Group-level Arousal and Valence Recognition in Static Images: Face, Body and Context

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Motivation

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Learning context

Bored??

Retail context

Like???

Enjoy????

Image Retrieval

Related works

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From individual emotion to group emotion

- Group Happiness Intensity (Dhall et al. 2012)

Related works

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	Data	Features	Classifier	Categories	No of Labelers
Dhall et.al FG'15	417 images	**Face** -Facial action unit -PHOG+LPQ **Scene context**	Multiple kernel learning	**Valence** Positive, neutral, negative	3/image
Ours	250 images	**Face** -Geometric -Local Appearance -Global Appearance **Body HOG** **Context**	KNN	**Arousal** High, medium, low **Valence** Positive, neutral, negative	15/image

Data

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Our requirements

- Various emotions in the whole database
- A group of people on each image

Existing databases

- Static Facial Expressions in the Wild (SFEW)[1]
  - Various emotions
  - Single person
- Annotated Face in the Wild(AFW)[2]
  - Multiple people
  - No various emotions, 90% happy, no emotion annotation
- HAPpy PEople Images (HAPPEI) [3]
  - Multiple people
  - All are happy

[1] Dhall, et al. "Static facial expression analysis in tough conditions: Data, evaluation protocol and benchmark." 2011.
[2] Zhu, et al"Face detection, pose estimation, and landmark localization in the wild.", 2012.
[3] Dhall, et al. Finding happiest moments in a social context, ACCV 2012.

Data Collection and Annotation

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Our database

- Collected images from Internet
- Each image was annotated by 15 raters along Arousal-Valence

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Data Collection and Annotation

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Annotation questionnaire

Valence

- Positive
- Neutral
- Negative

Activity

- High
- Medium
- Low

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Inter-rater agreement

	Cronbach's α
Arousal	0.85
Valence	0.96

Theories for group emotion

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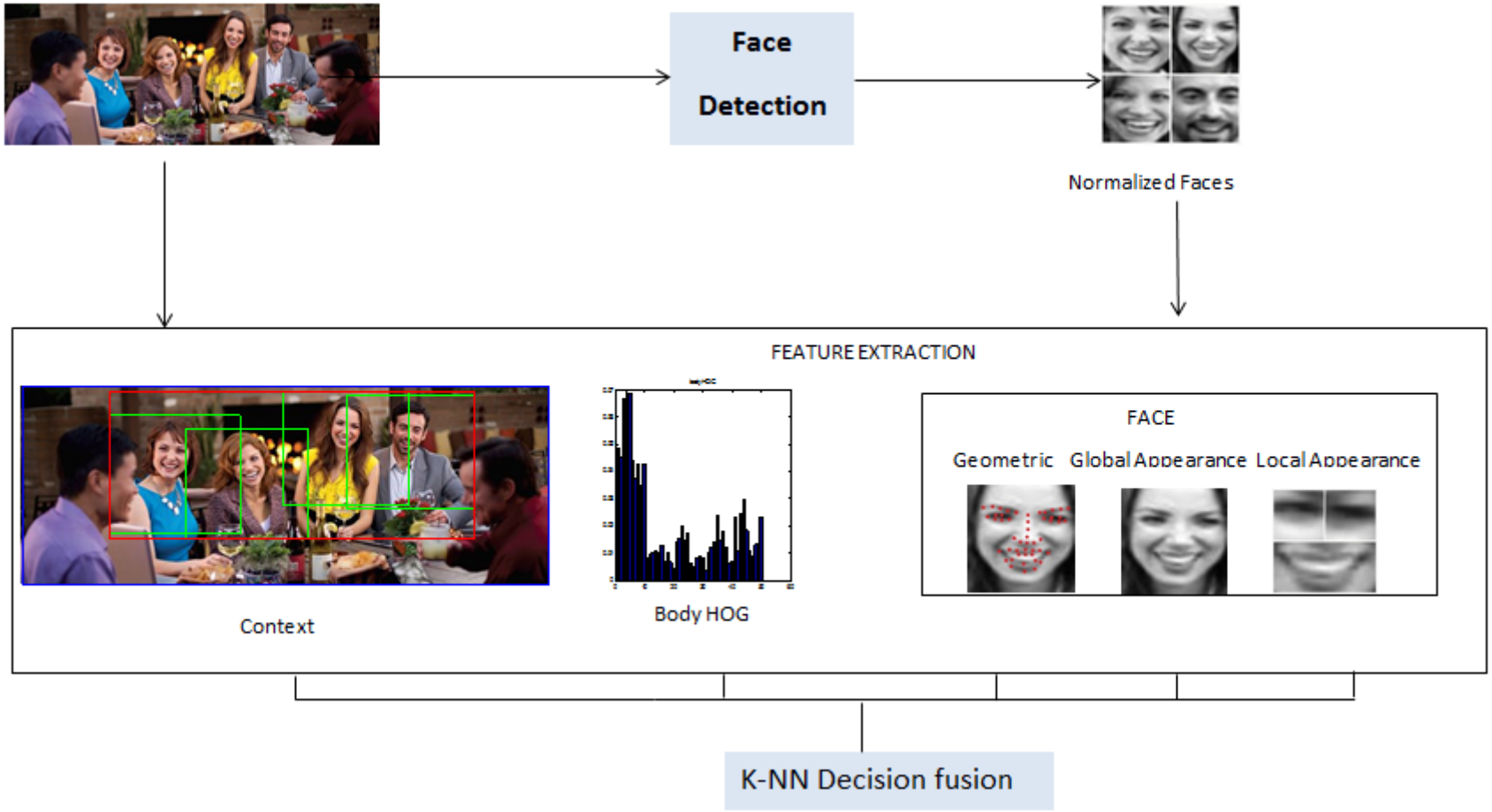
Top-down

