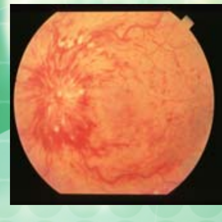
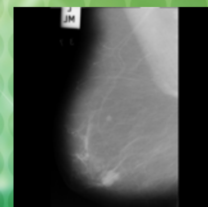

Medical Image Texture Analysis: A Case Study with Small Bowel, Retinal and Mammogram Images

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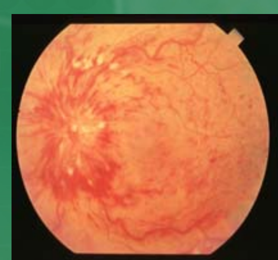
Computerized Applications

- Computers and software are performing many of our daily tasks

Navigation

Search the Internet

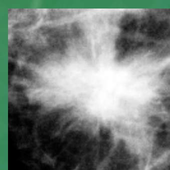


Analyze Medical Images (CAD)

Software-Based Medical Devices

Computer-Aided Radiology

Computer-Aided Diagnosis (CAD)

 →  → Diagnosis

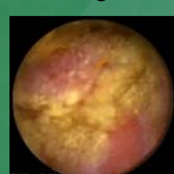
- Biomedical image processors aim to mimic the function of the physician
- Logical to create CAD systems to understand image content in the same manner as humans

Investigate human texture perception for CAD

Texture in Medical Images

Small Bowel Images

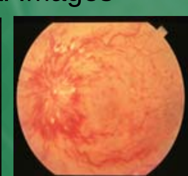
Normal



Abnormal

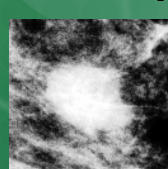
Retinal Images

Normal

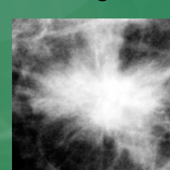


Abnormal

Mammogram Images



Benign



Malignant

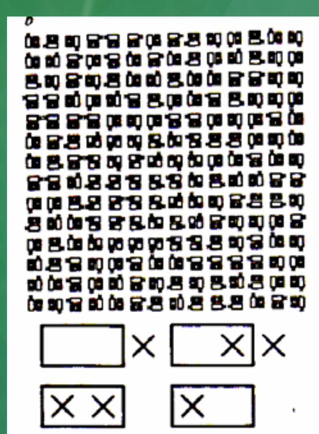
Image Texture

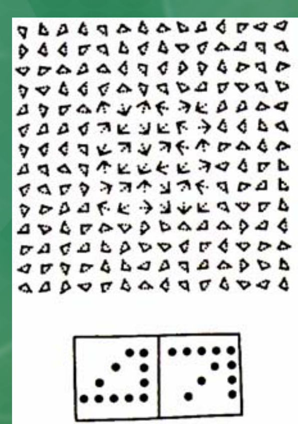
- Texture is one of the most important means to classify images[1]
  - Texture appears to differentiate between normal and abnormal pathologies
- This work designs a computer-aided diagnosis system, which mimics human texture perception

[1] R.M. Haralick, K. Shanmugam, and I. Dinstein. Textural features for image classification. IEEE Transactions on System, Man, Cybernetics, 3(6):610–621, Nov. 1973.

Human Texture Perception

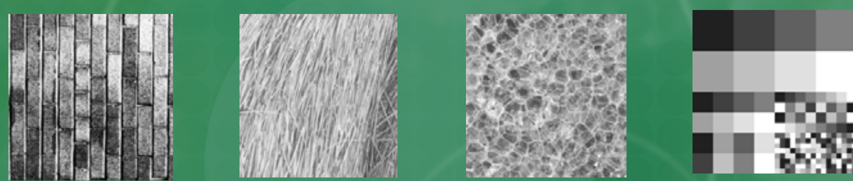
Textons[2]: Elementary units of texture





[2] B. Julesz. Textons, the elements of texture perception, and their interactions. Nature, 290(5802):91–97, Mar. 1981.

Human Texture Perception



- Relies on identification of textons[2]:
  - Differentiation between global and local texture events → ***Multiscale Texture Analysis***
  - Orientation, frequency, position and scale are important identifiers → ***Features must be ROBUST to translations, scale and rotation***

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[2] B. Julesz. Textons, the elements of texture perception, and their interactions. Nature, 290(5802):91–97, Mar. 1981.

Proposed Scheme

Modeling Human Texture Perception for CAD

Realization of global and local texture events

Multiscale Transform → *Feature Extraction* → *Feature Selection* → *Classification*

Robust quantification of texture which considers scale, rotation, position, etc.

