Empowering Whisper as a Joint Multi-Talker and Target-Talker Speech Recognition System

Lingwei Meng, Jiawen Kang, Yuejiao Wang, Zengrui Jin, Xixin Wu, Xunying Liu, Helen Men

The Chinese University of Hong Kong, Hong Kong SAR, China

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HyorinJung

Index

Background

Prior adaptation methods: Multi-talker speech recognition.

Cascade systems

- 1)Separate → 2)recognize
- suffer from objective mismatch and limited joint optimization

End-to-end (E2E)

- ASR methods (PIT, HEAT, SOT) show promise
- but usually need training from scratch or full fine-tuning

Background

Prior adaptation methods: Target-Talker ASR.

Goal : Efficiently recognize one target speaker's speech in multi-talker conditions

- End-to-end approaches have shown remarkable progress

Limitation

- However, they generally require:
  - External modules (e.g., x-vector, ECAPA-TDNN)
  - Internal embedding extractors
- Usually, only the target speaker's transcript is produced, while non-target speech is ignored.
- Speaker-attributed ASR can handle multiple speakers, but requires embeddings for all speakers
- Only one prior work addressed joint multi- and target-talker ASR, but still depends on an external extractor

Introduction

Main Contributions:

- Novel joint ASR framework — transcribes **multi-talker speech** while highlighting the **target speaker** without any speaker embedding extractor.
- Parameter-efficient & loosely coupled — only a small number of trainable parameters.
- State-of-the-art performance on LibriMix / LibriSpeechMix (English) and strong zero-shot generalization on AishellMix (Mandarin)

Introduction

Method

- **Whisper (Foundation Model)** : Serves as the base encoder-decoder model, providing robust pre-trained speech representations
- **Sidecar Separator** : Separates mixed embeddings from multiple speakers within Whisper’s encoder layers
- **Target Talker Identifier (TTI)** : Identifies the target speaker’s embedding flow dynamically using a 3-second enrollment cue
- **Soft Prompt Embedding** : Adapts the Whisper decoder to multi-/target-talker ASR tasks through lightweight soft prompt tuning

Background

Whisper as the Speech Foundation Model

- Whisper is an attention-based encoder–decoder speech recognition model.
- Trained on massive web-scale labeled speech data
- Widely used beyond ASR as a speech foundation model
- Inspired by its versatility, this study extends Whisper to handle joint multi-talker and target-talker ASR tasks efficiently

Background

Empowering Whisper as a Multi-Talker ASR System

- SS + Whisper >> converts a well-trained single-talker ASR model into a multi-talker ASR model
- The SS is a temporal convolutional network inserted between the early encoder layers
- It consists of stacked 1-D dilated convolutional blocks inspired by Conv-TasNet.
- Since the shallow encoder layers of ASR capture more acoustic than linguistic information, the SS separates mixed embeddings into speaker-specific representations by generating talker-dependent masks.

Background

Placement in Whisper:

- The Sidecar Separator, along with two additional 1-D Conv layers, is placed after the 2nd encoder block.
- It generates masks corresponding to each speaker,
  which are element-wise multiplied with the mixed embeddings to obtain separated speaker embeddings.
- The remaining encoder blocks and decoder then process each branch to produce the final transcriptions for each speaker.

