

6.869 Advances in Computer Vision: Learning and Interfaces

Spring 2005

Tuesday and Thursday; 2:30 to 4:00pm in 36-153

Announcements

Course Information

- Syllabus
- Problem Sets and Exams
- Grading and Requirements
- Internet Resources

Contacts

<http://courses.csail.mit.edu/6.869>

Contacts

Instructor

Professor William T.
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Office Hours

By Appointment

Teaching Assistant

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Office Hours

Monday, Wed. 4-5pm in
32-D451

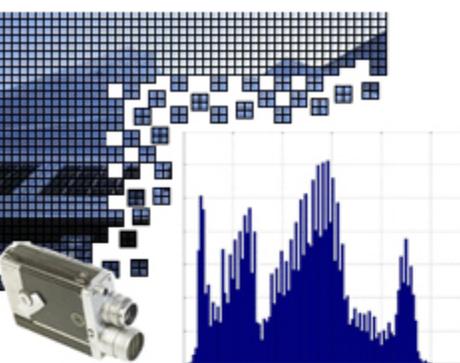


All offices are located on the fourth and fifth floor of the Dreyfoos building (Stata Center).

If you cannot attend our normally scheduled office hours, please send e-mail to schedule an alternate appointment.

Administration

- Syllabus
- Grading
- Collaboration Policy
- Project



6.869 Advances in Computer Vision: Learning and Interfaces

Spring 2005

Syllabus

The topics studied in this course will include:

- Image statistics, image representations, and texture models
- Color Vision
- Graphical models, Bayesian methods
- Markov Random Fields, applications to low-level vision
- Approximate inference methods
- Statistical classifiers
- Clustering & Segmentation
- Object recognition
- Tracking and Density Propagation
- Visual Surveillance and Activity Monitoring

Course Calendar

Lecture	Date	Description	Readings	Assignments	Materials
1	2/1	Course Introduction Cameras and Lenses	Req: FP 1.1, 2.1, 2.2, 2.3, 3.1, 3.2	PS0 out	
2	2/3	Image Filtering	Req: FP 7.1 - 7.6		
3	2/8	Image Representations: Pyramids	Req: FP 7.7, 9.2		
4	2/10	Image Statistics		PS0 due	
5	2/15	Texture	Req: FP 9.1, 9.3, 9.4	PS1 out	
6	2/17	Color	Req: FP 6.1-6.4		
7	2/22	Guest Lecture: Context in vision			
8	2/24	Guest Lecture: Medical Imaging		PS1 due	
9	3/1	Multiview Geometry	Req: Mikolajczyk and Schmid; FP 10	PS2 out	
10	3/3	Local Features	Req: Shi and Tomasi; Lowe		

11	3/8	Bayesian Analysis			
12	3/10	Markov Random Fields Belief Propagation		PS2 due	
13	3/15	Model Based Recognition	Req: FP 18.1-18.5, Lowe	EX1 out	
14	3/17	Discriminative Models		EX1 due	
	3/22-3/24	Spring Break (NO LECTURE)			
15	3/29	Face Detection and Recognition I	Req: FP 22		
16	3/31	Face Detection and Recognition II		Project proposal due	
17	4/5	Segmentation and Clustering	Req: FP 14, 15.1-15.2, Comaniciu and Meer	PS3 out	
18	4/7	Segmentation and Fitting	Req: FP 15.3-15.5, 16		
19	4/12	Tracking I	Req: FP 17		
20	4/14	Articulated Tracking and Shape Inference	Req: FP Extra Chapter	PS3 due	
	4/19	No class (Patriot's Day Holiday)			
21	4/21	Approximate Inference Methods		PS4 out	

Course requirements

- Two take-home exams
- Five problem sets with lab exercises in Matlab
- No final exam
- Final project

Grading

- Problem sets are graded check, check-plus, check-minus
- Contribution to grade:
 - 5 problem sets: 30 %
 - 2 take-home exams: 40%
 - final project: 30%

Collaboration Policy

Problem sets may be discussed, but all written work and coding must be done individually. Take-home exams may not be discussed. Individuals found submitting duplicate or substantially similar materials due to inappropriate collaboration may get an F in this class and other sanctions.

Project

The final project may be

- An original implementation of a new or published idea
- A detailed empirical evaluation of an existing implementation of one or more methods
- A paper comparing three or more papers not covered in class, or surveying recent literature in a particular area

A project proposal not longer than two pages must be submitted and approved by April 1st. I can provide ideas or suggestions for projects.

Problem Set 0

- Out today, due 2/12
- Matlab image exercises
 - load, display images
 - pixel manipulation
 - RGB color interpolation
 - image warping / morphing with `interp2`
 - simple background subtraction
- All psets graded loosely: *check, check-, 0.*
- (Outstanding solutions get extra credit.)



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Publications: Selected, grouped by topic

All publications

Patents

Biography, CV, and Research Statement

MIT Computer Science and Artificial Intelligence Laboratory
in a Center - Directory



Vision

- What does it mean, to see? “to know what is where by looking”.
- How to discover from images what is present in the world, where things are, what actions are taking place.

Vision

- What does it mean, to see? “to know what is where by looking”.
- How to discover from images what is present in the world, where things are, what actions are taking place.

Why study Computer Vision?

- One can “predict the future” (and avoid bad things...)!
- Images and movies are everywhere; fast-growing collection of useful applications
 - building representations of the 3D world from pictures
 - automated surveillance (who’s doing what)
 - movie post-processing
 - face finding
- Greater understanding of human vision
- Various scientific questions
 - how does object recognition work?

What is object recognition?

- People draw distinctions between what is seen
 - This could mean “is this a fish or a bicycle?”
 - It could mean “is this George Washington?”
 - It could mean “is this poisonous or not?”
 - It could mean “is this slippery or not?”
 - It could mean “will this support my weight?”
 - Area of research:
 - How to build programs that can draw useful distinctions based on image properties.

The course, in broad categories

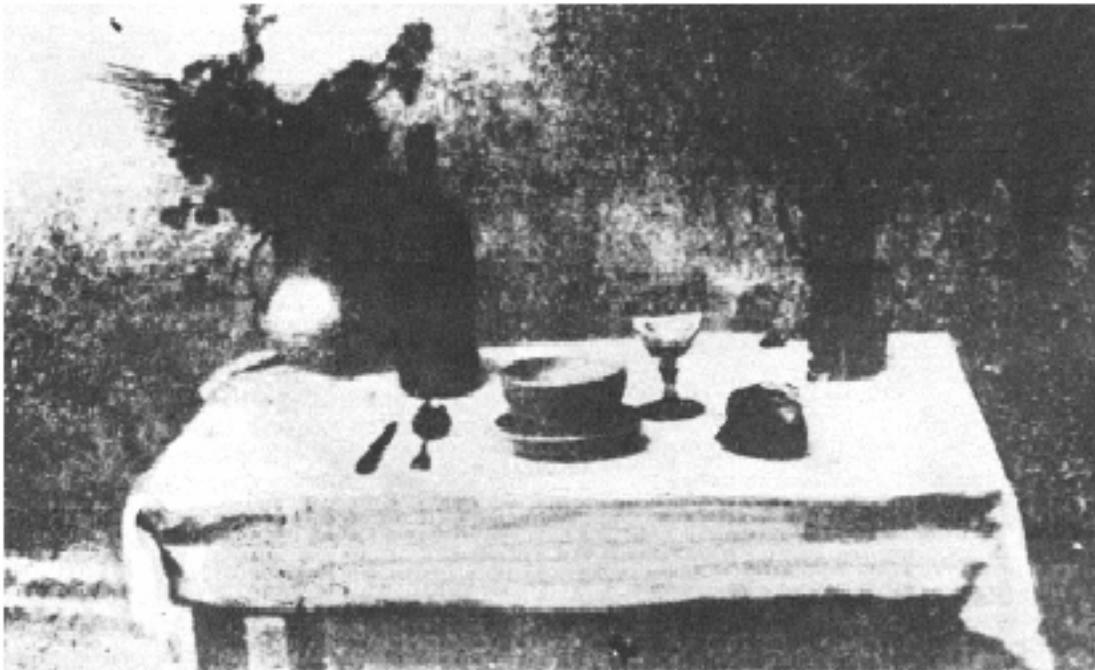
- Images and image formation
- Low-level vision
- High-level vision
- Implementations and applications

Computer vision class, fast-forward



Images and image formation

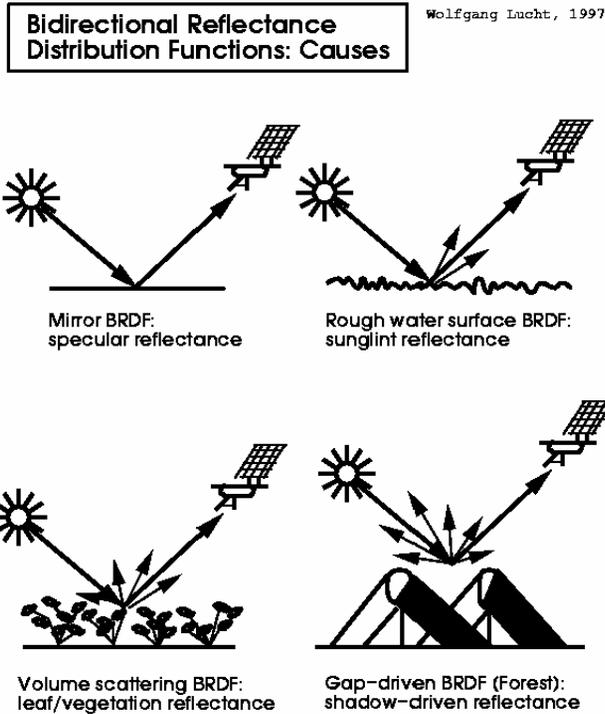
Cameras, lenses, and sensors



- Pinhole cameras
- Lenses
- Projection models
- Geometric camera parameters

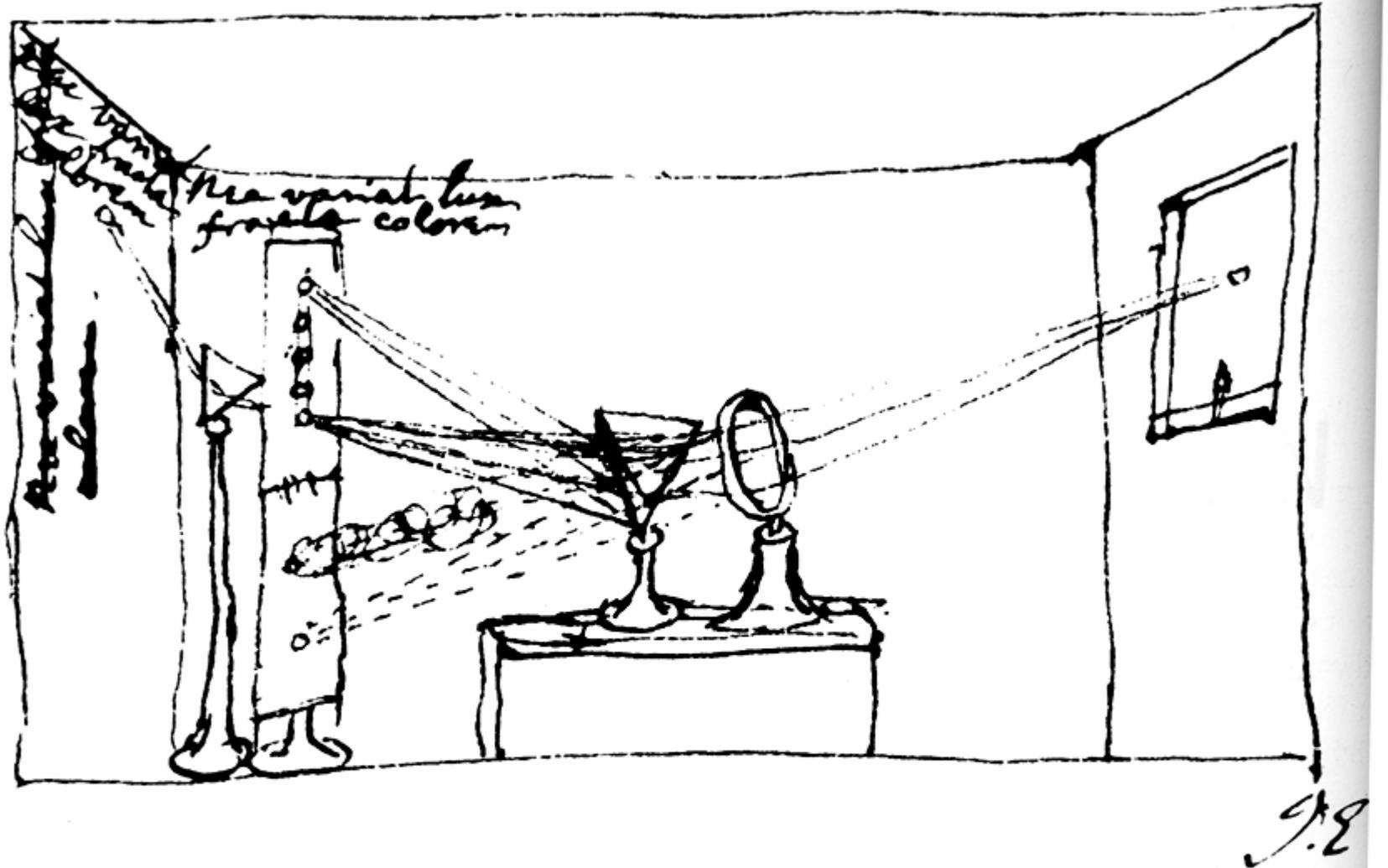
Figure 1.16 The first photograph on record, *la table servie*, obtained by Nicéphore Niepce in 1822. *Collection Harlinge-Viollet*.

Radiometry...not covered (see 6.801)



Wolfgang Lucht

Color



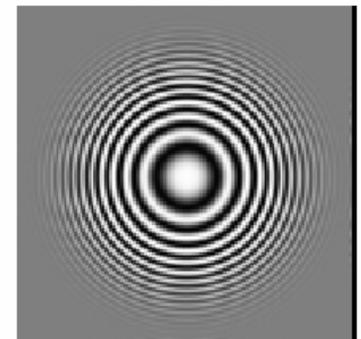
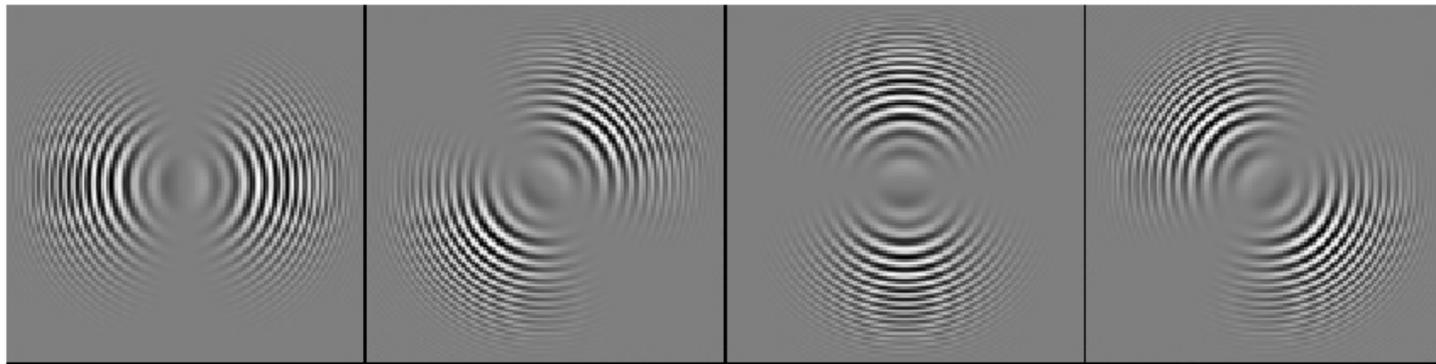
4.1 NEWTON'S SUMMARY DRAWING of his experiments with light. Using a point source of light and a prism, Newton separated sunlight into its fundamental components. By reconverging the rays, he also showed that the decomposition is reversible.

From Foundations of Vision, by Brian Wandell, Sinauer Assoc., 1995

Low-level vision

Image filtering

- Review of linear systems, convolution
- Bandpass filter-based image representations
- Probabilistic models for images



Oriented, multi-scale representation

Image

SIFT (scale invariant feature transforms)



David Lowe,
IJCV 2004

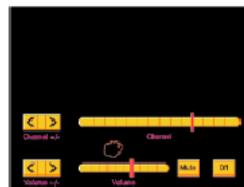
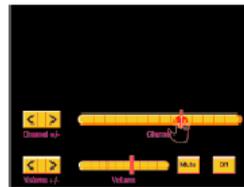
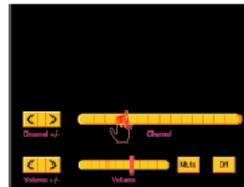
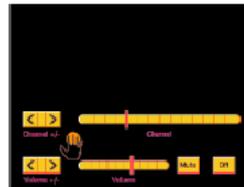
Figure 13: This example shows location recognition within a complex scene. The training images for locations are shown at the upper left and the 640x315 pixel test image taken from a different viewpoint is on the upper right. The recognized regions are shown on the lower image, with keypoints shown as squares and an outer parallelogram showing the boundaries of the training images under the affine transform used for recognition.

Non-linear filtering, and applications

viewer



television display



template



image



Normalized correlation

12 Sample session of television viewing. (a) Television is off, but searching for the trigger gesture. (b) Viewer shows trigger gesture (open hand). Television set turns on and hand icon and graphics overlays appear. (c) The hand icon tracks the user's hand movement. User changes controls as with a mouse. (d) User has moved hand icon to change channel. (e) User closes hand to leave control mode. After one second, the hand icon and controls then disappear.

