Single Organ Segmentation
Filters for Multiple Organ Segmentation

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Objective & Contributions

- Create automatic multiple-organ segmentation in Computed Tomography (CT) studies using pixel-level texture classification

- Apply single organ segmentations for each organ of interest in parallel

- Remove redundant pixel labels by comparing the region sizes and average probabilities over contested pixels.
Background

- Gray-level based segmentation
  - Gray-levels alone are not sufficient as many soft tissues have overlapping gray level ranges

- Shape-based segmentation
  - Organ shapes are different across different slides and across different patients

- Texture-based segmentation
  - Texture is expected to be homogenous and consistent across multiple slides for the same organ
Our Proposed Approach

- Applying, in parallel, single organ texture-based segmentation for each organ of interest

- Single-organ filtering:
  - Obtained via: 1) binary classification; 2) adaptive split-and-merge algorithm; and 3) region growing

- Remove redundant pixel labels by comparing of the region sizes and average probabilities over contested pixels.
Single Organ Segmentation

- Probability image of the organ of interest: Binary classification model obtained using pixel-based texture features
- Adaptive split-and-merge segmentation algorithm: Remove the noise introduced by misclassified pixels
- Region growing algorithm: Determine organ boundaries
Pixel-level Texture Extraction

Enhanced CT Images ➔ Features Extraction ➔ Feature Images ➔ Pixel-level classification ➔ Organ Probability Images ➔ Adaptive Split-&-Merge ➔ Adaptive Region Growing ➔ Organ Segmentation
Pixel-level Texture Extraction

- Consider texture around the pixel of interest.
- Capture texture characteristic based on estimation of joint conditional probability of pixel pair occurrences $P_{ij}(d, \theta)$.
  - $P_{ij}$ denotes the normalized co-occurrence matrix of specify by displacement vector $(d)$ and angle $(\theta)$.
Pixel-level Texture Extraction

Enhanced CT Images → Features Extraction → Feature Images → Pixel-level classification → Organ Probability Images → Adaptive Split- &- Merge → Adaptive Region Growing → Organ Segmentation
Classification

- Pixel-based texture classification: Classification and Regression Tree (C&RT) classifier is used to derive a set of rules for classifying pixels based on texture.

- Example of a rule,

  \[
  \text{IF} \quad [f_1(d, \theta; \gamma) < 0.34, 0.65 < f_5(d, \theta; \gamma) \leq 0.8]
  \]

  \[
  \text{THEN} \quad \text{Liver with}
  \]

  \[
  \text{PROBABILITY} = .9,
  \]

  denotes a rule obtained from a terminal node in which 90% of the pixels found at that node where indeed organ pixels.
Pixel-level Classification

- Liver Classification at a pixel level for different probability threshold
  
  (a) liver classification at 100%
  (b) liver classification at 90%
  (c) liver classification at 80%,
  (d) liver classification at 70%
Adaptive Split & Merge Segmentation

Enhanced CT Images → Features Extraction → Feature Images → Pixel-level classification → Organ Probability Images → Adaptive Split-&-Merge → Adaptive Region Growing → Organ Segmentation
Adaptive Split & Merge Segmentation

Probability Image → Initial Seed at 90% → Split & Merge at 85% → Split & Merge at 80%
Region Growing

Enhanced CT Images → Features Extraction → Feature Images → Pixel-level classification → Organ Probability Images → Adaptive Split- &- Merge → Adaptive Region Growing → Organ Segmentation
Region Growing

Split & Merge at 80%
Region growing at 70%
Region growing at 60%
Segmentation Result
Multiple Organ Segmentation

To merge all single organ filters, each of the pixels in the set of single-organ images are compared based on the following:

1. A pixel has not been classified, the pixel remains unclassified in the final segmentation.
2. A pixel has only labeled in one instance of a single-organ segmentation, that pixel retains its label in the final segmentation.
3. A pixel has multiple labels, a decision will be made based on
   - Size of the region containing that pixel
   - Average probability of the labels for each pixel in the region
Experimental Results

- **Data**
  - Normal CT studies from Northwestern Memorial Hospital (NMH) PACS.
  - DICOM format of size 512 by 512 and having 12-bit gray level resolution.

