CS516 Assignment2 Report

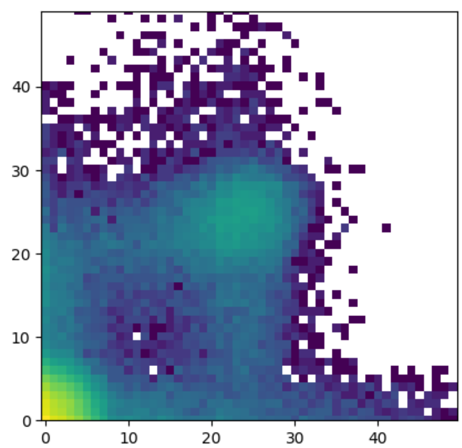
Group member: Yukuan Hao, Liang GU

Part1

(1) BrainMRI_1&BrainMRI_2

bin=50

The coordinates of this joint histogram are divided based on the size of

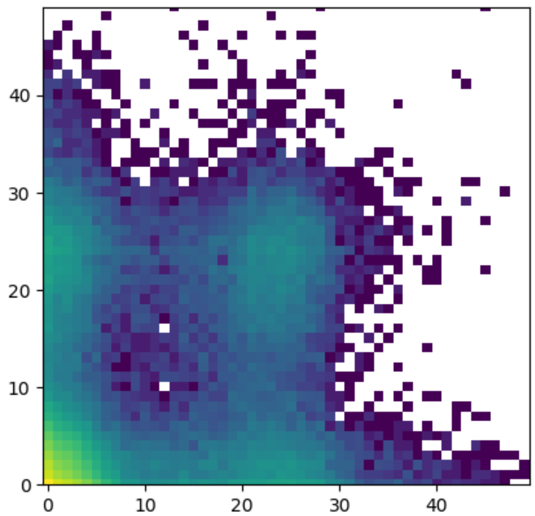


bin.

These two images overlap a lot around the diagonal from (0,0) to (30,30), and separate to the two sides of diagonal.

(2) BrainMRI_3&BrainMRI_4

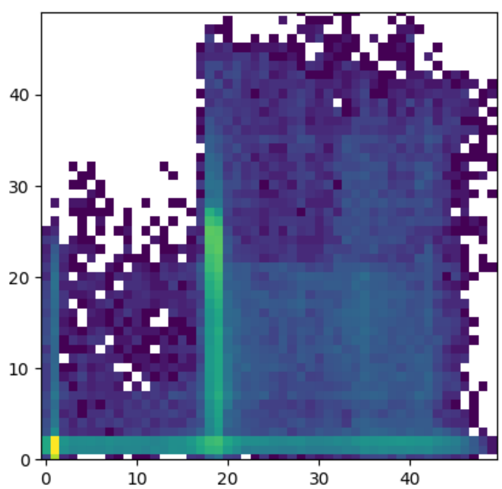
bin=50



The pixels of two images occur in the same place more in the bin of 40 than the first set of images above.

(3) I5&J5

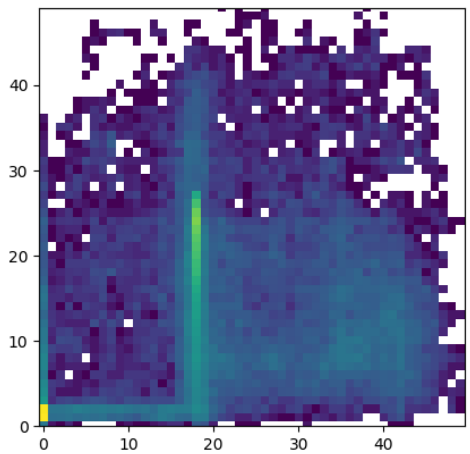
bin=50



The overlaps can be seen from x=17 to x=50, and there is no overlaps occur in the section from (0,30) to (17,40).

(4) I6&J6

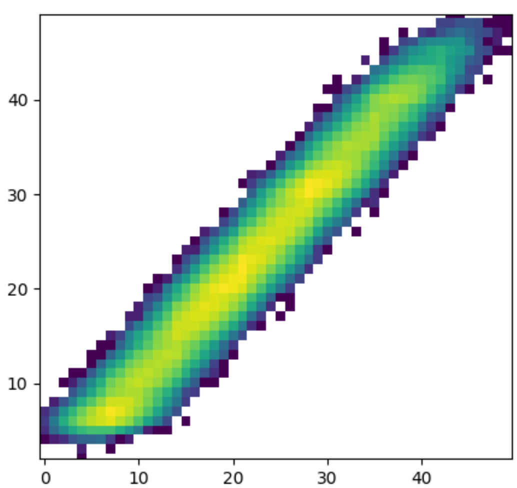
bin=50



They overlap more evenly than third set of images.

(5) I1&J1

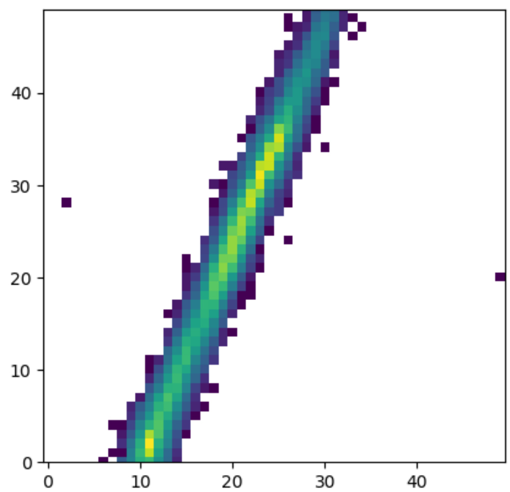
bin=50



Two images overlap along the diagonal for the high similarities

(6)I2&J2

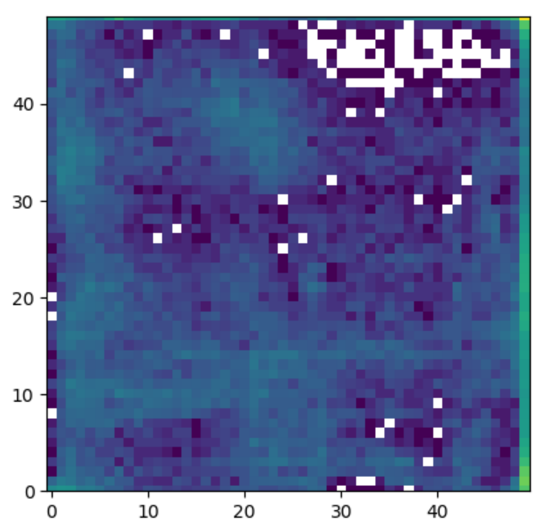
bin=50



Two images overlap only along the line from (0,10) to (30,50) indicating that all the value of pixels in the image J have the same increase as image I.

