Interactive Construction of 3D Models from Panoramic Mosaics

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Abstract

This paper presents an interactive modeling system that constructs 3D models from a collection of panoramic image mosaics. A panoramic mosaic consists of a set of images taken around the same viewpoint, and a transformation matrix associated with each input image. Our system first recovers the camera pose for each mosaic from known line directions and points, and then constructs the 3D model using all available geometrical constraints. We partition constraints into *soft* and *hard* linear constraints so that the modeling process can be formulated as a *linearly-constrained least-squares* problem, which can be solved efficiently using QR factorization. The results of extracting wire frame and texture-mapped 3D models from single and multiple panoramas are presented.

1 Introduction

A great deal of effort has been expended on 3D scene reconstruction from image sequences (with calibrated or uncalibrated cameras, e.g., [FSL+95]) using computer vision techniques. Unfortunately, the results from most automatic modeling systems are disappointing and unreliable due to the complexity of the real scene and the fragility of the vision techniques. Part of the reason is the demand for accurate correspondences (e.g., point correspondence) required by many computer vision techniques such as stereo and structure from motion. Moreover, such correspondences may not be available if the scene consists of large untextured regions.

Fortunately, for many real scenes, it is relatively straightforward to interactively specify corresponding points, or lines, or planes. For example, building interiors and exteriors provide vertical and horizontal lines and parallel and perpendicular planes. These constraints have been exploited in several interactive modeling systems. For example, PhotoModeler[1] is a commecial product which constructs 3D models from several images, using photogrammetry techniques and manually specified points. Explicit camera calibration is therefore necessary. The TotalCalib system[2], on the other hand, estimates the fundemental matrix from a few selected matched points [BR97]. It then predicts other possible matching points from one image to others. In Becker's modeling system[3], the problem of lens distortion (encounted in images taken with wide field of view lens) is also considered [BB95]. By employing the known structure of building exteriors, the Facade system[4] directly recovers a solid 3D model (blocks) from multiple images [TDM96].

Our system differs from previous interactive modeling systems in that we use multiple panoramic image mosaics (therefore large fields of view), instead of multiple images (generally small fields of view). A panoramic mosaic is a collection of images taken from the same viewpoint, and registered together to form one large image. Panoramas offer several advantages over regular images. First, we can decouple the modeling problem into a zero baseline problem (building panoramas from images taken with rotating camera) and a wide baseline stereo or structure from motion problem (recovering 3D model from one or more panoramas). Second, the camera calibration problem is implicitly recovered as part of the panorama construction [Ste95, KW97, SK97]. Due to recent advances, it is now possible to construct panoramas even with hand-held cameras [SS97b].

Previous work on 3D reconstruction from multiple panoramas [MB95, KS96] has not attempted to exploit important regularities present in the environment, such as walls with known orientations. Fortunately, the man-made world is full of constraints such as parallel lines, lines with known directions, planes with lines and points on them, etc.. Using these constraints, we can construct a fairly complex 3D model from even a single panorama. Of course the model recovered is only up to a scale, unless we have some knowledge of the scene (e.g., length or width of a room). Using multiple panoramas, more complete and accurate 3D models can be constructed.

We introduce our interactive modeling system in Sec-

[1] www.photomodeler.com

[2] www.inria.fr/robotvis/personnel/sbougnou

[3] sbeck.www.media.mit.edu/people/sbeck

[4] www.cs.berkeley.edu/debevec/Research

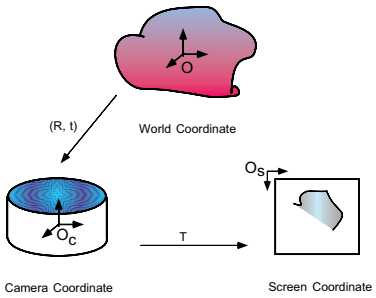


Figure 1: Coordinate systems.

tion 2, explain how to estimate camera orientations using known line directions in Section 3, recover line directions and plane normals in Section 4, and recover camera translations in Section 5. Section 6 presents our approach of combining all possible constraints to form a linearly-constrained least-squares problem. Techniques for building models from multiple panoramas are discussed in Section 7. Examples of 3D models from single and multiple panoramas are shown in Section 8. We close the paper with a discussion of potential extentions to the system.

