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ELIMINATION OF TYPE II ERRORS IN FEATURE BASED IMAGE MATCHING: A COMPARATIVE EVALUATION OF GEOMETRIC TRANSFORMATION METHODS

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ABSTRACT

Detection and elimination of type II errors has been a fundamental step towards realizing high quality matches in feature-based image matching algorithms. However, choosing the most appropriate outlier detection method that would yield the desired result has been a problem for several users of image matching algorithms. This has made it necessary for studies on the performance of outlier detection methods for elimination of type II errors in feature-based image matching. This study evaluated the performance of three geometric transforms, namely; Affine, Projective, and Conformal transform for detection and elimination of type II errors in feature-based image matching. SURF features were detected and extracted from a stereo pair of images of University of Ilorin senate building acquired at close-range. Initially, 10% of type II errors were matched with 90% correctly identified points using hamming distance. Subsequently, 20, 30, 40, 50, 60, 70, 80, and 90% of type II errors were matched with 80, 70, 60, 50, 40, 30, 20, and 10% of correctly identified points respectively, in stages. At each stage the three transforms were used to detect and eliminate type II errors from the correctly matched points. Performance of the three transforms were evaluated based on their efficacy in detecting and eliminating type II errors, and their robustness in identifying correctly matched points. The results showed that Conformal transform had the best performance with a complete detection and elimination of 90% type II errors from correctly matched points, while Affine and Projective transform eliminated 85% and 75% type II errors respectively. The paper concluded that Projective, Affine, and Conformal transform could be used in feature-based image matching to completely detect and eliminate 75%, 85%, and 90% type II errors respectively from correctly matched points.

Keywords: Type II errors, Image matching, outlier detection, geometric transforms, RANSAC.

1.0 INTRODUCTION

Image matching is the establishment of point-to-point correspondence between two or more images, through the process of feature detection, extraction and analysis to determine similarity between images (Habib *et al,* 003; Mikolajczyk and Schimid, 2003; Zhang and Feng, 2018). Accurate image matching has been a fundamental requirement for several applications in photogrammetry, including; image registration, relative orientation and 3D reconstruction from images (Heipke, 1998; Habib *et al*, 2003; Masoud and Hoff, 2016). Image matching has also found applications in several fields, including; medicine, agriculture, engineering, face recognition, computer vision, robotics, and automatic surveillance (Karami et al, 2015; Chen *et al*, 2019).

However, the presence of errors due to false matches usually reduce the performance of several image matching algorithms. Errors in image matching occur as type I errors when real matches are not detected by a matching algorithm, and as type II errors when an algorithm mismatches a feature (Pena, 2011). Although almost all image matching algorithms are error prone (Ruzgiene and Forstner, 2005), recent studies have shown that type I and type II error mostly occur in feature-based image matching algorithms where certain distance threshold is been set to determine matching pairs (Bostanchi *et al*, 2017; Chen *et al*, 2019).

In order to overcome the effects of type II errors (mis-match) on several applications of image matching, outlier detection and elimination methods are usually introduced to eliminate errors (mis-match) in image matching. Nonetheless, the particular method to be applied to effectively remove a particular type of error has been a source of burden to several users of image matching algorithms (Malik *et al*, 2014; Templ *et al*, 2019).

Several outlier detection techniques have been introduced in various research works to eliminate errors in image matching. The research work of Bian *et al* (2017), used Grid based motion statistics (GMS) algorithm to distinguish some false and true matches, while the research work of Rodriguez *et al* (2018), introduced hyper-descriptor to eliminate false matches in a fast-affine invariant image matching. Elsewhere is the research work of Zhao *et* *al* (2018), where an Epipolar Geometric Constraint (EGC) model was introduced into the traditional GMS and PROSAC algorithm. The resulting algorithm which they named GMS-EGCPROSAC was used to eliminate outliers (mis-match) in image matching.

It has been noted that geometric transformation methods, including Random Sample Consensus (RANSAC) algorithm and its variants usually detect and eliminate outliers in the process of coordinate transformation (Janika and Rapinski, 2014). While several research investigations have shown that RANSAC and its variants usually produce wrong results when the percentage of outliers in a dataset exceeds 45 – 50% (Beckouche *et al*, 2011; Janicka and Rapinski, 2014; Zhao *et al*, 2020), the efficacy of geometric transformation methods such as Affine, Projective, and Conformal transform in detecting and eliminating type II errors in feature-based image matching has not been investigated. This study investigates the efficacy of three geometric transforms (Affine, Projective, and Conformal) for detection and elimination of type II errors in feature-based image matching.

