Attention-based Multimodal Speech Emotion Recognition

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Speech Emotion Recognition (SER)

- Real-time analysis of human speech to detect and classify emotions, enhancing human-computer interaction
- Applications
  - Mental health support
  - Customer service optimization
  - etc
- Machine Learning
  - Advanced algorithms
  - Deep learning
  - Natural language processing (NLP)

Multimodal SER

- Integration of multiple data sources, such as audio, facial expressions, and body language, for comprehensive emotion recognition
- Improved Performance
  - Enhanced accuracy
  - Contextual understanding
  - etc
- Expansive Applications
  - Supports sentiment analysis
  - Remote education
  - etc

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Background

- SOTA methods focus on two main sub-areas
  - Representation of multimodal data
  - Feature fusion
- Initiative: A recent paper compared the effectiveness of self- and cross-attention on traditional features [1]
- Research Gap: No one compared the effect of self- and cross-attention on self-supervised features
- Idea: Pre-trained models for feature extraction (representation), compare self- and cross-attention for feature fusion

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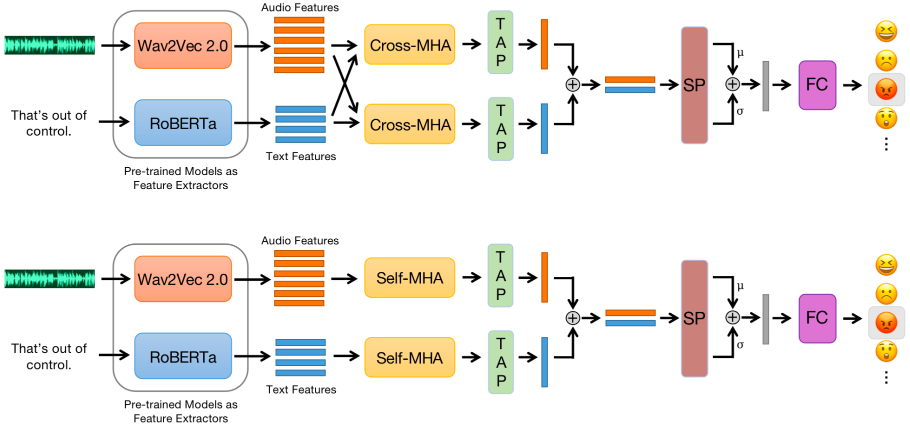
Proposed Models



IEMOCAP Dataset

- 12 hours of emotional interactions in scripted/unscripted settings
- Recordings from 5 male and 5 female speakers
- Speech audio clips and ground-truth text transcripts with emotion labels

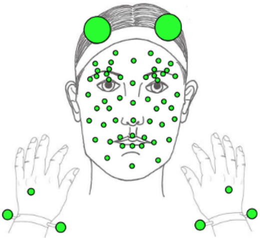


Figure 1. Marker layout. In the recording, fifty-three markers were attached to the face of the subjects. They also wore wristbands (two markers) and headband (two markers). An extra marker was also attached on each hand.

Training

- Trained the models on each fold of data for a maximum of 50 epochs
- Two strategies used
  - Learning rate scheduling
  - Early stopping
- Evaluated the models using the four metrics after each epoch on both the validation and test sets

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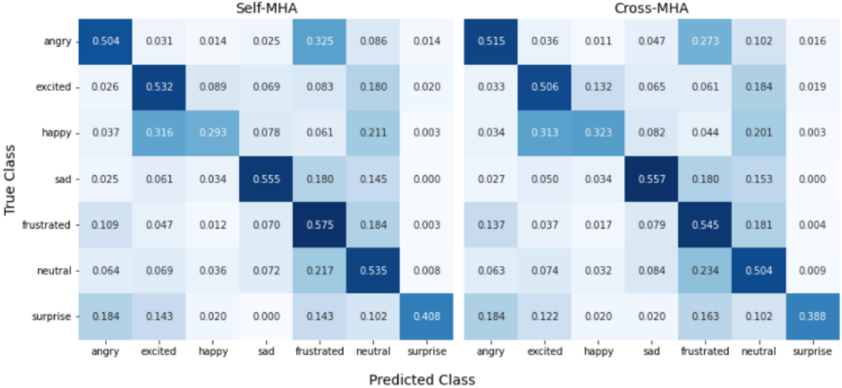
Experimental Results

	WA	UWA	WF1	UWF1
Random	0.138 ± 0.002	0.135 ± 0.004	0.151 ± 0.002	0.126 ± 0.002
Audio	0.398 ± 0.018	0.342 ± 0.006	0.367 ± 0.016	0.335 ± 0.007
Text	0.506 ± 0.027	**0.492 ± 0.029**	0.498 ± 0.025	0.475 ± 0.022
MDRE [x]	0.491 ± 0.039	0.466 ± 0.056	0.482 ± 0.035	0.470 ± 0.041
Self-MHA	**0.522 ± 0.014**	0.486 ± 0.020	**0.519 ± 0.016**	**0.488 ± 0.014**
Cross-MHA	0.509 ± 0.009	0.477 ± 0.027	0.509 ± 0.009	0.478 ± 0.024

- Self-attention model outperforms the cross-attention model
- Self-attention model outperformed all four baseline models
- Text modality can provide loads of valuable emotion information

Experimental Results



- Frequent confusion between some emotion classes
  - Angry vs Frustrated
  - Happy vs Excited
- Relatively poor performance on recognizing the class "surprise"

Ablation Study

	WA	UWA	WF1	UWF1
Self-noSP	0.514 ± 0.022	0.464 ± 0.042	0.507 ± 0.027	0.473 ± 0.046
Self-CLS	0.505 ± 0.008	0.461 ± 0.019	0.504 ± 0.009	0.468 ± 0.021
Self-MHA	**0.522 ± 0.014**	**0.486 ± 0.020**	**0.519 ± 0.016**	**0.488 ± 0.014**

	WA	UWA	WF1	UWF1
Cross-noSP	0.498 ± 0.005	0.442 ± 0.021	0.493 ± 0.005	0.448 ± 0.024
Cross-CLS	**0.518 ± 0.011**	0.451 ± 0.020	**0.512 ± 0.010**	0.456 ± 0.022
Cross-MHA	0.509 ± 0.009	**0.477 ± 0.027**	0.509 ± 0.009	**0.478 ± 0.024**

- Decreased performance without statistical pooling layer
- Use BERT's CLS token as the text feature
  - Decreased performance for self-attention model
  - Increased weighted accuracy and weighted F1 score for cross-attention model

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Limitations

Self-attention is more effective for multi-modal emotion recognition

- Limited dataset (IEMOCAP only)
- Suboptimal hyperparameter tuning

Future Work

- Improve the model's ability to distinguish between confused emotion classes
- Integrate video components in multi-modal models

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References

[1] Vandana Rajan, Alessio Brutti, and Andrea Cavallaro. Is cross-attention preferable to self-attention for multi-modal emotion recognition? In *ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 4693–4697. IEEE, 2022.