IEEE Computer Graphics and Applications, 18, no. 3, 1998

Models of texture



Parametric model



Non-parametric model

A Parametric Texture Model based on Joint Statistics of Complex Wavelet Coefficients

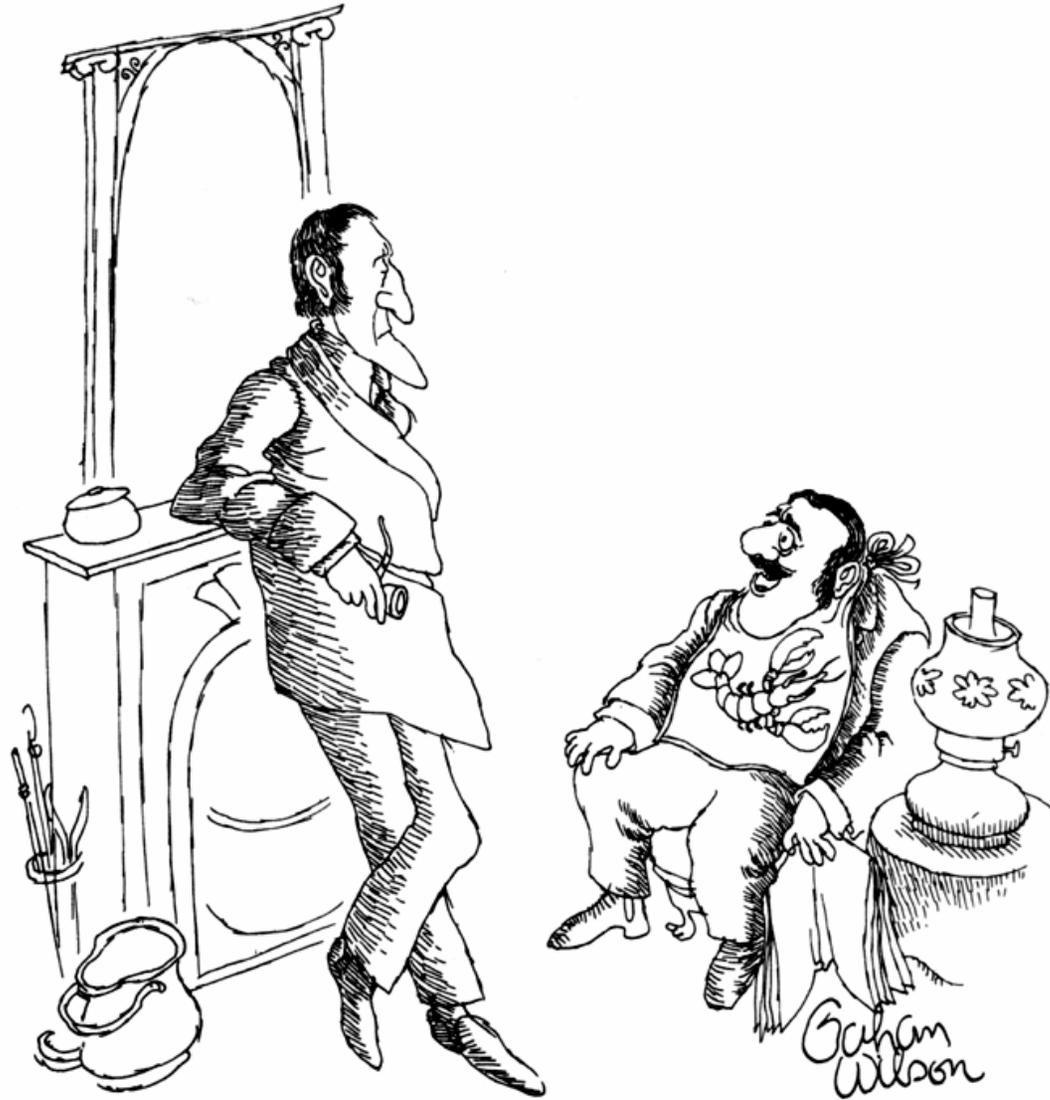
J. Portilla and E. Simoncelli, International Journal of Computer Vision 40(1): 49-71, October 2000.

© Kluwer Academic Publishers.

A. Efros and W. T Freeman, Image quilting for texture synthesis and transfer, SIGGRAPH 2001

Learning and vision

Bayesian framework for vision



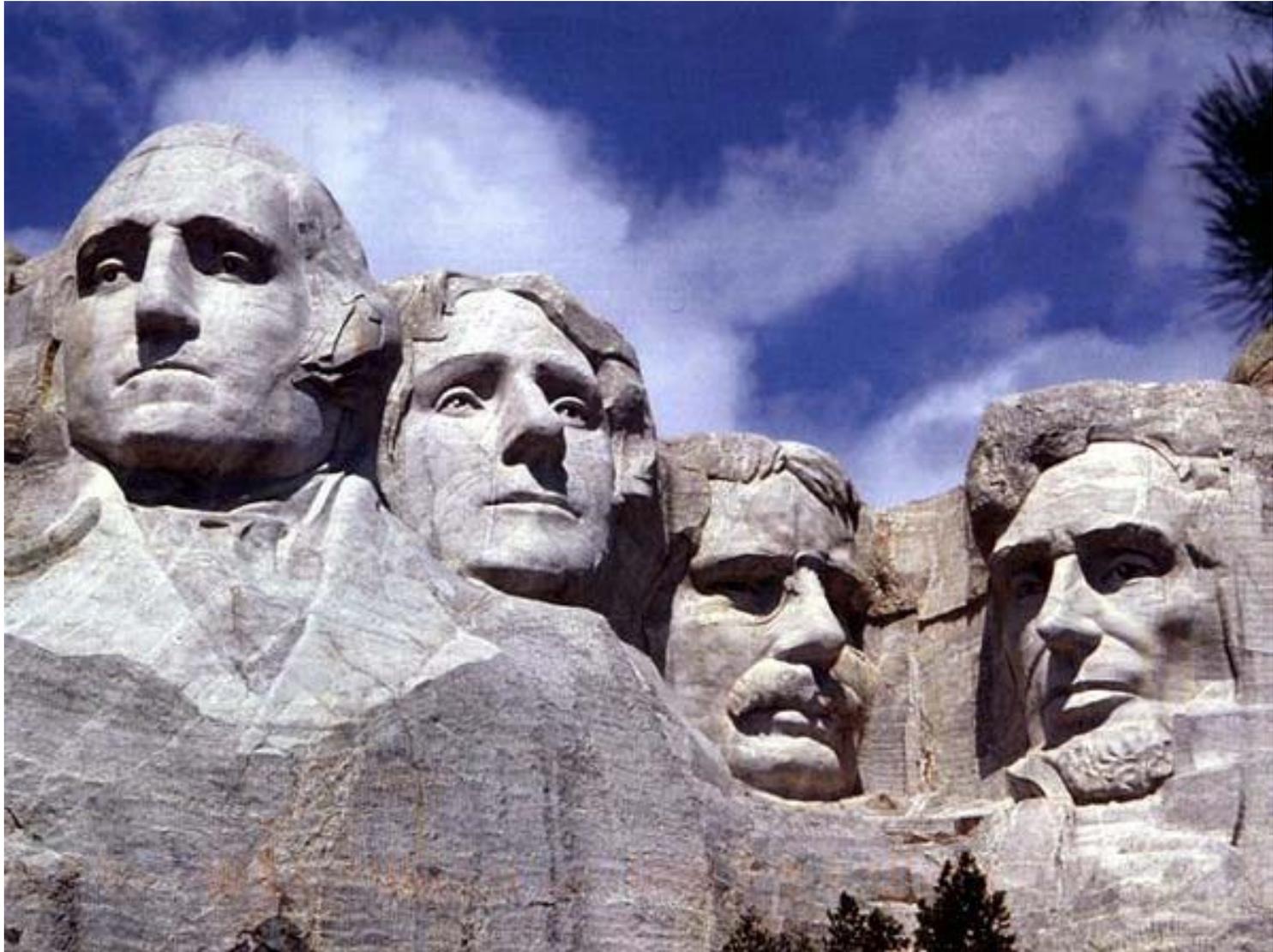
“Good lord, Holmes! How did you come to know
I’d seafood for lunch?”

Bayesian framework for vision



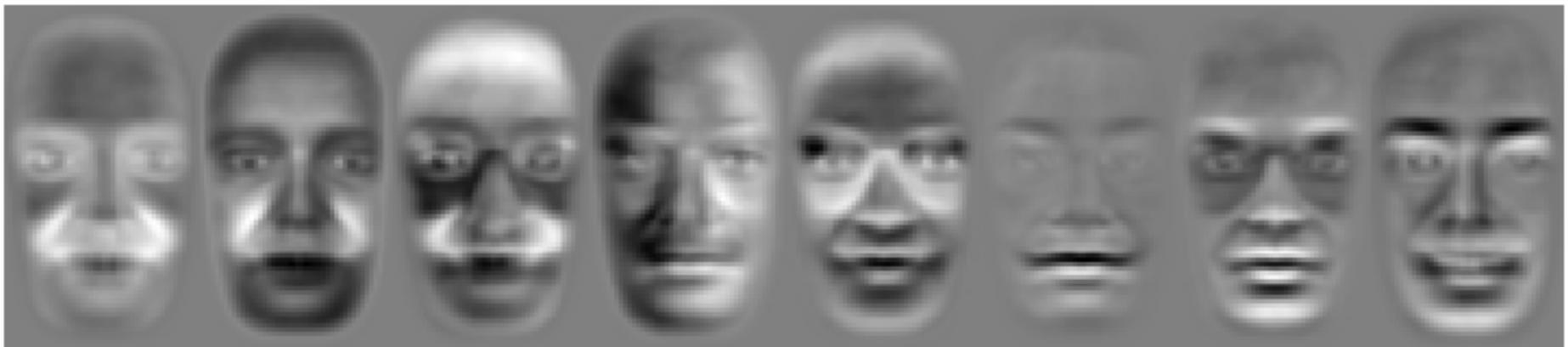
Coincidental appearance of face profile in rock?

Bayesian framework for vision

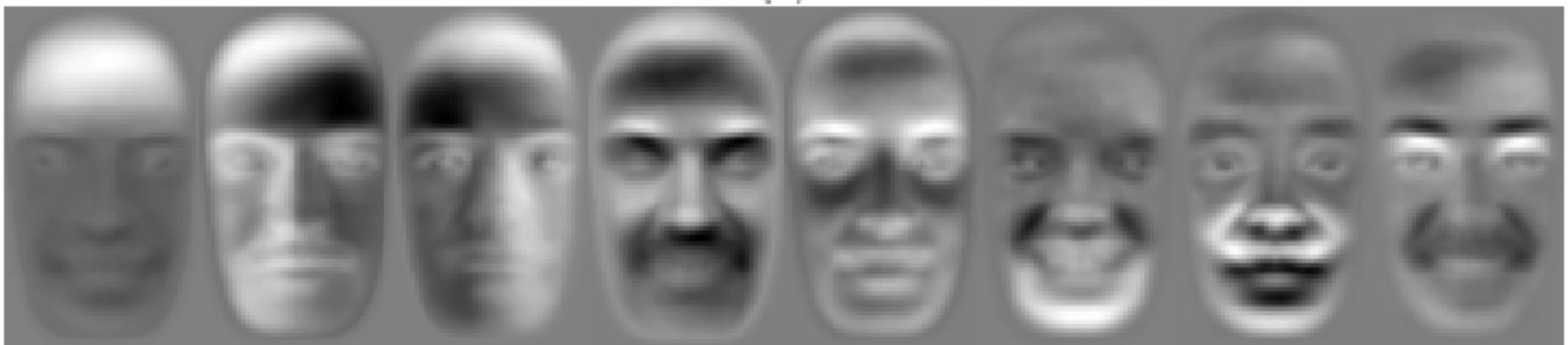


Coincidental appearance of faces in rock?

Eigenfaces: linear bases for faces



(a)



(b)

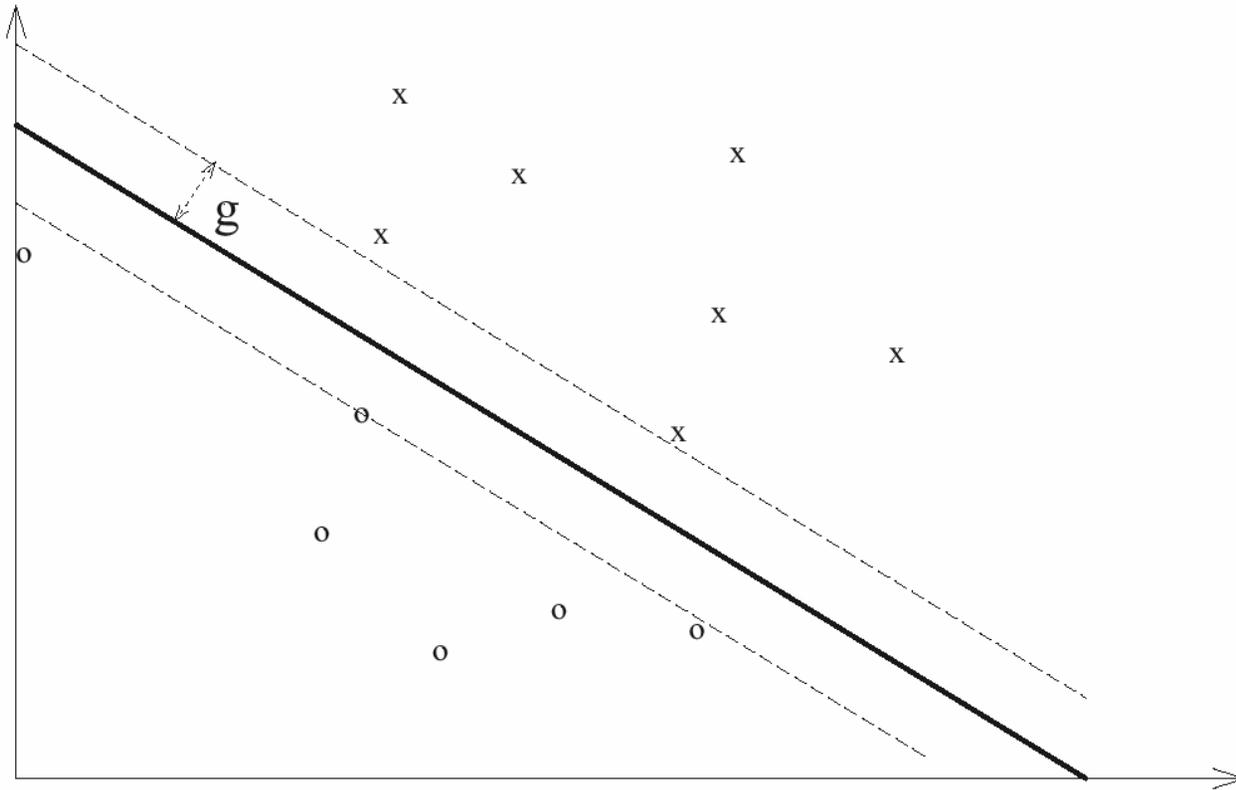
Figure 6: “Dual” Eigenfaces: (a) Intrapersonal, (b) Extrapersonal

Statistical classifiers



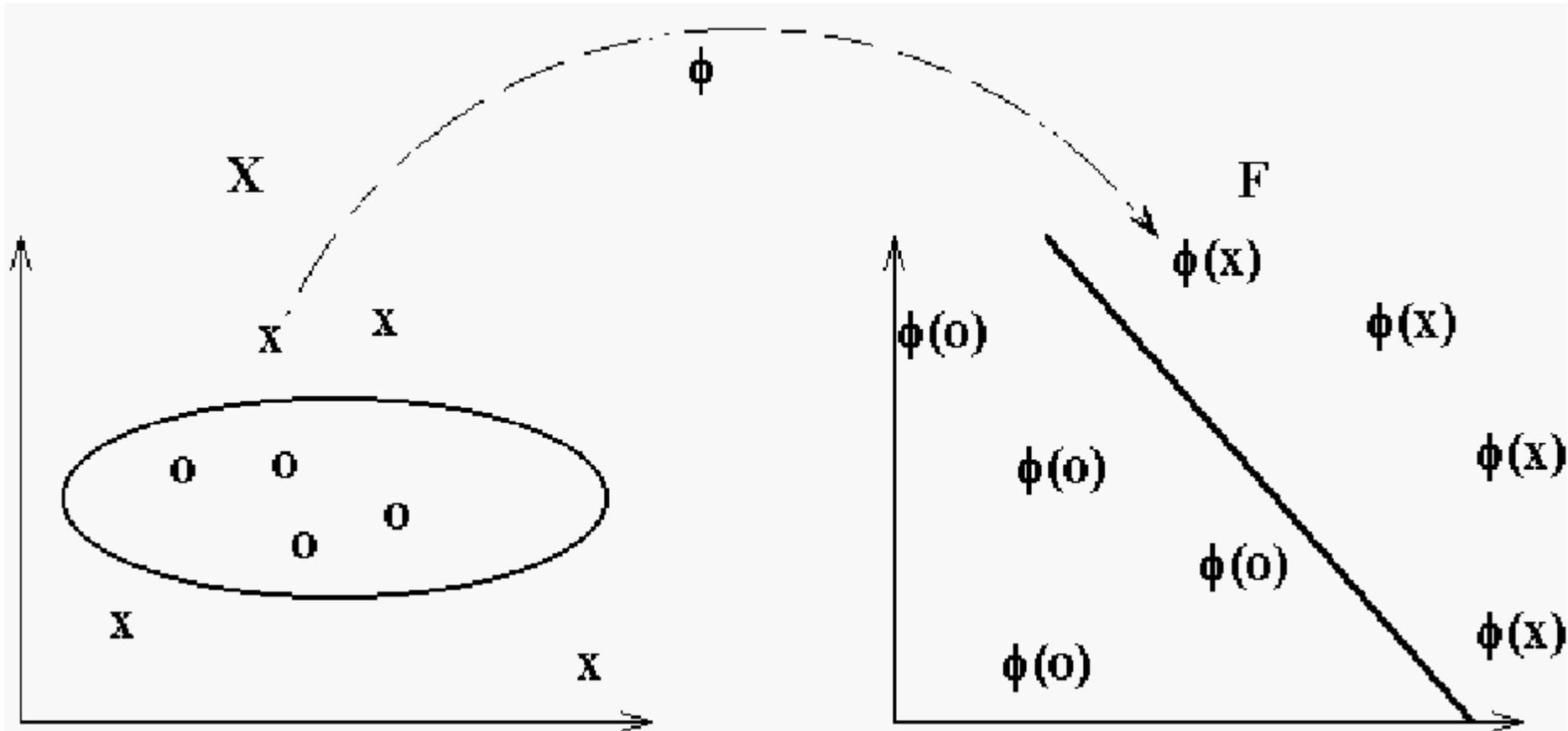
- MIT Media Lab face localization results.
- Applications: database search, human machine interaction, video conferencing.

Support vector machines and boosting



Large-margin classifier

Support vector machines and boosting



“The kernel trick”

Recent, now classic, paper on face detection:

Rapid Object Detection Using a Boosted Cascade of Simple Features

Paul Viola Michael J. Jones

Mitsubishi Electric Research Laboratories (MERL)

Cambridge, MA

Most of this work was done at Compaq CRL before the authors moved to MERL

Face Detection Goal



Many Uses

- User Interfaces
- Interactive Agents
- Security Systems
- Video Compression
- Image Database Analysis

Use of context for object detection



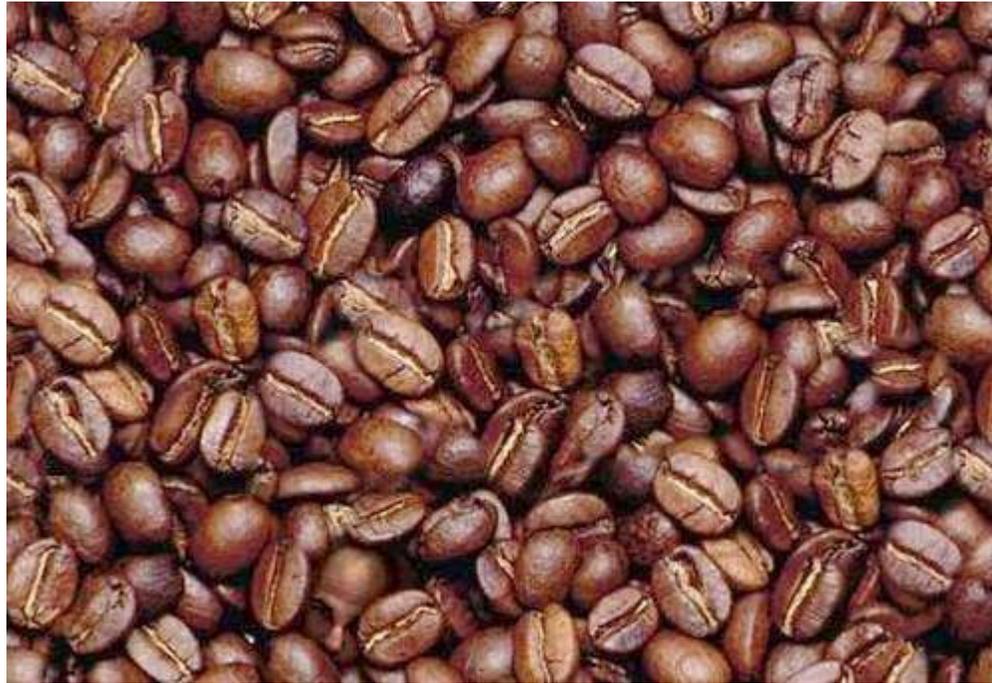
car



pedestrian

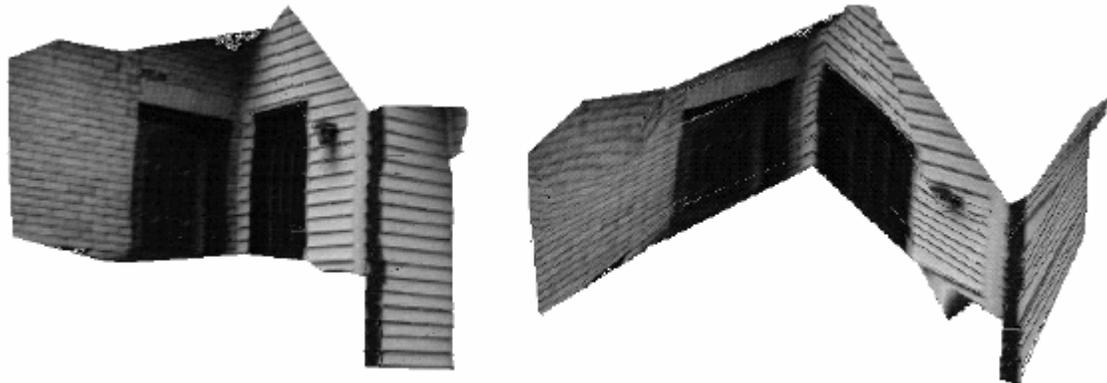
Identical local image features!

