

# Lesson 9: 3D Vision

1. Introduction
2. Camera Model
3. Calibration
4. Stereo Vision
5. Correspondence Search
6. Other 3D techniques



# 1. Introduction

- Cameras get a 2D projection of a 3D scene
- 3D reconstruction needs two or more images
  - 2 cameras: binocular stereo
  - 3 cameras: trinocular stereo
  - 1 single moving camera (SFM: structure from motion)
- Needs a model of the camera geometry and optics
- Main difficulty: search for correspondences
  - Given an element in one image (a point, edge, region,...), find it on the other images



## 2. Camera Model (Tsai)

- Projection of a point on an image:

$$\mathbf{u} = \text{Proj} (\mathbf{x}_w, \theta_c)$$

$$\mathbf{x}_w = \begin{pmatrix} x_w \\ y_w \\ z_w \end{pmatrix}$$

3D point coordinates

$$\mathbf{u} = \begin{pmatrix} u \\ v \end{pmatrix}$$

Coordinates on the image

$$\theta_c = \begin{pmatrix} \theta_{int} \\ \theta_{ext} \end{pmatrix}$$

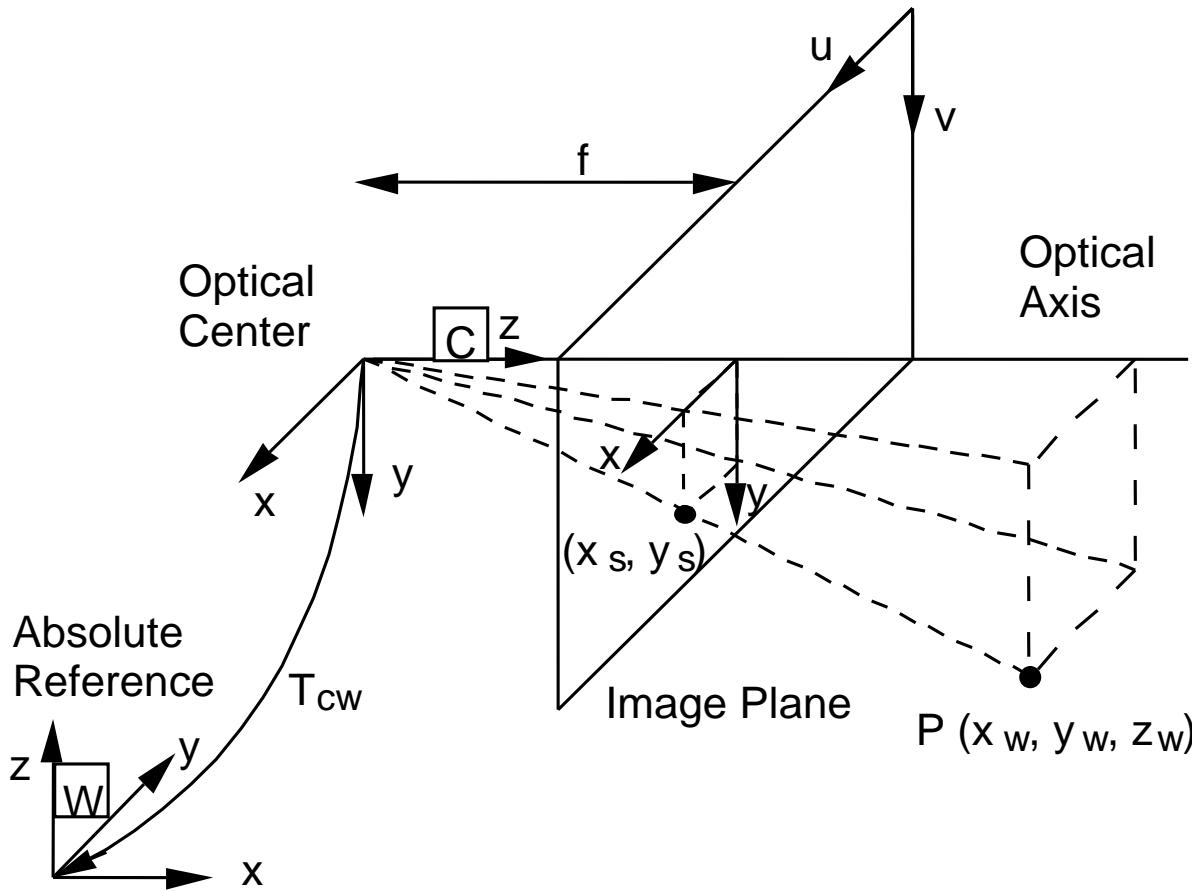
Camera parameters

- Intrinsic camera parameters
  - Camera geometry and optics
  - Image acquisition system (for analog cameras)
- Extrinsic camera parameters
  - Camera 3D position and orientation
- Calibration: experimental determination of camera parameters



# Tsai's Camera Model (1)

## 1) Transformation to camera reference



Coordinates relative to the Camera:

$$\mathbf{x}_c = \mathbf{R}_{cw} \mathbf{x}_w + \mathbf{t}_{cw}$$

$$\mathbf{x}_c = \begin{pmatrix} x_c \\ y_c \\ z_c \end{pmatrix}$$

Position and Orientation of  $W$  relative to  $C$ :

$$\mathbf{t}_{cw} = \begin{pmatrix} x_{cw} \\ y_{cw} \\ z_{cw} \end{pmatrix}$$

$$\mathbf{R}_{cw} = \begin{pmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{pmatrix}$$



# Homogeneous Transformations

$$\begin{pmatrix} x_c \\ y_c \\ z_c \\ 1 \end{pmatrix} = \begin{pmatrix} \mathbf{R}_{cw} & \mathbf{t}_{cw} \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x_w \\ y_w \\ z_w \\ 1 \end{pmatrix} = \mathbf{T}_{cw} \begin{pmatrix} x_w \\ y_w \\ z_w \\ 1 \end{pmatrix}$$

Position and Orientation of W relative to C

Position and Orientation of C relative to W

$$\mathbf{T}_{wc} = \mathbf{T}_{cw}^{-1} = \begin{pmatrix} \mathbf{R}_{cw}^T & -\mathbf{R}_{cw}^T \mathbf{t}_{cw} \\ 0 & 1 \end{pmatrix}$$

- Orientation defined by 3 angles:

Rotation Order

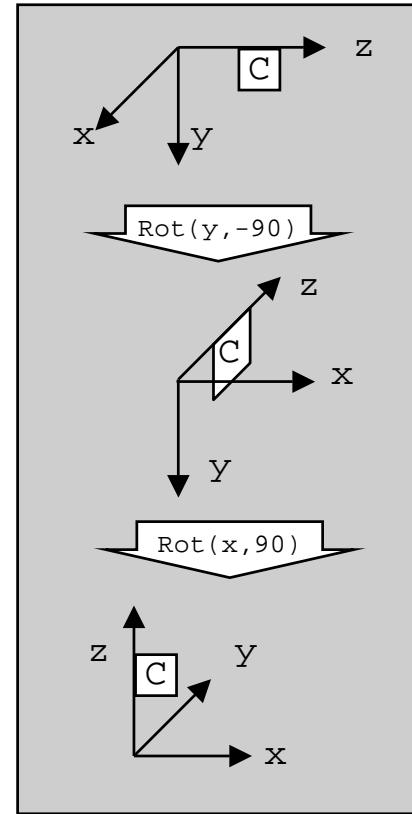
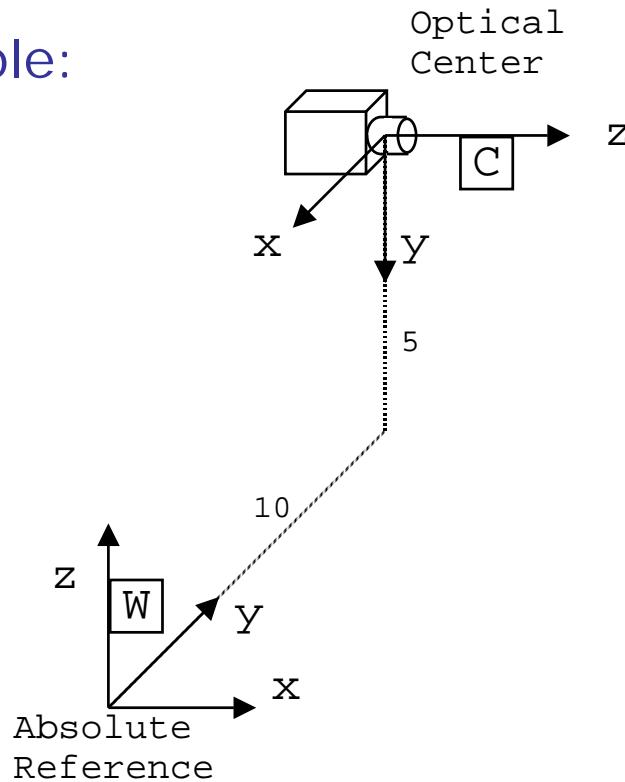
$$RPY(\phi, \theta, \psi) = Rot(z, \phi) Rot(y, \theta) Rot(x, \psi) =$$

$$RPY(\phi, \theta, \psi) = \begin{pmatrix} C\phi C\theta & C\phi S\theta S\psi - S\phi C\psi & C\phi S\theta C\psi + S\phi S\psi \\ S\phi C\theta & S\phi S\theta S\psi + C\phi C\psi & S\phi S\theta C\psi - C\phi S\psi \\ -S\theta & C\theta S\psi & C\theta C\psi \end{pmatrix}$$



