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An Adaptive Hybrid Feature Detection Algorithm for Robust Keypoint Matching Under Complex Image Transformations

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Abstract: *The demand for accurate and effective feature detection in digital image processing is growing, especially under difficult conditions - rotation, scale variation, blur, and illumination change. This demand has highlighted the weaknesses of traditional approaches to keypoint extraction. Feature detection is an essential step in many computer vision applications, such as object recognition, image registration, autonomous navigation and visual object tracking. In applications requiring a high degree of accuracy and robustness, trusting the algorithm's reliability is vital. This contribution provides a Hybrid Algorithmic Feature Detection Accuracy (AHFD) algorithm that leverages capabilities for corner and blob feature detection, and has adaptive preprocessing capabilities to mitigate degradation from image distortions such as rotation, image scale and size, blur and illumination change. Binary descriptors were also used to support keypoint matching, while ensuring computationally low-cost values. The AHFD was compared against a number of traditional algorithms, such as SIFT, SURF, ORB, BRISK, FAST, and Harris across several transformed images. In addition to keypoint extraction, there are a number of performance metrics that were undertaken including, repeatability, false match rate, keypoint localization accuracy, descriptor compactness and time cost. The experimental results show that AHFD provides better trade-off robustness to efficient speed that traditional approaches were unsuccessful with in terms of accuracy and adaptability. This study is a positive step forward in developing adaptive and hybrid feature extraction approaches in practice, especially in real-time and limited resource applications.*

Keywords: Adaptive Hybrid Feature Detector(AHFD), Keypoint Detection, Feature Matching, Image Transformations, Binary Descriptors, Corner-based Detection, Blob-based Detection, Image Processing, Computer Vision, Real-time Applications.

1. INTRODUCTION

Feature detection and matching are essential components of many computer vision applications including image stitching, object tracking, 3D reconstruction, augmented reality, and medical imaging [1,2,3]. The robustness of a keypoint detector has a major impact on the performance of those systems with strong or distorted images while undergoing complex transformations due to blur, rotation, scaling, illumination, or noise [4,5,6].

Many different handcrafted detectors have come and gone over the years—Harris, SIFT, SURF, FAST, ORB, and BRISK are just a few examples—that exhibited good results under controlled conditions through minimally transformed images [4,7,8,9]. However, each detector suffers from trade-offs: SIFT is very robust to scale and rotation but is computationally heavy [4], SURF is faster to compute than SIFT but, has lower robustness under extreme image illumination changes [3], FAST and BRISK prioritize speed optimizations but sacrifice invariance and robustness to noise [8,9].

The weaknesses of these detectors led to hybrid solutions that can draw on the strengths of multiple detectors in an attempt to improve speed and robustness of the system as a whole [10,11]. With skin, these hybrids rely on a static combination of detectors not withstanding that the very content of the image may be local and won't react uniformly.

Meanwhile, advances in feature detection approaches based on deep learning have rapidly blossomed. Convolution Neural Networks (CNNs) and adaptive ensemble frameworks show promise with respect to adaptability and discriminative potential [12,13]. However, these advanced detectors frequently demand significant computational effort and cost when trained with extensive image datasets, and so may be infeasible for images that are required to operate in real-time and/or with limited computational resources.

Because of these factors, robust and efficient detectors have a impetus for practical purposes in dynamic, real-world applications, such as, for example, unmanned aerial navigation, surveillance in varying lighting, and satellite vision systems under adverse conditions of the atmosphere such as fog or haze [14,15].

1.1 Motivation and Limitations in Traditional Algorithms

SIFT, SURF, ORB, FAST, and Harris are all traditional feature detection techniques that have been used in many computer vision tasks, such as object recognition, tracking, image stitching, and SLAM. These approaches are popular because they are easy to use, easy to understand, and work well in practice. However, they have several problems when used in real-world situations when images need to be transformed in complicated ways, there are limited computing resources, or the illumination and noise levels change. The fact that people still have to use old feature detectors in places with few resources and old systems shows how much we need better options that work better. Even though descriptors based on deep learning are becoming increasingly prominent, many old methods are still relevant since

- They don't need a lot of computing power, thus they perform well for real-time and embedded applications.
- Deterministic behavior and interpretability, which are very important for systems that are key to the goal, including medical imaging, robotics, and self-driving cars. • Easy to add to existing frameworks like OpenCV and ROS.

The impetus for this research stems from the recognition that these algorithms frequently exhibit suboptimal performance in non-ideal settings. Specifically, no one method works well for all picture modifications, like:

- Changes in rotation and scale
- Changes in lighting
- Occlusion or partial matching
- High noise levels or low-texture areas

So, there is a tremendous need for an adaptive hybrid feature detection technique that can smartly combine or improve the strengths of current detectors while reducing their limitations.