The world, to a face detector



Structure from Motion

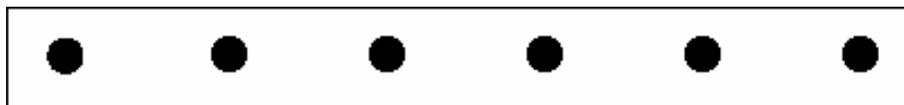
What is the shape of the scene?



Segmentation (perceptual grouping)

How many ways can you segment six points?

(or curves)



Not grouped



Proximity



Similarity



Similarity

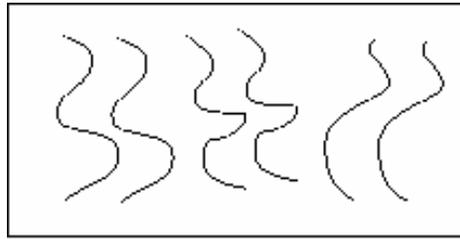


Common Fate

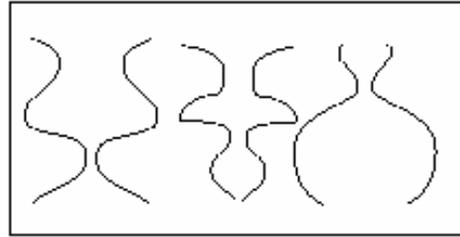


Common Region

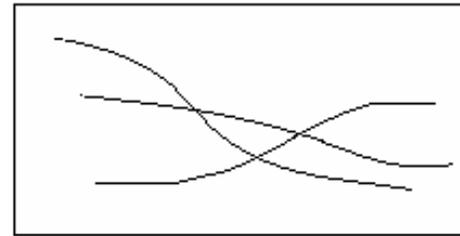




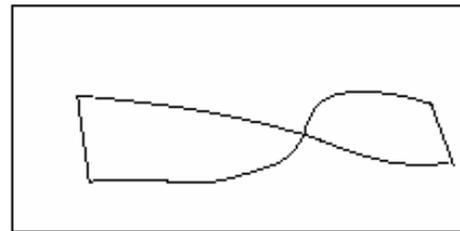
Parallelism



Symmetry



Continuity



Closure

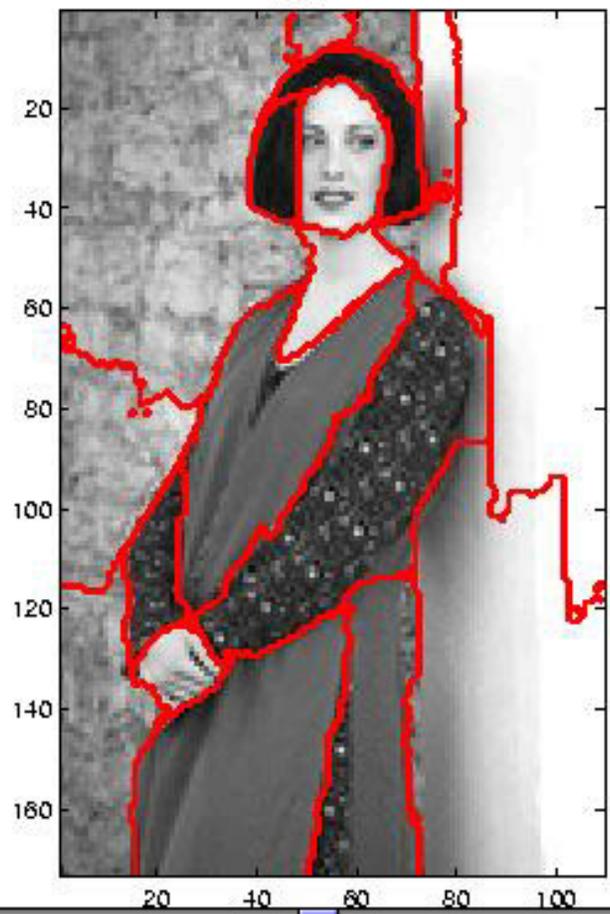
Segmentation

- Which image components “belong together”?
- Belong together=lie on the same object
- Cues
 - similar colour
 - similar texture
 - not separated by contour
 - form a suggestive shape when assembled

Back Forward Reload Home Search Netscape Images

Location: <http://HTTP.CS.Berkeley.EDU/~leungt/Gro/> What's Related

corel img # 181087
grps: 19



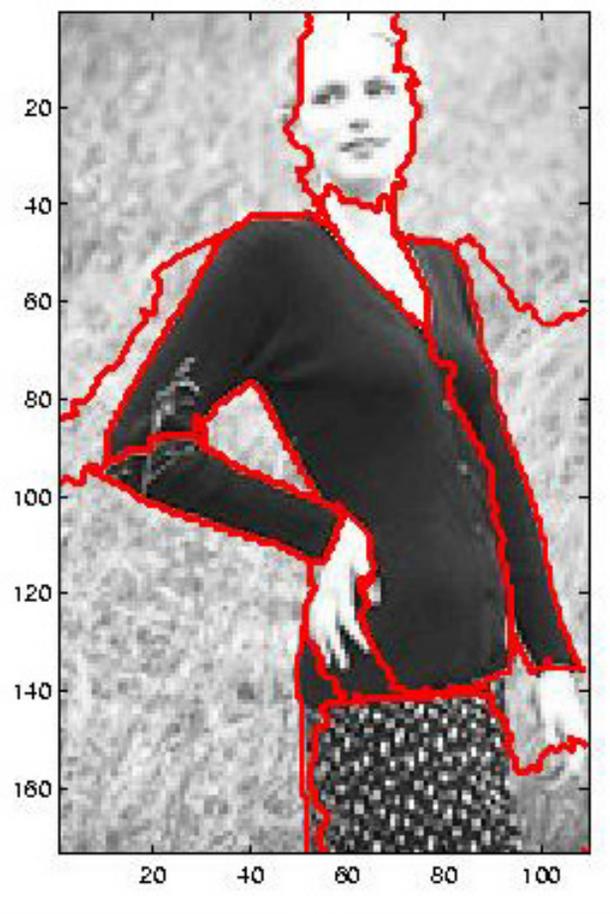
23% of 51K (at 273 bytes/sec)

Netscape: Image Segmentation

Back Forward Reload Home Search Netscape Images

Location: <http://HTTP.CS.Berkeley.EDU/~leungt/Gro/> What's Related

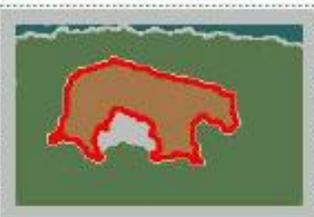
corel img # 181000
grps: 15



23% of 51K (at 273 bytes/sec)



Query image: 108019



Query blobs

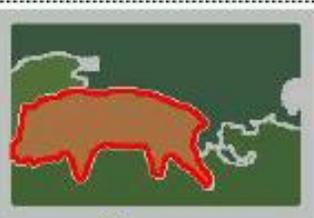
feature importance:

	overall	color	texture	location	shape
blob	very	very	somewhat	not	not
background	somewhat	very	not	not	not

Querying from 35000 images (2000 returned by the filter).



1: 108044 (score = 0.99)

[New query](#)

2: 108023 (score = 0.98)

[New query](#)

3: 108006 (score = 0.98)

[New query](#)

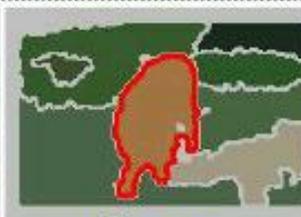
4: 108029 (score = 0.98)

[New query](#)

5: 108051 (score = 0.98)

[New query](#)

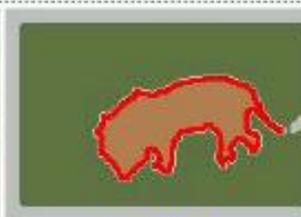
6: 108084 (score = 0.97)

[New query](#)

7: 108037 (score = 0.97)

[New query](#)

8: 108004 (score = 0.97)

[New query](#)

Applications

Tracking

Follow objects and estimate location..

- radar / planes
- pedestrians
- cars
- face features / expressions

Many ad-hoc approaches...

General probabilistic formulation: model density over time.

Tracking

- Use a model to predict next position and refine using next image
- Model:
 - simple dynamic models (second order dynamics)
 - kinematic models
 - etc.
- Face tracking and eye tracking now work rather well



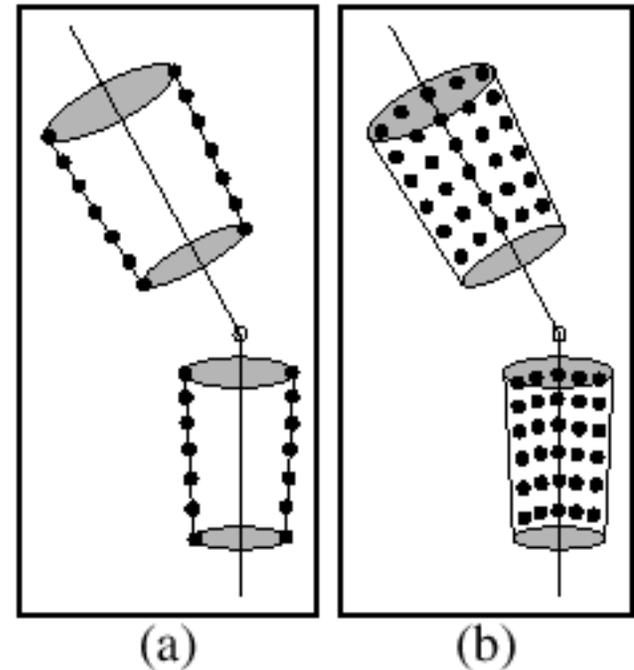
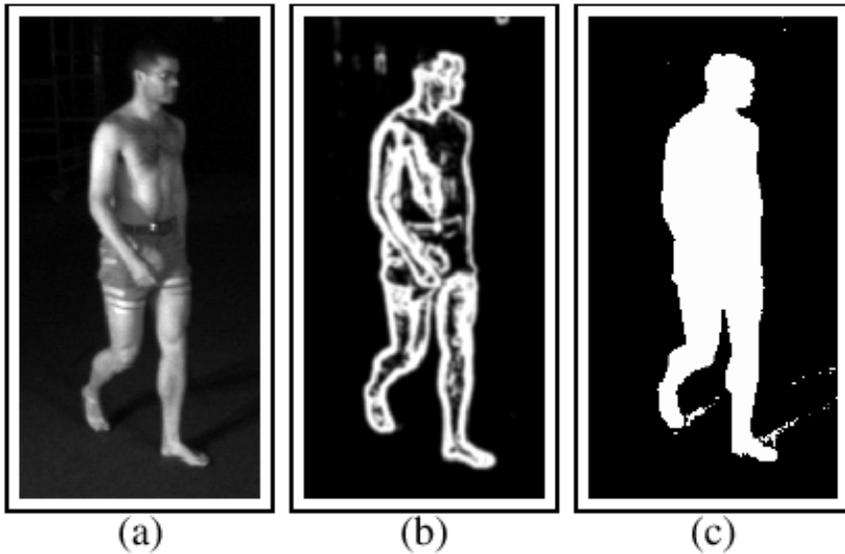






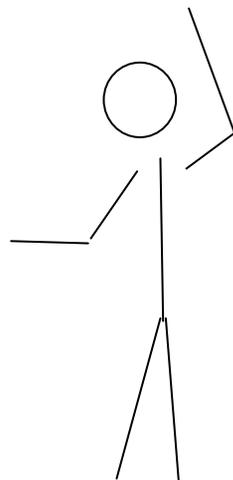
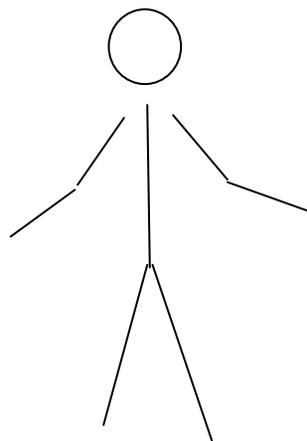


Articulated Models



Find most likely model consistent with observations....(and previous configuration)

Articulated tracking



- Constrained optimization
- Coarse-to-fine part iteration
- Propagate joint constraints through each limb
- Real-time on Ghz pentium...

slow



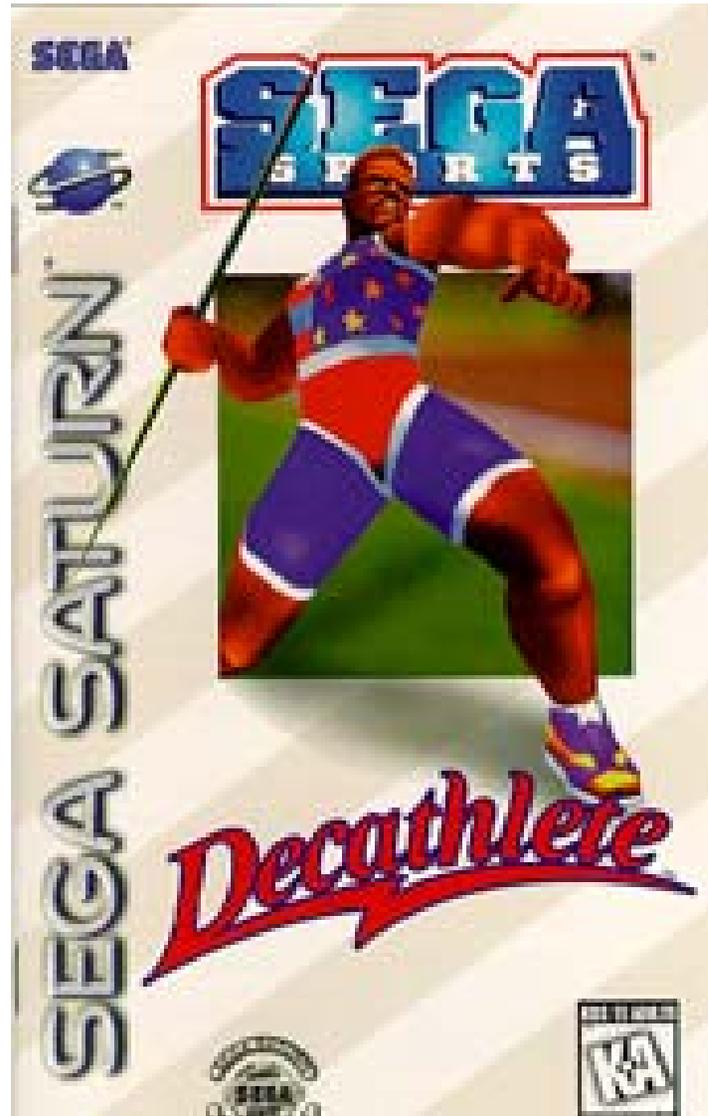
Computer vision applications as ocean-going vessels



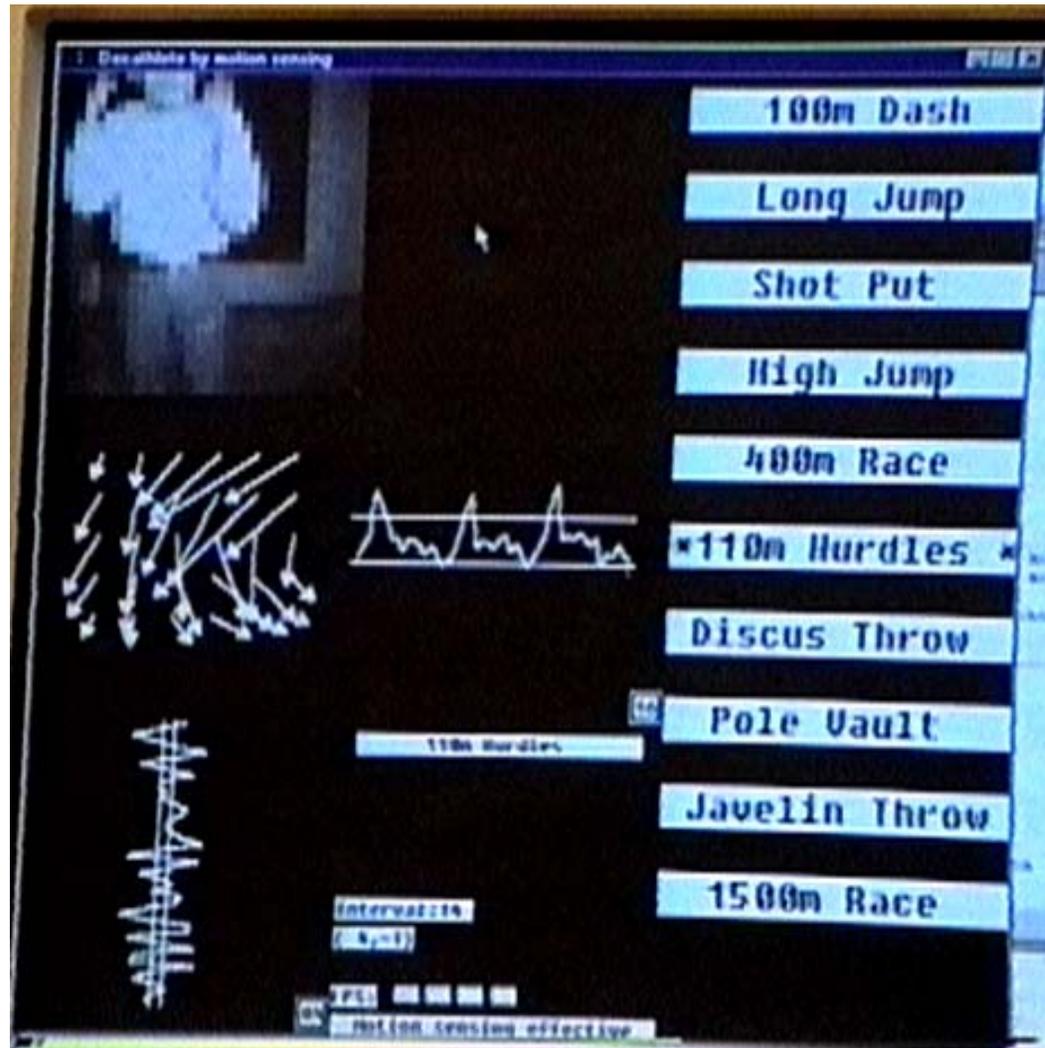
**this
application**



Game: Decathlete



Optical-flow-based Decathlete figure motion analysis



Decathlete 100m hurdles



Decathlete javelin throw



Companies and applications

- Cognex
- Reactrix
- Poseidon
- Mobileye
- Eyetoy
- Identix
- Roomba

- aquatic safety
- installed sites
- about us
- contact us
- news
- events
- site map
- select your country

Here is a partial list of our installed sites:

USA

- [McCoy Natatorium, Penn State University](#)
University Park
Pennsylvania, USA



- [YMCA Southcoast, New Bedford Division](#)
New Bedford
Massachusetts, USA

- [Medina Community Recreation Center](#)
Medina
Ohio , USA

- [Metro Atlanta YMCA - Carl E. Sanders Family YMCA](#)
Buckhead
Georgia , USA



- [Heritage YMCA Group - 95th St. Family Center](#)
Naperville
Illinois, USA



- [The Sarasota Family YMCA Pools](#)
Florida, USA

- [The Fort Wayne Community Schools' Pool](#)
Indiana, USA

- [The St. Cloud School District Pools](#)
Minnesota, USA

EUROPE

Poseidon saved a life here! ▶



THE LIFEGUARD'S THIRD EYE

[Home](#)[The System](#)[Aquatic safety](#)[Installed sites](#)[About us](#)[Contact us](#)[News](#)[Events](#)[Site map](#)[Select your country](#) 

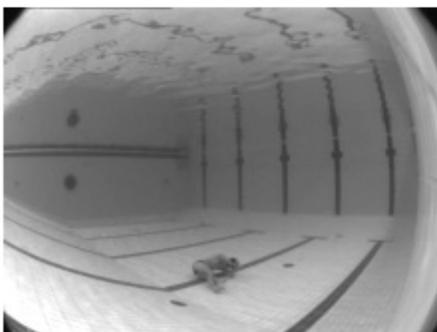
Poseidon saves a life

[Back](#) 

Ancenis – November 28, 2000

A young French teenager was out for his usual swim one night. Suddenly something went wrong. He sank to the bottom of the pool, unseen by the lifeguards on duty. Poseidon detected him, alerted the lifeguards, and he was saved. In less than thirty seconds.

