Two-Dimensional DICOM Feature Points and Their Mapping Extraction for Identifying Brain Shifts

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***Abstract*—In order to model organ deformation precisely, we extract numerous feature points and also their mapping correspondences from two layered two-dimensional Digital Imaging and Communications in Medicine (DICOM) images. In this study, we first selected the same image twice (the 68th image) from 124 layered two-dimensional DICOM images, and then two consecutive images (the 68th and 69th) and two that were far apart (the 55th and 80th). Next, two-dimensional feature points were extracted from these images, and their mapping was searched. We utilized the two-dimensional image feature point extraction/correspondence algorithms scale-invariant feature transform (SIFT), KAZE, Accelerated KAZE (AKAZE), and oriented FAST and rotated BRIEF (ORB) from OpenCV with real DICOM files to confirm that the aforementioned extraction and mapping was possible. According to our results, although the method for searching for matches by only looking for similar feature points in the vicinity of a certain feature point required slightly more calculation time than the method of looking for matches across the entire DICOM area, in the end it did decrease the number of mistaken matching correspondences.**

***Index Terms*—DICOM, OpenCV, Python, feature points, KAZE, AKAZE, ORB, SIFT, cranium**

I. Introduction

The brain is the most important organ in the human body, and it has many regions that must remain uninjured for a person to have a good quality of life (QOL). If the brain does inadvertently become injured, then complications or sequelae may develop. Furthermore, the boundaries between normal and abnormal regions are difficult to determine, and sequelae can develop if a surgeon goes too far when removing malignant tumors, while conversely the patient survival rate decreases when too much of a malignant tumor is left behind.

In light of this, we must be able to deftly handle brain shifts that occur during surgery on the brain. A brain shift is a phenomenon in which the brain deforms as it sinks toward its base when spinal fluid is lost after a craniotomy or gravity acts upon the brain. During a neurosurgical procedure, this results in intraoperative changes in the location, position, and form of malignant tumors, cerebral thrombosis, cerebral infarctions, and other regions shown in preoperatively produced Digital Imaging and Communications in Medicine (DICOM) files.

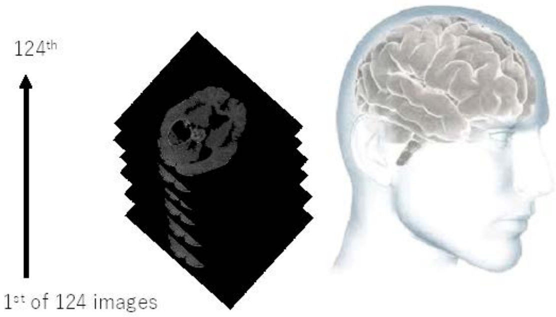

Figure 1. Numbering of two-dimensional DICOM images.

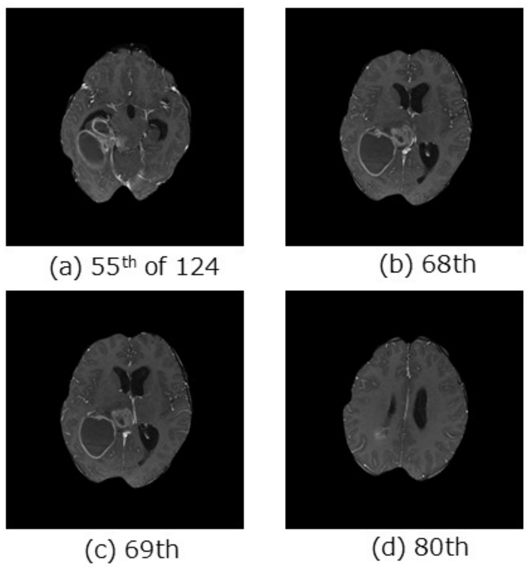

Figure 2. Some of the 124 layered two-dimensional images.

While the ultimate goal of this study is to model these brain shifts, in order to produce the basic data to achieve this numerous feature points were extracted from DICOM files and mapped into two two-dimensional DICOM images (Fig. 1 and Fig. 2). If matches are determined between preoperative and postoperative DICOM files,

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which is not carried out in this study, then it should be possible to identify which areas of the brain are deformed and by how much during the process of surgery. Using this information, our future plan is to utilize a large amount of matching data in order to successfully model brain shifts (i.e., identify the rheological parameters of regions such as malignant tumors, thrombi, blood vessels, and nerves), calculate brain shifts by inputting the area of an incision that will be monitored during surgery, and display visualizations of this for physicians [1]-[7].

