Investigating the Performance of Co-occurrence Matrix in Characterizing Brain MR images

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Introduction

- Texture analysis is a promising tool for clinical decision making, however;
- Several factors affect its performance and are still not completely understood.
- For routine use in clinical environments texture analysis needs to be standardized.

Objectives

- Assessment of the discriminating power of several co-occurrence matrix (COM) measures obtained for small ROI (~ 100 pixels) located in 3 normal regions and 1 pathologic region of the brain

Data and Methods

I. Methods of COM calculation:

- Classical approach for 2D ROI in a single slice (method “2D”).
  - Four angles at distance d = 1 pixel were studied.
- Averaging approach using multiple 2D ROI in consecutive slices (method “2DM”).
  - Averaging COMs for 3 ROIs at 4 different angles gives direction-independent average COM (sum of 4 directional COMs).
  - ROIs in consecutive slices are at exactly the same position.

Data and Methods

I. Methods of COM calculation (cont.):

- 3D approach (method “3D”) on a volume of interest (VOI).
  - 13 angles in 3D were studied
  - The associated 13 COMs were summed to give a direction-independent COM.
  - ROIs forming the VOI are located in consecutive slices at exactly the same location.

Data and Methods

II. Grey-level depths and derived COM measures

- COMs were calculated for three grey-level depths:
  - 32 GL (5 bits per pixel).
  - 64 GL (5 bits per pixel).
  - 128 GL (5 bits per pixel).
- Five COM measures were calculated from each matrix:
  - Angular Second Moment
  - Inverse Difference Moment
  - Entropy
  - Contrast
  - Correlation.

Data and Methods

II Co-occurrence Histograms (COH)

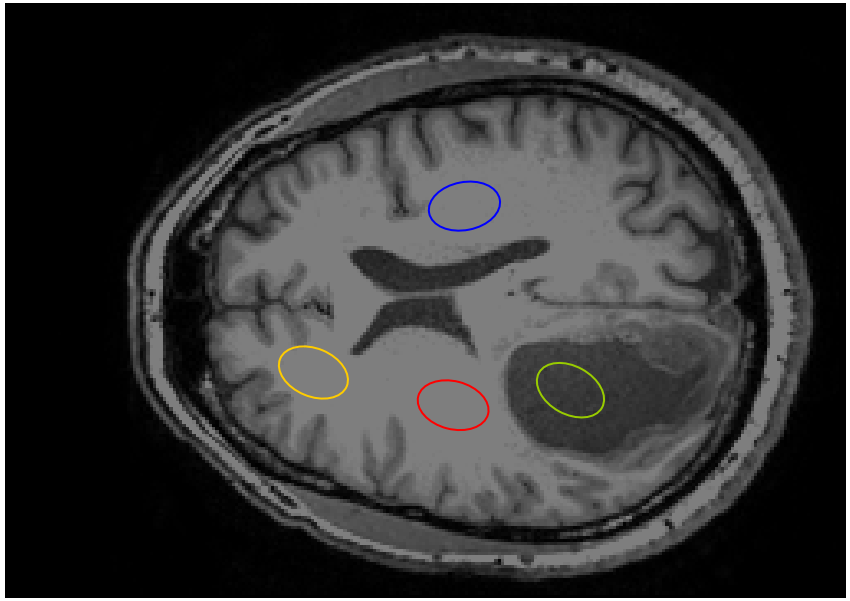
- COH are 2D representations of the of grey level's joint probabilities within a certain distance and angle.
- COH illustrate graphically the distribution of joint probabilities and how those are modified by pathological conditions.
- COH are less practical for large matrices (higher number of bpp) but they can be used to spot certain ranges in those matrices.
- In this study COH were plotted for 5 bpp matrices.

Data and Methods

IV. Patients

Four regions/volumes were identified on 7 patients (COST B21 glioblastomas Database) :

- Peritumoral WM
- Homolateral WM
- Contralateral WM
- Tumor



Data and Methods

V. Software and implementation.

- All COM methods (2D, 2DM, 3D) derived 5 COM measures and were implemented using MATLAB.

- Feature selection (Fisher coefficient) and Classification (Linear Discriminant Analysis) was performed for the 5 COM measures using the MaZda software.

