Associative tracking and recognition in video

Dmitry O. Gorodnichy
Institute for Information Technology,
National Research Council Canada
http://synapse.vit.iit.nrc.ca/memory

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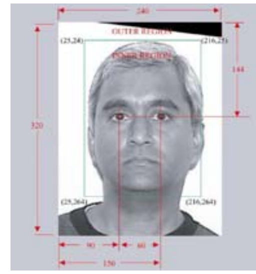
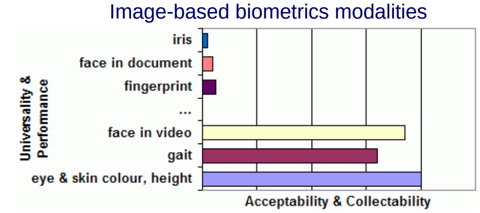
Proper treatment of video-based tasks

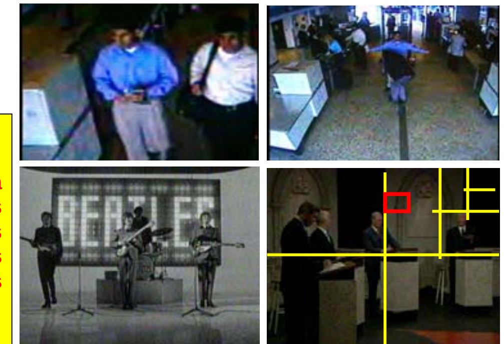
ICAO-conformed passport photograph (presently used for forensic identification)





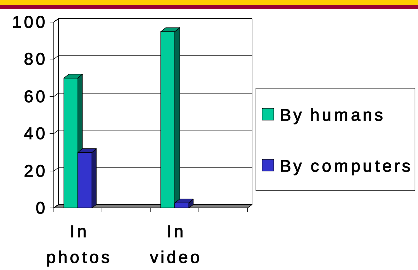
Photographic facial data and video-based facial data are two different modalities:
→ different nature of data
→ different biometrics
→ different approaches
→ different applications
→ different testing benchmarks

❖ In video: faces ***are meant to be*** of low quality and resolution (~ 10-20 pixels IOD)



Images from surveillance cameras (of 11/9 hijackers) and TV.
NB: VCD is 320x240 pixels

Proper tasks for Video Recognition



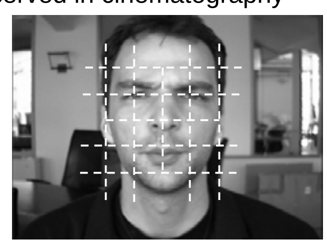
Face recognition systems performance
(from NATO Biometrics workshop, Ottawa, Oct. 2004)

Goal:
– NOT *"in making video data of better quality"* (as seen by Face Recognition Grand Challenge – www.frvt.com),
– BUT in **finding approaches & *applications* most suited for low-quality video-based data**

Good applications of video recognition (esp. wrt faces)
1. Multi-object tracking (in particular, multi-face tracking)
   a. Back-tracking,
   b. Multi-camera tracking: simultaneous and in sequence
   ASSOCIATIVE TRACKING
2. Recognize what has been already seen
   – limited class number classification / Video annotation
   ASSOCIATIVE RECOGNITION

Applicability of 160x120 video

According to face anthropometrics
-studied on BioID database
-tested with Perceptual Vision interfaces
-observed in cinematography



Face size	½ image	¼ image	1/8 image	1/16 image
In pixels	80x80	40x40	20x20	10x10
Between eyes-IOD	40	20	10	5
Eye size	20	10	5	2
Nose size	10	5	-	-
FS	√	√	√	b
FD	√	√	b	-
FT	√	√	b	-
FL	√	b	-	-
FER	√	√	b	-
FC	√	√	b	-
FM / FI	√	√	-	-

FS,FD,FT,FL,FER,FC,FM/I = face segmentation, detection, tracking, localization, expression recognition, classification, memorization/identification

√– good
b – barely applicable
- – not good

Main conclusions for video-surveillance-based biometrics:

1. If IOD < 10, no face-based biometrics is possible. Use body biometrics !
2. If IOD > 10, face-based recognition is possible, but mainly for limited #faces !

