TEAM BLOB

Blob Segmentation

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THE BLOB

Abstract

Given a set of placental histology slides our goal was to isolate blobs and their corresponding vessels, then compare the results for accuracy.

Goals? What goals?
Our Project

- Examine different preprocessing applications
- Apply various blob segmentation methods
- Take a hand sketching of isolated blobs and compare methods
- Determine accuracy

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Break it Down

IN CASE YOU FORGOT
HISTOLOGY SLIDES
PREPROCESSING
FROM ZERO TO IMAGE PROCESSING
TRIAL AND ERROR
TRIAL AND ERROR
K-MEANS METHOD
CHAN VESE
EDGE DETECTION
HISTOGRAM METHOD
WATERSHED
NO ONE'S PERFECT
SKETCH IT OUT!
SKETCH IT OUT!
SKETCH AND SCAN
COMPARISONS
CONCLUSION
WHO NEEDS A LIFE?

What is a Histology Slide?
Original Histology Slide

A Histology slide the microscopic image of a perpendicular bisection of the placenta. It portrays the maternal and fetal tissues as 2-D cross-sectional blobs.

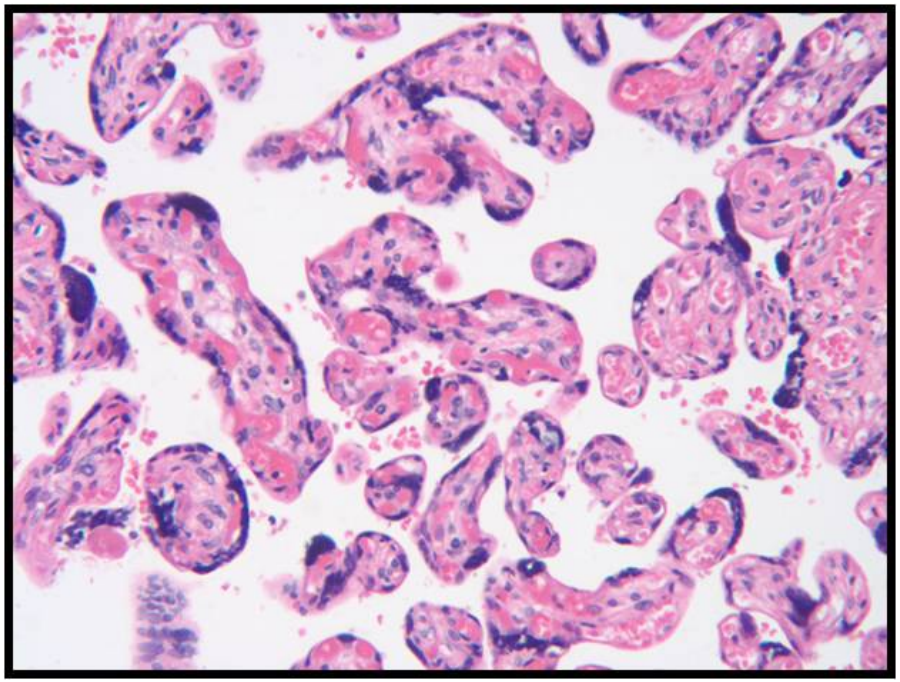

Figure: Original Image

What is a Histology Slide?
A Closer Look at The Blob

FULL SLIDE → VILLUS → BLOOD VESSELS/ CELL NUCLEI

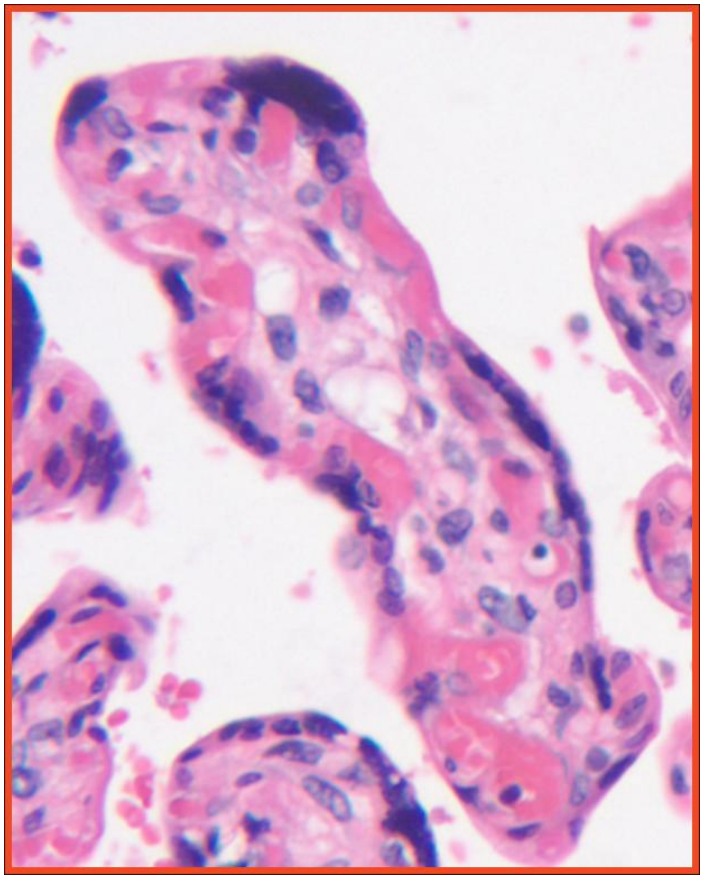

Figure: Zoomed In

Color Me Mine
Different Color Channels

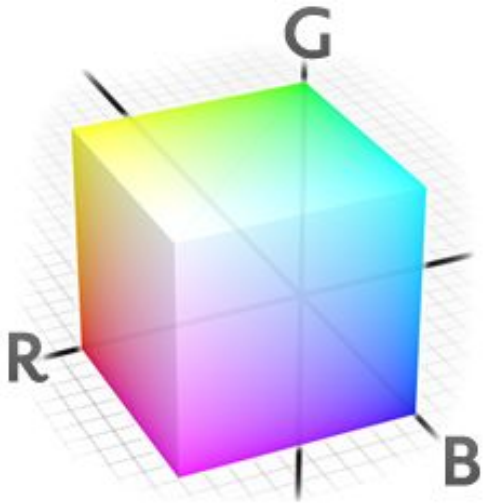

Figure: RGB

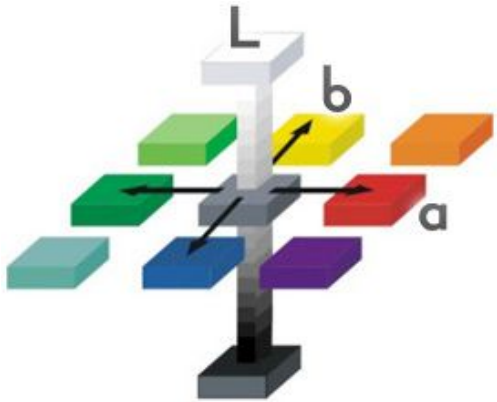

Figure: Lab

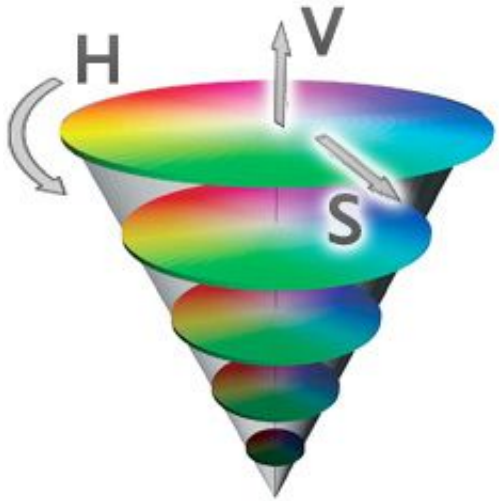

Figure: HSV

Color me Mine
RGB Color Space

R: red, G: green, B: blue

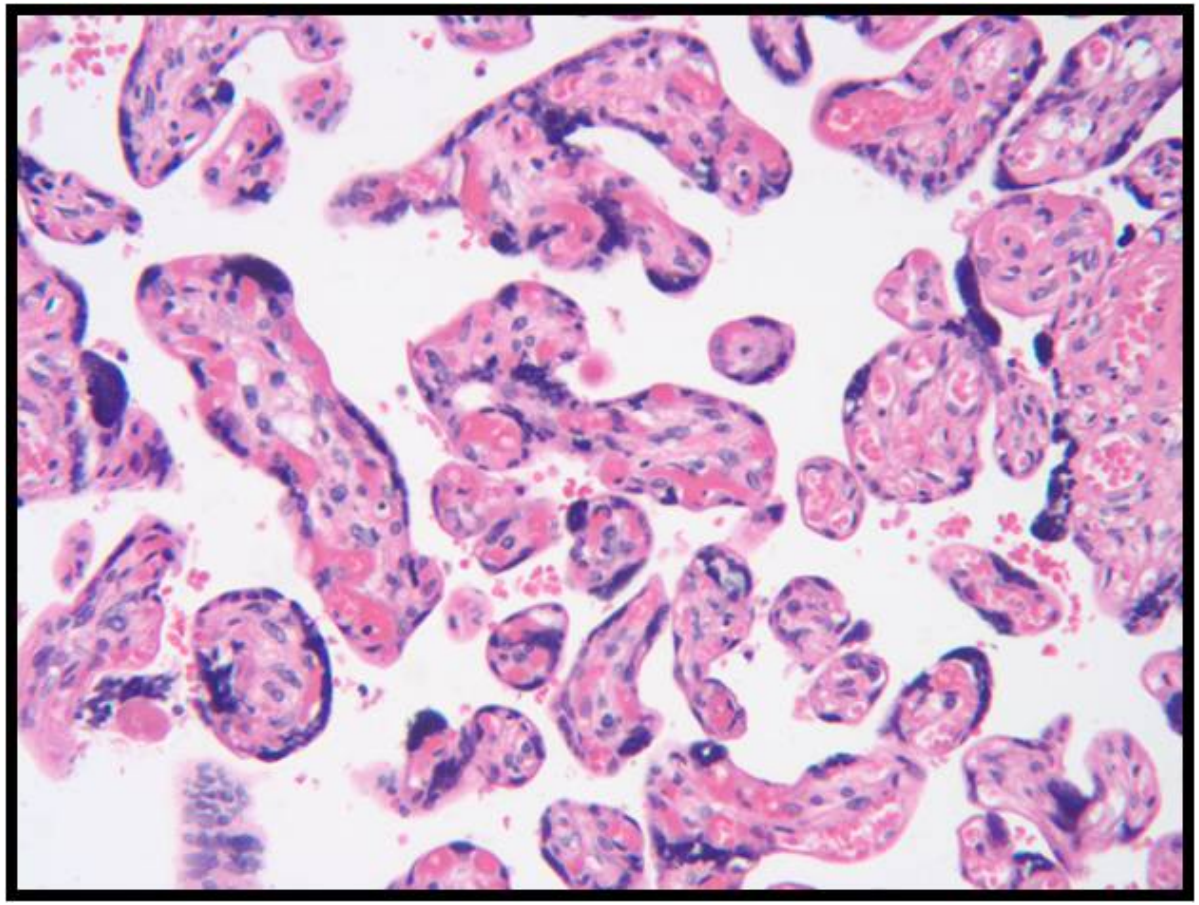

Figure: Original Image in RGB

Lab Intensity Corridoring
Lab Color Space

"L": lightness of color, "a": redness vs. greenness, "b": yellowness vs. blueness

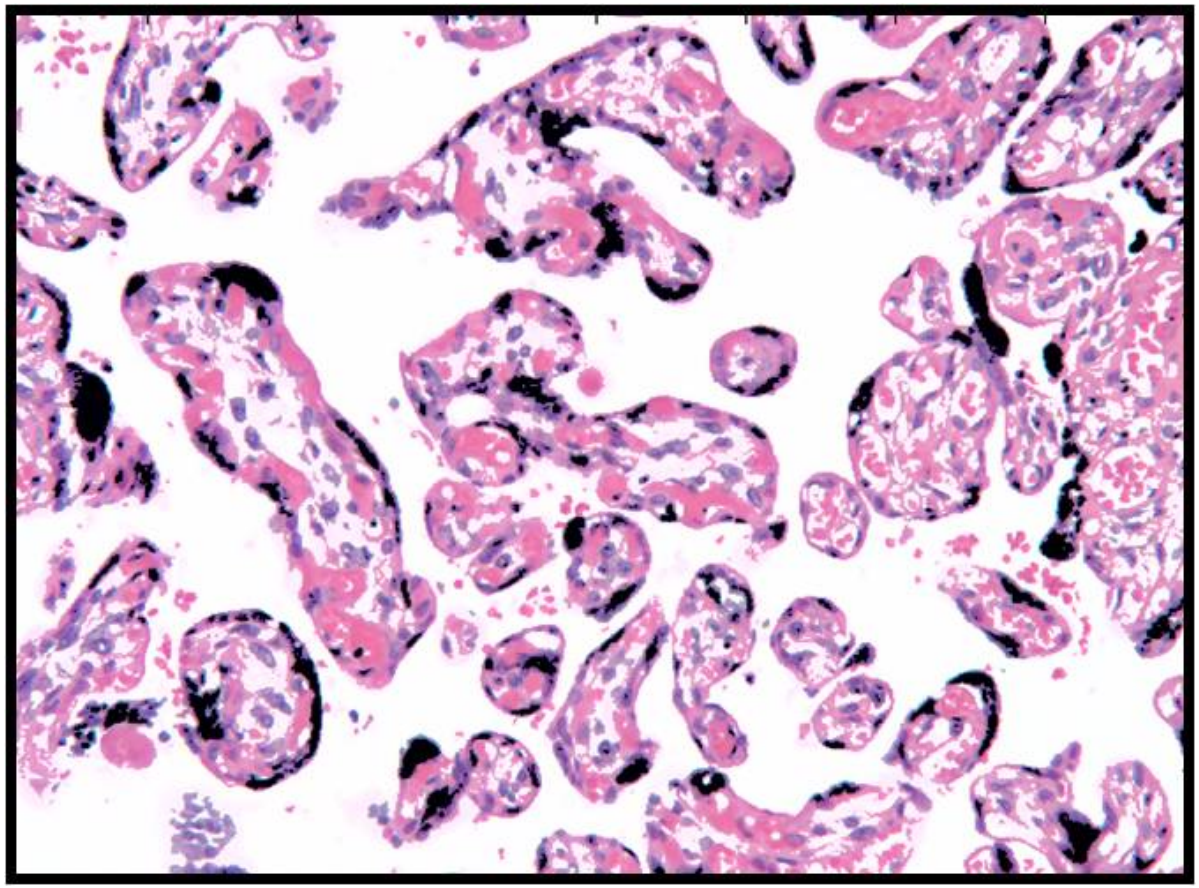

Figure: Lab Corridoring Image

H: Hue, S: Saturation, V: Value

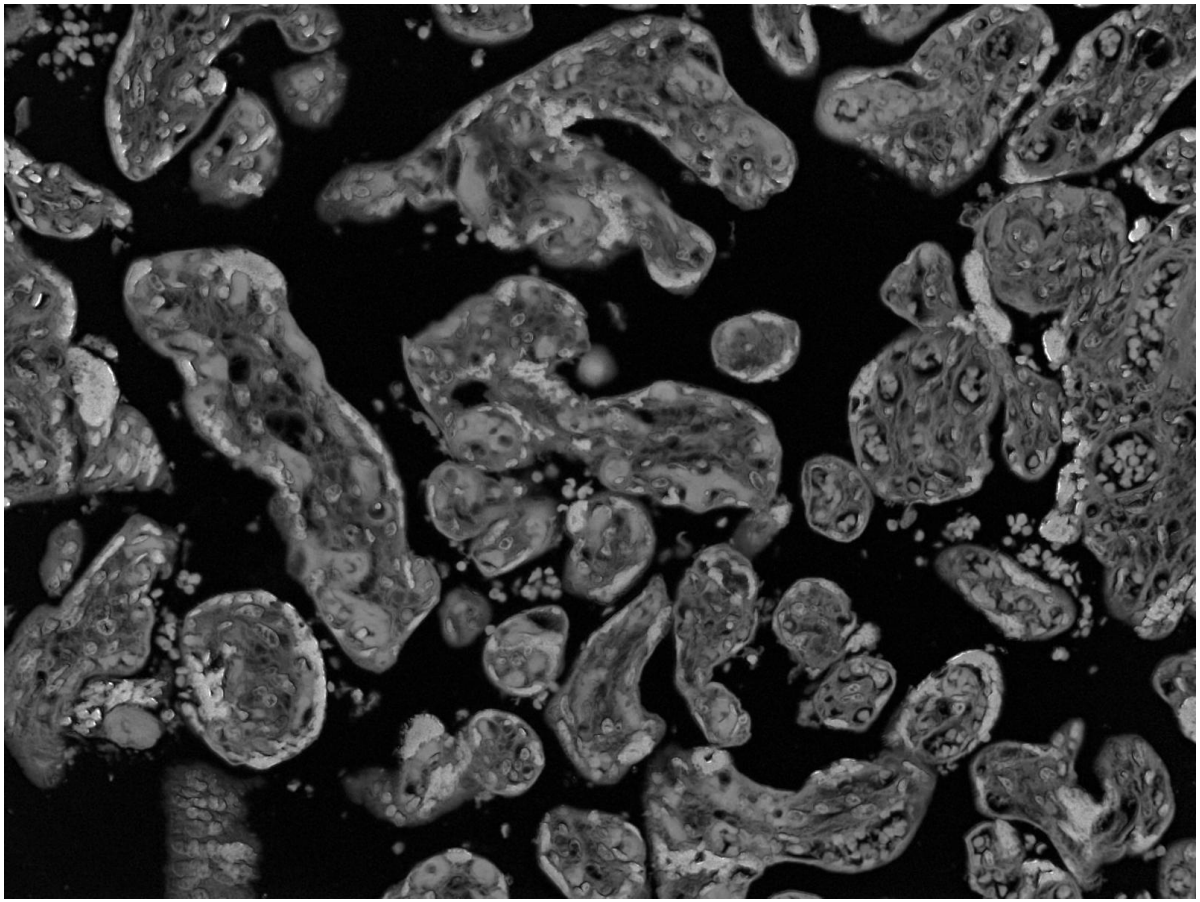

Figure: Original Image in the Saturated Channel

Quantifying Clinically Significant Features of Placental Histology Images: a Method

By: Morten Andersen , David Belangery, Radina Droumeva, Jenny Lix, Gilbert Moss, Gabriela Palauk August, 2008

1. Similar project: Segmentation of Placental "Blobs"
   - Uses K-means Segmentation with Mahalanobis Distance Metric
2. Potential for Comparison
   - Lesson Learned: Data Set Determines Algorithm

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Results Using Their Method
Our Histology Image

