NN Modelling of Physical Properties

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NEURAL NETWORK MODELS OF PHYSICAL PROCESSES

Modelling allows to simulate the behavior of a system for a variety of initial conditions,excitations and systems configurations - often in a much shorter time than would be required to physically build and test a prototype experimentally

- The ***quality and the degree of the approximation*** of the model can be determined only by a validation against experimental measurements.

- The ***convenience*** of the model means that it is capable of performing extensive parametric studies, in which independent parameters describing the model can be varied over a specified range in order to gain a global understanding of the response.

⇒ A more relevant model might be one which provides results more rapidly - even if a degradation in a solution accuracy results.

Analog Computer vs. Neural Network Tools for Physical Processes Modelling

- Both the Analog Computers and the Neural Networks are *continuous modelling devices*.

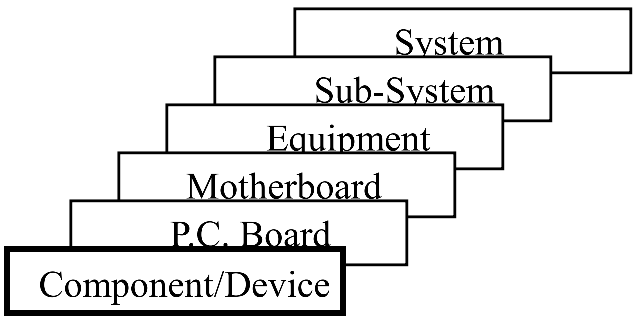
- The Analog Computer (AC) allows to *solve the linear or nonlinear differential and/or integral equations representing mathematical model* of a given physical process. The coefficients of these equations must be exactly known as they are used to program/adjust the coefficient-potentiometers of the AC's computing -elements (OpAmps). The AC doesn't follow a sequential computation, all its computing elements perform simultaneously and continuously.
  As an interesting note, "because of the difficulties inherent in analog differentiation the [differential] equation is rearranged so that it can be solved by integration rather than differentiation." [A.S. Jackson, *Analog Computation*, McGraw-Hill Book Co., 1960].

- The Neural Network (NN) doesn't require a prior mathematical model. A *learning algorithm* is used to adjust, sequentially by trail and error during the learning phase, the synaptic-weights/ coefficient-potentiometers of the neurons/computing-elements. As the AC, the NN don't follow a sequential computation, all its neuron performing simultaneously and continuously. The neurons are also integrative-type computing/processing elements.

NN Modelling of
3D Electromagnetic Fields for a
Virtual Prototyping Environment

EMC Modelling for Electronic Design Automation

EMC Design Levels



Optimum Approach to EMC Design

- {Design+Test+Analysis} **Synergy**
- **EMC_Behavior** = $\mathcal{F}$ (Design_Principle, Analysis&Modeling&Simulation_Tools, Test_Methodology&Instrumentation)

- Multiple PCBs can be integrated in any way as desired to define a complete electronic system, including mechanical parts.

- The final system can be ***interactively*** tested on an ***enhanced-reality virtual work-bench*** as a final product, by ***concurrently*** running what-if experiments in a ***multi-domain*** *(*mechanical, electrical, thermal)environment.

⇨ The design cycle is shortened, the cost of the tests is reduced, the quality of the product is improved, and the time-to-market is reduced.

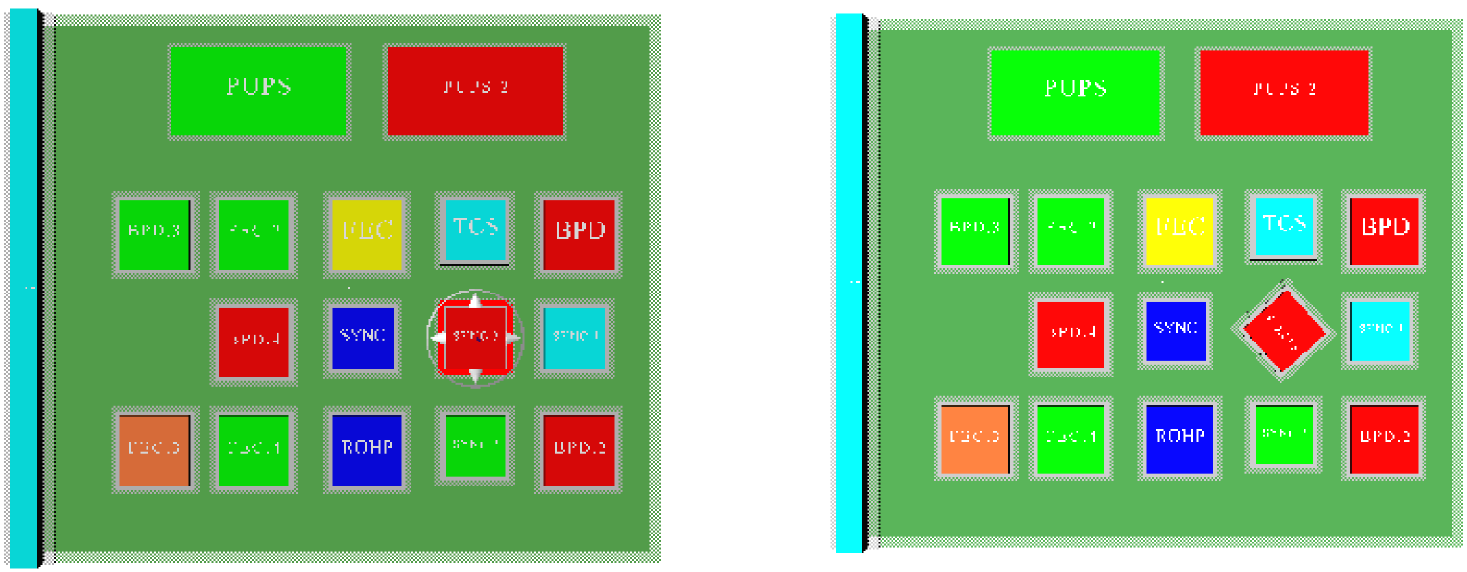
EM Virtual Prototyping Environment for the Interactive Design of Very High Speed Circuits

- **user-centered**, **task driven** point of view;

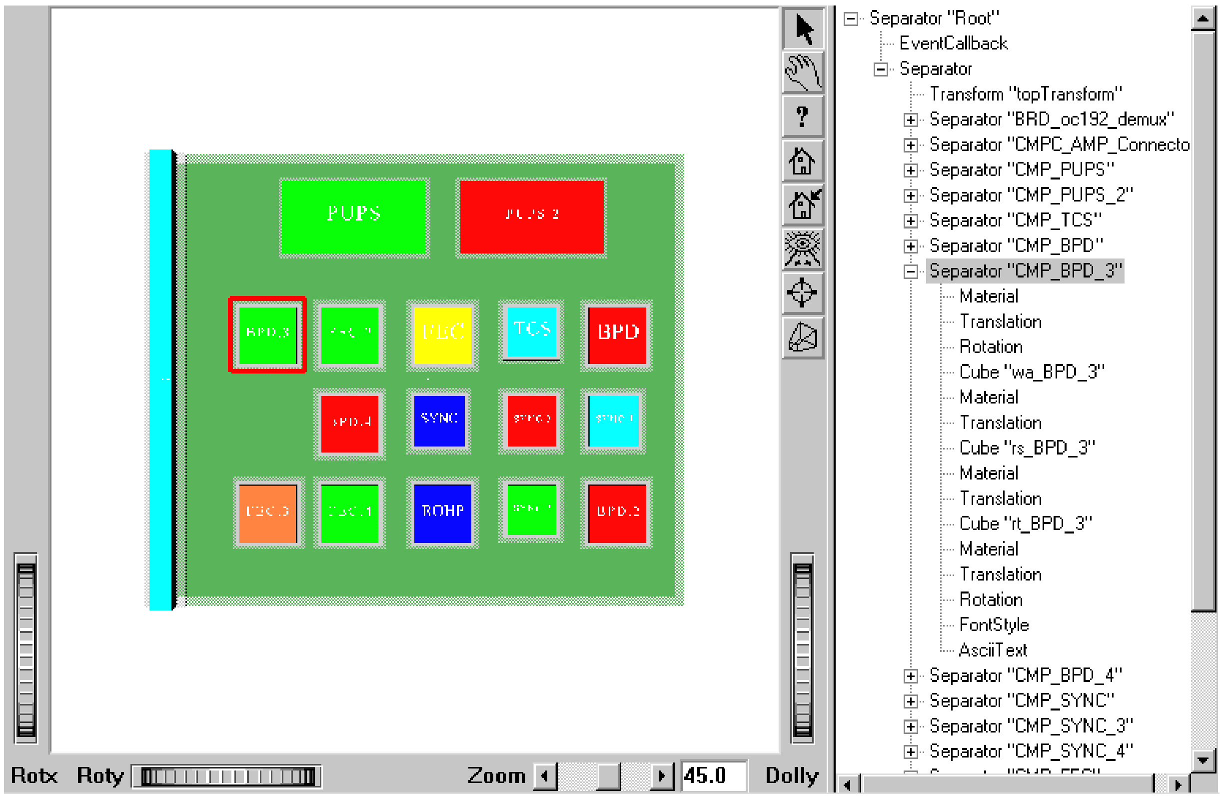
- **interactive functions**:
  (i) walk-through the 3D virtual world;
  (ii) specify material, electrical, and thermal specifications of circuit components;
  (iii) 3D manipulation of the position, shape, size, of the circuit components and layout;
  (iv) visualization the electrical wave forms, **3D Electromagnetic (EM) field** and thermal field effects in different regions of the electronic circuit.

- 3D scenes are composed of multiple objects: boards, components, connectors.
  - any object is characterized by its usual 3D geometric shape and *safety-envelopes* (the 3D geometric space points where the intensity of a given field radiated by that object becomes smaller than a specified threshold value), each type of field (EM, thermal) will have its own safety-envelope (the geometric safety-envelope being the object shape itself);
  - any object can be selected/becomes *active* by attaching a manipulator to it;

- The ***main objective*** is to detect a collision caused by a linear transformation (translation, rotation or scaling) between the selected object and the other objects in the scene.
  - for each transformation of the selected/active object, the program updates the 3D geometric parameters and the bounding box of the object;
  - then the program checks for collision between the safety-envelopes selected object and those of the other objects in the scene;
  - when a collision is detected, the active object returns to its position just before the collision

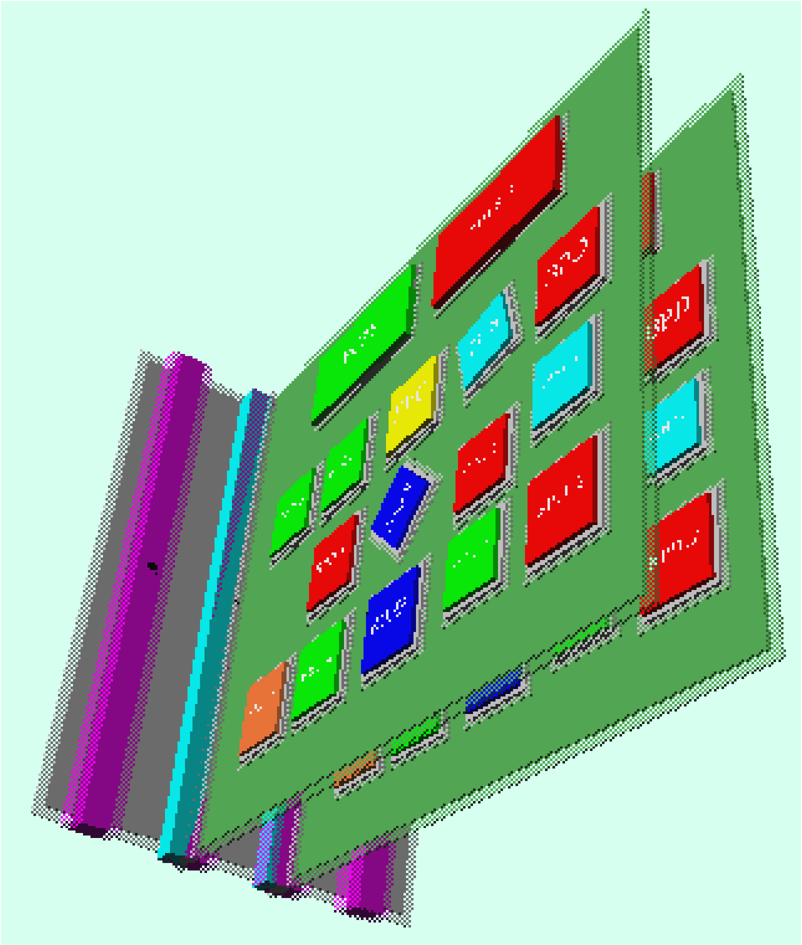


Rotation-translation manipulator dragger



Editing material properties

Assembling multiple PCBs



Electromagnetic Compatibility (EMC) Modelling Methods

- *circuit theory* to describe the conducted disturbances (such as overvoltages, voltage dips, voltage interruptions, harmonics, common ground coupling);

- *equivalent circuit* with either *distributed* or *lumped parameters* (such as in low frequency electromagnetic field coupling expressed in terms of mutual inductances and stray capacitances, field-to-line coupling using the transmission line approximation, and cable crosstalk);

- formal solutions to *Maxwell's equations* and the appropriate field boundary conditions (as for example in problems involving antenna scattering and radiation).

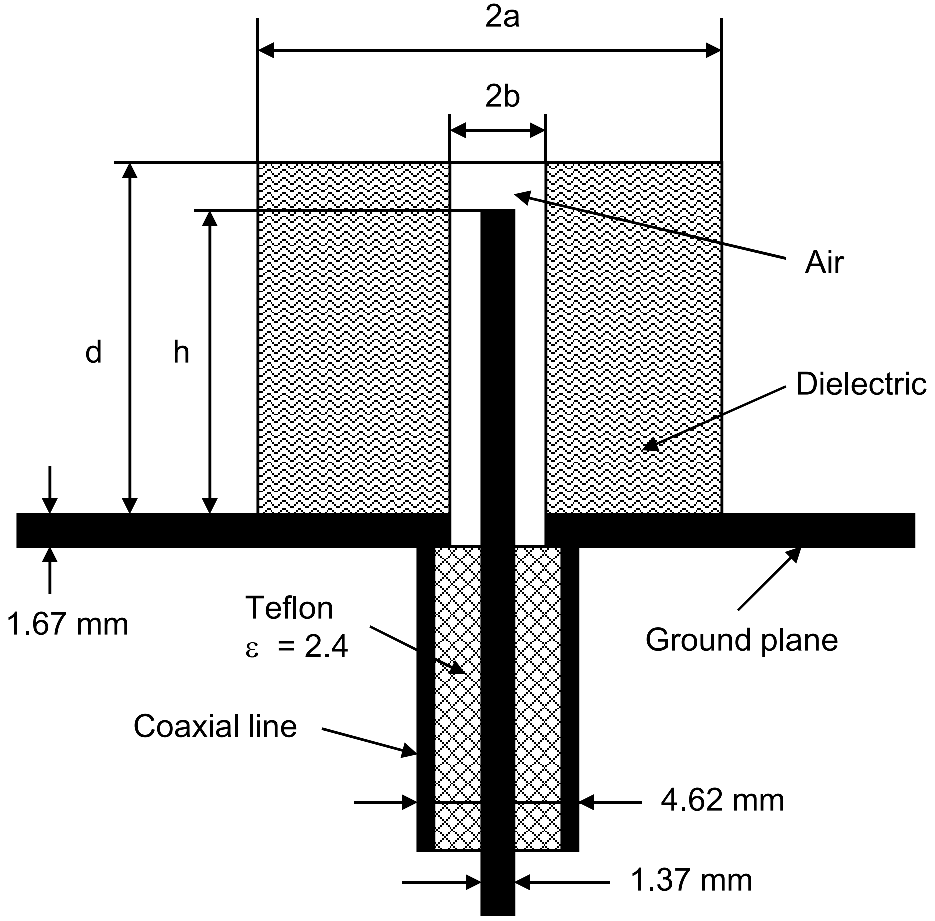
Parallel and Distributed Processing Techniques for Electromagnetic Field Solution

* **Classical numerical EM modelling** using sequential algorithms such as TLM (transmission-line matrix) or FEM (finite element method) is computer intensive, particularly as spatial discretization, geometry complexity, and domain size requirements become more demanding.