Background

Log-Mel Spectrogram

$$X \in \mathbb{R}^{D \times T}$$

CNN Down-sampling

Encoder

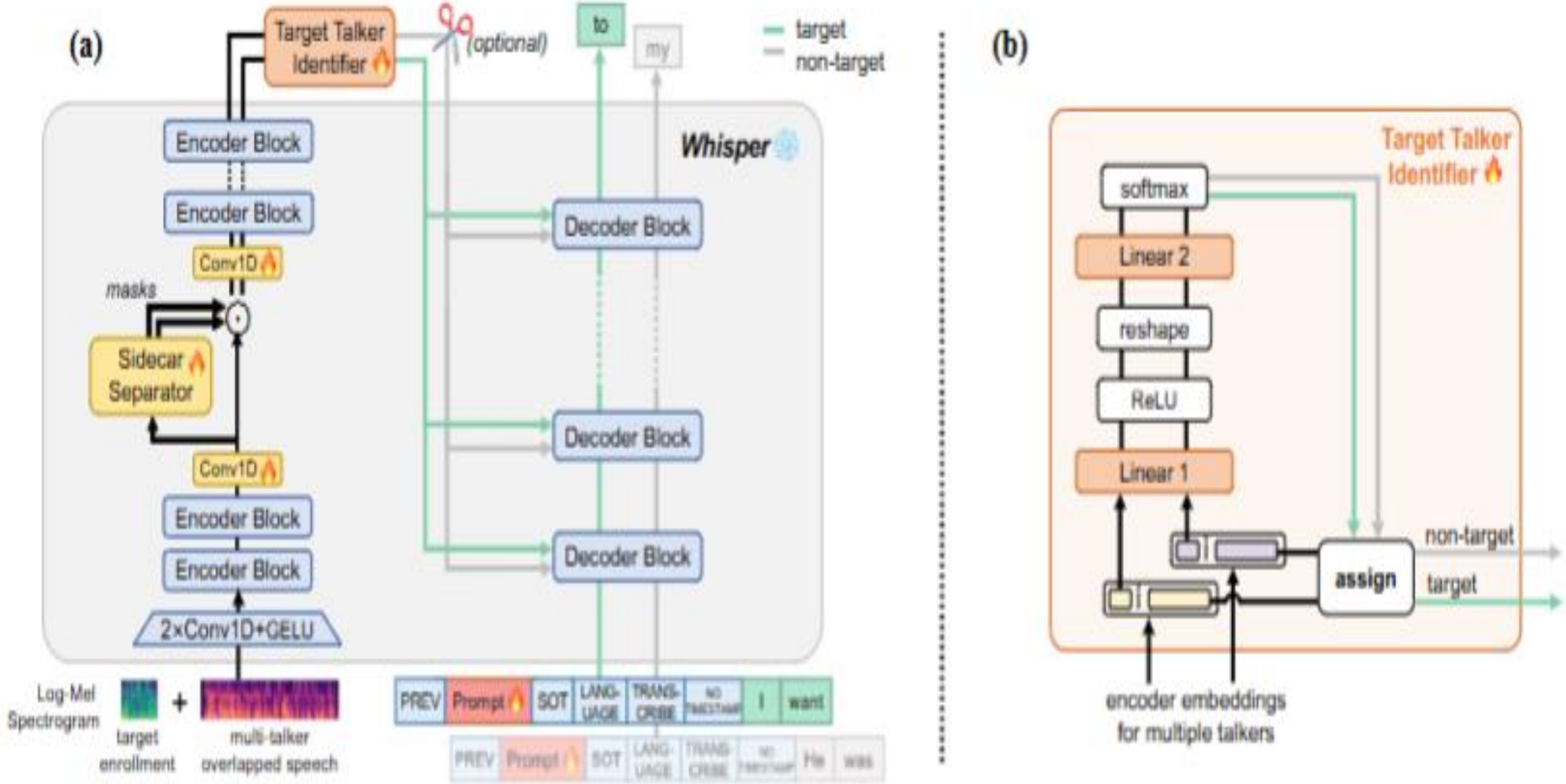
$$H_e = \text{Encoder}(\text{Conv}(X))$$

Decoder

$$\hat{y}_m = \text{Decoder}(s, \hat{y}_{1:m-1}, H_e)$$

- s : special token sequence
  ex<|PREV|>, decoder prompt,
<|SOT|>, <|LANGUAGE|>,
<|TRANSCRIBE|>, <|NO-TIMESTAMP|>

Text


(a)
Target Talker Identifier
(optional)
to
my
target
non-target
Whisper
Encoder Block
Encoder Block
Conv1D
masks
Sidecar Separator
Conv1D
Encoder Block
Encoder Block
2×Conv1D+GELU
Decoder Block
Decoder Block
Decoder Block
Log-Mel Spectrogram
target enrollment
multi-talker overlapped speech
PREV
Prompt
SOT
LANG-UAGE
TRANS-CRIBE
I
want
He
was
(b)
Target Talker Identifier
softmax
Linear 2
reshape
ReLU
Linear 1
assign
non-target
target
encoder embeddings for multiple talkers

Background

Target Talker Identifier (TTI)

- Introduces target-talker ASR capability into the system
- During the forward process :
  - Encoder outputs (from multiple speakers) are divided into:
    - Prefix segment — corresponds to the *3-second enrollment speech*
    - Main segment — corresponds to the *multi-talker speech*
- The prefix segment is sent to the TTI module,
  which determines which branch belongs to the target talker.
- Only the main segment of the target branch is passed to the Whisper decoder for transcription.

