Fast Approach for Stereo Balancing Mapping Function

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ABSTRACT

This paper presents an effective approach to minimize recursive computations for balancing stereo pairs by using disparity vector errors and its directional histogram. A stereo balancing function is computed from the correspondent pixels between two images, and a simple approach is to find the matching blocks of two images. However, this procedure requires recursive operation, and its computation cost is very high. Therefore, in this paper, we propose an efficient balance method using structural similarity index and a partial re-searching scheme to reduce the computation cost considerably. For this purpose, we determine if re-searching for each block is necessary or not by using the errors and the directional histogram of disparity vectors. Experiment results show that the performance of the proposed approach can save the computations significantly with ignorable image quality degradation compared with full re-search approach.

Keywords: stereo balancing, block matching, recursive computation

1. INTRODUCE

Stereo image pairs have been widely used in many research and practical fields. However, there exists an imbalance between the stereo image pair when each of them is acquired under different environments such as different ISO property, focus, and lens characteristics. The imbalance causes severe problems for examples in disparity estimation and correspondent point detection, because such works depend on the brightness and spatial information of images [1]. The imbalance in stereo pairs can be solved by finding a mapping relationship between a reference and its distorted images. The mapping relationship is efficiently obtained by using histogram specification (HS) which is a special version of histogram equalization. Many HS-based methods such as direct mapping including single mapping law (SML) and group mapping law (GML), dynamic histogram warping (DHW), and ordering techniques were proposed [2][3][4]. In order to compute a more robust relationship, we need to know the correspondent pixels between stereo images. The pixels are obtained by block matching approach, and a mapping relationship is estimated by using them. However, the mapping relationship (balancing function) may not be correct because of imbalance between the given stereo pair. To resolve this problem, the mapping function should be estimated recursively with high computational burdens. Therefore, in this paper, we propose a partial re-searching method to minimize the computational cost. In particular, we employ structural similarity index (SSI)[5] as an efficient method for estimating the balance function.

Overall procedures of the proposed scheme are shown in Fig. 1. First, we estimate a balancing function from the inputted images, and it is used to transform the target image. To take matching error into account, we compute new matching blocks using the transformed target image repeatedly, and then estimate a new balancing function again. At this point, to find a new matching block, we use the calculated disparity vector in previous stage, and partial re-searching is conducted instead of full re-searching. Here, we search the limited number of the blocks containing the large matching errors or the different disparity-vector direction compared with neighboring blocks. These procedures are repeated until a convergence condition, which is described in Section 2, is satisfied.

In this paper, the previous HS method and the proposed method for balancing stereo pair are presented in Section 2. The balancing function is estimated by using SSI. The proposed partial re-searching method is described in Section 3. Using the error value of disparity vector and direction histogram, we determine if each block needs to be re-searched or not. Results of the proposed algorithm with several stereo images are presented in Section 4. Finally, conclusions are given in Section 5.

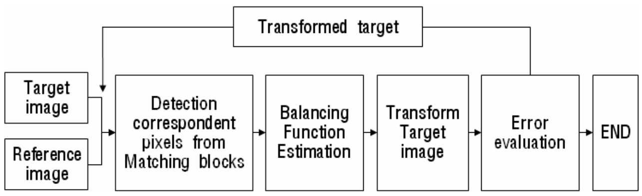


Fig. 1: A block diagram of the proposed algorithm.

2. STEREO BALANCING

In this section, several methods for balancing stereo images, in this section, are discussed. Balance methods of stereo images can be classified into two categories. First, the mapping relation is found between the true color values and the obtained colors from each camera. Second, the transform between the reference and target images is found. The second approach is generally simpler and does not need additional constraints. In this paper, we follow the latter approach and estimate the balancing function using HS.

2.1 Histogram specification

HS is a useful method of histogram modification for image enhancement or balancing. Specifically, it transforms the histogram of an image to a specified histogram in order to modify the gray-level range of a given image. HS converts the image so that it has a particular histogram (reference image) as specified. Therefore, using HS, the target image can be balanced by the histogram of a reference image. Let c_r and c_t be the cumulative histograms of the reference and target images. Then, they are presented by

$$c_r = g(i) = \int_0^i h_r(x)dx, \quad c_t = f(j) = \int_0^j h_t(v)dv \quad , \tag{1}$$

where $h_r(u)$ and $h_t(v)$ are the histograms for the given two images. In HS, the transformation function is given by the following relation, $t(j)=i=g^{-1}(c_t)$. Only, in continuous case, the HS can give correct results. However, in discrete case, Eq. (1) is expressed as

$$c_r = T_r(i) = \sum_{i=0}^{k} h_r(x) \quad \text{and} \quad c_t = T_t(j) = \sum_{j=0}^{l} h_t(v) \quad . \tag{2}$$

Therefore, the approximation errors due to quantization and rounding off are unavoidable. Several attempts have been made so far to improve the performances.