# Homogeneous Transformations

- Example:



$$\mathbf{R}_{cw} = \text{Rot}(z, 0) \text{Rot}(y, -90) \text{Rot}(x, 90) = \begin{pmatrix} 0 & -1 & 0 \\ 0 & 0 & -1 \\ 1 & 0 & 0 \end{pmatrix}$$

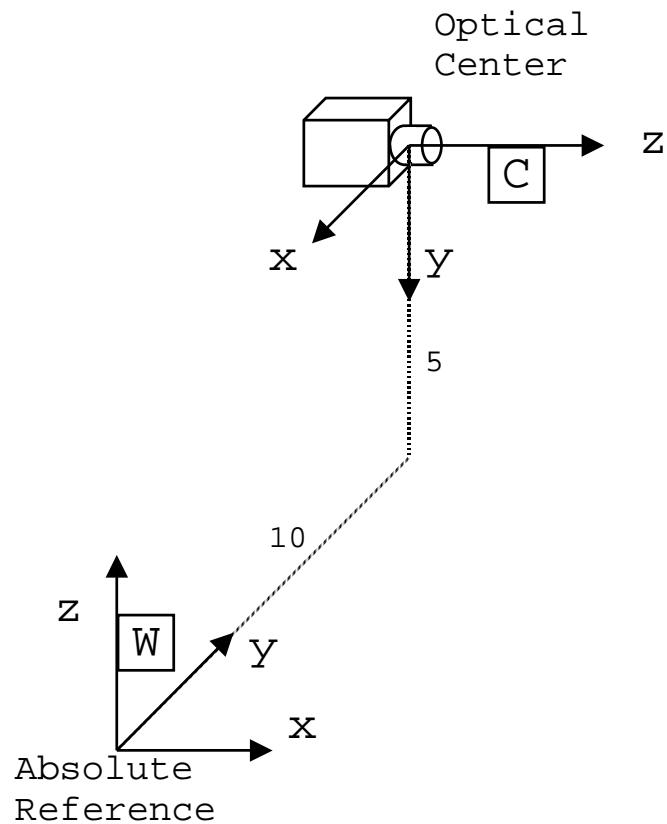
$\overset{\wedge}{x} \quad \overset{\wedge}{y} \quad \overset{\wedge}{z}$

Projection of W's  
axis on reference C



# Homogeneous Transformations

- Example:



$$T_{cw} = \begin{pmatrix} 0 & -1 & 0 & 10 \\ 0 & 0 & -1 & 5 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

$$T_{wc} = T_{cw}^{-1} = \begin{pmatrix} 0 & 0 & 1 & 0 \\ -1 & 0 & 0 & 10 \\ 0 & -1 & 0 & 5 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