2 Interactive modeling system

Our modeling system uses one or more panoramas.[5] For each panorama, we draw points, lines, and planes, set appropriate properties for them, and then recover the 3D model. These steps of interactively drawing geometric items, setting up properties, and modeling can be repeated in any order to refine or modify the model. The modeling system attempts to satisfy all possible constraints in a consistent and coherent way.

2.1 Representation

Three coordinate systems are used in our work (Figure 1). The first is the world coordinate system where the 3D model geometry (planes, lines, vertices) is defined. The second is the ''2D'' [6] camera coordinate system (panorama coordinates). The third is the screen coordinate system where zoom and rotation (pan and tilt, but no roll) are applied to facilitate user interaction. While each panorama has a single 2D coordinate system, several views of a given panorama can be open simultaneously, each with its own screen coordinate system.

We represent the 3D model by a set of points, lines and planes. Each point is represented by its 3D coordinate $\mathbf{x}$. Each line is represented by its line direction $\mathbf{m}$ and points on the line. Each plane is defined by $(\mathbf{n}, d)$ where $\mathbf{n}$ is the normal, d is the distance to the origin, and $\mathbf{n} \cdot \mathbf{x} + d = 0$ or $(\mathbf{n}, d) \cdot (\mathbf{x}, 1) = 0$. A plane consists of a set of vertices and lines on it.

Each ''2D'' model consists of a set of ''2D'' points and lines extracted from a panorama. A panorama consists of a collection of images and their associated transformations. A 2D point $\tilde{\mathbf{x}}$ (i.e., on a panorama) represents a ray going through the 2D model origin (i.e., camera optical center).[7] Likewise, a 2D line (represented by its line direction $\tilde{\mathbf{m}}$) lies on the ''line projection plane'' (with normal $\tilde{\mathbf{n}}_p$) which passes through the line and 2D model origin (Figure 2).[8] Therefore, a line direction in a 2D model can not be uniquely determined by two points in 2D model.

Note that line directions and plane normals have a sign ambiguity. These ambiguity problems will be discussed in Section 3.

2.2 Modeling steps

Many constraints exist in real scenes. For example, we may have known quantities like points, lines, and planes. Or we may have known relationships such as parallel and vertical lines and planes, points on a line or a plane. With multiple panoramas, we have more constraints from corresponding points, lines and planes.

Some of these constraints are bilinear. For example, a point on a plane is a bilinear constraint in both the point location and the plane normal. However, plane normals and line directions can be recovered without knowing plane distance and points. Thus, in our system we decouple the modeling process into several linear steps:

- recovering camera orientations ($\mathbf{R}$) from known line directions
- estimating plane normals ($\mathbf{n}$) and line directions ($\mathbf{m}$)
- recovering camera translations ($\mathbf{t}$) from known points
- estimating plane distances (d), vertex positions ($\mathbf{x}$)

These steps are explained in detail in the next sections.

3 Recovering camera rotation

We discuss in this section how to recover camera orientations from known line directions. The camera poses describe the relationship between the 2D models (panorama coordinate systems) and the 3D model (world coordinate system).

To recover the camera rotation, we use lines with known directions. For example, one can easily draw several vertical lines at the intersections of walls and mark them to be parallel to the Z axis of the world coordinate system.

[5] Our system can handle calibrated (non-panoramic) images as well — these are simply treated as simple, narrow field of view panoramas. However, the recovered estimates (e.g., vanishing points and hence camera orientations) will not be as accurate with narrow field of view images.

[6] Each point (or pixel) on the panorama has only two degrees of freedom because its distance from camera is not known.

