

# Tumour Classification By Volumetric Image Analysis

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**Abstract**—This research review covers techniques available for the classification of tumours in the human body considering practical implications and stage interfacing. An architecture is proposed that follows basic image processing conventions but with an additional sub-module that provides non-technical confidence informations for a domain expert. The purpose of which is to classify tumours contained in medical images. All image processing stages are considered only for the case of volumetric images. Using a third dimension scales up complexity because of the amount of data available but has the potential to yield better results than a 2D approach. Common techniques are reviewed and a selection is made on how to populate the architecture. Human supervised deployment is considered whether stand-alone or as an extension to existing medical review software.

## I. INTRODUCTION

THIS research review covers the use of volumetric image analysis in medicine to accurately classify tumours. The problem is to be approached by considering only the general case where no specific area of the human body is considered. Rather than trying to classify lung or brain tumours individually the goal is to consider what tumours have in common and given an entire image of a human body is it possible to classify tumours in any given section? The motivation behind this is to make the most of medical scanning. Dosages of radiation, cost and simply the time required are all reasons to reduce the number of scans needed. Making the most of any data gathered is a constructive method of scan frequency reduction. The objective is to provide a recommendation for a system to be implemented such that a medical practitioner could use it as a tool for diagnosis.

The architecture in Fig. 1 is the framework of the system to be recommended; inspired by those discussed in [1]–[5]. A chain of stages leads from raw data gathered from the patient to a diagnosis from a classification algorithm. A confidence sub-block enables the domain expert to view the performance of the entire system without knowing the intricacies of operation; this requires processing to be explained with respect to their domain. In medicine a threshold has to be selected carefully as false negatives in diagnosis are unjustifiable.

Raw data is captured from the patient and passed to system for pre-processing then feature extraction. Input patterns are produced dependent on a pre-determined list of known useful features. Feature reduction and normalisation is then used to frame the data as such to make the most of the classification algorithm.

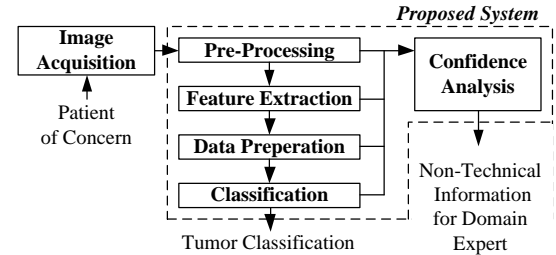


Fig. 1. Proposed system architecture.

## II. IMAGE ACQUISITION

A standard X-ray medical scan is tuned to produce and image of human bone. The rays are attenuated by different materials in the body, more so by dense regions of bone, and the image is gained from this attenuation effect. This uses a single source and substrate to capture the image. Taking multiple images from many different angles gathers more information and a 3D image can be made by stitching these together. Fig. 2 describes the physical process of gathering data to be used in Computed Tomography (CT). A ring allows images to be capture from 360° in a single plane then by moving in the orthogonal plane, in Fig. 2 through the paper, a full volumetric image of the patient can be made.

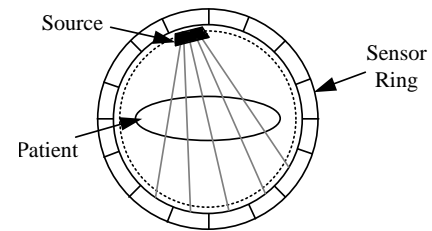


Fig. 2. Acquiring data from Computed Tomography. Adapted from [6].

Any method of non-invasive image capturing in 2D can therefore be expanded to work in 3D by using the CT principle. Different methods have tradeoffs such as radiation dosages and resolution. Ultrasound is a method of image acquisition with the advantage of a small processing overhead allowing internal organs to be viewed in real-time which is beneficial because it allows practitioners to view internal physical movement. It can be used for CT but higher resolution methods are usually favoured such as X-ray and Magnetic Resonance Imaging (MRI).

There are also other non-intrusive methods that do not use electromagnetic or ultrasonic waves. Hand palpitation is a common technique used by medical practitioners to gain an impression of abnormalities near the surface of the human body. Electromechanical apparatus employing the same technique can be used transfer the geometry of a growth to a volumetric image [7], [8]. Only part of the area under inspection is visible so the technique has obvious drawbacks.

Data is typically stored as a series of greyscale 2D images which are slices of the scan. The image viewer will build 3D images as and when required using these slices. The common medical standard for these images is DICOM which holds the slices, relative position and also patient information [9]. Viewing the data naturally proves problematic because it is 3D data shown in an isometric fashion on a 2D screen. Viewing software provides interactive images as shown in Fig. 3 which allows the user to move three slices to gain an impression of the region.

