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Abstract - *This paper presents an ameliorated version of the Zitnick and Kanade stereo algorithm. The novelties in our algorithm are the use of a balanced correlation window, the use of a new factor in the calculation of initial matching values which expresses the possibility of matching between two pixels and a new iterative function for the refinement of the initial matching values. Experimental results are evaluated on synthetic and real images and a comparison of our results to those of many state-of-the-art methods, using the ground truth data supplied by the University of Tsukuba, is presented.*

Keywords: Stereo matching, occlusion detection, fuzzy matching possibilities, balanced window

1 Introduction

Stereo matching is one of the traditional problems of stereo vision. It aims to rebuild 3D scenes from two or several images taken from slightly different points of view. Stereo vision techniques can produce dense disparity maps using matching techniques. Matching techniques use neighbourhood of the pixels (local support area) to compute a similarity value between pixels in the reference image and pixels in the target image. The choice of the support window size is critical to produce a dense disparity map with a minimum of matching errors rate. The basic assumption in stereo matching states that, under certain conditions, there exists a great similarity between the values of the pixels corresponding to the same physical parts of the observed scene (the support window). Those conditions consist of the closeness between the points of view and the stability of the lighting conditions. An initial matching cost is used to measure the similarity between the intensity of the supports windows of the two pixels tested for the correspondence. The choice of the correlation criterion influences the quality of the disparity map [9]. A good correlation criterion makes it possible to clearly discriminate good pairing among all the candidate pixels and must be robust to various forms of noise. In [1], Aschwanden and Guggenbühl made a comparative study for several correlation criteria. Experimental results of this study have shown that the best criteria, which are robust to conditions of view points, are ZSSD, ZNSSD and ZNCC. Another study in [6] confirmed these results and also showed that the traditional Euclidean distance criterion SSD remains very powerful under certain constraints of view points. Recent surveys in [11] for evaluations of cost functions shows that the performance of a matching cost can depend also on the algorithm that uses the cost. Classical correlation based techniques suffer from weakness problems near image edges and discontinuities. A small size of the local support area reduces this problem but increases the influence of noise, thing that decreases the number of successful matching. For those reasons, disparity maps, generated based only on the lightening similarity, show a relatively high error rate. To mitigate these problems, some works used the continuity assumption of the disparity function in a local area [15, 18, 25]. Other works used an adaptive size of the local support area to reduce matching errors near edges and discontinuities [13, 14, 2].Another challenge for stereo vision is occlusion. Occlusion detection is important in vision and robotic applications.

In this paper, an ameliorated version of the Zitnick and Kanade algorithm is presented. In paragraph 2 the original algorithm is briefly presented. In paragraph 3, we present our ameliorated version of the algorithm. In paragraph 4, experimental results are given to evaluate the performance of our algorithm.

2 Zitnick and Kanade algorithm

In [25], Zitnick and Kanade were based on the two assumptions for a stereo vision algorithm, proposed in [15, 16] by Marr and Poggio, to propose a cooperative stereo algorithm with explicit occlusion detection. The first assumption is the uniqueness assumption. It states that at most a single unique match exist for each pixel. The second assumption states that disparity is generally continuous, i.e., smooth within a local neighbourhood. Zitnick and Kanade have proposed a 3D disparity space to utilize these two assumptions. Assuming that the images have been rectified to have disparities only along the Y-coordinate axis, the

dimensions, they used, are line r, column c and disparity d. Each element (r,c,d) of the 3D disparity space projects to the pixel (r,c) in the reference image and the pixel (r,c+d) in the right image. Within the element (r,c,d), the estimated value of matching between the pixels (r,c) and (r,c+d) respectively of the reference image and the right image is held. To obtain smooth and dense disparity map, they proposed an iterative update function to refine the initial matching values $L_0(r,c,d)$ calculated using a function of image intensities, such as normalized correlation or squared differences. They denoted $L_n(r,c,d)$ the value assigned to element (r,c,d) at iteration n. They use the continuity assumption to iteratively average match values using fixed box shaped 3D local support area with fixed width height and depth. They defined $S_n(r,c,d)$ as the sum of all matching values within the box centred in (r,c,d). Initial values $L_0(r,c,d)$ are updated using the iterative function given in (2).

$$S_n(r,c,d) = \sum_{(r',c',d') \in \text{Local support box}} L_n(r+r',c+c',d+d') \quad (1)$$

$$L_{n+1}(r,c,d) = L_0(r,c,d) \left(\frac{S_n(r,c,d)}{\sum_{\text{inhibition}} S_n(r'',c'',d'')} \right)^{\alpha} \quad (2)$$

The inhibition area is denoted by the set of elements which overlap element (r,c,d) when projected onto an image. That is, each element in the inhibition area projects to pixel (r,c) in the left image or to pixel (r,c+d) in the right image.

