Improving Accuracy and Efficiency of Spin-Image Algorithm using Interest Points Detection for 3-D Surface Registration

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***Abstract*— In Three-dimensional (3D) objects, the aim is to detect a few prominent structures, which can be used, instead of the whole object, for applications like object registration, recognition, retrieval and mesh simplification. The Interest Points Detection (IPD) on 3D mesh data is a significant tool in computer vision and pattern recognition. In this paper we present a IPD algorithm on 3D manifold triangular meshes using extension of the Harris operator and computing their corresponding descriptors. We propose extension of Harris operator using Fitted Quadratic Surface (EHOFQS) for IPD. The proposed algorithm has been applied to the task of 3D surface registration. An interest point detection and combine with a spin image algorithm to register 3D images data. This method make use of the Harris Operator Extension method of IPD on 3D manifold triangular meshes in Barycentric coordinates. Using this approach, we can extract the object correctly and effectively in noise situation. The unique advantage of this framework is its applicability to triangular meshes models. Experimental results show the quality of this IPD with EHOFQS was measured using the repeatability criterion and EHOFQS is faster than EHOGFP. It can provide sufficient information for surface registration. On a different number of models are shown to demonstrate more accurate and effectively results for global registering 3D Objects triangular meshes for three pairs of corresponding interest points features.**

Keywords*— *Harris operator; Interest points detection; Barycentric coordinates; Fitted Quadratic Surface

I. Introduction

Applications such as mesh registration and recognition usually necessitate that same interest points are detected in different mesh representations of a 3D object. Because of that, The interest points detection (IPD) should have two important parameters : the repeatability and the accuracy. This paper proposes an extension of the IPD methods using Harris Operator Extension method on 3D manifold triangular meshes on Barycentric coordinates. This method is combined with a spin image algorithm for registration and recognition. The advantages of this proposed method is that the objects are extracted more correctly and effectively in noise situation. As surface acquisition 3D range images are becoming more popular and widely used for the 3D geometric data in many applications of geometric modeling, computer graphics and computer vision, such as 3D object registration and recognition, feature detection, discrete surface segmentation, rendering and shape recovery. In 3D object registration, such features are usually local around a point in the sense that for a given point in the scene its closeness is used to determine the corresponding feature. This task consists of two major phases, namely the identification of appropriate points, often referred to as interest points, feature points, salient points or key points and the way in which the information in the near of that point is encoded in a descriptor or description vector. They are those points which are distinctive in their locality. ([1]–[3],[4]–[6],[7],[8],[9]).

In this paper we present the IPD method together with a feature descriptor for points in 3D range data through 3D Harris operator extension, local covariance computation, PCA (Principal Component Analysis) and Barycentric coordinates. The outer forms are often rather unique so that their explicit use in the interest point extraction and the descriptor calculation can be expected to make the overall process more effectively and accurate. For this purpose, we also present a method to extract those points.

A well-known IPD algorithm called extension of Harris operator using Gaussian function points (EHOGFP) has been widely used for this task [10]. However, EHOGFP is very sensitive to outlier points and noise. To address the noise and computational problem, a fast and accurate measure is desired. In this paper, we propose IPD algorithm using the Harris operator [11] named extension of Harris operator using Fitted Quadratic Surface (EHOFQS). EHOFQS can be viewed as a special Harris operator extended to 3-D space for IPD. In our method, we construct a combined extension of Harris operator and fitted quadratic surface .

This paper addresses the above issue by proposing a 3D object IPD algorithm based Barycentric coordinates. This framework gives a unique and viewpoint-independent description of a local shape. We introduce a method for interest points extracting the local features from 3D manifold triangular meshes data. Finally, Our proposed method is applied on a variety of 3D models with different noise levels to demonstrate its accurate and effectiveness.

The block diagram of our method is shown in Fig. 1. Given a 3D manifold triangular mesh, the main process is experimented in a vertex-wise mode. The overall process consists of five steps. Firstly, our algorithm performs a 3D acquisition data of images around a vertex. Secondly, the subsequent tasks are experimented over this local neighborhood on Barycentric coordinates. Thirdly, the neighborhood is computed so that it is prepared for a fitted a quadratic surface to the set of transformed points. Using least square approach, we discover a paraboloid form. This surface is a good representation phase of the locality and we take and put it as an local image. Fourth, we propose to calculate derivatives using a smoothing over the surface. We can use these derivatives for computing the Harris response for each vertex. Finally, our method determines the final set of IPD. A prelude work version of our method has been presented in a international conference paper [12].

