Intelligent Pattern Recognition , Applications and Big Data, in Interactive Learning Environment©

Prof. Patrick Wang, *Ph.D.*

Fellow, IAPR, ISIBM, WASE

IEEE & ISIBM Outstanding Achievement Awardee

NSC Chair Professor, NTUST, Taiwan

Zijiang Visiting Chair Professor, ECNU, CQU, Tongji, China

iCORE Visiting Professor, Calgary U., Canada

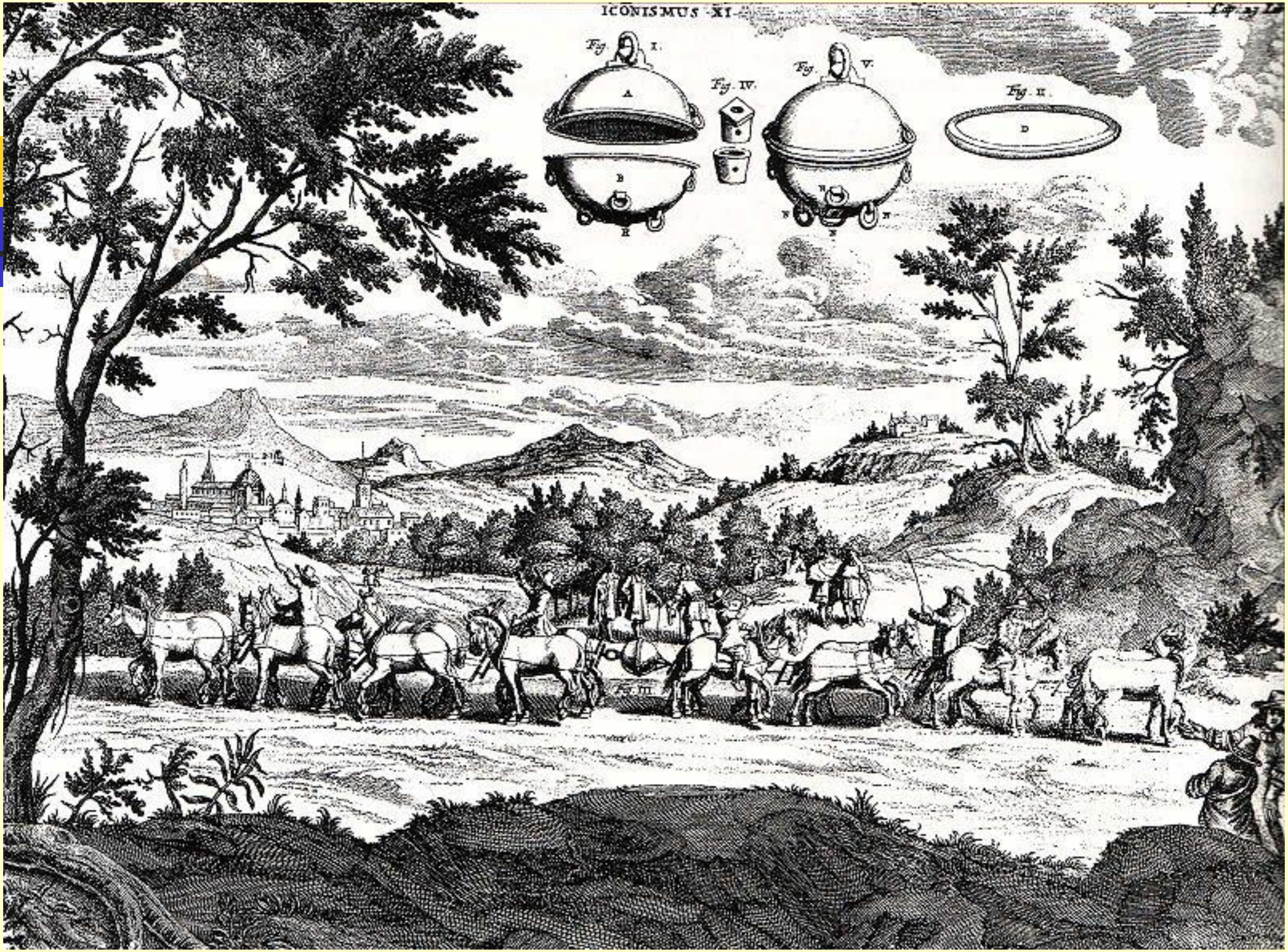
Otto-von-Guericke Distinguished Guest Professor, Magdeburg U., Germany

Northeastern University, Boston, USA

patwang@ieee.org , pa.wang@neu.edu

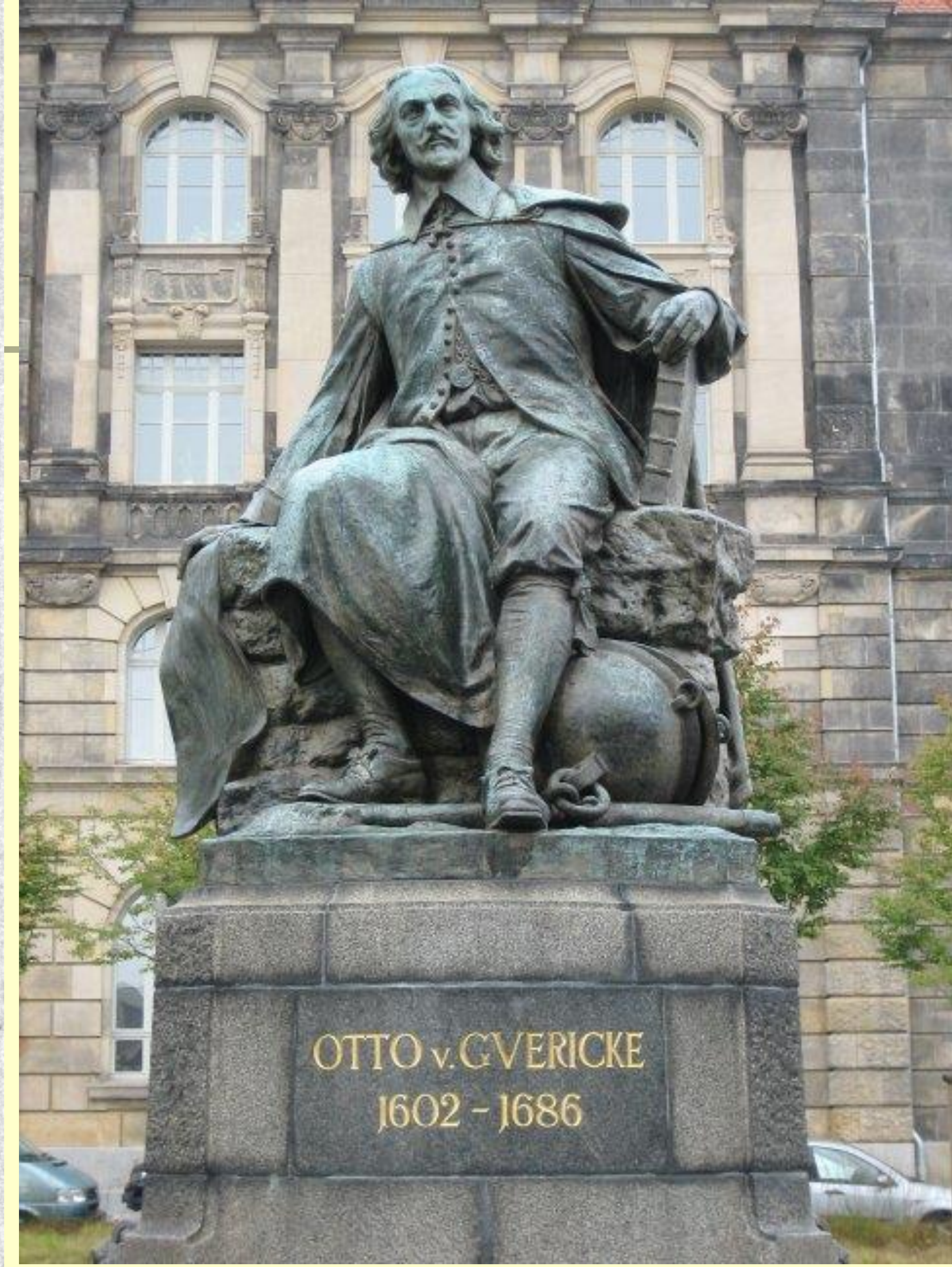
Table of Contents

Otto von Guericke, **(1602 - 1686)** engraving by Anselmus von Hulle, (1601-1674)



Kupferstich Gaspar Schotts zu von Guerickes Halbkugel-Experiment


33.
Je le sçais, où se trouve mieux
Cette vertu presque magique,
Sçavament nommée électrique;
Jeunes Beautés, c'est dans vos yeux.
33 l'Electricité


OTTO v.GVERICKE
1602 - 1686

OTTO-VON-GUERICKE-UNIVERSITÄT MAGDEBURG

Der Rektor

Prof. Dr. H. Böttger

Otto-von-Guericke-Universität Magdeburg · Postfach 4120 · D-39016 Magdeburg

Professor Richard Freeland
President
Northeastern University
360 Huntington Avenue
Boston, MA 02115

USA

Otto-von-Guericke-Universität Magdeburg
Universitätsplatz 2
D-39106 Magdeburg

Tel. (03 91) 67 18543
Fax (03 91) 67 11157

Ihre Zeichen, Ihre Nachricht vom | Unsere Zeichen | Datum

8 Nov 1996

Collaboration with the Otto-von-Guericke-University of Magdeburg

Dear Professor Freeland,

It has been an honour to have one of your faculty members, Dr. Patrick Wang, as our distinguished Otto-von-Guericke Visiting Professor for Imaging Sciences with us for the past month.

This professorship is assigned only every other year and for a topic of particular current interest. It reflects the committment to excellence in research and our current emphasis on Imaging Sciences.

I hope that this visit by Professor Wang will lead to collaboration between our scientists and lead to an exchange of students. Should you plan a trip to Europe, we would be delighted to welcome you here in Magdeburg.

For your information, I enclose a broshure describing our activities and profile.

Sincerely,

i.V. J. Stett

Professor Harald Böttger

NORTHEASTERN UNIVERSITY 1898 CENTENNIAL 1998

OFFICE OF THE PRESIDENT

Northeastern University, 110 Churchill Hall, Boston, MA 02115

617.373.2101 fax 617 373 5015

December 19, 1996

Professor Harald Böttger, Rektor
Otto-Von Guericke-Universität Magdeburg
Postfach 4120
D-39016

Dear Professor Böttger:

Thank you for your letter of November 8, 1996. We are pleased to learn that Dr. Patrick Wang, one of our distinguished Computer Science faculty, was honored with the Otto-von-Guericke Visiting Professorship this past fall.

Northeastern is always interested in exploring the possibility of faculty and student exchanges with international institutions. We look forward to receiving more information about the collaborations and/or exchanges you would propose so that we might better determine whether such programs would be of mutual interest.

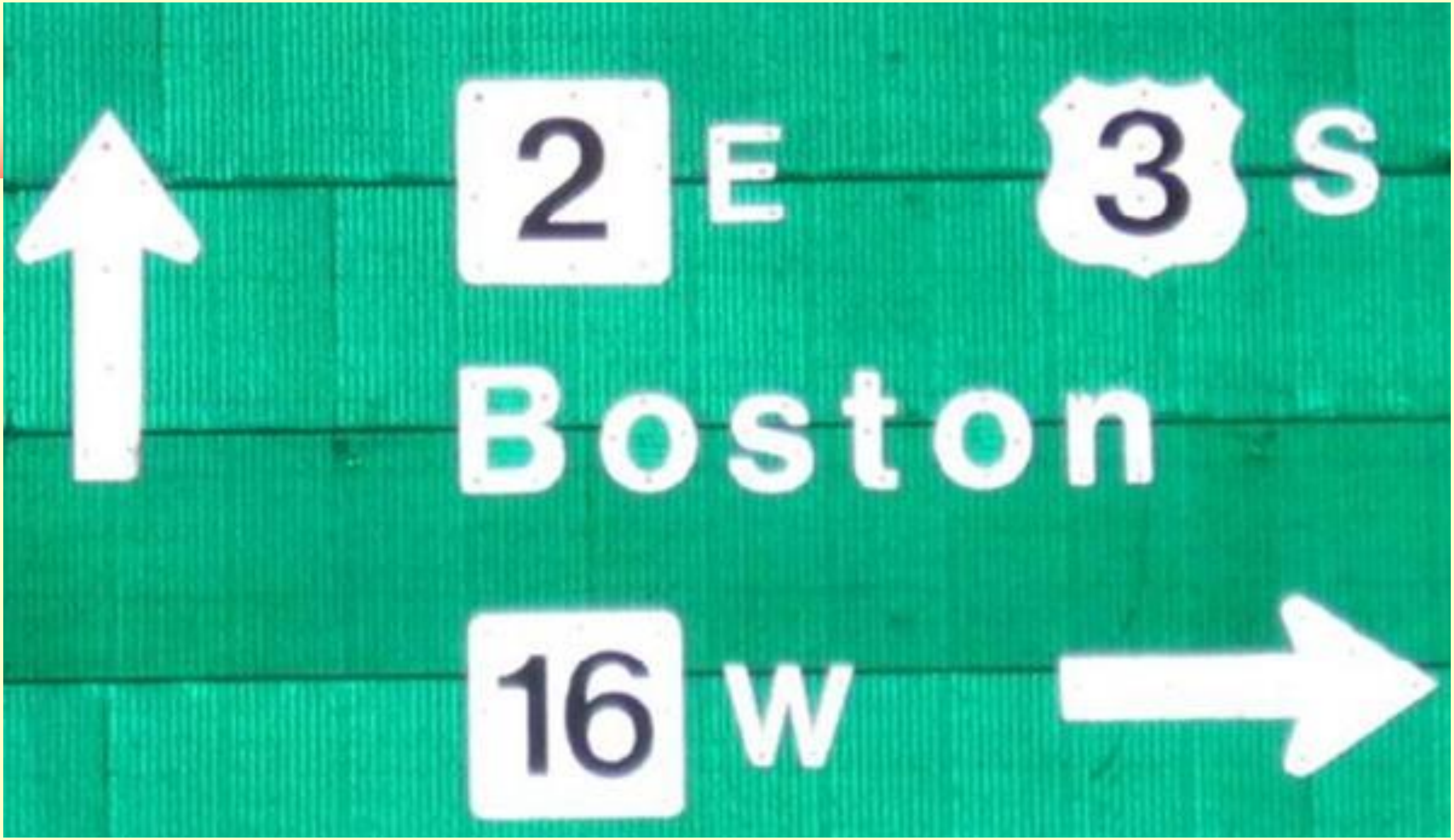
In the meantime, may I extend my best wishes for the holidays and the new year.

Sincerely,

Richard M. Freeland
President

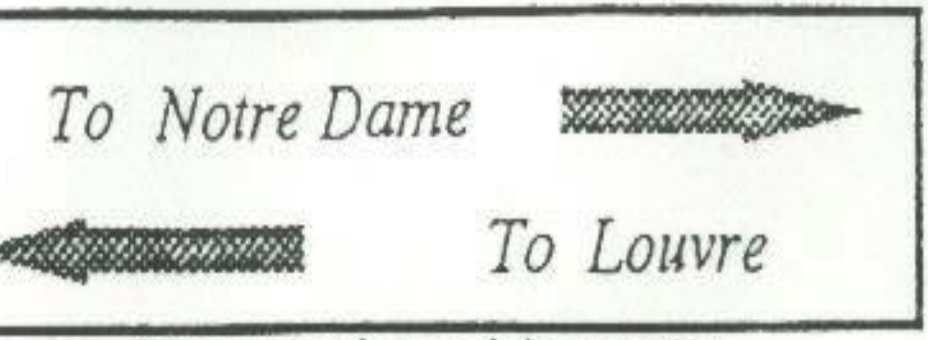
cc: Provost Michael Baer
Professor Patrick Wang


WHAT'S THE DELAY?
ROAD TO RECOV
GO
MY WAY
DO NOT NOT ENTER
NO LEFT TURN
SPEED LIMIT 30
BUSINESS
ERIC ALLIE


2 E
3 S
Boston
16 W

CHARLES ST
KEEP RIGHT
ONE WAY
ONE WAY
KEEP RIGHT
Oops, No I meant the First
You'll have to go round again
(M32,M4)
(M32)
Take the second exit
Look I said I was Sorry
ROAD ADVISORY SIGN 300m
LEFT
2 W 16 E 3 N
Harvard Sq.
2 E 16 W 3 S
Boston
Harvard Sq.
WEST VILLAGE A
WEST VILLAGE B
WEST VILLAGE C
WEST VILLAGE E
WEST VILLAGE G
WEST VILLAGE H
WILLIS HALL
SWITCH

An emergency sign lacks direction



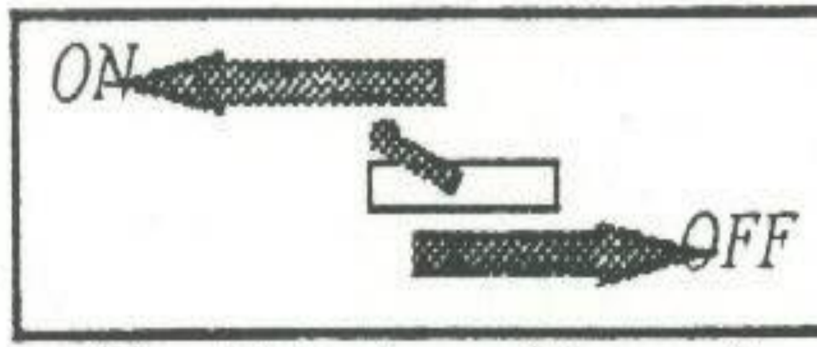
Not good (ambiguous)

Should be (unambiguous)

Emergency Switch

ot good and dangerous(ambiguous)

Emergency Switch



Should be (unambiguous)


Country, State(Province), City, Street, Number, Last Name, First Name
美国麻州波士顿杭亭屯街東北大學王巍教授
Scanning, Parsing, Searching and Matching (natural sequence, no backtracking needed)
First Name, Last Name, Street Number, City, State(Province), Country
Prof. Patrick Wang, Northeastern Univ, 360 Huntington Ave, Boston, MA 02115 USA
Scanning, Parsing, Searching and Matching (unnatural sequence, backtracking needed)
Year, Month, Day
(No backtracking needed)
Day, Month, Year
(Needs backtracking)

Artificial Intelligence

Using computers to solve problems that normally can be solved by human beings

Machine emulation of human behaviors (Natural Beings)
仿真,人類行為,模仿人類

Examples:

OCR: Optical Character Recognition

Robots

Speech Recognizer

Machine Aided Assistant

ATM Machine : Automatic Deposit/Withdrawal etc

Pattern Recognition

Cognize: To Learn(with Brain)

Re-cognize: To Cognize after Learning

Pattern: Class of Objects that satisfy common properties (Characteristics)

Finite versus Infinite Patterns

Examples:

Finite: Today's audience

Infinite: Integers

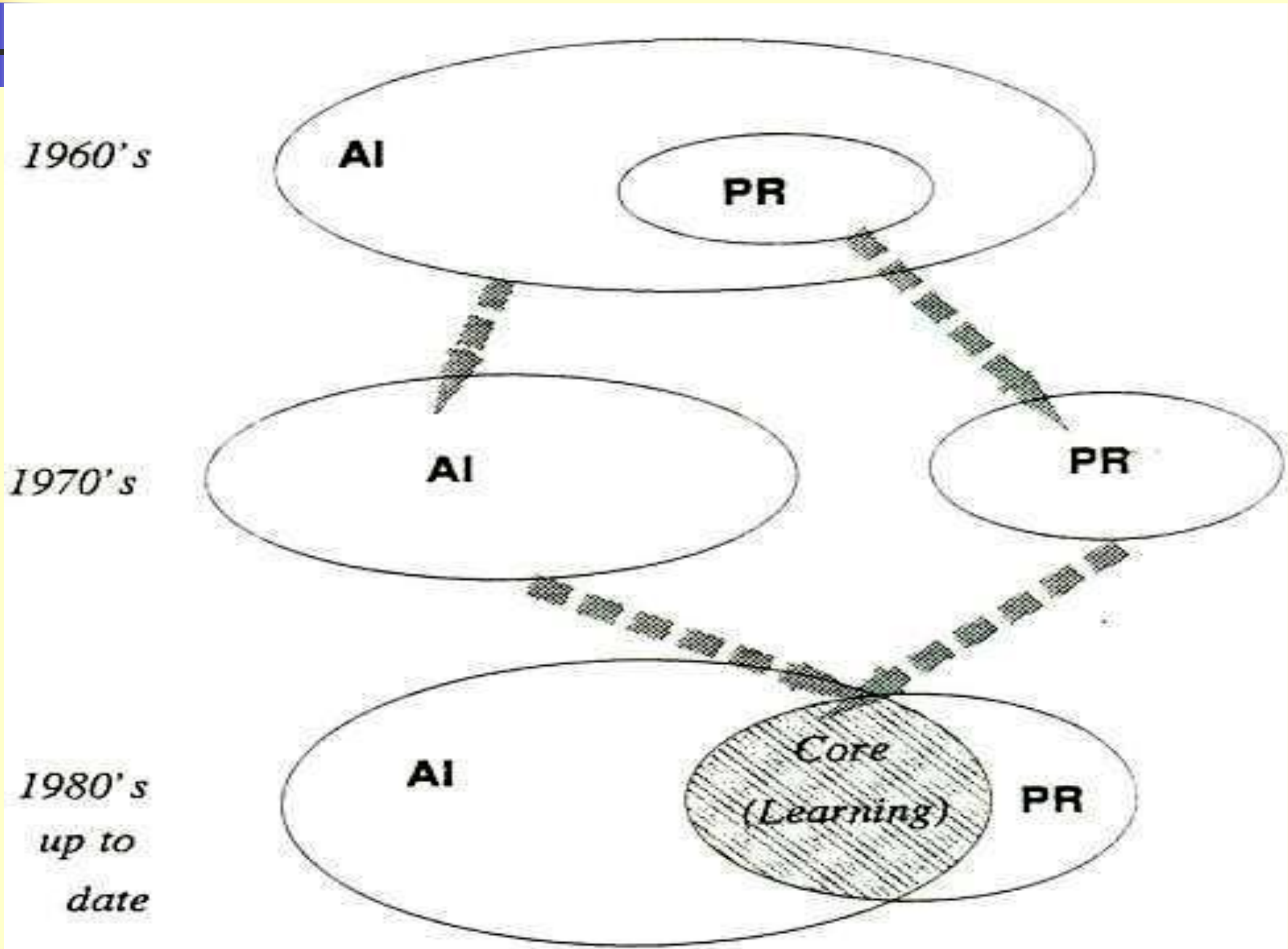
Real Numbers

All English Alphabets

Human Faces, Fingerprints, Voices, Handwritings, Signatures

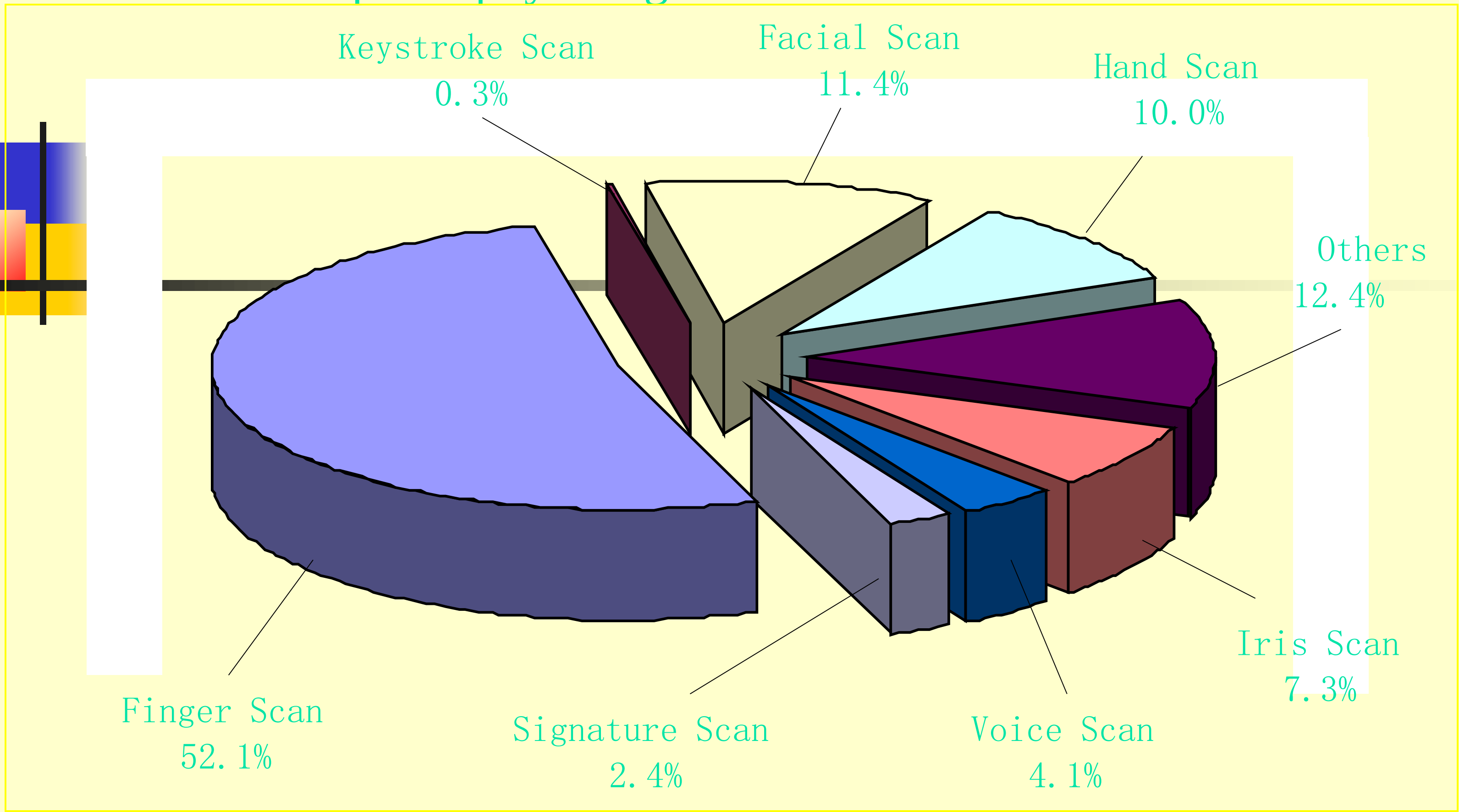
etc

PR (Pattern Recognition) and AI (Artificial Intelligence)



What are Biometrics?

Biometrics are automated methods of recognizing a person based on the acquired physiological or behavioral characteristics



Percentage of usage (Source: International biometric group)

Why Biometric Technologies?

For Security Reasons

A Scenario

Two Al Qaeda suspects were recently taken into custody by U.S. immigration authorities as they tried to enter the United States after their fingerprints were matched with ones lifted by U.S. military officials from documents found in caves in Afghanistan.

Example 1:

SFinGe - **S**ynthetic **Fin**gerprint **Ge**nerator

developed at the **Biometric Systems Lab,** University of Bologna – ITALY, is utilized to:

- *compare* different fingerprint matching algorithms
- *train* pattern recognition techniques that require large learning-sets (e.g. neural network)
- easily *generate* a large number of "*virtual users*" to develop and test medium/large-scale fingerprint-based systems (e.g. AFIS)

Fingerprints

"Perhaps the most beautiful and characteristic of all superficial marks (on human body) are the small furrows with the intervening ridges and their pores that are disposed in a singularly complex yet even order on the under surfaces of the hands and feet."

Francis Galton, Nature, June 28, 1888

Fingerprints: New Era

- Border security
- Financial fraud
- User convenience

New deployments need

- Cheap & compact sensors
- Fully automated matching

Disney World, Orlando

Throughput: 100K/day, 365 days/ year

Dermatoglyphics

- Ridged (friction) skin on fingers, palms & soles
- Derma (skin) + glyphē (carve): study of ridged patterns

Fingerprint Formation

- Ridge formation starts at 1 or 2 focal points and spreads over the fingertip
- Localized ridge units merge to form ridges at ~10.5 weeks estimated gestational age

Fake Documents

The nineteen 9/11 terrorists had a total of 63 valid driver licenses

US-VISIT

~ 60 million visitors have been processed through US-VISIT; 1,100 criminals denied entry

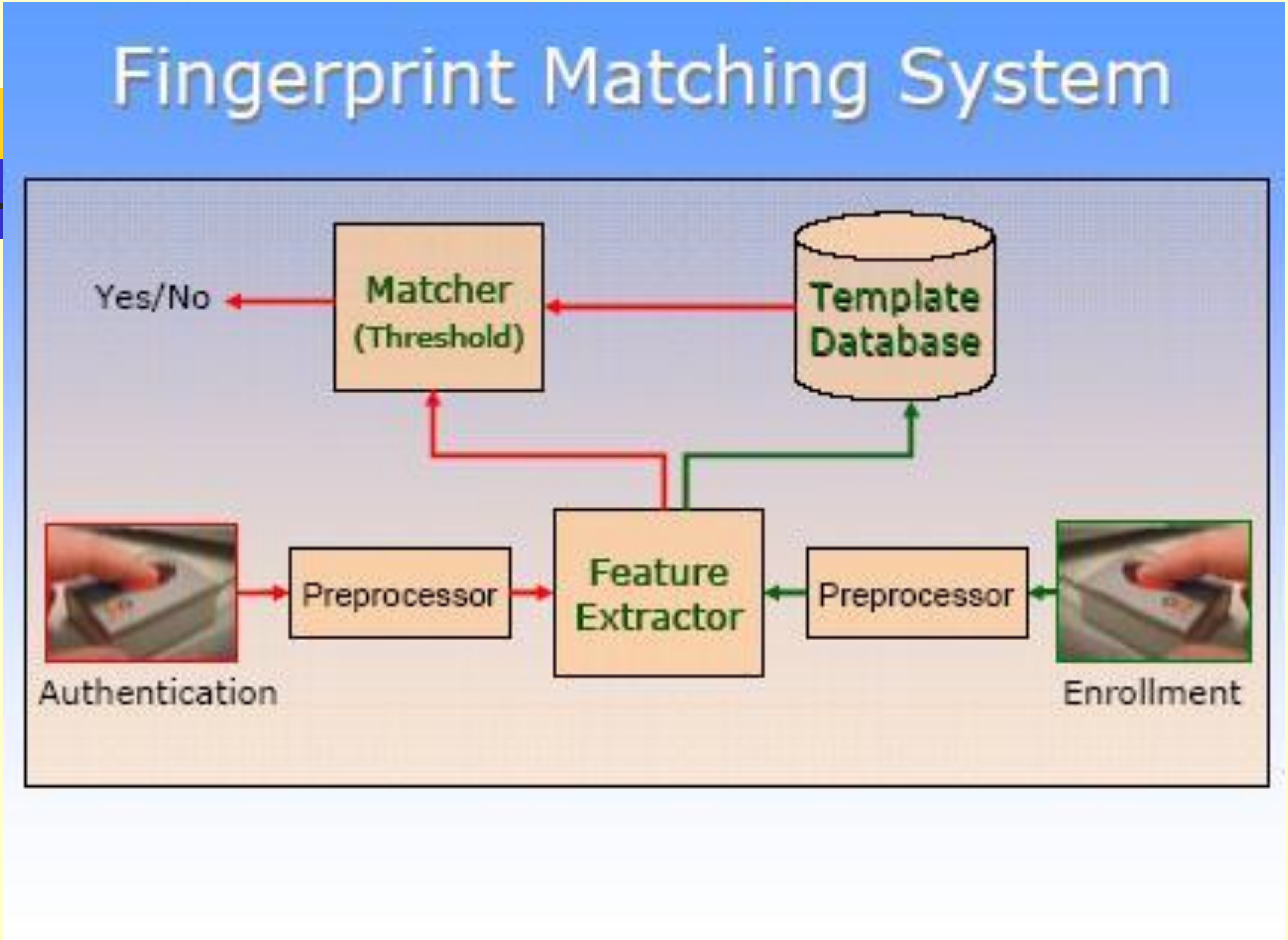
Hong Kong Smart Identity Card

HK Smart ID Card

- Security: Prevent misuse of stolen cards
- Convenience: e-Certificate
- Service: electronic government services
- Travel: Passenger Clearance System

PAY BY TOUCH™

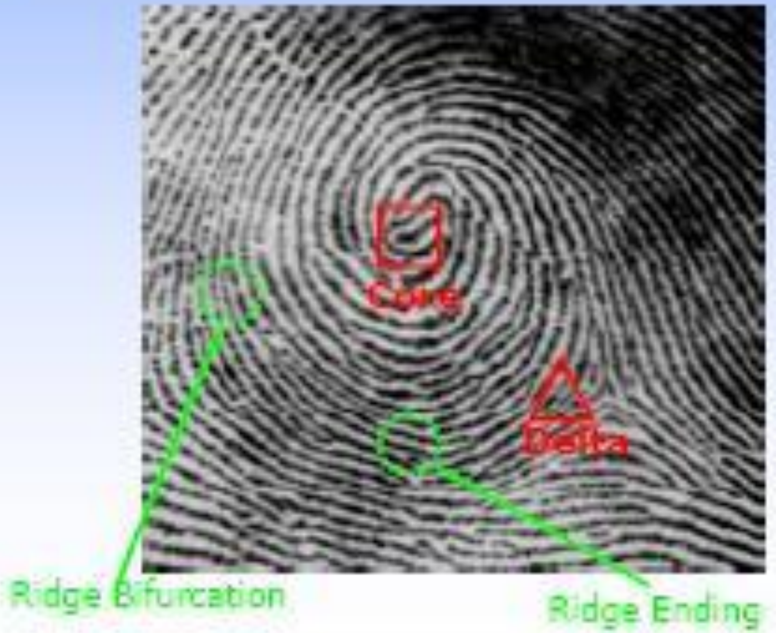
Customer pay by fingerprints; no need for cards/cash

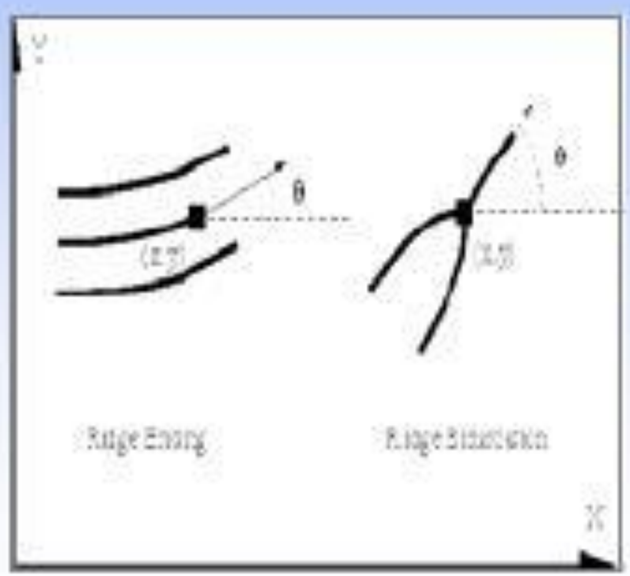


Fingerprint Matching System
Yes/No
Matcher
(Threshold)
Template
Database
Authentication
Preprocessor
Feature
Extractor
Preprocessor
Enrollment

Features

- Local ridge characteristics (minutiae): ridge endings and bifurcations
- Singular points (core and delta): discontinuity in ridge orientations

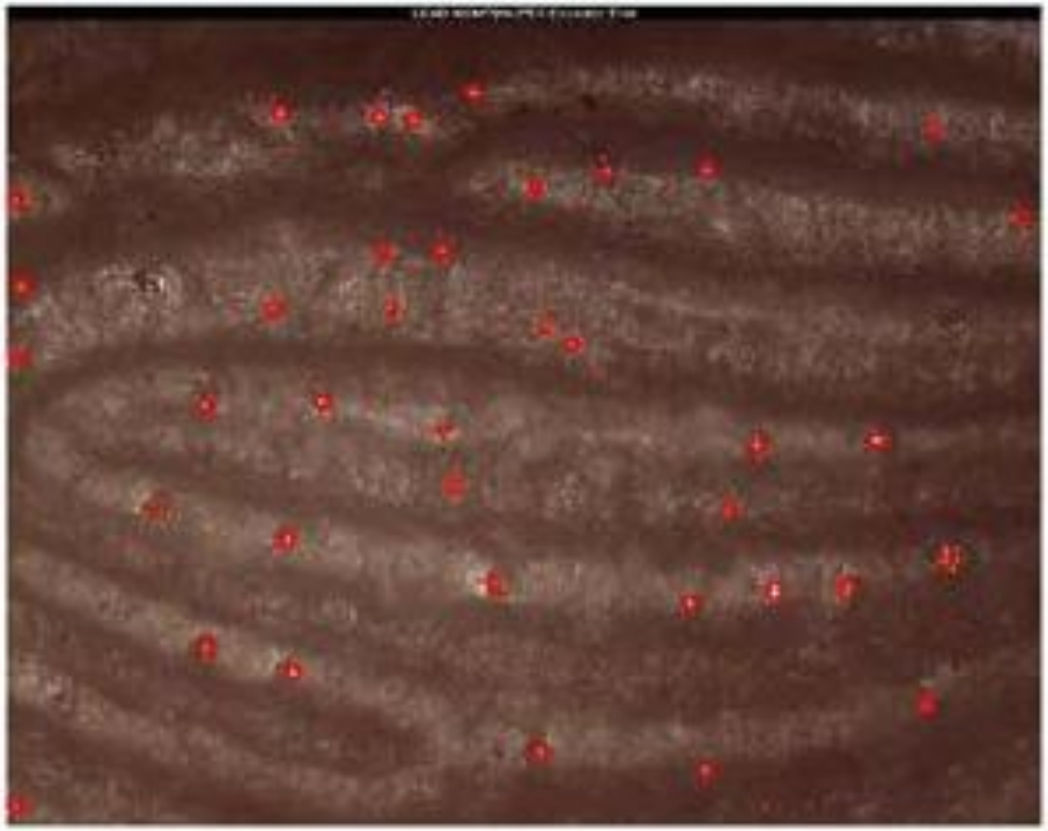




Extended Feature Set

'It is NOT the points, but what's in between the points that matters' Edward German, *latent print examiner*

High Resolution Sensors



Are Fingerprints Unique?

"Only Once during the Existence of Our Solar System Will two Human Beings Be Born with Similar Finger Markings" *Harper's headline, 1910*

"Two Like Fingerprints Would be Found Only Once Every 10^{48} Years" *Scientific American, 1911*

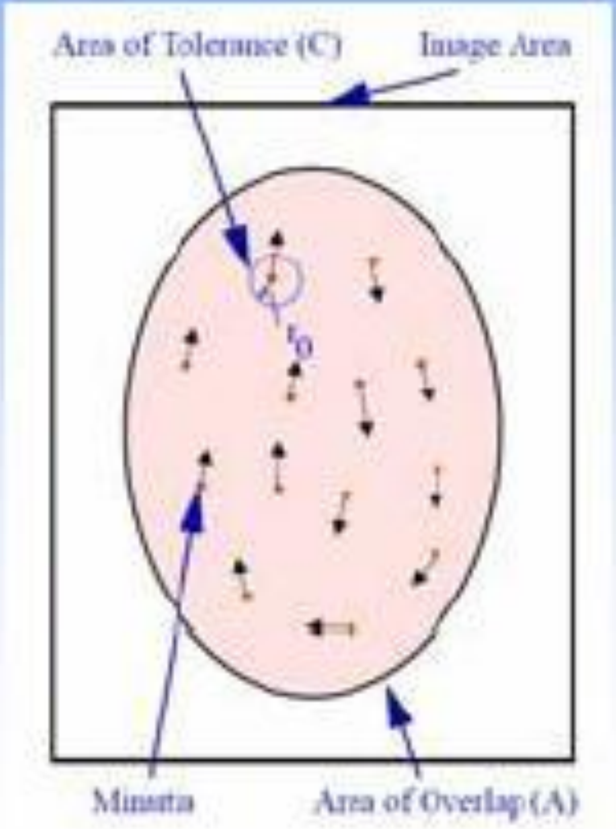
The uniqueness of fingerprints has been accepted over time because of relentless repetition and lack of contradiction

Challenges to Uniqueness

- *Daubert vs. Merrell Dow, 1993*
  - Test of hypothesis
  - Known or potential error rate
  - Peer reviewed and published
  - General acceptance
- Challenges *(USA v. Byron Mitchell, 1999)*
  - Error rate is not known
  - Uniqueness has not been tested

Probability of Random Correspondence

- Given two fingerprints with m & n minutiae, what is the probability they will share q minutiae?



1. m=n=52, q=12
   PRC = 4.4×10^{-3}
   (Observed value = 3.5×10^{-3})

2. m=n=52, q=26
   PRC = 3.4×10^{-14}

M = A/C=413 (NIST-4 database)

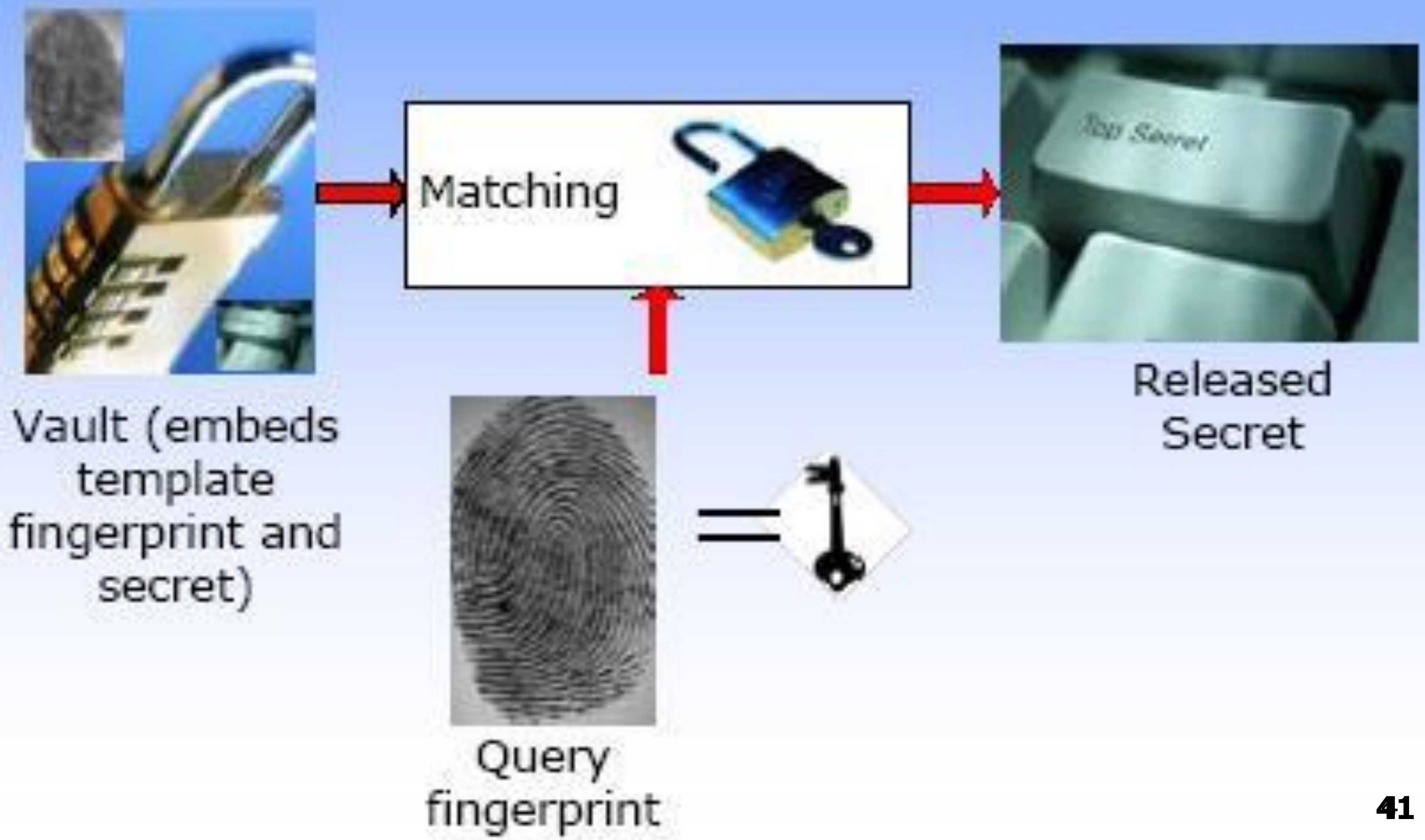
Match on Card

Biometric Smart Card
(UPEK Inc.)

Biometric Key Chain
(Privaris, Inc.)

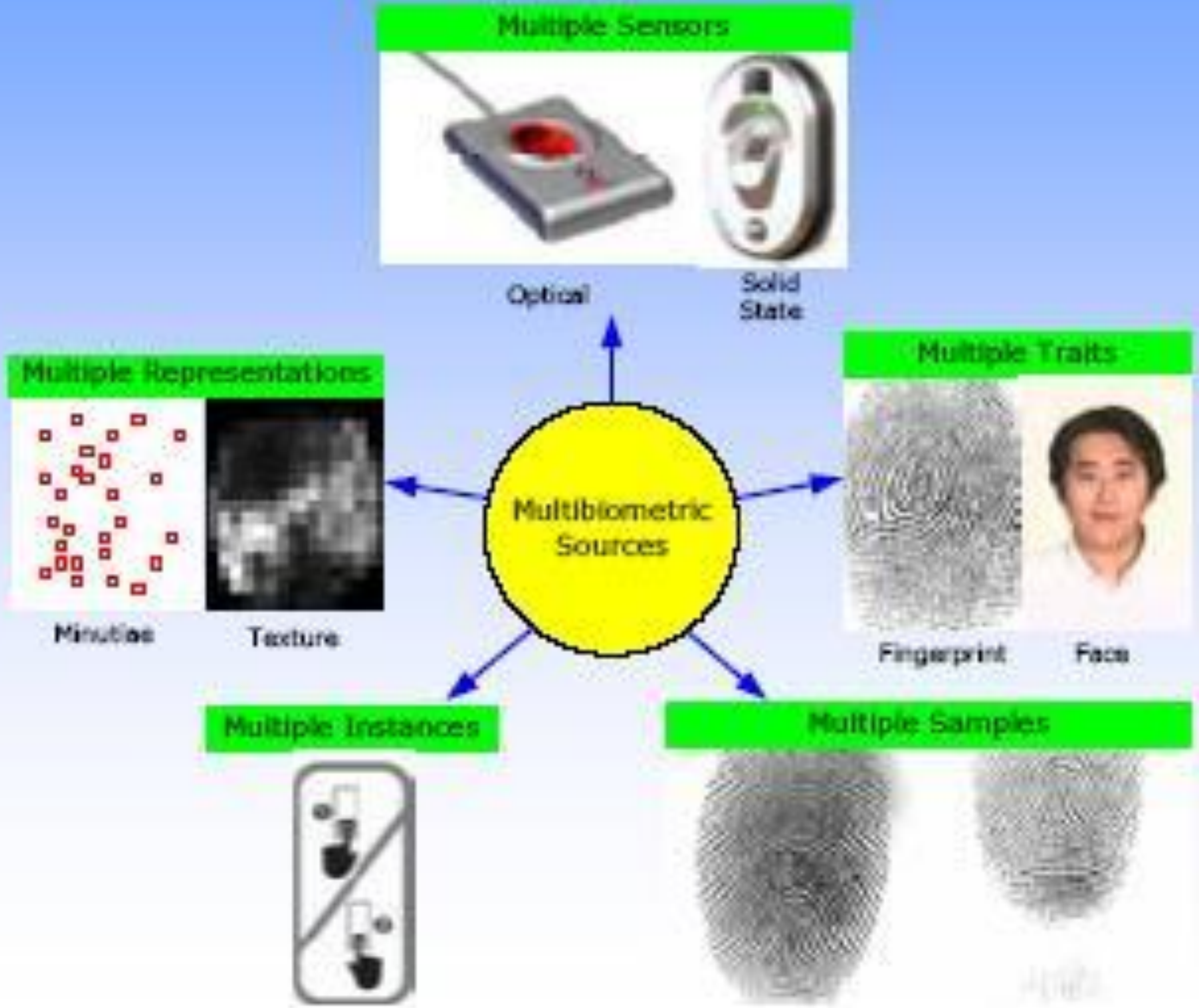
Fingerprint Fuzzy Vault

Secure an encryption key with fingerprint so only the authorized user can access the secret



Multibiometrics

Failure to enroll, spoof attacks, error rate



Summary

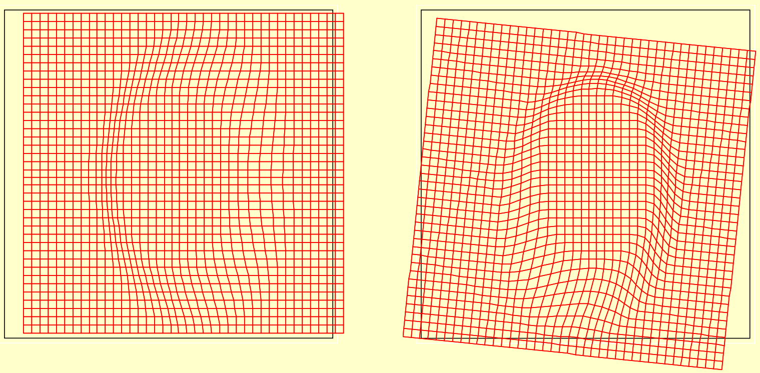
- Fingerprint recognition is the earliest & largest deployment of pattern recognition
- Fingerprints are believed to be fail proof, but commercial systems have finite error rates
- Many societal needs (identity theft, financial fraud, security) require robust, accurate & cost-effective fingerprint matchers
- It is a proving ground for pattern recognition

Example 2: generation of synthetic signature

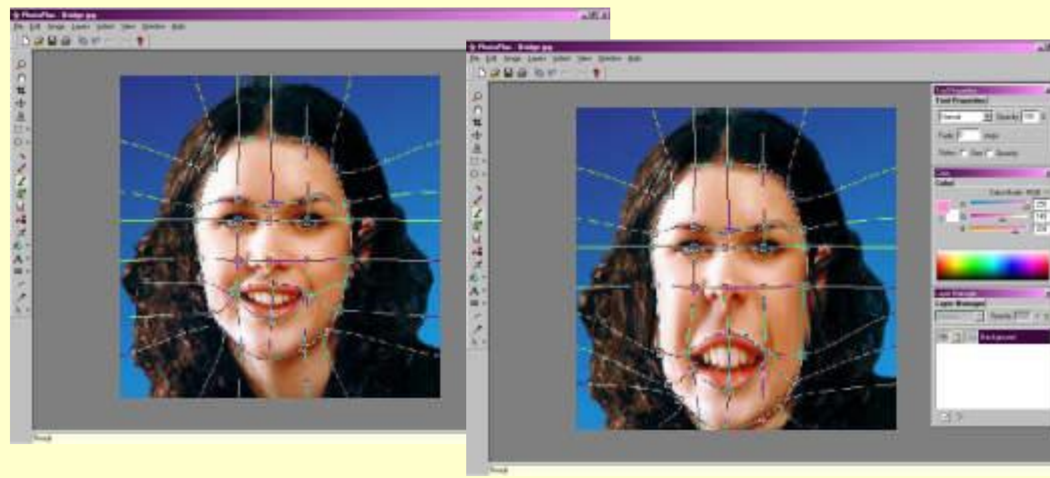
- Modeling segments (conics, splines)
- Assembling (desegmentation) of 2-D model
- Modeling by deformation
- 3-D model (pressure in on-line model)

Example 3: **Privacy protection:**

- After enrollment, a true object (e.g. image of face, fingerprint or voice signal) is intentionally distorted using irreversible transform - *Cancelable biometrics* (Ratha, Connell, Bolle, 2001)

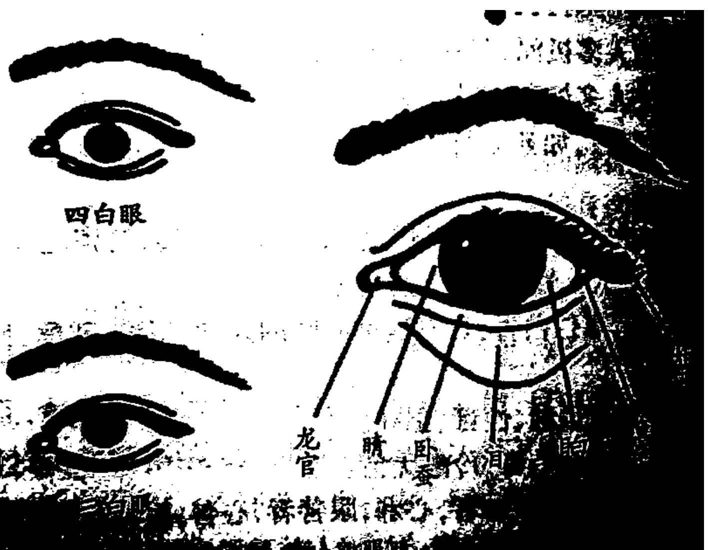


Skin distortion (fingerprint) (source: Biometric Systems Lab, University of Bologna)

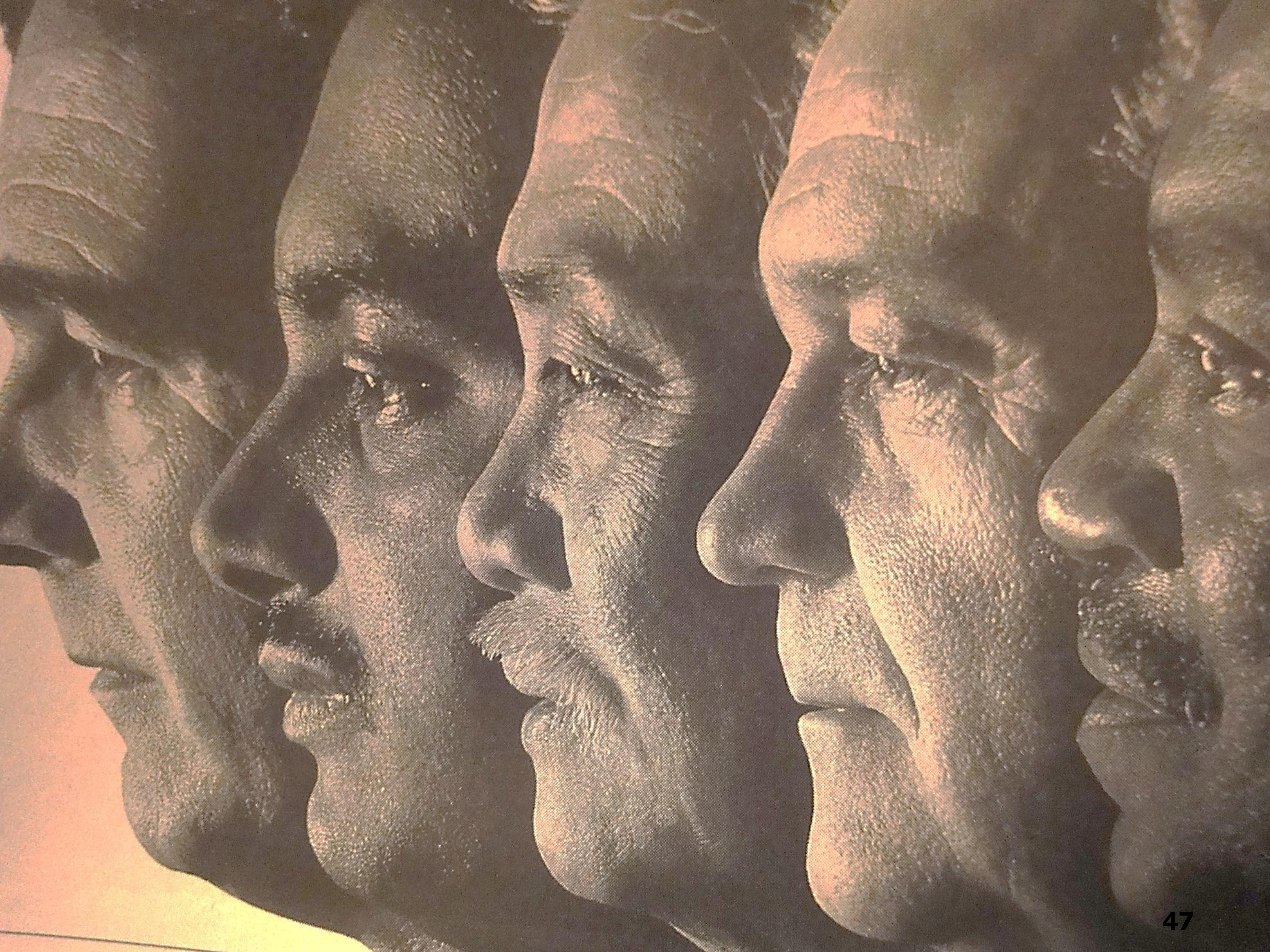


Face image is warped with bilinear interpolation (source: Serif Inc.)

FACE ANALYSIS and RECOGNITION



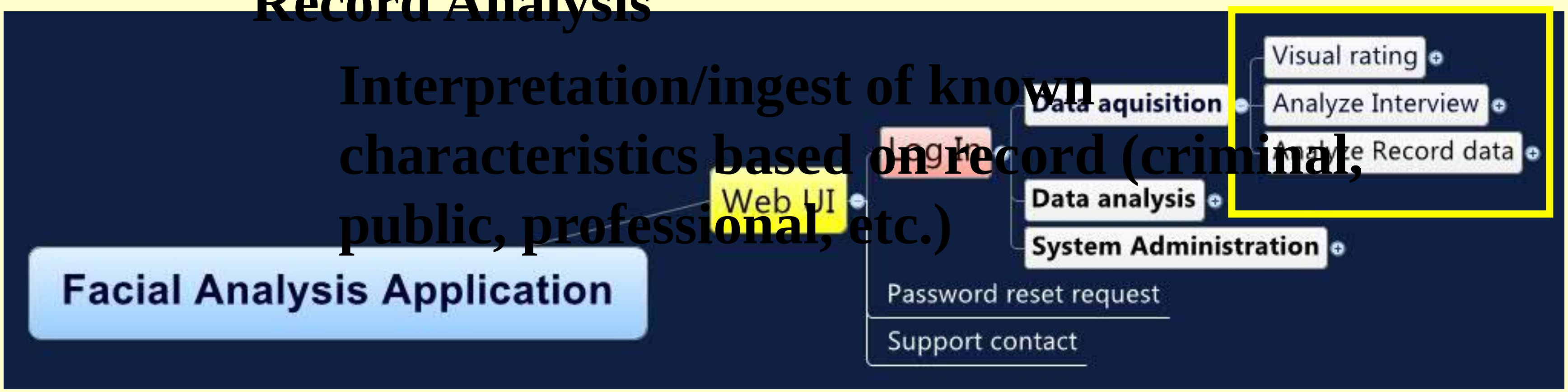
- Aileen Wuornos: Female Serial Killer
  From 1989 to 1990, prostitute Aileen Wuornos murdered seven men in Florida, later claiming they had raped her. She shot each man several times. She welcomed her pending execution, telling the Florida Supreme Court, “I’m one who seriously hates human life and would kill again.” She was put to death by lethal injection in 2002; the following year, Charlize Theron played her in the movie “Monster,” and ended up winning an Oscar.



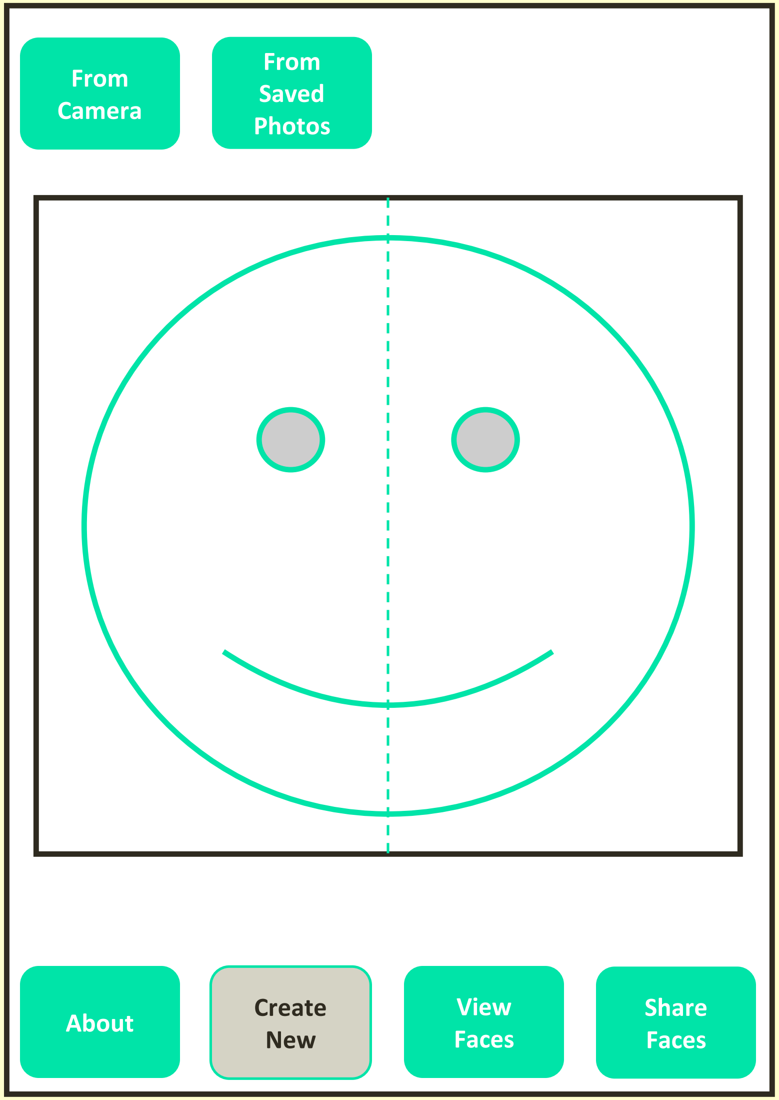
Application Components

Data Acquisition

- **Visual Rating**
  - **Interpretation/ingest of physical facial features**
- **Interview Analysis**
  - **Interpretation/ingest of psychological interview**
- **Record Analysis**
  - **Interpretation/ingest of known characteristics based on record (criminal, public, professional, etc.)**



Create New Face Screen

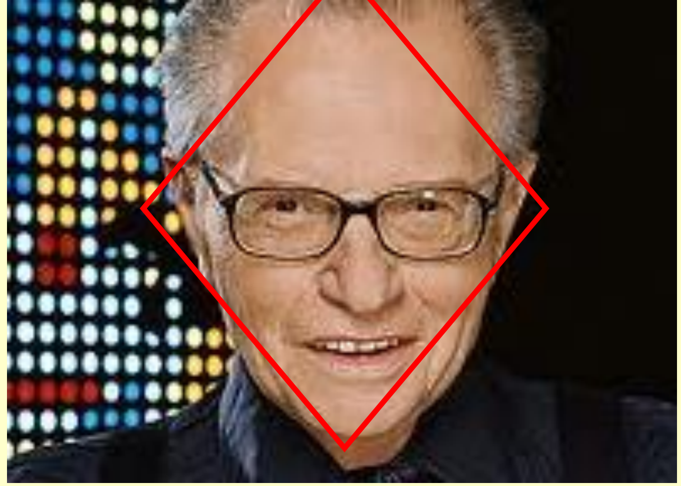


Here is where new face images will be setup and created.

You will first need to select from:

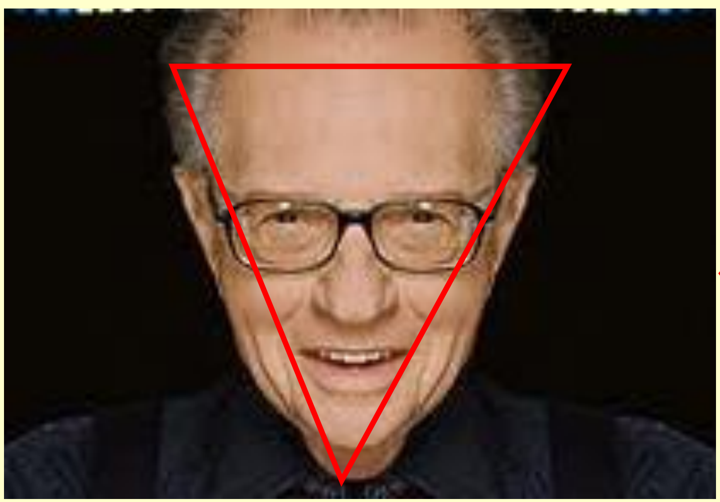
Camera or Saved Photos.

This screen will allow the user to adjust the image using zoom, pan, and rotate to get the image to align with the overlay template as close as possible.



Original Photo

Normal Face



Right Composite

Left Composite

Original Photo

Normal Face

Right Composite

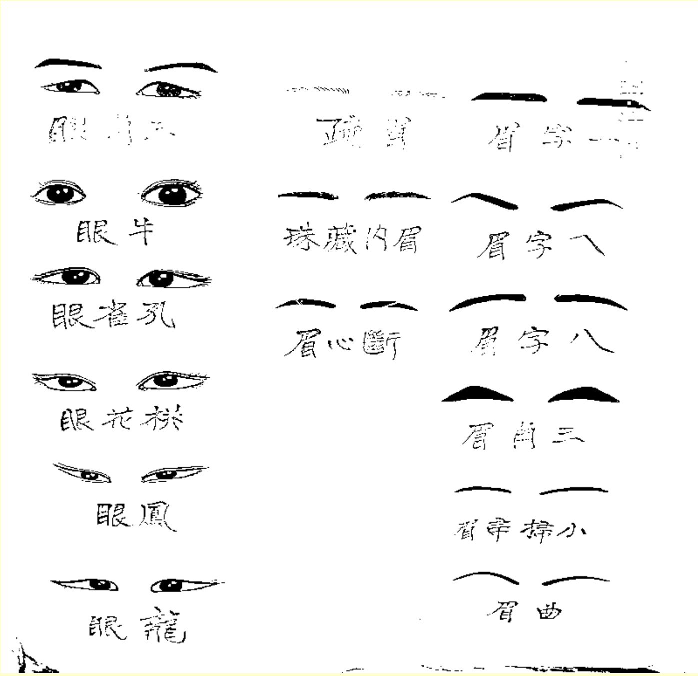
Left Composite

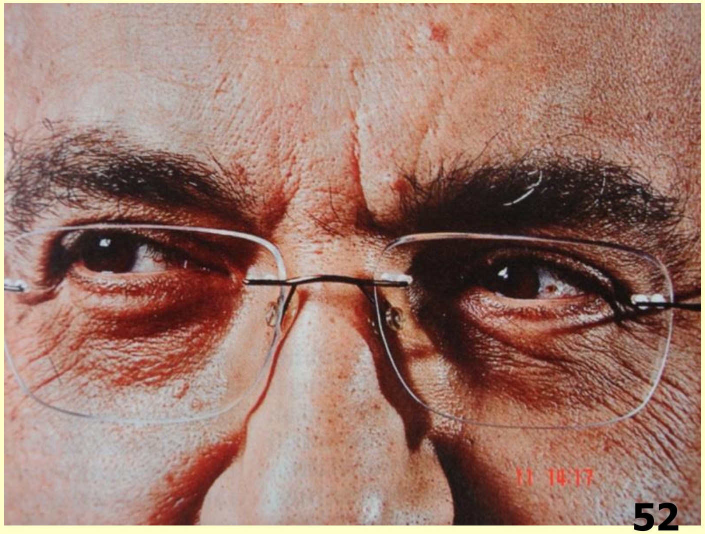
Face Characteristics

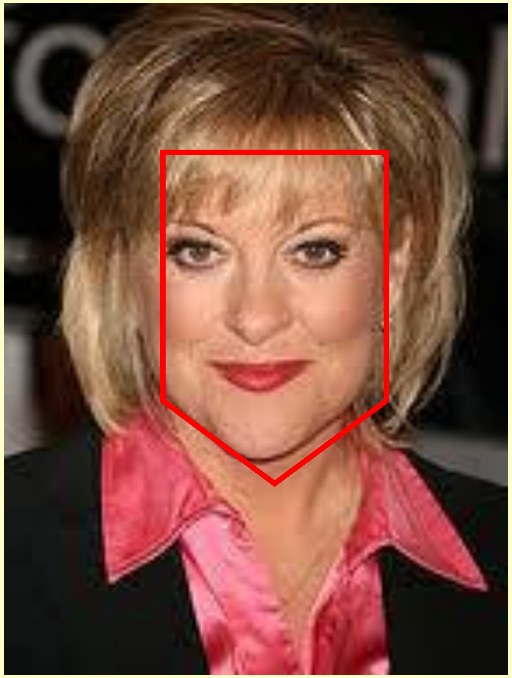
The appearance of a face and its Features are partially genetically related and partially reflect its habitual use and what his/her life had been through.