Zitnick and Kanade algorithm can be summarized as follows:

1. Prepare a 3D array, (r,c,d): (r,c) for each pixel in the reference image and d for the range of disparity.
2. Set initial match values L_0 using a function of image intensities, such as normalized correlation or squared differences.
3. Iteratively update match values L_n using (2), until the match values converge.
4. For each pixel (r,c), find the element (r,c,d) with the maximum match value.
5. If the maximum match value is higher than a threshold, output the disparity d, otherwise classify it as occluded.

The implementation of this algorithm gave satisfactory results but not as good as described in [25]. In fact, it generates matching errors near discontinuities and image edges. In this paper, we propose improvements to mitigate these problems.

3   Our stereo matching algorithm

In the Zitnick and Kanade algorithm, the function used to determine the corresponding pixels uses only the similarity between the supports area of the pixels which increases the error rate near discontinuities. For this reason, we present in this section a fuzzy sets based factor which express the similarity between the grey scales levels of the pixels tested for the correspondence. Two pixels having the same grey level are possible corresponding pixels. That is why we have called this factor the possibility factor. In the section 3.1 we present the balanced support window we have used. Section 3.2 presents the function we used to calculate the initial matching costs. In the section 3.3, the fuzzy possibility factor used to reinforce the initial matching costs is explained. Section 3.4 presents the iterative function we have used to refine the matching costs. Section 3.5 presents the occlusion detection mechanism.

3.1   Balanced support window

The choice of the support window is a crux of correspondence search. The window should be large enough to cover sufficient area in textureless regions, while small enough to avoid crossing depth discontinuities. For acquiring more exact results not only in homogeneous regions but also at depth discontinuities, many methods have been proposed [3, 22, 23, 24, 13, 8, 10]. Several works have used an adaptive support-weight approach [24, 22, 8 , 4]. In our implementation, we use a distance based weight approach. In this method adaptive support weights are assigned to pixels in a 2w sized support window based on the spatial proximity to the center of the support window. We used the Euclidean distance. The weighting of the point (r+i,c+j) is given by the equation 3:

$$w_{ij} = e^{-\frac{\sqrt{(i^2+j^2)}}{\mu}} \quad (3)$$

With μ is an empirical constant. The support window can be seen like a mask with fuzzy contours, i.e. its edge is progressive (the coefficients can take all real values between 0 and 1, instead of being a binary value: 0 or 1 in the case of a traditional mask).

3.2   Initial matching costs

The function we have used to calculate the similarity costs between pixels is given in equation (4).

$$C_0(r,c,d) = \frac{1}{4w^2 I_{max}} \sum_{i=-w}^{w} \sum_{j=-w}^{w} w_{ij} \left| I(r+i,c+j) - I(r+i,c+j+d) \right| \quad (4)$$

The values of $C_0(r,c,d)$ are between 0 and 1. A value of $C_0(r,c,d)$ closest to 0 indicates a high correspondence probability between the left image pixel (r,c) and the right image pixel (r,c+d). Let $L_0(r,c,d)$ be the value defined by the expression in (5).

$$L_0(r,c,d) = 1 - C_0(r,c,d) =$$

$$1 - \frac{1}{4w^2 I_{max}} \sum_{i=-w}^{w} \sum_{j=-w}^{w} e^{-\frac{\sqrt{(i^2+j^2)}}{\mu}} |I(r+i,c+j) - I(r+i,c+j+d)| \qquad (5)$$

Corresponding pixels will have values of L_0 close to 1. However, values of L_0 close to 1 do not necessarily indicate a correspondence between the pixels. In fact, this correlation criterion takes into account only the difference of intensities between the neighbourhoods of the two pixels. This criterion is unreliable since it uses a static representation of the matching error. In the next paragraph, we introduce a fuzzy factor which informs about the possibility of correspondence between two pixels.

