

# Interactive Texture Segmentation using Random Forests and Total Variation

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Interactive image segmentation is the task of semi-automatically separating a foreground object  $\mathcal{F}$  from image background  $\mathcal{B}$ . Usually, two steps are required to perform this task: (i) Generation of a hypothesis describing the likelihood that a certain pixel belongs to  $\mathcal{F}$ , and (ii) regularization to prevent overfitting of the hypothesis.

**Hypothesis** The segmentation quality depends on a strong description for  $\mathcal{F}$  and  $\mathcal{B}$ . In order to model hypotheses based on different high-level features, we need an efficient learning algorithm capable of handling arbitrary input data. Random Forests (RFs) are fast to compute while yielding state-of-the-art performance in machine learning and vision problems. Their parallel structure dedicates them to GPU implementations. Recently, an online version of RFs has been proposed [2], which renders retraining of the whole forest upon additional user input unnecessary.

**Regularization** Edge information can provide valuable information during regularization. Therefore, a wide range of segmentation algorithms are based on the minimization of the Geodesic Active Contour (GAC) energy. As already shown in [3], continuous minimization approaches have the advantage of low memory consumption, no discretisation errors and high parallelization potential compared to discrete methods such as graph cuts. By implementing them on the GPU, continuous algorithms obtain speeds comparable to discrete methods.

**Framework** We propose a tool comprising the extraction of features, Random Forest classification and convex energy minimization, all implemented on a GPU. We use the following convex minimization problem

$$\min_u \left\{ E_p = \int_{\Omega} g |\nabla u| dx + \lambda \int_{\Omega} u f dx \right\},$$

with  $\Omega$  the image domain,  $f: \Omega \rightarrow \mathbb{R}$  the hypothesis, and  $u: \Omega \rightarrow \{0, 1\}$  the binary labeling into foreground and background. Letting  $u$  vary continuously in the interval  $[0, 1]$  leads to convexity, thus, we can find a globally optimal solution. This solution is obtained by minimizing the energy with a fast primal-dual algorithm.

Using graphics processors speeds up the whole segmentation process to a few seconds and allows for convenient user interaction. In the experiments, we compare our framework to the continuous approach TVSeg [3] and the graph based framework GrabCut [1].

Method	Features	Hypothesis	Regularization
Unger <i>et al.</i> [3]	Color	Histograms	<b>TV</b>
Rother <i>et al.</i> [1]	Color	GMM	Graph Cut
Our approach	<b>arbitrary</b>	<b>RF</b>	<b>TV</b>

Table 1: Comparison of methods, bold faced letters indicate GPU implementations.



Figure 1: Segmentation results on artificial data using different methods.

**Experiments** Figure 1 shows how incorporating high-level features allows for segmentation of textured objects from isochromatic images. In figure 2, we compare the results of GrabCut, TVSeg and our approach with hand-labelled segmentations of natural images from the Berkeley Segmentation Dataset. Figure 3 shows results on medical data using iterative refinement by reseeding training points in previous segmentations.

Constraints	TVSeg	GrabCut	Our approach
	 90.0%	 73.8%	 <b>94.6%</b>
	 59.9%	 86.3%	 <b>96.3%</b>
	 99.4%	 89.4%	 <b>99.6%</b>

Figure 2: Quantitative evaluation, accuracy rates are given in percent of correct pixels compared to hand-labelled ground truth.

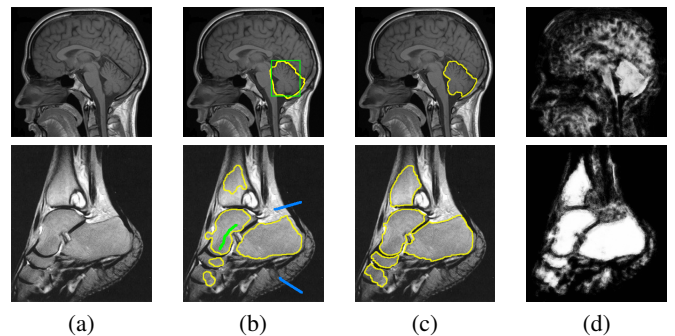


Figure 3: The original image (a) is segmented using rectangular or brush stroke constraints (b). The intermediate segmentation is used to retrain the forest resulting in better hypothesis and segmentation (c,d).

- [1] Carsten Rother, Vladimir Kolmogorov, and Andrew Blake. GrabCut: interactive foreground extraction using iterated graph cuts. *ACM Transactions on Graphics*, 23(3):309–314, 2004.
- [2] Amir Saffari, Christian Leistner, and Horst Bischof. Online random forests. Technical Report 09/02, Institute for Computer Graphics and Vision, Graz University of Technology, 2009.
- [3] Markus Unger, Thomas Pock, Werner Trobin, Daniel Cremers, and Horst Bischof. TVSeg - interactive total variation based image segmentation. In *Proceedings 19th British Machine Vision Conference*, 2008.

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