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A Complementary Local Feature Descriptor for Face Identification

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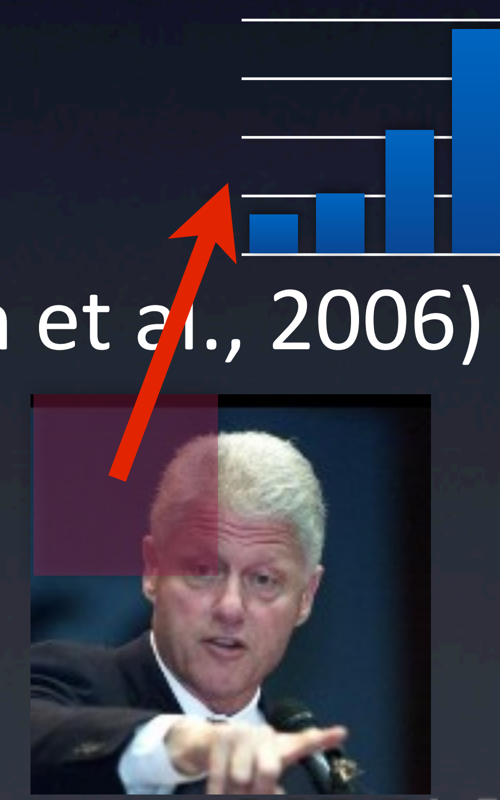
Agenda

- Background
  - Brief review of previous works
  - Motivation
- Introduction of CCS-POP feature
- Discriminative dimension weighting by partial least squares
- Experimental Results
- Conclusion

Existing Feature Descriptors for Face Identification

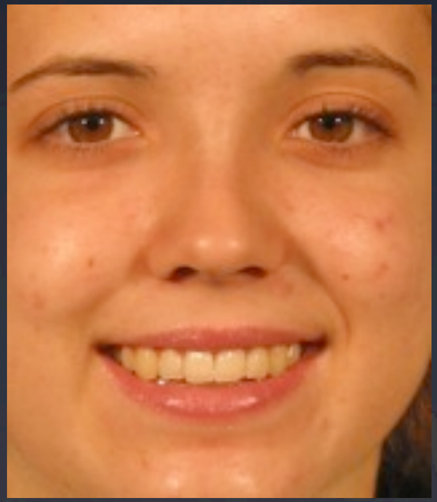
- Successful feature descriptors capture
  - Shape information with different scales
    - e.g. Gabor (D. Gabor, 1946)
  - Edge information
    - e.g. Histograms of oriented gradients (HOG) (Dalal and Triggs, 2005), SIFT (Lowe 1999)
  - Micro-edge information
    - e.g. Local binary patterns (LBP) (Ahonen et al., 2006)
- Compact representation of features
  - Using histogram in a sub-window



Motivation

- Compact representation of features
  - Using histogram in a sub-window
- It has a trade-off
  - Pro
    - Spatial invariance within the sub-window
  - Con
    - Losing location specific information

[Example: HOG]



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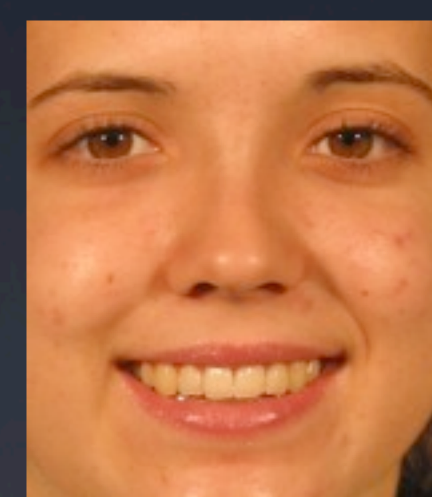

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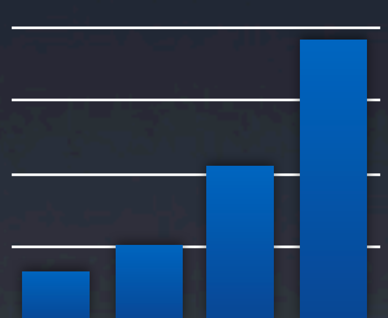
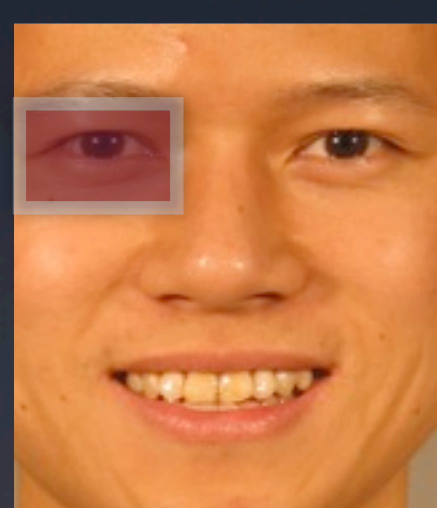
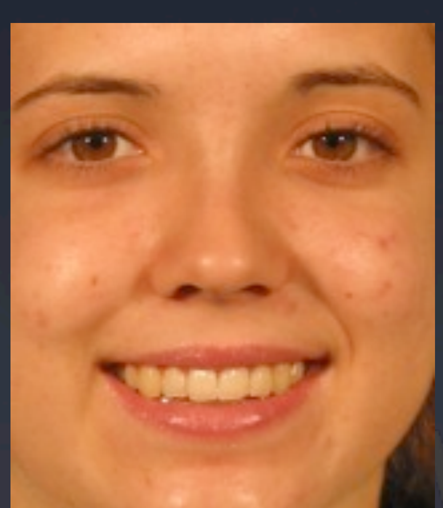