⇩

* More efficient **parallel and distributed computing** techniques must be developed to reduce the execution time for these methods so that they can be used in commercial CAD software. Speed of execution is particularly important when the field analysis is to be coupled with optimization, which may require several hundred analyses to be performed within a reasonable time. ⇨ **NN models**

☆ NN modeling of the 3D EM field radiated by a dielectric-ring resonator antenna



- *I. Ratner, H.O. Ali, E.M. Petriu, "Neural Network Simulation of a Dielectric Ring Resonator Antenna," J. Systems Architecture, vol. 44, No. 8, pp. 569-581, 1998.*

>> NN modeling of dielectric-ring resonator antenna EMF

Maxwell's equations: $\nabla \times \overline{H} = (\sigma + j\omega\varepsilon)\overline{E}$

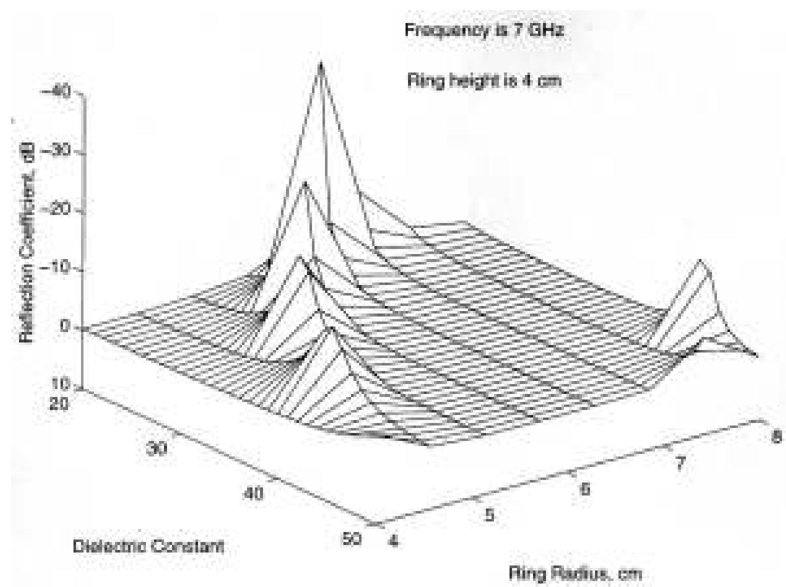
$\nabla \times \overline{E} = -j\omega\mu\overline{H}$

$$\nabla \times \nabla \times \overline{H} = -j\omega\mu\,(\sigma + j\omega\varepsilon)\overline{H}$$

Finite Element Method (*FEM*)

1400 frequency steps 2-16 GHz;

31 dielectric constants; a = d = 5.14 mm

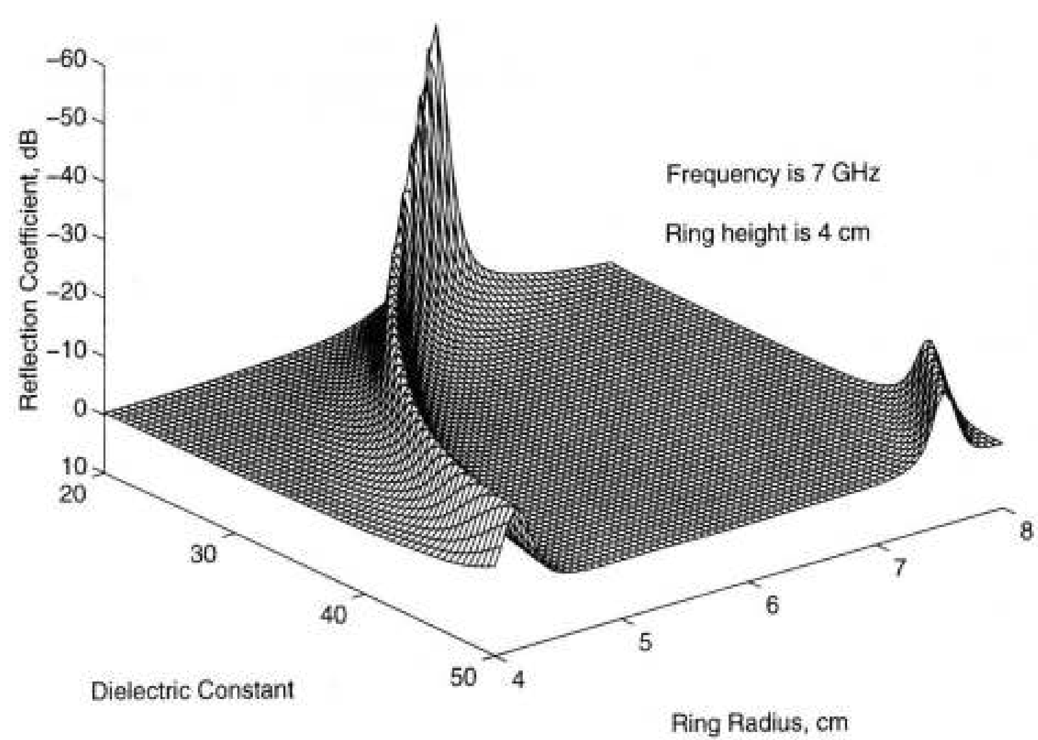


>> NN modeling of dielectric-ring resonator antenna EMF

FEM numerical Solution => **1.3×10^5 s** on SPARC 10 UNIX

NEURAL NETWORK

- Two input neurons (frequency, dielectric constant) + Two hidden layers (5 neurons each, with hyperbolic tangent activation function) + One output linear neuron;
- Backpropagation using the Levenberg-Marquard algorithm;
- **55 s** /200 epochs to *train the NN off line*on SPARC 10 UNIX station;
- **0.5 s** to *render on line5,000 points* of the EM field surface- model, SPARC 10 UNIX.



MODEL CALIBRATION

The whole idea of virtual prototyping relies on the ability to develop ***models conformable to the physical objects and phenomena*** which represent reality very closely.

There is a need for ***calibration techniques able to validate the conformance with the physical reality of the models*** incorporated in the new prototyping tools.

Experimental Measurements

- The EM field training data are conveniently obtained as analytical estimations of far-field values in 3D space and frequency from near-field data using the finite element method combined with method of integral absorbing boundary conditions.

- The near field data could be obtained analytically and/or by physically measuring EM field values at for given frequency values and 3D space locations.

- This approach allows to replace the usual cumbersome open site far-field measurement technique by anechoic chamber measurements.

The amount and extent of the area of measurements is significantly reduced by collecting data in the near-field only and calculating then the far-field values using Poggio's equation:

$$H\left(r'\right)=\frac{1}{4\pi}\int_{s1}\left[\,G\left(r,r'\right)\frac{\partial H(\,r)}{\partial n}-H(\,r)\frac{\partial G\left(r,r'\right)}{\partial n}\right]dS_1$$

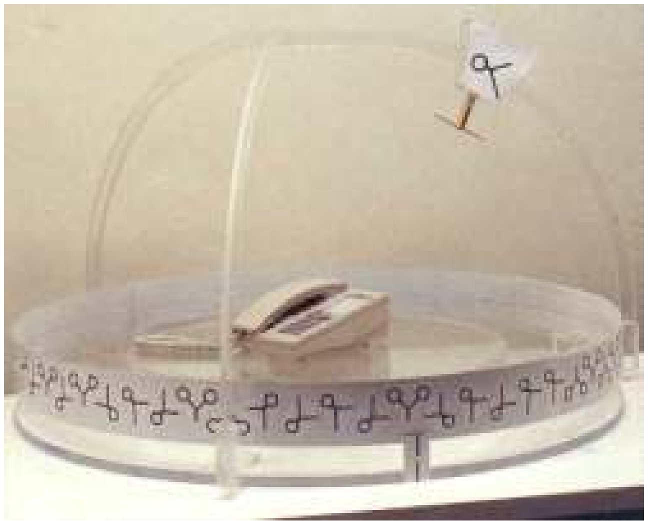
where:

-S_1 is the surface on which measurements are made, closed or made closed,

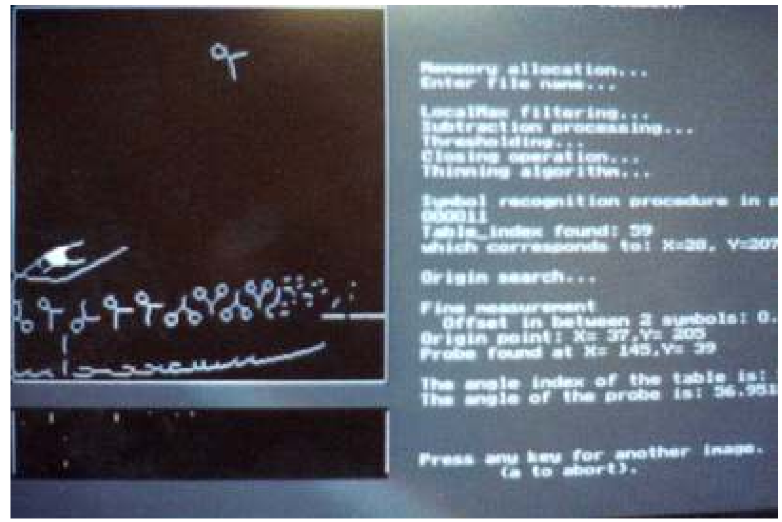
-n is the normal to S_1 and

is the free space Green’s function.

- *This equation states that if the field values and their derivatives are known on a closed surface enclosing all inhomogeneities, then the field outside the surface can be calculated.*



Experimental setup for the noninvasive measurement of the 3D near field data

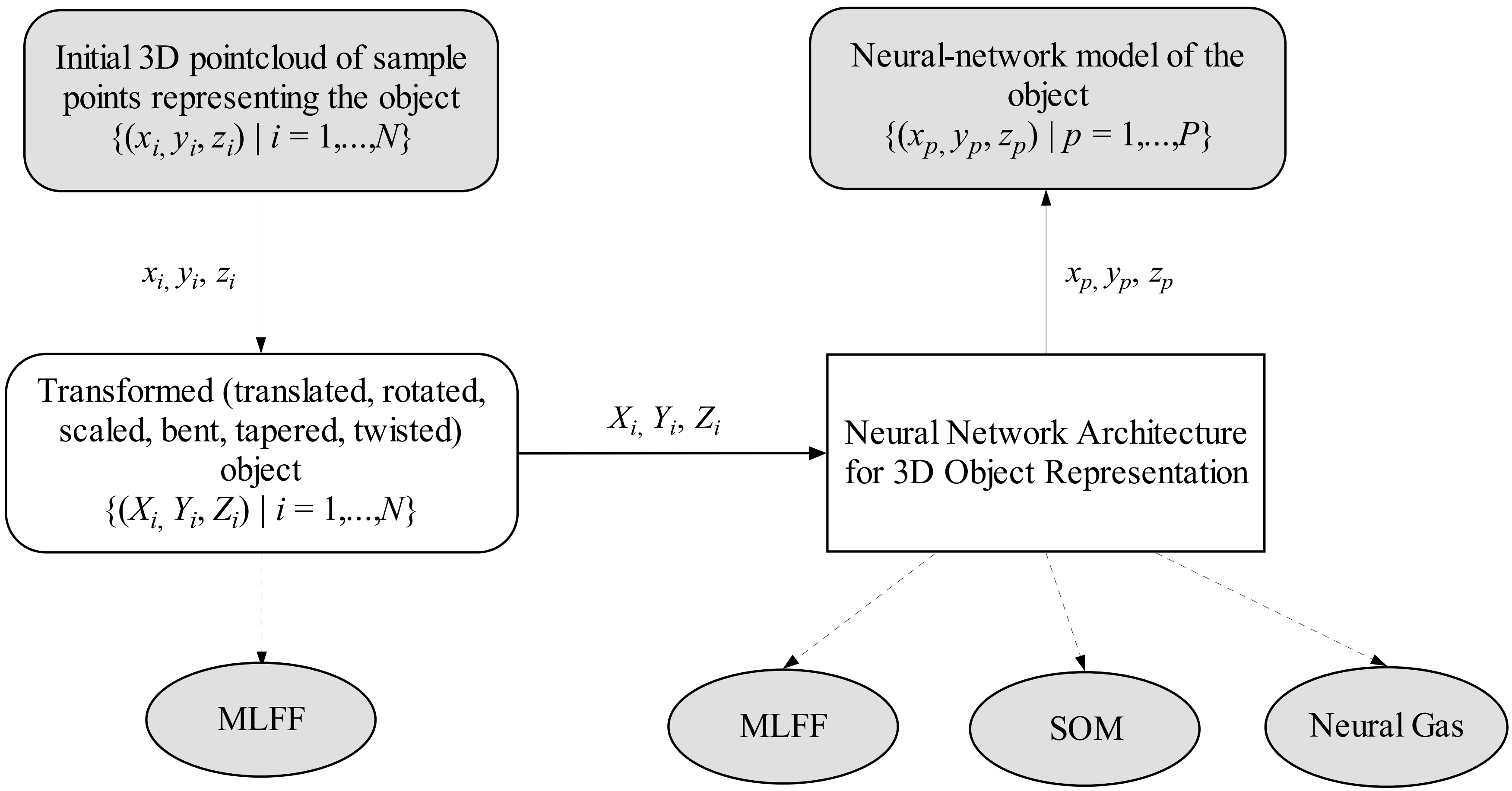


Computer vision recovery of the 3D position of the EM probe

Neural Network Modeling of 3D Objects

Compare the performance of three NN architectures used for 3D Object modelling:

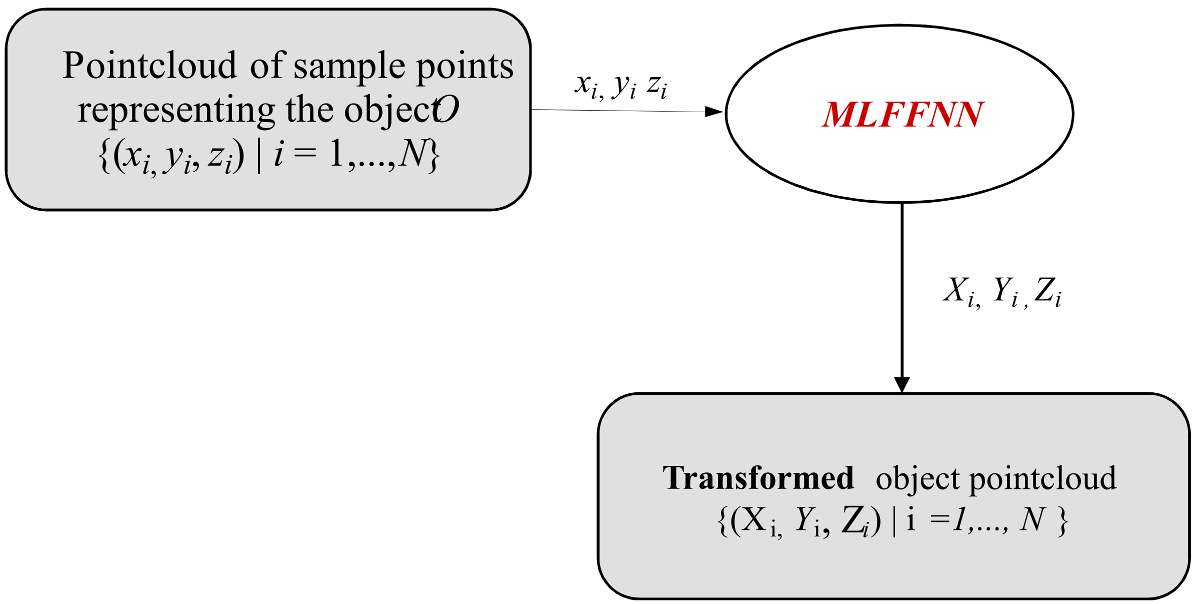
- Multilayer Feedforward Neural Network (*MLFFNN*)
- Self-Organizing Map (*SOM*)
- Neural Gas Network



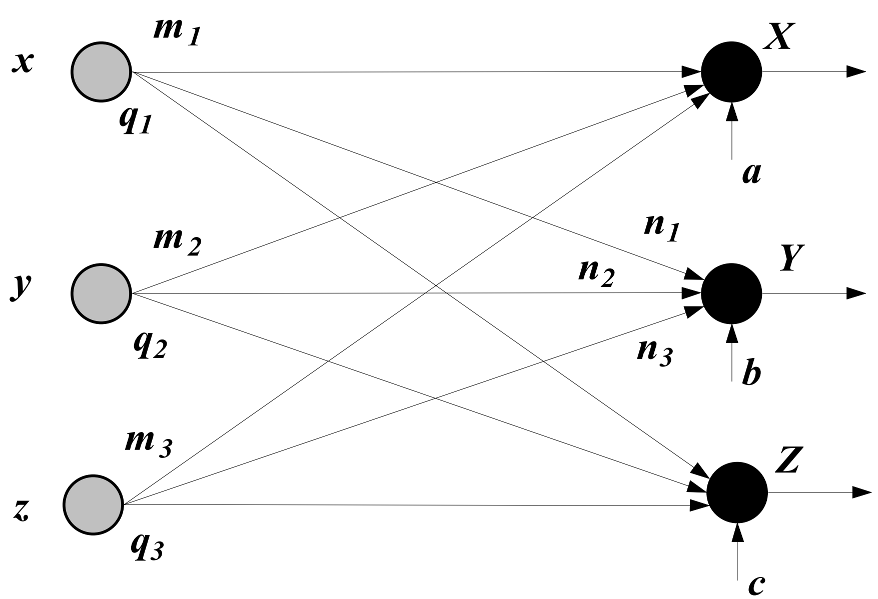
Transformation Function:

translation, rotation, scaling,

and deformations (bending, tapering, twisting)



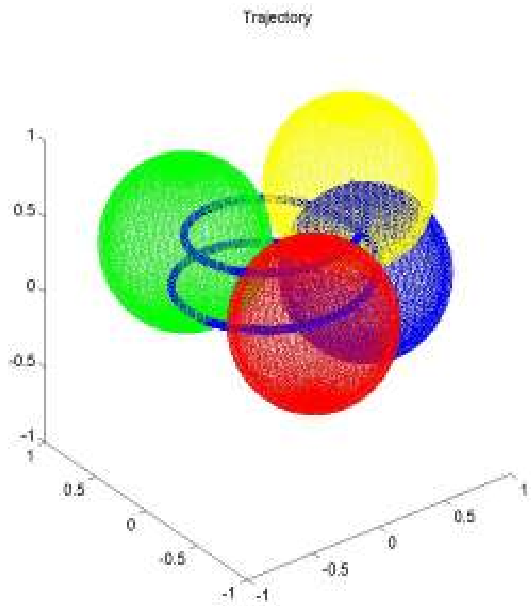
Transformation Function – NN Architecture

