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Performance Evaluation of Feature Detectors and Descriptors with Close-Range Solar Panel Images

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***Abstract*—Recent advancements in photovoltaic (PV) systems for power generation necessitate continuous inspection, fault detection, and maintenance to maximize energy production. While prior research has primarily focused on image processing and algorithms using long-range shots of PV systems, this study evaluates existing feature detectors and descriptors for processing close-range thermal images of solar panels. Utilizing a dataset captured with the FLIR Duo Pro R camera, which includes variations such as camera angle rotation, motion blur, and different times of day, we assessed the performance of various feature detectors (SIFT, FAST, AKAZE, BRISK, ORB) and descriptors (SIFT, FREAK, ORB, SURF, BRISK) with FAST as a keypoint detector. Additionally, the study examines the impact of different color maps (JET, RAINBOW, HOT, COOL, BONE, GRAY) on these metrics. Our results indicate that AKAZE is the most effective detector, while SURF is the most robust descriptor, particularly when used with multichromatic, high-contrast color maps like JET and RAINBOW. These findings provide a basis for improving various applications, such as image stitching and object detection, and have potential future work in PV fault detection.**

I. INTRODUCTION

The growing interest in renewable energy sources, particularly solar energy, has highlighted the importance of maintaining the efficiency and reliability of photovoltaic (PV) systems. Advanced PV systems have become more accessible, necessitating periodic inspection, fault diagnosis, and maintenance. Physical inspections of solar panels are often unreliable, leading to the adoption of drones and aerial thermography to detect faults. However, this method is less effective in desert environments where solar power is abundant. Long-range imaging loses resolution and detail, making it hard to detect small faults like micro-cracks or minor hotspots. Additionally, dust, heat haze, and air turbulence can distort thermal images in these settings.

This paper evaluates the performance of feature detectors and descriptors on close-range thermal images of solar panels. These images are crucial in various computer vision applications, such as facilitating tasks like image alignment and object recognition, which can aid in PV system fault diagnosis and inspection. Thermal images are well-suited for detecting temperature variations indicative of faults; however, most algorithms are optimized for visible light images, which may not perform well with thermal data due to temperature variation, emissivity, and surface characteristics that present challenges for feature detection.

We collected a dataset of close-range thermal images using a FLIR Duo Pro R thermal camera at different times, distances, and angles. To simulate real-life challenges, pre-processing involved applying varying transformations in particular motion blur and rotation on the images followed by different color maps: JET, RAINBOW, HOT, COOL, BONE from [1] and GRAY to enhance thermal data visualization. Existing algorithms: SIFT [2], FAST [3], AKAZE [4], BRISK [5] and ORB [6] were evaluated for feature detection, while SIFT [2], FREAK [7], ORB [6], SURF [8] and BRISK [5] algorithms were evaluated for feature description. The evaluation metric for detectors was repeatability scores [9], and performance [10] was used for descriptors.

The contributions of this paper are twofold: First, we conduct a comprehensive evaluation of various feature detectors (SIFT, FAST, AKAZE, BRISK, ORB) and descriptors (SIFT, FREAK, ORB, SURF, BRISK) using a dataset of close-range thermal images of solar panels captured under real-world conditions. Second, we analyze the impact of different color maps on the performance of these algorithms, providing insights into how color mapping affects thermal image processing. Our findings reveal that AKAZE is the most effective detector and SURF the most robust descriptor, particularly with high-contrast color maps.

II. RELATED WORK

This paper evaluates feature detection and description algorithms on close-range thermal images of solar panels. Previous studies, such as [11], offer comprehensive views of feature descriptors and detectors, including SIFT, SURF, and BRIEF, using datasets like Oxford. Hietanen et al. [12] compared BRIEF, BRISK, ORB, and FREAK on Caltech and ImageNet images, assessing performance through repeatability scores. However, these studies often rely on static images with minimal real-world discrepancies.

Boyraz et al. [13] utilized an indoor robot-captured dataset, finding FAST-SURF, SIFT-SURF, and ORB-BRIEF optimal for accuracy and speed. The trend of evaluating algorithms on readily available datasets continued until [14] suggested their potential in image stitching, with AKAZE outperforming others, albeit on synthetic data.

