ORIGINAL PAGE
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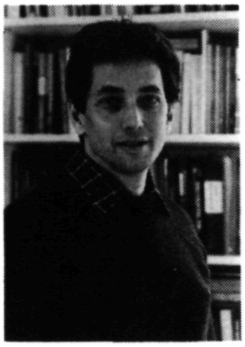

Stephen Grossberg, Ph.D.

Boston University
Boston, Massachusetts

Dr. Grossberg received his graduate training at Stanford University and Rockefeller University, and was a professor at the Massachusetts Institute of Technology before assuming his present position at Boston University. He is professor of mathematics, psychology, and biomedical engineering at Boston University, where he founded and is the director of the Center for Adaptive Systems. He is also the director of the university's new graduate program in cognitive and neural systems. In addition, Dr. Grossberg is president of the International Neural Network Society and coeditor-in-chief of the society's journal, Neural Networks. During the past few decades, Dr. Grossberg and his colleagues at the Center for Adaptive Systems have pioneered and developed a number of the fundamental principles, mechanisms, and architectures that form the foundation for contemporary neural network research.

EMERGENT INVARIANTS OF SELF-ORGANIZING NEURAL NETWORKS FOR PATTERN RECOGNITION AND ROBOTICS

Abstract

Described are several real-time neural network architectures that are capable of self-organizing invariant behavioral properties in applications to sensory pattern recognition, cognitive information processing, and adaptive sensory-motor control. These invariants include a similarity invariant that arises in adaptive pattern recognition and cognitive information processing; a position invariant that arises in determining the location of a target with respect to the head; and a synchrony invariant that enables motor systems with multiple degrees of freedom, such as arms and speech articulators, to generate flexible and synergetic planned movements.

EMERGENT INVARIANTS OF SELF-ORGANIZING NEURAL NETWORKS FOR PATTERN RECOGNITION AND ROBOTICS

Stephen Grossberg

A lecture delivered at
The 1988 First Joint Technology Workshop
on Neural Networks and Fuzzy Logic

May 2, 1988
Lyndon B. Johnson Space Center
Houston, Texas

EMERGENT INVARIANTS

A KEY PROBLEM OF INTELLIGENT BEHAVIOR

SELF-ORGANIZED

DISCOVERY

LEARNING

PRODUCTION

OF INVARIANT BEHAVIORAL PROPERTIES BY A REAL-TIME NEURAL NETWORK

MANY DIFFERENT TYPES

INVARIANT	BEHAVIOR
SIMILARITY	RECOGNITION
POSITION	TARGETING
SYNCHRONY	MULTI-JOINT MOVEMENT

SIMILARITY INVARIANT RECOGNITION

HOW DOES A NEURAL NETWORK LEARN TO RECOGNIZE SIMILAR PATTERNS AS EXEMPLARS OF A SINGLE CATEGORY?

ADAPTIVE RESONANCE THEORY (1976)
A R T

1. EXPLAIN AND PREDICT
BEHAVIORAL AND NEURAL DATA

PSYCHOLOGICAL REVIEW, 1980
1982
1986

STUDIES OF MIND AND BRAIN,
REIDEL, 1982

THE ADAPTIVE BRAIN, VOLS. I + I
ELSEVIER/NORTH-HOLLAND, 198

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2. MATHEMATICAL + COMPUTATIONAL
ANALYSES
ARCHITECTURE DEVELOPMENT

GAIL CARPENTER, ART 1 + 2

ADAPTIVE RESONANCE THEORY

STABLE SELF-ORGANIZATION OF RECOGNITION CODES FOR ARBITRARY SEQUENCES OF ANALOG OR DIGITAL INPUT PATTERNS.

(GAIL CARPENTER)

ART 1 - DIGITAL WORLD

(<u>CVGIP</u>, JAN., 1987)

ART 2 - ANALOG OR DIGITAL WORLD

(<u>APPLIED OPTICS</u>, NOV., 1987)

WHY DO WE PAY ATTENTION?

WHY DO WE LEARN EXPECTATIONS ABOUT THE WORLD?

HOW DO WE COPE SO WELL WITH UNEXPECTED EVENTS?

— WHEN WE ARE ON OUR OWN, WITHOUT A TEACHER?

HOW DO WE KNOW WHAT COMBINATIONS OF FACTS

ARE PREDICTIVE?
IRRELEVANT?

HOW DO WE QUICKLY RECOGNIZE FAMILIAR FACTS

WITHOUT HAVING TO SEARCH EVERYTHING ELSE THAT WE KNOW

MAIN IDEA

TOP-DOWN ATTENTIVE FEEDBACK
ENCODES

LEARNED EXPECTATIONS
THAT

SELF-STABILIZE LEARNING
IN RESPONSE TO

ARBITRARY TEMPORAL SEQUENCE
OF INPUT SPATIAL PATTERNS

IN

REAL-TIME

ATTENTIVE INFORMATION PROCESSING ⇄ LEARNING AND MEMORY

4 TYPES OF ATTENTIONAL MECHANISM

ATTENTIONAL PRIMING

ATTENTIONAL GAIN CONTROL

ATTENTIONAL VIGILANCE

INTERMODAL COMPETITION

ART
ARCHITECTURE RESOLVES KEY DESIGN TRADE-OFFS

STABILITY-PLASTICITY DILEMMA

HOW DOES A REAL-TIME SYSTEM SWITCH BETWEEN ITS STABLE AND PLASTIC MODES WITHOUT AN EXTERNAL TEACHER?

HOW CAN IT BE PLASTIC TO IMPORTANT EVENTS

AND STABLE TO IRRELEVANT EVENTS?

TOO STABLE	TOO PLASTIC
↓	↓
RIGID	CHAOTIC

SYSTEMS THAT ARE SENSITIVE TO

NOVELTY

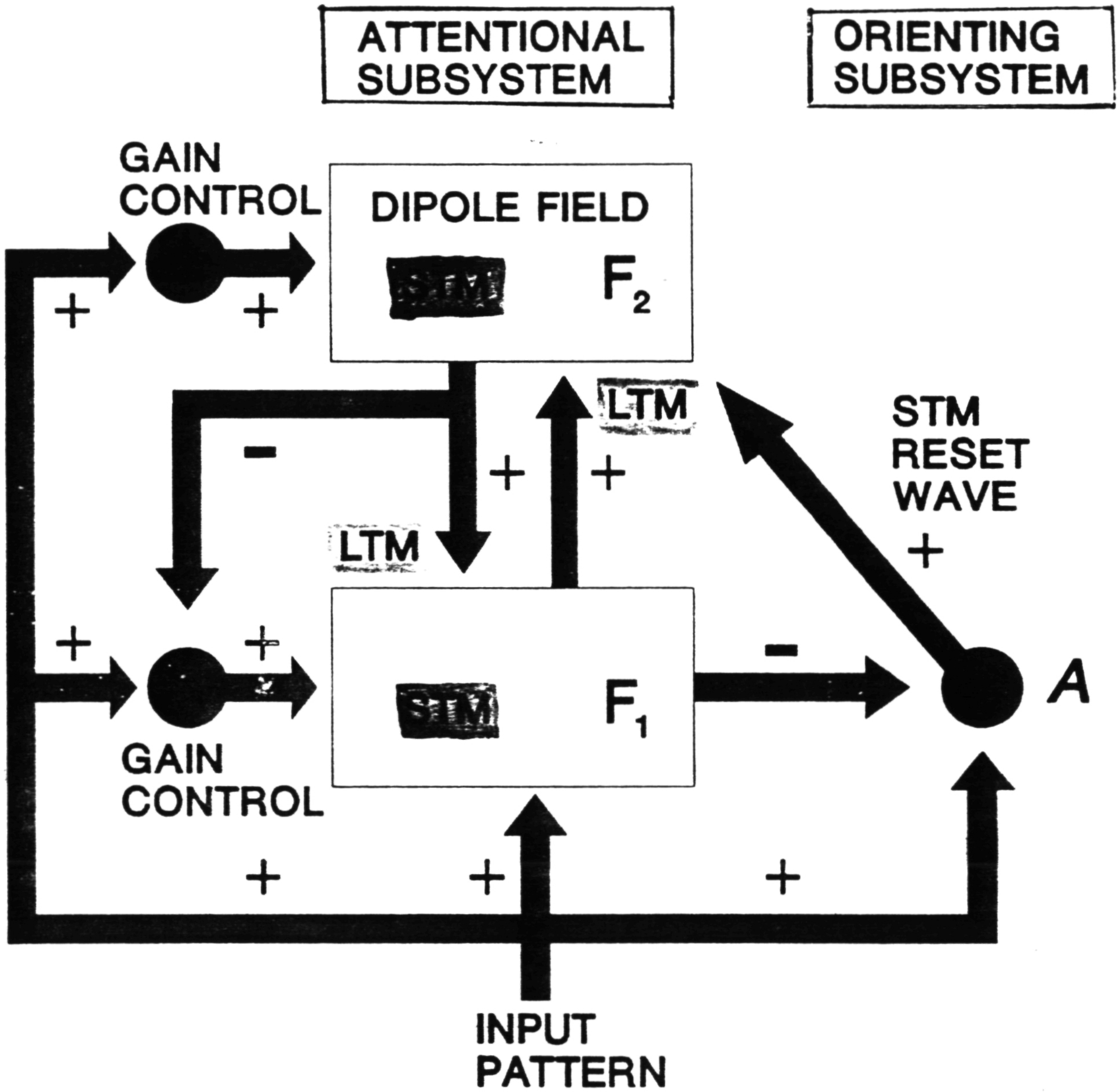
UNEXPECTED EVENTS RAPIDLY REORGANIZE INFORMATION PROCESSING NOT "JUST" MATCHING!

ART

MULTIPLE INTERACTING MEMORY SYSTEMS

ATTENTIONAL SUBSYSTEM	⟷	ORIENTING SUBSYSTEM
EXPECTED EVENTS		UNEXPECTED EVENTS
FAMILIAR EVENTS		UNFAMILIAR EVENTS

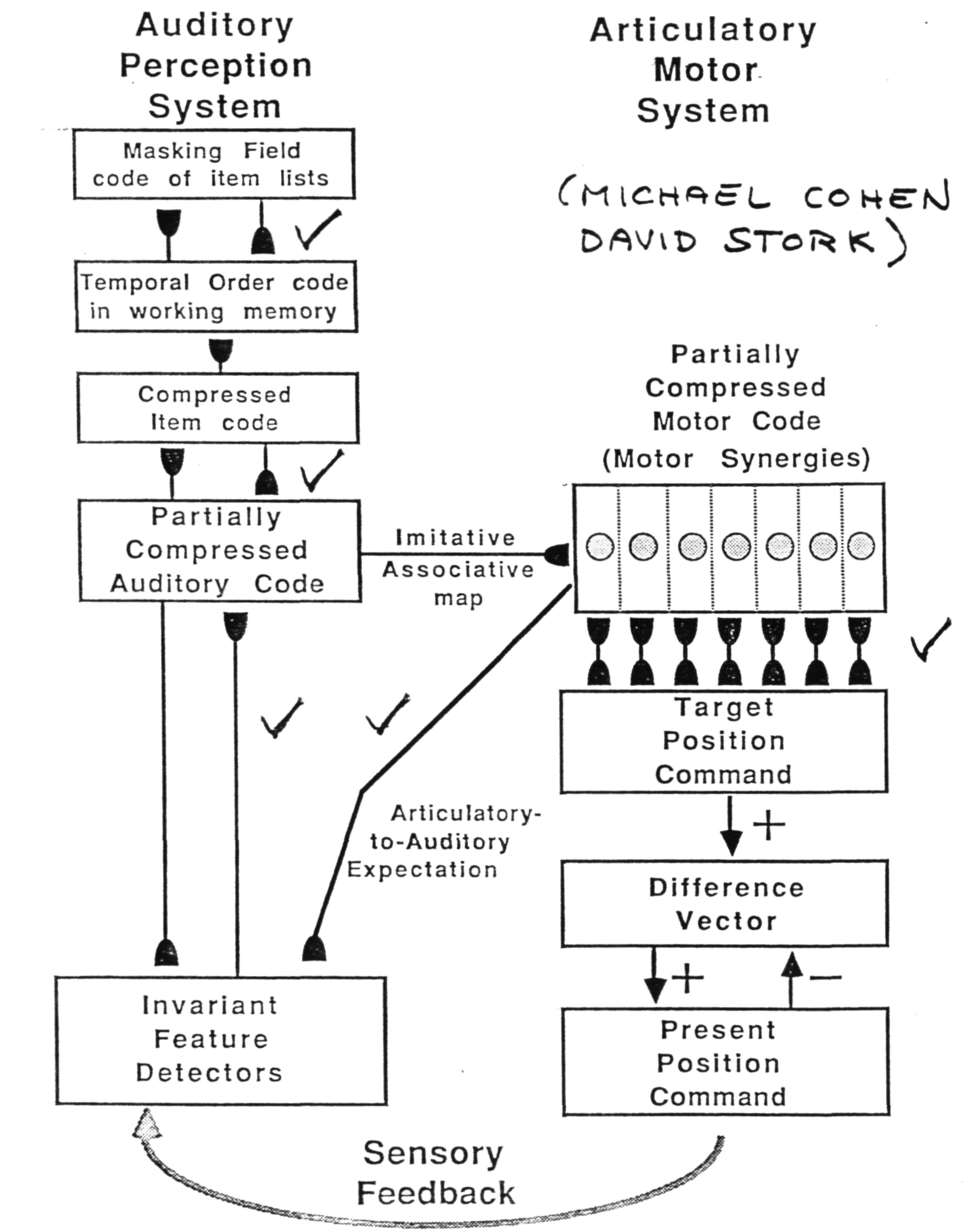
ART 1 ARCHITECTURE



NONSPECIFIC CONTROL STRUCTURES

NEURAL MODULATORS
AROUSAL

SPEECH PERCEPTION + PRODUCTION



61

ADAPTIVE RESONANCE SYSTEM	AUTOASSOCIATORS BOLTZMANN MACHINE BACK-PROPAGATION
SELF-ORGANIZE BUILDS INTERNAL CODES AND EXPECTATIONS	EXTERNAL TEACHER SOURCE OF PRE-CODED EXPECTED OUTPUT
SELF-STABILIZE WORLD KEEPS GOING INTERNAL MEMORY BUFFER	CAPACITY CATASTROPHE CODE WASHES AWAY WITH TOO MANY INPUTS SHUT OFF WORLD!
USE FULL CAPACITY	CAN'T USE FULL CAPACITY $\sim .15n$
MAINTAIN PLASTICITY RETAIN POTENTIAL FOR NEW LEARNING INDEFINITELY UNEXPECTED INPUTS	TERMINATE LEARNING TOO SOON? TOO LATE? JUST RIGHT! OMNISCIENT TEACHER
LEARN IN APPROXIMATE-MATCH PHASE BUFFERED AGAINST FREQUENT NOISE LOCAL MINIMA? NO!	LEARN IN MISMATCH PHASE WASHED AWAY BY FREQUENT NOISE STEEPEST DESCENT

HOW TO AVOID
SPURIOUS MEMORY STATES
LOCAL MINIMA?

USE NOISE 
EXTERNAL PARAMETERS $(T \to T_c$

CRITICAL SLOWING DOWN

NOT REAL-TIME!

TOO DIFFUSE!

ART SOLVES ANOTHER
TRADE-OFF

$$\boxed{\left\{\begin{matrix}\text{ADAPTIVE}\\ \text{SEARCH}\end{matrix}\right\} - \left\{\begin{matrix}\text{RECOGNITION}\\ \text{SPEED}\end{matrix}\right\}}$$

<u>SELF-ADJUSTING PARALLEL</u>
<u>MEMORY SEARCH</u>
ACTIVELY REORGANIZES
ENERGY LANDSCAPE
AS IT QUICKLY
<u>TESTS HYPOTHESES</u>
ABOUT THE WORLD

ART	
SELF-ADJUSTING MEMORY SEARCH REMAINS EFFICIENT IN ARBITRARY ENVIRONMENT AT ARBITRARY STAGE OF LEARNING	SEARCH TREE FIXED
DIRECT ACCESS NO SEARCH AS RECOGNITION INVARIANTS BECOME FAMILIAR SEARCH MECHANISM AUTOMATICALLY DISENGAGES	SEARCH TIME INCREASES WITH CODE COMPLEXITY LOG (n)

TIME TAKEN TO RECOGNIZE YOUR PARENTS AT

AGE 5 ?
20 ?
35 ?

LEARN IN APPROXIMATE-MATCH STAGE AT END OF SEARCH ON EACH TRIAL

ACCESS FAMILIAR RECOGNITION CODE | REFINE IT BASE ON NEW INFORMAT

ACCESS UNCOMMITTED RECOGNITION CODE | START A NEW CODE

HOW YOU MATCH

DETERMINES WHAT YOU CAN

STABLY LEARN

FAST INFORMATION PROCESSING (STM)

REAL-TIME!

LEARNING (LTM)

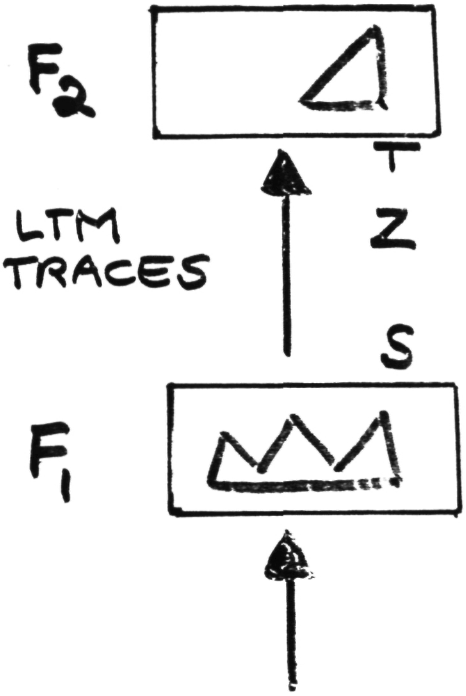
INTENTIONALITY!

