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Novel approach to detect HDR scenes and determine suitable frames for image fusion.

Sphurti Bhoskar; Nanyang Technological University; Singapore. Ramakrishna Kakarala; Picartio, Inc.; Santa Clara, California

Abstract

In this paper, a novel method for automatically detecting High Dynamic Range (HDR) scenes is proposed along with a method for determining suitable frames for fusion. The proposed algorithm finds its application in multi-exposure image fusion systems, such as consumer digital cameras etc. And, it is of interest to minimize computation by avoiding redundant image fusion. The proposed algorithm makes use of two or more auto-exposure bracketed frames to determine the degree of details in form of Momentum Value (MV). MV is computed region-wise for each frame when available. After accumulating MVs for all bracketed frames, they are compared region-wise to select frames that captures maximum information. If more than one frame is required to get maximum MV for all regions, then the scene can be judged to have dynamic range higher than that of the camera. And, the frames with maximum MV are used for fusion. The proposed approach consumes approximately 2.5% of the computation efforts compared to+ image fusion. Effectively, proposed method leads to significant saving in computations and enhances quality of fused HDR image.

Introduction

For photographers, it is challenging to reliably capture scene having both extremes of lighting conditions, dark and bright. They are termed as High Dynamic Range (HDR) scenes. Such scenes may include person standing in front of a bright light source (e.g. window) or a landscape at sunrise etc. The contrast observed by human eye may not be captured by cameras in single shot, due to limited dynamic range of image sensors. This problem is addressed by capturing multiple exposure shots to fuse them to match scene dynamic range and is called HDR photography. This requires significant system resources and it is wasteful to do so for scenes where such image fusion is not needed. It is necessary to automatically detect HDR scene and avoid such redundant image fusion. Selection of frames for fusion plays important role in resource consumption and resultant image quality. Hence it is of great interest to select minimum number of needed frames to capture maximum scene details with least computations.

Objective

Multi-exposure image fusion to enhance image dynamic range leads to significant increase in computation effort and it is susceptible to undesired artifacts. Before using image fusion, it is necessary to assess its need by comparing scene dynamic range with that of the camera. It is also important to optimize number of frames to fuse by selecting only necessary frames. This paper proposes efficient and accurate method to determine scene dynamic range using only image sensor data. This approach includes mathematical model of spatially varying degree of scene details, called Momentum Values (MV). The proposal addresses both the issues of automatic HDR scene detection and suitable frame identification simultaneously. While doing so, it is kept in mind that, the same approach can be applied to systems having image sensor of any dynamic range to capture any dynamic range scene. Proposed approach involves assessment of lost details, and ordering of usable frames for building HDR image that represents dynamic range of scene. Effectively a method of detecting HDR scene using existing hardware is proposed along with suggesting the frames to be used for fusion further.

Auto-HDR and Auto Exposure Bracketing(AEB)

To simplify and enhance user experience by hiding complex decision making, Auto-HDR feature is introduced. This feature can be broken down in three steps as automatic detection of HDR scene, selection of appropriate frames and fusion of frames to build HDR image. It was found that, later two are prevalent in commercial cameras and the first step is proposed in this paper. Auto Exposure Bracketing(AEB) is a critical tool to implement Auto-HDR feature. Auto Exposure Bracketing(AEB) is the technique of automatically taking two or more shots of the same scene using a different exposure setting for each one. Different exposure settings include both over exposed and under exposed (lighter and darker) with respect to current exposure setting EV(0) i.e. given by auto-exposure of camera. The exposure value is varied in terms of step size +/- 2 or +/-1 etc.(EV(+2) referring to over-exposed and EV(-2) to under-exposed, for example)

Literature Survey

Significant research has been done in capturing multiple frames with different exposure settings i.e. AEB. [10] Describes Auto Exposure Bracketing(AEB), its implementation and limitations. These AEB images are further fused to get a resultant image which capture scene details missing in individual frame but present in collective frame-set. [5] explains optimal HDR image fusion in JPEG domain using multi-exposure frames. In this context, [8, 7] provides some suggestions to reduce or eliminate artifacts such as ghosting etc. [3, 6], makes suggestions for identifying appropriate exposure settings for images to be merged. In present paper, suitable frames for fusion are decided based on amount of information contained in each frame. And, redundant frames with no addition details can be avoided to simplify fusion process. Degree of focus can serve as measure of information in each frame. Significant number of publications deal with fo-

