Weight Optimization for a Neural Network using Particle Swarm Optimization (PSO)

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October 27, 2006

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Lecture Information

Neurocomputing

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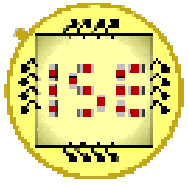
Institute of Integrated Sensor Systems



Dept. of Electrical Engineering and Information Technology

University of Kaiserslautern

Fall Semester 2006

What did we learn?

Back Propagation

Digital Neural Network Hardware

Analog Neural Network Hardware

Neural Network Visualization

Technical Real World Problems

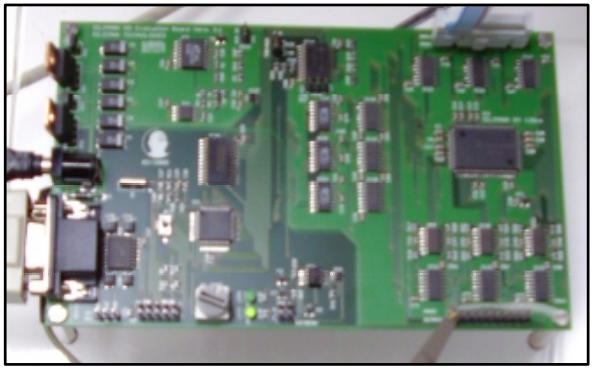
Neurocomputing Project

Weight Optimization for a Neural Network using Particle Swarm Optimization (PSO)

```
// Initialize from File
COptimizationPSO pso(4, 3, 75, 40);
pso.LoadTrainingData("Iris_train.txt");
pso.SetActivityFunctionInput("linear");
pso.SetActivityFunctionHiddenNeurons("tanhyp");
pso.SetActivityFunctionOutput("saltus", 0);
```

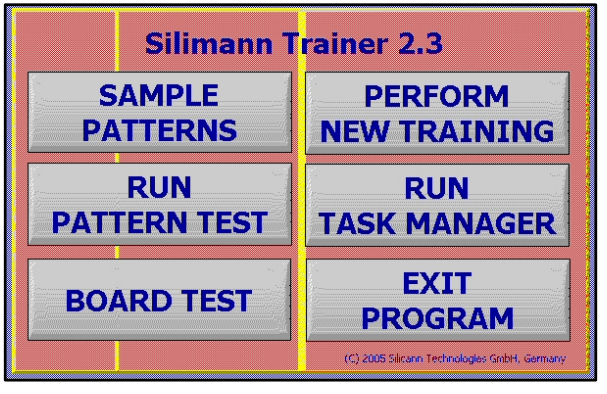
Implementation of offline training of the weights for the Silmann neural network

Silimann Evaluation Board



Neurocomputer

Silimann Trainer Software



Silimann 120cx evaluation board

Silimann 120cx evaluation board

- Neurocomputer
- Max: 10-6-10 network
  => (10 input neurons, 6 hidden neurons and 10 output neurons)
- Feed forward neural network
- Output:

$$O = \left[I^T \bullet W_1^T \right] \bullet W_2^T$$

3-4-2 feed forward network matrix example

$$\begin{bmatrix} out_1 \\ out_2 \end{bmatrix} = \left[\begin{bmatrix} in_1 \\ in_2 \\ in_3 \end{bmatrix}^T \bullet \begin{bmatrix} w1_{1,1} & w1_{2,1} & w1_{3,1} \\ w1_{1,2} & w1_{2,2} & w1_{3,2} \\ w1_{1,3} & w1_{2,3} & w1_{3,3} \\ w1_{1,4} & w1_{2,4} & w1_{3,4} \end{bmatrix}^T \right] \bullet \ldots$$

$$\ldots \begin{bmatrix} w2_{1,1} & w2_{1,2} & w2_{1,3} & w2_{1,4} \\ w2_{2,1} & w2_{2,2} & w2_{2,3} & w2_{2,4} \end{bmatrix}^T$$

Example from Silimann Neuromanual 1.2

Particle Swarm Optimization (PSO)