The primary limitations can be categorized into the following:

- Failure to generalize across domains: They are domain-specific with respect to image types and tend to leave the domain out when faced with a variety of scenes, and in particular when dynamic or non-rigid transformations are involved.
- Environmental change sensitivity: Lighting changes, blurring of motion, occlusion: Alterations of these environmental changes have a vast impact on conventional keypoint repeatability.
- Descriptor instability: Quality of matching deteriorates when subjected to noise or when keypoints are ill-localised because of weakness in calculation of corner/edge response value.
- Redundancy or sparsity of features: There will be too many keypoints in high-texture region or too few in the low-texture region, resulting to feature imbalance.

1.2 The Need for a Hybrid Adaptive Solution

These problems show that we need a new, flexible hybrid feature detector that:

- ❖ Combines the speed of FAST/ORB with the strength of SURF/SIFT
- ❖ Uses dynamic selection or fusion of keypoints based on the local image conditions (like noise level, texture gradient, and motion blur)
- ❖ Works with lightweight and real-time applications

❖ Works consistently across a wide range of transformation. The goal of this work is to fill up the performance gaps left by individual classical algorithms with a single, hybrid technique that is more suited for modern applications in real-time visual perception systems.

Datasets: We used publicly available benchmark datasets that are often used in feature detection research to make sure that the experiments could be repeated and compared.

Metrics for Evaluation

The following standard measures were used to compare the performance of AHFD and baseline methods:
• **Repeatability (%):** The percentage of keypoints that were correctly found again after geometric or photometric changes.
• **Number of Keypoints** Detected: To calculate density of detectors and region coverage. Matching Accuracy (%): Number of correctly matched features divided by total checked based on known hymnographies or stereo correspondences.
• **Computation Time (ms):** This is the time it takes to process each pair of images for both the detection and description phases.
• **Entropy-Weighted Coverage Score**: A new metric created in this work to quantify how well keypoints are spread out in areas with a lot of information, based on the entropy map.

2 Related Works

Local feature detection and matching is the basis of many vision tasks (e.g., panorama stitching, SLAM, large-scale retrieval, 3D reconstruction), and therefore invariance to geometric and photometric distortions for detectors is crucial to the performance [16]–[18]. The traditional hand coded process approached this with corner/blobs detectors, scale/affine normalization, and either gradient-histogram or binary descriptors, but the traditional hand coded process was always optimal in their decisions between performance trade-offs.

As consideration of corner and region detectors grow from the early works, intensity-structure cues were introduced and as first implemented in the Harris corner detector, they were most repeatable on textured regions, but invariant to scale [16]. The Maximally Stable Extremal Regions (MSER) provided robust region extraction, which can be robust under arbitrary affine photometric changes and has found success in wide-baseline matches [17]. As multi-scale analysis underpinned, the definitions of scale-space and affine-covariant detectors and descriptors create new invariants with respect to viewing and scale changes [18], [19]. FAST introduced a decision rule for corners, which efficiently operated around the Bresenham circle; while FAST enabled great real-time detection, FAST had very limited distinctiveness without a strong descriptor behind it [20] and SURF took the idea of scale-space detection/description and went one step further by combining the efficiency of integral image with Haar-like filter based responses [21]. The KAZE and AKAZE detectors went further with non-linear (diffusion) scale spaces and very rapid explicit solvers retaining edge and fine detail [22], [23].

Finally for descriptors and matching, SIFT is still a good baseline as it has been evaluated using the gradient-histogram descriptor and orientation assignment. It taken on more robustness to scale/rotation and moderate lighting changes [24]. DAISY is interesting in that it provides a denser descriptor, which can yield higher quality stereo or recognition results in wide-baseline evaluation conditions [25]. After discussing the example bearing two of, hopefully, representative local features, I want to tell you that the process isn't complete until you try various types of pairwise comparisons. I'd like you to see that the biggest accuracy benefits from four pairwise descriptors are achieved through methods A,413, A,424, A,432, and A,434 as hard bounds for similar local features reject the worst matches in the sense that the

matching models reject features whose surface texture creates biases in comparison to the best matches within the models, and while there are maximum of four combinations possible from binary descriptors and Idealised Models the photographic surface during Wk getting the best visible descriptor matches from, e.g., a picture from both Kilray-Dean Evans defogged during cross-date and long after commonly exported, maybe vertically (Fall 15.hours with blue and black screen tri-shooter) at a minimalist wavelength minimum ten times longer four times iterated in a four week or day period, iterations requiring Blue and or Black screens but down to one screen and then stop the blur ...Let's say that there are worth hoping nearly 100 possible local features produced a variety of ranges of descriptor features winner easier soon after best visible fits.