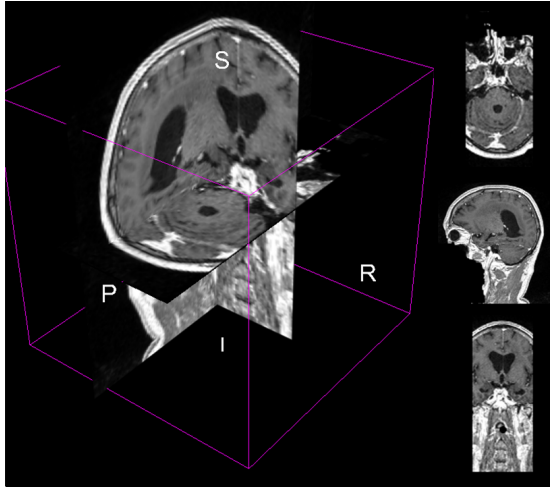


Fig. 3. An MRI scan of a healthy brain taken from [10] and rendered by [11].

The analogue of a pixel (picture element) in 2D image is called a voxel (volumetric element) in a 3D image. This is exactly the same idea but with an extra dimension to form a cube [12]. They can be considered cubes but also points which may make visualisation and processing easier to understand. Fig. 4 describes how voxels are packed and three different neighbourhoods that can be considered when inspecting one voxel. Considering voxels to have larger neighbourhoods can increase the time complexity of some algorithms.

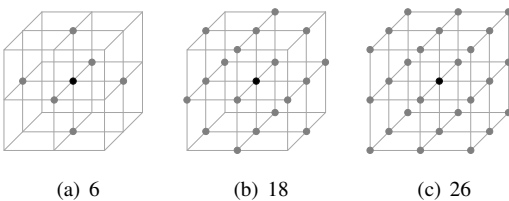


Fig. 4. Voxel Neighbourhoods [12].

### III. PRE-PROCESSING

The provided raw data needs to be converted from the delivery format from the acquisition technology to a 3D matrix ready for generic processing. Watermarking, which may have been inserted for human review, should also be removed at this stage. This is trivial in theory but requires a database of artefacts or manual review to accomplish. There are also techniques, not considered in this paper, which can be applied just to the slices of a volumetric image which may be used to reduce processing overheads [13].

There are different techniques available to enhance the image captured or ensure it is correctly formatted for further processing. This is considered as a mapping from an original image to a new image,  $I \mapsto I'$ , using only information from the original image.

#### A. Histogram Operations

An image histogram is a mapping from an image to a 2D plot of the frequency of voxel intensity; possible since voxels can have a discrete value of intensity within a fixed range. This contains information on the type of material seen in the image, if it can be determined from intensity, and how much of that material is used to form the entire image. Image enhancement can be performed using point operations with information from the histogram. This is a very fast method of image enhancement as it is direct voxel-to-voxel mapping; see Eq. 1. Normalisation stretches the histogram to cover all available values of intensity therefore improving contrast. Equalisation attempts to flatten the histogram by distributing intensity [14].

$$I'(u, v, w) = \alpha(u, v, w)I(u, v, w) \quad (1)$$

#### B. Spatial Filtering

Spatial filters use the neighbourhood of voxels to create a new value for each voxel in an image. The original image is mapped to a new image through a filter kernel, as described in Eq. 2. The filter kernel is a fixed dimension sub-image with a weighting on each voxel that is applied to every voxel in the original image. This is spatial convolution. If the filter kernel contains all ones it is known as a *box filter* and performs smoothing on the image to remove noise. A Gaussian filter performs better by placing a higher weighting on the central voxel and less on the extreme voxels [12].

$$I'(u, v, w) = \sum_{(i,j,k) \in R_H} I(u+i, v+j, w+k)H(i, j, k) \quad (2)$$

#### C. Frequency Filtering

The Fourier transform, as used spatially on 2D images, can be extended to 3D images. A Discrete Fourier Transform (DFT) for a  $N \times N \times N$  voxel image is held in Eq. 3. The spatial filtering process performs convolution so once an image is in the frequency domain the same effects can be achieved using multiplication. It may prove more efficient to filter an image in the frequency domain rather than space if the required

filter kernel is large. Band-pass and notch filter operations can also be performed in the frequency domain. Eq. (4) provides the same result as Eq. (2) using the increase transform implied from Eq. (3).

$$F_{u,v,w} = \frac{1}{N^{\frac{3}{2}}} \sum_{x=-\frac{N}{2}}^{\frac{N}{2}-1} \sum_{y=-\frac{N}{2}}^{\frac{N}{2}-1} \sum_{z=-\frac{N}{2}}^{\frac{N}{2}-1} I_{x,y,z} e^{-j\frac{2\pi}{N}(ux+vy+wz)} \quad (3)$$

$$\mathbf{I}' = \mathcal{F}^{-1}(\mathcal{F}(\mathbf{I}) * \mathcal{F}(\mathbf{H})) \quad (4)$$

#### D. Anisotropic Diffusion

Anisotropic diffusion is a powerful technique used to enhance images where it is possible to remove noise yet retain edges. The technique has been expanded from common 2D applications to 3D medical usage on MRI data [15]. The diffusion effect has the same outcome as a low pass filter with reasonably adjusted values for  $\Delta t$  and the decay constant. The spatial scalar  $\mathbf{k}$  is a function of the image and on edge must preserve edge by setting  $k(x_{edge}, y_{edge}, z_{edge}, t) = 0$ . Using Eq. (5) an iterative approach is provided in Eq. (6) where the original image is the value of  $\mathbf{I}$  at time zero. Iteration monitoring and reasonable scalar values in the function  $\mathbf{k}$  are required to produce a good outcome. Edge detection methods to be used for  $\mathbf{k}$  are discussed in [14] but for edge critical processing Canny edge detection is suitable [16].

