Joint Patch and Multi-label Learning for Facial Action Unit Detection

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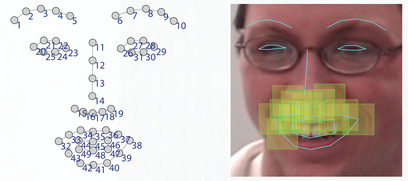
Problem

- Facial Action Unit (AU) detection

- Observations

(1) AUs describe region-based muscle movements; there are local dependencies between features.



(2) The combinations of AUs produce basic expressions; there are co-occurence and competition between AUs.

likely co-occur { 1 2 } { 6 12 }

rarely co-occur { 23 24 }

- Objectives

(1) Identify discriminative patch subset for each AU (patch learning)

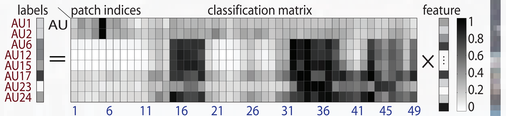
(2) Incorporate AU relations into model learning (multi-label learning)

patch learning

$$\min_{\mathbf{W}} L(\mathbf{W},\mathcal{D}) + \alpha\Omega(\mathbf{W}) + \Psi(\mathbf{W},\mathbf{X})$$

multi-label learning

where $L(\mathbf{W},\mathcal{D}) = \sum_{l=1}^{L} \sum_{i\in\mathcal{I}_l} ln(1+exp(-y_{il}\mathbf{w}_l^\top \mathbf{x}_i))$

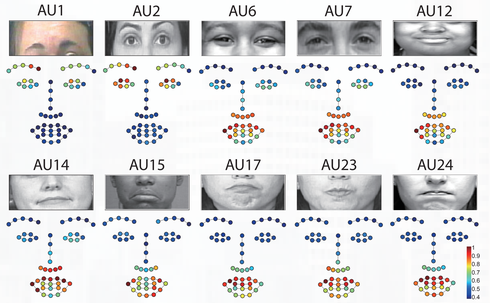


Patch Learning (PL)

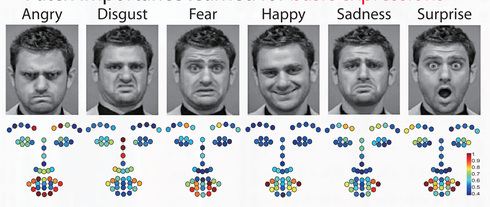
- Model

$$\min_{\mathbf{W}} L(\mathbf{W},\mathbf{D}) + \alpha\Omega(\mathbf{W}), \text{ where } \Omega(\mathbf{W}) = \sum_{l=1}^{L}\sum_{p=1}^{49} \|\mathbf{w}_l^p\|_2$$

- Patch importance learned for AUs

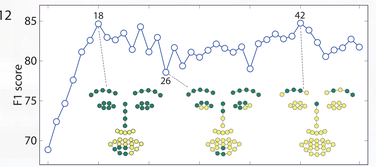


- Patch importance learned for basic expressions



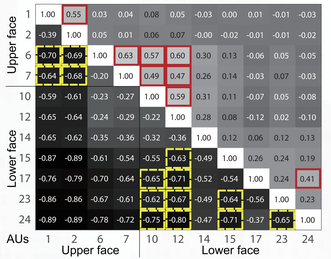
- The number of patches vs performance

▲F1-Norm of AU12 on CK+ dataset



Multi-label Learning (ML)

- Observed AU relations



- AU relations discovered from >350,000 frames

AU relations	AU groups
Positive correlation	(1,2), (6,7), (6,10), (7,10), (6,12), (7,12), (10,12), (17,24)
Negative competition	(1,6), (1,7), (2,6), (2,7), (10,17), (10,23), (10,24), (12,15), (12,17), (12,23), (12,24), , (15,23), (15,24), (23,24)

- Model

$$\min_{\mathbf{W}} L(\mathbf{W},\mathcal{D}) + \Psi(\mathbf{W},\mathbf{X})$$

$$\Psi(\mathbf{W},\mathbf{X}) = \beta_1 PC(\mathbf{W},\mathbf{X},\mathcal{P}) + \beta_2 NC(\mathbf{W},\mathbf{X},\mathcal{N})$$

▲ Regularizer with positive correlation:

$$PC(\mathbf{W},\mathbf{X},\mathcal{P}) = \frac{1}{2}\sum_{(i,j)\in\mathcal{P}} \gamma_{ij}\|\mathbf{w}_i^\top\mathbf{X} - \mathbf{w}_j^\top\mathbf{X}\|_2^2$$

▲ Regularizer with negative competition [2]:

$$NC(\mathbf{W},\mathbf{X},\mathcal{N}) = \sum_{i=1}^{N}\sum_{n=1}^{|\mathcal{N}|}(\sum_{j\in\mathcal{N}_n}|\mathbf{w}_j^\top\mathbf{x}_i|)^2$$

[1] S. Taheri, Q. Qiu, and R. Chellappa. Structure-preserving sparse decomposition or facial expression analysis. TIP, 23(8):3590–3603, Aug 2014.

