DUAL-EXPOSURE IMAGE REGISTRATION FOR HDR PROCESSING

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ABSTRACT

In this paper we present a method for registering a pair of differently exposed Low Dynamic Range (LDR) images for the purpose of rendering a High Dynamic Range (HDR) image. In general, the images are captured from a moving camera and/or contain moving objects. Therefore, proper registration is required to enable HDR rendering. However, even for equally exposed images, registration is an ill posed problem where errors are expected for a wide range of image pairs. The problem only becomes more challenging for a pair of differently exposed images. We propose an adaptive registration error detection and correction method to address this issue. By combining Optical Flow with the proposed correction method, we achieve state-of-the art results as shown in numerous experiments. The proposed method is simple and has low-complexity, hence allowing for an easy and efficient implementation.

Index Terms— Image Registration, Optical Flow, HDR

1. INTRODUCTION

The majority of cameras available on the market fail to capture the full range of details of a scene enclosing dark and bright regions. The generated LDR image contains either details in the bright areas or in the dark parts of the scene, depending on the exposure settings. These hardware-related limitations motivate the development of HDR Imaging (HDRI) approaches, which tackle this particular problem by computationally increasing the dynamic range in the input LDR's. The underlying concept is to merge the input LDR's into one image with a larger dynamic range [1]. The most common HDRI method is based on the computation of the scene radiance map by estimating the inverse camera response function (CRF) [2] [3] [4]. Alternative approaches such as Exposure Fusion [5] which are independent on the camera intrinsic parameters are gaining popularity.

However, the main limitation of HDRI techniques is related to image misalignment due to camera and/or scene motion, which creates visible artifacts, such as ghost effects. In this context, various methods are proposed to deal with this issue. The most sophisticated set of methods align the input LDR's to a reference image by estimating the motion information using Optical Flow. Optical Flow offers higher accuracy and has a broader range of applications since it can deal with all types of motion (arbitrary camera and scene motion). Additionally, Optical Flow is more suitable for scenarios involving video HDR. In [6], Kang et al. proposed a technique based on a global alignment operation followed by a refinement step using local Optical Flow [7]. Although this method presents clear advantages over conventional de-ghosting approaches, the lack of a global Optical Flow estimation affects the accuracy of the final motion vectors, especially in flat regions. Alternatively, Zimmer et al. propose a method [8] based on a dense gradient-based Optical Flow approach with a minimization of an energy function. They assume that the gradient remains constant under varying exposure settings. The final HDR is constructed based on a generated displacement map and the estimated motion information. However, the final results of some sequences still suffer from artifacts caused by erroneous motion information. Alternatively, methods based on variants of the *PatchMatch* algorithm [9] such as in [10] and [11] align the input LDR's to a reference image without computing motion vectors. However, these approachs depend on the quality of the reference image and the performance of the registration, which fails again in particular cases. More recently, Hafner et al. introduced a method in [12] based on the computation of a displacement map using Optical Flow. The estimation of the motion incorporates the specific CRF and adapts the regularization terms of the energy function to the differently exposed input LDR's. Therefore, a lack in accuracy of the CRF could affect the quality of the estimated motion information and the registration operation generally.

Our approach advances upon the methods proposed in [6, 8, 11, 10, 12] by introducing an adaptive, low-complexity correction step which improves the performance of the Optical Flow-based registration and the quality of final HDR. In addition, no prior information about the exposure ratio and the CRF are required. Furthermore, the robustness of the proposed registration approach allows for using a smaller number of input LDR images with higher exposure ratio.

2. OUR APPROACH

In this paper we propose a method for registering input LDR's based on motion estimation and subsequent detection and correction of optical-flow related artifacts. First we choose a reference image from the input LDR's (usually 2 images), then we reduce the difference in luminance between the input images. This step is essential for the estimation of the motion vectors. The gained motion information will be used for image registration using Optical Flow, followed by a post-processing step for distortion suppression and accuracy enhancement. Finally, the HDR image of the reference is rendered. The main contribution of this paper is:

- An adaptive method for detecting and correcting geometrical errors caused by erroneous registration.

