CS 250
VLSI Design
Lecture 7 – Project Introduction (Part 2)

2012-9-13

John Wawrzynek

Jonathan Bachrach

Krste Asanović

Today's lecture by John Lazzaro

TA: Rimas Avizienis

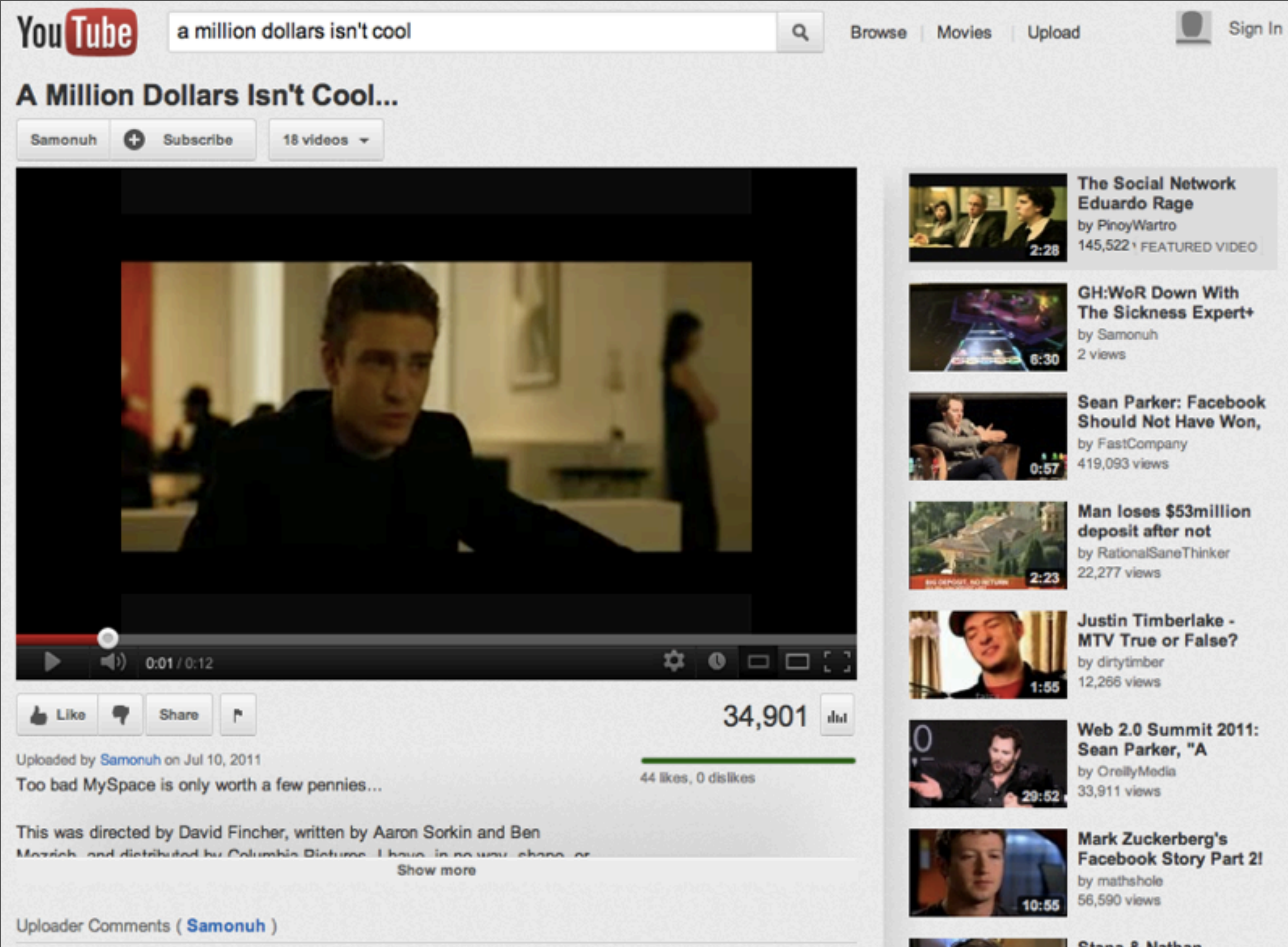
www-inst.eecs.berkeley.edu/~cs250/

Today's lecture:

- **Histogram filters**
- **Face detection**
- **Diffusion processing**
- **SIFT Keypoints**
- **Stereopsis**

- **More on power and energy**
(see end of Lecture 5 PDF for these slides)

Histogram Filters


YouTube
a million dollars isn't cool
Browse
Movies
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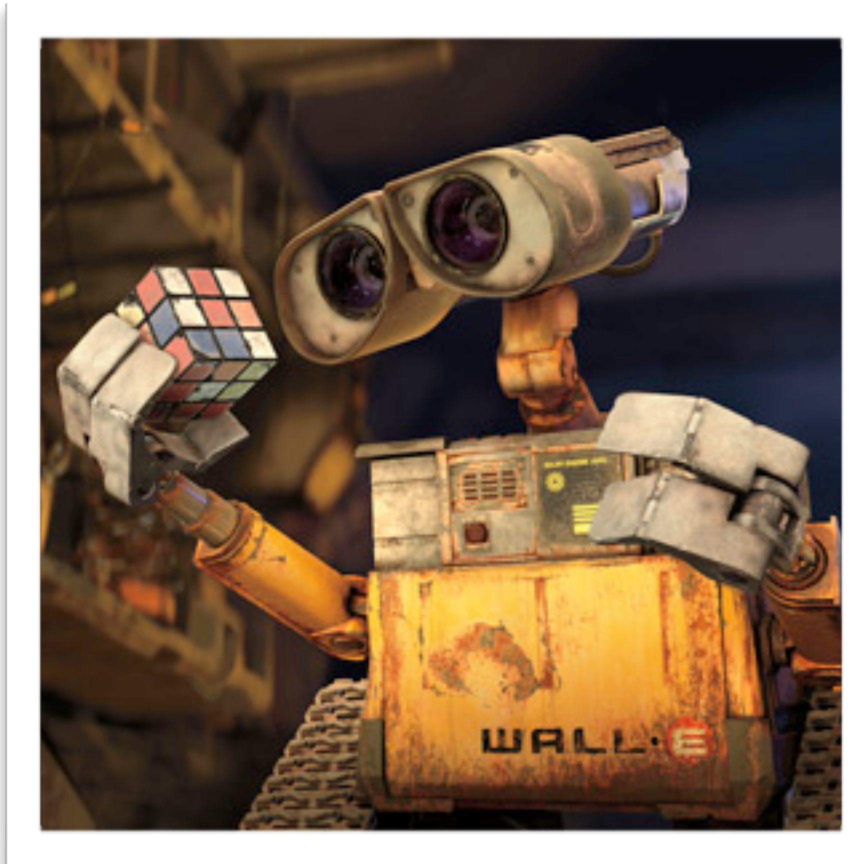
A Million Dollars Isn't Cool...
Samonuh
Subscribe
18 videos
0:01 / 0:12
Like
Share
34,901
Uploaded by Samonuh on Jul 10, 2011
Too bad MySpace is only worth a few pennies...
44 likes, 0 dislikes
This was directed by David Fincher, written by Aaron Sorkin and Ben
Show more
Uploader Comments (Samonuh)
The Social Network Eduardo Rage
by PinoyWartro
145,522
FEATURED VIDEO
2:28
GH:WoR Down With The Sickness Expert+
by Samonuh
2 views
6:30
Sean Parker: Facebook Should Not Have Won,
by FastCompany
419,093 views
0:57
Man loses $53million deposit after not
by RationalSaneThinker
22,277 views
2:23
Justin Timberlake - MTV True or False?
by dirtytimber
12,266 views
1:55
Web 2.0 Summit 2011: Sean Parker, "A
by OreillyMedia
33,911 views
29:52
Mark Zuckerberg's Facebook Story Part 2!
by mathshole
56,590 views
10:55

