DETECTING IMAGE POINTS OF DIVERSE IMBALANCE

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ABSTRACT

Imbalance oriented selection scheme was recently proposed to select good candidates of interest points [1]. In this paper, we propose a method to quantify the local diversity of imbalance of an image point, which provides us a new interest strength assignment scheme. We test the proposed approach by repeatability evaluation and stereo matching and obtain promising results.

Index Terms— Interest points, imbalance, diversity

1. INTRODUCTION

Many existing interest point detectors include two basic steps: one step is to assign interest strength to images by certain filtering techniques such as Gaussian derivative and its variants [2, 3], Difference of Gausssian [4], and Laplacian [5]; the other step is to select a candidate set by non-maximum suppression. The interest points are then defined as the candidates of largest strengths.

A new candidate selection scheme, called imbalance oriented selection, was recently proposed to address sparsely-textured images. This scheme chooses image points whose zero-/first-order intensities can be clustered into two imbalanced classes as candidates. Unlike the non-maximum suppression, under imbalance oriented selection, there can be more than one interest point in a local window, which not only preserves good candidates in sparsely-textured images, but also improves the localization accuracy of interest points. Extensive experiments on repeatability evaluation were presented to confirm this advantage of imbalance oriented selection in [1]. However, the detector developed in [1] still follows the conventional filter based interest strength assignment scheme, and it is difficult for the detector to distinguish interest points from edge points if images are textureless.

In this paper, we propose to investigate the local diversity of imbalanced points. The basic idea is to categorize imbalanced points by the so-called index of the maximum difference [1] (details are given in Section 2). Fig. 1 shows an example of an image point of most diverse imbalance in an image of two polygons.

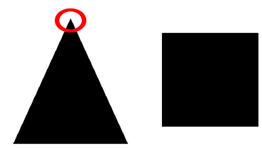

Fig. 1. The most diverse imbalanced point.

2. IMBALANCE ORIENTED SELECTION

Imbalance oriented selection aims to minimize the occurrences of edge points [1]. Since edge points have similar local appearances (i.e., not distinctive to each other), they increase the chance of mismatching in the higher-level applications. Edge points can be characterized as points of balanced local appearances. As shown in Fig. 2 (a), intensities are supposed to change slightly at the same side of an edge while they change significantly across an edge. Here, $n = 8$ directions are considered. A long (short) arrow indicates a strong (weak) intensity change along the associated direction. The number of long arrows is equal to the number of short arrows, which indicates the balance nature of an edge point. Fig. 2 (b) shows a case where the number of long arrows is not equal to the number of short arrows, which characterizes an interest point as an imbalanced point.

In [1], the authors proposed a sorting based approach to cluster the arrows into the two classes, as illustrated in the lower part of Fig. 2 (a) and (b). More specifically, the approach first sorts those first-order changes in increasing order, and then look for the first-order change whose difference with the next first-order change is maximum. The rank of this first-order change is called the *index of the maximum difference*, e.g., the circled numbers in Fig. 2 (a) and (b). In [1], the authors further consider a point whose index of maximum difference is larger than $n/2$ as a redundant point because of its co-occurrence of a certain point whose index of maximum difference is less than $n/2$.

It is clear that a larger n (more directions) gives more precise characterization of the imbalance of an image point. However, a larger n also increases computational cost. In this paper, we apply Bresenham's line algorithm to efficiently extract line segments for the computation of first-order change

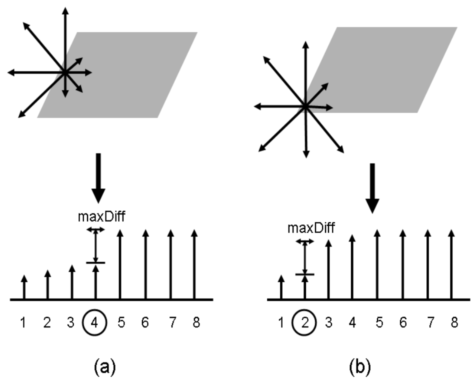

Fig. 2. (a) An edge point of balanced local appearance, where the index of maximum difference is 4 (half of 8 directions); (b) An imbalanced point, where the index of maximum difference is 2.

in each direction in order to reduce the computational cost.

