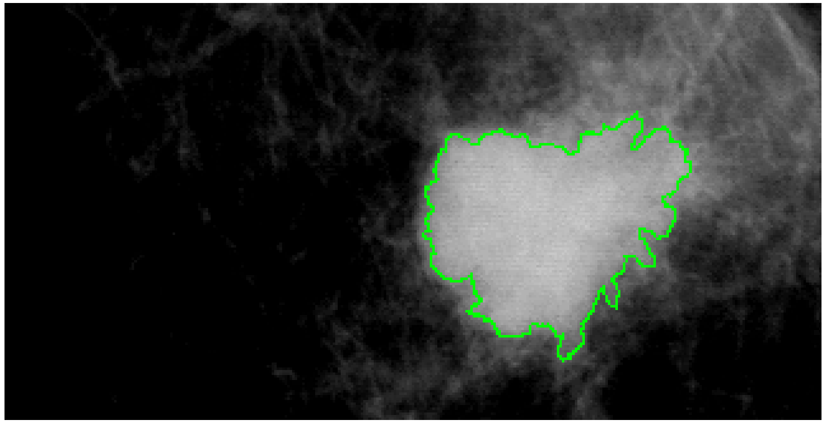
Mammographic Mass Shape Characterization using Neural Networks



H. Georgiou[1](xgeorgio@hol.gr), D. Cavouras [2](cavouras@hol.gr), N. Dimitropoulos[3], S. Theodoridis[1](stheodor@di.uoa.gr).

[1] Informatics Dept., University of Athens, TYPA buildings, Univ. Campus, 157 71, Athens.
[2] Medical Instrument Technologies Dept., 12210, Athens.
[3] Medical Imaging Dept., EUROMEDICA Medical Center, 2 Mesogeion ave, Athens.

Abstract

The purpose of this project is the automated classification of mammographic masses according to the contour shape in one of five predefined categories, which can be indicative to the degree of benignancy or malignancy of the mass.

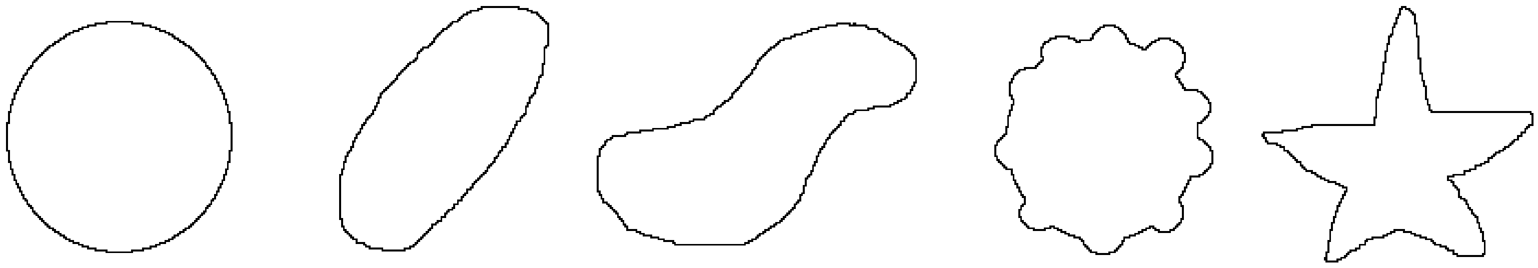
The contour shape of the mass retrieved from mammographic images was used to classify the mass as knotty (round, oval, lobulated, nodular) or stellate type. The morphology of the mass can be usefull in their characterization as benignant or malignant.

The mammographic mass border line was constructed using histogram thresholding techniques. The classification of shapes in one of the five categories was performed by using Pattern Recognition techniques and with the use of Neural Network (NN). Eleven attributes of the border line were used as input, calculated as the radial distance from the mass center, while the five classification categories were used as output. The internal network topology included 1 hidden neuron layer with 8 neurons. A set of patterns was used for the training phase and another one for the evaluation phase of the system.

The precision of correct classification of the masses in one of the five predefined morphologic categories was nearly 90%. The largest classification error percentage (5%) was noted between masses with round and nodular shape.