The rest of this paper is organized as follows: Section 2 describes our software and data used in this research. In section 3, we explain four kinds of extraction/correspondence algorithm for layered two-dimensional image feature points. Then in section 4, we show results of experiments with brain DICOM files. Finally, a discussion of the study is provided in section 5.

II. Software and Data

This chapter will describe the software employed in this study.

A. OpenCV

OpenCV (Open Source Computer Vision) is an open source computer vision library. It offers a variety of functions required to process images and videos on a computer, and can be used for both academic and commercial purposes, as it is distributed on a BSD license. In addition, one of its distinguishing characteristics is that it can be employed in a wide variety of situations, because it is compatible with multiple platforms.

B. Python

Python is a highly functional and extremely dynamic programming language, which is utilized in applications in a variety of fields. It is often compared to languages such as Java. It has a high-level, dynamic data types, and its procedural code makes the syntax very easy to read. Furthermore, it can be used in a wide range of operating systems such as Windows, Linux, and Mac.

C. DICOM

DICOM refers to a format of medical imaging taken with computed tomography (CT) or magnetic resonance imaging (MRI). It is a standard that defines communication protocols between medical imaging equipment, which was developed by the American College of Radiology and the National Electrical Manufacturers Association. After an image is taken, it is saved in BMP format on a server in a lossless or lossy format.

III. Extraction/Correspondence Algorithms for Layered Two-Dimensional Image Feature Points

What is generally desired from Simultaneous Localization and Mapping (SLAM), which is utilized with robots and cameras that move freely in three-dimensional environments, is the brightness, scale, rotation, and affine invariance of feature quantities in two-dimensional images. However, in a patient's layered two-dimensional DICOM files, everything other than the brightness remains virtually unchanged. In addition, using the cranium and incision as landmarks, the scale and rotation in multiple DICOM files from the same patient can easily be aligned using Visualization Toolkit (VTK).

The brightness varies according to the CT or MRI imaging parameters and the type of contrast dye. Accordingly, imaging is carried out using imaging parameters and contrast dye that allow for a consistent spread of feature point groups throughout the organ. In addition, when the brightness differs from that of the same patient's past DICOM files in the brain database, they will be normalized using VTK. OpenCV has been used to research algorithms such as scale-invariant feature transform (SIFT), KAZE, Accelerated KAZE (AKAZE), and oriented FAST and rotated BRIEF (ORB) [8]-[11], which are defined below, for use as extraction/correspondence algorithms for layered two-dimensional image feature points (Fig. 3).

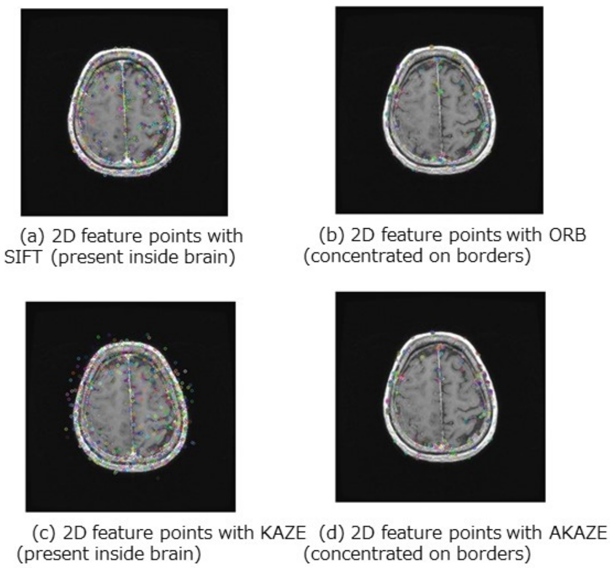


Figure 3. Feature points extracted from an actual patient's two-dimensional DICOM slice images.