(AI VS. SEARLE)

SPATIAL LOGIC

BASIC CODING STRUCTURE

COMPETITIVE LEARNING



COMPRESSED STM CODE, OR REPRESENTATION

$T = ZS$ ADAPTIVE FILTER

STM ACTIVITIES ACROSS A FIELD OF FEATURE DETECTORS

PREPROCESSED INPUTS

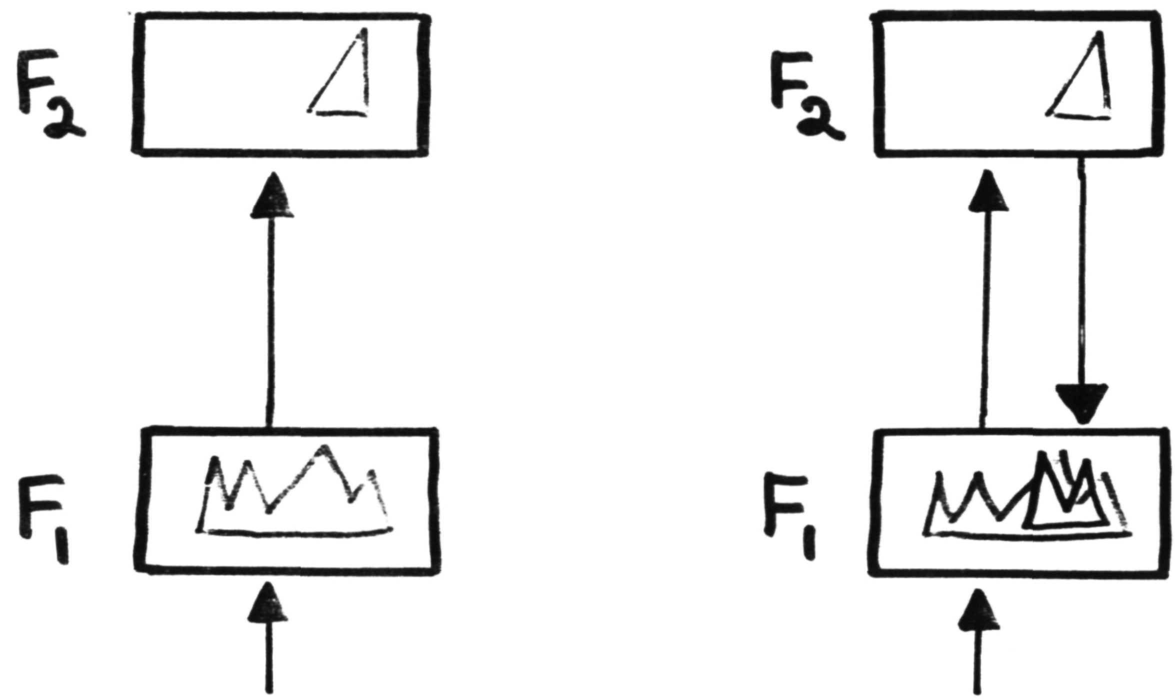
THEOREM (1976)

SUCH A SYSTEM CAN STABLY LEARN A RECOGNITION CODE IF THE INPUT PATTERNS ARE NOT TOO NUMEROUS OR DENSE.

IN GENERAL, **UNSTABLE!** ⇒ ART.

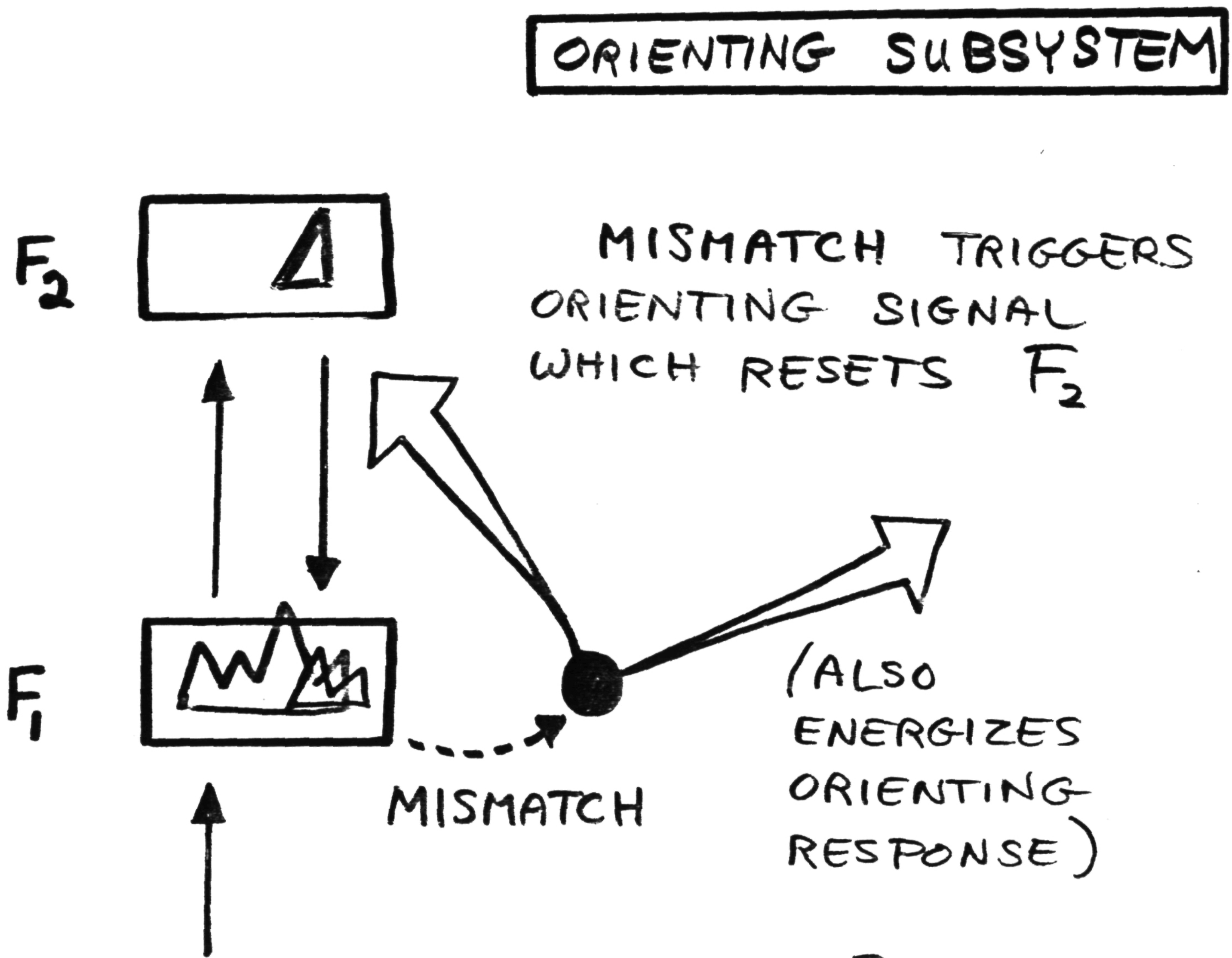
RECENT LEARNING CAN WASH AWAY OLDER LEARNING

LEARNED TOP-DOWN EXPECTANCIES, OR {PROTOTYPES / TEMPLATES}, CAN STABILIZE LEARNING IN RESPONSE TO AN ARBITRARY SEQUENCE OF PATTERNS



HOW? { MATCHING AT F_1 OF BU AND TD PATTERNS STABILIZES LEARNING

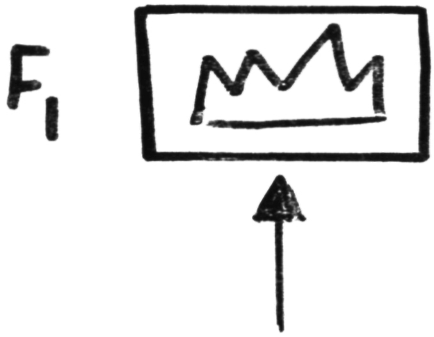
A "BIG ENOUGH" MISMATCH AT F_1 QUICKLY RESETS THE F_2 CODE BEFORE NEW LEARNING CAN OCCUR



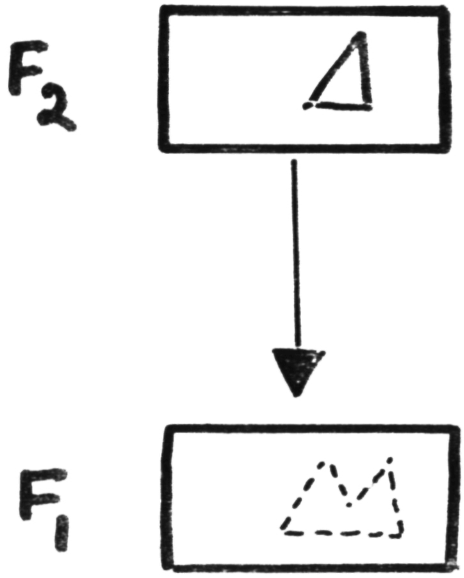
WHEN?

HOW TO MATCH BU AND TD AT F_1?

RECONCILE 2 REQUIREMENTS



1. AUTOMATIC REGISTRATION OF BU INPUT PATTERNS



2. TD PRIME CAN BE SUBLIMINA

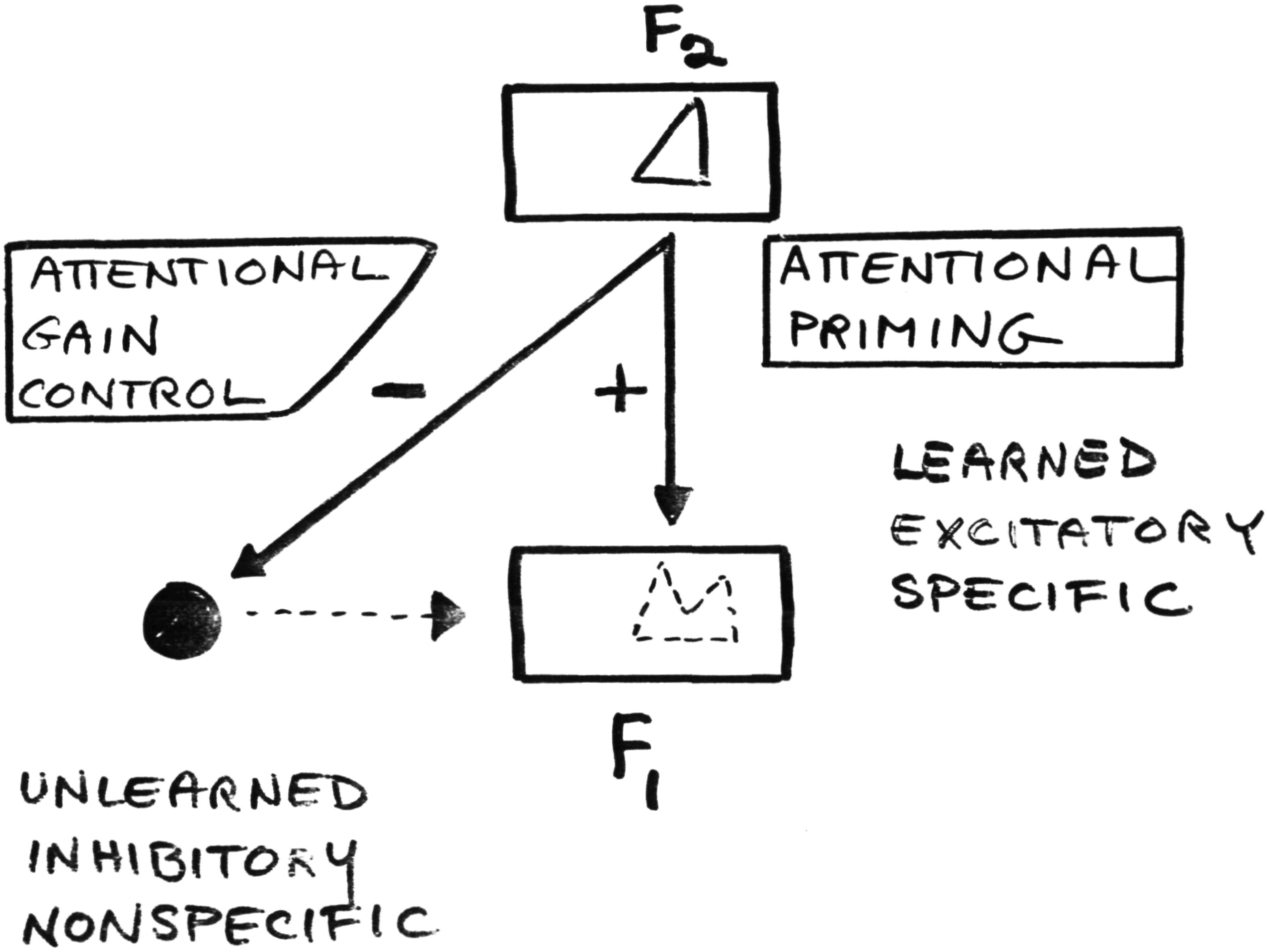
EXPECTANCY
INTENTIONALITY

SPATIAL LOGIC

INTENTIONALITY → LOGIC

HOW CAN F_1 KNOW THE DIFFERENCE BETWEEN BU AND TD SIGNALS?

FUNDAMENTAL DISTINCTION



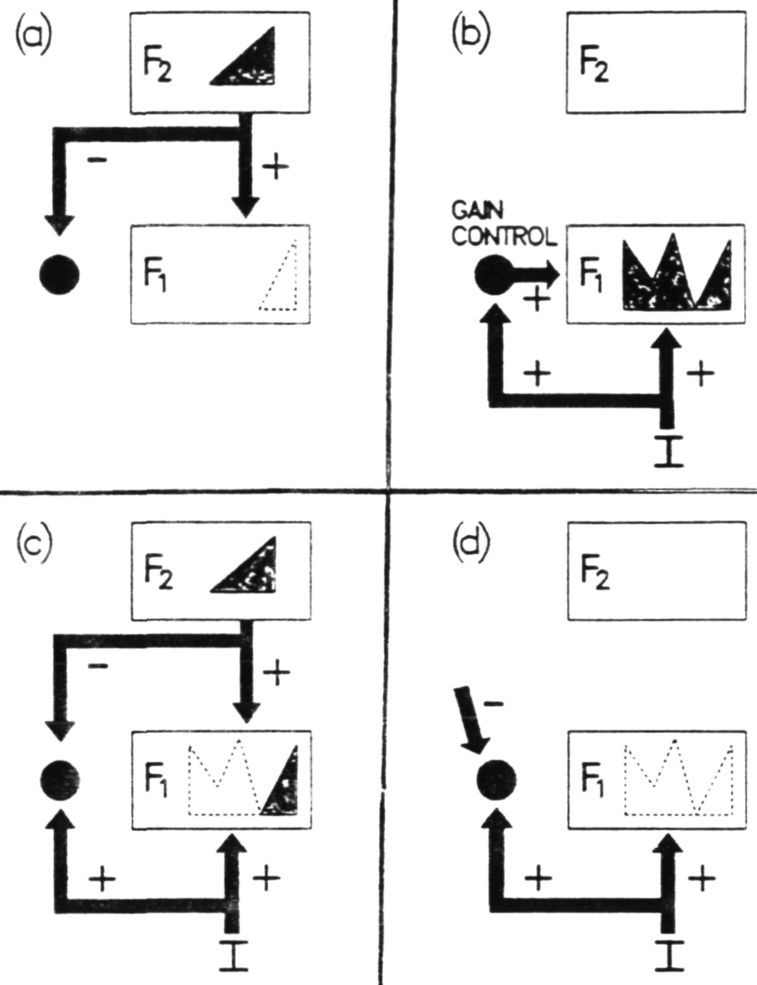
ATTENTIONAL GAIN CONTROL ⇒ MATCHING RUL

$\frac{2}{3}$ RULE

TD PRIME

BU INPUT

TD MATCH BU



"SPATIAL LOGIC"

INTERMODAL COMPETITION

INTENTIONALITY ~ LOGIC

$\frac{2}{3}$ RULE MATCHING

IS NECESSARY FOR

STABLE LEARNING

GIVEN ARBITRARY INPUTS.

HOW YOU <u>MATCH</u>
DETERMINES
WHAT YOU CAN STABLY <u>LEARN</u>

$\frac{2}{3}$ RULE +

WEBER LAW RULE
ASSOCIATIVE DECAY RULE } NON-HEBBIAN ASSOCIATIVE LEARNING RULE (LTM)

VIGILANCE RULE } RESET (STM)

ALL RULES EMERGE AS

PROPERTIES OF

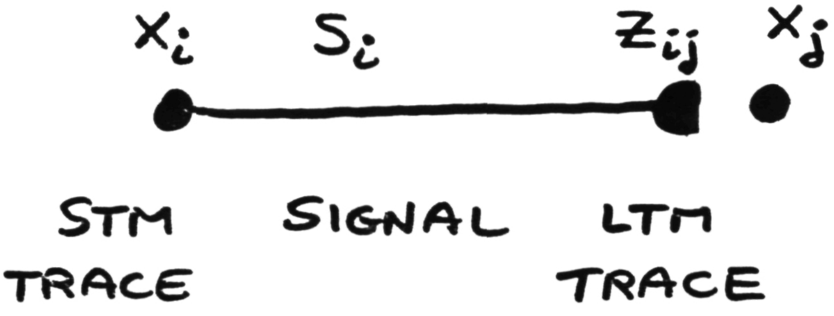
NETWORK INTERACTIONS

NO EXTERNAL PROGRAM

NO PREWIRED SEARCH STRATEGY

SHOW HOW "INDEX" OF CATEGORY CAN REMAIN INVARIANT AS THE CATEGORICAL CRITERIA ARE REFINED.

