Performance comparison of ORB, SURF and SIFT using Intracranial Haemorrhage CTScan Brain images

Ammar Oad[1], Karishma Kumari[2], Imtiaz Hussain Koondhar[2], Bacha Hammad[3], Feng Dong[1], Rajkumari Oad[1]

[1] Faculty of Information Engineering, Shaoyang University, Shaoyang 422000, China.
[2]Isrra University Hyderabad Sindh Pakistan.
[3] Department of Emergency Medicine, the Second Xiangya Hospital, Central South University, 139 Renmin Road, Changsha 410011, China.
Email: ammar.oad@hnsyu.edu.cn, karishmakumari27@gmail.com, imtiaz@yahoo.com, dongfeng@stu.shmtu.edu.cn, rajkumarioad_88@yahoo.com, khanmalakshah786@gmail.com

Corresponding Author: Ammar Oad, ammar.oad@hnsyu.edu.cn

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***Abstract*:** Medical images play a very important role in making the right diagnosis for the doctor and in the patient's treatment process. Using intelligent algorithms makes it possible to quickly distinguish the lesions of medical images, and it is especially important to extract features from images. Feature extraction is an important step in image classification. It allows the representation of the content of images as perfectly as possible. The intention of this study is to certain overall performance assessment among the feature detector and the descriptor method, especially while there are numerous combos for assessment. Three techniques were decided on for the feature descriptors: ORB (Oriented FAST and Rotated BRIEF), SIFT (Scale Invariant Feature Transformation), and SURF (Accelerated Robust Feature) and to calculate matching evaluation parameters, for example, the number of key points in the image, Execution time required for each algorithm and to find the best match. The dataset was taken from Kaggle, which contained 170 CTScan images of the brain with intracranial hemorrhage masks. The bruteForce method is used to achieve feature matching. Performance analysis shows the discriminative power of various combinations of detector and descriptor methods. SURF algorithm is the best and most robust in CTScan imaging to help medical diagnosis.

Index Terms: scale-invariant feature transform (SIFT), speed up robust feature (SURF), oriented FAST, rotated BRIEF (ORB), Image matching.

1. Introduction

Medical image is the main carrier and important carrier of modern medical alternative language description. Medical image analysis is a modern image analysis technology that integrates mathematical modeling, artificial intelligence, integrated medical imaging, digital image processing, and other multidisciplinary. [1]. Feature matching is an important technique to identify a single object in different images. It helps machines to construct recognition of a specific object from multiple perspectives. [2]. Image processing may be performed by extracting features for identification, classification, diagnosis, classification, clustering, recognition, and detection. [3]. There are many bio-medical imaging technologies available such as Radiography (X-ray image), CT-Scan, ECG, Ultrasound, MRI, etc [4]. These images are unlike typical photographic images primarily as they disclose internal anatomy as contrasting to an image of surfaces. [5]. There are many feature-based techniques are used in computer vision applications, such as the HARRIS detector, Scale Invariant Feature Transform (SIFT), Principal Component Analysis SIFT (PCA-SIFT), Bag of Features (BOF), Features from Accelerated Segment Test (FAST), Speed-up Robust Feature detector (SURF), and Oriented FAST and Rotated BRIEF (ORB) [6]. In this paper, Image matching methods based on ORB, SURF, and SIFT algorithms are reviewed and implemented on the Intracranial Hemorrhage CTscan image dataset using OpenCV in Python to compare ORB, SURF and SIFT in terms of key points, time spent, best matching.

The rest of this paper is organized as follows: Section 2 presents an overview of the three image-matching techniques SIFT, SURF, and ORB. In Section 3, we represent the literature review. In Section 4, Matcher of Images have been discussed. In Section 5, the material and methods have been presented. In Section 6, Simulation results have been discussed. Section 7 concludes the paper.