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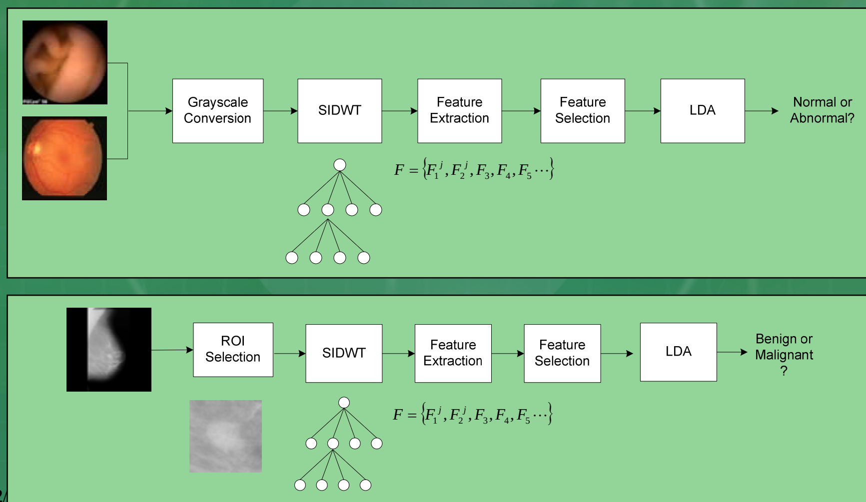
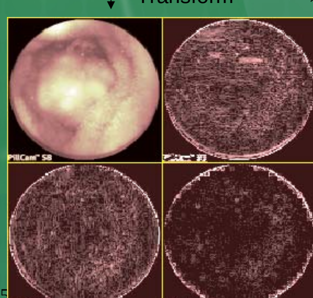
Block Diagrams



Wavelet Transformed Images

Small Bowel Lymphoma

Wavelet Transform

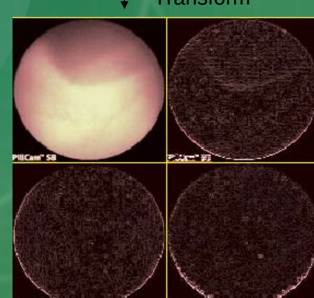


Pathology appears as heterogeneous texture (rapidly changing intensity)

Normal regions are very uniform (slowly varying intensity)

Healthy Small Bowel

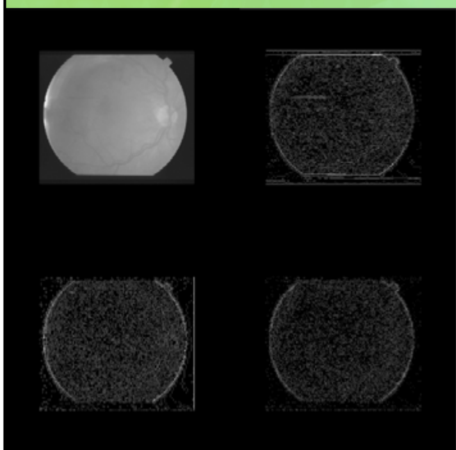
Wavelet Transform



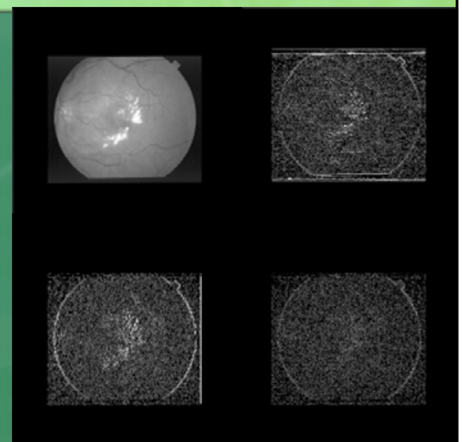
Note: Contrast enhancement was performed on the wavelet transformed images for visualization purposes

Wavelet Transformed Images

Normal Retinal Image



Diabetic Retinopathy



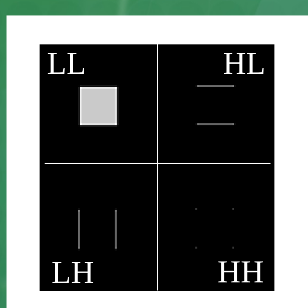
Normal regions are very uniform (slowly varying intensity)

Pathology appears as heterogeneous texture (rapidly changing intensity)

Note: Retinal images were converted to grayscale first

Development of a ***Novel*** Feature Set for Medical Images

DWT-based GCMs



Subband	GCM(s) Computed
HL	$p(l_1, l_2, 1, 0°)$
LH	$p(l_1, l_2, 1, 90°)$
HH	$p(l_1, l_2, 1, 45°)$, $p(l_1, l_2, 1, 135°)$
LL	$p(l_1, l_2, 1, 0°)$, $p(l_1, l_2, 1, 45°)$, $p(l_1, l_2, 1, 90°)$, $p(l_1, l_2, 1, 135°)$

Since each subband isolates different frequency components, the directions of the GCMs are selected so that they can capture localized, oriented, edge information

