EVIC 2005

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ASPECTOS TEÓRICOS Y PRÁCTICOS DE LÓGICA DIFUSA

Fuzzy Logic: Theory and Applications

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EVIC 2005:
Fuzzy Logic Theory & Applications: Topics

Dec. 14, 14:30 – 16:15:

- Basics
- Examples & Applications
  - HERE & NOW

Dec. 14, 16:30 -18:00

- Simulations of Linguistic Fuzzy Models
  - AT “LABORATORIO DE SISTEMAS INTELIGENTES”, LOCATED ON THE 3rd FLOOR OF THE BUILDING “LABORATORIO DE ELECTROTECNOLOGIAS”

Fuzzy Set Theory

- Motivation : There are several situations in the real world where object classes have membership categories which are not precisely defined

- Fuzzy logic associates uncertainty to the data set structure (Lotfi Zadeh, 1965)

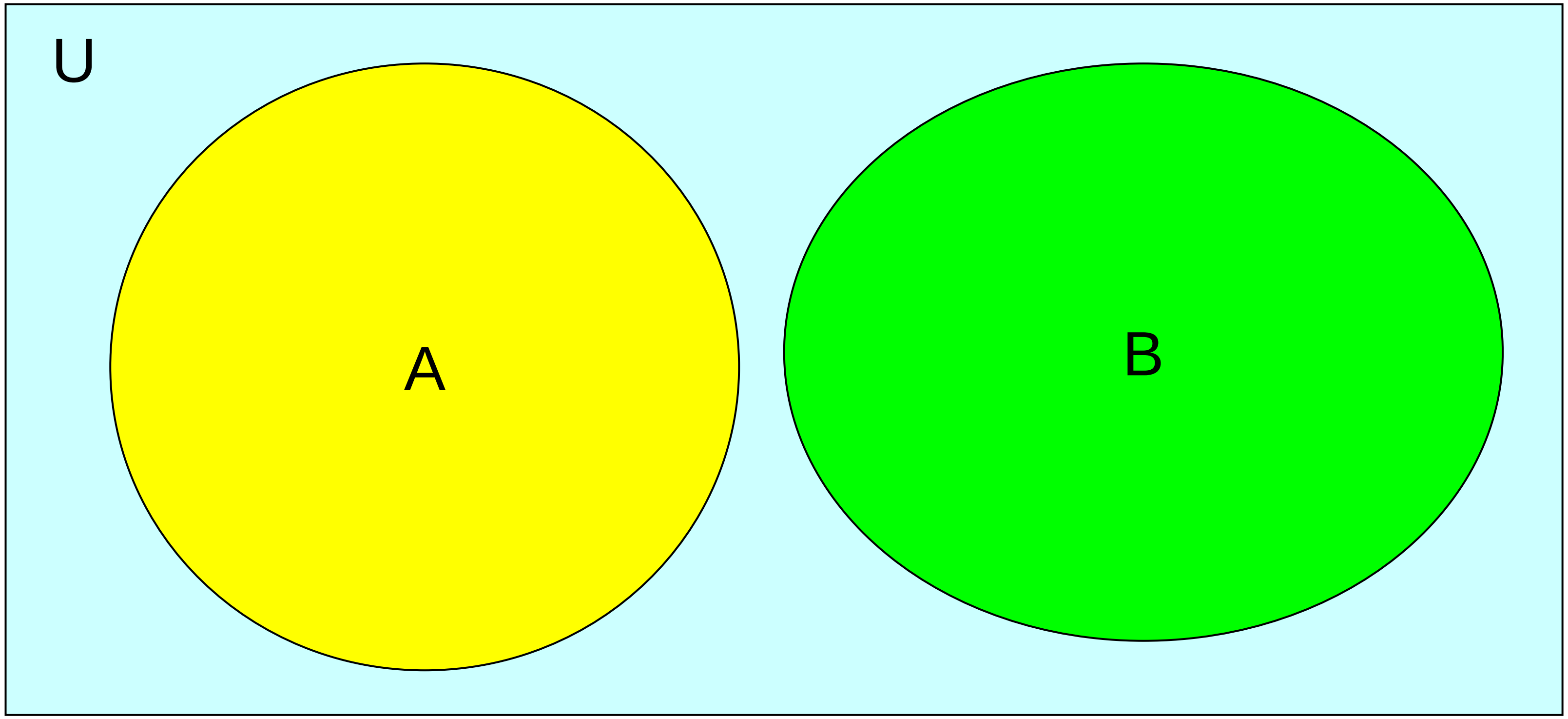
- The elements of a fuzzy set are ordered pairs of data specifying the value and membership grade

Crisp vs. Fuzzy Sets

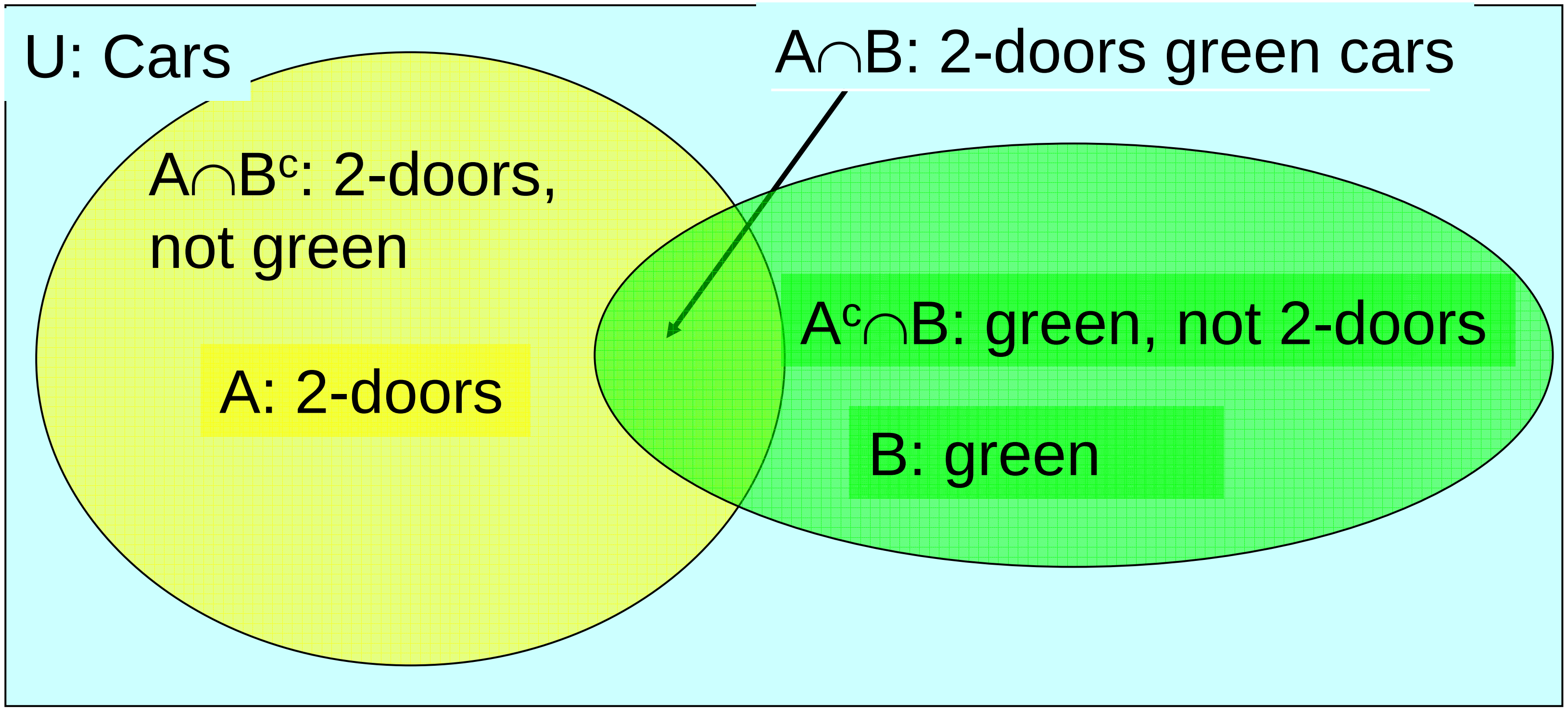
- “Crisp” Sets”: an element is either a member or not a member of a given set

- **Fuzzy Sets**:
  - \+ membership grade
  - \+ allows the formalization of concepts such as “tall”, “small”, “cold”, “fast”:
    - vastly used
    - essentially not precise

Crisp Sets Representation: Venn Diagram

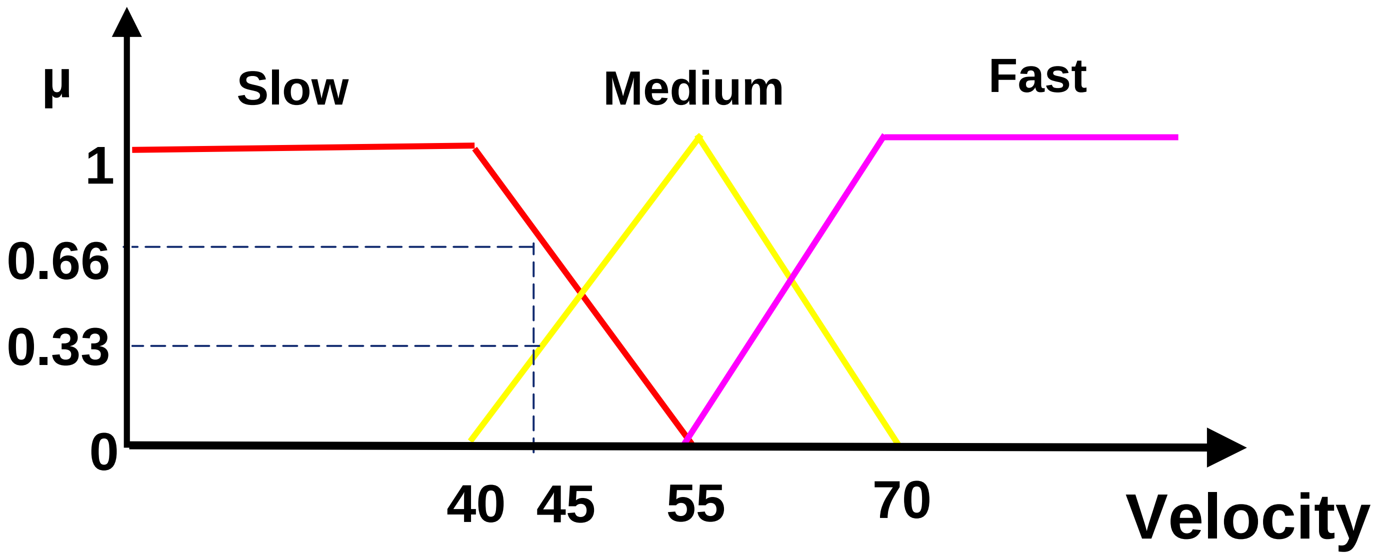


Venn Diagram: Example of Crisp Sets



Fuzzy Sets Example 1: Velocity

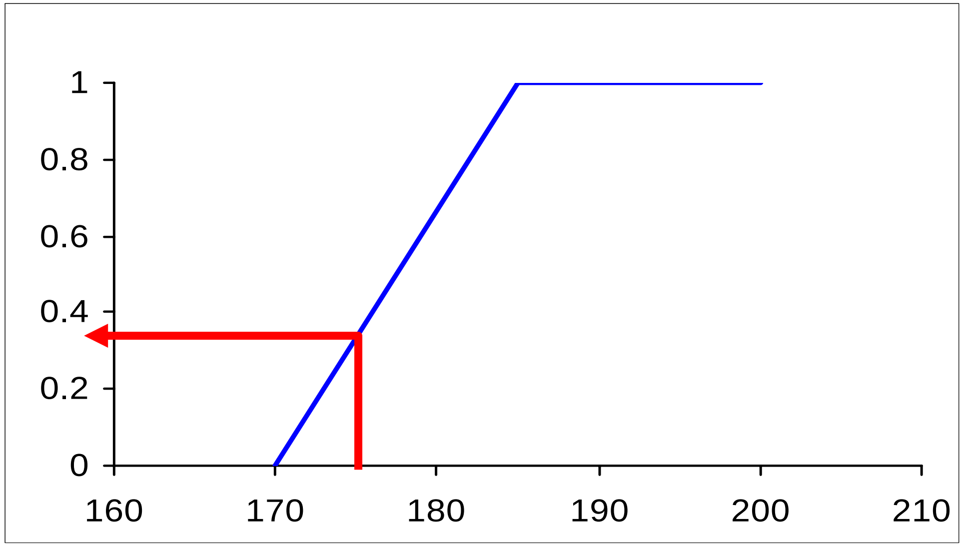
- Slow: “a velocity around 40 km/h or less”
- Medium : “a velocity around 55 km/h”
- Fast: “a velocity over 65 to 70 km/h approx.”



Fuzzy Sets Example 2: Tall Men

Membership grade:
Usually normalized between 0 and 1

(0 and 100%)



High (cm)

A man who is 175 cm is 33% member of the “Tall” men set.

Examples: “Crisp” vs. Fuzzy Sets

- The three-legged tables — Crisp

- The tall men — Fuzzy

- The high-frequency waves — Fuzzy

Fuzzy Variables and Membership Functions

A variable can be characterized by different linguistic values, each one represented by a fuzzy set.

Each element of the universe has a membership grade to a given set, which can be described by a function:

- **“Crisp” Sets**: $\mu_A(a): U \rightarrow \{0, 1\}$

- **Fuzzy Sets**: $\mu_A(a): U \rightarrow [0, 1]$

$[0, 1] \Leftrightarrow 0 - 100\%$

Observer Dependency on the Membership Grade

Basically, the membership grade is subjective, and context dependant.

Examples:

- Distance: How many meters is “far away”?
  - a) If you are walking
  - b) If you are travelling by car
- Temperature: “warm” and “cool” depends on:
  - a) If you are a furnace operator
  - b) If you refer to room temperature
  - c) If you refer to superconductors

The Membership Grade

The membership grade is given by the membership function.

The membership grade is not a probability. It can be described as “the compatibility between an object and the concept represented by the fuzzy set”.

Example:

Paul is 50 years old. His membership grade to the fuzzy set of “young” people is 0.3.

a) It means there is a 30% compatibility of his age to the “young” people concept.

b) It does not mean there is a 30% probability he is “young”.

Possibilistic Distribution

A function describing the truth grade of a statement is a possibilistic distribution.

There are analogies with a probabilistic distribution, but there are also significant differences, such as that the sum of possibilities may not be equal to one. It is not a description of groups or populations, but of individuals.

An event may have possibility =1, but very low probability.

Example:

It is perfectly possible that a person eats 4 eggs for breakfast (possibility=1) but it has a low probability (probability =0.03)

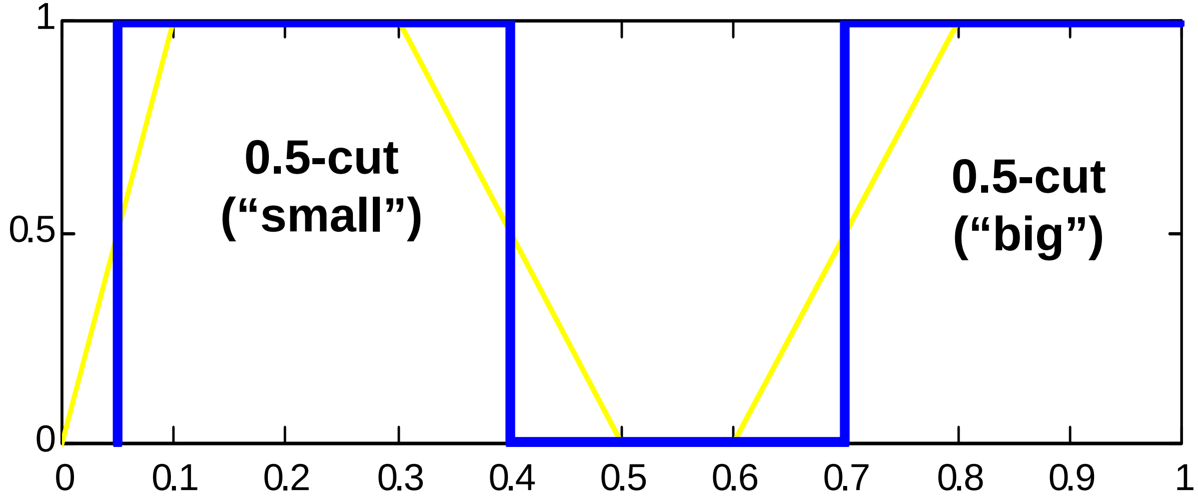
Crisp Sets Defined by a Fuzzy Set

Support: Crisp set including all elements with non-zero membership grade

Core: Crisp set including all elements with membership grade 1

α-cut: ${}^{\alpha}A = \{ x \mid A(x) \geq \alpha \}$, $0 \leq \alpha \leq 1$

Example: $\alpha = 0.5 \Rightarrow \alpha$-cut(“small”) = 0.5-cut(“small”)



Fuzzy Sets Allow a Better Representation of Some Kinds of Uncertainty

	Type 1 uncertainty	Type 2 uncertainty
Origin	Random behavior of physical systems	Human processes: sensation, perception, cognition, reasoning, thinking
Examples	- Random vibrations of a machine - Random fluctuations of electrons in a magnetic field - Gas difusion	- Perception and cognition of the physical environment through our natural sensors (vision, hearing, smell, touch and taste) - Perception of pain
Theory for analysis	Statistics (mean, variance)	Fuzzy SetsTheory

Reasoning in Computers vs. Humans

Decision-making in computers usually involves questions with clear yes-or-no type answers.

Humans usually do not think in such precise categories. Most of human reasoning has some grade component or context association.

For example:

- It is dangerous to drive on a slippery road
- A complex circuit has to be designed with high reliability (i.e. very low rejection index)

Fuzzy vs. Boolean Logic

Classic or bivalent or Boolean Logic requires a statement to be either true or false.

Fuzzy Logic allows truth grades, allowing approximate reasoning. Before fuzzy logic there were other developments in multi-valued logic, such as the work by Lucasiewicz.

Linguistic Fuzzy Models & Concepts

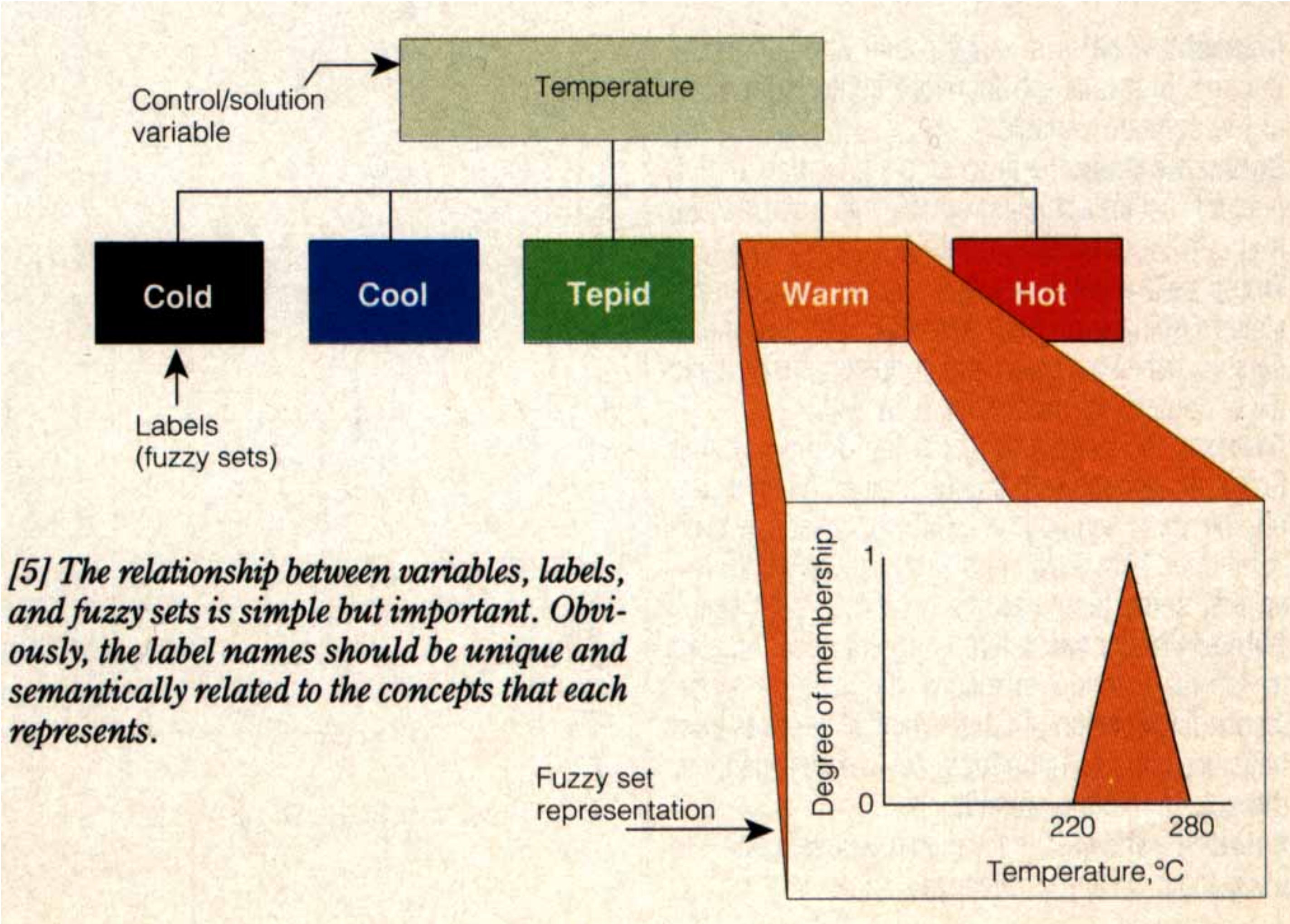
- Linguistic fuzzy models are based on heuristic rule sets where the input and output linguistic variables are represented by fuzzy sets

- A **linguistic variable** has set of **linguistic terms** associated, to describe it.