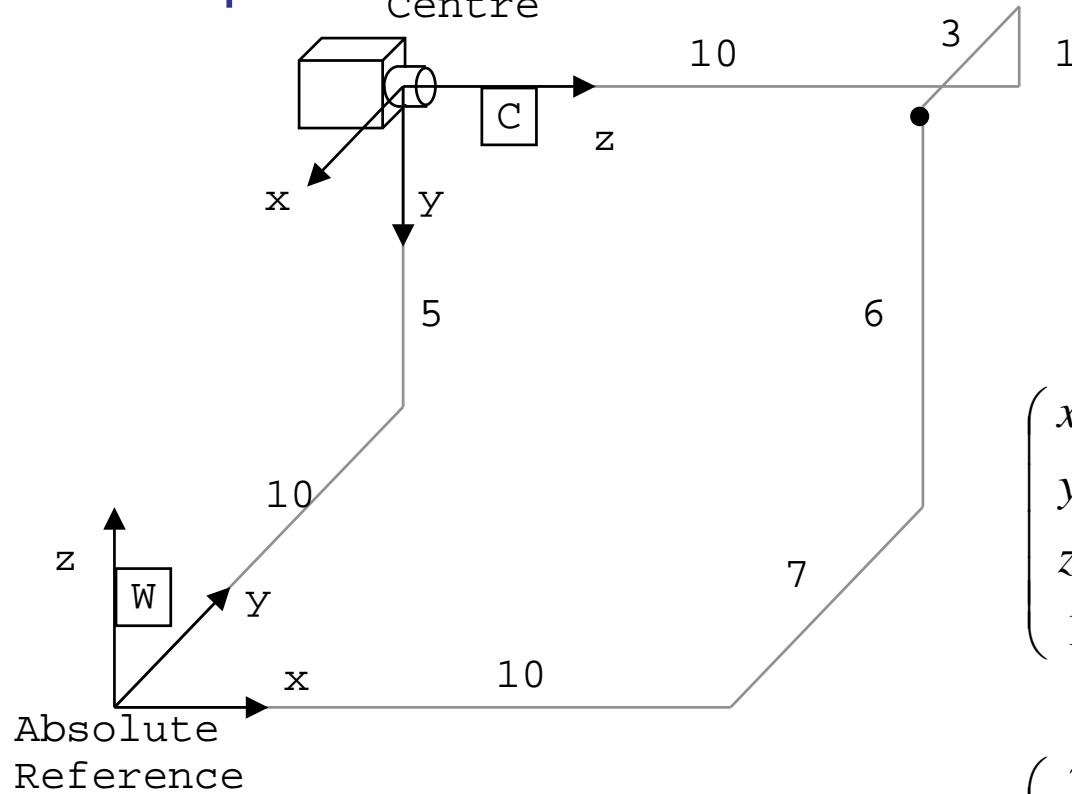


Projection of C's  
axis on reference W



# Homogeneous Transformations

- Example: Optical Centre

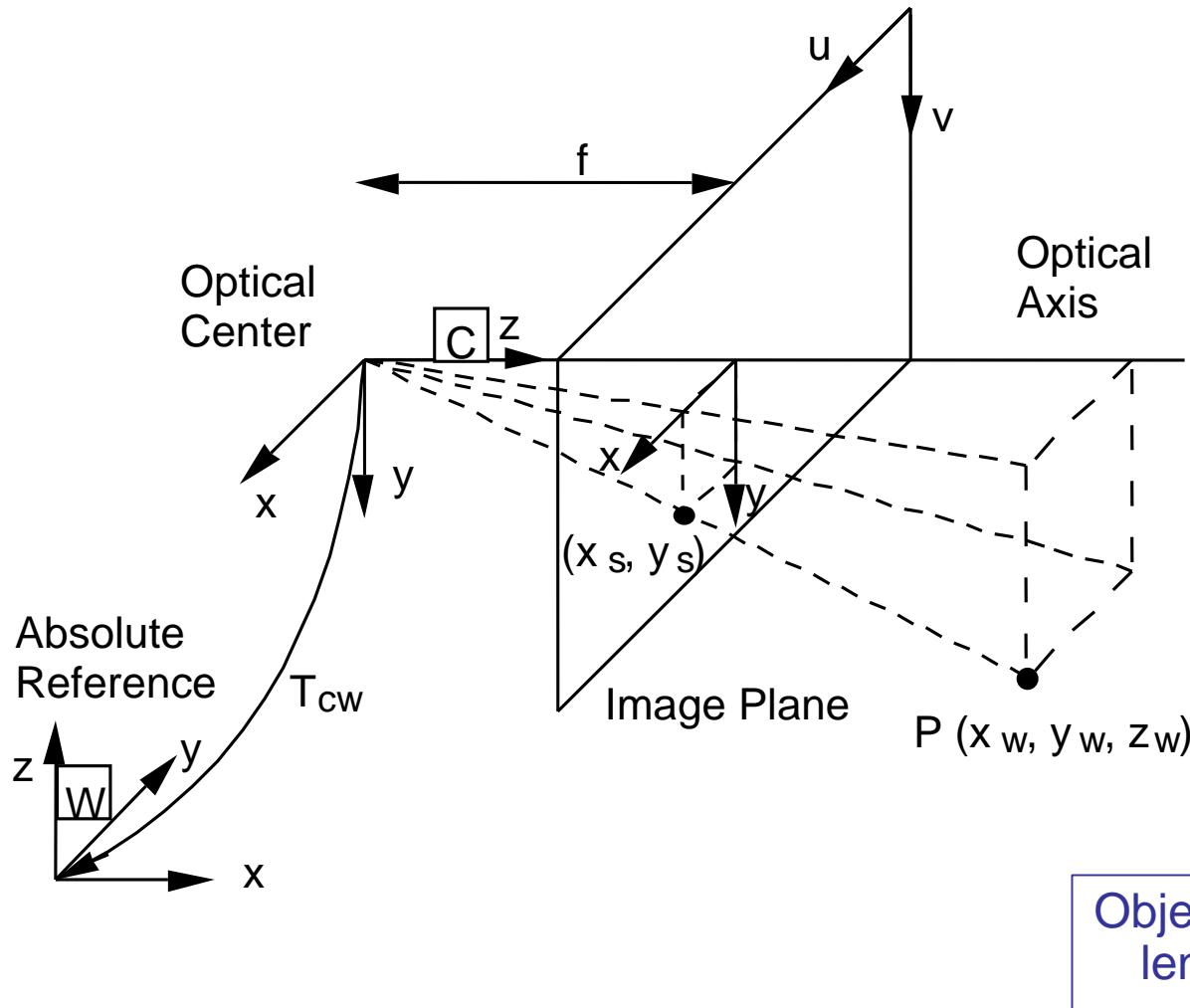


$$\begin{pmatrix} x_c \\ y_c \\ z_c \\ 1 \end{pmatrix} = \begin{pmatrix} \mathbf{R}_{cw} & \mathbf{t}_{cw} \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x_w \\ y_w \\ z_w \\ 1 \end{pmatrix} = \mathbf{T}_{cw} \begin{pmatrix} x_w \\ y_w \\ z_w \\ 1 \end{pmatrix}$$

$$\begin{pmatrix} 3 \\ -1 \\ 10 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 & -1 & 0 & 10 \\ 0 & 0 & -1 & 5 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 10 \\ 7 \\ 6 \\ 1 \end{pmatrix}$$

# Tsai's Camera Model (2)

## 2) Theoretical projection on image sensor



$$\mathbf{x}_{st} = \begin{pmatrix} x_{st} \\ y_{st} \end{pmatrix}$$

$$x_{st} = f \frac{x_c}{z_c}$$

$$y_{st} = f \frac{y_c}{z_c}$$

Objective's focal length (mm)



# Tsai's Camera Model (3)

## 3) Radial distortion

- Noticeable for wide lenses:  $f < 12$  mm

$$\mathbf{x}_{sd} = \begin{pmatrix} x_{sd} \\ y_{sd} \end{pmatrix}$$

Distorted coordinates

Theoretical undistorted coordinates

$$x_{st} = x_{sd} (1 + k_1 r^2)$$

Radial distortion coefficient

$$y_{st} = y_{sd} (1 + k_1 r^2)$$

$$r^2 = {x_{sd}}^2 + {y_{sd}}^2$$



# Tsai's Camera Model (4)

## 4) Transform to pixel coordinates

Coordinates where the optical axis intersects the image plane (in pixels)

$$\mathbf{u} = \begin{pmatrix} u \\ v \end{pmatrix}$$

$$u = C_x + \frac{x_{sd}}{d_x} s_x$$

$$v = C_y + \frac{y_{sd}}{d_y}$$

Horizontal correction factor (for analog cameras)

Pixel size on the sensor (mm)

- Example for a CCD analogic camera:

Acquiring all the lines

$$d_y = d_{cy}$$

or

$$d_y = 2d_{cy}$$

Acquiring half the lines

$$d_x = d_{cx} \frac{N_{sx}}{N_{tx}}$$

Pixels per line on the sensor

Pixels per line on memory



# Tsai's Camera Model (4)

- Example: camera Pulnix TM-6 (analogic)
  - Pixels: 752(H) x 582 (V)
  - Cell size: 8.4 $\mu$ m x 8.2  $\mu$ m

a) Sampling 512(H) x 512(V)

$$d_x = 8.4 \times 10^{-3} \frac{752}{512} = 12.34 \times 10^{-3} \text{ mm}$$

$$d_y = 8.2 \times 10^{-3} \text{ mm}$$

$$PAR = \frac{d_x}{d_y} = 1.5$$

PAR: Pixel Aspect Ratio

b) Sampling 768(H) x 512(V)

$$d_x = 8.4 \times 10^{-3} \frac{752}{768} = 8.2 \times 10^{-3} \text{ mm}$$

$$d_y = 8.2 \times 10^{-3} \text{ mm}$$

square pixel  
PAR = 1



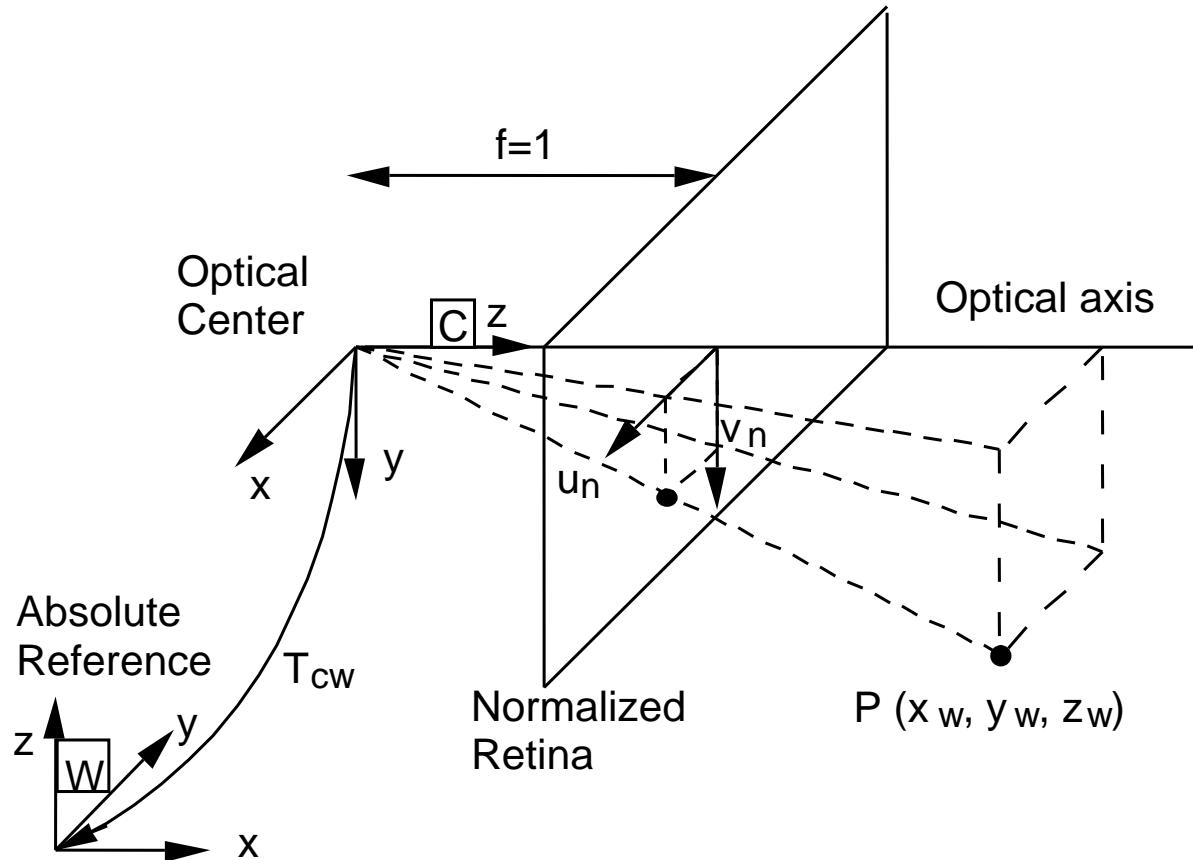
# Tsai's Camera Model (summary)