- group-as-a-whole
- use group-level information

Bottom-up

- group-as-sum-of-its-parts
- start with individuals

Our Methodology



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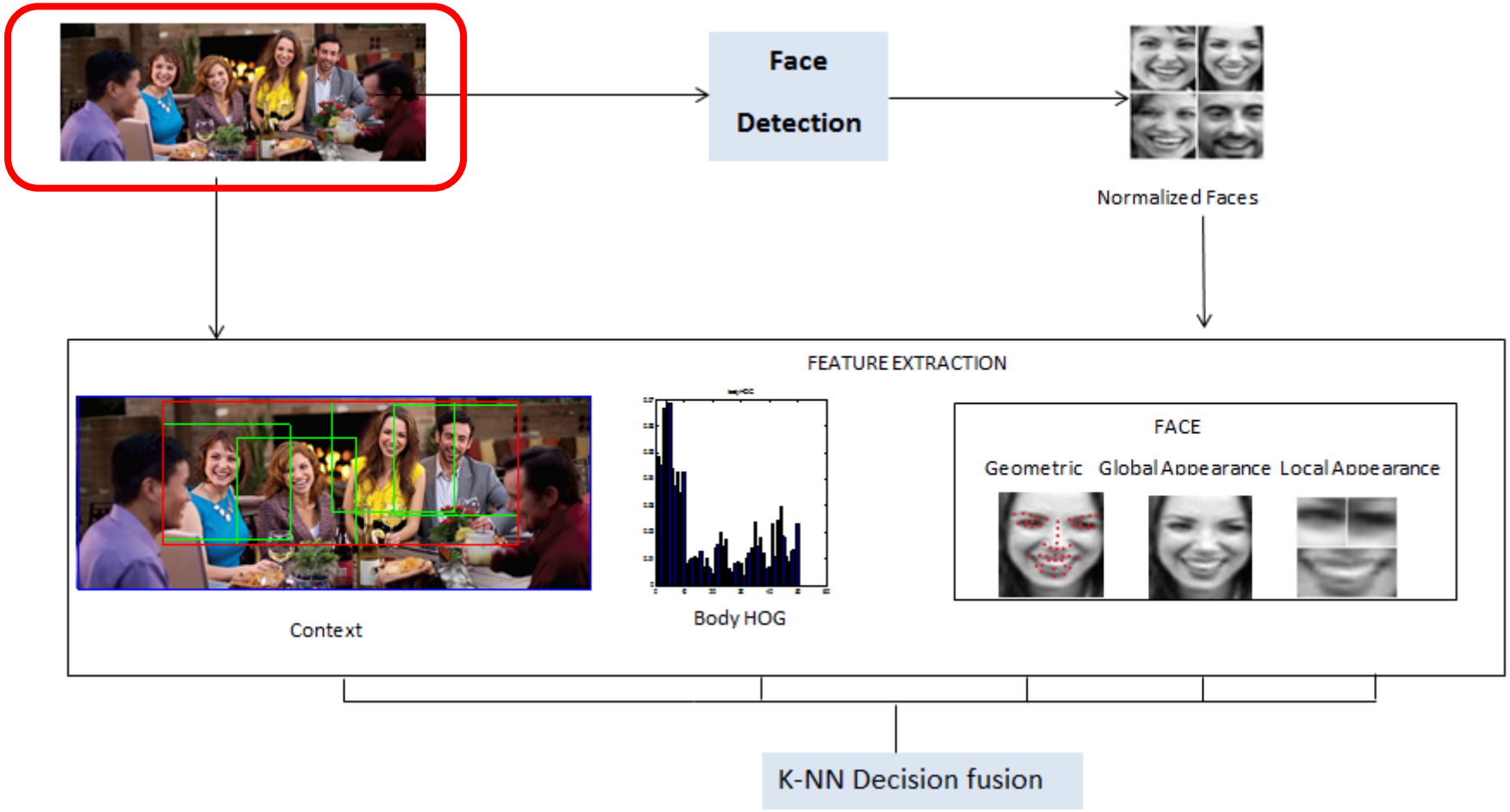

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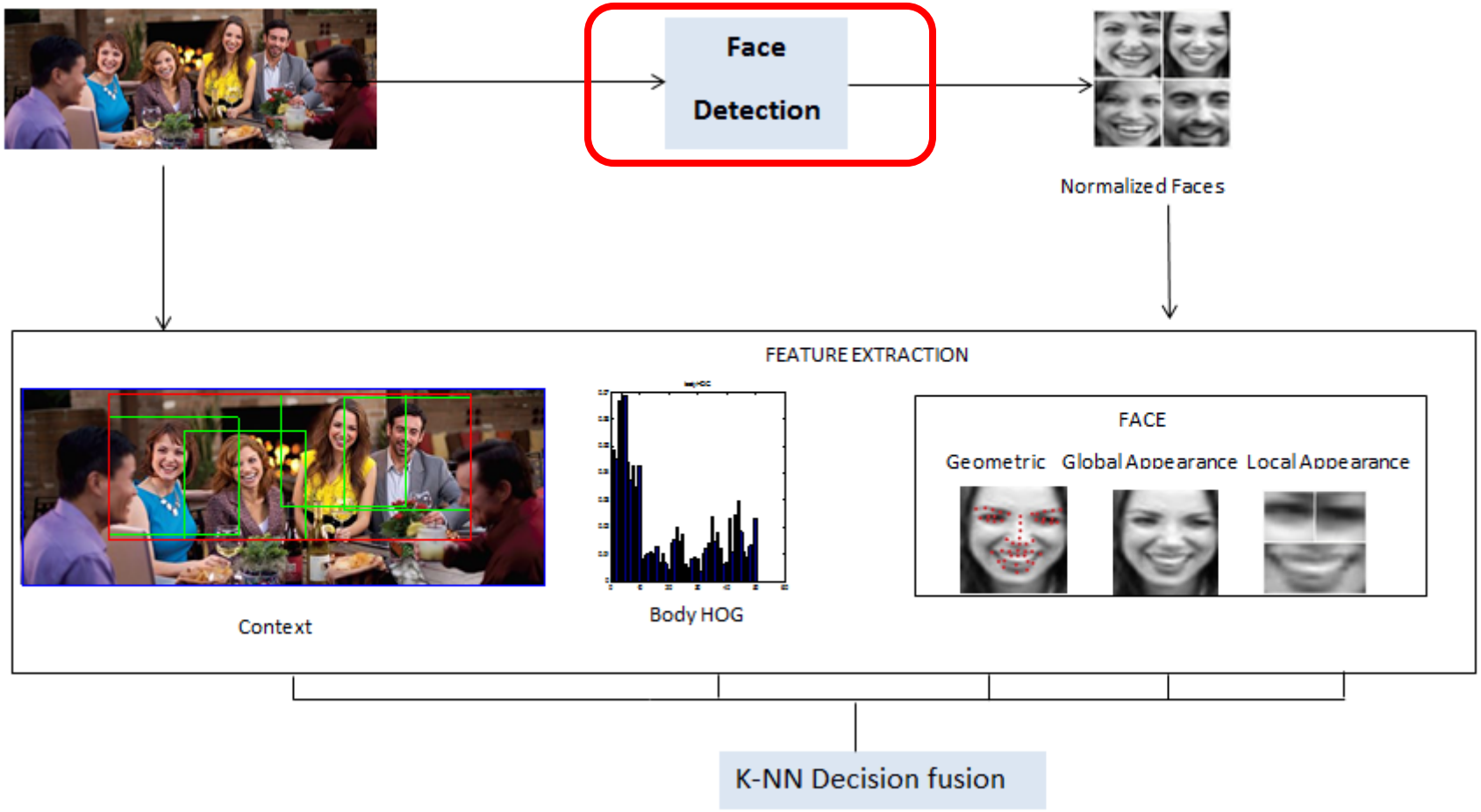