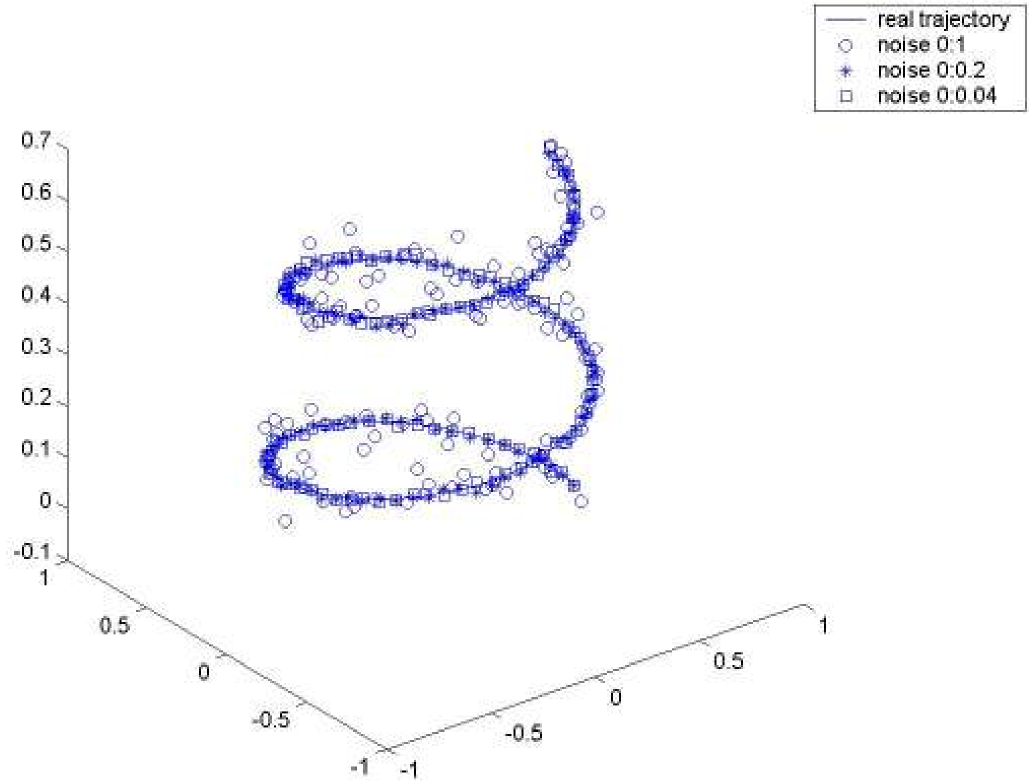


$$m_1 = a_1 \cos\theta \cos\varphi$$
$$m_2 = a_1(\cos\theta \sin\varphi \sin\psi - \sin\theta \cos\psi)$$
$$m_3 = a_1(\cos\theta \sin\varphi \cos\psi + \sin\theta \sin\psi)$$
$$n_1 = a_2 \sin\theta \cos\varphi$$
$$n_2 = a_2(\sin\theta \sin\varphi \sin\psi - \cos\theta \cos\psi)$$
$$n_3 = a_2(\sin\theta \sin\varphi \cos\psi - \cos\theta \sin\psi)$$
$$q_1 = -a_3 \sin\varphi$$
$$q_2 = a_3 \cos\varphi \sin\psi$$
$$q_3 = a_3 \cos\varphi \cos\psi$$

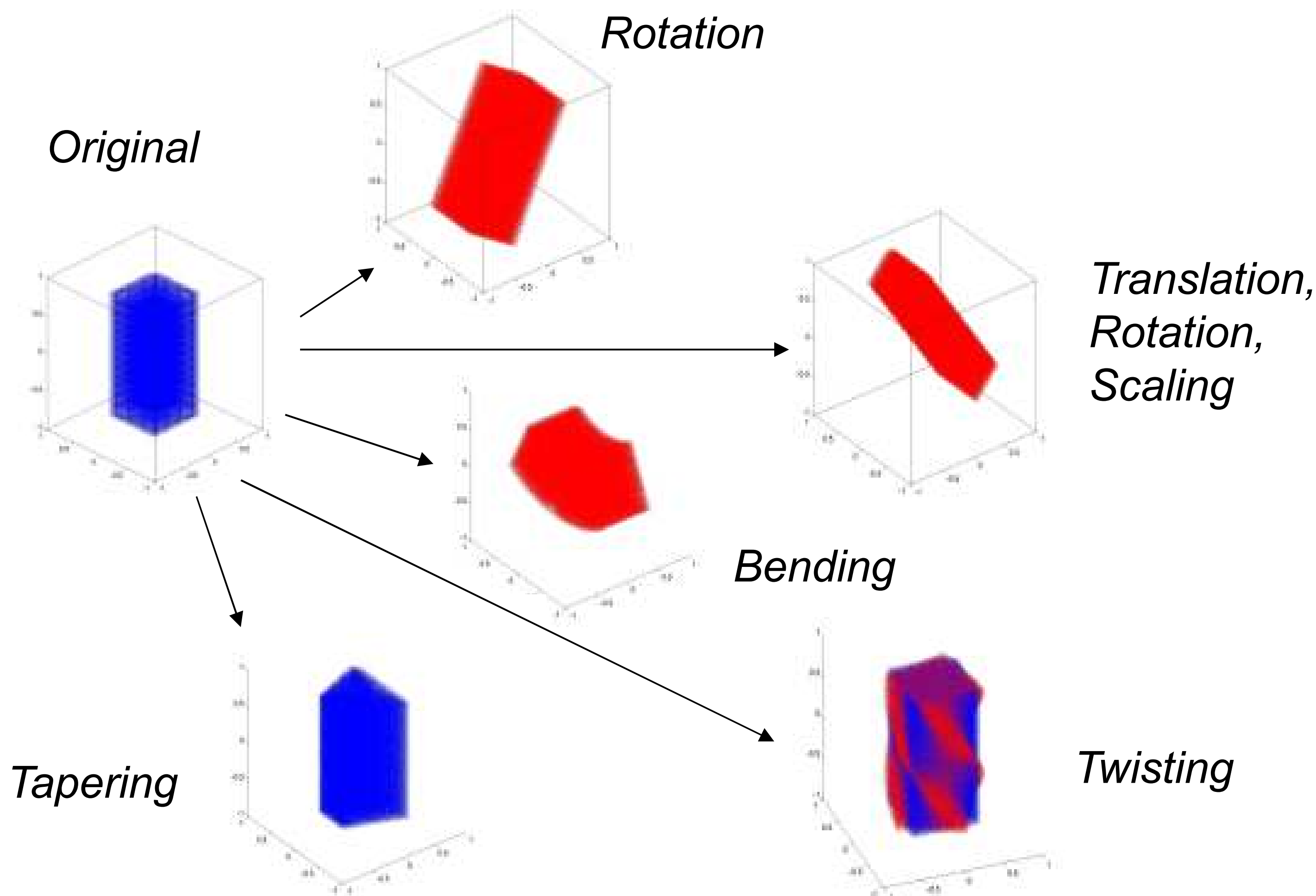
Transformation Function - Training Mode

Motion Estimation



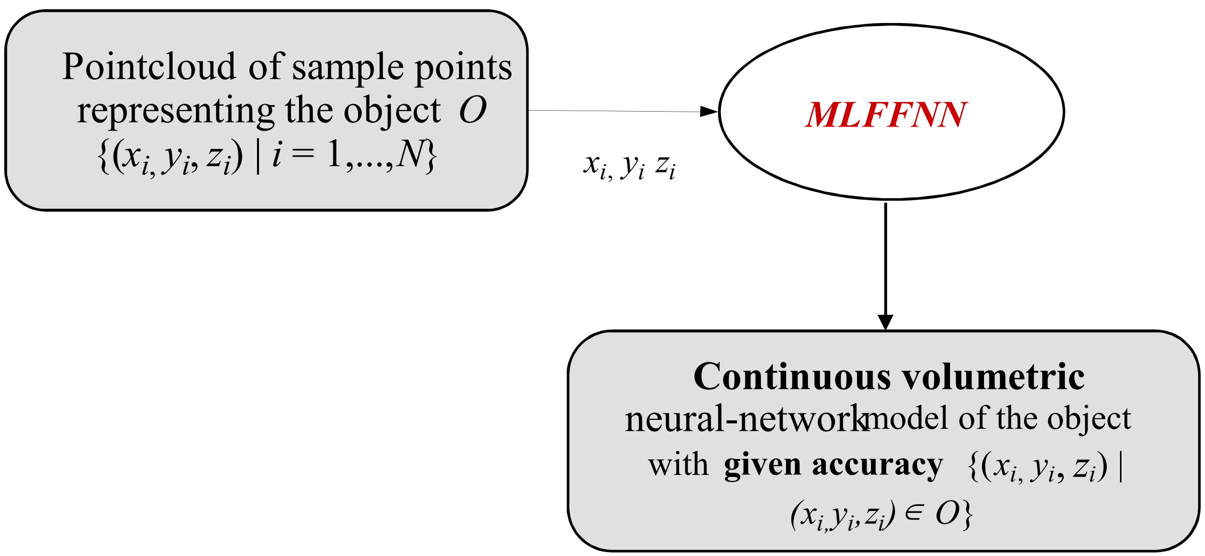


Transformation Function - Generation Mode

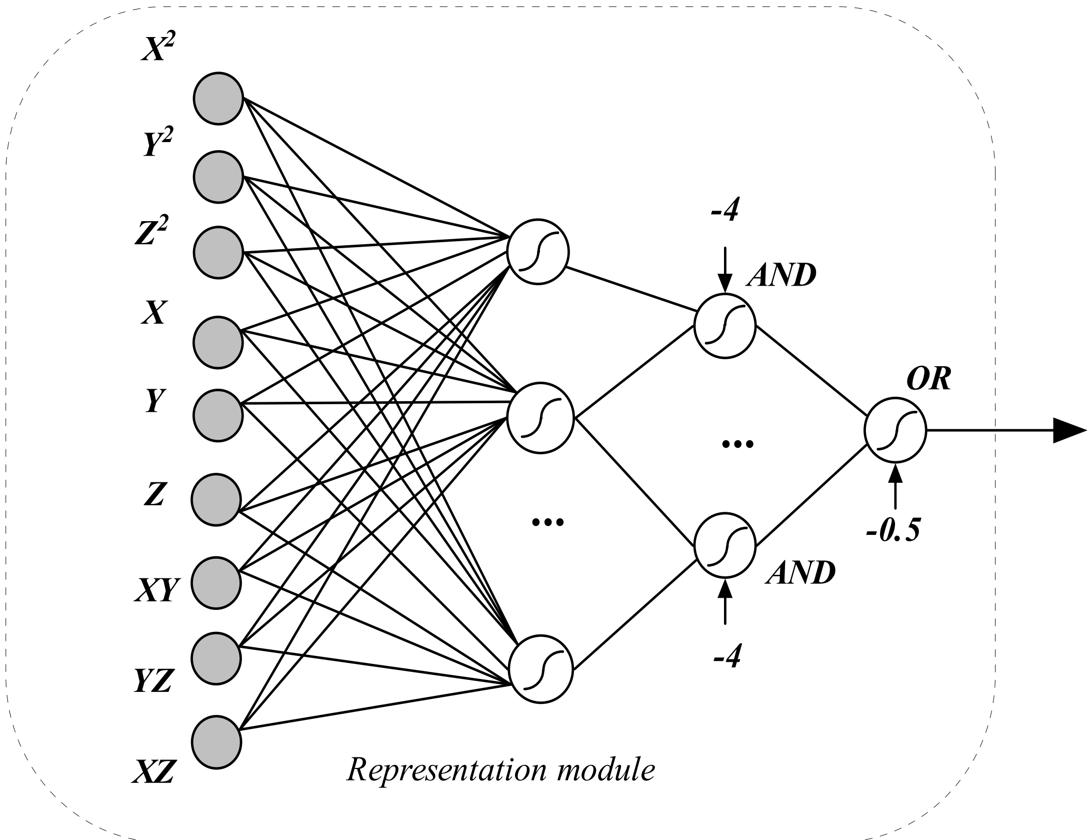


MLFF Representation

generates a value proportional to the distance between an input point and the modeled object surface

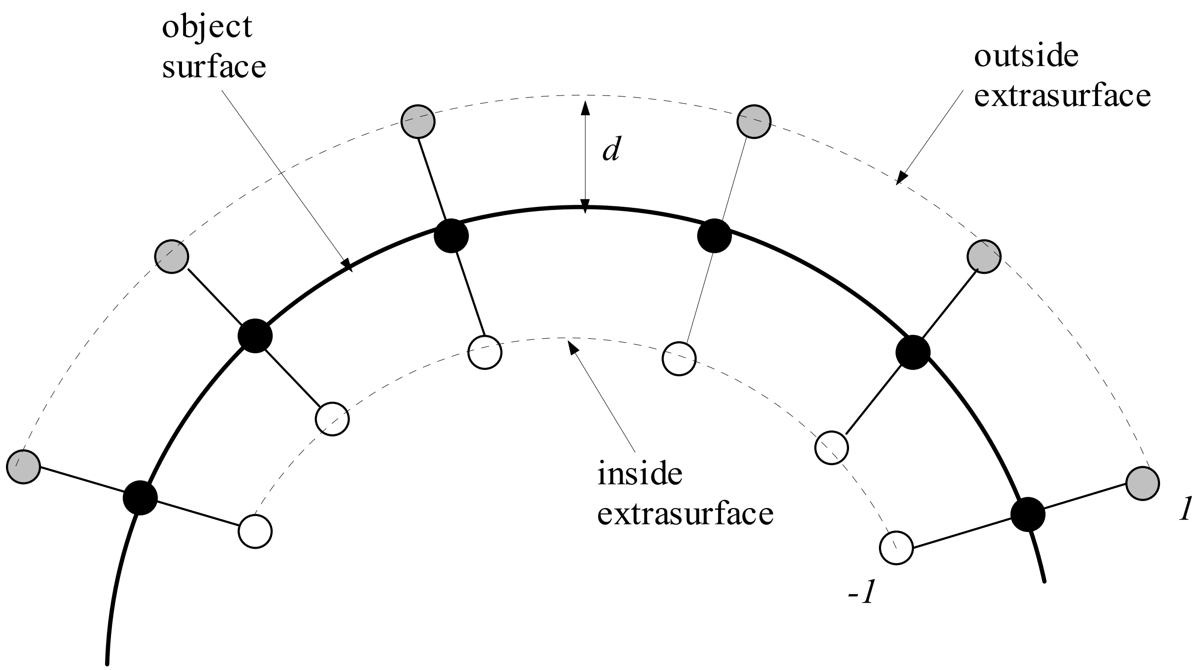


MLFFNN Representation – NN Architecure



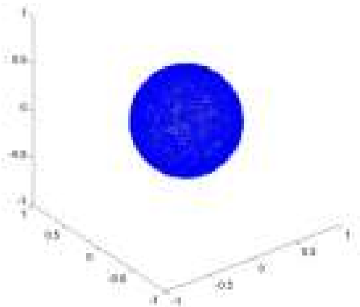
- **Activation Function**
  - sigmoid
- **Training/Testing Data**
  - normalized points in the [-1 1 –1 1 –1 1] cube
- **Learning**
  - supervised
  - scaled-gradient descent backpropagation

MLFFNN Representation - Training Mode

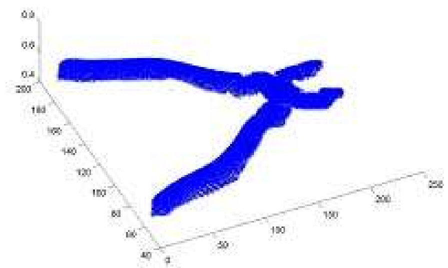


- Models objects given as pointclouds
- **Decisions**:
  - inputs to use
  - number of neurons in hidden layer
  - values for training parameters
  - number of extrasurfaces and distance

MLFFNN Modelling - Results

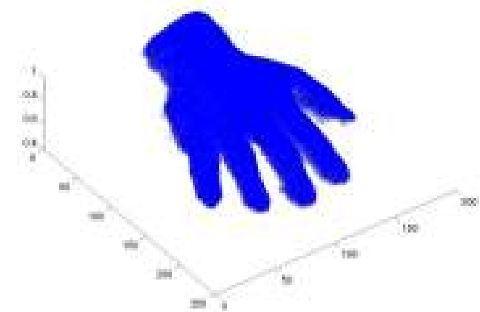


250 points, 6-3-1, 1 extrasurface, d=0.055, 550 epochs, mse: 0.14, 7 min.

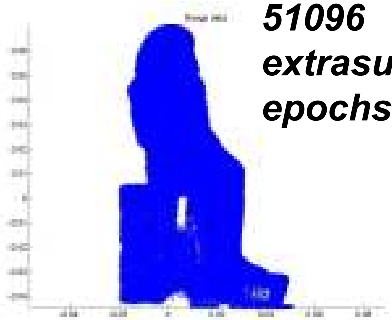


7440 points, 8-4-1, 5 extrasurfaces, d=0.055, 1100 epochs, mse: 0.24, 1 hr

19080 points, 10-5-1, 5 extrasurfaces, d=0.055, 1200 epochs, mse: 0.35, 2.8 hrs.

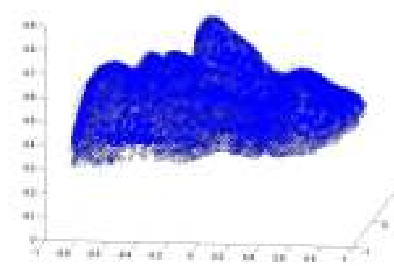


19000 points, 14-7-1, 4 extrasurfaces, d=0.055, 1100 epochs, mse: 0.4, 3.3 hrs

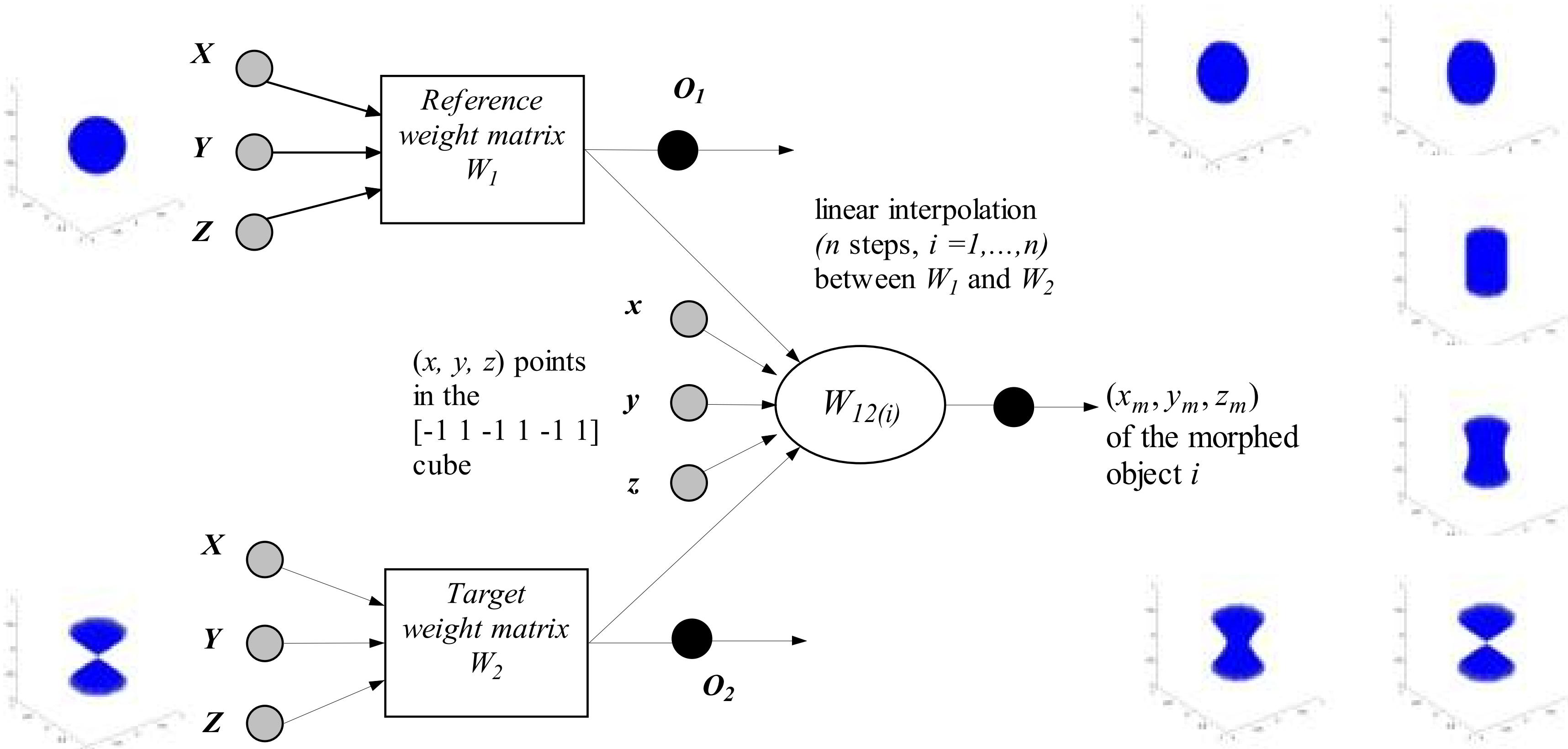


51096 points, 20-10-1, 5 extrasurfaces, d=0.055, 2000 epochs, mse: 0.67, 5.2 hrs.

