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On Shape And the Computability of Emotions

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On Shape and the Computability of Emotion

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  - ACM Multimedia 2012, Nara, Japan
  - **Keywords:** Human Emotion, Psychology, Shape Features

Introduction

- Images suggest emotions
- Aroused emotion prediction vs. Emotion detection (facial recognition, etc.)
- Psychological theories
  - Human affective response ⇔ low level features
    - Appart from the semantic content
- Challenges
  - Multiple emotions
  - Subjectivity

Introduction
Investigated factors

Introduction
Other?

Introduction

Other? → perceptual shapes

- Roundness [4, 5, 21]
  - Anger, happiness
  - Curved contours → positive feelings
  - Sharp transitions → negative bias
- Complexity of shapes [3]
  - Humans visually prefer simplicity

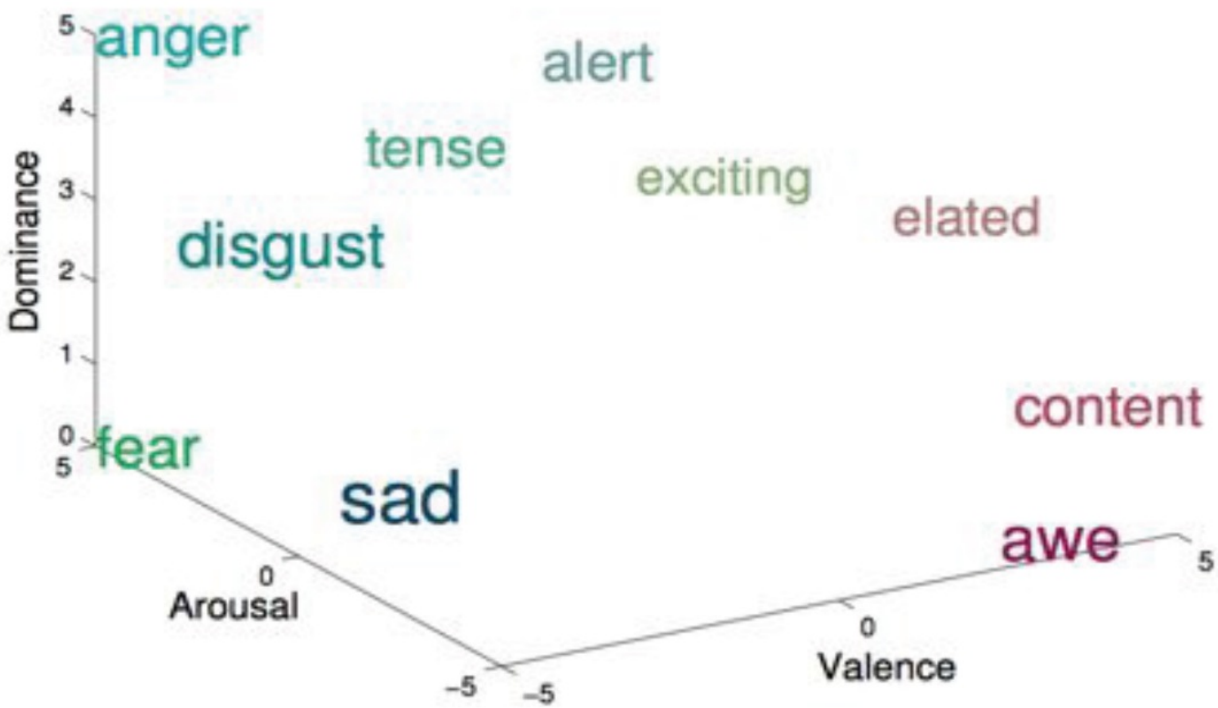
Introduction

*Affect dimensions**

- **Valence**: type of emotion
  - from positive to negative
- **Arousal**: intensity of emotion
  - from excited to calm
- **Dominance:** ranges from no control to full control (can be used to distinguish emotional states when they are similar in both arousal and valence)

* [Bradley et al., 2007; Lang et al., 1998; Lindquist et al., 2011]

Introduction
Dimensional representation of emotions



Introduction

Dataset

- IAPS: International Affective Picture System [15]
  - 1’182 images
  - User ratings on the 3 basic dimensions of affect: valence, arousal and dominance

Dimensions	Mean	Stdev
Valence	7.09	1.41
Arousal	3.55	2.32
Dominance	6.23	2.31

Related work

- Mainly through training classifiers on visual features [11, 26, 18]
  - Color, composition
  - Categorical emotions: Happiness, anger, sad
- Bag of colors, Fisher vectors [9]
- Shape characterization (through Zernike features, edge statistics features, object statistics, and Gabor filters) [27]
- Emotion-histogram & bag-of-emotion [24]