Background

- B: 배치 크기 (Batch Size)
- S: 화자 수 (Number of Talkers)
- 150: 시간 프레임 수 (Time Frames), 각 프레임은 20ms이므로 150프레임은 3초에 해당합니다.
- C: 채널 수 (Number of Channels)

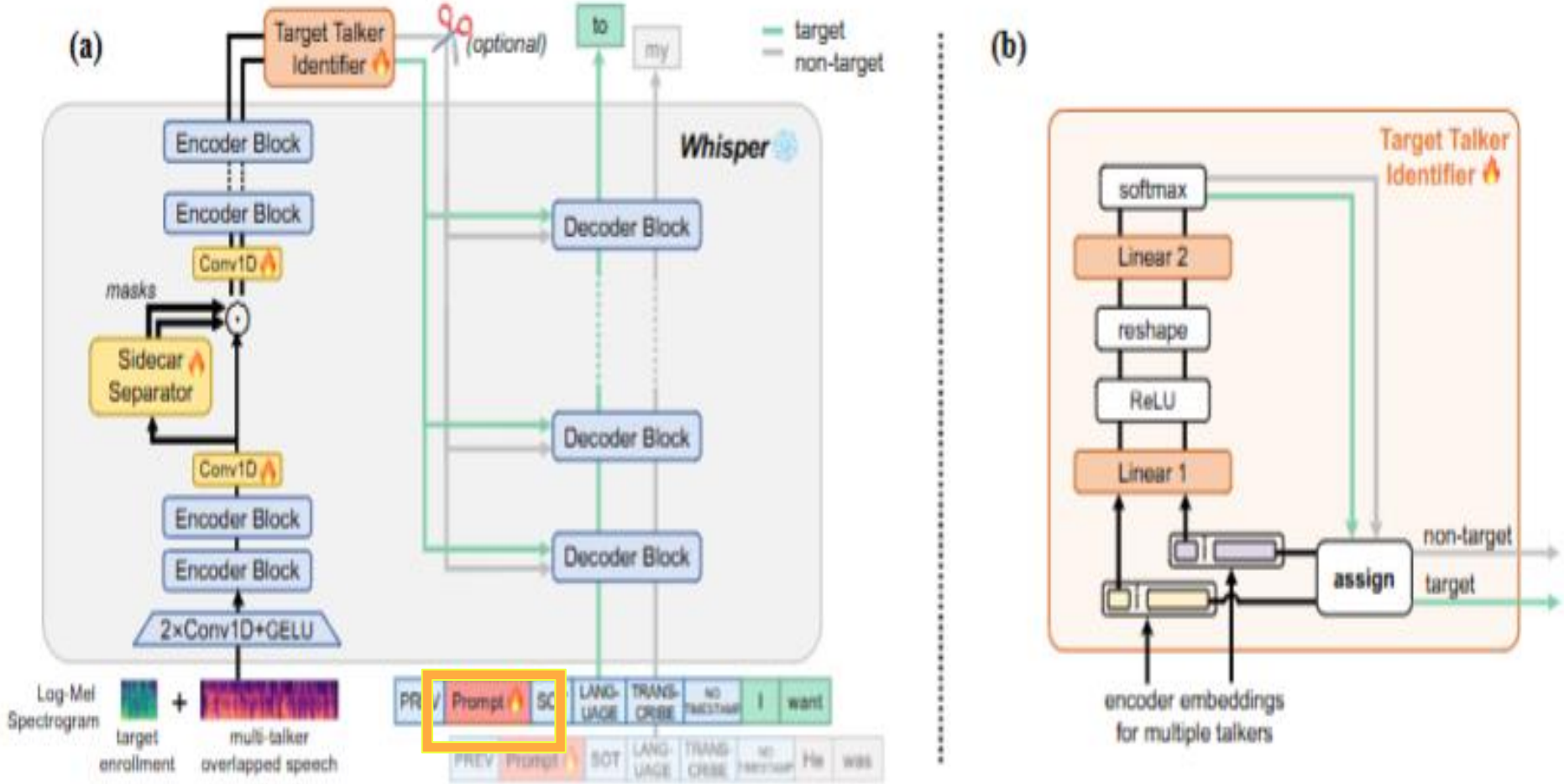
How TTI Works

Step	Operation	Output shape
1	Prefix segment input	(B × S, 150, C)
2(reshape)	Linear layer + ReLU	(B × S, 150, 1)
3(softmax)	Squeeze(크기1차원 제거) + reshape → Linear + Softmax	Probability (B, S) of each branch being the target speaker
	Select target branch (highest probability)	Minimal computational overhead

Background

Soft Prompt Tuning

- Whisper model text prompt tokens >> prefixes in the decoder input sequence to specify tasks and conditions
- Combine this inherent property of Whisper with
  Soft Prompt Tuning >> To adapt the model efficiently
  for multi-talker and target-talker ASR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Background

How It Works

- A learnable embedding (soft prompt) is inserted between <|PREV|> and <|SOT|> tokens — where hard prompts are usually placed
- The position of the soft prompt is masked when calculating loss, since the model doesn't need to generate it
- The soft prompt embedding is updated as the model learns to transcribe multi-talker speech

Experiments : Setting

Datasets

- **English datasets:**
  a. **LibriMix** : 2- and 3-speaker fully overlapped mixtures (Libri2Mix, Libri3Mix)
  b. **LibriSpeechMix** : partially overlapped mixtures (random delay)

- **Mandarin dataset:**
  a. **Aishell1Mix** : generated from Aishell-1 corpus