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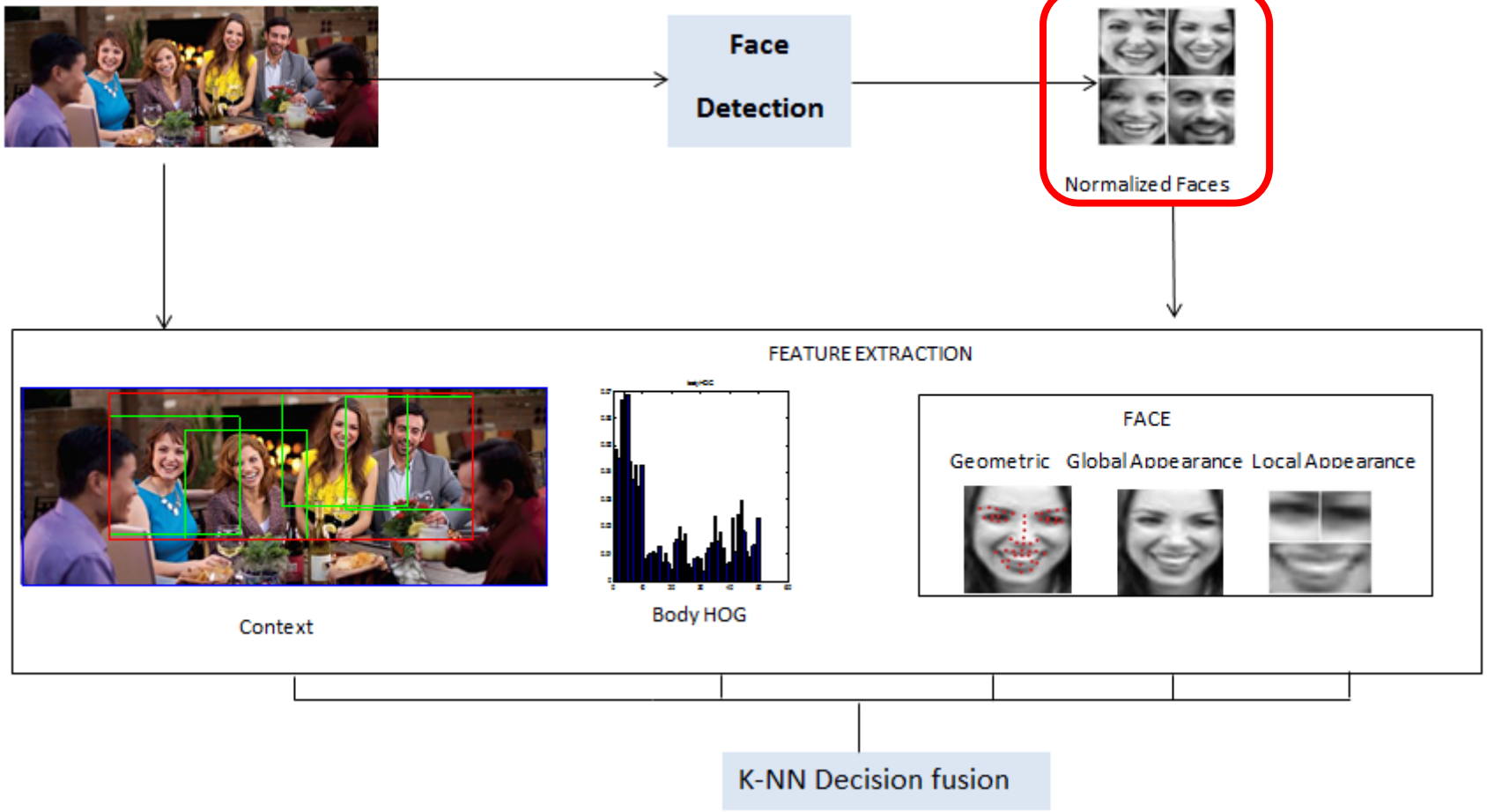

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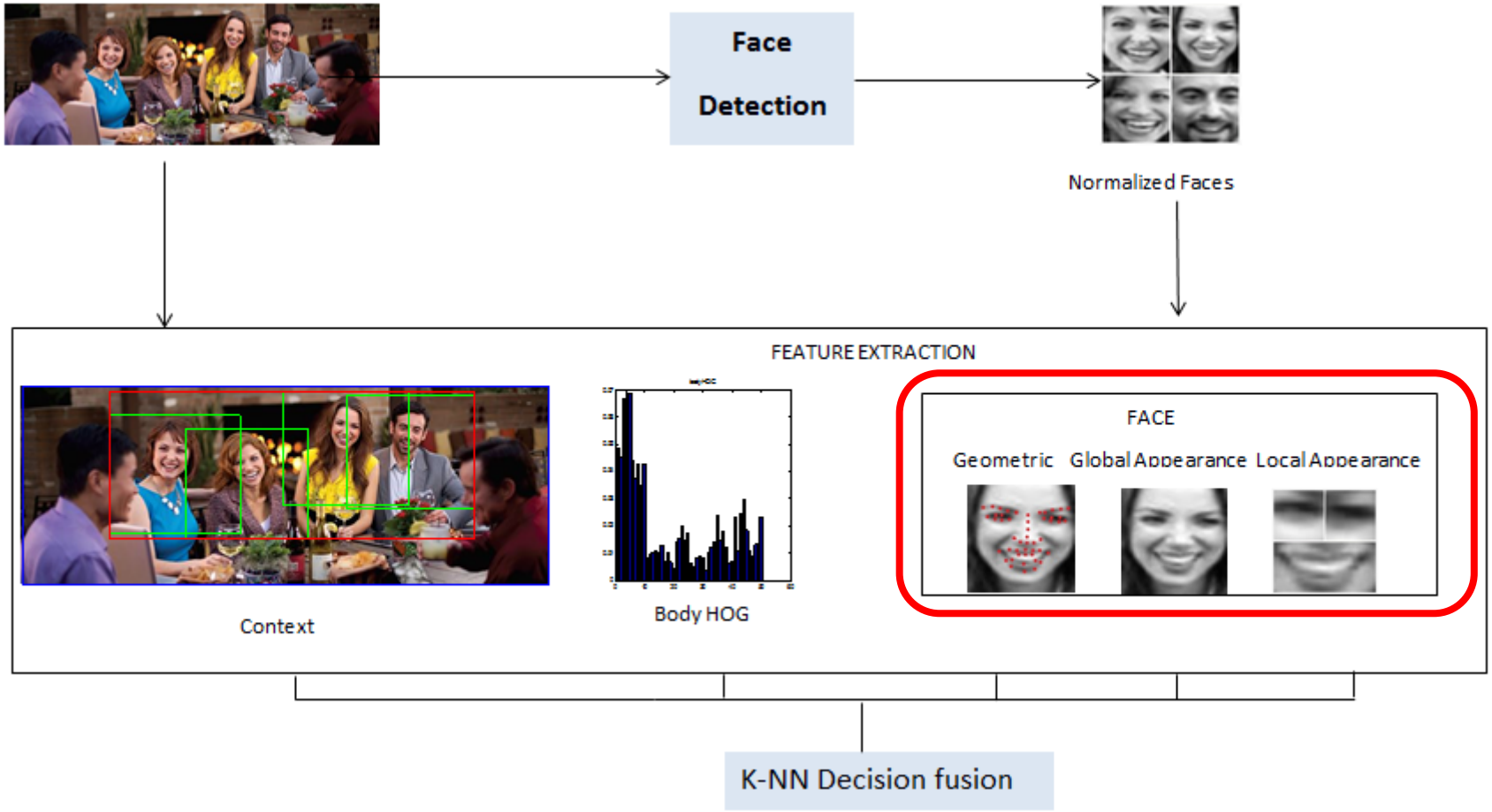

