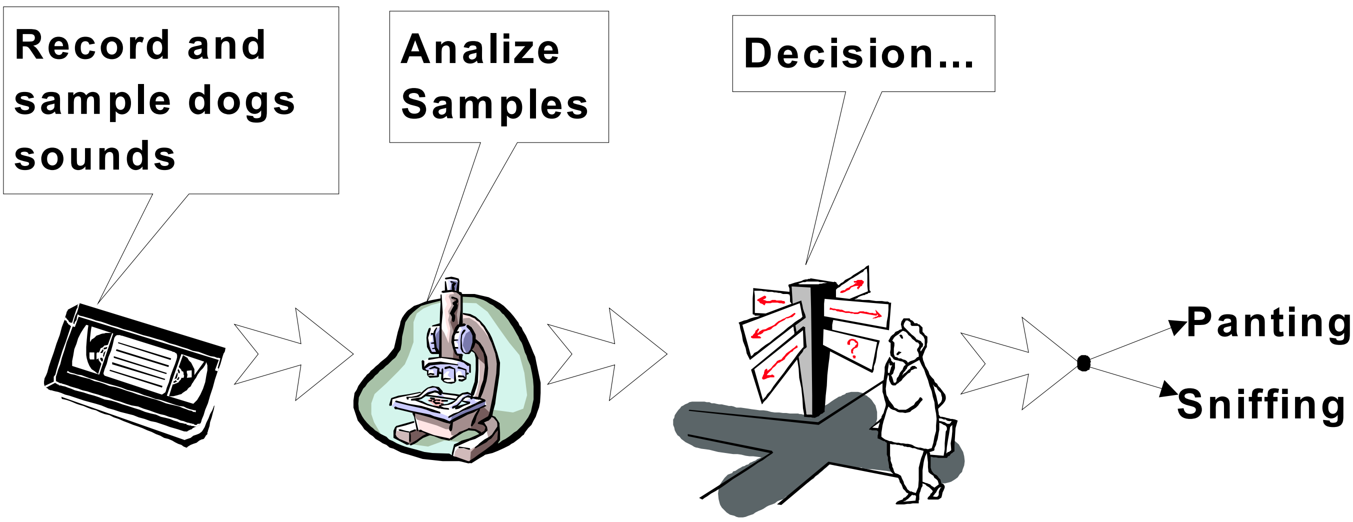
# Detection and Discrimination of Sniffing and Panting Sounds of Dogs

Ophir Azulai(1,4), Gil Bloch(1,5), Yizhar Lavner (1,2), Irit Gazit (3) and Joseph Terkel (3).

1. Signals and Image Processing Lab (SIPL), Faculty of Electrical Engineering, Technion IIT, Haifa, Israel (http://www-sipl.technion.ac.il)
2. Computer Science, Tel-Hai Academic College, Upper Galilee, Israel.
3. Department of Zoology, George S. Wise Faculty of Life Sciences Tel-Aviv University, Tel Aviv 69978, Israel.
4. IBM research lab, Haifa, Israel.
5. Mellanox Technologies LTD.

# Motivation

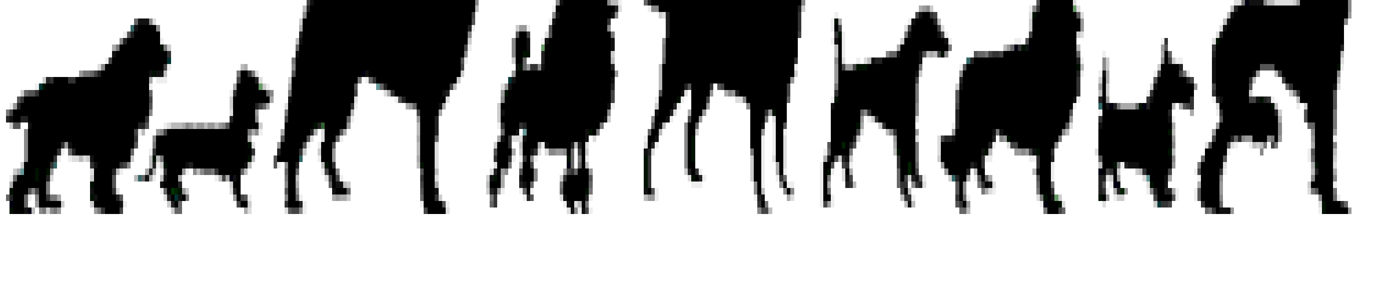
**Dogsí acute sense of smell enables them to accurately identify many types of odors.**
**- Detection of drugs.**
**- Detection of explosives.**
**- Finding people.**
**- Other special tasks.**
**Target: controlling dogsí behavior suggests many potential applications.**