1.2. Image Matching Techniques Overview

1.2.1. SURF*:* (Speed up Robust Features) algorithm is based on multi-scale space theory and the feature detector is based on Hessian matrix. Since Hessian matrix has good performance and accuracy. In image I, x = (x, y) is the given point, the Hessian matrix H(x, σ) in x at scale σ, it can be define as

$$\boldsymbol{H(X,\sigma)} = \begin{bmatrix} \boldsymbol{Lxx(X,\sigma)} & \boldsymbol{Lxy(X,\sigma)} \\ \boldsymbol{Lxy(X,\sigma)} & \boldsymbol{Lyy(X,\sigma)} \end{bmatrix} \quad (1)$$

Where Lxx (x, σ) is the convolution result of the second order derivative of Gaussian filters ∂^ (2) 〖∂x〗 ^2 (σ) with the image I in point x, and similarly for Lxy (x, σ) and Lyy (x, σ). SURF creates a "stack" without 2:1 down sampling for higher levels in the pyramid resulting in images of the same resolution. Due to the use of integral images, SURF filters the stack using a box filter approximation of second-order Gaussian partial derivatives. Since integral images allow the computation of rectangular box filters in near constant time [7] For Abstract and Index Terms, no first-line indentation. Alignment: left and right-justify your columns. Left-Aligned your table captions, and figure captions. Center-justify your tables and figures. Use automatic hyphenation and check the spelling. Digitize or paste down figures.

1.2.2. SIFT: SIFT descriptor based on multiple scale-spaces was presented by Lowe in 2004. For Space Extreme Detection. First of all, images between two adjacent octaves are down-sampled by a factor of 2. Multichannel Gaussian functions are adopted to smooth images belonging to different octaves. Thus, the Gauss pyramid is established. The DoG space pyramid is generated by the difference of Gauss pyramid between two adjacent scales belonging to the same octave. Then the DoG space pyramid is established. Consider the following:

$$\mathbf{L}\ (\mathbf{x},\mathbf{y},\boldsymbol{\sigma}) = \mathbf{G}(\mathbf{x},\mathbf{y},\boldsymbol{\sigma}) * \mathbf{I}\ (\mathbf{x},\mathbf{y}), \quad (2)$$

$$\mathbf{DoG}\ (\mathbf{x},\mathbf{y},\boldsymbol{\sigma}) = \mathbf{L}\ (\mathbf{x},\mathbf{y},\mathbf{k}\boldsymbol{\sigma}) - \mathbf{L}\ (\mathbf{x},\mathbf{y},\boldsymbol{\sigma}), \quad (3)$$

where σ represents the scale factor and $I(x, y)$ is the input image. Also, $*$ is the convolution operation in x and y. Meanwhile, (x, y, σ) is the representative of the Gaussian function with different scale-space kernels. In order to detect extreme points from the scale space, the pixel point is compared with its neighbor points in a $3 * 3*3$ cube consisting of three adjacent intervals belonging to the same octave. This pixel point is chosen as the candidate point on the condition that it is a local extreme with regard to the extreme detection cube.

1.2.3. Keypoints Localization: is to perform a detailed fit to the nearby data for location, scale, and the ratio of principal curvatures. Low contrast points and unstable points with strong edge responses are discarded to improve the robustness of key points. Firstly, Taylor's expansion of the scale-space formula with regard to each candidate point is adopted. The specific steps are shown as follows. These candidate points with low contrast values will be discarded from the candidate points. Consider

$$\mathbf{D}\ (\mathbf{X}) = \mathbf{D} + \frac{\boldsymbol{\partial D^T}}{\boldsymbol{\partial X}}\boldsymbol{X} + \frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{X^T}\frac{\boldsymbol{\partial^2 D}}{\boldsymbol{\partial X^2}}\boldsymbol{X}, \quad (4)$$

Where $X = (x, y, \sigma)\ T$ is the offset from this point. The accurate position of extreme key point $\hat{X}$ is found by calculating the derivative of function D regarding point X. [8]

1.2. 4. ORB: ORB is a fusion of the FAST key point detector and BRIEF descriptor with some modifications. Initially, to determine the key points, it uses FAST. Then a Harris corner measure is applied to find top N points. FAST does not compute the orientation and is a rotation variant. It computes the intensity-weighted centroid of the patch with located corner at center. The direction of the vector from this corner point to centroid gives the orientation. Moments are computed to improve the rotation invariance. The descriptor BRIEF poorly performs if there is an in-plane rotation. In ORB, a rotation matrix is computed using the orientation of patch and then the BRIEF descriptors are steered according to the orientation. [9] ORB descriptor was based on the BRIEF descriptor, but has an efficient calculation of the interest point's orientation and a variance and correlation analysis of interest points to deliver best results. [10].