In the following, a description of the mentioned steps is provided for the case of two input LDR's.

2.1. Image Registration

We propose to estimate the motion vectors for the registration using a gradient-based Optical Flow algorithm developed by *C. Liu* [13]. This algorithm is based on an image-pyramid approach for minimizing the energy $E(\mathbf{v})$

$$E(\mathbf{v}) = \int_{\mathbf{x}} [\phi(I_0(\mathbf{x}+\mathbf{v}) - I_1(\mathbf{x})) + \alpha\theta(\mathbf{v})]\, d\mathbf{x}, \quad (1)$$

where $I_j(\mathbf{x})$ is the pixel intensity of image j at location $\mathbf{x}$, $\phi()$ is a robust distance function, α is the smoothness term weight and $\theta()$ is a robust, piecewise smoothness term for the flow vector $\mathbf{v}$. However, Optical Flow methods based on the luminance constancy assumption between the input images, such as in [13], can not be used directly on differently exposed LDR's, as it is the case for HDRI. Performing image alignment directly on the input LDR's with average varying luminance leads in this case to severe artifacts in the registered images. Therefore it is mandatory to match the luminance of the input images prior to the motion estimation step. To this end, we propose to use Histogram Matching (HM) [14] [15]. Examples of registration errors are shown in Figure 2. The registered images present notable artifacts, mainly due to wrong motion vectors. Erroneous motion vectors are also likely to occur in occluded areas due to different camera perspective between the images.

2.2. Error Detection and Classification

The proposed algorithm for errors detection and correction starts with the calculation of the intensity difference image between the processed reference image and its registered counterpart (outcome of the motion estimation step):

$$D(i,j) = |I_{Processed}(i,j) - I_{Registered}(i,j)|, \quad (2)$$

The underlying idea is to detect the geometrical distortions using the difference image. This requires to set an adaptive threshold, which enables to distinguish between difference values resulting form normal **color differences** (a.c.a color errors) between the processed reference and the registered image, and difference values corresponding to the **geometrical errors** caused by erroneous registration. Additionally, we assume that the difference values of geometrical errors are larger, however they are less frequent than the difference of the color errors values. Based on these assumptions, we compute the histogram of the difference image. The desired threshold corresponds to the difference value which marks the abrupt decrease of the number of pixels inside the histogram (see Figure 1). We detect the threshold T_c for each color channel

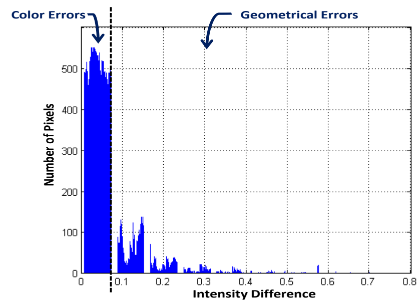

Fig. 1: Histogram of the difference image - Blue channel

by

$$T_c = \underset{T_c^i}{\arg\max}\, |T_c^i - T_c^{i+1}|, i = 0, ..., N-2, \quad (3)$$

where T_c^i is the bin center color value of the bin number i out of N bins.

In some cases, the detection of geometrical errors can produce false positives (outliers), where **color errors** are detected as **geometrical errors**. To make the detection less sensitive to outliers, we propose the following method. For each pixel in the difference image, we count the number of channels N_c with values larger then the corresponding thresholds. We introduce a parameter P, provided by the user, to enable a second thresholding. The parameter P controls the tolerance of the proposed approach towards outliers. Finally, the detection process is performed as follows:

if $N_c = 3$ **then**
  Pixel is confirmed as a geometrical error.
else if $N_c = 2$ **then**
  $D_{avr} = (D_{color1} + D_{color2})/2$
  $T_{avr} = (T_{color1} + T_{color2})/2$
  if $|D_{avr} - T_{avr}| > P$ **then**
    Pixel is confirmed as a geometrical error.
  end if
else if $N_c = 1$ **then**
  if $|D_{color} - T_{color}| > P$ **then**
    Pixel is confirmed as a geometrical error.
  end if
end if

