Exposure Control using Bayesian Optimization based on Entropy Weighted Image Gradient

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Abstract—Under- and oversaturation can cause severe image degradation in many vision-based robotic applications. To control camera exposure in dynamic lighting conditions, we introduce a novel metric for image information measure. Measuring an image gradient is typical when evaluating its level of image detail. However, emphasizing more informative pixels substantially improves the measure within an image. By using this entropy weighted image gradient, we introduce an optimal exposure value for vision-based approaches. Using this newly invented metric, we also propose an effective exposure control scheme that covers a wide range of light conditions. When evaluating the function (e.g., image frame grab) is expensive, the next best estimation needs to be carefully considered. Through Bayesian optimization, the algorithm can estimate the optimal exposure value with minimal cost. We validated the proposed image information measure and exposure control scheme via a series of thorough experiments using various exposure conditions.

I. INTRODUCTION

For a vision based robot navigation, perceptual sensors have been dominantly implemented in many vision based approaches, such as visual simultaneous localization and mapping (SLAM), visual odometry, and tracking. Visual sensors can provide essential motion estimation even when kinematic odometry is unavailable, as for drones and caterpillar-type mobile robots. Many vision-based approaches, unfortunately, assume that there is little variation in brightness, so their cameras operate with fixed exposure or in auto-exposure mode. However, as many researchers have reported, these vision-based algorithms are vulnerable to illumination changes. For example, a robot that moves from outdoors to indoors may fail to navigate correctly due to the large difference in brightness. Image saturation may occur due to indoor light sources or biased luminance from windows. Another example involves omnidirectional cameras (in which several images are stitched together). Because each camera faces a different direction, light conditions between the cameras can substantially vary, thus causing discontinuity.

The most common way to overcome this problem is to use a camera’s built-in automatic exposure control. However, this control scheme is based on the amount of irradiation, so its ability to cope with a large brightness change is limited. Furthermore, the total amount of irradiation may not be the dominant factor in robot vision. Features and image details are widely used in robotics applications; in these cases, the image gradient (not the total irradiation) captures the level of information within an image. This finding has been already noted by [1] and [2].

In this paper, we search for an optimal exposure value (i.e., sample C in the Fig. 1). In achieving this objective, we share the same philosophy as these previous researches. Similar to the previous studies we assume that the image with the largest gradient value that use weighted gradients to minimize noise is the most appropriate exposure time. Unlike previous methods, our method uses gradients to effectively incorporate image saturation status in the consideration of entropy. Using this newly devised metric, we introduce a control scheme that features Bayesian optimization. The proposed method contributes by extending the conventional approaches and automatic exposure control in the following aspects.

- We introduce an entropy-based image information measure by incorporating the images entropy; we thus handled the saturations less heuristically.
- The proposed control scheme is data-driven and requires few user parameters. When shifting between night and day, the incoming images exposure level is automatically adjusted accordingly.

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Fig. 1: Illustration of camera exposure value and image information. (a) Five sample images with different exposure values. (b) Plot of image information with respect to the camera exposure value. We plot the sum of entropy weighted image gradient for each image. Among five samples, C presents the maximum image information when both entropy and gradients are considered.
• We use Bayesian optimization to find the optimal exposure value through an internal prediction phase; it also shortens the optimization time.

II. RELATED WORK

For a High Dynamic Range (HDR) environment, merging multiple images have been popular in researches. In lieu of selecting one single optimal exposure, exploiting multiple images with various exposure value also provides a solution to the exposure problem [3], [4]. These approaches, however, require multiple cameras and images. Studies have also been conducted on the use of camera exposure times to control for HDR environments. In this control-based approach, the process of determining the optimal camera exposure starts with the definition of the best image. Overall irradiation is one metric for measuring the level of image information. Another method is to use the intensity histogram of the image to find the appropriate brightness value. Recently, there are other approaches to find the correct exposure time using entropy information and to find the exposure time with the highest gradient metric of the image for robot vision. We summarize the following three approaches for adjusting exposure time.