NON-HEBBIAN ASSOCIATIVE LAW



↑↓ GATED LEARNING AND MEMORY DECAY

$$\frac{d}{dt} z_{ij} = \epsilon f(x_j)\left[-z_{ij} + S_i\right]$$

STEEPEST DESCENT

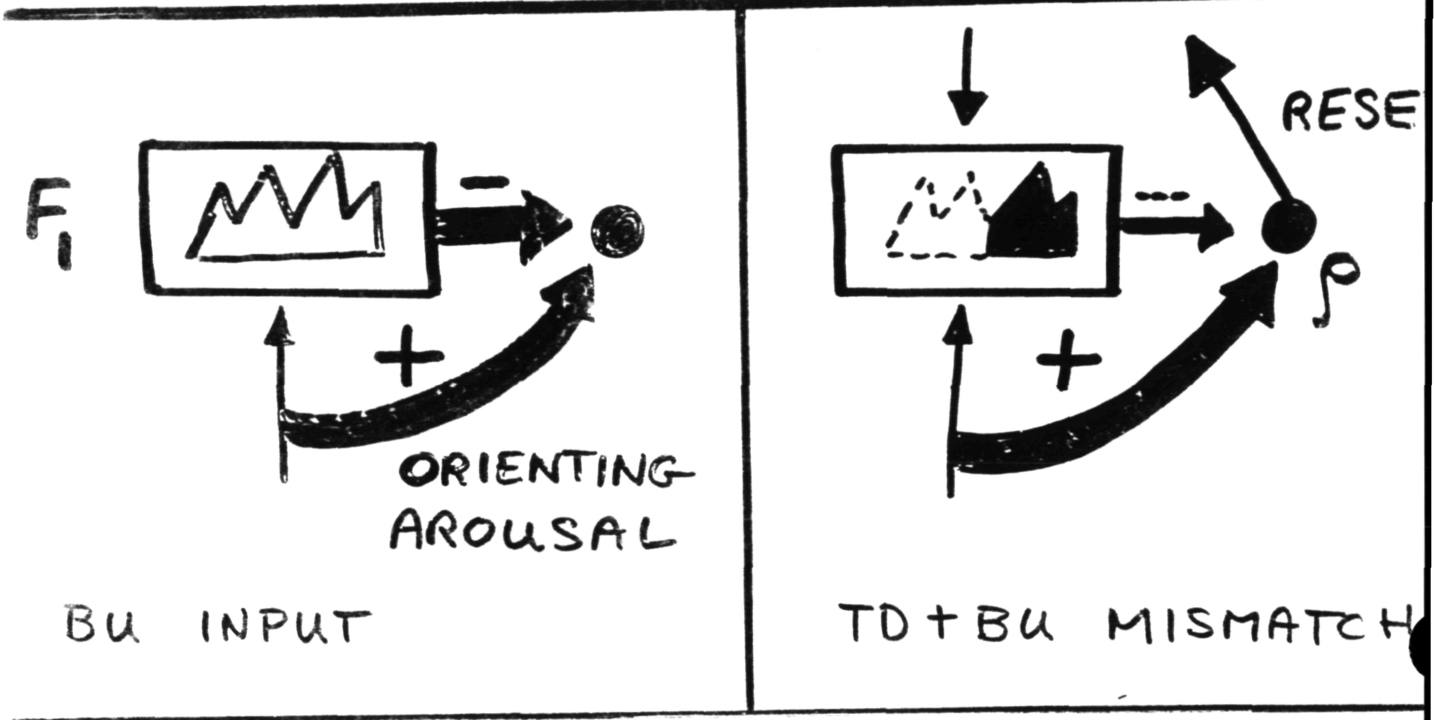
THEORY: GROSSBERG, 1969

EXPERIMENTS: RAUSCHECKER + SINGER, 1979

LEVY et al, 1983.

VIGILANCE RULE:

F_1 MISMATCH $\Rightarrow$ F_2 RESET



ORIENTING SUBSYSTEM

1. $\frac{2}{3}$ RULE $\Rightarrow$ TD CAN SUPPRESS A PORTION OF F_1 STM PATTERN

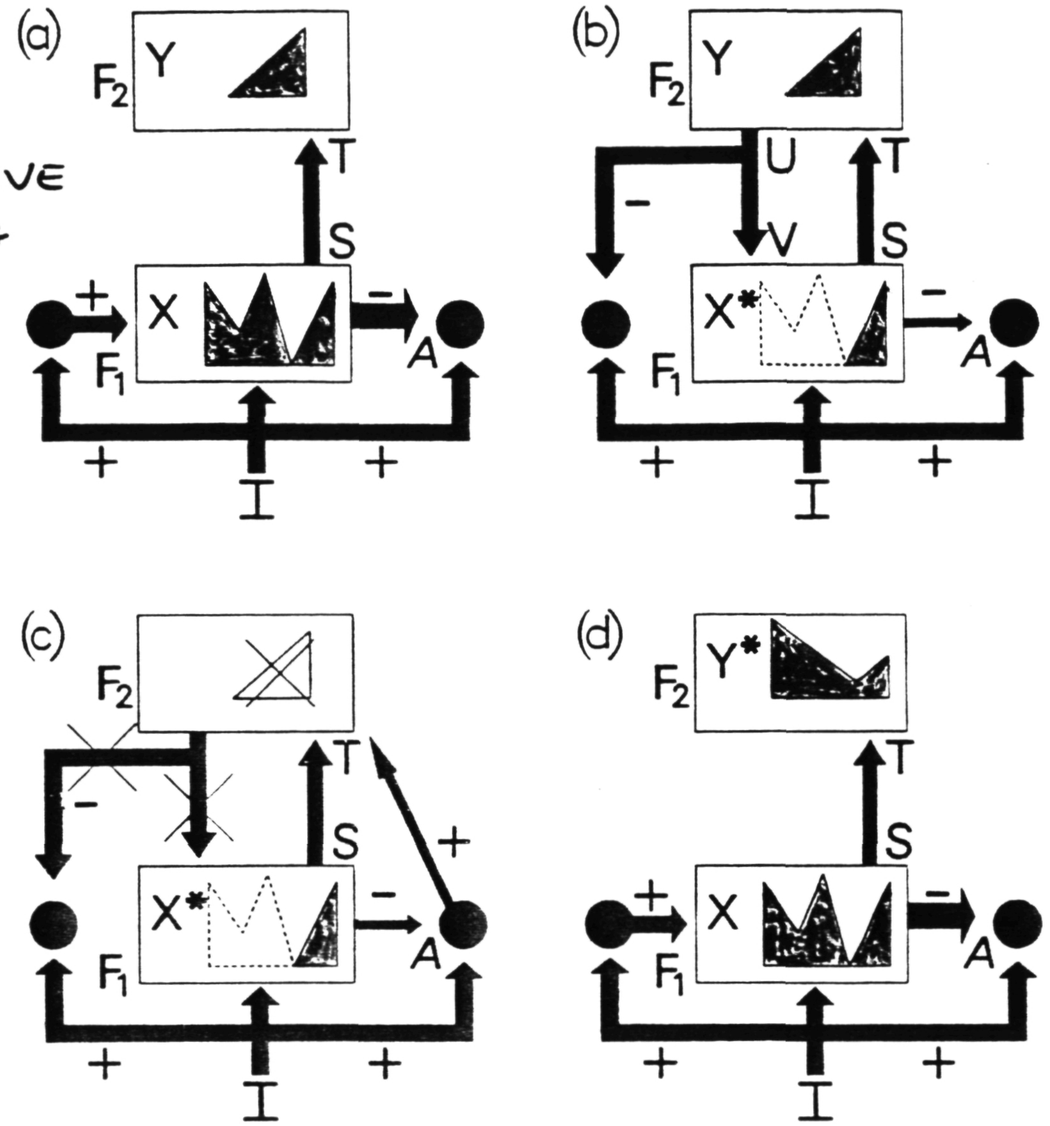
2. F_2 RESET IF

DEGREE OF MATCH $< \rho =$

VIGILANCE PARAMETER

ART 1 SEARCH CYCLE

COMPETITIVE LEARNING (1969-76)

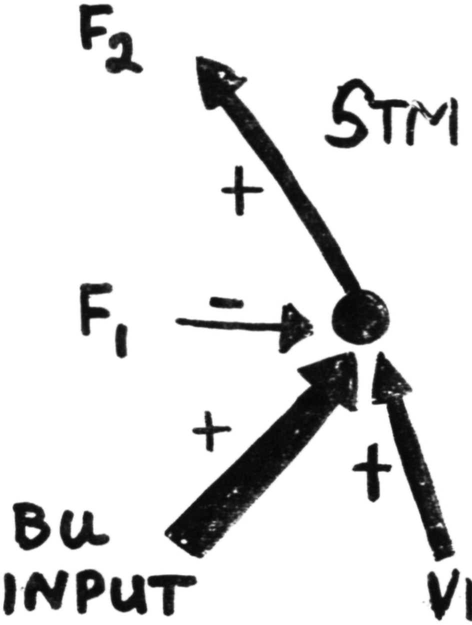


DIRECT ACCESS = NO RESET THEOREM:

DEEP FACT: SYSTEM CONVERGES TO THE NO RESET CASE IN RESPONSE TO AN <u>ARBITRARY</u> LIST OF INPUTS.

(CARPENTER + GROSSBERG, CUGIP, JAN. 1987)

VIGILANCE PARAMETER ρ



STM RESET (NONSPECIFIC AROUSAL)

RESET OF F_2 WHEN DEGREE OF MATCH $< \rho$

VIGILANCE SIGNAL

LOW VIGILANCE $\Rightarrow$ COARSE CATEGORIES

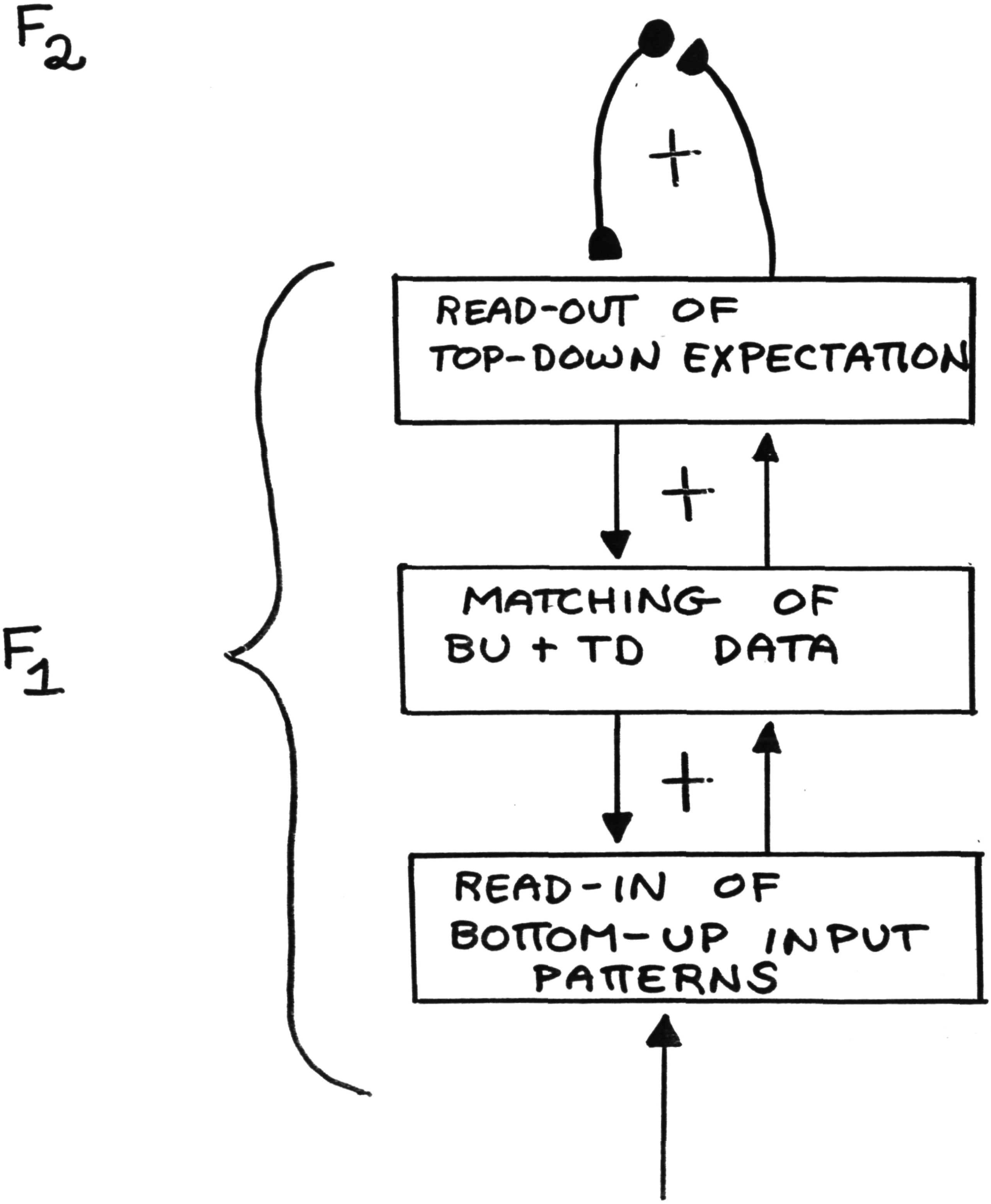
HIGH VIGILANCE $\Rightarrow$ FINE CATEGORIES

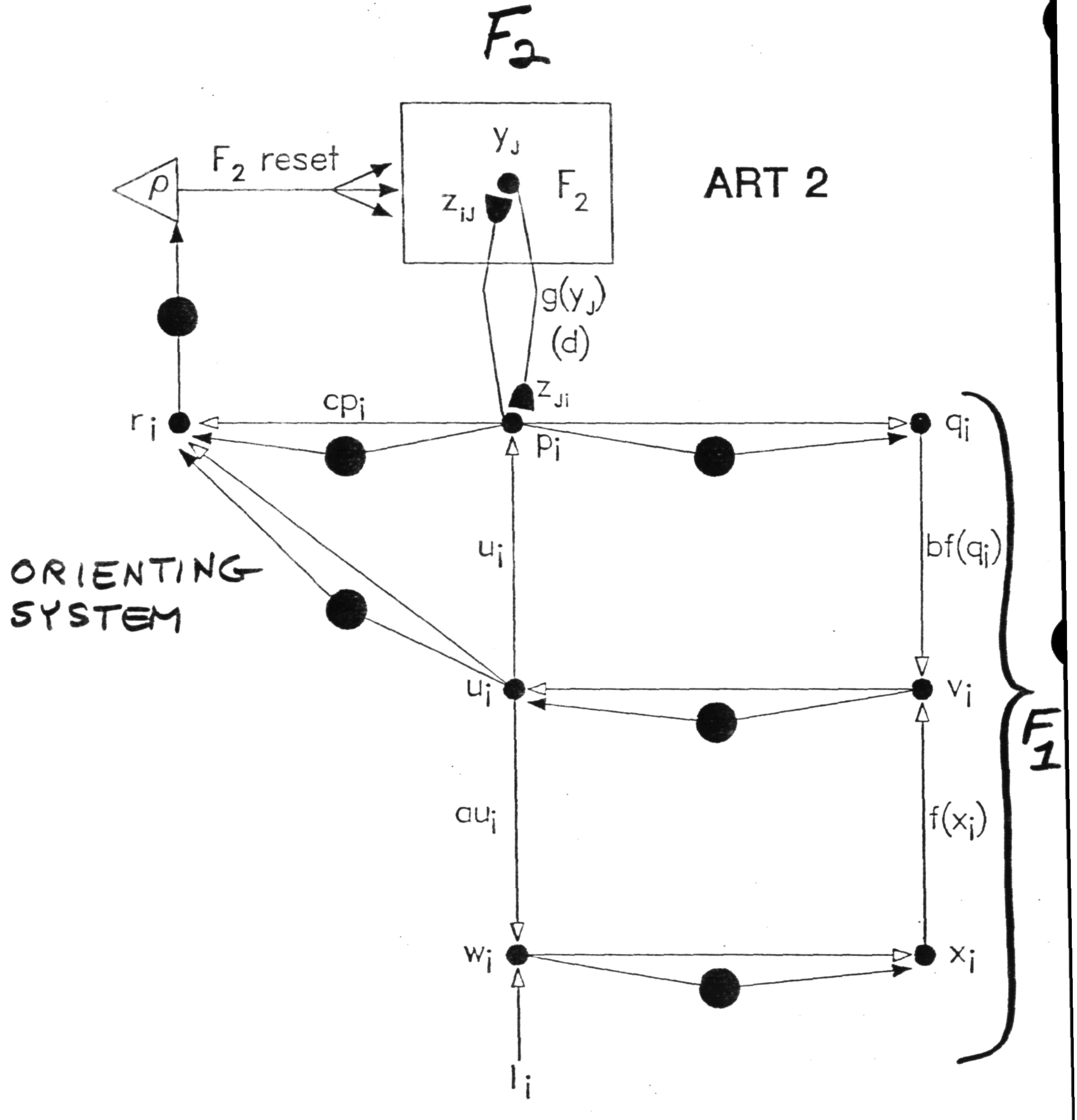
IF BEHAVIORAL FAILURE (e.g., PUNISHMENT) $\Rightarrow$ INCREASED VIGILANCE ($\rho \uparrow$),

SYSTEM AUTOMATICALLY LEARNS FINER CATEGORIES

eg ESKIMO NAMES FOR BLUE SKY.