"You are absolutely right - lesson number one in image processing - you need to carefully choose and adapt methods for application-specific requirements" -Radina Droumeva

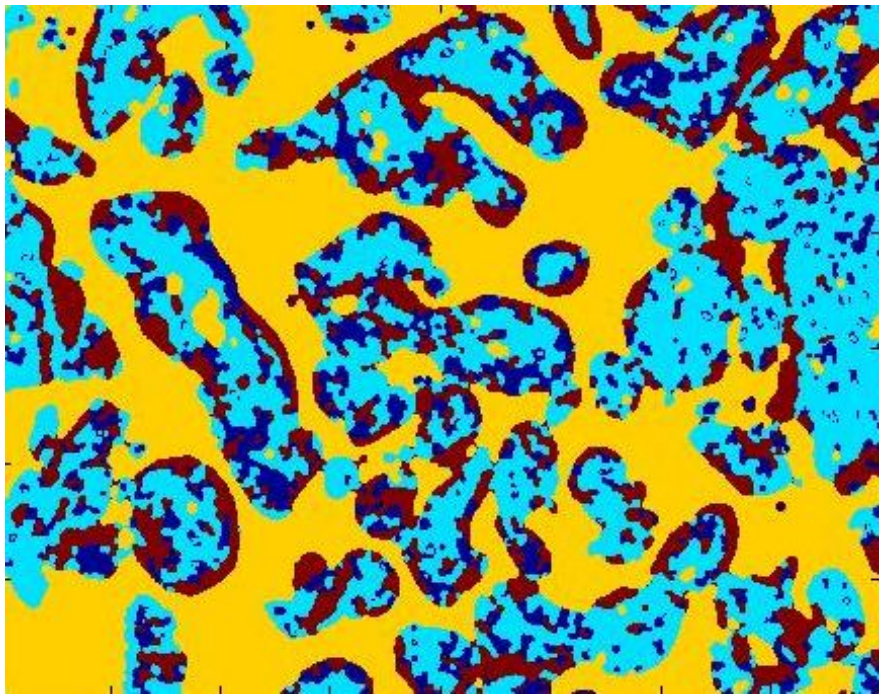

Figure: Resulting Histology Image

No One's Perfect
Reference Algorithm

Problems with their Method

1. Image Resolution
2. Difficulties Distinguishing: shades of pink/red
3. Predetermined Color Markers
4. Sensitive to Blob Boundaries

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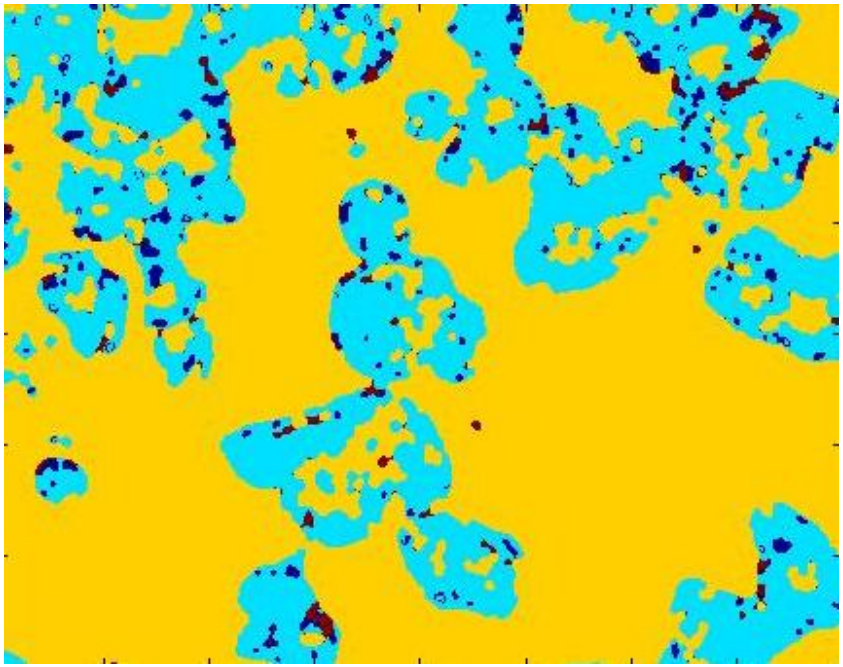

Figure: Resulting Histology Image 2

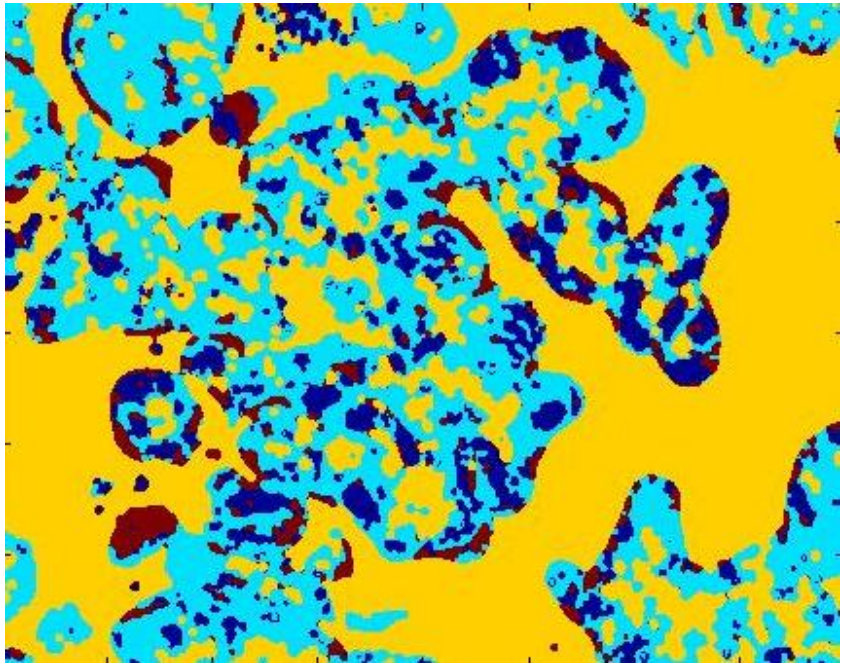

Figure: Resulting Histology Image 3

Methods We Tried

1. K-means
   - Euclidean
   - Mahalanobis
2. Chan Vese
3. Edge Detection
4. Watershed
5. Histogram

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Verbal Break Down

Euclidean Distance - Lab Space

1. Matlab's built in K-Means Algorithm
2. 4 vs. 5 Cluster Centers
   - 4: Lumps light pink with light purple, some pink with red
   - 5: Separates Red, Pink, Light Purple, Blue, and White effectively
3. Blobs are the inverse of the White Segmentation
4. Result: Slow but reasonably effective "Discrete Method"

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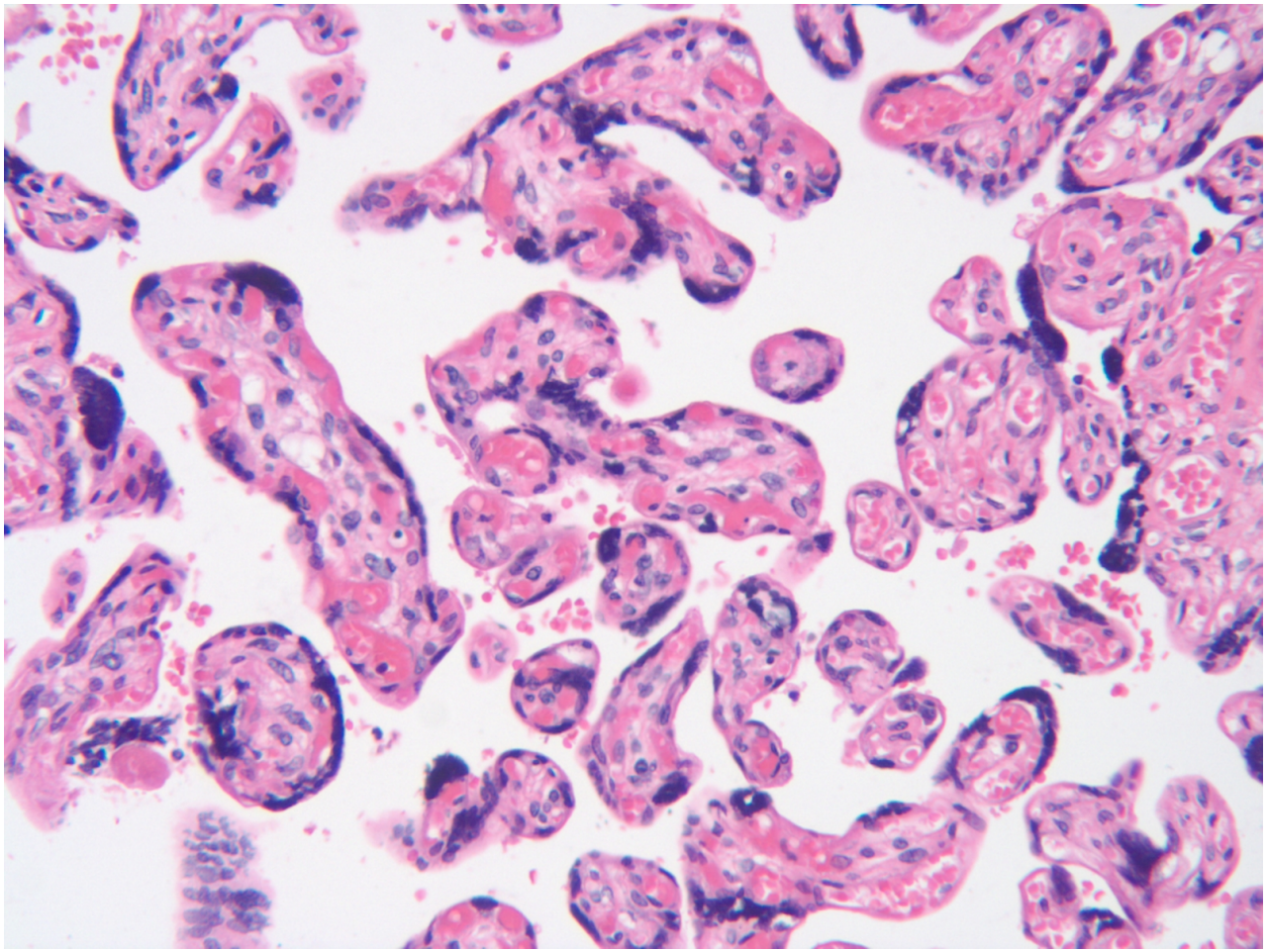

Figure: Histology Slide 1

K-means Killer
K-means Euclidean Method Results

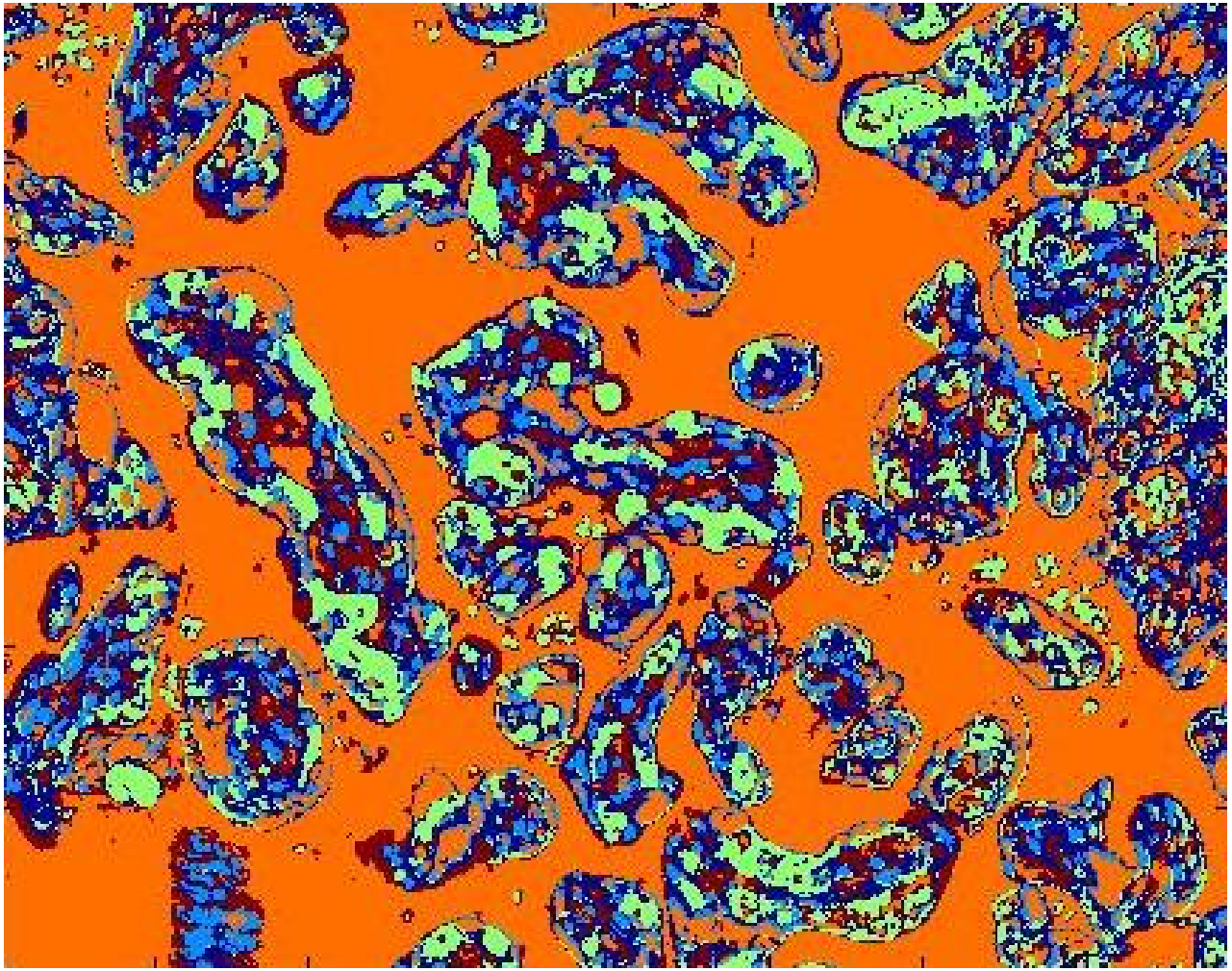

Figure: Total Segmentation 1

K-Means Euclidean Proves Promising

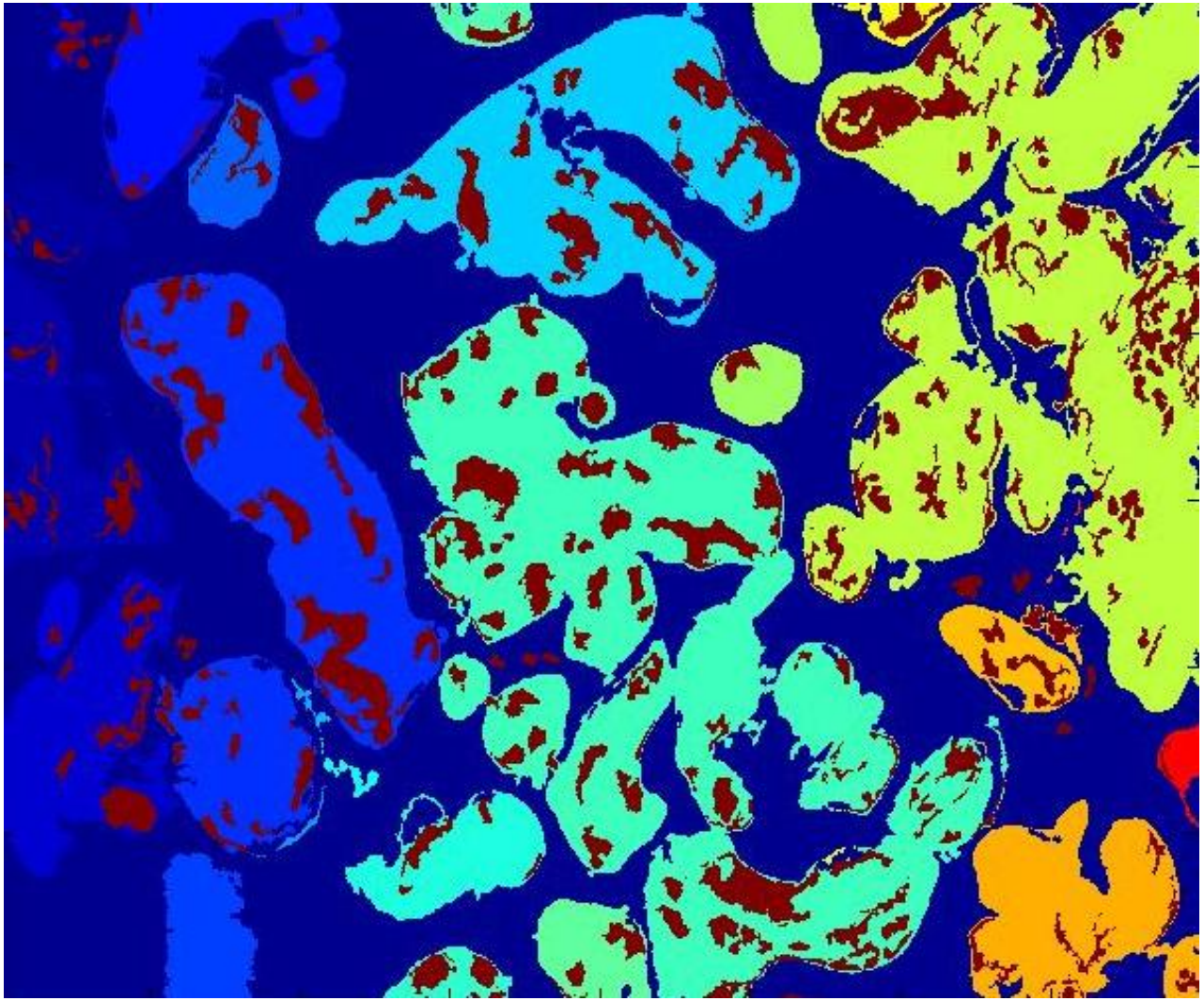

Figure:

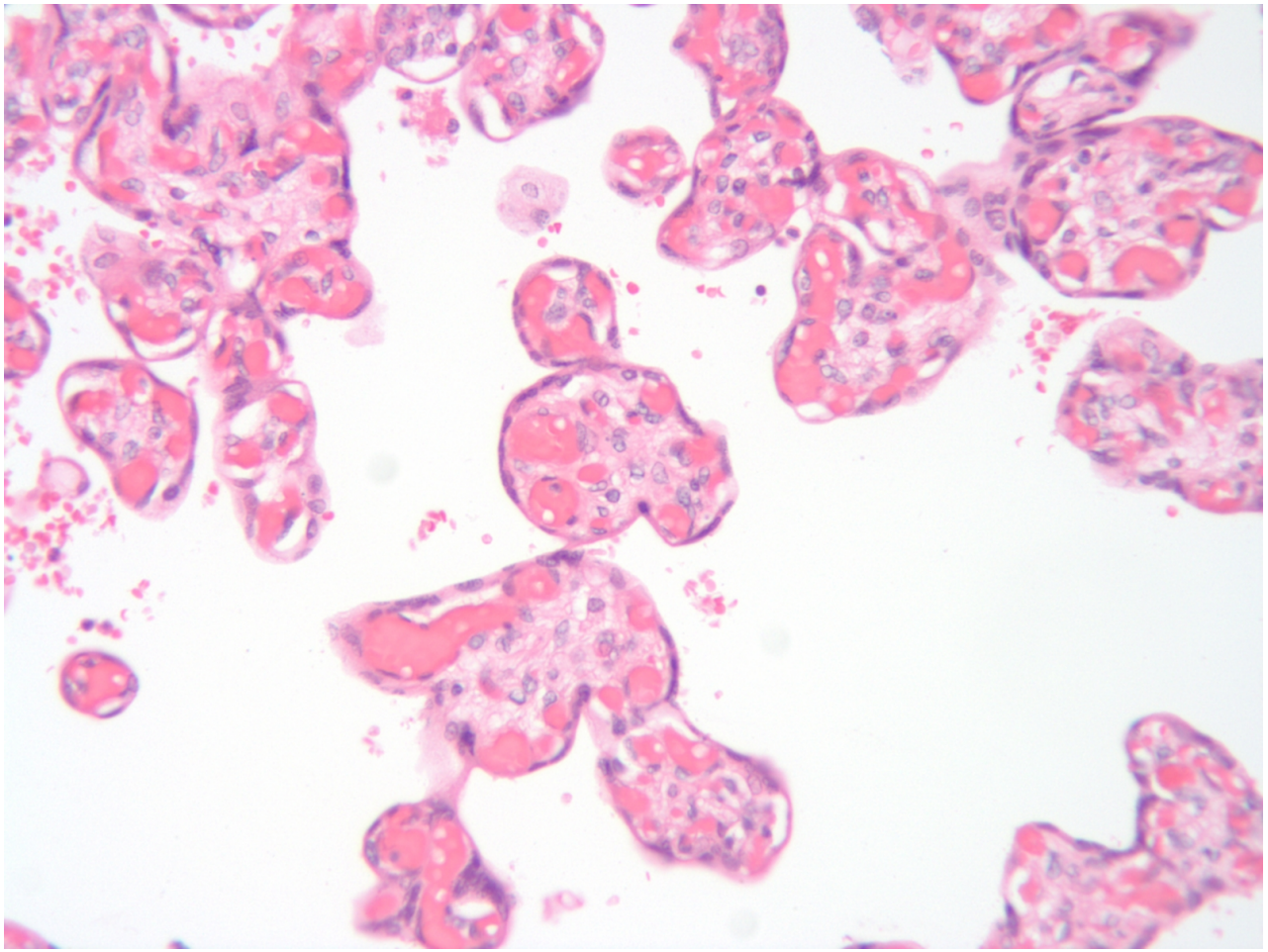

Figure: Histology Slide 2

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K-means Euclidean Method Results

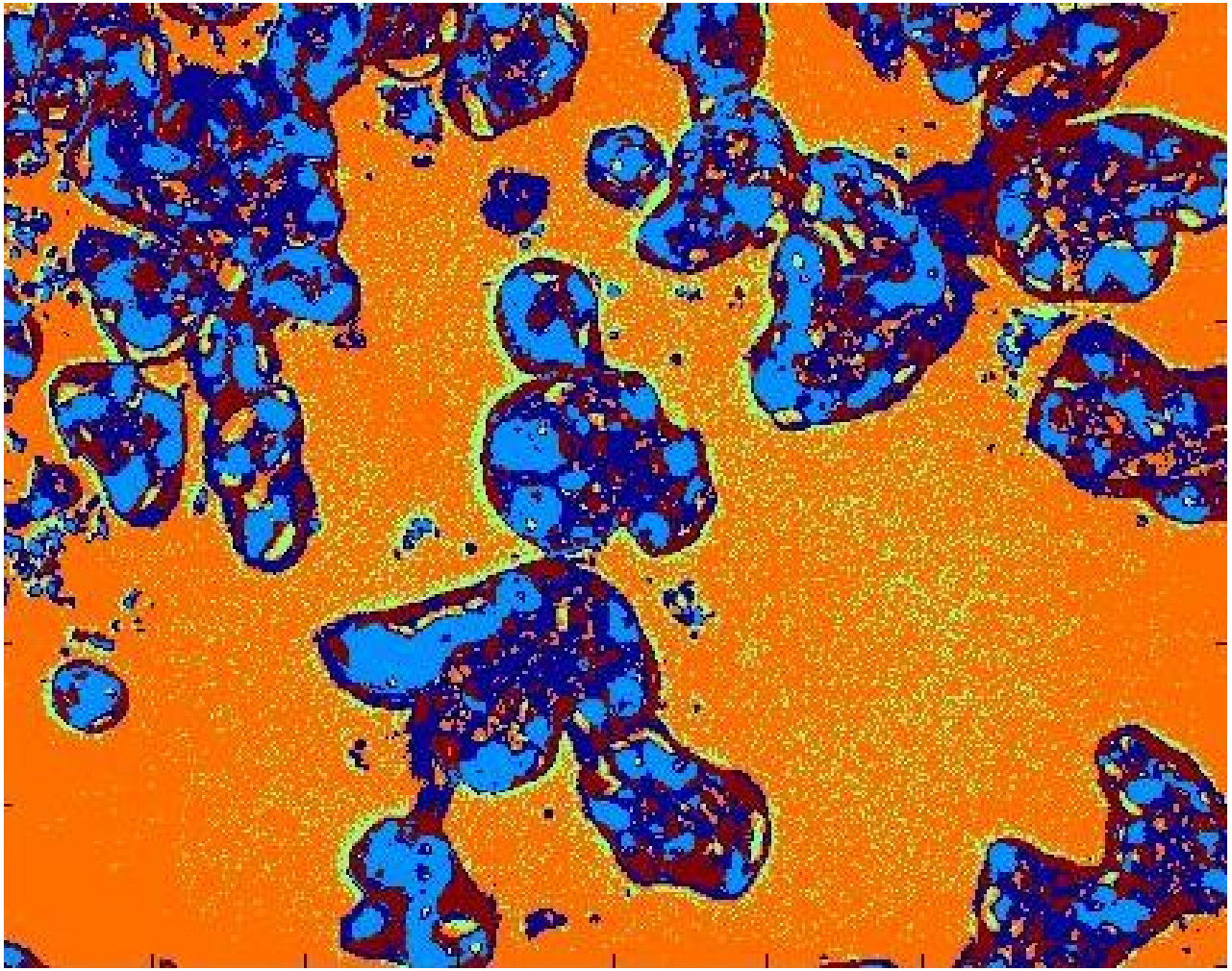

Figure: Total Segmentation 2

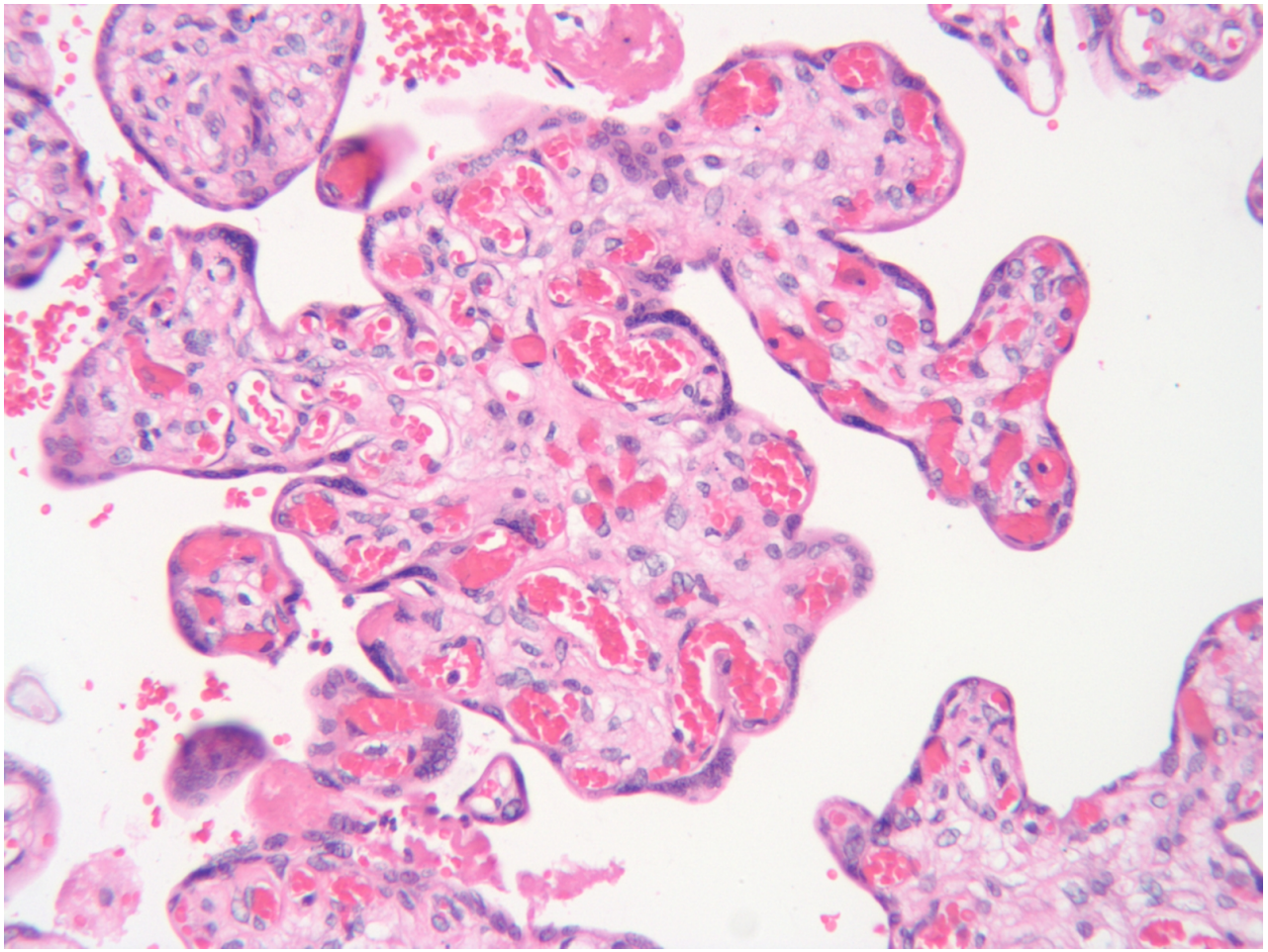

Figure: Histology Slide 3

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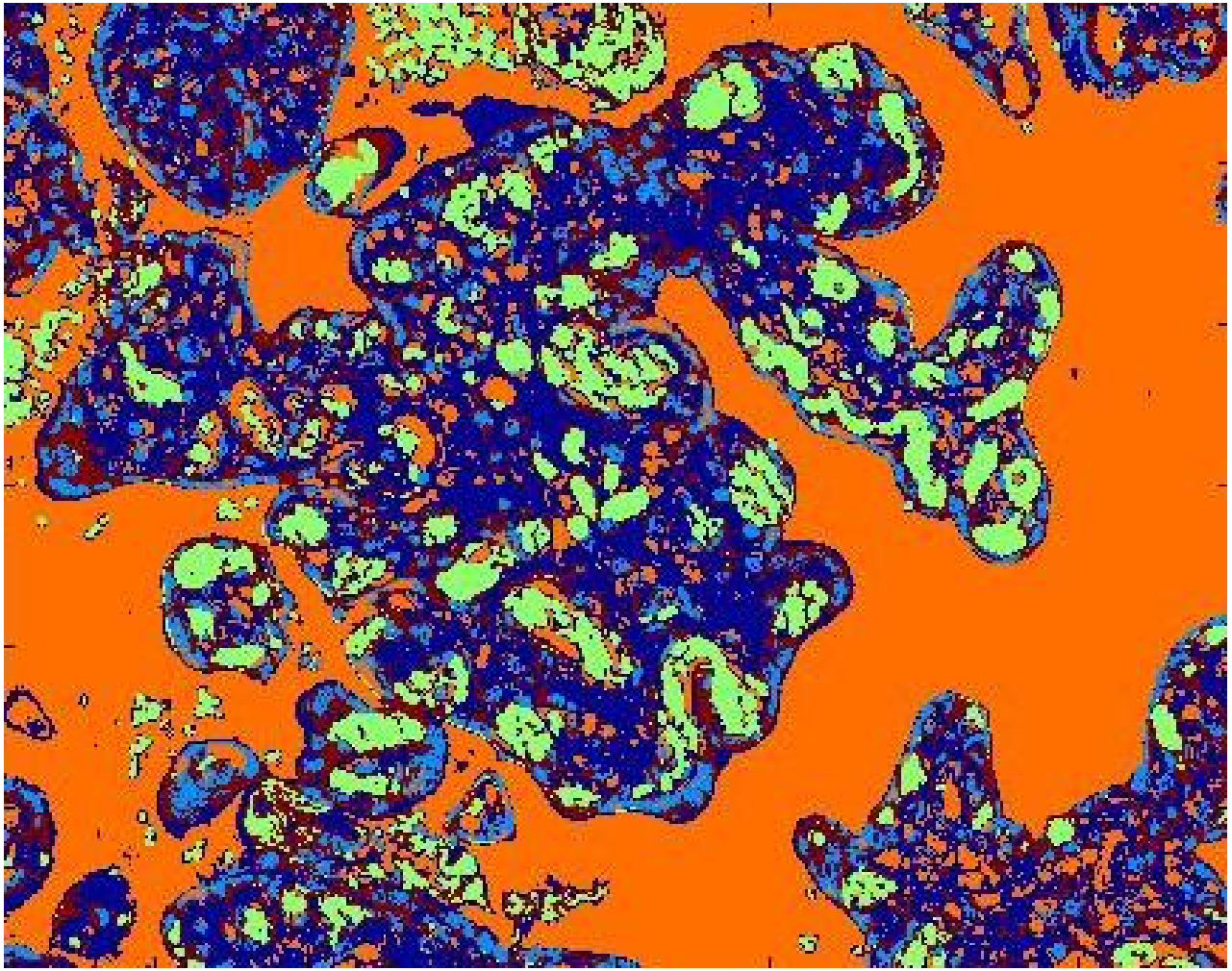

Figure: Total Segmentation 3

K-means Killer
Mahalanobis Distance in RGB Space

Verbal Break Down

1. Weights distance to an absolute color marker
   - Set by variance in each channel of RGB color space
   - Result: Using fixed color markers across variant variance structures creates segmentation distortions
2. Further Work Ideas
   - Use the Covariance Matrix of a single representative image
   - Use the Covariance of the entire population of images
   - Report the "Volatility of Volatility" in the image set as indicator of likely success

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K-means Killer
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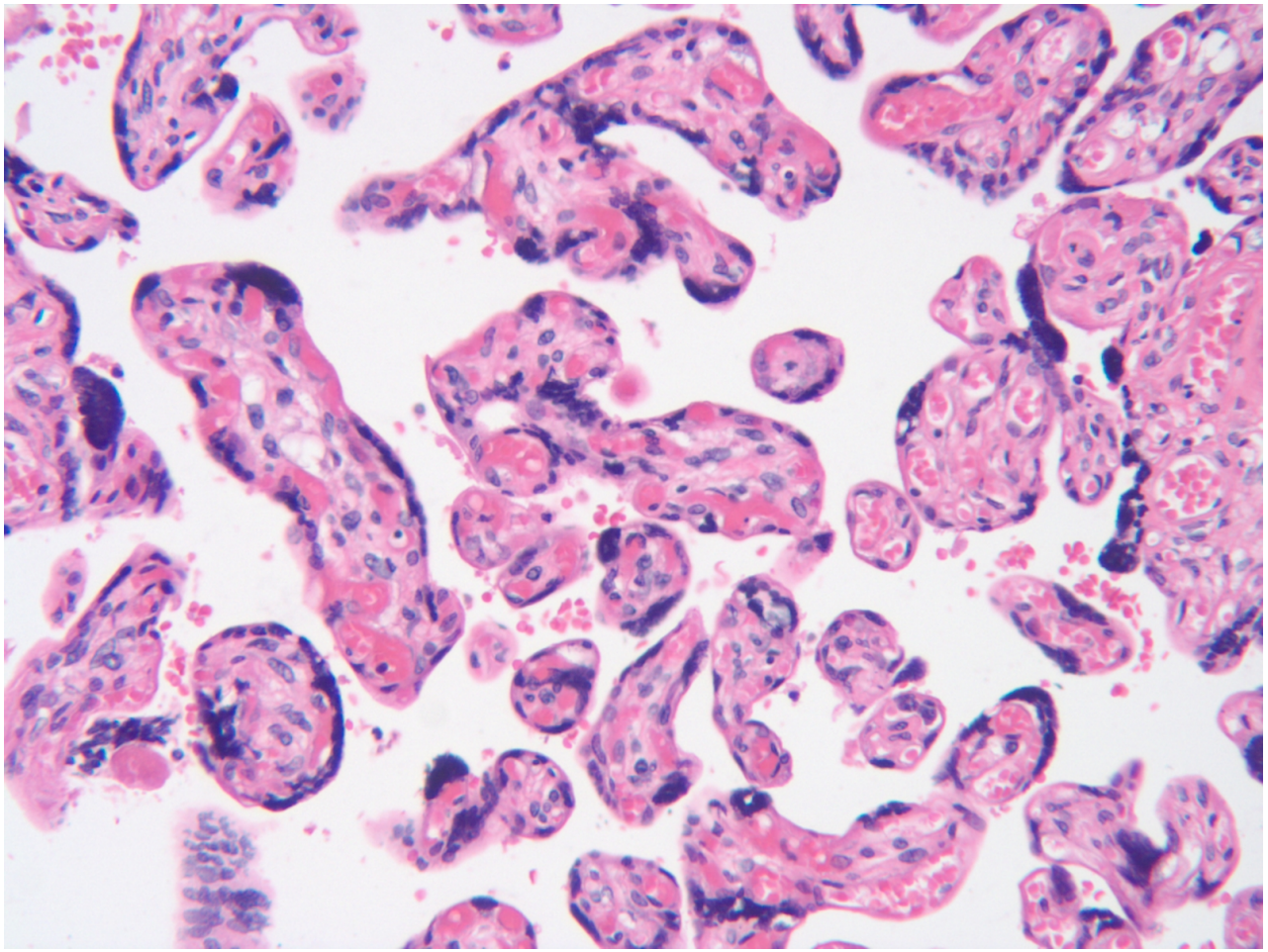