1) Image intensity: Image intensities are used to mask out bright or dark areas of an image. This ensures that the regions of interest are accurately exposed [5]. This method can be extended to the image histogram and to the regions of interest within each RGB channel [6]. These intensity-based methods are well-suited to a particular known environment, but they may not be suitable for the HDR case.

2) Image entropy: The exposure time of the image with the highest entropy is suitable for the robot vision [7] as the entropy indicates the level of diversity within an image. However, since image entropy involves a probabilistic model, estimating exposure times in HDR environments is not straightforward, so camera parameters must be adjusted using empirical methods.

3) Image gradient: Recent approaches have been based on the image with the largest gradient sum being the best-exposed image. In [1], synthetic images of various brightness levels were generated using a set of the gamma function. The exposure time was determined to be the sum of gradient magnitude. Another similar approach used the gradient magnitude, which is more robust, by computing the percentage of each pixel gradient value [2].

The above-mentioned metrics are used to control exposure time. In their approaches, a predefined function is used to determine the exposure time depending on the captured image intensity. However, recent researchers have found that the image gradient is a more appropriate metric for robotics applications. Shim [1] generated seven discrete synthetic images using gamma correction and found the maximum value from among the generated images, then mapped to the corresponding exposure time. However, the images generated using gamma correction might be different from the real image obtained from the camera. Zhang [2] used the photometric response function to find the exposure time. First, the derivative of the squared gradient was calculated, and then, a photometric response function was substituted to measure the gradient change according to the exposure time.

These two approaches are more appropriate for robotics application because they focus on the image gradient. However, because these methods only consider gradient metric, their solutions show limitations on handling the image saturation problem. Our method manages the saturated regions using entropy information, thus enabling robust exposure adjustments that are suitable for robot vision. Furthermore, our control method learns incoming images to compute the appropriate exposure time via Bayesian optimization.

III. ENTROPY WEIGHTED GRADIENT

The proposed method consists of the image metric computation module and the control module. The overview of the method is as in Fig. 2. First, we compute the gradient and entropy of the query image. Next, we minimize the noise in the image gradient through the weights calculated from entropy. Entropy also creates a saturation mask and uses the activation function to supplement the overall metric. When the metric calculation is complete, it is repeated until the Gaussian process finds the optimal value.
A. Entropy based Weight Function

We start by reviewing image entropy and gradient. For an image $I$, the simple image gradient is represented as derivative to $x$ and $y$ direction, and the magnitude of the gradient at a pixel $i$ is denoted by $\| \nabla I(i) \|^2$.

For image entropy, we adopt the definition proposed by [8]. The image entropy for a discrete random variable, $H_i$ as shown below

$$H_i = -\sum_k P(i_k) \log_2(P(i_k))$$  \hspace{1cm} (1)

while $P(\cdot)$ is the probability associated with the number of gray levels ($k$). Using this entropy, the weight of an image pixel is defined as below:

$$w_i = \frac{1}{\sigma} \exp \left\{ \frac{(H_i - \text{mean}(H_i))^2}{2\sigma^2} \right\}.$$  \hspace{1cm} (2)

Here $\sigma$ is the variance and $i$ is the location of the pixel. Lastly, we normalize the entropy based weight function.

$$W_i = \frac{w_i}{\sum_{i=0}^N w_i}$$  \hspace{1cm} (3)

This weight assign a large value for the pixel with rare intensity (i.e., high entropy) and a small value for the common pixels.

B. Saturation considered Activation Function

Depending the entropy level, we define an activation function $\pi(\cdot)$.

$$\pi(H_i) = \frac{2}{1 + \exp(-\alpha H_i + \tau)} - 1, \hspace{0.5cm} 0 \leq H_i \leq 1$$  \hspace{1cm} (4)

The activation function is based on the hyperbolic tangent model while $\alpha$ provides curve characteristics of the transition (Fig. 4). The $\alpha$ determines the balance between the image entropy and the image gradient. The larger the $\alpha$ value, the faster the saturation region is controlled, and the gradient information decreases rapidly. Reversely, with small $\alpha$, the algorithm considers more gradient components. The value of $\tau$ determines the shift in the exposure time axis. If the entropy is close to zero, the image contains no information (i.e., it is saturated). That is, $\tau$ determines the pixel value with minimum entropy level that can be determined as a saturated pixel.