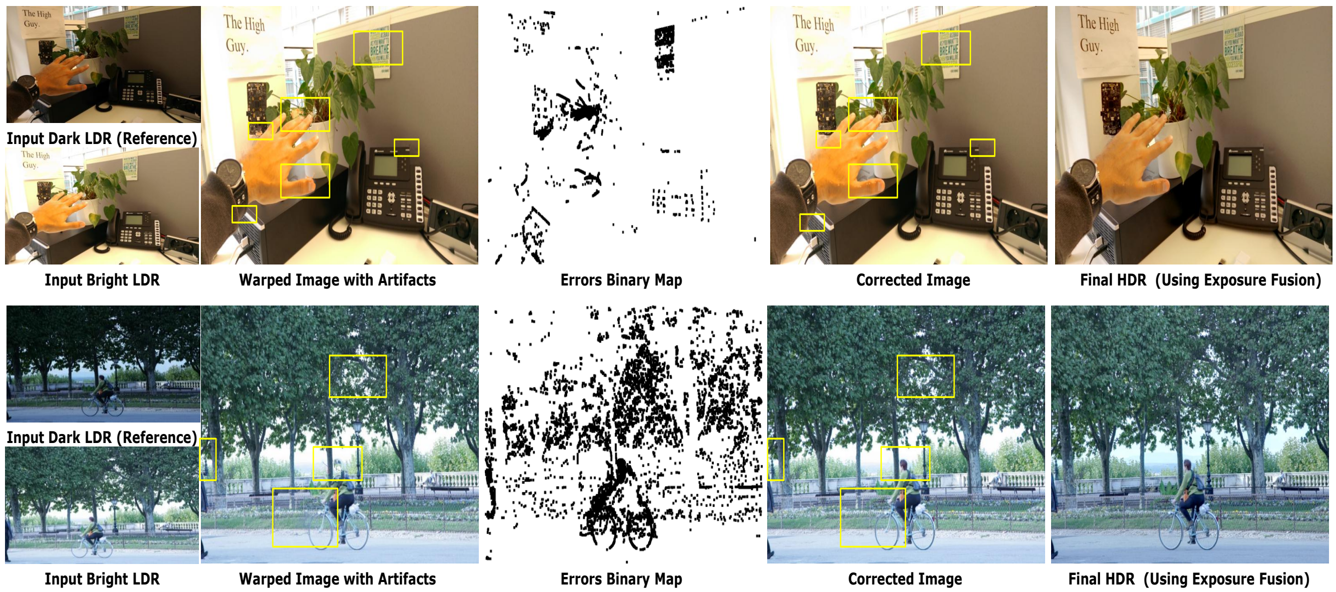

Fig. 2: Results of the optical flow-based registration and the correction results along with corresponding binary maps. The artifacts caused by wrong motion vectors are marked under yellow boxes, and can be also located using the binary maps. The corrected images show less distortions than the registered images.

Note that if the parameter P is set to 0, a pixel difference value is considered as erroneous if at least 1 color channel difference is larger than the corresponding threshold.

Based on the previously described steps, we generate a binary map containing the locations of the detected geometrical errors which need to be corrected (Figure 2). Using the generated map, we first replace the values of the detected errors using the original values from the processed reference image (result of histogram matching). We propose a window-based approach for replacing the erroneous values in order to avoid creating additional texture noise by replacing single pixels in large flat areas.

In the next step of the correction algorithm, we apply a Gaussian low-pass filter to the corrected pixels. This allows for reducing the difference between the corrected areas and the surrounding regions.