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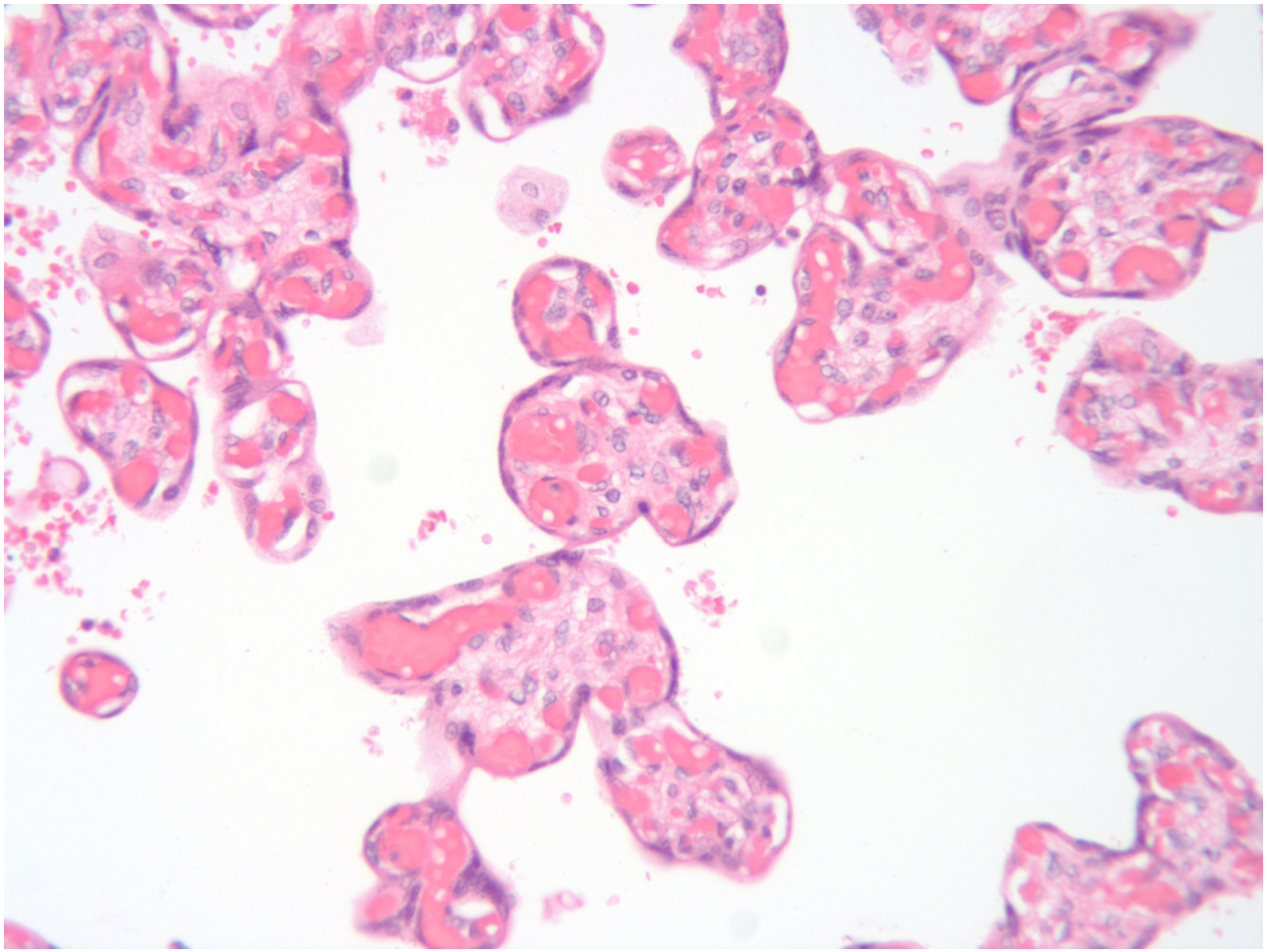


Figure: Histology Slide 2

K-means Killer
Original Image

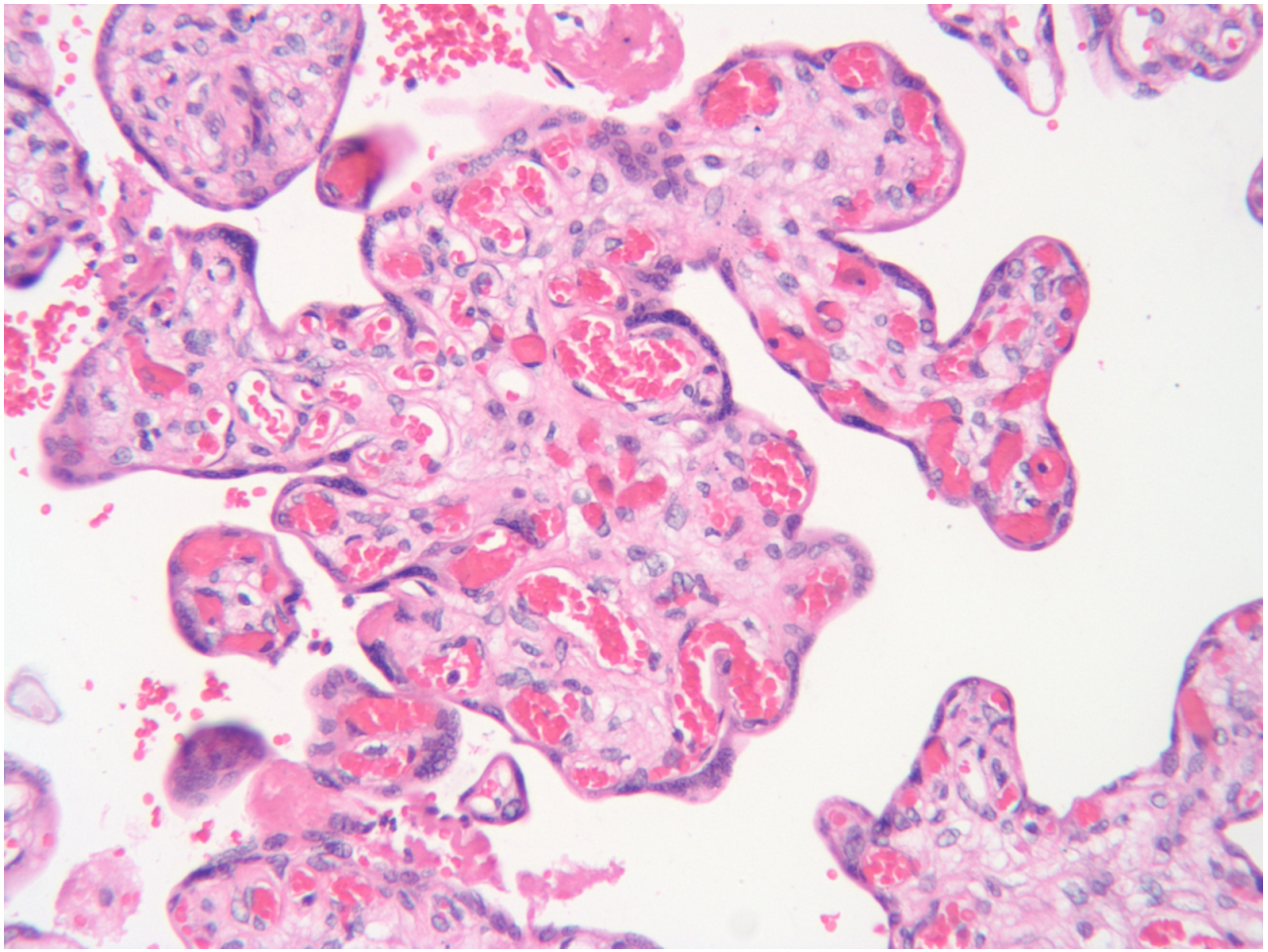
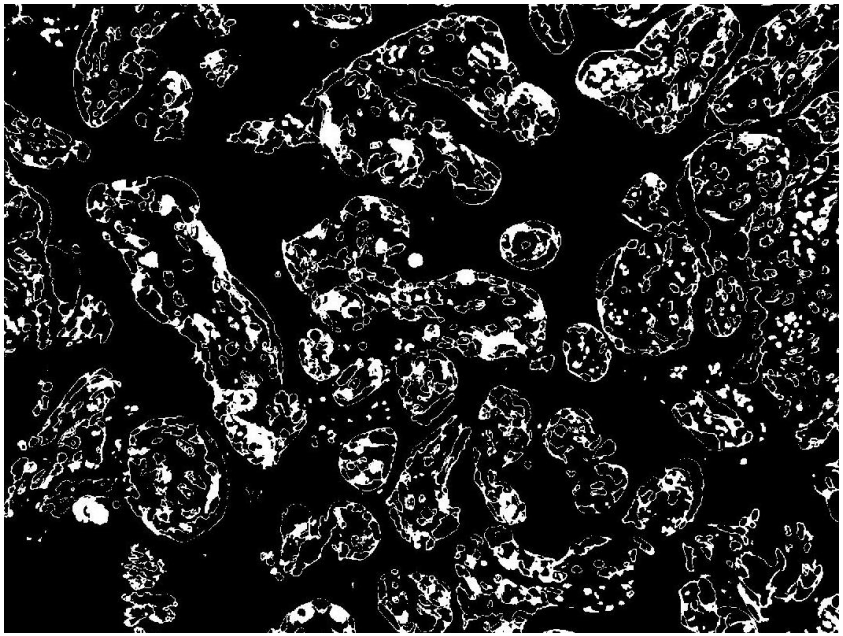


Figure: Histology Slide 1

K-Means, Mahalanobis, RGB Space
Histology Slide Calibrations



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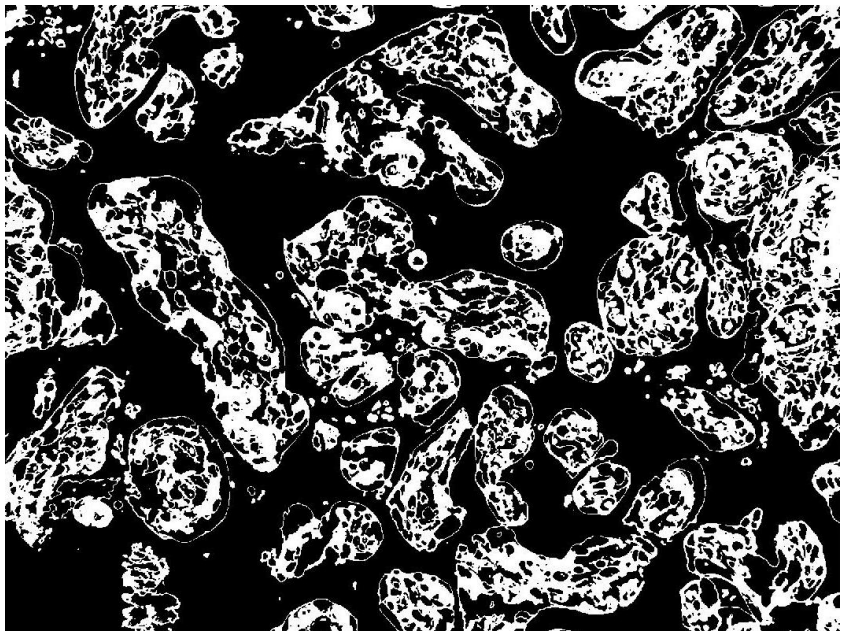
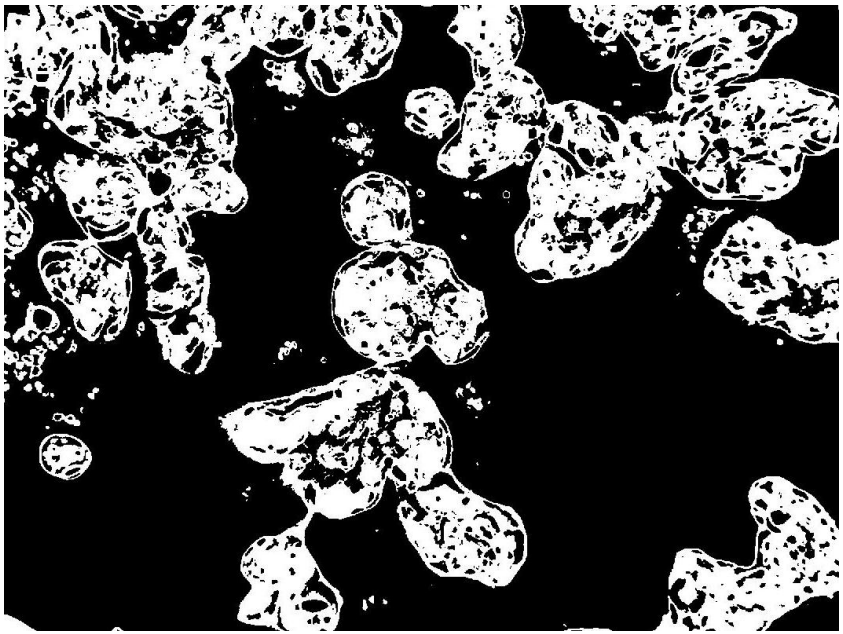


Figure: Calibration 2

K-Means, Mahalanobis, RGB Space
Histology Slide Calibrations



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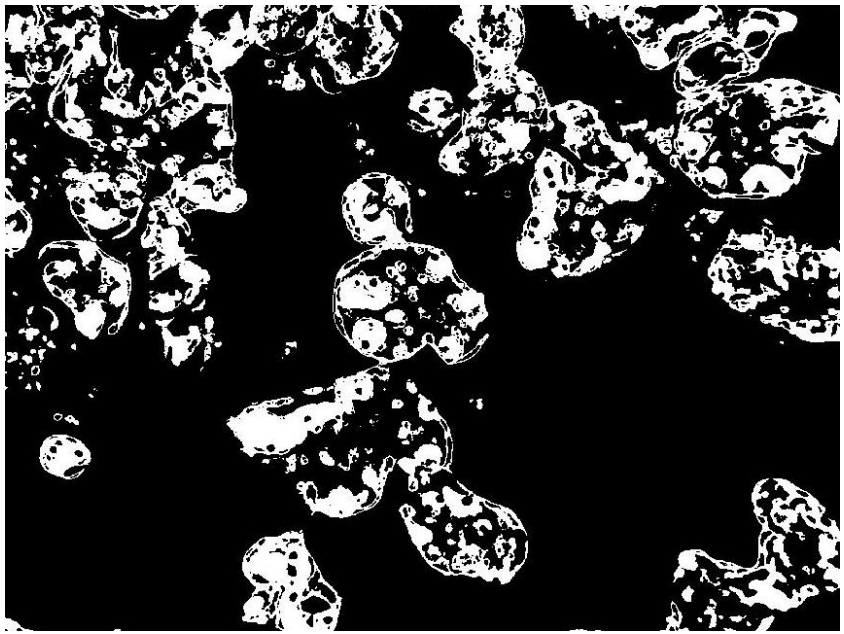

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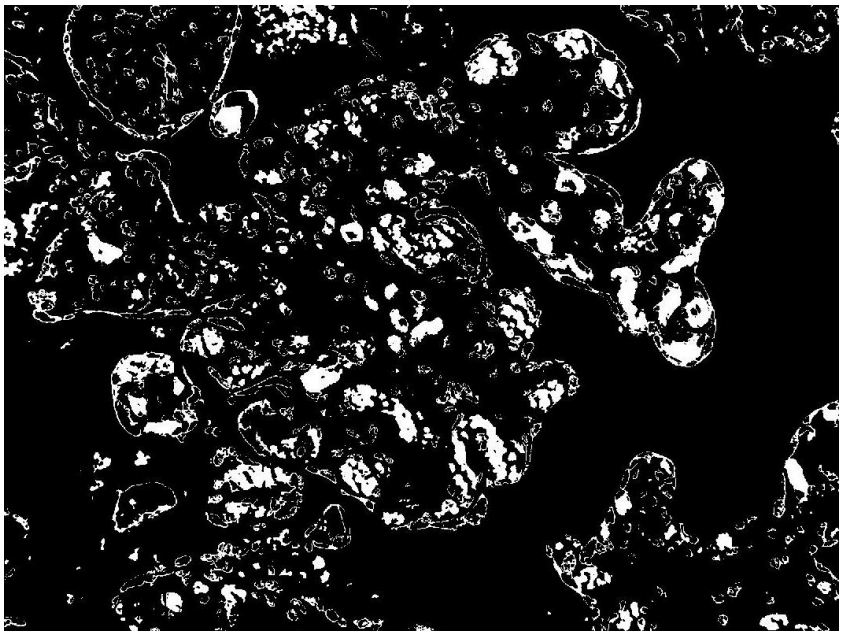

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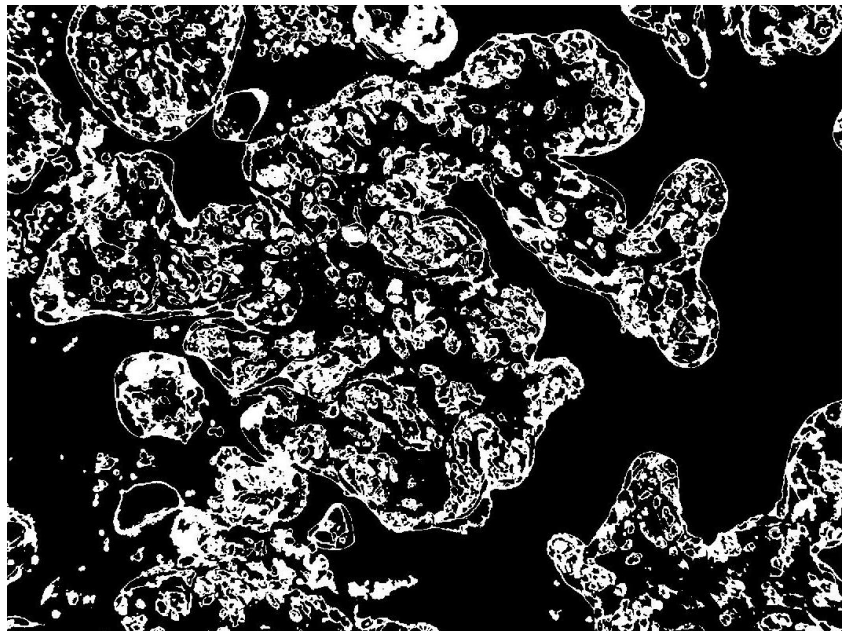

Figure: Calibration 2

Verbal Break Down

1. RGB $\rightarrow$ LAB
2. Mahalanobis calculation in the L, a, and b planes.
3. Distance in Light Intensity Value weighted in the Mahalanobis calculation
4. Result: Removes distortion from the Mahalanobis calculation