Those features and patterns can be classified into groups .

Those feature can be associate with personality and psychological characteristics

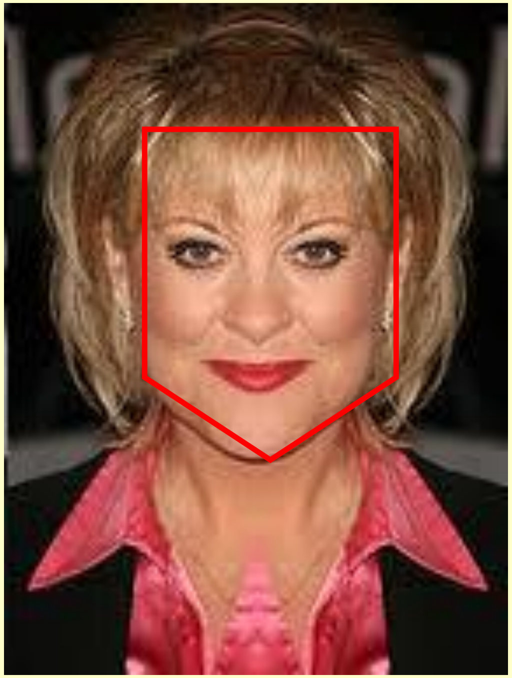




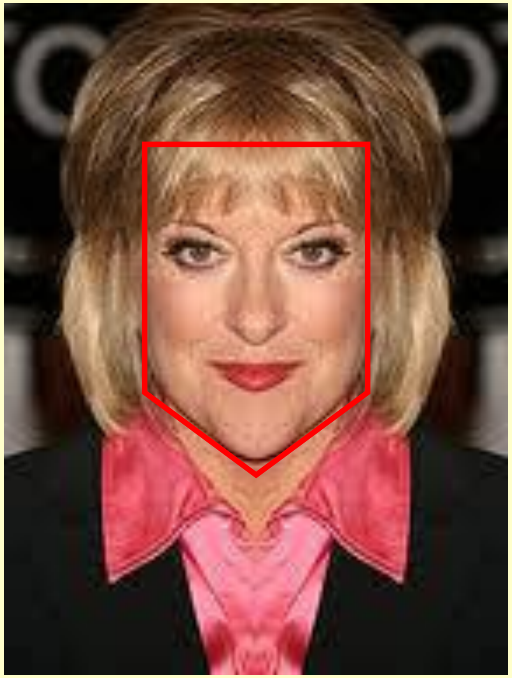


Original Photo

Normal Face



Right Composite
Public Fa



Left Composite
Private Face

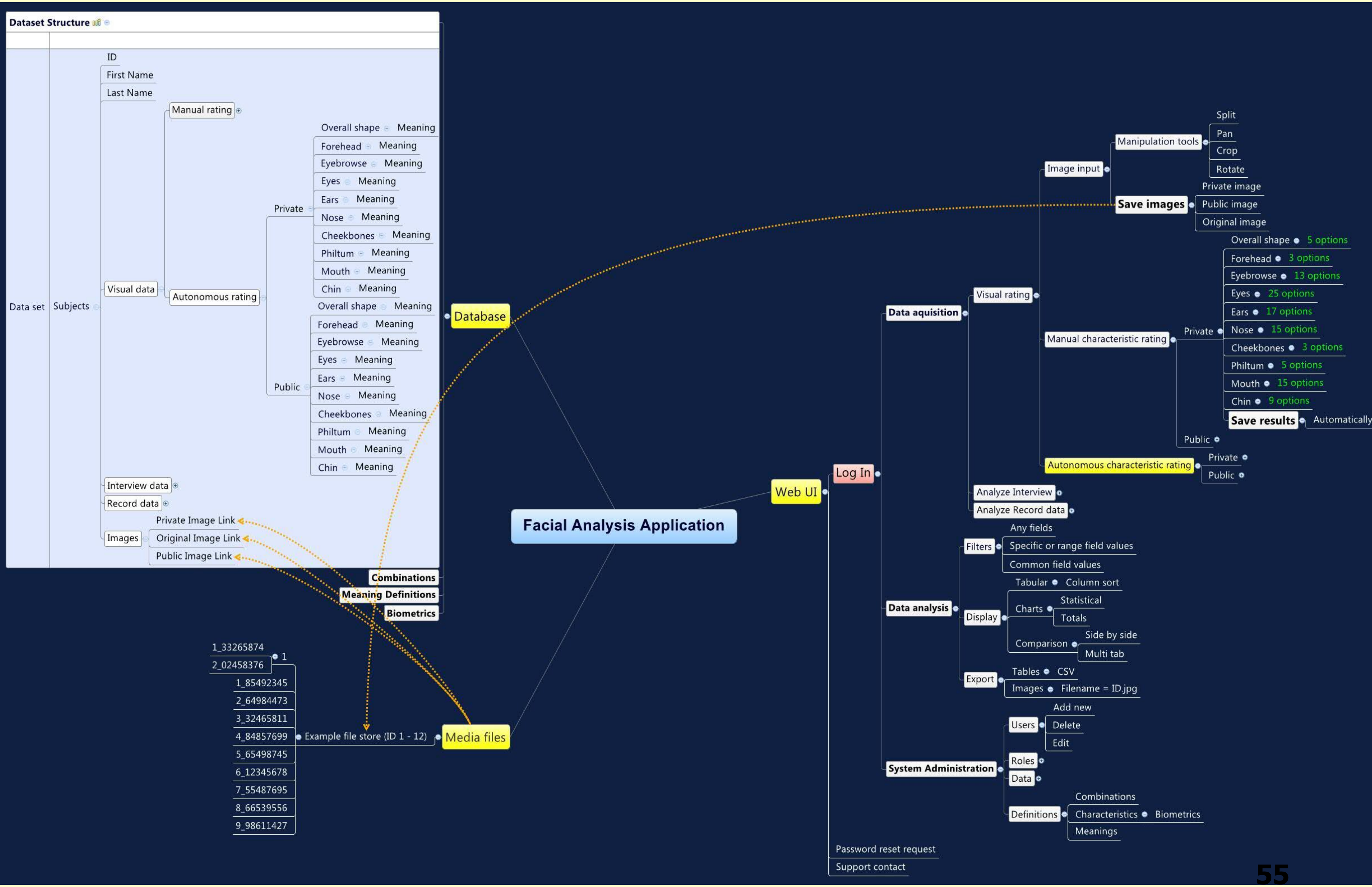
Facial Analysis Application Overview

Our facial analysis application consists of two different components:

- **The first is designed to help the user categorize or identify suspects: a potential terrorist, serial killer, suicide bomber.**

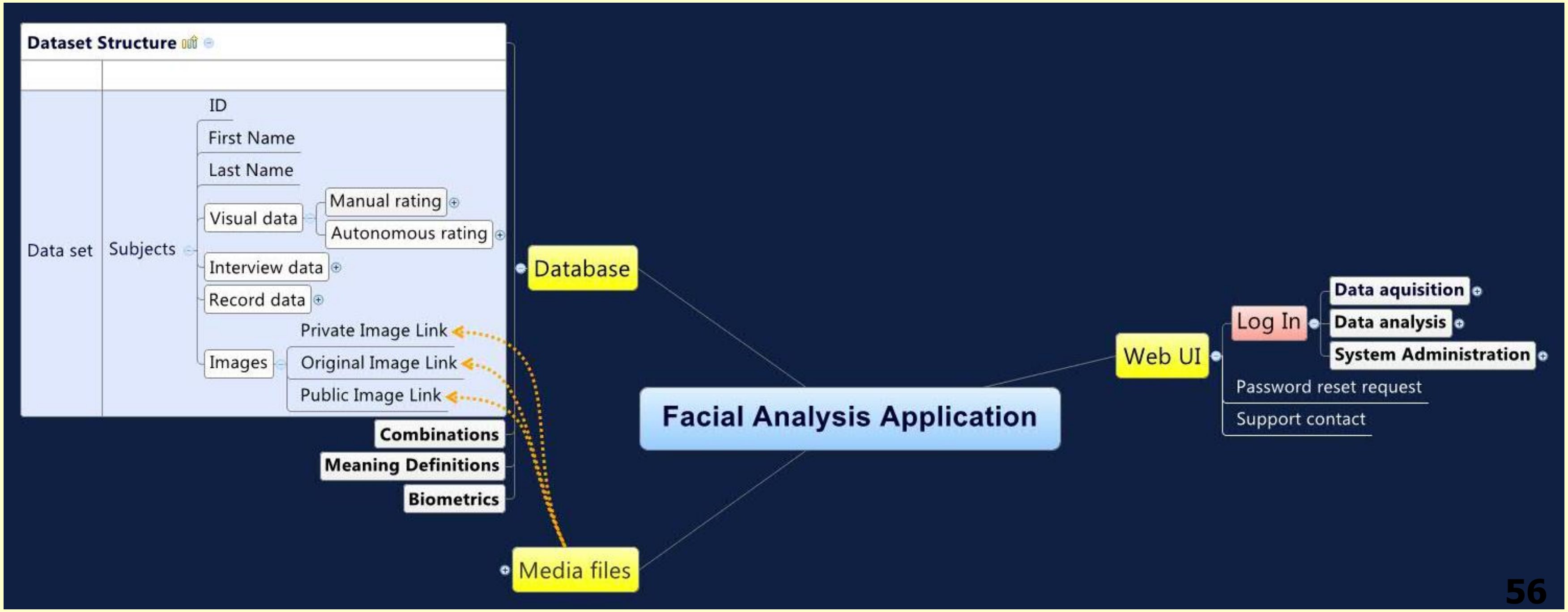
- **The second component is designed to help the user interrogate suspects more successfully.**

Facial Analysis Application Overview



Facial Analysis Application Overview

Through the use of a computer analysis application, we will be able to compare facial traits of known criminals and use that information to identify potential suspects:



Application Components

Back-End

Database

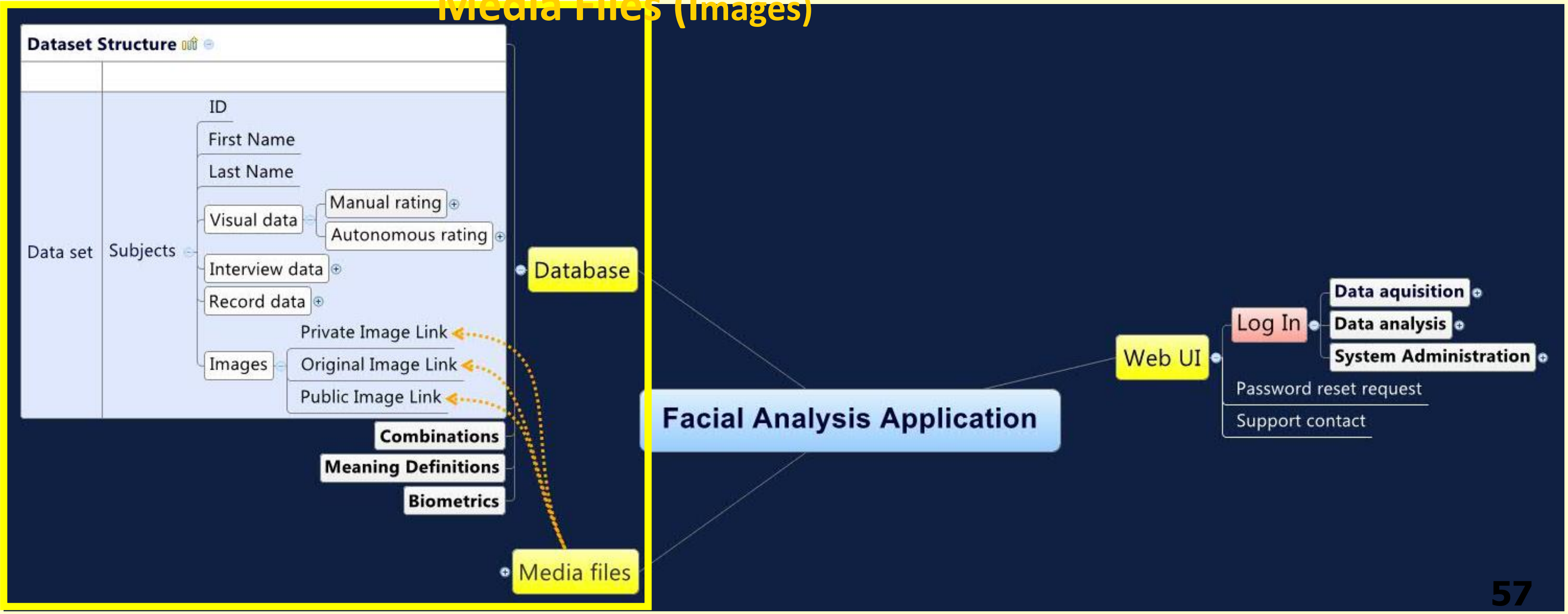
Biometrics

Feature Definitions

Personality Records (criminal, public, professional)

Psychological Interview Assessment

Media Files (images)



Application Components

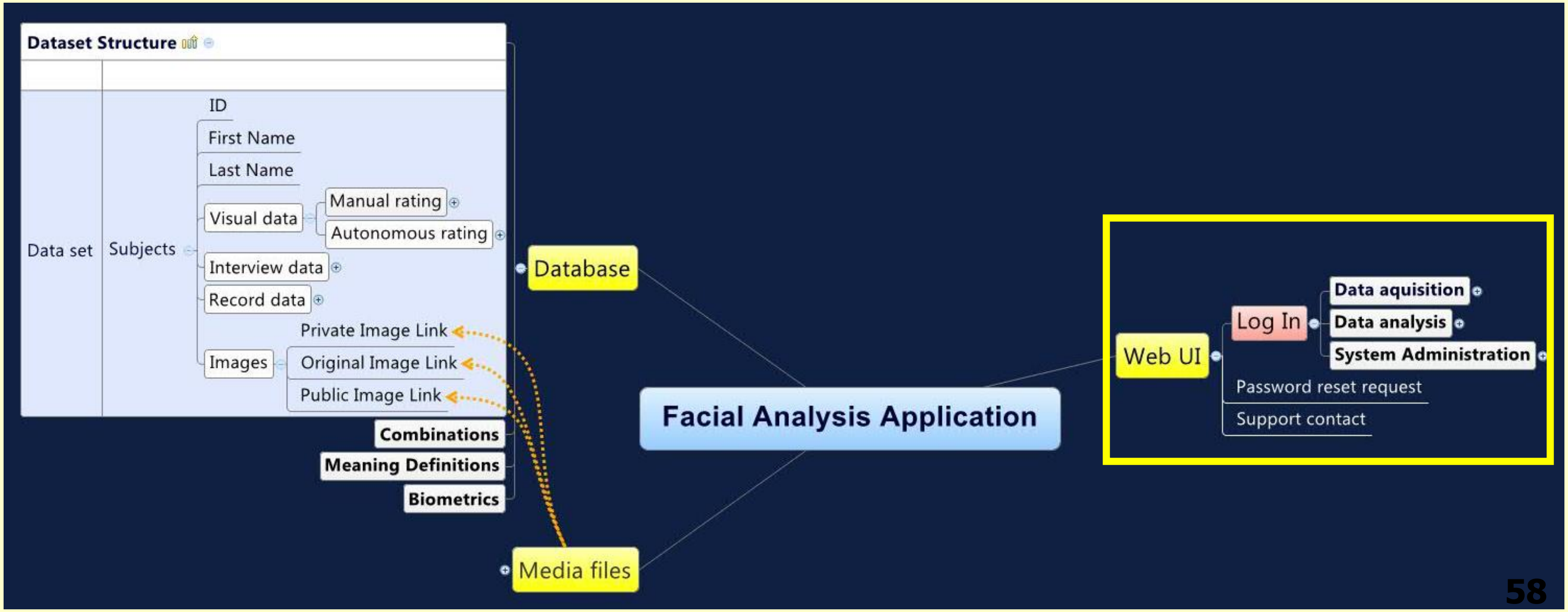
Front-End

Web Based Interface

Data Acquisition

Data Analysis

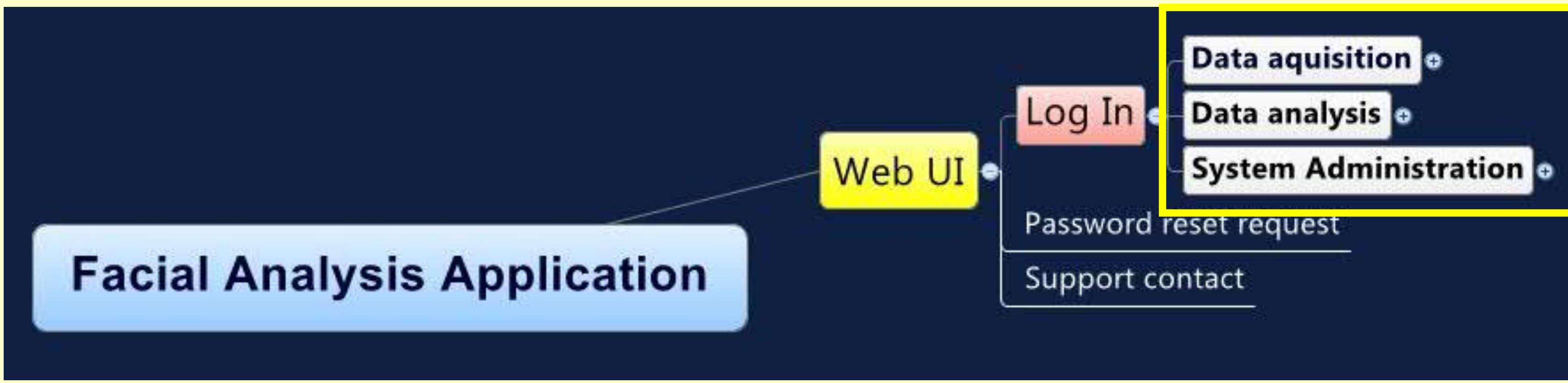
System Administration



Application Components

3 Primary Functions

- **Data Acquisition**
- **Data Analysis**
- **Administration**



Facial Analysis Application Overview

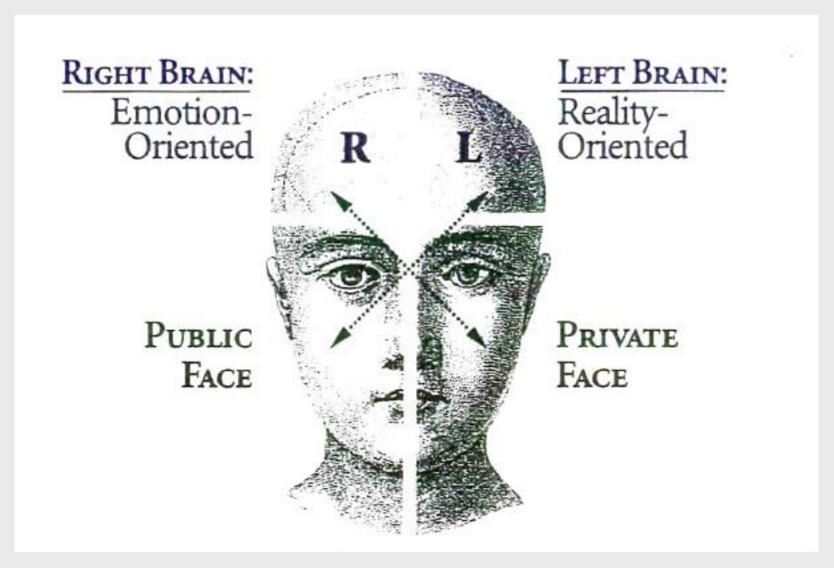
Our facial analysis application consists of two different components:

- **The first is designed to help the user categorize or identify suspects: a potential terrorist, serial killer, suicide bomber.**

- **The second component is designed to help the user interrogate suspects more successfully.**

Asymmetric Facial Analysis

The application will help reveal the private life of a suspect for greater results during interrogation. Scientists have shown that the right hemisphere of the brain has greater control over the left side of the body and the left hemisphere of the brain has greater control over the right side. Further research has identified that the right side of the brain controls the intuitive, creative, holistic, imaginative areas and deals with emotions and feelings. The left side of the brain controls the language skills, solving problems, a verbal, analytic processing side.

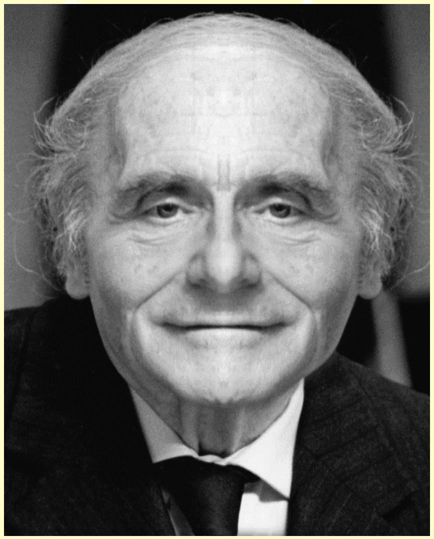


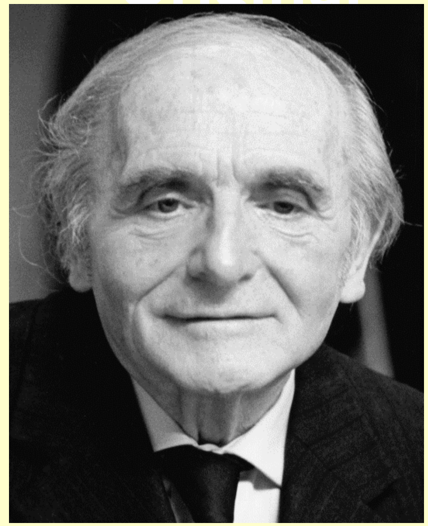
Public / Private Examples

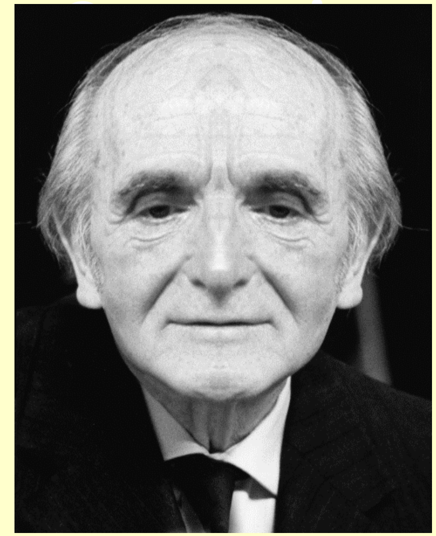
Right

Original

Left





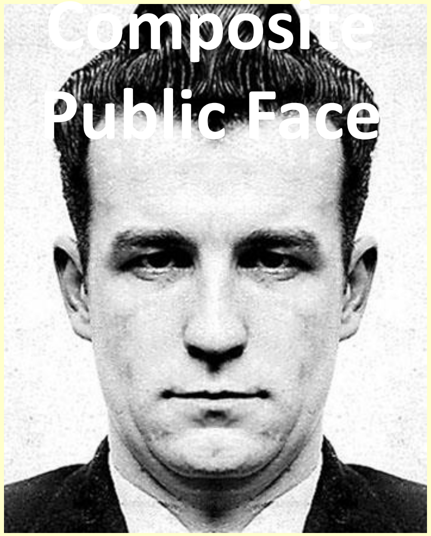


Klaus Barbie

Leader of Nazi Gestapo unit in 1942. Convicted of crimes against humanity.

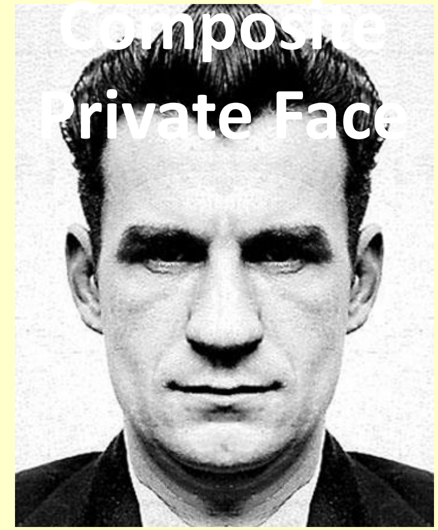
Public / Private Examples

Right Composite Public Face



Original

Left Composite Private Face

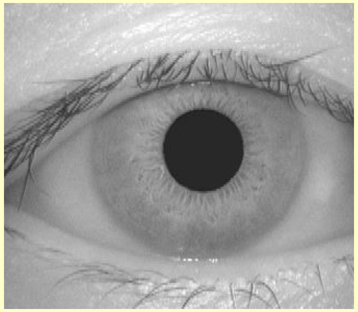


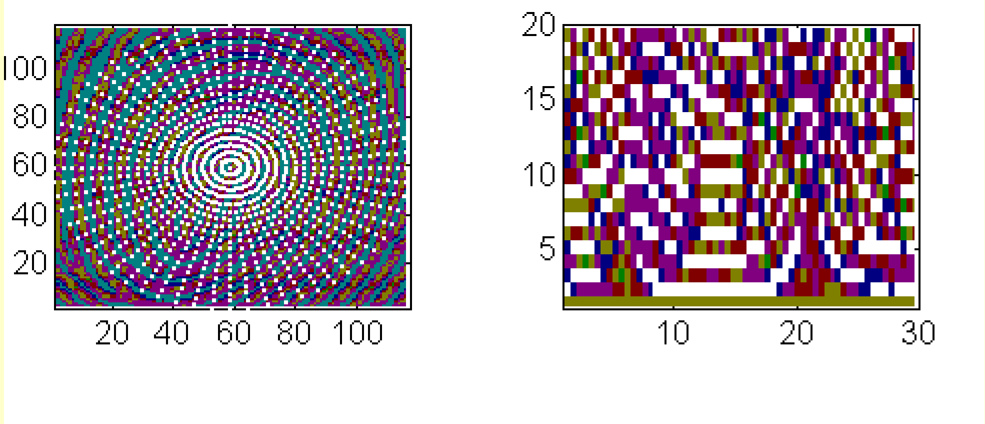
Peter Manuel

Convicted serial killer. Murdered nine people.

Some More Examples:

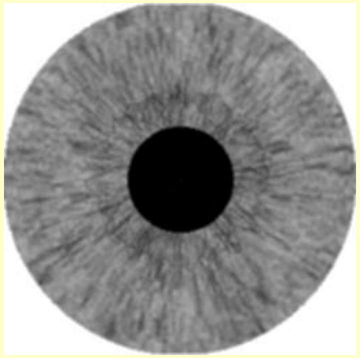
- Generation of synthesis fingerprints
- Generation of synthetic signatures (handwriting modeling is a relevant problem)
- Iris recognition and synthesis
- Information fusion in biometrics
- Speech-to-animated-face (with Biologically Inspired technologies group at NASA's JPL)

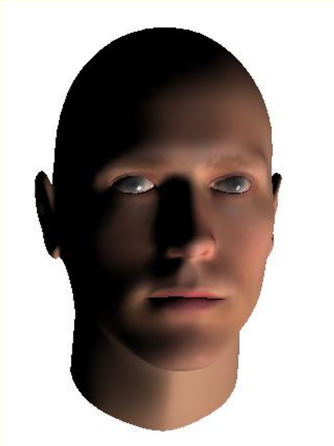




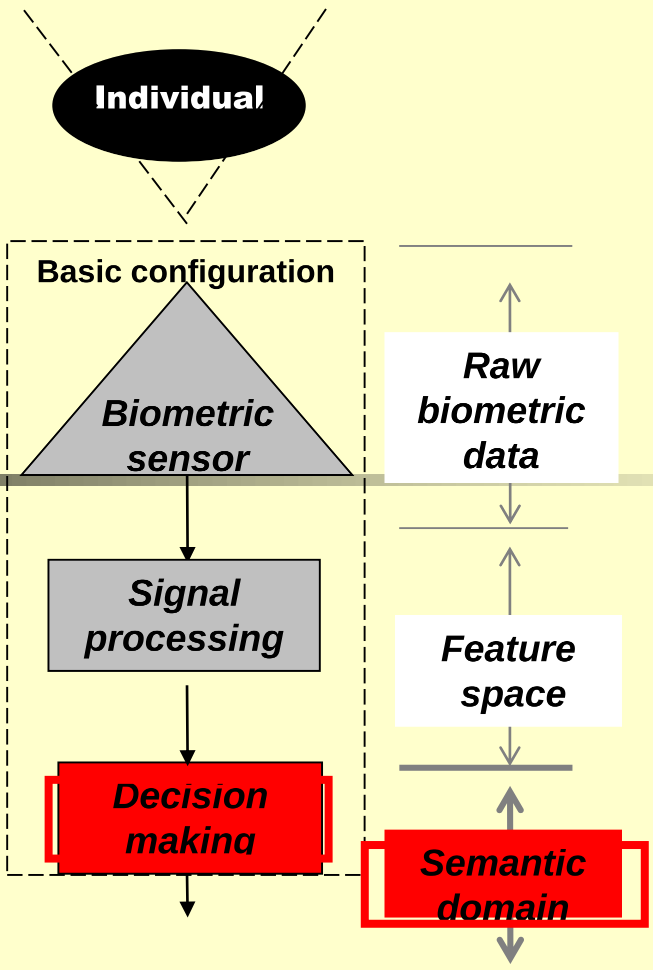
Where do we need biometrics?

- Traditional application: human identification
- Recent advances:
  - Early warning paradigm
  - Designing simulators for HQP training systems
  - Sensing in robotics

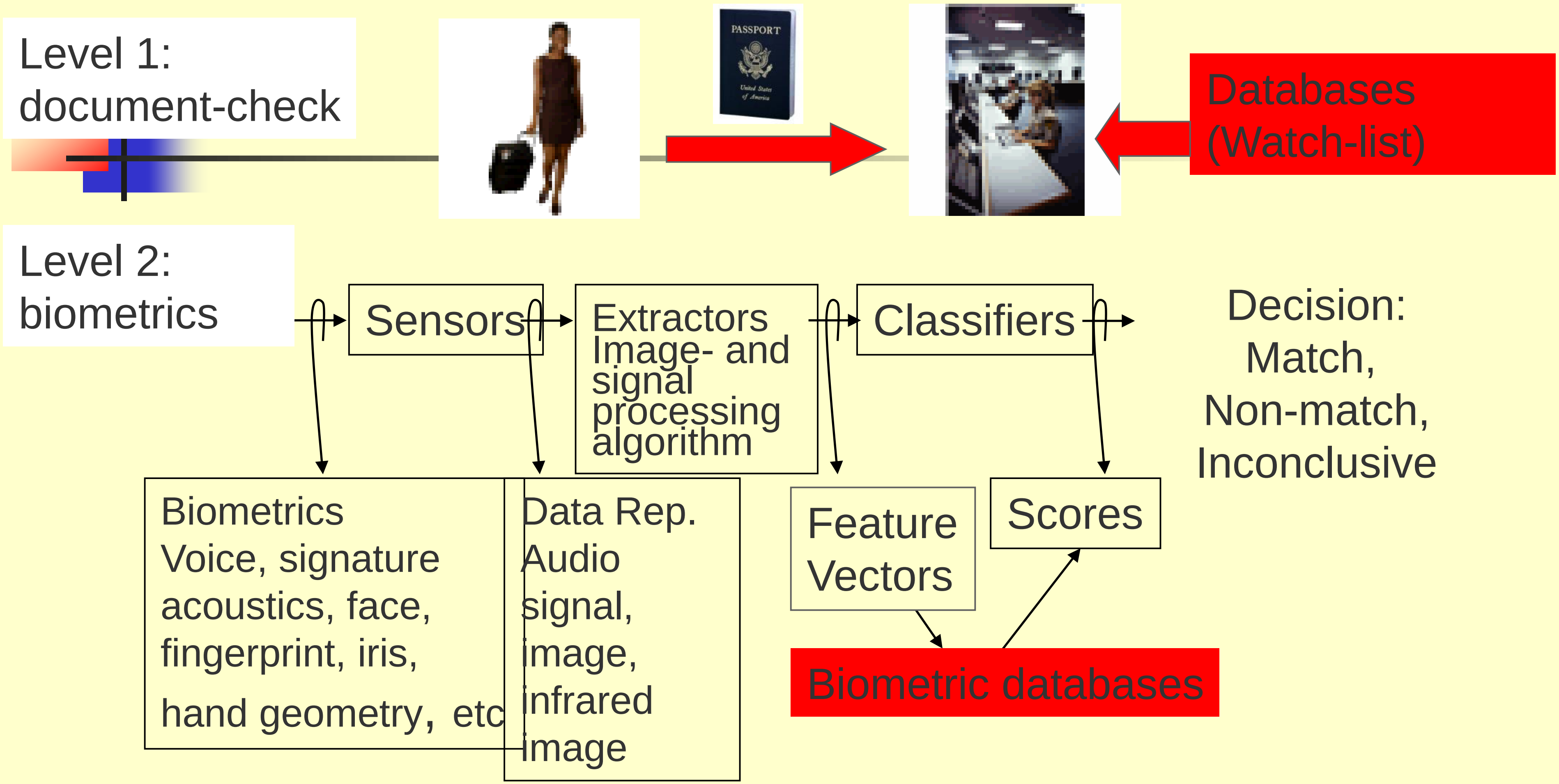




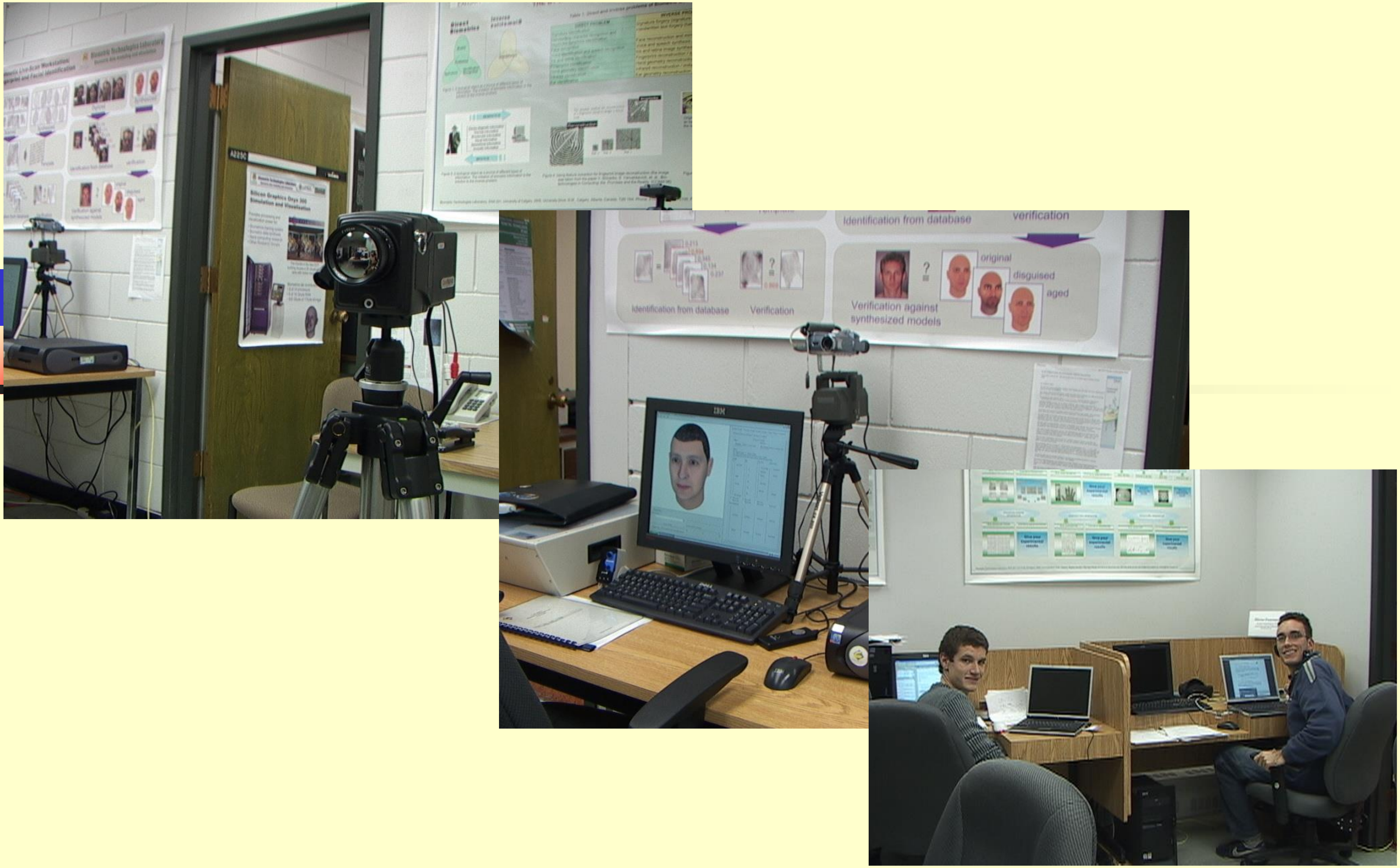
Early detection and warning



Application: physical access control system

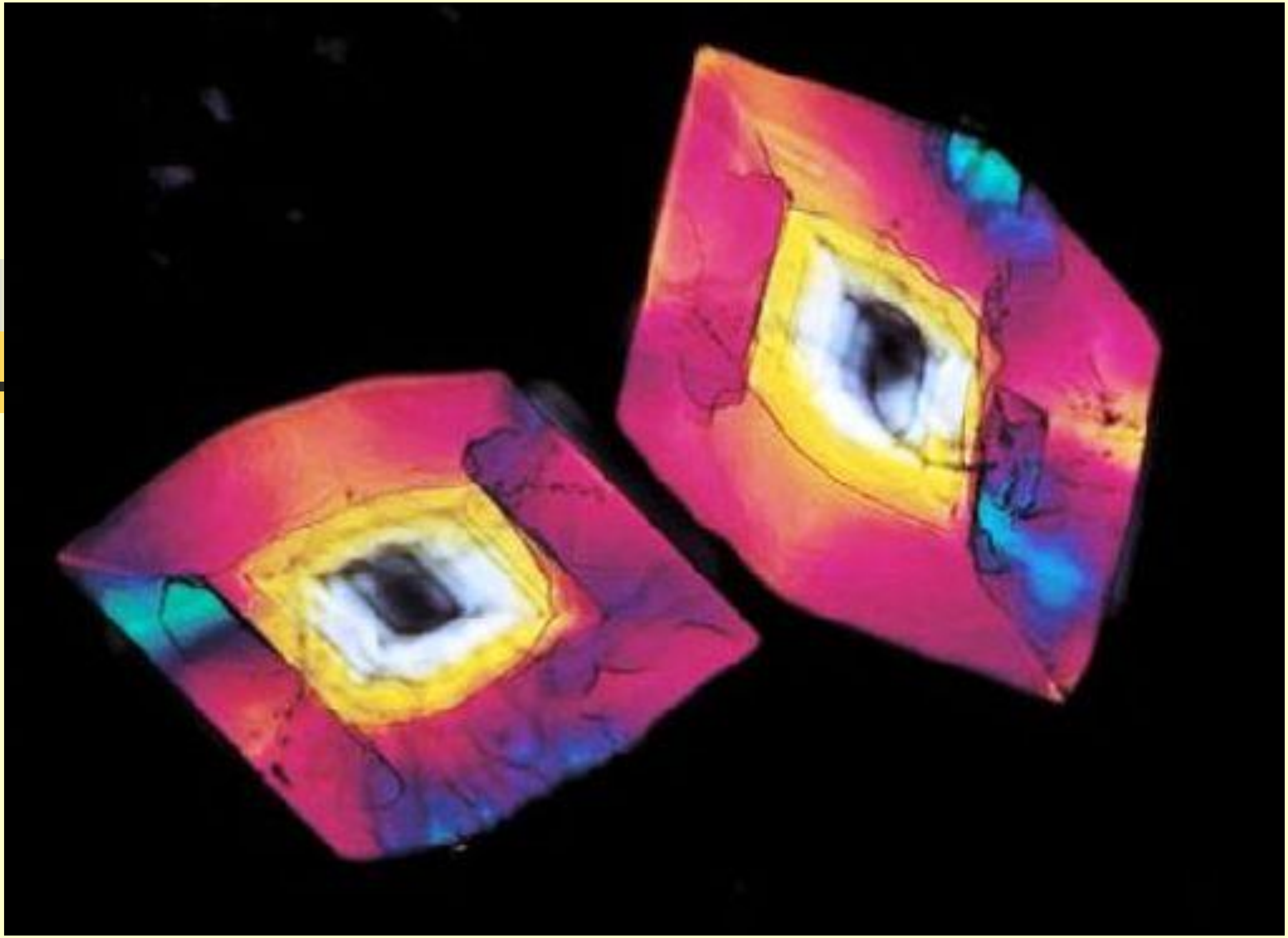


Laboratory experiments



Infrared Images

Sex Hormone



Early warning system components:

Infrared biometrics and decision support

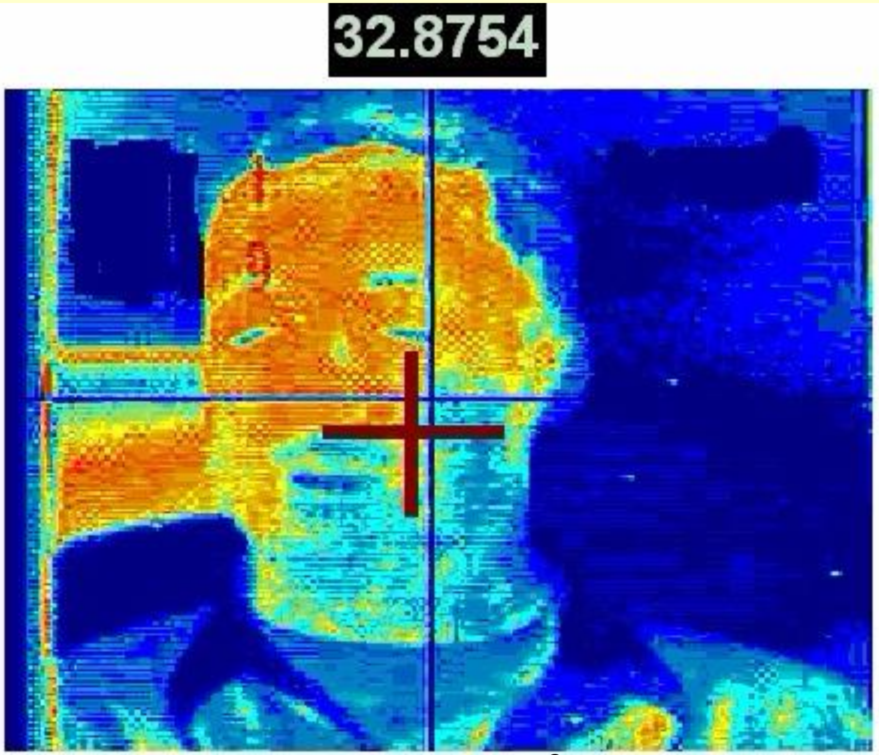
- Supports facial analysis

- Skin temperature evaluation

- Detection of disguise: wig and other artificial materials, and surgical alternations

- Evaluation of blood vessel flow (modeling expressions)

- Other physiological / medical measurements (alcohol / drug abuse)



Temperature value 32.8754 ^{0}C is detected in a point

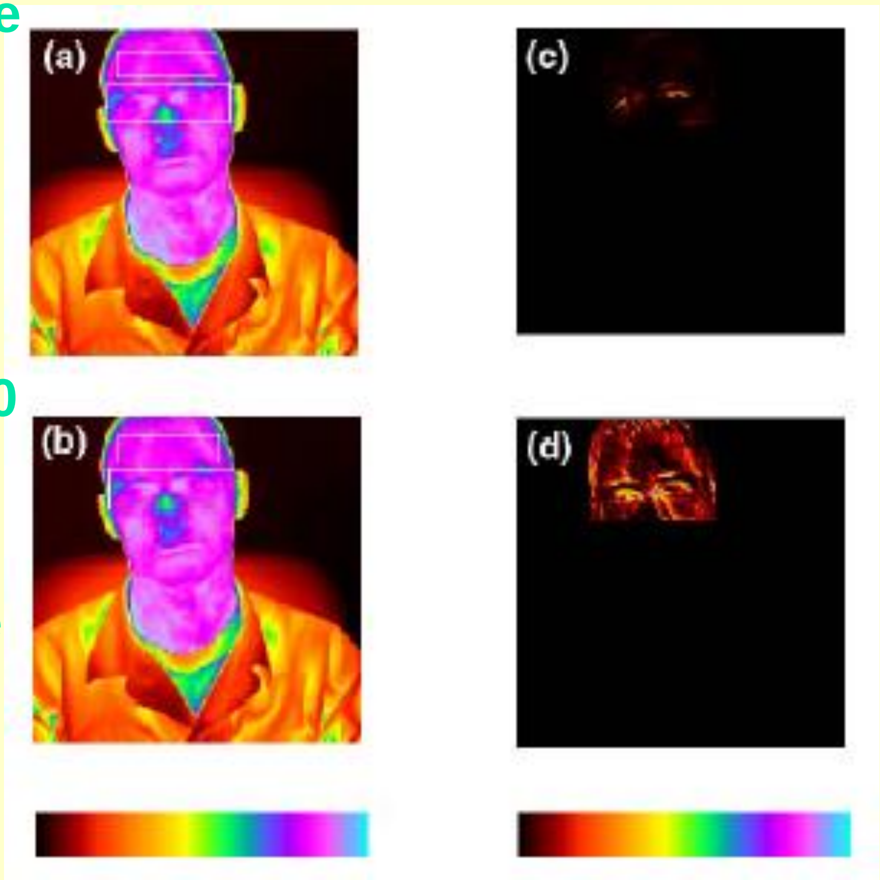
Mid-infrared: 3-5 μm, far-infrared: 8-12 μm

Early warning system components:

Blood flow rate analysis (from infrared)

Thermal image of subject at the beginning of answering the question “Do you have that stolen $20 on you right now?”

Thermal image of subject at the end of answering the question



Visualization of the blood flow rate from the upper rectangle of (a)

Visualization of the blood flow rate from (b). The difference is significant (from I. Pavlidis’ report)

Early warning system: decision making support

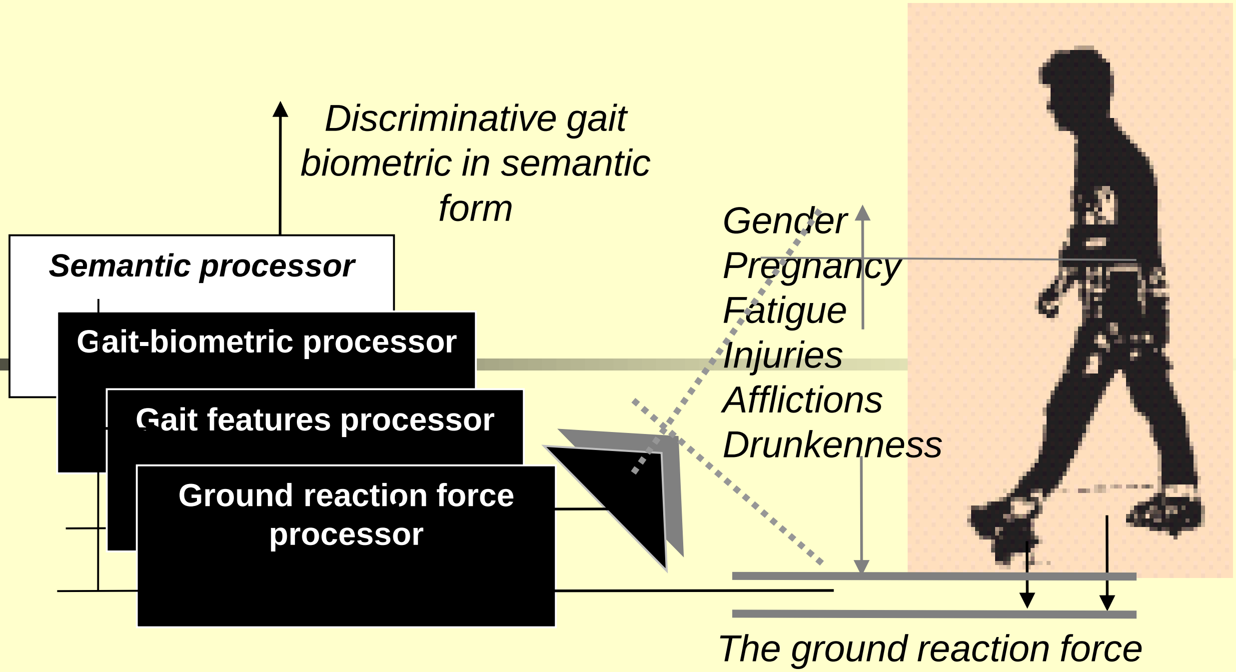
Example: Recommendation (in semantic form)

Time: 00.00.00:
Screened person: 45
Warning level: 04
Specification: Drug or alcohol consumption, level 03
Possible action:

1. Direct to the special inspection
2. Register with caution

Early warning security access control system:

Gait biometrics analysis and decision-making assistance



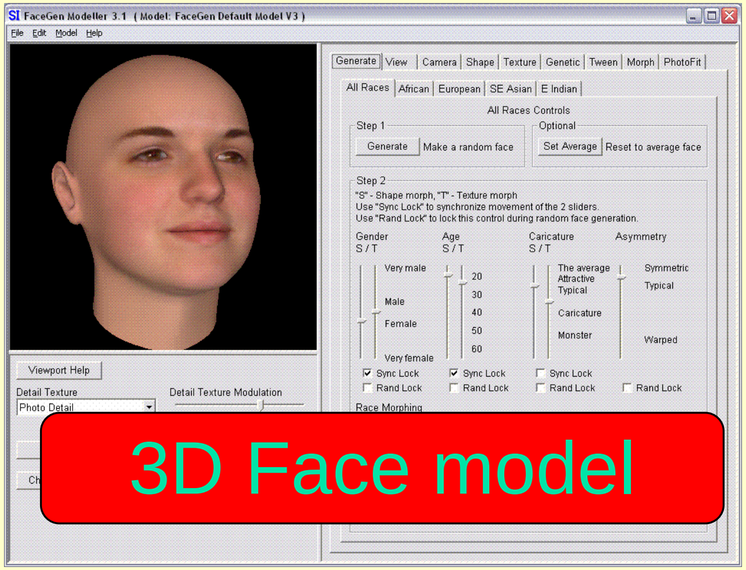
Principle Component Analysis (PCA):

Face capturing

Fitting points

0001001001010011010
0100100100101100100
1000100000100101011010
0100101001001001000
...

File (mesh/colour)



3D Face model

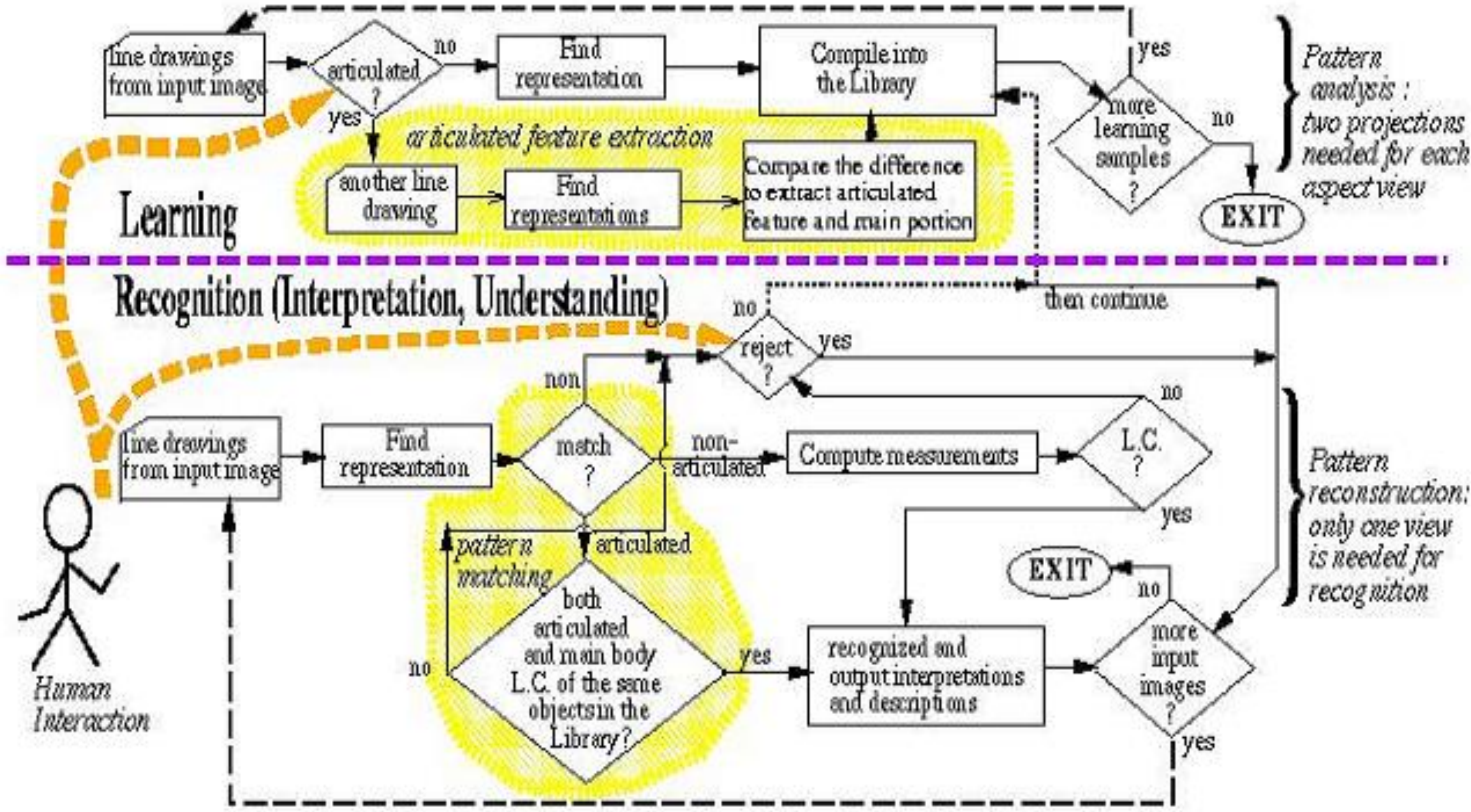
Perspectives: humanoid robots

- **Emotion synthesis**
- **Robot speech**
- **Sensing in robotics**

Robot head developed by Dr. Marek Perkowski at Portland State University

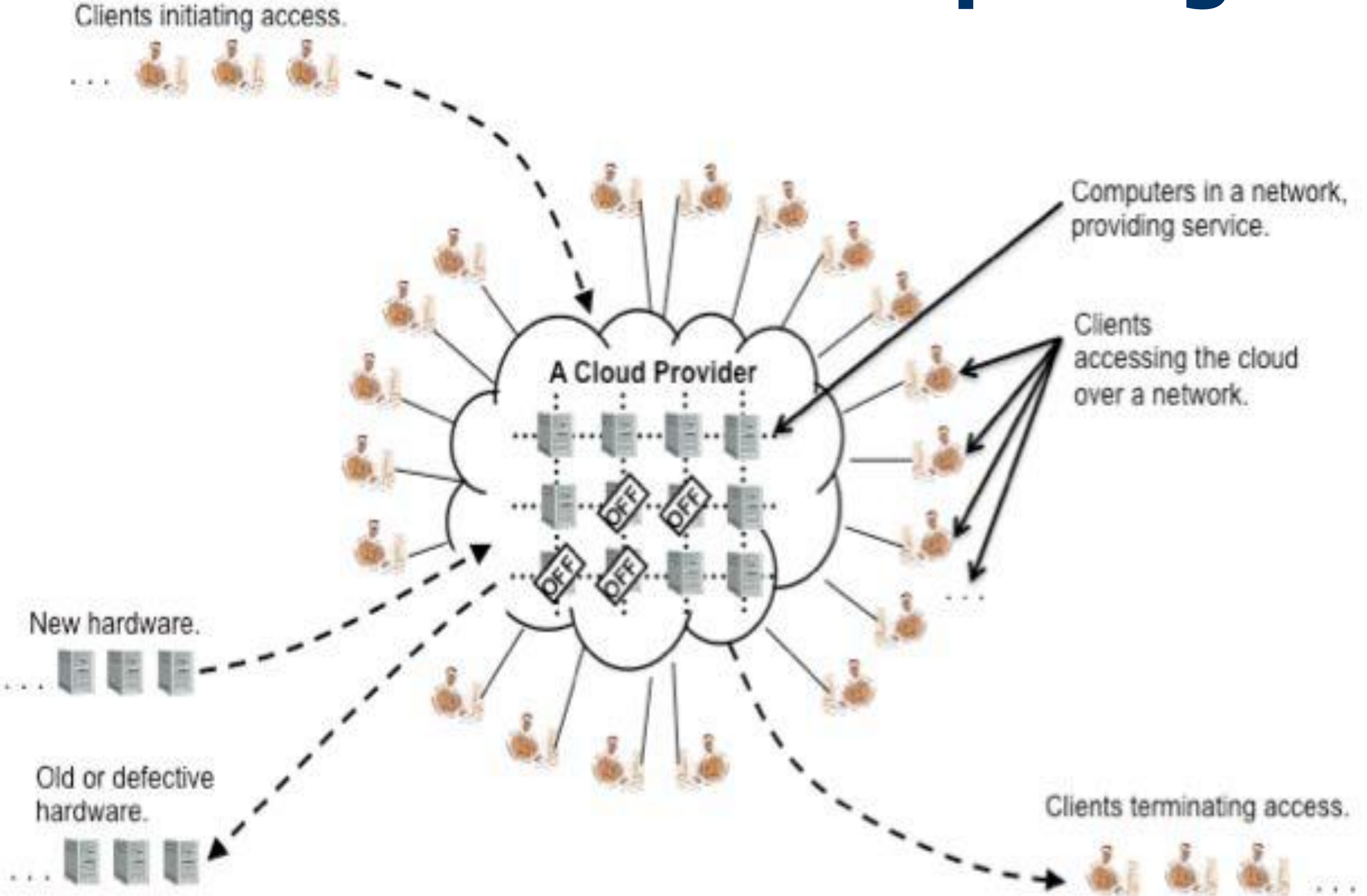
- What is Measurement ?
- Just a Comics Joke?
- No! More Than That
- It's *Similarity and Pattern Matching!*


PASQUALE, WILL YOU TAKE OUT THE GARBAGE, PLEASE ?
YOU'RE CLOSER !
ACTUALLY, I BELIEVE YOU'RE CLOSER !
DO YOU MEASURE GARBAGE FROM FEET OR NOSES ?



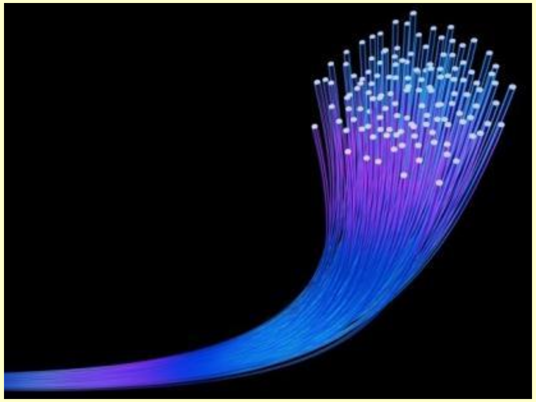
line drawings from input image
articulated ?
no
yes
Find representation
Compile into the Library
yes
more learning samples ?
no
EXIT
Pattern analysis : two projections needed for each aspect view
articulated feature extraction
another line drawing
Find representations
Compare the difference to extract articulated feature and main portion
Learning
Recognition (Interpretation, Understanding)
then continue
reject ?
non
line drawings from input image
Find representation
match ?
non-articulated
Compute measurements
L.C. ?
Pattern reconstruction: only one view is needed for recognition
pattern matching
articulated
both articulated and main body L.C. of the same objects in the Library?
recognized and output interpretations and descriptions
more input images ?
EXIT
Human Interaction

What is Cloud Computing?



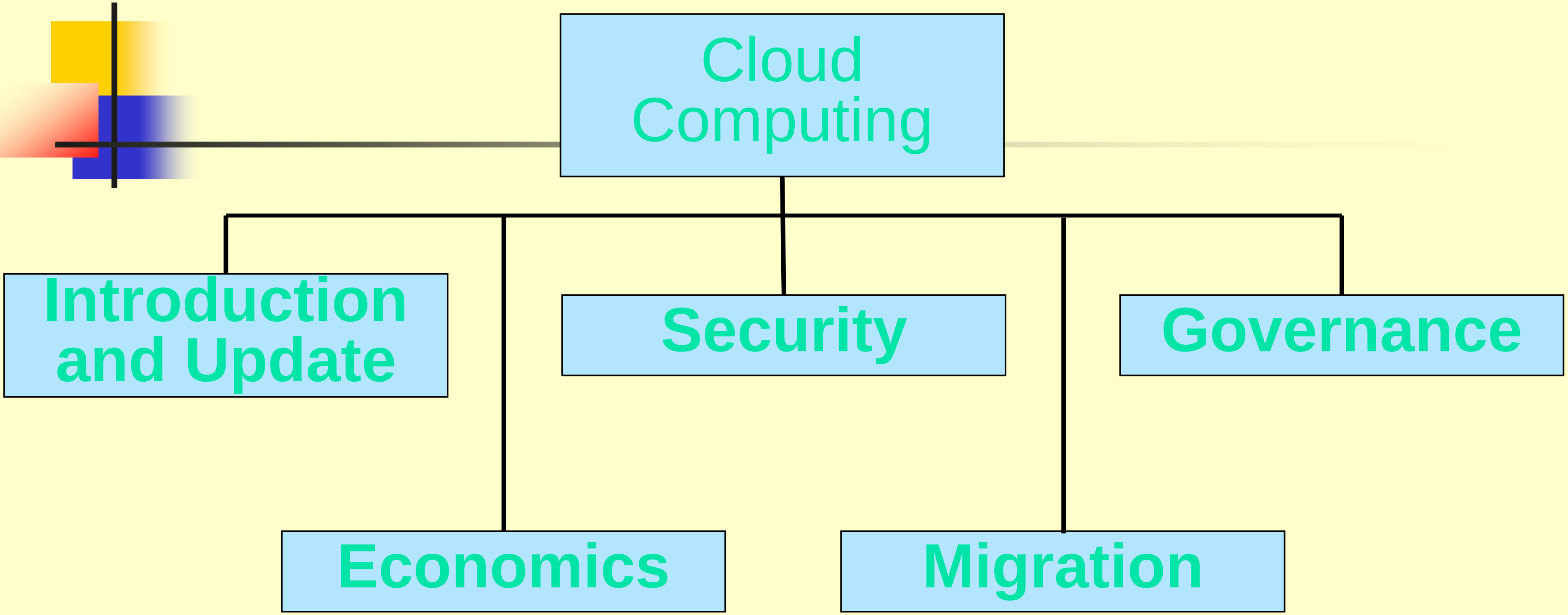
Cloud Computing

Unlike manufacturing processes that produce uniform products over time, Cloud Computing not only requires software engineers to design unique solutions for a specific business context, it also requires moving the application and data outside the physical control of the organization. This differentiates cloud computing from many other business and technical activities. Software professionals do not work with physical entities, but rather with ideas and materials that are unseen and uncontrollable by the end users.



As a result, cloud computing projects must be well managed, which may be difficult to accomplish under sometimes stressful and unique business conditions.

Cloud Computing: Breakdown of Topics



The topic of Cloud Computing **is divided into** five ***Level-1*** **topics as depicted in the graphic above. The introduction and update will change from time to time based on the inherent unsettled nature of the cloud environment and market. We will begin our discussions with an Introduction to Cloud Computing.**

Pattern Recognition

- Cognition (Learning)
- Re-Congition
- Classification
- Identification
- Verification
- Clustering

3D Object Recognition

Table of Contents

Linear Combination

- Object 1 A1
- Object 2 A2
- Object 3 A3
- Object 4 A4
- Object A4= a A1+ bA2 +cA3 +d

3D Recognition Background

- Widely used
  - industrial parts inspection
  - military target identification
  - CAM/CAD engineering design
  - image/vision understanding, interpretation, visualization, and recognition

3D Recognition Background

- Recognition 3D objects
  - Rigid Objects
    - Fixed shapes
  - Deformable Objects
    - Variable shapes
  - Articulated Objects
    - Fewer methods proposed

3D Recognition Background

- Our approach—Extended Linear Combination Method (LC)
  - Simpler preprocessing
  - Simpler and faster computation
  - Applicable to many articulated object rcognition, understanding, intrpretation, and visualization

THEORY

- Extended Linear Combination Method (LC)
  - based on the observation that novel views of objects can be expressed as linear combination of the stored views (from learning)
  - It identifies objects by constructing custom-tailored templates from stored two-dimensional image models.

