ID: P4-28-SS05

The T05 System for The VoiceMOS Challenge 2024: Transfer Learning from Deep Image Classifier to Naturalness MOS Prediction of High-Quality Synthetic Speech

Our codes
https://github.com/sarulab-speech/UTMOSv2

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Introduction

Automatic MOS Prediction

Machine learning system that predicts Mean Opinion Score (MOS) of synthetic speech (e.g., UTMOS [1])

- ✓ Reducing the costs of human-based subjective evaluations
- ✓ Achieving highly reproducible evaluation
- ✗ Suffering from the bias observed in the training data

RQ: Can we develop a MOS predictor suitable for high-quality synthetic speech?

Our Contributions: The Development of UTMOSv2

MOS predictor designed for comparing high-quality synthetic speech

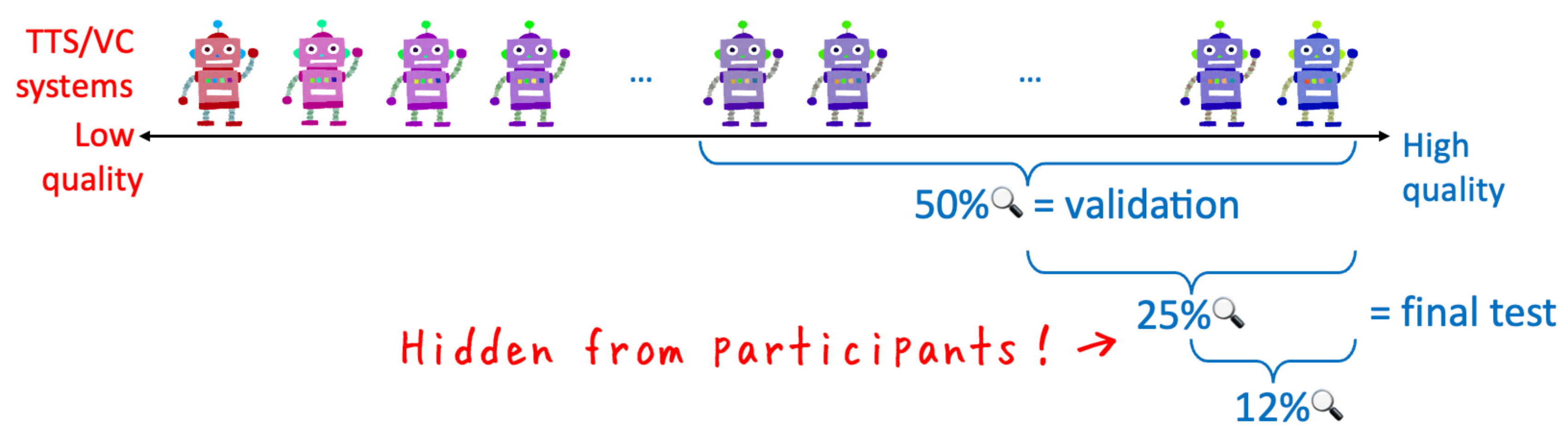
✨ UTMOSv2 achieved 1st place in 7/16 evaluation metrics ✨
✨🏆 and 2nd place in the remaining 9 metrics 🏆✨
✨ in the VoiceMOS Challenge (VMC) 2024 Track 1 [2] ✨

Publicly available on GitHub (scan the QR code above)

Our UTMOSv2 for The VMC 2024 Track 1

The VMC 2024 Track 1

Dataset: Zoomed-in MOS test results of BVCC [3]



