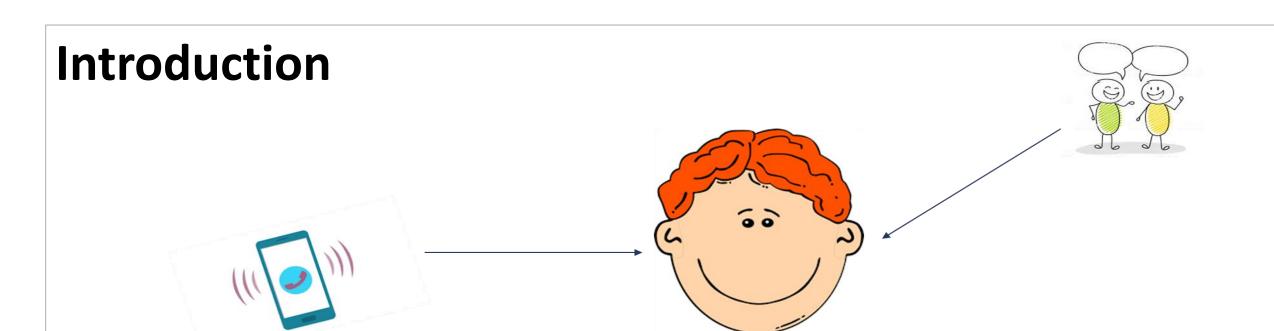
DCASE2021 Workshop on Detection and Classification of Acoustic Scenes and Events

WHAT MAKES SOUND EVENT LOCALIZATION AND DETECTION DIFFICULT? INSIGHTS FROM ERROR ANALYSIS

T. N. T. Nguyen*, K. N. Watcharasupat*, Z. J. Lee, N. K. Nguyen, D. L. Jones[†], W. S. Gan*

nguyenth003@e.ntu.edu.sg

*School of EEE, Nanyang Technological University, Singapore [†]Department of ECE, University of Illinois at Urbana-Champaign, USA



Problem: Polyphonic sound event detection and localization (SELD)

Challenges of SELD task: Noise, reverberation, interference, polyphony, non-stationarity, association between sound classes and directions of arrival (DOA), etc...

Objective: Understand the major sources of errors in SELD task. Approach: Error analysis on different SELD models and datasets.

Proposed error analysis method

- Focus: polyphony, moving source, class-location interdependence, and class-wise performance.
- Use two public datasets for SELD
 - > TAU-NIGENS Spatial Sound Events 2020 (TNSSE 2020) [1]
- > TAU-NIGENS Spatial Sound Events 2021 (TNSSE 2021) [2]
- Use two SELD systems that ranked second in the team categories of the DCASE 2020 and 2021 SELD challenges, respectively.
- System outputs are divided into segments of 1 second. Ground truth is used to group these segments into different categories such as polyphony (0, 1, 2, and 3 sources), static and moving sources, etc., in order to evaluate the SELD performance in each category.

SELD Datasets

Characteristics	TNSSE 2020	TNSSE 2021
Channel format	FOA	FOA
Moving sources	\checkmark	\checkmark
Ambiance noise	\checkmark	\checkmark
Reverberation	\checkmark	\checkmark
Unknown interferences	×	\checkmark
Maximum degree of polyphony	2	3
Number of target sound classes	14	12
Evaluation split	eval	test

References

- [1] A. Politis, S. Adavanne, and T. Virtanen. "A dataset of reverberant spatial sound scenes with moving sources for sound event localization and detection". In DCASE Workshop, 2020.
- [2] A. Politis, S. Adavanne, D. Krause, A. Deleforge, P. Srivastava, and T. Virtanen, "A Dataset of Dynamic Reverberant Sound Scenes with Directional Interferers for Sound Event Localization and Detection," arXiv, 2021.
- [3] T. N. T. Nguyen, D. L. Jones, and W. Gan, "Ensemble of sequence matching networks for dynamic sound event localization, detection, and tracking," In DCASE Workshop, 2020.
- [4] T. N. T. Nguyen, K. N. Watcharasupat, N. K. Nguyen, D. L. Jones, and W.-S. Gan, "DCASE 2021 Task 3: Spectrotemporally-aligned Features for Polyphonic Sound Event Localization and Detection," DCASE2021 Challenge, Tech. Rep., 2021.