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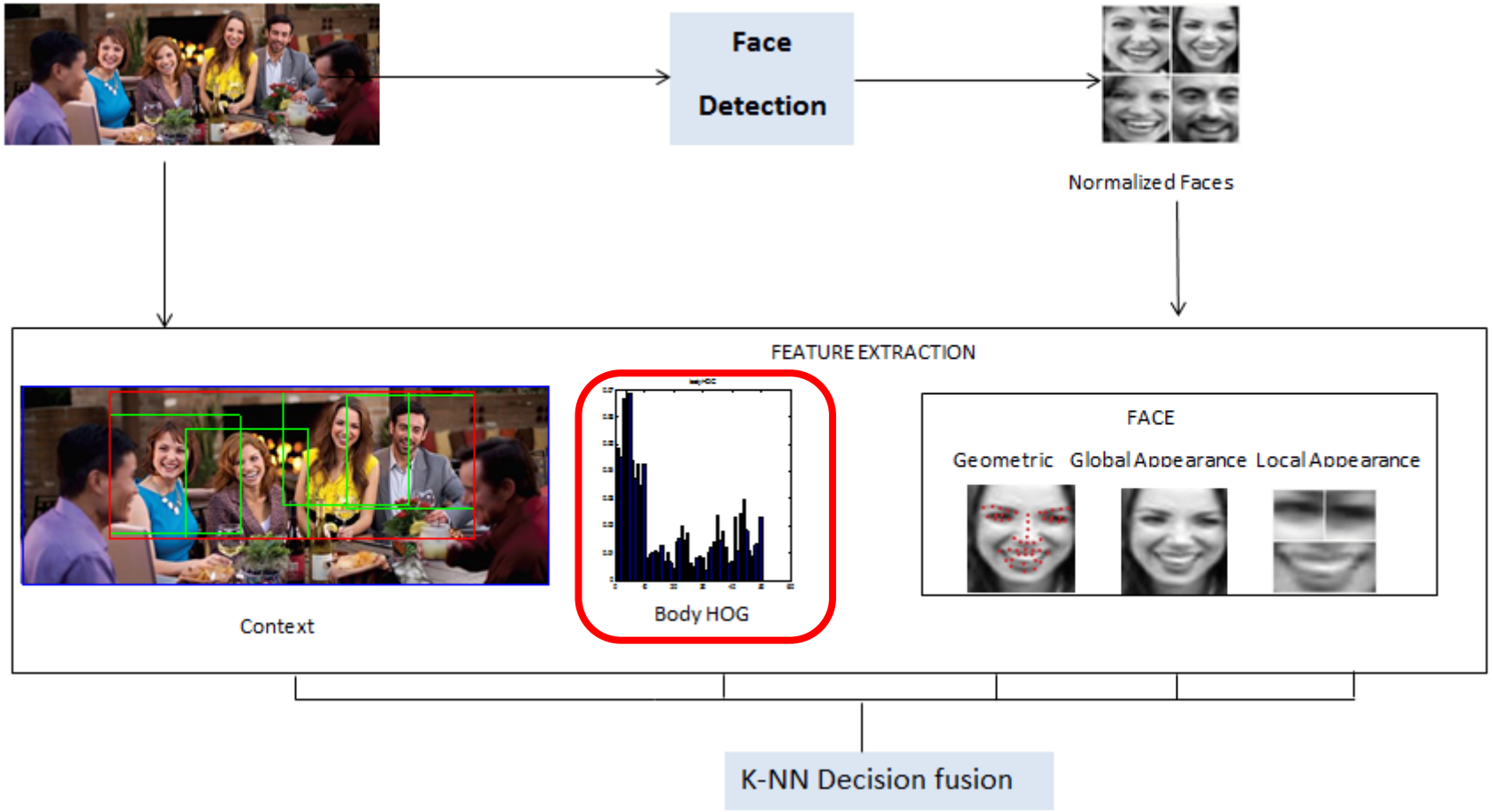

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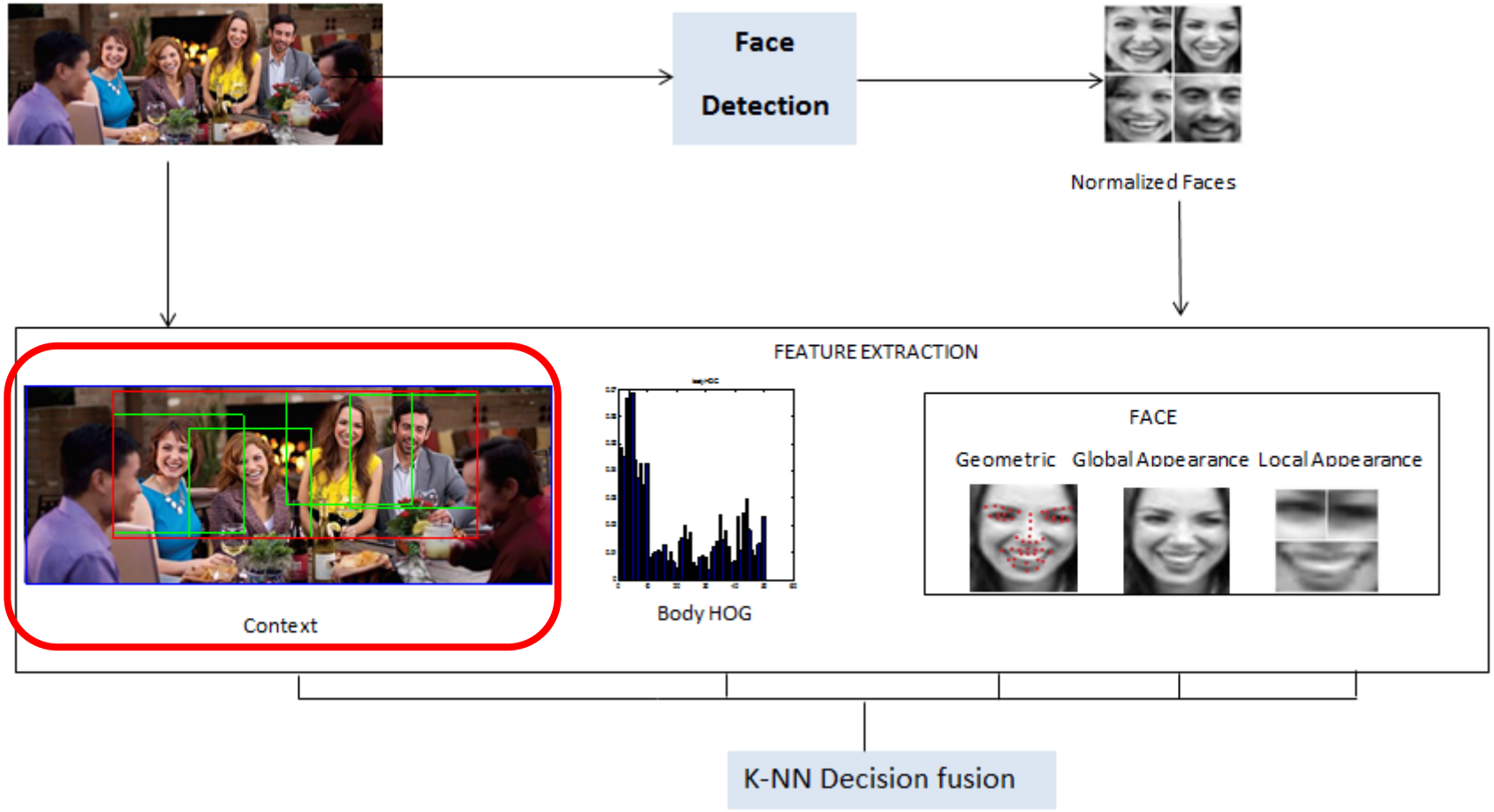