[2] Y. Zhou, R. Jin, and S. Hoi. Exclusive lasso for multi-task feature selection. In AISTATS, 2010.

JPML Optimization

- Joint solution with ADMM:

$$\min_{\mathbf{W}_1,\mathbf{W}_2} L(\mathbf{W}_1,\mathcal{D}) + \alpha\Omega(\mathbf{W}_1) + \Psi(\mathbf{W}_2,\mathbf{X})$$
$$\text{s.t. } \mathbf{W}_1 = \mathbf{W}_2$$

▲ Algorithms

Algorithm 1 Patch learning (PL)

Input: Training data $\mathcal{D}=\{(\mathbf{x}_i,\mathbf{y}_i)\}_{i=1}^N$, ML matrix $\mathbf{W}_2$, Lagrange multiplier of ADMM ρ and $\mathbf{U}$, learning rate η_1, and penalty parameter α.

Output: PL matrix $\mathbf{W}_1 \in \mathbb{R}^{D\times L}$ with sparse groups of rows.

1: **for** $\ell = 1,\ldots,L$ **do**
2: $\mathbf{w}_\ell^{(0)} = \frac{1}{D}\mathbf{1}_D$, $\mathbf{v}^{(0)} = \frac{1}{D}\mathbf{1}_D$, $a^{(0)}=1$, $t=0$; // Initialization
3: **while** not convergence **do**
4: $\mathbf{z}^{(t)} = \mathbf{v}^{(t)} - \eta_1(\nabla L(\mathbf{w}_\ell^{(t)},\mathcal{D}) + \mathbf{u}_\ell^{(t)} + \rho(\mathbf{w}_\ell^{(t)} - \mathbf{w}_2^{(t)}))$;
5: **for** $p = 1,\ldots,49$ **do**
6: $\mathbf{w}_{\ell_p}^{(t+1)} = I(\|\mathbf{z}^{(t)}\|_2 > \alpha)(1 - \frac{\alpha\eta_1}{\|\mathbf{z}^{(t)}\|_2})\mathbf{z}^{(t)}$;
// $\mathbf{w}_{\ell_p}^t$ is the p-th patch within the ℓ-th column of $\mathbf{W}_1$
7: **end for**
8: $a^{(t+1)} = \frac{2}{t+3}$;
9: $\mathbf{v}^{(t+1)} = \mathbf{w}_\ell^{(t+1)} + (\frac{1-a^{(t)}}{a^{(t)}}a^{(t+1)})(\mathbf{w}_\ell^{(t+1)} - \mathbf{w}_\ell^{(t)})$;
10: $t = t+1$;
11: **end while**
12: **end for**

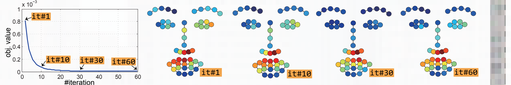
Algorithm 2 Multi-label learning (ML)

Input: Training data $\mathcal{D}=\{(\mathbf{x}_i,\mathbf{y}_i)\}_{i=1}^N$, PL matrix $\mathbf{W}_1$, Lagrange multiplier of ADMM ρ and $\mathbf{U}$, learning rate η_2, penalty parameter β_2, and accuracy control parameter μ.

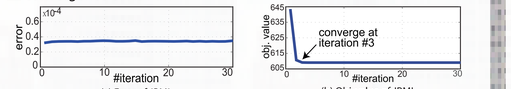
Output: ML matrix $\mathbf{W}_2 \in \mathbb{R}^{D\times L}$.

