BMPRE: An Error Measure for Evaluating Disparity Maps

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Abstract— **The percentage of Bad Matched Pixels (BMP) is widely used for evaluating disparity maps. It counts the number of differences between estimated disparity values and ground-truth values that exceed a threshold. A small error is counted in the same way that a large one by computing this measure. Moreover, the BMP ignores the inverse relation between depth and disparity. Although, the percentages of BMP are equal, those disparity maps may produce different 3D reconstructions. The Mean Relative Error (MRE) is calculated as an average of ratios of error magnitudes against true disparity values. It considers the inverse relation between depth and disparity. However, using the MRE, every deviation from ground-truth is considered as an error, regardless the application domain for which the disparity map was estimated. In this paper, an error measure devised for evaluating disparity maps is introduced. The introduced measure combines the advantages of the BMP and the MRE. It allows a user to declare what an estimation error is – using a threshold – and considers both, the error magnitude and the inverse relation between depth and disparity. The proposed measures is termed BMPRE and it determines estimation errors in a widely adopted way by the community and, at the same time, offers not only information, but flexibility, about the impact of those errors in the context of a 3D recovery process. Comparative analysis and experimental evaluation show that the BMPRE allows a fair evaluation of disparity maps, which impacts on a quantitative comparison of stereo correspondence algorithms.**

Stereo vision; quantitative evaluation; error measure; disparity maps.

I. Introduction

Stereo correspondence is a geometric relation between the projections of a point in 3D space into a stereo image pair. Stereo correspondences arise in a natural way when a 3D scene is captured from slightly different viewpoints. However, for a captured point in one image, it is not known beforehand where its corresponding lies, neither if it really exits. This lack of information is known as the stereo correspondence problem. This problem can be addressed by a stereo correspondence algorithm, which takes as input a stereo image pair, and produces as output an estimated disparity map. Disparity is the shift between corresponding points. If the disparity of a point is known, its depth can be recovered by a triangulation process. A stereo camera system is sketched in Fig. 1. C_l and C_r are the optical centres, and the distance between them is termed the baseline – B. The distance from the optical centres to the left – π_l – and the right – π_r – image planes is the focal length –f. The point P in 3D space is at a distance Z from the stereo camera system. The projections of the point P, into the π_l and the π_r image planes, are the corresponding points p_l and p_r, respectively.

A quantitative comparison of Stereo Correspondence Algorithms (SCAs) is required in order to measure the progress in the field [3, 12]. A comparison of SCAs can be addressed by a quantitative evaluation of disparity maps [14]. Most of approaches available in the literature for evaluating disparity maps are based on ground-truth data [13]. In these approaches, estimated disparity maps are compared against disparity ground-truth data using an error measure. Computed error scores are indicators of SCAs performance [2]. Among the different error measures available in the literature, the Bad Matched Pixels (BMP) percentage is widely used [12]. It counts the quantity of disparity estimation errors exceeding a threshold fixed by a user. A value of 1 pixel is commonly used as a threshold. In this case, a corresponding point assignation laying at more than one pixel of distance from the true correspondence is considered as an estimation error. This error definition can be seen as the main advantage of the BMP measure. In fact, this error definition may be useful in applications domains on which estimated disparity maps are used for generating novel rendered views. Those new views are observed by humans, whom may be incapable of detecting most of generated artefacts by disparity estimation errors. Although the estimated depth of a point may be closer or farther to its true 3D world position according to the disparity estimation error, the estimation error magnitude does not cause any difference in the obtained score by computing the percentage of BMP. Moreover, an estimation error of a same magnitude may have different impact on a 3D recovery process due to the inverse relation between depth and disparity. However, the BMP does not consider this relation.