Mass Shape Classification

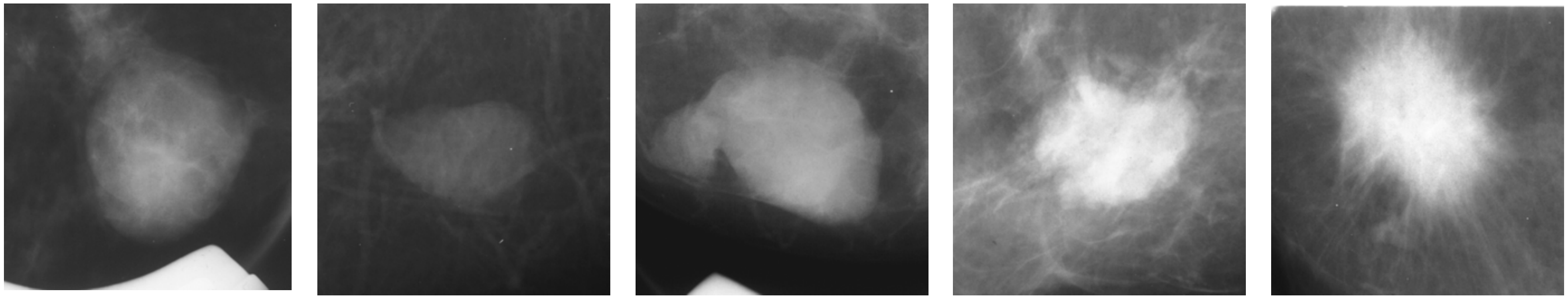
- Contour shape of the mass retrieved from mammographic images
- Mass classification as nodular (round, oval, lobulated, microlobulated) or stellate type



- May be of value to mass characterization as benign or malignant

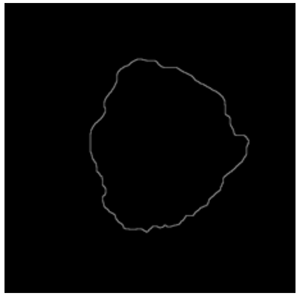
Material & Methods

Step-1: Image processing for mass shape determination employing histogram thresholding techniques