K-means Killer
Mahalanobis in Lab Space

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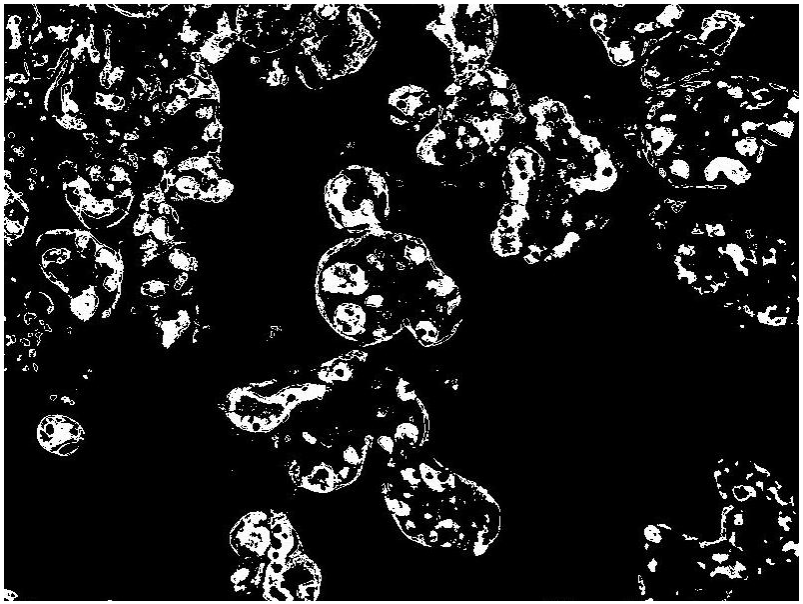

Figure: Segmented Vessels

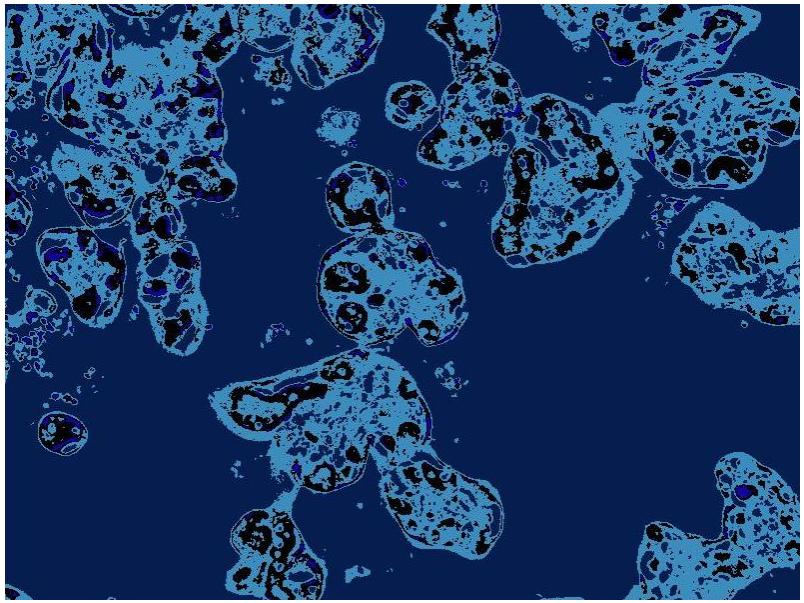

Figure: Total Segmentation

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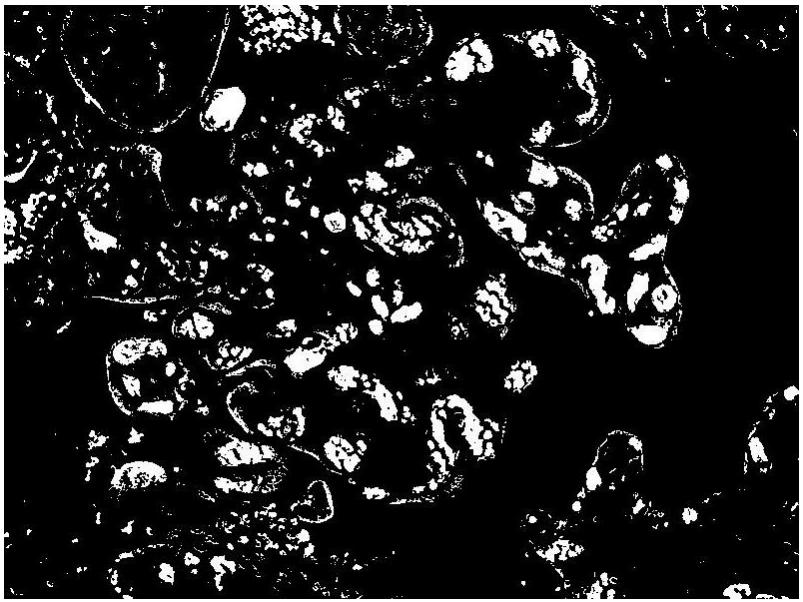

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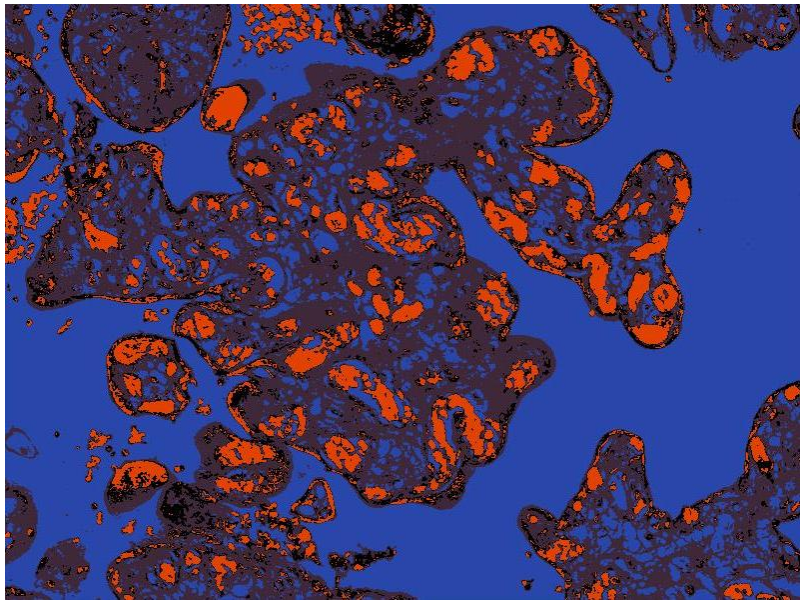

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Mumford-Shah functional outline provided by: Zoltan Kato

Mumford-Shah functional

- Let f be differentiable on $\bigcup R_i$ and allowed to be discontinuous across Γ.
  $E(f,\Gamma) = \mu^2 \iint_R (f-g)^2 dxdy + \int_R \int_\Gamma \|\nabla f\|^2 dxdy + v|\Gamma|$
- The smaller E, the better (f,Γ) segments g
  - f approximates g
  - f (hence g) does not vary much on R
  - The boundary Γ is as short as possible
- Dropping any term would cause $infE = 0$

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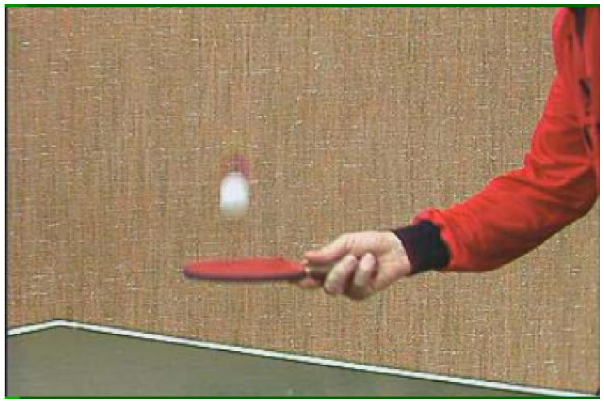
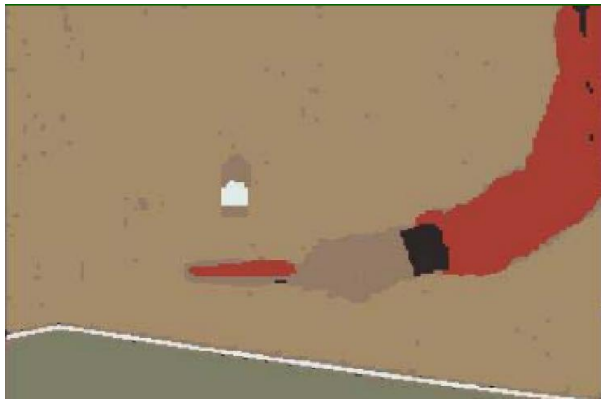
Chan Vese Method
Cartoon Image Example

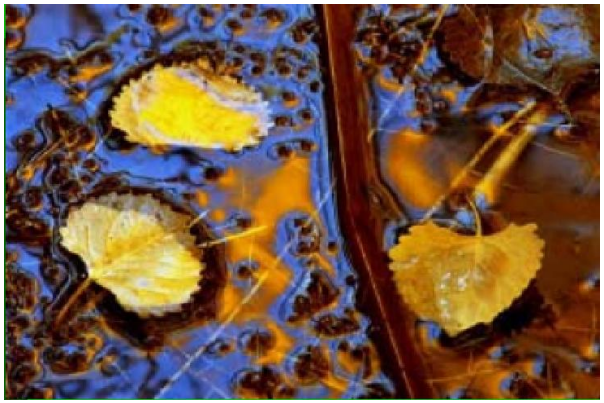
Cartoon Image Example provided by: Zoltan Kato



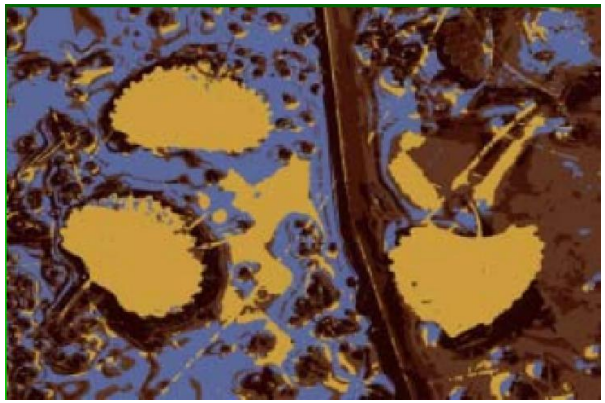
(a) Example Image 1



(b) Example Image 1 After



(c) Example Image 2



(d) Example Image 2 After

Chan Vese is a Work in Progress

Chan Vese Method Results

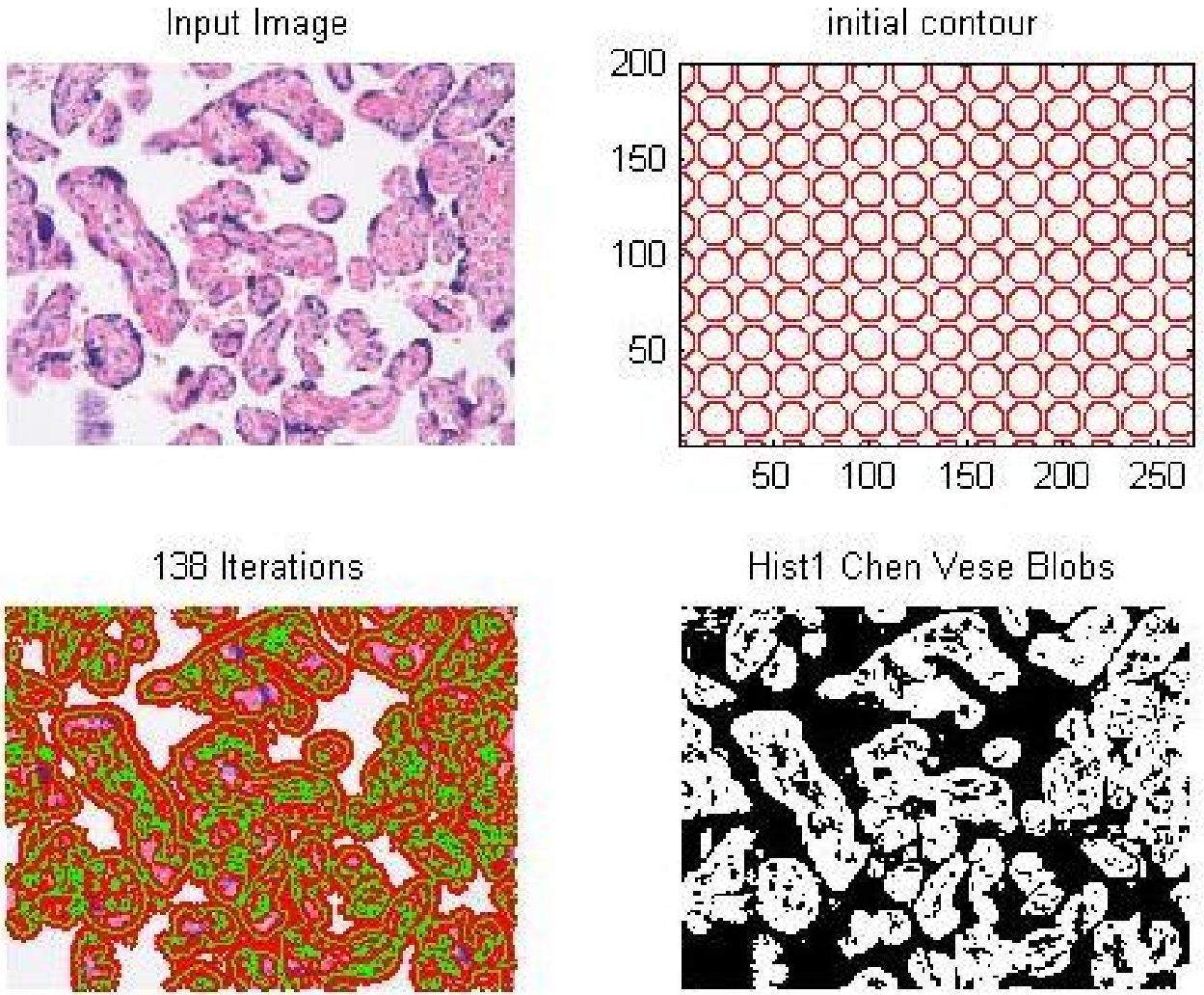


Figure: Using Histology Slide 1

Chan Vese is a Work in Progress
Still Needs Work

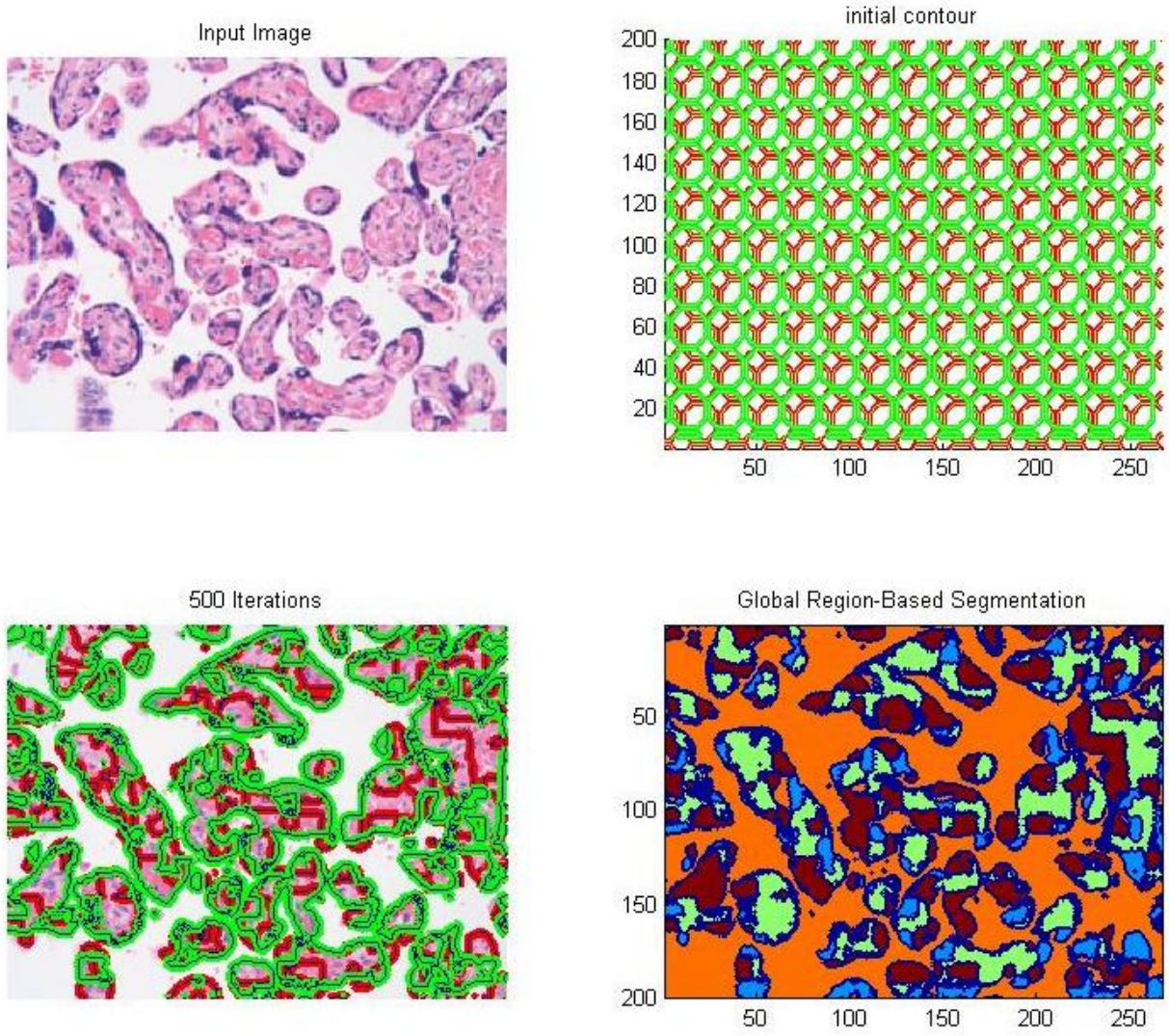


Figure: Using Histology Slide 1

Edge Detection Inspection
Edge Detection Method

Verbal Break Down

1. Find Binary Image
2. Use Canny Edge Detection
3. Merge Disjoint Regions

Edge Detection Inspection
Edge Detection Method

Verbal Break Down

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2. Use Canny Edge Detection
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Edge Detection Inspection
Edge Detection Method

Verbal Break Down

1. Find Binary Image
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Edge Detection Inspection
Edge Detection Method

