The goal is :

robust

pure python

Fennema-Notestine C, Ozyurt I B, Clark C P, et al. Quantitative evaluation of automated skull-stripping methods applied to contemporary and legacy images: Effects of diagnosis, bias correction, and slice location[J]. Human brain mapping, 2006, 27(2): 99-113.

This article compare with these 4 method to do skull-strip：

BET　3dIntracranial (AFNI)　HWA　BSE

’’HWA and BSE were more robust across diagnostic groups compared with 3dIntracranial and BET. With respect to specificity, BSE tended to perform best across all groups, whereas HWA was more sensitive than other methods.’’

Hwang H, Rehman H Z U, Lee S. 3D U-Net for skull stripping in brain MRI[J]. Applied Sciences, 2019, 9(3): 569.

Evaluate 3D u-net network , compare with BSE, ROBEX, and Kleesiek's method

Subject I.D.	Dice Coefficient			Sensitivity			Specificity		
	BSE	ROBEX	3D UNet	BSE	ROBEX	3D UNet	BSE	ROBEX	3D UNet
A00061276	0.9435	0.9568	0.9908	0.8883	0.9413	0.9853	0.9929	0.9710	0.9962
A00061387	0.9547	0.9431	0.9911	0.9186	0.9530	0.9865	0.9876	0.9342	0.9956
A00061709	0.9583	0.9528	0.9888	0.9306	0.9512	0.9890	0.9838	0.9543	0.9885
A00061711	0.9663	0.9467	0.9896	0.9435	0.9395	0.9856	0.9876	0.9531	0.9935
A00061806	0.9637	0.8793	0.9876	0.9313	0.8511	0.9797	0.9939	0.9015	0.9953
A00062210	0.964	0.9508	0.9913	0.9336	0.9216	0.9891	0.9923	0.9774	0.9934
A00062248	0.9585	0.9579	0.9914	0.9208	0.9434	0.9858	0.9933	0.9713	0.9969
A00062266	0.9482	0.9546	0.9915	0.8919	0.9521	0.9863	0.9989	0.9569	0.9966
A00062282	0.9587	0.9466	0.9897	0.9314	0.9519	0.9826	0.9838	0.9417	0.9967
A00062288	0.9674	0.9473	0.9905	0.9438	0.9397	0.9842	0.9895	0.9542	0.9968
A00062351	0.9554	0.9488	0.9909	0.9235	0.9328	0.9907	0.9846	0.9633	0.9912
A00062917	0.9557	0.9549	0.9897	0.9278	0.9338	0.9839	0.9813	0.9741	0.9954
A00062934	0.9197	0.9451	0.9921	0.8329	0.9409	0.9887	0.9935	0.9487	0.9954
A00062942	0.9608	0.9507	0.9922	0.9225	0.9164	0.9877	0.9962	0.9817	0.9966
A00063008	0.9705	0.9588	0.9915	0.9437	0.9334	0.9883	0.9957	0.9823	0.9947
A00063103	0.9544	0.9602	0.9884	0.9116	0.9434	0.9794	0.9935	0.9757	0.9972
A00063326	0.9436	0.9503	0.9896	0.8956	0.9372	0.9811	0.9864	0.9621	0.9979
A00063368	0.953	0.9478	0.9861	0.9030	0.9370	0.9751	0.9985	0.9575	0.9967
A00063589	0.9607	0.9512	0.9916	0.9349	0.9440	0.9877	0.9846	0.9577	0.9956
A00064081	0.9647	0.9511	0.9923	0.9296	0.9209	0.9888	0.9974	0.9785	0.9958
Mean	0.9561	0.9477	**0.9903**	0.9179	0.9342	**0.9853**	0.9908	0.9599	**0.9953**
Standard deviation	0.0113	0.0168	0.0016	0.0260	0.0221	0.0040	0.0055	0.0192	0.0022

Table 3. Comparison of mean and standard deviation for J Kleesiek's method and 3D U-Net. The best values are emboldened.

Tips:

About 3D U-Net:

https://arxiv.org/abs/1606.06650
3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation

''redundant''

deepbrain: Extractor

https://github.com/iitzco/deepbrain/blob/master/README.md

Extractor runs a custom U-Net model trained on a variety of manual-verified skull-stripping datasets.

’’Why choose Extractor over others (e.g. BET FSL, ANTs, PINCRAM)?

1.Extractor is **fast**. It's CNN was implemented on Tensorflow and carefully designed to be as small as possible. < 2 second extraction on GPU or 20 second on i5 CPU

2.Running Extractor is **easy**. Don't need to provide any complicated parameters (like brain templates or prior probability masks), just with the brain MRI is enough.

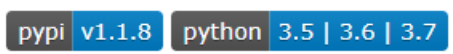
3.Extractor is **accurate**. It does not fail in some cases where others (specially BET) fails.’’