2.0 MATERIALS AND METHODS

This study employed three geometric transforms namely; Affine, Projective, and Conformal transform to detect and eliminate type II errors in feature-based image matching. The aim is to assess the performance of each method in terms of its effectiveness to identify and eliminate type II errors (image mis-match), and its robustness in identifying correct matches (inliers).

2.1 Data Acquisition

In this study, an amateur camera (Nikon D800) was used at close range to collect two overlapping (stereo) images of University of Ilorin senate building. The images were strategically taken such that an image pair have an end lap of 80 to 85%. This percentage of overlap is necessary so that part of the first image is duplicated in the second image (Wolf *et al*, 2014).

Figure 1: Stereo image of UNILORIN senate building acquired at close range

2.2 Data Processing

A program written in MATLAB programming language was used to carry out the process of feature detection and extraction, feature matching, elimination of outliers, and evaluation of matching accuracy. A flow chart for program implementation is shown in figure 2.

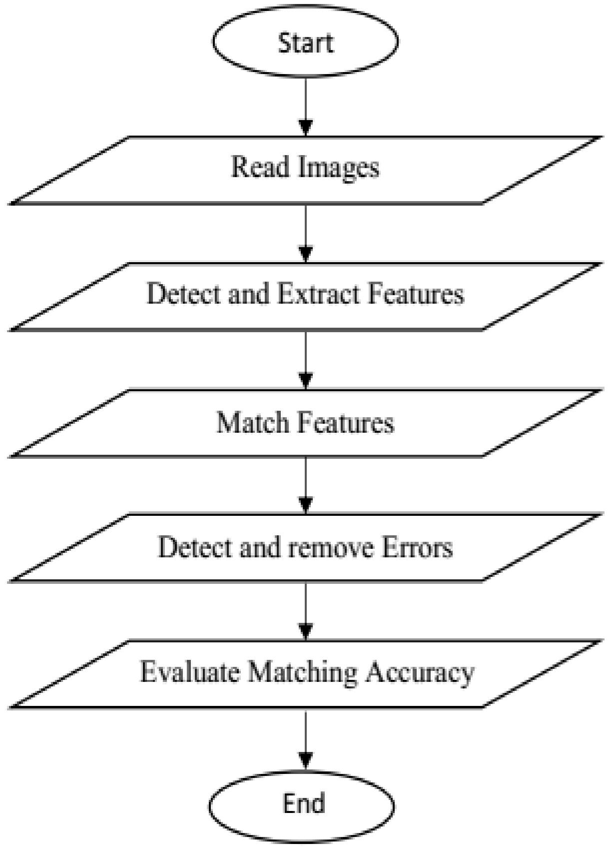

Figure 2: Flow chart for program implimentation

Speed Up Robust Features (SURF) were detected and extracted on both stereopair, while Hamming distance was used to match the extracted features. The study was carried out in stages. At the first stage, 10% of type II error (mis-match) was introduced into 90% correctly matched points. After a matching process using hamming distance, each geometric transform was used to detect and remove errors from the matched features. At subsequent stages, an error of 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, was introduced to 80%, 70%, 60%, 50%, 40%, 30%, 20%, and 10% of correctly matched points respectively. Just like the first stage, a matching process was carried out at each stage, while each geometric transform was used to detect and remove errors. Details are shown in table 1.

Table 1: % of type II errors (mis-match) introduced to correctly matched points at each stage

Stage	Number of correctly matched points	Number of type II errors (mis-match) introduced	Total Number of Points
1	100 (100%)	0 (0%)	100
2	90 (90%)	10 (10%)	100
3	80 (80%)	20 (20%)	100
4	70 (70%)	30 (30%)	100
5	60 (60%)	40 (40%)	100
6	50 (50%)	50 (50%)	100
7	40 (40%)	60 (60%)	100
8	30 (30%)	70 (70%)	100
9	20 (20%)	80 (80%)	100
10	15 (15%)	85 (85%)	100
11	10 (10%)	90 (90%)	100
12	5 (5%)	95 (95%)	100
13	0 (0%)	100 (100%)	100

