Deep Learning for Computer Vision

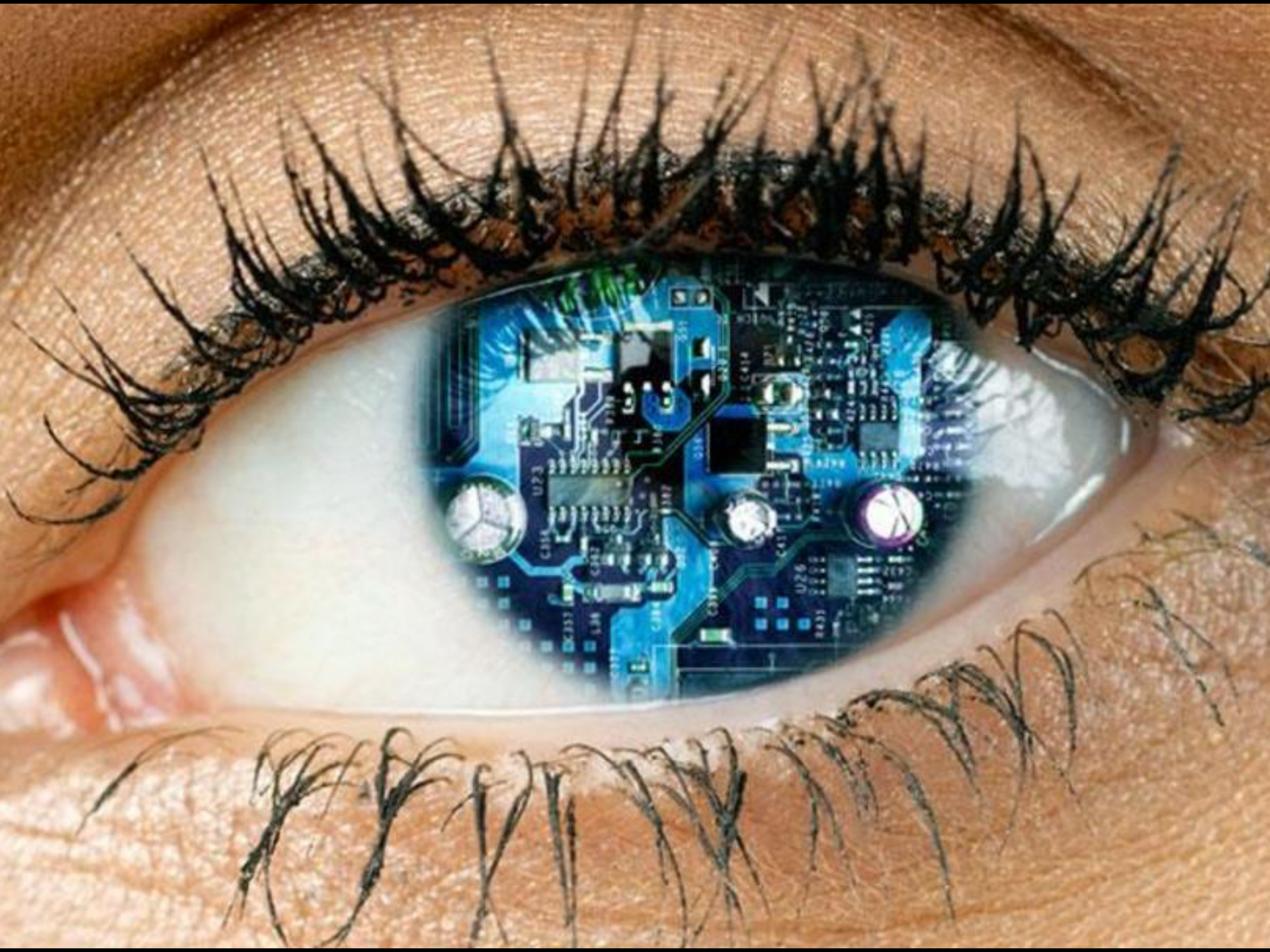
Lecture 1: An Introduction to Old-School Computer Vision

Peter Belhumeur

Computer Science
Columbia University

08 02 22 97 38 15 00 40 00 75 04 05 07 78 52 12 50 77 91 08
49 49 99 40 17 81 18 57 60 87 17 40 98 43 69 48 04 56 62 00
81 49 31 73 55 79 14 29 93 71 40 67 53 88 30 03 49 13 36 65
52 70 95 23 04 60 11 42 69 24 68 56 01 32 56 71 37 02 36 91
22 31 16 71 51 67 63 89 41 92 36 54 22 40 40 28 66 33 13 80
24 47 32 60 99 03 45 02 44 75 33 53 78 36 84 20 35 17 12 50
32 98 81 28 64 23 67 10 26 38 40 67 59 54 70 66 18 38 64 70
67 26 20 68 02 62 12 20 95 63 94 39 63 08 40 91 66 49 94 21
24 55 58 05 66 73 99 26 97 17 78 78 96 83 14 88 34 89 63 72
21 36 23 09 75 00 76 44 20 45 35 14 00 61 33 97 34 31 33 95
78 17 53 28 22 75 31 67 15 94 03 80 04 62 16 14 09 53 56 92
16 39 05 42 96 35 31 47 55 58 88 24 00 17 54 24 36 29 85 57
86 56 00 48 35 71 89 07 05 44 44 37 44 60 21 58 51 54 17 58
19 80 81 68 05 94 47 69 28 73 92 13 86 52 17 77 04 89 55 40
04 52 08 83 97 35 99 16 07 97 57 32 16 26 26 79 33 27 98 66
88 36 68 87 57 62 20 72 03 46 33 67 46 55 12 32 63 93 53 69
04 42 16 73 38 25 39 11 24 94 72 18 08 46 29 32 40 62 76 36
20 69 36 41 72 30 23 88 34 62 99 69 82 67 59 85 74 04 36 16
20 73 35 29 78 31 90 01 74 31 49 71 48 86 81 16 23 57 05 54
01 70 54 71 83 51 54 69 16 92 33 48 61 43 52 01 89 19 67 48

Find these pixels in this image:



They aren’t there.

08 02 22 97 38 15 00 40 00 75 04 05 07 78 52 12 50 77 91 08
49 49 99 40 17 81 18 57 60 87 17 40 98 43 69 48 04 56 62 00
81 49 31 73 55 79 14 29 93 71 40 67 53 88 30 03 49 13 36 65
52 70 95 23 04 60 11 42 69 24 68 56 01 32 56 71 37 02 36 91
22 31 16 71 51 67 63 89 41 92 36 54 22 40 40 28 66 33 13 80
24 47 32 60 99 03 45 02 44 75 33 53 78 36 84 20 35 17 12 50
32 98 81 28 64 23 67 10 26 38 40 67 59 54 70 66 18 38 64 70
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24 55 58 05 66 73 99 26 97 17 78 78 96 83 14 88 34 89 63 72
21 36 23 09 75 00 76 44 20 45 35 14 00 61 33 97 34 31 33 95
78 17 53 28 22 75 31 67 15 94 03 80 04 62 16 14 09 53 56 92
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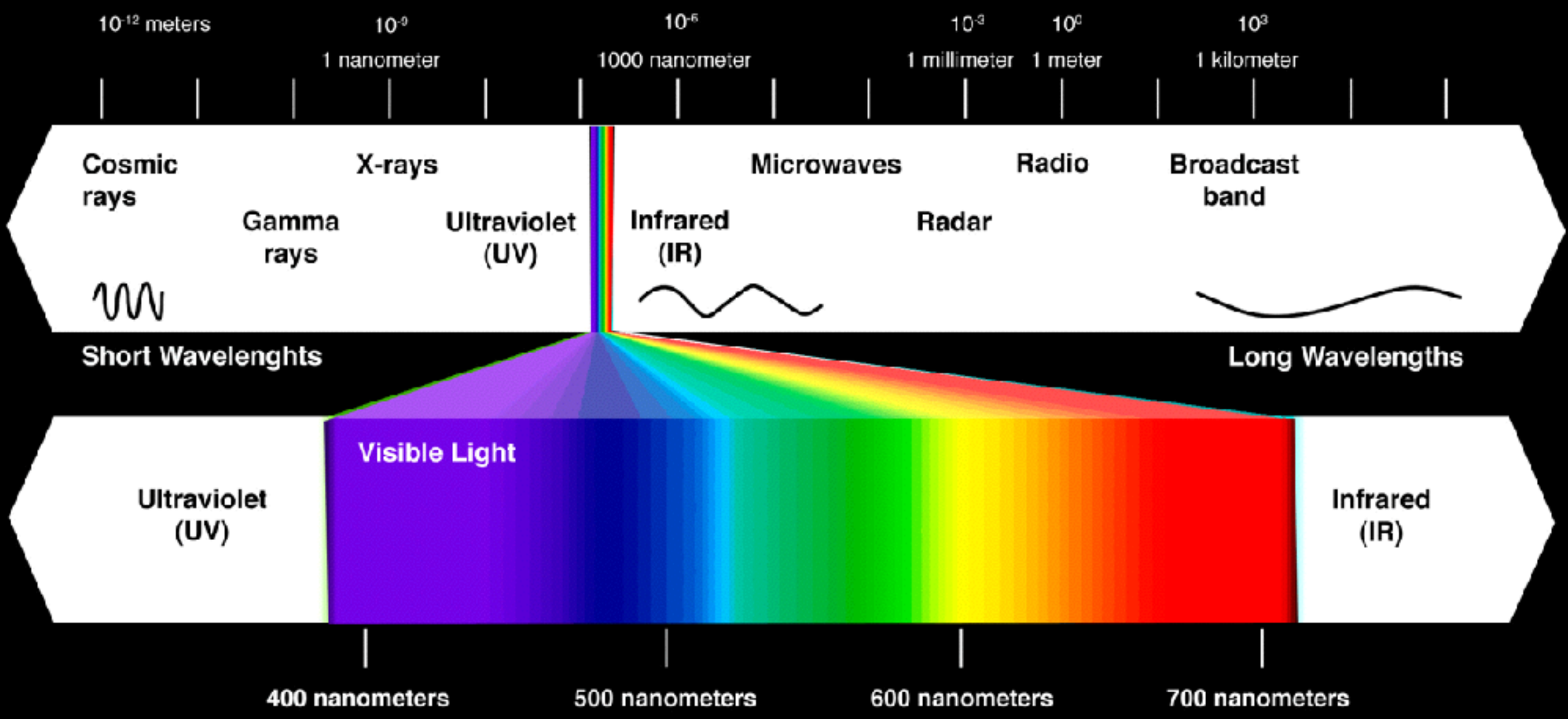
19 80 81 68 05 94 47 69 28 73 92 13 86 52 17 77 04 89 55 40
04 52 08 83 97 35 99 16 07 97 57 32 16 26 26 79 33 27 98 66
88 36 68 87 57 62 20 72 03 46 33 67 46 55 12 32 63 93 53 69
04 42 16 73 38 25 39 11 24 94 72 18 08 46 29 32 40 62 76 36
20 69 36 41 72 30 23 88 34 62 99 69 82 67 59 85 74 04 36 16
20 73 35 29 78 31 90 01 74 31 49 71 48 86 81 16 23 57 05 54
01 70 54 71 83 51 54 69 16 92 33 48 61 43 52 01 89 19 67 48

