IMPROVED SCENE CAPTURE IN UNFAVORABLE LIGHTING CONDITIONS

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ABSTRACT

Real world scenes have huge intensity variations which are not in the control of the capture process. While human eye has an excellent dynamic range that enables us to visualize precise contrast variations and dynamically adapts to illumination variations, the dynamic range of conventional imaging devices is limited because of the physical constraints of the sensors. As a result of limited capabilities of the sensors, image saturation is observed often when lighting conditions are unfavorable (very bright, dark or uneven). In such scenarios, the captured image will have some optimally illuminated parts while some parts may undergo saturation (underexposure or overexposure). This makes the captured scene visually unappealing and the capture suffers from significant information loss. In this work, we propose an imaging solution to recover the scene information lost due to saturation, and hence, produce a better quality image ensuring no or minimal saturation.

***Index Terms*—** computational imaging, image blending, image saturation, unfavorable lighting

1. INTRODUCTION

Human eye has remarkably good capability to adjust to changes in lighting conditions and contrast variations. On the contrary, traditional imaging devices have a limited dynamic range due to the physical constraints of image sensors. As a result, images captured in very low or high lighting conditions substantially lack information about the scene being photographed that renders the scene capture futile. In case of low lighting conditions, the camera sensor does not generate sufficient voltage leading to a low signal-to-noise ratio (SNR) leading to what is known as sensor underexposure or blackwashing of images. On the other hand, in brightly lit scenes, the intensity value of pixels at the highly illuminated regions of the scene gets clipped to the maximum permissible output resulting in sensor overexposure or whitewashing of images.

Both kinds of bad lighting conditions create irreparable damage to the captured images because of the pixel values getting saturated at lower or higher end of the intensity scale. This makes images perceptually unappealing to human eyes as well as unsuitable for machine vision based applications due to the loss of feature information. The only way to avoid such a problem would be to carefully control the illumination conditions. However, the illumination field is not in the control of the capture process: it is for the capture process to adapt to what is provided by the scene.

Conventional techniques to handle image saturation involve adjustment of camera parameters. Typical methods utilize two parameters: exposure time and aperture size. However, each parameter has its own disadvantages. Reduction of exposure time implies faster shutter speeds resulting in an alteration of blur induced motion effects as well as reduction in light levels across the view. The latter might reduce or eliminate whitewash, but can lead to increase in blackwash. If aperture size is reduced, apart from reduction in light levels, the visual depth of field is affected which is often undesirable. Another acceptable approach is usage of Neutral Density (ND) filter that attenuates all light entering the lens over the entire visual field resulting in reduction of whitewash at the cost of increasing blackwash. Also, ND filters require manual intervention for proper adjustment which is not feasible for real time imaging applications. To avoid these issues, we adjust the camera gain facilitating faster capture time hence, reducing the possibility of blur induced motion effects. Moreover, tuning camera gain is more convenient as compared to other parameters. Furthermore, our solution aims to handle both blackwashing and whitewashing of images simultaneously. The proposed approach eliminates manual intervention in the capturing process and is easy to integrate with current imaging devices.

Although, image saturation is very common when photography is done in non-uniformly illuminated environments, no significant research effort has been recorded in the past to solve this issue in bright light scenarios. On the other hand, there has been a considerable amount of research done in the field of imaging in low light environments. Eisemann and Durand [1] and Toyama et al [2] designed a method where information obtained from image captured with flash is combined with the one captured with no flash in an attempt to enhance the image captured in low ambient illumination. Masaki et al [3] proposed a method for pedestrian detection using far infrared images. Additionally, there have been efforts in the domain of image enhancement to improve the perceptual information in images. Enhancement techniques can be global [4], [5], [6] or local [7]. However, in the context of image saturation, image enhancement methods are not expected to generate output images with sufficient details about the scene due to the information loss during scene capture.