- Projection model:  $\mathbf{u} = \text{Proy}(\mathbf{x}_w, \theta_c)$
- 1. Transform to camera:  $\mathbf{x}_c = \mathbf{R}_{cw}\mathbf{x}_w + \mathbf{t}_{cw}$
- 2. Theoretical projection:  $x_{st} = f \frac{x_c}{z_c}$        $y_{st} = f \frac{y_c}{z_c}$
- 3. Radial distortion:  $x_{st} = x_{sd}(1 + k_1 r^2)$        $y_{st} = y_{sd}(1 + k_1 r^2)$   
 $r^2 = {x_{sd}}^2 + {y_{sd}}^2$
- 4. Transform to pixels:  $u = C_x + \frac{x_{sd}}{d_x} s_x$        $v = C_y + \frac{y_{sd}}{d_y} s_y$
- Known parameters:  $d_x, d_y$
- Parameter to Calibrate:
  - » Extrinsic:  $\mathbf{t}_{cw}, \mathbf{R}_{cw}$
  - » Intrinsic:  $f, k_1, C_x, C_y, s_x$



# Normalized Retina

- Is an ideal retina (without distortion) placed at focal distance  $f = 1$



The projection only depends on the extrinsic camera parameters:

$$\mathbf{u}_n = \text{Norm\_proj}(\mathbf{x}_w, \theta_{ext})$$

$$\mathbf{x}_c = \mathbf{R}_{cw}\mathbf{x}_w + \mathbf{t}_{cw}$$

$$u_n = \frac{x_c}{z_c}$$

$$v_n = \frac{y_c}{z_c}$$

$$\mathbf{u}_n = \begin{pmatrix} u_n \\ v_n \end{pmatrix}$$

Normalized coordinates (mm)



# Normalized Retina

- Each pixel can be transformed from the real retina to the normalized retina:

$$\mathbf{u}_n = \text{Normal}(\mathbf{u}, \theta_{int})$$

$$x_{sd} = (u - C_x) \frac{d_x}{S_x} \quad y_{sd} = (v - C_y) d_y$$

$$r^2 = {x_{sd}}^2 + {y_{sd}}^2$$

$$x_{st} = x_{sd} (1 + k_1 r^2) \quad y_{st} = y_{sd} (1 + k_1 r^2)$$

$$u_n = \frac{x_{st}}{f} \quad v_n = \frac{y_{st}}{f}$$



### 3. Calibration

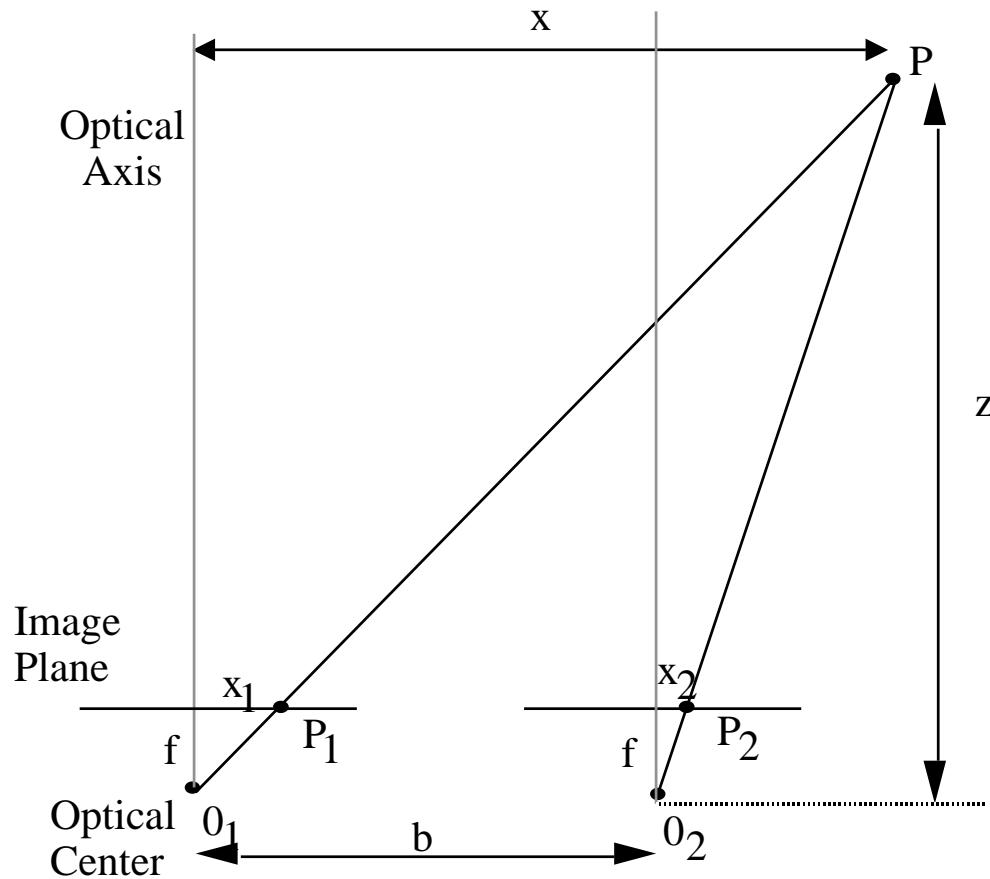
- Cameramodel:  $\mathbf{u} = \text{Proj}(\mathbf{x}_w, \theta_c)$
- Put a pattern with  $N$  points, in known positions:  
 $(\mathbf{x}_{w1}, \dots \mathbf{x}_{wN})$
- Take an image and compute the point coordinates in the image:  
 $(\mathbf{u}_1, \dots \mathbf{u}_N)$
- Obtain the set of parameters  $\theta_c$  that minimizes the squared error:  
$$\sum_{i=1}^N [\mathbf{u}_i - \text{Proj}(\mathbf{x}_{wi}, \theta_c)]$$

In order to compute all the parameters, the pattern must be 3D



## 4. Stereo Vision

- Simplest case: parallel cameras with no distortion



$$x_1 = f \frac{x_{c1}}{z_{c1}} = f \frac{x}{z}$$

$$x_2 = f \frac{x_{c2}}{z_{c2}} = f \frac{x-b}{z}$$

$$z = \frac{bf}{x_1 - x_2}$$

- Depth depends on the disparity:  $x_1 - x_2$



# Stereo Vision

- General case: real cameras in arbitrary positions
  - Using the normalized retinas:

$$\begin{aligned}\mathbf{x}_{c_k} &= R_{c_k w} \mathbf{x}_w + \mathbf{t}_{c_k w} \\ &= \begin{pmatrix} r_{11k} & r_{12k} & r_{13k} \\ r_{21k} & r_{22k} & r_{23k} \\ r_{31k} & r_{32k} & r_{33k} \end{pmatrix} \mathbf{x}_w + \begin{pmatrix} x_{c_k w} \\ y_{c_k w} \\ z_{c_k w} \end{pmatrix}\end{aligned}$$

$$\begin{aligned}u_{n_k} &= \frac{x_{c_k}}{z_{c_k}} & v_{n_k} &= \frac{y_{c_k}}{z_{c_k}} \\ \mathbf{r}_{1k} \mathbf{x}_w + x_{c_k w} &= u_{n_k} (\mathbf{r}_{3k} \mathbf{x}_w + z_{c_k w}) \\ \mathbf{r}_{2k} \mathbf{x}_w + y_{c_k w} &= v_{n_k} (\mathbf{r}_{3k} \mathbf{x}_w + z_{c_k w})\end{aligned}$$

$$\begin{pmatrix} x_{c_k} \\ y_{c_k} \\ z_{c_k} \end{pmatrix} = \begin{pmatrix} \mathbf{r}_{1k} \mathbf{x}_w + x_{c_k w} \\ \mathbf{r}_{2k} \mathbf{x}_w + y_{c_k w} \\ \mathbf{r}_{3k} \mathbf{x}_w + z_{c_k w} \end{pmatrix}$$

where:

$$\mathbf{r}_{ik} = (r_{i1k} \quad r_{i2k} \quad r_{i3k})$$

$$\begin{aligned}\mathbf{A}_k \mathbf{x}_w + \mathbf{b}_k &= 0 \\ \mathbf{A}_k &= \begin{pmatrix} \mathbf{r}_{1k} - u_{n_k} \mathbf{r}_{3k} \\ \mathbf{r}_{2k} - v_{n_k} \mathbf{r}_{3k} \end{pmatrix} \\ \mathbf{b}_k &= \begin{pmatrix} x_{c_k w} - u_{n_k} z_{c_k w} \\ y_{c_k w} - v_{n_k} z_{c_k w} \end{pmatrix}\end{aligned}$$