3.3 Fuzzy matching possibility factor

In the thesis [5], based on the assumption that projections of the same point of 3D-space have comparable light intensities, Comby have proposed a grey scale classification of the pixels. He has defined two dual classes of pixels; white pixels and black pixels (see Figure 1). Each pixel is represented by its degree of membership to the white class μ_{white} and its degree of membership to the black class μ_{white}.
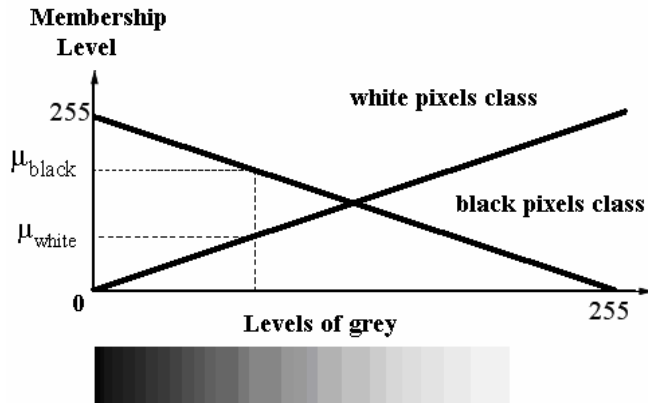

Figure 1: Grey scale classification of pixels; white pixels and black pixels [5].

In our application, the two images are taken simultaneously from two close points of view. Thus, the grey level conservation assumption is rigid. We can estimate that two corresponding pixels belong to the same grey class.

In the correlation criterion described previously, only the difference of intensities between the pixels neighbourhoods is taken into account to determine corresponding ones. This criterion is unreliable since it uses a static representation of the matching error.

In fact, more the support area is wide, more precise the statistics will be, but less reliable it will be. The lack of reliability is related to the ambiguous areas such as image edges and occluded zones. For this reason, we proposed to introduce a fuzzy sets based factor into the correlation criterion. This factor expresses the degree of membership of the two pixels to a same grey class. To not disadvantage the pairing of pixels of average grey level, we refined the classification proposed by in [5] into three grey classes; black, white and average (see Figure 2). Membership functions of grey classes are Gaussian centred in 0, 127.5 and 255 and with a standard deviation of 76.5. Membership functions we have used for the three grey classes are given in (6), (7) and (8).

$$\mu_{black}(x) = e^{-\left(\frac{x}{76.5}\right)^2} \qquad (6)$$

$$\mu_{average}(x) = e^{-\left(\frac{x-127.5}{76.5}\right)^2} \qquad (7)$$

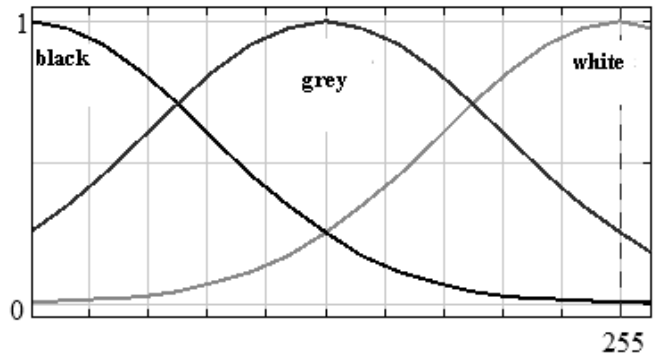$$\mu_{white}(x) = e^{-\left(\frac{x-255}{76.5}\right)^2} \qquad (8)$$

Figure 2: three-level classification of pixels: black, grey and white

The level grey scale conservation assumption for two pixels m1 and m2 belonging respectively to the left image and the right image can be summarized by the three following fuzzy rules:

If (m1 is black) and (m2 is black) then ((m1 and m2 are correspondent pixels) is possible)

If (m1 is average) and (m2 is average) then ((m1 and m2 are correspondent pixels) is possible)

If (m1 is white) and (m2 is white) then ((m1 and m2 are correspondent pixels) is possible)

Let $\mu_{black}(m)$, $\mu_{average}(m)$ and $\mu_{white}(m)$ be the degrees of membership of the pixel m respectively to the black pixels class, the average pixels class and the white pixels class. We denote by $\pi(m_1,m_2)$ the degree of possibility to have m_1 and m_2 as corresponding pixels. The three rules given previously are interpreted respectively by equations (9), (10) and (11).

