COMPLEMENTARITY OF FEATURE POINT DETECTORS

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Abstract: The goal of this paper is to provide a study on complementarity of feature point detectors. Many studies have been proposed on these detectors but none deals with complementarity in details. We introduce an evaluation of eleven well-known detectors based on new criteria used to characterize complementarity. The complementarity is computed with spatial distribution and contribution measures as well as repeatability and distribution gains of the association of two detectors.

1 INTRODUCTION

Many applications in computer vision rely on some characteristic points called feature points (or point of interest). Their detectors are designed to select the most distinctive points in an image so they are easy to match without ambiguities. We asked ourselves the following question: if different feature point detectors select the most distinctive points in an image, do they return the same points ? In other words, we propose to study the complementary of several feature point detectors. Previous evaluations studied detection criteria such as repeatability or information content and matching criteria such as recall and precision rates. We propose to study the complementarity of feature point detectors based on new criteria: spatial distribution and complementarity measures. The idea is to find out which are the most complementary detectors in order to combine them when needed. Initially, this evaluation is proposed on small-baseline stereo image pairs since feature points may be used for instance in application such as stereo matching (Lhuillier and Quan, 2002) or fundamental matrix estimation (Hartley and Zisserman, 2004).

First, previous work on feature point detectors is described. Second, the new criteria to measure complementarity are introduced. Finally, the results of our experimentations are discussed before the conclusion.

2 PREVIOUS WORK

2.1 Feature point detection

Feature points are distinctive points within an image. Therefore, they are used in many applications such as tracking, indexation or stereo matching. There are different families of detectors: contour based, intensity based, parametric model based methods (Schmid et al., 2000). We focus on intensity based methods since they are widely used. They are based on the following steps: (i) computation for each pixel of a response value based on local grey level variations ; (ii) non maxima suppression ; (iii) post processing (edge response elimination, subset selection, subpixel localisation). In this section we describe briefly the first step for the well known detectors: Moravec, Harris, Kitchen-Rosenfeld, Beaudet, SUSAN, FAST, SIFT, SURF, Harris-Laplace, Hessian-Laplace and Kadir.

■ **Fixed scale detectors** The response is computed using a fixed window size.

Moravec (MO) The response is based on an auto-correlation measure based on four directions (Moravec, 1977).

Harris (HA) The response is based on a generalisation of the auto-correlation measure on every shift directions. It defines an auto correlation matrix, then the response is obtained from this matrix. Several variants were given (Harris and Stephens, 1988; Noble, 1988; Shi and Tomasi, 1994).

Kitchen-Rosenfeld (KR) The response is based on the curvature of the grey level gradients (Kitchen and Rosenfeld, 1982).

Beaudet (BE) The response is based on the determinant of the Hessian matrix (second derivatives) (Beaudet, 1978).

SUSAN (SU) The response is based on the area in the neighbourhood of the same intensity as the current pixel (Smith and Brady, 1997).

FAST (FA) The response is based on the configuration of the grey levels on a circle centred on the current pixel (Rosten and Drummond, 2006).

■ **Multi scale detectors** The response is computed using different window sizes (or image resolutions).

SIFT (SI) The response is based on the grey level Laplacian computed using a difference of Gaussian (Lowe, 1999).

Harris-Laplace, Hessian-Laplace (HAL, HEL) The response is based on Harris or the Hessian matrix but the detected feature points must also be maxima in the scale space of the Laplacian (Mikolajczyk and Schmid, 2004).

SURF (SR) The response is based on the determinant of the Hessian matrix. The detected feature points must also be maxima in the scale space of the determinant of the Hessian (Bay et al., 2006).

Kadir (KA) The response is based on the grey level histogram entropy of the neighbours of the current pixel (Kadir et al., 2004).