A. AKAZE

AKAZE is an improved version of the KAZE algorithm. It employs a unique form of description called the Modified-Local Difference Binary (M-LDB). The scale space produced by the Gaussian filter (linear dispersion filter) used in SIFT and SURF is isotropic. This causes the edges of objects to become blurred, and local characteristics always be picked up properly. In order to resolve this issue, nonlinear and anisotropic scale space is utilized.

B. KAZE

KAZE is a feature quantity named after the Japanese character for wind, which is calculated using a nonlinear dispersion filter. Compared to SURF and SIFT, it powerfully detects changes in objects such as expansions, reductions, and rotations. Although Gaussian filters generally stand up well against noise, their disadvantage is that they erase feature quantities in flat regions owing to image smoothing. KAZE is useful in many situations, because it can eliminate noise while preserving feature quantities in flat regions.

C. ORB

ORB, is an alternative to SIFT and SURF that can be freely employed, because it has not been patented. It combines a FAST key point detector and a BRIEF feature descriptor. Key points are detected using FAST, and the Harris corner scale is used to narrow down these candidates to the top N items. In addition, an image pyramid is used to generate multiscale features. For feature point matching, a multi-probe locality-sensitive hashing (LSH) is utilized, which is an improved version of the existing LSH. ORB is considerably faster than SURF or SIFT. The ORB descriptor performs better than SURF, and ORB is a good choice for tasks such as creating panoramic images with equipment that is not highly functional.

D. SIFT

SIFT is able to pick up feature points as usual, even when affected by lighting or in the presence of an expansion, reduction, or rotation. Some of its primary uses are to ascertain minute features and produce panoramic pictures. This is why SIFT stands up well against changes in brightness, scale, and rotation, where changes in scale are recognized using the difference of Gaussians DoG on 26 dimensions, rotational changes are recognized using adjacent voxels and threshold processing, and brightness changes are recognized by the normalization of feature vectors (128 dimensions).

Finally, when an octree or similar is utilized to process a DICOM file through binary space partitioning, the feature point correspondence between DICOM files moves from a full search to partial search to be completed. In general, in organ deformation three-dimensional feature points only move within the area surrounding them, making it unnecessary to perform a full search using SLAM or PTAM with robots or cameras that can move freely in three-dimensional environments. In addition, searches of each layer region can be conducted through parallel processing with GPGPU multi-cores, and although this has not yet been implemented, it will provide a method of further speeding up the processing.

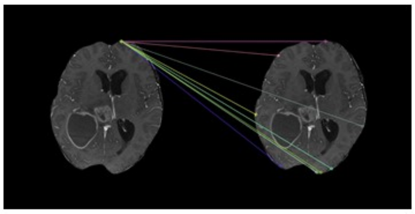
IV. RESULTS OF EXPERIMENTS WITH BRAIN DICOM FILES

A brain shift is the situation in which, after a craniotomy in a neurosurgical procedure, spinal fluid is lost and the brain sinks owing to the effect of gravity. This causes discrepancies between DICOM files produced preoperatively and the actual lesion sites to be operated on, leading to a marked drop in surgical accuracy when DICOM files are used in the removal of malignant tumors.

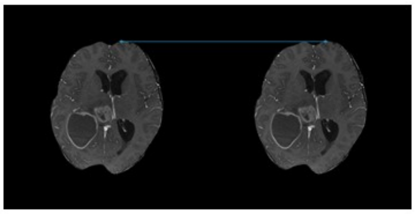
In this chapter, we first verify the method of extracting feature points from one layered two-dimensional DICOM image in the order of the strongest similarity with the feature points in the other layered two-dimensional DICOM image. Next, because a normal layered two-dimensional DICOM image contains few feature points around the periphery of or within the brain, and exhibits a bias towards these locations, the Canny edge detection algorithm and a Sobel-filter edge detection algorithm are utilized to generate a large number of feature points across a wide area of the brain DICOM file. Then, these are employed to select pairs from the 124 layered two-dimensional DICOM images in a combined manner, including pairs with the same image twice, and the pair with the maximum number of mapped feature points is determined. This process automatically extracts regions in which brain shift has occurred. If two images with the same number have the maximum amount of mapped points, then we know that brain shift has not occurred. Conversely, if the pair with the maximum number of mapped points consists of images with different numbers, then we know the location where brain shift has occurred. Finally, the two-dimensional image feature point extraction/correspondence algorithms SIFT, KAZE, AKAZE, and ORB are utilized to extract and create correspondences between feature points from total and local searches, and the required calculation time, number of feature points extracted, and number of points mapped for the two searches are compared.

