Imperial College London

The ACE challenge – corpus description and performance evaluation

James Eaton, Nikolay D. Gaubitch,
Alastair H. Moore, and Patrick A. Naylor

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Motivation

- We wish to accurately estimate T_{60} and DRR blindly from noisy reverberant speech to help improve speech enhancement and speech recognition

- The impact of noise and reverberation is significant on speech processing
- Environmental noise is typically inconsistently modeled
- Multi-channel devices are now commonplace

- Gaubitch *et al*. 2012 study showed that a wider study of noise impacts on T_{60} estimators was merited

Aim

- Develop a novel corpus of realistic multi-channel noisy reverberant speech for the acoustic characterization of environments (ACE)
- Run an international research challenge with colleagues in the field - the *ACE Challenge* - to
  - Determine the state-of-the-art in T_{60} and DRR estimation in noise in full-band and ISO frequency bands, single and multi-channel
  - Stimulate research in blind acoustic parameter estimation, both during the challenge and afterwards

Content

- ACE corpus
- ACE Challenge tasks, datasets and process
- ACE Challenge results
- Conclusion

ACE corpus

ACE corpus

- Components
  - Anechoic speech
  - Measured acoustic impulse responses (AIRs)
  - Noise recorded under the same conditions as the AIRs
  - T_{60} and DRR measurements
  - Room dimensions and source/microphone positions
  - Software tools for generating datasets
- Noisy reverberant speech is created by convolving the speech with AIRs and then adding the noise associated with that AIR

Anechoic speech recordings

- Speech recorded at TU Delft anechoic chamber
- 4 male talkers (Development)
  - Describe the place where you live?
  - How do you get to work?
- 5 male, 5 female (Evaluation)
  - Favourite colour?
  - Which town/city do you live in?
  - Describe the place where you live
  - How do you get to work?
  - Count from zero to nine

TU Delft Delft University of Technology

Corpus AIR and noise capture

Corpus impulse response and noise capture

- 7 rooms in Imperial College London
  - 2 offices, 2 meeting rooms, 2 lecture rooms, and building lobby
- 2 source-microphone configurations per room
  - Near, far
- 50 channels of audio (noise and AIRs) per source-microphone configuration
  - 2-channel laptop array (Chromebook pixel)
  - 3-channel mobile array (DPA4060)
  - 5-channel cruciform array (DPA4060)
  - 8-channel linear array (DPA4060)
  - 32-channel spherical array (Eigenmike)
- Noises: Ambient, fan, babble
- 4-7 “babblers” depending on room size
- AIRs captured using exponential sine sweep method (Farina *et al*. 2000)

Ground truth calculations

- EDC

$$EDC(n) = \int_n^{\infty} h^2(\tau)\, d\tau,$$

  - where h is the measured impulse response at discrete time, n

- T_{60} then calculated using non-linear fit method of Karjalainen *et al*. 2002
- DRR

$$DRR = 10\log_{10} \frac{\sum_{n=n_d-n_0}^{n_d+n_0} h^2(n)}{\sum_{n=0}^{n=n_d-n_0} h^2(n) + \sum_{n=n_d+n_0}^{n=\infty} h^2(n)}$$

  - where direct path arrives at sample time n_d and n_0=2.5ms

- All calculations per room, per microphone configuration, per channel, fullband (FB) and in ISO frequency bands (SB)

Ground truth values

Name	L (m)	W (m)	H (m)	Vol. (m^3)	T_{60} (s)	Mic. pos. 1 DRR min. (dB)	Mic. pos. 1 DRR max. (dB)	Mic. pos. 2 DRR min. (dB)	Mic. pos. 2 DRR max. (dB)
Office 1	4.8	3.3	3.0	47	0.34	−2.7	13	−0.55	6.6
Office 2	5.1	3.2	2.9	48	0.39	−0.44	13	−2.3	9.5
Meeting Room 1	6.6	4.7	3.0	92	0.44	−2.0	11	−3.1	7.6
Meeting Room 2	10.3	9.2	2.6	250	0.37	−2.6	11	1.1	12
Lecture Room 1	6.9	9.7	3.0	200	0.64	−0.82	15	0.87	7.9
Lecture Room 2	13.4	9.2	2.9	360	1.25	−0.37	13	−3.7	6.4
Building Lobby	5.1	4.5	3.2	72	0.65	−0.94	13	−2.5	8.1

Noisy reverberant speech

Laptop
Office 1 – Long
Fan noise - 10 dB SNR

Laptop
Building Lobby – Short
Babble noise – 0 dB SNR

ACE Challenge tasks, datasets and process

ACE Challenge tasks

- Participants may submit results for one or more blind estimation tasks for one or more algorithms

- T_{60} in fullband
- T_{60} in 1/3rd octave (ISO) frequency bands
- DRR in fullband
- DRR in 1/3rd octave (ISO) frequency bands

- All tasks can be performed in either single or multi-channel

ACE challenge process

- Organizers produce Development and Evaluation datasets
  - Development set includes ground truth
  - Evaluation set is fully blind
- Participants use the Development dataset to train their algorithms
- Participants run their algorithms on the Evaluation dataset and submit their results
- Organizers return results and ground truth values
- Participants write up their work in a conference paper
- Participants present their results in a workshop
- Results are published in the proceedings

Timeline

Phase 0

Oct 2012 Conception at IWAENC 2012
May 2014 Announcement at ICASSP 2014 Florence
Jul-Nov 2015 recordings

Phase 1

Jan 2015 Development dataset released
Mar 2015 Evaluation dataset released
Apr 2015 Phase 1 results submissions received

Phase 2

Jun 2015 Phase 2 results submissions received
Jul 2015 Paper submissions received