$$\pi(m_1, m_2) = \min(\mu_{black}(m1), \mu_{black}(m2)) \quad (9)$$

$$\pi(m_1, m_2) = \min(\mu_{average}(m1), \mu_{average}(m2)) \quad (10)$$

$$\pi(m_1, m_2) = \min(\mu_{white}(m1), \mu_{white}(m2)) \quad (11)$$

The aggregation of the three rules gives the final expression of the matching possibility degree (12). $\pi(m_1,m_2)$ lies between 0 and 1. More the degree of possibility is close to 1 more it is «possible» that m1 and m2 be corresponding pixels.

Thereafter, we will use the notation: $\pi(r,c,d)=\pi(m_1,m_2)$ with $m_1=(r,c)$ and $m_2=(r,c+d)$.

$$\pi(m_1, m_2) = \max[\ \min(\mu_{black}(m1), \quad \mu_{black}(m2)),$$
$$\min(\mu_{average}(m1), \mu_{average}(m2)), \quad (12)$$
$$\min(\mu_{white}(m1), \quad \mu_{white}(m2))\ ]$$

3.4 Our iterative function

To refine the initial matching values we used a new iterative function simpler than the one used by Zitnick and Kanade. We have used a box centred in (r,c,d), whose dimensions are $(R_{local}, C_{local}, D_{local})$, as local support. Assuming that the disparity is continue in a local support zone, we iteratively average the initial matching values in this box using the function described in (13).

$$M_n(r,c,d) =$$
$$\frac{1}{8R_{local}C_{local}D_{local}} \sum_{r'=-R_{local}}^{R_{local}} \sum_{c'=-C_{local}}^{C_{local}} \sum_{d'=-D_{local}}^{D_{local}} L_0(r+r',c+c',d+d') \quad (13)$$

The update function we used to have final matching costs is given in (14). α and β are empirical constants. α is the inhibiting constant and β is the possibility constant.

$$L_{n+1}(r,c,d) = \left[M_n(r,c,d)\right]^{\alpha} \left[\pi(r,c,d)\right]^{\beta} L_0(r,c,d) \quad (14)$$

3.5 Occluded zone detection

Occlusion detection is a major part in stereo vision problem. Several heuristic methods have been used to detect occluded zones. In [20], a competitive approach of occlusion detection has been implemented. In the first step, this approach generates a dense disparity map in which matching conflicts are labelled. In the second step, occlusions are extracted among these conflicts by using maximum-value rule. In [19], occlusion detection is based on the disparity map consistency. In [21], Bayesian networks are used to detect occlusions; this method is robust to noise. Other methods tried to explicitly detect the occlusions using intensity edges [12] or two-dimensional correlation [7].

In our approach, we have introduced a fuzzy factor that expresses the possibility of correspondence in the initial matching value. This factor plays first fiddle in occlusion detection since it is close to 0 if the pixels do not belong to the same intensity class. Actually, when a pixel in the reference image is occluded in the right image, it has a weak probability to be in the same class of intensity as the pixel that hides it in the right image In fact, provided mutually occluded areas within the disparity range do not have similar intensities, all match values corresponding to occluded pixels will be small since the possibility factor is close to 0. After the match values have converged, we can determine if a pixel is occluded by finding the element with the greatest match value along its line of sight. If the maximum match value is below a threshold, the pixel is labelled as occluded.

4 Experimental Results

In this part, we have carried some experiments in order to validate our approach. We have used real and synthetic pairs of rectified images. The threshold to detect occlusion is 0.003.

4.1 Random dot stereogram

Figure 3 (a) and (b) shows a pair of synthetic images with random noise. In order to compare our results with the results of Zitnick and Kanade, we have used the same synthetic pair of images in [25].

Table 1 shows a comparison of the two algorithms after 5 iterations with a 3x3x3 local support area size for $\alpha=4$ and $\beta=2$. The table shows that our algorithm gives better results in terms of percentage of disparities found correctly and percentage of detected occlusions. The major improvement is in the term of percentage of true occlusions found. Our algorithm detects 83.13% of occlusions against 61.82% for Zitnick and Kanade algorithm.