STM INVARIANCE UNDER READ-OUT OF MATCHED TOP-DOWN LTM

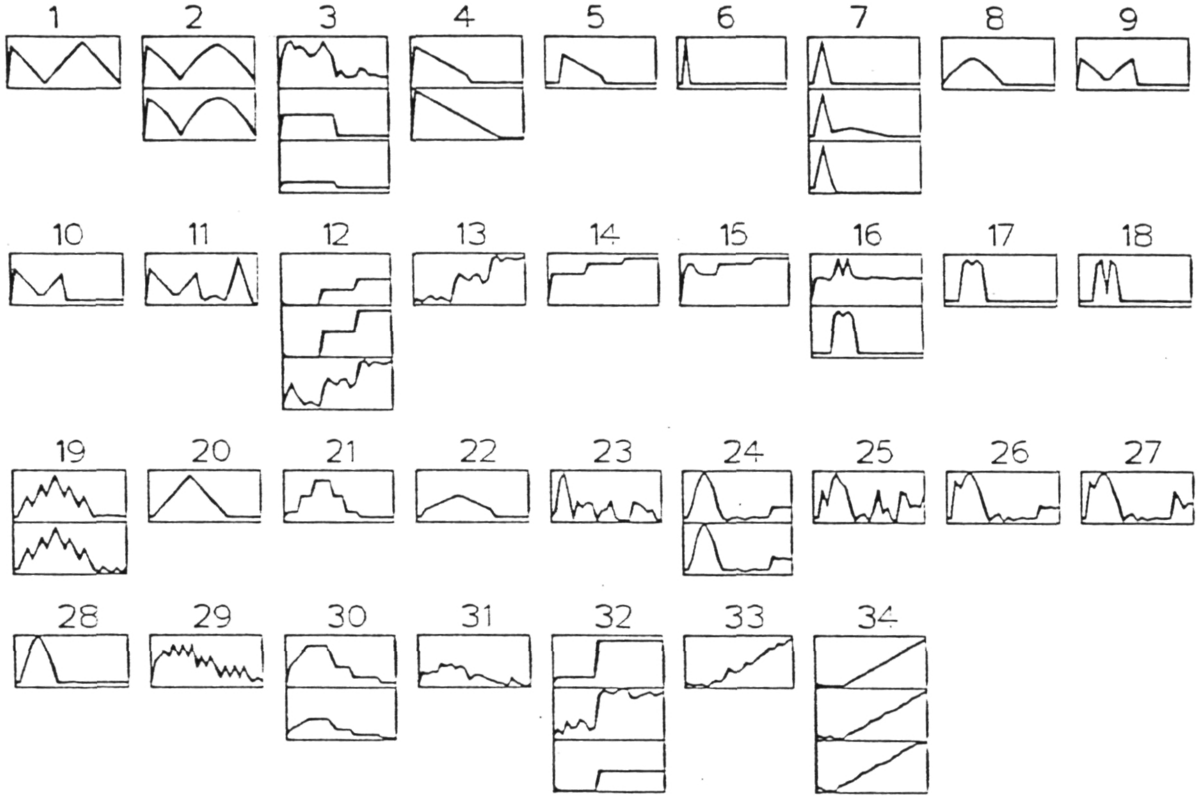




F2
ART 2
F2 reset
yJ
ziJ
F2
g(yJ)
(d)
zJi
ri
cpi
pi
qi
ui
bf(qi)
ORIENTING
SYSTEM
ui
vi
F1
aui
f(xi)
wi
xi
Ii

ART 2 GROUPING OF 50 INPUT PATTERNS INTO 34 RECOGNITION CATEGORIES ON 1 LEARNING TRIAL

FAST!



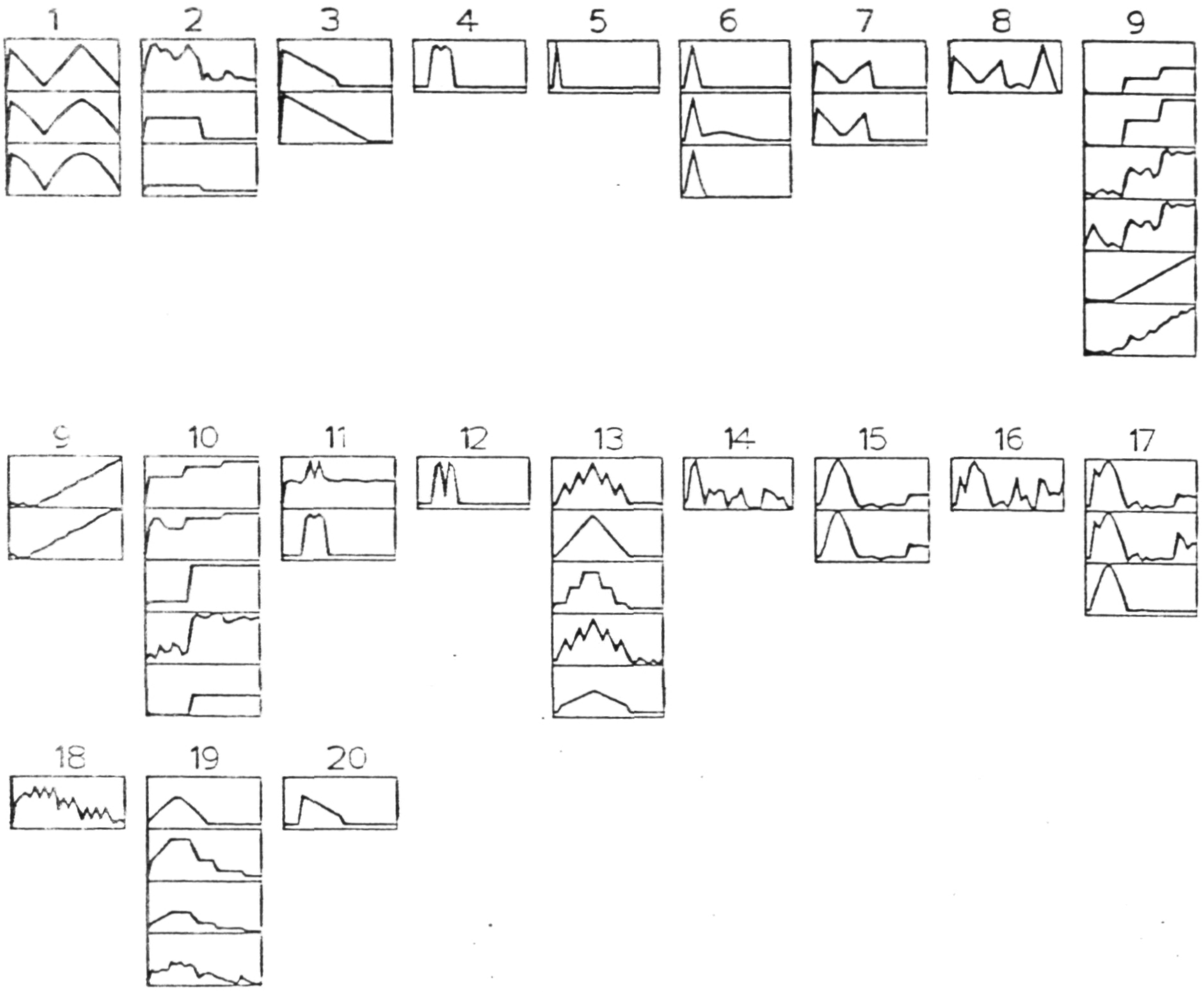
THEREAFTER

STABLE CATEGORIES

DIRECT ACCESS

NO SEARCH

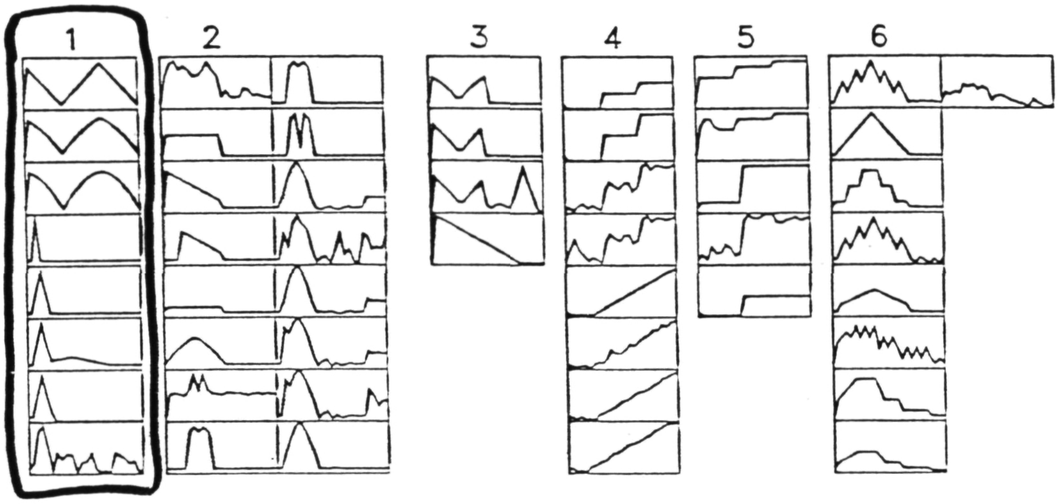
LOWER VIGILANCE - 20 INSTEAD OF 34 CATEGORIES



VERY LOW VIGILANCE ⇒ NO SEARCH

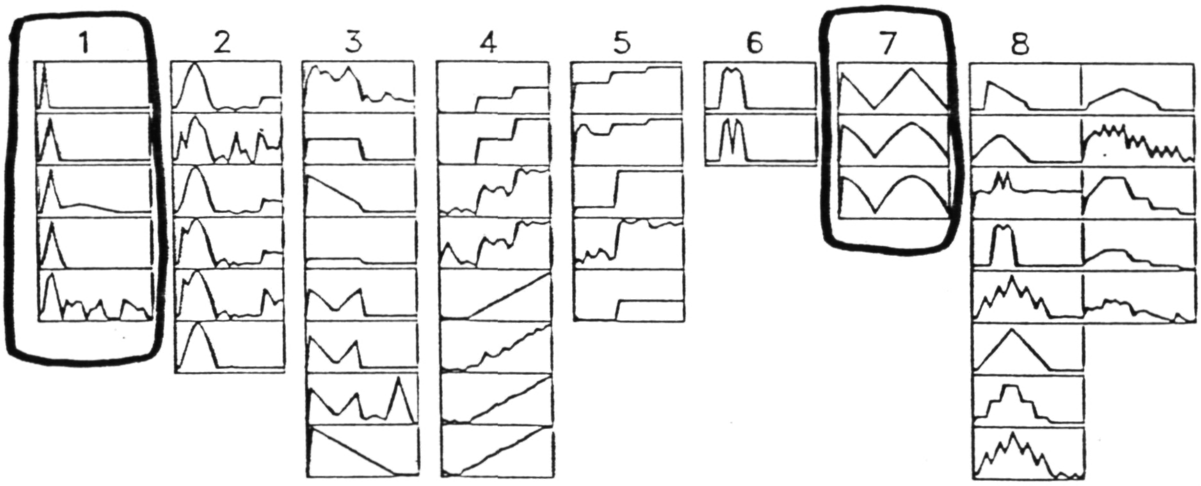
FIRST PRESENTATION

(a)



THIRD PRESENTATION ONWARDS

(b)



USE SIMILARITY INVARIANT

TO CONSTRUCT FRONT-END

FOR SIZE
ROTATION
TRANSLATION

INVARIANT RECOGNITION

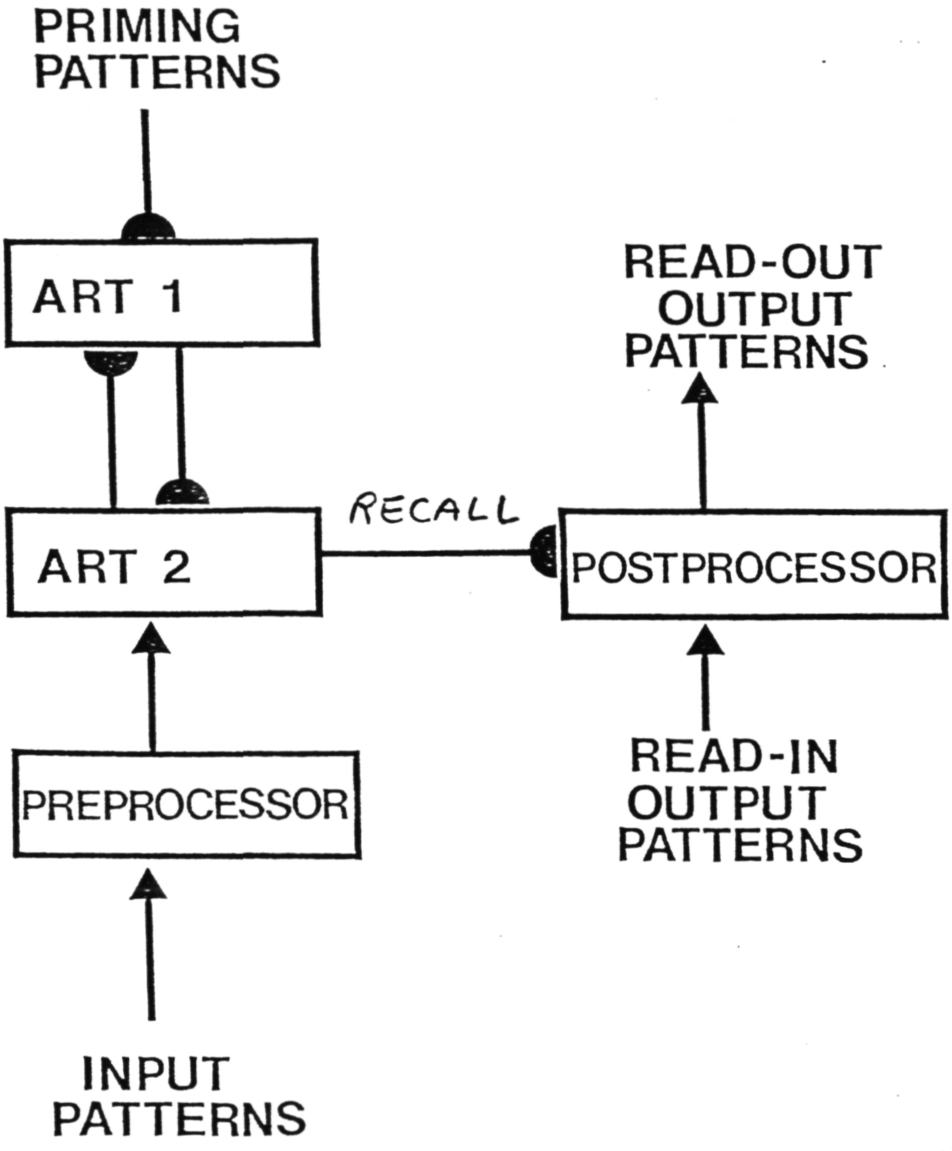
LASER RADAR → BOUNDARY SEGMENTATION

→ FOURIER-MELLIN

→ ART 2

THE 3 R'S:

RECOGNITION
REINFORCEMENT
RECALL



ASSOCIATIVE FAN-IN (INSTARS)	RECOGNITION
ASSOCIATIVE FAN-OUT (OUTSTARS)	RECALL

POSITION INVARIANT

TARGETING

HOW TO COMPUTE THE POSITION OF A TARGET WITH RESPECT TO THE BODY?

... IN A SELF-ORGANIZING SELF-CORRECTING WAY.

(MICHAEL KUPERSTEIN)
1986

POSTERIOR PARIETAL CORTEX

ACTION (ROBOTICS)

POSITION INVARIANT

HOW TO COMPUTE THE POSITION OF A TARGET?

EYE MOVEMENTS

TARGET POSITION = POSITION OF THE LIGHT ON THE RETINA

PRESENT POSITION = POSITION OF THE EYE IN THE HEAD

TARGET POSITION − PRESENT POSITION

= DIFFERENCE VECTOR

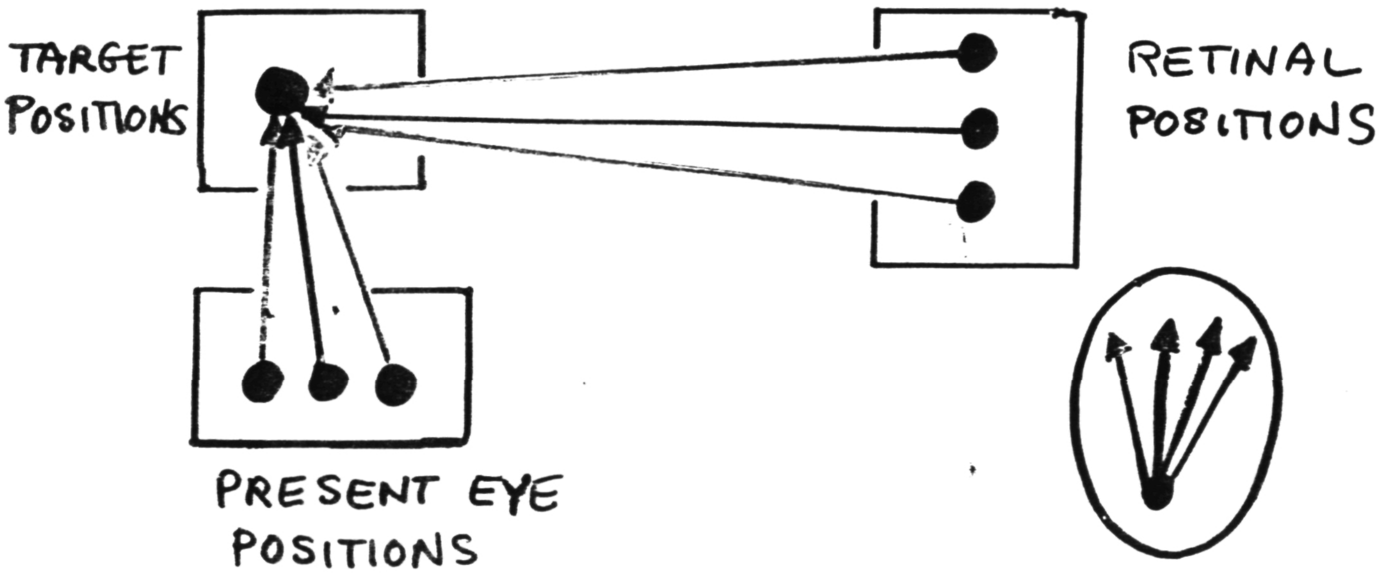
COMPUTES HOW FAR EYE MUST MOVE.

