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M. Asselin, J.P.B. O'Connor, R. Boellaard, N.A. Thacker and A. Jackson

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Imaging Science and Biomedical Engineering Division,
Medical School, University of Manchester,
Stopford Building, Oxford Road,
Manchester, M13 9PT.



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Review

Quantifying heterogeneity in human tumours using MRI and PET

Marie-Claude Asselin^a, James P.B. O'Connor^a, Ronald Boellaard^b, Neil A. Thacker^a, Alan Jackson^{a,*}

^a Wolfson Molecular Imaging Centre, University of Manchester, UK

^b Department of PET Research, VU University Medical Center, Amsterdam, The Netherlands

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Abstract Most tumours, even those of the same histological type and grade, demonstrate considerable biological heterogeneity. Variations in genomic subtype, growth factor expression and local microenvironmental factors can result in regional variations within individual tumours. For example, localised variations in tumour cell proliferation, cell death, metabolic activity and vascular structure will be accompanied by variations in oxygenation status, pH and drug delivery that may directly affect therapeutic response. Documenting and quantifying regional heterogeneity within the tumour requires histological or imaging techniques. There is increasing evidence that quantitative imaging biomarkers can be used *in vivo* to provide important, reproducible and repeatable estimates of tumoural heterogeneity.

In this article we review the imaging methods available to provide appropriate biomarkers of tumour structure and function. We also discuss the significant technical issues involved in the quantitative estimation of heterogeneity and the range of descriptive metrics that can be derived. Finally, we have reviewed the existing clinical evidence that heterogeneity metrics provide additional useful information in drug discovery and development and in clinical practice.

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1. The significance of tumour heterogeneity

Most tumours demonstrate biological heterogeneity^{1–3} including heterogeneity in genomic subtypes, variations in the expression of growth factors and pro and anti-angiogenic factors^{4–9} and variations in the tumoural

microenvironment. These can present as differences between tumours in different individuals. For example, O⁶-methylguanine-DNA methyltransferase, a DNA repair enzyme, is silenced by methylation of the gene promoter in 50% of glioblastoma (GBM), contributing to chemosensitivity, and improved survival.¹⁰

Heterogeneity also occurs within individual tumours with regional variations in proliferation, cell death, metabolic activity, vascular structure and other factors. Increasingly there is also recognition that relapse and metastatic behaviour result to a large extent from cancer

* Corresponding author. Address: Wolfson Molecular Imaging Centre, 27 Palatine Rd., Withington, Manchester M20 3LJ, UK. Tel.: +44 161 275 0040; fax: +44 161 275 0003.

E-mail address: alan.jackson@manchester.ac.uk (A. Jackson).

stem cells which exist in distinct micro-environmental niches.^{11–14}

Experimental evidence has shown that vascular heterogeneity can be associated with disease progression, therapeutic response and malignancy.^{15,16} Despite this, information concerning heterogeneity is rarely utilised even in imaging based studies and there is no consensus concerning the choice of descriptive metrics.^{17,18}

2. Studying and quantifying tumour heterogeneity with imaging biomarkers (IB)

Studying heterogeneity within solid tumours requires histological^{19–22} or imaging data.^{17,23} Histological biomarkers offer high spatial resolution and biological specificity but are difficult to localise, subject to sampling errors and can seldom be repeated. Imaging biomarkers can provide spatial information, are minimal or non-invasive and can be repeated.^{24–26} Modern imaging systems produce digital data but the development of IB requires the development and validation of acquisition and analysis techniques.

2.1. Magnetic Resonance Imaging (MRI) biomarkers

There has been particular interest in the use of diffusion weighted imaging (DWI) and dynamic contrast enhanced MRI (DCE-MRI). Other MRI IB such as magnetisation transfer contrast imaging, arterial spin labelling and novel targeted MRI contrast agents have yet to find widespread application.²⁷

DWI sensitises MRI to water diffusion within the extravascular extracellular space (EES) and is affected by the size and configuration of the cellular population. Quantitative metrics reflect freedom of diffusion (ADC (Apparent Diffusional Coefficient)) and the magnitude of anisotropy, e.g. FA (Fractional Anisotropy). Preclinical and clinical data show that DWI can be used to assess regional cellularity, aggressiveness, to predict suitable therapies and monitor response.^{28,29}

DCE-MRI uses dynamic acquisition of images during and after the injection of intravenous contrast agent.^{30,31} Signal changes can be transformed to absolute concentration of contrast allowing analysis using pharmacokinetic models. Measured parameters typically include vascular fraction (v_p), size of the EES (v_e) and contrast transfer coefficient (K^{trans}). DCE-MRI has been widely employed in early phase trials of antiangiogenic and vascular disrupting therapies. Although DCE-MRI requires the injection of intravenous contrast this does not limit repeated examinations.