Some images from the drowning:



[Download what the cameras saw \(Animated gif: 7MB\)](#) 



- [Applications](#)
- [Technologies](#)
- [Products](#)
- [Get Brochures](#) 

A Single-Camera Driving Assistance System on Chip



Motion magnification

And...

- Visual Category Learning
- Image Databases
- Image-based Rendering
- Medical Imaging

Skills learned from this class

- Goal: You'll be able to go to a computer vision conference and understand what's going on in most of the presentations.
- You'll have the skills and awareness of the literature to start building the vision systems you want.

Cameras, lenses, and calibration

Today:

- Camera models
- Projection equations
- Calibration methods

Images are projections of the 3-D world onto
a 2-D plane...

7-year old's question

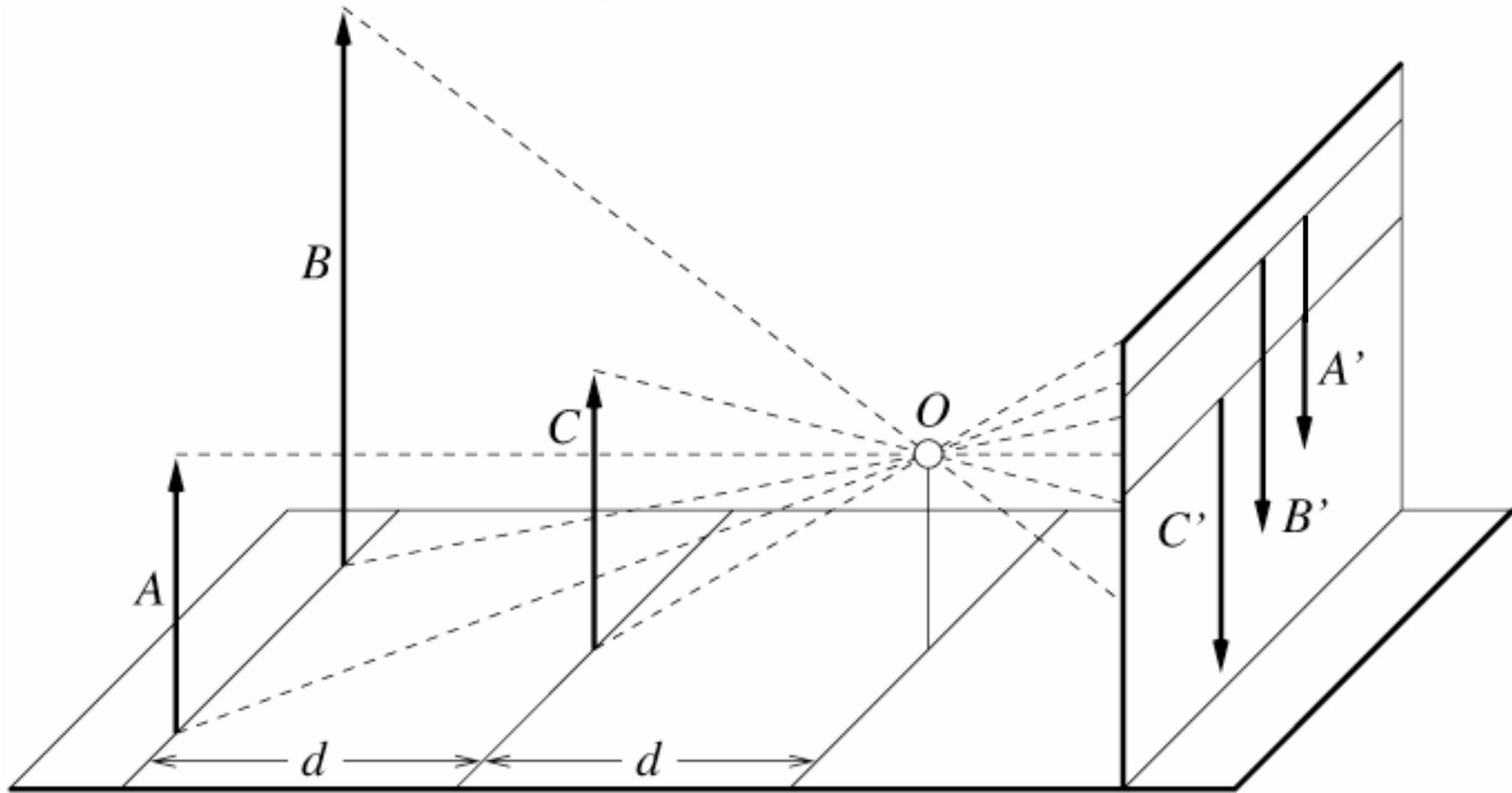


Why is there no image on a white piece of paper?

Pinhole cameras

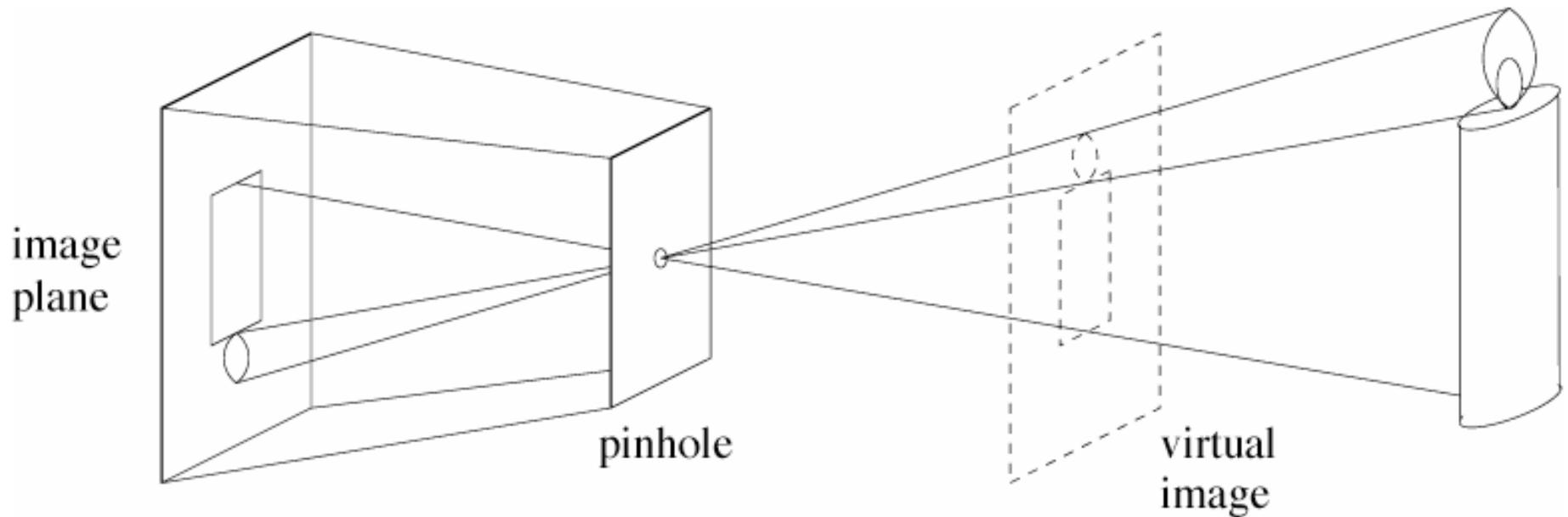
- Geometry

Distant objects are smaller



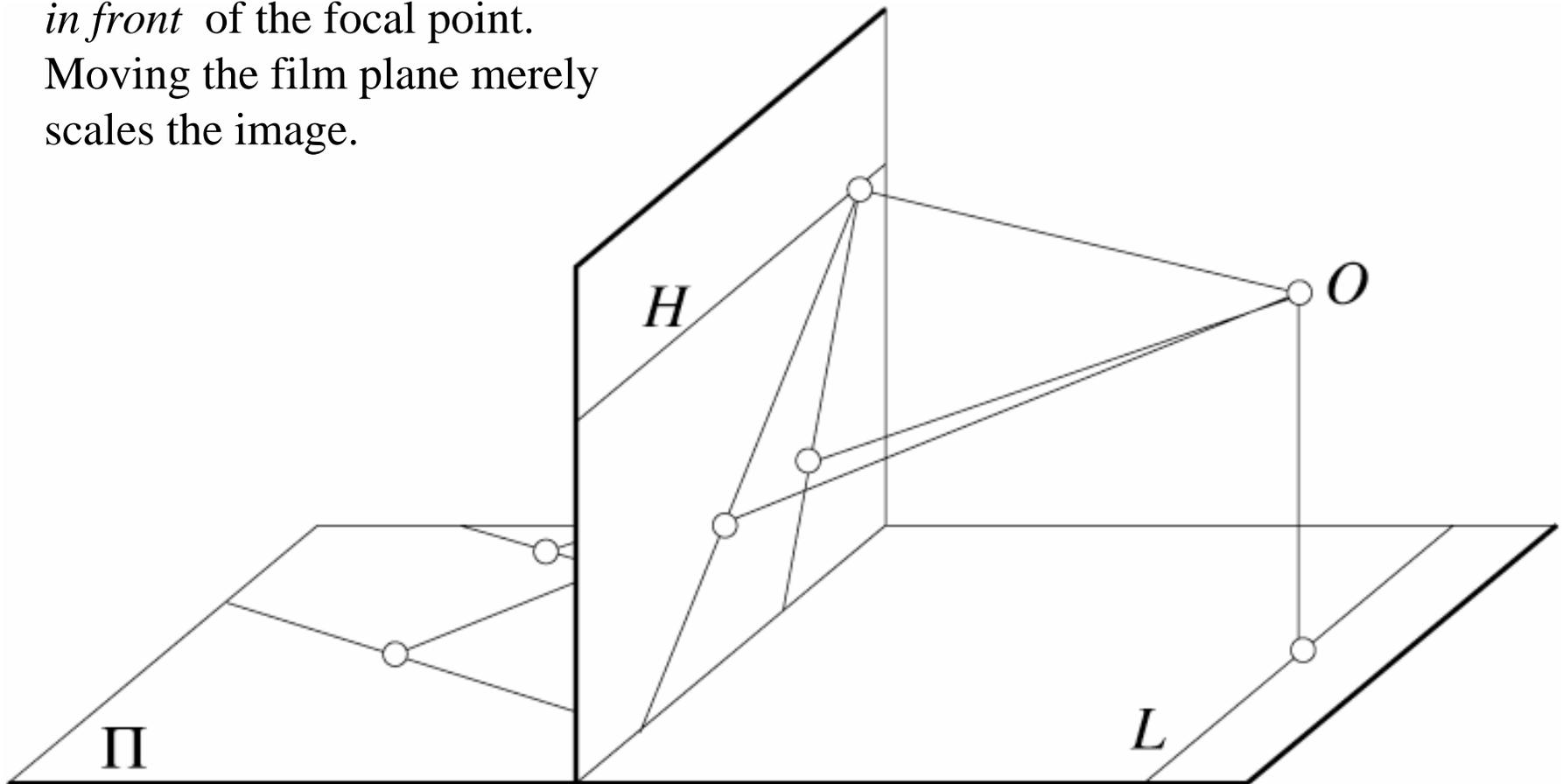
Virtual image, perspective projection

- Abstract camera model - box with a small hole in it

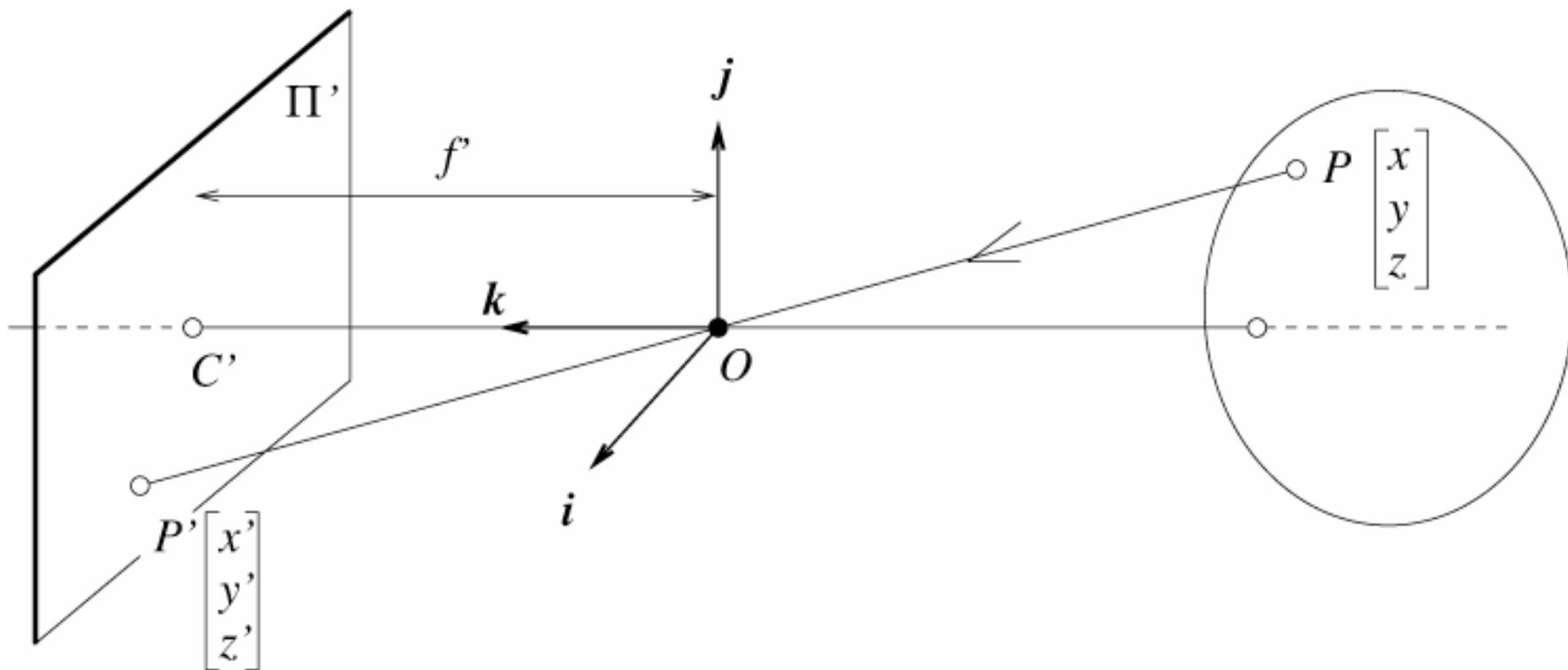


Parallel lines meet

Common to draw film plane
in front of the focal point.
Moving the film plane merely
scales the image.