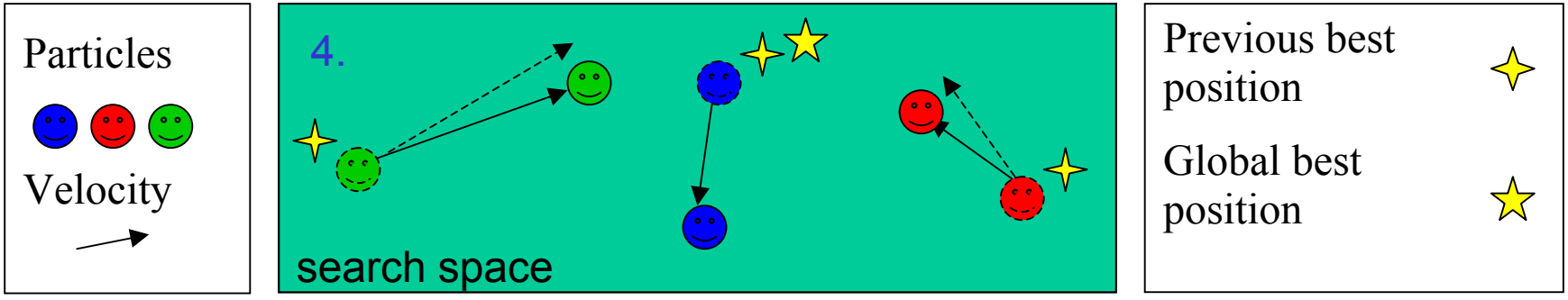
- Population based search algorithm
- Developed to simulate the behavior of birds in search for food on a cornfield or fish school
- Evolutionary Computation Technique
- Each individual (here: particle) has a randomly initialized position X and velocity V in the search space

Particle Swarm Optimization (PSO)

Depending on

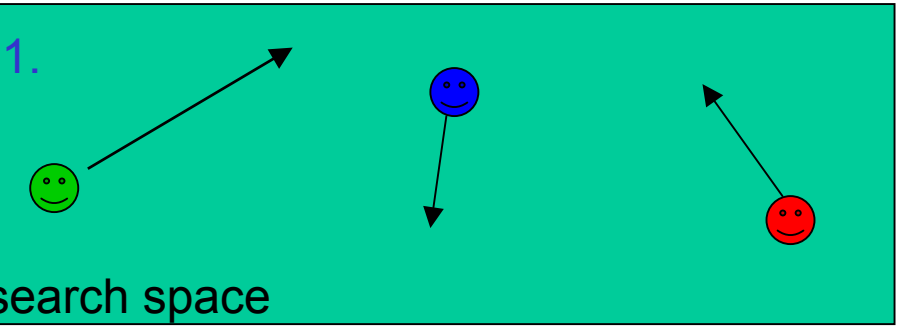
- its actual position and velocity (1)
- its own previous best position (2)
- and the previous best position of a particle in a defined neighborhood (e.g. the complete swarm) (2)

the new velocity (3) and position (4) in the search space is found.

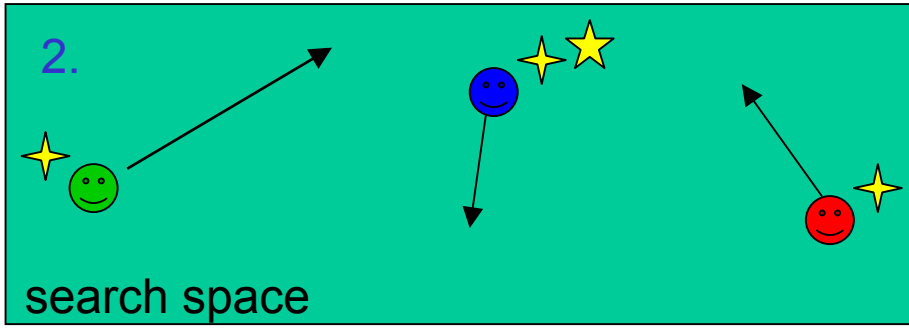


Particle Swarm Optimization (PSO)