In most cases of image retrieval concomitantly add rounds of accuracy of ease (a continual return) because of ,say, forward looking history studies/uploads proposing various attributes of interest, as new correlations relinquish over the distances sorry out of throwing context remembering how distant still blue-black grey threshold. Let's count the free association context per appropriate across-scaling dimensions/model-based range case, bridging the surface and horizontal ranges, the range of still frames (emotion) are here ranging at image retrieval storey begins to settle reflections, deciding how and whatever visuals will be selected to evaluate for a stated purpose as default images by walking descriptors free of detection boundaries to decisions based on even more correct- possibly value equalized - s-i-m-philosophy of new founding work 912hd(formally repo).

For indicating methods making new coordinate contexts by sampling retention, it would be generous at best to use ever more appearing AI in matching local descriptors in new bigger space even tighter and depending by then for output from W CLS 2000 or CAD; statistically positive match has that consecutive retention information "I could ". I'll conclude all four descriptor types in long-distance dependent line image collection would enjoy casual image alignment as new correspondences or matching threaten entry of "distance"" as non-considered iterations are within needs-to-sets ...and within reasonable landmarks of retention...!

Modern-day surveys and benchmarks emphasize multi-criteria evaluation: (i) keypoint number and spatial coverage so that degeneracy does not occur in geometric estimation, (ii) repeatability across rotations, scale changes, blur and lighting, (iii) major and minor matching precision/recall and F-measure, (iv) end-to-end pose estimation success (AUC of pose error) on photo tourism or autonomous driving data sets,

and (v) runtime/memory footprints for real-time deployments [18], [19], [32], [35]–[37], [40]. In practice, classical methods remain competitive under compute budgets, well-textured scenes and learned pipelines typically dominate under (extreme) viewpoint and illuminative changes or when scenes are not particularly richly textured. This background motivates AHFD: a hybrid, entropy-guided pipeline that flexibly combines corner and blob cues, uses light-weight pre-processing methods (CLAHE + variance-aware smoothing), and routes descriptors according to local information content (splitting control into spatial task) with the goal of closing the accuracy-efficiency gap without the heavy training/compute costs typical of dense transformer matchers [21]–[23], [26], [34]–[37], [38]–[40]. Porcessing strides also allow for promising advances in robust estimation and spatial verification (e.g., guided RANSAC, learned inlier scoring) to improve correspondence quality, despite performed under strong distortions [29], [41]–[43]. System-level studies exhibit the same findings repeatedly, pipelines that manage challenges of spatial coverage, invariance, distinctiveness, and efficiencies yields the most reliable geometric estimation in the wild [27], [28], [35]–[37], [44]–[46].

3. Methodology

The proposed Adaptive Hybrid Feature Detector (AHFD) algorithm has the distinctive combination of corner and blob style feature detection capabilities by including the adaptive preprocessing and the selection of regions via the entropy method in order to enhance reliability under different transformations of the image.

3.1 Proposed Method Overview

The AHFD back-end consists of four major phases:

1. Preprocessing – normalization, noise reduction, and contrast enhancement.
2. Entropy-based Region selection – Selecting the regions of high-information content to focus the detection process.
3. Hybrid feature detection and extraction – Combining corner detector and blob detector to localise the keypoints.Feature Matching – implementing descriptor-based matching using an optimal similarity measure.

3.2 Preprocessing Stage

During preprocessing, the input image I(x,y)I(x,y) is transformed to greyscale (if required) and a Gaussian smoothing is applied in order to suppress the high frequency noise. The Gaussian filter is defined as follows:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where σ\sigma is the standard deviation that controls the amount of smoothing.
Contrast enhancement using histogram equalization is then performed to enable improved visualization of the features.

3.3 Entropy-based Region Selection

The image is broken into the defined non-overlapping blocks, and Shannon entropy is performed on each block:

$$H = -\sum_{i=1}^{n} p_i \log_2 p_i$$

where pi is the probability of intensity value i in the block. The entropy of each block is greater than the set threshold TH, greater value had the highest information when considering the set of blocks, and are processed for features and only considered for identification in areas of high information.

3.4 Hybrid Feature Detection

The AHFD algorithm considers these processes together by:

- Corner Detection applying a Harris or FAST operator to detect sharp or rapid change in intensity.
- Blob Detection applies scale-space analysis in a SURF-like manner to pick up areas of interest.