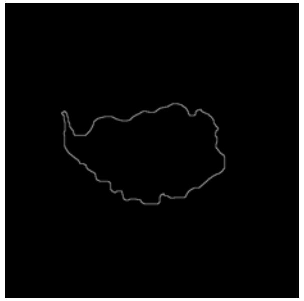


Round Oval Lobulated Nodular Stellate

Material & Methods



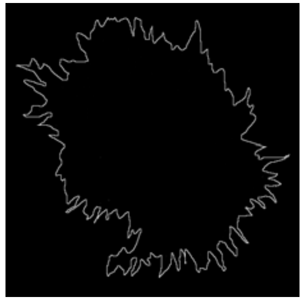
Round



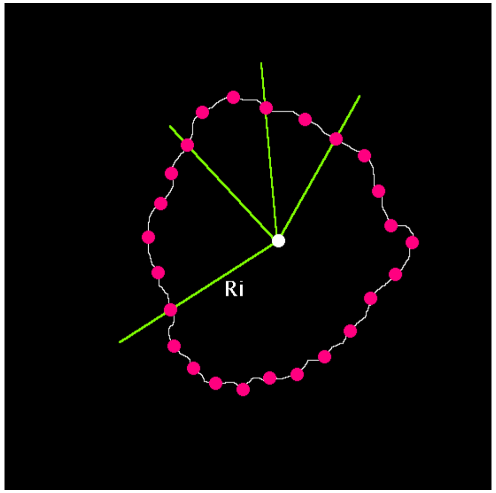
Oval

Lobulated

Nodular



Stellate

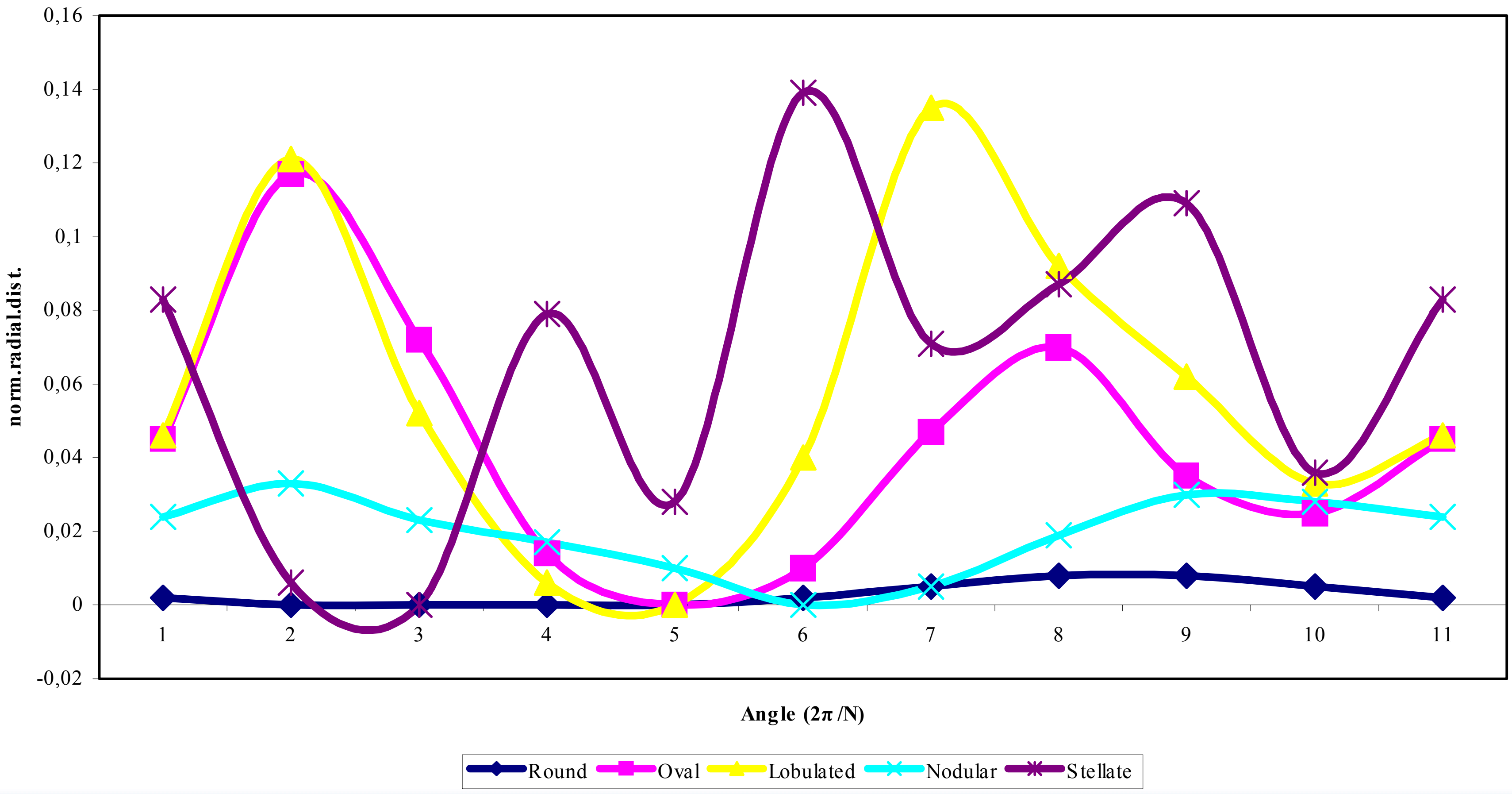


Step-2: Boundary line determination

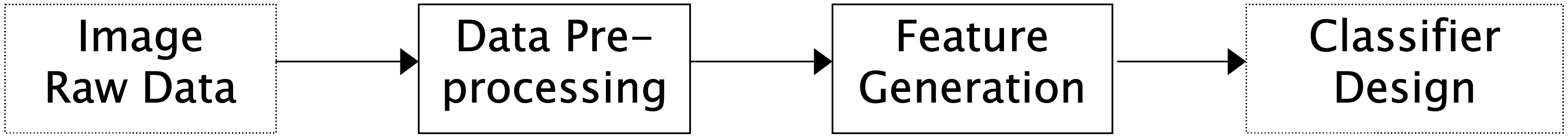
Step-3: Retrieve shape boundary using radial distance from mass center

Material & Methods

Unfolded normalized shape boundary curves (11-point)



Classifier Design



- Generate feature set from raw data
- Use most effective features
- Train classifier with feature set