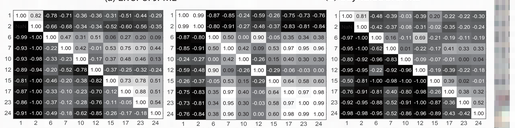
1: $\mathbf{W}_2^{(0)} = \frac{1}{D}\mathbf{1}_{D\times L}$, $\mathbf{V}^{(0)} = \frac{1}{D}\mathbf{1}_{D\times L}$, $a^{(0)}=1$, $t=0$; // Init.
2: **while** not convergence **do**
3: $\mathbf{U}^{(t)} = (1-a^{(t)})\mathbf{W}_2^{(t)} + a^{(t)}\mathbf{V}^{(t)}$;
4: $\mathbf{H}_t = \mathbf{0}_{L\times D}$;
5: **for** $i = 1,\ldots,N$ **do**
6: $\mathbf{z}_i = \min(1, \max(-1, \frac{\mathbf{U}^{(t)\top}\mathbf{x}_i}{\rho}))$;
7: $\eta_i = \mathbf{z}_i^\top\mathbf{U}^{(t)\top}\mathbf{x}_i - \frac{\rho}{2}\|\mathbf{z}_i\|_2^2$;
8: $\mathbf{H}_t = \mathbf{H}_t + \eta_i(\mathbf{z}_i\mathbf{x}_i^\top)$;
9: **end for**
10: $\mathbf{V}^{(t+1)} = \mathbf{V}^{(t)} - \frac{1}{\mu}(\mathbf{H}_t^\top - \mathbf{u} + \rho(\mathbf{W}_2 - \mathbf{U}^{(t)})) + \nabla PC(\mathbf{U}^{(t)})$;
11: $\mathbf{W}_2^{(t+1)} = (1-a^{(t)})\mathbf{W}_2^{(t)} + a^{(t)}\mathbf{V}^{(t+1)}$;
12: $a^{(t+1)} = \frac{2}{t+3}$;
13: $t = t+1$;
14: **end while**

▲ Convergence of patch learning



▲ Convergence of ADMM





(c) Relation matrix in CK+ (d) it#1 Patch Learning (e)it#30 JPML

★ The difference of correlation coefficent between (c) and (d) is 0.51, and that between (c) and (e) is 0.15

[3] L. Zhong, Q. Liu, P. Yang, B. Liu, J. Huang, and D. N. Metaxas. Learning active facial patches for expression analysis. In CVPR, 2012.

[4] X. Zhang, M. H. Mahoor, S. M. Mavadati, and J. F. Cohn. A lp-norm mtmkl framework for simultaneous detection of multiple facial AUs. In WACV, 2014

[5] P. Lucey, J. F. Cohn, T. Kanade, J. Saragih, Z. Ambadar, and I. Matthews. The extended Cohn-Kanade dataset (CK+): A complete dataset for action unit and emotion-specified ex- pression. In CVPRW, 2010.

[6] M. A. Sayette et al. Alcohol and group formation a multimodal investigation of the effects of alcohol on social bonding. Psychological science, 2012.

[7] X. Zhang et al. A high-resolution spontaneous 3D dynamic facial expression database. In Automatic Face and Gesture Recognition Workshop, 2013.

Experiments

- Settings

▲ SIFT descriptor on pre-determined 49 facial landmarks

▲ Leave-one-subject-out protocol

- Metrics

$$\text{F1-Norm} = \frac{2s\cdot R\cdot P}{s\cdot R + P}, \qquad \text{F1-Event} = \frac{2\cdot ER\cdot EP}{ER+EP}$$

- Methods

▲ SP-SVM: Self-defined Patches SVM

▲ SPSD [1]: Structure Preserving Sparse Decomposition

▲ LSVM: Linear SVM

▲ LL1: L1-regularized logistic regression

▲ APL [3]: Active Patch Learning

▲ MT-MKL [4]: Multi-Task Multiple Kernel Learning

▲ JPML: Our method

- CK+ [5]

▲ 593 posed videos from 123 subjects

	F1-Norm						
AU	SP-SVM	SPSD	LSVM	LL1	MT-MKL	ML	APL	JPML
1	61.8	44.4	85.8	83.4	73.0	**89.0**	86.4	**[90.0]**
2	63.9	47.9	90.9	87.4	87.8	**92.7**	86.6	**[93.0]**
6	61.7	34.2	**75.3**	**76.2**	61.9	70.7	70.8	74.2
7	60.0	50.8	**[70.8]**	**70.0**	–	61.6	62.8	66.7
12	65.5	47.4	**[80.7]**	80.0	73.3	75.2	76.6	**[80.7]**
14	66.3	59.9	**67.7**	**67.7**	–	–	**[69.5]**	–
15	65.8	53.4	67.5	66.7	67.8	61.9	**79.2**	**73.6**
17	60.4	62.2	**80.5**	**80.5**	68.3	80.3	80.0	**[83.5]**
23	66.2	65.0	69.3	69.8	–	69.7	**83.5**	**74.3**
24	68.3	65.8	71.1	**71.4**	–	67.5	**75.9**	65.9
AA.	64.0	52.3	**76.0**	75.3	–	–	**[77.1]**	–
AR.	63.7	51.5	76.9	76.2	72.0	74.3	**77.0**	**[78.0]**

- GFT [6]