Table 1 : The percentage of disparities found correctly, the percentage of detected occlusions, and the percentage of the true occlusions found for 3x3x3 local support area size for α=4 and β=2 using the random dot stereo pair, comparison of our algorithm with Zitnick and Kanade algorithm.

Algorithm	% Disparities Correct	% Occlusions Correct	% Occlusions detected
Zitnick et Kanade	98,1	89,35	61,82
Our algorithm	99	95,84	83,13

Figures 3 (c), 3 (d) and 3 (e) represents respectively true disparity map, disparity map found using Zitnick and Kanade algorithm and disparity map found using our algorithm. The disparity map found by our algorithm shows better quality compared to the Zitnick and Kanade map. The contours are clearer in our disparity map. Figure 4 shows that our algorithm converges more quickly than Zitnick and Kanade algorithm. Initial rate of disparities found correctly by our algorithm is noticeably higher than Zitnick and Kanade initial rate. Our algorithm reaches a rate of correct disparities of 99.3% in 7 iterations. This same rate is reached after 17 iterations by the algorithm of Zitnick and Kanade.

Figure 4: Convergence rate of our algorithm and Zitnick and Kanade algorithm for α= 4 and β=2 over 17 iterations using the random dot stereogram.

4.2 Head scene provided by the university of Tsukuba

Figure 5 (a) and (b) pair of images provided by the University of Tsukuba. Figure 5 (c) represents the ground truth disparity map. Figure 5 (d) shows the disparity map generated by our algorithm after 50 iterations. Our results an improvement near discontinuities compared to Zitnick and Kanade results.
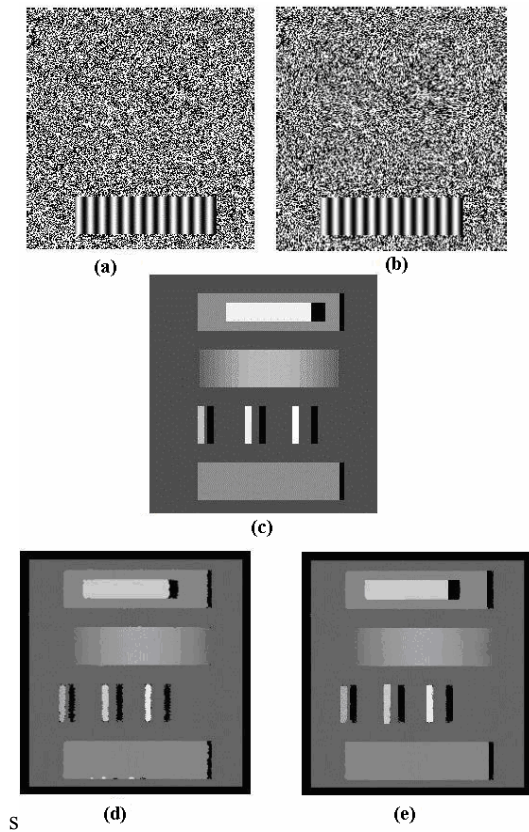
Figure 3: Synthetic scene, 50 percent density; (a) reference (left) image, (b) right image, (c) true disparity map, black areas are occluded, and (d) disparity map found using 3x3x3 local support area with Zitnick et Kanade algorithm, (e) disparity map found using 3x3x3 local support area with our algorithm, black areas are detected occlusions.
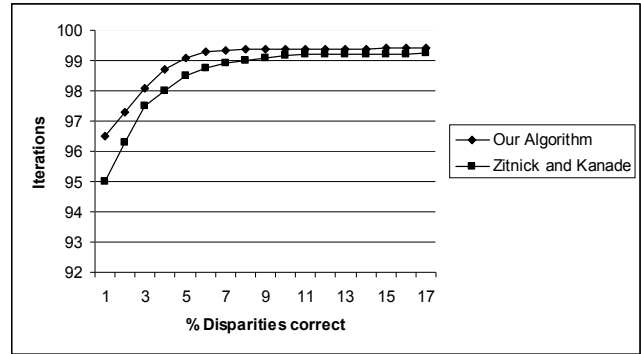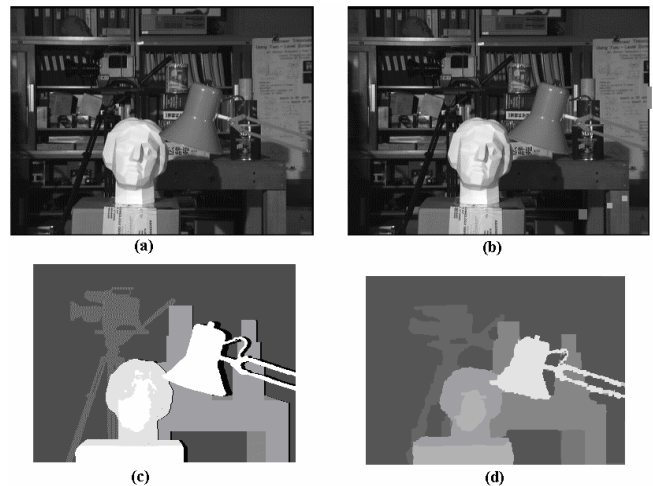
Figure 5: Head scene provided by the University of Tsukuba. (a) Reference (left) image, (b) right image, (c) ground truth disparity map with black areas occluded, provided courtesy of the University of Tsukuba, (d) disparity map found using our algorithm with a 5x5x3 local support area, black areas are detected occlusions.

