Texture Feature Analysis for Prediction of Postoperative Liver Failure Prior to Surgery

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ABSTRACT

Texture analysis of preoperative CT images of the liver is undertaken in this study. Standard texture features were extracted from portal-venous phase contrast-enhanced CT scans of 36 patients prior to major hepatic resection and correlated to postoperative liver failure. Differences between patients with and without postoperative liver failure were statistically significant for contrast (measure of local variation), correlation (linear dependency of gray levels on neighboring pixels), cluster prominence (asymmetry), and normalized inverse difference moment (local homogeneity). Though texture features have been used to diagnose and characterize lesions, to our knowledge, parenchymal statistical variation has not been quantified and studied. We demonstrate that texture analysis is a valuable tool for quantifying liver function prior to surgery, which may help to identify and change the preoperative management of patients at higher risk for overall morbidity.

1. PURPOSE

Partial hepatectomy is the most effective and only potentially curative treatment for primary and secondary hepatic tumors. Postoperative liver failure after hepatic resection is a life-threatening complication with high volume centers reporting an operative mortality rate of less than 5%[1] with careful patient selection.[2] Postoperative morality and liver failure rates are higher for major resections and therefore a major concern. Studies have shown that the percentage of functional liver parenchyma remaining after surgery is a good predictor of hepatic dysfunction.[3–5] Cross sectional imaging studies are typically used to assess the health of the parenchyma with respect to steatosis (fatty changes) or liver cirrhosis (excess connective tissue) but no metrics exist for quantifying liver functional capacity.[6] In this work, we relate features extracted using standard image processing techniques from CT images to postoperative liver dysfunction and demonstrate that parenchymal variations (at the texture level) observable prior to surgery appear to predict postoperative dysfunction.

Texture analysis has been used to augment lesion diagnosis and characterization[7] with specific applications in the liver including detecting colorectal liver metastases,[8] classifying lesions (colorectal liver metastases, hepatocellular carcinoma, and benign),[9] and quantifying texture in colorectal cancer patients with no metastases.[10] To our knowledge, texture analysis in the parenchymal (functional) regions of the liver has not been studied and in particular, variations in these regions have not been correlated with postoperative dysfunction, the topic under investigation in this paper.

2. METHODS

The institutional database at Memorial Sloan-Kettering Cancer Center was queried for patients that underwent major hepatic resection (right or extended right hepatectomy). A case-matched study design was used in an attempt to eliminate possible confounding effects of clinically established factors associated with postoperative hepatic dysfunction. Comparisons were performed between the patients who underwent major hepatic resection with postoperative liver failure or dysfunction complications and a matched group of patients with no postoperative liver failure or dysfunction. Patients were matched 2:1 by procedure (right lobectomy or right trisegmentectomy), remnant liver volume (RLV, defined as the percentage remaining of functional liver volume compared with percentage of preoperative functional liver volume), and year of the procedure. In total, the study group consisted of twelve patients with liver failure within six months following surgery compared to a control group of twenty-four patients with no liver failure for a total of 36 patients. All patients had undergone conventional portal-veinous phase contrast-enhanced CT prior to surgery consistent with the standard of care at our institution. Since postoperative liver failure is a rare occurrence at our institution due to careful patient selection, these 12 patients represented all of the patients with postoperative liver failure and the requisite imaging protocol in the database.

Liver, tumors and bile ducts, and the portal and hepatic veinous systems were segmented from CT scans using Scout Liver (Pathfinder Therapeutics Inc, Nashville, TN). Tumors, ducts, and vessels were subtracted from the segmented liver region using custom software developed with C++ and the Visualization Toolkit (Kitware Inc., Chapel Hill, NC) such that only the parenchymal regions of the liver remained for analysis. Pixel values were converted to Hounsfield units. Attenuation values above 300 and below 0 were thresholded from the scans and therefore excluded from analysis. All scans were scaled using conventional image normalization.

Texture analysis was undertaken to characterize the variation (not the value) of brightness in the CT scans and to determine potential differences in our study group. Standard gray-level co-occurrence matrices (GLCM) were used to quantify spatial differences in pixel pairs in the scans. The GLCM was constructed with the parameters representing the distance between pixel pairs and the direction (alignment) of the pixel pairs. In our implementation, the number of gray levels was set to 32, the directions were $0°$, $45°$, $90°$, and $135°$, and the distances were varied from 8 to 32 pixels to investigate the effect of distance on feature detection. In total, 18 texture features were implemented in Matlab; the extraction and analysis were fully automated. The eleven primary features analyzed were autocorrelation, contrast, correlation, cluster prominence, cluster shade, dissimilarity, energy, entropy, and homogeneity, which correspond to observable characteristics in the image that translate to some radiographic description or visual cue. An additional set of features characterizes the complexity and nature of gray-level variations in the image, which provide statistical descriptors that may not relate directly to radiographic interpretation. These seven derivative features, used to augment classification, are maximum probability, sum average, sum entropy, difference entropy, difference variance, information measure of correlation, and homogeneous inverse difference. The mathematical details of these feature statistics have been previously described.[11–13]

