# Dense Stereo Correspondence Using Combined Similarity Measurement

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Abstract—This paper presents a new real-time stereo correspondence method based on combined similarity guided filter. measurement and Many stereo correspondence methods use color intensity value as pixel similarity measurement, color intensity value is sensitive to noise, exposure, light and etc, so error correspondence rates of these methods are high. Gradient value is more robust to these factors than intensity, so we introduce the gradient value into the similarity measurement, and the linear combination of both measurements composes combined similarity measurement. Guided filter has edge-preserving character as bilateral filter, but runs faster than it, we use guided filter as adaptive support weight of the neighbored pixels in a finite squared support window. The experimental results demonstrate that our real-time approach performs much better compared with other local methods using different similarity measurements, whether in accuracy or robustness to radiometric distortions, according to the widely-used Middlebury stereo benchmarks.

## *Index Terms*—Stereo correspondence, Guided filter, Combined similarity, Gradient value

## I. INTRODUCTION

Dense stereo correspondence is one of the key and difficult problems in computer vision. In recent years, much research has been carried out for this problem, and great improvement has been achieved. According to [1], stereo correspondence algorithm is classified as local and global algorithms. Global methods can obtain highaccuracy disparity map, but it is difficult for users to determine the parameters with high complexity and it is not appropriate for real-time applications. Local approaches can achieve disparity map quickly, but the precision is low especially in depth discontinuity regions, and many researchers have focused on this problem.

The similarity measurement used in most local stereo correspondence algorithms at present is based on pixel color intensity, in other words, the corresponding pixels in the two views should have equal intensity. But the corresponding pixels in different views may not have the same intensity value due to image noise, repetitive (or weakly) texture and radiometric distortion, which make the correspondence result extraordinarily sensitive to intensity changes. To overcome this problem, some local dense stereo correspondence methods often aggregate the correspondence cost of the pixels in the support region around every pixel, with the implication that all pixels in the region have the same disparity as the central pixel. By using the support window, the image ambiguity is reduced to a certain extent, however, if the support window locates on depth discontinuity region, the disparities of the pixels do not equal, which conflicts with the implication of the aggregating and results in the socalled "foreground fattening" phenomenon. To achieve correct correspondence result in both regions, the support window should vary adaptively for every pixel, and many approaches have been put forward. Adaptive support window methods[2,3] and multiple support window methods[4,5] improve the correspondence result to a certain extent, but the shape and size of the support window are restricted, and can not make each pixel truly adaptive in the entire image regions especially in depth discontinuity regions. To work this problem out, some segmentation based methods [6] segment the image in the preprocessing stage, but accurate color segmentation is difficult and time-consuming for rich texture images.

Another improved approach is adaptive supportweight[7](the bilateral filter in fact), the size of the square support window is constant, and each pixel in the window has a different adaptive support weight, which depends on color similarity and proximity degree with the central pixel, and follow the principles of Gestalt visual. The correspondence result is satisfactory for a local approach and can be comparable to global ones. However, the running time is too long, and the method can not be used in real-time applications. Some accelerated versions of the method have been proposed [8, 9], but the improvement effects are not obvious.

The pixel-based correspondence cost in above-cited ones depend on the color intensity or gray level values only, which make the correspondence result error-prone. Four reasons have been introduced in [10] and proposed to measure the pixel similarity using the truncated pixel gradient ("Gradient" for abbreviatory), the accuracy of the result disparity map is improved, but the improvement is rather insignificant, because the pixel color intensity was ignored entirely. Conversely, the method has better robustness to radiometric distortions. In 2011, guided filter aggregation approach [11, 12] ("Costfilter" for abbreviatory) was proposed, and the method is not only the best performing local stereo correspondence method, but also the best performing real-time method. The pixel similarity in "Costfilter" is the truncated absolute difference of intensities and gradient modulus in x direction, the stereo correspondence performance is rather good (ranks 19), but it is not robust to radiometric

distortion because the gradient modulus in y direction and gradient phase were neglected entirely.