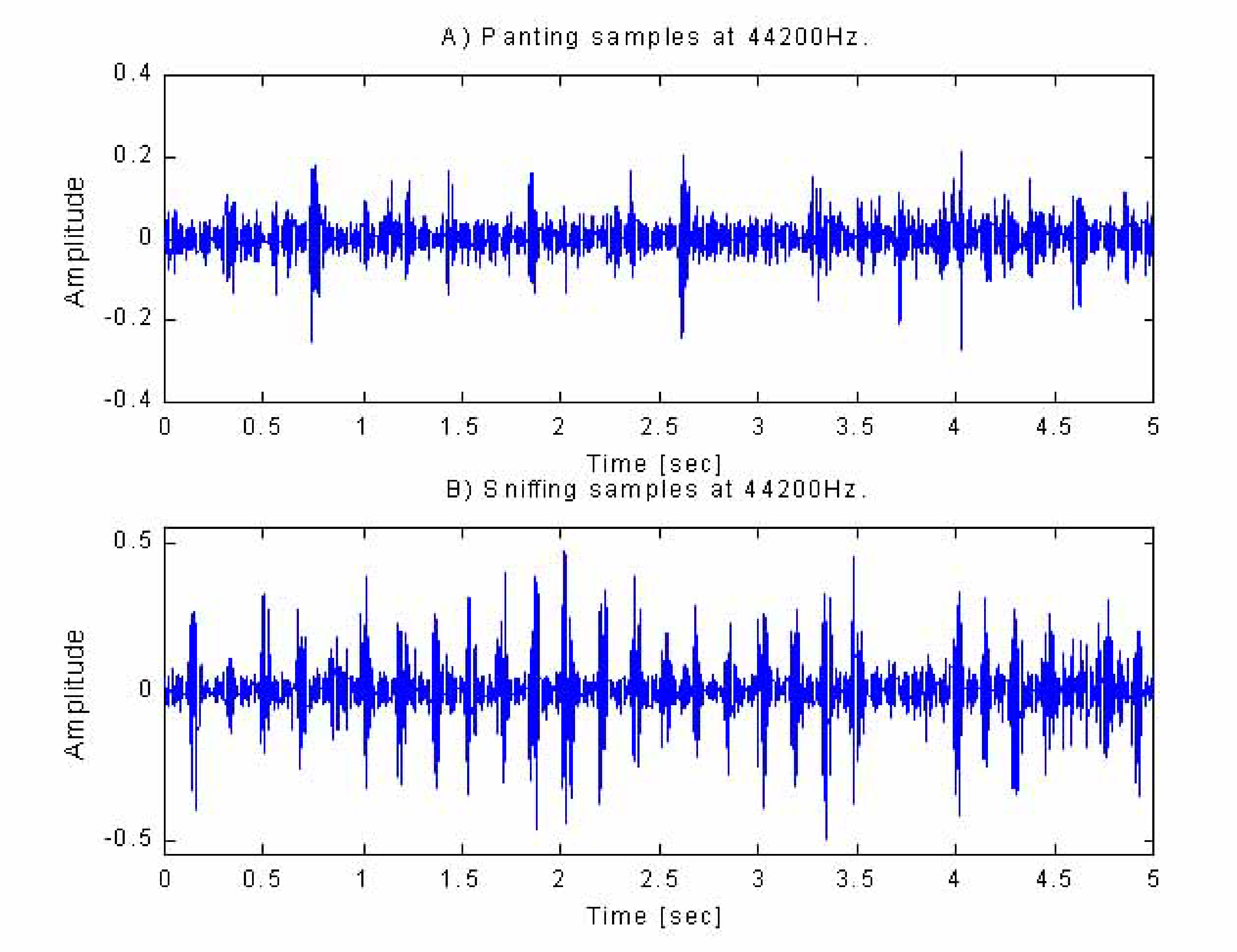
# Abstract

Dogsí acute sense of smell enables them to accurately identify many types of odors. This ability serves in the detection of drugs and explosives, finding people, and other special tasks. The possibility of controlling dogsí behavior suggests many potential applications.

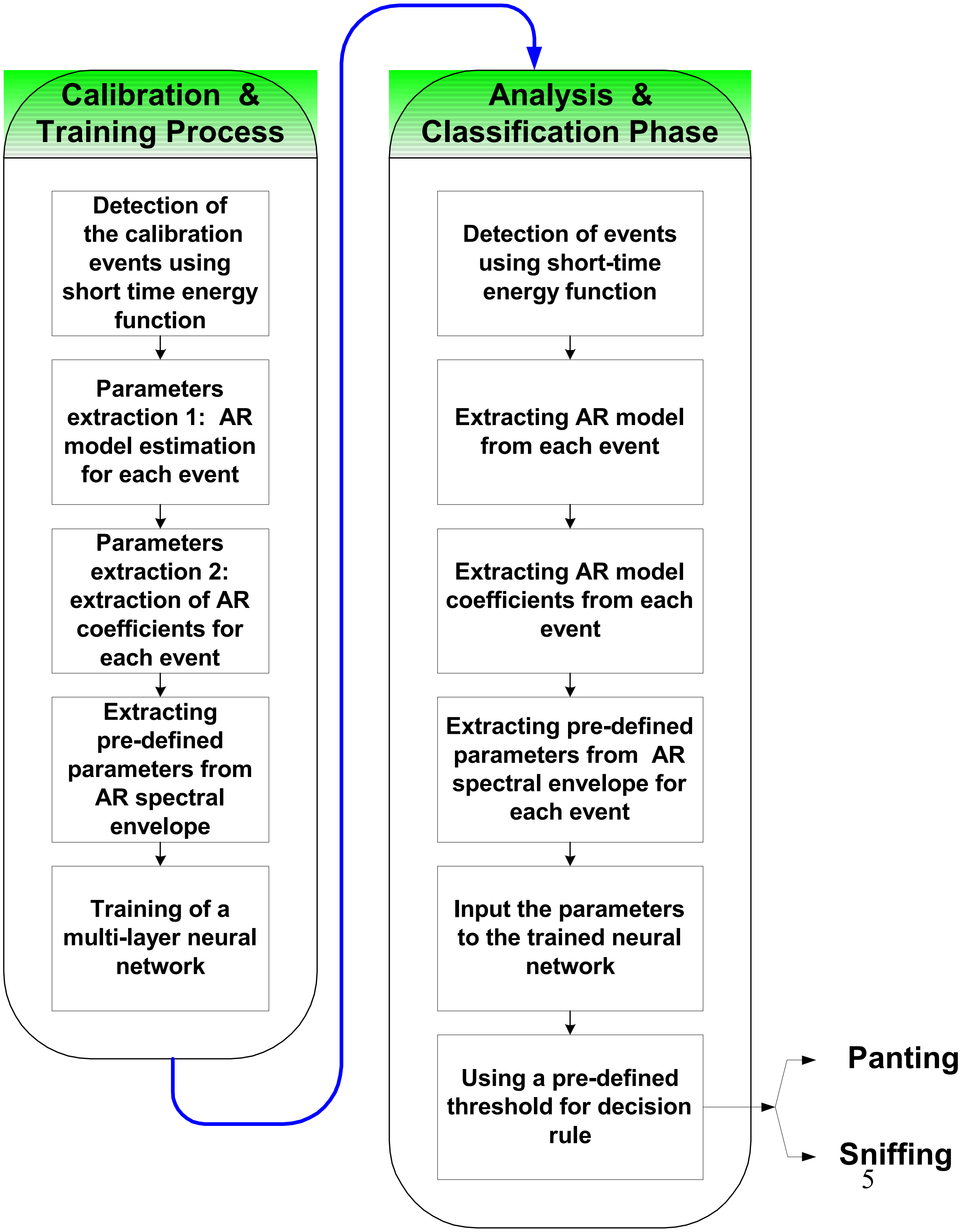
For this purpose, an automatic system for recognition of panting and sniffing according to their corresponding acoustic signals was developed. The system consists of three main components: analysis, training and discrimination. In the analysis stage the events were detected using short-time energy and zero-crossing rate functions. Features for discrimination were extracted utilizing an autoregressive model or by means of a Mel-frequency cepstrum. A few parameters of the spectral envelope were selected, based on their discrimination ability. In the training stage, a feedforward neural network was trained, using labeled signals. Alternatively, a fuzzy K-nearest neighbor algorithm can be used. Correct identification of up to 96.8% was achieved in the discrimination stage.



