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Distilling Cross-Temporal Contexts for Continuous Sign Language Recognition

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➢ Motivation and Contribution

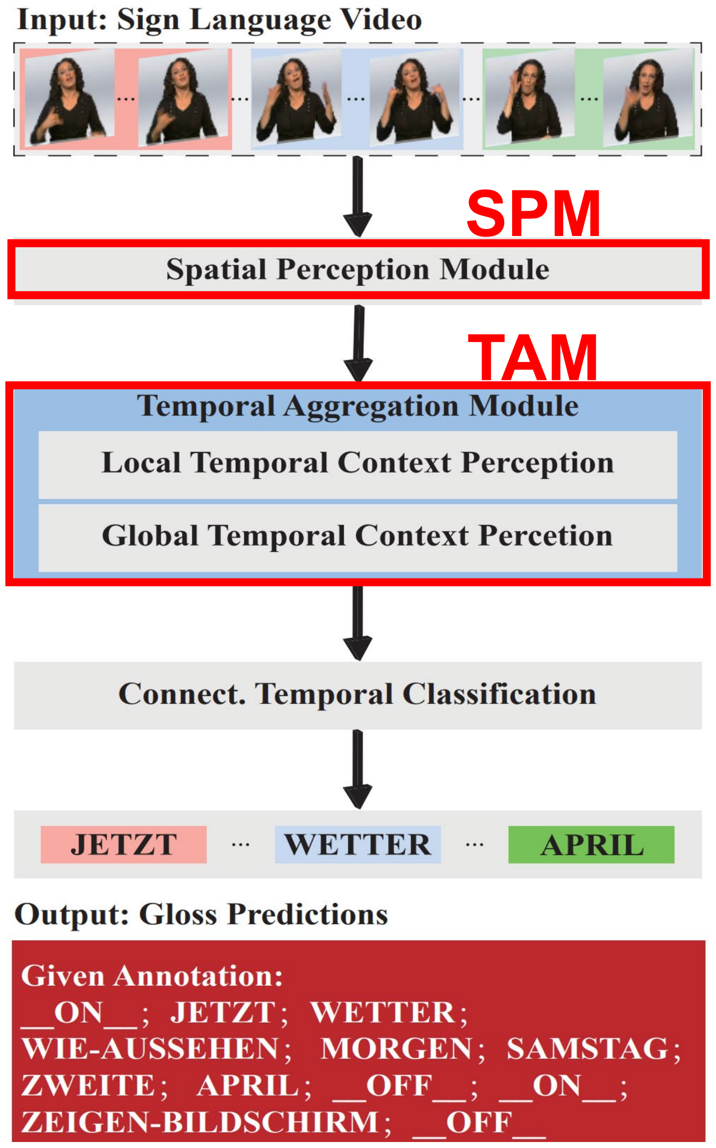
- **Motivation:**
  - The spatial perception module tends to be undertrained.
  - However, we have no idea about the desired temporal aggregation module.

- **Contribution:**
  - We extensively study the limitation and desirable properties of the temporal aggregation module and find it should be a shallow one and have high temporal aggregation capability.
  - We propose the cross-temporal context aggregation (CTCA) that a shallow temporal aggregation module has capable of incorporating local-global temporal contexts and the linguistic prior.

➢ The SOTA framework of CSLR

- Spatial Perception Module (SPM):
  - Spatial feature extraction.
- Temporal Aggregation Module (TAM):
  - Local-global temporal feature extraction, which is crucial to recognition performance.
  - It includes the local temporal perception module (1D-TCNs), and the global temporal perception module (BLSTM).
- Sequence prediction:
  - Connectionist temporal classification (CTC) function.

