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

Standard Machine Learning (ML) approach for audio classification:

- Preprocessing: STFT, Harmonic decomposition, ...
- Feature extraction: Energy, MFCC, ...
- ML Classifier: GMM, Neural Networks, ...
- ML Model

Our approach to real-time audio classification:

- Preprocessing: STFT: \( S = (S[1], ..., S[N]) \)
- Feature extraction: \( p(f|\theta) \) using \( S \)
- ML Model

3. SOUND MODELS

Normalized spectrum:

\[
S_{m}[n] = \frac{|s_{m}[n]|^2}{\sum_{p=1}^{M_{k}} |s_{p}[p]|^2}
\]

Mixture model:

\[
p(f|\theta_{m}) = \sum_{m=1}^{M_{k}} \pi_{m} \pi_{m}(f, s_{m})^2.
\]

Model likelihood for binned data:

\[
\mathcal{L}(\theta_{m}) = p(S|\theta_{m}) = \prod_{i=1}^{N} \left( \int_{f[n]} p(f|\theta_{m})df \right)^{\sum_{j}}.
\]

4. IDENTIFY NEW SOUNDS

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

Aggregate the likelihoods:

\[
p\left(S^{1} | C_{j}^{1}\right), \quad p\left(S^{2} | C_{j}^{2}\right), ..., p\left(S^{R} | C_{j}^{R}\right)
\]

Conditional probabilities of the groups \( G_{j}^{i} \):

\[
p\left(G_{j}^{i} | S\right) = \frac{p\left(S^{i} | G_{j}^{i}\right)p\left(G_{j}^{i}\right)}{\sum_{j} p\left(S^{i} | G_{j}^{i}\right)p\left(G_{j}^{i}\right)}.
\]

Aggregate the probabilities over \( R \) buffers:

\[
p(G_{j}|S) = \prod_{r=1}^{R} p\left(G_{j}^{r} | S\right).
\]

Final decision (for every group of \( R \) buffers):

\[
\hat{G}_{j} = \arg\max_{G_{j}} p\left(G_{j} | S\right).
\]

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>46.8</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 10^6 )</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

