Segmenting the Substantia Nigra in Ultrasound Images for Early Parkinson Diagnosis

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CARS 2007
Parkinson’s Disease (PD) is caused by death of dopamine producing cells in the Substantia Nigra (SN).
Motivation

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- Symptoms do not occur until substantial parts of SN have been irreparably damaged.
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- Neuroprotective drugs can shelter neurons in preclinical state.
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- Parkinson’s Disease (PD) is caused by death of dopamine producing cells in the Substantia Nigra (SN).
- Symptoms do not occur until substantial parts of SN have been irreparably damaged.
- Neuroprotective drugs can shelter neurons in preclinical state.
- Early identification of individuals at risk (1% of pop.) needed.
Recent findings

- Transcranial sonography (TCS) detects features correlating to PD at a very early state.
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- Very observer-dependent!
Transcranial sonography (TCS) detects features correlating to PD at a very early state.

SN shows hyperechogenicity in ultrasound images of the brain stem in about 90% of patients.

Differences not visible on CT or MRI scans.

Finding is based on manual image analysis.

Very observer-dependent!

Goal of this work

(Semi-)Automatic method to determine hyperchogenic SN region.
Ultrasound examination is performed from the temporal acoustic bone window.
Image Acquisition

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- Closer half of brain stem is analysed.
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Segmentation method outline

- Semi-automatic approach
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1. Manual segmentation of brain stem by clinical expert
Segmentation method outline

- Semi-automatic approach

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2. Preprocessing of brain stem region
Segmentation method outline

- Semi-automatic approach

1. Manual segmentation of brain stem by clinical expert
2. Preprocessing of brain stem region
3. Segmentation of SN region
Preprocessing

1. Border attenuation
   - Brain stem ROI may contain bright pixels from surroundings.
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1. **Border attenuation**
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   - Low-pass filter ROI mask image, use as attenuating mask.
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2. SN enhancement
   - SN lies approximately in middle third of ROI.
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   - SN lies approximately in middle third of ROI.
   - Fit ellipse to ROI.
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SN Segmentation

- SN is brightest spot in preprocessed image.

Introduction

Methods

Discussion

Kier, Cyrus, Seidel, Hofmann, Aach
SN Segmentation

- SN is brightest spot in preprocessed image.
- Threshold image with heuristically determined threshold.
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- Binary image with speckle noise effects:
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- Threshold image with heuristically determined threshold.
- Binary image with speckle noise effects:
  1. SN is interrupted by black spots.
  2. Small bright spots outside SN remain.

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Segmenting Substantia Nigra in US Images

Kier, Cyrus, Seidel, Hofmann, Aach
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Dilate again with circle element to include smaller objects which have been separated by remaining speckle.
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SN region size can automatically be determined and used as a diagnostic measure.
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Observer dependence is reduced, measure is reproducible.

Automatic segmentation of brain stem would remove observer dependence completely.

By using ultrasound this measure is fast, inexpensive, and uncomplicated to use on immobile patients.

Different from CT or MRI results.

Preliminary results comparing automatic and manual segmentation are very promising.

Method has to be validated in a clinical study.
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Presented method helps in developing a fast, cost-effective, and observer-independent preclinical predictor for Parkinson’s disease.
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Thank you for your attention!