INTERNATIONAL JOURNAL OF SCIENTIFIC PROGRESS AND RESEARCH (IJSPR) ISSN: 2349-4689
Issue 144, Volume 48, Number 02, June 2018

Robust Image Fusion Through Structural Patch Decomposition with Mean Filter

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Abstract - It propose a simple yet effective Structural Patch Decomposition with Mean Filter (SPDMF) approach for multi-exposure image fusion (MEF) that is robust to ghosting effect. It decomposes an image patch into three conceptually independent components: signal strength, signal structure, and mean intensity. Upon fusing these three components separately then reconstruct a desired patch and place it back into the fused image. This novel approach benefits MEF in many aspects. First, as opposed to most pixel-wise MEF methods, the proposed algorithm does not require post-processing steps to improve visual quality or to reduce spatial artifacts. Second, it handles RGB color channels jointly and thus produces fused images with more vivid color appearance. Third and most importantly, the direction of the signal structure component in the patch vector space provides ideal information for ghost removal. It allows us to reliably and efficiently reject inconsistent object motions then a chosen reference image without performing computationally expensive motion estimation. Now compare the proposed algorithm with SPD-MEF methods on different images (with camera and object motion). Extensive experimental results demonstrate that the proposed algorithm not only outperforms previous MEF algorithms on static scenes but also consistently produces high quality fused images with little ghosting artifacts for dynamic scenes. Moreover, it maintains a lower computational cost compared with state-of-the-art MEF de-ghosting schemes.

Index Terms—Multi-Exposure Image Fusion, High Dynamic Range Imaging, Structural Patch Decomposition, De-ghosting, Structural Patch Decomposition with Mean Filter, RGB.

1. INTRODUCTION

Multi-exposure image fusion (MEF) is considered an effective quality enhancement technique that is widely adopted in consumer electronics. MEF takes a sequence of images with different exposure levels as inputs and synthesizes an output image that is more informative and perceptually appealing than any of the input images. MEF fills the gap between high dynamic range (HDR) natural scenes and low dynamic range (LDR) pictures captured by normal digital cameras. Comparing with typical HDR imaging techniques which first construct an HDR image from the source sequence and then tone-map it to an LDR image, MEF bypasses the intermediate HDR image construction step and directly yields an LDR image that can be displayed on standard viewing devices.

Since first introduced in 1980’s, MEF has been an active research topic and attracted an increasing amount of attention in recent years. With many MEF algorithms at hand, it becomes pivotal to compare their performance, so as to find the best algorithm as well as directions for further advancement. Because the human visual system (HVS) is the ultimate receiver in most applications, subjective evaluation is a straightforward and reliable approach to evaluate the quality of fused images. Although expensive and time consuming, a comprehensive subjective user study has several benefits. First, it provides useful data to study human behaviors in evaluating perceived quality of fused images. Second, it supplies a test set to evaluate and compare the relative performance of classical and state-of-the-art MEF algorithms. Third, it is useful to validate and compare the performance of existing objective image quality assessment (IQA) models in predicting the perceptual quality of fused images. This will in turn provide insights on potential ways to improve them. Over the past decade, substantial effort has been made to develop objective IQA models for image fusion applications. Most of them are designed for general purpose image fusion applications, not specifically for MEF, and some of them can only work with the case of two input images. Furthermore, little has been done to compare them with (or calibrate against) subjective data that contains a wide variety of source sequences and MEF algorithms.

2. RELATED WORK

Chenwei Deng et. al, Multi-exposure image fusion is becoming increasingly influential in enhancing the quality of experience of consumer electronics. However, until now few works have been conducted on the performance evaluation of multi-exposure image fusion, especially colourful multi-exposure image fusion. Conventional quality assessment methods for multi-exposure image fusion mainly focus on grayscale information, while ignoring the color components, which also convey vital visual information.

Seungcheol Choi et. al, This paper proposes a method for fusing multi-exposed images that can operate on digital cameras or smart phones. The proposed method consists of an automatic exposure bracketing algorithm that determines which exposures to capture and a newly proposed multi-exposure image fusion algorithm. This fusion algorithm attempts to improve the fusion performance on the basis of the recently proposed no-reference image-quality metrics, noting that the exposure change affects the change in the local luminance details, contrast, and colour fullness of a pixel.

Kede Ma et. al, We propose a multi-exposure image fusion (MEF) algorithm by optimizing a novel objective quality measure, namely the colour MEF structural similarity (MEF-SSIMc) index. The design philosophy we introduce here is substantially different from existing ones.

Hui Li et. al, We propose a simple yet effective structural patch decomposition (SPD) approach for multi-exposure image fusion (MEF) that is robust to ghosting effect. We decompose an image patch into three conceptually independent components: signal strength, signal structure, and mean intensity.

Sujoy et. al, A multi-exposure and multi-focus image fusion algorithm is proposed. The algorithm is developed for colour images and is based on blending the gradients of the luminance components of the input images using the maximum gradient magnitude at each pixel location and then obtaining the fused luminance using a Haar wavelet-based image reconstruction technique.

