detect similarities across patients we performed dimensionality reduction using the t-distributed stochastic neighborhood embedding (t-SNE) followed by a Gaussian Mean Shift Clustering. ANOVA tests for each descriptor and each cluster were performed to find statistically significant differences. A repeated measurements model was fitted at each cluster to evaluate within-cluster trends for patients with and without toxicity (Fig. 1).

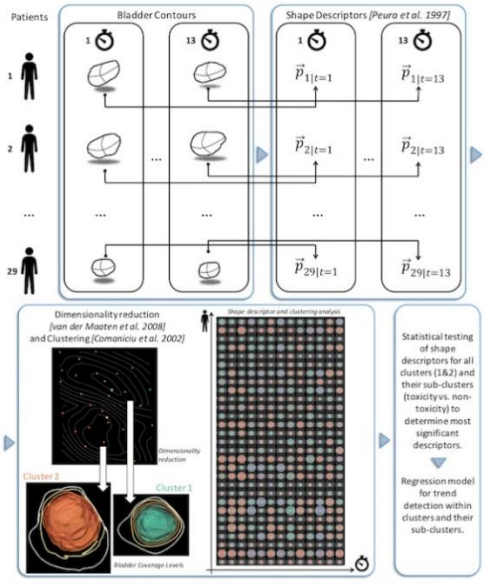


Figure 1. The workflow of our followed approach. Each patient bladder is described by 17 basic shape descriptors, and machine learning for dimensionality reduction and clustering is used to determine the two most important clusters (excl. outliers) in the data. Then, statistical testing and regression modelling is used to detect which of the 17 shape descriptors are more important.

**Results**

Two clusters with distinct shape characteristics comprised 85% of the patients while a third cluster (15%) included outliers. Clusters remained similar when data from the entire RT course was pooled in the t-SNE classification. Significant differences between cases and controls were observed at each cluster in seven descriptors (convexity and elliptic variance along the three principal axes, and compactness). In cluster 1 (small bladder volumes) more convex and round bladders shapes were associated with higher toxicity risk, while in cluster 2 (large bladder volumes) more concave and elliptical shapes were associated with higher risk of toxicity (Fig. 2).

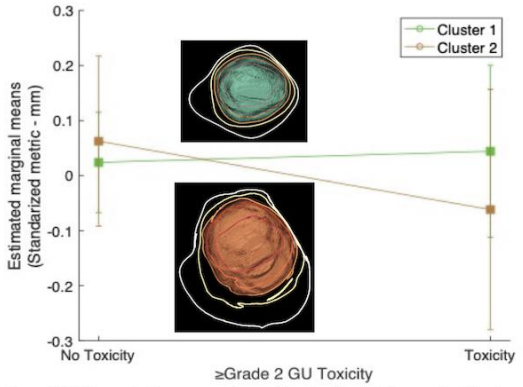


Figure 2. Fit to repeated measurements models using the data from each of the two clusters identified in the tSNE classification (only first week of treatment). The model for each cluster included the 7 shape descriptors not highly correlated (Pearson Coeff. < 0.6) and showing significant differences between patients presenting toxicity and those free from toxicity. For each cluster a sketch of the population average and quartiles bladder shape (at the central slice) are showed.

**Conclusion**

Bladder shape changes occurring during the first week of treatment show potential to predict the risk of developing late GU toxicity after RT for prostate cancer. Patient-specific changes in bladder shape might be related to the exposure of the most radiosensitive areas of the bladder to high doses.

**PO-0963 A novel normalisation technique for voxel size dependent radiomic features in oesophageal cancer**

P. Whybra[1], C. Parkinson[1], K. Foley[2], J. Staffurth[2], E. Spezi[1]

*[1]Cardiff University, School of Engineering, Cardiff, United Kingdom ; [2]Cardiff University, School of Medicine, Cardiff, United Kingdom*

**Purpose or Objective**

In oncology, radiomic studies hope to identify quantitative imaging features that predict survival and therapy response. To be clinically useful, features need to be robust. For 3D features that measure tumour heterogeneity, isotropic voxels are advised to ensure no directional bias [1]. Normally, PET/CT scans are not isotropic and require interpolation. The voxel size chosen is important; resampling a scan to smaller dimensions increases the number of voxels in a region of interest (ROI). An intrinsic dependency between common features and number of voxels in a ROI has been found [2]. This study evaluates methods to improve feature robustness and introduces a novel normalisation technique for voxel size dependent radiomic features in oesophageal cancer (OC).