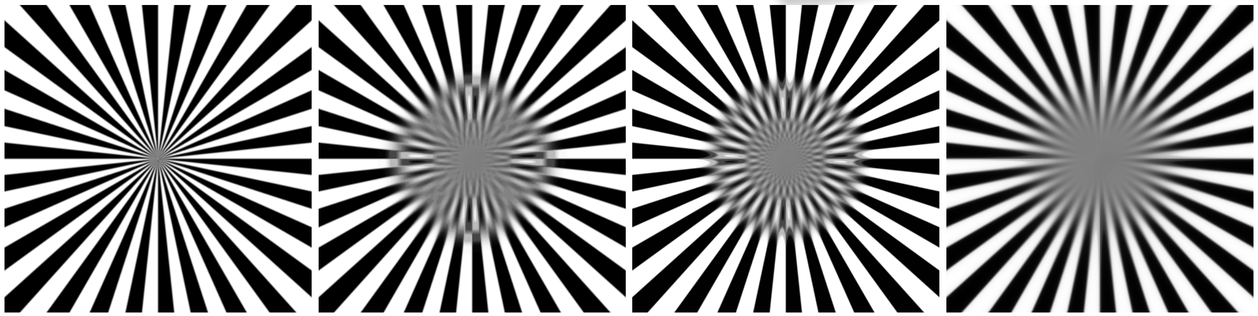
Smoothed Local Histogram Filters

Michael Kass
Pixar Animation Studios

Justin Solomon
Pixar Animation Studios and Stanford University

Photo filters with a Pixar aesthetic





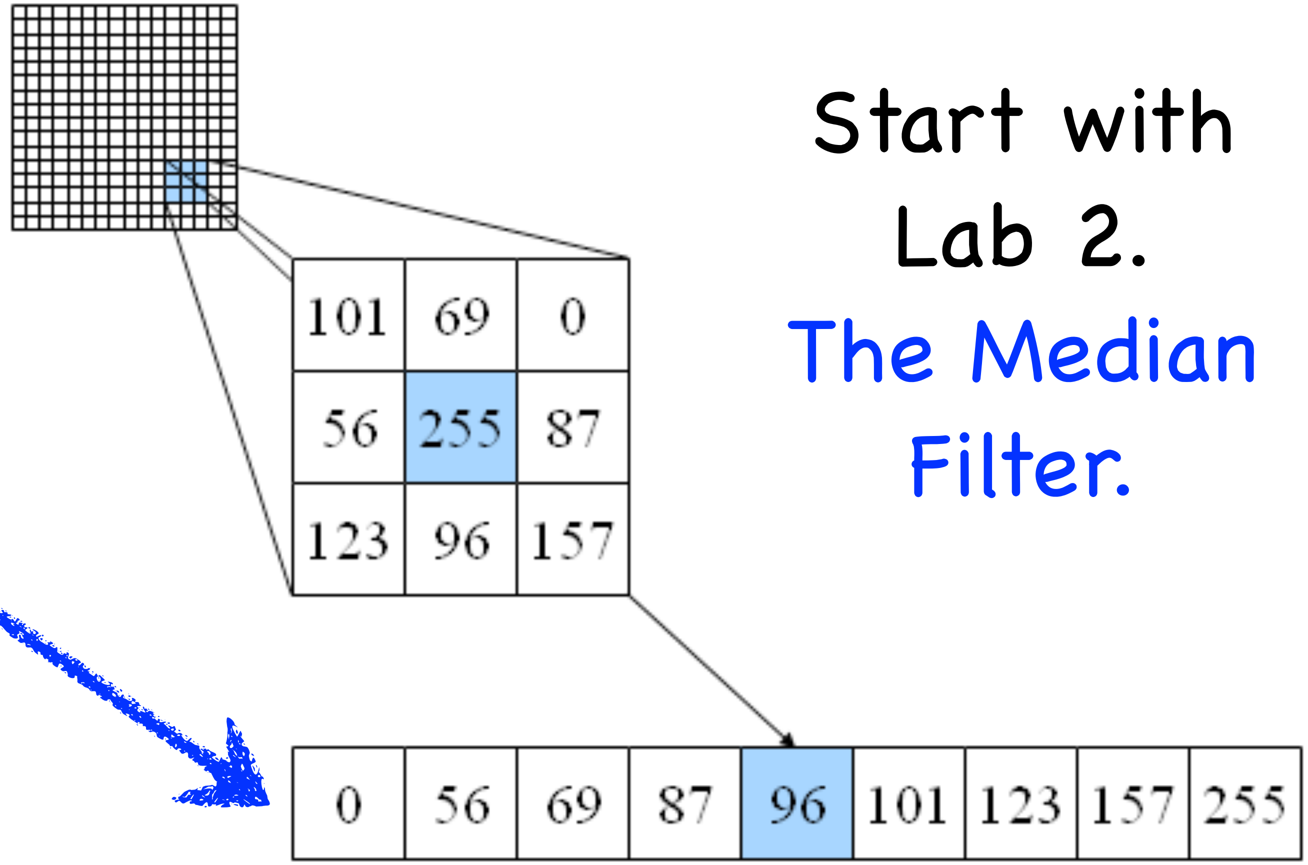
Test image

Previous state of the art

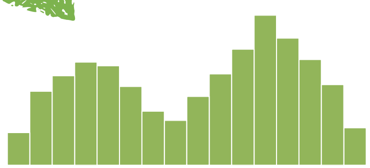
This paper

How it works:

We can interpret the sorted array as a histogram. We could set the output pixel to be the largest mode, etc ... not just the median



Start with Lab 2. The Median Filter.



The pictures look better if we generalize histograms ...

The paper shows an efficient way ...

(a) Original.

