

Advances in CT imaging processing and application

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Strokes are bad

From AHA Stroke statistics 2013 report¹:

- Of all strokes, 87% are ischemic and 10% are intracerebral hemorrhagic strokes, whereas 3% are subarachnoid hemorrhage strokes (GCNKSS, NINDS, 1999).
- Each year, $\approx 795,000$ people experience a new or recurrent stroke, 610,000 new, 185,000 recurrent.
- On average, **every 40 seconds**, someone in the United States has a stroke (90 strokes/hour)
- Intracerebral hemorrhage has a **high mortality rate**; **38%** survive the first year²

¹ Go, Alan S., et al. "Heart disease and stroke statistics—2013 update a report from the American Heart Association." *Circulation* 127.1 (2013): e6-e245.

² Qureshi, Adnan I., et al. "Spontaneous intracerebral hemorrhage." *New England Journal of Medicine* 344.19 (2001): 1450-1460.

Strokes affect the elderly

From Italian Longitudinal Study of Aging (ILSA) (N =5,632 individuals aged 65-84)

- Incidence for first-ever stroke was **9.51** (95% CI: 7.75-11.27) per 1,000 person years and **12.99** (95% CI: 10.99-14.98) including recurrent stroke (total incidence).
- Crude mortality was **49.2%** among first stroke patients and 15% among persons without stroke³

³ Di Carlo, Antonio, et al. "Stroke in an elderly population: incidence and impact on survival and daily function." Cerebrovascular Diseases 16.2 (2003): 141-150.

Stroke Trial Data I'm using

- Intracerebral (bleeds mainly in tissue, ICH) or Intraventricular (bleeds into ventricles, IVH) Hemorrhage trials
- Minimally Invasive Surgery plus rt-PA for ICH Evacuation (**MISTIE**)

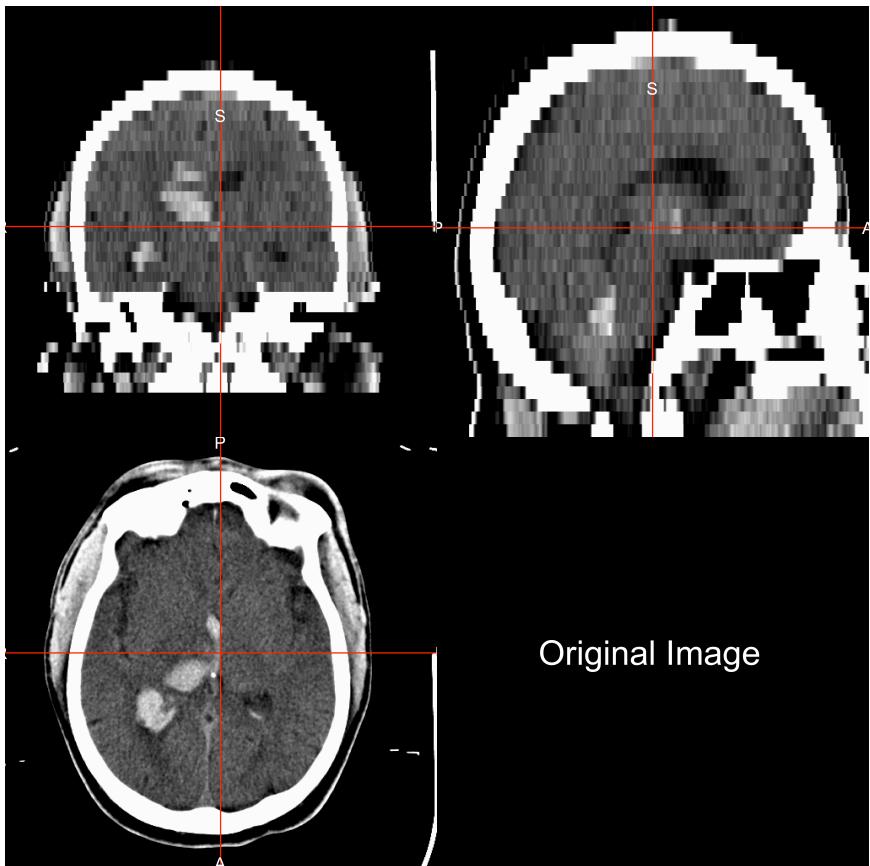


- <http://braininjuryoutcomes.com/mistie-about>

CT is NOT MRI (specifically not T1/T2)

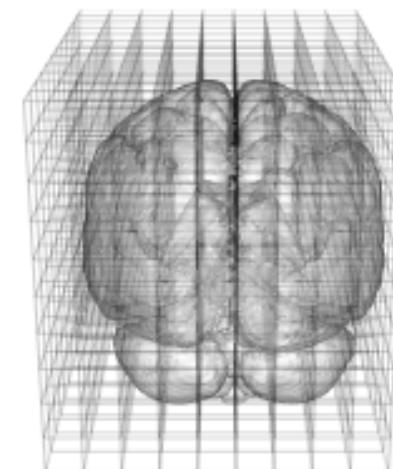
	CT	MRI
Domain	Diagnostic	Diagnostic/Research
Units	Houndsfield Units	Arbitrary
Template	One exists	MNI Standard
Measures	Measures humans/rooms/beds	Measures Humans
Methods	?	Many

CT Scan Characteristics



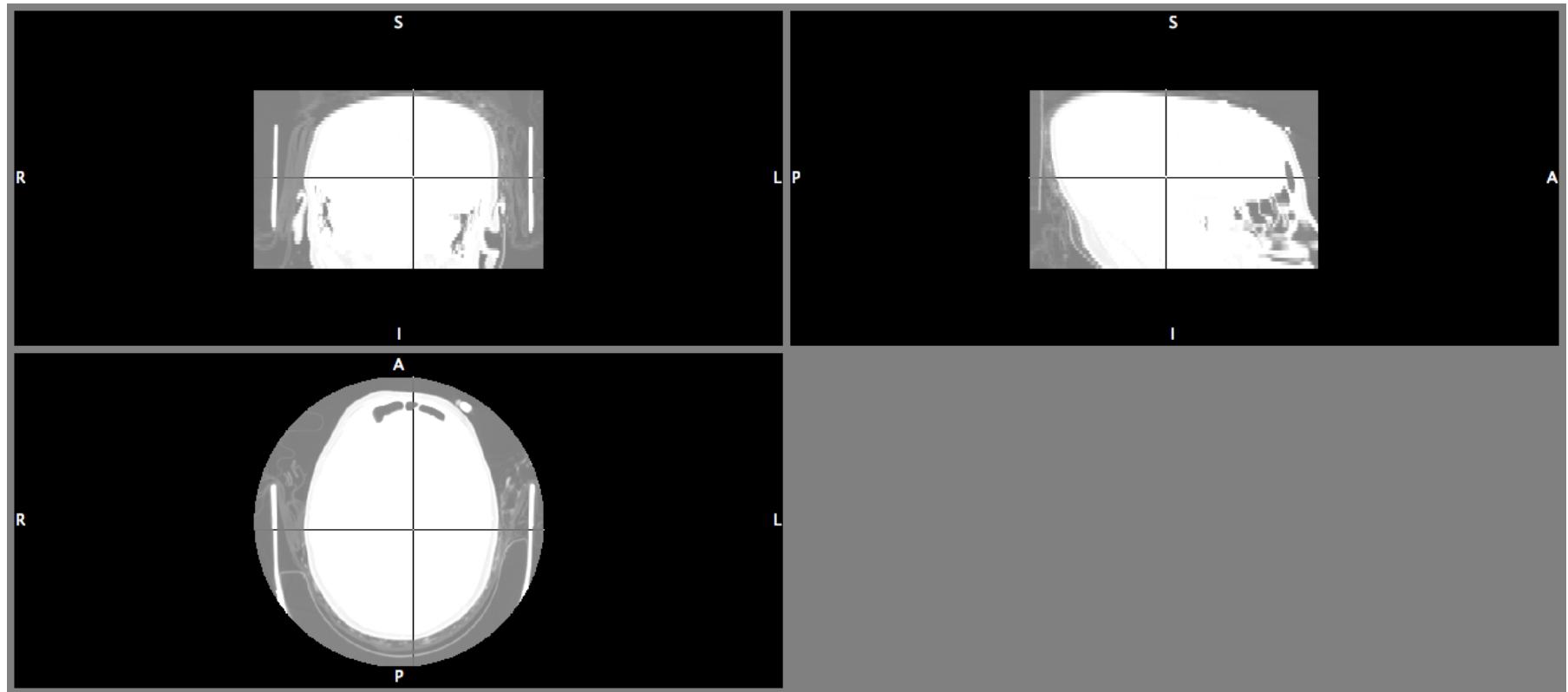
- Data are in Hounsfield Units (HU), which are "standardized"
- Bone – high intensity (1000 HU)
- Air – low intensity (-1000 HU)
- Water - 0 HU
- Tissue \approx 0 - 100 HU