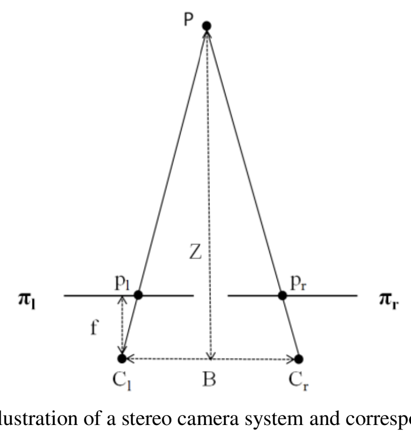

Figure 1. Illustration of a stereo camera system and corresponding points

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On the other hand, the Mean Relative Error (MRE) is an unbounded measure based on the ratio between the estimation error magnitude and the true disparity value [9]. Thus, an estimation error is weighted according to the real true disparity value. In this way, an estimation error, of a same magnitude, implies a larger error for a smaller true disparity – a far point –, and a smaller error for a larger true disparity – a close point. Obtained scores using the MRE are consistent with the inherent error of a stereo vision system [5]. However, the MRE is sensitive to extreme values and missing estimations. Moreover, it does not allow ant adjustment according to a specific application domain.

For the sake of completeness, disparity estimation errors are illustrated in Fig. 2. The left view of the Tsukuba stereo image pair and its associated ground-truth disparity map are shown in Fig. 2(a), and Fig. 2(b), respectively [12, 14]. Fig. 2(c) and Fig. 2(d) show erroneously estimated disparity maps. The map illustrated in Fig. 2(c) contains errors at the library – in the background –, whilst the map illustrated in Fig. 2(d) contains errors at the lamp – in the foreground. Fig. 2(e) and Fig. 2(f) show corrupted disparity maps by adding salt and pepper noise. The disparity maps illustrated in Fig. 2(e) and Fig. 2(f) contain a similar quantity of errors of different magnitude. Table I contains the BMP percentage, the MRE score and the Peak Signal-to-Noise Ratio (PSNR) calculated using disparity maps in Fig. 2. It can be observed that disparity maps, with different levels of estimation errors, may obtain the same BMP percentage. Consequently, the BMP percentage may be not appropriate for evaluating the accuracy of an estimated disparity map. In contrast, the scores obtained by the MRE are in concordance with the scores obtained using the PSNR.

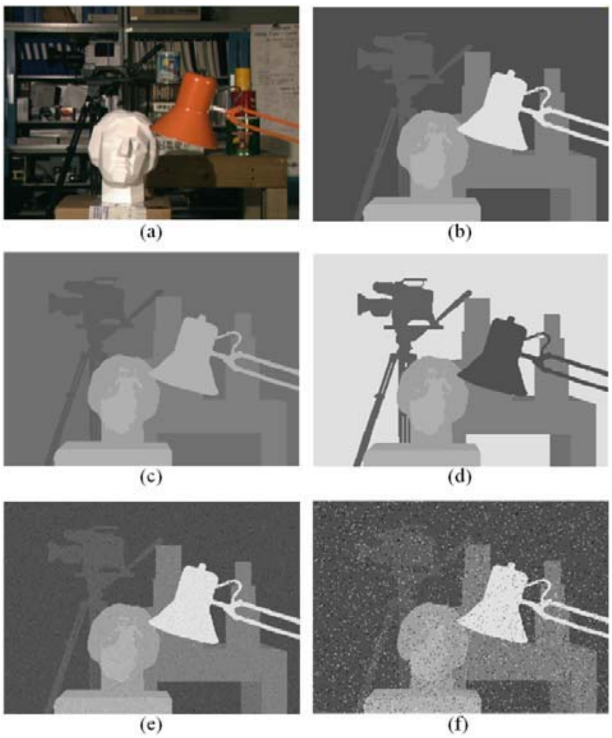

Figure 2. The Tsukuba stereo image: (a) the left view, (b) the ground-truth map, (c) and (d) erroneous disparity maps, (e) and (f) noised disparity maps

TABLE I. OBTAINED BMP PERCENTAGE, MRE AND PSNR USING FIG. 2(C), FIG. 2(D), FIG. 2(E), AND FIG. 2(F)

	BMP	MRE	PSNR
Fig. 2 (c)	64,30	0,245	18,90
Fig. 2 (d)	64,30	1,081	6,35
Fig. 2 (e)	4,99	0,016	30,52
Fig. 2 (f)	4,99	0,061	18,59

In this paper, an error measure for quantitatively evaluating disparity maps is presented. The proposed measure is termed BMPRE. It is based on the BMP and the MRE. The use of the proposed measure allows a proper and fair evaluation of disparity maps considering both: the quantity of disparity estimation errors and the impact of those errors according to the inverse relation between depth and disparity. Innovative evaluation results are obtained using the proposed measure. The paper is structured as follows. Related works are discussed in Section II. The proposed measure is introduced in Section III. Experimental evaluation is shown in Section IV. Finally, conclusions are stated in Section V.