Against this background, we propose a novel imaging solution to recover the scene information lost due to saturation, and hence produce a better quality image. The proposed method involves two stages: (i) acquisition of series of gain-shifted images, and (ii) blending of the captured images to obtain the output image having no or minimal image saturation with significantly improved scene information. Furthermore, we propose two approaches for the acquisition stage. The first approach involves acquisition of images using a programmable LCD-based Neutral Density (ND) filter. The other approach captures the series of gain-shifted images using a conventional camera upgraded with a firmware that enables the camera gain to vary linearly from a low value to a reasonably high value. While the second approach can work on any camera whose firmware can be updated, the hardware based approach allows the user to capture the scene using the proposed hardware if the camera firmware is not accessible for modification. The following stage of our solution aims to fuse the relevant information captured in each image of the gain-shifted sequence of images. Image fusion can be achieved by incorporating luminance information via fusion methods such as Gaussian pyramid blending [8], gradient based blending [9], wavelet blending [10] and alpha blending [11]. Computationally intensive methods such as feature tracking over time-varying light fields [12] have also been proposed. The blending algorithm used in our solution incorporates the contribution of each image to the scene information content and is tailored to better visibility and no saturation in the output.

2. PROPOSED SOLUTION

Our solution involves two stages: acquisition of sequence of gain-shifted images and blending of these images to obtain the output with no or minimal saturation and considerably improved scene information. We first describe the acquisition processes both hardware and firmware based approaches followed by the description of the blending algorithm.

2.1. Hardware Based Acquisition Process

In this method, we utilize the automatic gain control (AGC) of the camera to obtain a sequence of images at different illumination levels using a programmable LCD based time varying ND filter.

When the LCD is turned ON (opaque) from OFF (transparent) position, the gain of the camera AGC starts rising due to significantly low illumination reaching the sensor and attains the greatest value as shown in Fig. 1. Again, when the LCD is turned OFF, the reverse happens- LCD becomes transparent and camera gain starts going down and after some time reaches its minimum. During a single ON/OFF cycle, the LCD goes through different transparency levels, and therefore the camera gain traverses between its minimum and maximum values in such a way that maximum LCD opacity corresponds to maximum camera gain. This time window provides the user with multiple attenuation levels and hence, enables the capturing device to obtain multiple gain shifted versions of the scene capture. Given the time constant of the LCD opacity change on the application of a step voltage, a suitable switching interval for the LCD ON/OFF cycle will ensure considerable change of camera gain across consecutive frames.

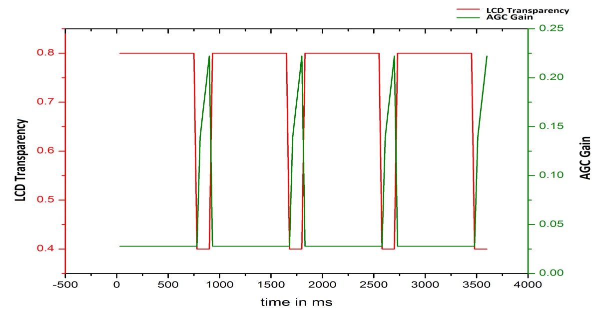


Fig. 1. Variations of camera AGC gain and LCD transparency

Despite the promising results, this method might be challenging to implement on large scale applications such as cameras for personal use and industries involving machine vision applications because of the additional hardware requirement.

2.2. Firmware Based Acquisition Process

In this method, the series of gain-shifted images is captured using any conventional camera upgraded with a firmware update that enables the camera gain to vary linearly from a low value to a reasonably high value. This is possible to achieve with programmable cameras.

This method does not require any additional hardware, and therefore it is convenient to integrate with the currently available imaging devices. Moreover, this approach allows the user to exercise control over the camera gain during scene capture as opposed to the ND filter approach which relies on the camera AGC making the process hardware-specific.

