OPTIMISING DELINEATION ACCURACY OF TUMOURS IN PET FOR RADIOTHERAPY PLANNING USING BLIND DECONVOLUTION

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Positron emission tomography (PET) imaging has been proven to be useful in radiotherapy planning for the determination of the metabolically active regions of tumours. Delineation of tumours, however, is a difficult task in part due to high noise levels and the partial volume effects originating mainly from the low camera resolution. The goal of this work is to study the effect of blind deconvolution on tumour volume estimation accuracy for different computer-aided contouring methods. The blind deconvolution estimates the point spread function (PSF) of the imaging system in an iterative manner in a way that the likelihood of the given image being the convolution output is maximised. In this way, the PSF of the imaging system does not need to be known. Data were obtained from a NEMA NU-2 IQ-based phantom with a GE DSTE-16 PET/CT scanner. The artificial tumour diameters were 13, 17, 22, 28 and 37 mm with a target/background ratio of 4:1. The tumours were delineated before and after blind deconvolution. Student's two-tailed paired *t*-test showed a significant decrease in volume estimation error ($p < 0.001$) when blind deconvolution was used in conjunction with computer-aided delineation methods. A manual delineation confirmation demonstrated an improvement from 26 to 16 % for the artificial tumour of size 37 mm while an improvement from 57 to 15 % was noted for the small tumour of 13 mm. Therefore, it can be concluded that blind deconvolution of reconstructed PET images may be used to increase tumour delineation accuracy.

INTRODUCTION

Accurate tumour delineation in 18F-fluoro-2-deoxy-D-glucose (FDG) positron emission tomography (PET) images has been shown to be important in optimising quality and effectiveness in radiotherapy planning since a high precision determination of the metabolically active region is necessary^(1–5). However, the poor resolution and high noise in PET images make this task extremely difficult. The partial volume effect (PVE) that partially results from the lack of resolution in PET distorts the shape of the structures, and therefore, the real contours of the tumours cannot be accurately assessed^(6, 7).

Various schemes have been devised and evaluated with the purpose of reliable delineation of tumours in order to improve the consistency and reduce inter-observer and intra-observer variabilities with respect to the manual method^(8, 9). Of those, the thresholding methods are the most frequently used in clinical practice. Sobel operators, deformable active contour (AC) methods, clustering methods and stochastic modelling are among the multitude number of approaches proposed for lesion delineation in PET images.

In parallel, methods have been developed for correcting the PVE^(10, 11). These methods are mainly based on enhancing spatial resolution during reconstruction or determining correction factors by using anatomical information⁽¹¹⁾.

Few studies have investigated the effect of PVE on the tumour delineation accuracy. In⁽¹²⁾, the impact of partial volume effect correction on the predictive and prognostic values of baseline 18F-FDG PET images was studied. In⁽¹³⁾, a comparative assessment of threshold-based methods for estimating tumour volume and standardised uptake value in 18F-FDG PET is given using a PVC scheme based on binary mask deconvolution with a measured point spread function (PSF).

In this study, we aim to use a blind deconvolution technique⁽¹⁴⁾ in order to recover the real tumour shapes. This technique has the advantage that the PSF of the imaging system does not need to be known. The blind deconvolution estimates the PSF of the imaging system in an iterative manner in a way that the likelihood of the given image being the convolution output is maximised. This technique can be implemented either as part of reconstruction or separately after reconstruction. The blind deconvolved images can then be processed manually or by well-known computer-aided delineation techniques. In this study, blind deconvolution is applied to PET images that were reconstructed using a standard filtered back-projection method. Then, the accuracy of tumour delineation in PET images is evaluated by determining the error in estimated tumour volumes with respect to a multitude of object delineation

techniques, namely manual delineation, AC, active gradient vector flow (GVF), spline AC and spline GVF⁽¹⁵⁾.