In this paper, on the basis of analysis of "Costfilter" method and "Gradient" method, we propose a new similarity measurement combines the color intensity and the gradient value, namely combined similarity measurement, which is in fact the linear combination of both measurements. Jointly with the aggregation step of adaptive support weight using guided filter, disparity is calculated based on WTA principle and with post processing, the accuracy of the resulting disparity maps is improved, the robustness to radiometric distortion is enhanced, while the efficiency keeps constant. The new combined similarity measurement is described in Section 2. The adaptive support weight method based on guided filter is interpreted in Section 3. In Section 4, the stereo correspondence performance and the robustness to radiometric distortion of the new proposed combined similarity measurement are analyzed and compared with three well known similarity measurements, "Gradient" method, "Costfilter" method and color intensity-based method("Intensity" for abbreviatory). We conclude our paper in section 5.

#### II. COMBINED SIMILARITY MEASUREMENT

We measure the pixel-based similarity using combined similarity measurement, which is the linearity combination of color intensity and gradient value.

Color intensity of image, which directly reflects relative degree of brightness of the color of the pixels, is the key factor describing the human eyes' perception of color. There are some commonly-used similarity cost functions, such as summed absolute differences (SAD), summed squared differences (SSD), normalized cross correlation (NCC). It has been shown that SAD is the fastest one in computation and has some advantages over NCC and SSD [13], so we use SAD of the color intensity as the similarity measurement of intensity, which can be expressed as:

$$\mathbf{M}(\mathbf{p},\mathbf{d}) = \sum_{c \in \{r,g,b\}} \left| f_l^c(p) - f_r^c(p-d) \right|$$
(1)

Where  $f_l^c(p)$  is the intensity of the color band c(r,g,b) of the pixel p in the left view,  $f_r^c(p-d)$  is the same of the pixel p-d in the right view.

The gradient of an image corresponds to the direction along which the grey value of the image changes most remarkably. In other words, the change of image intensity can be described by image gradient. As edge detection is seeking the local maximum and the direction of image gradient, gradient value can be used to reflect image edge or skeleton to some extent. This can be observed from Fig.1, the gradient modulus map and gradient phase map of image "cones" are shown. Gradient has better robustness against image noise, differences in sampling and local brightness changes between image views [10] (three important sources of error in methods relying on color intensity similarity of corresponding pixels).



Left view of "Cones"

Gradient modulus map



Figure 1. Gradient modulus and gradient phase map of a color image

Gradient value is composed of gradient modulus *m* and gradient phase *p*. Suppose f(x,y) represents a gray image, the gradient of f(x,y) is defined as a vector  $\nabla \mathbf{f} = \begin{bmatrix} Gx \\ Gy \end{bmatrix}$ , Gx and Gy is the differences in

*x*(horizontal) and *y*(vertical) direction. The modulus *m* of  $\nabla \mathbf{f}$  is  $m = \sqrt{Gx^2 + Gy^2}$ . For simplicity, we use an approximate form  $m = |\mathbf{Gx}| + |\mathbf{Gy}|$  instead to calculate *m*. The phase of  $\nabla \mathbf{f}$  is  $\phi = \operatorname{arctg}(\mathbf{Gy} / \mathbf{Gx})$ . The rate of change (modulus *m*) and the direction of the greatest rate of change (phase  $\phi$ ) provide different information about neighborhood of a pixel and have different invariance

properties with respect to radiometric distortion. Neither the modulus nor the phase is affected by additive (offset) changes in the input images. Multiplitive variations (gain) affect the modulus but not the phase, and the parameter  $\alpha$  controls the sensitivity of the algorithm to radiometric differences between images. So phase and modulus are separating and the weights of both are not equal, as expressed in (2):

$$G(p,d) = \sum_{c \in \{r,g,b\}} (\alpha | m_l^c(p) - m_r^c(p-d) | + f(|\phi_l^c(p) - \phi_r^c(p-d)|))$$
(2)

Where,  $m^c$  and  $\phi^c$  are the modulus and phase of the gradient operator applied to the color band c(r,g,b) respectively,  $\alpha$  is the weight of modulus. Through our practical experiments, the best value for  $\alpha$  is 0.12 (the

same to [10]), and *f* is a function to limit the range of difference of phases of the two corresponding pixels to  $[0, \pi]$ .

$$f(x) = \begin{cases} x, & if (0 \le x \le \pi) \\ 2\pi - x, & if (\pi < x < 2\pi) \end{cases}$$
(3)

The combined similarity measurement C(p,d) is expressed as:

 $C(p,d) = \beta \min\{M(p,d), T_c\} + (1-\beta)\min\{G(p,d), T_g\}$ (4)

Where C(p,d) is the correspondence cost of pixel pwhen disparity is d, M(p,d) and G(p,d) are the color intensity and gradient value similarity measurement of pixel p, Tc and Tg are the truncation value of color intensity and gradient value respectively, which can limit the influence of outliers.  $\beta$  is used to balance the relative importance of the color intensity and gradient value in the combined similarity measurement, or the relative importance of the accuracy of stereo correspondence and robustness to radiometric distortion.

