

计算机视觉与模式识别

Computer Vision and Pattern Recognition

Motion & Optical Flow

3D motion field, 2D image motion, Apparent motion, Optical flow computation (Nonparametric methods), KLT feature tracking

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Outline

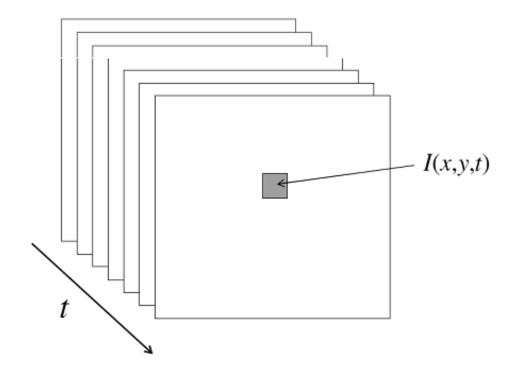
- Motion
 - Applications
 - ✓ e.g. Time to Collision (TTC)
- Motion Field (3D&2D motion field)
 - Derivation
 - Visual navigation & structure for motion
- Apparent motion &Optical Flow (Non-parametric)
 - Brightness constancy constraint
 - Aperture problem
 - Lucas-Kanade flow
 - Iterative refinement
 - Global parametric motion
 - Coarse-to-fine estimation
- KLT Feature Tracking



Video

Video

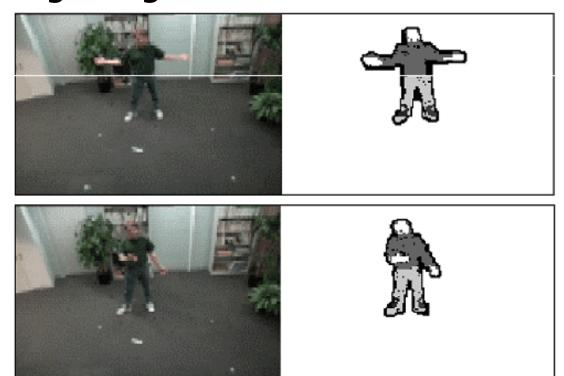
- A video is a sequence of frames captured over time
- The image data is a function of space (x, y) and time (t)





Background subtraction

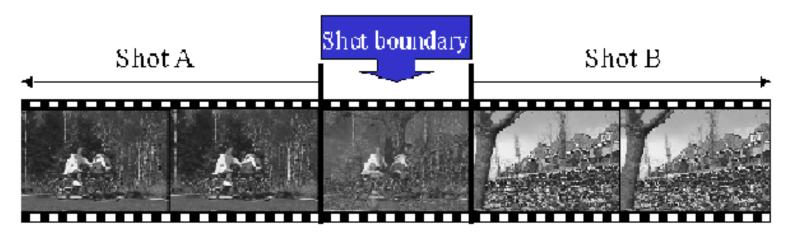
- A static camera is observing a scene.
- Goal: separate the static background from the moving foreground.





Shot boundary detection

- Commercial video is usually composed of shots or sequences showing the same objects or scene.
- Goal: segment video into shots for summarization and browsing (each shot can be represented by a single key-frame in a user interface).
- Difference from background subtraction: the camera is not necessarily stationary.

