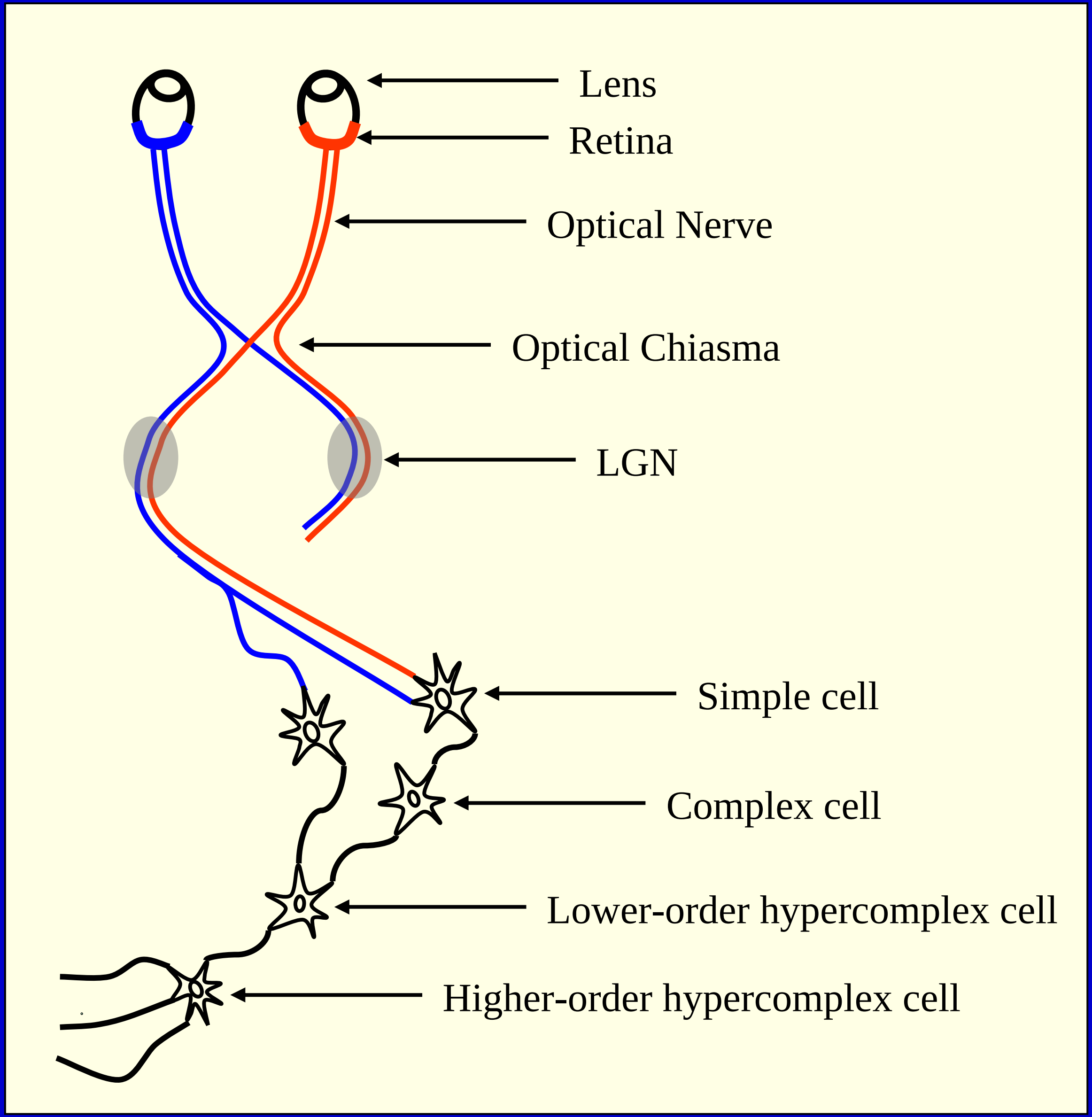
Genetic Selection of Biologically Inspired Receptive Fields for Pattern Recognition:

handwritten digit classification and face recognition

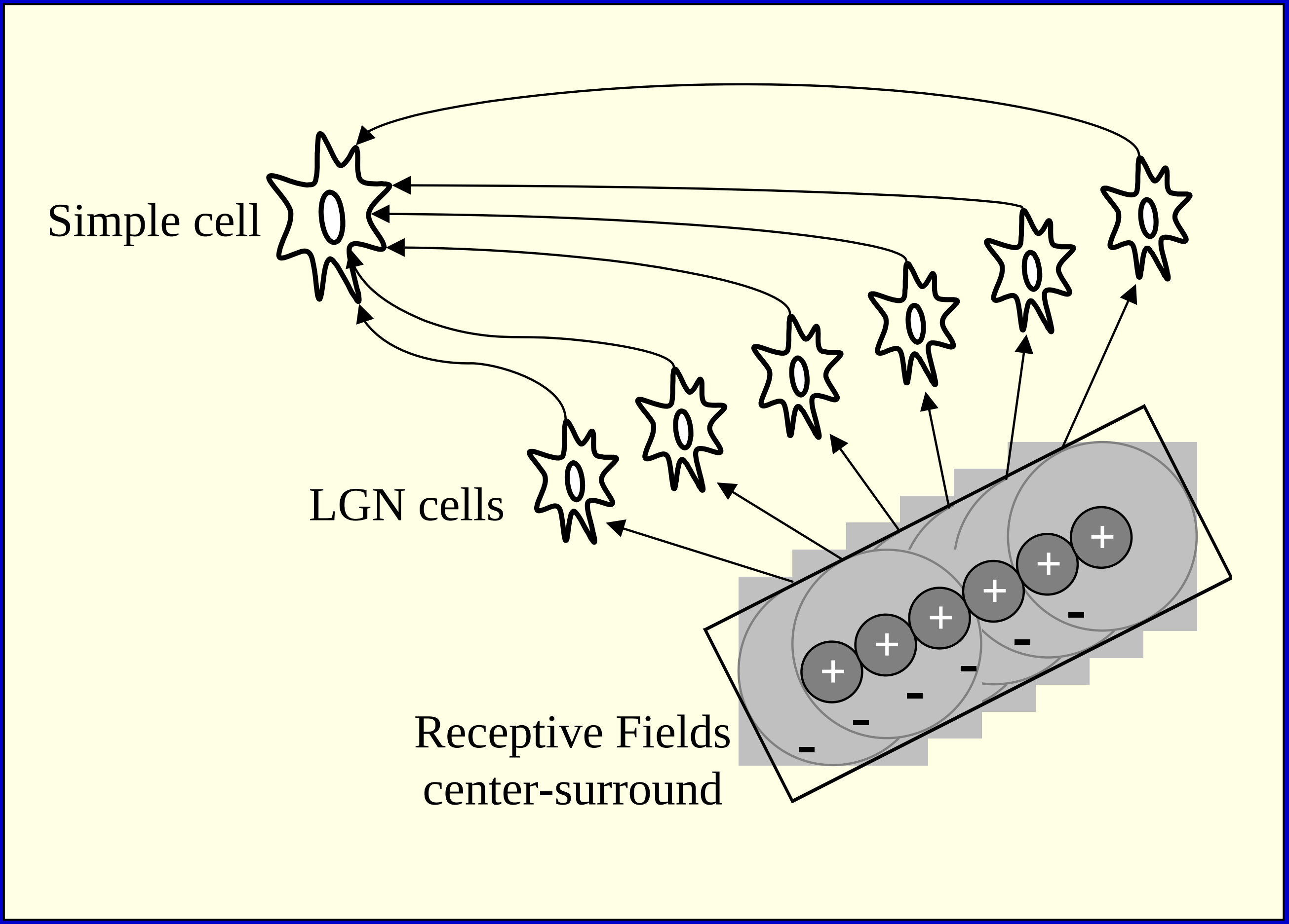
Objectives

- Propose a method for **automatic design of biologically inspired receptive fields** in a neural network model for pattern recognition.
- Show that **Genetic Algorithms** allow to determine an appropriate configuration of the receptive fields.
- Apply the method to the **problems** of handwritten digit classification and face recognition.
- Show that **biologically inspired receptive fields** improve the classification performance of neural networks.

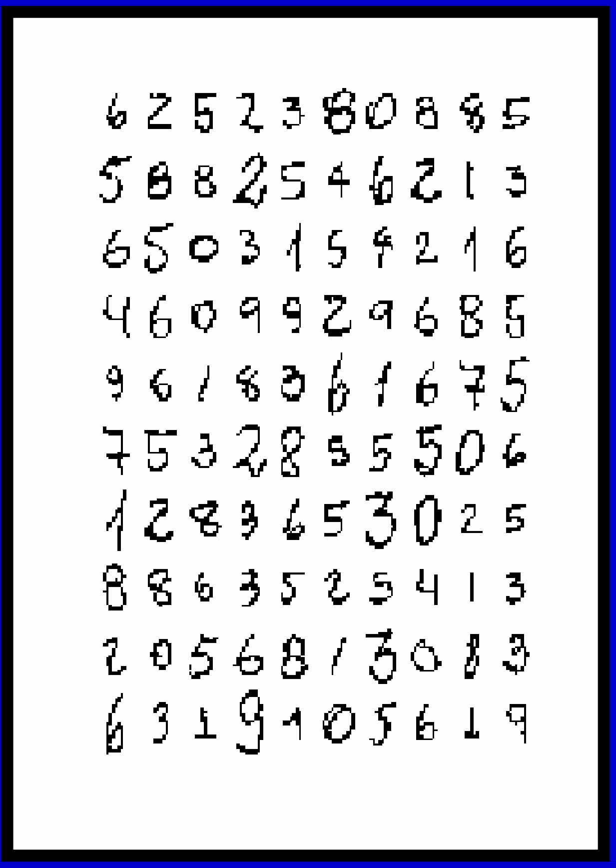
Introduction:Visual Path in Mammals



Introduction: Simple Cell Receptive Field

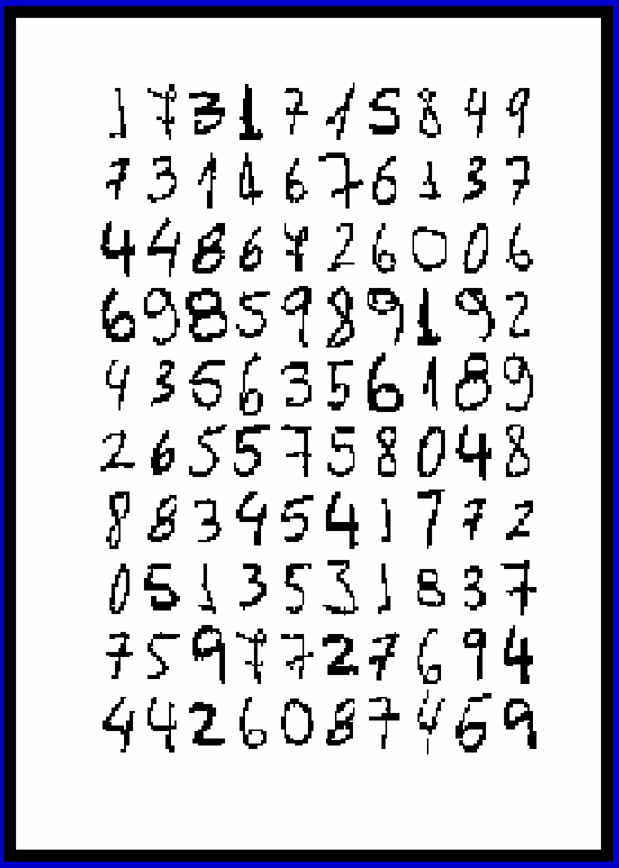


Handwritten Digit Database: Samples



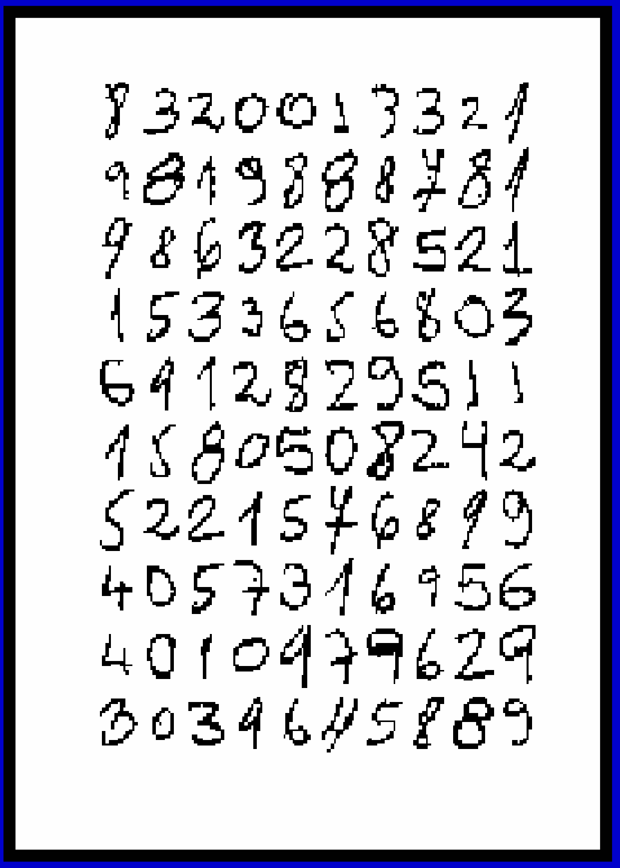
TRAINING

(1,837)



VALIDATION

(918)



