Tissue classification with smooth boundary regularized KNN

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Introduction

In this work we present a machine learning method with similar properties as the well known k-nearest-neighbor algorithm, but with an additional spatial regularization. The method can be used for tissue classification in medical images where several image frames are available for each data point (pixel/voxel.)

The suggested method provides:

- **Tissue regions of regular shape**
- **Low sensitivity to errors in training data**
- **Low sensitivity to noise**
- **Fast calculation**

Mathematical framework

Based on a the variational image segmentation framework by Mumford and Shah [1] we have the following discrete segmentation model:

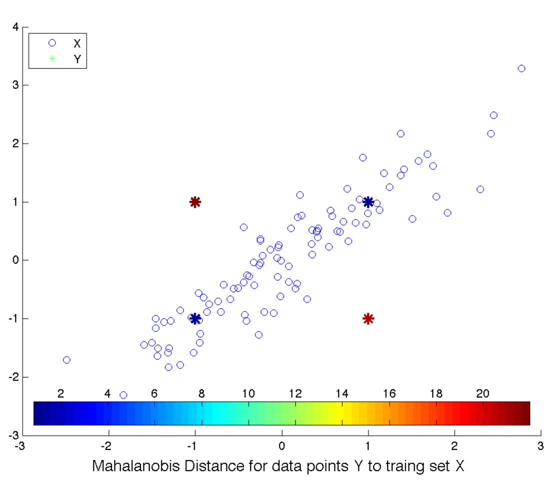
The domain Ω is segmented into two regions S and T, $S \cup T = \Omega$, $S \cap T = \emptyset$, by the minimization

$$\min_{S,T} \sum_{v \in S} C_s(v) + \sum_{v \in T} C_t(v) + \alpha B(S,T). \quad (1)$$

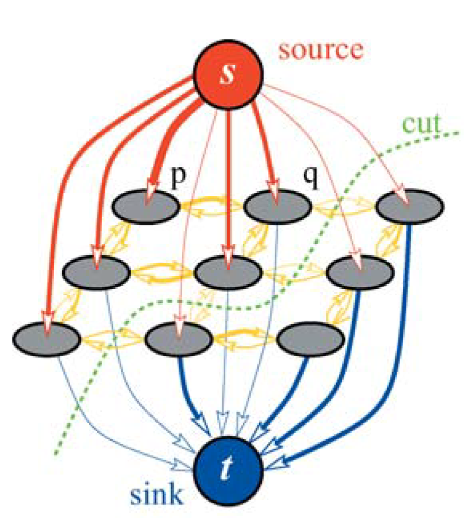
$C_s(x)$ and $C_t(x)$ are data-fidelity terms and can be seen as the similarity between point x and some pre-defined property of region S or T. The last term $B(S,T)$ is a discrete boundary measure.

We use the Mahalanobis distance to a user-defined training-set as data-fidelity term.

The Mahalanobis distance describes the distance from a point to a point-cloud.



An efficient solution of the minimization problem (1) can be computed using graph cuts as described in [2,3].