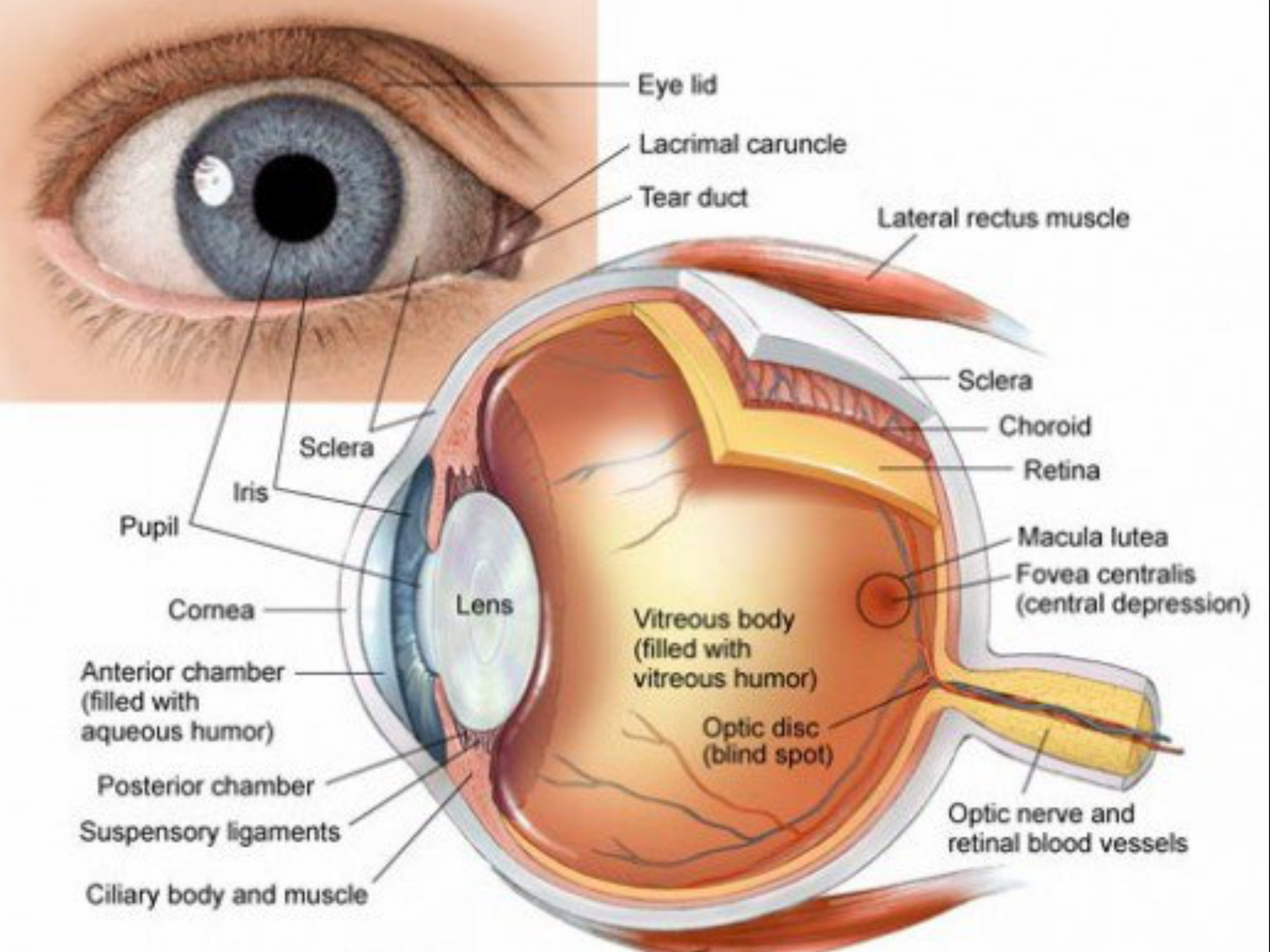
When you strip away the machinery of the human visual system, you have to start at the beginning…

What is vision?


10^{-12} meters
10^{-9}
1 nanometer
10^{-6}
1000 nanometer
10^{-3}
1 millimeter
10^{0}
1 meter
10^{3}
1 kilometer
Cosmic rays
Gamma rays
X-rays
Ultraviolet (UV)
Infrared (IR)
Microwaves
Radar
Radio
Broadcast band
Short Wavelenghts
Long Wavelengths
Visible Light
Ultraviolet (UV)
Infrared (IR)
400 nanometers
500 nanometers
600 nanometers
700 nanometers

Light

Visible light **travels in straight lines** and is not bent or diffracted by objects that we interact with like animals, buildings, furniture, etc.


Eye lid
Lacrimal caruncle
Tear duct
Lateral rectus muscle
Sclera
Choroid
Retina
Macula lutea
Fovea centralis
(central depression)
Optic nerve and
retinal blood vessels
Optic disc
(blind spot)
Vitreous body
(filled with
vitreous humor)
Lens
Sclera
Iris
Pupil
Cornea
Anterior chamber
(filled with
aqueous humor)
Posterior chamber
Suspensory ligaments
Ciliary body and muscle

Distant Object

50 Meters

Cornea

Changes in Lens Shape

Retina

Vitreous Humor

Sclera

Optic Nerve

Nearby Object

25 Centimeters

Cornea

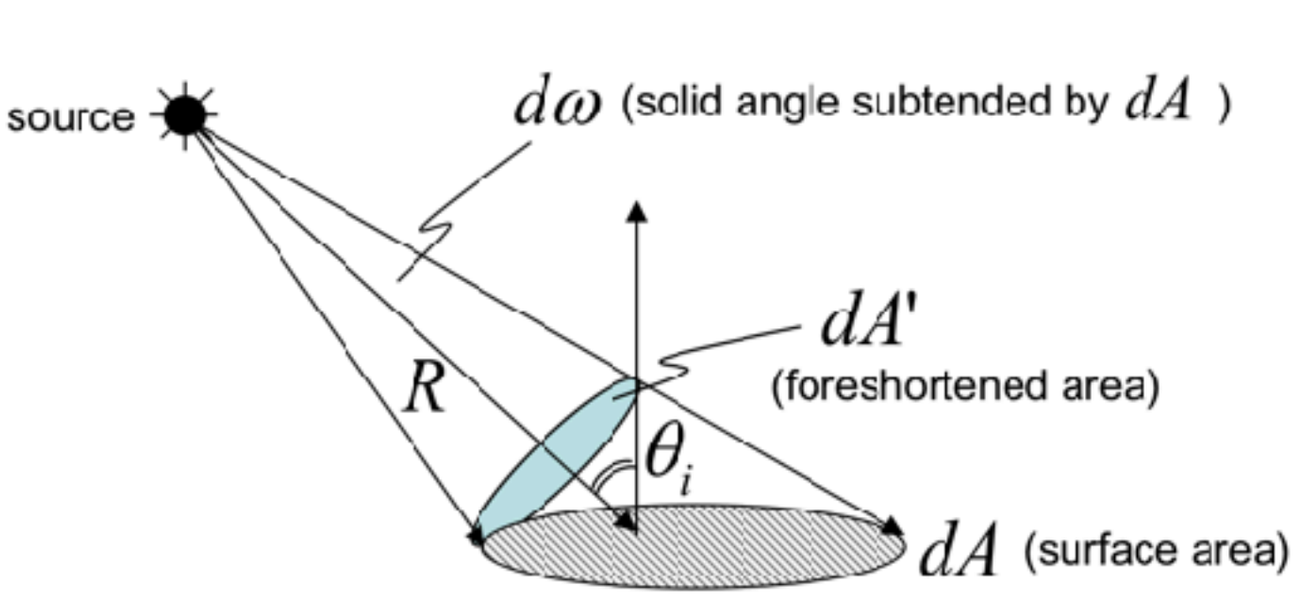
Optic Nerve

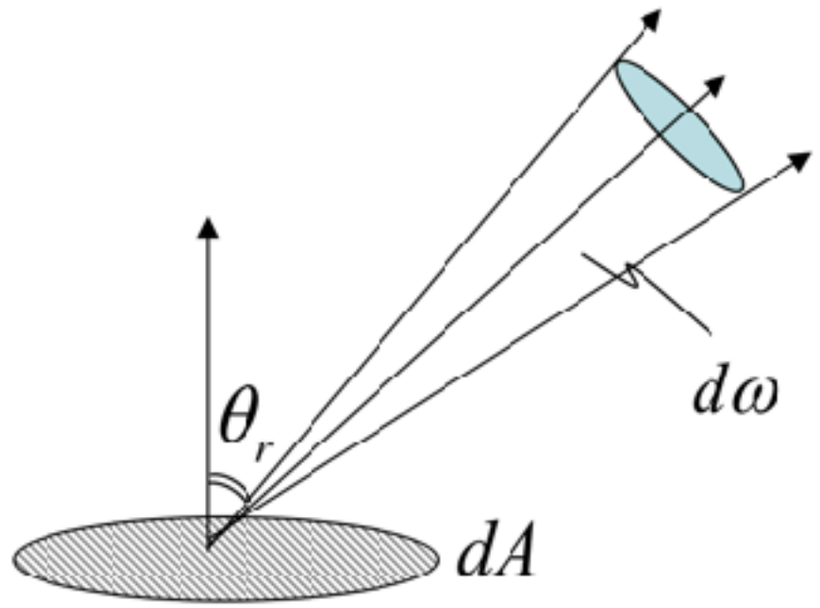
So what can vision measure?

- **radiance** ≈ how much light is reflected by the surface in a particular direction

- **radiance** = the radiant flux emitted by a *surface*, per unit solid angle per unit *projected* area

Radiometric Concepts





(1) Solid Angle : $d\omega = \dfrac{dA'}{R^2} = \dfrac{dA\cos\theta_i}{R^2}$ (steradian)

What is the solid angle subtended by a hemisphere?

(2) Radiant Intensity of Source : $J = \dfrac{d\Phi}{d\omega}$ (watts / steradian)

Light Flux (power) emitted per unit solid angle

(3) Surface Irradiance : $E = \dfrac{d\Phi}{dA}$ (watts / m^2)

Light Flux (power) incident per unit surface area.

Does not depend on where the light is coming from!

(4) Surface Radiance (tricky) :

$$L = \frac{d\Phi}{(dA\cos\theta_r)\ d\omega}$$ (watts / m^2 steradian)

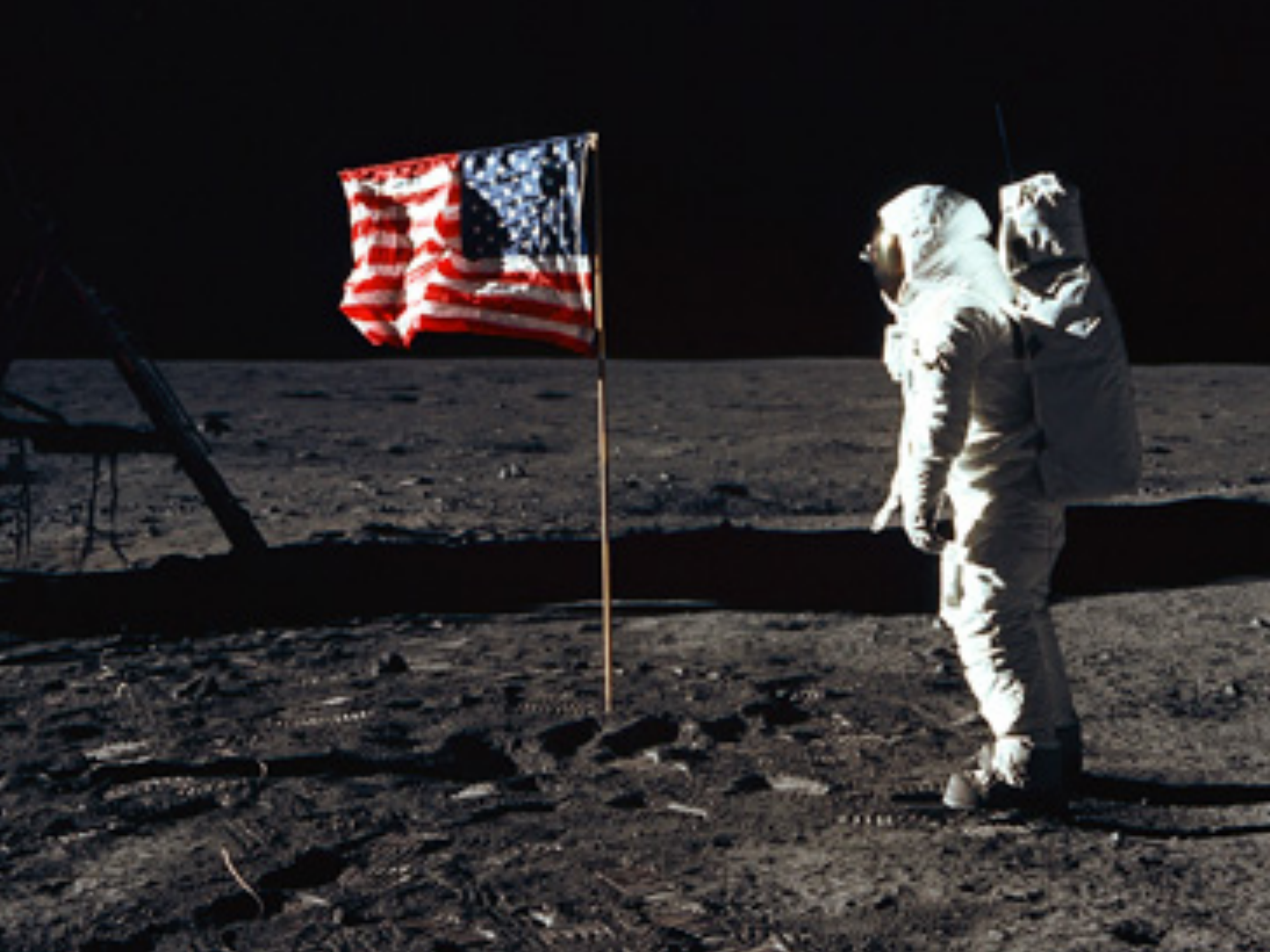
- Flux emitted per unit foreshortened area per unit solid angle.
- L depends on direction θ_r
- Surface can radiate into whole hemisphere.
- L depends on reflectance properties of surface.

