Binaural Model-Based Source Separation and Localization

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Abstract

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When listening in noisy and reverberant environments, human listeners are able to focus on a particular sound of interest while ignoring interfering sounds. Computer listeners, however, can only perform highly constrained versions of this task. While automatic speech recognition systems and hearing aids work well in quiet conditions, source separation is necessary for them to be able to function in these challenging situations.

This dissertation introduces a system that separates more than two sound sources from reverberant, binaural mixtures based on the sources’ locations. Each source is modelled probabilistically using information about its interaural time and level differences at every frequency, with parameters learned using an expectation maximization (EM) algorithm. The system is therefore called Model-based EM Source Separation and Localization (MESSL). This EM algorithm alternates between refining its estimates of the model parameters (location) for each source and refining its estimates of the regions of the spectrogram dominated by each source. In addition to successfully separating sources, the algorithm estimates model parameters from a mixture that have direct psychoacoustic relevance and can usually only be measured for isolated sources. One of the key features enabling this separation is a novel probabilistic localization model that can be evaluated at individual time-frequency points and over arbitrarily-shaped regions of the spectrogram.

The localization performance of the systems introduced here is comparable to that of humans in both anechoic and reverberant conditions, with a 40% lower mean absolute error than four comparable algorithms. When target and masker sources are mixed at similar levels, MESSL’s separations have signal-to-distortion ratios 2.0 dB higher than four comparable separation algorithms and estimated speech quality 0.19 mean opinion score units higher. When target and masker sources are mixed anechoically at very different levels, MESSL’s performance is comparable to humans’, but in similar reverberant mixtures it only achieves 20–25% of human performance. While MESSL successfully rejects enough of the direct-path portion of the masking source in reverberant mixtures to improve energy-based signal-to-noise ratio results, it has difficulty rejecting enough reverberation to improve automatic speech recognition results significantly. This problem is shared by other comparable separation systems.
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List of Abbreviations

ASR   Automatic Speech Recognition
BRIR  Binaural Room Impulse Response
BSS   Blind Source Separation
CASA  Computational Auditory Scene Analysis
DCT   Discrete Cosine Transform
DERTM Direct-path, Early echoes, and Reverberation, of Target and Masker
DFT   Discrete Fourier Transform
DP    Direct-path
DUET  Degenerate Unmixing Estimation Technique
EM    Expectation Maximization
FFT   Fast Fourier Transform
GCC   Generalized Cross-Correlation
GMM   Gaussian Mixture Model
HRIR  Head-Related Impulse Response
HRTF  Head-Related Transfer Function
ICA   Independent Component Analysis
IID   Independent and Identically distributed
IIPM  Ideal Interaural Parameter Mask
ILD   Interaural Level Difference
IPD   Interaural Phase Difference
ITD   Interaural Time Difference
JND   Just-noticeable difference
KDE   Kernel Density Estimator
MAA   Minimum Audible Angle
MESSL Model-based EM Source Separation and Localization
MMSE  Minimum Mean Squared Error
MOS   Mean Opinion Score
PDF   Probability Distribution Function
PESQ  Perceptual Evaluation of Speech Quality
PHAT  PHAse Transform
RMS   Root-Mean Square
SAR   Signal-to-Artifact Ratio
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>SDR</td>
<td>Signal-to-Distortion Ratio</td>
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<tr>
<td>SIR</td>
<td>Signal-to-Interferer Ratio</td>
</tr>
<tr>
<td>SNR</td>
<td>Signal-to-Noise Ratio</td>
</tr>
<tr>
<td>SNRI</td>
<td>Signal-to-Noise Ratio Improvement</td>
</tr>
<tr>
<td>SRT</td>
<td>Speech Reception Threshold</td>
</tr>
<tr>
<td>STFT</td>
<td>Short-Time Fourier Transform</td>
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<tr>
<td>TMR</td>
<td>Target-to-Masker Ratio</td>
</tr>
<tr>
<td>TRINICON</td>
<td>TRiple-N ICA for CONvolutive mixtures</td>
</tr>
<tr>
<td>WDO</td>
<td>Windowed-Disjoint Orthogonal(ity)</td>
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