Phase 3

July 2015 Acceptance notified
Oct 2015 Satellite workshop at WASPAA 2015

Development dataset

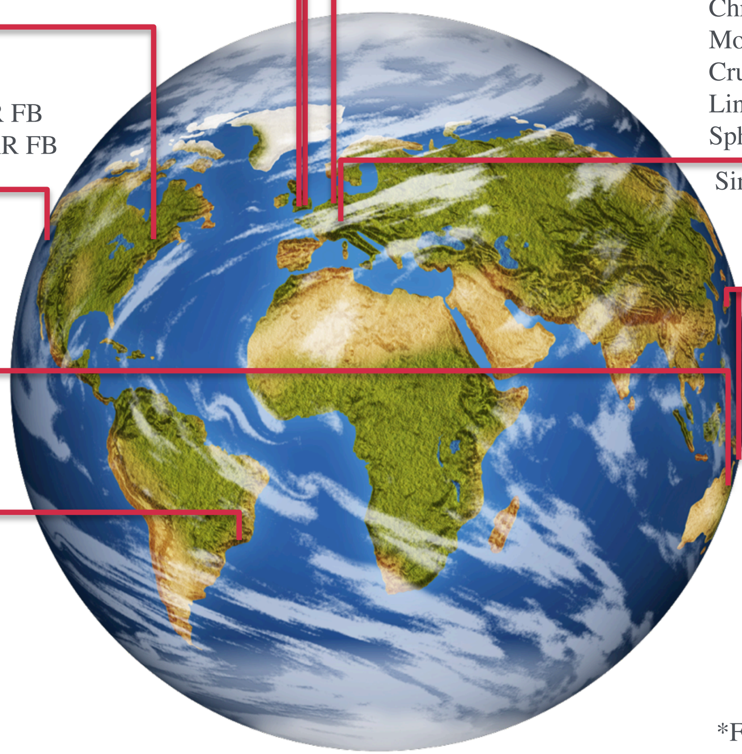
- 288 files
  - 4 male talkers
  - 2 utterances
  - 3 SNRs: 0 dB, 10 dB, and 20 dB
  - 3 noises: Ambient, fan and babble
  - 2 rooms each with 2 source-microphone configurations (near, far)
- 6 microphone arrays
  - 1, 2, 3, 5, 8, and 32 channel
  - Single channel based on channel 1 of 8-channel array
- T_{60} and DRR ground truth provided per channel, in fullband and in 1/3$^{\mathrm{rd}}$ octave frequency bands

Evaluation dataset

- 4500 files
  - 10 talkers: 5 male and 5 female
  - 5 utterances
  - 3 SNRs: -1 dB, 12 dB, and 18 dB
  - 3 noises: Ambient, fan and babble
  - 5 rooms each with 2 source-microphone positions (near, far)
- 6 microphone arrays
  - 1, 2, 3, 5, 8, and 32 channel
  - Single channel based on channel 1 of 5-channel array
- Fully blind
  - Files numbered in random permutation per microphone array
  - Ground truth not provided

ACE Challenge results

Global participation



NUANCE — Single, T_{60}, DRR FB*

Imperial College London — Single, T_{60} FB; Chromebook, DRR FB & SB*

Fraunhofer IDMT / Hearing4all / Carl von Ossietzky Universität Oldenburg — Single, T_{60}, DRR FB; Chromebook, T_{60}, DRR FB; Mobile, T_{60}, DRR FB; Cruciform, T_{60}, DRR FB; Linear, T_{60}, DRR FB; Spherical, T_{60}, DRR FB

MuSAE Lab INRS — Single, T_{60}, DRR FB; Mobile, T_{60}, DRR FB; Cruciform, , T_{60}, DRR FB; Chromebook, T_{60}, DRR FB

FAU Friedrich-Alexander Universität Erlangen-Nürnberg / RWTH Aachen University — Single, T_{60} FB & SB

Microsoft Research — Single, T_{60} FB

The University of Auckland Faculty of Engineering / NTT — Mobile, DRR FB

Australian National University — Spherical, DRR FB

CEFET/RJ / UFRJ COPPE — Single, T_{60}, DRR FB

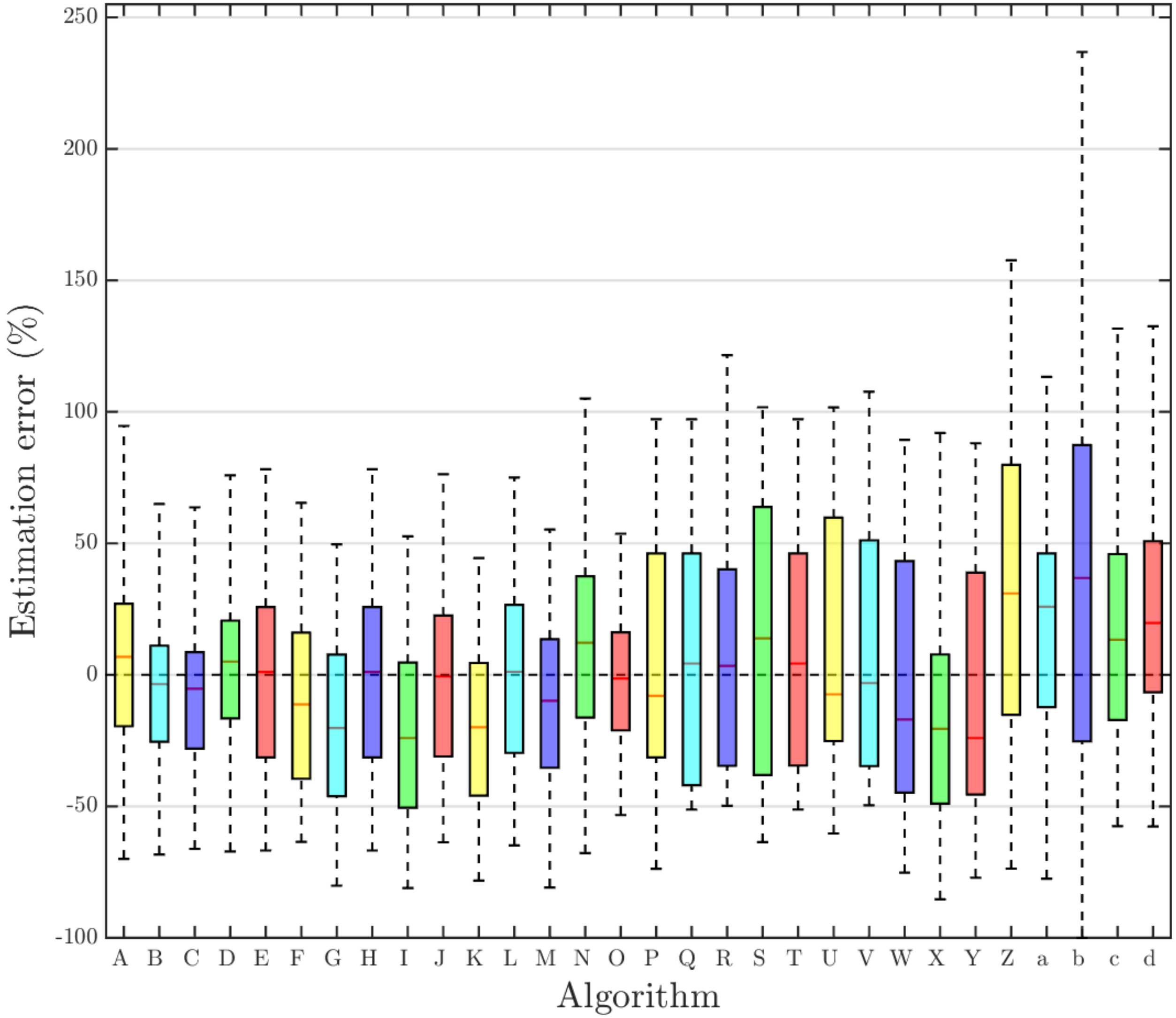
*FB – Full band
SB – Sub-band in ISO preferred frequency bands

