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Three Dimensional Binary Edge Feature Representation for Pain Expression Analysis

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Outline

- Background
- Feature Descriptor: 3D-BE
- Feature Evaluation
- Target Action Unit Selection
- Pain Detection Experiment and Evaluation
- Conclusion

Background

- Traditionally, pain assessment relies on subjective rating scales.

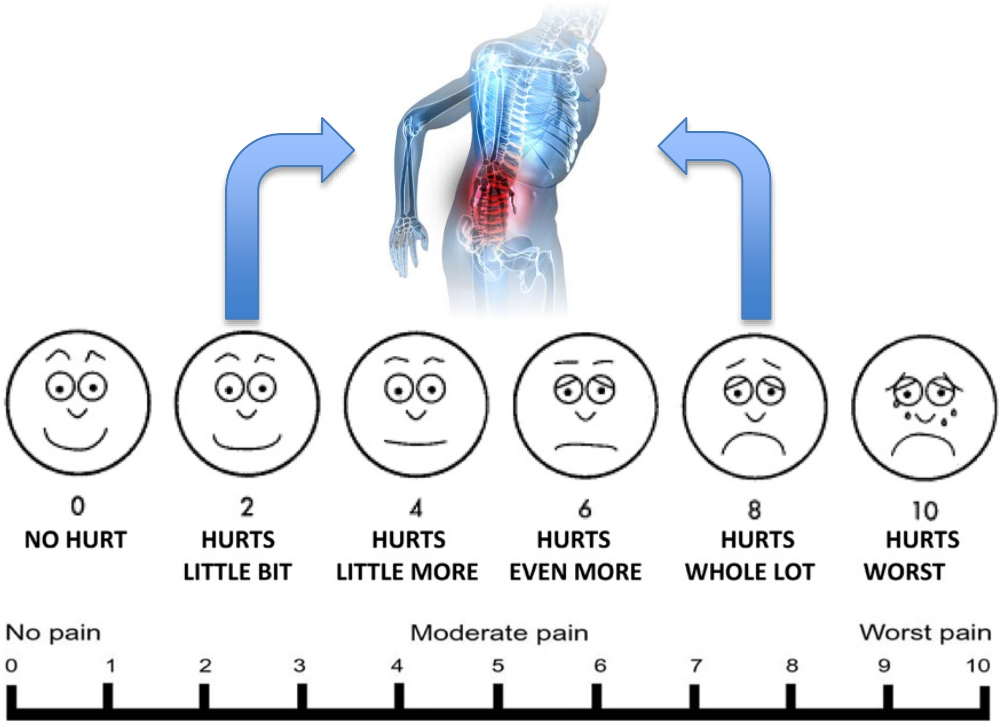


Image courtesy: disabilityintersections.com

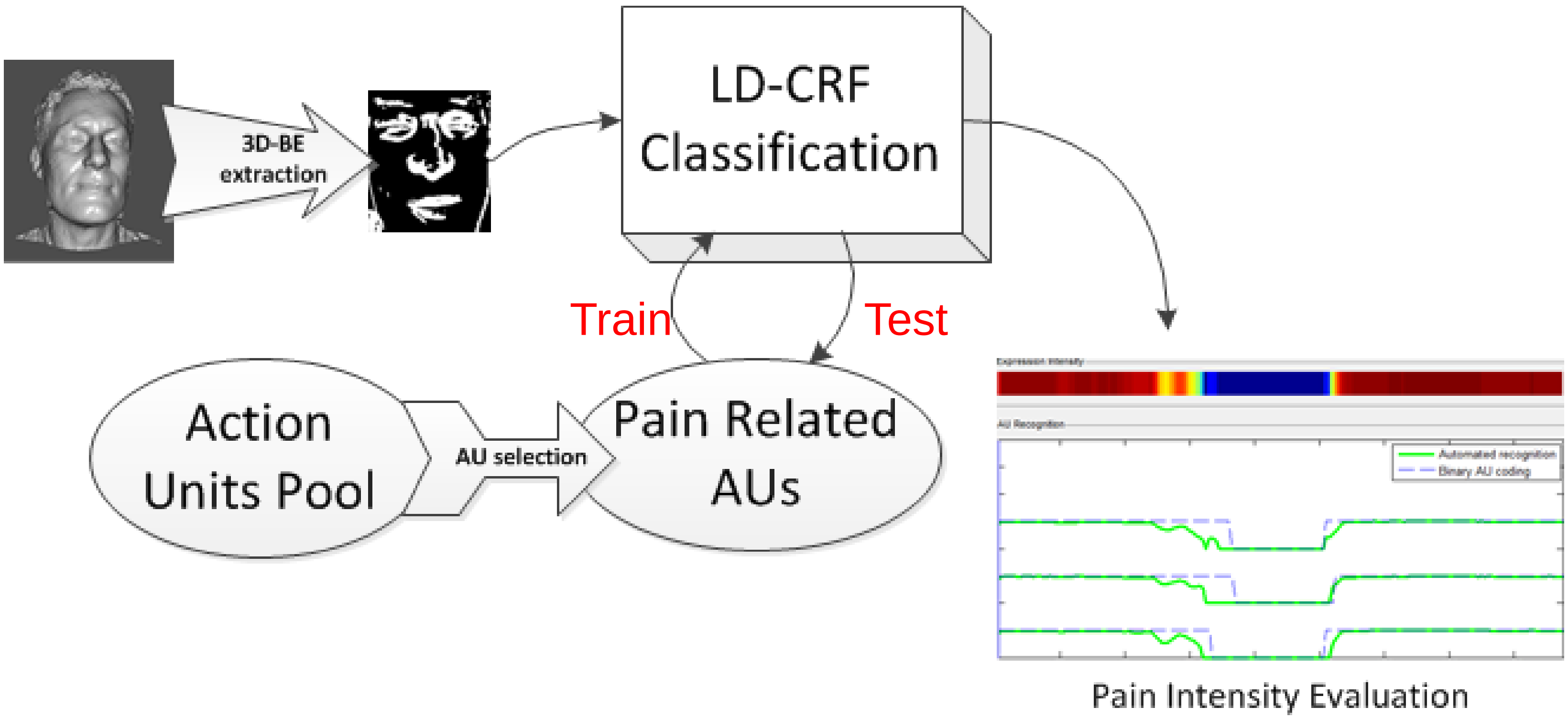
Background

- Previous work
  - G. Littlewort, M. Bartlett, et al. "Faces of pain: automated measurement of spontaneous all facial expressions of genuine and posed pain." *ACM ICMI 2007*
  - P. Lucey, J. F. Cohn, et al. "Automatically detecting pain using facial actions." *ACII* 2009

Background

- Limitation of 2D image based pain assessment
  - *Sensitive to head motion, illumination change*
  - *Missing important depth information*
  - *Not investigating the temporal evidence*
- What can we get from the dynamic 3D pain sequence?
  - *A natural representation of human face to explore new features*
  - Learning from the temporal information to detect pain in un-segmented sequence

Proposed Approach



Feature Descriptor

- Sketch is descriptive to carry expression information.