If the entropy value is lower than the threshold ($H_{thres} = 0.05$ in our implementation) value, the region is considered to be saturated, and the entire gradient is reduced by the activation function. In general, the sum of the gradients continues to increase even if the saturation region is large. This is because the gradient magnitude in the less saturated regions continues to increase. However, by adding weight to the saturation region using entropy, we can find the proper exposure time for a rapidly changing environment.

C. Entropy Weighted Image Gradient

We then generate a saturation mask using our previous method [9]. The change of entropy is near zero under saturation. Using this property, we generate a binary saturation mask $M$ and use the mask value for a pixel $i$, $M_i$. Therefore, our entropy mask is as follows.

$$M_i(H_i) = \begin{cases} 0, & H_{thres} \leq H_i \leq 1 \\ 1, & 0 \leq H_i < H_{thres} \end{cases}$$  \hspace{1cm} (5)

If the entropy determines that pixel $i$ is saturated, the entropy mask is one, otherwise it is mapped to zero.

Using image gradient, entropy, saturation mask and the activation function, we propose following the entropy weighted image gradient as Fig. 3(c). The entropy weighted gradient for pixel $i$ is

$$g_i = W_i \| \nabla I(i) \|^2 + \pi(H_i) M_i(H_i) W_i \frac{1}{N} \sum_{j=0}^{N-1} \| \nabla I(j) \|^2$$  \hspace{1cm} (6)

When calculating weighted gradient ($g_i$) for a pixel $i$, we consider weight from (3), activation function and entropy from (4), and image gradient. Our final metric for image
information measure is then the sum of the entropy weighted gradient for total number of pixels \((N)\) as

\[
G_{ewg} = \sum g_i. \tag{7}
\]

D. Evaluation of Entropy Weighted Image Gradient

In this section, we compare our image information measure to gradient based image information metrics of previous methods \([1], [2]\). For both indoor and outdoor environments, we captured a static scene with a changing exposure value. For outdoor environment, we controlled the exposure time from 100 \(\mu s\) to 5000 \(\mu s\) by 100 \(\mu s\) step size. As the indoor scene was darker, we collected the data exposures varying from 3000 \(\mu s\) to 40000 \(\mu s\) by increasing 1000 \(\mu s\). For this exhaustively collected dataset, we compare the best exposure time by each method.

In Fig. 5, we plot each metric with respect to the exposure time for a single image. Different exposures were selected because the evaluation of the image varies according to the base metric. The environment becomes brighter as the exposure value increases, and the light source and its reflection create a saturation region. The gradient in the unsaturated region thus becomes larger. The other approaches sacrifice saturation in some regions to gain more detail in the unsaturated region. The proposed metric, however, compensates for the saturated region by adding entropy information. Therefore, we can find the exposure time that minimizes the loss of image information.

IV. EXPOSURE CONTROL

A. Bayesian Optimization

In this section, we describe the exposure control scheme based on Bayesian optimization. Existing exposure control methods involve complex computations because they require calculations of image metrics according to synthetic exposure changes. We find Gaussian process optimization to be suitable, as using this allows us to get optimal exposure using the proposed metric with minimal querying exposures. By adopting Gaussian process optimization \([10]\), we construct an exposure controller as Bayesian inference. The expression of the predictive distribution is

\[
\mu(x^*_e) = k_T^T(K + \sigma_n^2 I)^{-1} \mathbf{y} \tag{8}
\]

\[
\sigma^2(x^*_e) = k(x^*_e, x_e) - k_T^T(K + \sigma_n^2 I)^{-1}k_e, \tag{9}
\]
where \( \mu \) and \( \sigma \) indicate mean and covariance of the estimated image metric. Kernel matrices \( K = [k(x_i, x_j)]_{x_i, x_j \in X} \), and \( K_x = [k(x_i, x^*)]_{x_i \in X} \) are computed by the vernal function \( k(\cdot, \cdot) \). We select Squared Exponential (SE) for the kernel function. Inputs \( X = (x_0, \cdots, x_m) \) and \( Y = (y_0, \cdots, y_m) \) are training points that represent the camera exposure and the related image metric.