MANY COMBINATIONS OF RETINAL POSITION AND EYE POSITION GENERATE

ONE POSITION OF THE LIGHT IN HEAD COORDINATES

LEARNING A

1. MANY-TO-ONE TRANSFORM
2. INVARIANT MAP

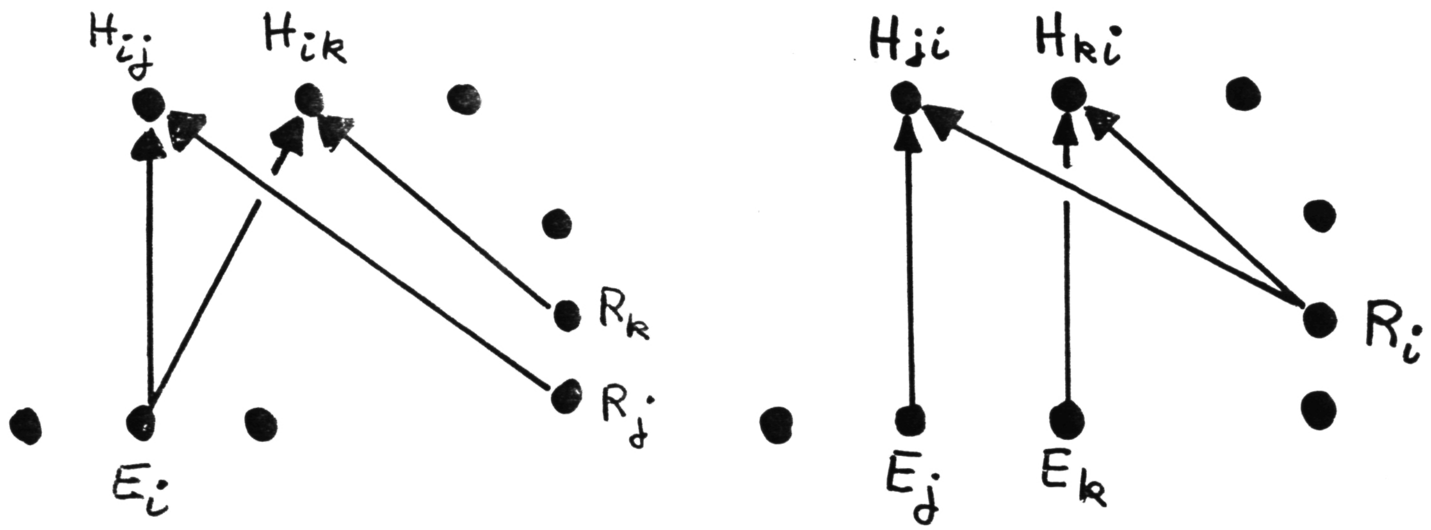


3. SELF-REGULATING AND SELF-CORRECT
(SELF- REPAIRING)

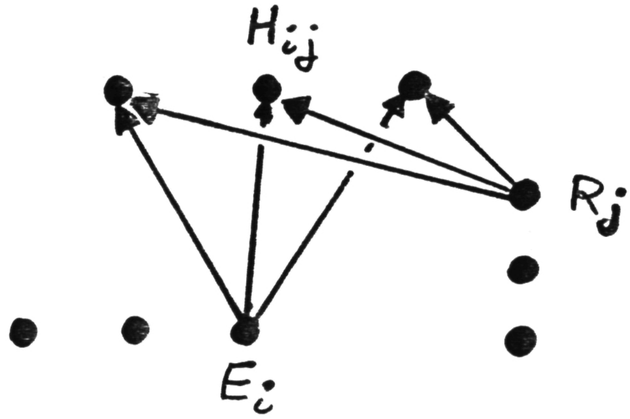
KEY DIFFICULTY (DISTRIBUTED)

EACH R POSITION AND E POSITION CAN ACTIVATE MANY TARGET POSITIONS IN H COORDINATES

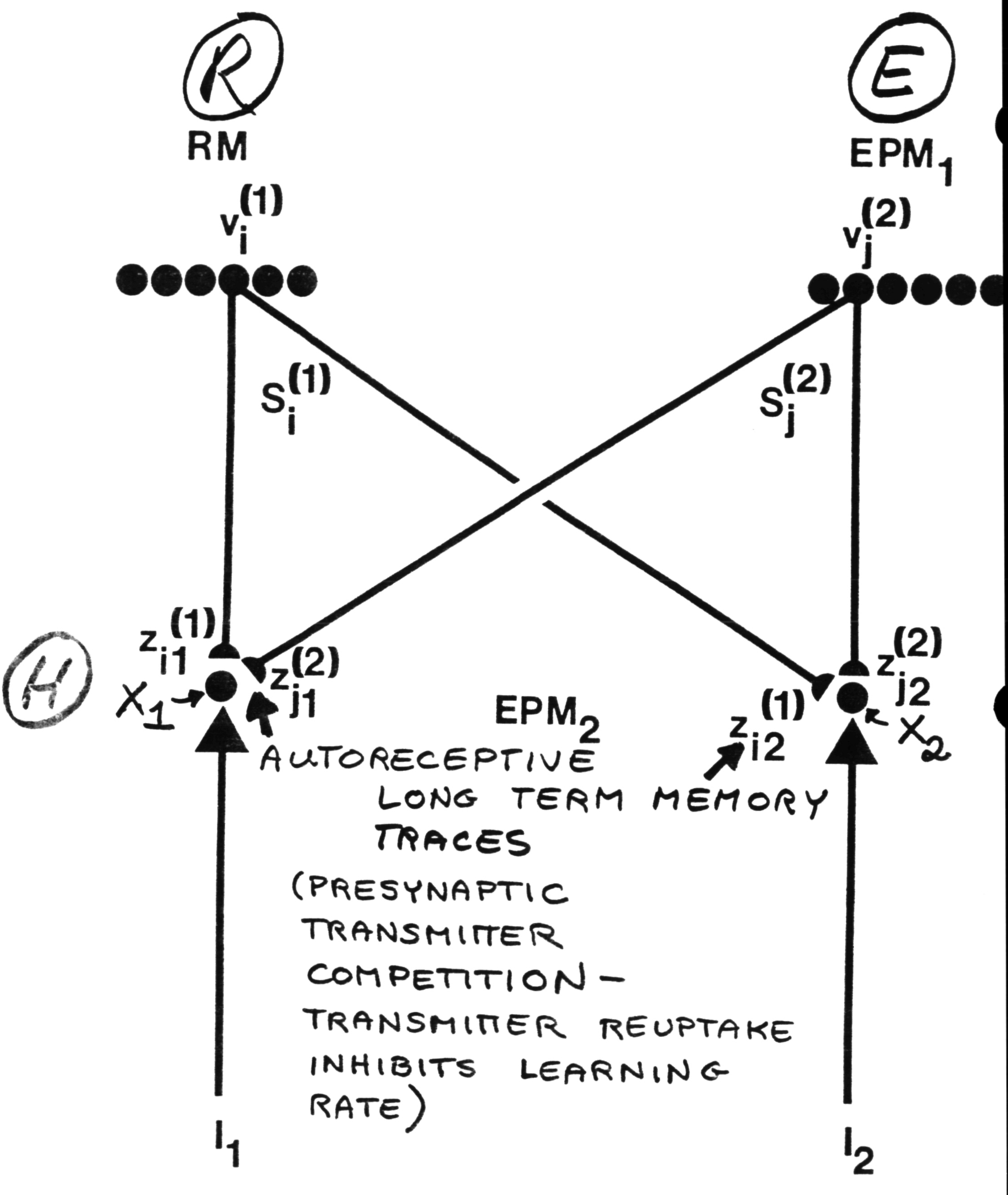
LEARNING



PERFORMANCE



LEARNING A GLOBALLY CONSISTENT RULE BY A DISTRIBUTED NETWORK INTERACTION.



CAN VARY THE # OF R AND E COMBINATIONS

A SPECIALIZED ADDITIVE MODEL!

FAST
SHORT TERM MEMORY:

HEAD-CENTERED PATTERN

$$\frac{d}{dt} x_i = -x_i + I_i + z_i$$

SLOW
LONG TERM MEMORY:

$$z_i = \underbrace{\sum_j S_j^{(1)} z_{ji}^{(1)}}_{\text{EYE}} + \underbrace{\sum_k S_k^{(2)} z_{ki}^{(2)}}_{\text{HEAD}}$$

$$\frac{d}{dt} z_{ji}^{(1)} = \epsilon S_j^{(1)} \left[-A z_{ji}^{(1)} + B x_i - C z_i \right]$$

AUTORECEPTOR TERM

$$\frac{d}{dt} z_{ki}^{(2)} = \epsilon S_k^{(2)} \left[-A z_{ki}^{(2)} + B x_i - C z_i \right]$$

RANDOM INPUTS: $S_j^{(1)}, S_k^{(2)}$.

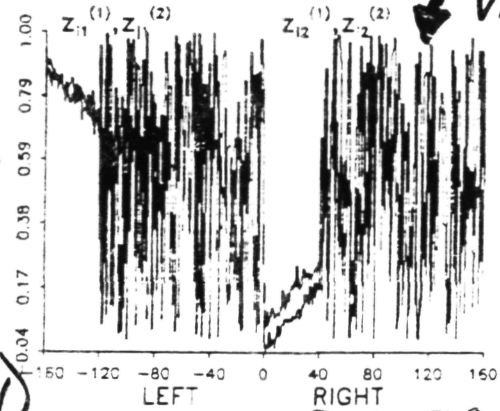
VERY LARGE SINGULAR STOCHASTIC SYSTEM OF ODE'S, TO ADAPTIVELY TRANSFORM VISUAL DATA INTO AN INVARIANT, SELF-REGULATING TARGET POSITION MAP IN HEAD COORDINATES.

INVARIANT SELF-REGULATING LTM MA

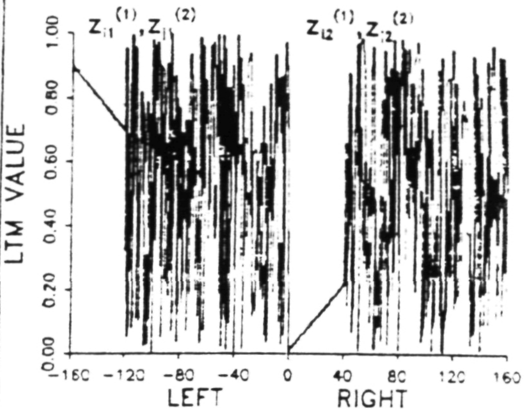
DURING LEARNING | AFTER LEARN

RANDOM INITIAL LTM VALUES

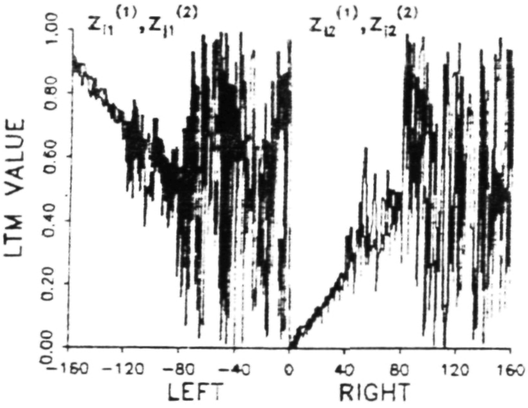
LTM MAPS (RET., AND EYE POSITION)



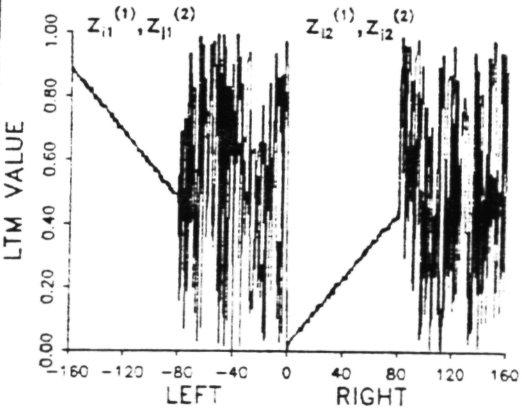
(a) POSITION



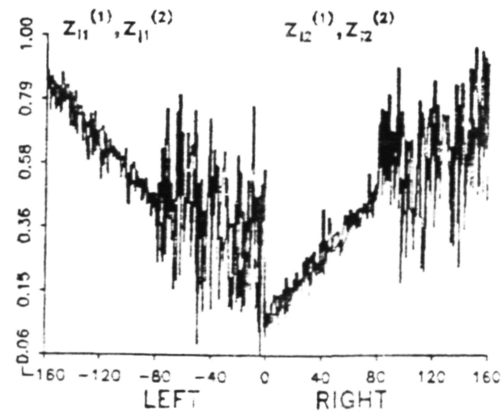
(b)



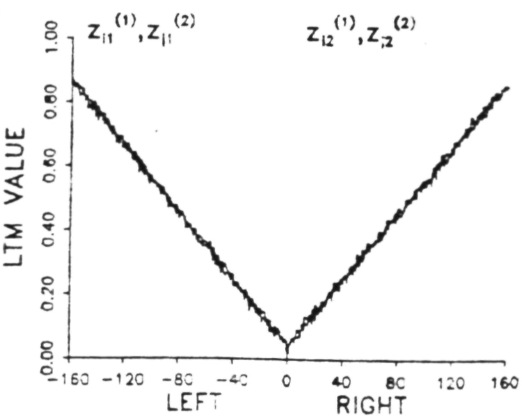
(c) MORE COMBINATIONS



(d)

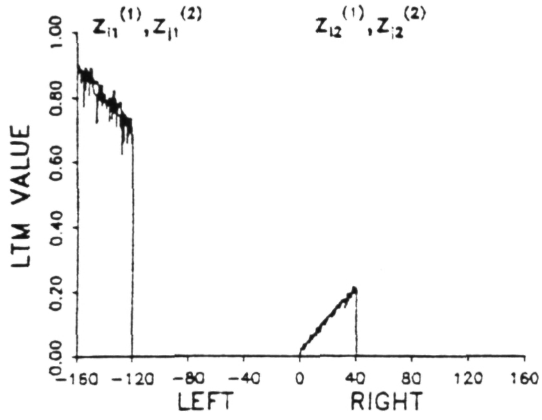


(e) STILL MORE COMBINATIONS

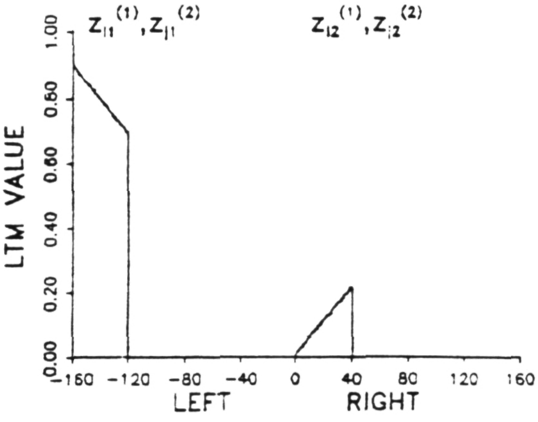


(f)

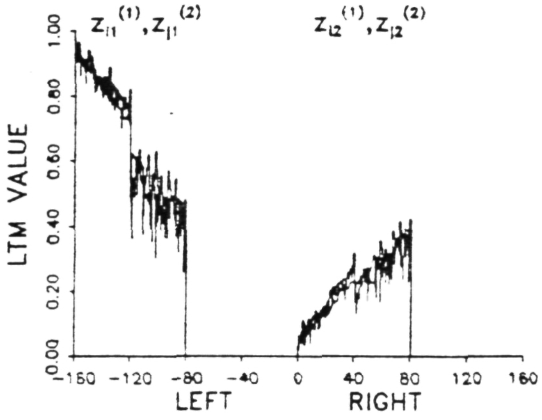
VERY INSENSITIVE TO NOISE!



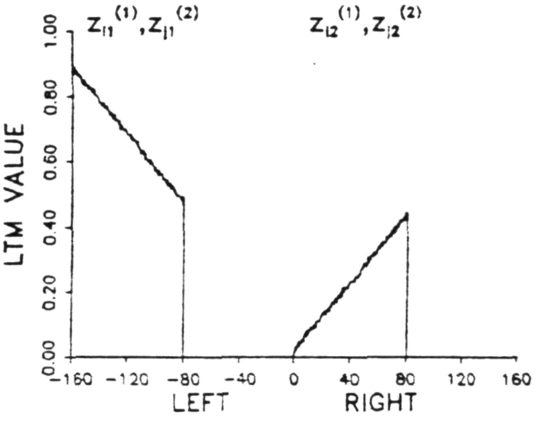
(a)



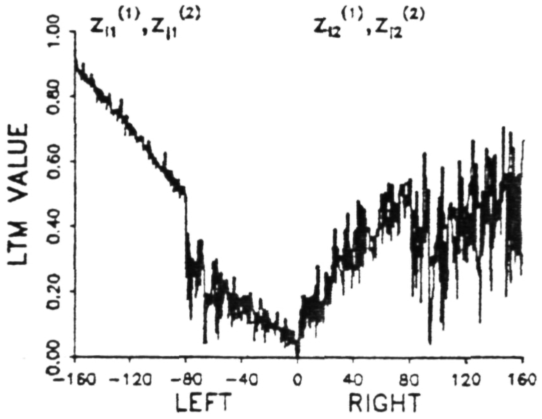
(b)



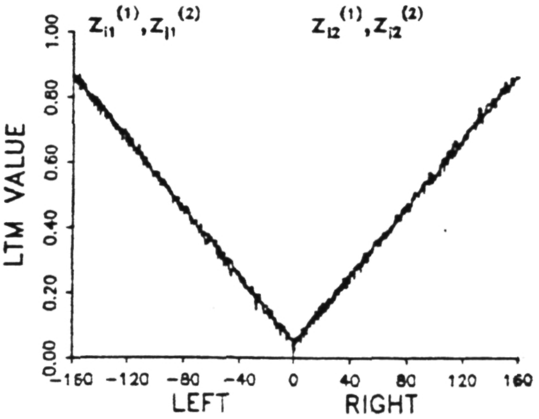
(c)



(d)



(e)



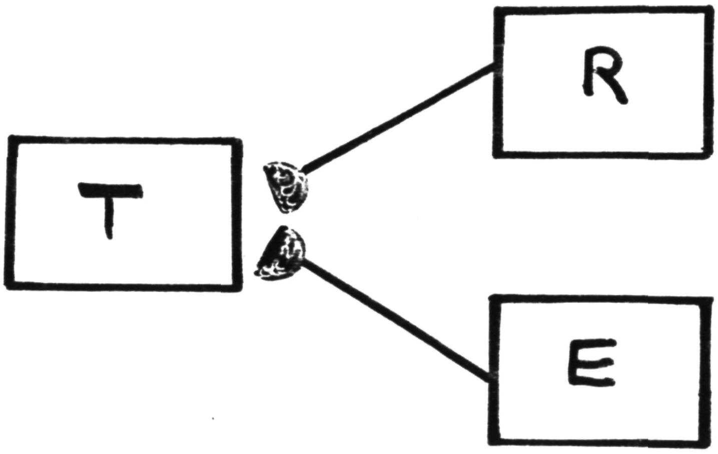
(f)

SOLUTION

NEURAL DYNAMICS OF ADAPTIVE SENSORY-MOTOR CONTROL, 1986
(MICHAEL KUPERSTEIN)

SPECIALIZED ADDITIVE MODEL!