2.2 Previous evaluations

Repeatability When two images of a same scene taken under different conditions are submitted to a feature point detector, it is desirable that the returned points are repeated: the two projections of a scene point are detected in the two images. In other words, a feature point in an image is repeated if its correspondent in the other image is also detected as a feature point. The repeatability rate of a detector is the percentage of repeated points from an image to another. If this rate is high when a transformation between the two images is large (rotation, scale change, perspective change, light change), this detector is robust to that transformation (Schmid et al., 2000; Mikolajczyk and Schmid, 2004; Gil et al., 2009).

Information content This value represents how much the feature points of an image are distinct to each other. The more distinctive the feature points are, the less ambiguous they are to match. A descriptor is computed for each feature point and the Mahanalobis distance is used to normalize each component (Schmid et al., 2000).

Complementarity The complementarity is measured in (Mikolajczyk et al., 2005) in an object recognition context. A clustering algorithm is applied to the feature points, then the number of points from each detector is computed for each class. Ideally, each class must contain points from the same detector only.

3 PROPOSED EVALUATION

We propose to extend and modify the previous criteria with the following ones:

- *spatial distribution* – distribution of feature points is measured in depth discontinuity areas and computed region wise ;
- *complementarity* – complementarity of two detectors is measured in three ways: contribution measure ; repeatability gain and distribution gain.

The repeatability is taken into account by the complementarity measures, therefore, we propose to compute it using the definition below.

3.1 Repeatability

Let $\mathbf{p}^{I}_{i,j}$ be the pixel at the i$^{\text{th}}$ row and j$^{\text{th}}$ column in the image I. Let $\mathbf{d}^{I_1}_{i,j}$ be the disparity vector such as $\mathbf{p}^{I_2}_{i',j'} = \mathbf{p}^{I_1}_{i,j} + \mathbf{d}^{I_1}_{i,j}$ where $\mathbf{p}^{I_2}_{i',j'}$ is the pixel in the right image which is the projection of the same scene entity as $\mathbf{p}^{I_1}_{i,j}$. Let ε be a tolerance margin in pixels. We use the following definitions:

- *repeated point* – a feature point $\mathbf{p}^{I_1}_{i,j}$ in the image I_1 is repeated if a feature point $\mathbf{p}^{I_2}_{i',j'}$ has been detected in the image I_2 within a distance lower than ε from its theoretical correspondent, *i.e.* $||(\mathbf{p}^{I_1}_{i,j} + \mathbf{d}^{I_1}_{i,j}) - \mathbf{p}^{I_2}_{i',j'}|| < \varepsilon$.
- *repeatability rate* – the repeatability rate for a detector D and an image pair (I_1, I_2) is given by:

$$\text{rep}\,(I_1, I_2) = \frac{\text{rep}_D\,(I_1 \to I_2) + \text{rep}_D\,(I_2 \to I_1)}{2} \tag{1}$$

with

$$\mathrm{rep}_D(A \rightarrow B) = \frac{\#\text{ feature pts. of A repeated in B}}{\#\text{ feature points in A}} \quad (2)$$

3.2 Spatial distribution

Distribution in depth discontinuity areas Depth discontinuity areas are located near the boundaries between homogeneous depth regions. They result in grey level variations. However, the grey level of the background may be locally different for two correspondents which makes such pixels harder to match than pixels in other areas. Feature point detectors tend to select points in areas where high grey level variations occur and therefore may return points in depth discontinuity areas. Thus, we compute the following measure:

$$\mathrm{DA} = \frac{\#\text{ feature points in depth discontinuity areas}}{\#\text{ feature points}} \quad (3)$$

Region wise distribution The regions are extracted using a color segmentation algorithm. The idea is based on the hypothesis that pixels with more or less the same color belong to the same object part (and therefore have more or less the same disparity value). For a detector D, the region wise distribution score is:

$$\mathrm{RD}_{D,S} = \frac{\#\text{ regions holding at least one feature point}}{\#\text{ regions}} \quad (4)$$

where S is a segmentation map. A low ratio reveals a lack of feature points or a bad distribution over the different regions of the image.