2.2. Positron emission tomography (PET) biomarkers

PET provides unique biological specificity, allowing dynamic or static imaging of biological molecules

labelled with positron emitting isotopes (e.g. ¹⁵O, ¹⁸F, ¹¹C). The technique is associated with a significant radiation dose, which limits repeated measurements, especially when used in combination with computer tomography (CT). Nonetheless, experimental designs with repeated examinations and/or imaging with multiple radiotracers is possible. The most widely used PET tracer in oncology is fluoro-2-deoxy-D-glucose (FDG) radiolabelled with ¹⁸F. FDG follows the same initial metabolic pathway as glucose but, after conversion by hexokinase, its metabolite FDG-6-phosphate becomes trapped in cells at a rate proportional to that of glucose utilisation. In cancer cells glycolysis is elevated and FDG uptake is increased. Following administration the time course of radioactivity in tissues reflects the transport of the radiotracer and enzymatic activity, either of which may be altered. When an input function is available, the rate constants describing these processes can be estimated using a kinetic model and combined to give the influx rate constant (K_i). Alternatively, radioactivity can be measured over a fixed period at a given time following administration and normalised to yield a standard uptake value (SUV). Some of the other radiotracers in use for oncologic applications include [¹⁵O]H₂O for the measurement of blood perfusion, [¹⁸F]3'-deoxy-3'-fluorothymidine (FLT) for cellular proliferation and [¹⁸F]fluoromisonidazole (FMISO) for hypoxia. Several anti-cancer drugs have also been radiolabelled and their distribution imaged by PET.

3. Technical considerations

3.1. Impact of data quality

Unfortunately, data from individual voxels will vary in the signal-to-noise ratio so that the confidence limits on the calculation of a parameter will vary across the parametric map. It is important to realise that an analysis of heterogeneity patterns must take into account potential inaccuracies in the calculation of individual pixel values which may require labelling some pixels as un-analysable or deriving parameters that allow direct estimation of the confidence limits.^{18,32} Assessments of heterogeneity should therefore take such correlations into account via the use of the appropriate Mahalanobis distance measures, or equivalent.

Heterogeneity analysis of PET images is further confounded by partial volume effects due to the limited spatial resolution and high noise level. In their simulation study, van Velden et al.⁶⁵ denoised (using an edge-preserving bilateral filter) and corrected the heterogeneous tumours for partial volume (using van Cittert deconvolution with Gibbs priors) improving the accuracy of the heterogeneity metric derived from the area under the curve (AUC) of cumulative intensity–volume histograms. Other heterogeneity metrics are likely to be more

sensitive to these effects. In addition to post-processing the reconstructed images, the image reconstruction parameters impact on noise and spatial resolution and influence the reliability of certain heterogeneity metrics more than others.³³ The level (whole tumour, subregions or voxel) at which heterogeneity analyses can reliably be performed is also limited by motion and co-registration for longitudinal studies and multi-tracers and/or multi-modality studies. Radiotracer uptake heterogeneity has been shown to impact tumour delineation, the extent of which depends on the segmentation method.³⁴ Conversely, tumour delineation will influence heterogeneity metrics, with some being more sensitive to boundaries than others, e.g. cumulative histogram (Fig. 1).³⁵

4. Methods for quantifying heterogeneity

4.1. Use of selective regions of interest (ROI)

Manual selection of small regions of interest with high/low values has been used for both DWI and DCE-MRI data.^{36–40} The technique is simple and inter-observer variations may be of minimal importance where large variations are present. However, this approach is not recommended for therapeutic trials or treatment monitoring.⁴¹ Subjective or semi-quantitative methods for grading the severity of heterogeneity have also been proposed but show significant⁴² inter-observer variations and poor reproducibility.^{43–45}

Rim enhancement patterns led to a quantitative approach to describe radial heterogeneity on MR^{46,47} where the tumour is divided into concentric circles and mean or median parameter values plotted against band number. This has been widely used in animal stud-

ies,^{48,49} but cannot be applied when heterogeneity patterns are not radial, which is often the case in human tumours.

