

Enhancing Image Registration Leveraging SURF with Alpha Trimmed Spatial Relation Correspondence

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Abstract. In medical image registration, traditional approaches such as Harris corner detector, Oriented FAST and Rotated Brief (ORB), and scale invariant feature transform (SIFT) encounters several challenges for achieving precise alignment. These challenges arise from their limited ability to adapt scale, rotation, and illumination variations. To confront these challenges, the proposed methodology leverages the speeded-up robust features (SURF) algorithm for feature point extraction. Additionally, it employs the alpha trimmed spatial relation correspondence (ATSRC) algorithm as an efficient alternative to the conventional random sample consensus (RANSAC) method to effectively eliminate mismatches. In the pre-processing phase, the reference image undergoes Gaussian filtering to remove noise, and subsequent normalization is applied. Furthermore, feature detection is performed on both the reference and target images using SURF. A brute force (BF) matcher is applied, followed by alpha trimmed spatial relation correspondence to remove outliers. The process continues with computing the homography matrix and generating the registered image. Numerous experiments are conducted on monomodal and multimodal medical images acquired from the Kaggle dataset. The proposed methodology outperforms existing technique by significantly improving mutual information (MI) from 2.53 to 3.654, 2.257 to 3.17389 and cross correlation (CC) from 0.9219 to 0.95475.

Keywords: Image registration · SURF feature extraction · Multimodal medical images

1 Introduction

Image registration (IR) is the process of aligning two medical images, whether monomodal or multimodal to depict the same scene [17]. In this case, one image serves as the reference (source) while the other acts as a target (template) image. The objective of IR is to achieve precise alignment between source and template image, which enables integration of information from both images to generate accurate and robust register image. Medical image registration approaches may be broadly classified into two

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categories: area-based and feature-based. The area-based method identifies the transformation model between two images without separating their features by utilizing an optimization algorithm. Medical imaging modalities can be broadly categorized into two types: functional images, such as single-photon emission computerized tomography (SPECT) and positron emission tomography (PET), which reveal soft tissues and their internal activities, and anatomical images, such as computed tomography (CT), magnetic resonance imaging (MR), and ultrasound (US), which display detailed structures of body organs. IR comprises of three essential components: rigid [25] transformation model, evaluation metrics, and feature extraction techniques. Rigid transformation model aims to find out the best transformation for image alignment by simulating geometric changes using rotation, scaling, and translation. Afterwards, alignment accuracy of the images is evaluated using several kinds of similarity metrics. Structural similarity index measure (SSIM), root mean square error (RMSE), and mutual information (MI) [4] are extensively utilized metrics. MI, peak signal to noise ratio (PSNR), cross correlation (CC), SSIM are maximized, while MSE is minimized, to achieve the successful registration. Finally, image registration employs a variety of feature extraction and matching algorithms, such as oriented FAST rotated BRIEF (ORB), SIFT, and SURF, brute force (BF) matcher. Monomodal and multimodal are two major categories that are used for image registration. Monomodal image registration refers to the alignment of images for same modality, such as MR-MR or CT-CT. In contrast, multimodal image registration involves categorizing images with a variety of modalities, like CT-MR scans. The integration of CT and MRI scans through registration methods improves the precision of patient data for a variety of applications including tracking tumour growth [14], confirming treatments [17] (such as surgery or radiotherapy), and facilitating clinical applications like tracking tumour growth and surgery planning. This paper introduces an innovative method that amalgamates SURF with Alpha trimmed spatial relation correspondence combined with affine transformation. This approach aims to speed up the feature detection process in images and enhance the registration speed of medical images by removing outliers. The proposed technique undergoes experimental testing on both monomodal and multimodal images. Finally, its performance is assessed based on evaluation metrics through experiments as compared to existing state-of-the-art methods [15, 27].

The key contributions of proposed methodology for the registration of multimodal/monomodal medical images are outlined as follows:

- A novel image registration method by hybridizing SURF feature extractor with alpha-trimmed spatial relation correspondence to effectively remove outliers.
- Extensive experiments are carried out to validate that SURF suits best for feature extraction as compared to ORB, SIFT as well as Harris corner detection algorithm. In addition, experiments state that ATSRC outperforms for removing outliers while RANSAC fails to generate register image.
- Efficacy of proposed methodology is experimentally proven by comparing with existing state-of-art approaches considering MI and cross- correlation as an evaluation metrics which explicitly states that the proposed approach outperforms.