[7] We use the notation $\tilde{\mathbf{x}}$ for a 2D point, $\mathbf{x}$ for a 3D point, and $\hat{\mathbf{x}}$ for a 3D point whose position is known. Likewise for line directions, plane normals, etc..

[8] If a pixel has the screen coordinate $(u, v, 1)$, its 2D point on the panorama is represented by (u, v, f) where f is the focal length.

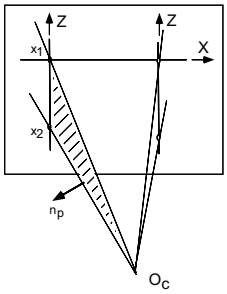


Figure 2: Camera rotation from 3 line directions.

3.1 Minimum condition

Lemma 1 (Minimum condition) *Given two vertical lines and a horizontal line, the camera rotation matrix can be recovered.*

Each line forms a projection plane (with normal $\tilde{\mathbf{n}}_p$) through the camera origin. Given two points $\tilde{\mathbf{x}}_1$ and $\tilde{\mathbf{x}}_2$ on a line, the plane normal can be computed by the cross product $\tilde{\mathbf{n}}_p = \tilde{\mathbf{x}}_1 \times \tilde{\mathbf{x}}_2$ (Figure 2). The length of $\tilde{\mathbf{n}}_p$ is a good confidence (or certainty) measure of the normal $\tilde{\mathbf{n}}_p$.

Let the camera rotation $\mathbf{R} = [\mathbf{r}_x \mathbf{r}_y \mathbf{r}_z]$. Each vertical line parallel to the Z axis (and the plane formed with the origin) gives a constraint $\tilde{\mathbf{n}}_p \cdot \mathbf{r}_z = 0$.

From two known vertical lines, $\tilde{\mathbf{n}}_{p1} \cdot \mathbf{r}_z = 0$, and $\tilde{\mathbf{n}}_{p2} \cdot \mathbf{r}_z = 0$, we have $\mathbf{r}_z = \tilde{\mathbf{n}}_{p1} \times \tilde{\mathbf{n}}_{p2}$. Note that there is a sign ambiguity for the recovered $\mathbf{r}_z$. If we have more vertical lines, we can formulate the recovery of $\mathbf{r}_z$ as a standard minimum eigenvalue problem.

With a known horizontal line (e.g., parallel to the X axis), we have a constraint on $\mathbf{r}_x$ ($\tilde{\mathbf{n}}_{pj} \cdot \mathbf{r}_x = 0$). Thus $\mathbf{r}_x = \mathbf{r}_z \times \tilde{\mathbf{n}}_{pj}$ because $\mathbf{r}_z \cdot \mathbf{r}_x = 0$. Again there is a sign ambiguity for the recovered $\mathbf{r}_x$. Finally $\mathbf{r}_y = \mathbf{r}_z \times \mathbf{r}_x$ completes $\mathbf{R}$.

Obviously, the camera rotation can also be computed if two horizontal lines (e.g., parallel to the X axis) and a vertical line are known.

3.2 Overconstrained problem

Lemma 2 (General condition) *Given at least two sets of parallel lines of known directions, the camera rotation matrix can be recovered.*

We now show how to incorporate all constraints to recover camera pose using unit quaternion. As shown above, if we have a pair of parallel lines with ''line projection plane'' normals as $\tilde{\mathbf{n}}_{pj}$ and $\tilde{\mathbf{n}}_{pk}$, the line direction $\tilde{\mathbf{m}}_i$ can be estimated as $\tilde{\mathbf{n}}_{pj} \times \tilde{\mathbf{n}}_{pk}$. Again, rather than normalizing $\tilde{\mathbf{m}}_i$, we can leave it unnormalized since its magnitude denotes own confidence in this measurement. Given the true line direction $\hat{\mathbf{m}}_i$ in the world coordinate, we can formulate the camera pose recovery as

$$\arg\max_{\mathbf{R}} \sum_{i=1}^{N} \hat{\mathbf{m}}_i \cdot (\mathbf{R}^T \tilde{\mathbf{m}}_i) \tag{1}$$

with $N \geq 2$, which leads to a maximum eigenvalue problem using unit quaternion.