At the limited spatial resolution of PET images, homogeneous radiotracer uptake in an ellipsoid would appear to progressively decline away from the centre and the deviation from this model has been used to quantify heterogeneity in FDG uptake⁵⁰ and found to be a predictor of outcome in 234 sarcoma patients.⁵¹

4.2. Cluster analysis

Cluster analysis is attractive since it will, in theory, allow identification of tumour components with common properties. It also maintains information regarding spatial relationships of tissue subtypes. Cluster analysis has been used in a small number of animal studies but has yet to be applied in human MR data.^{52,53}

In a multi-imaging biomarker study,⁵⁴ 13 cancer patients underwent DCE-MRI for the estimation of blood volume and blood flow, static FDG PET for the measurement of glucose metabolism and static [¹⁸F]-galacto-RGD (arginine-glycine-aspartate) for imaging the $\alpha_v\beta_{3/5}$ integrin receptors. After delineating the whole tumour on the fused PET images, the distribution of SUVs at the voxel level were clustered into four regions using preset thresholds for the two tracers on a scatter-plot: high FDG and RGD, high FDG and low RGD, low FDG and high RGD and low FDG and RGD. Significant differences in blood volume but not blood flow were detected between regions of both high glucose metabolism and $\alpha_v\beta_{3/5}$ expression and regions of both low glucose metabolism and $\alpha_v\beta_{3/5}$ expression. No significant correlation was found between the MR and

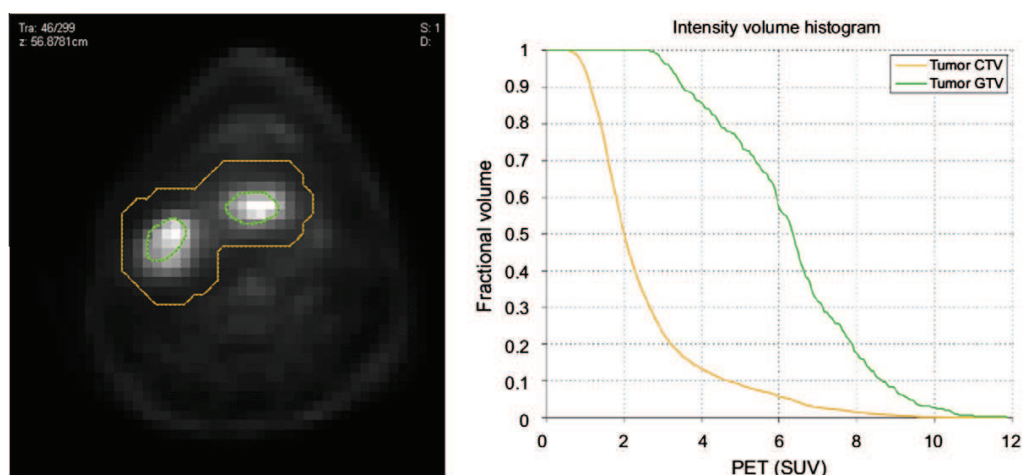


Fig. 1. Pre-treatment FDG scan of the head and neck cancer showing different tumour delineations are representing clinical (brown) and gross (green) tumour volume (Left). Intensity-volume histograms showing the difference depending on the choice of region of interest (right). (Adapted from³⁵ with permission).

PET biomarkers when the tumours were analysed as a whole.

4.3. Selective classification

One simple method is to measure the fraction of pixels that enhance after contrast administration (EnF (enhancing fraction)). EnF has been shown to support differentiation between, and to predict formal measurements of v_p and K^{trans} in low and high grade glioma.^{55,56} EnF provided predictive information in ovarian, cervical and colorectal cancers^{16,57,58} and a phase I trial of CNTO 95 showed that enhancing fraction can predict stable and progressive disease in the absence of clear treatment effects.⁵⁹

