AESTHETICS ASSESSMENT OF IMAGES CONTAINING FACES

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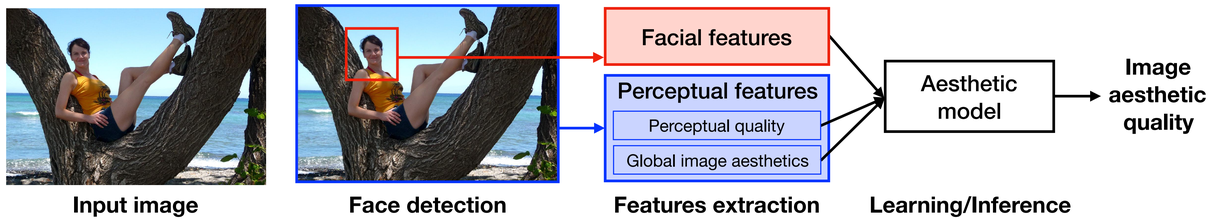
Abstract

This paper introduces a method for aesthetic quality assessment of images with faces. We exploit three different Convolutional Neural Networks to encode information regarding perceptual quality, global image aesthetics, and facial attributes; then, a model is trained to combine these features to explicitly predict the aesthetics of images containing faces. Experimental results show that our approach outperforms existing methods for both binary, i.e. low/high, and continuous aesthetic score prediction on four different databases in the state-of-the-art.

Facial Image Aesthetic Estimation



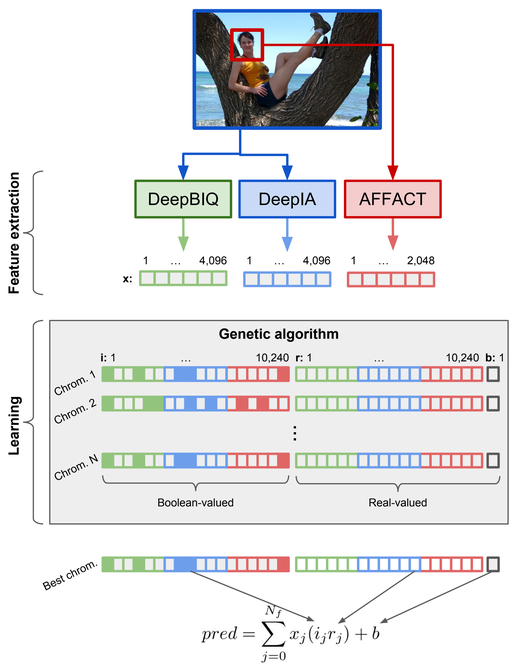
Perceptual features	• **DeepBIQ** model [2] (shortly IQ): perceptual quality metrics (noise, exposure, quality, JPEG quality, and sharpness); • **DeepIA** model [3] (shortly IA): global image aesthetics concepts, such as composition, brightness, contrast, color, etc.
Facial features	Alignment-Free Facial Attribute Classification Technique (**AFFACT**) [4], shortly FA: facial attributes encoding.

Datasets

Four state-of-the-art databases:

- **CUHKPQ:** 3,148 photos annotated respectively with high and low aesthetic quality.
- **HFS:** 250 headshot photos (7 images of 20 subjects + 110 portrait images). Scores between 1 and 6 (average of 25 individual scores).
- **FAVA:** subset of the AVA dataset containing images with faces. Value between 1 and 10 (average of 210 individual scores).
- **Flickr database:** 500 images (portraits or group of faces). Scores range [0-10].

Genetic Algorithm (GA)



Experiments

Two sets of experiments:

- considering the whole image
- considering only the face regions

Executed in the following configurations:

		Binary class.	Regression
SV		SVM	SVR
GA	# Individuals	100	100
	# Generations	200	250
	Fitness	Hinge loss	Smooth-L1 loss
	Crossover	80%	85%
	Elitism	7%	10%
Metrics		GCR	LCC

For each experiment:

- **10-fold cross validation** is performed by randomly selecting the training and testing images
- **10 repetitions** to avoid sampling bias

Results

Aesthetic quality estimation results for each database by extracting perceptual features from the **whole image**.

IQ	IA	FA	#features	GA	GCR (%) CUHKPQ	FAVA	Flickr
✓			4,096		93.2	63.6	64.3
	✓		4,096		97.2	67.4	71.6
		✓	2,048		97.0	70.0	66.2
✓		✓	6,144		97.2	70.0	67.6
✓	✓		8,192		97.4	63.0	73.6
	✓	✓	6,144		98.2	71.2	73.6
✓	✓	✓	10,240		98.2	71.2	74.0
✓	✓	✓	8,300	✓	97.5	70.7	73.9

IQ	IA	FA	#features	GA	LCC FAVA	Flickr
✓			4,096		0.38	0.36
	✓		4,096		0.51	0.57
		✓	2,048		0.55	0.48
✓		✓	6,144		0.57	0.51
✓	✓		8,192		0.36	0.56
	✓	✓	6,144		0.62	0.62
✓	✓	✓	10,240		0.61	0.61
✓	✓	✓	10,229	✓	0.62	0.61

Comparison with state-of-the-art methods for all the considered databases.

Methods	CUHKPQ GCR (%)	HFS GCR (%)	HFS LCC	FAVA GCR (%)	FAVA LCC	Flickr GCR (%)	Flickr LCC
Lienhard [6]	94.8	79.3	0.73	67.1	0.51	69.3	0.49
Kairanbay [5]	-			65.3	-	-	-
Proposed	98.2	79.0*	0.76*	71.2	0.61	74.0	0.61

*These results are obtained by extracting perceptual features from face region.

References

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