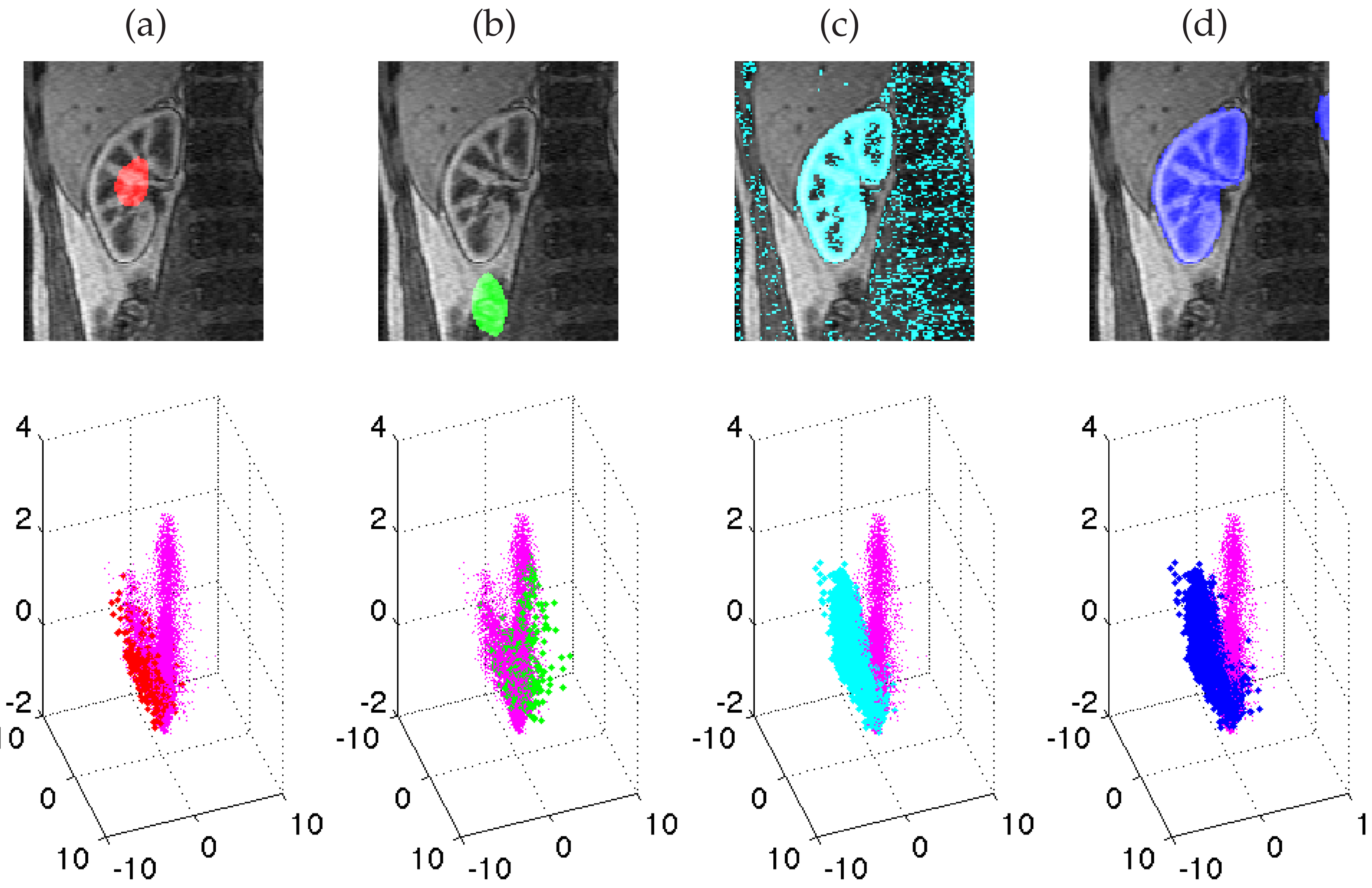
Adapted from [3]

All data points are represented by a node (gray) and assigned to the sink (blue) and the source (red) by edges weighted according to the data fidelity terms. The yellow edges correspond to similarities between neighboring data points

The graph based algorithm is based on the min cut/max-flow principle and allows for a fast solution of the minimization in (1).

Kidney data example

This example uses kidney MRI with contrast[1]. The tissue will be classified by its ability to absorb contrast and the timing of the absorption. 11 image frames are used to form a high dimensional feature space. The image sequence has only minor disturbence from respiration. In the example below we extract all compartments of the kidney within one operation



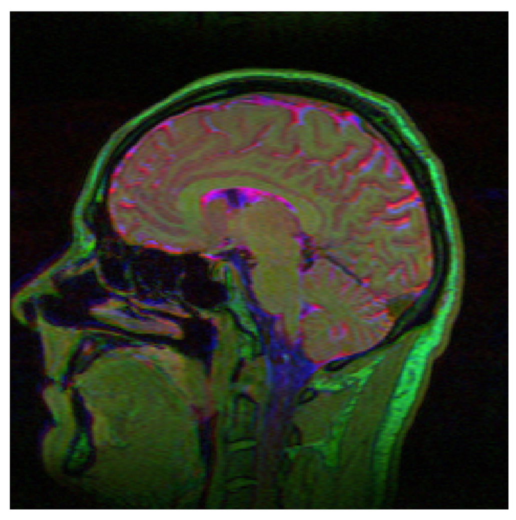
First row: *(a) Object training set, (b) Background training set, (c) classification using KNN, (d) classification using suggested method.* ***Second row:*** *Feature space representation corresponding to first row. (The feature space is projected down to three dimensions for visualization purposes)*