4.4. Histogram analysis

The intensity histogram allows a range of descriptive parameters including: range, mean, median, standard deviation (SD), skewness, kurtosis, entropy and various percentile cut-off values.^{46,60–63} A growing number of studies demonstrate important changes in response to treatment using histogram analysis that were not seen on whole tumour measurements.^{46,64} It must be realised that all information concerning spatial relationships within the tumour is lost. El Naqa et al.³⁵ introduced the cumulative intensity–volume histogram in which the volume is plotted as a function of image intensity that is equal to or higher than a certain value and from which various metrics can be extracted, e.g. percentage volume having at least a given percentage intensity. van Velden et al.⁶⁵ assessed the AUC of this plot as the quantitative index of uptake heterogeneity in simulated tumours and static FDG images. Although this heterogeneity metric characterised a rim pattern, it appeared less sensitive to heterogeneous radiotracer distribution and to a heterogeneous response than the simpler inverse of the coefficient of variation (mean/SD).

4.5. Texture mapping

Textural analysis provides a method to re-introduce spatial information. The available techniques include grey-level spatial co-occurrence matrices, and convolution based area representation (such as Gabor and Wavelet filters). Co-occurrence matrices measure the probability of finding a voxel with some grey level value at specific relative angle and distances. These can then be used to calculate a number of textural characteristics, including “contrast” and “entropy” (Fig. 2).

Texture analysis has been used in breast cancer to improve distinction between benign and malignant lesions.^{66,67} It has the disadvantage that the simplicity of derived parameters results in responses that are counter-intuitive with regard to the underlying variation in

tumour structure. El Naqa et al.³⁵ were among the first to explore textural features in static FDG images to predict treatment outcome. The combination of texture energy with the intensity–volume histogram was found to predict disease persistence in 14 patients with cervix cancer whereas overall survival in nine patients with head and neck cancer could be predicted with excellent power by combining shape extent with the intensity–volume histogram. Tixier et al.⁶⁸ compared global (distribution histogram), regional (intensity–size zone matrix) and local (co-occurrence matrix) features on static FDG images for their capacity to classify 41 patients with oesophageal cancer with respect to response to chemoradiotherapy and showed that local homogeneity and entropy as well as regional intensity and size–zone variabilities could identify non-responders, partial and complete responders with higher sensitivity than SUV measurements (Fig. 2).

4.6. Spatial geometric approaches

Here individual parameters are interpreted as the height on an extruded 4D hypervolume. Geometric features like surface area, volume, surface to volume ratio and box-count fractal dimension can be calculated and used as quantitative descriptors of heterogeneity.^{18,69} Clinical studies show increased discriminative power between low-grade and high-grade glioma and increased ability to predict outcome in colorectal metastatic disease in response to bevacizumab.¹⁶ Dimitrakopoulou-Strauss et al.⁷⁰ first used the box-counting method on time–activity curves from dynamic FDG, [¹⁵O]H₂O and 6-[¹⁸F]fluoro-L-DOPA (as a potential radiotracer for melanin synthesis) images from 11 metastatic melanoma patients, and did not find evidence of heterogeneous distribution within the manually delineated lesions. However, when combined with SUVs and kinetic parameters in discriminant analysis, fractal dimension improved the differentiation of sarcomas from dynamic FDG images.⁷¹

5. Clinical evidence for value of heterogeneity metrics

Increasing numbers of clinical studies demonstrate the ability of heterogeneity metrics to provide additional, important information relating to tumour phenotype, therapeutic response and prognosis.

5.1. Heterogeneity in DWI metrics

Early studies in glioma showed that mean values of [ADC] were less clinically relevant than the minimum values (minADC). A negative correlation between minADC and Ki-67 has been demonstrated in high-grade glioma and the use of a minADC cutoff value of 0.009 mm²/s for the differentiation between high and