TESTING

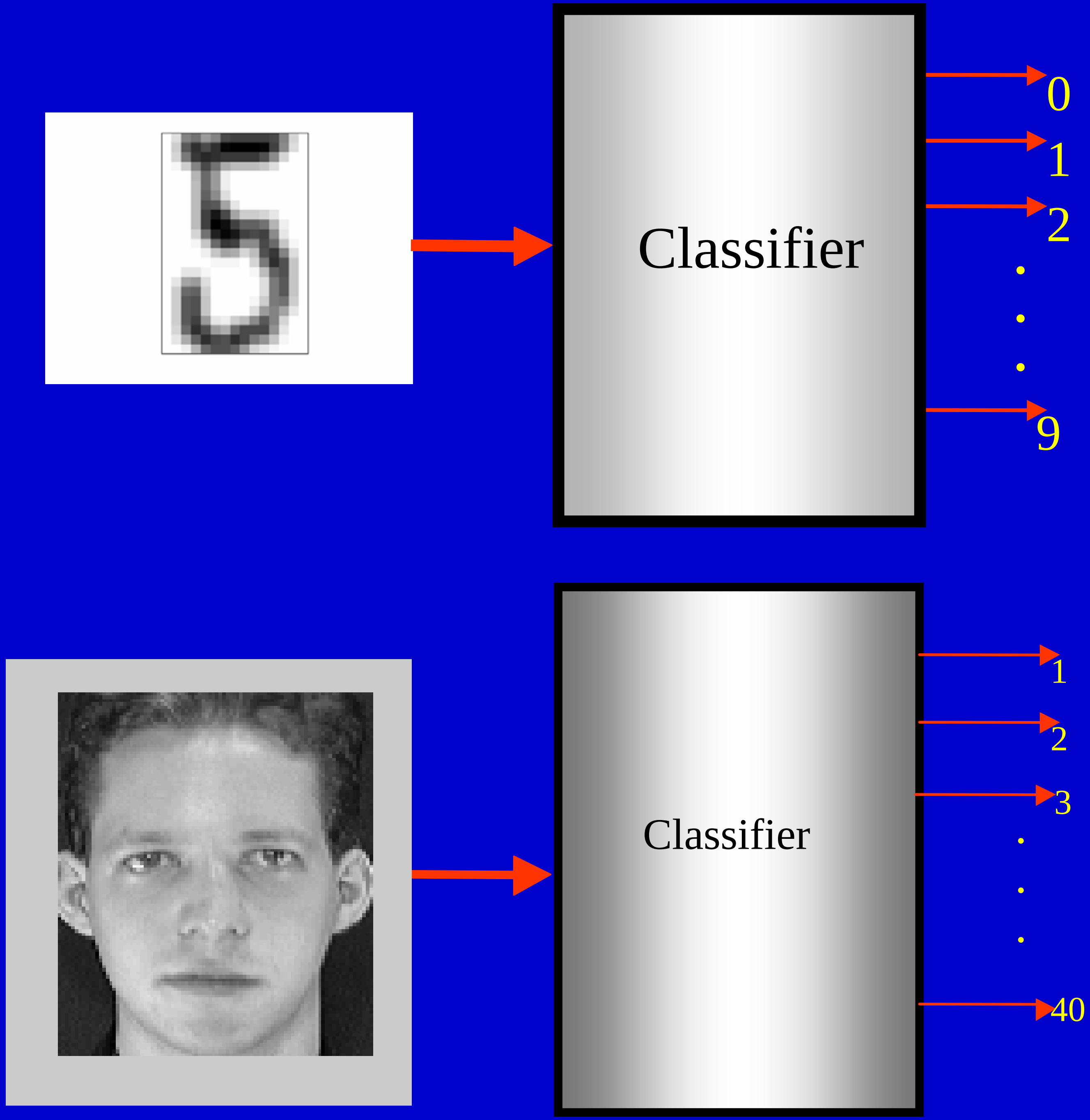
(919)

Face Database: Samples

TRAINING (160)

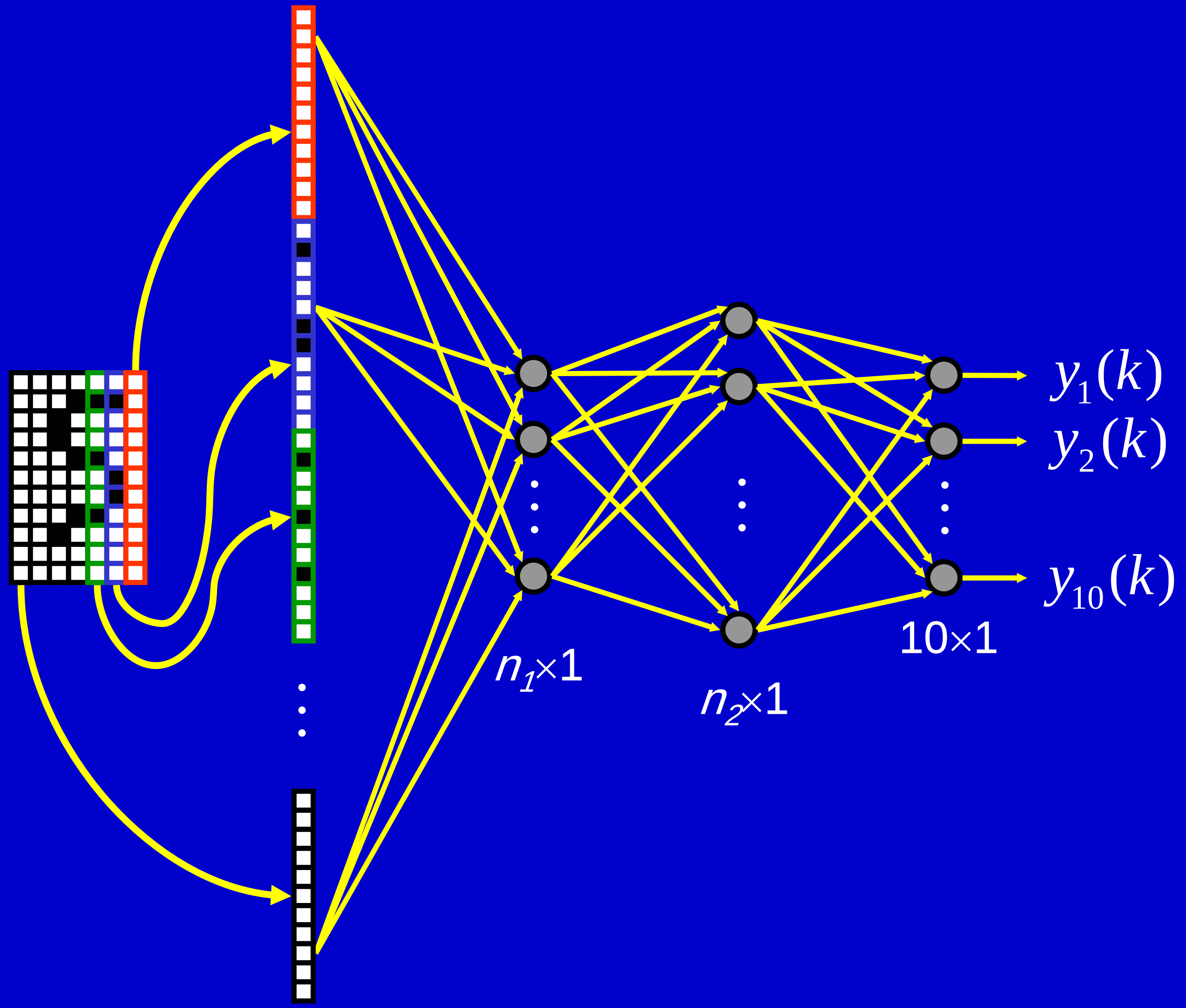
VALIDATION (120)

TESTING (120)