METHODS AND MATERIALS

Phantom data

Data from a NEMA NU-2 IQ-based phantom scanned with a GE DSTE-16 PET/CT scanner were used in this study. The phantom contained $^{68}\text{Ge}/^{68}\text{Ga}$ with 271-day half-life for ^{68}Ge 89 %. The artificial tumour diameters were 13, 17, 22, 28 and 37 mm with a target/background ratio of 4:1 and a background activity level being measured as 0.44 uCi/ml. Data for this study were acquired from the PET scanner operating in three-dimensional (3D) mode. Image voxel sizes were $2.73 \times 2.73 \times 3.27$ mm. The matrix size was $128 \times 128 \times 47$. Data acquisition time was 5 min. A 3D filtered backprojection reconstruction algorithm was used. More details on the phantom and data processing can be found in^(16, 17). One should note that the PVE is known to exist in the output volumetric image along the three x , y and z axes.

Blind deconvolution

A blind deconvolution algorithm was applied in order to restore the reconstructed phantom images.

A recent analysis and evaluation of blind deconvolution algorithms is given in⁽¹⁴⁾. Blind deconvolution is the problem of recovering a higher-resolution version of an input image when the PSF is unknown. The problem is to decompose the image y as

$$y = m \times x + n \quad (1)$$

where x is a sharp image, $\times$ denotes the convolution operator, m is the PSF whose spread is small compared with the image size and n is the noise contribution.

The method used in this work maximises the likelihood that the image obtained by convolving the resulting deblurred image with the resulting PSF is an instance of the blurred image assuming Poisson's noise statistics, using an iterative Lucy–Richardson-based algorithm that was implemented in Matlab (MATLAB Release 2012b, The MathWorks, Inc., Natick, MA, United States). The algorithm iteratively updates the PSF of the camera. Structured noise or streaks were assumed to not affect the delineation process (Figure 1a and b).

Delineation strategies

In addition to manual free delineation using the cursor, the following interactive methods have been employed⁽¹⁵⁾.

Figure 1. (a) The 3D surface plot for the original reconstructed image. (b) The 3D surface plot for the deconvolved image.

AC

This algorithm determines the object's boundary in a noisy image by applying a gradient magnitude filter. It is quicker than the 2D spline AC algorithm but is also more sensitive to noise in the image.

Active GVF

GVF or the gradient vector flow snake is an extension of the AC method and it calculates a GVF field of forces by using generalised diffusion equations and the components of the gradient of the image edge map. Then, a pair of decoupled linear partial differential equations is solved in order to diffuse the gradient vectors of a map computed from the image.

Spline AC

This algorithm works by fitting a spline to the data. It is slower than the AC algorithm; however, it has a better noise performance.

Spline GVF

Spline GVF is the combination of the GVF force and the spline AC. The B-spline assures contour

smoothness and therefore avoids the rigidity parameters of the traditional GVF snake.

The parameters used by the various delineation strategies implemented in MIPAV [version 7.0.1 (05 April 2013)] have been set to their default values as suggested by the software⁽¹⁸⁾. For the AC method, the scale of the Gaussian has been set to 2.0, the number of iterations was 50 and the smoothness was set to 2.0. In effect, the results depend on these initial settings. The default settings for all the delineation functions can be found in MIPAV⁽¹⁸⁾.

Error evaluation

The error in estimated volume is given by

$$EV = \frac{V_{\text{det}} - V_{\text{true}}}{V_{\text{true}} \times 100 \%} \quad (2)$$

where V_{det} is the determined volume, and V_{true} is the true volume⁽⁹⁾.

Figure 2. The larger contour shows the one obtained for the deconvolved image, while the outer contour is needed for the algorithm to start.