The rest of the paper is structured as follows: literature review is discussed in Sect. 2, whereas the proposed methodology for medical image registration method is described

in Sect. 3. The experimental and comparison results showcased in Sect. 4 whereas, conclusion and future directions is presented in Sect. 5.

2 Literature Survey

This section outlines the rigid medical image registration method proposed by many academics. Traditional techniques for image registration observed issues with speed, precision, and mismatched feature points, especially in medical, SAR, remote sensing, and histopathology slide images. Moreover, SIFT limits in efficient descriptor representation, preventing precise image alignment. The proposed approach further addresses these challenges by providing robust image alignment along with efficient feature extraction. Furthermore, it improves feature matching by using the best method for finding outliers, like alpha-trimmed spatial relation correspondence.

Engin *et al.* [10] had demonstrated the technique which leverages the combined SIFT and SURF descriptors, significantly improved alignment precision, especially with SIFT-based feature matching. Wu *et al.* [26] described the method which combines SURF and FREAK, leveraging robust feature extraction and strong regional description abilities, ensuring precise matching through rough matching and RANSAC-based filtering. Sreeja *et al.* [24] highlights modifications of SIFT and SURF for SAR image alignment, aiming to enhance registration accuracy and applicability across various SAR image processing applications [7]. Li *et al.* [18] presented the technique which combines SIFT with a feature point pair verification mechanism, leveraging affine transformation invariance and angle constraints for more accurate image registration. Darshana *et al.* [9] described their strengths and weakness of SIFT and SURF of each parameters like scale, rotation, blur, and speed. Sedaghat *et al.* [22]. Had outlined an improved SURF detector and AB-SIFT descriptor for robust feature extraction and correspondence establishment, followed by blunder detection using LGTM and accuracy enhancement using OLSM [6]. Ihmeida *et al.* [16] had recommended SIFT and SURF, renowned for their invariance and robustness, to improve SAR image alignment. Sabry *et al.* [21] had evaluated ORB as an alternative to address these limitations, assessing its performance against SIFT in various scenarios including multi-image feature extraction and real-to-sketch image matching [13]. Oad *et al.* [20] had studied ORB, SIFT, and SURF algorithms using a dataset of 170 CT Scan brain images in aiding medical diagnosis. Arora *et al.* [4] had demonstrated the combination of affine transformation as well as optimization technique for rigid medical image registration [3, 5]. Adhikari *et al.* [1] had focused on feature-based registration, evaluating ORB, KAZE coupled with RANSAC, GC-RANSAC, and MAGSAC + +. Hamzehei *et al.* [15] had integrated SIFT and ResNet50 for feature extraction and adaptive likelihood-based outlier detection using Maximum Likelihood Estimation Sample Consensus (MLESAC) for medical image registration [12]. Li *et al.* [19] had studied the Shi-Tomasi algorithm with SIFT to enhance efficiency, utilizing PROSAC for mismatch removal, significantly reducing matching time [2].

3 Proposed Methodology

Step 1. The source (reference) and target images undergo pre-processing using a Gaussian filter for noise reduction prior to normalization. Afterwards, normalization is conducted to standardize the image data consistently (Fig. 1).

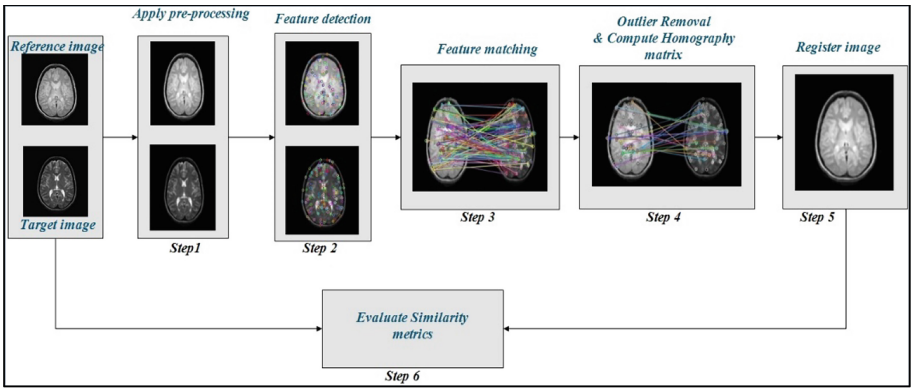


Fig. 1. Framework of proposed methodology

Step 2. Following pre-processing, identify distinctive features in the images using SIFT, SURF, and ORB. SIFT detects keypoints by scale and orientation, SURF finds blob-like structures using Haar wavelets, and ORB identifies corners using binary descriptors for efficiency.