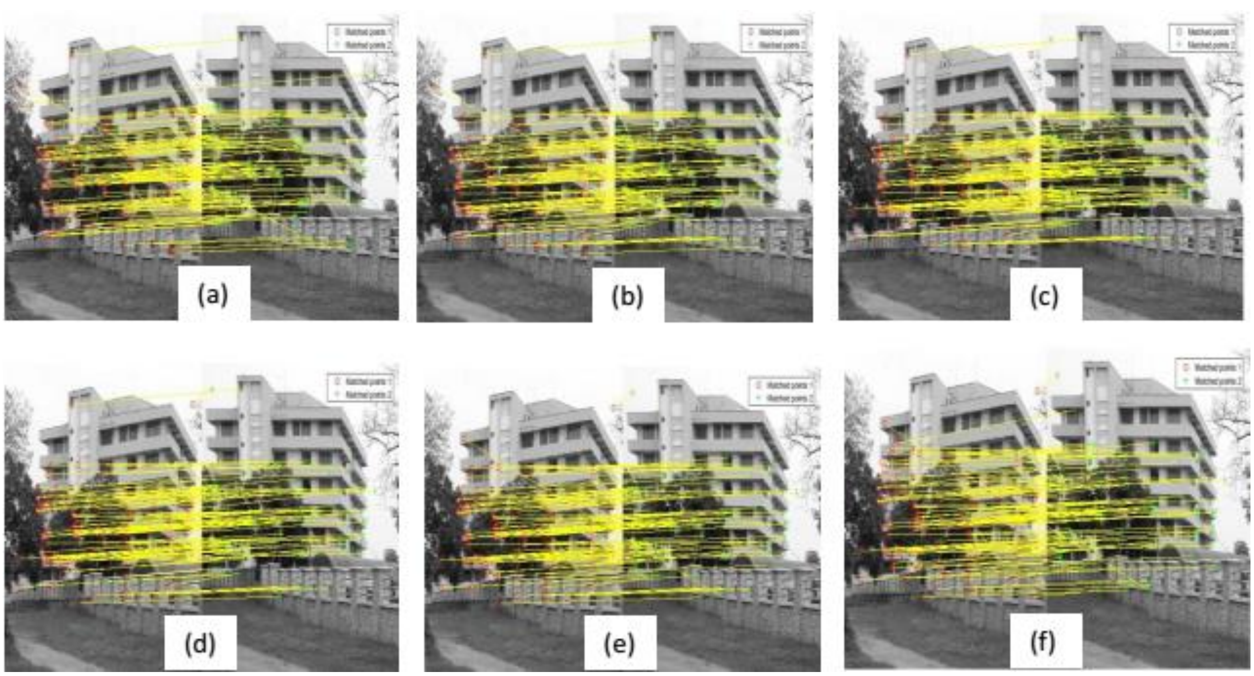

Figure 3: (a) 90% correct matches with 10% typeII errors (b) 70% correct matches with 30% typeII errors (c) 50% correct matches with 50% typeII errors (d) 40% correct matches with 60% typeII errors (e) 30% correct matches with 70% typeII errors (f) 10% correct matches with 90% typeII errors

Performance of each transform was evaluated based on its effectiveness in eliminating type II errors (number of errors eliminated at each stage), and its robustness in identifying correctly matched points (number of inliers detected at each stage). A comparative analysis was made between the three transforms to detemine which of them had the best performance.

3.0 RESULTS AND DISCUSSION

Results of type II errors detected and eliminated as well as the percentage of correctly matched points (inliers) detected at each stage by the three transforms is presented in table 2. Successful implementation of the three geometric transforms shows that 2D Affine transform detected and completely eliminated 85% of type II errors contained in the matched image features, with a number of correct matches (inliers) ranging from 6 – 18 been detected, (see table 2). Figure 4 shows performance of the three transforms in eliminating type II errors and detecting inliers from a set of matched points that contains 50% type II errors and 50% correctly matched points. Visual representation of the performance of the three transforms at all other stages are presented in the appendix section of this paper.

