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HIGH DYNAMIC RANGE IMAGE ACQUISITION

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Abstract

In this paper we recommend a novel method for high dynamic range image acquisition (HDRI) which is performed by combining multiple images taken with different exposures and estimating the irradiance values of each pixel, under various types of occlusion (object to object and object to scene occlusion) and scale change of object (small or large object) in real-time video. This is a common process for HDRI acquisition. In our approach firstly we apply some methods in original images like grey conversion, binary conversion, filter conversion, image resize, image sharpening to remove noise and to avoid minute changes in the image. By using the MAP (Maximum a Posteriori) estimation we can easily estimates displacement, occlusion and saturated regions simultaneously. In this paper we present the efficient and accurate multiple exposure fusion technique for HDRI acquisition to address the problems.

Key Terms—Multiple Exposure, High Dynamic Range Image, MAP Estimation.

I. INTRODUCTION

A. Background

In this paper first we will see that by adapting to lights in any viewing condition, the human visual system can capture a wide dynamic range of irradiance (about 14 orders in log unit), It is very important in many applications to capture wide range of irradiance of natural scene and store it in each pixel. Also it is one of the most promising applications of computer vision and has a very wide range of applications. In the last 10 years, the higher growth has been attained by it. Over recent years, much research has been devoted to high dynamic range image which is widely used for high quality rendering with image based lighting. Now it is most interesting and active area of research and this HDRI imaging technologies have been developed and some high dynamic range sensors are commercially available. They are used for in-vehicle cameras, Surveillance in night vision and high contrast photo development, robot vision etc.

In the last decade, to capture the HDRI, many techniques have been proposed based on the multiple-exposure principle, in which we merge some photographs shot with multiple exposures to construct the HDRI. Many of the techniques assume that a scene is static during taking photographs. The motion of the objects causes motion blur and ghosting artifacts. Although in some fields such as video coding and stereo vision, many of the displacement estimation methods are proposed, simply applying them into the multiple exposure fusion often fails since the intensity levels of the images are significantly different due to the failure of camera response curve estimation, and more importantly the low and high exposure causes black- and white-out to some regions of the images, respectively, in which correspondence between the images is hard to find. Some time in case of low exposure, noises such as thermal noise and dark current sometimes make the displacement estimation difficult.

In this paper we can construct the HDRI by taking into displacements, under and over-exposures (saturation) and occlusion. The displacement vectors as well as the occlusion and the saturation are detected by the MAP estimation. In our method we do not need to estimate accurate motion vectors but displacement to the pixel with the closest irradiance, while the conventional methods try to estimate the motion accurately. The occlusion and the saturation are clearly classified and then treat it separately, which results in the accurate removal of ghosting artifacts. This relaxation improves the final quality of the HDRI.

The HDRI is constructed by combining multiple types of images taken by camera. And the procedure for this HDRI acquisition is informally described as follows:

1) The images are acquired with different exposure settings. In our method, we assume that the exposures are set by changing shutter speed while the aperture is fixed, and we obtain a set of ordinary low dynamic range images with 8 bits/channel. In general there is a nonlinear relationship between the pixel values of the 8 bit images acquired by a camera and the values of actual irradiance. The photometric camera calibration is used to compensate this nonlinearity which is defined below and it is mainly performed for the input images.

A.1 Photometric Camera Calibration

The relationship between the irradiance *i* and the amount of lights *L* that we measure through some sensor can be expressed by

$$L = i \cdot t \qquad (1)$$

where *t* is exposure time (shutter speed).

In many camera sensors, the captured signal *L* is recorded at more than 8 bits in so-called the "raw image" format. The raw image is nonlinearly transformed through some image processing such as the gamma correction. Then the pixel is quantized to 8 bits. We assume that the nonlinearly transformed 8 bit images are obtained as an input. For convenience, we set the range of *i* to [0, 1]. To accurately retrieve the irradiance, we need to compensate for the nonlinearity by estimating the transform. Here we approximate it by a single curve and call it "camera response curve" denoted by

$$I = g(L) \qquad (2)$$

If one uses the raw images and an image sensor has linear sensitivity characteristics, this photometric calibration can be skipped. To accurately retrieve the irradiance, a dequantization procedure is necessary. However since we may assume that the image is densely quantized and the quantization error hardly affects the quality of the HDR acquisition, we ignore the quantization effect. Among the existing methods for the calibration problem, we adopt Mitsunaga et al.'s method to find *g*, in which the curve is approximated by a low order polynomial using multiple images and the values of exposure ratios between the images. Once the curve is estimated, the irradiance is derived from (1) and (2) as

$$I = g^{-1}(I)/t$$

In our method, the multiple exposure images are taken by varying the exposure time of a camera with other settings fixed. After that we will merge the images to create the HDRI.