A. Feature Point Extraction Using AKAZE, and Matching of Those Points

Here, we first used the feature point extraction/correspondence algorithm AKAZE to extract the top 10 most similar feature points to feature point A in one image (Fig. 4(a)). Then, from those 10 feature points we selected the one in the most similar position to feature point A as the nearby feature point (Fig. 4(b)).



(a) 10-point mapping of certain feature points



(b) Feature point mapping with only nearby point remaining

Figure 4. (a) DICOM image's top 10 feature points in terms of the similarity to feature points in another DICOM image. (b) Feature points among the top 10 most similar points that are near their original positions.

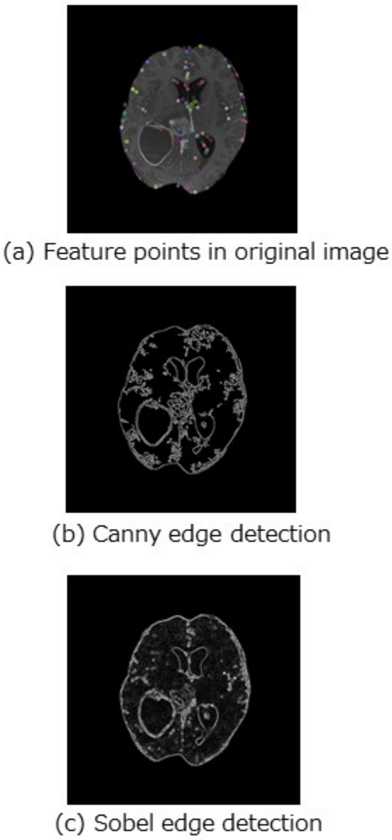


Figure 5. (a) Original DICOM image feature point grouping. (b) Image of Canny edge extraction from original DICOM image. (c) Image of Sobel-filter at extraction from original DICOM image.

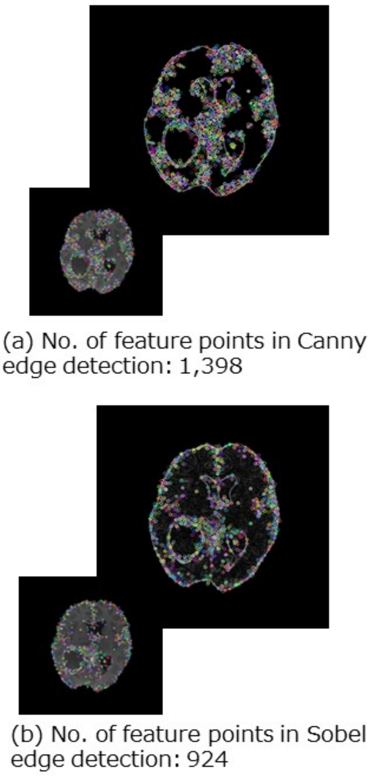


Figure 6. (a) Feature points from Canny edge detection (total 1,398 points). (b) Feature points from Sobel-filter edge detection (total 924 points).

In the original layered two-dimensional DICOM image, the number of feature points that appear is insufficient, and the points are scattered rather than appearing over a wide range in the brain (Fig. 5(a)). To resolve this problem, we applied the Canny edge detection algorithm and a Sobel filter to the layered two-dimensional DICOM image to produce a large number of edges, and feature points were generated from these (Fig. 5(b), (c)). As shown in Fig. 5 and Fig. 6, this edge detection method solidly increased the number of feature points, and spread those points across a wide area (Fig. 6).

B. *Mapping in Original Layered Two-Dimensional DICOM Images and the Maximum-Number Pair*

Here, the feature points of the original layered two-dimensional DICOM images are extracted, these points are mapped, and the pair of images that produces the maximum number of mapped points is identified. As shown in Fig. 7, the original number of feature points is small, meaning that the number of map points is also small. Furthermore, mapping is biased toward the periphery of the brain, and not many points appear within the brain, which is where they are needed to detect brain shifts. We can interpret this as meaning that it is not possible to detect brain shifts using the original layered two-dimensional DICOM images as they are.