1.3. Literature Review*:* Surbhi Gupta et.al, an efficient and exact face recognition algorithm is proposed based on the integration of feature extraction using SURF and SIFT algorithms. Test results in the dataset of FACE 94, Yale2B, ORL, FERET and M2VTS show that the proposed method is efficient and robust [11]. The descriptor generator module has been modified to improve algorithm performance. The SIFT algorithm consists of modules: key factor detection module and descriptor era module. Compared to current solutions, the rate of the descriptor era module has been increased 15 times and the time to extract features has also been reduced. The Algorithm must be resistant to noise and must be able to identify features quickly. The calculation speed of the algorithm must be very slow for use in modern equipment and systems [12]. Feature point comparison based on BRISK and ORB algorithms and algorithm improvement and feature point extraction experiments combining the advantages of the two are carried out. The accuracy of matching pyramid images between data sources is high. (1) When the number of pyramidal layers in the ORB algorithm is 8, the matching precision of pyramidal images between data sources is high. (2) Combining the characteristics of BRISK and ORB, optimize and improve the algorithm, so that the algorithm has excellent lighting robustness and fast computing power, as well as BRISK scale invariance [13]. Shaharyar Ahmed Khan et.al, Provides a comprehensive comparison of the descriptors for the SIFT, SURF, KAZE, AKAZE, ORB, and BRISK function detectors. Test results provide new and valuable information and insights for making key choices in vision-based applications. The precision of SIFT and BRISK is taken into account the very best of all sorts of geometric transformations, whereas SIFT is considered the foremost correct algorithm [14]. Daliyah S et.al, a new feature detection algorithm is proposed to solve some shortcomings of its SIFT and SURF algorithms. The proposed algorithm is called the accelerated and powerful scale invariant attribute transformation (SRSIFT) algorithm. It improves the speed of the SIFT algorithm and maintains its robustness. Improved the distribution accuracy of real BKP in the currency margin, which is better than the other two algorithms [15]. Ebrahim Karami et.al. For different types of transformations and distortions, such as scaling, rotation, noise, fisheye distortion, and clipping, three different image matching techniques are compared. In order to achieve this goal, different transformation styles are applied to the original image, and appropriate evaluation parameters are displayed, such as the amount of key points within the image, the matching rate, and also the execution time needed for every algorithm. ORB is that the quickest algorithm, SIFT works best in most cases [16]. M. Hanmandlu An effective algorithm has been developed to systematically locate the focus in the fingerprint after multiple events. This method uses the SIFT points detected in the fingerprint image as possible candidate points to determine the center point. The SIFT method eliminates noise and parasitic points, thereby minimizing the possibility of detecting false points in the heart. It is observed that the proposed method can detect the center point even in the extreme case where the center point is located at the edge of the fingerprint [17]. Shuvo Kumar Paul et al, In the presence of different geometric and photometric transformations, eight detectors and eight descriptors were compared and evaluated. The goal is to compare these methods to understand which combination produces the best performance in terms of speed and accuracy. On the detector, FAST, AGAST, and ORB detect more key points on average, and the speed is significantly faster. Descriptors generally work best when combined with KAZE and AKAZE detectors. In terms of descriptors, BRIEF, LUCID, ORB are faster than other methods, and AKAZE always produces better results by matching key points [18]. Ertugrul BAYRAKTAR et.al, explained detailed comparisons of detector performance and feature description methods, especially when different combinations of them are used for image comparison. This study covers five feature detection methods, including Fast Segmentation Test (FAST), Powerful Independent Core function and Binary Orientation (BRIEF) (ORB), Strong Acceleration Function Powerful (SURF) and Scale Invariant Functional Transformation (SIFT). Binary Robust Invariant Scalable Points (BRISK) and five other feature description methods are BRIEF, BRISK, SIFT, SURF and ORB. Results showed that when analyzing different combinations of feature detector descriptors, there is a tradeoff between different performance standards and parameters. If a series of rotations are matched, the algorithm will find weak features and will not match due to a predefined threshold [19]. Yin Fei et.al, proposed a new method to extract features by combining medical images. There are at least three major improvements compared to conventional SR-based synthesis methods. Three crystal structures proposed to improve the quality of the SR-based synthesis method for extracting structural and energetic features of the original image. Experimental results showed that the proposed fusion method can subjectively and objectively achieve better results than the conventional fusion method [20]. Shruthishree S.H and Harshvardhan Tiwari Some basic concepts of medical imaging have been explained. Note that not all of these regions are fully resolved, and all algorithms described here have the potential to be significantly improved. Curvature control flow has proven to be a suitable tool for many image processing tasks, and has a significant impact on engineering knowledge. The mathematical tasks of medical imaging are still important, and the skills required are included in most of the major fields of mathematics [21]. Chaoqun Ma et.al, an integrated ORB algorithm based on local dynamic thresholds defined in the ORB quad tree (QTORB) and a high-level quad tree is proposed. QTORB is based on the ORB's algorithm and focuses on finding and improving feature extraction steps and feature description procedures. First, a local dynamic feature point extraction method based on the threshold is applied. This method can evenly extract feature points in an image. Once the features have been extracted, this document does not appear to be too concentrated and duplicated by managing and optimizing the features based on the fourth approach proposed by MRA. The proposed QTORB algorithm can efficiently perform uniform distribution of features, assuming that the accuracy and real-time are essentially equivalent to the ORB algorithm and related extension algorithms. [22]