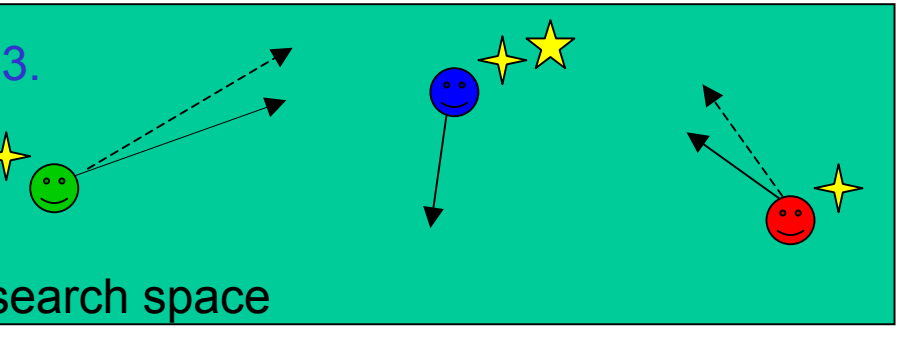
1. Actual position and velocity



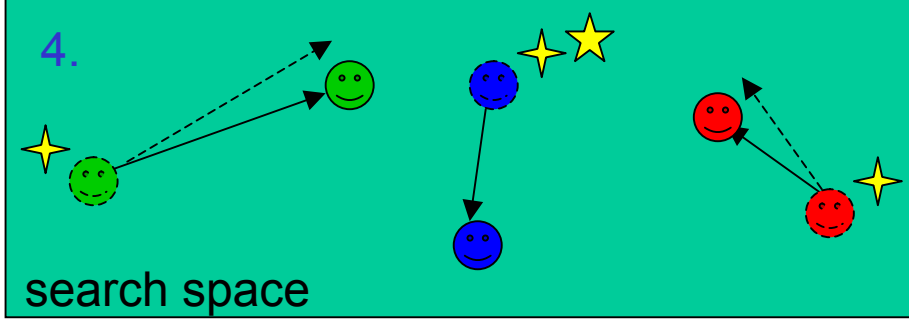
2. Local and global best position



3. New velocity



4. New position



Particles Velocity | Previous best position Global best position

Particle Swarm Optimization (PSO)

$$V_{t+1}^{i} = V_t^{i} + C_1 R_1 \cdot (XLB_{t'}^{i} - X_t^{i}) + C_2 R_2 \cdot (XGB_{t''}^{n} - X_t^{i})$$

$$X_{t+1}^{i} = X_t^{i} + V_{t+1}^{i}$$

V: velocity of particle *i* at time *t* / *t* +1,

X: position in the search space

XLB: best previous position of the particle *i* with *t'* < *t* (**X** **L**ocal **B**est)

XGB: best previous position of a particle in the n- neighborhood (e.g. the complete swarm) of the particle. (**X** **G**lobal **B**est)

C_1 and C_2 are positive constants, usually in the range [1,4]

R_1 and R_2 are two random functions taking values in the range [0,1].

Software Implementation PSO

Hardware restrains:

- Max: 10-6-10 network

  => 10 input neurons, 6 hidden neurons and 10 output neurons

  => max. (10+1)*6 + (6+1)*10 = 136 weights (= parameters) for the PSO

=> Those network parameters can be easily changed in the program

- Input (data) and output files (basically: weights of the NN) of the software must be compatible to the “Silimann Trainer” files.
- Those values must lie in the range [-1,1].

```
CHIP_TYPE
Silimann 120cx
TASK_ID
1
TEMPERATURE
22
MAX_WEIGHT
-1.0000
MIN_WEIGHT
1.0000
BIAS_VALUE
1.0000
INPUT_CHIP
-0.4765;0.2250;-0.7780;-0.8250;0.0000;0
-0.5824;-0.1500;-0.7780;-0.8250;0.0000;
```

Part of a net-file for „Silimann Trainer“

Software Implementation PSO

Software design:

- Implementation of a standard PSO
- The number of features, classes and samples must be known (Constructor) before loading any data from a file.
- Adjustable PSO Parameters:
  - Swarm size (Constructor),
  - Constants C_1 and C_2 (Constructor),
  - Maximum/minimum velocity
  - Boundaries of the search space

```
COptimizationPSO pso( nNoInputParam
                    , nNoClasses, nNoTrainSamples
                    , nNoParticles, fConst1,
fConst2);
```

Constructor call for a pso run.
Note: each parameter in the constructor has a default value. COptimizationPSO pso( ) will call pso(10, 10, 1, 20, 2, 2)

```
pso.LoadTrainingData(„iris_train.txt“)
```

Loading training data.

```
pso.SetVRange(0.6);
```

Set minimum/maximum velocity.

```
pso.SetXMinMax (-1, 1);
```

Set boundaries of the search space.

