COMPARISON OF FEATURE MATCHING TECHNIQUES IN 2D-3D CONSTRUCTION FOR MEDICAL APPLICATIONS

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ABSTRACT

3D medical imaging is a rapidly growing market, gaining traction among researchers for its advanced capabilities in visualizing anatomical structures, which in turn helps in detecting anomalies and severe health conditions, guiding surgical procedures, and improving patient outcomes. Though it has the potential to be an integral part of medical procedures, it has some hindrances that need to be addressed for efficiency and reliability. In this paper, we compared various hand-crafted image processing algorithms such as SIFT, SURF, ORB, and AKAZE used for feature detection and mapping that play a crucial role in improving the accuracy of the 3D conversion of medical images. We used Computed Tomography (CT) scan data of the pancreas to study algorithms, compared them on multiple parameters, and it was observed that ensembling multiple algorithms provide a 3D construction with improved accuracy for medical imaging.

Index Terms— Feature Descriptor, Feature Matching, 3D Construction, Medical Imaging

1. INTRODUCTION

With doctors increasingly counting on data to make better decisions, reliance on technology becomes inevitable. While 3D medical imaging already crossed a 200 million dollar market share, it is expected to be an integral of medical procedures by 2035 or sooner [1]. 3D medical imaging employs modern image processing techniques to convert a set of 2D images into a 3D model without the need for additional hardware resources.

The 2D to 3D conversion process involves collecting 2D images of various angles and detecting the features to be matched with the rest of the images. This result is then used to find the depth information to convert it into a 3D model. The accuracy of the 3D model reproduced depends on the number of features detected and matched among images [2]. Thus, it is important to find the best feature descriptor algorithms to produce better results.

The dataset used for this study has been taken from the National Institutes of Health Clinical Center, it was collected by performing abdominal contrast-enhanced CT scans on 82 healthy subjects (53 male and 27 female) aged between 18-76 years [3] [4] [5]. The CT scan of one of the subjects was taken and used for this analysis .

2. RELATED WORK

Various computational methods have been introduced using a variety of image processing techniques to acquire precise 3D information from 2D images to construct 3D medical models. Recently, several research studies have demonstrated the effectiveness of feature-matching algorithms in medical 3D image construction.

An experiment carried out by H.Madzin et al. used the Harris-Laplace method to extract features from each slice, then locate and match identical features in each slice using Scale-Invariant Feature Transform (SIFT) to construct a 3D Lung cancer cell [6]. It demonstrates that, despite having distinct frames of view, this approach was able to extract similar features. A similar feature matching-based technique was proposed by Zhang et al. for reconstructing the femur bone from a collection of 2D X-ray pictures using SIFT [7]. This method effectively produced the 3D information. Overall, SIFT is widely used for feature matching, particularly in applications where robustness to geometric and photometric transformations is critical [8].

In his research on the 3D construction of the human pelvis from 2D CT slices, P Kemancay et al. designed a methodology based on Speeded-Up Robust Features (SURF) in combination with a Sum of Squared Distances (SSD) matching algorithm [9]. SURF uses Haar wavelet response to compute image gradients, which allows it to perform feature detection and description more quickly than SIFT [10].

K. P. Win et al. proposed a methodology based on Oriented FAST and Rotated BRIEF (ORB) for stitching biomedical images [11]. In the experiment, various feature detectors such as Harris detector, SIFT, SURF and ORB were compared. Out of all, ORB performed the best. Introduced by E Rublee et al., ORB builds on two existing algorithms - the FAST (Features from Accelerated Segment Test) keypoint detector and the BRIEF (Binary Robust Independent Elementary Features) descriptor [12]. ORB improves on these algorithms by using a modified version of the FAST algorithm that is rotation-invariant and orientation-sensitive and using a modified version of BRIEF that is rotation-invariant and scale-invariant, making it more robust to changes in the scale and rotation of key points.

