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Active Illumination Control in Low-Light Environments using NightHawk

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Abstract. Subterranean environments such as culverts present significant challenges to robot vision due to dim lighting and lack of distinctive features. Although onboard illumination can help, it introduces issues such as specular reflections, overexposure, and increased power consumption. We propose NightHawk [1], a framework that combines active illumination with exposure control to optimize image quality in these settings. NightHawk formulates an online Bayesian optimization problem to determine the best light intensity and exposure-time for a given scene. A novel feature detector-based metric quantifies image utility and serves as the cost function for the optimizer. We built NightHawk as an event-triggered recursive optimization pipeline and deployed it on a legged robot navigating a culvert beneath the Erie Canal. Preliminary results demonstrate improvements in feature tracking (50-200%) and estimation accuracy. Further experiments including integration with a visual odometry system are currently underway.

Fig. 1. Active illumination and exposure control on Boston Dynamics Spot and Unitree Go2 robots, inspecting Culvert 110 under Erie Canal.

1 Introduction

Environmental illuminance significantly affects the performance of robot perception algorithms, as it influences image brightness and directly impacts the effectiveness of feature detection and matching methods. Standard vision sensors, including monocular, RGB-D, and stereo cameras, rely on auto-exposure (AE) to adjust settings like exposure-time (shutter speed), sensor gain (ISO), and aperture for optimal image capture. While AE performs well in well-lit scenarios, it struggles in extreme environments. Several exposure control methods have been proposed [11], [9], [7], [3], [10], [5] to alleviate such challenges. These methods use image utility metrics that quantify the quality of images for feature detection such as M_{shim} [7], $M_{softperc}$ [11] and NEWG [4]. They use image

[1] Supplementary results, datasets and code can be found at droneslab.github.io/NH

gradients as most classic feature detectors exploit gradients for key-point detection, but often fall short in challenging low-light or varying-light conditions. Integrating an onboard light source offers a promising solution by augmenting scene illumination. However, naive control of onboard lighting can introduce undesirable artifacts such as specular reflections [1] and overexposure.

Our motivation stems from our efforts to inspect culverts beneath the Erie Canal in western New York. These culverts are long pipes with a 1-meter diameter that extend across the canal. As shown in Figure 1, they are dimly lit with extreme light variations at the entrances. They are characterized by repeating textures and features, posing a significant challenge for visual estimation. Our key contributions are - (i) Novel image utility metric (M_{feat}) based on a modern learning-based feature detector that effectively quantifies feature performance, (ii) An active illumination and exposure control framework (NightHawk) which uses online Bayesian optimization to find optimal external-light intensity (P) and exposure-time (Δt), and (iii) Experimental validation in a challenging subterranean environment—a 66-meter-long, 1-meter-diameter culvert beneath the Erie Canal—to demonstrate enhanced feature matching performance. We have extensively experimented with localization, mapping and reconstruction in the culvert, but only discuss feature matching in this abstract due to space limitations.

2 NightHawk Design

NightHawk is an external light and camera exposure-time control algorithm that uses event-triggered Bayesian Optimization to provide optimal lighting and camera configuration. This section describes the image utility metric and illumination control strategy.

2.1 Image Utility

Effective exposure control requires a reliable mechanism to quantify image quality. Conventional auto-exposure (AE) mechanisms rely on irradiance aimed to maintain a mean intensity of 50% or 128 (8-bit). Prior approaches proposed by [7], [11], [4] control exposure by using image gradient-based utility metrics.

$$M_{\text{feat}} = \left(\frac{1}{N}\sum_{i=1}^{N} R_i\right) \cdot \left(\frac{1}{N}\sum_{i=1}^{N} Q_i\right)^2 \quad (1)$$

Recently, there have been numerous learning-based feature detectors (e.g., SiLK[2], R2D2[6]) that are trained in a self-supervised manner to estimate probabilities of being "interesting" per pixel. Further, detectors such as R2D2 explicitly output repeatability and reliability tensors aligned with image dimensions, enabling a more nuanced assessment of feature quality. Inspired by this literature, our intuition is to leverage such probabilities as direct feedback to assess image utility.

To quantify image utility, we utilize R2D2 as the base feature detection network. We compute the product of the mean repeatability and the square of the mean reliability that yields a single scalar value (denoted as M_{feat} in Equation 1) per image. This metric describes the image's utility for successful feature detection. The square of the reliability mean amplifies its influence on the final score, reflecting the critical role of descriptor confidence in accurate matching performance. Here, R_i is repeatability per pixel, Q_i is reliability per pixel and N is the total number of pixels.