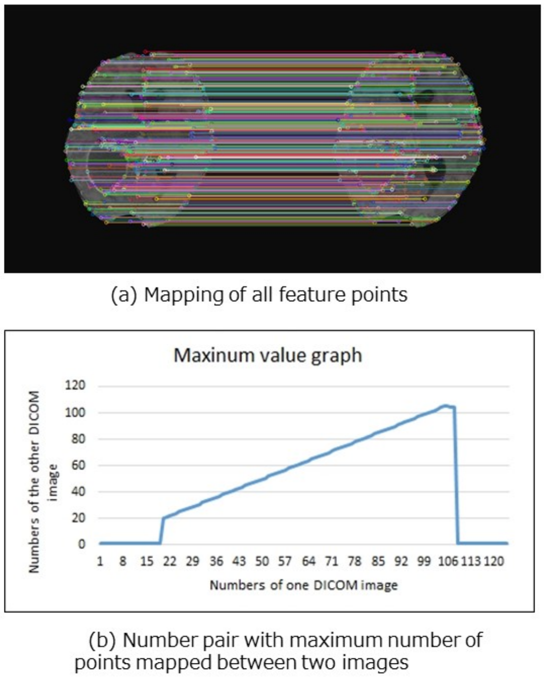
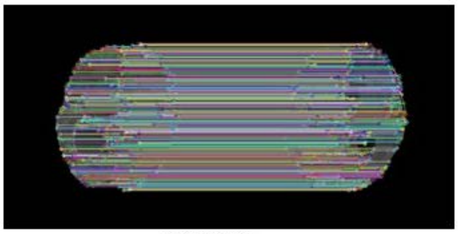


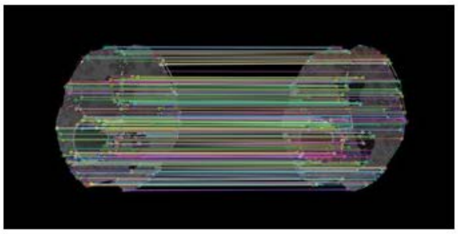
Figure 7. (a) Mapping set for original layered two-dimensional DICOM images. (b) Number of paired, layered two-dimensional DICOM images that produce the maximum number of map points.

C. *Mapping in Layered Two-Dimensional DICOM Images Processed with Canny Edge Extraction Algorithm and the Maximum-Number Pair*

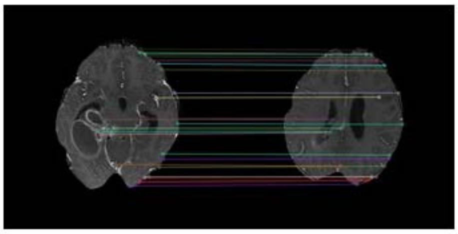
Here, we extracted mapping sets and the numbers of the pair of images with the maximum number of points mapped from the layered two-dimensional DICOM images processed using the Canny edge extraction algorithm. First, Fig. 8 (a), (b), and (c) present the results of matches taken from the pairings of number 68 and number 68, number 68 and number 69, and number 55 and number 80 from the 124 two-dimensional DICOM images. These results reveal that the number of feature points and the number of mapped points is far higher in images with edge detection than in the original images, and that these points appear across a wide area: not only around the periphery of the brain but also within it. Next, image pairs were selected from the 124 images, including pairs that contained images with the same number, and the pair with the maximum number of matches was extracted (Fig. 8(d)). These results show that image pairs with the same number had the highest number of matches.



