SAT-Net: Self-Attention and Temporal Fusion for Facial Action Unit Detection

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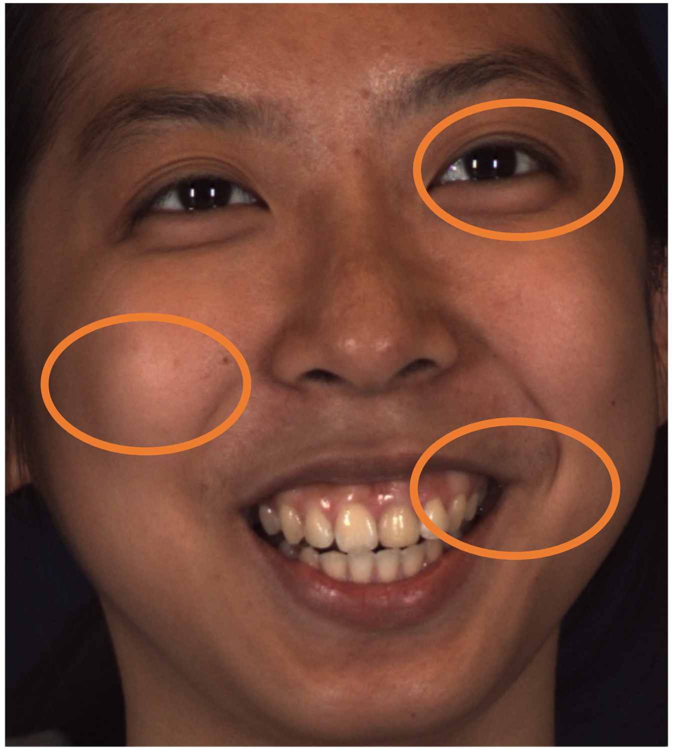
What Is Facial Action Units?

Facial action units (FAUs) are facial muscle actions at certain facial locations defined by Facial Action Coding System (FACS) Ekman, R. (1997)

AU index	Au Name
1	Inner Brow Raiser
2	Outer Brow Raiser
4	Brow Lowerer
6	Cheek Raiser
7	Lid Tightener
10	Upper Lip Raiser
12	Lip Corner Puller
14	Dimpler
15	Lip Corner Depressor
17	Chin Raiser
23	Lip Tightener
24	Lip Pressor