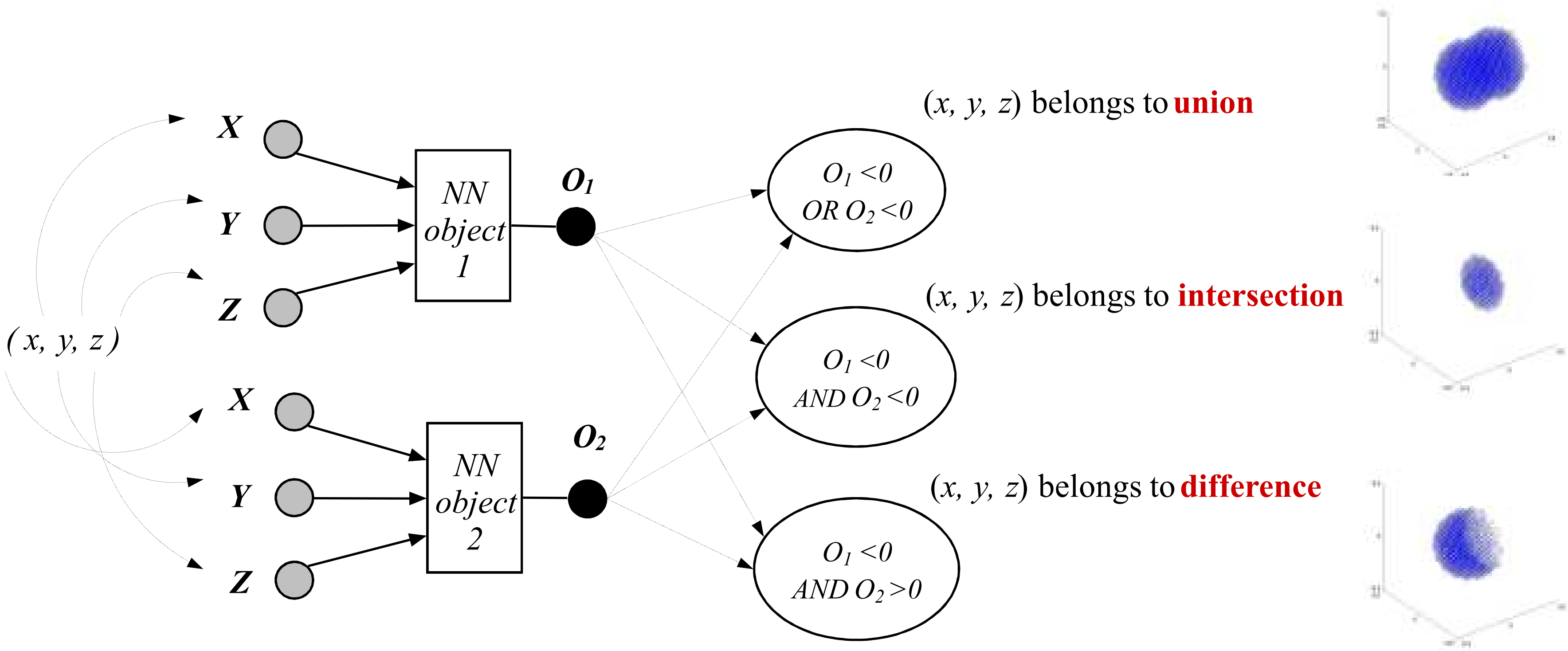
2500 points, 12-6-1, 2 extrasurfaces, d=0.06, 1020 epochs, mse: 0.39, 45 min.



MLFFNN Representation – Applications ⇨ Object Morphing

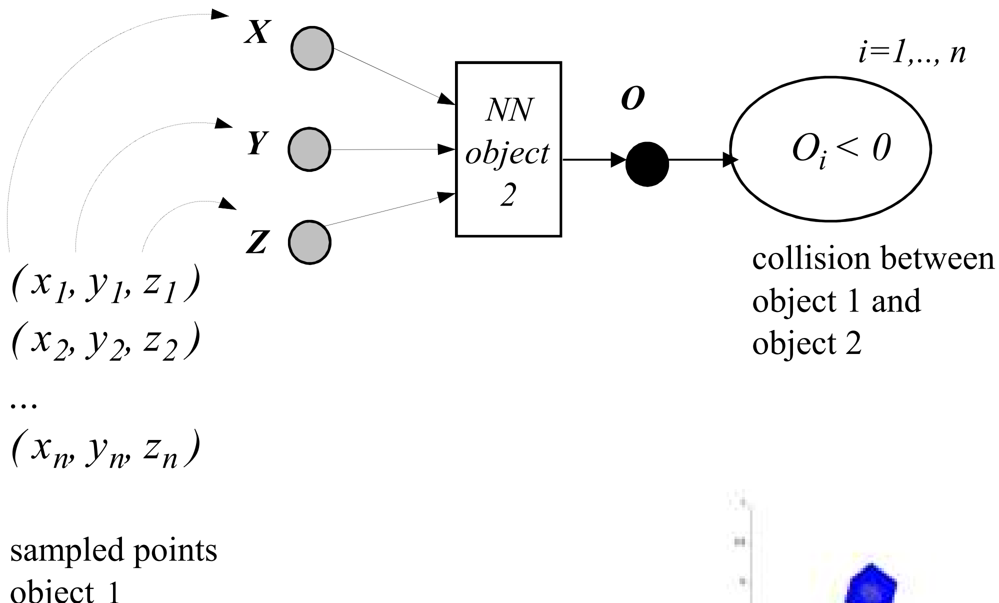


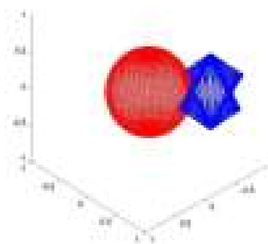
MLFFNN Representation – Applications ⇒ *Set Operations*



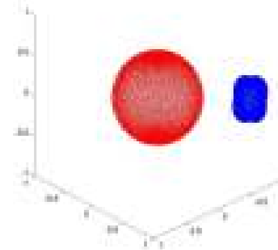
MLFFNN Representation – Applications

Object Collision Detection





96.56%



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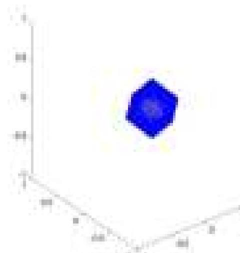

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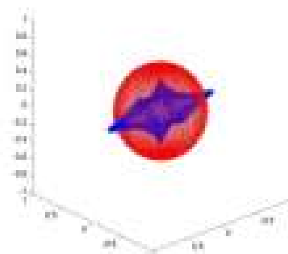

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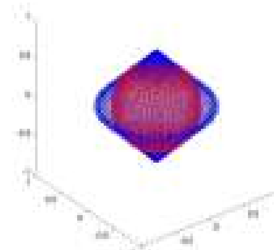

97
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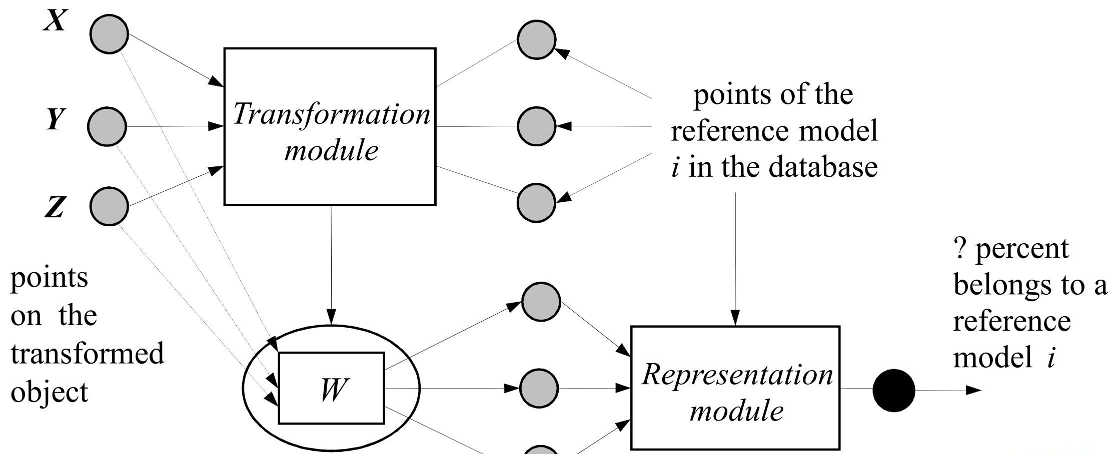
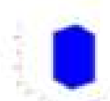
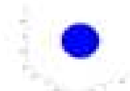
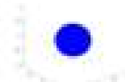
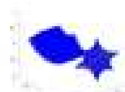
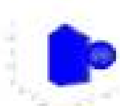
MLFFNN Representation – Applications ⇨ *Object Recognition*



				
	2.4%	4.9%	1.6%	99.1%
	93.3%	3.3%	91.7%	3.1%
	95%	99.1%	5.78%	98.3%
	91.7%	6.6%	1.6%	92.5%

MLFFNN Modelling – Summary

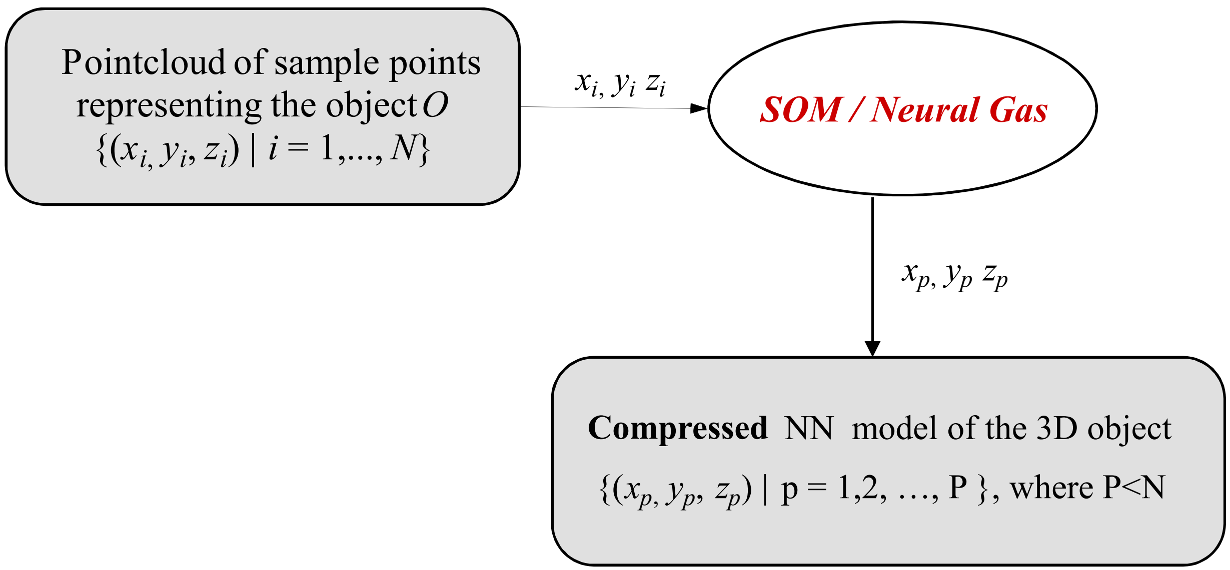
Advantages

- simple and compact (weights+architecture)
- less memory usage
- continuous volumetric model (though trained with surface)
- information about the entire object space
- provides desired accuracy
- represents objects of varied complexity
- preserves details
- morphing, set operations, recognition, collision detection (convenience)

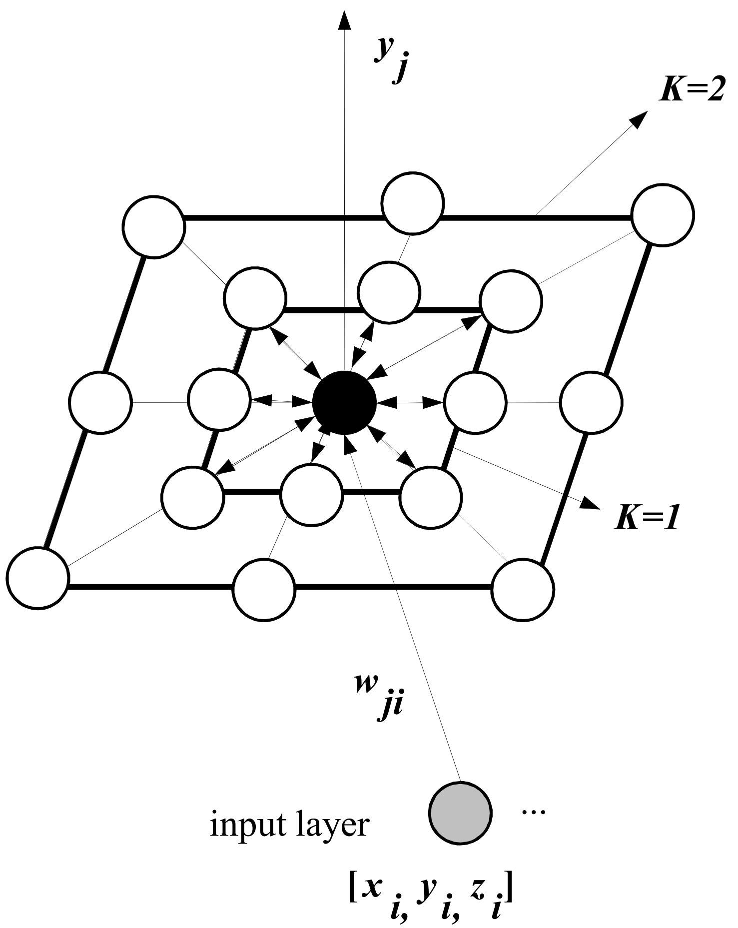
Disadvantages

- computationally expensive (for both learning and rendering)
- lack of local control of the object

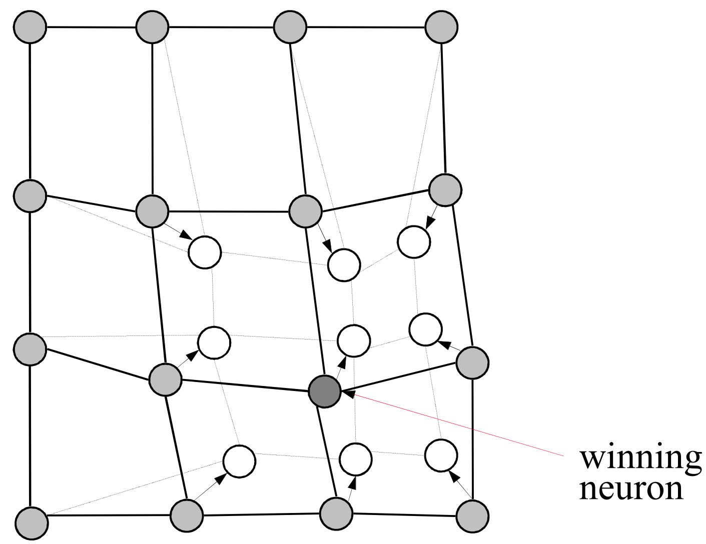
SOM and Neural Gas
- Compressed Representation Models



