



Article A Phantom Study to Investigate Robustness and Reproducibility of Grey Level Co-Occurrence Matrix (GLCM)-Based Radiomics Features for PET

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Supplemental Table

| Study (group) | # of Pa- tients | Machine | Cancer Type | Smoothing | Dose and Tracer | Metrics | Quantisa- tion | Segmentation | Direction | Tumor Size (baseline) | Tumor Size (after treat- ment) | Prediction of Response |
|--|-----------------------|---|------------------------------|---|---|--|--|--|---|-----------------------------------|---|--|
| Hatt (2011). IN- SERM France [1] | 25 | Biograph PET/CT Sie- mens | Non-small cel lung cancer | Ordered sub- sets maximiza- tion algorithm l (4 iterations, 8 subsets). At- tenuation cor- rection using CT data. | 45–60 min | Measuring using COV, lobec- tomy, CT im- ages, MATV | | 2 manual delinea- tions on CT, I50, adaptive (Nestle) and FLAB | | | | Relationship between vol- umes and impact of size and uptake in heterogeneity |
| Tixier (2011). INSERM France [2] | 41 | PET/CT Gem- ini; Phillips | Esophogeal | 3D row action maximum likelihood algorithm (2 iteration, re- laxation 0.05 & 3D gaussian post filtering of 5 mm in FWHM) | avg. 54 min | SUV, intensity his- togram, voxel alignment matrix, intensity—size zone matrix, co- occurrence, neigh- bourhood intensity- difference matrix. ROC curves | discrete val- ues. 64 is subsequent- | and then delineat- | n 13 differ- ent angu- lar direc- tion | | | Homogeneity and entropy significantly differentiate between non- responders with others (partial or complete re- sponders). No significant differences between |
| Tixier (2012). INSERM France [3] | 16 | PET/CT Gem- ini; Phillips relaxation parameter 0.05 | Esophogeal | | 2 min acquisi- tion time, 60 min after injecting 6 MBq/kg | 8 parameters for histogram, 17 for co- occur- rence/intensity-size zone | 8,16,32,64,12 8 | Primary was first identified by expe- rienced nuclear medicine physician and then delineat- ed automatically using fuzzy locally adaptive | 13 differ- nent angu- | Larger than 10 cm ³ | Reproducibil- ity study (En- tropy is the most repro- ducible). En- tropy, homo- geneity and dissimilarity | |

Table S1. Relationships of textural features with tumor heterogeneity for different parameters and methods.

| | | | | | | | | Bayesian algorithm (FLAB) | | | are preferred features |
|--|-----|-------------------------------|--|---|-----------------------------------|---|--|---|--|---|---|
| Hatt (2013). IN- SERM France [4] | 50 | Philips Gemi- ni PET/CT | Locally ad- vanced oe- sophageal | laxation pa- rameter 0.05, 5 mm 3D Gaussian post filtering, 4 × 4 × 4 voxel grid sampling) | 5 MBq/kg 60 min before scan | AUC-CSH -only those shown as robust for differ- ent reconstruction, acquisition &reproducibility -entropy, homoge- neity, dissimilarity, intensity variability, size-zone variabil- ity, zone percent- age, high intensity emphasis. (pre- ferred) Correlations as- sessed using Pear- son's correlation coefficient Bland-Altman as- sessed variability of image derived pa- rameter AUC-ROC | | Delineated in 3 ways: 42% of SU- V _{max} threshold; adaptive threshold accounted for tu- mor/background difference; Fuzzy locally adaptive Bayesian (FLAB) | | | Heterogeneity parameter more depend- ent on delinea- tion than PVC. Entropy and homogeneity were robust to delineation and PVC |
| Tixier (2014). INSERM France [5] | 102 | Philips Gemi- ni PET/CT | Non-small cel lung cancer | CT-based at- tenuation cor- rection and a 3D row- action maxi- mum likeli- hood algo- rithm with a previously optimized protocol (2 | 1 | | A 64-gray- level quanti- zation was used. | FLAB was exploited in this work using 2 or 3 classes to ade- quately cover the entire MATV, including low-uptake re- gions. | Local features were comput- ed over 13 direc- tions | Primary tu- mors with a MATV larger than 3 cm ³ | Change of size is not explicit- ly reported. Homogeneity, entropy and dissimilarity |