Photos vs Video

Photos:
- **High spatial resolution**
- **No temporal knowledge**

Video:
- **Low spatial resolution**
- **High temporal resolution**

(Individual frames of poor quality)

E.g. faces:

Photos:
- in controlled environment *(similar to fingerprint registration)*
- "nicely" forced-positioned
- 60 pixels IOD

Video:

Taken in unconstrained environment (in a "hidden" camera setup)
- don't look into camera
- even don't face camera
- 10-20 pixels IOD (intra-ocular distance)

Yet (for humans), video (even of low quality) is often much more informative and useful than a photograph !

Video processing implies accumulation over time:
in recognition and esp. in learning!

Why associative memorization?

Techniques to accumulate knowledge (i.e. learn data) over time:

- Histograms – simple count of the same values (in 1D, 2D)
- Next level: Correlograms (geometric histogram) – count of pixels and their inter-relationships
- NEXT level: Associative memorization – not just a count of pixel values and pair-wise pixel relationships, but also takes in account the entire picture of the data: PAST DATA and ALL PRESENT DATA

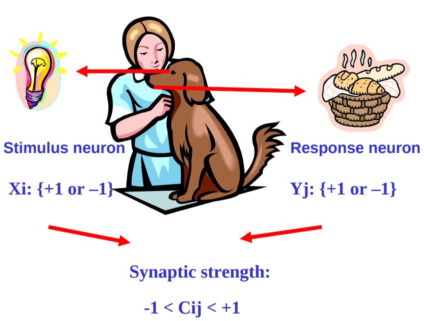
All of these learn data in real-time
All of these recognize data in real-time

From visual image → to saying name

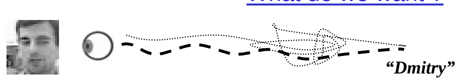
From neuro-biological prospective, memorization and recognition are two stages of the associative process:

From receptor stimulus R → to effector stimulus E

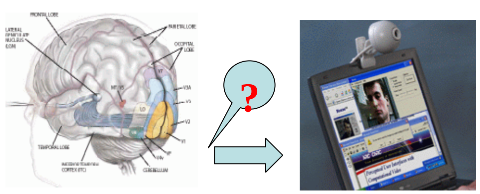
Main associative principle



What do we want ?



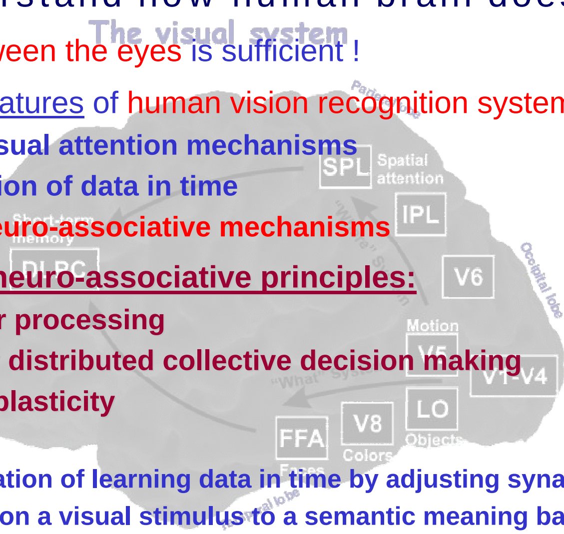
- To model associative processing



Main question of learning: ***How to update synaptic weights Cij as f(X,Y) ?***

Keys to resolving association problem

To understand how human brain does it



I. 12 pixels between the eyes is sufficient !

II. Main three features of human vision recognition system:

1. **Efficient visual attention mechanisms**
2. **Accumulation of data in time**
3. **Efficient neuro-associative mechanisms**

