# Nano-scale fault tolerant machine learning for cognitive radio


Jaakko Peltonen[1], Mikko A. Uusitalo[2], and Joni Pajarinen[1]

[1]Helsinki University of Technology, Department of Information and Computer Science, P.O.Box 5400, FI-02015 TKK, FINLAND

[2]Nokia Research Center, Nanosystems, 11-13 Itämerenkatu, Helsinki 00180, NOKIA GROUP, FIN 00045, FINLAND

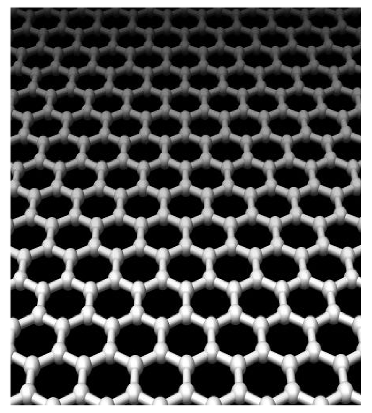
Jaakko.Peltonen@tkk.fi
Mikko.A.Uusitalo@nokia.com
Joni.Pajarinen@tkk.fi



**One-sentence summary:** We introduce the first architecture proposal for nano-scale cognitive radio and show that it performs well under a physically reasonable error model.


## Background

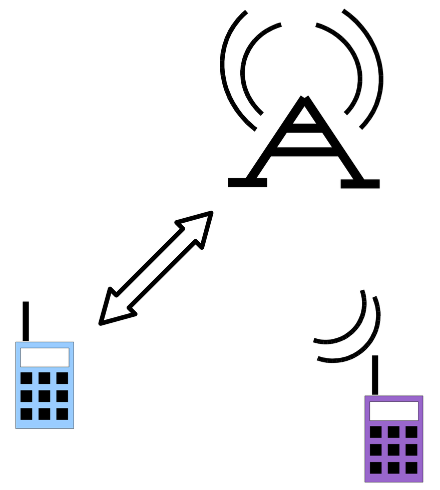
**Nanotechnology**



- Manipulation of matter at the scale of 1 to 100 nm
- *Nanocomputing* is a major attraction of nanotechnology:
  - Large numbers of components can be packed on a small device
  - Closely connected components can operate faster
  - Less power is needed at smaller scales
- State of the art:
  - Manufacturing and analyzing components like nanowires
  - Theoretical proposals of architectures or at best abstract simulations

**Cognitive radio**

- Optimal radio channel usage requires analysis of the radio environment
- At simplest a classification problem: each radio channel is classified either "occupied" or "free"
- Nanocomputing can operate with less power than conventional electronics and could allow integration of cognitive radio into a single handheld device

