A Theory of Possibility for Reliable Correspondence Search

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Abstract: In this paper we present a new theory of possibility for correspondence search. The proposed theory is based on fuzzy modeling of stereoscopic constraints. It defines a possibility of matching and a possibility of unmatching for each pair of pixels from the two stereo images. We estimate the initial disparities using a confidence degree calculated using the proposed possibilities. An adaptive support window, whose weights are computed using initial disparities, is used in a SAD aggregation function to calculate final disparity map. Experimental results and comparison with other algorithms are presented to demonstrate the performance of our approach.

Keywords: Correspondence search, adaptive window, Fuzzy logic, Theory of possibility, Stereoscopic Constraints, Occlusion detection

1. INTRODUCTION

Correspondence search is the most important and costing task of stereo vision. Classical correlation based techniques suffer from weakness because of two main problems. The first problem is the choice of the support window size. In one hand, a small size of the window increases the influence of the noise. In the other hand, a large window covers regions with different depths and gives unreliable support. For this reason, unlike the existing methods that try to find an optimal size of the support window, we adjusted the support-weight of each pixel in a given support window. The amount of the support that the central pixel receives from a pixel in the support window should depend on the distance separating the two pixels and the local variation of disparity. There have been some researches for adaptive support window (Hoff & Narendra, 1989) (Panton, 1978), (Luo et al. 2008), (Bekaert et al. 2007), (Sizintsev & Wildes, 2010), (Nalpantidis & Gasteratos, 2010). The difficulty of a locally adaptive support weight approach based on disparity variation lies in the difficulty of evaluating and using disparity variances since the disparity is what we intend to calculate (Levine et al. 1973). The second problem is that area based approaches are generally reliable only when the following criteria are satisfied: The lighting source must ideally be a point source at infinity; the surfaces in the scene should ideally be Lambertian; the amount of figural dissimilarity or distortion between the views is small. In many situations where stereo is applied, idealized environments and light sources cannot be assumed. In these situations, classical correlation metrics are not sufficient to have reliable matches. The use of imprecise techniques such as fuzzy logic can solve this problem (Nieradka & Butkiewicz, 2009), (Medeiros et al. 2010), (Ghazouani et al. 2010). In this paper we propose a theory of possibility to estimate initial disparities. We use the estimated disparities to compute the support-weights of a pixel in a given support window. We use this window in a SAD aggregation function to search for correspondences.

2. THE THEORY OF POSSIBILITY

In this section we propose reliable fuzzy metrics based on stereoscopic constraints to be used for the estimation of initial disparities. Without loss of generality, we assume that stereo pairs are rectified to have the baseline parallel to the Y-axis and the disparity is supposed to be only along the Y-coordinate.

We define a 3D disparity space whose dimensions are r, c and d respectively to designate row, column and disparity. Each element (r, c, d) of the disparity space is projected to pixel (r, c) on the reference image and the pixel $(r, c + d)$ on the matching image. Element (r, c, d) refers to the pairing of the pixel (r, c) in the reference image and the pixel $(r, c + d)$ in the matching image and $L(r, c, d)$ is the associated matching cost.

2.1 Possibility of Matching

Similarity constraint states that the projections of the same physical point have comparable light intensities. The major part of stereo matching approaches use this constraint in a static correlation criterion that calculates the difference of illumination between two areas of the stereo images. This correlation measure, based on numerical distances of intensities, is particularly disturbed by changes caused by non ergodic phenomena, such as the change of the point of view, partial occlusion, sampling, scanning, ... These changes can be hardly modeled by simple normal laws. In our approach, we propose to model the similarity constraint by a fuzzy measure, which is more robust to noise and changes. This measure expresses the degree of membership of two pixels to a same grey class. We define a grey scale classification of pixels. Three classes are defined; black, white and average pixels. Membership functions of these grey classes (given by equation 1) are Gaussian centred in 0, 127.5 and 255.

$$\mu_{class}(m) = exp\left(-\frac{(I(m) - c_{class})^2}{2\sigma^2_{class}}\right) \tag{1}$$

I(m) is the intensity at the pixel m, c_{class} and σ_{class} are respectively the center and the standard deviation of the class under consideration. Based on this classification, we give the following proposition.

Proposition 1. The pairing of the pixels m_1 and m_2, from the two stereo images, is possible if the two pixels belong to the same grey class. That means (m_1 is black AND m_2 is black) OR (m_1 is white AND m_2 is white) OR (m_1 is average AND m_2 is average).