Linear Combination

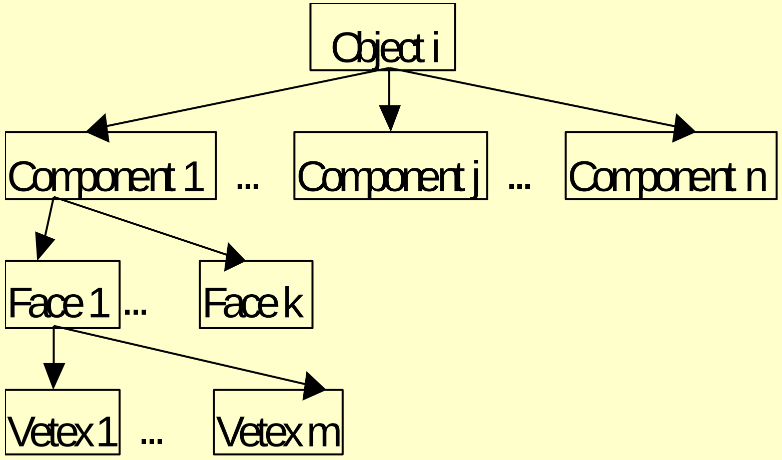
- model
  - an image consists of a list of feature points observed in the image

Linear Combination

- **Recognition:** An unknown object is matched with a model by comparing the points in an image of the unknown object with a template-like collection of points produced from the model

System Desgin

- Visulazation
  - Structured objected Method
  - a model consists of several images - minimally three for a polyhedra



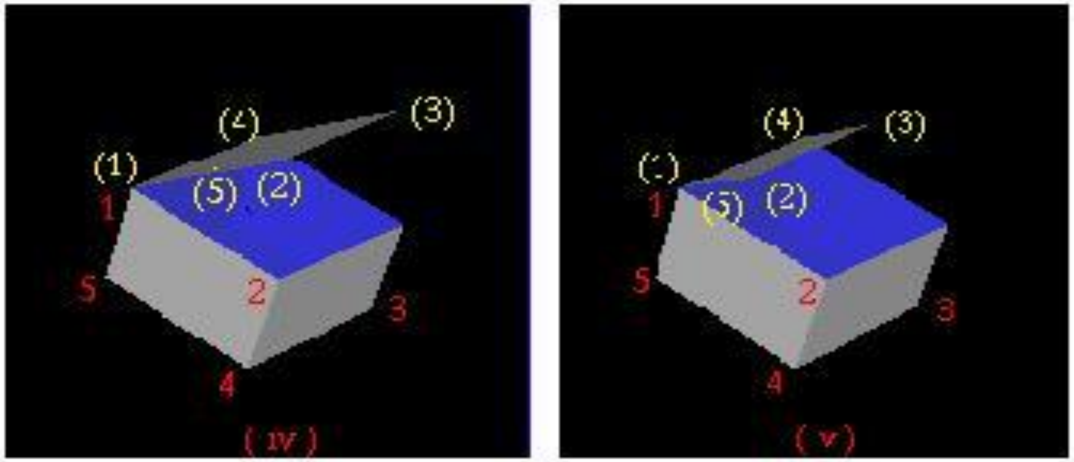
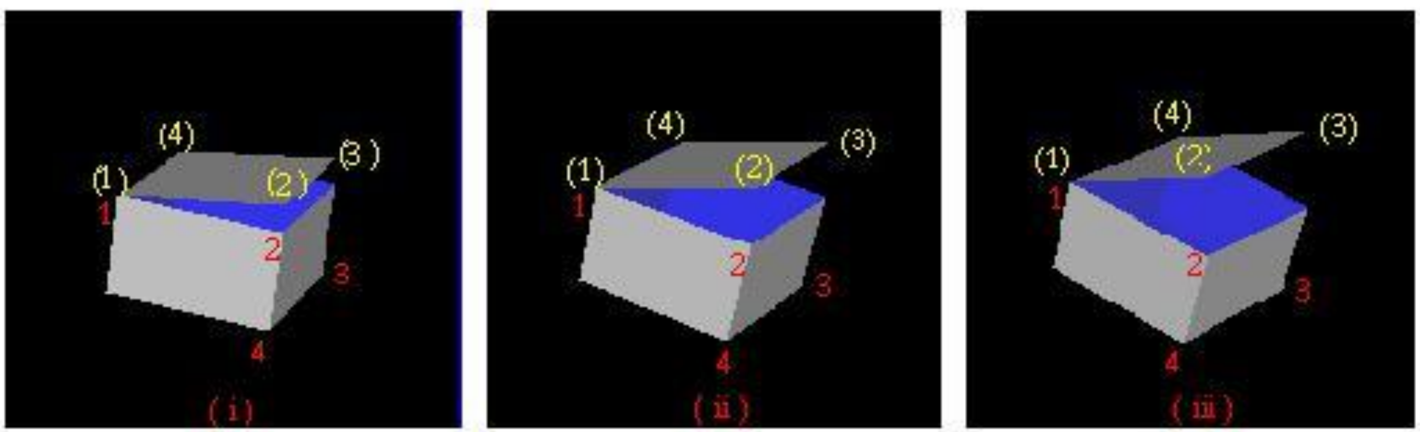


Figure 3.1 Articulated object recognition
(i), (ii) and (iii) are model images of
the closet, (iv) is another view of the same
closet,and (v) is the image of a different closet



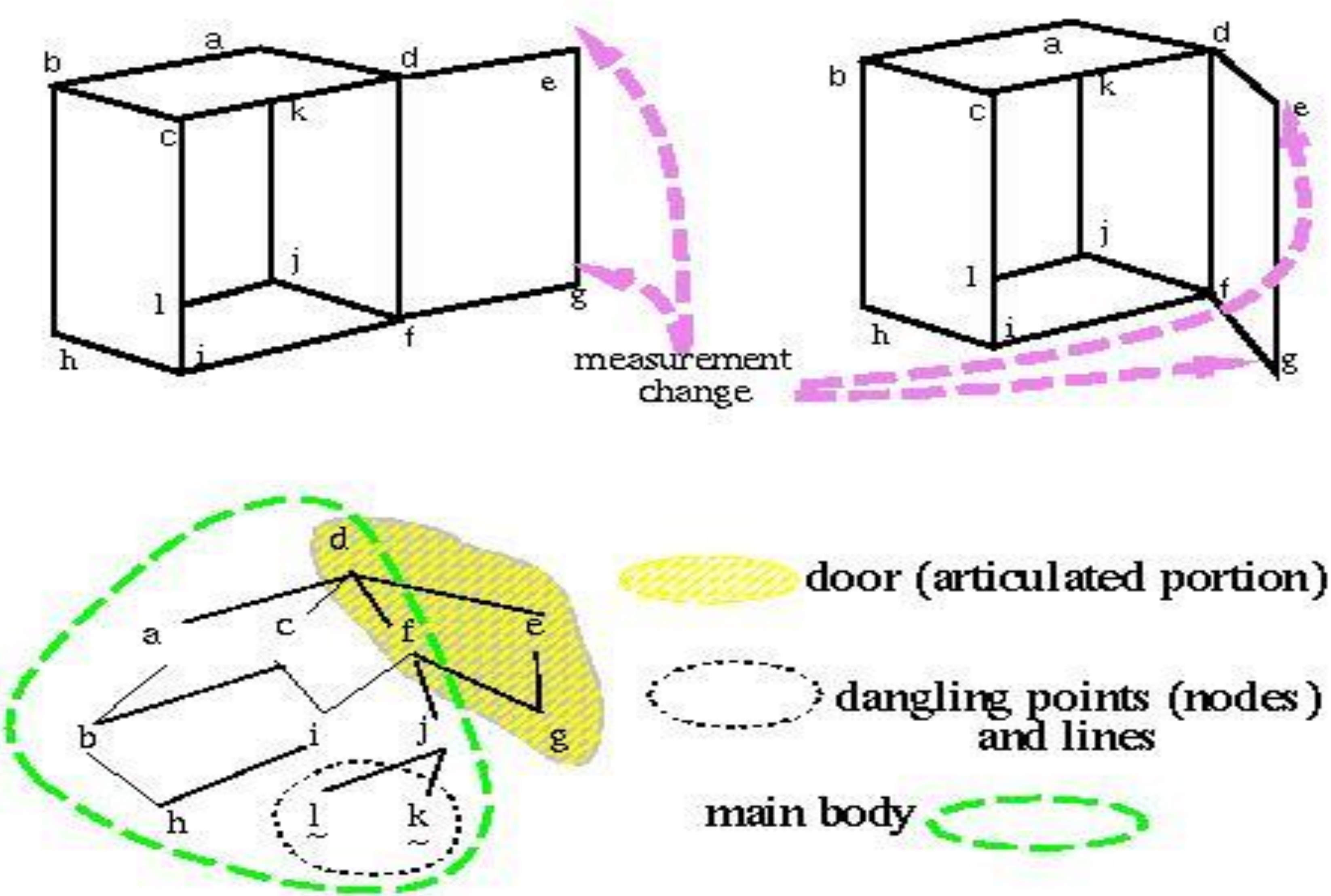


Figure 2.3 An example of articulated feature extraction

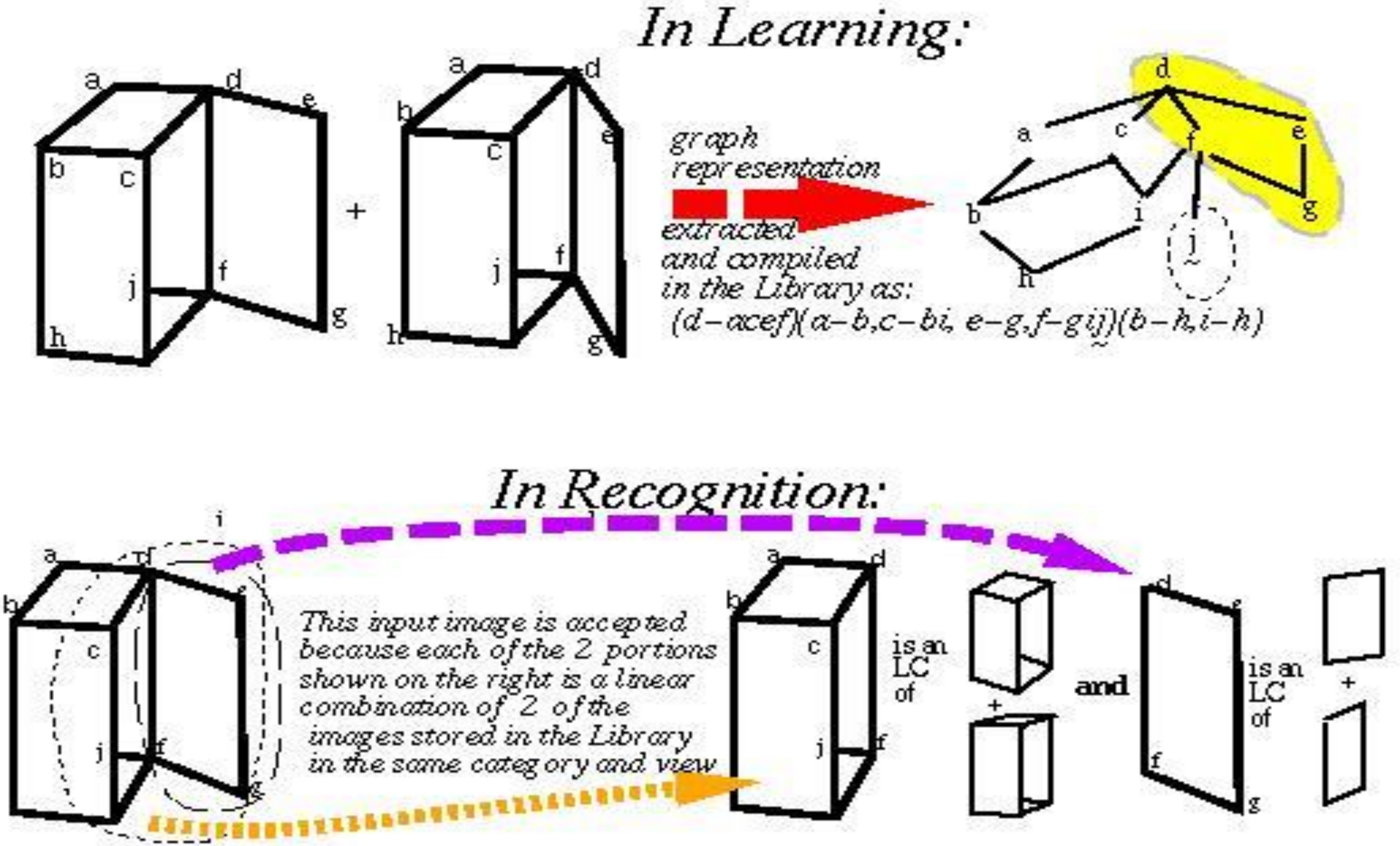
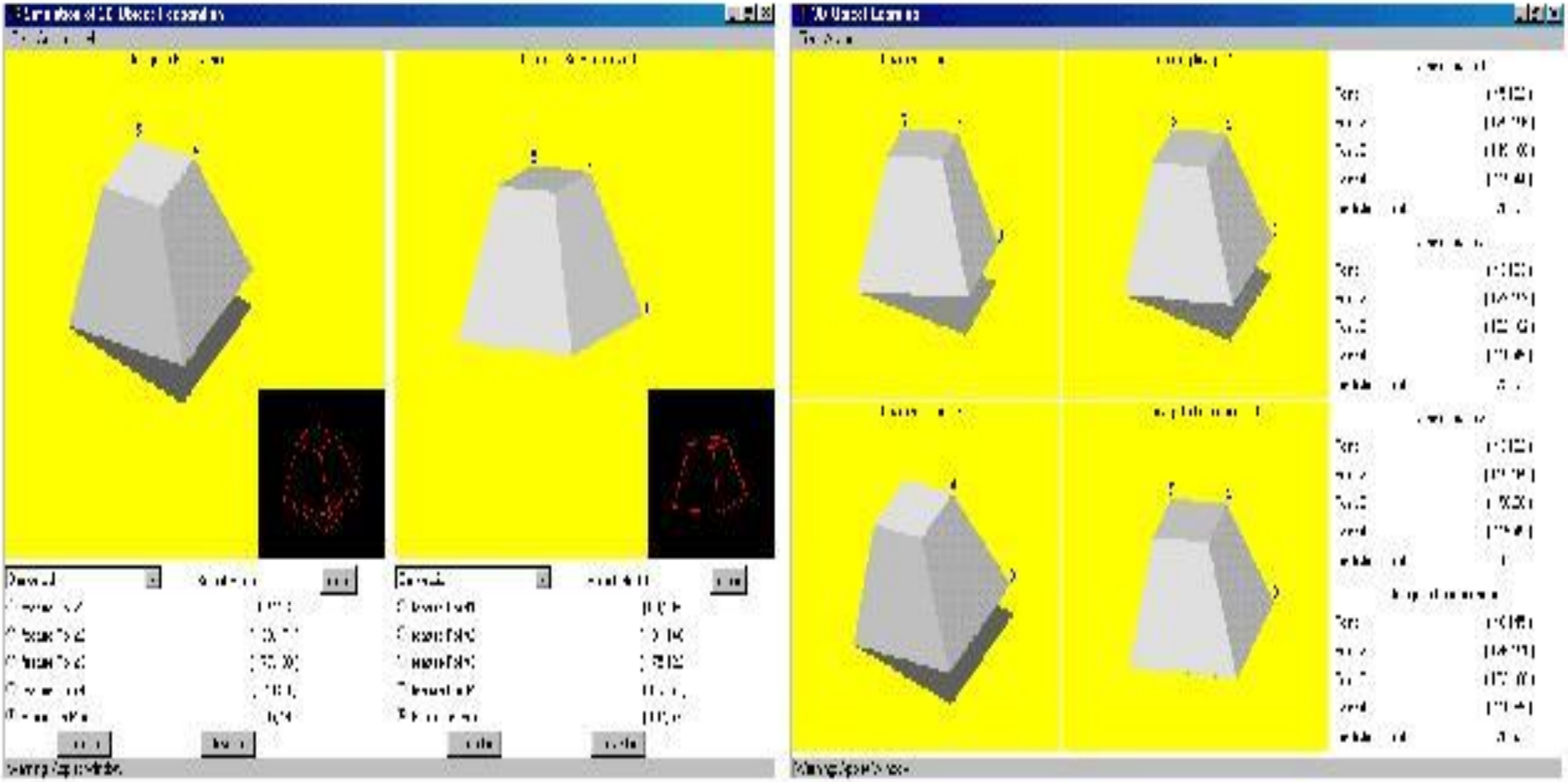


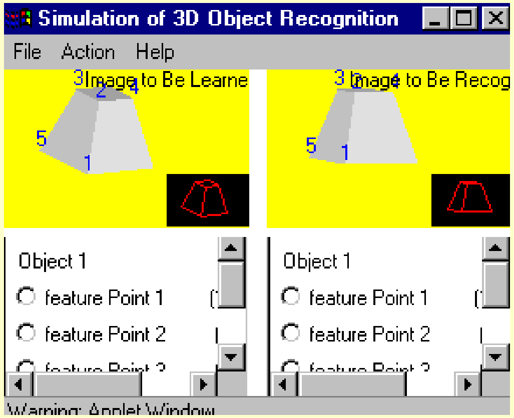
Figure 2.4 An example of pattern matching (learning and recognition)

HOUGH TRANSFORM

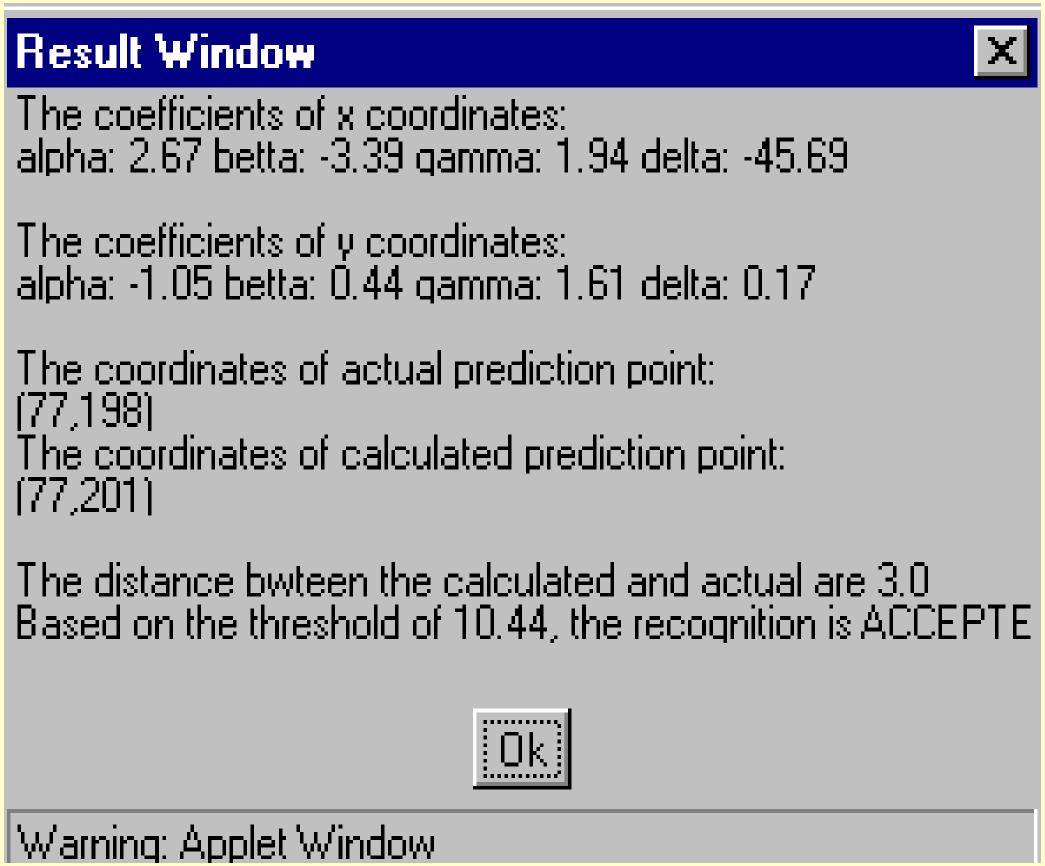


Experiments

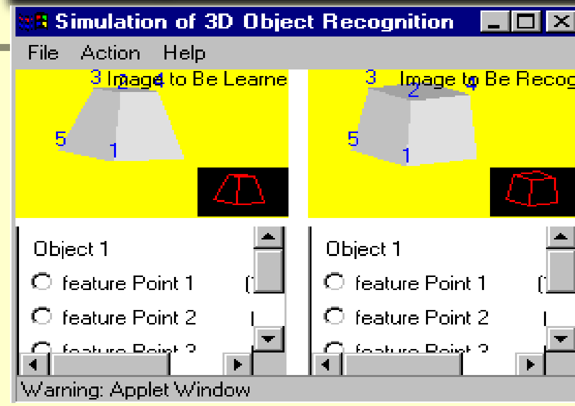
- Experitment-1
  - Match same objects

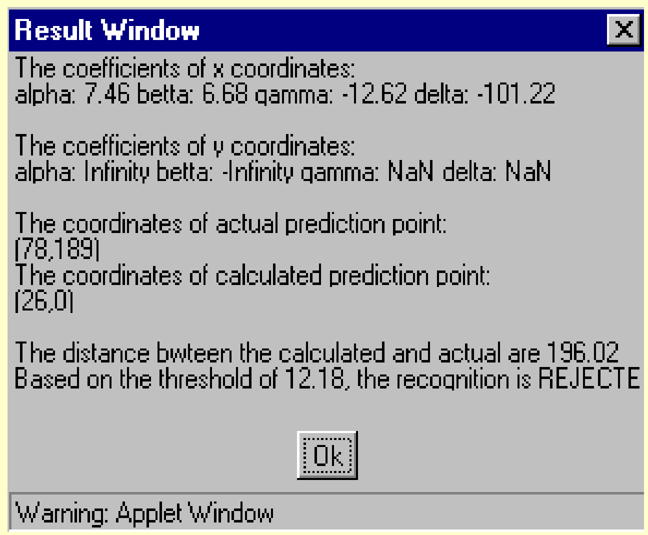


Experiment-1 Result

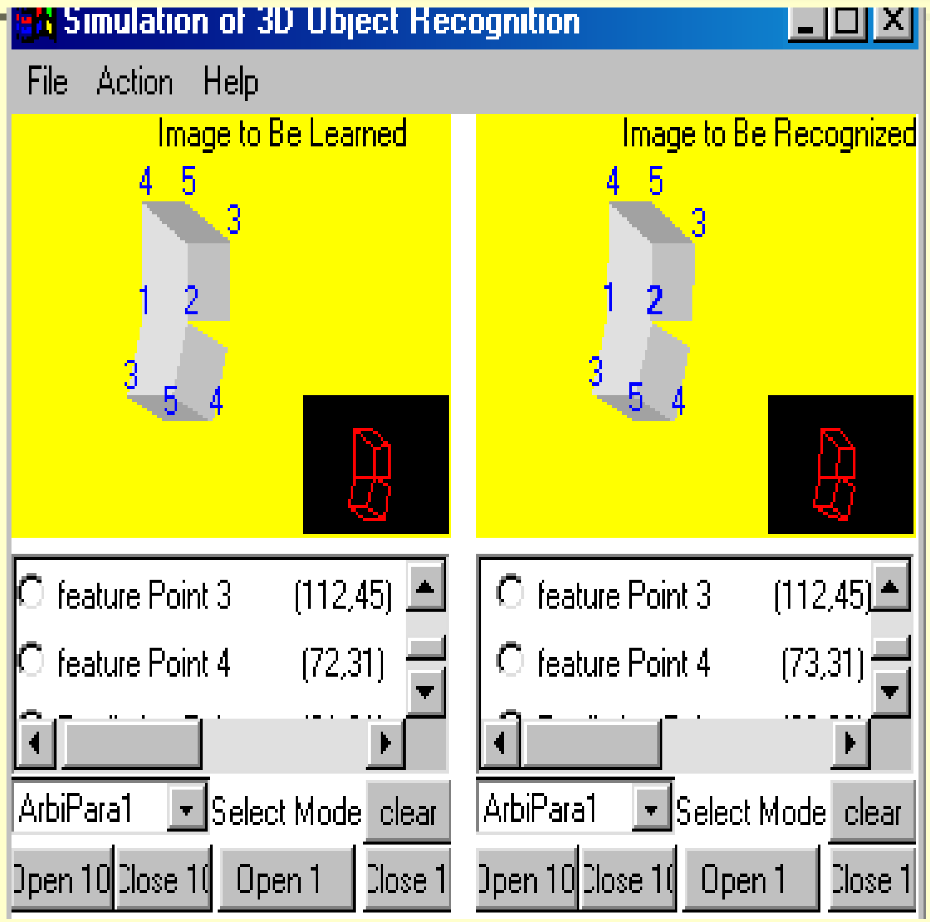


Experiment-2

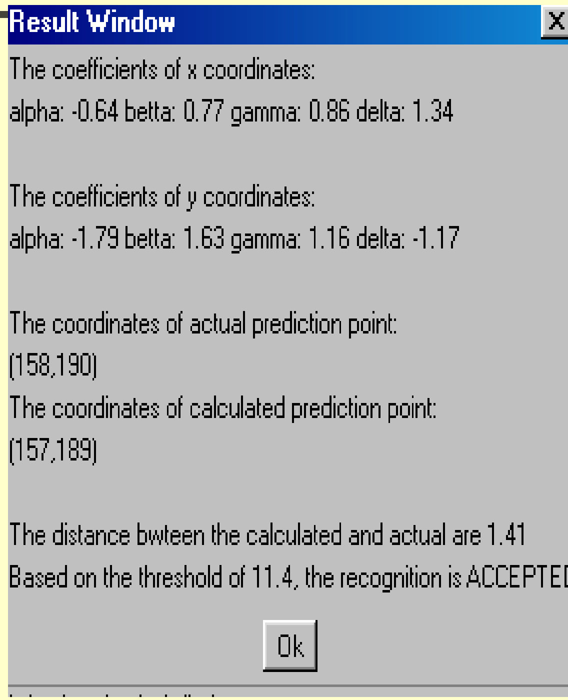


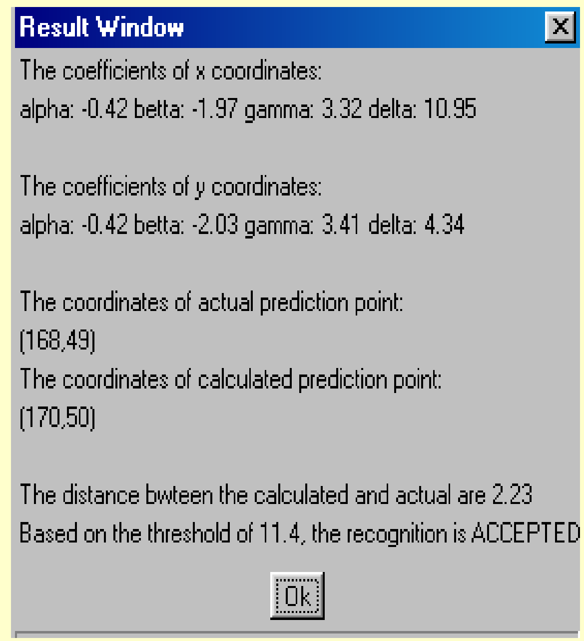


Experiment-3 …

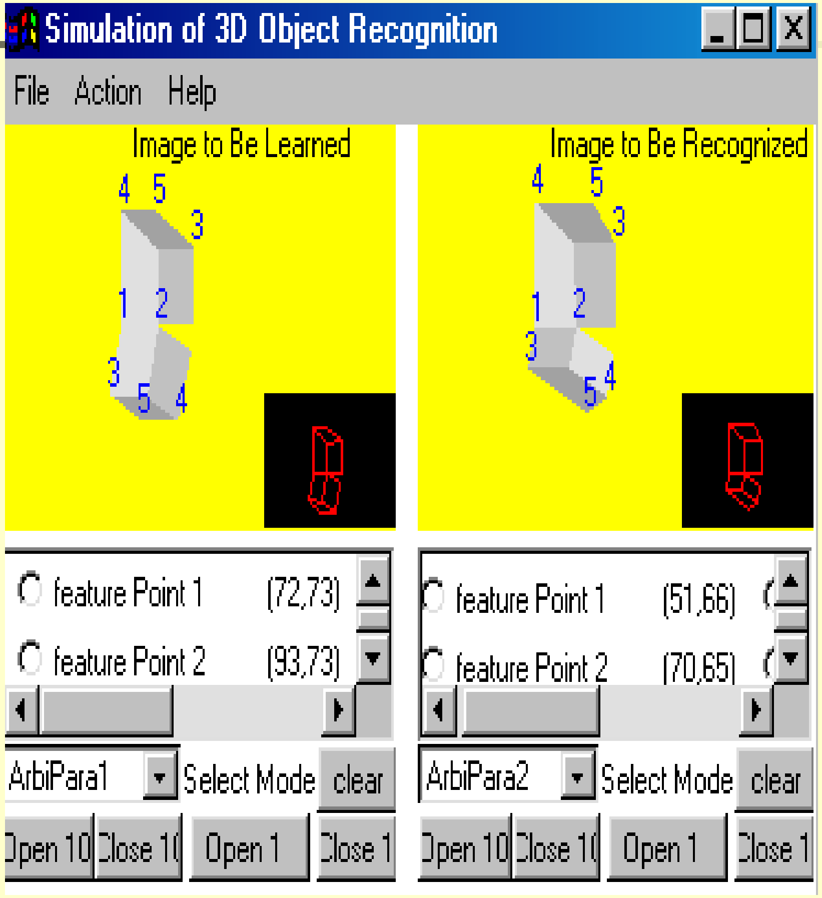


Experiment-3 Result





Experiment-4



Experiment-4 Result

Result Window

The coefficients of x coordinates:
alpha: 0.76 betta: 1.75 gamma: -1.36 delta: -18.21

The coefficients of y coordinates:
alpha: 0.67 betta: 1.29 gamma: -1.17 delta: 25.0

The coordinates of actual prediction point:
(143,138)
The coordinates of calculated prediction point:
(126,131)

The distance bwteen the calculated and actual are 18.38
Based on the threshold of 11.4, the recognition is REJECTED

Ok

Rejected

Rejected Too

Result Window

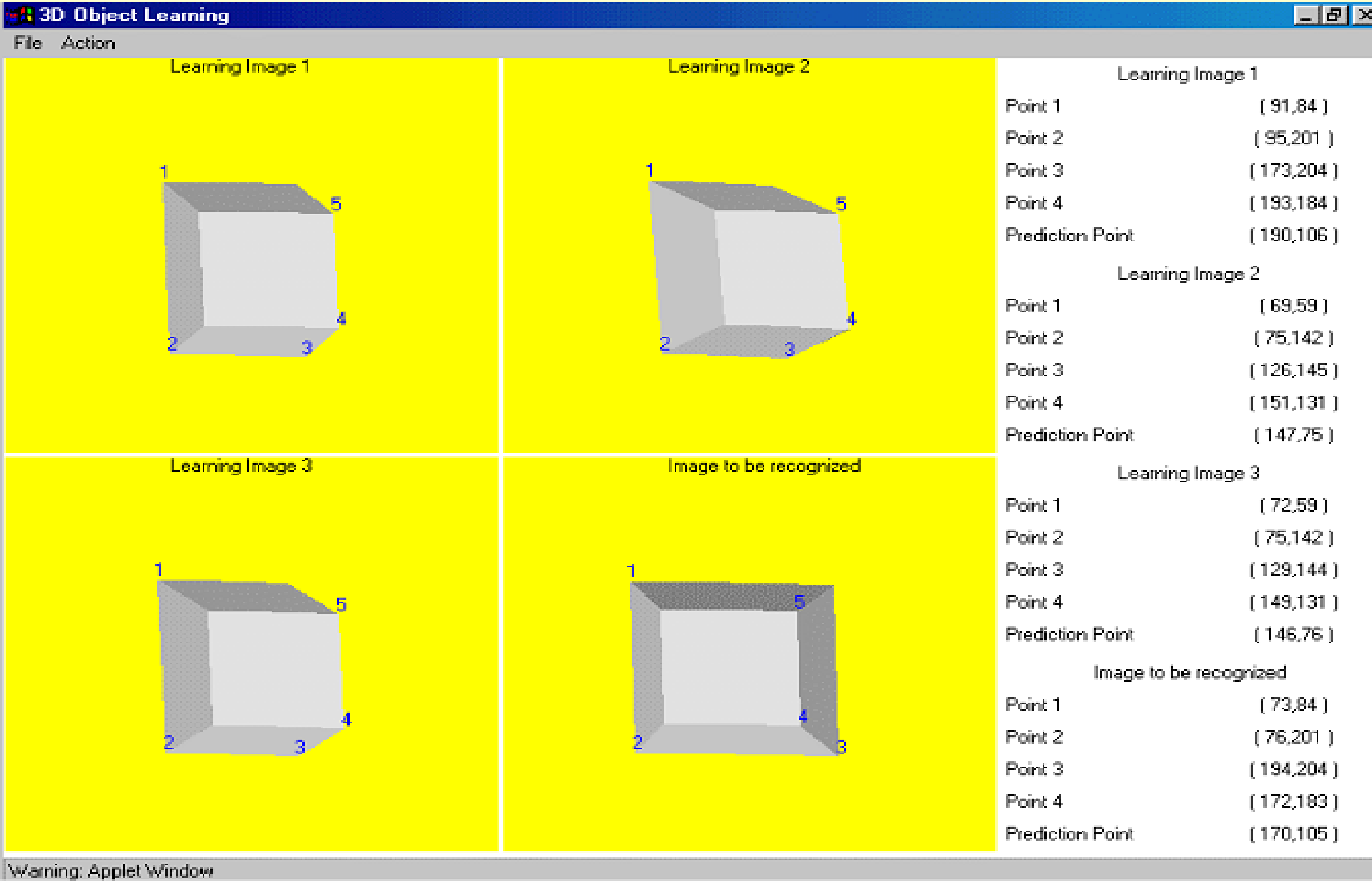
The coefficients of x coordinates:
alpha: 1.0 betta: 0.41 gamma: -0.31 delta: -11.61

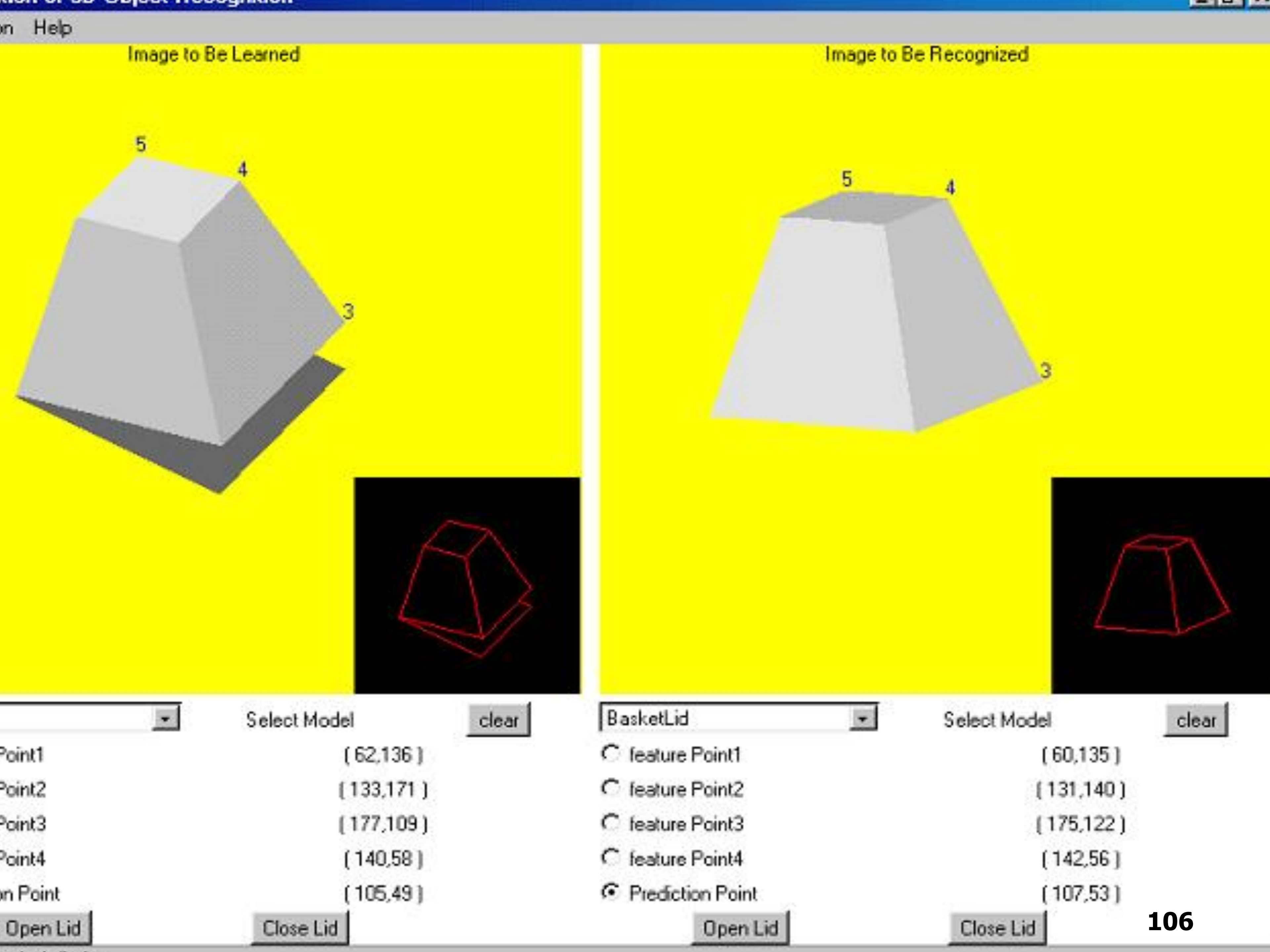
The coefficients of y coordinates:
alpha: NaN betta: Infinity gamma: -Infinity delta: NaN

The coordinates of actual prediction point:
(133,34)
The coordinates of calculated prediction point:
[illegible]

The distance bwteen the calculated and actual are 37.16
Based on the threshold of 11.4, the recognition is REJECTED

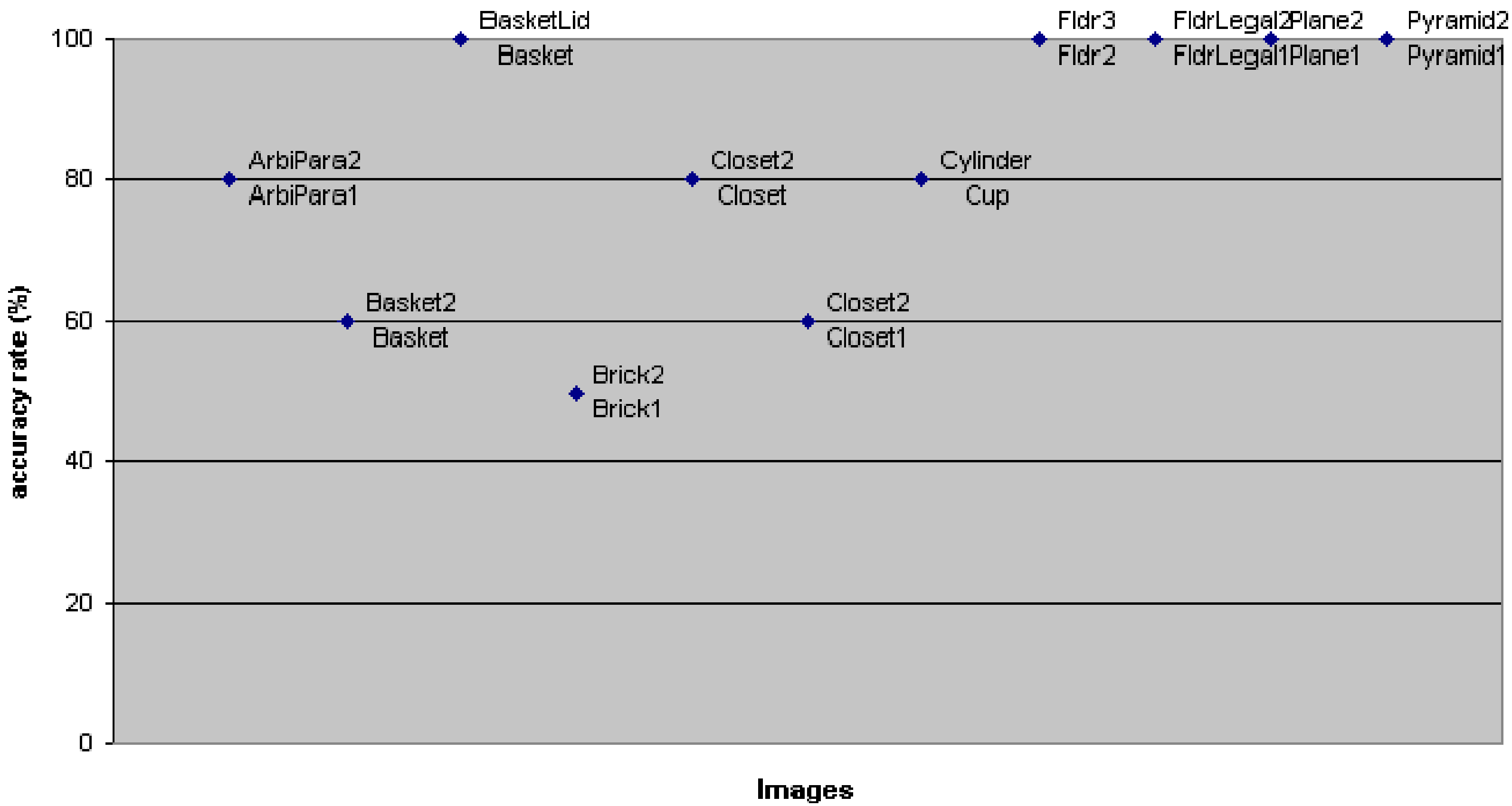
Ok

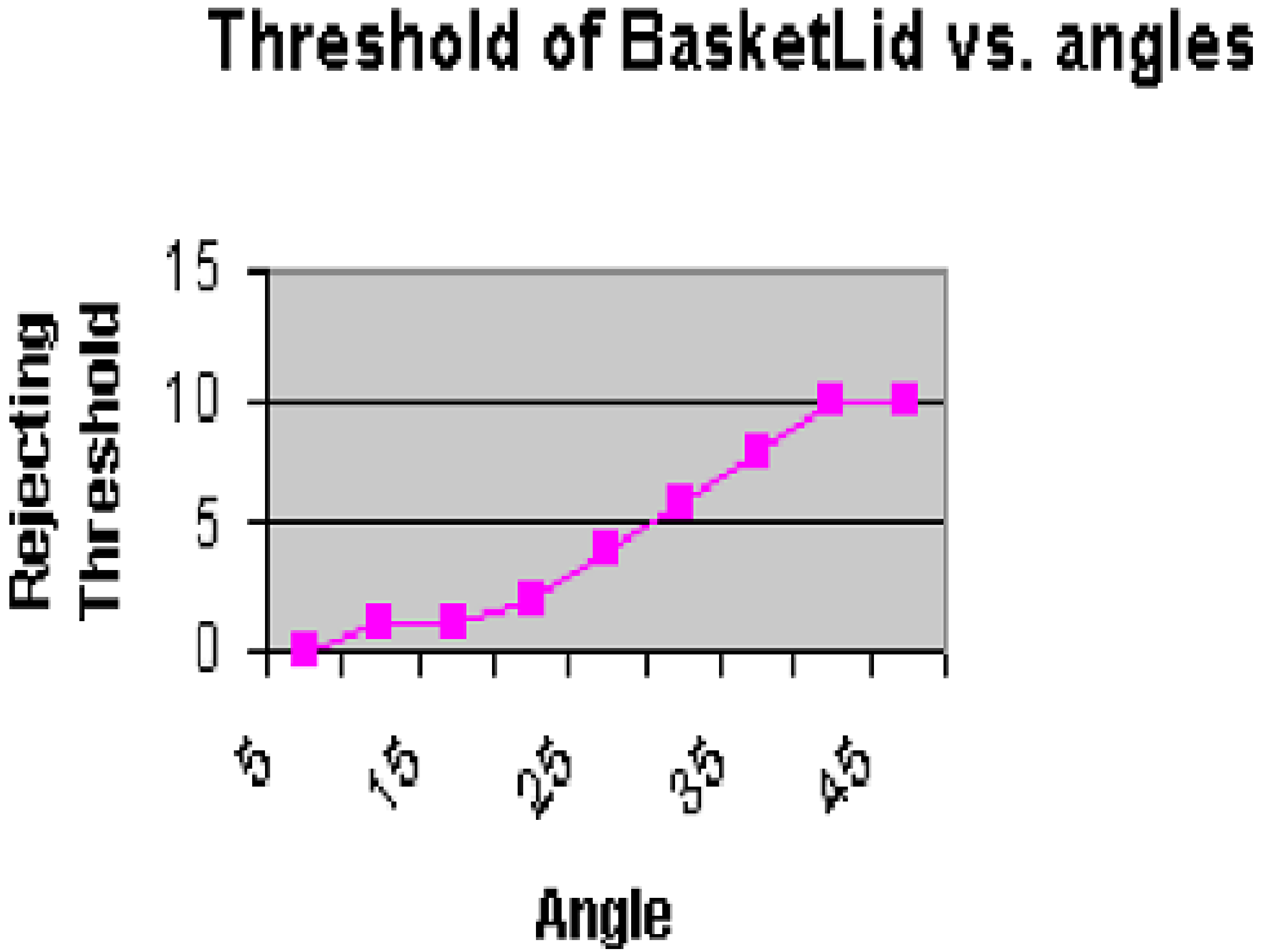

3D Object Learning
File
Action
Learning Image 1
Learning Image 2
Learning Image 3
Image to be recognized
1
2
3
4
5
Learning Image 1
Point 1 (91,84)
Point 2 (95,201)
Point 3 (173,204)
Point 4 (193,184)
Prediction Point (190,106)
Learning Image 2
Point 1 (69,59)
Point 2 (75,142)
Point 3 (126,145)
Point 4 (151,131)
Prediction Point (147,75)
Learning Image 3
Point 1 (72,59)
Point 2 (75,142)
Point 3 (129,144)
Point 4 (149,131)
Prediction Point (146,76)
Image to be recognized
Point 1 (73,84)
Point 2 (76,201)
Point 3 (194,204)
Point 4 (172,183)
Prediction Point (170,105)
Warning: Applet Window



on Help
Image to Be Learned
5
4
3
Image to Be Recognized
5
4
3
Select Model
clear
Point1 (62,136)
Point2 (133,171)
Point3 (177,109)
Point4 (140,58)
on Point (105,49)
Open Lid
Close Lid
BasketLid
Select Model
clear
feature Point1 (60,135)
feature Point2 (131,140)
feature Point3 (175,122)
feature Point4 (142,56)
Prediction Point (107,53)
Open Lid
Close Lid

Recognition Result of side view 5%




Threshold of BasketLid vs. angles
Rejecting Threshold
15
10
5
0
5
15
25
35
45
Angle

橫看成嶺側成峯
遠近高低各不同
不識廬山真面目
只緣身在此山中

Looking from one side, mountains, from the other side, ranges
Far, near, high, low, all different
I can hardly recognize the true face of the Lu Shan mountain
Simply because I am in the middle of it

Written by Su Dong-po, 11th Century. Translated by P. Wang,

Color Biometric Imaging Analysis

Items to be discussed:

- Clustering and K-means algorithm
  - Statistical
  - Unsupervised
- Color Representation and Color Image Segmentation

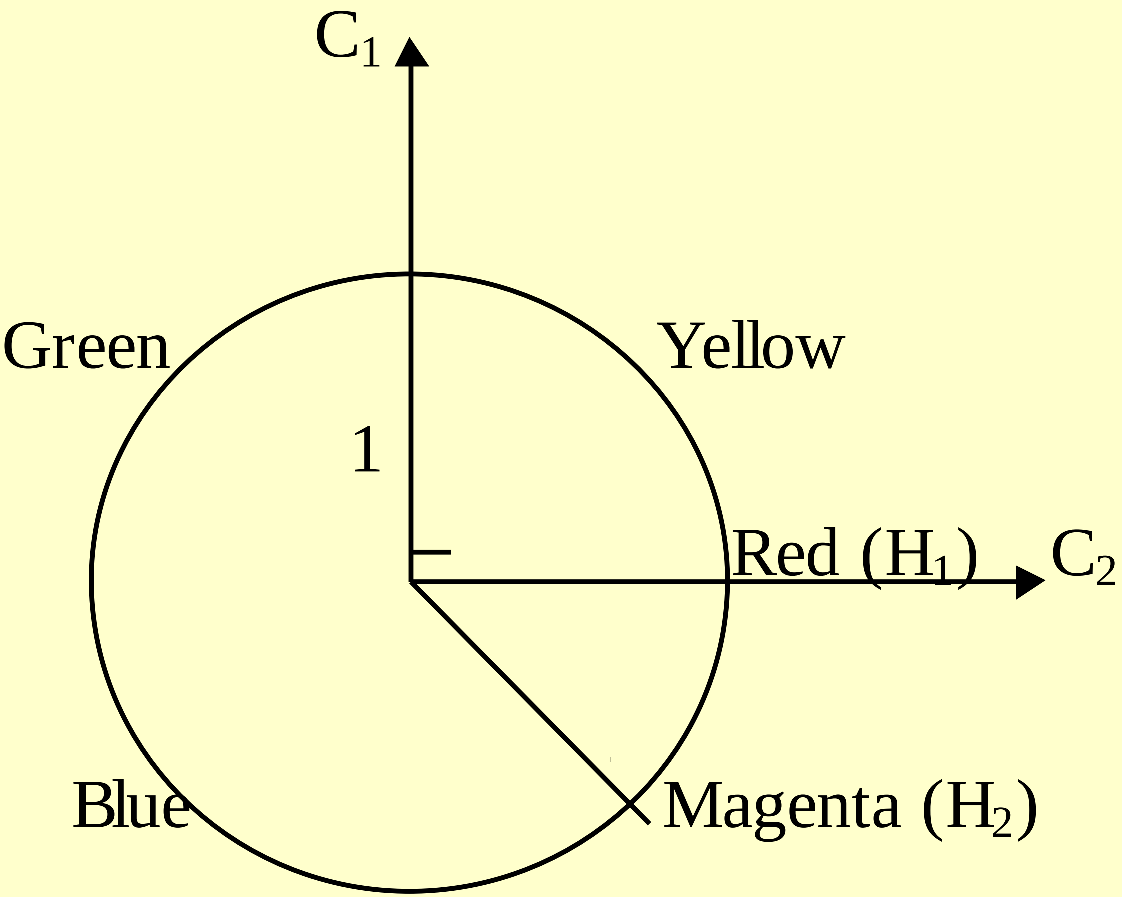
Supervised Classification and minimum distance classification

- Minimum Distance Classification
  - Supervised
  - Find the center of known patterns of each class

$$\lambda_i = \frac{1}{N_i} \sum_{x \in Ci} x$$

  - Classify unknown patterns into the class that is "closest" to it.

Color Image Segmentation: Hue Component



Color Image Segmentation

- Task:
  - Study the K-means algorithm in ***hue space***.
- Interesting:
  - Periodical Circular Property of hue component
  - new Measure of Distance.
- Problem:
  - K-means algorithm is based on the measure of distance and definition of center

Hue Component Clustering

- Definition 1: ***Distance*** of Hue Values
- Definition 2: ***Directed Distance*** of Hue Values
  - Tricky: ***Addition*** of Directed Distance
- Definition 3: ***Interval and Its Midpoint*** in H Space.
- Definition 4: ***Center*** of a Set of Points in Hue Space
- Theory: ***Euclidean Theory of Center*** in Hue Space

Hue Component Clustering

- Definition 1: ***Distance*** of Hue Values

$$d(H_1, H_2) = \begin{cases} |H_1 - H_2| & |H_1 - H_2| \le \pi \\ 2\pi - |H_1 - H_2| & |H_1 - H_2| > \pi \end{cases}$$

Hue Component Clustering

- **Definition 2: *Directed Distance* of Hue Values**

$$\bar{d}(H_1, H_2) = \begin{cases} H_2 - H_1 & |H_2 - H_1| \le \pi \\ H_2 - H_1 - 2\pi & |H_2 - H_1| \ge \pi, H_2 \ge H_1 \\ 2\pi - (H_1 - H_2) & |H_2 - H_1| \ge \pi, H_1 \ge H_2 \end{cases}$$

- **Tricky: Addition of Directed Distance**
  - **the following vector addition property no longer holds:**

$$\vec{d}(H_1, H_3) = \vec{d}(H_1, H_2) + \vec{d}(H_2, H_3)$$

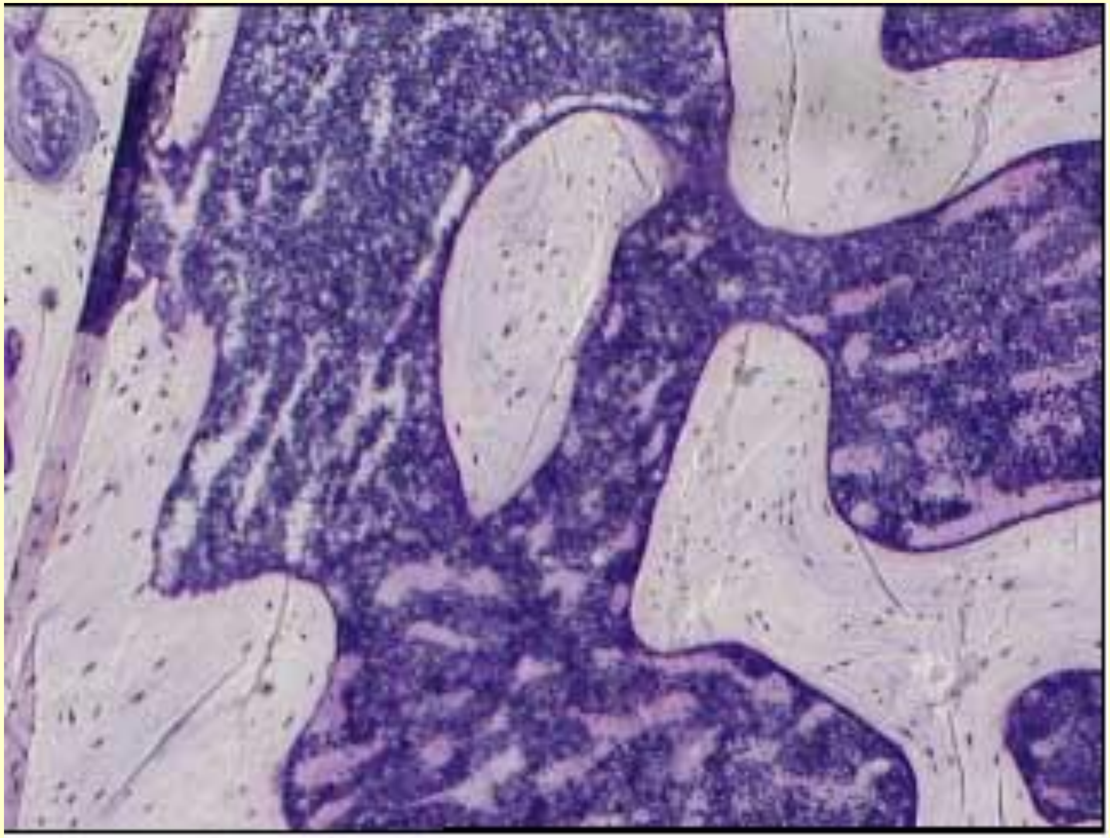
Hue Component Clustering

- Revisit definition: ***Interval and Its Midpoint*** in H Space.
- Revisit definition : ***Center*** of a Set of Points in Hue Space
- Revisit the Proof of Theory: ***Euclidean Theory of Center*** in Hue Space

Color Image Segmentation

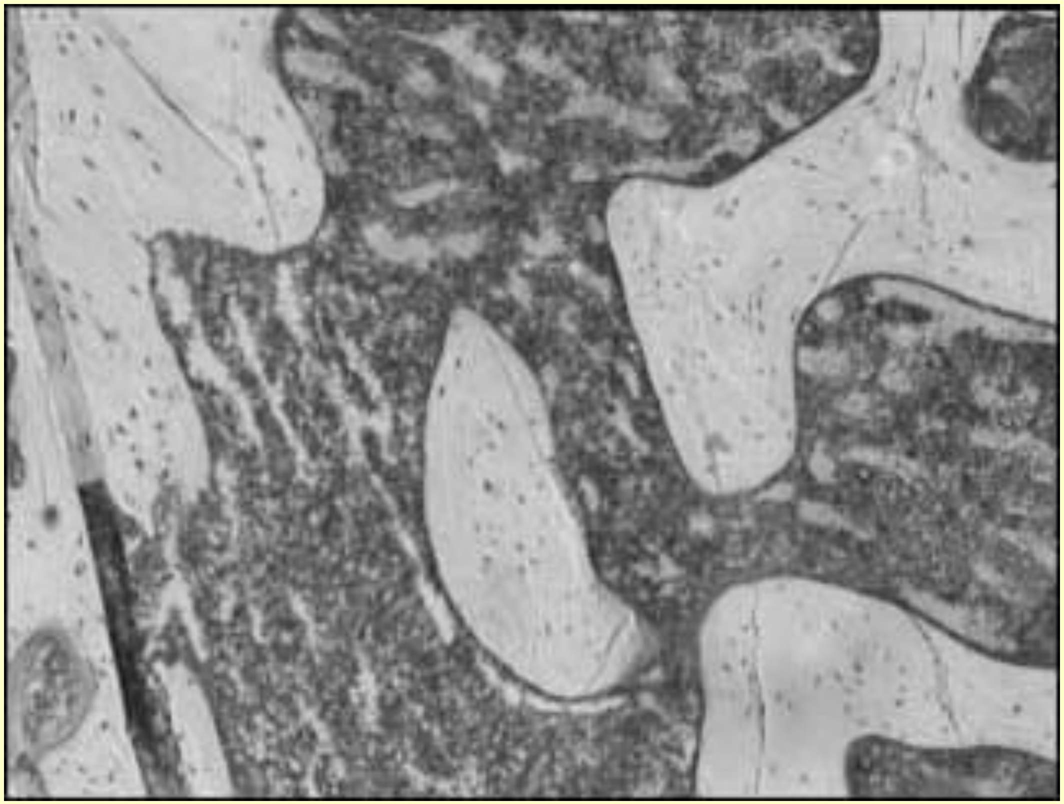
- I and H components are of Interest.
- Good color image segmentation algorithms should consider and combine both
  - Variation of light intensity and occlusion:
    hue component is better
  - Color information is lost:
    Intensity component is better
- Fuzzy member function is introduced

Color Image Segmentation - Experiment 1
Intensity Distinguishable



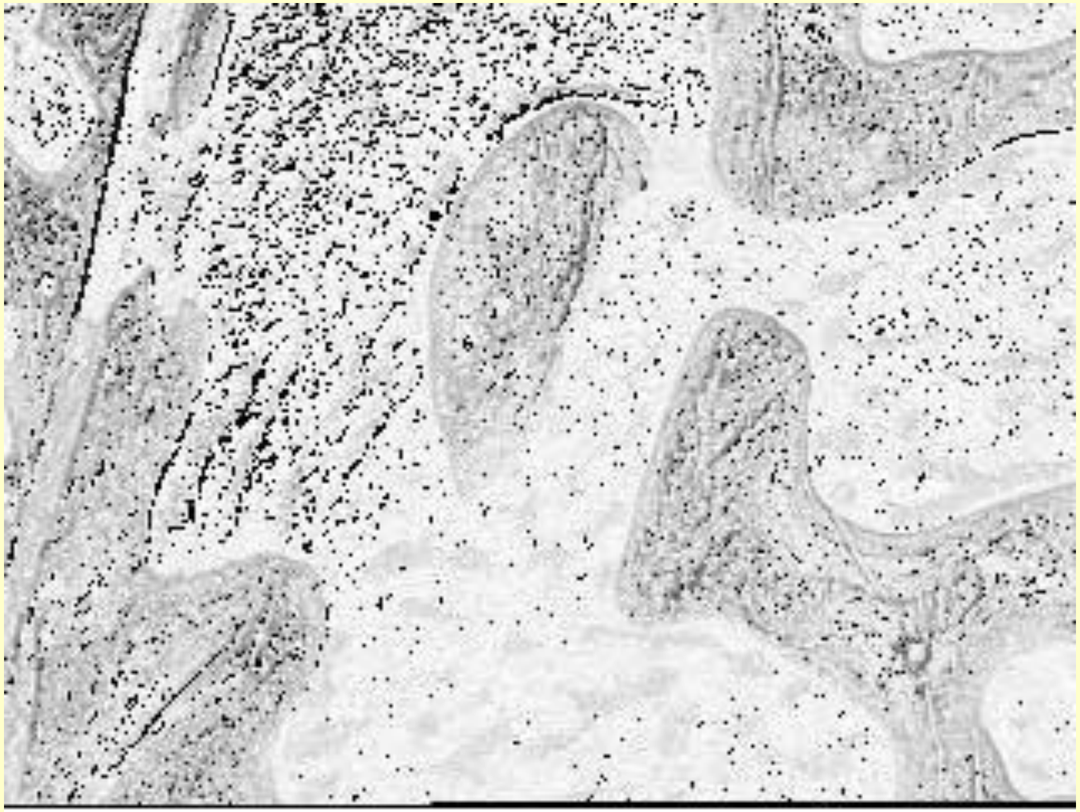
(a) Original color image

Color Image Segmentation - Experiment 1
Intensity Distinguishable



(b) Intensity image

Color Image Segmentation - Experiment 1
Intensity Distinguishable



(c) Hue image

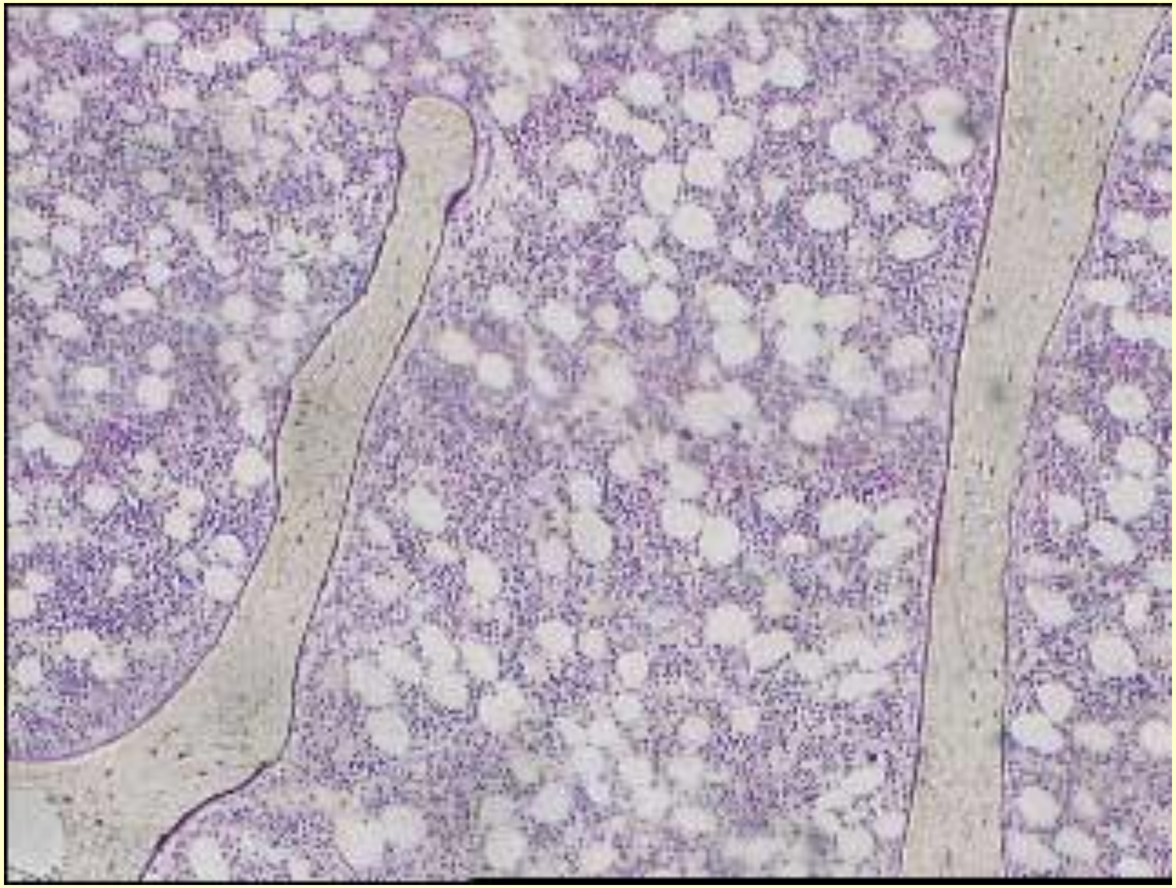
Color Image Segmentation – Experiment
Intensity Distinguishable