FAUs by index



AU 6, AU7, AU12 are activated in a happy face

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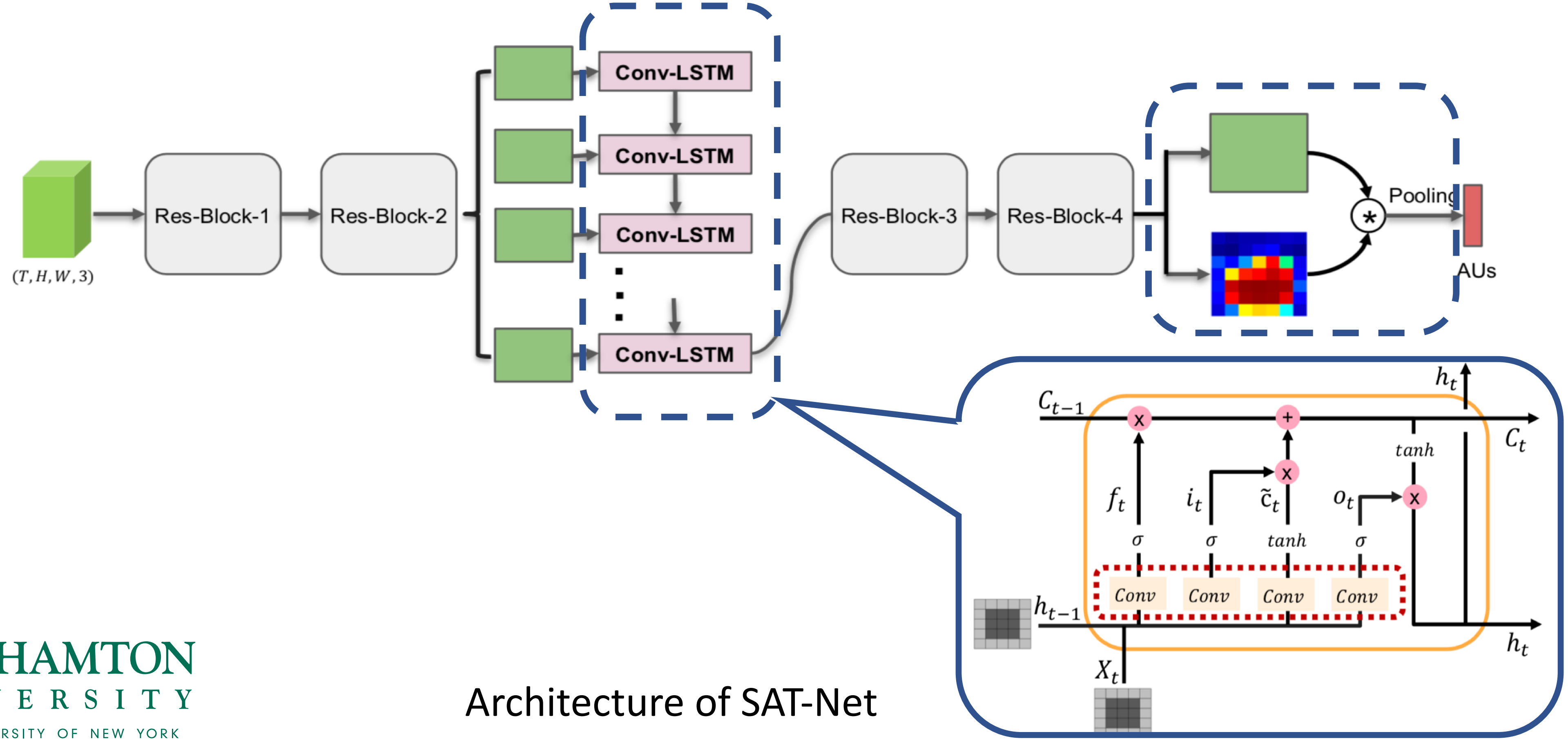
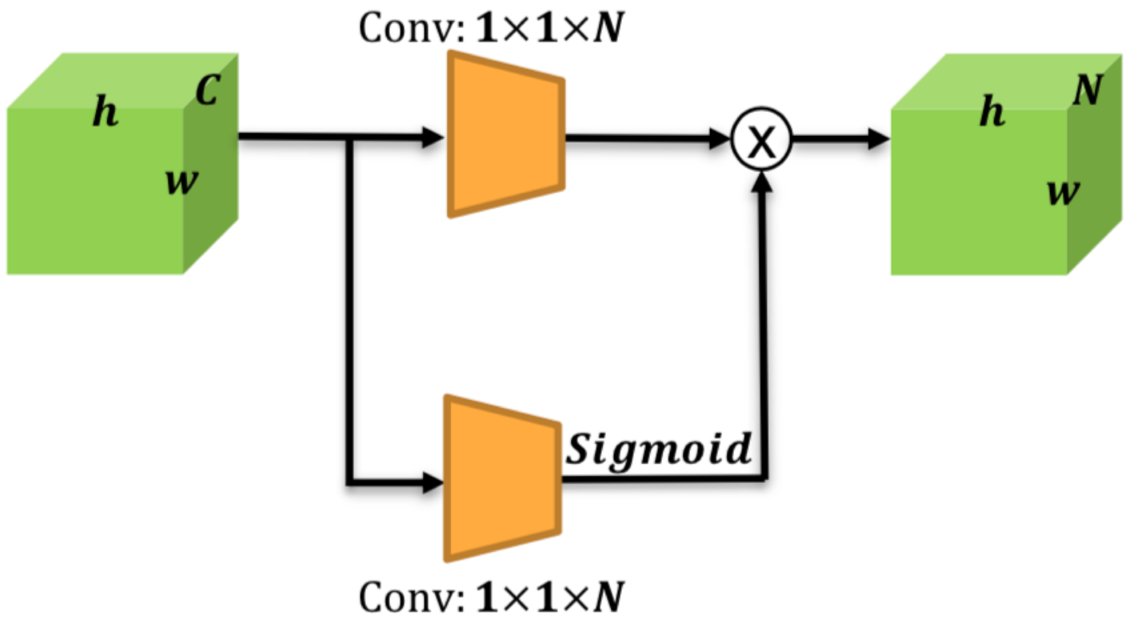
What Is Facial Action Units?