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cus measurement from accuracy and efficiency point of view. [1, 2, 4, 13, 11, 12, 14, 16, 17, 19, 20], Provide some focus measurement techniques primarily in frequency domain. Apart from this, [15] suggests an optimal way of measuring focus using histogram approach, where spatial variation of pixel value is not considered but only value variations are considered. [18]Uses "difference between mean and median of image" for assessing appropriate exposure values and detect existence of HDR scene. In the process of evaluating relevant image information, one can be mislead by effect of high frequency noise. Hence filtering out the such noise is necessary and low pass filter can be employed for this purpose. [9] Describes high pass and low pass filers for image processing.

Novelty

In this paper, a single method to find both solutions to detect HDR scene and suitable frames for fusion is proposed. There are limited publications addressing this issue. [3] suggests saturated or dark pixel count to select appropriate exposure frames. However, these image statistics may not only be because of camera sensor dynamic range limitation. They can be result of nature of scene. [18] utilizes radiant mapping for this purpose which is significantly computation heavy. Comparatively, approach presented in present paper needs very few computations. Approach specified in [18] necessarily involve HDR fusion and subsequent comparison for determining appropriate frames for fusion etc. This approach is extremely computation heavy as it requires several HDR fusions. Multi-frame fusion as suggested in [21] is employed for comparison of computation efforts. It is observed that, compared to fusion, only 2.43 % of the computation efforts are required for HDR scene detection by our approach. It also results in selecting minimum number of best suitable frames needed for fusion. Hence subsequent image fusion leads to retrieval of maximum possible scene details in efficient manner.

Problem identification

A computationally lighter qualifier for image fusion is required. AEB is commonly used to capture necessary frames with different EV for image fusion. It is expected that, all AEB frames collectively cover dynamic range of scene. Identification for such exposure bracketing limits is not covered in this algorithm. If single frame can capture entire scene details, then no fusion is necessary. In short, camera's dynamic range is greater or equal to that of the scene dynamic range. However, if more than one frame is needed to cover scene dynamic range, the converse is true and multiple image frames are needed to be fused to improve dynamic range of captured image. It is also necessary to accurately select least number of best suitable frames to capture maximum scene details. HDR fusion is susceptible to many image artifacts such as ghosting or edge softening etc. Hence it is also important to select minimum necessary frames only for fusion. Such redundancy removal serves computational efficiency and reduction of image artifacts. Effectively there are two problems which need solution. First is to calculate minimum number of frames needed to capture scene details which are spread across entire dynamic Range. And second is to identify best suitable frames, to capture maximum possible scene details. By nature of HDR scene, it is obvious that, some region of scene are too dark and some may be too bright to be captured by camera simultaneously. This clearly means that, there is need to asses scene details region-wise across all frames. It is also crucial to define appropriate measure of scene details to make such assessment. To define such a measure, calculable difference across available frames need to be understood and formulated. The degree of loss of scene intensity variation can serve the purpose as elaborated next. For given EV, camera's dynamic range window is fixed. Any light intensity beyond these limits result in clipped limiting values. E.g. for brighter regions values clipped to max pixel value. And for darker regions they are made zero or lowest value. Effectively there is loss of pixel value variations near either or both extremes of pixel values. So, comparative assessment of such degree of pixel value variation in specific scene regions can serve as measure of interest, in present context. If the same measure for all regions across all frames is organized, this provides sufficient infrastructure to solve both of above mentioned problems. It is also necessary to optimize memory and CPU requirements of intended computations to efficiently qualify image fusion. Following example 1 explained need of HDR scene detection .