3. DIVERSITY OF IMBALANCE

Imbalanced points can be contiguous. The underlying rationale is that regions such as the one around a triangle vertex contain rich geometry information, and thus deserve more number of interest points. Fig. 3 (a) shows the zoom-in upper region of the triangle overlaid by a number of detected imbalanced points labeled by their indices of maximum difference, where the number of directions n is set to be 64 (we will fix this number in the rest of this paper). This figure shows a typical behavior of imbalance oriented selection different from non-maximum suppression. The distribution of the index of maximum difference in the region (Fig. 3 (a)) supports the above rationale very well.

We can observe, from Fig. 3 (a), that an imbalanced point closer to the boundary of the corner region has smaller index of maximum difference, which is consistent with the intuition very well. However, due to digitization phenomenon (discrete space), we also observe certain counter-intuitive example, e.g., the pixel labeled by 6, in the bottom-left part of the illustrated image.

We propose an approach to address the digitization challenge by introducing the diversity of imbalance. More specifically, for each imbalanced point p, we accumulate the occurrence of imbalanced points of different index of maximum difference in its neighborhood $O(p)$. So, the number of occurrence (denoted by o) of imbalanced points in a neighborhood implies the rank of imbalance diversity of a point p. We quantify the rank of diversity by the number $n/2 - o$ (note that o is never over $n/2$). Smaller ranks indicate higher diversity. Fig. 3 (b) shows the zoom-in upper region of the triangle overlaid by a number of detected imbalanced points labeled by diversity strength, where $O(p)$ is a 7×7 window. Roughly speaking, the most diverse points are in the middle of the cluster of imbalanced points detected in the corner region.

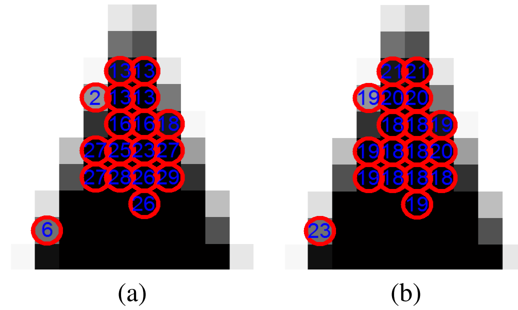

Fig. 3. Zoom in a corner region of the triangle: (a) showing the index of maximum difference; (b) showing the diversity strength

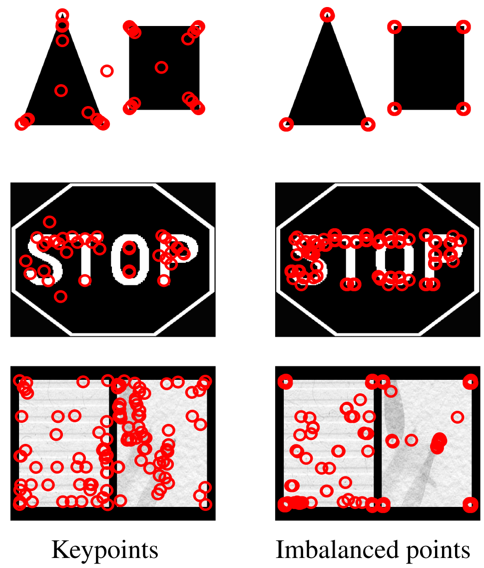

Fig. 4. Keypoints vs. imbalanced points.

Fig. 4 presents the interest points detected by the proposed detector and keypoint detector on three images of different types of textures: polygon, stop sign, and wallpaper. The keypoints detected in the polygon image illustrate a common phenomenon of scale-space point detectors.