Also, we introduce two acquisition functions for searching query exposures: maximum variance (MAXVAR) [10] and maximum mutual information (MAXMI) [11]. In the main algorithm (Algorithm 1), instead of linearly searching for exposure candidates, the optimal exposures are determined via querying exposure values using Gaussian process optimization. The optimal exposure is selected as the value that represents the maximum estimated image metric of final Gaussian process inference.

The exposure searching procedure terminates after few steps; a detailed view of optimization is shown in Fig. 6, in which the querying procedure terminates after five steps for MAXMI and seven steps for MAXVAR. Initial evaluation started at the minimum exposure time provided by the camera, while fast convergence achieved from the Bayesian-based approach. The details of the acquisition functions are explained in Algorithm 2. When we use MAXMI as the acquisition function, the optimizer converges faster than MAXVAR. Because MAXVAR mode is based on an exploration task, the function requires more query exposures to estimate an optimal exposure. However, the estimated mean using MAXVAR is closer to the truth metric function than MAXMI. The overall steps and exposure times for MAXMI and MAXVAR are five steps with 29300 \( \mu s \) and seven steps with 69200 \( \mu s \), respectively. Using these characteristics, we can selectively choose the type of acquisition function according to the purpose.

V. EXPERIMENT

For validation, we performed three types of experiments. First, we compared the number of image features from each approach. Second, we compared the proposed exposure control to the built-in auto-exposure control. Lastly,
we checked the efficiency of our approach by measuring the required frame for exposure adjustment under rapidly changing illumination. A multimedia file attached to this paper exposure.mp4 also presents the resulting images from the proposed exposure control.

The experimental setup is as in Fig. 8. A stereo camera rig was prepared. One camera ran the proposed control scheme, while the other camera was set up for auto-exposure. When running the tests, the camera rig was installed on a mobile platform as shown in Fig. 8(a).

A. Intensity based Feature Tracking Comparison

The first set of tests was conducted to evaluate feature extraction performance. We evaluated our image using the Oriented FAST and Rotated BRIEF (ORB) feature [12]. In this test scenario, the mobile robot underwent illumination change when entering indoors from outdoors. The code from Shim and Zhang was not available, and we validated that our metric was capable of selecting the best exposure for the feature tracking. For this purpose, the robot moved in a step-by-step manner while taking a sequence of images with varying exposure times at each step. In six steps (from T1 to T6) were considered in this test. Among the series of images in each step, we selected the best image by following other approaches. One control scheme was set to manual and always selected 1000 µs. The selected images from each method are plotted in Fig. 7.

Feature tracking usually fails to handle saturation re-
Our Method

Auto Exposure

F
A B C D E
G H I J
F
A B C D E
G H I J

Fig. 9: Indoor Experiment using our exposure control. The first row image sets are the images by the auto exposure control, and the second image sets are the result using our control scheme.

TABLE II: The number of tracked ORB features for Fig. 9 using the automatic exposure (AE) and our method (EWG).

<table>
<thead>
<tr>
<th>Frame</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
<th>I</th>
<th>J</th>
</tr>
</thead>
<tbody>
<tr>
<td>AE</td>
<td>0</td>
<td>0</td>
<td>175</td>
<td>167</td>
<td>6</td>
<td>163</td>
<td>164</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>EWG</td>
<td>180</td>
<td>202</td>
<td>206</td>
<td>137</td>
<td>108</td>
<td>170</td>
<td>147</td>
<td>34</td>
<td>37</td>
<td>210</td>
</tr>
</tbody>
</table>

regions in rapidly changing lighting conditions. All three methods (Shim’s, Zhang’s and ours) adjusted the exposure and outperformed the manual exposure case. Shim’s and Zhang’s methods embraced more saturation to increase the overall gradient. Our method, however, incorporates entropy to detect the saturation and thus tries to gain more gradient while minimizing image saturation. Overall, the results more reliably matched the feature points.