So what can vision measure?

- so vision can measure the amount of light reflected back toward the eye by each point in the field of view as a function of time

- NOT size
- NOT weight
- NOT smell
- NOT temperature
- NOT chemical composition…

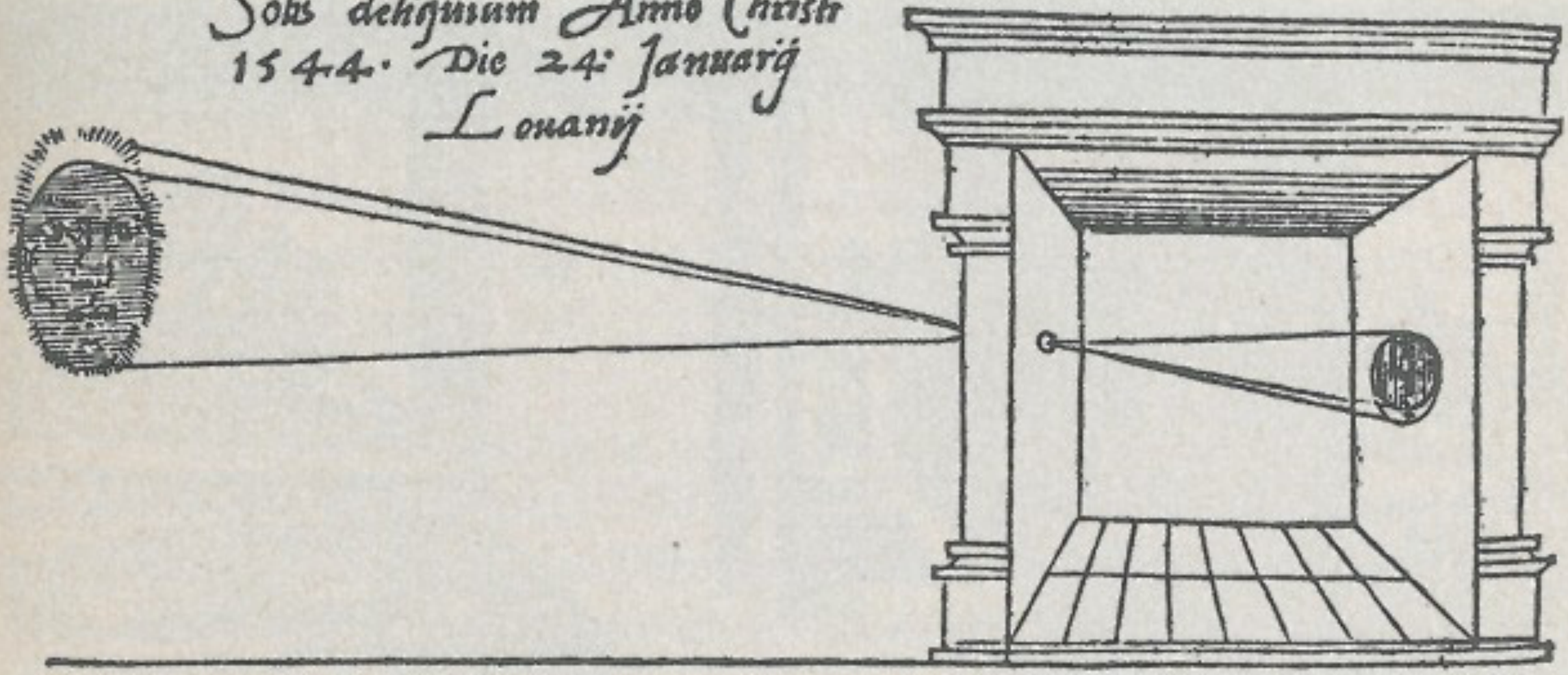
But from vision we can infer an awful lot based on innate or learned experience…



But what about computers?

Leonardo da Vinci’s
Codex Atlanticus (1490)

Camera Obscura

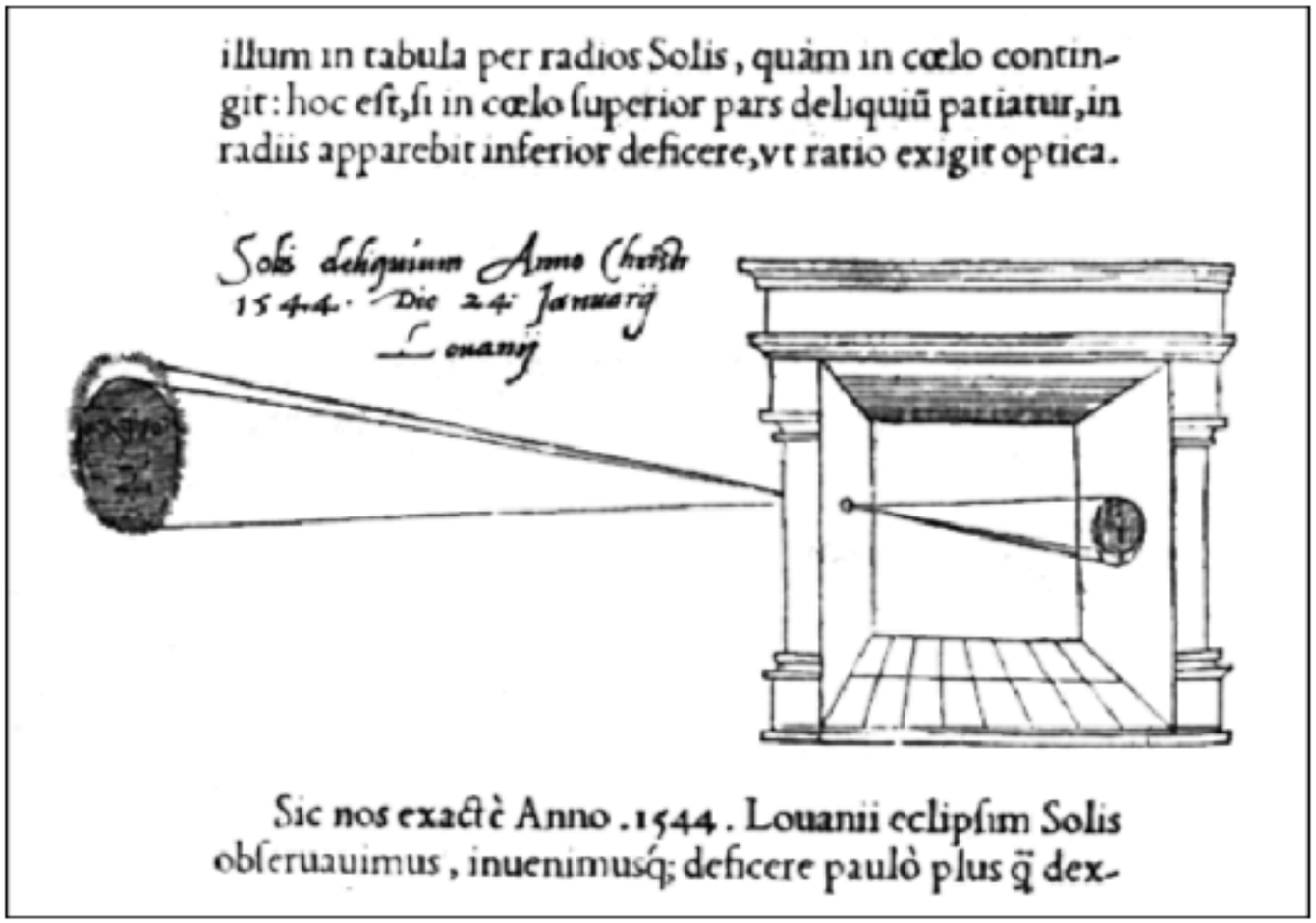


Camera Obscura

Gemma Frisius' 1545 De Radio Astronomica and Geometrica

Camera Obscura (1490)

Next


illum in tabula per radios Solis, quàm in cœlo contingit: hoc est, si in cœlo superior pars deliquiũ patiatur, in radiis apparebit inferior deficere, vt ratio exigit optica.

Solis deliquium Anno Christi 1544. Die 24. Januarij Louanij

Sic nos exactè Anno .1544. Louanii eclipsim Solis obseruauimus, inuenimusq; deficere paulò plus q̃ dex-

A camera obscura is a dark box with a small hole in the front. Light passes through this hole and lands on the back of the box, casting an upside-down version of the scene. Although this idea had been understood by scholars for hundreds of years, Leonardo da Vinci (1452-1519) was the first to write a detailed description of the camera obscura in his *Atlantic Codex* in 1490. An astronomer named Gemma Frisius (1508-1555) was the first to draw a camera obscura around 1545.

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Printed in Great Britain

RECEPTIVE FIELDS, BINOCULAR INTERACTION AND FUNCTIONAL ARCHITECTURE IN THE CAT'S VISUAL CORTEX

BY D. H. HUBEL AND T. N. WIESEL
From the Neurophysiology Laboratory, Department of Pharmacology Harvard Medical School, Boston, Massachusetts, U.S.A.

(*Received* 31 *July* 1961)

What chiefly distinguishes cerebral cortex from other parts of the central nervous system is the great diversity of its cell types and interconnexions. It would be astonishing if such a structure did not profoundly modify the response patterns of fibres coming into it. In the cat's visual cortex, the receptive field arrangements of single cells suggest that there is indeed a degree of complexity far exceeding anything yet seen at lower levels in the visual system.

In a previous paper we described receptive fields of single cortical cells, observing responses to spots of light shone on one or both retinas (Hubel & Wiesel, 1959). In the present work this method is used to examine receptive fields of a more complex type (Part I) and to make additional observations on binocular interaction (Part II).

This approach is necessary in order to understand the behaviour of individual cells, but it fails to deal with the problem of the relationship of one cell to its neighbours. In the past, the technique of recording evoked slow waves has been used with great success in studies of functional anatomy. It was employed by Talbot & Marshall (1941) and by Thompson, Woolsey & Talbot (1950) for mapping out the visual cortex in the rabbit, cat, and monkey. Daniel & Whitteridge (1959) have recently extended this work in the primate. Most of our present knowledge of retinotopic projections, binocular overlap, and the second visual area is based on these investigations. Yet the method of evoked potentials is valuable mainly for detecting behaviour common to large populations of neighbouring cells; it cannot differentiate functionally between areas of cortex smaller than about 1 mm^2. To overcome this difficulty a method has in recent years been developed for studying cells separately or in small groups during long micro-electrode penetrations through nervous tissue. Responses are correlated with cell location by reconstructing the electrode tracks from histological material. These techniques have been applied to

Hubel and Wiesel's 1962 single cell recordings in the cat's visual cortex

Visual Cortex

Mapping receptive fields

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

PROJECT MAC

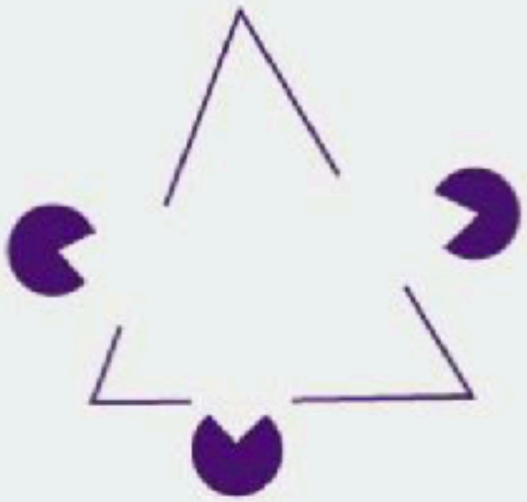
Artificial Intelligence Group July 7, 1966
Vision Memo. No. 100.

THE SUMMER VISION PROJECT

Seymour Papert

The summer vision project is an attempt to use our summer workers effectively in the construction of a significant part of a visual system. The particular task was chosen partly because it can be segmented into sub-problems which will allow individuals to work independently and yet participate in the construction of a system complex enough to be a real landmark in the development of "pattern recognition".