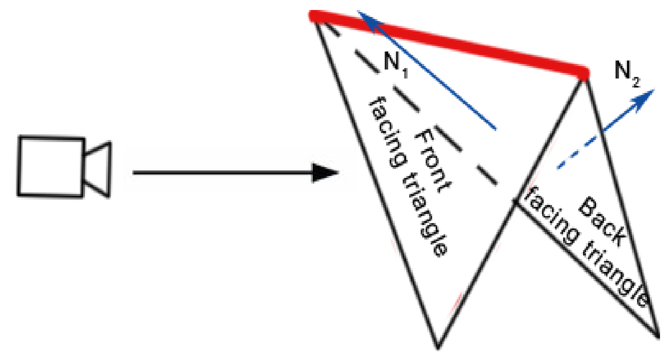
PORTRAIT D'HENRI MARTIN, PABLO PICASSO

NON-PHOTOREALISTIC RENDERING OF BP4D-Spon

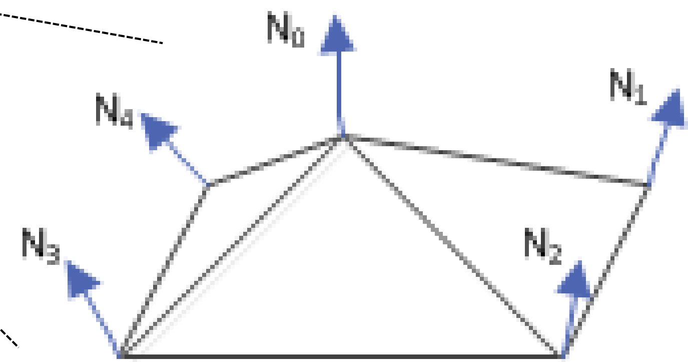
Feature Descriptor

- A close look at the 3D edge

$$N_1 \bullet N_2 = |N_1||N_2|\cos\alpha < 0$$

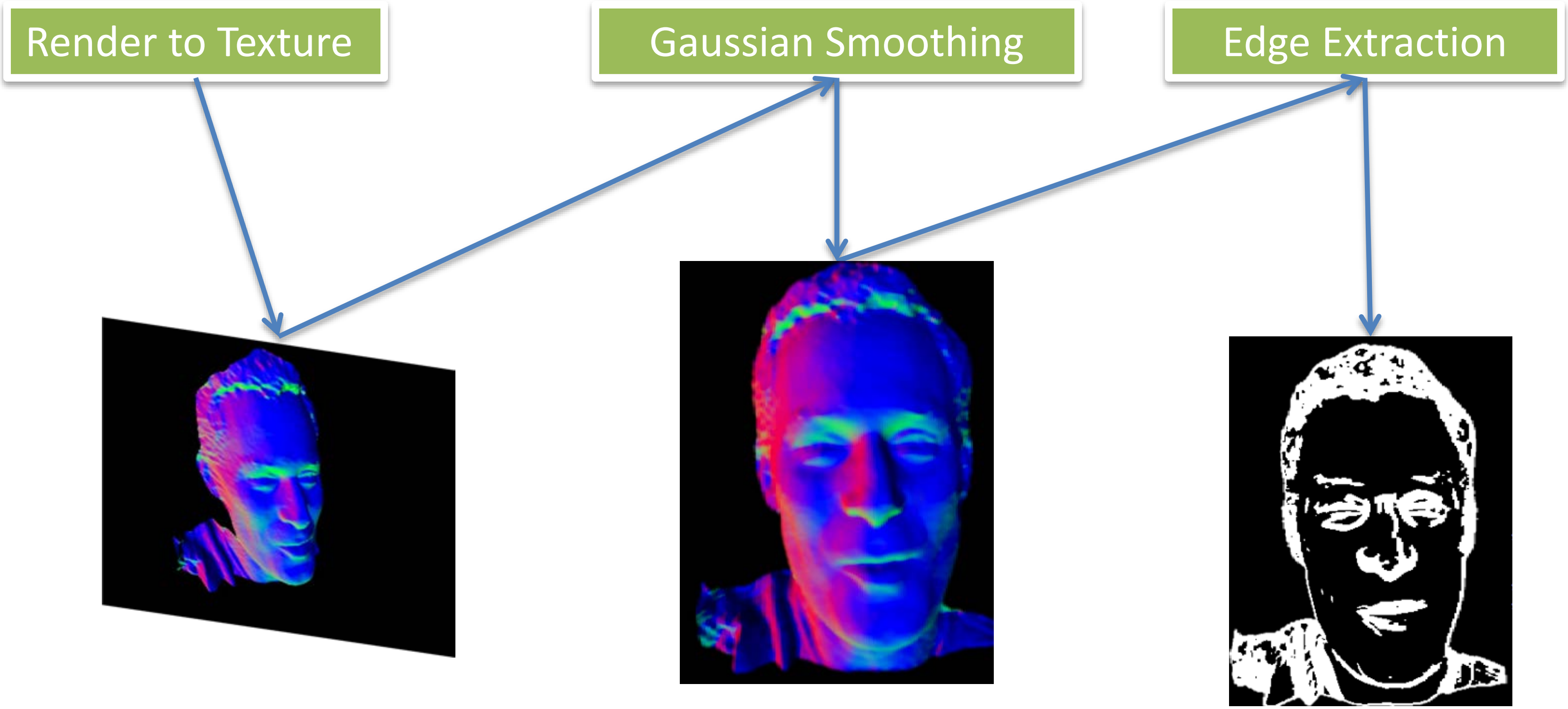