Software Implementation PSO

- Each layer of the NN has its own activity function (e.g. to limit the output to a defined range).
  - Linear: no restriction of the NN outputs
  - Tanhyp: hyperbolic tangent, -> restriction to values in the range [-1, 1].
  - Saltus: step function, global threshold s, -> restriction to values {-1, 1}.
- More activity functions can be easily implemented.

```
pso.SetActivityFunctionInput(„satus", s);
```

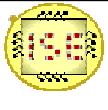
Set activity function input layer.

```
pso.SetActivityFunctionHiddenNeuron(„tanhyp");
```

Set activity function hidden neurons.

```
pso.SetActivityFunctionOutput(„linear");
```

Set activity function output layer.



Software Implementation PSO

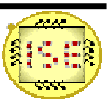
- Evaluation of the fitness of a swarm particle

  - PMSE: percentage of mean square error. PMSE of all N neural network outputs o_i is calculated for all P pattern samples (t_{pi}: desired result).

  - EC: Sum of classification errors EC_p for all pattern samples. If the maximum neural network output max[o_{pi}] corresponds to $t_{pi} = 1$ -> $EC_p = 0$, else $EC_p = 1$.

$$PMSE = 100 * \frac{1}{N \cdot P} \sum_{p=1}^{P} \sum_{i=1}^{N} (o_{pi} - t_{pi})^2$$

PMSE for fitness evaluation.



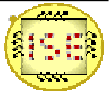
Software Implementation PSO

- Evaluation of the fitness of a swarm particle
  - EC2: like EC, but the minimum difference mdiff = max[o_{pi}] - o_{pj} ($j \neq i$) must be greater than a predefined threshold to generate an error $EC_p = 0$.
  - Further fitness computation functions are implemented as well. See the source code for more information.

```
pso.SetFitnessFunction(„PMSE“);
```

Set fitness function.

Note: At the current state, only one of these parameters (PMSE, EC, …) can be applied to optimize the weights of the neural network (the other parameters are computed for each particle and displayed during the optimization as well). The PSO minimizes the selected fitness parameter.



Software Implementation PSO

Further important Functions

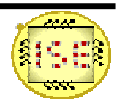
- InitializePSO(Key): Sets the seed point for all used random numbers. (Key == 0: the system time is used as key).

Call these function for every generation:

- ComputeFitness(): Computes the fitness for all particles.
- UpdateVelocity(): Computes and sets the new velocity and position for all particles.

```
Generation: 15
Part.    EC ECBest PMSE          PMSEBest    MMAbsEr   MMAbsErBest EC2   EC2Best   MinDiff MinDiff
Best
P:  0,   6 /   6,  67.7806 /  58.3469,   1.4137 /   1.3202,  45 / 25, 497.2561 / 319.3004
P:  1,   7 /   2,  97.1177 /  60.8921,   1.6867 /   1.2939,  54 / 33, 573.4517 / 393.3214
P:  2,   6 /   5,  84.2057 /  62.1747,   1.5680 /   1.4147,  49 / 31, 531.1514 / 362.5492
P:  3,   5 /   5,  77.1243 /  72.6785,   1.5051 /   1.3293,  62 / 46, 640.8151 / 501.9556
P:  4,   8 /   8,  82.1889 /  59.7241,   1.5810 /   1.3426,  36 / 34, 421.5658 / 399.3183
P:  5,   5 /   5,  95.2502 /  66.4836,   1.6446 /   1.4429,  44 / 25, 489.3828 / 312.9446
```