If Pixel value is plotted in Z axis and X-Y axis plane shows special distribution of pixel values, 3D vision of Image can be seen. For easy viewing the orthogonal view of the image is shown. First image on the left side shows above mentioned view of an image captured with low exposure time. And image on the Right shows its high exposure time counterpart. It is clearly visible that, in high exposure time image, significant pixels reach their ceiling value (256). And variations in most of the image region showing building pillars are lost and details are blown off. Effectively, only white regions without any shades or edges in them are seen. However, lower exposure image do not suffer from this and all variations in the same regions can be seen. Effectively, it can be said that, to capture details of building pillars in image, low exposure time need to be used.

On the other hand, the images shown in 2 shows a bird, whose details are suppressed in image captured with low exposure time. The bird appears dark and it can be seen that most of the details of the bird are suppressed. But in high exposure image, more variations in pixel values and details are clearly visible. Effectively, it can be said that, to capture details of the bird in image, high exposure time is needed.

As both of the requirements arise from same scene, at least two exposure captures and image fusion are needed to combine details from both captures. So it can be said that, the scene is worthy of being captured by HDR photography. Effectively, if the multiple exposure frames are used, then, details in image for pillars can be picked from low exposure image and for details of birds high exposure image details can be used. Hence the fused image can represent maximum details i.e. spacial distribution of pixel values. In sum, both problems, 'determining HDR scene' and 'identifying frames to be fused in case of HDR' are addressed in this paper.

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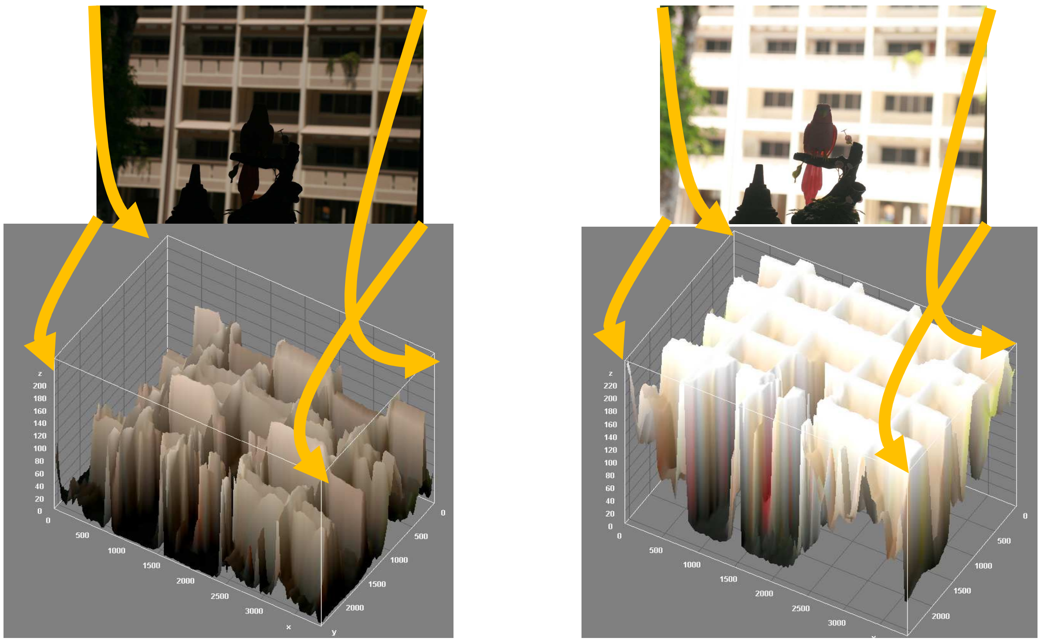

Figure 1: Loss of details due to saturation:In high exposure image on right, variations in most of the image region showing building pillars are lost and details are blown off. These image regions are seen as white flat regions without any variation in form of edges. These details are captured by low exposure image on left