- EXAMPLE: If **temperature** is interpreted as a linguistic variable, then its term set could be

  {very_cold, cold, tepid, hot, very_hot}

Example of Fuzzy Variable: Temperature



[5] The relationship between variables, labels, and fuzzy sets is simple but important. Obviously, the label names should be unique and semantically related to the concepts that each represents.

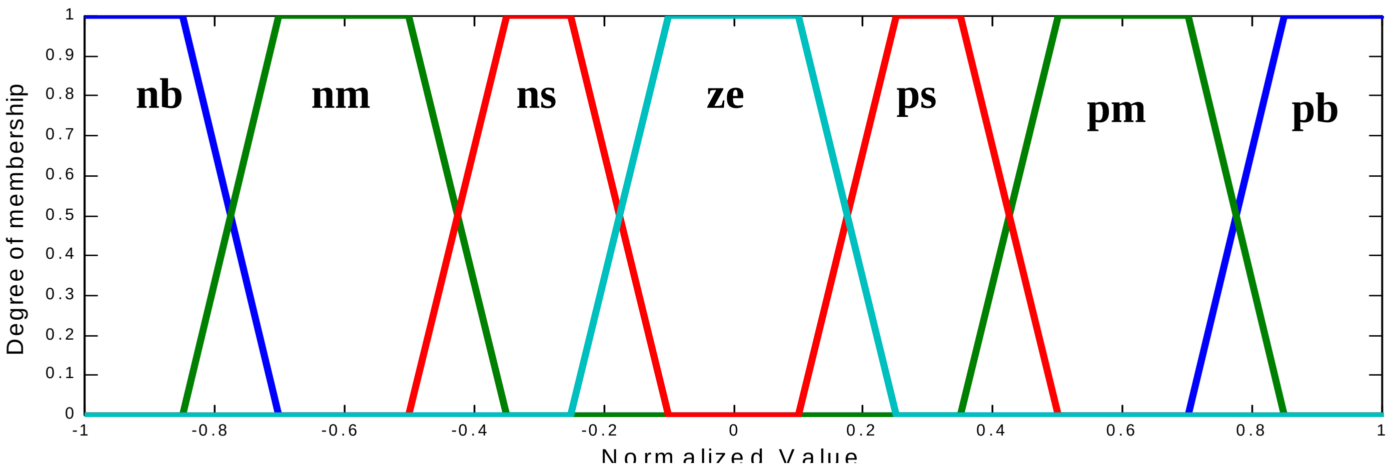
From E.Cox."Fuzzy Fundamentals". IEEE Spectrum Oct.1992

Associating Fuzzy Sets to a Variable

The **universe of discourse** of a variable is the range it covers in the “real world”.

The **dynamic range** is the range in which the variable is “observed”; it can be **normalized** by mapping it to [-1, 1].

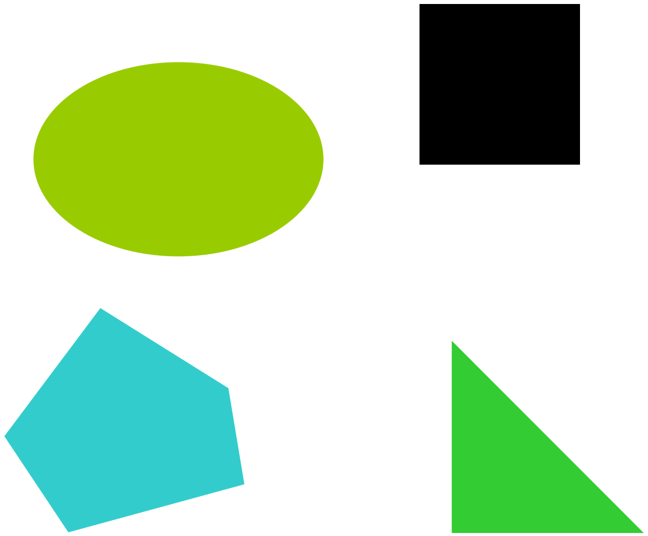
Linguistic terms or **fuzzy labels** or **fuzzy numbers** are defined for the variable (in the example below: 7 sets).



Convexity: Crisp Sets

A is convex $\Leftrightarrow \forall\, a,b \in A, \forall\lambda \in [0,1]: (\lambda a + (1-\lambda)\, b) \in A$

Examples:



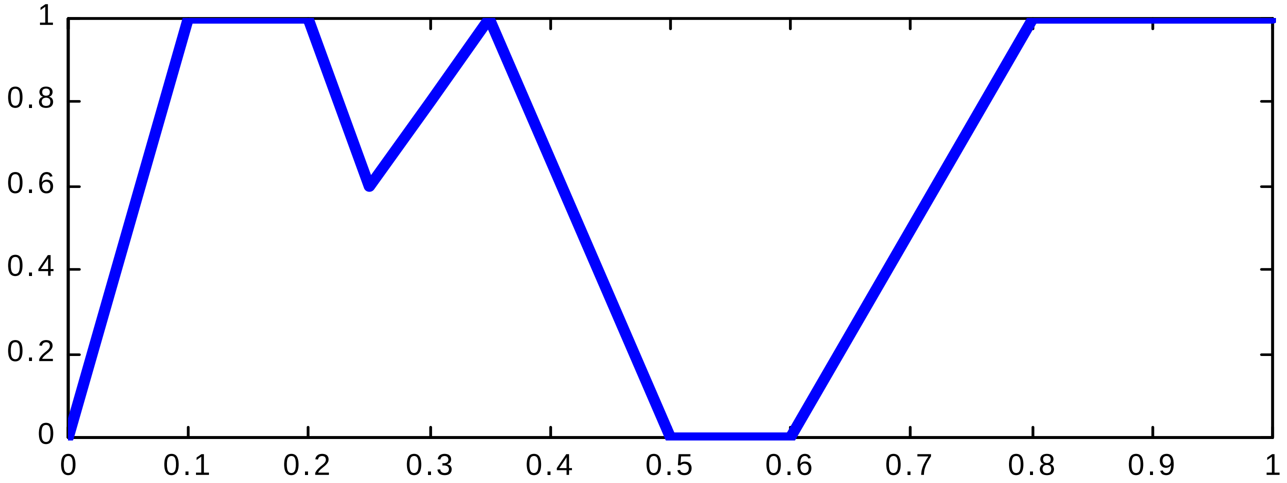
convex

non-convex

Convexity: Fuzzy Sets

A is convex $\Leftrightarrow$

$\forall$ a,b $\in$ A, $\forall\lambda \in[0,1]$: $\mu_A(\lambda a + (1-\lambda)\, b\,) \geq \min(\mu_A(a), \mu_A(b))$



Most fuzzy sets applied to practical applications are convex.

Operations on Fuzzy Sets

Intersection of fuzzy sets, as the other fuzzy operations, are generalizations of the corresponding classical set operations.

Unlike crisp sets, there is no unique way to represent the intersection or the other sets operations, but **a class of binary functions**. The determination of the particular functions depends on each application.

Intersection on Fuzzy Sets: t-norm

Triangular norm or **t-norm** is any function with following properties:

1) $N_T(a,b) = N_T(b,a)$;

2) $N_T(N_T(a,b), c) = N_T(a, N_T(b, c))$;

3) if $(a \leq c) \Rightarrow N_T(a,b) \leq N_T(c,b)$

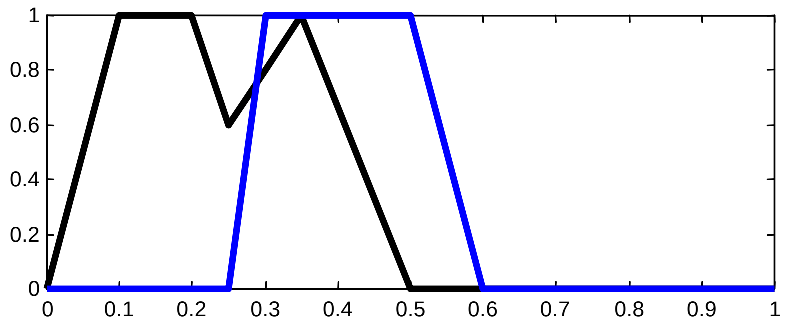
4) $N_T(a,1) = a$.

Popular t-norms in engineering applications are

$\mathbf{(A \cap B)(x) = \min\{A(x), B(x)\}}$ and

$\mathbf{(A \cap B)(x) = A(x) * B(x)}$

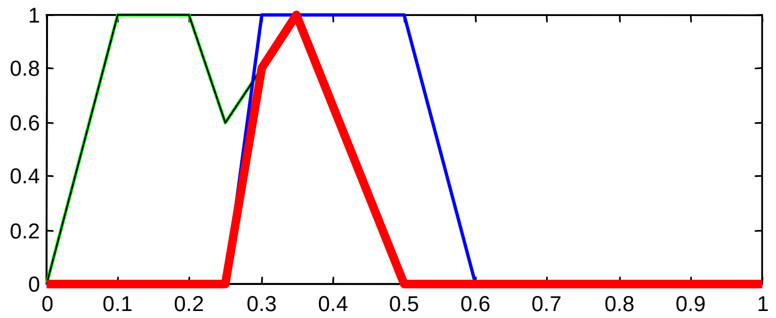
T-norm: Example



Fuzzy sets:

A (green)

B (blue)



$(A \cap B)(x) = \min\{A(x), B(x)\}$

Union on Fuzzy Sets: t-conorm

Triangular conorm or **t-conorm** or s-norm is any function with following properties:

1) $N_S(a,b) = N_S(b,a)$;

2) $N_S(N_S(a,b), c) = N_S(a, N_S(b, c))$;

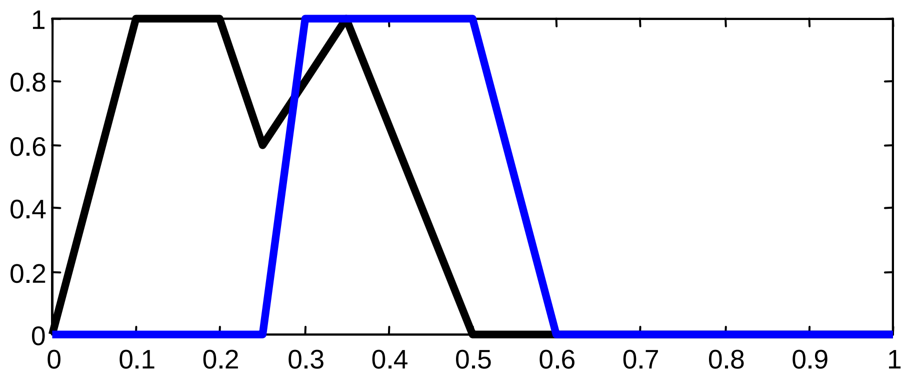
3) if $(a \leq c) \Rightarrow N_S(a,b) \leq N_S(c,b)$

4) $\mathbf{N_S(a,0) = a.}$

Most applications in engineering use the t-conorm

$$\mathbf{(A \cup B)(x) = \max\{A(x),B(x)\}}$$

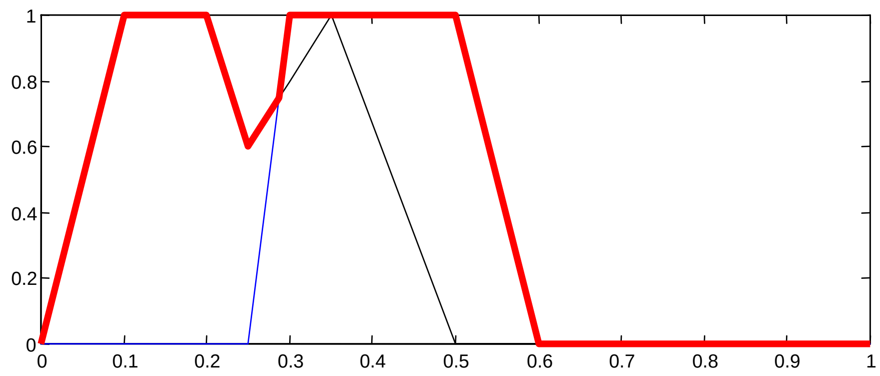
T-conorm: Example



Fuzzy sets:

A (green)

B (blue)



$(A \cup B)(x) = \max\{A(x), B(x)\}$

Complement on Fuzzy Sets

The **fuzzy complement** is any function with following properties:

1) $N_C(0) = 1;$

2) if $(a \leq b) \Rightarrow N_C(a) \geq N_C(b), \quad \forall\, a,b \in [0, 1]$

3) $N_C(N_C(a)) = a;$

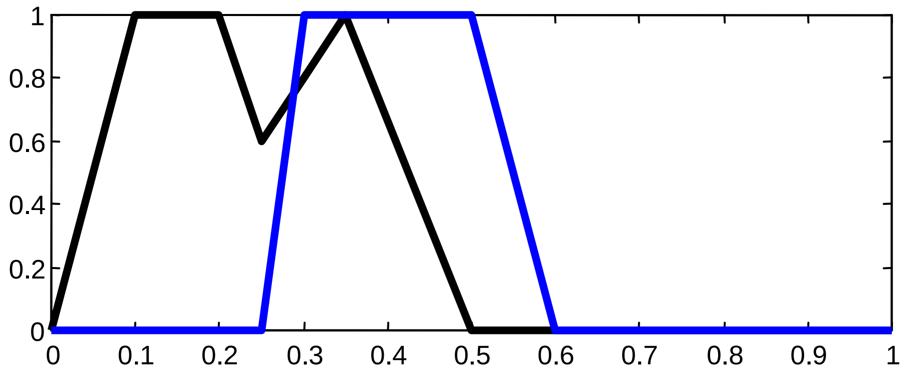
Most practical applications use

$$\mathbf{N_C(a) = 1\text{-}a} \quad \text{(complement of 1)}$$

Max -Min Properties

Min is the function with the highest outputs of the **t-norms** class

Max is the function with the lowest outputs of the **t-conorms** class



Fuzzy Logic Control

There are different methodologies to integrate fuzzy logic to automated control

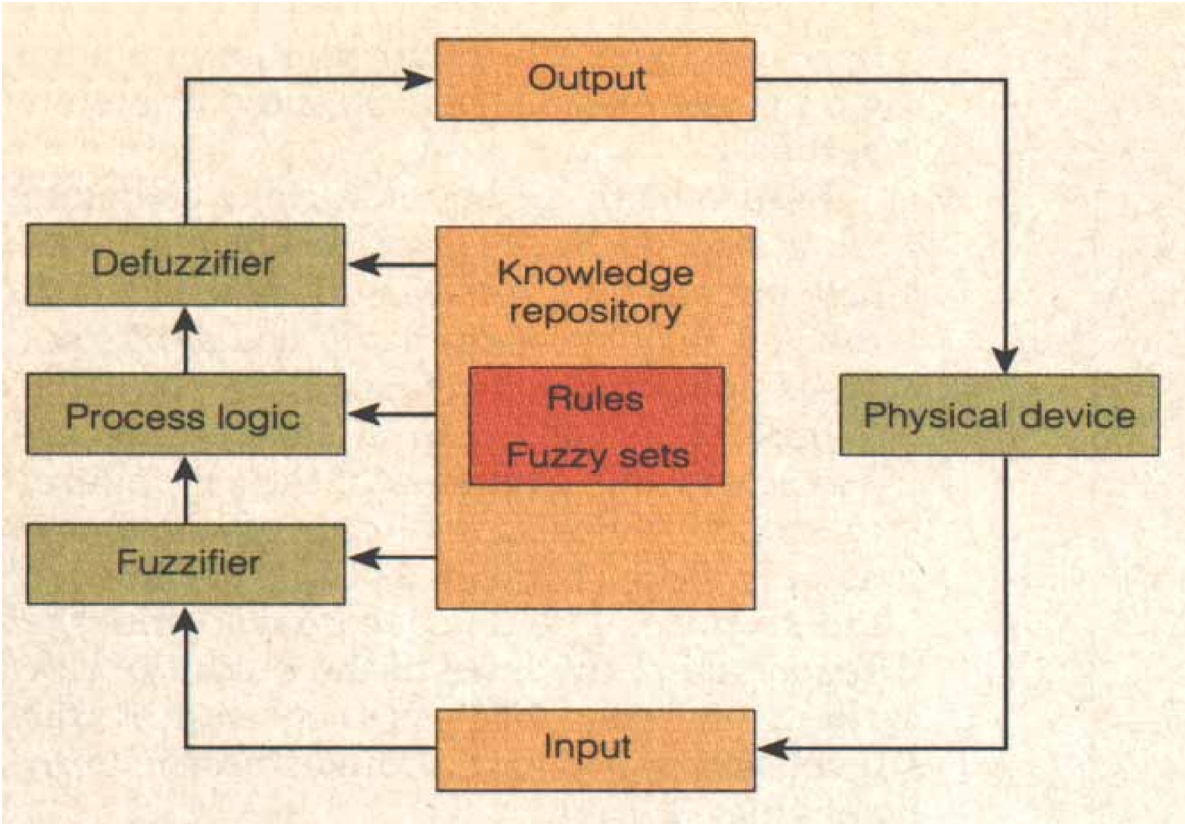
- Linguistic fuzzy models (Mamdani)
- Takagi & Sugeno fuzzy models

The “**Mamdan**i” view of control design:

Classic Control: Model the plant

Fuzzy Logic Control: Model the controller (i.e. the plant operator)

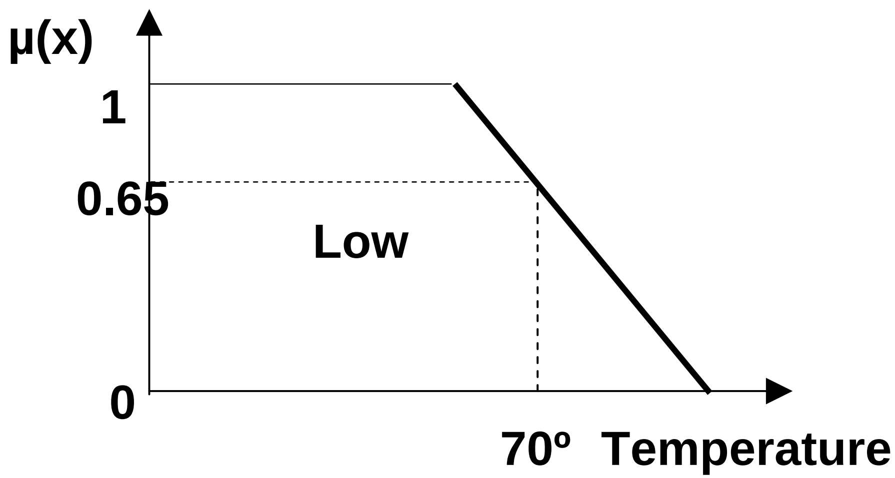
Fuzzy Logic Control Scheme



The **inference engine** applies the **knowledge base** to the fuzzified inputs

Fuzzification Interface

- The Fuzzifier transforms the input variables to fuzzy variables
  - Example: 70 º $\rightarrow$ “Low 0.65”



Knowledge Base & Fuzzy Rules

The **Knowledge Base** contains the linguistic rules and the membership functions information of the fuzzy sets.

The “knowledge” of a rule-based system is in its **fuzzy rules set.**

Each fuzzy rule is typically of the form

If (condition 1, condition 2, ...)
then (consequence 1, consequence 2 ...).

Fuzzy Rules

The fuzzy rules are **triggered** using **approximate reasoning** to obtain the desired results.

The **inference engine** calculates the output variables fuzzy sets from the input variables by using the rules and the fuzzy inference.

The classic (Boolean) implication **p$\Rightarrow$q** is replaced by a **fuzzy implication**. There are several different fuzzy implications. In control **Mamdani**'s implication is widely used.

Mamdani's (or Engineering) Implication

Rule: If a is A then b is B.