2.3. Blending Algorithm

The second stage of our method involves fusion of the information captured in the sequence of gain-shifted images to generate an output image with no or minimal saturation. It is evident that the image regions optimally illuminated at lower gains are overexposed at higher gains, however, the regions that are underexposed at lower gains are optimally illuminated at higher gains. Therefore, all images in the series contain some relevant information about the scene. The data needs to be combined suitably in order to get a visually appealing and detailed output image. The images mainly vary at illumination levels and tuning the gain might also increase underexposed or overexposed pixels in individual images, therefore the proposed algorithm takes the input from each image with each pixel contributing based on its intensity level. The proposed blending algorithm is as follows.

Let $I^k_{i,j}$ be the intensity of the image I_k at pixel (i,j), I_k being the k^{th} image in the gain-shifted sequence. For n-bit image representation, $I^k_{i,j}$ lies between 0 to $(2^n - 1)$.We calculate the weight $\alpha^k_{i,j}$ applicable to $(i,j)^{th}$ pixel of k^{th} image using (1).

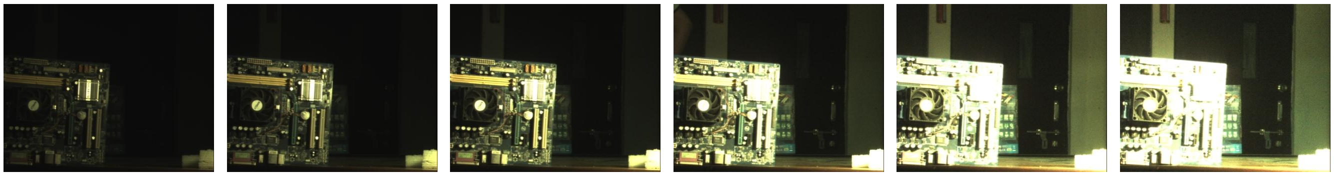


Fig. 2. Gain shifted images of a motherboard placed on a table in a non-uniformly lit environment captured using hardware approach.

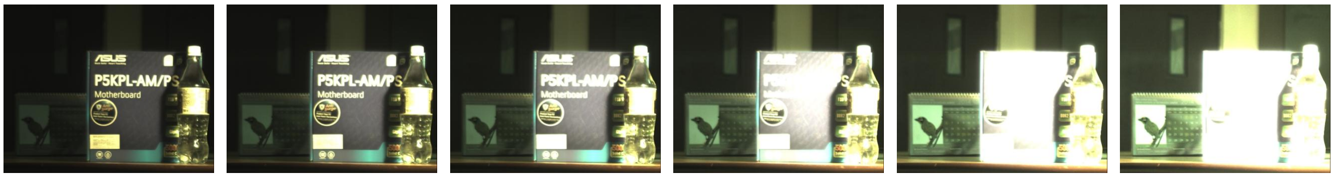


Fig. 3. Gain-shifted images of a bottle placed on a table in an unevenly illuminated environment using firmware approach. The gain ranges from 2 dB to 24 dB at a linear increment of 4 dB.

$$\alpha_{i,j}^{k} = \left[\lambda \mathcal{N}(I_{i,j}^{k}, \mu, \sigma) + c\right] \tag{1}$$

Where the function $\mathcal{N}$ is given by (2).

$$\mathcal{N}(x, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \tag{2}$$

Here λ is a scaling factor (suitable values $1000 \leq \lambda \leq 5000$), μ represents the scale midpoint which is 2^{n-1} for n-bit quantization (128 in 8-bit image representation), c controls the desired contrast in the output (suitable values $20 \leq c \leq 40$) and σ defines the output image sharpness (suitable values $20 \leq \sigma \leq 60$). After pixel weights for all the images in the sequence have been obtained, the final image I is obtained using the relation given by (3) for each pixel (i, j) of the image I.

$$I_{i,j} = \sum_{k=1}^{K} \beta_{i,j}^{k} I_{i,j}^{k} \tag{3}$$

where $\beta_{i,j}^{k}$ is the normalized weight given by (4).

$$\beta_{i,j}^{k} = \alpha_{i,j}^{k} / \sum_{k=1}^{K} \alpha_{i,j}^{k} \tag{4}$$

The output image obtained by fusion of the gain-shifted images is given by I.