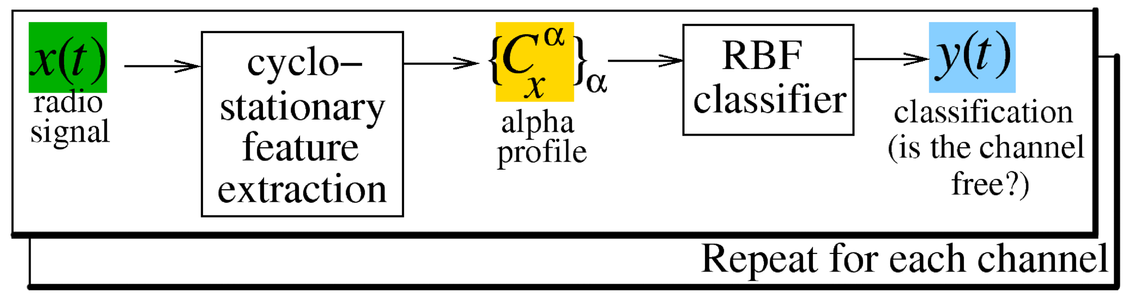


Cognitive radio scanning the radio environment for unused channels

**Fault tolerance**

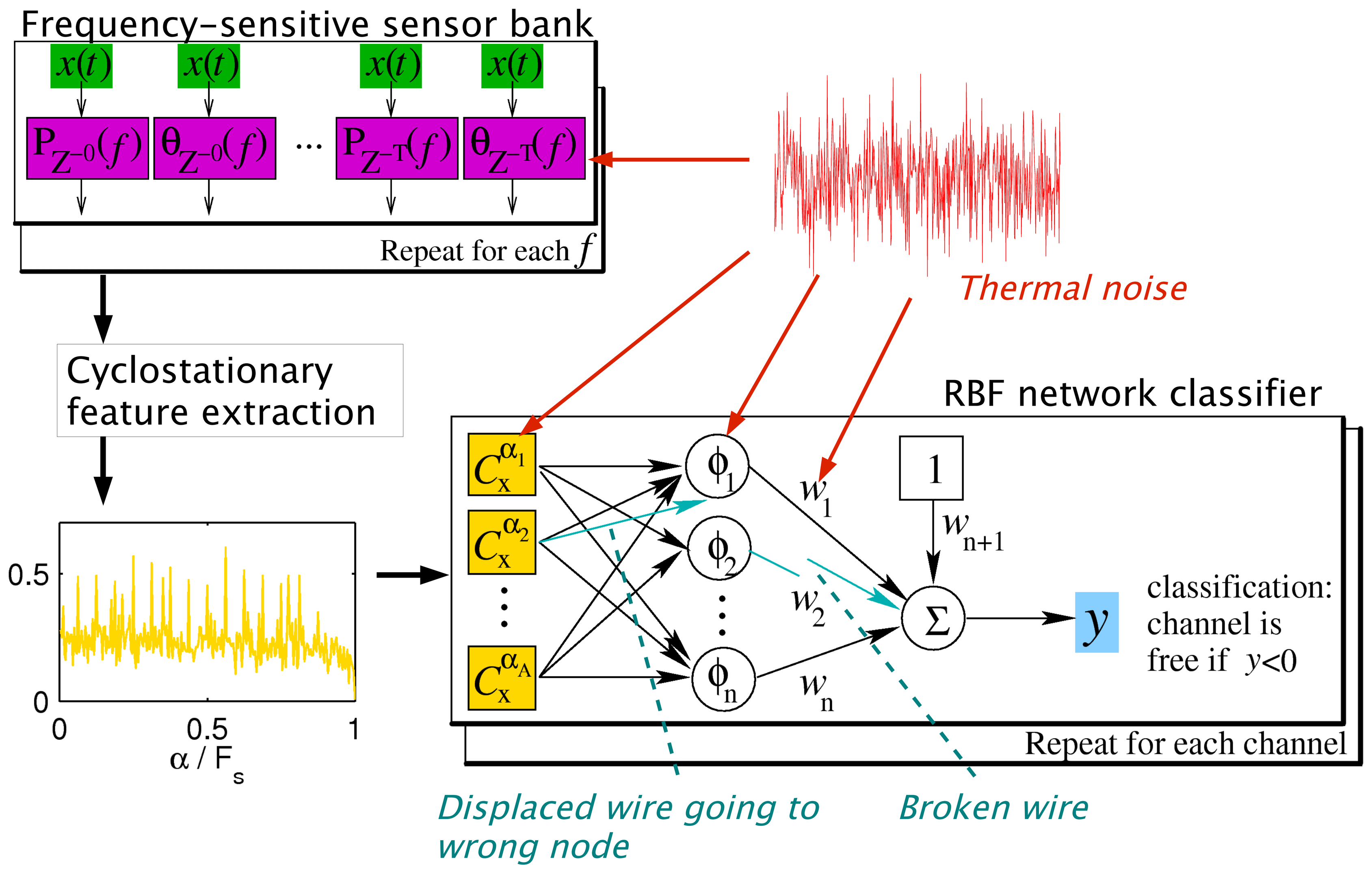
- Because of the nano-scale implementation, our proposed system needs tolerance against noise and broken and displaced elements
- We investigate broken and displaced wires and thermal noise
- Injection of faults into a radial basis function (RBF) network during training makes the system more fault tolerant