Related work

- 1st to model categorical emotions: Machajdik and Hanbury [18]
  - Discrete emotional categories modelisation
  - Color, texture, composition, content, semantic level features (#faces)
- Kansei system: 23 words pairs (e.g., like-dislike, warm-cool, etc.) [23]
- Universal, distinctive and comprehensive representation of emotions [25]
- But, interrelationship among types of emotions ignored

Concept

- Leveraging shape descriptors → capture emotions evoked by images
- SotA [7, 20]: straightness, sinuosity, linearity, circularity, elongation, orientation, symmetry & mass of a curve
- Choice: Roundness-angularity & simplicity-complexity characteristics
  - Psychologists: influence human beings affect

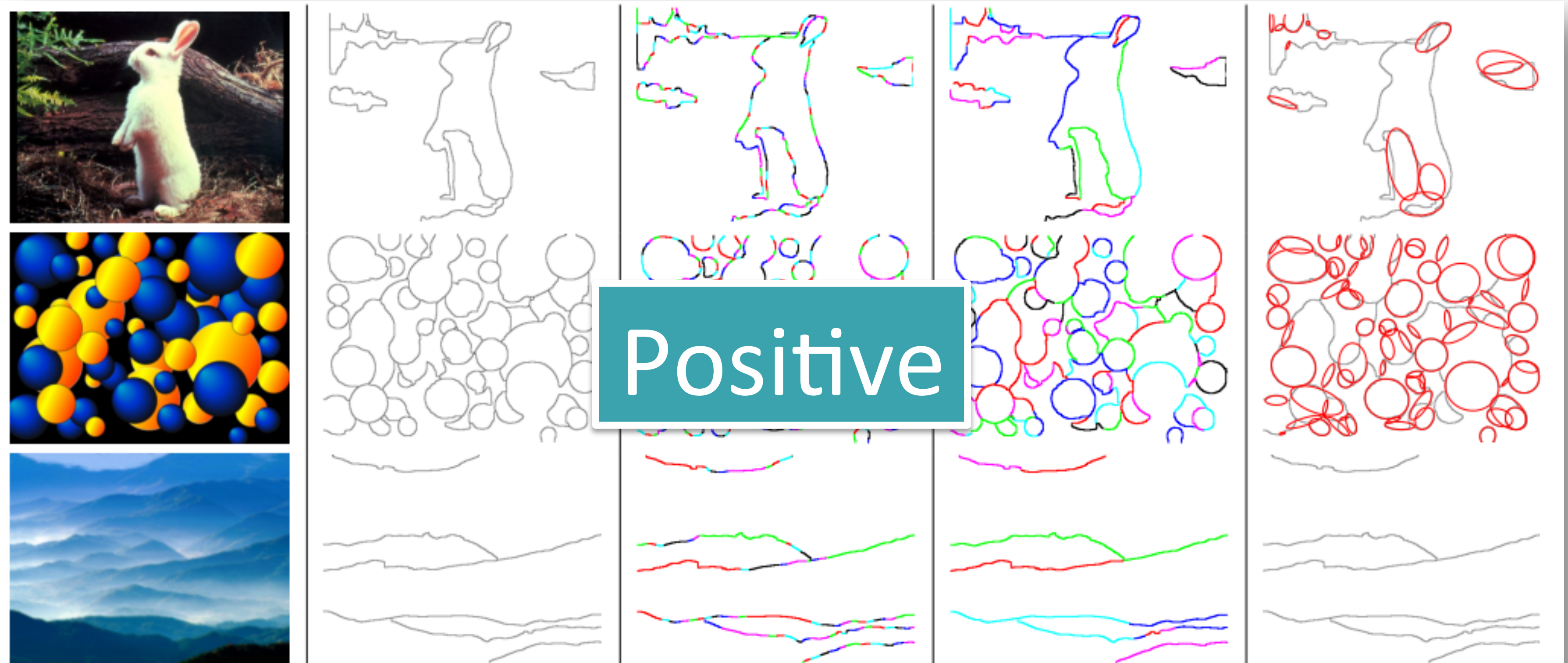
Concept

Perceptual shapes *(derived from [8])*

- Framework for extracting perceptual shapes:
  - Complexity-Simplicity
  - Roundness-Angularity
- Shape features
  - Line segments
  - Angles
  - Continuous lines