(d) Segmentation by hue

Color Image Segmentation - Experiment 1
Intensity Distinguishable

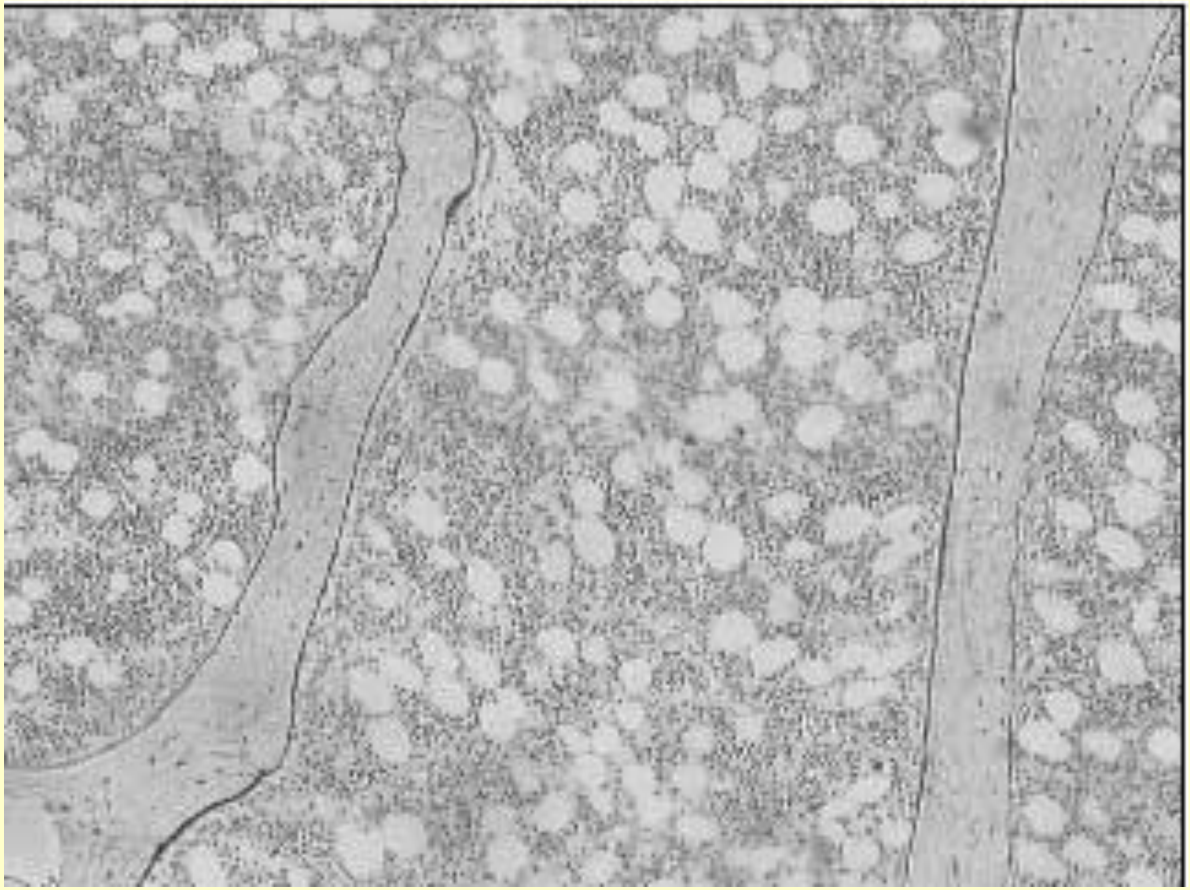
(e) Segmentation by hue and intensity

Color Image Segmentation - Experiment 2
Hue Distinguishable



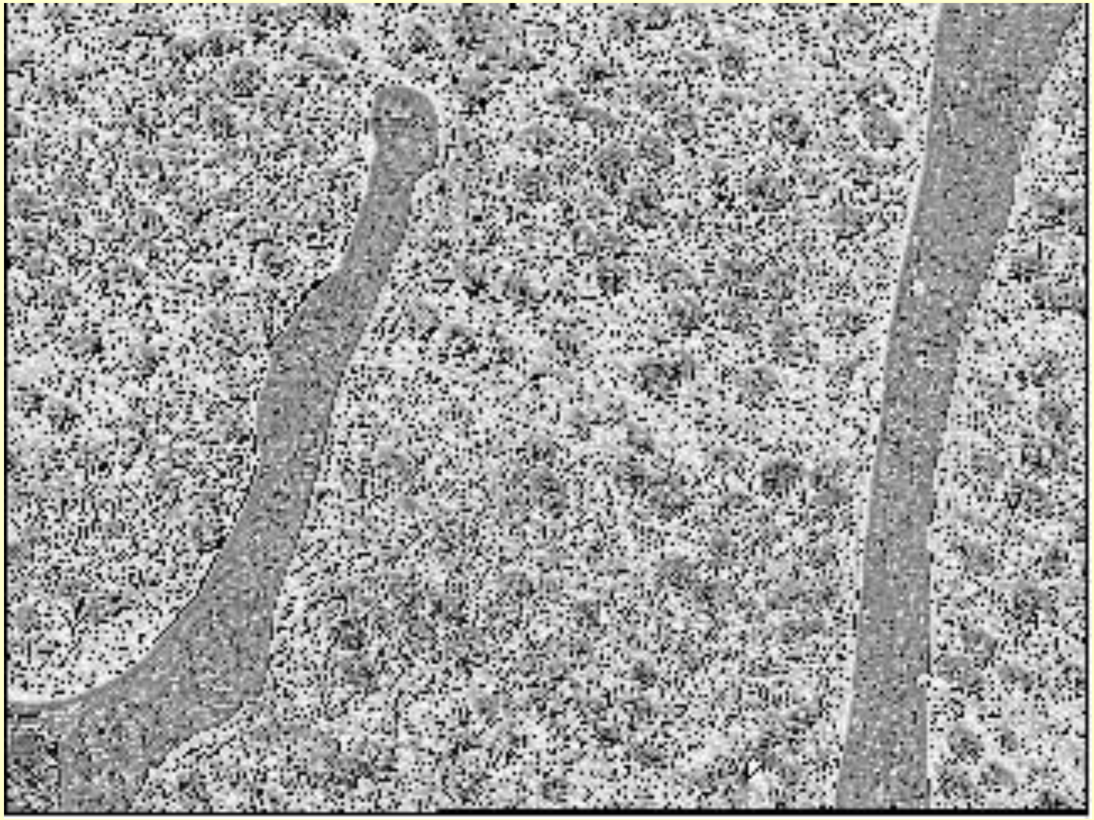
(a) Original color image

Color Image Segmentation - Experiment 2
Hue Distinguishable



(b) Intensity image

Color Image Segmentation - Experiment 2
Hue Distinguishable

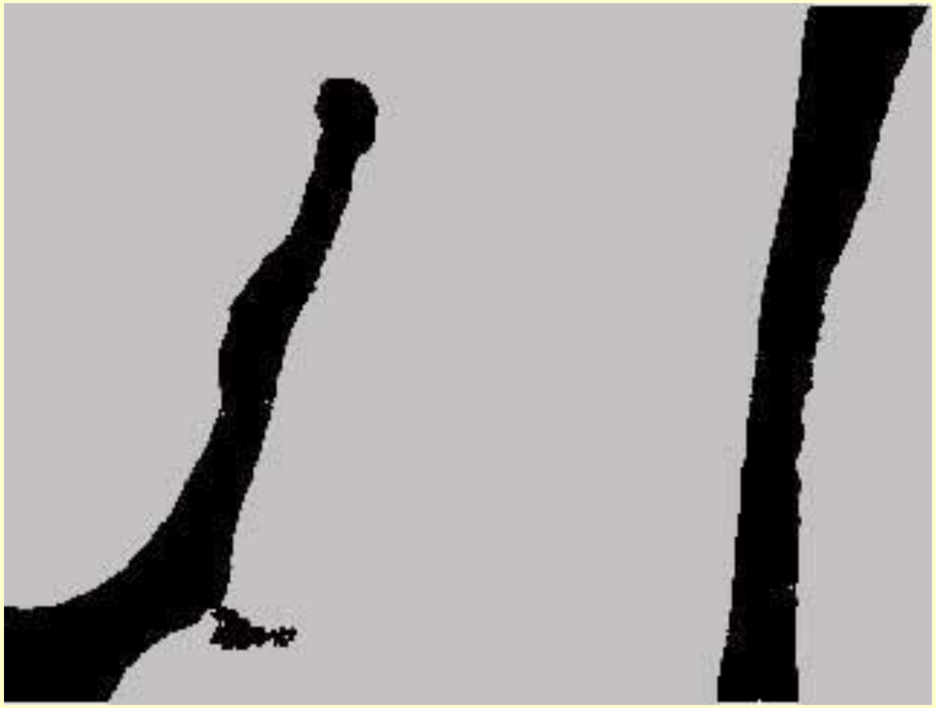


(c) Hue image

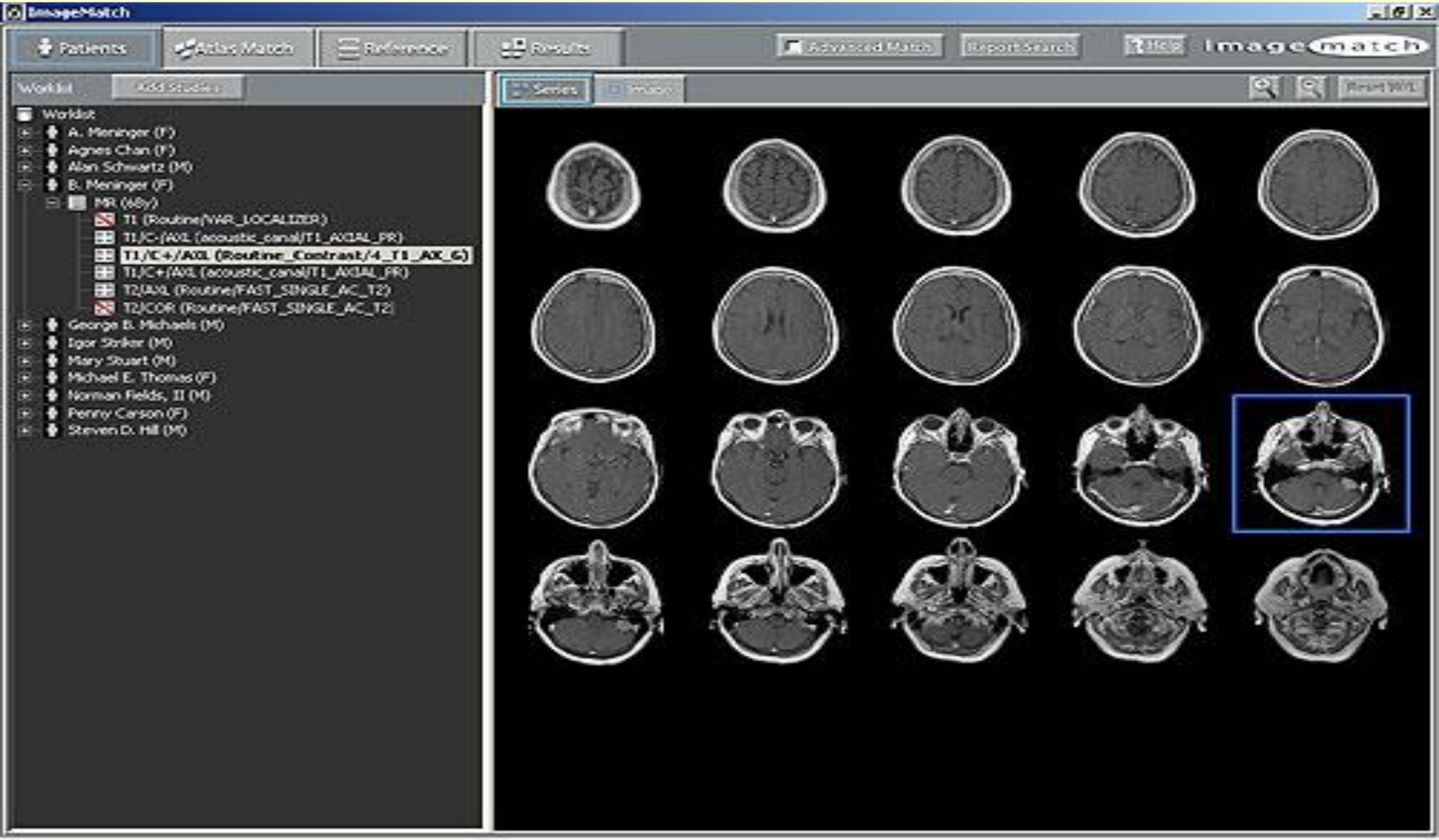
Color Image Segmentation - Experiment 2
Hue Distinguishable

(d) Segmentation by intensity

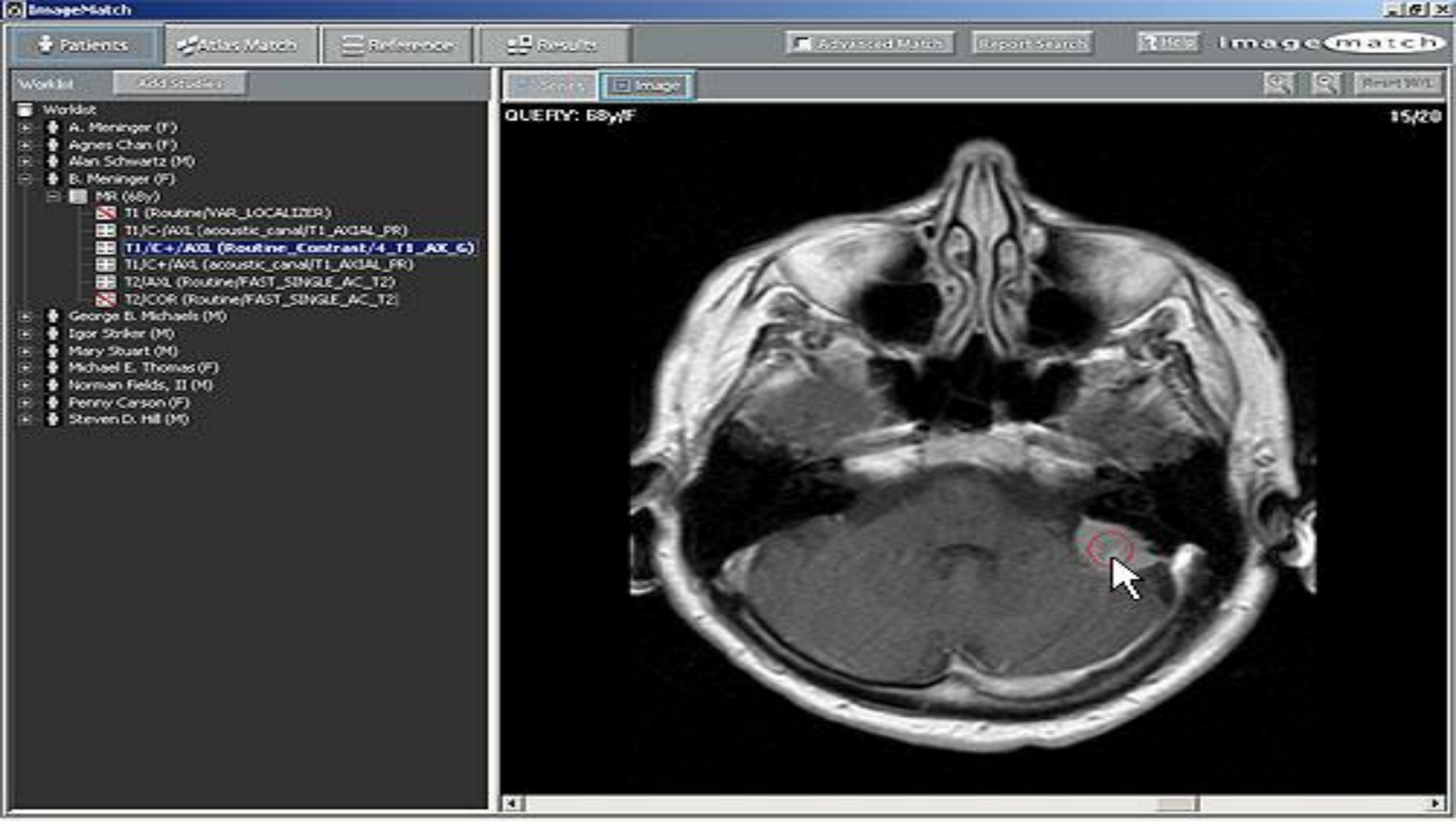
Color Image Segmentation - Experiment 2
Hue Distinguishable



(e) Segmentation by hue and intensity



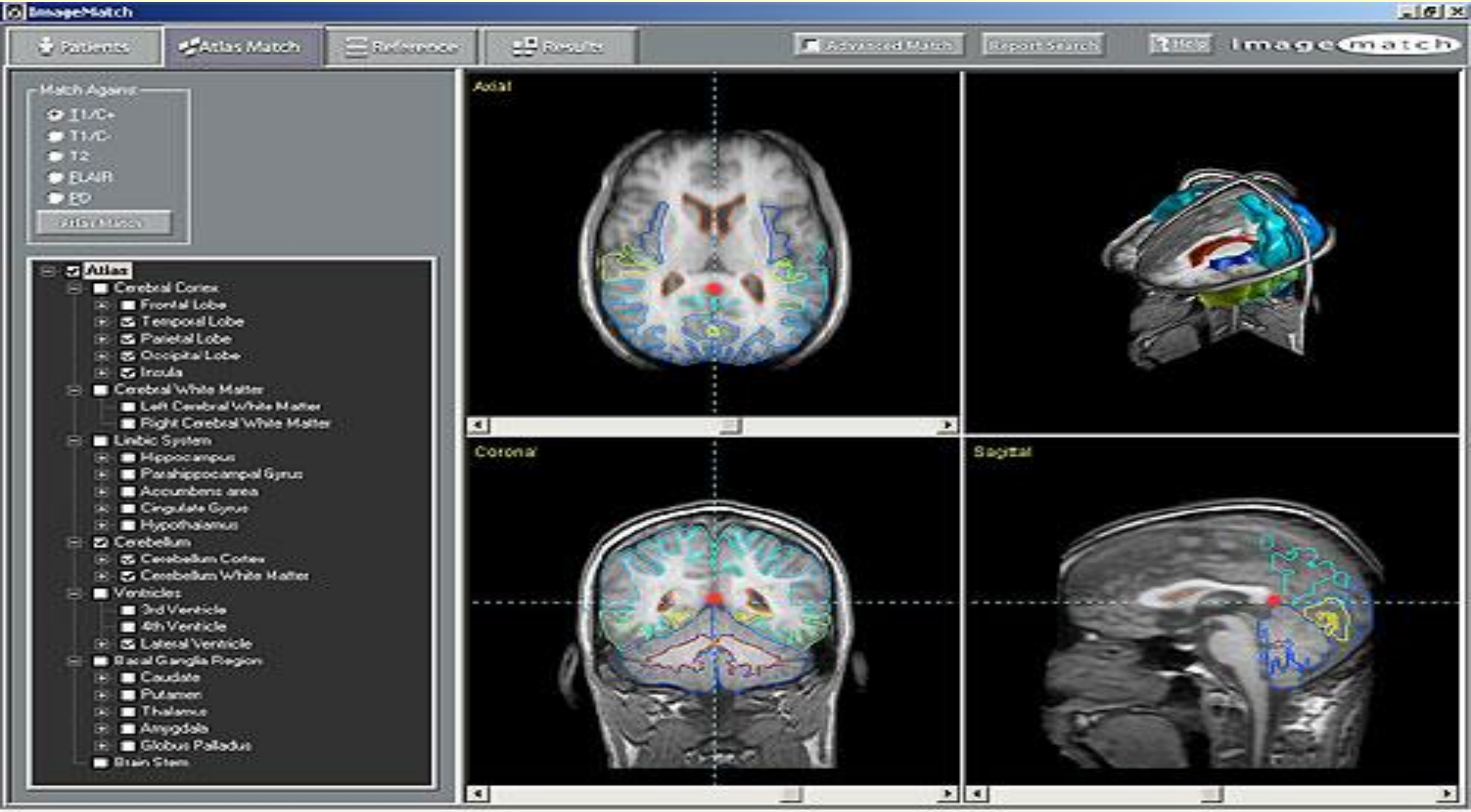
With Image Match, you can submit your own DICOM studies to find similar cases in the MDOL database within seconds. Once you have identified your query case, Image Match allows you to view all the images in the study.



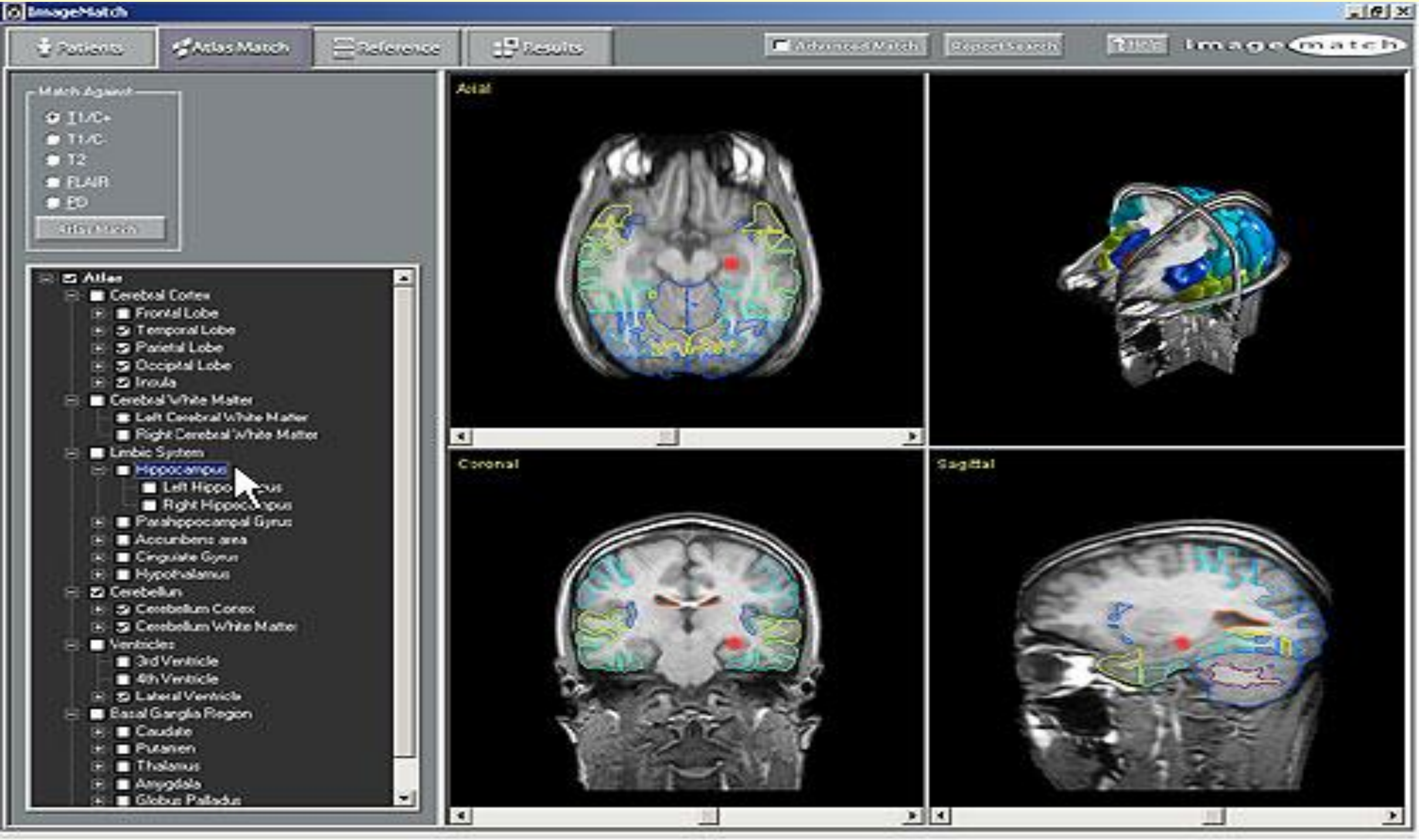
After choosing the image that best represents the pathology of the case, double-clicking on the region where pathology is shown will activate the Image Match search engine and automatically transfer you to the *Results* page.

Within seconds, you are presented with a side-by-side comparison of your image to the most similar image in the MDOL database. You can browse through thumbnail representations of match results . . .

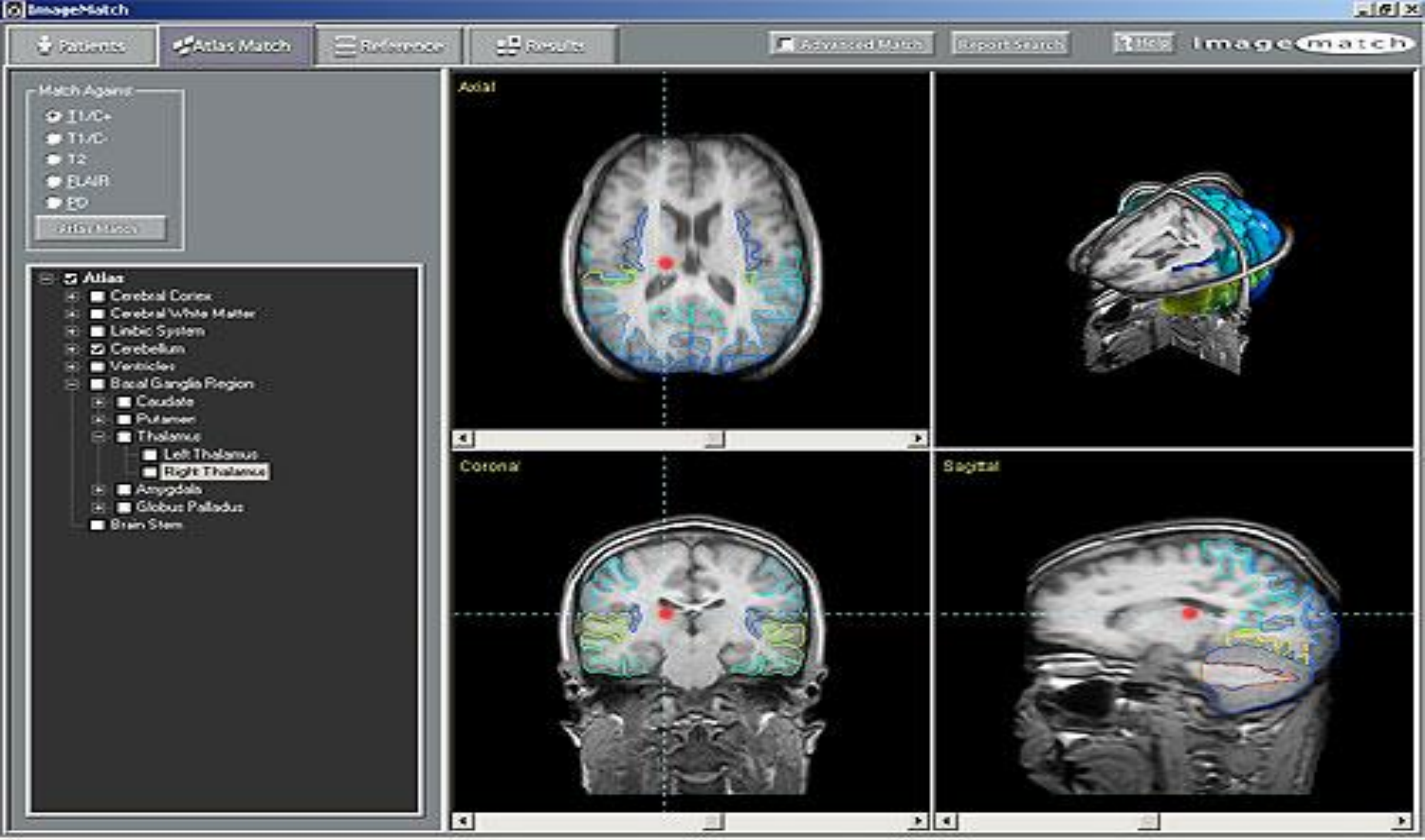
. . .view the corresponding clinical reports of the match results, filter match results by disease class or sub-class, view the entire imaging series and explore prototypical image examples and textbook information related to the pathology under review.



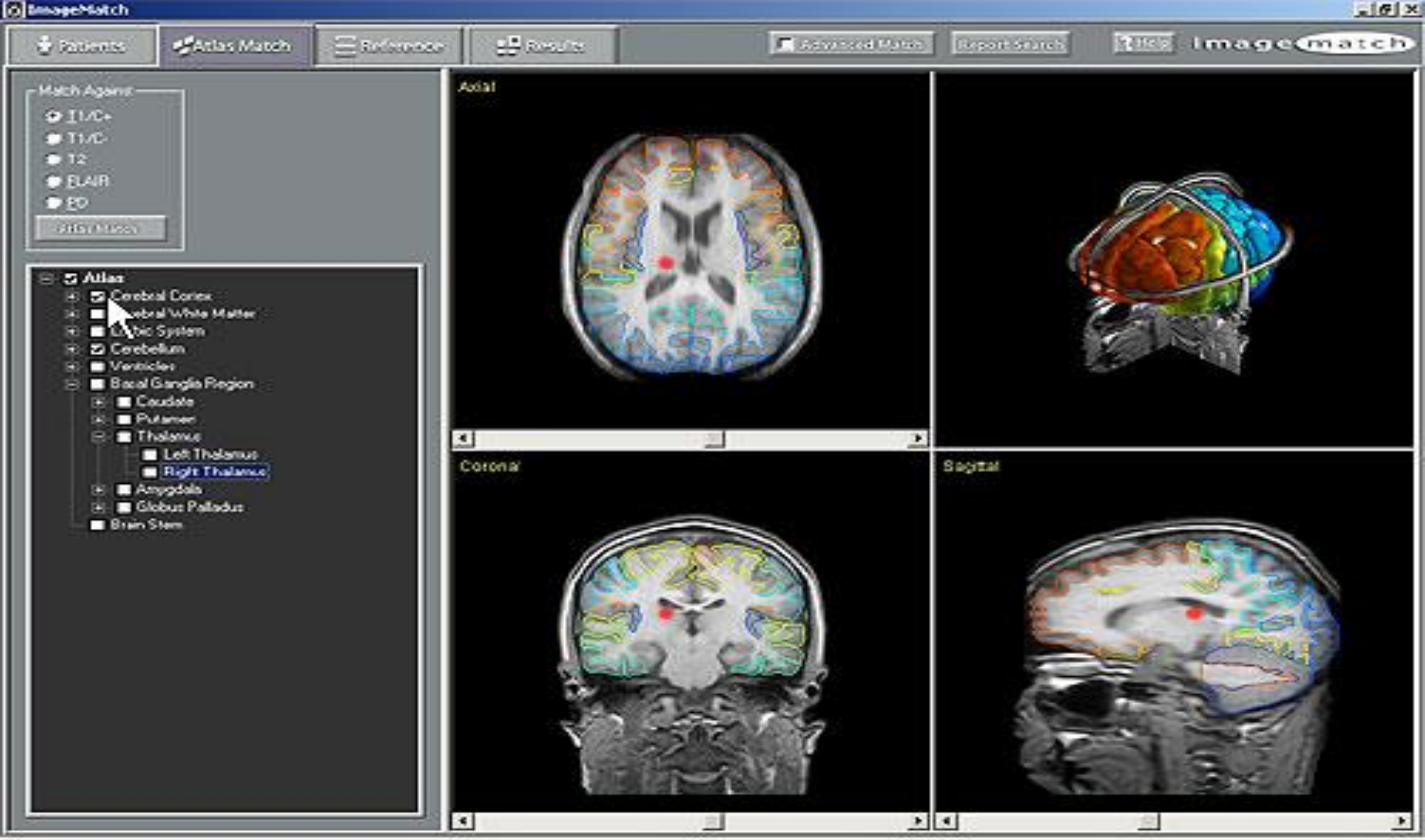
The Image Match *Atlas* page allows you to simply query the MDOL database by a region of interest that is indicated in a tri-plane view of a normal brain. It also proves to be an important reference tool for students and residents in training.



The interactive 3D atlas enables you to locate specific anatomical regions of the brain with ease. In the index, double-clicking on an anatomical label moves the ROI markers (•) to the appropriate regions in each of the axial, coronal and sagittal views.

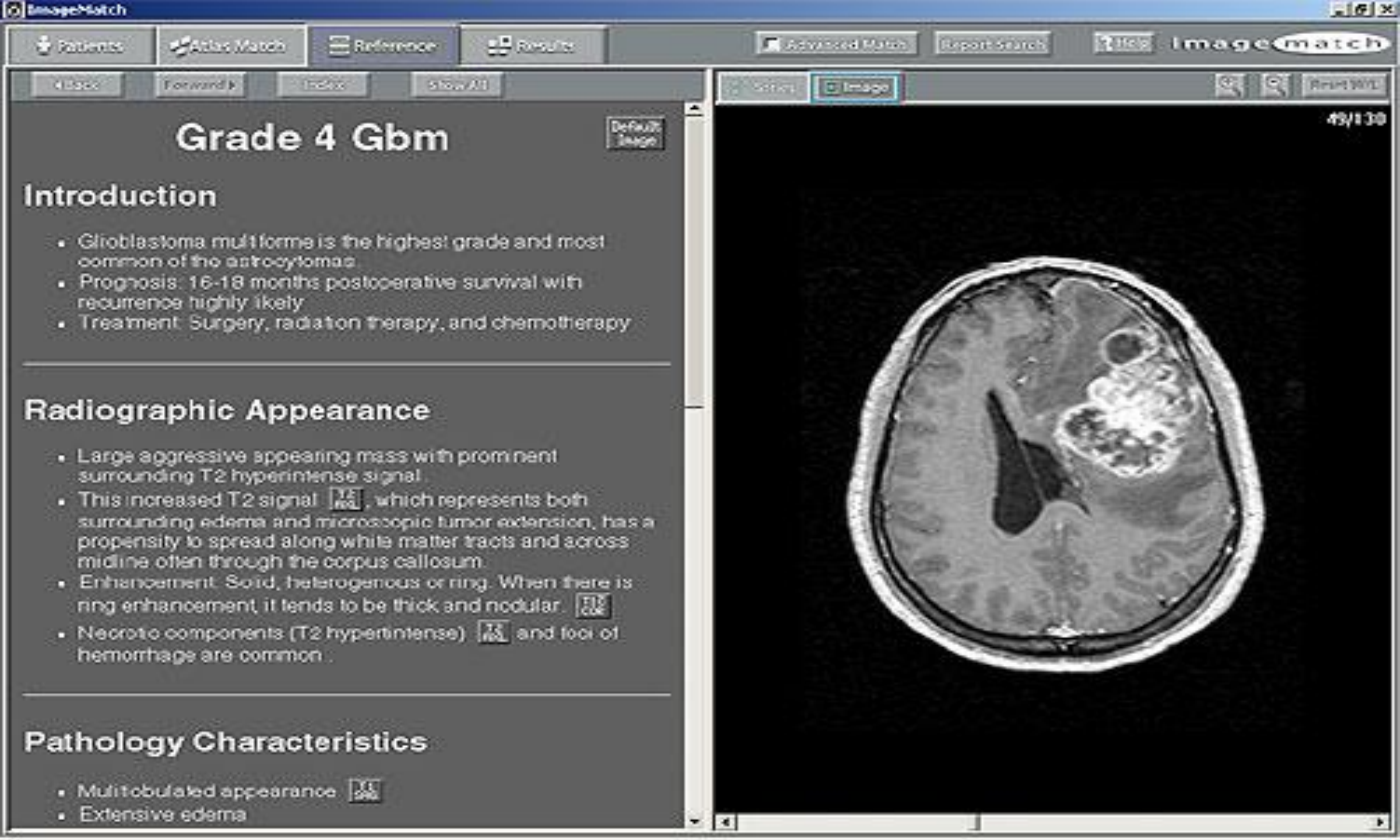


Conversely, clicking on a region on any 2D image highlights the corresponding anatomical label in the index.



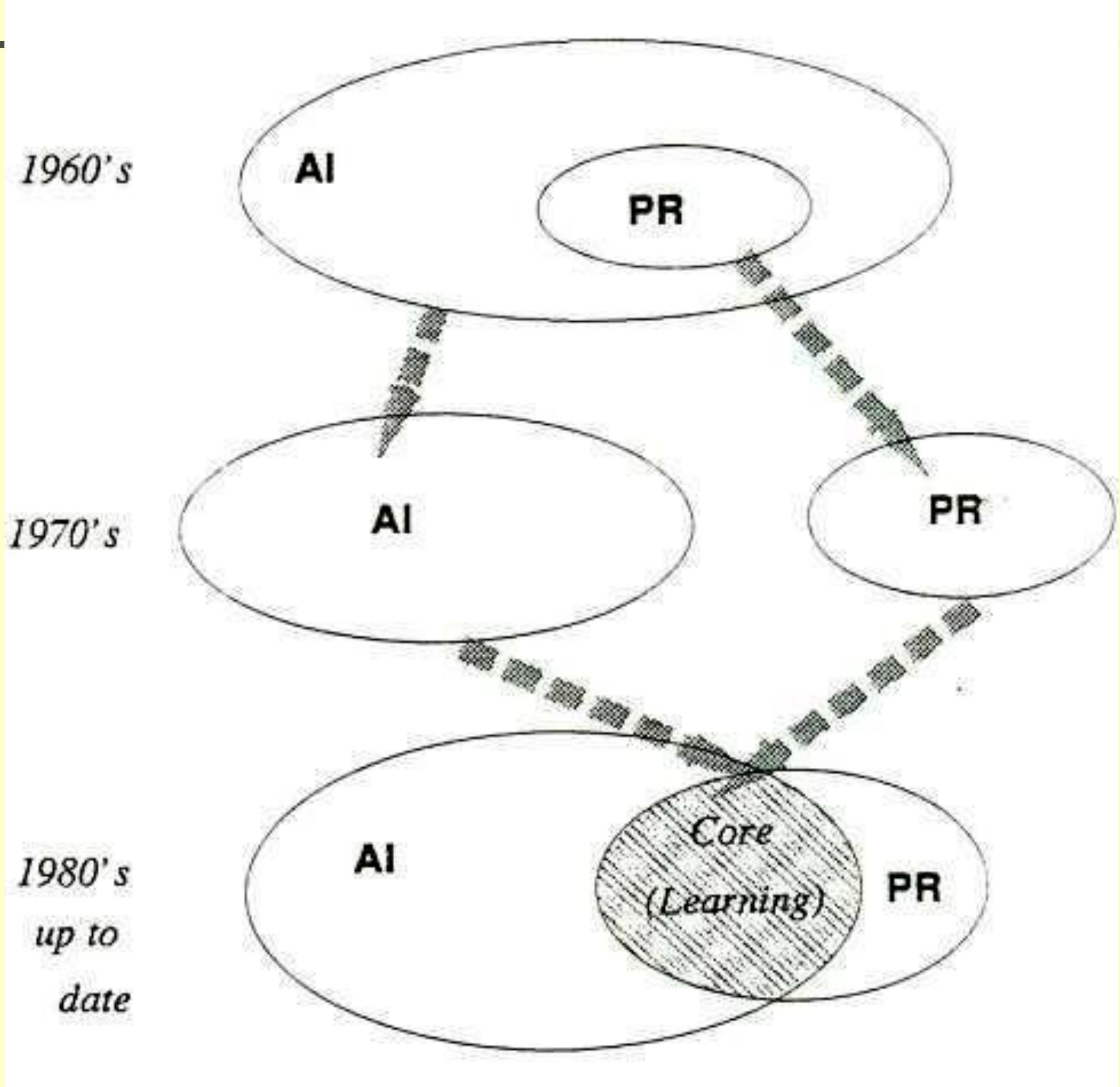
Marking the checkboxes displays the anatomy in the 3D rendering.

Once you have located an ROI, double-clicking on that region activates the Image Match search engine and again transfers you to the *Results* page. You will then immediately have access to patient cases in the MDOL database that best exemplify the differential diagnosis relevant to the selected location.

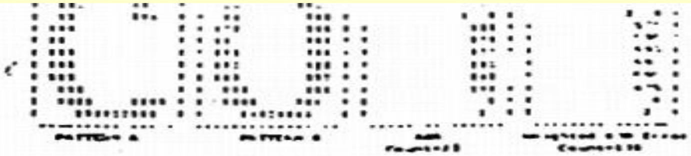


The Image Match *Reference* page offers an index of all the pathologies represented in the MDOL database. Every disease state has a corresponding *Reference* page that displays prototypical image examples and textbook information.

PR (Pattern Recognition) and AI (Artificial Intelligence)



Statistical Pattern Recognition



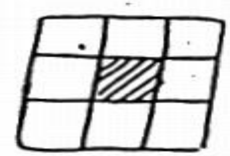
Example of exclusive or $\oplus$ pattern for "c" and "o".

Example of exclusive or + pattern for pair of "e"s

Exclusive or $\oplus$

A	B	A $\oplus$ B
0	1	1
1	0	1
1	1	0
0	0	0

Weighted $\oplus$

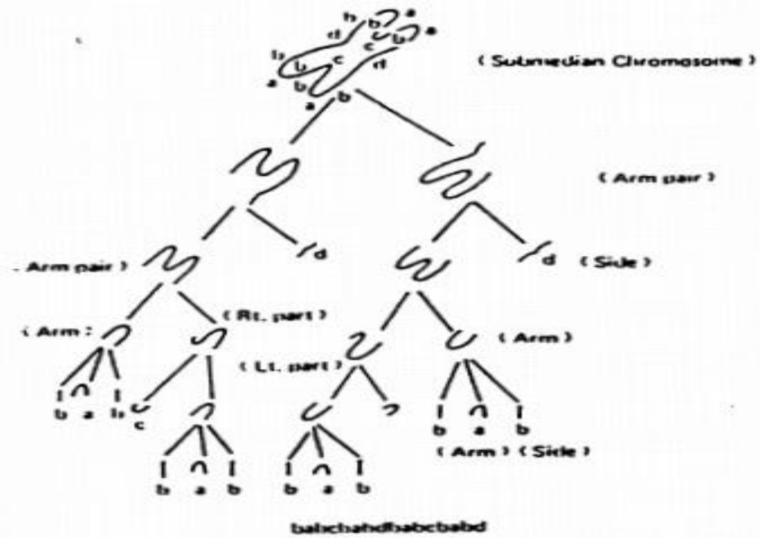


$$E = \sum_{C=1}^{Nc} \sum_{R=1}^{Nr} A(C, R) + B(C, R)$$

$$D(U,C) = \sum_{I=1}^{Nf} | Fc(I) - Fu(I) |$$

If pixel = 1

Syntactical Pattern Recognition



(a)

$G = (V_N, V_T, P, \langle Submedian \rangle)$

where V_N = {<Submedian>, <Arm pair>, <Lt. part>, <Rt. part>, <Arm>, <Side>}

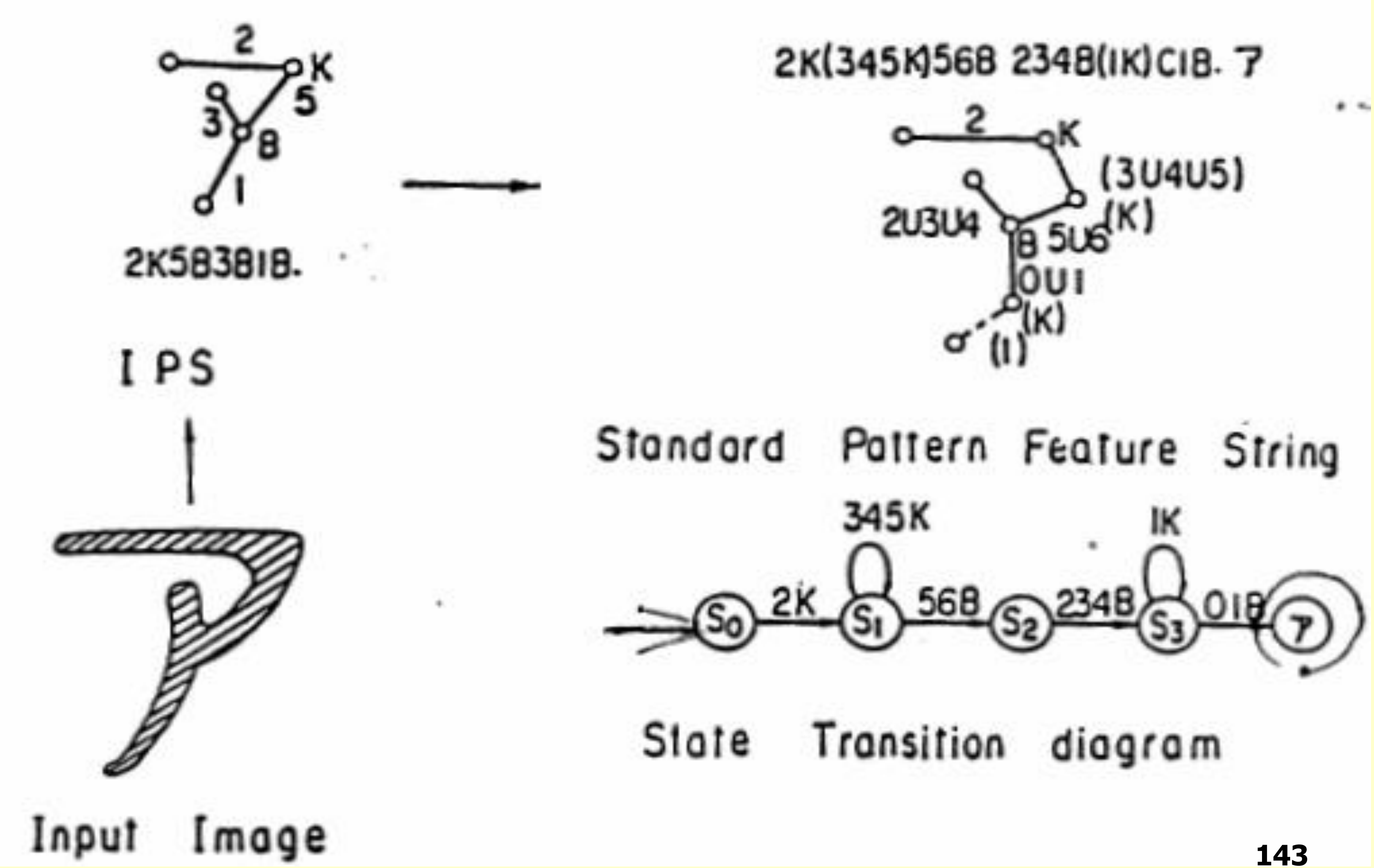
$V_T = \{\overset{\cap}{a}, \overset{|}{b}, \overset{\cup}{c}, d\}$

and P: <Submedian> → <Arm pair> <Arm pair>
<Arm pair> → <Arm pair><Side>
<Arm pair> → <Arm><Rt. part>
<Arm pair> → <Lt. part><Arm>
<Rt. part> → c<Arm>
<Lt. part> → <Arm>c
<Arm> → b<Arm>
<Arm> → <Arm>b
<Side> → b<Side>
<Side> → <Side>b
<Arm> → a
<Side> → b
<Side> → d

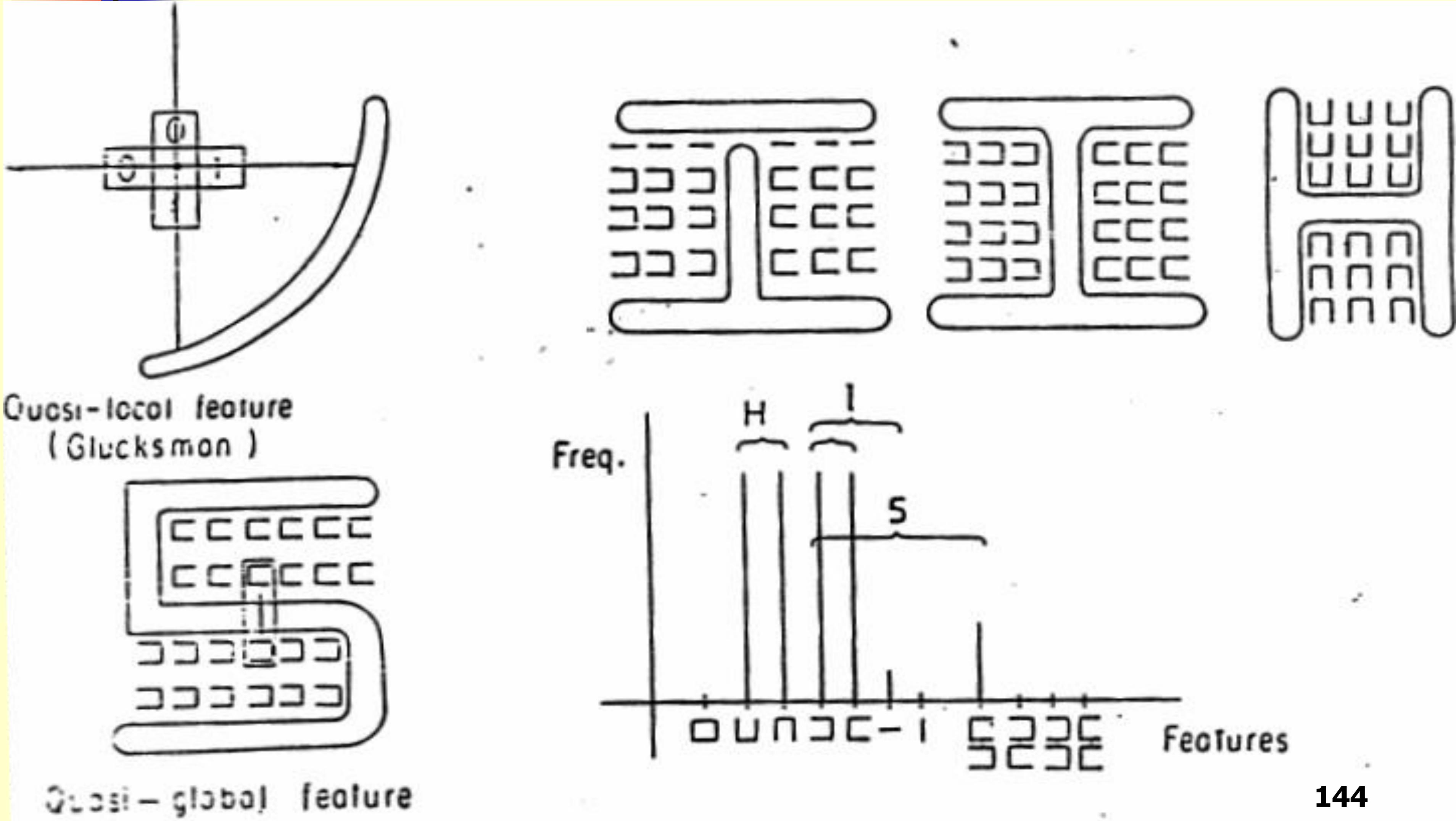
(b)

(a) Hierarchical Structure of a submedian chromosome
(b) A CFG generating (a)

Structural Pattern Recognition



Histogram Pattern Recognition



An Example : Chinese Words, Learning, AI, and PR

Word: A sequence of characters group

together, that make sense (semantically sound, have meanings)

Grammatically speaking:

Syntax => Semantics => Pragmatics

Structure Interpretation Implementation

A typical Data (Image, Vision) handling paradigm is as follows:

Data (Syntax) → Processing

Information → Knowledge → Actionable Intelligence (Semantics)

--> Decision Support

→ Executable actions (Pragmatics)

For example:

A=B + C * D Syntax

Load C

Muliply D Semantics

Add B

Store A

0001 0001 0011 0011=> “2”

0002 0002 0010 0010=> “3”

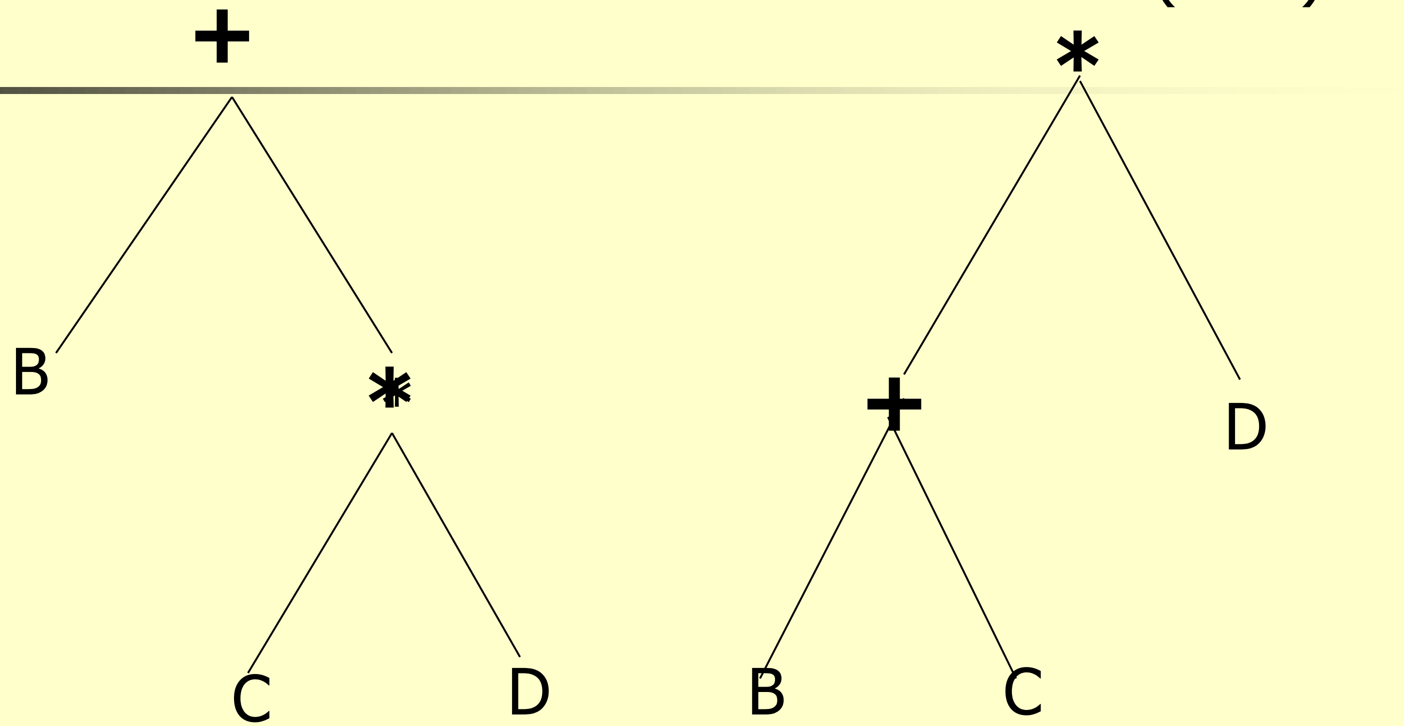
0003 0003 0010 0010=> “4”

0004 0004 0001 Mem A : 0001=> 2->6->10

Implementation

A=B+(C*D)

A=(B+C)*D

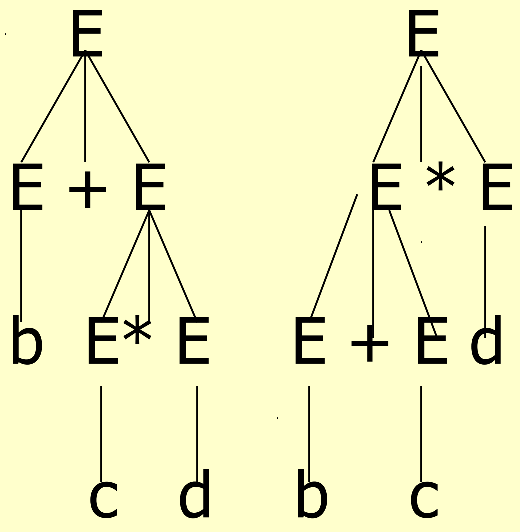


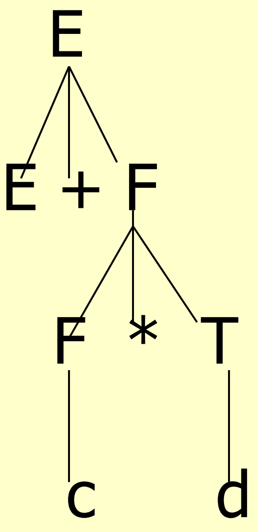
Problem of Ambiguity

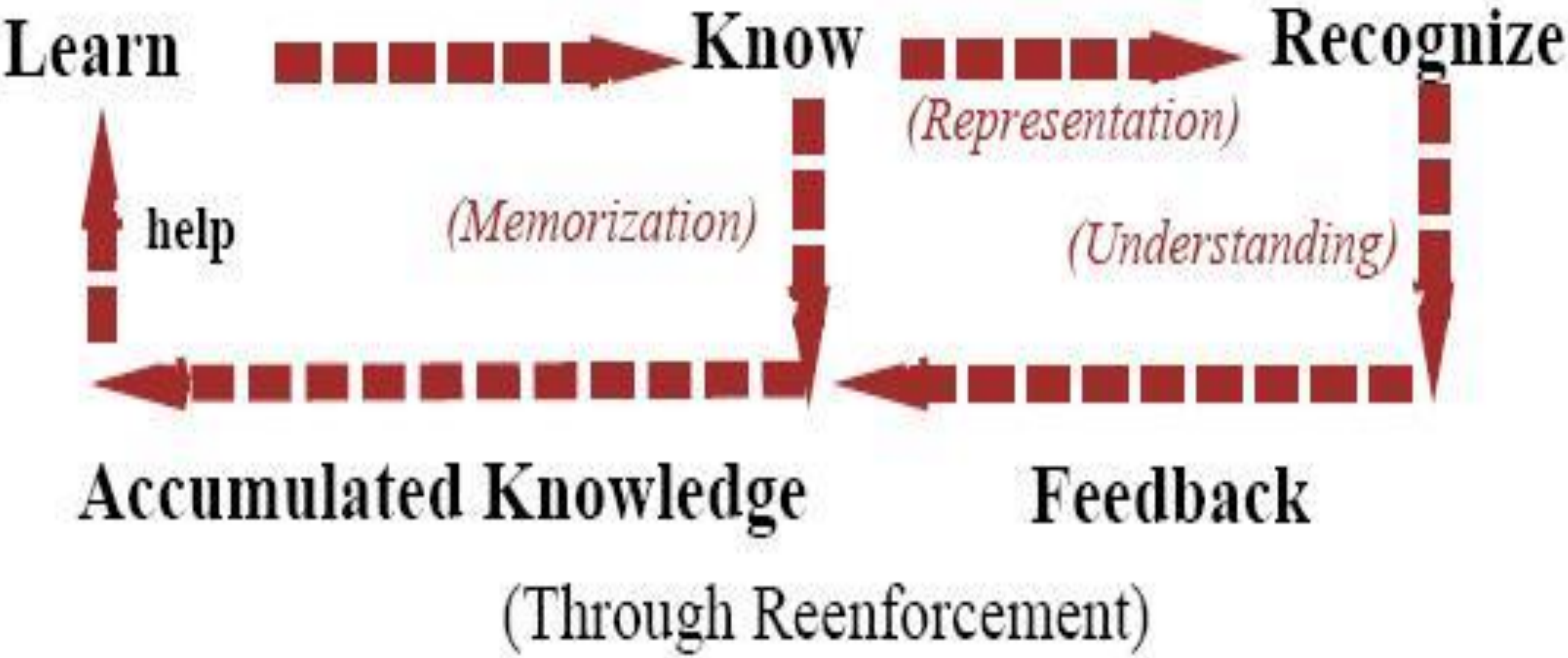
Ambiguous =>Disambiguate=>Unambiguous

E -> E + E
E -> E * E
E -> a|b|c|d

E -> E + F
F -> F * T
T -> a|b|c|d



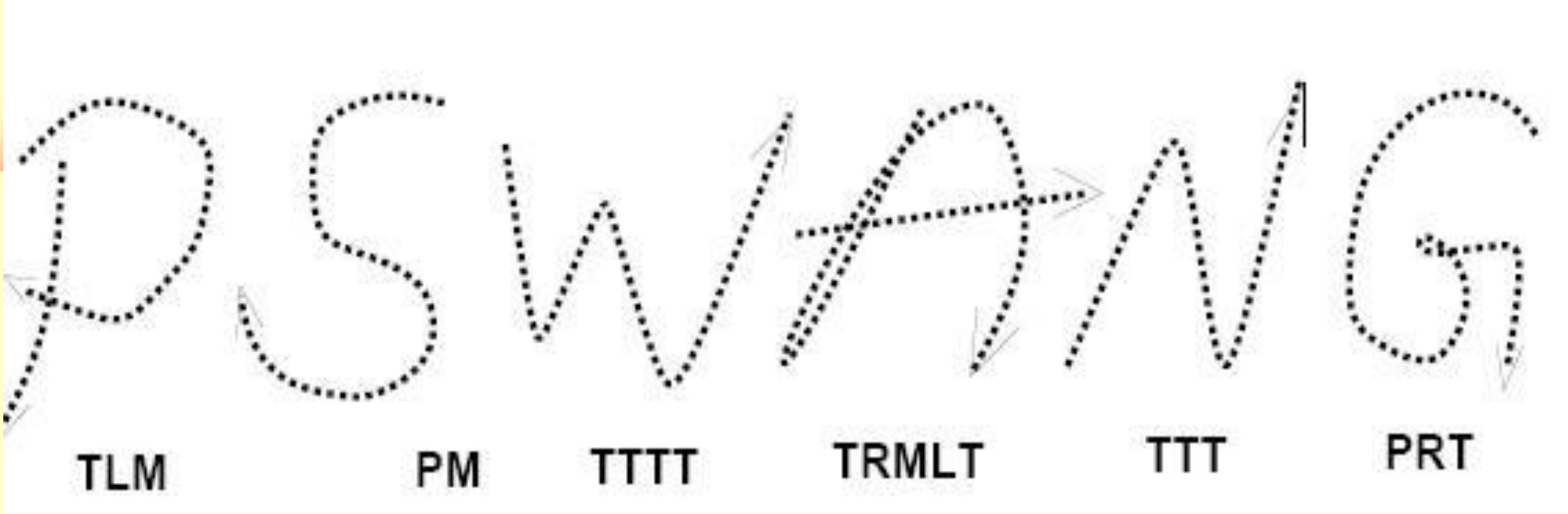




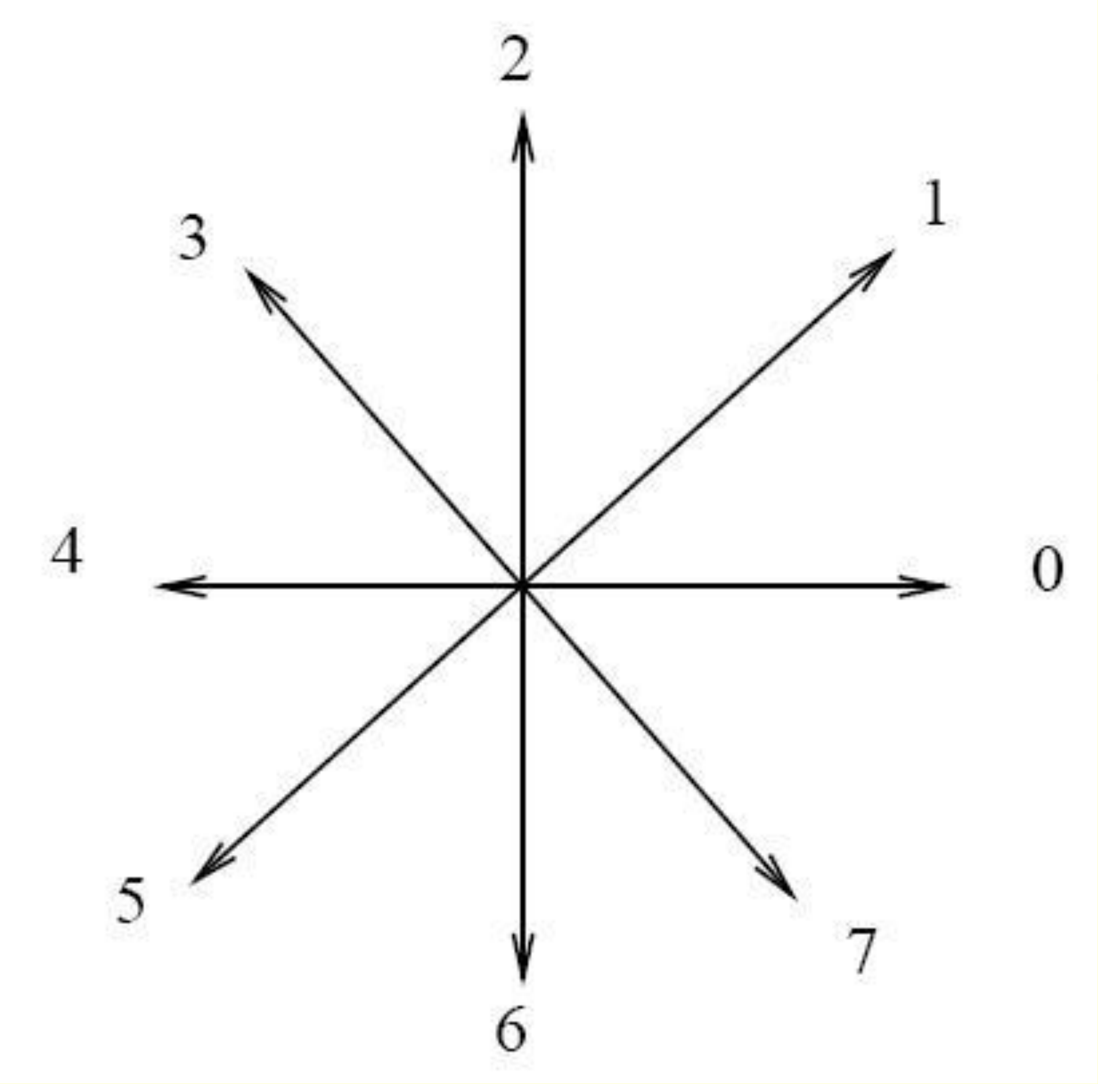
Learning Cycle:
knowledge, recognition, understanding, representation

Code	Symbols	Code	Symbols
M	O	TM	S
MLT	J	TLTTT	M
MM	M	TRM	DP
P	C L U	TRLMLT	AF
PLT	EGQ	TRMLTLT	E
PLTLT	E	TRMM	B
PM	S	TRMRM	BR
PRT	G	TRBT	R
PT	G	TRTTLT	AFK
TLM	DPJ	TRTTLTLT	E
TLMM	BR	TRTTT	N
TLMRM	B	TRTTT	M
TLMT	R	TT	LV
TLT	X Y T	TTLT	J
TLTLT	AFHIKNYZ	TTLTLT	E
TLTLTLT	E	TTT	ZNS
TLTT	N	TTTT	WM
TLTTM	B		

Berthod and Maroy(BM) Method dictionary



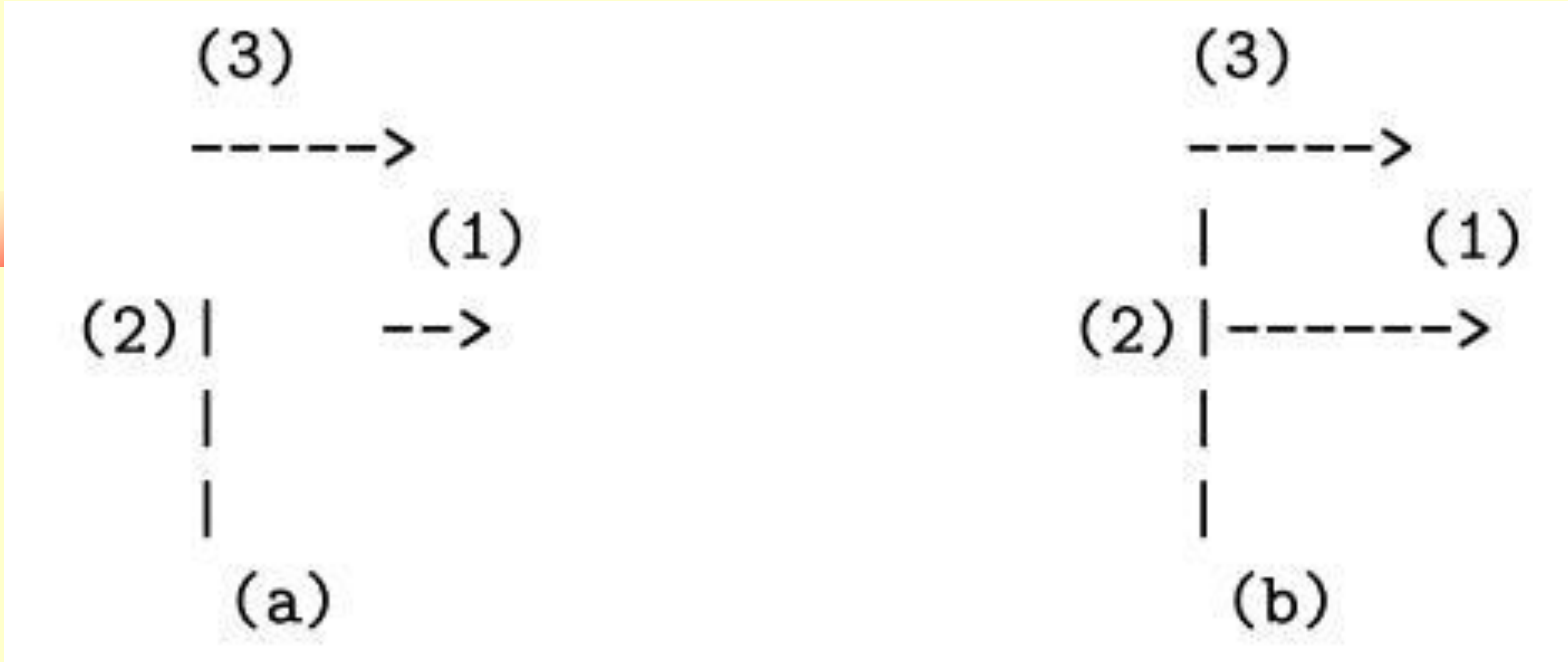
BM code examples



Freeman Chain Coding

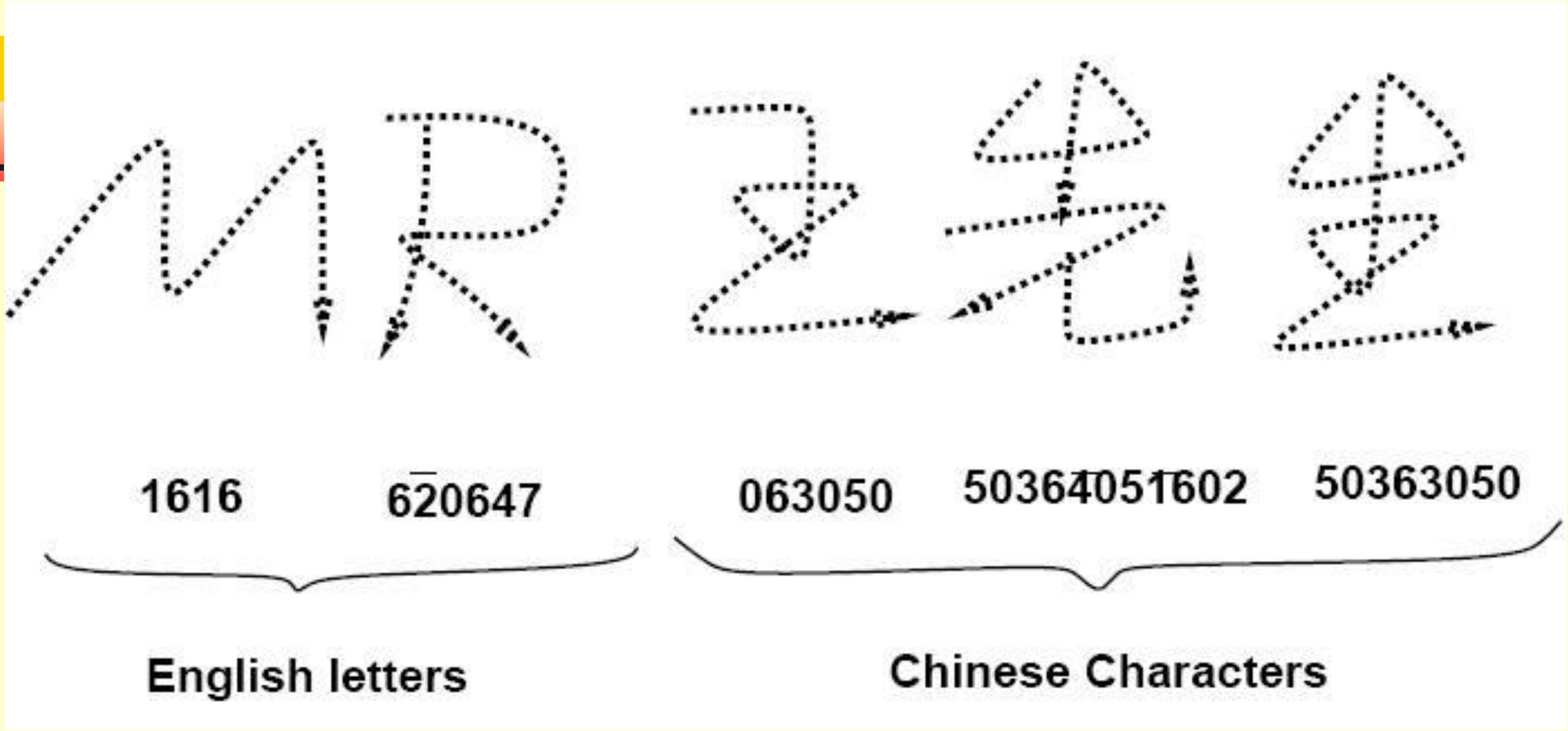
Extended FCC (EFCC) Dictionary

$046\overline{2}0\overline{5}0$	E	$0765\overline{2}6$	P
$0\overline{4}6$	T	$0\overline{4}6\overline{2}0$	F
$046\overline{2}050$	E	$0\overline{4}64$	J
$0\overline{4}6\overline{4}0$	I	161	N
21	V	2121	W
245670123406	G	2716	M
3456701	CO	4560	C
$46\overline{2}0$	F	$46\overline{2}0\overline{5}0$	E
4675	S	560	C
5670123	CO	$5670123\overline{6}7$	Q
575	S	$5\overline{1}6\overline{3}0$	A
$5\overline{1}7\overline{1}5$	N	$5\overline{1}7\overline{3}0$	A
$5\overline{2}7$	XY	61	L
602	U	$61\overline{5}7$	K
620657	R	62065765	B
6275	DP	$64\overline{2}0$	J
670	L	67012	U
$6\overline{1}57$	K	$6\overline{1}6\overline{3}0$	H
$6\overline{2}0657$	R	$6\overline{2}065765$	B
$6\overline{2}0765$	DP	$6\overline{2}71$	N
$6\overline{2}716$	M	$6\overline{2}75$	DP
$6\overline{2}7575$	B	$6\overline{3}0$	T
7171	W	72	V
$7\overline{1}5$	Y	$7\overline{2}5$	X



0 4 6 2 0   0 3 6 2 0

Some examples of IEFCC



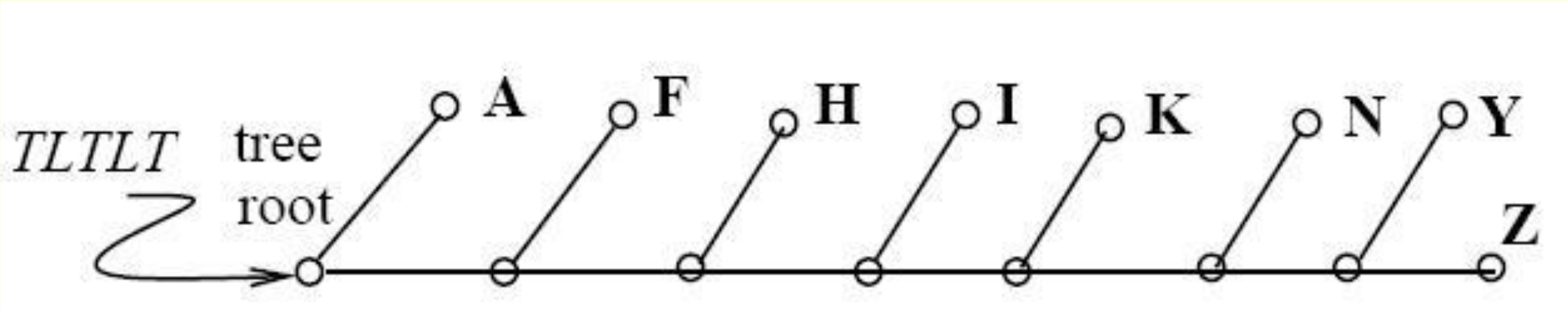
Some more examples of EFCC (and IEFCC with bars removed)

0462050	E	076526	P
046	T	04620	F
0462050	E	0464	J
04640	I	161	N
21	V	2121	W
245670123406	G	2761	M
3456701	CO	4560	C
4620	F	0462050	E
4675	S	560	C
5670123	CO	567012367	Q
575	S	51630	A
51715	N	51730	A
527	XY	61	L
602	U	6157	K
620657	R	62065765	B
6275	DP	6420	J
670	L	67012	U
6157	K	61630	H
620657	R	62065765	B
620765	DP	6271	N
62715	M	6275	DP
627575	B	630	T
7171	W	72	V
715	Y	725	X

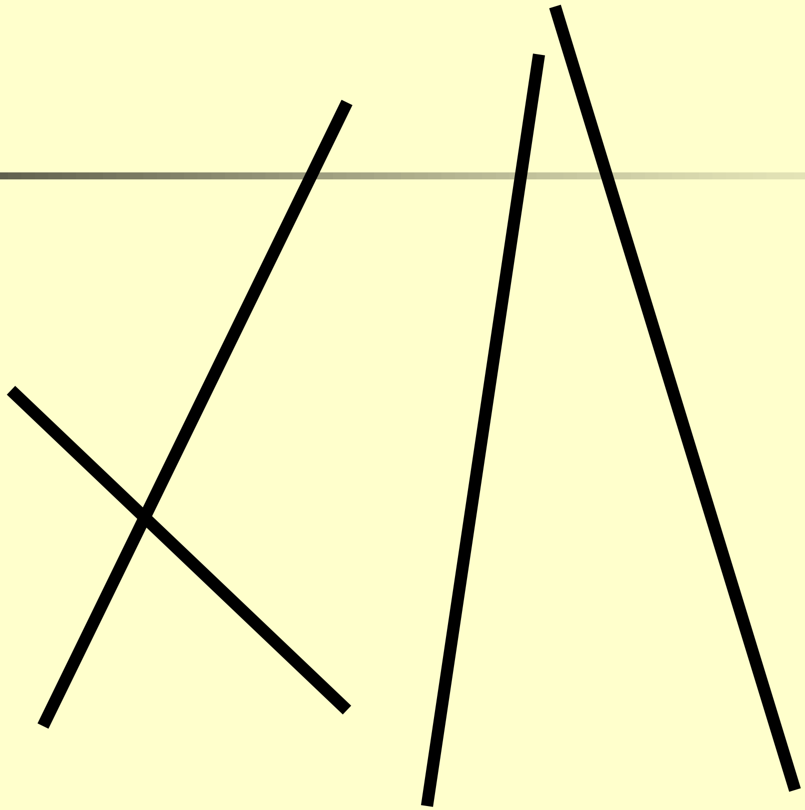
Improved EFCC(IEFCC) Dictionary

- **IEFCC**：

more accurate, efficient, less ambiguous, and no backtracking needed



Backtracking of BM method => Extremely time consuming



A doomed miss-recognition as “E” (TLTLTLT)

Chinese words: really hard to Learn? Understand? Recognize? Memorize?