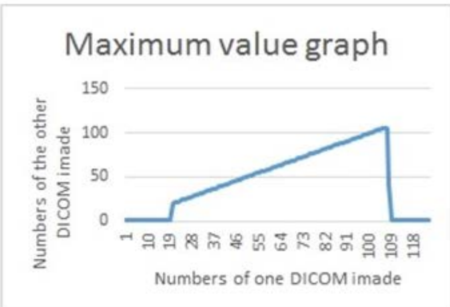
(a) 68×68



(b) 68×69

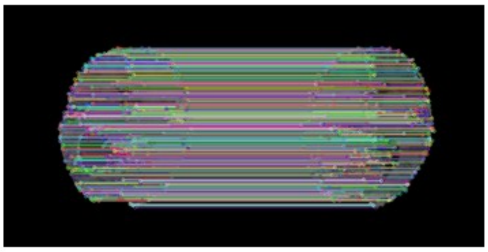


(c) 55×80

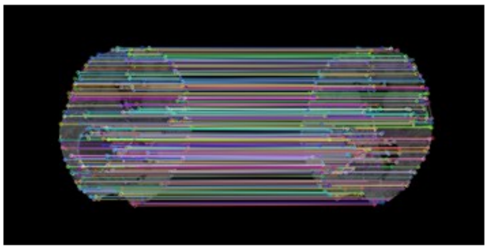


(d) Number pair with maximum number of points mapped between two images

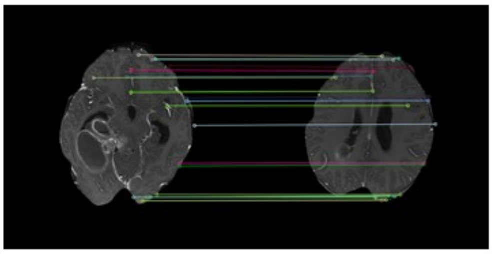
Figure 8. (a), (b), and (c) Results of matches taken from the pairings of number 68 and number 68, number 68 and number 69, and number 55 and number 80 from the 124 two-dimensional DICOM images processed with the Canny edge detection algorithm. (d) The pair with the maximum number of matches when pairs were selected from the 124 images, including pairs that contained images with the same number.



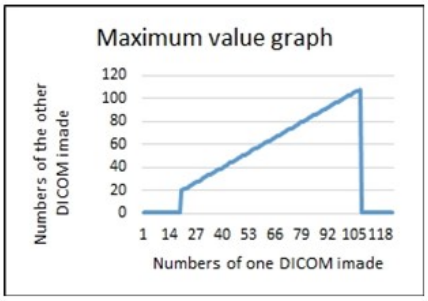
(a) 68×68



(b) 68×69



(c) 55×80



(d) Number pair with maximum number of points mapped between two images

Figure 9. (a), (b), and (c) Results of matches taken from the pairings of number 68 and number 68, number 68 and number 69, and number 55 and number 80 from the 124 two-dimensional DICOM images processed with the Sobel-filter edge detection algorithm. (d) Pair with the maximum number of matches when pairs were selected from the 124 images, including pairs that contained images with the same number.

D. Mapping in Layered Two-Dimensional DICOM Images Processed with the Sobel Filter and the Maximum-Number Pair

Here, the mapping and maximum-number pairs were reproduced in the layered two-dimensional DICOM images processed with the Sobel filter. First, Fig. 9 (a), (b), and (c) present the results of matches taken from the pairings of number 68 and number 68, number 68 and number 69, and number 55 and number 80 from the 124 two-dimensional DICOM images. These results reveal that the number of feature points and the number of mapped points is considerably higher in images with edge detection, and that those points appear across a wide area: not only around the periphery of the brain but also within it. Next, pairs were selected from the 124 images, including pairs that contained images with the same number, and the pair with the maximum number of matches was extracted (Fig. 9(d)). These results show that image pairs with the same number had the highest number of matches.

TABLE I. CALCULATION TIME, NUMBER OF EXTRACTED FEATURE POINTS, AND NUMBER OF POINTS MAPPED FOR A FULL SEARCH AND VICINITY SEARCH OF DICOM FILES USING THE FEATURE POINT EXTRACTION/CORRESPONDENCE ALGORITHMS SIFT, KAZE, AKAZE, AND ORB

Algorithm	SIFT	ORB	KAZE	AKAZE
Full search (processing time [seconds])	0.34	0.01	0.82	0.18
Vicinity search (processing time [seconds])	0.70	1.03	0.98	0.39
Difference in search time for both searches (seconds)	-0.36	-1.02	-0.16	-0.21
Number of feature points in image 1 (points)	450	500	162	198
Number of feature points in image 2 (points)	472	500	190	226
Number of mapped points (full [points])	274	291	112	151
Number of mapped points (vicinity [points])	192	352	106	143
Difference in number of mapped points (points)	82	-61	6	8