Concept

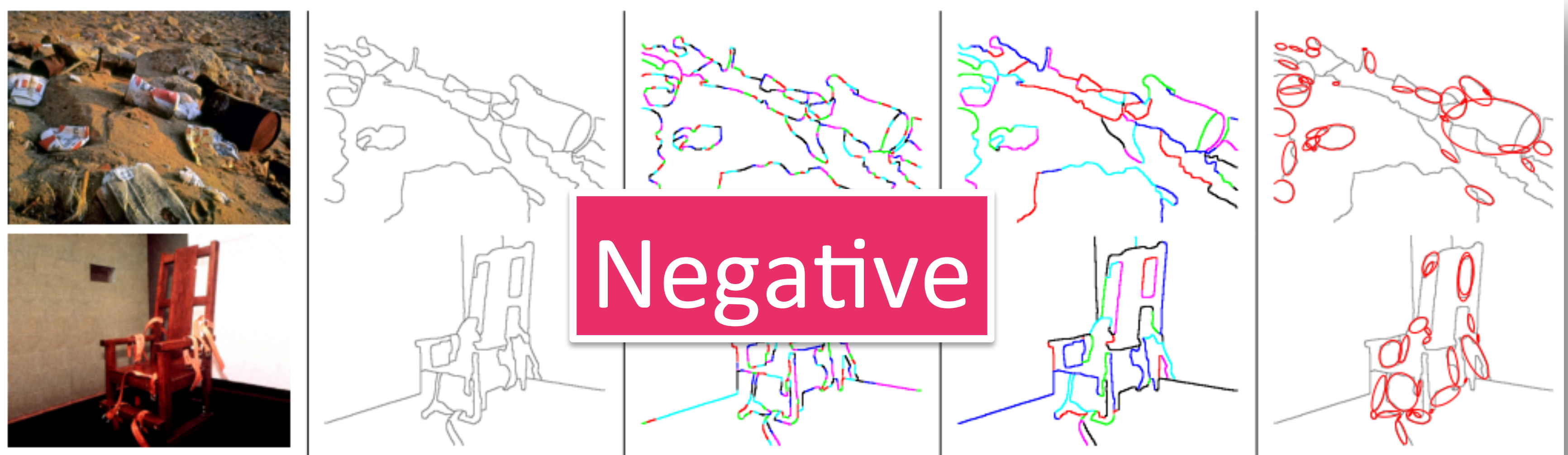
- Perceptual shapes of images with high valance



(a) Original (b) Contours (c) Line segments (d) Continuous lines (e) Ellipse on curves

Concept

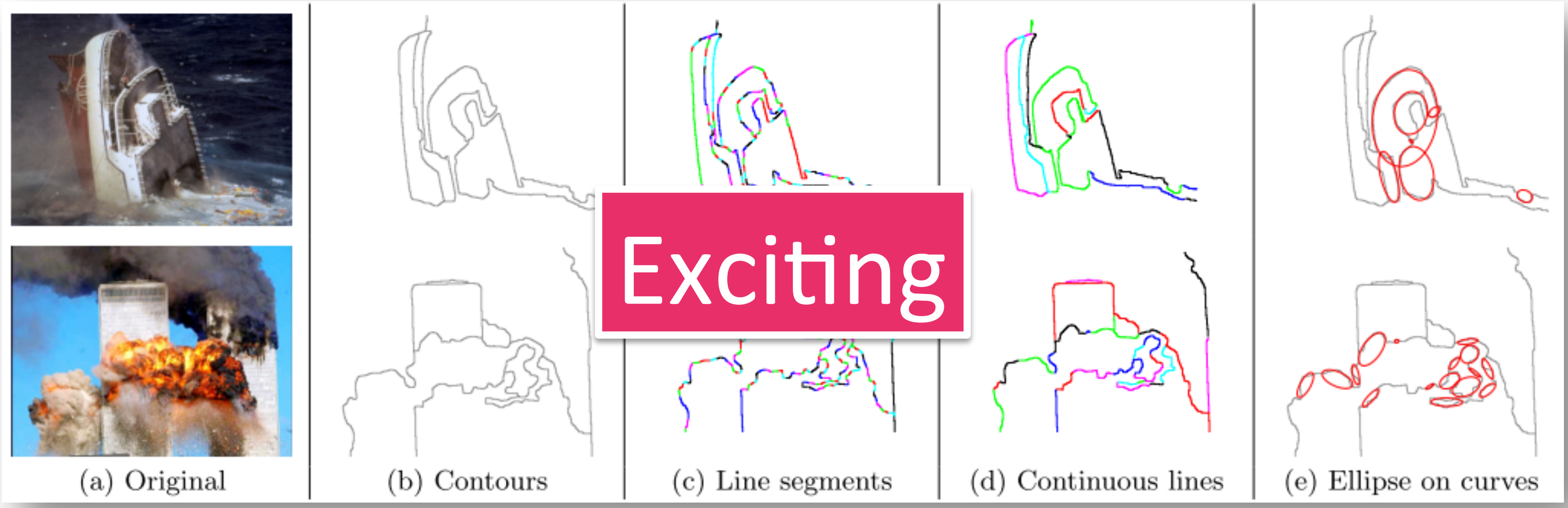
- Perceptual shapes of images with low valance