#### III. ADAPTIVE SUPPORT WEIGHT BASED ON GUIDED FILTER

With guided filter [14], the aggregated correspondence cost is expressed as:

$$C'(p,d) = \sum_{q} W_{p,q}(I)C(q,d)$$
(5)

Where q is a pixel in the support window of pixel p,  $W_{p,q}$  is the support weight of q with regard to p, the value depends on the guidance image I, which is the reference image. For simplicity, we use a grayscale guidance image I to interpret the support weight.

$$W_{p,q}(I) = \frac{1}{|\omega|^2} \sum_{k:(p,q)\in\omega_k} (1 + \frac{(I_p - \mu_k)(I_q - \mu_k)}{\sigma_k^2 + \varepsilon}) \quad (6)$$

Where  $\mu_k$  and  $\sigma_k^2$  are the mean and variance of *I* in a squared window  $\omega_k$  with dimensions  $\gamma \times \gamma$ , centered at pixel k.  $|\omega|$  is the number of pixels in the window  $\omega_k$ , and  $\varepsilon$  is a parameter to determine "flat patch" or "high variance". The patches with variance  $\sigma^2$  much smaller than  $\varepsilon$  are smoothed, where those with variance much larger than  $\varepsilon$  are preserved. The support weight of (6) can be simply transited to RGB images as (7):

$$W_{p,q}(I) = \frac{1}{|\omega|^2} \sum_{k:(p,q)\in\omega_k} (1 + (I_p - \mu_k) (\sum_k + \varepsilon U)^{-1} (I_q - \mu_k)^T)$$
(7)

 $I_p$ ,  $I_q$  and  $\mu_k$  are 1×3 vectors,  $\sum_k$  is the 3×3

covariance matrix, and U is a  $3 \times 3$  identity matrix.

## IV. EXPERIMENTS

We conduct two experiments. One to select the best value of  $\beta$  and evaluate the accuracy of our combined similarity measurement, and another to compare robustness to radiometric distortion of our method with

other local methods using different similarity measurements. The experimental images are 4 stereo pairs ("Tsukuba", "Venus", "Teddy" and "Cones") and other 6 test images, available at http://www.middlebury.edu/stereo/. The experiments are carried out on the platform of Windows XP on desktop PC 2GHz processor and 2GB memory.

To obtain the disparity map, we compute the disparity by selecting the minimal (winning) aggregated correspondence value for each pixel using WTA (Winner-Take-All) manner as:

$$d_p = \arg\min C'(p,d) \quad (d \in D) \tag{8}$$

Where D is the possible disparity set. In order to make the disparity of the left view and right view consistent, we compute the disparity map d' of the right image I' in the similar method to the left image. After left-right cross consistency check, we mark a pixel in the left disparity map d as invalid if the disparity of its corresponding pixel in d' changes. The invalid disparities are then appointed to the smallest valid disparity value of the nearest pixel which locates on the same scan line. The simple replacing will produce streak artifacts in the disparity map. To erase the noise, we carry out the bilateral filter to the replaced pixels. We do not refine the disparity map, so the disparity is integer, because: other local methods compared with ours have not sub-pixel refinement too, and the goal of this paper is to highlight the effect of the combined similarity measurement.

## A. Accuracy Comparison with Other Similarity Measurements

We evaluate the accuracy performance of our combined similarity measurement using the 4 stereo pairs, and the error threshold is 1 pixel. The parameters in our algorithm are same for the four pairs:

$$\{\alpha, Tc, Tg, \varepsilon, \gamma\} = \{0.12, 0.031, 0.017, 0.0001, 9\}$$

 $\beta \in [0,1]$ . Especially, when  $\beta = 0$ , our similarity measurement degenerates to the gradient measurement, and when  $\beta = 1$ , is the frequently-used intensity similarity measurement. We submit the disparity map to the authoritative testing website Middlebury, the feedback stereo evaluation results are shown in Tab. 1. The numbers in the table represent the percentage of bad pixels for all pixels ("all"),for pixels in non-occluded regions ("nonc"),and for pixels in regions near depth discontinuities ("dis"), and the average of the 12 percentages ("Ave").We can see, when  $\beta = 0.1$ , all of the percentages are lowest among all values of  $\beta$ . So the best value of  $\beta$  is 0.1.we use it in the second experiment.

