ECE 638
Topics on Image Analysis

Module 65.0 Content Color Dependent Screening

Jan Allebach

Electronic Imaging Systems Laboratory (EISL)

Purdue University

6 December 2021

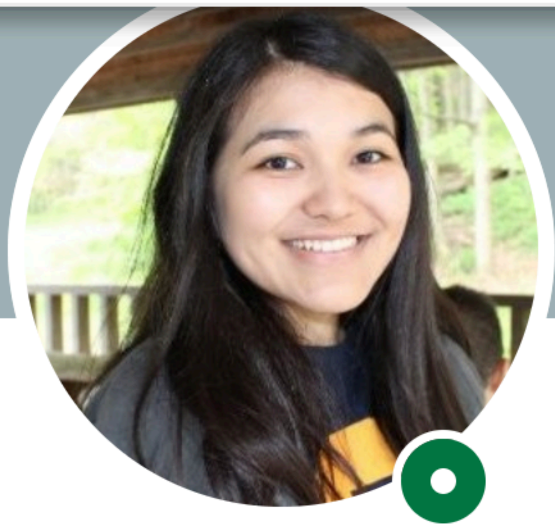
Synopsis (1/2)

- Binary segmentation
  - Otsu's method
  - Twice Otsu method
  - Valley emphasis method
- Clustering methods
  - K-means algorithm (unsupervised)
  - Choosing the number of clusters
    - Elbow method
    - Other approaches
  - Spatiochromatic feature space
  - K-nearest neighbors (supervised)

Synopsis (2/2)

- Edge-based methods
  - Sobel operator
  - Color-aware Sobel operator
- Adaptive bilateral filter
- Connected components
- Edge-thinning
- Morphological operations

About the authors (1/2)



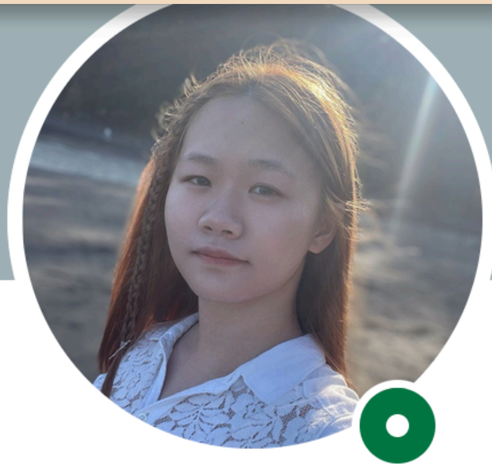
Altyngul Jumabayeva · 1st

Postdoctoral Scholar at Nazarbayev University

Nazarbayev University · Purdue University

West Lafayette, Indiana, United States · Contact info

About the authors (2/2)



Yang Yan · 1st

Looking for internship. PhD student on computer vision, machine learning, image/video processing , and color science.

Purdue University College of Engineering

West Lafayette, Indiana, United States · Contact info

The Source

YANG YAN'S PRELIMINARY EXAMINATION

*IMPROVED CONTENT-COLOR-DEPENDENT SCREENING (CCDS): ADAPTIVE BILATERAL FILTERING AND COLOR-AWARE SOBEL EDGE DETECTOR**

Major Professor: Jan P Allebach

Committee Members: George T.-C. Chiu

Fengqing Maggie Zhu

Michael D. Zoltowski

Purdue University, West Lafayette, IN

PURDUE UNIVERSITY | School of Electrical and Computer Engineering

1

* This work was supported by HP Indigo Division, Rehovat, ISRAEL.

Outline

Introduction

- Color halftoning background
- CCDS motivation and goal

CCDS Flow Diagram

- Cluster map
- Segmentation map
- Merged map
- CCDS halftoning image generation

Results

- Comparisons
- Psycho-physical Experiment Results

Summary

- Contributions
- Future Work

Outline

Introduction

- Color halftoning background
- CCDS motivation and goal

CCDS Flow Diagram

- Cluster map
- Segmentation map
- Merged map
- CCDS halftoning image generation

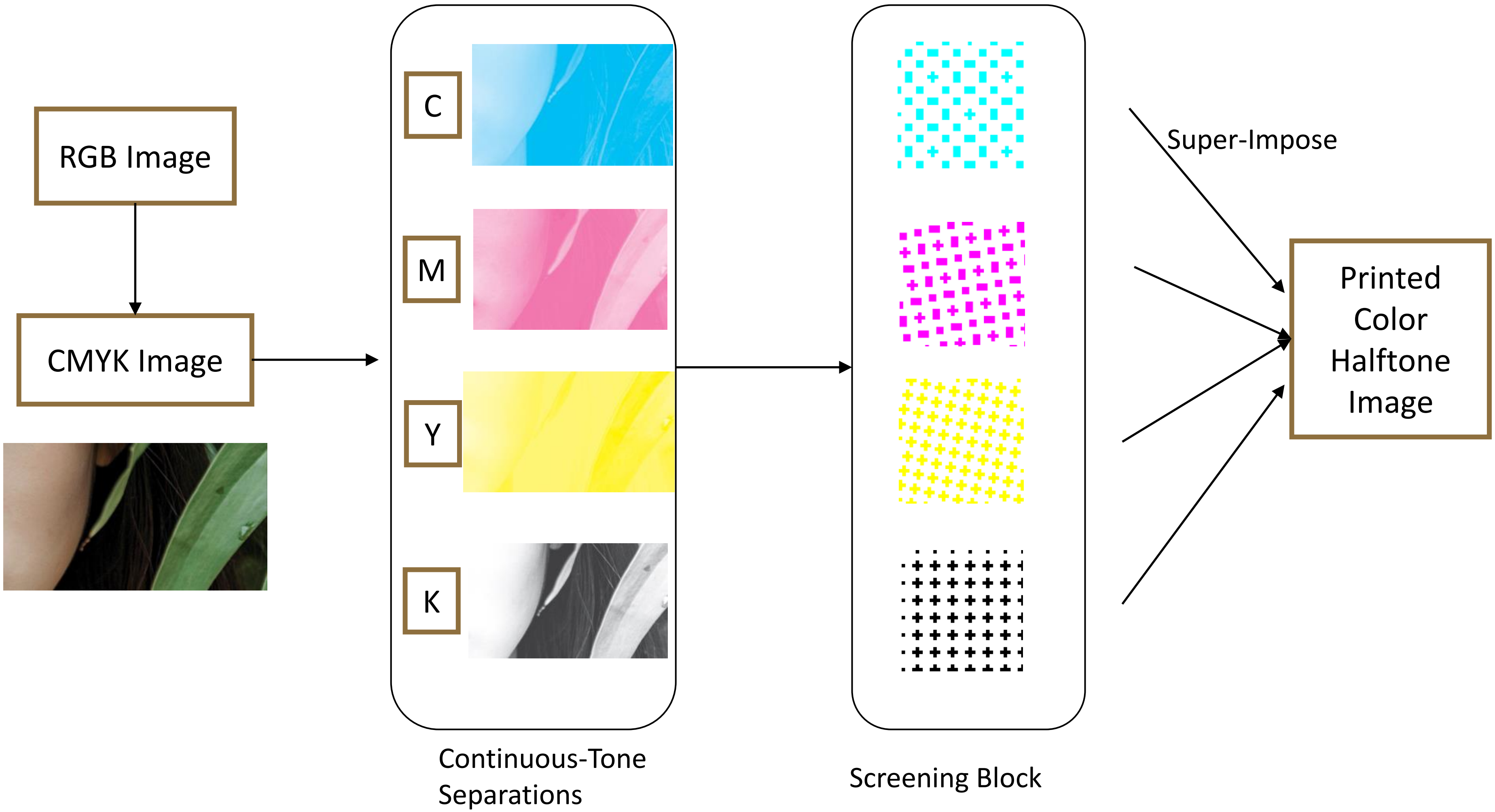
Results

- Comparisons
- Psycho-physical Experiment Results

Summary

- Contributions
- Future Work

Color Halftoning Process for Printing



Halftone Screen Set Used

The screen set used for this project:

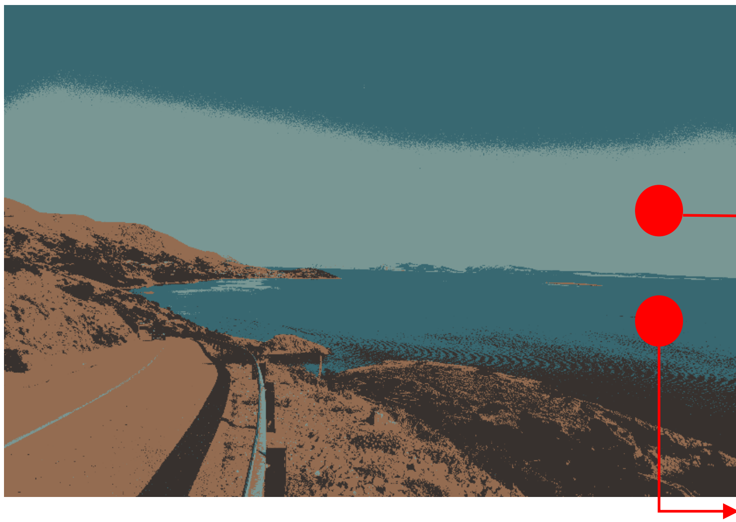
Screen Index	Indigo parameters (m, n, l (TileSize))	Periodicity matrix	Periodicity matrix (fractional)	Screen frequency (lpi)	Screen angle (°)	Tile Size
1	[3, 2, 1, 13]	$N_1 = \begin{bmatrix} 2 & -3 \\ 3 & 2 \end{bmatrix}$	$N_1 = \begin{bmatrix} 2 & -3 \\ 3 & 2 \end{bmatrix}$	225.43	56.31	13
2	[27, 27, 1, 216]	$N_2 = \begin{bmatrix} 4 & -4 \\ 4 & 4 \end{bmatrix}$	$N_2 = \begin{bmatrix} 4 & -4 \\ 4 & 4 \end{bmatrix}$	143.68	45	216
3	[56, 8, 1, 200]	$N_3 = \begin{bmatrix} 0.5 & -3.5 \\ 3.5 & 0.5 \end{bmatrix}$	$N_3 = \begin{bmatrix} 1/2 & -7/2 \\ 7/2 & 1/2 \end{bmatrix}$	229.89	81.87	200
4	[2, 3, 1, 13]	$N_4 = \begin{bmatrix} 3 & -2 \\ 2 & 3 \end{bmatrix}$	$N_4 = \begin{bmatrix} 3 & -2 \\ 2 & 3 \end{bmatrix}$	225.43	33.69	13

Printer resolution is 812.8 dpi.

T. Frank, O. Haik, A. Jumabayeva, J. P. Allebach and Y. Yitzhaky, "New Design for Compact Color Screen Sets for High-End Digital Color Press," in IEEE Transactions on Image Processing, vol. 29, pp. 3023-3038, 2020, doi: 10.1109/TIP.2019.2955295.

Content-Color-Dependent Screening Motivation

Given a fixed 4-tuple of color absorptance values, different screen assignments can yield very different halftone qualities.