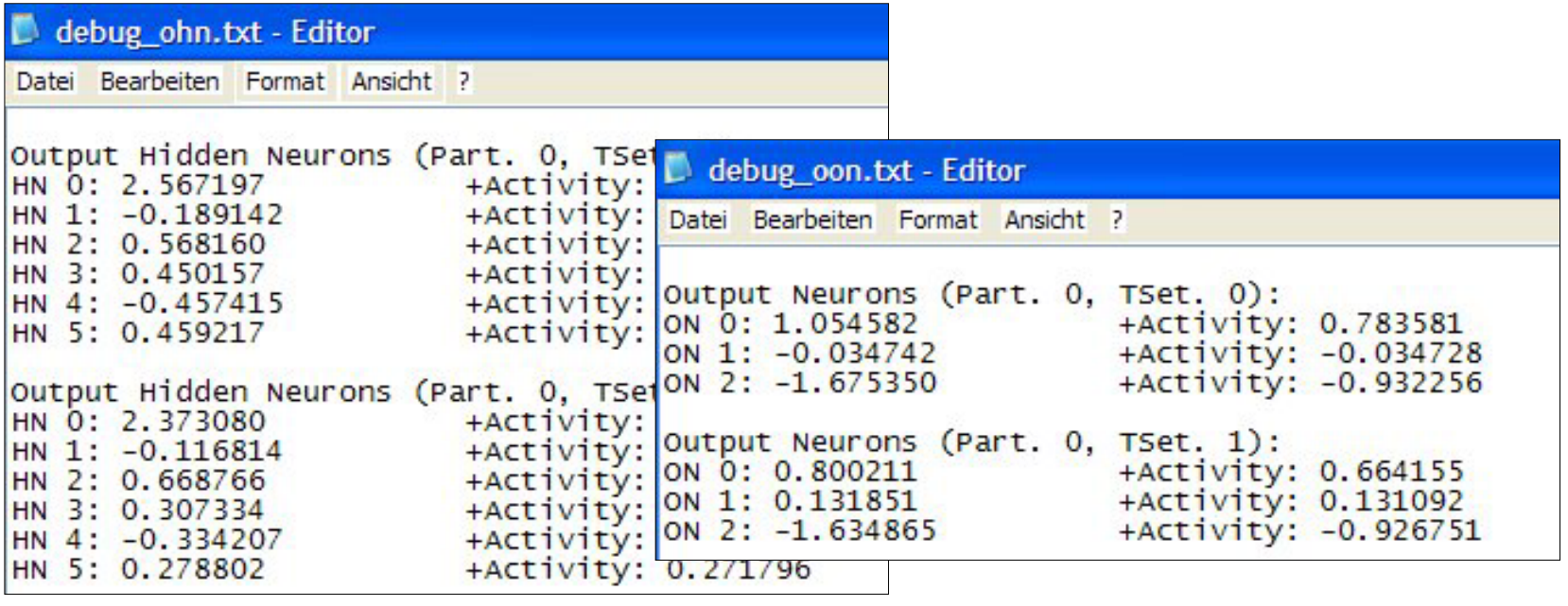
Output of the fitness parameters during the optimization.



Software Implementation PSO

Multiple debugging options increase the comprehensibility of the software

- For example: Output of the hidden and output neurons (to screen or to file)

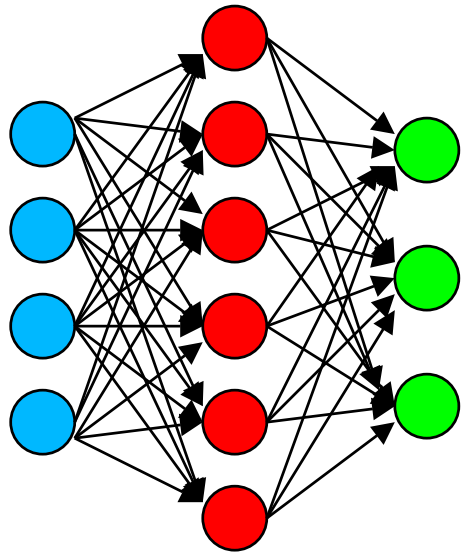


Iris Data

Iris Plants Database

- The data set contains 3 classes of 50 instances each, where each class refers to a type of iris plant.
  - 4 Parameters: sepal length and width, petal length and width

