RawNeXt: Speaker verification system for variable-duration utterances with deep layer aggregation and extended dynamic scaling policies

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Overview

❖Speaker verification (SV): The task of determining whether the identity of an anonymous voice matches the target speaker

❖Problems: Variable-duration input utterance degrades the reliability of SV system
- Insufficient speaker-specific information of short utterance
- SV systems operating in a fixed way with manually designed layers

❖Proposed model: **RawNeXt**
- **Apply deep layer aggregation**: Enhance speaker information by iteratively and hierarchically aggregating features
- **Propose extended dynamic scaling policy**: Process features according to the length of the utterance
- 28.7% and 28.4% relative improvement compared to baseline for full-length result and mean result of 1,2, and 5s lengths for the VoxCeleb1 evaluation set

Baseline architecture with raw waveform

❖Input feature of models: Raw waveform
1. Data-driven manner on less-processed data can extract discriminative representations suitable for SV tasks
2. Minimal hyper-parameter search of acoustic feature pre-processing

❖DNN architecture: A variant of ResNeXt[1]
- Contain the grouped convolutional layers (Number of group: 32)
- Input: Raw waveform (59,049 sample)
- Output: Speaker embedding (512 dim)

❖Detailed architecture

Level	Block structure	# Blocks	Output
Convs	Conv(3, 3, 128)	1	2,187×128
	Conv(3, 1, 128) Maxpool(3)	2	
Stage 0	Conv(1,1,256) Conv(3,1,256), C=32	2	729×256
Stage 1	Conv(1,1,256) Maxpool(3)	4	243×256
Stage 2	Conv(1,1,512) Conv(3,1,512), C=32	4	81×512
Stage 3	Conv(1,1,512) Maxpool(3)	2	27×512
Pooling	ASP	1	1,024
Embedding	FC(512)	1	512

Experiments & Results

❖ Experiment configurations
- Training dataset: VoxCeleb2
  - 6,112 speakers
- Evaluation dataset: VoxCeleb1
  - 40 speakers
- Batch size: 320
- Test utterance duration : 1s, 2s, 5s and full length
- Performance comparison : Equal error rate (EER)
- Optimizer: AMSGrad
- Training epoch: 80
- Weight decay: 10^{-4}
- Learning rate (LR): $10^{-3} \rightarrow 10^{-7}$

❖ Exp1: Comparison with recently proposed SV system for variable-duration utterances
- Proposed RawNeXt outperforms other models for all test conditions
- Compared to baseline, 28.7% improvement for full-length test / 28.4% improvement for mean result of 1,2, and 5-sec lengths
- RawNeXt demonstrates superior generalization and robustness to variable-length utterances