Definition Considering two pixels m_1 and m_2 from the two stereo images, we define $\Pi(m_1, m_2)$ as the possibility of matching between the two pixels by expressing proposition 1 using classical fuzzy logic operators. $\Pi(m_1, m_2)$ is a measure of co-membership to a same grey class. It reflects how much it is possible to have m_1 and m_2 as corresponding pixels. $\Pi(m_1, m_2)$ is given by (2).

$$\Pi(m_1, m_2) = \max\begin{pmatrix} \min(\mu_{black}(m_1), \mu_{black}(m_2)), \\ \min(\mu_{average}(m_1), \mu_{average}(m_2)), \\ \min(\mu_{white}(m_1), \mu_{white}(m_2)) \end{pmatrix} \tag{2}$$

$\mu_{class}(m)$ is the degree of membership of the pixel m to the class under consideration. The possibility of matching ranges between 0 and 1.

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

2.2 Possibility of Unmatching

Supposing that the observed objects are opaque and the disparity is not significant, the uniqueness constraint stipulates that an object whose projection is a pixel on the first image has a projection that is a pixel in the second image. Using such a constraint reduces the number of potential matches of a pixel in the reference image. This constraint can be used only to modify an initial pairing distribution to have a new distribution with less violation to the uniqueness constraint. Referring to the possibilities of matching, a match (r, c, d) violates the uniqueness constraint if there is a match (r, c, d') with $d' \neq d$ and $\Pi(r, c, d) < \Pi(r, c, d')$.

Definition Considering two pixels $m_1 = (r, c)$ and $m_2 = (r, c + d)$ from the two stereo images, we define $\Pi_U\overline{(r, c, d)}$ as a *possibility of unmatching* relatively to the uniqueness constraint. $\Pi_U\overline{(r, c, d)}$ reflects how much the pairing of the pixel (r, c) in the reference image and the pixel $(r, c + d)$ in the matching image violates the uniqueness constraint. $\Pi_U\overline{(r, c, d)}$ is given by (3).

$$\Pi_U\overline{(r, c, d)} = \sup_{d' \neq d} \{\Pi(r, c, d') > \Pi(r, c, d)\} \tag{3}$$

Under some conditions defined in (Faugeras, 1993), the ordering of pixels is preserved across the images. This constraint can be formulated by the following proposition.

Proposition 2. Considering two pixels m_1 and m_2, respectively from the reference and the matching image. If m_1 and m_2 are projections of the same physical point M then all the pixels on the right (respectively left) of the pixel m_1 are on the right (respectively left) of the pixel m_2.

By extension we can express the dual negative proposition (proposition 3).

Proposition 3. Considering two pixels m_1 and m_2, respectively from the reference and the matching image. If m_1 and m_2 are projections of the same physical point M then all the pixels on the right (respectively left) of the pixel $m_1$can not be on the left (respectively right) of the pixel m_2.

In other words, a match (r, c, d) violates the ordering constraint if there is a match (r, c', d') that verifies : $(c < c'$ $AND\ c + d > c' + d')$ OR $(c > c'\ AND\ c + d < c' + d')$ AND $(\Pi(r, c, d) < \Pi(r, c', d')$). Based on this analysis, we give the following definition.

Definition Considering two pixels $m_1 = (r, c)$ and $m_2 = (r, c + d)$ from the two stereo images, we define $\Pi_O\overline{(r, c, d)}$ as the *possibility of unmatching* relatively to the ordering constraint. $\Pi_O\overline{(r, c, d)}$ reflects how much the pairing of the pixel (r, c) in the reference image and the pixel $(r, c + d)$ in the matching image violates the ordering constraint. $\Pi_O\overline{(r, c, d)}$ is given by (4).

$$\Pi_O\overline{(r, c, d)} = \max\begin{pmatrix} \sup\limits_{\substack{c' > c \\ d' < d - (c' - c)}} \{\Pi(r, c', d') > \Pi(r, c, d)\}, \\ \sup\limits_{\substack{c' < c \\ d' > d + (c - c')}} \{\Pi(r, c', d') > \Pi(r, c, d)\} \end{pmatrix} \tag{4}$$

Definition We define a global unmatching possibility by merging unmatching possibilities relatively to uniqueness constraint and ordering constraint. *Global unmatching possibility*, given by (5), expresses how much the pairing of the pixel (r, c) in the reference image and the pixel $(r, c + d)$ in the matching image violates the stereoscopic constraints.

