# Automated Colorectal Tumour Segmentation in DCE-MRI using Supervoxel Neighbourhood Contrast Characteristics

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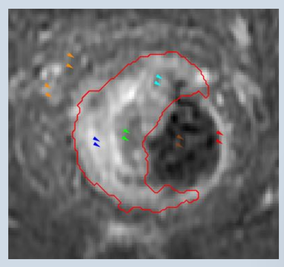
## Introduction

- **Dynamic contrast enhanced MRI** provides characteristic tissue signal enhancement curves for assessment of tissue perfusion.
- DCE-MRI is becoming a key modality for monitoring **tumour progression** and **response**
- Colorectal tumours exhibit **heterogeneity** in signal enhancement both within the tumour and surroundings (Fig 1)
- Accurate tumour segmentations are required for tumour analysis and characterisation
- Considerable **inter-rater variability** demonstrates the need for a robust and consistent segmentation approach in DCE-MRI
- However, automated DCE-MRI colorectal tumour segmentation is currently **unexplored**



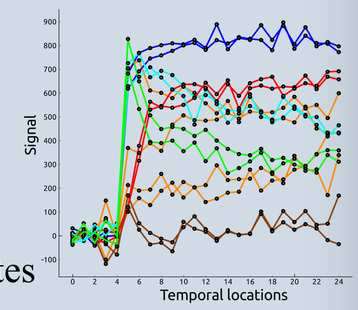



Fig 1. Signal enhancement curves for the tumour and surrounding tissue. This figure illustrates the heterogeneity in the tumour, as well as similarities between subregions of the tumour.

## 1. Colorectal DCE-MRI cases

- **23 patients** with rectal adenocarcinomas
- 1.5T GE with **SPGR DCE-MRI** sequence
- **T2-weighted** high resolution images were **delineated** by expert radiologists because of the challenge of delineating 4D DCE-MRI directly
- However, there is still considerable **variability** between experts due to **mucinous tumours**, **wall thickening** and **complex anatomy**
- Tumour masks are then **aligned** and **registered** with DCE-MRI baseline scan
- Aligned using patient coordinates
- Non-rigid registration to correct for small motion between scans.

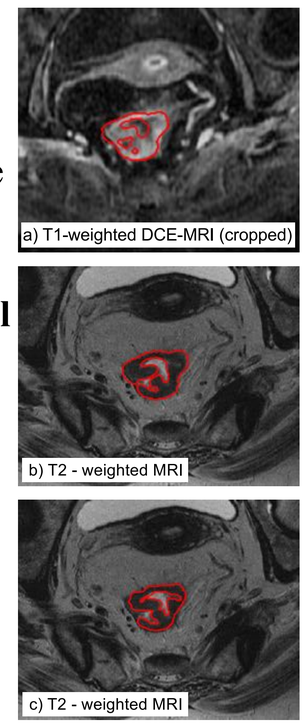



Fig 2. Colorectal MRI images with annotations a) DCE-MRI axial slice (with tumour annotation) b,c) Corresponding T2 MRI showing the inter-rater variability of the delineation

## 2. Preprocessing

- Foreground detection and **automatic cropping**
- Preprocessing of the tumour ROI with **partial supervoxel** coverage
- Enhancement curve **normalisation**
- Detection of **injection time**

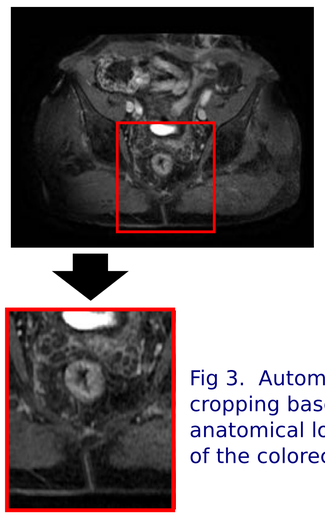


Fig 3. Automated cropping based on anatomical location of the colorectum

## 3. PCA-SLIC supervoxels

- **Voxel enhancement** represented by principal components (**b**)

$$\mathbf{b} = \Phi^T(\mathbf{x} - \overline{\mathbf{x}})$$

- **Simple linear iterative clustering** (SLIC) extended for contrast enhanced 4D imaging by **coupling** with **PCA** modes of enhancement

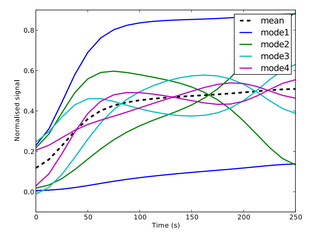



Fig 4. Two standard deviations of the first 4 modes of variation from the mean enhancement curve

| | |
|---|---|
| Feature distance ($d_f$) | $d_f^2 = \frac{1}{n}\sum_k^n (b_{jk} - b_{ik})^2$ |
| Spatial distance ($d_s$) | $d_s^2 = \sum_k^3 (x_{jk} - x_{ik})^2$ |
| $D = \sqrt{d_f + (d_s/r)}$ | $r = \frac{s}{\text{compactness}}$ |

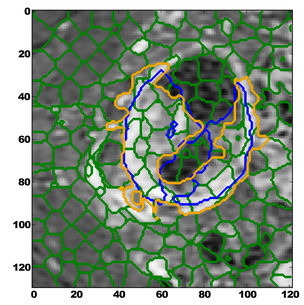


Fig 5. Supervoxel cross sections and ROI on a single slice and temporal location of the 4D DCE-MRI

