CONTOUR DETECTION

CS 766 Computer Vision
University Of Wisconsin-Madison

Haiyan Yang

Shuo Han

Yuting Liu

OUTLINE

I. Background
II. Previous Work
III. Our approaches
IV. Results
V. Application
VI. Q & A

CHAPTER I

BACKGROUND

- Contour detection → fundamental problem
- Our goal: achieve BETTER results
- Methodology:
    - Probability of Boundary
    - Sparse Code Gradient
    - Sketch Tokens

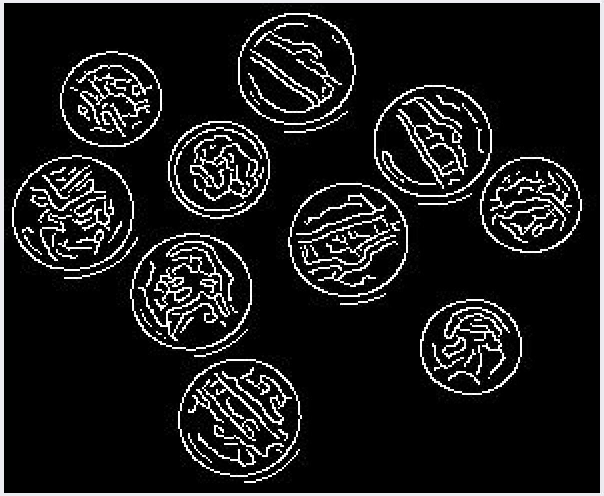


Fig. Example of canny edge detector

CHAPTER II

PREVIOUS WORK

- Early approaches: aimed at finding sharp discontinuities in the brightness channel.
- Recent approaches: estimate probability of boundary using changes in lightness, color and texture.

CHAPTER III

APPROACHES

- Three approaches implementations

I. Probability of Boundary

II. Sparse code gradient

III. Sketch tokens

- Compare performances of three implementations
- Applications based on resulted contour images

APPROACH I

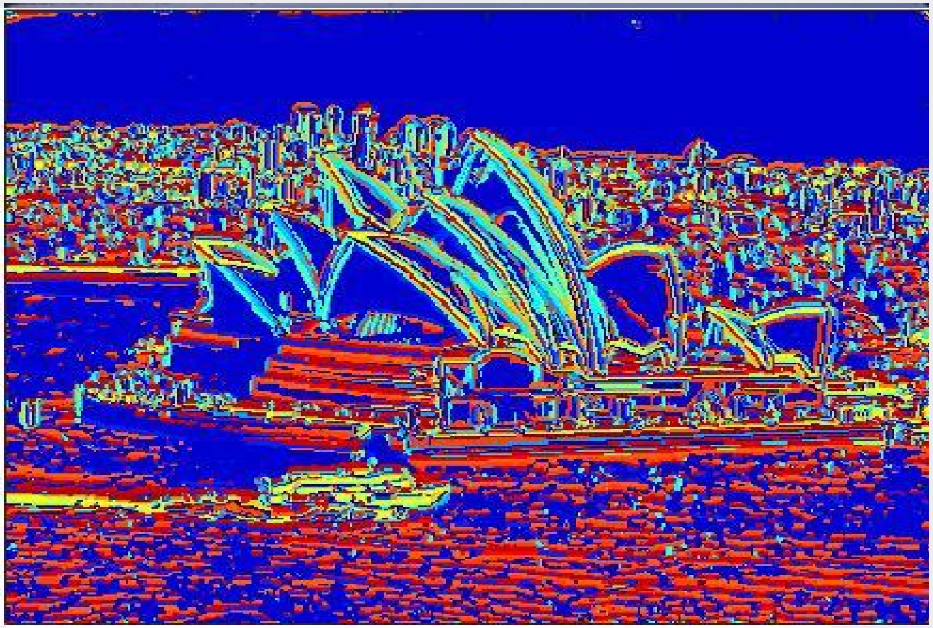
PROBABILITY OF BOUNDARY

- Get the information about lightness, color and texture.
- Quantify the changes in those channels.
- Combine those changes in different channels to represent the probability of boundary.

