Advances in Automatic Quantification of White Matter Hyperintensities

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Topics

White Matter Disease
Clinical Importance of WMH Quantification

WMH Automated Algorithms
MICCAI WMH Challenge
White Matter Disease

White matter hyperintensities (WMH, also known as leukoaraiosis), are widely observed in the ageing population.

The abnormal signal, explained by a change in the fat/water ratio, reflects injury to the white matter.

Multiple sclerosis and other demyelinating diseases primarily affect white matter leading to characteristic WMH.

Longitudinal segmentation of age-related white matter hyperintensities. C.H. Sudre et al. / Medical Image Analysis 38 (2017)
Clinical Impact of WMH

WMHs are common in patients with cardiovascular risk factors such as hypertension, diabetes; and cerebrovascular disease

WMH’s are associated with increased risk of functional decline, dementia, and death

Quantitation and longitudinal monitoring of WMH is of major importance in clinical medicine, cerebrovascular research and drug trials in multiple sclerosis
Quantifying WMH

Growing need for reliable quantification of WHM to better understand their diagnostic and prognostic value in both healthy and diseased populations

Lesion size, location, total WMH burden and overall white matter volume

Visual rating scales: Fazekas scale, Scheltens scale and the age-related white matter changes (ARWMC) scale
Quantification Challenges

- Visual scales are seldom comparable (Scheltens et al. 1998)
- Lack critical clinically important information about spatial distribution of WMH
- Visual scales are not appropriate when examining longitudinal progression of WMH (Prins et al. 2004)
- Show poor sensitivity to clinical group differences (Mantyla et al. 1997)
- High intra-subject and inter-subject variability (van den Heuvel et al. 2006)

Manual quantification of WMH areas is more reliable, but the processing involved is far too cumbersome and time consuming for practical utility.
Quantification Challenges

Voxel-wise WMH maps can be used to quantitate and better understand relationship between WMH and specific symptoms

Semi-automated voxel-based morphometry requires considerable manual processing and lack generalizability across different MRI hardware and scanning technique for widespread application

Need – accurate, objective and automated method to quantitate and spatio-temporally map WMH with adaptive perpetual learning capability
Algorithmic WMH Segmentation and Quantification
Automated WMH Algorithms

‘in-house’ algorithms

Study or protocol specific

Small sample sizes

Not evaluated on publicly available data set
BIANCA

Automated Algorithm

Multiple MRI protocols

Key options
BIANCA

Automated Algorithm: Requires retraining
Multiple MRI protocols: By protocol
Key options: Adapted to each dataset
WMH Challenge
Aim: Directly compare methods for automatic segmentation of WMH

Many published techniques

Issues:
- Different ground truth
- Different evaluation metrics
- Different data sets
Organisation

Main organizer

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## WMH Segmentation Challenge

**Task:** automatically segment WMH on brain MR images (T1 and FLAIR)

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WMH Segmentation Challenge

**Task:** automatically segment WMH on brain MR images (T1 and FLAIR)

**Method:**
- Participants download training data
- Tool is trained and containerized with Docker
- Organizer (me) runs all tools on all test data
WMH Challenge – Reference Standard

WMH manually segmented by Observer 1 (O1), then peer reviewed corrected by Observer 2 (O2)

Binary masks created from annotations used as ground truth

Currently gathering Observer 3 (O3) segmentations, estimate is inter-observer Dice of 0.8
Deep, Multi-scale, Convolutional Network

WMH Positive

WMH Negative

FC 400

FC 200
WMH Model Highlights
Skull stripping using FSL

399,716 positive patches
550,000 negative patches

Upsampled high-intensity negative FLAIR

ReLU, Dropout in FC layers, Batch Norm
No pooling, mini-batch size of 768
Example Auto-Segmented Scans
Key Metrics in Automated Quantification

- Total WMH Volume
- Total # of Lesions
- Localization of Lesions
- Registration of WMH to atlas

Longitudinal monitoring
- Progression, Regression, Stability
- New Lesions
- Lesion Growth
The Challenge of Accurate Detection

Initial

One year later
The Problem of Quantification and Longitudinal Monitoring

Ten years ago

Current
What next:

• Additional training data
• Additional validation
• Deploy for clinical use
Thank you