The equation of projection



The equation of projection

- Cartesian coordinates:

- We have, by similar triangles, that

- $(x, y, z) \rightarrow (f x/z, f y/z, -f)$

- Ignore the third coordinate, and get

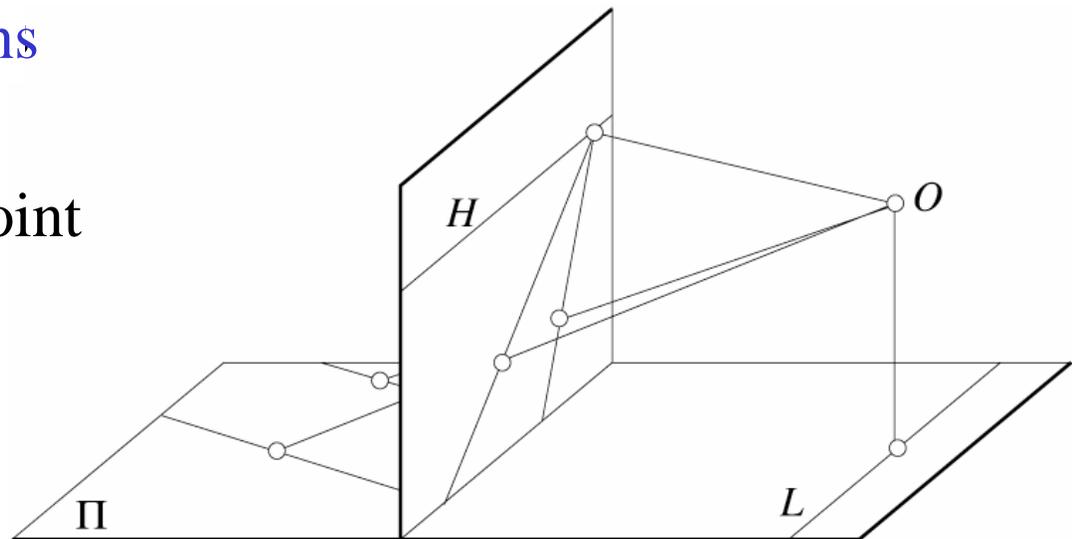
$$(x, y, z) \rightarrow \left(f \frac{x}{z}, f \frac{y}{z}\right)$$

Vanishing points

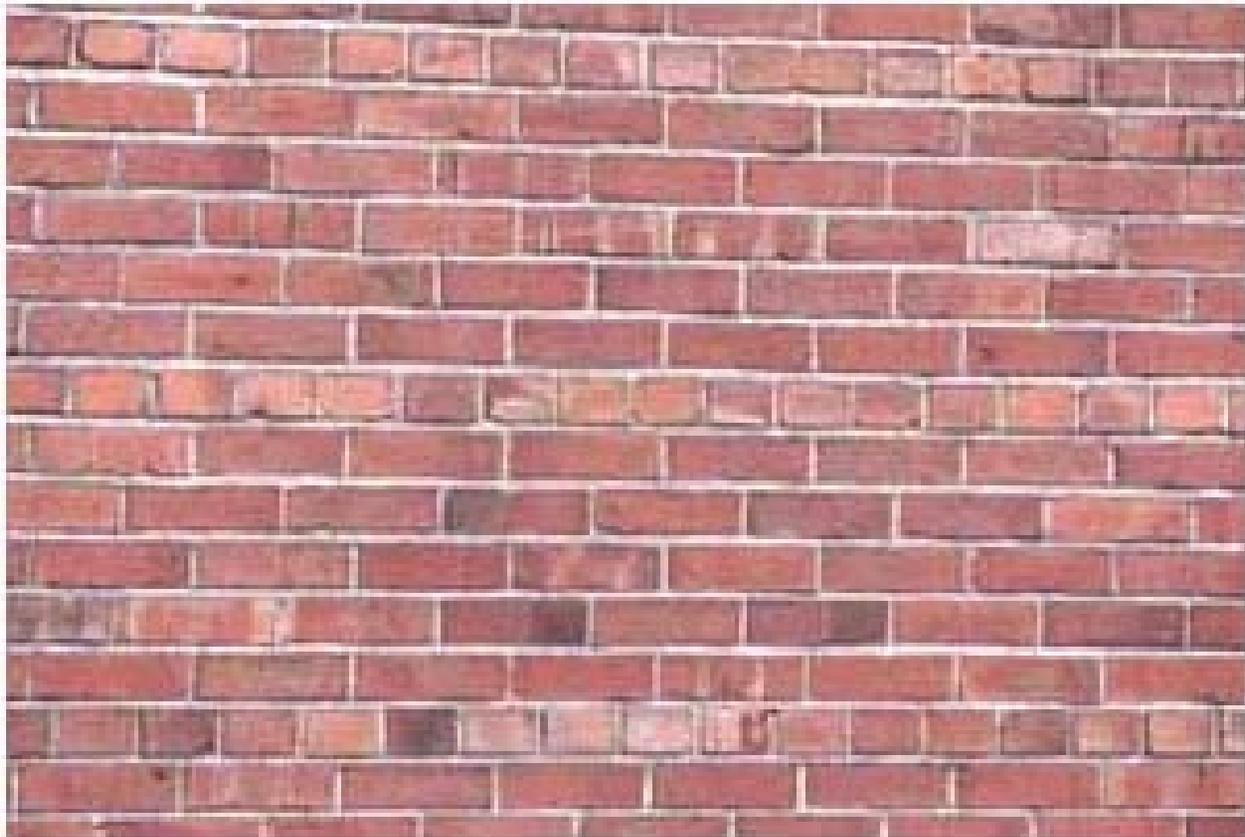
- Each set of parallel lines (=direction) meets at a different point
 - The *vanishing point* for this direction
- Sets of parallel lines on the same plane lead to *collinear* vanishing points.
 - The line is called the *horizon* for that plane
- We show this on the board...

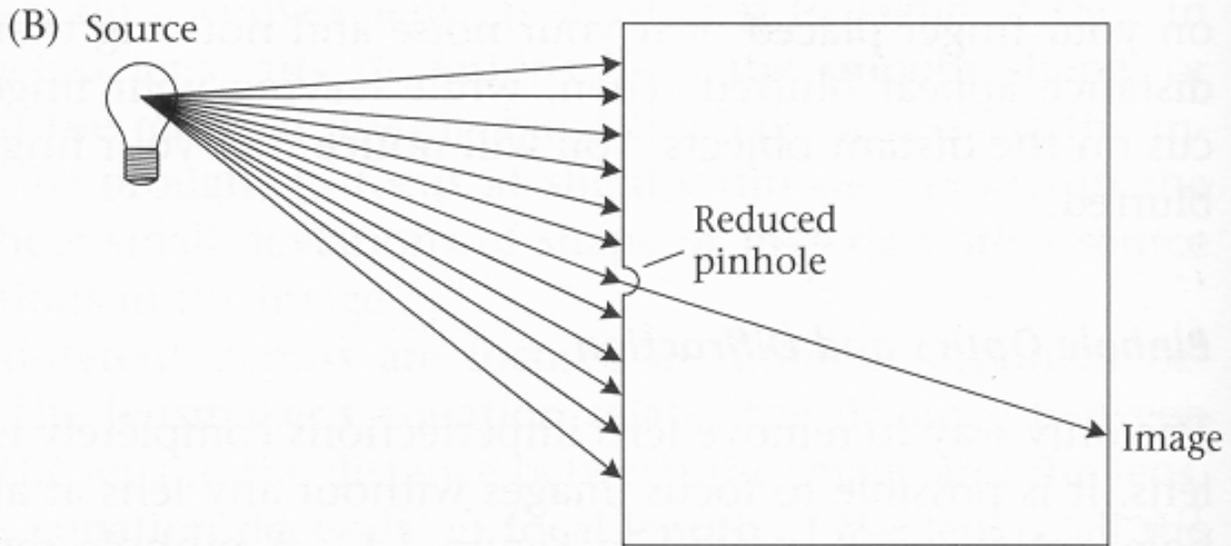
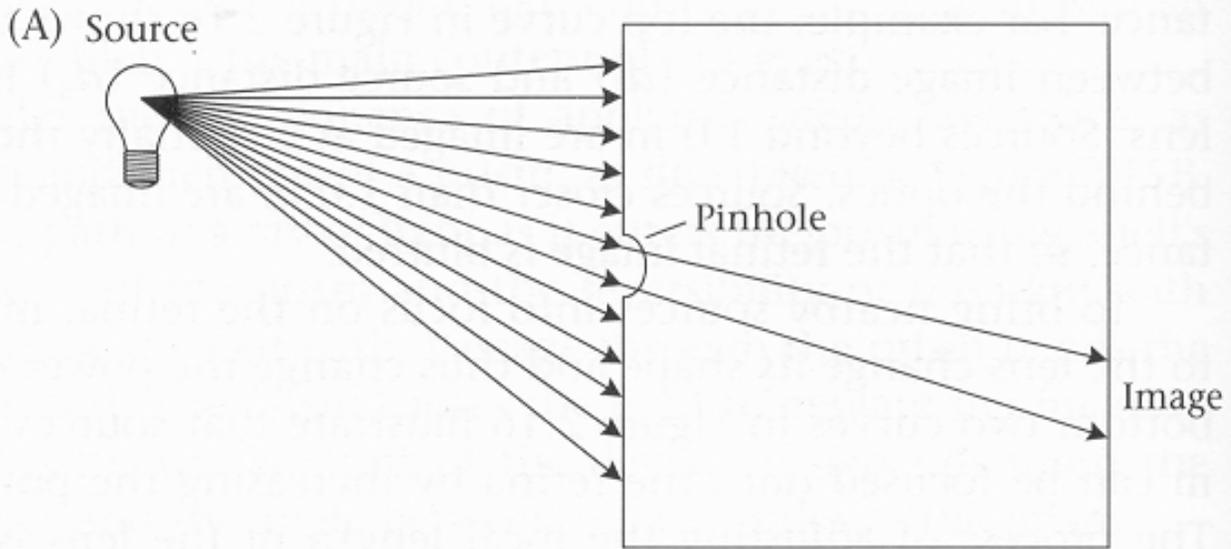
Geometric properties of projection

- Points go to **points**
- Lines go to **lines**
- Planes go to **the whole image**
or a **half-plane**
- Polygons go to **polygons**
- Degenerate cases
 - line through focal point to **point**
 - plane through focal point to **line**



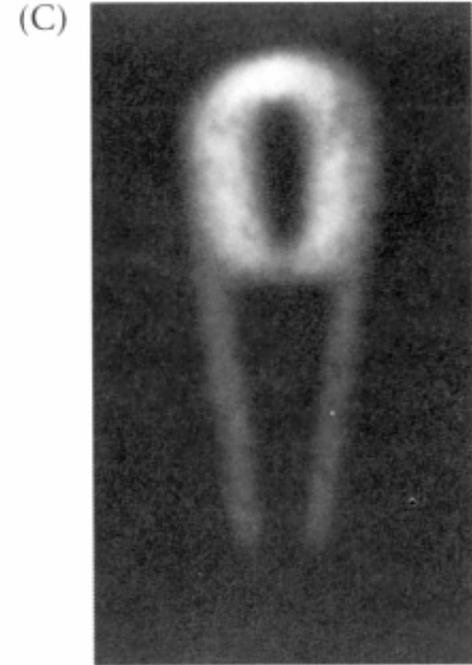
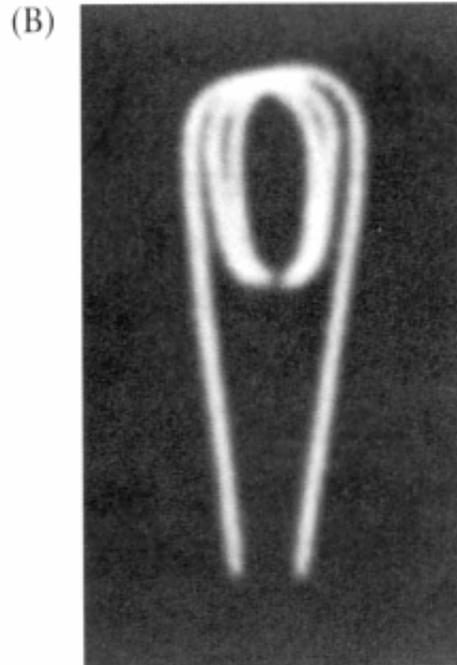
What if you photograph a brick wall head-on?





Pinhole camera demonstrations

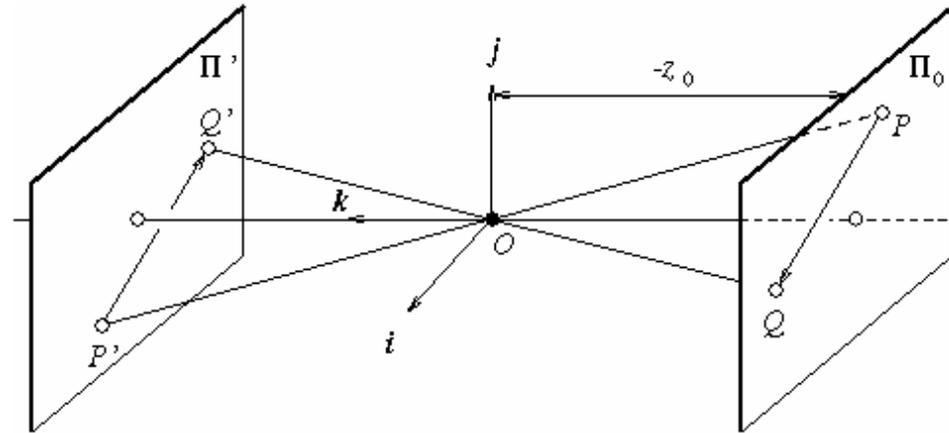
- Film camera, box, demo. Apertures, lens.
- The image is the convolution of the aperture with the scene.



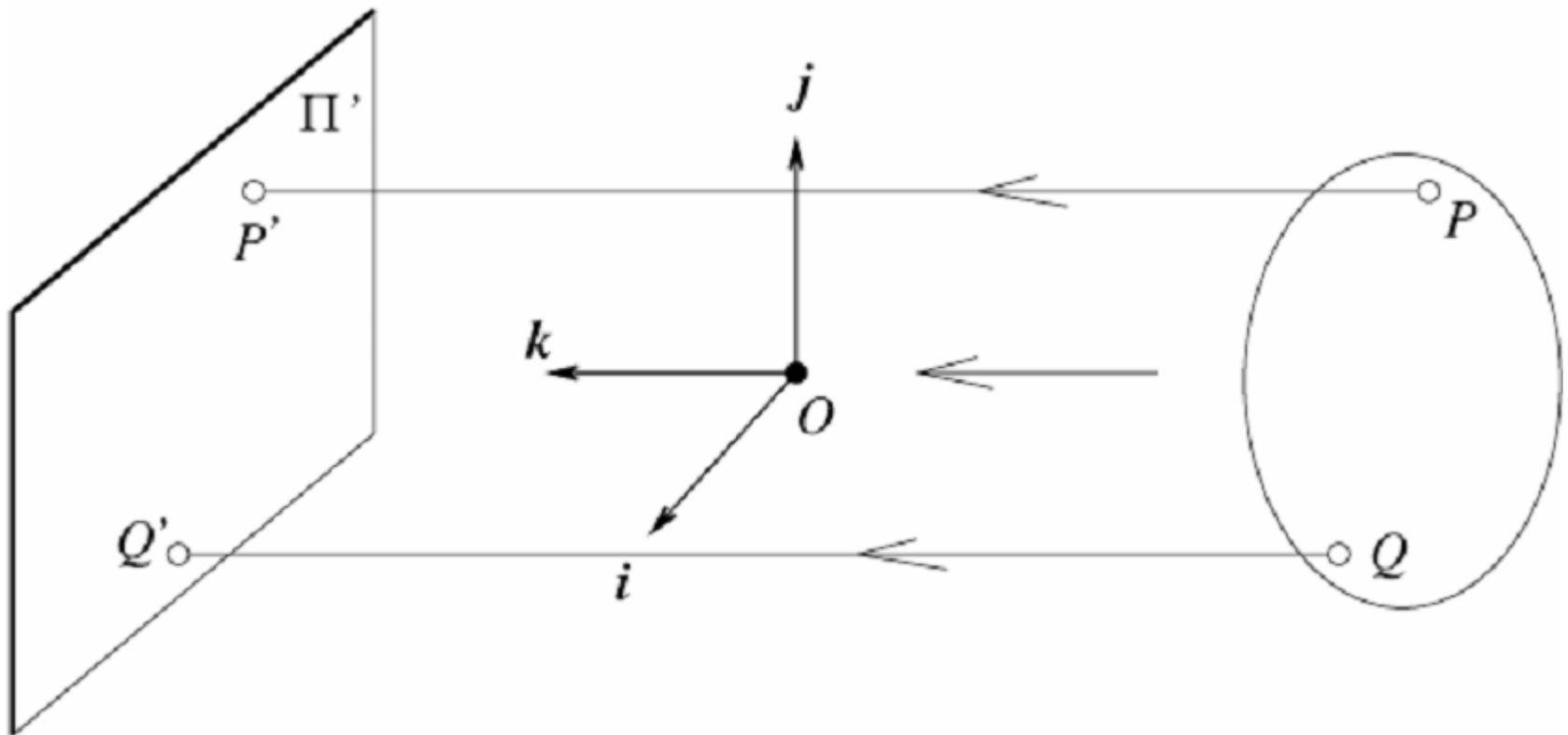
2.18 DIFFRACTION LIMITS THE QUALITY OF PINHOLE OPTICS. These three images of a bulb filament were made using pinholes with decreasing size. (A) When the pinhole is relatively large, the image rays are not properly converged, and the image is blurred. (B) Reducing the size of the pinhole improves the focus. (C) Reducing the size of the pinhole further worsens the focus, due to diffraction. From Ruechardt, 1958.

Weak perspective

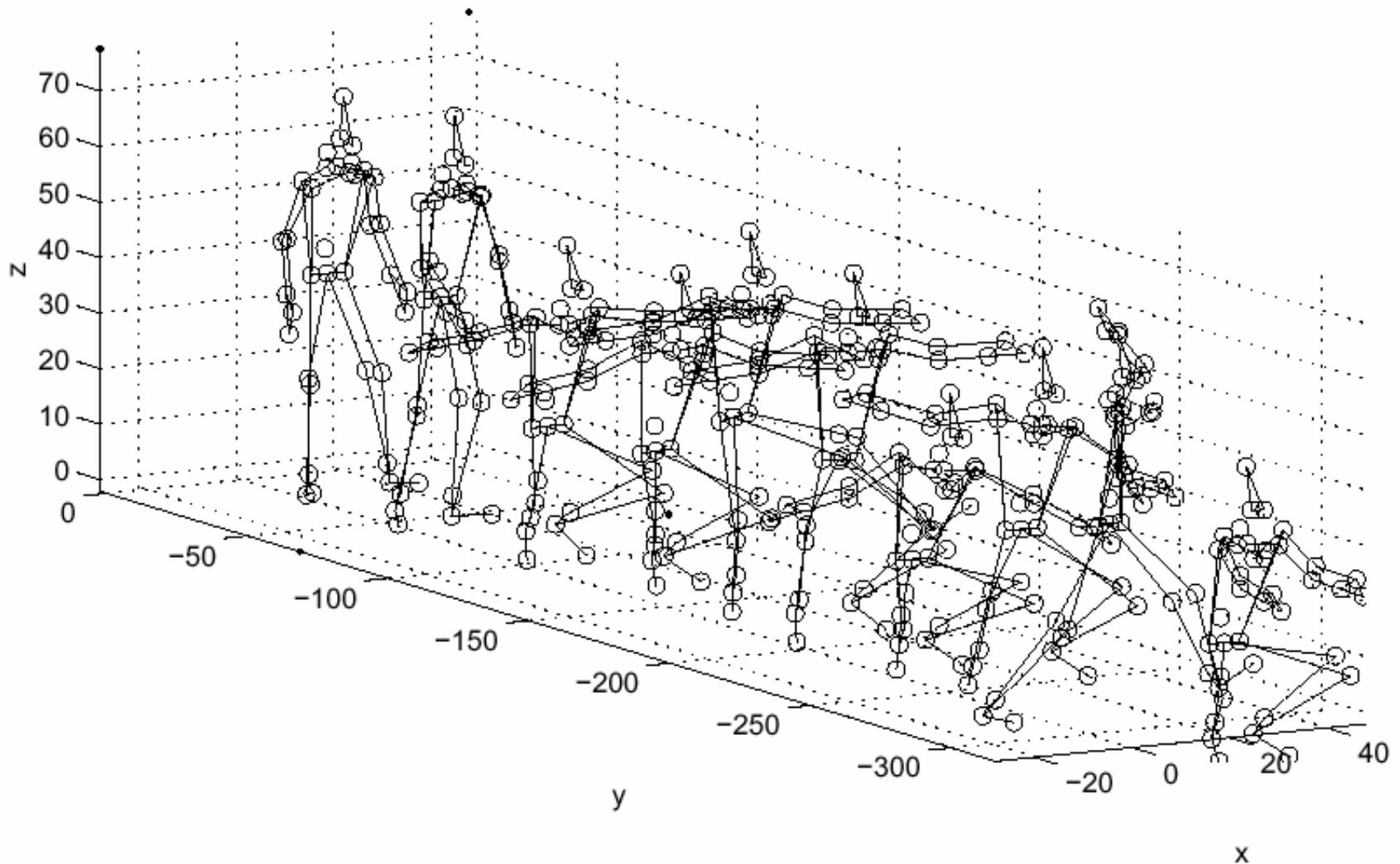
- Issue
 - perspective effects, but not over the scale of individual objects
 - collect points into a group at about the same depth, then divide each point by the depth of its group
 - Adv: easy
 - Disadv: wrong



Orthographic projection



Example use of orthographic projection: inferring human body motion in 3-d



Advantage of orthographic projection

Our simplified rendering conditions are as follows: the body is transparent, and each marker is rendered to the image plane orthographically. For figural motion described by human motion basis coefficients $\vec{\alpha}$, the rendered image sequence, \vec{y} , is:

$$\vec{y} = PU\vec{\alpha}, \quad (1)$$

where P is the projection operator which collapses the y dimension of the image sequence $U\vec{\alpha}$.