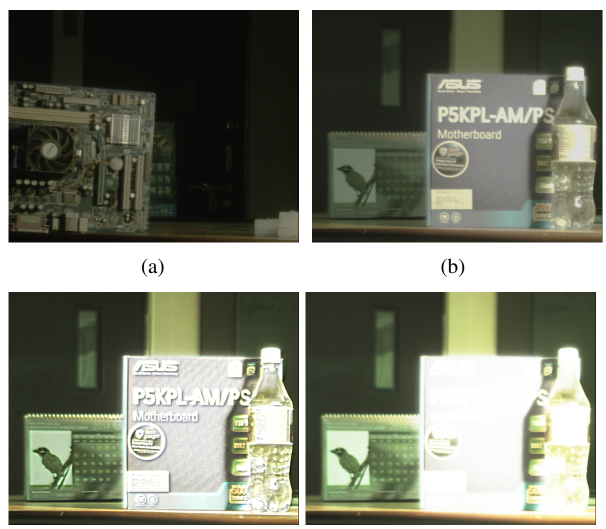
3. RESULTS AND DISCUSSION

To validate our solution, we present one set of experiments each for the hardware based acquisition method and the firmware based method. Both share the blending algorithm.

For the hardware method evaluation, a controllable ND filter was developed using PCF8814 based 65×96 pixels matrix LCD, as described in Section 2.1. The filter was triggered using microcontroller to toggle between ON/OFF states periodically with time period less than capturing duration. In our case, the switching cycle time was set to 2 seconds with duty cycle $1:5$. The LCD panel has maximum opacity when ON and maximum transparency when OFF. Images at relevant timestamps are shown in Fig. 2 and the corresponding output is shown in Fig. 4(a).

For validation of the firmware based approach as described in Section 2.2, we captured a series of gain-shifted images as shown in Fig. 3 using a programmable camera Epic PIXCI Silicon Video Camera which is controlled by a software named XCAP Imaging Software. The resultant HDR image for this dataset is shown in Fig. 4(b).

Additional datasets and results for both methods can be found on the link: http://goo.gl/igAwVt



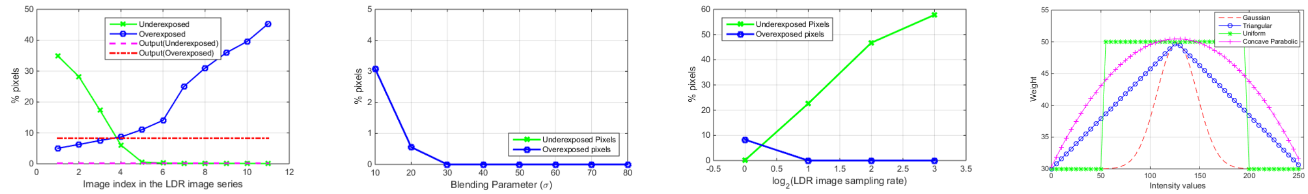
(a) (b)

(c) (d)

Fig. 4. (a) Output image corresponding to image series in Fig 2 using the proposed bending algorithm ($\lambda = 1000$, $\sigma = 30$, $c = 40$). Output image corresponding to LDR image series in Fig 3 using (b) IB ($\lambda = 1000$, $\sigma = 20$, $c = 40$), (c) GP, (d) MWV

3.1. Objective Assessment

In view of the fact that we are performing photography in unfavorable lighting conditions, the amount of saturation (blackwashing and whitewashing) present in the output image becomes an important metric to monitor. Thus, we use the percentage of saturated (underexposed and overexposed) pixels as the measure of image quality. Fig. 5(a) shows percentage of blackwashed pixels and whitewashed pixels in the series of images (acquired using the firmware method) obtained from one gain sweep cycle. This evidently illustrates



(a) (b) (c) (d)

Fig. 5. (a) Percentage of underexposed and overexposed pixels in the image sequence for the dataset in Fig. 3 and the output image in Fig. 4(b); (b) Variation of percentage of underexposed and overexposed pixels with standard deviation of the function ($\lambda = 1000$, $c = 40$) described in the algorithm. (c) Variation of percentage of underexposed and overexposed pixels with sampling rate of image sequence ($\lambda = 100$, $\sigma = 20$, $c = 40$), (d) Different distributions for weights over intensity scale.