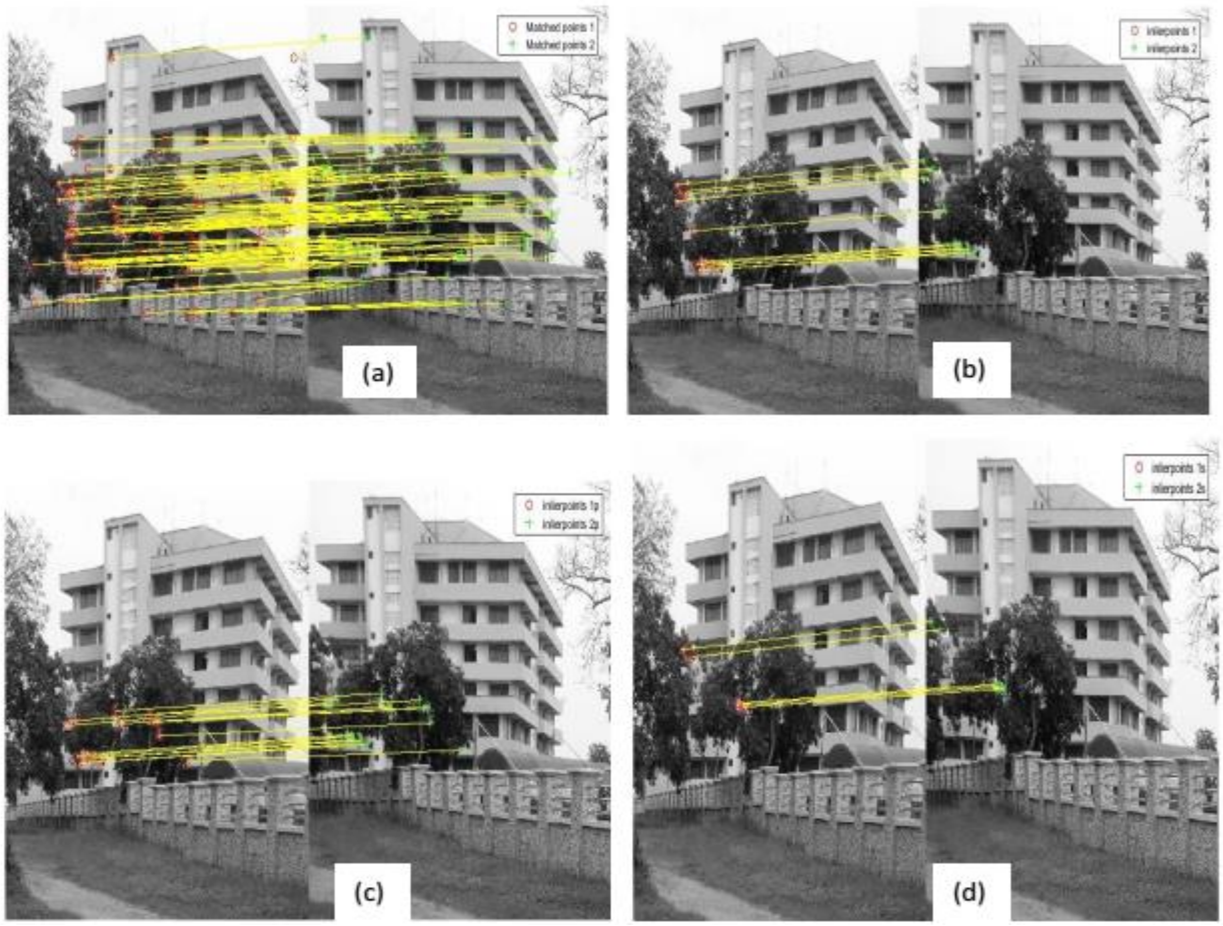

Figure 4: Detection and elimination of type II errors by tree transforms: (a) Set of matched points containing 50% type II errors and 50% correctly matched points (inliers). (b) Detected inliers after eliminating type II errors using Affine transform. (c) Detected inliers after eliminating type II errors using Projective transform. (d) Detected inliers after eliminating type II errors using Conformal transform.

At stages where the percentage of type II error is above 85%, the transform failed to completely eliminate all errors, while also detecting wrong matches as inliers. Basically, this

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performance can be related to the fact that the 2D affine transform is a six parameters model that requires a minimum of three corresponding points to determine the six parameters of the transform (Ghilani and Wolf, 2014). Hence, with a sufficient percentage of matched points, it selects the best set of matches that conforms to the model to determine the transformation parameters, thereby eliminating outliers (wrong matches). However, its robustness is quite poor, as there are a number of correctly matched points it could not detect at each stage.