# Stereo Vision

- 3D point reconstruction from n images
  - Three unknowns:  $x_w, y_w, z_w$
  - Two equations in each image k:

$$\mathbf{A}_k \mathbf{x}_w + \mathbf{b}_k = 0$$

- System of linear equations (over-determined):

$$\mathbf{A} \mathbf{x}_w + \mathbf{b} = 0$$

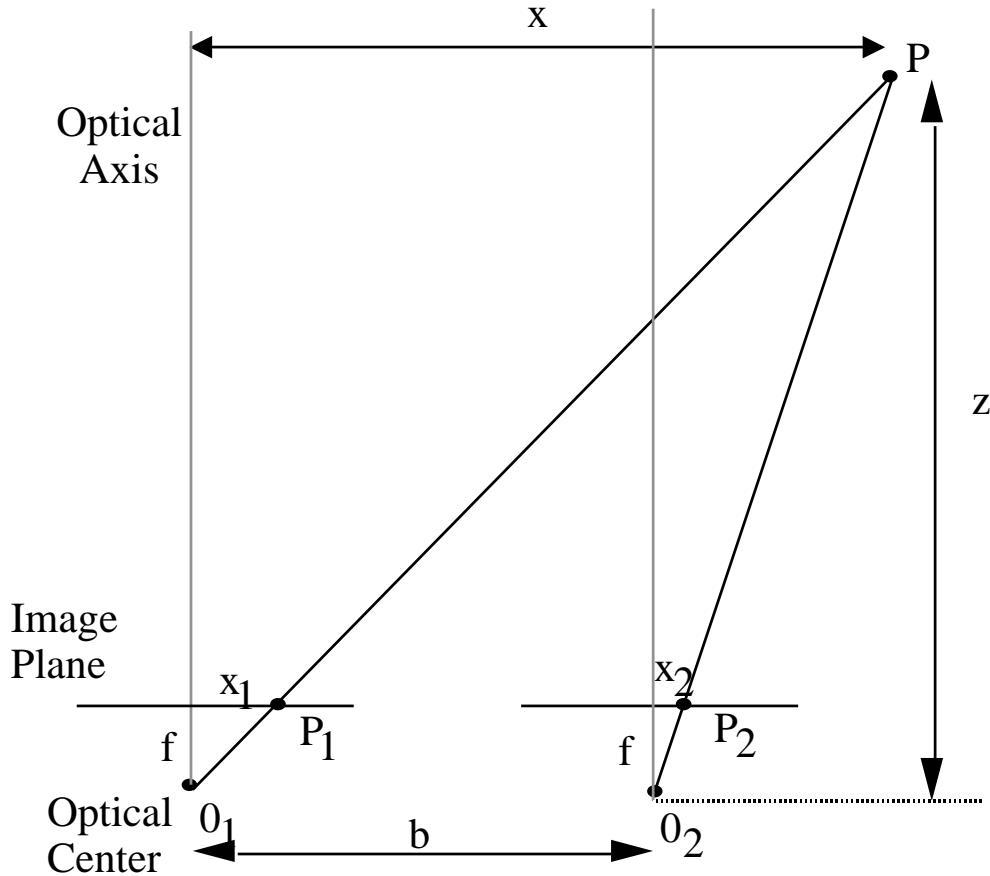
$$\mathbf{A} = \begin{pmatrix} \mathbf{A}_1 \\ \dots \\ \mathbf{A}_n \end{pmatrix} \quad \mathbf{b} = \begin{pmatrix} \mathbf{b}_1 \\ \dots \\ \mathbf{b}_n \end{pmatrix}$$

- Least Squares Solution:

$$\mathbf{x}_w = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b}$$



# Example: parallel cameras



$$R_{c_1w} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$R_{c_2w} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$t_{c_1w} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

$$t_{c_2w} = \begin{pmatrix} -b \\ 0 \\ 0 \end{pmatrix}$$

- Choosing as absolute reference  $W = C_1$



# Example: parallel cameras

- Linear system:

$$\begin{pmatrix} 1 & 0 & -u_{n1} \\ 0 & 1 & -v_{n1} \\ 1 & 0 & -u_{n2} \\ 0 & 1 & -v_{n2} \end{pmatrix} \begin{pmatrix} x_w \\ y_w \\ z_w \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ -b \\ 0 \end{pmatrix} = 0$$

- Analytical solution:

$$z_w = \frac{b}{u_{n1} - u_{n2}}$$

$$x_w = u_{n1} \frac{b}{u_{n1} - u_{n2}}$$

$$y_w = v_{n1} \frac{b}{u_{n1} - u_{n2}}$$

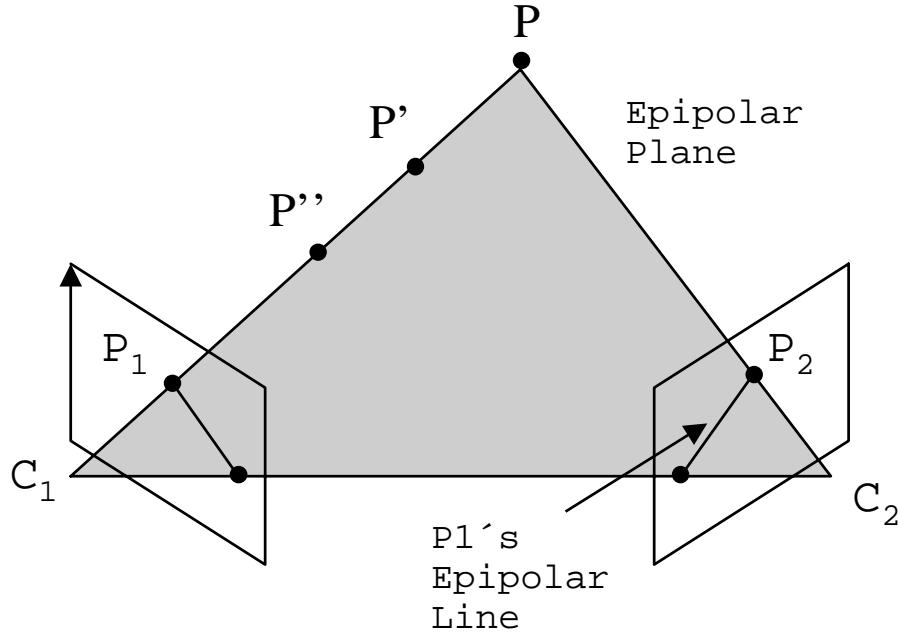
$$v_{n1} = v_{n2}$$



- Epipolar constraint: The corresponding points must be on the same row in both images