However, the resulting camera rotation $\mathbf{R}$ can still be ambiguous due to the sign ambiguities in line directions $\tilde{\mathbf{m}}$. We solve this problem by specifying a few vertices with known coordinates, rather than asking the user to specify a direction for each line.

3.3 Line direction from parallel lines

More generally, the line direction recovery problem can be formulated as a standard minimum eigenvector problem. Because each ''line projection plane'' is perpendicular to the line (i.e., $\tilde{\mathbf{n}}_{pi} \cdot \tilde{\mathbf{m}} = 0$), we want to minimize

$$e = \sum_i (\tilde{\mathbf{n}}_{pi} \cdot \tilde{\mathbf{m}})^2 = \tilde{\mathbf{m}}^T (\sum_i \tilde{\mathbf{n}}_{pi} \tilde{\mathbf{n}}_{pi}^T) \tilde{\mathbf{m}}. \tag{2}$$

This is equivalent to finding the vanishing point of the lines [CW90]. The advantage of the above formulation is that the sign ambiguity of $\tilde{\mathbf{n}}_{pi}$ can be ignored. When only two parallel lines are given, the solution is simply the cross product of two line projection plane normals.

4 Estimating plane normals

Once we have camera pose, we can recover the scene geometry (i.e., points, lines, and planes). Because of the bilinear nature of some constraints (such as points on planes), we recover plane normals ($\mathbf{n}$) before solving for plane distances (d) and points ($\mathbf{x}$). If a normal is given (north, south, up, down, etc.), it can be enforced as a hard constraint (see Section 6.1). Otherwise, we compute the plane normal $\mathbf{n}$ by finding two line directions on the plane.

If we draw two pairs of parallel lines (a parallelogram) on a plane, we can recover the plane normal. Because $\mathbf{R}$ has been estimated, and we know how to compute a line direction ($\tilde{\mathbf{m}}$) from two parallel lines, we obtain $\mathbf{m} = \mathbf{R}^T \tilde{\mathbf{m}}$. From two line directions $\mathbf{m}_1$ and $\mathbf{m}_2$ on a plane, the plane normal can be computed as $\mathbf{n} = \mathbf{m}_1 \times \mathbf{m}_2$.

A rectangle is a special case of parallelogram. We can recover the plane normal of a rectangle if we have 3 lines of the rectangle. As with the parallelogram, we get one line direction $\mathbf{m}_1$ from 2 parallel lines. And because $\mathbf{m}_1 \cdot \mathbf{m}_2 = 0$ and $\mathbf{n}_{p2} \cdot \mathbf{m}_2 = 0$, where $\mathbf{n}_{p2} = \mathbf{R}^T \tilde{\mathbf{n}}_{p2}$, we obtain the other line direction $\mathbf{m}_2 = \mathbf{m}_1 \times \mathbf{n}_{p2}$. Unlike [Har89], we do not need to know specify all four corners of a rectangle.

Using the techniques described above, we can therefore recover the surface orientation of an arbitrary plane (e.g., tilted ceiling) provided either we can draw a parallelogram (or rectangle) on the plane.

5 Recovering camera translation

A point on a 2D model (panorama) represents a ray from the camera origin through the pixel on the image. This constraint can be expressed in different ways. For example, we can relate each point in 3D model to its 2D counterpart by a scale k, i.e.,

$$(\mathbf{x} - \mathbf{t}) = k\mathbf{R}^T\tilde{\mathbf{x}}. \tag{3}$$

Alternatively, the 3D point should lie on the ray represented by the 2D point,

$$(\mathbf{x} - \mathbf{t}) \times \mathbf{R}^T\tilde{\mathbf{x}} = 0, \tag{4}$$

which is equivalent to

$$(\mathbf{x} - \mathbf{t}) \cdot (\mathbf{R}^T\tilde{\mathbf{p}}_j) = 0, j = 0, 1, 2, \tag{5}$$