SAT-Net: features generated from Res-Block-2 are sequentially fed into Conv-LSTM.
Self-Attention: learning feature maps and attention masks at the same time, after which attended features map are pooled for predictions.



Architecture of SAT-Net

Self-Attention Module



Self-Attention Module in SA-Net/SAT-Net, C, N stand for the number of input and output channels, h and w are the spatial resolution of feature maps

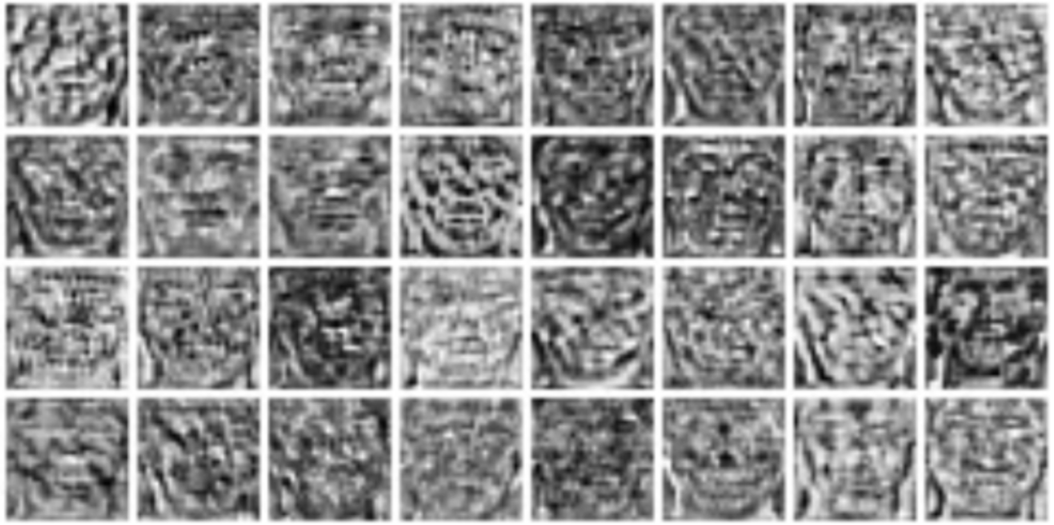
Datasets for AU Recognition

BP4D:
23 female and 18 male subjects with diverse ethnicities and backgrounds.
Each subject performes 8 tasks, a total of 328 emotional sequences.
~ 140,000 frames have valid AU occurrence codes.

DISFA:
12 female and 15 male subjects. More than 100, 000 annotated images
5 level intensity: 0 means the absent, and 5 the most expressive. > 1 as occurred
The data imbalance issue is more severe than that of BP4D.