(7)I3&J3

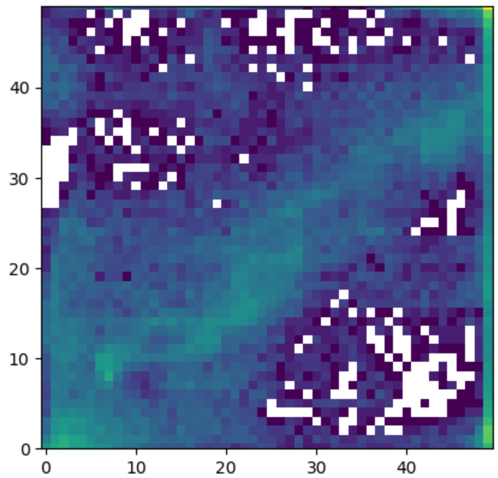
bin=50



The overlapping parts are dispersed evenly. There are a part of loss around the coordinates of (40,40)

(8)I4&J4

bin=50



The overlapping parts are more concentrated than similar set of images above.

2. To verify that

$$\sum_{i,j} H_{I,J}(i,j) = n \cdot p$$

The value of pixels in joint histogram at place [i, j] represent the number of pixel when image1's pixel value equal to i and image2's pixel value equal to j at same place, so the sum of the pixel value in joint histogram equal to all the pixel number in image1 or image2(image1 and image2 have same number of pixels)

Part2

(1) BrainMRI_1&BrainMRI_2

SSD: 87100357.0

CORR: 0.6998209575711278

MI: 0.52758521

The ssd is low meaning that the level of differences is low. The correlation coefficient is higher than MI, these two images have higher linear correlation than the possibility of distribution.

(2) BrainMRI_3&BrainMRI_4

SSD: 192411158.0

CORR: 0.33871188113182205

MI: 0.30387227

The SSD is much higher than the first set of images. The correlation coefficient and mutual information are about 0.3, so these two images have a lower similarity.

(3) I5&J5

SSD: 699888797.0

CORR: 0.6564367191426469

MI: 0.55488207

The ssd is extremely high while the correlation coefficient and mi is not low, so these two images have fewer difference in linear correlation and distribution of pixel than the difference of shape.

(4) I6&J6

SSD: 425536176.0

CORR: 0.7802495447255012

MI: 0.67485632

Corr is better than MI, therefore, these two images have better linear correlation than the distribution of joint possibility. The ssd is smaller than the above set of images, showing that these two images have higher value of similarity.

(5) I1&J1

SSD: 26574152.0

CORR: 0.978182428141388

MI: 1.5549331

These two images have extremely high value of similarity in linear and joint possibility distribution, and also the ssd is low, which means that this set has a lot similarity.

(6) I2&J2

SSD: 473379387.0

CORR: 0.9962134367832854

MI: 2.22874888

The correlation coefficient and mi are both high but the SSD shows a high value of the difference between two images. That is the reason why this set of images has the same structure and distribution of pixels, but they look different.

(7) I3&J3

SSD: 870751839.0

CORR: 0.14339070113716768

MI: 0.66875862

The ssd is extremely high and the correlation coefficient is pretty low, while the mi is much higher than correlation coefficient. The linear correlation is weak, but their distribution of different value of pixels are more similar.

(8) I4&J4

SSD: 362261357.0

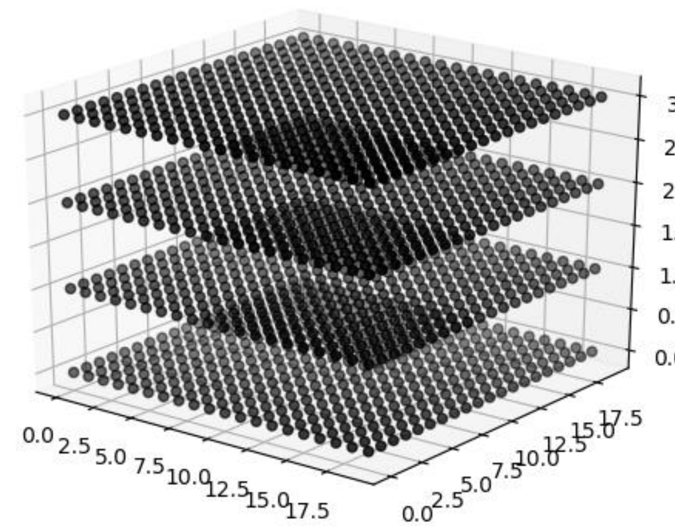
CORR: 0.5640342309868849

MI: 1.0241533

The ssd is lower than the above set, so these two images have more similarity. The linear correlation becomes better than the above set and also the distribution is closer.

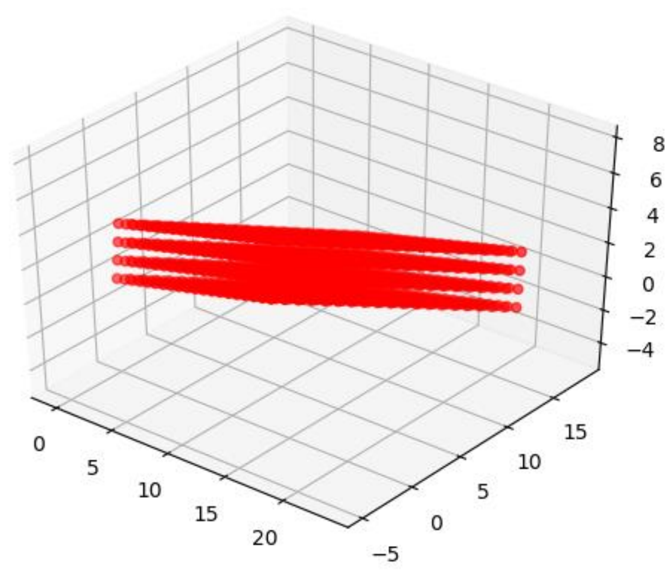
Part 3

3d grid:



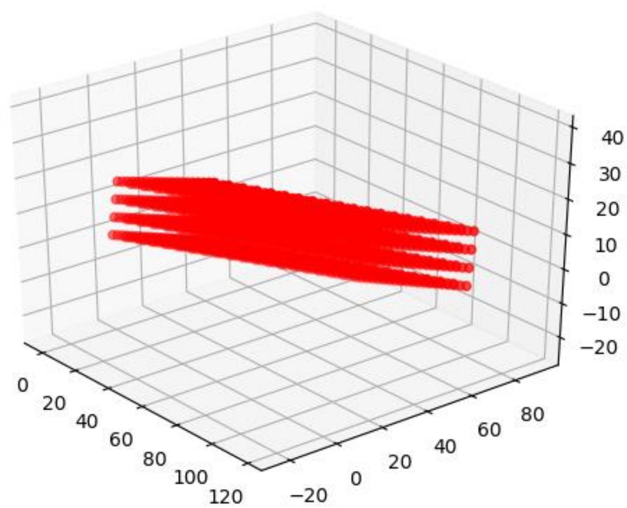
Rigid transform:

Theta=15 Omega=15 Phi=15 p=1,q=2,r=3

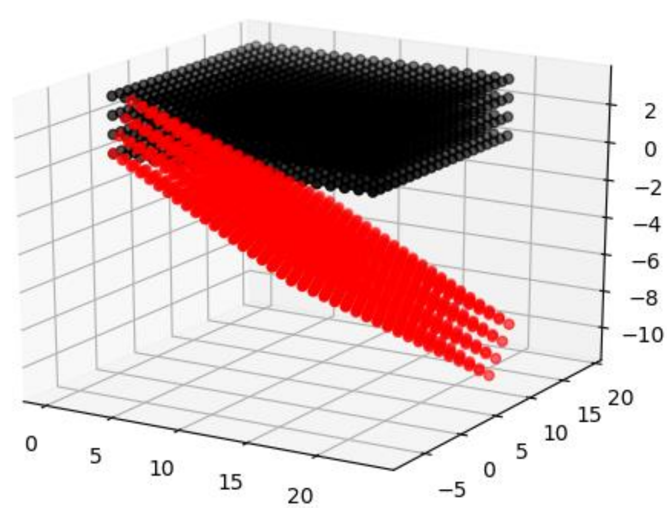


Affine transform

Theta=15 Omega=15 Phi=15   p=1,q=2,r=3 Scale=5

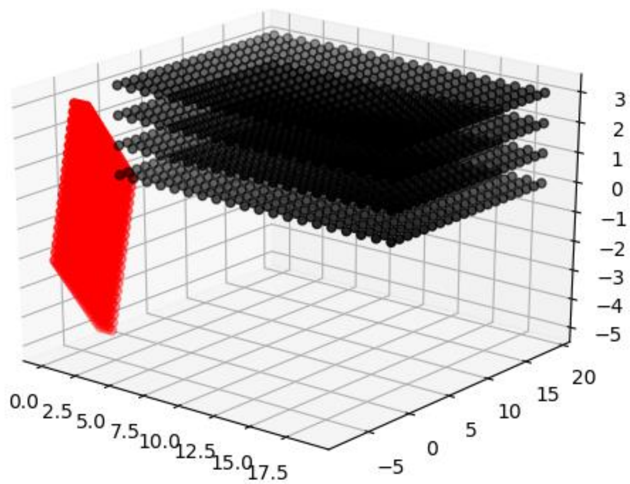


M1:



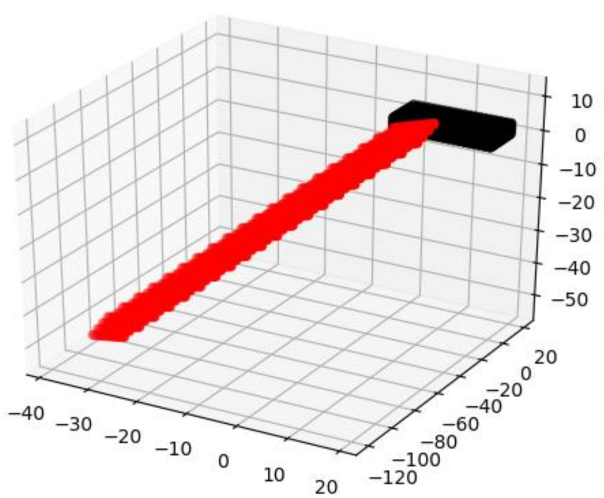
Rotation No Shearing   No Scaling No Translation

M2:



Rotation Scaling Shearing Translation

M3:

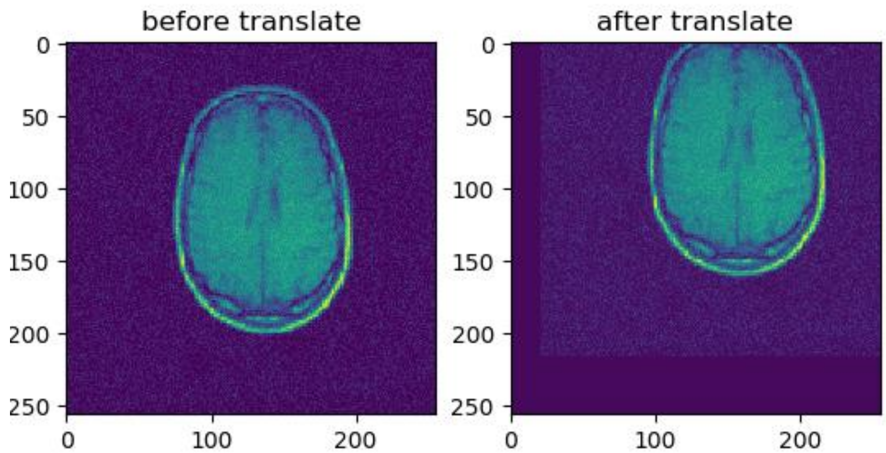


Rotation   Shearing   Scaling   No Translation

Part4

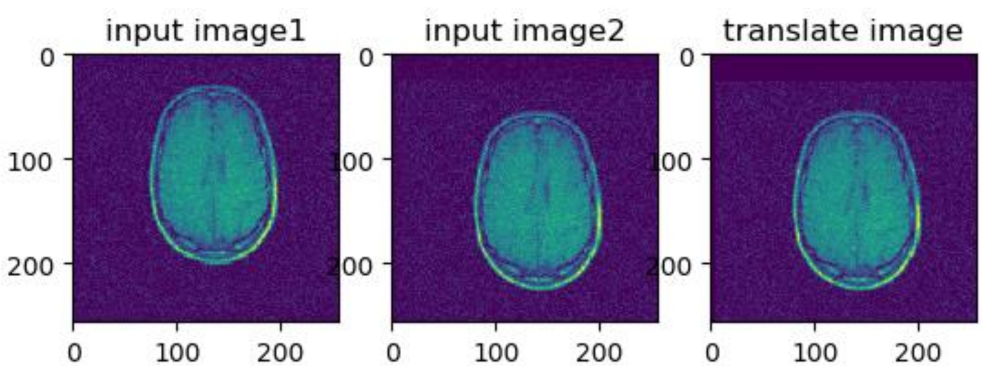
A).