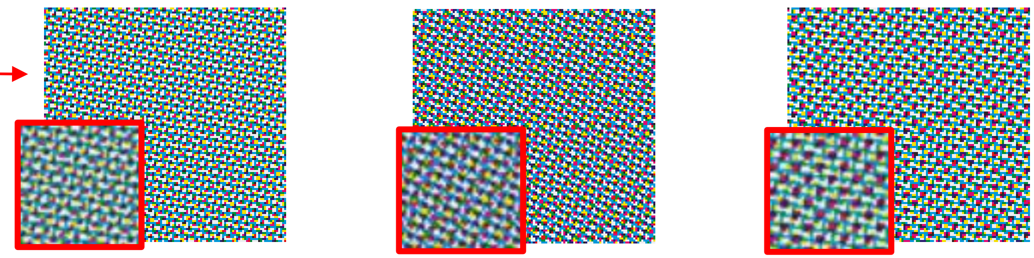
Cluster Map

(color displayed in the image is the average absorptance value of the pixels in the same color cluster)

Configurations:

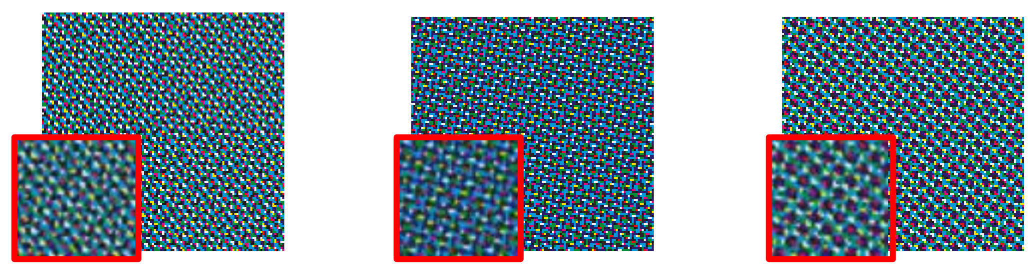
Absorptance value (C,M,Y,K)= $(0.59, 0.25, 0.33, 0.01)$

3412   1324   3214



Best Configuration

Absorptance value (C,M,Y,K)= $(0.88, 0.42, 0.39, 0.11)$



Best Configuration

Above images are 100% and150% zoom-in of the corresponding halftone patches.

Outline

Introduction

- Color halftoning background
- CCDS motivation and goal

CCDS Flow Diagram

- Cluster map
- Segmentation map
- Merged map
- CCDS halftoning image generation

Results

- Comparisons
- Psycho-physical Experiment Results

Summary

- Contributions
- Future Work

Goal of Content-Color-Dependent Screening

Given an image, cluster colors into K_{color} clusters, assign a unique screen configuration to each cluster, halftone the image using different configurations for the corresponding clusters.

In the example below, we will apply different configurations (switching the CMYK screen assignments) to the 3 clusters, cluster #1: configuration #1 (2431), cluster #2: configuration #2 (1324), cluster #3: configuration #3 (3124).

Figure 1: CMYK image.

cluster #1 (2431)
$\boldsymbol{\mu}_1 = (a_c, a_m, a_y, a_k) = (0.68, 0.63, 0.70, 0.72)$

cluster #2 (1324)
$\boldsymbol{\mu}_2 = (a_c, a_m, a_y, a_k) = (0.36, 0.46, 0.58, 0.14)$

cluster #3 (3124)
$\boldsymbol{\mu}_3 = (a_c, a_m, a_y, a_k) = (0.68, 0.36, 0.79, 0.26)$

Figure 2: Segmentation using K-means algorithm. $K_{color} = 3$

PURDUE UNIVERSITY | School of Electrical and Computer Engineering

A. Jumabayeva, T. Frank, Y. Ben-Shoshan, R. Ulichney and J. Allebach, "Content-color-dependent screening (CCDS) using regular or irregular clustered-dot halftones," 2018 7th European Workshop on Visual Information Processing (EUVIP), Tampere, 2018, pp. 1-6, doi: 10.1109/EUVIP.2018.8611727.

Outline

Introduction

- Color halftoning background
- CCDS motivation and goal

CCDS Flow Diagram

- Cluster map
- Segmentation map
- Merged map
- CCDS halftoning image generation

Results

- Comparisons
- Psycho-physical Experiment Results

Summary

- Contributions
- Future Work

Flow Diagram
for Content-Color-Dependent Screening (CCDS)

CMYK Image

K-means to cluster the image into K clusters

K is determined by elbow method

Cluster Map

Assign each segment in segment map a cluster label according to cluster map

Merged Map

Assign best halftone screen ordering according to mean absorptance values for each segmented region $\boldsymbol{\mu}_i = [a_{c,i}, a_{m,i}, a_{y,i}, a_{k,i}]$

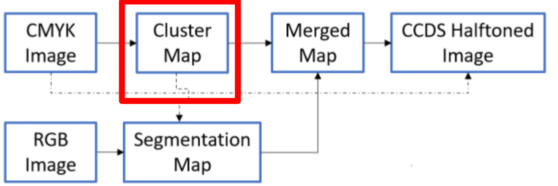
CCDS Halftoned Image

Edge detection to segment the image into S segments

RGB Image

Segmentation Map

Outline



Introduction

- Color halftoning background
- CCDS motivation and goal

CCDS Flow Diagram

- Cluster map
- Segmentation map
- Merged map
- CCDS halftoning image generation

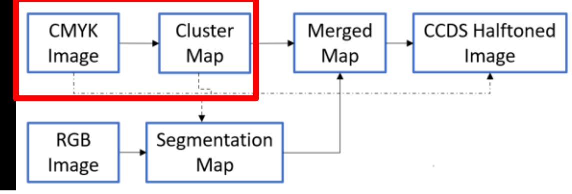
Results

- Comparisons
- Psycho-physical Experiment Results

Summary

- Contributions
- Future Work

Determine the No. of Clusters
—Elbow Method



- Elbow Method proposed to traverse the K parameter from 1 to k and calculate the W. Intuitively, this W is same to the K-means objective function.

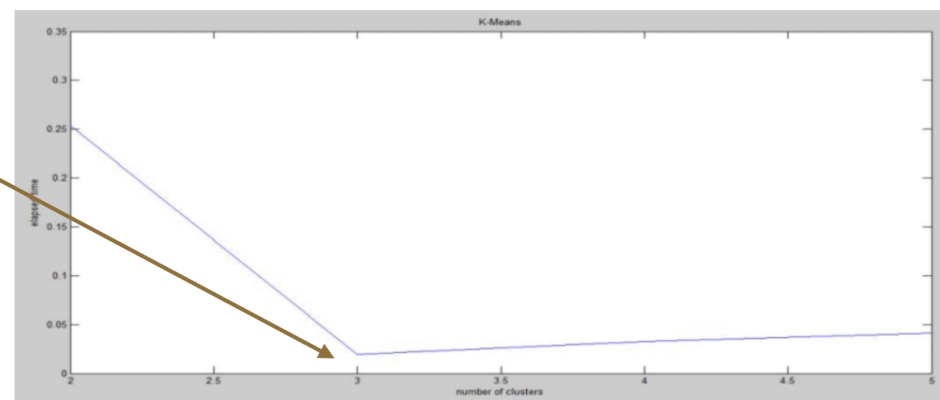
- Calculate the sum of intra-cluster distance between points in a given cluster C_k containing n_k points.

$$D_k = \sum_{x_i \in C_k} \sum_{x_j \in C_k} \left\| x_i - x_j \right\|^2 = 2n_k \sum_{x_i \in C_k} \| x_i - x_k \|^2$$

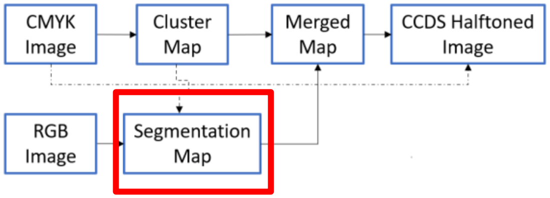
- Calculate the sum of all cluster normalized D_k:

$$W_k = \sum_{k=1}^{K} \frac{1}{2n_k} D_k$$

An elbow point can be found.



Outline



Introduction

- Color halftoning background
- CCDS motivation and goal

CCDS Flow Diagram

- Cluster map
- Segmentation map
- Merged map
- CCDS halftoning image generation

Results

- Comparisons
- Psycho-physical Experiment Results

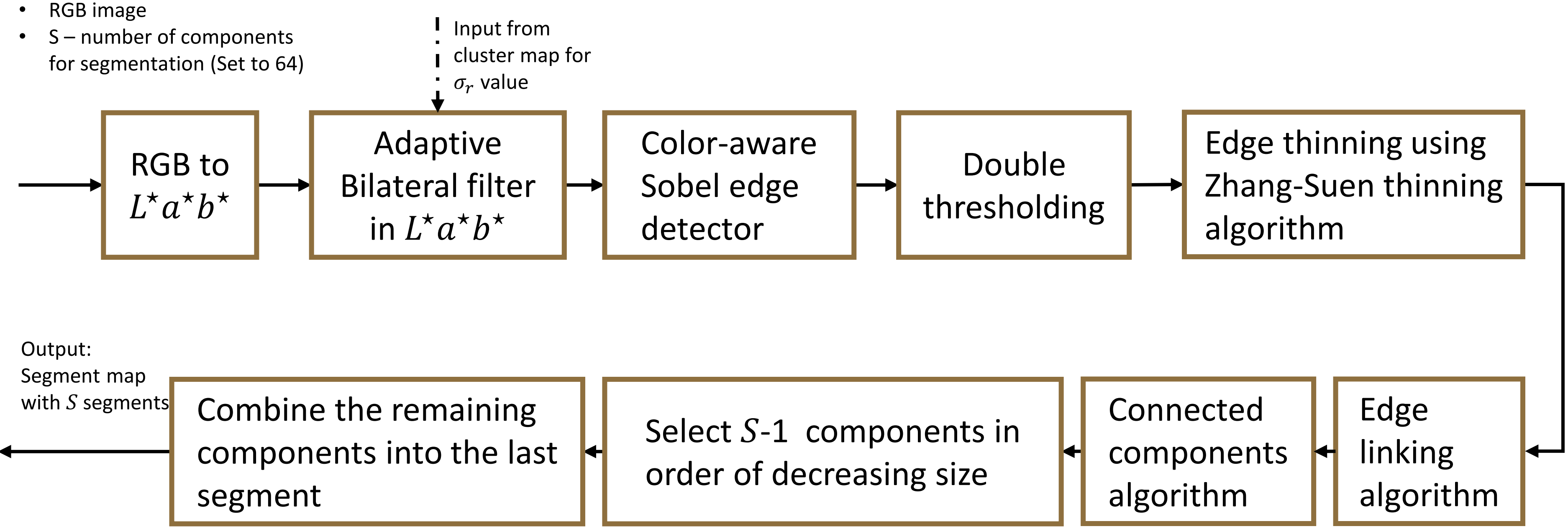
Summary

- Contributions
- Future Work

for

Generating the Segmentation Map

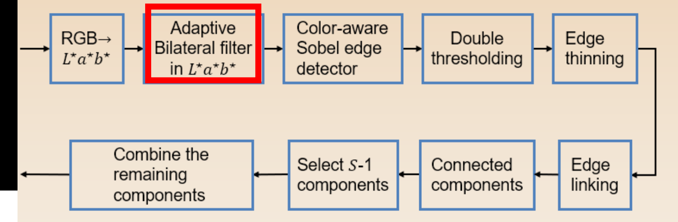
Inputs:
- RGB image
- S – number of components for segmentation (Set to 64)



The edge pixels are NOT included as one of the components.