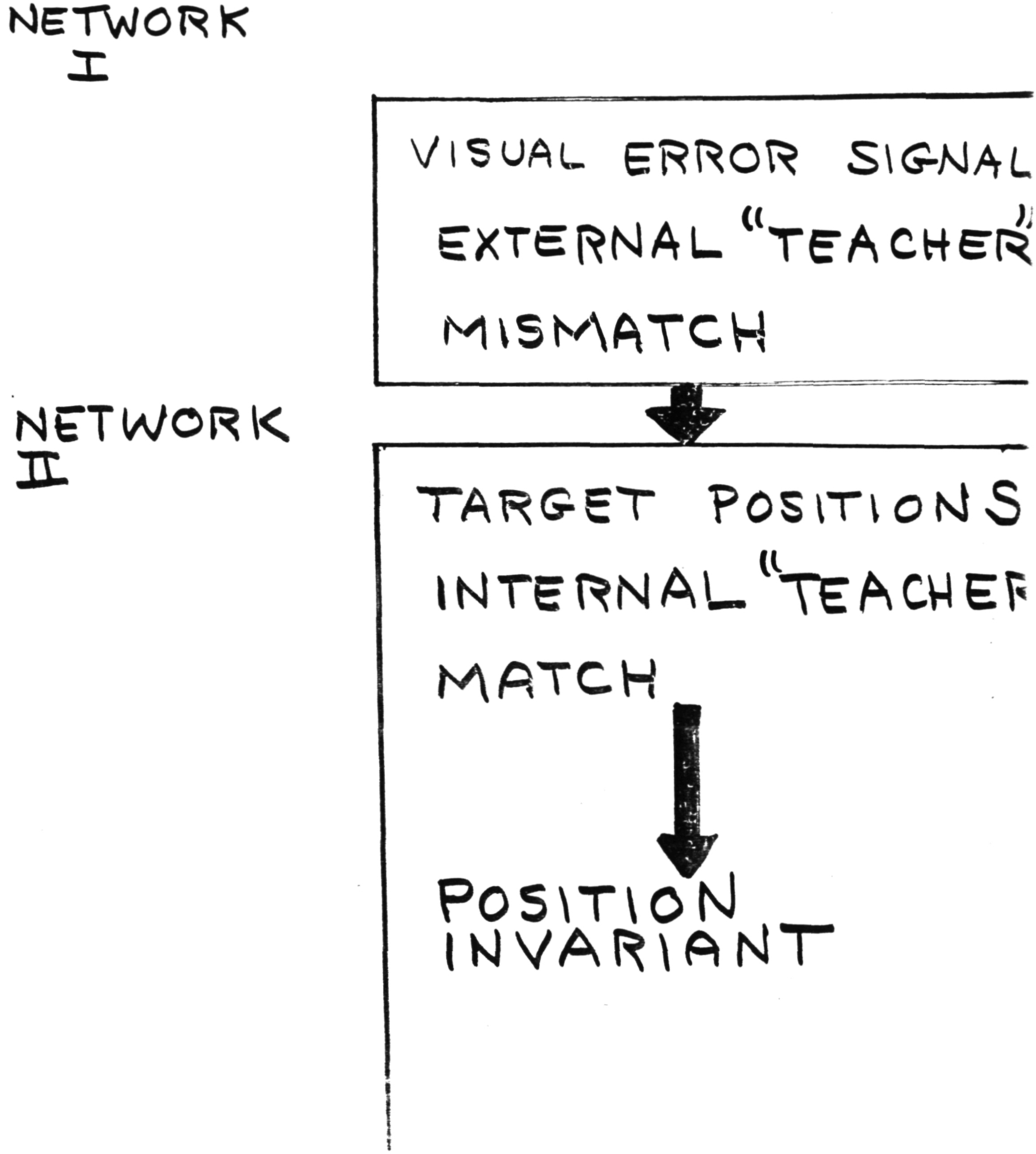
WHERE DO YOU GET GOOD TARGET POSITIONS TO LEARN?!



HOW TO GET STARTED?!
INFINITE REGRESS

VISUALLY REACTIVE MOVEMENT SYSTEM

VISUAL ERROR SIGNALS
MISMATCH


NETWORK I
VISUAL ERROR SIGNAL
EXTERNAL "TEACHER"
MISMATCH
NETWORK II
TARGET POSITIONS
INTERNAL "TEACHER
MATCH
POSITION INVARIANT

TO OVERCOME INFINITE REGRESS:

NETWORK HIERARCHY OF DEVELOPING MOVEMENT SYSTEM

FUNCTION	ANATOMY
1. VISUALLY REACTIVE MOVEMENTS	(SUPERIOR COLLICU[LUS], CEREBELLUM, VISUA[L] CORTEX, ...)
↓	
2. ATTENTIONALLY MODULATED MOVEMENTS	(PARIETAL CORTE[X], ...) TARGET POSITIONS
↓	
3. PLANNED INTENTIONAL MOVEMENT SEQUENCES WHICH DERIVE THEIR ACCURACY FROM (1), BUT CAN IGNORE VISION'S MOMENTARY DEMANDS.	(FRONTAL CORTEX, ...)

MANY FUNCTIONALLY CHARACTERIZED ARCHITECTURES

~ MANY SPECIALIZED BRAIN REGIONS

SYNCHRONY INVARIANT

MULTI-JOINT MOVEMENT

(ARM,
SPEECH ARTICULATORS, ...)

HOW ARE MOVEMENT RATES OF MUSCLES ADJUSTED IN PARALLEL SO DIFFERENT AMOUNTS OF CONTRACTION OCCUR IN EQUAL TIME?

(DANIEL BULLOCK)

PLANNED VS. AUTOMATIC CONTROL

HUMANS

PLAN

1. TARGET POSITION

   WHERE WE WANT TO MOVE

2. SPEED

   HOW FAST TO MOVE

AUTOMATIC

3. PRESENT POSITION

4. UNEXPECTED LOADS AND INERTIAS

5. CHANGES IN MOTOR PLANT

VECTOR

INTEGRATION

TO

ENDPOINT

MODEL

(DANIEL BULLOCK)

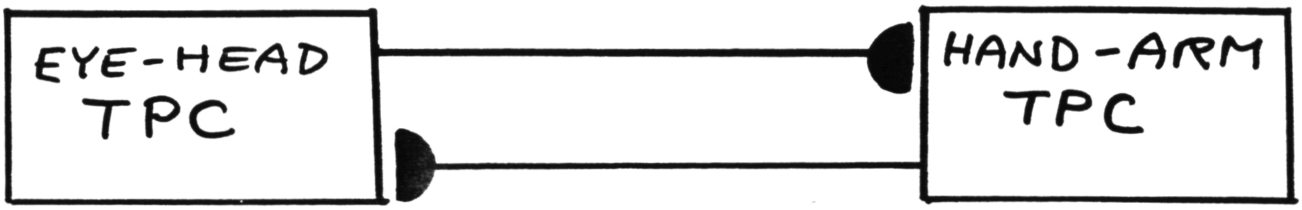
KEY QUESTION:

HOW DO WE LEARN HOW TO REACH WITH AN ARM AN OBJECT THAT WE SEE WITH OUR EYES?

WHAT INFORMATION IS AVAILABLE IN REAL-TIME ON WHICH TO BASE THE LEARNING PROCESS?

PIAGET!

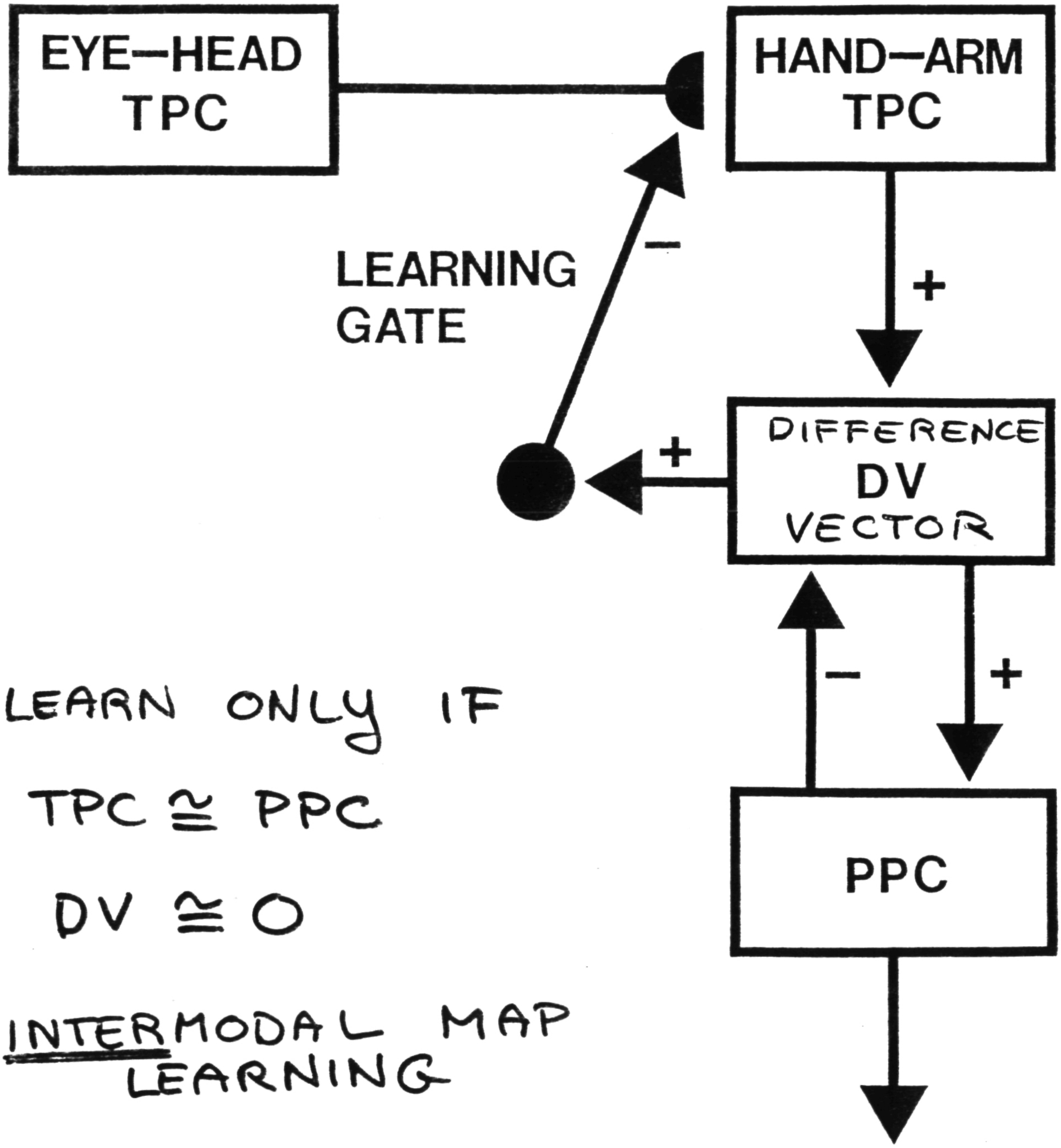
LEARNED ASSOCIATIVE MAP BETWEEN TARGET POSITION CODES
T P C



CIRCULAR REACTION (PIAGET)

HOW DOES HAND-ARM TPC GENERATE A SYNCHRONOUS TRAJECTORY

NEED AUTOMATIC COMPENSATION FOR PRESENT POSITION (PPC)



LEARN ONLY IF

TPC ≅ PPC

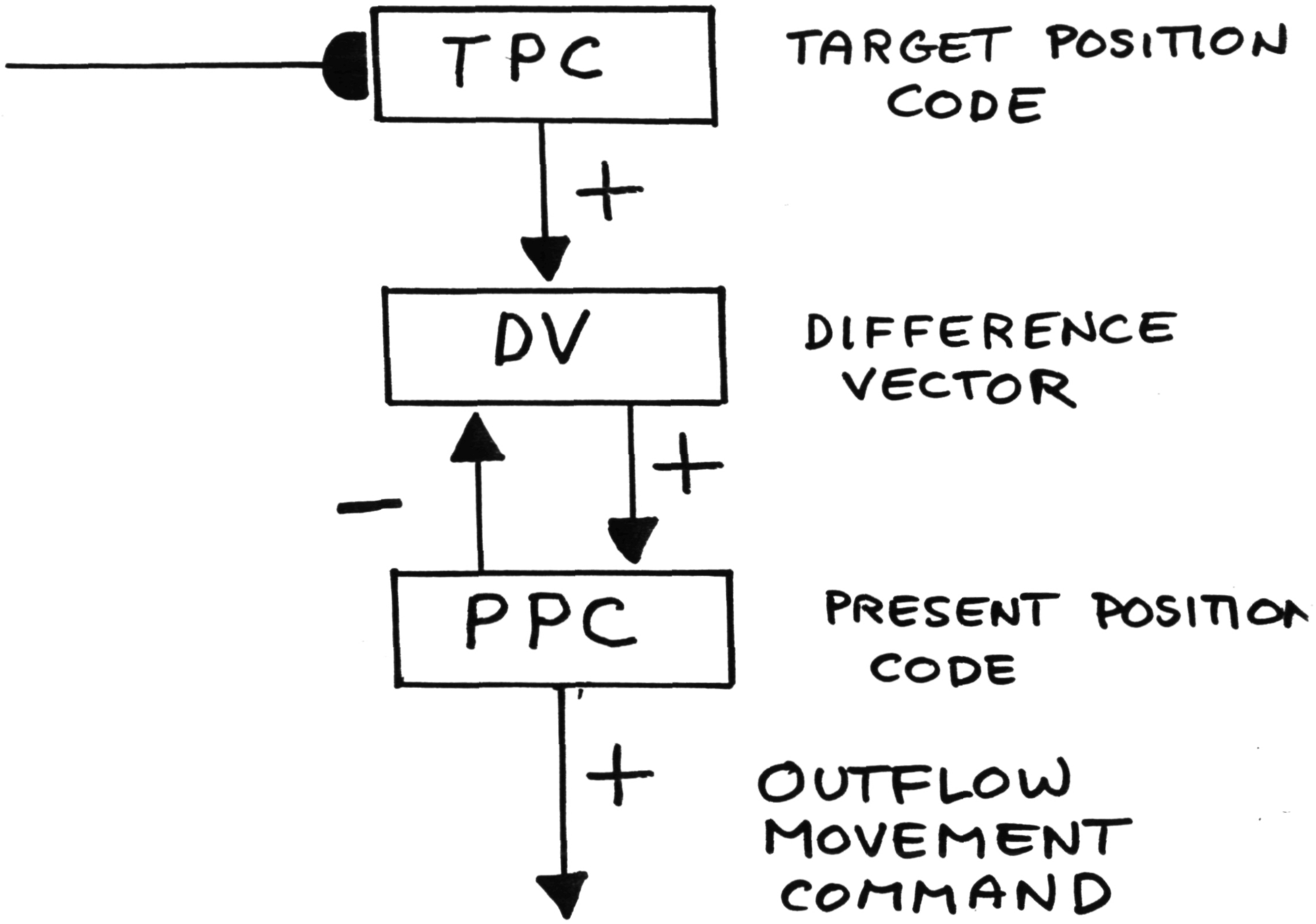
DV ≅ 0

INTERMODAL MAP LEARNING

INTRAMODAL TRAJECTORY FORMATION

Figure 14

VITE MODEL

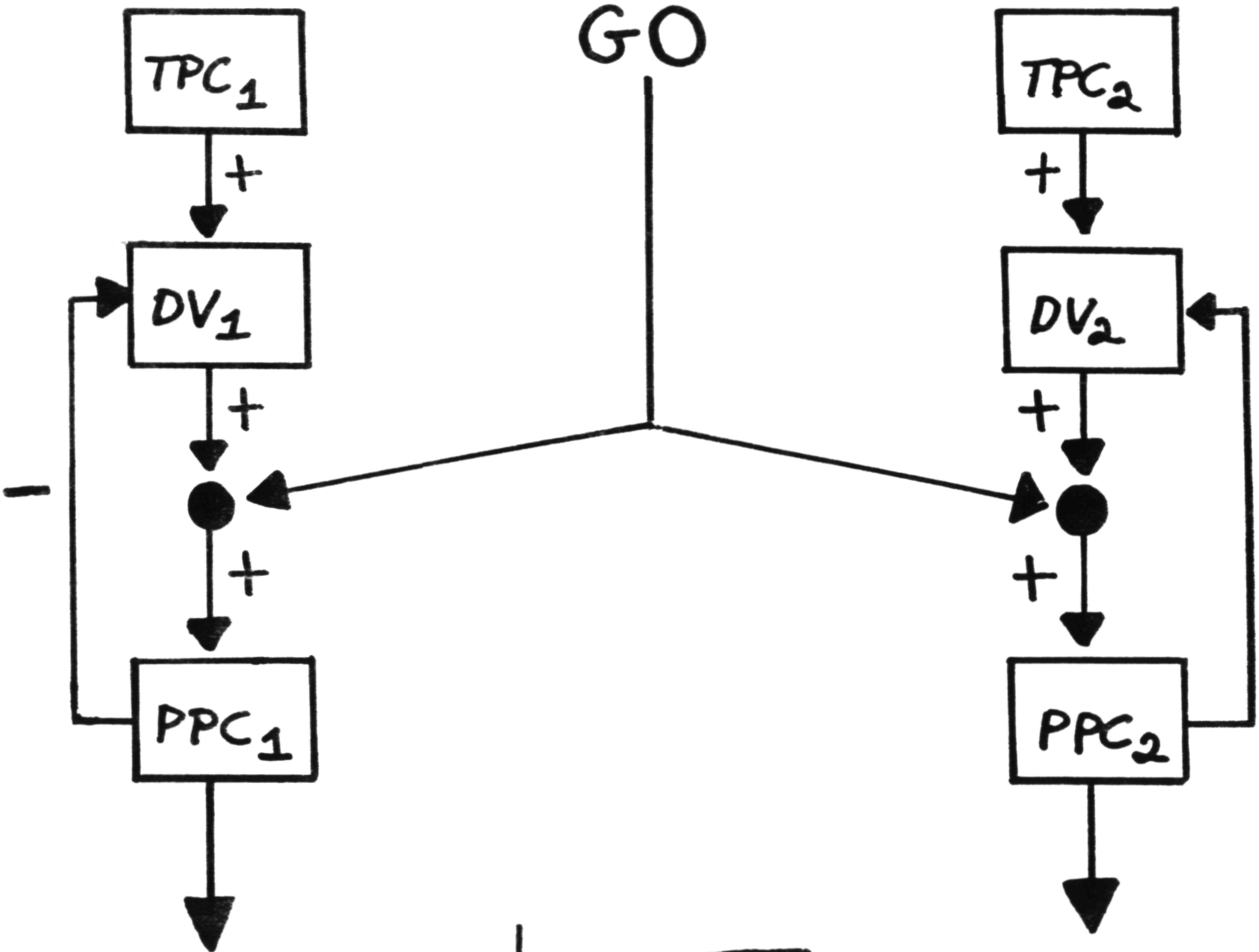


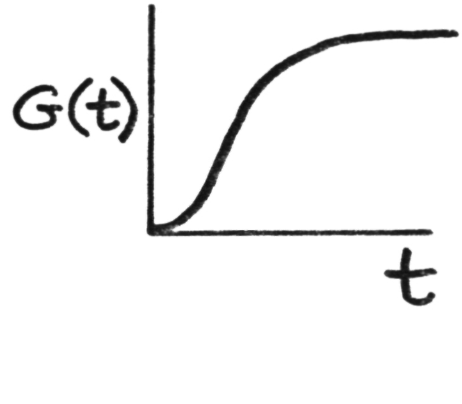
DV IS ADDED TO PPC UNTIL PPC = TPC AND DV = 0.