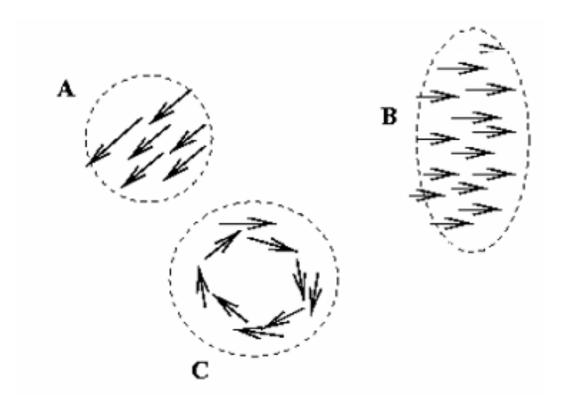




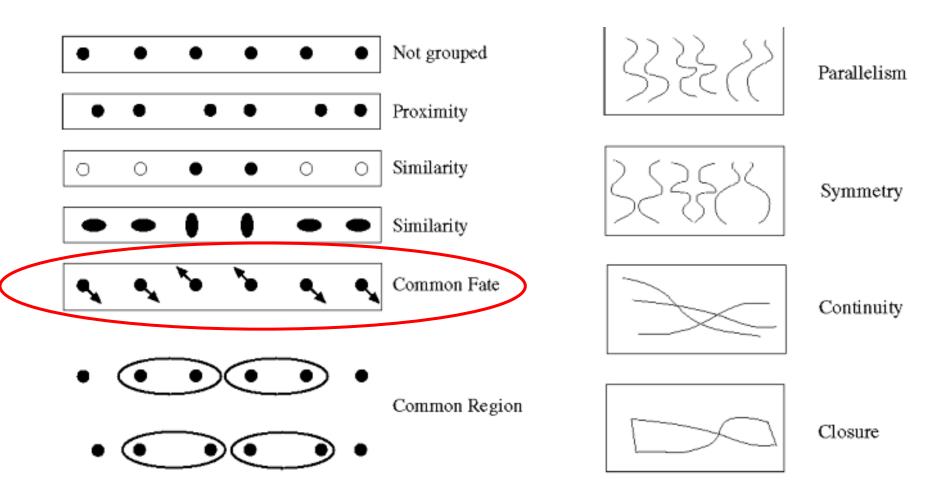
- Shot boundary detection
 - For each frame, compute the distance between the current frame and the previous one: (measure between frames)
 - Pixel-by-pixel differences
 - Differences of color histograms
 - Block comparison
 - ➤ If the distance is greater than some threshold, classify the frame as a shot boundary.



- Motion segmentation
 - Segment the video into multiple coherently moving objects



Computer Vision and Pattern Recognition Motion and Perceptual Organization



Sometimes, motion is the only cue

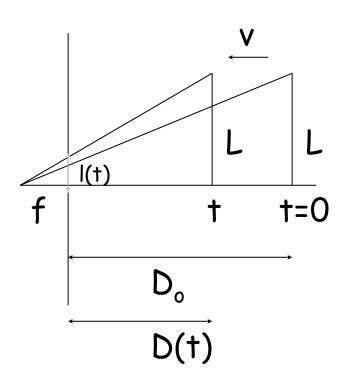
Slide credit: Svetlana Lazebnik



Uses of Motion

- Estimating 3D structure
 - Directly from optic flow
 - Indirectly to create correspondences for SfM
- Segmenting objects based on motion cues
- Learning dynamical models
- Recognizing events and activities
- Improving video quality (motion / image stabilization)
- Time to Collision

Computer Vision and Pattern Time to Collision Recognition



An object of height L moves with constant velocity v:

- ·At time t=0 the object is at:
 - $D(0) = D_0$
- ·At time t it is at

$$\cdot D(t) = D_0 - vt$$

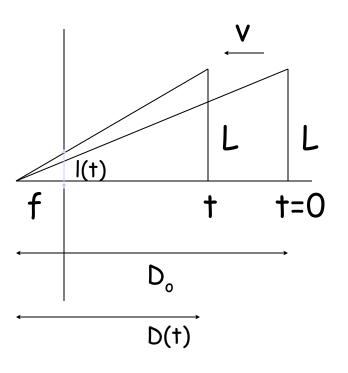
•It will crash with the camera at time:

$$\cdot D(\tau) = D_o - v\tau = 0$$

$$\cdot \tau = D_o/v$$

计算机视见与模式识别 Time to Collision

The image of the object has size I(t):



$$l(t) = \frac{fL}{D(t)}$$

Taking derivative wrt time:

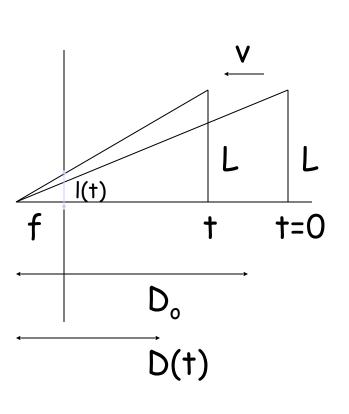
$$l'(t) = \frac{dl(t)}{dt} = fL \frac{d(1/D(t))}{dt}$$

$$l'(t) = fL \frac{-1}{D^2(t)} \frac{d(D(t))}{dt}$$

$$l'(t) = fL \frac{v}{D^2(t)}$$

$$\frac{d(D(t))}{dt} = -v$$

Computer Vision and Pattern Time to Collision

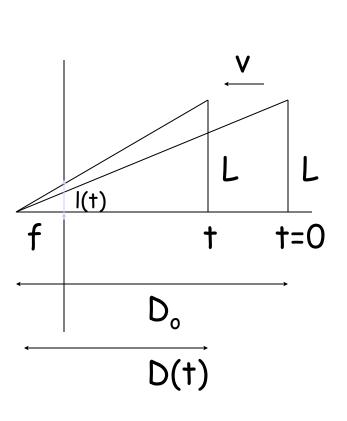


$$l'(t) = fL \frac{v}{D^2(t)}$$

$$l(t) = \frac{fL}{D(t)}$$

And their ratio is:

$$\frac{l(t)}{l'(t)} = \frac{fL}{D(t)} \frac{D^2(t)}{fLv} = \frac{D(t)}{v} = \tau$$



$$l'(t) = fL \frac{v}{D^2(t)}$$

$$l(t) = \frac{fL}{D(t)}$$

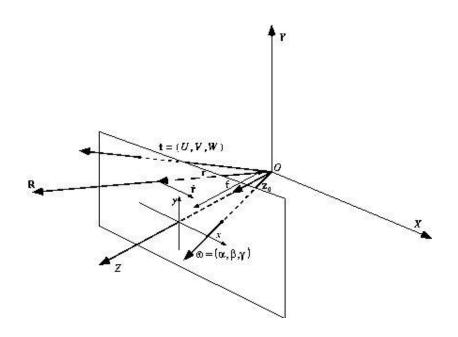
Can be directly measured from image

And time to collision:

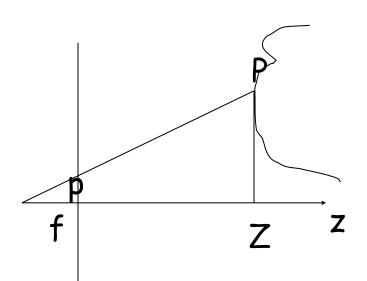
$$\tau = \frac{l(t)}{l'(t)}$$

Can be found, without knowing L or Do or v!!

Passive Navigation and Structure from Motion



The system moves with a rigid motion with translational velocity $\mathbf{t} = (t_x, t_y, t_z)^T$ and rotational velocity $\mathbf{\omega} = (\omega_x, \omega_y, \omega_z)^T$. Scene points $\mathbf{R} = (X, Y, Z)^T$ project onto image points $\mathbf{r} = (x, y, f)$ and the 3D velocity $\dot{\mathbf{R}} = (V_x, V_y, V_z)$ of a scene point is observed in the image as velocity $\dot{\mathbf{r}} = (u, v.0)$ Consider a 3D point P and its image:



$$P = \left[\begin{array}{c} X \\ Y \\ Z \end{array} \right]$$

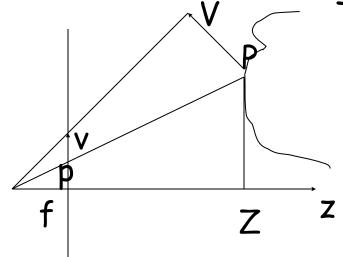
$$p = \left[\begin{array}{c} x \\ y \\ f \end{array} \right]$$