$$\sum^{4}(1 - N_o \bullet N_i) \geq t$$



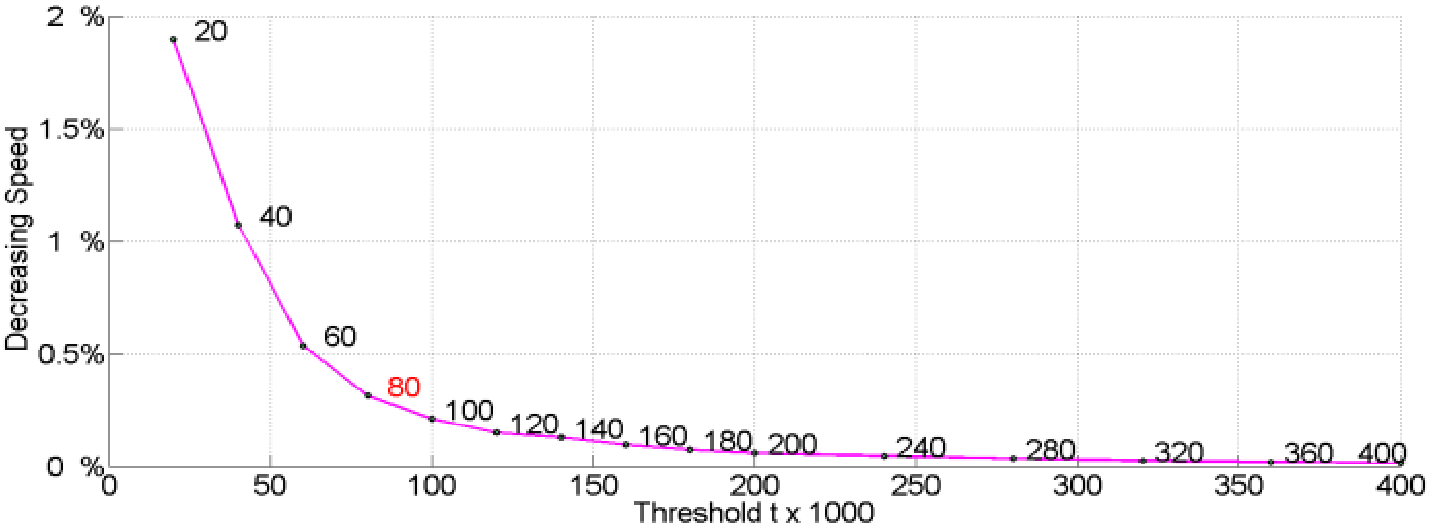
Feature Descriptor

- Normal map based rendering



Feature Descriptor

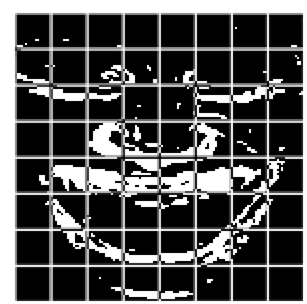
- An optimal threshold ***t*** is chosen based on the edge decreasing speed.