2)We select a main image from the multiple exposure images. For each of the other images, the displacement from the main image, which is mainly due to object movements, is found. In practice we select an image with medium exposure as the main image in a default setting. Furthermore occlusions and under- and over-exposed regions are found for the images. This is done by the MAP based motion compensation method in Section III.

3)To improve the accuracy for discriminating the occlusion and the saturation (i.e. under- and over-exposed regions), we employ the post processing in Section III where we use the algorithm to determine the regions of the occlusion and the saturation and then we can easily obtain the displacement vectors except in these areas. Finally we combine the images to create the HDRI which is necessary in this paper.

B. Challenges

Sometimes, there are some challenges occurred during taking photographs they are:

B.1 Occlusion

B.2 Displacement vector

B.3 Saturation

These challenges are overcome by using the MAP estimation. MAP estimation is defined by Maximum a posteriori estimation, a maximum a posteriori probability (MAP) estimate is a mode of the posterior distribution. This MAP can be used to obtain a point estimate of an unobserved quantity on the basis of empirical data. It is closely related to Fisher's method of maximum likelihood (ML), but employs an augmented optimization objective which incorporates a prior distribution over the quantity one wants to estimate. This MAP estimation can also therefore be seen as a regularization of ML estimation.

This MAP (Maximum a posteriori) estimation can be computed in several ways:

1. This is done by analytically, especially when the mode(s) of the posterior distribution can be given in closed form. This case is when conjugate priors are used.
2. By using the numerical optimization such as the conjugate gradient method or Newton's method. This usually requires first or second derivatives, which have to be evaluated analytically or numerically.
3. Map estimation also computed by modification of an expectation-maximization algorithm. This does not require derivatives of the posterior density.
4. This is also done by Monte Carlo method which is using the simulated annealing.

By using this MAP estimation we can easily detect the challenges that occur during taking photographs (Displacement vectors, occlusion and saturation).

B.1 Occlusion

Occlusion means object is occluded by other things partially of fully. It can be of two types object to object occlusion and object to scene occlusion.

B.1.1 Object to Object Occlusion:

When there are more than two objects in a scene then sometimes one object can cover other object partially or fully. Figure1 illustrates an example of partial and complete occlusion.

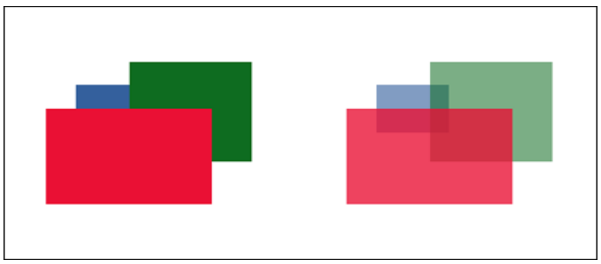


Figure 1. Object to Object Occlusion

B.1.2 Object to Scene Occlusion:

Sometimes the background object can cover foreground object (object of interest) partially or fully. When foreground object is occluded by some stationary background object (like pillar, table, chairs etc.) partially, it means that only some parts of foreground objects (object of interest) are visible then it is called partial occlusion. If the foreground object (object of interest) is occluded by some stationary object of the background completely, it means none of the part of foreground object is visible then it is called a complete occlusion. Figure 2 shows an example of partial occlusion.