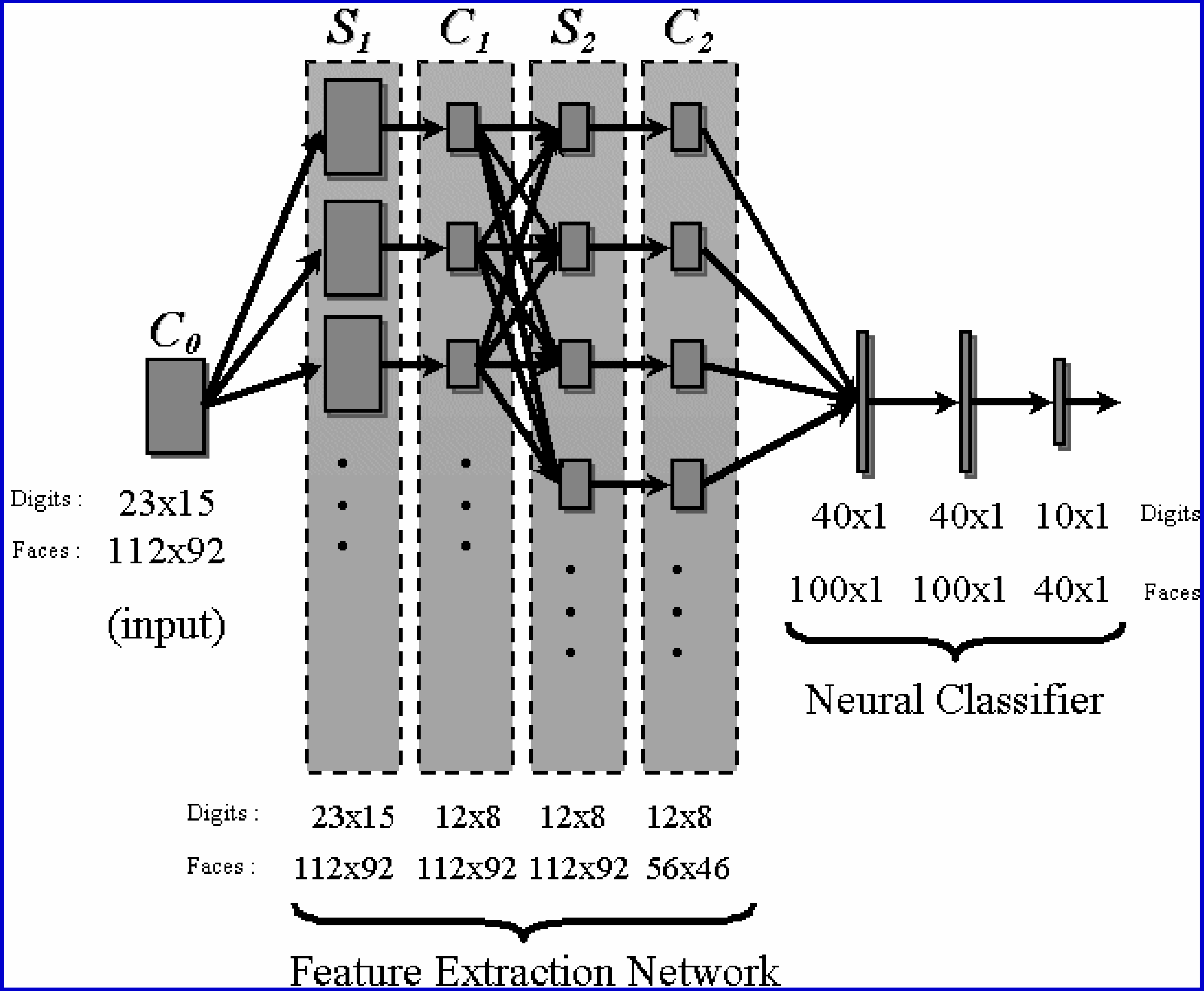


Classifier
0
1
2
9
Classifier
1
2
3
40

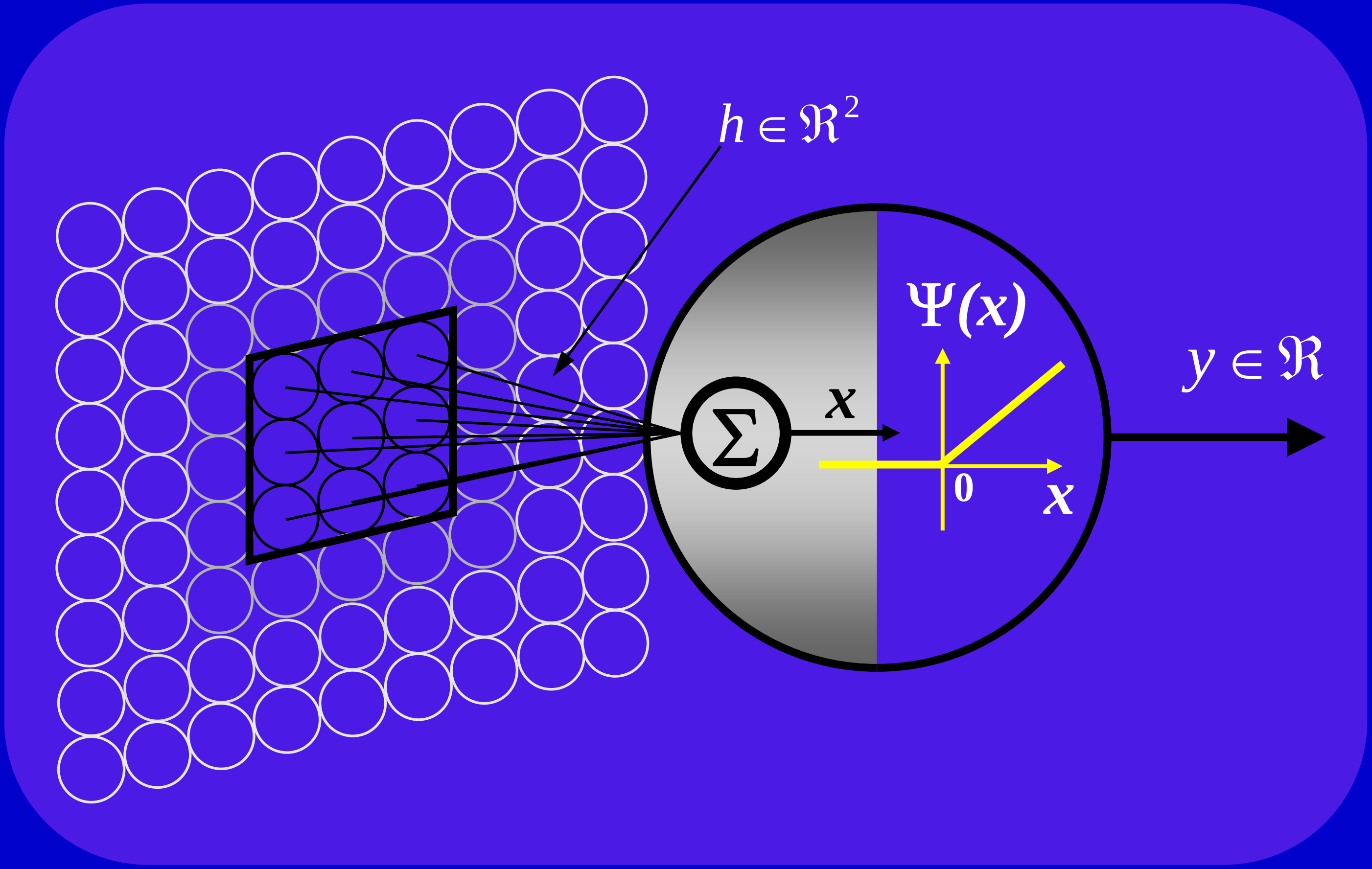
Perceptron Architecture



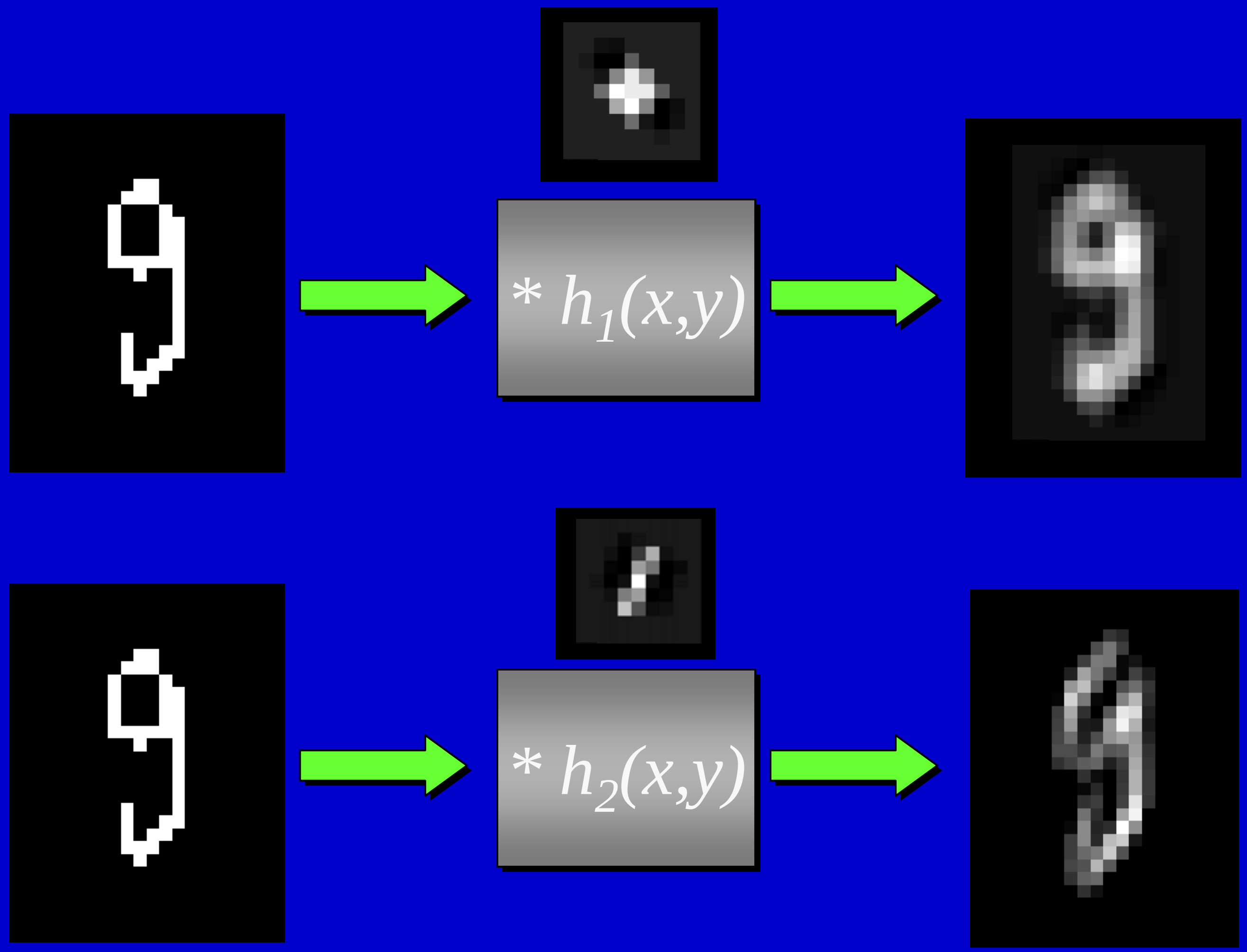
Convolutional NN Architecture



Convolutional Network's Units



Receptive fields as filters



Feature Detection & Scale Reduction

C plane convolution

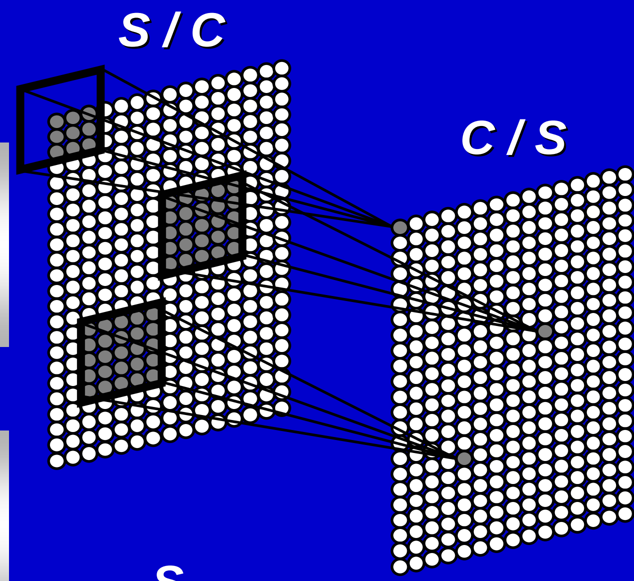
$$C_l^k(i,j) = \Psi\left(\sum_{m=1}^{Sx_l^k}\sum_{n=1}^{Sy_l^k} S_l^k(m,n)\cdot hc_l^k(i-m, j-n)\right)$$

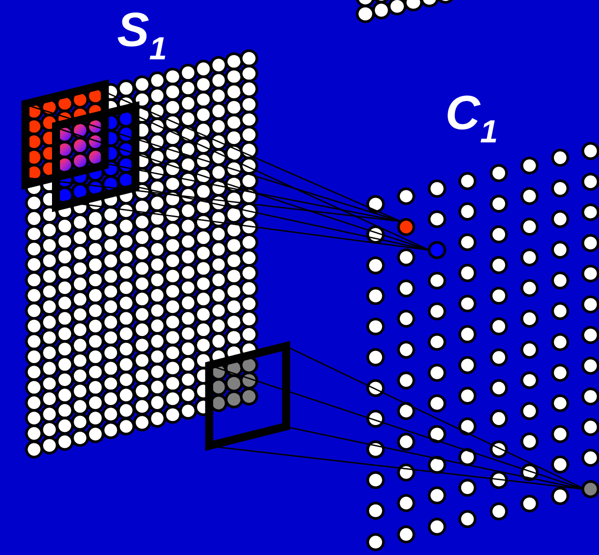
S plane convolution

$$S_l^k(i,j) = \Psi\left(\sum_{r=1}^{R_l}\sum_{m=1}^{Cx_{l-1}^r}\sum_{n=1}^{Cy_{l-1}^r} C_{l-1}^r(m,n)\cdot hs_l^k(i-m, j-n)\right)$$

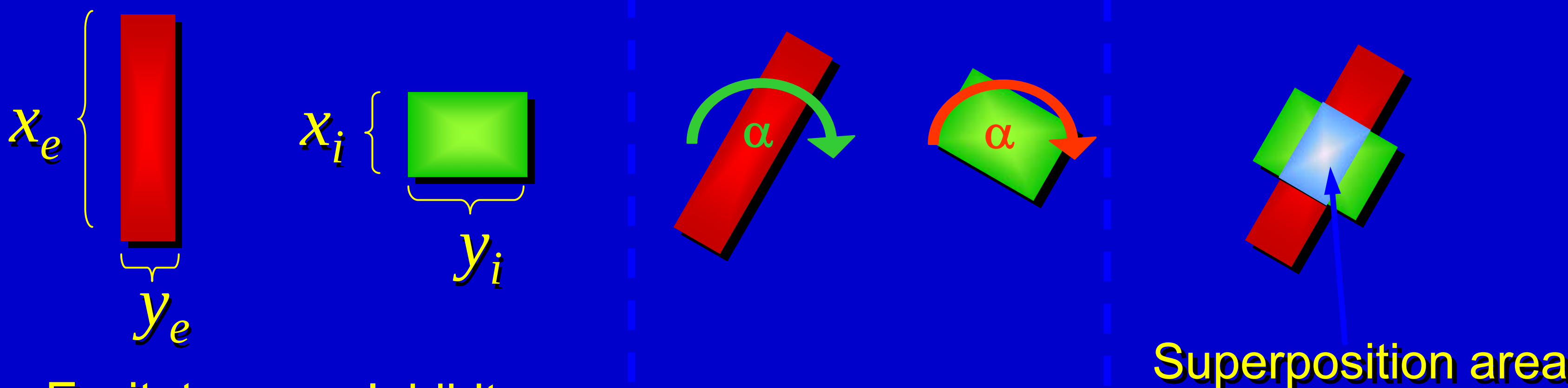
Scale reduction

$$C_1^k(i,j) = \Psi\left(\sum_{m=1}^{Sx_1^k}\sum_{n=1}^{Sy_1^k} S_1^k(m,n)\cdot hc_1^k(2i-m, 2j-n)\right)$$





Receptive Fields Construction



Excitatory Component

Inhibitory Component

Stage 1

Dimension Assignment

Stage 2

Rotation

Stage 3

Additive Superposition and *Bias*

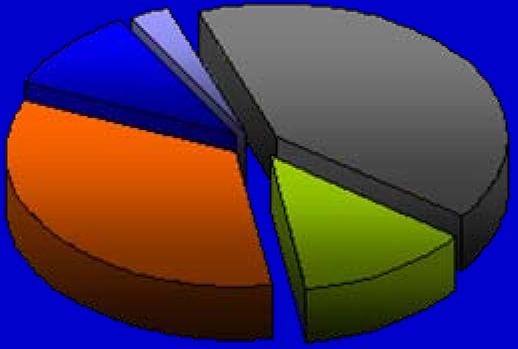
Genetic Algorithm

Fitness: The fitness f_i is the classification performance on a validation database of 918 handwritten digits. The training set is composed of 1,837 handwritten digits.

Coding: The parameters encoded for the genetic algorithm for each plane of each hidden layer are the x_e, y_e, x_i, and y_i dimensions, the orientation α and *bias* as well the number of planes per layer.

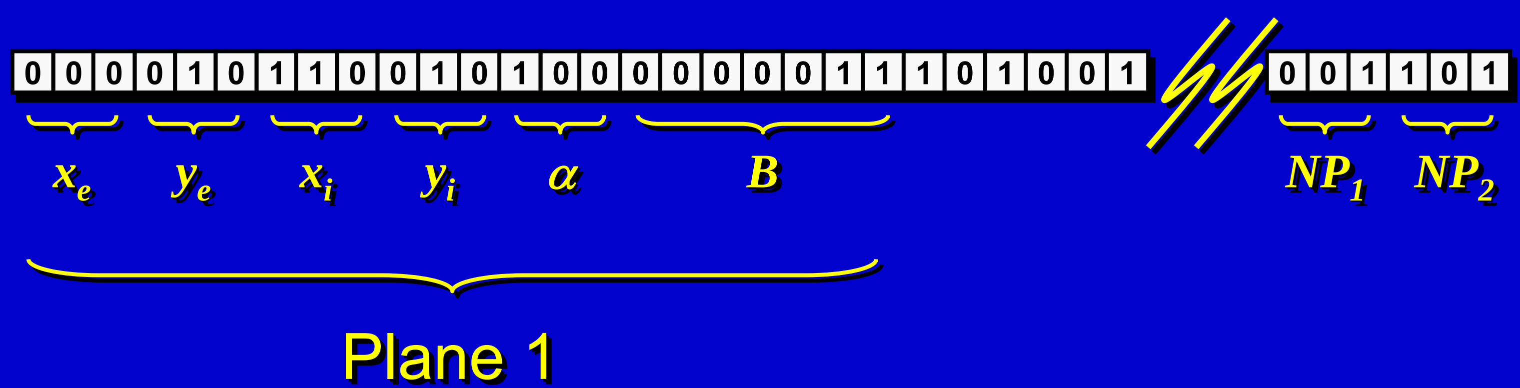
Selection: Proportional Selection.

$$P_i = \frac{f_i}{\sum_{k=1}^{N} f_k}$$



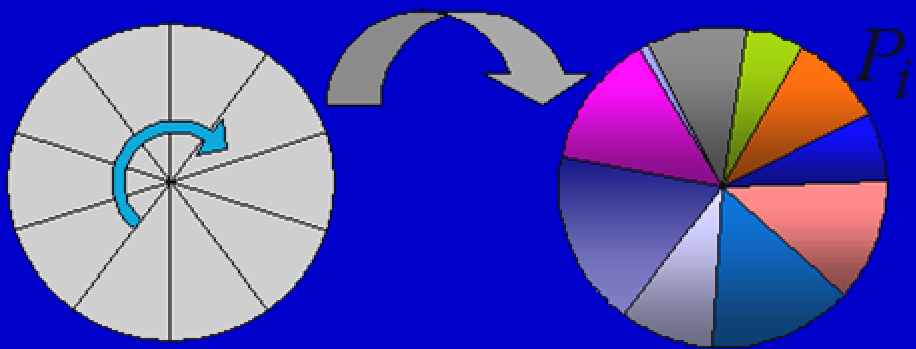
Coding

Parameter	Units	Number of bits	Minimum value	Maximum value	Step
x_e	Pixels	3	1	8	1
y_e	Pixels	3	1	8	1
x_i	Pixels	3	1	8	1
y_i	Pixels	3	1	8	1
α	Degrees	3	0	157.5	22.5
B	no dimension	7	0	1	0.0079
NP_1	no dimension	3	1	8	1
NP_2	no dimension	3	1	8	1

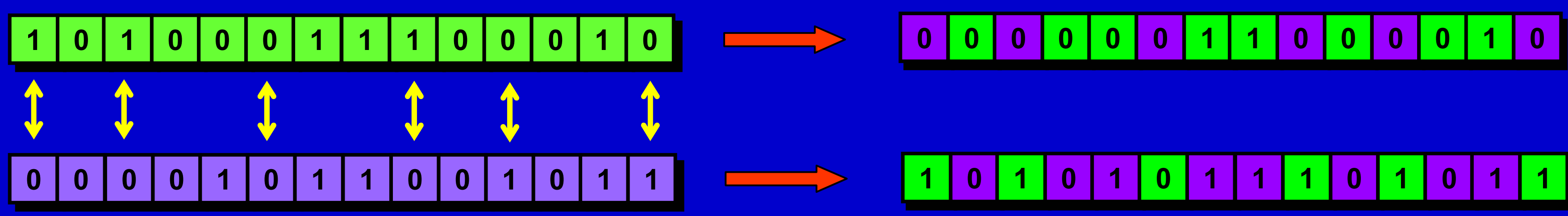


Genetic Algorithm 2

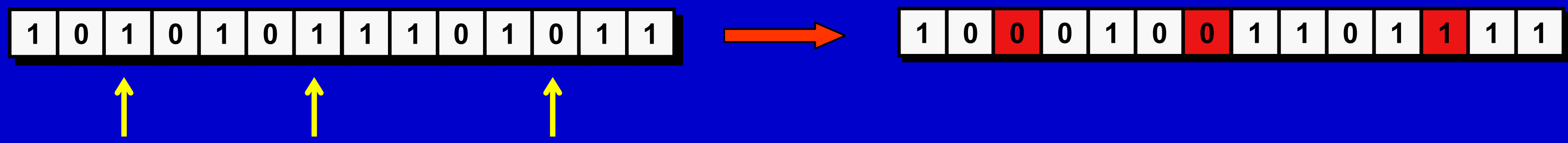
Sampling : Stochastic Universal Sampling.