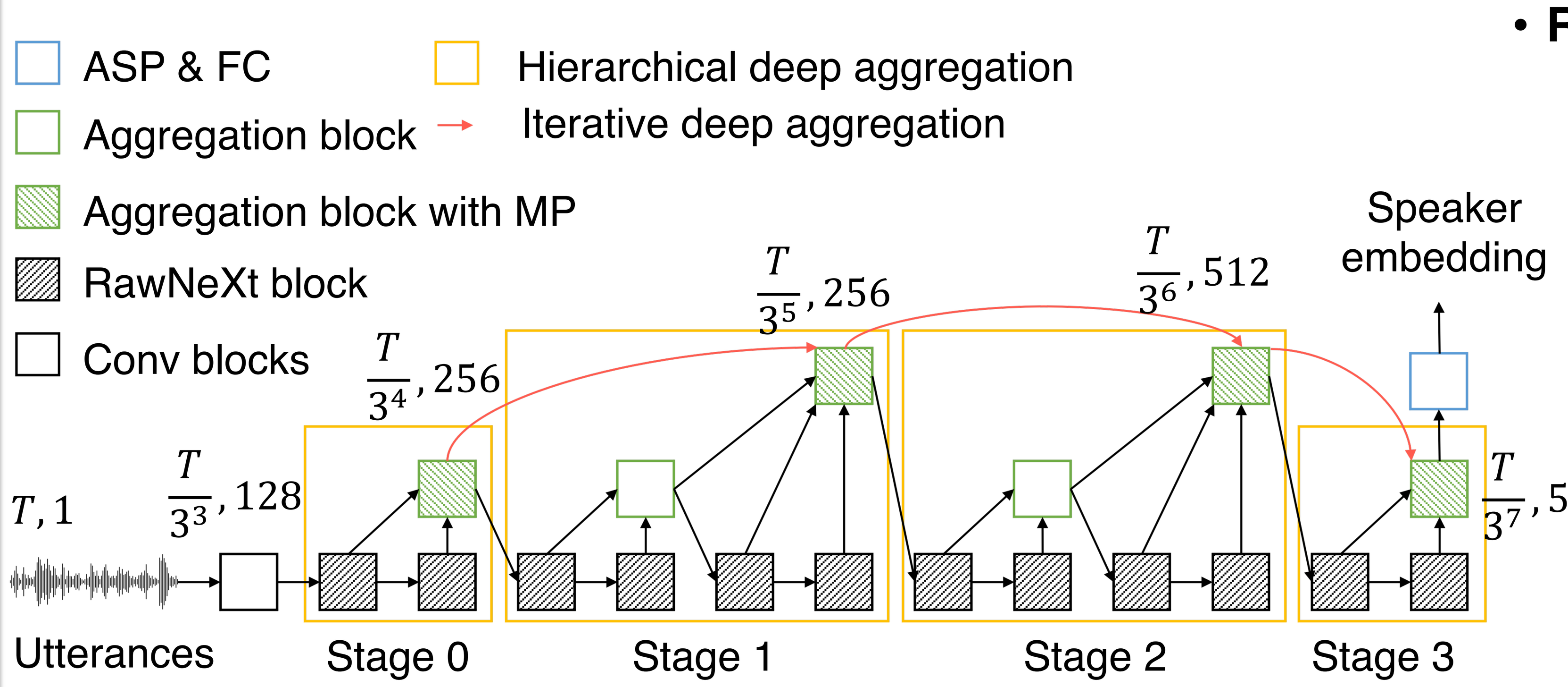
Model	Input Feature	Loss Function	Test utterance length (EER, %)			
			1s	2s	5s	full
MESA+FPM[4]	MFB-64	A-Softmax	5.92	3.38	2.17	1.98
ResNet34[5]	MFB-40	Softmax+PN	4.49	2.88	2.04	1.91
ResNeXt	Waveform	Softmax	6.12	3.68	2.45	2.16
RawNeXt	Waveform	Softmax	**4.47**	**2.58**	**1.72**	**1.54**

RawNeXt with Deep Layer Aggregation & Extended Dynamic Scaling Policy

❖Combining features of multiple layers for variable-duration SV
- Yield context-rich representations by merging intermediate features of various time scales

1.Deep layer aggregation (DLA)[2]
- Apply to derive speaker embeddings by fusing features in a more iterative and hierarchical manner for utterances of various lengths
- Iterative deep aggregation module: Enrich temporal context information by merging the different time resolution of features
- Hierarchical deep aggregation module: Enhance spectral context information by combining the feature channels of different levels
- Aggregation block: Learn to select important information from the multiple inputs and project it into a single output

- **RawNeXt structure**



- f_i^r :1d convolutional layer of the i-th path in the r resolution branch
- D: Downsampling function(average pooling layer)
- U_i^r: Upsampling function (transposed convolutional layer)
- σ: Batch normalization layer & rectified linear unit