Table 2: % of outliers and inliers detected by the three transforms at each stage

Stage	Number of correctly matched points	Number of type II errors (mis-match) introduced	Total Number of Points	% of outlier detected by transform			% of Inliers detected by transform		
				Affine	Projective	Conformal	Affine	Projective	Conformal
1	100 (100%)	0 (0%)	100				17	47	8
2	90 (90%)	10 (10%)	100	10	10	10	14	41	8
3	80 (80%)	20 (20%)	100	20	20	20	8	33	7
4	70 (70%)	30 (30%)	100	30	30	30	16	37	3
5	60 (60%)	40 (40%)	100	40	40	40	15	21	5
6	50 (50%)	50 (50%)	100	50	50	50	11	15	5
7	40 (40%)	60 (60%)	100	60	60	60	11	15	5
8	30 (30%)	70 (70%)	100	70	70	70	9	9	5
9	20 (20%)	80 (80%)	100	80	78	80	7	4	3
10	15 (15%)	85 (85%)	100	85	83	85	6	6	3
11	10 (10%)	90 (90%)	100	86	85	90	0	2	3
12	5 (5%)	95 (95%)	100	91	90	92	0	0	0
13	0 (0%)	100 (100%)	100	96	95	97	0	0	0

Similarly, the 2D projective transform completely detected and eliminated up to 75% type II errors present in matched image features, with a number of correct matches (inliers) ranging from 5 to 47 being detected. At stages where the percentage of type II errors exceeded 75%, the transform failed to detect and eliminate all errors, while it also detected wrong matches

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as inliers. The 2D projective transform is an eight parameter transform that requires a minimum of 4 corresponding points to determine the eight parameters of the transform (Ghilani and Wolf, 2014). Just like the affine transform, the projective transform selects the best set of matches (inliers) to determine a geometric transform, thereby eliminating outliers (wrong matches). The projective transform has proven to be quite robust in detecting correct matches (inliers) in the presence of few type II errors (see table 2, column 9), as it could detect a number of correct matches at the 1st, 2nd, and 3rd stage where the percentage of type II error present in the matched image features is within 0 to 30%.

The 2D conformal transform detected and completely eliminated 90% of type II errors present in matched image features, with a number of correct matches (inliers) ranging from 3 to 8 being detected (see table 2). At stages where the percentage of type II error exceeded 90%, the transform failed to detect and eliminate all errors. The 2D Conformal transform is also known as the four parameters similarity transform that requires a minimum of two corresponding points to determine the four parameters of the transform (Ghilani and Wolf, 2014). With a sufficient percentage of matched image features, it selects the best set of matches to determine geometric transformation parameters, thereby eliminating outliers (wrong matches). However, robustness of conformal transform in detecting inliers is very poor, as there are a number of correctly matched features at each stage which it could not detect (see table 2, column 10).

A comparative evaluation of the three transforms in terms of their effectiveness in detecting and eliminating type II errors (shown in figure 6), reveals that Conformal transform has the best performance with the capability of completely eliminating 90% of Type II errors from matched image features, followed by Affine transform with the capability of completely detecting and eliminating 85% type II errors, while the projective transform has the least performance with a capability of detecting and eliminating 75% of type II errors from matched image features.