where $\tilde{\mathbf{p}}_0 = (-x_2, x_1, 0)$, $\tilde{\mathbf{p}}_1 = (-x_3, 0, x_1)$ and $\tilde{\mathbf{p}}_2 = (0, -x_3, x_2)$ are three directions perpendicular to the ray $\tilde{\mathbf{x}} = (x_1, x_2, x_3)$. Note that only two of the three constraints are linearly independent.[9] Thus, camera translation $\mathbf{t}$ can be recovered as a linear least-squares problem if we have two or more given points. Given a single known point, $\mathbf{t}$ can be recovered only up to a scale. In practice, it is convenient to fix a few points in 3D model, such as the origin $(0, 0, 0)$. These given points are also used to eliminate the ambiguities in recovering camera pose.

For a single panorama, the translation $\mathbf{t}$ is set to zero if no point in 3D model is given. This implies that the camera coordinate coincides with the 3D model coordinate. We should point out that it is not necessary to recover camera translation independently; it can be solved for along with plane distance and points as shown in the next section.

6 Estimating the 3D model

6.1 Hard and soft constraints

Given camera pose, line directions, and plane normals, recovering plane distances (d), 3D points ($\mathbf{x}$), and camera translation $\mathbf{t}$ if desired, can be formulated as a linear system consisting of all possible constraints. By differentiating hard constraints from soft ones, we obtain a least-squares system with equality constraints. Intuitively, the difference between soft and hard constraints is their weights in the least-squares formulation. Soft constraints have unit weights, while hard constraints have very large weights [GV96].

Some constraints (e.g., a point is known) are inherently hard, therefore equality constraints. Some constraints (e.g., a feature location on a 2D model or panorama) are most appropriate as soft constraints because they are based on noisy image measurements. But most constraints can be considered as either hard or soft. It is a design decision why and when those constraints should be considered hard. Table 1 lists all constraints used in our modeling system. Again, we use the notations $\hat{\mathbf{m}}$ and $\hat{\mathbf{n}}$ to represent the given line direction $\mathbf{m}$ and plane normal $\mathbf{n}$, respectively.

[9] The third constraint with minimum $\|\tilde{\mathbf{p}}_i\|^2$ is eliminated.

Type	Constraint	n	Soft	Hard
Known point	$\hat{\mathbf{x}}_i$	3		x
Known plane	$\hat{d}_i$	1		x
$\|$ planes	$d_i - d_j$	1		x
Point/model	$(\mathbf{x} - \mathbf{t}) \cdot \mathbf{p}_j = 0$	2	x	
Point/plane	$\mathbf{x}_i \cdot \hat{\mathbf{n}}_k + d_k = 0$	1		x
Point/plane	$\mathbf{x}_i \cdot \mathbf{n}_k + d_k = 0$	1	x	
Points/line	$(\mathbf{x}_i - \mathbf{x}_j) \times \hat{\mathbf{m}} = 0$	2		x
Points/line	$(\mathbf{x}_i - \mathbf{x}_j) \times \mathbf{m} = 0$	2	x	
known length	$\mathbf{x}_i - \mathbf{x}_j = c\hat{\mathbf{m}}$	3		x
known length	$\mathbf{x}_i - \mathbf{x}_j = c\mathbf{m}$	3	x	

Table 1: Hard and soft constraints (the third column n represents the number of constraints)

Take a point on a plane for an example. If the plane normal $\hat{\mathbf{n}}_k$ is given, we consider the constraint $(\mathbf{x}_i \cdot \hat{\mathbf{n}}_k + d_k = 0)$ as hard. This implies that the point has to be on the plane, only its location can be adjusted. On the other hand, if the plane normal $\mathbf{n}_k$ is estimated, we consider the constraint $(\mathbf{x}_i \cdot \mathbf{n}_k + d_k = 0)$ as soft. This could lead to an estimated point that is not on the plane at all. So why not make the constraint $(\mathbf{x}_i \cdot \mathbf{n}_k + d_k = 0)$ hard as well?

