



Role of Lexical Boundary Information in Chunk-Level Segmentation for Speech Emotion Recognition

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Outline

1. Motivation

- **2.** Lexical-based Segmentation
- **3.** Experimental Results and Analysis
- 4. Conclusions & Future Works







Motivation



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Chunk-level modeling for speech emotion recognition (SER)



Step2: Chunk-level model training

Motivation

4



Dynamic chunk segmentation [1]



[1] W.-C. Lin and C. Busso, "Chunk-level speech emotion recognition: A general framework of sequenceto-one dynamic temporal modeling," IEEE Transactions on Affective Computing, vol. Early Access, 2022.

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Motivation

5



Time-based chunk segmentation

- Split data chunks without considering their actual lexical boundaries
- E.g., dynamic chunk segmentation



Lexical-based Segmentation

Lexical chunk segmentation

- Factor C: number of chunks to split
 => fixed or number of spoken words
- Factor W: chunk window size
 => fixed or word-level alignment boundary
- Result in different combinations, e.g., FixedW-VariedC (FW-VC)

The model does NOT consider the semantic meaning of words, still an SER task!



Lexical-based Segmentation

Visualization of different options











Lexical VariedW-VariedC (VW-VC)







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Experimental Results and Analysis

Multimodal Signa Processing Labo

Experimental Setting

8

- Datasets: <u>IEMOCAP</u> and <u>MSP-Podcast v1.10</u> [2]
- Acoustic features: <u>LLDs</u> and <u>wav2vec2</u> [3]
- Model arch: <u>LSTM</u> chunk-level encoder + <u>Multi-Heads Self-Attention</u> aggregation
- Emotion: <u>arousal</u>, <u>dominance</u>, and <u>valence</u>
- Evaluation metric: <u>concordance correlation coefficient</u> (CCC)

The only difference is how we segment the data chunks!

[2] R. Lotfian and C. Busso, "Building naturalistic emotionally balanced speech corpus by retrieving emotional speech from existing podcast recordings," IEEE Transactions on Affective Computing, vol. 10, no. 4, pp. 471–483, October-December 2019.

[3] A. Baevski, Y. Zhou, A. Mohamed, and M. Auli, "wav2vec 2.0: A framework for self-supervised learning of speech representations," in Advances in Neural Information Processing Systems (NeurIPS 2020), vol. 33, Virtual, December 2020, pp. 12 449–12 460.



Experimental Results and Analysis



Performance comparison summary

	MSP-Podcast v1.10									
Method	CovrR/OvrR	LLDs (CCC)			Wav2Vec2 (CCC)					
	[%]	Aro.	Val.	Dom.	Aro.	Val.	Dom.			
tFW-FC	99/50	0.528	0.216*	0.430	0.604	0.352	0.478			
FW-FC	90/56	0.529	0.191	0.423	0.598	0.344	0.475			
VW-FC	57/35	0.534	0.170	0.427	0.595	0.352	0.460			
FW-VC	94 / 68	0.544*	0.141	0.455*	<mark>0.620</mark> *	0.349	0.497*			
VW-VC	82/0	0.546*	0.118	0.459*	0.613*	0.336	0.492*			
cFW-VC	99/65	0.562 [†]	0.207*	0.468 [†]	0.616*	0.343	0.499*			
	IEMOCAP									
		•	IEN	MOCAP	•					
Method	CovrR/OvrR		IEN LDs (CC	MOCAP CC)	Wav2	2Vec2 (0	CCC)			
Method	CovrR/OvrR [%]	Li Aro.	IEN LDs (CC Val.	MOCAP CC) Dom.	Wav2 Aro.	2 <i>Vec2</i> (0 Val.	CCC) Dom.			
Method <i>tFW-FC</i>	<i>CovrR/OvrR</i> [%] 99 / 79	Li Aro. 0.614	IEN LDs (CC Val. 0.353	MOCAP CC) Dom. 0.406	Wav2 Aro. 0.709*	2 <i>Vec2</i> (0 Val. 0.554	CCC) Dom. 0.531			
Method <i>tFW-FC</i> <i>FW-FC</i>	<i>CovrR/OvrR</i> [%] 99 / 79 82 / 83	Li Aro. 0.614 0.593	IEN LDs (CC Val. 0.353 0.257	MOCAP CC) Dom. 0.406 0.411	Wav2 Aro. 0.709* 0.700	2Vec2 (0 Val. 0.554 0.537	CCC) Dom. 0.531 0.539			
Method <i>tFW-FC</i> <i>FW-FC</i> <i>VW-FC</i>	<i>CovrR/OvrR</i> [%] 99 / 79 82 / 83 47 / 71	Li Aro. 0.614 0.593 0.595	IEN LDs (CC Val. 0.353 0.257 0.279	MOCAP CC) Dom. 0.406 0.411 0.409	Wav2 Aro. 0.709* 0.700 0.688	2Vec2 (Val. 0.554 0.537 0.532	CCC) Dom. 0.531 0.539 0.526			
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Method <i>tFW-FC</i> <i>FW-FC</i> <i>VW-FC</i> <i>FW-VC</i> <i>VW-VC</i>	<i>CovrR/OvrR</i> [%] 99 / 79 82 / 83 47 / 71 81 / 67 61 / 0	Li Aro. 0.614 0.593 0.595 0.633* 0.626*	IEN LDs (CC Val. 0.353 0.257 0.279 0.378 0.395*	MOCAP CC) Dom. 0.406 0.411 0.409 0.451* 0.433	Wav2 Aro. 0.709* 0.700 0.688 0.713* 0.719 *	2Vec2 (0 Val. 0.554 0.537 0.532 0.582* 0.577*	CCC) Dom. 0.531 0.539 0.526 0.538 0.558*			





Knowing the precise word boundary (i.e., VariedW) does NOT bring significant performance benefits!

* means statistically significant better performance over other approaches without a marker

† means the results are statistically significant better than all other approaches



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Experimental Results and Analysis



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			IEN	МОСАР)					
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Knowing how many chunks use to split (i.e., depending on the number of words) is crucial!

* means statistically significant better performance over other approaches without a marker

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Conclusions & Future Works



Conclusion

- We found a minor role of word-level timing boundaries for chunk-level SER
- We found that splitting data chunks according to number of words is the key leads to better chunk-level SER

Future Work

Multimodal segmentation and benefits for modeling (e.g., video-speech-text)





Welcome to join our poster session in ICASSP 2023 Paper ID: 4354 Session Date/Time: 6/8/2023 14:00:00 (EEST) Session Name: Speech Emotion Recognition: Multimodality



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