After completing a survey of the existing research, we have chosen four feature descriptor algorithms - SIFT, SURF, ORB, and AKAZE (Accelerated Kernels for Adaptive and Zeroth-Order Extension) for our analysis. Out of these, SIFT and SURF are Gradient Based Descriptors, ORB is Binary Based Descriptor and AKAZE is Hybrid Feature Descriptor. Introduced by P. F. Alcantarilla et al., AKAZE is based on the KAZE (Kernels for Adaptive and Zeroth-Order Extension) algorithm. It computes feature descriptors directly from the image gradient magnitude and orientation which makes it significantly faster than other feature-based algorithms [13].

Taking inspiration from these explorations, we carried out the analysis of different feature descriptor algorithms on the Pancreas CT dataset.

3. METHODOLOGY

3.1. Image Preprocessing

Initially, we take the pancreas CT scan dataset and perform gray-scaling to ensure that images are consistent in terms of color representation. This reduces the complexity of the calculation and fastens the processing time.

3.2. Feature Detection

Features are detected in each image using the inbuilt OpenCV feature detector algorithms - SIFT, SURF, ORB, and AKAZE. These features may include points, blobs, edges, or other distinctive patterns in the image.

3.3. Feature Description

A feature descriptor is computed for each detected feature, which encodes the local appearance of the feature using a set of numerical values. The descriptor should be unique and invariant to certain transformations, such as rotation, scale, and illumination changes.

3.4. Feature Matching

The descriptors of features in one image are compared with those in another image to find potential matches. This is typically done using a distance metric, such as Euclidean distance or Hamming distance, and a threshold to determine which matches are valid.

3.5. Outlier Rejection

Not all potential matches will be valid, as some may be caused by noise or other factors. We use the RANSAC algorithm to remove incorrect matches and improve the accuracy of the feature matching.

3.6. Ensembling

The output received is inspected for various parameters such as the number of features detected between the two images, features matched before and after removing outliers, and computation time. Based on the ranking we ensemble the best algorithms to find the best combination.

3.7. 3D Reconstruction

Once corresponding points or features have been identified in multiple images, the 3D structure is reconstructed by projecting the matched points in a 3D space.

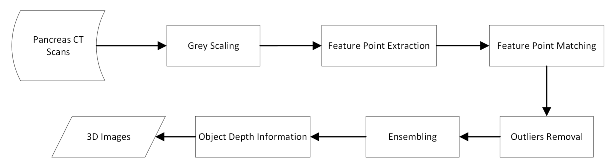


Fig. 1. Pipeline used for Analysis and 3D Construction

4. ANALYSIS

The analysis of four feature descriptor algorithms for medical CT images produced interesting results. The data in Table 1 shows the features detected from two images and the feature matching results with outliers and without outliers for the four algorithms. Compared to ORB and SIFT, SURF and AKAZE produced a greater number of key points, with SURF identifying the most key points. The maximum and least number of feature matches were produced by SURF and SIFT respectively. Following RANSAC, SURF produced a higher number of matches followed by AKAZE and SIFT, with ORB identifying the least matches.

Algorithm	Features	Outliers	Without Outliers
SIFT	1265	233	225
SURF	3541	772	742
ORB	500	237	185
AKAZE	1306	319	316

Table 1. Features detected in both the images

For feature generation, ORB and AKAZE were computationally most efficient. When it comes to feature matching, SURF and ORB took more time as compared to SIFT and AKAZE. The computing times of the feature generators and feature matching for four algorithms are shown in Table 2.

Algorithm	Descriptor Generator	Feature Matching
SIFT	$238.46ms$	$4.29ms$
SURF	$234.21ms$	$15.89ms$
ORB	$0.9ms$	$15.85ms$
AKAZE	$0.9ms$	$8.01ms$