**Material and Methods**

18F-FDG PET images (scanned and segmented with the same protocol) from 441 OC patients (training=353, validation=88) were included [3]. Standardised and validated [1] in-house feature extraction algorithms were used. Voxel intensities were discretised with a fixed bin width (0.5 SUV). Five selected features recommended for voxel normalisation [2] were extracted from the original scan dimension and 5 isotropic sizes. Patients were ranked based on the feature result of the original dimension. Surface models were generated on the training dataset to normalise each feature using the voxel size and feature value. A concordance correlation coefficient (CCC) was used to determine reproducibility between features extracted from the original dimension and a range of interpolated voxel sizes.

**Results**

Fig.1 shows development of a surface model and results for a selected feature, run length non-uniformity (RLNU). Fig.2 is a feature heatmap of the CCC results for each voxel dimension for the validation dataset. There are 3 versions of each feature; standard (CCC 0.16-0.96), voxel number normalised (CCC 0.08-0.99), and surface model normalised (CCC 0.95-0.99). Features normalised with a surface model performed the best in each case.

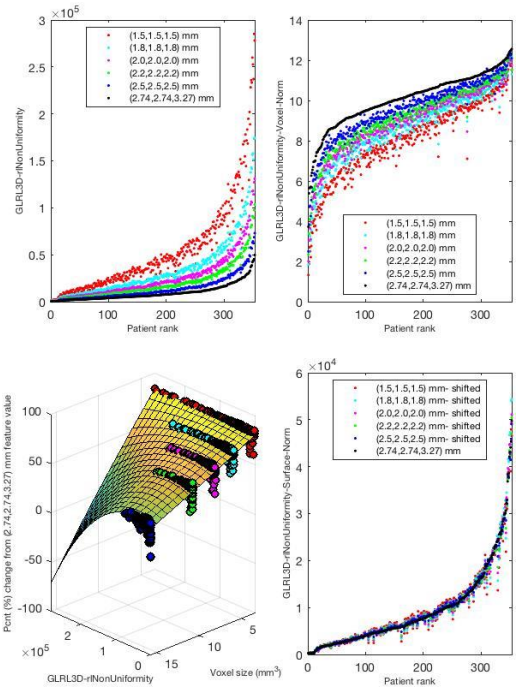


**Fig.1:** Results for RLNU (training). **TOP**: (left) feature calculated at each voxel dimension against patient rank. (right) Feature normalised by voxel number in ROI. **BOTTOM**: (left) Surface model to calculate feature change. (right) Surface model shifted result.

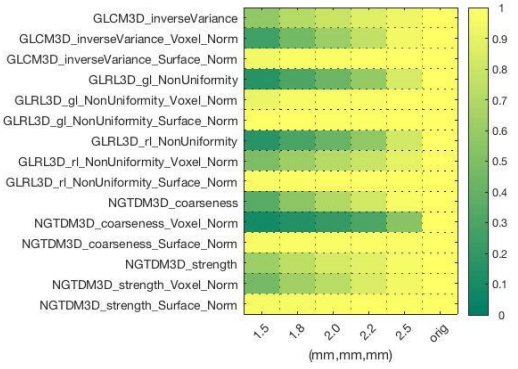


**Fig.2:** CCC heatmap for each feature (validation dataset)

**Conclusion**

We developed, tested and validated a novel normalisation technique for voxel size dependent radiomic features. On-going work aims at validating the proposed approach on other imaging modalities.