| | | | iterations; re- | range, 22 <mark>3–</mark> | | | | |
|----------------------|-----|----------------------------|--------------------------|---------------------------|---------------------|-------|---------------|------------------|
| | | | laxation pa- | 690) | | | | |
| | | | rameter, | | | | | |
| | | | 0.05; 5 mm in | | | | | |
| | | | full width at | | | | | |
| | | | half maximum | | | | | |
| | | | 3D Gaussian | | | | | |
| | | | post filtering; | | | | | |
| | | | $4 \times 4 \times 4$ mm | | | | | |
| | | | voxels grid | | | | | |
| | | | sampling) | | | | | |
| Hatt (2015). IN- | 555 | | | | | | FLAB | |
| SERM France [6] | 555 | | | | | | TLAD | |
| | | | Ordered- | 10 100 | | | | |
| | | | subset expec- | | | | | |
| | | | tation maxi- | (median, | | | | |
| | | Hybrid | mization (sub- | , | | | | |
| | | PET/CT scan- | set and itera- | the admin- | | | | 3 months after |
| Kidd (2008). | | ner (Biograph Cervical car | tion are not | istration of | H (dV/dT) is heter- | | 40% threshold | treatment. |
| Washington [7] | 72 | LSO 2, Sie- cer | mentioned) | 15–20 mCi | ogeneity | | | Change of size |
| , , dorini Gron [,] | | mens Medical | post recon- | FDG, with | | | | is not explicit- |
| | | Solutions) | | imaging times | 3 | | | ly reported |
| | | Solutions) | Gaussian filter | | | | | |
| | | | (5 mm full | 4 min/bed | | | | |
| | | | width half | position | | | | |
| | | | maximum) | | | | | |
| | | | Ordered- | 42–120 min | | | | |
| | | | subset expec- | (median, | | | | |
| | | Hybrid | tation maxi- | 65 min) after | | | | |
| | | PET/CT scan- | mization (sub- | the admin- | | | | |
| Brooks (2011). | | ner (Biograph Cervical car | , | istration of | The standard devia- | | | Change of size |
| Washington [8] | 73 | LSO 2, Sie- cer | tion are not | 15–20 mCi | tion, skewness | 8 bit | 40% threshold | is not explicit- |
| , asing ton [0] | | mens Medical | mentioned) | FDG, with | and kurtosis | | | ly reported |
| | | Solutions) | , | imaging times | 2 | | | |
| | | controllay | struction | of 2– | , | | | |
| | | | Gaussian filter | | | | | |
| | | | Gaussian filter | 4 mm/bed | | | | |

| Brooks (2013). Washington [9] | Hybrid PET/CT scan- ner (Biograph Cervical car LSO 2, Sie- cer mens Medical Solutions) | (5 mm full) positionwidth halfmaximum)Ordered-subset expec-42–120 mintation maxi-(median,New heterogeneitymization (sub-65 min) aftermetric the spherici-set and itera-the admin-tion are notistration of 15entioned)to 20 mCiaccrued deviationpost recon-FDG, withfrom smootheststructionimaging times gradients (ζ) as im-Gaussian filterof 2 toage heterogeneity(5 mm full4 min/bedmaximum) | 40% threshold | Compared against experi- enced expert |
|-------------------------------------|---|--|--|---|
| Brooks (2013). 8 Washington [10] | n = 58 Siemens Bio- graph 2 Cervical can n = 27 cinoma Siemens Bio- graph 40 | maximum) $n = 58$ OSEM 8 sets 2iterations and5.3 mm postreconstructionGaussiansmoothing $n = 27$ OSEM 8 sets 4iterations and 4 mm post reconstructionGaussiansmoothing $n = 27$ OSEM 8 sets 4iterations and 4 mm post reconstructionGaussiansmoothing (9)most recentBiograph 40image setsunderwent anadditionalpoint-spread | 40% threshold (The oncologist then made slight manu- al adjustments to the ROI to remove any obvious non- tumor pixels such as those compris- ing bladder or bowel regions) | Size was not explicitly men- tioned |