Evaluation metrics

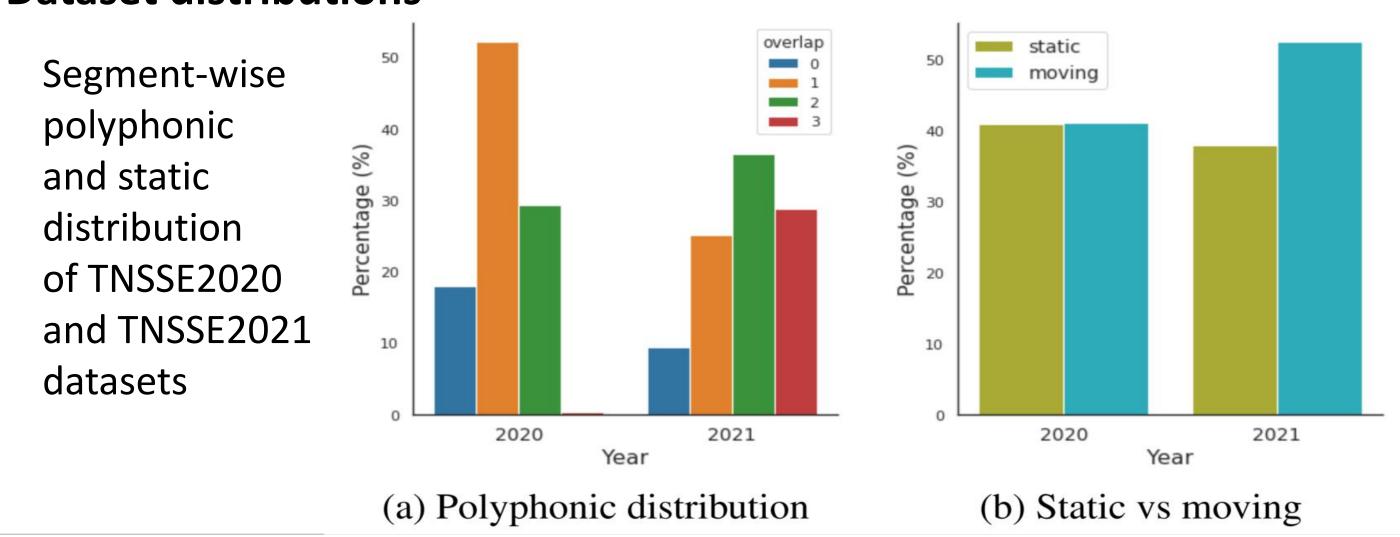
- Sound event detection (SED): Location-dependent error rate $(ER_{< T})$ and F1 score $(F_{\leq T})$. T is DOA threshold (typical value is 20°)
- \triangleright $ER_{\leq T} = substitution + deletion + insertion error rate$
- $F_{\leq T} = 2 \frac{precison * recall}{precison + recall}$
- DOA estimation: Class-dependent localization error (LE_{CD}) (in degrees) and localization recall (LR_{CD})

SELD systems

Year	System	$\text{ER}_{\leq 20^\circ}$	$F_{\leq 20^\circ}$	LE_{CD}	LR_{CD}
2020 (eval)	Baseline [9] #1: USTC'20 [25] #2: NTU'20 [27]	0.69 0.20 0.23	0.413 0.849 0.820	23.1° 6.0 ° 9.3°	0.624 0.885 0.900
2021 (test)	Baseline [11] #1: Sony'21 [26] #2: NTU'21 [23]	0.73 0.43 0.37	0.307 0.699 0.737	24.5° 11.1° 11.2°	0.448 0.732 0.741

- NTU'20: ensemble of sequence matching networks, evaluated on the evaluation split of the TNSSE2020 dataset [3].
- NTU'21: ensemble of SELDnet-like networks, trained on SALSA features, evaluated on the test split of the TNSSE2021 dataset [4].