Classes of algorithm submitted – T_{60}

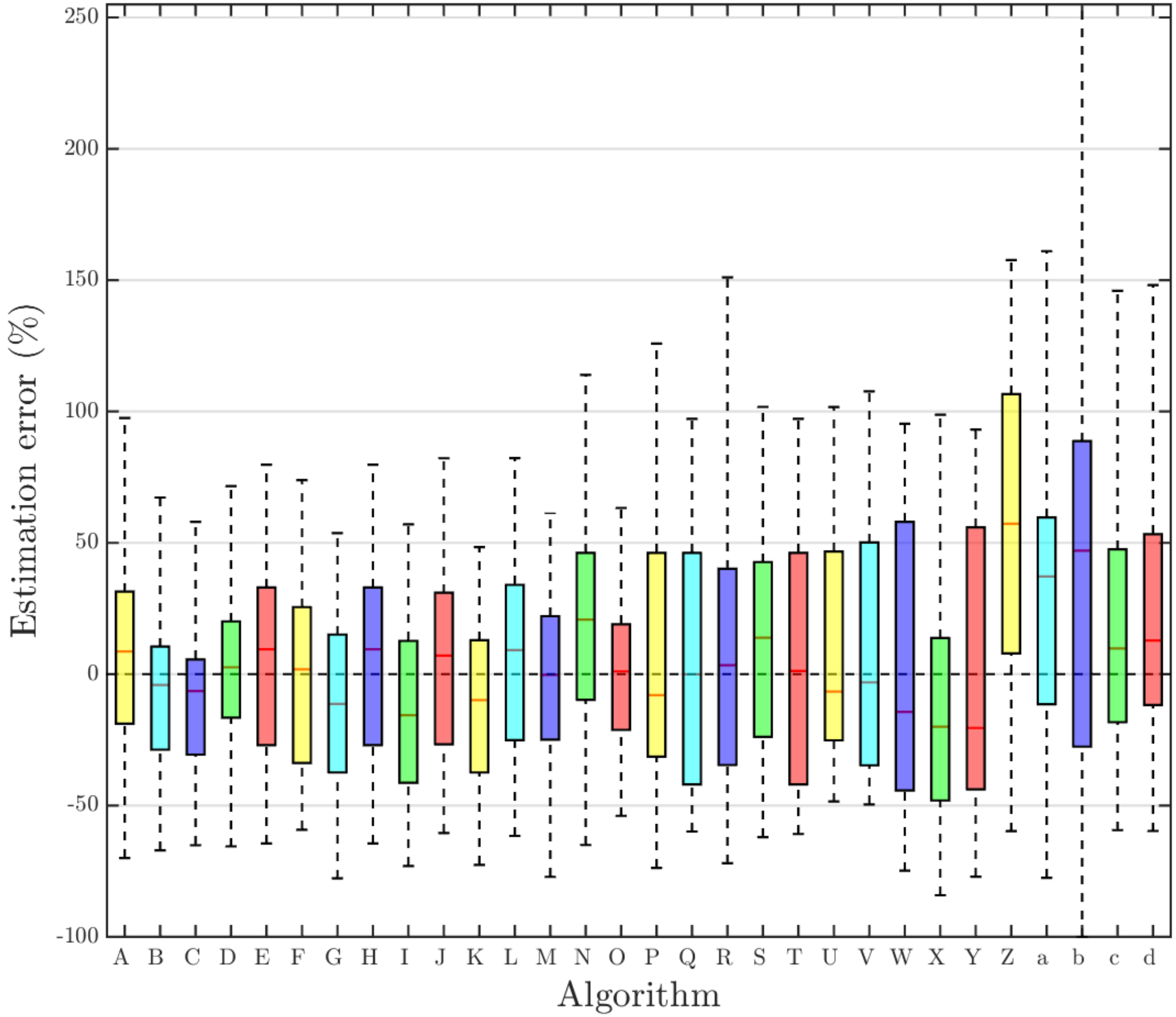
- Analytical
  - Maximum Likelihood
- Single feature mapping
  - Blur Kernel
  - Speech-Reverberation-Modulation-Ratio (SRMR)
  - Spectral decay distributions (SDD)
  - Analysis of free decay regions
- Machine learning
  - Speech recognition features
  - 2D Gabor (auditory inspired)