Orthography can lead to analytic solutions

have our multi-dimensional gaussian,

$$\text{Prior probability} \quad P(\vec{\alpha}) = k_2 e^{-\vec{\alpha}' \Lambda^{-1} - \vec{\alpha}}, \quad (3)$$

where k_2 is another normalization constant. If we model the observation noise as i.i.d. gaussian with variance σ , we have, for the likelihood term of Bayes theorem,

$$\text{Likelihood function} \quad P(\vec{y}|\vec{\alpha}) = k_3 e^{-|\vec{y} - P U \vec{\alpha}|^2 / (2\sigma^2)}, \quad (4)$$

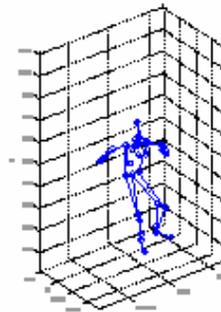
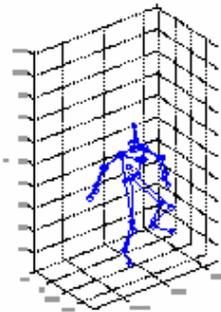
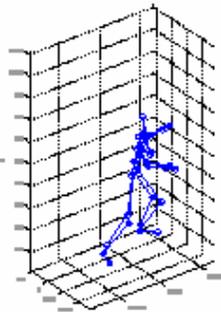
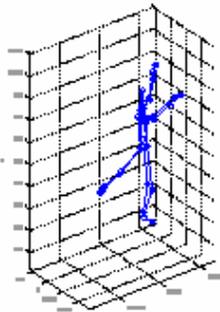
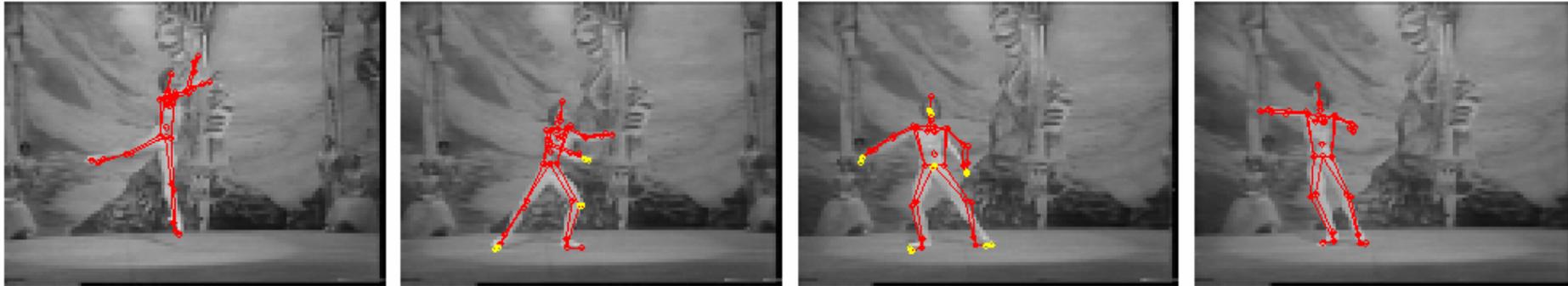
with normalization constant k_3 .

The posterior distribution is the product of these two gaussians. That yields another gaussian, with mean and covariance found by a matrix generalization of “completing the square” [7]. The squared error optimal estimate for α is then

$$\alpha = S U' P' (P U S U' P' + \sigma I)^{-1} (\vec{y} - (P \vec{m})) \quad (5)$$

Analytic solution for inferred 3-d motion

Results

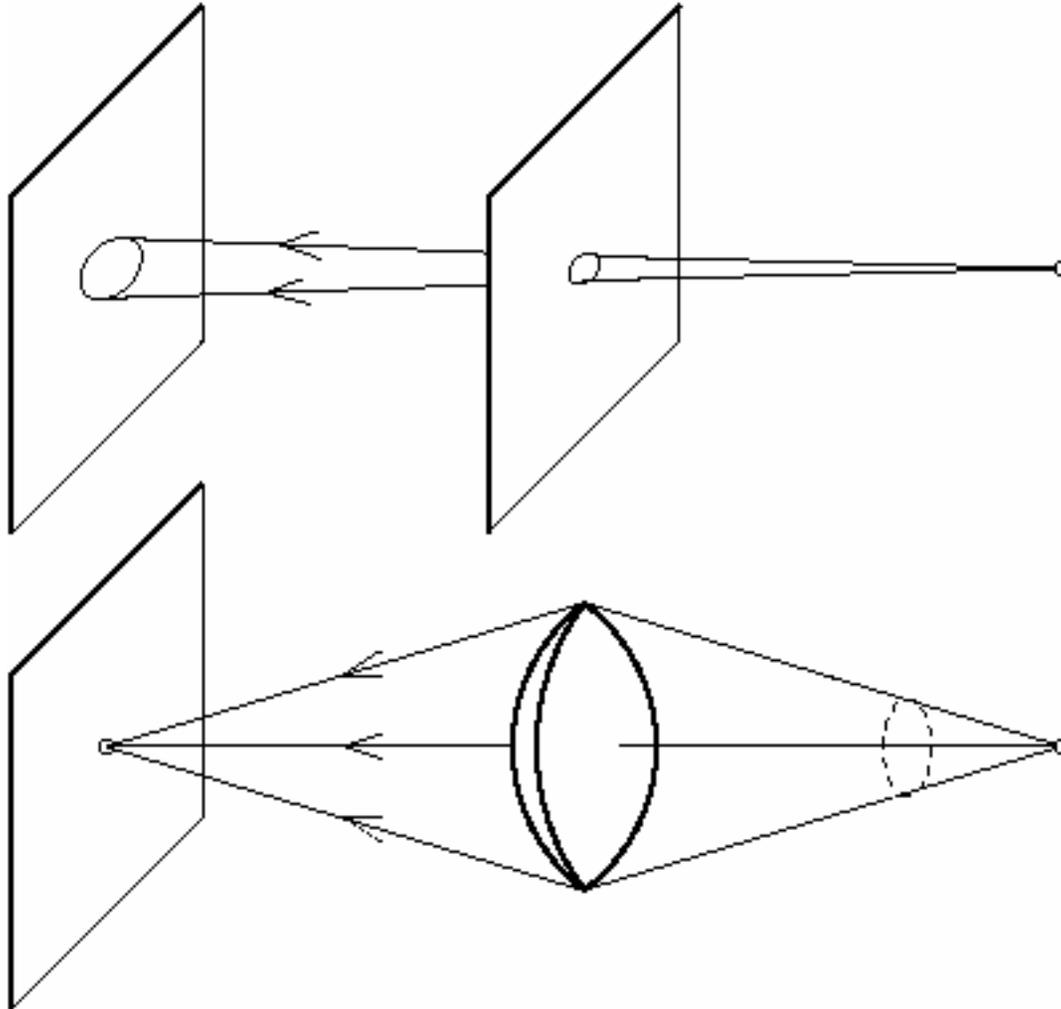


But, alas

“The results for the simplified problem appear promising. However serious questions arise because of the simplifying assumptions, which trivialize a number of the hard issues of the problem in the real world. Eg. scaling effects that arise from perspective projection are ignored, by assuming orthographic projection. ...”

Reviewer's comments

The reason for lenses

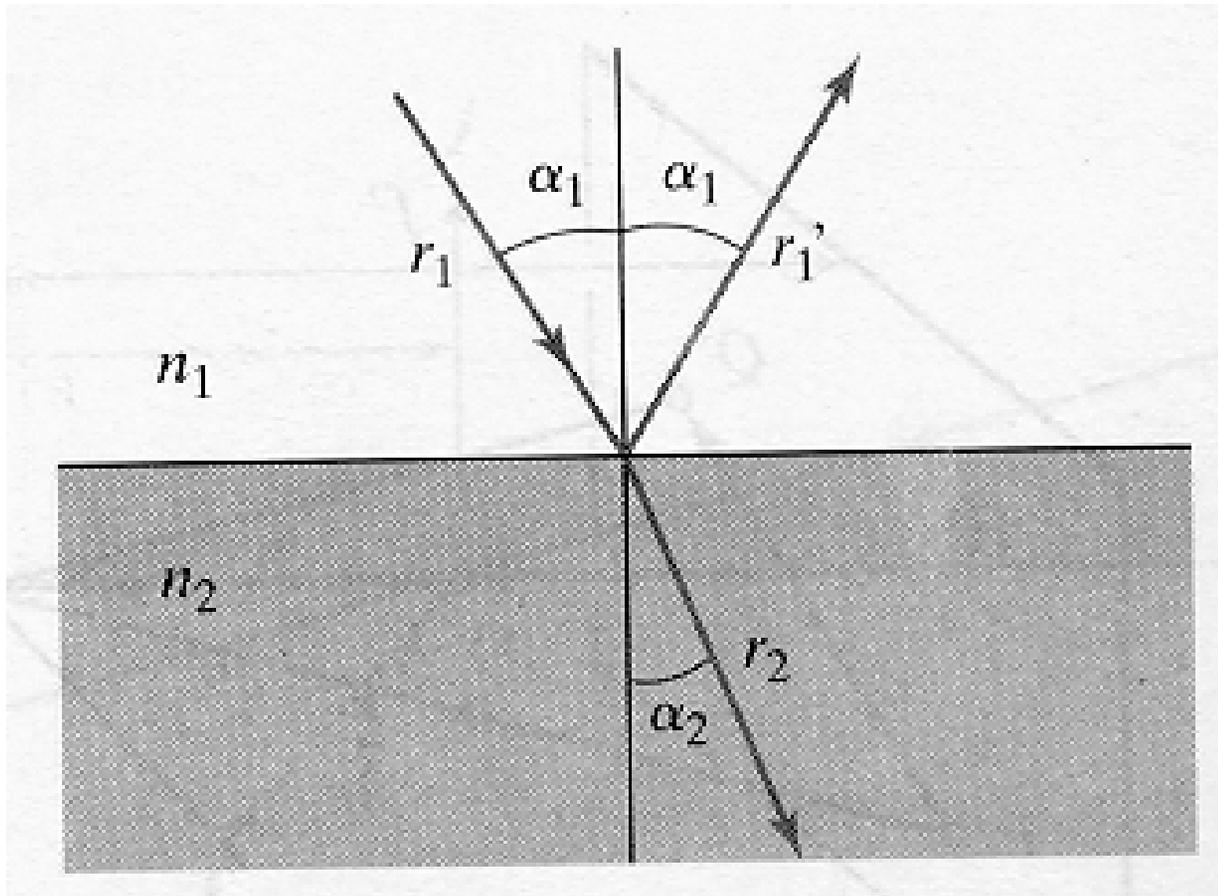


Water glass refraction



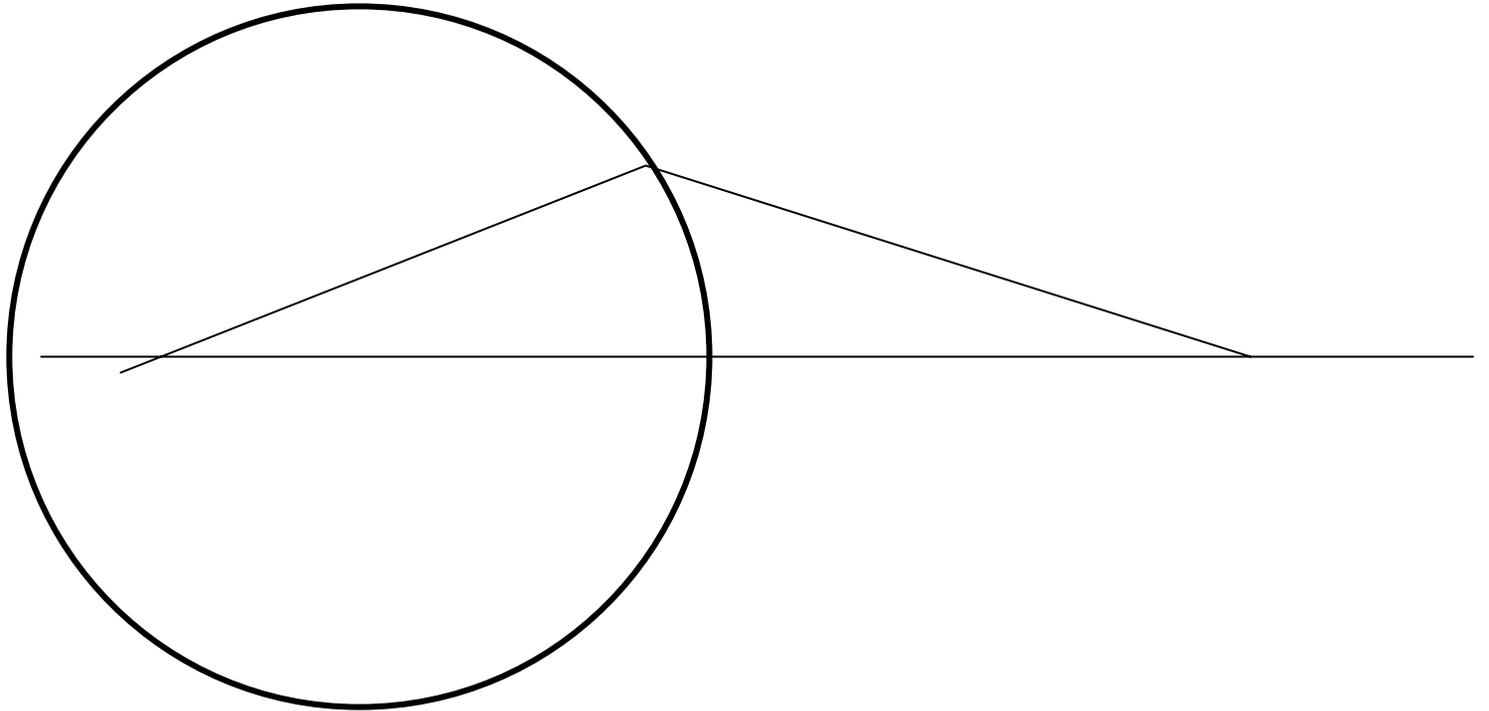
http://data.pg2k.hd.org/_exhibits/natural-science/cat-black-and-white-domestic-short-hair-DSH-with-nose-in-glass-of-water-on-bedside-table-tweaked-mono-1-AJHD.jpg

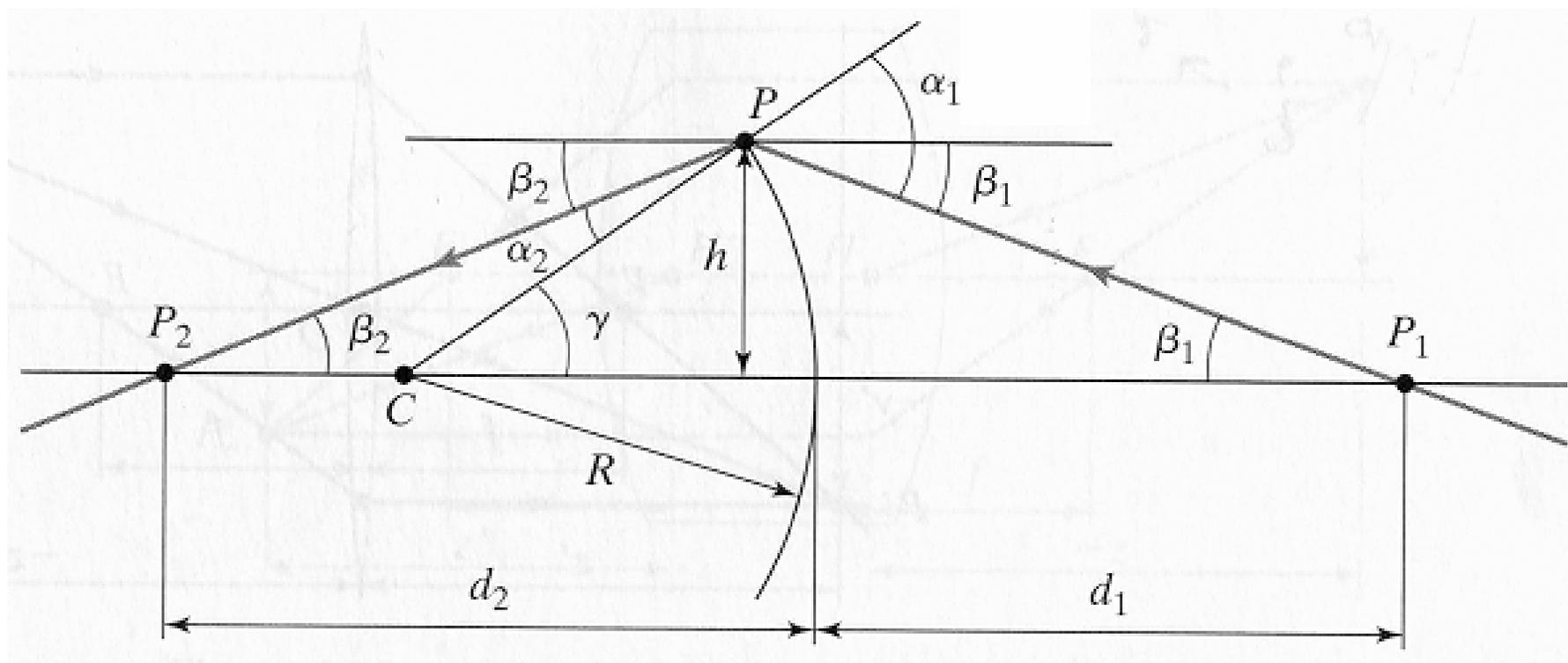
Snell's law



$$n_1 \sin(\alpha_1) = n_2 \sin(\alpha_2)$$

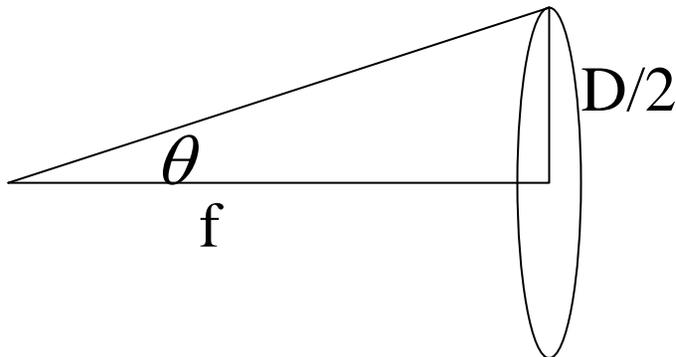
Spherical lens





First order optics

$$\sin(\theta) \approx \theta$$



$$\theta \approx \frac{D/2}{f}$$

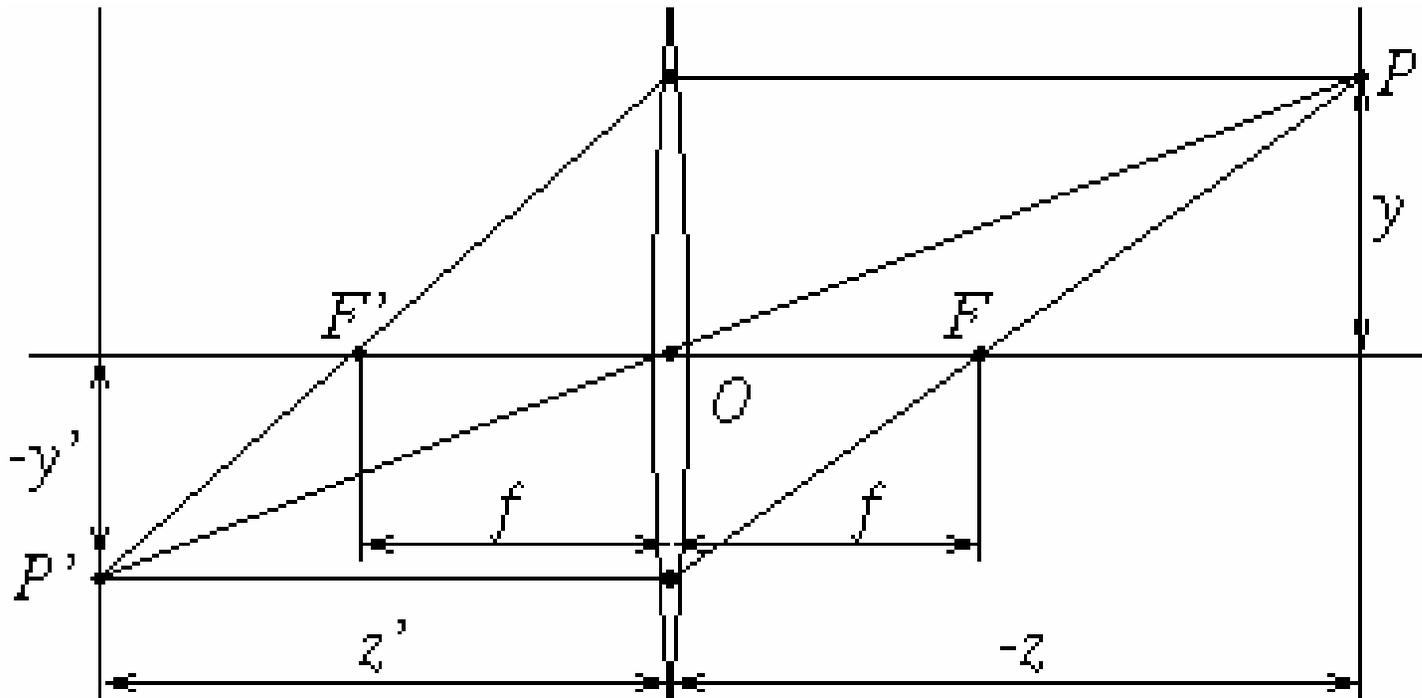
Paraxial refraction equation

$$\alpha_1 = \gamma + \beta_1 \approx h \left(\frac{1}{R} + \frac{1}{d_1} \right)$$

$$\alpha_2 = \gamma - \beta_2 \approx h \left(\frac{1}{R} - \frac{1}{d_2} \right)$$