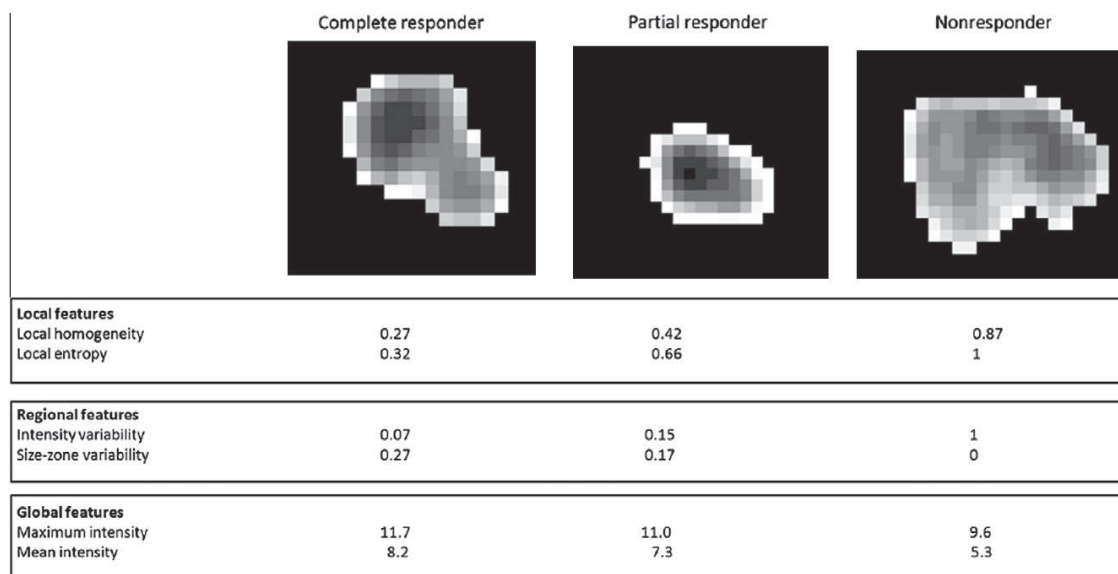


Fig. 2. Examples of textural features extracted from baseline ^{18}F -FDG PET images in patients with oesophageal cancer showing variations in textural features between complete responders, partial responders and non-responders. (Adapted from⁶⁸ with permission).

low-grade neuroepithelial tumours provided the best combination of sensitivity (85.4%) and specificity (71.0%).³⁸ These low values of ADC are believed to reflect hyper-cellular areas where proliferation is high and the size of the EES consequently reduced.

5.2. Detecting and predicting treatment response with DWI heterogeneity metrics

The distribution of pre-treatment ADC values in glioblastoma predicted progression free survival with bevacizumab therapy and optimal separation was obtained by use of a cut-off value derived from distribution histograms.⁷² Researchers from the University of Michigan spatially registered pretreatment to early post treatment maps of ADC and demonstrated that although mean values of ADC in tumours showed no predictive value, the presence of significant numbers of pixels showing early changes in ADC values was highly predictive.^{73–75} This approach, labelled the parametric response map (prm; vide infra), is being increasingly adopted in studies of cerebral tumours. However, prm is invalidated by the treatment induced spatial distortion restricting its application in extra-cerebral tumours.

Clinical evidence for DWI heterogeneity measures has also been demonstrated in extra-cranial tumours. In 12 patients with 48 metastatic liver lesions from colorectal cancer, positive correlations were observed between minADC and reduction ratio in response to arterial infusion chemotherapy with 5-fluorouracil.⁷⁶ A study of minADC and prognosis in endometrial cancer found correlations between minADC of the primary tumour and FIGO stage ($P = 0.001$), depth of myome-

trial invasion ($P < 0.001$), cervical involvement ($P = 0.003$), lymph node metastasis ($P = 0.027$), ovarian metastasis ($P < 0.001$), peritoneal cytology ($P = 0.027$) and tumour maximum size ($P < 0.001$). A low minADC was also associated with reduced survival ($P < 0.001$) and ADCmin was an independent factor for disease recurrence ($P = 0.019$).³⁷ A further study in endometrial cancer concluded that quartile ADC had a strong relationship with the invasiveness of endometrial carcinomas, while mean ADC value did not.⁷⁷

5.3. Heterogeneity in DCE-MRI metrics

Peripheral contrast enhancement is a common feature of aggressive tumours and, in the breast, is used as a diagnostic indicator of malignancy.¹⁵ Heterogeneity in vascular features has been associated with decreased survival, poor therapeutic response and increased metastatic potential in a range of systemic tumour types.^{12,62,78,79}

5.4. Detecting and predicting treatment response with DCE-MRI heterogeneity metrics

An early study of high-grade glioma showed that the 95th percentile of the distribution of K^{trans} predicted overall survival whilst median values did not.⁸⁰ Galban and colleagues applied the prm technique to DCE-MRI⁸¹ showing that direct pixel-by-pixel comparison of CBV values from images acquired before and one and three weeks after therapy provided more accurate prediction of survival than overall percentage change.

