Signal Intensity and Texture Feature Analysis in Contrast-Enhanced Liver MRI for Chronic Liver Disease Diagnosis

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INTRODUCTION: Chronic liver disease (CLD) involves a process of progressive destruction and regeneration of the liver parenchyma leading to fibrosis and cirrhosis. Early detection and accurate staging of CLD is important because liver transplantation is the only treatment for advanced cirrhosis with liver failure. Patients with CLD and metastatic liver tumors use cross-sectional imaging for a routine diagnostic testing. But the ability to measure the severity of CLD has been lacking in image-based tests. Consequently, clinicians have relied upon indirect measures derived from clinical status and blood or tissue tests that are neither highly sensitive nor specific to early disease or to small changes in disease progression. Thus, this work focuses on a computer-aided diagnosis (CAD) for assessing the level of regional liver function and aiding diagnostic decision making based on signal intensity change and texture feature analysis in contrast-enhanced MR image.

METHODS: Contrast agent is taken up to various degrees by functioning hepatocytes, and the paramagnetic property of the contrast agent shorten the longitudinal relaxation time (T1) of the liver causing an increase in signal intensity in T1-weighted MRI. Hepatobiliary-specific contrast agent such as gadoxetate disodium (Gd-EOB-DTPA, Eovist or Primovist, Bayer HealthCare) allows data acquisition up to the hepatobiliary phase at 20 minutes after injection of contrast agent. ***1. Signal Intensity Analysis*:** For a computation of the slope at the hepatobiliary phases (3-20 minutes), the signal intensity points over the liver parenchyma are subtracted by the signal intensity at the start of the hepatobiliary phase (3 minutes), then normalized by the peak of aorta signal as follows: $(S_k - S_{3\,\min}) / S_{aorta\ peak}$. A mean slope can be computed using the geometry of a rectangle triangle (dashed line in Figure 1) with the same area as the sum of trapezoidal areas among discrete times 3-20 min as follows: $\sum_{p\in\Omega}^{N}\{2/(20-3)^2 \sum_{k=1}^{4} A_k\}/N$ where A_k is the area of k-th trapezoidal division and p indicates the voxel in the liver parenchyma region and N is the number of voxels of interest. ***2. Texture Feature Analysis*:** The hepatic fibrosis or cirrhosis can be reflected by the reticular enhancement patterns over the liver parenchyma in the equilibrium phase. To extract these patterns on the MR image, we use the 2-D Gabor filter [1] to perform edge detection with eight different orientation. The computed Gabor energy is then performed with anisotropic non-classical receptive field inhibition [2] that reduces influence of stimuli in the surroundings and enhances the linear structure. From the filtered image, the ratio of linear structure is computed (Figure 2). The rest of texture features are generated from the grey level co-occurrence matrix (GLCM) [3] that examines textures with the spatial relationship of neighboring pixels within a radius of three pixels. ***3. Classification*:** A supervised classifier based on a multivariate normal distribution model and maximum a posteriori (MAP) decision rule was applied for the classification. The performance of the classifier was evaluated via leave-one-out cross-validation.

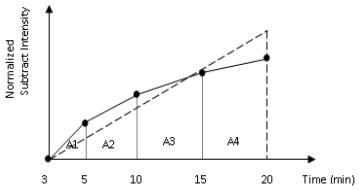

Figure 1. Mean slope in hepatobiliary pahse (3-20 minutes).

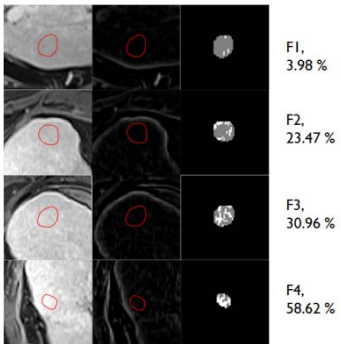

Figure 2. Reticular enhancement patterns and linear structure ratio related to the degree of liver fibrosis.

RESULTS: For 14 patients with known pathologic scores, quantitative result of the mean slope was significantly different from the normal group based on a one-tailed t-test (***p*-value of 0.0039**). The mean slope was highly correlated with the degree of fibrosis (r=0.8186), suggesting its potential for assessing the progress of liver fibrosis (Figure 3). From the GLCM in 126 regions of interest with known fibrotic scores assigned by experts, we independently ranked all the possible texture features by class separability criterion (e.g., fisher score), and the most correlated six features: **the ratio of linear structure, entropy, dissimilarity, inverse difference, sum average, and variance**. The leave-one-out cross-validation test of the supervised MAP classifier resulted in 55% matching with no error, 37% matching with a score error of one (Figure 4), with **the prediction accuracy with a score error no more than one being 92%**. Figure 5 illustrates the colormap representation of the predicted fibrosis score over the entire liver region, which could significantly aid clinicians in interpreting medical images comprehensively with increased throughput.

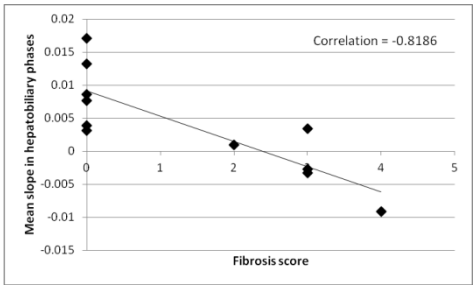

Figure 3. Correlation of the degree of liver fibrosis score and the mean slope in hepatobiliary phase.

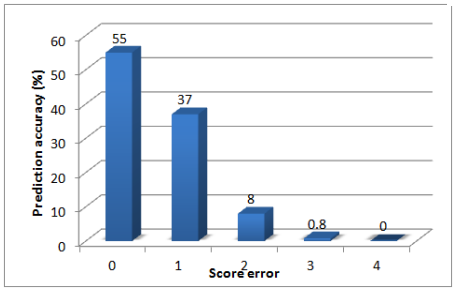

Figure 4. The prediction accuracy determined by leave-one-out cross validation of supervised MAP classifier.

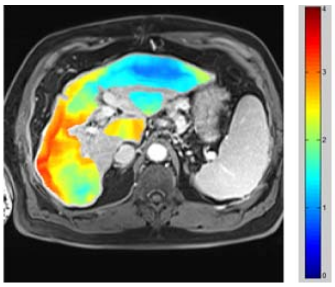

Figure 5. A colormap representation of predicted fibrosis scores over the entire liver.

CONCLUSION: The mean slope in hepatobiliary phase and texture features in the equilibrium phase of contrast-enhanced MRI were able to predict liver pathology scores, making them use in computer-aided diagnosis of liver disease. Further validation using a larger patient population is needed to establish its clinical utility.

REFERENCES: **[1]** J.R. Movellan, *Open Source Document*, 2002. **[2]** C. Grigorrescu et al., *Image Processing, IEEE Transactions on*, vol. 12, no. 7, pp. 729-739, 2003. **[3]** R. M Haralick et al., *IEEE Transactions on Systems, Man, and Cybernetics*, vol. SMC-3, No.6, pp. 610-621, 1973.