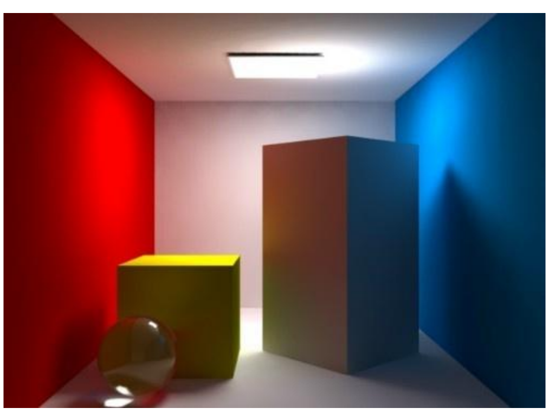


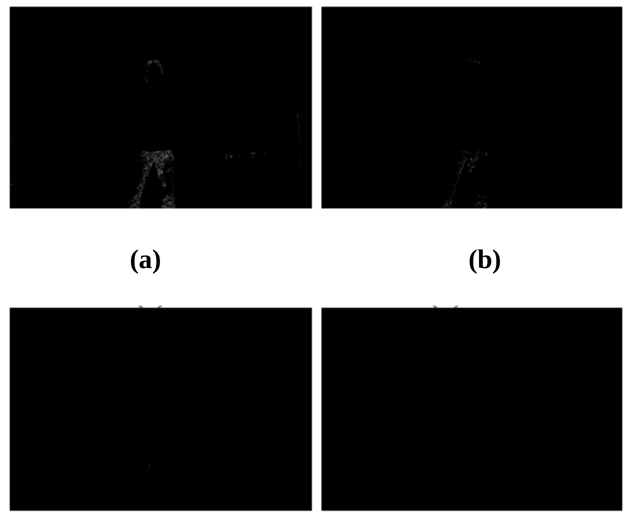
Figure 2. Object to Scene Occlusion

B.2 Displacement vector

The displacement vector is defined by the displacement in images which is mainly due to object movements and that displacement vectors should be smooth. In the displacement estimation, we simply search the closest value for each pixel.

B.3 Saturation

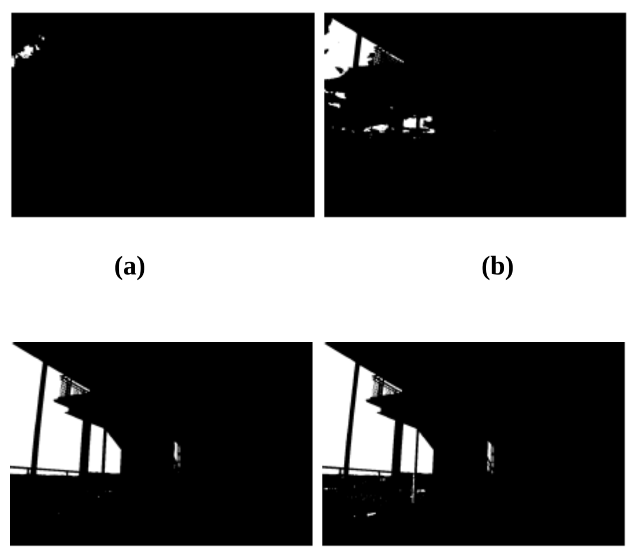
Regions of the saturation, that is, under- and overexposure in image.



(a) **(b)**

(c) **(d)**

Figure 3. Under-Exposure map



(a) **(b)**

(b) **(d)**

Figure 4. Over-Exposure map

In theses image we can see Under-exposure and Overexposure map.

II. RELATED WORK

A number of literature surveys have been done about object detection, segmentation and tracking in the video surveillance. We present the survey, which deals with only those works which is related to our thesis study in any context.

Pernkopf and O'Leary[1]&[2] presented an approach for inspection of machined high precision surfaces such as bearing rolls. They used the geometric setup of light sectioning. Only few inspection systems based on range imaging are reported in the literature.

Newman and Jain[3] defined the task of inspection as follows: Inspection is the process of determining if a product deviates from a given set of specifications. They proposed the image processing techniques, which plays a crucial role in the growing field of automatic surface inspection.

Fernandes et al.[4] proposed a system for the continuous inspection of cast aluminium, where up to 15 different types of defects have to be detected and classified and that are usefull for this image acquisition.

Stefani et al.[5] in this paper of high dynamic range image acquisition they demonstrated an industrial inspection arrangement for inspection of continuously extruded cylindrical products which effectively detected defects at a speed up to 10 m/s.