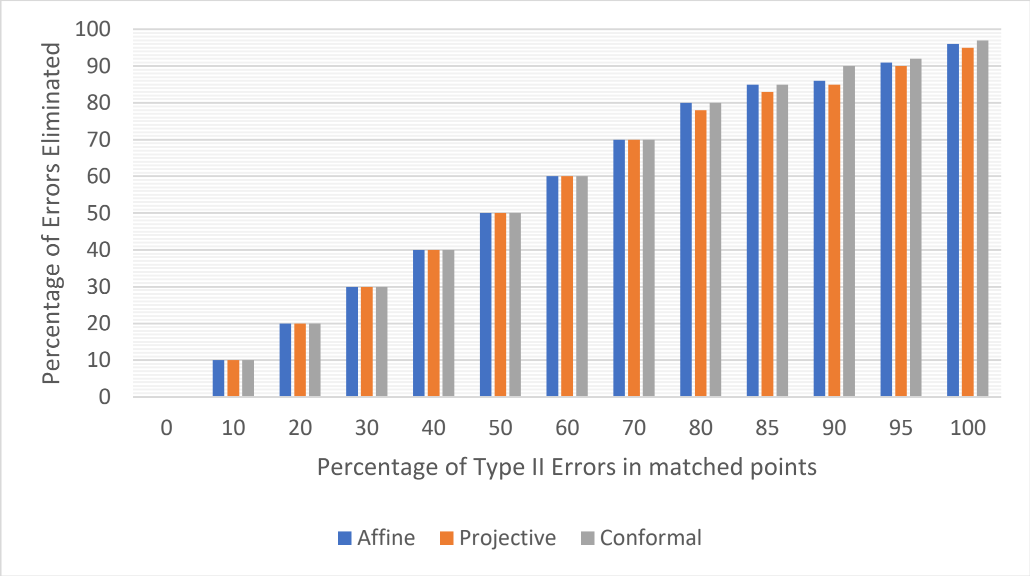

Figure 5: Comparison of type II error detection and elimination capabilities of Affine, Projective and Conformal transform, in feature-based image matching

However, in terms of robustness in detecting correct matches (inliers) while eliminating errors (see figure 6), the projective transform has the best performance.

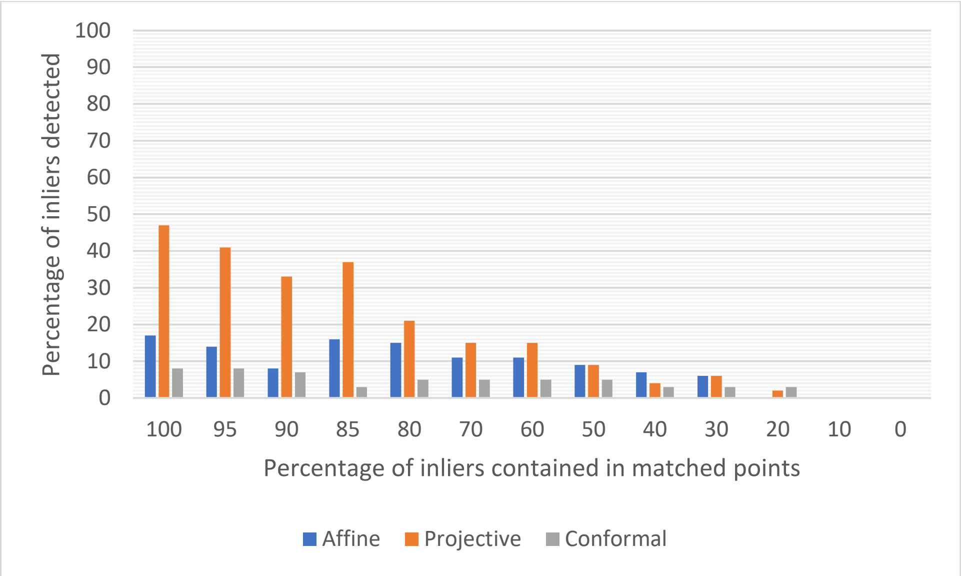

Figure 6: Comparison of inlier detection capabilities of Affine, Projective and Conformal transform, in feature-based image matching

4.0 CONCLUSION

This study evaluated and compared the efficacy of three geometric transforms namely; Affine, Projective and Conformal transform for detection and elimination of several percentage of type II errors in feature-based image matching. Findings from the study have shown that Projective, Affine, and Conformal transform can completely eliminate up to 75%, 85%, and 90% type II errors respectively, from correctly matched image features. The study also revealed that the capability of the three transforms in detecting correct matches (inliers) from erroneous matches is poor, however the Projective transform performed better than Affine and Conformal transform when the percentage of type II errors contained in matched image features is within 0 to 30%. The Authors believe that further studies are necessary to determine techniques that can improve the inlier detection capability of the three transforms.

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Appendices

A1(a): set of matched points containing 90% type II error & 10% correctly matched points
A2(a): set of matched points containing 10% type II error & 90% correctly matched points
A3(a): set of matched points containing 40% type II error & 60% correctly matched points
A4(a): set of matched points containing 70% type II error & 30% correctly matched points
(b), (c), (d): Detected inliers after eliminating type II errors using; Affine, Projective and Conformal transform, respectively.