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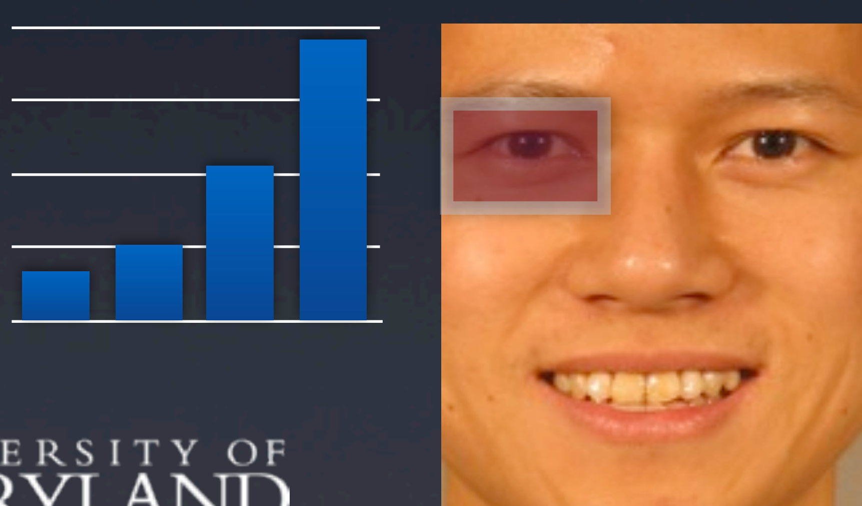

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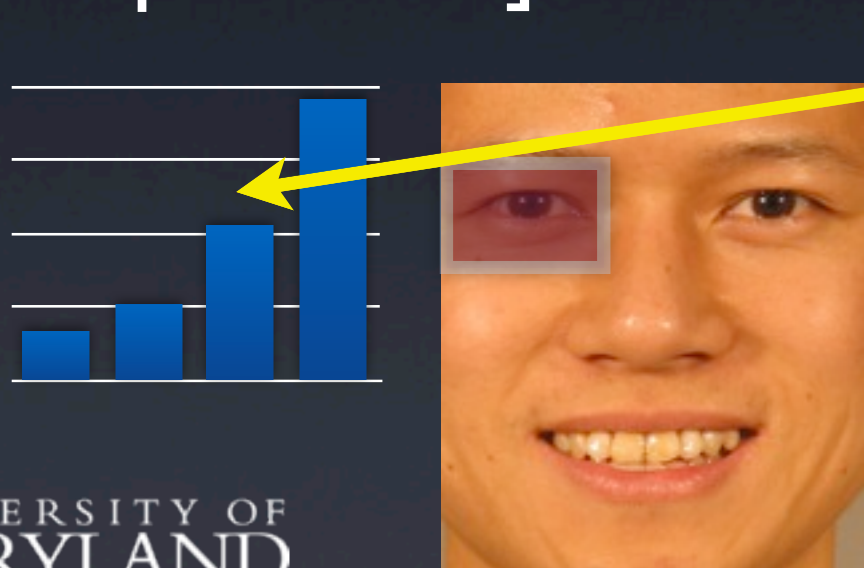
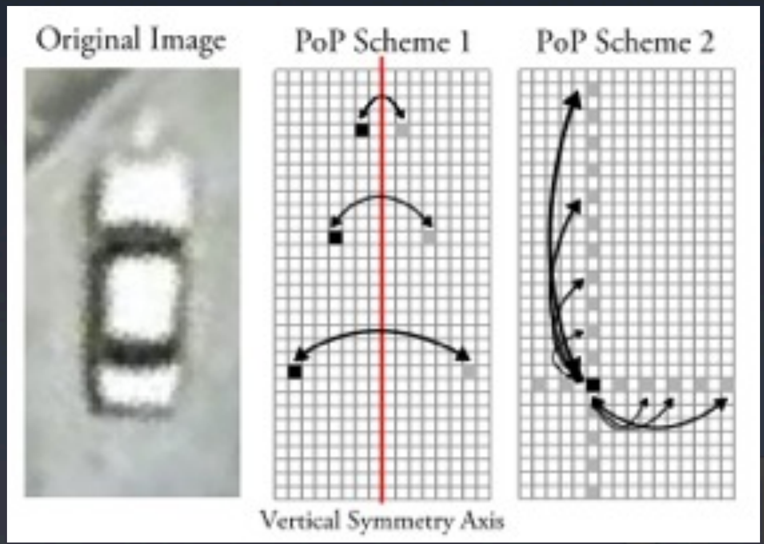
[Example: HOG]

Only Different here!