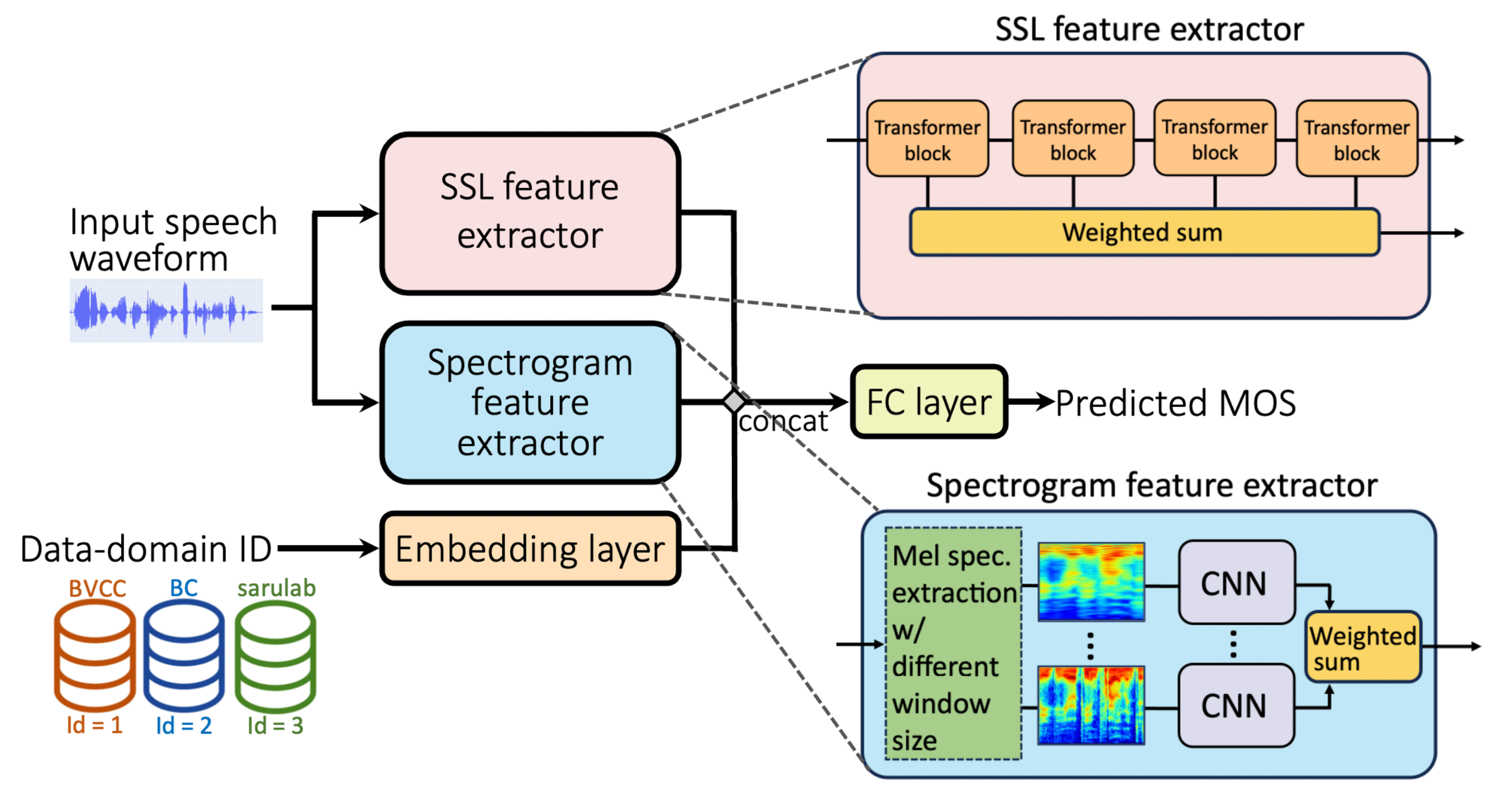
- No official training dataset for zoomed-in MOS tests
  → Our team conducted 50% zoomed-in MOS test using BVCC & published the results as "sarulab-data" (sarulab).

