Real-time Audio Classification based on Mixture Models

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1. INTRODUCTION

Standard Machine Learning (ML) approach for audio classification:
- Input sound: \( x = (x[1], ..., x[P]) \)

<table>
<thead>
<tr>
<th>Preprocessing</th>
<th>Feature extraction</th>
<th>ML Classifier</th>
</tr>
</thead>
<tbody>
<tr>
<td>STFT, Harmonic decomposition, ...</td>
<td>Energy, MFCC, ...</td>
<td>Mixture model</td>
</tr>
</tbody>
</table>

Our approach to real-time audio classification:
- Input sound: \( x = (x[1], ..., x[P]) \)
  - STFT: \( S = (S[1], ..., S[N]) \)
- Fit mixture model: \( p(f|\theta) \) using \( S \)

\[ D = \{ \hat{\theta} \} \]

2. CREATE A DICTIONARY OF MODELS

How the sounds are grouped and splitted:
- Group of sounds: \( G_1, ..., G_n \)
- Sounds: \( C_{i1}, ..., C_{iL} \)
- Sound buffers: \( C_{ij1}, ..., C_{ijK} \)

Split a sound into buffers with a window size \( T \) and an overlap \( D \):

Modeling of each buffer with a mixture model [2]:
- Magnitude
- Spectrum
- Model

3. SOUND MODELS

Normalized spectrum:
\[ S_{\alpha}[n] = N \frac{|s_{\alpha}[n]|^2}{\sum_{\beta=1}^{M} |s_{\alpha}[\beta]|^2} \]

Mixture model:
\[ p(f|\theta_{\beta}) = \sum_{m=1}^{M_{\beta}} \pi^{(m)}_{\beta} \phi^{(m)} f, \quad \phi^{(m)} = \frac{\sigma^{(m)}}{\sigma^{(m)^2}} \]

Model likelihood for binned data:
\[ L(\theta_{\beta}) = p(S|\theta_{\beta}) = \prod_{n=1}^{N} \left( \int_{f[n]} p(f|\theta_{\beta}) df \right) S[n] \]

4. IDENTIFY NEW SOUNDS

Test sounds \( S \): Split with window size \( T \) and consider groups of \( R \) buffers.

Aggregate the likelihoods:
\[ p(S|\theta_{G_i}) \]

Conditional probabilities of the groups \( G_i \):
\[ p(G_i|S) = \frac{p(S|G_i)p(G_i)}{\sum_{j=1}^{R} p(S|G_j)p(G_j)} \]

Aggregate the probabilities over \( R \) buffers:
\[ p(G_i|S) = \prod_{r=1}^{R} p(G_i|S_r) \]

Final decision (for every group of \( R \) buffers):
\[ \hat{G}_r = \arg\max_{G_i} p(G_i|S) \]

5. RESULTS & DISCUSSION

Cross-Validation Good classification rate (%)
(Comparison with state-of-the-art methods)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>A-Volute ESC-50 ESC-10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our algorithm</td>
<td>96.5 94.0 96.0</td>
</tr>
<tr>
<td>Parametric</td>
<td>73.6 45.5 73.5</td>
</tr>
<tr>
<td>Non-parametric</td>
<td>46.6 53.2 76.0</td>
</tr>
<tr>
<td>Human</td>
<td>91.8 81.3 95.7</td>
</tr>
</tbody>
</table>

Parametric method: standard GMM with standard features [1]
Non-parametric method: Deep ConvNet with spectrogram features [3]

Complexity
(Example on the A-Volute database)

<table>
<thead>
<tr>
<th></th>
<th>( O(\text{Number of operations}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our algorithm</td>
<td>( 28 \times 10^6 )</td>
</tr>
<tr>
<td>Parametric method</td>
<td>( 2 \times 10^3 )</td>
</tr>
<tr>
<td>Non-parametric method</td>
<td>( 14 \times 10^6 )</td>
</tr>
</tbody>
</table>

6. RESOURCES

Website available with free demonstrator of the method:

7. REFERENCES