

CONTRIBUTION: LESION HETEROGENEITY CHANGE FOR PREDICTING RESPONSE

Early therapy response prediction, employing biomarkers such as the longitudinal scans are used for the response evaluations. Nonethemography (**PET**) imaging the tumor metabolic activity, turned out to the baseline scan prior treatment has been recently found to be corbe the defactor mode of evaluation in longitudinal studies. Tradition-relating well with the final outcome [1]. The aim of this study is to ally, the first order intensity based feature estimates extracted from establish the significance of tumor texture in follow up evaluations.

 $[^{18}F]$ -fluorodeoxyglucose (FDG) followed with positron emission to- less, lesion heterogeneity computed from the higher order textures of

CLINICAL LESIONS: $[^{18}F]$ -FDG PET/CT SCANS

15 chemo-naive first-line patients suffering from metastatic colorec- investigated for early response. 1-5 lesions were expert identified per tal cancer (mCRC) and treated with cetuximab were selected for patient and analyzed. Sagittal, coronal and axial orthogonal slices the study. Baseline $[^{18}F]$ -FDG PET scans were acquired prior to of the PET (left) and blended PET/CT (right) of a subject in the

treatment and the follow up scanned at 1 week post treatment was cohort is displayed below. Expert marking is also visible in the slices.





PET LESION DELINEATION





A block overview of various modules investigated in this longitudina study is schematically represented above.

Illustration of the **FLAB** [2] algorithm, on the process of extracting a typical PET lesion, with initialization followed by step-by-step iterations demonstrated in a clock-wise manner.



ON USING TEXTURAL INFORMATION FROM LONGITUDINAL PET SCANS FOR PREDICTING TUMOR RESPONSE

¹Medical Imaging Research Center, UZ Leuven 2 ESAT/PSI/MIC, 3 Nuclear Medicine, 4 Gastroenterology, KU Leuven, Belgium ⁶IBBT-KU Leuven Future Health Department ⁵icoMetrix NV, Leuven, Belgium *jose.george@uzleuven.be



COVARIATES / FEATURE ESTIMATES

- Traditional feature (\mathbf{TrF}) estimates employed in this longitudinal study included 4 SUV-based, 1 volume-based and their 2 combinations constituting 7 **TrF** covariates.
- Textural features (\mathbf{TxF}) employed in this longitudinal study included 7 from ALCC, 11 from ALRL, 11 from ALSZ, 5 from **ALDC** and 19 from **ALHS** constituting 53 \mathbf{TxF} covariates.
- > Activity level co-occurrence matrix [3] entries $ALCC_{ij}$ express the frequency of co-occurrences of (i, j) activity level pairs.
- \Rightarrow Activity level run length matrix [4] elements **ALRL**_{ij} represent the frequency of i^{th} activity level's j runs in 13 directions.
- \Rightarrow Activity level size zone matrix [5] entries $ALSZ_{ij}$ is updated when i^{th} activity level has a zone with j voxels.
- > Activity level difference matrix [6] **ALDC** consists of mean deviation of activity level relative to the neighbourhood.
- \Rightarrow Activity level histogram descriptive statistics **ALHS** were also computed and investigated.

DATA ANALYSIS

- \Rightarrow To compute a marker per subject, response indices (**RI**) computed for each lesion feature were accumulated either taking the **maximum** relative change $(\max\{\delta FS_{(\%)}\}_{locions})$ or the relative change **cum**ulated $(\delta \sum {FS}_{lesions(\%)})$ over all lesions.
- \Rightarrow The baseline dynamic range of **TrF** estimates were investigated.
- and analyzed. The regression coefficients were projected back to the feature set so as to compute the 'marker'.
- \Rightarrow The time dependent receiver operating characteristics (**ROC**) [7] were determined relating the continuous 'marker' with the continuous 'outcome'. The time to progression (**TTP**) was used as the 'outcome' information in our studies.
- For more realistic evaluation, a leave one-out cross validation (LOOCV) was performed to investigate the model fitting.
- \Rightarrow In LOOCV, the regressor was fit with features from all subjects except one. The regressor was then tested on the remaining subject. This procedure was repeated for each subject to find the respective marker value.
- The concordance measure (C_{τ}) [8] was determined by weighted integration of the individual area under curve (AUC).
- AUC at TTP > 4 months (AUC_{TTP4}) was also computed.
- \rightarrow For multivariate feature selection (**MVFS**), univariate analysis was performed using a Cox model and significant features giving p < 0.25 were selected. Selected features (FS) are then used for creating the multivariate Cox model.
- \Rightarrow The current clinical standard **EORTC criteria** [9] and **PER-CIST 1.0** [10] (using SUV - body weight) were studied.
- \Rightarrow With **MVFS**, 2 predictive models, **pMVFS-max** and **pMVFS**cum, were presented.
- \Rightarrow The statistical difference of survival curves was analyzed using logrank test.

 \mathbf{TxF} - \mathbf{ALSZ} [5]

 $\mathbf{TxF} - \mathbf{ALDC}$ [6]

 $\textbf{Jose George}^{1,2,6\star}, \textbf{Kathleen Vunckx}^{1,3}, \textbf{Sabine Tejpar}^4, \textbf{Christophe M. Deroose}^3, \textbf{Johan Nuyts}^{1,3}, \textbf{Dirk Loeckx}^{1,2,5,6} \& \textbf{Paul Suetens}^{1,2,6} \\ \textbf{Sabine Tejpar}^4, \textbf{Christophe M. Deroose}^3, \textbf{Johan Nuyts}^{1,3}, \textbf{Dirk Loeckx}^{1,2,5,6} \& \textbf{Paul Suetens}^{1,2,6} \\ \textbf{Sabine Tejpar}^4, \textbf{Christophe M. Deroose}^3, \textbf{Johan Nuyts}^{1,3}, \textbf{Dirk Loeckx}^{1,2,5,6} \& \textbf{Paul Suetens}^{1,2,6} \\ \textbf{Sabine Tejpar}^4, \textbf{Sa$