# Panting and Sniffing Signals

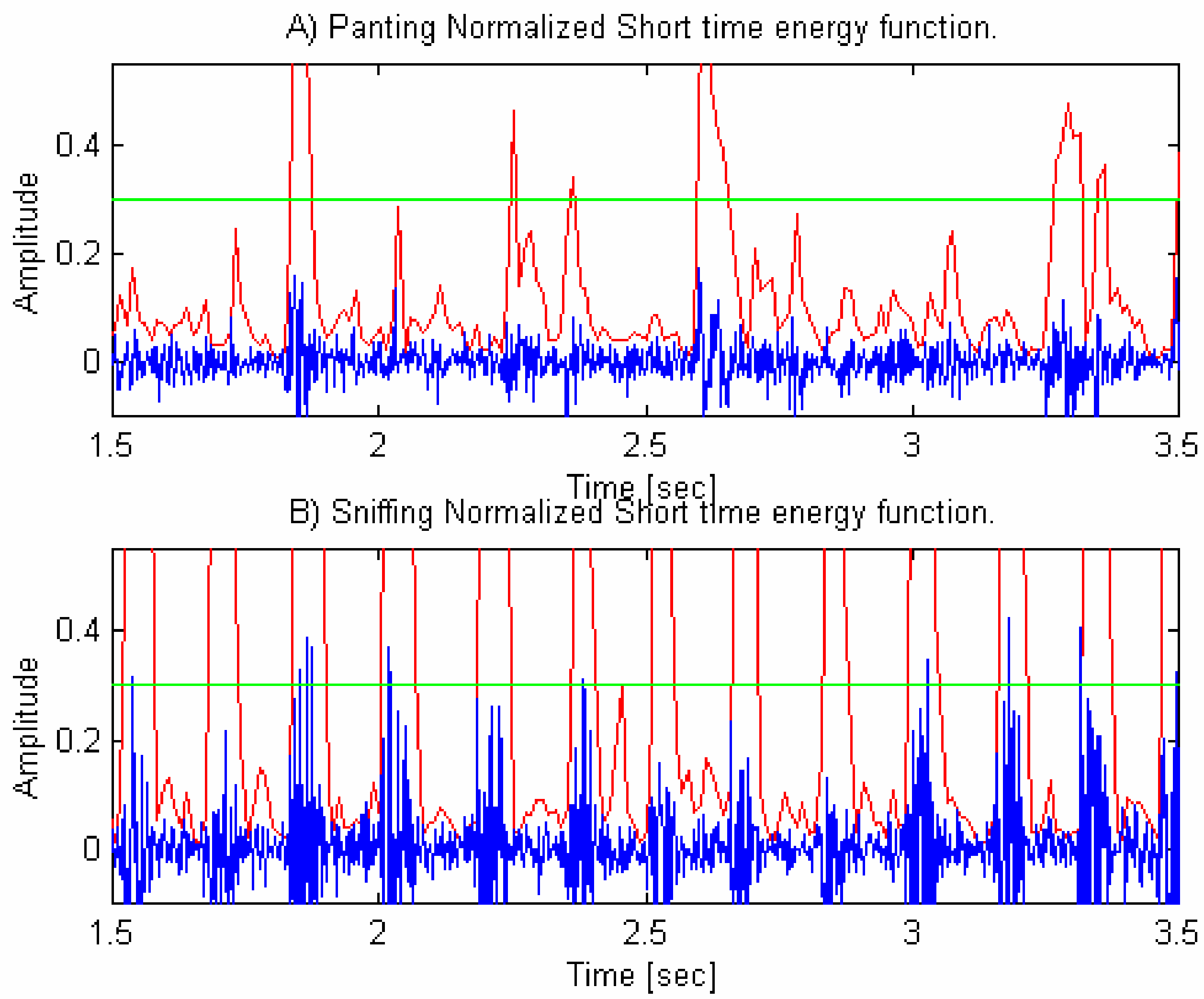


# Discrimination Method 1



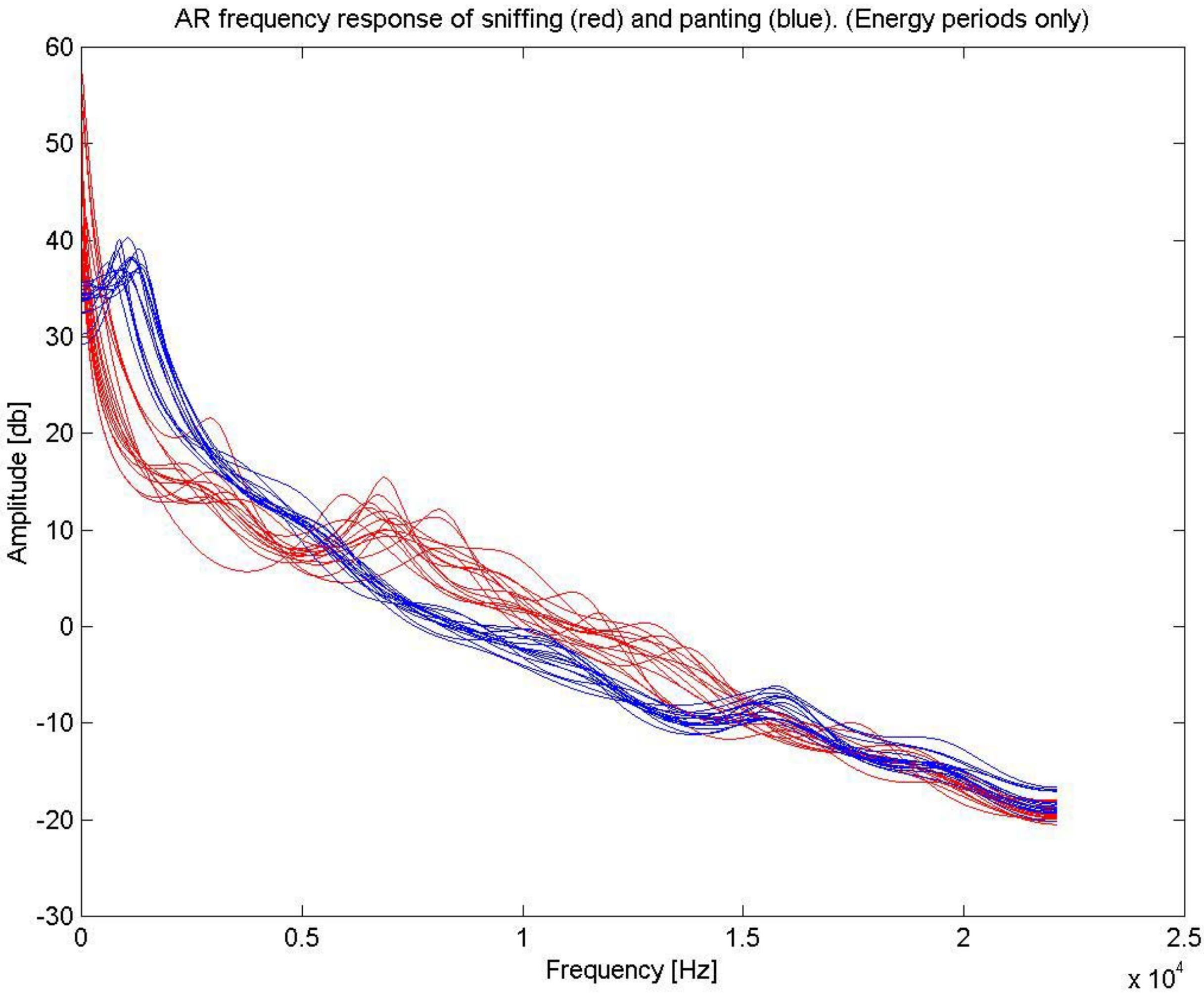
# Events Detection

Using Normalized Short Time Energy Function



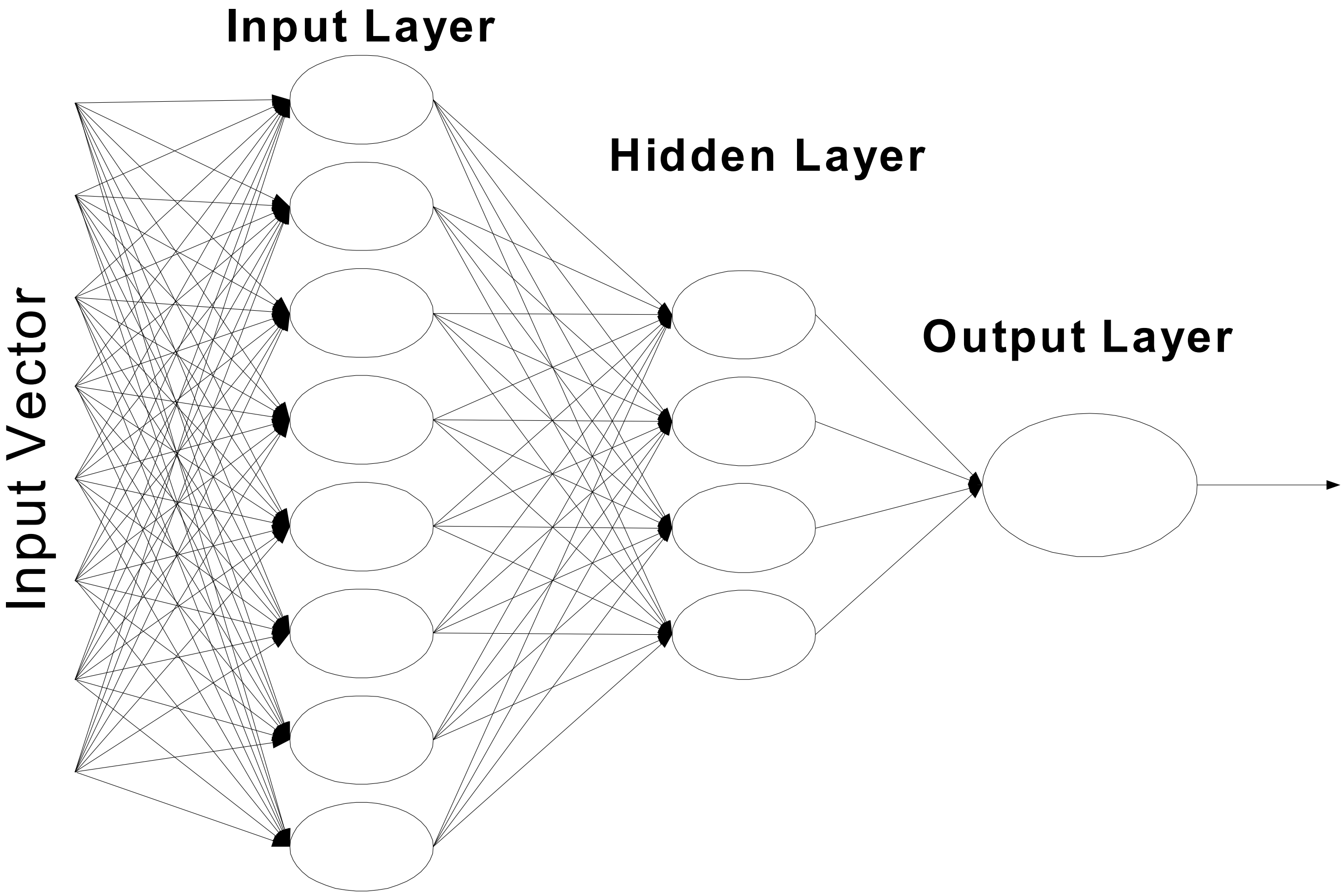