(a) Original (b) Contours (c) Line segments (d) Continuous lines (e) Ellipse on curves

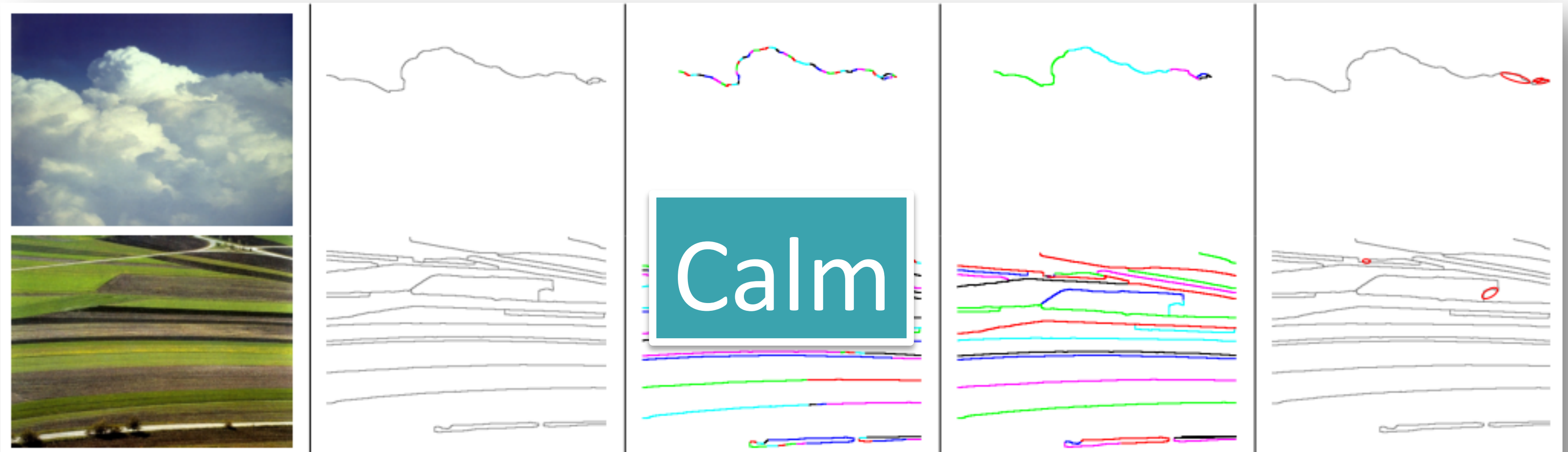
Concept

- Perceptual shapes of images with high arousal



Concept

- Perceptual shapes of images with low arousal

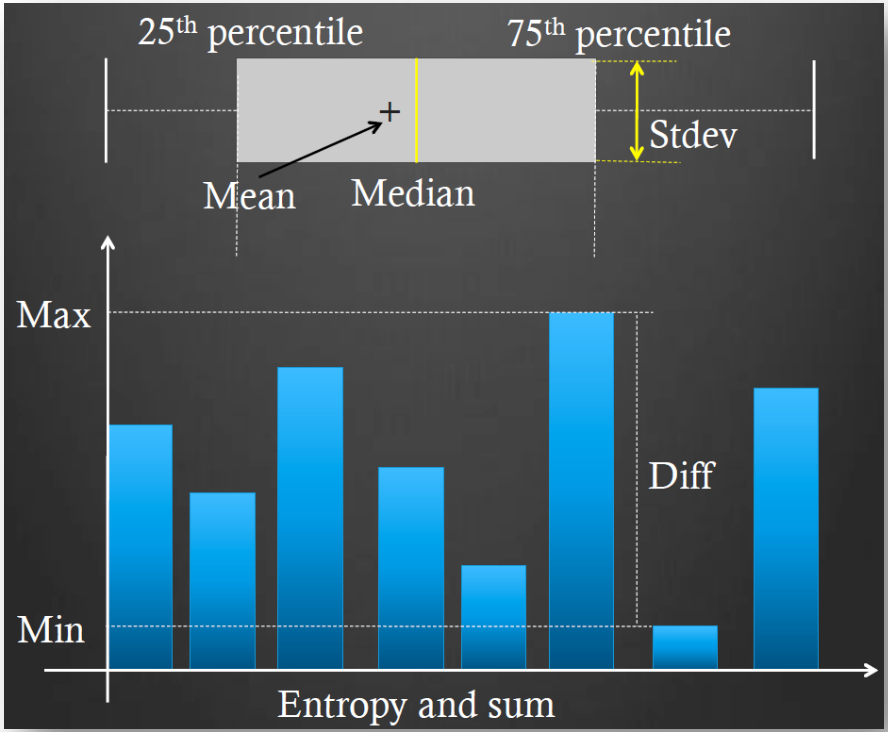


(a) Original (b) Contours (c) Line segments (d) Continuous lines (e) Ellipse on curves