Early proposed SML algorithm to map h_t to h_r finds k and l that minimize $|T_r(i)-T_t(j)|$. Since it is intuitive and straightforward one-to-one mapping, the results produce considerable rounding off error. GML [2] algorithm, to decrease the errors, considered many-to-one mapping using an integer function $f(l)$ that satisfies $0\leq f(0)\leq f(l)\leq\ldots\leq f(N-1)\leq M-1$ instead of k. It is obvious that the GML makes more close results to the desired one than the SML. However, since matching errors are accumulated and propagated, GML make artifacts such as spikes. To minimize the errors, DHW [3] considered one-to-many mapping by finds k and l that minimize a cost function using dynamic programming. While the cost function can be efficiently minimized via dynamic programming, DHW algorithm does not achieve exact HS. To achieve exact HS, Dinu Coltuc [4] used an ordering relation which induces a strict ordering among image pixels. In order to induce such an ordering the pixel neighborhood is taken into account. That is, the pixels which have a same gray-level are ordered by the local averages of the pixels. Until the pixels are completely ordered, a size of closed neighborhood is expended. This method can achieve correct histogram specification, but it is not suitable for stereo balancing problem because there is not any consideration about the pixels of non-overlapped region. In this paper, we are focused on balancing whole pixels of a target image.

2.2 Stereo balancing using structural similar -ity index

We use the structural similarity index (SSI) for balancing. SSI computes the quality of an image by comparing the correlations in luminance, contrast, and structure, locally, between the reference and target images and averaging these quantities over the entire image [5]. The SSI of each pixel between two images is calculated as

$$SSI(x,y) = \frac{(2\mu_1\mu_2 + C_1)(2\sigma_{12} + C_2)}{(\mu_1^2 + \mu_2^2 + C_1)(\sigma_1^2 + \sigma_2^2 + C_2)} \quad . \tag{3}$$

Where, μ_1 and μ_2 are the means of each image, σ_1 and σ_2 are the standard deviations of each image, σ_{12} is the square root of covariance of the reference and target images, and C_1 and C_2 are constants.

When the corresponding pixels in a stereo pair are extracted, we can find the number of mapping levels $w(i)$ and a minimum mapping levels $k(i)$ for each input level i from histogram specification in a target image. In case of $w(i)>1$, the input pixels at the ith level will be mapped into multi levels as $i \rightarrow [k(i), \cdots, k(i)+w(i)-1]$. For this case, we use the mean of SSIs to find an optimal mapping level. From a reference I_r, a target I_t, and a transformed-target image $I_{t'}$, the local SSIs are computed as

$$SSI_{rt} : I_r \leftrightarrow I_t, \; SSI_{rt'} : I_r \leftrightarrow I_{t'}, \; SSI_{tt'} : I_t \leftrightarrow I_{t'} . \tag{4}$$

Next, the mean values of the $SSIs$, $MSSI_{rt}(i)$ and $MSSI_{rt'}(i)$, for each level in the reference image are calculated from $SSI_{rt}(x,y)$ and $SSI_{rt'}(x,y)$ at (x,y) location, respectively. Then, a structural variation measure $EM(i)$ between the given target and the GML transformed-target images at each level i is defined by

$$EM(i) = MSSI_{rt'}(i) - MSSI_{rt}(i) . \tag{5}$$

The $EM(i)$ is close to zero at all levels when the occluded region and imbalance do not exist. In case of $EM(i)>0$, it indicates that the transformed-image is similar to the reference more than the given target one. Based on the preceding observations, the pixels mapped into the multi levels can be handled properly by finding the level where the difference between the $SSItt'(x,y)$ of each pixel and the EM values of each level at the mapping interval is minimum. Therefore, a balancing function can be written by

$$B(i) = \underset{k(i)<j<k(i)+w(i)-1}{\arg\min} \left(SSI_{tt'}(x,y) - EM(j)\right) . \tag{6}$$