- Xiaojun Feng, Jan P. Allebach, "Measurement of ringing artifacts in JPEG images," Proc. SPIE 6076, Digital Publishing, 60760A (17 February 2006);
- B. Zhang and J. P. Allebach, "Adaptive Bilateral Filter for Sharpness Enhancement and Noise Removal," in IEEE Transactions on Image Processing, vol. 17, no. 5, pp. 664-678, May 2008, doi: 10.1109/TIP.2008.919949.
- Zhang, T. Y., and Ching Y. Suen. "A fast parallel algorithm for thinning digital patterns." *Communications of the ACM* 27.3 (1984): 236-239.
- Benhamza, Karima, and Seridi, Hamid. "Canny Edge Detector Improvement Using an Intelligent Ants Routing." *Evolving Systems*, 2019, pp. Evolving systems, 2019–08-26.

Segment Map
— Adaptive Bilateral Filtering



- Choosing σ_r value for bilateral filtering according to images

Spatial Domain (Gaussian)
Spatial Smoothing

Range Domain
Contrast Preserving

$$\mathcal{BF}\{I_k[i_0,j_0]\} = \frac{1}{N}\sum_{i=i_0-w}^{i_0+w}\sum_{j=j_0-w}^{j_0+w}\exp\left(-\underline{\frac{(i-i_0)^2+(j-j_0)^2}{2\sigma_d^2}}-\underline{\frac{\Delta E^2(I_k[i,j],I_k[i_0,j_0])}{2\sigma_r^2}}\right)I_k[i,j]$$

, where k $= L, a^*, b^*$ for the k of I_k

Cluster Map → Group pixels with same cluster labels

↓

Calculate the ratio between the Range Domain value and the Spatial Domain Value $R_{k,[i_0,j_0]}$

↓

R_k is $R_{k,[i_0,j_0]}$ averaged over the window size.

↓

Calculate $\sigma_{r,k}^2$
(Since the pixels with same cluster labels should construct relatively smooth area, the filter should works approximate a Gaussian filtering.
Here $\sigma_{r,k}^2 = 2\cdot\sigma_d^2\cdot R_k$ is applied.)

$$R_{k,[i_0,j_0]} = \frac{\Delta E^2(I_k[i,j],I_k[i_0,j_0])}{(i-i_0)^2+(j-j_0)^2}$$

$$R_k = \frac{1}{N}\sum_{i=i_0-w}^{i_0+w}\sum_{j=j_0-w}^{j_0+w}\left(R_{k,[i_0,j_0]}\right)$$

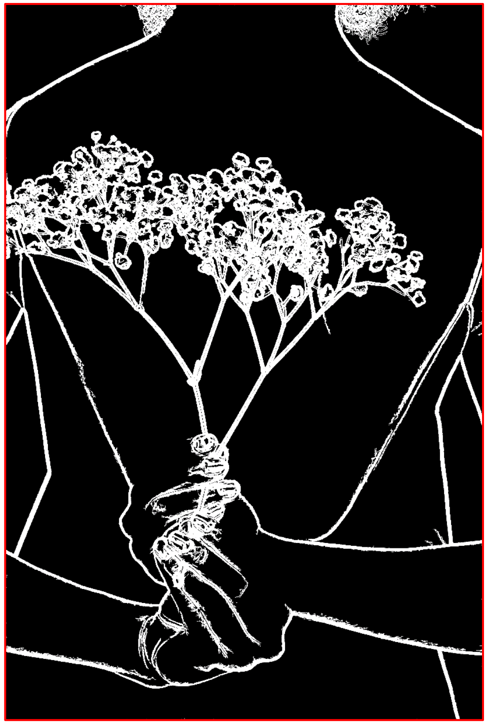
$$\sigma_{r,k}^2 = 2\cdot\sigma_d^2\cdot R_k$$

The value of σ_r is adaptive according to each image and each cluster k.

Adaptive Bilateral Filtering
— Benefits of Adaptive σ_r

Example Image: woman4, with the same $\sigma_d = 2\%$ of the diagonal of the image

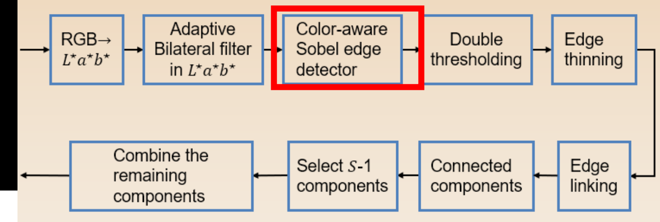
Edge Map after bilateral filtering with fixed σ_r



Edge Map after bilateral filtering with cluster-dependent σ_r

Adaptive bilateral filtering with cluster-dependent σ_r removes clutter, while preserving important edges.

Color-Aware Sobel Edge Detector



- PSFs (point spread functions) of FIR horizontal and vertical derivative filters are

$$H = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}, V = \begin{bmatrix} 1 & 2 & -1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

- To obtain the gradient magnitude

$$|g[i,j]| = \sqrt{g_H^2[i,j] + g_V^2[i,j]}$$

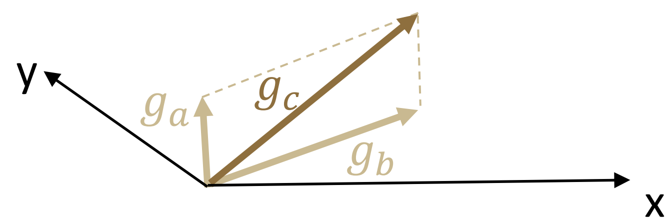
- To obtain the gradient direction:

$$\theta[i,j] = \text{atan}\left(\frac{g_V[i,j]}{g_H[i,j]}\right)$$

We apply the Sobel operator to the L, a, and b channels separately and obtain the gradient magnitudes $|g_L[i,j]|$ for the L channel, and $|g_C[i,j]|$ for the chroma channel**, respectively.**

The latter is defined by vector addition between g_a and g_b:

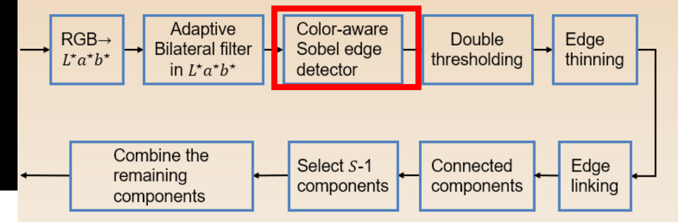
$$|g_C[i,j]| = |g_a[i,j]|\angle\theta_a[i,j] + |g_b[i,j]|\angle\theta_b[i,j]$$



$$Edge\ Map = thr(|g_L|) \cup thr(|g_c|)$$

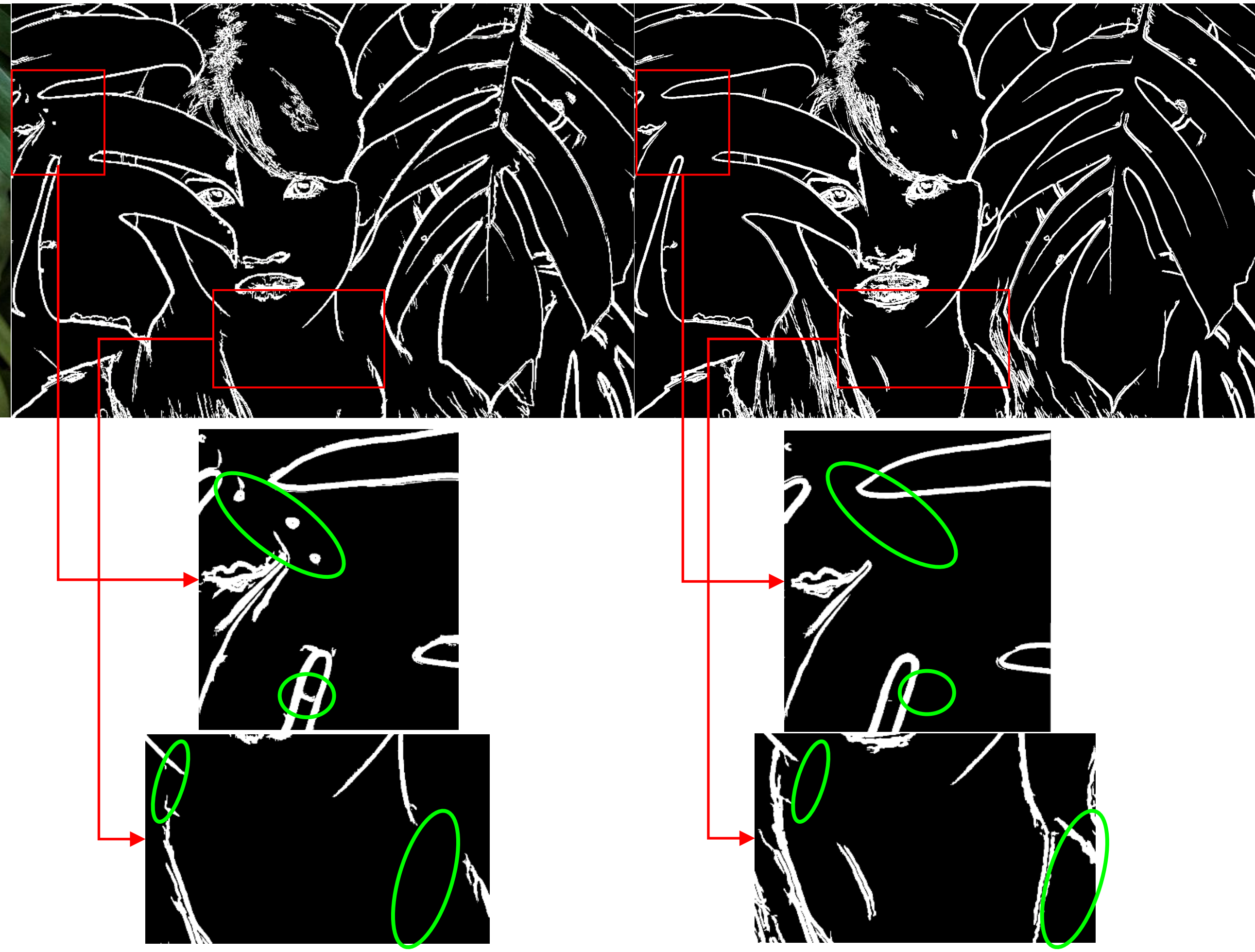
Concepts for Chroma and Hue:
Gevers, Theo, et al. *Color in computer vision: fundamentals and applications*. Vol. 23. John Wiley & Sons, 2012.