Dataset distributions



Effect of polyphony

	2020 2021						
Metrics	1	2	All	1	2	3	All
↓ER<20°	0.108	0.331	0.232	0.349	0.338	0.394	0.372
$\downarrow Substitution$	0.029	0.072	0.052	0.093	0.104	0.129	0.114
↓ Deletion	0.042	0.155	0.103	0.091	0.137	0.182	0.152
↓ Insertion	0.038	0.104	0.078	0.164	0.096	0.083	0.105
↑F<20°	0.930	0.765	0.845	0.784	0.763	0.704	0.737
↑ Precision	0.932	0.788	0.875	0.757	0.780	0.746	0.756
↑ Recall	0.928	0.743	0.833	0.813	0.747	0.666	0.719
\downarrow LE _{CD}	5.6	13.4	9.4	6.8	10.3	13.5	11.2
\uparrow LR _{CD}	0.930	0.775	0.846	0.816	0.764	0.701	0.741



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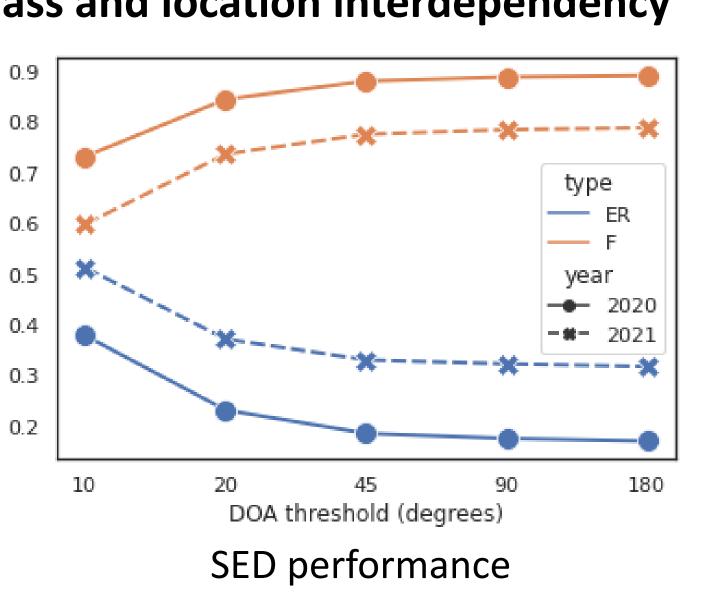
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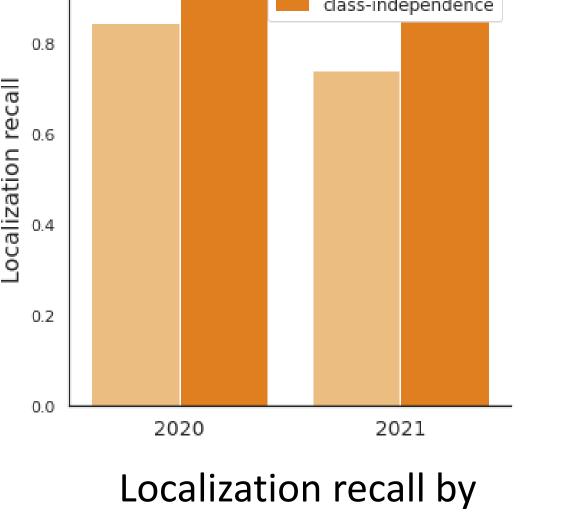
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Effect of moving sound sources