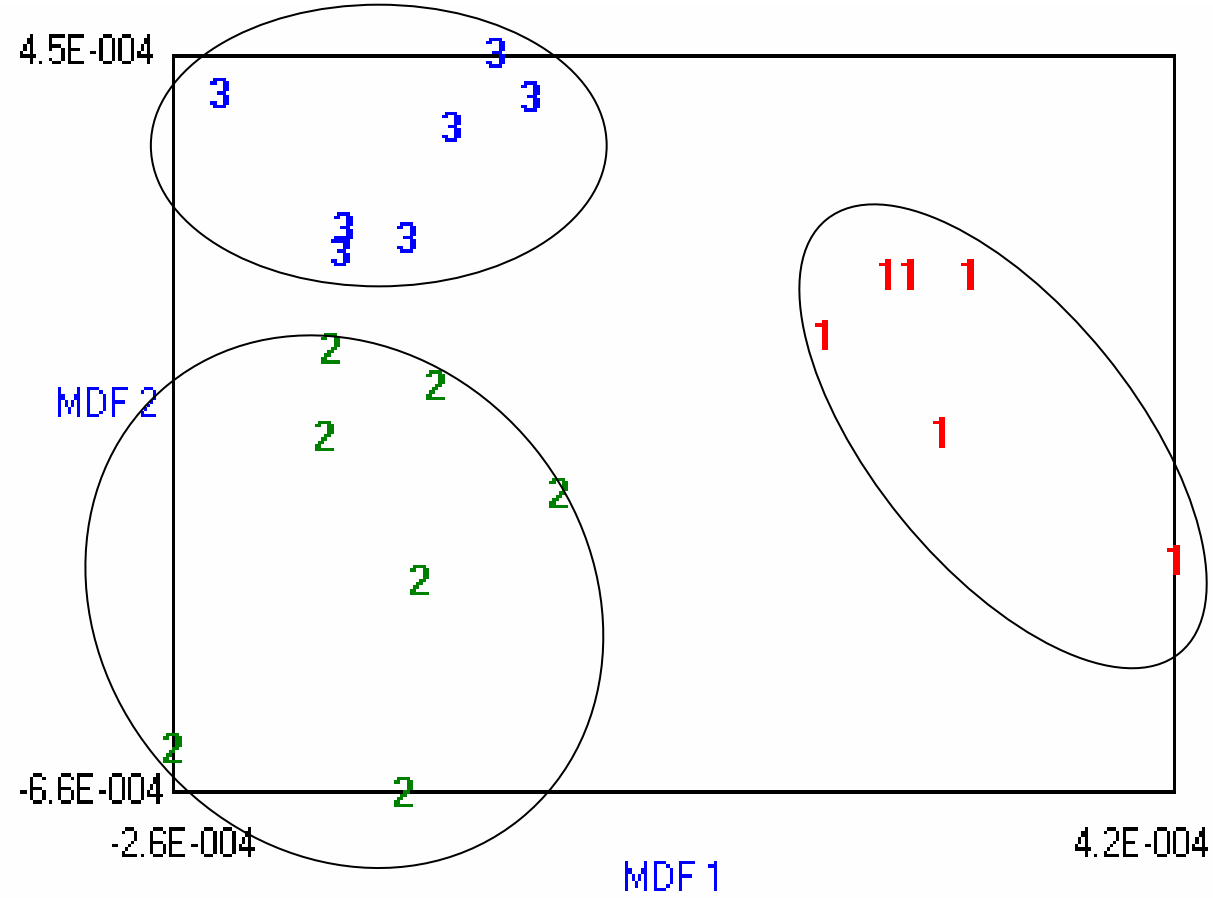
Results

Characterizing Peritumoral WM from other WM

Calculation approach	32 bpp		64 bpp		128 bpp	
	PT vs. (HL and CL) Misclassification	HL vs. CL overlapping	PT vs. (HL and CL) Misclassification	HL vs. CL overlapping	PT vs. (HL and CL) Misclassification	HL vs. CL overlapping
3D	1	4	1	0	0	0
2DM (average of all ROIs)	1	6	3	3	1	1
ROI3	0	2	0	3	0	2
ROI2	5	2	2	0	0	1
ROI1	0	2	0	1	0	3

- For most classification results for all methods, PT was separated from other two overlapping WMs.
- HL and CL were totally separated using 64 and 128 bpp in 3D method (feature overestimation? or true histological evidence?).
- The number of errors decreased for increasing the number of bits-per-pixel (bpp).
- The averaging method 2DM didn't improve results compared to single slice 2D method.
- Higher dynamic range might be better for simple 2D calculation but could be misleading for more complex calculations.