Uniform Crossover



Mutation



Genetic Selection & Training Parameters

Genetic Selection

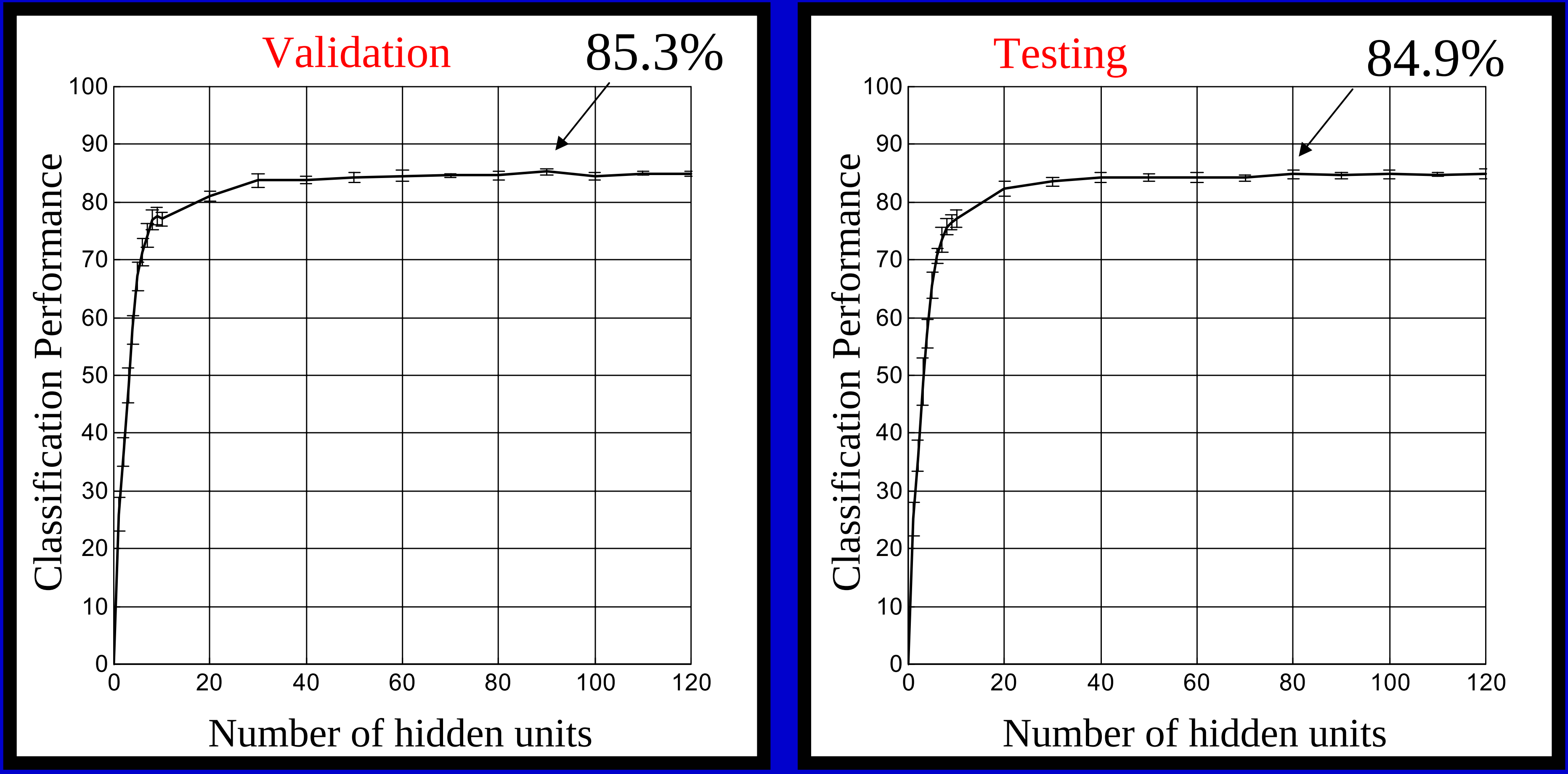
- Population size : 20 individuals
- Uniform crossover probability : 0.5
- Mutation probability : 0.001

Training

- Training algorithm : Backpropagation
- Learning rate : 0.2
- Momentum : 0.2
- Training epochs per individual : 200
- Perceptron activation function :

$$\frac{1}{1+e^{-x}}$$

MLP - Handwritten Digit Problem (HDP): Classification Performance versus Number of Hidden Units

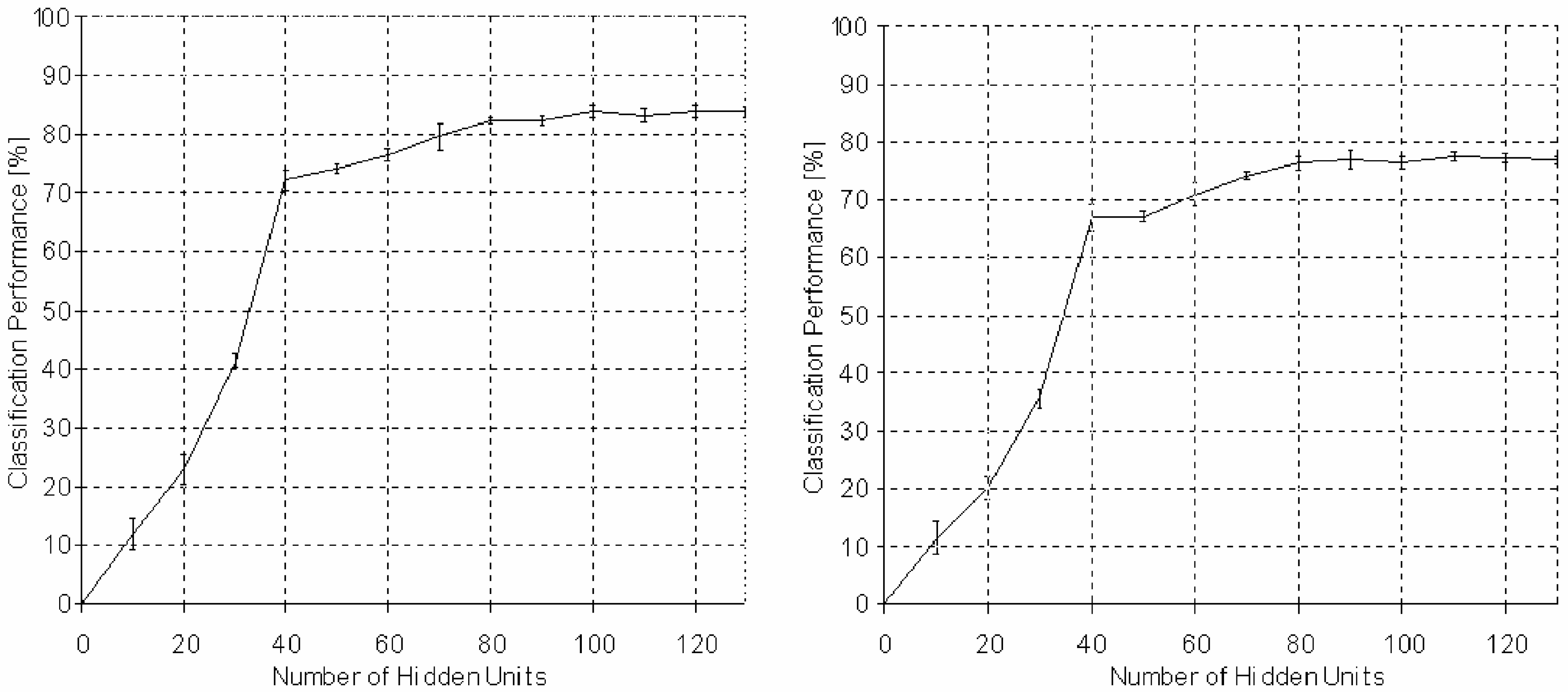


Database Training: 1837, Validation: 918, Testing: 919

MLP - Face Recognition Problem (FRP): Classification Performance versus Number of Hidden Units

Validation: 84.9%

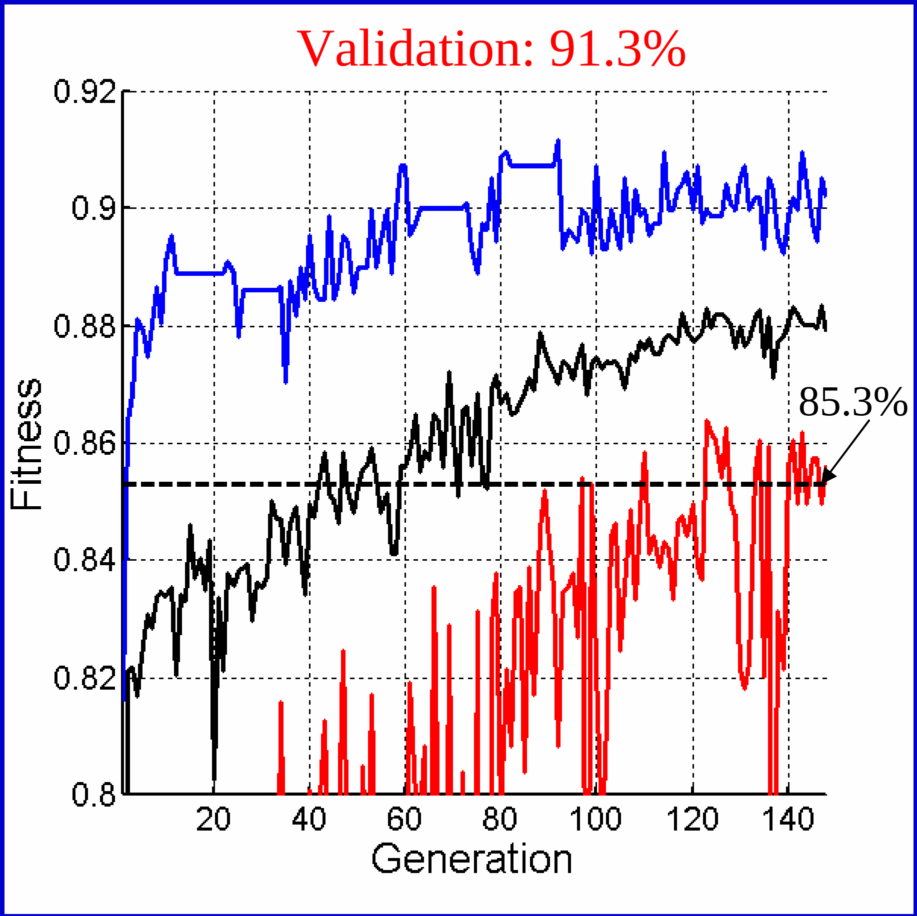
Testing: 77.5%

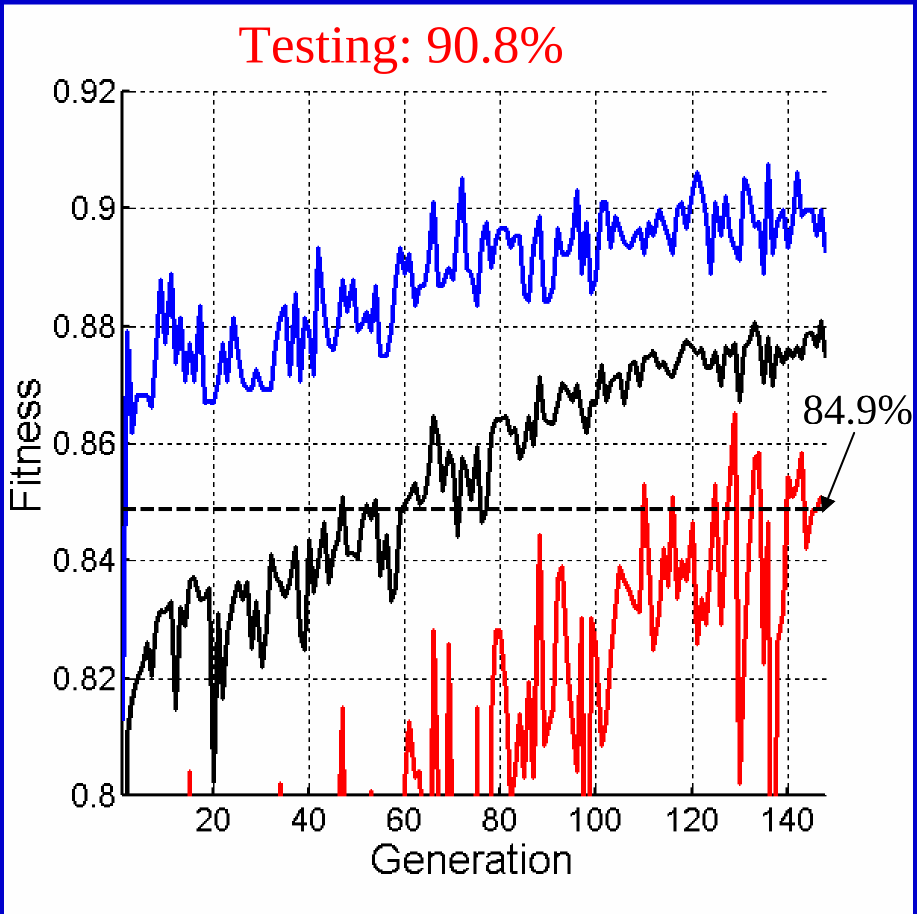


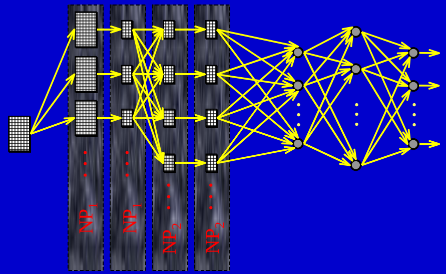
(c) (d)