E. *Comparison of Calculation Time, Number of Extracted Feature Points, and Number of Points Mapped for a Full Search and Vicinity Search Using the Feature Point Extraction/Correspondence Algorithms SIFT, KAZE, AKAZE, and ORB*

Here, the two-dimensional image feature point extraction/correspondence algorithms SIFT, KAZE, AKAZE, and ORB were utilized to extract and create correspondences between feature points from total and local searches, and the required calculation time, number of extracted feature points, and number of mapped points were compared. As shown in Table 1, we learned that vicinity searches, which require the vicinity to be checked, required more time to calculate than full searches, which do not. This was true for all algorithms. Furthermore, for the algorithms SIFT, KAZE, and AKAZE the vicinity searches eliminated mistaken correspondences, decreasing the number of mapped points. However, for the ORB algorithm, the vicinity search extracted more mappings than the full search using one-way confirmation (feature points b1 through b10 in the two-dimensional DICOM image B are selected in order of the strongest similarity with feature point ai in the two-dimensional DICOM image A, and among these the point located closest to feature point a is selected as bi and matched) or two-way confirmation (the feature point in the two-dimensional DICOM image B with the strongest similarity to the feature point a in the two-dimensional DICOM image A is selected as feature point b, and then the feature point in the two-dimensional DICOM image A with the strongest similarity to feature point b in the two-dimensional DICOM image B is selected as feature point a, and there is determined to be a match if a=a'). In terms of the confirmation accuracy, this is because one-way confirmation is less strict than two-way confirmation.

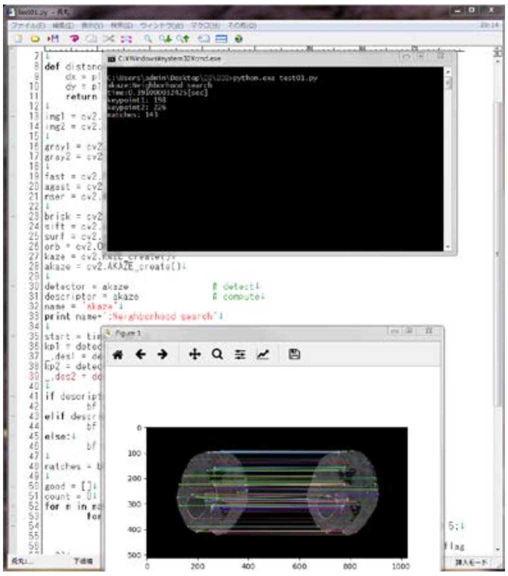


Figure 10. Results of feature-point mapping in the vicinity search with AKAZE.

Finally, Fig. 10 presents the results of feature-point mapping in a vicinity search, while Fig. 11 shows the same for a full search. Fig. 12 presents the results of feature-point mapping for the vicinity search with ORB, while Fig. 13 shows the same for a full search.

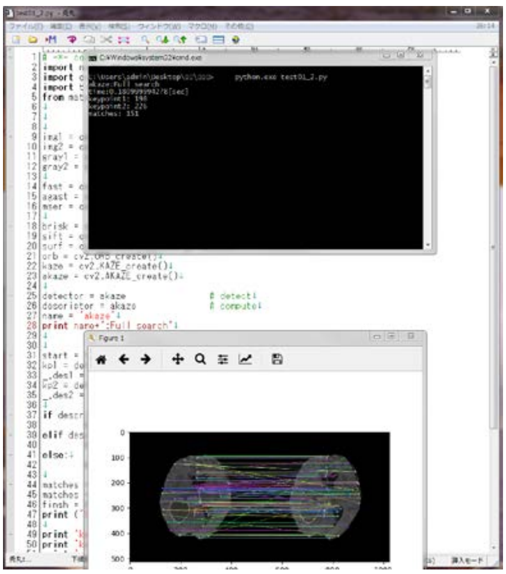


Figure 11. Results of feature-point mapping in full search with AKAZE.