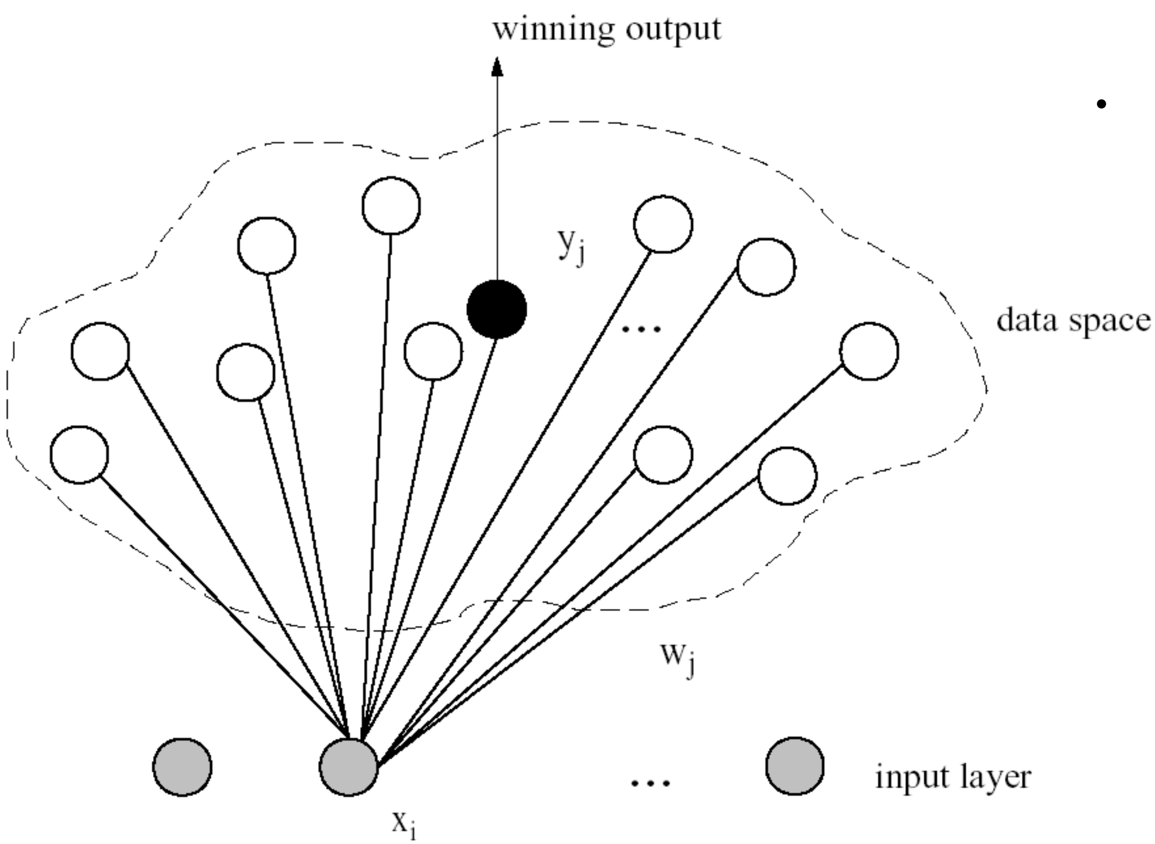
SOM Representation – NN Architecture



- **Activation Function**
  - soft competition
- **Learning**
  - unsupervised



Neural Gas Representation – NN Architecture



- **Activation Functions**:
  - soft competition
  - neighbourhood ranking
- **Learning**
  - unsupervised

SOM and Neural Gas Modelling - Results

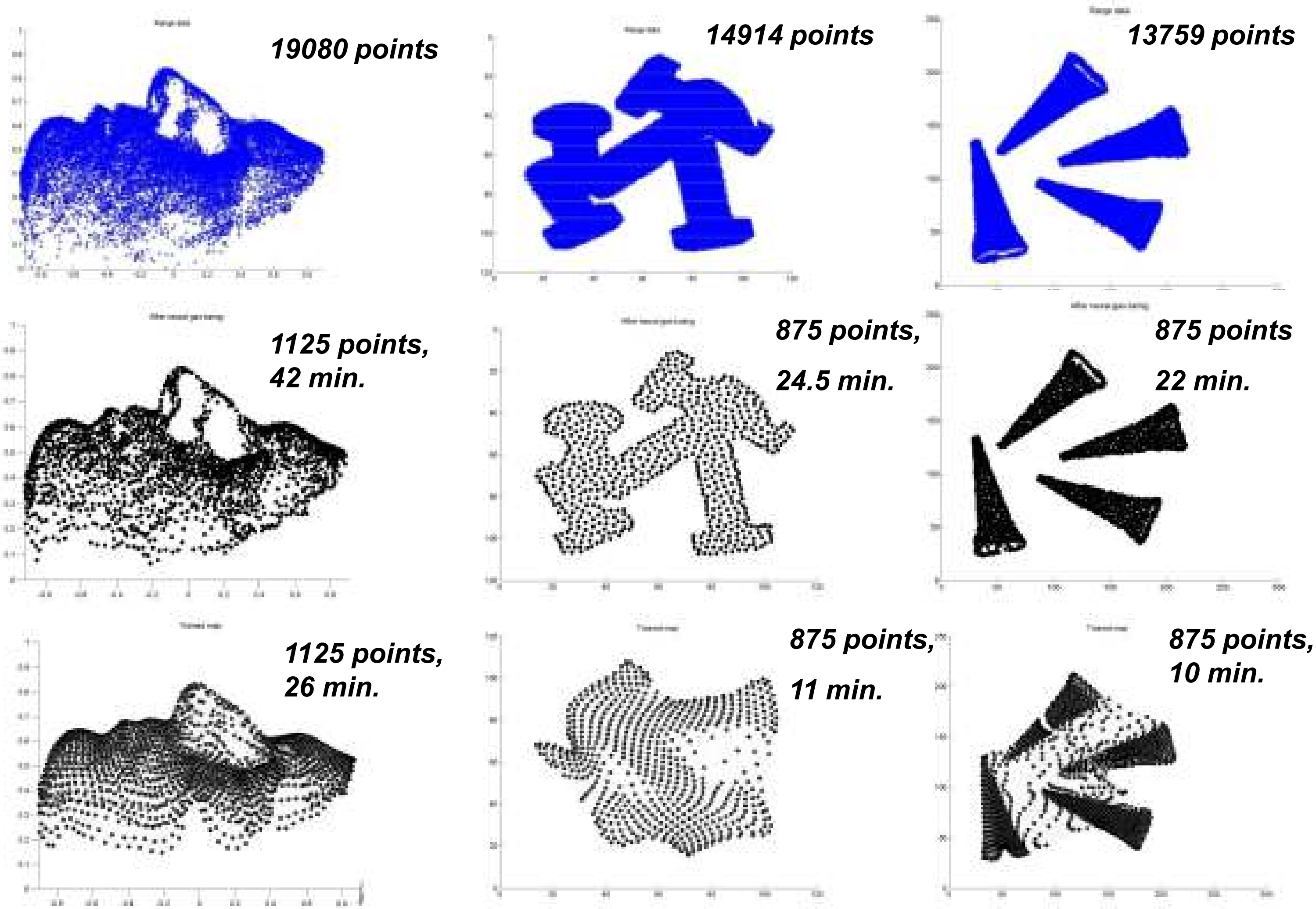
Initial pointcloud

Neural Gas

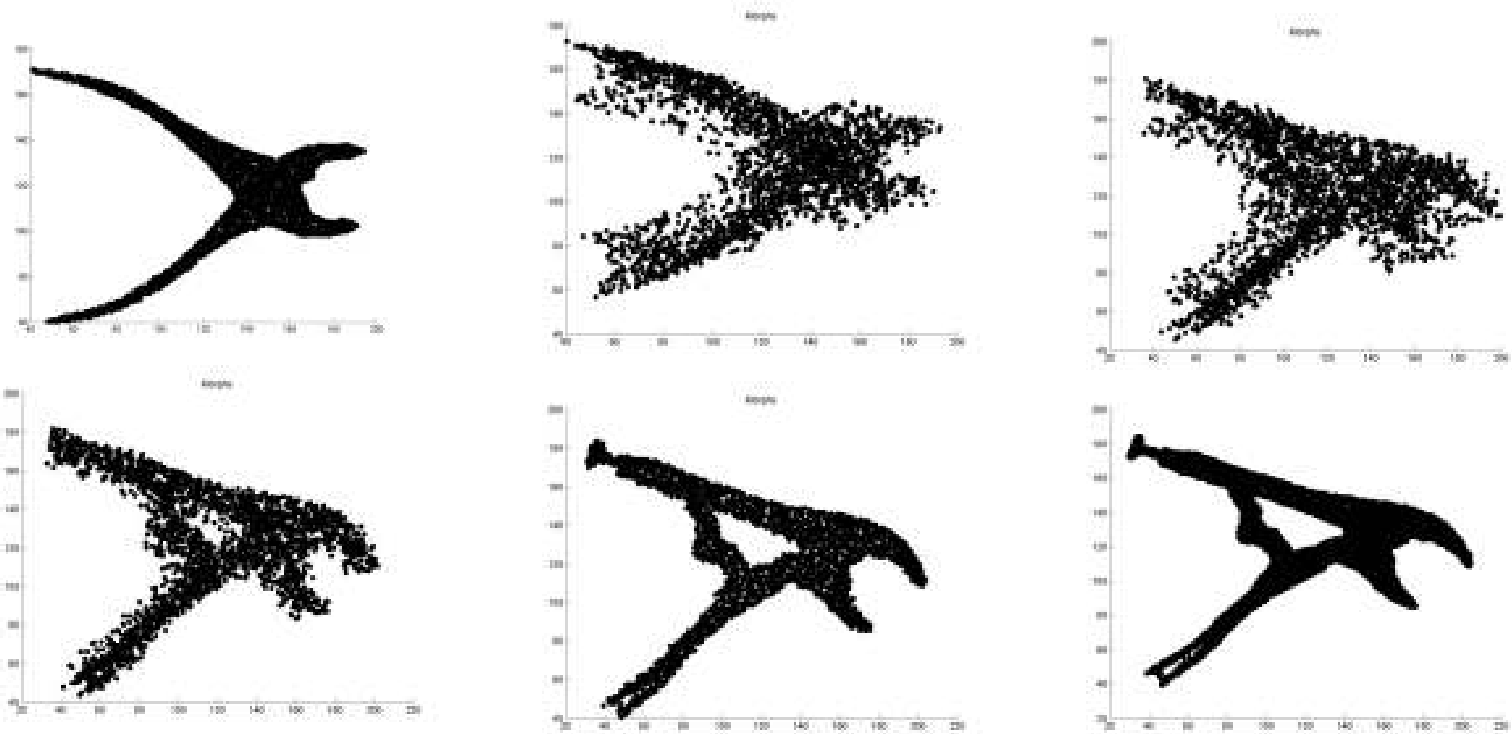
er= 0.0098

SOM

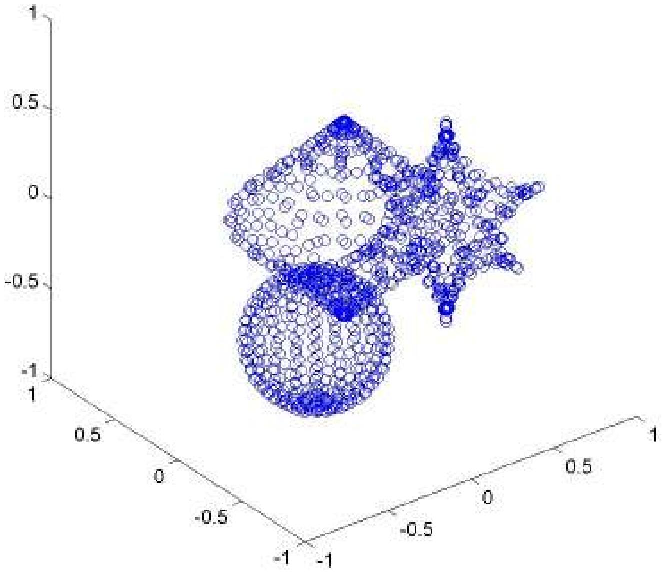
er= 0.0125

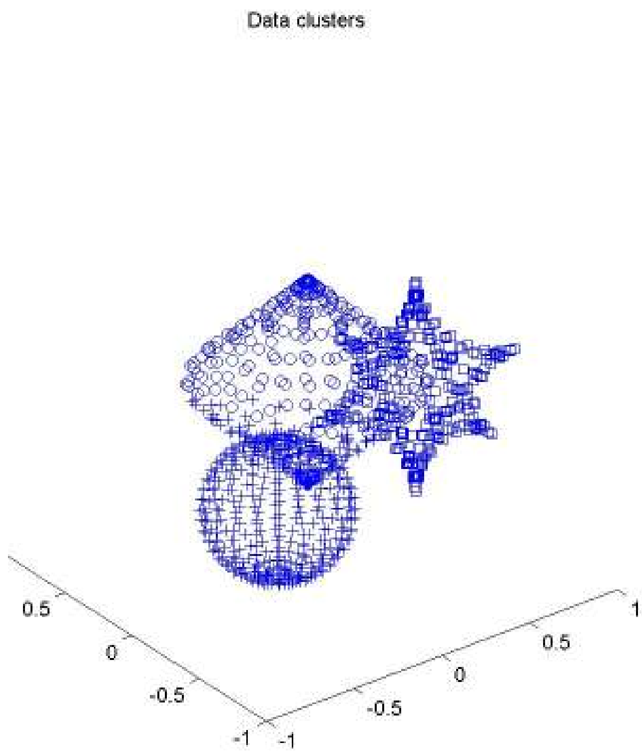


SOM and Neural Gas Modelling – Applications ⇨ *Object Morphing*



SOM and Neural Gas Modelling – Applications ⇨ *Segmentation*





SOM and Neural Gas Modelling – Summary

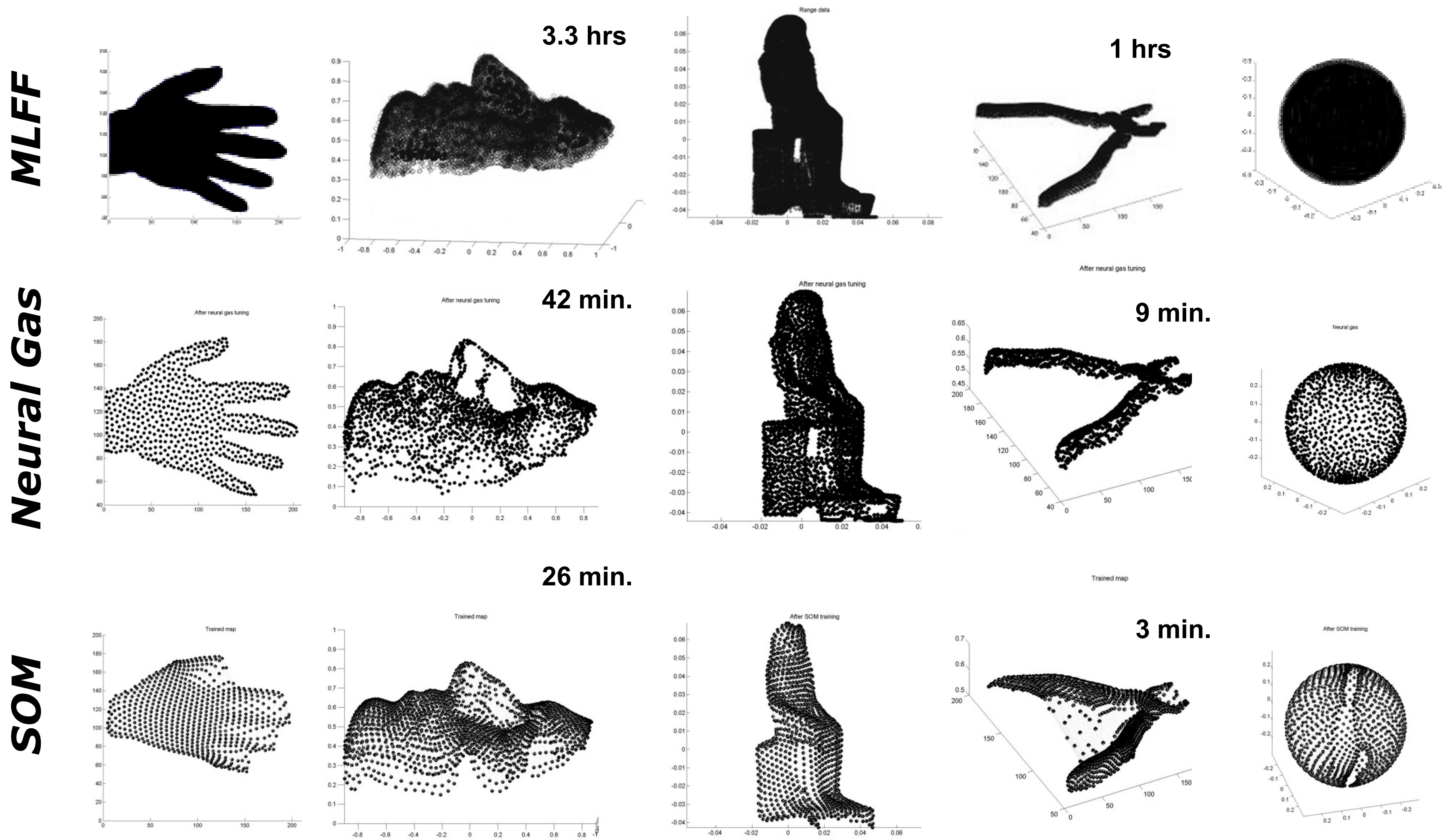
Advantages

- simple and compact (weights)
- compressed
- less memory usage
- desired accuracy
- objects of varied complexity
- details
- morphing, motion detection, segmentation

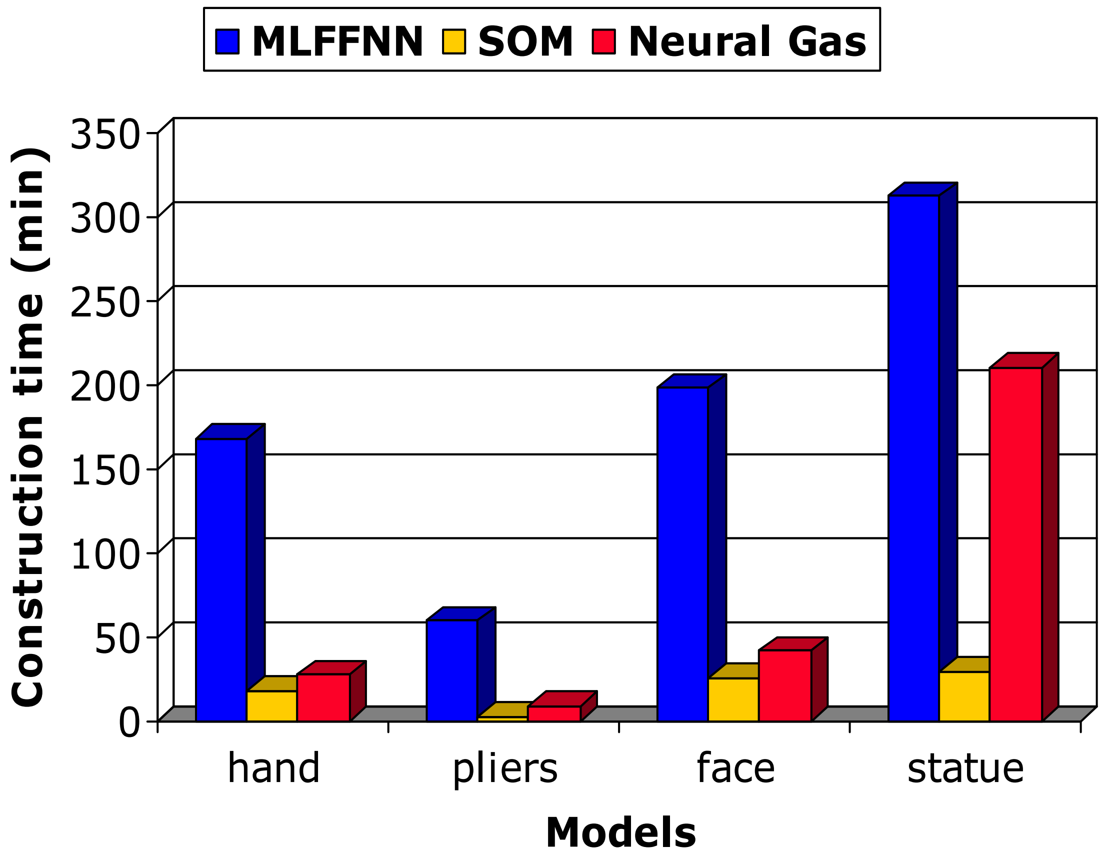
Disadvantages

- computational expensive for high accuracy
- no information about the object space
- no direct surface representation