3. EXPERIMENTAL RESULTS

We tested the performance of our registration procedure using Optical Flow on a variety of real world images. Figure 2 shows the results of the correction step after registration using the estimated motion vectors. The correction method is able to remove most of the artifacts caused by erroneous motion estimation, despite the large displacements and the large exposure ratio between the input LDR's. This can be seen using the provided binary maps, which indicate the locations of the erroneous motion-related artifacts. In addition, we assess the performance of the proposed approach by comparing it to available ground truth images (Table 1). To this end, we used two stereo sets from the *Middlebury College Dataset* [16], which provide the ground truth images needed for the comparison. In addition, we created 3 more test sets using a smart phone as capturing device. These test sets are shown in Figure 3. The PSNR values show that the Optical Flow-based image registration is improved through the proposed correction approach. Additionally, values from the smart phone pairs 2 and 3 show that our approach improves the result of registration, although the latter may cause a drop in the PSNR in comparison to HM.

In addition, Figure 4 shows a crop from the HDR rendering using our algorithm applied to the multi-exposed non-aligned LDR's provided by [8], in comparison to their rendered HDR. This sequence was considered by the authors of [8] as a failure case, due to large motion in the scene. However, our algorithm is able to register and correct motion-related artifacts, which improves the quality of the final HDR.

Furthermore, Figure 5 represents the comparison between our the registration results of our approach and the results the Patch-Based algorithm presented in [11]. The comparison shows that our technique can achieve similar or better results using the proposed correction method. The halo effect created by the matching operation of the patches is not present in our results. However, few warping errors are still visible in our results.

Set	Histogram Matching (dB)	Warped Image (dB)	Warped and Corrected (dB)
Moebius [16]	28.8395	30.5053	31.7769
Baby [16]	27.1475	29.9598	30.997
Smart Phone Pair 1	32.7442	31.2759	33.5491
Smart Phone Pair 2	35.125	35.0174	36.015
Smart Phone Pair 3	30.0961	31.4755	33.5176

Table 1: PSNR values resulting from the comparison of different intermediate results (histogram matching, warping) and our proposed approach, against available ground truth images. The used sets are shown in Figure 3

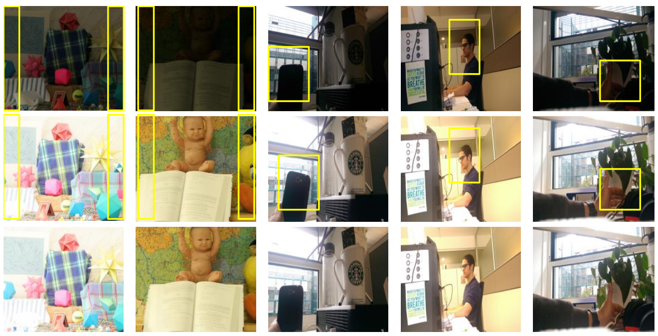

Fig. 3: Sets used for the quantitative evaluation of the proposed approach (see Table 1). First row contains the input dark LDR's (**reference**). Second row represents the input bright LDR's and finally the third row shows the ground truth bright version of the reference images. Yellow boxes indicate where the motion occurred.

Fig. 4: Comparison of the performance of our registration with the results of [8].

4. CONCLUSION

In this paper we propose a correction method to be applied after image registration to improve motion HDR applications. Especially in cases where just two differently exposed low-dynamic range images are available, we show the benefit of improved registration in numerous experiments. This is particularly important for enabling video HDR applications. The

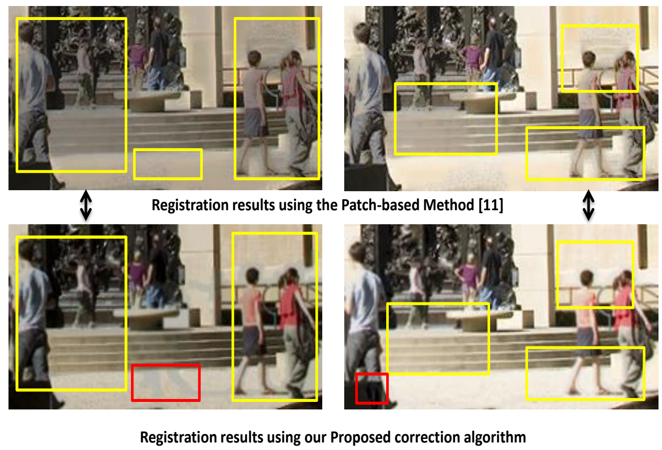

Fig. 5: Comparison of the registration results using our approach with the results of the method presented in [11]. In this case, the reference image was registered to 2 darker input LDRs with large scene motion. Yellow boxes indicate where our results performed better and red boxes designate areas where our algorithm missed the correction of the artifacts. *Images courtesy of Orazio Gallo and Jan Kautz* [17].

suggested technique shows that it is possible to deal with arbitrary scene and camera motion without using computationally expensive and complex algorithms.