1.4. Matchers: Matchers Matching Algorithms (or Matchers) are methods that determine which characteristics represented in the descriptors of two images are similar according to their criteria. Chances of finding a pattern in an image increases with the number of similar features found. Brute force matchers available in OpenCV are simple. Each feature of the first descriptor is compared with all features of the second descriptor according to a distance metric with the closest pair returned. A minimum distance value determines whether the pair will be considered relevant or not. A brief description of the matching algorithms used is presented next according to. In the following equations, V1 and V2 are the feature vectors of the two images, M the size of the vectors and v1[i] and v2[i] are the ith element of the respective vector. The BruteForce-L1 algorithm uses the L1 metric distance, also known as Manhattan or City Block, to determine the distance between floating point descriptors as shown in

$$\boldsymbol{d = (V1, V2) = \sum_{i=1}^{M} |v_1\ [i] - v_2\ [i]} \qquad (5)$$

BruteForce is used by floating points descriptors and the considered distance is L2, also known as Euclidean Distance. This method requires more processing power than BruteForce L1 since it is a quadratic function as shown in [23]

$$\boldsymbol{D = (V1, V2) = \sqrt{\sum_{i=0}^{M} (v_1\ [i] - v_2\ [i])^2}} \qquad (6)$$

1.5. Material and Methods: The experiments are carried out on a laptop with CPU 2.20 GHz processor, 8 GB RAM, and Windows 10 as an operating system. All detectors like (ORB, SURF and SIFT) are implemented in python using OpenCv ver '3.4.2' library. The code is taken from the given link https://docs.opencv.org/4.5.2/dc/dc3/tutorial_py_matcher.html. The dataset computed-tomography-images-for-intracranial-hemorrhage-detection-and-segmentation-1.0.0 for Medical images have been download from https://www.kaggle.com/vbookshelf/computed-tomography-ct-images. From the dataset only four folders of CTScan images were taken each folder contained 26 images. Simply two images the first and second taken from dataset to be compared by the detectors (ORB, SURF and SIFT) with each other, means each folder provided 13 pairs of images, overall it provided 52 pairs for all images.