The organization of this paper is as follows. The Harris Operator using Gaussian Function Points is provided in Sect. 2. Feature Description Method for IPD is presented in Sect. 3. In Sect. 4, we construct pairwise surface registration. In Sect. 5, we present the experimental results using EHOFQS, comparison with EHOGFP for IPD and its application in Surface Registration. Finally, Sect. 6, concludes this study and suggest directions for future work.

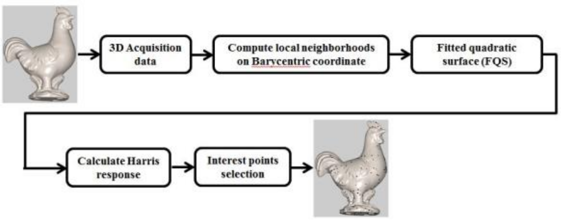

Fig. 1. Interest Points Detection algorithm.

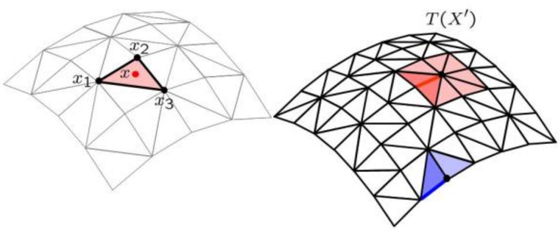

Fig. 2. Barycentric coordinates on manifold triangular mesh.

II. HARRIS OPERATOR

A. *Using Gaussian Function Points*

The traditional (2D) interest interest points detector for images was proposed by Harris and Stephens [11], and has gained popularity due to its strong invariance to rotation, scale, illumination variation and image noise. The 2D Harris interest points detector is based on the local auto-correlation surface (ACS), which compute how stable this metric is with respectto small variations in position Δx by comparing an image patch against itself. Glomb [10] experimented a technique similar to Harris and Stephens [11] interest points detector for 3D data images. It is performed to analyze the matrix E as eigenvalues. This matrix is made up of enough local information related to the structure of neighborhood. The views of an input object (range images) in the creation of point clouds are first converted into manifold triangular meshes. The definition of a data structure for boundary representations, such as manifold triangle meshes, involves the topological entities coding (with the linked up geometric information) and of a suitable subset of the topological relationships between such entities. The Fig. 2 show a data structure of 3D object.

In this paper, we confine our discussion to the IPD that are designed to work on 3D manifold triangular mesh models. First, We intend to carry out vertices and Vk the neighborhood considering k rings around v. We calculate the centroid and translate into the origin of the Barycentric coordinates system. Then, we compute the best fitting plane to the translated points based on principal component analysis in a local neighborhood. Next, the set of points is rotated so that the normal of the fitting plane is the z-axis. EHOGFP, computing in in the 3D manifold triangular mesh for each candidate costs too much computational time. In order to solve these possible problems, a EHOFQS proposed here to calculate derivatives for IPD.

B. *Using Fitted Quadratic Surface*

Derivatives calculation perform to fit a quadratic surface to the set of transformed points. Using least square approach, we discover a paraboloid of the form [13]. The difficulty raise up because in the original expression the derivatives are discrete functions and our derivatives are continuous functions. To solve this problem, we propose to apply the integration of the derivatives with a continuous Gaussian function as follows [7]. Because our method use Barycentric coordinates ([14][12]), then if the object tessellation is uniform, i.e., almost all triangles in the manifold triangular mesh have the same size, we can use a constant number of rings to all points, or use the points contained in a ball of radius r and centered in point v.

III. Feature Description Method

Johnson and Hebert [1] introduced Spin images (SI) method in the seminal work of a feature description method to characterize the properties of 3D object with respect to a single oriented point. It is a surface representation that uses 2D images to describe 3-D oriented points. Each spin-image is a local surface descriptor calculated at an oriented point (p,n) (3D point with normal vector) by encoding two of the three cylindrical coordinates of the its surrounding points. The spin-image X for a surface point p is a 2D histogram in which each pixel is a bin that stores the number of neighbours that are a distance a from n and a depth b from its tangent plane P. More precisely, it is assume that all the 3D data given as mesh triangular of 3D Objects Mesh = V,E where V are the vertices and E the edges.

