A FORMAL METHOD FOR SELECTING EVALUATION METRICS FOR IMAGE SEGMENTATION

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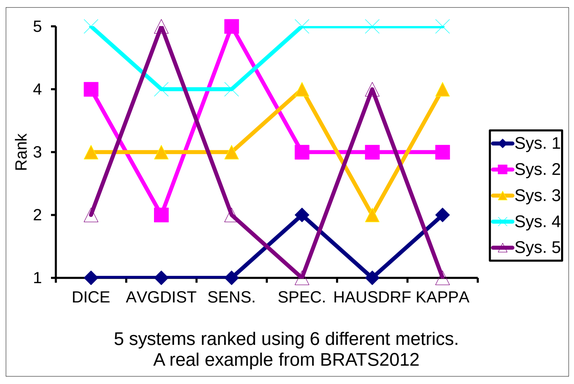
MOTIVATION

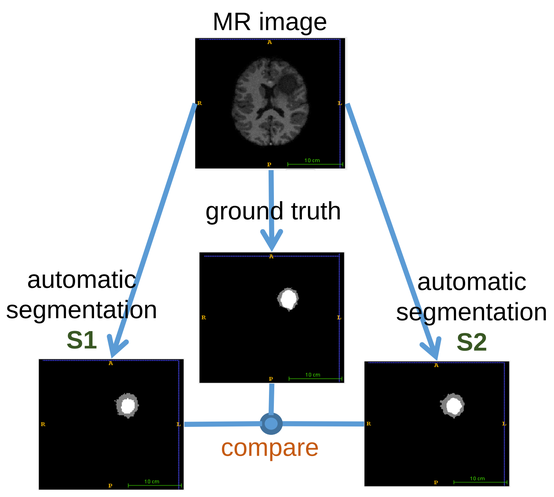
✓ Dozens of evaluation metrics have been used to evaluate medical image segmentations in order to rank the systems that produced them.

✓ But each metric produces a ranking that may be different from the other rankings.



5 systems ranked using 6 different metrics.
A real example from BRATS2012

✓ Also, evaluation is dependent of the evaluation task.



metric 1: S1 is better than S2
metric 2: S2 is better than S1
decision: **????**

✓ An effective identification of the state-of-the-art systems requires consistent selection of the evaluation metrics.

✓ There is a lack of a formal way to select evaluation metrics.

GOAL

A formal method for choosing the most suitable metric(s) from a metric pool to evaluate the quality of medical segmentations taking into account:

i. the segmentations being evaluated

ii. the segmentation task.

STRATEGY

Measuring the metric bias to the different properties of the segmentations being evaluated.

➢ This is achieved by analyzing how the average scores of subsets of the segmentations correlate when the subsets are selected (i) randomly and (ii) according to properties of the segmentations.

METHOD

I. Define a set of properties.

II. Measure the metric bias to each property.

III. Select the metric(s) with the lowest sum of biases over all properties.

✓ Any properties, e.g. segment size, class imbalance, noise, smoothness, roundness, shape signature, etc.

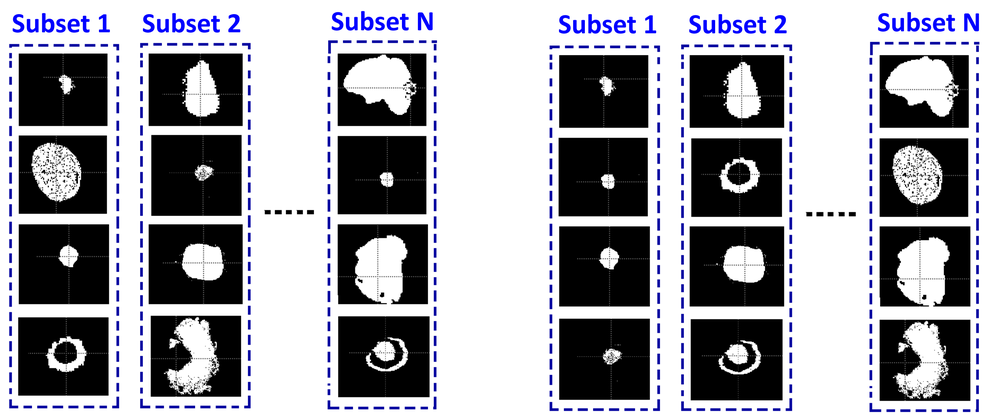
✓ The example bellow illustrates measuring the metric bias to segment size.