Early studies, such as [10], explored non-visible images, emphasizing transformations like rotation and scaling. This study adopts a similar framework, assessing feature detectors and descriptors on thermal images. It reveals no clear winners

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but confirms the feasibility of detecting features beyond the visible spectrum.

Mouats et al. [9] bridged the gap between visible and thermal images, finding Fast-Hessian with FREAK effective for thermal navigation. Shi et al. [15] evaluated monocular thermal images for robot navigation, with BRIEF achieving high precision. In facial recognition, [16] showed thermal imagery's robustness to lighting, outperforming visible images in low-light conditions but struggling with facial expressions and heat variations.

This paper builds on these insights, focusing on evaluating feature detectors and descriptors for thermal images to enhance fault detection in PV systems.

III. METHODOLOGY

In this section, we discuss the dataset, its pre-processing, and the evaluation framework for both experiments: detectors and descriptors. The evaluation follows a similar approach to [9] and [10] for detectors and descriptors, respectively.

A. Dataset

Our dataset consists of 710 thermal images of solar panels captured using the FLIR Duo Pro R camera at a close range. To ensure the reliability of the dataset, we divided it into two subsets based on the time of day: early morning(8 am) and midday(12 pm). Within each time of day, the images were further subdivided by camera angles: 0 degrees and 30 degrees. For each of these angles, we captured images at different distances: 10, 15, 20, 25, 30, and 35 cm from the solar panel.

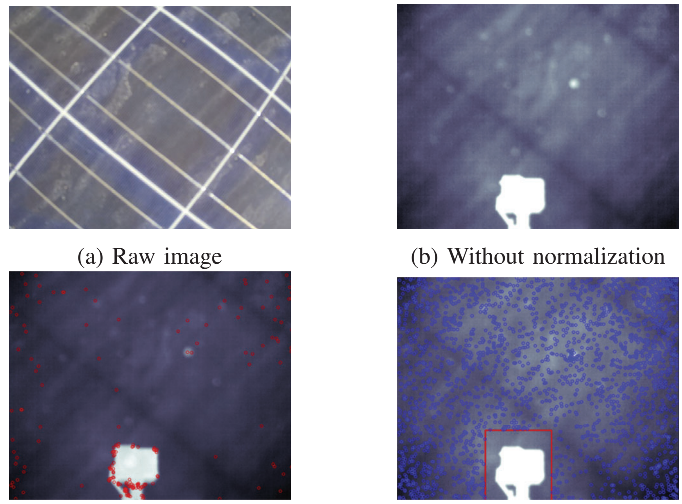
We applied various transformations to simulate real-life conditions:

- **Motion Blurring:** with kernel sizes: 4, 8, 12, 16, 20
- **Rotation:** with angles ranging from 0 to 345 in 15 degrees increments

B. Preprocessing

During pre-processing, we addressed shadows of the camera and the photographer on the thermal images. Furthermore, in our 12pm dataset, direct sunlight created hot spots on the solar panel, leading to a relatively uniform temperature range across the rest of the panel. This sharp contrast hindered feature detection. To mitigate this, we identified shadow areas and created bounding boxes around them using a vision transformer model from [17]. To exclude the shadow areas from the feature detection, we first determined the true minimum and maximum temperature values outside the bounding boxes. This was essential for applying min-max normalization on the images before applying the color maps, ensuring that the sharp temperature values captured inside the bounding boxes were not accounted for in the color map range. Proper normalization ensured that intensity changes between pixels were more pronounced, aiming at improving feature detection in thermal images.

The color maps that encompass a range of characteristics were selected for performance evaluation of detector sand descriptors are listed in Table I.



(a) Raw image
(b) Without normalization
(c) With normalization
(d) With shadow exclusion and normalization

Fig. 1: Feature detection before and after normalization and shadow exclusion with BONE color map.

TABLE I: Selected color maps for Performance Evaluation

Type of color map	Spectrum	Characteristics
JET	Blue to Red	High contrast, commonly used, good for highlighting differences.
HOT	Black to Red to Yellow to White	High contrast and brightness emphasizes high values.
COOL	Cyan to Magenta	Softer contrast, visually distinct, good for distinguishing features.
RAINBOW	Blue to Green to Red	High contrast, covers a wide spectrum range, visually appealing.
BONE	Shades of Gray to White	Low contrast, perceptually uniform, good for subtle variations.
GRAY	Shades of Gray	Uniform contrast, ideal for intensity variations without color.