(a) Existing CSLR framework

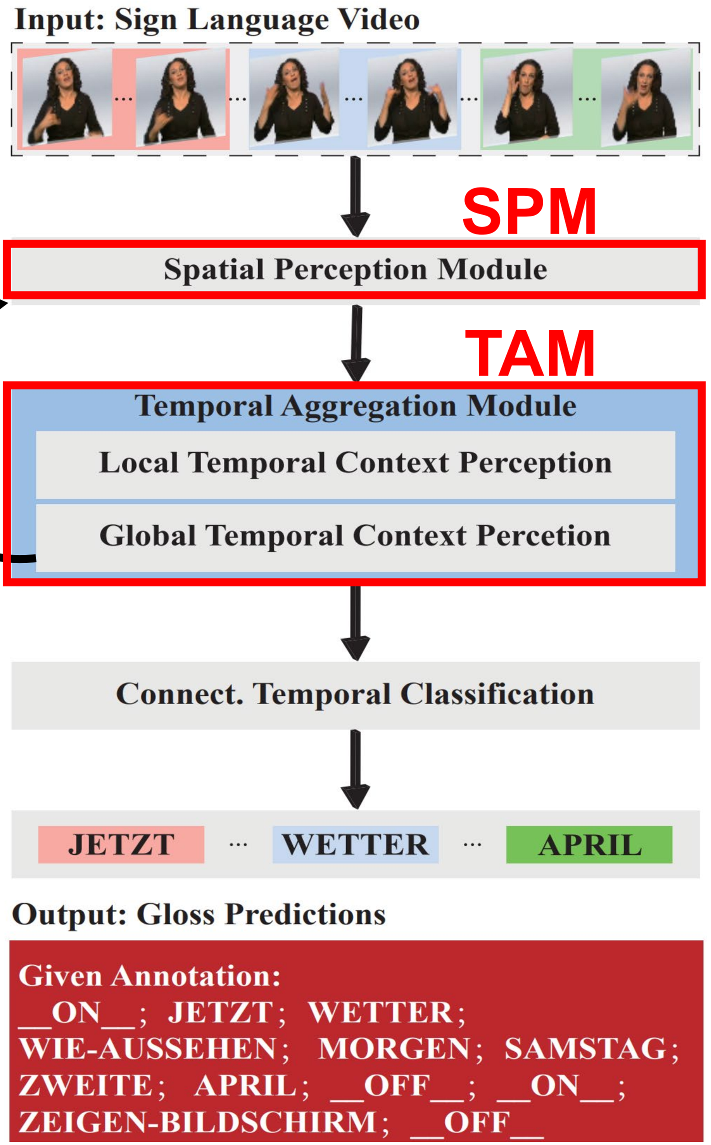


➢ Motivation

- The spatial perception module tends to be undertrained due to the easy overfitting temporal aggregation module and the objective function[1-3].

Insufficient feedback information

(a) Existing CSLR framework



- What are the effects of the TAM on the SPM?
- What are the properties of the desired TAM?

1. Ronglai Zuo and Brian Mak. C^{2}SLR: Consistency-enhanced continuous sign language recognition. In CVPR, 2022.
2. Aiming Hao, Yuecong Min, and Xilin Chen. Self-mutual distillation learning for continuous sign language recognition. In ICCV, 2021.
3. Junfu Pu, Wengang Zhou, and Houqiang Li. Iterative alignment network for continuous sign language recognition. In CVPR, 2019.

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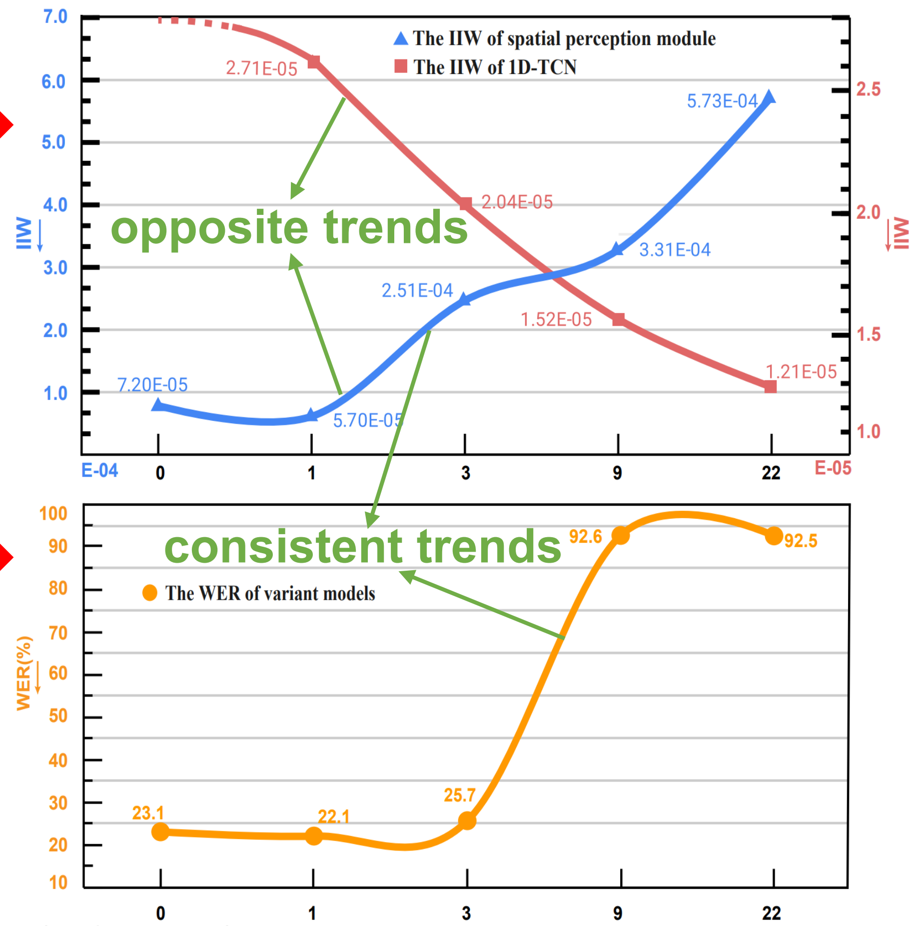
➢ Empirical Studies and Analysis