Takao Jinno[6] have proposed the method of MAP estimation to estimate the displacements, occlusion and saturation regions simultaneously and also construct the new motion blur free HDRIs. He suggested various of challenges that are object to object scene occlusion and camera motion etc.

Masahiro Okuda[7] demonstrates that the HDRI acquisition algorithm is accurate even for images with large motion. In this paper he proposed a method for the multiple exposure fusion.

Nayar et al. [8] Determining shape and reflectance of hybrid surfaces by photometric sampling. show an approach of an extended light source resulting in an increased diffuse reflection component compared to the specular component.

Johannesson [9] addresses the problem of occlusion as one of the major problems of light sectioning methods. Either an occlusion is induced by the laser so that no contour line is projected on the area viewed with the camera (laser occlusion) or the camera is not able to visualize the area illuminated by the laser (camera occlusion).

III. PROPOSED METHOD

In this, we have described our methodology. Each block described the processing technique. Every block describes the steps for Image Acquisition. Each block has its own characteristics. It means by each block, the images are being processed and output of each is given to as input in next processing block. Figure 5 shows the steps of our proposed work for object Image Acquisition. Each steps defined different process for the Image Acquisition.

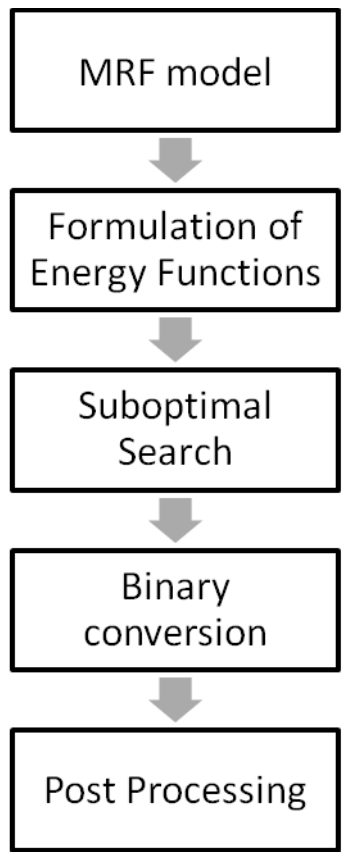


Figure 5. Flowchart of the Proposed System

A. MRF model

In this paper, we propose an algorithm of the HDRI estimation based on the MRF model. This MRF is stands for Markov random field model. The compensation is usually done by two steps, Global motion and Local displacement compensation steps. In our method we assume that the global motion (e.g. motion caused by camera shake) has been already compensated by some image alignment algorithm. In this section we focus on the local displacement compensation.

In our situation, the displacement estimation may fail due to (I) occlusion, (II) saturation, that is, under- and over-exposure, and (III) differences in intensity caused by the failure of the camera response curve estimation.

Fig.6 illustrates an example of two exposures, where some regions of the high exposure image is over-exposed (white region in (a)) and under-exposed (black region in (b)). There may be three types of regions where correspondence between the images is hard to find: occlusion (marked by light gray in (c)), saturation (overexposure marked by white), and both of the two (dark gray).

In our approach, we simply search the closest value within a window for the hole caused by the occlusion, while in the saturated area we do not compensate for the motion. For the regions where pixel intensities vary between images due to failure of the camera response curve estimation, we treat them the same way as the occlusion.

In the end, we need to estimate the following two classes as well as the displacement vectors.

Class I: Regions that include the occlusion and intensity

mismatch caused by the failure of the camera response curve estimation.