Learn

Understand

Recognize

Memorize

(Core of A.I. and P.R.)

Characteristics of Chinese Characters

- Two Dimensional
- Non-alphabetical
- Basically Pictorial
- Confined in a rectangle (or square)
- 5,000 years of history
- Used by more than 1.3 billion people today! (and rapidly increasing)

Six Methodologies(六書)

- 1. Hsiang-Hsing, imitative drafts (象形)
- 2. Chih-Shih, indicative letters (指事)
- 3. Hui-I, Logical aggregates (會意)
- 4. Hsing-Sheng, phonetic complex (形聲)
- 5. Chuan-Chu, derived generalized (轉注)
- 6. Chia-Chieh, borrowing (假借)

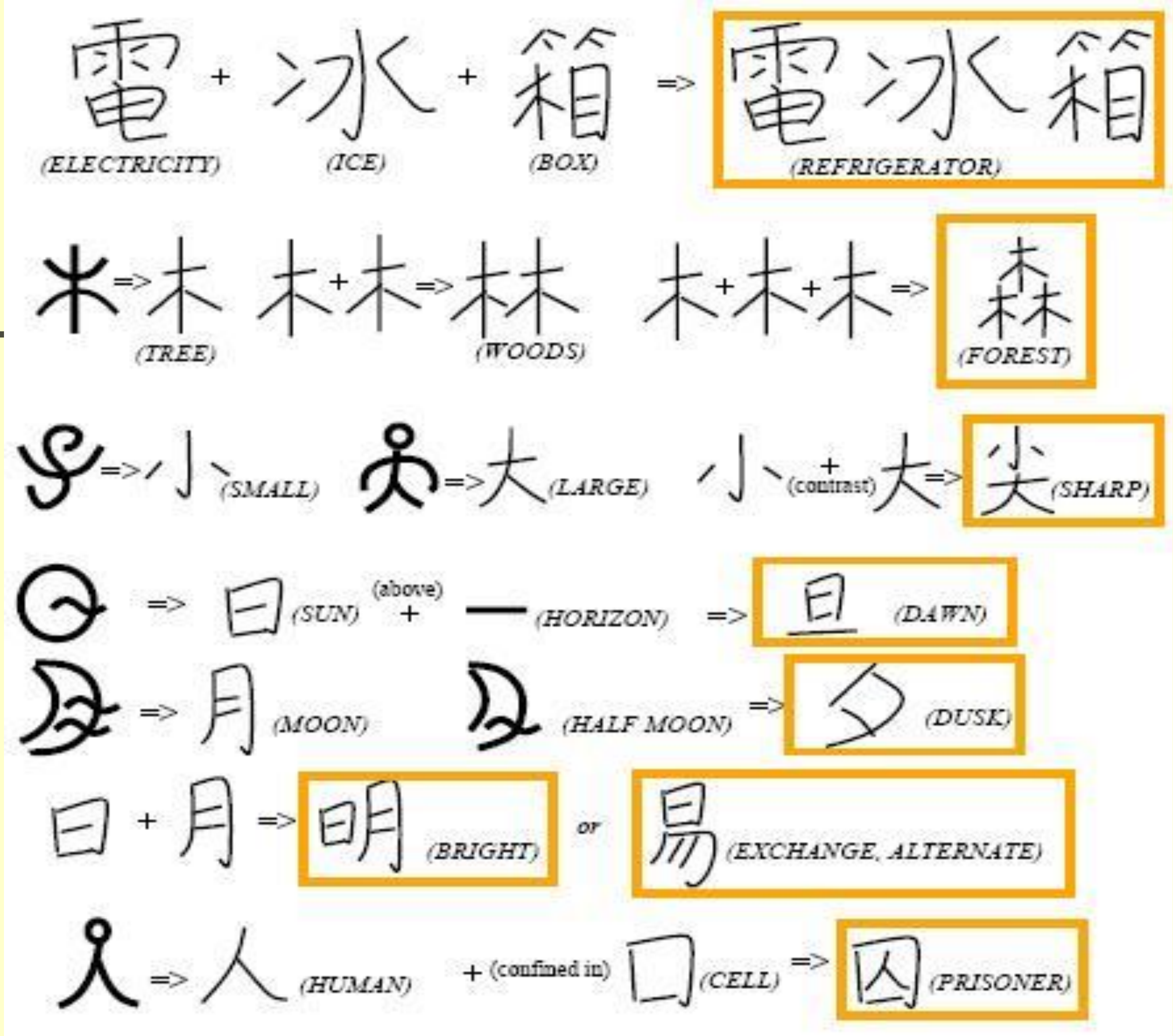
Artificial Intelligence人工智能(慧)

- Imagery 形象
- Syntax-Phonetics-Semantics 形,音,意結合
- Logic Connection Between Words 字與字之間的關聯(共同特徵,圖形)
- Induction, Implied Meanings: 語意延伸性

  1. Logic 邏輯性

  2. Semantic Network 語意網

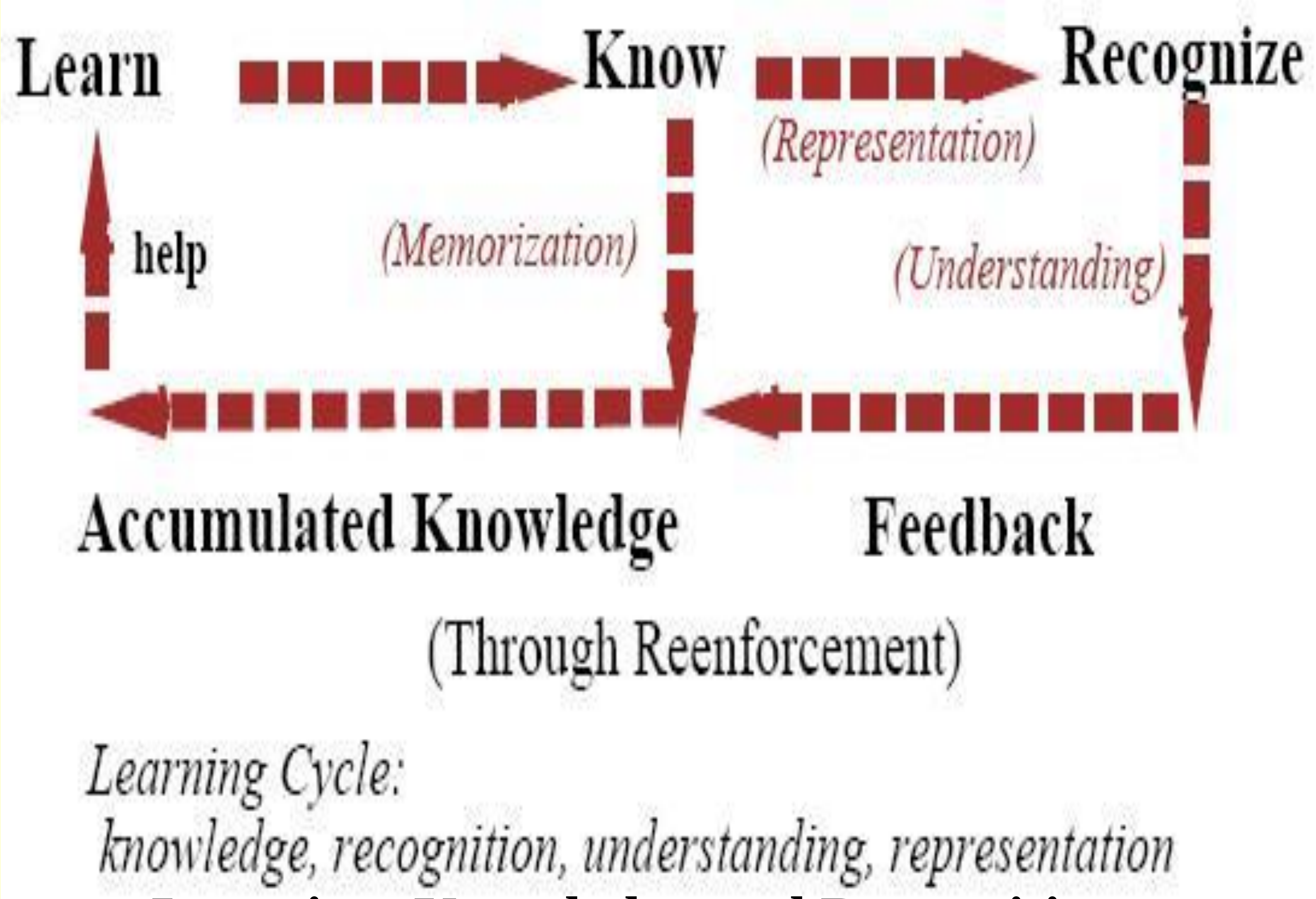
  3. Knowledge Representation 知識表達



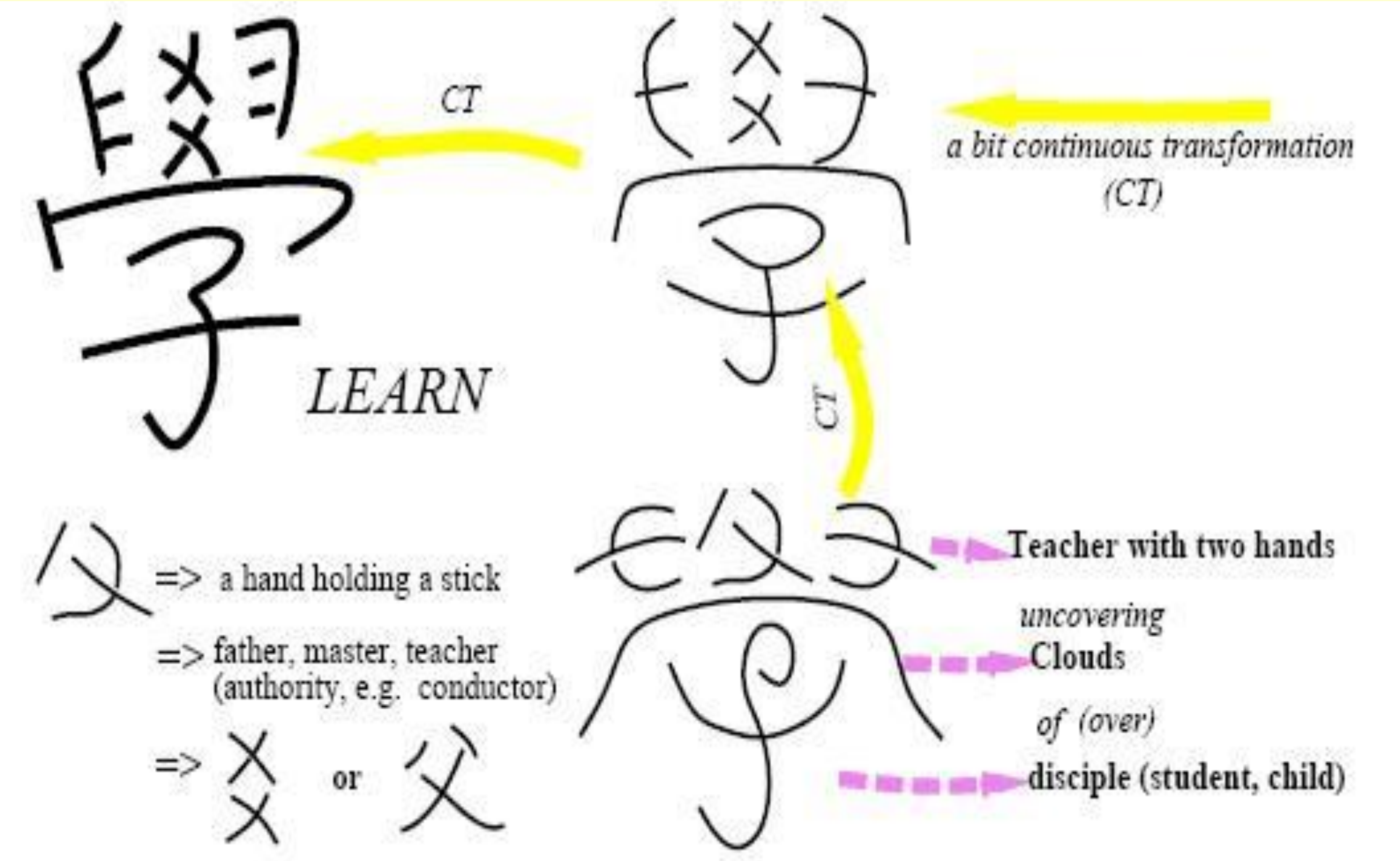
Chinese words:

Pictorial, Semantics, Logical Connections


BPO that helps you find value by
seeing the wood for the trees.



Learning, Knowledge and Recognition

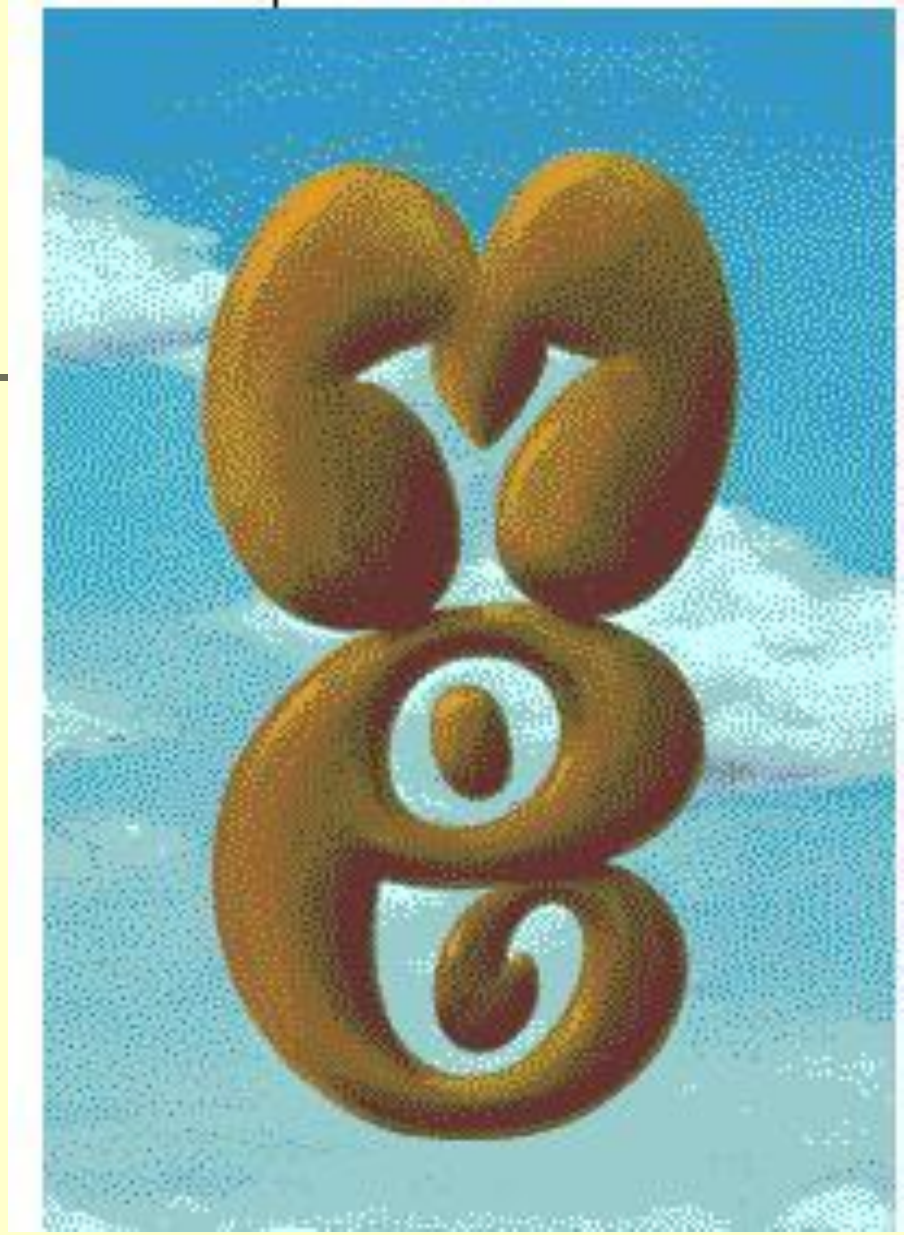


The character "Learn"

Teach or Learn? or Both?Mirror Image LEREN (Dutch)


Love ? or Hate ?

Good ? Or Evil ?



You ? or Me ?

Optical Illusion:

one word? or two words ?

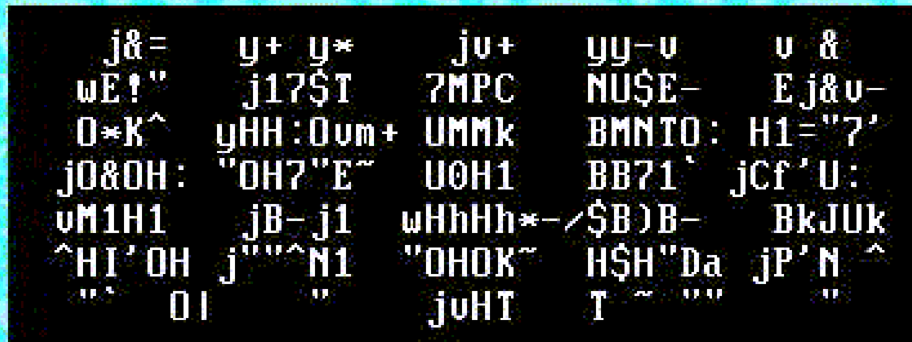
O lny srmat poelpe can raed tihs.
I cdnuolt blveiee taht I cluod aulaclty uesdnatnrd waht I was rdanieg. The phaonmneal pweor of the hmuan mnid, aoccdrnig to a rscheearch at Cmabrigde Uinervtisy, it deosn't mttaer in waht oredr the ltteers in a wrod are, the olny iprmoatnt tihng is taht the frist and lsat ltteer be in the rgh it pclae. The rset can be a taotl mses and you can sitll raed it wouthit a porbelm. Tihs is bcuseae the h uamn mnid deos not raed ervey lteter by istlef, but the wrod as a wlohe. Amzanig huh? yaeh and I awlyas tghuhot slpeling was ipmorantt! if you can raed tihs psas it on !!

Psas Ti ON !

IF YOU CAN READ THIS YOU HAVE A STRONG MIND!

7H15 M3554G3
53RV35 7O PR0V3
H0W 0UR M1ND5 C4N
D0 4M4Z1NG 7H1NG5!
1MPR3551V3 7H1NG5!
1N 7H3 B3G1NN1NG
17 WA5 H4RD BU7
N0W, 0N 7H15 LIN3
Y0UR M1ND 1S
R34D1NG 17
4U70M471C4LLY
W17H 0U7 3V3N
7H1NK1NG 4B0U7 17,
B3 PROUD! 0NLY
C3R741N P30PL3 C4N
R3AD 7H15.
PL3453 F0RW4RD 1F
U C4N R34D 7H15.

用心看



今天下午，我收到朋友轉寄來的一封E-m@il，打開一看是一個黑色方塊上面堆了一些類似亂碼的白色文字，而排列方式也毫無規則可言，完全不知道那是什麼東西。不過朋友附上原始說明文字：請一定要後退至少兩公尺看。我是有點半信半疑，近看都看不清楚，何況是向後退兩公尺！

我的位子不大，我只好儘可能將椅子往後退，並將身體盡力後仰，螢光幕上還是一片黑白相間的無意義圖案。我知道我朋友不是隨便轉信的人，這封E-m@il一定有點道理，我決定站起來，一步一步往後退，當我與螢光幕距離超過兩公尺的時候，我終於看清楚這個圖了，一堆亂碼似的文字正隱藏著五個大而清楚的中文字。你也一定看的出來！

我又走回電腦前面，這些文字又變回亂碼，沒錯！這個圖一定要距離兩公尺以上才看得清楚，或許是某個電腦高手寄給戀人的情書吧！

想想看，小時候上美術課時，大家都好像是大畫家，每畫個兩筆就要往後退幾步，檢視一下畫面的整體平衡，這是一個很自然的動作，從來不必經過思考。但是在每個人的人生中，有多少人會後退一下呢？大家都是不斷地要求自己前進再前進，就算出了什麼岔子也是立刻換一條繼續前行，似乎都忘了後退一步，反而可以看出事情的全貌。

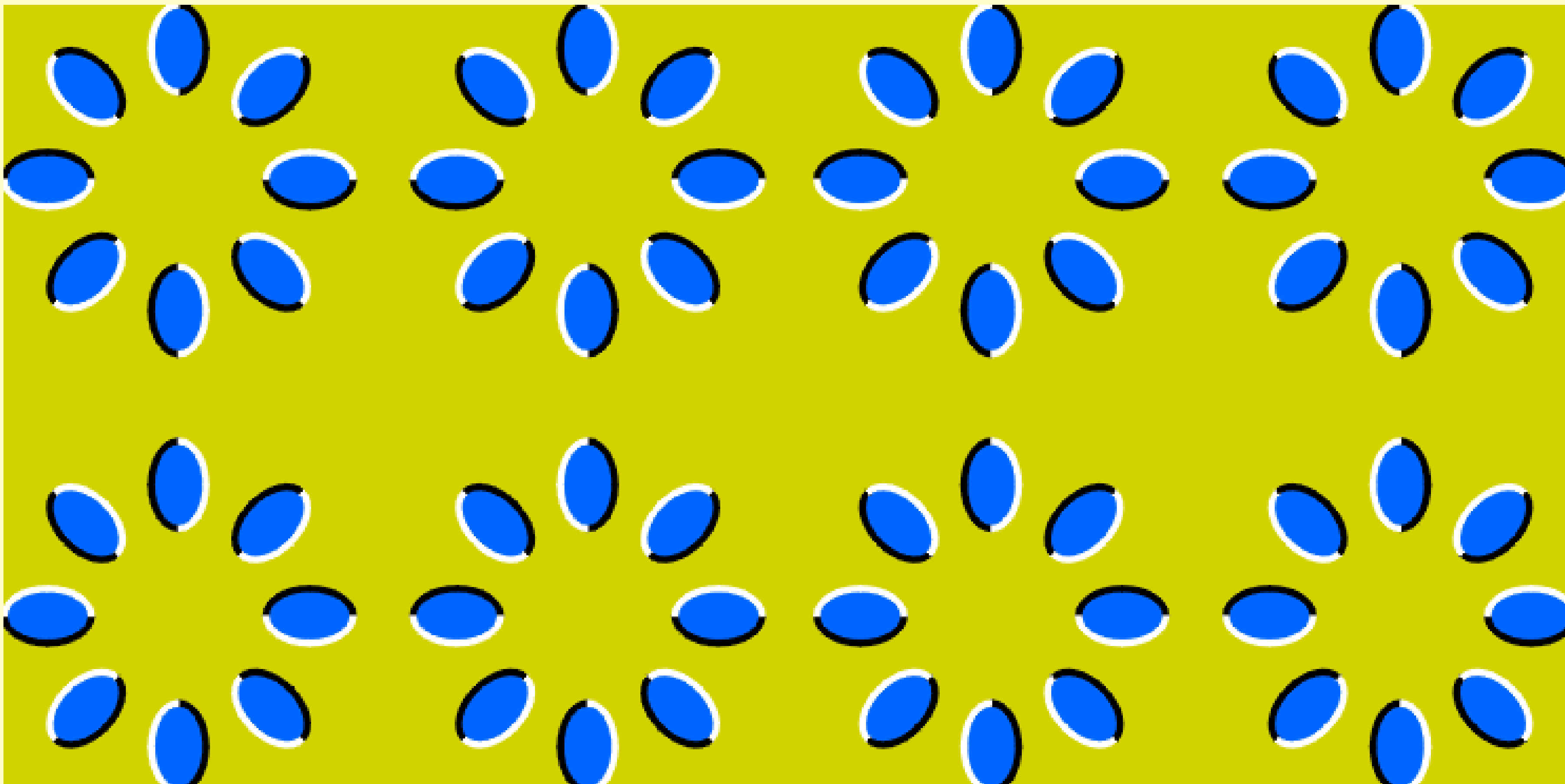
也許向後退，在你亂碼似的人生中，可以發現一個美麗溫柔的秘密！

Optical Illusions and Visual Phenomena

幻覺和視覺現象

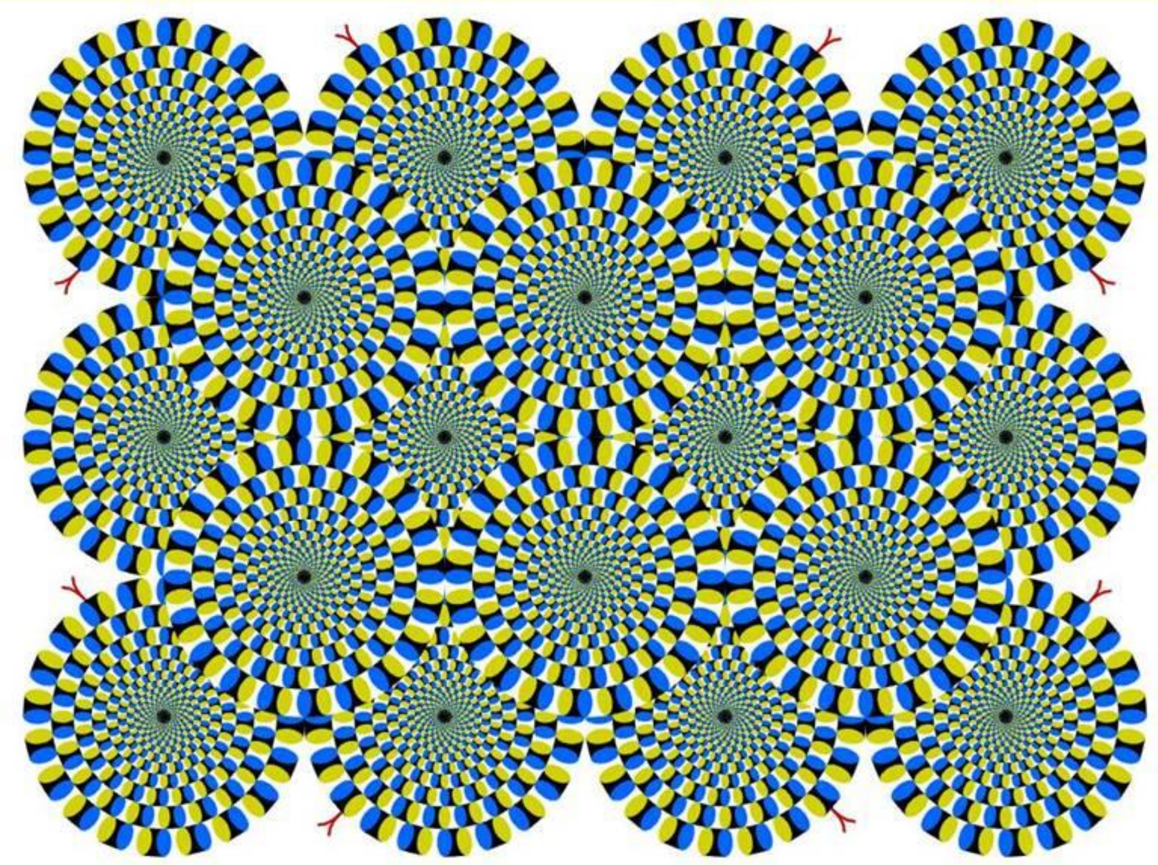
Want to confuse your eyes and brain a bit?
想讓你的眼睛和大腦陷入迷亂？那麼看一下下面的圖片...

Yes? Then you might want to have a look at the following pics ..

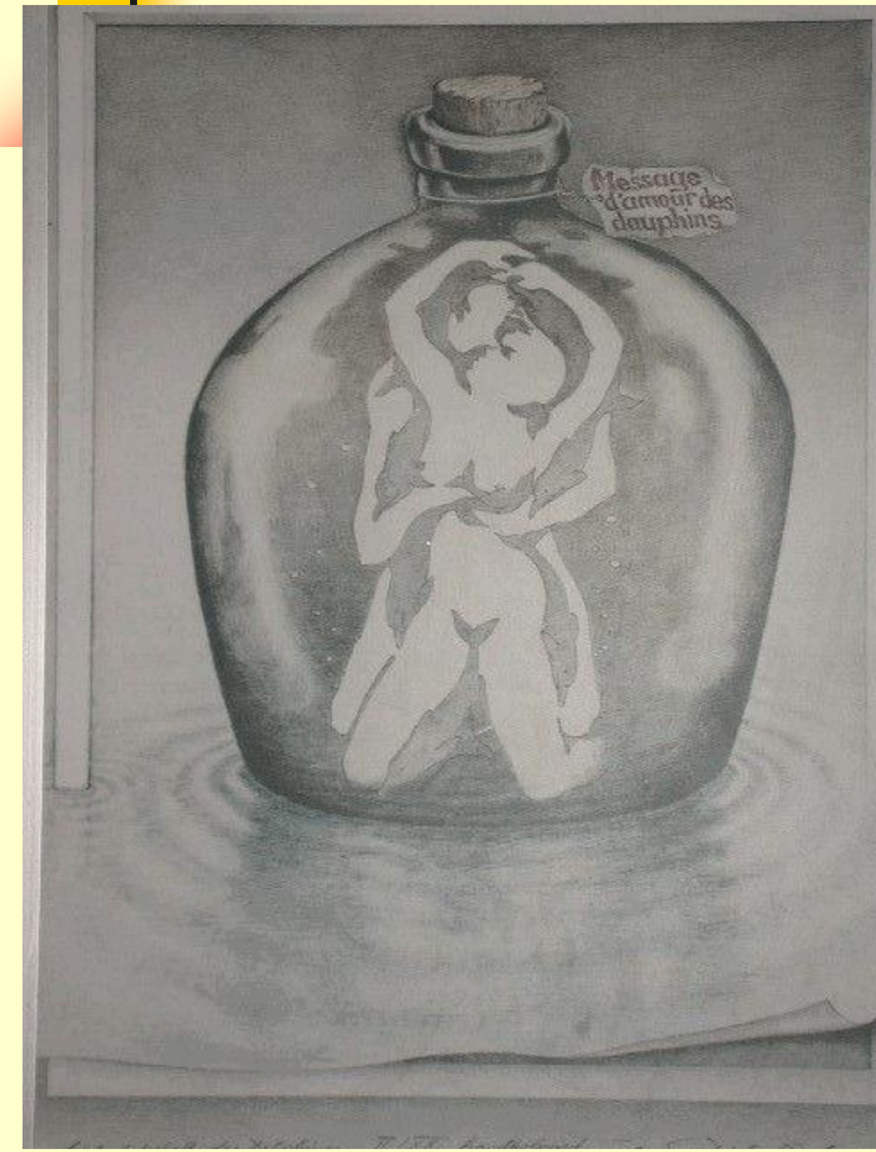


If something‘s rotating – go home, you need a break

如果感到有東西在轉動 – 你該回家休息一下了！



Take a look at the picture? What do you see?
看一下這幅照片，看到什麼了？

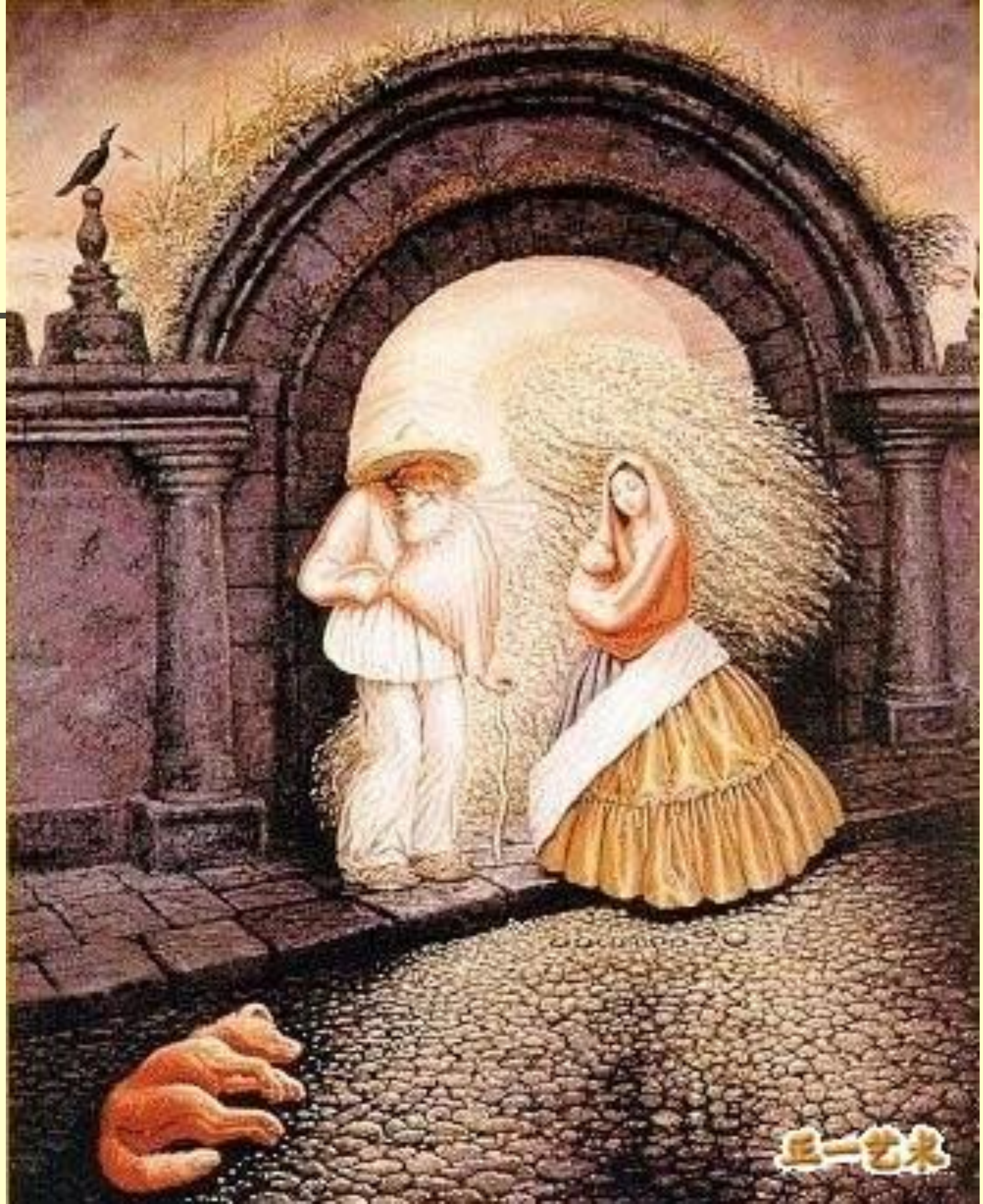


Research has shown that young children cannot identify the intimate couple because they do not have prior memory associated with such a scenario.
研究结果表明，孩子們看不出這對親密的夫妻，因為他們没有與之相關的先行記憶

Children see nine dolphins.
孩子們看到的是9隻海豚。

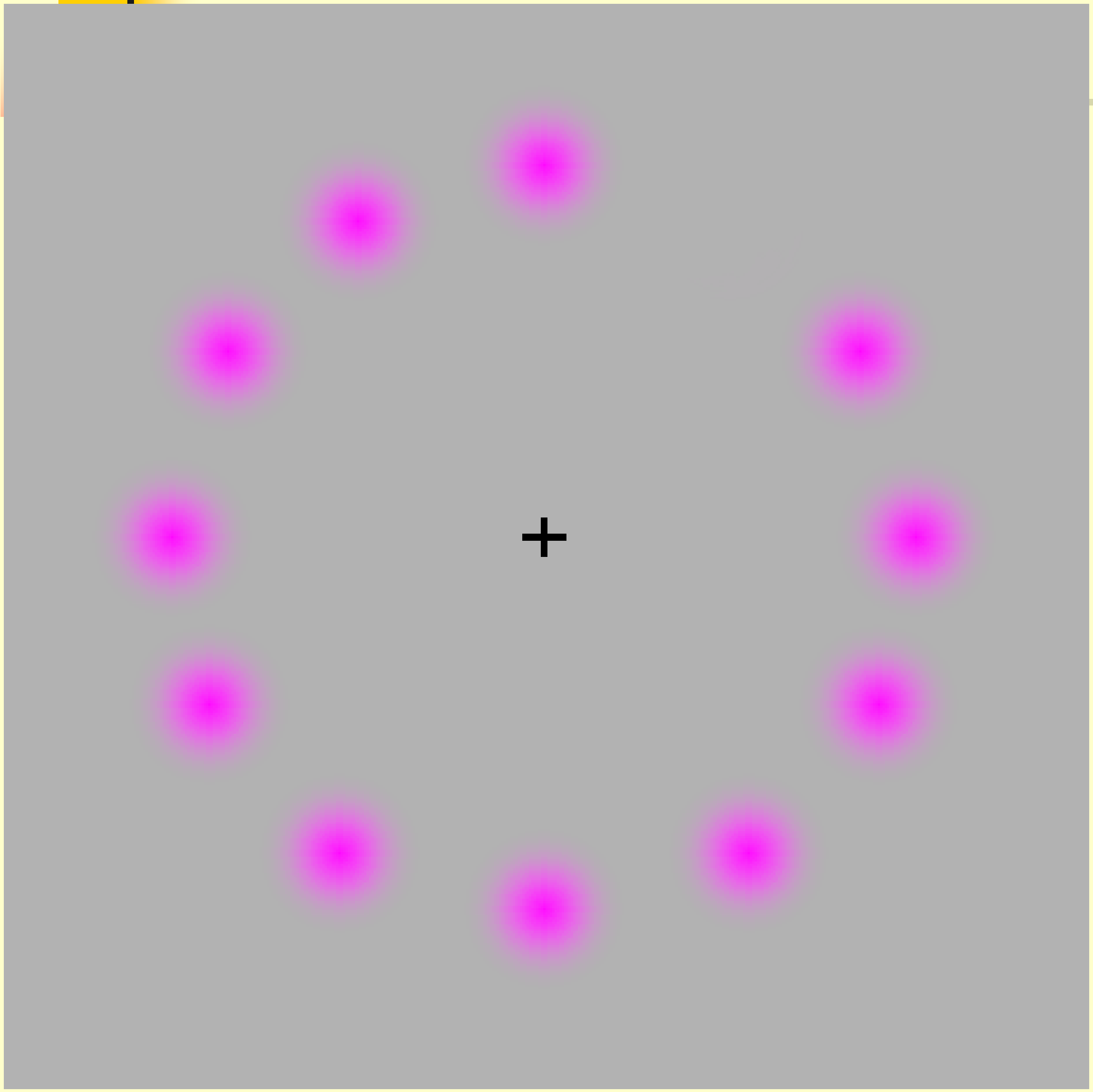
This is a test to determine if you already have a corrupted mind. If it is hard for you to find the dolphins within six seconds, your mind is indeed corrupted.
這個測試用於判斷你的頭腦是否已被腐蝕。如果你在6秒之内還難以看到海豚的話，你的頭腦的確遭到了腐蝕。

Bill Clinton? Or Girl? Or Both?



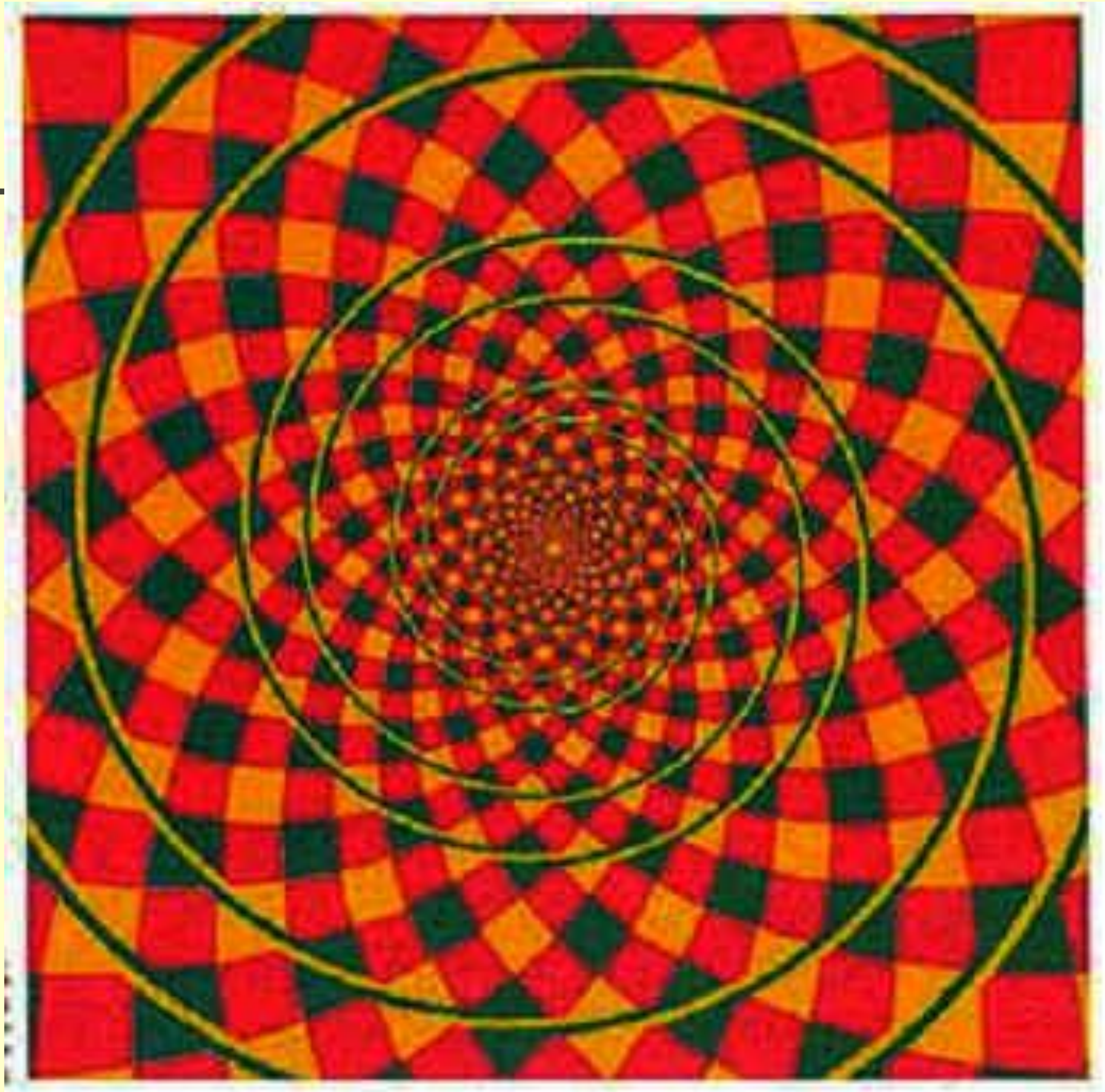

BEFORE 6 BEERS
AFTER 6 BEERS

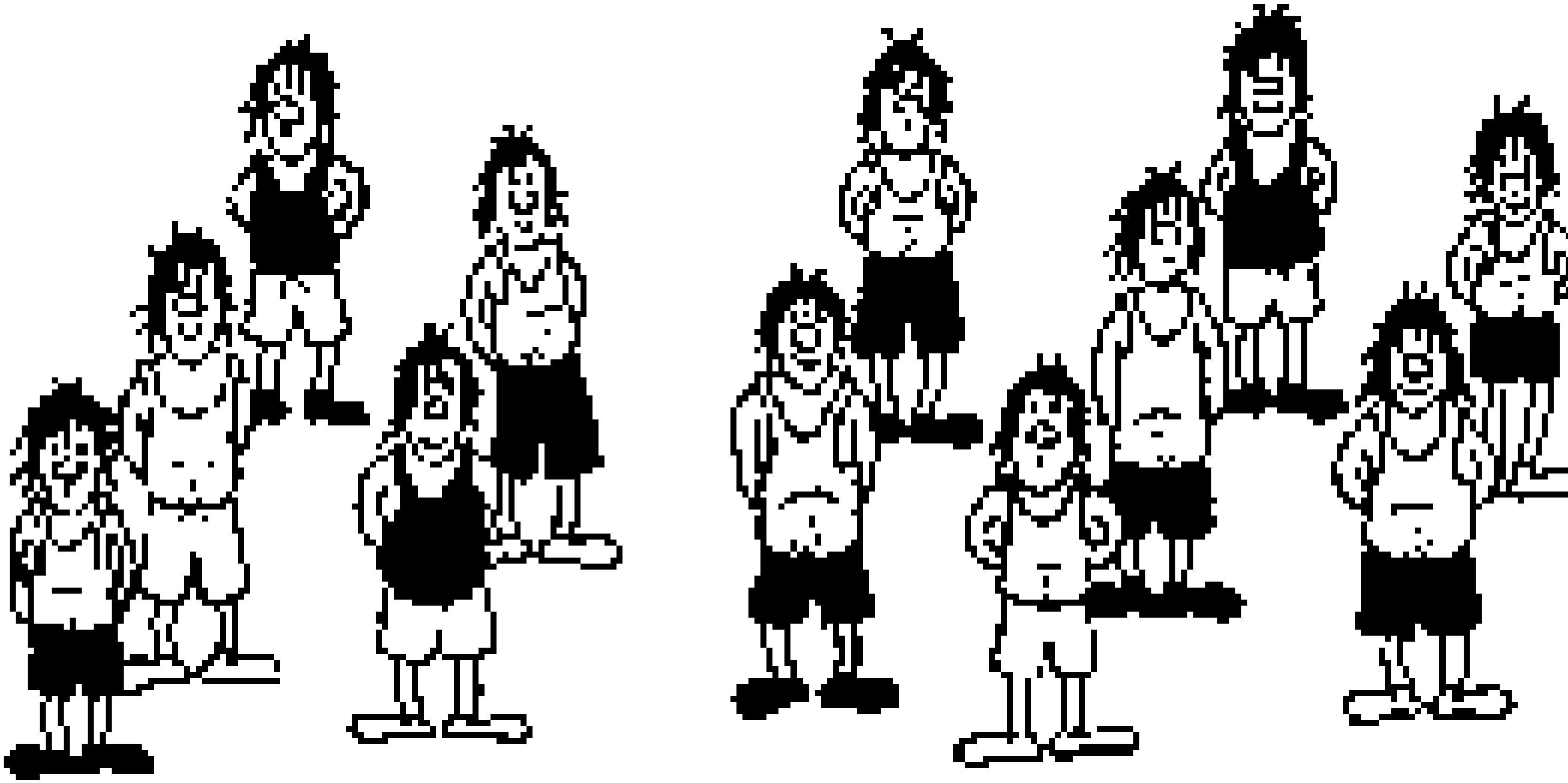
Concentrate on the cross in the middle, after a while you will notice that this moving purple dot will turn green!
把目光集中在中間的十字，你會發現，移動的紫點會變綠

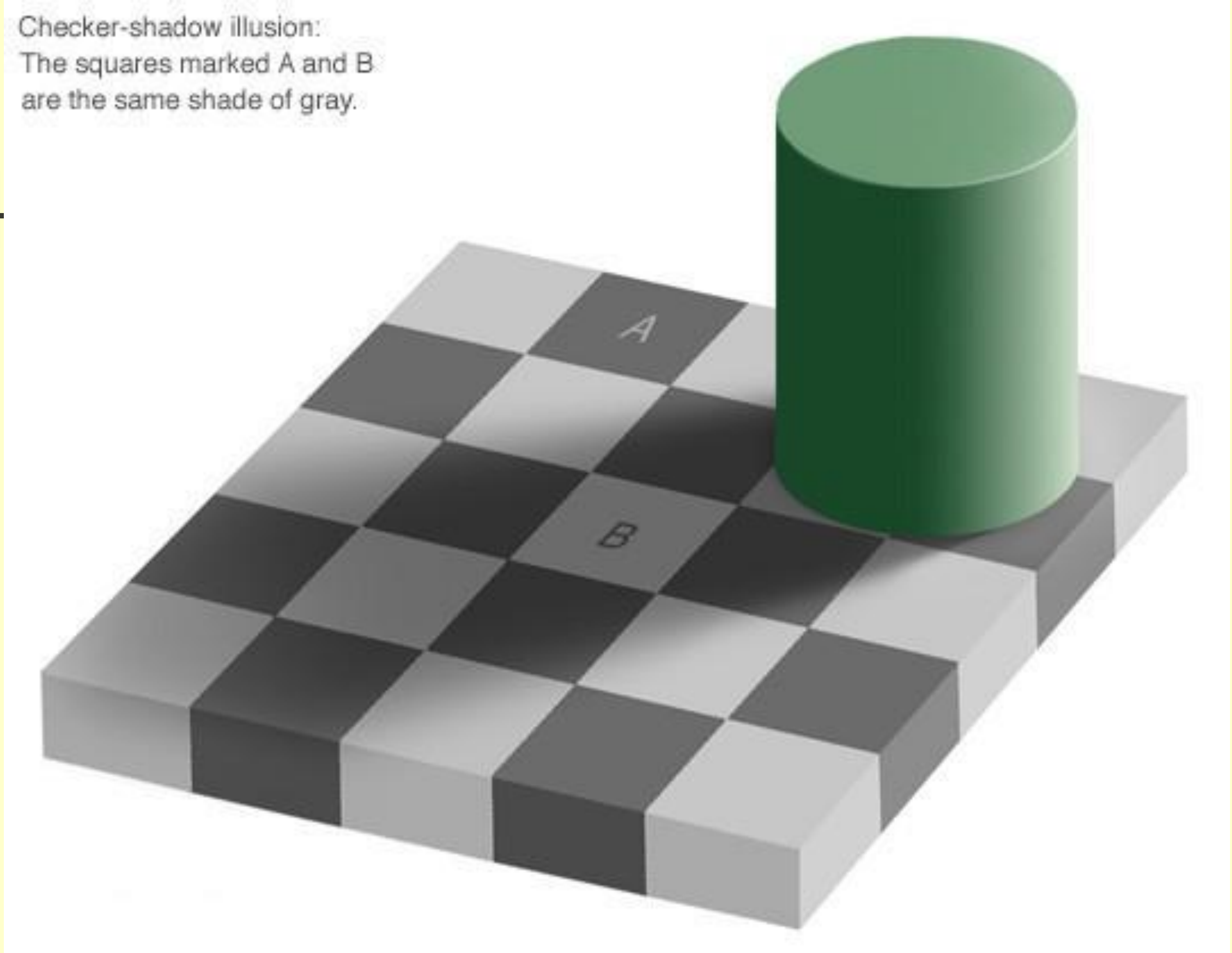


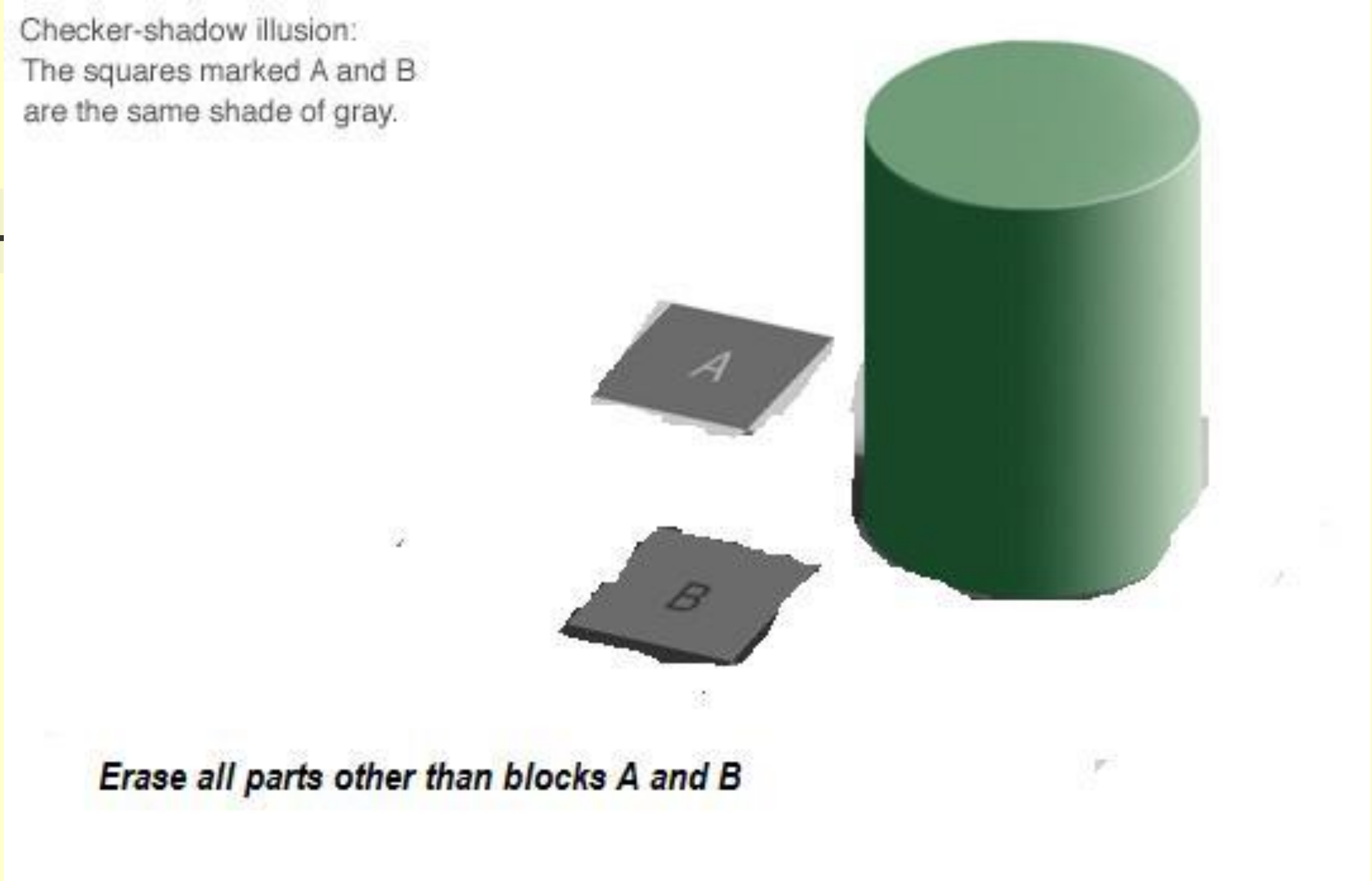
Look at the cross a bit longer and you'll notice that all dots except the green one will disappear.
盯住十字，時間再長一點，你會發現，除了綠色的點外，其他所有的點都消失了。

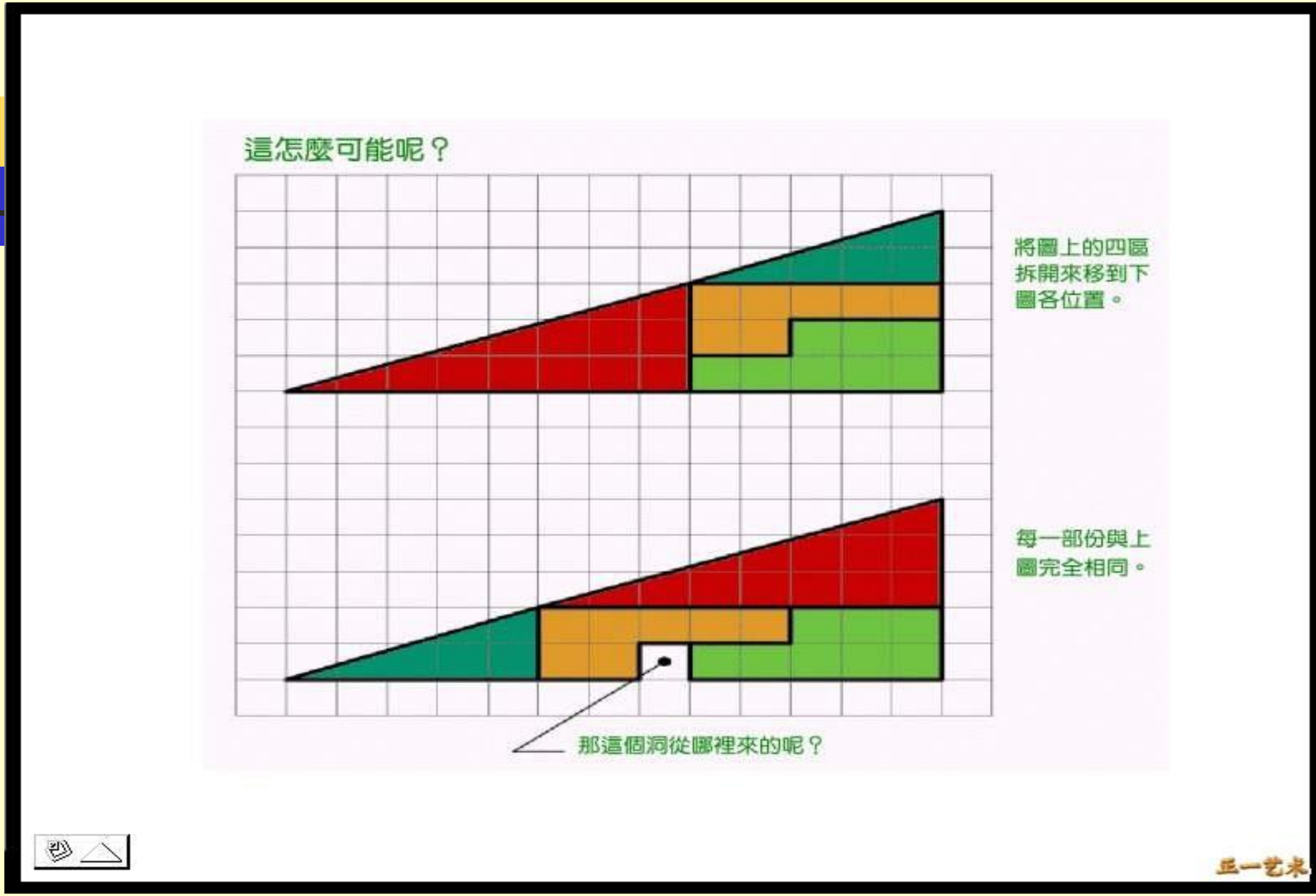
Coil or circle? 是螺旋的還是圓形的？






Checker-shadow illusion:
The squares marked A and B
are the same shade of gray.
A
B

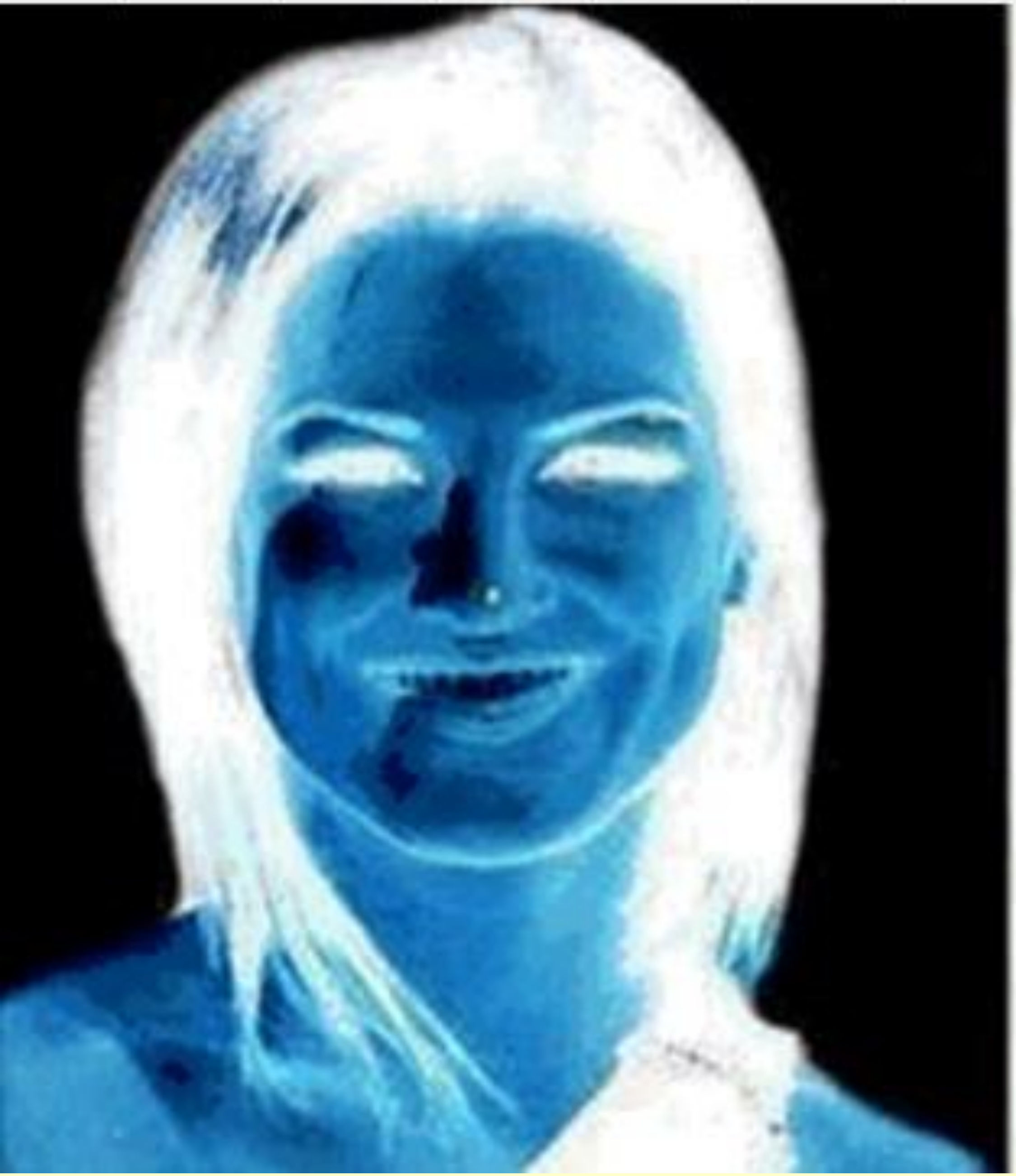

Checker-shadow illusion:
The squares marked A and B
are the same shade of gray.
A
B
Erase all parts other than blocks A and B



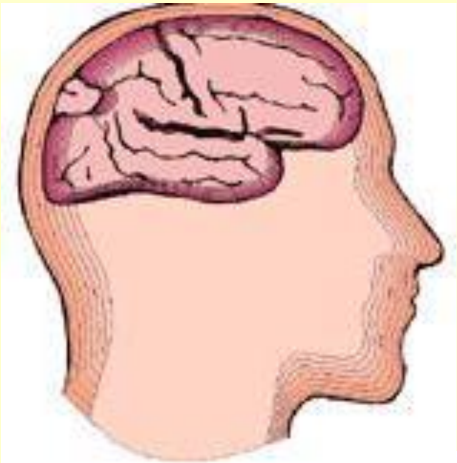
45 = 44 (45-1) ?

