Automated separation of low quality and artifact spectra by pattern recognition in the processing of MR spectral images

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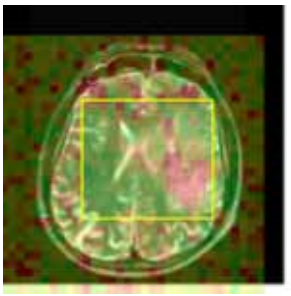
Abstract
The presence of noise and artifacts is a characteristic in the processing of magnetic resonance data, in particular in applications at the frontier of technical development. In the following, a methodology will be proposed, which automates the decision of a human operator about the quality and interpretability of an MR spectrum. The primary application will be - in conjunction with a following diagnostic classification - in the automated processing of high resolution MR spectral images, in particular in the detection of brain tumor.

Introduction
The standard approach in the analysis of MR spectral images is the resonance line quantification, but also pattern recognition has shown its value e.g. in the classification of short echo time data [Devos]. Both approaches are able to map relevant diagnostic information to nosologic images, which can easily be interpreted by a radiologist, even without detailed technical knowledge in the signal processing of MR spectra [Szabo].
However, one feature hinders the direct interpretation of such maps: In the presence of noise or artifacts, results can only be trusted after visual inspection and reassurance that the fitting procedure has worked successfully, or that the spectrum has a sufficient data quality for a meaningful pattern recognition, respectively. Such a manual procedure of the operator sets clear limits to the applicability of highly resolved spectral images (and 3-dim spectral volumes) with thousand of single spectra, which are the future of MR spectral imaging [Dydak].
Quality or error maps are proposed, to give additional information to the operator in such situations, e.g., by mapping the residuals after a quantification or by information theoretic criteria about the line fit [Young, Vanhamme]. However, rather than providing detailed knowledge about the presence of typical artifacts, these approaches give information about the stability of the fitting procedure. Also, these approaches are not applicable when a pattern recognition is preferred in the diagnostic analysis of the spectral image.
So, we present a methodology, which mimics typical decisions of a human operator in the assessment of the quality of a spectrum and which is applicable both together with quantification and pattern recognition. Frequent artifacts and the signal-to-noise (SNR) ratio are explicitly learned by a supervised pattern recognition and unknown -not yet learned- artifacts are detected by an unsupervised extension of this algorithm.



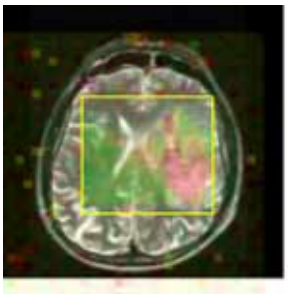


Fig 1: *Separation of low quality spectra in a diagnostic map. (red tumor, green normal, PRESS box indic. yellow)*

Methods
Data: A set of 36 spectral images (32*32 voxels, TE 135, Siemens MAGNETOM Vision, 1.5 T) were acquired at the German Cancer Research Center (dkfz) within routine diagnostics from patients with brain tumor. After water peak removal and correction of the B0-shift, the absolute spectra were labeled manually according to the signal quality. Citeria for "noise" spectra were insufficient SNR, and the presence of artifacts like unremoved baselines, strong shifts, or extra resonances (due to technical reasons) within the spectral region of interest (Choline, Creatine, NAA, lipid, lactate - region). Approximately 10% out of the 36 864 spectra were classified as "nice" spectra.
Classifier: On this data we trained a nonlinear classifier ("randomForest", a decision tree ensemble classifier [Breiman]) using the full spectrum of the region between choline and lactate as input after a binning of the spectral vector. In addition to the labeled data of this binary classification, the "noise" class of the training data was augmented by further random samples of the spanned feature space, allowing to detect and separate spectra with a - so far - unknown (artifact) pattern. The output of this procedure, the quality score, was the relative number of votes from the tree ensemble (between 0 and 1, with a threshold of 0.5 for classification).
Evaluation: A leave-'one patient'-out scheme was chosen in the evaluation of the test error. Hyperparamters of the classifier were kept fix to default parameters. For comparison, the SNR was also assessed for all spectra.

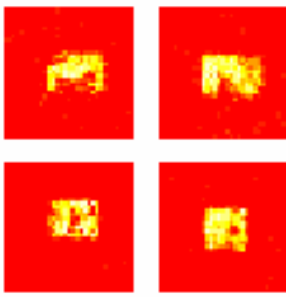


Fig 2: *Quality maps of spectral images from the training set.*

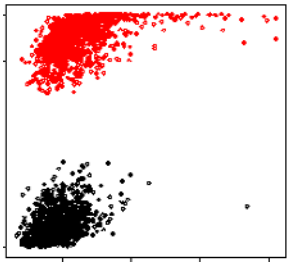


Fig 3: *SNR vs. quality score. x-axis SNR, y-axis score, red: high quality spectra, black::low*

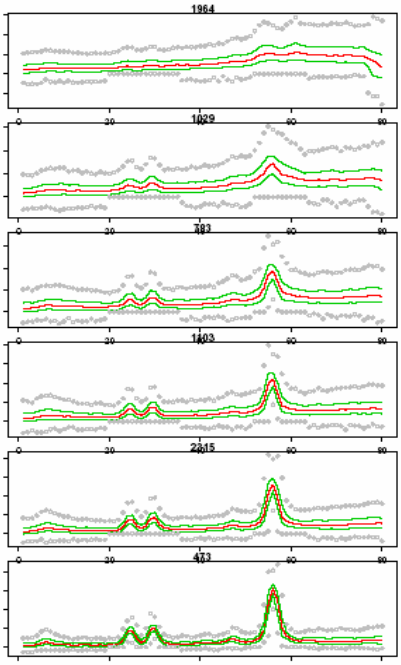


Fig 4: *Robust averages (median, quartiles, outlier) of spectra grouped according to the quality score.*

Results
All regions of high signal quality were localized. Excited regions (PRESS box) of the spectral images typically show a considerable number of low quality spectra. These areas were reliably detected as well [figs. 1, 2]. When grouping the spectra according to the quality score, we observe a smooth transition between low and high quality spectra, both in terms of artifact contamination and noise level [cp. fig. 4]. Comparing the proposed quality score with the SNR, we observe, that the SNR is not able to separate all the spectra, which were disregarded by an human operator [cp. fig. 3]. Overall, we observe a test error of 1.07%, which is comparable to the training error and most probably the result of ambivalent training labels.

Discussion
The proposed method is applicable, when a sufficient number of training spectra is available for a certain diagnostic problem. We find that the proposed methodology is easily transferable to other settings. So far, we applied it to spectral images of the brain (both tumor patients [figs. 1, 2] and healthy volunteers [figs. 3, 4]) and of the prostate (results not shown). Although we do not have experience with short TE spectra, we expect the method to be also applicable in that situation.
Overall, we are able to present an approach for a machine-based quality assessment of MR spectra, which is another step in the automation of an analysis of MR spectral images and which has the potential to reduce time and effort of the human operator considerably.

References
[Devos] J Magn Reson 2004; [Szabo] Nature Med 2000; [Dydak] MRM 2003; [Young] MRM 2000; [Vanhamme] MRM 2001; [Breiman] Machine Learning 2001