

## Anatomy as a parameter in multiparametric MRI-based predictive algorithms

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### Introduction

Multiparametric algorithms combining diffusion-weighted (DWI) and perfusion-weighted (PWI) MRI have been shown to predict tissue infarction more accurately than using any single imaging modality [1]. However, a limitation of the existing algorithm is that the intrinsic variations in both normal and pathophysiologic states are not taken into consideration. For example, normal white matter cerebral blood flow values are at ischemic levels for gray matter and thus, white matter may need a different statistical model of infarction risk than gray matter. The purpose of this study is to investigate whether incorporation of anatomical information into multiparametric MRI-based algorithms improves prediction.

### Patients and Methods

Acute stroke patients receiving conservative treatment (no thrombolysis) (n=12) within 6 hours of symptom onset were retrospectively analyzed. Median scan time was 3 h. All patients underwent a protocol of acute DWI/PWI and a 7-day follow-up (F/U) MRI on a 1.5 T scanner (Siemens). Apparent diffusion coefficient (ADC) maps were calculated from the DWI. The low b-value (b=0) and high b-value (b=1000) images were used as the T2 weighted image and isotropic DWI (iDWI) maps. CBF, CBV and mean transit time (MTT) maps were calculated using singular value decomposition [2] with an arterial input function selected from the ipsilateral hemisphere. Delay maps were measured as the time of the residue function peak [3]. Acute DWI/PWI images were coregistered to the F/U image and to the ICBM-152 brain that is in a stereotaxic coordinate system (MNI Autoreg) [4]. All images were normalized with respect to contralateral normal white matter values producing relative values. Infarcted tissue was delineated on the F/U by a neuroradiologist. Non-infarcted tissue was defined as all remaining tissue in the ipsilateral hemisphere.

Using the ICBM probabilistic brain atlas [5], gray matter (GM), white matter (WM) and cerebral spinal fluid (CSF) probability maps were generated for each patient. Fig 1 shows example classifications for a patient imaged 2 h from symptom onset. Relative T2, ADC, iDWI, CBF, CBV, MTT and Delay maps were then used as parameters for training a supervised learning algorithm using a generalized linear model (GLM) whose output is the likelihood of infarction [1]. GLM coefficients were derived for each of the three tissue types. All training was performed using jack-knifing [1] to avoid biasing from training and testing on the same dataset. To generate an overall risk map, the predicted output for each tissue type was combined using a weighted average. The predicted results of this anatomically-weighted GLM (wGLM) risk map was compared to results from standard GLM (sGLM) algorithms [1]. Sensitivity and specificity were calculated along with receiver operating characteristic curves. Area under the curves (AUC) was calculated and compared (paired one-sided Wilcoxon test). The root mean squared errors (RMSE) of the predictions were calculated in the ipsilateral hemisphere and compared (paired Wilcoxon test).

### Results

Fig 2 shows the individual GM, WM, and CSF predicted risk of infarction for the same patient shown in Fig 1. Fig 3 shows the acute T2, iDWI and MTT as well as the predicted risk map from the combined anatomically-weighted wGLM and standard sGLM risk map along with F/U. wGLM appears more specific especially at lower risk values than sGLM. GLM models incorporating anatomical information performed significantly better than the simple GLM in terms of AUC ( $P < .05$ ). Furthermore, the RMSE was significantly lower ( $p < .001$ ) in wGLM ( $.21 \pm .09$ ) than in sGLM ( $.23 \pm .08$ ).

### Discussion

Incorporation of anatomical information into MRI-based predictive algorithms improved prediction of tissue outcome in acute stroke patients. Because the technique coregistered the acute T2 MRI to Talairach space without reliance on F/U, this approach is applicable to prospective studies where the follow-up imaging is not known. Furthermore, since the resulting risk maps are in a stereotaxic-coordinate system, anatomic lesion locations of areas at highest risk can be used as an additional parameter in algorithms that predict clinical functional outcome [6]. Because of the increased accuracy and negligible computational overhead, anatomically-weighted GLM is preferable over standard GLM for clinical stroke diagnosis and prognosis.

References 1. Wu O; *Stroke*. 2001; 32, 933-42. 2. Østergaard L; *MRM*. 1996; 36, 715-25. 3. Wu O; *MRM*. 2003; 50, 164-74. 4. Collins DL; *JCAT*. 1994; 18, 192-205. 5. Mazziotta J; *Philos Trans R Soc Lond B Biol Sci*. 2001; 356, 1293-322. 6. Menezes NM; ISMRM 11th Meeting; 2003.

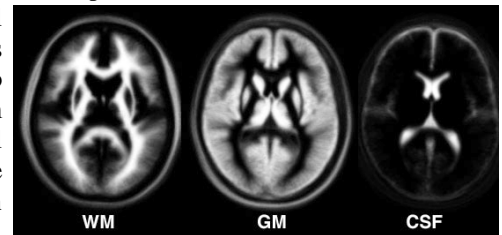


Fig. 1: Example WM, GM, CSF probability maps

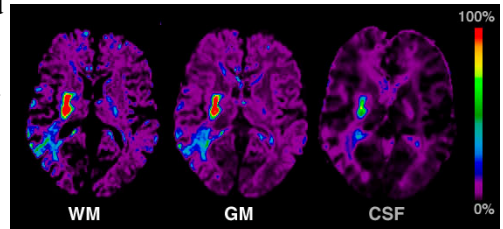


Fig 2: Risk maps generated by WM, GM, and CSF predictors

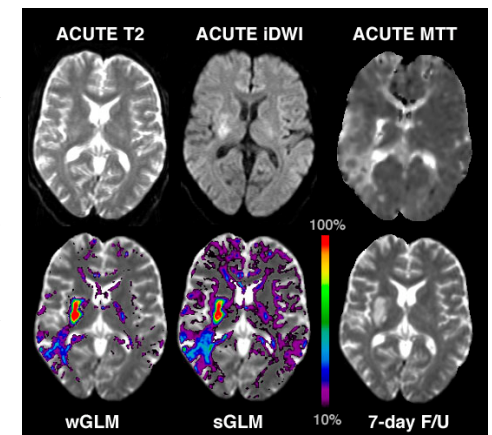


Fig 3: Acute T2, iDWI, MTT, wGLM, sGLM and F/U