II. RELATED WORK

An estimated disparity map is compared against a disparity ground-truth map using error measures such as the Mean Absolute Error (MAE), the Mean Square Error (MSE), and the Root Mean Square Error (RMSE), among others. However, the above measures do not properly distinguish between disparity maps with a lot of small errors and disparity maps with a few large errors [9].

The R-SSIM measure is an adaptation of the Multi-Scale Structural Similarity (MS-SSIM) [17]. It was proposed in [8] for comparing estimated disparity maps against disparity ground-truth data, under the assumption that the main components of the MS-SSIM – luminance, contrast and structure – find their counterpart in disparity maps –as depth, surface roughness and 3D structure. The R-SSIM is capable of handling missing data in both, the disparity map under evaluation and in disparity ground-truth data. Obtained results using the R-SSIM and the BMP are statistically correlated. The discussion of the analogy between components of MS-SSIM and the properties of a disparity map is not properly addressed. Consequently, the motivation for using the R-SSIM measure may turn weak [2].

The BMP is presented in [12] and is defined as follows:

$$\varepsilon(x,y) = \begin{cases} 1 \text{ if } |D_{true}(x,y) - D_{estimated}(x,y)| > \delta \\ 0 \text{ if } |D_{true}(x,y) - D_{estimated}(x,y)| \leq \delta \end{cases}, \quad (1)$$

$$BMP = \frac{100\%}{N} \sum_{(x,y)}^{N} \varepsilon(x,y), \quad (2)$$

where $D_{true}(x,y)$ is the disparity ground-truth value at (x,y) pixel position, $D_{estimated}$ is the estimated disparity value at (x,y) pixel position, N is the amount of compared pixels, and δ is an error threshold. It can be seen as a binary function. None of the above measures consider the inverse relation between depth and disparity.

The Sigma-Z-Error (SZE) measure is based on the absolute difference between the recovered depth by the ground-truth disparity and the recovered depth by the estimated disparity [2]. It inherently considers the estimation error magnitude and the inverse relation between depth and disparity. It is formulated as follows.

$$\mathrm{SZE} = \sum_{(x,y)}^{N} \left| \frac{f * B}{D_{\mathrm{true}}(x,y) + \mu} - \frac{f * B}{D_{\mathrm{estimated}}(x,y) + \mu} \right|, \quad (3)$$

where μ is a small constant to avoid data instability due to possible missing estimations. The SZE fulfils the properties of a metric. Nevertheless, it is unbounded. Moreover, although disparity ground-truth data generation requires of a complex setup, values of f and B may be not available. In this case, obtained error scores by the SZE measure are up to a scale factor. In fact, the SZE is suited to be used in robotic related domain applications, or, in general, to domain applications where the final observer or user of a 3D reconstruction is not a human.

The use of the MRE for evaluating disparity maps is proposed in [9]. This unbounded measure considers the inverse relation between depth and disparity, without requiring additional information about the stereo camera system. It is sensitive to missing data and extreme error values. It is formulated as follows.

$$\mathrm{MRE} = \frac{1}{N} \sum_{(x,y)}^{N} \frac{|D_{\mathrm{true}}(x,y) - D_{\mathrm{estimated}}(x,y)|}{D_{\mathrm{true}}(x,y)}. \quad (4)$$

The disparity gradient and the disparity acceleration indices are proposed in [21] for evaluating disparity maps in the absence of disparity ground-truth data. These indices aim to measure the smoothness of the estimated map considering disparity changes on neighbouring regions. The difference between a noisy value (i.e. an estimation error) and a disparity discontinuity is determined by a threshold. However, no information is provided about how the thresholds can be fixed. Moreover, proposed indices ignore the fact that an estimated map may vary smoothly, but being totally wrong. Consequently, these indices may be not suited for properly evaluating estimated disparity maps.