APPROACH I

PROBABILITY OF BOUNDARY

- How to get the information about texture?

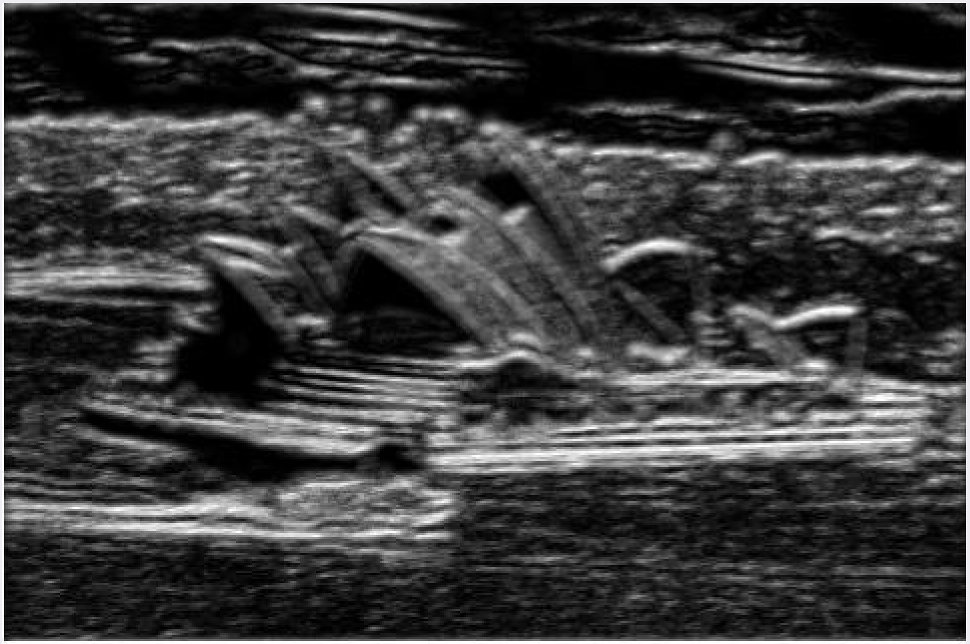


1. Arbelaez, Pablo, Michael Maire, Charless Fowlkes, and Jitendra Malik. "Contour detection and hierarchical image segmentation."Pattern Analysis and Machine Intelligence, IEEE Transactions on33, no. 5 (2011): 898-916.