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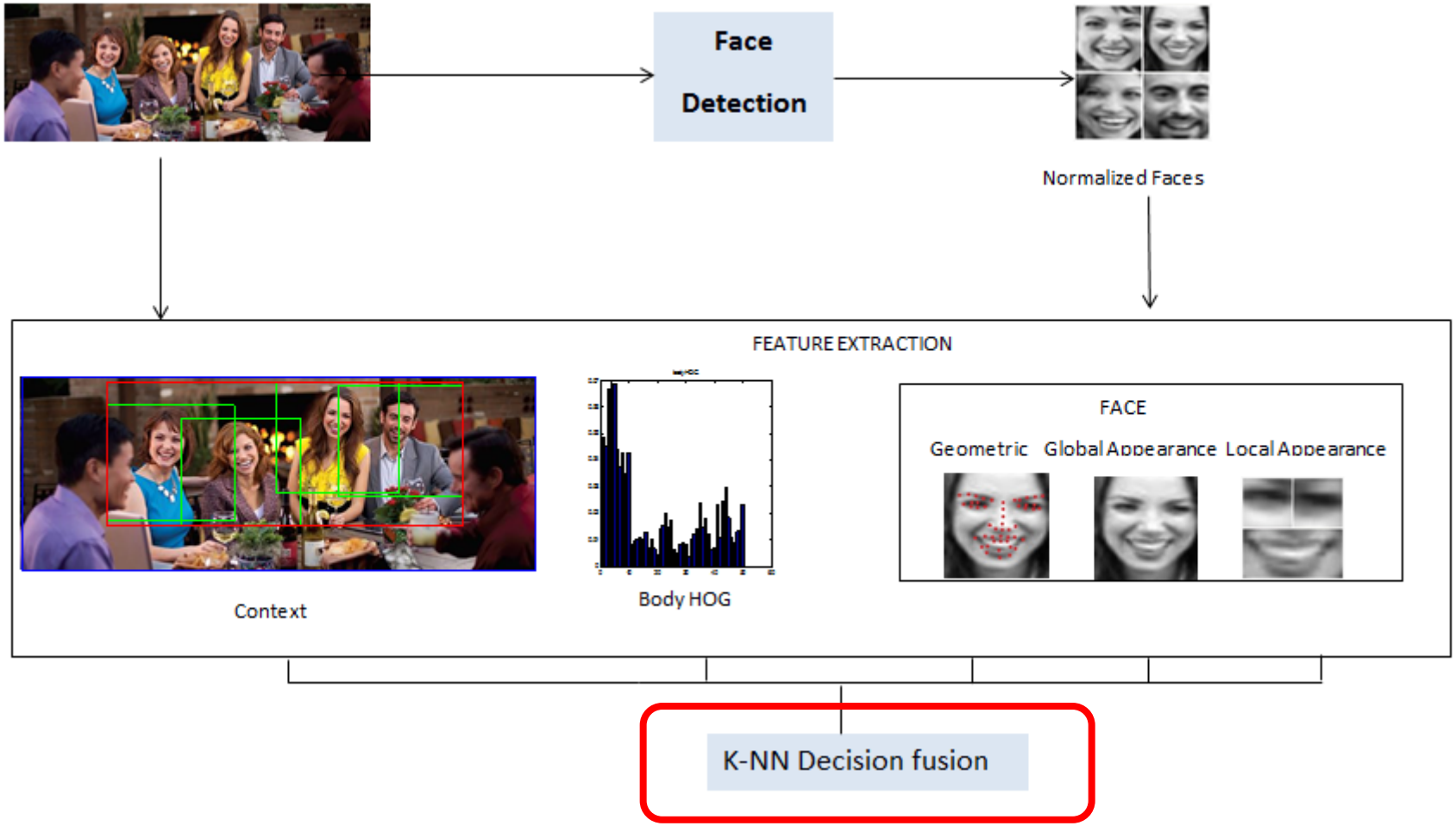
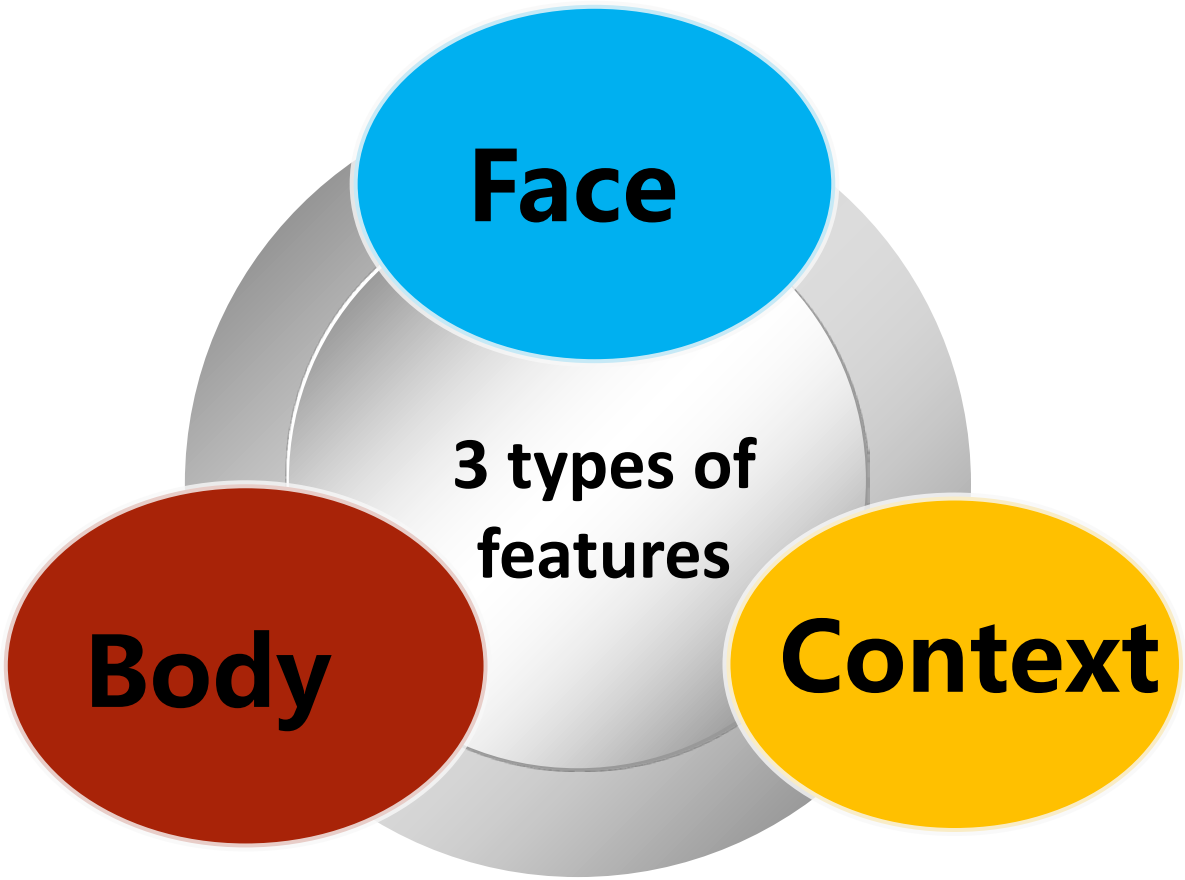