A1

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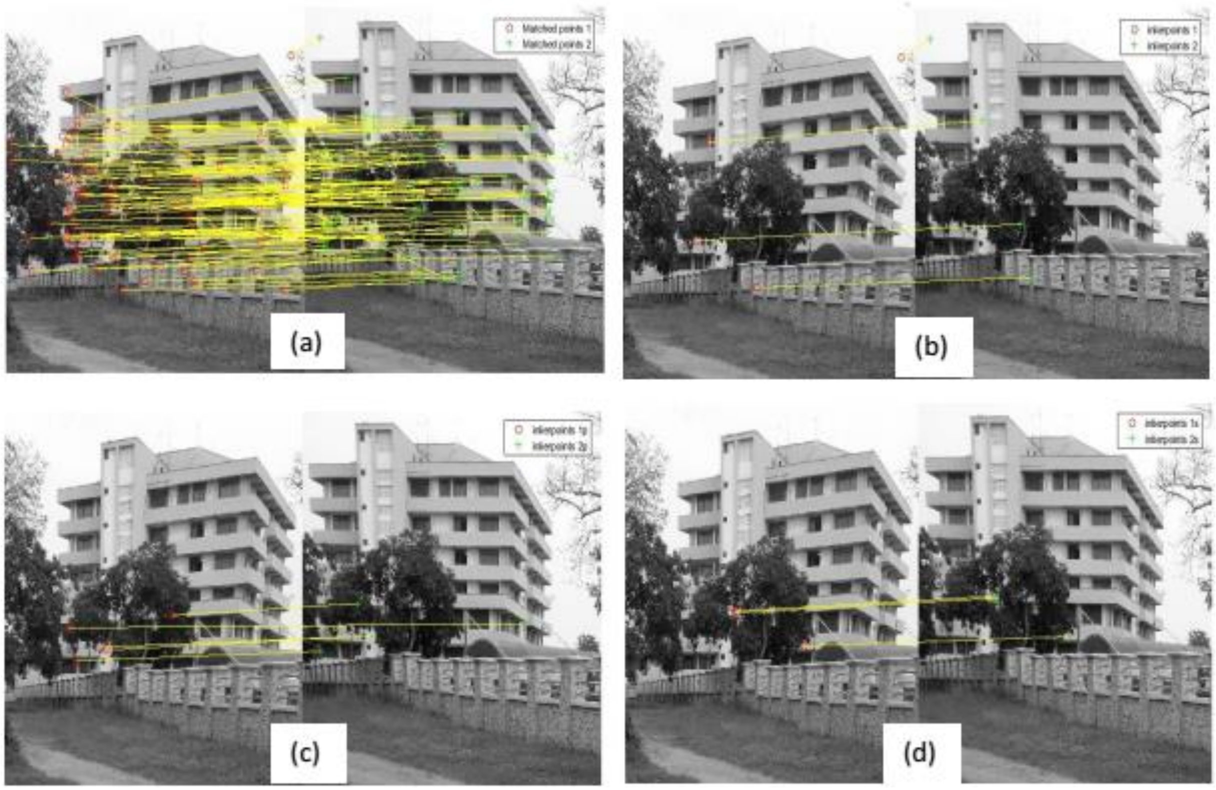

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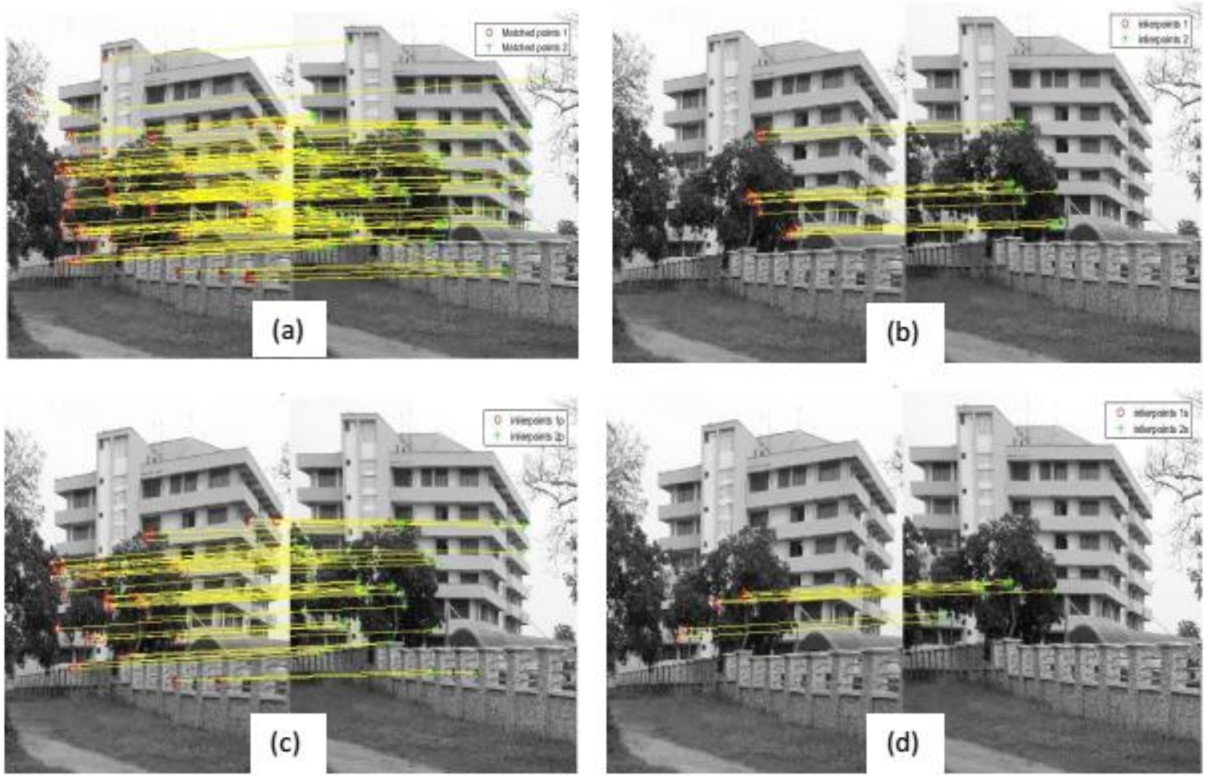