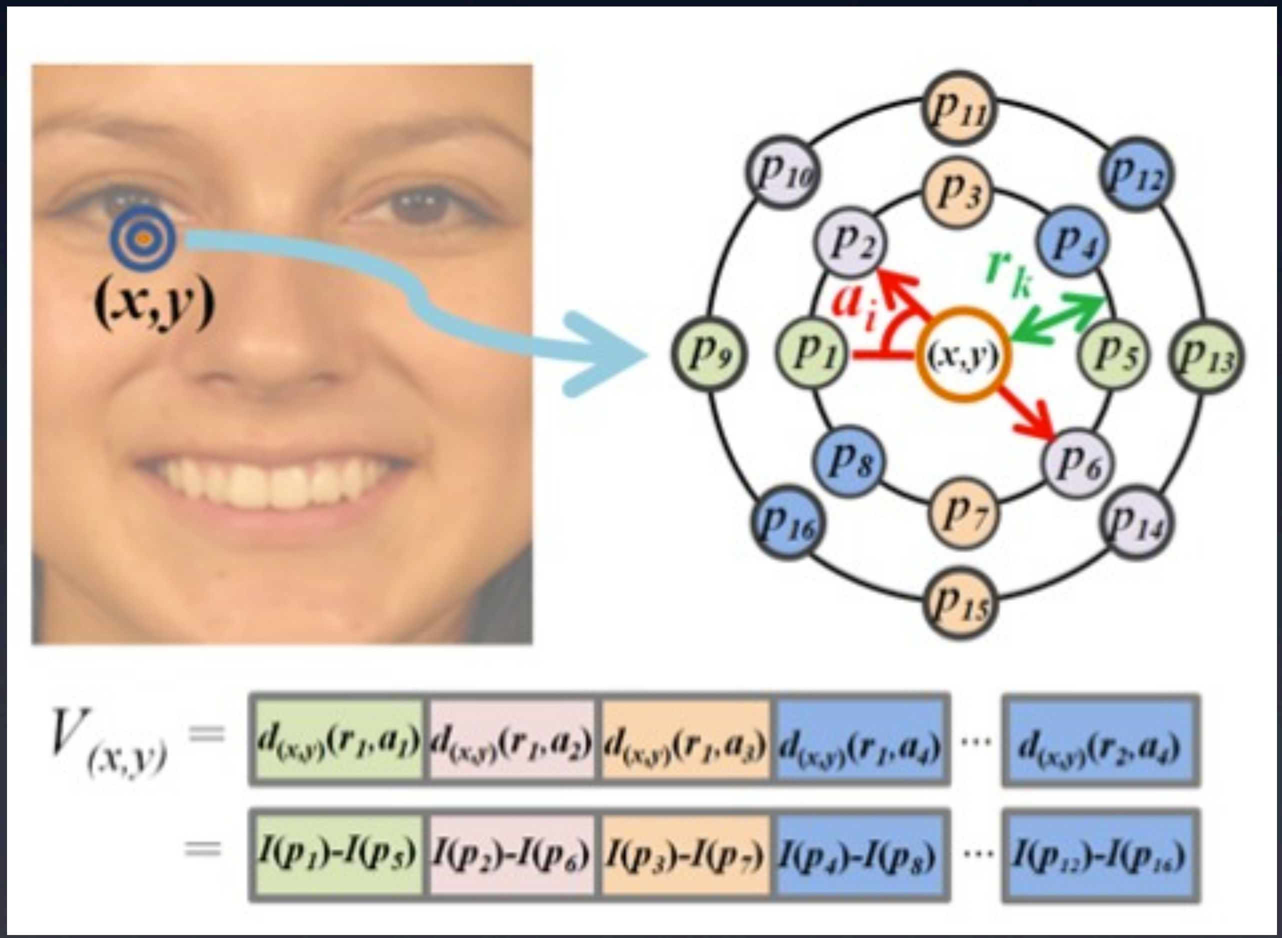
Location Specific Descriptors

- Gabor (D. Gabor, 1946)
  - Shape or big edge information centering at a pixel
- Pairs of Pixels (POP) (Kembhavi *et al.*, 2010)
  - Pixel-wise information: from micro-edge to distant symmetric pairs
  - Can have discriminative weights on each pixel pairs by partial least squares
  - But only good at well aligned rectangular objects (usually man-made objects)



Introducing CCS-POP

- Circular Center Symmetric-Pairs of Pixels
  - Generalizing the POP for natural objects with multiple radius and various directions
  - Similar information to LBP and its variants
    - but no histogramming and encoding with magnitude



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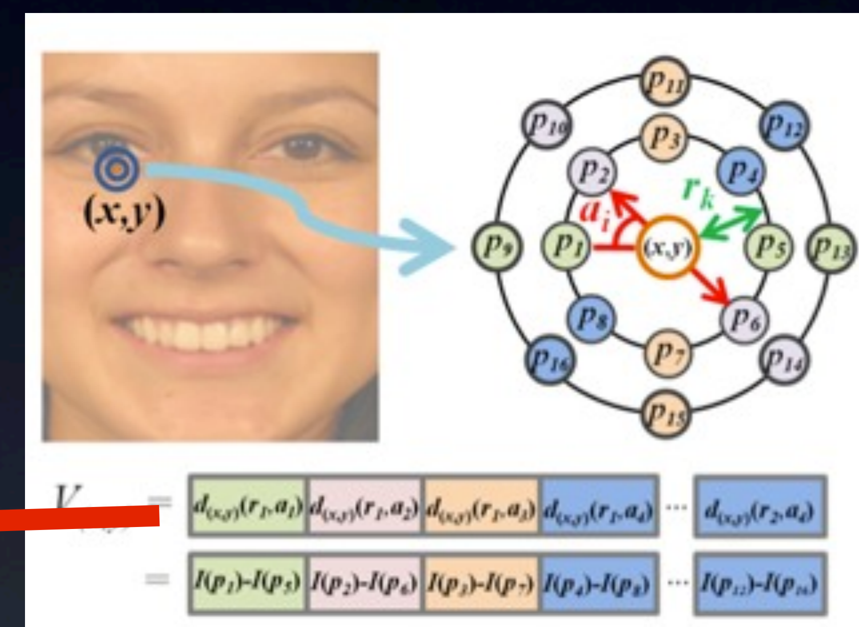
Magnitude Information

- Due to extreme illumination variation, pixel difference information (w/ magnitude) in micro scale (few pixels away) might be very noisy
  - Solution: truncation threshold (T_t)



$$d_{(x,y)}(r_k, a_i)$$

$$= \begin{cases} d_{(x,y)}(r_k, a_i), & |d_{(x,y)}(r_k, a_i)| < T_t, \\ \mathrm{sgn}(d_{(x,y)}(r_k, a_i)) \cdot T_t, & |d_{(x,y)}(r_k, a_i)| \geq T_t, \end{cases}$$

Curse of Dimensionality

- CCS-POP gives very high dimensional features
  - \# of dim = # of radii X # of sampled points X # of pixels
  - It might have noisy information
  - But less dimensionality than POP