MLFF, SOM, and *Natural Gas* Modelling – Performance Comparison
Training Time



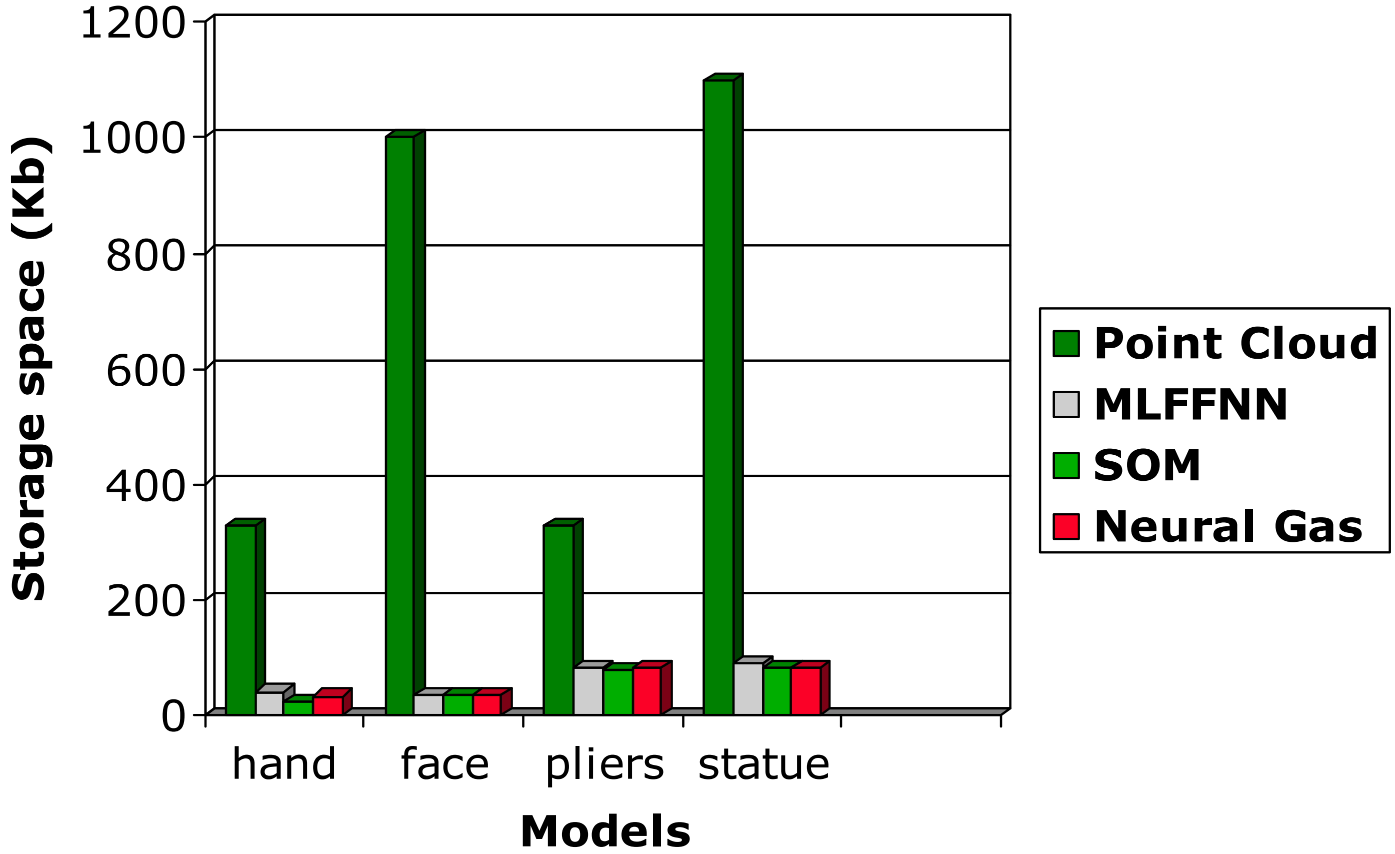
MLFF, SOM, and *Natural Gas* Modelling – Performance Comparison



- **MLFNN**
  - computational time = construction time + generation time+rendering
- **SOM and Neural Gas**
  - computational time =

    construction time + rendering

MLFF, *SOM*, and *Natural Gas* Modelling – Performance Comparison
Compactness



MLFF, SOM, and *Natural Gas* Modelling of 3D Objects

CONCLUSIONS

- The use of neural network modeling advantageous mainly for simplicity and compactness
- ***MLFNN*** – continuous model, information on the entire object space, many applications, but time consuming
- ***SOM and Neural Gas*** – compressed model while maintaining the properties of the object, very good accuracy, less time consuming
- The use of different techniques depends on the application requirements.

Neural Network Adaptive Sampling of 3D Surface Elastic Properties

Recovery of the elastic material properties requires touching each point of interest on the explored object surface and then conducting a strain-stress relation measurement on each of the touched points.

Tactile probing is a time consuming Sequential operation

Find fast sampling procedures able to minimize the number of the sampling points by selecting only those points that are relevant to the elastic characteristics.

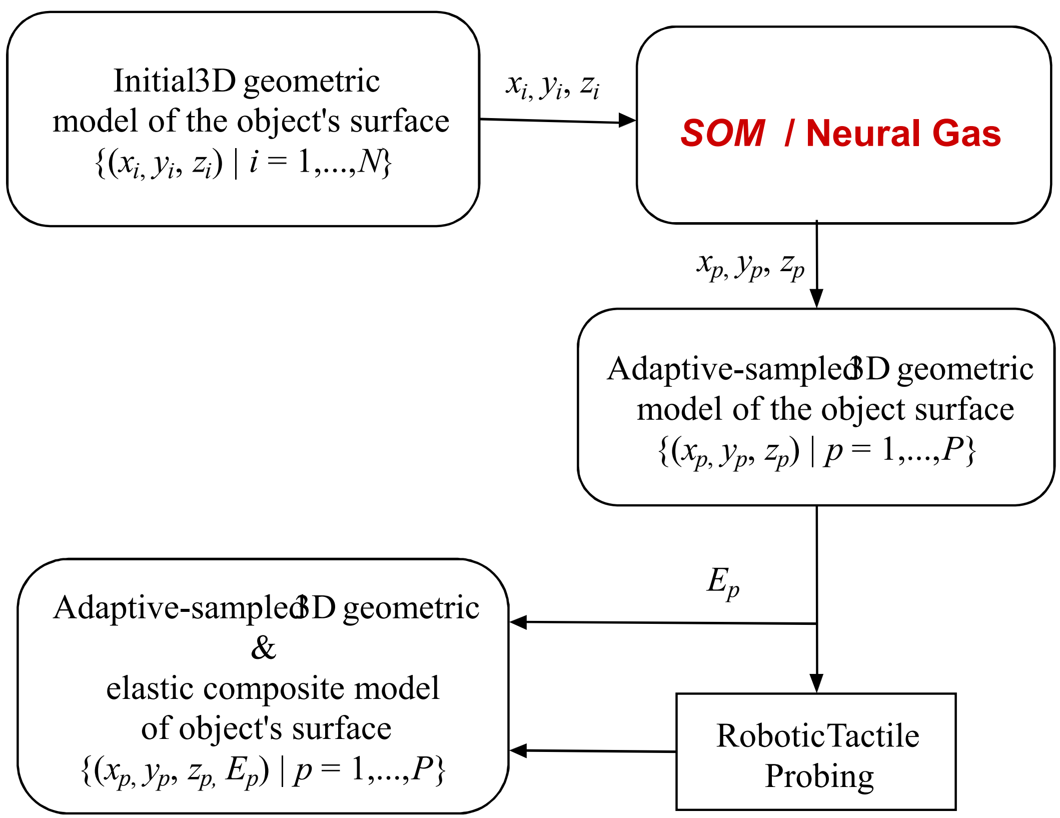
non-uniform adaptive sampling algorithm of the object's surface, which exploits the SOM (*self-organizing map) ability to find optimal finite quantization of the input space.*

The elastic behaviour at any given point (x_p, y_p, z_p) on the object surface is described by the Hooke's law:

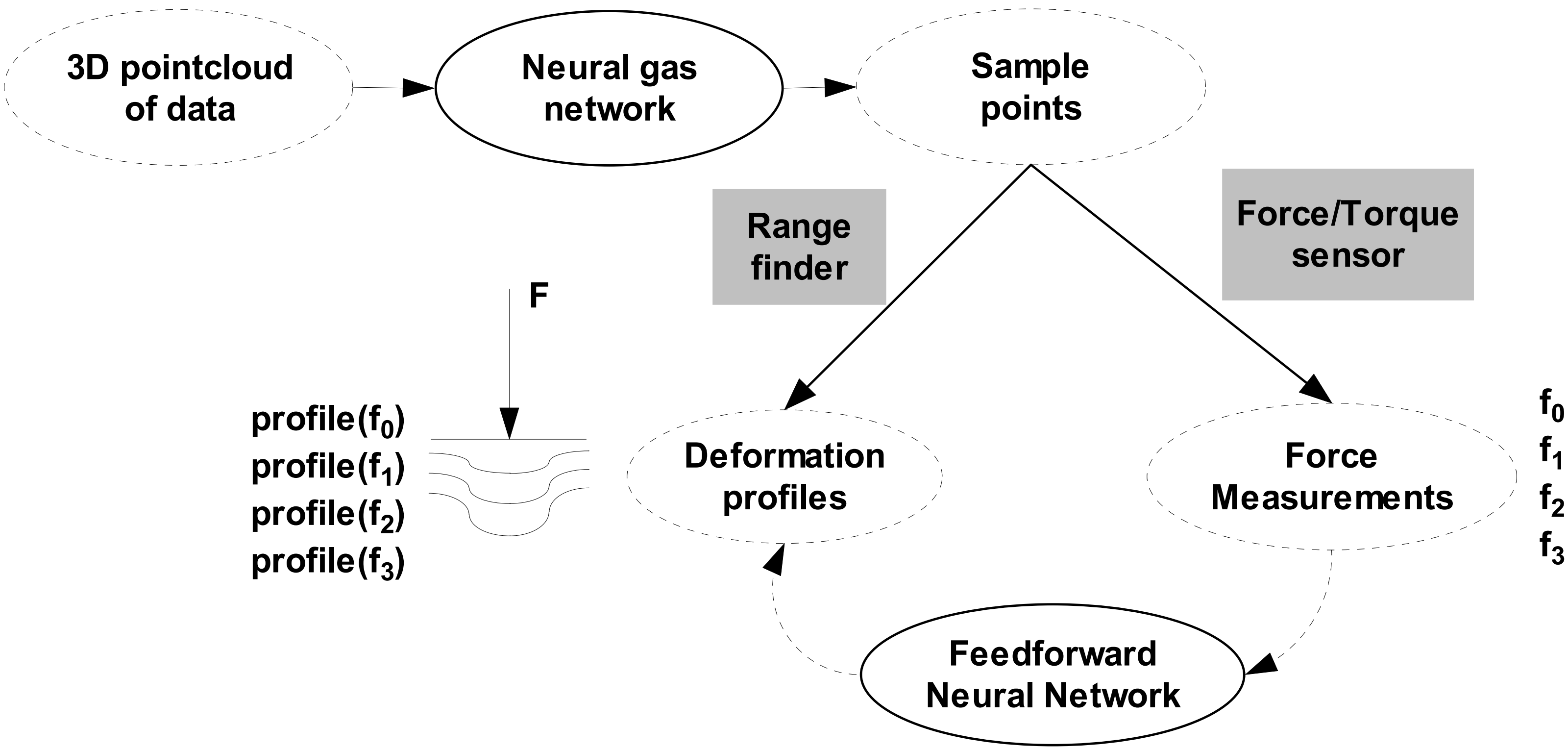
$$\begin{cases} \sigma_p = E_p \cdot \varepsilon_p & if\ 0 \leq \varepsilon_p \leq \varepsilon_{p\max} \\ \sigma_p = \sigma_{p\max} & if\ \varepsilon_{p\max} < \varepsilon_p \end{cases}$$

where E_p is the modulus of elasticity , s_p is the stress, and e_p is the strain on the normal direction.

Adaptive Sampling Control of the Robotic Tactile Probing of Elastic Propertiesof 3D Object Surfaces

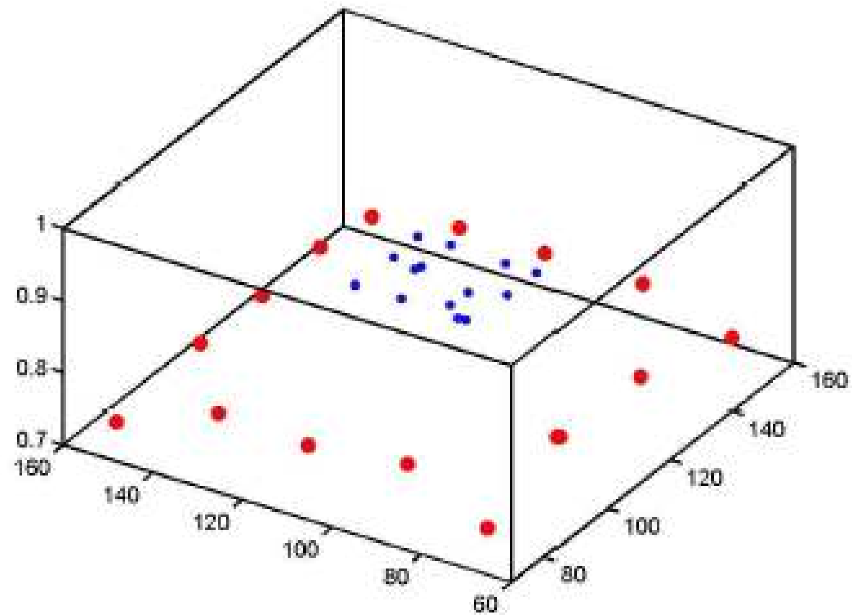


Neural Network Mapping an Clustering of Elastic Behavior from Tactile and Range Imaging

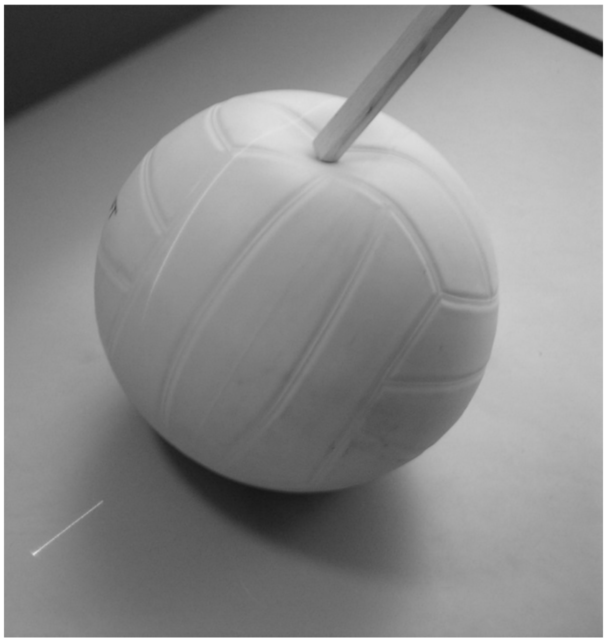


Starting from a 3D point-cloud, a **neural gas NN** *yields a reduced set of points on the 3D object's surface which are relevant for the tactile probing*. The density of these tactile probing points is higher in the regions with more pronounced variations in the geometric shape. A **feedforward NN** *is then employed to model the force/displacement behavior of selected sampled points* that are probed simultaneously by a force/torque sensor and the active range finder.

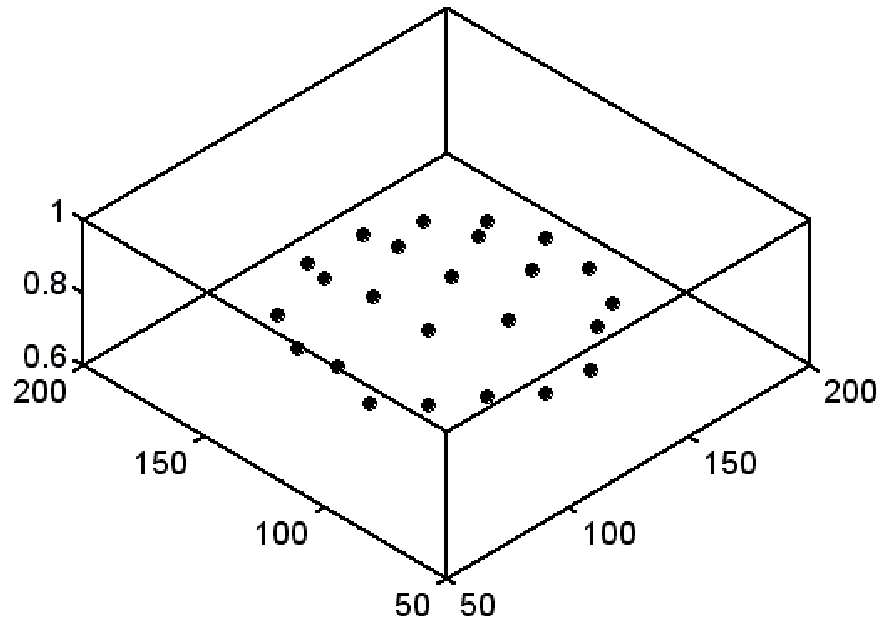
Variable elasticity object used
for experimentation.