3.3 Complementarity

Contribution measure Let $\mathcal{P}_{D_1}$ be the set of the feature points returned by a detector D_1 and $\mathcal{P}_{D2}$ the set of the feature point returned by a detector D_2. The contribution of D_2 over D_1 is given by:

$$\mathrm{contribution}_{D_2|D_1} = \frac{\mathrm{card}\{\mathcal{P}_{D_2}\} - \mathrm{card}\{\mathcal{P}_{D_1} \cap \mathcal{P}_{D_2}\}}{\mathrm{card}\{\mathcal{P}_{D_1}\}} \quad (5)$$

where the intersection $\mathcal{P}_{D_1} \cap \mathcal{P}_{D_2}$ is computed considering two points $\mathbf{p}^I_{i,j}$ and $\mathbf{p}^I_{i',j'}$ of an image I as the same point when $||\mathbf{p}^I_{i,j} - \mathbf{p}^I_{i',j'}|| < \varepsilon$. The higher this value is with a high ε, the larger the differences are between the two sets $\mathcal{P}_{D_1}$ and $\mathcal{P}_{D_2}$. This measure is illustrated by figure 1.

$\mathcal{P}_{\mathrm{HA}}$ $\quad$ $\mathcal{P}_{\mathrm{BE}} - (\mathcal{P}_{\mathrm{HA}} \cap \mathcal{P}_{\mathrm{BE}})$

Figure 1: This figure shows on the left all the feature points returned by HA and on the right the contribution of BE, *i.e.* the feature points returned by BE which are different from the ones already returned by HA ($\varepsilon = 3$). It also shows the segmentation map (each color represents one region).

This contribution measure is not symmetric since the cardinalities of each detector are different, therefore in order to get an objective idea of the complementarity of the union of two detectors (D_1, D_2), we compute:

$$\begin{aligned}\mathrm{contribution}(D_1, D_2) &= \mathrm{contribution}(D_2, D_1)\\ &= \min(\mathrm{contribution}_{D_2|D_1}, \mathrm{contribution}_{D_1|D_2})\end{aligned} \quad (6)$$

Repeatability gain The repeatability is computed independently for the detectors D_1 and D_2. It is then computed with $D_1\&D_2$ which represents the union $\mathcal{P}_{D_1} \cup \mathcal{P}_{D_2}$. The gain of repeatability is given by:

$$\mathrm{gain}_{\mathrm{rep}_{D_1\&D_2}} = \mathrm{rep}_{D_1\&D_2} - \max\left(\mathrm{rep}_{D_1}, \mathrm{rep}_{D_2}\right) \quad (7)$$

Distribution gain The spatial distribution is computed independently for the detectors D_1 and D_2. It is then computed with $D_1\&D_2$ which represents the union $\mathcal{P}_{D_1} \cup \mathcal{P}_{D_2}$. The gain of distribution is given by:

$$\begin{aligned}\mathrm{gain}_{\mathrm{RD}_{D_1\&D_2,S}} =& \mathrm{RD}_{D_1\&D_2,S}\\ &- \max\left(\mathrm{RD}_{D_1,S}, \mathrm{RD}_{D_2,S}\right)\end{aligned} \quad (8)$$

where S is a segmentation map.

4 DATA SET

4.1 Stereo pairs

Stereo pairs from the Middlebury data set[1] are used for this experimentation[2]. They present issues such as occlusions and depth discontinuities. They are epipolar rectified and the ground truth is known. However, deformations between two images is not as important as it could occur in applications such as indexation.

[1] vision.middlebury.edu/stereo/data/

[2] We use the pairs named *aloe*, *art*, *bowling1*, *cloth1*, *cloth4*, *cones*, *dolls*, *midd2*, *moebius*, *plastic* and *teddy*.