VISION

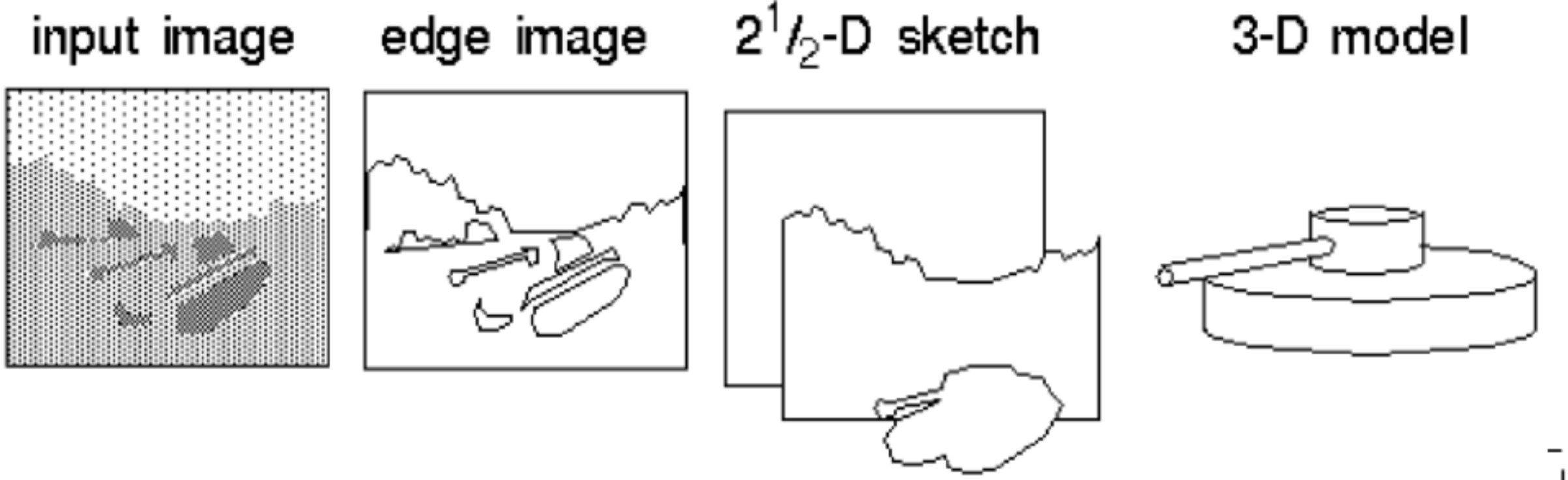


David Marr

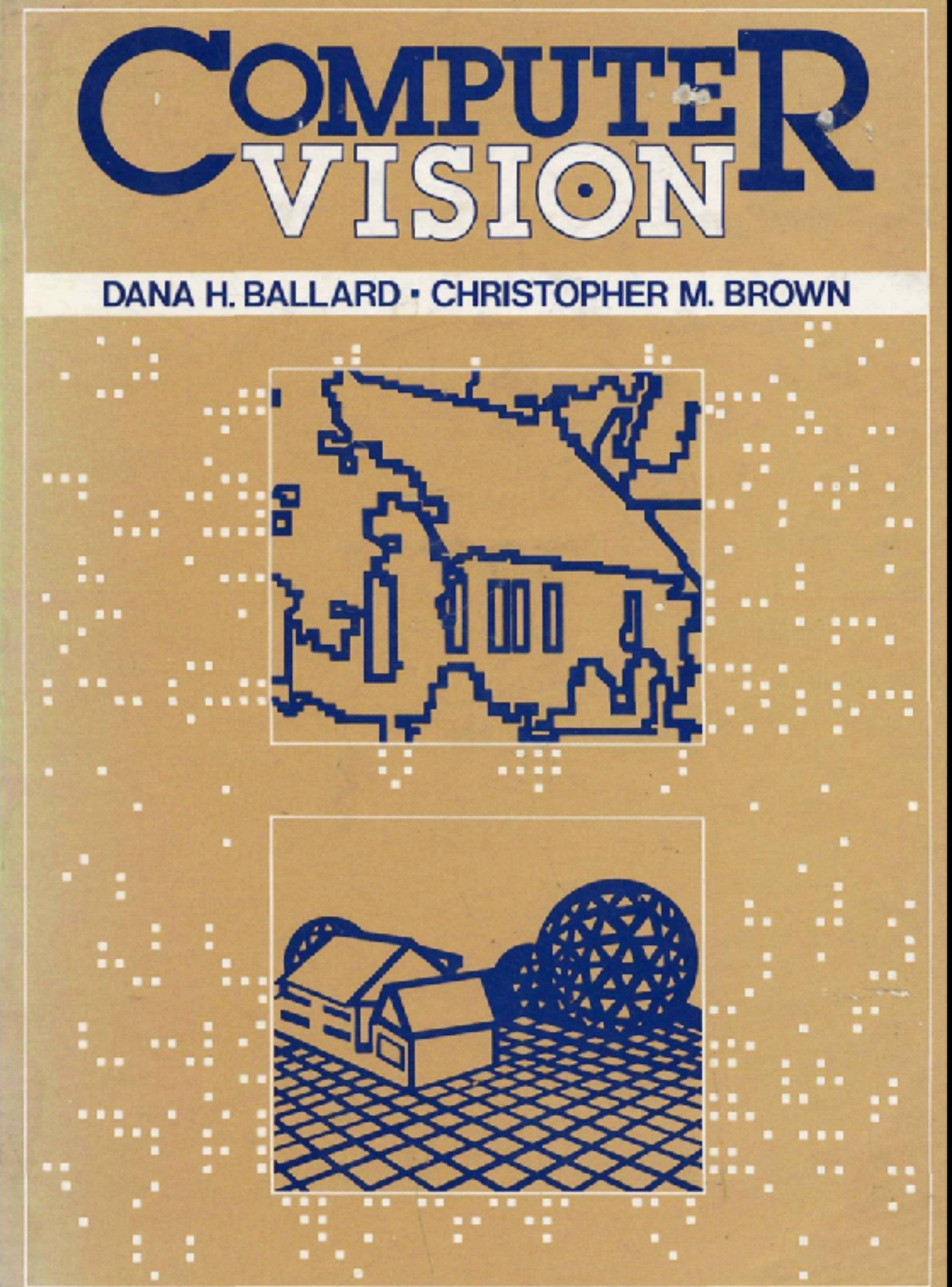
FOREWORD BY
Shimon Ullman

AFTERWORD BY
Tomaso Poggio

Vision from a 1970s neuroscience perspective



Stages of Visual Representation, David Marr



Vision from a 1982
computer science perspective

(3.57) as closely as possible and also is locally smooth [Horn and Schunck 1980]. In this case as well, the Laplacians of the two velocity components, $\nabla^2 u$ and $\nabla^2 v$, can measure local smoothness.

Again using the method of Lagrange multipliers, minimize the flow error

$$E^2(x, y) = (f_x u + f_y v + f_t)^2 + \lambda^2[(\nabla^2 u)^2 + (\nabla^2 v)^2] \tag{3.58}$$

Differentiating this equation with respect to u and v provides equations for the change in error with respect to u and v, which must be zero for a minimum. Writing $\nabla^2 u$ as $u - u_{av}$ and $\nabla^2 v$ as $v - v_{av}$, these equations are

$$(\lambda^2 + f_x^2)u + f_x f_y v = \lambda^2 u_{av} - f_x f_t \tag{3.59}$$

$$f_x f_y u + (\lambda^2 + f_y^2)v = \lambda^2 v_{av} - f_y f_t \tag{3.60}$$

These equations may be solved for u and v, yielding

$$u = u_{av} - f_x \frac{P}{D} \tag{3.61}$$

$$v = v_{av} - f_y \frac{P}{D} \tag{3.62}$$

where

$$P = f_x u_{av} + f_y v_{av} + f_t$$

$$D = \lambda^2 + f_x^2 + f_y^2$$

To turn this into an iterative equation for solving $u(x, y)$ and $v(x, y)$, again use the Gauss-Seidel method.

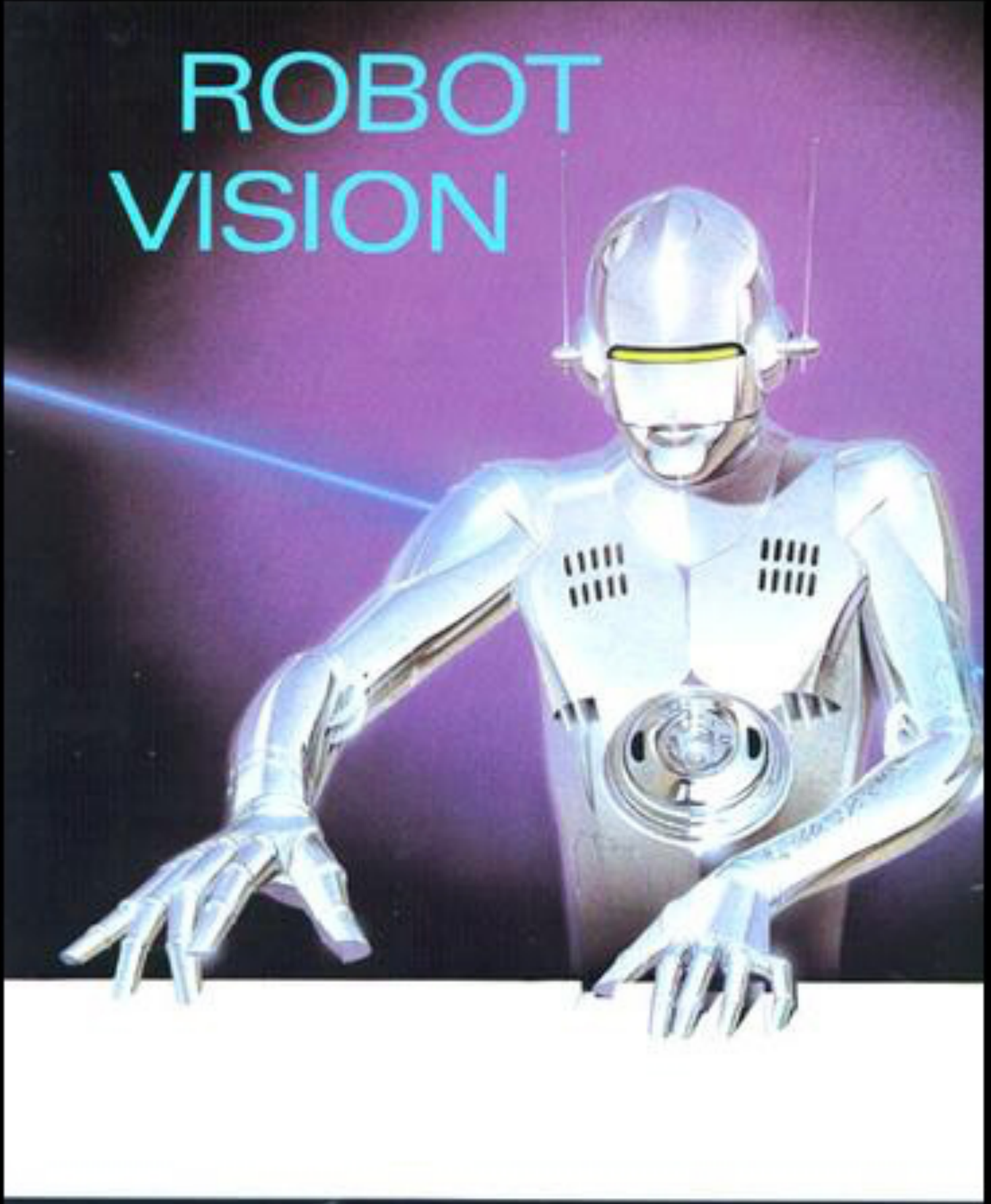
Algorithm 3.4: Optical Flow [Horn and Schunck 1980].

$k = 0$.
Initialize all u^k and v^k to zero.
Until some error measure is satisfied, do

$$u^k = u_{av}^{k-1} - f_x \frac{P}{D}$$

$$v^k = v_{av}^{k-1} - f_y \frac{P}{D}$$

As Horn and Schunck demonstrate, this method derives the flow for two time frames, but it can be improved by using several time frames and using the final solution after one iteration at one time for the initial solution at the following time frame. That is:



Vision from a 1986
electrical eng. perspective

for some m. This is the *Poisson* distribution. We can calculate the average number liberated in time T as follows:

$$\sum_{n=1}^{\infty} n e^{-m} \frac{m^n}{n!} = m e^{-m} \sum_{n=1}^{\infty} \frac{m^{n-1}}{(n-1)!}.$$

But

$$\sum_{n=1}^{\infty} \frac{m^{n-1}}{(n-1)!} = \sum_{n=0}^{\infty} \frac{m^n}{n!} = e^m,$$

so the average is just m. We show in exercise 2-18 that the variance is also m. The standard deviation is thus $\sqrt{m}$, so that the ratio of the standard deviation to the mean is $1/\sqrt{m}$. The measurement becomes more accurate the longer we wait, since more electrons are gathered. Again, the ratio of the "signal" to the "noise" only improves as the square root of the average number of electrons collected, however.

To obtain reasonable results, many electrons must be measured. It can be shown that a Poisson distribution with mean m is almost the same as a Gaussian distribution with mean m and variance m, provided that m is large. The Gaussian distribution is often easier to work with. In any case, to obtain a standard deviation that is one-thousandth of the mean, one must wait long enough to collect a million electrons. This is a small charge still, since one electron carries only

$$\epsilon = 1.602192\ldots \times 10^{-19} \text{ Coulomb}.$$

Even a million electrons have a charge of only about 160 fC (femto-Coulomb). (The prefix *femto-* denotes a multiplier of 10^{-15}.) It is not easy to measure such a small charge, since noise is introduced in the measurement process.