Database Training: 160, Validation: 120, Testing: 120

Genetic Selection of Receptive Fields: HDP







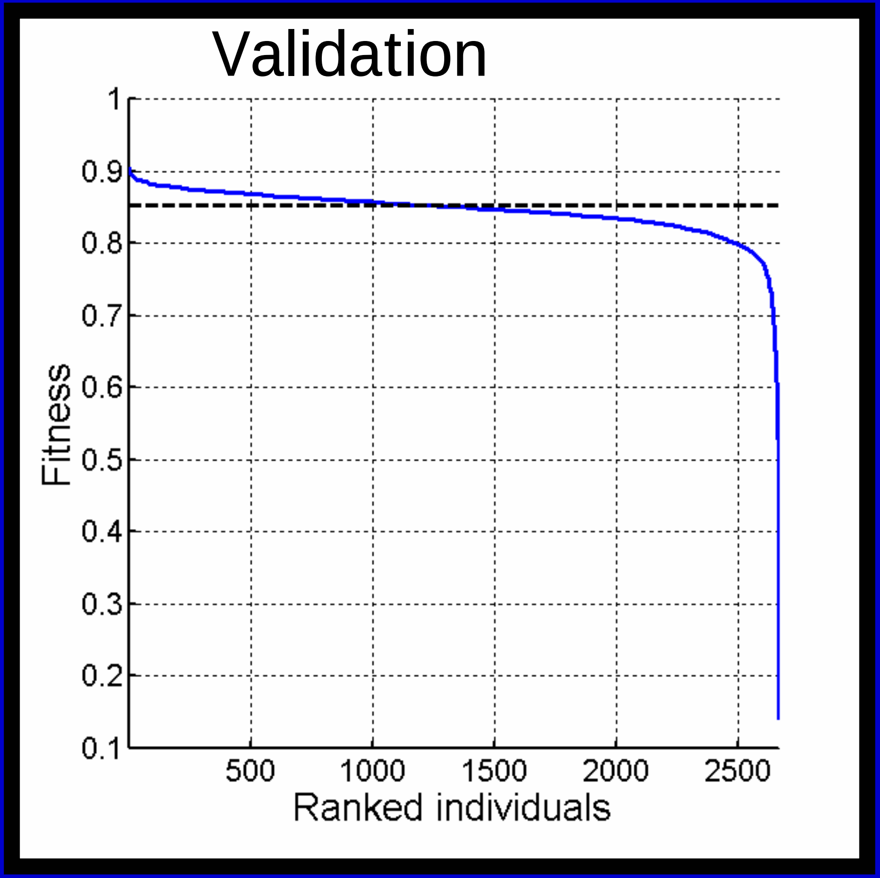
Best individual

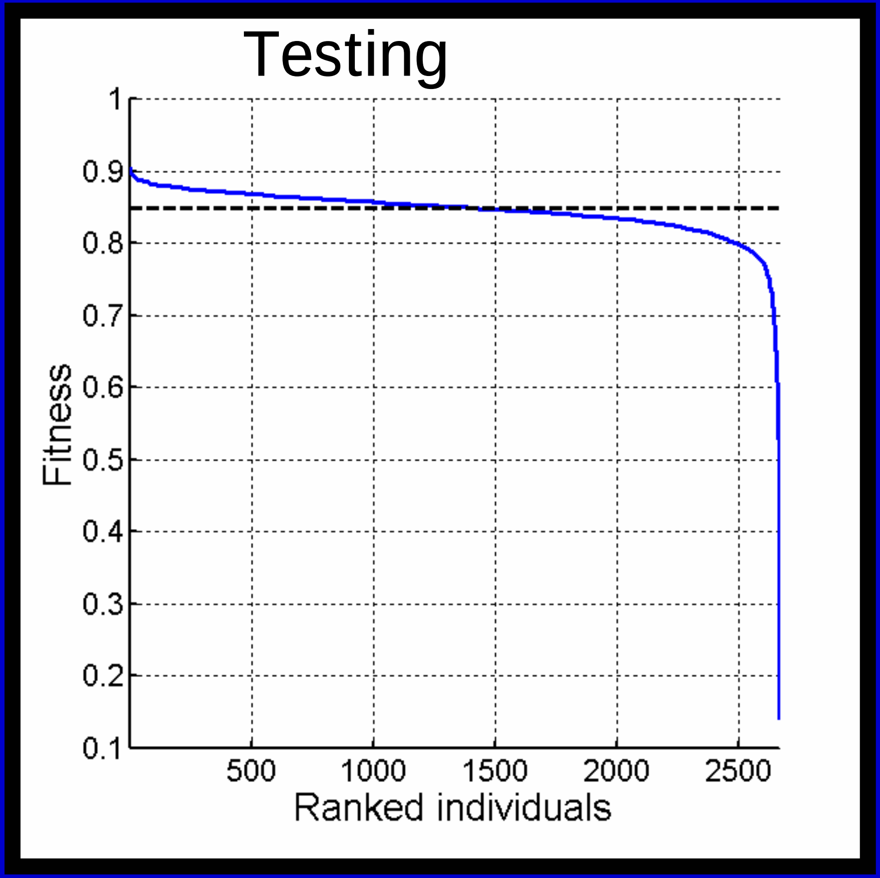
Worst

Averange

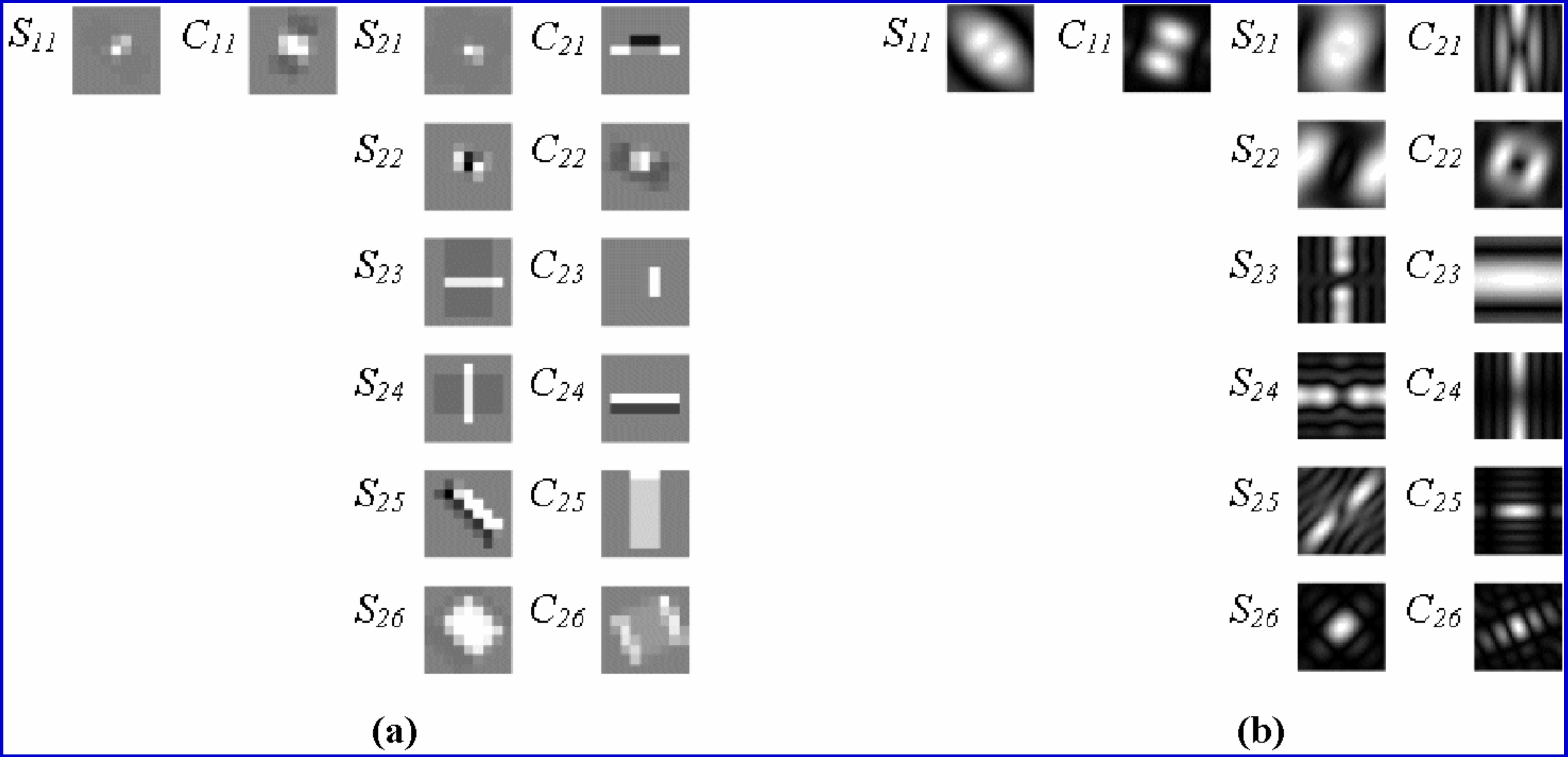
Perceptron

Ranked Individuals: HDP

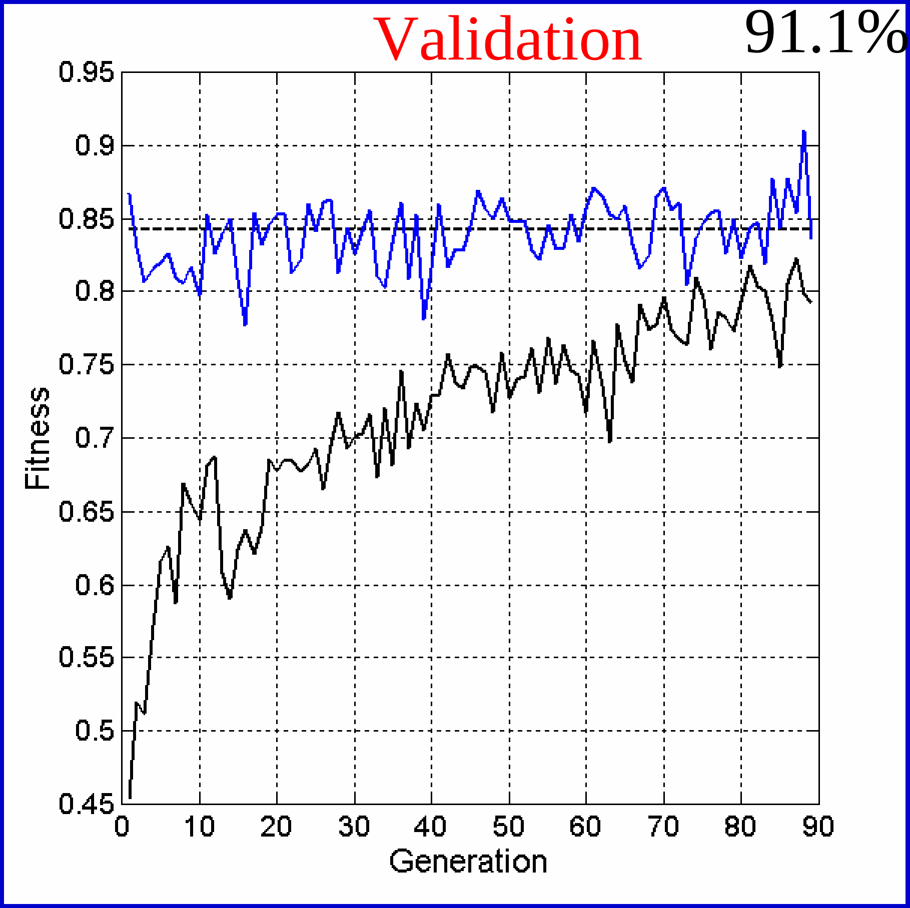


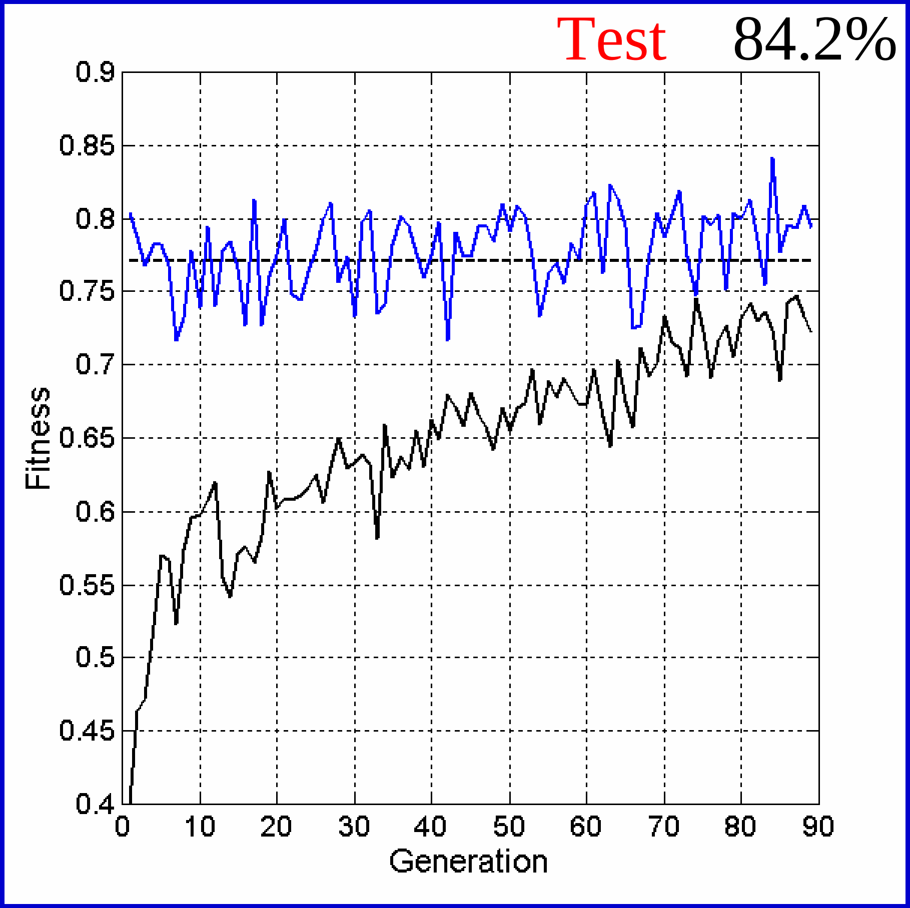


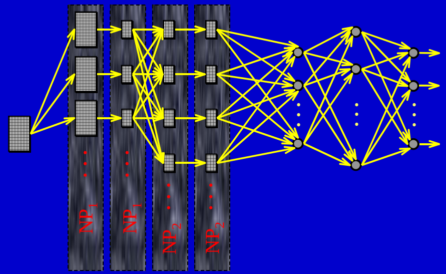
Ranked Individuals:HDP



Genetic Selection of Receptive Fields: FRP





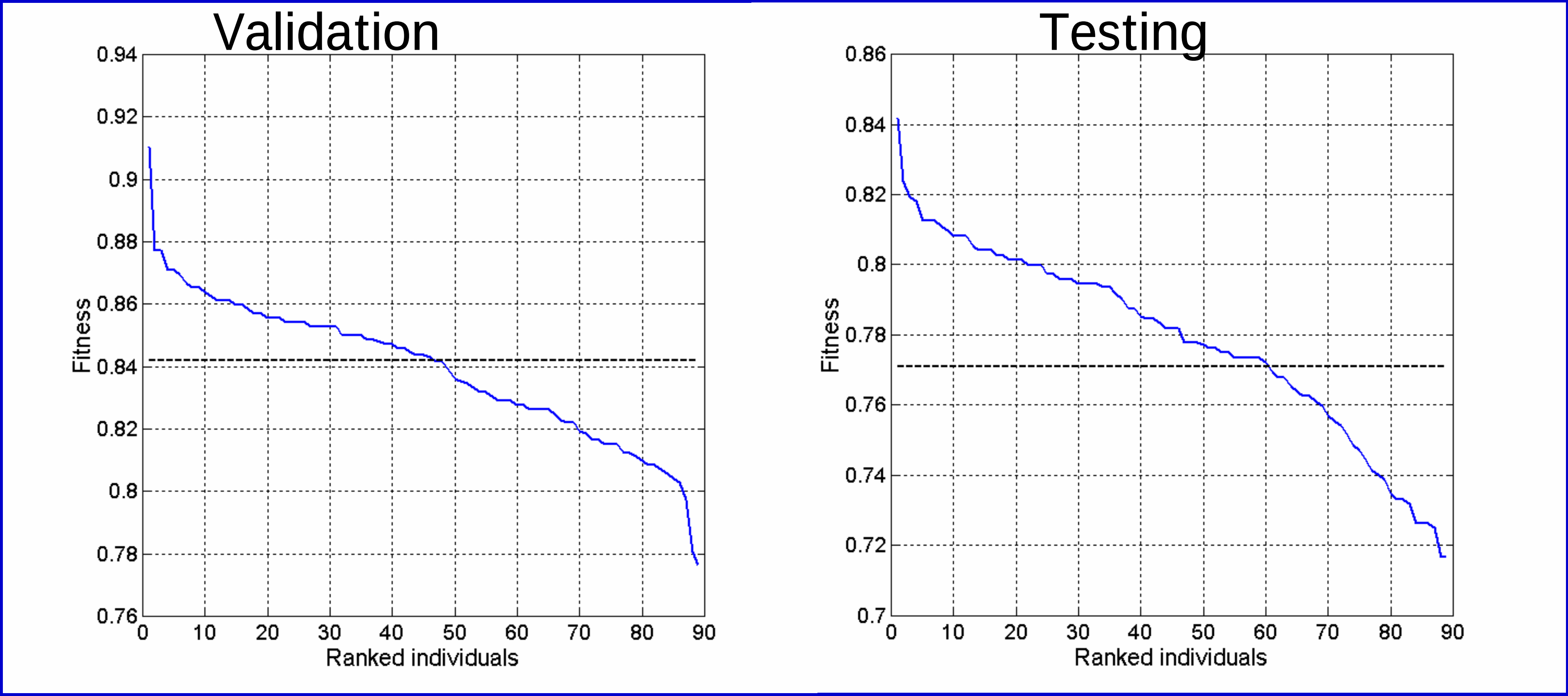


Best individual

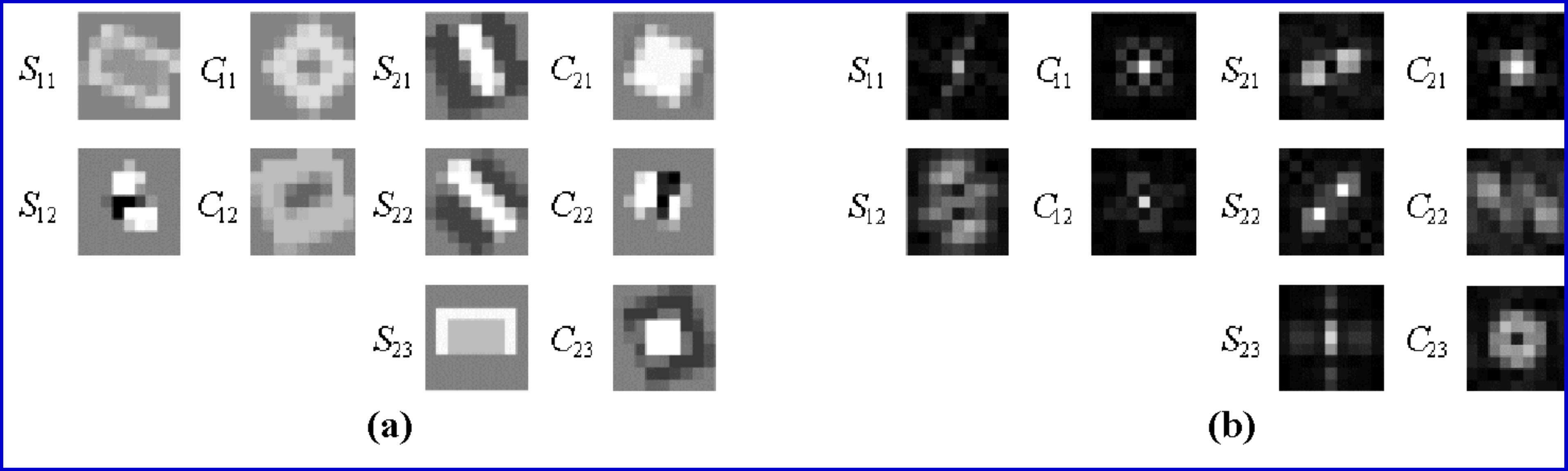
Averange

Perceptron

Ranked Individuals: FRP



Ranked Individuals: FRP



Comparison among different models

Problem	Fully Connected *MLP* Model [%]	*FEN+MLP* Classifier [%]
Handwritten Digit Recognition	84.9	90.8
Face Recognition	77.5	84.2

Kohonen's Maps: HDP

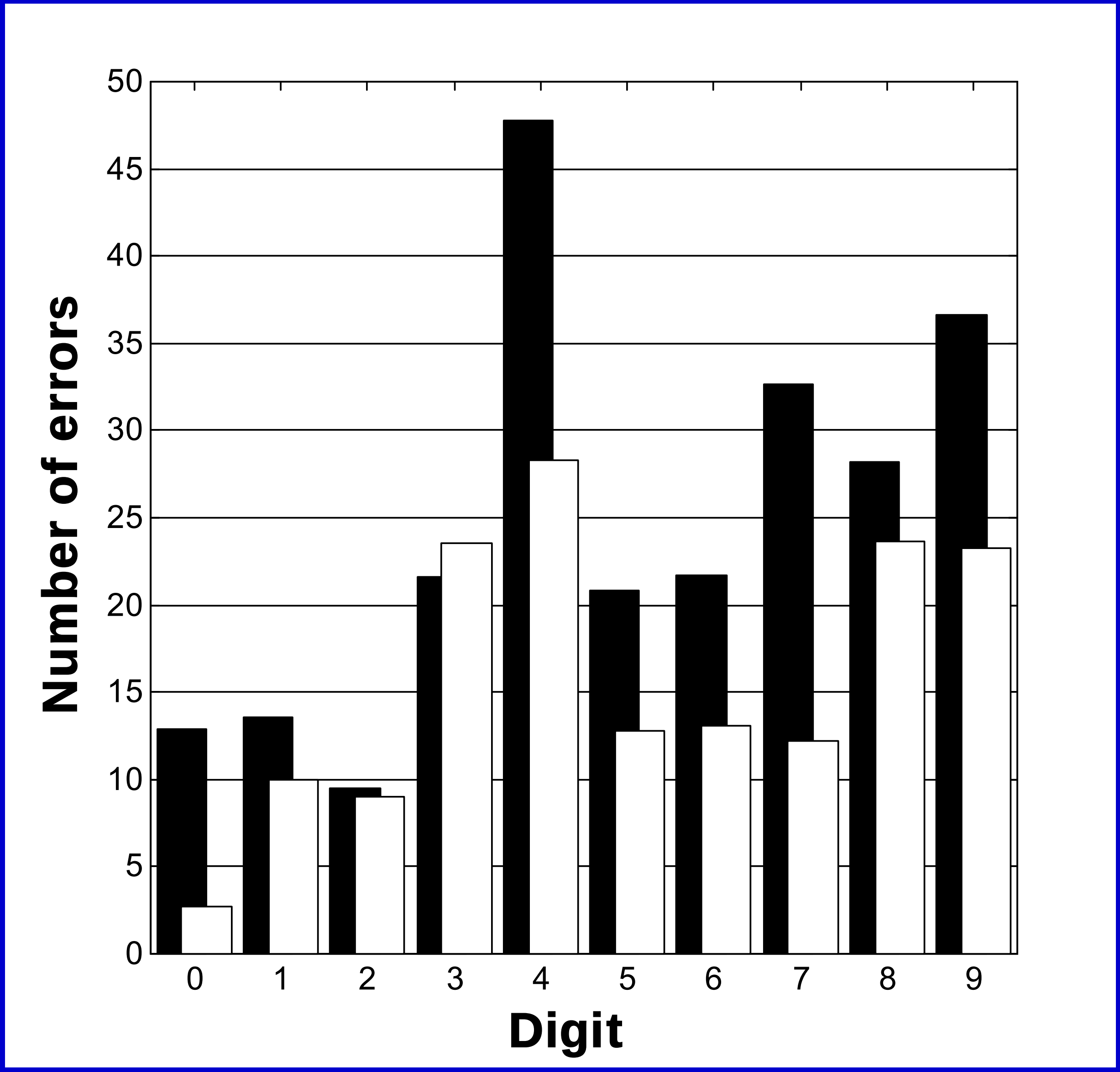
0	0	0	6	6	6	6	6	6	6	6	8	5	5	5	5
0	6	0	6	6	6	6	6		6		8	5	5	5	5