Given a vertex P $\in$ V. The spin image axis are the normal to the point P, and a perpendicular vector to this normal. The former one is called β and the latter one α. The support region of a spin image is a cylinder centered on P, and aligned around its normal. From this, each point of the model is assigned to a ring with a height along β, and a radius along α as shown in Fig. 3. The similarity of two spin-images is measured by calculating their correlation coefficient.

The registration of two different views are performed by finding the correspondences between points on the surfaces using the similarity of their spin-images. Correspondence pairs with highest similarity that are geometrically consistent are selected to estimate the rigid transformation that registers the surfaces. As the surface positions chosen to compute spin-images are selected randomly, this may reduce the accuracy of the registration as a result of missing important geometric structures. By incorporating our feature selection framework into the spin-image algorithm, we can improve interest points features in the matching process and the accurate as the number of features is significantly smaller than the number of randomly selected points [1].

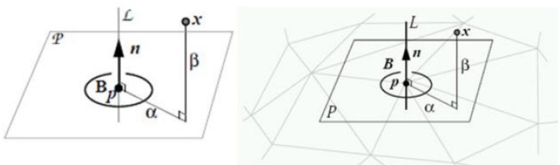

Fig. 3. Spin Image.

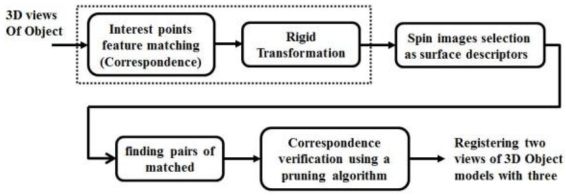

Fig. 4. 3D object registration algorithm.

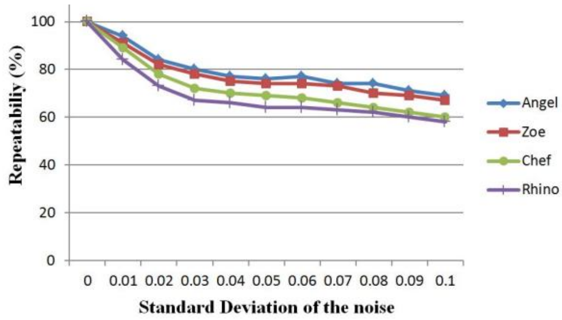

Fig. 5. Repeatability IPD.

IV. Pairwise Surface Registration

The registration of 3D datasets such as range images (or views) is performed pairwise and it can be divided in two steps. First, the views are coarsely registered and second, the 3D registration is refined with a fine registration algorithm as shown in Fig. 4.

Coarse registration is furthered by a fine registration algorithm which iteratively refines the initial coarse registration. By finding the match that registers the largest number of interest point features between the two range images, the best transformation is able to be estimated. This transformation can be follow refined using a variant of the Iterative Closet Point (ICP) algorithm [15],[16]. To solve among the set of all rigid transformation using the solution to the local minimization problem . Then, Spin images selection as surface descriptors and finding pairs of matched. Next, Correspondence verification using a pruning algorithm[17]. Last, Registering two views of 3D Object models with three pairs of corresponding features.

V. Experimental Results

Our proposed a framework feature extraction method was tested on a variety of standard 3D models. The IPD extracted from four different 3D models. The ’Chef’, ’Parasaurolophus’, ’Buddha’, ’Dragon’, ’Chicken’ and ’Rhino’ models could be downloaded from the Mian’s web side as in [3] and [18]. The ’Dragon’ and ’Buddha’ models were found from the Stanford 3D Scanning Repository as in[19]. The ’Angel’, ’Bigbird’ and ’Zoe’ models were taken from B. Taati Queen’s Range Image and 3-D Model Database from Queen university web side as in [20] and [21]. It can be analyzed from the figures that most of the salient positions in the models such as locations close the noses, mouths or eyes of the Buddha and Chef, the tail of the Rhino, Angel and zoe together with many others were selected as feature points, as shown in Fig. 5.

The comparison between the number of interest points and the number of vertices in each model as shown in Table I.