Features Before and After Temporal Fusion

(a) SA-Net feature maps



(b) SAT-Net feature maps

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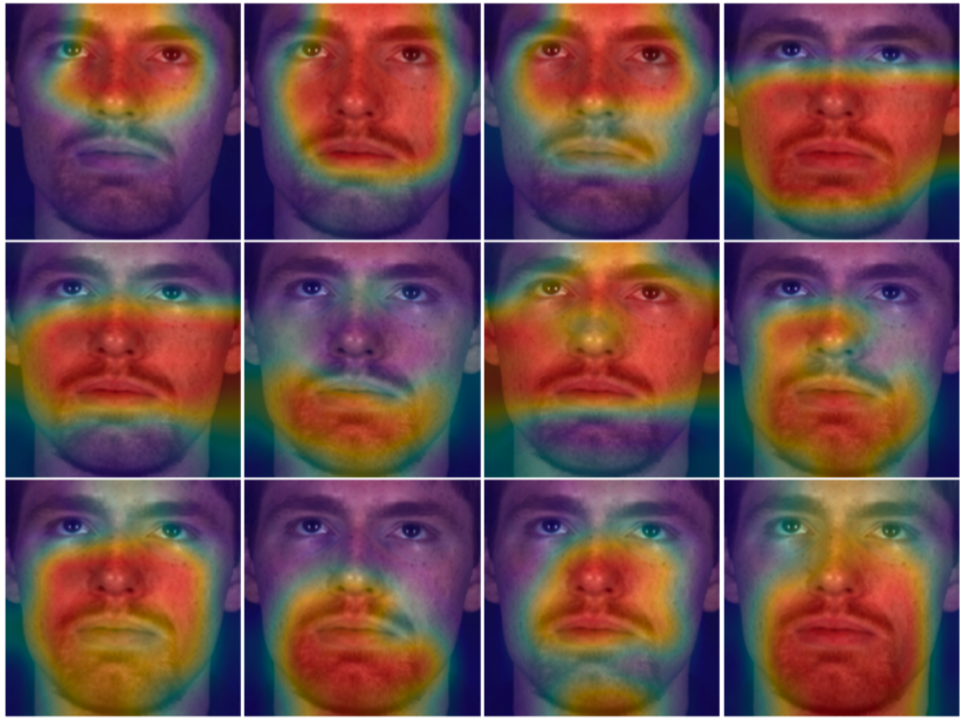
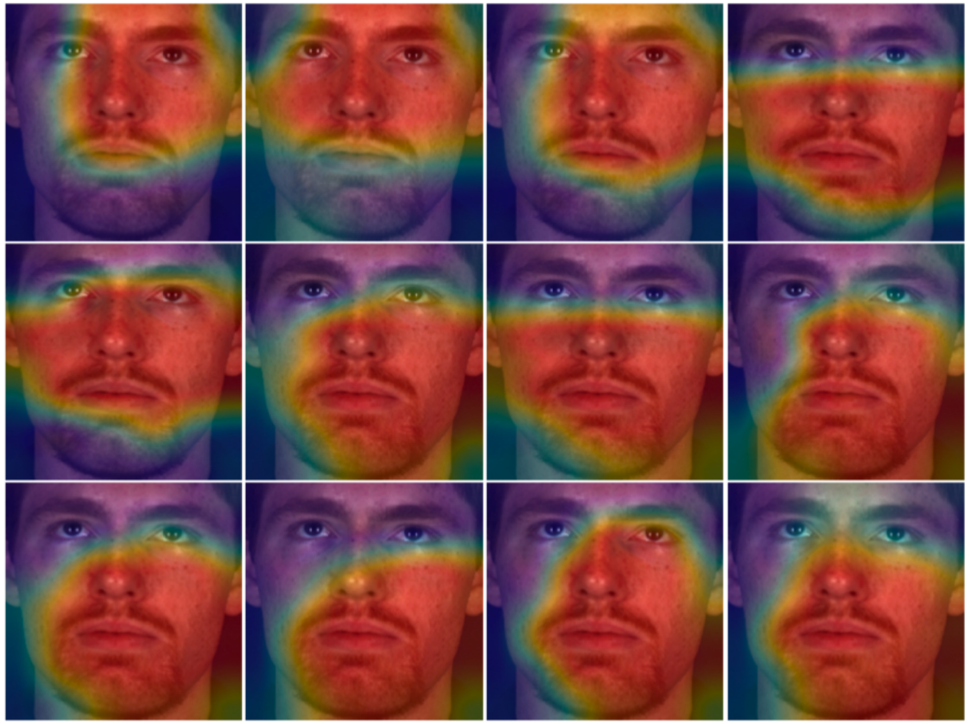
Self-learned Attention maps



(a) SA-Net attention maps



(b) SAT-Net attention maps

AU 1 Inner Brow Raiser	AU 2 Outer Brow Raiser	AU 4 Brow Lowerer	AU 6 Cheek Raiser
AU 7 Lid Tightener	AU 10 Upper Lip Raiser	AU 12 Lip Corner Puller	AU 14 Dimpler
AU 15 Lip Corner Depressor	AU 17 Chin Raiser	AU 23 Lip Tightener	AU 24 Lip Pressor