Benefits of New Color Aware Sobel Edge Detector



Example Image: woman3

Edge Maps



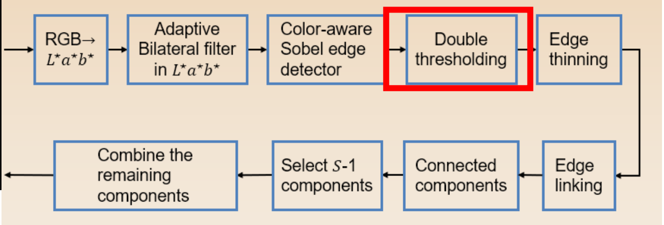
Feature Comparison (New vs. Old):

- Edges are more continuous.
- Isolated features are removed.

Old: $thr(\sqrt[2]{|g_L[i,j]|^2 + |g_a[i,j]|^2 + |g_b[i,j]|^2})$

New: $thr(|g_L|) \cup thr(|g_c|)$

Segment Map — Double thresholding



- **The double thresholding algorithm uses 2 thresholds:**

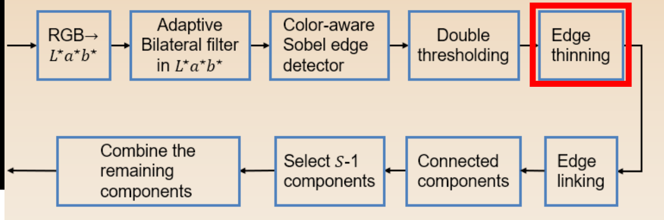
$$T_{high} \text{ and } T_{low}.$$

- **A pixel at** $[m, n]$ **is called a strong pixel if** $|g_{Lab}[i,j]| > T_{high}$.
- **A pixel at** $[m, n]$ **is called a weak pixel if** $|g_{Lab}[i,j]| \leq T_{low}$.
- **All other pixels are called candidate pixels.**
- **Iterate the steps below until there are no more changes:**
  - In each position $[i, j]$, discard the pixel if it is weak; output the pixel if it is strong.
  - If the candidate pixel $[i, j]$ is connected to a strong pixel (8x8 connectivity), output this candidate pixel; otherwise, do not output the candidate pixel.

PURDUE UNIVERSITY | School of Electrical and Computer Engineering

Fang, M., Yue, G., & Yu, Q. (2009). The study on an application of Otsu method in Canny operator. In Proceedings. The 2009 International Symposium on Information Processing (ISIP 2009) (p. 109). Academy Publisher.

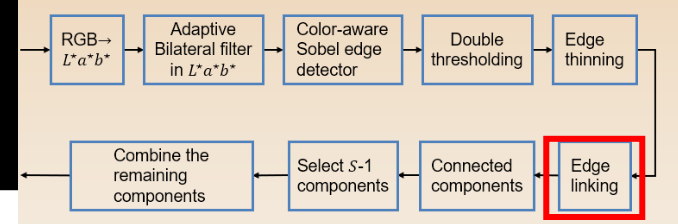
Edge Thinning



- The goal of thinning algorithms is to take a binary image and draw a 1 pixel wide skeleton of that image while retaining the shape and structure of the full image.
- The Zhang-Suen Thinning algorithm is probably the most used thinning algorithm. Devised in 1984, the algorithm is what is called a 2-pass algorithm, meaning that for each iteration it performs two sets of checks to remove pixels from the image.

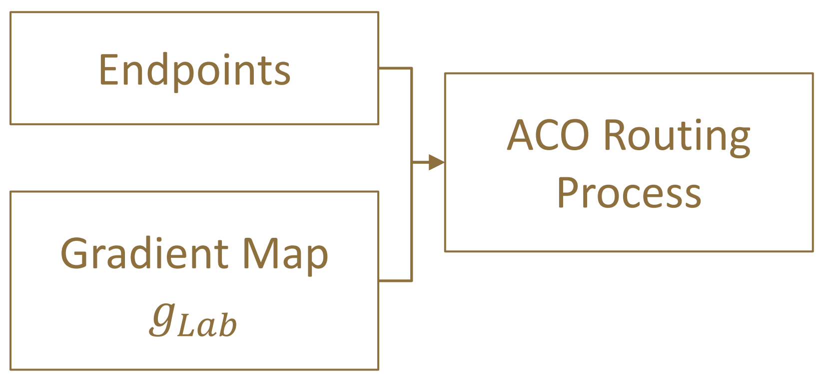
Zhang, T. Y., & Suen, C. Y. (1984). A fast parallel algorithm for thinning digital patterns. *Communications of the ACM*, *27*(3), 236-239.

Edge Linking Algorithm



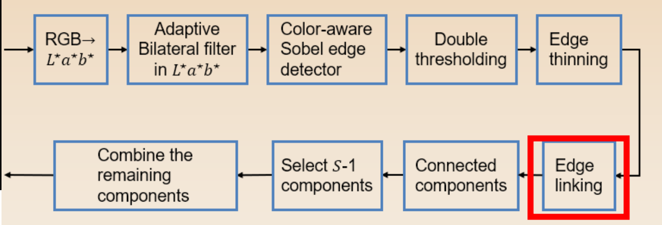
Ant Colony Optimization (ACO) algorithm

- The endpoints are extracted from the thinned edges.
- These end points are used as the initial starting positions of the virtual ants.
- The missing pixels edges are iteratively retraced through the movements of ants depositing pheromone trails.
- This pheromone quantity is updated locally after each ant moves and globally after the all the ant movements.



Benhamza, K., & Seridi, H. (2021). Canny edge detector improvement using an intelligent ants routing. *Evolving Systems*, *12*(2), 397-406.

Edge Linking Algorithm — Details



Preparation:

- Find all the edge endpoints based on the thinned edges.
- The endpoint type(N,S,W,E,NW,NE,SW,SE) for every endpoint is saved to record where the edge comes from.
- Heuristic matrix w is rotated according to the endpoints type.

  Example of an ant comes from south:

1/2	1	1/2
1/4	Ant	1/4
1/12	1/20	1/12

- Calculate the gradient magnitude variation map V_g based on the gradient magnitude map g_{lab}.

$$V_g(i,j) = \max(|g_{lab}[i-1,j-1] - g_{lab}[i+1,j+1]|, \\ |g_{lab}[i-1,j+1] - g_{lab}[i+1,j-1]|, \\ |g_{lab}[i-1,j] - g_{lab}[i+1,j]|, \\ |g_{lab}[i,j-1] - g_{lab}[i,j+1]|)$$

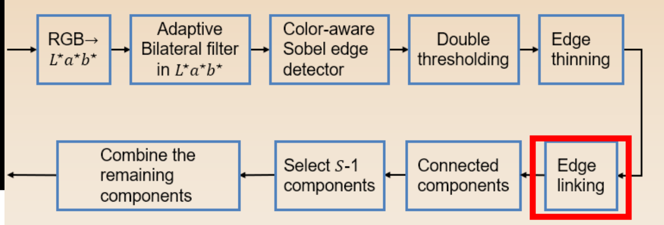
Initialization:

- The number of ants is equal to the number of edge endpoints.
- Pheromone trail matrix is initialized as $\tau^0(i,j) = \frac{V_g(i,j)}{V_{g,max}}$,

  where i, j are position of the pixels, $V_{g,max}$ is the maximum value of matrix V_g.

Benhamza, K., & Seridi, H. (2021). Canny edge detector improvement using an intelligent ants routing. *Evolving Systems*, *12*(2), 397-406.

Edge Linking Algorithm — Details



Probability Transition Matrix (the probability for an ant's movements from one pixel to another)

- For n^{th}movement, k^{th} endpoints, $P_{(p,q)}^{n} = \frac{(\tau^{n-1}(p,q))^{\alpha} w^{\beta}}{\sum_{(p,q)\in\Omega_k}(\tau^{n-1}(p,q))^{\alpha} w^{\beta}}$,

where (p, q) are the locations of neighbors of the k^{th} endpoints, α, β are two constant characterizing the influence of the pheromone matrix τ and the heuristic matrix w respectively. Here $\alpha = 0.5$, $\beta = 1$.

- Among the 8 neighbors, the position with the largest probability is where the ant moves to.

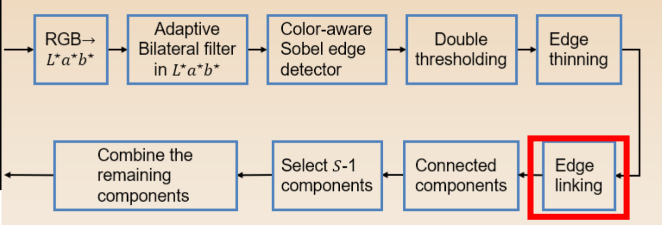
Pheromone update rule:

- Local pheromone update: $\tau^{n}(i, j) = (1 - \Psi) \cdot \tau^{n-1}(i, j) + \Psi \cdot \tau^{0}(i, j)$,
  where $\Psi \in [0,1]$ denotes the local pheromone evaporation ratio.
- Global pheromone update: $\tau^{n} = \begin{cases} (1-\rho)\tau^{n-1} + \rho/D_{n-1} & \text{If the pixel is selected to be moved to} \\ \tau^{n-1} & \text{Otherwise} \end{cases}$

where D_{n-1} is the path length travelled by the ant, $1/D_{n-1}$is the pheromone amount deposited by the ant, ρ is the evaporation constant. Here, $\rho = 0.5$.

Benhamza, K., & Seridi, H. (2021). Canny edge detector improvement using an intelligent ants routing. *Evolving Systems*, *12*(2), 397-406.

Edge Linking Algorithm — Details

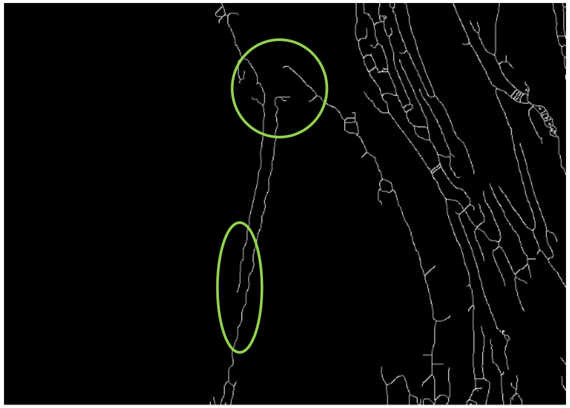


Stop criteria:

- If the maximum number of iterations is reached.
- If some portion of the ants has successfully travelled from one edge segment to another.
- If the ant come cross another ant's path, it stops and the other ant returns to its own original segment.