In breast cancer patients, receiving cytotoxic chemotherapy for locally advanced disease, the SD

and kurtosis of enhancement amplitude before therapy predicted subsequent radiological response. Furthermore, tumours that responded had a significant reduction in the SD of enhancement amplitude and showed a change from a heterogeneous distribution into a more homogeneous one.⁸² In a similar study, patients surviving for more than five years were found to have a significantly less heterogeneous distribution of relative signal intensity (RSI) in the baseline DCE-MRI distribution than non-survivors.⁸³ Padhani et al. found that changes in vascular heterogeneity quantified by the range of K^{trans} distributions at the end of cycle two were predictive of both clinical and histopathologic responses after three to six cycles of therapy.⁸⁴

The 10th percentile of the distribution of relative signal intensity was found to better predict tumour recurrence after radiotherapy in patients with cervical carcinoma than mean or median values.⁴⁵ A more recent study quantified heterogeneity using the percentiles of voxel signal intensities in the plateau phase of enhancement curves. Low values of the 5th to 20th percentiles were correlated with poor primary tumour control and short disease-free survival. The 5th percentile measured at two weeks of therapy provided the best prediction for eight-year primary tumour control.⁸⁵

In colorectal cancer, a study of 10 patients with 26 colorectal cancer liver metastases treated with bevacizumab and FOLFOX6 demonstrated that 86% of the variance in post treatment shrinkage could be explained by a model combining baseline measurements of v_e , tumour enhancing fraction (EnF), and microvascular uniformity ($R^2 = 0.86$, $P < 0.00005$).¹⁶

5.5. DCE-MRI heterogeneity metrics in clinical applications

Early work with T2* based DCE-MRI in brain tumours described a close relationship between grade and cerebral blood volume (CBV).^{39,40} Subsequently, the use of parametric maps combined with image guided biopsy, has become a common clinical practice.⁸⁶ Similarly, evidence that regional increases in CBV precede other indicators of malignant dedifferentiation in low-grade glioma has led to the introduction of DCE-MRI in surveillance protocols.⁸⁷

Considerable evidence of the clinical value of heterogeneity metrics has also accrued in breast cancer imaging. Early work demonstrated that measurements of SD of parameters such as K^{trans} within a ROI significantly improve diagnostic accuracy when attempting to distinguish malignant from benign lesions.⁶⁰ Heterogeneity of enhancement patterns are now included in the ACR Breast Imaging-Reporting and Data System (BI-RADS) MRI lexicon.¹⁵

5.6. Heterogeneity in PET metrics

The majority of heterogeneity analyses have been performed on static images since they are more widely available than dynamic images and less noisy than parametric maps. However, SUVs are kinetically heterogeneous, being influenced by transport and trapping mechanisms. Kinetic modelling of dynamic scans may be required when comparing heterogeneity of different biomarkers if one is to interpret the differences between different modalities and/or multiple radiotracers⁵⁴ and take full advantage of the specificity of PET.

5.7. Detecting and predicting treatment response with PET heterogeneity metrics

In a large cohort of 234 sarcoma patients before neoadjuvant chemotherapy or surgical resection, the heterogeneity metric defined as the percentage of variability in voxelwise FDG uptake that is not explained by an ellipsoidal pattern was a stronger independent predictor of survival than SUV.⁵¹ Tumours with highly heterogeneous metabolism likely have a high metastatic potential associated with poor patient outcome. However, there was only a weak association of the heterogeneity metric with the presence of necrosis, the histological hallmark of high grade in this cancer on CT and MR images available for 77 of these patients.

Heterogeneity in radiotracer uptake holds the potential to be incorporated into treatment planning for radiotherapy. Individualisation of treatment for head and neck cancer based on hypoxia PET imaging with FMISO has recently been proposed and its clinical feasibility for intensity-modulated radiation therapy theoretically assessed.⁸⁸ Taking into consideration heterogeneity of hypoxic regions could contribute to the identification of patients who would benefit from a segmented dose escalation focused to the hypoxic target.

6. Summary and conclusions

Quantification of tumour heterogeneity has the potential to add valuable information to clinical imaging studies. The choice of metrics for heterogeneity is uncertain and may differ between applications. Moreover, the technical challenges of producing meaningful heterogeneity metrics are significant and, in particular, issues associated with variation in data quality must be addressed.

Conflict of interest statement

None declared.

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