Audio Event Detection for Automatic Scene Recognition

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June 20, 2015

Outline

1. Introduction
2. Audio Event Detection
3. Scene Recognition
4. Evaluation
5. Demo

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1. Introduction
   - Problem Description
   - Approach
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Problem Description

In this project, our problem is to recognize a scene where an audio is recorded. Sound example:

Play Sound

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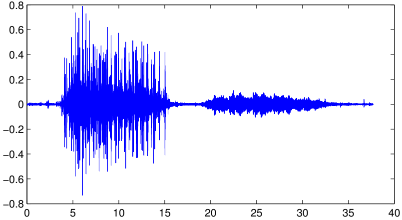

$\Rightarrow$ *concert*

Our Approach

Our approach is to detect the audible events in a clip.
Then infer the scene from the detected events.

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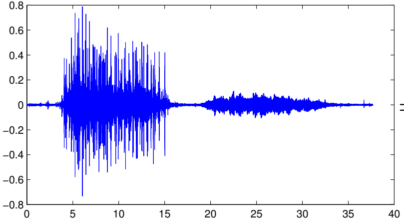
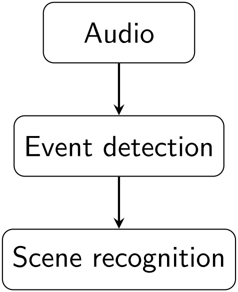


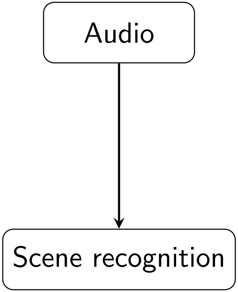
$\Rightarrow$ *applause, instrument* $\Rightarrow$ *concert*

Our Approach vs. Other Approaches

Our approach:



Other approaches:



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1. Introduction
2. Audio Event Detection
   - Audible Event Taxonomy
   - Audio Data
   - Preprocess and Feature Extraction
   - Event Model
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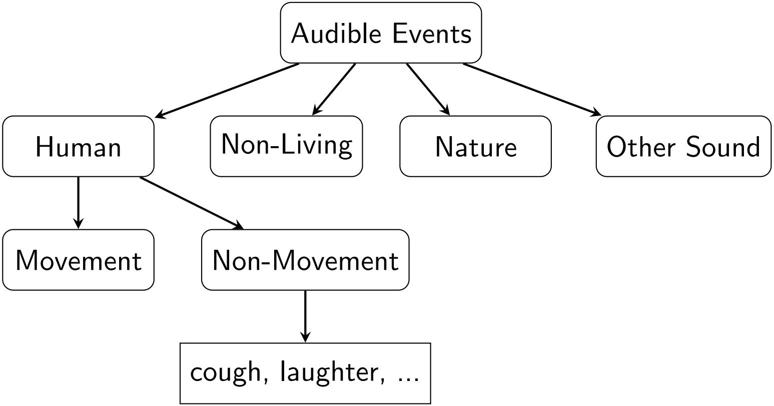
We labelled common audible events into 4 classes, there are 120 events in total.



Audio Data

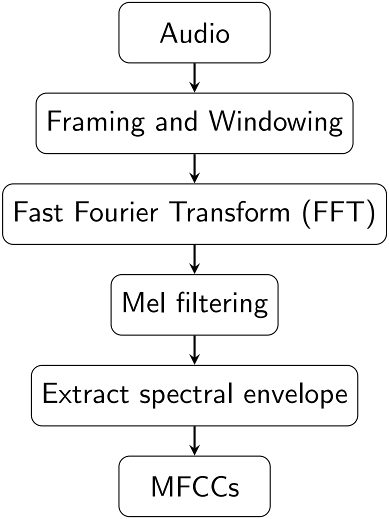
We download the audio data for events from Sound Search Engines (SSEs).
For example, when query “cough” in SSE:

Noise Reduction

denoise here

Feature Extraction

The features we extracted from audios are Mel-Frequency Cepstral Coefficients (MFCCs).