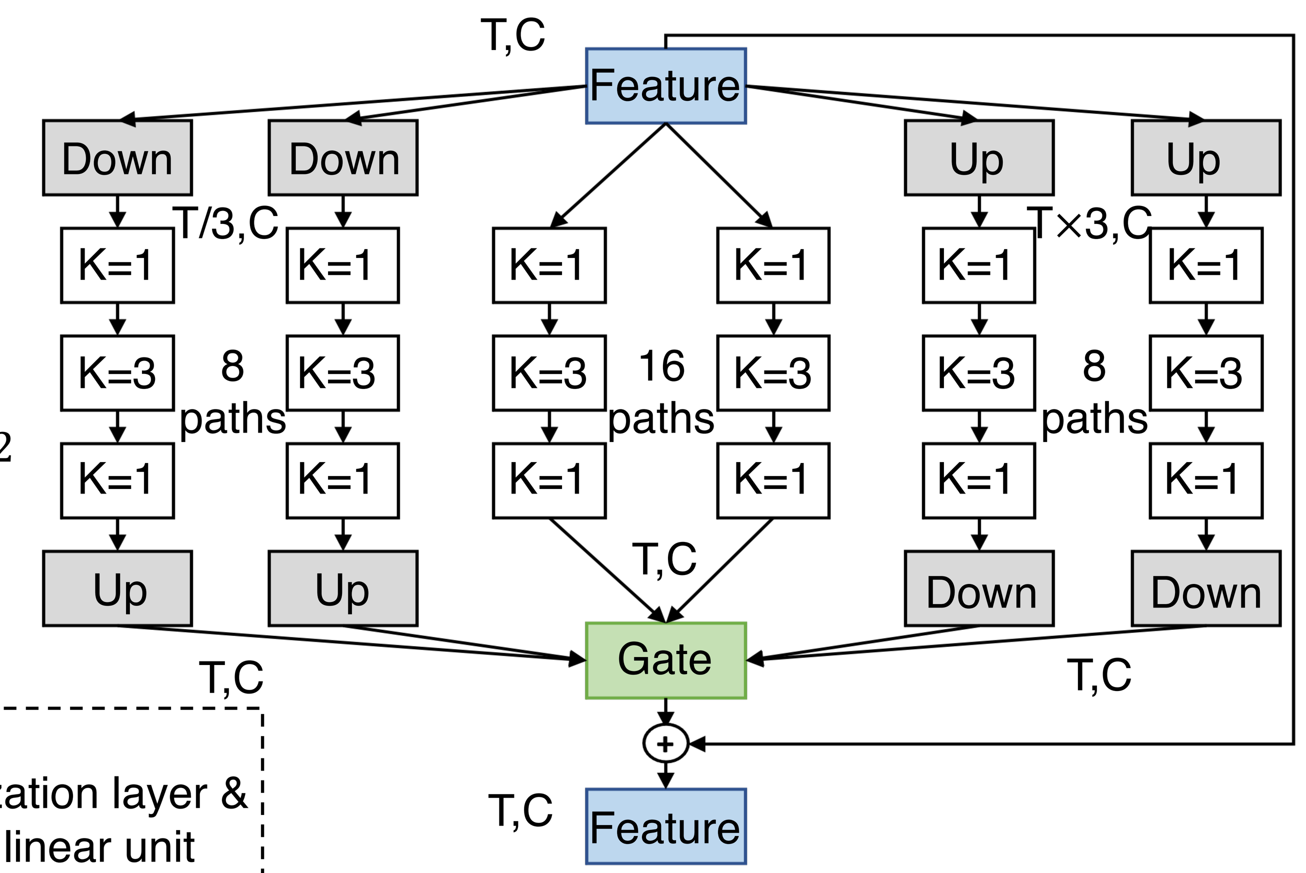
❖Elastic[3]: Processing images with various scales in vision tasks
- Learn a scaling policy from data by combining the features output by the original path and downsampling path of each block

2.Extend dynamic scaling policy (EDSP)
- Propose for utterance of arbitrary lengths based on Elastic
- Utilize three resolution branches and a gate module
- Low, original, and high resolution branches: Feature extraction with receptive fields of different sizes

$$F^l(x)=\sum_{i=1}^{8} U_i^l(f_i^l(D(x))),\quad F^o(x)=\sum_{i=1}^{16} f_i^o(x),\quad F^h(x)=\sum_{i=1}^{8} D(f_i^h(U_i^h(x)))$$