▲ 50 2-minute spontaneous videos from 50 participants

	F1 Norm							F1 Event						
AU	SPSVM	SPSD	LSVM	LL1	ML	APL	JPML	SPSVM	SPSD	LSVM	LL1	ML	APL	JPML
1	29.9	33.0	53.0	52.0	**[66.7]**	44.1	**58.0**	**17.8**	12.2	**[20.6]**	17.8	11.5	11.5	15.9
2	60.2	34.7	51.3	45.1	**[64.4]**	43.6	**63.2**	**[21.2]**	12.9	19.6	16.8	12.5	**16.6**	15.0
6	**[77.2]**	34.8	74.7	75.2	57.3	**77.2**	**[79.6]**	46.6	21.6	33.2	42.3	25.5	**50.3**	**[50.8]**
7	56.5	40.3	**72.7**	70.5	67.6	**[73.6]**	**[73.6]**	41.3	25.3	38.2	34.4	34.3	**47.9**	**[54.7]**
10	74.6	41.8	75.8	**77.5**	–	**[78.6]**	–	**45.6**	25.6	30.7	41.2	37.9	–	**50.2**
12	77.1	76.2	79.2	80.2	67.1	**81.3**	**[84.1]**	47.9	**48.6**	47.9	48.4	15.3	**[53.6]**	46.7
14	64.1	**68.9**	68.5	**[70.4]**	–	66.7	–	42.1	49.0	42.1	**55.0**	–	**[60.6]**	–
15	47.2	30.1	45.8	65.3	66.3	**[67.1]**	**66.2**	16.4	10.6	**39.1**	**[39.7]**	17.8	16.9	**37.9**
17	51.8	32.8	47.6	46.8	67.1	**[74.5]**	**72.0**	33.8	22.9	38.3	**38.9**	27.1	**[48.7]**	38.8
23	49.7	35.9	38.8	43.5	**[66.9]**	**63.9**	60.0	25.9	18.0	**35.4**	28.4	28.6	35.0	**[37.6]**
24	51.1	35.3	56.6	59.2	67.1	**79.0**	**[79.3]**	18.7	12.9	**27.3**	25.0	26.7	19.2	**[35.5]**
AA.	56.5	42.3	59.8	55.4		**[67.1]**		31.1	23.4	34.2	34.6		**[36.3]**	
AR.	53.6	39.4	57.0	51.3	65.6	**65.9**	**[70.7]**	38.3	19.7	32.5	32.0	22.1	**32.7**	**[37.0]**

- BU4D [7]

▲ 48 spontaneous videos from 41 participants

	F1 Norm							F1 Event						
AU	SPSVM	SPSD	LSVM	LL1	ML	APL	JPML	SPSVM	SPSD	LSVM	LL1	ML	APL	JPML
1	22.9	27.6	40.6	35.6	**[58.6]**	**56.0**	55.5	9.5	10.6	13.0	11.7	14.9	**17.1**	**[17.5]**
2	15.8	15.8	32.1	24.1	56.9	**60.2**	**[62.7]**	7.6	7.6	11.5	10.3	14.0	**16.0**	**[17.2]**
6	45.5	54.6	59.4	**75.2**	62.9	75.0	**[75.7]**	21.9	27.9	17.2	21.1	15.6	**[32.7]**	**30.0**
7	44.1	56.0	55.7	**[70.5]**	66.7	64.3	**66.7**	22.9	**30.5**	20.5	23.6	17.1	**[33.7]**	26.3
10	50.1	55.6	63.0	**[74.3]**	–	**72.9**	–	29.7	32.8	22.0	**34.1**	–	**41.0**	–
12	46.5	54.9	62.5	82.0	67.1	**[82.3]**	**81.4**	28.4	30.6	23.4	25.0	20.5	**[41.3]**	**31.6**
14	44.2	52.7	51.5	61.2	–	**66.0**	–	19.3	28.3	23.5	29.3	–	**29.8**	–
15	13.2	40.5	49.6	56.3	66.0	**[68.4]**	**65.9**	**23.4**	22.9	23.9	18.6	20.4	13.1	**[30.1]**
17	42.3	46.9	40.3	63.4	66.7	**[69.2]**	**65.3**	19.3	21.9	21.2	25.6	20.8	**[33.5]**	**29.4**
23	11.3	23.9	42.1	57.2	67.1	**[68.0]**	**65.2**	**19.4**	19.6	**[21.8]**	19.0	20.6	16.2	**[27.7]**
24	7.3	47.3	21.3	69.5	66.7	**[78.1]**	**77.3**	17.7	18.4	19.0	**[23.1]**	20.4	13.2	**[26.4]**
AA.	29.3	42.1	47.1	59.5	–	**[68.7]**	–	18.9	21.8	19.7	23.1	–	**[24.6]**	–
AR.	25.3	39.4	44.8	57.7	64.3	**[68.5]**	**68.4**	15.9	19.9	19.0	21.1	18.3	**22.2**	**[26.2]**