- Model Generalizability Metric:
  - IIW (the compression of information stored in weights)[1].
- Observations:
  - The effects of chain depth on the capability of SPM and TAM have completely opposite trends.
  - SPM: has higher effects on the final prediction.
- TAM desired properties:
  - SPM desires a shallow TAM.
  - TAM desires a deeper architecture.



1. Zifeng Wang, Shao-Lun Huang, Ercan Engin Kuruoglu, Ji-meng Sun, Xi Chen, and Yefeng Zheng. Pac-bayes information bottleneck. In ICLR, 2022.

➢ The conflict caused by shallow TAM

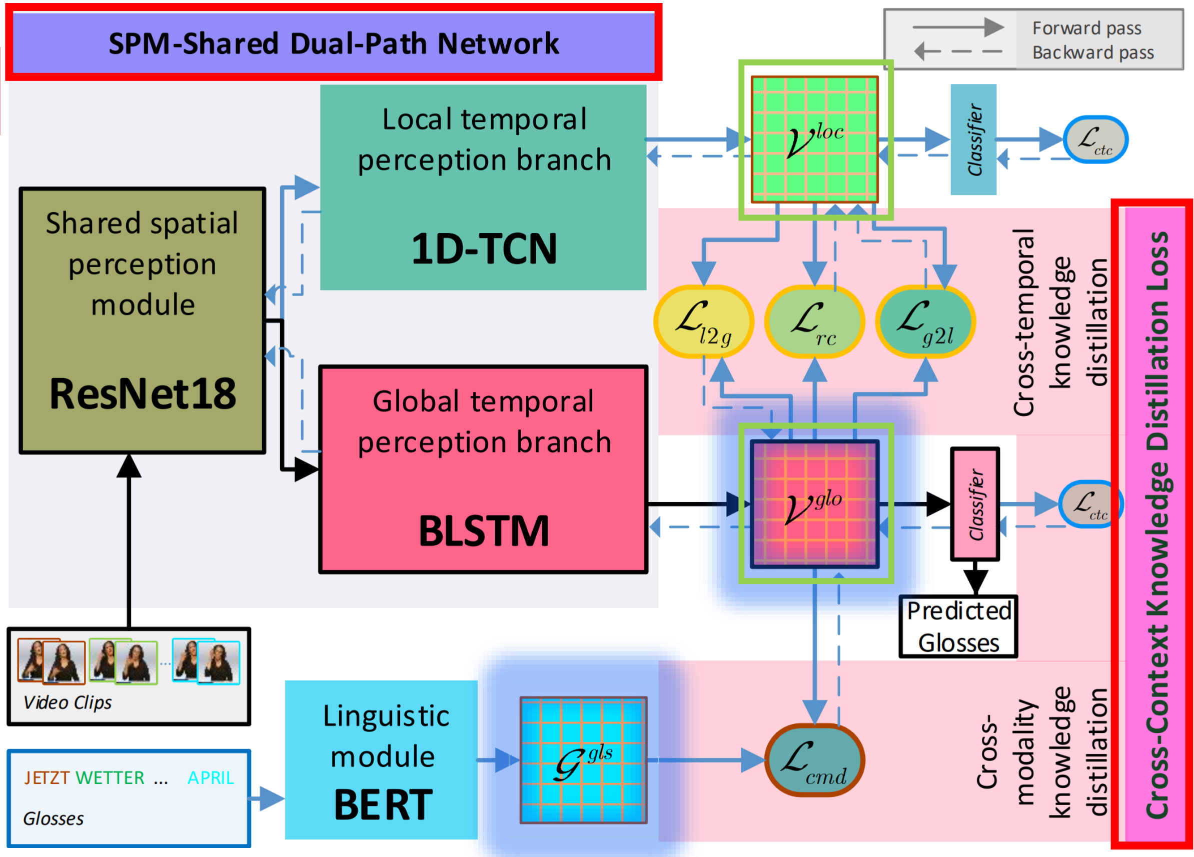
- Advantage:
  - Shallow TAM allows more thorough training of the spatial perception module.