Using pinhole camera equation:

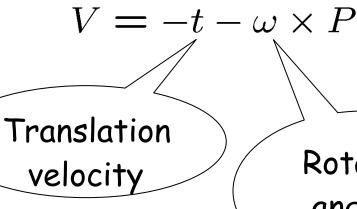
$$p = \frac{fP}{Z}$$



Relative motion



The <u>relative velocity</u> of P wrt camera:

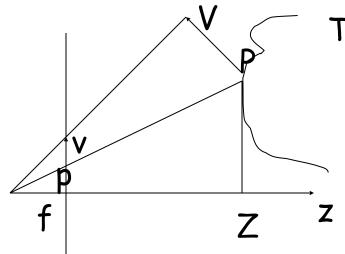


$$t = \left[\begin{array}{c} t_x \\ t_y \\ t_z \end{array} \right]$$

$$\omega = \left[\begin{array}{c} \omega_x \\ \omega_y \\ \omega_z \end{array} \right]$$

Rotation angular velocity

Computer Vision and Pattern 3D Relative Velocity:



The relative velocity of P wrt camera:

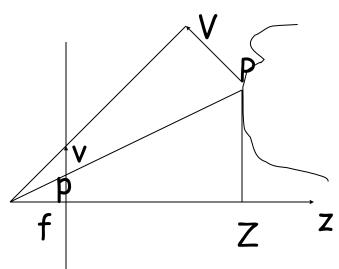
$$V = -t - \omega \times P$$

$$\begin{bmatrix} \vdots \\ \mathbf{z} \end{bmatrix} \mathbf{z} \qquad t = \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix} \omega = \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} P = \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

$$V_x = -t_x - \omega_y Z + \omega_z Y$$

$$V_y = -t_y - \omega_z X + \omega_x Z$$

$$V_z = -t_z - \omega_x Y + \omega_y X$$



$$p = \frac{fP}{Z}$$

Taking derivative wrt time:

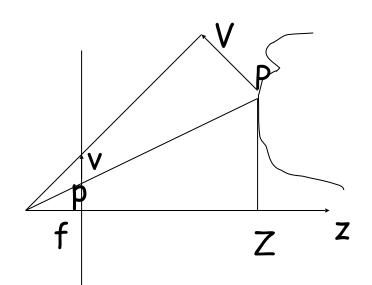
$$\frac{dp}{dt} = \mathbf{v} = \frac{d\frac{fP}{Z}}{dt}$$

$$= \mathbf{v} = \frac{d\frac{fP}{Z}}{dt} = \frac{f}{Z^2} \left[\frac{dP}{dt} \cdot Z - P \cdot \frac{dZ}{dt} \right]$$