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Solution → Discriminative dimension reduction by Partial Least Squares[1]

[1] W.R.Schwartz et al., A Robust and Scalable Approach to Face Identification, ECCV 2010

Partial Least Squares

- A supervised dimension reduction technique by maximizing covariance of weighted independent variable (X) and weighted dependent variable (Y)

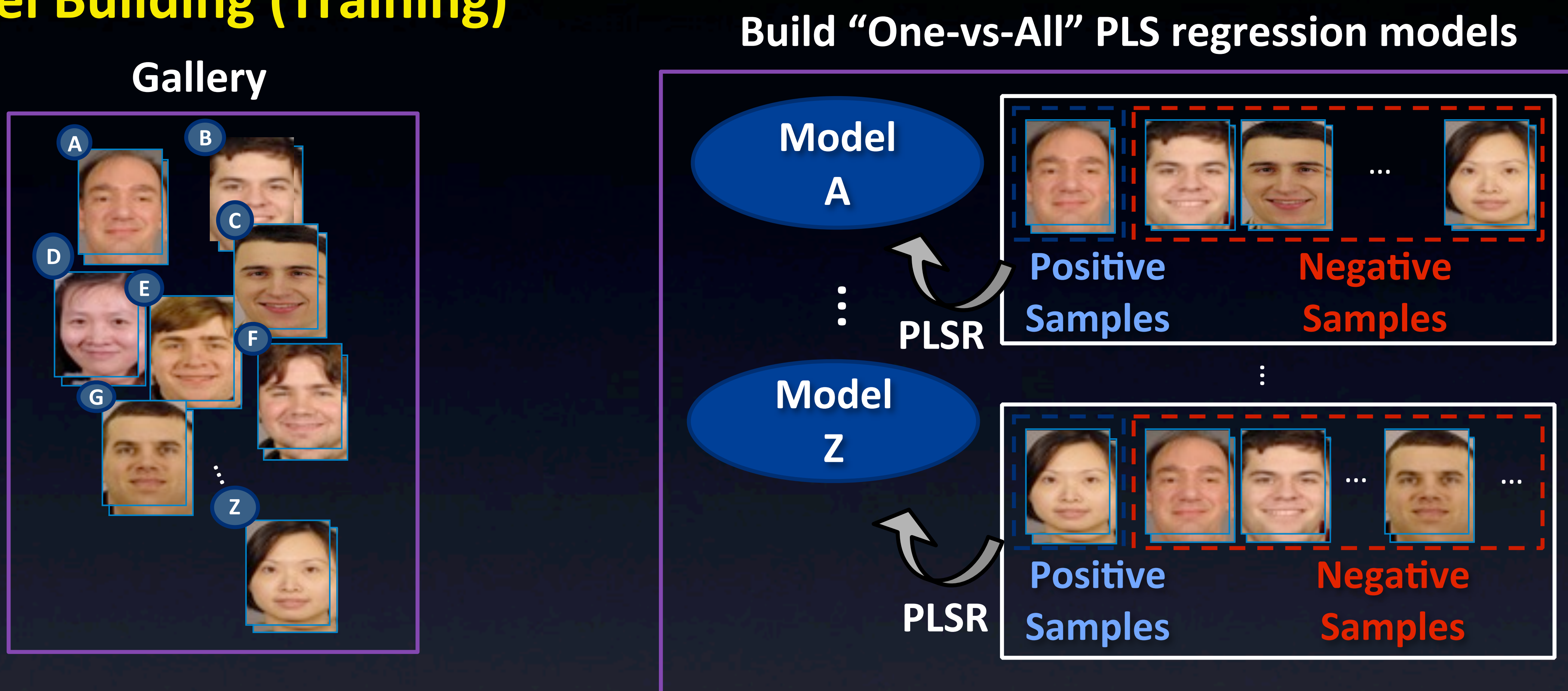
$$cov(t,u)^2 = \max_{|w|=1} cov(Xw, Y)^2$$

- Using NIPALS algorithm[1] to obtain the regression solution from X to Y

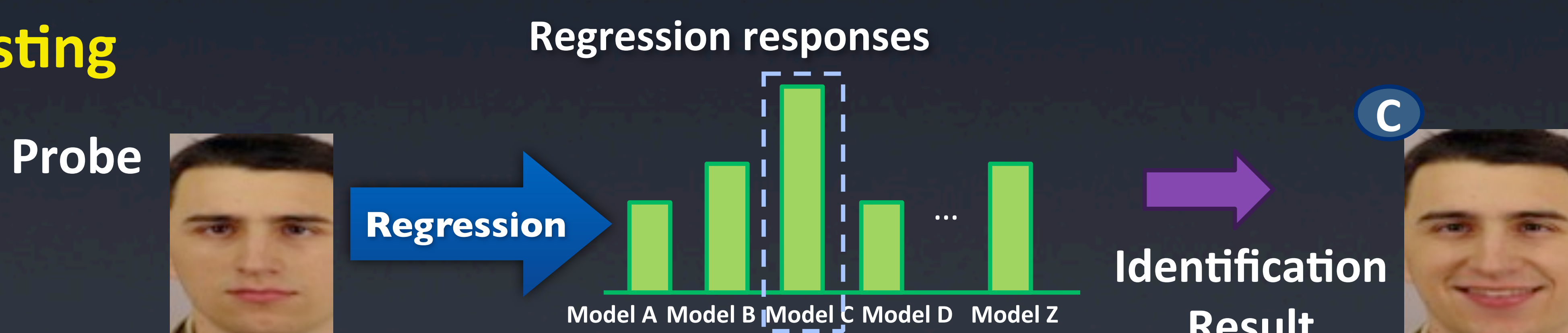
[1] H. Wold, Partial Least Squares, 1985

Discriminative Weighting Using Partial Least Squares[1]

