Fully automatic segmentation of stained histological cuts

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Abstract

The paper describes an automatic unsupervised segmentation of stained histological sections, which would be suitable for further registration of series of stained consecutive histological cuts. We combine some already existing methods – Gaussian Mixture model of colour histogram, superpixels to increase the robustness and speed, and the Graph Cut method to obtain compact segmentation. We show the experimental results on both synthetic and real histological images. For synthetic images we reach mean classification error for 4-class segmentation of about 3%. The unsupervised segmentation on real images provides always a reasonable object, which is important for future segmentation-based registration.

Method

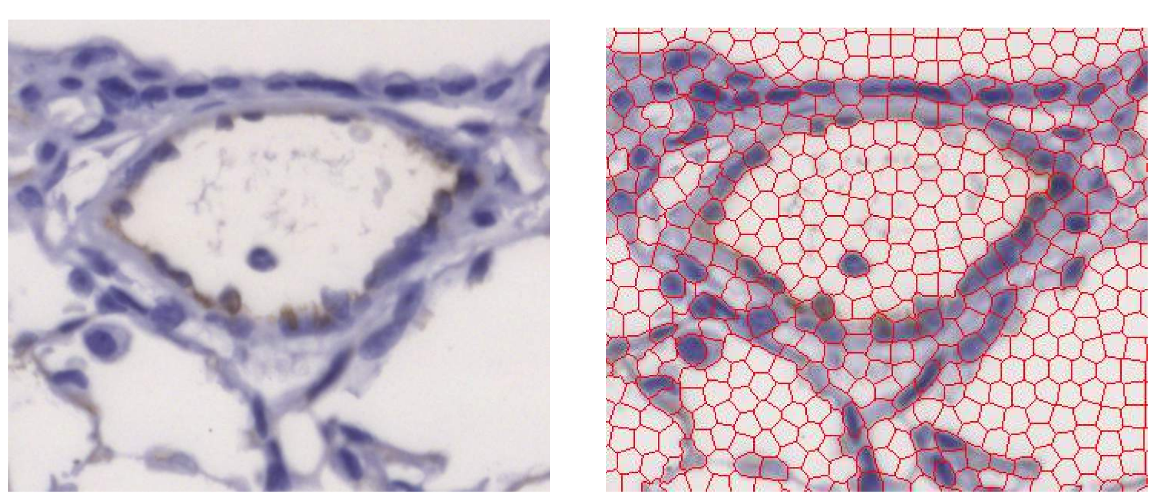
1. SLIC superpixel segmentation;
2. colour descriptors;
3. estimation of Gaussian Mixture Models (GMM);
4. Graph Cut segmentation.

SLIC superpixels

Simple linear iterative clustering (SLIC) [1] superpixel segmentation is based on k-means with features space

$$x = [\text{CIELAB color}; \text{position}]$$

on limited region $2K \times 2K$ where K is grid size.

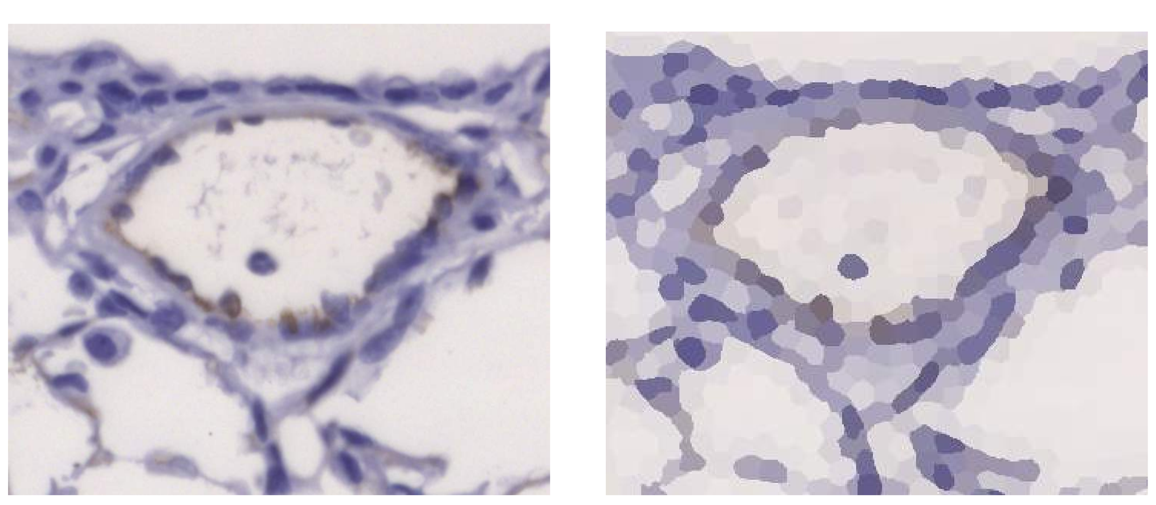


Sample of original image. SLIC superpuxel segmentation.

