Detection and Discrimination of Sniffing and Panting Sounds of Dogs

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Motivation

Dogs’ 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 dogs’ behavior suggests many potential applications.
Abstract

Dogs’ 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 dogs’ 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

A) Panting samples at 44200Hz.

B) Sniffing samples at 44200Hz.
Discrimination Method 1

Calibration & Training Process

- Detection of the calibration events using short-time energy function
- Parameters extraction 1: AR model estimation for each event
- Parameters extraction 2: extraction of AR coefficients for each event
- Extracting pre-defined parameters from AR spectral envelope
- Training of a multi-layer neural network

Analysis & Classification Phase

- Detection of events using short-time energy function
- Extracting AR model from each event
- Extracting AR model coefficients from each event
- Extracting pre-defined parameters from AR spectral envelope for each event
- Input the parameters to the trained neural network
- Using a pre-defined threshold for decision rule

Input: Panting, Sniffing
Events Detection

Using Normalized Short Time Energy Function

A) Panting Normalized Short time energy function.

B) Sniffing Normalized Short time energy function.
AR model spectral envelope

AR model of 10th order

AR frequency response of sniffing (red) and panting (blue). (Energy periods only)
Neural Network

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

Input Layer

Hidden Layer

Output Layer

Input Vector

Schematic drawing of a typical neuron.
Discrimination Method 2

**Calibration & Learning Phase**
- Detectin of the Calibration events
- MFCC extraction from each event
- Finding the most separable MFC coefficients
- Creating Event Feature Vectors (EFV) for each event

**Analysis & Classification Phase**
- Calculating the MFCC's of the signal
- Calculating the EFV's of the signal
- Classification using fuzzy KNN
- Decision rule for event location
Calculation of MFC Coefficients

MFCC Calculation

- Framing
  - Windowing
    - |FFT|
      - Mel-filtering
        - LOG
          - DCT
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 \( K=3 \)

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

- \( U_{ij} \) Membership degree of the \( J \)-th vector in the class \( i \).
- \( M \) Weighting parameter.
- \( X \) Test vector
- \( X_j \) The \( J \)-th nearest neighbour vector.
Membership Function

Classification results using Fuzzy KNN
## Comparison between the two methods

### Calibration and Training Process:

<table>
<thead>
<tr>
<th>#</th>
<th>Phase</th>
<th>Method 1</th>
<th>Method 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Event Detection</td>
<td>Using short time energy function</td>
<td>Manually</td>
</tr>
<tr>
<td>2.</td>
<td>Estimation of model parameters</td>
<td>AR model frequency response</td>
<td>MFCC</td>
</tr>
<tr>
<td>3.</td>
<td>Parameters extraction</td>
<td>Manually</td>
<td>Most Separable</td>
</tr>
<tr>
<td>4.</td>
<td>Feature vector</td>
<td>Extracted parameters</td>
<td>EFV</td>
</tr>
<tr>
<td>5.</td>
<td>Calibration and training</td>
<td>Neural Network Training</td>
<td>Setting the membership Degree of labeled events</td>
</tr>
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</table>
Comparison between the two methods

Continued

Analysis and Classification Process:

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<td>Neural Network</td>
<td>Fuzzy KNN</td>
</tr>
<tr>
<td>5.</td>
<td>Decision rule</td>
<td>Pre-defined threshold</td>
<td>Not yet defined</td>
</tr>
</tbody>
</table>
### Results

Results using first method:

<table>
<thead>
<tr>
<th>Dog Name</th>
<th>File Name</th>
<th>Events Num.</th>
<th>Error #</th>
<th>Error Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sonia</td>
<td>SoniaHeavyPant</td>
<td>97</td>
<td>2</td>
<td>2%</td>
</tr>
<tr>
<td></td>
<td>SoniaSniff</td>
<td>41</td>
<td>1</td>
<td>2.5%</td>
</tr>
<tr>
<td>Rondo</td>
<td>RondoPant</td>
<td>159</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>RondoSniff</td>
<td>82</td>
<td>3</td>
<td>3.7%</td>
</tr>
<tr>
<td></td>
<td>RondoSniff2</td>
<td>183</td>
<td>12</td>
<td>6.6%</td>
</tr>
<tr>
<td>Ben</td>
<td>BenHeavyPant</td>
<td>80</td>
<td>40</td>
<td>50%</td>
</tr>
<tr>
<td></td>
<td>BenFoodSniff</td>
<td>189</td>
<td>40</td>
<td>22%</td>
</tr>
</tbody>
</table>
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.