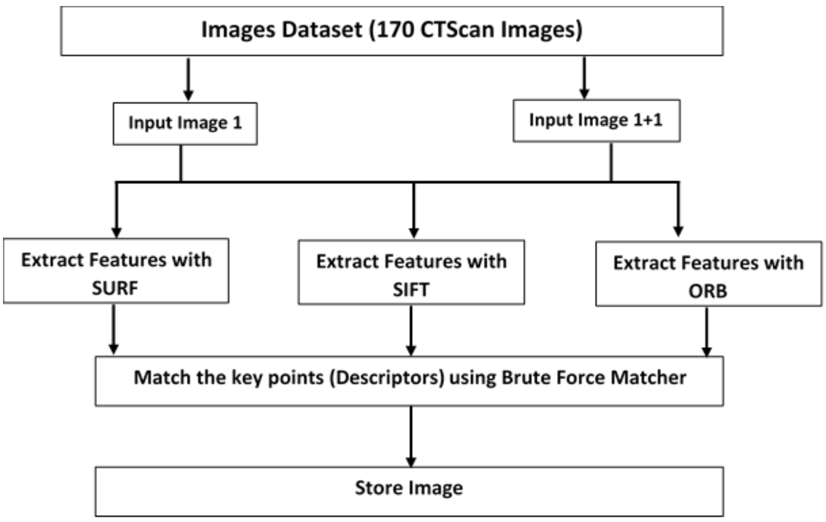


Figure 01: Prototype:

1.5.1. Prototype: An Image dataset that contains 170 brain CTScan images, two images have been taken for image matching, image 1 and image 2 then on both images SURF, SIFT and ORB are applied to find the of key points, time spent, and best matching individually. BruteForce method is used to achieve feature matching and then both images are saved. 1.6. Simulation Results: In this Section, we investigated SIFT, SURF, and ORB in terms of key points, feature detections. All three ORB, SURF and SIFT algorithms with L1 and L2 distance implemented in python and executed.

1.6. Results and Discussion: The results shows that an average best match rate for the same set of images for ORB is 250.0192308, for SURF is 884.3269231 and for SIFT is 349.1730769 that is shown in Table 01. This clearly shows that for the same set of CTScan images the SURF shows 634.3100002 more matches than ORB and 535.1538462 more matches than SIFT. An average key points of Image 1, key points image 2, best matches using L1 distance, best matches using L2 distance and time taken in seconds of 13 pairs of 26 CTScan brain images with ORB, SURF and SIFT are shown in Table 02, Table 03 and Table 04. The combined average scores of ORB, SURF and SIFT is shown in Table 01. The results shows that the SURF has got highest number of Key points in both paired images and best matches than ORB and SIFT, but takes 0.416862992 seconds more time with ORB and 0.424220163 seconds with SIFT. If we compare ORB with SIFT we come to know that SIFT has got more key points and best matches with L1 and L2 distance then ORB and takes less time than that the ORB takes. The time difference between ORB and SIFT is 0.007357171 seconds shown in Table 01. The graphical representation of comparison of ORB, SURF and SIFT is shown in Figures 5(A), 5(B), Figure 6, Figures 7(A), 7(B), and 7(C). Feature match for ORB, SIFT and SURF are shown in Figure 02, 03 and 04. Figure 08: This is Pie chart to represent time in seconds taken by ORB, SURF and SIFT. It has also been proved from result that SURF algorithm has taken more time than other algorithms, while other algorithm the ORB and SIFT have equal time. Shown in Figure 08.

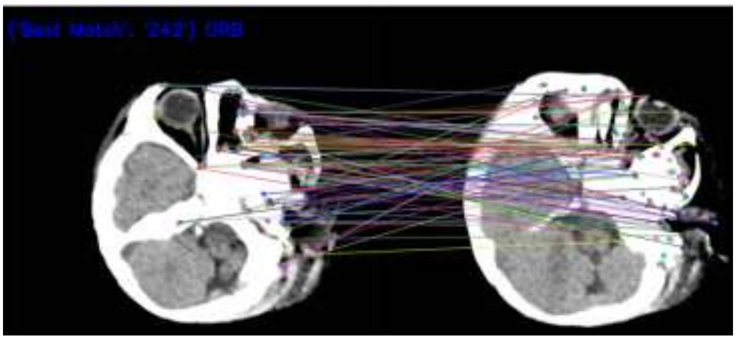


Figure 02: Best Match using L1 and L2 with ORB.