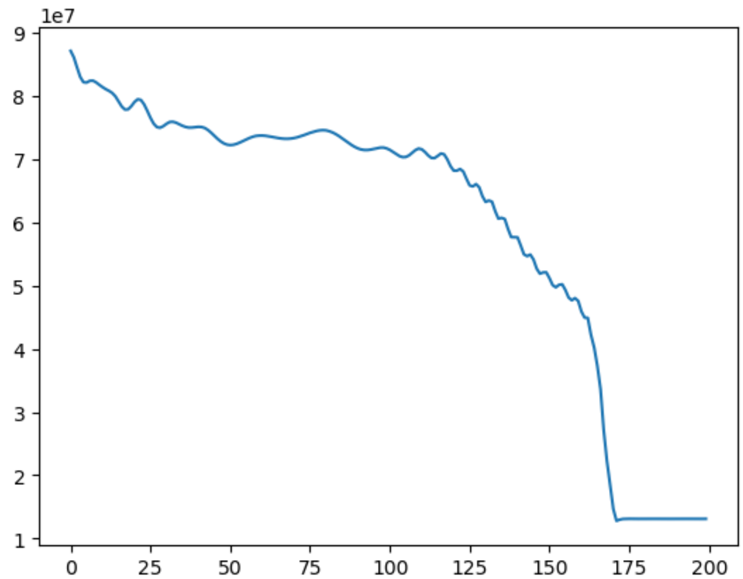
Here is the output of the function translate(I,P,Q),we choose BrainMRI_1.jpg as input, and we set p=20,q=-40, here is the result:



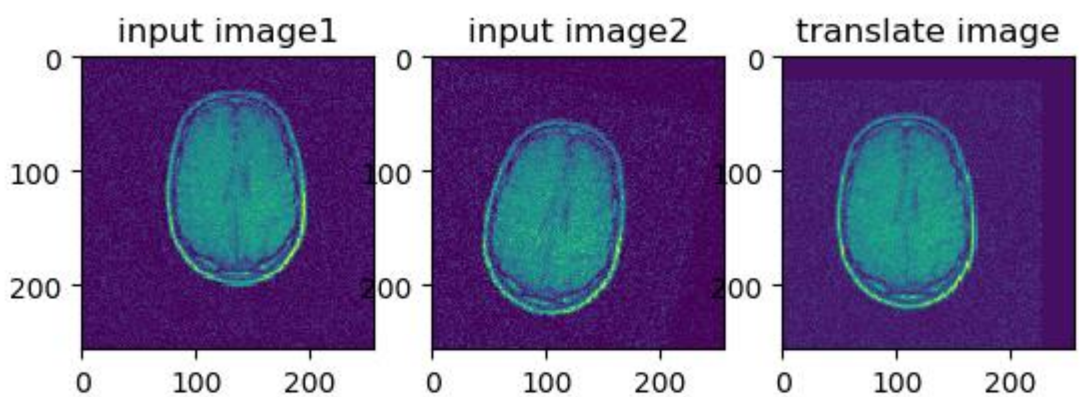
B).We use Lucas-Kanade method (iterative solution) to minimizing SSD, we set 200 as the default maximum iteration, here is our result:

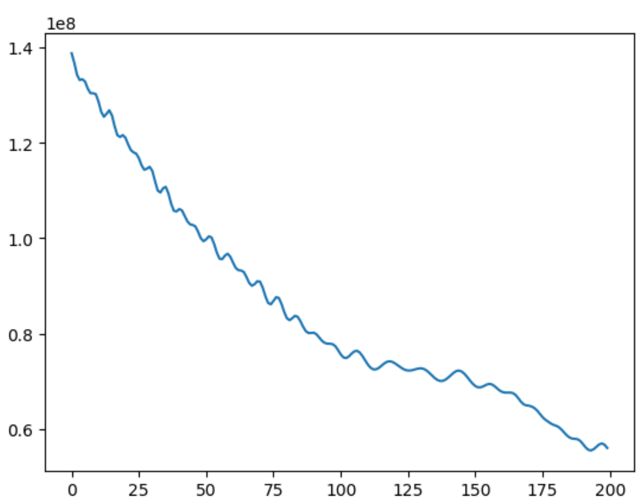
Input images: BrainMRI_1.jpg, BrainMRI_2.jpg



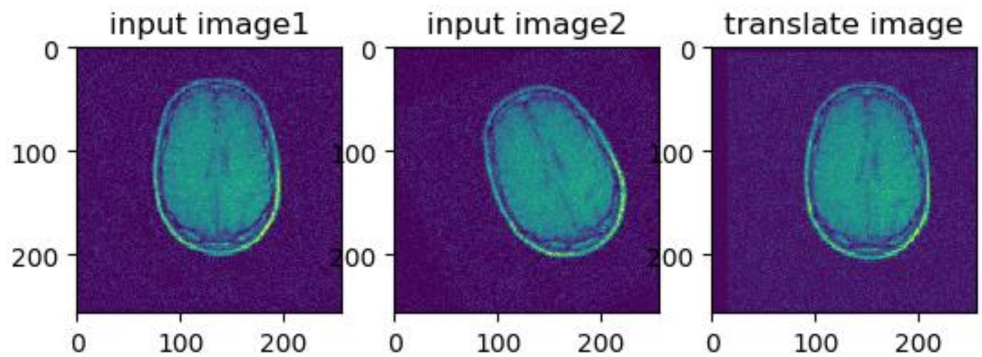


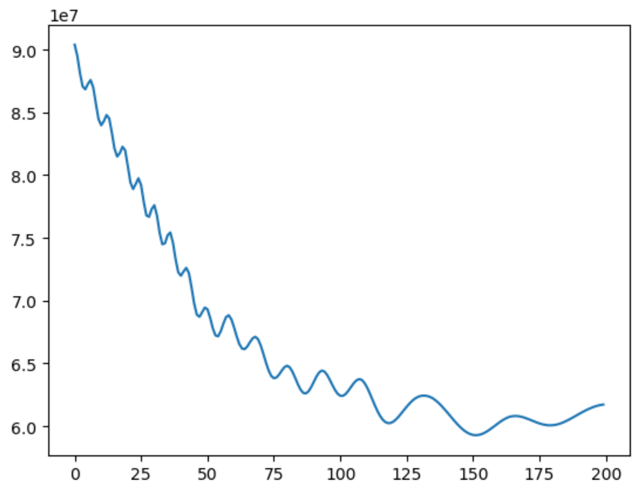
Input images: BrainMRI_1.jpg, BrainMRI_3.jpg





Input images: BrainMRI_1.jpg, BrainMRI_4.jpg



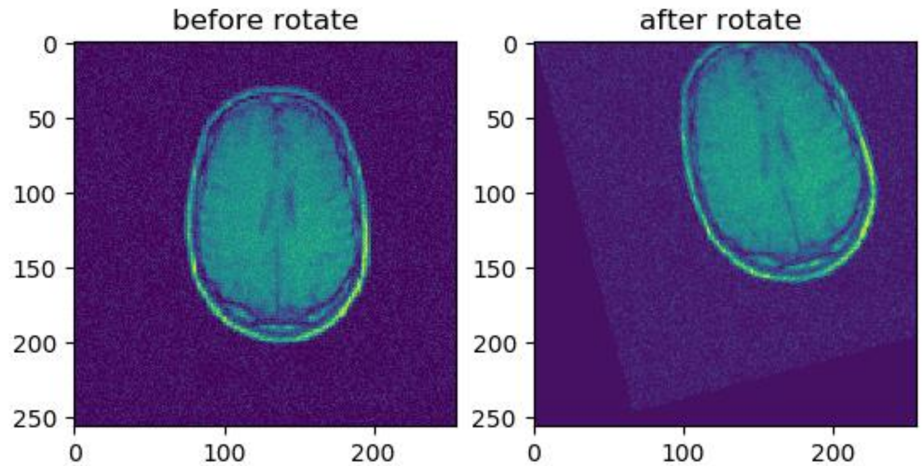


The result analysis:

Overall, those three pair images' SSD curve is decreasing, but those curves are fluctuation in detail.