APPROACH I

PROBABILITY OF BOUNDARY

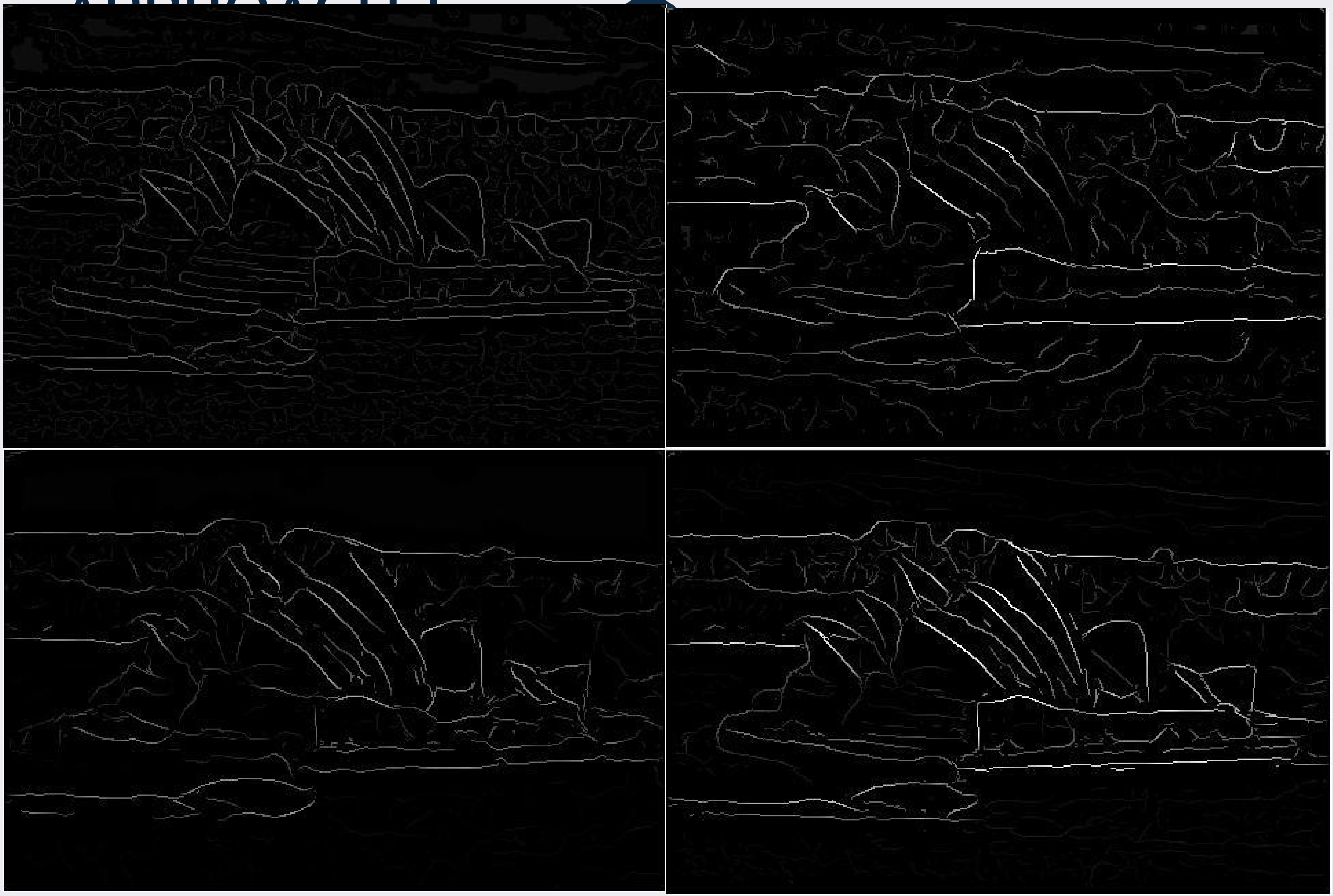
- How to quantify the changes in different channels?



$G(x, y, \theta)$

1. Arbelaez, Pablo, Michael Maire, Charless Fowlkes, and Jitendra Malik. "Contour detection and hierarchical image segmentation."Pattern Analysis and Machine Intelligence, IEEE Transactions on33, no. 5 (2011): 898-916.

APPROACH I



1. Arbelaez, Pablo, Michael Maire, Charless Fowlkes, and Jitendra Malik. "Contour detection and hierarchical image segmentation."Pattern Analysis and Machine Intelligence, IEEE Transactions on33, no. 5 (2011): 898-916.

APPROACH II

SPARSE CODE GRADIENT

Improve Probability of Boundary with:

- K-SVD Dictionary Learning

Generalizes k-means & learns dictionaries of code-words from unsupervised data

$$\min_{D,X} \|Y - DX\|_F^2 \; s.t. \forall i, \|x_i\|_0 \leq K; \; \forall j, \|d_j\|_2 = 1$$

- Y : image patches extracted from image
- X : associated sparse code matrix
- D : dictionary
- $\|\cdot\|_F$: Frobenius norm
- Minimize reconstruction error

1. Xiaofeng, Ren, and Liefeng Bo. "Discriminatively trained sparse code gradients for contour detection." *Advances in neural information processing systems* 2012: 584-592.