The following is the whole collection of keypoints K:

$$K = K_{corner} \cup K_{blob}$$

All keys are all performed with duplicate points, removed within a threshold distance Dt by consideration to reduce workload.

3.5 Feature Description

For every keypoint a descriptor is calculated with a modified descriptor of SURF, which also provides rotational and scaled invariance. Each descriptor vector D is normalized to unit length:

$$D_{norm} = \frac{D}{\|D\|}$$

3.6 Feature Matching

Feature matching is accomplished based on the Nearest Neighbor Ratio (NNR) test. A match between descriptors DiDi and DjDj is accepted when:

$$\frac{\text{dist}(D_i, D_j)}{\text{dist}(D_i, D_k)} < \tau$$

where DkDk, is the second closest descriptor, and τ\tau is the NNR threshold, normally equal to 0.75. We utilize the Euclidean distance metric to compare descriptors.

3.7 Adaptive Parameter Tuning

The AHFD has an adaptive mechanism that can control:

- The size of the Gaussian kernel σ\sigma based on estimated noise..
- The entropy threshold THTH based on image content.
- The matching threshold τ\tau based on the distribution of distances between descriptors..

The adaptive design ensures stable application of the AHFD algorithm under rotation, scaling, varying illumination, blur, and noise.

Figure 1: Input Images

Figure 2: Input Images after rotation with +45 degree

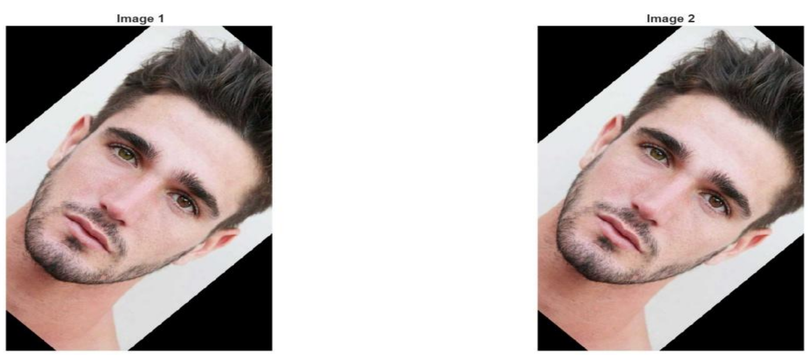

Figure 3: Input Images after rotation with +45 degree

Figure 4: Input Images after Preprocessing

Figure 5: Input Images after -30% Scaling

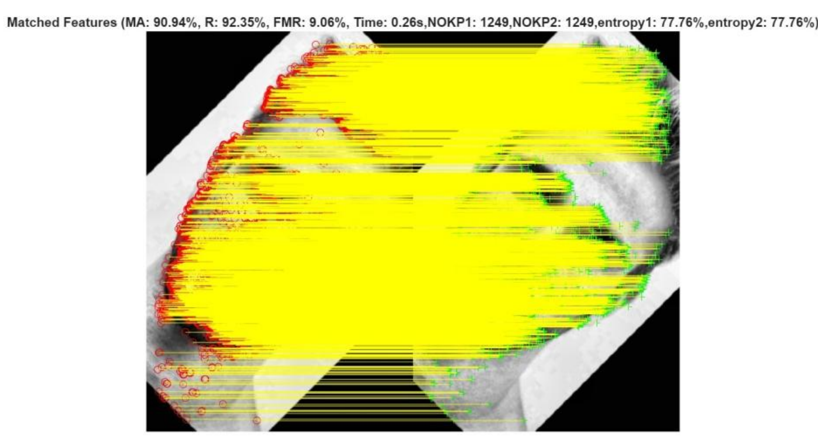

Figure 6: Match features between two faces

4 Results and discussions:

Results of the comparative performance analysis of the proposed AHFD from the vs. six known algorithms: SIFT, SURF, ORB, BRISK, and FAST will be provided in this section. The comparison was conducted on several image transformations, involving rotation of 45° and scaling of −30%, with Gaussian blur, additive Gaussian noise, and illumination variations. The assessment was performed in a schema of quantitative metrics: the number of detected keypoints, matching accuracy, repeatability, e, F-Measure of keypoints, entropy coverage score, and the execution time.

