Recurrent neural networks for polyphonic sound event detection in real life recordings

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Overview

1. Introduction

2. Method

3. Evaluation
Goal: detect *which* sources are active, *beginning* and *ending* moments.
Polyphonic sound event detection

- A multilabel classification task.
- Map input signal to class labels in short time windows (~50ms)
Polyphonic sound event detection

- A multilabel classification task.
- Map input signal to class labels in short time windows (≈50ms)
Previous work

Context dependent
- GMM+HMM
- Nonnegative matrix factorisation (NMF)

Context independent
- Deep feedforward neural networks (FNN)
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**Context independent**
- Deep feedforward neural networks (FNN)
System overview
System overview

Annotations

Feature extraction

Data augmentation

BLSTM training

car engine

dog barking  dog barking

footstep  footstep  footstep

Method
System overview

[Diagram showing a system overview for feature extraction and BLSTM training, with annotations for car engine, dog barking, and footstep.]
System overview

Feature extraction

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RNNs for polyphonic SED
March 24, 2016
Log mel energies, ZMUV, split in sequences at three different timescales (10, 25, 100 frames).

The data needs to be annotated: each class is marked as active (1) or inactive (0) in each frame.
Feature extraction

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Recurrent neural network (RNN)

For an input sequence \(\{x_1, ..., x_T\}\), compute a sequence of hidden activations \(\{h_1, ..., h_T\}\) and output vectors \(\{\hat{y}_1, ..., \hat{y}_T\}\) as

\[
h_t = \mathcal{F}(W^{xh}x_t + W^{hh}h_{t-1} + b^h) \tag{1}
\]

\[
\hat{y}_t = \mathcal{G}(W^{hy}h_t + b^\hat{y}) \tag{2}
\]

**Figure:** On the left, a recurrent neural network with 1 hidden layer and a single neuron. On the right, the same network unfolded in time over \(T\) steps.
Bidirectional RNN (BRNN) \(^1\)

**Figure:** A bidirectional recurrent neural network with one hidden layer and two hidden neurons unfolded in time.

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\(^1\)Schuster et al., IEEE Trans. on Sgn. Processing (1997)
Model

- **Bidirectional RNN with LSTM units (BLSTM)**
- Multiple stacked recurrent hidden layers
- One output vector for each frame ("sequence to sequence")
- Output layer with sigmoids predicts posterior probabilities for each class of being active. Multilabel $\rightarrow$ no softmax
- At test time threshold predictions for binary activities
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Data augmentation

Three techniques:
- Block mixing
- Time stretching
- Sub-frame time shifting

All performed directly in the time-frequency domain, on the extracted features.
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**Dataset**

**CASA** 61 classes from 10 contexts, real life recordings.
18 hours. 5 folds of training, validation and test.
Average polyphony 2.53

Augmentations:
- ×16 all combined (in the tables + DA)
  - Block mixing: 20 blocks per context, mixing 2 at the time ×9.5
  - Time stretching: stretching coeff \{0.7, 0.85, 1.2, 1.5\} ×4.25
  - Sub-frame time shifting: three times ×3
### Dataset

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![Bar chart showing polyphony distribution]

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Evaluation

Metrics

Overall metric is the average of the scores in each of the 10 contexts.

1. Framewise F1
2. 1-second F1
Neural nets used in the experiment

- 40 input neurons, each reading one band of the log mel energies
- 4 recurrent (BLSTM) hidden layers
- 200 LSTM blocks in each (100 forwards, 100 backwards)
- 850K parameters in total
- Optimizer: RMSprop
- Objective function: RMSE (cross entropy didn’t work as well)
- Package: Currennt (CUDA/C++)
- 5 nets trained from random init for each fold, then pick the best on validation.
- At test time 100-frames sequences, threshold at 0.5
- Also tests using only LSTM (no bidirectional)
- No smoothing step required, RNN takes care of temporal continuity
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Results

Comparing to the approach in [Cakir et al., 2015], which uses a FNN (MLP with maxout) with 1.6M parameters (double those of the RNN), where the outputs are smoothed using a median filter.

Table: Overall $F_1$ scores, as average of individual contexts scores, for the FNN, the proposed LSTM and BLSTM, and BLSTM with data augmentation (+DA).

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<th>$F_{1_{AvgFram}}$</th>
<th>$F_{1_{1-sec}}$</th>
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<tr>
<td>FNN [Cakir et al., 2015]</td>
<td>58.4%</td>
<td>63.0%</td>
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<td>LSTM</td>
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BLSTM+DA improves the performance over the FNN by relative 15.1% and 6.8% for $F_{1_{AvgFram}}$ and $F_{1_{1-sec}}$ respectively.
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## Results — individual contexts

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<th>Context</th>
<th>FNN</th>
<th>BLSTM</th>
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<tr>
<td>basketball</td>
<td>70.2%</td>
<td>77.4%</td>
<td>78.5%</td>
</tr>
<tr>
<td>beach</td>
<td>49.7%</td>
<td>46.6%</td>
<td>49.6%</td>
</tr>
<tr>
<td>bus</td>
<td>43.8%</td>
<td>45.1%</td>
<td>49.4%</td>
</tr>
<tr>
<td>car</td>
<td>53.2%</td>
<td>67.9%</td>
<td>71.8%</td>
</tr>
<tr>
<td>hallway</td>
<td>47.8%</td>
<td>58.1%</td>
<td>54.8%</td>
</tr>
<tr>
<td>office</td>
<td>77.4%</td>
<td>79.9%</td>
<td>74.4%</td>
</tr>
<tr>
<td>restaurant</td>
<td>69.8%</td>
<td>76.5%</td>
<td>77.8%</td>
</tr>
<tr>
<td>shop</td>
<td>51.5%</td>
<td>61.2%</td>
<td>61.1%</td>
</tr>
<tr>
<td>street</td>
<td>62.6%</td>
<td>65.3%</td>
<td>65.2%</td>
</tr>
<tr>
<td>stadium</td>
<td>58.2%</td>
<td>61.7%</td>
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</tr>
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<td>average</td>
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Results — polyphony

Quite robust to polyphony increase

![Graph showing F1 score for different polyphony levels]
Demo time!
Discussion

1. RNNs improve over FNNs in polyphonic SED, and with half the parameters.
2. Overfitting, the main issue encountered $\implies$ much more data needed.
3. Data augmentation helps slightly reducing overfitting.
4. Quite robust to high polyphony.
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