The number of electrons liberated from an area δA in time δt is

$$N = \delta A\, \delta t \int_{-\infty}^{\infty} b(\lambda)\, q(\lambda)\, d\lambda,$$

where $q(\lambda)$ is the quantum efficiency and $b(\lambda)$ is the image irradiance in photons per unit area. To obtain a usable result, then, electrons must be collected from a finite image area over a finite amount of time. There is thus a trade-off between (spatial and temporal) resolution and accuracy.

A measurement of the number of electrons liberated in a small area during a fixed time interval produces a result that is proportional to the irradiance (for fixed spectral distribution of incident photons). These measurements are quantized in order to read them into a digital computer.

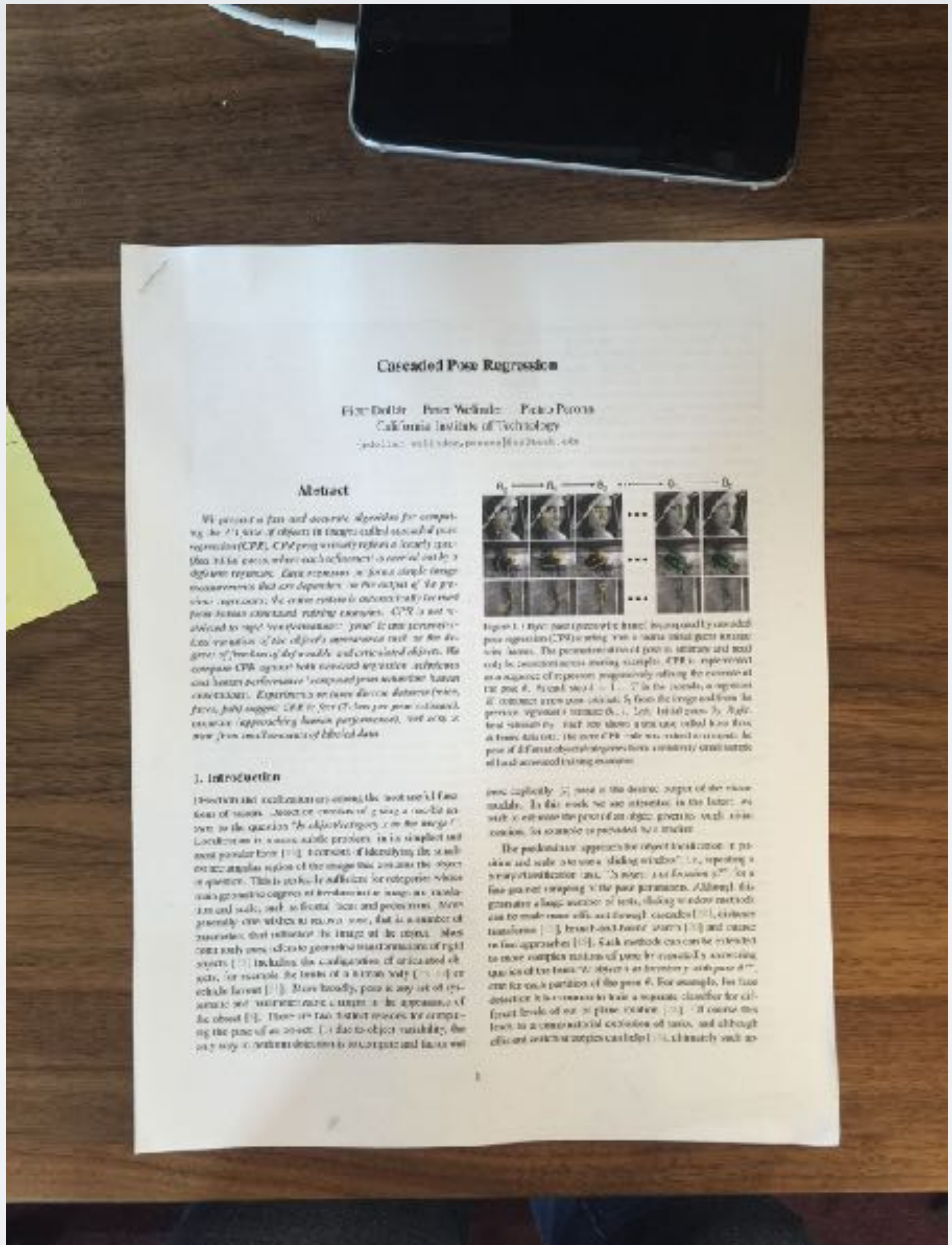
Computer Vision Algorithm: Document Scanner