Model Building (Training)



Testing



[1] Schwartz *et al.*, A Robust and Scalable Approach to Face Identification, ECCV 2010

Experimental Results

Datasets

- FRGC Ver. 1.0

Gallery

Probe

  - Exp1: (G) 1 controlled image, (P) 1 controlled image (mostly illumination variations)
  - Exp2: (G) 4 controlled images, (P) 1 controlled image
  - Exp4: (G) 1 controlled image, (P) multiple uncontrolled images
- FERET
  - fa: Gallery
  - fb: expression variations
  - fc: different lighting variations
  - dup1, dup2: time gap (expression and lighting, uncontrolled)

Effect of Not Using Histogram

- Raw LBP is a feature of LBP information (binary pixel difference with a single radius) without histogramming
- Weighted by PLS regression

FRGC

Descriptor	Dim.	Exp.1	Exp.2	Exp.4
LBP	16,128	85.4	96.8	13.0
Raw LBP	176,640	94.4	98.7	59.9

FERET

Descriptor	Dim.	fb	fc	$dup1$	$dup2$
LBP	6,400	57.7	26.8	18.3	10.3
Raw LBP	96,800	89.8	73.7	68.7	53.0

➡ Given a discriminative weighting scheme, histogramming prevents better performance

➡ But the feature dimension of Raw LBP is prohibitive

CCS-POP

- Far less number of dimension than Raw LBP
  - 176,640 → 44,160 (75% less)
  - Comparable performance
- Using color information (only in FRGC dataset)
  - Better performance (Especially in Exp. 4)
  - Triple the feature dimensions (44,160 → 132,480)
- Less number of dimension by simple color information (CI)
  - 132,480 → 60,042 (55% less)
  - Maintaining the performance

FRGC

Color	Dim.	Exp.1	Exp.2	Exp.4
Raw LBP	176,640	94.4	98.7	59.9
Gray	44,160	96.1	99.0	59.4
R,G,B	132,480	96.5	99.4	67.3
Gray+CI	60,042	96.7	99.3	67.6

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Effect of Truncation Threshold

- Truncation threshold improves performance on the experiments with FRGC dataset

FRGC

T_t	Exp.1	Exp.2	Exp.4
No threshold	91.6	97.2	57.7
5	96.7	99.3	67.6

Comparison to Other Descriptors

FRGC

Descriptor	Dim.	Exp.1	Exp.2	Exp.4
Intensity	22,080	41.3	51.3	3.5
POP	607,520	83.2	94.0	29.3
LBP	16,128	85.4	96.8	13.0
MSLBP	32,256	95.2	98.9	30.9
HOG	49,860	97.5	99.4	64.5
Gabor	54,401	97.0	99.5	66.6
CCS-POP	60,042	96.7	99.3	67.6

FERET

Descriptor	Dim.	fb	fc	$dup1$	$dup2$
Intensity	12,100	75.1	52.6	39.5	31.2
POP	242,000	79.7	69.1	47.2	42.7
LBP	6,400	57.7	26.8	18.3	10.3
MSLBP	12,800	92.8	29.4	56.5	49.1
HOG	24,336	94.1	98.5	76.9	76.9
Gabor	29,187	97.0	97.9	79.4	76.1
CCS-POP	24,200	91.9	72.7	69.3	53.4