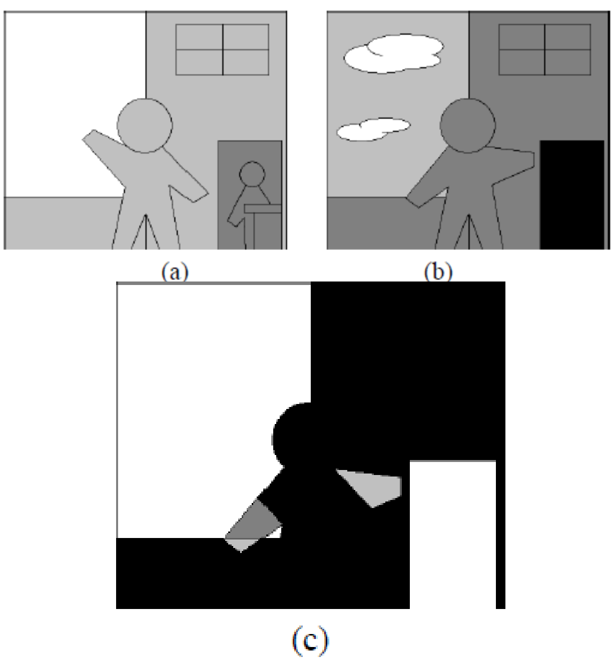


Figure 6. Example of multiple Exposure Images: (a) high exposure, (b) Low Exposure, (c) Occlusion (gray) and Saturation (white)

Class II: Regions of the saturation, that is, under- and overexposure.

In this class the regions of saturation which is under-and over exposure which is shown in fig.3 and fig,4. Here we introduce a probability model for the estimation of the displacement between two images and the regions of the two classes.

In this framework, the exposure time of all the images are known and the images have been made linear to irradiance values by the photometric camera calibration method.

B. Formulation of Energy Functions

In our case, difference in pixel values and its corresponding pixels are sensitively affects the quality of the final HDRI. While an accurate motion estimation is not necessary, we use the minimum value.

The term $U(\boldsymbol{i}^p|\boldsymbol{d}, \bar{\boldsymbol{o}}, \bar{\boldsymbol{s}}, \boldsymbol{i}^q)$ characterizes the image $\boldsymbol{i}^p$ with $\boldsymbol{d}$, $\bar{\boldsymbol{o}}$, $\bar{\boldsymbol{s}}$, and $\boldsymbol{i}^q$ given. In most cases the function is defined by the l_1-norm or l_2-norm error between the blocks of $\boldsymbol{i}^q$ and $\boldsymbol{i}^p$. In our case, since the difference in pixel values of $\boldsymbol{i}^q$ and its corresponding pixels in $\boldsymbol{i}^p$ sensitively affects the quality of the final HDRI while an accurate motion estimation is not necessary, we use the minimum value of the difference,

$$e(k,l) = \min_{(m,n)\in\mathcal{N}^1_{k,l}} \|i^q_{k,l} - i^p_{m,n}\|^2 \tag{3}$$

where $N^1{}_{k;l}$ is a block of pixels around the center pixel (k, l). We use the block of 31x31. The above error assumes that the pixel $\boldsymbol{i}^q{}_{k;l}$ and its corresponding displaced pixel in $\boldsymbol{i}^p$ ideally coincides.

Considering these, we define the energy function,

$$U(\boldsymbol{i}^p|d,\bar{o},\bar{s},\boldsymbol{i}^q) = \sum_{(k,l)\in\Lambda} \bar{o}_{k,l}\cdot\bar{s}_{k,l}\cdot e(k,l) \tag{4}$$

This equation excludes the occlusion and the saturation from the cost function.

From (3) and (4) formula we will define the Energy Function formula (5). Since the displacement generally occurs due to object movements, the displacement vectors should be smooth. Thus we define the energy function as follows

$$U(d|\bar{o}, \bar{s}, i^q) = \sum_{(k,l)\in\Lambda} \bar{o}_{k,l} \cdot \bar{s}_{k,l} \cdot \left\{ \sum_{(m,n)\in\mathcal{N}^2_{k,l}} \|d_{k,l} - d_{m,n}\|^2 \right\} \quad (5)$$

where $N^2{}_{k;l}$ is a block around the center pixel (k, l). Note that we use different notations for $N^1{}_{k;l}$ and $N^2{}_{k;l}$ since they have different sets of sites on neighborhood. In practice, we use 3x3 blocks. This Formulation of Energy Functions is basically used for Image Acquisition.

C. Suboptimal Search

The nonlinearity makes the minimization problem hard to solve directly. To address the difficulty, some relaxation algorithms have been proposed such as simulated annealing and the mean field theory. The former has high computational complexity. The latter can relieve the complexity but it is not straightforward to apply it to our problem. In our method, instead, we adopt a suboptimal approach. In our search, the estimations of the displacement, the occlusion and the saturation are performed independently. In the estimation algorithm, we adopt a block-based search for the occlusion and the saturation, while a pixel-based search is performed for the displacement.

