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A Critical Analysis of Design Flaws in the Death Star

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Abstract

English

The English abstract.

Afrikaans

Die Afrikaanse uittreksel.

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Nomenclature

Variables and functions

$p(x)$	Probability density function with respect to variable x .
$P(A)$	Probability of event A occurring.
ε	The Bayes error.
ε_u	The Bhattacharyya bound.
B	The Bhattacharyya distance.
s	An HMM state. A subscript is used to refer to a particular state, e.g. s_i refers to the i^{th} state of an HMM.
\mathbf{S}	A set of HMM states.
\mathbf{F}	A set of frames.
\mathbf{o}_f	Observation (feature) vector associated with frame f .
$\gamma_s(\mathbf{o}_f)$	A posteriori probability of the observation vector \mathbf{o}_f being generated by HMM state s .
μ	Statistical mean vector.
Σ	Statistical covariance matrix.
$L(\mathbf{S})$	Log likelihood of the set of HMM states \mathbf{S} generating the training set observation vectors assigned to the states in that set.
$\mathcal{N}(\mathbf{x} \mu, \Sigma)$	Multivariate Gaussian PDF with mean μ and covariance matrix Σ .
a_{ij}	The probability of a transition from HMM state s_i to state s_j .
N	Total number of frames or number of tokens, depending on the context.
D	Number of deletion errors.
I	Number of insertion errors.
S	Number of substitution errors.

Acronyms and abbreviations

AE	Afrikaans English
AID	accent identification
ASR	automatic speech recognition
AST	African Speech Technology
CE	Cape Flats English
DCD	dialect-context-dependent
DNN	deep neural network
G2P	grapheme-to-phoneme
GMM	Gaussian mixture model
HMM	hidden Markov model
HTK	Hidden Markov Model Toolkit
IE	Indian South African English
IPA	International Phonetic Alphabet
LM	language model
LMS	language model scaling factor
MFCC	Mel-frequency cepstral coefficient
MLLR	maximum likelihood linear regression
OOV	out-of-vocabulary
PD	pronunciation dictionary
PDF	probability density function
SAE	South African English
SAMPA	Speech Assessment Methods Phonetic Alphabet

XXX - flat earth buildings assumption XXX - try 512 x 512 XXX - different datasets

0.1. Rotational Estimators

0.1.1. Introduction

Rotational estimators are critical in image alignment and pose estimation tasks. In this project, rotational estimators are employed to align UAV-captured images when GPS data is unreliable. The accuracy of rotational alignment directly impacts the estimation of translational shifts and image similarity. These steps are crucial to ensuring reliable navigation in GPS-denied environments.

Four methods were selected for rotational estimation based on their applicability, computational efficiency, and accuracy. Other methods were considered but ultimately excluded due to their efficiency or accuracy.

0.1.2. Methods

- **Homography Estimation:** A method supporting 8 degrees of freedom (DoF), accounting for rotation, scaling, translation, and perspective correction. It is suitable for complex transformations but may introduce unnecessary errors when perspective correction is not needed.
- **Affine Estimation:** A method with 6 degrees of freedom that handles rotation, scaling, and translation without perspective correction. It is computationally efficient and offers sufficient transformation handling for most tasks.
- **2x2 Rotation Matrix:** A simplified method that accounts only for rotational and translational freedom. It lacks support for scaling and perspective, making it less effective for complex transformations.
- **Vector-based Estimation:** A direct estimation of rotation using vectors derived from image points. This method lacks robust outlier removal and complexity, limiting its effectiveness for real-world applications.

Conclusion: These methods were chosen to provide a range of complexity and computational efficiency, with homography and affine estimation being the primary focus due to their broader applicability in image transformations.

0.1.3. Improvement Techniques

To enhance the accuracy and robustness of these methods, the following improvement techniques were applied:

- **Lowe’s Ratio with KNN:** Filters out ambiguous matches by comparing the best match with the second-best match, effectively eliminating outliers, especially in repetitive or noisy data.
- **RANSAC (Random Sample Consensus):** A robust outlier removal technique that iteratively refines the inlier set to accurately estimate transformations.
- **Confidence Thresholds:** Filters out matches or keypoints below a certain confidence level. In practice, this technique performed worse than Lowe’s Ratio and RANSAC, and when used alongside them, it reduced accuracy due to over-filtering.
- **Confidence Weightings:** Adjusts the influence of each match based on its confidence score. Similar to confidence thresholds, this technique led to decreased stability by over-filtering.

Conclusion: The combination of Lowe’s Ratio and RANSAC was the most effective in improving accuracy and robustness. Confidence thresholds and weightings were found to be redundant.