4.2 Implementation details

The programs provided by the detector authors is used when available: HAL[3], HEL[4], SU[5], FA[6], SI[7], SR[8] and KA[9]. Our own implementation is used for the other detectors. For each detector, the following parameters can have an influence on the result:

- *response window size* (for fixed scale detectors) – the smaller this size is, the more the detector is able to select small structures but the greater the noise sensitivity is. On the other hand, the greater this size is, the larger the smoothing effect is and the greater localization errors are.
- *non maxima suppression window size* – the smaller this size is, the larger the number of detected feature points is but these feature points may be close to each other.
- *response threshold* – a threshold on the response value is often used in order to get rid of false responses. The higher this value is, the smaller the number of feature points is.

It would be interesting to study the influence of each parameter on the result but this exhaustive evaluation is difficult to analyse. Moreover, for the detectors implemented by their authors, we do not always have the possibility to change all the settings. A normalization would also be necessary on all the different values in order to make them comparable. Facing this issue, we decided to fix these parameters once for all for each detector. For the detectors we implemented, we used parameter values that give good results with our experimentations. For the the other detectors, we used the default values given by their authors.

5 RESULTS

5.1 Repeatability

The repeatability rep_D of a detector D is given by computing the mean value of the repeatability rates found over the data set. The repeatability is measured by taking $\varepsilon \in \{0, 1.5, 3\}$. The results for repeatability are shown in figure 2. The detectors with the best repeatability are HA, FA and SI. For $\varepsilon = 0$

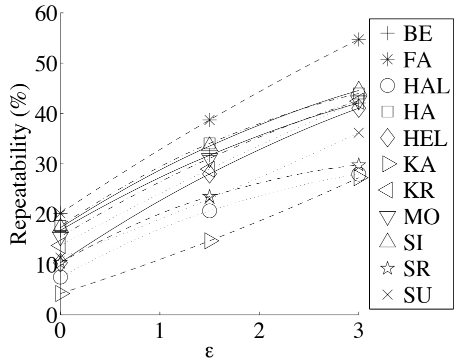

Figure 2: Repeatability scores rep_D for the tested detectors. All the feature points are taken into account, therefore feature points in occluded areas decrease the score. The notations are defined in § 2.1.

the repeatabilities are very low. Therefore, a "feature points to feature points" matching strategy is not advisable when high precision is required. We recommend a "feature points to neighbours of feature points" matching strategy to settle this issue.

5.2 Spatial distribution

The results for the depth discontinuity distribution are shown in table 1. The depth discontinuity areas are computed using the provided ground truth disparity maps, see § 4.1. The results for the region wise distribution are shown in table 1. The EDISON[10] program is used to compute two segmentation maps: (i) an "under" segmentation $S1$ giving about 100 regions for each image ; (ii) a "medium" segmentation $S2$ giving about 500 regions for each image (see figure 1).

The most significant criteria, where the biggest differences are obtained, are $\text{RD}_{D,S2}$ and Card. HAL detector returns very few points and consequently gives also the worst $\text{RD}_{D,S2}$. On the other hand, HA detector seems to obtain the best compromise between cardinality, DA and $\text{RD}_{D,S2}$. According to these results, the best compromises is obtained by the detectors HA, FA and SI.

5.3 Complementarity

Contribution measure This measure is computed over all the feature points and over the repeated points with $\varepsilon = 3$ (we consider this value as the minimum distance between two different points) in one hand and $\varepsilon = 12$ (large enough value to see which detectors return complementary feature points away from each other) on the other hand. The results are shown

[3] robots.ox.ac.uk/~vgg/research/affine/

[4] robots.ox.ac.uk/~vgg/research/affine/

[5] users.fmrib.ox.ac.uk/~steve/susan/index.html

[6] svr-www.eng.cam.ac.uk/~er258/work/fast.html

[7] cs.ubc.ca/spider/lowe/keypoints/siftDemoV4.zip

[8] vision.ee.ethz.ch/~surf/

[9] robots.ox.ac.uk/~timork/salscale.html

[10] caip.rutgers.edu/riul/research/code/EDISON/

Table 1: Mean cardinalities (Card.), mean of the distribution measures in depth discontinuity (DA), and mean of the region based distribution measure (RD) with segmentation $S1$ ans $S2$. For each column the best result is shown in bold.

