School of Engineering / Yr Ysgol Peirianneg

Dependency of patient risk stratification on PET target volume definition in Oesophageal cancer

Author(s) [1]Parkinson C, [2]Foley K, [1]Whybra P, [3]Hills R, [4]Roberts A, [5]Marshall C, [6]Staffurth J, [1,6]Spezi E

[1]Cardiff University, School of Engineering, UK. [2]Division of Cancer & Genetics, UHW, Cardiff UK, [3]Clinical Trials Unit, Cardiff University UK. [4]Clinical Radiology, UHW, Cardiff, UK. [5]Wales Research & Diagnostic PET Imaging Centre, UK. [6]Velindre Cancer Centre, UK.

Introduction

A personalised approach to therapy is hoped to improve Oesophageal cancer survival rates. Recently, the inclusion of radiomic features extracted from PET images into prognostic models has gained substantial interest. However, radiomic features are dependent on the target volume definition (TVD) [1]. Many automatic PET segmentation methods (PET-AS) exist and are regularly used for feature extraction.

Aims & Objectives

The aim of this study is to investigate the dependency of patient risk stratification on TVD, defined by different PET-AS, when prognostic models are developed with radiomic features.

Materials & Methods

Consecutive patients (n=427) with biopsy-proven Oesophageal cancer staged with PET/CT were included. Patients received 4MBq/kg of ^{18}F-FDG before image acquisition at 90 minutes. In each case, the Metabolic Tumour Volume (MTV) was defined using Clustering Means (KM2), General Clustering Means (GCM3), Adaptive Thresholding (AT) and Watershed Thresholding (WT) PET-AS. Table 1, describes PET-AS implementations. All tumour segmentations were reviewed by a radiologist to ensure accuracy. Prognostic models using identical clinical data but different radiomic features defined by each segmentation method were developed. Changes in patient classification between risk groups were analysed. A p-value of <0.05 was considered statistically significant. Primary outcome was overall survival (OS).