3. RESULTS

Figure 2 shows a single slice from two preoperative CT volumes from different patients. The image shown in Figure 2(A) is a representative sample from a patient that had no postoperative liver failure and (B) is a representative sample from a patient with postoperative liver failure. The values for each of the texture features obtained from gray-level occurrence matrices are summarized below the figure for these patients.

The feature values did not vary with direction (0, 45, 90, and 135), which suggests a consistent texture for liver parenchyma in contrast-enhanced portal venous phase CT without anisotropy. Therefore, the feature values were averaged over all of the directions, a common approach reported in the literature. The size of the neighborhood (pixel distance) was varied to determine an optimal distance for this application. It appears that a pixel distance between 12 and 32 has a similar capacity to distinguish features between liver failure and no liver failure patients. Since texture analysis measures pixel variation across this neighborhood, regions of less than four pixels likely correspond to imaging unit noise and are therefore not expected to distinguish parenchymal differences.

Four texture features were significantly different in the control group (n=24) compared to the patients in the liver failure/dysfunction group (n=12). Boxplots for the seven statistically interesting features obtained from gray-level occurrence matrices are provided in Figure 3. Compared to the features in the control group, the contrast and cluster prominence features increased in the patients with liver failure/dysfunction, whereas the correlation and normalized inverse difference moment features decreased in value. Contrast, a measure of local variation in the image, showed significantly more variation in the liver failure group compared to the control patients (pixel distance = 12, $p<0.10$). Correlation is a measure of the linear dependency of gray levels on neighboring pixels, with higher values indicating similar gray-level regions; the control group had much less variation than the liver failure group (pixel distance = 12, $p<0.05$). Cluster prominence, an assessment of image