III. **Main three neuro-associative principles:**

3.1 Non-linear processing

3.2 Massively distributed collective decision making

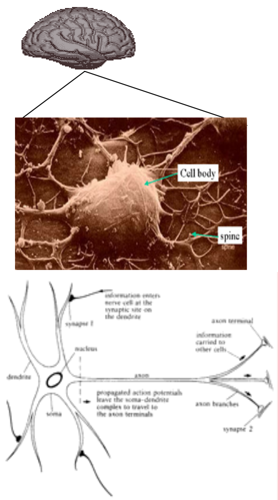
3.3 Synaptic plasticity

for:

a) accumulation of learning data in time by adjusting synapses

b) association a visual stimulus to a semantic meaning based on the computed synaptic values

Lessons from biological memory



- Brain stores information using synapses connecting the neurons.
- In brain: *10^{10} to 10^{13}* interconnected neurons
- Neurons are either in rest or activated, depending on values of other neurons Yj and the strength of synaptic connections: Yi={+1,-1}
- Brain is a network of "binary" neurons evolving in time from initial state (e.g. stimulus coming from retina) until it reaches a stable state – attractor.

$$Y_i(t+1) = \mathrm{sign}\left(\sum_{j=1}^{N} C_{ij} Y_j(t)\right)$$

- Attractors are our memories!

Refs: Hebb'49, Little'74,'78, Willshaw'71

Learning process

Learning rules: *From biologically plausible to mathematically justifiable*

$$\boxed{C_{ij}^{m} = C_{ij}^{m-1} + \Delta C_{ij}^{m}}$$

- Hebb (correlation learning): $\Delta C_{ij}^{m} = \frac{1}{N} V_i^m V_j^m$ is of form $\Delta C_{ij}^{m} = \alpha F(V_i^m, V_j^m)$
- Better however is of form: $\Delta C_{ij}^{m} = \alpha F(C_{ij}^{m-1}, V_i^m, V_j^m)$
- Should be of form: $\boxed{\Delta C_{ij}^{m} = \alpha F(C^{m-1}, V^m)}$
- Widrow-Hoff's (delta) rule: $\mathbf{C}^{k+1} = \mathbf{C}^{k} + \alpha(\vec{V} - \mathbf{C}^{k}\vec{V})\vec{V}^T$
- **We use *Projection Learning* rule:** $C_{ij}^{m} = C_{ij}^{m-1} + \frac{(v_i^m - s_i^m)(v_j^m - s_j^m)}{E^2}$, $E^2 = \|\vec{V}^m - \mathbf{C}^{m-1}\vec{V}^m\|^2$

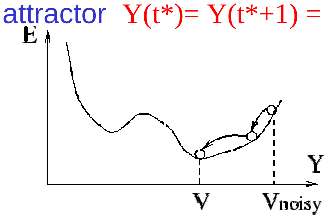
It is most preferable, as it is:

- both incremental and takes into account relevance of training stimuli and attributes;
- guaranteed to converge (obtained from stability condition $V^m = CV^m$);
- fast in both memorization and recognition; also called *pseudo-inverse rule*: $\mathbf{C} = \mathbf{V}\mathbf{V}^{+}$

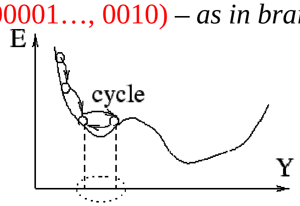
Refs: Amari'71,'77, Kohonen'72, Personnaz'85, Kanter-Sompolinsky'86,Gorodnichy'95-'99

Recognition process

- Each frame initializes the system to state Y(0) = (01000011…, 0000) from which associative recall is achieved as a result of convergence to an attractor Y(t*)= Y(t*+1) = (01000001…, 0010) – *as in brain…*



Static attractor



Dynamic attractor

- Effector component of attractor (0010) is analyzed. Possible outcomes: S00 (none of nametag neurons fire), S10 (one fires) and S11 (several fire)
- Final decision is made over several frames:

```
0000100000
0000000000
0000100000
0000100000
```

```
0000100000
0010100000
0000100000
0000100000
```

```
0000100000
0000010000
0000100000
0000100000
0000100000
```

(e.g. this is ID=5 in all these cases)

From video input to neural output

1. face-looking regions are detected using rapid classifiers.
2. they are verified to have skin colour and not to be static.
3. face rotation is detected and rotated, eye aligned and resampled to 12-pixels-between-the-eyes resolution face is extracted.
4. extracted face is converted to a binary feature vector (Receptor)
5. this vector is then appended by nametag vector (Effector)
6. synapses of the associative neuron network are updated