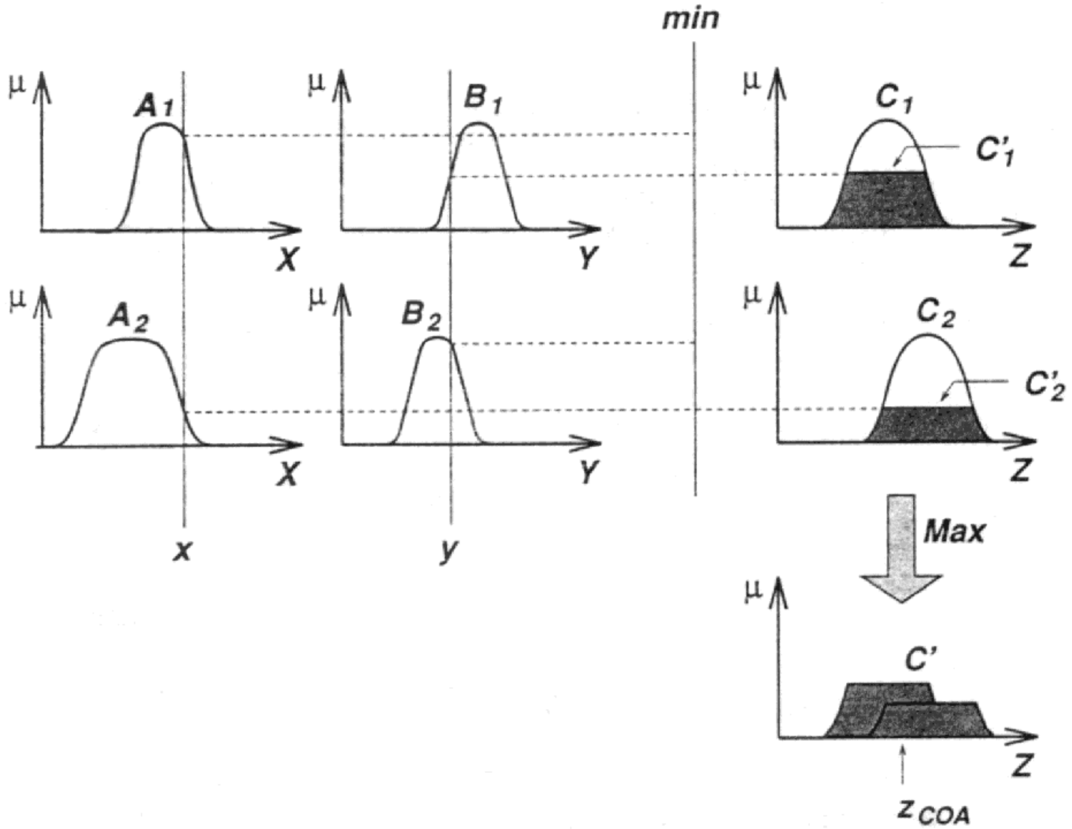
If the rule is triggered, then a T-norm is applied on $\mu_A(a)$*B.
Using min:

$$\forall\ b \in U_B: \mu_{B(A \Rightarrow B)}(b) = \min\{ \mu_A(a), \mu_B(b)\}$$

i.e. the membership grade of a to A limits the membership of b to B.

The result $\mu_{B(A \Rightarrow B)}$ of the rule is a cut-off version of original $\mu_{B.}$

Mamdani's Fuzzy Inference Example: 2-Inputs, 2-Rules, 1-Output



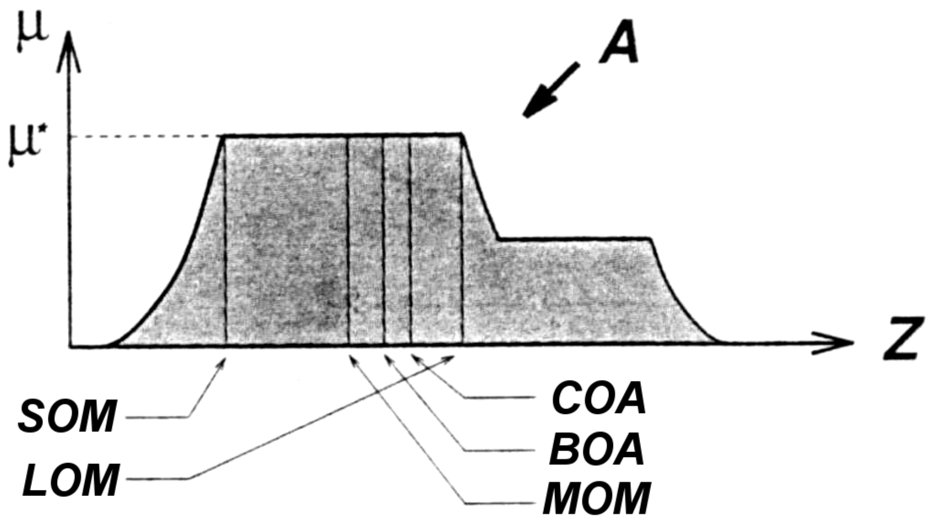
R1: If x is A1 and y is B1 then z is C1

R2: If x is A2 and y is B2 then z is C2

Result: Combination of rule outputs

Output: A crisp number is obtained by a defuzzifying method.

Defuzzifying methods

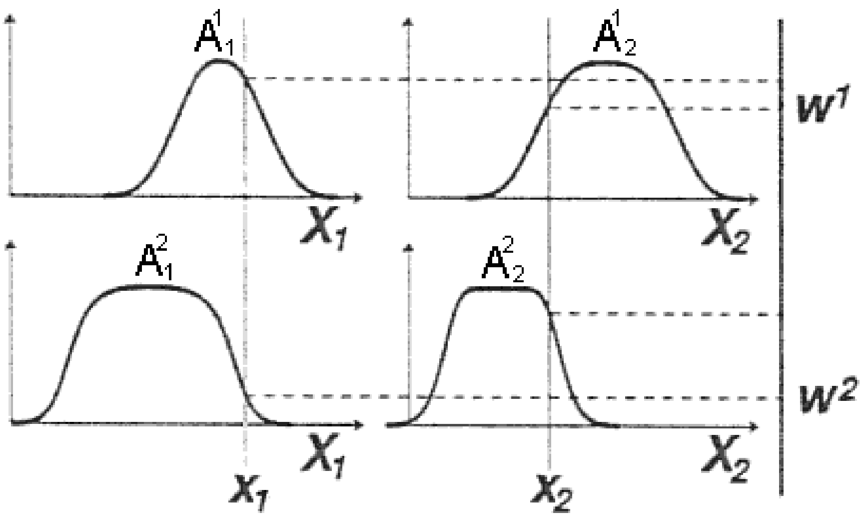


There are different defuzzifying methods, which will render different crisp results.

A widely used method is Center of Area (COA): The output is given by the center of gravity of the area described by the union of membership functions.

Sugeno Type Fuzzy Inference System

It is a mix between a concepts-based fuzzy system and an equations-based analytic system.



$$y^1 = a_0^1 + a_1^1 x_1 + a_2^1 x_2$$

$$y^2 = a_0^2 + a_1^2 x_1 + a_2^2 x_2$$

$$y = \frac{w^1 y^1 + w^2 y^2}{w^1 + w^2}$$

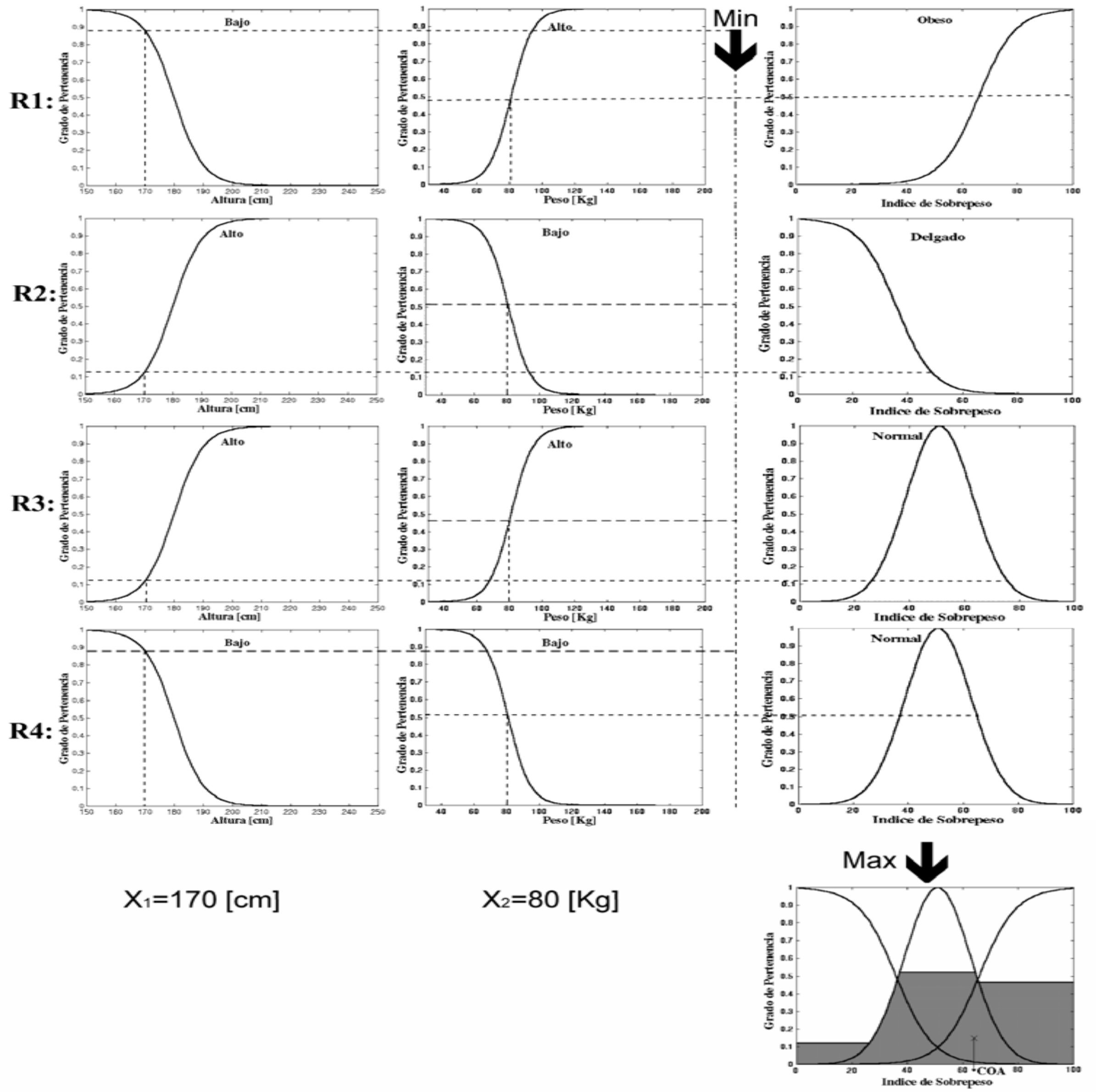
$$y = \bar{w}^1 y^1 + \bar{w}^2 y^2$$

The output of each rule $\mathbf{y^i}$ is a first order polynomial. The inputs membership grades determine the output relative weight. No defuzzifier is needed, since the output **y** is a crisp number.

Fuzzy Logic: Examples & Applications

- Diet planner tool (fragment)
- What’s the fuzz?
- Basketball team coach
- Handwritten digits recognition (prototypes & fuzzy rules)
- Classification of sleep stages in infants
- Sleep spindles detection in infant polysomnograms
- Fraude en telecomunicaciones

Fuzzy Inference Example: Diet Planner



R1-R4: Rules defining whether a person is obese, normal or thin.

The diagram shows a Mamdani inference, with COA output.

Alternatively, if the output should be a concept, it is given by the rule with the highest membership grade. In the example: R4.

Not that different...

It’s been here before. An opinion that focuses on applications.

Get the fuzz out

The article ‘‘Fuzzy logic flowers in Japan’’ [July, pp. 32–35] reminds me of what happened when artificial intelligence was ‘‘discovered’’ a few years ago. At that time, I worked for Hydro-Quebec and, almost as a hobby, I had developed an expert system capable of analyzing the events taking place in our very complex and critical extrahigh-voltage network. The information contained in the network’s data bank was very rich and complete, and the expert system was able to read the data bank, determine a difference between voluntary and involuntary events, and, after 30 seconds, print a very complete sequence, down to the millisecond, of what had happened.

I developed the system even though I did not know at the time that I was using inference motors, forward and backward chaining, and other related subtleties. These I discovered later when the scholars jumped onto the wagon and organized congresses, symposia, and fancy conferences using satellites—at which, after inventing a new dedicated jargon, they pontificated first about intelligence and then about expert systems, complicating practically everything that up until then had been logical and simple, without, finally, ever producing anything of practical value.

After reading about fuzzy logic, I am afraid history is repeating itself. Many years ago I headed a group of very experienced control engineers who, using a minicomputer, developed a control system for a hydroelectric generating plant. No fancy equations, no sophisticated models, no specially developed software. Everything—from starting the optimal number of units to synchronizing them to the network and managing the load—was automatic and had been programmed by plain engineers using the ‘‘good enough’’ approach. It worked beautifully.

At the time none of us knew about fuzzy logic, and even today I could do it again without reading a book about the matter. Right now, the Japanese are inundating the market with washing machines, cameras, car electronics, videos, etc., using this old common sense logic, which has been newly christened ‘‘fuzzy logic.’’ If North American industry gets fooled again by scholars into thinking that this is a very academic and complex theory requiring a dedicated vocabulary and specialized studies, as with artificial intelligence, it is going to take a long time before we can compete with the Japanese in this area.

Sergio del Pozo
Westmount, Que., Canada

Forum, IEEE Spectrum Oct.1992

Basketball Team Coach

A basketball trainer has to select team members:

Conditions:

- Height
- Good performance

“Classic” solution:

- Height > 185 cm
- Out of 16 basket shots, score at least 13: 13/16

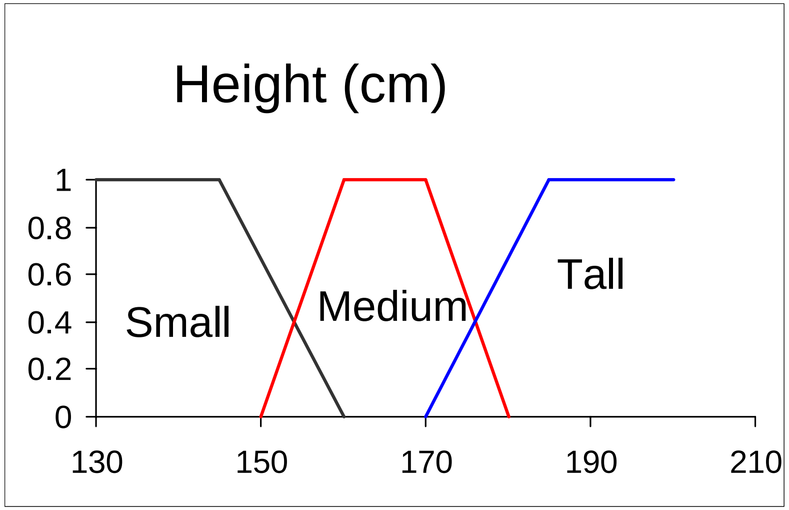
Results of a Selection Process Using a “Classic” Solution

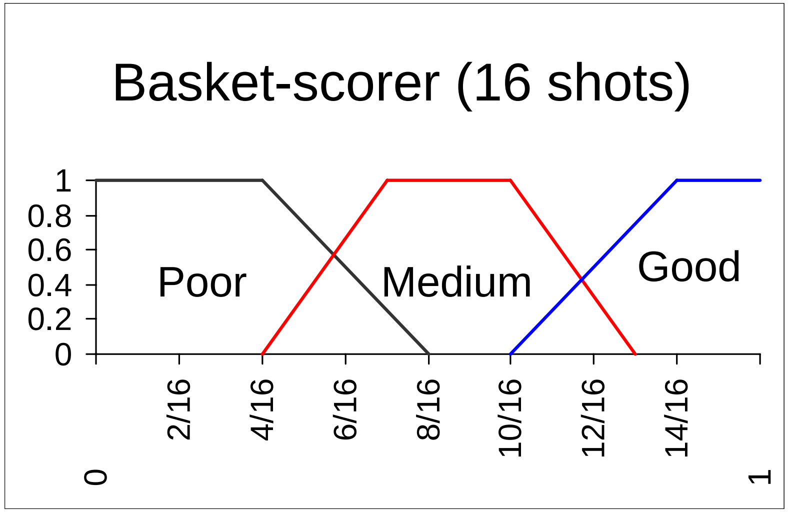
Candi-date	Height (cm)	Basket-score (16 shots)		"Classic" selection score
A	167	12		0
B	169	6		0
C	175	15		0
D	179	12		0
E	183	16		0
F	186	13		1
G	187	12		0
H	190	10		0
J	200	13		1

An Alternative to a “Classic” Solution

<u>Using Fuzzy Sets</u>:

- Fuzzy numbers are defined for each variable
- Variables combination using fuzzy logic





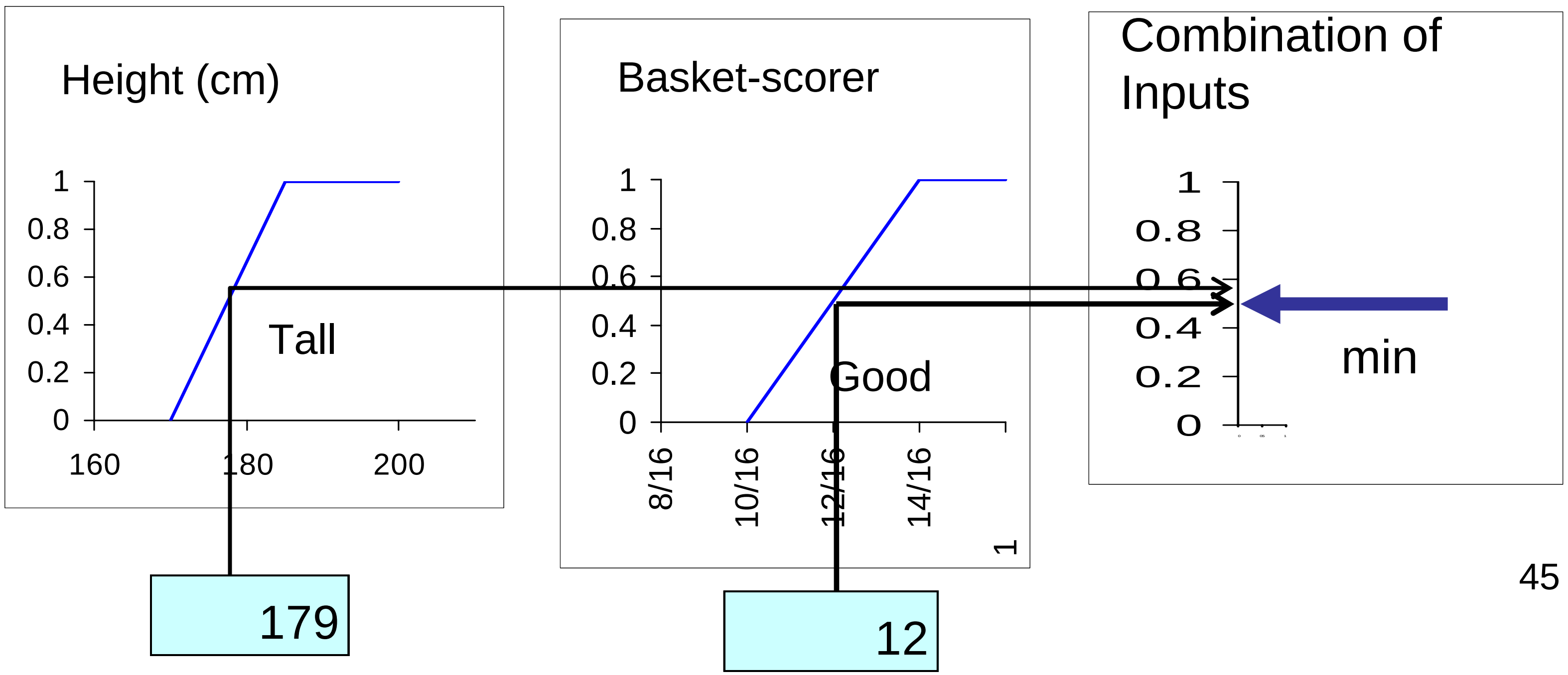
Selection Process Using Fuzzy Logic: Example

A successful candidate:

- "**Tall**" in Height

- "**Good**" in Basket-scorer

Candi-date	Height (cm)	Basket score (16 shots)	Fuzzy score
D	179	12	0,50



Fuzzy Logic Approach Provides a Ranked Output

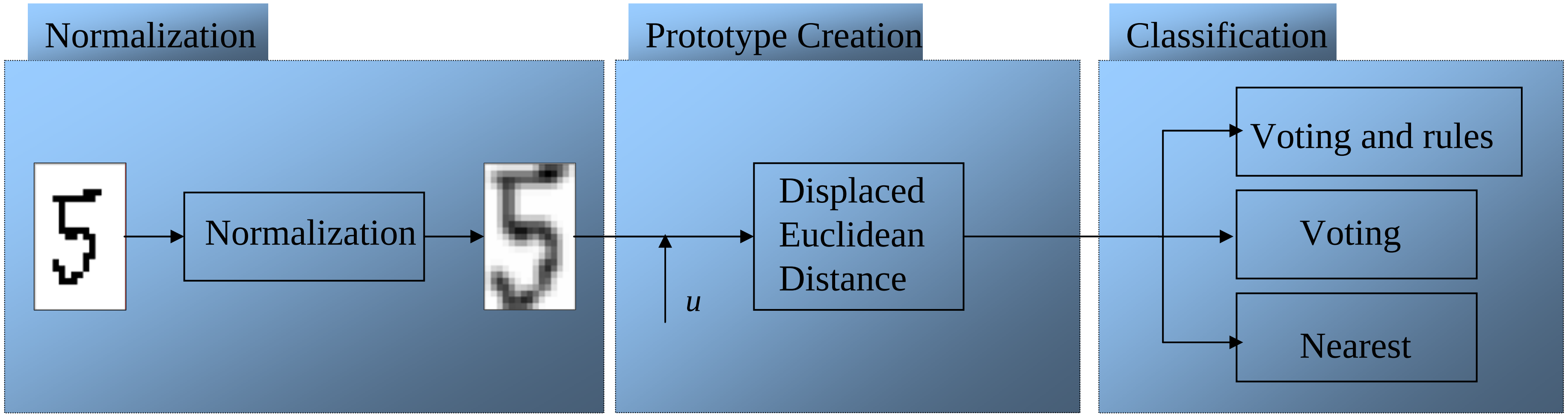
Candi-date	Height (cm)	Basket-score (16 shots)		"Classic" selection score		"Classic" selection score
E	183	16		0		0.87
F	186	13		1		0.75
J	200	13		1		0.75
D	179	12		0		0.5
G	187	12		0		0.5
C	175	15		0		0.33
A	167	12		0		0
B	169	6		0		0
H	190	10		0		0

Avoids excluding a great basket scorer, 183 cm height.