Three classes were separated using 3D COM with 128 bpp



1 Peritumoral WM

2 Homolateral WM

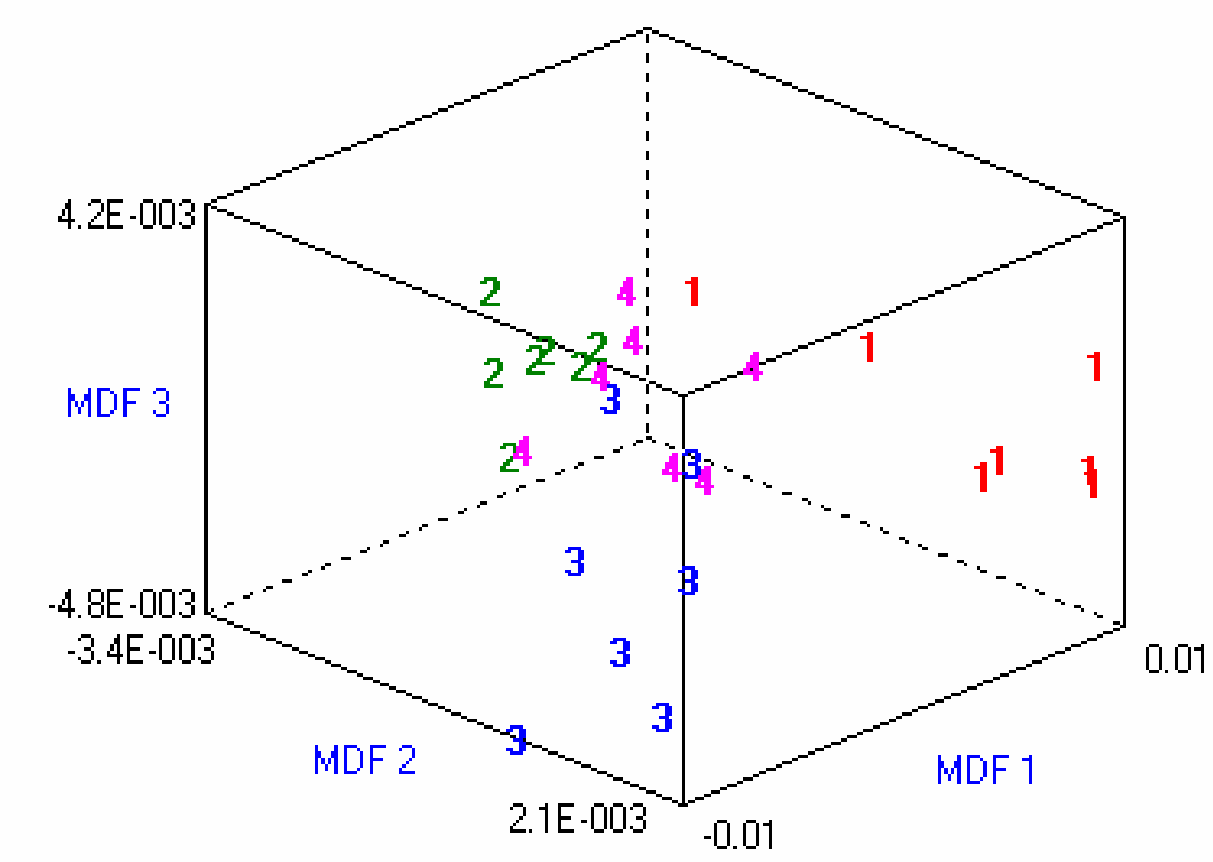
3 Contralateral WM

Characterizing tumor (n=7) from WM (n= 7 x 3)

Calculation approach	32 bpp		64 bpp		128 bpp	
	FN	FP	FN	FP	FN	FP
3D	0	0	0	0	2	2
2DM	1	1	1	0	1	0
ROI3	1	0	1	0	1	0
ROI2	1	0	1	0	1	0
ROI1	2	1	1	0	1	1

• Results for 32, 64, 128 GL COMs for all methods were comparable except for the 3D method, which had a higher number of errors.

3D COM for 32 bpp has separated one tumor class, one Peritumoral WM class (zero errors) and one overlapping WM class containing HL and CL regions.



