Tumour Detection By Volumetric Image Analysis

Author: Mr Ashley J. Robinson

Email: ajr2g10@ecs.soton.ac.uk

Supervisor: Professor Mark S. Nixon

Full Report: www.ajrobinson.org/tumour.pdf

This research review covers the use of volumetric image analysis in medicine to accurately detect the presence of tumours in the human body. The problem is to be approachedd by considering the general cases therefore concentration is not set on a specific area of the body. Rather than trying to classify lung or brain tumours individually the goal is to consider what features tumours have in common. Given an entire image of a human body is it possible to classify the presence of a tumour in any given section whilst using the same approach?

The motivation behind this is to make the most of medical scanning. Dosages of radiation, cost and capture time are all reasons to reduce the number of required patient scans. Thoroughly inspecting any data gathered is a constructive method of scan reduction. A practical end objective is used to provide direction to research and maximise the resultant impact. This is to provide an implementation recommendation for a tool that can assist with medical practitioner diagnosis.

Tumour Features

All tumours that can occur in the human body are caused by aabnormalities in cell growth [2]. Tumours are dense areas of cells and can be either benign or malignant. Malignant tumours are considered cancers because they invade nearby normal tissue and spread therefore making them an area of concern.

Fig. 1 Hyperproliferation leading to a benign then malignant tumour [2].

Pre-Processing

Original

Anisotropic Diffusion

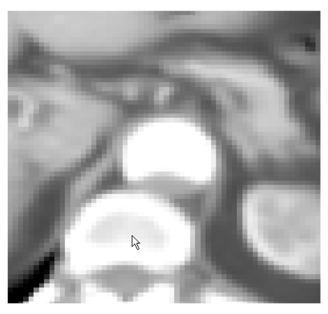

Fig. 2 Example smoothing [1].

Anisotropic diffusion is a powerful technique used to enhance images where it is possible to remove noise yet retain clear edges. The technique has been expanded from common 2D applications to 3D medical usage on MRI data [19]. The diffusion effect has the same outcome as a low pass filter with reasonably adjusted values for resolution, □t, and the decay constant, k. The spatial scaler decay constant is a function of the image and time which must preserve edges by setting iterative approach is provided in Eq. (6) where the original image is the

Anisotropic diffusion is a powerful technique used to enhance images where it is possible to remove noise yet retain clear edges. The technique has been expanded from common 2D

$$\frac{\partial \mathbf{I}}{\partial t} = \mathbf{k}(\mathbf{I})\nabla^2\mathbf{I}, \;\; \mathbf{k}, \mathbf{I} \in \mathbb{R}^4$$

$$\mathbf{I}_{t+\Delta t} = \mathbf{I}_t + \Delta t \mathbf{k}(\mathbf{I}_t)\nabla^2\mathbf{I}_t$$

Eq. 1 Volumetric Anisotropic Diffusion

Feature Extraction

The active contour model is a method for flexible shape extraction and has been thoroughly trialled in 2D [18]. Volumetric implementations are state of the art and have been successfully applied to prostate, nerve fibre and artery segmentation [22]–[24]. These are not pure active contours and emulate behave by segmenting 2D regions then using volumetric growth algorithms to actively converge upon a 3D shape. This works for certain parts of human anatomy but typically known geometry is required to influence the growing algorithm. Pure active contours could improve performance and using current research it is possible to expand dimensionality. The

The active contour model is a method for flexible shape extraction and has been thoroughly trialled in 2D [18]. Volumetric implementations are state of the art and have been successfully applied to prostate, nerve fibre and artery segmentation [22]–[24]. These are not pure active contours and

$$E = \int_0^1 \int_0^1 E_{int}(\mathbf{v}) + E_{ext}(\mathbf{v}) + E_{con}(\mathbf{v}) \, dr \, ds$$

$$E_{int} = \alpha(r,s)\left|\nabla \mathbf{v}\right|^2 + \beta(r,s)\left|\nabla^2 \mathbf{v}\right|^2$$

$$E_{ext} = w_l \mathbf{I} + w_e |\nabla \mathbf{I}|^2 + w_t E_c(\mathbf{I})$$

Eq. 2 Active Surface Contours

Feature Selection

Commonly large datasets contain some features in the input space will be have no effect upon or even reduce the performance of a classifier. It is naive to use just the raw image data. Tumour features for extraction have been considered in section III which already removes some redundant information. Mapping input data into a lower dimensional space is possible and can improve performance but if ill-applied can remove key features. A brute-force approach would find the optimal combination of features but the input space is expected to be too large, 2n is a challenge even moderate value of n, to be