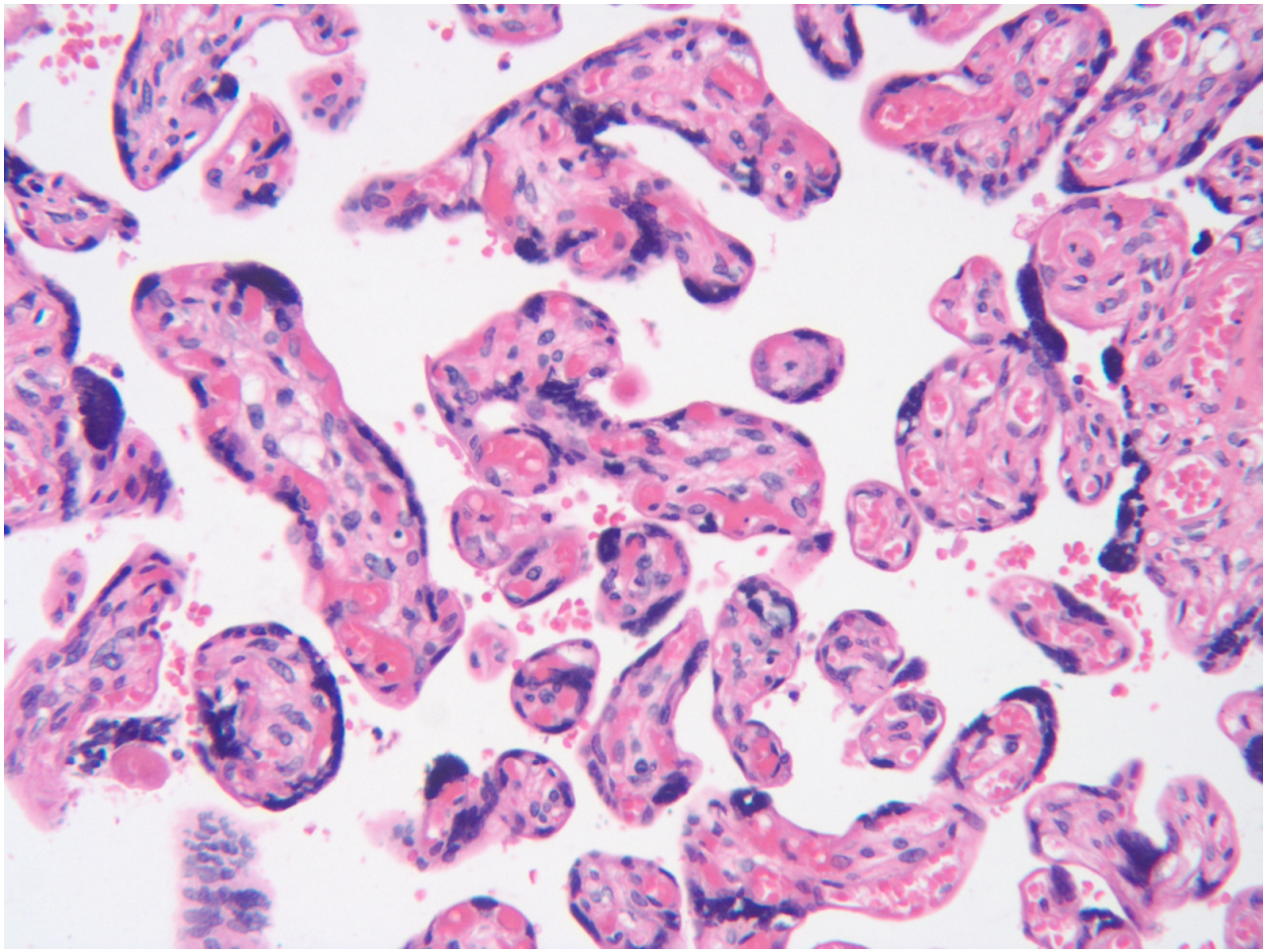

Figure: Histology Slide 1

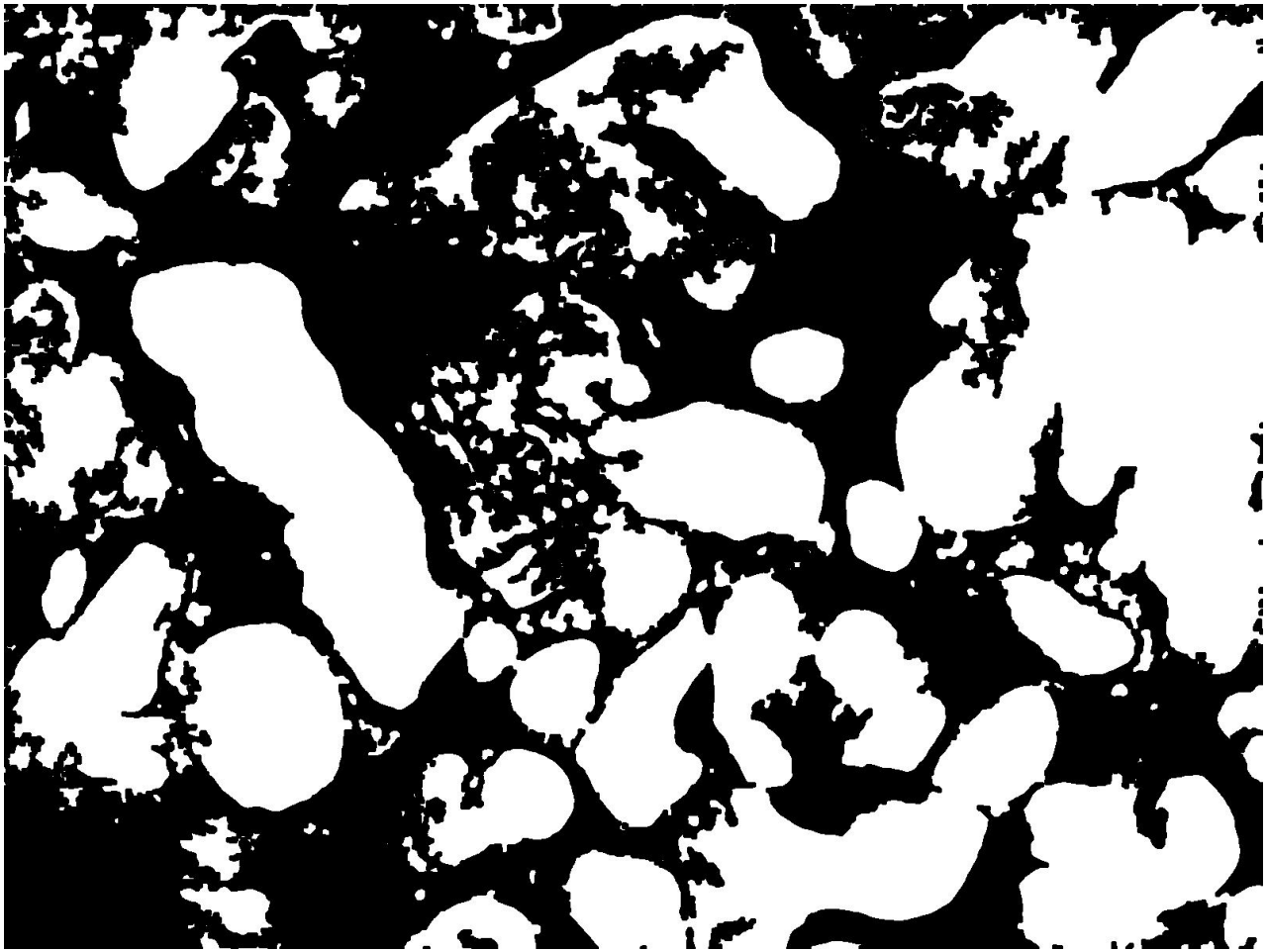

Figure: Black and White of Original 1

Edge Detection Method Results
Blobs Only

Figure: Segmented Blobs of Original 1

Edge Detection Method Results
Blobs and Vessels

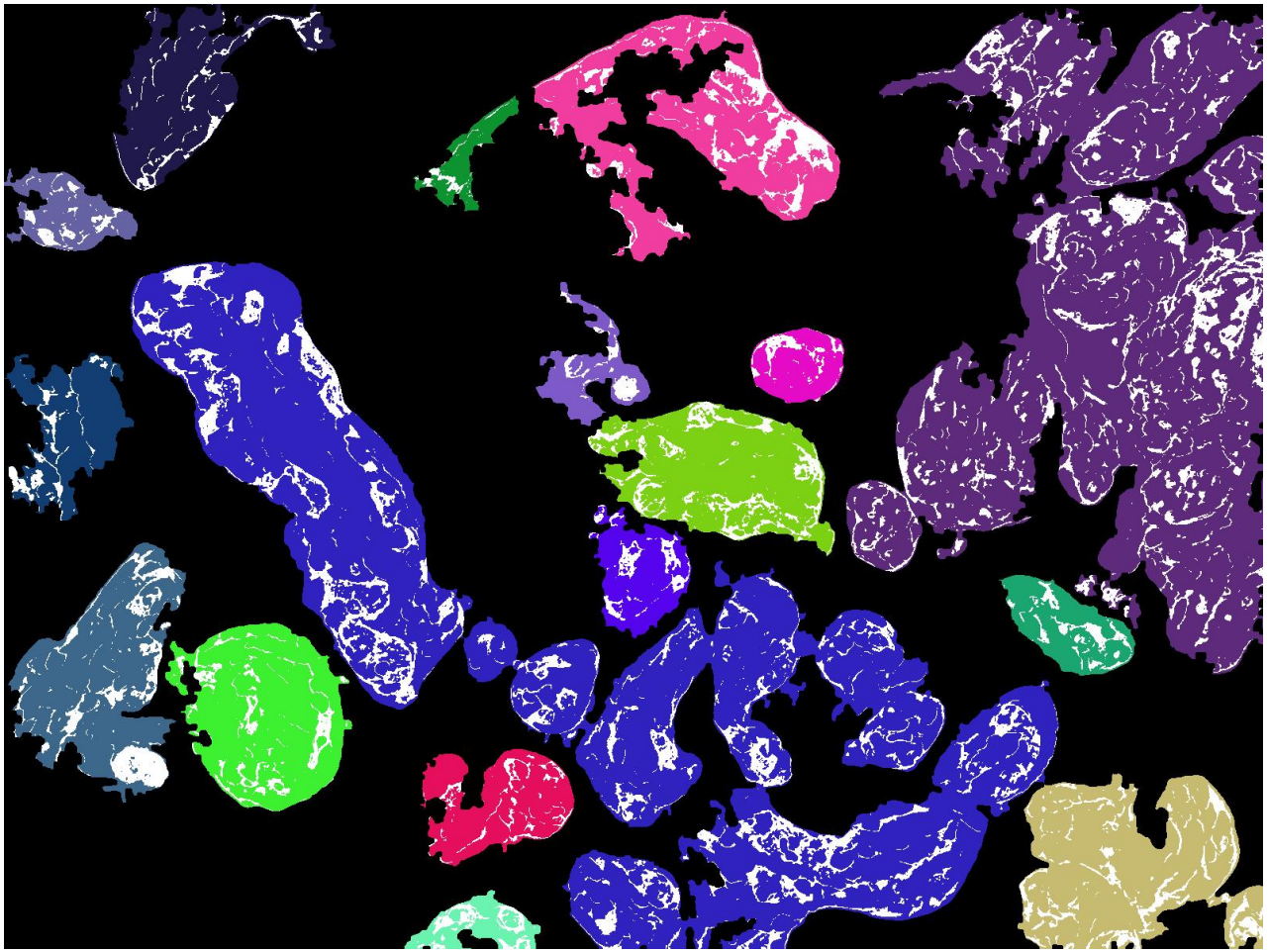

Figure: Segmented Blobs and Vessels of Original 1

Verbal Break Down

1. RGB $\rightarrow$ HSV
2. Use Histogram to Find Blobs
3. Morphological Operations on binary image

Verbal Break Down

1. RGB $\rightarrow$ HSV
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Verbal Break Down

1. RGB $\rightarrow$ HSV
2. Use Histogram to Find Blobs
3. Morphological Operations on binary image

Histogram Method Results
Blobs Only

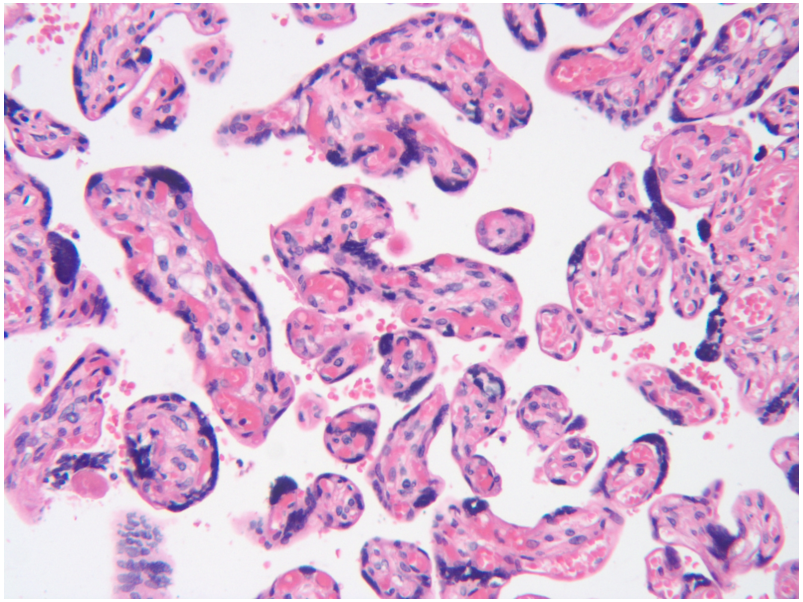

Figure: Original

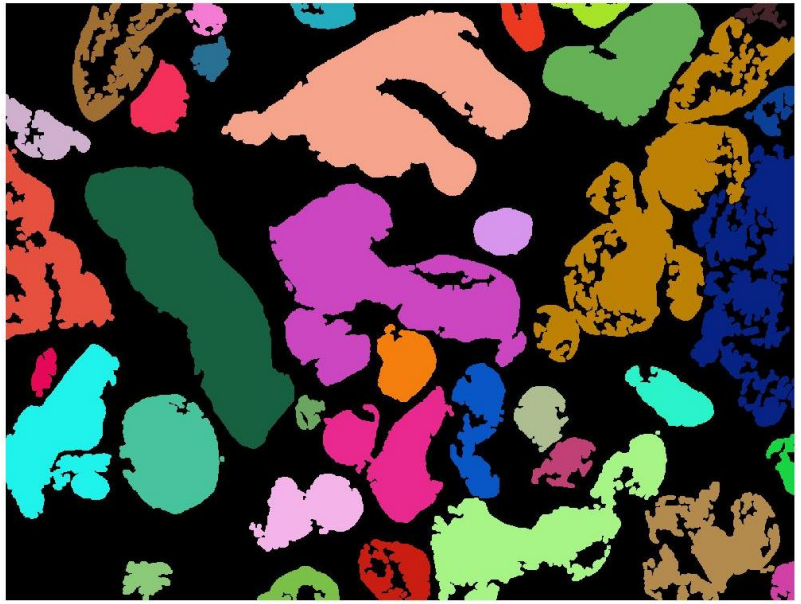

Figure: Blobs Segmented

Histogram Method Results
Blobs Only

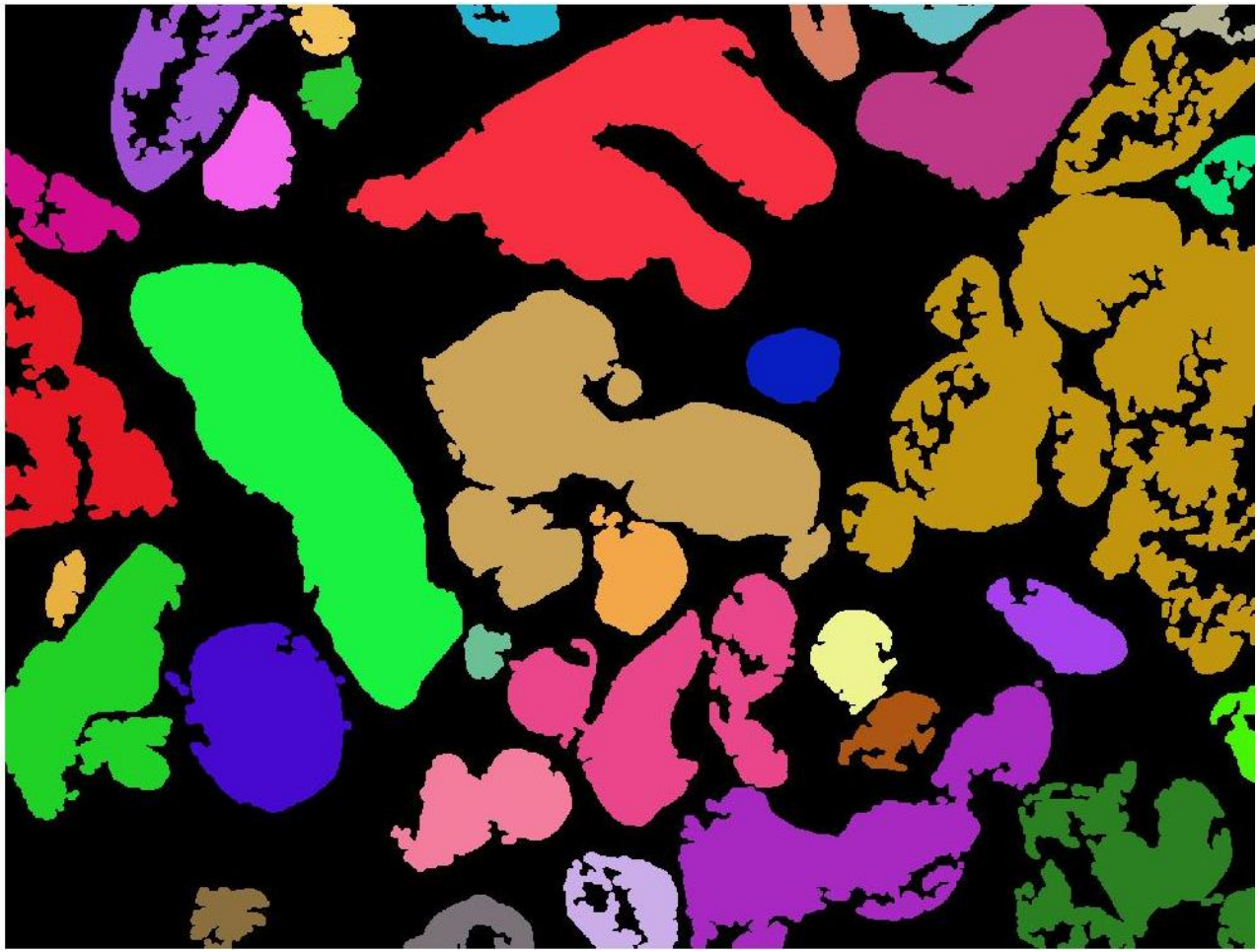

Figure: Blobs Segmented Take 2

Histogram Method Results
Blobs and Vessels

Color blobs indicate Villi and white indicates the blood vessels.