4	6	1	5	5	5	0	5	8	8	8	8	8	3	5	6
6	6			5	5	5	5	8		3	3	3	3	6	6
6	6	2	5	5	5	5	2	2	3	3	2	2	3		0
6	6		5	5		5	2	2	2		2	2	2	3	0
6	6	5	0	5	5	3	2	2	2	2	4	6	7	6	6
8	8	5	5		3	3	2	2	2		8	6	7	1	1
8	8	5	3	3	3	3	2	2	8	8	8	4	1	1	7
8	8	5		3	3	1	8	8	8	8	8	4	7	4	7
8	8	8	3	3	3	3	8		8	8	8	9	1	1	1
8	8	8	3	3	3	3	4	9	7	9	9	9	1	1	1
8	8	3	3	3	7	9	4	9	7	4	7	4	1	1	1
8	5	3	3	9	9	4	9	4	4	7	4	7	3	1	4
3	5	9	9	4	4	4	9	9	4	3	1	7	9	1	1
3	9	9	9	4	4	4	4	9	1	1	1	1	1	4	7

Original Database

0	0	0	6	6	6	6	6	6	2	2	2	2	3	8	8
0	0	0	6	6	6	4	6	6	2	2	2	2	8	8	8
0	0	2	1	6	6	6	6	6	8	2	2	2	8	8	8
5	5	1	1	5	5	6	6	6	3	5	3	3	3		8
5	5		1	2	5	1	6	6	5	3	3	3	3	3	3
5	5	5	5	8	8	8	6		1		3	3	3	3	3
5	5	5	5	8	8	8	8	1	1	3	3	5	5	5	5
5	5	5	9	7	8	7		1	1	1	3	5	5	3	5
5	5	0	3	1	7	1	1	1	1	1	9			5	8
5	3	8	1	1	7	8	1	1	1	1	9	9	9	9	9
3	2	2	1	1	1	4	4	1	1	4	4	9	9	9	9
3	3	8	1	1	7	4	4	4	4	4	4	9	9	9	9
3	2	6	8	8	1	1	4	0	9	4	9	9	4	4	4
6	6	3	3	1	1	1	8	8	8	9	4	7	7	4	4
6	2	0	2	1	1	1	3	8	9	7	4		7	4	4
4	0	0	0	1	1	9	9	3	7	4	6	7	7	2	4