We use Gaussian Mixture Models to train the features.

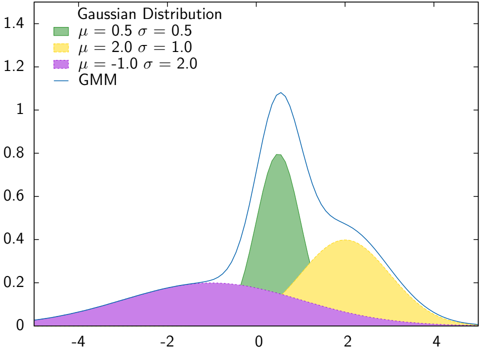


Figure: GMM with three components

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1. Introduction
2. Audio Event Detection
3. Scene Recognition
   - Scene-Event Map
   - Audio Segmentation
   - Scene Inference
4. Evaluation
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Scene Extraction

We use the scripts for movies, plays and TV series to extract the scenes.
Below is a script example. We call it a *context*, including a scene, and some descriptive sentences.

INT. LEONARD'S BATHROOM - Night Leonard turns on the light, revealing a shower, toilet and sink. He removes toiletries from the grocery bag and places them inside.

Scene Extraction

We use Natural Language Process (NLP) tools to process a context, and eliminate the following type of words:

- Person names
- Time indicator
- Adjective, determiner, ...

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Table: Top 10 Occurred Scenes

Scene	Occurrence
house	3537
office	3259
apartment	2919
room	2580
bedroom	2257
car	1699
street	1622
kitchen	1431
living room	1374
tardis	1259

Scene-Event Relation Mining

We first match audible events in a context, and count their occurrence.

INT. LEONARD'S BATHROOM - Night Leonard turns on the light, revealing a shower, toilet and sink. He removes toiletries from the grocery bag and places them inside.

Scene-Event Relation Mining

Based on the idea of Term-Frequency-Inverse Document Frequency (TFIDF), we calculate two scores of an event e, to a scene s.

1. $TF = log(1 + f(e,s))$
   $f(e,s)$ is the number of contexts e appears in all contexts under scene s.
2. $IDF = 1 + log(\frac{N}{N_e})$
   N is the number of scenes. N_e is the number of scene that event e appears.

These two scores are then multiplied, and used as the importance of an event to a scene.

$$TFIDF = TF \times IDF \tag{1}$$

Table: An example of scene-event map

Scene	Top 10 events ranked by TF-IDf
bathroom	running+water, toilet, faucet, toothbrush, shower, drawer, drain, talk, paper, bowl
beach	seagull, sand, boat, talk, wave, sea, car, laughter, drink, wood, running
concert	piano, applause, crowd, chorus, child, cry, talk
forest	tree, wood, dirt, talk, running, bird, river, car, leaf, grass, wind
kitchen	drawer, cutlery, microwave, dish, kettle, talk, bowl, phone, toaster, running+water
office	desk, drawer, page+turn, talk, phone, printer, paper, chair, leaf, typewriter
park	talk, car, tree, laughter, dog, child, grass, crowd, running, phone
restaurant	talk, drink, laughter, phone, car, leaf, paper, dish, ring, chair, write
street	car, truck, subway, talk, traffic, engine, siren, phone, running, laughter
subway station	subway, train, car, tube, talk, pace, crowd, metal, phone, vehicle

Audio Segmentation

In testing, we segment the audio into smaller parts for event detection. We set two thresholds based on the following two features:

1. Frame Energy
   The averaged energy of a frame, calculated as:

$$E_i = \frac{\sum_{n=1}^{N} (x_i(n))}{N} \tag{2}$$

2. Spectral Centroid
   The "center" of frequency, calculated as:

$$C_i = \frac{\sum_{k=1}^{N} k \times Amp(k)}{\sum_{k=1}^{N} Amp(k)} \tag{3}$$

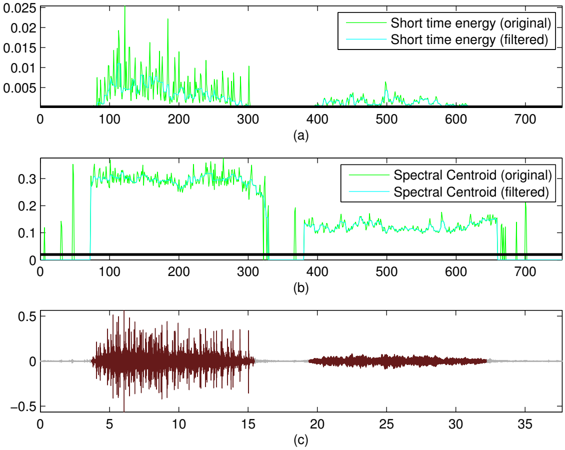

Figure: A segmentation example

Scene Inference

For each segment, we evaluate it with our trained GMMs.
Then we rank events by their posterior scores, the top three events are chosen as the candidates. We add the TFIDF scores to scene which contain the detected events.

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   - Event Detection Evaluation
   - Scene Recognition Evaluation
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Event detection F-measure with different component numbers.

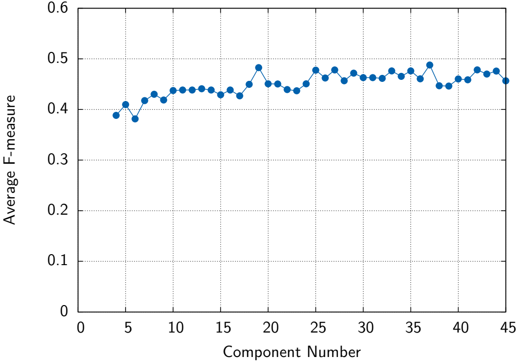

Figure: F-measure for different component number

We compare our event detection with other systems.

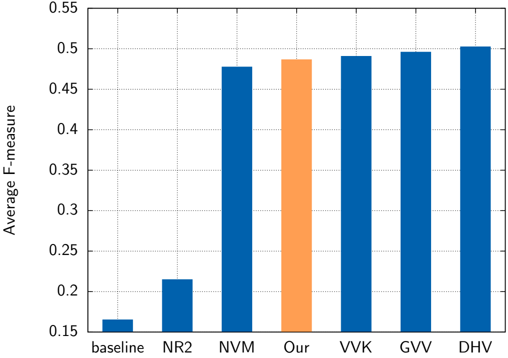

Figure: Event Detection F-Measure

Denoise Evaluation

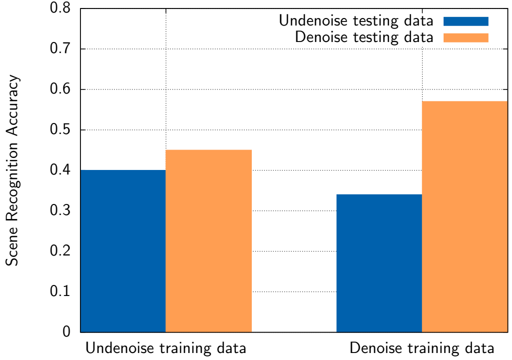

Figure: Recognition accuracy for our different models

Scene Recognition Evaluation

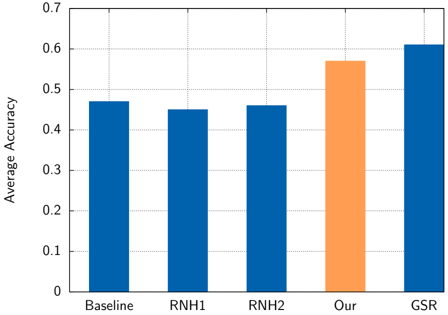

Figure: Recognition accuracy for 10 audio scenes

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Demo

Live demo for our system.

Acknowledgement

I would like to thank my advisor Kenny Q. Zhu, and my friend Xinyu Hua for their help in this project.

Thank you!

Any Question?