FPGA-Based Face Detection System Using Haar Classifiers

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Face Detection

Robust Real-Time Face Detection

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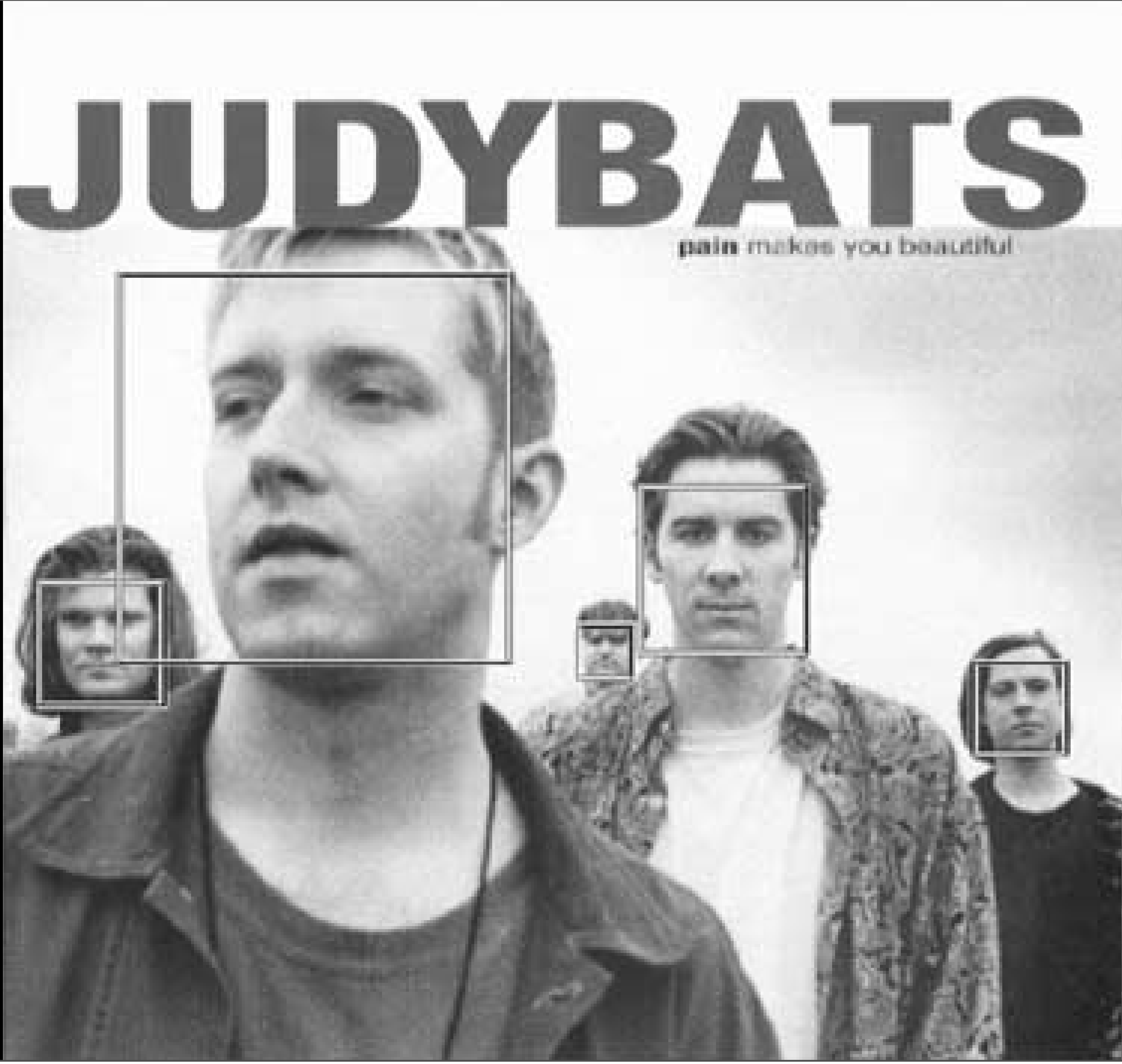
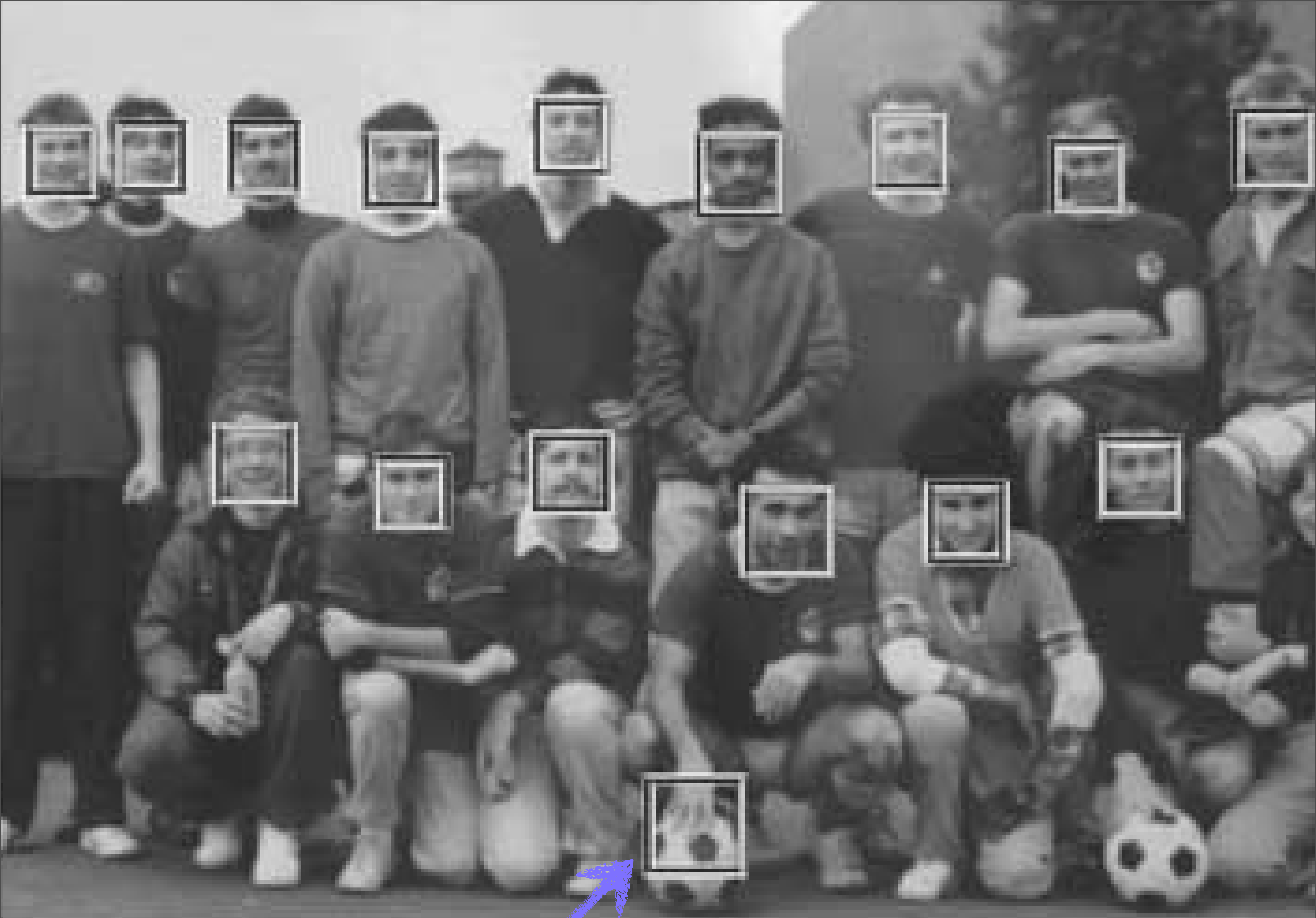
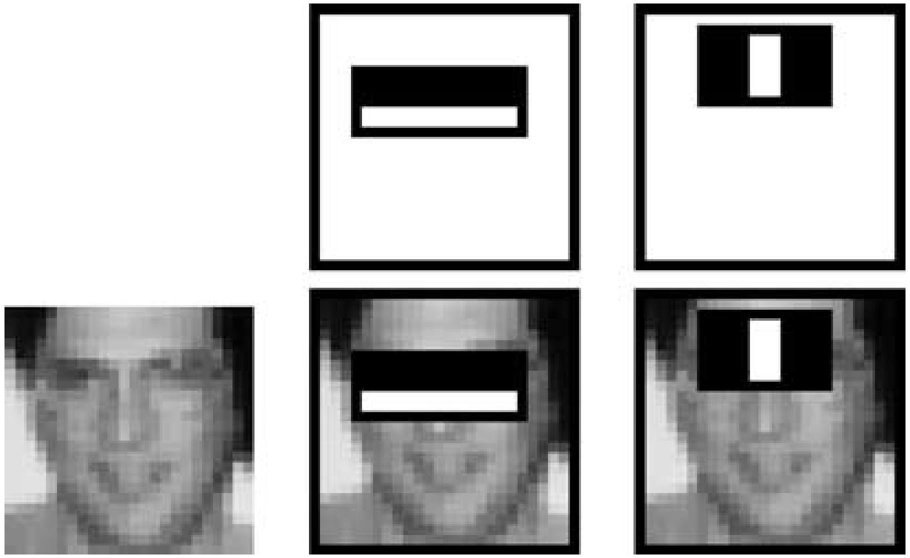

JUDYBATS
pain makes you beautiful



False positive

False negatives

How it works:



Harr Filters ($f(x)$):

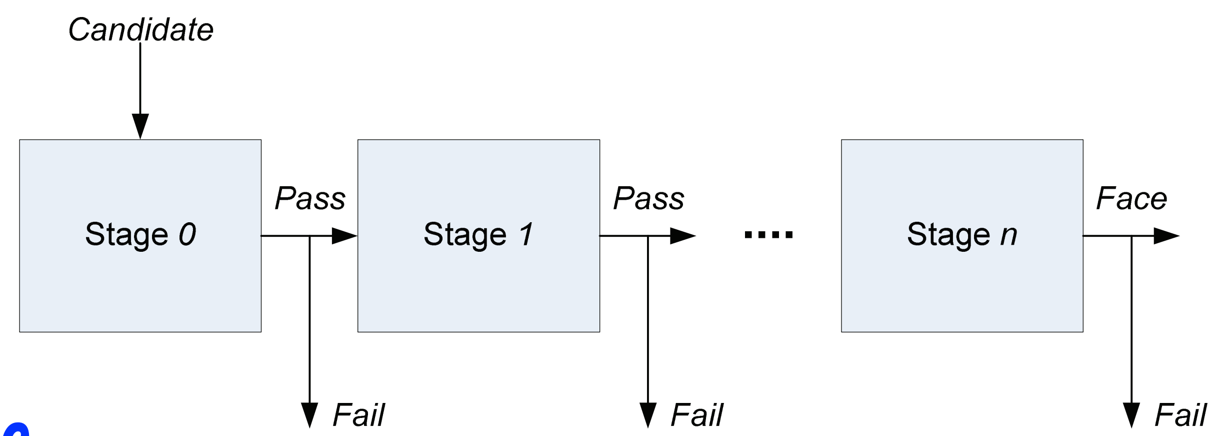
Add pixels under white regions, subtract pixels under black regions.

