

Image Formation and Analysis (Formation et Analyse d'Images)

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ENSIMAG 3 - MMIS Option MIRV

First Semester 2010/2011

Lesson 3

11 Oct 2010

Calibrating a Camera Model

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Calibrating a Camera Model

The Complete Camera Model

$$P^i = C_r^i P_c^r T_s^c P^s = M_s^i P^s$$

$$\begin{bmatrix} w i \\ w j \\ w \end{bmatrix} = M_s^i \begin{bmatrix} X_s \\ Y_s \\ Z_s \\ 1 \end{bmatrix}$$

and thus

$$i = \frac{w i}{w} = \frac{M_s^1 \cdot P^s}{M_s^3 \cdot P^s} \qquad j = \frac{w j}{w} = \frac{M_s^2 \cdot P^s}{M_s^3 \cdot P^s}$$

or

$$i = \frac{w i}{w} = \frac{M_{11} X_s + M_{12} Y_s + M_{13} Z_s + M_{14}}{M_{31} X_s + M_{32} Y_s + M_{33} Z_s + M_{34}}$$

$$j = \frac{w j}{w} = \frac{M_{21} X_s + M_{22} Y_s + M_{23} Z_s + M_{24}}{M_{31} X_s + M_{32} Y_s + M_{33} Z_s + M_{34}}$$

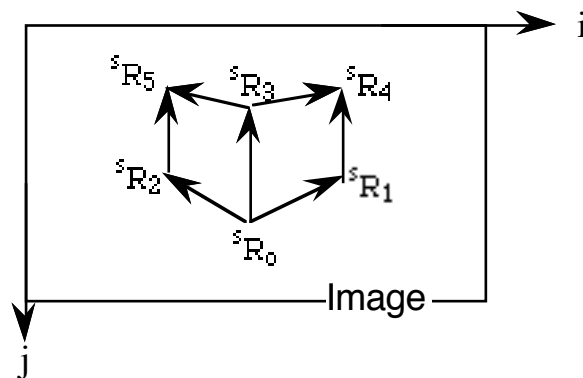
Calibrating the Camera

How can we obtain M_s^i ? By a process of calibration.

Observe a set of at least 6 non-coplanar points whose position in the world is known.

R_k^s for $k=0,1,2,3,4,5$ (s are the scene coordinate axes $s=1,2,3$)

For example, we can use the corners of a cube. Define the lower front corner as the origin, and the edges as unit distances.



The matrice M_s^i is composed of $3 \times 4 = 12$ coefficients. However because, M_s^i is in homogeneous coordinates, the coordinate m_{34} can be set to 1.

Thus there are $12 - 1 = 11$.

We can determine these coefficients by observing known points in the scene. (R_k^s).

Each point provides two coefficients. Thus, for 11 coefficients we need at least $5 \frac{1}{2}$ points. With 6 points the system is over-constrained.

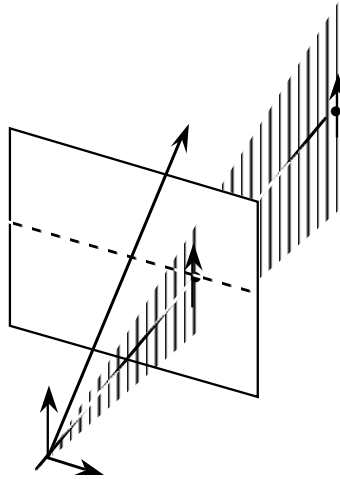
For each known calibration point R_k^s given its observed image position P_k^s , we can write:

$$i_k = \frac{w_k i_k}{w_k} = \frac{M_s^1 \cdot R_k^s}{M_s^3 \cdot R_k^s} \quad j_k = \frac{w_k j_k}{w_k} = \frac{M_s^2 \cdot R_k^s}{M_s^3 \cdot R_k^s}$$

This gives 2 equations for each point.

$$(M_s^1 \cdot R_k^s) - i_k (M_s^3 \cdot R_k^s) = 0 \quad (M_s^2 \cdot R_k^s) - j_k (M_s^3 \cdot R_k^s) = 0$$

Each pair of equations corresponds to the planes that pass through the image row and the image column of the observed image point P_k^s



The equation $(M_s^1 \cdot R_k^s) - i_k (M_s^3 \cdot R_k^s) = 0$ is the vertical plane that includes the projective center through the pixel $i=i_k$.

The equation $(M_s^2 \cdot R_k^s) - j_k (M_s^3 \cdot R_k^s) = 0$ is the horizontal plane that includes the projective center and the row $j=j_k$.