D	Card.	DA%	$\mathrm{RD}_{D,S1}$%	$\mathrm{RD}_{D,S2}$%
BE	967	28	**100**	78
FA	**2243**	27	**100**	83
HAL	293	35	94	30
HA	989	**25**	99	**86**
HEL	1252	32	**100**	73
KA	638	29	99	61
KR	1153	31	**100**	81
MO	845	27	97	62
SI	1662	29	99	82
SR	303	31	99	49
SU	922	29	**100**	74

Table 2: Contribution measures taking into account all the feature points. For each couple of detectors $D_1\&D_2$, we show $\text{contribution}_{D_2|D_1}$. $\varepsilon = 3$ on the first row and $\varepsilon = 12$ on the second row. To find out which detector is the most complementary with HA and $\varepsilon = 3$, for instance, look at the HA row and column (here in blue). It shows that it is HEL. For each detector and each ε value, the best result appears in bold.

	BE	FA	HAL	HA	HEL	KA	KR	MO	SI	SR
FA	17 4	0 0								
HAL	20 2	9 1	0 0							
HA	55 2	28 2	15 0	0 0						
HEL	**58** 10	**56** **10**	9 0	**67** 6	0 0					
KA	56 **19**	28 12	40 **9**	56 **9**	49 **15**	0 0				
KR	**58** 8	18 2	23 1	62 1	**73** 9	58 **20**	0 0			
MO	39 2	4 0	39 8	42 10	53 5	**85** **27**	27 1	0 0		
SI	37 7	28 3	16 1	56 2	**58** 10	45 **20**	51 5	31 2	0 0	
SR	23 3	13 1	**70** 8	25 1	3 0	38 9	26 2	46 **12**	10 1	0 0
SU	42 3	6 0	36 3	42 1	55 6	**92** **30**	33 2	45 3	32 3	39 5

in table 2 (the measures are computed over all the features points) and in table 3 (the measures are computed over the repeated feature points). According to these results, the most complementary detectors are KA+SU, KA+MO and KR+HEL. By reading these tables, we can see for instance that by taking the union HA+SI, we add in the worst case 67% of new repeated feature points within a distance of $\varepsilon = 3$ pixels of each other and 2% of new repeated feature points within a distance of $\varepsilon = 12$ (*i.e.* at least 12 pixels farther than the already computed feature points).

Table 3: Contribution measures taking into account the repeated feature points (see table 2 for notations).

	BE	FA	HAL	HA	HEL	KA	KR	MO	SI	SR
FA	18 6	0 0								
HAL	19 2	7 1	0 0							
HA	52 3	30 3	12 0	0 0						
HEL	61 13	**51** 12	8 1	**75** 6	0 0					
KA	34 **17**	19 **14**	71 **11**	33 **7**	32 **16**	0 0				
KR	**68** 9	17 2	22 1	60 1	**72** 11	42 **22**	0 0			
MO	46 2	5 0	36 10	44 0	55 6	**82** **31**	35 1	0 0		
SI	42 8	27 4	15 1	67 2	**63** 13	29 **21**	53 6	34 2	0 0	
SR	21 3	9 1	**85** 12	20 1	3 0	64 11	24 2	42 13	8 1	0 0
SU	42 3	5 1	43 3	36 1	47 7	**85** **37**	35 2	62 3	29 3	41 5

Table 4: Repeatability gain. For each couple of detectors $D_1\&D_2$, we show $\text{gain}_{\text{rep}_{D_1\&D_2}}$ ($\varepsilon = 3$). To determine which detector is the most complementary in terms of repeatability with HA, for instance, look at the HA row and column (here in blue), it shows that it is HEL. For each detector, the best result appears in bold.