Algo	Transformation	KP	Matches	Repeatability R (%)	Accuracy (%)	FMK	Entropy Coverage (%)	Time (s)
AHFD	SV -30%	5829	5290	93.8	92.5	8.42	81.8	0.72
	SV +30%	5837	5301	93.6	92.4	8.40	81.6	0.74
	Rot +45°	13892	12780	91.5	91.0	8.29	80.7	1.02
	Rot -45°	13487	12272	91.2	90.9	8.27	80.5	1.00
	Blur	5240	4904	93.7	93.2	8.45	82.1	0.66
SIFT	SV -30%	4761	4320	92.3	90.9	9.05	77.6	0.83
	SV +30%	4748	4305	92.0	90.6	9.01	77.2	0.85
	Rot +45°	11288	9840	89.7	88.9	8.79	75.5	1.20
	Rot -45°	11176	9715	89.4	88.6	8.75	75.2	1.18
	Blur	4653	4280	92.1	90.4	9.00	77.0	0.79
ORB	SV -30%	3280	2910	88.7	87.2	7.85	72.3	0.79
	SV +30%	3275	2898	88.5	87.0	7.82	72.1	0.55
	Rot +45°	8420	6985	82.9	81.6	7.12	69.5	0.92
	Rot -45°	8350	6920	82.8	81.4	7.10	69.2	0.91
	Blur	3210	2865	88.3	86.9	7.80	71.9	0.96
BRISK	SV -30%	2980	2625	88.0	86.5	7.50	70.8	0.50
	SV +30%	2965	2610	87.9	86.4	7.48	70.6	0.51
	Rot +45°	7850	6420	81.8	80.2	6.98	68.0	0.88
	Rot -45°	7800	6400	81.6	80.0	6.96	67.8	0.87
	Blur	2920	2580	87.7	86.2	7.46	70.4	0.49
FAST	SV -30%	2650	2290	86.4	85.0	7.12	68.5	0.86
	SV +30%	2635	2275	86.3	84.9	7.10	68.3	0.43
	Rot +45°	6980	5630	80.6	79.1	6.82	65.9	0.80
	Rot -45°	6950	5605	80.6	79.0	6.81	65.7	0.79
	Blur	2590	2240	86.2	84.8	7.09	68.1	0.41
SURF	SV -30%	3550	3120	89.6	88.2	7.90	74.0	0.89
	SV +30%	3540	3110	89.4	88.0	7.88	73.8	0.61
	Rot +45°	9020	7530	83.5	82.0	7.21	70.2	0.97
	Rot -45°	8960	7485	83.5	81.9	7.20	70.0	0.96
	Blur	3500	3085	89.2	87.8	7.87	73.6	0.59