$$\frac{\partial \mathbf{I}}{\partial t} = \mathbf{k}(\mathbf{I}) \nabla^2 \mathbf{I}, \quad \mathbf{k}, \mathbf{I} \in \mathbb{R}^4 \quad (5)$$

$$\mathbf{I}_{t+\Delta t} = \mathbf{I}_t + \Delta t \mathbf{k}(\mathbf{I}_t) \nabla^2 \mathbf{I}_t \quad (6)$$

#### IV. TUMOR FEATURES

Before features can be extracted from an image it must be clear what features will be useful to a classification algorithm. Reducing dimensionality through feature reduction can often prove more effective than lower dimensional projection methods; discussed in Section ???. The recommendation of feature selection can come from domain knowledge or convergence on a subset that will provide a sufficiently low training error using an iterative tuning algorithm [17], [18]. A combination of both suits this purpose where domain knowledge may over-recommend features and a machine learning approach can prune as required for the subset.

There are hundreds of types of tumours that can occur in the human body but they are all caused by abnormalities in cell growth [19]. Tumours are dense areas of cells in the human body 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; these are broken down into three categories. *Carcinomas* where cells line the body and internal organs account for 90% of human cancers. *Leukemias* and *Lymphomas* which occur in the blood and lymph systems account for 8%. *Sarcomas* are solid regions of connective tissue which are rare.



(a) Brain [20] (b) Lung [21] (c) Liver [22]

Fig. 5. Example MRI images containing tumors.

Whether the tumor lines the host or grows independently the key to feature extraction is to differentiate normal and abnormal cell density. Figure 5 contains examples of identified tumors in different organs. The brain (5(a)) and lung (5(b)) images are far simpler than the liver image (5(c)). An image of a liver will contain other organs so these must be considered when trying to extract features.

#### V. FEATURE EXTRACTION

High level feature extraction of volumetric shapes should be used on the input image. These high intensity regions may be organs walls or bones but should also include potential tumors.

##### A. Active Contours

Expanding upon common 2D implementations active contours can be used to extract shape information from volumetric images. Eq. (7) contains the standard energy minimisation function expanded for volumetric images [14], [23].

$$E = \int_0^1 E_{int}(\mathbf{v}) + E_{ext}(\mathbf{v}) + E_{con}(\mathbf{v}) ds, \quad \mathbf{v}(s) \in \mathbb{R}^3 \quad (7)$$

#### VI. FEATURE SELECTION

Commonly large datasets contain some features in the input space which will have no effect upon or even reduce the performance of a classifier. It is naive to use just the raw image data. Tumor features for extraction have been considered in section IV which already makes better use of data. Mapping input data into a lower dimensional space is possible and can improve performance but if ill-applied can remove key features. Although a brute-force would approach would find the optimal combination of features the input space is expected to be too large to be completely shattered within reasonable execution time.

##### A. Sequential Floating Search (SFS)

This heuristic algorithm is applied to tumor classification in [3]. It is possible to start from either the full or empty set of features then iteratively add and remove features to improve the performance of the classifier. A performance function is required for set comparison. Listing 1 contains the algorithm starting from an initial subset of no features and repeated until convergence.

```

1.  Z = {}, Y = {All}
2.  Z = Z + Y(Best)
3.  X = Z - Z(Worst)
4.  if (f(Z-) > f(Z))
      Z = X
      goto 3
   else
      goto 2

```

Listing 1. SFS Algorithm

### B. Genetic Algorithm (GA)

This a stochastic approach that uses a population of potential solutions to converge on a sub-optimal output. A GAs have been applied to tumor feature

### C. Principle Component Analysis (PCA)

PCA is a common technique used for dimensionality reduction by identifying dimensions of the least variance. These dimensions can then simply be removed but if the effect of a low variance dimension is important to classification this can reduce performance.

## VII. CLASSIFICATION

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

### A. Artificial Neural Networks (ANNs)

ANNs contain summation nodes where data is propagated through weighted connections resulting in a final output. As a supervised technique parametric weights are trained by propagating the error backwards through the network. Multilayer nets can provided non-linear separation functions and increase the number of layers only increase the possible function complexity.

### B. Support Vector Machines (SVMs)

An SVM classifier builds a separation margin supported by the close data points draw a separation function from the middle of this margin.

### C. Boosting

Boosting is the practice of combining different techniques together and drawing an output based on many sub-classifier.

## VIII. CONCLUSIONS

It is clear that this tool can't be used as a hard and fast method of tumour diagnosis but instead as a valuable tool for image reviewers. Software packages designed for medical image review, such as [11], have bidirectional interfaces to custom extensions. Implementing this system as an extension would remove many overheads required in data handling but reduce the scope for optimisation. The feedback from the entire process would be a checklist which the user must manually review and waive if incorrectly identified.

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