FPCRL: Feature Projection and Contrastive Representation Learning for End-to-End Speech Translation

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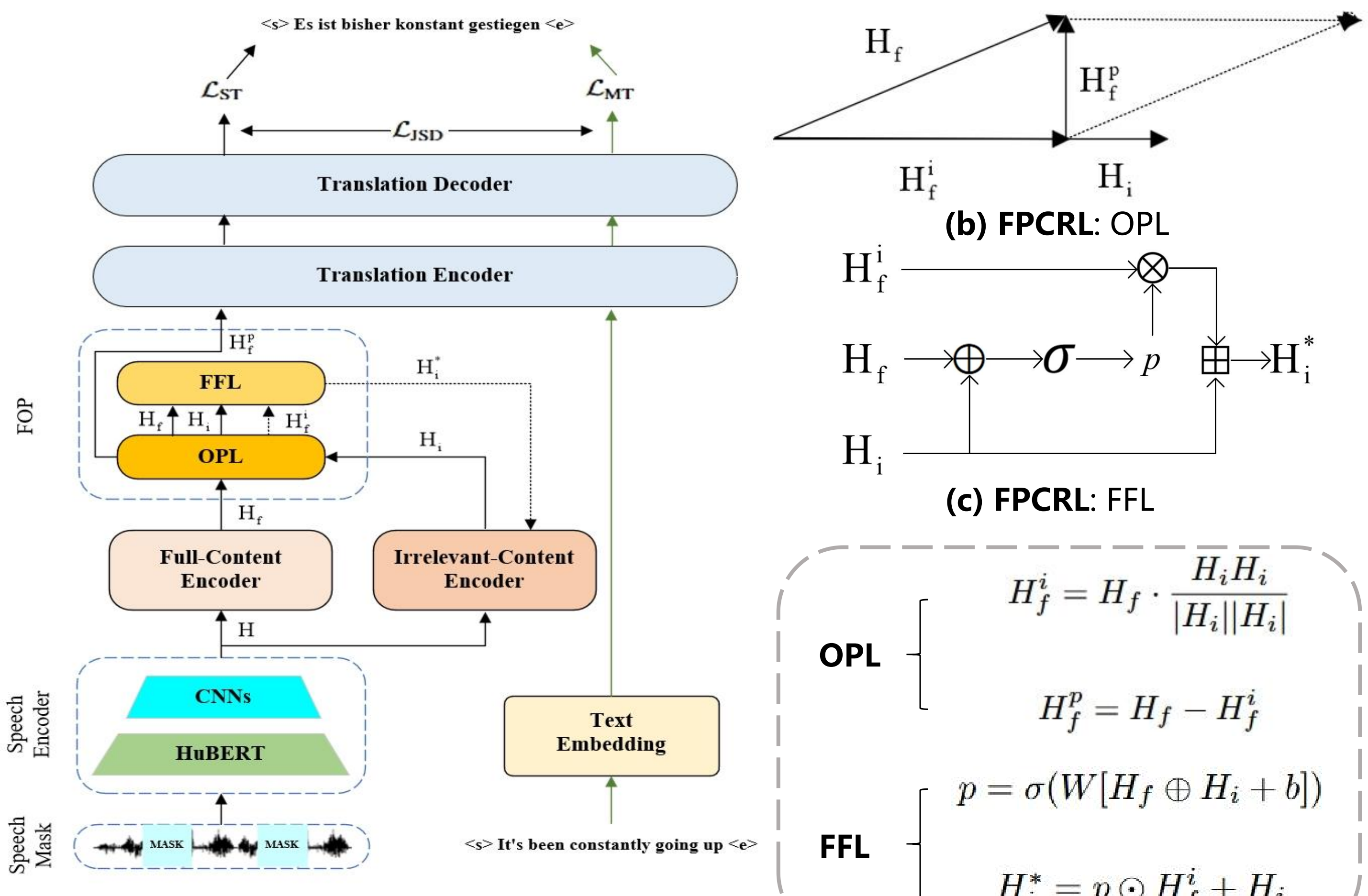
All Neural Network roads lead to Rome