Pre-processing trick makes computing large numbers of Harr filters on an image efficient.

A few filters make a "weak" classifier:

$$h(x, f, p, \theta) = \begin{cases} 1 & \text{if } pf(x) < p\theta \\ 0 & \text{otherwise} \end{cases}$$

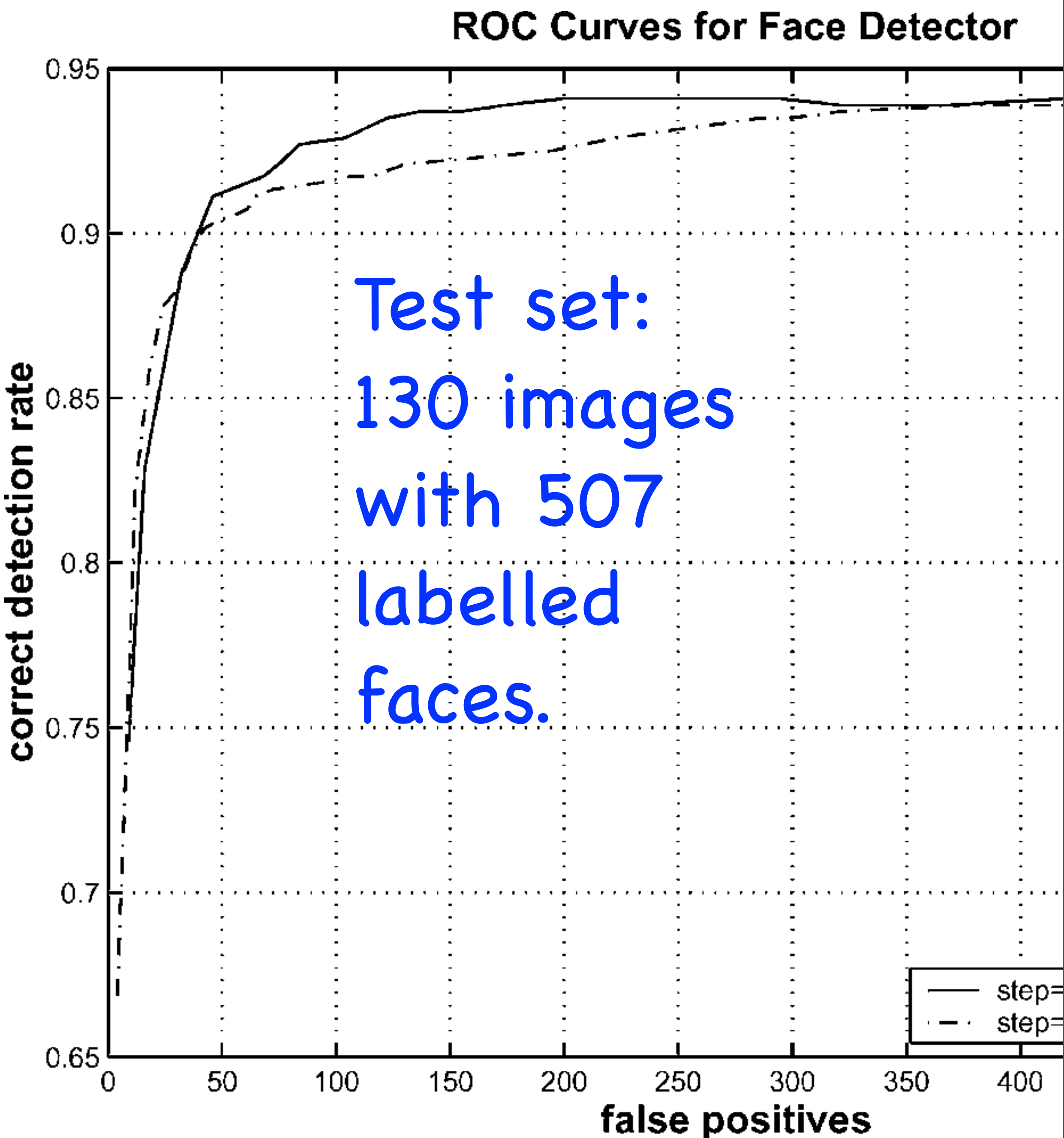
About 2100 weak classifiers create a "cascade":



Stepped over entire image ...

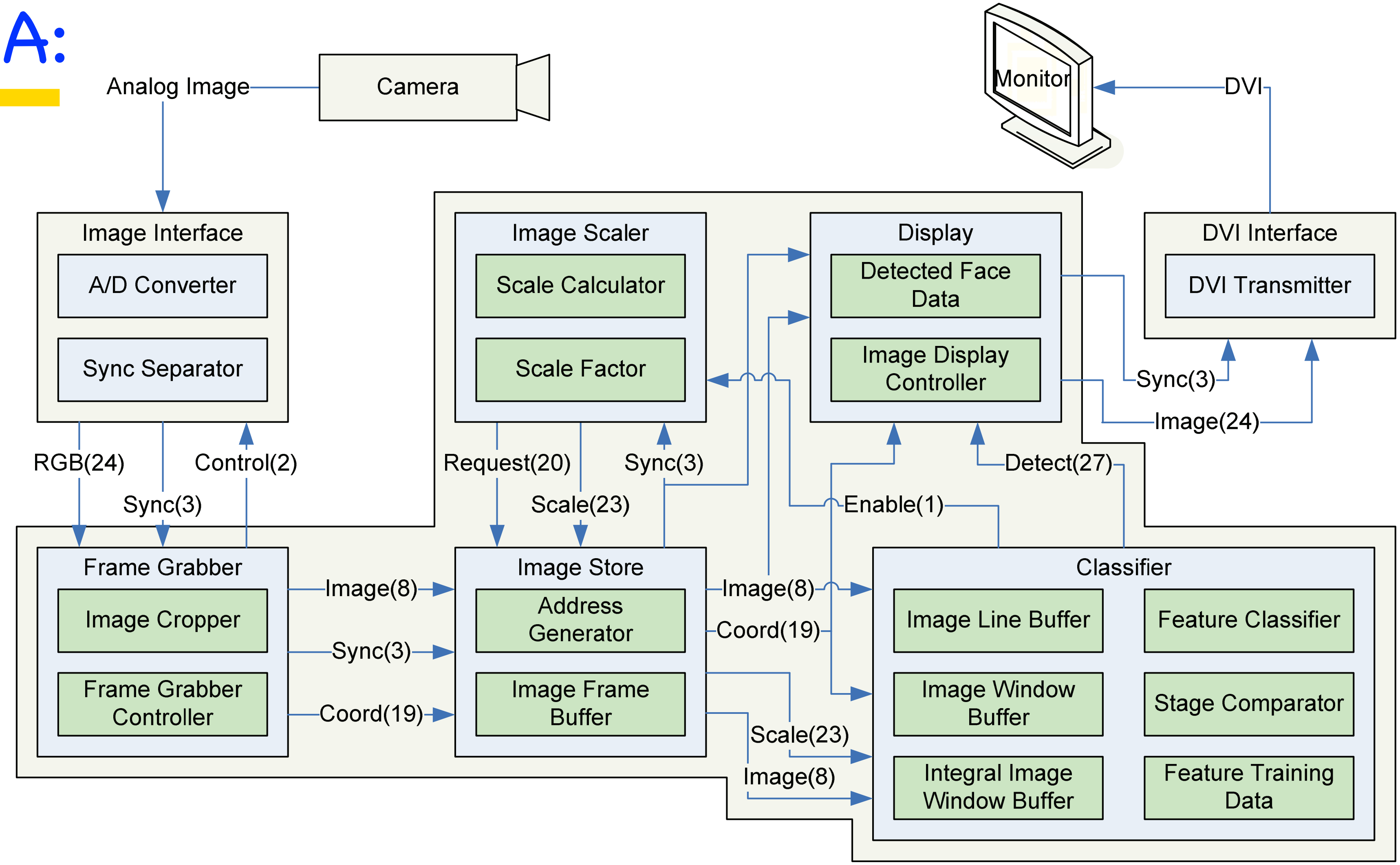
Performance:

Classifiers trained on a labelled face database.