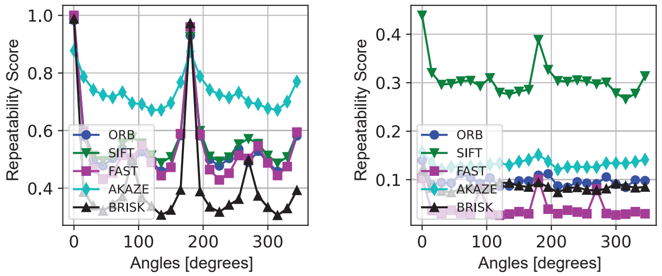
C. Feature Detectors

We assessed the performance of the following algorithms: SIFT, AKAZE, ORB, BRISK, and FAST, following a similar approach to [9]. Our evaluation metric for the performance of the feature detectors is the repeatability score shown in Eq. 1 similar to [9].

$$\text{Repeatability Score} = \frac{|\text{Correspondences}|}{|\text{K1}|} \tag{1}$$

where $|\text{K1}|$ represents the number of keypoints in the original image. The correspondences refer to the number of features in the common region of the two images, which in our case is the entire image.

To find the correspondences and avoid bias towards any descriptor, we formed bounding boxes with dimensions of 30 pixels around each detected keypoint, then we compared the bounding boxes for the keypoints of both images and counted the ones with an overlap error less than or equal 30% as correspondence. We averaged the repeatability score for each detector to evaluate performance across the entire dataset.



(a) Jet color map (b) Cool color map

Fig. 2: Evaluation of Feature Detectors on 8am dataset under rotation across all color maps.

Repeatability scores ranged from 0 to 1; values closer to 1 indicated better performance of the feature detector, reflecting its ability to detect the same features across different images or conditions consistently.

D. Feature Descriptors

Following the methodology outlined by [10], our study focuses on the following feature descriptors: SIFT, SURF, ORB, BRISK, and FREAK. We used the FAST algorithm for feature detection to evaluate the feature descriptors' performance. FAST was selected for its compatibility with all the descriptors and its established efficiency in computer vision. Additionally, using FAST as a standardized feature detection process across all experiments facilitated a fair and consistent assessment of the descriptors' performance.

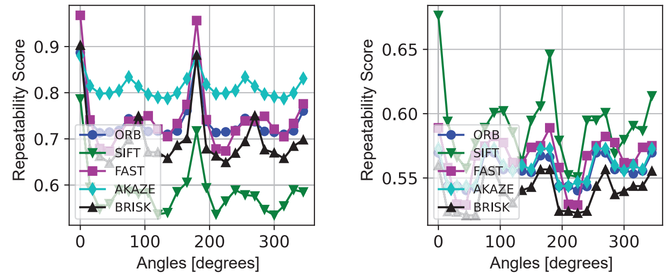
After pre-processing the images, keypoints were detected using the FAST algorithm. Transformations were then applied to the images, and feature descriptors were computed for both the original and transformed images. The performance of each descriptor was quantitatively assessed by calculating the ratio of correct matches between the original and transformed images to the total number of keypoints in the original image. To evalaute the performance across the entire dataset, the performance value was averaged for each descriptor. Performance values ranged from 0 to 1, where 1 represented perfect matching and 0 indicated no matches. Higher values indicated better descriptor performance, reflecting the descriptor's ability to maintain correspondences despite transformations.

IV. RESULT ANALYSIS

In this section, we provide a detailed analysis of the results obtained from evaluating various feature detectors and descriptors on close-range thermal images of solar panels. We systematically assess the performance of each algorithm under different real-world conditions, including variations in camera angle, motion blur, and time of day. Additionally, we thoroughly examine the impact of different color maps on the accuracy and robustness of feature detection and matching.