Evaluation Metrics:

- **MSE (Mean Squared Error)**
- **SRCC (Spearman's Rank Correlation Coefficient)**
- LCC (Linear Correlation Coefficient)
- KTAU (Kendall's Tau)

- Evaluation for each utterance (Utterance-level)
- Evaluation for each speech synthesis system (System-level)

UTMOSv2



① Fusion of SSL/spectrogram features → See Exp. 1
- Using pretrained speech SSL model / image classification model as powerful feature extractors for MOS prediction

② Multi-stage learning strategy → See Exp. 2
1) Pretrain each feature extractor independently
2) Train the last FC layer
3) Fine-tune the whole system

③ Data-domain encoding → See Exp. 3
- Condition the MOS predictor on the data domain ID

Experimental Evaluation with 12% Zoomed-in BVCC

Experimental Setup (See our paper for more details)

Traning Dataset	BVCC [3], Blizzard Challenge 2008〜2011 [4,5,6,7], SOMOS [8], sarulab (Mixup [15] was used as the data augmentation)
Feature Extractor	SSL: wav2vec2.0-base [9] (pretrained on LibriSpeech [10]) Spectrogram: EfficientNetV2 [11] (pretrained on ImageNet [12])
Optimizer	AdamW [13] w/ cosine annealing scheduler [14] (The learning rates were tuned for each experiment)
Training Objective	Minimizing contrastive loss [1] + MSE
Checkpoint Selection	5-fold cross-validation based on the average system-level SRCC (The primal metric for the VMC 2024 Track 1)

Exp. 1: Effects of Feature Fusion

	Utterance-level		System-level	
	MSE ↓	SRCC ↑	MSE ↓	SRCC ↑
UTMOSv2	0.459	**0.579**	0.288	**0.854**
w/o SSL	**0.357**	0.516	**0.188**	0.770
w/o Spec.	0.673	0.529	0.497	0.793
SSL-MOS [16]	0.741	0.417	0.589	0.609
UTMOS [1]	0.541	0.300	0.378	0.367

✓ ①The fusion improved SRCC

✓ ②Achieved higher performance than the baselines (SSL-MOS, UTMOS)

Exp. 2: Comparison of Multi-Stage Learning

	Utterance-level		System-level	
	MSE ↓	SRCC ↑	MSE ↓	SRCC ↑
UTMOSv2	0.459	**0.579**	0.288	**0.854**
w/o Stage 1	0.342	0.505	0.108	0.816
w/o Stage 2	**0.293**	0.423	**0.097**	0.672

✓ The multi-stage learning process improved SRCC

【Reference】
[1] Saeki et al., INTERSPEECH 2022, [2] Huang et al., SLT 2024, [3] Huang et al., INTERSPEECH 2022,
[4] Karaiskos et al., BC Workshop 2008, [5] Black et al., BC Workshop 2009,
[6] Black et al., BC Workshop 2010, [7] King et al., BC Workshop 2011,
[8] Maniati et al., INTERSPEECH 2022, [9] Baevski et al., NeurIPS 2020,
[10] Panayotov et al., ICASSP 2015, [11] Tan et al., ICML 2021, [12] Deng et al., CVPR 2009,
[13] Loshchilov et al., ICLR 2019, [14] Loshchilov et al., ICLR 2017, [15] Zhang et al., ICLR 2018,
[16] Cooper et al., ICASSP 2022.

Exp. 3: Investigation on Training Dataset

The data domain ID specified for MOS prediction

	BVCC		BC		SOMOS		sarulab	
System-level	MSE ↓	SRCC ↑	MSE ↓	SRCC ↑	MSE ↓	SRCC ↑	MSE ↓	SRCC ↑
All datasets	0.288	**0.854**	**0.088**	**0.851**	**0.056**	0.844	**0.058**	**0.838**
w/o BVCC	-	-	0.343	0.832	0.128	**0.846**	0.101	0.836
w/o BC	**0.145**	0.819	-	-	0.069	0.823	0.122	0.805
w/o SOMOS	0.224	0.696	0.221	0.682	-	-	0.221	0.700
w/o sarulab	0.282	0.647	0.102	0.661	0.186	0.690	-	-

✓ Training on all datasets generally yielded the best performance

✓ Removing SOMOS or sarulab degraded the performance
→ SOMOS/sarulab datasets were important for the zoomed-in MOS prediction