| Brooks (2015). Washington [11] | 27 pa- tients as well as sim- ulation | Siemens Bio- graph 40 | Cervical car- cinoma | function/time- of-flight cor- rection) OSEM 8 sets 4 iterations and 4 mm post reconstruction Gaussian smoothing (9 most recent Biograph 40 image sets underwent an | Dissimilarity, ho- mogeneity, energy and entropy | 8-bits (i.e., 256 gray levels) | threshold to com- lar dire pare with the simu- tion | After 3 months |
|-----------------------------------|---|---|-------------------------|--|--|--------------------------------------|---|---|
| | tients as well as sim- | | | Gaussian smoothing (9 most recent Biograph 40 image sets | mogeneity, energy | 256 gray | original data. Re- 26 diff peated with 50% ent ang threshold to com- lar dire | After 3 months |
| Orlhac (2014). France [12] | colo- rectal | MCC— Discovery LS System. NSCLC and 3C: Gemini TF PET/CT | MCC, NSCLC and BC | MCC—OSEM with 2 iter 28 subsets and Gaussian post filtering (FWHM = 5.45 mm). NSCLC and BC: BLOB-OS-TF with 2 iter and 33 subsets | | | Adaptive thresh- olding and 40% fixed threshold | VOI greater than 5 mL used for texture analysis (77 voxels for MCC and 78 voxels for NSCLC and BC). MCC > 5.0030 cm ³ . NSCLC and BC > 4.9920 cm ³ |

| | cer)] | | | | | | | | |
|---|-------|---|--|---|--|--|---------------|---|--|
| Cheng (2013). Taiwan [13] | 70 | Healthcare). 9 × Biograph | Orapharynge- al squamous cell carcinoma (Head & neck) | tation maxi- | -imaged 50 min after injection -370 to 555 MBq | SUV histogram analysis, GLCM, NGTDM, -Spearman correla- tion coeff., | 4, 16, 32, 64 | PMOD 3.3 software package | |
| Galavis (2010). Wisconsin [14] | 20 | PET/CT | Adrenal gland carcinoma, | Ordered sub- set expectation maximization algorithm (4 iterations, 14 | 10 mCi | 8 first order, 23 co- occurrence, 11 grey level run length matrix, 5 neigh- bouring grey level, 3 neighbourhood grey tone difference matrix | | | |
| Willaime (2013). Hammersmith. London [15] | 15 | ECAT 962/HR+ scanner (CTI/Siemens) | Breast cancer | OSEM itera- tive recon- struction method (360 iterations, 6 subsets). Fil- tered back projection to validate re- sults | 153–381 MBq for 95 min | -SUV, Coefficient of variation, Skew- ness, Entropy, area under a cumulative histogram curve, GLCM, GLSZM, NGTDM, Homoge- neity, Complexity. -Normality of rela- tive distances as- sessed using Shapiro-Wilk. -Limits of repeata- bility were calculat- ed. | | Regions of interest were drawn manu- ally | |

| 11 (for test retestECAT Exact -normalization and attenua- tion weightedLeijenaar (2013). cohort). Test-retest.MATOM Sen- sation 16ordered subset expectationNetherland [16]ter- ter- ECAT ACCEL for other co- hortECAT ACCEL subsets)maximization (2 iteration, 16 | Gray level co- occurrence (GLCM), Equally 50% for test retest 26 differ- gray level run- gray level run- spaced bins cohort. Manual ent angu- of 0.5 units delineation for lar direc- of SUV other cohort tion ces (GLSZM) | Test-retest and inter ob- server |
|--|---|--|
|--|---|--|

| Lopez (2015). Spain [17] | 38 | Discovery STI 16 PET CT | ^E NSCLC | OSEM with manufacturer recommended parameters | FDG (370 MBq) | Energy, entropy, contrast, correlation and homogeneity are calculated using GLCM | SUV greater than 2.5 | 13 differ- ent angu- lar direc- tion | kelationship between het- erogeneity, metabolic parameters and patholog- ic staging |
|-----------------------------|------|-----------------------------------|-----------------------|--|------------------|---|-------------------------|---|---|
| El Naqa (2009) [18] | 14/9 | PET/CT Sie- mens bio- graph | Cervix/head & neck | Ordered sub- set' expecta- tion maximi- zation algo- rithm | | SUV, Intensity- volume histogram, co-occurrence, shape based, spearman's rank. ROC curve | | | |

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