Capturing emotion from shape

Statistical measures

- *Minimum, Maximum*
- *0.75 quantile, 0.25 quantile*
- *Diff(0.75 quantile, 0.25 quantile)*
- *Diff(max, min)*
- *Sum*
- *Total number*
- *Median*
- *Mean*
- *Standard deviation*
- *Entropy*



Capturing emotion from shape

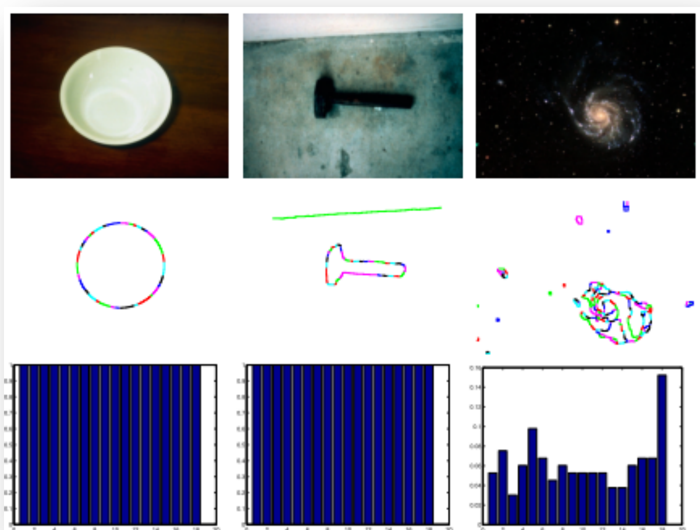
Line segments → structure

- *Short straight lines generated by fitting nearby pixels*
- Orientation: represent feelings (calm & stability)
  - Horizontal: peace & calm
  - Vertical: strength
- Length: simplicity vs complexity
  - Long lines: simple
  - Shorter lines: complex contours
- Mass of the image
  - May indicate associated relationships among line segments within visual design [3]

Capturing emotion from shape
Line segments

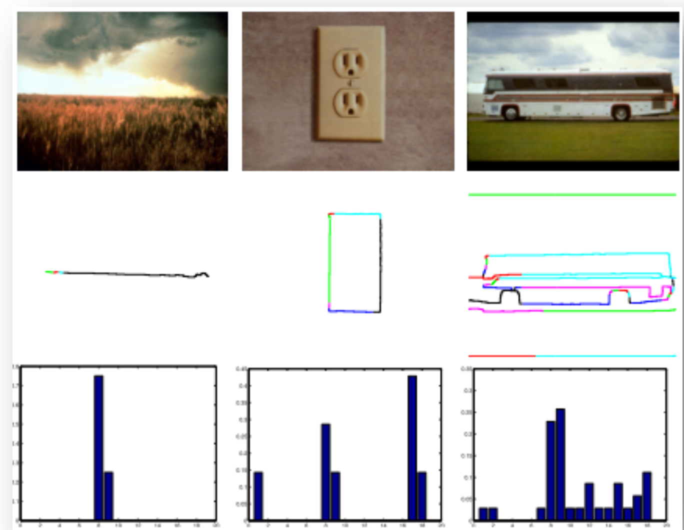
- Mean value of length of line segments (and associated orientation histograms)

Low



VS

High

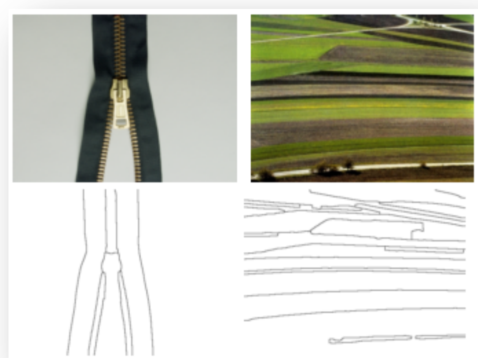


Capturing emotion from shape

Continuous lines → simplicity-complexity

- *Connection of intersecting line segments having the same orientations*
- Degree of curving
  - f(l)= length(l) / N
    - N: #points on continuous line l
- Length
- Line count
  - Total #continuous/open/closed lines