$$\Pi\overline{(r, c, d)} = \max(\Pi_U\overline{(r, c, d)}, \Pi_O\overline{(r, c, d)}) \tag{5}$$

3. THE PROPOSED CORRESPONDENCE SEARCH ALGORITHM

3.1 Initial Disparities

Using matching possibility and unmatching possibility we attribute to each pairing (r, c, d) a *matching confidence degree* defined by (6).

$$\tau(r, c, d) = \frac{\Pi(r, c, d)}{1 + \lambda \Pi\overline{(r, c, d)}} \tag{6}$$

Where λ is a scaling constant. The matching confidence degree $\tau(r, c, d)$ expresses how much we can trust the pairing of the pixels (r, c) and $(r, c + d)$ regarding the chromatic values of the two pixels and the stereoscopic constraints satisfied by their pairing. This confidence degree will be used as initial matching cost to estimate initial disparities. The best disparity is selected by comparing the confidence degrees across all disparities. The disparity of the maximum confidence degree is defined as the best disparity.

Notation Thereafter, we will use the notation $d_0(r, c)$ for the initial disparity of the pixel (r, c) determined using the defined confidence degrees. The initial disparity function associates to each pixel (r, c) in the reference image its corresponding pixel $(r, c+d_0(r, c))$ in the matching image.

3.2 Adaptive support-weights

The choice of the support window is a crux of correspondence search. For acquiring more exact results, several works have used an adaptive support-weight window (Yoon & Kweon, 2006), (Veksler, 2002), (Gu et al. 2008), (Boykov et al. 1998), (Yang et al. 2009), (Zhai et al. 2009), (Mattoccia, 2010). In our implementation, we use a support-weight approach in order to increase the reliability of matching. In this approach, based on the coherence principle used by Pradzny (Pardzny, 1985), we examine candidate matches by calculating how much support they receive from their local neighbourhood. The coherence principle states that neighboring disparities, if corresponding to the same 3D object, should be similar. Two neighboring pixels with similar disparity should support each other, while pixels with dissimilar disparities should not inhibit with each other. To incorporate this idea into a stereo matching algorithm we define a support-weight function based on distances and initial disparities.

$$w(i, j) = \frac{1}{\mu\sqrt{2\pi}\sqrt{i^2 + j^2}} \exp\left(\frac{-|d_0(r, c) - d_0(r + i, c + j)|}{2\mu^2(i^2 + j^2)}\right) \tag{7}$$

Where $w(i, j)$ is the amount of the support that central pixel (r, c) of the support window receives from the pixel $(r+i, c+j)$. $\sqrt{i^2 + j^2}$ is the Euclidean distance between the two pixels. $d_0(r, c)-d_0(r+i, c+j)$ is the difference between initial disparities at the two pixels. $w(i, j)$ is inversely proportional to the difference of disparities. More distant pixels in the support window exert less influence in the final disparities calculus; and the more distant the two points are, the less seriously their difference of disparities is considered.

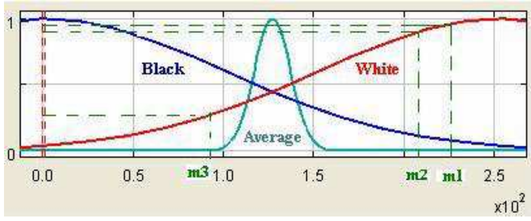

Fig. 1. Empirical fitting of the membership function standard deviations.

3.3 Final Disparities and occlusion handling

The absolute difference of intensity, which is given by (8), is used as the matching cost computation. $I_r(r, c)$ is the pixel intensity at (r, c) in the reference image and $I_m(r, c+d)$ is the intensity of pixel shifted in horizontal by the disparity value, d, from (r, c) in the matching image. A 2w-sized window with adaptive support weights, as already described, is used to calculate the aggregation cost $C(r, c, d)$ given by (9).

$$C_0(r, c, d) = |I_r(r, c) - I_m(r, c + d)| \tag{8}$$

$$C(r, c, d) = \frac{1}{4w^2 I_{max}} \sum_{i=-w}^{i=w} \sum_{j=-w}^{j=w} w(i, j) C_0(r + i, c + j, d) \tag{9}$$