- Several joint approaches simultaneously estimating T_{60} and DRR
- Mainly fullband submissions – 1 submission in frequency bands

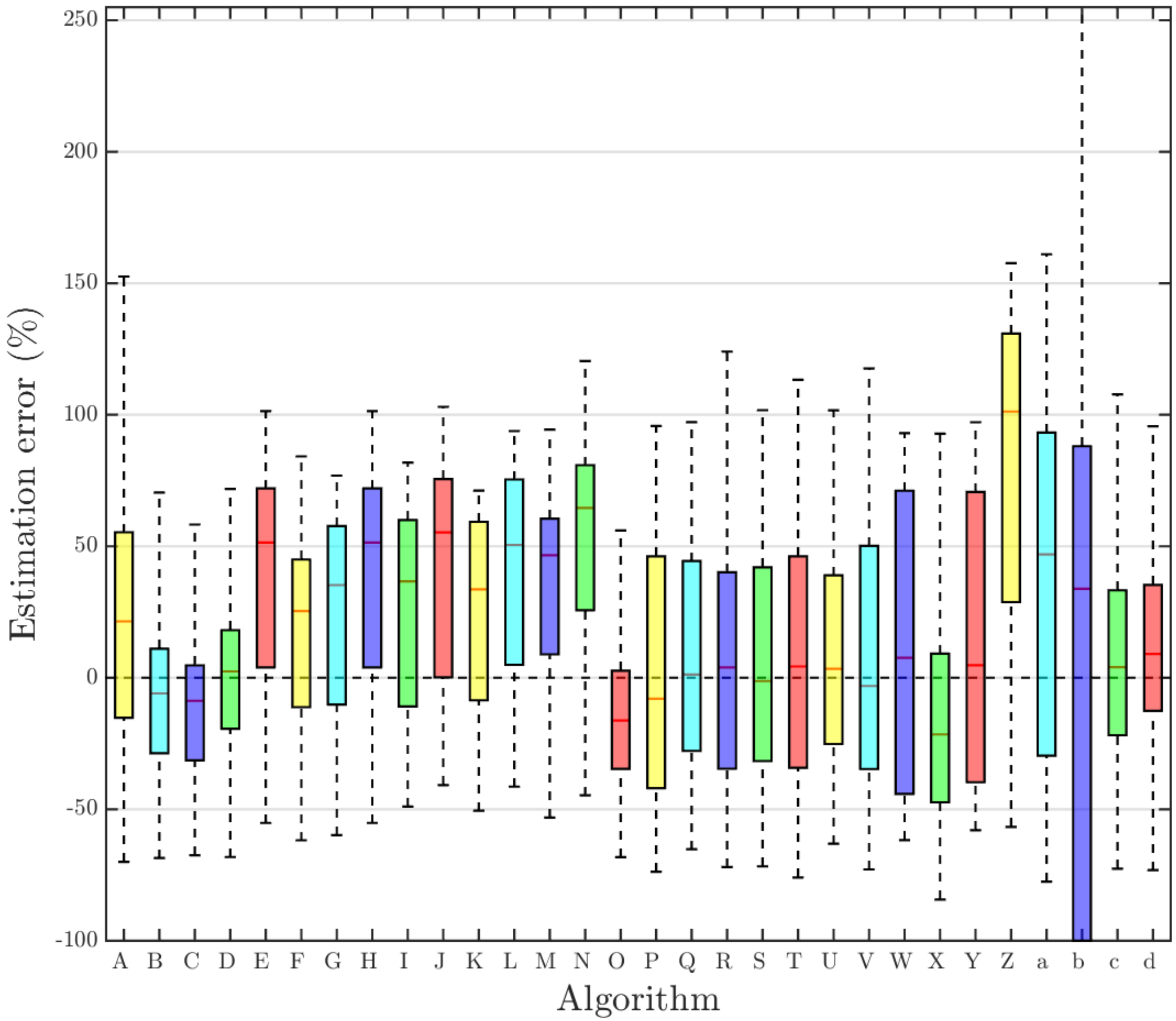
Results: T_{60}, Babble, 18dB SNR



Results: T_{60}, Babble, 12dB SNR



Results: T_{60}, Babble, -1dB SNR



Results: T_{60}, Babble, 18dB SNR

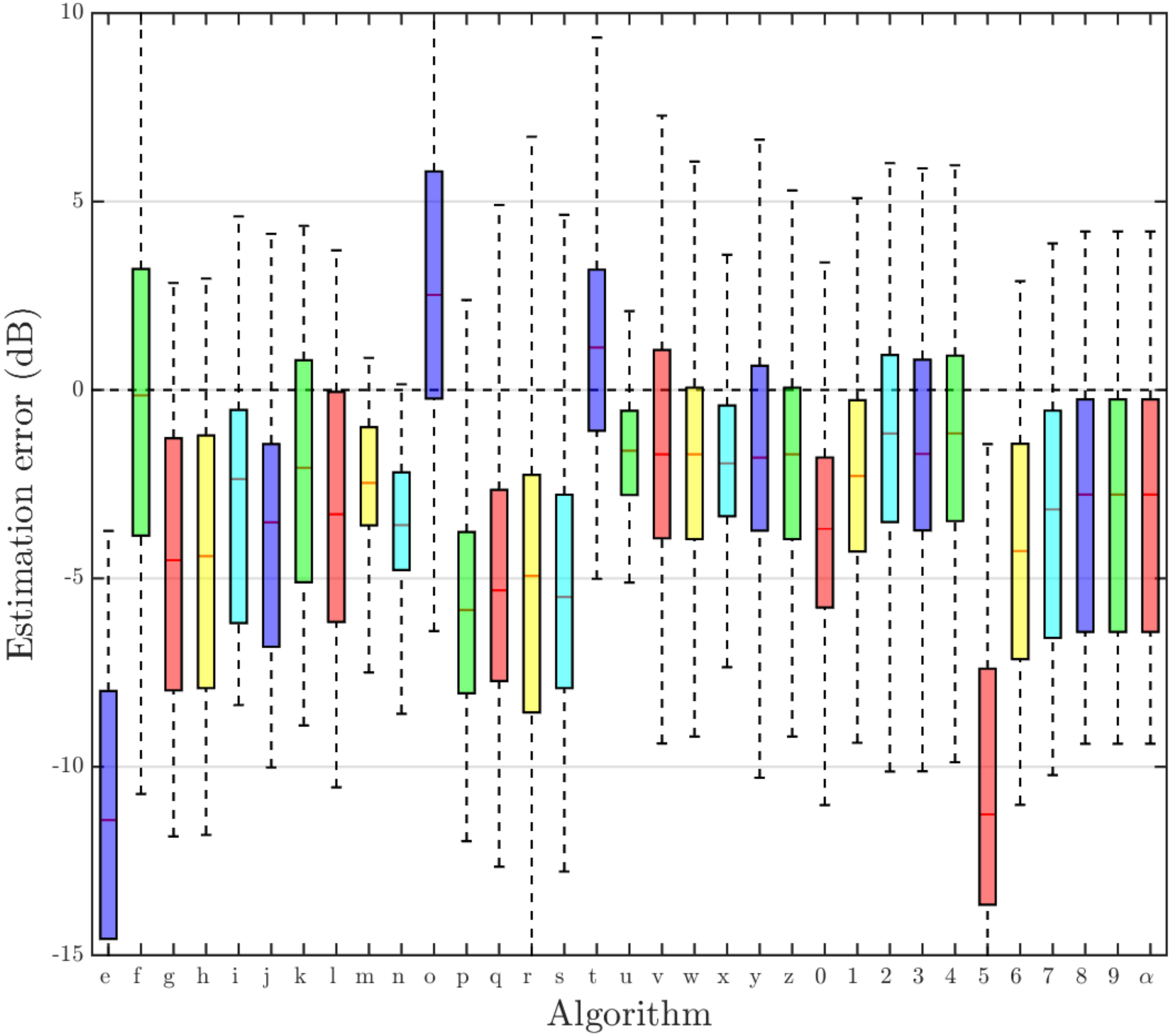
Label	Algorithm	Mic. Config.	RTF	Bias	MSE
A	Baseline algorithm for fullband RTE [1]	Single	0.0428	-0.0546	0.102
B	DCT-based fullband RTE [1]	Single	0.99	-0.1	0.0698
C	Octave subband-based fullband RTE [1]	Single	0.911	-0.112	0.064
D	Model-based subband RTE [1]	Single	0.443	-0.0665	0.0905
E	Sec. 2.4. NSRMR [2]	Single	0.572	-0.116	0.119
F	Per acoustic band SRMR: SRMR$\times k$ Sec. 2.5. [3]	Single	0.579	-0.152	0.108
G	SRMR Sec. 2.3. [3]	Single	0.457	-0.207	0.152
H	NSRMR Sec. 2.4. [3]	Single	0.572	-0.116	0.119
I	SRMR Sec. 2.3. [3]	Mobile	1.26	-0.204	0.128