Feature Extraction



Feature Extraction

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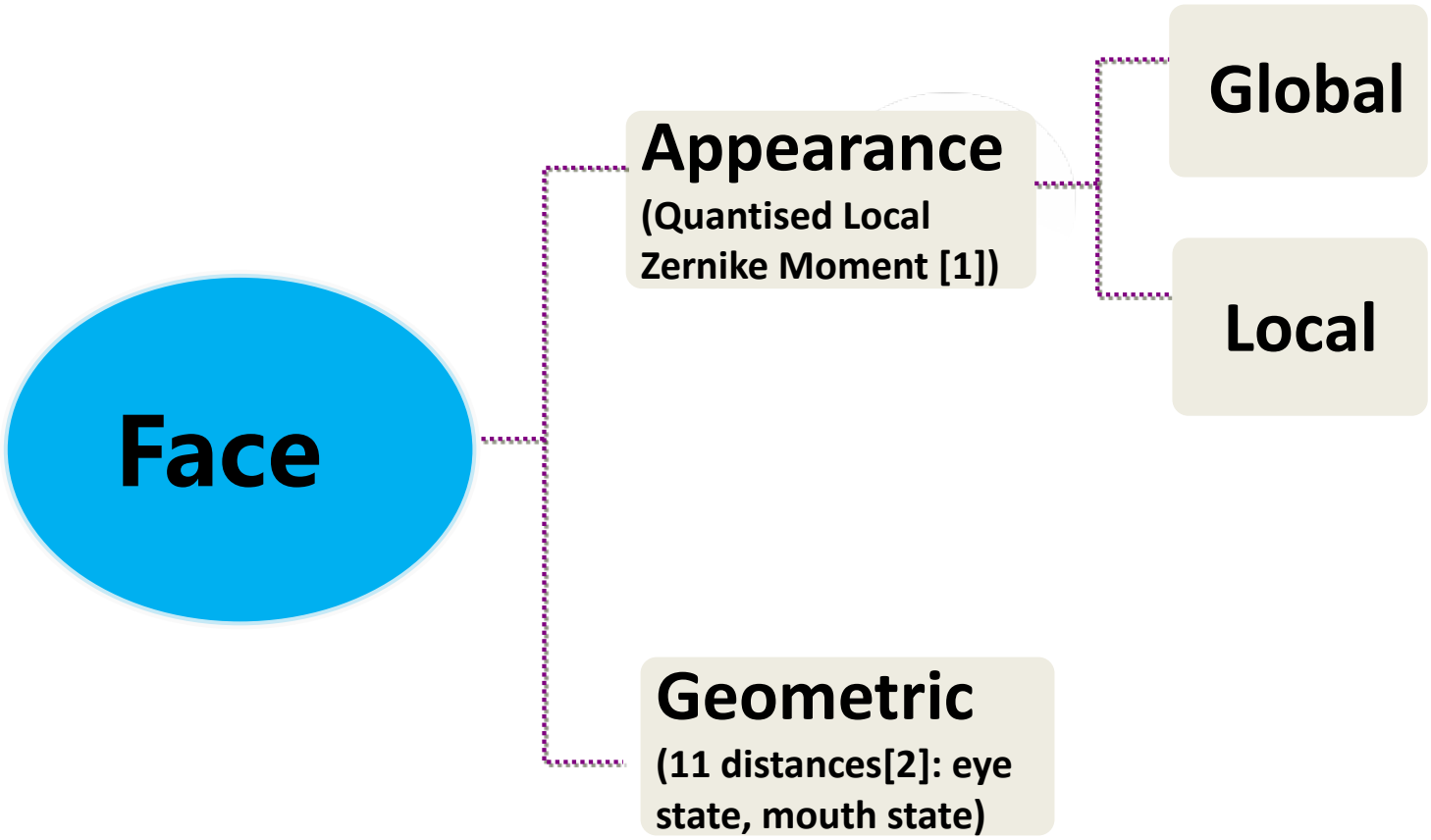
Face

Feature Extraction



[1] Sariyanidi, et al. "Local Zernike Moment Representation for Facial Affect Recognition." 2013.
[2] Akakın, et al. "Robust classification of face and head gestures in video." 2011.

Feature Extraction

- **Face**
  - **Appearance** (Quantised Local Zernike Moment [1])
    - **Global**
    - **Local**
  - **Geometric** (11 distances[2]: eye state, mouth state)

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(Quantised Local Zernike Moment [1])

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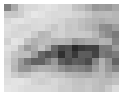

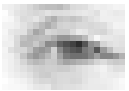

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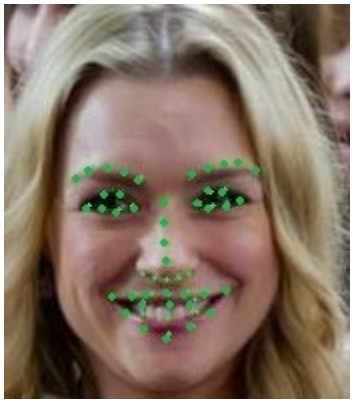

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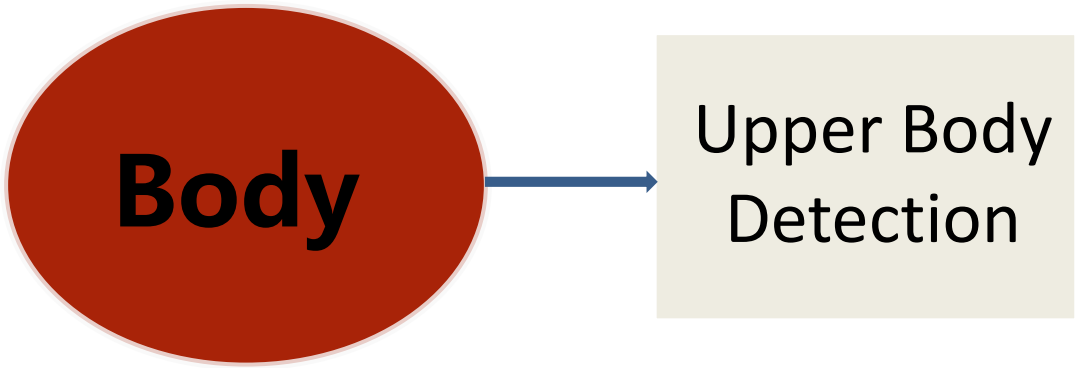

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Feature Extraction

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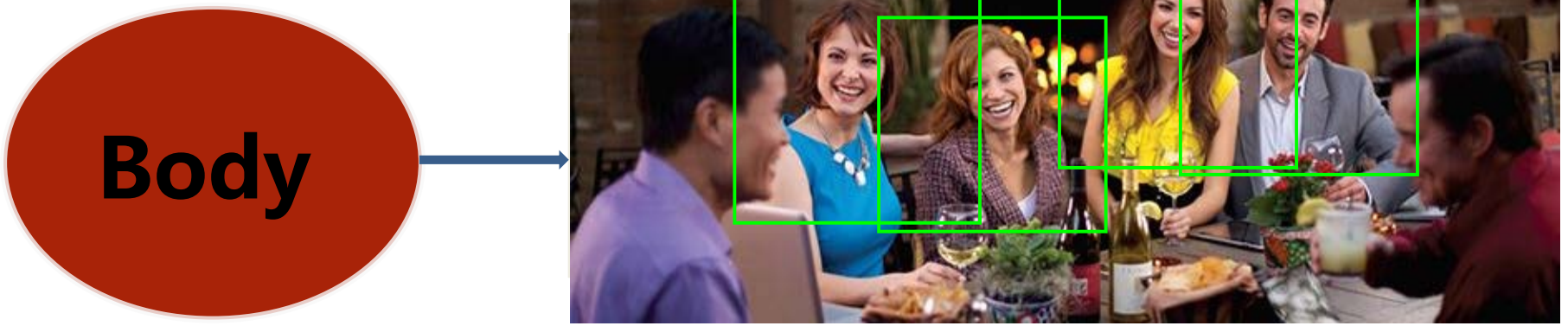