The final matching cost is given by (10). For the final disparity computation step, the best disparity is selected by comparing the final costs across all disparities. In our approach, we used a winner-take-all method (Bekaert et al. 2007) to find the disparity at each pixel position. The disparity of the maximum final cost is defined as the best disparity. The disparity selected for every pixel position defines the final disparity map.

$$L(r, c, d) = \frac{[\tau(r, c, d)]^\alpha}{C(r, c, d)} \tag{10}$$

In our approach, we explicitly detect occluded areas by examining final matching costs. The proposed confidence degree used in the final matching cost allows discrimination of false correspondences. Having the final matching costs, we can determine if a pixel is occluded by finding the element with the greatest matching cost along its line of sight. If the maximum matching value is below a threshold, the pixel is labelled as occluded.

4. EXPERIMENTAL RESULTS

For all the experiments, we set $\sigma_{black} = \sigma_{white} = 7.071$ and $\sigma_{average} = 2.236$ (1), $\lambda = 0.45$ and $\alpha = 0.6$ (10). These values were empirically determined. Fig. 1 shows fuzzy membership functions of the defined classes. Using the defined classification, we can have significant values of the matching possibilities. As shown in Fig. 1, $\Pi(m1, m2) = 0.9$ and $\Pi(m1, m3) = 0.26$. Fig. 2 shows different initial disparity maps for Tsukuba stereo pair using confidence degrees with different values of the scaling constant λ used in (6). Best initial disparity map is found using $\lambda = 1$.

Fig. 3 (a) and (b) show a pair of synthetic images with random noise. Fig. 3 (c) is the theoretical disparity map. Fig. 4 Shows disparity maps generated by our algorithm using 4×4, 12×12, 18×18 and 24×24 local support

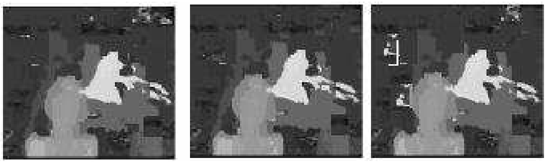

Fig. 2. Initial disparity maps found using (from the left to the right) $\lambda = 0.5$,$\lambda = 1$ and $\lambda = 0.5$

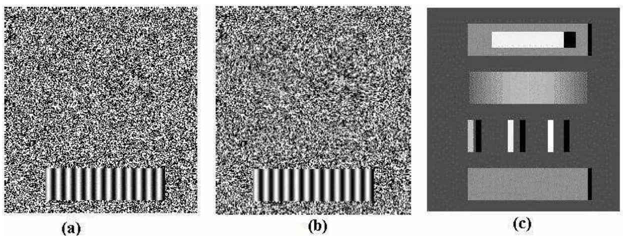

Fig. 3. Synthetic scene, 50% density (a) reference image, (b) right image, (c) true disparity, black areas are occluded

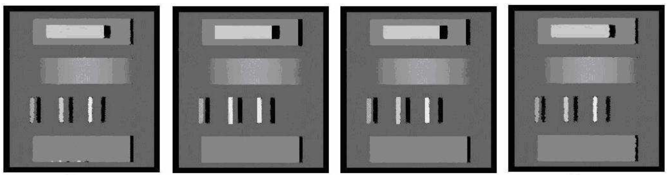

Fig. 4. Disparity maps found using (from the left to the right) 4×4, 12×12, 18×18, and 24×24 local support, black areas are detected occlusions.

window. The best disparity map is found using 12×12 local support window. For all next experiments we set $\lambda = 1$ and use a 12×12 local support window ($w = 6$).

To evaluate the performance of our stereo matching approach, we used a test bed proposed by Shcarstein and Szeliski (Scharstein & Szeliski, 2002) and updated by Yoon et al. in (Yoon & Kweon, 2005). We evaluated the proposed approach on these test data sets: Tsukuba, Venus, Sawtooth and Map. The error rate, defined by Scharstein and Szeliski in (Scharstein & Szeliski, 2002), measures the percentage of pixels in which the absolute difference between the result and the theoretical disparity map is greater than 1 pixel. It provides a useful qualitative measure for performance comparison of different algorithms.

Fig. 5 shows the results of stereo matching for the four standard stereo images. For comparison, we include the results of window based methods. The results show that our algorithm achieves a good performance in conventionally challenging regions such as untextured and discontinued regions. This is due to the efficient calculus of the support weights in the correlation window and fuzzy reliable estimation of initial disparities. Table 1 shows quantitative results for stereo matching using true disparity maps in different stereo pairs. Table 2 and Table 3 show, respectively, quantitative results in discontinued and untextured regions. The results demonstrate that the proposed approach has comparable performance and even best then state-of-the-arts.