Sampling points selected with
the neural gas network.

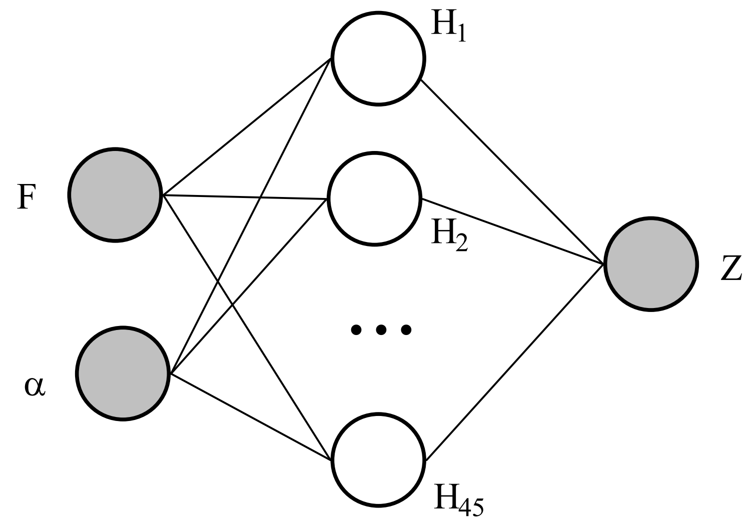


Elastic ball used
for experimentation.



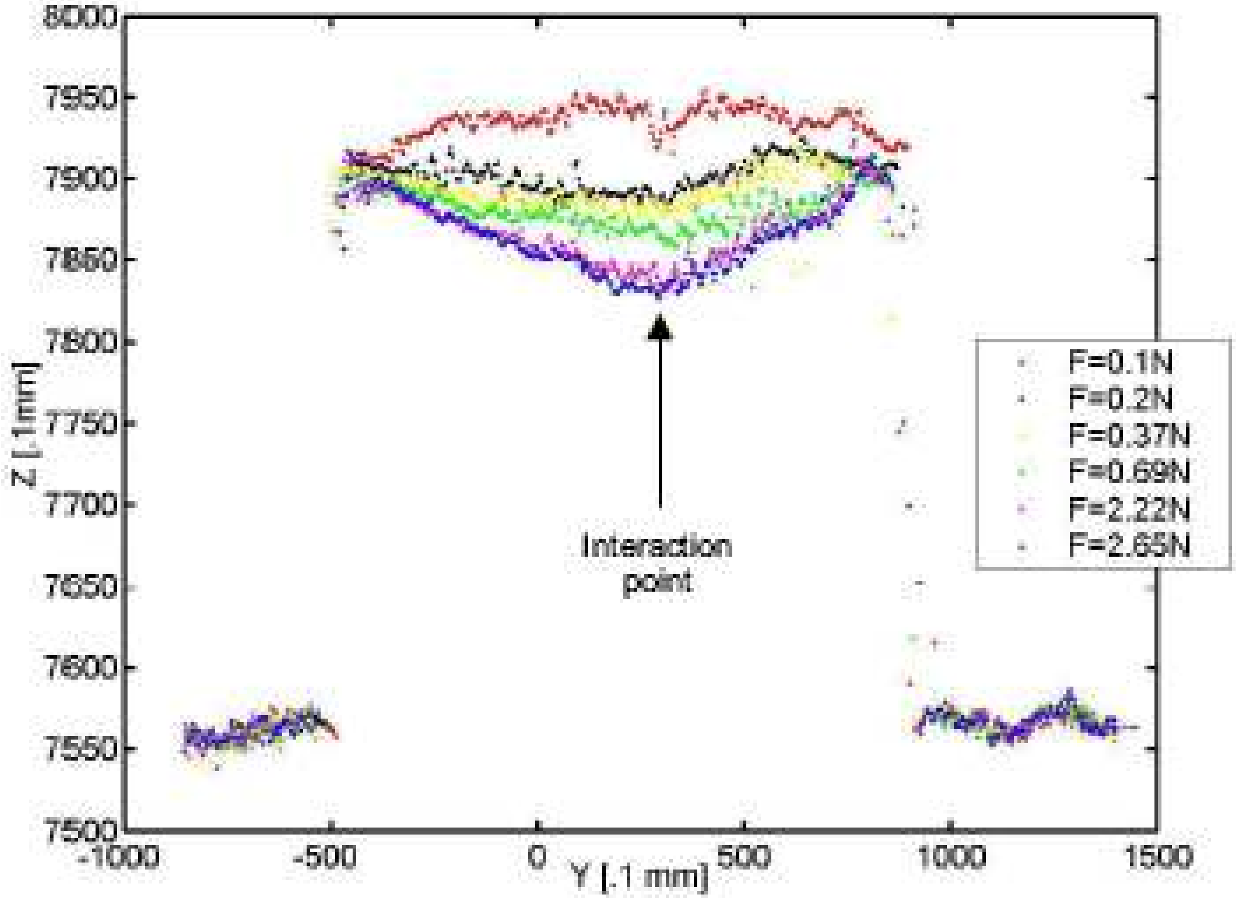
Sampling points selected with
the neural gas network for the ball.

Different magnitudes of a normal force are applied successively on the selected sampling points using the probe attached on the **force/torque sensor** and a range profile is collected with the **laser range finder** for each force magnitude.

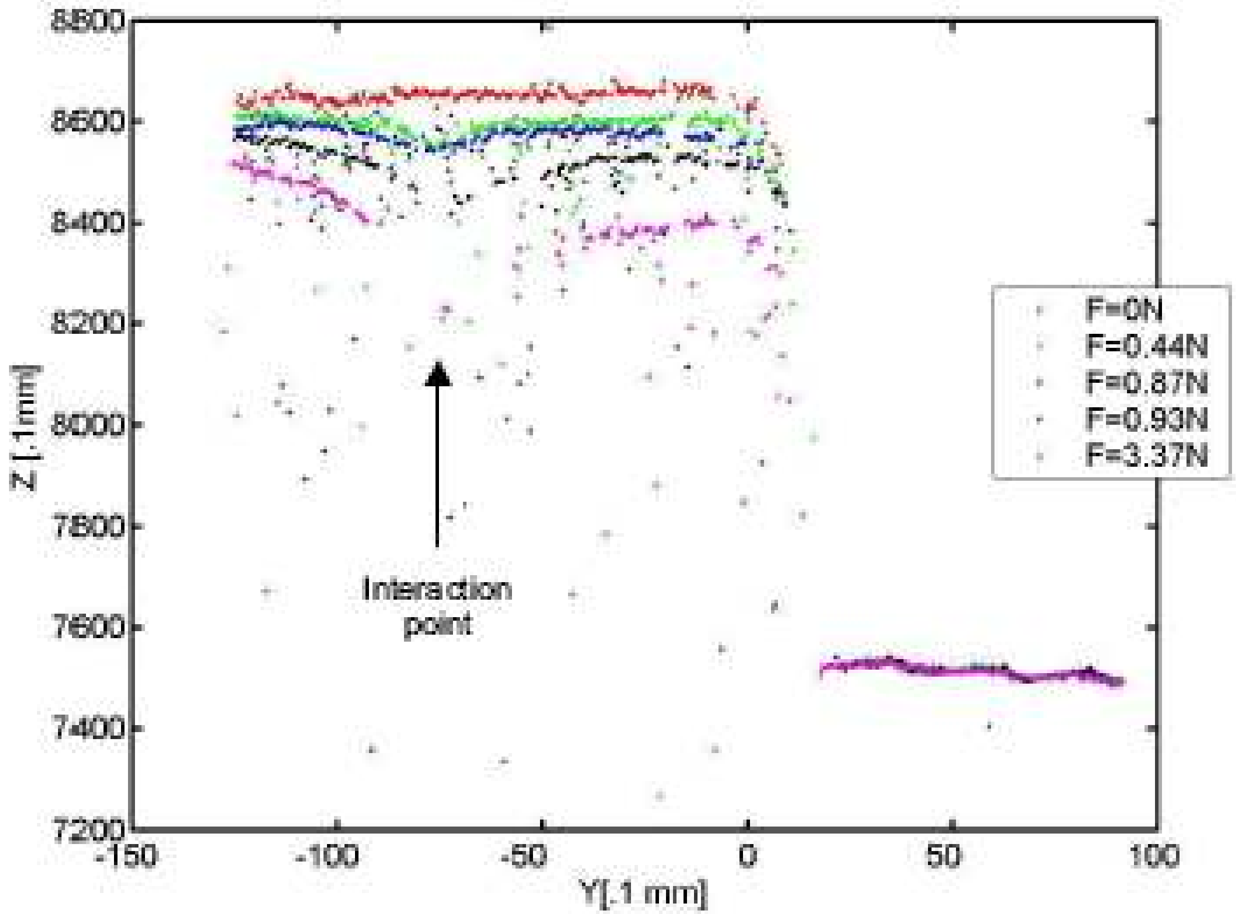


There is no need to recover the explicit displacement information from the range profiles. Instead the NN models use the raw range data as a function of applied force, F, without explicitly defining values for the displacement. For each cluster of similar elasticity, a feed-forward NN with two input neurons (F and a), 45 hidden neurons (H_1-H_{45}) and one output neuron (Z), is used to learn the relation between forces and the corresponding geometric profiles provided by the range finder.

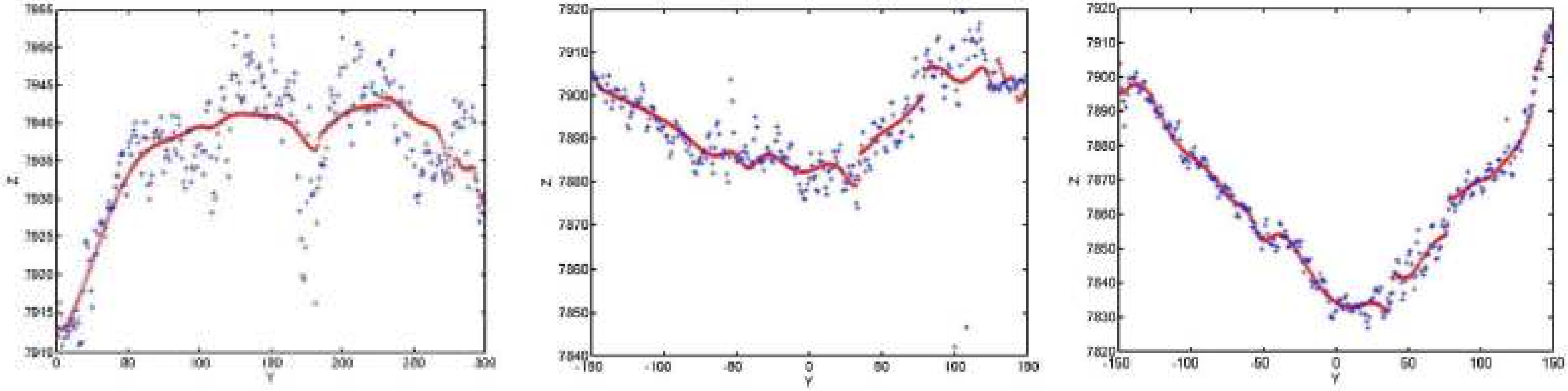
The NN associated with each material were trained for 10,000 epochs using the Levenberg-Marquardt variation backpropagation algorithm with the learning rate set to 0.1. The whole data set is used for training in order to provide enough samples. The training takes approximately 10 min. on a Pentium IV 1.3GHz machine with 512MB memory. For the rubber, the sum-squared error reached during training is 3.7×10^{-3}, for cardboard is 3.5×10^{-2} while for the foam is 2.2×10^{-2}. As expected, the error is lower for the rubber where data is more compact and less noisy, while it remains slightly higher for the cardboard and even higher for the foam. But in all cases, excellent convergence is achieved.



Deformation profiles for semi-stiff material (cardboard).

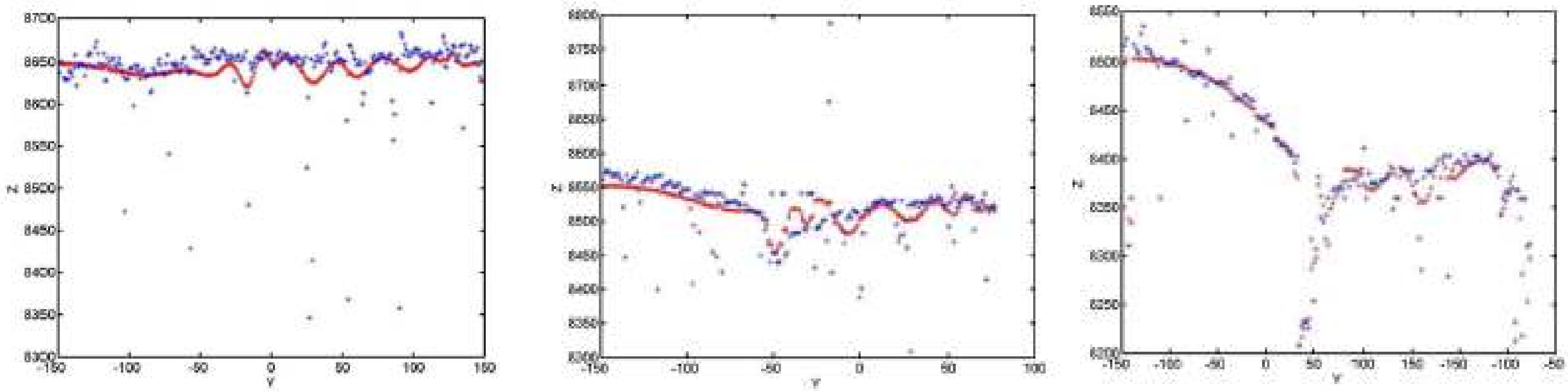


Deformation profiles for smooth material (foam).



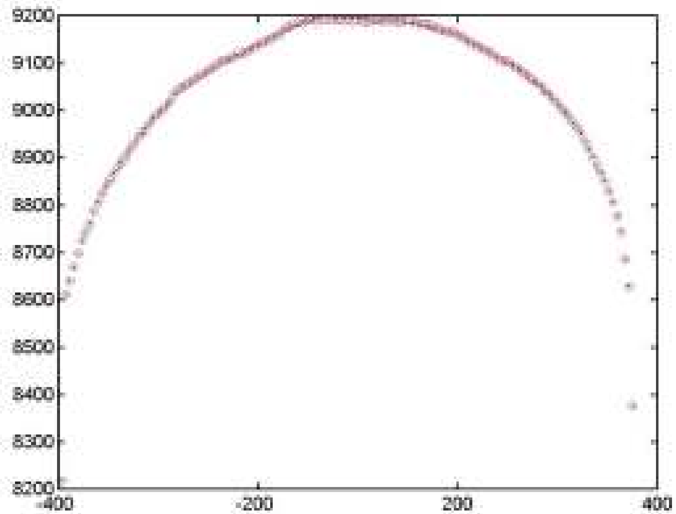
(a) (b) (c)

Real and modeled deformation curves using neural network for semi-stiff material (cardboard) under a normal force of: a) F=0.1N, b) F=0.37N, and c) F=2.65N.

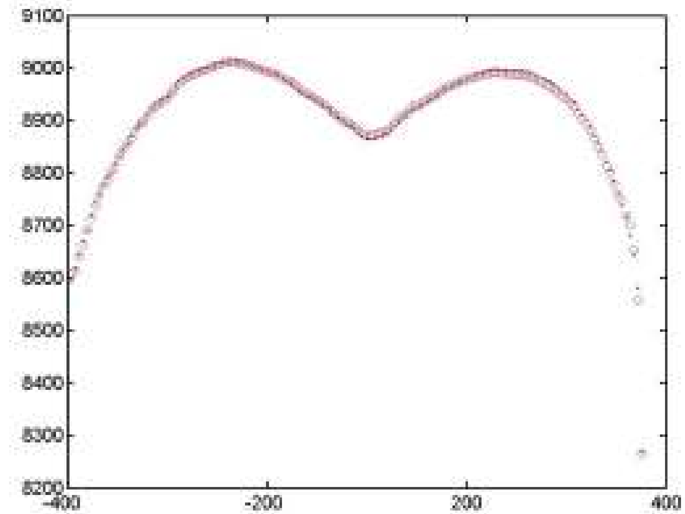


(a) (b) (c)

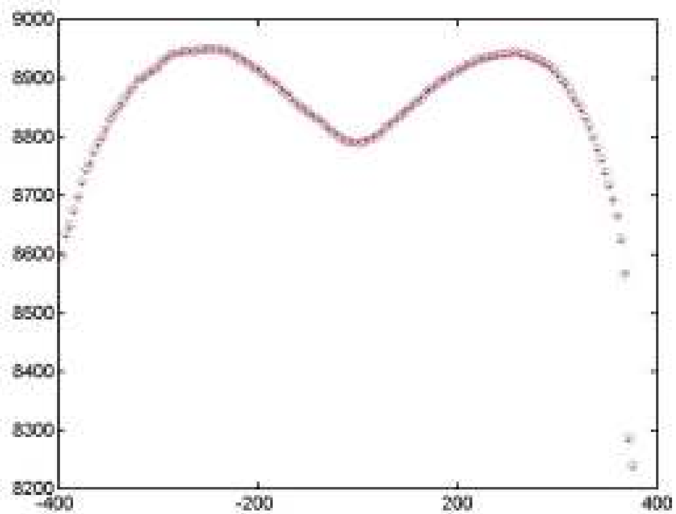
Real and modeled deformation curves using neural network for smooth material (foam) under a normal force of: a) F=0N, b) F=0.93N, and c) F=3.37N.