## TABLE I.

Three percentages of BAD pixels when  $\,eta\,$  varies

β	Tsukuba			Venus			Teddy				Ave		
	nonc	all	dis	nonc	all	dis	nonc	all	dis	nonc	all	dis	
0	1.89	2.22	8.27	0.36	0.54	3.75	7.31	12.9	17.4	3.80	9.38	10.7	6.54
0.1	1.82	2.18	8.20	0.27	0.46	2.69	6.78	12.3	16.3	2.77	8.17	7.85	5.82
0.2	1.97	2.33	8.40	0.30	0.50	2.73	8.47	13.7	17.5	2.59	8.04	7.37	6.16
0.3	2.17	2.54	8.51	0.35	0.57	3.10	9.24	14.2	17.8	2.79	8.16	7.83	6.44
0.4	2.21	2.57	8.70	0.41	0.66	3.66	9.58	14.4	18.3	3.56	8.93	8.88	6.83
0.5	2.23	2.60	8.62	0.46	0.72	4.12	9.82	14.6	18.7	4.33	9.63	9.83	7.14
0.6	2.30	2.68	8.66	0.53	0.80	4.74	10.0	14.8	18.9	5.51	10.8	11.2	7.58
0.7	2.38	2.76	8.85	0.64	0.91	5.50	10.4	15.2	19.5	7.80	12.9	13.4	8.35
0.8	2.43	2.81	8.92	0.75	1.03	5.90	10.8	15.6	20.0	10.3	15.1	16.1	9.14
0.9	2.51	2.90	9.00	0.88	1.17	6.34	11.3	16.0	20.9	12.1	16.8	18.3	9.86
1.0	2.57	2.95	8.99	1.26	1.56	6.81	11.7	16.5	21.4	13.4	18.0	20.30	10.4

Tab.2 lists the website feedback stereo evaluation results of ours and other local methods. Our method produces excellent results (Fig.3.), ranks 36<sup>th</sup> out of 135 methods at the time of submission. The result of method HEFB is better than ours, but it relies on special hardware and relevant software, and ours can be implemented on general platform. Especially, the accuracy of our method

is higher than "Gradient" method (ranks 63), and the time complexity is slower than it, because we use guided filter instead of bilateral filter as the adaptive support weight. When compared with "Costfilter" method, the accuracy of ours is a little slower than it (ranks 19), but the runtime remains almost unchanged.



(a) Left image

Figure 2. Dense disparity maps for the four images



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Algorithm	Rank	Tsukuba			Venus			Teddy			Cones			Ave
		nonc	all	dis	nonc	all	dis	nonc	all	dis	nonc	all	dis	
AdapWeig[7]	67	1.38	1.85	6.90	0.71	1.19	6.13	7.88	13.3	18.6	3.97	9.79	8.26	6.67
SegSup[6]	53	1.25	1.62	6.68	0.25	0.64	2.59	8.43	14.2	18.2	3.77	9.87	9.77	6.44
AdRanDis[16]	37	1.19	1.42	6.15	0.23	0.34	2.50	7.80	13.6	17.3	3.62	9.33	9.72	6.10
Costfilter[11,12]	19	1.51	1.85	7.61	0.20	0.39	2.42	6.16	11.8	16.0	2.71	8.24	7.66	5.55
Ours	36	1.82	2.18	8.20	0.27	0.46	2.69	6.78	12.3	16.3	2.77	8.17	7.85	5.82
GradAdapWg[10]	63	2.26	2.63	8.99	0.99	1.39	4.92	8.00	13.1	18.6	2.61	7.67	7.43	6.55
FBS[17]	74	2.38	2.80	10.4	0.34	0.92	4.55	9.83	15.3	20.3	3.10	9.31	8.59	7.31
DCB[15]	111	5.90	7.26	21.0	1.35	1.91	11.2	10.5	17.2	22.2	5.34	11.9	14.9	10.9
VSW[18]	58	1.62	1.88	6.98	0.47	0.81	3.40	8.67	13.3	18.0	3.37	8.85	8.12	6.29
HEBF[19]	13	1.10	1.38	5.74	0.22	0.33	2.41	6.54	11.8	15.2	2.78	9.28	8.10	5.41