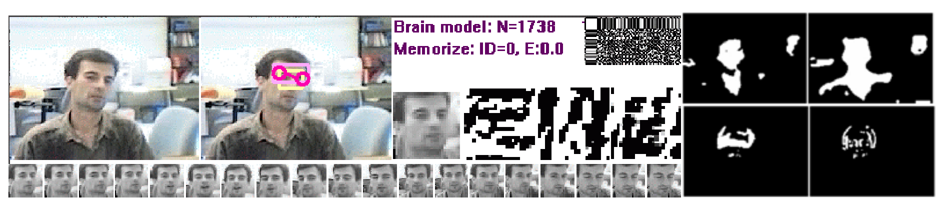


Table 2: Neural response in time.

```
Recognition of 05b.avi
*22 -1.0 -0.6 -1.2 -0.7 -0.7 +0.1 -0.5 -1.1 -1.1 -0.7 -1.0
.24 -1.1 -0.6 -1.2 -0.8 -0.8 -0.3 -0.7 -1.3 -1.0 -0.5 -1.3
*26 -1.1 -1.0 -1.0 -0.6 -1.0 +0.2 -0.6 -1.2 -1.1 -0.8 -1.6
...
*70 -1.0 -0.5 -1.1 -0.3 -1.0 +0.4 -0.9 -1.2 -1.3 -1.1 -0.8
+72 -0.8 -0.1 -1.1 +0.2 -1.3 +0.1 -0.6 -0.9 -0.5 -0.9 -0.7
.74 -1.1 -0.5 -1.0 -0.3 -1.3 -0.3 -1.0 -1.0 -1.0 -0.9 -0.8
```

Time weighted decision:

a) neural mode: all neurons with PSP greater than a certain threshold Sj>S0 are considered as ``winning";
b) max mode: the neuron with the maximal PSP wins;
c) time-filtered: average or median of several consecutive frame decisions, each made according to a) or b), is used;
d) PSP time-filtered: technique of a) or b) is used on the averaged (over several consecutive frames) PSPs instead of PSPs of individual frames;
e) any combination of the above.

S10 - The numbers of frames in 2nd video clip of the pair, when the face in a frame is associated with the correct person (i.e. the one seen in the 1st video clip of the pair), without any association with other seen persons. - best (non-hesitant) case

S11 - ... when the face is not associated with one individual, but rather with several individuals, one of which is the correct one. - good (hesitating) case

S01 - ... when the face is associated with someone else - worst case

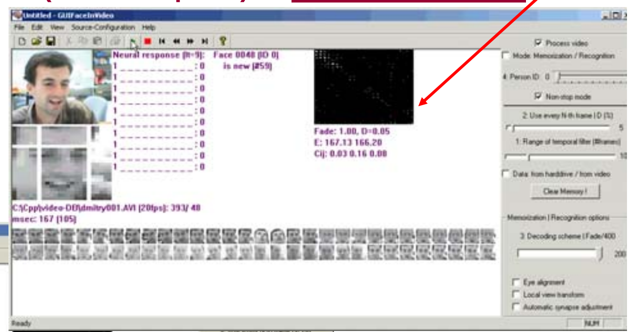
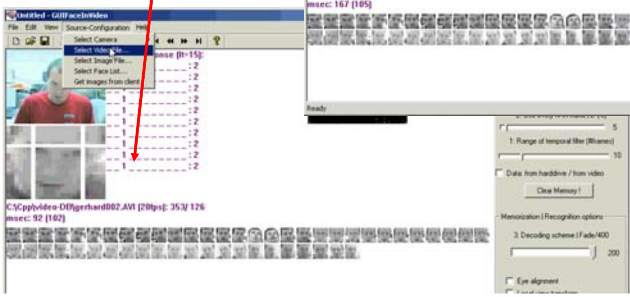
S02 - ... when the face is associated with several individuals (none of which is correct) - wrong but hesitating case

S00 - ... when the face is not associated with any of the seen faces - not bad case