The threshold for explicit occlusion detection is set to 0.65. Tsukuba Ground truth pairs shows 84003 labeled as non-occluded and 1902 pixels labelled as occluded. Among the 84003 non-occluded pixels, our algorithm has correctly matched 82842 pixels, wrongly matched 988 pixels and labelled 181 pixels as *occluded*. Among the 1902 occluded pixels, our algorithm has correctly labelled 1798 pixels and wrongly labelled 104 pixels as *non-occluded*. The percentage of occlusion detection is 94.53%.

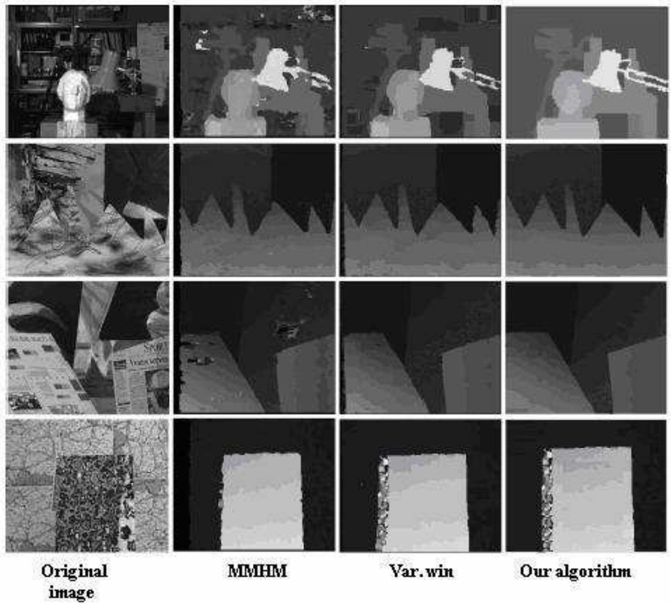

Fig. 5. Results for (from the top to the bottom) Tsukuba, Swatooth, and Venus and Map images pairs.

Table 1. Performance comparison of stereo Correspondence Search Algorithms

	Tsuk.	Swat.	Venus	Map
Proposed method	1.38	1.33	1.11	0.3
Adapt.Wgt(Yoon&Kweon 05)	1.51	1.14	1.14	1.47
Var. win. (Veksler, 03)	2.35	1.28	1.23	0.24
Graph cut (Boykov et al. 01)	1.94	1.30	1.79	0.31
Tree DP (Veksler, 05)	1.77	1.44	1.21	1.45
Comp. win. (Veksler, 01)	3.36	1.61	1.67	0.33
MMHM (Mühlmann et al. 02)	9.76	4.76	6.48	8.42

Table 2. Performance comparison in discontinued regions

	Tsukuba	Swatooth	Venus
Proposed method	6.85	6.78	5.95
Adpt.Wgt(Yoon&Kweon05)	7.24	5.48	4.49
Var. win(Veksler, 03)	12.17	7.09	13.35
Graph cut(Boykov et al.01)	9.49	6.34	6.91
Tree DP(Veksler, 05)	9.48	6.87	5.04
Comp. win(Veksler, 01)	12.91	7.87	13.24
MMHM(Mühlmann et al.02)	24.39	22.49	31.29

Table 3. Performance comparison in untextured regions

	Tsukuba	Swatooth	Venus
Proposed method	0.73	0.82	0.12
Adpt.Wgt(Yoon&Kweon05)	0.65	0.27	0.61
Var. win(Veksler, 03)	1.65	0.23	1.16
Graph cut(Boykov et al.01)	1.09	0.06	2.61
Tree DP(Veksler, 05)	0.38	0.84	1.41
Comp. win(Veksler, 01)	3.54	0.45	2.18
MMHM(Mühlmann et al.02)	13.85	1.87	10.36

5. CONCLUSION

In this paper, we have proposed a theory of possibility to estimate initial disparities. We defined a support-weight function based on estimated disparities. We used the proposed support-weights in an aggregation function to find final disparity map. The proposed algorithm explicitly detects occlusion by comparing maximum matching costs to a threshold. Experimental results have demonstrated that our algorithm gives comparable performance and even best than state-of-the-art methods

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