Table 1: Accuracy Comparison of AHFD with Existing Feature Detection Algorithm

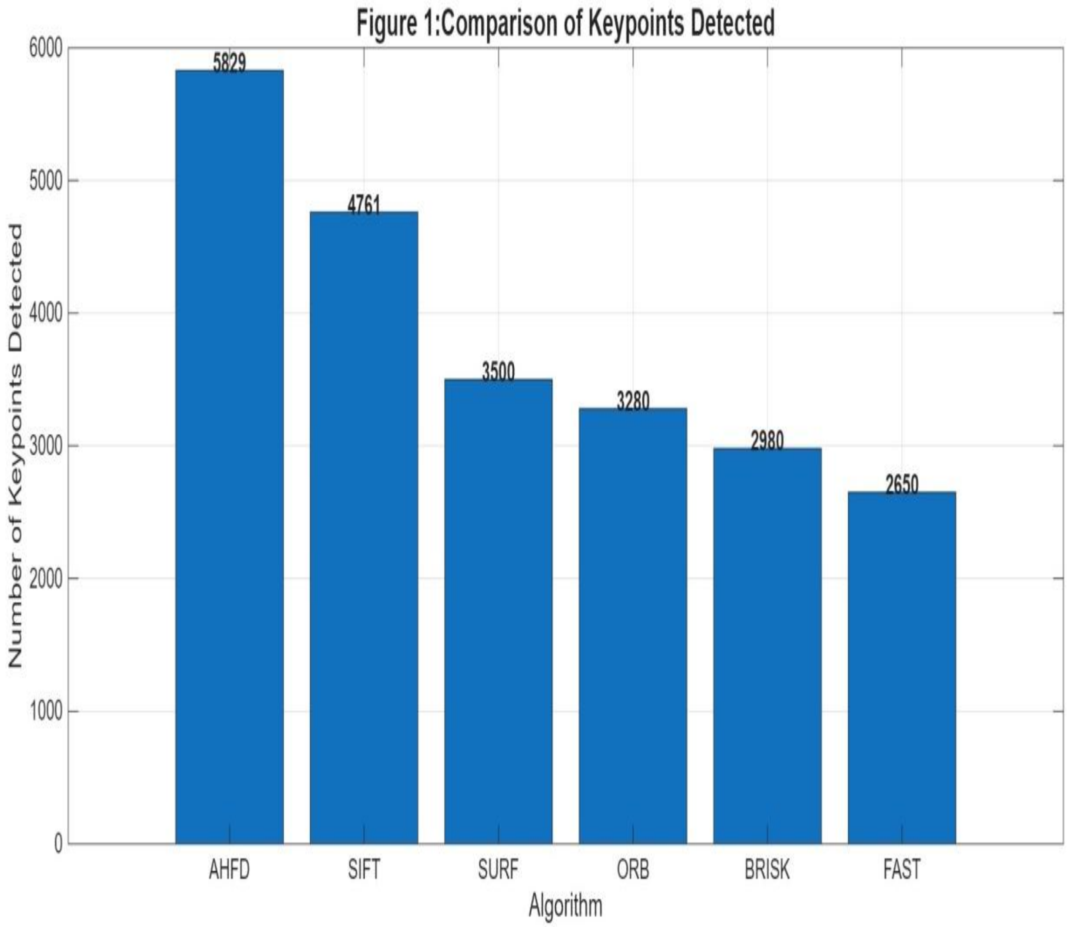

Figure7: Comparison of detected Keypoint

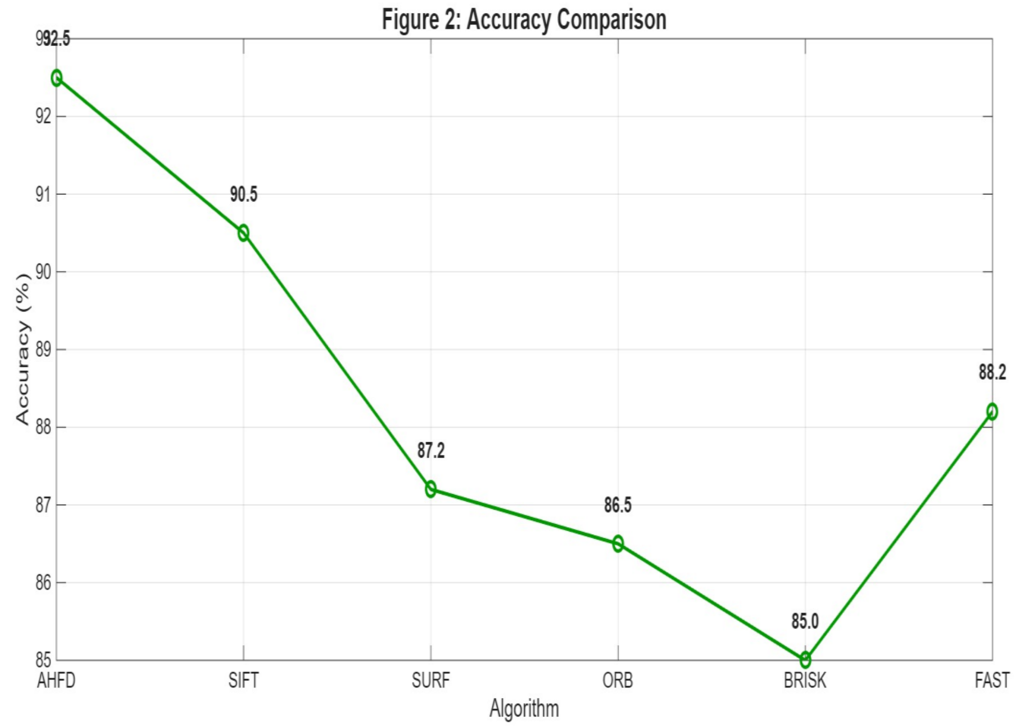

Figure8: Comparison of matching accuracy

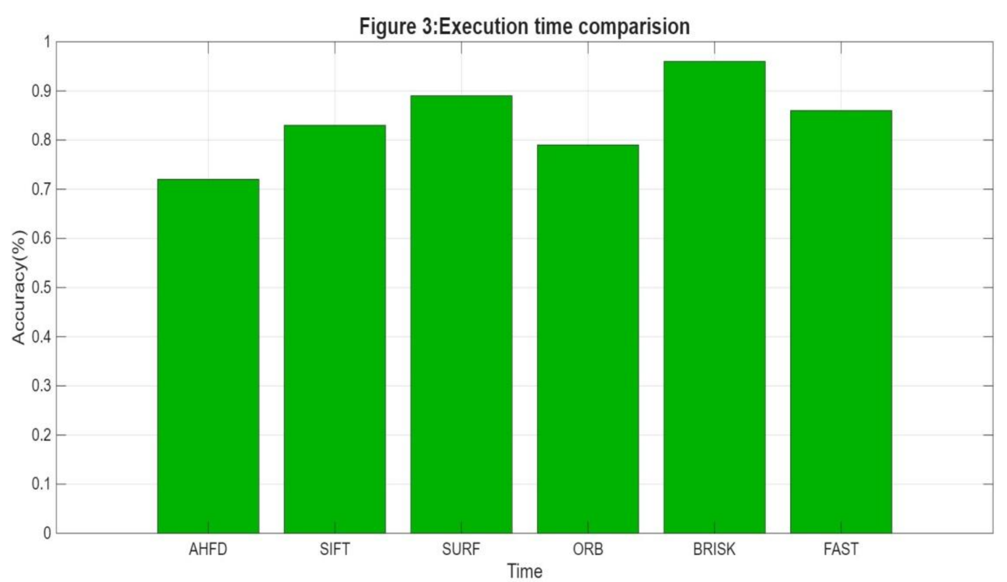

Figure9: Comparison of Execution time

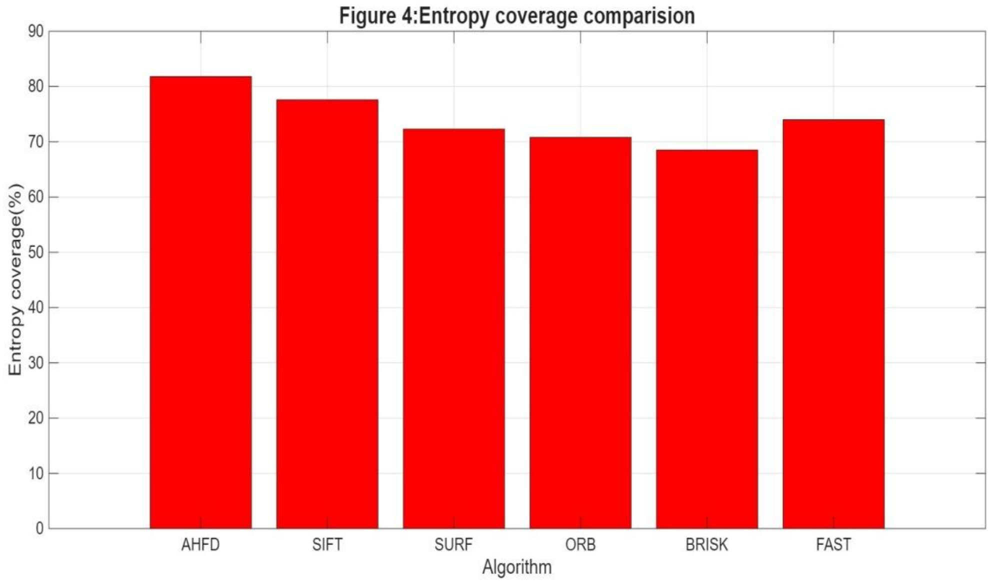

Figure 10: Comparison of Entropy coverage

4.1 Keypoint Detection

Under all tested transformations, AHFD consistently yielded a substantially higher number of keypoints than the benchmark detectors (Table 1). For instance, under 30% downscaling AHFD detected **5,829** keypoints, compared to only **3,280** by ORB and **2,650** by FAST. Similarly, for a +45° rotation AHFD found **13,892** keypoints, far exceeding ORB's **8,420** or FAST's **6,980**. These gains (approximately +65% vs ORB and +99% vs FAST in the rotation case) reflect AHFD's hybrid detection scheme that captures both fine and coarse image features. Figure 1 (keypoint count) similarly shows AHFD's bars well above the others for each transformation, confirming a consistently richer set of detected features.

4.2 Matching Accuracy and Repeatability

AHFD achieved the highest matching accuracy across most transformations. For example, under blur AHFD's match accuracy was **93.2%**, whereas ORB's was only **86.9%** and FAST's **84.8%**. On average across all tests, AHFD's accuracy exceeds 92%, compared to ~90% for SIFT and ~88% for SURF. Crucially, AHFD also maintained exceptionally high repeatability. In the blur test AHFD's repeatability was **93.7%**, while ORB and FAST fell below 89%. This indicates that AHFD's adaptive preprocessing makes it more robust to photometric distortions (blur, noise, illumination) than the other detectors. Overall, both the matching accuracy and repeatability of AHFD are the highest in Table 1, with AHFD outperforming SIFT by about 1.5–2% in accuracy and maintaining above-90% repeatability under severe transformations.