4. EXPERIMENTS

In this section, we will first test the repeatability of the proposed detector, and then its performance on stereo matching.

4.1. Repeatability evaluation

We test the repeatability of the proposed detector across image rotations, compared with the imbalanced point detector [1] and keypoint detector [4]. We follow the definition of ϵ-

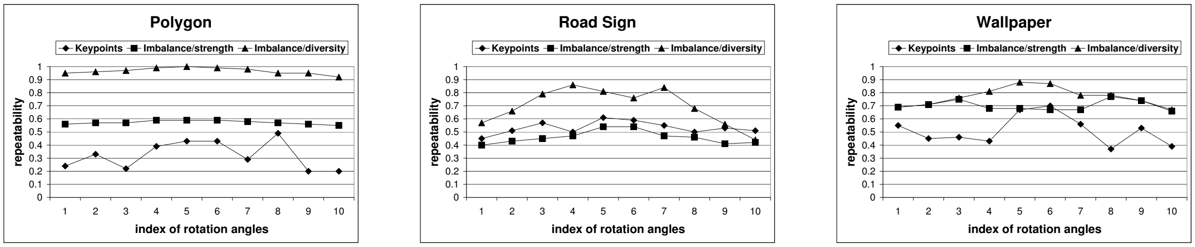

Fig. 5. Repeatability

repeatability rate proposed in [2]. The range of rotation angles is $\theta_i = -45^\circ + (i-1) \times 10, i = 1 \ldots 10$.

Fig. 5 shows the $\epsilon = 1.5$ repeatability rate, on three images in Fig. 4. Note that the first image is basically textureless (some edge points have blending intensities though), the second one contains simple intensity information, and the third one contains sparse textures. It is very interesting that the proposed detector performs extremely well on the textureless polygon image while the keypoint detector performs extremely poor. For the image of a stop sign, it is still clear for us to observe the superiority of diversity based detector over filter based detector. For the wallpaper image (of more textures), the proposed detector achieves the highest repeatability rate too.

4.2. Stereo matching

We now test the proposed detector, compared with the keypoint detector (with SIFT descriptor) [4], on stereo matching with epipolar geometry estimation [6]. It is well-known that the estimation of epipolar geometry is sensitive to mismatching and inaccurate localization. So stereo matching and epipolar geometry estimation can test not only the localization accuracy of detected image points but also the distinctiveness of the local appearances of detected image points. For an imbalanced point, we use its 5×5 window normalized by its local orientation as the descriptor, where the orientation is estimated by applying SVD to the distribution of neighboring imbalanced points.

Given an image, we apply vertical or horizontal perspective transformation to synthesize the second image. This approach provides a convenient way to evaluate estimated point correspondence. Note that the epilines associated with the vertical perspective transformation are expected to be horizontally parallel, and the epilines associated with horizontal perspective transformation are expected to be vertically parallel. Similar to [4], we apply the commonly used scheme to estimate point correspondence and epipolar geometry, i.e., first initialize point correspondence by correlation of the descriptors of detected points, and then apply RANSAC to prone outliers.

Fig. 6 shows the results of matched points and estimated epilines on three different types of sparsely-textured images: face, wall paper, and sky. The left two columns are results obtained from the keypoint detector, and the right two columns from the proposed detector. We can observe that the epilines computed from the proposed detector are perfectly consistent with the expectation.

5. CONCLUSIONS

In this paper, we propose a novel detector that detects image points based on the diversity of imbalance. It differs from existing detectors that apply conventional filtering techniques, e.g., Gaussian, DoG, and Laplacian, to assign interest strength. By repeatability evaluation and stereo matching, we have shown the superiority of proposed detectors.