PPC <u>NOT</u> INFLOW!

HOW IS SPEED CONTROLLED?

NONSPECIFIC, MULTIPLICATIVE GO SIGNAL





GO MECHANISM (VITE)

IS FUNCTIONALLY HOMOLOGOUS TO

ATTENTIONAL GAIN CONTROL (ART)

IS FUNCTIONALLY HOMOLOGOUS TO

AROUSAL SOURCE (AVALANCHE)

⋮

A GENERAL DESIGN PRINCIPLE

FACTORIZATION OF PATTERN + ENERGY

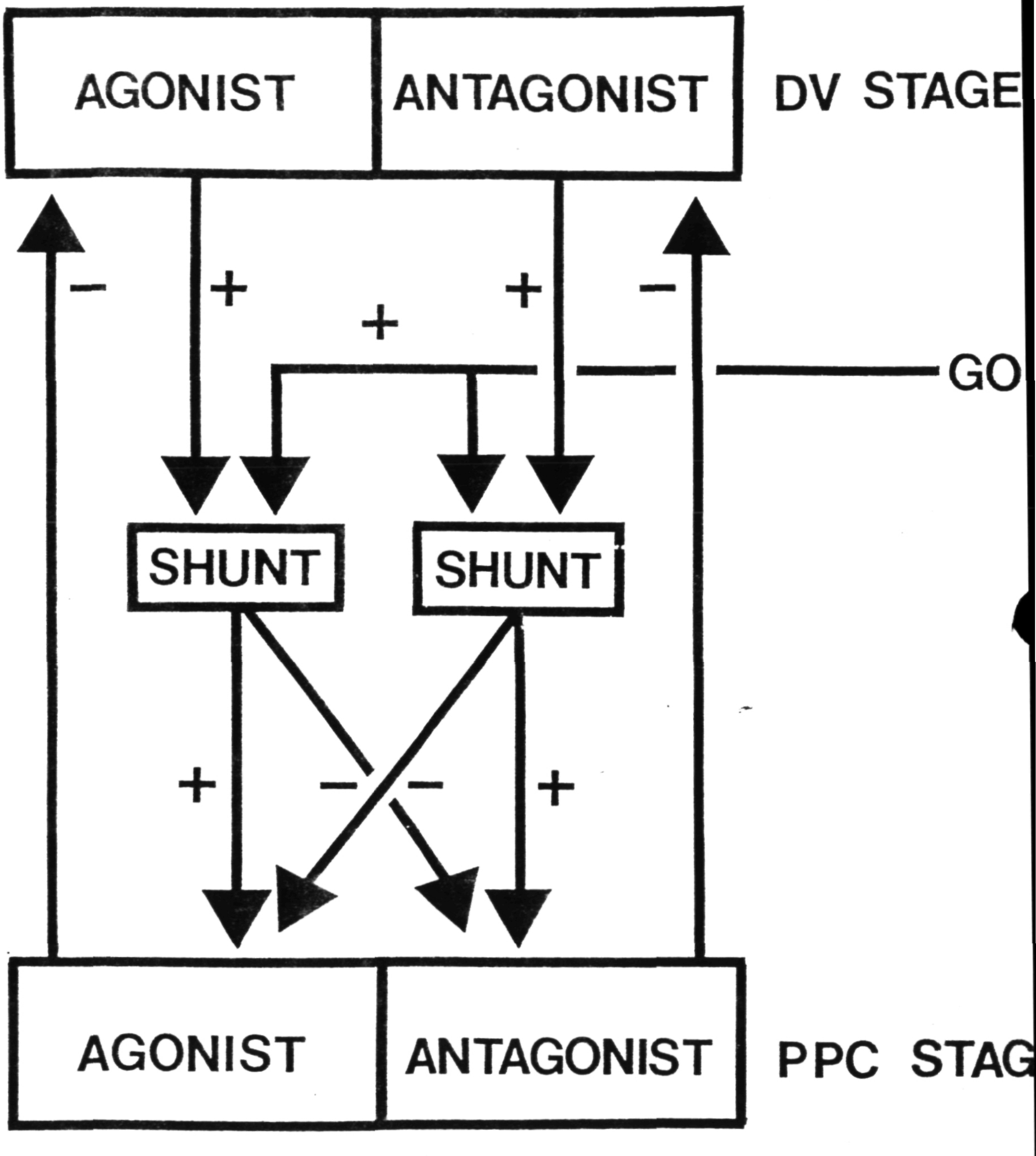
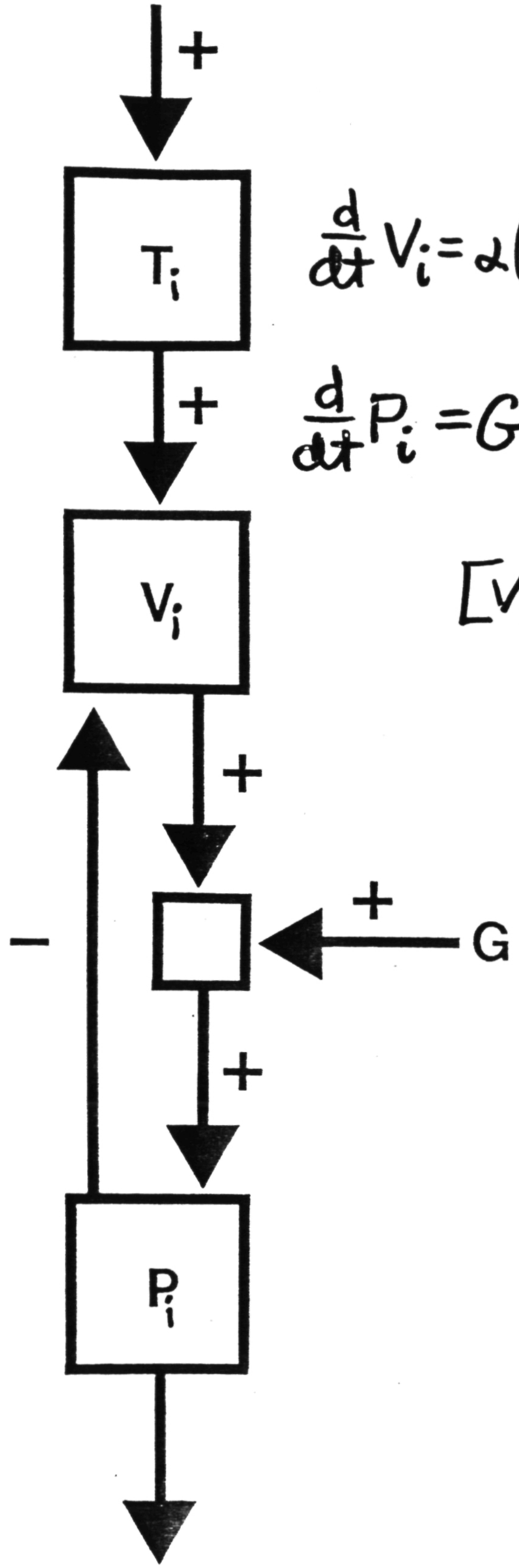

AGONIST
ANTAGONIST
DV STAGE
+
+
+
−
−
GO
SHUNT
SHUNT
+
−
−
+
AGONIST
ANTAGONIST
PPC STAG

Figure 16



$$\frac{d}{dt}V_i = \alpha\left(-V_i + T_i - P_i\right)$$

$$\frac{d}{dt}P_i = G(t)\max(V_i, 0)$$

$$[V_i]^+ = \max(V_i, 0)$$

DIGITAL SWITCH OF TPC
SMOOTH SYNCHRONOUS TRAJECTORY

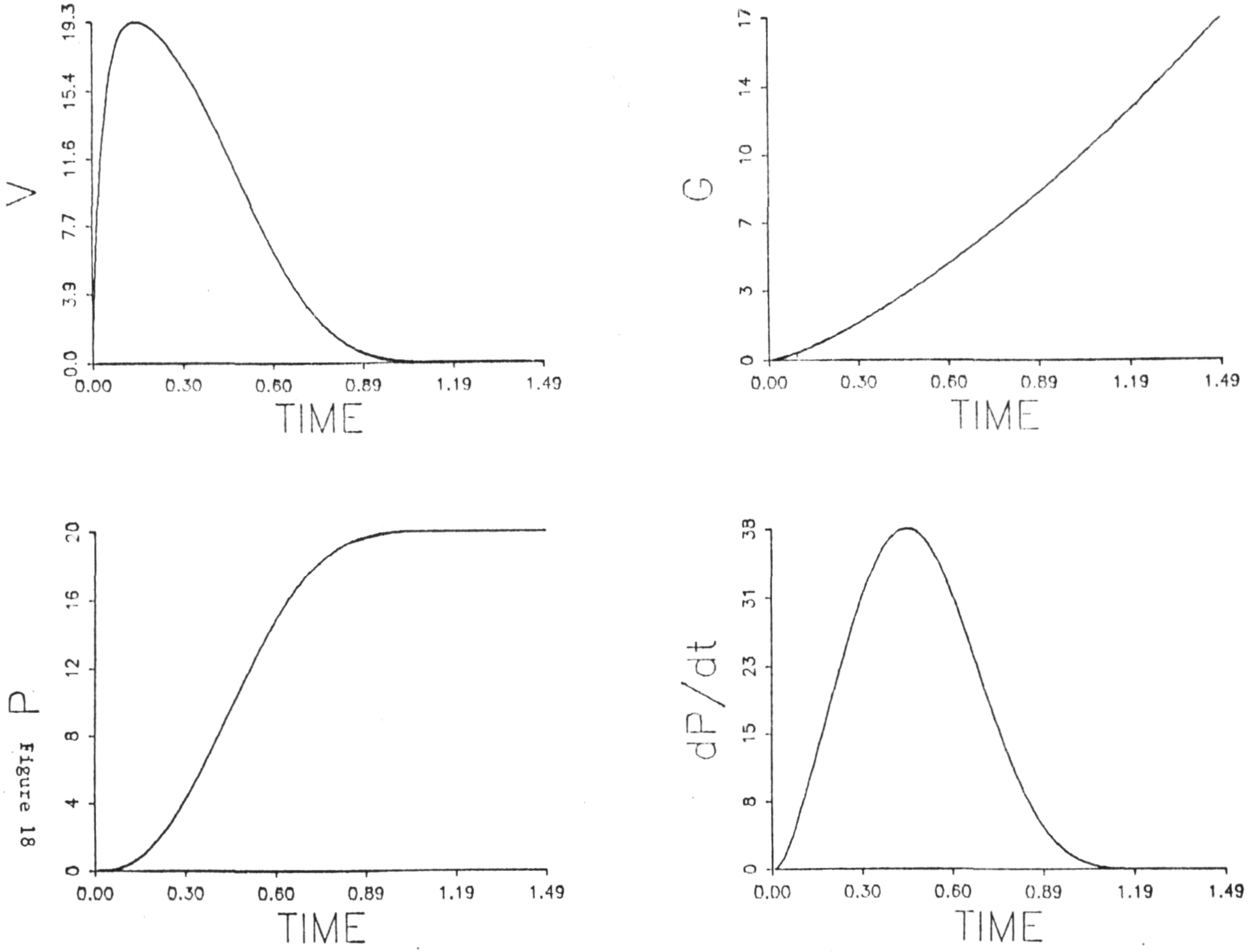


Figure 18

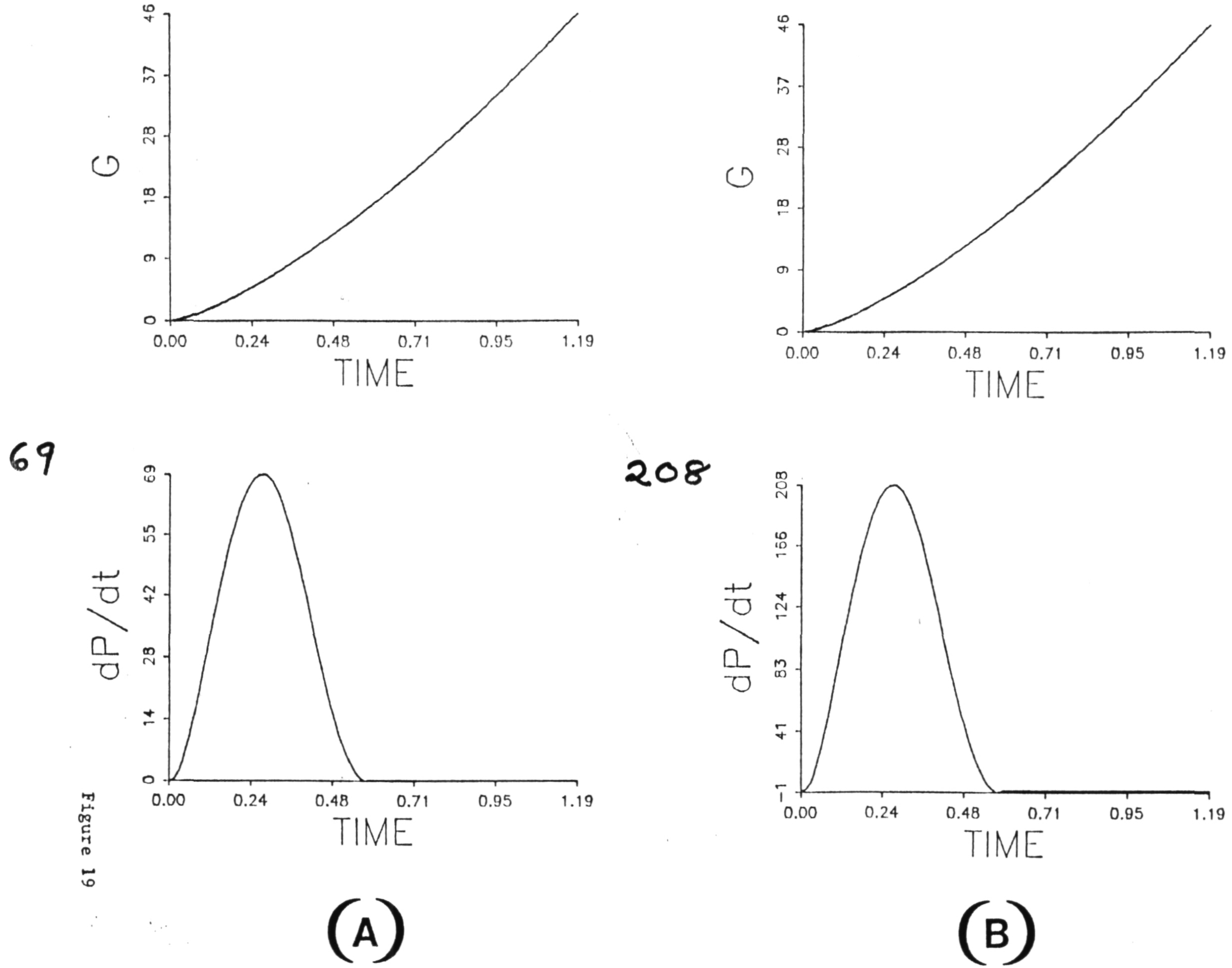

G
TIME
dP/dt
TIME
69
208
0
9
18
28
37
46
0.00
0.24
0.48
0.71
0.95
1.19
14
42
55
-1
41
83
124
166
(A)
(B)

Figure 19

SYNCHRONY AND DURATION INVARIANCE

GIVEN

$$\frac{d}{dt}V = \alpha(-V + T - P)$$

$$\frac{d}{dt}P = G(t)\max(V, 0),$$

WITH $V(0) = 0$.

SWITCH T FROM $T = T_0$ TO

$T = T_1 > T_0$ AT $t = 0$.

PROVE:

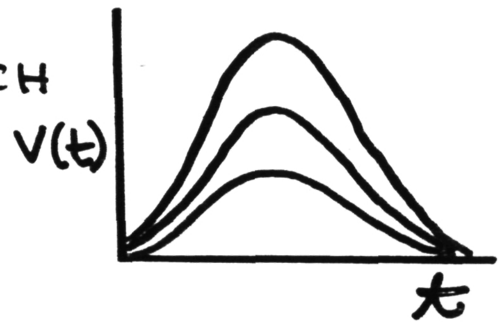
$$P(t) = P(0) + (T_1 - T_0)\,q(t)$$

WHERE $q(t)$ IS INDEPENDENT OF T_0 AND T_1.