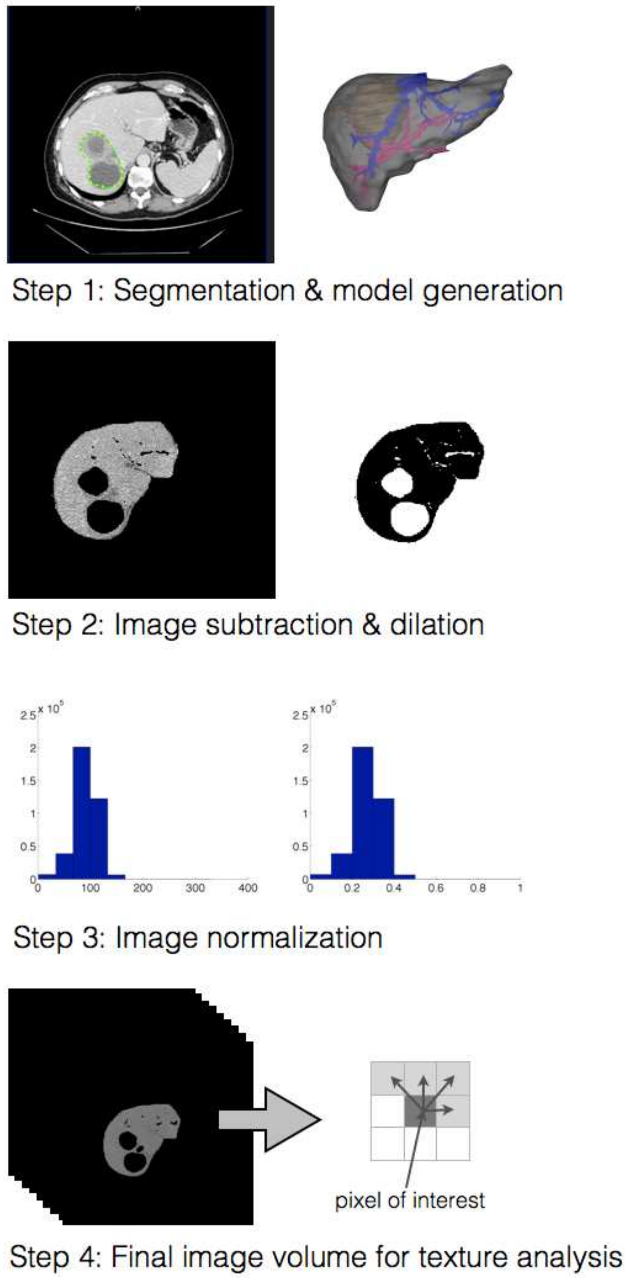
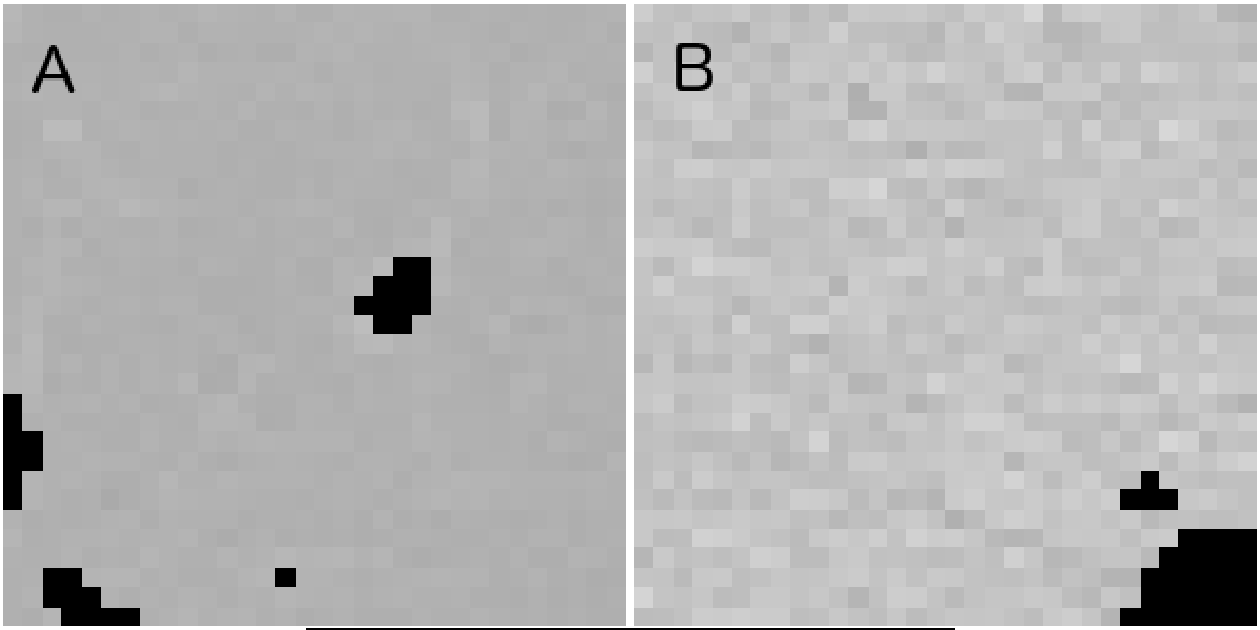


Figure 1. Image quantification of preoperative CT images for prediction of postoperative hepatic dysfunction from image segmentation (step 1) to texture analysis (step 4).



Texture Feature	NLF	LF
Contrast	7.0	17.0
Correlation	8.8×10^{-2}	2.3×10^{-2}
Cluster Prominence	2.9×10^{2}	10.2×10^{2}
Dissimilarity	2.0	3.3
Entropy	3.9	4.9
Homogeneity	4.7×10	3.4×10
Inv. Diff. Mom. Norm.	99.3×10^{-2}	98.4×10^{-2}

Figure 2. Comparison of preoperative CT texture (pixel distance = 24): (A) patient with no postoperative liver failure or dysfunction and (B) patient with postoperative liver failure or dysfunction. Black areas indicate non-parenchymal regions excluded from analysis.

asymmetry, was greater in the liver failure patients (pixel distance = 24, $p<0.10$). The normalized inverse difference moment is a measure of the local homogeneity of an image, where high values indicate homogeneity. These values were very slightly lower in the liver failure group, suggesting less homogeneity (pixel distance = 16, $p<0.10$). These observations are supported by the differences in dissimilarity (pixel distance = 16, $p=0.14$), entropy (randomness, pixel distance = 24, $p=0.18$), and homogeneity (pixel distance = 16, $p=0.17$) texture features, which although failing to meet statistical significance in this analysis, could potentially inform further classification of the study groups in a larger data set. These data suggest that further classification should incorporate texture features at multiple pixel distances.

To summarize, the texture of the liver parenchyma from preoperative CT images of patients with postoperative liver dysfunction was significantly more varied, less symmetric, and less homogeneous than that of the control group and with no directional dependence, evidenced in Figure 2.