APPROACH II

SPARSE CODE GRADIENT

- Orthogonal Matching Pursuit (OMP)
- – Iteratively greedy algorithm to find “best match” at each step
- – Compute per–pixel level sparse code (5 x 5 image patch in our implementation)
- Multi-scale Pooling
- - Use oriented half-discs at each pixel
- - Each orientation with two half-discs rectangle to represent
- Linear SVM Classifier

- Multi-scale contrast information for classifying a location in image whether it’s edge or not

1. Xiaofeng, Ren, and Liefeng Bo. "Discriminatively trained sparse code gradients for contour detection." *Advances in neural information processing systems* 2012: 584-592.

APPROACH II

SPARSE CODE GRADIENT

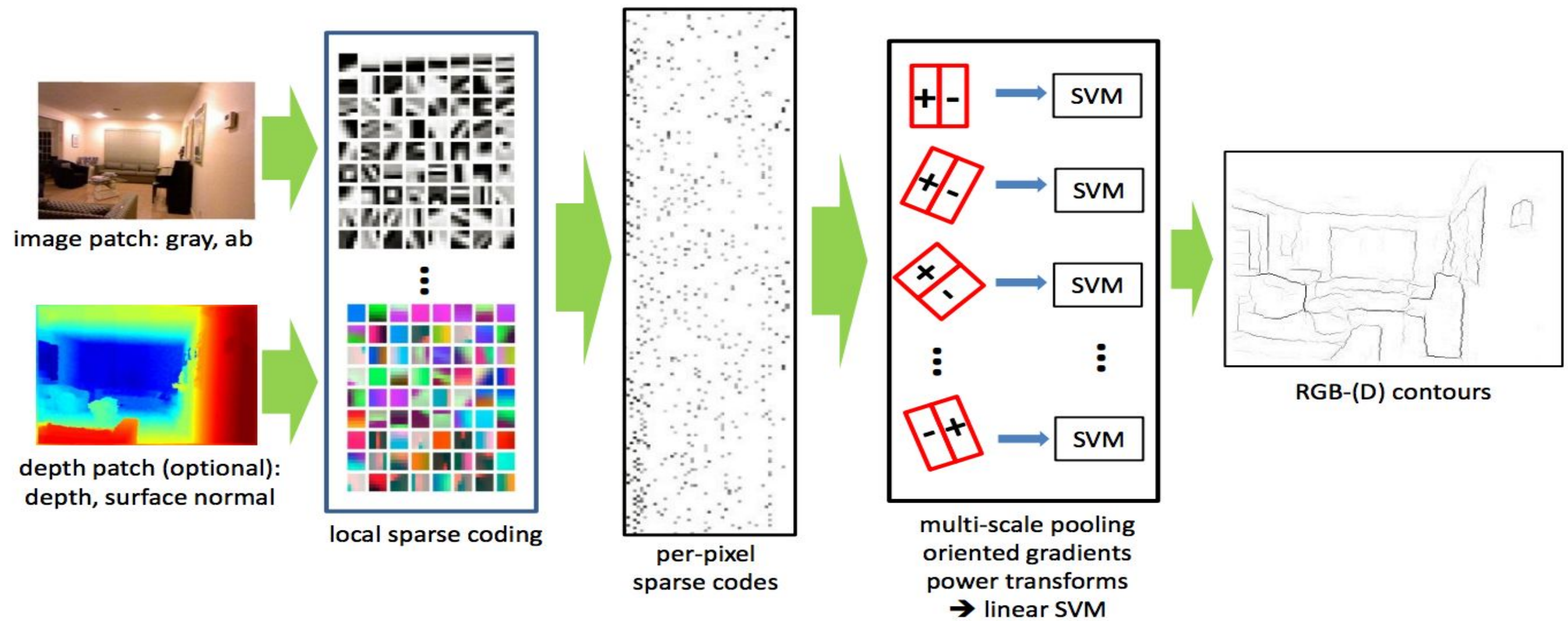


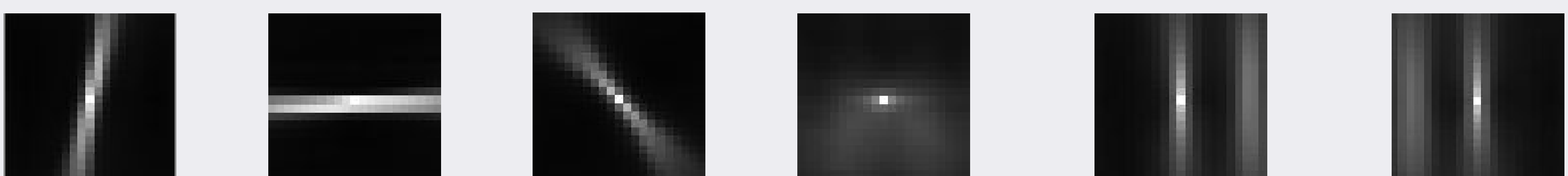
Fig. Illustration of contour detection with Sparse code gradient[1]

1. Xiaofeng, Ren, and Liefeng Bo. "Discriminatively trained sparse code gradients for contour detection." *Advances in neural information processing systems* 2012: 584-592.

APPROACH III

SKETCH TOKENS

- A set of token classes
  - Represent local edge structures
- Unsupervisedly learned from hand drawn sketches
  - Extract patches centering at contour pixels from binary sketch images
  - Compute DAISY descriptors on those patches
  - Perform clustering on the descriptors using K-means algorithm



APPROACH III

SKETCH TOKENS

- How to detect sketch tokens?
  - By supervised learning (classification)
- Feature extraction (from patches)
  - Color, gradient and oriented gradient channels
  - Self-similarities $f_{ijk} = g_{jk} - g_{ik}$
- Classification
  - Total class number = # of sketch token classes + 1
  - Use random forest -- efficient for multi-class problems
    - Predicts the probability of each class

SKETCH TOKENS

- Use trained model for contour detection
  - Compute the probability of a contour at the center pixel
    - P (contour) = Σ P (sketch token) = 1 - P (background)
  - Perform a standard non-maximal suppression to find the peak response of a contour