A new suboptimal search strategy suitable for feature selection in very high-dimensional remote sensing images (e.g., those acquired by hyperspectral sensors) is proposed. Each solution of the feature selection problem is represented as a binary string that indicates which features are selected and which are disregarded. In turn, each binary string corresponds to a point of a multidimensional binary space. Given a criterion function to evaluate the effectiveness of a selected solution, the proposed strategy is based on the search for constrained local extremes of such a function in the above-defined binary space. In particular, two different algorithms are presented that explore the space of solutions in different ways.

D. Binary Conversion

Binary images are images whose pixels have only two possible intensity values: zero or one. They are normally displayed as black and white. Numerically, the two values are: 0 for black, and either 1 or 255 for white. The foreground image which we get from third step is grey level image so for doing further processing we will convert it into binary image. Figure7 shows the representation of binary image. For converting gray level image into binary image following steps are used:

1. Find the intensity of each pixels in gray scale image
2. Compare each intensity value to some threshold value, I used threshold value 80.
3. If intensity value is greater than threshold value then change the intensity value to 255 or 1(white).
4. Else change the intensity value to 0 (black)

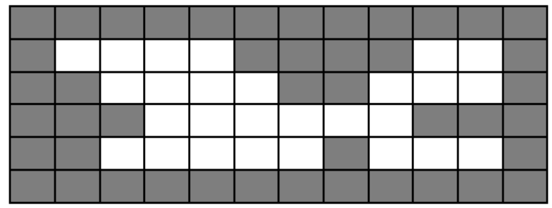


Figure 7. Block Diagram of Binary Image[10]

E. Post Processing

By using an algorithm, we can determine the regions of the occlusion and the saturation and obtain the displacement vectors except in these areas. Next it is necessary to combine the images using the information. The Post-Processing Workflow Profile provides the means to organize and schedule post-processing tasks and to monitor their progress and completion.

PWF is a natural / logical extension of the Scheduled (Acquisition) Workflow Profile and provides the capabilities to sustain and optimize several tasks typically performed after image acquisition in preparation for the following image interpretation (reporting). It specifies transactions to support a seamless flow of information for typical post-processing tasks such as:

- Quality control
- Image reconstruction
- Computer Aided Detection
- 3D views generation

Some benefits of Post Processing

- Improves the efficiency of post-processing tasks providing the users with ready-made worklists (to-do lists) where they can simply pick the next task to perform and have immediate access to relevant patient and procedure information and to the images to be processed
- Time and efforts are greatly reduced, as users don't have to manually search or inquire for patient and procedure data, nor do they have to handle paper or film

- Consistency and integrity of patient and clinical information can easily be maintained as the integrated systems can preserve the proper correlation of patient demographics, order information and procedure data with the generated images and post-processing results
- The status of the post-processing tasks (scheduled, in progress, completed) can be closely monitored to facilitate performance statistics and to derive provisions for improvements of the imaging department's efficiency
- Notification of completion of procedures can be used by scheduling systems to initiate preparations for follow-up actions such as image interpretation (reporting) or setting-up additional diagnostic or patient treatment procedures
- Details of the effectively performed tasks and utilized resources and materials are essential input for an accurate charging of radiological services

Enabling an unobstructed information flow from system to system

- Eliminates the need of redundant and error-prone manual re-capture of data
- Ensures consistency and integrity of patient data and
- Allows the medical staff to focus on the tasks at hand rather than having to deal with the deficiencies of non-integrated devices and IT systems

The Post-Processing Workflow Integration Profile addresses the following functions and systems interactions:

- **Planning** – a scheduling system (RIS, PACS) assembles and prepares the data needed to perform certain post-processing tasks.
- **Provide Worklists** – a post-processing workstation (3D Workstation) queries the scheduling system for worklists (lists of 3D post-processing tasks to be preformed) and presents the information to the user.
- **Post-Process**ing – the workstation user selects (claims) a certain task to work on, retrieves the images pertinent to the selected task, performs the appropriate post-processing procedures and generates additional results (reconstructed images, measurements, findings) to be stored. The correlation of patient, procedure, images and results information can be properly maintained.