- Disadvantage:
  - However, a shallow TAM cannot well capture both local and global temporal context information.

➤ Cross-Temporal Context Aggregation (CTCA)

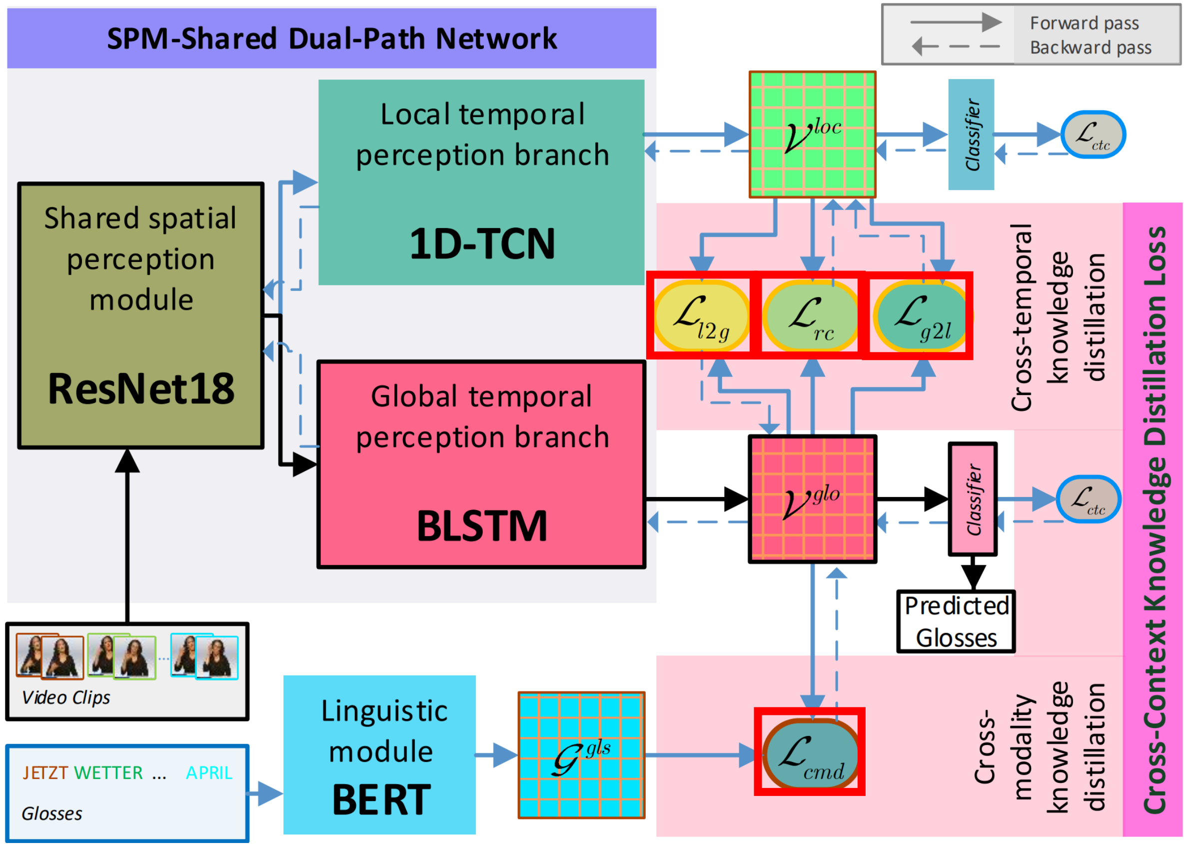
- SPM-Shared Dual-Path Network (SDPN): designed for a shallow TAM allows more thorough training of the SPM.

