RIFNOM: 3D Rotation-Invariant Features on Normal Maps

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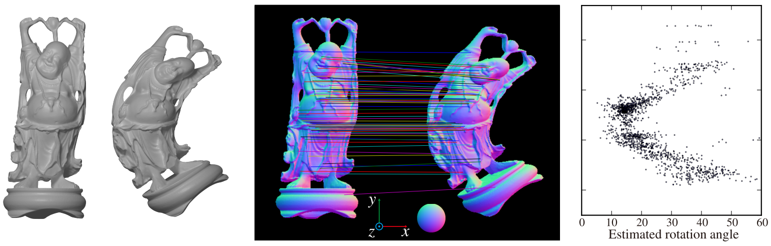

Figure 1: *Left: Images captured from Happy Buddha and deformed one. Middle: Interest point matching between normal maps with RIFNOM features. Right: Estimated rotation angles between corresponding interest points. The vertical axis of the graph corresponds to the vertical locations of the interest points on the original Happy Buddha.*

Abstract

This paper presents 3D rotation-invariant features on normal maps: RIFNOM. We assign a local coordinate system (CS) to each pixel by using neighbor normals to extract the 3D rotation-invariant features. These features can be used to perform interest point matching between normal maps. We can estimate 3D rotations between corresponding interest points by comparing local CSs. Experiments with normal maps of a rigid object showed the performance of the proposed method in estimating 3D rotations. We also applied the proposed method to a non-rigid object. By estimating 3D rotations between corresponding interest points, we successfully detected deformation of the object.

CCS Concepts

•***Computing methodologies*** → *Interest point and salient region detections; Matching;*

1. Introduction

Estimation of object motion is an important task in computer vision and has many applications, such as camera tracking [KM07]. One of the approaches to tackle this problem uses intensity image features and has achieved high accuracy [ANB13]. However, such image features depend on surface intensity or textures, so it is difficult to accurately extract correspondences between images of textureless objects. Several methods have been proposed to extract correspondences between images independently from surface textures by detecting interest points in 3D point clouds or normal maps. One of these normal-map-based approaches succeeded in extracting features from textureless objects [SAS15]; however, it cannot deal with continuous 3D rotation, and the rigid body assumption is needed to estimate object motion.

In this paper, we propose a method called 3D rotation-invariant features on normal maps (RIFNOM) to solve these problems. We assign a rotation-invariant local coordinate system (CS) to each pixel by using neighbor normals to extract RIFNOM features. These features can be used to perform interest point matching between normal maps. Comparison between local CSs of the corresponding interest points provides a 3D rotation estimate for each pair, so the rigid body assumption is not needed in the proposed method. Deformation of a non-rigid object can be detected by applying this method.

2. RIFNOM features

Definition of local CSs

In order to extract 3D rotation-invariant features, we assign a local CS (Σ_L) to each pixel, as shown in Fig. 2. The local z axis is set as a normal of the pixel $\vec{n}_c$. Let D be a disk perpendicular to the local z axis with a radius of R, and we assume that every neighbor normal is on disk D. Note that the disk is deformed by perspective projection onto the normal map. When the disk is small, we can approximate it as an elliptic plate. We define $\vec{n}'_i$ $(i = 1, 2, \dots N)$ by

DOI: 10.2312/egp.20181016

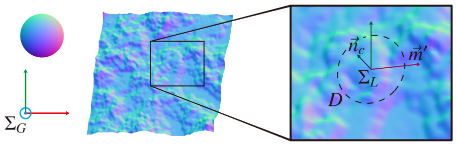

Figure 2: *Local CS Σ_L is assigned to each pixel. Local z axis and x axis are set as $\vec{n}_c$ and $\vec{m}'$, respectively.*

subtracting local z components from neighbor normals $\vec{n}_i$ on disk D as: $\vec{n}_i' = \vec{n}_i - (\vec{n}_c \cdot \vec{n}_i)\vec{n}_c$. The local x axis is determined as the direction of mean vector $\vec{m}' = 1/N \sum_{i=1}^{N} \vec{n}_i'$, and the local y axis is set as the cross product of the local z axis and the x axis. The local CS obtained at each pixel can be used to perform 3D rotation estimation.

