Cross Attentional Audio-Visual Fusion for Dimensional Emotion Recognition

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Outline

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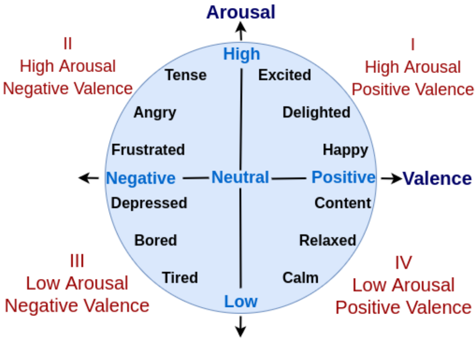
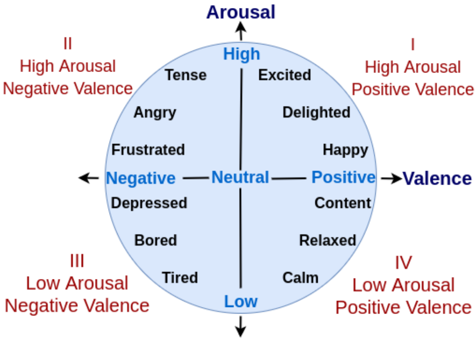
Dimensional Emotion Recognition



Dimensional Emotion Recognition



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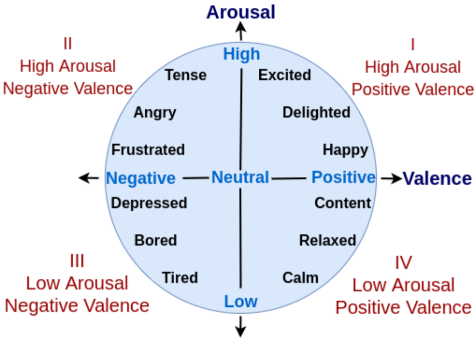

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- Valence denotes the range of emotions from very sad (negative) to very happy (positive)

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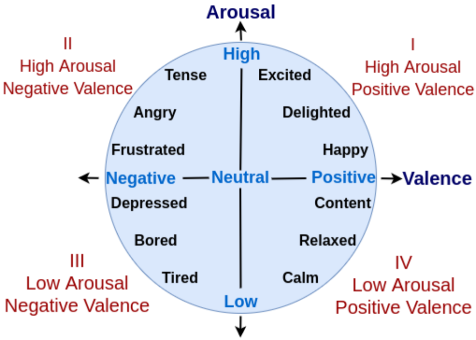

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- Valence denotes the range of emotions from very sad (negative) to very happy (positive)
- Arousal reflects the energy or intensity of emotions from very passive to very active

A-V Fusion for Dimensional Emotion Recognition

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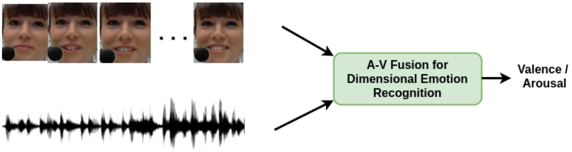

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- How to handle wide range of variations in vocal expressions due to speaker identity-bias, background noise, etc ?

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A-V Fusion Approaches for Dimensional Emotion Recognition

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- [Parthasarathy and Sundaram, 2021] explored transformers with cross modal attention, where cross attention is integrated with self attention

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- Though attention models have been explored with transformers, they fail to capture the complimentary relationship of A-V modalities
- The semantic relevance among A-V features are not effectively captured in the existing approaches

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- The training mechanism has three major modules : V Network, A Network and Cross-Attentional A-V Fusion

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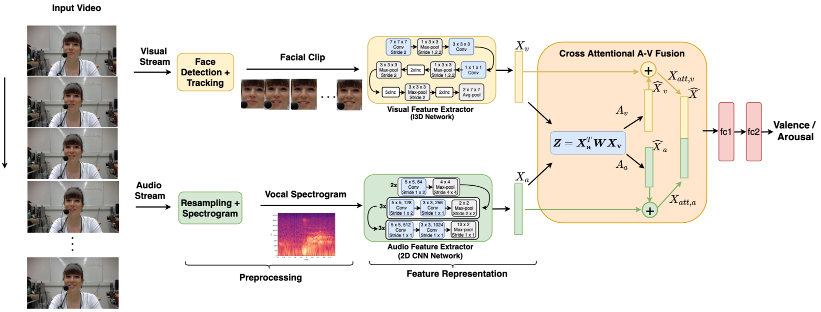