$$= \frac{f}{Z^2} \left[V.Z - P.V_z \right]$$

the velocity of p

$$\mathbf{v} = f \frac{V}{Z} - p \frac{V_z}{Z}$$

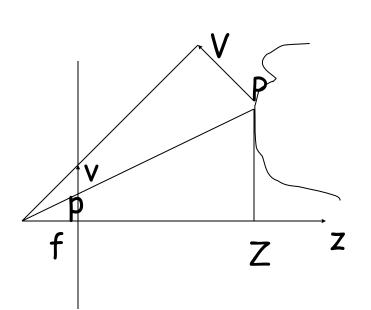


$$v = f\frac{V}{Z} - p\frac{V_z}{Z}$$

$$v_x = u = f \frac{V_x}{Z} - x \frac{V_z}{Z}$$

$$v_y = v = f \frac{V_y}{Z} - y \frac{V_z}{Z}$$

$$v_z = f \frac{V_z}{Z} - f \frac{V_z}{Z} = 0$$



$$u = f \frac{V_x}{Z} - x \frac{V_z}{Z}$$

$$v = f \frac{V_y}{Z} - y \frac{V_z}{Z}$$

$$V_x = -T_x - \omega_y Z + \omega_z Y$$

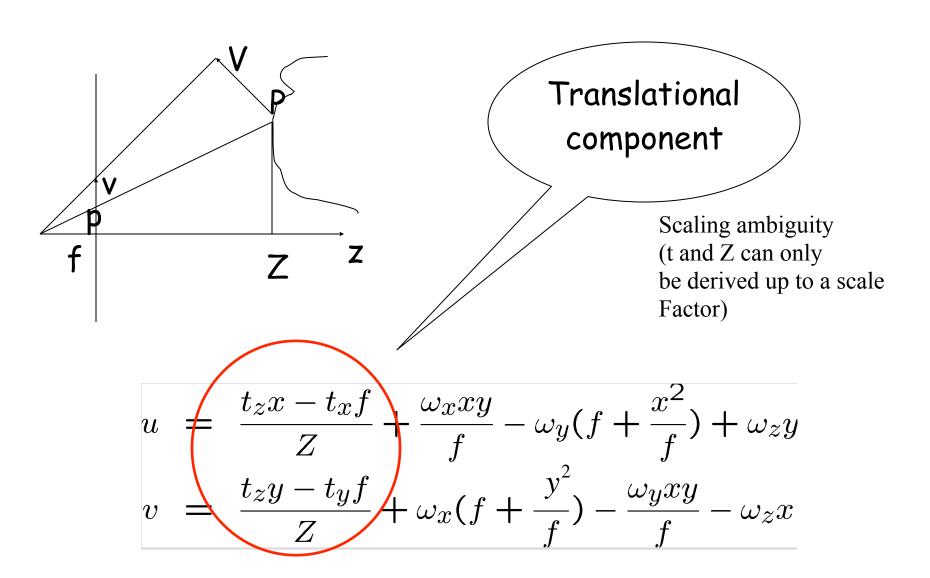
$$V_y = -T_y - \omega_z X + \omega_x Z$$

 $V_z = -T_z - \omega_x Y + \omega_y X$

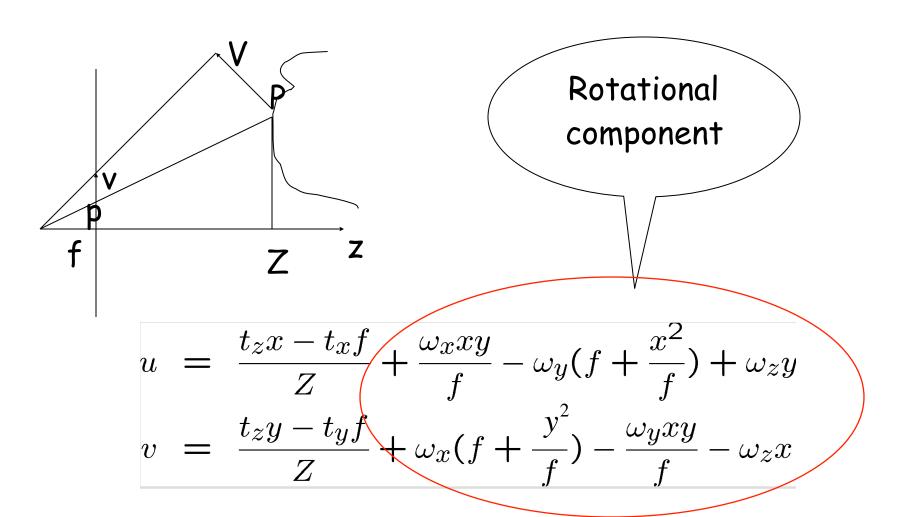
$$u = \frac{t_z x - t_x f}{Z} + \frac{\omega_x xy}{f} - \omega_y (f + \frac{x^2}{f}) + \omega_z y$$

$$v = \frac{t_z y - t_y f}{Z} + \omega_x (f + \frac{y^2}{f}) - \frac{\omega_y xy}{f} - \omega_z x$$