Step 3. In this step, feature matching is carried out using brute force matcher and K-nearest neighbors (KNN) with an aim to align similar features across the entire dataset for subsequent analysis.

Step 4. After feature matching step, next step is to compute homography estimation and apply outlier removal techniques such as alpha trimmed spatial relation correspondence, RANSAC, spatial trimmed correspondence, PROSAC, and LORANSAC, aiming to eliminate inconsistent or erroneous feature correspondences.

Step 5. Compute the registered image, leveraging the transformations derived from the processed data to create a unified representation of the images.

Step 6. Evaluate the similarity metrics (SSIM, PSNR, MI, and cross-correlation) to quantify the resemblance between the reference and registered images to provide insights into their alignment and similarity.

4 Experimental and Comparison Results

This section exhibits the effectiveness of the proposed methodology using evaluation metrics (SSIM, MI, RMSE, PSNR and CC) to analyse monomodal and multimodal medical images. Furthermore, we determine the extracted features, number of matches and visual quality of reference and target image.

4.1 Experimental Results

All experiments are conducted on the PYTHON 3.9.4 platform, using a system equipped with 16.0 GB RAM and a 2.80 GHz Intel(R) Core TM I7-1165G7 CPU. In order to analyze both monomodal and multimodal medical images, the proposed methodology employs two distinct Kaggle datasets [11, 23] for validating the scheme. Furthermore, the experiments are performed on monomodal and multimodal medical images as shown in Fig. 2(a1–a8) and (a9–a16) respectively. These CT and MRI monomodal and Multimodal medical brain images with dimensions of (256 × 256) in (Fig. 2a1–a16) are the reference images that are taken into consideration for the analysis. Following, the reference and target images undergo pre-processing as shown in Fig. 2(a1–a16) and (b1–b16) respectively. Subsequently, key point extraction is performed on both the pre-processed reference and target image as depicted in Fig. 2(c1–c16) and (d1–d16) respectively. Following that, a brute force matcher is employed to identify matches, and alpha-trimmed spatial relation correspondence is employed to remove outliers as displayed in Fig. 2(e1–e16) and (f1–f16) respectively. This process ensures the detection of the most suitable matches, which eventually results in the generation of the registered image as depicted in Fig. 2(g1–g16).

As depicted in Table 1, the quantitative analysis of the proposed methodology (SURF-ATSRC) is compared to traditional approaches (Harris corner detection, ORB, SIFT).

Table 2 and Fig. 3 illustrate that across all monomodal and multimodal test images, the register image of proposed methodology performs better in terms of assessment metrics including MI, RMSE, SSIM, CC, and PSNR. Bold value in Table 2 states higher similarity metrics corresponding to the proposed methodology.

4.2 Comparative Results

A comparative analysis is conducted between proposed methodology and recently developed feature extraction technique [12] to assess its performance in monomodal medical image registration. In order to provide a fair comparison, the identical image with [12, 27] are analyzed. Monomodal and multimodal test image, namely MRI-T1 and CT, obtained from [15, 27] with dimensions of 256 × 256, as shown in Fig. 3. The results depicted in Tables 3 and 4 illustrates that the proposed methodology achieves an effective registered image with higher MI and CC value (Fig. 4).