# AR model spectral envelope

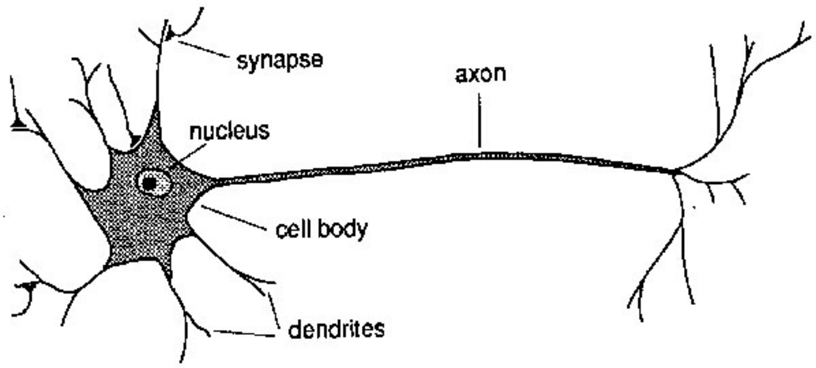
## AR model of 10th order



# Neural Network

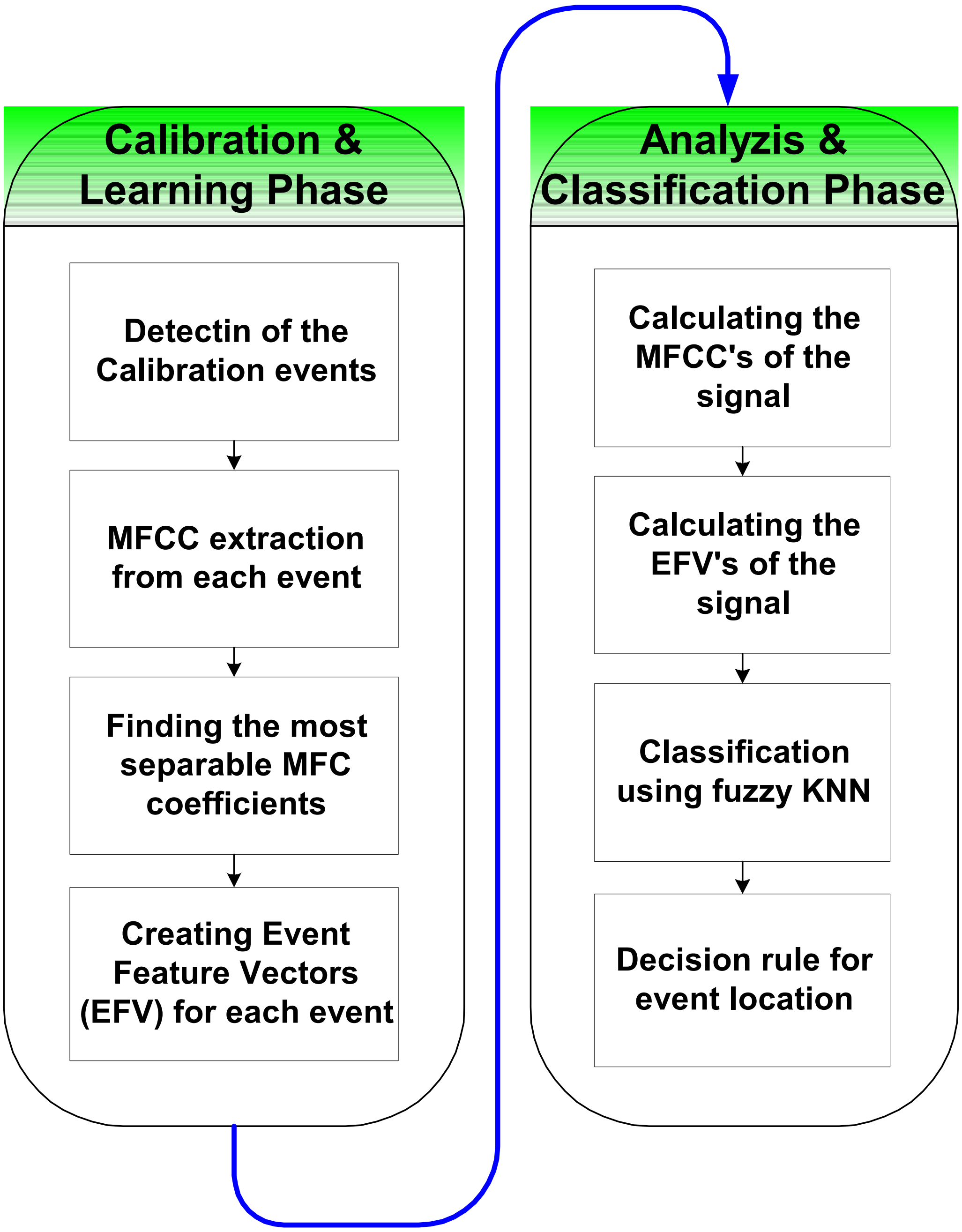
Using three layers, feed forward network with back propagation learning method