J	NSRMR Sec. 2.4. [3]	Mobile	1.58	-0.106	0.0924
K	SRMR Sec. 2.3. [3]	Crucif	2.1	-0.2	0.137
L	NSRMR Sec. 2.4. [3]	Crucif	2.63	-0.104	0.105
M	SRMR Sec. 2.3. [3]	Chromebook	0.833	-0.173	0.145
N	NSRMR Sec. 2.4. [3]	Chromebook	1.04	-0.0642	0.111
O	QA Reverb [4]	Single	0.398	-0.0854	0.058
P	Single baseline [5]	Single	0.0579	-0.054	0.098
Q	Single [5]	Single	0.0579	-0.0373	0.0974
R	Laptop [5]	Chromebook	0.0588	-0.056	0.0891
S	Mobile [5]	Mobile	0.0555	-0.0197	0.086
T	Cruciform [5]	Crucif	0.057	-0.0431	0.097
U	Linear [5]	Lin8Ch	0.0618	-0.0359	0.0897
V	Spherical [5]	EM32	0.0576	-0.0518	0.0876
W	NIRAv1 [6]	Single	0.906	-0.126	0.132
X	NIRAv2 [6]	Single	0.901	-0.176	0.228
Y	NIRAv3 [6]	Single	0.906	-0.14	0.133
Z	Blur Kernel [7]	Single	8.88	0.102	0.107
a	Blur Kernel with Sliding Window [8]	Single	0.438	-0.026	0.108
b	SDD [9]	Single	0.0224	0.793	141
c	SDDSA-G [10]	Single	0.0162	0.0104	0.0681
d	SDDSA-G retrained [11]	Single	0.0155	0.0931	0.0836