In tensor notation

given $P^i = \begin{pmatrix} wi \\ wj \\ w \end{pmatrix}$ we write : $P^i = M_s^i R^s$

with k scene points, R_k^s and their image correspondences P_k^i we can write

$$P_k^i = M_s^i R_k^s$$

with $i \cdot w = P_k^1/P_k^3$ et $j \cdot w = P_k^2/P_k^3$ for each image point k , there are two independent equations

$$\begin{pmatrix} p^1 \\ p^2 \\ p^3 \end{pmatrix} = \begin{pmatrix} wi \\ wj \\ w \end{pmatrix} \text{ donc } \begin{pmatrix} i \\ j \\ 1 \end{pmatrix} = \begin{pmatrix} p^1/p^3 \\ p^2/p^3 \\ 1 \end{pmatrix}$$

and with $P_k^3 = M_s^3 R_k^s$

$$i = p^1/p^3 = M_s^1 R_k^s / M_s^3 R_k^s \Rightarrow i M_s^3 R_k^s - M_s^1 R_k^s = 0$$

$$j = p^2/p^3 = M_s^2 R_k^s / M_s^3 R_k^s \Rightarrow j M_s^3 R_k^s - M_s^2 R_k^s = 0$$

We can write this as:

$$\begin{pmatrix} R^1 & R^2 & R^3 & 1 & 0 & 0 & 0 & 0 & -iR^1 & -iR^2 & -iR^3 & -i \\ 0 & 0 & 0 & 0 & R^1 & R^2 & R^3 & 1 & -jR^1 & -jR^2 & -jR^3 & -j \end{pmatrix} \begin{pmatrix} \mathbf{M}_1^1 \\ \mathbf{M}_2^1 \\ \mathbf{M}_3^1 \\ \mathbf{M}_4^1 \\ \mathbf{M}_1^2 \\ \mathbf{M}_2^2 \\ \mathbf{M}_3^2 \\ \mathbf{M}_4^2 \\ \mathbf{M}_1^3 \\ \mathbf{M}_2^3 \\ \mathbf{M}_3^3 \\ \mathbf{M}_4^3 \end{pmatrix} = 0$$

For N non-coplanair points we can write 2N equations.

$$\mathbf{A} \mathbf{M}_s^i = 0.$$

We then use least squares to minimize the criteria:

$$\mathbf{C} = \|\mathbf{A} \mathbf{M}_s^i\|$$

For example, give a cube with observed corners

$$\begin{array}{lll} P_o^L = (101, 221) & P_1^L = (144, 181) & P_2^L = (22, 196) \\ P_3^L = (105, 88) & P_4^L = (145, 59) & P_5^L = (23, 67) \end{array}$$

Least squares will give:

$$\mathbf{M}_s^i = \begin{pmatrix} 55.886873 & -79.292084 & 1.276703 & 101.917630 \\ -22.289319 & -17.878203 & -134.345576 & 221.300658 \\ 0.100734 & 0.038274 & -0.008458 & 1.000000 \end{pmatrix}$$

Alternate Derivation using the Cross product

In classic matrix notation:

$$\vec{P} \times \mathbf{M}_s^i \vec{R} = 0$$

The term \vec{R} can be factored to set $\vec{P} \vec{R} \times \mathbf{M}_s^i = 0$

This gives
$$\begin{pmatrix} 0 & -wR^s & jwR^s \\ -wR^s & 0 & -iwR^s \\ wR^s & -wR^s & 0 \end{pmatrix} \begin{pmatrix} \mathbf{M}_s^1 \\ \mathbf{M}_s^2 \\ \mathbf{M}_s^3 \end{pmatrix} = 0$$

Where \vec{R} and \mathbf{M}_s^i are vectors. Thus:

$$\begin{pmatrix} 0 & 0 & 0 & 0 & wX & wY & wZ & w1 & -jwX & -jwY & -jwZ & -jw1 \\ -wX & -wY & -wZ & -w & 0 & 0 & 0 & 0 & -iwX & -iwY & -iwZ & -iw1 \\ wX & wY & wZ & w & -wX & -wY & -wZ & -w & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \mathbf{M}_1^1 \\ \mathbf{M}_2^1 \\ \mathbf{M}_3^1 \\ \mathbf{M}_4^1 \\ \mathbf{M}_1^2 \\ \mathbf{M}_2^2 \\ \mathbf{M}_3^2 \\ \mathbf{M}_4^2 \\ \mathbf{M}_1^3 \\ \mathbf{M}_2^3 \\ \mathbf{M}_3^3 \\ \mathbf{M}_4^3 \end{pmatrix} = 0$$

Any two of the equations are independent.

Homography between two planes.