4. DICUSSION

In this paper, we correlated postoperative liver dysfunction with texture features derived from preoperative images. The contributions described in this paper are not technical (existing texture features were studied) but clinical in nature. The impact of this work is clear: even though postoperative liver failure is a rare event, the ability to preoperatively predict patient outcome has direct impact on patient care and management. The next step in this research is to increase the number of study patients by including patients from other institutions, to build a classifier based on training data, toward prospective evaluation of CT images.

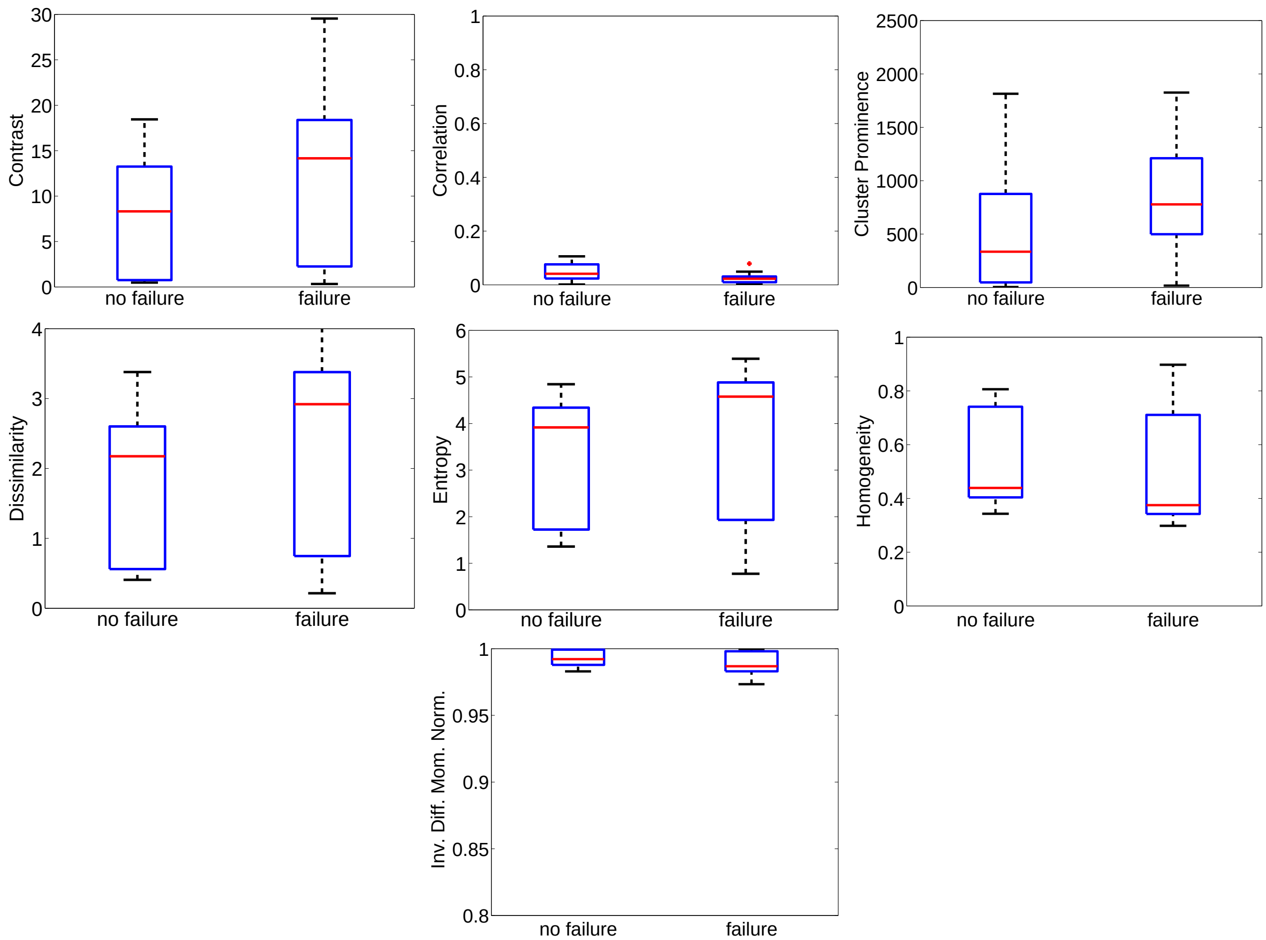


Figure 3. Comparison of preoperative CT texture (pixel distance = 24): box plots of texture feature values for patients with and without postoperative liver failure.

5. CONCLUSIONS

Texture features within parenchymal regions of the liver in preoperative CT images correlate to postoperative liver failure. Texture analysis is a valuable tool for quantifying liver function prior to surgery which may help identify patients at higher risk for overall morbidity.

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