Classes of algorithm submitted - DRR

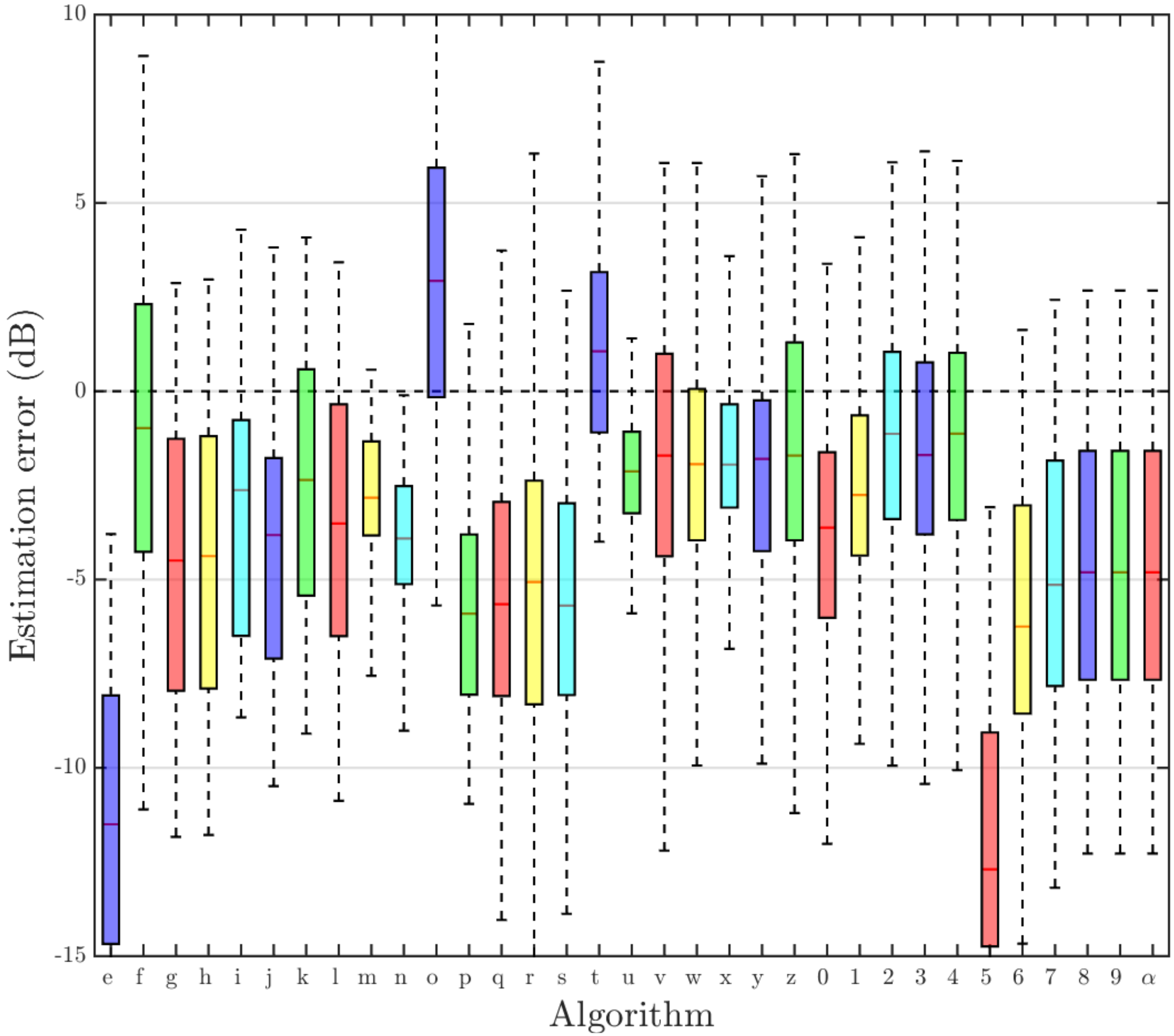
- Analytical
  - Beamforming
- Single feature mapping
  - Speech-Reverberation-Modulation-Ratio (SRMR)
  - Analysis of free decay regions
- Machine learning
  - Speech recognition features
  - 2D Gabor (auditory inspired)