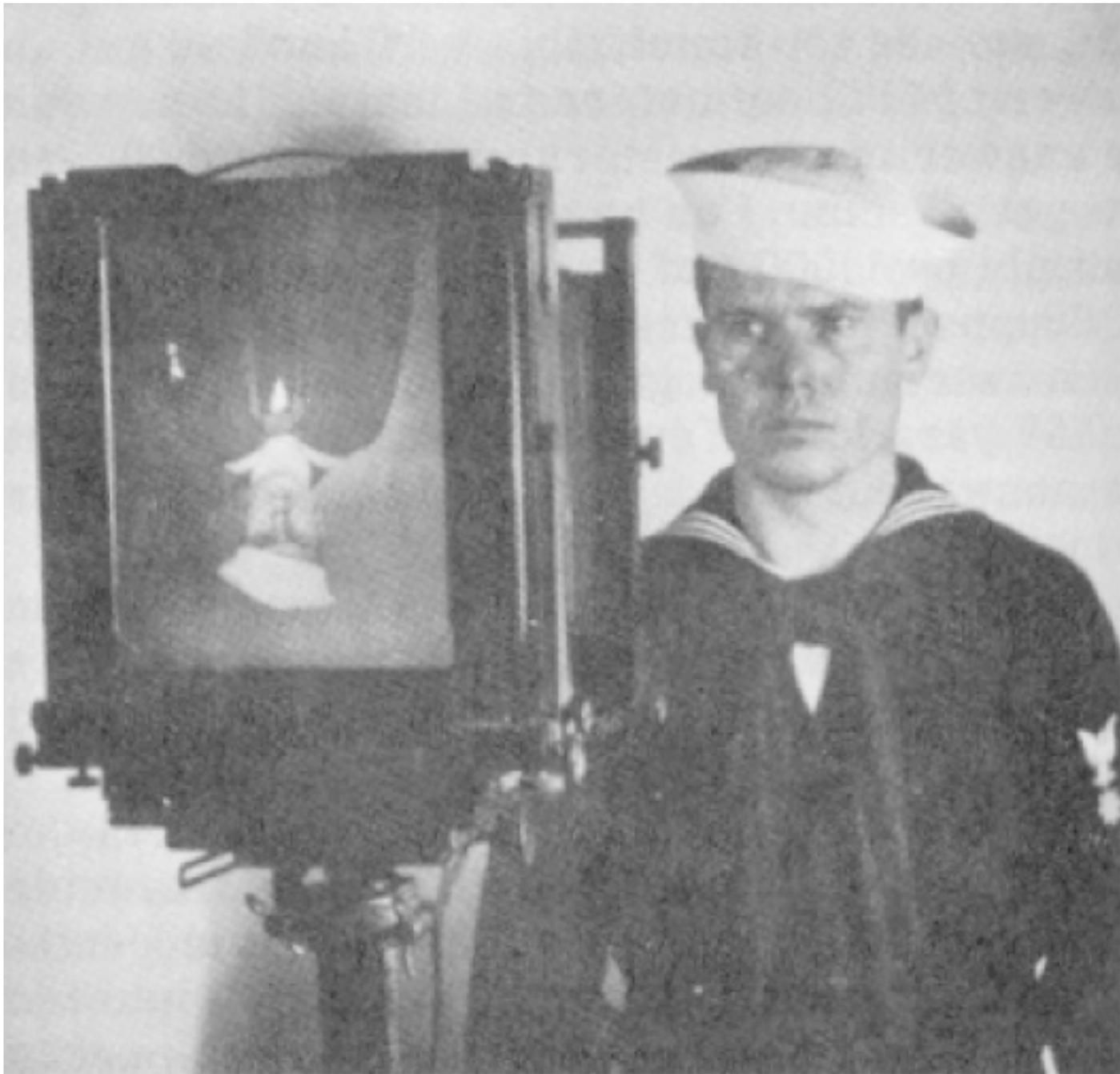
$$n_1 \alpha_1 \approx n_2 \alpha_2 \Leftrightarrow \frac{n_1}{d_1} + \frac{n_2}{d_2} = \frac{n_2 - n_1}{R}$$

The thin lens, first order optics



$$\frac{1}{z'} - \frac{1}{z} = \frac{1}{f}$$

$$f = \frac{R}{2(n-1)}$$



What camera projection model
applies for a thin lens?

Candle and laser pointer demo

More accurate models of real lenses

- Finite lens thickness
- Higher order approximation to $\sin(\theta)$
- Chromatic aberration
- Vignetting

Thick lens

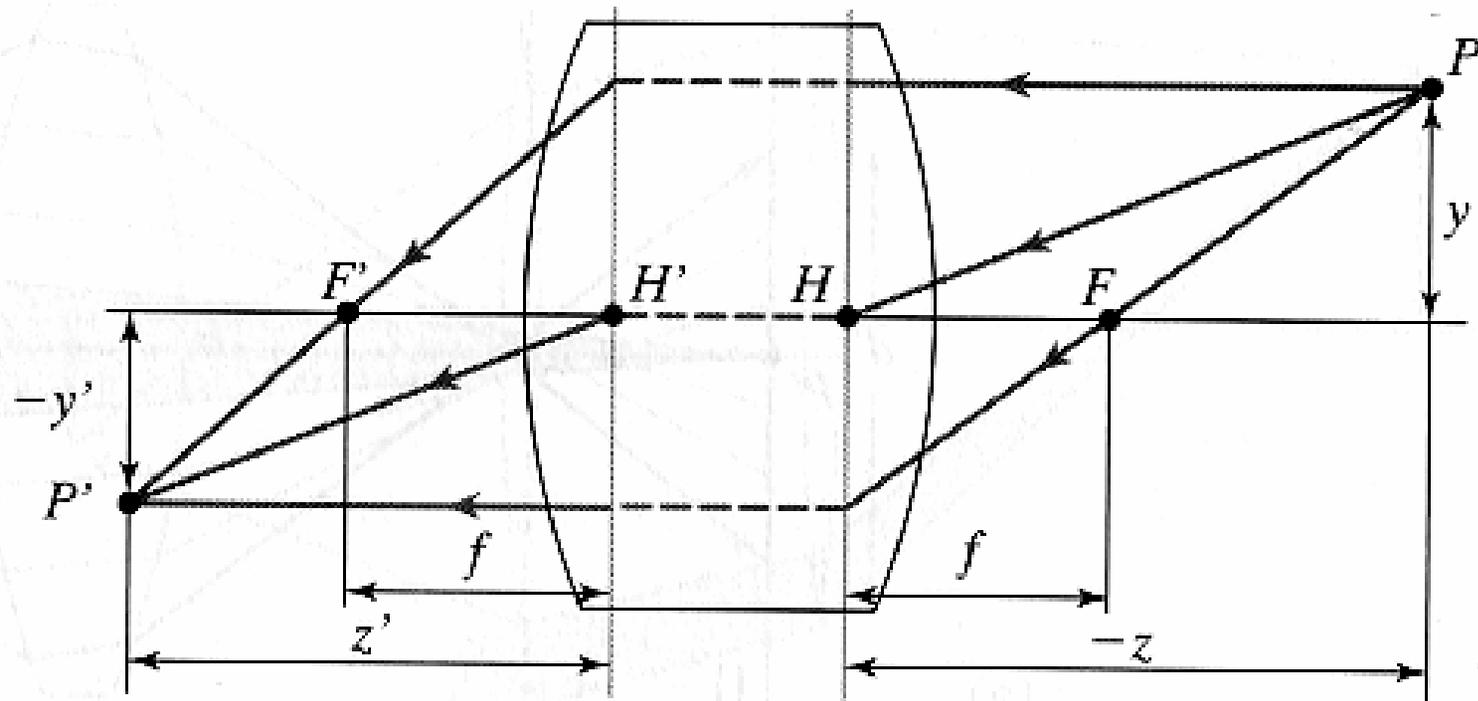
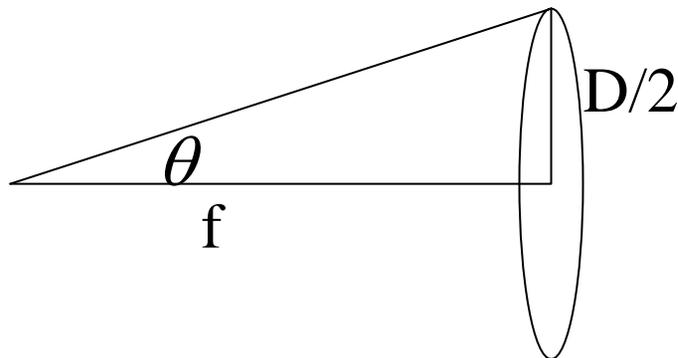


Figure 1.11 A simple thick lens with two spherical surfaces.

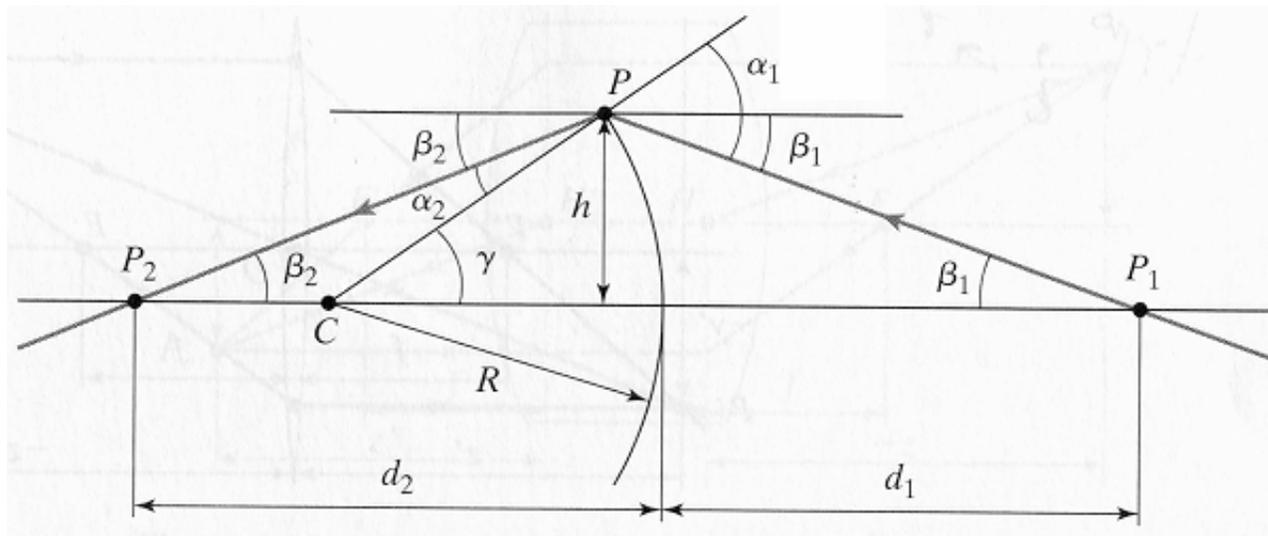
Third order optics

$$\sin(\theta) \approx \theta - \frac{\theta^3}{6}$$



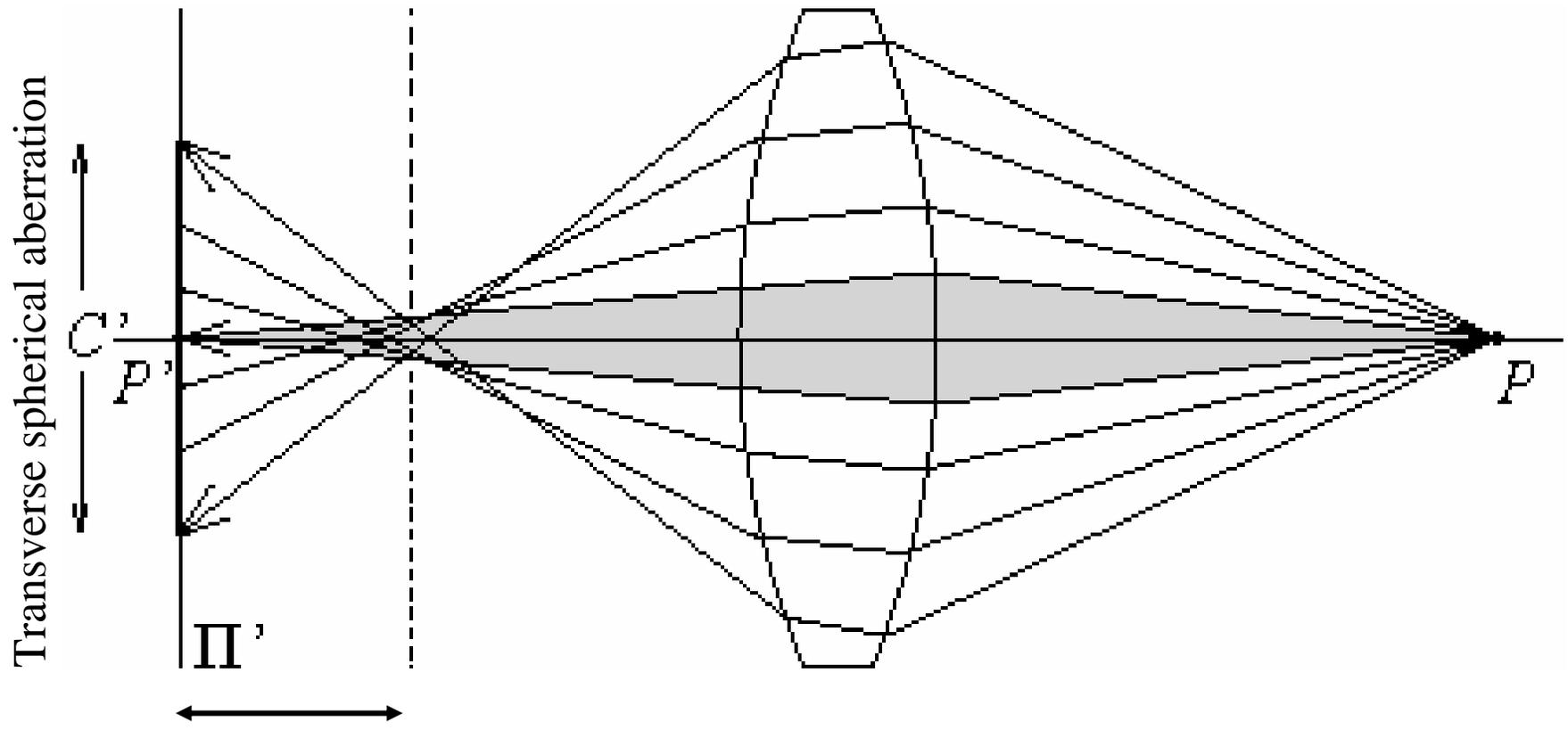
$$\theta \approx \frac{D/2}{f} - \frac{\left(\frac{D/2}{f}\right)^3}{6}$$

Paraxial refraction equation, 3rd order optics



$$\frac{n_1}{d_1} + \frac{n_2}{d_2} = \frac{n_2 - n_1}{R} + h^2 \left[\frac{n_1}{2d_1} \left(\frac{1}{R} + \frac{1}{d_1} \right)^2 + \frac{n_2}{2d_2} \left(\frac{1}{R} - \frac{1}{d_2} \right)^2 \right]$$

Spherical aberration (from 3rd order optics)

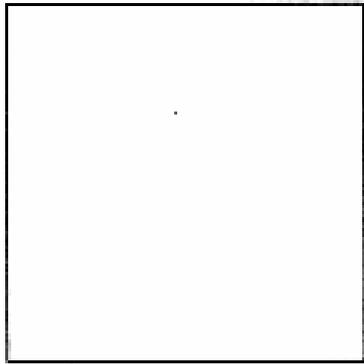


Longitudinal spherical aberration

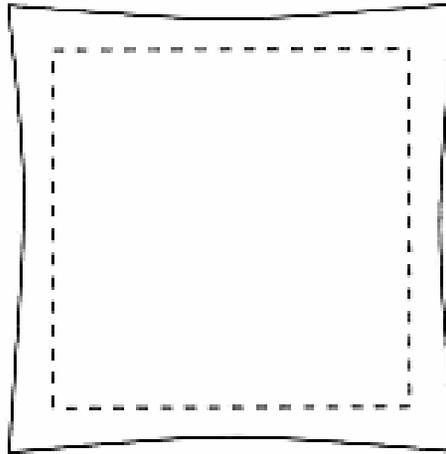
Forsyth&Ponce

Other 3rd order effects

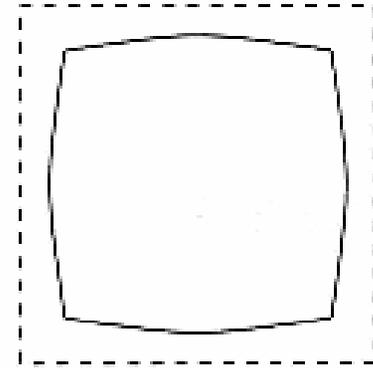
- Coma, astigmatism, field curvature, distortion.