This figure representing two CT scan brain images with best match score which 242 with ORB Algorithm.

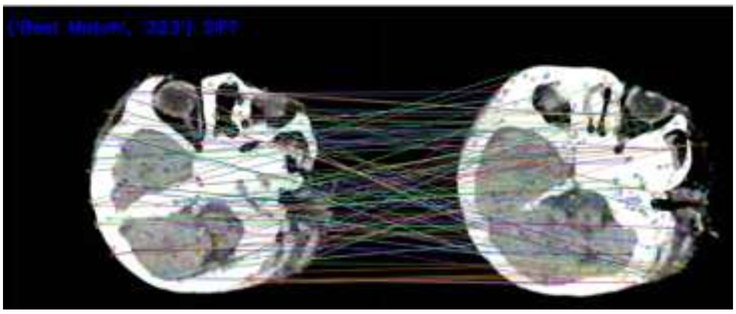


Figure 03: Best Match using L1 and L2 with SIFT

This figure representing two CT scan brain images with best match score which is 323 with SIFT Algorithm.

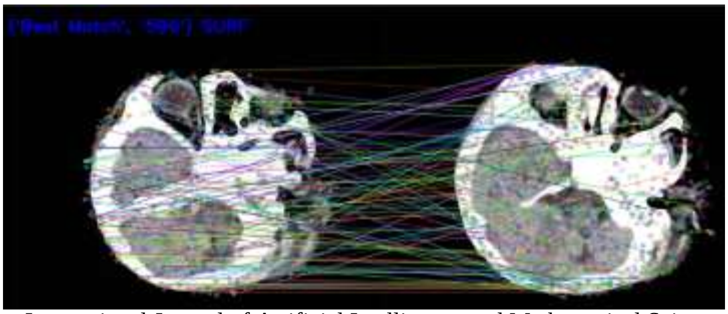
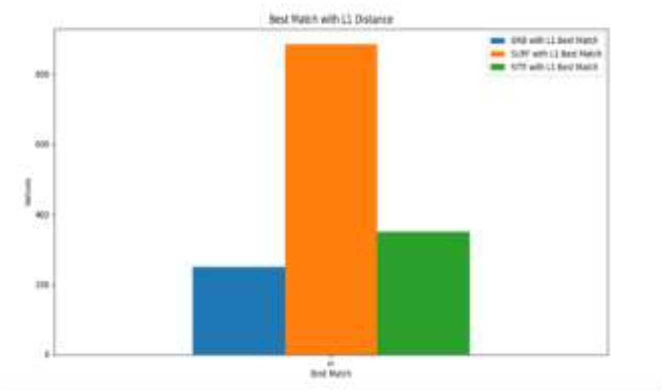


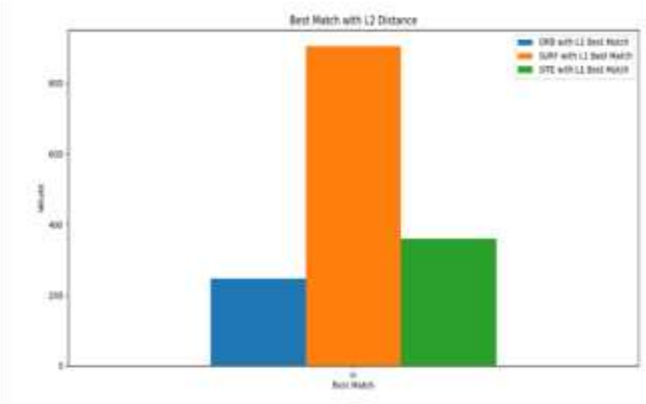
Figure 04: Best Match using L1 and L2 with SUR

This figure representing two CT scan brain images with best match score which is 596 with SURF Algorithm.