Not Good

Complementariness of CCS-POP

- For the challenging experiments in FRGC dataset
  - FRGC Exp.4

Improvement by CCS-POP
Original Performance

Improvement by CCS-POP
Improvement by Gabor
HOG

89.0%

82.4%

79.3%

68.4%   69.2%

Complementariness of CCS-POP

- For the challenging experiments in FRGC dataset
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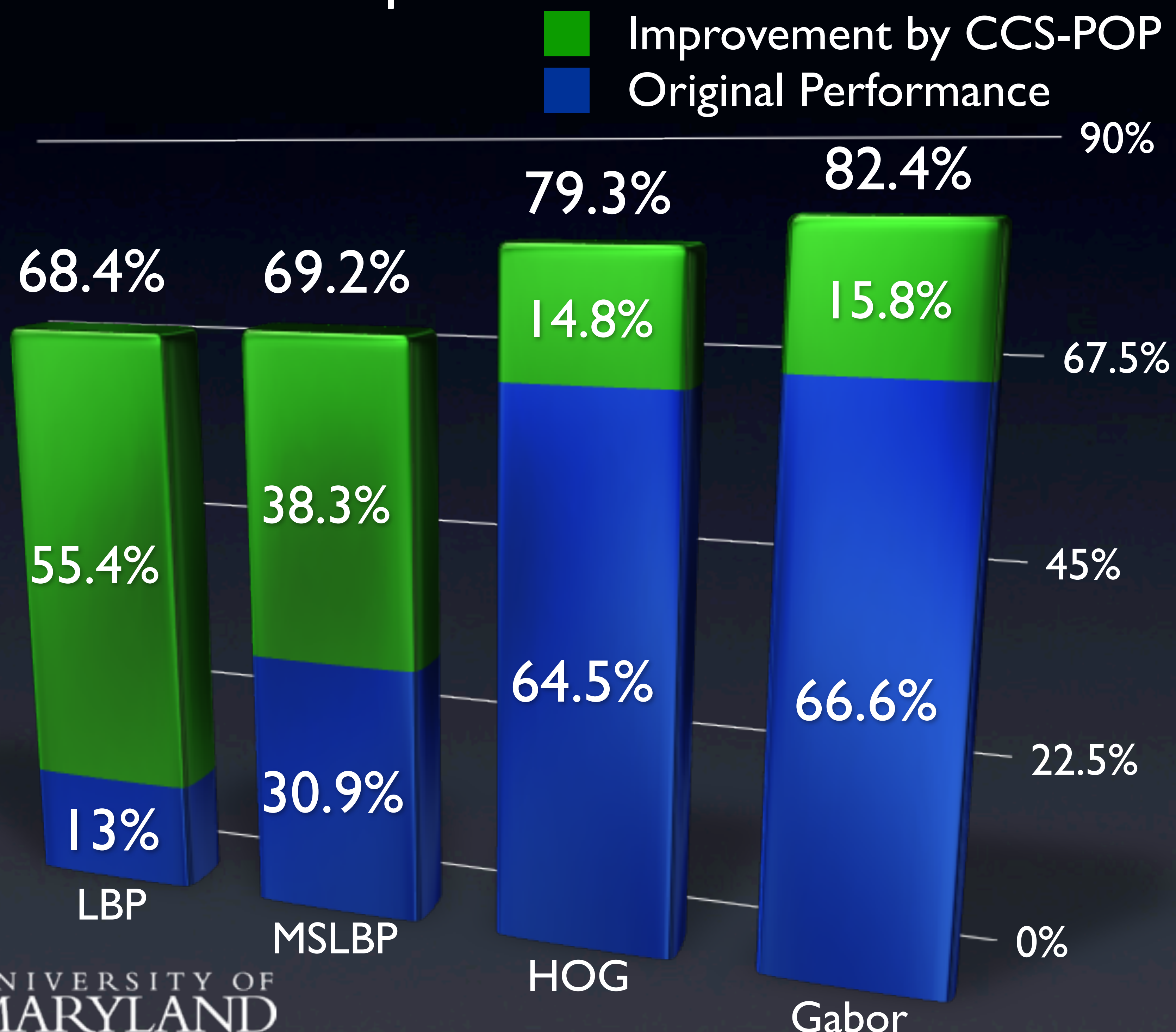
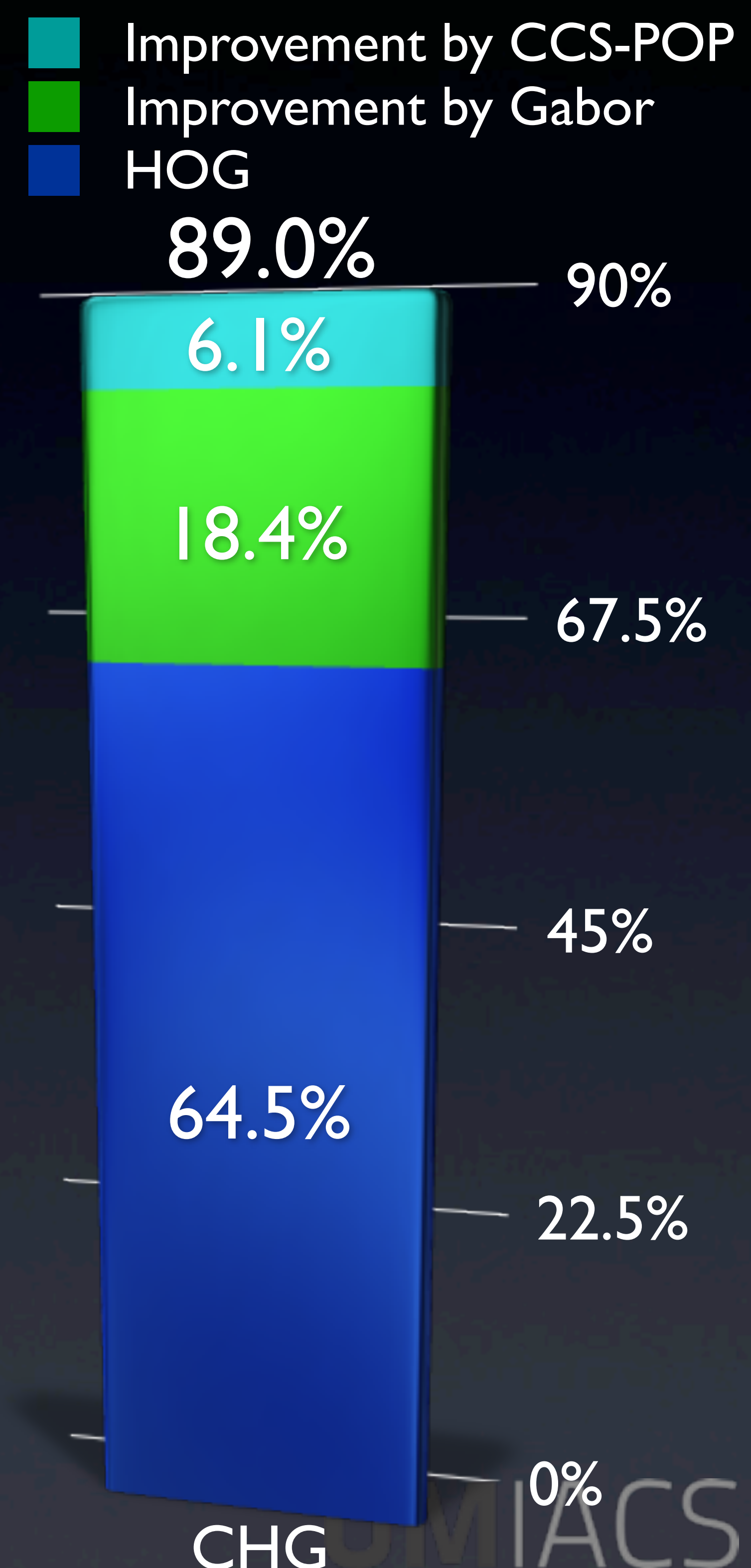