III. PROPOSED MEASURE

The BMPRE is devised by combining the advantage of the BMP – a clear and concise interpretation of a disparity estimation error –, and the advantages of the MRE – which considers both the error magnitude and the inverse relation between depth and disparity. It is defined based on the components formulated below.

Let Δ be the magnitude of an estimation error, computed as the absolute difference between the estimated disparity and the true disparity value.

$$\Delta(x,y) = |D_{\mathrm{true}}(x,y) - D_{\mathrm{estimated}}(x,y)|\,. \quad (5)$$

Let ρ be the ratio between Δ and the true disparity value – the relative error.

$$\rho(x,y) = \frac{\Delta(x,y)}{D_{\mathrm{true}}(x,y)}\,. \quad (6)$$

Let τ be a function for avoiding divisions by zero, defined as follows.

$$\tau(x,y) = \begin{cases} \rho(x,y) & \text{if } D_{\mathrm{true}}(x,y) > 0 \\ 0 & \text{otherwise} \end{cases}. \quad (7)$$

There is a special case related with true disparity values of zero. A disparity value of zero is associated, in theory, to a point laying at infinitum. In practice, a disparity value of zero may be assigned during the disparity estimation process to a point farther enough from the used stereo camera system, since such point exceeds the 3D recovering capabilities of the system (i.e. which is not capable of detect any shift between that point and its conjugate). Moreover, disparity values of zero may be used in disparity ground-truth maps for representing the absence of data. Thus, disparity values of zero require a special treatment during the evaluation process – which is handled in the proposed measure by the τ component.

The BMPRE measure is formulated as:

$$\mathrm{BMPRE} = \sum_{(x,y)}^{N} \begin{cases} \tau(x,y) & \text{if } \Delta(x,y) > \delta \\ 0 & \text{if } \Delta(x,y) \le \delta \end{cases}. \quad (8)$$

The relevance of considering both: the inverse relation between depth and disparity – the ρ component –, as well as the estimation error magnitude – the Δ component – is illustrated in Fig. 3. On one hand, Fig. 3(a) and Fig. 3(c) illustrate how estimation errors of a same magnitude – represented by points p'_r and q'_r respectively – may cause different triangulation errors –represented by points P' and Q', respectively. On the other hand, Fig. 3(b) and Fig. 3(d) illustrate how a larger estimation error magnitude increases triangulation errors.

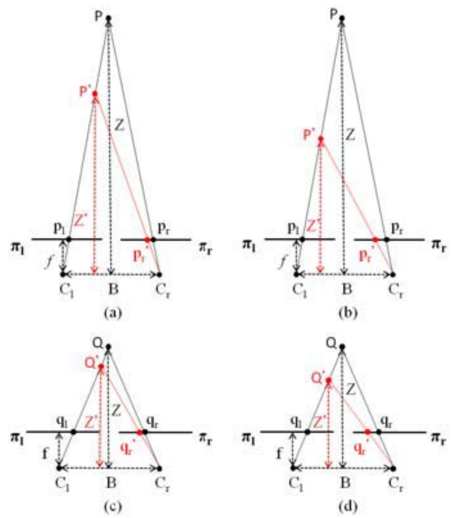

Figure 3. Relation bettwen disparity estimation errors and triangulation errors: (a) a small estimation error of a farther point, (b) a large estimation error of a farther point, (c) a small estimation error of a close point, and (d) a large estimation error of a close point

TABLE II. OBTAINED BMPRE SCORES AND PSNR OF RENDERED VIEWS USING MAPS ILLUSTRATED IN FIG. 2(C), FIG. 2(D), FIG. 2(E), AND FIG. 2(F)

	BMPRE	PSNR
Fig. 2 (c)	21.493,8	23,6
Fig. 2 (d)	94.882,1	19,8
Fig. 2 (e)	1.438,8	30,4
Fig. 2 (f)	30.904,8	28,4

Obtained scores by computing the BMPRE measure using disparity maps in Fig. 2(c), Fig. 2(d), Fig. 2(e), and Fig. 2(f) are shown in Table II. It can be observed that the BMPRE assigns different scores to each map according to its accuracy. Moreover, rendered views are generated based on disparity maps in above mentioned figures, and are evaluated using the PSNR. The highest error score obtained by the BMPRE is associated to the lowest PSNR value, and vice versa.

