Crowdsourced Pairwise Comparison for Source Separation Evaluation

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I. Introduction

• Automated objective methods of audio source separation evaluation are fast, cheap, and require little effort by the investigator, but their output often correlates poorly with human quality assessments.

Table I. Listening tests details

Web-based Multi-stimulus

Web-based Pairwise Comparison

0.78 0.82 0.96

0.69

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How do the scores from BSS-Eval, web-based pairwise comparison,

and web-based multi stimulus tests correlate to lab-based multi

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NORTHWESTERN

UNIVERSITY

stimulus?



NEW YORK UNIVERSITY

Subjective multi-stimulus listening tests are the gold standard for audio evaluation, but they are slow and onerous to run.

• Our previous work showed that a crowdsourced multi-stimulus listening test can produce results comparable to lab-based multi-stimulus tests [1], but they are limited to evaluating 12 or fewer stimuli and require groundtruth stimuli for reference.

• We present a web-based pairwise-comparison listening test for source separation evaluation that addresses these limitations while still promising to speed and facilitate conducting listening tests. We compare to multistimulus lab- and web-based tests (referred to as lab-MS and web-MS)

2. Baseline Dataset

PEASS Dataset [2]

I0 mixtures (5 music, 5 speech)

5 sec long w/ 2 - 7 sources each

▶ 8 test stimuli per mixture:

Reference

# of Participants	530	458
# of participants that passed hearing screening	336	345
# of Trials	1763	1444
Mean trials per condition	34	30
Mean trials per participant	3.3	3.2

Figure I. multi-stimulus (left) and pairwise (right) interfaces*



4. Quality Score Estimation



Are the web-based pairwise-comparison scores noisier than web- and lab-based multi stimulus scores?



3 anchors

4 source separation algorithm outputs
 MUSHRA multi-stimulus evaluations from 20 experts on 4 quality scales

3. Listening Test Procedure

Participants were recruited from Amazon's Mechanical Turk

Each participant was limited to one quality scale and could perform up to I0 trials

We collected at least 30 trials per condition (mixture / quality pair)

Steps:

Participants completed a quick hearing evaluation

Participants completed a training phase

For each trial, participants compared all pairs in a set: ⁸/₂ i.e., 28 pairs
For each pair, participants choose which of two stimuli is higher on a quality scale

• **Payment**: \$0.80 for first trial, \$0.50 for subsequent trials. Up to \$0.25

• We used a Thurstone model to estimate quality scores from pairwise preferences. The basic Thurstone model is as follows:

 $S_n \sim \text{Normal}(\mu_n, \sigma^2), \text{ for } n \in 1 : N$ $\Pr(a_i \succ a_j) = \Pr(S_i > S_j), \text{ for } i, j \in 1 : N ; i \neq j$ $= \Pr(S_i - S_j > 0)$ $= \Phi\left(\frac{\mu_i - \mu_j}{\sigma\sqrt{2}}\right)$

where for N items, S_n are the quality scale values with measurement error and μ_n are the latent quality scores. a_i and a_j are the two items in a paired comparison.

• Using this model, we fit the likelihood of our data for each quality scale using MCMC sampling (NUTS) and with priors chosen so that the resulting scores are on the same scale as the multi-stimulus scores.

5. Results

Table 2. Mean Pairwise Transitivity Statistics (N=10)

Quality Seels Transitivity Weak Stochastic Medium Stoch. Strong Stoch.

Score Estimation Method

Which test should I use?



bonus per trial based on consistency.

Quality scales:

Overall quality

Preservation of the target source

Suppression of other sources

Absence of additional artificial noises (additive artifacts)
Preservation of the target source (subtractive artifacts)
Lack of distortions to the target source (additive and subtractive artifacts)

new quality scale added to address confusion between additive and subtractive artifacts.

	Satisfaction Rate	Transitivity	Transitivity	Transivity
Overall Quality	0;91	0.97	0.93	0.61
Target Preservation	0.90	0.97	0.95	0.71
Suppression of Other Sources	0.92	0.99	0.94	0.60
Absence of Additional Artificial Noises	0.91	0.99	0.98	0.71
Lack of Distortion to the Target Source	0.93	1.00	0.99	0.73

References

[1] M. Cartwright, B. Pardo, G. Mysore, M. Hoffman. Fast and Easy Crowdsourced Perceptual Audio Evaluation. In Proc. of ICASSP, 2016.

[2] V. Emiya, E. Vincent, N. Harlander, and V. Hohmann, "Subjective and Objective Quality Assessment of Audio Source Separation," IEEE TASLP, vol. 19, pp. 2046-2057, 2011.