The reason is that we may end up with a very bad model if some of the estimated normals have large errors. One has to be cautious not to have too many hard constraints, which could conflict with one another or make other soft constraints insignificant.

6.2 Equality-constrained L-S

To satisfy all possible constraints, we formulate our modeling process as an equality-constrained least-squares problem. In other words, we would like to solve the linear system (soft constraints)

$$\mathbf{A}\mathbf{x} = \mathbf{b} \tag{6}$$

subject to (hard constraints)

$$\mathbf{C}\mathbf{x} = \mathbf{q} \tag{7}$$

where $\mathbf{A}$ is $m \times n$, $\mathbf{C}$ is $p \times n$.

A solution to the above problem is to use the QR factorization [GV96]. Suppose $\mathbf{C}$ is of full rank. Let

$$\mathbf{C}^T = \mathbf{Q}\begin{bmatrix} \mathbf{R} \\ 0 \end{bmatrix} \tag{8}$$

be the QR factorization of $\mathbf{C}^T$ where $\mathbf{Q}$ $(n \times n)$ is orthorgonal, $\mathbf{Q}\mathbf{Q}^T = \mathbf{I}$, and $\mathbf{R}$ is $p \times p$. If we define

$\mathbf{Q}^T\mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix}$, $\mathbf{AQ} = (\mathbf{A}_1, \mathbf{A}_2)$, where $\mathbf{A}_1$ is $m \times p$, $\mathbf{A}_2$ is $m \times (n-p)$, $\mathbf{x}_1$ is $p \times 1$, and $\mathbf{x}_2$ is $(n-p) \times 1$ we can recover $\mathbf{x}_1$ because $\mathbf{R}$ is upper triangular and

$$\mathbf{Cx} = \mathbf{CQQ}^T\mathbf{x} = \mathbf{R}^T\mathbf{x}_1 = \mathbf{q}. \quad (9)$$

Then we obtain $\mathbf{x}_2$ from the unconstrained least-squares $\|\mathbf{A}_2\mathbf{x}_2 - (\mathbf{b} - \mathbf{A}_1\mathbf{x}_1)\|^2$ because

$$\begin{aligned} \mathbf{Ax} - \mathbf{b} &= \mathbf{AQQ}^T\mathbf{x} - \mathbf{b} \\ &= \mathbf{A}_1\mathbf{x}_1 + \mathbf{A}_2\mathbf{x}_2 - \mathbf{b} \\ &= \mathbf{A}_2\mathbf{x}_2 - (\mathbf{b} - \mathbf{A}_1\mathbf{x}_1). \end{aligned}$$

Finally $\mathbf{x} = \mathbf{Q}\begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix}$.

If $\mathbf{C}$ is not of full rank, other approaches such as the elimination method [SS97a] can be used.

6.3 Decomposing the linear system

Before we can apply the equality-constrained linear system solver, we must check whether the linear system formed by all constraints is solvable. In general, the system may consist of several subsystems (connected components) which can be solved independently. For example, when modeling a room with a computer monitor floating in the space not connected with any wall, ceiling or floor, we may have a system with two connected components. To find all connected components, we use depth first search to step through the linear system. For each connected components we check that:

- the number of equations[10] is no fewer than the number of unknowns,
- the right hand side is a non-zero vector, i.e., some minimal ground truth data has been provided[11]
- the hard constraints are consistent.[12]

If any of the above is not satisfied, the system is declared unsolvable, and a warning message is then generated to indicate which set of unknowns cannot be recovered.

7 Multiple panoramas

To build 3D models from multiple panoramas, we do:

1. insert a new panorama
2. repeat steps of modeling from a single panorama to obtain a rough camera pose for current view
3. project the existing model onto the new panorama using the rough camera pose
4. fix up the predicted feature locations by dragging them to the right positions
5. recover a new model using all constraints available in the multiple panoramas.