In my opinion, the step size is an important reason that causes the SSD curve not directly decreasing. If we choose a large value of step size, there is a high possibility to miss the correct translation.

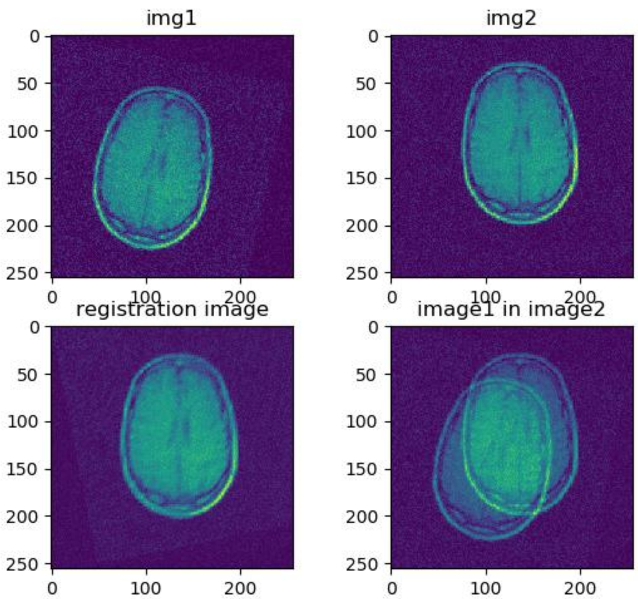
C). Here is the output of the function rotate(I, theta), we choose BrainMRI_1.jpg as input, and we set theta=15, here is the result:

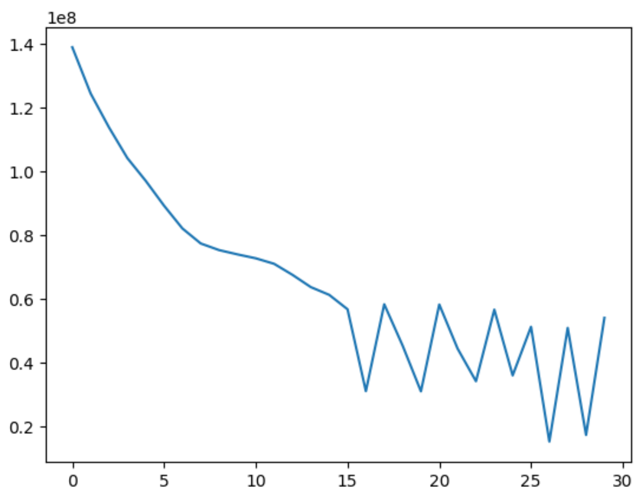


before rotate
after rotate
0
50
100
150
200
250
0
100
200

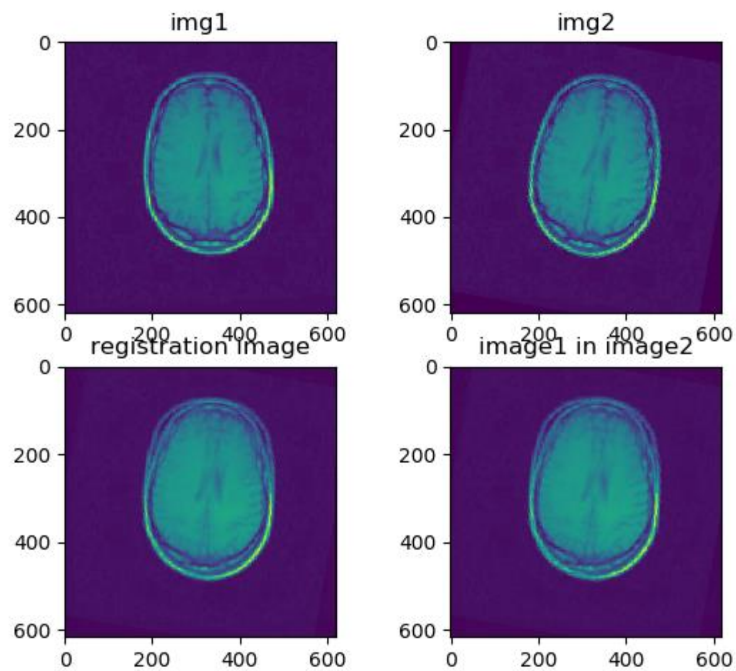
D).we calculate SSD derivatives to minimize SSD , here is the result :

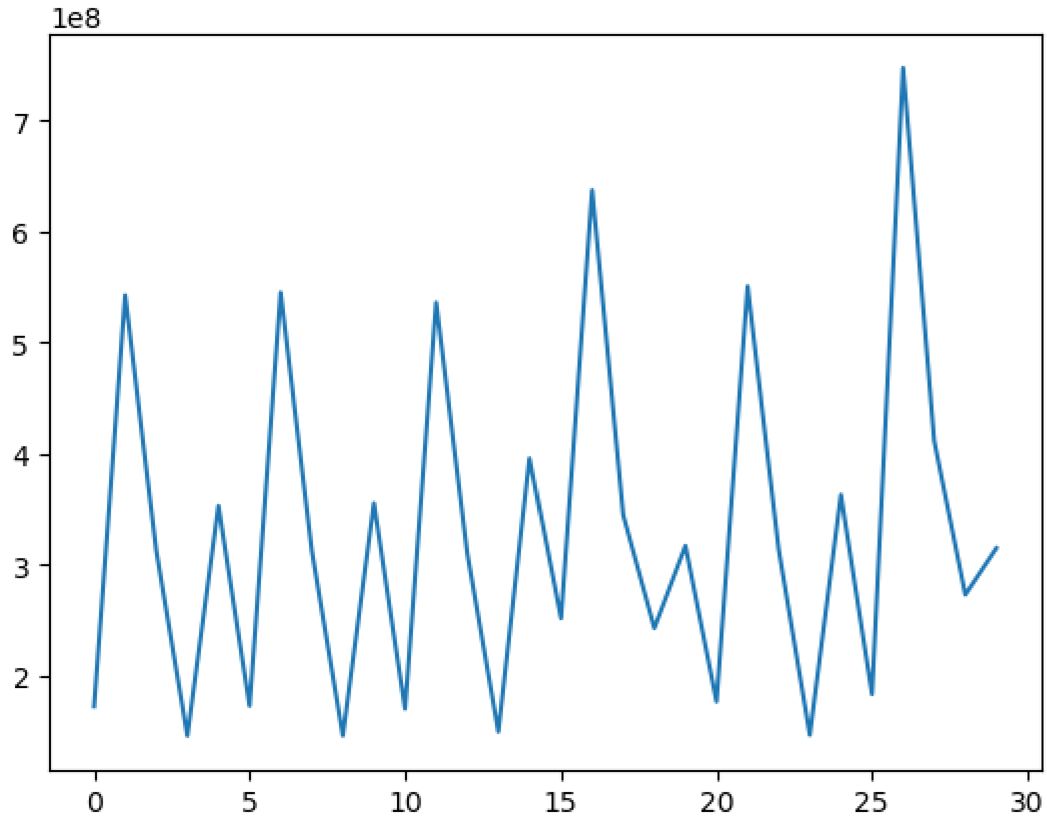
input image BrainMRI_1.jpg and BrainMRI_3.jpg:



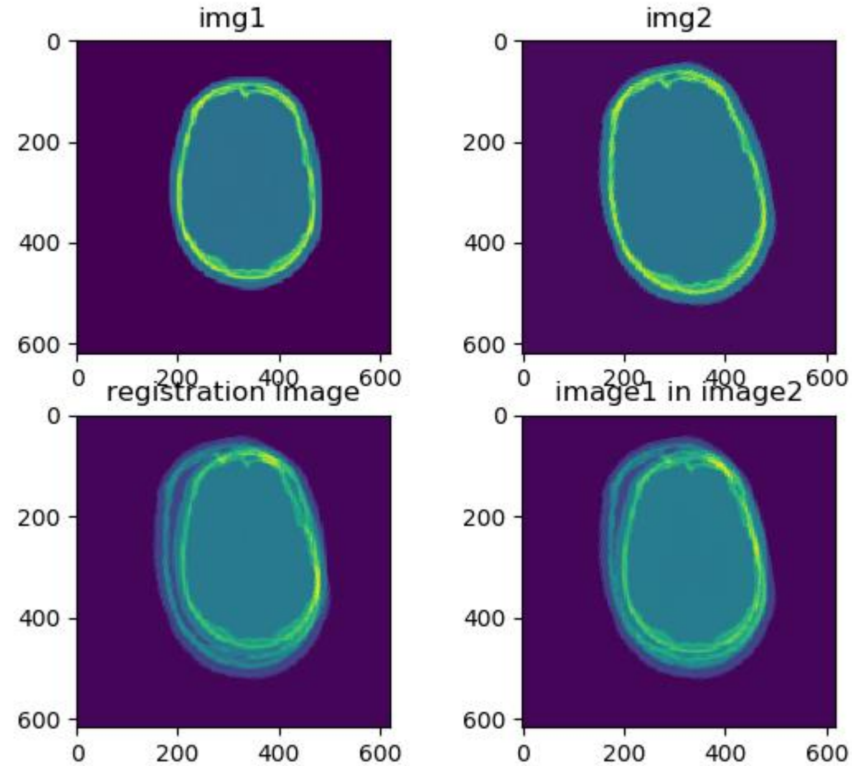


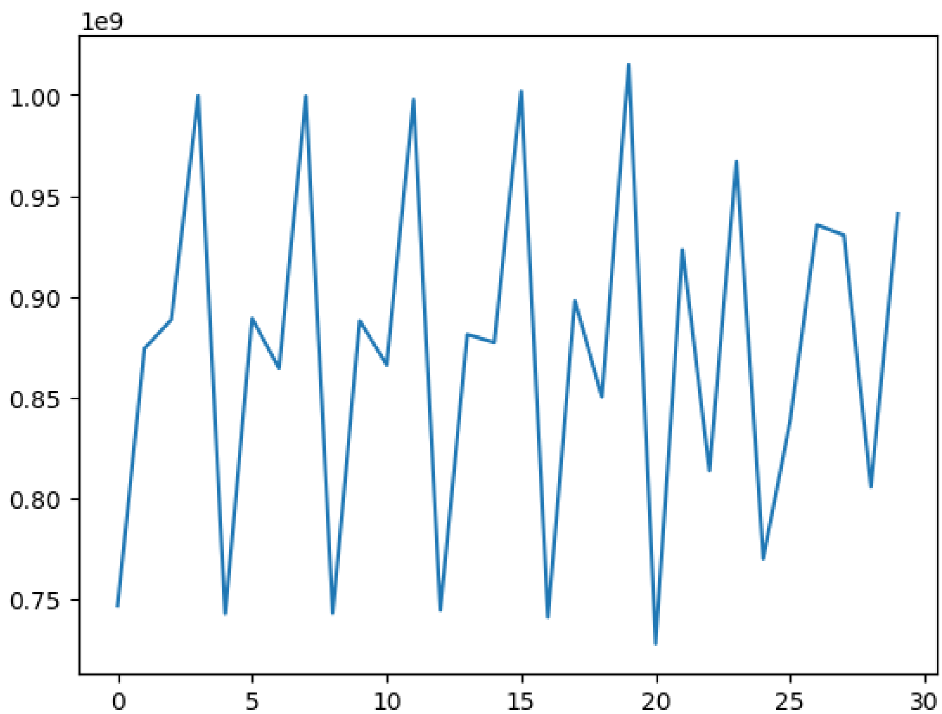
input image I5.jpg and I6.jpg:





input image J5.jpg and J6.jpg:


img1
img2
registration image
image1 in image2
0
200
400
600


1e9
1.00
0.95
0.90
0.85
0.80
0.75
0
5
10
15
20
25
30

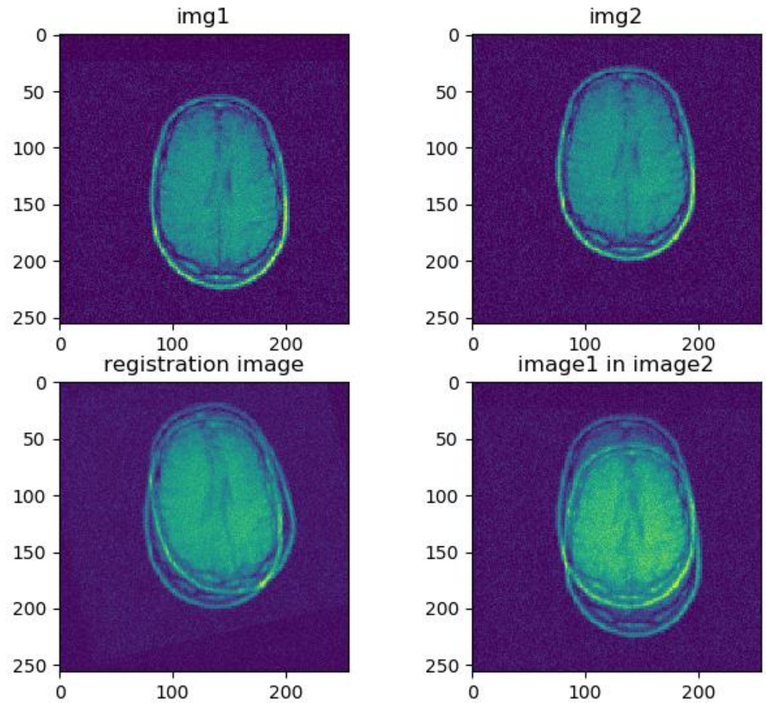
Result analysis:

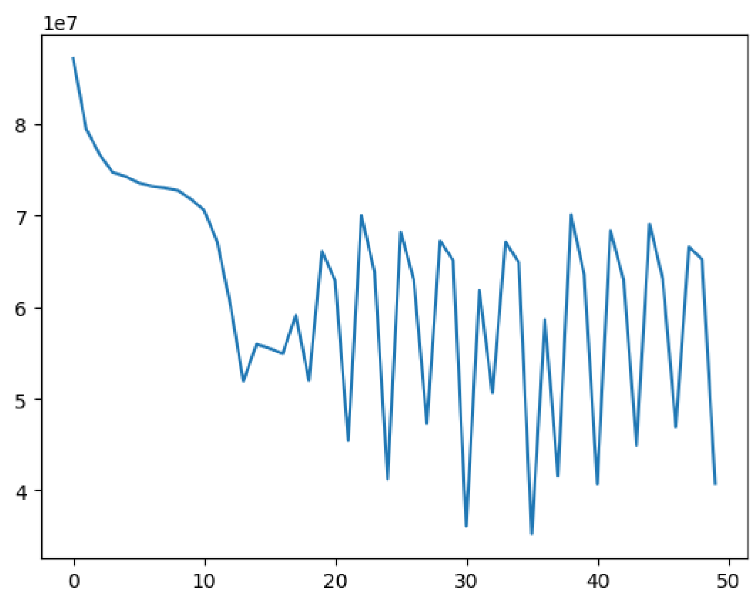
For BrainMRI_1.jpg and BrainMRI_3.jpg, our function gets a good result, SSD curve decrease directly before 15th iteration, but after 15th iteration the curve becomes fluctuation, I think it is because the angle is very close to the correct angle, and our function's iteration step miss that correct angle so the curve becomes fluctuation.

For I5.jpg and I6.jpg, our rotate function doesn't give us a good result, and the SSD curve is fluctuation because our function rotates the image from the top left, but I5.jpg seems to rotate the image from the center, so our function failed. In addition, if we put I5 and I6 in one image((I5+I6)/2), we can found those two images already trend to overlap, so the SSD curve is fluctuation.

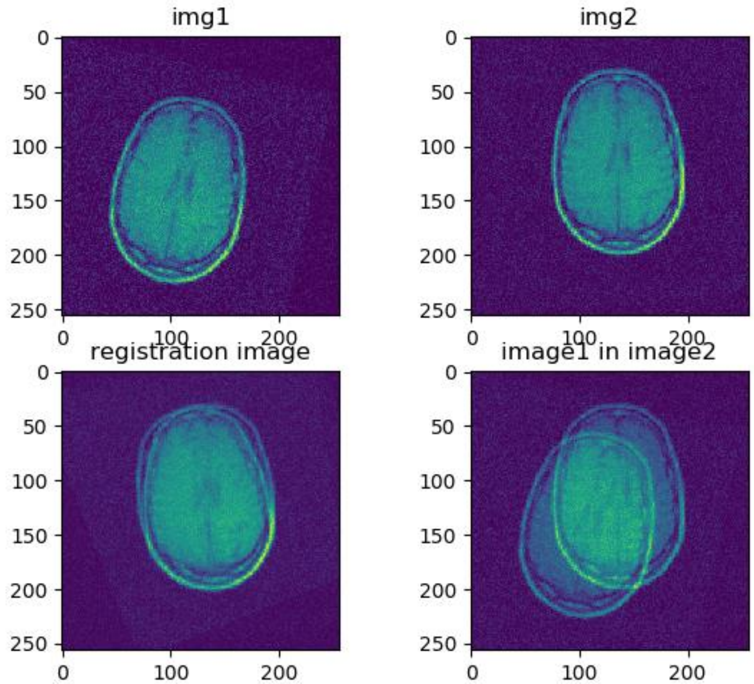
For J5.jpg and J6.jpg, our rotate function also doesn't give us a good result, and the SSD curve is fluctuation, I think J5.jpg not only do rotate step, but also do scale step, so our function failed.