	BE	FA	HAL	HA	HEL	KA	KR	MO	SI	SR
FA	1.55	0								
HAL	0.75	-0.36	0							
HA	3.77	0.32	-0.36	0						
HEL	4.48	**2.12**	0.36	**4.20**	0					
KA	-0.17	-1.69	-0.39	-0.38	2.03	0				
KR	**4.71**	0.22	0.90	3.88	**5.75**	1.81	0			
MO	3.78	-0.69	-0.62	3.11	**4.47**	-1.34	2.83	0		
SI	3.57	1.19	0.76	3.40	2.37	0.82	**4.98**	3.00	0	
SR	1.01	0.38	0.09	0.66	-2.06	1.48	**1.70**	0.82	-0.19	0
SU	3.53	-1.21	**1.65**	2.24	**5.00**	**2.60**	3.50	2.23	2.46	**2.63**

Repeatability gain The results are shown in table 4. They show which detectors are the most complementary in terms of repeatability. First, it shows the good complementarity of the following detectors KR+HEL, HEL+SU and KR+SI. Second, it shows which detector to use in combination to another in order to improve the repeatability. The best repeatability was given by FA, see § 5.1. Therefore, adding the feature points from the detector HEL can improve by 2.12% the repeatability of FA.

Distribution gain The segmentation S2 is used in our experimentation, see § 5.2. The results are shown in table 5. They show which detectors are the most complementary in terms of region based distribution. First, it shows the good complementarity of the

Table 5: Distribution gain. For each couple of detectors $D_1\&D_2$, we show $\text{gain}_{\text{RD}_{D_1\&D_2,S2}}$ ($\varepsilon = 3$) (see 4 for an example of how to read the table).

	BE	FA	HAL	HA	HEL	KA	KR	MO	SI	SR
FA	3.96	0								
HAL	2.23	1.30	0							
HA	**6.14**	5.11	1.19	0						
HEL	8.13	**7.80**	1.30	6.09	0					
KA	**8.53**	6.85	**7.09**	5.54	9.27	0				
KR	6.47	4.23	3.28	5.86	**7.98**	6.08	0			
MO	3.82	0.02	6.46	3.26	8.62	**12.07**	2.30	0		
SI	5.32	4.96	1.52	5.95	5.39	**6.88**	6.12	2.92	0	
SR	4.15	3.79	4.89	3.63	0.51	**11.58**	5.30	10.38	1.71	0
SU	6.16	0.10	3.30	4.18	**9.72**	**10.17**	3.20	3.27	4.45	7.12

Table 6: This table summarizes the most complementary detectors to Harris, FAST and SIFT in terms of contribution (Cont.) ($\varepsilon = 3$) (results are similar whether all the feature points or only the repeated points are taken into account), repeatability (R) and region based distribution (RD_{S2}).

D	Cont.	R	$\text{RD}_{D_1\&D_2,S2}$
HA	HEL	HEL	BE
FA	HEL	HEL	HEL
SI	HEL	KR	KA

following detectors KA+MO, KA+SU and KA+SR. Second, it shows which detector to use in combination to another in order to improve the spatial distribution. The best region based distribution was given by HA, see § 5.2. By reading table 5, we can see that adding the feature points from the detector BE can improve the distribution by 6.14% which gives a score of 86+6.14=92.14% for the union HA+BE.

Analysis These results can be read in two ways: (i) for each detector they give which detector is the most complementary in terms of contribution, repeatability and spatial distribution ; (ii) they give the most complementary detectors between them. The best compromises between repeatability and distribution are given by: Harris, FAST and SIFT. Table 6 summarizes the most complementary detectors to the detectors in terms of contribution, repeatability and region-wise distribution. The most complementary detectors between them are Kadir and SUSAN, Kitchen and Rosenfeld and Hessian-Laplace, Moravec and Kadir *i.e.* they return the most distinct sets of feature points.

6 CONCLUSION

We proposed an evaluation and a comparison of eleven well-known feature point detectors based on new criteria used to characterize spatial distribution and complementarity. This study aims to be helpful for any applications that need feature points well distributed in the image. It also helps to select the most complementary detectors in terms of region based distribution. This work will be extended on larger transformations between the images.

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