DOC SCANNER

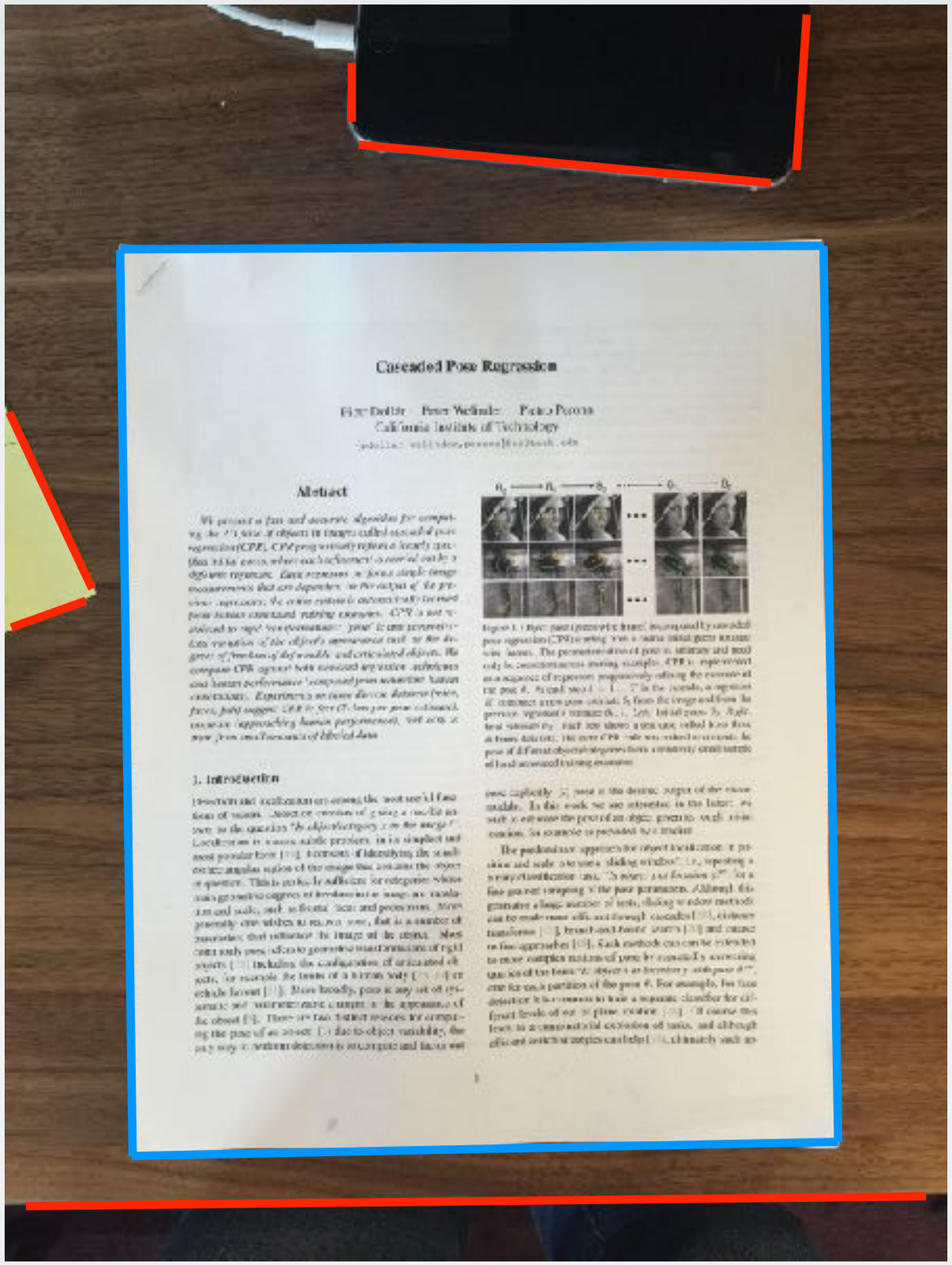
ML TEAM @ DROPBOX

Dropbox Tech Blog

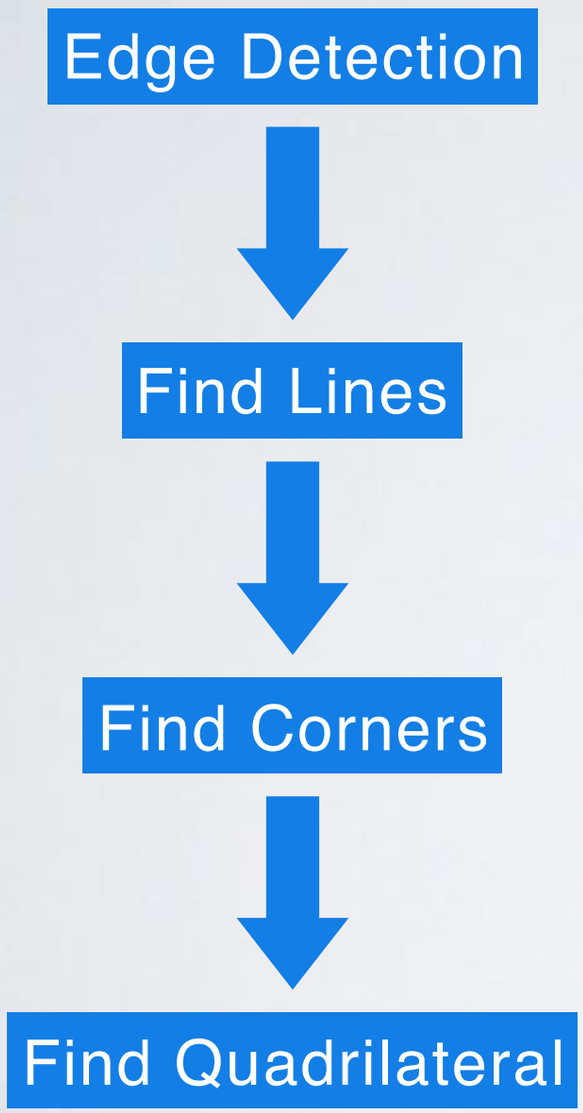
DOCUMENT DETECTION



DOCUMENT DETECTION



STEP BY STEP


Edge Detection
Find Lines
Find Corners
Find Quadrilateral

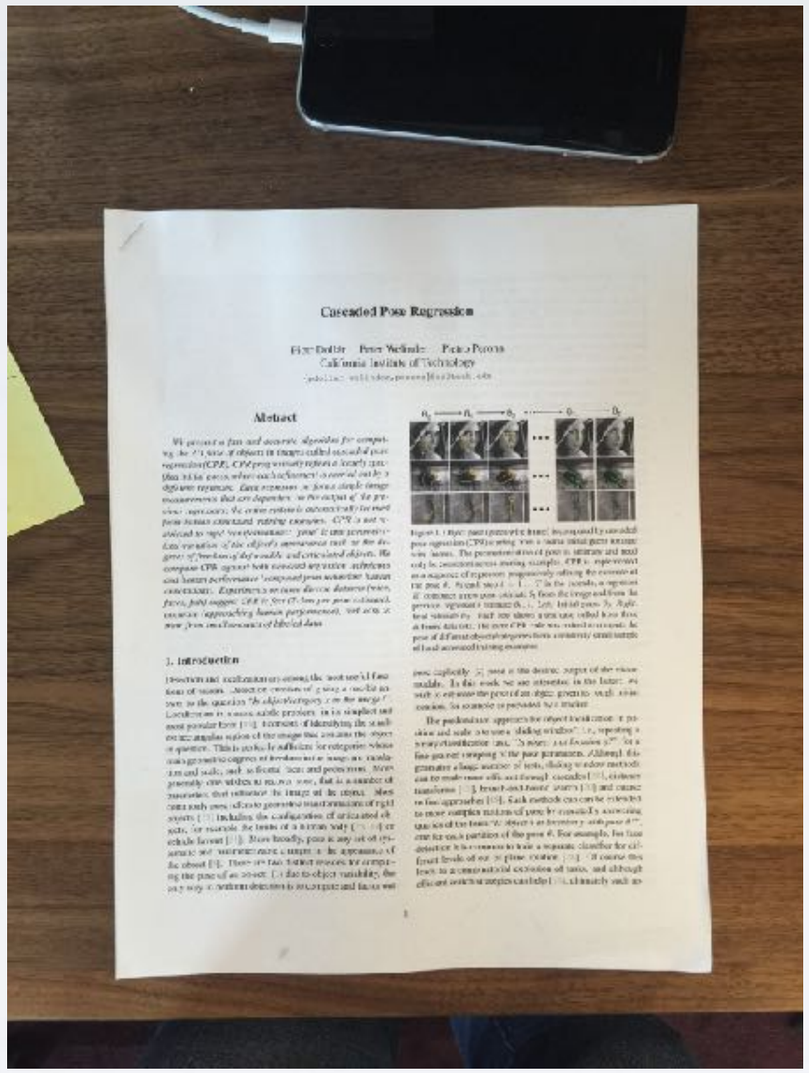
STEP BY STEP

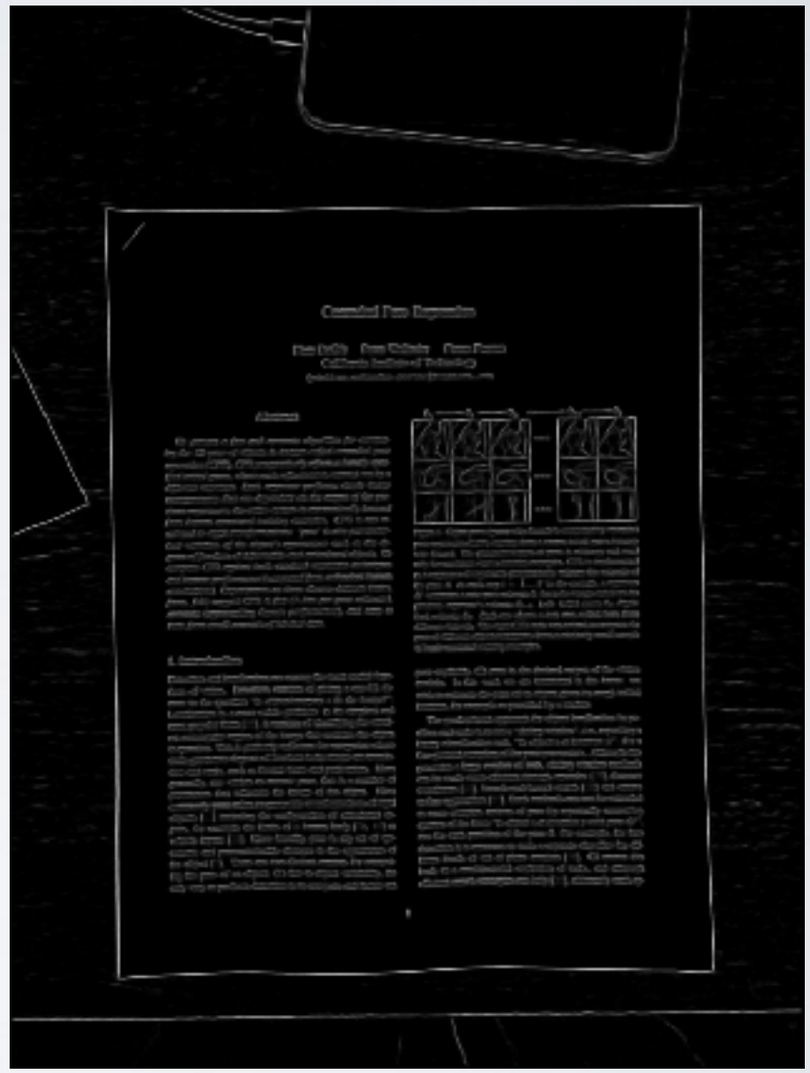
Edge Detection

Find Lines

Find Corners

Find Quadrilateral





ML-Based Detector

STEP BY STEP

Edge Detection

Find Lines

Find Corners

Find Quadrilateral

STEP BY STEP

Edge Detection

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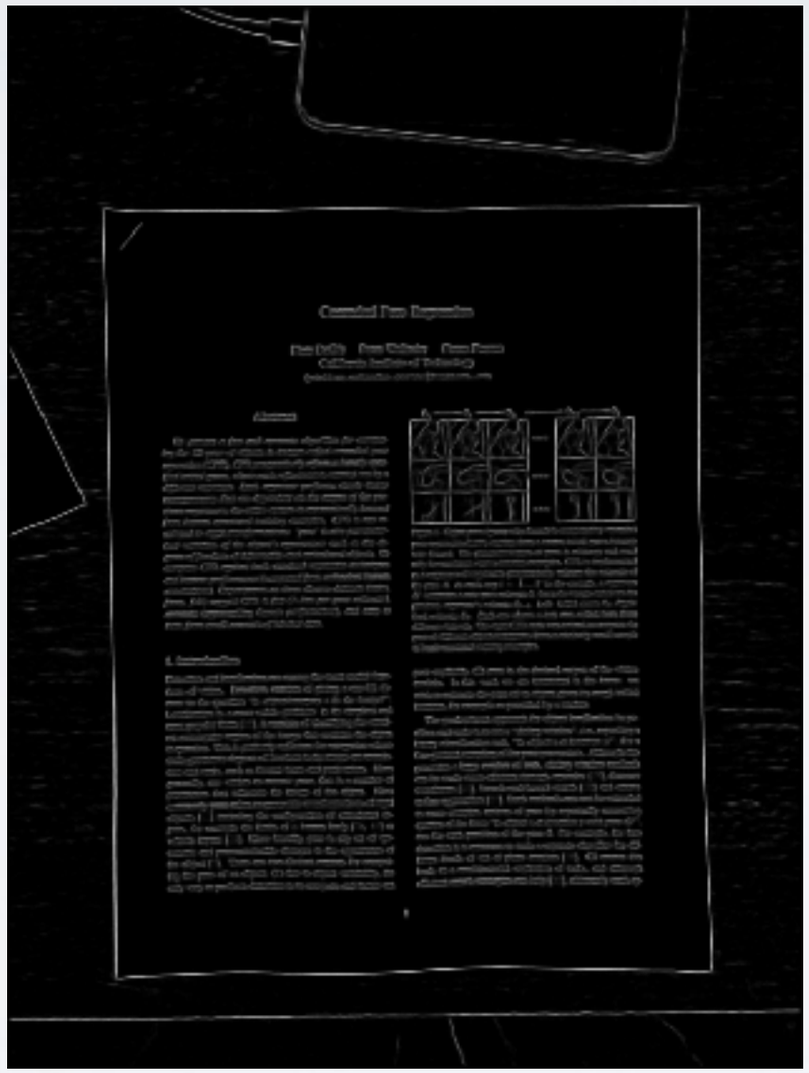
Find Corners

Find Quadrilateral



STEP BY STEP

Edge Detection

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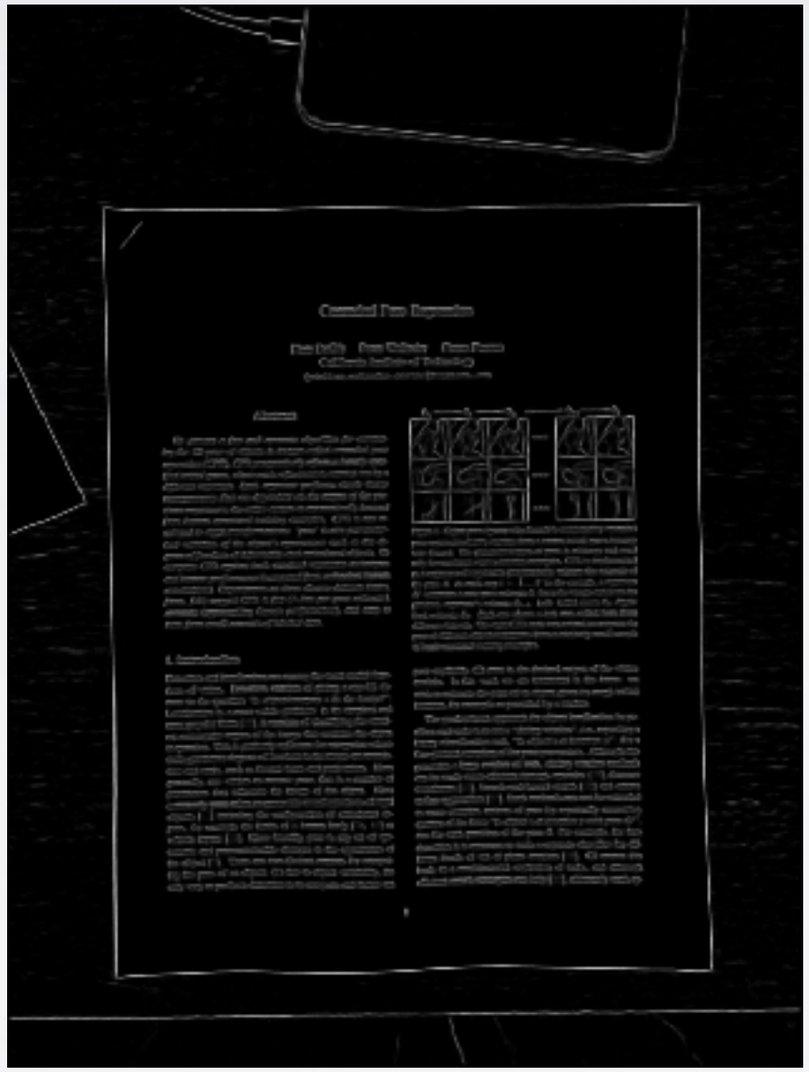
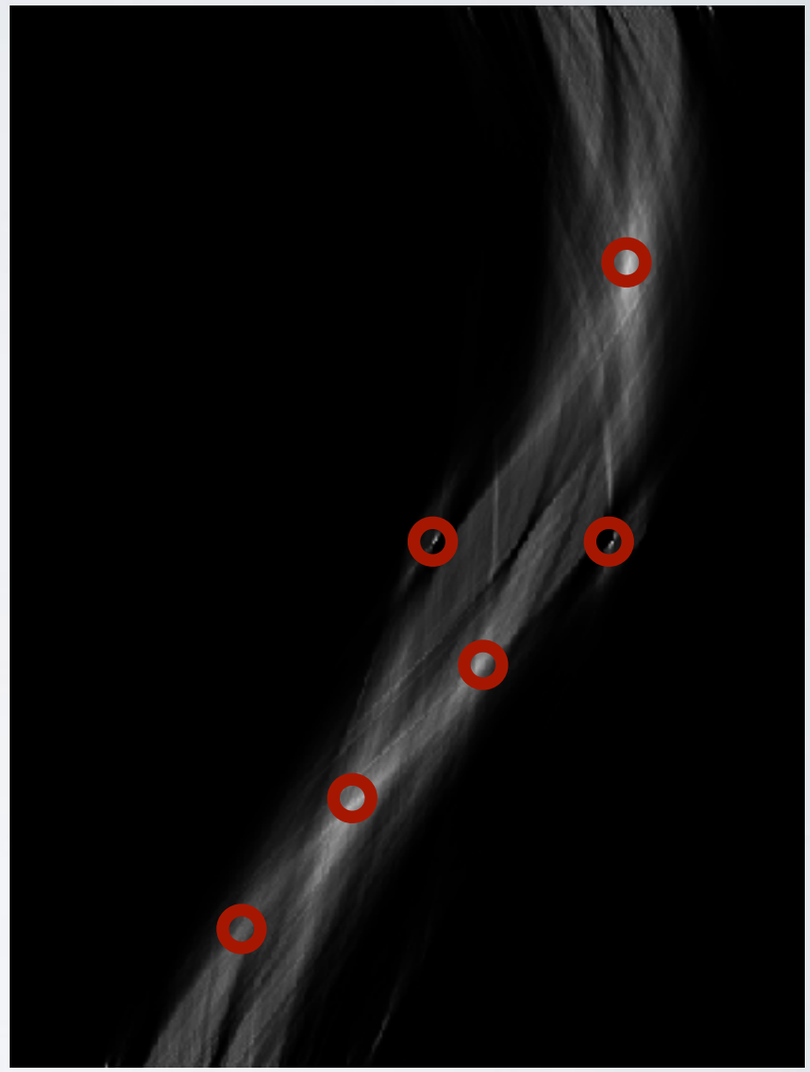
Find Quadrilateral