We evaluate M_{feat}'s performance and compare against other metrics in section 3 where M_{feat} shows strong correlation with feature matching performance.

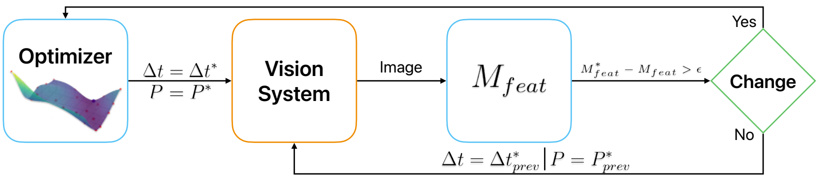

Fig. 2. Overview of the NightHawk pipeline

2.2 Illumination and Exposure Control

The illumination and exposure control problem is formulated as a multi-variable Bayesian optimization (BO) where the optimal value of the light-intensity (P) and exposure-time (Δt) are determined by maximizing our image quality metric M_{feat}. The Gaussian process (GP) provides the surrogate model to parameterize the influence of P and Δt with zero mean Gaussian noise $n = \mathcal{N}(0, \sigma_n^2)$.

NightHawk's overall architecture is illustrated in Figure 2 where the algorithm begins with BO to compute the optimal configuration (P^* and Δt^*) which provides the optimal M^*_{feat}. After applying the configuration, images are received by an image quality assessment module which checks the current metric value and compares it with the optimal. A threshold ϵ ($\epsilon > 0$) is provided by the user as the tolerance. As the robot moves, if $M^*_{feat} - M_{feat} > \epsilon$, the system triggers another round of optimization.

3 Experiments and Results

Figure 3 shows the metrics as well as feature matching performance between consecutive frames compared with our metric M_{feat}. Spearman correlation is used to quantify the relationship between each metric and feature matching.

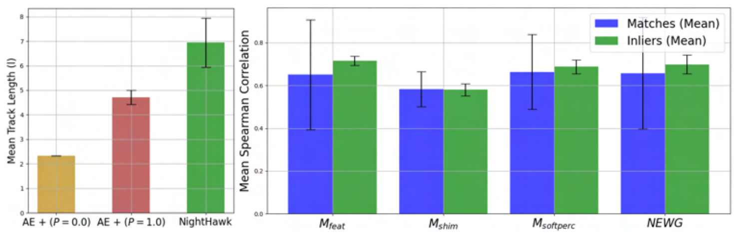

Fig. 3. Feature tracking performance of the 3 settings (left) where NightHawk shows improved feature tracking and lower exposure-times. Correlation of utility metrics (right) with feature detection/matching.

M_{feat} demonstrates a strong positive correlation with feature matching performance across five diverse feature detectors (AKAZE, Shi-Tomasi Corner , ORB, R2D2, and Superpoint) [8]. While $NEWG$ also exhibits comparable correlation, M_{feat} is more consistent with lower variance. Further, M_{feat}'s capacity to incorporate information from learning-based feature detectors distinguishes it from conventional metrics reliant solely on gradient-based features and enables a more comprehensive evaluation of image utility. Finally, M_{feat} offers a significant practical advantage when using learning-based features in visual estimation. A single computation for both feature extraction and quality assessment (e.g., when using R2D2 features) can help reduce compute overheads.

We deploy NightHawk on a Spot robot equipped with a FLIR Blackfly S camera and controllable 50W LED. NightHawk was implemented using ROS2, PyTorch, and Scikit-learn and runs online on an onboard NVIDIA Jetson. The optimization process takes about 20 seconds depending on the chosen hyperparameters. We conducted several teleoperated missions beneath the Erie Canal, capturing images under 3 camera configurations with fixed gain: (1) AE with no external lighting (built-in AE only), (2) AE with fixed external lighting (LED at constant 100%), and (3) NightHawk. Feature tracking performance for each setting is shown in Figure 3 while change in M_{feat} shown in Figure 4. The two baselines result in sub-optimal performance, without external light image utility and feature tracking is poor, although use of external light (at max intensity) improves feature tracking, it introduces artifacts such as a green-ish hue. NightHawk achieves superior average track lengths, and minimal exposure times (effectively reducing motion blur) while preventing artifacts due to reflections and over-exposure.