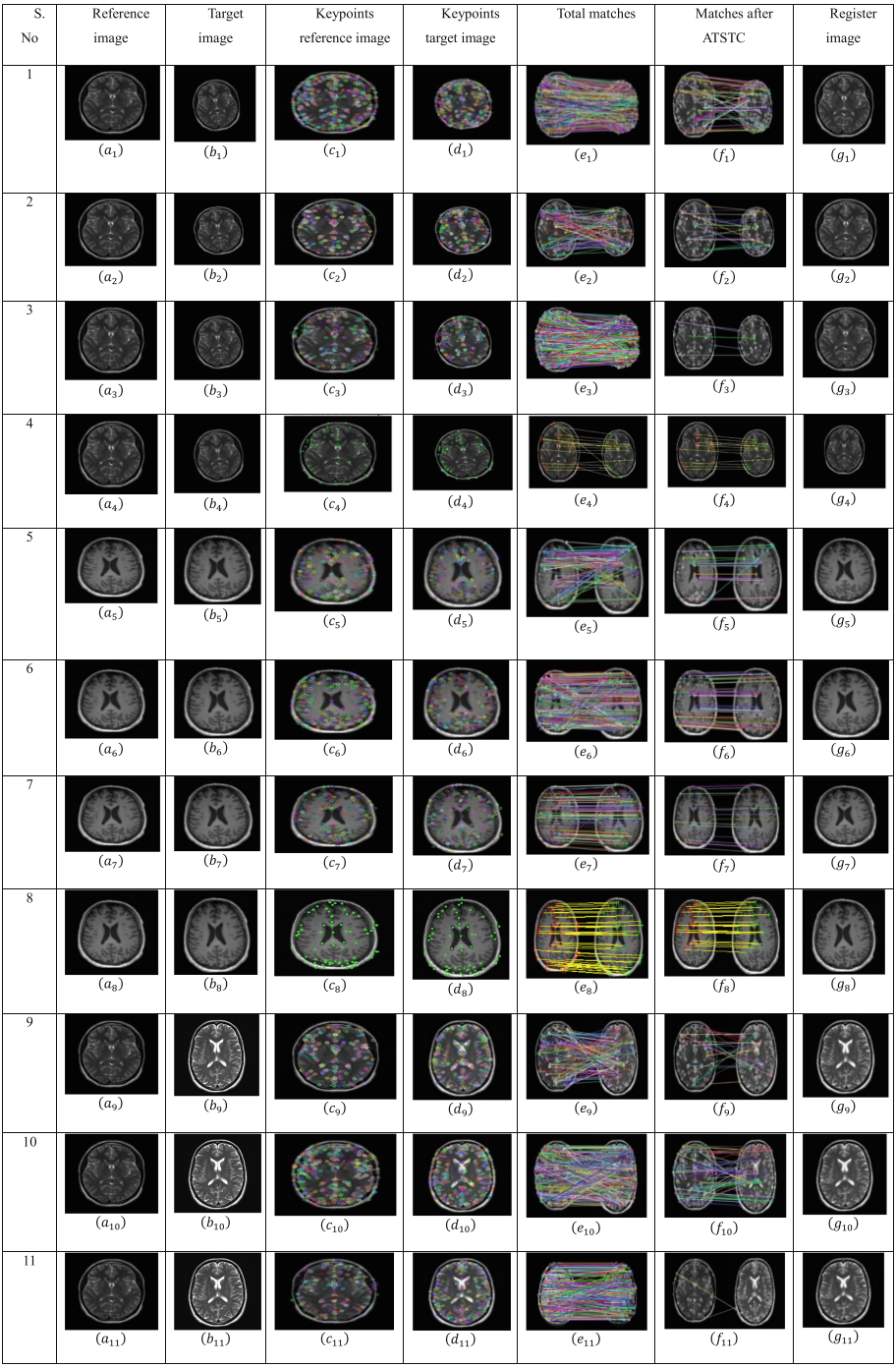


Fig. 2. Experiment conducted on various monomodal/multimodal medical images (a) Reference image (b) Target image (c) Keypoints of reference image (d) Keypoints of target image (e) Total matches (f) Matches after ATSRC (g) Register image