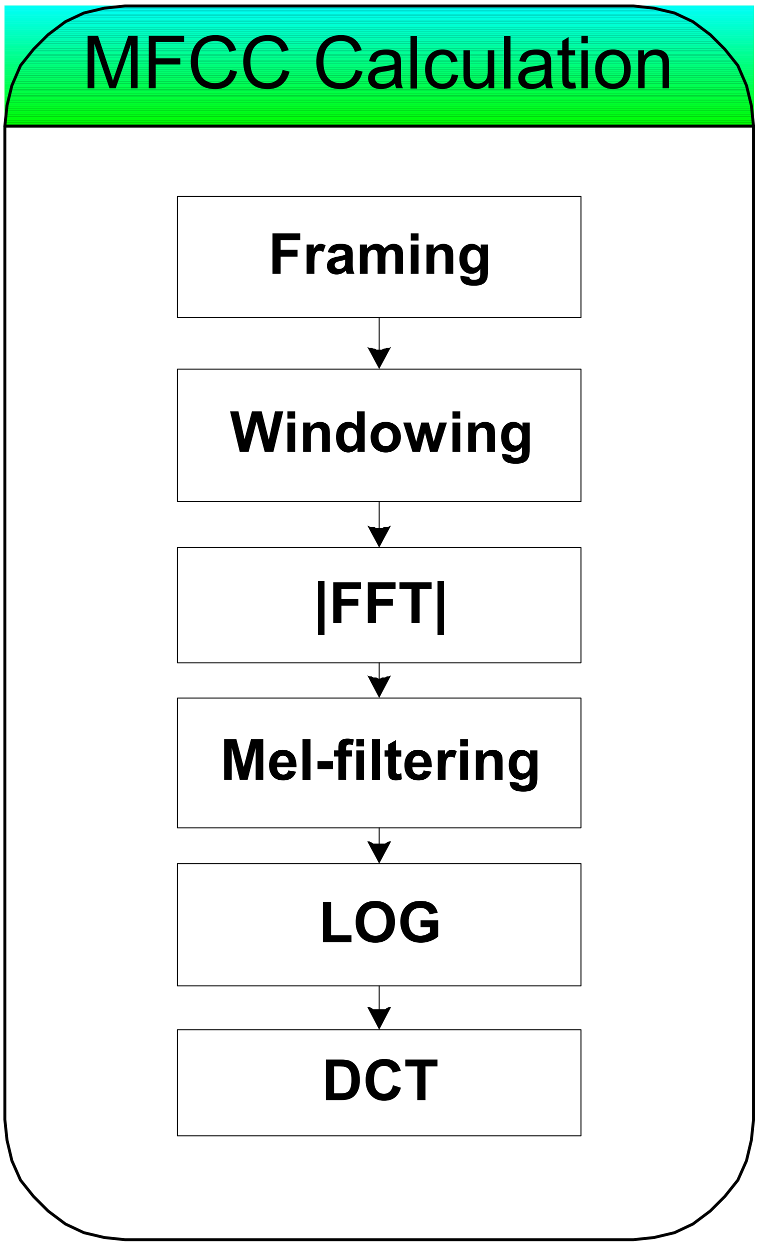




Schematic drawing of a typical neuron.