EXPLAINS LARGE PARAMETRIC DATA BASE

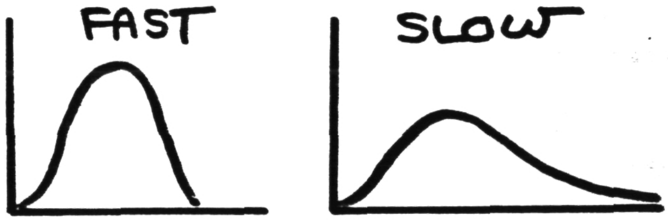
VELOCITY PROFILES FROM MOVEMENTS OF SIMILAR DURATION BUT UNEQUAL DISTANCE SUPERIMPOSE AFTER VELOCITY AXIS RESCALING

FREUND AND BÜDINGEN
ATKESON AND HOLLERBACH



VELOCITY PROFILE ASYMMETRY VARIES WITH DURATION

BEGGS AND HOWARTH
ZELAZNIK _et al_



(EVIDENCE AGAINST HOGAN'S MINIMUM JERK MODEL)

PRESENT POSITION COMMANDS ARE GRADUALLY UPDATED

BIZZI *et al*

(EVIDENCE AGAINST "SPRING-TO-ENDPOIN
MODELS)

LOGARITHMIC SPEED-ACCURACY TRADEOFF (FITTS' LAW)

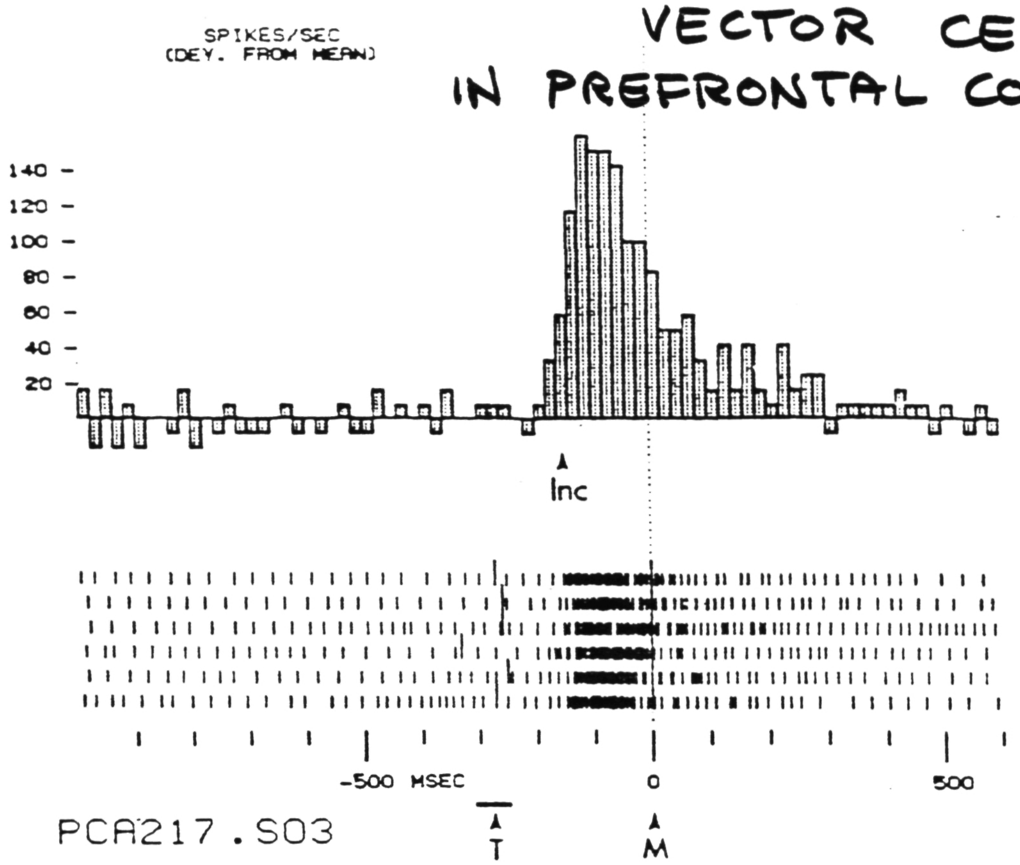
$$MT = a + b \log_2 \left(\frac{2D}{W} \right)$$

MT = MOVEMENT TIME

D = DISTANCE MOVED

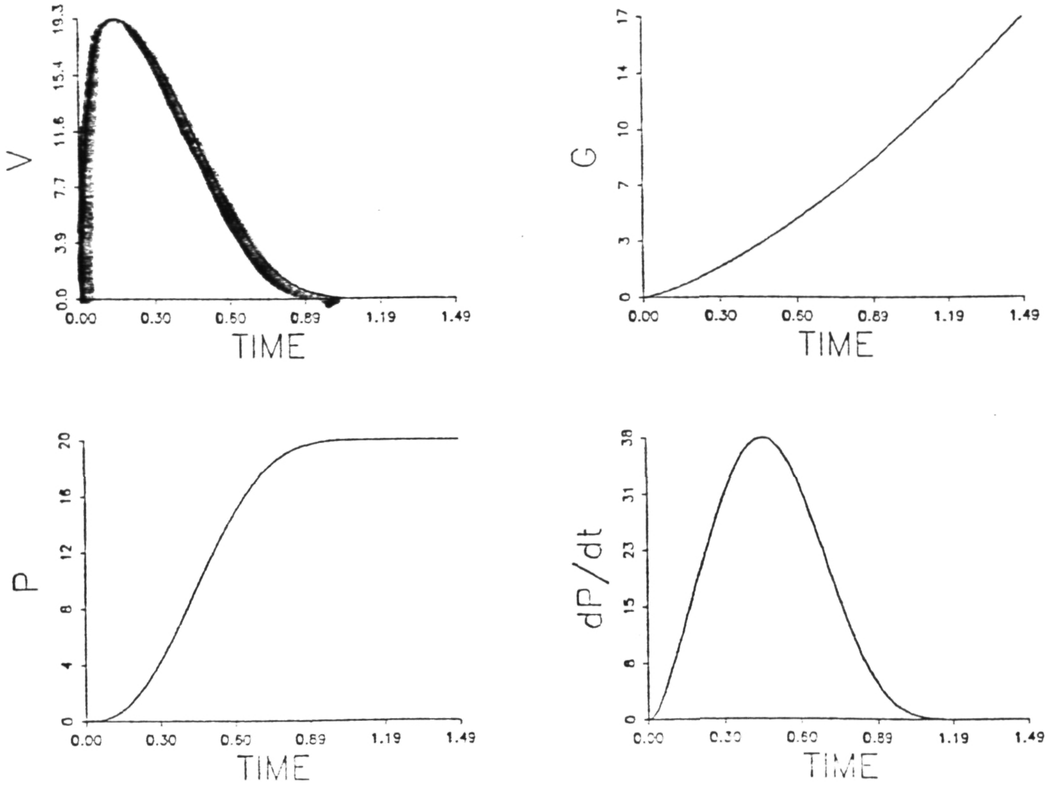
W = TARGET WIDTH

VECTOR CELL IN PREFRONTAL CORTEX



(GEORGOPOULOS et al; EVARTS AND TANJI)

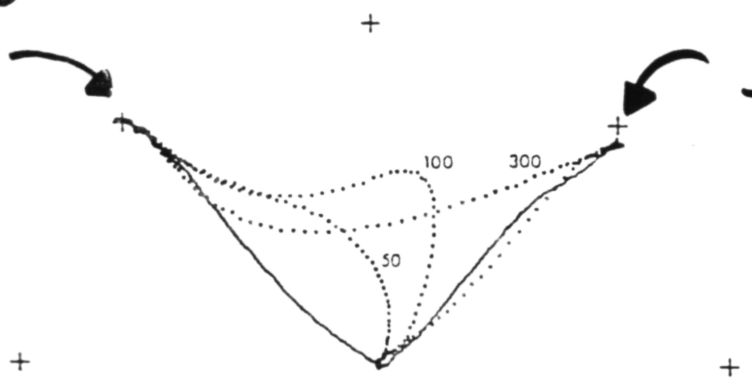
DV NODE IN VITE MODEL



AN ADAPTIVE EMERGENT PROPERT

SWITCHED TARGET

INITIAL TARGET



SEAMLESS TRAJECTORY CORRECTION AND "ANOMALOUS" MULTIPLICATION OF PEAK VELOCITY (GEORGOPOULOS et al)

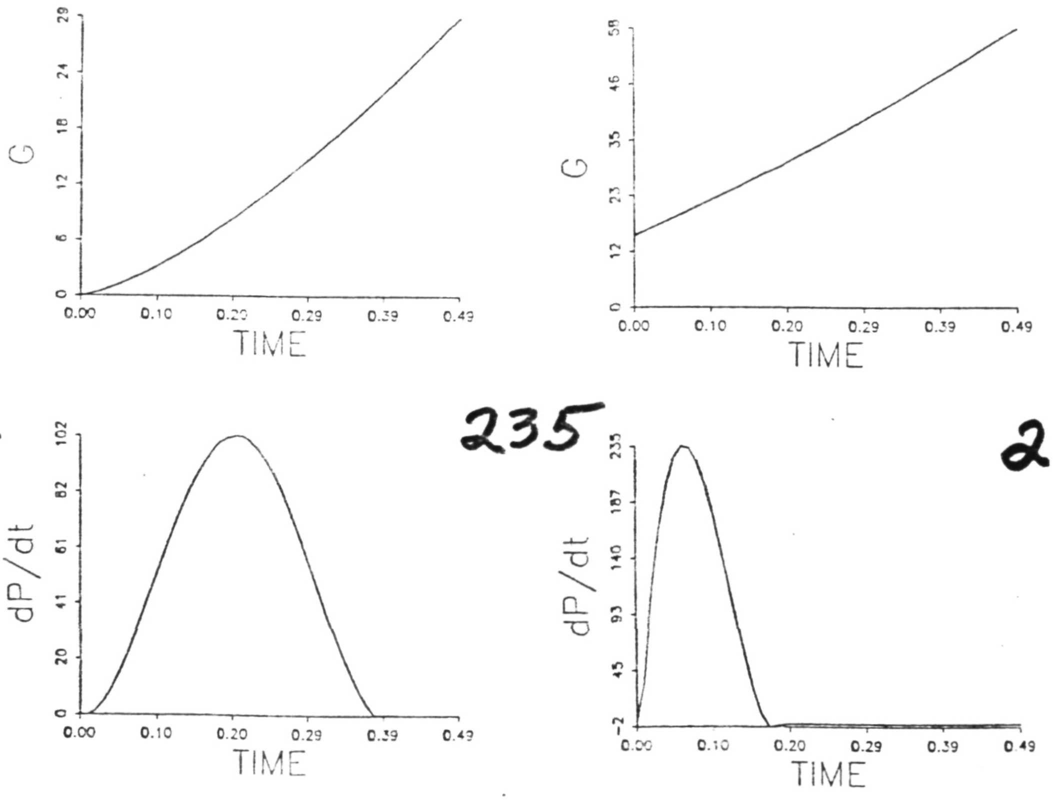
LOCAL VIOLATION OF FITTS' LAW

GO

102

235

2.3X



(A) (B)

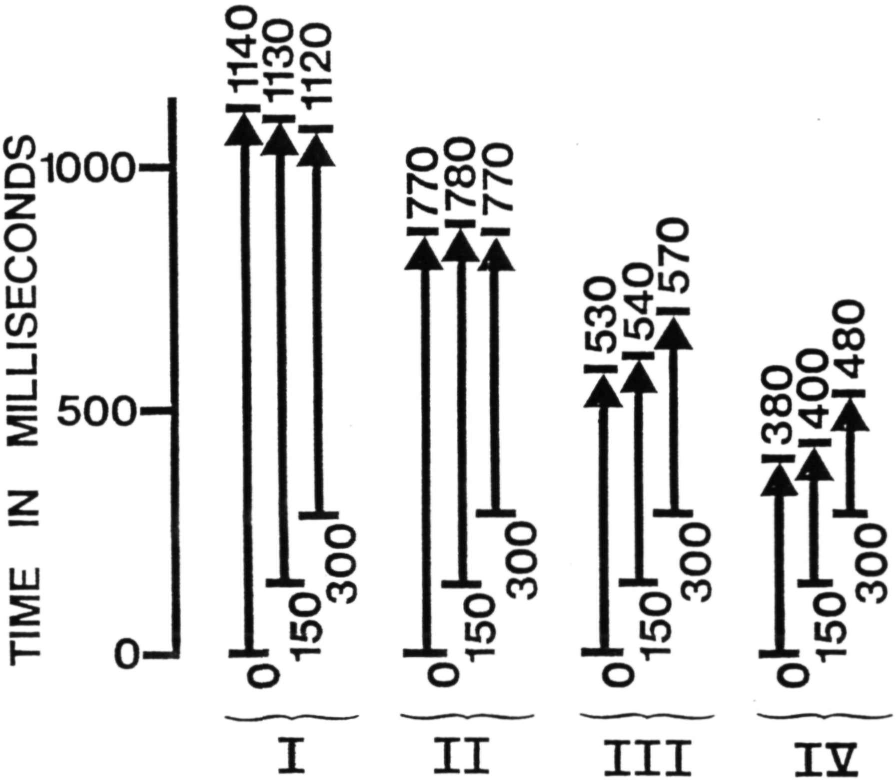
EQUIFINALITY

AUTOMATIC COMPENSATION FOR STAGGERED ONSET TIMES

⊥ SYNERGIST BEGINS CONTRACTION

SYNERGIST ENDS CONTRACTION

FAULT TOLERANT



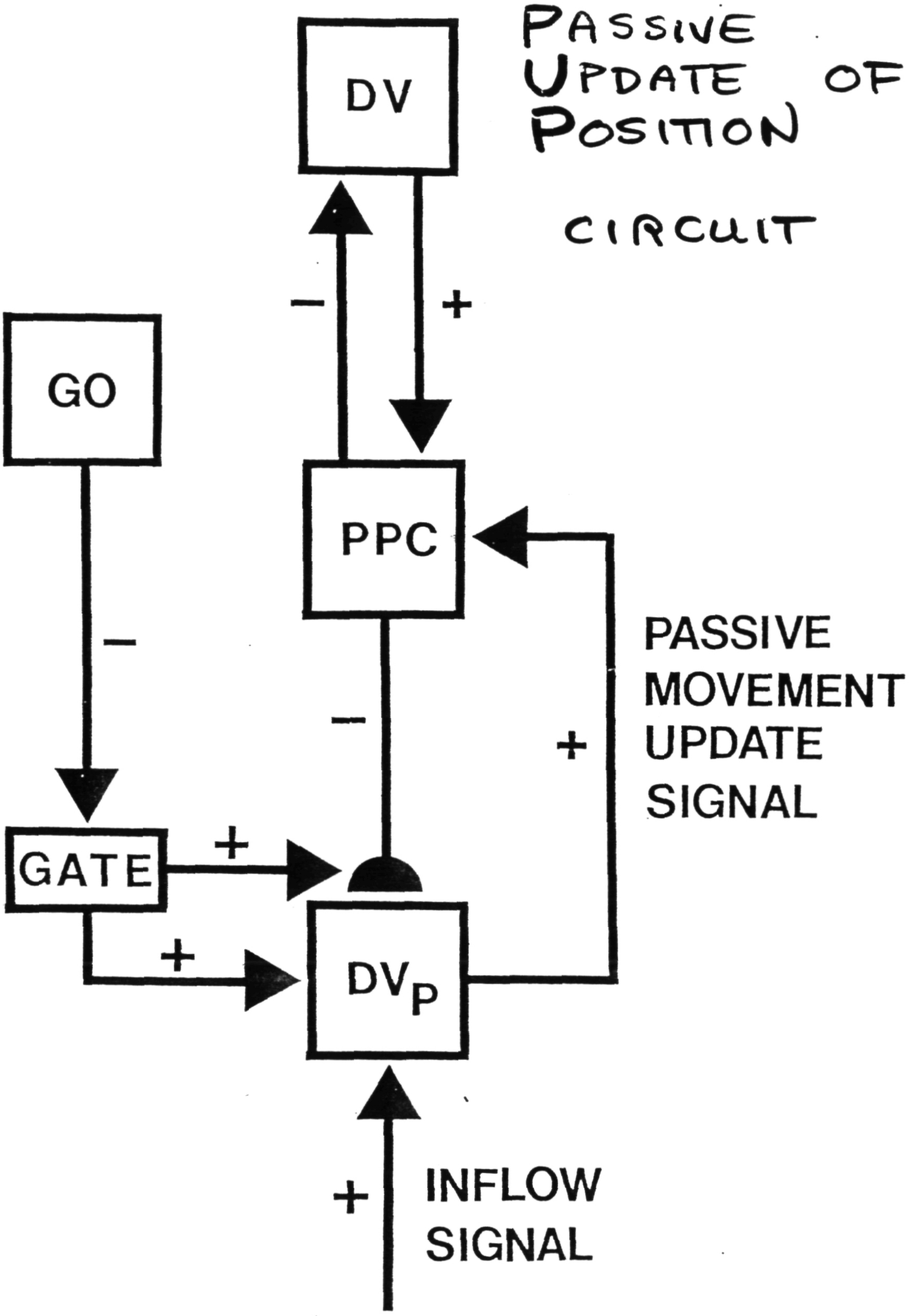
PRESENT POSITION

PASSIVE VS. ACTIVE MOVEME

GRAVITY
EXTERNAL FORCES

OUTFLOW VS. INFLOW

ADAPTIVE COORDINATE CHANGE



ADAPTIVE VECTOR ENCODER
ADAPTIVE COORDINATE CHANGE

VITE + PUP

VECTOR

$$\frac{d}{dt} V_i = \alpha(-V_i + T_i - P_i)$$

PPC

$$\frac{d}{dt} P_i = G[V_i]^+ + G_p[M_i]^+$$

$$G G_p = 0$$

OUTFLOW-INFLOW MATCH

$$\frac{d}{dt} M_i = -\beta M_i + \gamma_i I_i - z_i P_i$$

ADAPTIVE GAIN CONTROL (LTM

$$\frac{d}{dt} z_i = \delta G_p(-\epsilon z_i + [M_i]^+).$$

A MULTI-ARCHITECTURAL ADAPTIVE SYSTEM

MULTIPLE LEARNING PROBLEMS $\sim$ MULTIPLE CIRCUITS

SUMMARY

EMERGENT INVARIANT	BEHAVIOR
SIMILARITY	RECOGNITION
POSITION	TARGETING
SYNCHRONY	MULTI-JOINT MOVEMENT

SPECIALIZED INFORMATION PROCESSING

SPECIALIZED LEARNING LAWS

REAL-TIME NONLINEAR FEEDBACK

ALL EXAMPLES OF A FEW GENERAL EQUATIONS WITH SPECIALIZED PARAMETER CHOICES

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