- Cross-Context Knowledge Distillation (CCKD): enables the global perception module to achieve local-global temporal perception and be more discriminative.



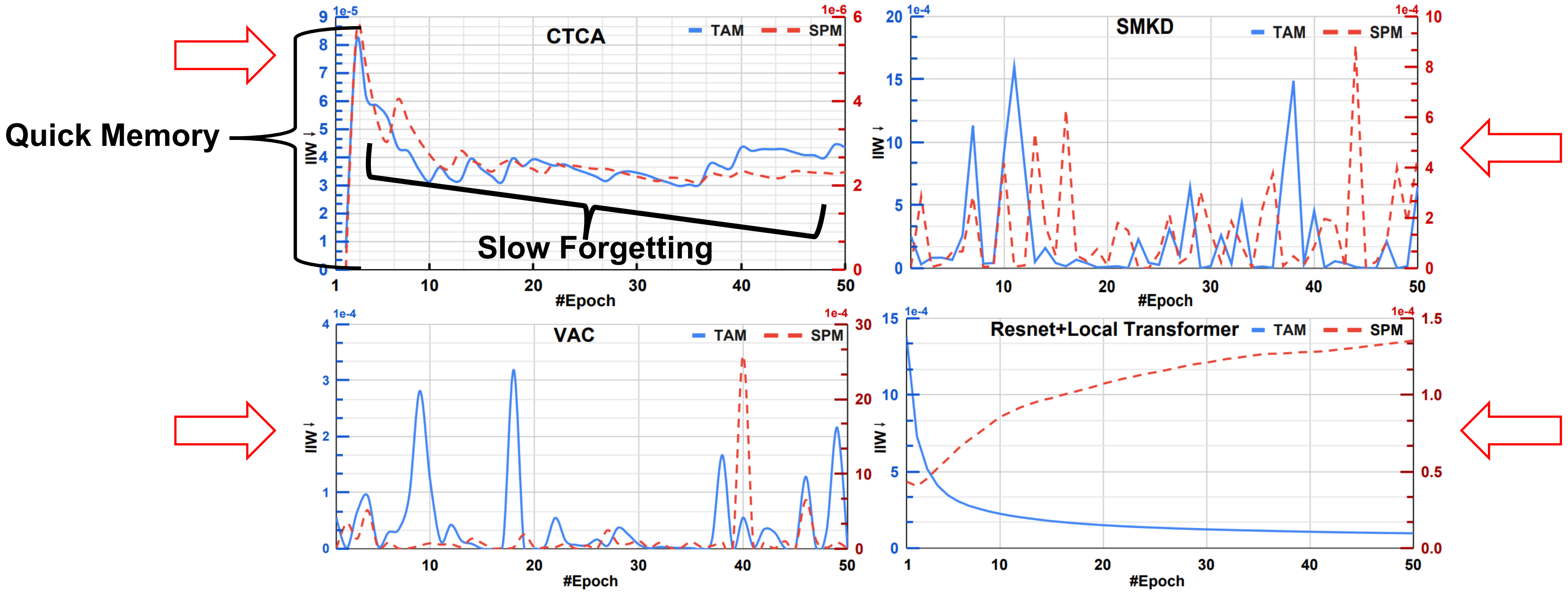
➤ Cross-Temporal Context Aggregation (CTCA)

- Cross-Context Knowledge Distillation:
- Cross-temporal knowledge distillation:
  - Local temporal context guidance loss: encourages V^{glo} to learn sign-wise context maintained in V^{loc}.
  - Global temporal context guidance loss: evolves distilling correlation among co-occurring signs to V^{loc}.
  - Reconstruction loss: reinforces the above cross-temporal context distillations.
- Cross-modality knowledge distillation: encourages V^{glo} to learn the inter-gloss discrimination indirectly.