no distortion

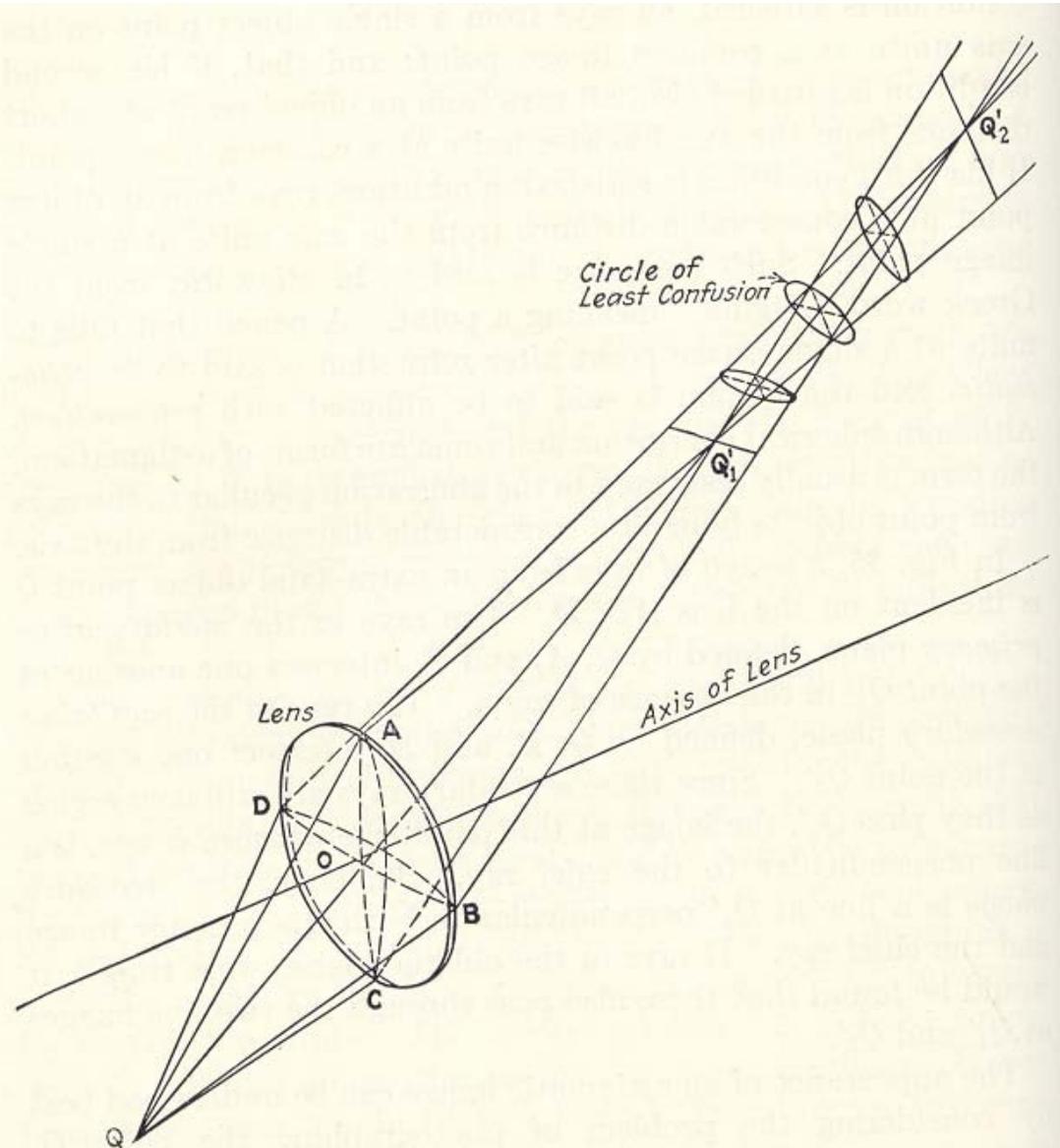


pincushion
distortion



barrel
distortion

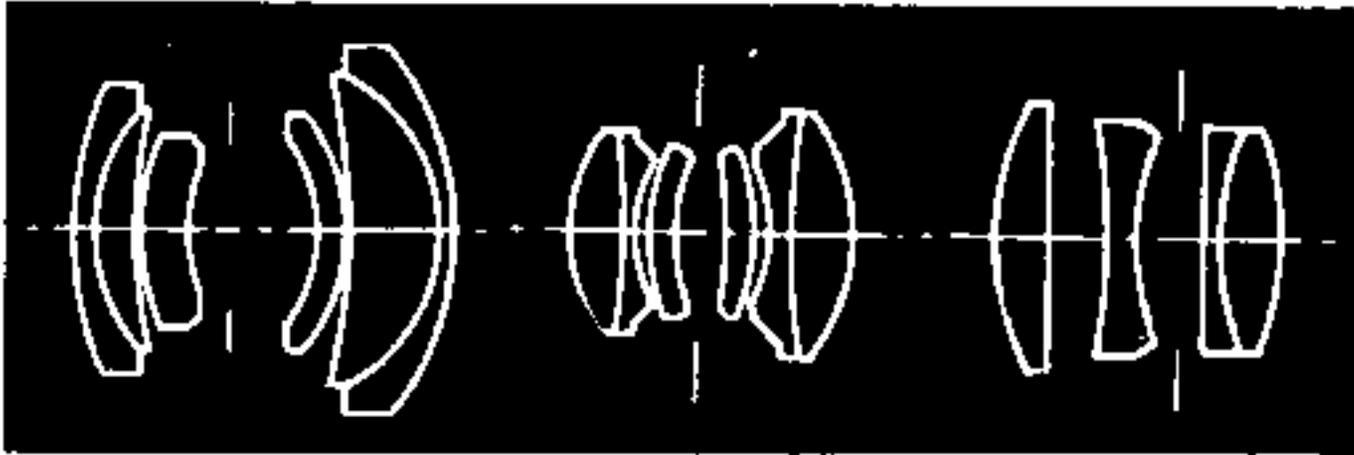
Astigmatic distortion



Hardy & Perrin,
The Principles of Optics, 1932

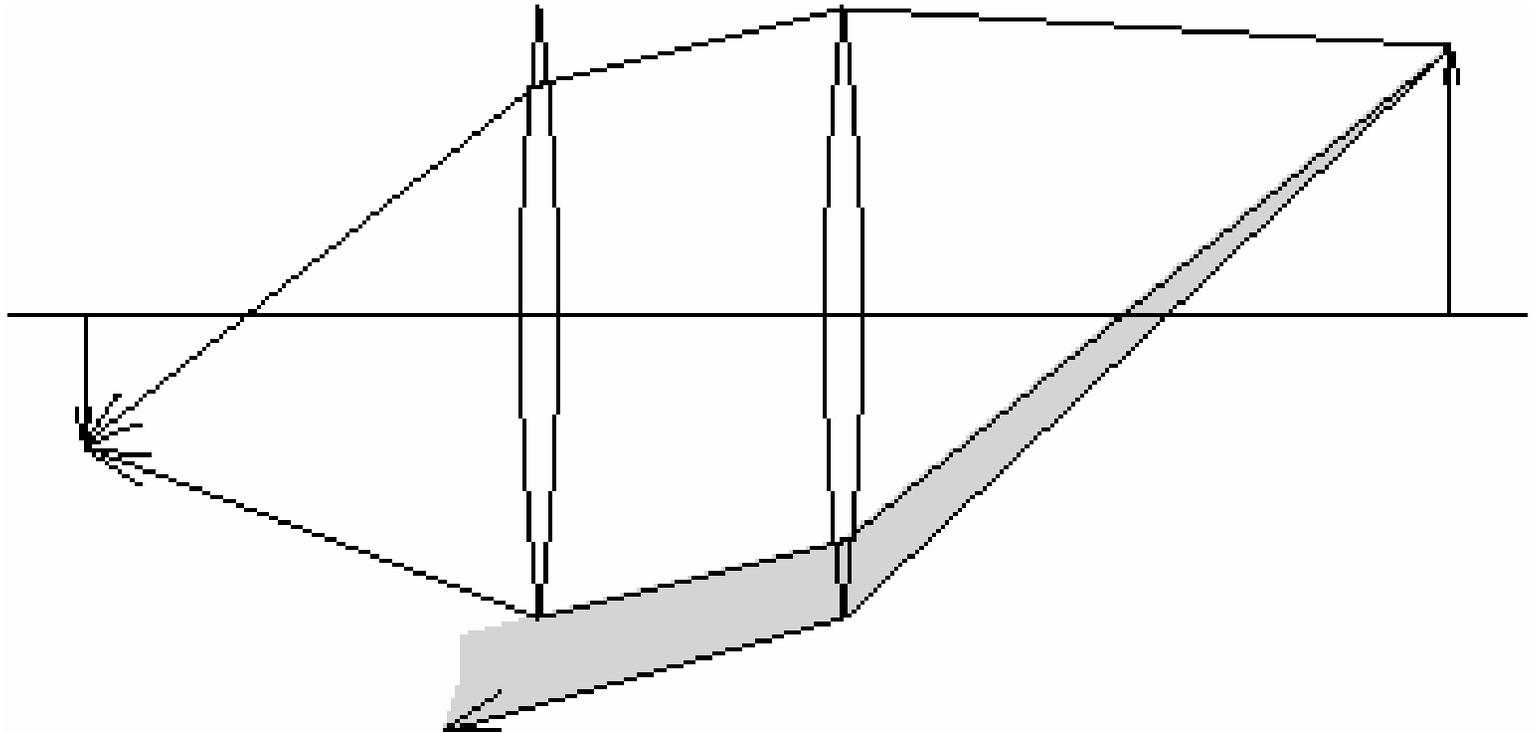
FIG. 45.—An illustration of the character of astigmatic images.

Lens systems



Lens systems can be designed to correct for aberrations described by 3rd order optics

Vignetting



Chromatic aberration

(great for prisms, bad for lenses)



Other (possibly annoying) phenomena

- Chromatic aberration
 - Light at different wavelengths follows different paths; hence, some wavelengths are defocussed
 - Machines: coat the lens
 - Humans: live with it
- Scattering at the lens surface
 - Some light entering the lens system is reflected off each surface it encounters (Fresnel's law gives details)
 - Machines: coat the lens, interior
 - Humans: live with it (various scattering phenomena are visible in the human eye)

Summary

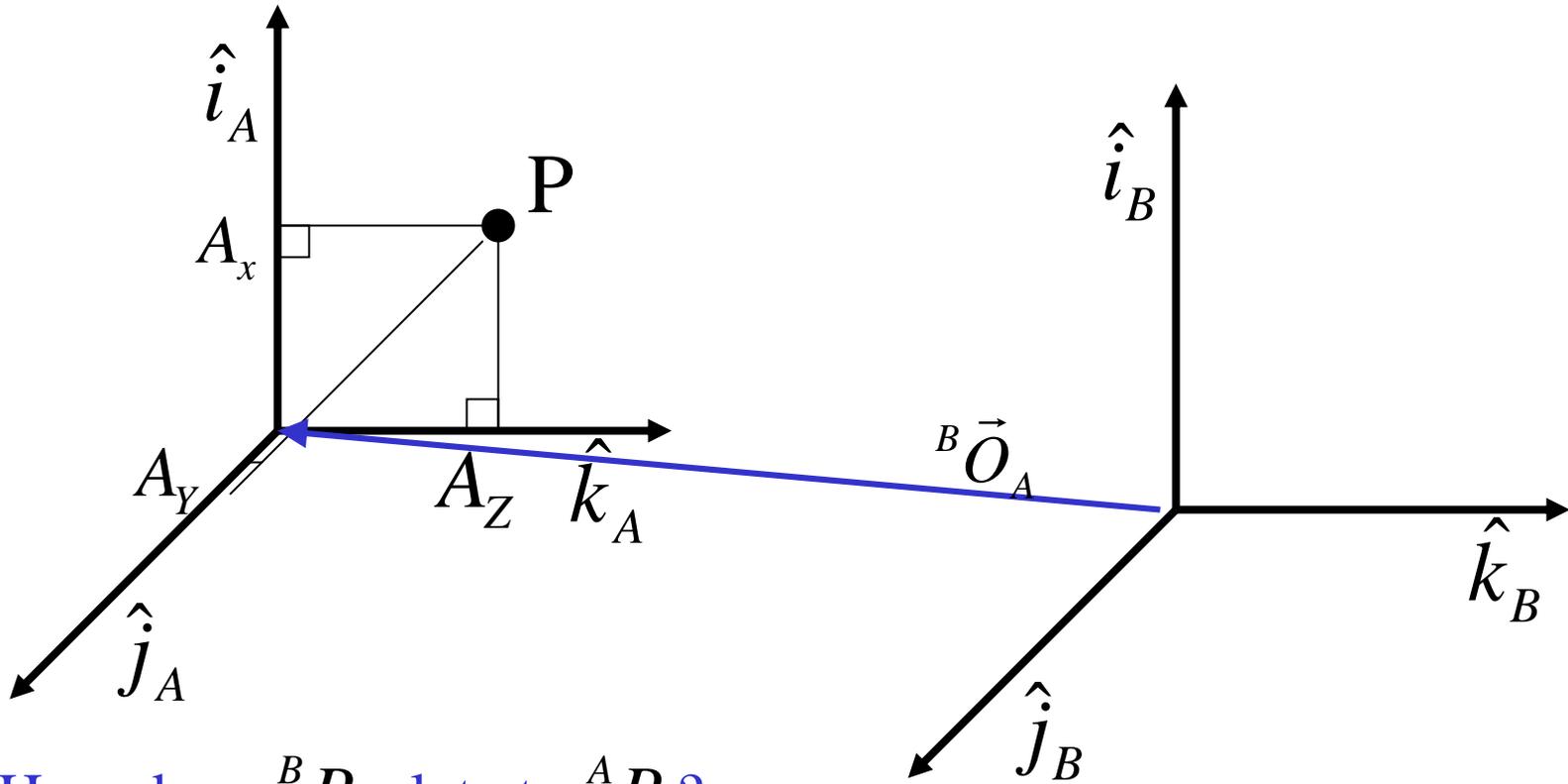
- Want to make images
- Pinhole camera models the geometry of perspective projection
- Lenses make it work in practice
- Models for lenses
 - Thin lens, spherical surfaces, first order optics
 - Thick lens, higher-order optics, vignetting.

Next

- how *positions* in the image relate to 3-d positions in the world.

Translation

$${}^A P = \begin{pmatrix} A_x \\ A_y \\ A_z \end{pmatrix} \quad {}^B P = \begin{pmatrix} B_x \\ B_y \\ B_z \end{pmatrix}$$



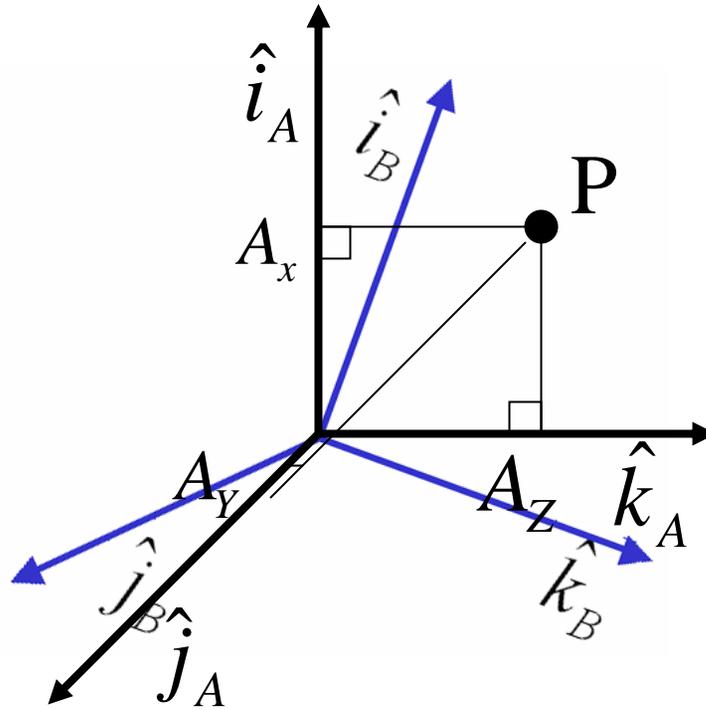
How does ${}^B P$ relate to ${}^A P$?

$${}^B P = {}^A P + {}^B O_A$$

Rotation

$${}^A P = \begin{pmatrix} A_x \\ A_y \\ A_z \end{pmatrix}$$

$${}^B P = \begin{pmatrix} B_x \\ B_y \\ B_z \end{pmatrix}$$

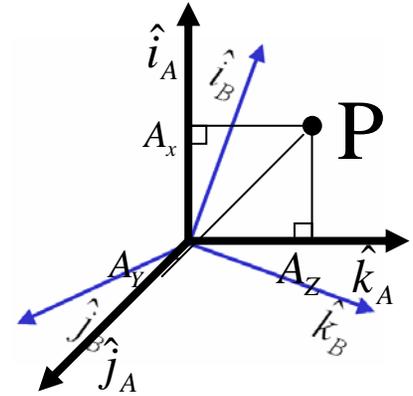


How does ${}^B P$ relate to ${}^A P$?

$${}^B P = {}^B_A R {}^A P$$

Find the rotation matrix

$$\text{Project } \overrightarrow{OP} = \begin{pmatrix} \hat{i}_A & \hat{j}_A & \hat{k}_A \end{pmatrix} \begin{pmatrix} A_X \\ A_Y \\ A_Z \end{pmatrix}$$



onto the B frame's coordinate axes.

$$\begin{pmatrix} B_X \\ B_Y \\ B_Z \end{pmatrix} = \begin{pmatrix} \hat{i}_B \cdot \hat{i}_A A_X & \hat{i}_B \cdot \hat{j}_A A_Y & \hat{i}_B \cdot \hat{k}_A A_Z \\ \hat{j}_B \cdot \hat{i}_A A_X & \hat{j}_B \cdot \hat{j}_A A_Y & \hat{j}_B \cdot \hat{k}_A A_Z \\ \hat{k}_B \cdot \hat{i}_A A_X & \hat{k}_B \cdot \hat{j}_A A_Y & \hat{k}_B \cdot \hat{k}_A A_Z \end{pmatrix}$$

Rotation matrix

this

$$\begin{pmatrix} B_X \\ B_Y \\ B_Z \end{pmatrix} = \begin{pmatrix} \hat{i}_B \bullet \hat{i}_A A_X & \hat{i}_B \bullet \hat{j}_A A_Y & \hat{i}_B \bullet \hat{k}_A A_Z \\ \hat{j}_B \bullet \hat{i}_A A_X & \hat{j}_B \bullet \hat{j}_A A_Y & \hat{j}_B \bullet \hat{k}_A A_Z \\ \hat{k}_B \bullet \hat{i}_A A_X & \hat{k}_B \bullet \hat{j}_A A_Y & \hat{k}_B \bullet \hat{k}_A A_Z \end{pmatrix}$$

implies

$${}^B P = {}^B R {}^A P$$

where

$${}^B R = \begin{pmatrix} \hat{i}_B \bullet \hat{i}_A & \hat{i}_B \bullet \hat{j}_A & \hat{i}_B \bullet \hat{k}_A \\ \hat{j}_B \bullet \hat{i}_A & \hat{j}_B \bullet \hat{j}_A & \hat{j}_B \bullet \hat{k}_A \\ \hat{k}_B \bullet \hat{i}_A & \hat{k}_B \bullet \hat{j}_A & \hat{k}_B \bullet \hat{k}_A \end{pmatrix}$$

Translation and rotation

Let's write ${}^B P = {}^B R {}^A P + {}^B O_A$

as a single matrix equation:

$$\begin{pmatrix} B_X \\ B_Y \\ B_Z \\ 1 \end{pmatrix} = \begin{pmatrix} - & - & - \\ - & {}^B R & - \\ - & - & - \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} | \\ {}^B O_A \\ | \\ 1 \end{pmatrix} \begin{pmatrix} A_X \\ A_Y \\ A_Z \\ 1 \end{pmatrix}$$