Error Assessment in Serial Morphometry: Application to Multiple Sclerosis

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- Problem Statement

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 - Voxel-wise classification consistency.
 - Intra-class correlation

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- Under-estimation of measurement error
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Background Problem Statemen

Background

- The measurement of brain atrophy has become an established method of estimating MS disease severity and progression.
- The atrophy is quantified by MRI morphometric measurements such as brain parenchymal fraction (*BPF*).
- Atrophy is a slow process and thus requires high level of measurement precision/sensitivity.

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Background

- The reliability of *BPF* and other morphometric measurements is frequently measured with scan-rescan experiments.
- In scan-rescan experiments two MRI's of the patient are obtained within a short interval (e.g., 30 minutes).
- Between the two imaging sessions patients may be asked to exit and re-enter the scanner area
- In the absence of true biological/structural change, any differences in the measurements from the two scans is attributed as measurement precision.

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Sources of error

Principal sources of error are:

- Patient re-positioning error
- Instrument variability (e.g., magnet and/or receiver coil)
- Algorithm specific errors (e.g., stochastic algorithms or nonlinear algorithm transfer function)

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Problem Statement

Questions:

- Is scan-rescan error a reliable indicator of real-life error?
- Can we analyze reliability of the scan-rescan error ?
- For a given image segmentation algorithm, how much change in BPF indicates "real change" ?
- Various techniques exist for error assessment: which one has greatest practical utility ?

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Datasets Error Measurement

Datasets Used

- 20 MS patients
- 5 MRI per patient (baseline MRI plus 4 weekly MRIs each).
- Axial dual-echo PDw/T2w protocol on a 1.5T
- Acquisition parameters
 - TE 30/80 ms, TR = 3000 ms
 - resolution: 0.93-by-0.93-by-3 mm
- None of the patients had received any form of therapy or steroids.

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Image analysis

- Template-driven segmentation algorithm (TDS) used for image segmentation
- Segmentated classes: White matter (*WM*), Gray matter (*GM*), Cerebro-spinal fluid (*CSF*).
- Brain Parenchymal Fraction (BPF) was computed as:

$$BPF = \frac{WM + GM}{WM + GM + CSF} = 1 - \frac{CSF}{ICC}$$

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Datasets Error Measurement

Error assessment techniques

We compare the following three methods to analyze measurement error:

- Standard error of measurement
- Voxel-wise classification consistency
- Intra-class correlation coefficient: a measure of agreement

Datasets Error Measurement

Standard error of measurement (SEM)

$$SEM = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\sigma_i^2}, \text{ where } \sigma_i = \sqrt{\frac{1}{M-1}\sum_{j=1}^{M}(x_{i,j}-\mu_i)^2}$$

M : no. of observers, *N* : no. of subjects $x_{i,j}$: measurement made by observer *j* for subject *i* Given the *SEM*, the threshold value (δ), that represents 95% of chabeyond chance is:

 $\delta = \sqrt{2} * 1.96 * SEM$

 δ is the threshold's which signify "real change" (with 95% certainty). **Voxel-wise classification consistency**

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Datasets Error Measurement

Intra-class correlation coefficient

$ICCoeff = \frac{variability in the BPF measurements of patients}{Total variability (from all sources)}$

$ICCoeff = \frac{MS_R - MS_E}{MS_R + (k-1)MS_E + \frac{k}{n} \cdot (MS_C - MS_E)}$

n denotes the number of images, MS_R is the mean square error between images, MS_E is the residual mean square error, MS_C is the mean square error between observers.

Table: Interpretation of ICCoeff

ICCoeff value	Strength of Agreement
ICCoeff < 0.4	Indicates poor reproducibility
0.4 < ICCoeff < 0.75	Indicates fair to good reproducibility
ICCoeff > 0.75	Indicates excellent reproducibility

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SEM Voxel-wise classification consistency. Intra-class correlation

Pair-wise comparisons of MR scans

Table: SEM and δ values for BPF, WM and GM for each of the four pair-wise comparisons. bMR denotes the baseline MRI.

		Pair of time-points compared			
		bMR &	bMR &	bMR &	bMR &
		week 1	week 2	week 3	week 4
BPF	SEM	0.0040	0.0048	0.0057	0.0055
	δ	0.0111	0.0134	0.0157	0.0154
WM	SEM	0.0046	0.0050	0.0053	0.0054
	δ	0.0128	0.0138	0.0146	0.0149
GM	SEM	0.0045	0.0055	0.0042	0.0044
	δ	0.0126	0.0151	0.0116	0.0122

Note for scan-rescan experiment: SEM = 0.0020, $\delta = 0.0056$

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SEM Voxel-wise classification consistency. Intra-class correlation

Comparison across multiple MR scans

Table: SEM and δ values for BPF, WM and GM variables obtained by comparing the measurements of these variables from multiple MR scans.

	No. of MRIs compared					
		2	3	4	5	
BPF	SEM	0.0040	0.0045	0.0047	0.0048	
	δ	0.0111	0.0125	0.0130	0.0133	
WM	SEM	0.0046	0.0048	0.0046	0.0047	
	δ	0.0128	0.0133	0.0127	0.0130	
GM	SEM	0.0045	0.0049	0.0043	0.0042	
	δ	0.0126	0.0135	0.0120	0.0115	

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Pair-wise comparisons







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Summary of pair-wise comparisons







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SEM Voxel-wise classification consistency. Intra-class correlation

Results

Table: *ICCoeff* for *BPF*, *WM* and *GM*, for each of the four pair-wise comparisons. bMR denotes the baseline MRI.

	Pair of time-points compared					
	bMR & bMR & bMR & bMR &					
	week 1	week 2	week 3	week 4		
BPF	0.9929	0.9898	0.9851	0.9860		
WM	0.9933	0.9926	0.9916	0.9912		
GM	0.9373	0.9195	0.9501	0.9448		

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Under-estimation of measurement error Future work

Scan-rescan experiments under-estimate measurement error:

- Measurement error in scan-rescan
- Previous work from our group (Wei, 2004) has shown that
 - SEM = 0.0020, $\delta = 0.0056$ (Scan-rescan)
 - SEM = 0.0040, δ = 0.0111 (two MRI taken a week apart)
 - the SEM from weekly measurements is 2 times greater than that from scan-rescan.

Utility of SEM

- By comparing various methods to quantify measurement variability we find that the *SEM* demonstrates highest practical utility.
- SEM is simple to compute and allows one to compute threshold's which signify real biological change (with 95% certainty).

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Table: *ICCoeff* for *BPF* for each of the four pair-wise comparisons. bMR denotes the baseline MRI.

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BPF	0.9929	0.9898	0.9851	0.9860		

- In our example, the scan-rescan *ICCoeff* was 0.998,
- Recall, an *ICCcoeff* > 0.75 denotes excellent agreement.
- Using only the *ICCcoeff* implies that there is no difference in the measurement error computed from a scan-rescan setting versus that quantified from weekly MRI.
- We have two methods which produce very contrasting results.

Under-estimation of measurement error Future work

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- Obtain or collect a weekly MRI data-set of healthy individuals
- Test the performance of multiple algorithms
- Limitations: Loss of spatial information.

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