Table 2. Time Taken for Feature Extraction & Matching

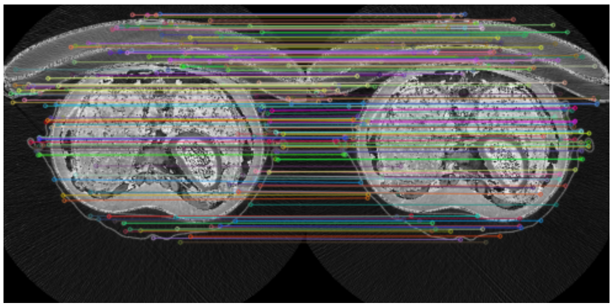


Fig. 2. Feature matching of SURF Algorithm

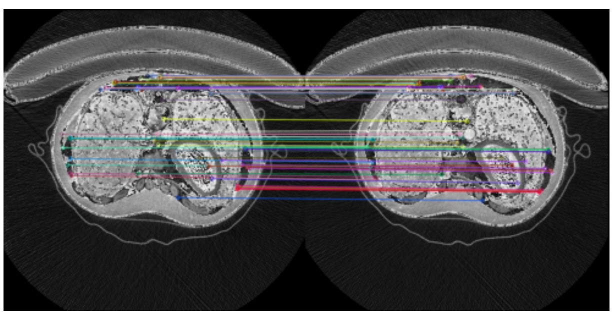


Fig. 3. Feature matching of ORB Algorithm

Fig. 2 shows the feature mapping of two medical CT images of the SURF algorithm. From our analysis, we observed that SIFT, AKAZE and SURF algorithms matched the key points over the edges of the images, with SURF proving to be the best algorithm for matching key points over edges. Furthermore, the data indicates that SURF has the highest number of matching points in both cases, with and without outliers.

On the other hand, ORB proved to be the perfect algorithm for detecting the edges inside the pancreatic part of the image as shown in Fig. 3. It matched the inner part of the images and had a higher number of matching points in inner region when compared to other algorithms.

Based on these findings, we decided to combine SIFT, AKAZE, and SURF with ORB to increase the number of matching points and improve the accuracy of 3D image construction.

5. ENSEMBLE

The performance of SIFT, AKAZE, SURF, and ORB was evaluated on pancreas CT images. These algorithms are ensembled to improve the accuracy and matching points for 3D image reconstruction. It was identified that the SURF-ORB ensemble outperformed the other ensemble algorithms by producing the highest number of matched features in both cases, with and without outliers. Furthermore, the analysis indicated that SURF-ORB was the most efficient algorithm for matching key points of both the inner and outer edges of the images, with double the value of points when compared with the other two ensemble algorithms. These findings suggest that the SURF-ORB ensemble may be a promising approach for feature extraction and matching in medical image processing. Table 3 below shows the performance of ensemble algorithms.

Ensemble	Features	Outliers	Without Outliers
SIFT - ORB	1765	470	410
SURF - ORB	4041	1009	750
AKAZE - ORB	1807	556	325

Table 3. Number of Features Detected and Features Matched

Table 4 shows the computational time of feature extraction and feature matching for three ensemble algorithms. The results indicate that the AKAZE - ORB algorithm has the fastest feature extraction and matching time while SURF - ORB algorithm has the slowest feature extraction and matching time.

Ensemble	Feature Extraction	Feature Matching
SIFT - ORB	$70.36ms$	$11.01ms$
SURF - ORB	$145.83ms$	$53.03ms$
AKAZE - ORB	$55.45ms$	$29.5ms$

Table 4. Time Taken for Feature Extraction & Matching

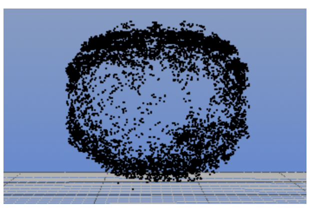
These results suggest that the AKAZE - ORB ensemble may be the most efficient algorithm. However, the SURF-ORB algorithm comes with a trade-off of high computational time, particularly during feature extraction. Despite this drawback, the SURF-ORB ensemble demonstrated impressive performance in terms of matching key points between images in both cases, with and without outliers.

6. 3D CONSTRUCTION

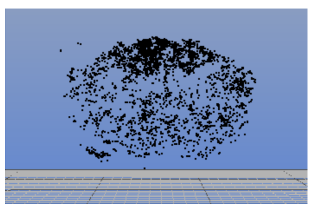
As the study uses the images obtained from CT Scan for analysis, various slices have been extracted from the pancreas dataset of a subject. Feature extraction is performed on the slices and the matches obtained after removal of the outliers have then been projected to the 3D space determined by the x,y coordinate based on the location of the matched feature point in the image while the z coordinate is computed based on the CT slice using the slice thickness parameter. This forms a sparse 3D point cloud.