IV. EXPERIMENTAL RESULTS

The result shows that the work done by us is how much effective and robust. We know that we can't claim that whether the work done by us is good or not unless it show fine results. This section represents the performance and efficacy of the work done by us. The measurements of performance have been shown by showing the result of our proposed.

First we make our image clear by converting them into binary conversion, grey conversion, and filter conversion, resize image.

A.Binary conversion

First we convert the original image into binary image as below Input Image is the original image and output image is the binary image.

Input Image:

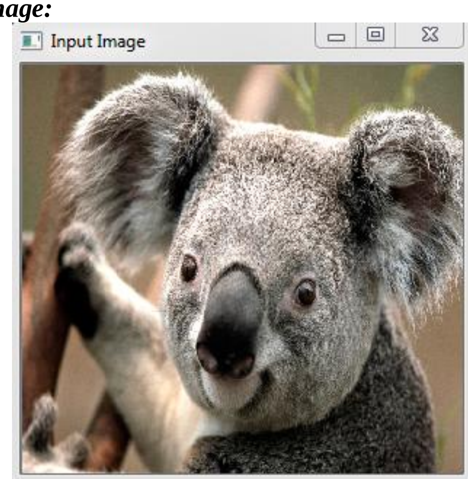


Figure 8. Original Image

Output Image:

Figure 9. Binary Image

B.Grey conversion

Here we have original image, we will convert it into the GreyScale Image which is shown as the Output Image below.

Input Image:

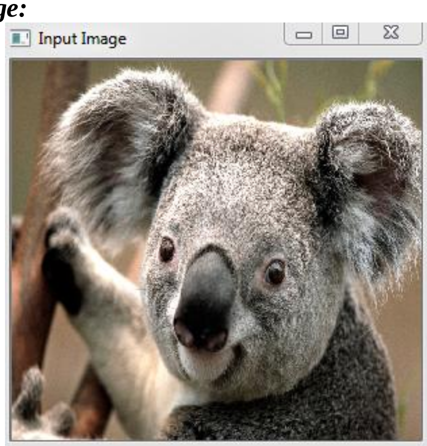


Figure 10. Original Image

Output Image:

Figure 11. GreyScale Image

C.Filter Conversion

In this we convert the original image into the Filter Conversion. Input Image is the Original Image and Output Image is the Filtered Image.

Input Image:

Figure 12. Original Image

Output Image:

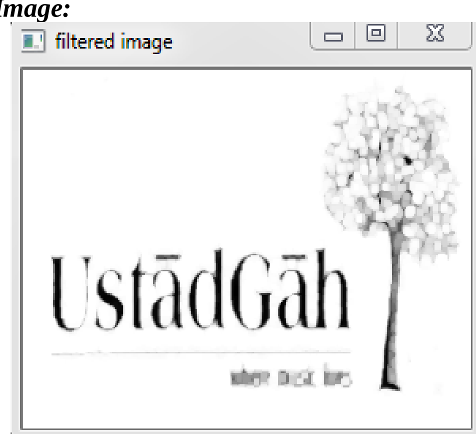


Figure 13. Filtered Image

D.Resize Image

Resizing Image is a very easy task as below shown figures Input Image is the original Image and Output Image is the Resized Image.

Input Image:

Figure 14. Original Image

Output Image:

Figure 15. Resized Image

E.Image Sharpening

From Sharpening Image we can see the picture clearly. As Shown below Images Input Image is the Original Image and Output Image is the Sharpened Image.

Input Image:

Figure 16. Original Image

Output Image:

Figure 17. Sharpened Image

V. CONCLUSION

We propose a method for the multiple exposure fusion. In the method, the MAP based method estimates occlusion, saturation and displacements between input images and then construct the HDRIs by removing the artifacts. While in the conventional work it is hard to eliminate the ghosting artifacts especially when large motion occurs, the proposed method can compensate for the effects of motion, occlusion and saturation and can obtain motion blur free HDRIs.

VI. FUTURE SCOPE

In the future we can implement this in security surveillance system, recognizing activity and to detect many complex activities, this would also help in automated surveillance as we can add any type of activity which can be suspicious. It can be also used in context based video retrieval to organize the videos in accord to actions.

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