Applying our algorithm to the head scene provided by the University of Tsukuba, 82% of initial matching was found correctly against 59% for Zitnick and Kanade algorithm. Table 2 shows comparison of our results with Zitnick and Kanade results after 12 iterations, using different local support area sizes (3x3x3, 5x5x3, 7x7x3), an inhibiting constant $\alpha=4$ and a possibility constant $\beta=2$. As shown in Table 2, more than 99% of disparities were correctly found using our algorithm. The best result was found using a 5x5x3 local support area size with an error rate of à.67%.

Table 2: The percentage of disparities found correctly, the percentage of detected occlusions that are correct, and the percentage of the true occlusions found for three different local support area sizes using the University of Tsukuba's stereo pair.

Local support area	% Disparities correct	% Occlusion correct	% Occlusion detected
3x3x3	98,21	77,13	74,19
5x5x3	99,33	89,49	68,29
7x7x3	98,57	81,73	61,62

A detailed analysis of the number of occluded and non occluded pixels found using our algorithm is shown in Table 3. Ground truth data provided by the University of Tsukuba shows 84003 labelled as "non-occluded" and 1902 pixels labelled as "occluded". Among the 84003 non-occluded pixels, our algorithm has correctly paired 83180 pixels, wrongly paired 642 pixels and labelled 181 pixels as "occluded". Among the 1902 occluded pixels, our algorithm has correctly labelled 1411 pixels and wrongly labelled 491 pixels as "non-occluded".

Table 3: The number of occluded and non occluded pixels found using our algorithm compared to the ground truth data provided by the University of Tsukuba. A 5 x5x3 area was used for the local support and the disparity values were allowed to completely converge.

	occluded	non occluded	Total
«occluded»	1411	181	1592
«non-occluded»	491	Correct: 3180 Incorrect: 642	84313
Total	1902	84003	85905

Ignoring the occluded pixels, 0.97% of the 84003 pixels were correctly paired by our algorithm, which is an excellent error rate. Table 4 shows comparison of several stereo algorithm results using the pair of images provided by the University of Tsukuba.

Our algorithm presents a significant improvement in error rate compared to the algorithm of Zitnick and Kanade [25]. The best error rate is given by Nakamura et al. [17] using multiple images and camera masking.

Table 4: Comparison of our algorithm with other algorithms.

Algorithm	Errors rate
Our Algorithm	0.9
Zitnick et Kanade [25]	1.4
GPM-MRF [3]	2.8
LOG-Filtered L1 [3]	9.0
Normalized correlation [3]	10.0
Nakamura et al. [17] (25 images)	0.3
Nakamura et al. [17] (9 images)	0.9

5 Conclusion

In this paper, we proposed a stereo approach based on the stereo algorithm of Zitnick and Kanade. It's a stereo matching algorithm that explicitly reflects the continuity and uniqueness assumptions. We have used a balanced correlation window and introduced a fuzzy factor to the initial matching values. This factor expresses the possibility of correspondence between two pixels according to a grey scale classification of pixels. We have proposed a new iterative function based on the continuity assumption to refine initial matching values. The results of our experiments confirm that our method offers a significant improvement in matching error rate and occlusion detection.

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