0.1.4. Initial Accuracy Testing

Initial tests were conducted using relatively optimal parameters, and the performance of each method was evaluated based on its Mean Absolute Error (MAE) in heading relative to the ground truth. The results are summarized below:

Method	MAE (heading)	Result
Homography	0.1207	Accurate
Affine	0.1129	Best-performing
2x2 Rotation Matrix	1.0277	Poor performance
Vector-based	7.3571	Poor performance

Table 1: Initial Testing Results (MAE - Mean Absolute GPS Error)

Conclusion: The affine method achieved the lowest MAE, making it the most accurate for aligning images. Homography performed slightly worse due to its additional degrees of freedom, which introduced unnecessary errors. The 2x2 rotation matrix and vector-based methods were unsuitable for the task due to their lack of transformation handling complexity. Based on these results, affine and homography were selected for further testing.

0.1.5. Accuracy in Global and Local Matching

To assess the overall suitability of the rotational estimators, it is crucial to evaluate their impact on the system as a whole. Focusing solely on heading errors does not capture

the full extent of how minor inaccuracies propagate through the system. By examining the Mean Normalized Error (MNE) in GPS coordinates, a more realistic understanding of the cumulative effect of small rotational errors and their influence on overall system performance is obtained.

Global Method	Local Method	Mean Normalized Error (GPS)
Homography	Homography	48.90
Homography	Affine	41.80
Affine	Homography	42.37
Affine	Affine	41.28

Table 2: Accuracy Comparison for Global and Local Matching Techniques (MNE - Mean Normalized Error)

Conclusion: The affine method consistently outperforms homography in both global and local matching scenarios. The significant reductions in GPS error, even with relatively minor decreases in rotational error, highlight the sensitivity of both methods to rotational inaccuracies. This underscores the critical importance of optimizing the accuracy of the rotational stage.

0.1.6. Time Constraints

Time efficiency was evaluated to assess the computational performance of each method. The table below summarizes the average, minimum, median, and maximum runtimes for each approach. Lower computation times enable higher frame rates, provide greater tolerance for minor errors, and allow for faster processing of larger search spaces, ultimately improving accuracy.

Method	Mean Time (ms)	Max Time (ms)	Min Time (ms)	Median Time (ms)
Affine	1.276	11.55	0.00	0.999
Homography	22.58	50.74	0.98	10.80

Table 3: Time Analysis for Affine and Homography Methods

Conclusion: Affine is significantly faster than homography, with a much lower mean and median runtime. The greater variability in homography's runtime (indicated by the difference between mean and median) is due to its handling of more complex transformations. Affine's speed makes it particularly well-suited for real-time UAV applications.

0.1.7. Robustness Testing

Robustness testing was performed to assess each method’s sensitivity to different parameter settings, such as RANSAC thresholds, Lowe’s ratio for match filtering, and keypoint confidence thresholds. These tests are essential to determine the methods’ reliability under varying conditions and data quality.

RANSAC Threshold Testing

We varied RANSAC thresholds to evaluate how sensitive each method is to outlier removal. A lower threshold implies more aggressive filtering, which reduces the number of keypoints but increases the reliability of those retained.

Threshold	Homography (Mean Heading Error)	Affine (Mean Heading Error)
0.2	0.1384	0.1089
0.5 (Default)	0.1207	0.1129
5	0.1249	0.1003
25	0.1222	0.0997
50	0.1226	0.1112

Table 4: Effect of RANSAC Thresholds on Heading Error

Conclusion: Both methods are robust to RANSAC threshold changes, but homography exhibits greater variability at lower thresholds, suggesting a weaker estimation capability when fewer keypoints are available.

Lowe’s Ratio Testing

We evaluated Lowe’s ratio to assess its impact on match filtering and rotational estimation accuracy. A lower ratio implies more aggressive filtering, reducing the number of matches but increasing their quality.

Lowe’s Ratio	Homography (Mean Heading Error)	Affine (Mean Heading Error)
0.6	0.1289	0.1098
0.7	0.1255	0.1006
0.8	0.1207	0.0997
0.9	0.1139	0.1111
0.95	0.1211	0.1054

Table 5: Effect of Lowe’s Ratio on Heading Error

Conclusion: Both methods are robust to changes in Lowe’s ratio.

Keypoint Confidence Threshold Testing

Keypoint confidence thresholds were varied to evaluate how each method performs with different levels of keypoint quality. Lower thresholds admit more keypoints but decrease the reliability of individual keypoints.

Keypoint Confidence Threshold	Homography (Mean Heading Error)	Affine (Mean Heading Error)
0.001	0.1404	0.1019
0.0008	0.1207	0.0974
0.0005	0.1247	0.0997
0.0002	0.1247	0.1024

Table 6: Effect of Keypoint Confidence Thresholds on Heading Error

Conclusion: Both methods are robust to changes in keypoint confidence thresholds, but affine remains more consistent at lower thresholds, maintaining lower mean errors with noisier keypoints.

Overall Robustness

In summary, affine consistently outperforms homography in terms of robustness, particularly in scenarios involving noisier or fewer keypoints. This makes affine the preferred method for handling datasets with varying quality and practical applications requiring stability under changing conditions.

0.1.8. Conclusion

Affine estimation is selected as the primary method for future work due to its superior accuracy, faster computation, and greater robustness. Its 6 degrees of freedom provide sufficient understanding of image transformations without introducing unnecessary errors from perspective correction.