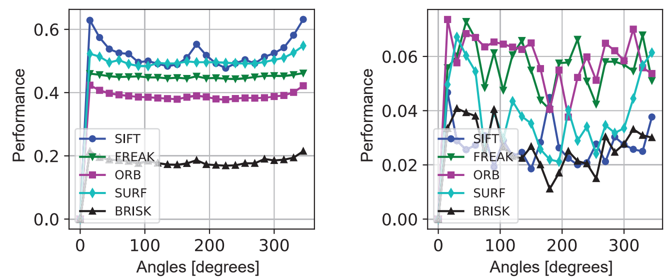
A. Rotation

For the feature detectors, Fig. 2 show the results for the 8am dataset. Although the repeatability scores were very sensitive to the angle change, AKAZE had the best score, consistently



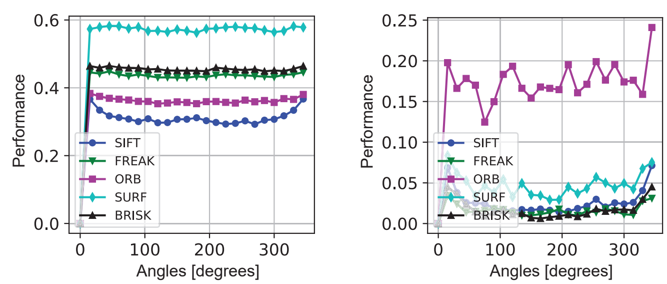
(a) Jet color map (b) Cool color map

Fig. 3: Evaluation of Feature Detectors on 12pm dataset under rotation across all color maps.



(a) Jet color map (b) Cool color map

Fig. 4: Evaluation of Feature Descriptors on 8am dataset under rotation across all color maps.

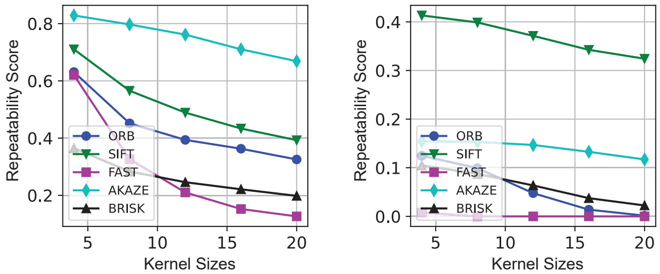


(a) Jet color map (b) Cool color map

Fig. 5: Evaluation of Feature Descriptors on 12pm dataset with rotation effect across all color maps.

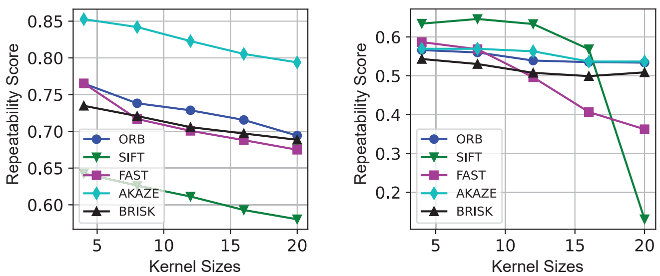
above 0.6 for most color maps. The 12 pm dataset, shown in Fig. 3 also showed similar behavior to the 8 am dataset, with AKAZE being the best detector, staying consistently above 0.8. The impact of color map selection on performance is evident, as detectors performed best with the JET color map compared to the COOL color map, which resulted in the lowest performance.

For the feature descriptors, Fig. 4 indicates that the best performance was achieved by SIFT with the JET color map, with scores ranging from 0.5 to 0.6, followed by the SURF color map. In the 12pm dataset, Fig. 5 shows that SURF outperformed other feature descriptors across all angles, achieving a performance of around 0.6. Notably, BRISK consistently exhibited the worst performance across all color maps and rotation angles. Among the color maps, JET provided the best performance with most descriptors, while COOL resulted in



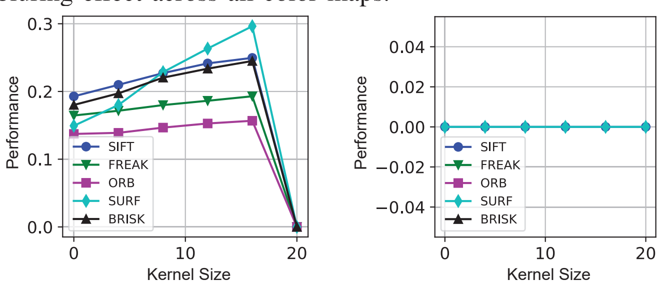
(a) Jet color map (b) Cool color map

Fig. 6: Evaluation of Feature Detectors on 8am dataset with bluring effect across all color maps.