STEP BY STEP

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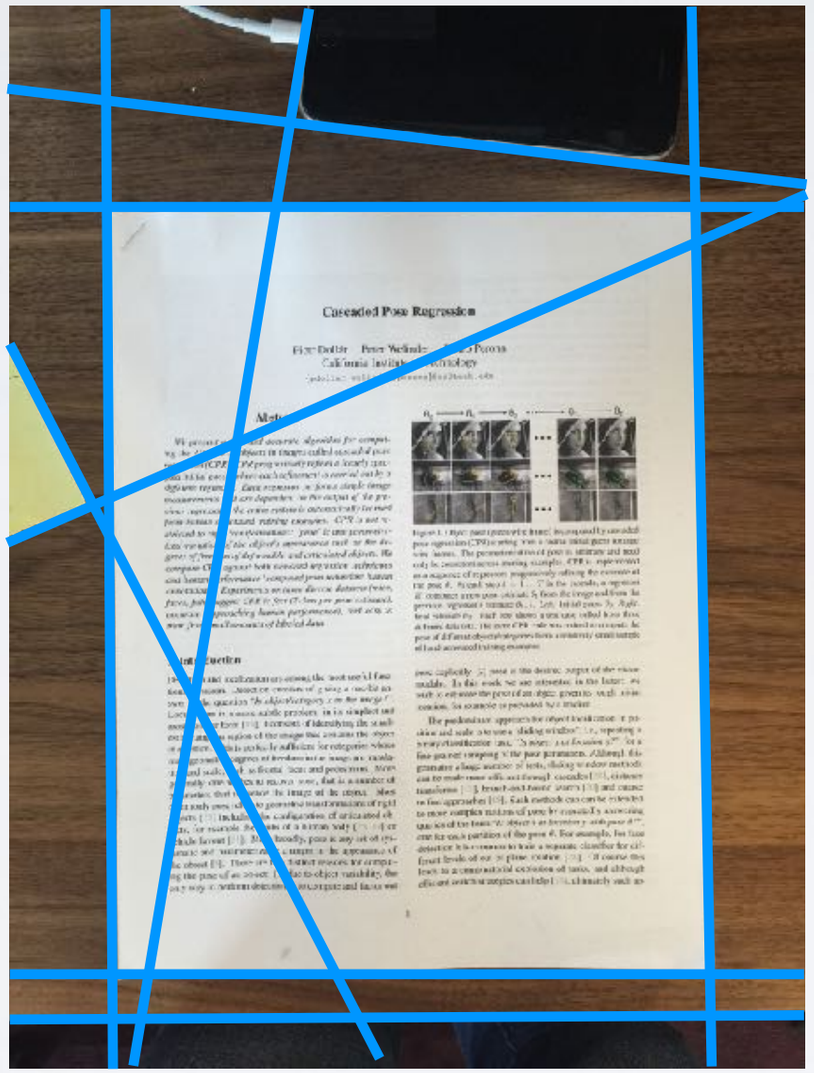

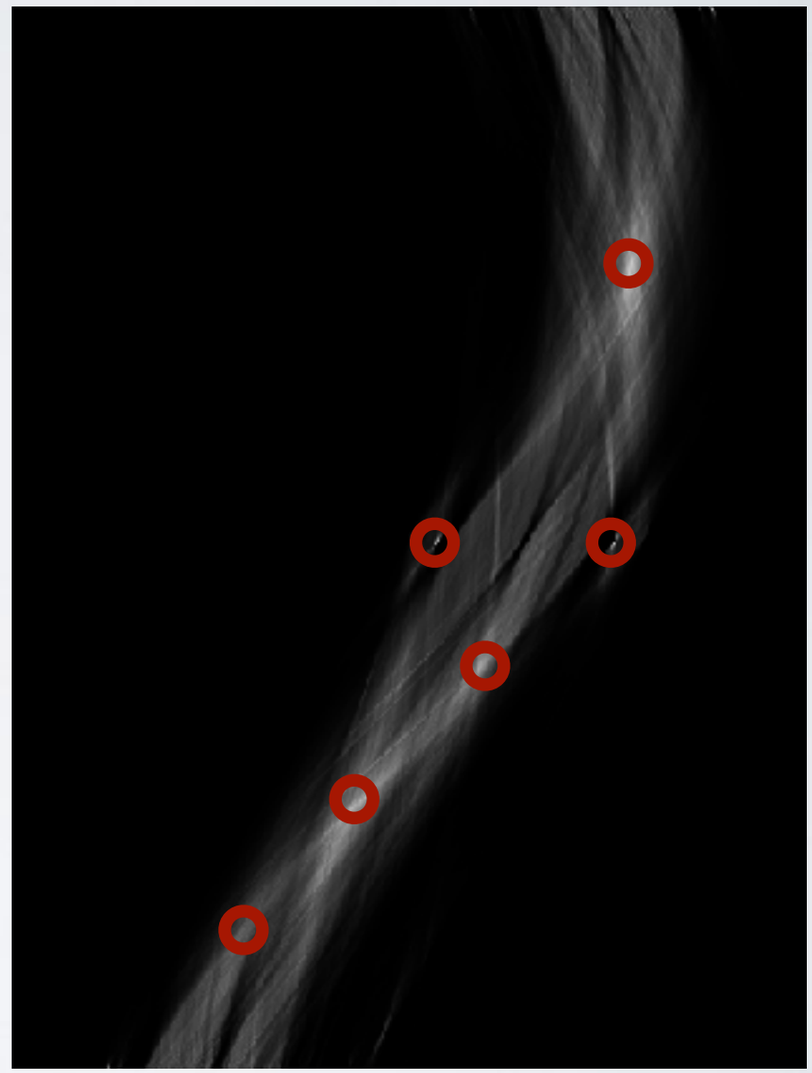

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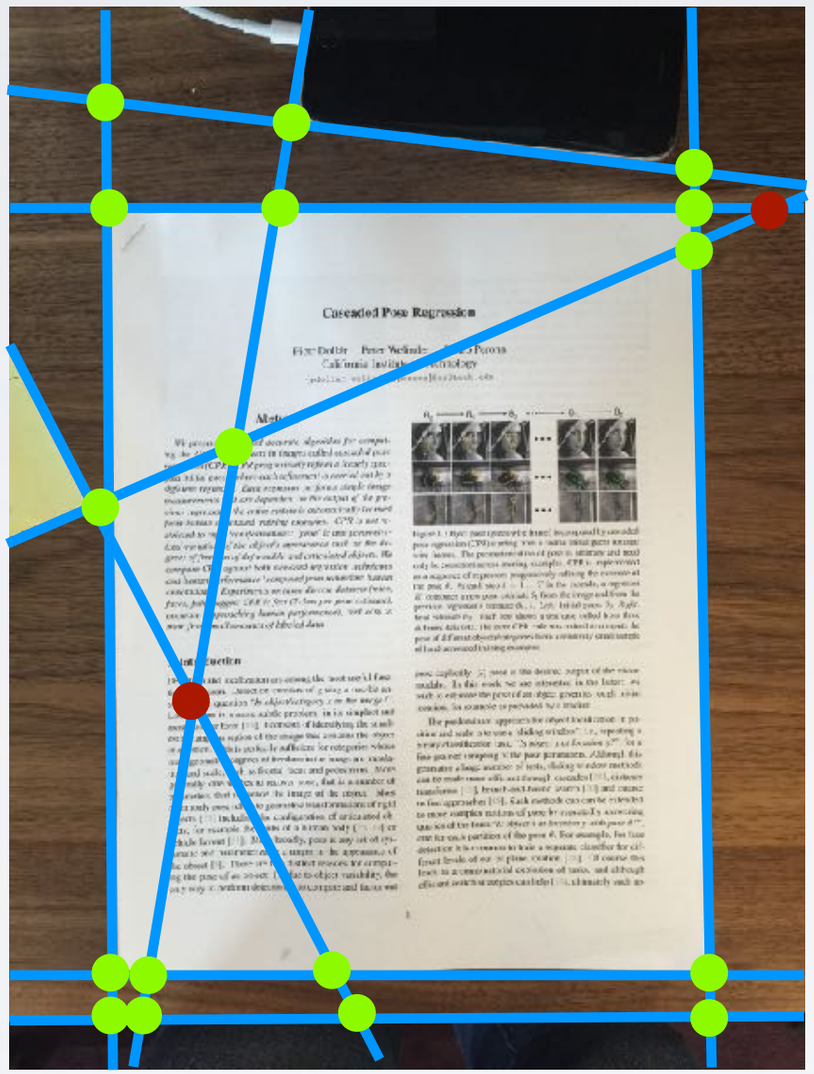

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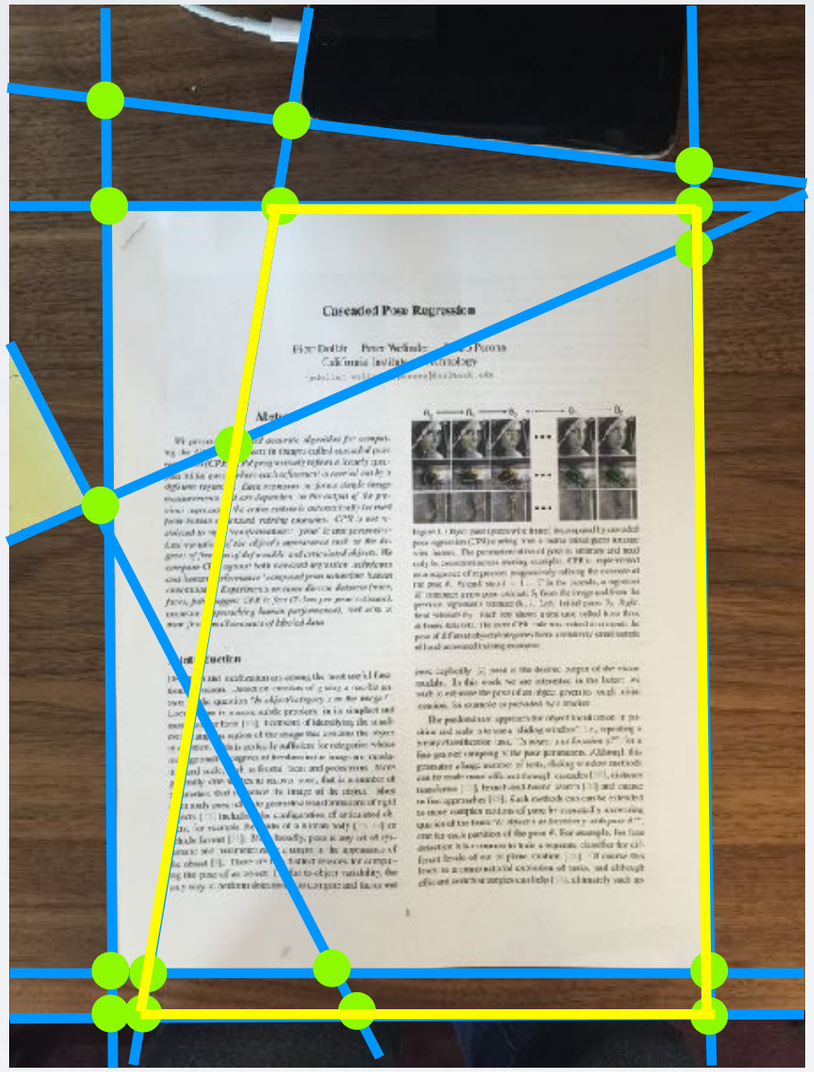

