

OBJECT RIGIDITY AND REFLECTIVITY IDENTIFICATION BASED ON MOTION ANALYSIS

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ABSTRACT

Rigidity and reflectivity are important properties of objects, identifying these properties is a fundamental problem for many computer vision applications like motion and tracking. In this paper, we extend our previous work to propose a motion analysis based approach for detecting the object's rigidity and reflectivity. This approach consists of two steps. The first step aims to identify object rigidity based on motion estimation and optic flow matching. The second step is to classify specular rigid and diffuse rigid objects using structure from motion and Procrustes analysis. We show how rigid bodies can be detected without knowing any prior motion information by using a mutual information based matching method. In addition, we use a statistic way to set thresholds for rigidity classification. Presented results demonstrate that our approach can efficiently classify the rigidity and reflectivity of an object.

Index Terms— Rigidity, Reflectivity, Mutual Information, Optic Flow

1. INTRODUCTION

Rigidity and reflectivity are significant properties of objects, identifying these properties is a fundamental problem of many computer vision applications like motion and tracking. Rigidity indicates an object's resistance to changing its shape. Reflectivity is commonly captured by means of bidirectional reflectance distribution function (BRDF) [1]. According to the surface reflectivity, objects are either diffuse or specular. Considering both the rigidity and reflectance, objects can be classified as four categories, namely, specular rigid, diffuse rigid, specular nonrigid and diffuse nonrigid, as shown in figure 1.

Detecting the rigidity and reflectance of an object would allow a computer vision system to rely more on appropriate measurements and improve performance. Methods for rapidly classifying the reflectivity and rigidity of an object would give the basis for automated recovery. However, the inference of rigidity and reflectance is difficult without additional information about the object's shape, the environment,



Fig. 1. From left to right: Specular rigid object; diffuse rigid object; specular nonrigid object; diffuse nonrigid object.

or lighting. Hence, most computer vision algorithms usually have strong assumptions about both the reflectivity and rigidity.

For example, structure from motion algorithms assume that the object is rigid. And it is difficult to extract the point motion information needed without diffusely reflective and patterned objects [2]. Although there are methods to handle both nonrigid structure from motion and shape from specular flow, these methods are derived under the assumption that the rigidity and reflective properties of the object are known [3, 4]. Previous methods for classifying material have largely relied on the ability to control the lighting in the scene, using multiple lights, structured lights, color, stereo, or combinations of these, see [5, 6, 7]. Oren and Nayar [8] developed a classification strategy to distinguish image points whose motions affected by specular reflectance from points behaving like diffuse reflectors based on caustic curves. Recently, we showed that the relative motions of object and observer provide a rich source of information for inferring object rigidity and reflectivity [9]. However, in that work, motion parameters are assumed to be known in advance.

In this paper, we extend our previous work and demonstrate that, without having any prior motion information, it is possible to detect rigid object motion for specular and diffusely reflecting surfaces by coupling the mutual information based motion parameter estimation and optic flow matching. We use a Procrustes analysis [10] of structure from motion [11] reconstructed 3D points to detect the reflectance of an rigid object. Besides, we also show how a statistic way of setting thresholds is utilized for the rigidity classification.

The presented results demonstrate that our approach can efficiently classify the rigidity and reflectivity of an object.

2. IDENTIFICATION SCHEME

In this section, we give an overview of the rigidity and reflectivity identification scheme. As shown in figure 2, the presented approach consists of two steps. The first step is to distinguish rigid and nonrigid bodies by coupling the motion estimation and optic flow matching. We use a combined global local differential method (CLG) for optic flow computation based on Bruhn et al. [12]. CLG yields accurate, dense flow fields that are robust against noise. To estimate motion parameters of objects, a mutual information based matching method, described in section 3, is employed.

It is shown in our previous work [9] that rigidity produces characteristic transformations in optic flows and it holds for objects with both diffuse and specular reflectance. Optic flow patterns of rigid motion bodies are the same up to the motion transformation. If there is sufficient matchable structures in the flow fields, rigidity can be identified by matching optic flows. However, in our previous work, the detection of rigidity assumes motion parameters are known. In this paper, no prior motion information is required. Motion parameters can be estimated by employing the mutual information based technique, and optic flow patterns are accordingly matched and measured in a quantitative way with the average angular error (AAE) [13]. Nonrigid objects tend to have higher AAE values, on the contrary, AAE values are lower for rigid objects. In this paper, we utilize a statistic way, detailed in section 4, to set thresholds for classifying the rigidity.