CHAPTER IV

RESULTS

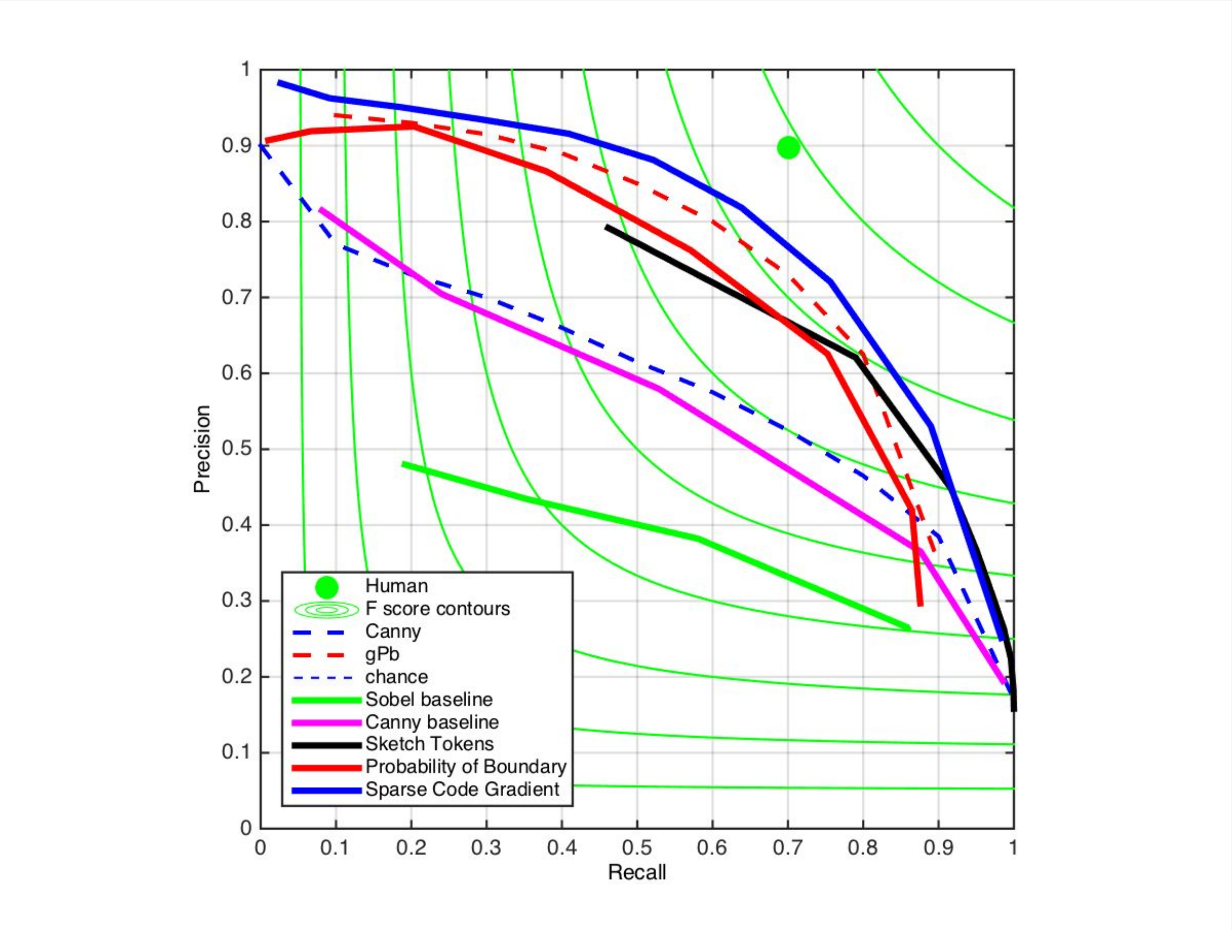
- Examples

Original Pb SCG Sketch Tokens

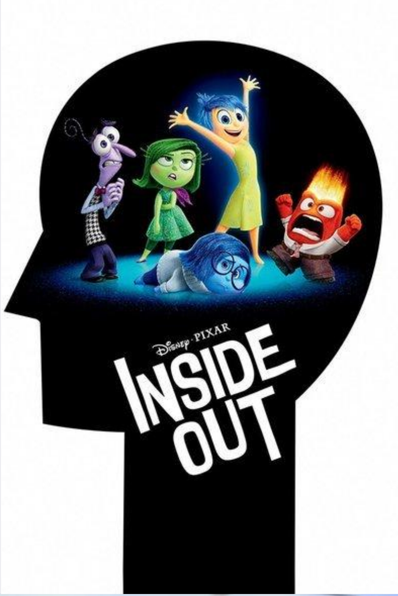
CHAPTER IV

RESULTS

- Precision-recall curve