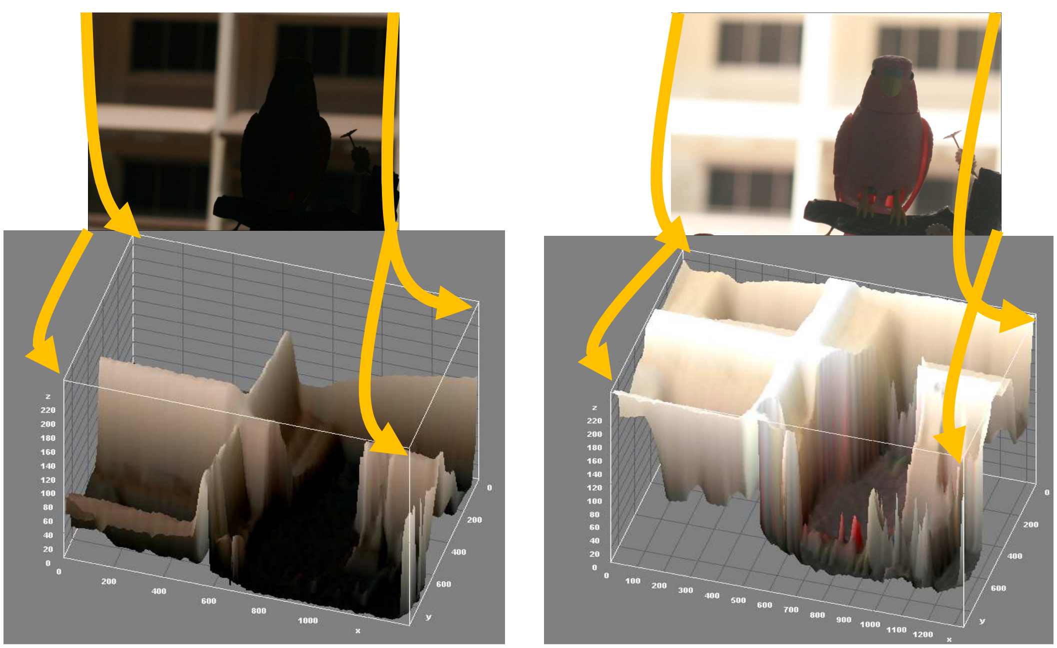

Figure 2: Loss of details due to pixel value suppressed to zero:In low exposure on left, image details in the object bird are lost and these details are visible in high exposure image on right. These image regions are seen as dark flat regions without any variation in form of edges

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Algorithm Definition

As discussed in previous section, all AEB frames are sequentially partitioned in smaller regions and relevant details are extracted, organized and further analyzed to receive binary conclusion of scene HDR detection and list of most usable frames. The process can be divided in to 5 steps as explained below and shown in Fig.3.

Proposed Algorithm

1. Divide input image frames into smaller regions of predefined size.
2. Suppress high frequency noise for all regions of all the frames
3. Compute 'degree of details'(MV) for each region for each available frame with different exposure time.
4. Identify frame ID which shows maximum degree of details(MV) for each region.
5. Identify if single frame is sufficient to capture all details. If not, the scene is HDR.
6. If the scene is HDR, record the unique frame IDs to be fused.

Steps other than 2 and 3 are data organization. Low pass filter is employed to suppress high frequency noise in step 2. For step 3, 'degree of details' is defined in problem identification section as degree of pixel value variations. Such variations can be divided in to pixel value variation and their spatial distribution. Pixel value variation can be easily identified by analyzing histogram of pixel values. Since histogram retains extremely reduced information, histogram based analysis is computationally light but information about spatial distribution is lost. Spatial distribution of pixel values define edges etc and can be measured by measuring special frequency etc. However such frequency domain analysis is computationally heavy. Since, the frames to be compared are for the same scene, spatial variation can be neglected and value variation can be safely chosen as measure of details. Different spatial frequency analysis as suggested in [1, 2, 4, 13, 11, 12, 14, 16, 17, 19, 20] and histogram based approach as suggested in [15] are analyzed. Approach from [15] is useful in this regard. Since the approach suggested is for auto-focus, it is assumed that all frames have same EV . As, in present case, AEB frames are used for analysis, their exposure values are different. Hence exposure value variations need to be compensated before comparing frames. In [15], mean of the image block is defined as