Just as the Coach (Human Expert) would do!

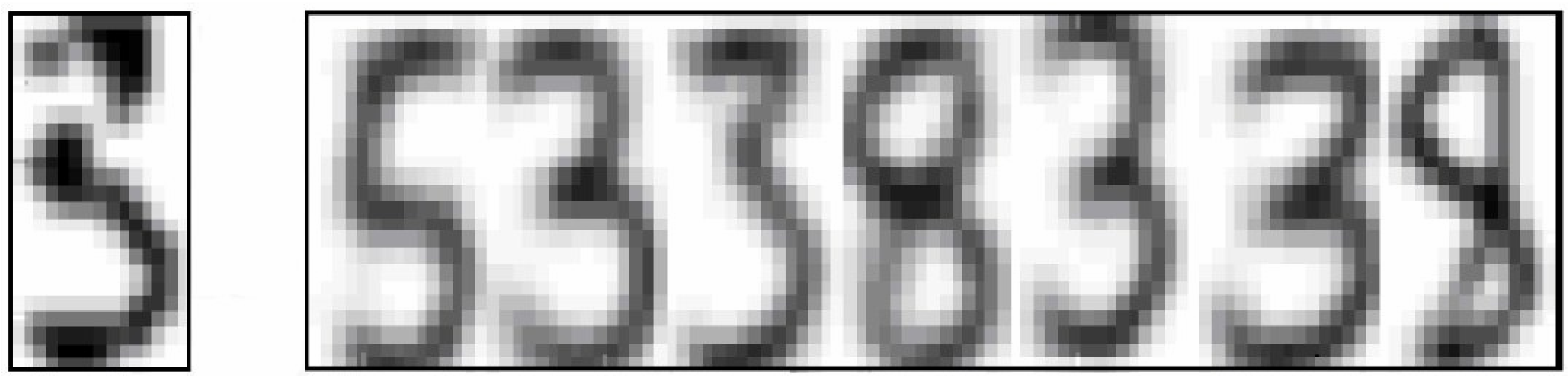
Handwritten Digits Recognition System Based on Prototypes and Fuzzy Rules

- Accurate classification of handwritten digits using prototypes:
  - Prototype creation using size normalization, limited shifting and Euclidean distance
  - Classification by identification to prototypes
- Addition of fuzzy rules to avoid confusions and increase classification performance



Classification Methods: Weighted Voting

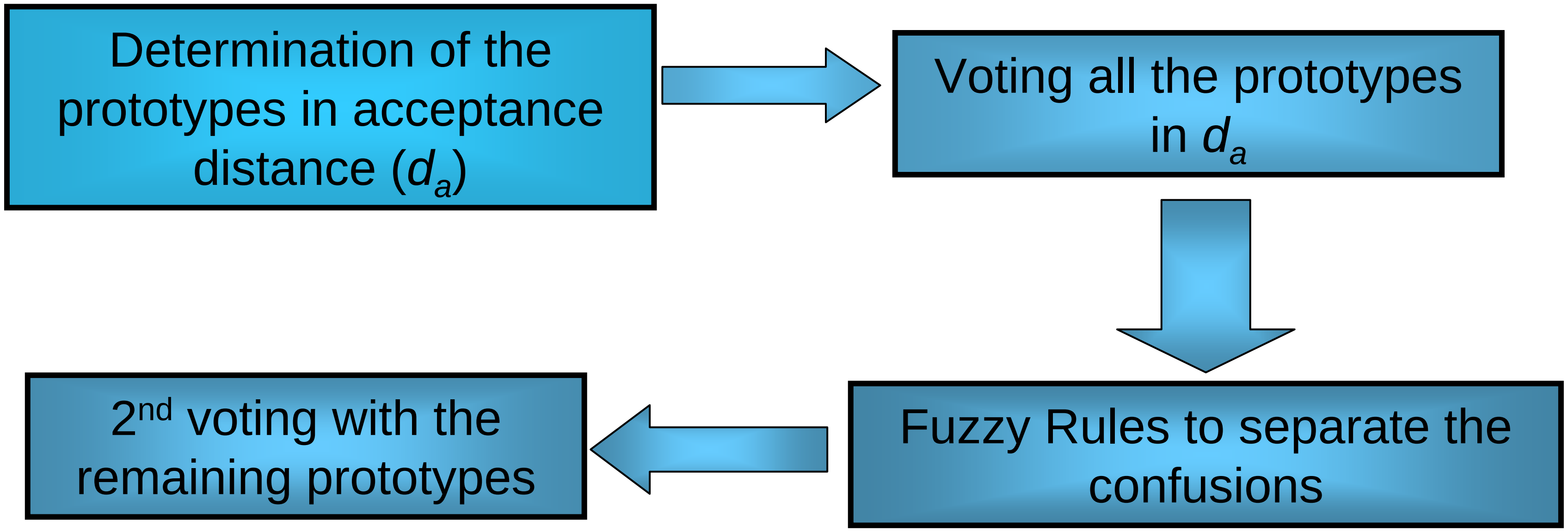
Class with highest score found by weighted voting among all prototypes inside an acceptance distance (d_a).



Pattern Prototypes inside acceptance distance

Weighted Voting + Fuzzy Rules

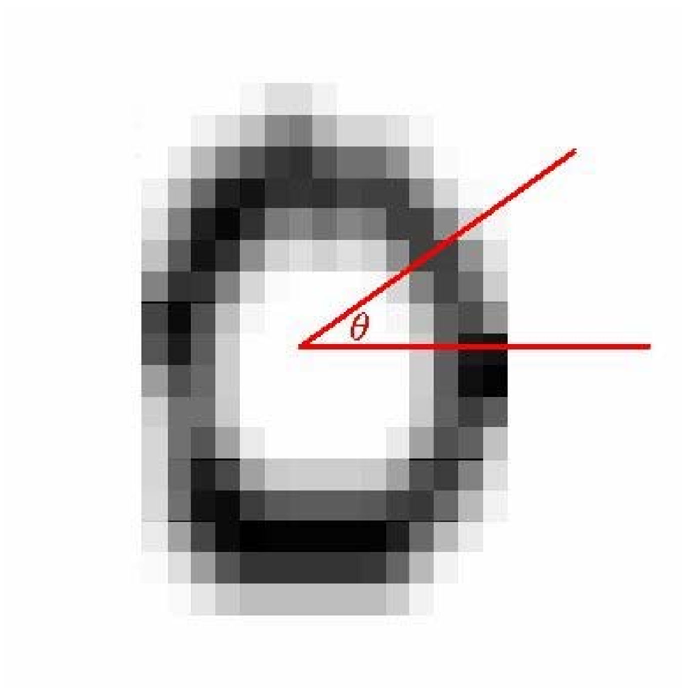
Fuzzy rules help in class pruning among prototypes inside acceptance distance (d_a)



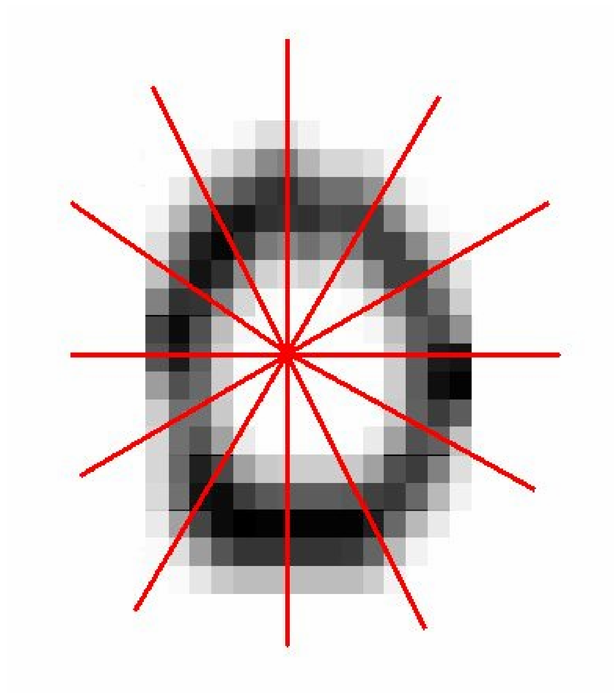
Fuzzy Rules for Digit Classification

- Aimed at solving most frequent confusions among digits
- Fuzzy Rules output:
  - 0 : ignorant
  - Positive (0,1]: to classify digit as class member
  - Negative [-1,0): to reject digit as class member
- Characteristics: based on aspects usually observed by a human in recognizing handwritten digits

Form Features are Rules Inputs (1): Closures in Different Angles

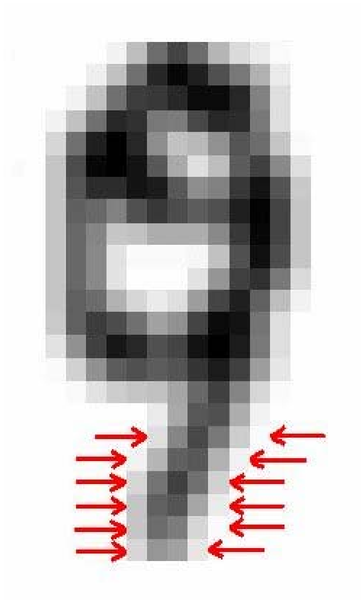


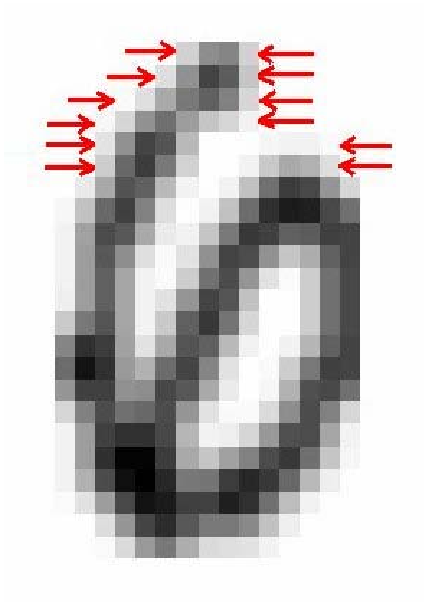
Boundary Pixels
Function (BPF)

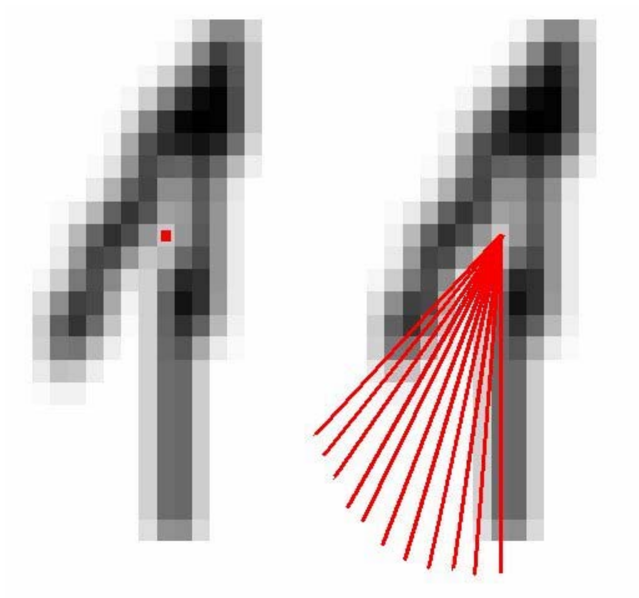


Closed Trace
Function (CTF)

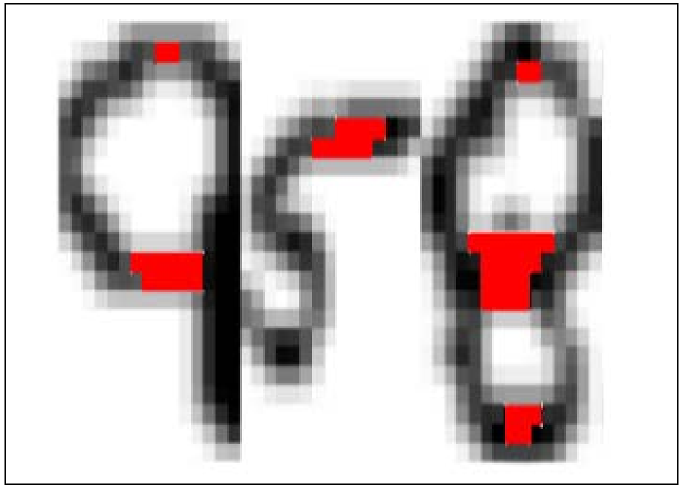
Form Features are Rules Inputs (2): Lines and Openings



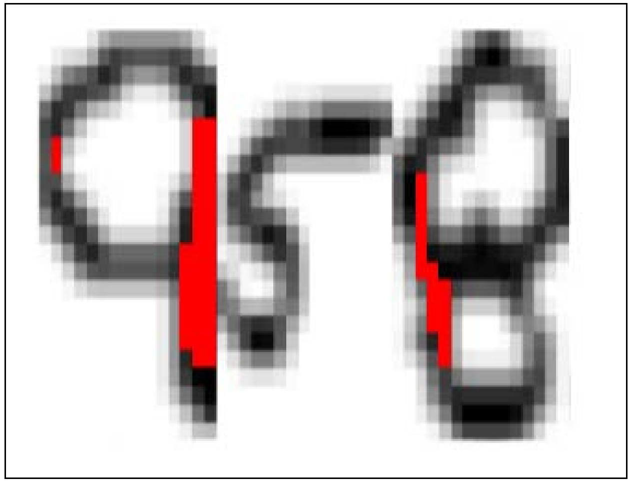




Form Features are Rules Inputs (3): Horizontal, Vertical and 45° Lines

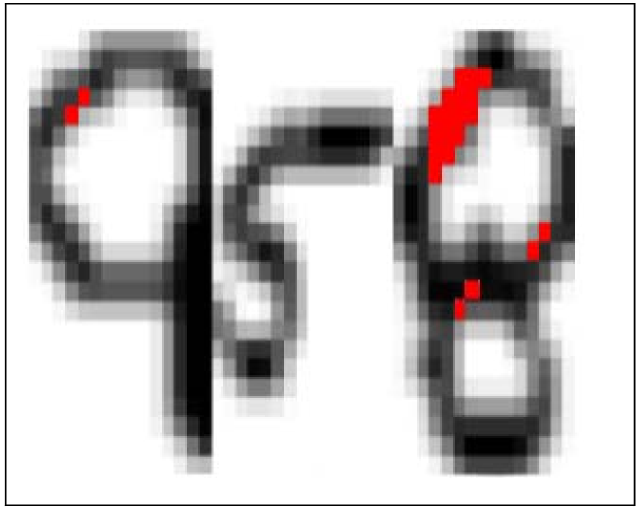


Horizontal Lines

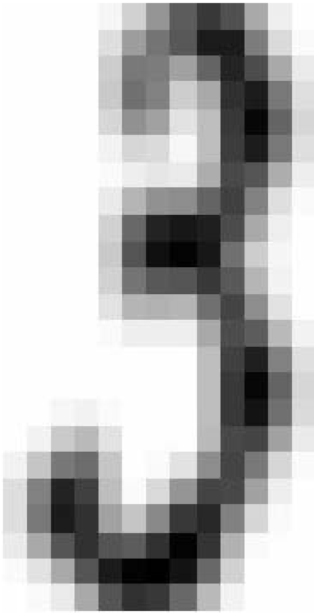


Vertical Lines

Lines in 45º



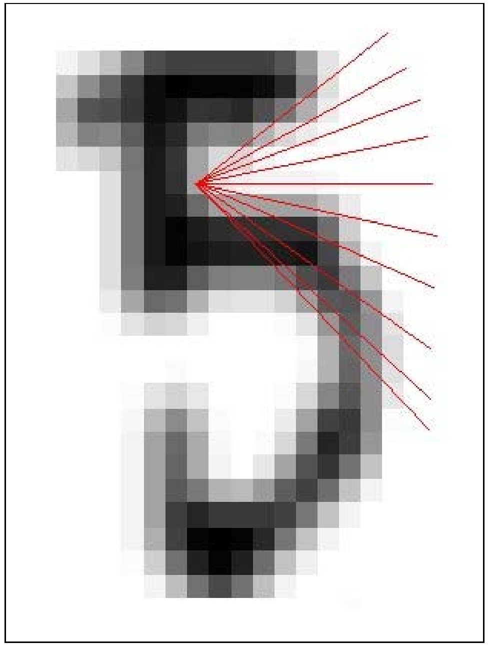
Fuzzy rule for number 3



$$R3 = \begin{cases} -1 & SSOL<0 \vee ISOL<0 \\ \begin{Bmatrix} 0.9\min\{SSOL,ISOL\} & MW > 7 \\ -1 & \sim \end{Bmatrix} & \sim \end{cases}$$

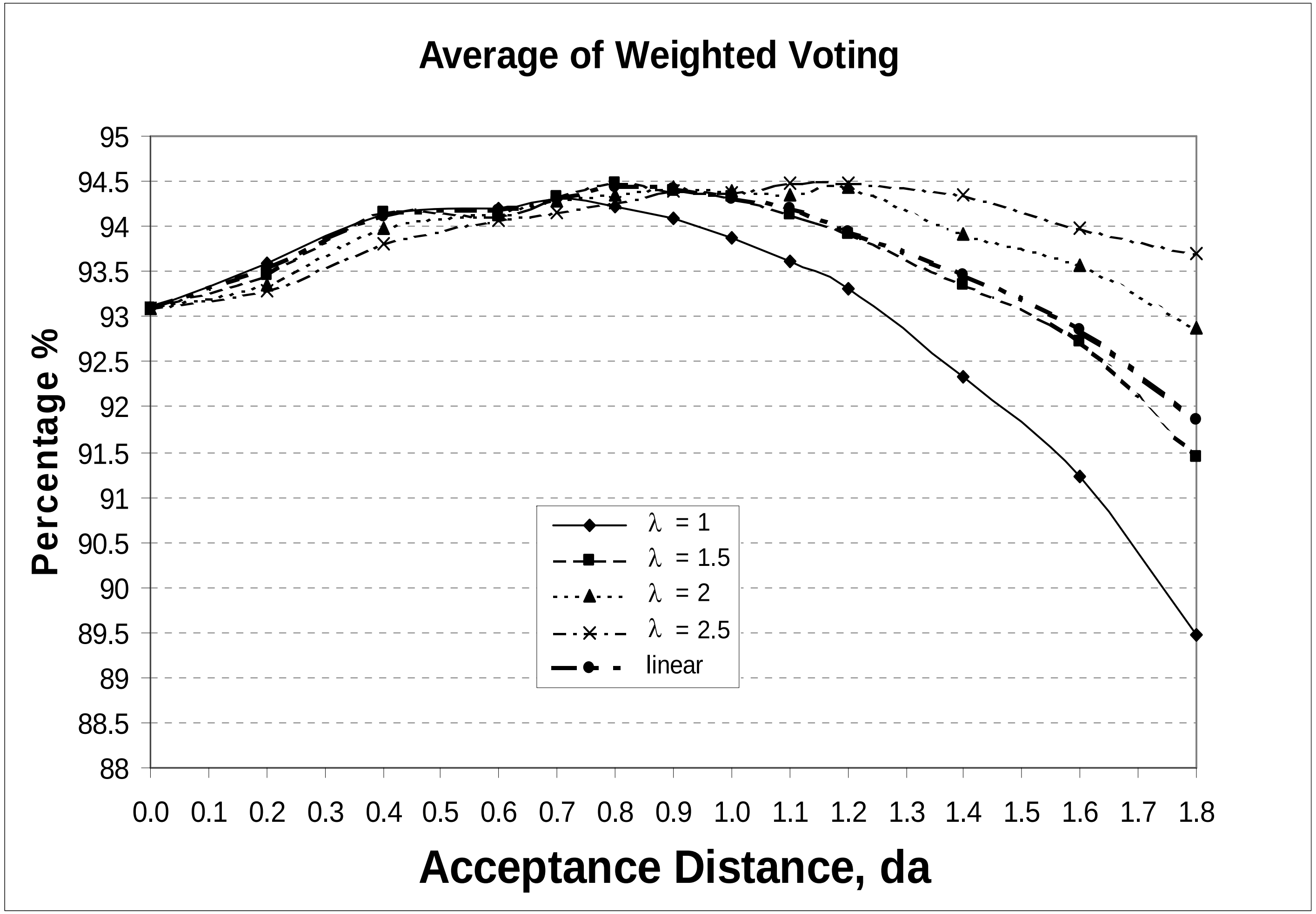
MW: Maximum width of the first 8 rows of the digit

