Applying Data Mining for the Characterization of Acute Stroke

M. Visser[1,2], R. Holthuizen[1], F. Hoogenraad[1], A. W. Simonetti[1], A. v. Muiswinkel[1], L. L. Latour[3], and C. Ciuhu[4]

[1]MR Image Handling Software, Philips Medical Systems, Best, Netherlands, [2]Eindhoven University of Technology (TU/e), Eindhoven, Netherlands, [3]National Institute of Neurological Disorders and Stroke (NINDS), Washington DC, United States, [4]Video Processing and Analysis, Philips Research, Eindhoven, Netherlands

Introduction: Stroke pathology is diverse and rapidly evolving over time, requiring multiple MR contrast mechanisms for accurate assessment of stroke sub-type, acuity, and potential risk/benefit of intervention. However, the use of MRI for selecting the appropriate acute therapy is hampered by immediate access to human expert interpretation in an emergency setting. Furthermore, lesion conspicuity on a single sequence (such as DWI) is not sufficient, and concordance/discordance across multiple sequences (such as DWI/PWI mismatch) is essential for comprehensive interpretation [1].

We propose a training-based expert system for automatic tissue classification to guide the physician in decision making. The approach relies on an expert observer to identify tissue-contrast classes within individual sequences and on multidimensional data mining to find combinations of classes having significant concordance. The training expert is then given the opportunity to select new functional classes based on these combinations, which can be used in final diagnosis. We present the results of an exploratory, retrospective study used to develop the expert system that is to be tested prospectively in the acute clinical setting.

Material and Methods: Imaging data on ten consecutive patients, having acute stroke in the MCA territory and consenting to a natural history protocol, was obtained using an Achieva 3.0 Tesla MR system (Philips Medical Systems, The Netherlands) at The Washington Hospital Center (Washington DC). The MR imaging series consisted of DWI and an apparent diffusion coefficient (ADC) maps, PWI and mean transit time (MTT) maps, gradient recalled echo (GRE) and pre-contrast fluid attenuated inversion recovery (FLAIR) scans.

All scans within the same examination were registered with respect to each other and small intensity variations between examinations were corrected using a linear intensity correction scheme. A human reader segmented tissue on individual series and assigned classes according to Table 1. The signal values of the ADC and MTT maps and GRE and FLAIR images for each delineated pixel were combined into a set of 4-element training vectors. These vectors were then stored in a database along with the class assignment by the expert, thus forming a feature space.

To identify combinations of classes, or *compound classes*, the data mining algorithm divided feature space into a mesh of equally sized hypercubes and counted the training vectors of each class within these hypercubes. If one particular class was predominant in a hypercube, then the hypercube was associated with that class. A hypercube was associated with a compound class, if multiple classes had approximately the same number of samples as the predominant class. The compound classes and their incidence in feature space were reported to the expert human observer, who optionally assigned a new or one of the existing classes to the hypercubes. Then, the bulk of the training vectors within a hypercube associated with a compound class was assigned to this class. See Figure 1 for an example of feature space before and after this procedure for a 2-dimensional situation. Originally, two classes (green and blue circles) exist with significant overlap. After the procedure, most of the vectors in the red hypercube are assigned to a new red compound class (red crosses), while the vectors in the other hypercubes remain unchanged (green and blue crosses).

A weighed k Nearest Neighbor algorithm (k-NN) [2] was used for classification within the feature space after data mining. The result of the classification was compared with the k-NN result based on the original feature space.

Note that we have allowed spatial overlap between segments of different classes. Such overlap would for example occur between diffusion and perfusion lesion segments [1]. Overlap results in training vectors with different class assignments at the same location in feature space. This decreases the performance of the k-NN classifier. Since aforementioned overlap increases the likelihood of hypercubes associated with compound classes, the expert observer could resolve this issue for those hypercubes by changing the class assignment of most training vectors from their initial classes to the classes defined by the expert after data mining.

Table 1 – Tissue and contrast classes delineated by the expert, including the series on which delineation was performed.

Tissue class	Color
Diffusion lesion on ADC	Green
Perfusion lesion on MTT	Blue
Flair lesion on FLAIR	Yellow
Gray matter on GRE	Tan
White matter on GRE	Purple

Table 2 – Combinations of tissue classes identified through data mining and the associated (unnamed) classes.

Compound classes (found by system)	Color
DIFF_LES **and** PERF_LES **and** (GM **or** WM)	Red
FLAIR_LES **and** (DIFF_LES **or** PERF_LES)	Yellow

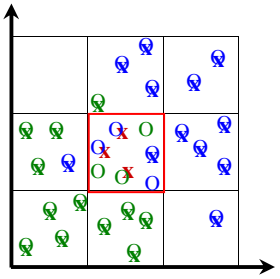

Figure 1 – Fragment of feature space with training vectors before (circles) and after data mining (crosses).

Results: Figures 2a through 2c show an example of an acute ischemic lesion in a stroke patient. Figure 2d shows the result of the characterization using only the classes of Table 1 and the feature space before data mining. A value of k=100 was chosen for the weighted k-NN classifier. The assignment of either the diffusion, perfusion or FLAIR class is arbitrary due to overlap of these classes in the training data. Table 2 shows two new classes identified through data mining as appearing consistently paired. Figure 2e shows the classification result using these classes and the updated feature space. Figure 2e improves on the classification result of Figure 2d by exposing regions with concurrent diffusion-perfusion deficiency (red) and FLAIR in combination with the two other lesion types or FLAIR exclusively (both yellow). Note that the definition of the yellow class causes more voxels to belong to that class than in Figure 2d, despite the fact that the FLAIR enhancements in these areas are marginal. This illustrates how choices in the definition of new classes can increase the performance of k-NN classifier.

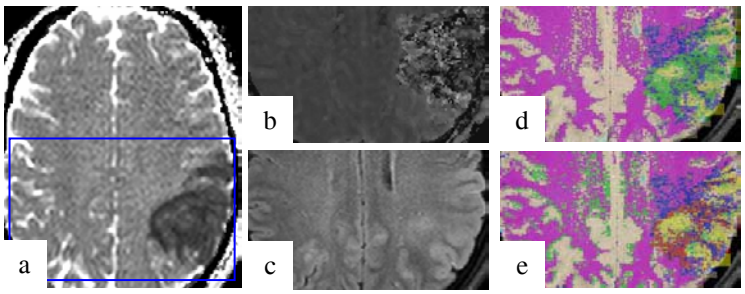

Figure 2 – Alphabetically: ADC, MTT, FLAIR, classification using the classes from Table 1 only, and using the additional classes of Table 2.

Discussion/Conclusion: We have created and successfully tested a training-based expert system for automatic tissue classification. We have shown that use of our data mining algorithm and the new compound classes defined by the expert observer in combination with the k-NN classifier can expose effects, which are not readily apparent using a single contrast, and this may improve the characterization result. Efforts are now focused on further developing automation and characterization, combined with extensive clinical testing in patients. Our efforts should result in an expert system to guide the physician in decision making in near-real time for both stroke and other pathologies.

References:

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