$$Mean(\mu) = \sum_{i=0}^{N-1} iP(i) \tag{1}$$

and Absolute Central Moment (ACM) is defined as

$$AbsoluteCentralMoment(ACM) = \sum_{i=0}^{N-1} |i-\mu|P(i) \tag{2}$$

Equation 2 rely on absolute deviation of pixel vales in image regions across frames with different exposure time. Therefore, it is necessary to get rid of absolute value variations for reliable comparison. In this regard, applying sigmoidal gain or attenuation to relevant frames as suggested by [5] can be used. Another computationally lighter approach is by normalizing ACM value with image mean. The later approach is used in this algorithm and is stated by eq 3. The resultant value is termed as MV i.e. Momentum Value.

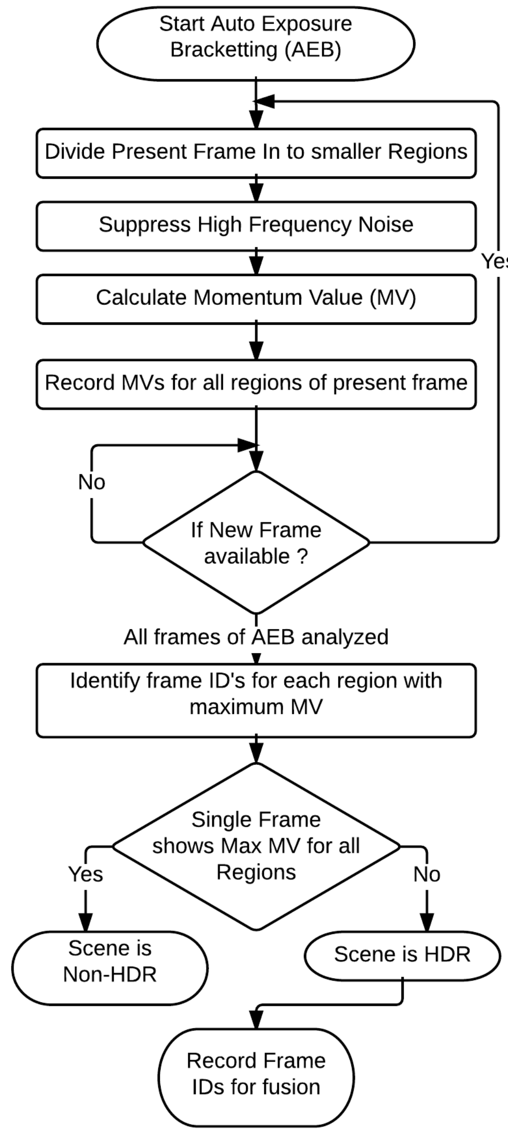

Figure 3: Flowchart: Algorithm for HDR scene detection

$$MomentumValue(MV) = \frac{\sum_{i=0}^{N-1} |i-\mu|P(i)}{\mu} \tag{3}$$

Momentum Value (MV) as computed in eq 3 is calculated for all regions in all frames. After accumulating mentioned statistics(MV) for all bracketed frames, they are compared region wise to select frames that captures maximum information. Comparison of MV across different regions of AEB frames can be done by tabulating the computations as shown in snippet of table 1. The last field of table 1 is frame ID of frames which represent maximum details as maximum MV value. Unique frame IDs in last column are retained to identify usable frames for fusion. If single ID is found, then image is considered non-

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Table 1: Image contents - statistical analysis

Sr.No.	Region Geometries				Momentum value			Maximum MV	Max MV frame ID
	X Start	Y Start	X Size	Y Size	Frame1	Frame2	Frame 3		
1	:	:	:	:	:	:	:	:	:
2	1	1	499	499	0.11	0.23	0.08	0.23	2
3	501	1	499	499	0.39	0.38	0.22	0.39	1
4	1001	1	499	499	0.40	0.68	0.16	0.68	2
5	1501	1	499	499	0.29	0.75	0.05	0.75	2
6	2001	1	499	499	0.43	0.69	0.18	0.69	2
7	2501	1	499	499	0.26	0.25	0.22	0.26	1
8	3001	1	499	499	0.14	0.29	0.11	0.29	2
9	3501	1	386	499	0.26	0.35	0.27	0.35	2
9	:	:	:	:	:	:	:	:	:

HDR. If more than one ID is found, then image is considered HDR. For detected HDR scenes, the unique IDs recorded are the usable frame IDs for HDR fusion. It is evident from this table that, only limited numbers are needed to be stored to represent scene details. Hence it can lead to very low memory utilization while switching among different AEB frames .