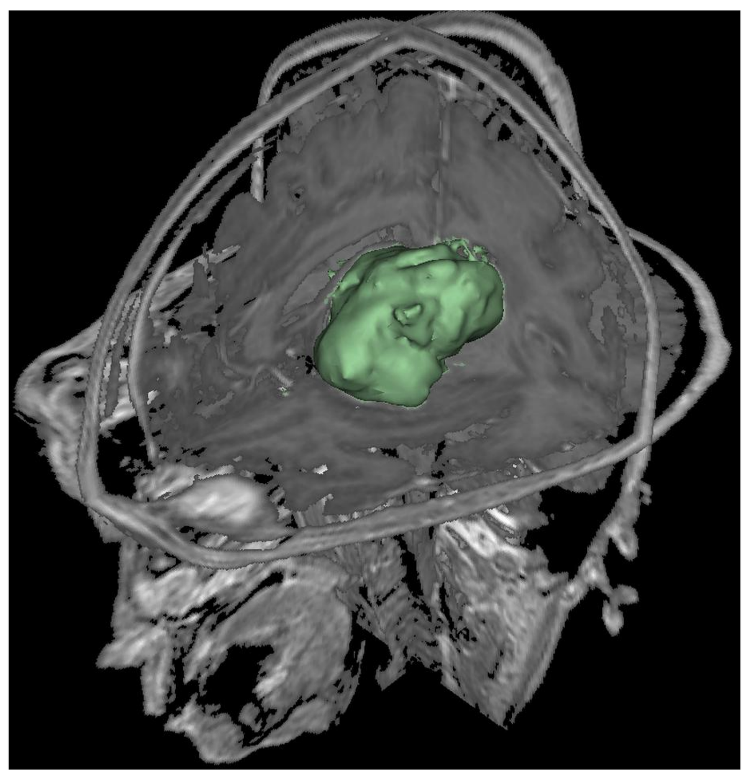

Fig. 3 A segmented volumetric brain tumour viewed in *3DSlicer* [3][4].

Classification

Classification must differentiate between extracted geometric shapes that are expected and those which may potentially be tumours. Tumours will also be attached to normal internal body parts so the classifier must be able to handle any abnormalities in organs. Supervised

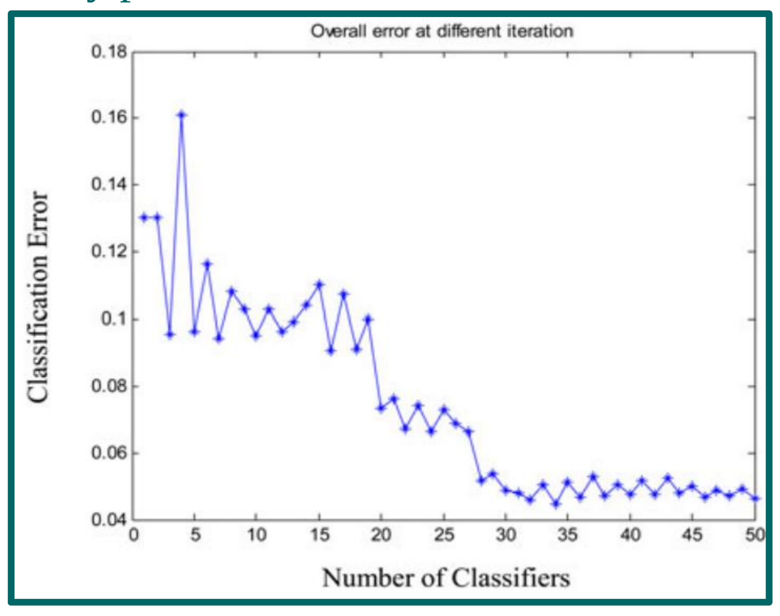

Fig. 4 Change in classification error as classifiers are added to the ensemble [5].

Classification must differentiate between extracted geometric shapes that are expected and those which may potentially be tumours. Tumours will also be attached to normal internal body parts so the classifier must be able to handle any abnormalities in organs. Supervised techniques for classification are considered even though datasets have not yet been.

Anisotropic diffusion is recommended to reduce noise because edge detection is important in later stages. This method can also by easily tuned by limiting iterations of the algorithm to match the image source. Edge detection is for required for both pre-processing and feature extraction. Canny edge detection produces significantly better results than simple filter kernels but at the expense of computation. Edge, curvature and active contour feature extraction techniques are recommended for implementation. To deal with amount of features PCA can be used to remove redundant components but also AdaBoost in conjunction with the classifier algorithm. SVMs are robust machine learning architectures and should defiantly provide at least weak hypothesises which should prove useful in the boosting algorithm.

Confidence Analysis

The confidence analysis unit will take noise informationfrom the initial image by differencing the input and output ofthe pre-processing stage. In feature extraction it can report on the quantity of shape extraction from an image. Dimensionality reduction will have no output as the reduction value is tuned prior to deployment. The binary classifier also has a nondiscrete output before hard thresholding which can used be used as a measure of confidence. This can also be used to adaptively control the number of boosting rounds.

References

[1] B. Nakhjavanlo, T. Ellis, P. H. Soan, and J. Dehmeshki, *3d medical image segmentation using level set models and anisotropic diffusion*, SITIS, 2011 7th Int. Con. on, Nov 2011, pp. 403–408.

[2] G. Cooper, *Elements of Human Cancer*, ser. Biology Series. Jones and Bartlett Publishers, 1992

[3] Eggar et al., *GBM Volumetry using the 3D Slicer Medical Image Computing Platform, CoRR*, 2013.

[4] 3DSlicer. [Visited] 06/05/14. [Online]. Available: http://www.slicer.org/

[5] Islam et al., *Multifractal texture estimation for detection and segmentation of brain tumors*, Biomedical Engineering, IEEE Transactions on, vol. 60, no. 11, pp. 3204–3215, Nov 2013.

UNIVERSITY OF Southampton

School of Electronics and Computer Science