- => 4 – 6 – 3 Neural Network
- => Training set: 25 instances of each class
- => Test set: 25 different instances of each class
- Sources:
  (a) Creator: R.A. Fisher
  (b) Donor: Michael Marshall
  (MARSHALL%PLU@io.arc.nasa.gov)
  (c) Date: July, 1988Evolutionary Computation Technique



4 – 6 – 3 Feed forward Neural Network

Iris Data

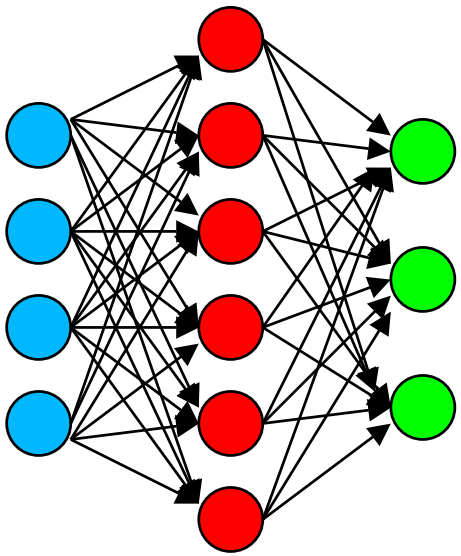
A Resulting Net-File weights:

(Optimization: 40 Particles, PMSE, hyptan-Activity for hidden and output neurons, C1, C2 = 2)

Results Optimization Offline:

Training 75/75 pattern, Test: 73/75 pattern correctly classified.

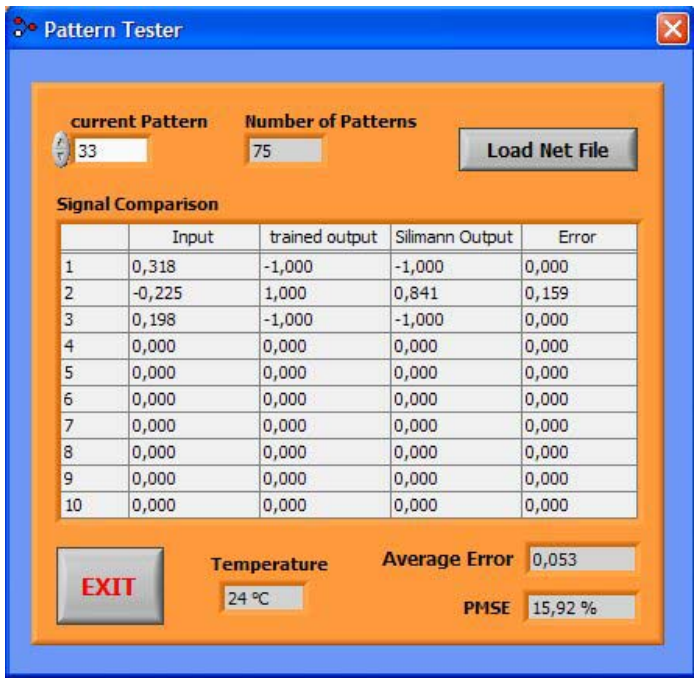
W1_TRAIN
0.1361;0.5477;0.3449;0.0754;-0.2446
-0.2446;0.3370;-0.8200;0.9504;0.2757
0.2757;0.4560;-0.4385;-0.1748;-0.0970
-0.0970;0.4672;0.3002;0.0073;0.8531
0.8531;0.5733;-0.5808;-0.0668;0.1156
0.1156;0.9243;-0.1257;-0.9057;0.8236
W2_TRAIN
0.1290;-0.7530;0.1069;0.9800;0.3467;-0.7851;0.9652
-0.8735;-0.0558;-0.3678;0.2691;0.3834;0.5740;-0.2593
0.1578;-0.3466;0.2025;0.1710;-0.7851;0.9503;-0.0766



