Automatic Quality Assessment of Diffusion Weighted Images

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Background and Purpose

Diseases like glaucoma affect the visual pathway in the brain. Diffusion Tensor Imaging enables the reconstruction of white matter fibers in vivo. For a reliable analysis the quality of the input data is discriminant.

The purpose of our work is to develop a method to **automatically discriminate between different quality levels** of diffusion weighted images.

Key Ideas

Three feature groups capture determinant quality criteria

- **Clustering:** Recognizability of relevant structures
- **Sharpness:** Separation of important components
- **Texture:** Generic image appearance

A Support Vector Machine classifies different quality levels

Data

Acquisition

- 3T-MRI scanner
- Imaging sequence: Single-shot, spin echo, echo planar imaging
- 230 x 230 mm^2 field of view
- Intra-slice-resolution: 1.8×1.8 mm^2, 5mm thickness
- 10 subjects scanned along 20 gradient directions
- Each scan on 1 image as 5×5 matrix (Fig. 1)
- 4 scans in each direction

Four quality levels by averaging scans in each direction are used

- **Level 1**: Original scan (No average)
- **Level 2**: Average of 2 scans in same direction
- **Level 3**: Average of 3 scans in same direction
- **Level 4**: Average of 4 scans in same direction

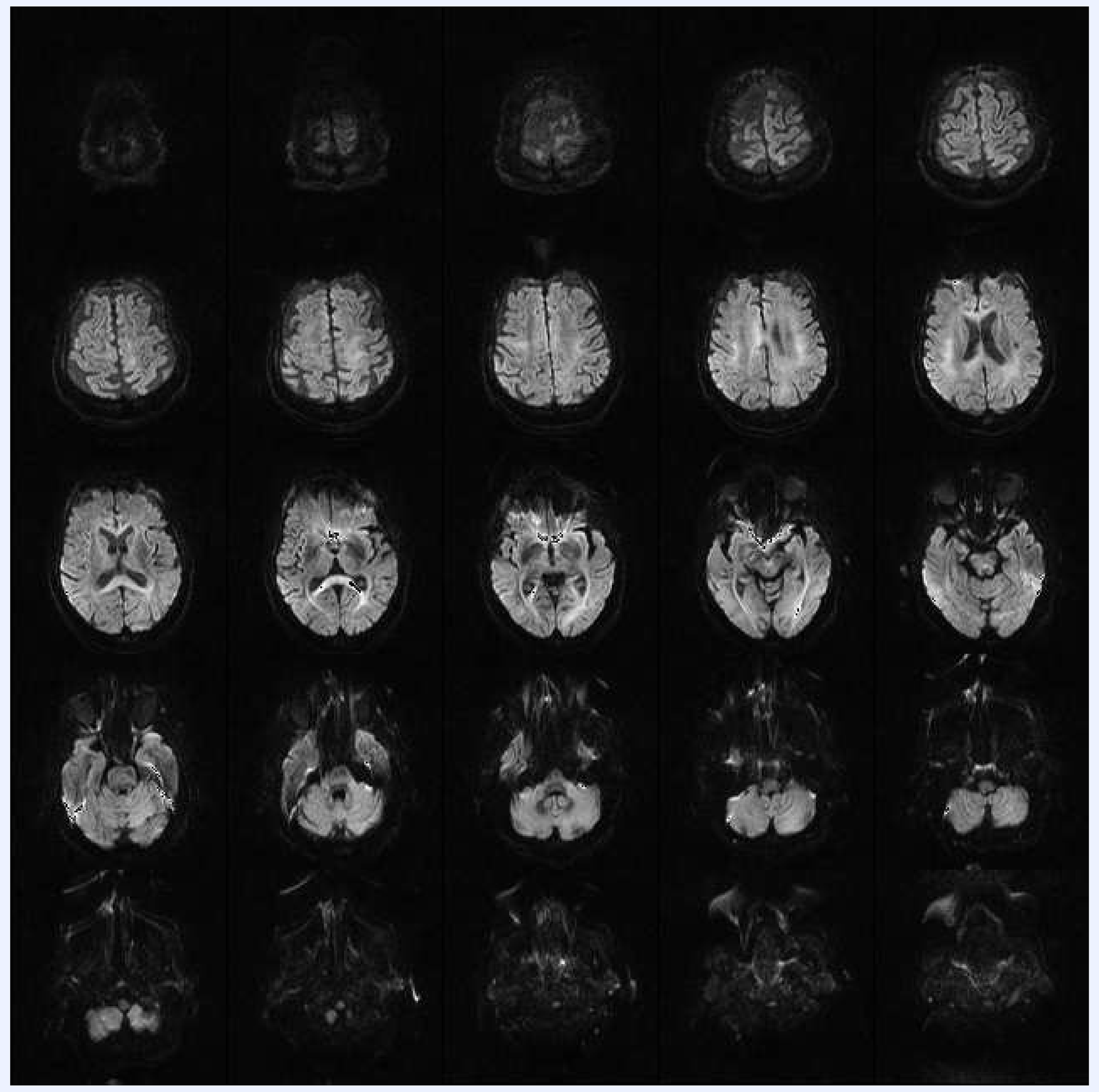

Figure 1: Example image of a diffusion weighted imaging dataset of a brain scan (average of 4 scans). The 25 slices are aligned in a 5×5 matrix.