- Each enrollment speech = **3-second clip** randomly sampled from LibriSpeech.

- Audio longer than **30 s** is time-stretched to fit Whisper’s input limit.

Experiments : Setting

Implementation Details

- At each training step:
  - 80% probability: multi-talker ASR training
  - 20% probability: joint multi-talker + target-talker ASR training
- Two losses are optimized:
  - ASR loss
  - TTI cross-entropy loss
- Both require speaker-order permutation assignment (to resolve label ambiguity)

Experiments : Setting

Model Settings and Evaluation Metrics

- Base models: Whisper-small, Whisper-medium,Whisper-large-v3
- Frozen weights; only train: Sidecar Separator, TTI module, Soft Prompt embeddings
- Optimizer: AdamW (lr: 2e-4 → 1e-4)
- Training: up to 200k steps on 8×NVIDIA V100 (batch=16)
- λ = 0.01 for TTI loss weight.
- Evaluation metrics:
  - Multi-talker ASR → WER/CER (permuta
  - Target-talker ASR → standard WER

Foundation Model	2-speaker	3-speaker
Whisper-small	8.69 M (3.47%)	8.79 M (3.51%)
Whisper-medium	13.16 M (1.69%)	13.29 M (1.71%)
Whisper-large	18.41 M (1.18%)	18.58 M (1.19%)

Experiments : Setting

Implementation Details

- The assignment is determined by Permutation Invariant Training (PIT): matching

$$\hat{\pi} = \arg\min_{\pi \in \mathcal{P}} \sum_{s=1}^{S} \text{Loss}_{\text{ASR}}(Y^s, R^{\pi(s)}) \Rightarrow L_{\text{ASR}} = \sum_{s-1}^{S} \text{Loss}_{\text{ASR}}(Y^s, R^{\hat{\pi}(s)})$$

- Final objective: $L = L_{ASR} + \lambda L_{TTI}$
- λ = 0.01
- No CTC loss is used, since Whisper was not trained with CTC.