Results:

Edge Map before edge thinning algorithm



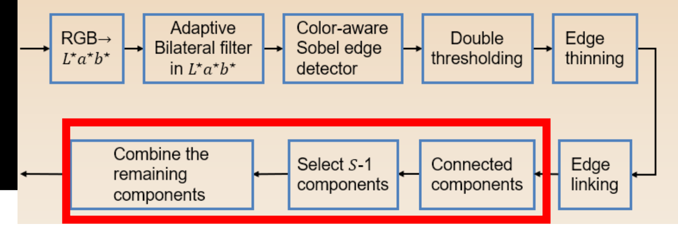
After Edge Thinning Before ACO

After Edge Thinning and ACO

School of Electrical and Computer Engineering

Benhamza, K., & Seridi, H. (2021). Canny edge detector improvement using an intelligent ants routing. *Evolving Systems*, *12*(2), 397-406.

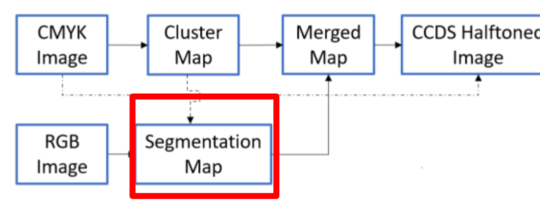
Generating the Segmentation Map



Flood fill the isolated black areas and mark them to be separated segments

Edge Map
(Edge pixels are highlighted to be white)

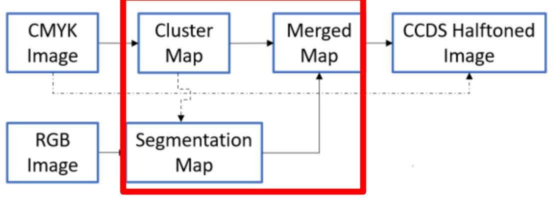
Segmentation Map
(Edge pixels are not one of any segment)



PURDUE UNIVERSITY
School of Electrical and Computer Engineering

Soille, P., *Morphological Image Analysis: Principles and Applications*, Springer-Verlag, 1999, pp. 173–174.

Outline



Introduction

- Color halftoning background
- CCDS motivation and goal

CCDS Flow Diagram

- Cluster map
- Segmentation map
- Merged map
- CCDS halftoning image generation

Results

- Comparisons
- Psycho-physical Experiment Results

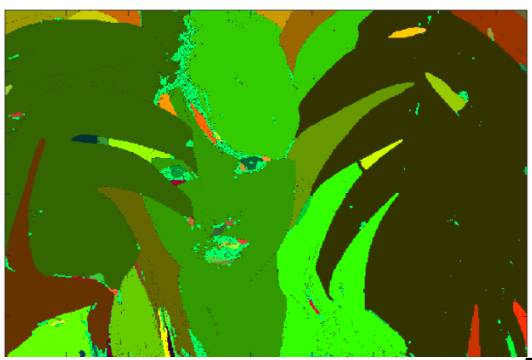
Summary

- Contributions
- Future Work

Generating Merged Map — Procedures

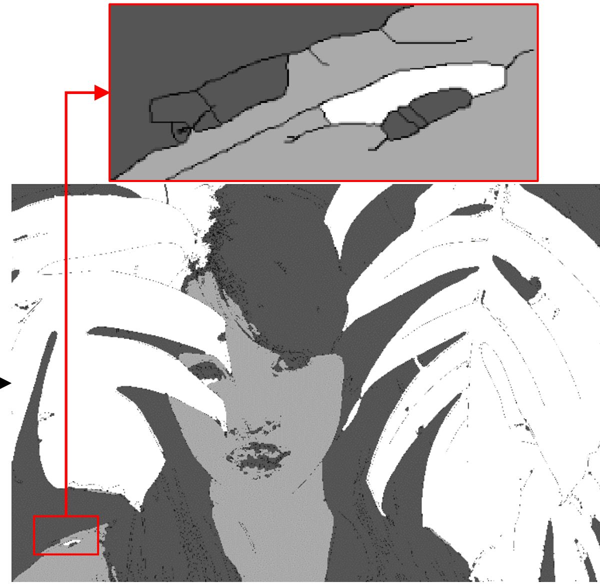
Cluster Map

(Cluster map is generated by K means. Pixels are colored with the average cluster color.)

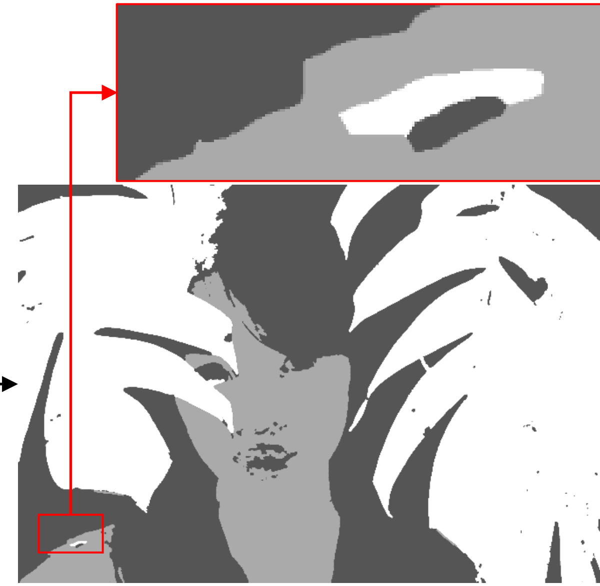


Segmentation Map

(Edge pixels are not one of any segment)



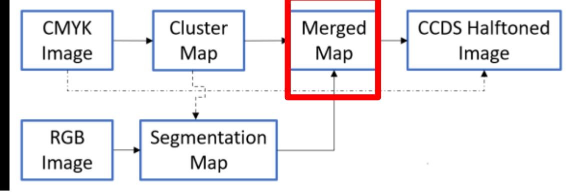
Each segment is labeled with the cluster label that corresponds to the largest number of pixels in that segment.



Edge pixels are merged with neighboring segments.

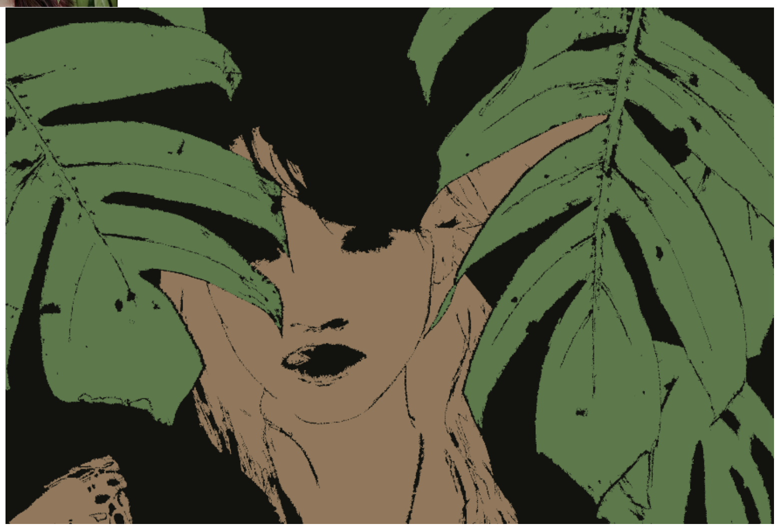
Small segments are merged to large segments by morphological closing

Generating Merged Map



Final Merged Map

(Each segment is displayed with mean absorptance values)



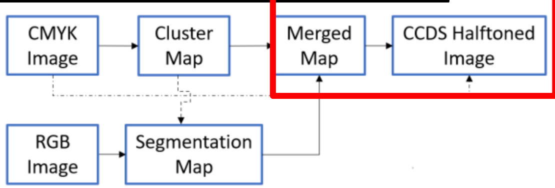
Merged map generated by previous CCDS algorithm.

Improvements with new adaptive bilateral filtering and new segmentation approach:

- Edge pixels are merged to neighboring segments.
- Parameters are not manually selected.
- No small segments.

A. Jumabayeva, T. Frank, Y. Ben-Shoshan, R. Ulichney and J. Allebach, "Content-color-dependent screening (CCDS) using regular or irregular clustered-dot halftones," 2018 7th European Workshop on Visual Information Processing (EUVIP), Tampere, 2018, pp. 1-6, doi: 10.1109/EUVIP.2018.8611727.

Outline



Introduction

- Color halftoning background
- CCDS motivation and goal

CCDS Flow Diagram

- Cluster map
- Segmentation map
- Merged map
- CCDS halftoning image generation

Results

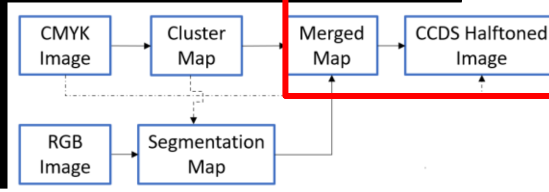
- Comparisons
- Psycho-physical Experiment Results

Summary

- Contributions
- Future Work

PURDUE UNIVERSITY | School of Electrical and Computer Engineering

Generating CCDS Halftoned Image — Overview



Input:
CMYK continuous-tone image

Halftone each segment using the best screen assignment

Output:
Content-color-dependent halftoned image

Input:
Merged map regions (indicate to which cluster number (1~ K) each pixel is assigned).

If the delta E values of a given screen assignment for two clusters are less than 0.5 from the delta E values of their best color assignments, the screen assignments of **the two clusters are merged to one**.

...

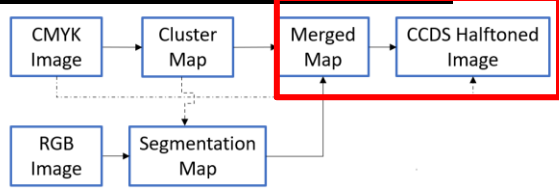
Merged map region mean absorptance values ($\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \dots, \boldsymbol{\mu}_K$, where $\boldsymbol{\mu}_i = [a_{c,i}, a_{m,i}, a_{y,i}, a_{k,i}]$)

For each $\boldsymbol{\mu}_i$, find the **best screen assignment** out of 24 possible screen assignments using spatiochromatic HVS model

A. Jumabayeva, T. Frank, Y. Ben-Shoshan, R. Ulichney and J. Allebach, "Content-color-dependent screening (CCDS) using regular or irregular clustered-dot halftones," 2018 7th European Workshop on Visual Information Processing (EUVIP), Tampere, 2018, pp. 1-6, doi: 10.1109/EUVIP.2018.8611727.
Jumabayeva, A., Frank, T., Ben-Shoshan, Y., Ulichney, R., & Allebach, J. (2016). HVS-based model for superposition of two color halftones. *Electronic Imaging, 2016*(20), 1-9.