Introduction

Speech-to-text translation is a cross-modal and multilingual translation task. To alleviate the modality gap and data scarcity of this task, recent research has primarily focused on aligning speech and text representations to unify cross-modal features and incorporating external knowledge via multi-task learning. Although significant progress has been achieved, there remains potential for improvement, particularly in enhancing translation performance by purifying speech representations to extract more content-relevant information. In this paper, we propose a framework based on feature projection and contrastive representation learning for speech translation, FPCRL, which is adaptable to various training settings. FPCRL introduces additional full-content and irrelevant-content encoders, which separately extract full and irrelevant information from speech. Through a feature projection module, irrelevant components are removed from the full content representations, yielding purified speech representations. Furthermore, the extracted content-irrelevant information is utilized to guide the training of the irrelevant-content encoder via contrastive representation learning. Experiments on the MuST-C En-De, CoVoST-2 De-En, and CoVoST-2 Fr-En benchmarks demonstrate that FPCRL achieves significant improvements across all datasets.
We open-source the model for future research at ***https://github.com/Akito-Go/FPCRL***.

Framework of FPCRL



(a) **FPCRL**: model (b) **FPCRL**: OPL (c) **FPCRL**: FFL

Main contributions:

- ***E2E ST Training Framework.*** We propose **a training framework FPCRL for E2E ST**, which can be applied in various settings. This framework purifies speech representations by introducing additional full-content and irrelevant-content encoders and employing a feature orthogonal projection method.
- ***Speech Purification and Feature Fusion.*** By leveraging the redundant content-irrelevant information extracted during **the purification process**, we introduce **a feature fusion method** to combine it with the output from the irrelevant-content encoder. This fusion further guides the encoder to effectively capture and learn the content-irrelevant information.
- ***Significant improvements.*** Experiments on the MuST-C En-De, CoVoST-2 De-En, and CoVoST-2 Fr-En benchmarks show that the methods we proposed can lead to significant improvements over strong E2E ST baselines across three settings: **transcript-free**, **multi-task**, and **expanded data**.

Methods

(a) Speech Mask:
We modify the speech input s to mask continuous segments and obtain the masked waveform s', which is utilized as the input of the model. Then we mask with a probability of 0.75 for each speech input. The selected speech input is then masked for at least 2 spans, each containing at least 3600 consecutive frames.

(b) Orthogonal Projection:
We use the OPL to remove content-irrelevant information from the full content representations and firstly project H_f onto H_i to extract the content-irrelevant information H_f^i. Then we obtain the expected purified speech representations H_f^p by removing H_f^i from H_f.

(c) Feature Fusion:
We fuse H_f^i and H_i into H_i^*, and the future fusion process automatically controls the selection of H_f^i based on H_f and H_i, and then adds the selected portion to H_i to obtain the fused features H_i^*.

(d) Contrastive Learning:
To further enhance the encoding ability of irrelevant-content encoder for content-irrelevant information, we leverage H_i and H_i^* for contrastive learning.

$$\mathcal{L}_{\text{CRL}} = -[\sum_{m=1}^{N} log\frac{sim(H_i, H_{im}^*)}{\tau} + \sum_{m=1}^{N}\sum_{n\neq m} log(1 - \frac{sim(H_i, H_{in}^*)}{\tau})]$$

(e) Consistency Constraints:
For the speech input s_i, we apply Gaussian noise with a perturbation level defined randomly by the signal-to-noise ratio $snr \in [5, 50]$ to obtain new noisy data: $\tilde{s_i} = s_i + Guss(s_i, snr)$ to verify the effectiveness of the FOP in removing content-irrelevant information.

$$\mathcal{L}_{\text{CST}} = \sum_{i=1}^{|D|} \| Mean(H_f^p) - Mean(\widetilde{H_f^p}) \|_2$$

(f) Loss Warm-up:
We propose a loss warm-up method, where the loss coefficient is initialized to a small value of 1e-8 at the beginning of training. As the number of training steps increases, the coefficient gradually increases to 1, allowing the loss to fully contribute to optimization.

Main Results

Evaluation Metrics:

- ✓ **BLEU**: An automatic metric used to evaluate the quality of machine-generated text, especially in translation tasks. It measures how closely a candidate translation matches one or more reference translations based on overlapping n-grams. Scores range from 0 to 1 (often shown as 0–100), with higher scores indicating better translation quality.

