MRI Texture Analysis for the Characterisation of Childhood Brain Tumours

Ahmed E. Fetit
Supervisors: Prof Theo Arvanitis, Prof Andrew Peet and Dr Jan Novak
Problem
UK Childhood Cancer Statistics:

![Bar chart showing cancer types and their frequencies among boys and girls.]

- **Leukaemia**: Highest frequency among both boys and girls.
- **Brain Other CNS and Intracranial Tumours**: 27% of cases.

Obtained from: Cancerresearchuk.org

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T2-Weighted MRI scans of two cases of paediatric brain tumours:

Medulloblastoma

Ependymoma

Obtained from: CCLG e-Repository
Initial characterisation of tumours from MRI scans is usually performed via radiologists’ visual assessment.

Different brain tumour types do not always demonstrate clear differences in physical appearance. Using conventional MRI to provide a definite diagnosis would lead to inaccurate results.

Current diagnosis gold standard: invasive histopathological examination.

Need for quantitative, accurate and non-invasive diagnostic aid → Texture?
Texture
What is ‘Texture’?

No universal definition.

In medical image processing: The spatial variation of pixel intensities
Based on pixel intensities -> Quantitative -> Captures patterns beyond human vision

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Textural Feature Extraction:

**Statistical:**
- First Order (Histogram) Features
- Second Order (Grey-Level Co-Occurrence Matrix) Features
- Higher Order (Grey-Level Run-Length Matrix) Features

**Transformation:**
- Wavelet

**Model-based:**
- Autoregressive Model
First Order (Histogram):

The lower the pixel intensity value, the darker the value

The histogram represents a count of the number of pixels in the image that have a certain grey value

- Mean
- Variance
- Percentiles
- Skewness
- Kurtosis
Texture Analysis Methods

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Texture Analysis Methods

Absolute Gradient:

Extract mean, variance, skewness, kurtosis

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Second Order (Grey-Level Co-Occurrence Matrix):

- Define a **direction** and a **distance**
- Count number of pixel pairs that have a certain sequence

### Example image

```
0 0 0 1 0 0 0
0 1 0 0 1 0 0 0
0 0 0 0 1 0 0 0
0 0 0 0 1 0 0 0
0 0 0 0 1 0 0 0
1 0 0 0 0 1 2 0
0 0 0 0 0 0 0 1
2 0 0 0 0 0 0 0
0 0 0 0 1 0 0 0
```

### GLCM for P0

```
1 2 3 4 5 6 7 8
1 5 6 5 8 1 2 3 4 5 7 1 4 5 7 1 2 5
```

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Some GLCM features include:

**Angular Second Moment (ASM):** Measure of local homogeneity; high ASM values indicate good homogeneity.

**Contrast (CON):** Estimates local variation; high CON values indicate low homogeneity.

**Entropy (ENT):** Measure of randomness within the image; high ENT indicates low homogeneity.

14 features. Formulae and explanation available at paper by Haralick et al 1973

**Textural Features for Image Classification**

ROBERT M. HARALICK, K. SHANMUGAM, AND ITS’HAK DINSTEIN

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Higher order (Grey-Level Run-Length Matrix):

Example image

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Grey-level 0 never appears alone

Grey-level 0 appears in a pair twice

*Run length matrices are computed for 0, 45, 90 and 135 degree directions

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Some GLRLM features include:

**Short Run Emphasis:** Measure of the proportion of runs in the image that have short lengths. Coarse textures tend to assume a high value.

**Long Run Emphasis:** Measure of the proportion of runs in the image that have long lengths. Smooth textures tend to assume a high value.

11 features; formulae and explanation available at

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Detailed Explanation of Techniques:


REVIEW

Texture analysis of medical images
G. Castellano*, L. Bonilha, L.M. Li, F. Cendes

Neuroimage Laboratory, Faculty of Medical Sciences, State University of Campinas, Brazil
Some Work in the Literature
Analysis Pipeline

MR imaging data -> Image Pre-processing -> Textural feature extraction -> Feature selection

Additional information

Classification -> Model evaluation

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Data
- 40 children with brain tumours
- Medulloblastoma, pilocytic astrocytoma and ependymoma
- T1, T2 and diffusion-weighted MRI

Supervised learning
- SVM classifier
- Classify tumour types
- Classify MB subtypes
- Randomly split data to training and testing sets
- Repeated 500 times

Preprocessing
- Normalisation to the mean value of white-matter
- Manual ROI segmentation

Results
- Up to 79% classification accuracy for tumour type classification, using T1 and T2-weighted images
- Up to 91% using diffusion weighted images

TA
- Histogram statistics
- GLCM
- In-house MATLAB software was used
**Data**
- 40 children with brain tumours
- Medulloblastoma, pilocytic astrocytoma and ependymoma
- T1, T2-weighted MRI

**Preprocessing**
- Manual ROI segmentation
- ImageJ software

**TA**
- Histogram statistics
- Autoregressive model
- GLCM
- GLRLM

**Supervised learning**
- PCA for dimensionality reduction
- Neural Network and LDA classifiers
- Leave-One-Out and 10-fold cross validation

**Results**
- PNN yielded 90% accuracy on T1 and 93% accuracy on T2 (Leave-One-Out)
- LDA’s results were noticeably poorer (around 57%).

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Anonymised T1 and T2-weighted MR Images (Secure database)

21 Children diagnosed with brain tumours

Tumours fall into:
• medulloblastoma (7),
• pilocytic astrocytoma (7)
• ependymoma (7)

(1) Want to see if we could use classifiers trained with textural features to discriminate between the tumour types
(2) Want to see if 3D TA leads to better classification performance
2D vs. 3D

2D: Each voxel has 8 immediate neighbours in 4 directions

3D: Each voxel has 26 immediate neighbours in 13 directions

Voxel spatial separation

T2-Weighted slice for one medulloblastoma case. Obtained from: CCLG e-Repository

Can 3D capture more information?
Analysis Pipeline

T1 and T2 weighted

Semi-automatic segmentation (Snake GVF)

Normalisation (mean +/- 3 std)

2D & 3D TA

Extract features

Supervised classification

Entropy MDL Discretisation

Does 3D TA improve classification?

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## Results

**Model validation used: Leave-One-Out**

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The use of 3D textural information extracted from MR images, instead of 2D features, has the potential to increase computerised classification of childhood brain tumours.
Future Work

Expand the study to include larger datasets in order to confirm the robustness of 3D TA under different protocols.

Investigate possible over-optimistic bias in the results:

3D-trained kNN yielded 100% with all metrics. ( Might be because feature selection was carried out outside the leave-one-out loop)
Questions?