 **iitzco** Work in 256 for segmenter — Latest commit `dbeff0e` on 24 Sep 2018

bin	Add pb loading method	last year
deepbrain	Work in 256 for segmenter	last year
imgs	Improve script	last year
.gitignore	Update gitignore	last year
LICENSE	Create LICENSE	last year
MANIFEST.in	edit manifest	last year
README.md	Update README	last year
requirements.txt	Add requirements.txt	last year
setup.py	Improve script	last year

README.md

DeepBrain



> Brain image processing tools using Deep Learning focused on speed and accuracy.

How to install

```
$ pip install deepbrain
```

BET

3dIntracranial (AFNI)

HWA

BSE

3D u-net network (deepbrain)

ROBEX

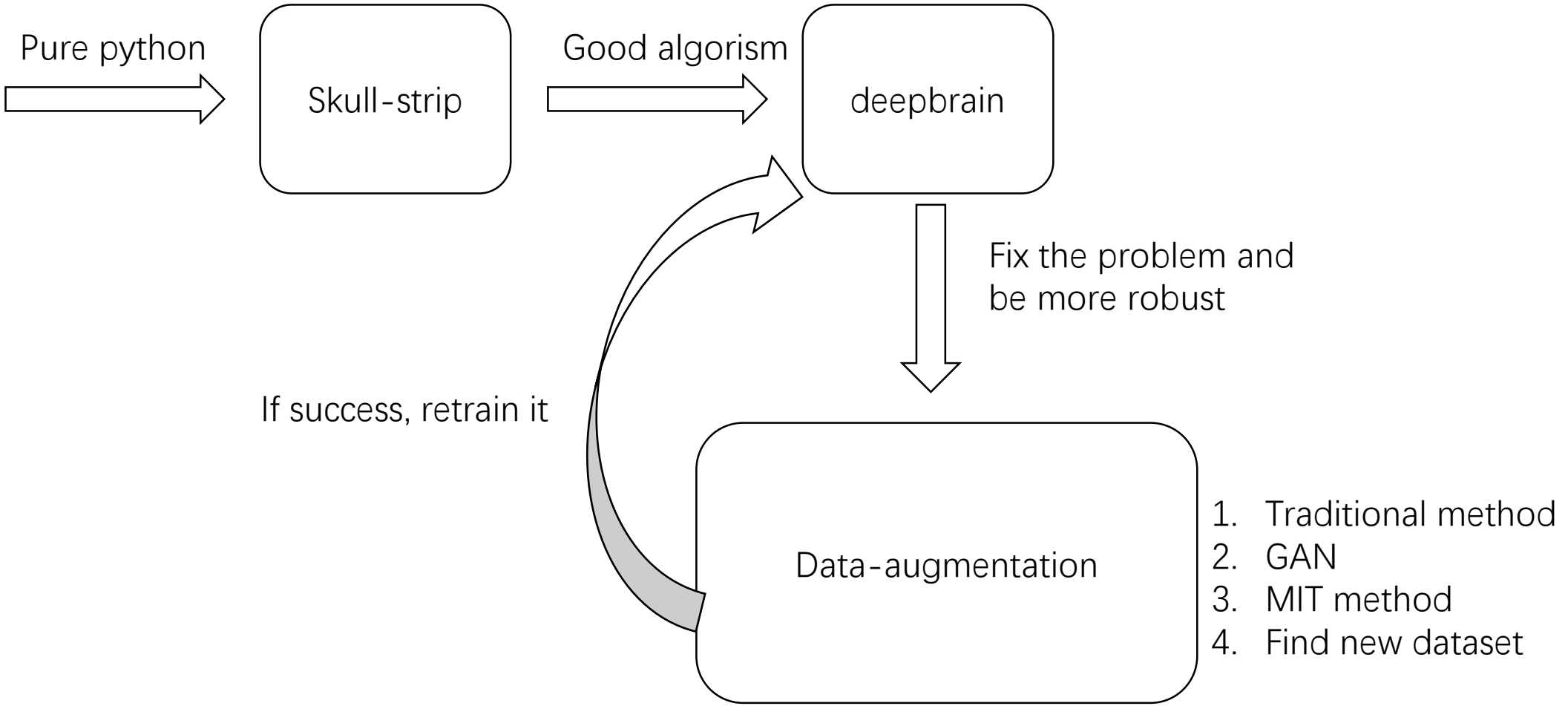
I think deepbrain is a very good benchmark.

1. Pure python
2. It performs well than other methods
3. Their trouble is not hard for us to solve:
    1. In my opinion, why Alex said deepbrain is not useful in some dataset is that they just train this model in 3 small dataset.
    2. We can use data augmentation method or find new dataset to train it.

As for data-augmentation:

1. Traditional method (e.g. flip, noise, rotate, image contrast, precision)
2. GAN
3. MIT method ‘Data augmentation using learned transformations for one-shot medical image segmentation’(http://www.mit.edu/~adalca/files/papers/cvpr2019_brainstorm.pdf)
4. Find new dataset

Conclusion


Pure python
Skull-strip
Good algorism
deepbrain
Fix the problem and
be more robust
If success, retrain it
Data-augmentation
1. Traditional method
2. GAN
3. MIT method
4. Find new dataset