## Proposed system



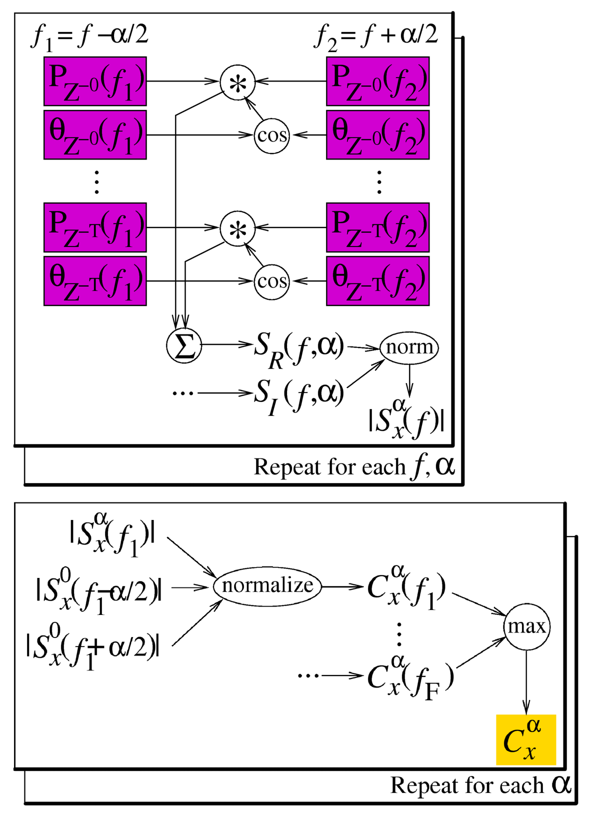

- Signal intercepted by frequency-sensitive sensor banks in the passive analog circuit (sensors for magnitude and phase at each frequency)
- Cyclostationary features are extracted from sensor banks
- Fault tolerant RBF network classifies the signal using the computed features
- Properties:
  - Feature extraction is generic in the sense that it could extract features from different kinds of cyclostationary signals
  - Whole system in nano-scale: minimizes nano/non-nano communication
  - RBF network parameters are trained and then manufactured into the device

## Error model




- Physically reasonable expected fault levels
- *Thermal noise*: Normally distributed noise is added to computing operations according to the physical signal/noise voltage proportions at each computing unit
  - Feature extraction: Noise on the frequency sensors and the extracted features
  - RBF network: Noise on the centroids, spreads, hidden units, wire weights
- Structural faults in the RBF network
  - *Broken wire*: 1% probability
  - *Displaced wire going to neighboring RBF network unit*: 0.1% probability
- The RBF network implementation needs nano-scale components for summation, multiplication and a Gaussian kernel function