	2020			2021		
Metrics	Static	Moving	All	Static	Moving	All
\downarrow ER $_{\leq 20^{\circ}}$	0.214	0.239	0.232	0.379	0.357	0.372
\uparrow F $_{\leq 20^{\circ}}$	0.854	0.841	0.845	0.731	0.745	0.737
\downarrow LE _{CD}	8.7	10.0	9.4	10.5	11.7	11.2
\uparrow LR _{CD}	0.847	0.846	0.846	0.725	0.751	0.741
\downarrow ER $_{\leq 180^{\circ}}$ \uparrow F $_{\leq 180^{\circ}}$	0.166	0.168	0.171	0.334	0.298	0.318
	0.898	0.891	0.892	0.778	0.800	0.789

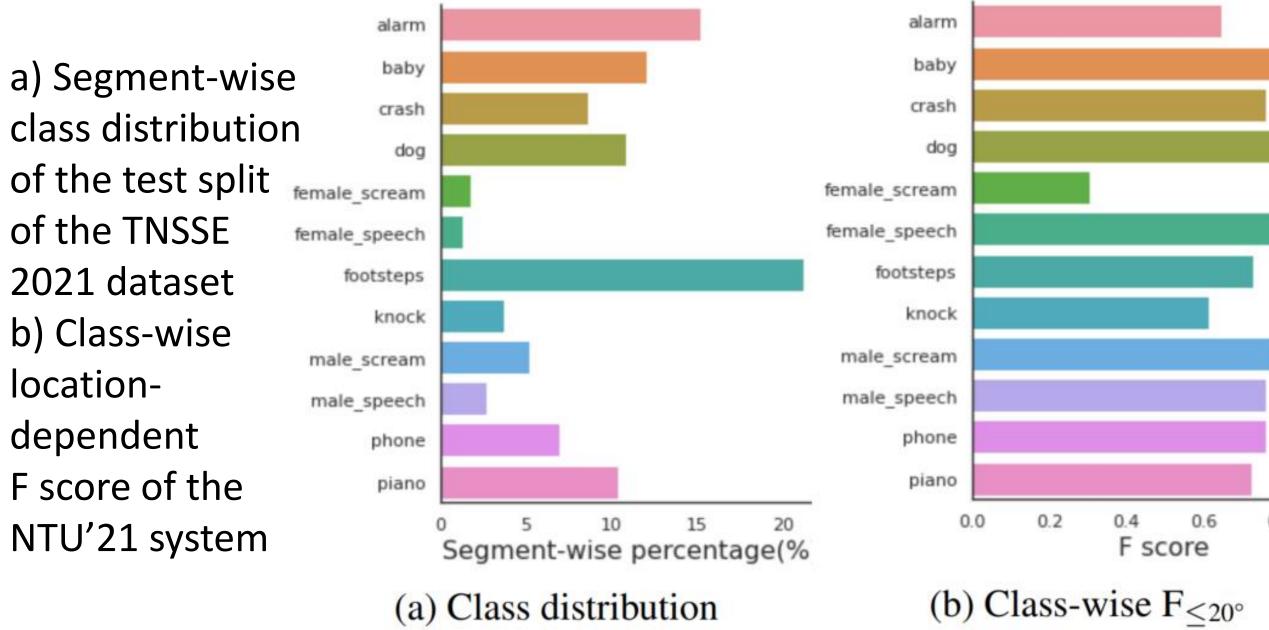
Class and location interdependency





across different DOA threshold

class dependencies Class-wise performance



Conclusion

- Polyphony and unknown interferences appear to be the biggest challenges for SELD task as SELD systems struggle to detect all events of interests (low recall and high deletion error).
- Unknown interferences lead to more substitution errors.
- $ER_{\leq T}$ is lowest for the polyphonic case that dominates the dataset.
- Moving sources mainly increase the localization errors.
- It is very challenging to further tighten the DOA threshold.
- High segment-wise representation of a class does not necessarily translate to high SED performance.