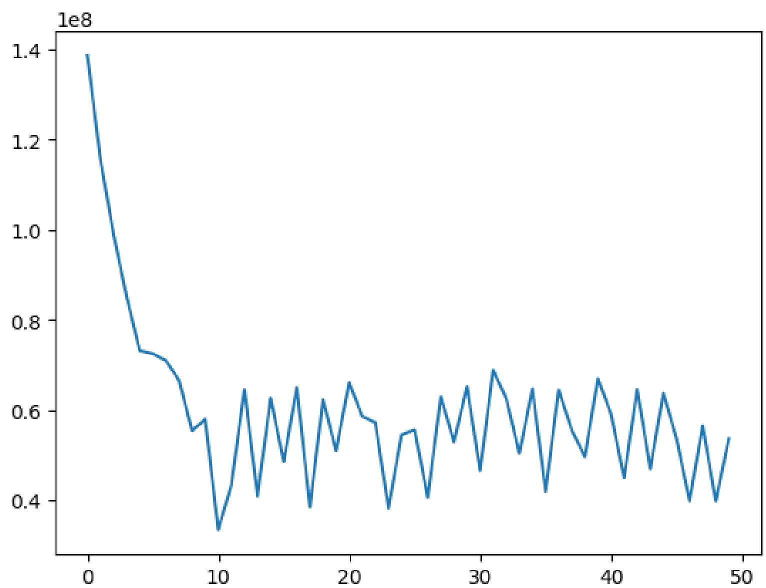
E).BrainMRI_1.jpg and BrainMRI_2.jpg



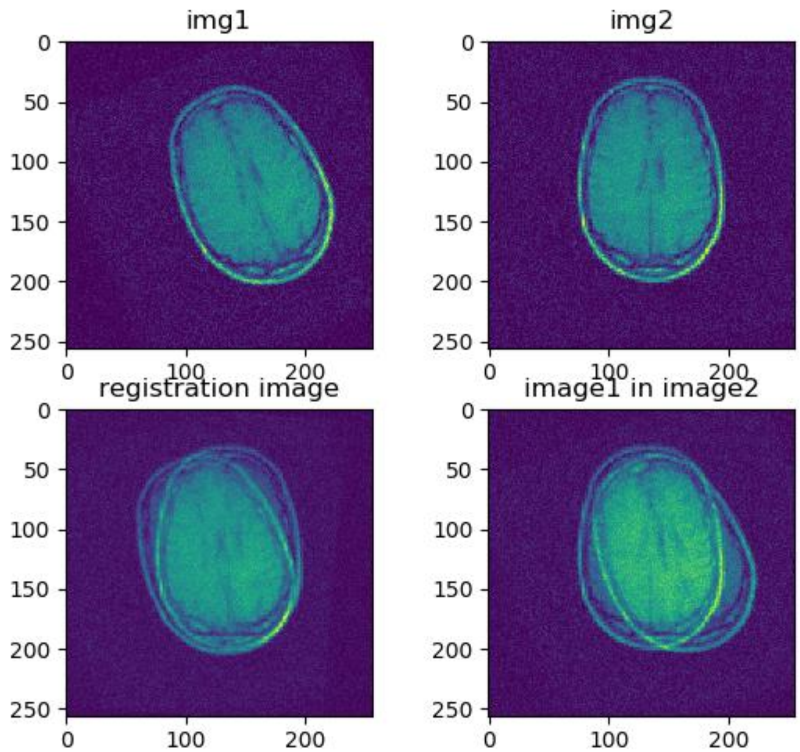


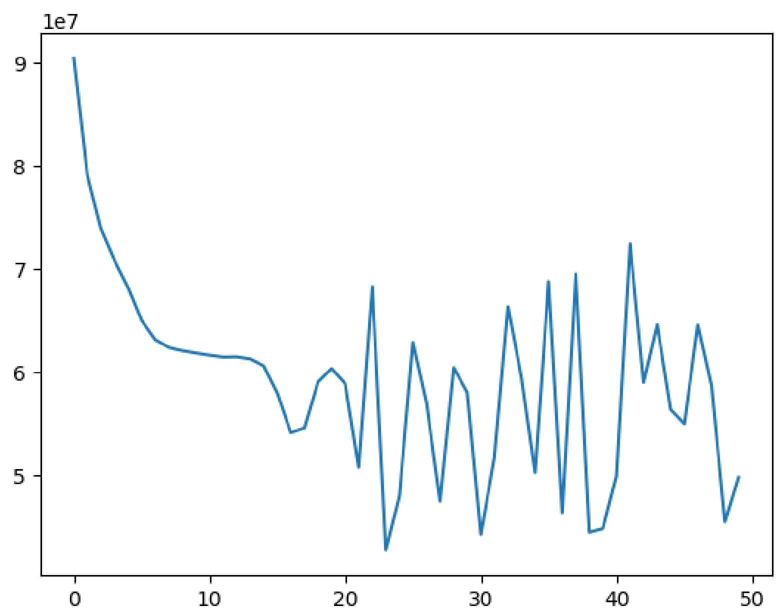
BrainMRI_1.jpg and BrainMRI_3.jpg





BrainMRI_1.jpg and BrainMRI_4.jpg



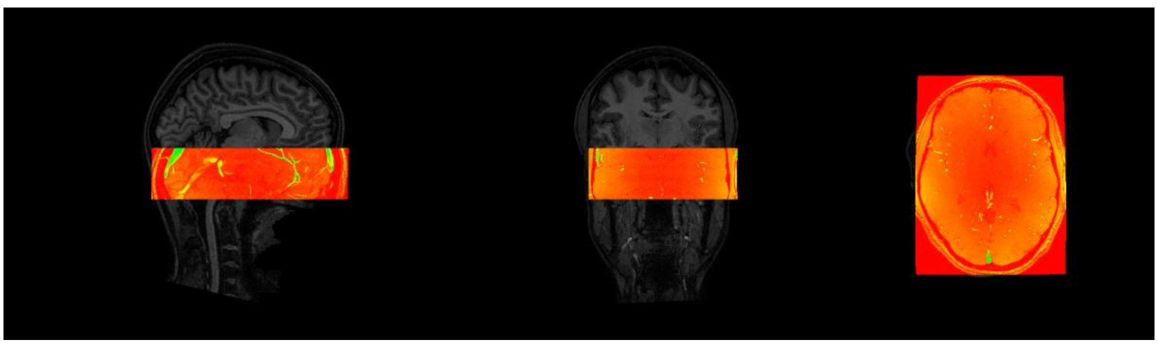


Result analysis

First pair images(BrainMRI_1.jpg and BrainMRI_2.jpg) and second pair images(BrainMRI_1.jpg and BrainMRI_3.jpg) have a good result, the registration converges, the third pair images(BrainMRI_1.jpg and BrainMRI_4.jpg) do not converge. In my opinion, our registration function uses a large number of step size, because I want to use a few iterations to get a good result, from the resulting image we can see all of the SSD curves are fluctuation at the end, and the image shows that images are very close to overlapping, so I guess our function takes big steps and miss the correct registration.

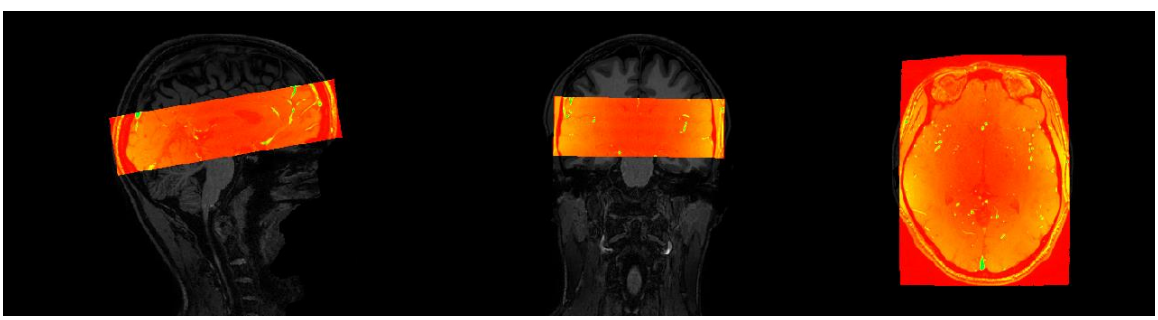
Part5

We use FSL to align tof.nii and t1.nii, there is our result, we use command "flirt -in tof.nii -ref t1.nii -out out.nii", we use Fsleyes to visualize images, here is t1.nii and tof.nii:



(The grayscale image is t1.nii, and the red color image is tof.nii.)

We can see tof.nii is not in the correct place in t1.nii, then we put our output image on t1.nii, and remove tof.nii, here is our result



(The grayscale image is t1.nii, and the red color image is our result.)