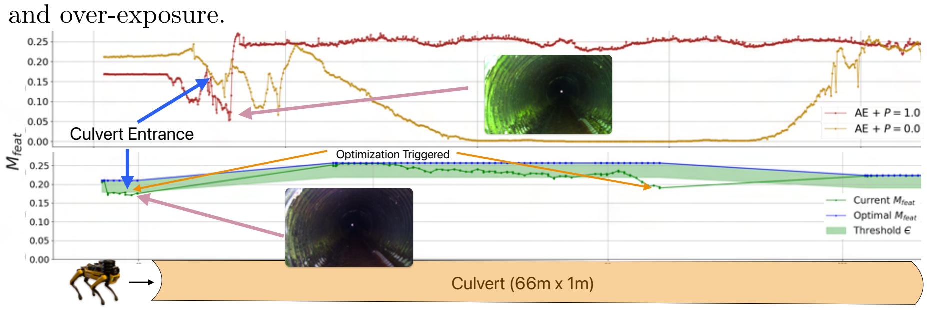

Fig. 4. Change in M_{feat} as the robot enters the culvert is shown in the 3 settings, AE with no external light results in underexposed images while adding a fixed (100%) light introduces artifacts such as a green-ish hue. Finally, with NightHawk, overall image utility is consistent, the sudden dips and green-ish hue at culvert entrance is prevented

4 Experimental Insights

Inspection in Low Light Conditions

Optimizing Adaptive Lighting: A key challenge in low-light and dynamic lighting environments for robot perception is the ability to adapt. Our observation is that controlling only exposure settings of a camera, or mounting a light that is switched on throughout the task gives suboptimal feature detection and tracking results. Controlling an adjustable light, identifying when the lighting conditions have changed, and adaptively reconfiguring the light as well as exposure jointly leads to much better feature detection/tracking (Figure 3) including a 47% improvement in feature tracking in our scenario. This also results in more robust robot perception as shown by the low variance in correlation in Figure 3.

Tuning to a given scenario: There are several tradeoffs in incorporating NightHawk into an inspection system. The optimization takes time as seen by the delays in execution (several seconds per run) once the optimization is triggered in Figure 4. We need to tune the threshold (ϵ) to ensure the optimization is not triggered too frequently to affect task execution while also not triggering too infrequently to affect useful image capture. In our executions, we have tuned the threshold to adjust to big changes - once when it goes from the outside into the culvert, and again when it is deep enough in the culvert that the lighting has completely changed. Note that NightHawk changes the light setting to 54% intensity when it enters the culvert, far less than the 100% setting in our baseline. This results in slightly lower scores as in Figure 4, but good feature matching accuracy in our application.

Integrating other perception services: In theory, we can increase exposure unboundedly to improve image capture. However, in most robot autonomy, there are other services such as localization and mapping that assume continuity through motion and a certain frame rate for efficient execution. Further, motion adds blur which is exacerbated by long exposure. We observe that adaptive lighting allows us to function at reasonable frame rate to cater to such services while improving inspection in the culvert environment.

Energy Efficiency: A side benefit is reduced energy expenditure. Our setup in Figure 2 has a 50W LED. The total power output of the robot is 150W. Keeping a light powered on at full intensity can severely limit the robot range and endurance.

Learning-based Metric

Our metric builds on ongoing research in learning-based feature detectors, and uses R2D2 [6]. The advantage of using our metric is that we can both compute the image utility as well as detect features in one pass. As demonstrated in Figure 3, it exhibits strong and reliable (low variance) correlation with feature detection and matching. Beyond our application, we believe that our metric can be widely applicable for applications requiring to only adjust auto-exposure, or even evaluate the image utility of a given scene for other purposes.

System Optimizations

Onboard Optimization: Optimization must efficiently execute on resource constrained robot hardware. We employ multi-threading and early stopping to accelerate convergence. Through this process, we reduced the latency of optimization from 70 seconds to 20 seconds.

Parameter Control and Feedback: The optimizer adjusts P, Δt, captures images, and receives feedback M_{feat}. ROS2 ensures time synchronization and precise hardware control. *Utility Computation:* M_{feat} is computed online at high rates by applying CUDA acceleration to down-sampled images, achieving approximately 15Hz on an NVIDIA Jetson while running other tasks on the CPU. *Event-triggered Maneuvers:* The optimizer can temporarily pause robot movement, determining optimal settings before proceeding to the next way-point. One promising solutions is to move this evaluation to the background in an predictive manner, which will significantly reduce the delay.

5 Conclusion and Future Plan

We propose NightHawk, an active illumination and exposure control method that improves visual estimation in low and varying light environments. We show preliminary results and the corresponding improvements of 50-200% in feature tracking when NightHawk is deployed to inspect a culvert. Experiments are planned to thoroughly evaluate NightHawk in adjoining culverts. In the full paper, we will also show visual estimation performance (localization, mapping) and include results from multiple culverts. We will also move the optimization to the background to minimize delay during experiments.

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