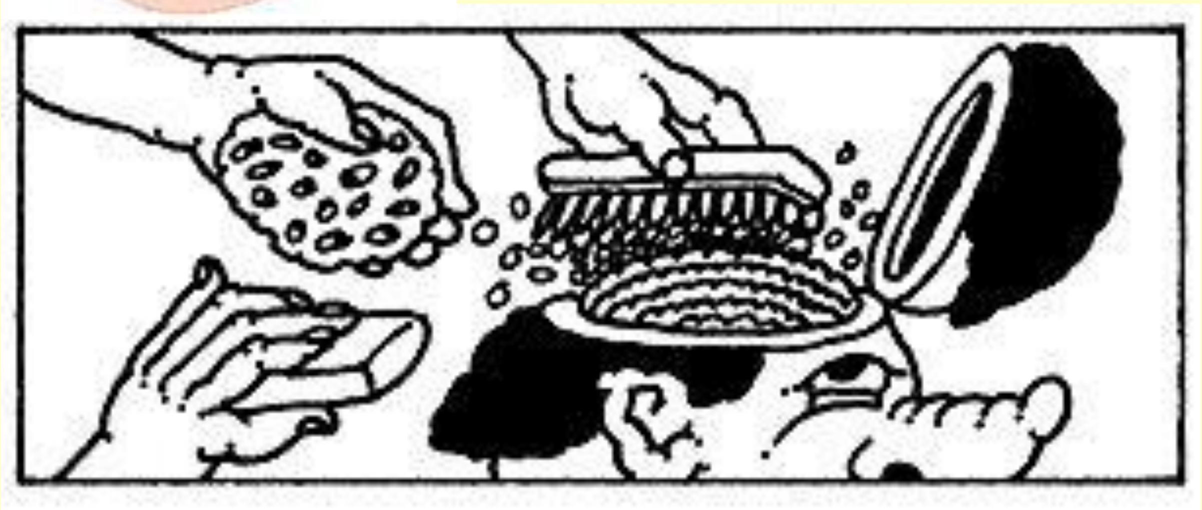
Follow the instruction below. 按照下面的指引

1) Stare at the 4 little dots on the middle of the picture for 30 seconds 盯住圖片正中間的4個小點達30秒
2) then look at a wall near you 然後往你附近的牆上看
3) a bright spot will appear 會出現一個明亮的東西
4) twinkle a few times and you`ll see a figure 閃過幾次後，你會看到一個頭像
5) What do you see? Or even WHO do you see? 看到什麼了？或者看到誰？



Our Incredible Brain: Think, Learn, Understand, Recognize, Illusion





Our Incredible Brain: Think, Learn, Understand, Recognize, Illusion

TEN GOLDEN RULES FOR TEACHING COMPUTER SCIENCE

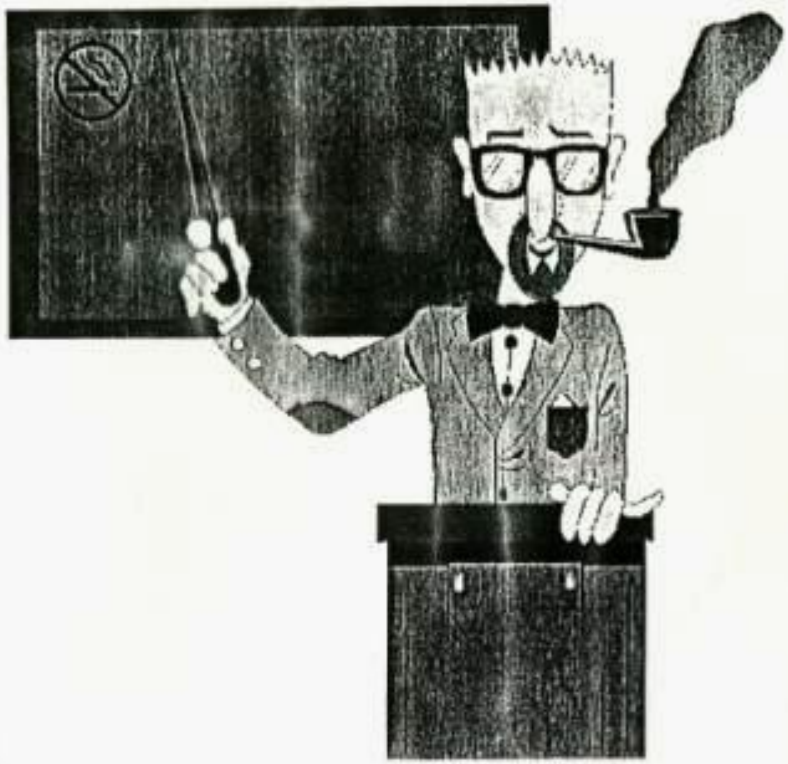
Andrew S. Tanenbaum

Dept. of Computer Science

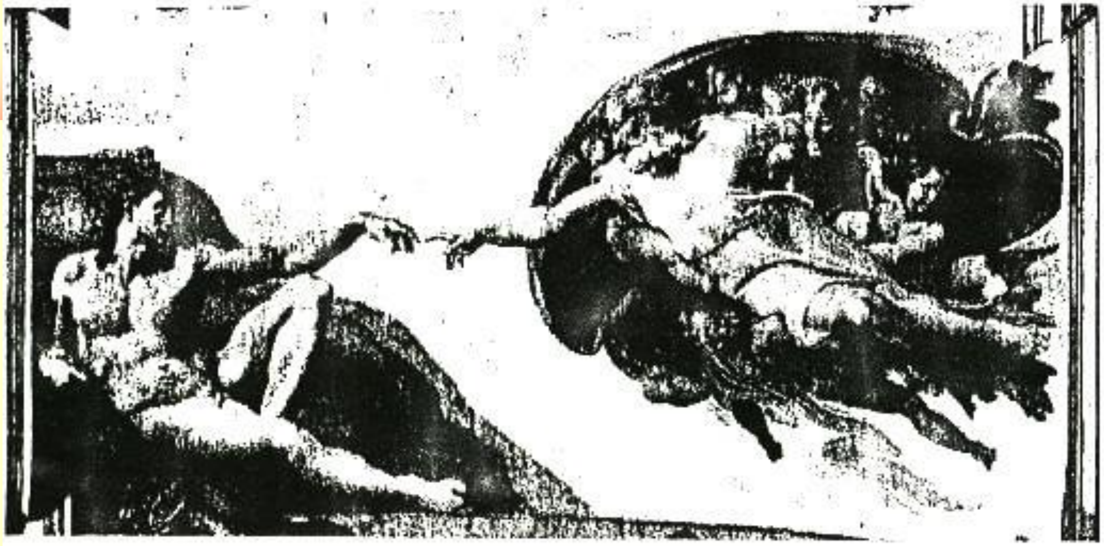
Vrije Universiteit

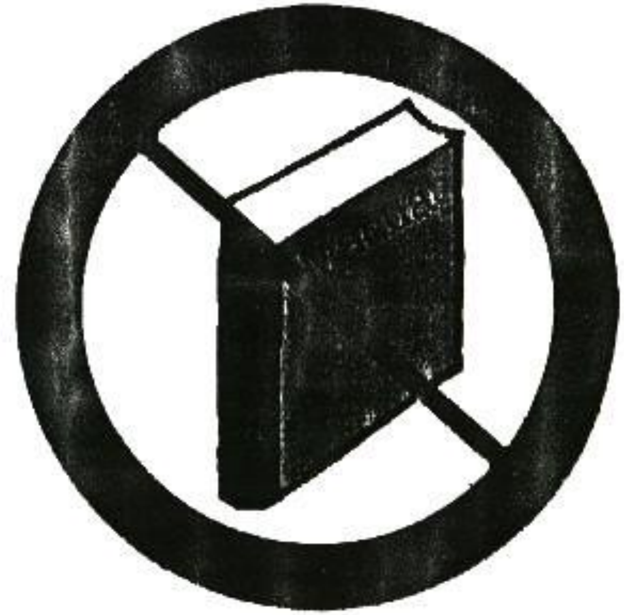
Amsterdam, The Netherlands

http://www.cs.vu.nl/~ast/

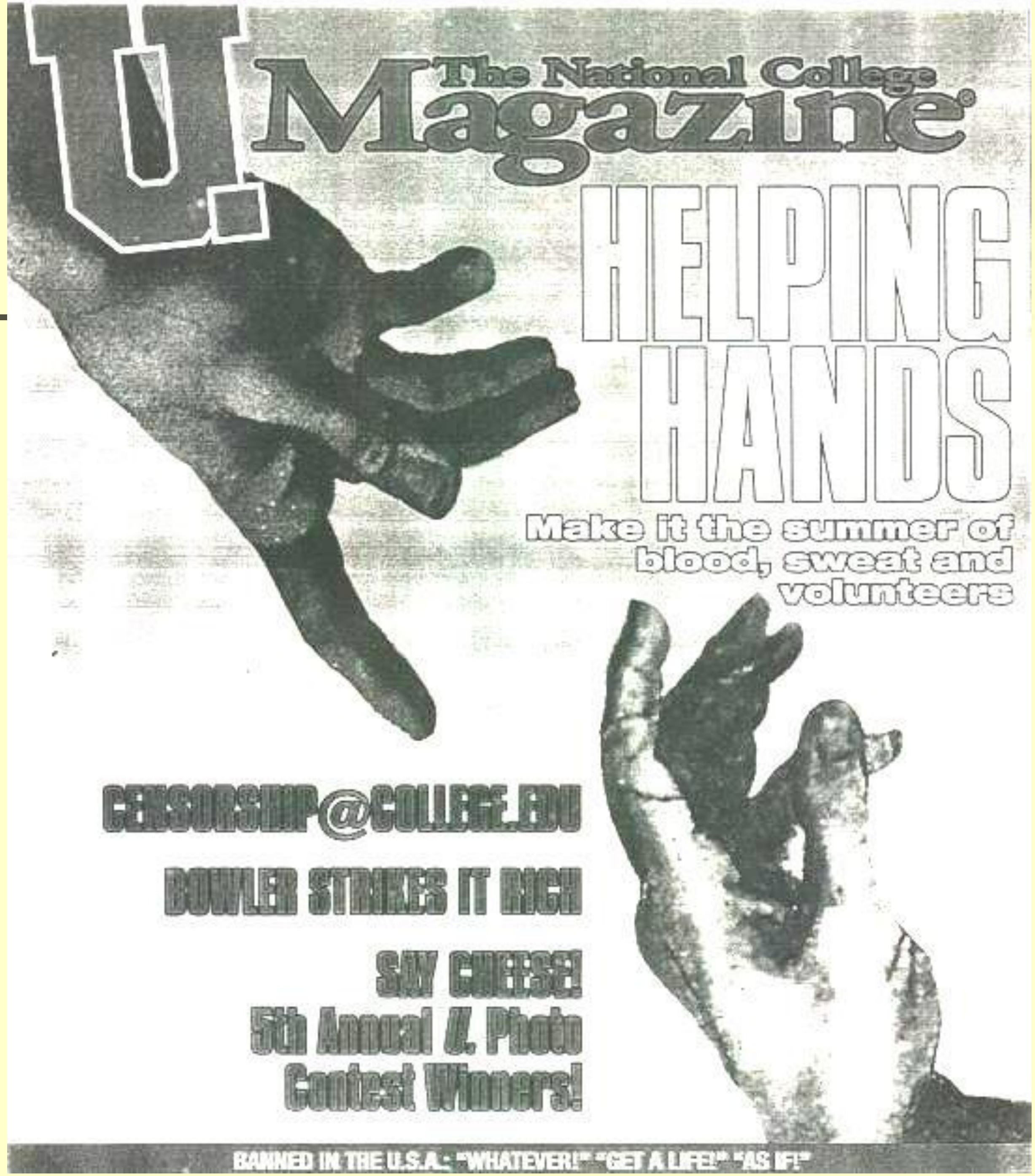


SCIENCE





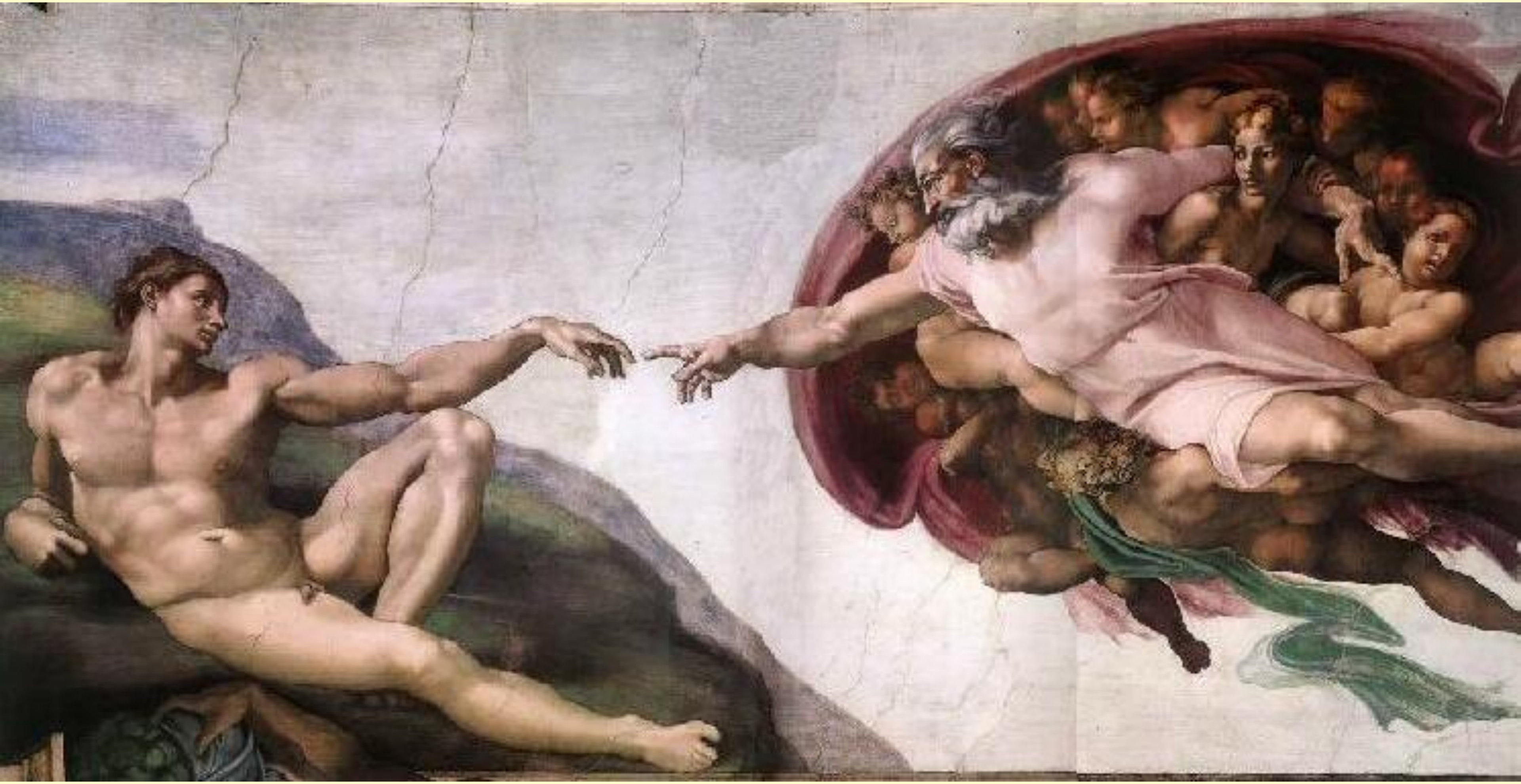
When God created the universe, like many implementers who came later, he did not bother writing any documentation


U.
The National College
Magazine
HELPING HANDS
Make it the summer of blood, sweat and volunteers
CENSORSHIP@COLLEGE.EDU
BOWLER STRIKES IT RICH
SAY CHEESE!
5th Annual U. Photo Contest Winners!
BANNED IN THE U.S.A.: "WHATEVER!" "GET A LIFE!" "AS IF!"

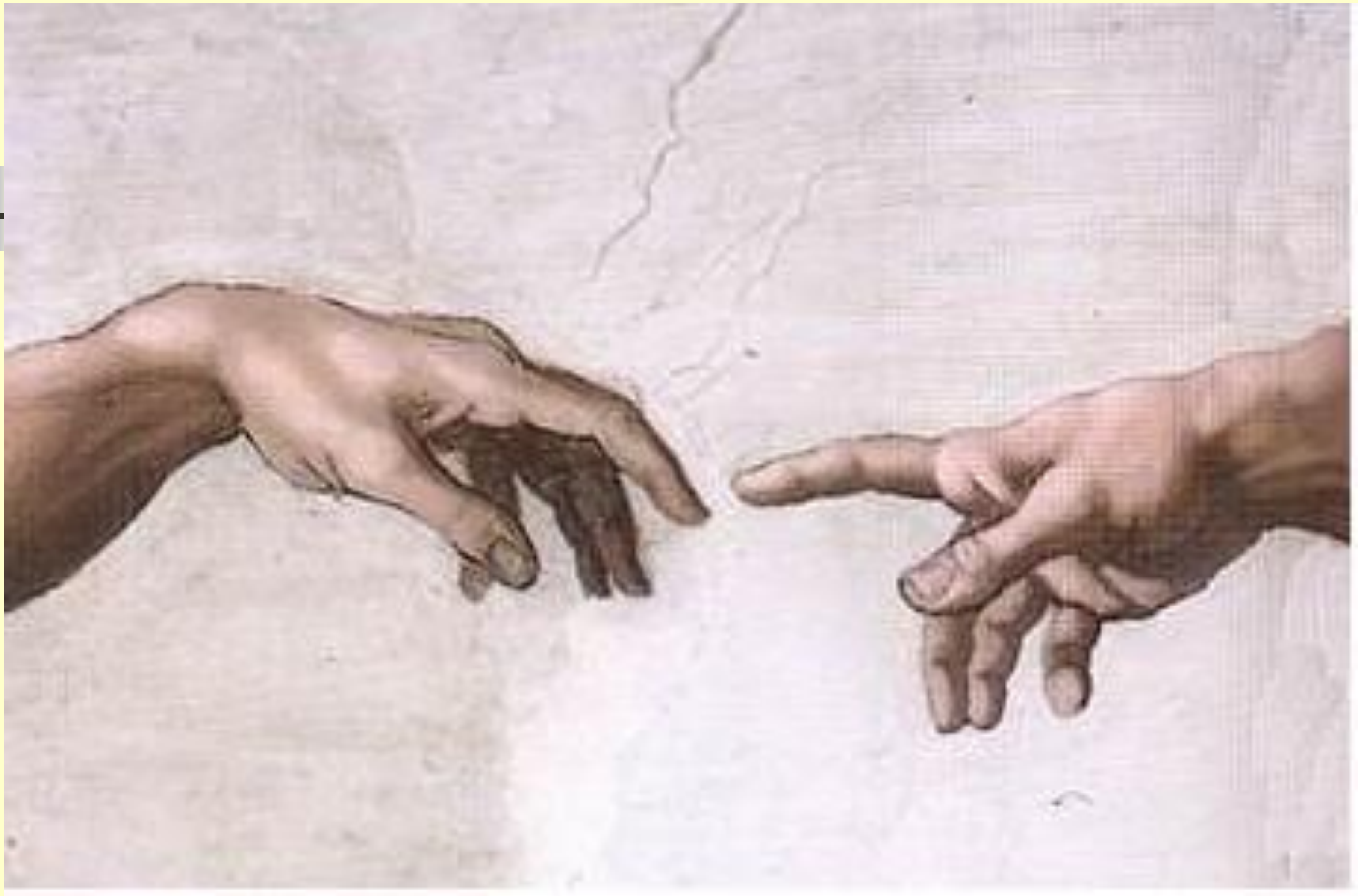
千禧年「郵」物

↑義大利廿五日發行了紀念二千年的郵票，這張郵資為四千八百里拉（二·四八歐元）的郵票畫面為一隻人手與一隻機器人手的碰觸，代表著過去與未來。這個形象是取材自米開蘭基羅在西斯丁教堂頂上的壁畫「亞當的創造」，不過畫中人的手是在左邊，右邊是上帝的手。

（法新社）

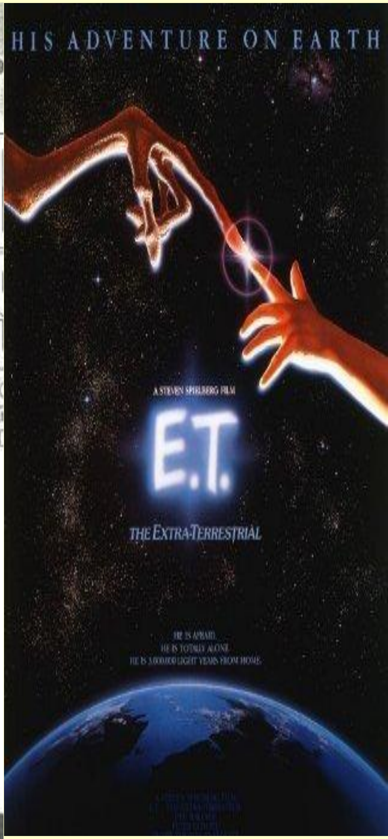


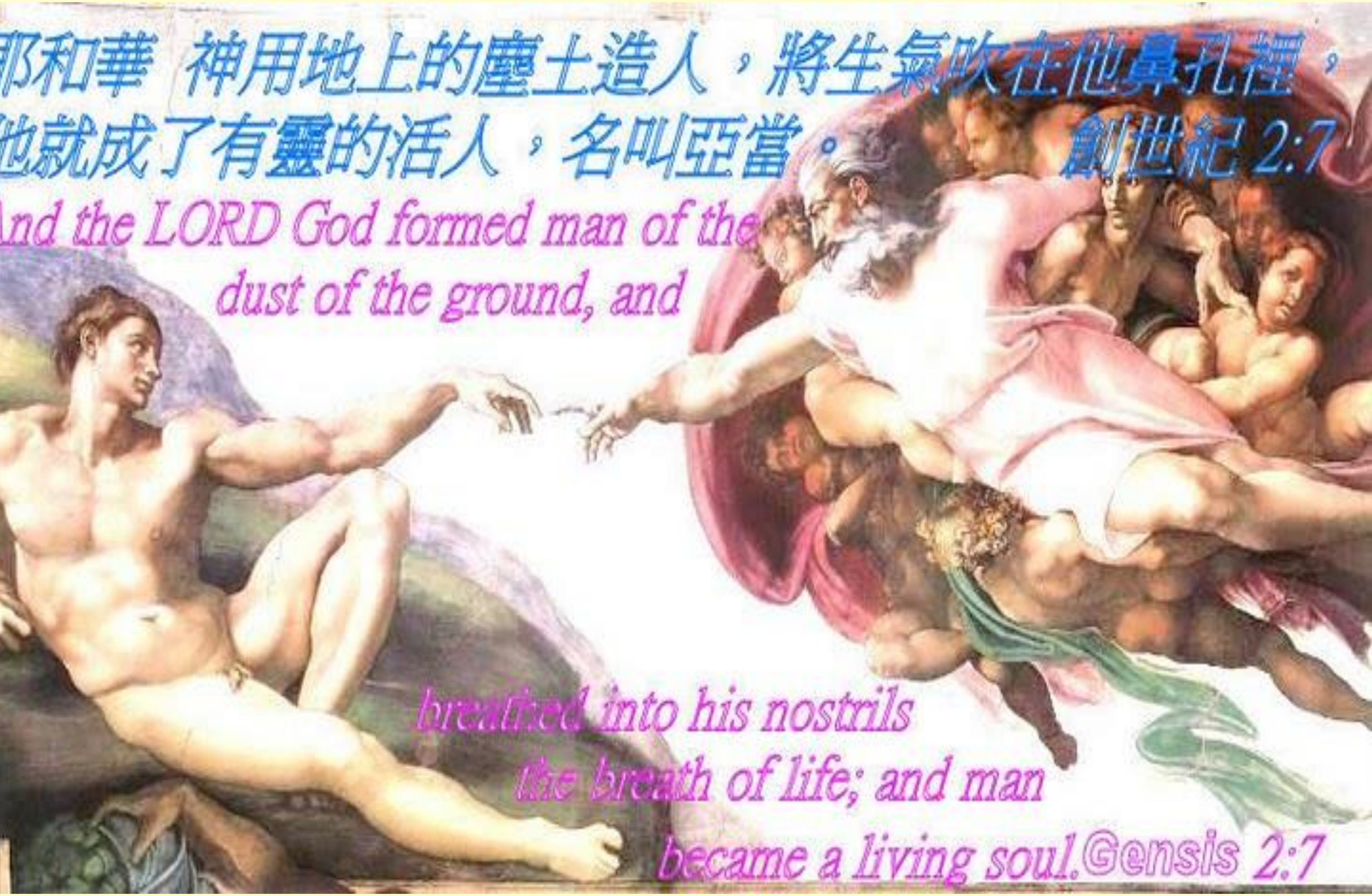
God Creates Adam, with LOVE --- Genesis
Michelangelo, Sistine Chapel Ceiling, Vatican



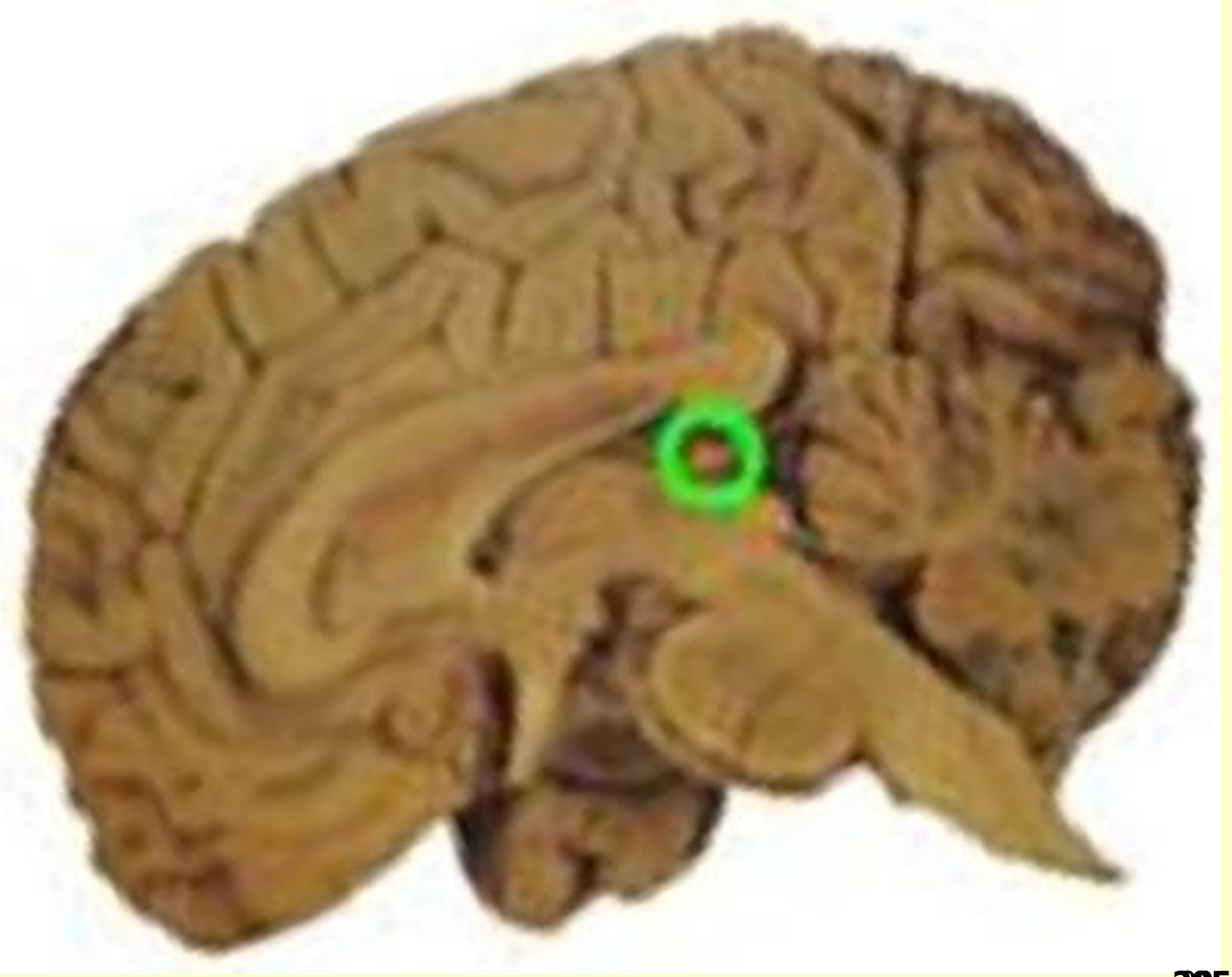

ITALIA
4800
€ 2,48
VERSO IL DUEMILA

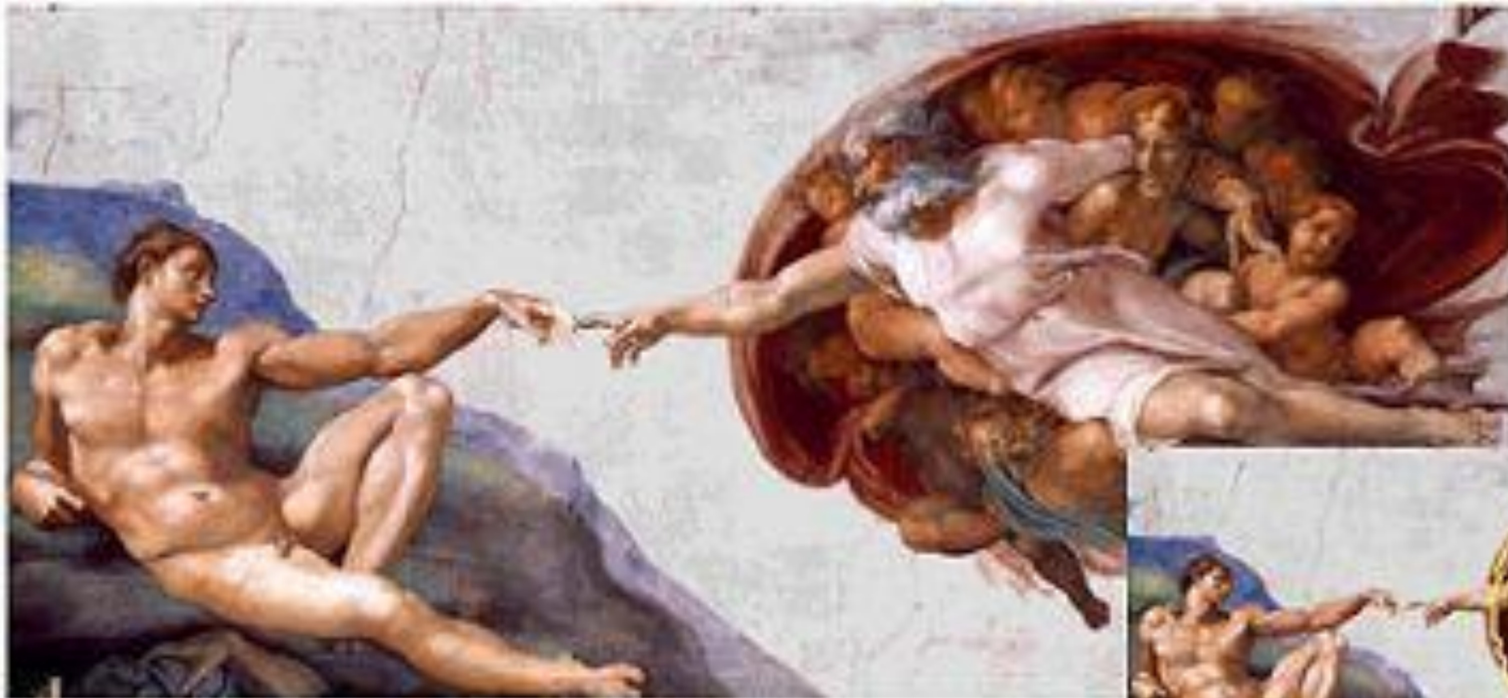

The National College
Magazine
CENSORSHIP@COLLEGE.EDU
SAY CHEESE!
Contest Winners!


HIS ADVENTURE ON EARTH
A STEVEN SPIELBERG FILM
E.T.
THE EXTRA-TERRESTRIAL

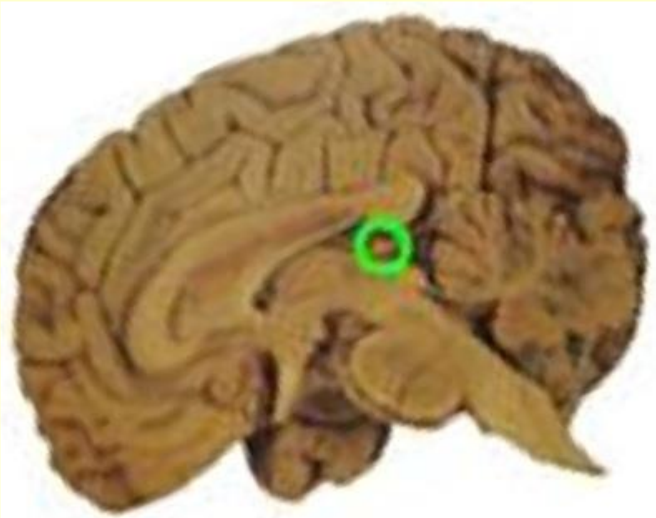

耶和華 神用地上的塵土造人，將生氣吹在他鼻孔裡，
他就成了有靈的活人，名叫亞當。
創世紀 2:7
And the LORD God formed man of the
dust of the ground, and
breathed into his nostrils
the breath of life; and man
became a living soul.
Gensis 2:7

米開朗基羅的曠世鉅作——
「創造亞當」壁畫（部份）



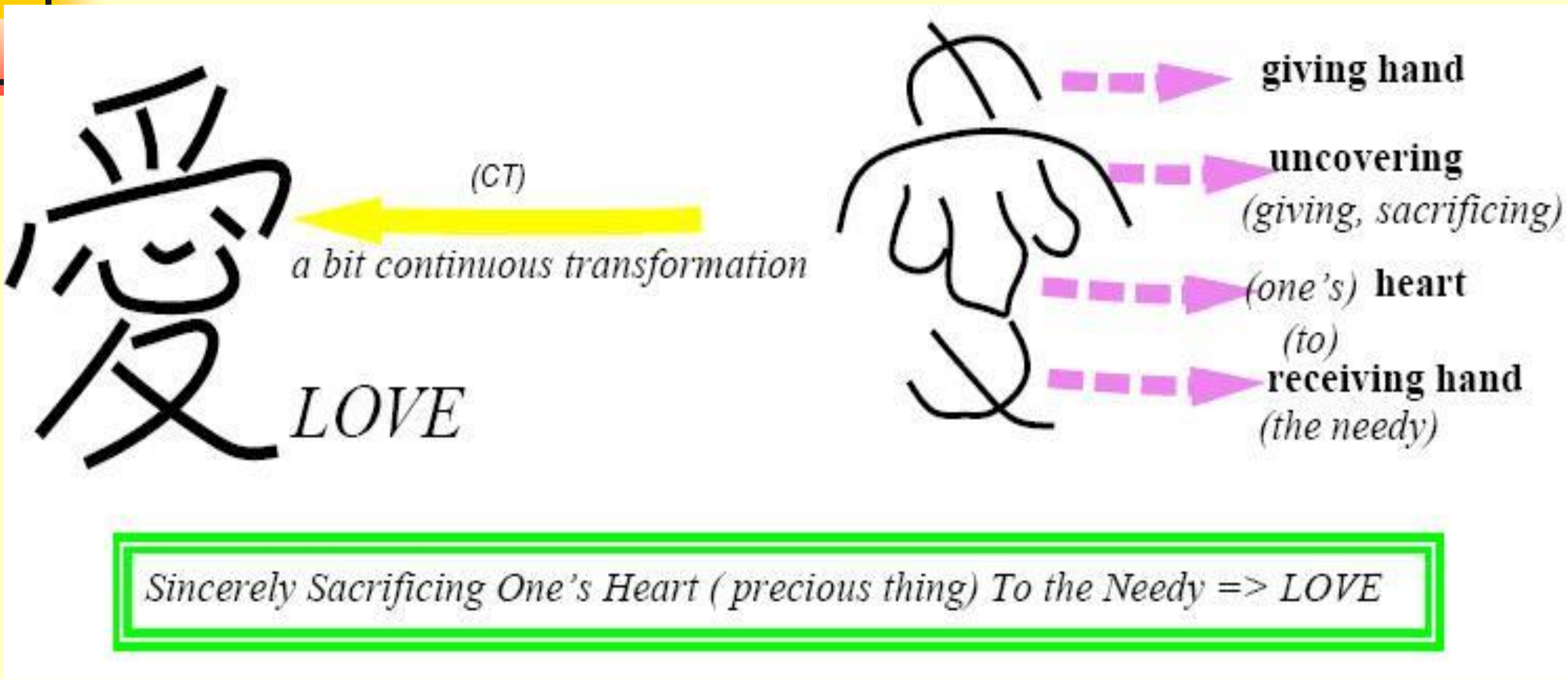


米開朗基羅的曠世鉅作——
「創造亞當」壁畫（部份）

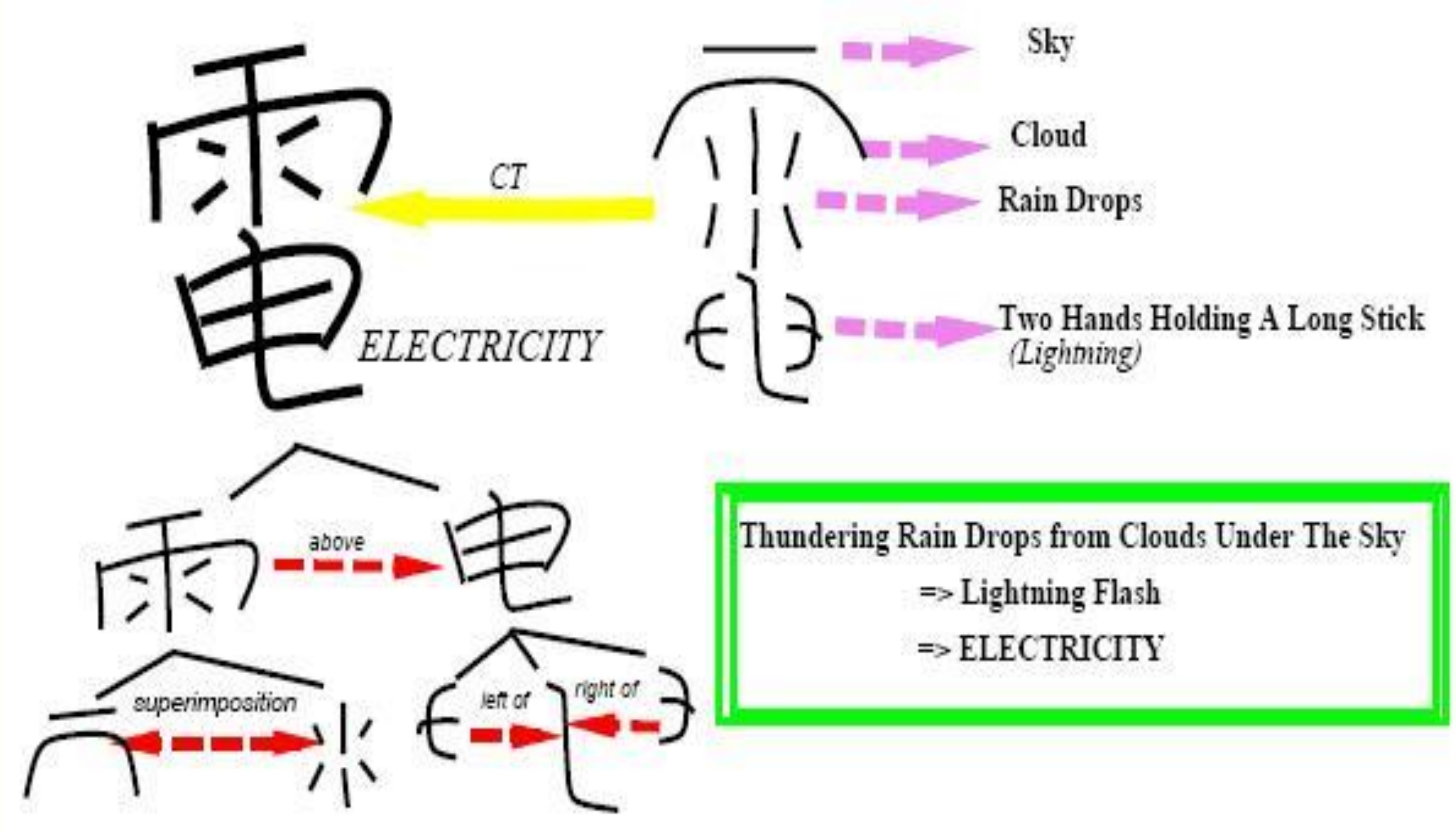



圖片來源：聯合報
頭殼摔破大腦剩一半 英男奇蹟存活
奇台語歌王達莊、金曲台語女歌手獎：曾心

BU Scientists implemented electrode into patients'brain for testing speech control.

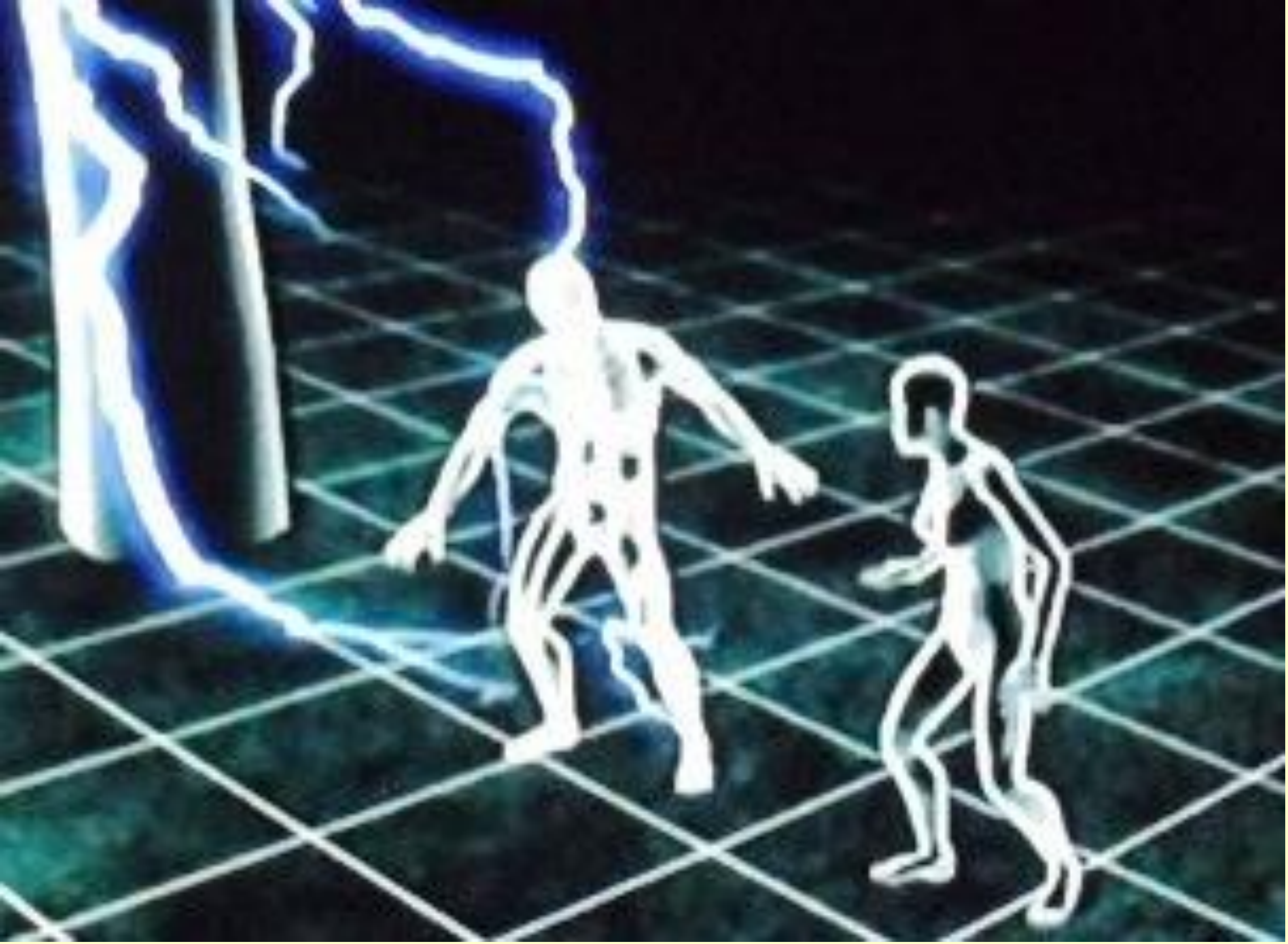


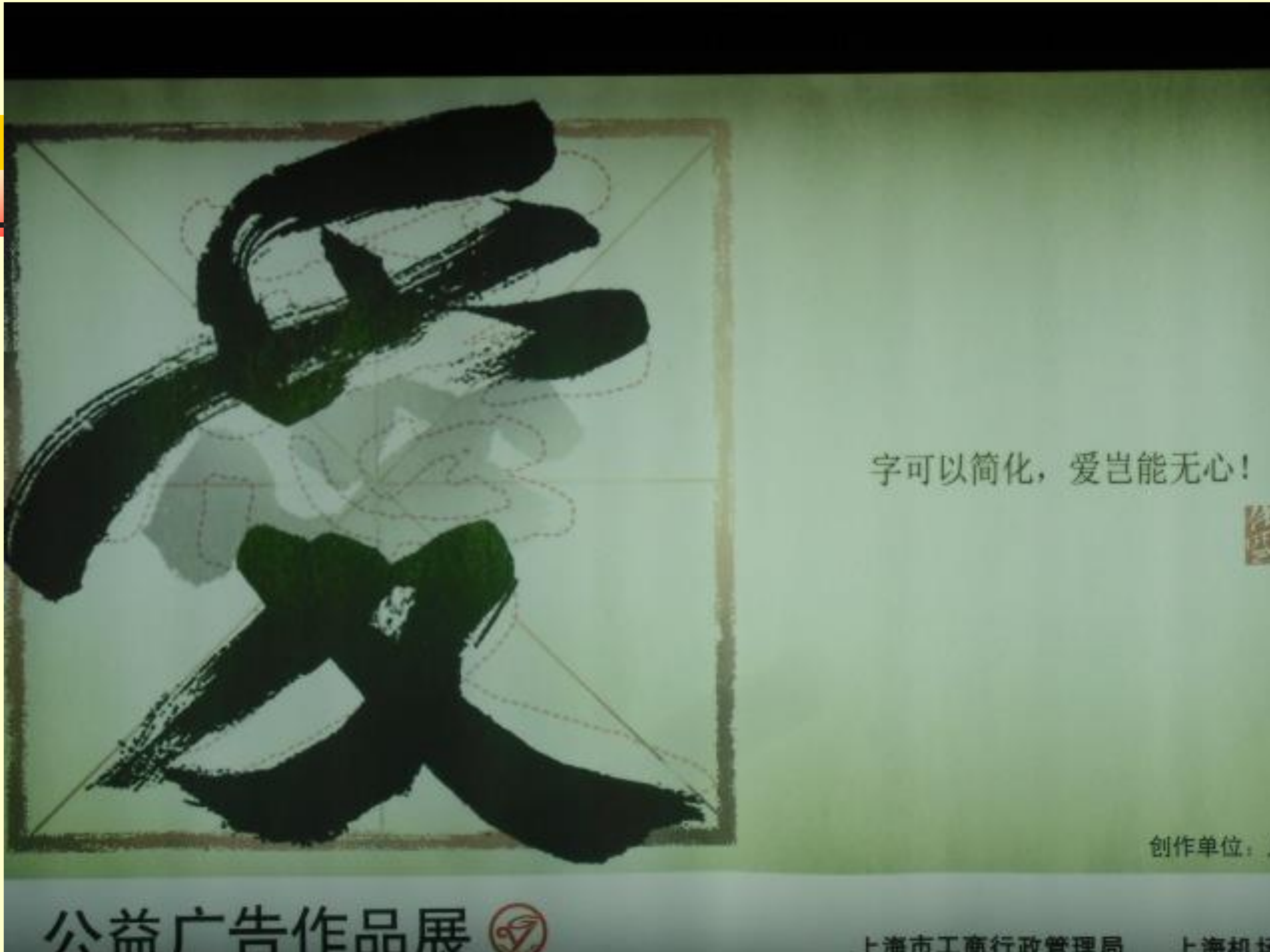
(CT)
a bit continuous transformation
LOVE
giving hand
uncovering
(giving, sacrificing)
(one's) heart
(to)
receiving hand
(the needy)
Sincerely Sacrificing One's Heart (precious thing) To the Needy => LOVE

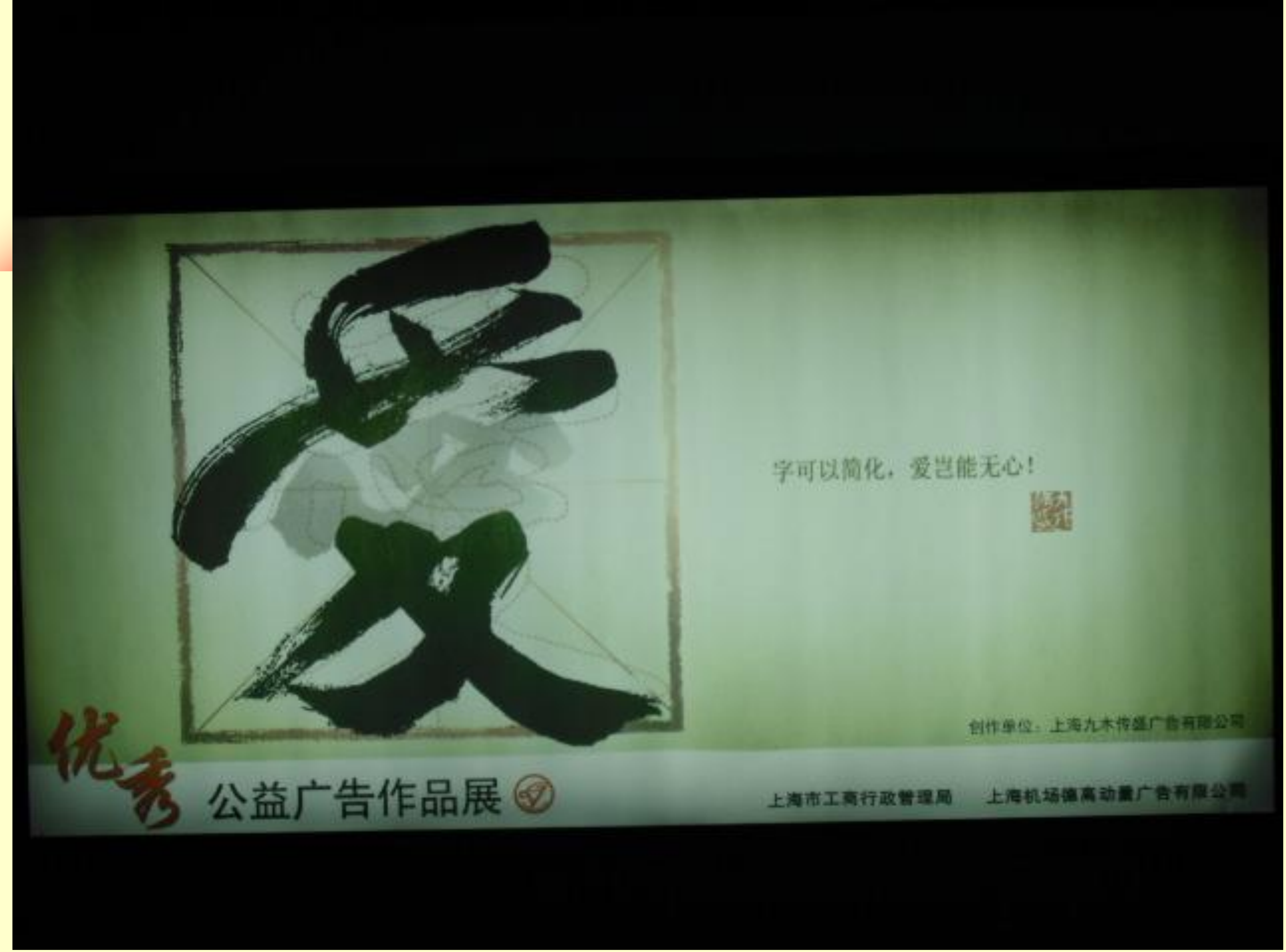


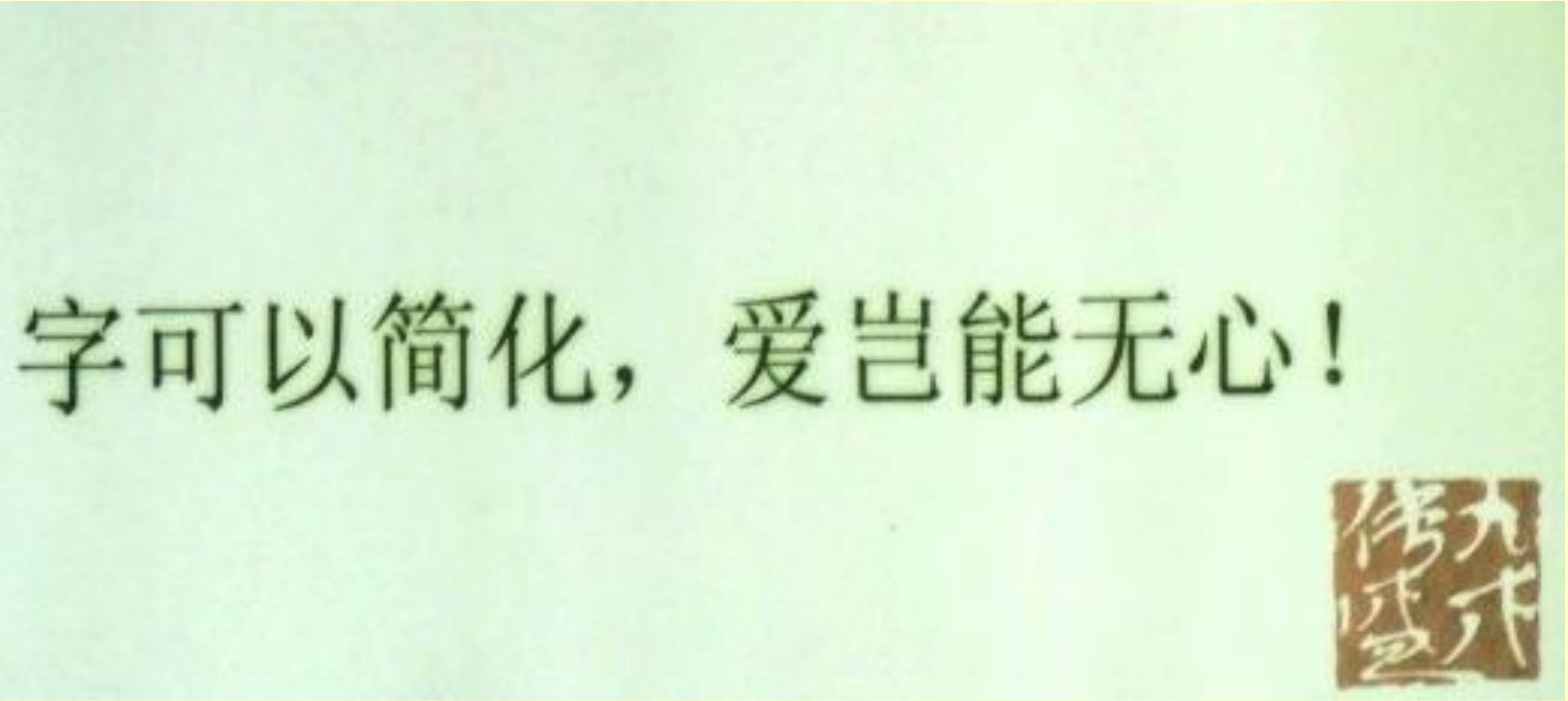
Electricity=> Sky + Cloud + Rain + Lightning

“長恨歌”白居易 :“排空馭氣奔如電 ”唐宪宗元和元年（806）



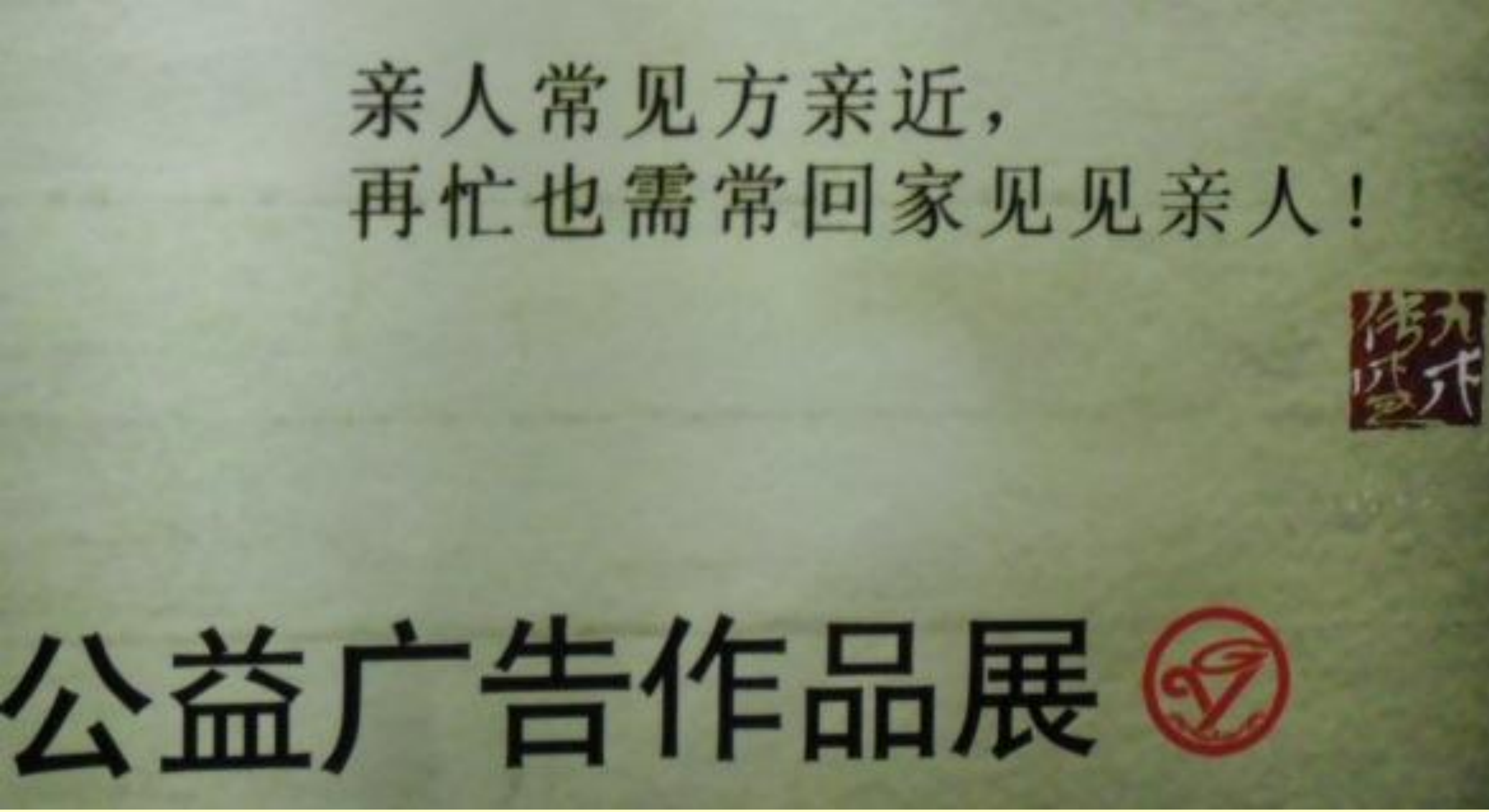

字可以简化，爱岂能无心！
创作单位：
公益广告作品展
上海市工商行政管理局
上海机场


字可以简化，爱岂能无心！
创作单位：上海九木传盛广告有限公司
优秀
公益广告作品展
上海市工商行政管理局
上海机场德高动量广告有限公司



Words can be simplified, but Love can not live without“ Heart ’


亲人常见方亲近，
再忙也需常回家见见亲人！
优秀
公益广告作品展
创作单位：上海九木传盛广告有限公司

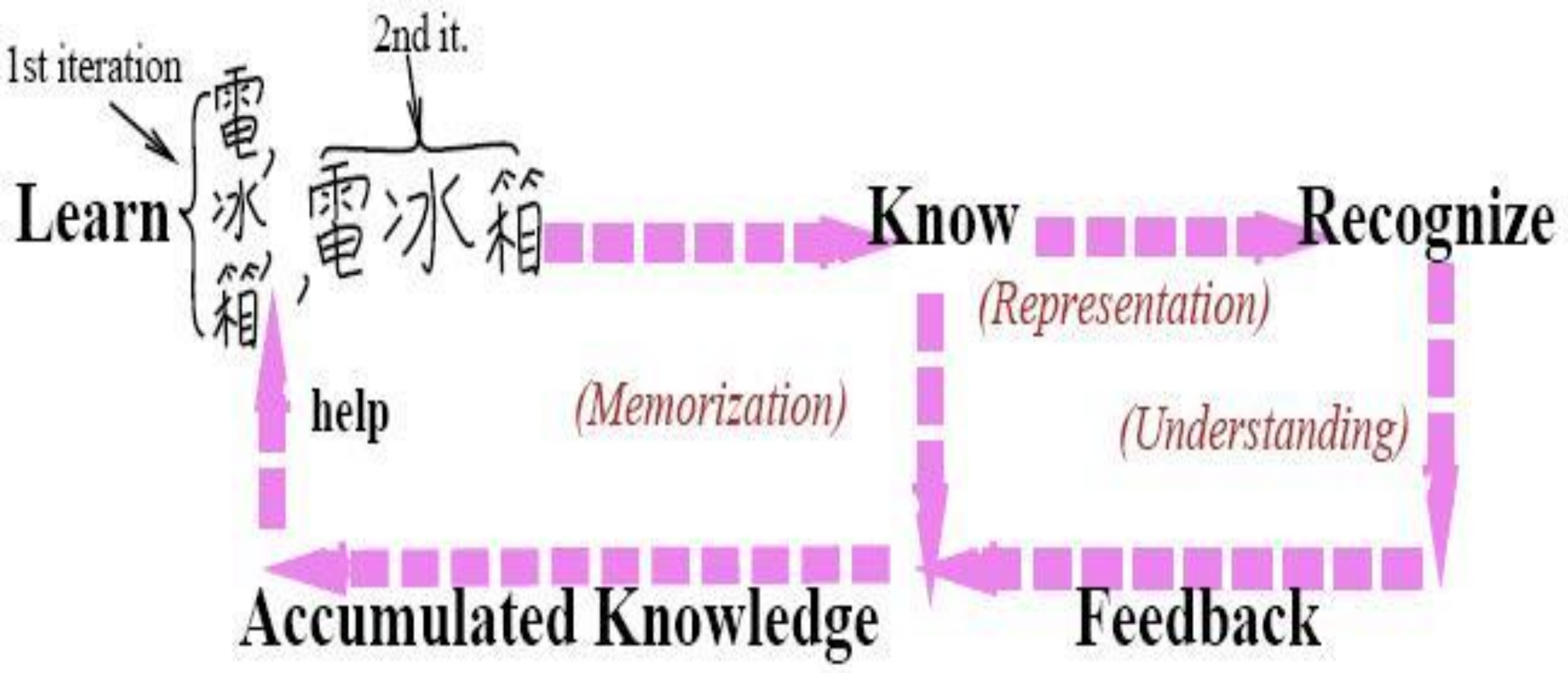


Relatives need to meet frequently to be intimate.

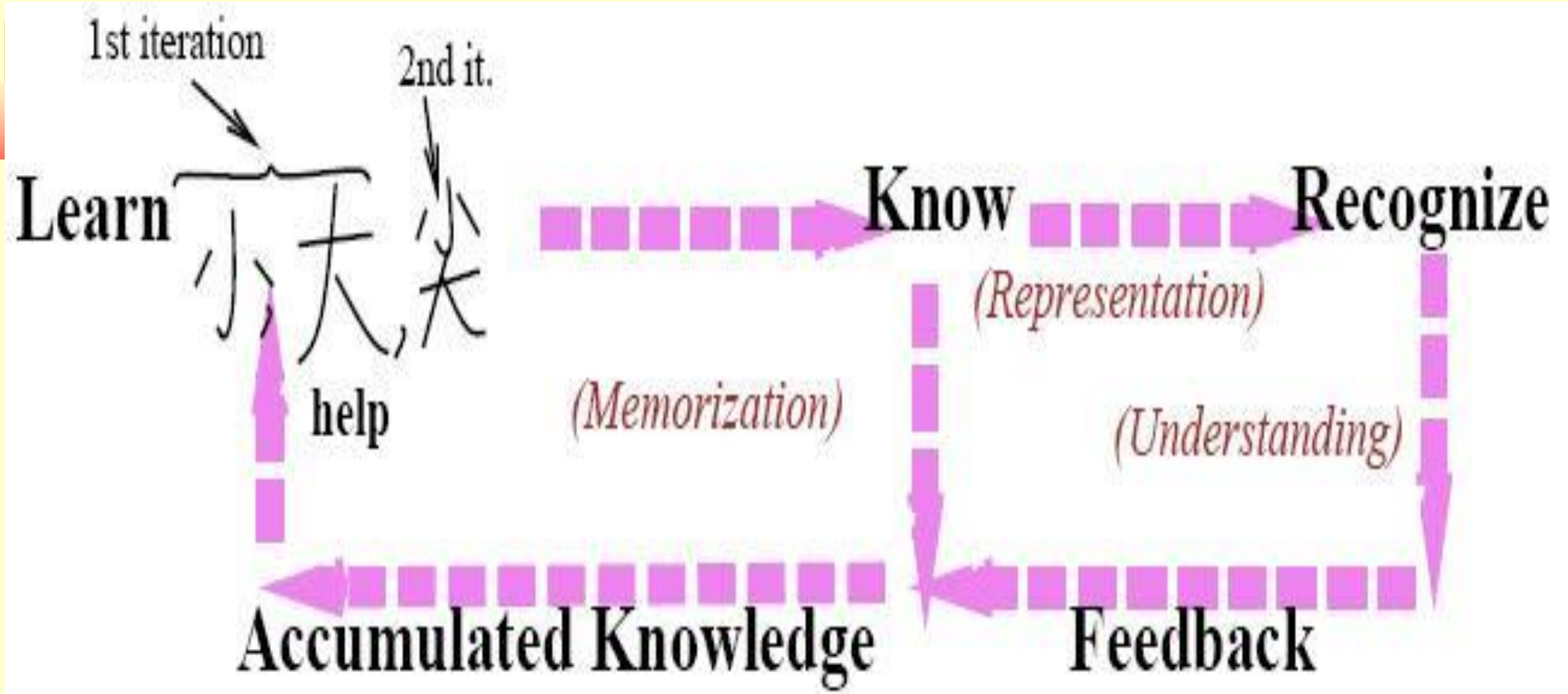
No matter how busy you are, you must return home to meet your relatives


亲人常见方亲近，
再忙也需常回家见见亲人！
优秀 公益广告作品展
创作单位：上海九木传播广告有限公司
上海市工商行政管理局
上海机场德高动量广告有限公司


爱
字可以简化，爱岂能无心！
优秀
公益广告作品展
创作单位：上海九木传播广告有限公司
上海市工商行政管理局
上海机场德高动量广告有限公司



Refrigerator=> Electrical + Ice + Box



Sharp => Large (Big) => Contrast <= Small

Hanzi vs Kanji

-----Original Message-----
From: Lambert Schomaker <SCHOMAKER@NICI.KUN.NL>
[SMTP:SCHOMAKER@NICI.KUN.NL]
Sent: Monday, December 23, 1996 1:57 AM
To: Multiple recipients of list SCRIB-L
Subject: Two WWW addresses (Archives and {K,H}an{j,z}i)

Dear Scrib-l subscribers,

I would like to draw you attention to two WWW addresses.