# 5. Correspondence Search

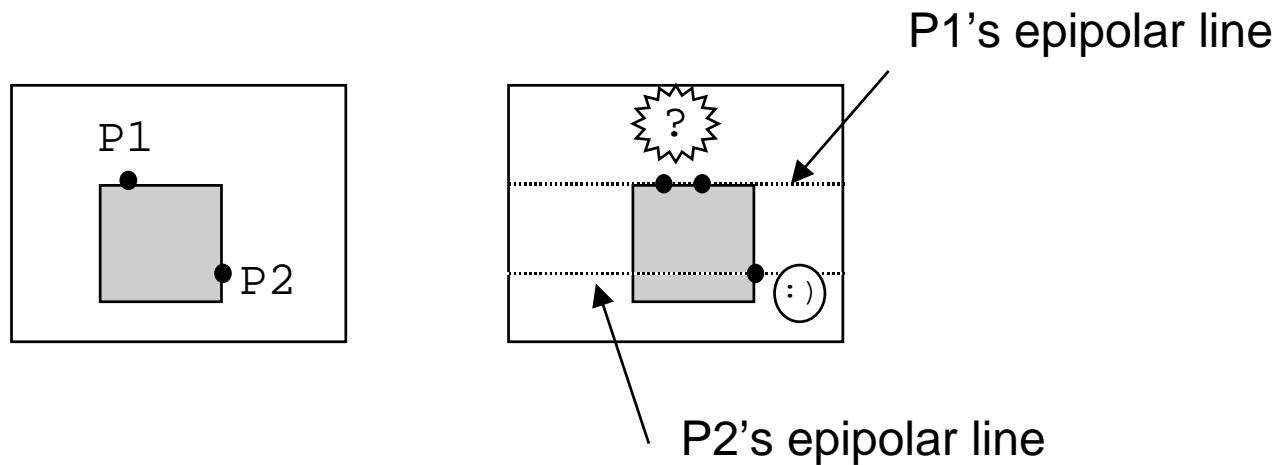
- Give a point  $P$ , its epipolar plane is  $PC_1C_2$
- Its projections  $P_1$  and  $P_2$  belong to  $P$ 's epipolar plane



- Epipolar constraint for  $P_1$ :
  - Given  $C_1$ ,  $C_2$  y  $P_1$ , compute the epipolar plane
  - Intersect the epipolar plane with the image plane 2 to obtain  $P_1$ 's epipolar line in image 2
  - The point corresponding to  $P_1$  must be on the epipolar line
- They can be several candidates  $P_2, P_2', \dots$

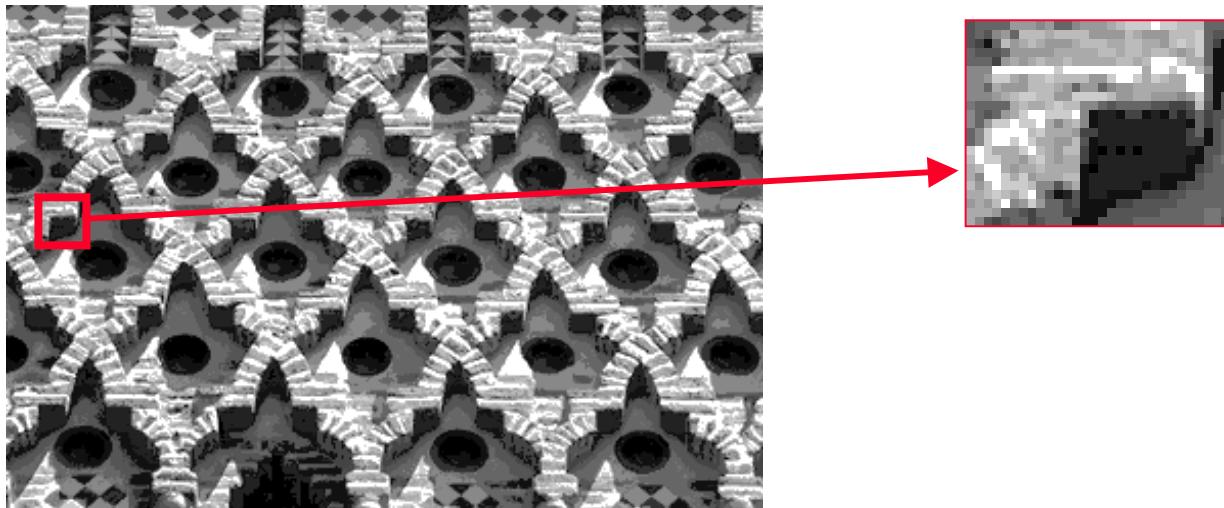
# Edge Correspondences

- Detect edge points in both images
- For each edge in image 1, search for an edge along its epipolar line having:
  - Similar gradient magnitude
  - Similar gradient orientation
- Contours oriented parallel to its epipolar line cannot be matched:



# Matching using Correlation

- For each pixel, take a local patch and search for a similar patch along the epipolar line on the second image



# Correlation

- Sum of Squared Differences SSD:

$$\sum_{i,j} (W_{ij}^a - W_{ij}^b)^2$$

Searched nxm patch  
from the first image

Each possible nxm patch  
on the second image

» Problematic if illumination changes

- Normalized Correlation:

$$\rho = \frac{\sum_{ij} (W_{ij}^a - \bar{W}_{ij}^a)(W_{ij}^b - \bar{W}_{ij}^b)}{\sqrt{\sum_{ij} (W_{ij}^b - \bar{W}_{ij}^b)^2} \sqrt{\sum_{ij} (W_{ij}^a - \bar{W}_{ij}^a)^2}} \quad \rho \in [-1,1]$$

»  $\rho$  close to 1: linear gray level relation  $\rightarrow$  correspondence

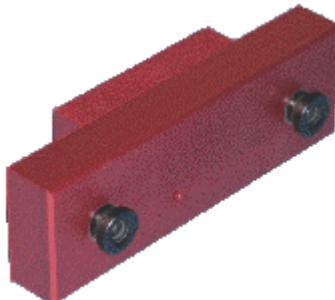


# Stereo using Correlation

- SRI Stereo Engine algorithm by Kurt Konolige

<http://www.ai.sri.com/~konolige/>

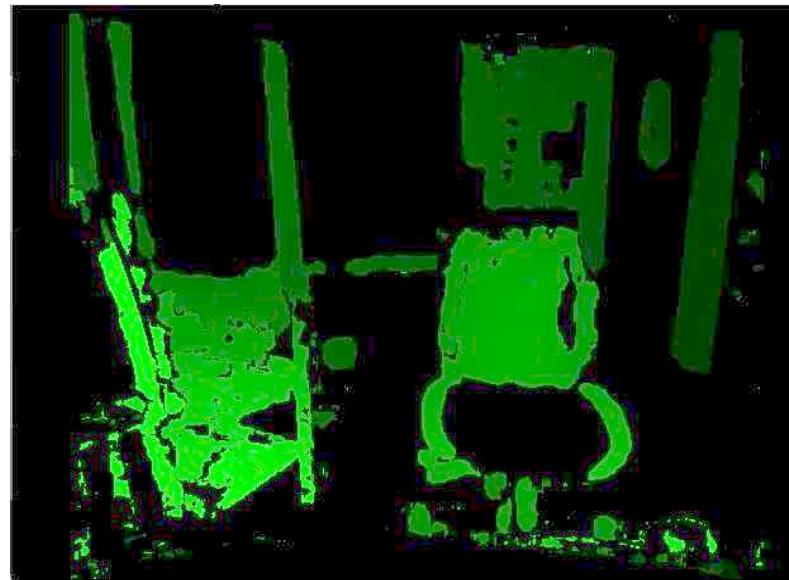
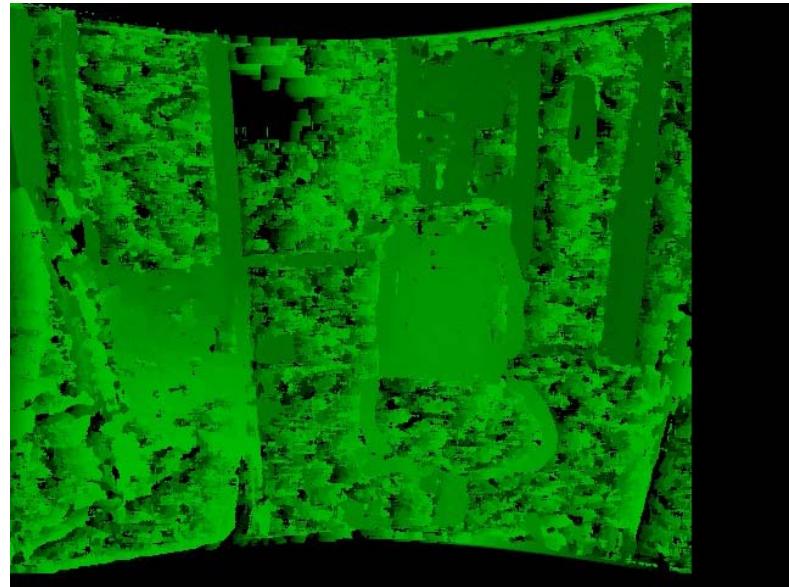
1. Rectification - remove distortion from images
2. Feature Extraction - Laplacian of Gaussian
3. Correlation - compute disparities by matching
4. Filtering - remove uncertain matches
5. 3D reconstruction - convert disparities to 3D points