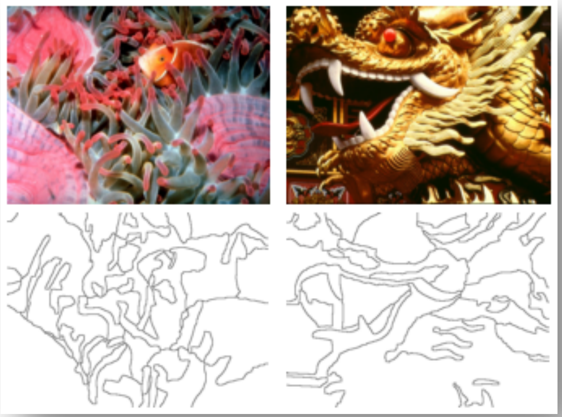
VS



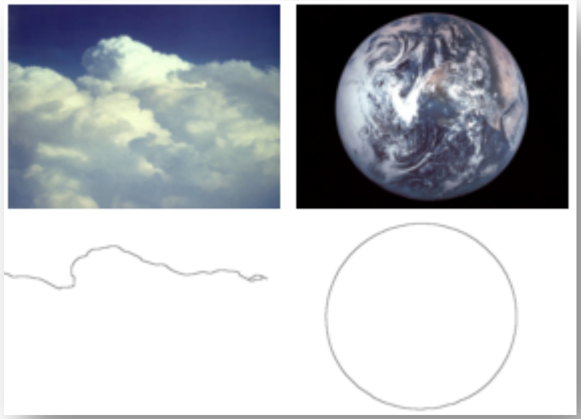
Capturing emotion from shape

Angles → simplicity/complexity

- *Calculated between each of any two intersecting line segments*
- Angle count
  - #angles
  - % of unique angles in the image
- Angular metrics

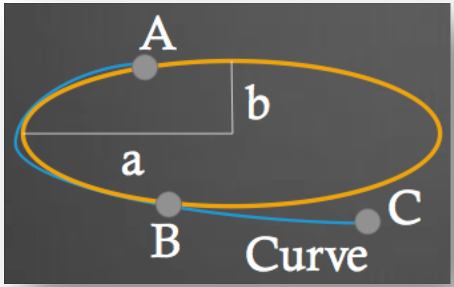


VS



Capturing emotion from shape

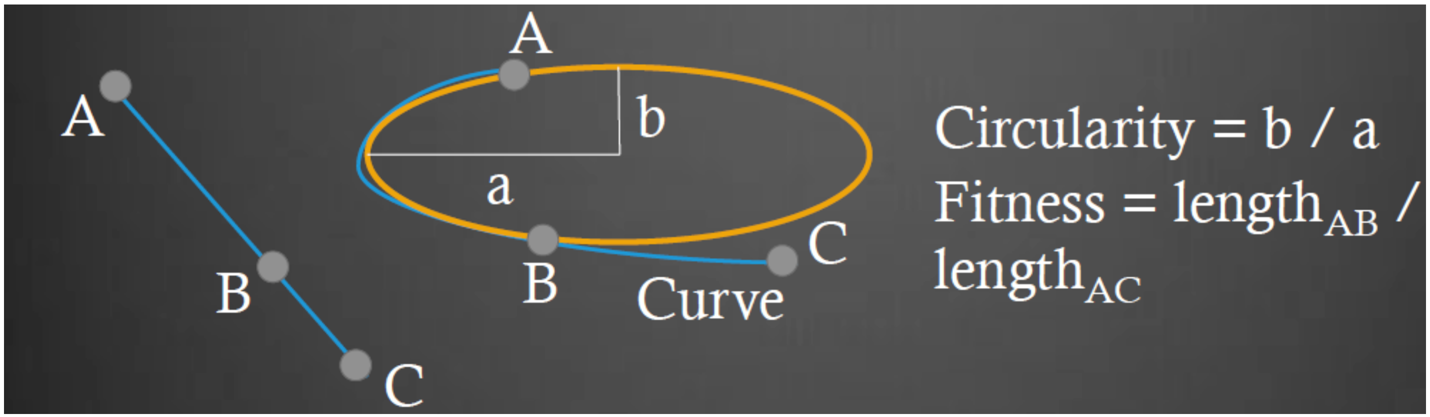
Curves → roundness



- *Subset of continuous lines*
- Fitness, area, circularity
  - Fitness: overlap between proposed ellipse and the curves (=b/a)
  - Circularity: ratio of the minor & major axes of the ellipse (=AB/AC)
- Mass of curves
  - Mean value & standard deviation of (x, y) coordinates
- Top round curves
  - Fitness, area & circularity for each top-3 curves

Capturing emotion from shape

Curves



[Fitness]

	(0.8,1]	(0.6,0.8]	(0.4, 0.6]	(0.2, 0.4]
Positive Img	2.12	9.33	5.7	2.68
Negative Img	1.42	7.5	5.02	2.73

[Circularity]