Feature Extraction

- Compute two statistical measures to "quantify" texture found in the wavelet transform
  - Relative uniformity (h) → $h = \sum_{l_1=0}^{L-1}\sum_{l_2=0}^{L-1} p^2(l_1, l_2, d, \theta)$
    - Quantifies the amount of homogeneity
  - Entropy (e) → $e = -\sum_{l_1=0}^{L-1}\sum_{l_2=0}^{L-1} p(l_1, l_2, d, \theta)\log\left(p(l_1, l_2, d, \theta)\right)$
    - Quantities amount of "roughness" or heterogeneity

Feature Selection/Classification

Feature Selection

- From all features, an exhaustive search was performed

Classification

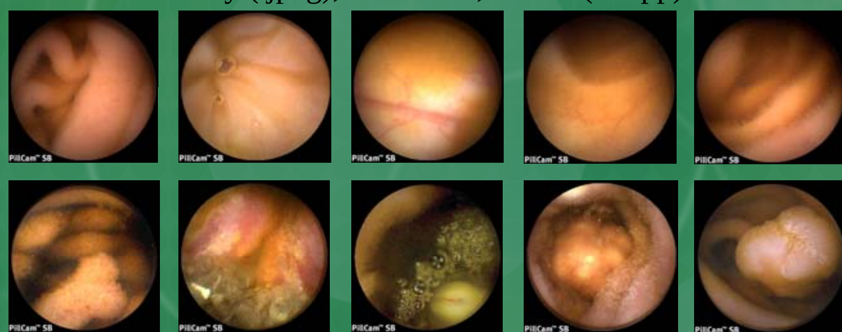
- Use Linear Discriminant Analysis (LDA) with leave-one-out method (LOOM) for small database for classification[4]

[4] K. Fukunaga and R.R. Hayes, "Effects of sample size in classifier design," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 11, no. 8, pp. 873 – 885, Aug. 1989.

Experimental Images

Small Bowel Images

Lossy (.jpeg), 256 x 256, colour (24bpp)



41 normal and 34 abnormal (submucosal masses, lymphomas, jejunal carcinomas, multifocal carcinomas, polypoid masses, Kaposi’s sarcomas, etc.)

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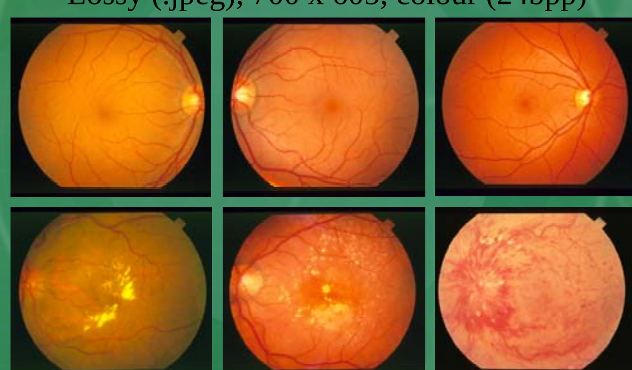
Image Database Source: Given Imaging Ltd. PillCam^{TM} Image Atlas. World Wide Web, 2006. http://www.givenimaging.com/.

Experimental Images

Retinal Images

Lossy (.jpeg), 700 x 605, colour (24bpp)



38 normal, 48 abnormal (exudates, large drusens, fine drusens, choroidal neovascularization, central vein and artery occlusion, arteriosclerotic retinopathy, histoplasmosis, hemi-central retinal vein occlusion etc.)

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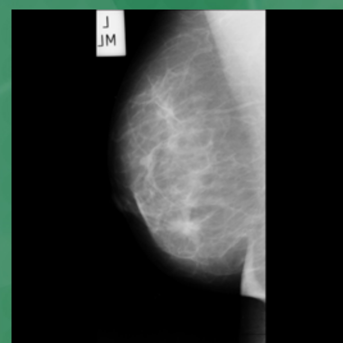
Image Database Source: M. Goldbaum. STARE - STructured Analysis of the Retina. World Wide Web, 2002. http://www.parl.clemson.edu/stare/

Experimental Images

Mammogram Images

Raw (.pgm), 1024 x 1024, grayscale (8bpp)



35 benign and 19 malignant lesions

Image Database Source: J. Suckling et al. MIAS Mammogram Database Exerpta Medica. World Wide Web. http://peipa.essex.ac.uk/info/mias.html

Results

Small Bowel Images

	Normal	Abnormal
Normal	35 (85%)	6 (15%)
Abnormal	5 (15%)	29 (85%)

Retinal Images

	Normal	Abnormal
Normal	30 (79%)	8 (21%)
Abnormal	7 (14.6%)	41 (85.4%)

Mammogram Images

	Benign	Malignant
Benign	28 (80%)	7 (20%)
Malignant	8 (42%)	11 (58%)

Conclusions

- Features were extracted in accordance to human perception model to achieve high classification rates
  - Local and global texture characteristics
  - Robust features
- Features were:
  - Robust to multiple pathologies
  - Database independent
  - Extracted from the compressed domain

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Future Work

- Incorporate colour-based GCMs (CCM)
- Segmentation of mammogram lesion prior to feature extraction
- Vessel segmentation prior to feature extraction

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