# Stereo using Correlation

- SRI Stereo Engine algorithm by Kurt Konolige  
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# Stereo using Correlation

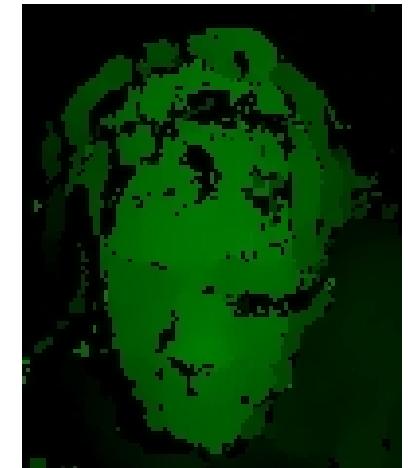
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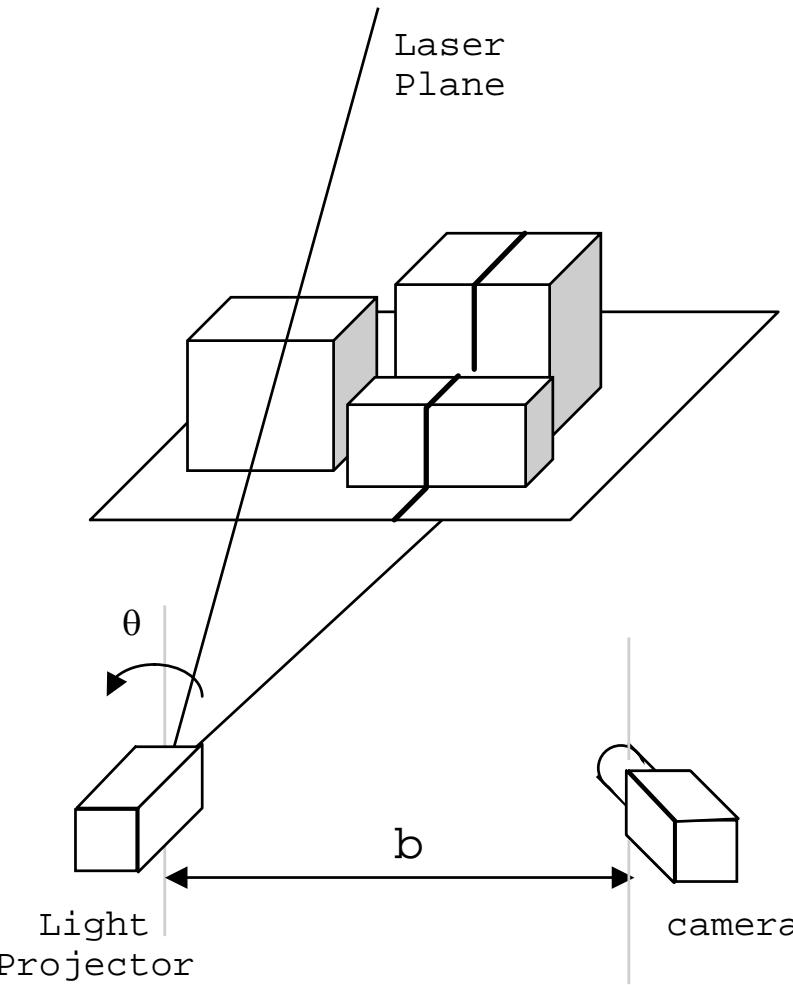
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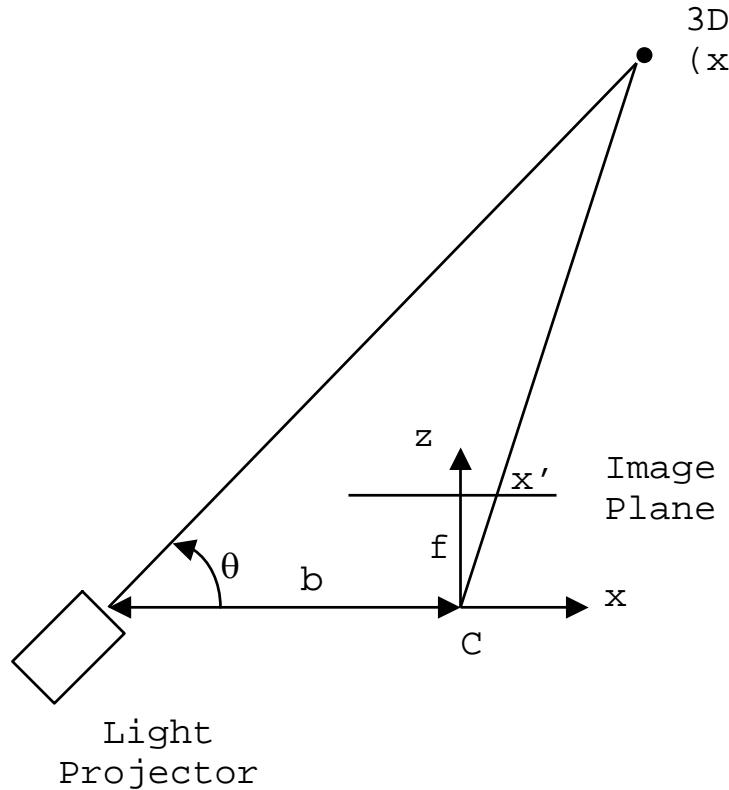
## 6. Other 3D techniques: Structured Light

- Sweep the scene with a laser point or a laser plane



# Structured Light

- 3D information from triangulation



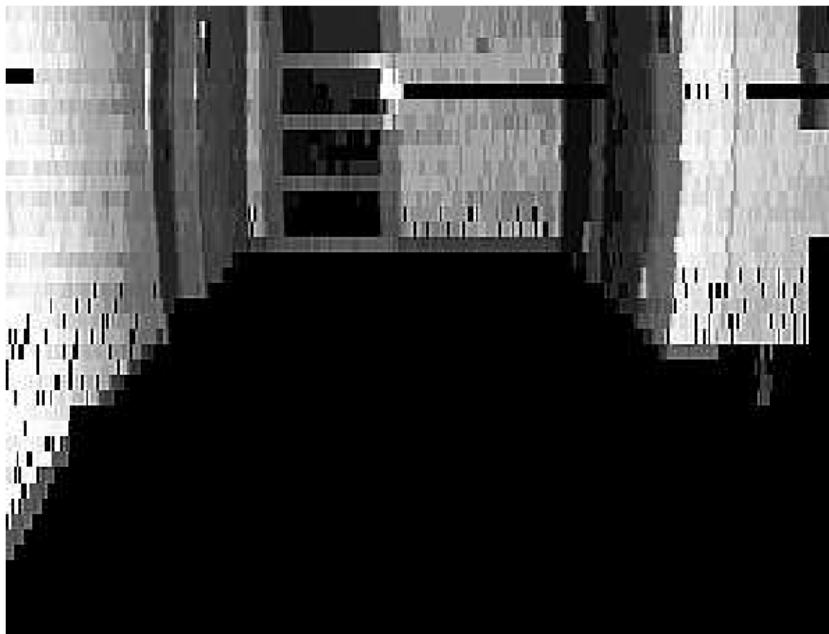
$$x' = f \frac{x}{z} \quad y' = f \frac{y}{z}$$

$$\tan \theta = \frac{z}{x + b}$$

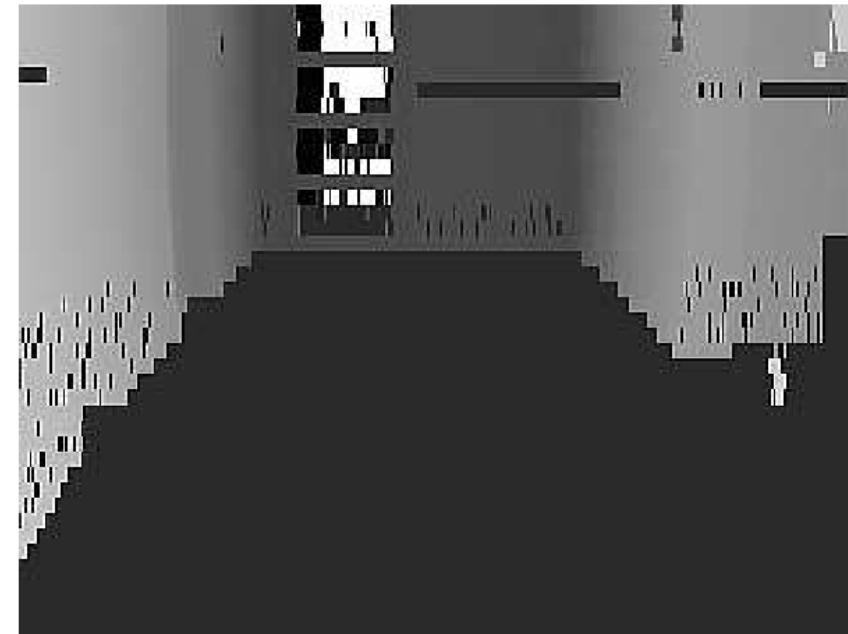
$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} = \frac{b}{f \cot \theta - x'} \begin{pmatrix} x' \\ y' \\ f \end{pmatrix}$$