- **Pixel-Level Texture Extraction**
  - Haralick co-occurrence feature with 9x9 window size

- **Pixel-based Texture Classification**
  - Binary Classification and Regression Tree (C&RT)
  - Randomly select pixels from one CT slide in which the organ of interest was present: 50% of total pixels are from the organ of interest class
  - Model evaluation: 66% for training and 34% for testing.
Experimental Results

Liver

Spleen

Kidney

10/13/2006

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Conclusion & Future Works

- The use of multiple segmentation filters is no longer an “all or nothing” approach in which every pixel in the image must have assigned a segment label;

- Segmentation can be iteratively improved as information on new organs becomes available to generate new segmentation filters.

Future works

- Three dimensional (3D) texture extraction and 3D segmentation algorithms.
- Generate hierarchical segmentations supported by ontological labels.
References

Questions
Haralick Texture

Entropy: measure the randomness of gray-level distribution
\[-\sum_{i}^{M} \sum_{j}^{N} P_{ij} \log P_{ij}\]

Energy: measure the occurrence of repeated pairs within an image
\[\sum_{i}^{M} \sum_{j}^{N} P_{ij}^2\]

Contrast: capture the local contrast in an image
\[\sum_{i}^{M} \sum_{j}^{N} (i - j)^2 P_{ij}\]

Homogeneity: measure the homogeneity of the image
\[\sum_{i}^{M} \sum_{j}^{N} \frac{P_{ij}}{|i - j|} ; i \neq j\]

Sum Average: provide the mean of the gray intensity within an image
\[\frac{1}{2} \sum_{i}^{M} \sum_{j}^{N} (iP_{ij} + jP_{ij})\]

Variance: estimate the variation of gray level distribution
\[\frac{1}{2} \sum_{i}^{M} \sum_{j}^{N} ((i - \mu_i)^2 P_{ij} + (j - \mu_j)^2 P_{ij})\]
Haralick Texture

Correlation: measure a correlation of pixel pairs on gray-levels
\[ \sum_{i}^{M} \sum_{j}^{N} \frac{(i - \mu_r)(j - \mu_c)P_{ij}}{\sqrt{\sigma_r^2 \times \sigma_c^2}} \]

Maximum Probability: represent the most predominant pixel pair in an image
\[ \max_{i,j} P_{ij} \]

Inverse Difference Moment: measure the smoothness of an image
\[ \sum_{i}^{M} \sum_{j}^{N} \frac{P_{ij}}{1 + (i - j)^2} \]

Cluster Tendency: measure the grouping of pixels that have similar gray-level values
\[ \sum_{i}^{M} \sum_{j}^{N} (i - \mu_r + j - \mu_c)^2 P_{ij} \]

where \( \mu_r, \mu_c, \sigma_r^2, \sigma_c^2 \) are the mean and variance of row and column defined as follow:
\[ \mu_r = \sum_{i}^{M} \sum_{j}^{N} iP_{ij}, \quad \mu_c = \sum_{i}^{M} \sum_{j}^{N} jP_{ij} \]
\[ \sigma_r = \sum_{i}^{M} \sum_{j}^{N} (i - \mu_r)^2 P_{ij}, \quad \sigma_c = \sum_{i}^{M} \sum_{j}^{N} (j - \mu_c)^2 P_{ij} \]
Clipped-binning

- **Clipped binning technique** (Lerman et al., 2006) is applied to enhance the contrast within the soft tissues necessary for good texture feature extraction.

- The clipped binning technique incorporates
  1. K-means algorithm that automatically determines the range of the gray levels for the soft tissues in the given CT images
  2. Gray-levels that are lower than the soft tissue range and the gray-levels that are higher than the soft tissue range will be assigned to the minimum bin and maximum bin, respectively; the gray values within the soft tissue range will be linearly divided into equal bins.