Methods: Clustering

The recognizability of 3 classes is investigated

1. Grey/white matter
2. Background
3. Remaining regions

→ The image is divided into corresponding clusters. The division will fail for low quality images.

Global description:

- k-means-clustering ($k = 3$)
- Initialization on random image points
- Clustering fails for low quality images

Features:

- *Cluster sizes* c_i of clusters C_i:

$$c_i = \frac{\#\{g_{xy} | g_{xy} \in C_i\}}{\{\#g_{xy} | g_{xy} \in Image\}} \quad (1)$$

- *Inter-cluster-differences* d_{ij} of cluster means m_i:

$$d_{ij} = m_i - m_j, \; i, j \in \{1, \ldots, k\}, \; i > j \quad (2)$$

Methods: Sharpness

The quality of separation of relevant classes is determined

→ The separation is dependent on edge information. Low quality images will show weak edges and low sharpness.

Local measurement:

- Gradient based sharpness metric for edge evaluation
- Identification of strong edges:
  1. Computation of gradient magnitude image G
  2. Detection of strong edge pixel: Magnitudes above $2\times$ mean value of G

Features:

- Number of strong edge pixels
- Average magnitude of strong edge pixels

Methods: Texture

The image appearance is evaluated

1. Common sharpness
2. Intensity homogeneity
3. Contrast

→ Texture statistics give information about the image appearance.

Texture metric:

- Haralick features
- Well established texture description method
- Statistics based on adjacent intensity pairs

Features:

- Entropy ↔ Sharpness
- Energy ↔ Homogeneity
- Contrast

Methods: Classification

- Support Vector Machine with linear kernel
- Normalized features
- 10-fold-cross-validation
- Determination of quality levels independent from scan direction

Results

The performance of assigning an image to its correct quality level was evaluated

For all quality levels:

- Minimum sensitivity of 0.96 at a specificity of 0.90
- Area under ROC curve higher than 0.97

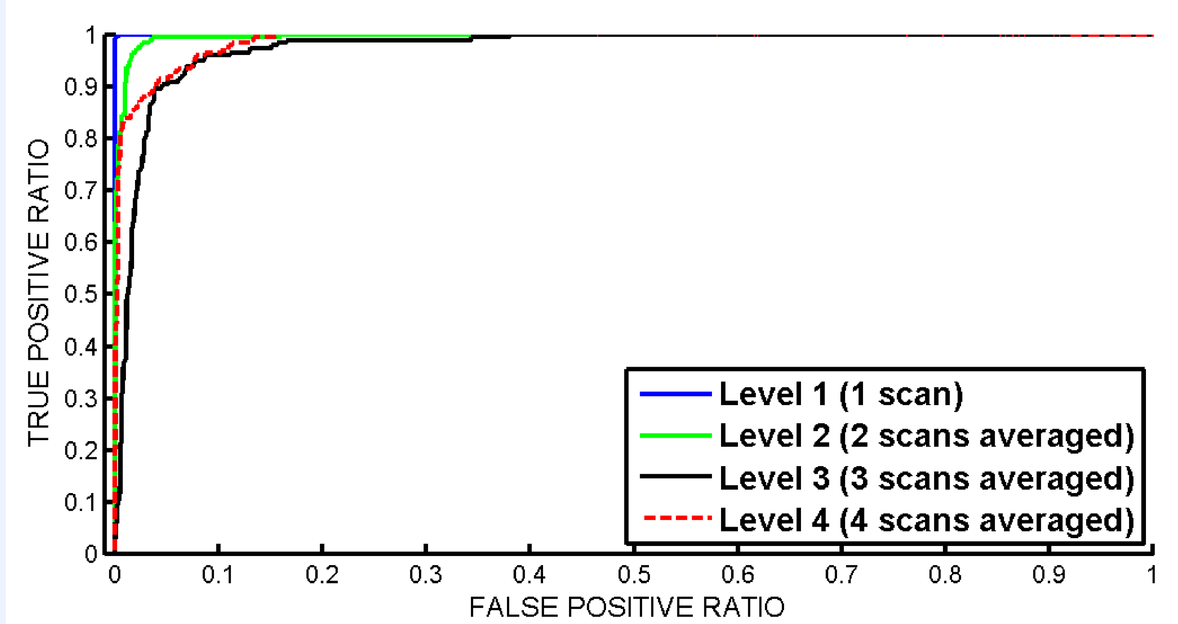

Figure 2: ROC curves for automatically **assigning images to their correct quality levels**.

Conclusion

1. We developed a **reliable and robust method for automated quality assessment** of different quality levels of diffusion weighted images.
2. In the future the algorithm has to be evaluated on a human graded gold standard.

Support

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Commercial Relationship

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References

[1] D. Le Bihan, J. Mangin, C. Poupon, C. Clark, S. Pappata, N. Molko, H. Chabriat. Diffusion Tensor Imaging: Concepts and Applications. Journal of Magnetic Resonance Imaging 13(4), pp. 534-546, 2001

[2] R. M. Haralick, K. Shanmugam and I. Dinstein, Textural Features for Image Classification, IEEE Transactions on Systems, Man and Cybernetics, SMC-3, 610–621 (1973)