(1) Random grouping

❑ Group the segmentations **randomly** into N subsets.
❑ Rank the subsets according to their average scores.
❑ Perform the same for each of the M metrics in a pool.

(2) Grouping by size

❑ Group the segmentations **according to segment size** into N subsets.
❑ Rank the groups according to their average scores.
❑ Perform the same for each of the M metrics in the pool.



(3) Ranking

❑ Now, you obtain **M rankings** from the random grouping (1) and **M rankings** from the grouping by segment size (2).
❑ **Analyzing these rankings** leads to the metric bias to the property used for grouping (segment size).

random grouping

	rank metric 1	rank metric 2	….	rank metric M
subset 1	….	….	….	….
subset 2	….	….	….	….
….	….	….	….	….
….	….	….	….	….
subset N	….	….	….	….

grouping by size

	rank metric 1	rank metric 2	….	rank metric M
subset 1	….	….	….	….
subset 2	….	….	….	….
….	….	….	….	….
….	….	….	….	….
subset N	….	….	….	….

(4) Analyzing correlation

❑ The correlation between rankings of the random subsets reflects the nature of the metrics (**base correlation**).
❑ But the change in this correlation in the second case reflects the **metrics bias to the property** used (segment size) (**biased correlation**).

(5) Repeat, other properties

❑ Repeat (1) to (4) with other properties.
❑ Each time, the metric bias is the difference between the base correlation and the biased correlation.
❑ For each metric, sum the bias to all properties to find the overall bias.

(6) Select metric(s)

❑ The overall bias (bias sum) is an indicator of the metric suitability.
❑ Metrics with the least overal bias are the most suitable.
❑ **Weights** can be used to reflect the **task specific issues**, i.e. properties with more importance for the task are assigned accordingly higher weights than other properties.

RESULTS

We propose a formal method for ranking a set of metrics according to their suitability for evaluating a specific segmentation set, given a specific evaluation task.

The method has been tested against a manual ranking of 20 evaluation metrics, done by a medical expert.

As shown in the table, the ranking of metrics produced automatically by the proposed method correlates with the manual ranking by the medical expert. The correlation value is 0.607.

Complete experiment details can be found in [1].

metric	manual		automatic	
	correl.	rank	bias	rank
Cohen's Kappa	0.818	1	33.5	2
Adjusted Rand Index	0.818	1	33.1	1
Interclass Correlation	0.818	1	33.5	2
Probabilistic distance	0.802	2	34.7	5
Dice	0.800	3	33.6	3
Average Distance	0.798	4	33.9	4
Accuracy	0.791	5	64.0	14
Rand Index	0.791	5	64.0	14
Variation of Inform.	0.791	6	62.0	13
Mutual Information	0.753	7	46.5	12
Mahalanobis Distance	0.701	8	37.7	7
Global Consistency Err.	0.670	9	69.8	15
Hausdorff Distance	0.663	10	35.5	6
Area u. curve (AUC)	0.647	11	42.0	8
Sensitivity	0.615	12	44.4	10
Precision	0.608	13	44.5	11
Volumetric Similarity	0.590	14	43.6	9
Specificity	0.398	15	78.6	16
Correl. btw. manual & automatic ranking				0.607

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REFERENCE

[1] Abdel Aziz Taha, Allan Hanbury, and OscarJimenez, "Test data and results of the automatic metric selection method," Tech. Rep., Vienna University of Technology, http://publik.tuwien.ac.at/files/PubDat 229008.pdf, 2014.