Parameters affecting performance of algorithm

As in proposed algorithm, there are no frequency domain computations involved, the computation time does not depend on scene variations. It was observed that, resolution of input image has linear impact on run-time of the algorithm. Hence reduced resolution of input frames can be used to optimize run-time of algorithm. While doing so, it is important to retain significant low frequency data of the image to avoid degradation in quality of results. To suppress high frequency noise, low pass filter is employed. Input image size reduction and low pass filtering can be achieved simultaneously by using image scaling which do not illuminate low frequency information. e.g. image resolution reduction can be achieved by means of binning. However, sub-sampling can be avoided as it may eliminate significant image information. Number of partitions do not significantly affect run-time but it affects the MV measurements. It was observed that for most scenes using approximately 20 partitions produced acceptable results. Other parameters which can affect the performance are choice of scene variation measure (e.g. MV), low pass filter and hysteresis used. However, presently these are not evaluated.

Experiments and Results

Images from various cameras including Samsung Galaxy S5 mobile, Cannon EOS 450D and Canon EOS Kiss X6i are used for evaluation and tuning of algorithm. Auto Exposure Bracketing using 3 frames with +/-1 or +/-2 EV are used. However the approach presented in present paper is applicable for any number of frames. For mathematical calculations GNU Octave 3.8.1 under Ubuntu Linux 14.01.1 is used. The code for this algorithm is at the git repository https://github.com/sphurti-bhoskarntu/HDR_scene_detection.git.

Stationary or almost stationary objects are used as scene composition to avoid issues related to large scale scene alteration. For training purpose, 31 sets of scenes with 3 frames each are tested. Images from all sources are made part of training data and algorithm is tuned accordingly. As algorithm is not expected to work reliably with scene having large scale motion, negative test case with large movement is deliberately added to test robustness. In initial experiments with training data, it was noted that noise was responsible for introducing variations which did not represent scene. To increase robustness, by suppressing noise, a low pass filter was introduced. After tuning algorithm using training data as above, consistent results were obtained. For example, figures [4] and [5] demonstrates set of images of two different scenes. Figure [4] represent HDR scene where frame 1, frame 2 and frame 3 i.e. frames with EV(0), EV(-2) and EV(+2) are required to be fused to capture entire dynamic range of scene. Whereas figure [5] represent a non-HDR scene. To represent this non-HDR scene only frame 2 i.e. frame with EV(-2) is sufficient.

When, algorithm produced consistent results with training data, the algorithm was employed to process testing data which included negative test case. All the test-cases except negative test-case passed and detected HDR scene reliably. For negative test-case, although scene was not HDR, it was reported as HDR scene due to large scale motion of a car which formed significant portion of image. The overall results were again verified by manual visual inspection and the result was approved as reliable. Table 2 summarizes results. Average run-time for HDR scene detection is approximately 2.5% of HDR fusion computation time. Hence, such detection may prove to be efficient qualifier for enabling HDR fusion in necessary conditions only. This will result in significant computation savings and eliminate softening of edges due to unnecessary fusion and other artifacts.