Test set: 130 images with 507 labelled faces.

On FPGA:



Modules	Slices Register	Slice LUTs	BRAMs	DSP 48Es
Total Classifier Module	18122	62890	21	0
Total Classifier Module	13245	45340	21	964

Virtex-5 LX 110
@15 frames/sec

IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 12, NO. 7, JULY 1990 629

Scale-Space and Edge Detection Using Anisotropic Diffusion

PIETRO PERONA AND JITENDRA MALIK

Diffusion Processing

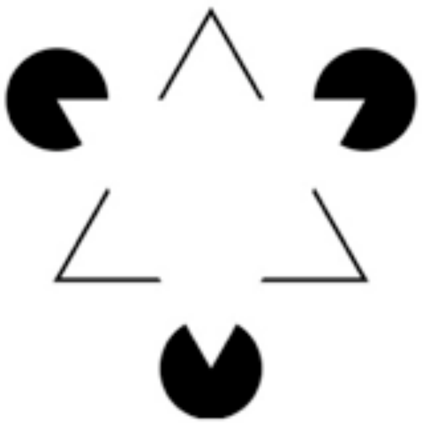
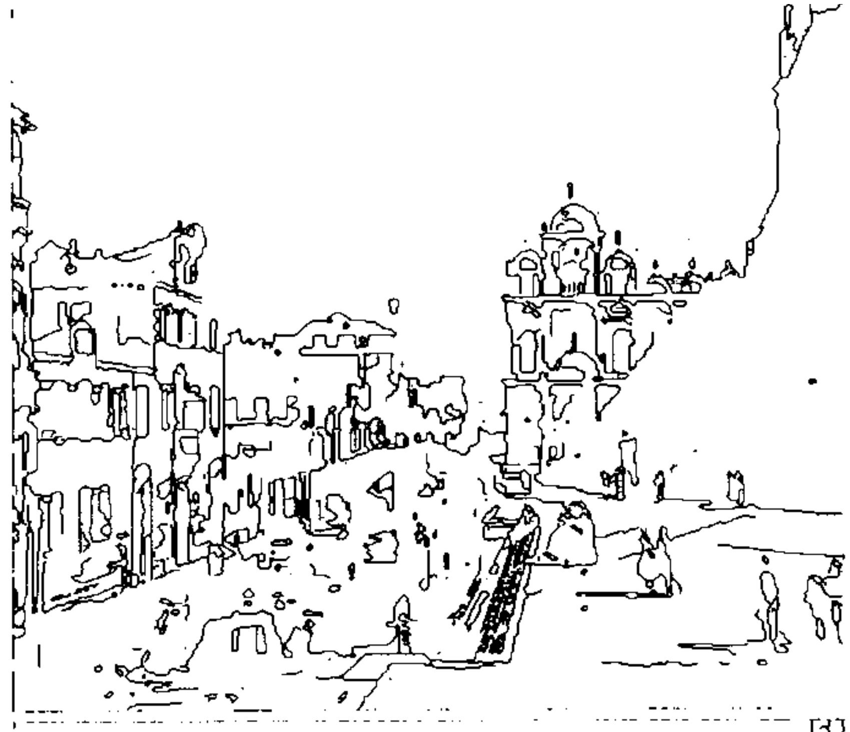


Table 1 Regularization in early vision

Problem	Regularization principle
Edge detection	$\int [(Sf - i)^2 + \lambda (f_{xx})^2]\, dx$

(a)

(b)



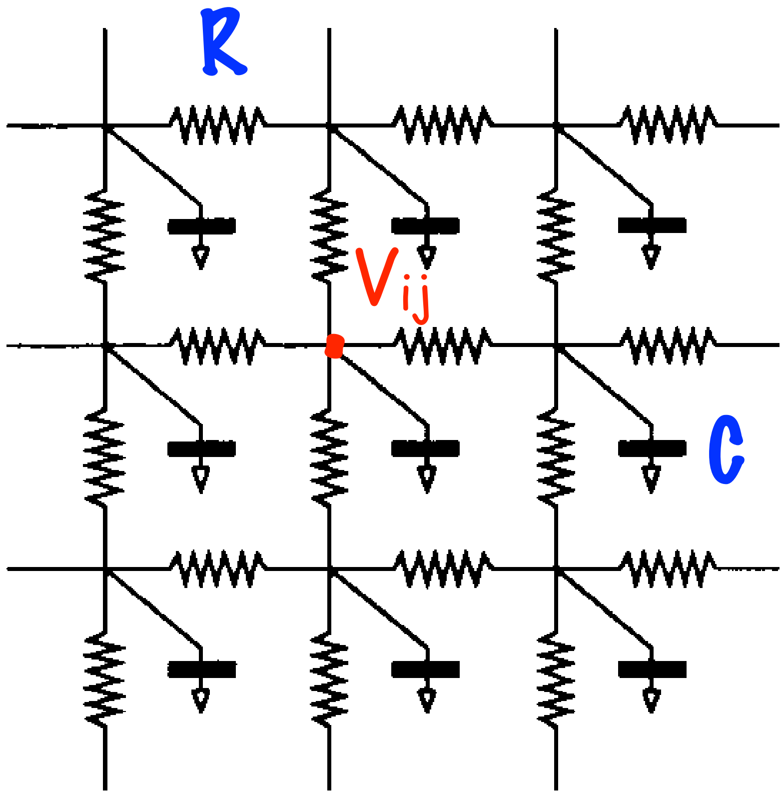
(a)

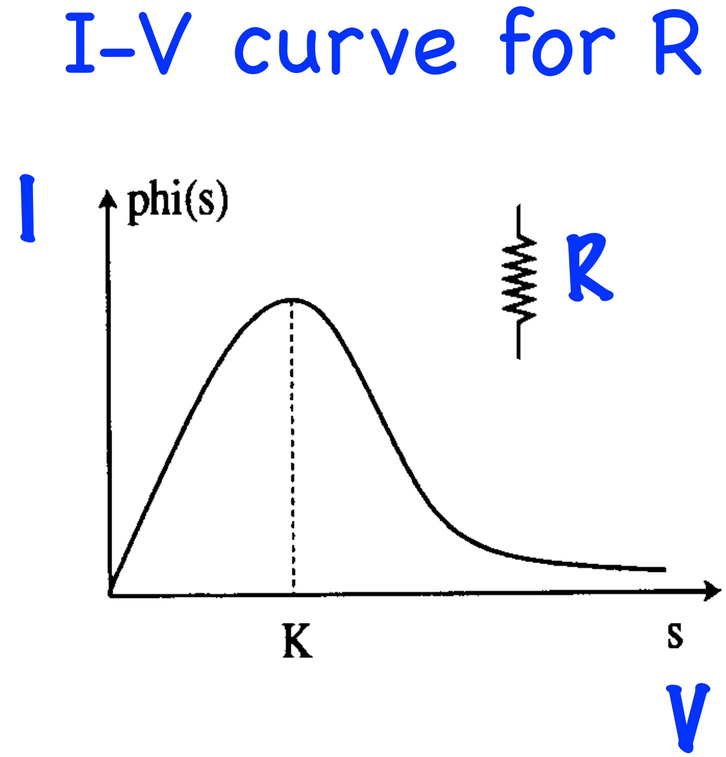
(b)

Edges detected using (a) anisotropic diffusion and (b) Gaussian smoothing (Canny detector).

How it works: "anisotropic heat equation solver"

A 2-D RC circuit (non-linear Rs) computes edges.





@t=0, set V_{ij} values to pixel values of input image.

Then let circuit settle. Final V_{ij}s form edge image

A digital implementation "simulates" the circuit.