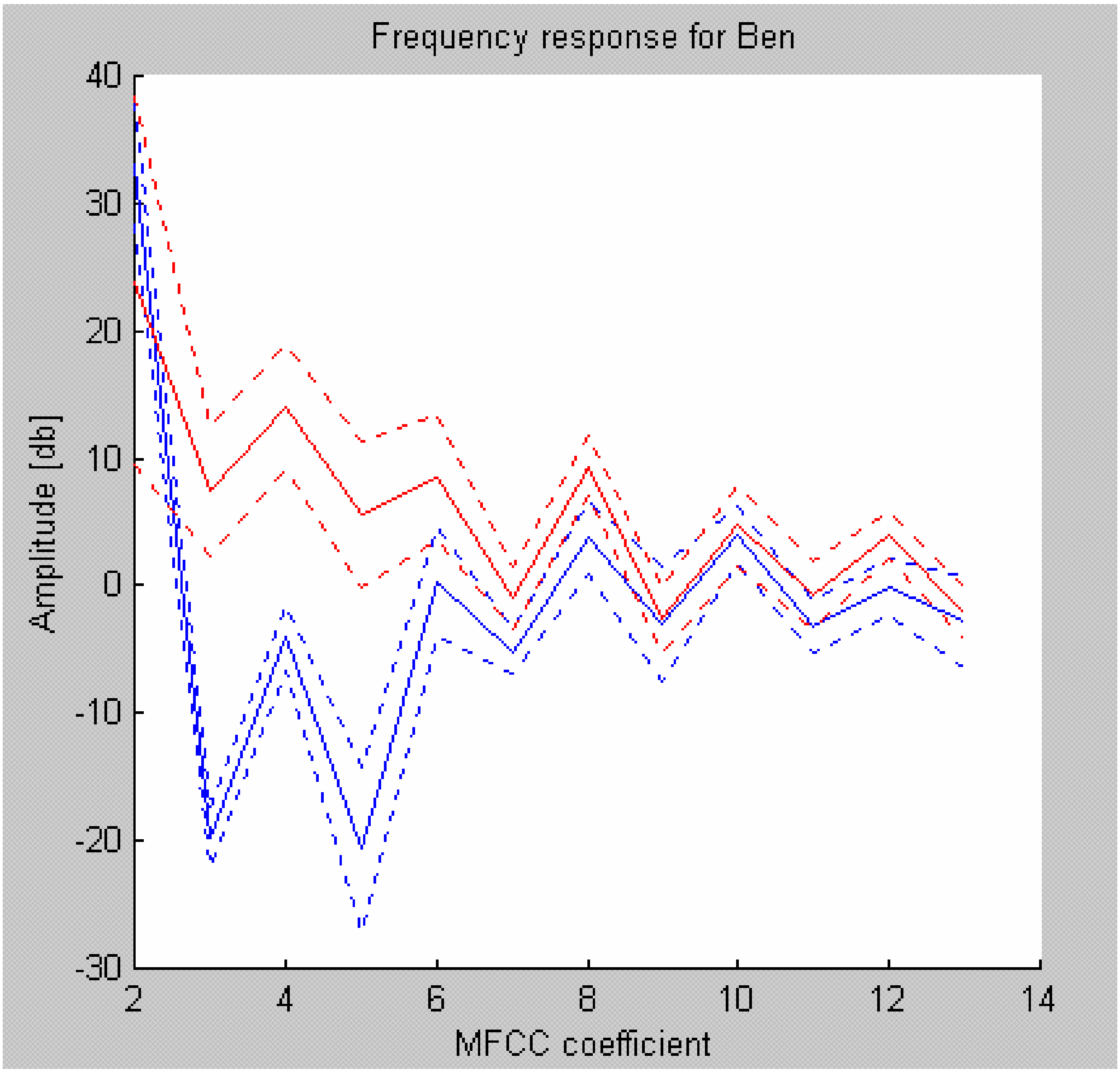
# Discrimination Method 2



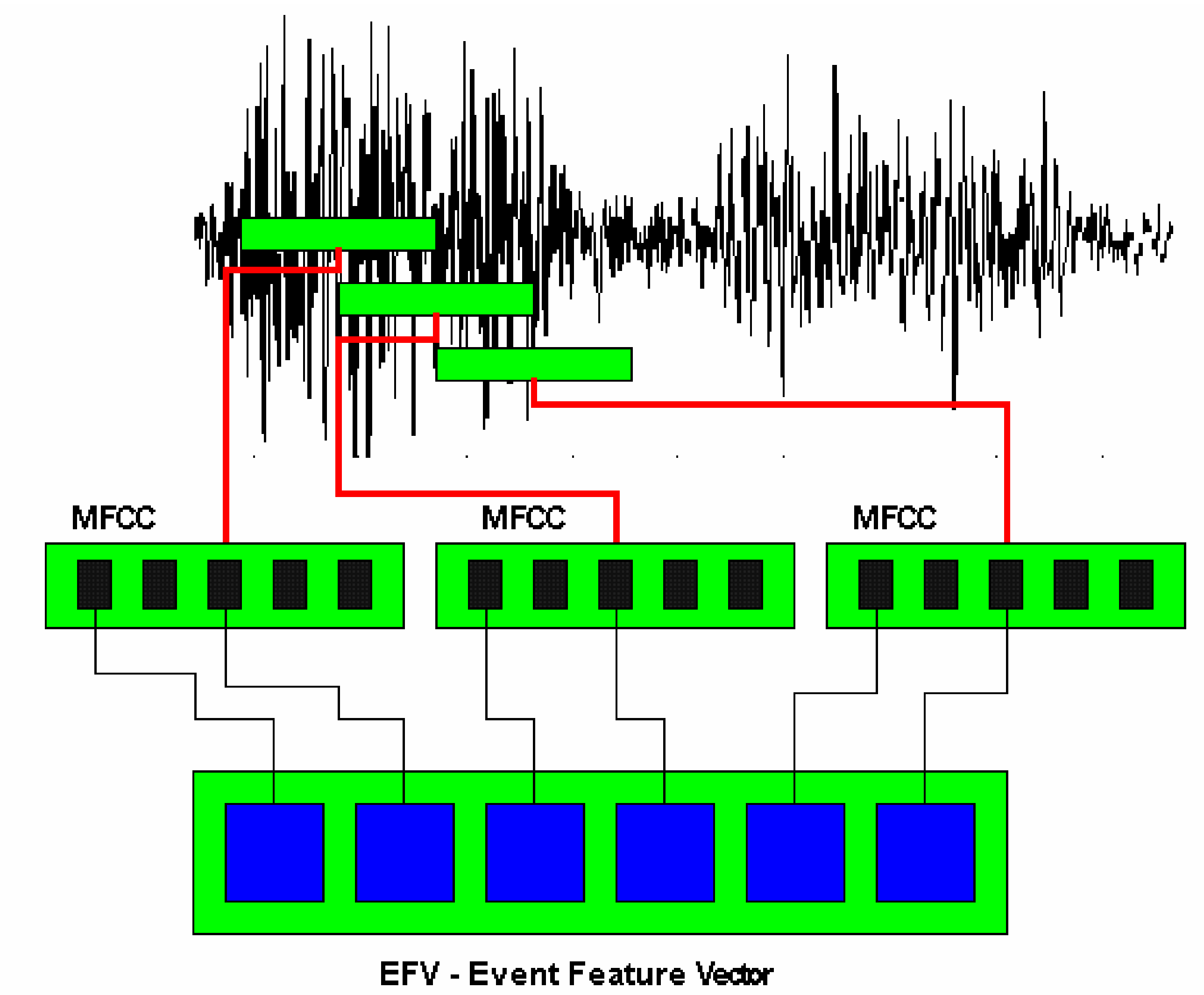
# Calculation of MFC Coefficients



# Mel-Frequency Cepstral Coefficients