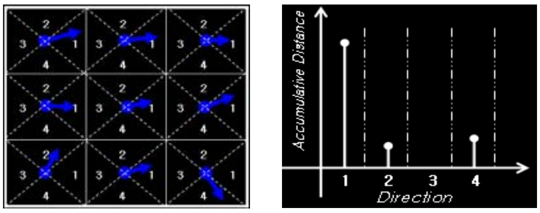
Finally, a target image is balanced by the function $B(i)$. However, the balancing function estimated from the inputted stereo images is not accurate in early stage due to block matching errors. Therefore, the estimated function needs to be optimized recursively. For the recursion, total structural error

$$E_n = \sum_{i=0}^{255} \left|EM(i)\right| \tag{7}$$

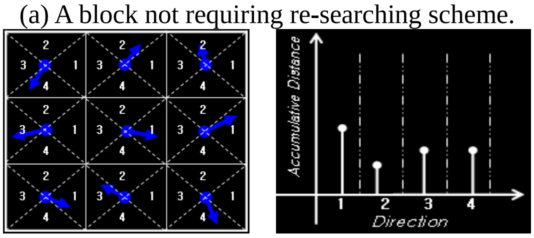
is defined, and the balancing function is repeatedly estimated until $E_{n-1}\leq E_n$. It is noted that the previously transformed target image is used in the current estimation instead of the GML transformed-target image.

3. A partial re-search for recursive estimation

As mentioned in the preceding sections, the computational cost is very high when a balancing function is estimated recursively. In order to minimize the cost, we employ a partial re-searching scheme to estimate disparity vectors again. Here, we make a decision on the validity of re-searching for each block based on disparity error (matching error) and directional histogram. Specifically, first, we use the disparity error of each block, which was estimated in the previous stage. Let $e(i)$ be the estimated error of ith block, m be mean error in the whole blocks, and $m_{near}(i)$ be the mean error of neighboring blocks at the ith blcok. Then, $m_{near}(i)/m$ indicates local fluctuation against global mean error, and $e(i)/ m_{near}(i)$ represents the variance of the ith block against local mean error. When any block needs re-searching, the matching error of the block may be larger than those of neighboring blocks, and can simultaneously satisfy $m_{near}(i)/m<e(i)/m_{near}(i)$. Therefore, re-searching the blocks are performed with the following conditions as



(a) A block not requiring re-searching scheme.



(b) A block requiring re-searching scheme.

Fig. 2: Disparity vectors and directional histogram.

$$\left(\frac{m_{near}(i)}{m} < \frac{e(i)}{m_{near}(i)}\right) \text{and} \max\left(e_{near}(i)\right) < e(i)\,. \tag{8}$$

Here, $max(e_{near}(i))$ is a largest error value in the neighboring blocks of the ith block.

Second, we use the directional histogram of disparity vectors to determine the validity of re-searching. For this purpose, the whole disparity vectors are clustered into 4-directions using k-means algorithm. Then, we can calculate a directional histogram of the ith block $dirH_i(n), n=1,2,3,4$ using the 8-neighboring blocks with the Euclidian distance $Dist^i_n(j)$ of disparity vectors as

$$dirH_i(n) = \sum Dist_n^i(j), i \neq j \tag{9}$$

where n is a directional bins. As shown in Fig. 2 (a), the directional histogram of a block is concentrated on one direction, and re-searching operation is not required for this block. In contrast, re-searching scheme is required for the case in Fig. 2 (b) since the distribution of the vector s indicates the high possibility of erroneous estimation. Therefore, in this paper, we consider the directional distribution of disparity vectors to determine the validity of re-searching as

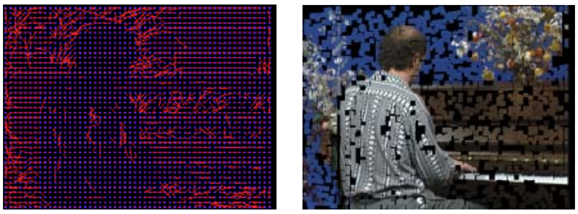
$$dirH_i(n) > k \times d_m(i), \text{for}\, n = m \tag{10}$$

where $d_m(i)$ is the distance of the ith block, and k is a constant value. If a block does not satisfy Eq. (10), the given block is re-searched. In summary, to re-compute the disparity vectors for partial blocks, we use the disparity estimation error and the directional histogram with Eq. (8) and Eq. (10). Fig. 4(a) and (b) show the re-searched disparity vectors from the partial and the whole blocks, respectively.


Fig. 3: Test stereo pairs.

4. SIMULATION RESULTS

This section describes a series of experiments to demonstrate the performance of the proposed algorithm, and also compares its results with full re-search algorithm. In experiment, we employed the fast full search algorithm based on a row-matching scheme [6] to find disparity vector or matching block, and the sum of difference (SAD) is used as an error criterion. The block size is 7 ×7 pixels, and the search window is 41×41. The imbalance-removal results on four stereo pairs, viz., 'Tshukuba', 'Sawtooth', 'Ship', and 'Piano' with the raster scanning order, as shown in Fig. 3, are compared. The target images of 'Tshukuba' and 'Sawtooth' pairs are modified by a commercial image processing tool, while 'Ship' and 'Piano' pairs are obtained from different cameras.