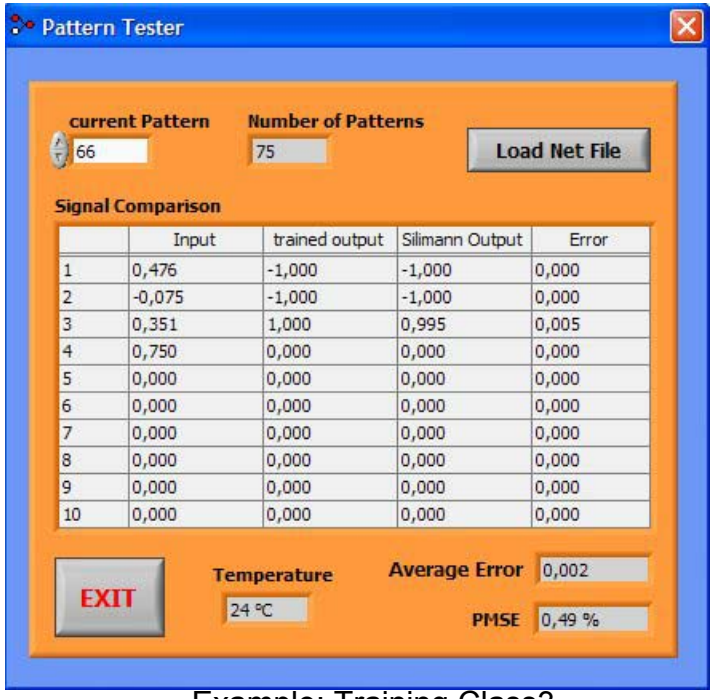
4 – 6 – 3 Feed forward Neural Network

Results: Iris Data 1

- Uploading of the trained weights to the Silimann Evaluation Board and testing of Training and Test pattern samples:



Example: Training Class2

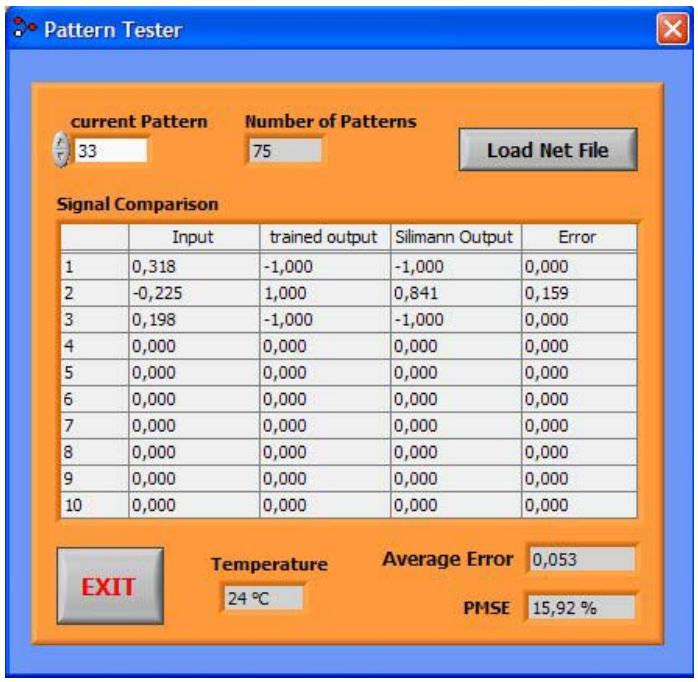


Example: Training Class3

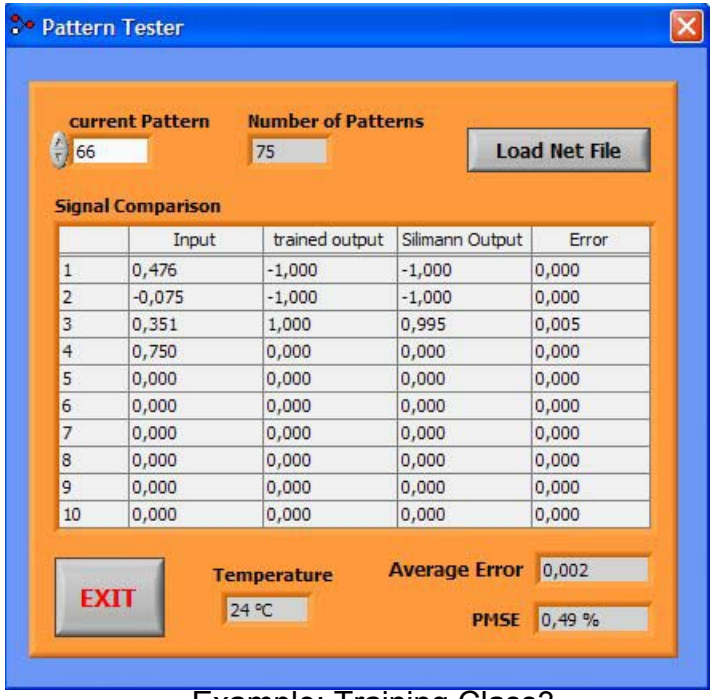
75 of 75 training patterns are correctly classified by the Silimann evaluation board