RESULTS AND DISCUSSION

The effect of the blind deconvolution algorithm on a slice⁽¹⁸⁾ of the phantom was examined using 3D surface plots given in Figure 1. It can be noted that the loss of resolution spreads the image counts and decreases the pixel values in the original image, with a consequence of errors in quantification⁽¹¹⁾. The goal of blind deconvolution is to correct for this effect and recover the real shapes of the objects. Ideally, the surface plot in Figure 1 should give perfect cylinders for the recovered slice image. It can be seen that the pixel values for spheres have been increased to somewhat higher levels in the deconvolved image, compensating for the signal loss due to the PSF.

Initially, a manual contour has been drawn on two images one for a large and the other for a small sphere in order to observe and test the effect of deconvolution. For the largest diameter artificial tumour of 37 mm, the accuracy in volume determination improved from 26 to 16 %, whereas for the smallest tested artificial tumour of 13 mm, the accuracy improved from 57 to 15 %. The tedious manual method is known to present large inter-observer and intra-observer⁽⁹⁾ variations.

Four computer-aided boundary detection methods have been utilised in order to estimate the boundaries of the spheres on both the original as well as the deconvolved images. The algorithms were given an approximate region of interest in order to start the search process.

It was observed that larger contours were detected after deconvolution. This can be explained by the fact that blind deconvolution aims to restore the shapes of the objects and that on the original reconstructed images, the contours are smaller since part of the counts has been spread by the PSF towards the lower end of the profiles. This is clearly illustrated in Figure 1a and b. Figure 2 gives an example of the contours obtained on both types of images.

Table 1 gives the volume estimation errors based on the original and deconvolved images by making use of the aforementioned delineation methods.

Note that the 13-mm sphere is not included in Table 1 for computer-aided methods since the results

Table 1. Volume estimation errors.

Sphere diameters (mm)	True volume (cc)	AC (error %)		Active GVF (error %)		Spline AC (error %)		Spline GVF (error %)	
		Original	Deblurred	Original	Deblurred	Original	Deblurred	Original	Deblurred
37	26.52	20.63	4.54	21.73	5.92	16.48	4.91	20.72	8.50
28	11.49	17.04	4.07	28.53	5.13	23.21	11.30	24.91	3.22
22	5.58	15.36	10.54	36.41	25.45	30.27	22.82	32.47	23.70
17	2.57	15.95	19.75	43.92	35.37	5.91	5.91	24.92	19.21

were not reliable. This is probably due to the large sampling size, that is the small 128×128 matrix size in this study. Another reason could be acquisition time used for this dataset. One should also recall that deconvolution after reconstruction is known to increase noise and therefore may add to the difficulties with small lesions.

The data suggest, however, that the blind deconvolution may be a fast and practical method for recovering tumour shapes for radiotherapy planning. The error rates are in the order of the rates given in a similar study for the uncorrected images⁽⁹⁾. However, significant gains in volume estimation accuracies were noted in our study with the blind deconvolved images. Student's two-tailed paired *t*-test showed a significant decrease in volume estimation error ($p < 0.001$) when blind deconvolution was used in conjunction with computer-aided methods. The average change in percentage error was 14.27 with a 95 % confidence interval of [6.02, 14, 27]. The interactive snakes methods were in general successful in determining the volume for large spheres.

CONCLUSIONS

Tumour volume estimation accuracy is very important for PET-based radiotherapy planning, which is known to improve the therapeutic effect and reduce side effects. In this study, blind deconvolution using maximum likelihood has been shown to decrease errors in tumour volume determinations in a phantom-based study. A NEMA phantom with ground truth was used to show this effect. It was seen that the AC method with blind deconvolution was able to give significantly diminished error rates (below 5 %) for large spheres. This represents an improvement with respect to a previous similar study without partial volume correction⁽⁹⁾. Blind deconvolution has the advantage that no prior knowledge of the PSF is needed.

Further work is needed to improve volume estimation accuracy for small tumours. The study will also be extended to include real patient images, operating conditions, as well as data acquisition and processing parameters (e.g. acquisition time, reconstruction algorithm and parameters). Repeatability with respect to acquisition and processing parameters and tumour characteristics should also be assessed. Delineation algorithm parameters as well as different deconvolution methods and parameters should also be considered.