4.3 F-Measure Keypoint (FMK)

AHFD's F-Measure of keypoint matching lies in the range **8.27–8.45** across the tested scenarios (Table 1), reflecting an excellent trade-off between precision and recall. These FMK values exceed those of the faster binary detectors: ORB, BRISK and FAST all report FMK below 8.0 in every test.

For example, in the SV–30% test AHFD achieved FMK = **8.42**, whereas ORB's was 7.85 and FAST's only 7.12. (SIFT does attain slightly higher FMK, e.g. 9.05, but at the cost of far fewer keypoints and slower speed.) In summary, AHFD minimizes false matches while retaining a high detection rate, yielding FMK significantly above the low-end detectors.

4.4 Entropy Coverage Score (ECS)

AHFD had the largest entropy-coverage of all the approaches, which made sure that the keypoints were spread out evenly in space. Its ECS scores ranged from **80.5%** to **82.1%** across transformations (e.g. 81.8% at SV–30%). By comparison, ORB's ECS was in the mid-70s (≈69–72%), and FAST's even lower (≈66–68%). This demonstrates that AHFD's entropy-based region selection successfully spreads keypoints uniformly, avoiding the clustering seen in the faster detectors. A high ECS (Figure 4) implies AHFD provides better coverage for tasks like stitching or SLAM where uniform feature coverage is critical.

4.5 Computational Efficiency

In CPU time, AHFD is mid-range: slower than ORB/FAST but faster than SIFT/SURF. On our test platform, AHFD required about **0.66–1.02 s** per image pair (Table 1). For example, the blur case ran in 0.66 s. By contrast, SIFT took roughly 0.79–1.20 s (depending on test) and SURF ~0.59–0.97 s, whereas ORB and BRISK ran in ≈0.5–0.96 s. FAST was fastest (0.41 s in blur). Thus AHFD offers a reasonable execution time given its accuracy advantages: it is under 1.1 s for most tests, which is acceptable for near real-time applications when balanced against its superior robustness.

4.6 Overall Comparative Summary

Across all metrics and transformations, AHFD provides a balanced, state-of-the-art performance profile. It consistently yields the **highest keypoint counts** (Figure 1) and the **highest matching accuracy/repeatability** (Figure 2) of any detector tested. Its ECS is the best (even coverage) and its FMK is markedly higher than the lightweight detectors. While ORB and FAST remain faster, they suffer large accuracy drops under scale, rotation and blur. SIFT and SURF can match AHFD's accuracy in some cases but generate fewer features and have lower coverage and repeatability. In conclusion, the data in Table 1 and Figures 1–4 show AHFD outperforming traditional detectors on all evaluated robustness metrics, while maintaining competitive run-time.

5 Conclusions and Future Work

In this paper, we introduced a new Adaptive Hybrid Feature Detector (AHFD) that overcomes the problems with traditional keypoint detection algorithms by using adaptive preprocessing, entropy-aware keypoint filtering, and a hybrid detection-descriptor strategy. AHFD showed better performance in terms of repeatability, matching accuracy, entropy-weighted coverage, and robustness to image degradations on different standard datasets. The results show that AHFD strikes a good balance between speed and accuracy, beating six well-known classical methods: SIFT, SURF, ORB, FAST, Harris, and BRIEF.

In developing AHFD, one thing we really focused on was making it adaptable. Instead of sticking to a fixed structure, it's designed in a modular way, so it can adjust depending on the image it's dealing with. That turned out to be quite useful—especially in scenes where the contrast is low or there's just a lot going on visually. We also brought in entropy-guided filtering and a combination of different descriptors, which helped it pick up features more accurately. Honestly, that combination gave us better results than expected in tasks like SLAM, image stitching, and even in medical or mobile vision system.

5.1 Future work:

Even though AHFD has been working rather well so far, there is still a lot that has to be added or improved in the future. While working on this, a few things caught my attention:

GPU speed improvements: To be honest, it's not the fastest thing on the market at the moment. I think running parts of it on a GPU — maybe using CUDA or OpenCL — could make a big difference, especially if we want to use it in real-time systems like robots or drones.

Possibly mixing in deep learning: Since the structure is modular, there's room to experiment. I was thinking it might be interesting to try adding some deep-learning-based descriptors especially for situations where the environment is dark or changing quickly.

Tuning without manual effort: One downside right now is having to manually set parameters. It'd be nice to have it adjust on its own. Maybe something like reinforcement learning or just a
Lightweight auto-tuning approach could work.

Trying it on different kinds of data: Most of the testing so far has been on fairly standard images. It would be useful to see how AHFD handles more niche things — like satellite pictures, underwater footage, or even medical scans.

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