A Cox proportional hazards regression model was fit with RIs MULTIVARIATE FEATURE SELECTION (MVFS) RESULTS

2 MVFS predictive models are presented below:

Selected	Univariate	Multivariate	Hazard	Multivariate				
Features	p-value	Cox Coeff.	Ratio	p-value				
$\mathbf{pMVFS}\text{-}\mathbf{max} \Rightarrow \operatorname{Cox} \operatorname{Coeff}_{FS} \times \max\{\delta FS_{(\%)}\}_{lesions}$								
SUV _{peak}	0.1529	0.0412	1.0421	0.1495				
$ALCC_{con}$	0.1711	-0.1271	0.8807	0.2817				
$ALCC_{epy}$	0.1992	-0.0391	0.9617	0.4153				
$ALCC_{dis}$	0.1654	0.1843	1.2024	0.1130				
$ALRL_{sre}$	0.2473	-0.6104	0.5431	0.0328				
$ALRL_{rp}$	0.2424	0.5219	1.6852	0.0315				
$ALDC_{con}$	0.1985	-0.002	0.9998	0.6759				
$\mathbf{pMVFS-cum} \Rightarrow \mathrm{Cox} \ \mathrm{Coeff}_{\mathrm{FS}} \times \delta \sum \{\mathrm{FS}\}_{lesions(\%)}$								
ALCC _{sam}	0.2283	-0.0919	0.9122	0.0387				
$ALCC_{idm}$	0.1606	-3.0988	0.0451	0.0649				
$ALCC_{hom}$	0.1645	4.2081	67.2291	0.0500				
$ALRL_{lrhae}$	0.2313	-0.0596	0.9422	0.3385				
$ALSZ_{sze}$	0.1557	0.0079	1.0080	0.6447				
$ALSZ_{szhae}$	0.2246	-0.0236	0.9767	0.3404				
$ALDC_{coa}$	0.1861	-0.0758	0.9270	0.0313				
$ALDC_{con}$	0.0885	0.1044	1.1101	0.0466				
$ALDC_{cpx}$	0.1159	-0.1928	0.8247	0.0579				
$ALDC_{txs}$	0.1748	0.0367	1.0374	0.1134				
$\operatorname{ALHS}_{\operatorname{aadmod}}$	0.1125	0.0503	1.0515	0.0585				

BASELINE DYNAMIC RANGE

The baseline dynamic range of \mathbf{TrF} are listed below:

TrF estimates	Minimum	Maximum	Median	SD^{\dagger}			
$SUV_{max} (g/mL)$	2.40	12.28	6.33	2.34			
$\mathrm{SUV}_{\mathrm{peak}} \ (g/mL)$	1.64	10.52	4.86	2.01			
$SUV_{mean} (g/mL)$	1.61	8.39	4.05	1.52			
TLV (mL)	0.48	$1,\!182.42$	5.71	155.91			
TLA (g)	2.11	$6,\!620.88$	29.58	878.20			
TLE (g^2/mL)	3.55	$38,\!963.30$	152.79	$5,\!138.32$			
SD: Standard Deviation							

- subject dichotomization.
- respect to **EORTC criteria**.
- For both EORTC criteria & PERCIST 1.0, hazard ratio (HR) of 0.71 means responders have a 29% less chance for progression \square REFERENCES: (\mathbf{TTP}) compared to non-responders.
- > However, both EORTC criteria & PERCIST 1.0 based dichotomization are less statistically significant (p=0.743).
- > In **pMVFS-max**, a positive Cox regression coefficient indicated that, an increase in $\max \delta SUV_{peak(\%)}$ for a subject will result in an increase in hazard for progression.
- > In **pMVFS-max**, ALRL_{sre} and ALRL_{sp} were found to be statistically significant in the multivariate Cox model.
- \Rightarrow In **pMVFS-cum**, ALCC_{idm} obtained higher statistically significance and lower **HR** (95.5% less chance for progression). Hence pp. 610–621, nov. 1973. a subject with a high $\delta \sum ALCC_{idm}\%$ will have less chance for [4] M. M. Galloway, "Texture analysis using gray level run lengths," Comput. progression (or high chance of response to treatment). Graph. Image Process., vol. 4, no. 2, pp. 172–179, June 1975.
- > In $\mathbf{pMVFS-cum}$, ALCC_{hom} obtained both high \mathbf{HR} and statistically significance. Hence a subject with a high $\delta \sum ALCC_{hom}$ % will have high chance for progression.
- \Rightarrow Both **pMVFS-max** (p=0.0497) and **pMVFS-cum** (p=0.0006) provided statistically significant cohort dichotomization.
- In **pMVFS-max**, responders were having 68% (HR=0.32) less chance for progression compared to non responders.
- \Rightarrow In **pMVFS-cum**, responders were having 74% (HR=0.26) less chance for progression compared to non responders.
- \Rightarrow Both **pMVFS-max** and **pMVFS-cum** provided better C_{\tau}, AUC_{TTP4} & LOOCV – C_{τ} estimates compared to **EORTC** criteria and PERCIST 1.0.

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• **PERCIST 1.0** gave better C_{τ} , AUC_{TTP4} & LOOCV - C_{τ} with

CONCLUSION

 \Rightarrow Both EORTC criteria & PERCIST 1.0 resulted in identical The results with the current data denoted an added value in using textural information for early therapy response evaluation. Moreover, therapy response could be predicted as early as 1 week post treatment using $\mathbf{TrF} \& \mathbf{TxF}$ feature estimates.

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