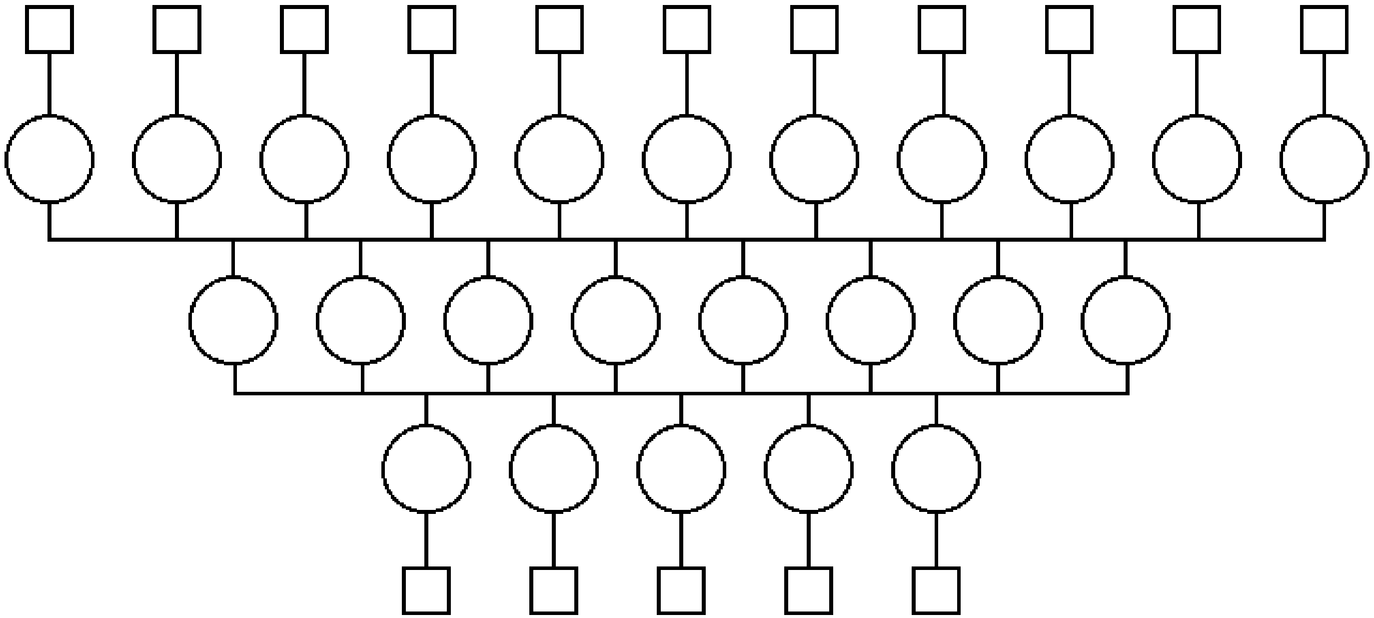
Neural Network Employed

Neural Network:

- feed-forward
- fully connected

Current topology:

- 11-point input vector
- 1 hidden layer (8 neurons)
- 5-class output vector



Classifier Specifications

Network Architecture:

Tolology

- Feed-forward fully connected Neural Network
- Sigmoid neuron activation
- Layers: 11-8-5 (inp-hid-out)

Training

- Back-Propagation method
- Leave-Half-Out on-line training
- Learing rates: l=0.15, m=0.05
- Less than 1000 epochs

Simulated data set:

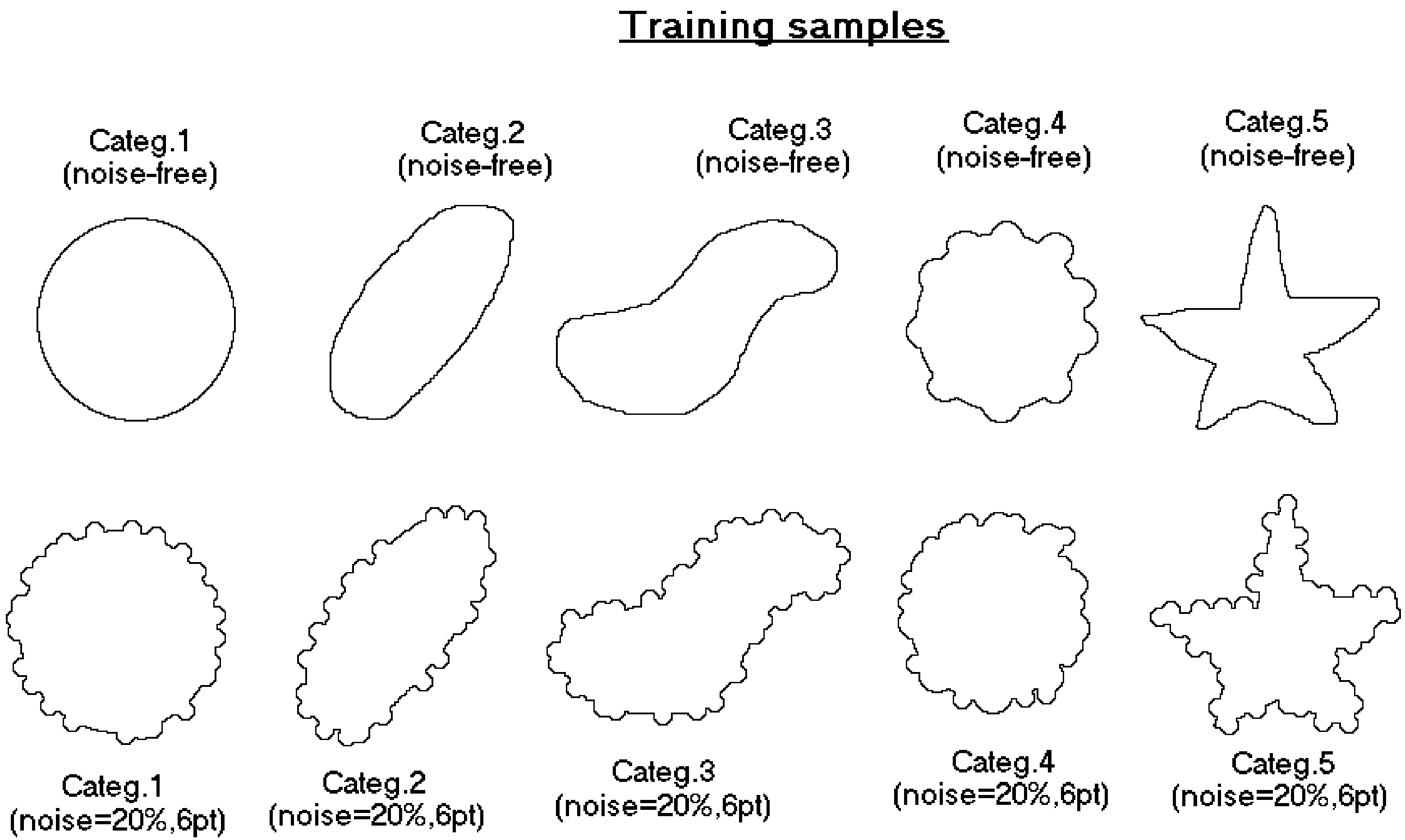
Training

- Disturb. probabilities: 10%-30%
- 100 patterns per class (5x100)
- 50% for training (253)
- 50% for validation (252)