Neuroimaging Data - voxels = 3D pixels



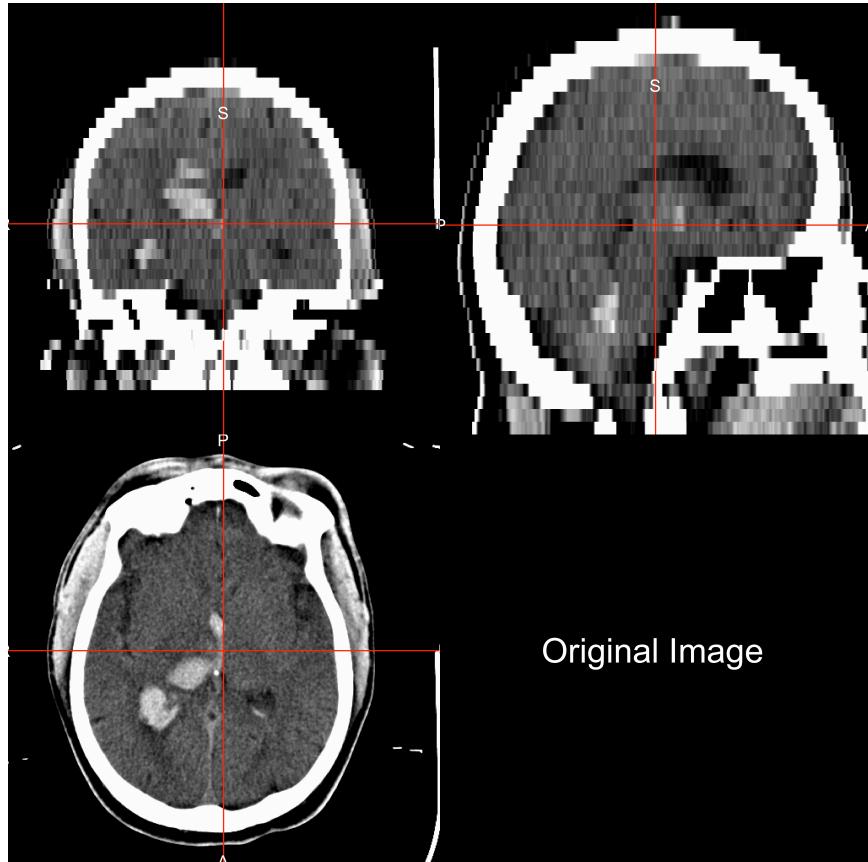
Problem: Human + Room + FOV

All "objects" captured

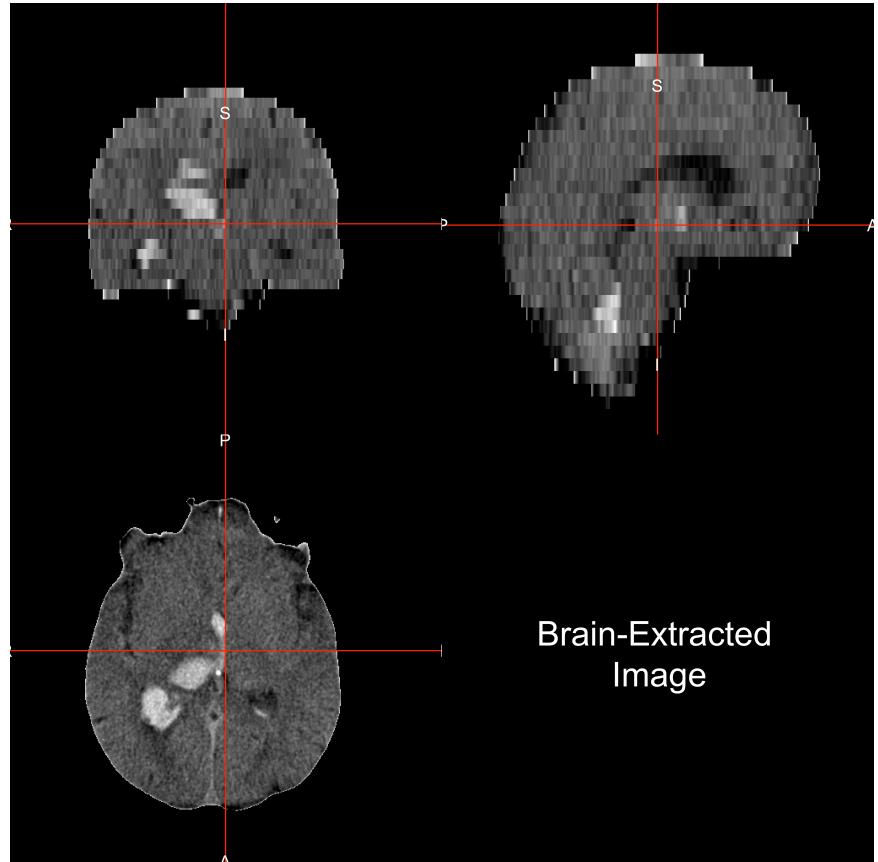


CT Skull Stripping: Goal

Want to go from this

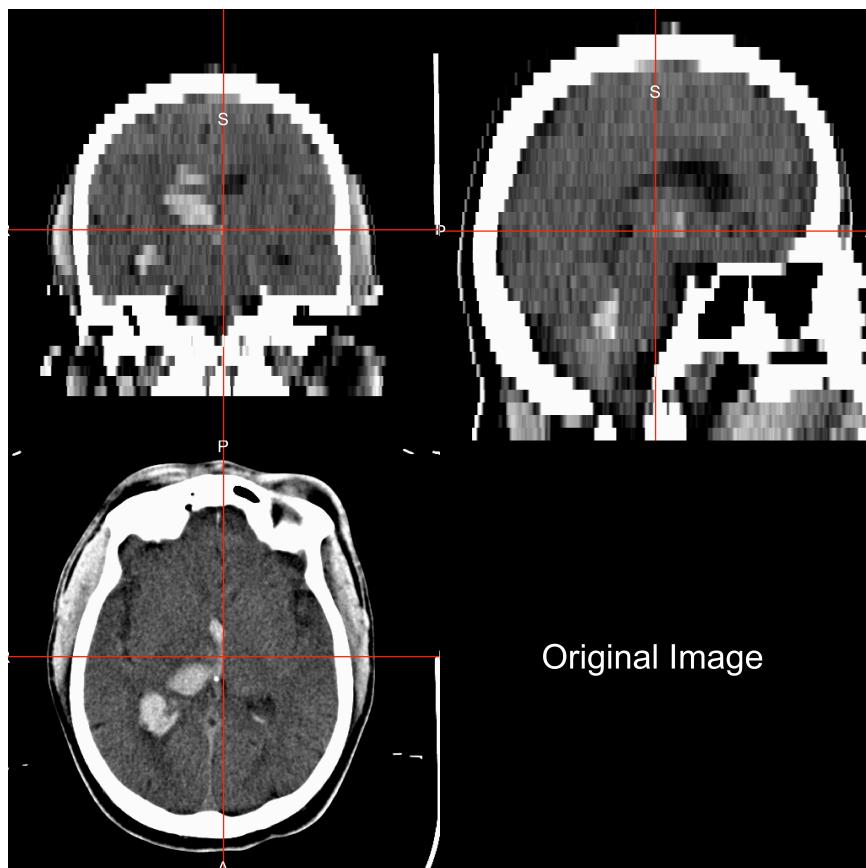


To This:



CT Skull Stripping: Step 1 - Threshold

Threshold 0- 100 HU:

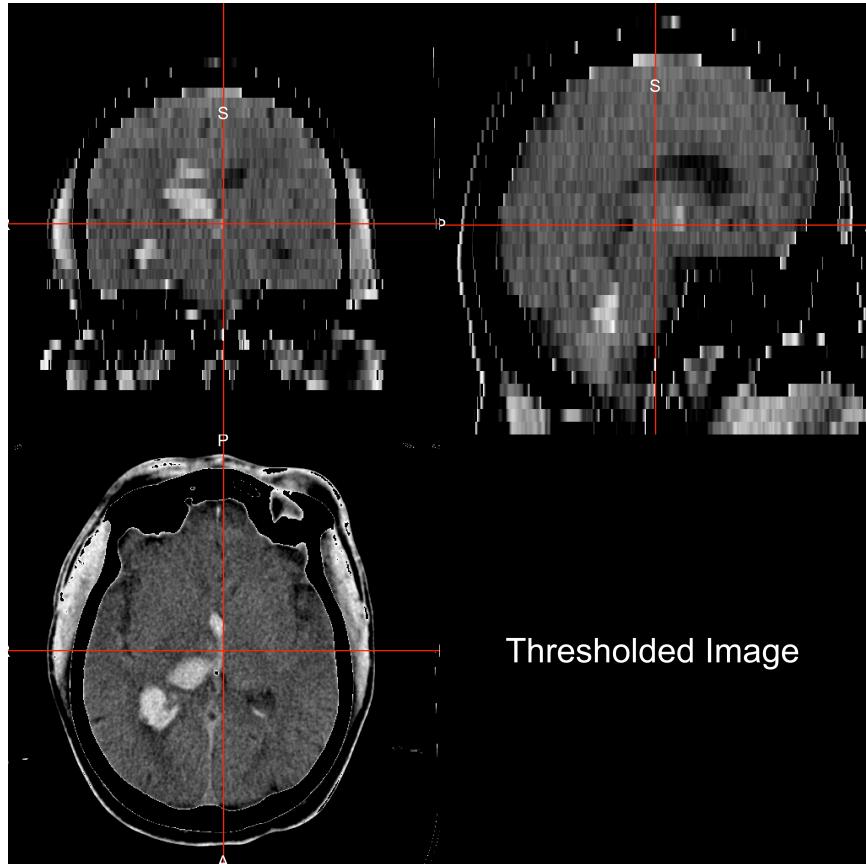


Result:

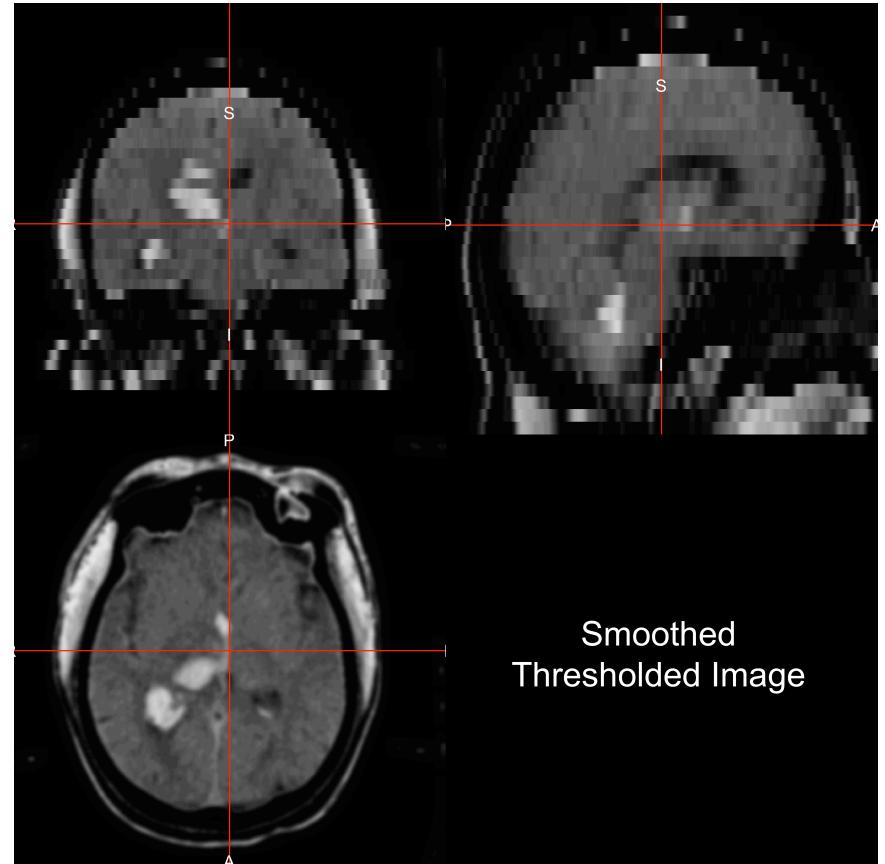


CT Skull Stripping: Step 2 - Smooth

Smooth Image with 1mm Gaussian



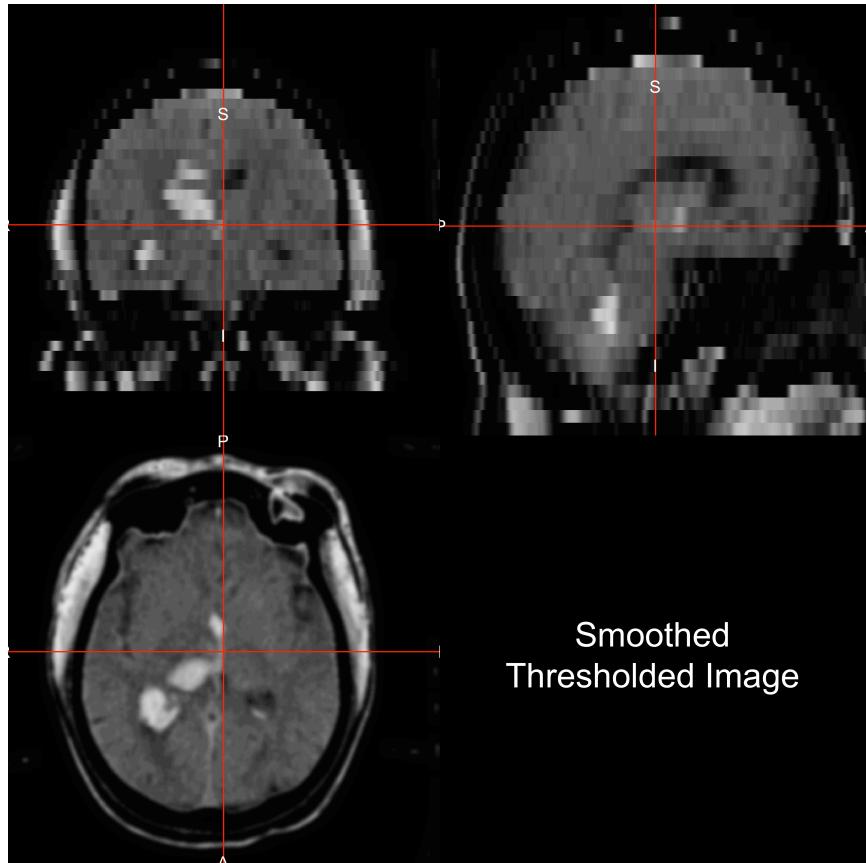
Result:



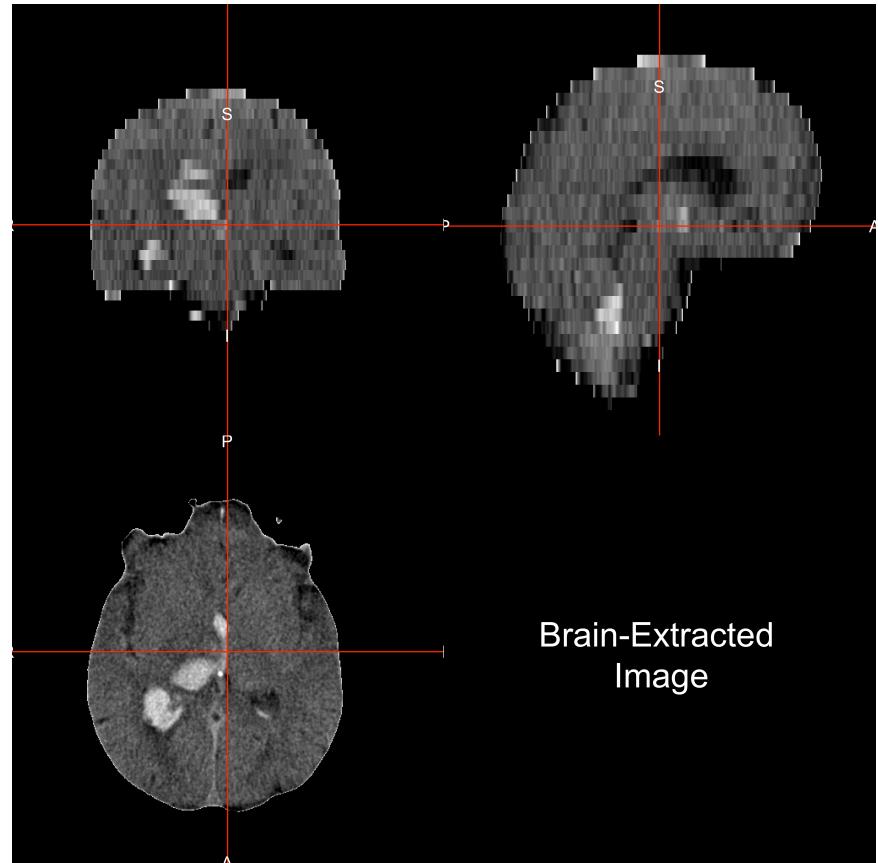
Smoothed
Thresholded Image

CT Skull Stripping: Step 3 - Run BET

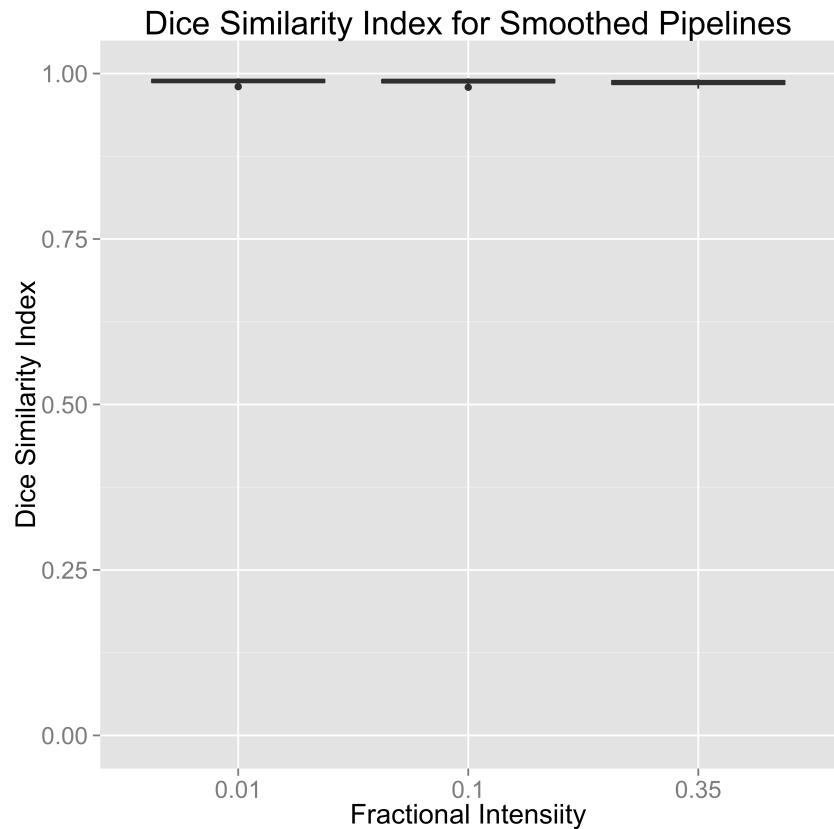
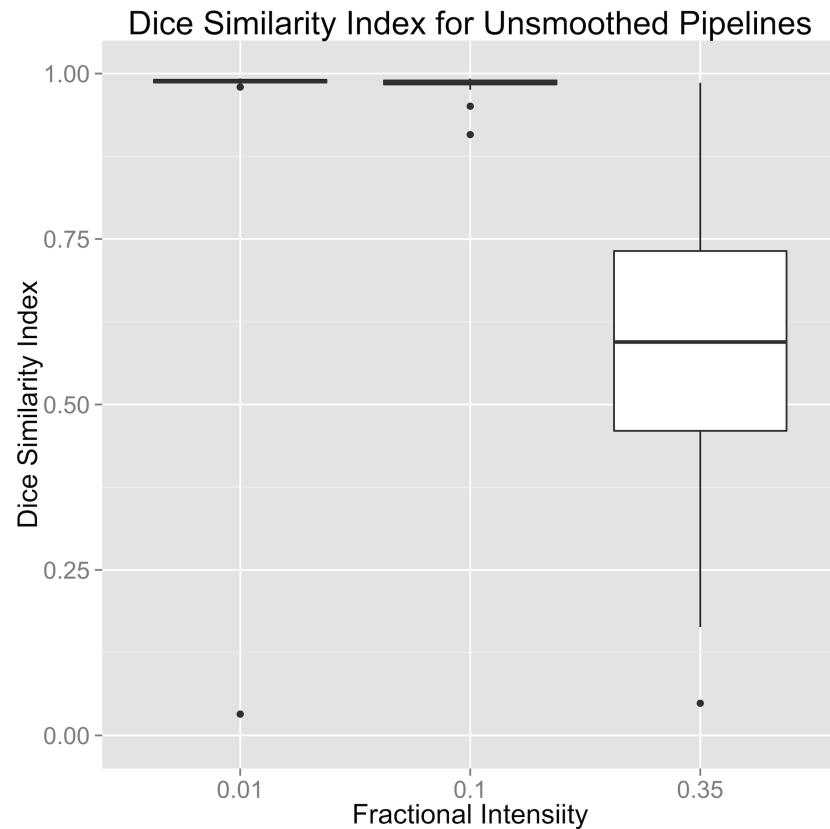
Run BET (Brain Extraction Tool) from FSL:



Result (Skull Stripped Image):