Colour descriptors

Colour descriptors on extracted superpixels as colour means.

$$s_j = \frac{1}{\|\Omega_j\|} \cdot \sum_{i \in \Omega_j} x_i$$

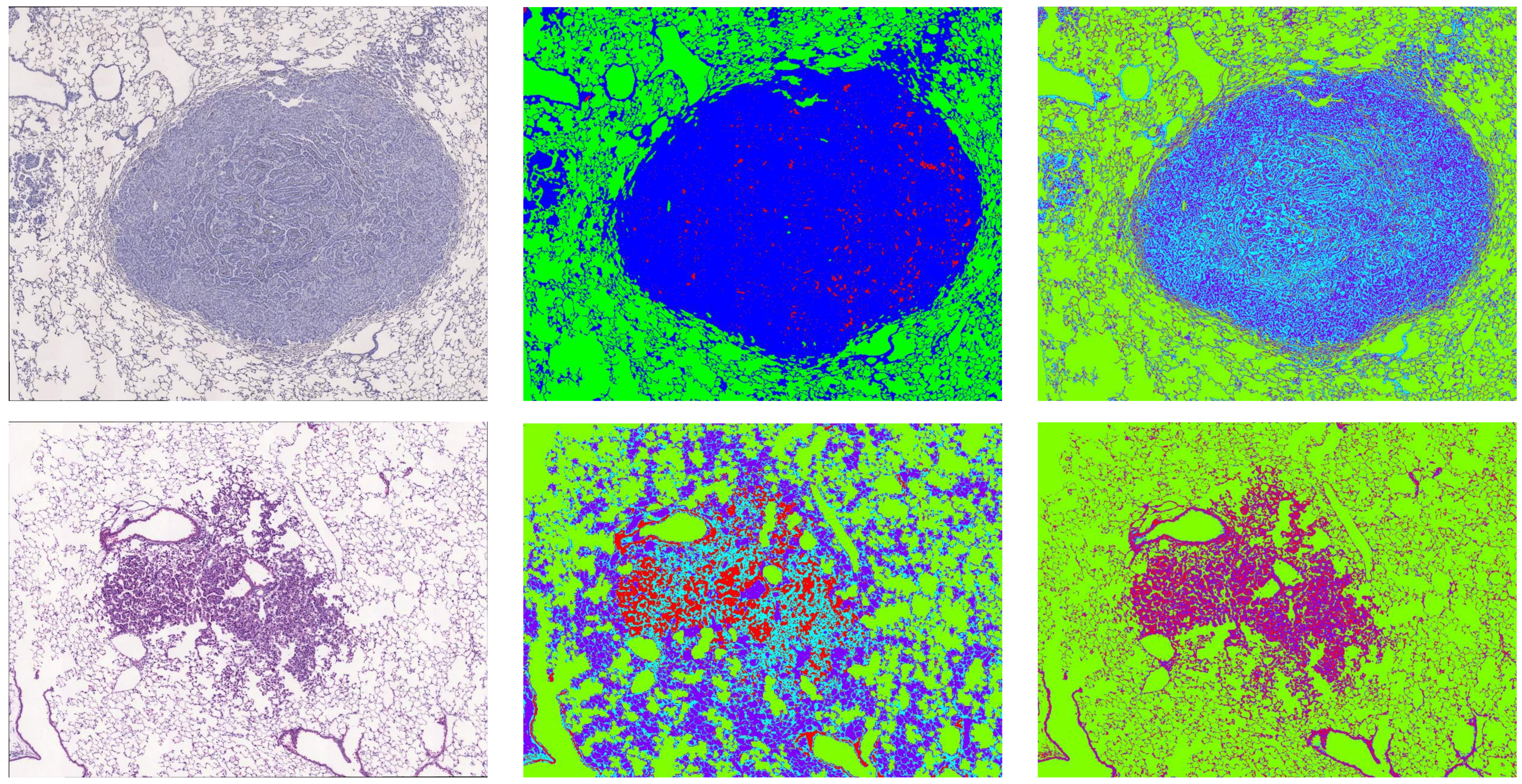


Sample of original image. Descriptors - colour means.