The projection of a plane to another plane is a degenerate case of the the project transform. In this case, the transform is bijective and reduces to a 3 x 3 invertible

This matrix can be used to rectify an image to a perpendicular view.

$$Q^B = H_A^B P^A$$

In classic notation

$$\begin{pmatrix} w \ x_B \\ w \ y_B \\ w \end{pmatrix} = H_A^B \begin{pmatrix} x_A \\ y_A \\ 1 \end{pmatrix} = \begin{pmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{pmatrix} \begin{pmatrix} x_A \\ y_A \\ 1 \end{pmatrix}$$

$$x_B = \frac{w \ x_B}{w} = \frac{m_{11} \ x_A + m_{12} \ y_A + m_{13}}{m_{31} \ x_A + m_{32} \ y_A + m_{33}}$$

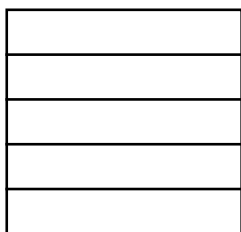
$$y_B = \frac{w \ y_B}{w} = \frac{m_{21} \ x_A + m_{22} \ y_A + m_{23}}{m_{31} \ x_A + m_{32} \ y_A + m_{33}}$$

In tensor notation:

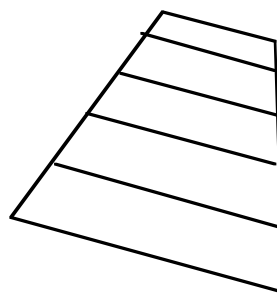
$$Q^B = H_A^B P^A$$

$$\begin{pmatrix} q^1 \\ q^2 \\ q^3 \end{pmatrix} = H_A^B \begin{pmatrix} p^1 \\ p^2 \\ p^3 \end{pmatrix} = \begin{pmatrix} h_1^1 & h_2^1 & h_3^1 \\ h_1^2 & h_2^2 & h_3^2 \\ h_1^3 & h_2^3 & h_3^3 \end{pmatrix} \begin{pmatrix} p^1 \\ p^2 \\ p^3 \end{pmatrix}$$

$$x_B = \frac{q^1}{q^3} \quad y_B = \frac{q^2}{q^3}$$



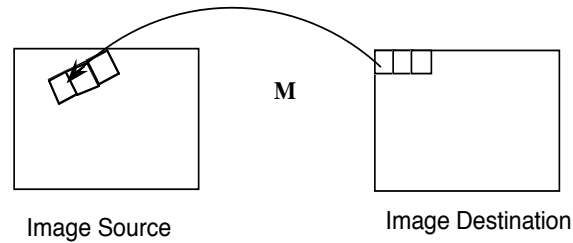
Image



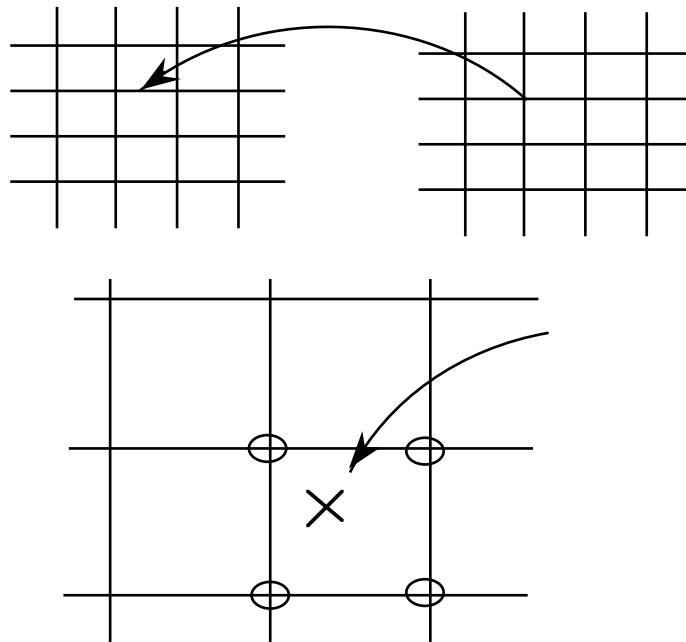
Homographic projection

Image Transformations

For each pixel in the destination image, (x_d, y_d) compute its position in the source image (x_s, y_s)



Determine the appropriate pixel value (intensity or color) for the source image and put this pixel value in the destination.

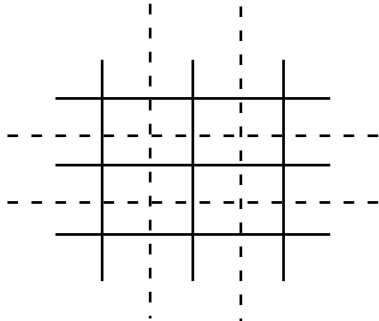


The problem is that the calculated pixel is a real number. To obtain a destination pixel value we need to interpolate. This can be done by

zeroth order:	Nearest neighbor
First order:	Linear or bilinear interpolation
second order	Cubic spline.