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Performance on BP4D

AU	JPML	DRML	CNN-LSTM	EAC	JAA	LP	$AR_{ConvLSTM}$	SRERL	ResNet	T-Net	SA-Net	SAT-Net
1	32.6	36.4	31.4	39.0	47.2	43.4	48.0	46.9	50.8	45.9	52.0	[**54.1**]
2	25.6	41.8	31.1	35.2	44.0	38.0	43.2	45.3	45.4	43.9	45.1	[**49.5**]
4	37.4	43.0	71.4	48.6	54.9	54.2	53.1	55.6	56.2	55.8	[**60.0**]	58.3
6	42.3	55.0	63.3	76.1	77.5	77.1	76.9	77.1	77.1	76.5	[**78.0**]	77.7
7	50.5	67.0	77.1	72.9	74.6	76.7	78.4	[**78.4**]	76.6	76.8	76.9	77.7
10	72.2	66.3	45.0	81.9	[**84.0**]	83.8	82.8	83.5	82.3	82.6	83.8	83.6
12	74.1	65.8	82.6	86.2	86.9	87.2	[**87.9**]	87.6	86.7	86.8	87.3	86.5
14	65.7	54.1	[**72.9**]	58.8	61.9	63.3	67.7	60.6	57.2	59.5	61.0	63.2
15	38.1	36.7	33.2	37.5	43.6	45.3	45.6	52.2	49.3	[**53.0**]	49.5	49.1
17	40.0	48.0	53.9	59.1	60.3	60.5	63.4	[**63.9**]	60.5	62.8	61.0	61.8
23	30.4	31.7	38.6	35.9	42.7	48.1	47.9	47.1	48.1	[**50.0**]	47.5	48.7
24	42.3	30.0	37.0	35.8	41.9	54.2	[**56.4**]	53.3	50.0	48.5	47.6	49.3
Avg	45.9	48.3	53.2	55.9	60.0	61.0	62.6	62.9	61.7	61.8	62.5	[**63.3**]

Table 1: Performance on BP4D

Performance on DISFA

AU	LSVM	APL	DRML	EAC	JAA	$AR_{ConvLSTM}$	SRERL	ResNet	SA-Net	T-Net	SAT-Net
1	10.8	11.4	17.3	41.5	43.7	26.9	[**45.7**]	29.8	32.3	36.6	41.2
2	10.0	12.0	17.7	26.4	46.2	24.4	[**47.8**]	29.3	33.1	32.5	33.1
4	21.8	30.1	37.4	[**66.4**]	56.0	58.6	59.6	56.6	62.3	64.9	63.0
6	15.7	12.4	29.0	50.7	41.4	49.7	47.1	[**57.3**]	52.2	53.1	56.4
9	11.5	10.1	10.7	[**80.5**]	44.7	34.2	[**45.6**]	35.5	33.3	35.8	43.0
12	70.4	65.9	37.7	[**89.3**]	69.6	71.3	73.5	71.8	71.2	74	73.1
25	12.0	21.4	38.5	[**88.9**]	88.3	83.4	84.3	84.6	84.0	82.2	82.9
26	22.1	26.9	20.1	15.6	58.4	51.4	43.6	55.2	59.6	55.7	[**60.6**]
Avg	21.8	23.8	26.7	48.5	56.0	50.0	55.9	52.5	53.5	54.3	[**56.7**]

Table 2: Performance on DISFA

Conclusion

- Our network utilized the **least training parameters** but achieves the state-of-the-art performance.

- Different from handcraft attention mechanism, we developed an AU label supervised **self-learned attention module** to enable the network to learn to pay more attention to different facial areas for the corresponding AUs

- We have also proposed to use **Conv-LSTM module** to fuse the temporal information into AU detection problems and proved to be feasible with temporal information as a supplement in facial action unit detection

Acknowledgement

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