Results: Iris Data 1

- Uploading of the trained weights to the Silimann Evaluation Board and testing of Training and Test pattern samples:



Example: Training Class2



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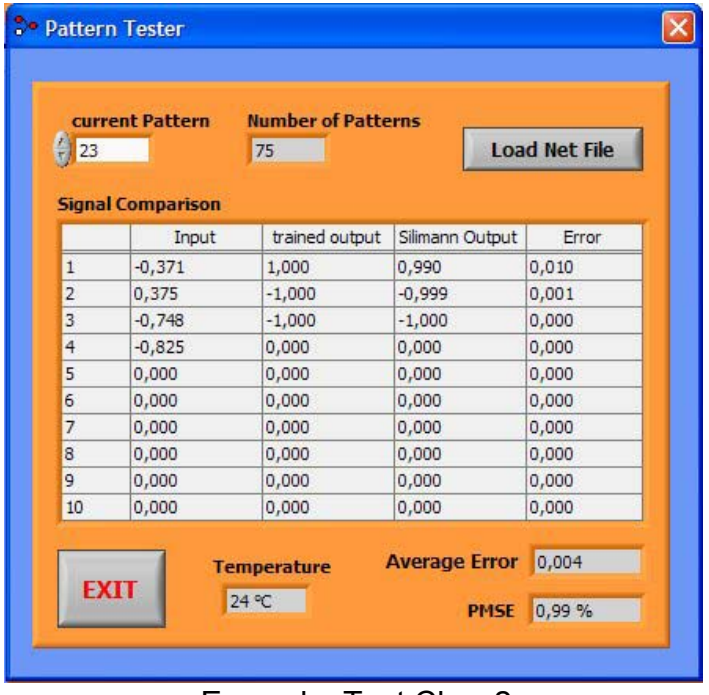
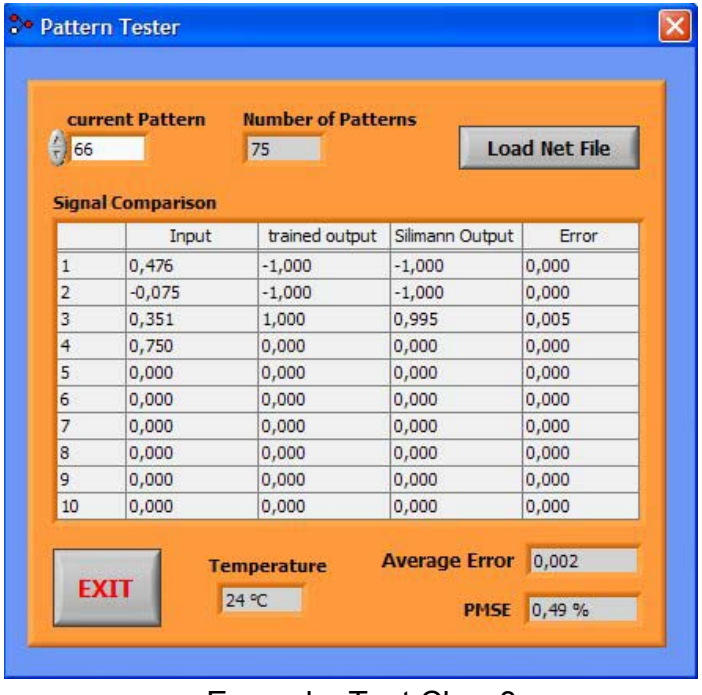


Example: Test Class2



Example: Test Class3

71 of 75 test patterns are correctly classified by the Silimann evaluation board

Questions