Complementariness of CCS-POP

- For the challenging experiment in FERET dataset
  - FERET dup2

Improvement by CCS-POP
Improvement by Gabor
HOG

Improvement by CCS-POP
Original Performance

84.6%

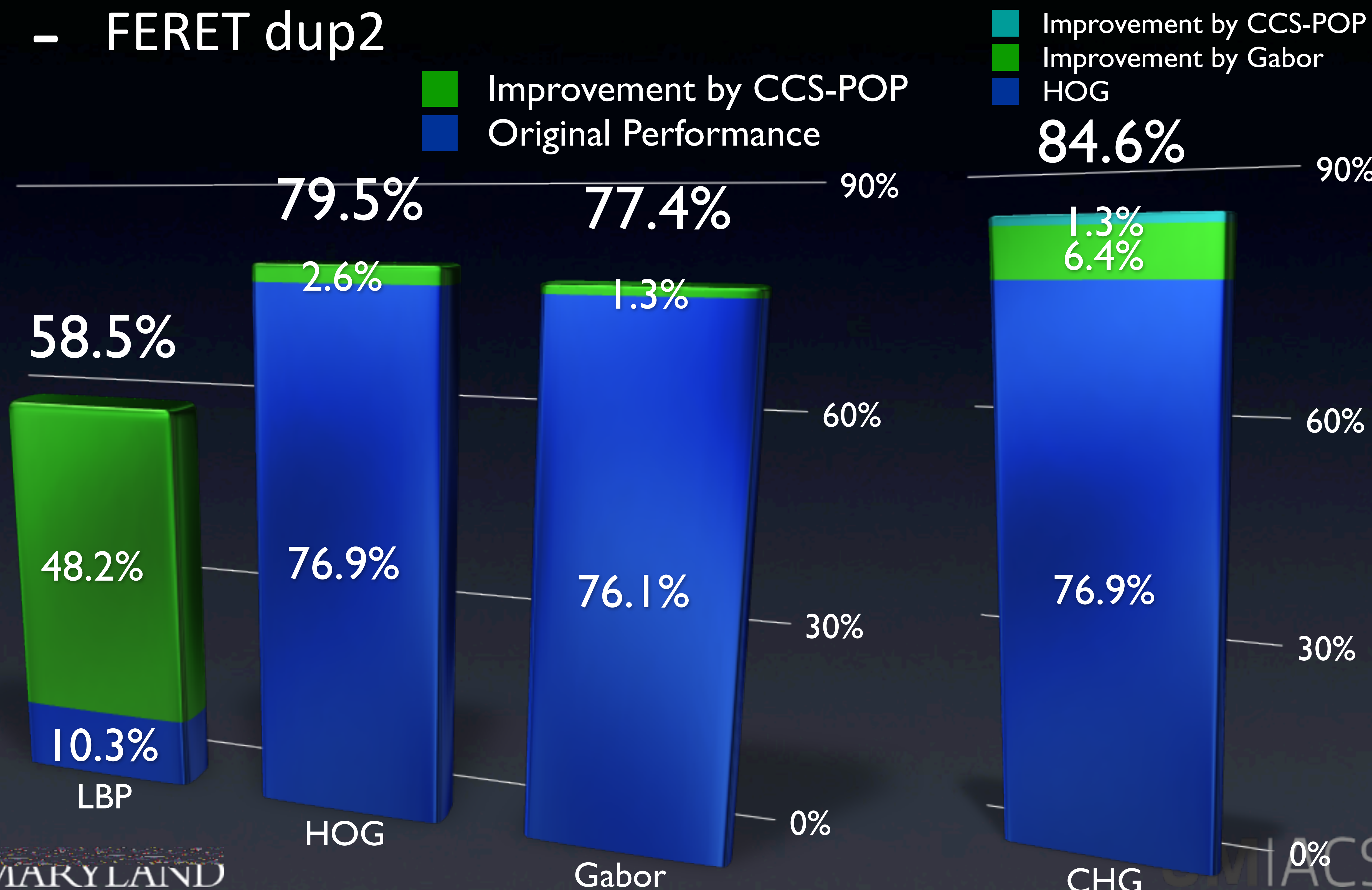
79.5%

77.4%

58.5%

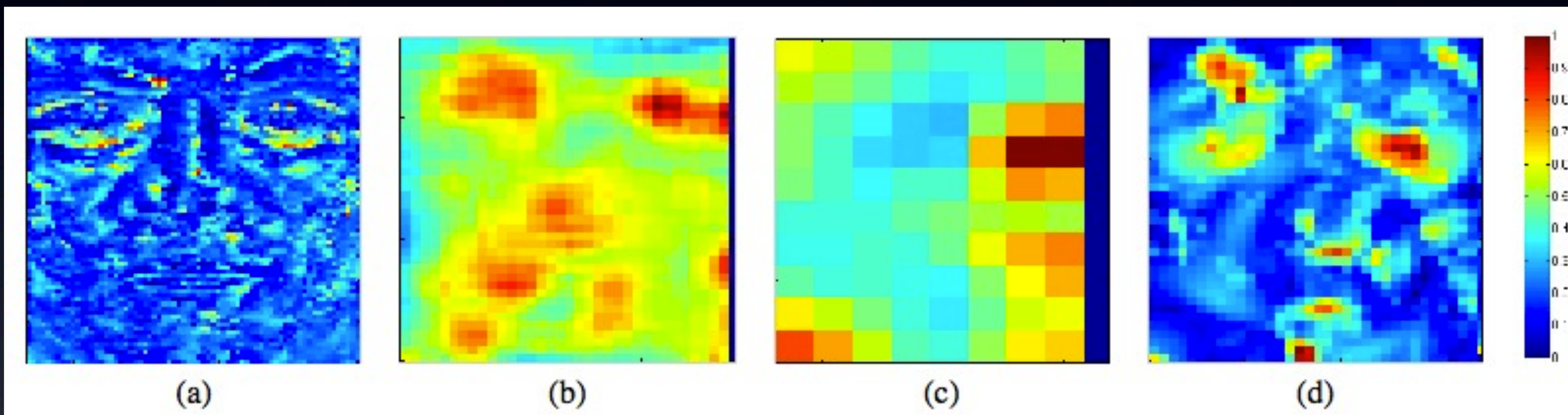
Complementariness of CCS-POP

- For the challenging experiment in FERET dataset
  - FERET dup2



Complementariness by Feature Weighting

- An example of heat maps of PLS regression for different features.