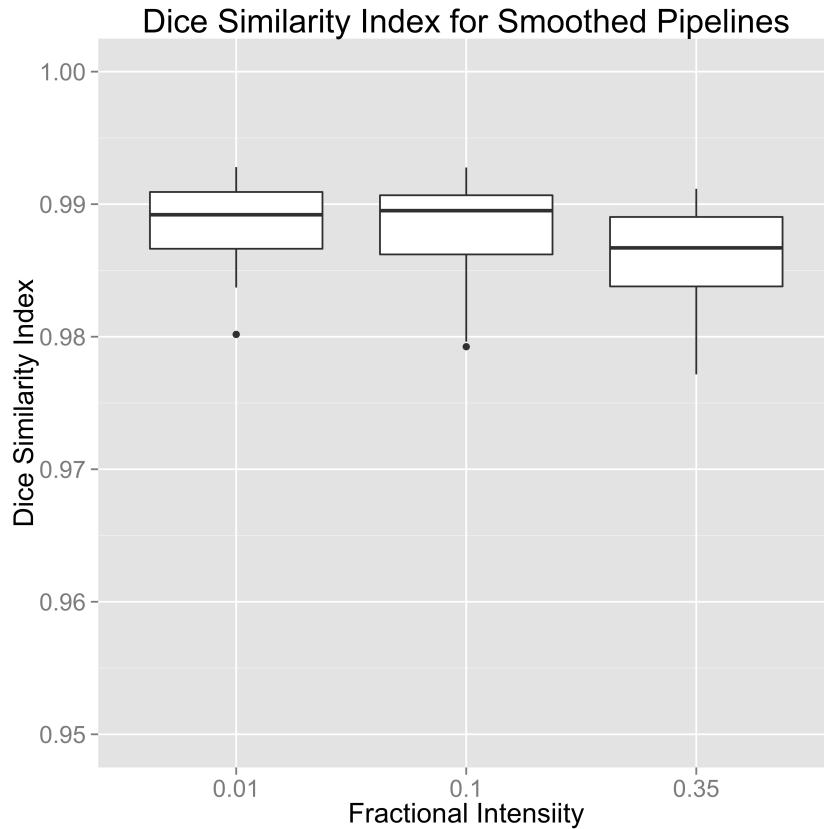


22 Scans: manual vs automatic skull stripping

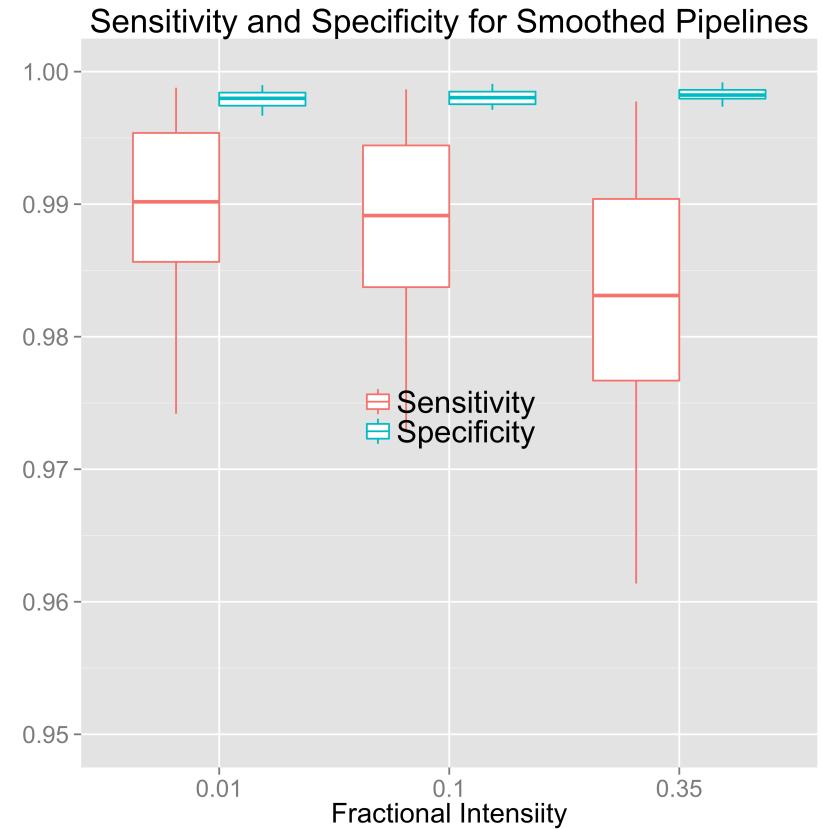


Validation: Choosing one pipeline to rule them all

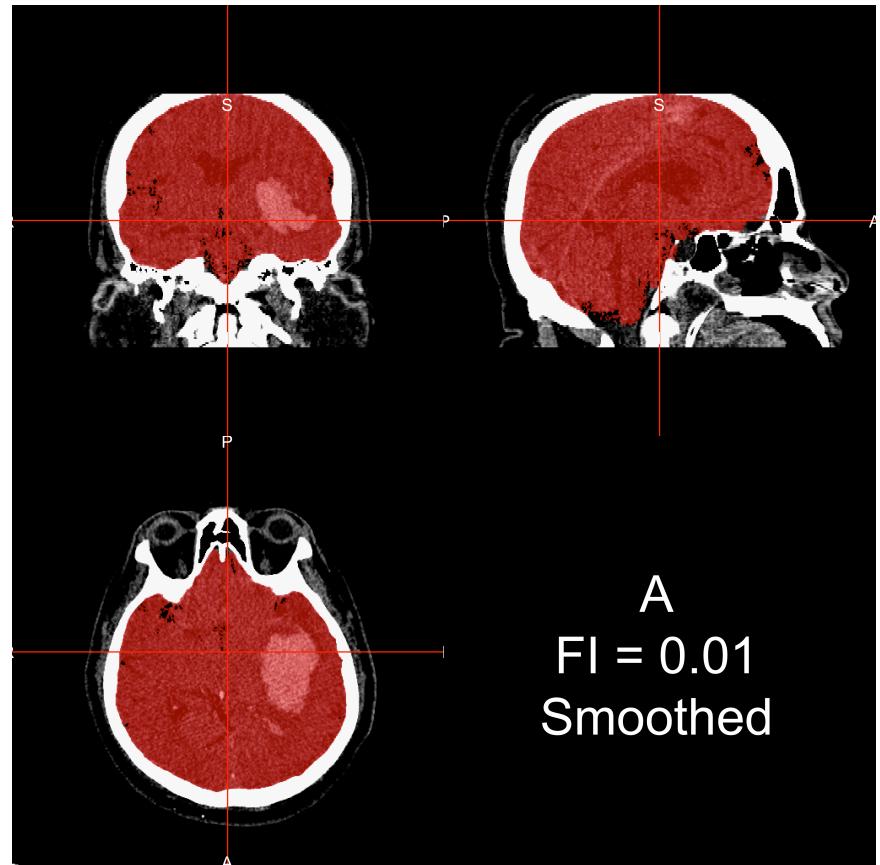
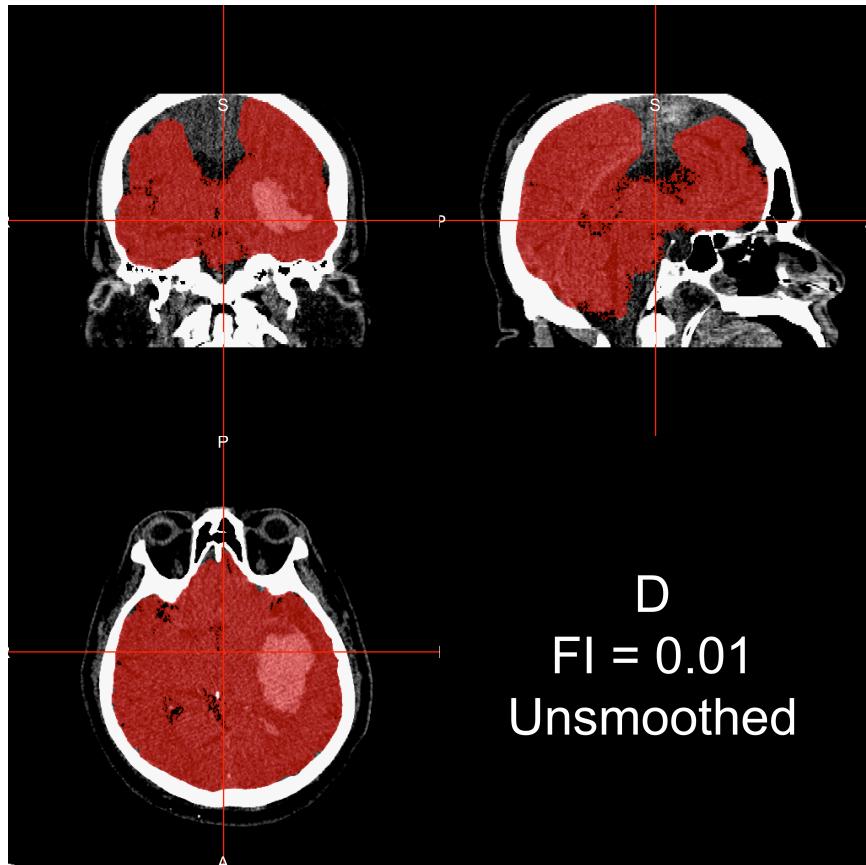
Note change of y-axis



Sensitivity/Specificity

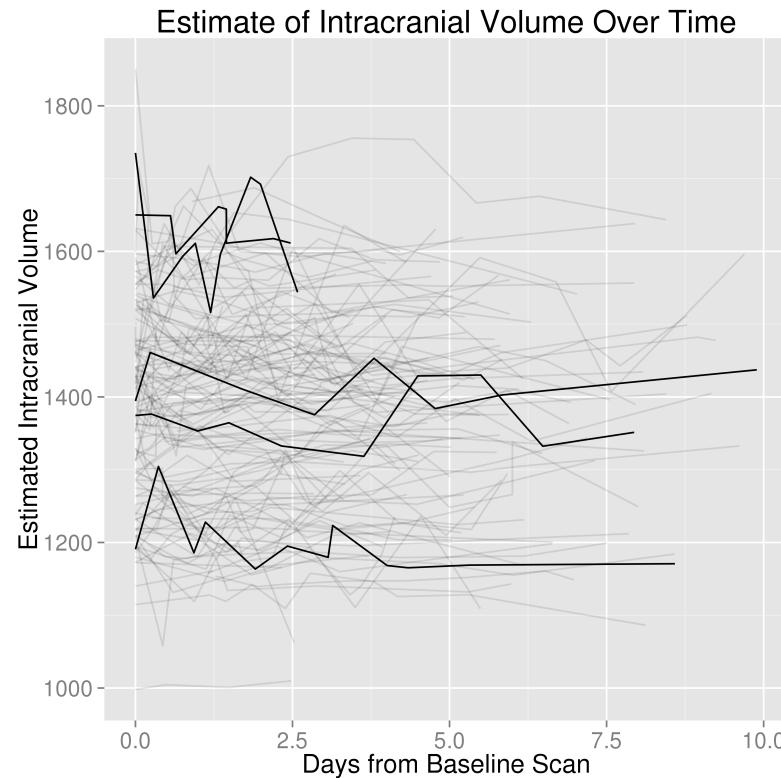


Validation: Smoothing Matters

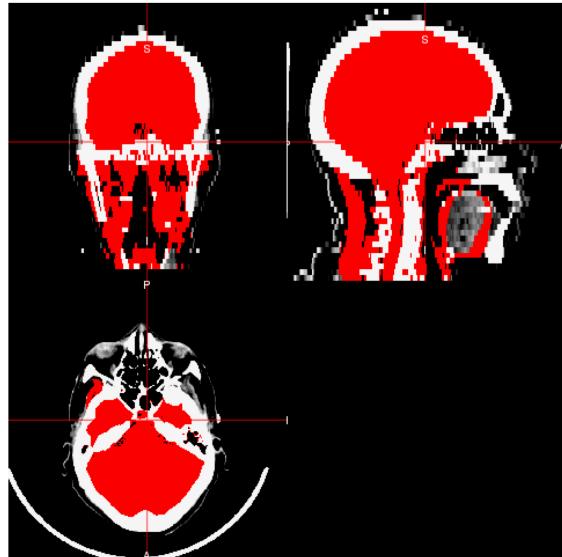


"But that was only 20 scans"

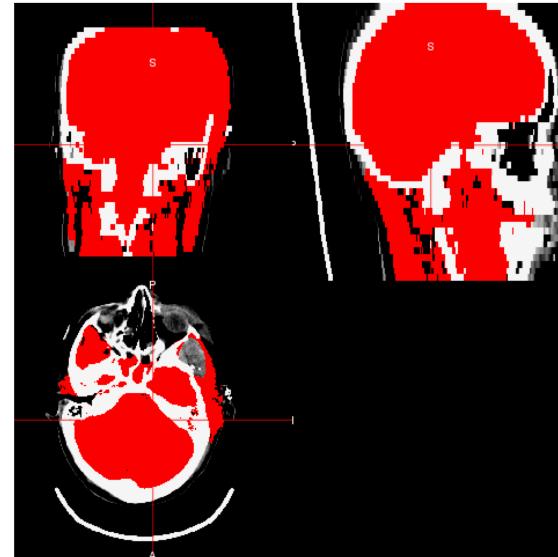
1062 images from 133 patients, excluding 115 scans for craniotomy or skull stripping failure (9.8%). Intraclass correlation estimate: 0.93, (95%CI : 0.91, 0.95).