The second step is to identify the object's reflectance. Similar to our previous work, for the specular rigid and diffusely reflective rigid objects, structure from motion analysis is applied and a Procrustes analysis is utilized to evaluate the variation of reconstructed 3D shapes across time. Based on an average shape change (ASC) measure [9], we are able to distinguish specular and diffuse rigid bodies.

3. MOTION PARAMETER ESTIMATION

To evaluate the optic flow matching in a quantitative way, the global transformation of object moving should be first estimated. A mutual information based method is employed to align the computed optic flow amplitude images for estimating the motion parameters. In [14], a novel image matching approach based on the alignment by maximization of mutual information was proposed. The basic idea is, given two images of the same scene or objects, when their mutual information is maximized, they are considered to be matched. The concept of mutual information is closely related to the entropy. For a discrete random variable X , the Shannon entropy is defined as

$$\begin{aligned} H(X) &= -E_X[\log(P(X))] \\ &= -\sum_{x_i \in \Omega_X} \log(P(X = x_i))P(X = x_i), \quad (1) \end{aligned}$$

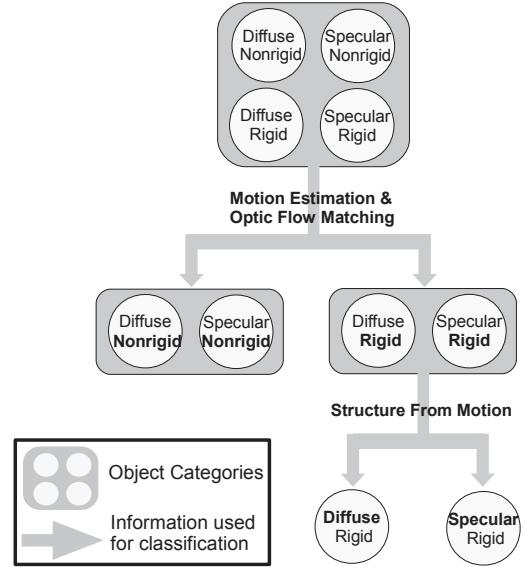


Fig. 2. Object rigidity and reflectance classification.

where E_X indicates the expected value function of X , $P(X)$ is the probability of X , Ω_X refers to the domain over which the random variable can range and x_i is an event in this domain.

Given two random variables X and Y , their joint entropy is defined as

$$H(X, Y) = -E_X[E_Y[\log(P(X, Y))]], \quad (2)$$

where E refers to the expectation, $P(X, Y)$ is the joint distribution of X and Y . The mutual information is then given by

$$I(X, Y) = H(X) + H(Y) - H(X, Y). \quad (3)$$

The way of matching two images is to find the transformation which gives the maximum mutual information. Let X be a random variable which ranges over the domain of an image m , $m(X)$ is thus a new random variable. If a transformation T is applied on m , we can get a mapped image n with $n(T(X))$ being a random variable. The mutual information of these two images is then given by

$$\begin{aligned} I(m(X), n(T(X))) &= H(m(X)) + H(n(T(X))) \\ &\quad - H(m(X), n(T(X))). \quad (4) \end{aligned}$$

Matching images m and n requires to find the transformation T by differentiating equation (4), that is

$$\begin{aligned} \frac{d}{dT} I(m(X), n(T(X))) &= \frac{d}{dT} H(n(T(X))) \\ &\quad - \frac{d}{dT} H(m(X), n(T(X))) \quad (5) \end{aligned}$$

To compute the transformation, the probability distribution should be first estimated. In this paper, we use a method

called Parzen windowing to estimate the random variable's probability density. Given a set S of n samples, the probability $P(X)$ of X occurring is the sum of the contributions of each sample s from S to $P(X)$. The contributions are functions of the distance between s and X . This results in the following definition of the probability of X given a sample s

$$P(X, S) = \frac{1}{n} \sum_{s \in S} W(X - s), \quad (6)$$

where the weighting function W is chosen to be a Gaussian function with the following form

$$g(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{x^2}{2\sigma^2}\right), \quad (7)$$

with σ being the variance of the Gaussian distribution. In order to maximize the mutual information, we use an optimization scheme proposed by [15]. A stochastic gradient method is employed to seek a local minimum of entropy and the gradient of the mutual information is computed in an iterative way by using a multi-scale scheme.

Based on the estimated motion parameters, optic flow patterns are accordingly transformed for further matching.