Figure: Blobs and Vessels Segmented

Is Watershed Dead?
Watershed Method

Verbal Break Down

1. Find Binary Image
2. Find Distance Transform of Image
3. Run Watershed on Distance Transform

Is Watershed Dead?
Watershed Method

Verbal Break Down

1. Find Binary Image
2. Find Distance Transform of Image
3. Run Watershed on Distance Transform

Is Watershed Dead?
Watershed Method

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1. Find Binary Image
2. Find Distance Transform of Image
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Is Watershed Dead?
Watershed Method

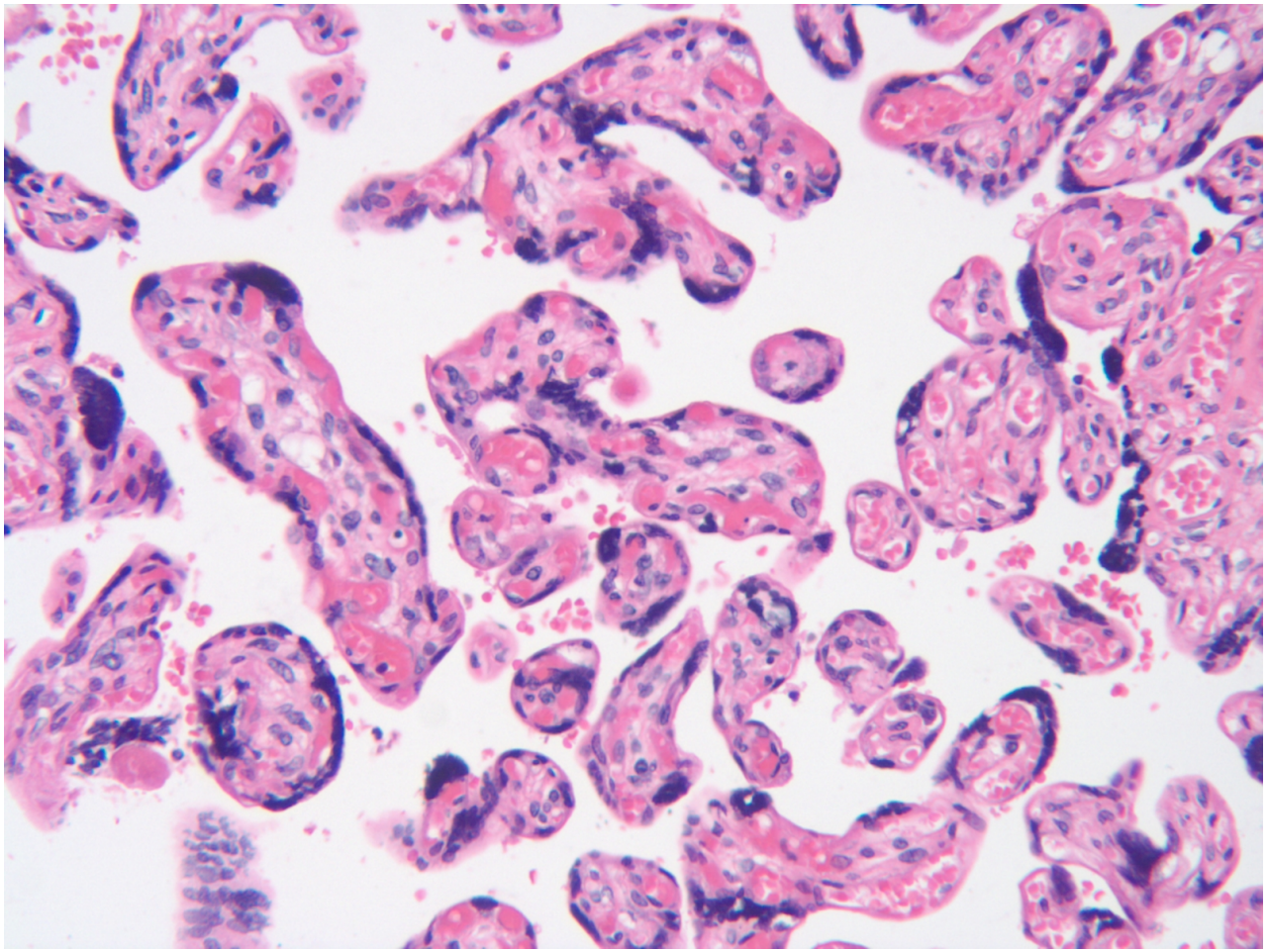

Figure: Histology Slide 1

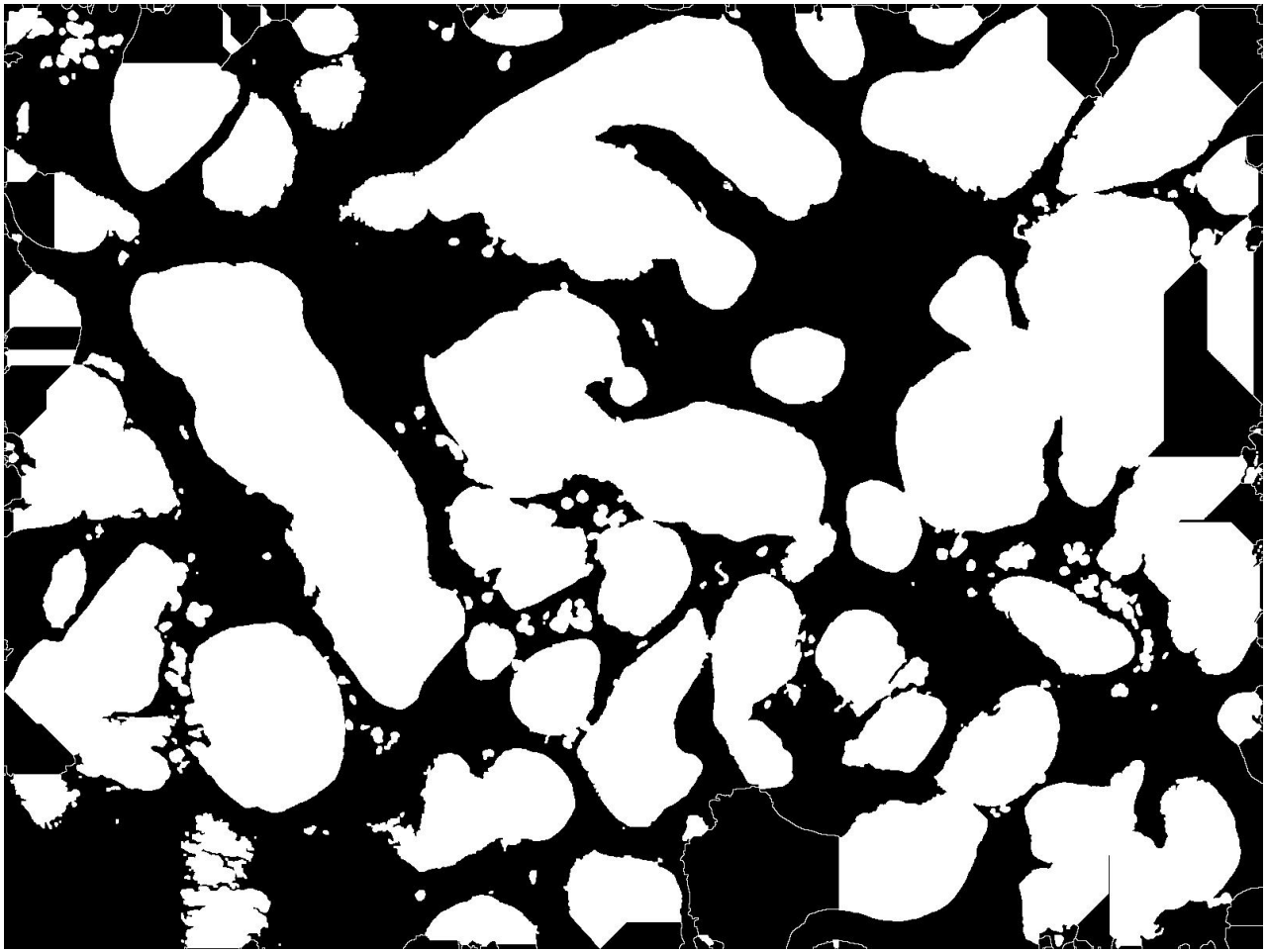

Figure: Black and White of Original 1

Watershed Method Results
Blobs Only

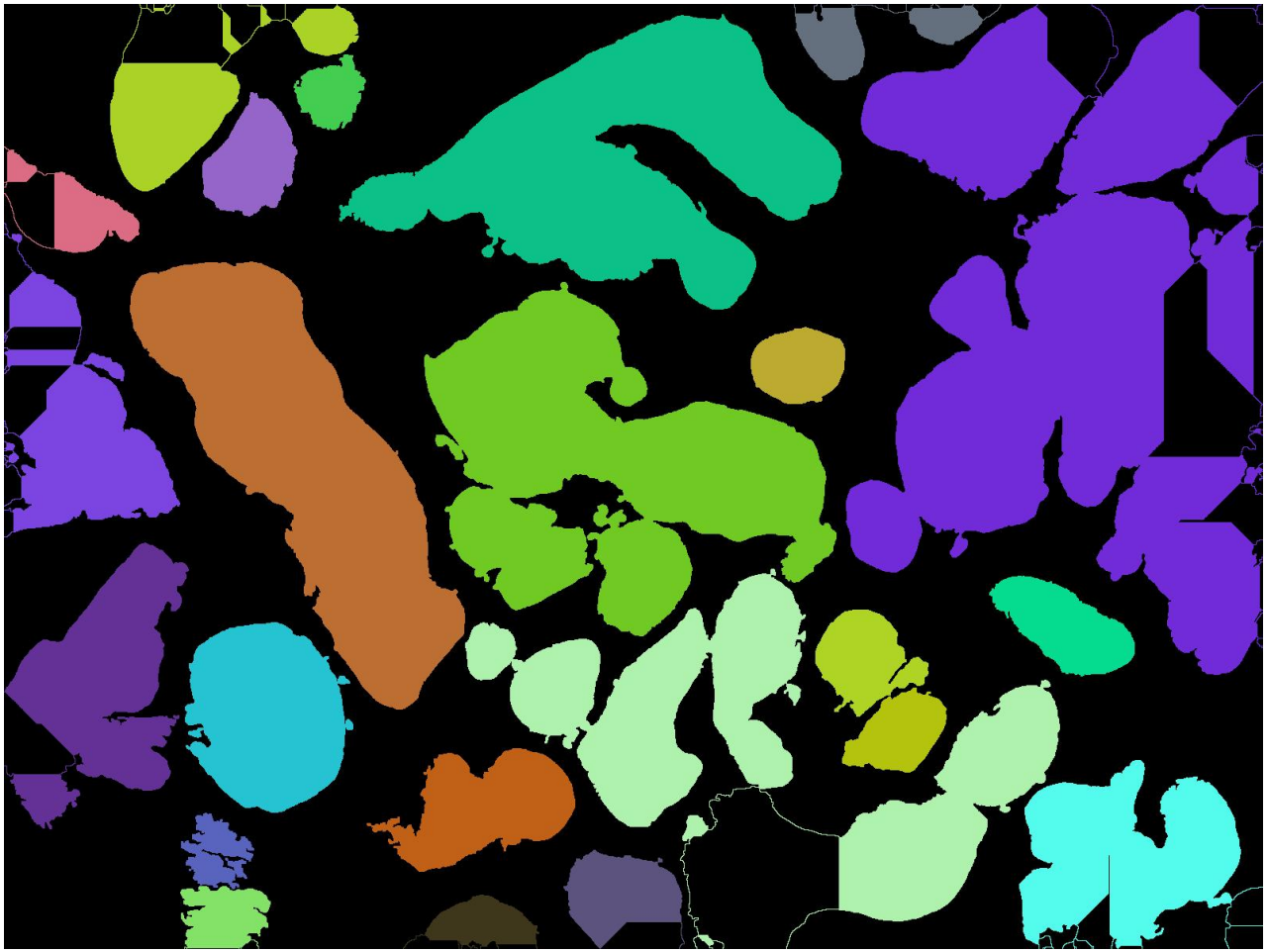

Figure: Segmented Blobs of Original 1

Watershed Method Results
Blobs and Vessels

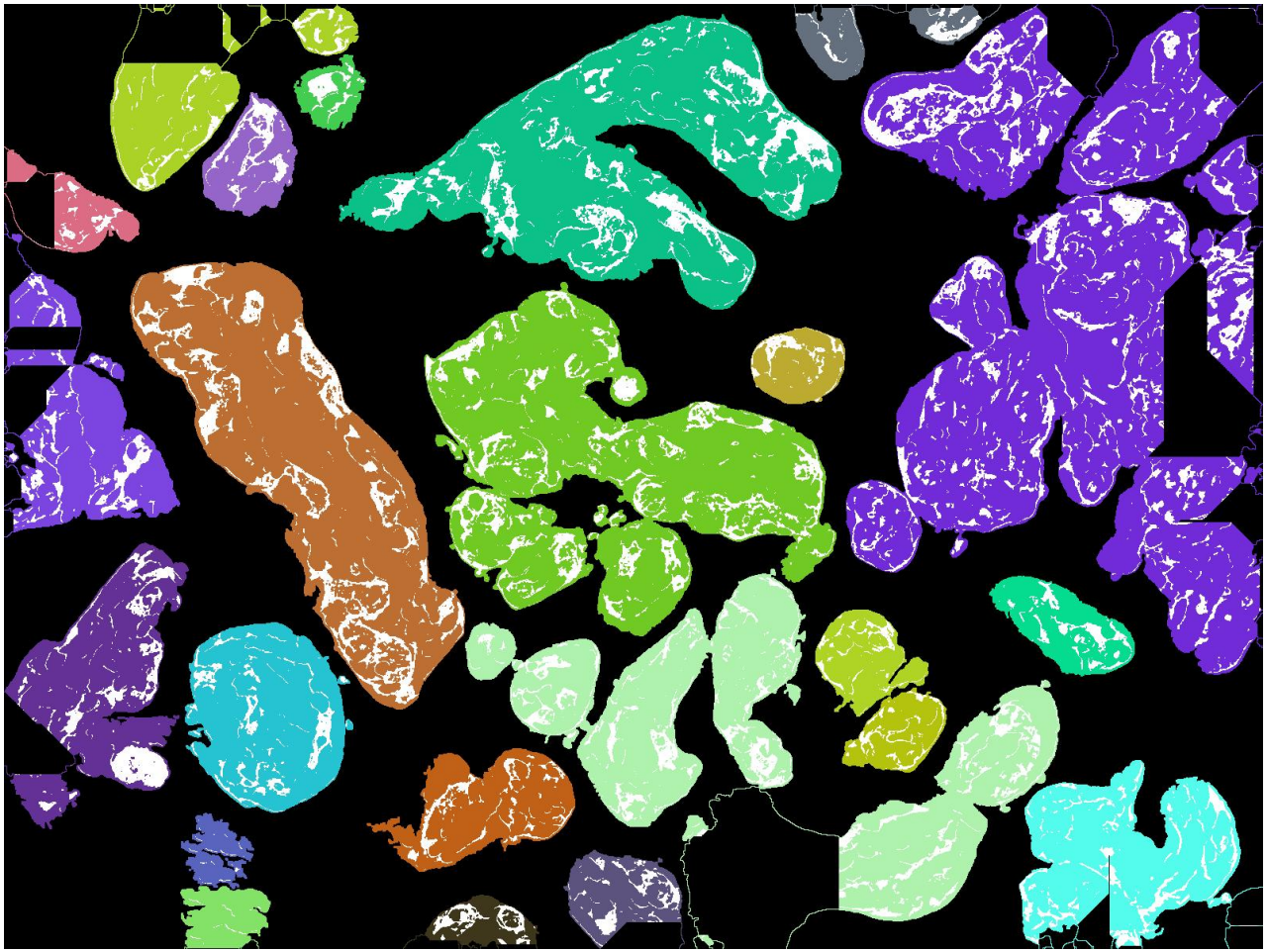

Figure: Segmented Blobs and Vessels of Original 1

Sketch and Scan
Hand-Tracings of Original Images

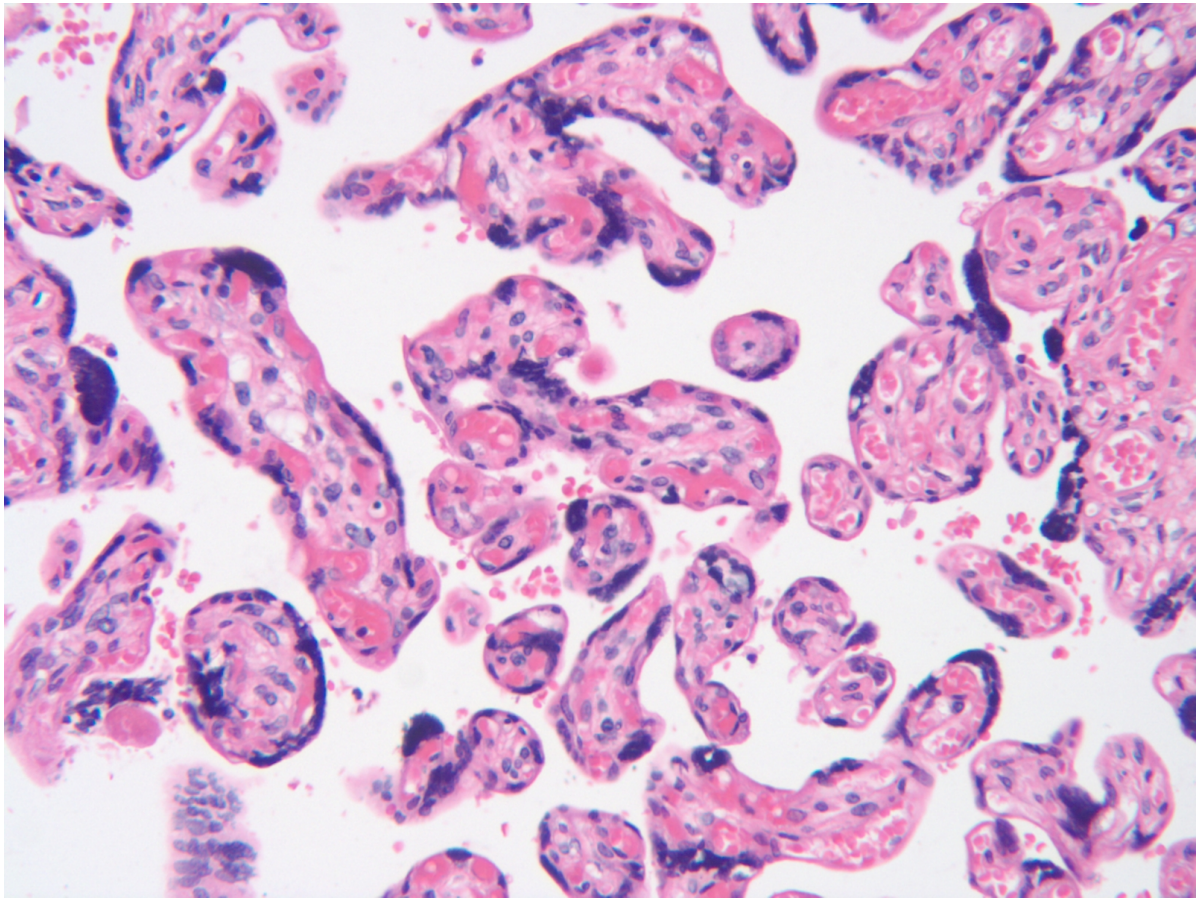

Figure: Histology Slide 1

Sketch and Scan
Hand-Tracings of Histology Slide 1

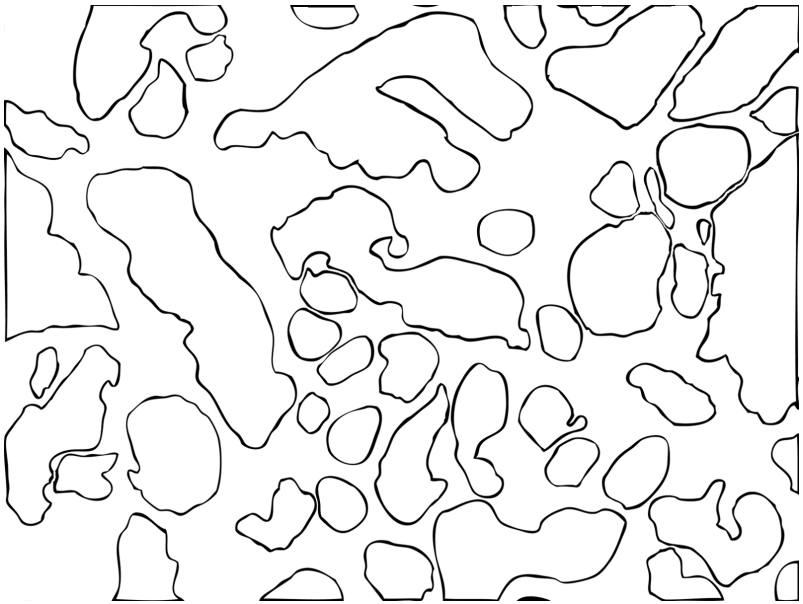

Figure: Outlined Blobs

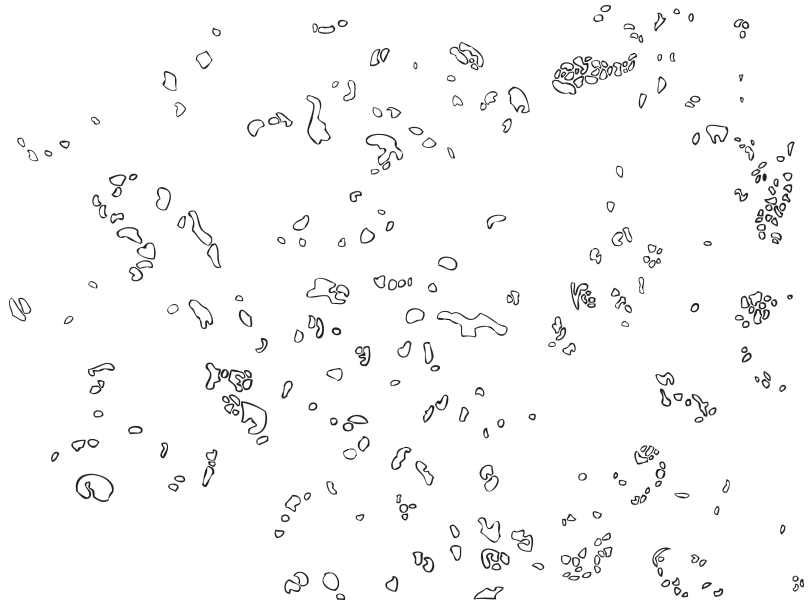

Figure: Outlined Vessels

Sketch and Scan
Hand-Tracings of Original Images