the excellent performance of the proposed blending algorithm generating output images with saturated pixels considerably less than any of the input images. Moreover, although the algorithm requires two parameters to be given by the user, the saturated count was observed to have no major dependencies on these parameters when chosen in a suitable range as shown in Fig. 5(b). These parameters allow the user to customize the contrast and sharpness of the output image, hence they can be more accurately termed as *user preferences* rather than essential blending parameters.

Furthermore, the experiments show that the output is not obtainable simply by clever selection from the range of input images; it is indeed significantly different from and superior to any one of the input images, and in essence, collects within it the useful part of the information contained in every one of them. Therefore, with increase in sampling rate of the images from the captured sequence, there is significant loss in information with increase in saturated pixels as shown in Fig. 5(c). Moreover, the algorithm as described in Section 2.3 uses the weights to possess Gaussian distribution over intensity spectrum $(0-255)$. We attempted to evaluate the performance of algorithm for various distributions as shown in Fig. 5(d) and saturation (underexposure and overexposure) in the resultant image was observed to be around 8% for all distributions.

Additionally, the gain-shifted images were blended using three algorithms: mean wavelet blending (MWV)[13], gaussian pyramid blending (GP)[14] and the proposed intensity-based algorithm (IB). Fig. 4(b),(c) and (d) show output images obtained using IB, GP and WV respectively for dataset in Fig. 3. The proposed algorithm has lower saturation counts as compared to other algorithms for all datasets (please refer to the link) as shown in Table 1.

Dataset	MWV	GP	IB
Motherboard	41	74	36
Bottle	42	32	8
Drone	49	44	35
Lamp	83	55	33

Table 1. Performance comparison of the proposed algorithm based on objective metric (Percentage of the image pixels saturated)

3.2. Subjective Assessment

Image quality is difficult to quantify and highly dependent on human perception. Hence, to evaluate the image quality of the output images, we use mean opinion score (MOS) as a metric to compare the quality of images. We conduct a survey on 158 users who give a rating to each of the three output images (obtained from blending algorithms MWV, GP, IB) on a scale of $0-10$ (0 implies completely saturated). The score is obtained by taking the mean of these ratings. The results of the survey have been reported for all datasets (please refer to the link) in Table 2. From the survey, it is evident that the proposed blending algorithm generates good quality image with no or minimal saturation.

Dataset	MWV	GP	IB
Motherboard	2.18	3.29	7.49
Bottle	1.72	2.49	8.13
Drone	5.02	4.37	8.14
Lamp	2.75	5.68	7.64

Table 2. Performance comparison of the proposed algorithm based on subjective metric (MOS)

4. CONCLUSION AND FUTURE WORK

In this paper, we presented imaging solutions that employ camera gain as the controlling parameter to manipulate the final image of the scene being captured in a manner that there appears no saturation (underexposure and overexposure) in the output. The proposed solution enables easy integration of feature of photography in unfavorable lighting conditions with the currently available imaging hardware by a firmware update. Moreover, for devices not capable to firmware modifications, we present a hardware based solution. The solutions differ in terms of gain control as well. While firmware based approach allows the user to vary the gain linearly from a low value to a reasonably high value, the hardware based approach manipulates the gain based on the camera AGC response giving less control to the user.

However, it is to be noted that the proposed method of gain swept imaging presumes that there is no motion in the scene being captured. Motion compensation techniques can be used to handle dynamic scenes so as to extend the idea of avoiding image saturation to videos. Also, since the capturing process is sequential over time, the captured images would also contain motion blur demanding further corrections. Moreover, the storage and processing capability requirements because of post-capture processing involved in this approach might also raise a concern. As an initial step to address this issue, acquisition of images in a single shot by optimizing intensity of each pixel on image sensor for saturation avoidance.

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