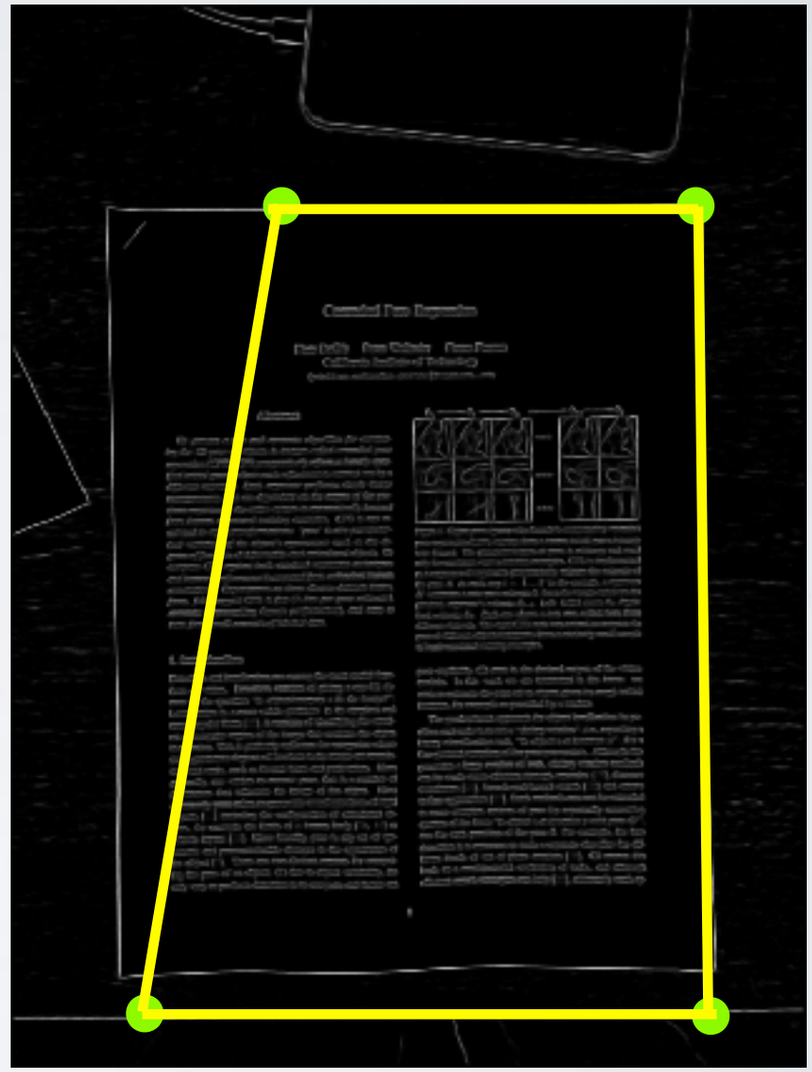

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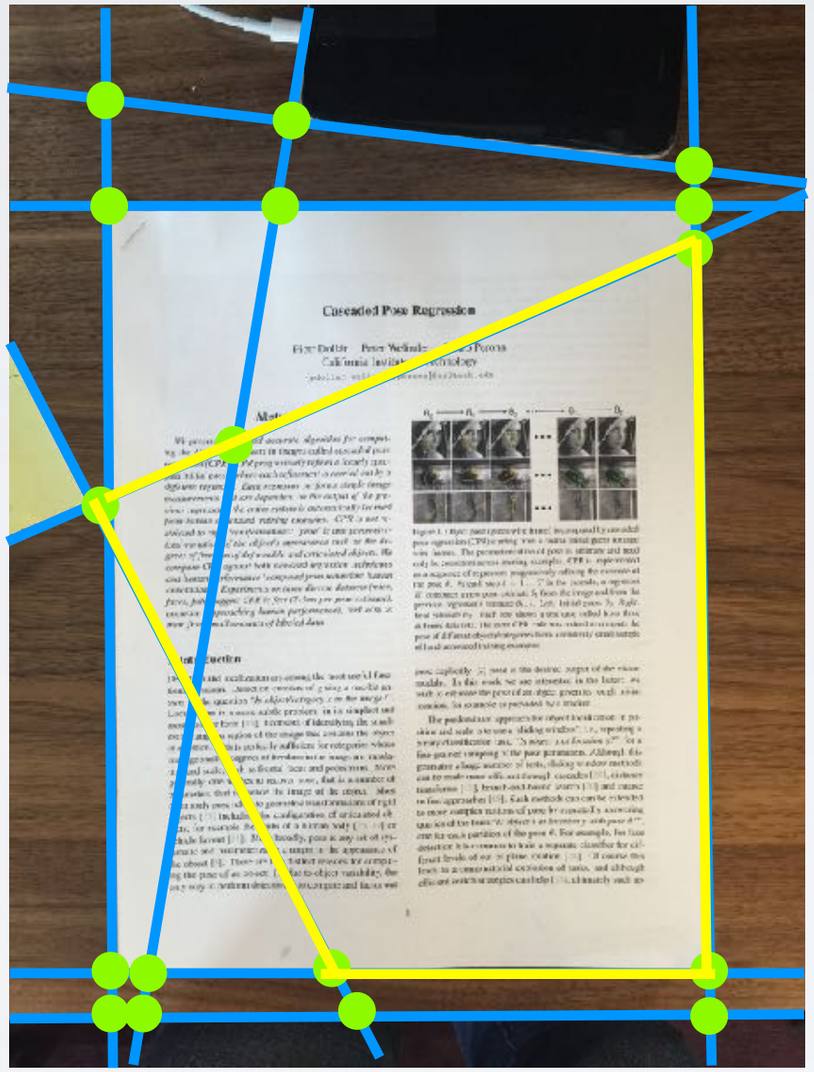
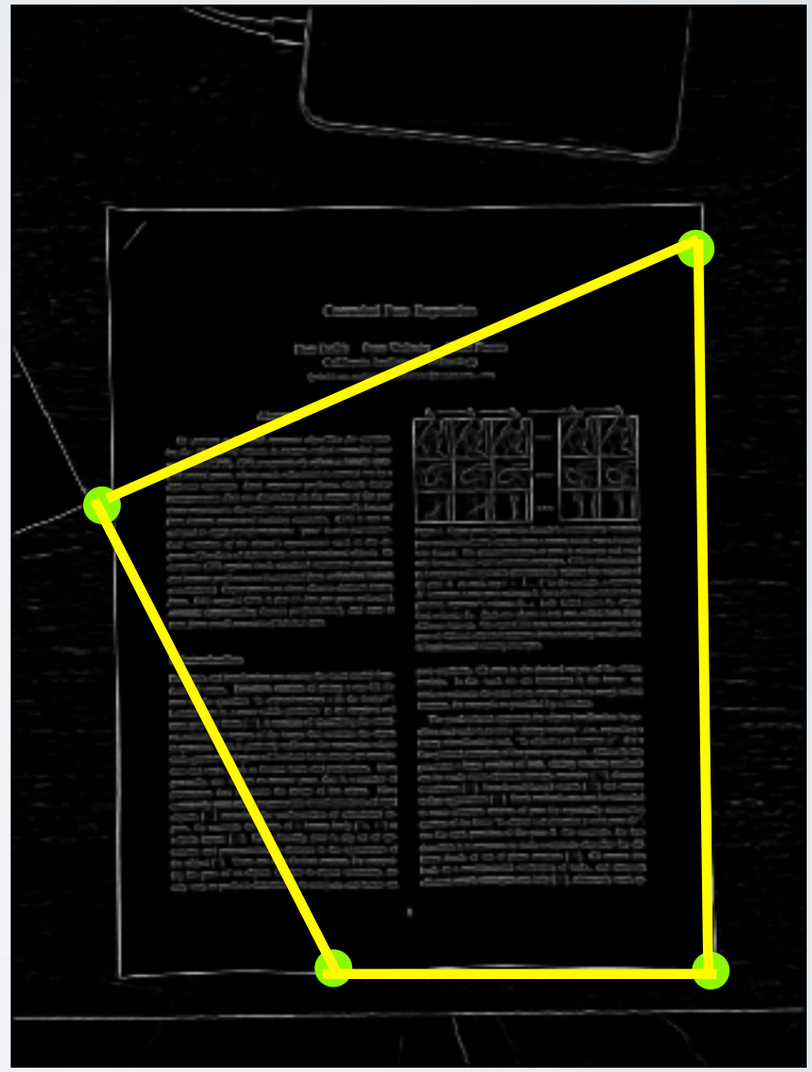
Find Corners

Find Quadrilateral





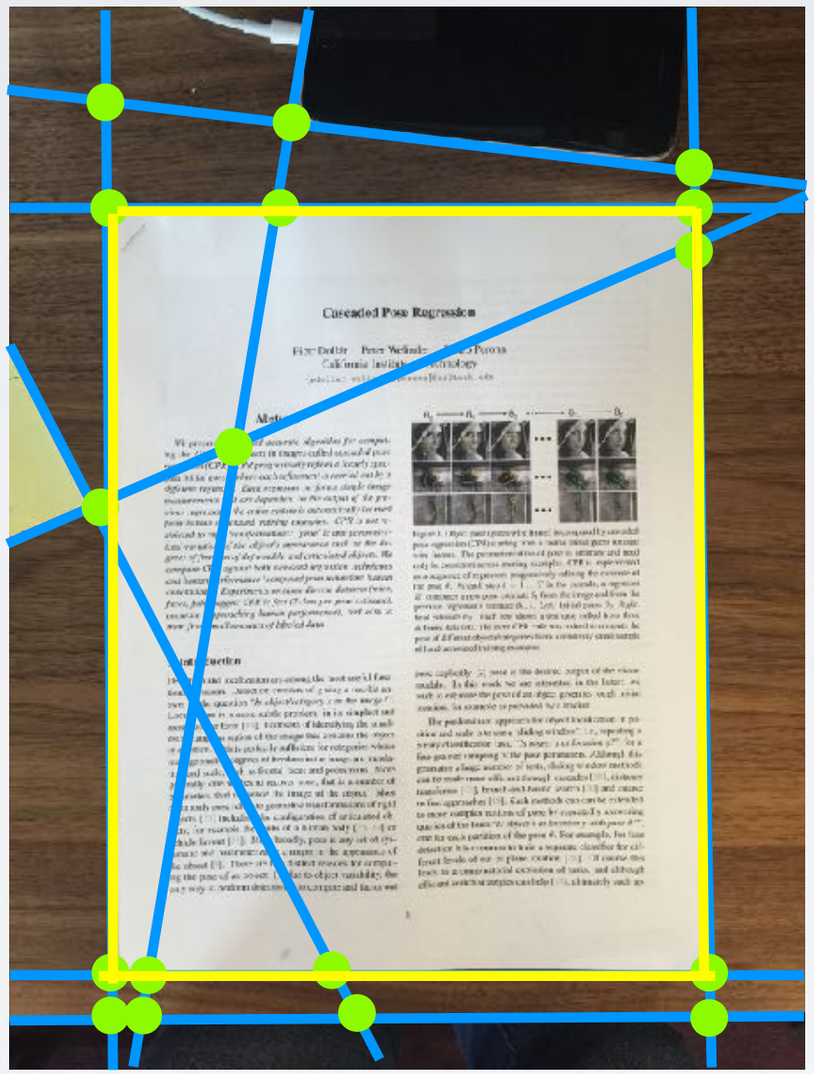
STEP BY STEP

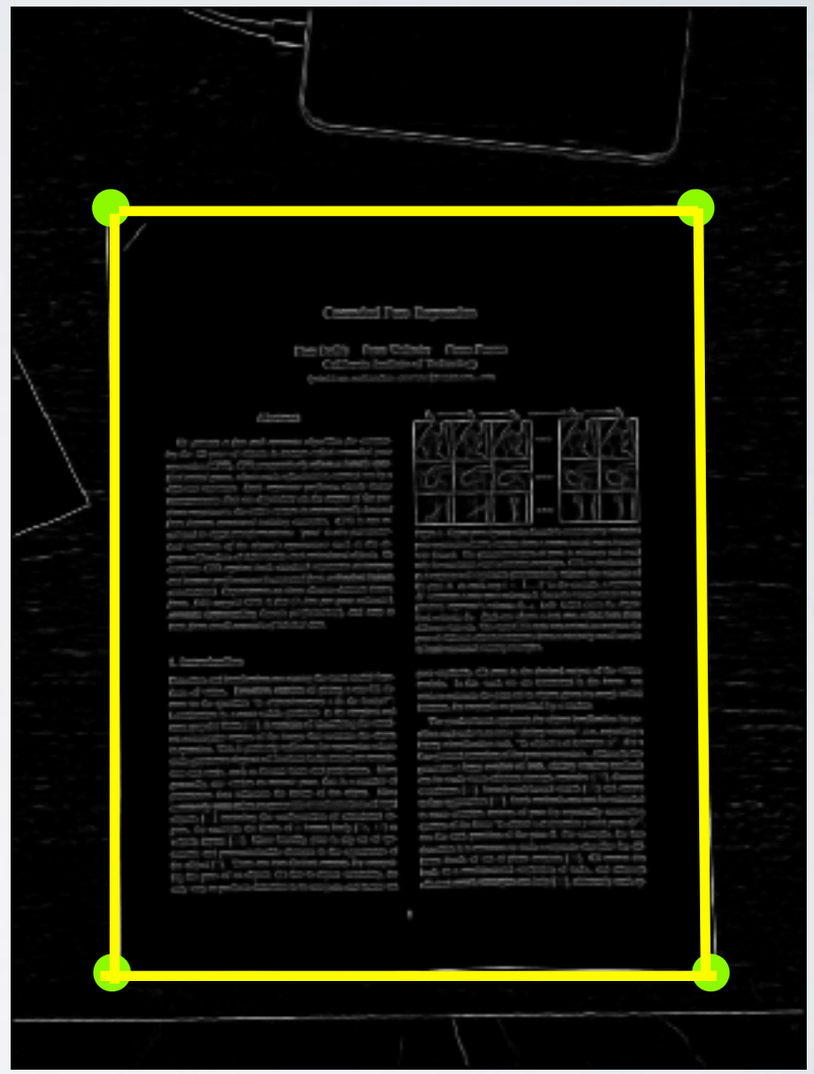
Edge Detection

Find Lines

Find Corners

Find Quadrilateral





REAL-TIME DEMO

Edge Detection

Find Lines

Find Corners

Find Quadrilateral