- Gate module: Selectively merge the activation of each branch according to the length of input utterance by using self-attention mechanism
- RawNeXt block with skip-path: $B(x)=\sigma(Gate(F^l(x),F^o(x),F^h(x))+x)$

- **RawNeXt block architecture**



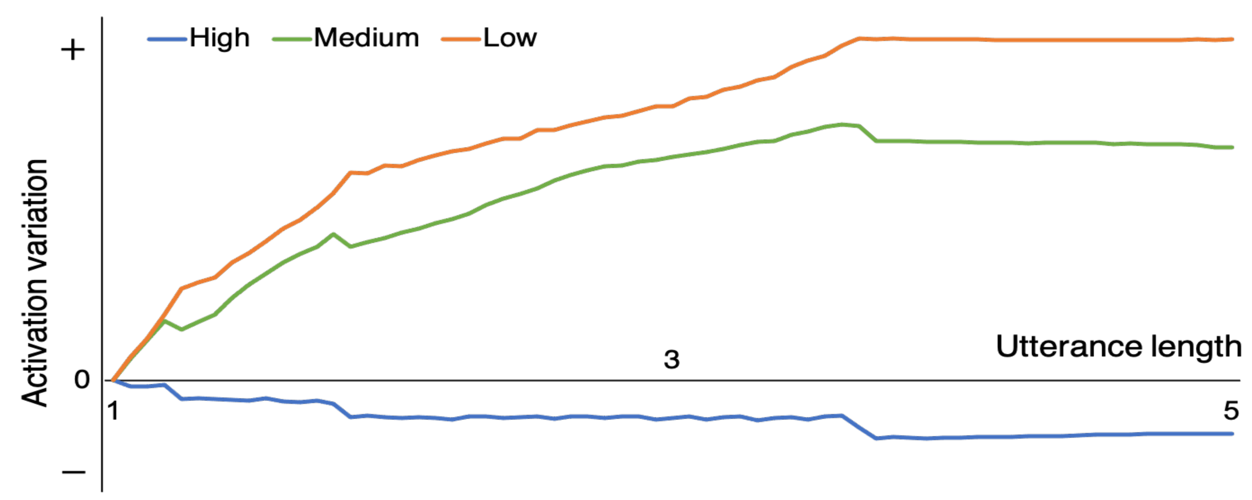
❖ Exp2: Ablation experiments of RawNeXt components
- #1: ResNext (Baseline), #7: RawNeXt (Proposed)
- Performance improves as each module is applied
- The motivations of each method are well aligned with the goal of variable-duration utterance SV

Model	D	E	G	U	Test utterance length (EER, %)			
					1s	2s	5s	full
#1	x	x	x	x	6.12	3.68	2.45	2.16
#2	o	x	x	x	4.82	2.98	2.08	1.93
#3	x	o	x	x	5.39	3.18	2.16	1.95
#4	o	o	x	x	4.66	2.94	2.13	1.94
#5	o	o	o	x	4.67	3.01	2.08	1.88
#6	o	o	x	o	4.65	2.81	1.94	1.82
#7	o	o	o	o	**4.47**	**2.58**	**1.72**	**1.54**

❖ Exp3: Variation score for mean activation of each resolution path according to the input utterance length
- Score at each r resolution branch by differences of mean activations between L and a 1-second utterance

$$S_L^r=\frac{1}{TC}\left(\sum_{t=1}^{T}\sum_{c=1}^{C}x_{Ltc}^r-\sum_{t=1}^{T}\sum_{c=1}^{C}x_{1tc}^r\right)$$

- RawNeXt extracts speaker information with appropriate resolutions by dynamically applying scaling policies according to the length of the utterance



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2. F. Yu et. al., Deep layer aggregation, CVPR 2018.
3. H. Wang et.al., Elastic: Improving cnns with dynamic scaling policies, CVPR 2019.
4. Y. Jung et. al., Improving multi-scale aggregation using feature pyramid module for robust speaker verification of variable-duration utterances, Interspeech 2020.
5. S. Kye et. al., Supervised attention for speaker recognition, SLT 2021.