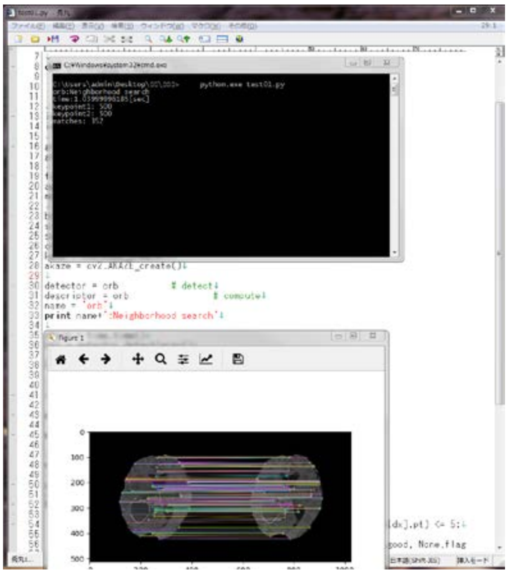


Figure 12. Results of feature-point mapping in vicinity search with ORB.

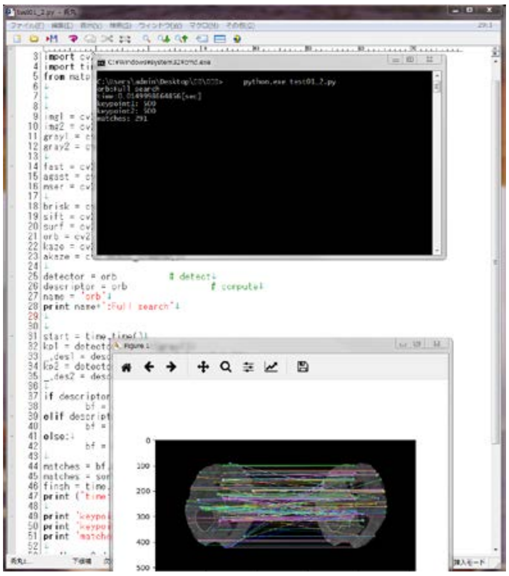


Figure 13. Results of feature-point mapping in full search with ORB.

V. CONCLUSIONS

This study used layered two-dimensional DICOM images from an actual patient to conduct basic experiments for identifying brain shifts. First, numerous feature points scattered on the surface of and within the brain in two-dimensional DICOM images were extracted, and the number of these points that are mapped was investigated by selecting pairs of 124 images. The results showed first that pairs with the same number had the highest number of mapped points. This indicates that a brain shift has not occurred in the DICOM file. If preoperative and postoperative DICOM files were to be used, then pairs with different numbers should have the highest numbers of mapped points, and it should be possible to estimate the location at which a brain shift occurs from the shape of the graph.

Next, we learned that in the original two-dimensional images, the number of feature points inside the brain was small. To improve this, we employed the Canny edge detection algorithm and a Sobel-filter edge detection algorithm to generate a large number of edges in the original two-dimensional images. As a result, we prepared a huge number of feature points around and inside the brain in the two-dimensional DICOM images. Then, we employed this result to map feature points in two copies of the same image (the 68th image), two consecutive images (the 68th and 69th), and two images that were far apart (the 55th and 80th). With these results, we produced a large number of mapped points, not only on the surface of the brain but also within it, and confirmed for all pairs that pairs of images with the same number produced the largest number of mapped points.

Finally, we used the feature point extraction/correspondence algorithms SIFT, KAZE, AKAZE, and ORB to study calculation time, number of extracted feature points, and number of points mapped for a full search and vicinity search of the DICOM files. In terms of the calculation time, the more difficult it was to calculate the distance, the longer the calculation time became for vicinity searches compared to full searches. Next, the fewer mistaken correspondences there were, the lower the number of matches for vicinity searches were compared to full searches when using the algorithms SIFT, KAZE, and AKAZE. However, as described in the previous chapter, the determination of matching is different in vicinity searches and full searches, and because determination is less strict in the former than in the latter vicinity searches only exhibited more matches than full searches when using the ORB algorithm.

ACKNOWLEDGMENT

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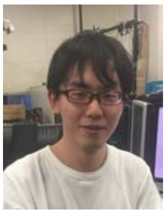

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