Fuzzy rule for number 5

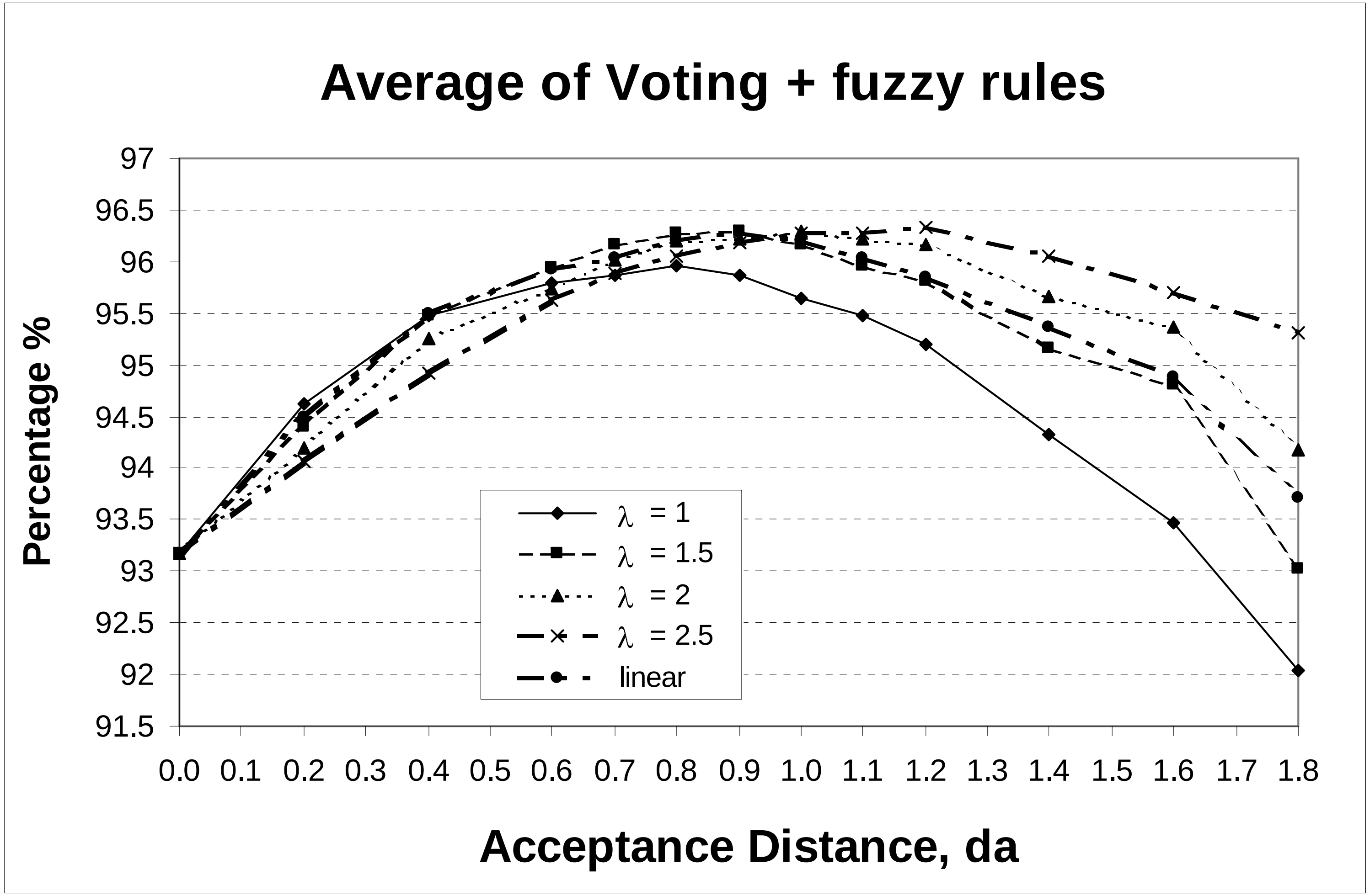


$$R5 = \begin{cases} -1 & SSOR<0 \vee ISOL<0 \\ \max\left\{ \begin{array}{l} 0.9 \min \{SSOR, ISOL, HLSF\} \\ 0.7 \min \{SSOR, ISOL, 45LF\} \end{array} \right\} & \sim \end{cases}$$

Results (1): Weighted Voting



Results (2): Voting + Rules



Results (3): Comparison

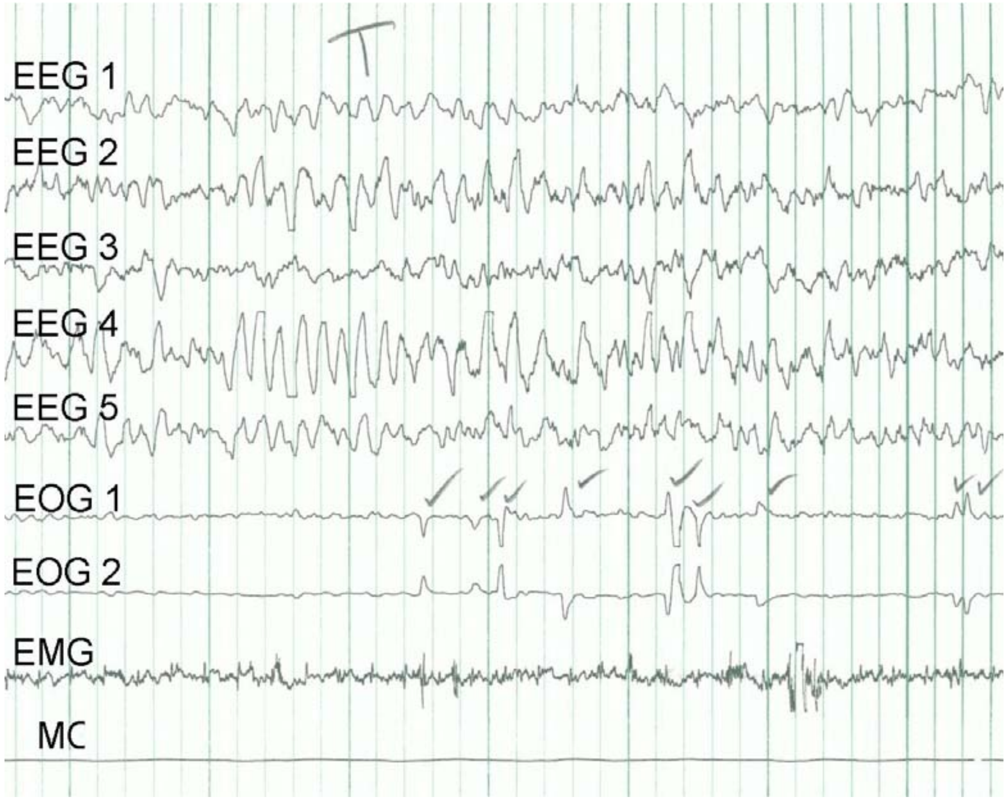
Method	Classification Criteria	Percentage of correct Classification %
Perceptron with shifting 345-80-80-10 (Average)	Max Output	94.6 ± 0.5
Perceptron with shifting (as above) 345-80-80-10 (Maximum)	Max Output	95.1
Euclidean Distance with shifting (Average)	Minimum Distance	93.1 ± 0.4
Euclidean Distance with shifting & voting (Average)	Voting	94.5 ± 0.3
Euclidean Distance with shifting, voting & rules (Average)	Voting + Rules	96.3 ± 0.4
Euclidean Distance with shifting, voting & rules (Maximum)	Voting + Rules	96.9

Database: 2361 training patterns, 1320 testing patterns

Classification of Sleep Stages in Infants: A Neuro-Fuzzy Approach

Bioelectrical and biomechanical signals are recorded, accumulating a large number of pages with graphical data

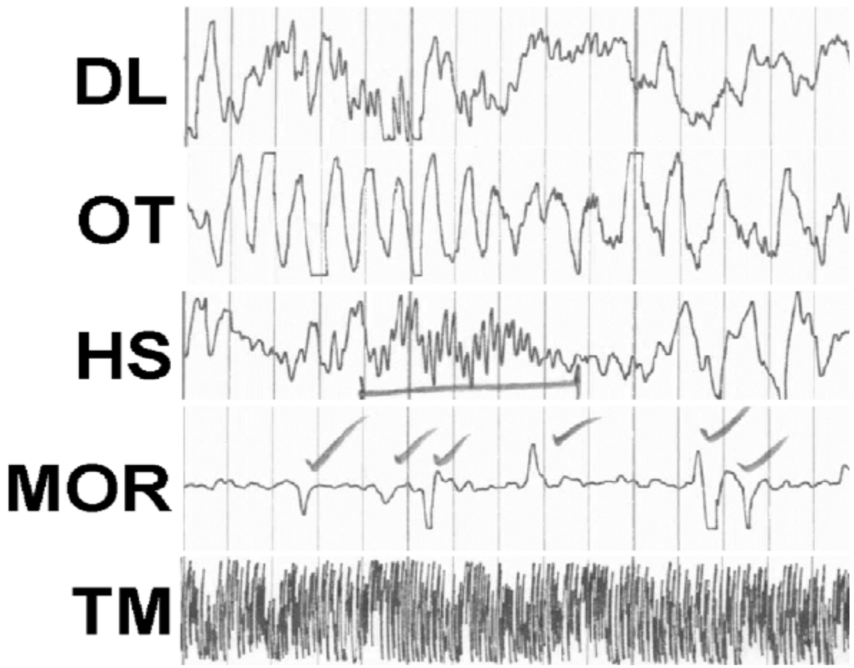
Polygraph Recording



Shown: Electroencephalogram (EEG) (5), Electrooculogram (EOG) (2), Electromyogram (EMG), Body movements (1 shown)

Not shown: Electrocardiogram (ECG), Abdominal ventilatory movements, nostrils airflow, body temperature, oxymetry

Sleep Classification (Visual Scoring)



The expert determines:

- Predominant background frequency range in the EEG (DL, OT)
- Presence of
  - sigma spindles (SS) in EEG,
  - rapid eye movements (REMov) in EOG
  - muscular tone (MT) in EMG

Other channels provide contextual information, such as body movements (BM) and cardiac activity (ECG).

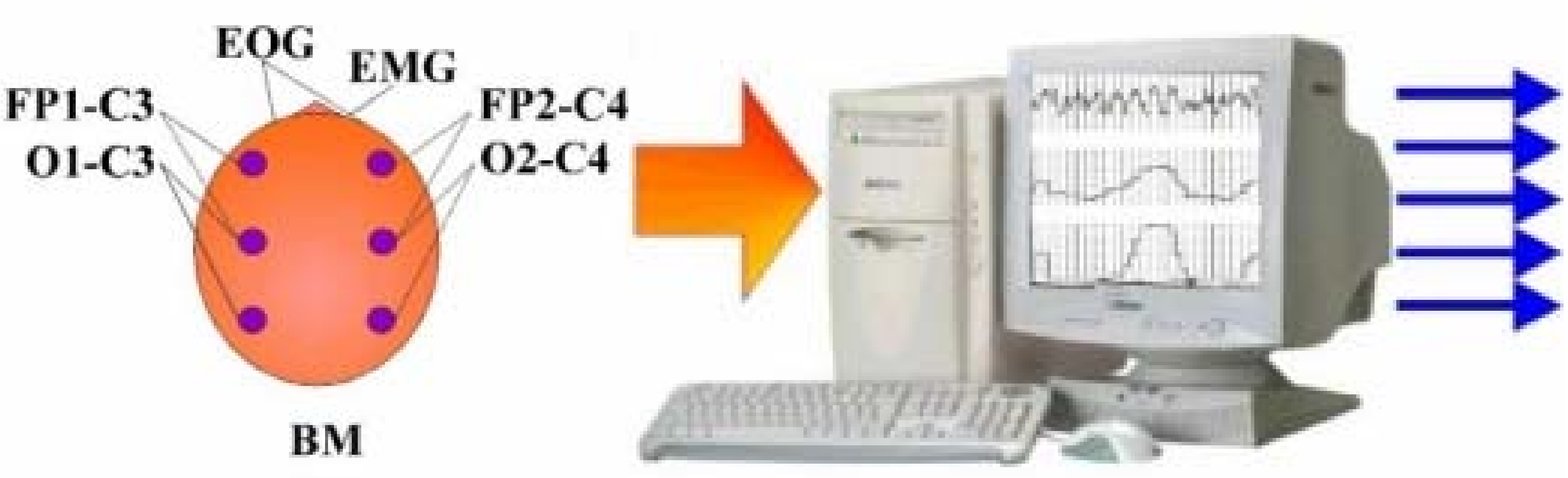
Sleep Classification Table

Pattern	Sleep States and Stages				
	NREM-I	NREM-II	NREM-III&IV	REM	WA
REMov	A	A	A	P	P
TH	P	X	X	P	X
SD	A	A	P	A	A
SS	A	P	X	A	A
MT	X	X	X	A	P

The expert determines the sleep state or stage applying rules. However, sleep classification is not completely standardized and usually experts from different research centers have slightly different approaches.

Each state or stage has a minimum duration of 1 minute.

Digital Data Acquisition for Automated Sleep Classification



Visual scoring is a very data intensive, complex, time-consuming task, with significant variability among scorers. Hence the interest to develop an automated system.

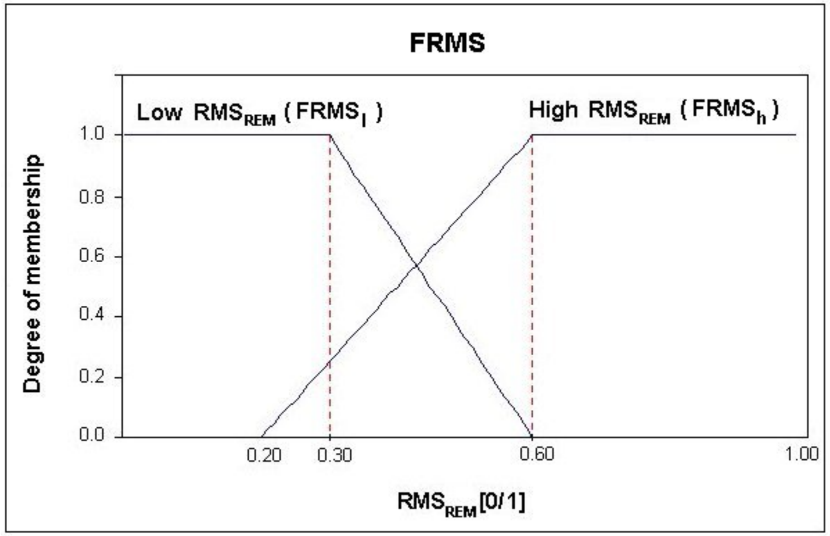
Automated Pattern Detection

SD
OT
SS
REMov
MT

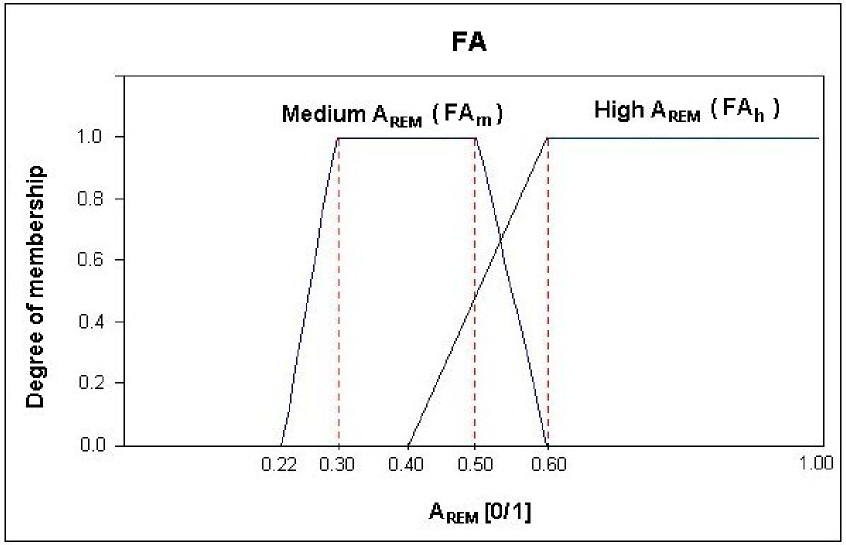
An automatic detection system scores the presence of each pattern. The outputs are either percentages of presence or quality indices of a given pattern per frame.

The outputs are normalized in the [0, 1] range.

Fuzzy REMov Scoring Variables



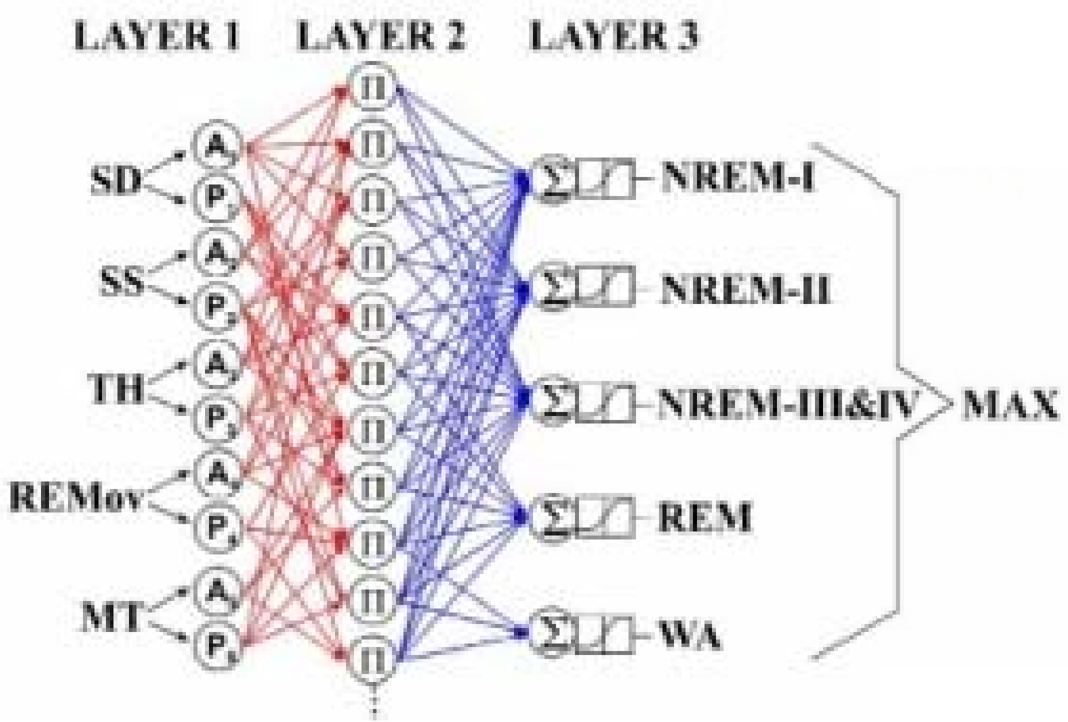
RMS Energy



Amplitude

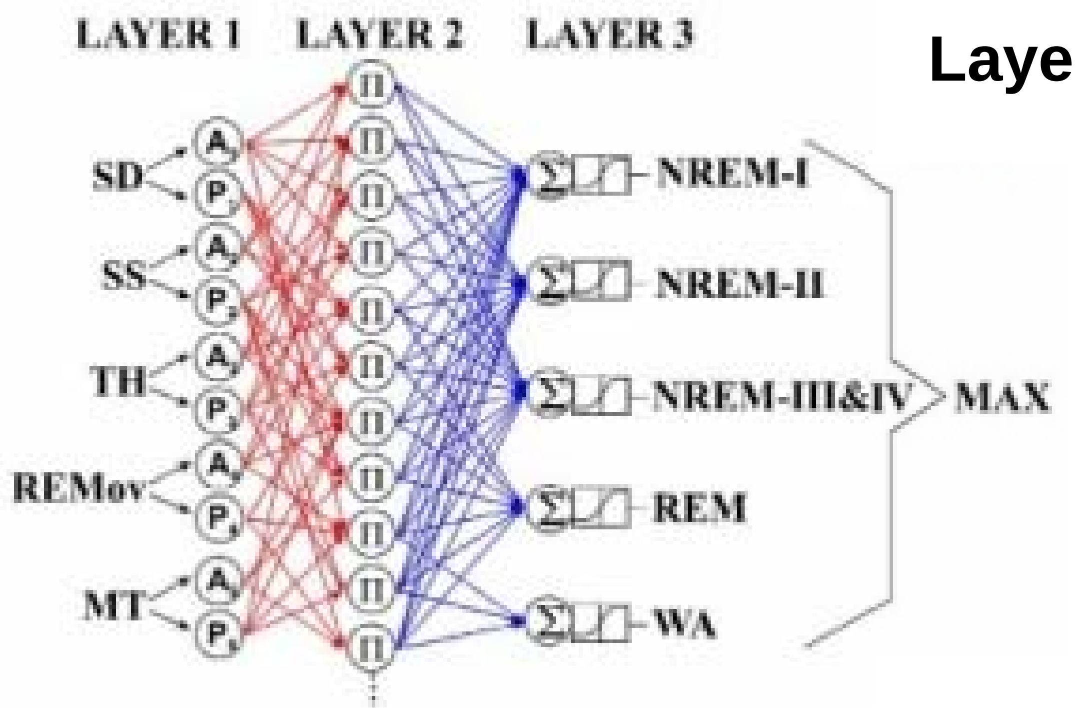
Neuro-Fuzzy Classifier (NFC) - 1

Layer 1: Fuzzification. Each input has fuzzy concepts for presence or absence of the pattern (P_i and A_i).



Layer 2: **Rules**. All possible combinations considering one fuzzy concept per input (P_i or A_i).

