Real-time Audio Classification based on Mixture Models
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1. INTRODUCTION

Standard Machine Learning (ML) approach for audio classification:

Input sound \( x = (x[1], ..., x[P]) \)

Preprocessing
STFT, Harmonic decomposition, ...

Feature extraction
Energy, MFCC, ...

ML Classifier
GMM, Neural Networks, ...

ML Model

Our approach to real-time audio classification:

Input sound \( x = (x[1], ..., x[P]) \)

Preprocessing
STFT: \( S = (S[1], ..., S[N]) \)

Fit Mixture Model

Dictionary

\( \mathcal{D} = \{ \theta \} \)

2. CREATE A DICTIONARY OF MODELS

How the sounds are grouped and split:

Group of sounds \( G_1 \) \( \cdots \) \( G_r \)

Sounds \( C_{ij} \) \( \cdots \) \( C_{iN} \)

Sound buffers \( \tilde{C}_{ij} \) \( \cdots \) \( \tilde{C}_{iN} \)

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:

\[ S_{jk}[n] = N^{-1} \frac{|s_{jk}[n]|^2}{\sum_{p=1}^{M_p} |s_{jp}[p]|^2} \]

Mixture model:

\[ p(f|\theta_{jk}) = \sum_{m=1}^{M_k} \pi_{jk}^{(m)} \frac{1}{2\pi} \left( f - \mu_{jk}^{(m)} \right)^2 \]

Model likelihood for binned data:

\[ \mathcal{L}(\theta_{jk}) = p(S|\theta_{jk}) = \prod_{n=1}^{N} \left( \int_{[s]} p(f|\theta_{jk})df \right) S_{jk}[n] \]

4. IDENTIFY NEW SOUNDS

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

Aggregate the probabilities over \( R \) buffers:

\[ \hat{G}_i = \arg \max_{G_i} p(G_i|S) \]

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</td>
</tr>
<tr>
<td>Parametric method</td>
<td>73.6</td>
</tr>
<tr>
<td>Non-parametric method</td>
<td>46.6</td>
</tr>
<tr>
<td>Human</td>
<td>91.8</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>( \mathcal{O}(\text{Number of operations}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our algorithm</td>
<td>( 28 \times 10^k )</td>
</tr>
<tr>
<td>Parametric method</td>
<td>( 2 \times 10^k )</td>
</tr>
<tr>
<td>Non-parametric method</td>
<td>( 14 \times 10^k )</td>
</tr>
</tbody>
</table>

6. RESOURCES

Website available with free demonstrator of the method:

7. REFERENCES

