of actual site measurements and diverse data sources complicates quantitative evaluation of model performance. Current systems often use relative criteria and human perception to verify the accuracy and credibility of reconstructed models. For example, a reconstructed model can be embedded in the original sensor data as a qualitative validation.[24] Because the sensor data is a physical measure of the real world, it's often the best and most accurate data available. Imagery (aerial photographs, ground images or video captured with high-resolution digital cameras, and terrain maps) can also help verify a geometry models' accuracy.[39] Although these techniques allow some verification of the models, they mostly act as ad hoc and sparse qualitative measures of accuracy. Reliable evaluation and confirmation of model accuracy requires better quantitative strategies, mathematical models, and algorithms integrated into modeling systems.

Future work

As data acquisition and modeling techniques advance, modeling and analysis systems are likely to include several characteristics to handle the increased data.

Future urban area databases will include building shells as well as their internal structure and everything relative to the environment—such as terrain, vegetation, and transportation and telecommunications networks. Real-time dynamic data such as external and internal building video, security data, traffic-flow measures, and air quality might all be accessible and projected into 3D visualizations based on urban models.

Future systems will need to accommodate the huge data arising from models of entire city, county, and nation models. Interactive query and visualization will require both hierarchical structures and multiresolution display methods.

Because of the distributed nature of future users of urban model databases, the system structure will need to change. The development of immersive user interfaces and increased Internet bandwidth will let users update, collaborate, and explore models remotely and interactively. ■

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