5. REFERENCES

[1] S. Mann and R. W. Picard, “On being undigital with digital cameras: Extending dynamic range by combining differently exposed pictures,” in *Proceedings of Image Science and Technology*, 1995, pp. 442–448.

[2] T. Mitsunaga and S. K. Nayar, “Radiometric Self Calibration,” in *IEEE Computer Society Conference On Computer Vision and Pattern Recognition*, vol. 1, 1999, pp. 374–380.

[3] P. Debevec and J. Malik, “Recovering High Dynamic Range Radiance Maps from Photographs,” in *Proceedings SIGGRAPH*, 1997, pp. 369–378.

[4] M. A. Robertson, S. Borman, and R. L. Stevenson, "Dynamic Range Improvement Through Multiple Exposures," in *International Conference on Image Processing*, vol. 3, 1999, pp. 159–163.

[5] T. Mertens, J. Kautz, and F. Van Reeth, "Exposure Fusion," in *Pacific Graphics*, 2007, pp. 369–378.

[6] S. Kang, M. Uyttendaeke, S. Winder, and R. Szelisk, "High Dynamic Range Video," in *ACM SIGGRAPH*, 2003, pp. 319–325.

[7] B. D. Lucas and T. Kanade, "An Iterative Image Registration Technique with an Application to Stereo Vision," in *Proceedings of Imaging Understanding Workshop*, 1981, pp. 121–130.

[8] H. Zimmer, A. Bruhn, and J. Weickert, "Freehand HDR Imaging of Scenes with Simultaneous Resolution Enhancement," in *EUROGRAPHICS*, 2011, pp. 319–325.

[9] C. Barnes, E. Schechtman, D. B. Goldman, and A. Finkelstein, "PatchMatch: A Randomized Correspondence Algorithm for Structural Image Editing," in *ACM Transactions on Graphics SIGGRAPH*, 2009.

[10] J. Hu, O. Gallo, K. Pulli, and X. Sun, "HDR Deghosting: How to deal with Saturation?" in *International Conference on Computer Vision and Pattern Recognition*, 2013, pp. 1036–1170.

[11] P. Sen, N. K. Kalantari, M. Yaesoubi, S. Darabi, D. B. Goldman, and E. Schechtman, "Robust Patch-Based HDR Reconstruction of Dynamic Scenes," in *ACM Transactions on Graphics SIGGRAPH Asia*, 2012, pp. 203–214.

[12] D. Hafner, O. Demetz, and J. Weickert, "Simultaneous HDR and Optic Flow Computation," in *International Conference on Pattern Recognition*, 2014, pp. 2065–2070.

[13] C. Liu, "Beyond Pixels: Exploring New Representations and Applications for Motion Analysis," Ph.D. dissertation, Massachusetts Institute of Technology, 2009.

[14] K. R. Castlman, *Digital Image Processing*. New Jersey: Prentice Hall, 1996.

[15] R. D. Gonzalez and R. E. Woods, *Digital Image Processing (3rd Edition)*. New Jersey: Prentice Hall, 2006.

[16] D. Scharstein and R. Szeliski, "A taxonomy and evaluation of dense two-frame stereo correspondence algorithms," in *IEEE Workshop on Stereo and Multi-Baseline Vision*, 2001, pp. 131–140.

[17] O. Gallo, N. Gelfand, W. Chen, M. Tico, and K. Pulli, "Artifact-free High Dynamic Range Imaging," 2009, pp. 1–7.