First, in order to make the browsing through Scrib-l discussions easier, there is:

http://www.cogsci.kun.nl/cgi-bin/lwgate/SCRIB-L/archives/

Second (in light of the recent discussion on Kanji) there is the following page:

http://hwr.nici.kun.nl/unipen/kanji/

****

Please note that I did not know that there was an alternative word for Kanji. Thus I created an alternative address:

http://hwr.nici.kun.nl/unipen/hanzi/

****

These pages are mainly intended for Westerners who scarcely get the opportunity to visualize Asian character sets on their screen.
I have extracted .gif images from Jim Breen's KANJIDIC.

Enjoy!

Hanzi vs Kanji

http://hwr.nici.kun.nl/unipen/hanzi/

Kanji and Hanzi

In respond to the request from Patrick Wang to add a link referring to **Hanzi**, the NICI has added this page.

You will be forwarded to the kanji webpage in 30 seconds.

According to Bob Davidson (Bob_Davidson@cpqm.mail.saic.COM):
"Hanzi are the semi-ideographic syllabic/whole-word characters that writers of Chinese use (regardless of their language/dialect); Kanji is a set of Japanese semi-ideographic characters, which were borrowed/derived from the Chinese Hanzi long ago."

The Most Difficult Chinese Character Hanzi

最難寫最難讀的一個漢字

念 biang 第二聲 (大陸的拼音法)

或者連讀:「比昂比昂」

陝西的一種麵食 biang biang 麵

康熙字典中有這個字。

關中的民謠:「一點撩上天，黃河兩道灣，八字大張口，言字往裡走，你一扭，我一扭;你一長，我一長;當中夾個馬大王，心字底月字旁，留個鉤掛麻談糖，推個車車逛咸陽」，就是寫這個字的順口溜。

註解:此字為陝西名吃 biang,biang 面的專用字！
古稱渭水biang,biang。
是古時人用渭河之水和面，做成寬如褲帶的麵條！

也是陝西八大怪之一。猶以咸陽的最為正宗(有圖為證)！

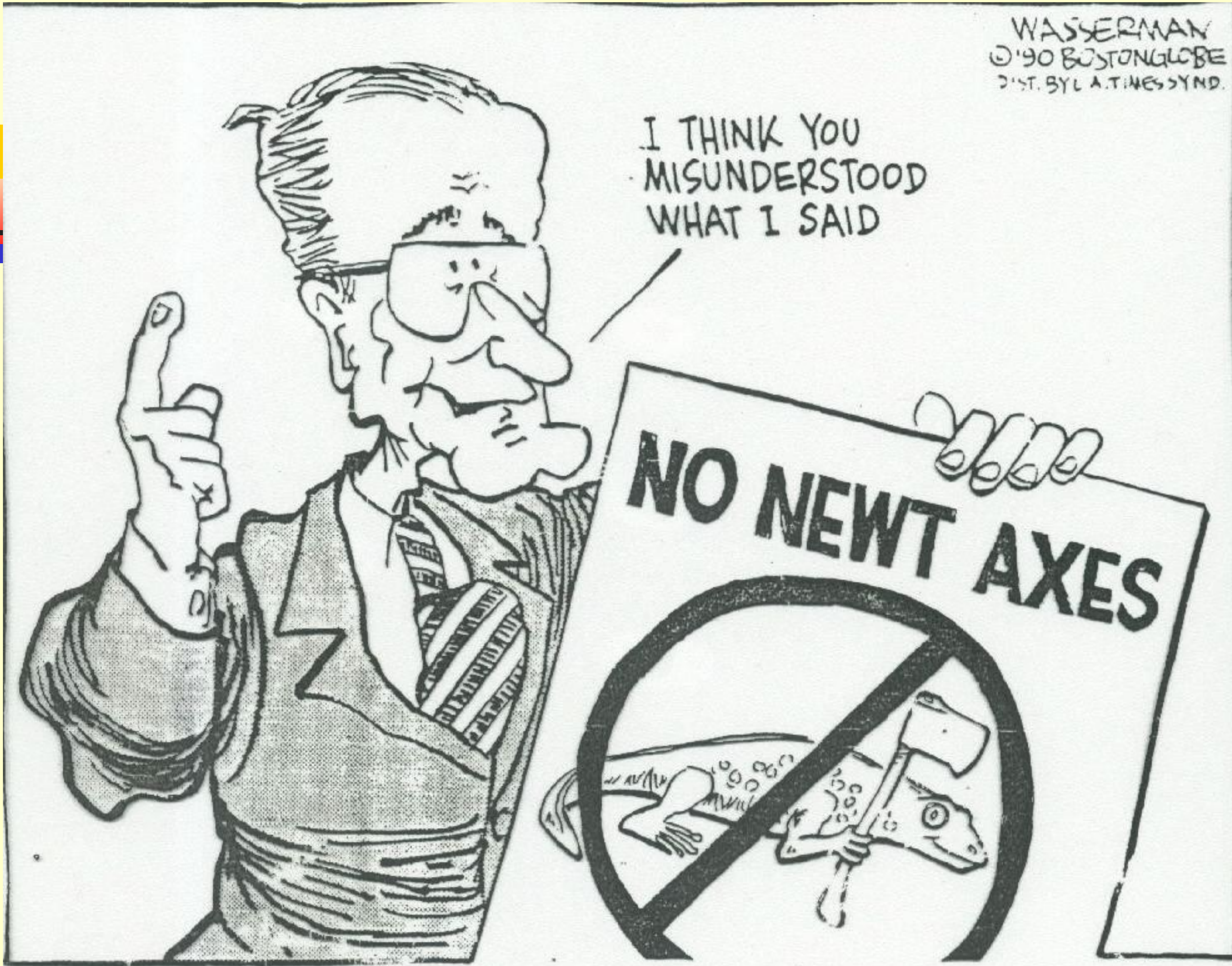
這家麵店的～招牌 Logo

這就是這家麵店的招牌麵

Future Research

- *Automatic Recognition*: **until now we only select feature points manually, we expect to implement automatic selection of correspondence points and recognition**
- *Threshold Selection*: **How to select appropriate threshold, which can optimize the final recognition result. It is a critical point which is still under research.**
- *Establishing an Imaging Database* **:Testing more Bio-Medical Data, and**
- **www.ccs.neu.edu/~pwang/3dpr**


HOLD IT!... THERE'S A TYPO, HERE.... THIS SAYS MOSCOW WANTS A LASTING PIECE IN THE PERSIAN GULF...!
SOVIET PLAN
IRAQ


WASSERMAN
©'90 BOSTON GLOBE
DIST. BY L.A. TIMES SYND.
I THINK YOU MISUNDERSTOOD WHAT I SAID
NO NEWT AXES

American humor.

British people understand English well.

Did Osama attend school in England?

Osama sent a messasge to Bush:

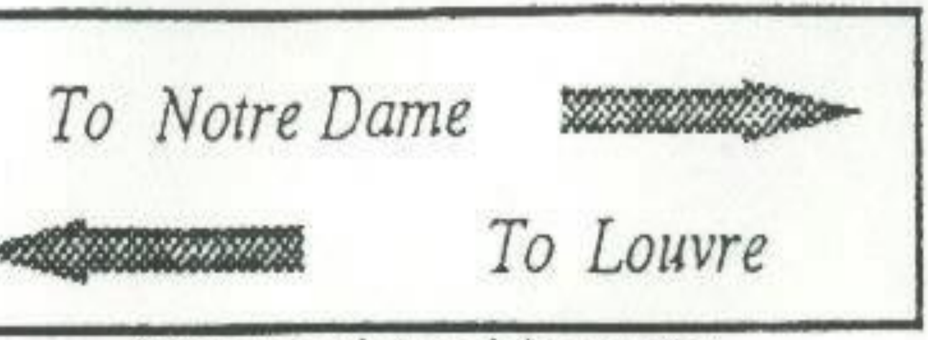
370HSSV 0773H

FBI: ? ? ?

CIA: ? ? ?

British: Upside Down !


OW!
WHAT HAPPENED? WHAT'S THE MATTER?
I GOT HIT ON THE FINGER WITH A FOUL TIP...
IS IT GOING TO BE ALL RIGHT? ARE YOU GOING TO BE ABLE TO PLAY?
I'M NOT SURE....I'LL HAVE TO FIND OUT
IT'S ALL RIGHT...I CAN PLAY!
THAT ISN'T EXACTLY WHAT I MEANT..
SCHULZ



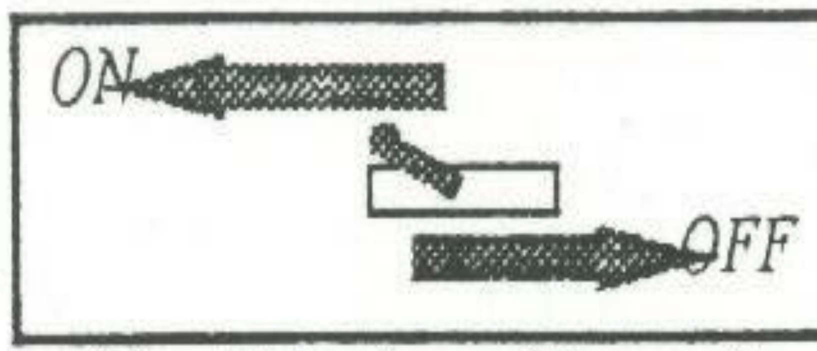
Not good (ambiguous)

Should be (unambiguous)

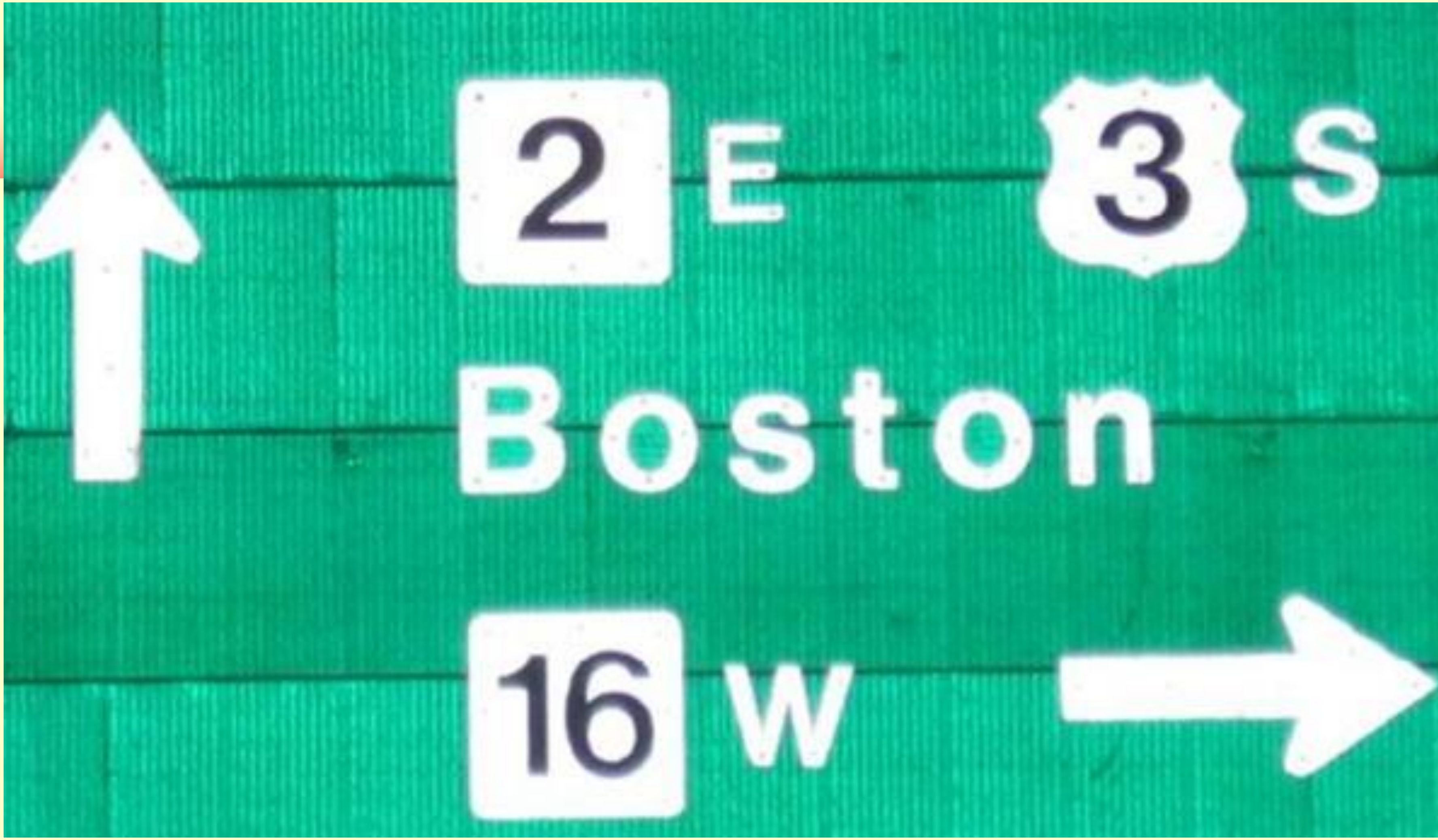
Emergency Switch

Not good and dangerous(ambiguous)

Emergency Switch



Should be (unambiguous)


2 E
3 S
Boston
16 W


2 E
3 S
Boston
16 W


2 E
3 S
Boston
16 W


2 E
16 W
3 S
Boston
Harvard Sq.

An emergency sign lacks direction

Boston subway trains. An emergency exit sign shown in the following photo image, saying: "TO OPEN DOOR MANUALLY, BREAK COVER, TURN HANDLE!" But this sign lacks direction of handle bar rotation : should the turn be clockwise ? or counter-clockwise ?

Notice that in emergency, one does not have time to hesitate, or cut and try ! One second delay may mean tens of lives lost !

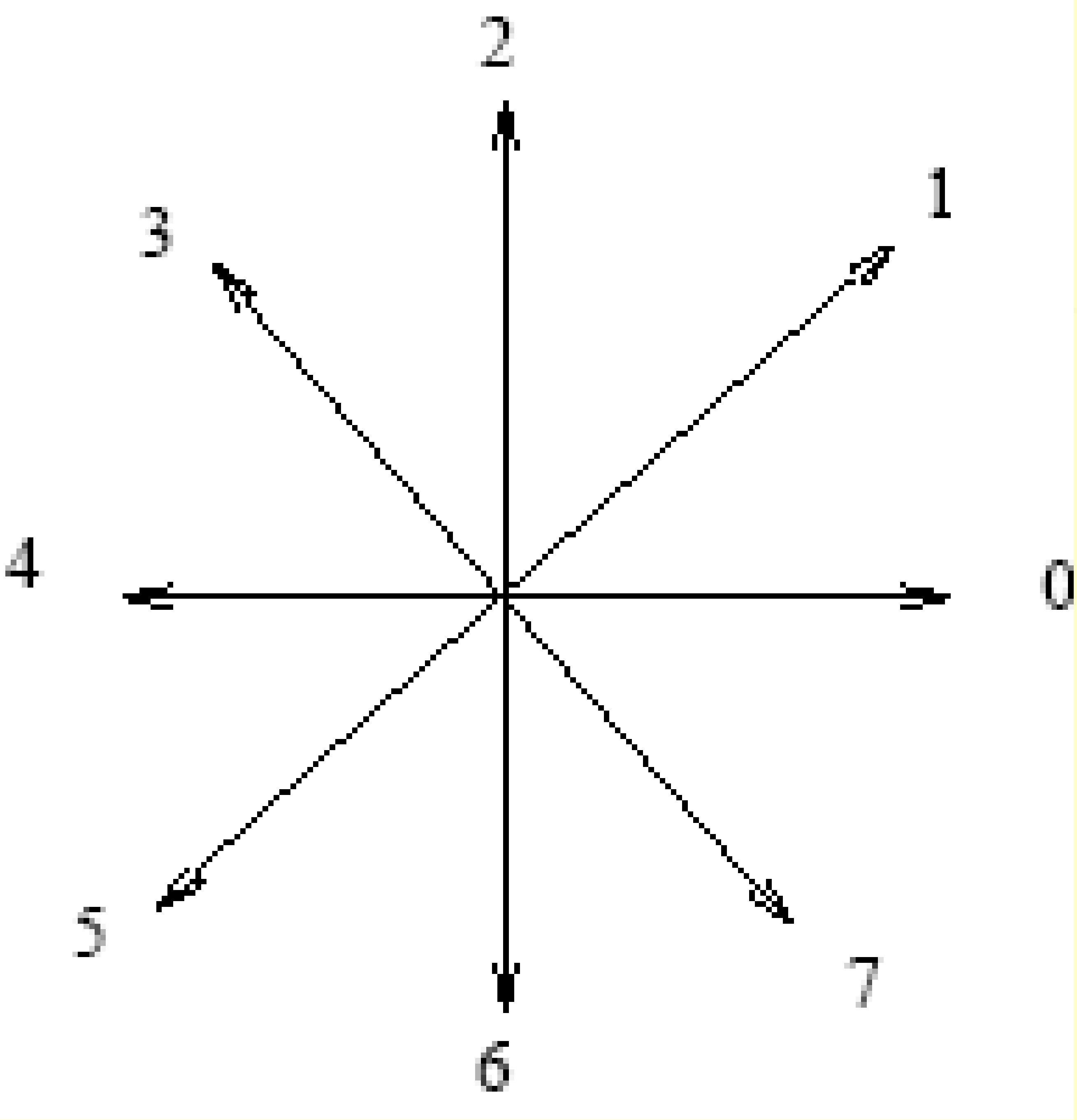
If we had enough alert and prevention in advance, disasters like 9/11 may never happen, and at least casualties may be much lower! Hope from now on, we all can ***learn the lesson, and be more cautious***, from ***hierarchical structure, ambiguity and PR point of view***, to ***save time, man power, energy cost***, ***money***, and best of all, it can ***save precious lives!*** See Figure 3.1

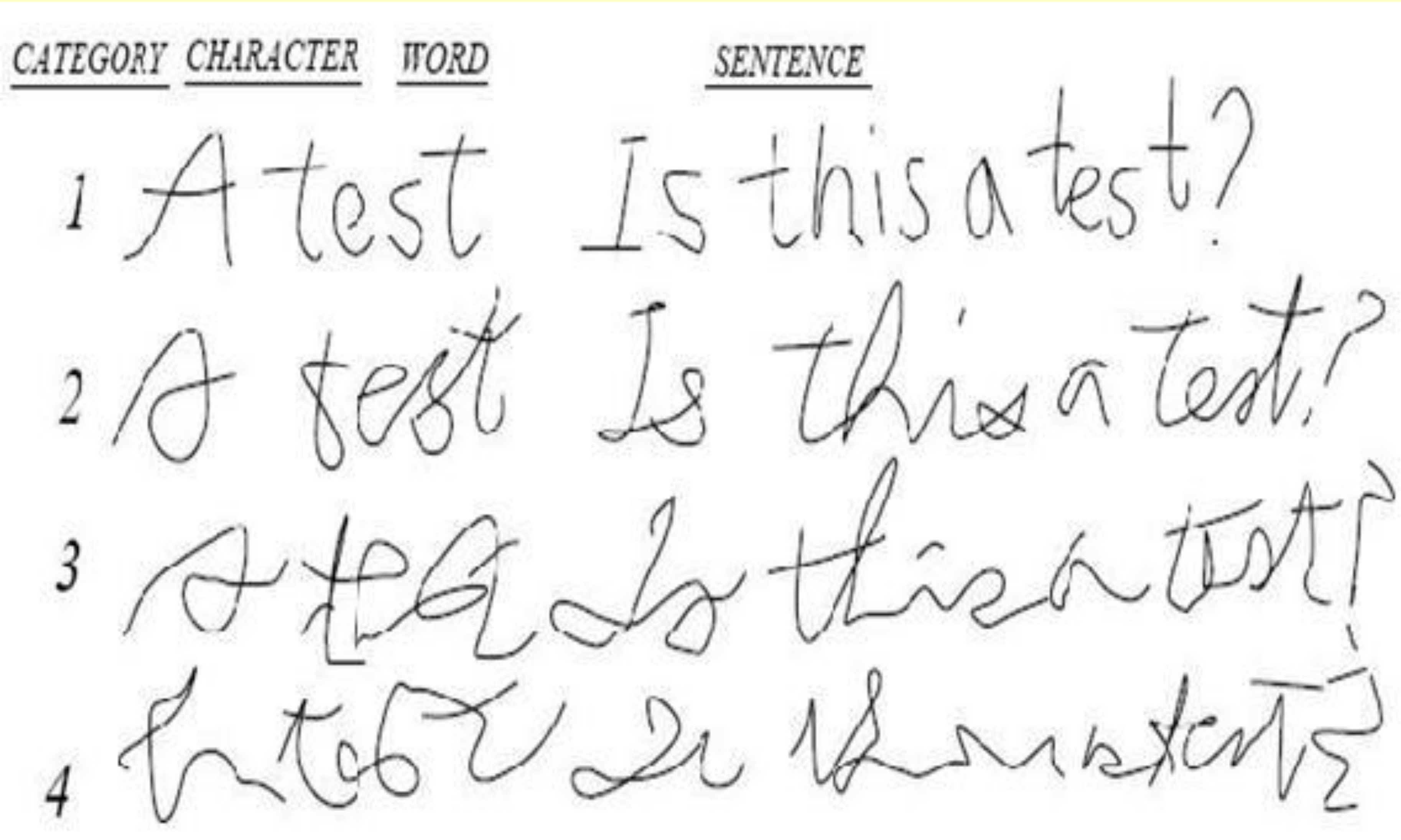

Disarmed
DITCHING
Armed
OPEN
EMERGENCY DOOR OPENING INSTRUCTIONS
ROTATE HANDLE TO FULL OPEN POSITION
PUSH DOOR OUTWARD • SLIDE INFLATES AUTOMATICALLY

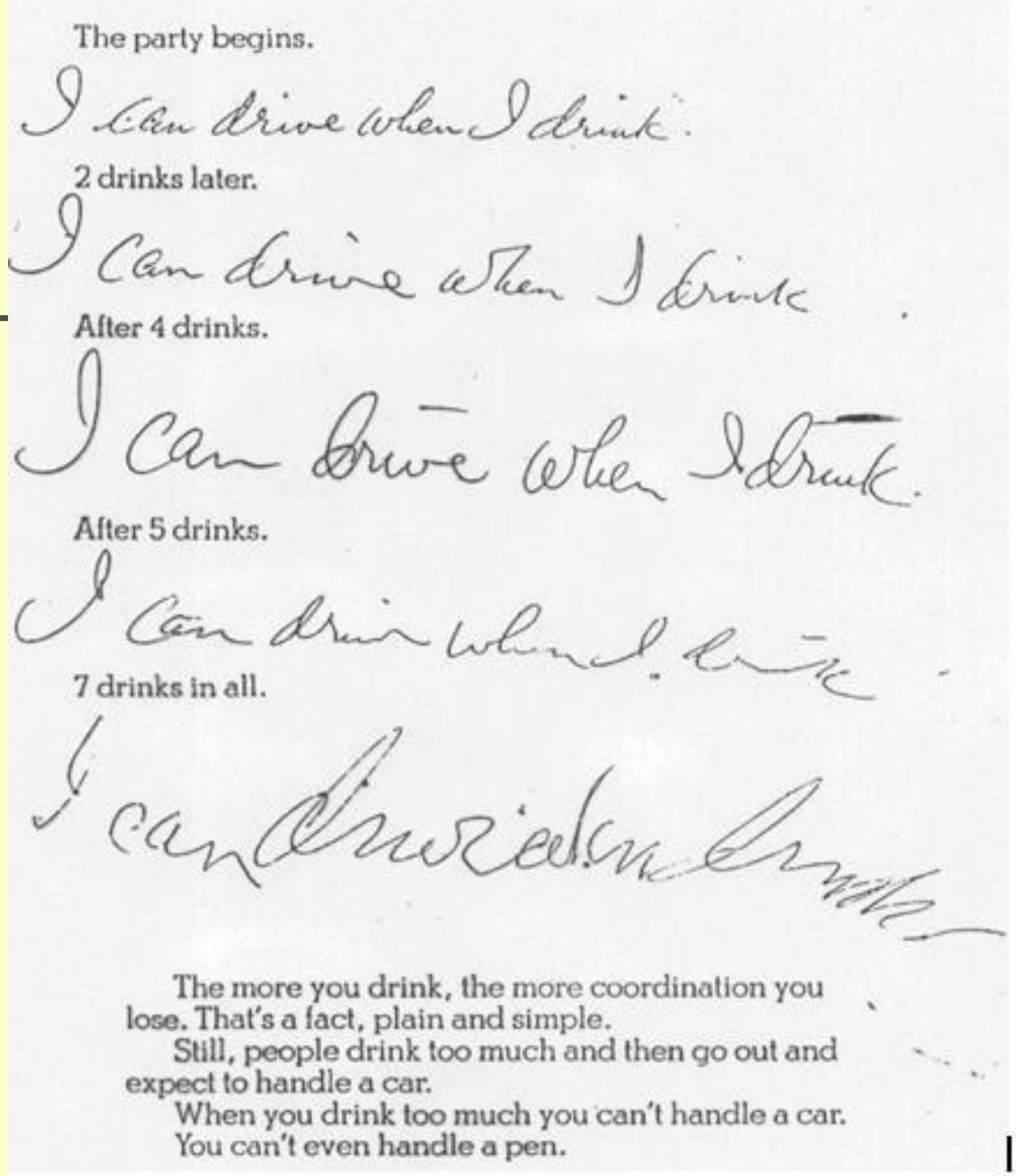

Disarmed
Armed
OPEN
No Cigarette
Disposal

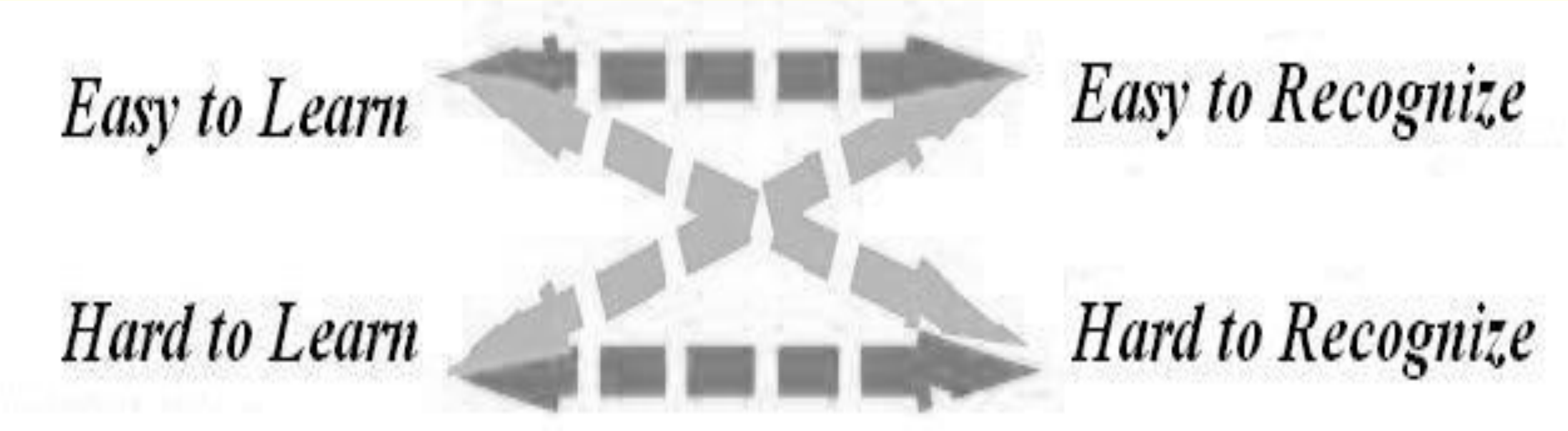

CHARLES ST
KEEP
RIGHT
ONE WAY
ONE WAY
KEEP
RIGHT
Oops, No
I meant
the First
You'll have to
go round again
(M32,M4)
(M32)
Take the
second exit
Look I said
I was Sorry
SIGN
300m
LEFT
2 W 16 E 3 N
Harvard Sq.
2 E 16 W 3 S
Boston
Harvard Sq.
WEST
VILLAGE A
WEST
VILLAGE B
WEST
VILLAGE C
WEST
VILLAGE E
WEST
VILLAGE G
WEST
VILLAGE H
WILLIS
HALL
SWITCH


WHAT'S THE DELAY?
ROAD TO RECOV
GO
MY WAY
DO NOT NOT ENTER
NO LEFT TURN
SPEED LIMIT 30
BUSINESS
ERIC ALLIE


2
1
3
4
0
5
7
6


CATEGORY
CHARACTER
WORD
SENTENCE
1 A test Is this a test?
2 A test Is this a test?
3
4


The party begins.
I can drive when I drink.
2 drinks later.
I can drive when I drink
After 4 drinks.
I can drive when I drink.
After 5 drinks.
7 drinks in all.
The more you drink, the more coordination you lose. That's a fact, plain and simple.
Still, people drink too much and then go out and expect to handle a car.
When you drink too much you can't handle a car.
You can't even handle a pen.


Easy to Learn
Easy to Recognize
Hard to Learn
Hard to Recognize

Country, State(Province), City, Street, Number, Last Name, First Name

美国麻州波士頓杭亭屯街東北大學王嵬教授

Scanning, Parsing, Searching and Matching (natural sequence, no backtracking needed)

First Name, Last Name, Street Number, City, State(Province), Country

Prof. Patrick Wang, Northeastern Univ, 360 Huntington Ave, Boston, MA 02115 USA

Scanning, Parsing, Searching and Matching (unnatural sequence, backtracking needed)

Year, Month, Day

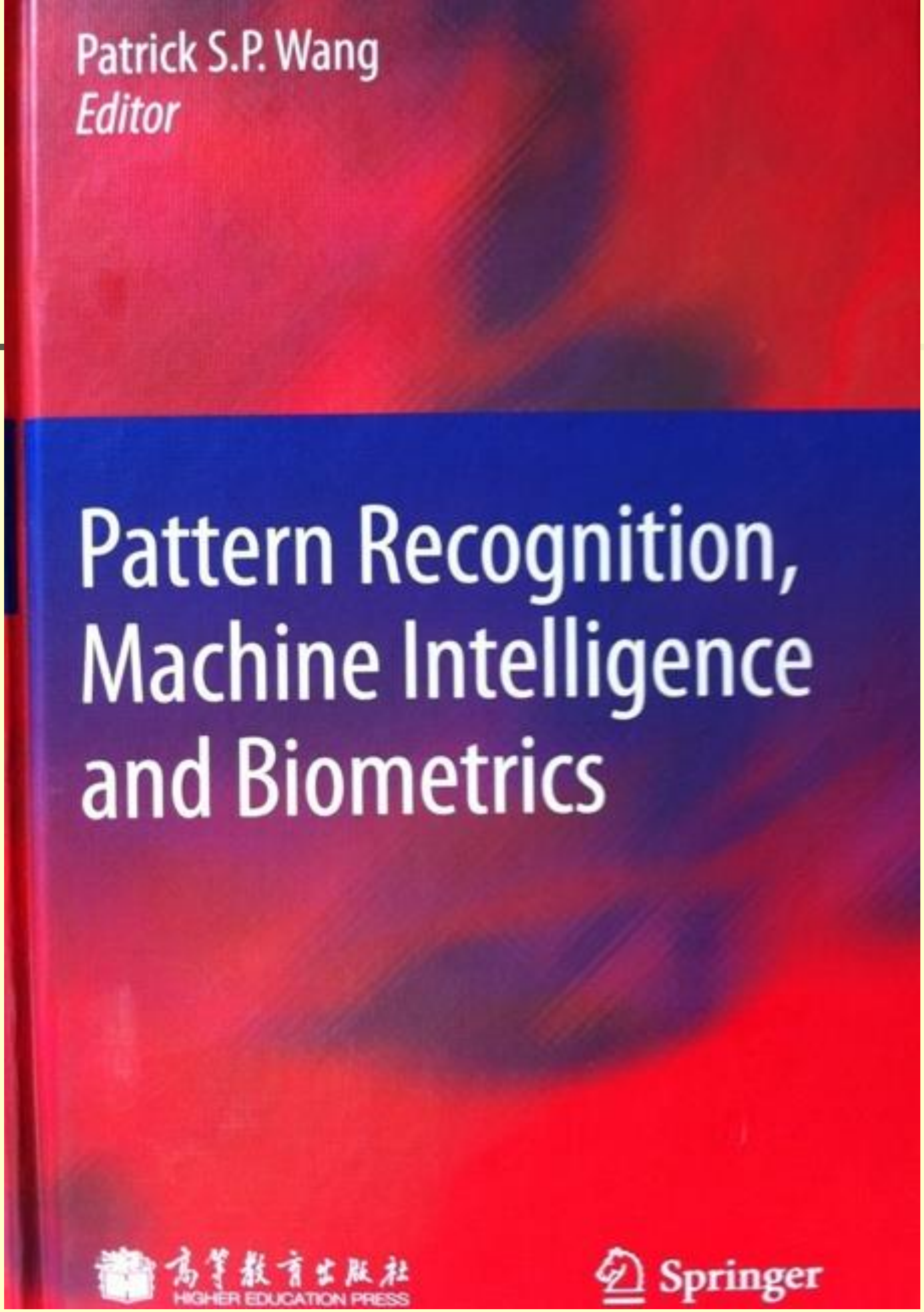
(No backtracking needed)

Day, Month, Year

(Needs backtracking)

References

- Patrick S.P. Wang, *Pattern Recognition and Machine Vision* -i Honor and Memory of Late Prof. King-Sun Fu, River, 2010
- S. N. Yanushkevich, D. Hurley and P. S. P. Wang ,SPECIAL ISSUE: *Pattern Recognition and Artificial Intelligence in Biometrics, IJPRAI* 2008, v22 no3
- Anil K. Jain, Arun A. Ross, Patrick Flynn, Handbook of Biometrics, Springer Verlag, 2007
- P. Wang and S. Yanushkevich, Biometrics Technolgies and Applications, AIA2007, Innsbruck, Austria, 226-233, Feb, 2007
- Yanushkevich S., Wang P., Srihari S., Gavrilova M, *Image Pattern Recognition: Synthesis and Analysis in Biometrics*, World Scientific Publishers (WSP), 2007 USA DHS CFP2010 reference
- P. Wang, Some Concerns on the Measurement for Biometrics Analysis and Applications, WSP, in *IPR: Synthesis and Analysis in Biometrics*, 2007, 321-338
- Yanushkevich S, Stoica A., Shmerko V., Popel D., Biometric Inverse Problems, CRC Press/Taylor&Francis, 2005


Patrick S.P. Wang
Editor
Pattern Recognition, Machine Intelligence and Biometrics
高等教育出版社
HIGHER EDUCATION PRESS
Springer

Lotfi A. Zadeh (left) and Patrick S.P. Wang (right)

Dear Patrick,

Many thanks for your message and the kind words.

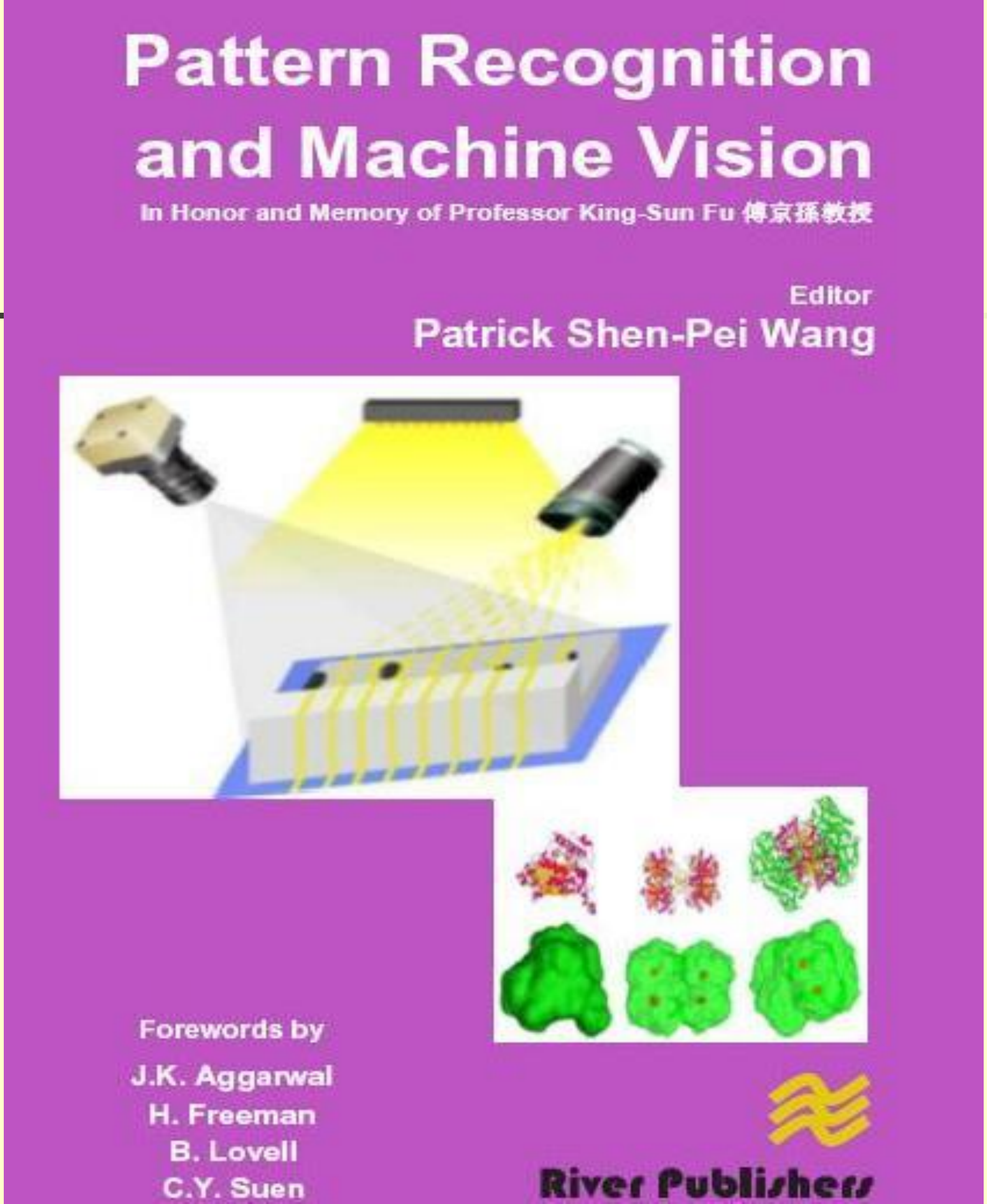
I appreciate very much what you wrote. As you know, I am highly impressed by your achievements. With regard to the foreword, I have a problem. After my heart attack in December 2008 my vision and my hearing have experienced a decline. Today, to read printed matter I have to use a magnifying glass. Reading messages does not present a problem but reading a book does. This is why writing a foreword — even to a book dedicated to my admired friend, K.S.Fu, would be stressful. It is a source of great regret for me not to be able to respond affirmatively to your invitation. Please keep in touch.

With my warm regards.

Sincerely,

Lotfi

Lotfi A. Zadeh
Professor in the Graduate School
Director, Berkeley Initiative in Soft Computing (BISC)


Pattern Recognition and Machine Vision
In Honor and Memory of Professor King-Sun Fu 傅京孫教授
Editor
Patrick Shen-Pei Wang
Forewords by
J.K. Aggarwal
H. Freeman
B. Lovell
C.Y. Suen
River Publishers

傅京孫

King-Sun Fu

(10/2/1930 [Nanking, China] – 4/29/1985 [D.C. , USA])

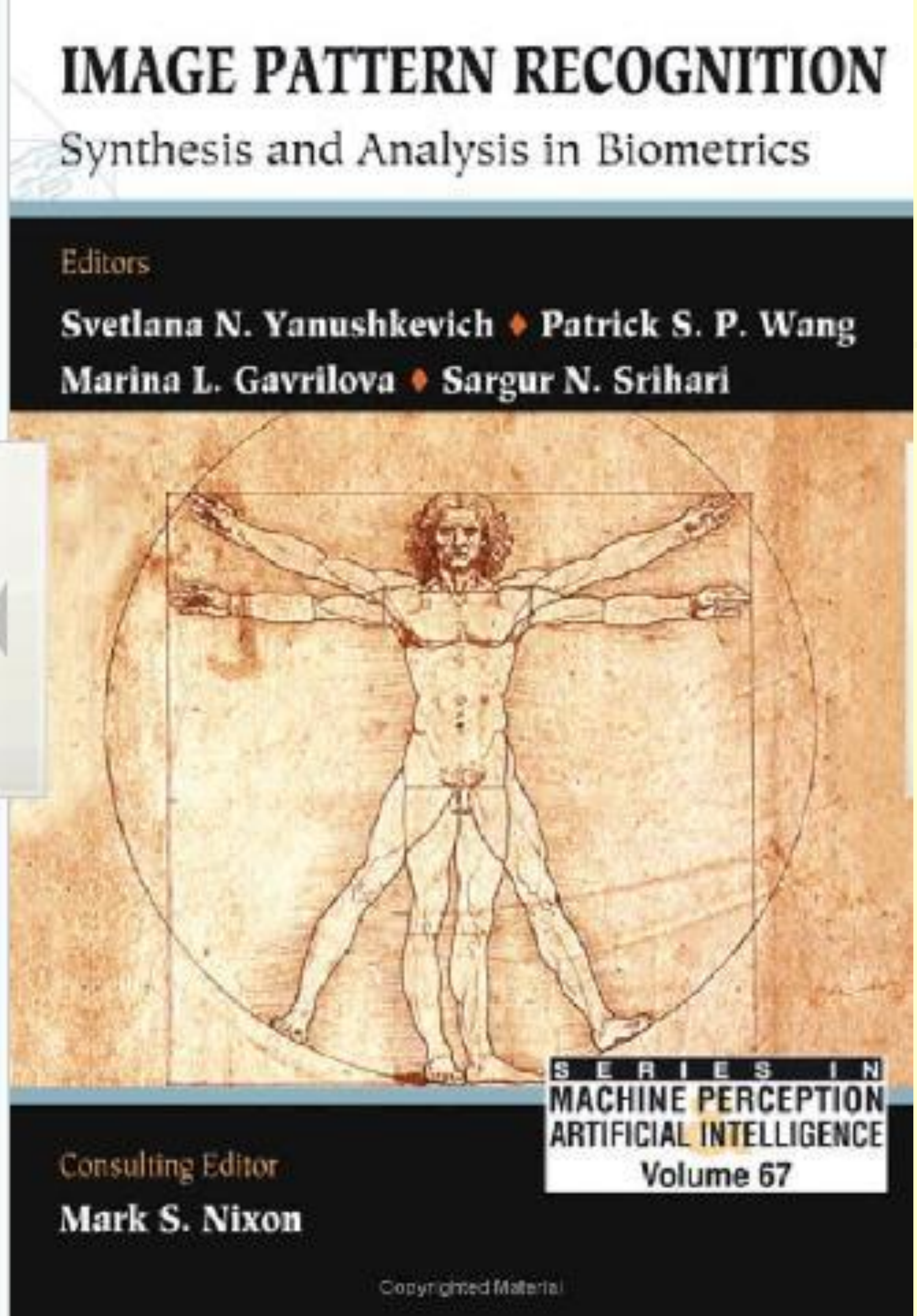


IMAGE PATTERN RECOGNITION
Synthesis and Analysis in Biometrics
Editors
Svetlana N. Yanushkevich ♦ Patrick S. P. Wang
Marina L. Gavrilova ♦ Sargur N. Srihari
SERIES IN
MACHINE PERCEPTION
ARTIFICIAL INTELLIGENCE
Volume 67
Consulting Editor
Mark S. Nixon
Copyrighted Material

Synthetic Biometrics

CALL FOR GRANTS PROPOSALS (CFP2010)

- DHS (S&T) SBIR FY-10.1 - H-SB010.1-005
  Department of Homeland Security **美国国土安全部**
  Opens: " November 18, 2009 - Closes: January 6, 2010 2:00pm EST

- **REFERENCE:**

Svetlana N. Yanuschkevich (Editor), **Patrick S. P. Wang** (Editor), Marina L. Gavrilova (Editor), Sargur N. Srihari (Editor), ***"Image Pattern Recognition: Synthesis and Analysis in Biometrics***," Series in Machine Perception and Artificial Intelligence – Vol. 67, World Scientific Publishing Co. Pte. Ltd., Imperial College Press, UK, 2007.

- **https://www.sbir.dhs.gov/**
- **https://www.sbir.dhs.gov/PastSolicitationDownload.asp#101005**


ISSN: 0218-0014
INTERNATIONAL JOURNAL OF PATTERN RECOGNITION AND ARTIFICIAL INTELLIGENCE
Volume 24 • Number 2 • March 2010
Editors-in-Chief
X Jiang
University of Münster, Germany
P S P Wang
Northeastern University, Boston, USA
World Scientific

INTERNATIONAL JOURNAL OF PATTERN RECOGNITION AND ARTIFICIAL INTELLIGENCE

EDITORIAL BOARD

Big Data , Image Analysis and Pattern Recognition

- **Big data** is a broad term for **data** sets so large or complex that traditional **data** processing applications are inadequate.
- Challenges include image analysis, especially biometrics images including audio and video data, capture, **data** curation, search, sharing, storage, transfer, visualization, and information privacy.

What is Big Data? - IBM

- Big data is being generated by everything around us at all times.
- Every digital process and social media exchange produces it.
- Systems, sensors and mobile devices transmit it. Big data is arriving from multiple sources at an alarming velocity, volume and variety.
- To extract meaningful value from big data, you need optimal processing power, analytics capabilities and skills.

What is changing in the realm of big data?

Big data is changing the way people within organizations work together.

It is creating a culture in which business and IT leaders must join forces to realize value from all data.

Insights from big data can enable all employees to make better decisions—deepening customer engagement, optimizing operations, preventing threats and fraud, and capitalizing on new sources of revenue.

But escalating demand for insights requires a fundamentally new approach to architecture, tools and practices.

Competitive advantage : Data is emerging as the world's newest resource for competitive advantage.

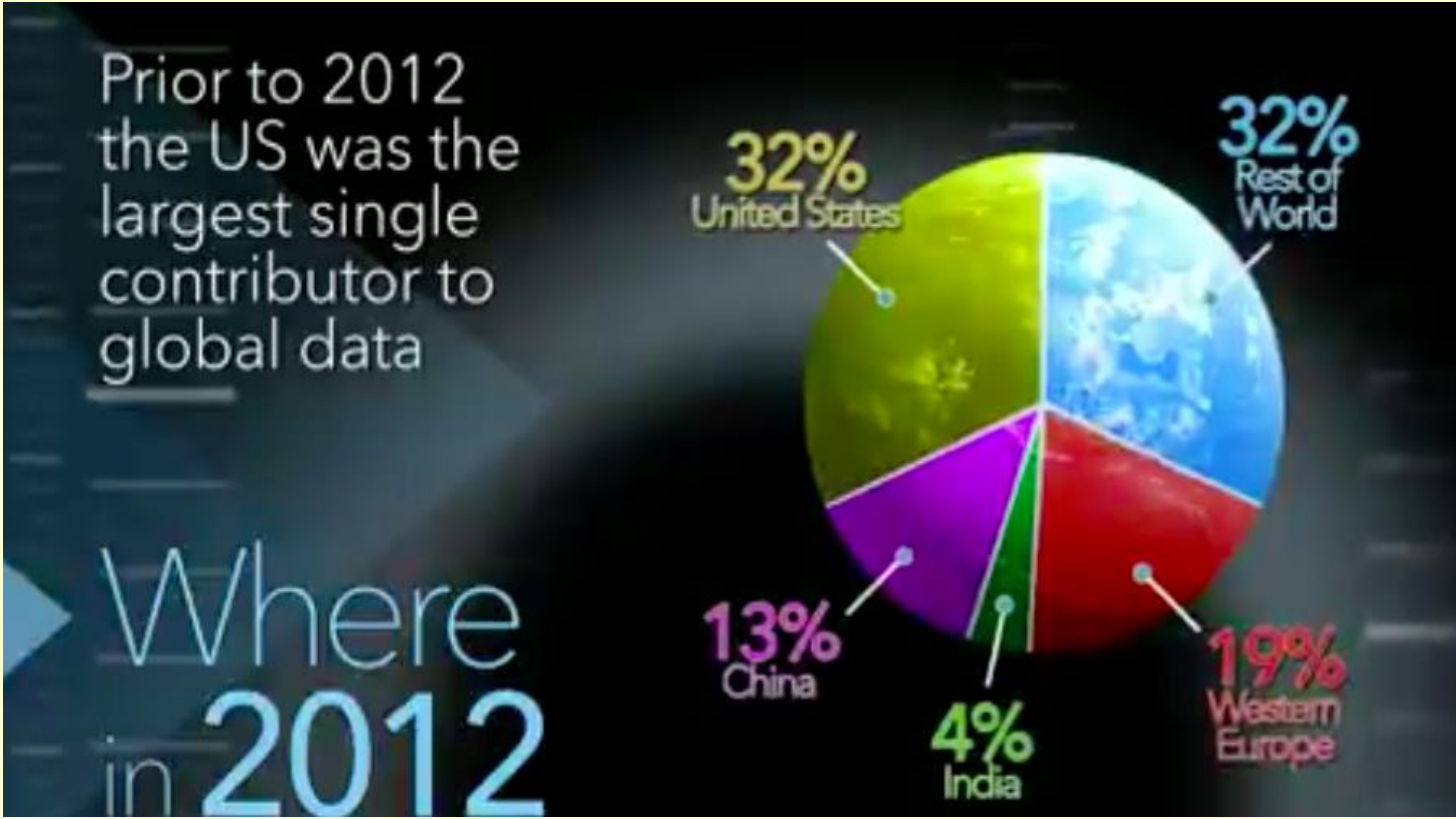
Decision making : Decision making is moving from the elite few to the empowered many.

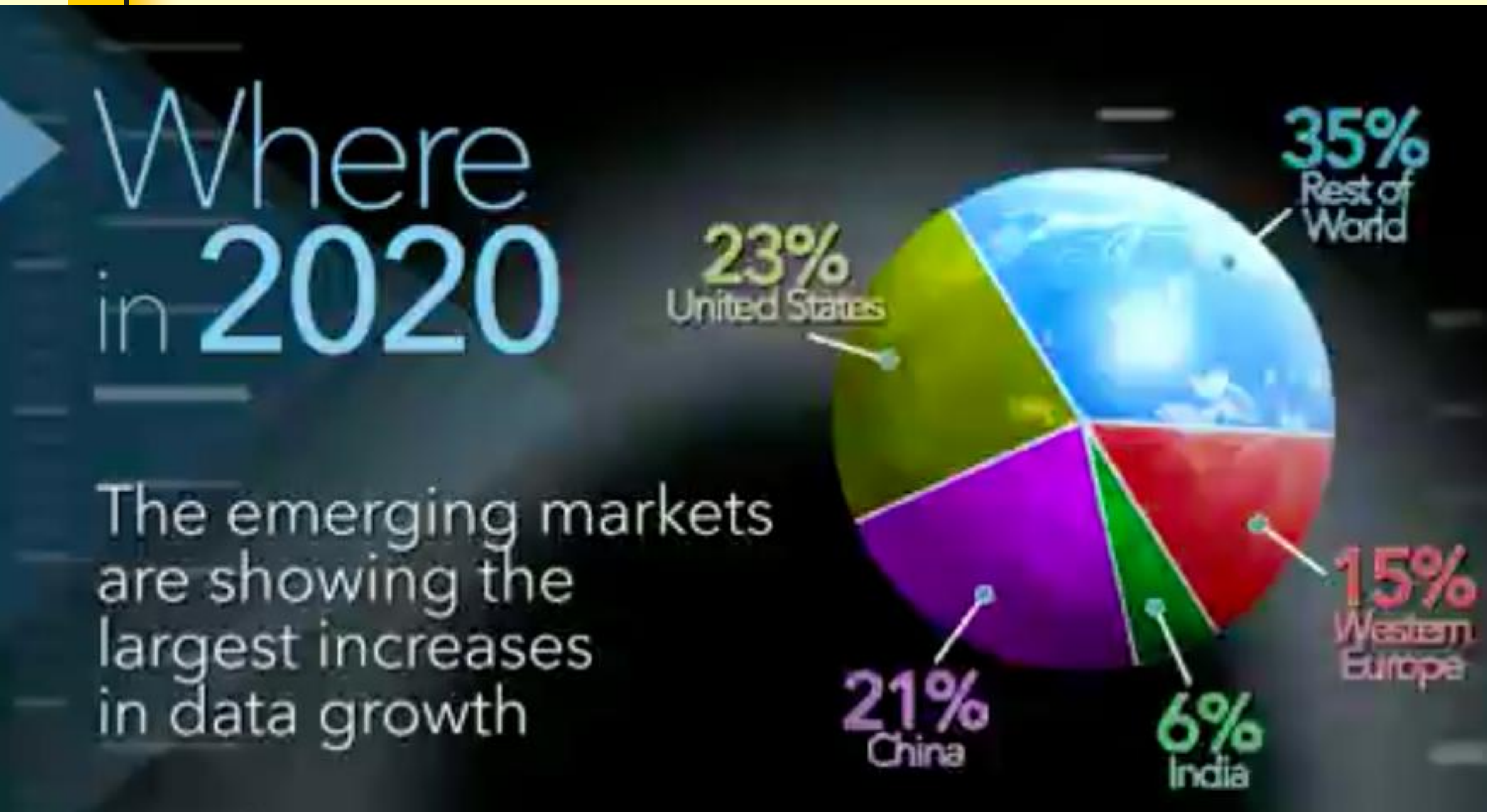
Value of data : As the value of data continues to grow, current systems won't keep pace.

http://www.sas.com/en_us/insights/big-data/what-is-big-data.html


By 2020
The total amount of data stored is expected to be...
50x
larger
than today
2012
2013
2014
2015
2016
2017
2018
2019
2020


The Digital Universe
All data that has been created and stored
Nearly half of which is unprotected


Prior to 2012 the US was the largest single contributor to global data
Where in 2012
32% United States
32% Rest of World
13% China
4% India
19% Western Europe


Where
in 2020
The emerging markets are showing the largest increases in data growth
23%
United States
35%
Rest of World
15%
Western Europe
6%
India
21%
China


Wisdom is the effective use of knowledge in decision making
VALUE
Wisdom
Knowledge
Information
Data

Big Data: Volume or Technology?

- While the term may seem to reference the volume of data, that isn't always the case. The term big data, especially when used by vendors, may refer to the technology (which includes tools and processes) that an organization requires to handle the large amounts of data and storage facilities. The term big data is believed to have originated with Web search companies who needed to query very large distributed aggregations of loosely-structured data.

An Example of Big Data

An example of big data might be petabytes (1,024 terabytes) or exabytes (1,024 petabytes) of data consisting of billions to trillions of records of millions of people—all from different sources (e.g. Web, sales, customer contact center, social media, mobile data and so on). The data is typically loosely structured data that is often incomplete and inaccessible.

1,024 Gigabytes = 1 Terabyte.
1,024 Terabytes = 1 Petabyte.
1,024 Petabytes = 1 Exabyte

(In 2000, 3 exabytes of information was created.)

1,024 Exabytes = 1 Zettabyte.

Big Data=> depends on complexity of problems

What is a terabyte? What is bigger than a terabyte? searchstorage.techtarget.com/answer/Whats-bigger-than-a-Terabyte

- Volume: big data doesn't sample. It just observes and tracks what happens
- Velocity: big data is often available in real-time
- Variety: big data draws from text, images, audio, video; plus it completes missing pieces through data fusion
- Machine Learning: big data often doesn't ask why and simply detects patterns
- Digital footprint: big data is often a cost-free byproduct of digital interaction

Big data can be described by the following characteristics:

- **Volume:**The quantity of generated data is important in this context. The size of the data determines the value and potential of the data under consideration, and whether it can actually be considered big data or not. The name 'big data' itself contains a term related to size, and hence the characteristic.
- **Variety:**The type of content, and an essential fact that data analysts must know. This helps people who are associated with and analyze the data to effectively use the data to their advantage and thus uphold its importance.
- **Velocity:** In this context, the speed at which the data is generated and processed to meet the demands and the challenges that lie in the path of growth and development.

More expanded version:

- **Variability:**The inconsistency the data can show at times—-which can hamper the process of handling and managing the data effectively.
- **Veracity:**The quality of captured data, which can vary greatly. Accurate analysis depends on the veracity of source data.
- **Complexity:**Data management can be very complex, especially when large volumes of data come from multiple sources. Data must be linked, connected, and correlated so users can grasp the information the data is supposed to convey.

Factory work and Cyber-physical systems may have a 6C system:

- Connection (sensor and networks)
- Cloud (computing and data on demand)[30][31]
- Cyber (model and memory)
- Content/context (meaning and correlation)
- Community (sharing and collaboration)
- Customization (personalization and value)

7D on Big Data Research

- Diversity on applications
- Diversity on data properties
- Diversity on goals / objectives
- Diversity on representations
- Diversity on infrastructures
- Diversity on algorithms
- Diversity on theoretical foundation

Result: Best-Effort Solutions

Big Data EveryWhere!

- Lots of data is being collected and warehoused
  - Web data, e-commerce
  - purchases at department/ grocery stores
  - Bank/Credit Card transactions
  - Social Network

How much data?

- Google processes 20 PB a day (2008)
- Wayback Machine has 3 PB + 100 TB/month (3/2009)
- Facebook has 2.5 PB of user data + 15 TB/day (4/2009)
- eBay has 6.5 PB of user data + 50 TB/day (5/2009)
- CERN's Large Hydron Collider (LHC) generates 15 PB a year

640K ought to be enough for anybody.

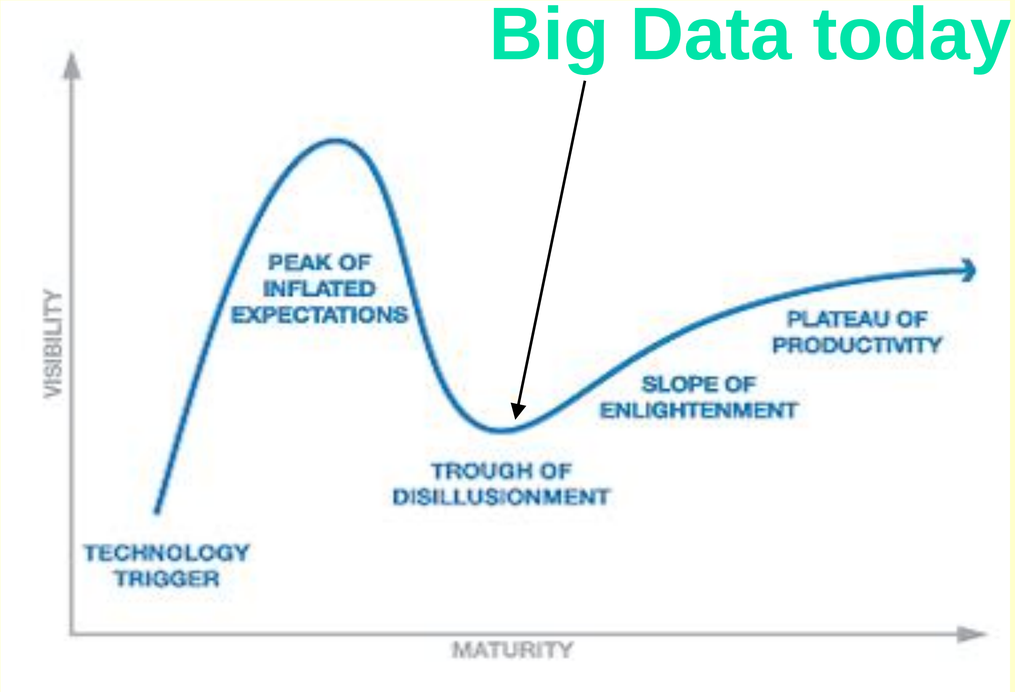
Gartner Hype Cycle

(Special Report: July 27, 2013)

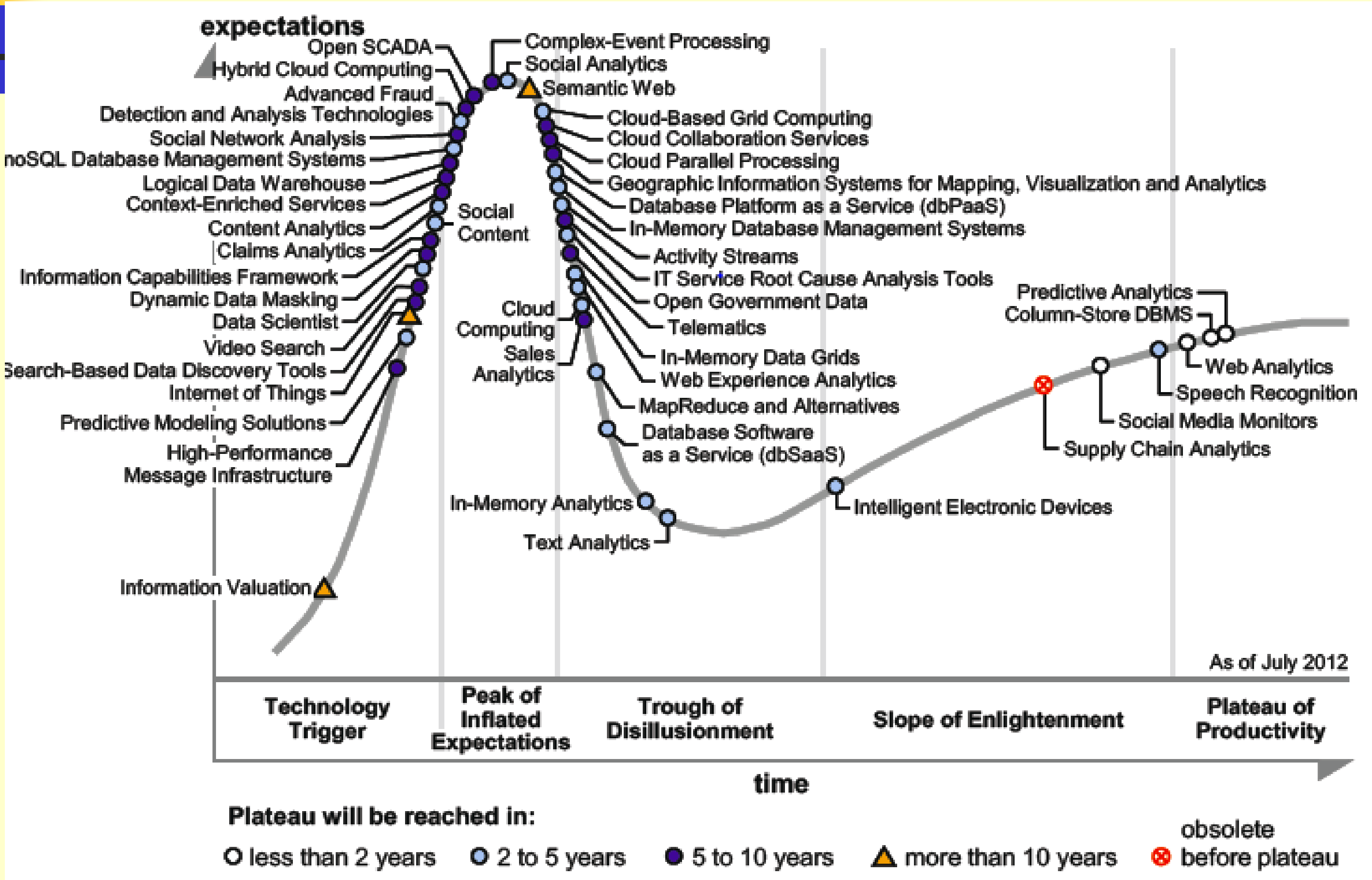
Big data is at the trough of disillusionment

- IBM
- Accel Partners
- Sumo Logic
- Trifacta
- RelateIQ
- Cloudera
- Hardoop

(10 times by 2016)

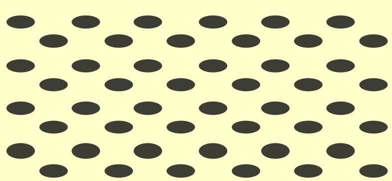


Gartner Hype Cycle
(Special Report: July 27, 2013)



Big Data and the 4 Vs

Volume

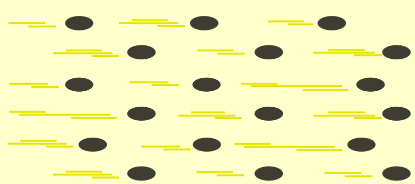


Very Large

IDC Analyze the Future

到2020年，数据总量达40ZB，人均5.2TB

Velocity

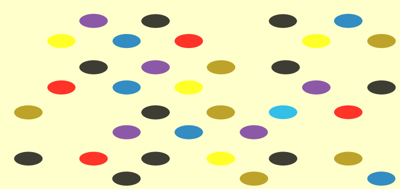


Very Fast

facebook

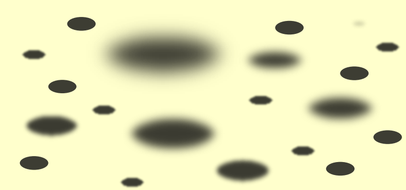
分享的内容条目超过25亿个/天，增加数据超过500TB/天

Variety

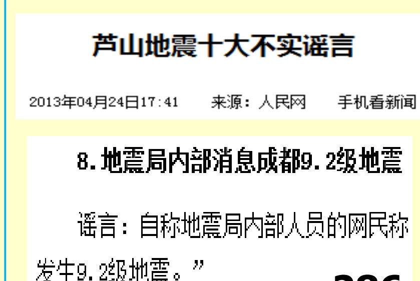


Multimodal

Veracity



True or False



芦山地震十大不实谣言

2013年04月24日17:41　来源：人民网　手机看新闻

8.地震局内部消息成都9.2级地震

谣言：自称地震局内部人员的网民称发生9.2级地震。”

Examples of Big Data

Over 1 trillion webpages (Google)

1.8 zettabytes in 2011

Transactions

Network

Courtesy of James Cheng

The Earthscope

- The Earthscope is the world's largest science project. Designed to track North America's geological evolution, this observatory records data over 3.8 million square miles, amassing 67 terabytes of data. It analyzes seismic slips in the San Andreas fault, sure, but also the plume of magma underneath Yellowstone and much, much more. (http://www.msnbc.msn.com/id/44363598/ns/technology_and_science-future_of_technology/#.TmetOdQ--uI)

Type of Data

- Relational Data (Tables/Transaction/Legacy Data)
- Text Data (Web)
- Semi-structured Data (XML)
- Graph Data
  - Social Network, Semantic Web (RDF), …

- Streaming Data
  - You can only scan the data once

What to do with these data?