Neuro-Fuzzy Classifier (NFC) - 2



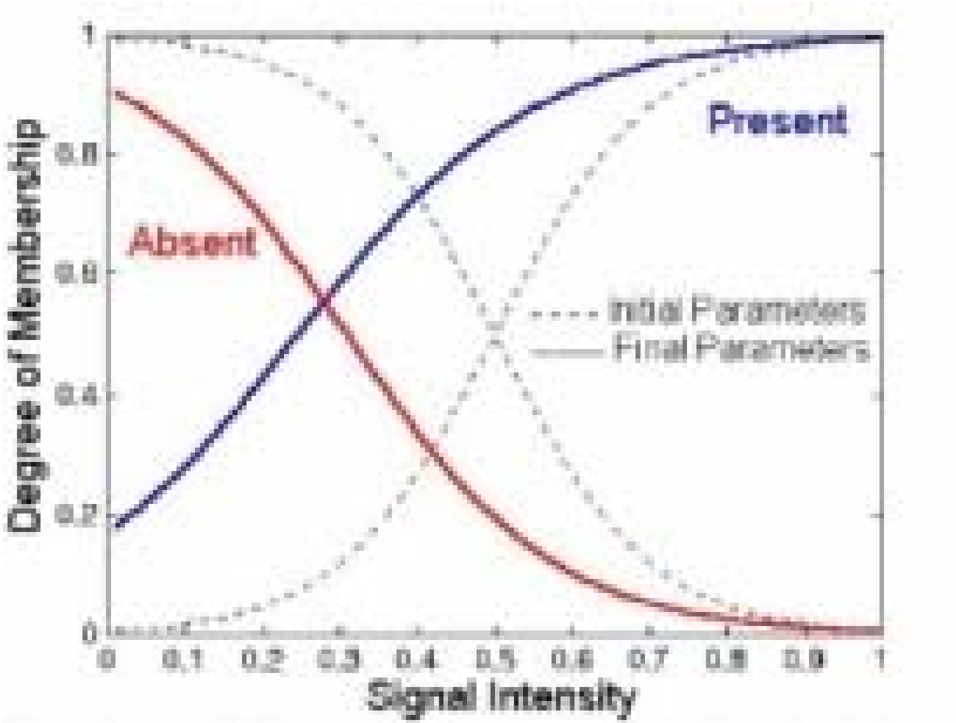
Layer 3: Class evaluation.

Linear combination of rules strength and sigmoidal function to establish class membership.

Classifier output: max μ(class)

NFC: Training to Establish Input Fuzzy Sets

P_i and A_i functions are same for all inputs when training starts.



(Example: SS)

Final parameters are unique to each input after training.

NFC: Post-Processing

Rules pruning algorithm:

- reduce number of rules
- tend to expert-like set of fuzzy if-then rules

State-duration algorithm (SDA) to ensure that every state-stage lasts at least one minute.

Rules Selection (Pruning Algorithm)

	Nº	DL	OT	HS	MOR	TM
	1	P	P	P	P	P
	2	P	P	P	P	A
	3	P	P	P	A	P
	4	P	P	P	A	A
	5	P	P	A	P	P
	6	P	P	A	P	A
R3	7	P	P	A	A	P
	8	P	P	A	A	A
	9	P	A	P	P	P
	10	P	A	P	P	A
	11	P	A	P	A	P
	12	P	A	P	A	A
	13	P	A	A	P	P
	14	P	A	A	P	A
	15	P	A	A	A	P
	16	P	A	A	A	A
	17	A	P	P	P	P
	18	A	P	P	P	A
	19	A	P	P	A	P
	20	A	P	P	A	A
	21	A	P	A	P	P
	22	A	P	A	P	A
R1	23	A	P	A	A	P
	24	A	P	A	A	A
	25	A	A	P	P	P
	26	A	A	P	P	A
	27	A	A	P	A	P
	28	A	A	P	A	A
	29	A	A	A	P	P
	30	A	A	A	P	A
R2	31	A	A	A	A	P
	32	A	A	A	A	A

Only a few rules survive the pruning algorithm for each output.

Example: NREM-I: Surviving rules:

R3: 7-8, R1: 23-24, R2: 31-32

(3 rules considering MT irrelevant).

R1 recovers the expert’s rule, and it is by far the most relevant. Classification without R1 drops performance to 19,7% for the class.

Performances of NFC, a Multi Layer Perceptron Neural Network (MLP) and the Expert's Rules

	Training	Validation	Test	Test with SDA
NFC	86.2 ± 0.1%	87.7 ± 0.2%	83.9 ± 0.4%	88.2± 0.5%
MLP	87.1 ± 0.7%	87.3 ± 0.4%	83.4 ± 0.6%	87.3 ± 0.9%
Expert's Rules	84.10%	87.20%	82.60%	86.70%

Evaluation on frame-by-frame basis except for the last column, which includes SDA filter.

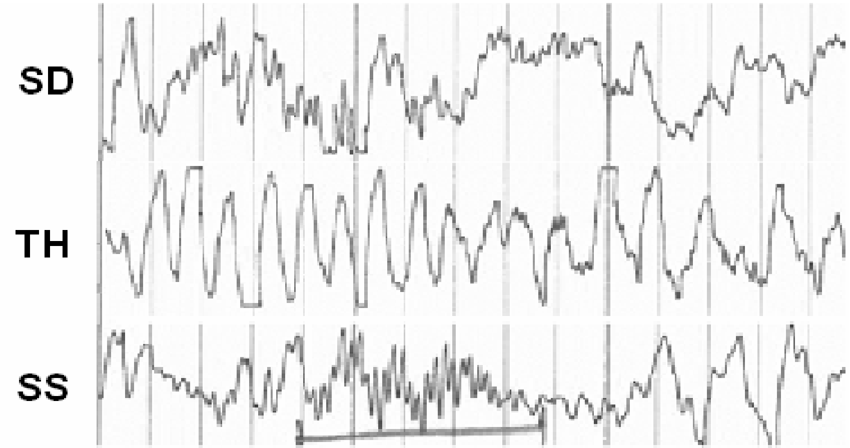
Dual Approach for Automated Sleep Spindles Detection within EEG Background Activity in Infant Polysomnograms

Objective: To improve automated sleep spindles (SS) detection within EEG activity using two approaches:

1. Amplitude - frequency analysis (Module 1)
2. Expert procedure (Module 2)

SS:
- characteristic of stage 2 quiet-NREM sleep
- aging, infant pathologies, memory processes

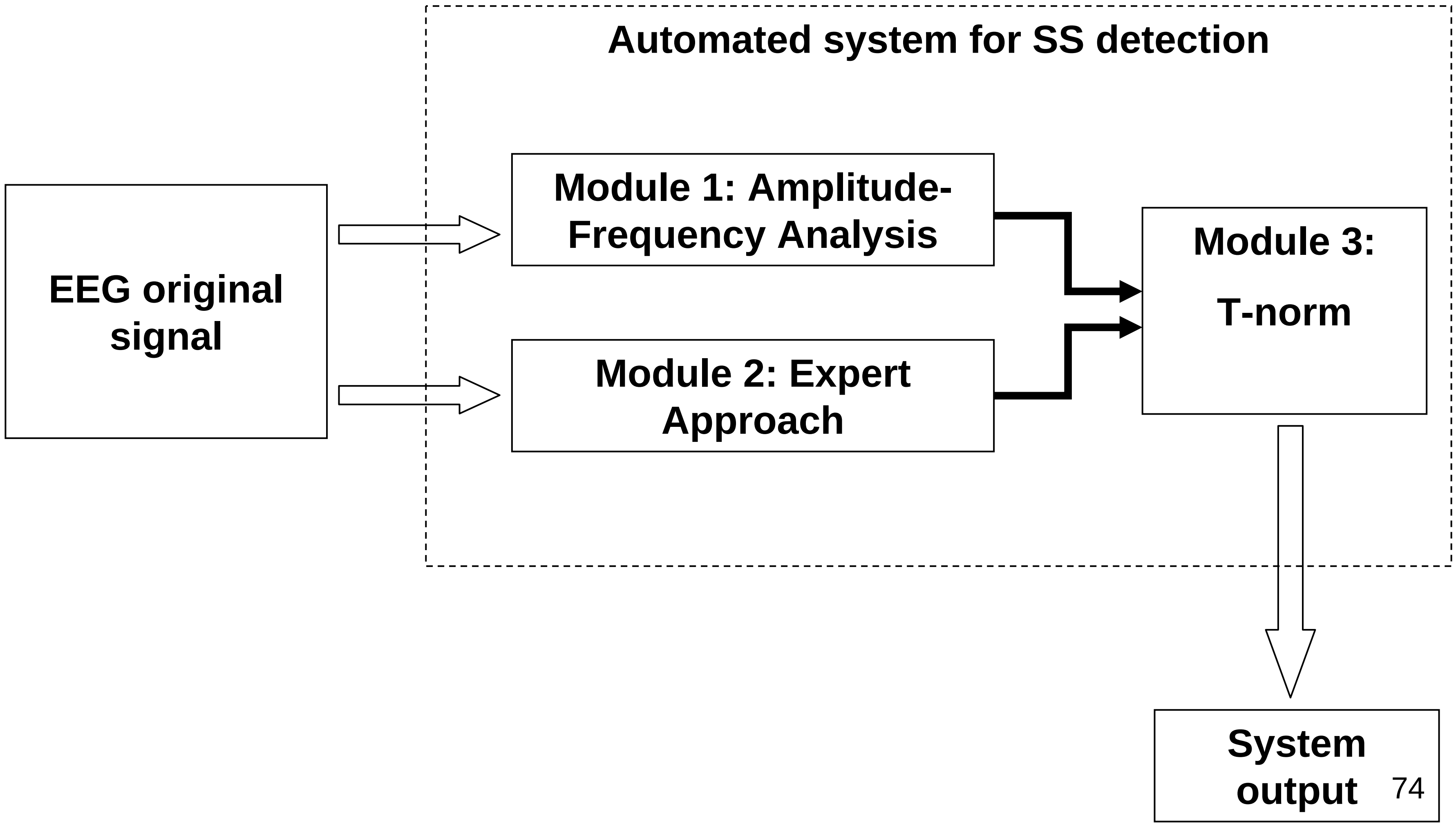
EEG Patterns for Sleep Classification



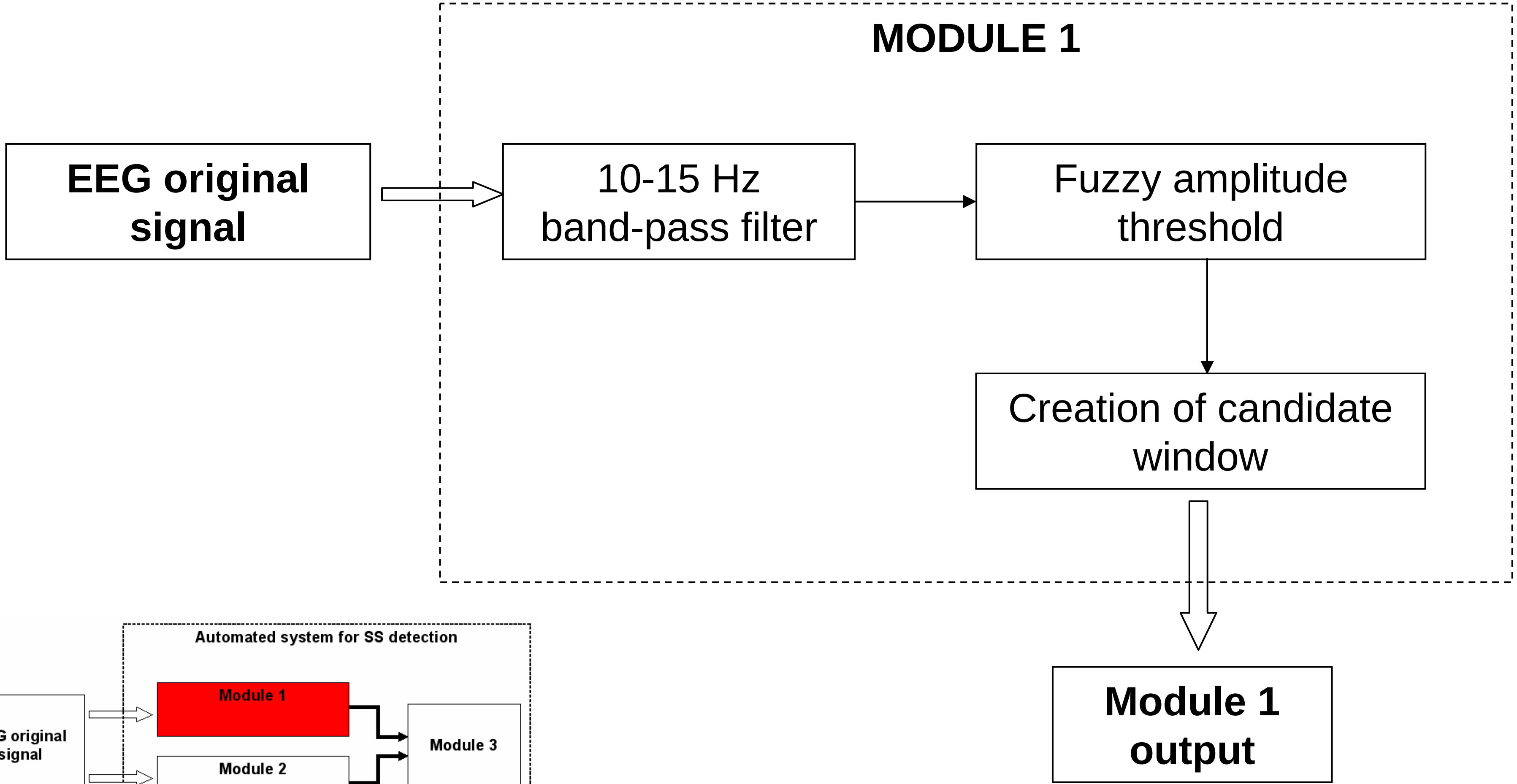
Background Activity: Slow Delta (SD) and Theta (TH) waves

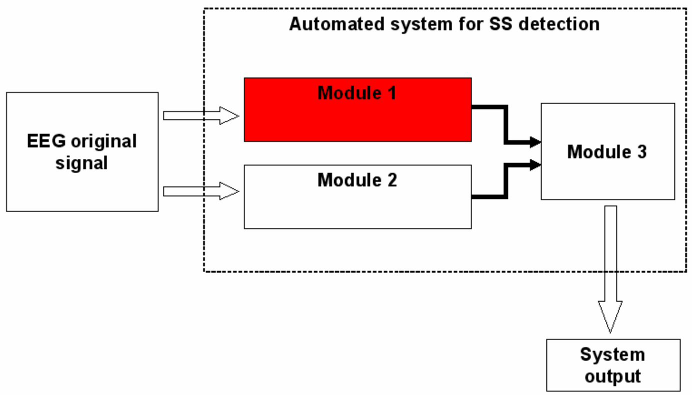
Events: Sleep Spindles (SS)

Proposed SS Detection System

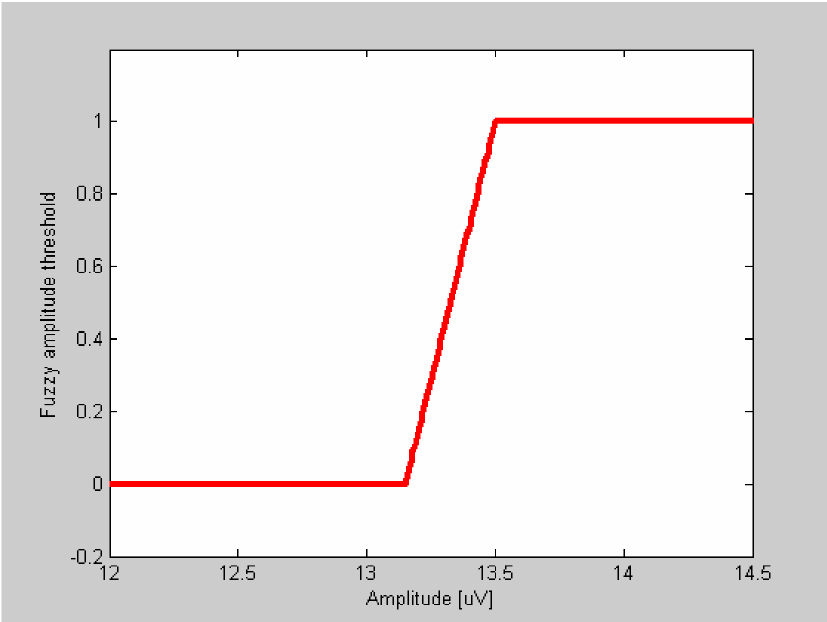


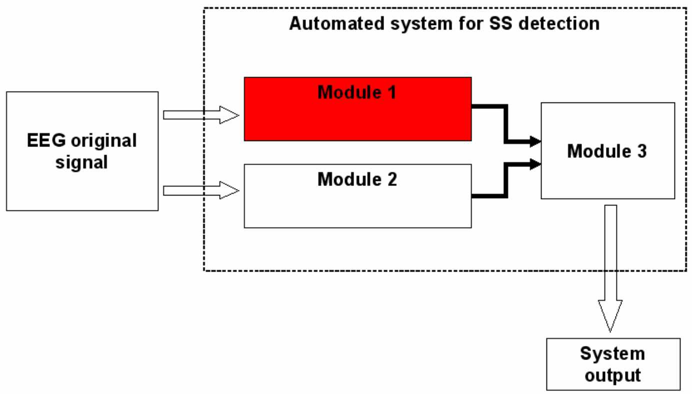
Module 1: Amplitude - Frequency Analysis





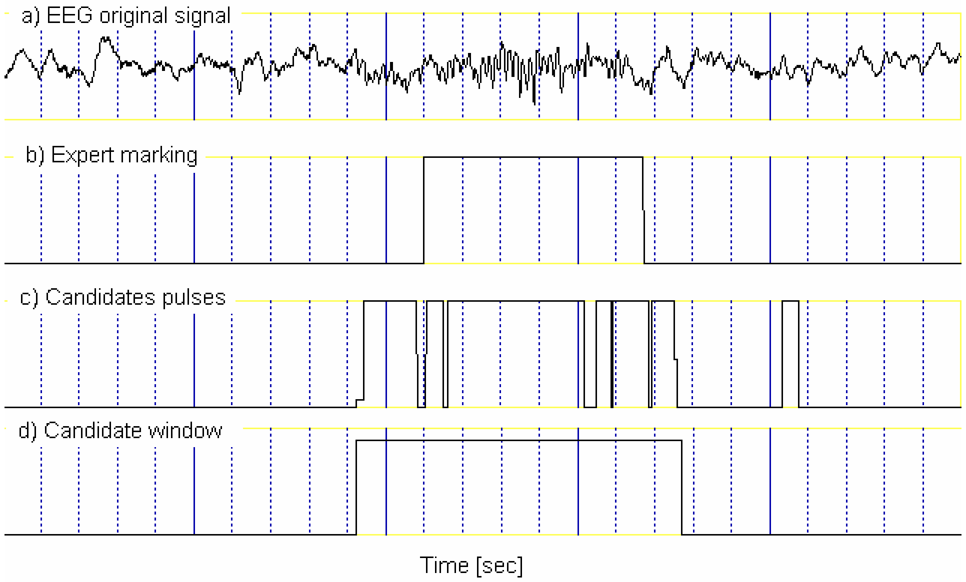
Module 1: Fuzzy Amplitude Threshold

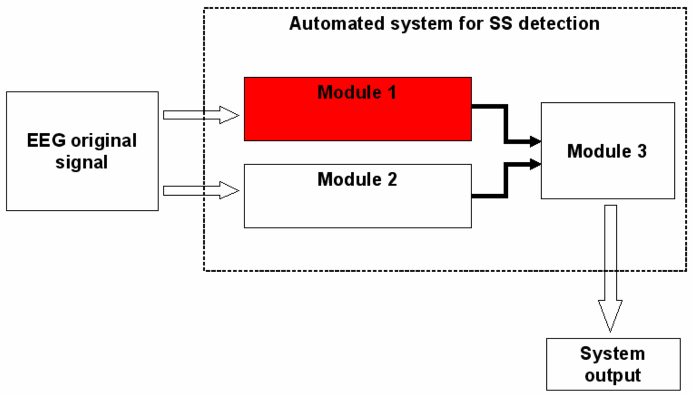




Search for candidate pulses:
- Sigma-band filter (10 - 15 Hz)
- Fuzzy amplitude threshold, FAp(h)

Module 1: Signal Processing





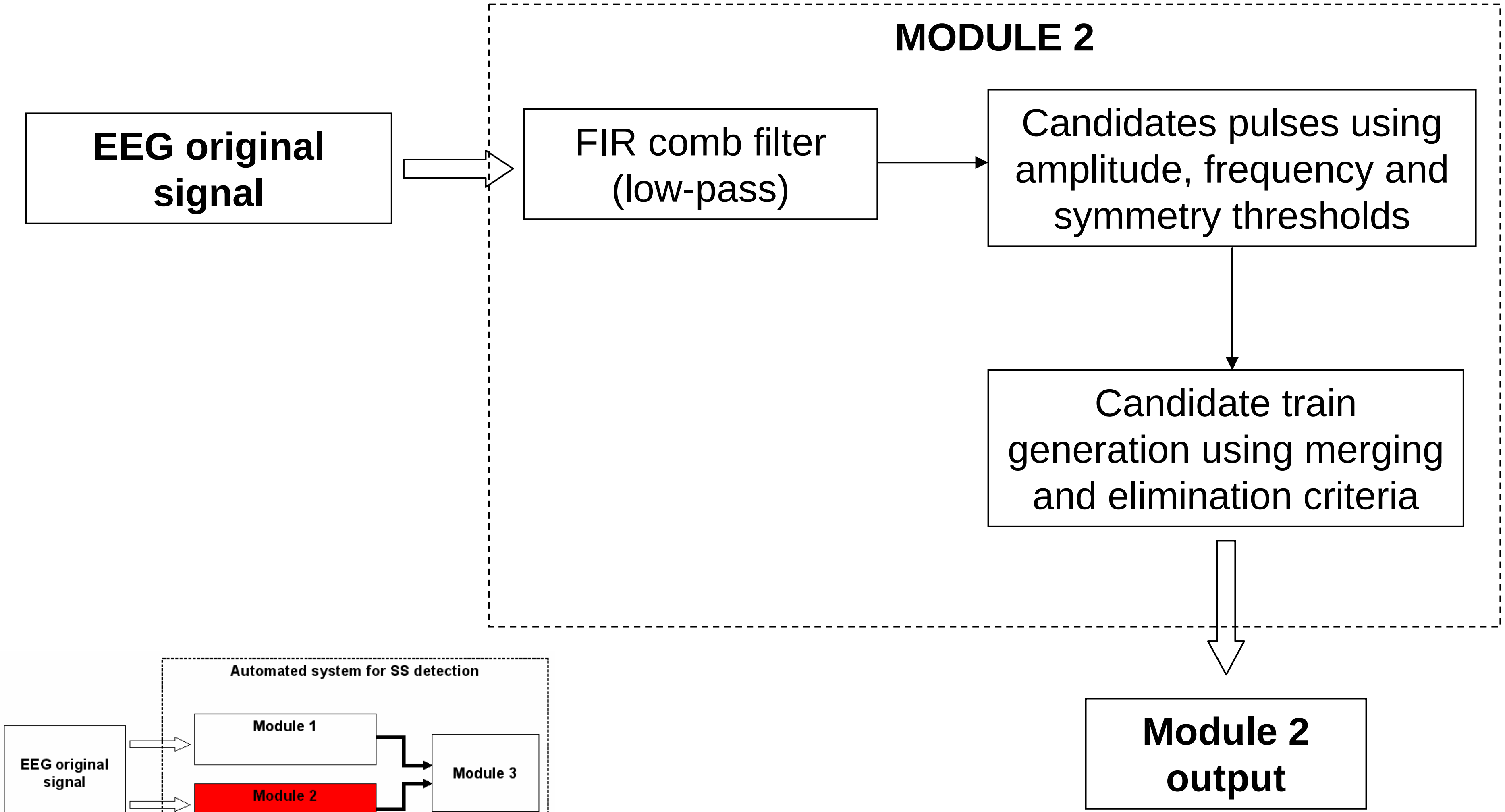
Consecutive candidate pulses are chained together in candidate window.