## 4. Supervoxel features

- **PCA dimensionality reduction** applied to the signal enhancement of each voxel in the image
- Features extracted from each **supervoxel** using mean and variance of **b**
- **Supervoxel connectivity** graph used to extract neighbourhood
- Rotationally invariant magnitude of the gradient used to capture variation in **neighbourhood features**

$$f = \{f_s, f_\nabla\}$$

Supervoxel features — Neighbourhood features

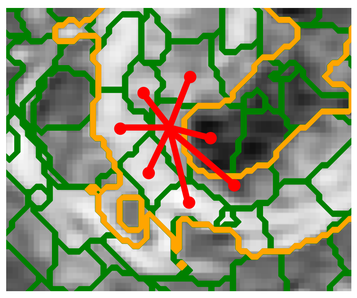


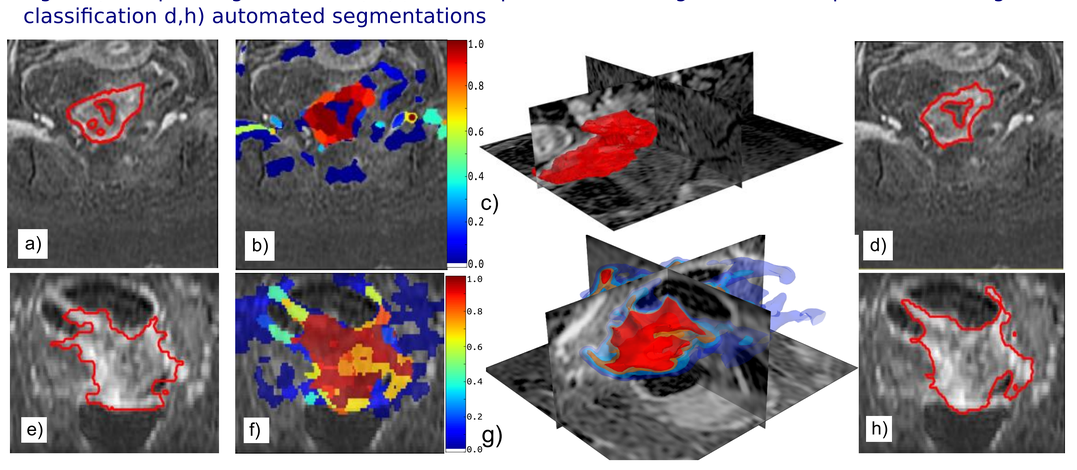
Fig 6. Cross section of the supervoxel representation and tumour ROI with illustration of the nearest neighbour connectivity for a single supervoxel. .

$$f_{\nabla i} = \sqrt{(f_{x+1} - f_{x-1})^2 + (f_{y+1} - f_{y-1})^2 + (f_{z+1} - f_{z-1})^2}$$

## 5. Learned representation

- Linear discriminant analysis and Random forests evaluated
- Classification applied to **individual supervoxels** of an unseen case
- **Tumour probability** assigned to each supervoxel

Fig 7. a,e) Expert segmentations, b,f) Tumour probabilities assigned to the supervoxels during classification d,h) automated segmentations




## Results

- **Leave-one-patient-out** cross validation
- First four patients used for parameter selection
- Correctly detected colorectal tumour location in **20 of 23 cases**
- **DICE overlap of 0.68 ± 0.15** with processed ground truth
- Close to **expert variability 0.73 ± 0.13** and **0.77 ± 0.10**
- Improvement on **fuzzy c-means** clustering **0.28 ± 0.17**
- Written in **Python** and **c++** with a run time of 3.7± 2.4 minutes per case (4 x faster than an expert of ~ 15 minutes)

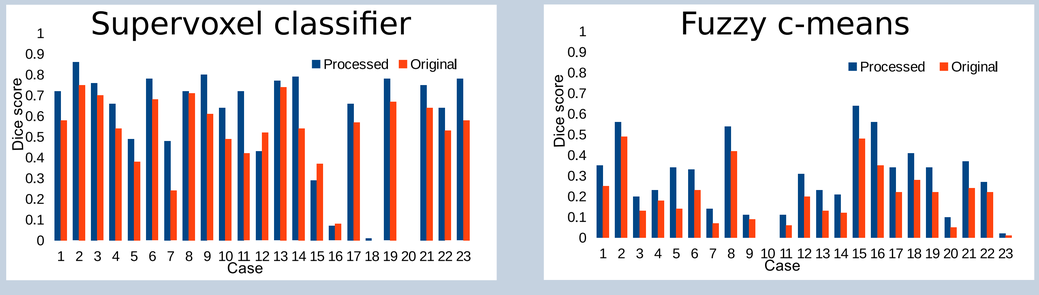



Fig 8. Dice score for the supervoxel classification method and fuzzy c-means method based on the processed ground truth and the original ground truth

Visualisations: www.birving.com/supplementary/Irving_MICCAI_2014.xhtml

## Summary and contributions

- We have introduced a novel method to **segment colorectal tumours** directly from **4D DCE-MRI** using the **signal enhancement patterns** of the tumour and surrounding regions
- This method aims to provide a **robust segmentation** approach to reduce the influence of expert **inter-rater variability**
- Future extensions will include an **explicit tumour and heterogeneity model** to further constrain the segmentation

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