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6. REFERENCES

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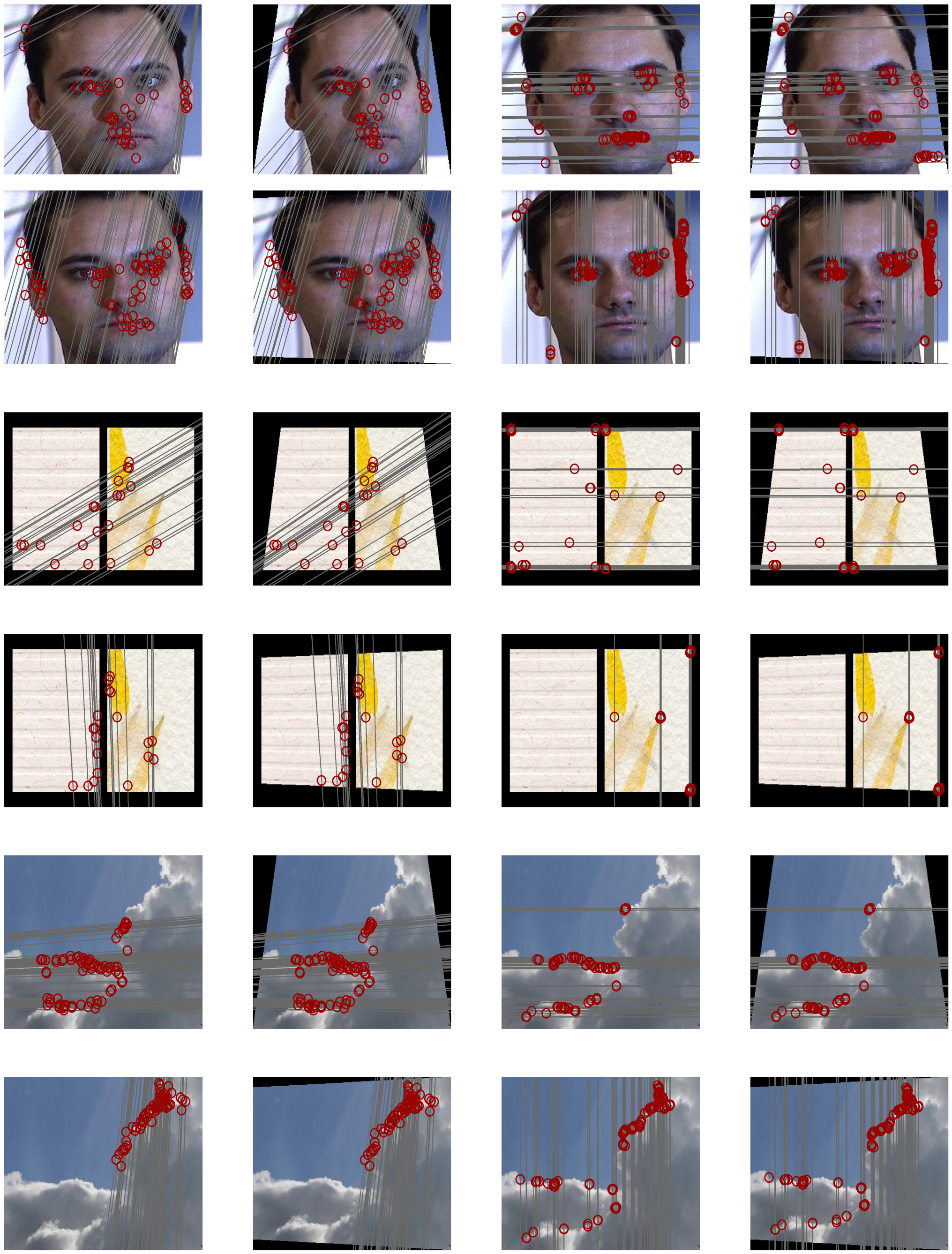

Keypoint detector　　　　Proposed detector

Fig. 6. Point matching and epipolar geometry estimation: Keypoint vs. Proposed