Ablation Study

Ablation:

- Tested prompt lengths {0, 2, 4, 8, 16}
- Best performance achieved at **soft prompt length = 4.**
- Too long → harder optimization (frozen model → longer sequences hurt)

Table 5: *Ablation study on soft prompt, evaluated by WER (%).*

	Soft Prompt Length				
System	0	2	4	8	16
Whisper-medium-SS-TTI	7.21	6.82	**6.56**	6.84	7.5
Whisper-large-SS-TTI	5.27	4.98	**4.66**	4.74	5.43

Table 2: *Multi-talker ASR on the test sets of LibriMix and LibriSpeechMix. Evaluated by WER (%). "SS" denotes "Sidecar Separator", "TTI" denotes "Target Talker Identifier".*

System	LibriMix		LibriSpeechMix	
	2spk	3spk	2spk	3spk
(a) WavLM Base+ PIT [9]	18.45	-	-	-
(b) C-HuBERT-Large [35]	7.80	-	-	-
(c) SURT [11]	-	-	7.20	-
(d) SOT-Conformer [27]	-	-	4.90†	**6.20†**
(e) D2V-Sidecar-DB [21]	9.69	33.91	7.49	11.94
(f) Whisper-small-SS	10.04	29.20	5.27	9.85
(g) Whisper-small-SS-TTI	9.39	26.76	5.18	8.61
(h) Whisper-medium-SS	6.95	22.58	4.32	7.80
(i) Whisper-medium-SS-TTI	6.56	21.47	4.01	7.50
(j) Whisper-large-SS	4.98	17.55	3.81	7.13
(k) Whisper-large-SS-TTI	**4.66**	**16.79**	**3.43**	6.80

† with extremely heavier training efforts.

Table 3: *Target-talker ASR on LibriMix and LibriSpeechMix. Evaluated by WER (%). "-limited" denotes using the same training data as in [24].*

System	LibriMix		LibriSpeechMix	
	2spk	3spk	2spk	3spk
WavLM-Base$^+$-TSE [9]	12.32	-	-	-
Whisper-TS-ASR [24]	11.98	-	-	-
Whisper-small-SS-TTI-limited	15.75	-	-	-
Whisper-medium-SS-TTI-limited	11.39	-	-	-
Whisper-large-SS-TTI-limited	10.79	-	-	-
Whisper-small-SS-TTI	11.81	30.52	8.89	15.85
Whisper-medium-SS-TTI	9.14	25.75	7.58	12.4
Whisper-large-SS-TTI	**7.97**	**21.97**	**6.99**	**11.4**

Table 4: *Zero-shot and one-batch-tuning multi-talker ASR on Aishell1Mix Mandarin dataset. Evaluated by CER (%).*

System	zero-shot	one-batch-tuning
Whisper-small-SS-TTI	55.87	28.95
Whisper-medium-SS-TTI	36.28	19.83
Whisper-large-SS-TTI	**28.94**	**17.81**

Experiments : Result

- Evaluated whether multilingual capability is retained after fine-tuning on English.
- Tested on AishellMix (Mandarin) – first use for multi-talker ASR.
- Two evaluation modes:
  - Zero-shot: directly tested without retraining
  - One-batch tuning: fine-tuned for one epoch on AishellMix
- Medium & large models show acceptable CER in zero-shot; further improved with minimal tuning.
- Confirms that Whisper's multilingual ability is preserved

Limitations

Limitations:

- Current method relies on **PIT**, requiring pre-defined max speaker count.
- Future work: explore **SOT / HEAT** to handle variable speakers.
- Large target-speaker delay can reduce accuracy.
- Plan to enhance **TTI** with longer contextual awareness (beyond 3 seconds).

Conclusion

- We proposed a novel methodology that harnesses Whisper,
  a speech foundation model, to jointly transcribe multi-talker speech
  while highlighting the target talker's speech,
  without any external speaker embedding extractor.
- Key components:
  1. **Frozen Whisper backbone**
  2. **Sidecar Separator** for embedding separation
  3. **Target Talker Identifier (TTI)** for on-the-fly target detection
  4. **Soft Prompt Tuning** for efficient task adaptation
- Extensive experiments show that our approach:
- Outperforms previous methods on LibriMix and LibriSpeechMix
- Achieves **strong zero-shot performance** on **AishellMix (Mandarin)**