Feature Descriptor

- Based on three expression invariant feature points, we register the face and get the feature region.

$$V = [p_{1,} p_2, \dots p_n],\ p_i = c_i \Big/ \sum_{i=1}^{n} c_i$$



Feature Evaluation

Method \ AU	3D-based Features			2D-based Features		
	3D-BE	Shape Index	Nebular	LBP-TOP Depth	LBP-TOP texture	Gabor texture
1	64.6	53.2	54.1	52.4	57.9	61.0
2	57.1	59.4	63.0	55.9	59.2	60.8
4	66.5	61.6	58.7	51.1	53.3	58.6
6	69.0	70.4	67.6	61.3	64.8	67.6
7	64.5	64.1	58.9	52.4	55.4	64.4
10	68.7	68.0	66.4	56.9	62.1	70.5
12	75.2	75.2	57.3	53.3	59.1	74.5
14	55.9	53.5	54.5	52.8	52.3	52.8
15	66.2	65.1	66.0	63.1	64.5	60.9
17	64.2	59.2	61.8	53.3	60.0	62.2
23	63.6	50.9	60.6	59.3	58.5	61.7
24	75.9	67.9	63.3	62.9	63.4	72.1
Avg.	66.0	62.3	61.3	56.2	59.2	63.9

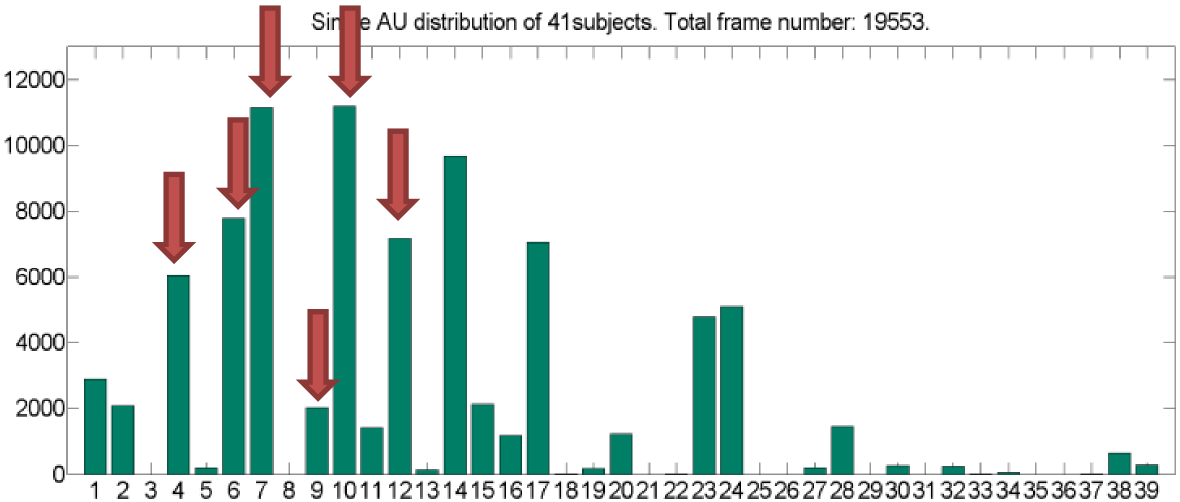
Target Action Units Selection

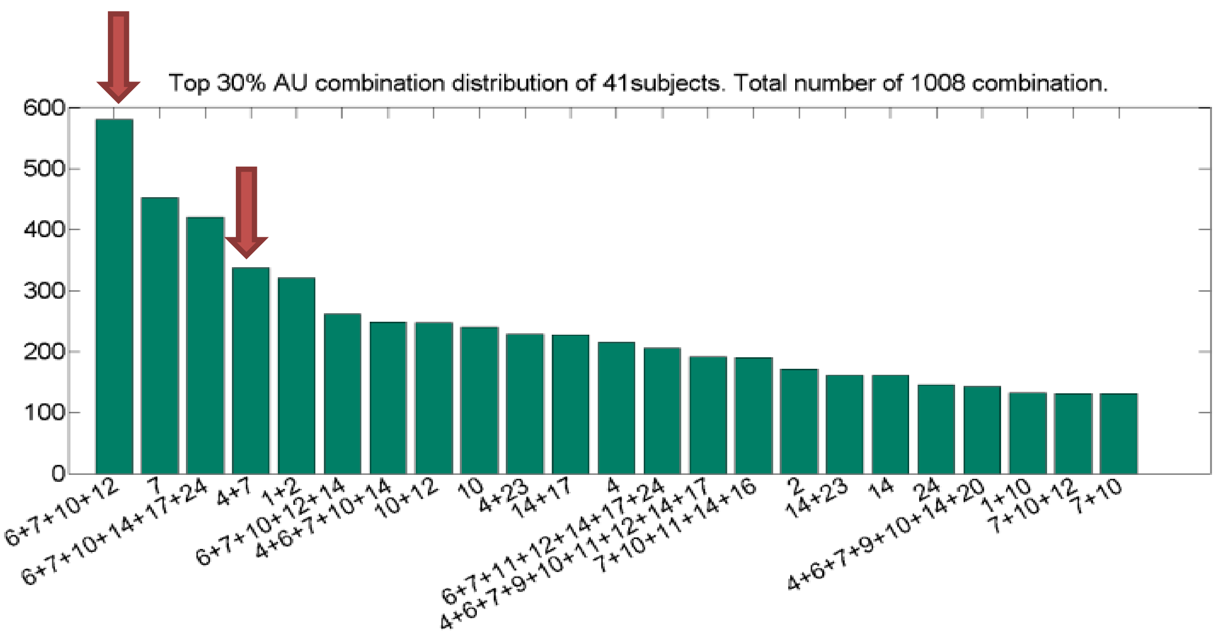
- Prkachin and Solomon selected pain related AU set including: AU4, 6, 7, 9, 10, 12, 20, 25, 26, 27 and 43 [PRKACHIN et al. 2008].
- They define the pain intensity scale (PSPI) as