To recover the 3D model using multiple panoramas, we use bundle adjustment, i.e., either we update $(d, \mathbf{x}, \mathbf{t})$ using linear least-squares, or we also update $(\mathbf{R}, \mathbf{m}, \mathbf{n})$ using full bilinearly constrained non-linear least-squares. However, to better handle feature measurements taken from different viewpoints, it is more optimal [Zha97] to modify Eq.(5) s.t.

$$\frac{(\mathbf{x} - \mathbf{t})}{\|\mathbf{x} - \mathbf{t}\|} \cdot (\mathbf{R}^T\tilde{\mathbf{p}}_j) = 0, j = 0, 1. \quad (10)$$

8 Experiments

We have implemented our system on a PC and tested it with single and multiple panoramas. The system consists of two parts: the interface (viewing the panorama with pan, tilt, and zoom control) and the modeler (recovering the camera pose and the 3D model). Figure 3 shows a spherical panoramic image on the left and a simple reconstructed 3D model on the right. The coordinate system on the left corner (red) is the world coordinate, and the coordinate system in the middle (green) is the camera coordinate. The panorama is composed of 60 images using the method of creating full-view panorama [SS97a]. Corresponding (6) texture maps (without top and bottom faces) are shown in Figure 4. Notice how the texture maps in Figure 4 have different sampling rates from the original images. The sampling is the best (e.g., Figure 4(b)) when the surface normal is parallel with the viewing direction from the camera center, and the worst (e.g., Figure 4(d)) when perpendicular. This also explains why the sampling on the left is better than that on the right in Figure 4(a).

Figure 5 shows two views of our interactive modeling system. Green lines and points are the 2D items that are manually drawn and assigned with properties, and blue lines and points are projections of the recovered 3D model. The system is easy to use. It took about 15 minutes for the authors to build the simple model in Figure 3. In 30 minutes, we can construct the more complicated model shown in Figure 6.

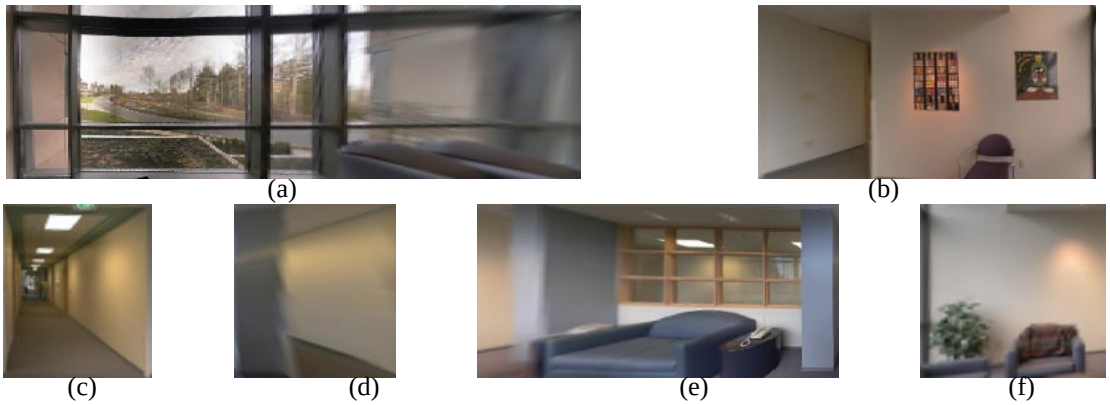
Figures 7 and 8 show an example of building 3D models from multiple panoramas. Figure 7 shows two spherical panoramas built from image sequences taken with a handheld digital video camera. Figure 8 shows two views of reconstructed 3D wireframe model from the two panoramas in Figure 7. Notice that the occluded middle area in the first panorama (behind the tree) is recovered because it is visible in the second panorama.

[10] This includes both hard and soft constraints.

[11] In principle, we can still solve the system without any ground truth for multiple panoramas, but this requires finding the unit norm solution of the homogeneous set of equations.