	(0.8,1]	(0.6,0.8]	(0.4, 0.6]	(0.2, 0.4]
Positive Img	0.96	2.56	5.1	11.2
Negative Img	0.73	2.19	4	9.75

Experiments

- 3 tasks
  1. Distinguish strong emotional content from emotionally neutral images
  2. Fit valence and arousal dimensions using regression methods
  3. Classification on discrete emotional categories

Experiments

Dataset

- Subsets of IAPS
  - Subset A (484 images)
    - ~~Images with facial expressions & human bodie~~
  - Subset B (394 images)
    - images with category labels (discrete emotions)
      - Generated by Mikels [19]: Anger, disgust, fear, sadness, amusement, awe, contentment, excitement
      - Comonly used → benchmark classification accuracy with results in Machajdik et al. [18]

Experiments (1)

Strong emotional content

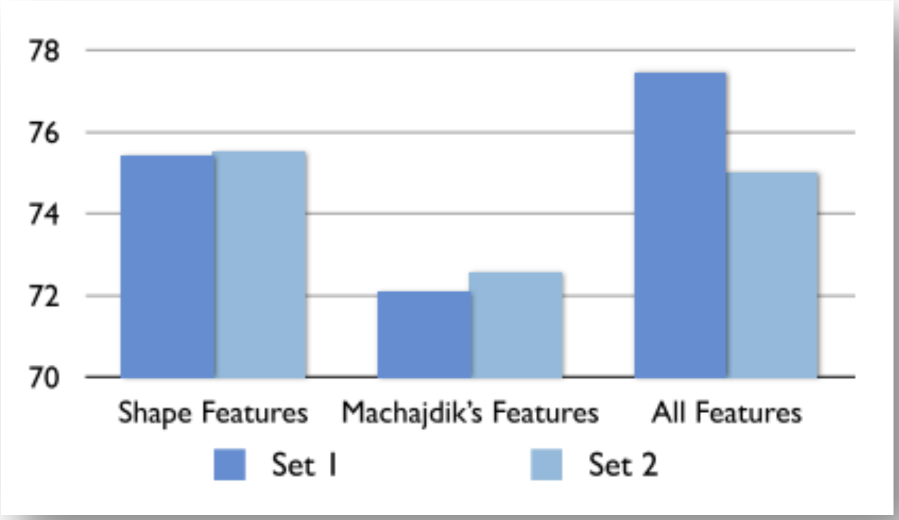
- Very high or very low valance and arousal ratings

  → Images with strong emotional content
- Subset A splited in 2 (Set 1, Set 2)
- Classification
  - SVM with RBF kernel
  - Trained with
    - Proposed shape features
    - Machajdik's features
    - Combined features
  - Feature selection with PCA

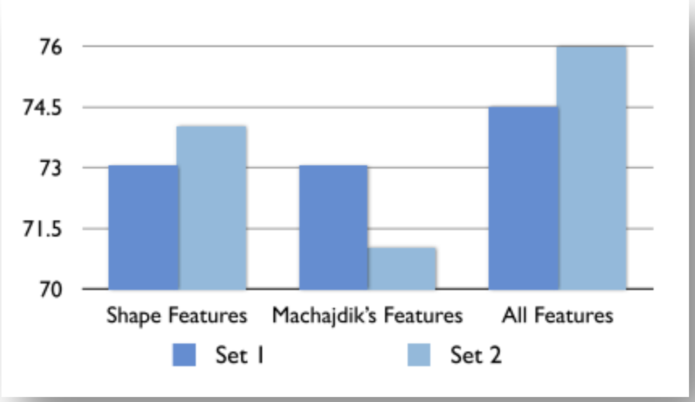
Experiments (1)

Strong emotional content

- Classification accuracy
  - Emotional/neutral images



Without PCA



With PCA feature selection

Experiments (1)

Strong emotional content

- Shape > Machajdik's features
- Combined features better
  - Intuitive: shape alone cannot represent well enough emotions → other image features help (color, composition, texture)
- Very complex/simple, round and angular images
  → strong emotional content & high valence values
- Simple structured images, very low degrees of curving
  → strong emotional content & high arousal values

Experiments (2)