  $$Pain = AU4 + (AU6||AU7) + (AU9||AU10) + AU43$$

- BP4D-Spontaneous database code 34 AUs for pain activity of 41 subjects [ZHANG, Yin, Cohn, et al. 2013].
- We start from the intersection of the two:
  - AU4, 6, 7, 9, 10, 12, 20, and 27.

Target Action Units Selection





AU4, 6, 7, 9, 10, 12, 20, and 27

AU4, 6, 7, 9, 10, 12

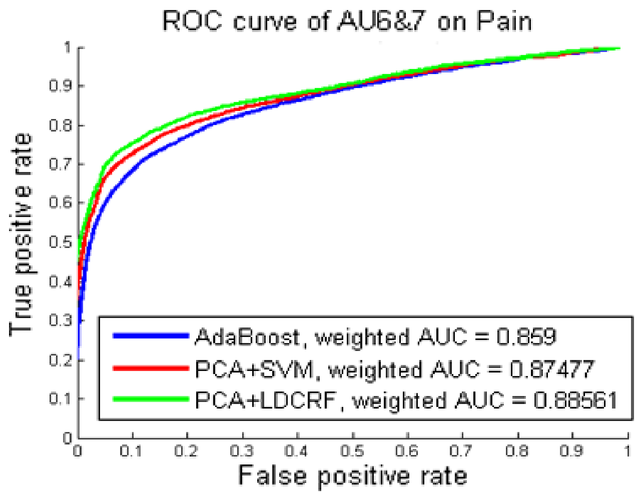
Target Action Units Selection

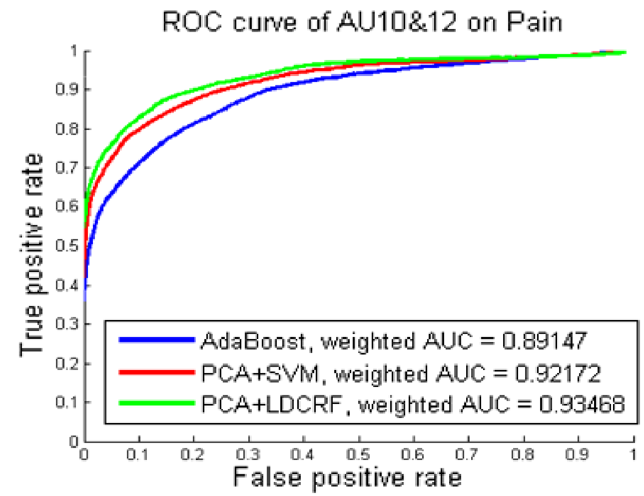
Task AU set	Happy	Sad	Startled	Embarrass	Fear	Upset	Disgust
4, 6, 7, 9, 10	0.0257	0.0196	0.0014	0.0005	0.0013	**0.2346***	0.0331
4, (6&7), (9&10)	**0.6041***	**0.2754***	0.0012	0.2113	**0.8187***	0.0245	0.0343
4, 6, 7, 10, 12	0.0042	0.0067	0.0019	0.0004	0.0007	**0.0992***	0.0290
4, (6&7), (10&12)	0.0052	**0.0546***	0.0040	7.0879×10^{-6}	0.0125	**0.3507***	0.0227
4, (6&7), 9, (10&12)	0.0074	0.0475	0.0034	9.7693×10^{-6}	0.0156	**0.3951***	0.0120
(6&7), 9, (10&12)	0.0003	1.0536×10^{-8}	0.0032	1.3646×10^{-7}	8.1435×10^{-5}	0.0307	0.0043