Interest point detection

Local CSs should be noise-robust to improve the repeatability of feature extraction. If $\|\vec{m}'\|$ is close to zero, the direction of the local x axis can be significantly changed by perturbations. Therefore, interest points should satisfy the following inequality: $\|\vec{m}'\|^2 > t_{\mathrm{mean}}$. Also, points in flat regions have poor uniqueness for interest point matching. Since normals are almost constant in flat areas, these areas are excluded by using the criterion: $1/N \sum_{i=1}^{N} \|\vec{n}_i' - \vec{m}'\|^2 > t_{\mathrm{var}}$. We perform interest point detection according to these two criteria.

Feature description

We use a polar grid on disk D and calculate the locations of the grid points in image coordinate system Σ_G. Then, we obtain a normal at each grid point by using bilinear interpolation. RIFNOM features are obtained by extracting local x and y components of the normals at the grid points. Let N_r and N_θ be the number of partitions in the radial direction and the angular direction, respectively. We obtain the feature vector length of $2N_rN_\theta$.

Interest point matching and rotation estimation

Here we compare feature f extracted in a reference normal map to those extracted in another normal map. The mean squared error (MSE) is used to define similarity between features. Let f_1' be the best match to f and f_2' be the second-best match. If $\mathrm{MSE}(f_1', f) < t_{\mathrm{diff}}$ and $\mathrm{MSE}(f_1', f)/\mathrm{MSE}(f_2', f) < t_{\mathrm{ratio}}$, then the match is accepted. By comparing local CSs between corresponding interest points, 3D rotation is estimated for each pair of interest points.

3. Experiments

To show the robustness to 3D rotation of the RIFNOM feature, we applied the proposed method to a rotated rigid object. The parameters were set as follows: $R = 10\,\mathrm{px}$, $N_\theta = 20$, $N_r = 10$, $t_{\mathrm{mean}} = 0.15$, $t_{\mathrm{var}} = 0.15$, $t_{\mathrm{diff}} = 0.2$, $t_{\mathrm{ratio}} = 0.7$. Fig. 3 shows the performance of the proposed method. Estimated rotation angles and axes were obtained by using the inverse of Rodrigues' rotation formula. We also confirmed the performance for more challenging cases, and details will be shown in the poster.

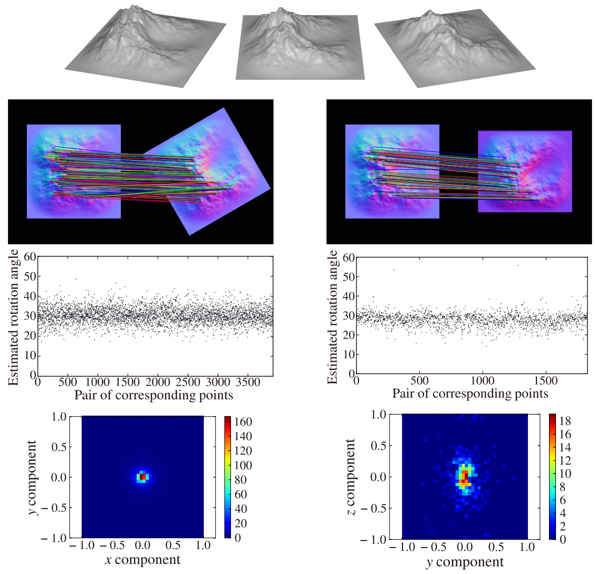

Figure 3: *The result for a rigid 3D model: Mountain. From the top, images of Mountain, interest point matching with RIFNOM features, estimated rotation angles, and estimated rotation axes. The mountain was rotated* 30 deg. *around the z axis (left) and the x axis (right), and we obtained 3918 and 1827 matches, respectively. For the sake of clarity,* 5% *of the accepted matches are drawn here.*

We also applied the method to a deformed object to show the performance of RIFNOM features in the case of non-rigid objects. We deformed Happy Buddha by rotating its upper and lower parts by −40 deg. and 40 deg. respectively around the z axis. After that, we rotated the whole body 15 deg. around the y axis, so the total rotation angles of its upper, middle, and lower parts were about 42.6 deg., 15 deg., and 42.6 deg., respectively. We successfully estimated rotations between corresponding interest points, resulting in the detection of deformation of the non-rigid object (Fig. 1).

4. Conclusion

This paper presents a method called 3D rotation-invariant features on normal maps. For each pair of corresponding interest points, we can estimate the 3D rotation by exploiting local CSs obtained at interest points. The performance of the method was shown in experiments with rigid and non-rigid objects. Future work will include introducing a scale space and binary descriptors and reducing computational costs.

References

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