SIFT Keypoints

Distinctive Image Features from Scale-Invariant Keypoints

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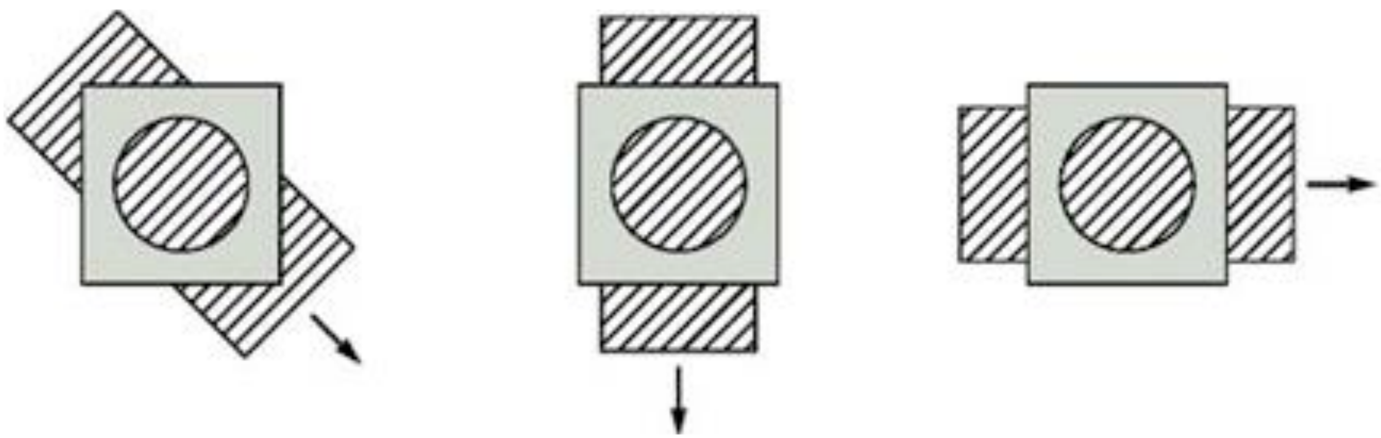
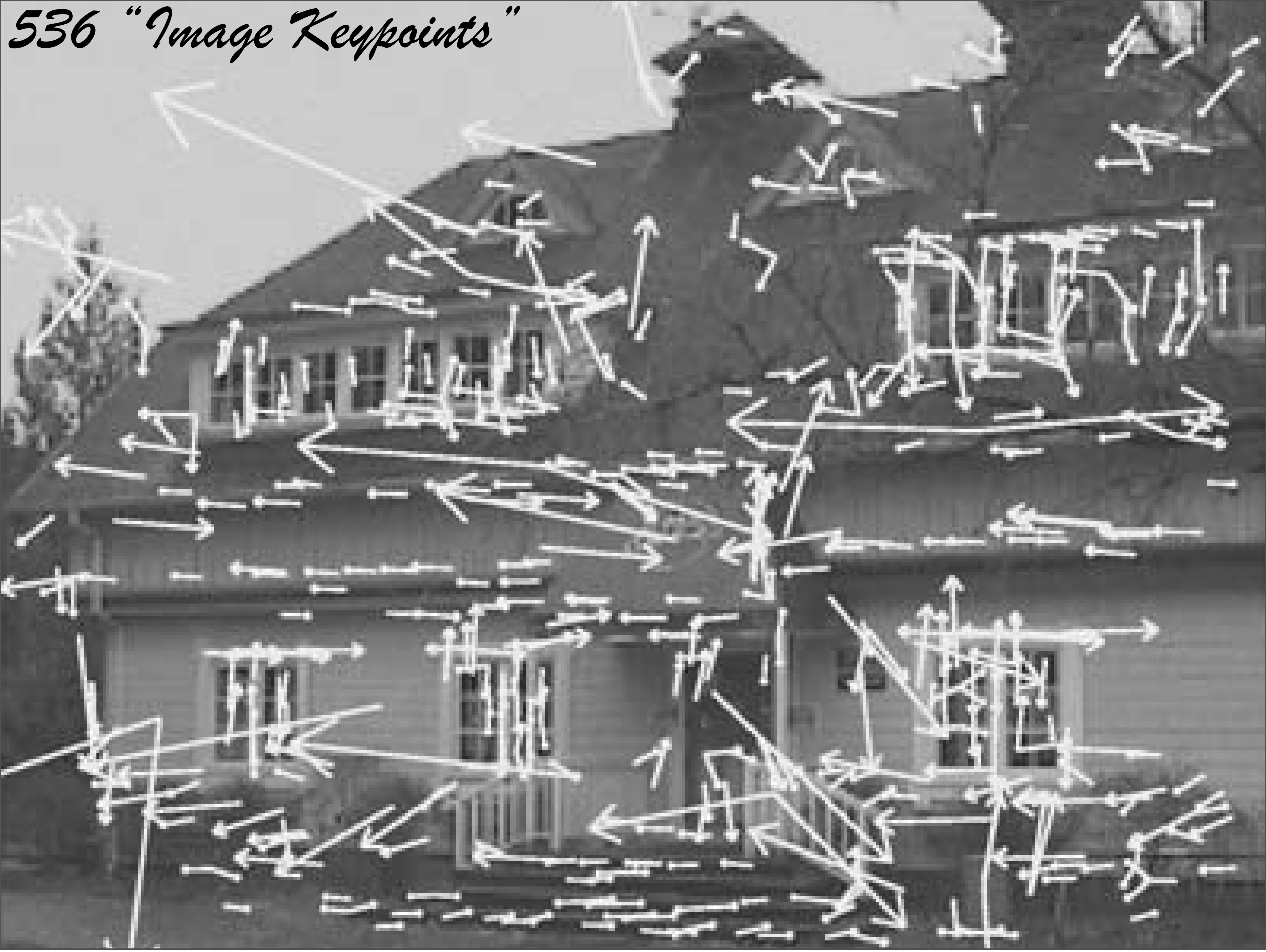
Received January 10, 2003; Revised January 7, 2004; Accepted January 22, 2004

SIFT Keypoints

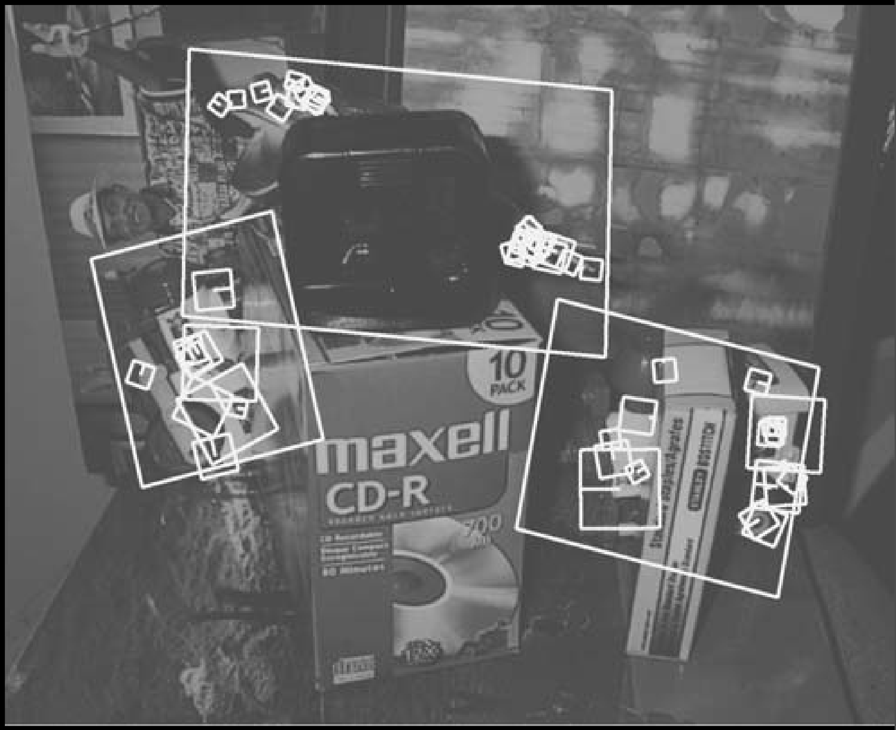
"Things change when you can match features"



536 "Image Keypoints"