(A)

Figure 05(A): ORB, SURF and SIFT with L1 distance.



(B)

Figure 05 (B): ORB, SURF and SIFT with L2 Distance

Figure 05 (A) and 05 (B) both are showing a bar chart of Best Matches, representing that SURF is having is at Highest Best Match values, after that SIFT is having Best Match values and finally the ORB has Best Match values.

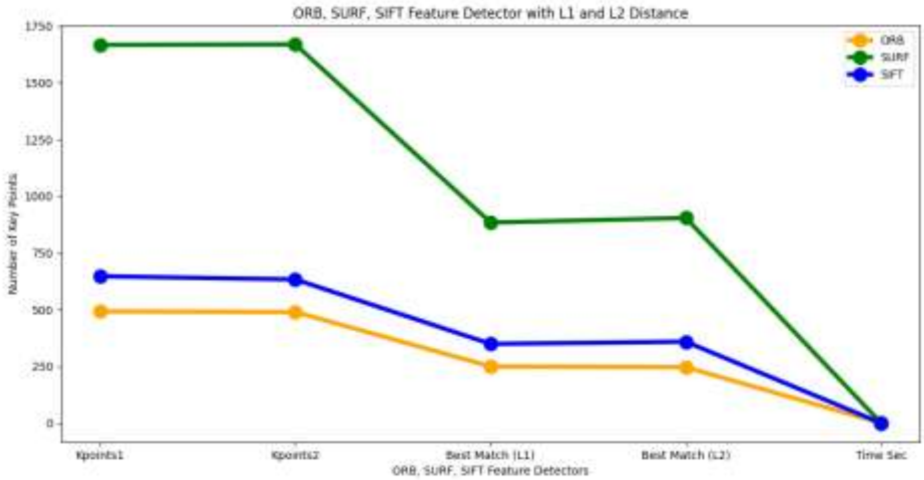
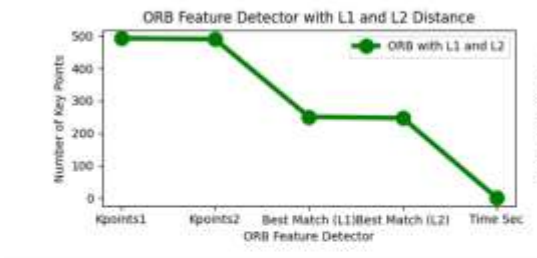
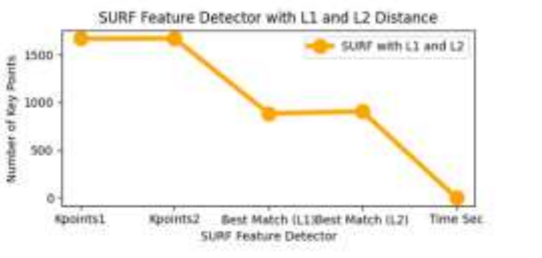


Figure 06: This graph shows key points, time taken and best for ORB, SURF and SIFT,

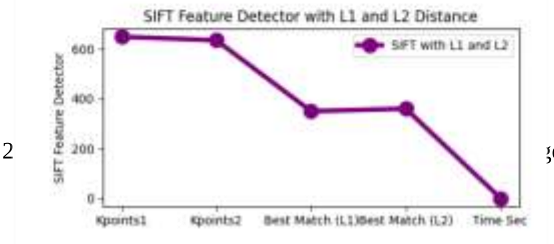
In this figure it can be seen that SURF is representing number of key points more than 1500, after that SIFT is representing more than 600 finally the ORF is representing near to 500 key points.



(A)



(B)



(C)

Figure 07: shows Individual key points, time taken and best with L1 and L2 distance for ORB in (A), SURF in (B), and (C) SIFT.

In this figure all three feature matching algorithms are representing the number of key points with L1 and L2 distance individually. The SURF algorithm is representing 1500 key points, the SIFT is representing more than 600 key points and finally the ORF is representing less than 500 key points.