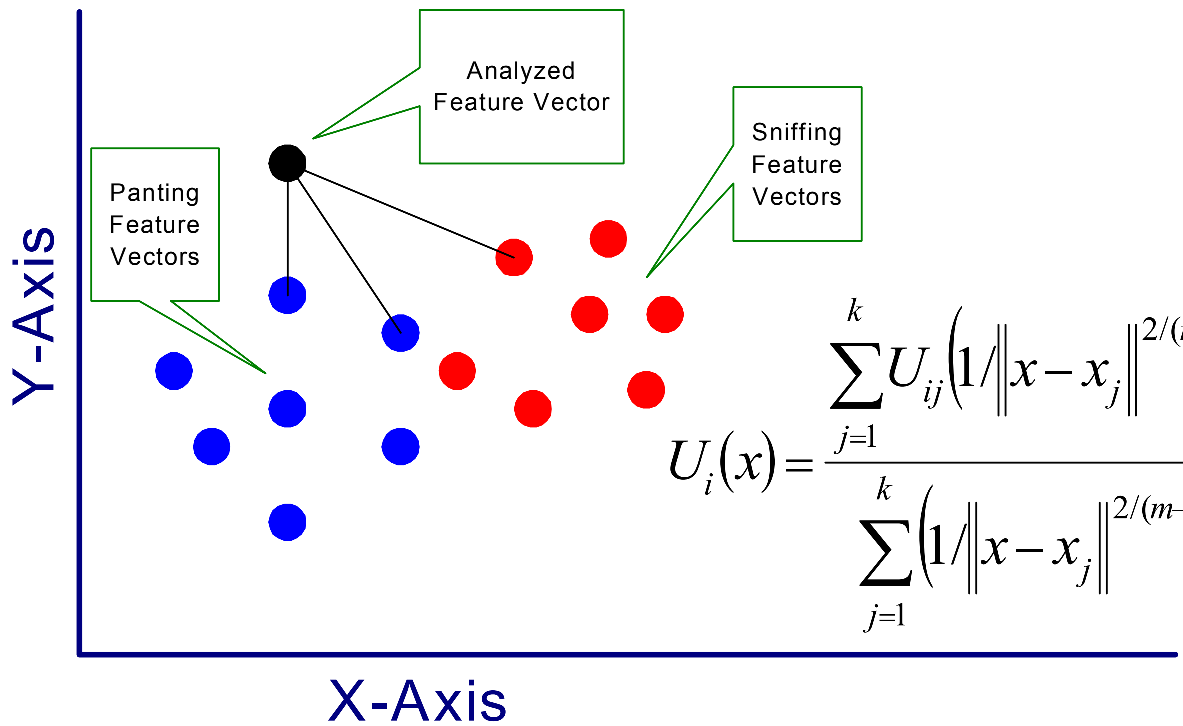
# Event Feature Vector




Calculating MFCC for some overlapping periods, choosing most separable coefficients and combining into one EFV.