- Aggregation and Statistics
  - Data warehouse and OLAP
- Indexing, Searching, and Querying
  - Keyword based search
  - Pattern matching (XML/RDF)
- Knowledge discovery
  - Data Mining
  - Statistical Modeling

Random Sample and Statistics

- *Population: is used to refer to the set or universe of all* entities under study.
- However, looking at the entire population may not be feasible, or may be too expensive.
- Instead, we draw a random sample from the population, and compute appropriate *statistics* from the sample, that give estimates of the corresponding population parameters of interest.

5.9	6.9	6.6	4.6	6.0	4.7	6.5	5.8	6.7	6.7	5.1	5.1	5.7	6.1	4.9
5.0	5.0	5.7	5.0	7.2	5.9	6.5	5.7	5.5	4.9	5.0	5.5	4.6	7.2	6.8
5.4	5.0	5.7	5.8	5.1	5.6	5.8	5.1	6.3	6.3	5.6	6.1	6.8	7.3	5.6
4.8	7.1	5.7	5.3	5.7	5.7	5.6	4.4	6.3	5.4	6.3	6.9	7.7	6.1	5.6
6.1	6.4	5.0	5.1	5.6	5.4	5.8	4.9	4.6	5.2	7.9	7.7	6.1	5.5	4.6
4.7	4.4	6.2	4.8	6.0	6.2	5.0	6.4	6.3	6.7	5.0	5.9	6.7	5.4	6.3
4.8	4.4	6.4	6.2	6.0	7.4	4.9	7.0	5.5	6.3	6.8	6.1	6.5	6.7	6.7
4.8	4.9	6.9	4.5	4.3	5.2	5.0	6.4	5.2	5.8	5.5	7.6	6.3	6.4	6.3
5.8	5.0	6.7	6.0	5.1	4.8	5.7	5.1	6.6	6.4	5.2	6.4	7.7	5.8	4.9
5.4	5.1	6.0	6.5	5.5	7.2	6.9	6.2	6.5	6.0	5.4	5.5	6.7	7.7	5.1

Table 1.2: Iris Dataset: `sepal length`

Statistic

- Let S_i denote the random variable corresponding to data point x_i , then a *statistic* $\hat{\theta}$ is a function $\hat{\theta} : (S_1, S_2, \cdots , S_n) \to \mathbb{R}$.

- If we use the value of a statistic to estimate a population parameter, this value is called a *point estimate of the parameter, and the statistic is called as an estimator of the* parameter.

Empirical Cumulative Distribution Function

$$\hat{F}(x) = \frac{\sum_{i=1}^{n} I(S_i \leq x)}{n}$$

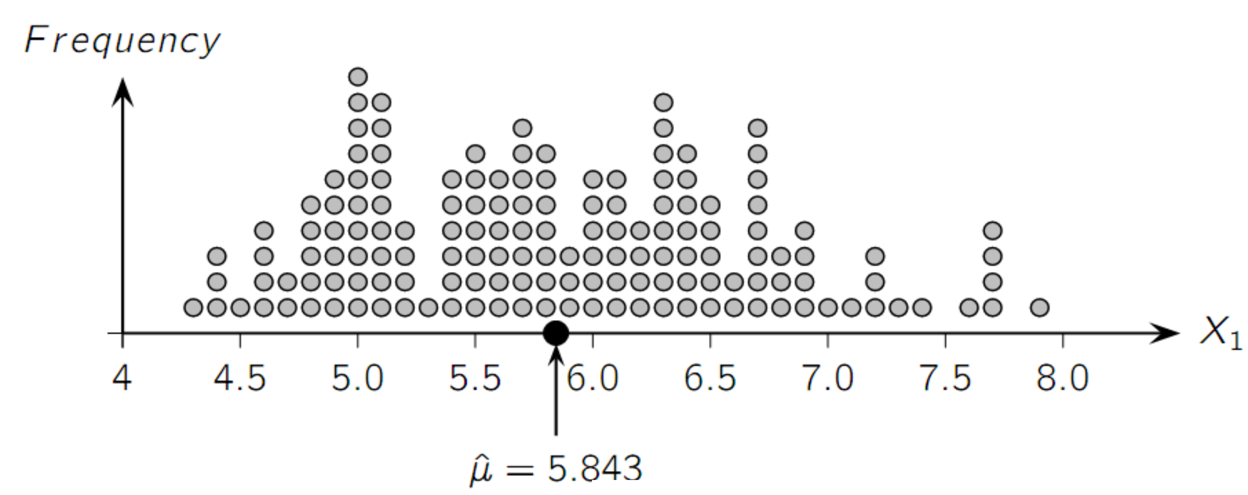
Where

$$I(S_i \leq x) = \begin{cases} 1 & \text{if } S_i \leq x \\ 0 & \text{if } S_i > x \end{cases}$$

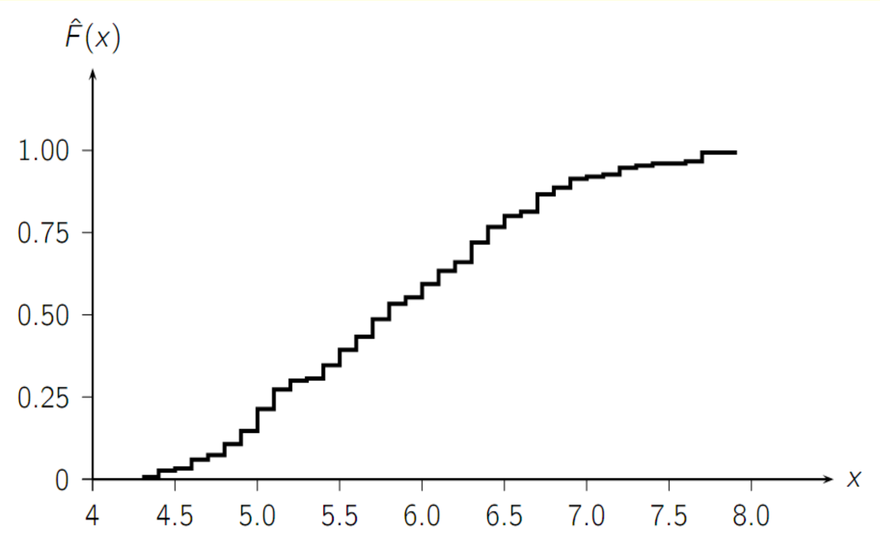
Inverse Cumulative Distribution Function

$$F^{-1}(q) = \min\{x : F(x) > q\} \qquad \text{for } q \in [0, 1]$$

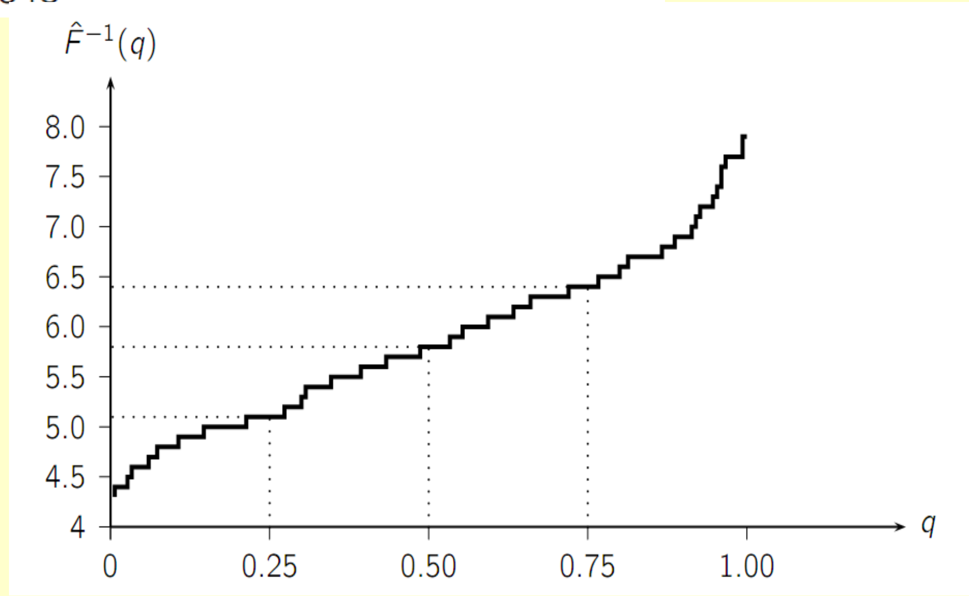
Example



Frequency
X_1
4
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
$\hat{\mu} = 5.843$



$\hat{F}(x)$
1.00
0.75
0.50
0.25
0
4
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
x



$\hat{F}^{-1}(q)$
8.0
7.5
7.0
6.5
6.0
5.5
5.0
4.5
4
0
0.25
0.50
0.75
1.00
q

Measures of Central Tendency (Mean)

Population Mean:

$$\mu = E[X] = \sum_x x\, f(x)$$

$$\mu = E[X] = \int_{-\infty}^{\infty} x f(x) dx$$

Sample Mean (Unbiased, not robust):

$$\hat{\mu} = \sum_x x \hat{f}(x) = \sum_x x \left(\frac{\sum_{i=1}^n I(S_i = x)}{n} \right) = \frac{\sum_{i=1}^n S_i}{n}$$

$$E[\hat{\mu}] = E\left[\frac{\sum_{i=1}^n S_i}{n} \right] = \frac{1}{n} \sum_{i=1}^n E[S_i] = \frac{1}{n} \sum_{i=1}^n \mu = \mu$$

Measures of Central Tendency (Median)

Population Median:

$$P(X \le m) \ge \frac{1}{2} \text{ and } P(X \ge m) \ge \frac{1}{2}$$

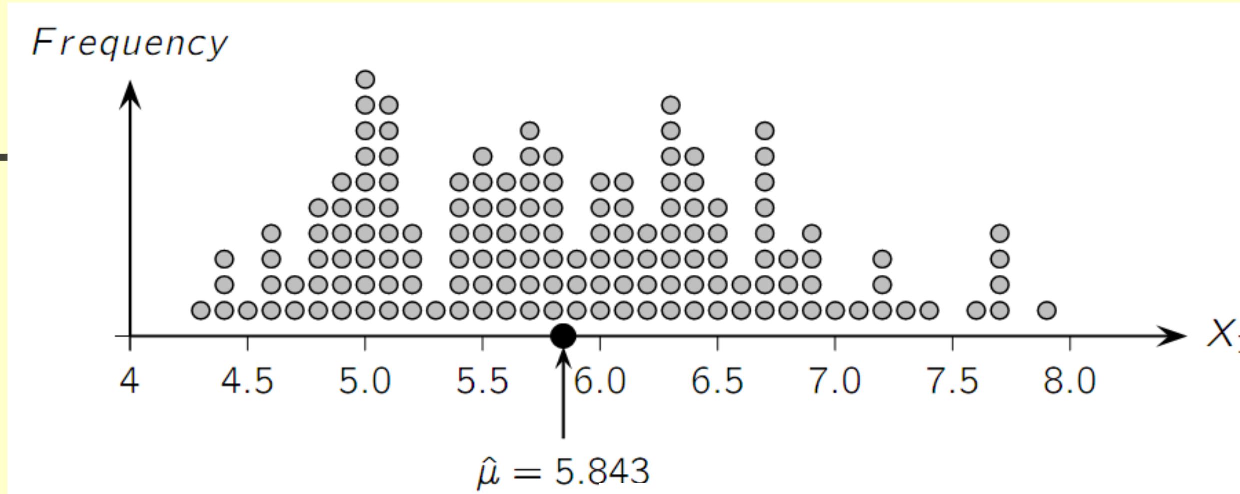
or

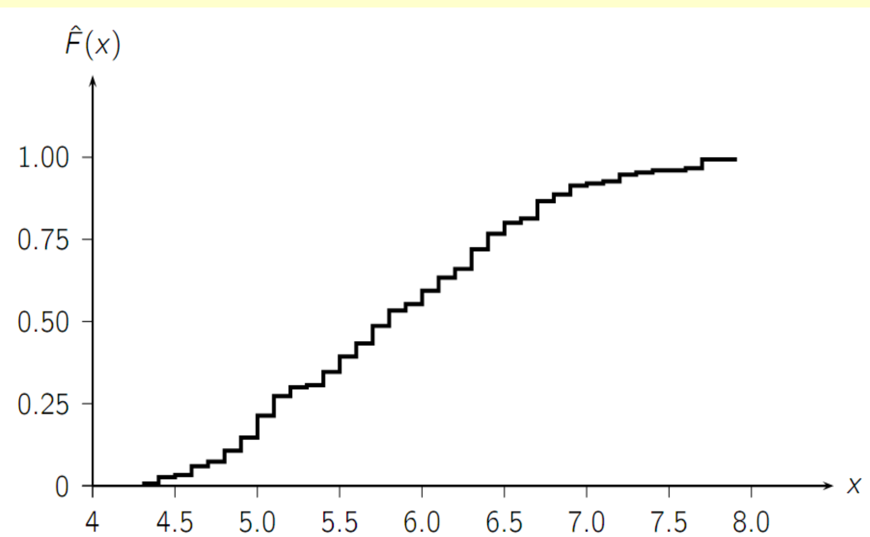
$$F(m) = 0.5 \text{ or } m = F^{-1}(0.5)$$

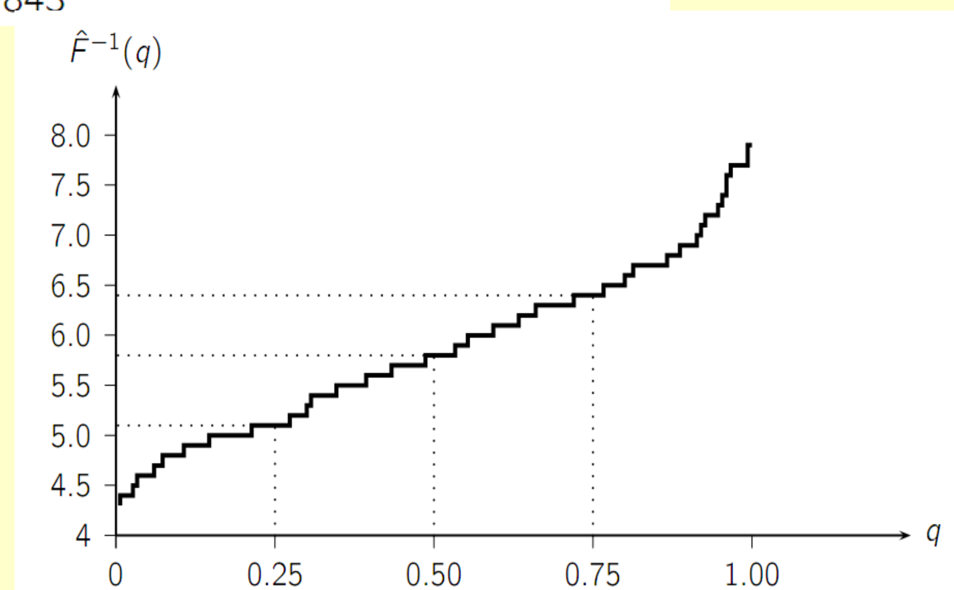
Sample Median:

$$\hat{F}(m) = 0.5 \text{ or } m = \hat{F}^{-1}(0.5)$$

E


Frequency
X_1
4
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
$\hat{\mu} = 5.843$


$\hat{F}(x)$
1.00
0.75
0.50
0.25
0
4
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
x


$\hat{F}^{-1}(q)$
8.0
7.5
7.0
6.5
6.0
5.5
5.0
4.5
4
0
0.25
0.50
0.75
1.00
q

Measures of Dispersion (Range)

Sample Range: $r = \max_x\{x\} - \min_x\{x\}$

$$\hat{r} = \max_i\{S_i\} - \min_i\{S_i\} = \max_i\{x_i\} - \min_i\{x_i\}$$

- **Not robust, sensitive to extreme values**

Measures of Dispersion (Inter-Quartile Range)

Inter-Quartile Range (IQR):

$$IQR = F^{-1}(0.75) - F^{-1}(0.25)$$

Sample IQR:

$$\widehat{IQR} = \hat{F}^{-1}(0.75) - \hat{F}^{-1}(0.25)$$

- **More robust**

Measures of Dispersion (Variance and Standard Deviation)

Variance:

$$var(X) = E[(X-\mu)^2] = \begin{cases} \sum_x (x-\mu)^2 f(x) & \text{if } X \text{ is discrete} \\ \int_{-\infty}^{\infty} (x-\mu)^2 f(x)\, dx & \text{if } X \text{ is continuous} \end{cases}$$

Standard Deviation:

$$\begin{aligned} \sigma^2 = var(X) = E[(X-\mu)^2] &= E[X^2 - 2\mu X + \mu^2] \\ &= E[X^2] - 2\mu E[X] + \mu^2 = E[X^2] - 2\mu^2 + \mu^2 \\ &= E[X^2] - (E[X])^2 \end{aligned}$$

Measures of Dispersion (Variance and Standard Deviation)

Variance:

$$var(X) = E[(X-\mu)^2] = \begin{cases} \sum_x (x-\mu)^2 f(x) & \text{if } X \text{ is discrete} \\ \int_{-\infty}^{\infty} (x-\mu)^2 f(x)\, dx & \text{if } X \text{ is continuous} \end{cases}$$

Standard Deviation:

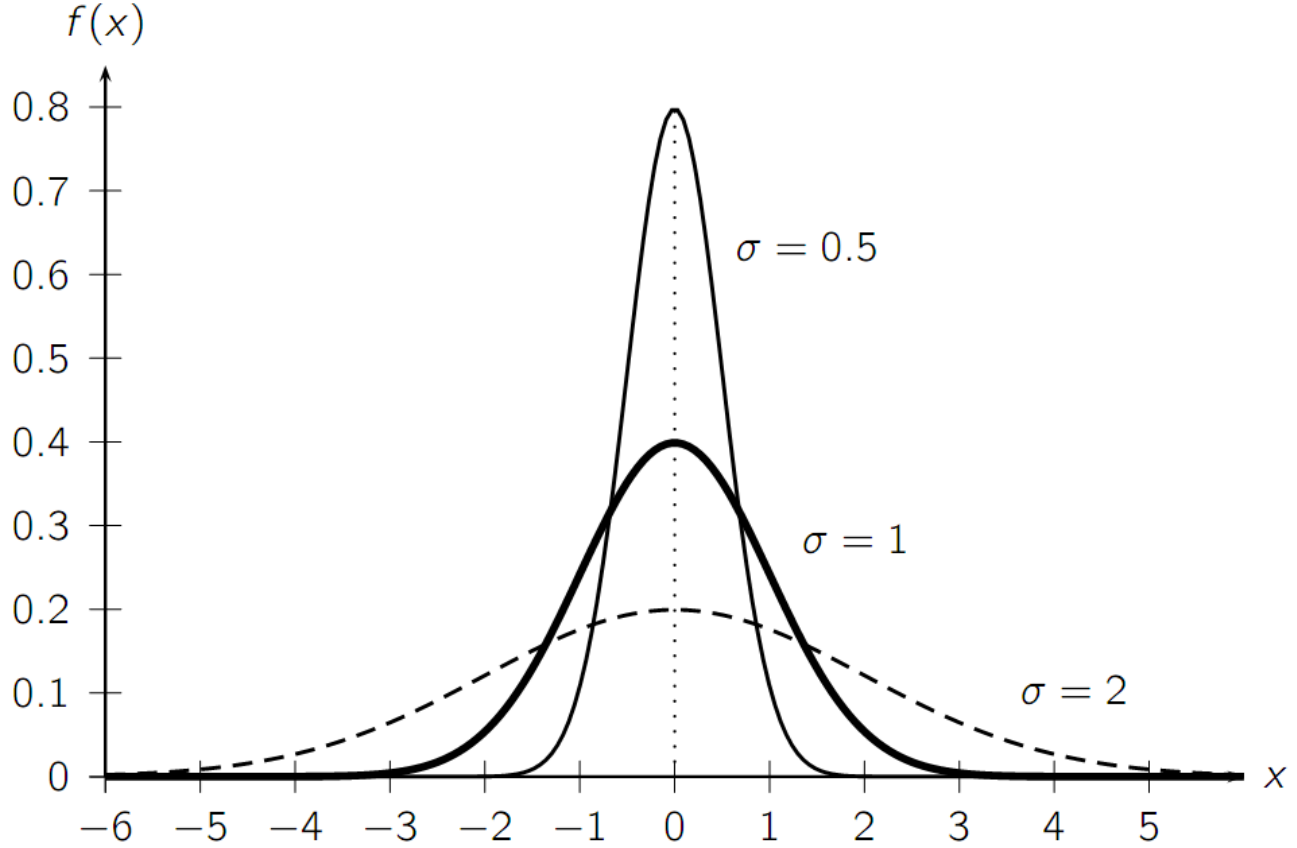
$$\begin{aligned} \sigma^2 = var(X) = E[(X-\mu)^2] &= E[X^2 - 2\mu X + \mu^2] \\ &= E[X^2] - 2\mu E[X] + \mu^2 = E[X^2] - 2\mu^2 + \mu^2 \\ &= E[X^2] - (E[X])^2 \end{aligned}$$

Sample Variance & Standard Deviation:

$$\hat{\sigma}^2 = \sum_x (x-\hat{\mu})^2 \hat{f}(x) = \sum_x (x-\hat{\mu})^2 \left(\frac{\sum_{i=1}^n I(S_i = x)}{n} \right) = \frac{\sum_{i=1}^n (S_i - \hat{\mu})^2}{n}$$

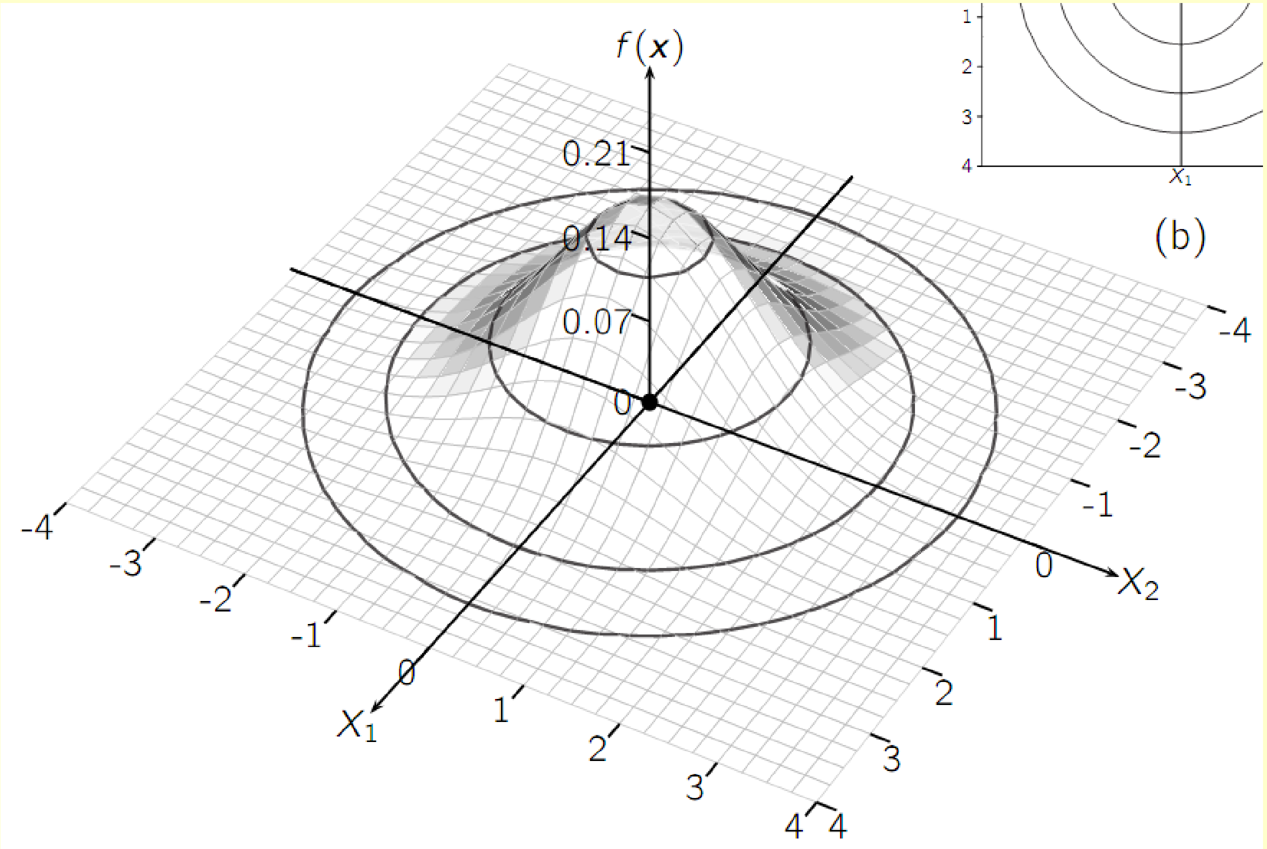
Univariate Normal Distribution

$$f(x|\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\}$$

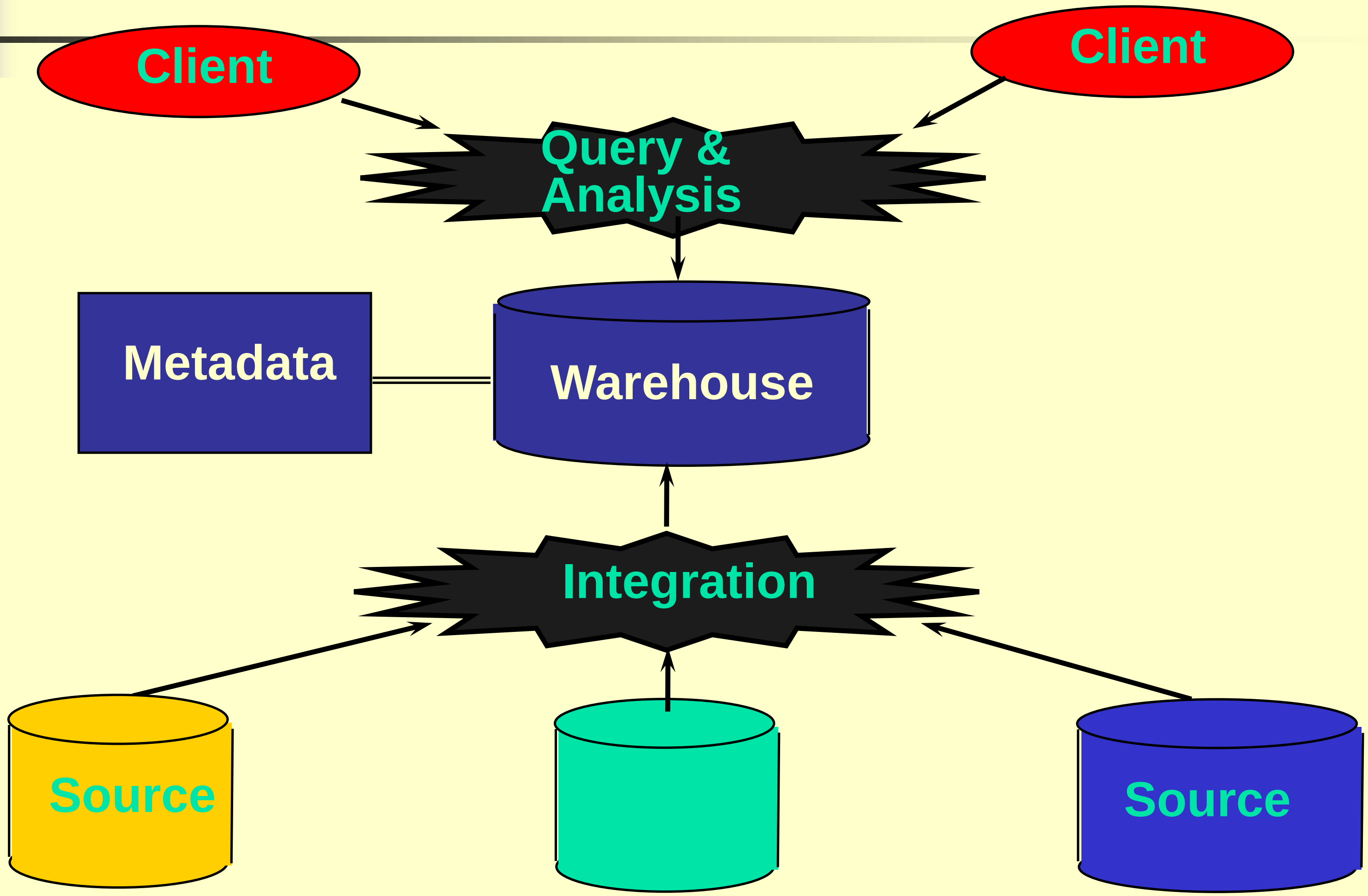


Multivariate Normal Distribution

$$f(\mathbf{x}|\boldsymbol{\mu},\boldsymbol{\Sigma}) = \frac{1}{(\sqrt{2\pi})^d\sqrt{|\boldsymbol{\Sigma}|}}\exp\left\{-\frac{(\mathbf{x}-\boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})}{2}\right\}$$



Warehouse Architecture

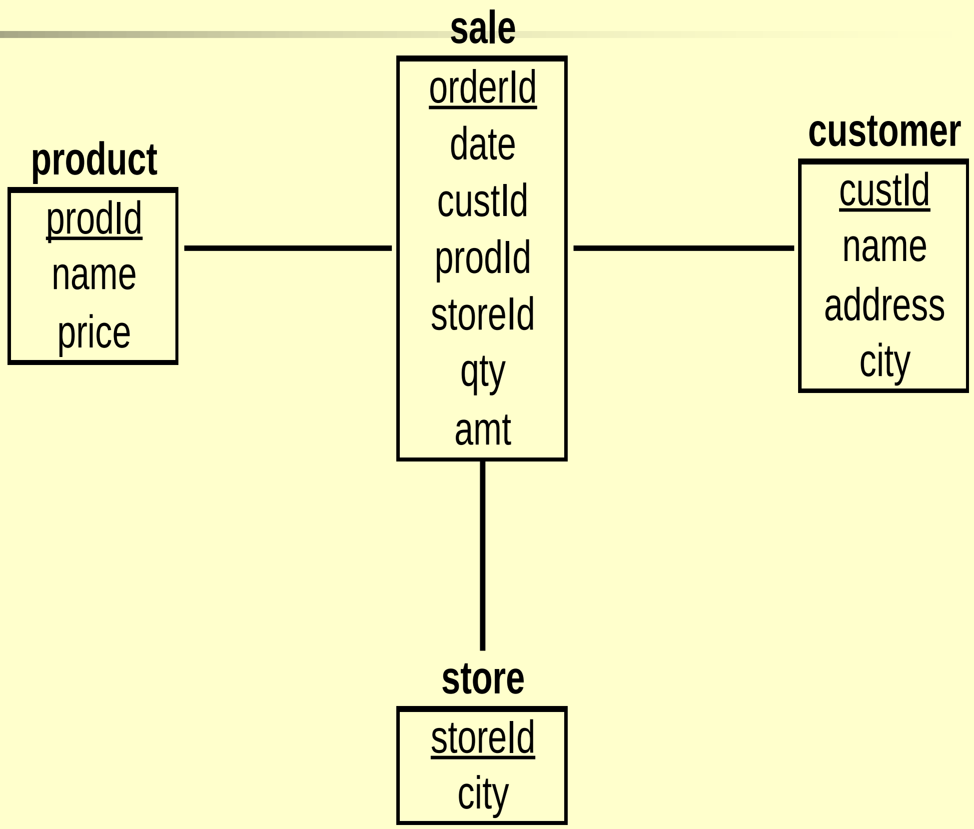


Star Schemas

- A *star schema* is a common organization for data at a warehouse. It consists of:
  1. *Fact table* : a very large accumulation of facts such as sales.
     - Often “insert-only.”
  2. *Dimension tables* : smaller, generally static information about the entities involved in the facts.

Terms

- Fact table
- Dimension tables
- Measures



Star

product	prodId	name	price
	p1	bolt	10
	p2	nut	5

store	storeId	city
	c1	nyc
	c2	sfo
	c3	la

sale	oderId	date	custId	prodId	storeId	qty	amt
	o100	1/7/97	53	p1	c1	1	12
	o102	2/7/97	53	p2	c1	2	11
	105	3/8/97	111	p1	c3	5	50

customer	custId	name	address	city
	53	joe	10 main	sfo
	81	fred	12 main	sfo
	111	sally	80 willow	la

Cube

Fact table view:

sale	prodId	storeId	amt
	p1	c1	12
	p2	c1	11
	p1	c3	50
	p2	c2	8

↔

Multi-dimensional cube:

	c1	c2	c3
p1	12		50
p2	11	8	

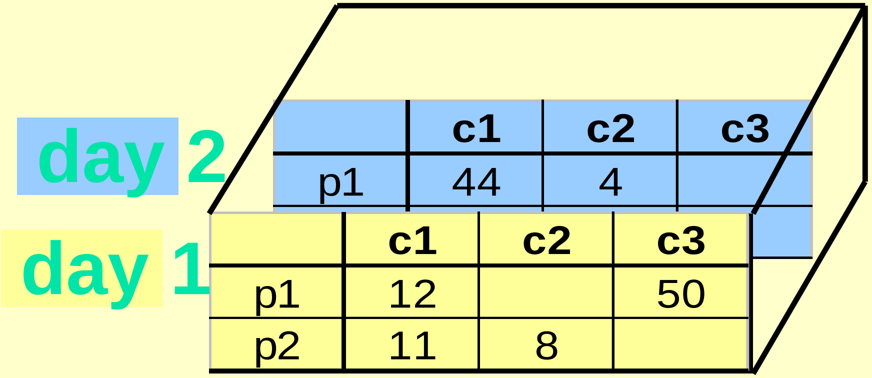
dimensions = 2

3-D Cube

Fact table view:

sale	prodId	storeId	date	amt
	p1	c1	1	12
	p2	c1	1	11
	p1	c3	1	50
	p2	c2	1	8
	p1	c1	2	44
	p1	c2	2	4

Multi-dimensional cube:



dimensions = 3

ROLAP vs. MOLAP

- ROLAP:
  Relational On-Line Analytical Processing
- MOLAP:
  Multi-Dimensional On-Line Analytical Processing

Aggregates

- Add up amounts for day 1
- In SQL: SELECT sum(amt) FROM SALE
  WHERE date = 1

sale	prodId	storeId	date	amt
	p1	c1	1	12
	p2	c1	1	11
	p1	c3	1	50
	p2	c2	1	8
	p1	c1	2	44
	p1	c2	2	4

⇨ **81**

Aggregates

- Add up amounts by day
- In SQL: SELECT date, sum(amt) FROM SALE
  GROUP BY date

sale	prodId	storeId	date	amt
	p1	c1	1	12
	p2	c1	1	11
	p1	c3	1	50
	p2	c2	1	8
	p1	c1	2	44
	p1	c2	2	4

ans	date	sum
	1	81
	2	48

Another Example

- Add up amounts by day, product
- In SQL: SELECT date, sum(amt) FROM SALE GROUP BY date, prodId

sale	prodId	storeId	date	amt
	p1	c1	1	12
	p2	c1	1	11
	p1	c3	1	50
	p2	c2	1	8
	p1	c1	2	44
	p1	c2	2	4

sale	prodId	date	amt
	p1	1	62
	p2	1	19
	p1	2	48

rollup →

← drill-down

Aggregates

- Operators: sum, count, max, min, median, ave
- "Having" clause
- Using dimension hierarchy
  - average by region (within store)
  - maximum by month (within date)

What is Data Mining?

- Discovery of useful, possibly unexpected, patterns in data
- Non-trivial extraction of implicit, previously unknown and potentially useful information from data
- Exploration & analysis, by automatic or semi-automatic means, of large quantities of data in order to discover meaningful patterns

Data Mining Tasks

- Classification [Predictive]
- Clustering [Descriptive]
- Association Rule Discovery [Descriptive]
- Sequential Pattern Discovery [Descriptive]
- Regression [Predictive]
- Deviation Detection [Predictive]
- Collaborative Filter [Predictive]

Classification: Definition

- Given a collection of records (*training set*)
  - Each record contains a set of *attributes*, one of the attributes is the *class*.
- Find a *model* for class attribute as a function of the values of other attributes.
- Goal: <u>previously unseen</u> records should be assigned a class as accurately as possible.
  - A *test set* is used to determine the accuracy of the model. Usually, the given data set is divided into training and test sets, with training set used to build the model and test set used to validate it.

Decision Trees

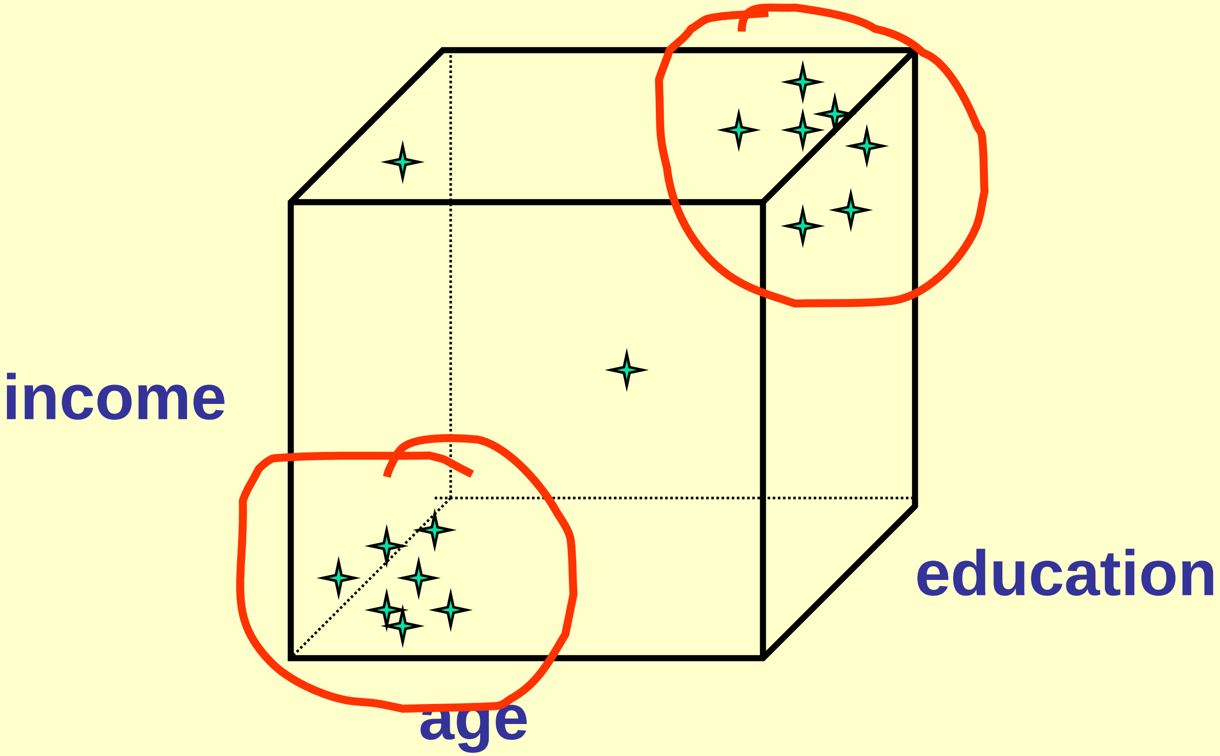
Example:

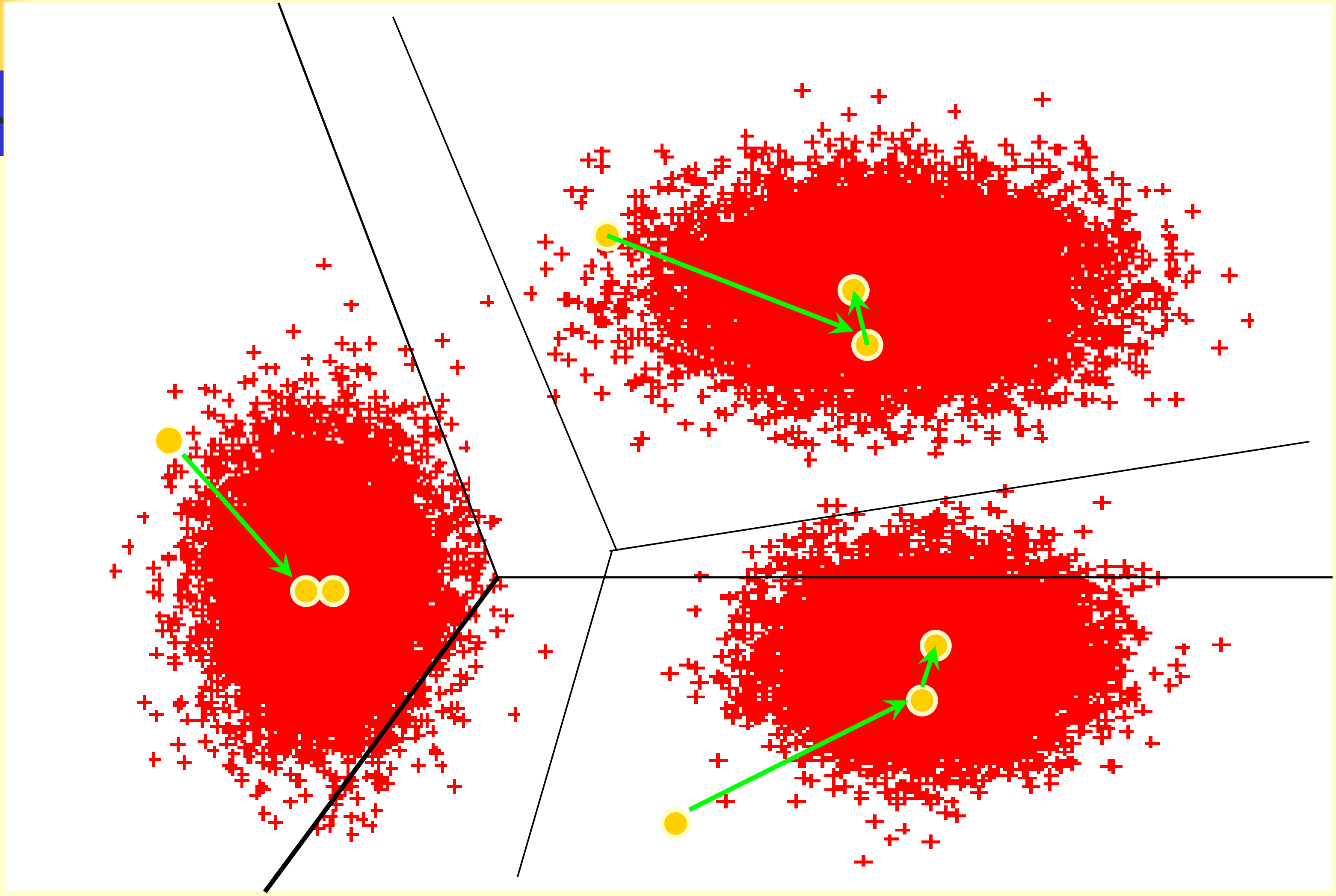
- **Conducted survey to see what customers were interested in new model car**
- **Want to select customers for advertising campaign**

sale	custId	car	age	city	newCar
	c1	taurus	27	sf	yes
	c2	van	35	la	yes
	c3	van	40	sf	yes
	c4	taurus	22	sf	yes
	c5	merc	50	la	no
	c6	taurus	25	la	no

training set

Clustering





Association Rule Mining

sales records:

transaction id	customer id	products bought
tran1	cust33	p2, p5, p8
tran2	cust45	p5, p8, p11
tran3	cust12	p1, p9
tran4	cust40	p5, p8, p11
tran5	cust12	p2, p9
tran6	cust12	p9

market-basket data

- **Trend: Products p5, p8 often bough together**
- **Trend: Customer 12 likes product p9**

Association Rule Discovery

- Marketing and Sales Promotion:
  - Let the rule discovered be

    {Bagels, … } --> {Potato Chips}
  - Potato Chips as consequent => Can be used to determine what should be done to boost its sales.
  - Bagels in the antecedent => can be used to see which products would be affected if the store discontinues selling bagels.
  - Bagels in antecedent *and* Potato chips in consequent => Can be used to see what products should be sold with Bagels to promote sale of Potato chips!
- Supermarket shelf management.
- Inventory Managemnt

Collaborative Filtering

- Goal: predict what movies/books/… a person may be interested in, on the basis of
  - Past preferences of the person
  - Other people with similar past preferences
  - The preferences of such people for a new movie/book/…
- One approach based on repeated clustering
  - Cluster people on the basis of preferences for movies
  - Then cluster movies on the basis of being liked by the same clusters of people
  - Again cluster people based on their preferences for (the newly created clusters of) movies
  - Repeat above till equilibrium
- Above problem is an instance of **collaborative filtering**, where users collaborate in the task of filtering information to find information of interest

Other Types of Mining

- **Text mining**: application of data mining to textual documents
  - cluster Web pages to find related pages
  - cluster pages a user has visited to organize their visit history
  - classify Web pages automatically into a Web directory
- **Graph Mining**:
  - Deal with graph data

Data Streams

- What are Data Streams?
  - Continuous streams
  - Huge, **Fast**, and Changing
- Why Data Streams?
  - The arriving speed of streams and the huge amount of data are beyond our capability to store them.
  - “Real-time” processing
- Window Models
  - Landscape window (Entire Data Stream)
  - Sliding Window
  - Damped Window
- Mining Data Stream

Streaming Sample Problem

- Scan the dataset once
- Sample K records
  - Each one has equally probability to be sampled
  - Total N record: K/N

Data Mining and Pattern Recognition for Large-Scale Scientific Data (Big Data)

We need an effective way to deal with data overload

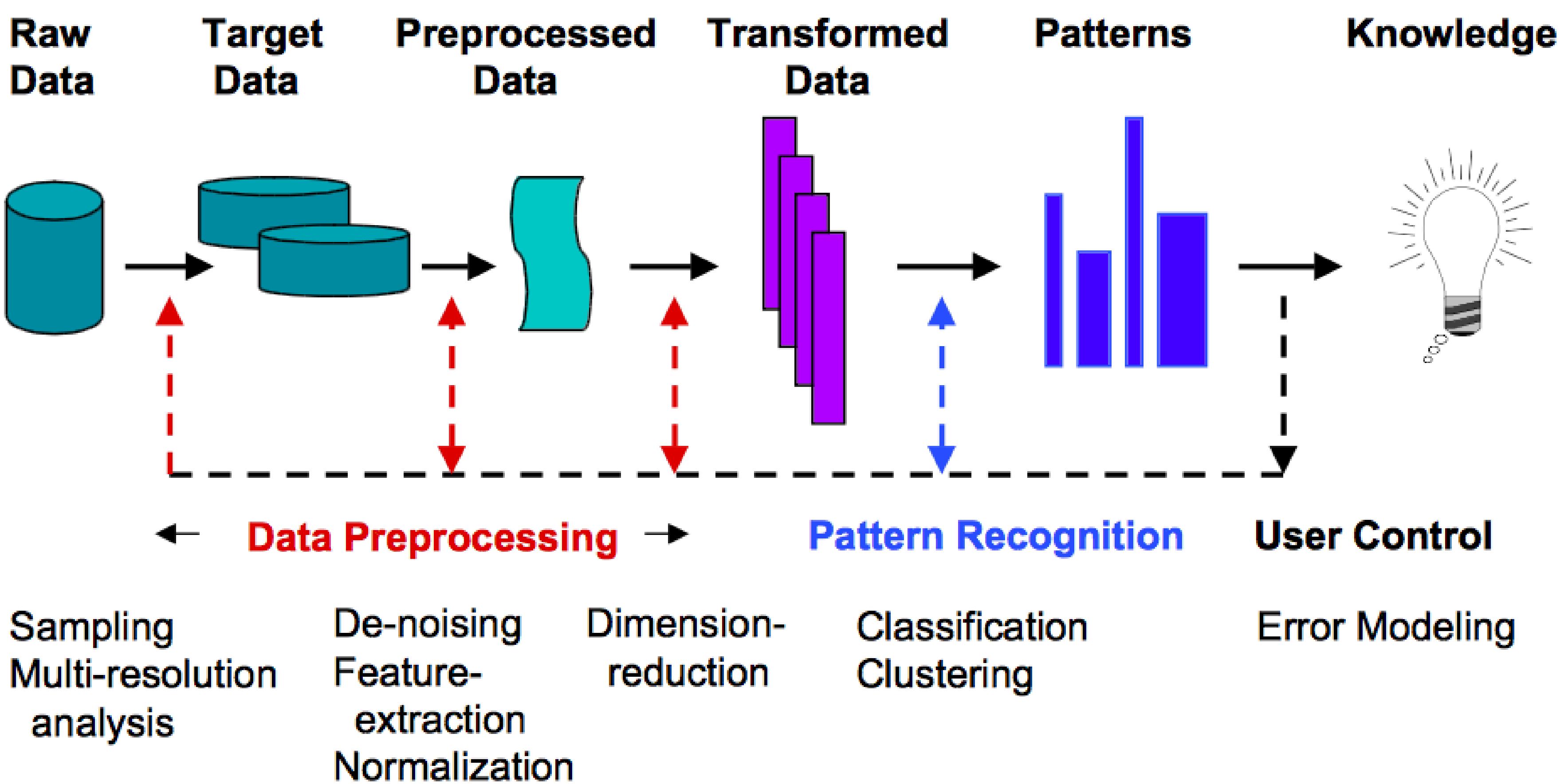
- Widening gap between data collection capabilities and data analysis abilities
  - Data from simulations, experiments, observations
  - Terabytes of data, soon to be petabytes
  - Complex data (images, time series data)
- Manual exploration and analysis is impractical
  - Poor utilization of resources
  - Potential loss of information

  => Need computational tools and techniques to work out automate the exploration and analysis of large, complex data sets

What do we mean by the terms Data Mining and Pattern Recognition?

- **Data Mining: Uncovering patterns, associations, anomalies, and statistically significant structures in data**
- **Pattern Recognition: Characterization of patterns in data**
- **Pattern: Arrangement or ordering with an underlying structure**
- **Feature: An extractable measurement or attribute**
- ***Images of Radio Emitting Galaxies with Bent-Double Morphology***

Data Mining: Key steps in an iterative and interactive process



Research for scaling data mining to large and complex data sets

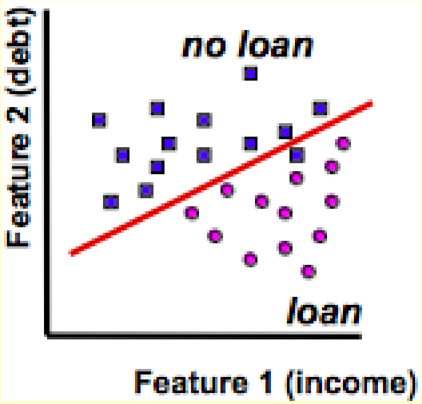
- Data pre-processing
- – Implement effective image processing algorithms
- – Investigate the use of multi-resolution analysis
- – Research methods for dimension reduction
- Pattern recognition algorithms
- – Consider different algorithms for an application
- – Implement in an object-oriented framework
- – Research ways of making them more effective and efficient
- – Examine accuracy versus computational effort issues
- Parallel implementation

Data pre-processing: a time-consuming but critical first step

- **Extraction of features:** image processing and wavelets
  - De-noising (noise elimination)
  - Multi-resolution analysis
- **Dimension reduction:** identification of key features
  - Features with greatest variance
    - Principal component analysis

Pattern Recognition: need for scalable classification and clustering algorithms

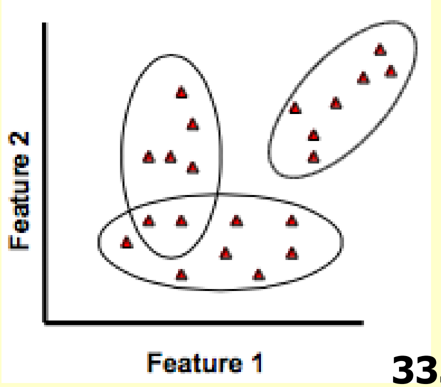
Classification: learn a function to map a data item into one of several predefined classes



- **Neural networks**
  - **Genetic algorithms**
  - **Simulated annealing**

Clustering: a task that identifies a finite set of clusters to describe the data

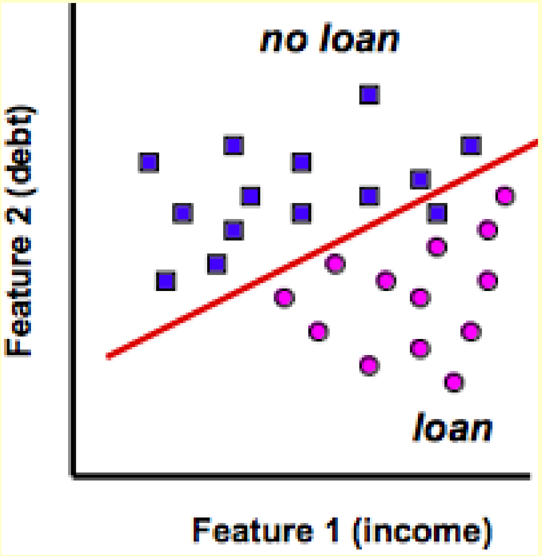
- **Graph theoretic techniques**
  - **Hypergraph partitioning**
  - **Promising for high dimensional data**



Pattern Recognition: need for efficient, accurate, and scalable classifiers

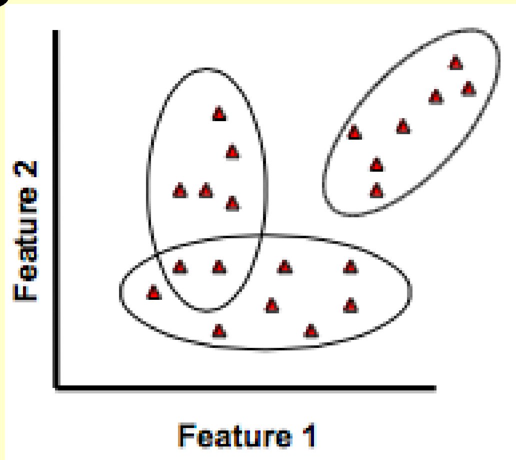
Classification: learning a function that maps a data item into one of several pre-defined classes

- **Neural networks: avoid local minima – Genetic algorithms – Simulated annealing**
- **Decision trees – attribute selection**
  - **– tree pruning**
- **Hybrid algorithms – techniques for combining classifiers**



Pattern Recognition: need for scalable and interpretable clustering algorithms

- **Clustering: a descriptive task that seeks to identify a finite set of clusters to describe the data**
- **Implement known techniques**
  - **k-means**
  - **fuzzy k-means**
  - **k-nearest-neighbors**
- **Graph theoretic techniques**
  - **hypergraph partitioning**
  - **initial promise for high dimensional data**



Large-scale pattern recognition can benefit several applications

- Visualization
- Computational steering
- Computer Security
- Verification and validation
- Global climate modeling
- Astrophysics (MACHO and FIRST)
- And so on …

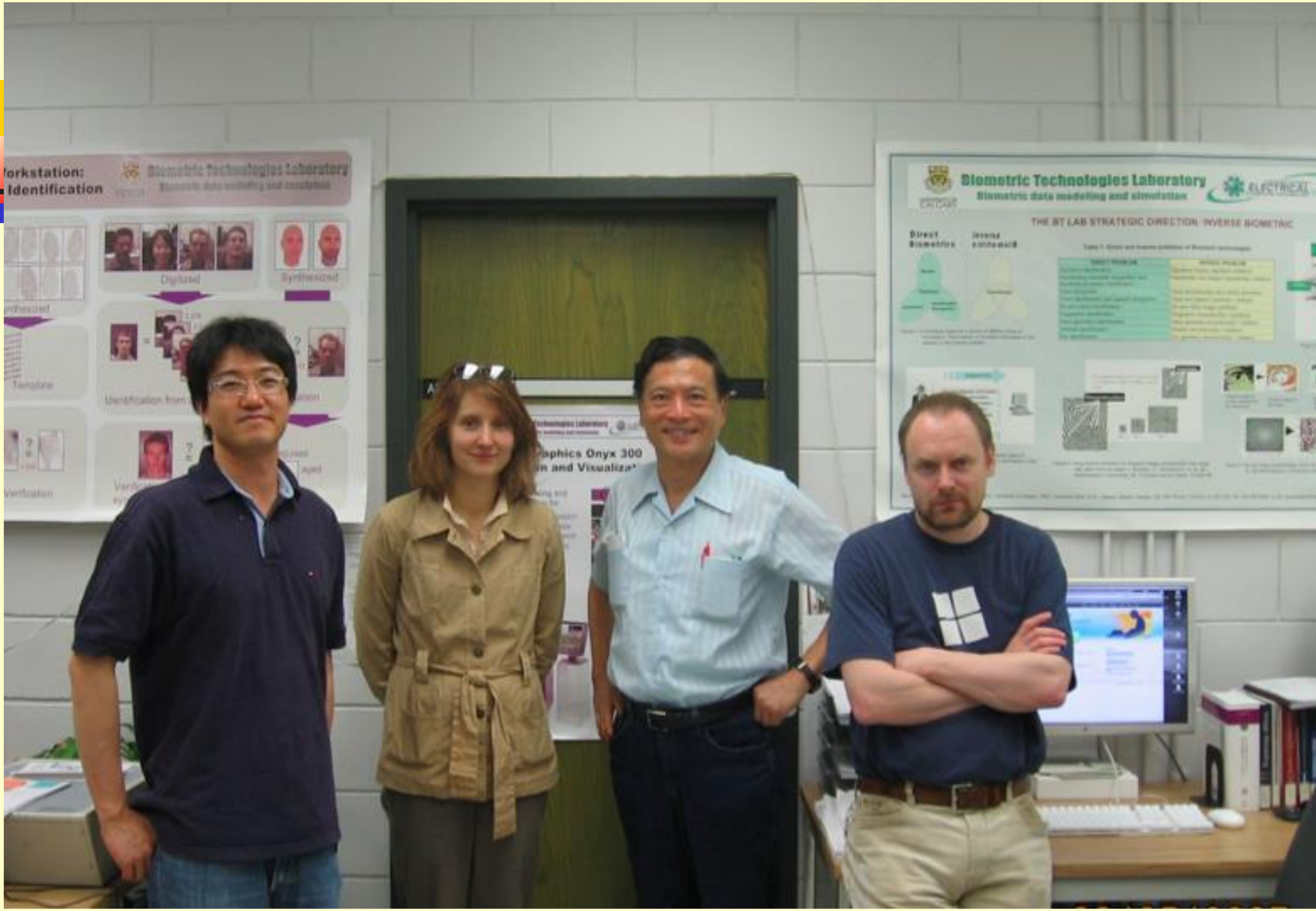
=> A capability for large-scale pattern recognition will strengthen our ability to perform science by providing an effective way to cope with data overload.

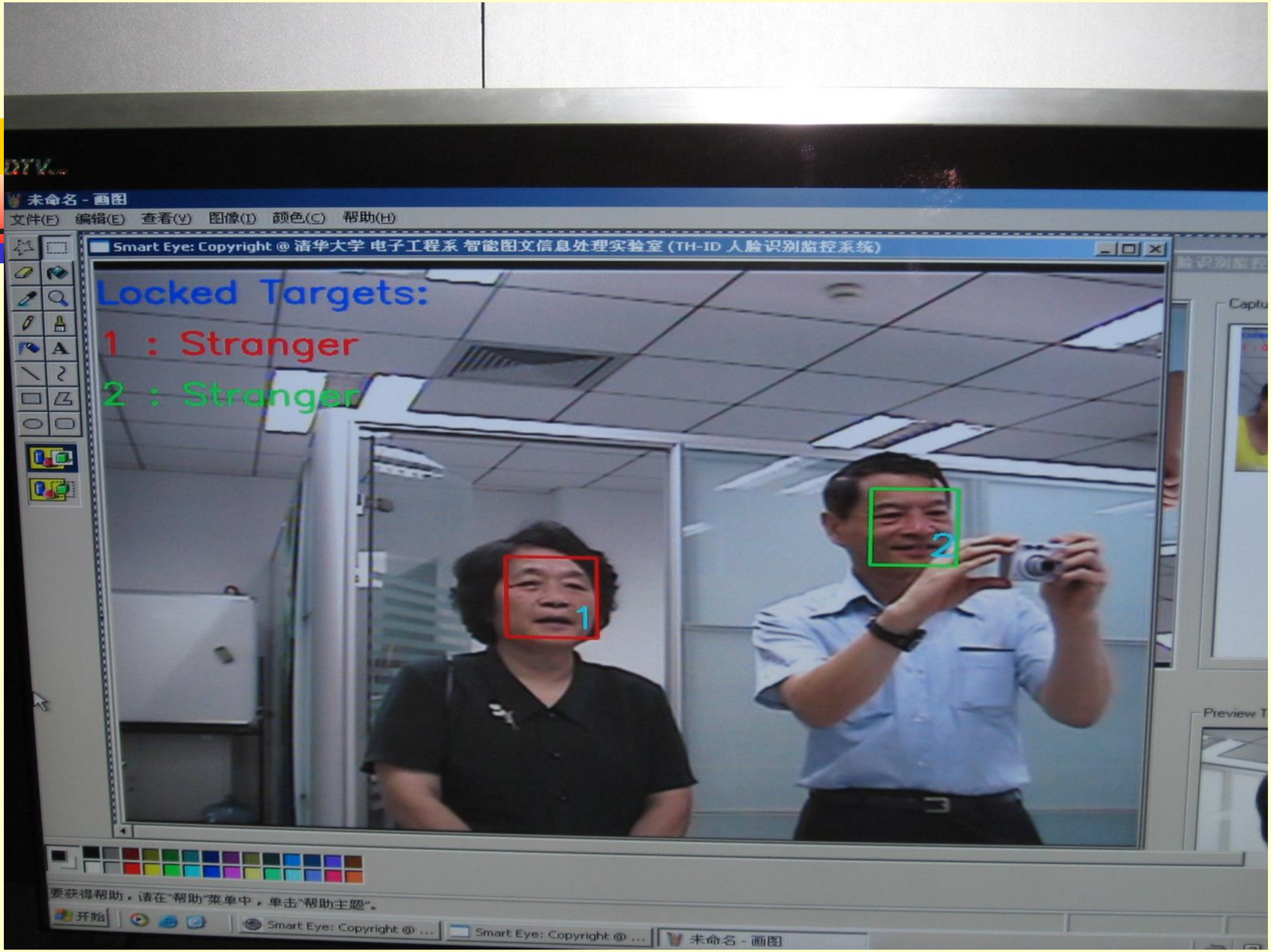
- Mark **Gahegan,** Centre for eResearch & Computer Science, University of Auckland
- **http://www.llnl.gov/CASC/sapphire**
- **kamath2@llnl.gov**

- Visualization in Big Data: A tool for pattern recognition in data stream.
- Victor Hugo Andrade Soares, Graduate in Information Systems, UFV , Joelson Ant^onio dos Santos, Graduate in Information Systems, UFV and Murilo Coelho Naldi, Phd. Adjunct Professor-III, UFV {victorhugoasoares, joelsonn.santos}@gmail.com, murilocn@ufv.br
- Revista de Sistemas de Informac ao da FSMA
  n. 15 (2015) pp. 30-39

Automation ?

Berlin, Germany (Deutschland)


Identification
Biometric Technologies Laboratory
Digitized
Synthesized
Template
Biometric Technologies Laboratory
Biometric data modeling and simulation
THE BT LAB STRATEGIC DIRECTION: INVERSE BIOMETRIC


未命名 - 画图
文件(F) 编辑(E) 查看(V) 图像(I) 颜色(C) 帮助(H)
Smart Eye: Copyright @ 清华大学 电子工程系 智能图文信息处理实验室 (TH-ID 人脸识别监控系统)
Locked Targets:
1 : Stranger
2 : Stranger
1
2
要获得帮助，请在"帮助"菜单中，单击"帮助主题"。
开始
Smart Eye: Copyright @ ...
Smart Eye: Copyright @ ...
未命名 - 画图

Sorry, They got the wrong person,
Prof. Theodo Pavidlis vs Bin Laden

Three Illustrations of Artificial Intelligence Applications: Distributive Intelligence

http://www.youtube.com/watch?v=Lo8xwNaHgBE

Bangkok Food Market: A Train Runs Through It

http://www.youtube.com/watch?v=TKjuaFE-zAY Firebrigade life save auction

http://www.youtube.com/watch?v=n_1apYo6-Ow Eating Machine

A Turing Machine – Overview

http://www.youtube.com/watch?v=E3keLeMwfHY

--- (Church) Turing Thesis

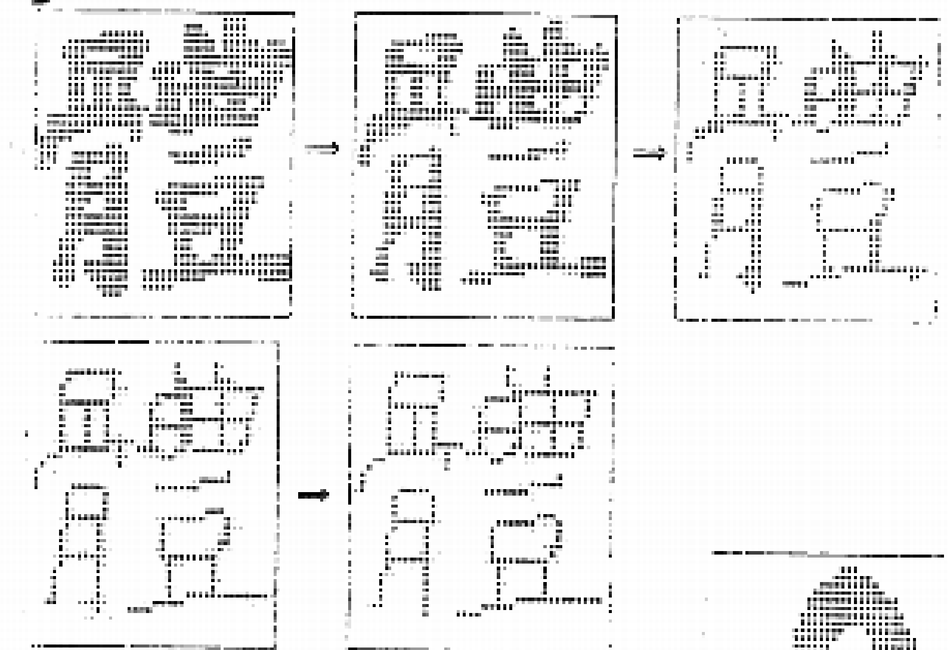
"Every effectively computable function is Turing Computable"

Robotic Walking Legs

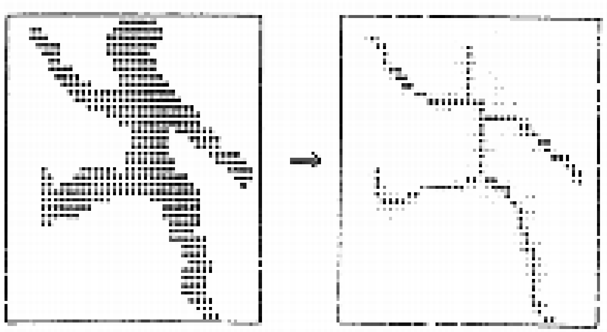
http://www.youtube.com/user/DynamicLegLocomotion

http://www.youtube.com/watch?v=xlOwk6_xpWo&feature=c4-overview-vl&list=PLF6F8912BDCE92E60

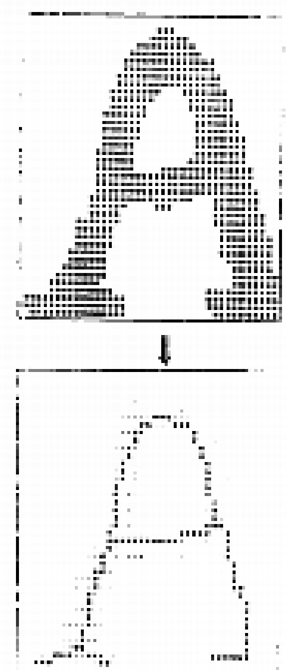
Thinning (Skeletonization): For Line-Drawing PR



The Chinese Character "龍"



A moving body



The English letter "A"

THINNING
(Skeletonization)