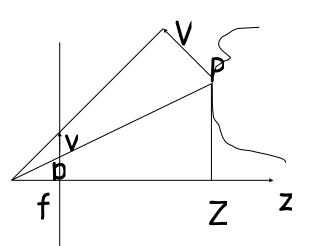








NOTE: The rotational component is independent of depth Z!



$$\mathbf{U}(x,y) = \frac{1}{Z(x,y)} \mathbf{A}(x,y) \mathbf{V} + \mathbf{B}(x,y) \boldsymbol{\omega}$$

$$\mathbf{A}(x,y) = \begin{bmatrix} -f & 0 & x \\ 0 & -f & y \end{bmatrix}$$

$$\mathbf{A}(x,y) = \begin{bmatrix} -f & 0 & x \\ 0 & -f & y \end{bmatrix} \qquad \mathbf{B}(x,y) = \begin{bmatrix} \frac{xy}{f} & -f - \frac{x^2}{f} & y \\ f + \frac{y^2}{f} & -\frac{xy}{f} & x \end{bmatrix}$$

$$V = \left[\begin{array}{c} t_x \\ t_y \\ t_z \end{array} \right]$$

$$\boldsymbol{\omega} = \left| \begin{array}{c} \boldsymbol{\omega}_x \\ \boldsymbol{\omega}_y \\ \boldsymbol{\omega}_z \end{array} \right|$$

Computer Vision and Pattern Recognition Translational flow field

$$tz \neq 0$$

$$u_{tr} = (x - x_o) \frac{t_z}{Z}$$

$$v_{tr} = (y - y_o) \frac{t_z}{Z}$$

where $p_o = (x_0, y_0) = \left(\frac{t_x}{t_z} \cdot f, \frac{t_y}{t_z} \cdot f\right)$ is the focus of expansion (FOE) or focus of contraction (FOC).

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$$t_{z} = 0$$

$$u_{tr} = -\frac{t_{x} \cdot f}{Z}$$

$$v_{tr} = -\frac{t_{y} \cdot f}{Z}$$

$$v_{tr} = \frac{t_{y} \cdot f}{Z}$$

where
$$p_0 = (x_0, y_0) = (\infty, \infty)$$
 is the focus of expansion (FOE) or focus of contraction (FOC).

All motion field vectors are parallel to each other and inversely proportional to depth!

Pure Translation:

Properties of the MF

- If $t_z \ne 0$ the MF is RADIAL with all vectors pointing towards (or away from) a single point p_o . If $t_z = 0$ the MF is PARALLEL.
- The length of the MF vectors is inversely proportional to depth Z. If $t_z \neq 0$ it is also directly proportional to the distance between p and p_o .

$$u_{tr} = (x - x_o) \frac{t_z}{Z}$$
$$v_{tr} = (y - y_o) \frac{t_z}{Z}$$



Pure Translation:

Properties of the MF

• p_o is the vanishing point of the direction of translation.

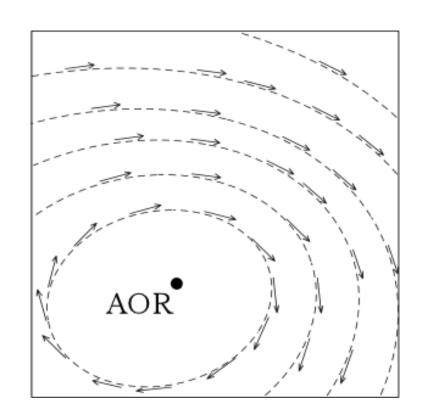
• p_o is the intersection of the ray parallel to the translation vector and the image plane.