CCDS Halftoned Image

— Merging Clusters Algorithm



Algorithm 1: Merging Clusters Algorithm

Result: The merged clusters

Initial $\Delta E_{1-hot} = \Delta E < 1.1 \cdot \Delta E_{opt}$;

Initial $\Delta E_{percent} = \Delta E / \Delta E_{opt}$;

Initialize a graph structure with C vertices;

for *cluster* A **do**

  for *screen assignment pair candidates* $[i, [A, B]]$ **do**

    Calculate $S_i = \Delta E_{percent}[i, A] + \Delta E_{percent}[i, B]$;

  end

  Find the smallest S_i value and assign it to be the edge value from vertex A to vertex B;

end

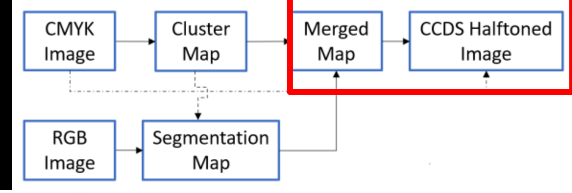
if *vertex* A *has more than* 1 *edge* **then**

  Assign the edge with the smallest edge value to be the only edge connected to vertex A;

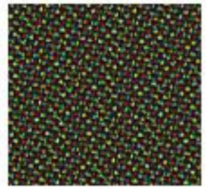
end

Remaining edges are the connecting the pairs of the merged clusters.;

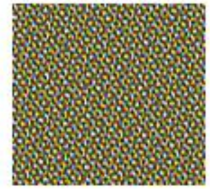
CCDS Halftoned Image
— Merging Clusters Algorithm - Example



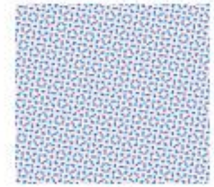
Cluster number:



1



2



3

Blue dots mark the best configuration among all the possible combinations.

Delta E Tables:

CMYK Image

Cluster Map before Merging

Cluster 1:

	CMYK	delta E
1	4321	4.88
2	4312	4.93
3	4231	5.41
4	4213	4.41
5	4132	5.49
6	4123	4.45
7	3421	5.02
8	3412	5.18
9	3241	5.01
10	3214	4.82
11	3142	5.18
12	3124	4.84
13	2431	5.48
14	2413	5.52
15	2341	5.08
16	2314	4.97
17	2143	5.65
18	2134	5.48
19	1432	5.50
20	1423	4.41
21	1342	4.86
22	1324	4.73
23	1243	4.47
24	1234	5.42

Cluster 2:

	CMYK	delta E
1	4321	3.47
2	4312	5.84
3	4231	5.25
4	4213	5.25
5	4132	5.74
6	4123	4.81
7	3421	3.41
8	3412	5.71
9	3241	5.23
10	3214	5.13
11	3142	5.85
12	3124	3.61
13	2431	5.15
14	2413	5.18
15	2341	5.18
16	2314	5.08
17	2143	5.25
18	2134	5.17
19	1432	5.74
20	1423	4.81
21	1342	5.98
22	1324	3.66
23	1243	5.30
24	1234	5.25

Cluster 3:

	CMYK	delta E
1	4321	1.19
2	4312	1.17
3	4231	2.40
4	4213	2.39
5	4132	1.34
6	4123	1.33
7	3421	1.19
8	3412	1.16
9	3241	2.96
10	3214	2.96
11	3142	1.52
12	3124	1.52
13	2431	2.09
14	2413	2.08
15	2341	2.62
16	2314	2.62
17	2143	2.08
18	2134	2.09
19	1432	1.34
20	1423	1.33
21	1342	1.62
22	1324	1.63
23	1243	2.11
24	1234	2.12

Cluster No. 2 will be merged with cluster No. 3, with screen assignment (3,4,2,1)

Outline

Introduction

- Color halftoning background
- CCDS motivation and goal

CCDS Flow Diagram

- Cluster map
- Segmentation map
- Merged map
- CCDS halftoning image generation

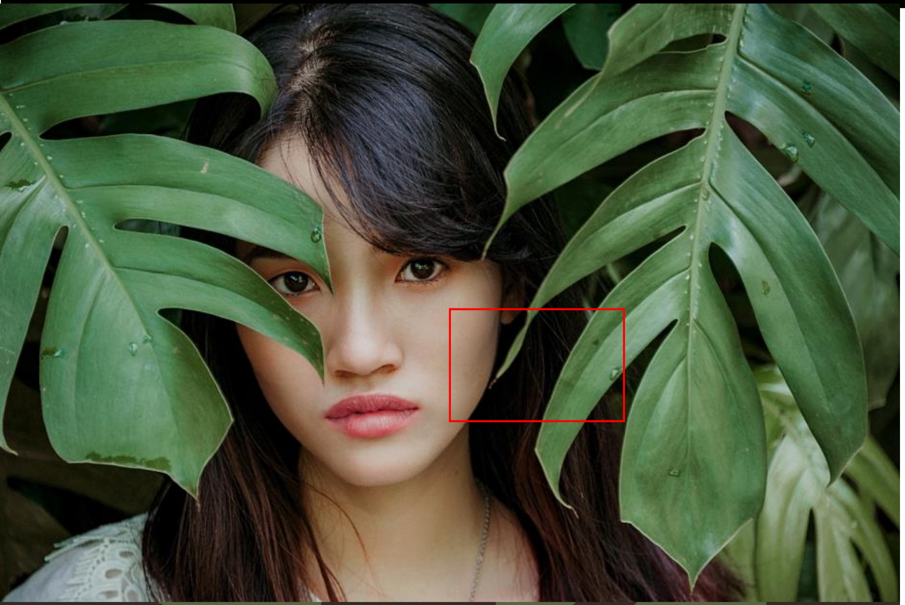
Results

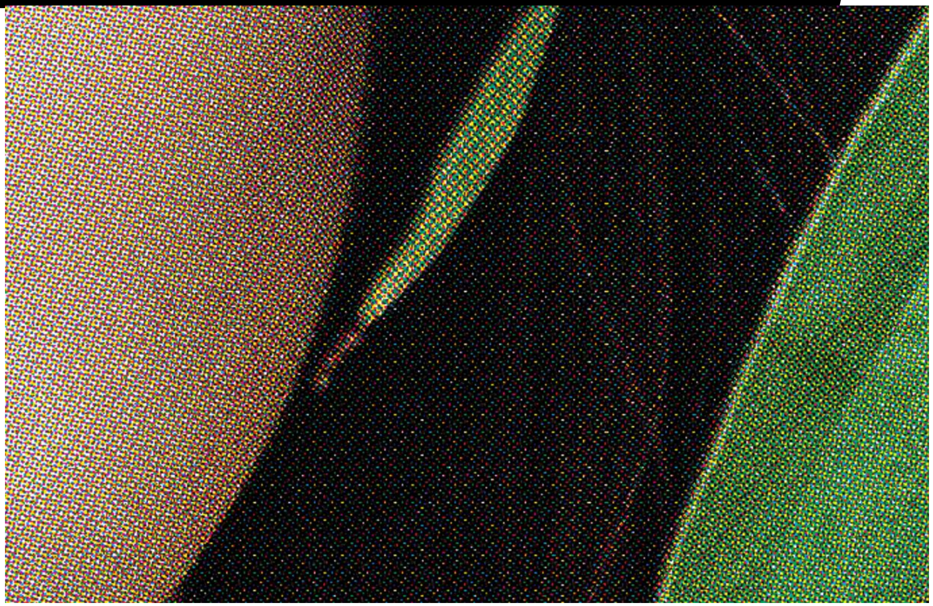
- Comparisons
- Psycho-physical Experiment Results

Summary

- Contributions
- Future Work

CCDS Halftoned Image Result

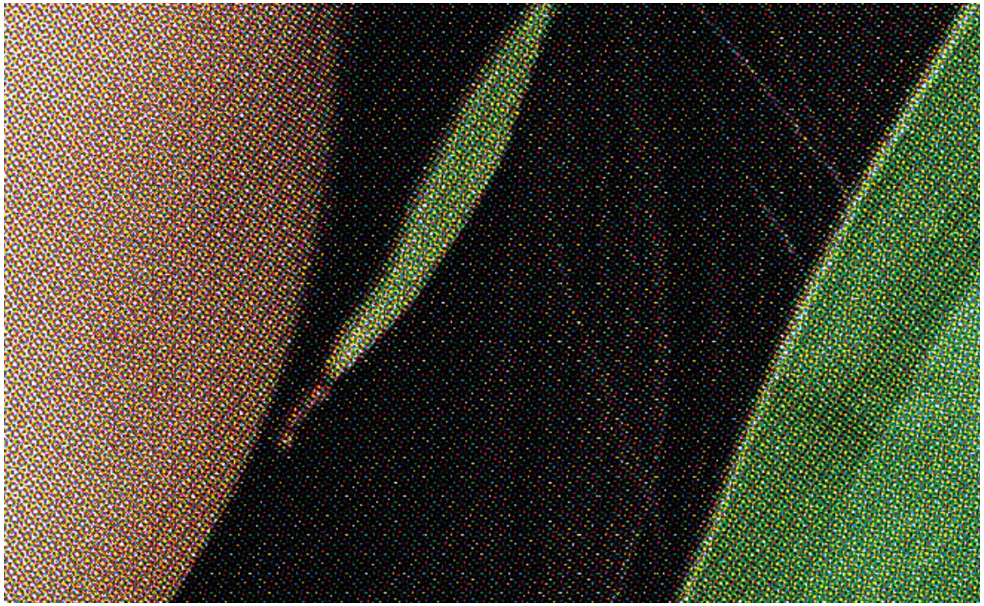


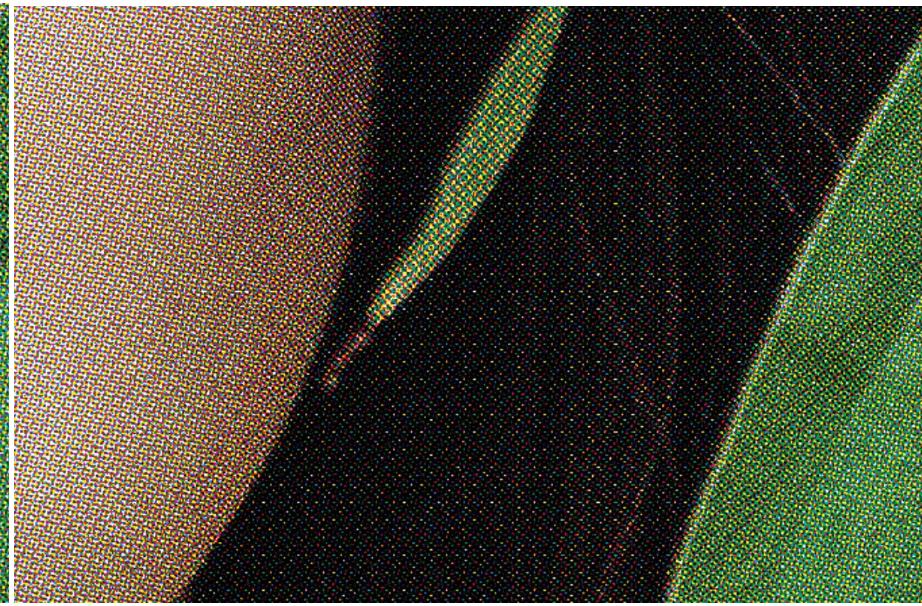


Above image is 180% zoom-in of the halftone image.

No texture discontinuity when switching screens.
No parameters that need to be manually selected.