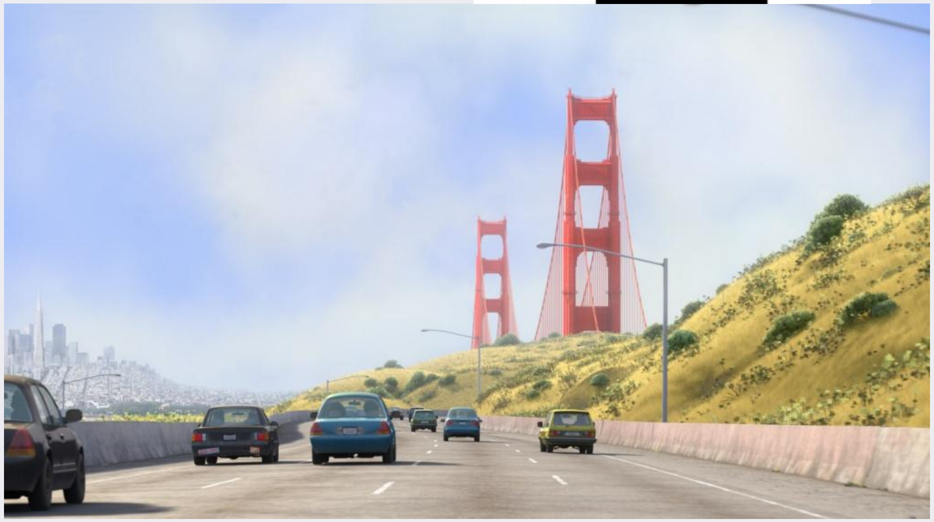


CHAPTER V



APPLICATIONS

- Cartoonify images from real scene pictures



CHAPTER V

APPLICATIONS

- Process of change an image into cartoon-style image

Input Image (Real-scene picture)