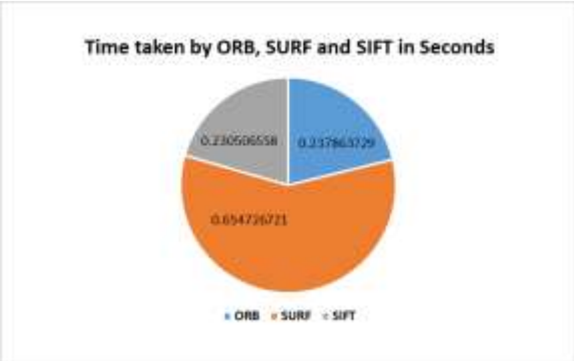


Figure 08: This is Pie chart to represent time in seconds taken by ORB, SURF and SIFT.
In this Pie chart it can be seen that the SURF algorithm has taken more time than other algorithms, while other algorithm the ORB and SIFT have equal time.

Table 01. An average key points, best matches and time taken by 13 Pairs of 26 CTScan brain images using L1 and L2 distance with ORB, SURF and SIFT.

Feature Detectors	Medical Images	Kpoints 1	Kpoints2	L1 Distance Best Match	L2 Distance Best Match	Time (Sec)
ORB	52 Pairs	492.5384615	489.6923077	250.0192308	246.5	0.237863729
SURF	52 Pairs	1667.807692	1670.115385	884.3269231	904.5576923	0.654726721
SIFT	52 Pairs	647.5769231	633.5	349.1730769	359.0384615	0.230506558

Table 02. An average key points, best matches and time taken by 13 Pairs of 26 CTScan brain images using L1 and L2 distance with ORB.

Dataset	Kp1	Kp2	L1	L2	Time (Sec)
CT Scan Brain 1 Dataset	500	500	254.2308	248.4615	0.245553
CT Scan Brain 2 Dataset	500	500	256.3846	252.0769	0.230675
CT Scan Brain 3 Dataset	487.8462	483.8462	243.9231	243.9231	0.236943
CT Scan Brain 4 Dataset	482.3077	474.9231	245.5385	241.5385	0.238284

Table 03. An average key points, best matches and time taken by 13 Pairs of 26 CTScan brain images using L1 and L2 distance with SURF.

Dataset	Kp1	Kp2	L1	L2	Time (Sec)
CT Scan Brain 1 Dataset	1556.462	1542.462	799.4615	830.5385	0.673333

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CT Scan Brain 2 Dataset	2237.154	2240.538	1206.077	1226.615	0.709325
CT Scan Brain 3 Dataset	1461.538	1502.462	804.7692	814.6154	0.616781
CT Scan Brain 4 Dataset	1416.077	1395	727	746.4615	0.619468

Table 04. An average key points, best matches and time taken by 13 Pairs of 26 CTScan brain images using L1 and L2 distance with SIFT

Dataset	Kp1	Kp2	L1 Best Match	L2 Best Match	Time (Sec)
CT Scan Brain 1 Dataset	774.6923	736.7692	424	422.6923	0.2421
CT Scan Brain 2 Dataset	969.3077	977.8462	522.2308	544.2308	0.253392
CT Scan Brain 3 Dataset	399.7692	401.5385	217.3846	228.0769	0.207511
CT Scan Brain 4 Dataset	446.5385	417.8462	233.0769	241.1538	0.219024

1. 7. Conclusion: In this paper, three different image matching techniques ORB, SURF and SIFT have been compared using Intracranial Hemorrhage CTScan Brain images and displayed the matching evaluation parameters such as the number of key points in images, the execution time required for each algorithm and best matches with L1 and L2 distance for Brain CTScan images. From the result, it can be concluded that the SURF has got highest key points for both L1 and L2 distance and best match, after that the SIFT algorithm has got more key points and best match than ORB algorithm. The SURF algorithm has taken more time than other algorithms, while other algorithm the ORB and SIFT have equal time.

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