[12] We can use QR decomposition of $\mathbf{C} = \mathbf{Q}_1\mathbf{R}_1$, or $\mathbf{R}_1\mathbf{x} = \mathbf{Q}_1^T\mathbf{q}$ to check if all zero rows of $\mathbf{R}_1$ correspond to zero entries of $\mathbf{Q}_1^T\mathbf{q}$.

Figure 3: 3D model from a single panorama.



(a) (b) (c) (d) (e) (f)

Figure 4: Texture maps (6) for the 3D model.

Figure 5: Two views of the interactive system.

Figure 6: A more complex 3D model from a single panorama.

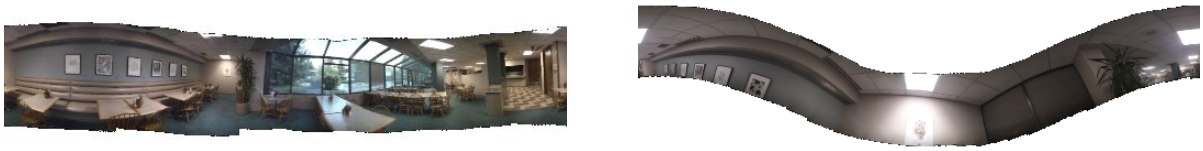


Figure 7: Two input panoramas of an indoor scene.

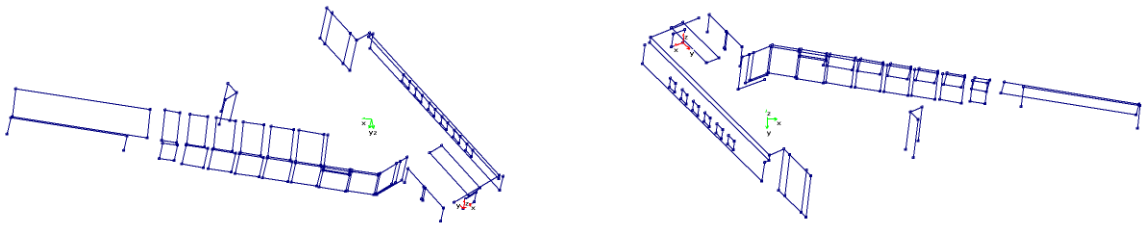


Figure 8: Two views of a 3D model from multiple panoramas.

9 Discussion and conclusions

In this paper, we have presented a system for interactively constructing 3D models from one or more panoramas. Our system decomposes the modeling process into a zero baseline problem (panorama construction) and a wide baseline problem (stereo or structure from motion). Our system first recovers the camera pose for each panorama from known line directions, and then constructs the 3D model using all possible constraints. In particular, we carefully partition the recovery problem into a series of linear estimation stages, and divide the constraints into ''hard'' and ''soft'' constraints so that each estimation stage becomes a linearly-constrained least-squares problem.

Our modeling system constructs accurate wire-frame and realistic texture-mapped 3D models. Our modeling approach has much less ambiguity than traditional structure from motion approaches because it uses wide field of view images and therefore obtains better estimate of camera rotation. It also exploits geometrical regularities and therefore obtains more accurate estimates of the 3D model. Our results show that it is desirable and practical for the modeling system to take advantage of as many regularities and priori knowledge about man-made environments [WH88] (such as vertice lines and planes) as possible.

We are working on several extensions to improve the usability of our system. For example, we have implemented an automatic line snapping technique which snaps lines to their closest edges present in the panorama. We also plan to incorporate automatic line detection, corner detection as well as inter-image correspondence and other feature detections to further automate the system. If we use more features with automatic feature extraction and correspondence techniques, robust modeling techniques should also be developed.

We are also actively studying the problem of inverse texture mapping. In particular, we want to develop techniques for optimally extracting texture maps from multiple panoramas, given an accurate 3D model or a rough 3D model. Another direction of future research is to apply multiple baseline stereo algorithms [KS96, TDM96] using the initial model from our interative system. Combining all of these into one interactive modeling system will enable users to easily construct complex photorealistic 3D models from images.

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