Best Rotator: Affine, AKAZE AND BF

Matching filtration techniques

Global point matching. In order to find an accurate rotational estimate, we need to ensure that the points we use in the inference are of sufficient quality and quantity. This involves filtering out lower quality keypoints while considering sufficient keypoints are still needed to remove noise from resolution and computation limits and distortion-based point differences. This means we need to filter the matches between images. The first is to remove ambiguous matches. This involves using Lowes Ratio's Test to ensure the

two best potential matches are sufficiently different based on their descriptors. Then, we can sort the matches according to how close the match is to its actual corresponding keypoint based on their descriptors. Finally, we can use homography and RANSAC to firstly estimate a model for the data points and reject any outliers to this model. Together, these steps remove ambiguity, ensure matches are of high quality, and remove outliers to ensure the best possible rotational estimate. The three parameters associated with each of these steps are:

- **Lowes Ratio Test:** This is the ratio of the distance of the best match to the second-best match. If this ratio is above a certain similarity allowed threshold, the match is considered ambiguous and removed.
- **Homography and RANSAC:** The homography and RANSAC model is used to estimate the transformation between the two images. The RANSAC threshold is the maximum distance a point can be from the model to be considered an inlier.
- **Keypoint Confidence Threshold:** This is the minimum confidence a keypoint must have to be considered in the matching process. This may be only keeping some number of the highest quality keypoints or keeping all keypoints above a certain similarity threshold. The former will be used as this ensures that we do not have to constantly adjust the threshold based on the dataset and quality, instead we are guaranteed to have a certain number of keypoints which is more important than being pedantic about the quality of the keypoints.

Note, this is tested on only the global matcher, and with multimethod, implying isolation in its effect on the rotational estimation. XXX this still now needs to be tested with the global matcher being the local matcher (added inferred effect) and on the local matcher. Testing Kp threshold confidences:

AKAZE NO FILTER: Percentage Deviation: [4.91698283] Preprocessing Global Detector: AKAZE, Preprocessing Global Matcher: BF, Global Matching Technique: Histogram, Local Detector: AKAZE, Local Matcher: BF Mean normalized GPS error: [65.07094916] Mean Heading Error: 0.8556339319426911 Mean Length of Keypoints: 2525.866666666667 Mean Global Time to Extract Keypoints: 0.2709 s Mean Number of Good Matches: 802.4396551724138 Range of Good Matches: 1524 Time taken to execute The Method: 45.7884 seconds

AKAZE 500 Percentage Deviation: [4.58746506] Preprocessing Global Detector: AKAZE, Preprocessing Global Matcher: BF, Global Matching Technique: Histogram, Local Detector: AKAZE, Local Matcher: BF Mean normalized GPS error: [62.34674896] Mean Heading Error: 0.9235667588307905 Mean Length of Keypoints: 2525.866666666667 Mean Global Time to Extract Keypoints: 0.4008 s Mean Number of Good Matches: 500.0 Range of Good Matches: 1524 Time taken to execute The Method: 62.8682 seconds

AKAZZE 300 Percentage Deviation: [4.53573965] Preprocessing Global Detector: AKAZE, Preprocessing Global Matcher: BF, Global Matching Technique: Histogram, Local Detector: AKAZE, Local Matcher: BF Mean normalized GPS error: [61.64376568] Mean Heading Error: 0.9238056255750251 Mean Length of Keypoints: 2525.866666666667 Mean Global Time to Extract Keypoints: 0.2578 s Mean Number of Good Matches: 300.0 Range of Good Matches: 1524 Time taken to execute The Method: 45.2109 seconds

Keypoints Allowed	No Filter	500	300	No Filter	500	300
Method	AKAZE			ORB		
GPS Error	65.07	62.35	61.64	54.10	56.72	60.64
Mean Number of Good Matches	802.44	500.0	300.0	718.15	500.0	300.0
Range of Good Matches	1524	1524	1524	0	0	0
Mean Length of Keypoints	2525.87	2525.87	2525.87	3000.0	3000.0	3000.0
Time Per Keypoint Extraction (s)	0.2709	0.4008	0.2578	0.0636	0.0916	0.0571
Time Taken (seconds)	45.79	62.87	45.21	48.08	47.3382	46.04

Table 7: Comparison of AKAZE and ORB Feature Matching Performance

From this table, its clear the optimal point for ORB is without filtering the matches given that ORB was running with only 3000 keypoints. For AKAZE, this point is at 300. This optimal point is based mainly on accuracy with consideration for no large time difference. As visible, ORB outperforms AKAZE in accuracy given roughly similar time constraints.

As visible, ORB outperforms AKAZE in accuracy given roughly similar time constraints. The time is also more consistent accross different datasets implying more robustness.

Chapter 1

Summary and Conclusion

Appendix A

Project Planning Schedule

This is an appendix.

Appendix B

Outcomes Compliance

This is another appendix.