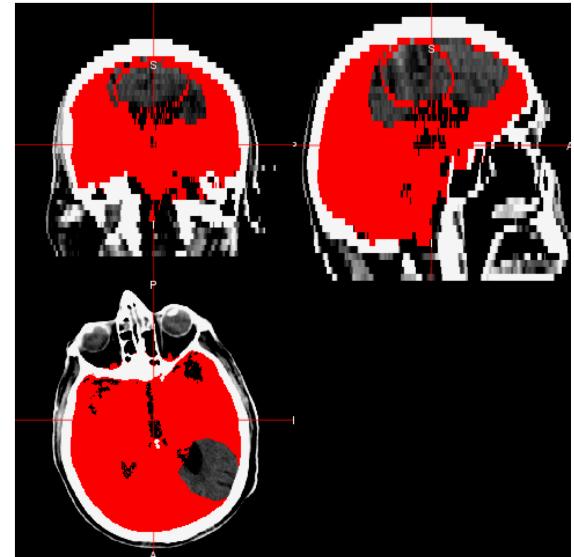
What about those "failures"



Much more area than the brain is imaged



Patient had a craniotomy



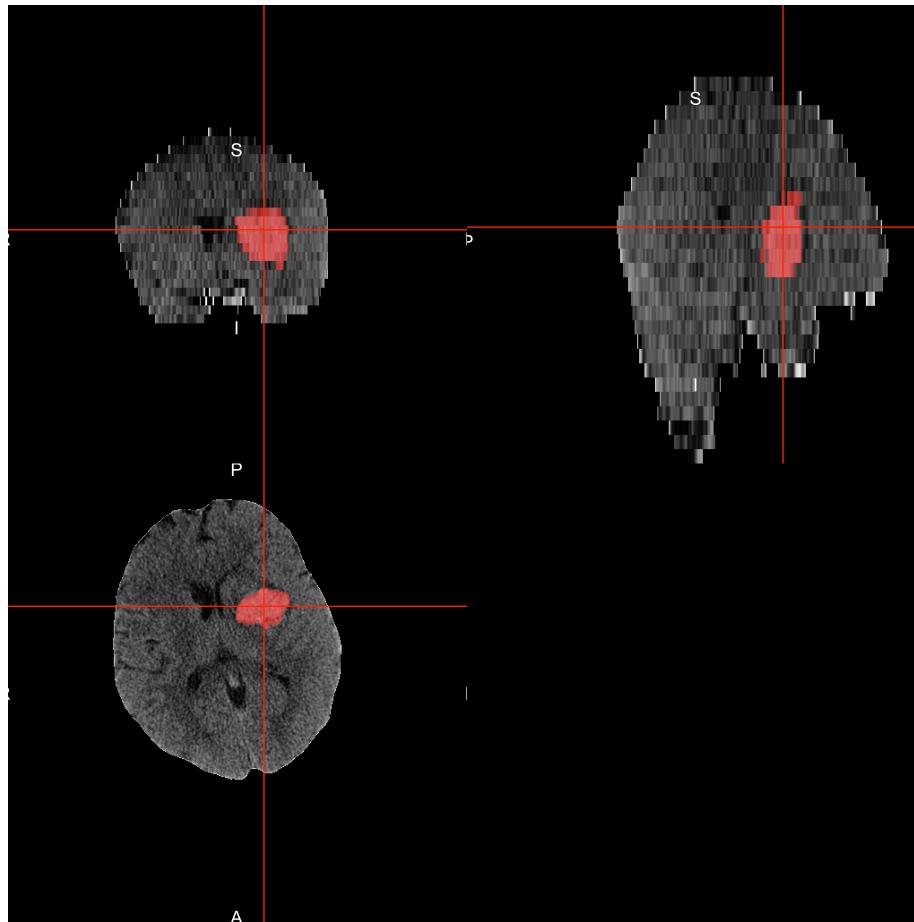
CT ventricles are low intensity or enlarged

Code to do this

- R code: http://bit.ly/CTBET_RCODE
 - Based on fslr - R package to interface with FSL
 - Paper submitted
- bash code: http://bit.ly/CTBET_BASH

ICH Prediction - data

- ICH are manually traced (gold standard)



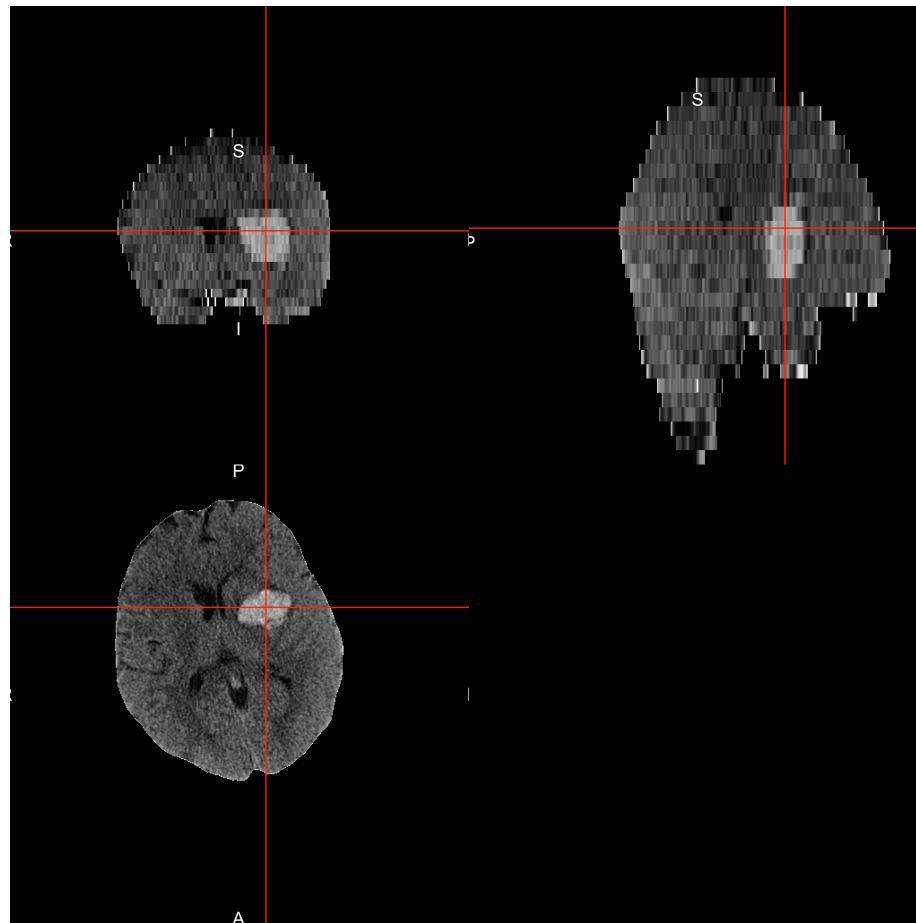
ICH Prediction - data

- ICH are manually traced (**gold standard**)
 - Time-consuming
 - Within and across-rater variability
- Can't do for large databases
 - Important for some processes, such as image registration

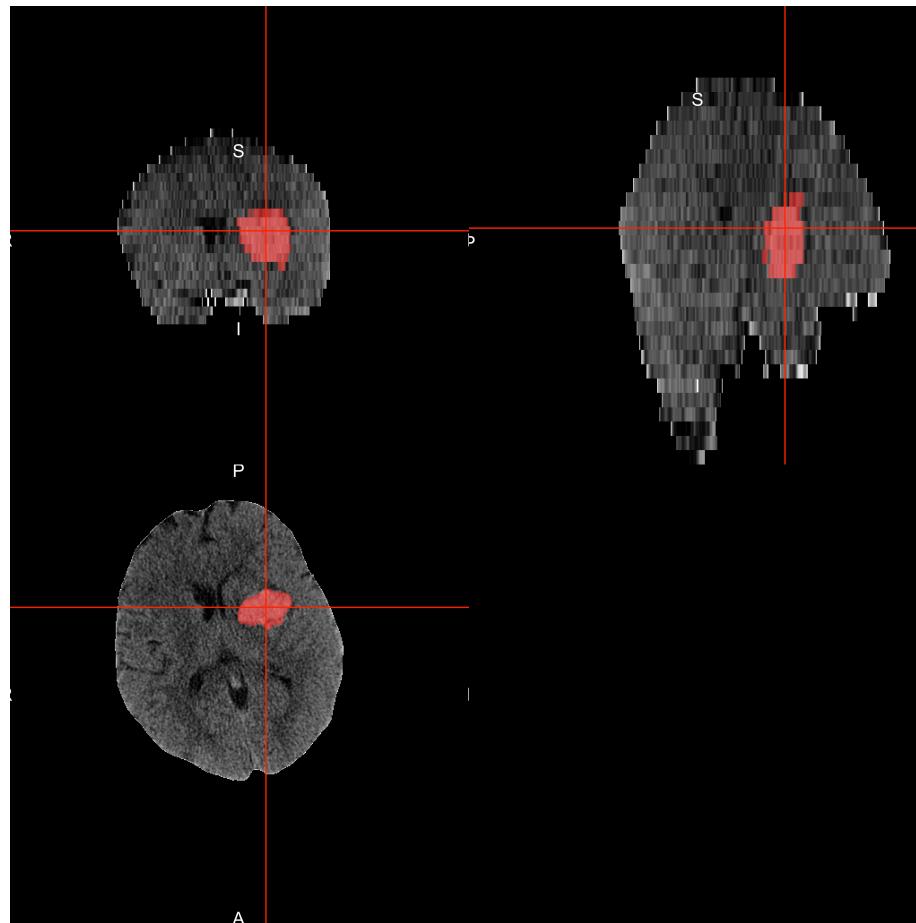
Primary Intracerebral Hemorrhage Prediction Employing Regression and Features Extracted from CT (PltchPERFECT)