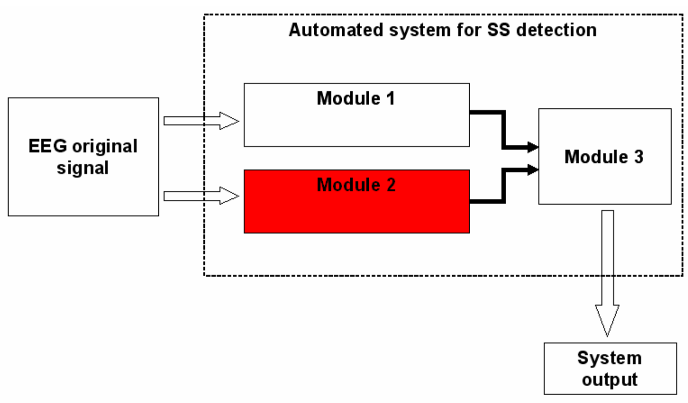
Candidate window with weighted amplitude:
$WA=(\Sigma FAp_i * t_i)/t_w$

Each candidate pulse i has duration t_i and amplitude Fap_i; t_w is the window time span,

$$\Sigma t_i \leq t_w$$

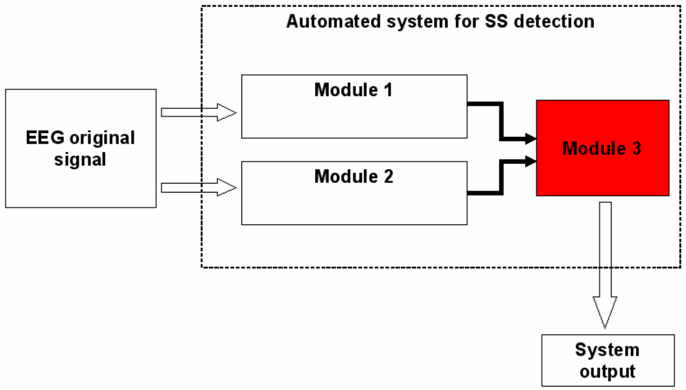
Module 2: Mimics an Expert Approach

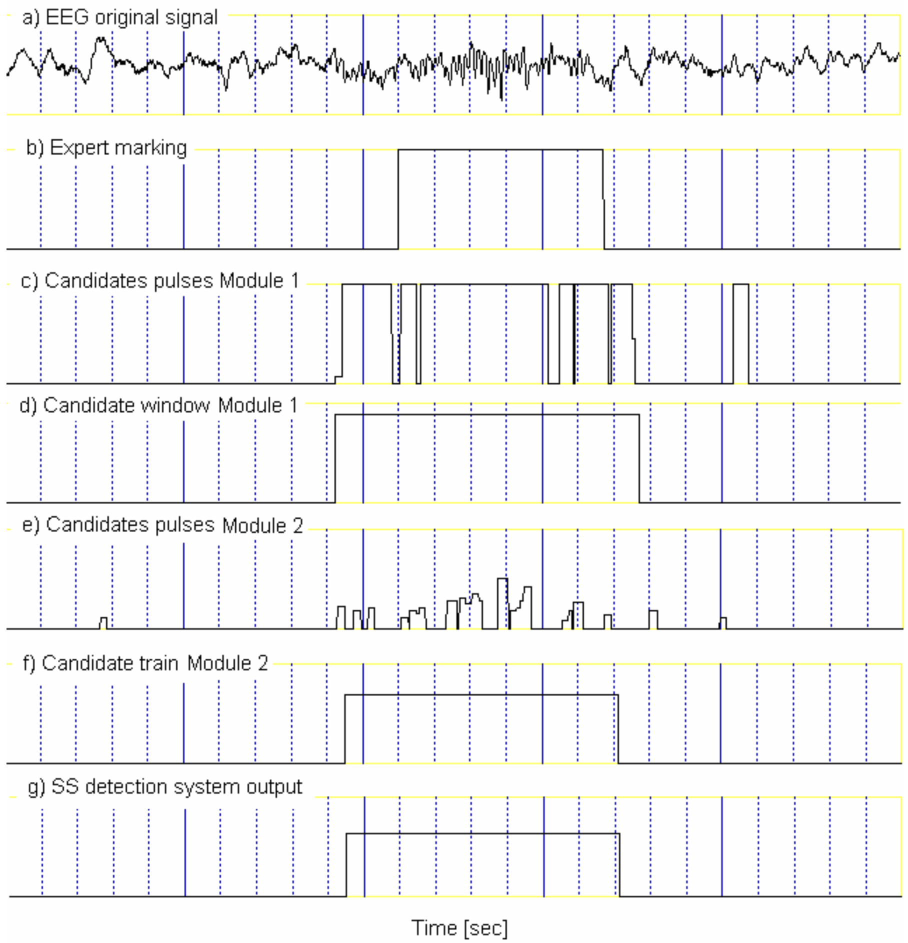




Module 3: T-norm Combines Outputs of Modules 1 and 2

SS presence required simultaneously in modules 1 and 2 to validate event.





Results on SS Detection

Low precision of each individual module (avg):

- Module 1: 19.3%
- Module 2: 33.0%

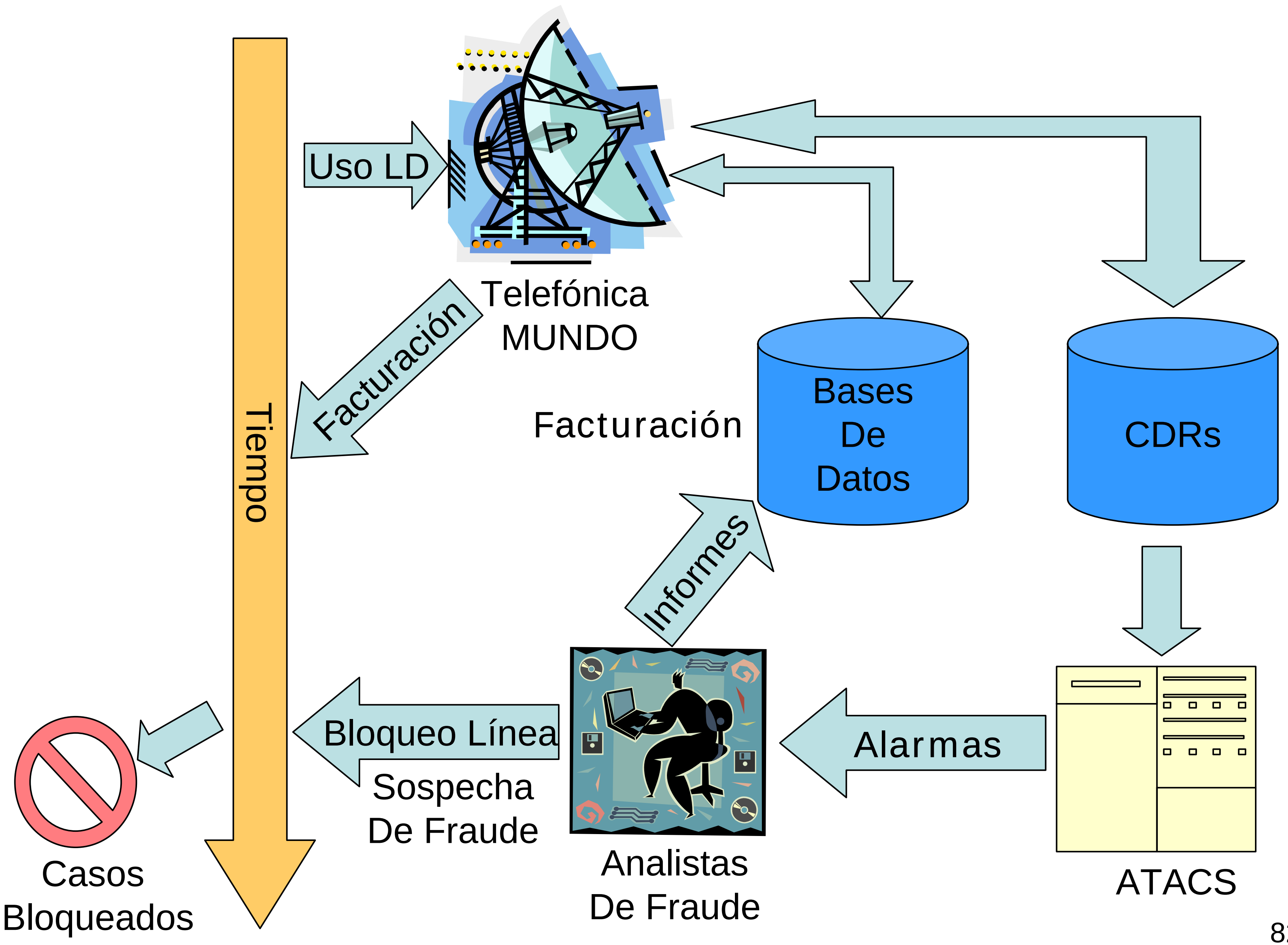
is enhanced by the combination of both modules: 91.9% (best run: 98.1%)

SS Detection Results on Test Data Set

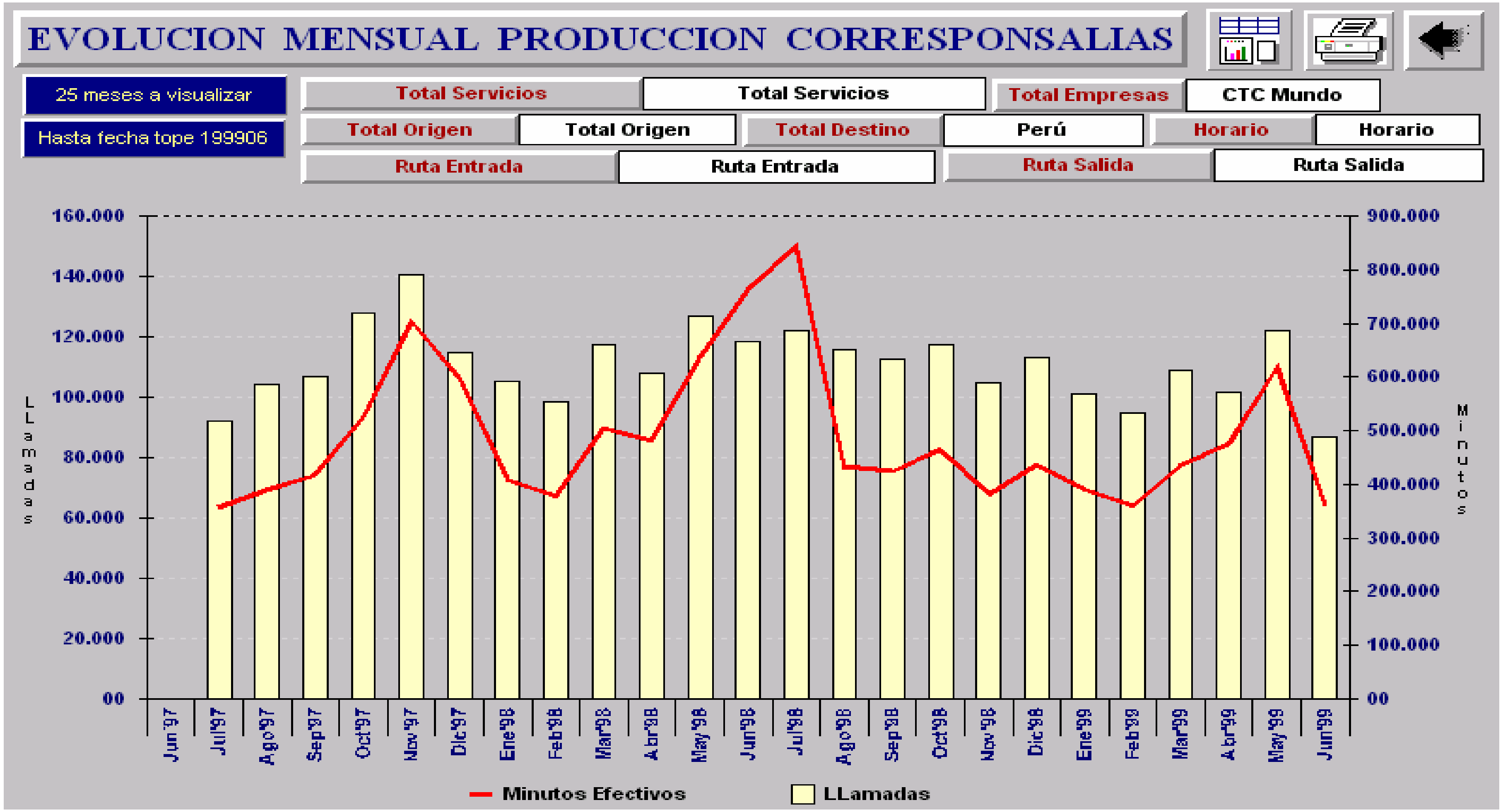
Recording	SS events		Expert-system agreement	Marked, but not detected	Detected, but not marked	Expert agreement rate	System precision
	Marked by expert	Automated detection					
CV061493	520	478	453	67	25	87.1%	94.8%
AM102793	283	288	251	32	37	88.7%	87.2%
TOTAL	**803**	**766**	**704**	**99**	**62**	**87.7%**	**91.9%**

Detección de Fraude en Telecomunicaciones: Caso CTC-MUNDO

- Primer Fraude detectado: Agosto 1996, llamadas Canadá con tarjetas de llamadas
- Enero 1997: Se desarrolla un sistema de detección “batch” de Fraude para tarjetas y celulares
- Octubre 1997: Se compra ATACS 4.0 (Advanced Telecommunication Abuse Control System)
- Noviembre 1997: Se detectan Fraudes a Líbano, Cook Island, Kuwait, etc.. (“call back” y “llamadas eróticas”)
- Enero 1998: Fraude masivo a Perú
- Junio 1998: Comienza operación de ATACS 4.0


Uso LD
Telefónica
MUNDO
Facturación
Facturación
Bases
De
Datos
CDRs
Tiempo
Informes
Bloqueo Línea
Sospecha
De Fraude
Alarmas
Casos
Bloqueados
Analistas
De Fraude
ATACS

Caso Típico de Fraude: Quiebre de tendencia por introducción de ATACS



Sistemas de Detección de Fraude y el Fraude de Suscripción

- En el mundo existen unos 30 sistemas comerciales de detección de fraude telefónico basado en información de tráfico

- Estos sistemas detectan el fraude una vez que ha ocurrido, ya sea en línea o a posteriori (Ej.: ATACS)

- Se propuso evaluar el riesgo de fraude antes de que ocurra, al momento de la suscripción de una nueva línea telefónica (FONDEF 1050)

Definición de Categorías de Clientes

- Fraudulento de Suscripción (S)

  Presentan un disparo de su cuenta dentro de 6 meses de la fecha de instalación, bloqueo por fraude, tráfico LDI

- Otros Fraudulentos (O)

  Presentan un disparo tardío de su cuenta o tienen deudas altas y más de 3 meses sin pagar

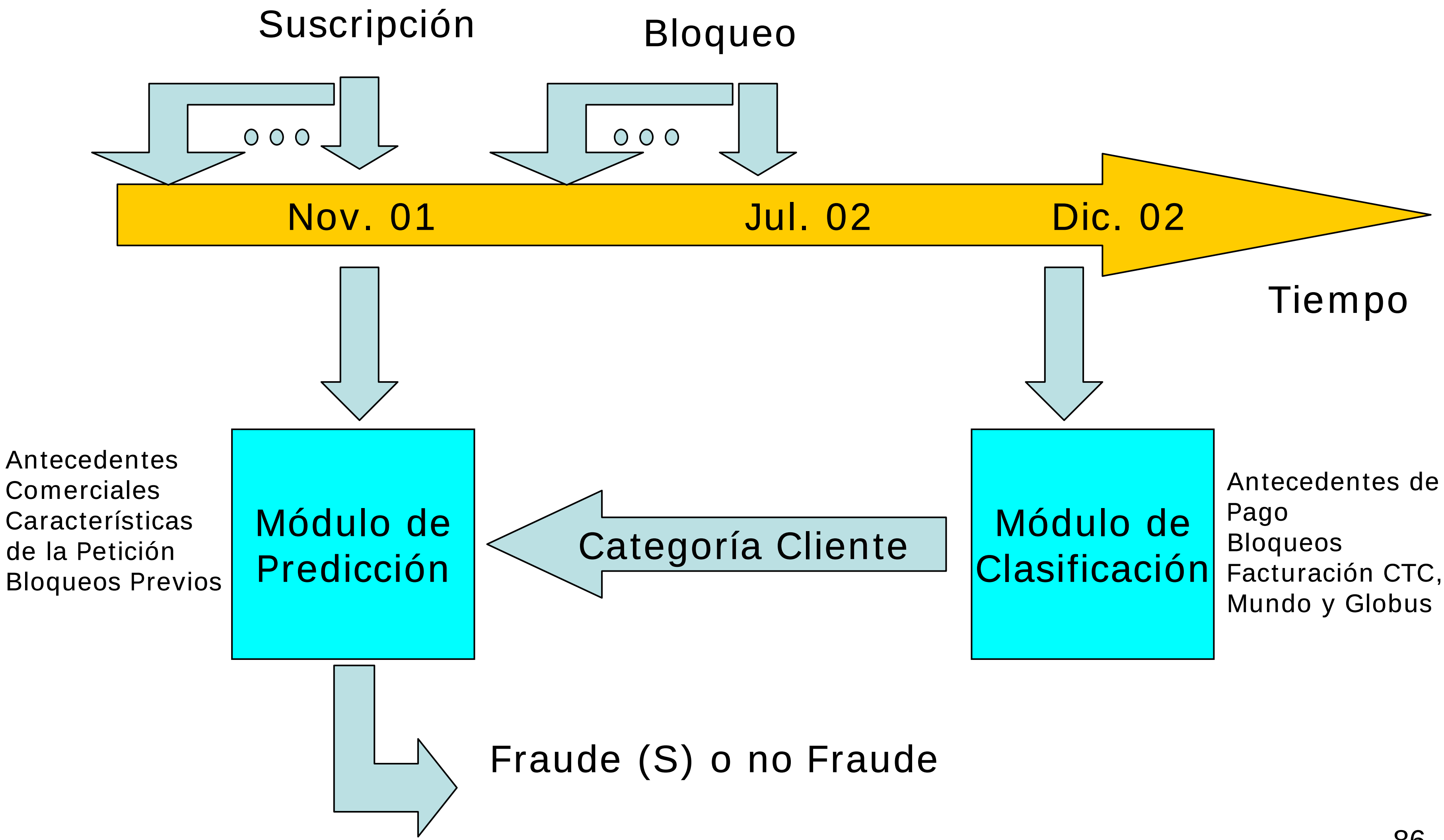
- Morosos (M)

  Incluye a los que frecuentemente se atrasan en pagar la cuenta, a los morosos ocasionales y a los morosos de suscripción que nunca pagan su cuenta

- Normales (N)

  No presentan más de una cuenta impaga o más de 30 días de retraso

Metodología



Módulo de Clasificación Automática

- Clasifica los clientes en 4 categorías: S, O, M, N

- Reglas basadas en lógica difusa permiten manejar conceptos difusos tales como Alto Riesgo (AR) y Bajo Riesgo (BR)

- Usa reglas del tipo:

  SI “X_1 es AR y X_2 es AR”

  ENTONCES “S”