Table 2: Results: Algorithm result Vs Visual confirmation

Image set category	Number of sample sets	Detection by Algorithm		Detection by visual confirmation	
		HDR	nonHDR	HDR	nonHDR
Training Data	31	20	11	20	11
Testing Data	32	12	20	12	20
Negative Test	1	1	0	0	1

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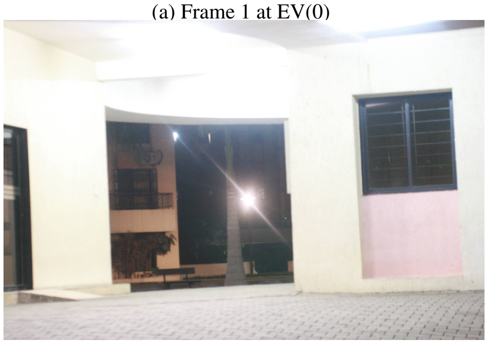
(a) Frame 1 at EV(0)

(b) Frame 2 at EV(-2)



(c) Frame 3 at EV(+2)

2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2

(d) Algorithm Outcome

Figure 4: Fig a,b and c are HDR Scene Images with Different Exposure. Figure d, is the algorithm outcome which shows maximum details of different regions of the scene are captured by different frames. And all 1,2 and 3 frames are required to be fused, to cover entire dynamic range of scene.

(a) Frame 1 at EV(0)

(b) Frame 2 at EV(-2)

(c) Frame 3 at EV(+2)

2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2

(d) Algorithm Outcome

Figure 5: Fig a,b and c are non-HDR Scene Images with Different Exposure. Figure d, is the algorithm outcome which shows maximum details of all regions of the scene are captured by single frame. Only frame b covers entire dynamic range of scene.

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Summary

An efficient and flexible way of automatic HDR scene detection is proposed. Existing generic features such as Auto Exposure Bracketing is used to generate necessary frames. Computation heavy steps are avoided to realistically make efficient assessment of HDR photography need. Theoretically the approach can be extended to cover any dynamic range of scene to be covered by any dynamic range camera. Experiments show that for motion free scenes the algorithm consistently provide accurate results. Algorithm shows consistent and accurate results also for scene consisting of minor motion. On the other hand, the algorithm is not reliable for scenes having significant motion. This scenario is acceptable since only stationary scenes, such as landscapes or scenes with a co-operative stationary objects are suitable for image fusion. In summary, a fast, low resource consuming algorithm to assess scene dynamic range compared to camera's ability is suggested. Proposed algorithm not only determines when the scene is HDR but also suggests which frames are to be used for better fusion, this is achieved with practically negligible computation efforts.

Future Work

In this paper, computation is minimized by simplifying image data as histogram to compute MV. Histogram data in form of MV is normalized to compensate effects of different EV across AEB frames. The same was found sufficiently accurate for all tests. If accuracy is to be further improved at the cost of computational efficiency, the MV computation can be replaced by approaches similar to the ones listed in [7-17] etc. Sigmoidal gain/attenuation as suggested in [5] etc. can replace MV normalization by simple scaling with image average etc. Best choice for low pass filter is not discussed here and can be a matter of future analysis. Image binning can be achieved within sensor itself or can be digitally computed. Comparative analysis of such binning with traditional low pass filter can also be considered in future. For implementing present algorithm, image is split into rectangular regions. Subsequently, comparison of MV for all regions is done. However intensity based regioning can lead to selection of limited number of regions for comparison and can lead to further reduction in computations. Scene with significant motion across different AEB frames are not suitable for image fusion. Such identification of large scale motion can also be used to disqualify scene for image fusion. Simplified motion detection algorithm can be used along with proposed algorithm.

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Author Biography

Sphurti Bhoskar is masters student pursuing M. SC. in Embedded Systems from Nanyang Technological University, Singapore. Previously she worked with ST Microelectronics Pvt. Ltd., India in R&D division. Currently she is working as Software Engineer in R&D division, Gemalto, Singapore. email: sphurti.k.bhoskar@gmail.com website:https://sites.google.com/site/bhoskarsphurti/ https://in.linkedin.com/in/sphurti-bhoskar-a3096672

Ramakrishna Kakarala received a BS in Computer Engineering from the University of Michigan (1986) and the PhD in Mathematics from the University of California, Irvine (1992). He has served on the faculties of the University of Auckland, New Zealand, and the Nanyang Technological University. In 2015, he co-founded Picartio, Inc., a Silicon Valley company devoted to cartoons and animation, and currently serves as its President.