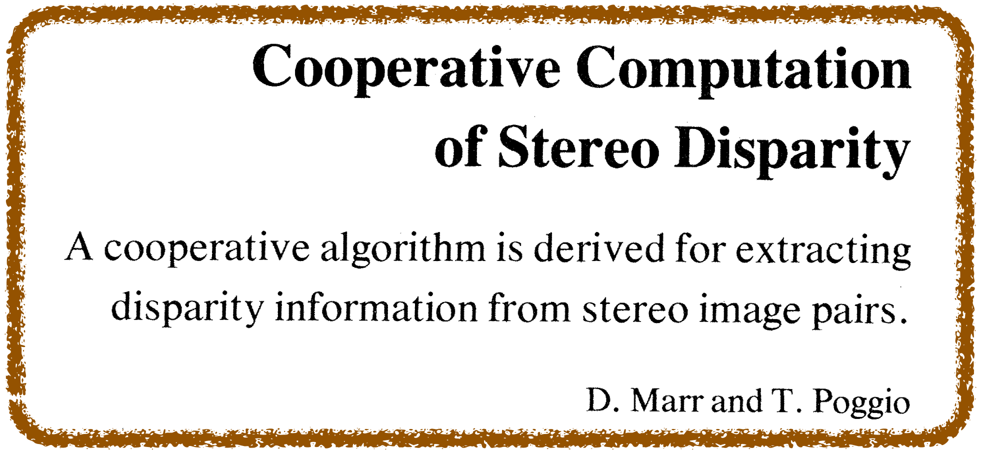
The features are invariant to image scale and rotation, and provide robust matching across a substantial range of affine distortion, change in 3D viewpoint, addition of noise, and change in illumination.



Training objects

"Where's Waldo?"

Works because of SIFT invariances.



Cooperative Computation of Stereo Disparity

A cooperative algorithm is derived for extracting disparity information from stereo image pairs.

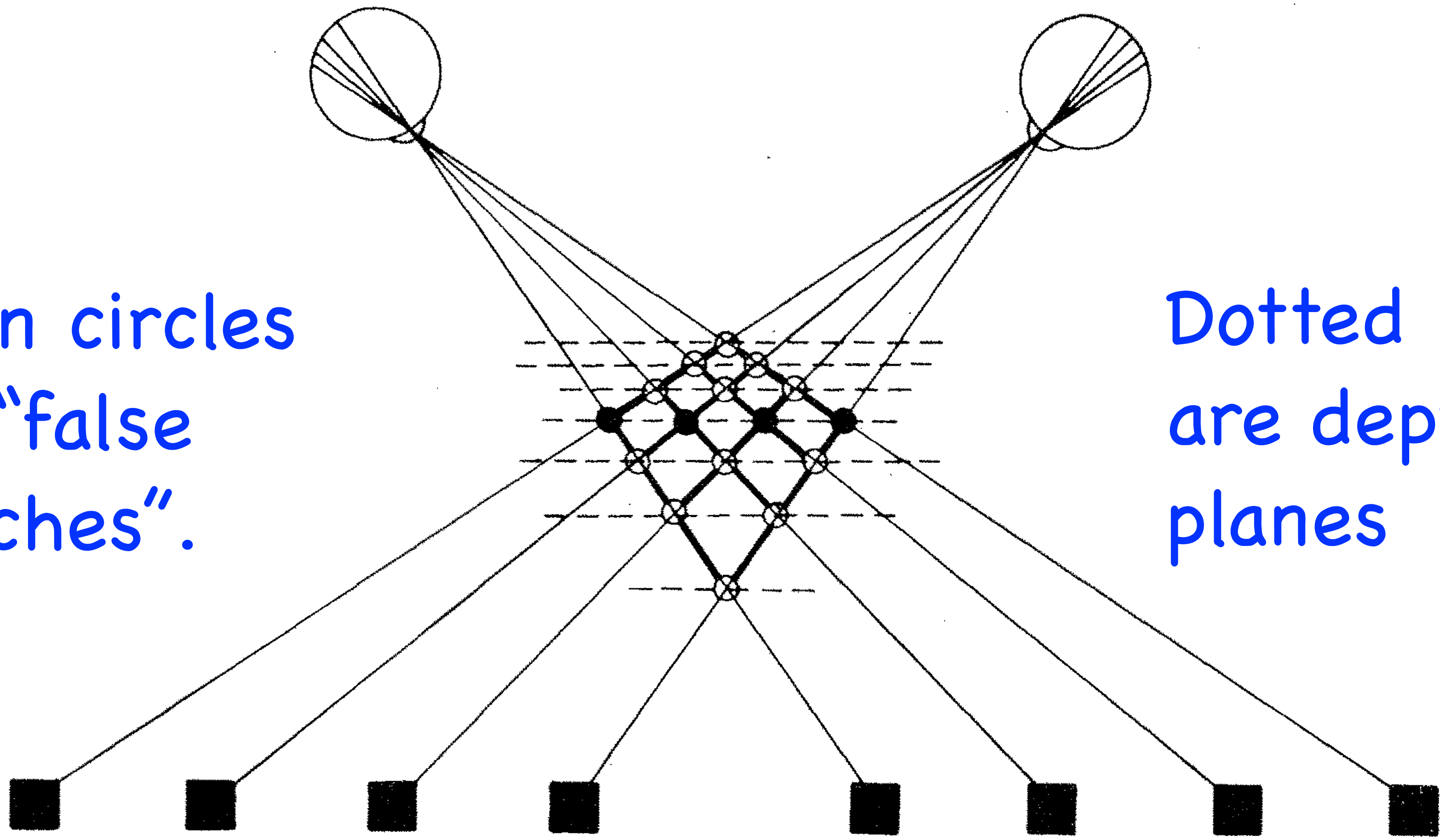
D. Marr and T. Poggio

Stereopsis

1-D Stereo

"Correspondence problem" -- find matching squares.

Open circles are "false matches".



Dotted lines are depth planes

Image seen by left eye

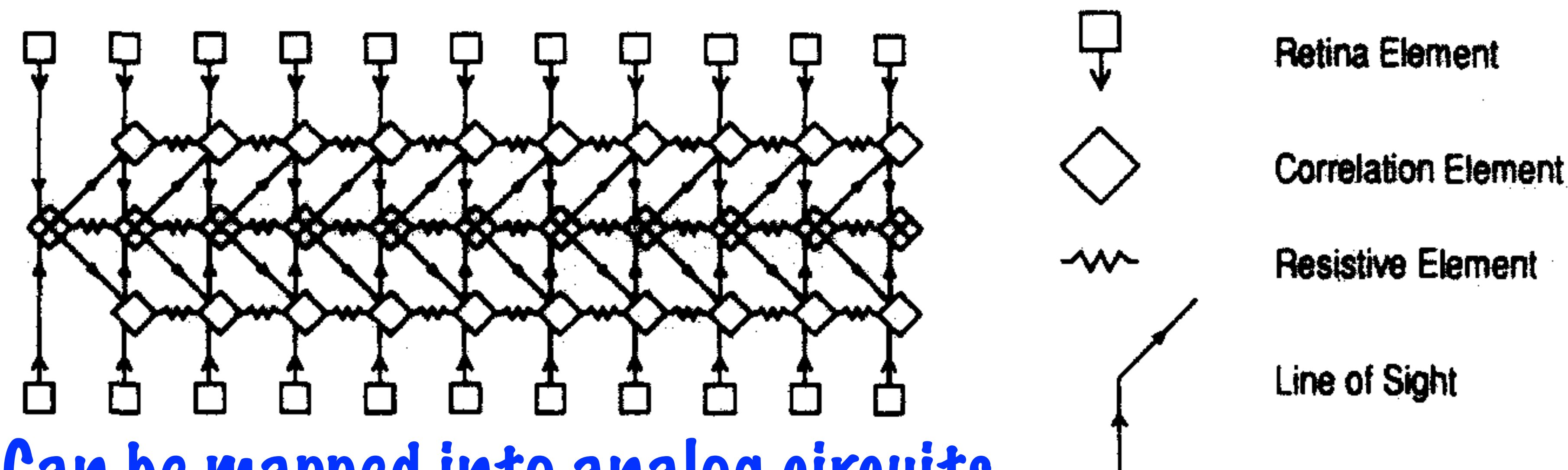
Image seen by right eye

"Cooperative algorithm"

Stereo $\quad \int \{[\nabla^2 G * (L(x,y) - R(x + d(x,y), y))]^2 + \lambda(\nabla d)^2\}\, dx\, dy$

Uniqueness: Only one match for an object seen in the two eyes.