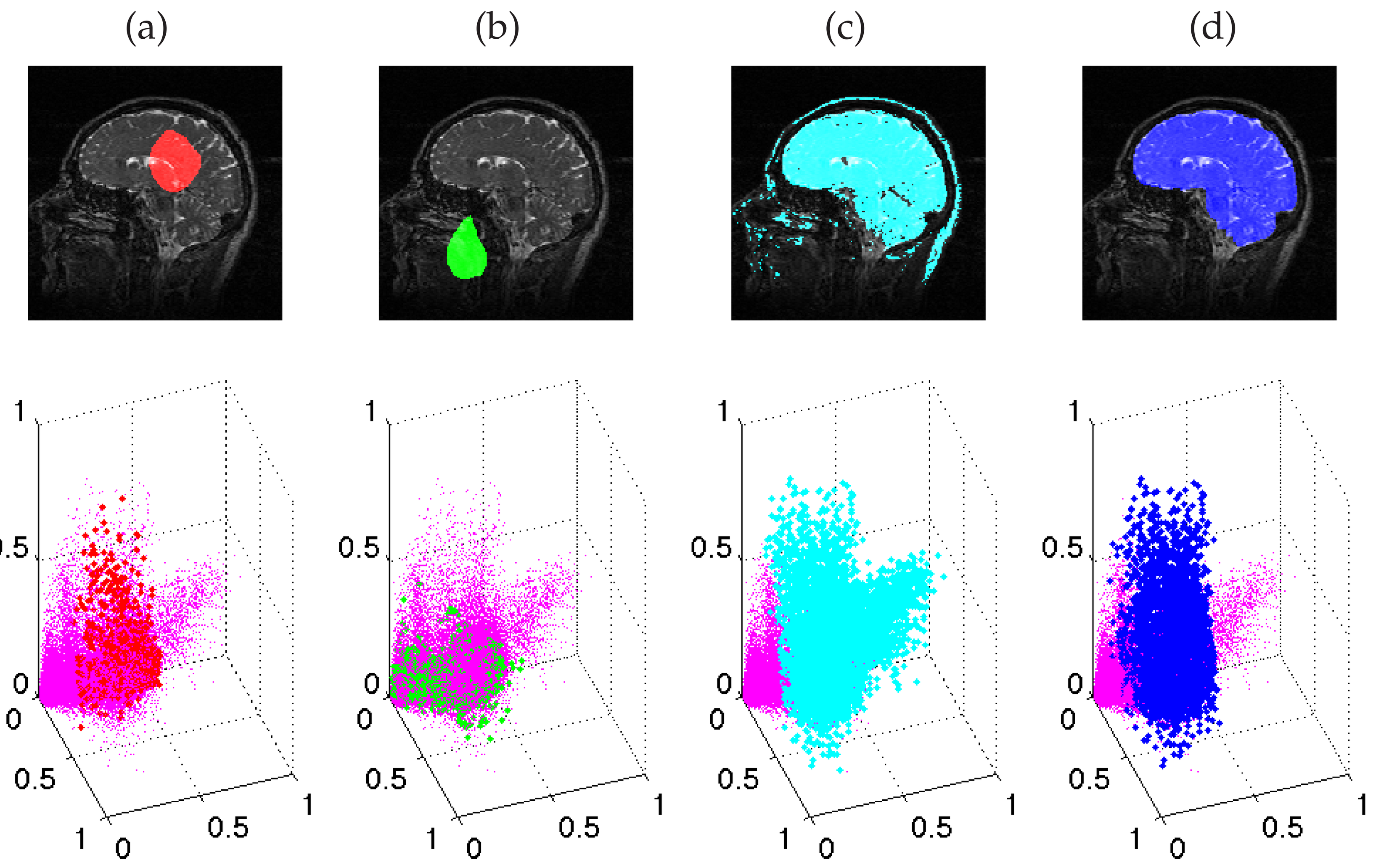
The improved classification quality is obtained by clustering data points with similar behavior over all the image frames (feature space), but at the same time force neighboring data points to belong to the same group.

[1] Courtesy of the "Kidney functional imaging project" headed by Prof. Jarle Rørvik

Brain data example

In this example we study a multispectral MRI dataset with the intention to extract the brain. The data includes one T1-weighted FLASH channel, one T2-weighted DESS channel and one T2-weighted PSIF channel [4]. One slice of the image data is expressed to the right in RGB image space. Note that the brain tissue has a color structure different from the most of the image, but the colors are in no way uniform.





First row: *(a) Object training set, (b) Background training set, (c) classification using KNN, (d) classification using suggested method.* ***Second row:*** *Feature space representation corresponding to first row.*

Further Work

This first implementation of the method only apply spatial regularization in 2D. Further work will include a 3D-implementation of the regularization and testing on a larger variety of 3D data.

We also aim to make a multi cluster edition of the method with a segmentation approach as in [5]. Further work will be available at:

folk.uib.no/eha070

Refrences

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