Transformed Database

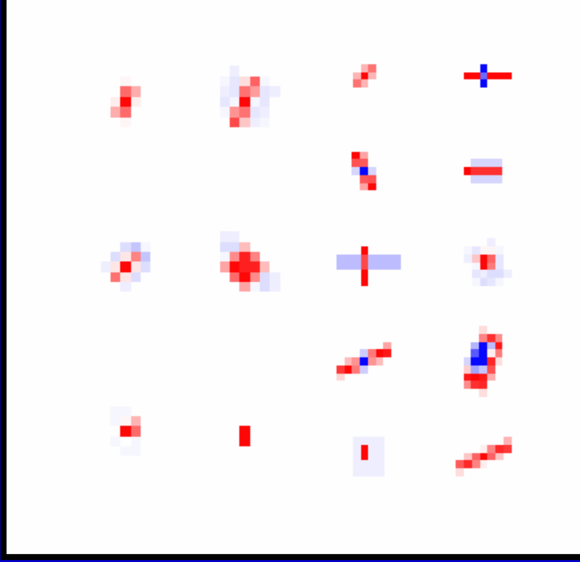
Confusions: HDP

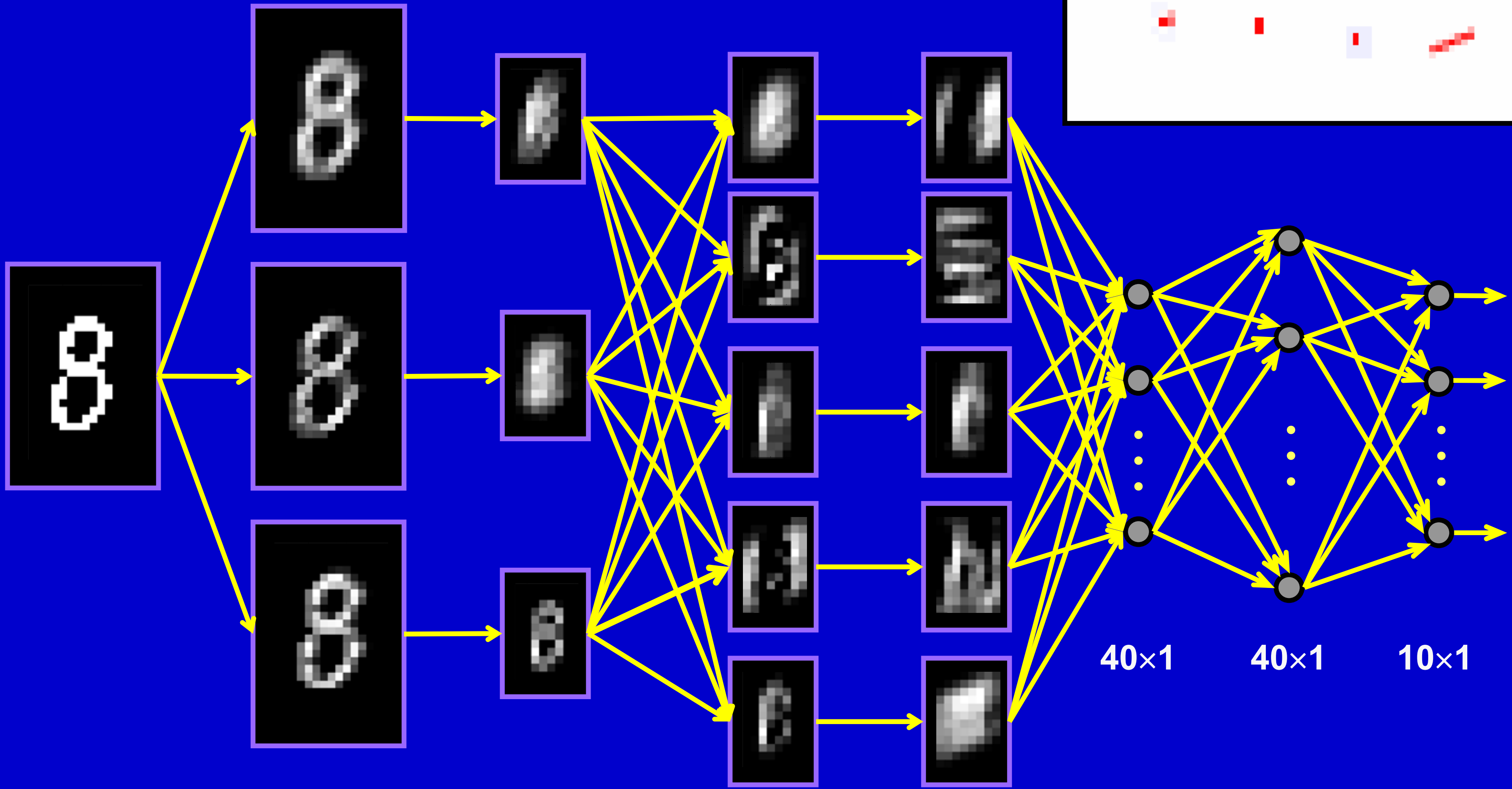


Original Database

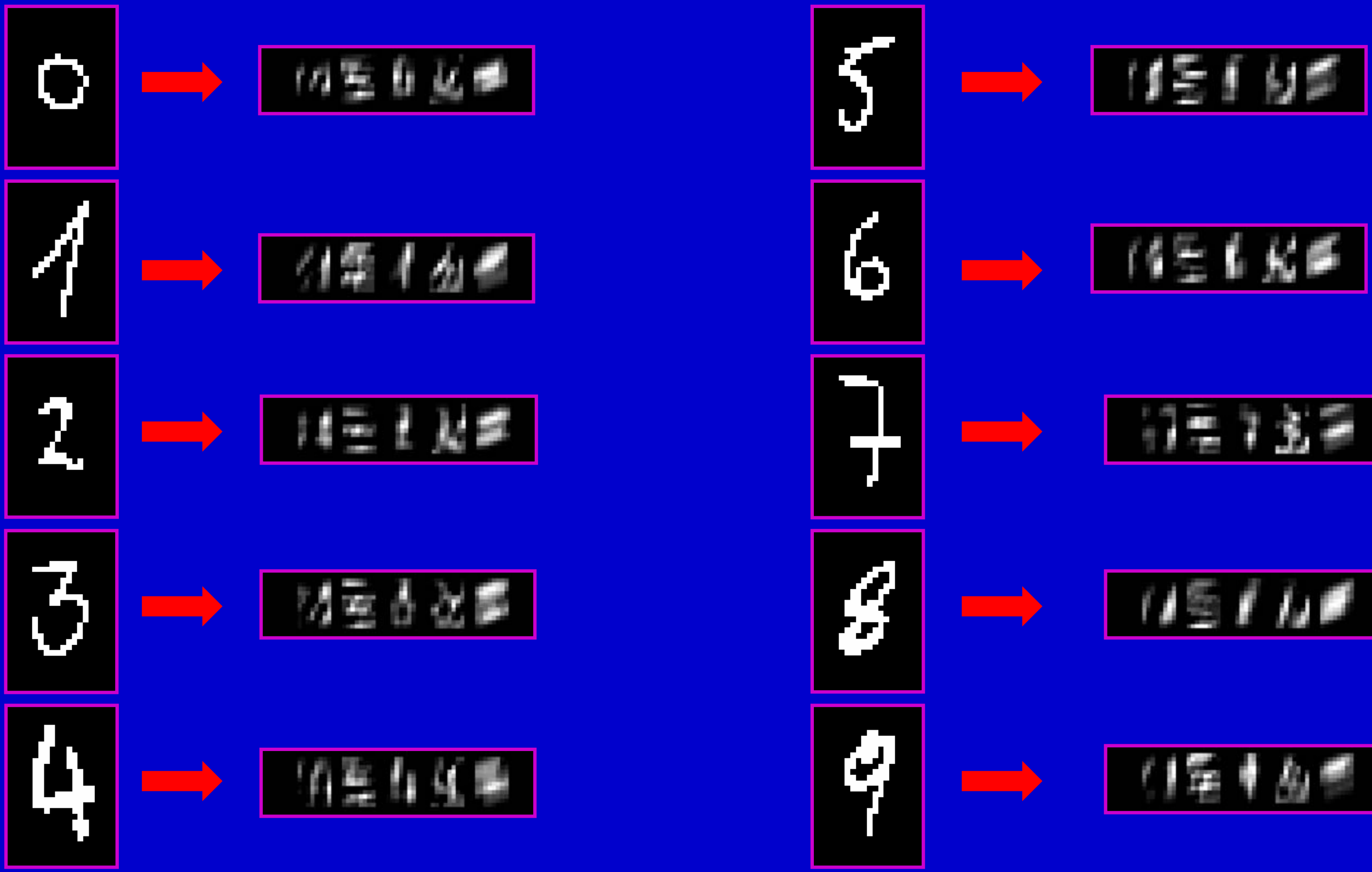
Transformed Database

One individual HDP (example)





Database Transformation: HDP



Genetic Design of Biologically Inspired Receptive Fields for Neural Pattern Recognition

Claudio A. Perez, *Member, IEEE*, Cristian A. Salinas, Pablo A. Estévez, *Member, IEEE*, and Patricia M. Valenzuela

***Abstract*—This paper proposes a new method to design, through simulated evolution, biologically inspired receptive fields in feed forward neural networks (NNs). The method is intended to enhance pattern recognition performance by creating new neural architectures specifically tuned for a particular pattern recognition problem. It is proposed a combined neural architecture composed of two networks in cascade: a feature extraction network (FEN) followed by a neural classifier. The FEN is composed of several layers with receptive fields constructed by an additive superposition of excitatory and inhibitory fields. A genetic algorithm (GA) is used to select the receptive fields parameters to improve the classification performance. The parameters are the receptive field size, orientation, and bias as well as the number of different receptive fields in each layer. Based on a random initial population where each individual represents a different neural architecture, the GA creates new enhanced individuals. The method is applied to the problems of handwritten digit classification and face recognition. In both problems, results show strong dependency between the NN classification performance and the receptive fields architecture. The**

ceeds from the retina to the inferotemporal cortex in the visual pathways [2], [7], [41].

A receptive field is the region of the sensor where an adequate stimulus elicits a response [8]. The receptive fields of retinal ganglion cells in mammals are organized in center/surround configurations [28]. The receptive fields from retinal and lateral geniculate nucleus (LGN) neurons have circular symmetry and they respond almost equally to all stimulus orientations [50]. Hubel and Wiesel built a comprehensive picture of the basic functional architecture of the visual cortex [27]. They defined "simple cells" as cells where it is possible to map the excitatory and inhibitory regions of the receptive field by monitoring the cell's response to a spot of light. The receptive fields of simple cells were implemented by overlapping the receptive fields of center/surround cells from LGN [25], [26]. Simple cells at the visual cortex have oriented receptive fields, and hence they

Local Matching Gabor

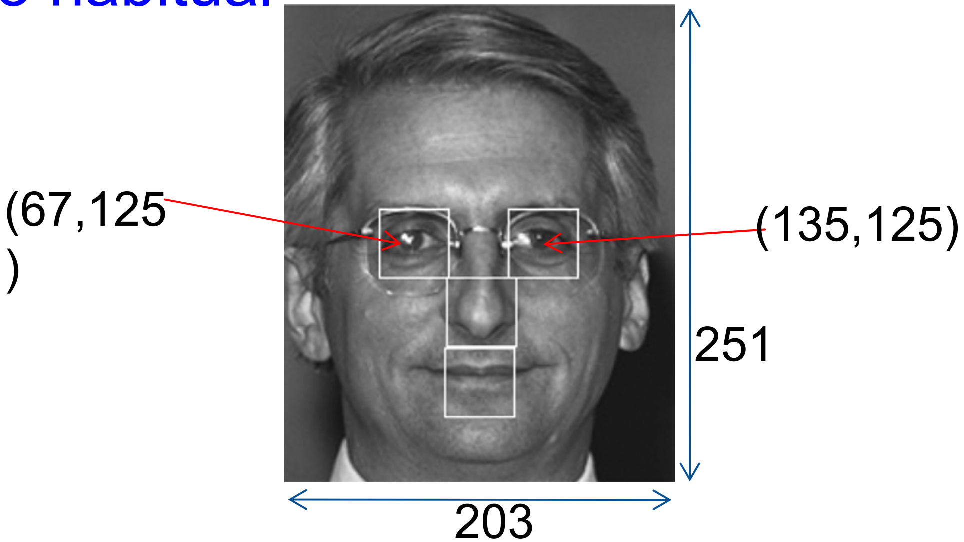
- [1] J. Zou, Q. Ji, and G. Nagy, "A comparative study of Local Matching Approach for Face Recognition," *IEEE Trans. on Image Processing, Vol. 16, No. 10, pp. 2617 – 2628, Oct. 2007.*

Diagrama de bloques

Alineamiento, escalamiento y recorte de caras → Extracción de características con Gabor Jets → Matching local y combinación por conteo Borda

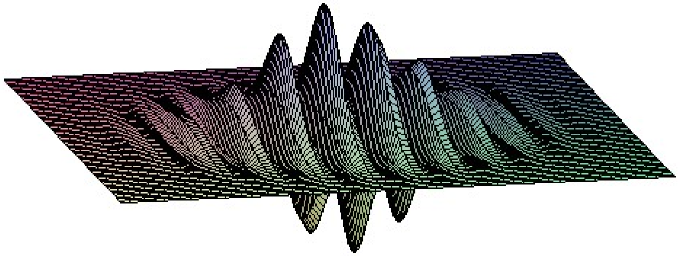
1) Alineamiento y Recorte

- Los ojos se posicionan en puntos fijos estimados con el promedio de las marcas de una base de entrenamiento ((67,125) y (135,125)). Esto implica escalamiento y rotación
- Se hace recorte de 203x251. Se incluye mayor área facial de lo habitual