TABLE II. PERFORMANCE COMPARISON OF SOME LOCAL METHODS

# B. Invariance to Radiometric Distortion

There are two sources of invariance to radiometric distortion in local methods. The first source is in the similarity measurement, and another is the aggregation method. Because the invariance due to the aggregation method is much less important than the invariance caused by the similarity measurement, we consider the invariance caused by the similarity measurement only. The radiometric robustness of the proposed gradient-based method("our"), the method("Gradient"),the intensity-based method("Intensity") and the cost filter method("Costfilter") were researched using 6 datasets and the ground truth disparities (Fig.3) provided by Hirschmüller and Scharstein[20]. Each dataset was taken under 3 different exposures and 3 different light source configurations, so there were 9 different images from each viewpoint with significant different radiometric characteristics. Fig.4 shows both exposure and lighting variations of the left image of the "Art" dataset. To highlight our combined similarity measurement, all of the 4 compared methods use the guided filter as the adaptive support weight. The parameters were the same as those in the first experiment, to evaluate whether the proposed method worked well with more complicated and challenging images (have severe radiometric differences) beside the 4 well-known image pairs (error threshold is 1 pixel also).

The test results are shown in Fig.5. The number in each one of the plots represents the average number of error pixels in unoccluded regions under an established exposure condition (Fig. 5(a)) or illumination condition (fig.5 (b)).The coordinates in the horizontal axis, for instance, in Fig. 5(b), 1/3 stands for a kind of test environment when the illumination configuration for the left image is the first one out of 3 and the illumination configuration for the right image is the third one out of 3, the exposure configuration keeps the same for both images. The number is the average of the test results under 3 different exposure conditions for 6 image datasets (18 different images in sum).



Figure 3. Left image(up) and ground truth disparity(down)of "Art", "Books", "Dolls", "Laundry", "Moebius" and "Reindeer"



Figure 4. Left image of "Art" under 3 different exposure and 3 different light conditions

Fig.5 (a) shows the test results for 9 different exposure combinations. All of the 4 methods have better performance when the two images are under the same exposure configurations than when they are under different exposure configurations. "Intensity" method is the worst one out of 4 methods, because pixel intensity is hypersensitive to radiometric distortion. Gradient-based similarity measurement method is much more robust to exposure differences than other 3 methods. When two images are under the same configuration, our algorithm produces fewer errors than "Gradient" method, a bit more than "Costfilter" method. When two images are under different configuration, ours possesses the same error rate as the "Gradient" method, and fewer error rates than "Costfilter" method, especially under 1/3 and 3/1 configurations.

The test results for 9 different lighting setting combinations are shown in Fig.5 (b). Our method is also much more robust to lighting differences than "Intensity" in every lighting condition. As mentioned before, phase is insensitive to offset and gain, and modulus is insensitive to offset and not to gain, different lighting generates complex radiometric differences (includes offset and gain), thus the erroneous pixels in our method and "Gradient" method (phase is considered in both methods) are fewer than in Fig.5 (a) when the lighting setting are different. When our method is compared with "Gradient", "Costfilter" methods, the same result is obtained as in Fig.5 (a).



Figure 5. Correspondence 3×3 left/right image combinations that differ in exposure (a) and lighting conditions (b)

## V. CONCLUSIONS

In this study, we present a new combined similarity measurement for stereo correspondence that is the linear combination of color intensity and gradient value, aggregate the correspondence cost using the fast and edge-preserving guided filter, compute the disparity using WTA principle, left-right cross consistency check and post processing. Experimental results show that the proposed method has three advantages: First, the accuracy of ours is much higher than color intensity based methods ("Intensity") or gradient value based methods ("Gradient"), is a bit lower than "Costfilter" method. Second, the proposed method uses the guided filter as the adaptive support weight, which has the edge-preserving property as the bilateral filter, but is faster than it. The time complexity is the same as "Costfilter", and is faster than "Gradient" method or "Intensity" method. Third, our algorithm has better robustness to radiometric distortions.

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