(a) Re-searching for whole blocks.


(b) Re-searching for partial blocks.

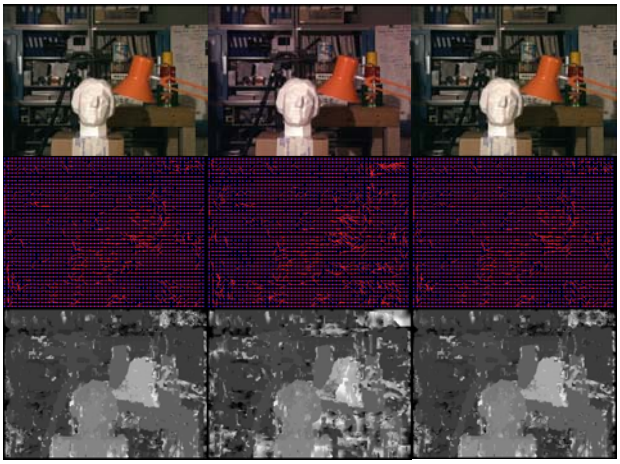
Fig. 4: Disparity re-searching results.

Table. 1: PSNR and the rate of time cost

	Full re-searching	Partial re-searching	Time cost (P/F rate)
Tshukuba	24.657	24.710	0.9535
Sawtooth	25.642	25.642	0.7596
Ship	37.239	37.238	0.6908
Piano	24.667	24.668	0.8582

First, we evaluated performance of the proposed re-search method. Fig. 4 (a) and (b) show an example for the full re-searching and the partial one, respectively, and Table. 1 shows the performance of each approach with respect to

PSNR and computational efficiency. In particular, the computational cost (P/F rate) is computed by the rate of the partial re-searching approach against the full re-searching one. It is easily seen that the proposed partial re-searching method gives good performance in P/F rate with even maintaining similar PSNR to the full re-searching approach. It is expected that P/F rate will be smaller as the inputted image size is getting bigger or the recursive number increases.



(a) Original (b) Imbalanced (c) After processing

Fig. 5: Results of the proposed algorithm.

Second, we evaluated the balancing performance of the proposed algorithm. Fig. 5 illustrates some graphical results. The first row images illustrate an original-, an imbalanced-, and its balanced-target images (B-image), respectively. The second and the third rows present the disparity vectors, which are computed between the balanced target and its reference images, and the disparity maps (DM-image), respectively. For objective performance evaluation, PSNR results from each algorithm are shown in Fig. 6. The PSNR in 'DM-image' is computed between the DM images estimated from the original target image and its balanced one by each method in Fig. 6. Similarly, the PSNR in 'B-image' is calculated between the reference and the compensated target images by the disparity vectors estimated from the balanced target ones. It is easily seen that the proposed method outperforms other methods with respect to PSNR. Especially, the PSNR scores in 'DM-image' are much higher than those in 'B-image'. This means that the proposed method, taking the structural information into consideration, is much more effective for solving stereo-image-pair imbalance problems. The proposed algorithm improves 3.83 dB and 5.91 dB on average for 'B-image' and 'DM-image', respectively, with the given test pairs than other methods.

5. CONCLUSION

In this paper, we presented an effective method to balance the stereo-image pair obtained from different environments. In particular, a partial re-searching scheme was introduced to minimize computational cost for estimating a balancing mapping function recursively. In order to evaluate the proposed scheme, several baseline approaches were compared with respect to PSNR, and it is verified that the result of the proposed one outperforms the other algorithms. Therefore, we believe that the proposed scheme can be an acceptable tool to remove the imbalance in stereo- pair related works.

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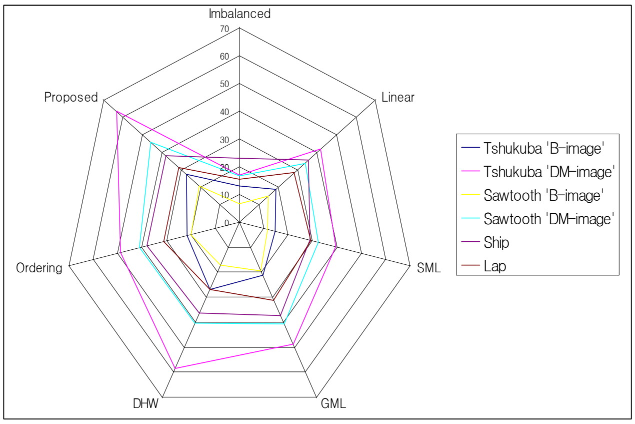

Fig. 6: PSNR comparison after balancing the target image.

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