计算机视觉与模式识别 Computer Vision and Recognition Recognition Recognition

$$u_r = \frac{\omega_x xy}{f} - \omega_y \left(f + \frac{x^2}{f} \right) + \omega_z y$$

$$v_r = -\frac{\omega_y xy}{f} + \omega_x \left(f + \frac{x^2}{f} \right) - \omega_z x$$

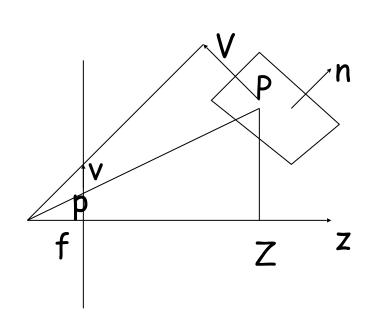
$$\begin{cases} u_r = 0 \\ v_r = 0 \end{cases} \Rightarrow \begin{cases} rx_0 = \frac{\omega_x}{\omega_z} f \\ ry_0 = \frac{\omega_y}{\omega_z} f \end{cases}$$



$$\left(\frac{\omega_x}{\omega_z}f, \frac{\omega_y}{\omega_z}f\right)$$
 is the point where the rotation axis pierces the image plane (AOR).

NOTE: The rotational component is independent of depth Z!

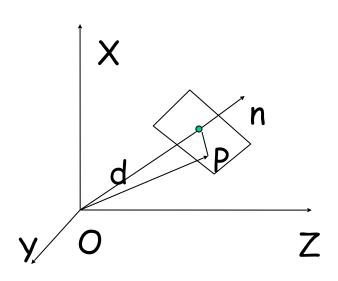
Computer Vision and Pattern Recognition Special Case: Moving Plane



Planar surfaces are common in man-made environments

Question: How does the MF of a moving plane look like?

Computer Vision and Patters pecial Case: Moving Plane Recognition



Points on the plane must satisfy the equation describing the plane.

Let

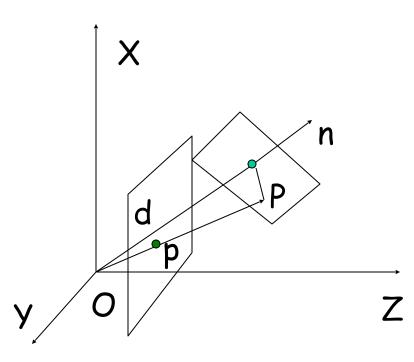
- •n be the unit vector normal to the plane.
- •d be the distance from the plane to the origin.
- •NOTE: If the plane is moving wrt camera, n and d are functions of time.

Then:

$$\mathbf{n}^T.\mathbf{P} = d$$

where
$$n = \begin{bmatrix} n_x \\ n_y \\ n_z \end{bmatrix}$$
 $P = \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$

Computer Vision and Patter Special Case: Moving Plane Recognition



Let
$$p = \begin{bmatrix} x \\ y \\ f \end{bmatrix}$$
 be the image of P

Using the pinhole projection equation:

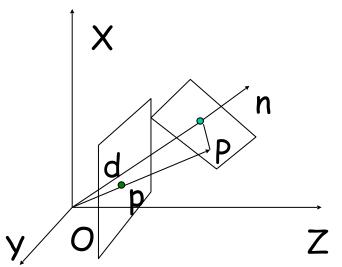
$$p = \frac{fP}{Z} \implies P = \frac{pZ}{f}$$

Using the plane equation:

$$\mathbf{n}^T.\mathbf{P} = d \longrightarrow \mathbf{n}^T.\mathbf{p}\frac{Z}{f} = d$$

Solving for Z:
$$Z = \frac{fd}{n_x x + n_y y + n_z f}$$

Computer Vision and Patter Special Case: Moving Plane Recognition



Now consider the MF equations:

$$u = \frac{t_z x - t_x f}{Z} - \omega_y f + \omega_z y + \frac{\omega_x x y}{f} - \frac{\omega_y x^2}{f}$$