2) Gabor Jets

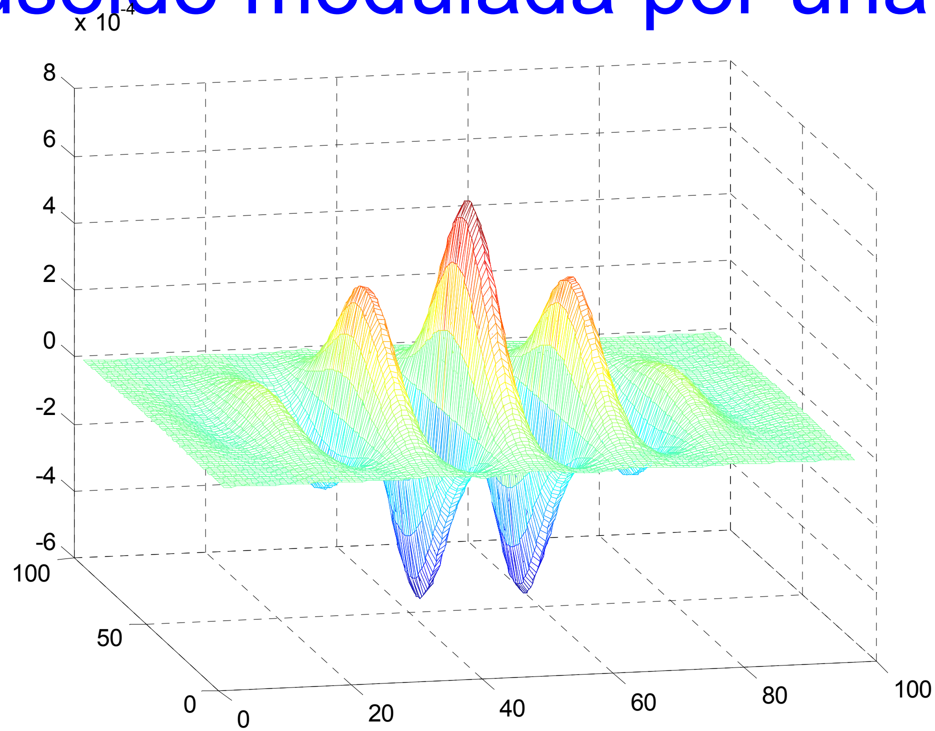
- Gabor Jet: Conjunto de funciones Gabor 2-D complejas que coinciden en posición y longitud de onda (λ), pero difieren en orientación



$$h(x,y;\sigma,\omega_0,\phi)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{1}{2}\frac{x^2+y^2}{\sigma^2}\right)\cos\left(\omega_0\left(x\cos\phi+y\sin\phi\right)\right)$$

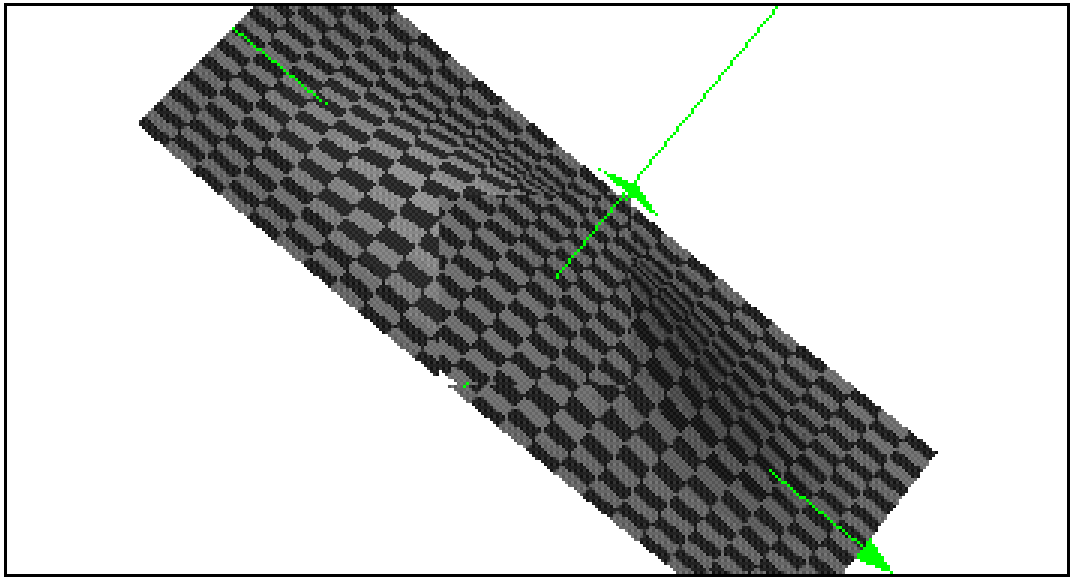
Filtros Gabor

- Sinusoide modulada por una Gaussiana

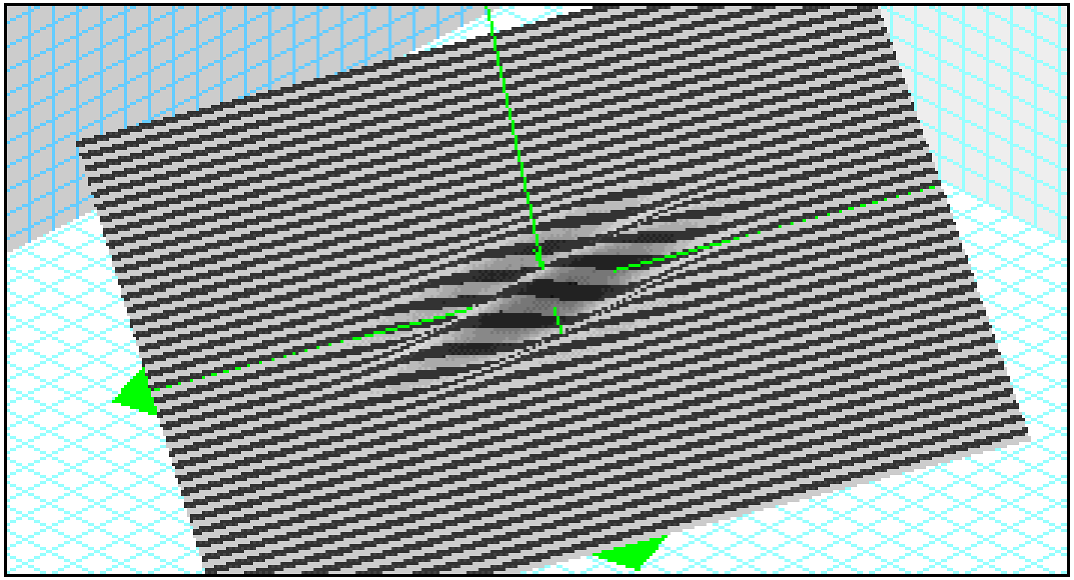


$$h(x,y;\sigma,\omega_0,\phi)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{1}{2}\frac{x^2+y^2}{\sigma^2}\right)\left[\exp\left(j\omega_0\left(x\cos\phi+y\sin\phi\right)\right)\right]$$

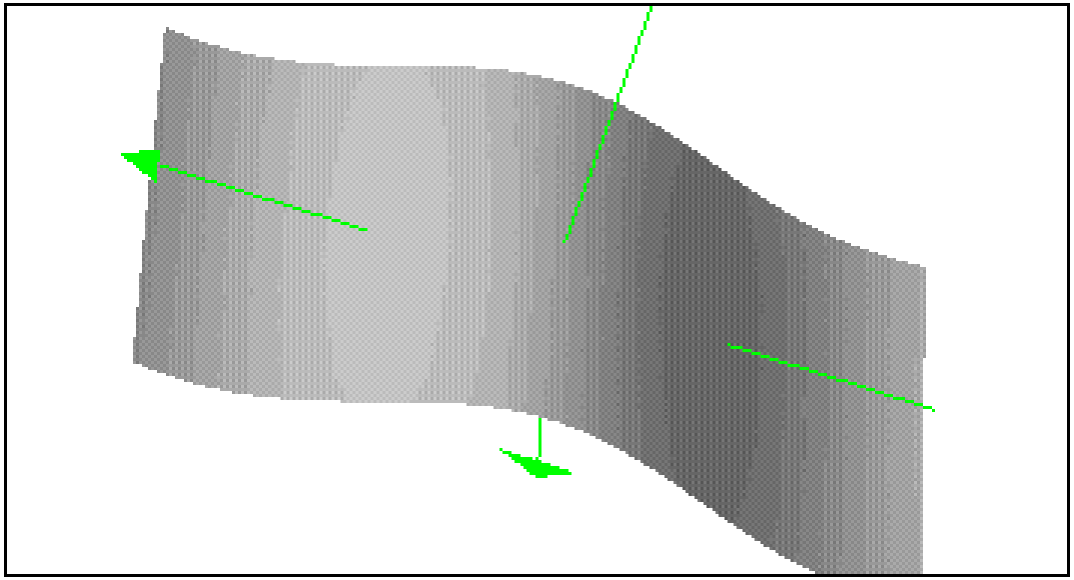
The Log kernel



Oriented Filters are steerable



Changing Scale at 0 Degrees



2) Gabor Jets

- Para un Gabor Jet se utilizan 8 orientaciones, equiespaciadas en el círculo. Se usa sólo amplitud, por lo que resulta vector de largo 8
- Los Gabor Jets se localizan uniformemente sobre la imagen, separados por una longitud de onda
- 4172 regiones a cinco escalas: 2420 a $\lambda=4$, 1015 a $\lambda=4\sqrt{2}$, 500 a $\lambda=8$, 165 a $\lambda=8\sqrt{2}$ y 72 $\lambda=16$

3) Clasificación y Combinación

- Cada Gabor Jet se compara con todos los candidatos utilizando el producto interno normalizado
- Los resultados de los 4172 clasificadores se combinan con Borda count
  - Se suman los puntajes asignados a cada candidato según ranking de cada clasificador

Resultados Paper [1] y Otros Métodos en FERET

Método	Fb	Fc	Dup1	Dup2
EBGM	95	82	59	52
LBP Weighted	97	79	66	64
LGBPHS	98	97	74	71
Local Matching Gabor [1]	99,5	99,5	85,0	79,5

Construcción de Gabor Jets

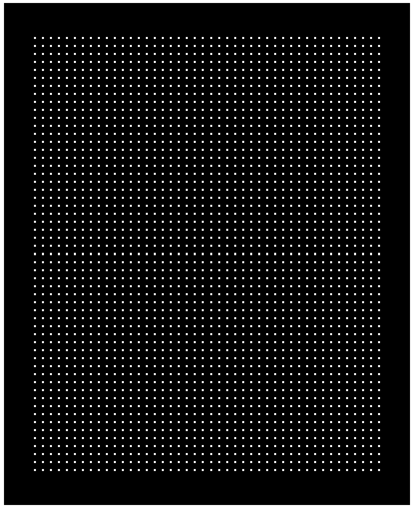
- Datos *paper* [1]:
  - 5 longitudes de onda (λ = 4, 4√2, 8, 8 √2, 16) y 8 orientaciones (φ = nπ/8 con n=0,..,7)
  - 4172 de Gabor Jets

λ	Nº
4	2420
4√2	1015
8	500
8√2	165
16	72

  - Jets separados en un λ

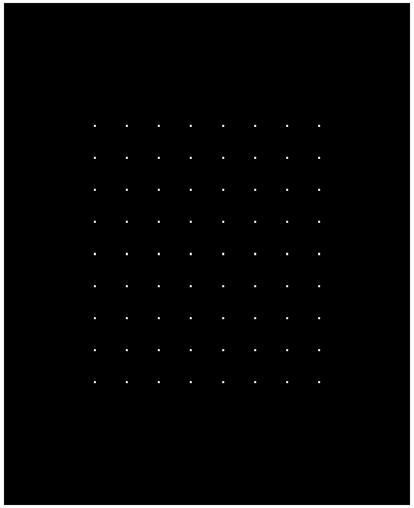
Construcción de Gabor Jets

- Grillas
  - Se llenaron partiendo del centro de la imagen
  - Distancia entre nodos = λ (entremedio hay λ-1 píxeles)



λ = 4

. . .



λ = 16

Construcción Gabor Jets

- Parámetros filtros Gabor
  - $\sigma = \lambda$
  - Tamaño ventana = $6\sigma + 1$ por lado

Base de Datos GrayFeret

- Imágenes de 256x384 en tonos de grises
- 5 subconjuntos:
  - Fa: 1196, 1 foto/individuo. Se utiliza como galería
  - Fb: 1195, 1 foto/individuo, mismo día, cámara e iluminación
  - Fc: 194,~1 foto/individuo, mismo día, diferente cámara e iluminación
  - Dup1: 722, ~2 fotos/individuo, hasta 34 meses de diferencia
  - Dup2: 234, ~2 fotos/individuo, por lo menos 18 meses de diferencia


Fa


Fb


Dup1


Dup2


Fa


Fc

Resultados LG, PCA y NeoFace en Yale

– Nº individuos: 15
– Galería: 1 fotos/individuo
– Prueba: 9 fotos/individuo
– Nº pruebas: 10

	%Identificación PCA*	%Identificación NeoFace con Coordenadas	%Identificación LocalGabor
Sin pre-proc	74,7 ± 12,4	77,0 ± 11,1	98,4 ± 1,8
Pre-proc básico	82,1 ± 8,0	76,3 ± 13,0	97,5 ± 2,0
C-LUX	**83,5 ± 7,1**	78,0 ± 15,7	98,3 ± 1,4
SQI sin optimización	77,5 ± 7,8	**79,1 ± 16,6**	98,3 ± 1,5
LN	68,3 ± 9,7		98,7 ± 1,6

*Nº componentes principales: 14

Resultados LG, PCA y NeoFace en Feret

- Nº individuos: 127
- Galería: 1 fotos/individuo
- Prueba: 3 fotos/individuo
- Nº pruebas: 4

	%Identificación PCA*	%Identificación NeoFace con Coordenadas	%Identificación LocalGabor
Sin pre-proc	77,6 ± 0,9	85,9 ± 1,1	96,2 ± 1,5
Pre-proc básico	**79,1 ± 2,1**	78,7 ± 1,7	95,4 ± 1,4
C-LUX	75,0 ± 1,1	**86,1 ± 2,1**	96,1 ± 1,3
SQI sin optimización	68,8 ± 3,2	80,8 ± 2,0	95,4 ± 1,6
LN	78,3 ± 1,8	79,7 ± 1,0	97,2 ± 1,5

*Nº componentes principales: 126