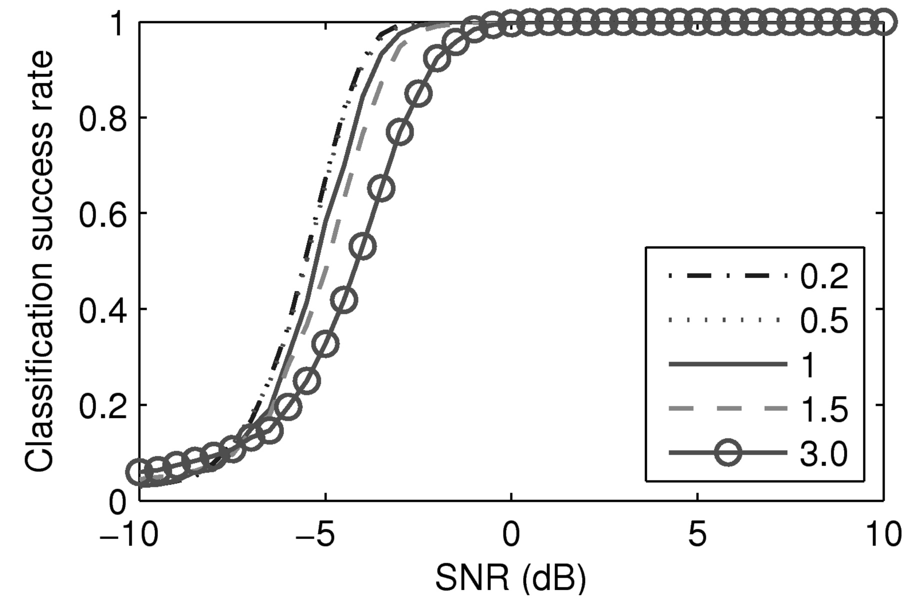
## Cyclostationary feature extraction



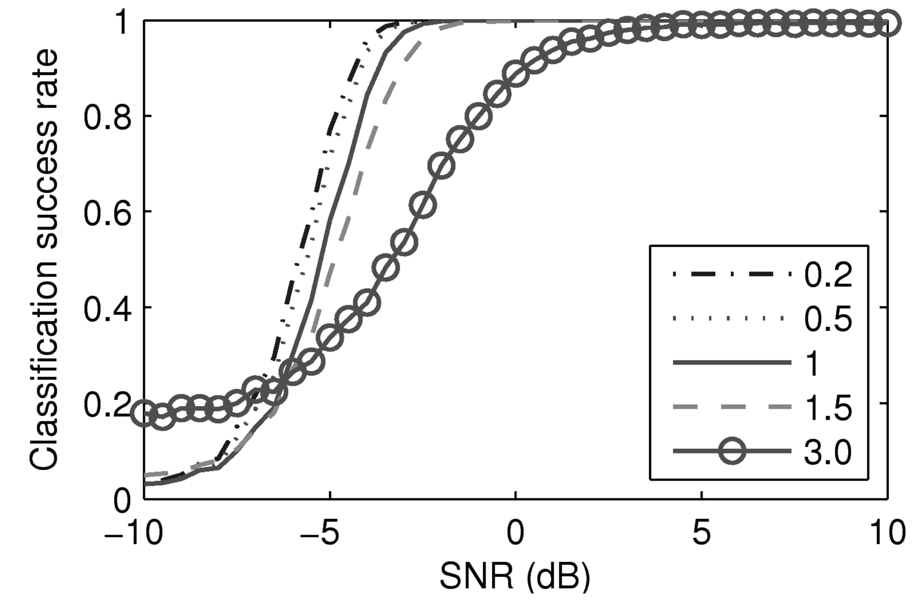

- Cyclostationarity describes a signal that has cyclically time varying statistical properties
- WLAN 802.11a signals have cyclostationary components
- We extract an *alpha profile*: For each cyclic frequency α the maximum of normalized spectral correlations over frequencies is computed
- The implementation needs nano-scale components for
  - Summation
  - Multiplication
  - Cosine of a difference of two angles $\cos(\theta_1-\theta_2)$
  - Norm of two inputs $\sqrt{x_1^2+x_2^2}$
  - Normalization of three positive inputs $\frac{x_1}{\sqrt{x_2 \cdot x_3}}$
  - The maximum of inputs

## Simulation results

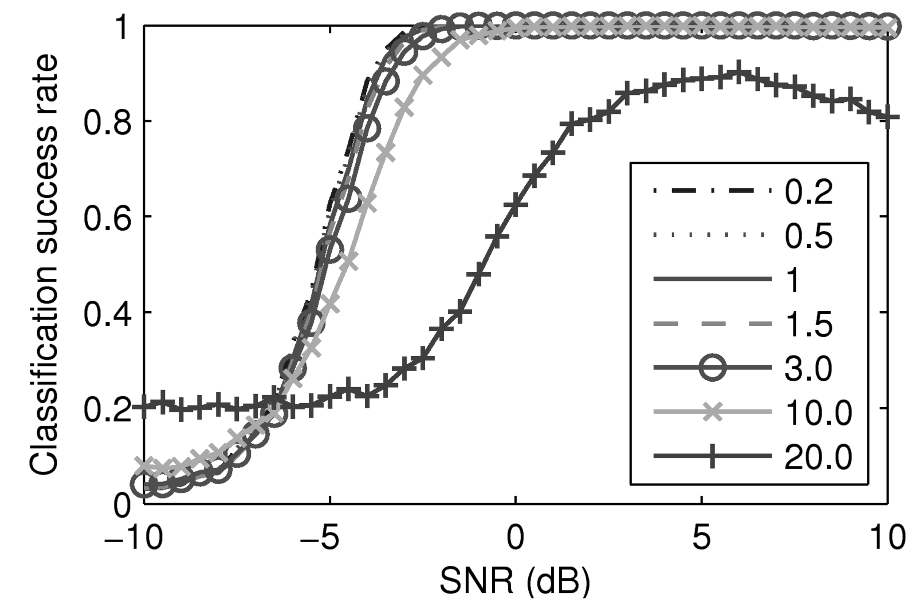
Classification success rate of signal samples (see the paper for noise samples) for varying levels of feature extraction noise faults.




Classification success rate of signal samples for varying levels of RBF network noise fault levels.




Classification success rate of signal samples for varying levels of RBF network structural faults.




**Experiments**

- In each experiment one fault type is studied at several fault levels, while holding the other fault types at the expected fault level 1
- "fault level" is used to multiply STDs of thermal noise and structural fault probabilities
- A WLAN 802.11a simulator generates the input signal
- Same fault levels were used for injecting faults in both training and testing

**Results**

- Small changes to the expected fault level have no major performance impact
- RBF network thermal noise seems to have largest effect on signal classification; this may be because signal voltage is lowest when it reaches the RBF network
- Moderate structural fault levels have little effect suggesting the RBF network contains enough redundancy

**Conclusions**

- First proposal for nano-scale implementation of a cognitive radio
- Performs well under expected fault levels
- Physically reasonable error model
- Works for different kinds of cyclostationary signals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