Multi organ segmentation in 2D ultrasound images of thyroid gland using speckle related pixels

presented by

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Outline

• Introduction
• Literature Review
• Proposed Segmentation Method
• Results, Conclusions and Future work
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Multi-Organ Segmentation

Multi organ segmentation in 2D ultrasound images of thyroid gland using speckle related pixels.
Speckles: Friend or Foe?

- Always treated as noise
- Filters for speckle noise removal:
  - PDE Based
    - SRAD, NMWD, RTAD [1-3]
- Statistically analyzed to have Rayleigh, K or Rician distribution for noise removal [4]
- 1st and 2nd order statistics developed assuming linear processing

Physics behind Speckle Formation

Interference  Scattering  Refraction  Reflection  Absorption

Objective

- To investigate into the practical importance and use of speckle related pixels in performing an unsupervised multi-organ segmentation of the US images of thyroid gland.
- Organs segmented in the thyroid gland:
  - Transverse scan: Thyroid, Carotid, Trachea and Muscles
  - Longitudinal scan: Thyroid and Muscles
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Segmenting the Thyroid Gland

• Necessary to:
  • Automatically detect nodules in the gland[7]
  • Automatically estimate volume of the gland[8]
  • To perform guided interventions[9]

• Existing algorithms:
  • are active contour based and require manual initializations[10]
  • Perform binary segmentation
    • Thyroid from image or
    • Nodules from thyroid

Multi-Organ Segmentation

- Extensively studied in CT imaging
- Few methods in Ultrasound Imaging of abdomen
- All algorithms are supervised
  - Use decision tree based classifiers
  - Use Haar or Haar like features for segmentation
- Need large databases of annotated datasets for training

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Flow Diagram

1. **Input US Image** → Extract FOV → Determine pixels associated with speckles → Classify the speckle related pixels into 3 echogenic classes

2. From Classify the speckle related pixels into 3 echogenic classes:
   - **Is Transverse?**
     - **Y**
       - **Segment Trachea** → **Segment Carotid** → **Segment Muscles** → **Segment Thyroid** → **Segment thyroid** → **Output segmented image**
     - **N**
       - **Segment Muscles** → **Segment Thyroid**
Speckle Extraction and Clustering

- Speckle extraction using second order partial derivative test:

  \[ \mathcal{F} = \{(x, y) : |H(f)| > 0 \text{ and } \frac{\partial^2 f(x, y)}{\partial^2 x} > 0\} \]

  \[ H(f) = \begin{pmatrix} \frac{\partial^2 f(x, y)}{\partial^2 x} & \frac{\partial^2 f(x, y)}{\partial x \partial y} \\ \frac{\partial^2 f(x, y)}{\partial y \partial x} & \frac{\partial^2 f(x, y)}{\partial^2 y} \end{pmatrix} \]

- Convolve with averaging kernel and cluster pixels

  \[ f_{\text{avg}}(x, y) = \begin{cases} f(x, y) \ast w(x, y) & \forall (x, y) \in \mathcal{F} \\ 0 & \text{otherwise} \end{cases} \]

- Hypoechoic if: \( n_a > n_b + n_e \)
- Hyperchoic if: \( n_b > n_a + n_e \)
- Isoechoic if: \( n_e > n_a + n_b \)

\[ n_a(x, y) = |F_w| : f_{\text{avg}}(x_i, y_i) > f_{\text{avg}}(x, y) + \tau; i \in w \]

\[ n_b(x, y) = |F_w| : f_{\text{avg}}(x_i, y_i) < f_{\text{avg}}(x, y) - \tau; i \in w \]

\[ n_e(x, y) = |F_w| : f_{\text{avg}}(x, y) - \tau < f_{\text{avg}}(x_i, y_i) < f_{\text{avg}}(x, y) + \tau; i \in w \]
On Transverse Scans

- Trachea is the hypoechoic component above the largest anechoic component attached at the bottom of image.
- Segmenting Carotid:

\[
F = \int_{\text{inside}(E)} |f(x, y) - \bar{E}_i|^2 \, dx \, dy + \int_{\text{outside}(E)} |f(x, y) - \bar{E}_o|^2 \, dx \, dy
\]

\[
\bar{E}_i = \frac{\int f(h, y) f_{ho}(x, y) E(x, y) \, dx \, dy}{\int E(x, y) \, dx \, dy}
\]

\[
\bar{E}_o = \frac{\int f(h, y) f_{ho}(x, y) (1 - E(x, y)) \, dx \, dy}{\int (1 - E(x, y)) \, dx \, dy}
\]
On Transverse Scans

- Muscles: Hypoechoic components above carotid
- Thyroid: Bounded on 3 sides by Carotid, Trachea and Muscles
- Anterior boundary estimated using gradients of speckle intensities

\[ g_y[t] = f(n_x(t), y), 1 \leq y \leq N \quad n_x = \{x : f_{hr}(x, y) > 0|y\} \text{ and } 1 \leq t \leq |n_x| \]

\[ x_{y,m} = \arg\max_{n_x} |\nabla g_y|, \]
On Longitudinal Scans

- Thyroid: Largest iso-echoic component in Image
- Anterior boundary estimated using gradients of speckles
- Muscles: Largest hypo-echoic component above the thyroid

\[ g(x) = \sum_{y=1}^{N} f_b(x, y) \]
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Results

• Tested on a dataset of 88 ultrasound images of the thyroid.
• Quantitatively validated on 32 images (20 in transverse and 12 longitudinal) using Dice co-efficient (DSC)

\[
\text{DSC} = \frac{2 \times \text{TP}}{2 \times \text{TP} + \text{FP} + \text{FN}}.
\]

<table>
<thead>
<tr>
<th>Anatomical Structures</th>
<th>Transverse Scans</th>
<th>Longitudinal Scans</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average Dice Co-efficient value</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Expert 1</td>
<td>Expert 2</td>
</tr>
<tr>
<td>Thyroid</td>
<td>0.8170 ± 0.0550</td>
<td>0.8179 ± 0.0557</td>
</tr>
<tr>
<td>Muscles</td>
<td>0.7321 ± 0.1233</td>
<td>0.8002 ± 0.1200</td>
</tr>
<tr>
<td>Carotid</td>
<td>0.8490 ± 0.0594</td>
<td>0.8356 ± 0.0757</td>
</tr>
<tr>
<td>Trachea</td>
<td>0.7753 ± 0.0907</td>
<td>0.7712 ± 0.1295</td>
</tr>
</tbody>
</table>
Conclusion and Future Work

• Conclusion
  • Speckle related pixels need not necessarily be treated as noise and be filtered from the images.
  • Clinically significant results can be obtained by incorporating information from speckles and employing it with standard segmentation algorithms.
  • Results can be improved if imaging related artefacts can be identified and removed from the images.

• Future work
  • To improve the overall performance of the algorithm
  • To extend the concept of multi-organ segmentation using speckle related pixels to other organs
Questions?