Takao Sakai et. al, We propose a hybrid method for multi-exposure image fusion in this paper. The fusion blends some images capturing the same scene with different exposure times and produces a high quality image. Based on the pixel-wise weighted mean, many methods have been actively proposed, but their resultant images have blurred edges and textures because of the mean procedure. To overcome the disadvantages, the proposed method separately fuses the means and details of input images.

3. METHODOLOGY

The algorithm of methodology Structural Patch Decomposition with Mean Filter (SPDMF) is as follows

Input: Source image sequence $\{X_k = \{X_k | 1 <= k <= K\}$

Step 1: Select the reference image Xr and create K - 1 latent images $\{X'_k\} = \{X'_k != r\}$ of Xr using IMF

Step 2: For each reference patch X_r do

Step 3: For each channel of color, e.g., Red channel, the blurred pixel of the red color is normally computed by

$$b[i,j] = \sum_{y=i-r}^{i+r} \sum_{x=j-r}^{j+r} red[y,x] * w[y,x]$$

Where red [i , j] is the red color and w[i, j] is the weighted Mean function of the pixel (i,j). However, to reduce the computational burden, the one-dimensional limited space blur (*1*-dim box blur)

Step 4: The Box blur algorithm assumes that the weighted function is a constant function lying within a square (box). That is

$$b[i,j] = \sum_{y=i-r}^{i+r} \sum_{x=j-r}^{j+r} red[y,x]/(2\cdot r)^2$$

Step 5: The one-dimensional box blur uses the computational technique called Divide & Conquer. It simplifies the Box blur algorithm into 2 steps

(1) Horizontal blur:

$$b_h[i,j] = \sum_{x=j-r}^{j+r} red[i,x]/(2\cdot r)$$

(2) Total blur:

$$b_t[i,j] = \sum_{y=i-r}^{i+r} b_h[y,j]/(2\cdot r)$$

Because Moreover to efficiently computing the Horizontal blur for each iteration, we have $b_h[i,j+1] = b_h[i,j] + red[i,j+r+1] - red[i,j-r]$

Step 6: Extract its co-located patches $\{x_k;\ x'_k \mid k != r\}$

Step 7: Check the structural consistency of $\{x_k\}$ using B_k.

Step 8: Reject inconsistent x_k compensated by X'_k.

Step 9: Compute $\hat{c}$, $\hat{s}$ and $\hat{l}$ separately

Step 10: Reconstruct the fused patch $\hat{\mathbf{x}} = \hat{c}\cdot\hat{\mathbf{s}} + \hat{l}$.

Step 11: end for

Step 12: Aggregate fused patches into $\hat{X}$.

Step 13: Obtain fused image in $\hat{X}$.

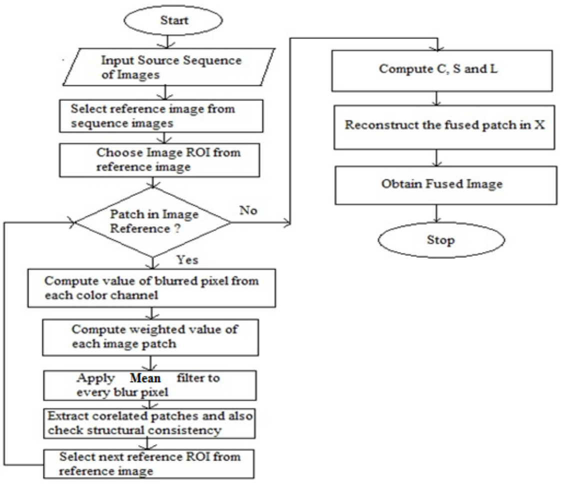

Figure 1: The System Architecture of SPDMF-MEF in Cloud Computing

4. RESULT AND ANALYSIS

The analysis of the existing work (SPD-MEF) and the proposed work (SPDMF-MEF) on the basis of different quality parameters are given in Table 1.

Table 1: Comparative analysis of SSIM, AET and MD for SPD-MEF and SPDMF-MEF

Image Index	Source Sequence Image	Size	SPD-MEF [1]			SPDMF-MEF		
			SSIM	AET	MD	SSIM	AET	MD
1	Balloons	339 x 512 x 9	0.969	10.21	206	0.981	9.87	187
2	Belgium house	384 x 512 x 9	0.973	10.72	216	0.978	10.11	192
3	Cave	384 x 512 x 4	0.985	4.83	251	0.992	4.18	211
4	Chinese garden	340 x 512 x 3	0.991	4.16	234	0.997	3.85	201
5	Farmhouse	341 x 512 x 3	0.993	3.97	238	0.997	3.51	206
6	House	340 x 512 x 4	0.960	4.86	236	0.985	4.16	204
7	Lamp	384 x 512 x 15	0.956	7.48	261	0.971	5.41	214
8	Landscape	341 x 512 x 3	0.993	4.36	238	0.998	3.15	203
9	Madison capitol	384 x 512 x 30	0.968	19.47	270	0.979	16.38	221
10	Office	340 x 512 x 6	0.990	8.37	241	0.996	7.62	204
11	Tower	512 x 341 x 3	0.986	4.61	282	0.991	3.24	226
12	Venice	341 x 512 x 3	0.984	3.96	287	0.989	3.57	229