# Other 3D techniques: Range Camera

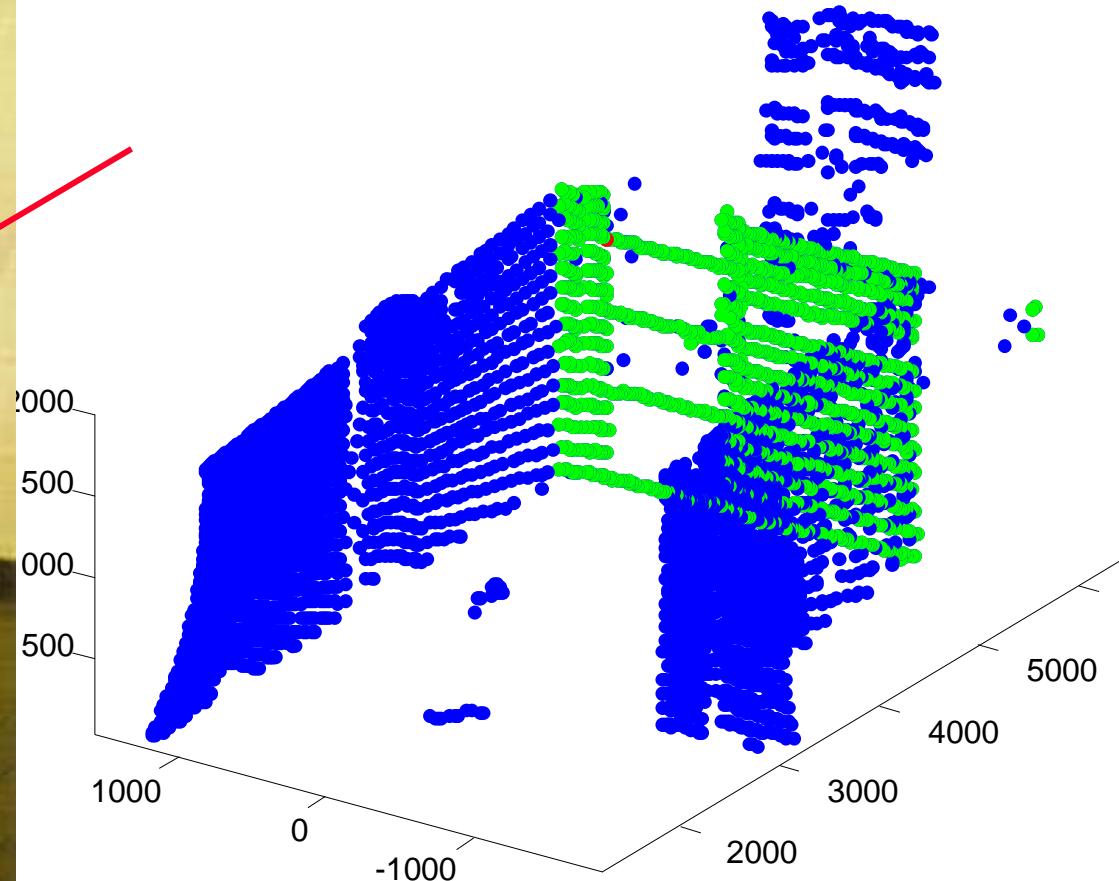
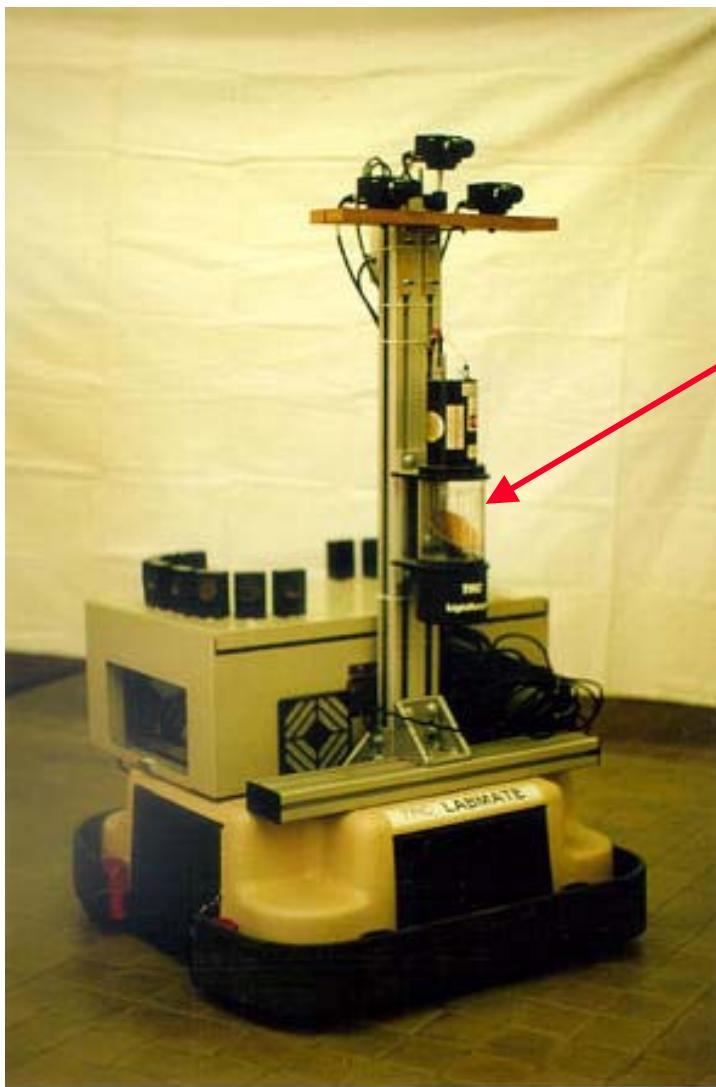


Intensity Image



Depth Image

# Other 3D techniques: 3D Laser Scanner

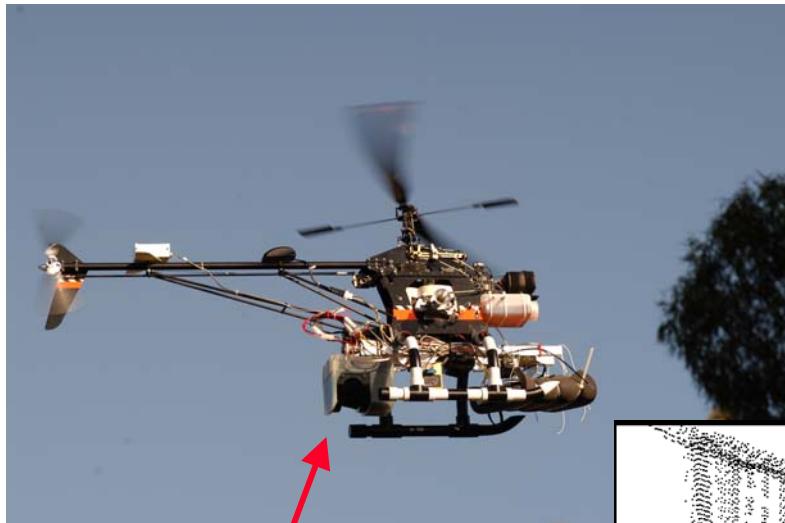


Otilio



# 2D Laser Scanner + Motion

- Scan Alignment and 3-D Surface Modeling with a Helicopter Platform by Sebastian Thrun, Mark Diel, and Dirk Haehnel, 2003 International Conference of Field and Service Robotics.



**2D Laser  
Scanner**