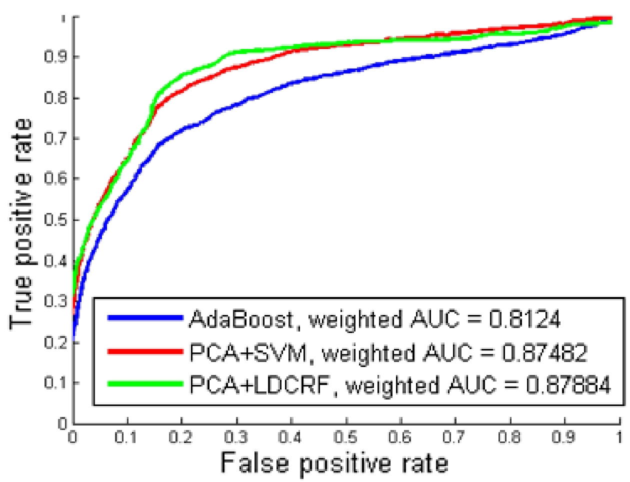
Pain Detection Experiment and Evaluation

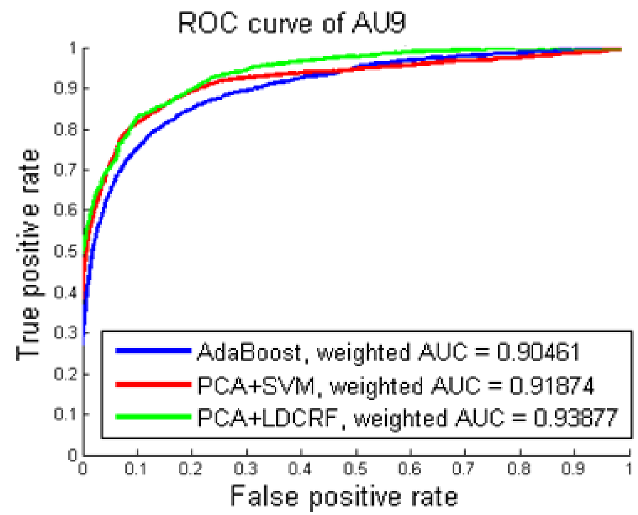
- Three classification models:
  - AdaBoost [VIOLA, JONES 2002]
  - Support Vector Machine (SVM) [LITTLEWORT, et al. 2007]
  - Latent-Dynamic Conditional Random Field (LDCRF) [MORENCY, et al. 2007]
- Methodology
  - 10-fold cross validation for the classifier parameters
  - Positive and negative data from two tasks (pain and no-pain)