IV. EXPERIMENTAL EVALUATION

Experimental evaluation is conducted using elements and methods of the A^* Groups [3] and the Middlebury [12] methodologies. The imagery test-bed [13] is composed by the Tsukuba, the Venus, the Teddy, and the Cones stereo images, and the error criteria are: points near depth discontinuities – *disc* –, non-occluded points – *nonocc* –, and the whole image – *all*. A total of 112 SCAs from the Middlebury's on-line ranking [14] were selected to be compared using the proposed measure, under the A^* Groups [3] and the Middlebury's evaluation models. Table III shows obtained BMPRE scores and BMP percentages calculated with estimated disparity maps using the ADCensus [10], the AdaptingBP [6], and the OutlierConf [18] stereo correspondence algorithms, and the Teddy stereo image. Obtained results indicate that the ADCensus stereo correspondence algorithm produces the smallest percentage of errors, and, simultaneously, that those errors have the largest magnitude. Table IV contains obtained ranks using the BMPRE and he BMP measures, disclosing the 25% of compared algorithms. Different ranks are assigned by the Middlebury's evaluation model to compared stereo correspondence algorithms when the BMPRE measure is used. It can be observed that discrepancies among assigned ranks may arise due to the error measure used, such as is the case of the GC+SegmBorder [14], the DistinctSM [20], the OverSegmBP [22], and the RegionTreeDP [7] algorithms. This may indicate that, when the BMP is used, the evaluation model is failing in determining the top-performer algorithms, by producing false negatives or missing accurate algorithms. Table V contains selected ranks for illustrating that the evaluation model can be affected by selecting an error measure. Thus, it may be producing false positives or concealing large disparity errors, due to considering the percentage of BMP.

There may be not a single error measure better than others under all circumstances. In fact, the BMPRE and the BMP measures share common principles that can be exploited using the A^* Groups evaluation methodology, which conceives the comparison of SCAs as a multi-objective optimisation problem [16]. This methodology can be used to find groups of algorithms showing the best trade-off according to the selected error criteria and measures. Table VI shows obtained results for the evaluation in areas near depth discontinuities using the BMPRE and the BMP measures.

TABLE III. ERROR SCORES OF SELECTED CORRESPONDENCE ALGORITHMS FOR THE TEDDY STEREO IMAGE

		ADCensus	AdaptingBP	OutlierConf
BMPRE	*nonocc*	990,35	**444,91**	703,48
	all	1.856,23	**886,97**	1.520,10
	disc	644,83	**382,48**	574,55
BMP	*nonocc*	**4,10**	4,22	5,01
	all	**6,22**	7,06	9,12
	disc	**10,89**	11,79	12,84

TABLE IV. ASSIGNED RANKS TO THE TOP-PERFORMER ALGORITHMS ACCORDING TO THE BMPRE ERROR SCORES AND BMP PERCENTAGES

Algorithm	BMPRE Rank	BMP Rank	Algorithm	BMPRE Rank	BMP Rank
AdaptingBP	1	2	PlaneFitBP	16	20
OutlierConf	2	6	**DistinctSM**	**17**	**34**
ADCensus	3	1	GeoSup	18	21
CoopRegion	4	3	SymBP+occ	19	22
DoubleBP	5	4	ObjectStereo	20	10
WarpMat	6	9	**OverSegmBP**	**21**	**35**
GC+SegmBorder	**7**	**13**	Undr+OvrSeg	22	12
SurfaceStereo	8	8	IterAdaptWgt	23	27
SubPixDoubleBP	9	7	CostFilter	24	15
RDP	10	5	MVSegBP	25	33
FeatureGC	11	18	ASSM	26	23
InfoPermeable	12	14	**RegionTreeDP**	**27**	**41**
AdaptOvrSegBP	13	17	ConfSuppWin	28	25
GlobalGCP	14	16	C-SemiGlob	29	28
PatchMatch	15	11	MultiResGC	30	30

TABLE V. SELECTED ALGORITHMS RANKS AND AVERAGED RANKS USING THE BMPRE ERROR SCORES AND THE BMP PERCENTAGES

	BMPRE Rank	BMPRE Averaged Ranks	BMP Rank	BMP Averaged Ranks
P-LinearS	39	41,75	19	27,00
GeoDif	38	38,58	24	30,58
AdaptDispCalib	42	43,58	26	31,50