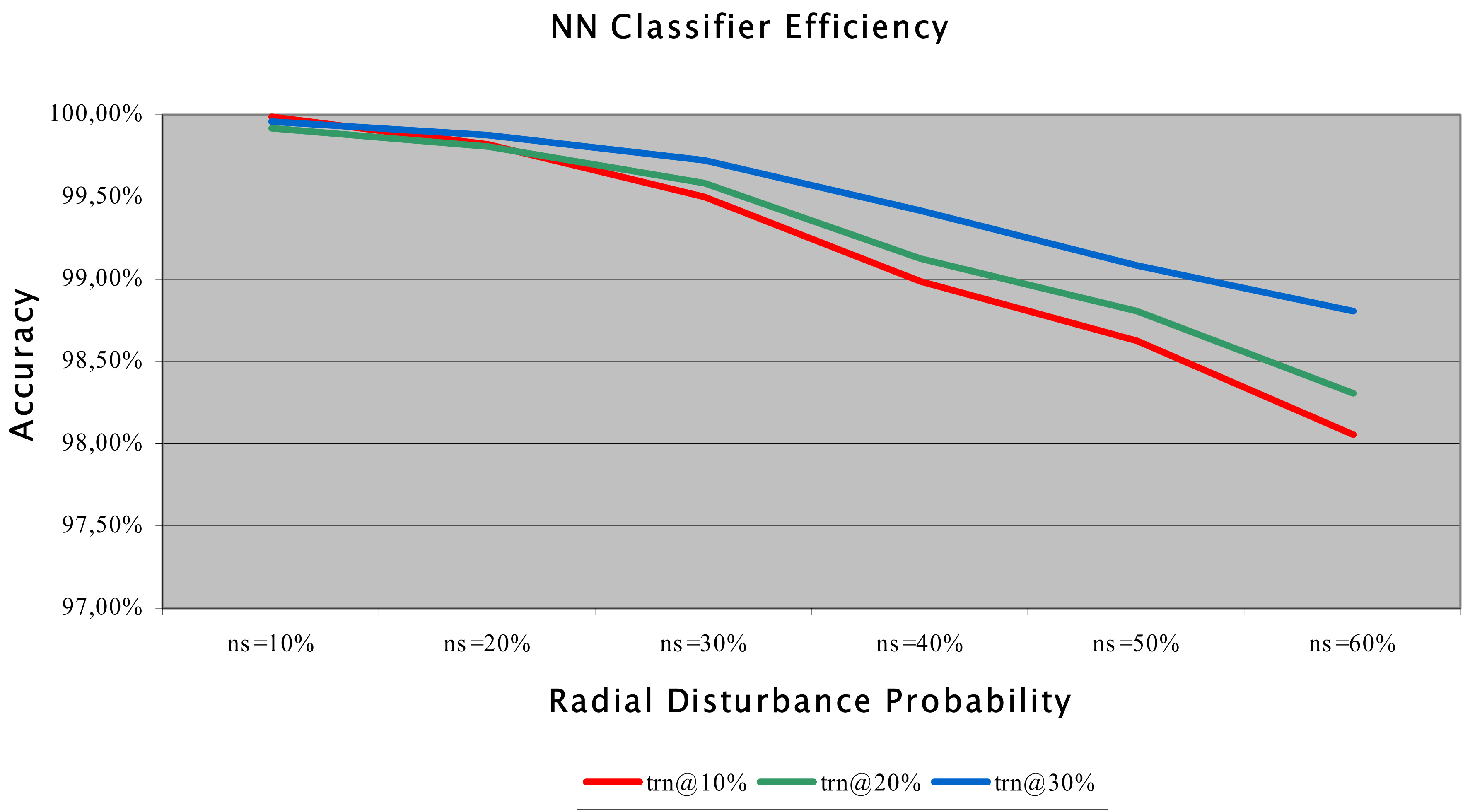
Evaluation

- 10% radial disturbance
- Disturb. probabilities: 10%-60%
- 1000 patterns per class (5x1000)

Simulated Contour Shapes



Classifier Results



Conclusions

- High Neural Network classification accuracy (>90%)
- Little degration in efficiency with large radial disturbances in each mass shape category
- Highest classification error (<5%) between round and nodular mass shapes
- Robust NN classifier design & implementation

References

[01] Khotaznad, «Classification of Invariant Image Representations using a Neural Network», IEEE Trans. on Acoustics, Speech and Signal Proc., vol.38, No 6, 1990.

[02] R. Gonzalez, R. Woods, «Digital Image Processing», Addison-Wesley Publishing Company, 1992.

[03] Lori Mann Bruce, Reza R. Adhami, «Classifying Mammographic Mass Shapes Using the Wavelet Transform Modulus-Maxima Method», IEEE Trans. on Medical Imaging, vol.18, No 12, 1999.

[04] Jong Kook Kim, Hyun Wook Park, «Statistical Textural Features for Detection of Microcalcifications in Digitized Mammogramms», IEEE Trans. on Medical Imaging, vol.18, No 3, 1999.

[05] Baoyu Zheng, Wei Qian, Laurence Clarke, «Digital Mammography: Mixed Feature Neural Network with Spectral Entropy Decision for Detection of Microcalcifications», IEEE Trans. on Medical Imaging, vol.15, No 5, 1996.

[06] Songyang Yu, Ling Guan, «A CAD System for the Automatic Detection of Clustered Microcalcifications in Digitized Mammogram Films», IEEE Trans. on Medical Imaging, vol.19, No 2, 2000.