Models	External Data Speech	ASR	MT	BLEU
Training in *transcript-free* setting				
Fairseq ST [5]	-	-	-	22.7
Revisit ST [41]	-	-	-	23.0
Self-training [17]	✓	✓	-	25.2
CCSRD [11]	✓	-	-	25.4
DUB [40]	✓	-	✓	26.2
SRPSE [15]	✓	-	-	**26.2**
W2V2-Transformer	✓	-	-	24.3
HuBERT-Transformer	✓	-	-	24.4
FPCRL	✓	-	-	25.7

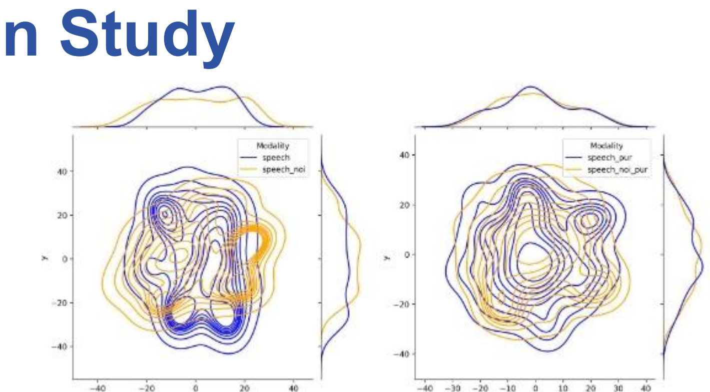
Models	External Data Speech	ASR	MT	CoVoST-2 De-En	Fr-En
Transformer-ST [35]	-	✓	-	17.1	26.3
Revisit ST [41]	-	-	-	14.1	26.9
Siamese-PT [43]	-	✓	✓	19.7	27.7
DUB [40]	✓	-	✓	19.5	29.5
FPCRL	✓	-	-	16.4	28.8
$\text{FPCRL}_{\text{MTL}}$	✓	-	-	**22.8**	**31.7**

Models	External Data Speech	ASR	MT	BLEU
Training in *multi-task* setting				
XSTNet [6]	✓	-	-	25.5
STEMM [7]	✓	-	-	25.6
ConST [8]	✓	-	-	25.7
CCSRD [11]	✓	-	-	26.1
M^3ST [42]	✓	-	-	26.4
SRPSE [15]	✓	-	-	26.9
CMOT [9]	✓	-	-	**27.0**
FPCRL	✓	-	-	26.8
Training in *expanded data* setting				
XSTNet [6]	✓	-	✓	27.8
CCSRD [11]	✓	-	✓	28.1
ConST [8]	✓	-	✓	28.2
STEMM [7]	✓	-	✓	28.7
CMOT [9]	✓	-	✓	29.0
SRPSE [15]	✓	-	✓	**29.2**
FPCRL	✓	-	✓	28.8

Ext. Main Results: comparison with baselines && multilingual verification

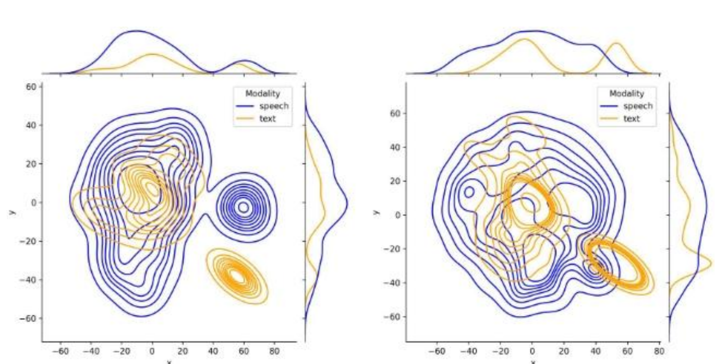
Ablation Study

Models	BLEU
Our FPCRL	**25.7**
w/o $\mathcal{L}_{\text{CST}}$	25.5
w/o Speech Mask	25.3
w/o $\mathcal{L}_{\text{CRL}}$	24.5
w/o OPL	24.3



(a) w/o purification (sim: 0.06). (b) w/ purification (sim: 0.12).

Models	LW_{CRL}	LW_{CST}	BLEU
$\text{FPCRL}_{\text{CRL}}$	0	-	24.8
	5k	-	25.1
	10k	-	25.3
	15k	-	**25.5**
$\text{FPCRL}_{\text{CRL-CST}}$	15k	0	24.9
	15k	5k	25.0
	15k	10k	25.5
	15k	15k	**25.7**



(a) w/o FPCRL (sim: 0.02). (b) w/ FPCRL (sim: 0.21).

Ext. Methods Evaluation: ablation studies && visualization