In above table, multi exposure fused images from Balloons to Venice dataset are compares in between of SPD-MEF and SPDMF-MEF (in Table 4.2). The value of MD (for SPDMF-MEF) is less than value of MD (for SPD). The value of SSIM (for SPDMF-MEF) is more than value of SSIM (for SPD-MEF). The value of AET (for SPDMF-MEF) is less than value of AET (for SPD-MEF).

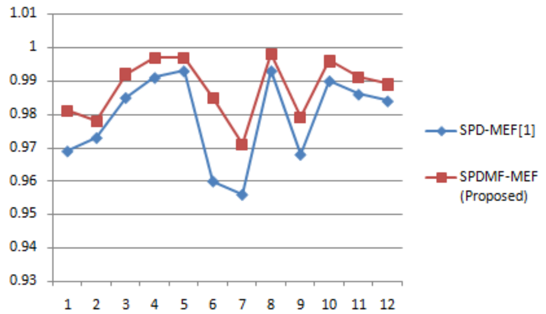

Figure 2: Graphical Analysis for SSIM in between of SPD-MEF[1] and SPDMF-MEF

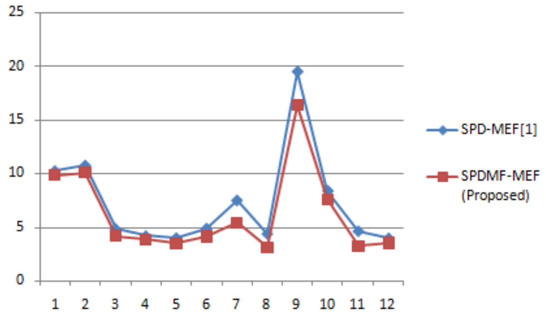

Figure 3: Graphical Analysis for AET in between of SPD-MEF[1] and SPDMF-MEF

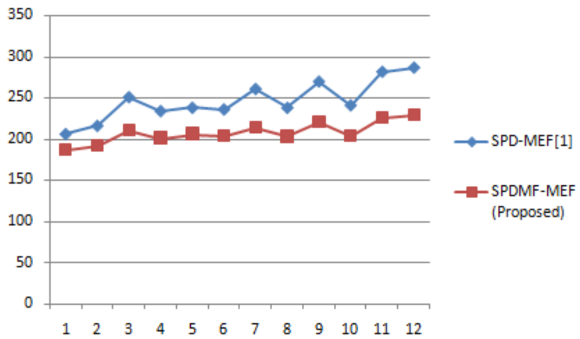

Figure 4: Graphical Analysis for MD in between of SPD-MEF[1] and SPDMF-MEF

Hence performance parameter for multi-exposure image fusion is more close to SPDMF-MEF instead of SPD-MEF[1]. Basically, the comparisons result tested on the basis of different image types and their types. The performance parameters for fused image (from Balloons to Venice Datasets) are compares in between of SPD-MEF and SPDMF-MEF (mentioned in table 4.2 and related figure). The performance of the proposed work (SPDMF-MEF) is better than the existing technique (SPD-MEF).

5. CONCLUSIONS

Novel structural patch decomposition with Mean filter (SPDMF) approach for MEF. Different from most pixel-wise MEF methods, SPDMF-MEF works on color image patches directly by decomposing them into three conceptually independent components and by processing each component separately then apply Mean filter for effective fusion process. As a result, SPDMF-MEF generates little noise in the weighing map and makes better use of color information during fusion.

Comprehensive experimental results demonstrated that SPDMF-MEF produces MEF images with sharp details, vivid color appearance and little ghosting artifacts while maintaining a manageable computational cost. The proposed SPDMF approach is essentially dynamic range independent. Therefore, it would be interesting to explore its potential use in HDR reconstruction to generate high quality HDR images with little ghosting artifacts.

6. SCOPE OF FUTURE WORK

Furthermore, reliable de-ghosting performance is achieved by using the direction information of the structure vector. Moreover, the application of SPDMF is not limited to MEF. As a generic signal processing approach, SPD has been found to be useful in image quality assessment of contrast-changed and stereoscopic images. It is worth considering whether SPD offers any insights that can be transferred to other image processing applications. In addition, although objective quality models for MEF algorithms begin to emerge, the models for objectively comparing MEF algorithms for dynamic scenes are largely lacking. Therefore, it is demanding to switch the focus from developing MEF algorithms for dynamic scenes to developing such objective quality models in order to conduct a fair comparison.

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