3D textural features of conventional MRI predict survival in childhood medulloblastoma

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Target Audience

Individuals interested in predicting survival prognosis of childhood brain tumours using non-invasive MR image analysis methods.

Purpose

Magnetic resonance imaging (MRI) is the key imaging technique used for visualising and managing childhood brain tumours. There has been an increasing interest in tumour characterisation using non-invasive MR image analysis methods, such as texture analysis (TA) over the past decade. However, much of this work focused on diagnostic classification of tumour types[1,2]. This raises the question: *If textural features could capture powerful patterns that aid the diagnosis of tumours, can they also be used to predict patients' survival prognosis?* The primary aim of this study was to determine whether TA of conventional MR images could predict the survival of paediatric medulloblastoma – the most common malignant brain tumour occurring in childhood.

Materials and Methods

- Data: The dataset consisted of pre-contrast T_1 and T_2-weighted MR images of 32 children who attended a single centre and were diagnosed with medulloblastoma. Images were acquired using a 1.5 T Siemens scanner with TE=8.7ms, TR=500ms for T_1 and TE=105ms, TR=4730ms for T_2. Snake GVF segmentation was used to extract regions of interest (ROIs), followed by ROI normalisation $(\mu+/-3\delta)$[3] in order to mitigate any variations in parameter settings across scans.
- TA: 3D textural features were calculated using histogram, absolute gradient, co-occurrence matrix (GLCM) and run-length matrix (GLRLM)[4,5].
- Identifying optimal features: a cut-off value of 4 years was chosen, and if patients survived until at least this point, they were categorised as having a 'good' prognosis. We proceeded by temporarily removing the data of the 10 patients who are still alive but have not reached the cut-off point, which reduced our cohort size to 22 patients. Entropy-minimum descriptive length (MDL) discretisation was used for feature selection, followed by the training of a Naïve Bayes classifier in a two-class problem, with the aim of classifying data as 'had died before 4 years' or 'had survived for at least 4 years'. Encouraging classification results allowed us to proceed by testing features using the Kaplan-Meier (KM) estimator.
- Statistical methods: the KM survival estimator was used to individually test each feature identified during the supervised classification stage, by examining whether a high feature value is associated with significant differences in survival time across the entire cohort of 32 patients. In order to test the study's primary hypothesis, the log-rank test was used with a chosen *p* value of 0.05.

Results

Using the log-rank test, we were able to identify 15 significant features that were able to successfully differentiate between good and poor survival prognoses (the significance values are reported in Table 1). All features were variations of *sum variance, sum of squares* and *angular second moment*, with different inter-pixel distances and directions of analysis. Fig 1 shows KM curves for three examples of the significant features.

Table 1. p-values for the fifteen textural features identified as significant.

Feature	*p*
Sum Variance (1,-1,0)	< 0.01
Sum Variance (1,0,0)	< 0.05
Sum Variance (2,-2,0)	< 0.01
Sum Variance (2,0,0)	< 0.01
Sum Variance (0,0,3)	< 0.01
Sum of Squares (1,1,0)	< 0.01
Sum of Squares (0,0,3)	< 0.05
Angular Second Moment (0,2,0)	< 0.05
Angular Second Moment (2,2,0)	< 0.01
Angular Second Moment (2,-2,0)	< 0.01
Angular Second Moment (3,0,0)	< 0.01
Angular Second Moment (0,3,0)	< 0.01
Angular Second Moment (3,3,0)	< 0.01
Angular Second Moment (4,0,0)	< 0.01
Angular Second Moment (4,4,0)	< 0.01

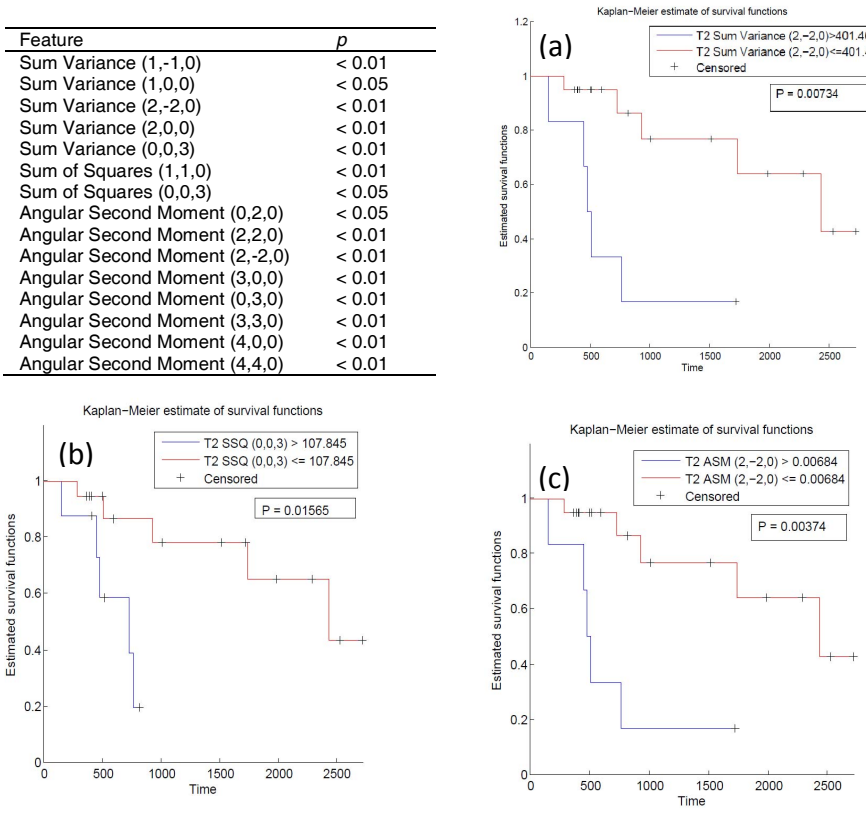

Fig 1. KM survival curves for three of the fifteen features identified to be of prognostic value: (a) Sum Variance (2,-2, 0); (b) Sum of Squares (0, 0, 3) (c) Angular Second Moment (2,-2, 0).

Discussion

Following diagnosis, determination of prognosis is an important step in tumour management, with implications that determine treatment options. Therefore, the identified features have the potential to advance clinical management of patients for therapy and the possibility to support more informed discussions with the patient's family. An interesting observation is that all 15 features were GLCM-based and extracted from T_2-weighted images. Future work will focus on cross-centre transferability of TA as a prognostic predictor, by testing the identified features on datasets acquired from different hospitals. Recent research efforts have identified glutamate as a biomarker for paediatric medulloblastoma[7]. Hence, identifying any inherent links between textural features and glutamate is an important future task.

Conclusion

3D textural features of conventional MRI were successfully used to predict the survival analysis of paediatric medulloblastoma.

References

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