Creación de Reglas: Ejemplos

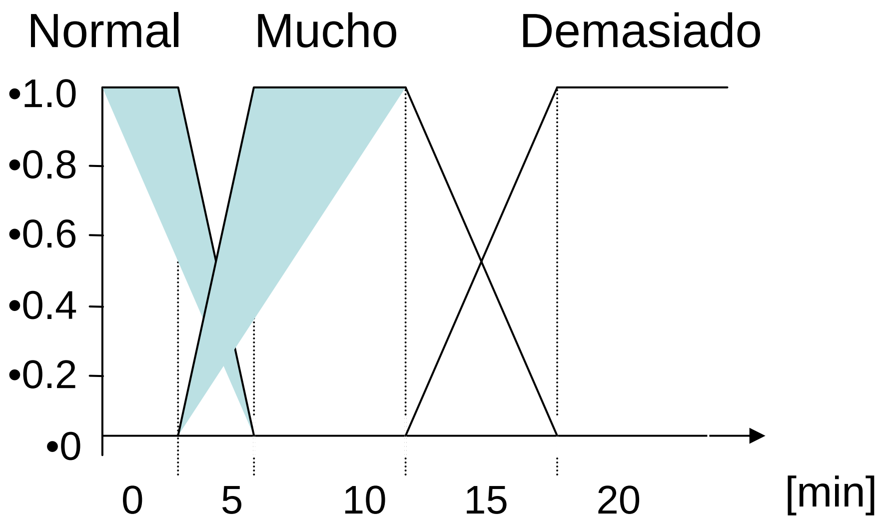
Con datos de tráfico telefónico tales como

- duración de las llamadas (difuso)
- tipo de lugar de origen y destino (nac. o internac.)
- tipo de teléfono de origen y destino (público o normal)
- país de destino sospechoso

Ej: "Si la duración de la llamada es 'larga', es internacional, se hace desde un teléfono público, y a un país sospechoso, entonces hay 'alto riesgo' de fraude"

Variable Difusa, Ejemplo 1: Duración de la llamada

Caso clientes personas masivas



Duración de la llamada

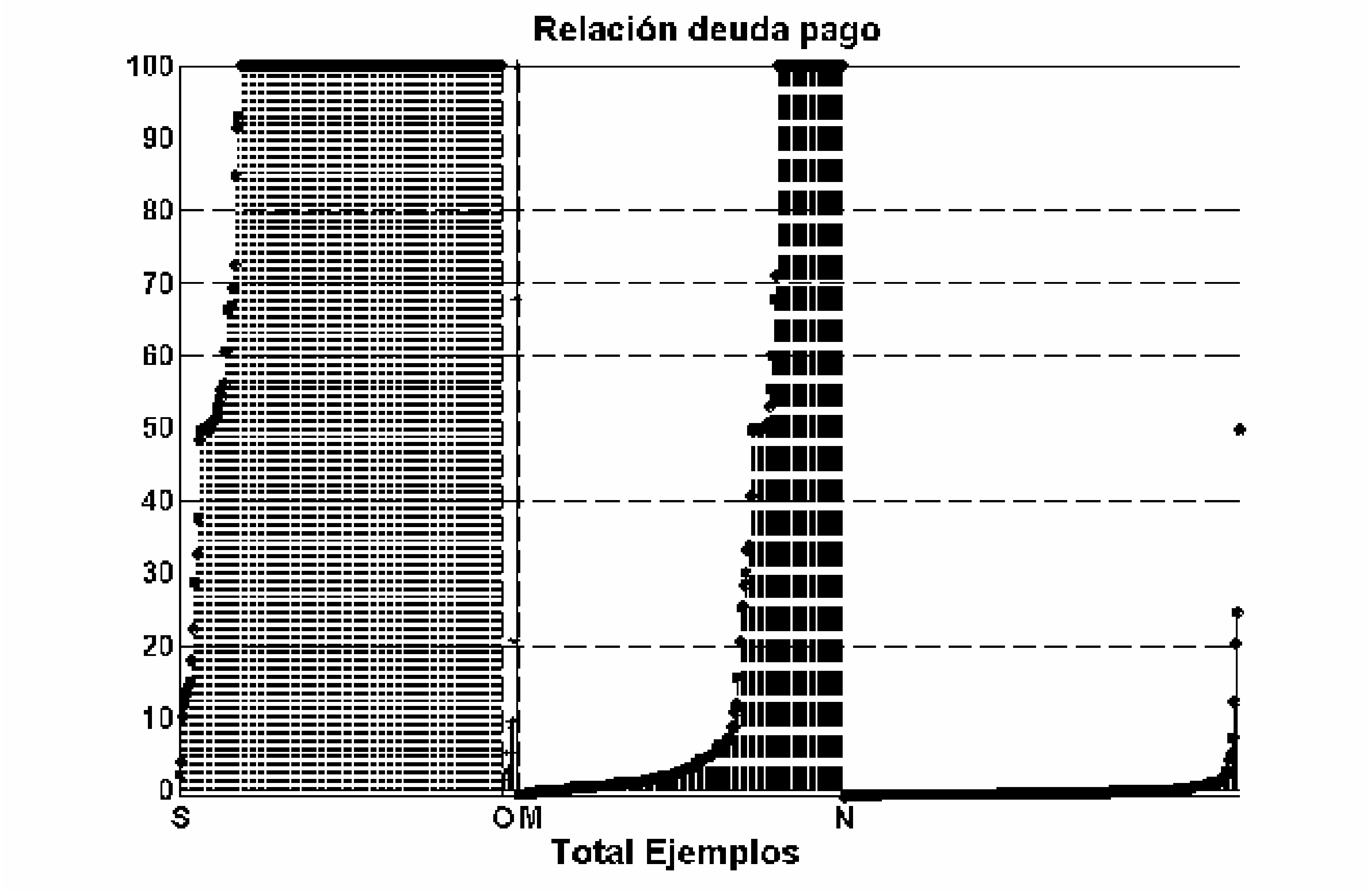
Variable Difusa, Ejemplo 2: Relación Deuda-Pago

Categoría	**Deuda**	**Pago**
Normales	$6.360	$40.140
Morosos	$101.274	$20.827
Fraudes de Suscripción	$1.720.954	$5.119

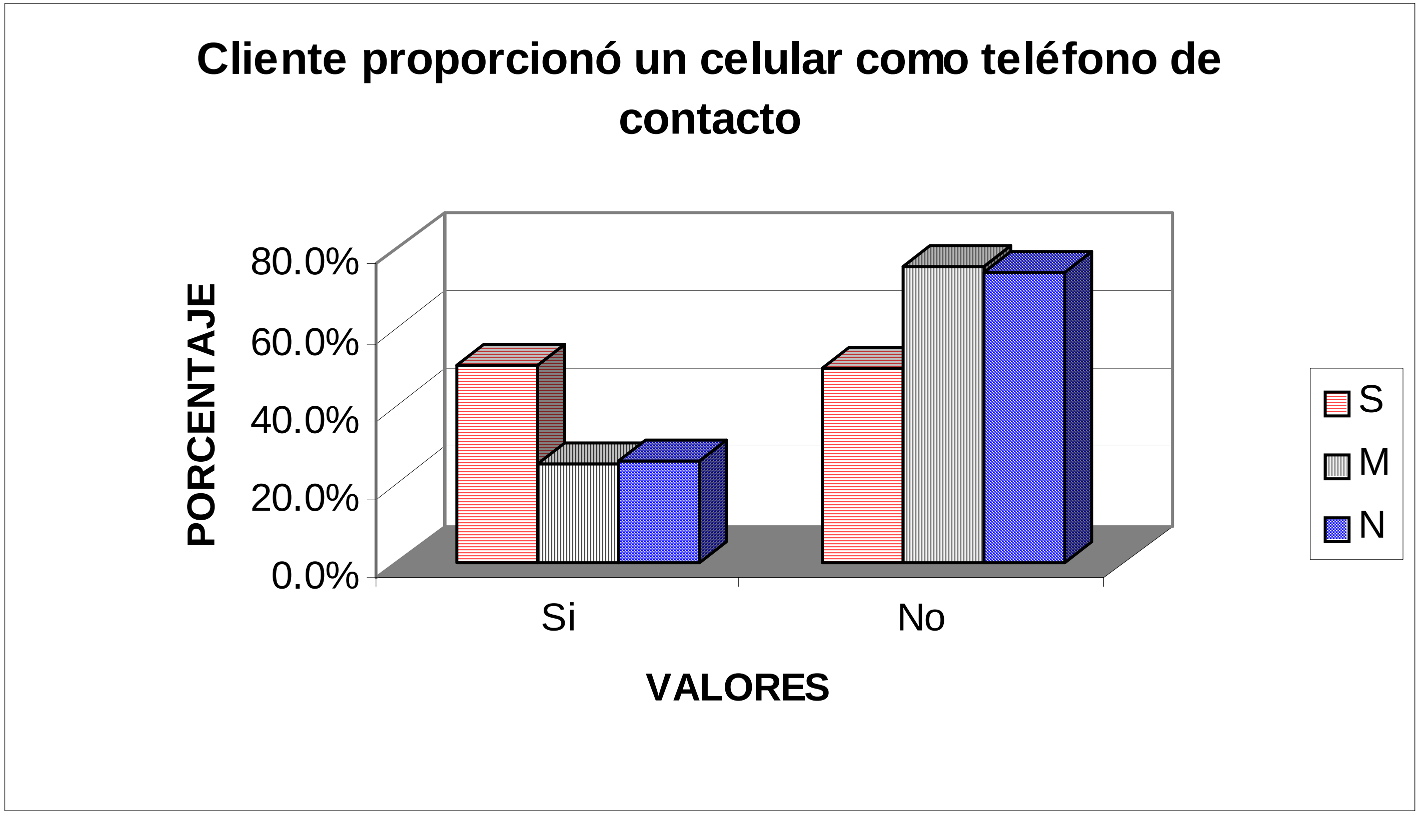
Montos promedio de deuda y pago por categoría:

- N/M: deuda último registro
- S: deuda al momento del bloqueo
- Pago: mensual

Variable Relación Deuda-Pago



Variable Difusa, Ejemplo 3: Teléfono de Contacto es Celular



Los porcentajes suman 100% por categoría

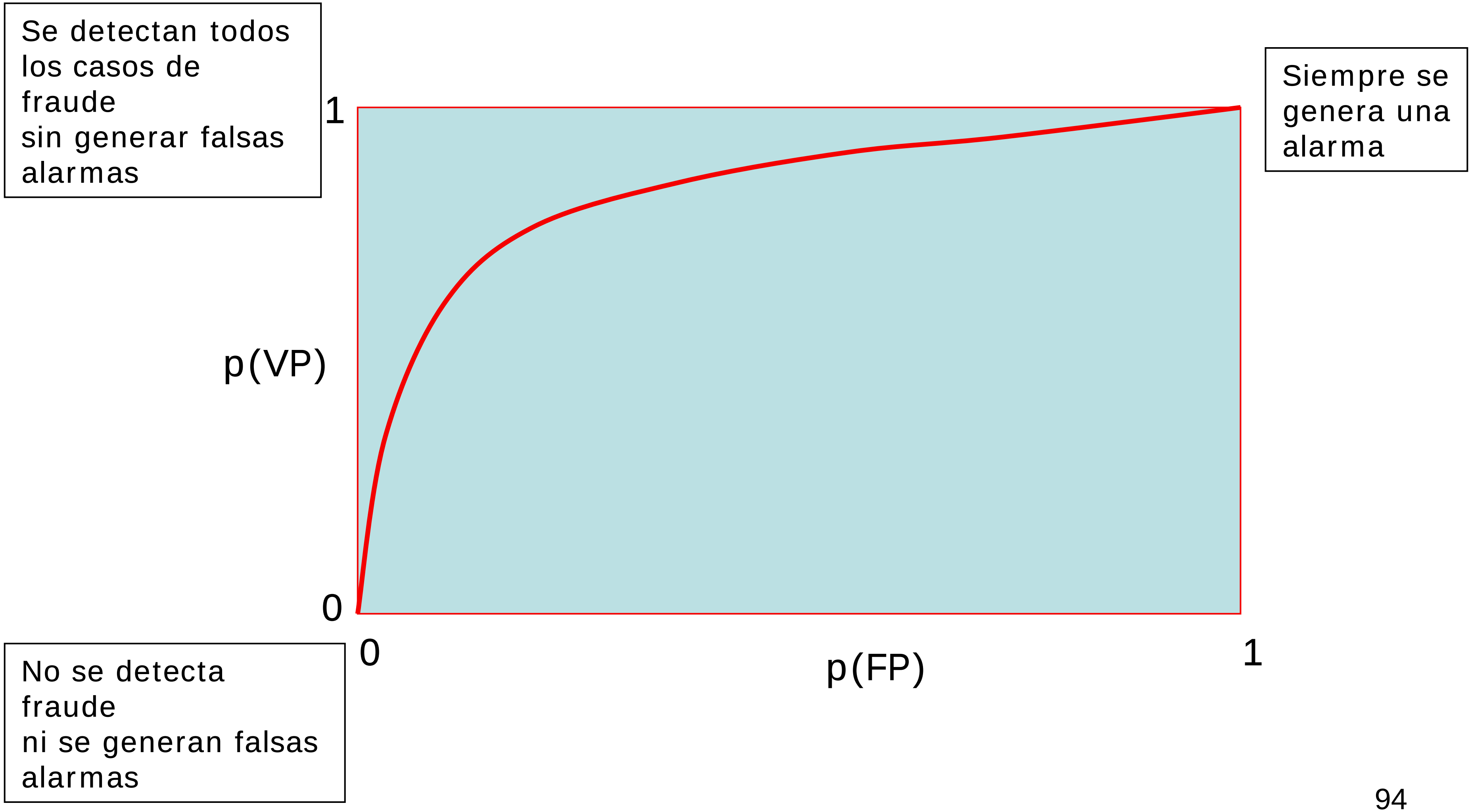
Fijación de Parámetros de Operación: Receiving Operator Characteristic

- Curva ROC grafica la tasa de Verdaderos Positivos p(VP) versus la tasa de Falsos Positivos p(FP)

$$p(VP) = \frac{\text{casos positivos bien clasificados}}{\text{total de casos positivos}}$$

$$p(FP) = \frac{\text{casos negativos mal clasificados}}{\text{total de casos negativos}}$$

Interpretación Curva ROC



Neuronal

Neuronal S.A.: start-up que nace a partir de Proyecto FONDEF
Busca aprovechar el desarrollo tecnológico y know-how propio.

Misión:

- Proveer soluciones de gestión sobre los datos para la detección, análisis, control y gestión de la empresa.
- Aplicar herramientas “inteligentes”, basadas en redes neuronales, lógica difusa, algoritmos genéticos y otros
- Contar con recursos especializados de consultoría, investigación y desarrollo
- Pesquisar en todo el mundo, adquirir y capacitar en las herramientas más adecuadas para cada caso

After the Break: Simulations of Linguistic Fuzzy Models

Laboratorio de Aplicaciones de Sistemas Difusos

Profesor Auxiliar: Leonardo Causa

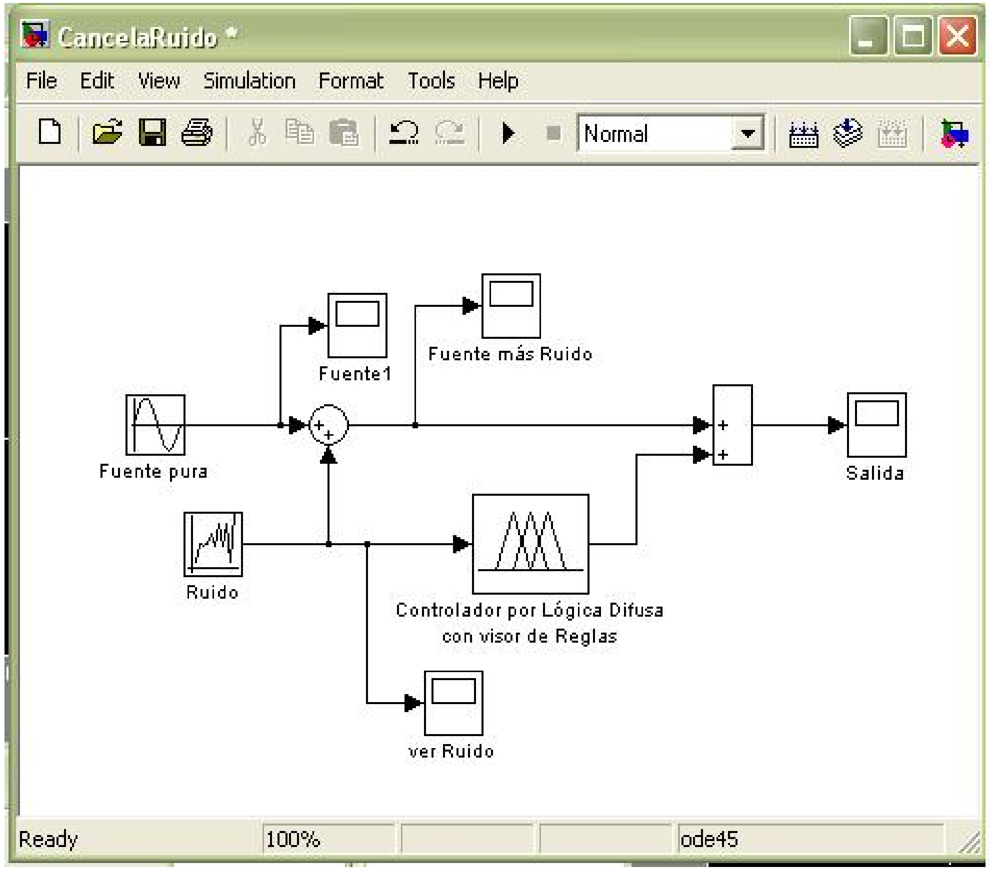
ATENCIÓN: NOTEN UBICACIÓN DEL LABORATORIO

Edificio de Electrotecnologías, Piso 3

Laboratorio de Sistemas Inteligentes

Trabajarán en grupos de 2 a 3 personas por computador

Experiencia Nº1: Cancelador de Ruido con un Controlador por Lógica Difusa (CLD)

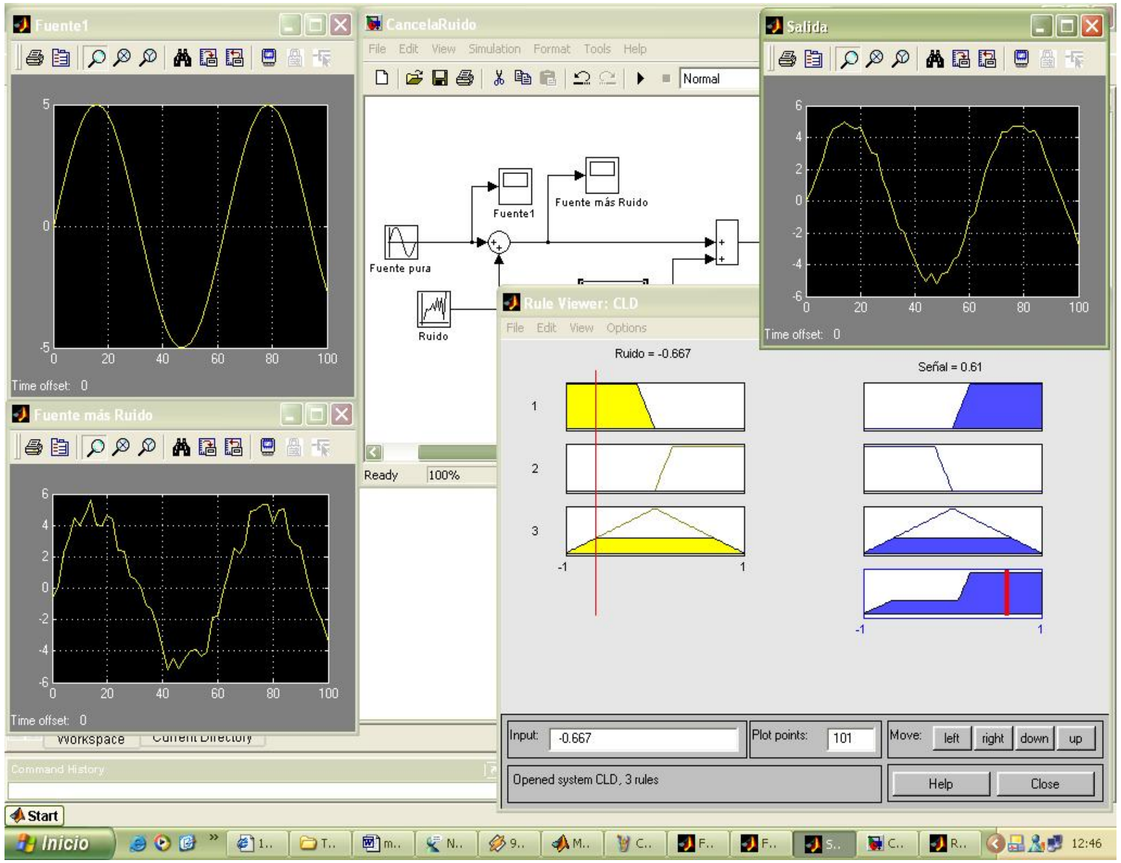


Para la simulación del CLD se utiliza Simulink de Matlab

Para visualizar formas de onda se utilizan visores

La simulación "corre" eligiendo "Start" en el menú "Simulation" o con el botón ">"

Cancelador de Ruido CLD: Simulación



Aparecen visores para las señales seleccionadas y un visor del CLD “on-line”

La experiencia contempla efectuar modificaciones al sistema y observar las consecuencias.

Experiencia Nº2: Sistema Experto “BUSCA-ZOO 2004”

Programado en Matlab

La interfaz hombre-máquina es muy importante para aceptación de sistemas de apoyo a la toma de decisiones.

El usuario ingresa su conocimiento a través de una interfaz tipo “regla deslizante”

La experiencia contempla efectuar modificaciones al sistema y observar sus consecuencias