# Fuzzy KNN

Fuzzy KNN with K=3




$$U_i(x) = \frac{\sum_{j=1}^{k} U_{ij}\left(1/\left\|x - x_j\right\|^{2/(m-1)}\right)}{\sum_{j=1}^{k}\left(1/\left\|x - x_j\right\|^{2/(m-1)}\right)}$$

Uij ñ Membership degree of the J-th vector in the class i.

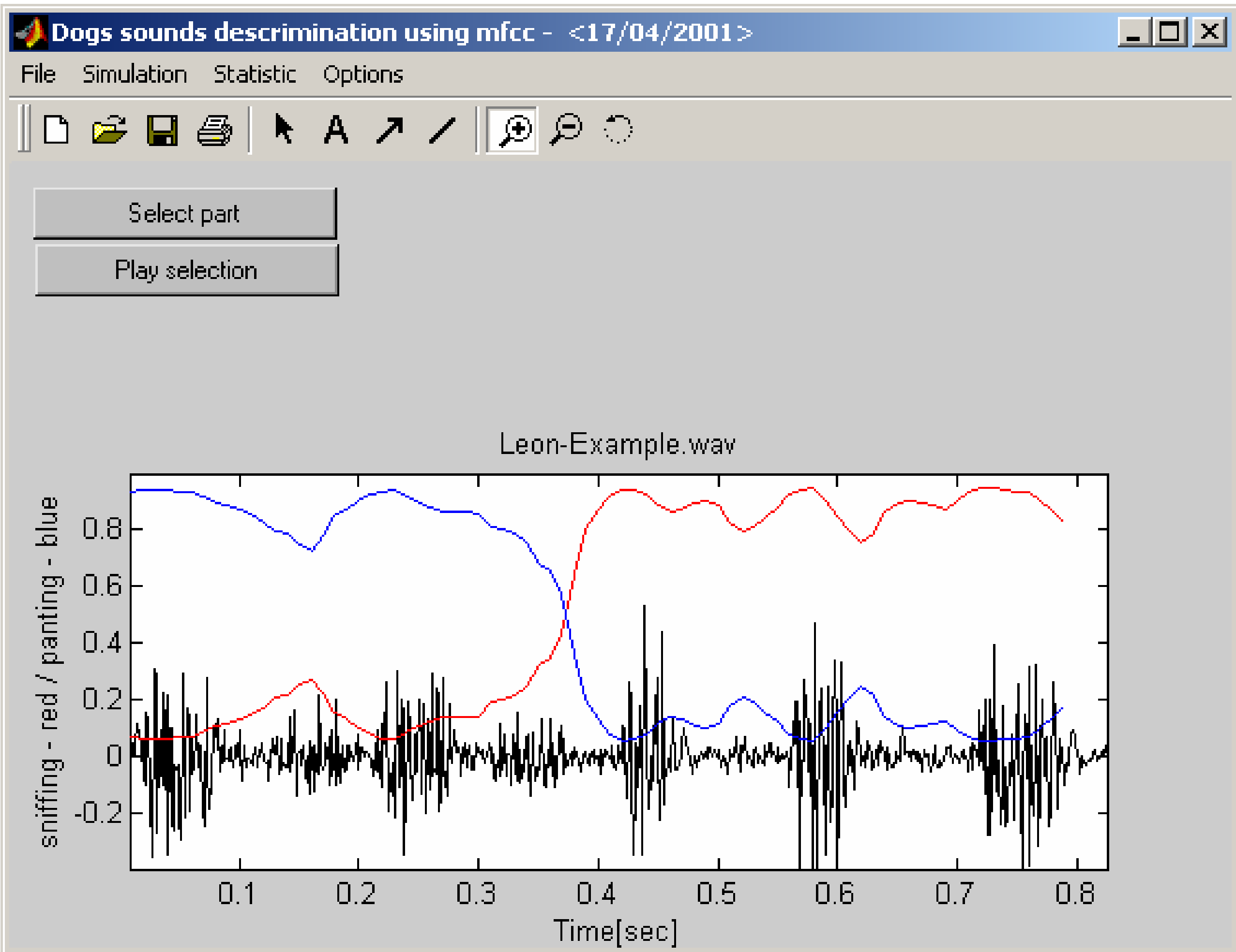
M ñ Weighting parameter.

X ñ Test vector

Xj ñ The J-th nearest neighbour vector.

# Membership Function

## Classification results using Fuzzy KNN



# Comparison between the two methods

Calibration and Training Process:

| # | Phase | Method 1 | Method 2 |
|---|---|---|---|
| 1. | Event Detection | Using short time energy function | Manually |
| 2. | Estimation of model parameters | AR model frequency response | MFCC |
| 3. | Parameters extraction | Manually | Most Separable |
| 4. | Feature vector | Extracted parameters | EFV |
| 5. | Calibration and training | Neural Network Training | Setting the membership Degree of labeled events |

# Comparison between the two methods

Continued

Analysis and Classification Process:

| # | Phase | Method 1 | Method 2 |
|---|---|---|---|
| 1. | Event Detection | Using short time energy function | - |
| 2. | Estimation of model parameters | AR model frequency response | MFCC |
| 3. | Feature vector | Extracted parameters | EFV |
| 4. | Classification | Neural Network | Fuzzy KNN |
| 5. | Decision rule | Pre-defined threshold | Not yet defined |

# Results

Results using first method:

| Dog Name | File Name | Events Num. | Error # | Error Rate |
|---|---|---|---|---|
| Sonia | SoniaHeavyPant | 97 | 2 | 2% |
| | SoniaSniff | 41 | 1 | 2.5% |
| Rondo | RondoPant | 159 | 0 | 0% |
| | RondoSniff | 82 | 3 | 3.7% |
| | RondoSniff2 | 183 | 12 | 6.6% |
| Ben | BenHeavyPant | 80 | 40 | 50% |
| | BenFoodSniff | 189 | 40 | 22% |

# Conclusions

1. Sniffing and Panting sounds have unique signature that enable discrimination between them.
2. The information needed for correct discrimination is coded in the frequency domain of the signal.
3. Detection of events should combine both feature vector and some other method like energy function or ZCR.