**References**

[1] A. Zwanenburg *et.al.*, "Image biomarker standardisation initiative" -arXiv:1612.07003

[2] M. Shafiq-Ul-Hassan *et.al.*,"Voxel size and gray level normalization of CT radiomic features in ESTRO_lung cancer," *Sci. Rep.*2018.

[3] K. G. Foley *et al.*, "Development and validation of a prognostic model incorporating texture analysis derived from standardised segmentation of PET in patients with oesophageal cancer," *Eur. Radiol.*, 2017.

## PO-0964 Stability and prognostic significance of CT radiomic features from oesophageal cancer patients

C. Piazzese[1], P. Whybra[1], R. Carrington[2], T. Crosby[3], J. Staffurth[4], K. Foley[5], E. Spezi[1]

*[1]Cardiff University, School of Engineering, Cardiff, United Kingdom ; [2]Velindre Cancer Centre, Medical Physics, Cardiff, United Kingdom ; [3]Velindre Cancer Centre, Department of Oncology, Cardiff, United Kingdom ; [4]Velindre Cancer Centre, Radiotherapy & Clinical Trials, Cardiff, United Kingdom ; [5]Cardiff University, School of Medicine, Cardiff, United Kingdom*

**Purpose or Objective**

Radiomics aims at extracting quantitative features from medical images. Several studies focussed on the potential value of radiomic analysis in predicting tumour response for oesophageal cancer (OC) patients using contrast enhanced CT images. However, in clinical practice contrast agents are not always administrable, making the development of a new radiomic model necessary. In this work, we investigated the usefulness of radiomic features extracted from contrast and non-contrast enhanced CT scans in the development of a prognostic model in OC.

**Material and Methods**

CT images and radiotherapy volumes of 213 patients from a clinical trial in OC[1]were processed with the CERR package[2]. Patients were divided into 3 groups: mixed group (MG) with contrast and non-contrast enhanced CT images (n=213), contrast group (CG) with contrast enhanced CT scans (n=138) and non-contrast group (nCG) with non-contrast enhanced CT data (n=75). Radiomic features were automatically extracted in 2D and 3D in compliance with the IBSI[3], using in-house developed data analytics software[4]. Stable features were selected as the ones with similar intra-groups distributions (Kruskal-Wallis test). Corresponding 2D and 3D stable features within each group were evaluated for differences (Wilcoxon signed rank test). Remaining filtered features and clinical characteristics were used to develop a prognostic model with the Cox regression method.

**Results**

A total of 119 2D and 3D features were computed from each group. The Kruskal-Wallis test excluded 82, 3 and 6 unstable features obtained from MG, from CG and from nCG, respectively (Fig. 1). Some stable features (6 for MG, 15 for CG and 17 for nCG) did not show a significant difference if extracted considering 1 tumour layer at a time or considering the whole tumour volume. Among stable features, 4 features showed no difference if obtained from 3D or 2D data and were stable in all the 3 groups. The Cox regression model, constructed with 8 clinical and radiomic variables, identified 1 feature (GLDZM zone distance variance) associated with survival (Table 1).

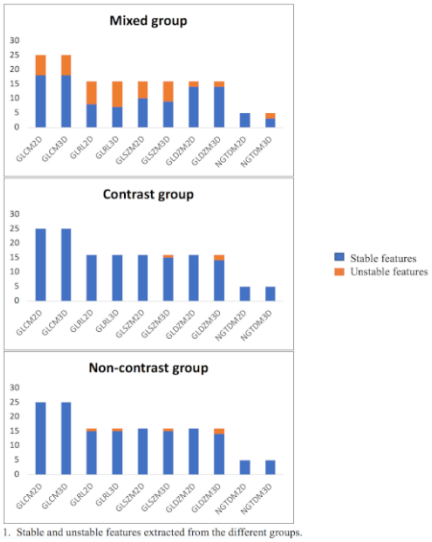


Figure 1. Stable and unstable features extracted from the different groups.

**Conclusion**

The prognostic model has identified 1 texture significantly and independently correlated with overall survival. This