- Creating predictor variables:
 - Raw intensity
 - Z-scores in all 3 planes with only brain image (skull stripped)
 - Indicator if intensity ≥ 40 (established threshold) & ≤ 80 HU
 - Local moments (mean, sd, skew, kurtosis)
 - Large smoothers
- Run a **logistic regression** with these
- Model built on 10 subjects

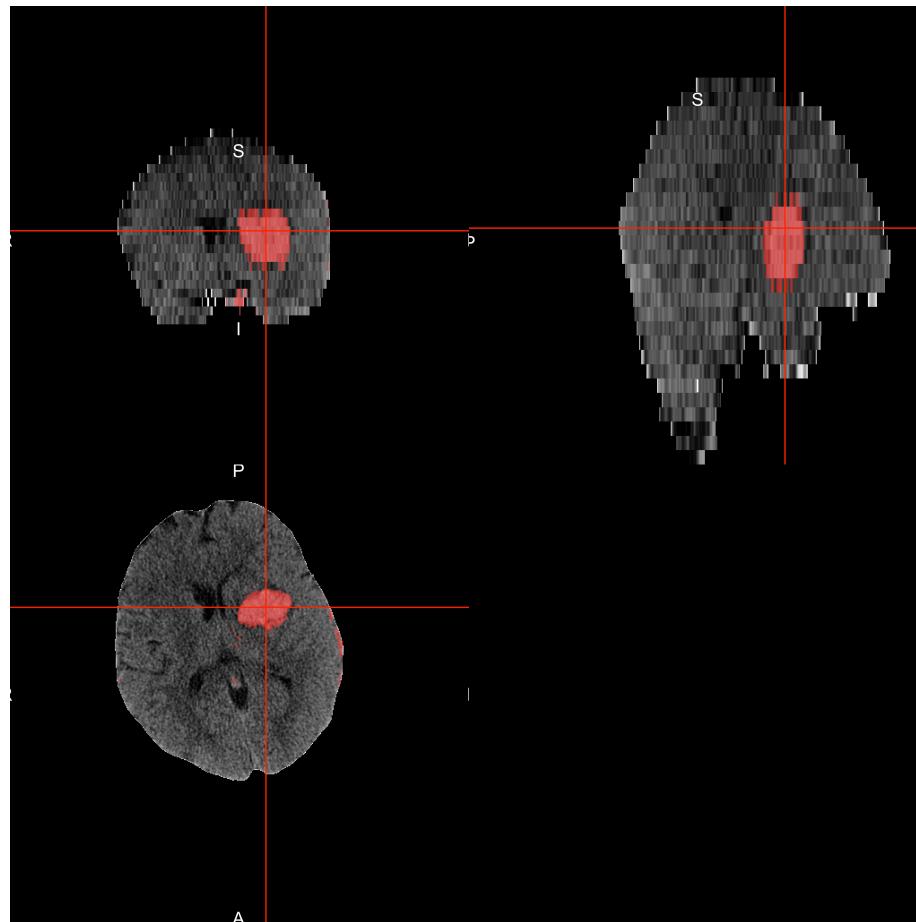
Example Output: Skull Stripped Image



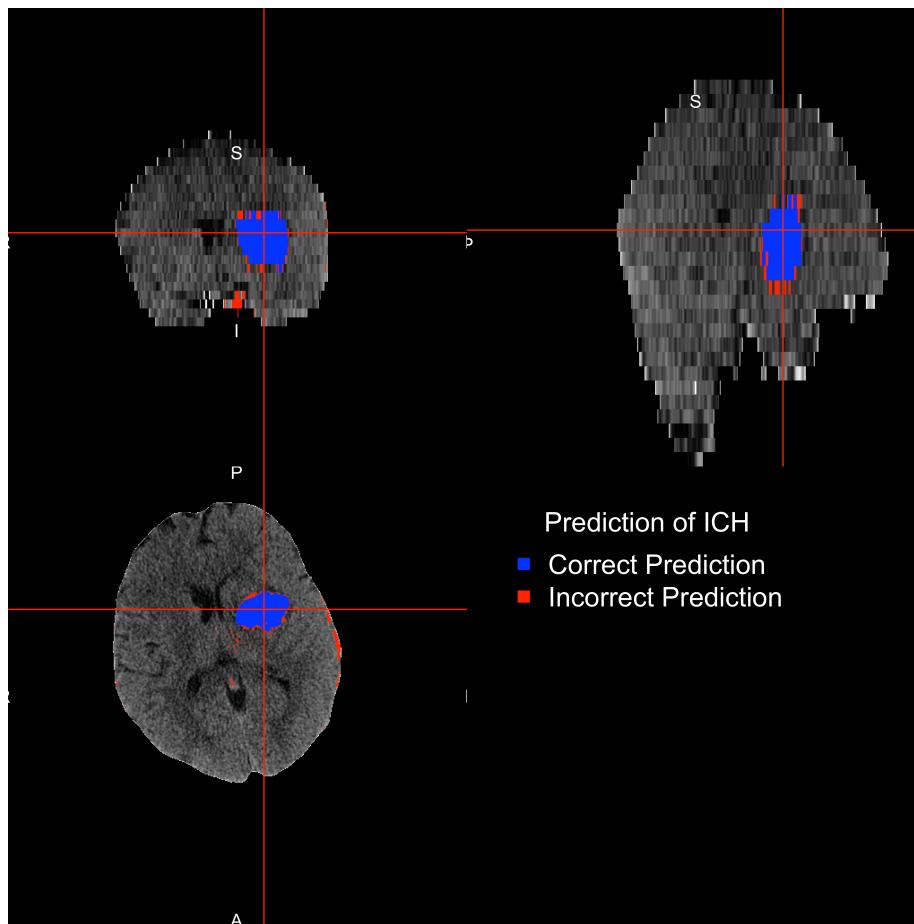
Example Output: Manual Segmentation



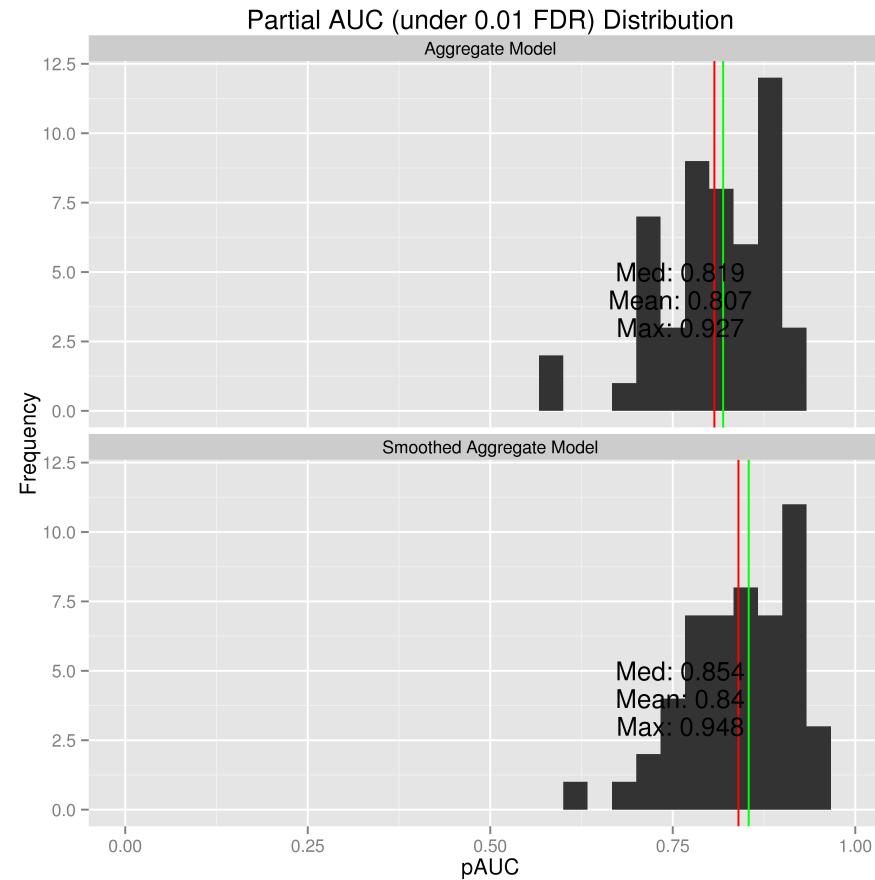
Example Output: Automatic Segmentation



Prediction Comparison



Prediction Result: Population



Conclusions and Extensions

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- Many new problems open and available
 - Can use these methods for **large datasets**
- Use for other diseases with CT imaging

Conclusions and Extensions

- Virtual International Stroke Trials Archive (VISTA)

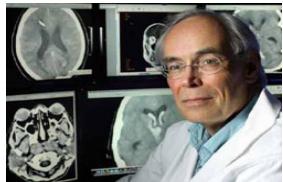
"The purpose is to create an international consortium of investigators and a repository of source MRI and CT images toward the objectives of standardization and validation of acquisition, analytic, and clinical research methods of image-based stroke research."