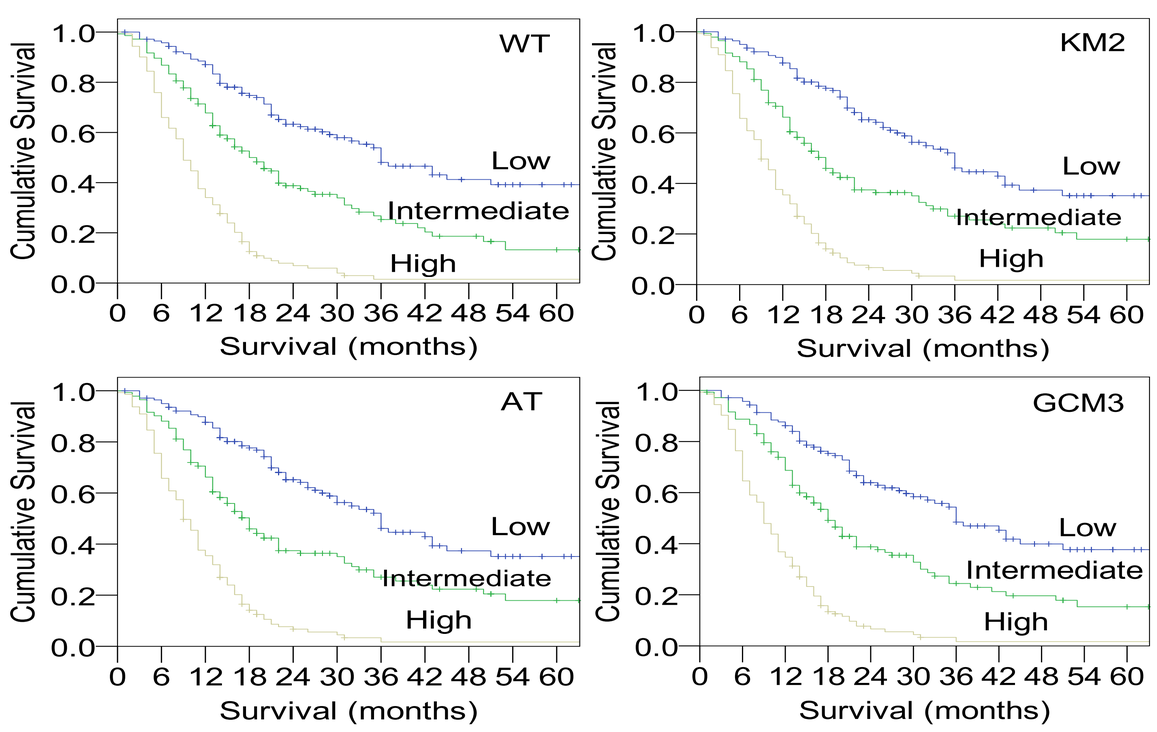

Figure 1 Risk stratification and OS for WT (Top Left), KM2 (Top Right), AT (Bottom Left), GCM3 (Bottom Right).

Results

The equations for each model from different segmentation methods are listed in Table 2. Age, treatment and radiological stage were significant variables in all prognostic models. Skewness was a significant variable in GCM3 and WT based models. Table 3 shows the number (percentage) of patients that changed risk stratification between developed prognostic models. Figure 1 shows the overall survival for the KM2, GCM3, AT and WT developed models. There was no significant difference in median OS between KM2, GCM3, AT and WT low-risk groups (P > 0.5), intermediate-risk (P > 0.5) and high-risk groups OS (P > 0.5).

Table 1: Descriptions of PET-AS used to delineate GTV_{PET}.

Algorithm	Description
AT	3D Adaptive iterative thresholding, using background subtraction
RG	3D Region-growing with automatic seed finder and stopping criterion
KM2/KM3	3D K-means iterative clustering with custom stopping criterion
FCM2	3D Fuzzy-C-means iterative clustering with custom stopping criterion
GCM3/GCM4	3D Gaussian Mixture Models-based clustering with custom stopping criterion
WT	Watershed Transform–based algorithm, using Sobel filter.
ATLAAS	A decision tree based segmentation methodology incorporating individual PET-AS included within this study.

Table 2: Equations of models developed from differing PET-AS methods.

Segmentation Method	Prognostic Model Equation
AT	(Age * 0.020) - (Treatment * 1.075) + (Stage * 0.144)
GCM3	(Age * 0.019) - (Treatment * 1.024) + (Stage * 0.142) - (Skewness * 0.789) + (Kurtosis * 0.632)
KM2	(Age * 0.020) - (Treatment * 1.075) + (Stage * 0.144)
WT	(Age * 0.018) - (Treatment * 1.063) + (Stage * 0.140) + (Skewness * 0.674) + (GLNU * 0.017)

Table 3: Number of (percentage) of patients that change risk stratification between models

Number of patients changing risk stratification (%)	AT based prognostic model	GCM3 based prognostic model	KM2 based prognostic model
GCM3 based prognostic model	66 (15.4)		
KM2 based prognostic model	0 (0.0)	66 (15.4)	
WT based prognostic model	57 (13.3)	73 (17.1)	57 (13.3)

Conclusion

Radiomic features are dependent on the PET-AS used and consequently influence patient risk stratification when incorporated into prognostic models. Methods used to define the metabolic tumour volume in PET radiomic studies should be standardised.

References

[1] B. Berthon, M. Evans, C. Marshall, N. Palaniappan, N. Cole, V. Jayaprakasam, T. Rackley, and E. Spezi, “Head and neck target delineation using a novel PET automatic segmentation algorithm,” Radiother. Oncol., vol. 122, no. 2, pp. 242–247, 2017.

[2] B. Berthon, C. Marshall, M. Evans, and E. Spezi, “ATLAAS: An automatic decision tree-based learning algorithm for advanced image segmentation in positron emission tomography,” Phys. Med. Biol., vol. 61, no. 13, pp. 4855–4869, 2016.

Poster number: PO-0931.

This work was partially funded by EPSRC-DTP grant number EP/M507842/1 and Velindre NHS Trust charitable funds project number 2016/11.