4. THRESHOLD SETTING

In order to distinguish rigid and nonrigid objects based on the AAE measures, a statistic way to set thresholds is utilized. Based on a computer generated diffuse rigid image sequence, we compute the corresponding optic flows and match them using the estimated motion parameters. The matched optic flow error data is assumed to have a Gaussian distribution. Then, we randomly generate two optic flow fields and make sure that their probabilities of having the same distribution with that of the diffuse rigid optic flow error are bigger than 0.8. Based on these two optic flow fields, corresponding AAEs are computed and regarded as the thresholds. Moving objects with AAEs below the thresholds are accordingly identified as rigid bodies. And the rest objects are classified as nonrigid.

5. EXPERIMENTAL RESULTS

To have a better evaluation of the presented approach, we work on four image sequences with real objects. Figure 3 shows four types of real objects: a shiny ballon (specular nonrigid), a diffusely reflective ballon (diffuse nonrigid), a shiny plate (specular rigid) and a box (diffuse rigid). For each sequence, the 1st, 60th and 100th frames are illustrated. All objects undergo a rotation with the view direction being the rotation axis. The deformation of nonrigid objects are manually made.

Using mutual information based matching, rotation angles are estimated as shown in figure 4. For every other 10 frames, we match the optic flow magnitude images with the model image (generated from the first two frames). It is revealed



Fig. 3. Rows from top to bottom: Specular nonrigid objects; diffuse nonrigid objects; specular rigid objects; diffuse rigid objects. Columns from left to right: 1st, 60th and 100th frames of the corresponding image sequences.

that estimated results of the rigid objects are very close to the ground truth. With the increase of deformation, estimated rotation angles of nonrigid objects are increasingly far away from the ground truth. However, since the mutual information of the two images are maximized, these angles with bigger errors enable more accurate optic flow matching than that based on the ground truth.

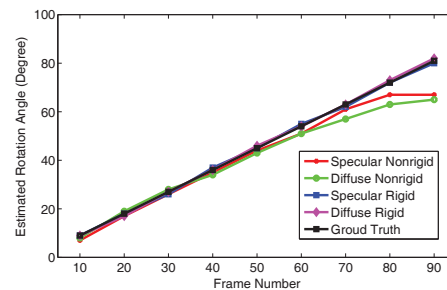


Fig. 4. Estimated rotation angles for four objects.

Using the estimated rotation angles, optic flows are matched for every other 10 frames and results are demonstrated in figure 5. It is shown that rigid objects have lower AAEs than the thresholds. Hence, nonrigid and rigid bodies can be distinguished.

We track object features across the duration of a sequence, and compute the ASC by comparing shape changes between the first and second 50-frame block. Figure 6 illustrates the average shape change measure for the specular and diffuse

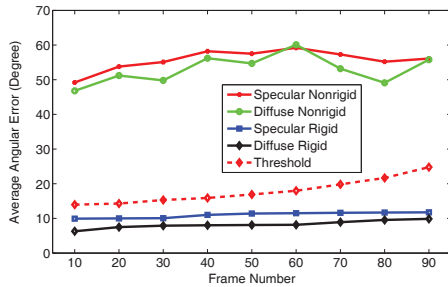


Fig. 5. Average angular errors between an initial flow field based on frames 1-2 and subsequent fields as a function of frame number.

rigid objects. Results demonstrate that the specular rigid object has much high values of average shape change, however, these values are much lower for the diffuse rigid objects. Based on the ASC measure, specular and rigid objects can be clearly classified.

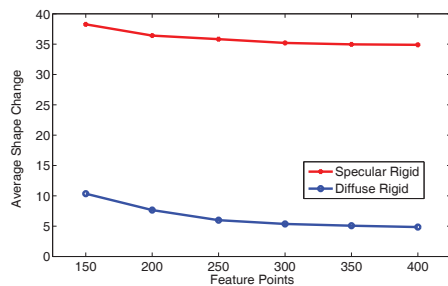


Fig. 6. Average shape change measure with respect to different feature points.

6. CONCLUSIONS

In this paper, we propose a motion analysis based approach to identify the rigidity and reflectivity of an object. Without having any prior motion information, rigid bodies can be classified by using a mutual information based motion parameters estimation and optic flow matching. In addition, a statistic way to set thresholds for classifying rigidity is utilized. To distinguish specular and diffuse rigid objects, we apply a Procrustes analysis of structure from motion reconstructed 3D points. Presented results demonstrate that our approach can efficiently classify an object's rigidity and reflectivity.

7. REFERENCES

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