CCDS Halftoned Image Result
—Comparison with Single Screening Configuration Halftone Process





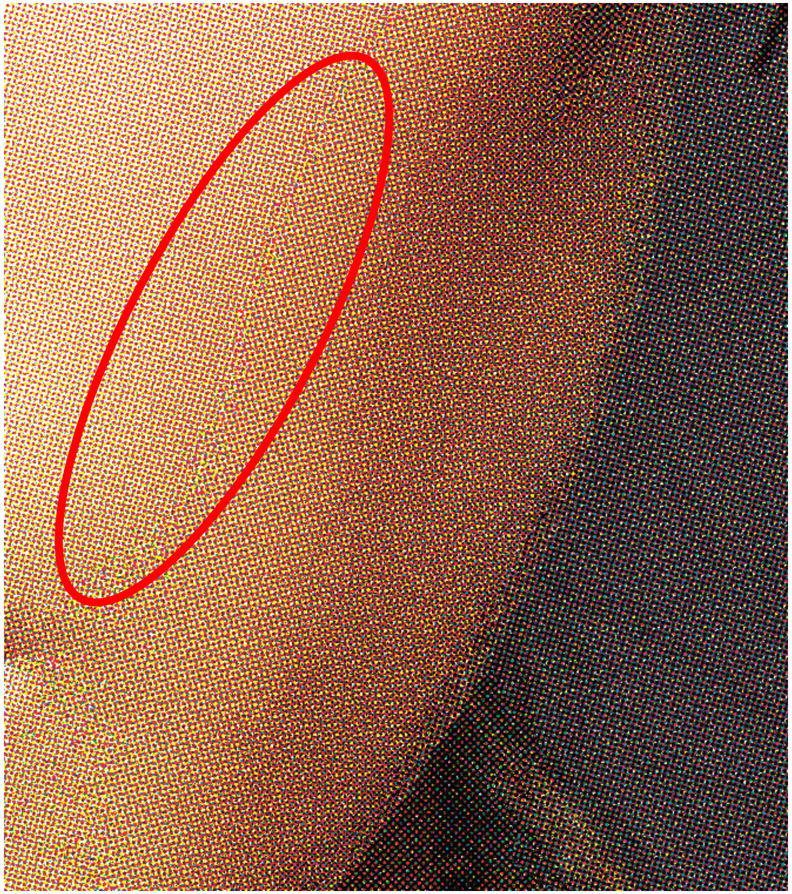
Above images are 180% zoom-in of the halftone image.

Halftone Image with single screen configuration (Best screen configuration according to the whole image.)

Updated CCDS Method with
adaptive bilateral filtering,
multi-channel edge detection,
and updated segmentation method.

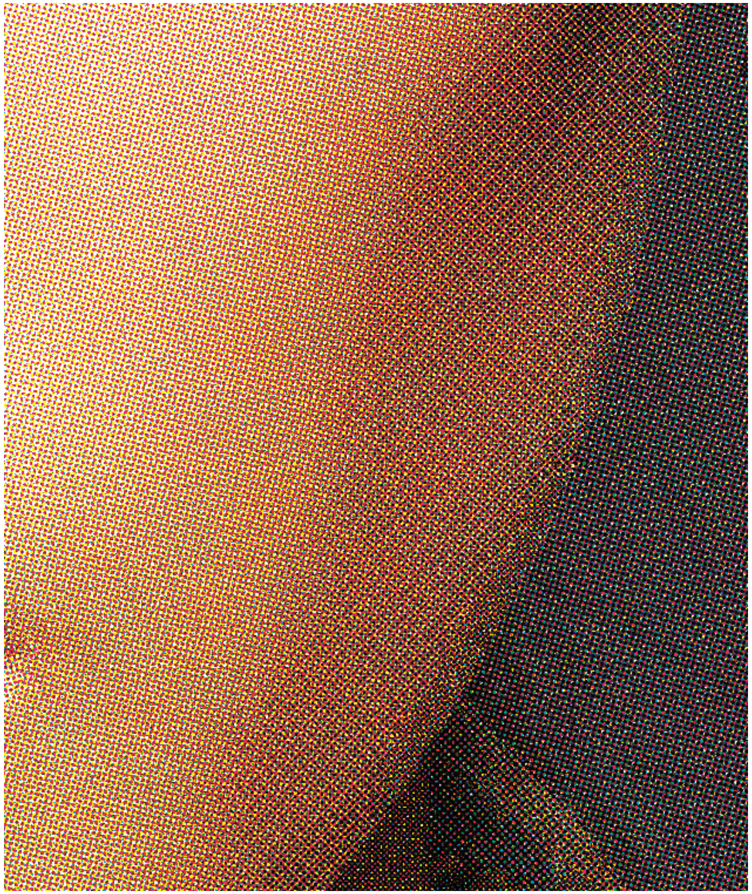
Less noise (smoother).

CCDS Halftoned Image Result
—Comparison with CCDS that is not Based on Edge Detection Process

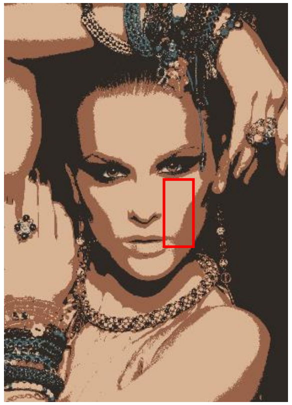


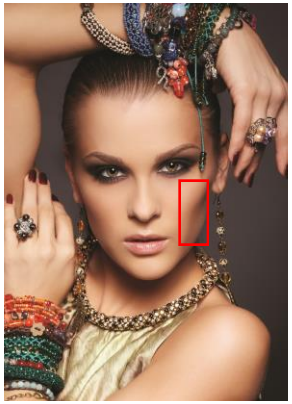
CCDS Method
Based on cluster map only
Not based on segmentation map

Note highlighted transition between different screen assignments



Updated CCDS Method with updated adaptive bilateral filtering, multi-channel edge detection, and updated segmentation method.





Outline

Introduction

- Color halftoning background
- CCDS motivation and goal

CCDS Flow Diagram

- Cluster map
- Segmentation map
- Merged map
- CCDS halftoning image generation

Results

- Comparisons
- Psycho-physical Experiment Results

Summary

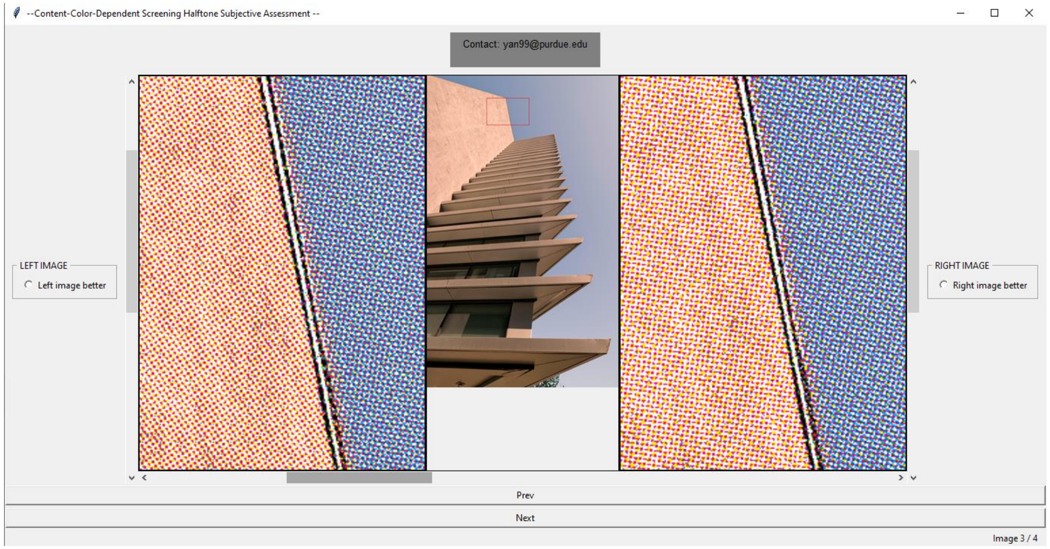
- Contributions
- Future Work

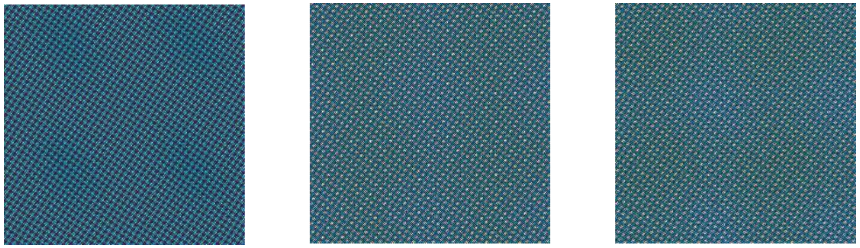
Contribution

- Added elbow method to determine the number of clusters.
- Developed a cluster-based adaptive bilateral filter.
- Developed the color-aware Sobel edge detector.
- Added edge linking based on ant colony optimization algorithm.
- Developed cluster merging algorithm based on graph structure.
- Performed a psycho-physical experiment to establish benefit of CCDS (near future).

Future Work

- Psychophysical experiment based on digital halftoning images will be performed.





Same absorptance, same screen,
only generated with different configuration.

But the color looks different.
This is an issue for color management.

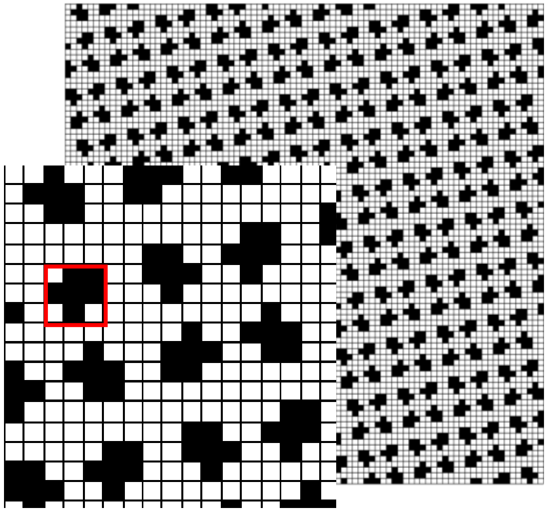
THANK YOU!

Indigo geometry
$[m, n, l, tileSize] = [6, 23, 1, 112]$.
Screen Frequency: 172.48 lpi.
Screen Angle: 14.62°.