(a)

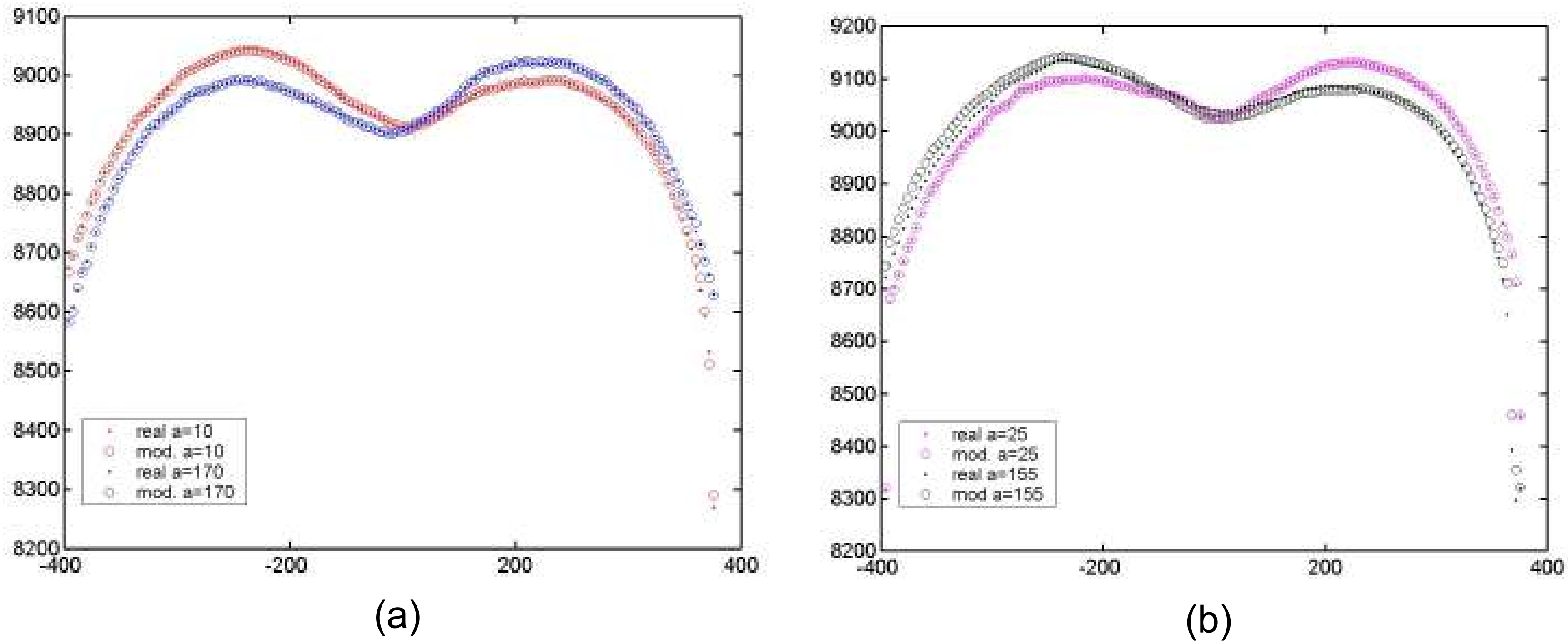


(b)



(c)

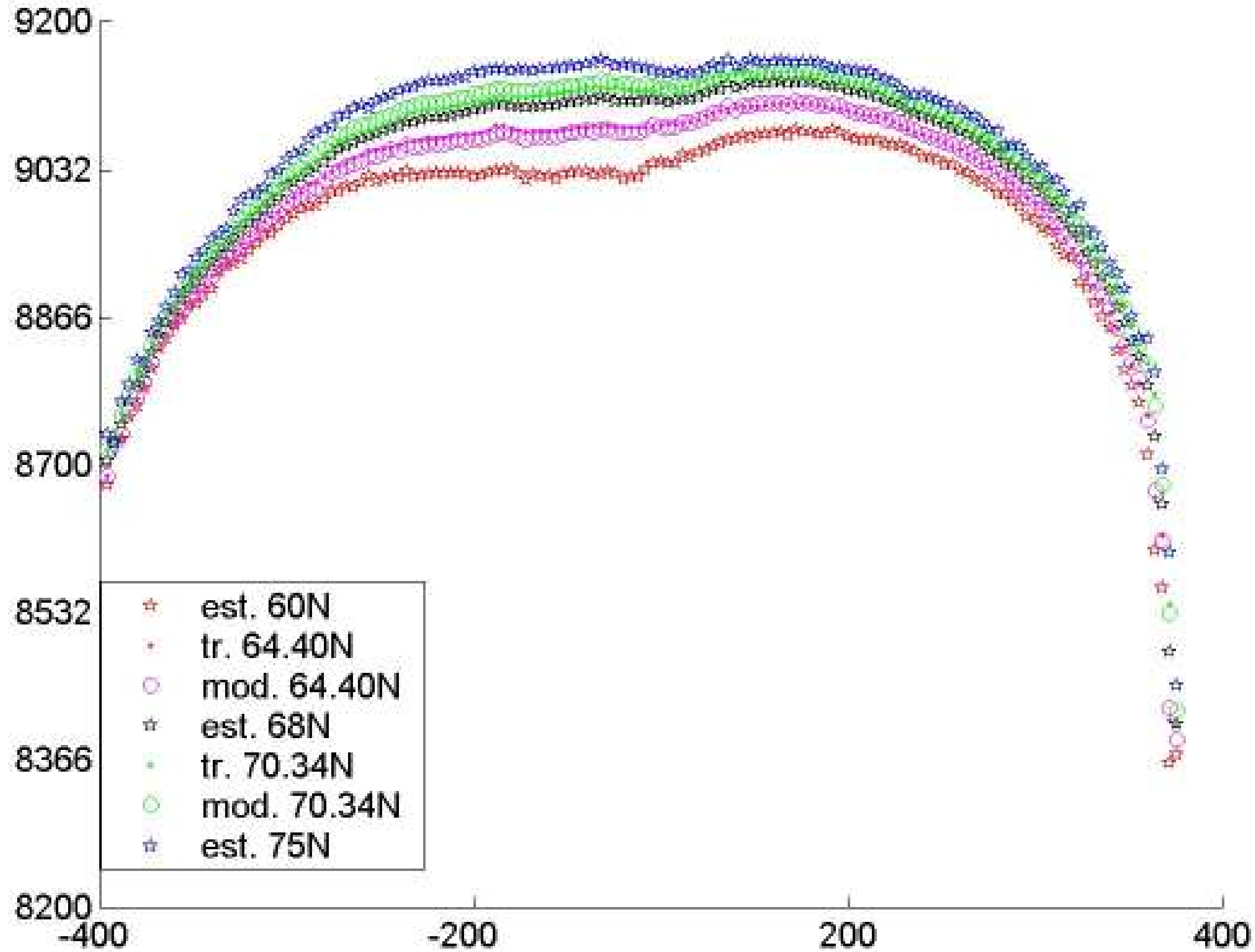
Real and modeled deformation curves using neural network for rubber under a normal force of: a) F=0N, b) F=65.52N, and c) F=80.5N.



Real and modeled deformation curves using neural network for rubber under forces applied at different angles:

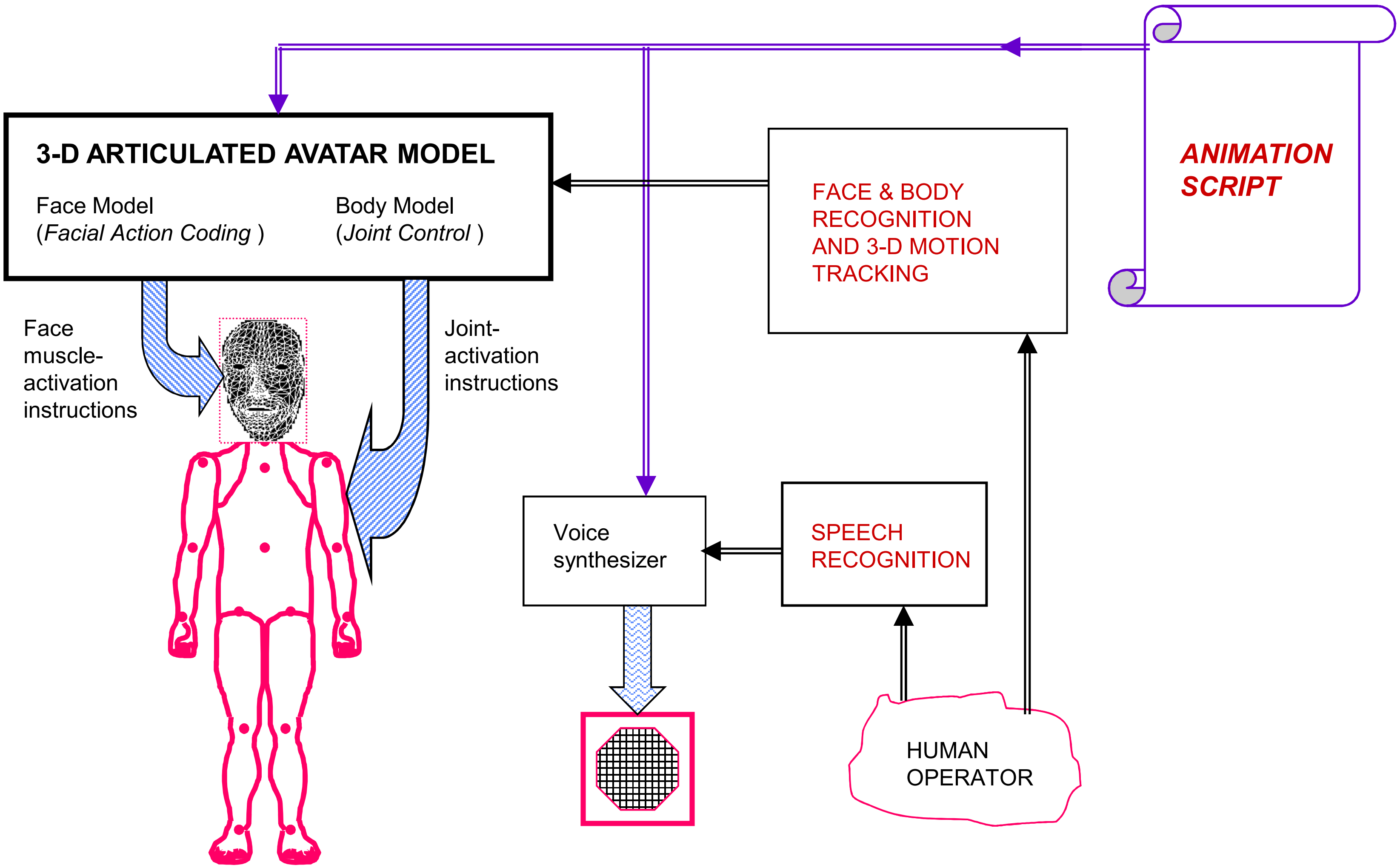
a) F=65N, a_1=10° and F=65N, a_2=170°,

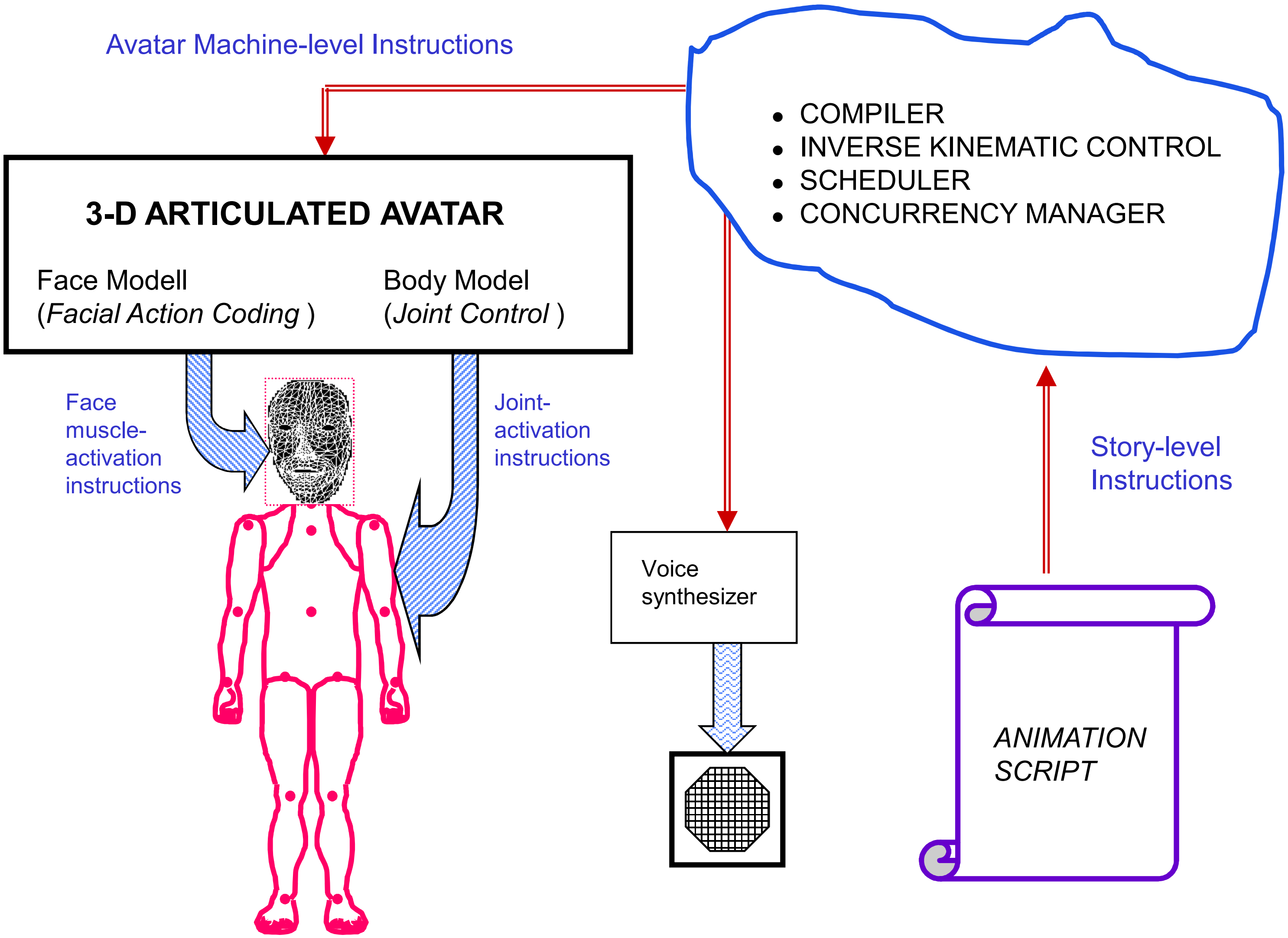
b) F=36N, a_1=25°, and F=36N, a_2=155



Real, modeled and estimated deformation profiles detail of estimated deformation profiles using neural network for rubber ball for increasing forces applied at 75-degree angle.

Modelling Avatar Behaviours in Interactive Virtual Environments.


3-D ARTICULATED AVATAR MODEL
Face Model
(Facial Action Coding)
Body Model
(Joint Control)
Face muscle-activation instructions
Joint-activation instructions
FACE & BODY RECOGNITION AND 3-D MOTION TRACKING
ANIMATION SCRIPT
Voice synthesizer
SPEECH RECOGNITION
HUMAN OPERATOR


Avatar Machine-level Instructions
COMPILER
INVERSE KINEMATIC CONTROL
SCHEDULER
CONCURRENCY MANAGER
3-D ARTICULATED AVATAR
Face Modell
(Facial Action Coding)
Body Model
(Joint Control)
Face muscle-activation instructions
Joint-activation instructions
Story-level Instructions
Voice synthesizer
ANIMATION SCRIPT

Scripting Language: Abstraction Levels

- Three levels of abstraction for the avatar animation scripting language:
  - Highest: story-level description
    - constrained English-like description
    - syntactic and semantic analysis to extract information such as: main player(s), action, subject and object of the action, relative location, degree, etc.
    - translate in a set of skill-level instructions, that may be executed sequentially or concurrently
  - Middle: skill-level macro-instructions
    - describe basic body and facial skills (such as walk, smile, wave hand, etc.)
    - each skill involves a number of muscle/joint activation instructions that may be executed sequentially or concurrently
  - Lowest: muscle/joint activation instructions
    - activation of individual muscles or joints to control the face, body or hand movement

Personalizing Skills

- Add “personality” to skill-level macro-instructions
  - different avatars may perform a certain skill in a “personalized” way
    - examples: “walk like Charlie Chaplin”
      “write like Emil”
  - there is a skill generalization/specialization relationship (similar to object-oriented systems) between
    - a generic skill
    - one or more specialized (or personalized) skills
- Personalizing skills
  - by using Neural Network models
    - off-line training
    - on-line rendering

STORY-LEVEL DESCRIPTION

…..
DanielA sits on the red chair.
DanielA writes "Hello" on stationary.
DanielA sees HappyCat under the white table and starts smiling.
HappyCat grins back.
……

SKILL-LEVEL ("MACRO") INSTRUCTIONS

…..
DanielA's right hand moves the pen to follow the trace representing "H".
DanielA's right hand moves the pen to follow the trace representing "e".
DanielA's right hand moves the pen to follow the trace representing "l".
DanielA's right hand moves the pen to follow the trace representing "l".
DanielA's right hand moves the pen to follow the trace representing "o".
……

SKILL-LEVEL MACRO-INSTRUCTIONS

…

DanielA’s right hand moves the pen to follow the trace representing “H”.

…

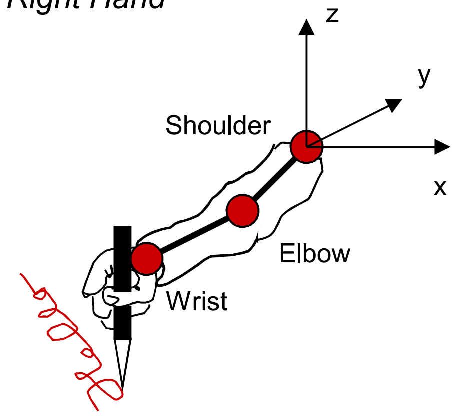
DanielA’s specific style of moving his right arm joints to write “H” (**NN model capturing DanielA’s writing personality**)

Rotate Wrist to a^i

Rotate Elbow to b^j

Rotate Shoulder to g^k

3-D Model of DanieA’s Right Hand



- M. Costa, P. Crispino, A. Hanomolo, and E. Pasero, "Artificial Neural Networks and the Simulation of Human Movements in CAD Environments", *International Conference on Neural Networks*, 1997, vol. 3, pp. 1781 -1784

Thank You!