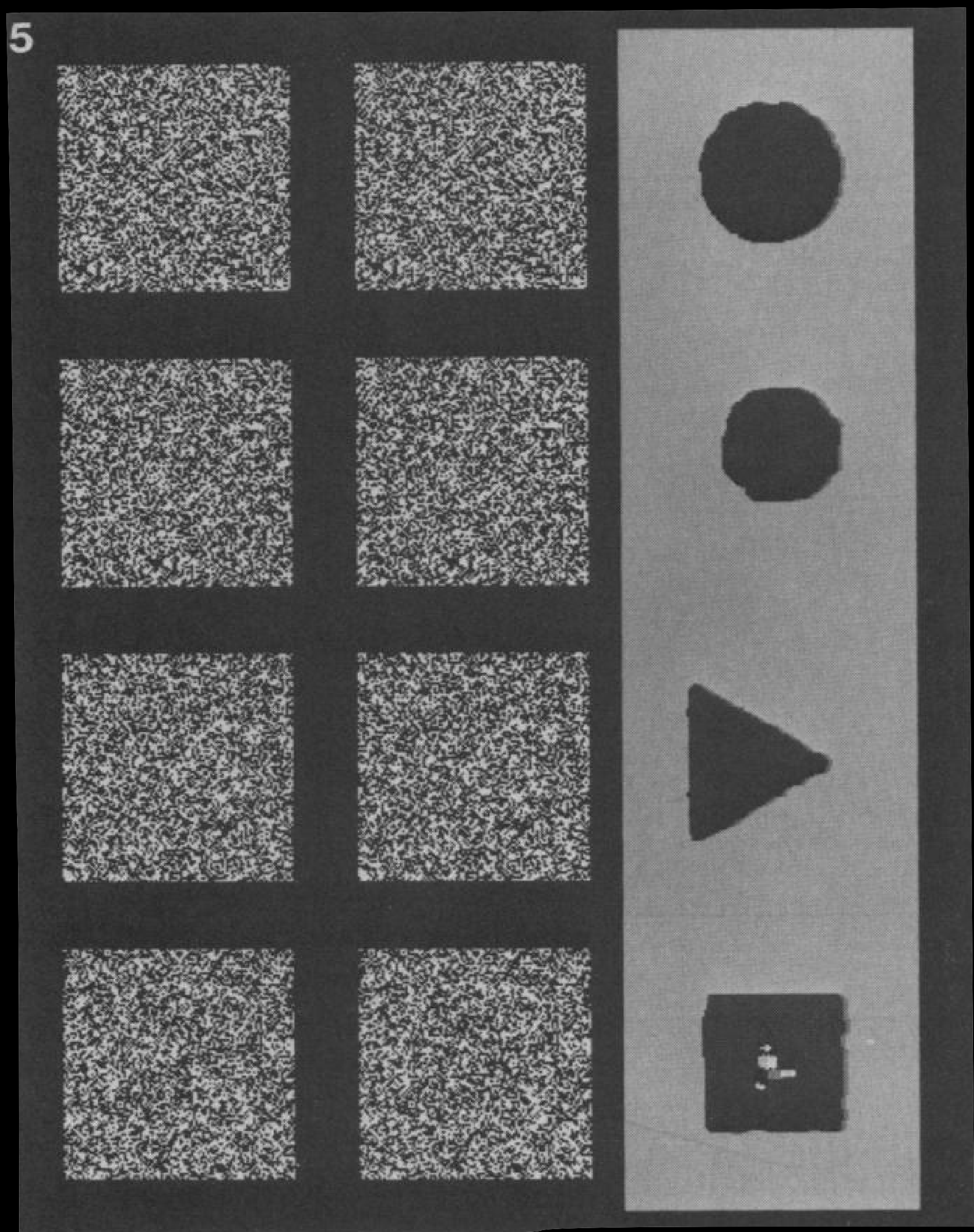
Smoothness: Objects are generally smooth in the depth plane.

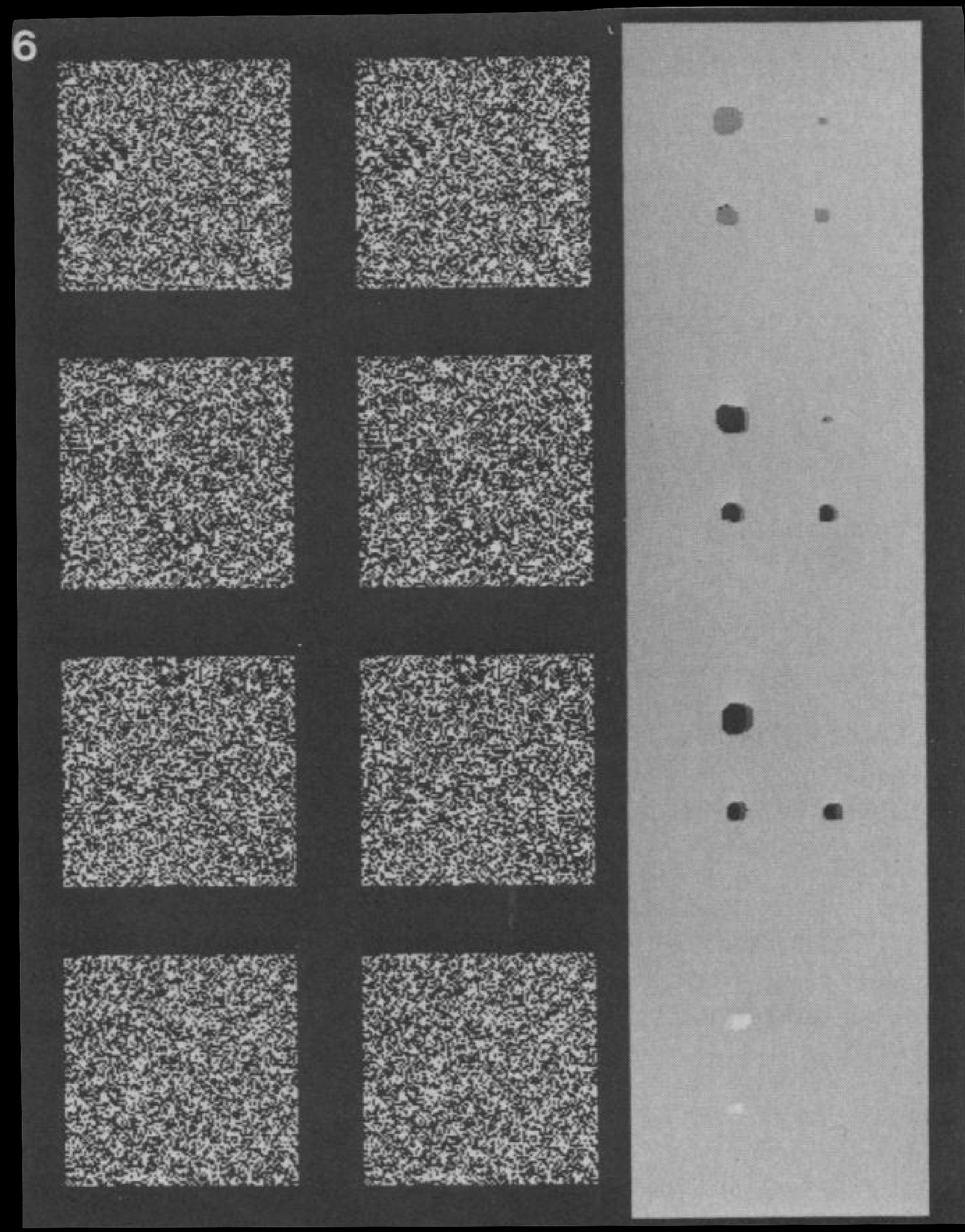


Can be mapped into analog circuits.

AN ANALOG VLSI IMPLEMENTATION OF THE MARR-POGGIO STEREO CORRESPONDENCE ALGORITHM.
M. Mahowald and T. Delbrück 216-76 Caltech, Pasadena, CA, 91125 USA

Algorithm in action





Next Week: Krste Asanović returns

Tue Sep 18	KA	Lecture 8: Overview of hardware design patterns.
Thu Sep 20	KA	Lecture 9: Memory and Memory Design Patterns.