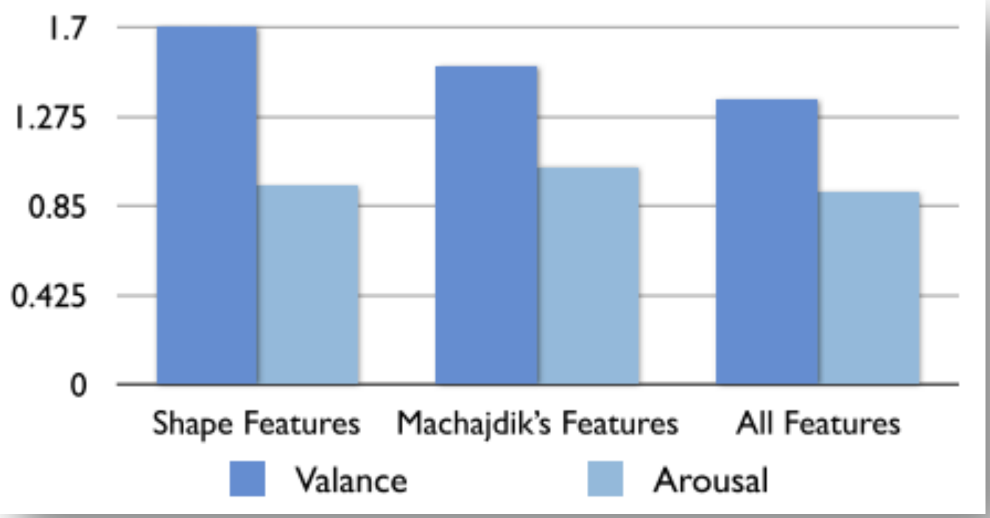
Fitting the dimensionality of emotions

- Model basic emotional dimensions
  - Tuple of valence & arousal values (1, 9)
  - Regression model learned dimensions separately
  - SVM regression with RBF kernel
- Result: visual shapes provide a stronger cue in understanding the valence as opposed to color/texture/ composition
- Valance ↔ angular count, fitness, circularity, orientation of line segments
- Arousal ↔ angle count, angle metrics, straightness, length span, orientation of curves

Experiments (2)

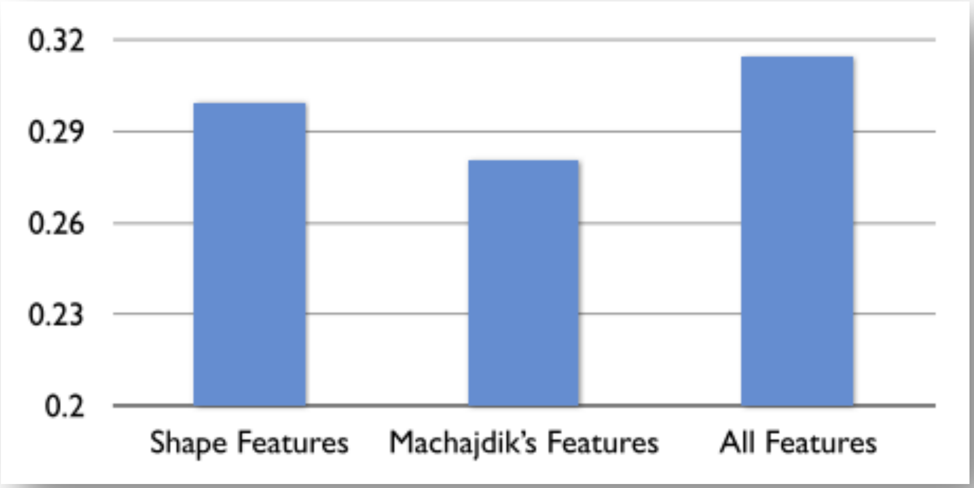
Fitting the dimensionality of emotions

- Mean squared error for the dimensions of valance and arousal



Experiments (3)
Classifying categorized emotions

- Classification of images into
  - Anger, disgust, fear, sadness, amusement, awe, contentment and excitement
- One-vs-all classification as in Machajdik et al. [18]
- SVM



Experiments (3)

Significant features to emotions

- Each of these shape features: >= 30% classification accuracy

Emotion	**Features**
Angry	Circularity
Disgust	Length of line segments
Fear	Orientation of line segments and angle count
Sadness	Fitness, mass of curves, circularity, and orientation of line segments
Amusement	Mass of curves and orientation of line segments
Awe	Orientation of line segments
Excitement	Orientation of line segments
Contentment	Mass of lines, angle count, and orientation of line segments

Conclusion

Main contributions

- Investigation of the correlation between visual shapes and aroused emotions
- Quantitatively model roundness-angularity and simplicity-complexity concepts
  - From the perspective of shapes
  - Using a dimensional approach
- Distinguish images with strong/weak emotional content

Conclusion

- Shape features can be used to predict aroused emotions from images
- It can be used alone, or with other features (color, texture, etc.)
  - Combination gives best results
- Different shape features for different types of emotions
- But, emotions are still subjective

Conclusion

- Multiple applications
  - Improve performance of keyword based image retrieval systems
  - Automatic emotional categorization of images/ movies collection
  - …
  - For me: help to find the best parts of a movie for a particular user profile

Main references

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