The 3D point cloud obtained displays the points which have been extracted and matched among the set of images passed as an input to the 3D construction algorithm. This 3D point cloud is analyzed based on the density of the points spread among the space, which determines that the algorithm has been successful in identifying key points and matching them across the entire area, i.e. both the external anatomical structure as well as the inner organs.

Fig. 4(a) depicts the point cloud generated using the SURF algorithm. From this visualization, it is evident that SURF is able to detect most feature points across the outer edges of the Pancreas. From Fig. 4(b), it is observed that even though ORB has a lower amount of feature points, it is able to detect a lot more features located in the interior region. Thus, as mentioned in the previous section, ensembling both SURF and ORB for 3D construction would give a better result as shown in Fig.5.



(a) SURF



(b) ORB

Fig. 4. 3D Point Cloud

From Fig. 5, it can be seen that ensembling SURF and ORB together for 3D construction improves the point cloud by including both the outer and inner feature points thus providing a better 3D construction.

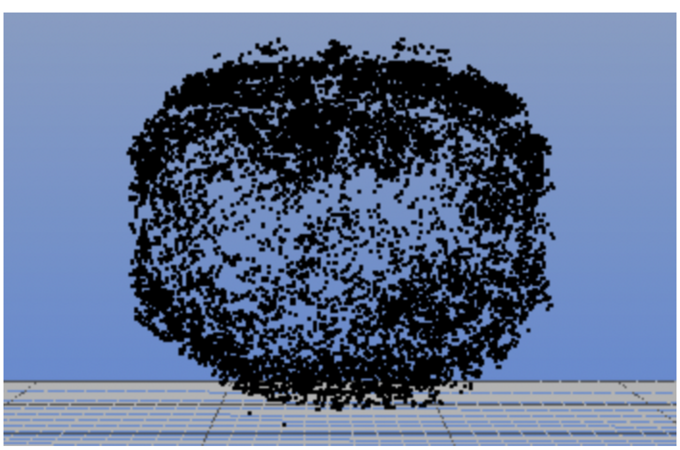


Fig. 5. 3D Point Cloud using Ensemble of SURF & ORB

7. RESULTS AND DISCUSSION

The study compared the performance of four feature descriptor methods for feature extraction and matching on medical CT images: SIFT, SURF, ORB, and AKAZE. The results revealed that SURF and AKAZE generated more key points than ORB and SIFT. SURF produced the most matching points, both with and without outliers, and it detects the outer edges of medical images effectively. ORB was discovered to be the best algorithm for detecting match points inside an image. Then, SIFT, AKAZE, and SURF were integrated with ORB to enhance the number of matching points and hence improve the accuracy and robustness of 3D image reconstruction.

Then a 3D point cloud was constructed from CT scan images of a subject's pancreas. This process involves extracting and matching feature points from the images, projecting them into a 3D space, and analyzing the density of the resulting point cloud. We projected the performance of two feature extraction algorithms in Fig. 4, SURF and ORB, and found that ensembling the two algorithms leads to better results, including the detection of both outer and inner feature points of the image. The resulting 3D point cloud provides a better representation of the subject's pancreas.

8. CONCLUSION AND FUTURE WORK

The primary challenge for our research is achieving high accuracy which is hindered by noisy images, artifacts, and the complexity of the anatomy. These factors affect the performance in feature matching which in turn impacts 3D reconstruction. We can further use deep learning techniques to improve the accuracy of feature-matching algorithms and 2D-3D reconstruction. Deep learning techniques can be also ensembled with our native image processing algorithms to get the best out of both worlds.

Medical imaging often involves the use of multiple modalities such as CT, MRI, etc. Matching features across different modalities can be challenging due to differences in image appearance and acquisition parameters. In future, we can focus on developing algorithms that can match features across multiple modalities and combining information from them can lead to more accurate 3D reconstruction.

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