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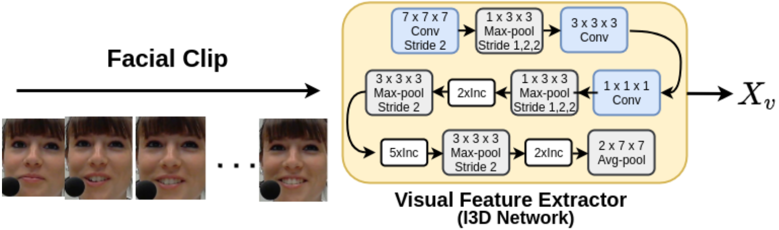

Audio Network

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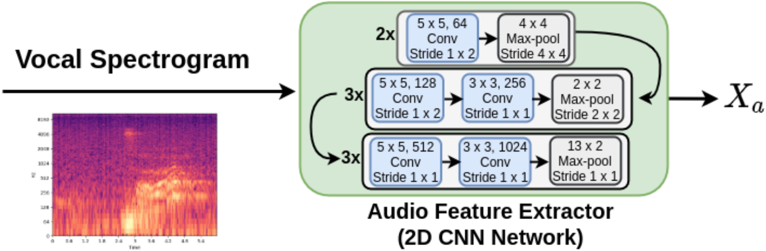

Cross Attentional AV Fusion

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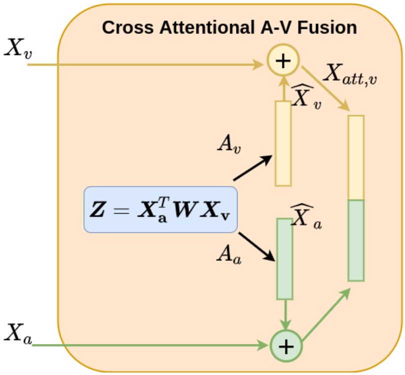

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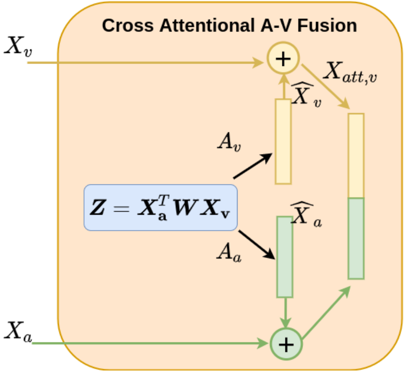

- The V features ($\boldsymbol{X_v}$) and A features ($\boldsymbol{X_a}$) features are fed to the cross attentional module

Cross Attentional Fusion

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- The cross correlation helps A-V features to interact between each other and gives a measure of semantic relevance across the modalities
- Cross correlation based cross attention was successfully applied in few shot classification [Hou et al., 2019] and weakly supervised action localization [Lee et al., 2021]

Cross Attentional AV Fusion

Cross Correlation matrix

$$\boldsymbol{Z} = \boldsymbol{X_a}^T \boldsymbol{W} \boldsymbol{X_v}$$

where $\boldsymbol{W}$: learnable parameter

$\boldsymbol{X_v}$: deep features of V modality of given video sequence

$\boldsymbol{X_a}$: deep features of A modality of given video sequence

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Cross Attention Weights

$$\boldsymbol{A_a}_{i,j} = \frac{e^{\boldsymbol{Z}_{i,j}/T}}{\sum_{k=1}^{K} e^{\boldsymbol{Z}_{k,j}/T}} \quad \text{and} \quad \boldsymbol{A_v}_{i,j} = \frac{e^{\boldsymbol{Z}^T{}_{i,j}/T}}{\sum_{k=1}^{K} e^{\boldsymbol{Z}^T{}_{i,k}/T}}$$

where $\boldsymbol{Z}_{i,j}$: ith row and jth column of $\boldsymbol{Z}$
T : softmax temperature

Cross Attentional AV Fusion

Attention Maps

$$\widehat{\boldsymbol{X_a}} = \boldsymbol{X_a}\boldsymbol{A_a} \quad \text{and} \quad \widehat{\boldsymbol{X_v}} = \boldsymbol{X_v}\boldsymbol{A_v}$$

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$$\widehat{\boldsymbol{X_a}} = \boldsymbol{X_a A_a} \quad \text{and} \quad \widehat{\boldsymbol{X_v}} = \boldsymbol{X_v A_v}$$

Final Attended features

$$\boldsymbol{X_{att,a}} = \tanh(\boldsymbol{X_a} + \widehat{\boldsymbol{X_a}})$$

$$\boldsymbol{X_{att,v}} = \tanh(\boldsymbol{X_v} + \widehat{\boldsymbol{X_v}})$$

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$$\boldsymbol{X}_{\boldsymbol{att,v}} = \tanh(\boldsymbol{X}_{\boldsymbol{v}} + \widehat{\boldsymbol{X}_v})$$

- The final attended features are further concatenated and fed to fully connected layers for valence / arousal prediction

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1. Dimensional Emotion Recognition
2. Motivation for Cross Attentional A-V Fusion
3. Proposed Approach
4. Results and Discussion
5. Conclusion