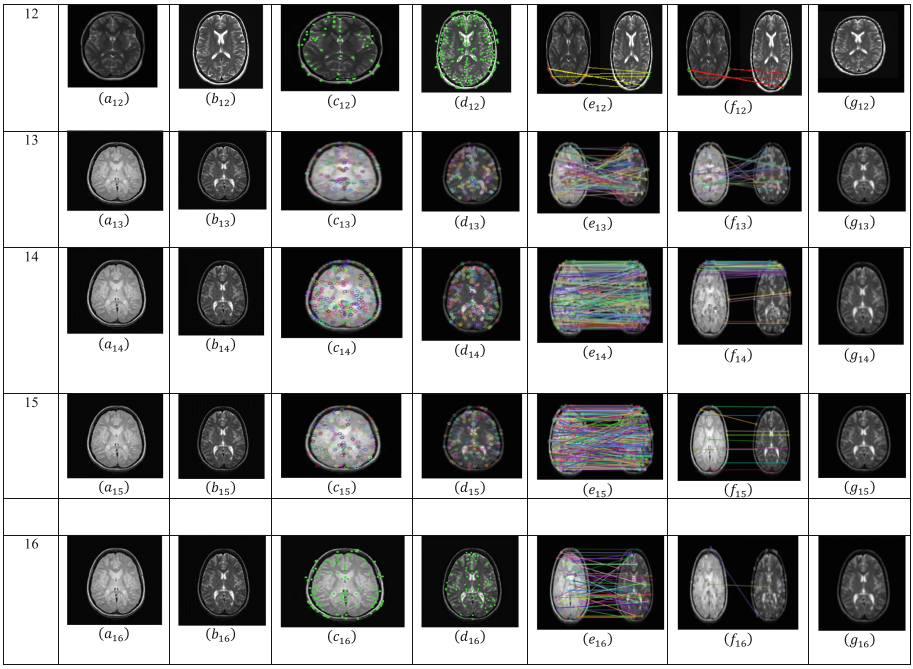


Fig. 2. (*continued*)

Table 1. Experimental outcomes on various monomodal/multimodal medical images taken from Kaggle dataset [11, 23]

S. No.	Images	Reference image keypoints	Target image keypoints	Total matches	Matches after ATSRC
1	MRI-Flair & MRI-Flair	467	423	350	68
2		372	396	126	25
3		158	130	630	5
4		53	48	17	12
5	MRI-T1 & MRI-T1	291	191	143	25
6		241	182	279	55
7		137	142	110	22
8		78	65	52	27
9	MRI- Flair & MRI-T2	372	394	131	22
10		467	334	366	69

(*continued*)

Table 1. (*continued*)

S. No.	Images	Reference image keypoints	Target image keypoints	Total matches	Matches after ATSRC
11		158	252	327	2
12		372	394	131	22
13	CT & MRI-T2	270	394	111	19
14		239	229	245	48
15		131	160	230	10
16		104	74	10	2

Table 2. Computed evaluation metric for monomodal and multimodal medical images

S. No.	Algorithm	RMSE	MSE	SSIM	PSNR	Cross correlation	MI
1	Harris corner detection	25.4532	647.86539	0.83652	29.8765	0.87654	2.0987
2	ORB	21.4321	459.33491	0.85142	31.3245	0.89643	2.31432
3	SIFT	18.4322	339.745997	0.86754	33.4562	0.91342	2.5432
4	**Proposed Methodology**	**16.5643**	**274.376034**	**0.87654**	**35.6754**	**0.93452**	**2.76532**
5	Harris corner detection	21.3574	456.14130	0.83212	31.53923	0.93924	2.39973
6	ORB	20.3428	455.51745	0.85295	34.54575	0.939354	2.69345
7	SIFT	20.6343	385.50573	0.86143	37.42513	0.95143	3.024265
8	**Proposed Methodology**	**17.5432**	**307.763866**	**0.89765**	**40.32456**	**0.96543**	**3.23452**
9	Harris corner detection	58.3421	3403.80063	0.76543	22.4568	0.7689	1.1532
10	ORB	54.6325	2984.71006	0.786543	24.6754	0.78654	1.4998
11	SIFT	50.9843	2599.39885	0.819872	26.7843	0.79834	1.8321
12	**Proposed Methodology**	**44.6543**	**1994.00651**	**0.832465**	**28.9765**	**0.81987**	**1.9876**
13	Harris corner detection	38.5821	1488.57844	0.70253	26.60862	0.80753	1.4547

(*continued*)

Table 2. (*continued*)

S. No.	Algorithm	RMSE	MSE	SSIM	PSNR	Cross correlation	MI
14	ORB	36.8765	1359.87625	0.72431	27.89765	0.83245	1.5432
15	SIFT	35.4536	592.55730	0.75326	29.75321	0.85423	1.85231
16	**Proposed Methodology**	**33.5432**	**1125.14627**	**0.76549**	**30.8765**	**0.86573**	**1.98654**