The results are summarized in Table. I for the same experiment. We compared the gradient sum of the images for each exposure time, the percentage of the saturated region identified by the histogram. As the table shows, the gradient metric method generally shows high values in bright images. In other words, the metrics using only the gradient methods are likely to be saturated by light conditions.

B. Exposure Control Using Bayesian Optimization

We performed additional experiments under various light conditions to verify our camera exposure control algorithm. Fig. 9 shows the results of applying the exposure control algorithm in an indoor corridor environment. We mounted the camera rig on a mobile robot and traveled along the corridor at night. The corridor was equipped with a motion-detecting-sensor to control the light, which turns on and off automatically as people passes. This sensor caused rapidly changing lighting conditions and prevented reliable robot navigation. We compared our exposure control scheme against the built-in auto-exposure control.

Auto-exposure admitted some level of saturation within an image. As can be seen in A and B in Fig. 9, the images showed a large saturation region from differences in brightness due to illumination. However, our method minimizes the saturation region and determines the proper exposure time of the maximum gradient information, so as to guarantee accurate feature matching. Another fatal problem caused by lighting conditions can be seen in images I and J in Fig. 9. If the light suddenly turns off and then on, the intensity-based auto exposure control will maintain a saturated image for about 30 frames until the correct exposure time is found. These conditions are easily encountered when passing through tunnels or going outdoors from indoors. Since our method uses the entropy information to prevent the saturation region from becoming large, we can cope with the rapid change in light.

Table. II shows the number of tracked ORB feature points. Note that the proposed method consistently maintained tracked features while the automatic exposure control reported initialization failure and tracking loss due to rapid illumination change (A, B, E, H, I).

C. Detailed Analysis Against Auto-exposure

The next experiment further compared the proposed approach in terms of adaptation speed. We intentionally turned the room light on and off repeatedly so that the light condition changed rapidly. While the illumination was changing radically, we counted the number of frames that each control scheme took until full adaptation.

Fig. 10 compares the experimental result between the auto-exposure and our exposure control method. Table. III shows the computational time analysis of this comparison experiment. Because the auto exposure mode searches for
Fig. 10: We examine image sequence until the optimal exposure time from each method. The rows of the figure are images obtained by maximum mutual information (MAXMI), maximum variance (MAXVAR), and automatic exposure functions respectively. The frame number appears on the top left corner of the image.

TABLE III: Computation time analysis for the experiment in Fig. 10. Each row of the table shows the optimal exposure time found by each method. The frame number of query images indicates the number of frames taken until the method finds the control target exposure. The final exposure time is the settled exposure time from each method.

<table>
<thead>
<tr>
<th>method</th>
<th>Start $\Delta t$ [µs]</th>
<th>Required frame No.</th>
<th>Final $\Delta t$ [µs]</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAXMI</td>
<td>9000</td>
<td>4 frames</td>
<td>8000</td>
</tr>
<tr>
<td>MAXVAR</td>
<td>8500</td>
<td>6 frames</td>
<td>8000</td>
</tr>
<tr>
<td>AE</td>
<td>11500</td>
<td>25 frames</td>
<td>9000</td>
</tr>
</tbody>
</table>

the optimal exposure value based on the intensity of pixels, it searches the image from the maximum exposure time and takes longer to become optimal. However, the proposed methods showed much more effective querying procedures (fewer query images). MAXMI mode searches the optimal value from the minimum exposure to the optimal exposure, and MAXVAR mode search the minimum and maximum exposures repeatedly. Our control methods start at 9 and 8.5 ms, respectively. We also trained 4 and 6 query images to determine the final exposure time of 8 ms. On the other hand, the automatic exposure control started at 11.5, ms and we confirmed that the exposure time of 9 ms was determined after approximately 25 frames.

VI. Conclusion

We proposed a new metric for determining exposure time that minimizes camera information loss. The proposed method combines the gradient and entropy information of an image to identify valuable or lost information and optimize image information. We also introduced a new way for machine learning-based control systems to learn real data quickly and to find the optimal value accurately and quickly. We found the optimal value when training about four query images through actual experiments and proved that our method is more suitable for robot vision than the existing method.

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