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REFERENCES

1. Lammering, G. *et al.* The use of FDG-PET to target tumors by radiotherapy. *Strahlenther. Onkologie*. **186**(9), 471–481 (2010).
2. Cheebsumon, P. *et al.* Impact of [18F] FDG PET imaging parameters on automatic tumor delineation: need for improved tumor delineation methodology. *Eur. J. Nucl. Med. Mol. Imaging*. **38**(12), 2136–2144 (2011).
3. Buijsen, J. *et al.* FDG-PET-CT reduces the inter-observer variability in rectal tumor delineation. *Radiother. Oncol.* **102**(3), 371–376 (2012).
4. Hatt, M. *et al.* Reproducibility of 18F-FDG and 3'-deoxy-3'-18F-fluorothymidine PET tumor volume measurements. *J. Nucl. Med.* **51**(9), 1368–1376 (2010).
5. Hatt, M. *et al.* Impact of tumor size and tracer uptake heterogeneity in 18F-FDG PET and CT non-small cell lung cancer tumor delineation. *J. Nucl. Med.* **52**(11), 1690–1697 (2011).
6. Soret, M., Bacharach, S. L. and Buvat, I. Partial-volume effect in PET tumor imaging. *J. Nucl. Med.* **48**(6), 932–945 (2007).
7. Cheebsumon, P. *et al.* Effects of image characteristics on performance of tumor delineation methods: a test-retest assessment. *J. Nucl. Med.* **52**(10), 1550–1558 (2011).
8. Wanet, M. *et al.* Gradient-based delineation of the primary GTV on FDG-PET in non-small cell lung cancer: a comparison with threshold-based approaches, CT and surgical specimens. *Radiother. Oncol.* **98**(1), 117–125 (2011).
9. Khamwan, K., Krisanachinda, A. and Pluempitwiriya, C. Automated tumor boundary delineation on 18F-FDG PET images using active contour coupled with shifted-optimal thresholding method. *Phys. Med. Biol.* **57**(19), 5995 (2012).
10. Hoetjes, N. J. *et al.* Partial volume correction strategies for quantitative FDG PET in oncology. *Eur. J. Nucl. Med. Mol. Imaging*. **37**(9), 1679–1687 (2010).
11. Erlandsson, K. *et al.* A review of partial volume correction techniques for emission tomography and their applications in neurology, cardiology and oncology. *Phys. Med. Biol.* **57**(21), R119 (2012).
12. Hatt, M. *et al.* Impact of partial-volume effect correction on the predictive and prognostic value of baseline 18F-FDG PET images in esophageal cancer. *J. Nucl. Med.* **53**(1), 12–20 (2012).
13. Tylski, P. *et al.* Comparative assessment of methods for estimating tumor volume and standardized uptake value in 18F-FDG PET. *J. Nucl. Med.* **51**(2), 268–276, (2010).
14. Levin, A. *et al.* Understanding blind deconvolution algorithms. *IEEE Trans. Pattern Anal. Mach. Intell.* **33**(12), 2354–2367 (2011).
15. McAuliffe, M. J. *et al.* Medical image processing, analysis and visualization in clinical research. *Computer-Based Medical Systems, 2001. CBMS 2001. Proceedings 14th IEEE Symposium on IEEE*, 381–386 (2001).
16. Clark, K. *et al.* The cancer imaging archive (TCIA): maintaining and operating a public information repository. *J. Digital Imaging*. **26**(6), 1045–1057 (2013).
17. The Cancer Imaging Archive. National Cancer Institute. RIDER PET-CT Phantom Data University of Washington, Society of Nuclear Medicine <http://cancerimagingarchive.net>.
18. MIPAV User's Guide. Volume I and II, National Institutes of Health for Information Technology (2008).