Experimental Setup

- We have evaluated our proposed approach on RECOLA and Fatigue (private) datasets
- RECOLA dataset has been used for various challenges such as AVEC 2015 and AVEC 2016, where 9 subjects are used for training and 9 for validation
- Fatigue is a private dataset, which has 27 videos captured from 18 participants, suffering from degenerative diseases inducing fatigue
- Concordance Correlation Coefficient (CCC) is used to measure the performance of the proposed approach

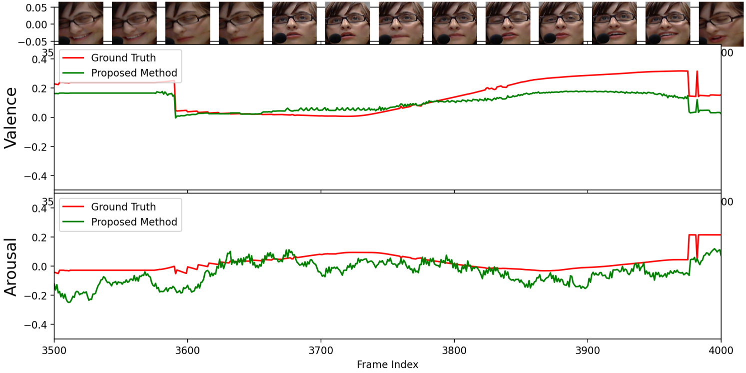
Ablation Study

- For V modality, we have explored 2D CNN and I3D model whereas for A modality, we have used the same deep network for all the experiments

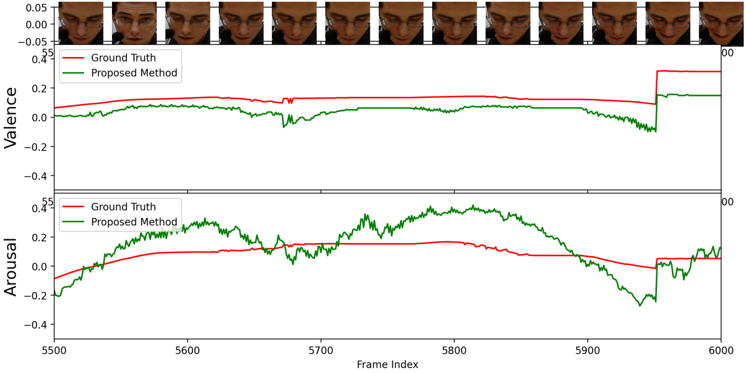
Table: **CCC performance of our proposed approach obtained with various components on the RECOLA dataset.**

Method: V + Fusion	**Valence**	**Arousal**
2D CNN + Feature Concatenation	0.538	0.680
2D CNN + LSTM	0.552	0.697
I3D + Feature Concatenation	0.579	0.732
I3D + Self Attention	0.623	0.787
I3D + Cross-Attention (ours)	0.685	0.835

Visualizations of valence and arousal predictions for subject "dev 1"



Visualizations of valence and arousal predictions for subject "dev 3"



Comparison with state-of-the-art approaches

Table: **CCC performance of the proposed and state-of-art models. All the results are presented on the RECOLA development set**

Method		Valence			Arousal		
		Audio	Visual	Fusion	Audio	Visual	Fusion
[He et al., 2015]	AVEC (2015)	0.400	0.441	0.609	0.800	0.587	0.747
[Han et al., 2017]	IVU (2017)	0.480	0.592	0.554	0.760	0.350	0.685
[Tzirakis et al., 2017]	IEEE JSTSP (2017)	0.428	0.637	0.502	0.786	0.371	0.731
[Ortega et al., 2019]	IEEE SMC (2019)	-	-	0.565	-	-	0.749
[Schoneveld et al., 2021]	PR Letters (2021)	0.460	0.550	0.630	0.800	0.570	0.810
Proposed Approach	Cross-Attention	0.463	0.642	0.685	0.822	0.582	0.835
Proposed Approach	2-stage Cross-Attention	0.463	0.642	0.690	0.822	0.582	0.838

Results with Fatigue (private) Data

Table: **CCC performance on Fatigue dataset.**

Method	**Fatigue**
Audio only (2D-CNN)	0.312
Visual only (I3D)	0.415
Feature Concatenation	0.378
Proposed Approach (Cross-Attention)	0.421

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Conclusion

- We propose a cross attentional A-V fusion model for dimensional emotion recognition
- Unlike prior approaches of A-V fusion, we focus on inter modal relationships to leverage the complementarity of A-V modalities
- Contrary to prior cross attentional models, we explored cross attention based cross correlation in the context of regression
- Extensive set of experiments conducted on RECOLA and Fatigue (private) datasets shows that the proposed approach clearly outperforms SOTA

Thank you for your attention!

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