Experiment and Evaluation









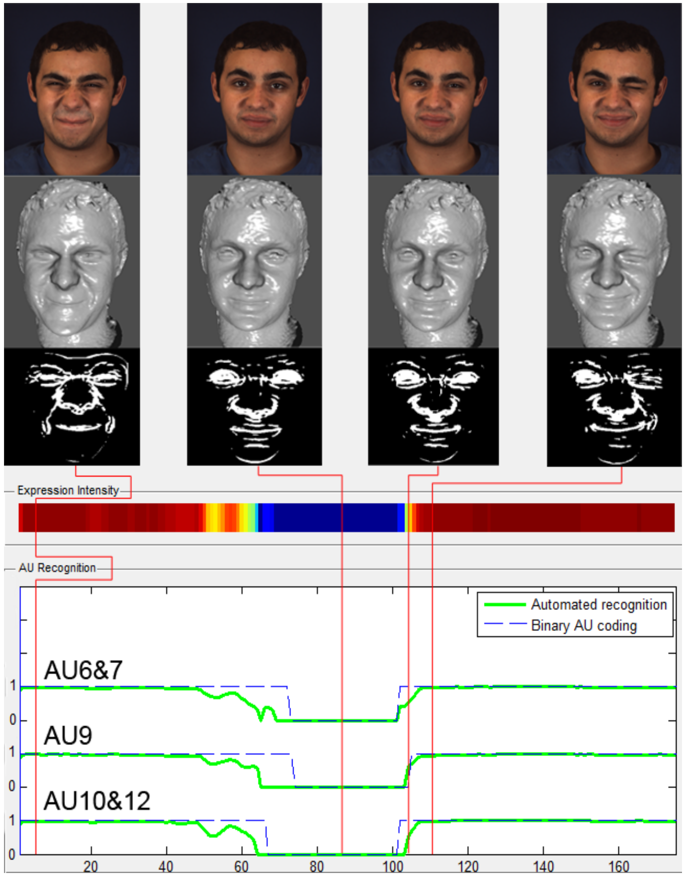
Pain Detection Experiment and Evaluation

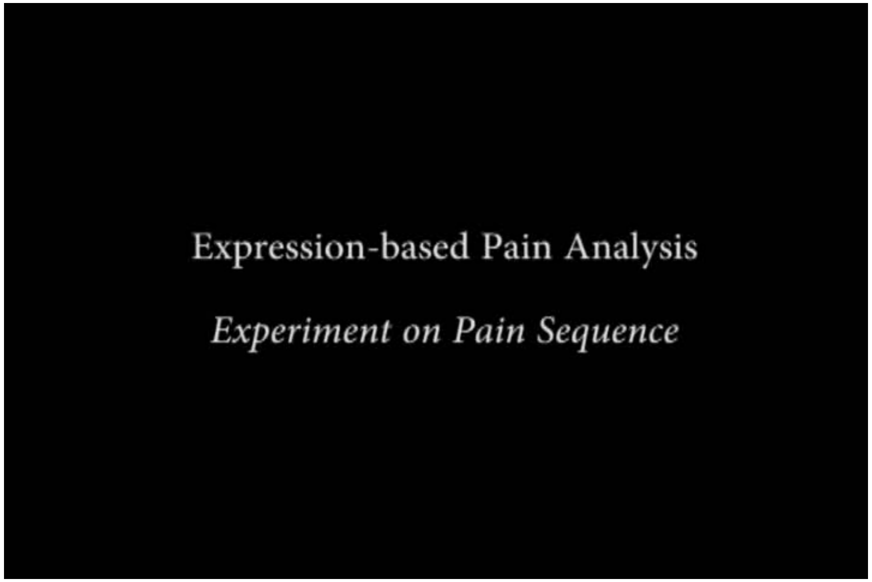
- We evaluate the consistency of log-likelihood from the classifier (LDCRF) with the intensity coding on AU6, 10, and 12.
- Different mapping functions may apply to the raw likelihood , and the result is divided into 5 isometric bins.

Type AU \	Linear mapping		6-th power mapping	
	MEAN	STD	MEAN	STD
6	1.949	0.998	1.312	0.924
10	1.678	0.959	1.243	0.842
12	2.130	1.053	1.436	1.033

Pain Detection Experiment and Evaluation

- Pain intensity detection





Conclusion

- A newly developed binary edge feature for 3D face model is introduced.
- An Action Units set has been found as a good indicator of genuine pain expression.
- LDCRF fits this un-segmented sequence classification.
- The classification result can be used to indicate the pain intensity.

Future Work

- Pain analysis based on different modality data.
- Investigate AU sets correlated to the other expressions.
- Apply the 3D-BE feature to RGB-D image stream for patient monitoring application.

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