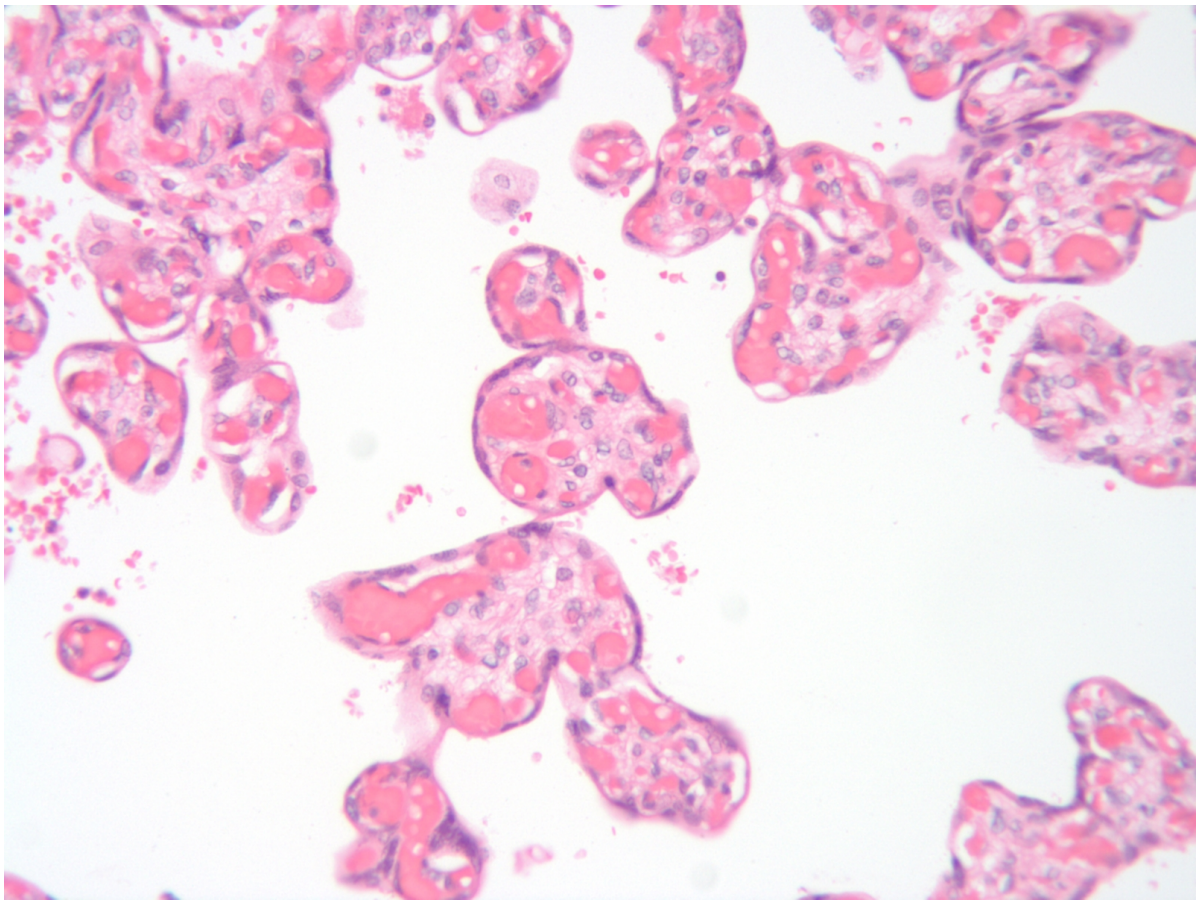

Figure: Histology Slide 2

Sketch and Scan
Hand-Tracings of Histology Slide 2

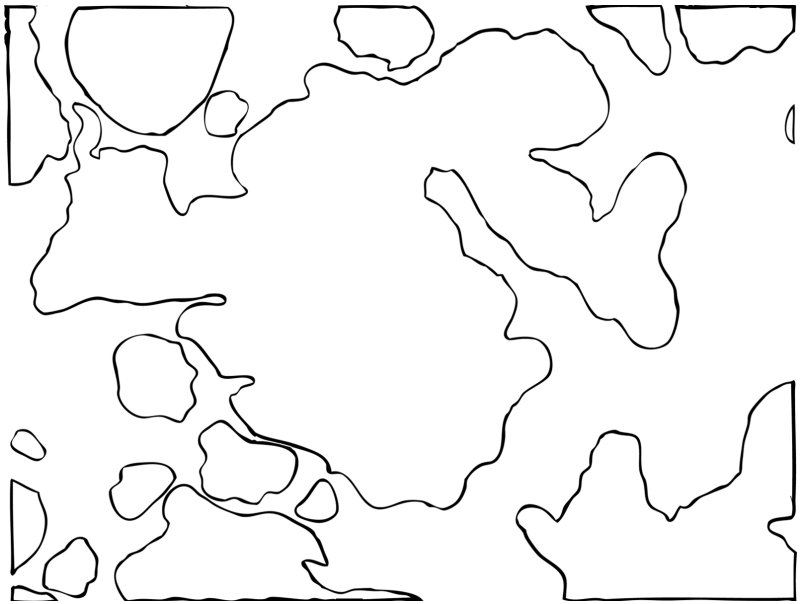

Figure: Outlined Blobs

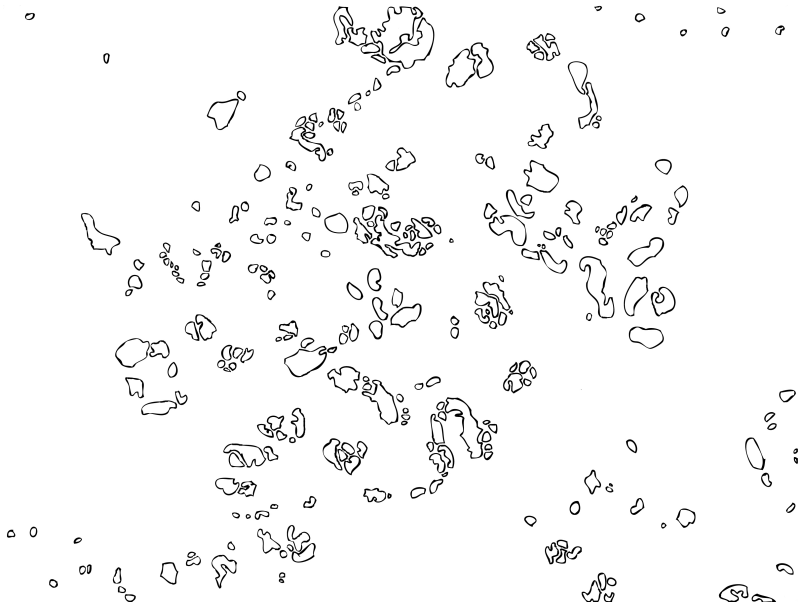

Figure: Outlined Vessels

Sketch and Scan
Hand-Tracings of Original Images

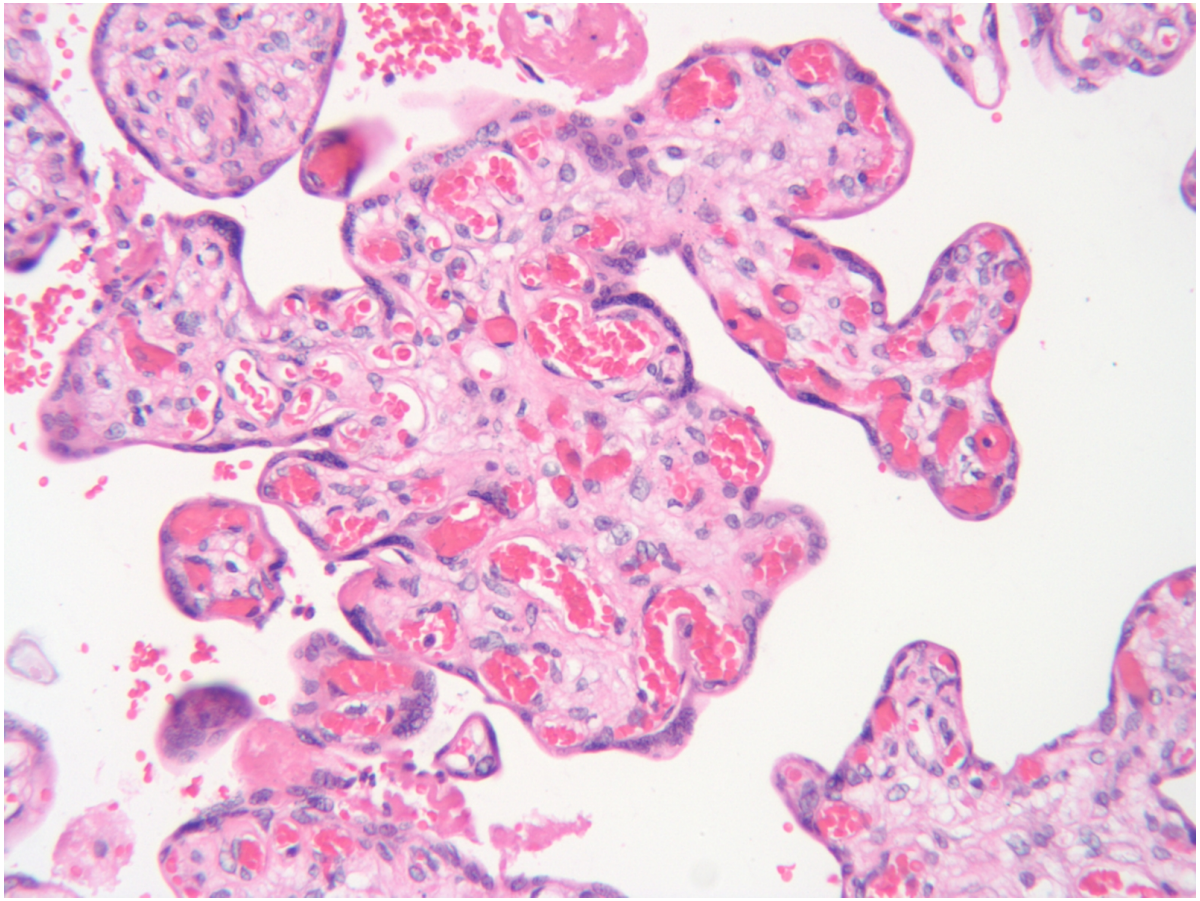

Figure: Histology Slide 3

Sketch and Scan
Hand-Tracings of Histology Slide 3

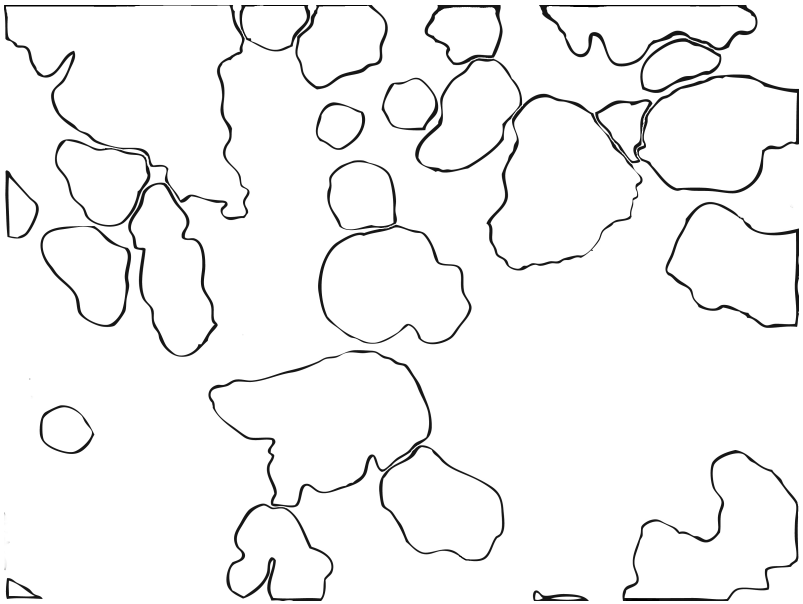

Figure: Outlined Blobs

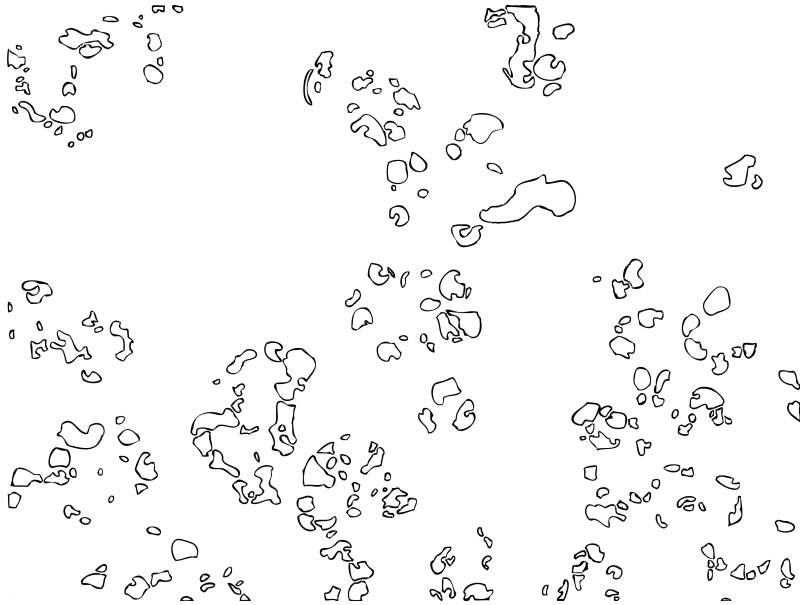

Figure: Outlined Vessels

Judging a Book by its Cover
Comparing Blob Area

Relative Error Comparison		
Method	Total Blob Area	Median Blob Area
KM Euclid	22.77%	N/A
KM Mahal RGB	24.714%	N/A
KM Mahal Lab	23.97%	N/A
Chan-Vese	25.77%	N/A
Edge Detection	11.76%	41.53%
Histogram	23.00%	27.89%
Watershed	17.00%	82.13%

Judging a Book by its Cover
Comparing Vessel Area

Relative Error Comparison		
Method	Total Vessel Area	Median Vessel Area
KM Euclid	53.17%	N/A
KM Mahal RGB	143.52%	N/A
KM Mahal Lab	39.47%	N/A
Chan-Vese	34.66%	N/A
Edge Detection	39.76%	32.74%
Histogram	45.79%	36.49%
Watershed	45.17%	163.88%

Conclusion
Future Ideas

1. Further Examination of Chan Vese Method
2. Combinations of Existing Methods
3. A Deeper Analysis of Our Data

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Questions?