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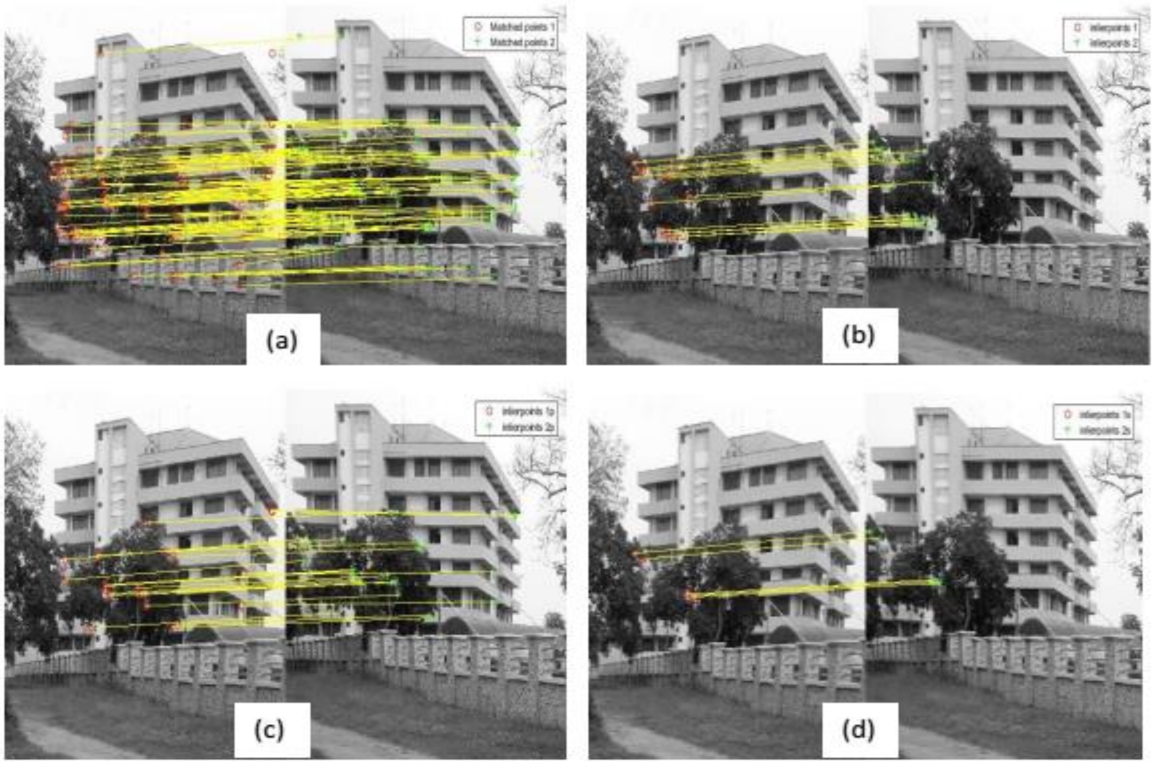

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