- Mainly fullband - 2 teams made subband submissions

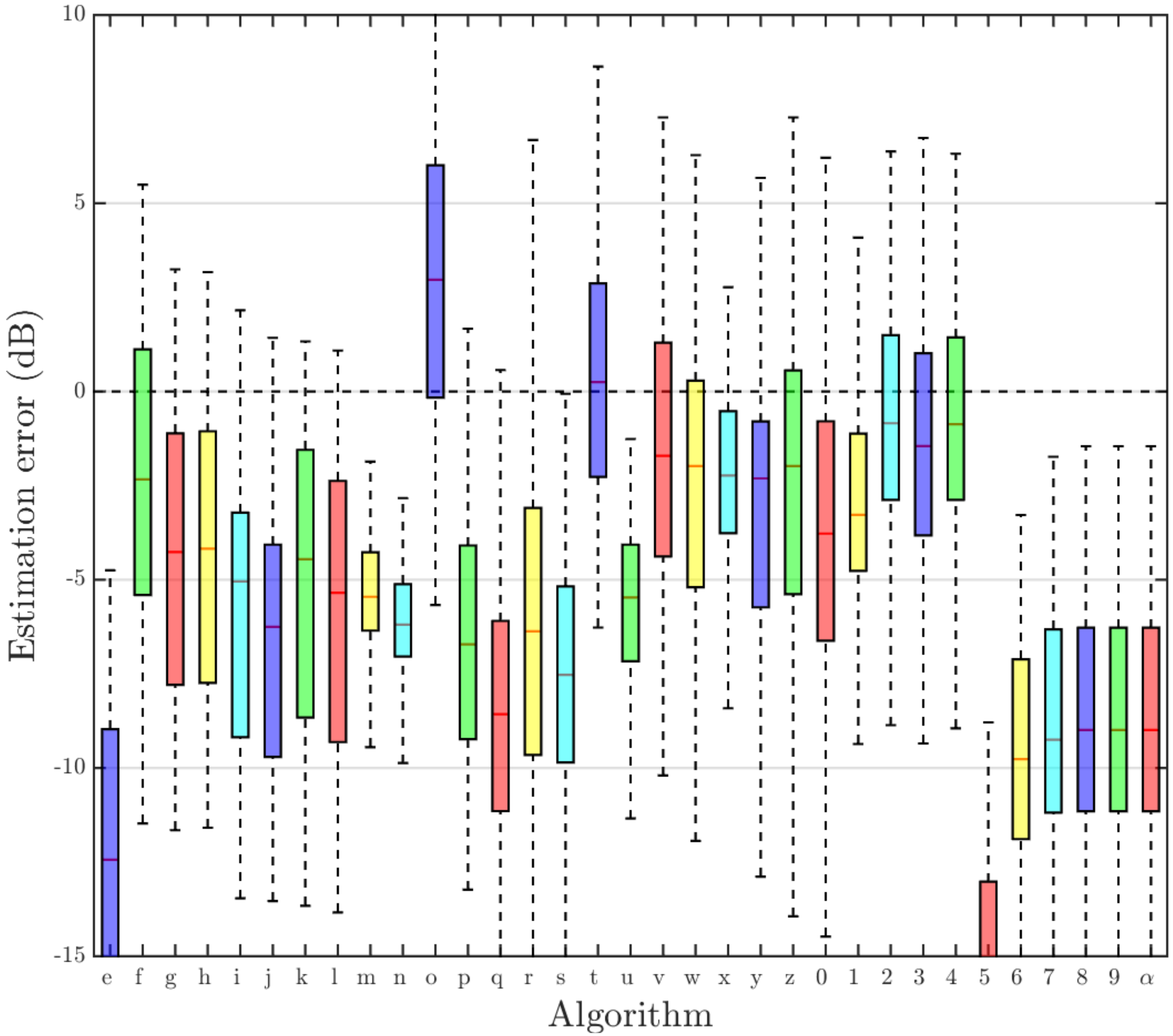
Results: DRR, Babble, 18dB SNR



Results: DRR, Babble, 12dB SNR



Results: DRR, Babble, -1dB SNR



Results: DRR, Babble, 18dB SNR

Label	Algorithm	Mic. Config.	RTF	Bias	MSE
e	Temporal dynamics [12]	Single	0.0823	-11.1	141
f	Per acoustic band SRMR: SRMR $\times k$ Sec. 2.5. [3]	Single	0.579	-0.337	21.5
g	OSRMR Sec. 2.2. [3]	Single	0.444	-4.29	34.9
h	NOSRMR Sec. 2.2. [3]	Single	0.534	-4.21	34.3
i	OSRMR Sec. 2.2. [3]	Mobile	1.26	-2.62	17.4
j	NOSRMR Sec. 2.2. [3]	Mobile	1.58	-3.66	24.2
k	OSRMR Sec. 2.2. [3]	Crucif	2.1	-2.24	18
l	NOSRMR Sec. 2.2. [3]	Crucif	2.63	-3.28	24.3
m	OSRMR Sec. 2.2. [3]	Chromebook	0.833	-2.6	11.1
n	NOSRMR Sec. 2.2. [3]	Chromebook	1.04	-3.76	18.5
o	QA Reverb [4]	Single	0.392	2.63	24.8
p	PSD est. in beamspace (Raw) [13]	Mobile	3.17	-5.85	40.9
q	PSD est. by twin BF [14]	Mobile	0.615	-5.13	40
r	Spatial Covariance in matrix mode [15]	Mobile	0.627	-5.09	51.7
s	PSD est. in beamspace v2 [13]	Mobile	0.843	-5.38	41.2
t	PSD est. in beamspace bias comp. [13]	Mobile	0.757	1.12	7.96
u	Particle velocity [16]	EM32	0.134	-1.62	5.28
v	Single baseline [5]	Single	0.0579	-1.54	15.5
w	Single [5]	Single	0.0579	-1.6	14.1
x	Laptop [5]	Chromebook	0.0588	-2.16	11.1
y	Mobile [5]	Mobile	0.0555	-1.76	13.8
z	Cruciform [5]	Crucif	0.057	-1.62	14.6
0	Linear [5]	Lin8Ch	0.0618	-3.56	23.3
1	Spherical [5]	EM32	0.0576	-2.2	13.5
2	NIRAv1 [6]	Single	0.906	-1.35	12.9
3	NIRAv2 [6]	Single	0.906	-1.67	12.8
4	NIRAv3 [6]	Single	0.906	-1.35	13
5	Blind est. of coherent-to-diffuse energy ratio [17]	Chromebook	0.019	-10.8	133
6	Null St. BF no NR [18]	Chromebook	0.0323	-4.11	27.4
7	Null St. BF spec. sub. [18]	Chromebook	0.0577	-3.27	22
8	Null St. BF S.S. Gerkmann [18]	Chromebook	0.0476	-3.02	20.6
9	Null St. BF filtered subbands [19]	Chromebook	0.778	-3.02	20.6
α	Null St. BF FFT derived subbands [19]	Chromebook	0.0448	-3.02	20.6

Top 3 summary results by category

- T_{60} full-band in babble noise

	Smallest mean-squared error	Smallest absolute bias
1	Octave Fullband MLRTE (FAU/RWTH Aachen)	SDDSA-G (Imperial College London)
2	QA_Reverb (UFRJ)	SRMR-4-40 (MuSAE Lab)
3	SDDSA-G (Imperial College London)	Blur Kernel with Sliding Window (Microsoft)