Smooth Filter

Contour detector

Smoothed Image

Edge Image

Get from our previous work

Use bilateral filter in our implementation

Non-photorealistic rendering

Find strong edge →
Filter corresponding pixel in
filtered image to 0

Cartoon Image

APPLICATIONS

- Example

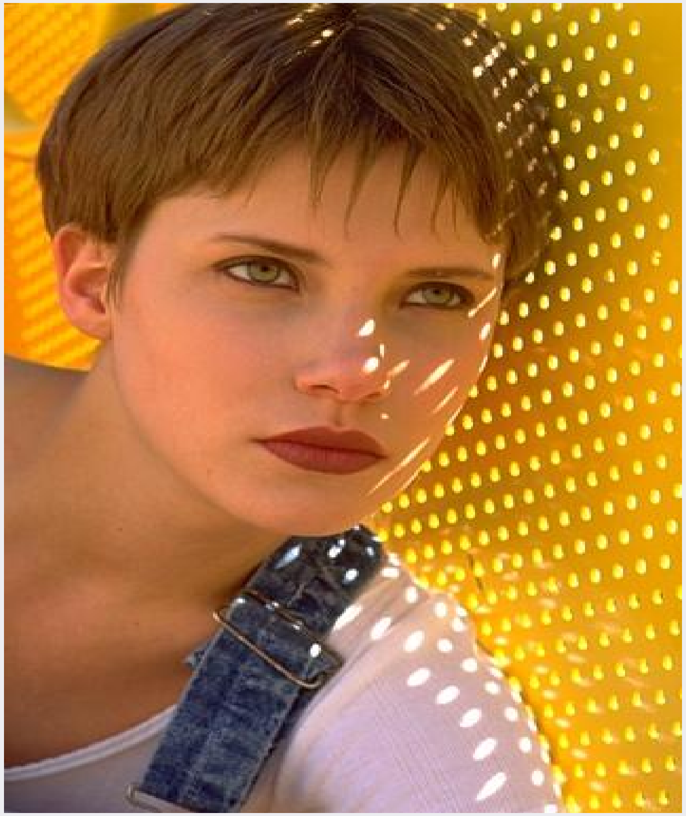


Fig. Input Image

CHAPTER V

APPLICATIONS

- Example

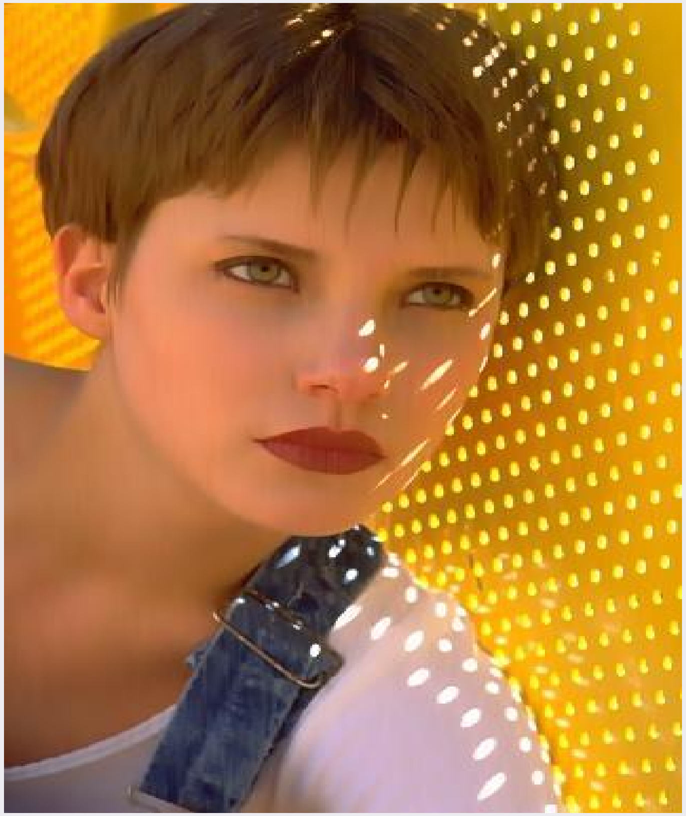


Fig. Smoothed Image

Fig. Edge Image

CHAPTER V

APPLICATIONS

- Example

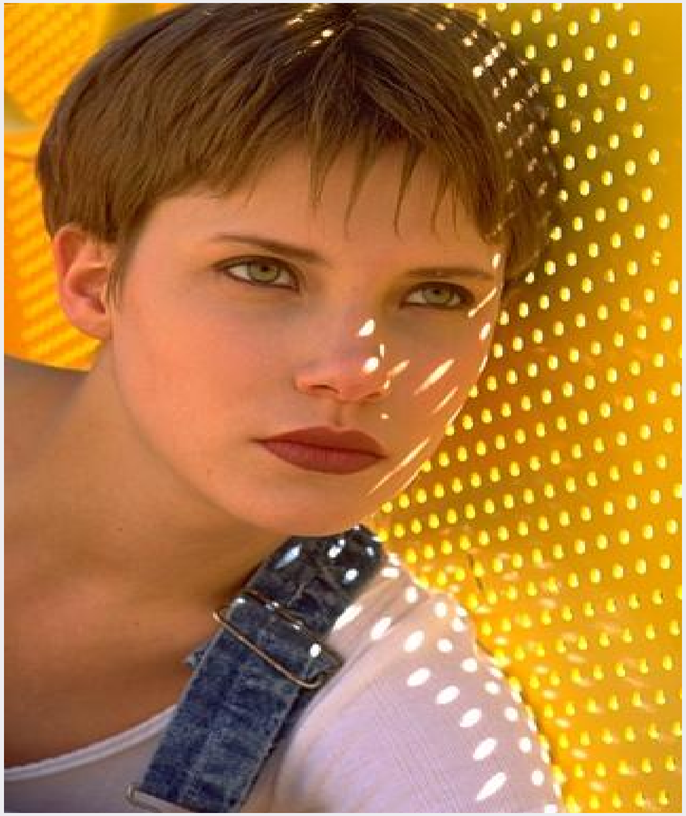


Fig. Input Image

Fig. Output Image

CHAPTER V

APPLICATIONS

- Comparison among outputs by our three methods

Probability of Boundary

Sparse Code Gradient

Sketch tokens

- Which one is your favorite?

CHAPTER VI

Future Work

- Better performance by tuning the parameters, adding more meaningful features and more powerful computational power
- Interesting applications

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CHAPTER VI

REFERENCE

- Arbelaez, Pablo, Michael Maire, Charless Fowlkes, and Jitendra Malik. "Contour detection and hierarchical image segmentation."Pattern Analysis and Machine Intelligence, IEEE Transactions on33, no. 5 (2011): 898-916.
- Xiaofeng, Ren, and Liefeng Bo. "Discriminatively trained sparse code gradients for contour detection." Advances in neural information processing systems 2012: 584-592.
- Lim, Joseph, C. Zitnick, and Piotr Dollár. "Sketch tokens: A learned mid-level representation for contour and object detection." InProceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3158-3165. 2013.

Q&A

Thank you