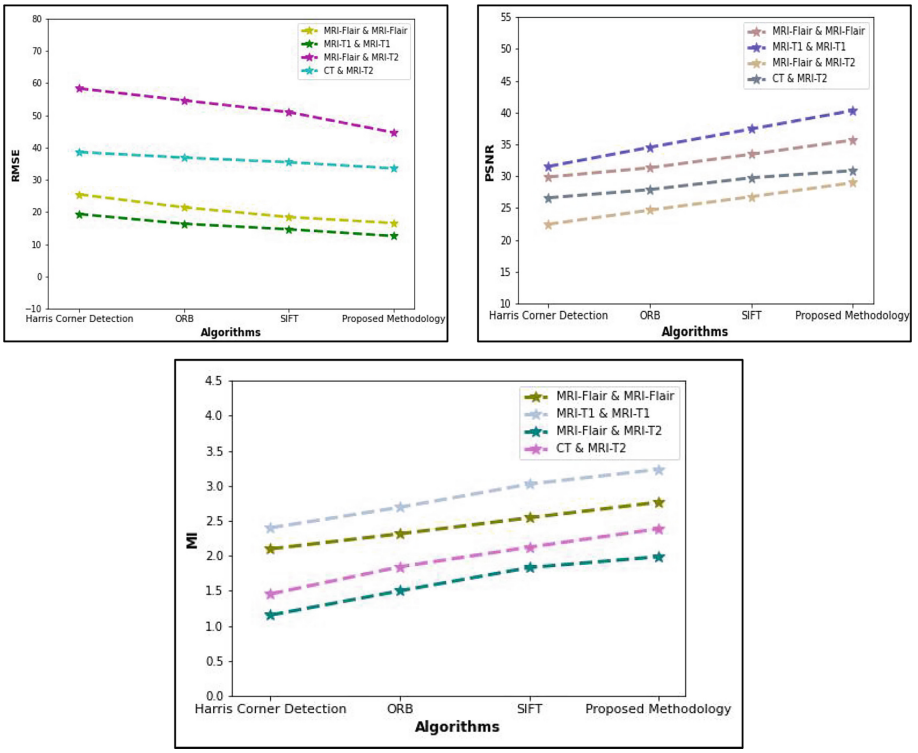


Fig. 3. Comparison of various similarity measures for medical images with proposed methodology

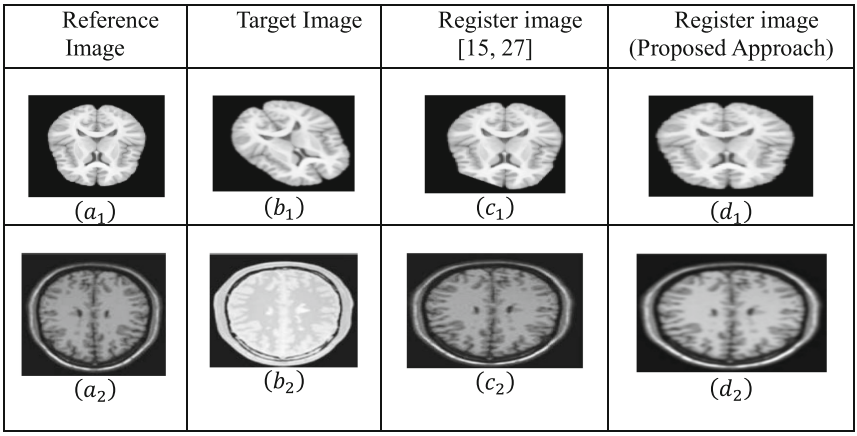


Fig. 4. Experimental comparison of [15, 27] and proposed approach for monomodal images from dataset [8]

Table 3. Comparison of MI for proposed methodology with existing scheme [15]

Transformation	Evaluation metric
	MI
MLESAC (Affine)	2.35
MLESAC (Rigid)	1.53
MLESAC (Rotated)	1.54
MLESAC (Translated) [15]	2.53
Proposed Approach	**3.654**

Table 4. Evaluation of proposed methodology with existing scheme [27] corresponding to MI and CC

Evaluation metric	MI	CC
P1-SURF [27]	2.2577	0.9219
Proposed Methodology	3.17389	0.95475

5 Conclusion and Future Work

Conventional medical image registration methods, including Harris corner detector, ORB, and SIFT fail to achieve precise alignment due to limitations in adapting to scale, rotation, and illumination variations. Moreover, in this paper introduces a novel image

registration method that amalgamates SURF with the alpha trimmed spatial relation correspondence method to achieve robust register image. The analysis systematically evaluated four feature detection algorithms, namely Harris corner, ORB, SIFT and SURF, along with an outlier detection algorithm, alpha trimmed spatial relation correspondence. Through experimental evaluation, it can be observed that employing SURF for key point extraction, in combination with efficient alpha trimmed spatial relation correspondence algorithm, outperformed traditional methods for reducing mismatches. The experimental results highlight the effectiveness of the proposed methodology in enhancing key similarity metrics, including MI, RMSE, PSNR, and SSIM, leading to optimal image alignment. The proposed method can be extended to integrate deep learning with a feature extraction algorithm, offering the potential for further improvements in overall registration performance.

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