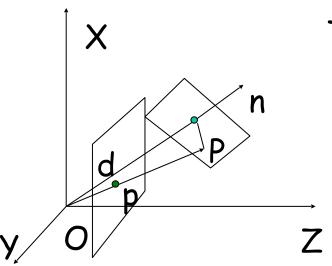
$$v = \frac{t_z y - t_y f}{Z} + \omega_x f - \omega_z x - \frac{\omega_y x y}{f} + \frac{\omega_x y^2}{f}$$

And Plug in:

$$Z = \frac{fd}{n_x x + n_y y + n_z f}$$



Special Case: Moving Plane



The MF equations become:

$$u = \frac{1}{fd}(a_1x^2 + a_2xy + a_3fx + a_4fy + a_5f^2)$$

$$v = \frac{1}{fd}(a_1xy + a_2y^2 + a_6fy + a_7fx + a_8f^2)$$

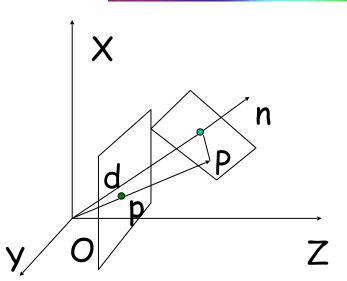
$$v = \frac{1}{fd}(a_1xy + a_2y^2 + a_6fy + a_7fx + a_8f^2)$$

where

$$a_1 = -d\omega_y + t_z n_x$$
 $a_2 = d\omega_x + t_z n_y$
 $a_3 = t_z n_z - t_x n_x$ $a_4 = d\omega_z - t_x n_y$
 $a_5 = -d\omega_y - t_x n_z$ $a_6 = t_z n_z - t_y n_y$
 $a_7 = -d\omega_z - t_y n_x$ $a_8 = d\omega_x - t_y n_z$



Special Case: Moving Plane



MF equations:

$$u = \frac{1}{fd}(a_1x^2 + a_2xy + a_3fx + a_4fy + a_5f^2)$$

$$v = \frac{1}{fd}(a_1xy + a_2y^2 + a_6fy + a_7fx + a_8f^2)$$

Q: What is the significance of this?

A: The MF vectors are given by low order (second) polynomials.

- •Their coeffs. a_1 to a_8 (only 8!) are functions of n, d, t and ω .
- •The same coeffs. (or MF) can be obtained with a different plane and relative velocity.



Moving Plane:

Properties of the MF

• The MF of a planar surface is at any time a quadratic function in the image coordinates.

• A plane $n^TP=d$ moving with velocity $V=-t-\omega x$ P has the same MF than a plane with normal n'=t/|t|, distance d and moving with velocity

$$V=|t|n-(\omega+nx t/d)x P$$

$$n'=t/|t| \longrightarrow n \times t=0$$

Visual navigation & structure for motion

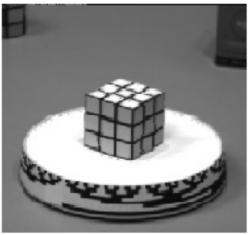
$$\mathbf{U}(x,y) = \frac{1}{Z(x,y)} \mathbf{A}(x,y) \mathbf{V} + \mathbf{B}(x,y) \boldsymbol{\omega}$$

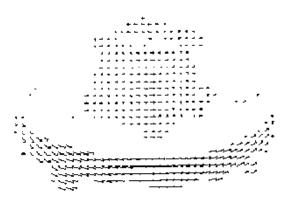
$$U(x,y)$$
 $Z(x,y); V; \omega$



The motion field is the projection of the 3D scene motion into the image







Direct methods

- Directly recover image motion at each pixel from spatio-temporal image brightness variations
- Dense motion fields, but sensitive to appearance variations
- Suitable for video and when image motion is small

Feature-based methods

- Extract visual features (corners, textured areas) and track them over multiple frames
- Sparse motion fields, but more robust tracking
- Suitable when image motion is large