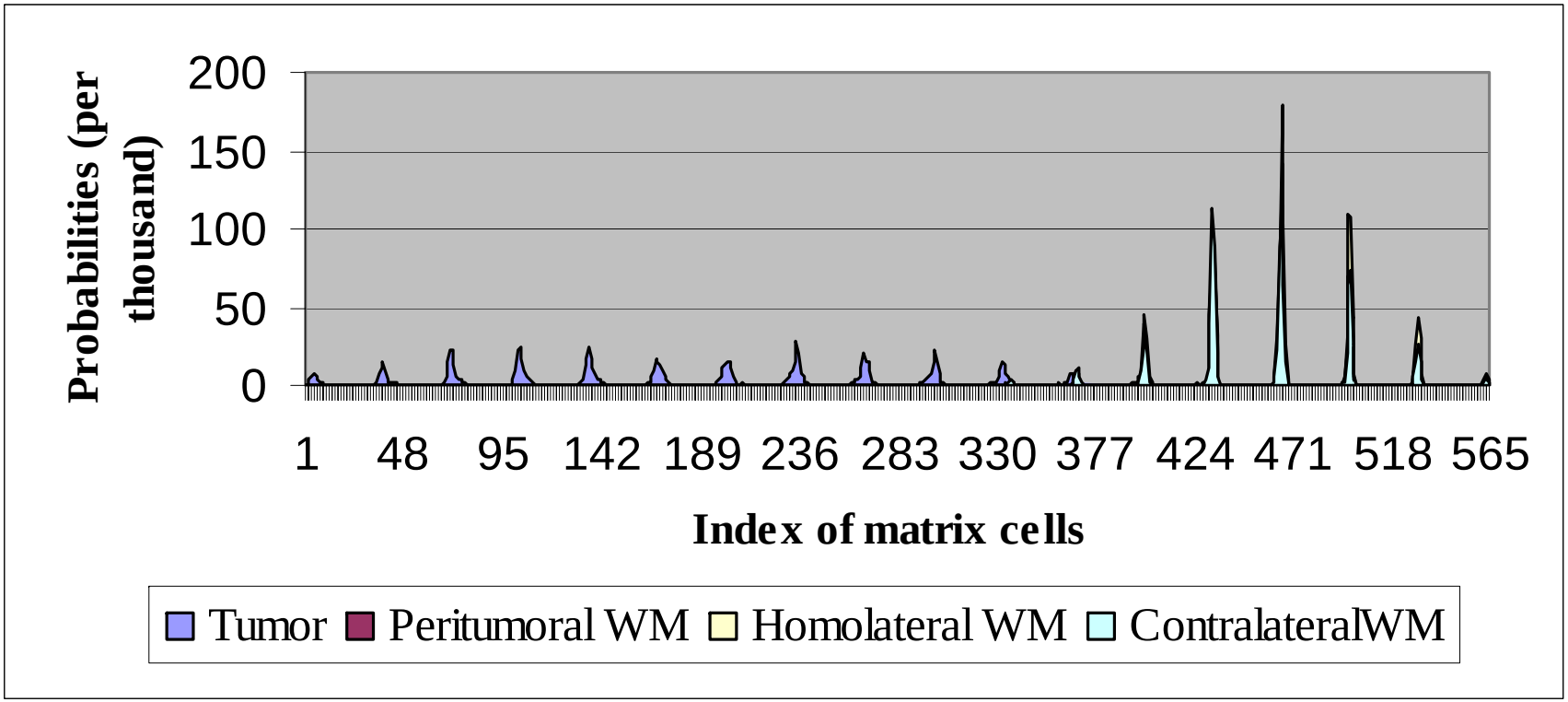
1 Tumor

2 Peritumoral WM

3 Homolateral WM

4 Contralateral WM

COH for 3D direction-independent Co-occurrence matrix



- The peaks from different WM regions overlap in position but don't have the same height.
- Each peak corresponds to a row (or column) in the COM.
- Each peak have a Gaussian form centered around the joint probability of similar GLs.
- All peaks make a Gaussian profile i.e GL distribution falls around a central value.

Discussion and Conclusion

- The Peritumoral WM has shown to represent a different class when other WM regions seemed to be overlapping. This is consistent with a previous done work in our group in Rennes University on isotropic voxels (M-Ghoneim et al, 2002, MRI). This was clear in both 2D or 3D methods.
- In WM characterization, the 3D methods showed more stability in results while the 2D ones seemed to be dependent on the ROI. Some ROI showed zero errors while others showed several errors for the same location.

Discussion and Conclusion

- Classification results depend on the accuracy and stability of the features extracted from the COM
- The stability of the features depend on the bpp used in calculating COM
- For homogenous structures like WM the accuracy of features increases by increasing the bpp and stability does not appear to be critical.
- For heterogeneous structures like tumors, increasing the bbp tends to “dilute” the discriminating features, i.e. the COM has (too) few entries per cell and yields instable classifiers.

Questions and Perspectives

- What would be the best normalization factor to use?
- HL and CL , are these belong to one class or different classes?
- More investigation for direction independent matrices.
- More investigation for COH.
- Standardization of the method?