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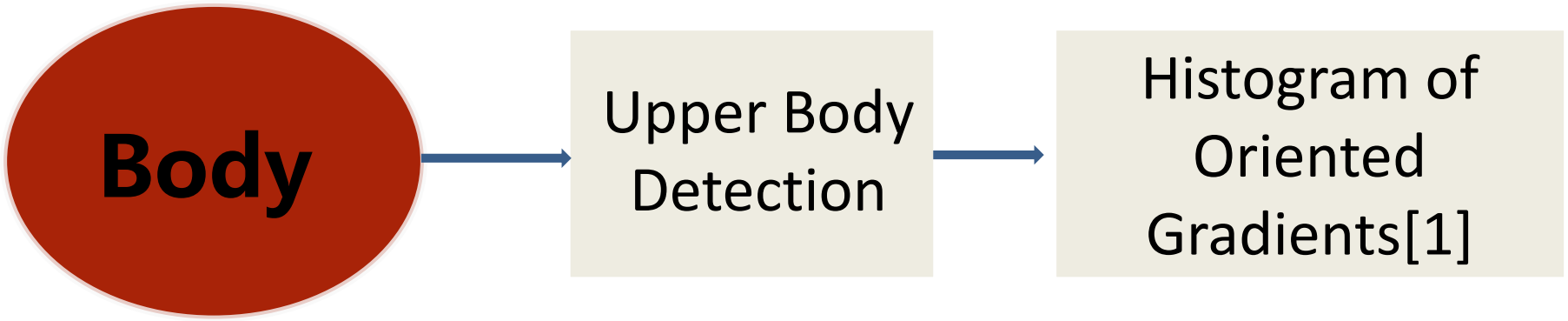

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Feature Extraction

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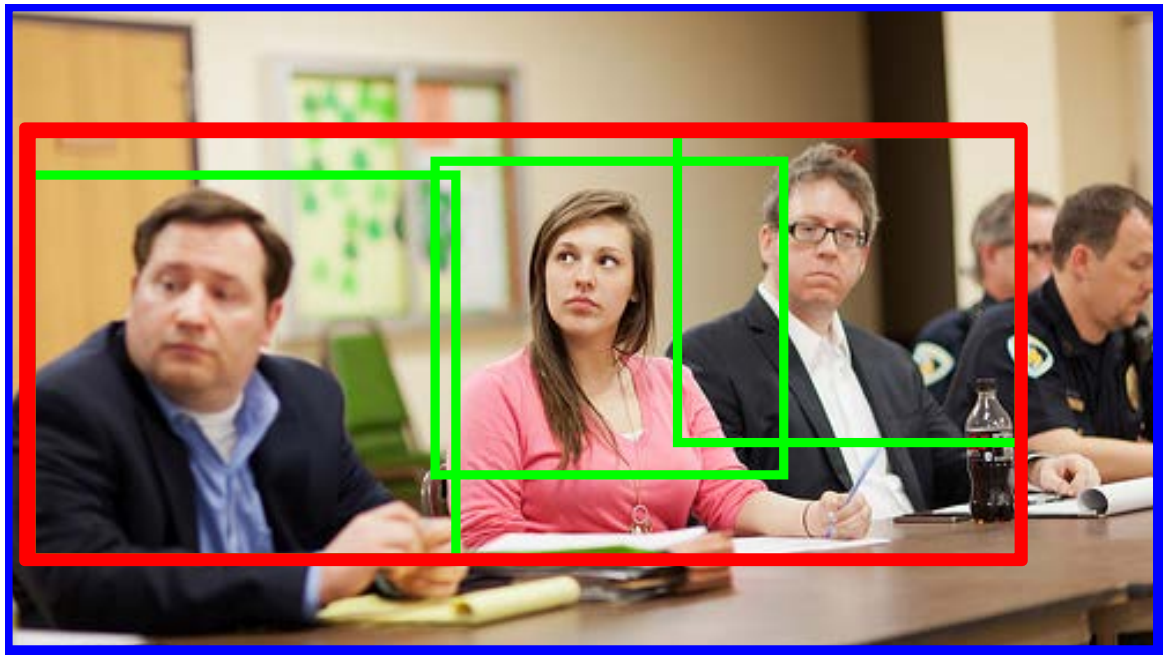
Context

1. Bodies' relative scale and location w.r.t bounding box
2. Bounding box's relative scale and location w.r.t Image



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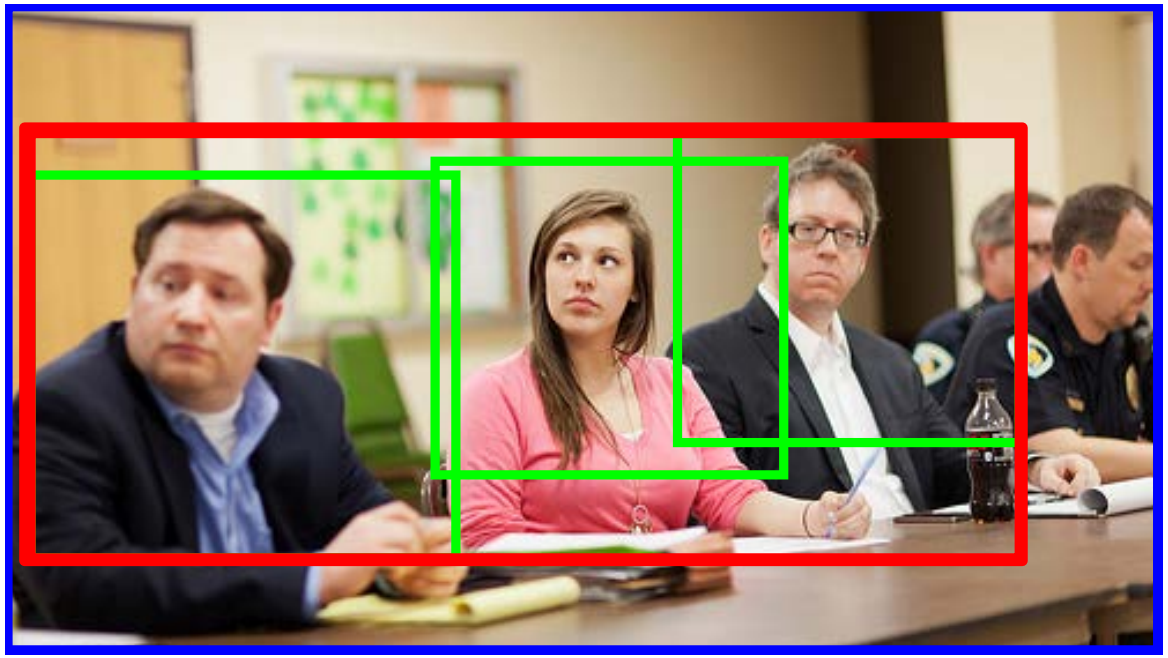

Experiment and Analysis

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Representation divided images into 3 groups based on number of faces, **2** faces**, 3** faces and **4-more** faces.