DEMO 1: User / Actor recognition

- ***Downloadable: Works with your web-cam or .avi file***
- **Shows tuning of name-stimulus associations (synaptic matrix) as you track a face in memorization (compare to 2D Histogram image)**
- **Shows associative recall (neurons spikes) as your track a face in recognition (compare to Histogram back projection)**

Limitation: memorizes < ~10 users (classes)

Tested using TV video and database

- **TV programs annotation**

(Recognize 4 party leaders in a show)

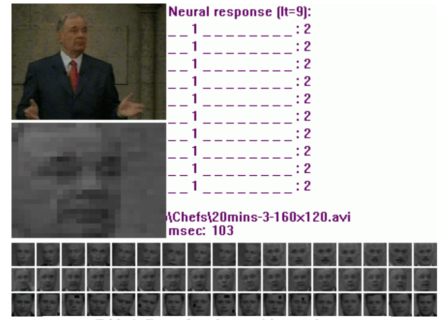


Table 1: Frame-based recognition results.

a) Basic case (N=1739):	S10	S11	S01	S 00	S02
ID 1	49	4	0	1	0
ID 2	175	0	3	8	0
ID 3	288	1	2	19	0
ID 4	163	1	11	98	0
ID 5	84	2	3	36	0
ID 6	202	2	3	15	0
ID 7	208	3	12	17	0
ID 8	353	3	8	38	0
ID 9	191	8	30	62	8
ID 10	259	0	10	24	17
Total:	1972	24	82	318	25
ID 0 (unknown face)	0	1	70	112	15

- IIT-NRC 160x120 video-based facial database (one video to memorize, another to recognize)

DEMO 2: Squash game

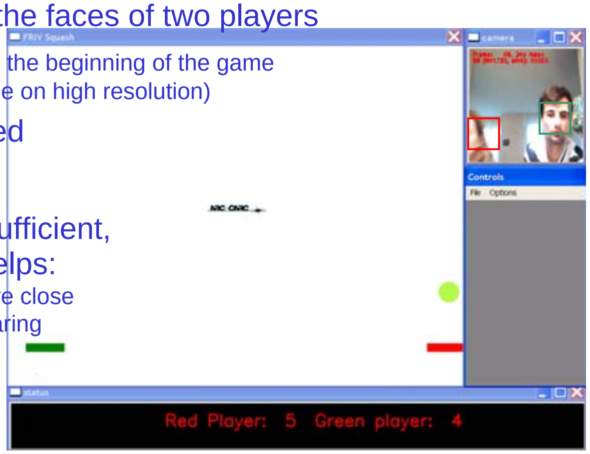
Two-face associative tracker.

(Face motion controls the squash racket (rectangle) to bounce the ball)

Setup: ~1 meter from camera. Game starts when two faces are detected.

- Extension of the face memorizing/recognizing demo to the case of two classes – the faces of two players
- Faces are first learnt in the beginning of the game (slow, due to FD in every frame on high resolution)

  then individually tracked by the learnt colour histogram reprojection (fast)
- When tracking is not sufficient, associative memory helps:
  - when reprojection areas are close
  - after occlusion or disappearing
- Synapses are updated
  - once in a while
  - when both are detected



More details

- Acknowledgements:
  - “Squash” game is implemented by Jason Salares (Carlton University)

- References:

  - Dmitry O. Gorodnichy, **Editorial: Seeing faces in video by computers.** *Image and Video Computing*, Vol. 24, No. 6 (Special Issue on Face Processing in Video Sequences, Editor: D.O. Gorodnichy), pp. 551-556, June 2006.
  - Dmitry O. Gorodnichy. **Video-based framework for face recognition in video.** Second Workshop on Face Processing in Video (FPiV'05) in Proc. of CRV'05, pp. 330-338, Victoria, BC, Canada, 9-11 May, 2005.
  - D.O. Gorodnichy, **Projection learning vs correlation learning: from Pavlov dogs to face recognition.** AI'05 Workshop on Correlation learning, Victoria, BC, Canada, May 8-12, 2005.

- **Open Source Associative Memory Library:**

  http://synapse.vit.iit.nrc.ca/memory/pinn