- DRR full-band in babble noise

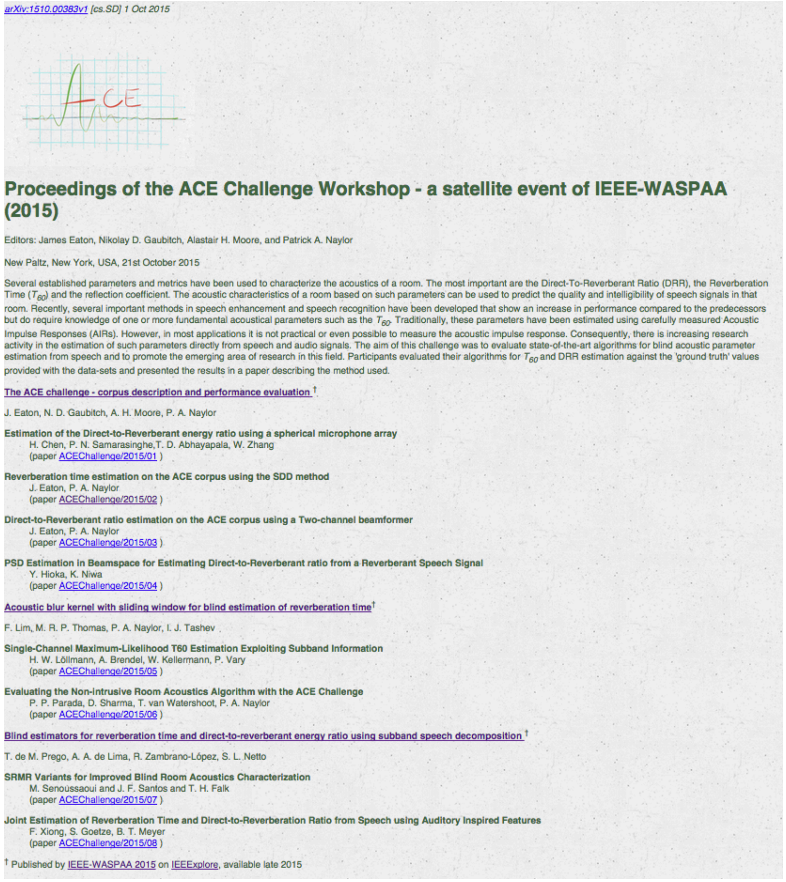
	Smallest mean-squared error	Smallest absolute bias
1	PSD estimation in beamspace bias comp. (University of Auckland/NTT)	PSD estimation in beamspace bias comp. (University of Auckland/NTT)
2	NIRAv1 (NUANCE)	NIRAv1 (NUANCE)
3	NIRAv3 (NUANCE)	NIRAv3 (NUANCE)

Results

- Noise causes significant bias in both tasks
- T_{60} results are more consistent than DRR showing that this is a more mature field
- Large MSE suggests that many DRR estimators may not yet give useful results, with the best method within 3 dB IQR
- Few frequency dependent entries – an emerging field

ACE Challenge Proceedings

- Coming soon:
  - Proceedings arXiv:1510.00383
  - ACE corpus on http://ace-challenge.org



arXiv:1510.00383v1 [cs.SD] 1 Oct 2015

Proceedings of the ACE Challenge Workshop - a satellite event of IEEE-WASPAA (2015)

Editors: James Eaton, Nikolay D. Gaubitch, Alastair H. Moore, and Patrick A. Naylor

New Paltz, New York, USA, 21st October 2015

Several established parameters and metrics have been used to characterize the acoustics of a room. The most important are the Direct-To-Reverberant Ratio (DRR), the Reverberation Time (T_{60}) and the reflection coefficient. The acoustic characteristics of a room based on such parameters can be used to predict the quality and intelligibility of speech signals in that room. Recently, several important methods in speech enhancement and speech recognition have been developed that show an increase in performance compared to the predecessors but do require knowledge of one or more fundamental acoustical parameters such as the T_{60}. Traditionally, these parameters have been estimated using carefully measured Acoustic Impulse Responses (AIRs). However, in most applications it is not practical or even possible to measure the acoustic impulse response. Consequently, there is increasing research activity in the estimation of such parameters directly from speech and audio signals. The aim of this challenge was to evaluate state-of-the-art algorithms for blind acoustic parameter estimation from speech and to promote the emerging area of research in this field. Participants evaluated their algorithms for T_{60} and DRR estimation against the 'ground truth' values provided with the data-sets and presented the results in a paper describing the method used.

The ACE challenge - corpus description and performance evaluation †

J. Eaton, N. D. Gaubitch, A. H. Moore, P. A. Naylor

Estimation of the Direct-to-Reverberant energy ratio using a spherical microphone array
H. Chen, P. N. Samarasinghe,T. D. Abhayapala, W. Zhang
(paper ACEChallenge/2015/01)

Reverberation time estimation on the ACE corpus using the SDD method
J. Eaton, P. A. Naylor
(paper ACEChallenge/2015/02)

Direct-to-Reverberant ratio estimation on the ACE corpus using a Two-channel beamformer
J. Eaton, P. A. Naylor
(paper ACEChallenge/2015/03)

PSD Estimation in Beamspace for Estimating Direct-to-Reverberant ratio from a Reverberant Speech Signal
Y. Hioka, K. Niwa
(paper ACEChallenge/2015/04)

Acoustic blur kernel with sliding window for blind estimation of reverberation time†

F. Lim, M. R. P. Thomas, P. A. Naylor, I. J. Tashev

Single-Channel Maximum-Likelihood T60 Estimation Exploiting Subband Information
H. W. Löllmann, A. Brendel, W. Kellermann, P. Vary
(paper ACEChallenge/2015/05)

Evaluating the Non-intrusive Room Acoustics Algorithm with the ACE Challenge
P. P. Parada, D. Sharma, T. van Watershoot, P. A. Naylor
(paper ACEChallenge/2015/06)

Blind estimators for reverberation time and direct-to-reverberant energy ratio using subband speech decomposition †

T. de M. Prego, A. A. de Lima, R. Zambrano-López, S. L. Netto

SRMR Variants for Improved Blind Room Acoustics Characterization
M. Senoussaoui and J. F. Santos and T. H. Falk
(paper ACEChallenge/2015/07)

Joint Estimation of Reverberation Time and Direct-to-Reverberation Ratio from Speech using Auditory Inspired Features
F. Xiong, S. Goetze, B. T. Meyer
(paper ACEChallenge/2015/08)

† Published by IEEE-WASPAA 2015 on IEEExplore, available late 2015

Imperial College London

Conclusion

- Outcomes
  - Research stimulated
  - State-of-the art determined
  - Corpus of multi-channel noisy reverberant speech freely available shortly
- Corpus applicable to T_{60} and DRR estimation, but also applicable to speech enhancement and speech recognition tasks such as de-reverberation
- Excellent cooperation from all researchers involved – many thanks for your participation!

Thank-you!

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