Classifier K-Nearest Neighbor

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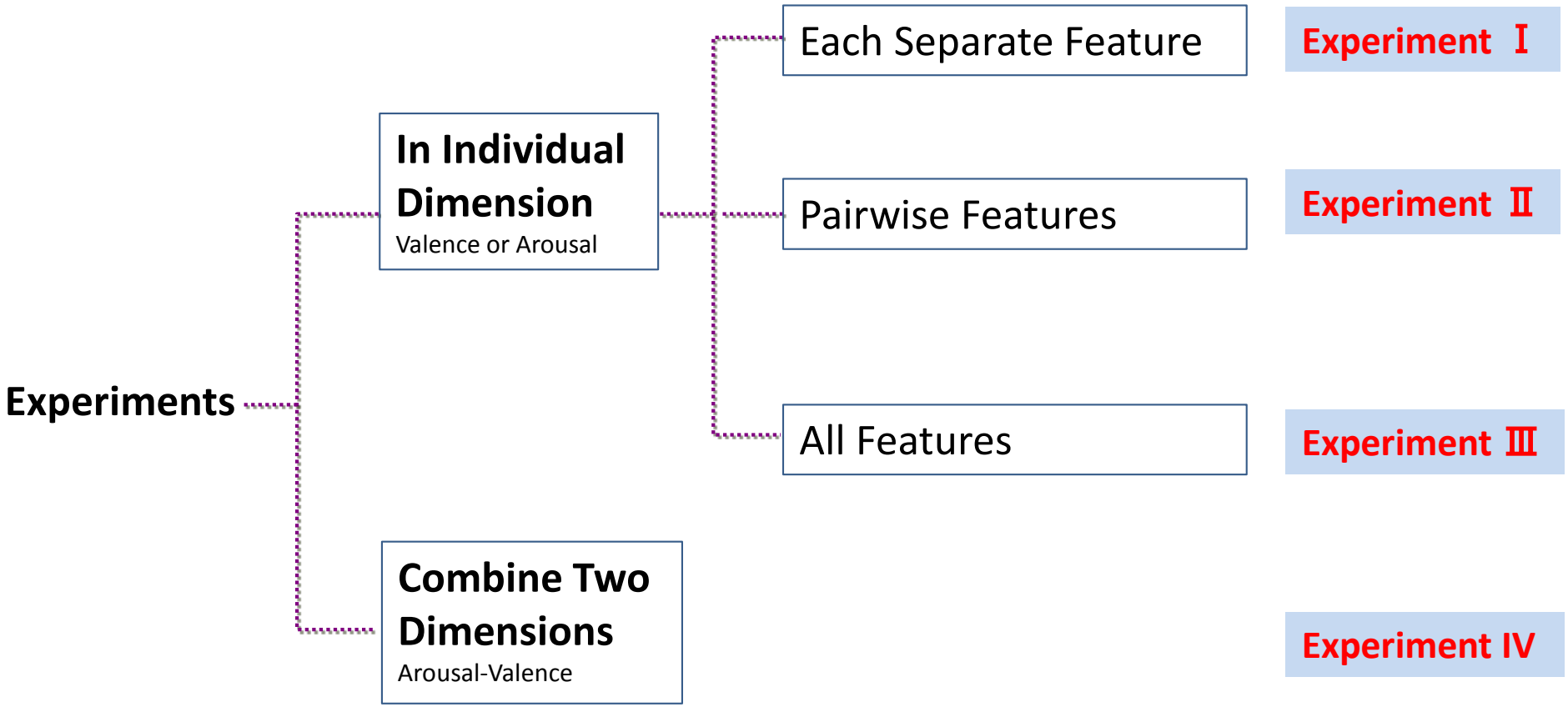

Experiment and Analysis

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Experiment Ⅰ: Different features independently

Faces / %	2 faces		3 faces		>= 4 faces		Mean	
	valence	arousal	valence	arousal	valence	arousal	valence	arousal
Geometric	**63**	56	48	55	**48**	49	**53**	**53**
Global QLZM	53	**57**	46	40	44	**52**	47	49
Part QLZM	37	33	**69**	**61**	28	43	44	45
Context	39	35	30	33	44	35	37	34
Body HOG	38	23	33	35	37	38	35	32

Experiment and Analysis

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Experiment Ⅱ: Pairwise features decision fusion

V: valence A: Arousal

Geometric	Global QLZM	Local QLZM	Context	Body HOG	2 faces / %		3 faces / %		>=4faces / %		Mean / %	
Face features					V	A	V	A	V	A	V	A
√	√				**55**	**57**	43	57	51	52	**49**	**55**
√		√			51	47	**56**	59	41	47	**49**	51
√			√		43	40	53	53	43	49	46	47
√				√	46	44	46	**62**	46	45	46	50
	√		√		39	36	38	33	**51**	33	42	34
	√			√	40	32	41	35	46	40	42	35
		√	√		36	30	33	31	53	40	40	33
		√		√	39	32	41	38	38	43	39	37
			√	√	31	40	33	31	43	35	35	35
	√	√			40	44	**56**	53	41	**56**	45	51

Experiment and Analysis

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Experiment Ⅲ: All features with decision fusion

V: valence A: Arousal

Face features	Context	Body HOG	2 faces / %		3 faces / %		>=4faces / %		Mean / %	
			V	A	V	A	V	A	V	A
√			47	**51**	53	51	44	54	48	52
√	√		47	44	48	57	57	**59**	50	**53**
√		√	**55**	49	56	46	48	56	53	50
√	√	√	45	40	**58**	**64**	**60**	50	**54**	51

Face features: geometric, local appearance, global appearance

Experiment and Analysis

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Experiment results IV: Combined Dimension

Face features	Context	Body HOG	2 faces / %	3 faces / %	>=4faces / %	Mean / %
√			28.33	40	31.11	33.15
	√		21.6	8	20	16.53
		√	18.33	20	26.67	21.67
√	√		**31.67**	40	**44.44**	**38.70**
√		√	28.33	**56**	35.56	**39.96**
√	√	√	28.33	44	35.56	**35.96**

V: valence A: Arousal

Face features: geometric, local appearance, global appearance

Representative Results

Representative Results

Representative Results

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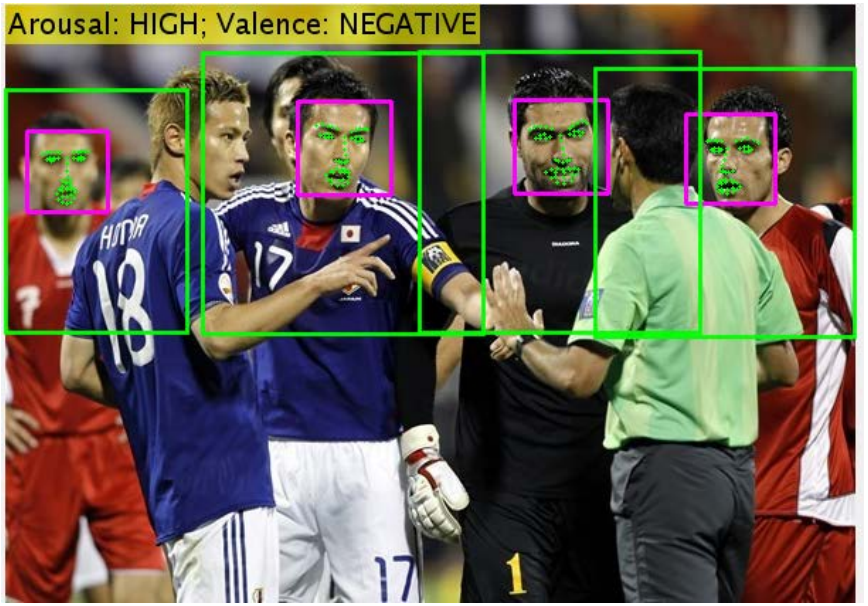

Conclusion and Future Work

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1. A new database for group emotion detection
2. Automatic group emotion detection along Arousal and Valence dimensions
3. A context feature and body-HOG feature used for group emotion detection

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Future work

1. Feature selection before fusion and classification
2. Experiment with more sophisticated classifiers
3. Test on a larger database

Thank you!

Questions?