Zero Order Interpolation.

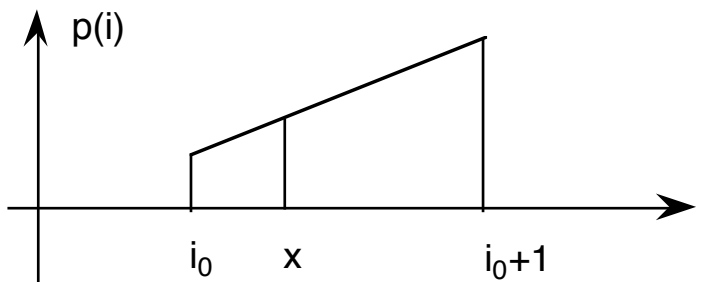
Use the pixel value of the position i_2, j_2 that is closest to the (x_B, y_B)
 This is essentially rounding (x_B, y_B) to the nearest integer value



The dashed lines represent decision lines

Linear Interpolation

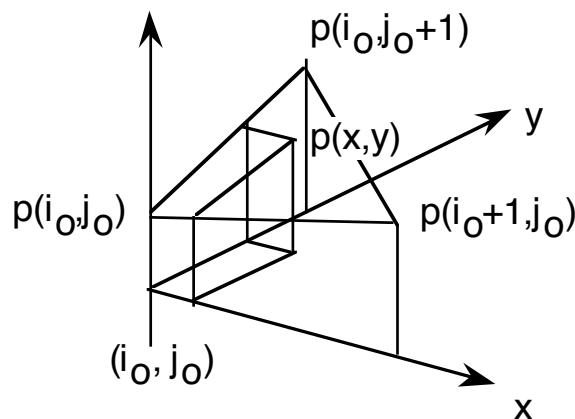
For a 1 D signal, interpolation, between pixel i_0 and its neighbor is $i_0 \leq x \leq i_0+1$



Calculate the slope : $m_x \equiv \frac{\Delta P}{\Delta x} = p(i_0+1) - p(i_0)$

Then: $p(x) = (x-i_0) m_x + p(i_0)$

In 2 D, linear interpolation is only valid in the triangle defined by the three points $p(i,j)$, $p(i+1, j)$, $p(i,j+1)$.



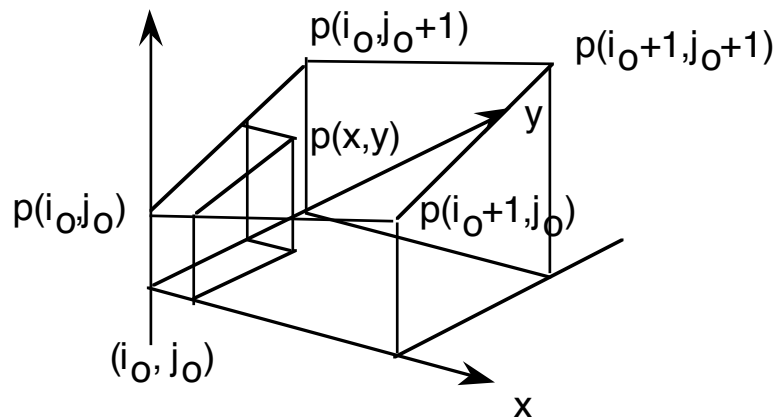
$$m_x \equiv \frac{\Delta P}{\Delta x} = p(i+1, j) - p(i, j)$$

$$m_y \equiv \frac{\Delta P}{\Delta y} = p(i, j+1) - p(i, j)$$

$$p(x, y) = m_x \cdot (x-i) + m_y \cdot (y-j) + p(i, j)$$

If we are closer to $p(i+1, j+1)$ the value is not accurate. It is better to use bilinear interpolation

Bilinear Interpolation:



The mathematical form is a hyperbolic paraboloid.

$$p(x, y) = a x + b y + c x y + d.$$

This is equivalent to the interpolation in y between a pair of points computed as interpolations in x at y and $y+1$.

Derivation :

$$a \equiv m_x = \frac{\Delta P}{\Delta x} = p(i+1, j) - p(i, j)$$

$$b \equiv m_y = \frac{\Delta P}{\Delta y} = p(i, j+1) - p(i, j)$$

$$c \equiv m_{xy} = p(i+1, j) + p(i, j+1) - p(i, j) - p(i+1, j+1)$$

$$d = p(i, j)$$

$$p(x, y) = a \cdot (x-i) + b \cdot (y-j) + c \cdot (x-i) \cdot (y-j) + p(i, j)$$