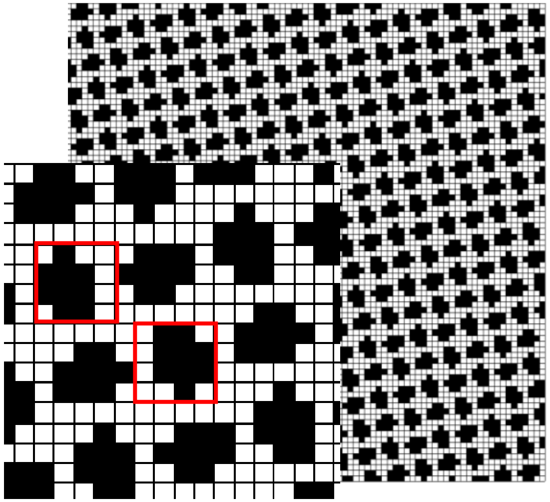
Irregular Screen Example

$$\mathbf{N} = \begin{bmatrix} 4.56 & -1.19 \\ 1.19 & 4.56 \end{bmatrix}$$

Microcell area: $\det \mathbf{N} = 22.21$



absorptance = 0.30



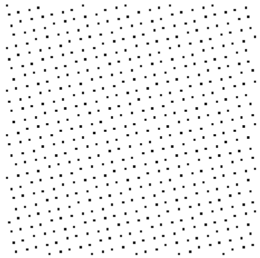
absorptance = 0.40

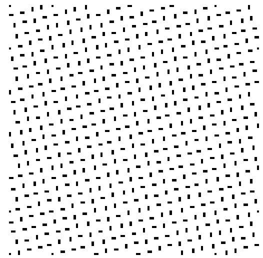
Irregular Screen Example

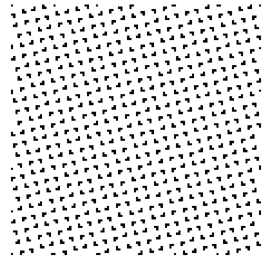
Indigo geometry
$[m, n, l, tileSize] = [6, 23, 1, 112]$.
Screen Frequency: 172.48 lpi.
Screen Angle: 14.62°.

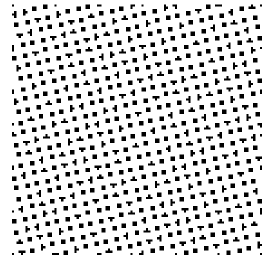
$$\mathbf{N} = \begin{bmatrix} 4.56 & -1.19 \\ 1.19 & 4.56 \end{bmatrix}$$

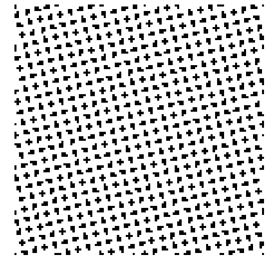
Microcell area: $\det \mathbf{N} = 22.21$

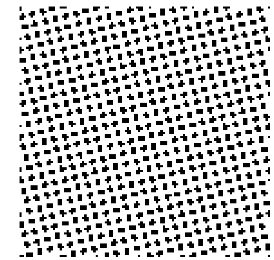

Absorptance = 1/24

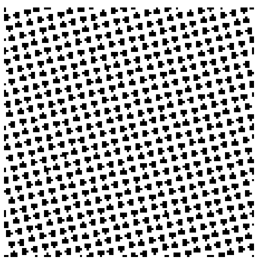

Absorptance = 2/24

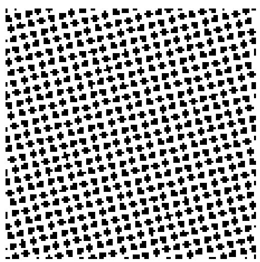

Absorptance = 3/24

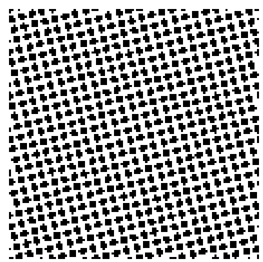

Absorptance = 4/24

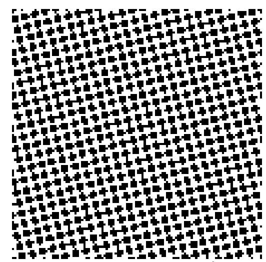

Absorptance = 5/24

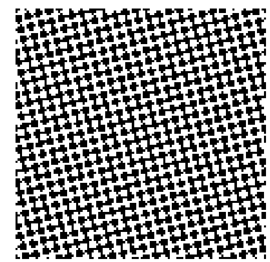

Absorptance = 6/24

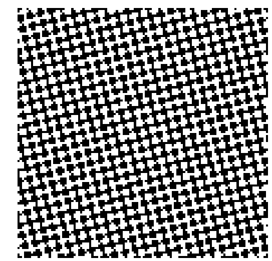

Absorptance = 7/24

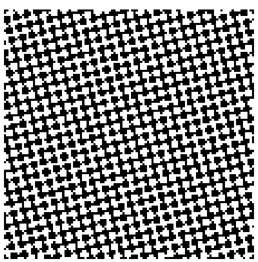

Absorptance = 8/24

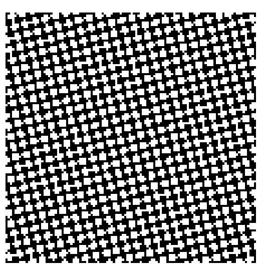

Absorptance = 9/24

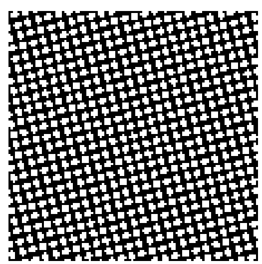

Absorptance = 10/24

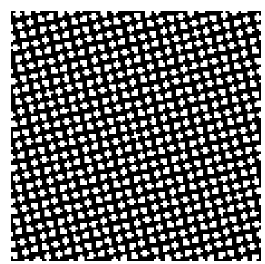

Absorptance = 11/24

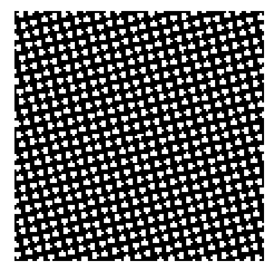

Absorptance = 12/24

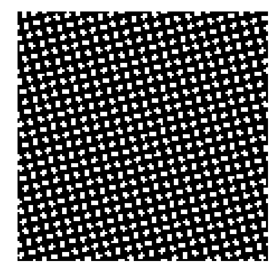

Absorptance = 13/24

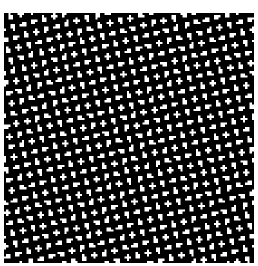

Absorptance = 14/24

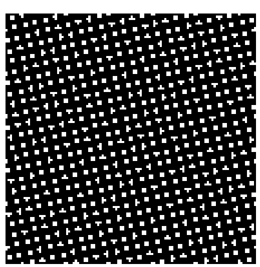

Absorptance = 15/24

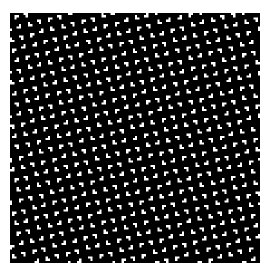

Absorptance = 16/24

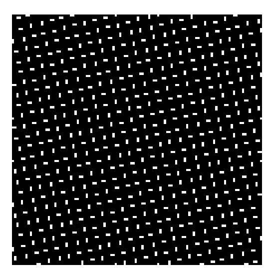

Absorptance = 17/24

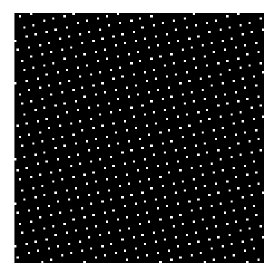

Absorptance = 18/24


Absorptance = 19/24


Absorptance = 20/24


Absorptance = 21/24


Absorptance = 22/24


Absorptance = 23/24


Absorptance = 1

CCDS HALFTONED IMAGE — REDUCING NO. OF CLUSTERS

For each $\boldsymbol{\mu}_i$, find the best color assignment out of 24 possible color assignments using HVS based model

Merge Clusters

Output:

- Best color assignment for each cluster
- Final assignment of number of clusters

	CMYK	delta E
1	4321	4.30
2	4312	7.00
3	4231	6.19
4	4213	4.97
5	4132	5.26
6	4123	4.27
7	3421	4.39
8	3412	6.29
9	3241	5.16
10	3214	5.12
11	3142	6.29
12	3124	4.45
13	2431	5.22
14	2413	5.12
15	2341	5.71
16	2314	5.36
17	2143	5.04
18	2134	5.05
19	1432	5.25
20	1423	4.25
21	1342	7.04
22	1324	4.13
23	1243	5.08
24	1234	6.19

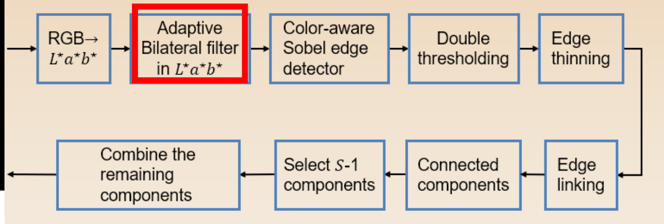
Best color assignment

Sample chart for each possible combination of the 4 screens applied to a certain absorptance value $\boldsymbol{\mu}_i$ in CMYK space.

Merge Clusters:

- If two clusters have common best color assignments or the delta E error is less than 0.5 from the delta E value of its best color assignment:
  - » These two clusters are merged.
  - » The number of clusters is reduced by 1.

Adaptive Bilateral Filtering



- Choosing σ_r value for bilateral filtering according to image

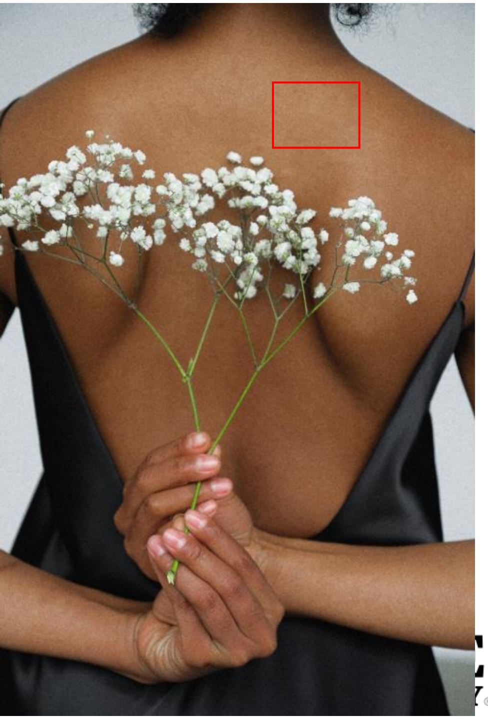
Spatial Domain (Gaussian) Spatial Smoothing

Range Domain Contrast Preserving

$$\mathcal{BF}\{I_k[m_0,n_0]\} = \frac{1}{N}\sum_{m=m_0-w}^{m_0+w}\sum_{n=n_0-w}^{n_0+w}\exp\left(\underbrace{-\frac{(m-m_0)^2+(n-n_0)^2}{2\sigma_d^2}}_{}\underbrace{-\frac{\Delta E^2(I_k[m,n],I_k[m_0,n_0])}{2\sigma_r^2}}_{}\right)I_k[m,n]$$

, where k $= L, a^*, b^*$ for the k of I_k

Image



Cluster Map

Since the pixels with same cluster labels should form a relatively smooth area, the filter should approximate Gaussian filtering.

Since $\sigma_d = 2\%$ of the diagonal of the image is fixed for the image, to force the bilateral filter to smooth an area considered to be “smooth”, σ_r is calculated according to each cluster.

The value of σ_r is adaptive according to each cluster within the image.