It can be observed that some algorithms show a good performance for a particular stereo image, according to both measures, such as the IterAdaptWgt algorithm [11] – in the Tsukuba image –, the FeatureGC algorithm [14] – in the Venus image –, the DoubleBP algorithm [19] – in the Teddy image –, and the ObjectStereo algorithm [1] – in the Cones image. Moreover, the evaluation also detects algorithms yielding conflictive results, such as the P-LinearS [4] and the PUTv3 [15], using the Teddy image. These algorithms show a small percentage of the BMP measure, but a large magnitude error of the BMPRE measure.

V. CONCLUSIONS

The contribution of this work consists in introducing the BMPRE measure. The introduced measure combines the strength of the BMP and the MRE measures, such as a concise definition of disparity estimation errors, and properly quantifying the error magnitude. In fact, the BMPRE considers, in a simple way, both the error magnitude and the inverse relation between depth and disparity. Moreover, the impacts of these considerations are not simple at all, since they allow a proper and deeper quantitative evaluation of disparity maps than the obtained using the BMP. In contrast to complex error measures that consider the inverse relation between depth and disparity, the BMPRE does not require additional information about the stereo camera system. Conducted experimental evaluation shows that the BMPRE is not only an alternative to use instead of the BMP, but also they can be used together, in order to provide effective data to evaluation models during an evaluation process, and supporting users' understanding about the performance of SCAs.

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TABLE VI. STEREO ALGORITHMS WITH THE BEST TRADE-OFF BETWEEN THE BMPRE ERROR MAGNITUDE AND THE BMP PERCENTAGE, USING DISC ERROR CRITERIA AND THE A* GROUPS EVALUATION MODEL.

Algorithms	BMPRE				BMP			
	Tsukuba	Venus	Teddy	Cones	Tsukuba	Venus	Teddy	Cones
DoubleBP	457,34	111,25	**360,47**	691,01	4,76	1,87	9,63	7,79
ADCensus	516,73	72,20	644,83	705,15	5,73	1,15	10,89	6,95
AdaptingBP	497,37	107,62	382,48	726,89	5,79	1,44	11,79	7,32
OutlierConf	437,99	130,25	574,55	632,00	4,74	2,40	12,84	6,99
CoopRegion	432,35	97,95	503,00	845,00	4,61	1,54	12,95	8,01
SubPixDoubleBP	499,91	113,24	371,21	703,90	5,98	1,74	10,01	7,91
RDP	420,83	122,78	792,50	725,38	5,00	1,89	12,57	7,38
PlaneFitBP	468,69	88,29	497,92	1.014,67	5,26	1,71	14,71	10,60
PatchMatch	750,09	127,19	483,78	649,64	9,31	2,62	9,62	7,11
ObjectStereo	603,04	392,01	491,01	538,04	6,36	4,61	11,18	**6,36**
AdaptOvrSegBP	484,88	71,75	764,87	937,67	5,64	1,47	16,42	8,84
Undr+OvrSeg	621,79	73,91	559,38	730,83	7,22	1,34	16,36	7,90
GC+SegmBorder	647,77	147,55	388,26	**435,66**	7,86	2,44	10,94	8,66
SurfaceStereo	545,19	195,99	392,06	757,55	6,78	2,61	**8,65**	8,26
MVSegBP	477,60	78,15	560,28	1.332,11	5,57	2,02	14,78	14,53
InfoPermeable	551,39	200,86	768,75	616,90	5,64	4,15	14,47	7,69
IterAdaptWgt	**375,31**	252,41	867,31	736,93	**4,59**	4,53	17,33	8,49
FeatureGC	550,22	**68,23**	707,87	1.031,78	5,82	**1,11**	18,46	11,15
LocallyConsist	474,12	92,37	1.628,21	1.125,40	5,67	1,63	16,95	9,72
ASSM	508,21	374,89	929,13	616,63	6,44	5,61	16,45	7,19
P-LinearS	497,54	352,56	923,35	846,00	5,92	5,71	15,88	6,71
PUTv3	1.157,32	348,69	1.391,17	803,46	9,42	5,72	18,29	6,56