➢ Generalizability of SPM and TAM

- "Quick Memory - Slow Forgetting" [1,2]



1. N. Tishby and N. Zaslavsky, "Deep learning and the information bottleneck principle," 2015 IEEE Information Theory Workshop (ITW), Jerusalem, Israel, 2015
2. Zifeng Wang, Shao-Lun Huang, Ercan Engin Kuruoglu, Ji-meng Sun, Xi Chen, and Yefeng Zheng. Pac-bayes information bottleneck. In ICLR, 2022.

➢ Comparison with state-of-the-arts

Table 1. Comparison with state-of-the-art methods on the RWTH-2014 dataset. (WER (%) the lower is the better).

Methods	Dev		Test	
	del/ins	WER	del/ins	WER
DNF	7.8/3.5	23.8	7.8/3.4	24.4
FCN	-	23.7	-	23.9
VAC	7.9/2.5	21.2	8.4/2.6	22.3
CMA	7.3/2.7	21.3	7.3/2.4	21.9
SMKD	6.8/2.5	20.8	6.3/2.3	21.0
C^2SLR	-	20.5	-	20.4
TLP	6.3/2.8	19.7	6.1/2.9	20.8
RadialCTC	6.5/2.7	19.4	6.1/2.6	20.2
CTCA(Ours)	6.2/2.9	19.5	6.1/2.6	20.1

Table 2. Comparison with state-of-the-art methods on the RWTH-2014T dataset. (WER (%) the lower is the better).

Methods	WER	
	Dev	Test
SLT	24.6	24.5
CNN+LSTM+HMM	22.1	24.1
BN-TIN+Transf	22.7	23.9
V-L Mapper	21.9	22.5
SMKD	20.8	22.4
C^2SLR	20.2	20.4
TLP	19.4	21.2
CTCA(Ours)	19.3	20.3

Table 3. Comparison with state-of-the-art methods on the CSL-Daily dataset. (WER (%) the lower is the better).

Methods	Dev		Test	
	del/ins	WER	del/ins	WER
LS-HAN	14.6/5.7	39.0	14.8/5.0	39.4
SLT(Gloss+Text)	10.3/4.4	33.1	9.6/4.1	32.0
FCN	12.8/4.0	33.2	12.6/3.7	32.5
BN-TIN+Transf	13.9/3.4	33.6	13.5/3.0	33.1
TIN+Iterative	12.8/3.3	32.8	12.5/2.7	32.4
CTCA(Ours)	9.2/2.5	31.3	8.1/2.3	29.4