Segmentation examples

lesion stain by CD31

lesion stain by H&E

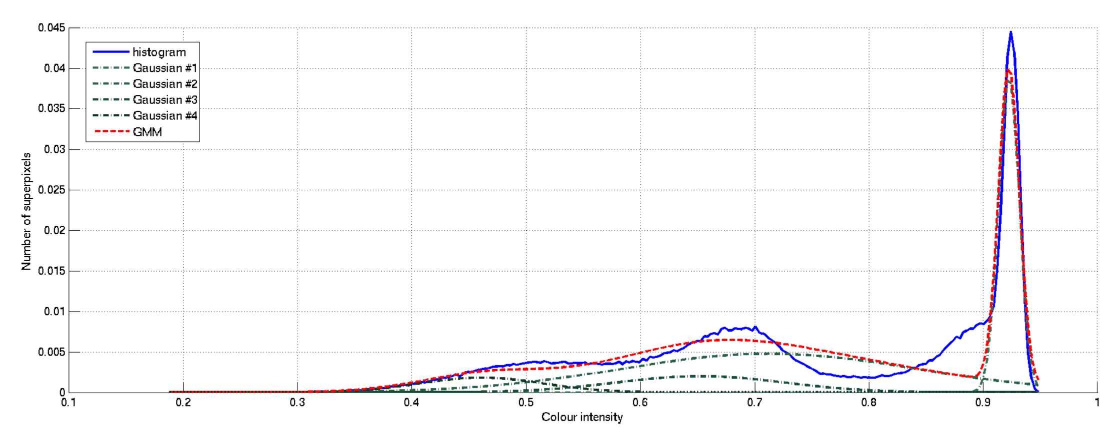


Original image | Automatic segmentation | Weka segmentation

GMM and EM estimation

Unsupervised learning of the probabilistic models of expected classes using the Expectation-Maximisation (EM) [2] algorithm initialised by K-means for Gaussian Mixture Models (GMM) [3].

$$p(\boldsymbol{s}_i|\theta_k) = N(\boldsymbol{s}_i, \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$$



Projection of descriptors.

Graph Cut segmentation

Graph Cut extract compact segmentation [4]

$$Y^* = \arg\min_Y \sum_i \overbrace{U(x_i, y_i)}^{\text{Unary term}} + \sum_{\substack{i \neq j \\ d(i,j) \leq 1}} \overbrace{B(y_i, y_j)}^{\text{Binary term}}$$

where the unary term defines assignment cost

$$U(x_q, y_q) = -\log(p(x_q|y_q) \cdot h(y_q))$$

and the binary term describes relation between labels

$$B(k, l) = \beta \cdot [\![k \neq l]\!]$$

Results

dataset	images	size ($x \cdot 10^3$ pixels)	relative error mean	relative error std
Synthetic	99	1.6×1.6	3.19%	4.88%
Lesions	5	18×15	24.6%	5.8%

Processing time for images with 9.000×7.500 pixels.

clustering	SLIC	desc.	GMM	GC	total
none	**0** s	**0** s	861.3 s	137.4 s	998 s
SLIC (7px)	131.6 s	0.4 s	**57.8** s	**12.9** s	**203** s

Conclusion

- unsupervised segmentation of large images of histological sections
- SLIC superpixels decrease dimensionality for Graph Cut segmentation
- segmentation with various a mount of details in segmented images
- useful for the registration of stained histological cuts

References

[1] R. Achanta and A. Shaji. SLIC Superpixels Compared to State-of-the-art Superpixel Methods. *Pattern Analysis and Machine Intelligence, IEEE*, 34(11):2274 – 2282, 2012.

[2] G. Xuan and W. Zhang. EM algorithms of Gaussian mixture model and hidden Markov model. *Image Processing*, 1:145–148, 2001.

[3] H. Permuter, J. Francos, and I. Jermyn. A study of Gaussian mixture models of color and texture features for image classification and segmentation. *Pattern Recognition*, 39(4):695–706, April 2006.

[4] A. Lucchi, K. Smith, and R. Achanta. Supervoxel-Based Segmentation of Mitochondria in EM Image Stacks With Learned Shape Features. *Medical Imaging, IEEE*, 31(2):474 – 486, 2012.

Graph Cut regularisation

Reg. | Original | 10^3 *(overlay)* | 10^3 | $3 \cdot 10^4$ | 10^5 | 10^5 *(overlay)*

lesion stain by H&E

lesion stain by CD31