CCS-POP HOG LBP Gabor

- CCS-POP captures pixel-wise micro information

Comparison to the Previous Works

FRGC

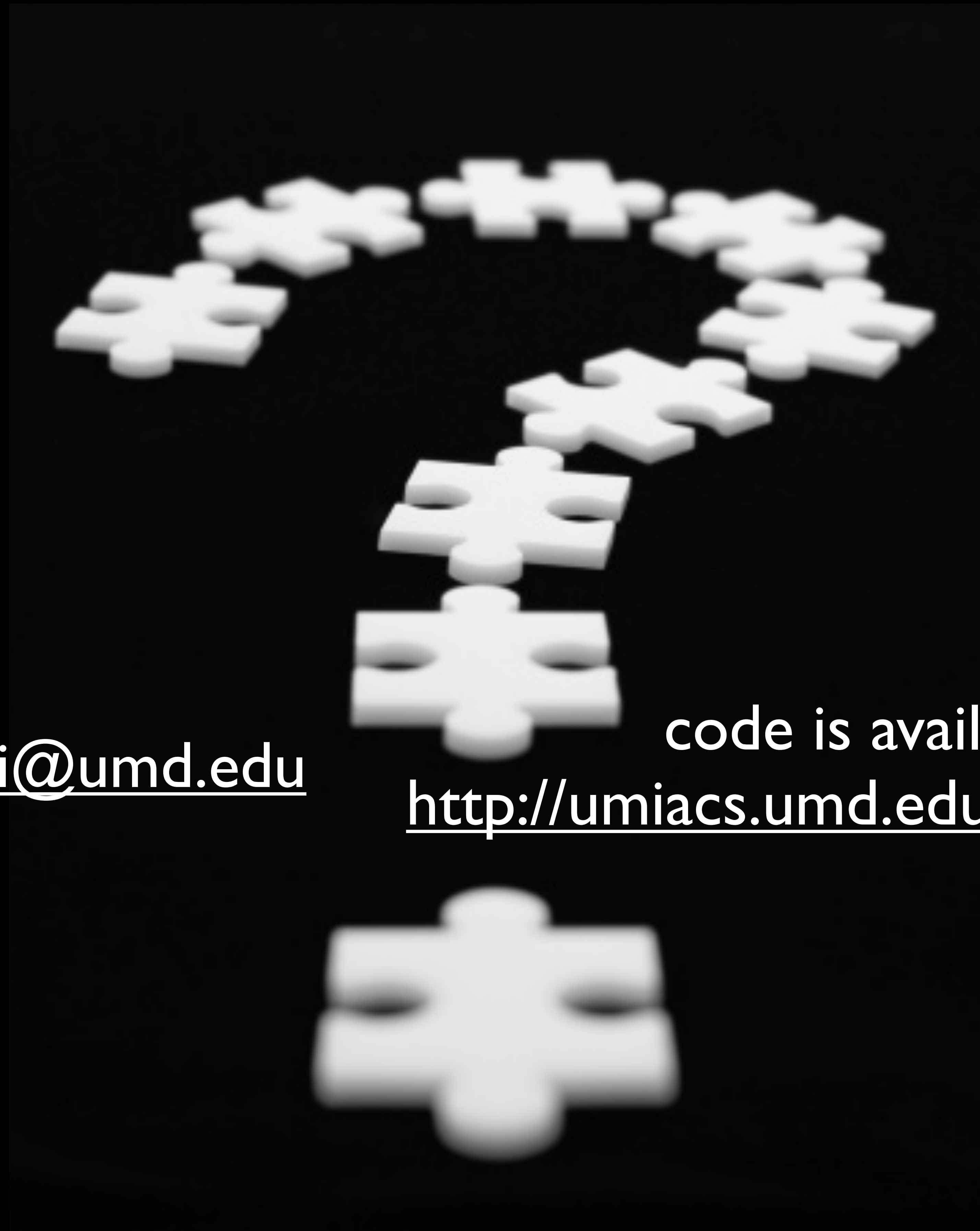
Method	Exp.1	Exp.2	Exp.4
PCA [17]	87.6	95.6	-
UMD [1]	94.2	99.3	-
BEE (from [27])	-	-	37.0
LC_1C_2 [27]	-	-	75.0
ROCA [10]	96.4	-	75.5
Liu [12]	-	-	78.0
Tan (from [8])	-	-	58.1
Holappa [8]	-	-	63.7
LPQ [20]	-	-	74.5
PLS [24]	97.5	99.4	78.2
CHG	**98.0**	**99.8**	**89.0**

FERET

Method	fb	fc	$dup1$	$dup2$
LGBPHS [36]	98	97	74	71
HGPP [35]	**97.6**	98.9	77.7	76.1
SIS [13]	91	90	68	68
POEM [30]	**97.6**	96	77.8	76.5
PLS [24]	95.7	**99.0**	80.3	80.3
CHG	97.5	98.5	**85.6**	**84.6**

Conclusion

- New feature descriptor (CCS-POP) generalizing POP for natural object (e.g. face) is proposed
- Empirically show the importance of not using histogram with a discriminative weighting scheme
- Complementary to existing descriptors
- Achieve state-of-the-art performance on both FRGC and FERET datasets



email: jhchoi@umd.edu

code is available in
http://umiacs.umd.edu/~jhchoi/ccspop

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