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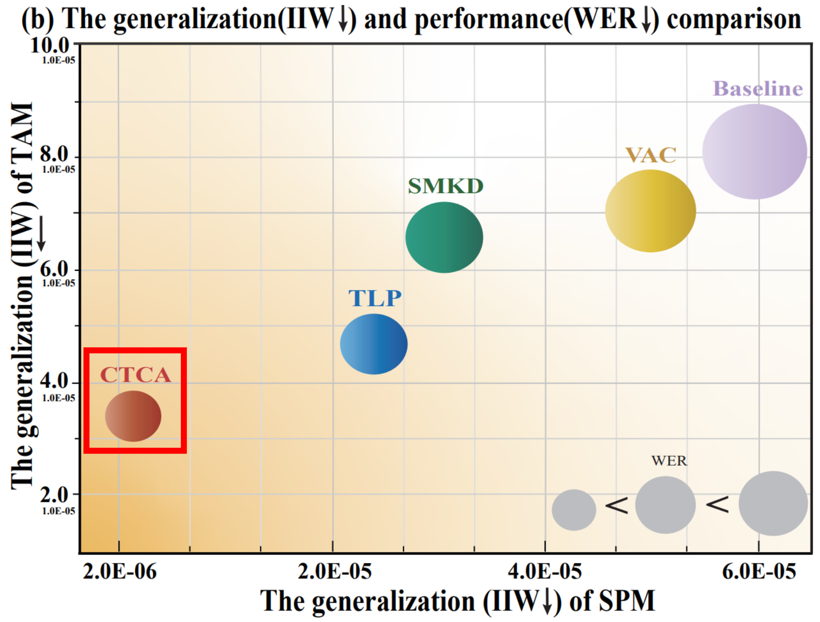
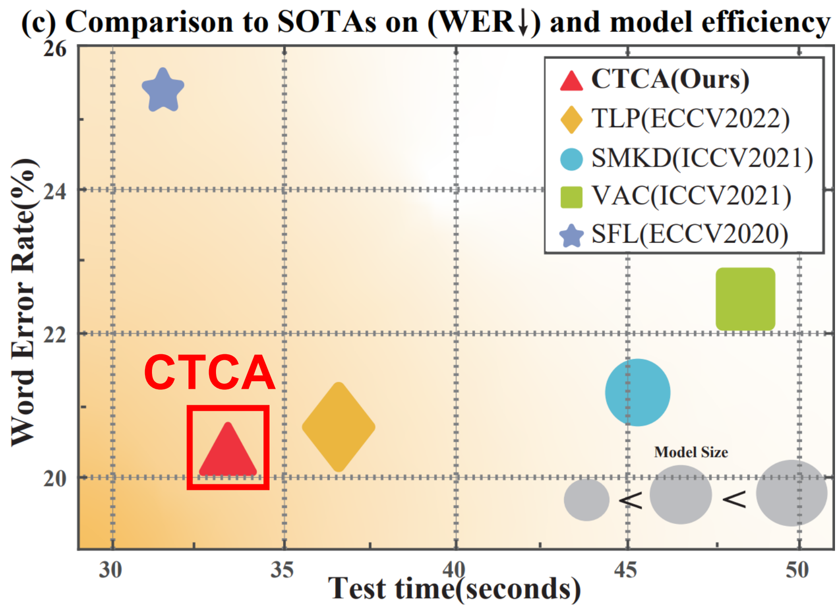
➢ Comparison with state-of-the-arts

- Better Generalizability, Smaller Parameter size
- Higher Performance, Faster Inference





Ablation Study

Table 5. Ablation study on cross-context knowledge distillation loss on the RWTH-2014.

Method	$\mathcal{L}_{ctd}$			$\mathcal{L}_{cmd}$	Dev	Test
	$\mathcal{L}_{l2g}$	$\mathcal{L}_{g2l}$	$\mathcal{L}_{rc}$			
Baseline	-	-	-	-	21.8	22.1
Vanilla	-	-	-	-	21.7	21.9
SDPN A	✓	-	-	-	21.0	21.1
SDPN A- $I(.;)$	✓	-	-	-	21.3	21.5
SDPN B	-	✓	-	-	20.8	20.7
SDPN C	✓	✓	-	-	20.4	20.6
SDPN D	✓	✓	✓	-	20.0	20.4
SDPN D-$\omega(.;)$	✓	✓	✓	-	20.2	20.6
SDPN E	-	-	-	✓	21.3	21.0
CTCA	✓	✓	✓	✓	19.5	20.1

Table 6. Comparison of different knowledge fusion schemes on the RWTH-2014. "Wasserstein" is the Wasserstein distance.

Methods	Knowledge fusion	Dev	Test
SDPN	-	21.7	21.8
	Vanilla distillation	21.6	21.6
	Wasserstein	21.6	21.5
	JMMD	21.3	21.3
	CKD	21.3	21.5
	CTCA ($\mathcal{L}_{l2g}$)	21.0	21.1
	concatenation	22.7	23.6
	point-wise addition	21.2	22.3
	attention	22.2	22.6

➢ Ablation Study

Table 7. Performance comparison of local temporal perception module with distinct temporal window widths on the RWTH-2014. Ft and Ft(d) correspond to the 1D temporal convolution layer with the kernel of t and dilation of d, respectively.

Method	variants	windows	Dev	Test
1D-TCN	F3-F3-F3	7*2	19.5	20.1
	F3(1)-F3(2)	7*2	19.8	20.3
	F5-F5	9*2	20.6	20.6
	F5-F5-F5	13*2	19.9	20.6
	F7-F7	13*2	20.1	20.3

Table 8. Comparison of CTCA with distinct global temporal perception modules (GTPM) on the RWTH-2014.

Method	variants	Dev	Test
GTPM-branch	BLSTM	19.5	20.1
	Dilated blocks	22.2	22.6
	Transformer	28.7	28.9
	Transformer+BLSTM	24.4	24.1

Thanks for your listening!