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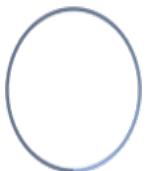
Thanks

- Main Collaborators



- Groups

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Johns Hopkins University

BI  **S**

- Funding

T32AG000247

NIA

RO1EB012547

NIBIB

RO1NS046309, RO1NS060910, RO1NS085211, NINDS

RO1NS046309, U01NS080824 and
U01NS062851

RO1MH095836

NIMH

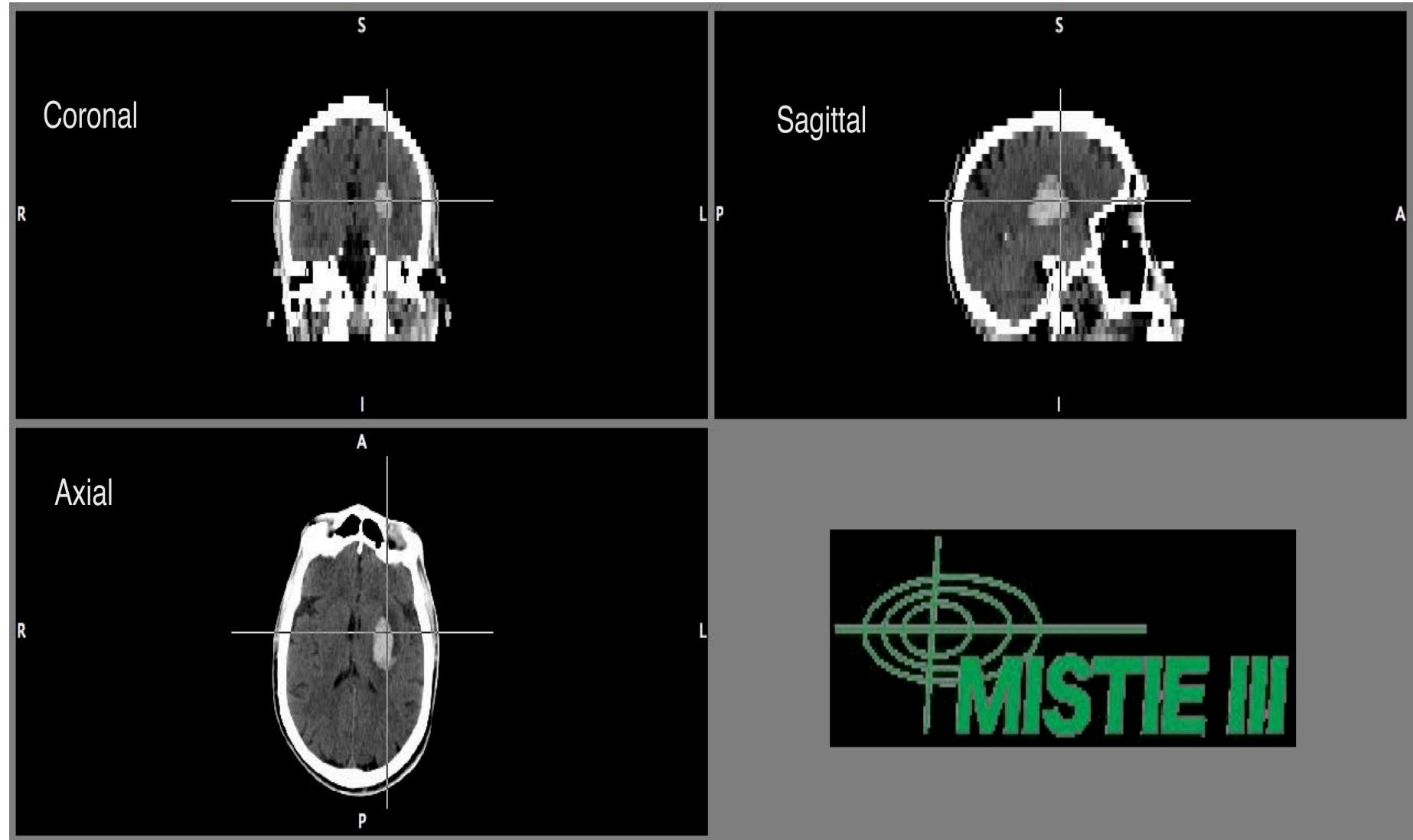
MISTIE Trial - Intracerebral Hemorrhage

- Number of patients: N = 123, number randomized: N = 96
- Inclusion criteria: age 18-80 years old

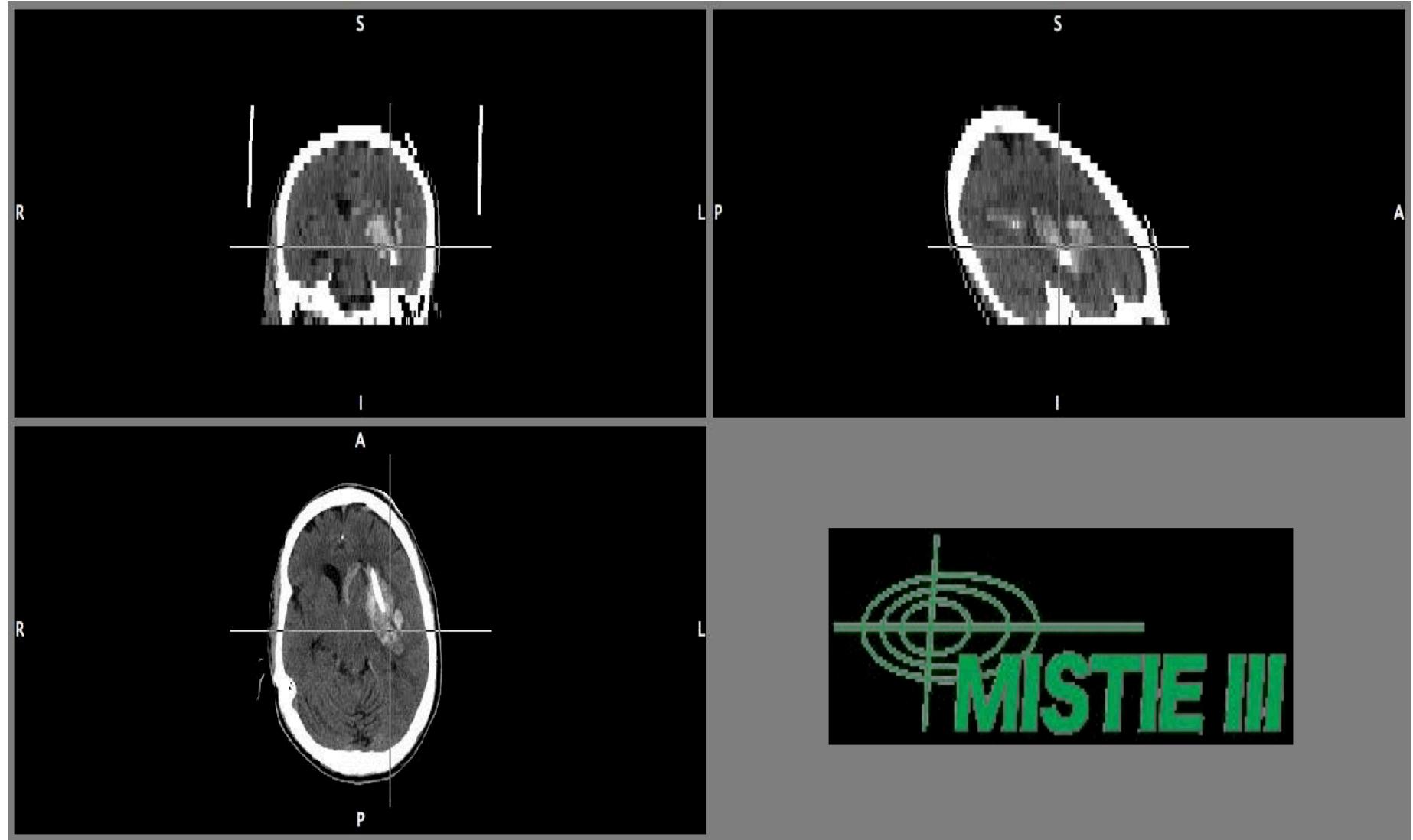
	Medical (N=42)	MIS (N=54)
	N% or Mean(SD)	
Age in Years: Mean (SD)	61.1 (12.3)	60.7 (11)
Age in Years: Median (IQR)	62 (49.5 - 73)	60 (54 - 69)
Gender: Male	28 (66.7%)	35 (64.8%)
Race		
Caucasian	23 (54.8%)	30 (55.6%)
African American	11 (26.2%)	18 (33.3%)
Hispanic	5 (11.9%)	4 (7.4%)
Other	3 (7.1%)	2 (3.7%)

- Over 65 years old: 36 (37.5%), Surgical: 18 (33.3%), Medical: 18 (42.9%)

An "Ideal" MISTIE Patient: ICH Formed



An "Ideal"" MISTIE Patient: Catheter Placed



An "Ideal" MISTIE Patient: Clearance!