(a) Jet color map (b) Cool color map

Fig. 7: Evaluation of Feature Detectors on 12pm dataset with bluring effect across all color maps.



(a) Jet color map (b) Cool color map

Fig. 8: Evaluation of Feature Descriptors on 8am dataset under blurring effect across all color maps.

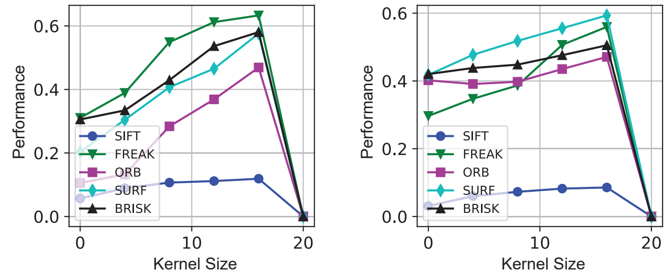
the lowest performance values.

Conclusively, AKAZE was the best detector, while SURF emerged as the best descriptor overall. The JET color map showed the best results across all angle rotations.

B. Motion Blurring

For the feature detectors, Fig. 6 show us that for the 8 am dataset, AKAZE outperformed the rest, and all of them showed a similar trend when the kernel sizes increased. JET and RAINBOW had the highest repeatability score ranges exceeding 0.8 among the color maps, while COOL had the lowest range, and the rest were almost similar. Considering the 12 pm dataset Fig. 7, we still concluded that AKAZE was the best detector and that JET and RAINBOW were the best color maps while COOL was the worst.

For the feature descriptors, Fig. 8 shows that for the 8 am dataset, the best performance achieved was by SURF with JET as a color map. Overall, SURF had the highest performance across all color maps, followed by BRISK. ORB had the worst performance with every color map. All the descriptor's performance dipped to 0 at kernel size 20, and across all color maps, the performance kept increasing linearly with the kernel size. Notably, COOL had the worst performance of 0 across all descriptors due to the lack of features.



(a) Jet color map (b) Hot color map

Fig. 9: Evaluation of Feature Descriptors on 12pm dataset with bluring effect across all color maps.

For the 12 pm dataset, Figure 9 FREAK, BRISK, and SURF were top contenders across all colormaps, and again, the highest performance was seen with JET colormap. However, for other colormaps, SURF consistently performed better with all the different color maps, whereas the performance of FREAK and BRISK dropped.

Overall, our results for motion blurring remained consistent with those of rotation, with AKAZE being the best detector and SURF being the best descriptor with the color map JET.

V. Conclusion and Future Work

In this paper, we conducted a comprehensive evaluation of various feature detectors (SIFT, FAST, AKAZE, BRISK, ORB) and descriptors (SIFT, FREAK, ORB, SURF, BRISK) using a dataset of close-range thermal images of solar panels captured with the FLIR Duo Pro R camera. Additionally, we analyzed the impact of different color maps (JET, RAINBOW, HOT, COOL, BONE, GRAY) on the performance of these algorithms. Our findings indicate that AKAZE is the most effective detector, and SURF is the most robust descriptor, mainly when used with high-contrast color maps such as JET and RAINBOW. These insights offer crucial direction for enhancing thermal image processing techniques, which can ultimately support efficient fault detection and maintenance in photovoltaic systems, although fault detection remains outside the immediate scope of this study.

In our future work, we plan to explore additional preprocessing techniques, such as histogram equalization, and implement thermal image stitching to create panoramas. We also aim to integrate high-quality feature detectors with robust descriptors, particularly SURF, to enhance the accuracy of thermal image stitching. Furthermore, we see potential in leveraging the inherent temperature gradient information in thermal images for feature extraction and matching, ultimately developing more effective methodologies for various applications in thermal imaging analysis and processing.

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