TABLE I. NUMBER OF INTEREST POINT DETECTION

No	Models	Number of vertices	IPD
1	Dragon	134559	3929 (2.92 percent)
2.	Rhino	79934	1287 (1.61 percent)
3.	Zoe	5002	166 (3.31 percent)
4.	Buddha	133127	2929 (2.22 percent)
5.	Parasaurolophus	184933	3458 (1.87 percent)
6.	T-rex	176508	2995 (1.70 percent)
7.	Chicken	135142	2608 (1.93 percent)
8.	Bigbird	5003	159 (3.17 percent)
9.	Cheff	176920	2672 (1.51 percent)
10.	Angel	4998	160 (3.14 percent)

It can be showed that the number of IPD is significantly smaller than the number of vertices in all 10 surfaces. Although the set of interest points contains just a small percentage of the manifold triangular surface data, it is still a sparse but well-described representation of the geometric structures in the model as evident. The extension of Harris operator combined with FQS (EHOFQS) for IPD in 3D manifold triangular meshes on Barycentric coordinates can be computed faster than EHOGFP measure. Fig. 6 shows the running time in the experiment for computing 400 Harris operator values.

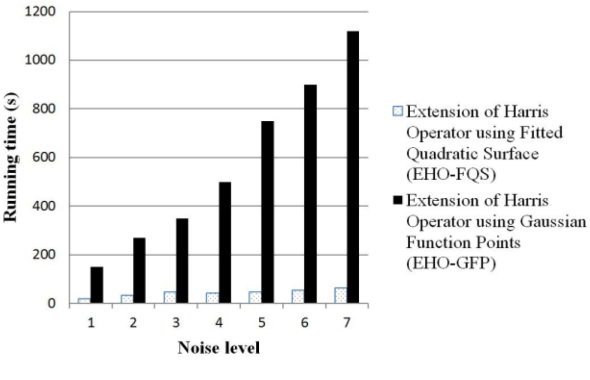

Fig. 6. Comparison EHO-GFP and EHO-FQS

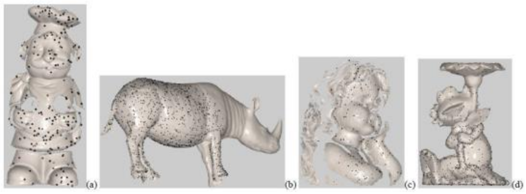

Fig. 7. Feature extraction results.

The noise which is used in the experiment is 1 to 7 and the has mean Gaussian noises from 0 to 100. Feature points detection from the Chef, Rhino, Zoe and Angel models for different levels of noise as shown in Fig. 7.

It can be looked from the figure that a large portion of local points feature from original, smooth surface are described in the noisy versions. In order to evaluate the repeatability of the feature points, white Gaussian Noise with standard deviation σ is set at various values: $\sigma = 0.05, 0.1, 0.2$ for chef and rhino, $\sigma = 0.05, 0.1, 0.2$ for Angel view and Zoe model. The impacts of noises on the surface Chef and Angel view models are shown in Fig. 8. The results show that the variation of local surface patches will increase. Overall, there would be more features points detected in noisy images compared the original one. The repeatability evaluation method that use in this work use as in [22]. At the level noise level $\sigma = 0.05$ nearly all of the features in the original model can be detected in the noisy surface. Even when the standard deviation of the noise goes to $\sigma = 0.2$, about 0.51 of the original features repeat in the noisy data. The 3D registration results as shown in Fig. 9 represent to register two different views and the correspondences of these features were searched through all vertices of the other view to improve the probability of finding matches. The results from Table II, III and IV show the comparisons of translation and rotation errors between the spin image and our proposed method. They can be analyzed that our proposed method overcome the spin image method in both the translation and rotation error metrics. Therefore, this proposed method a very suitable result for any global or coarse registration algorithm.

The SIs were selected features 201, 189, 105 and 114 for the Chef, Rhino, Angel and Zoe models as surface descriptors in order to perform 3D Registration with the IPD features proposed method. Our proposed method produced more accurate results as the average registration errors were 1.980, 1.783, 1.232 and 1.345 compared to 1.901, 1.701, 1.129 and 1.318 for the Chef, Rhino, Angel and Zoe models if using random points, respectively. Then, SIs are selected as surface descriptors in order to apply 3D surface registration using our proposed IPD features extraction. The pairwise registration as shown in Fig. 8 represent to register two different views and the correspondences of these features were searched through all vertices of the other view to improve the probability of finding matches.

TABLE II. COMPARISON OF REGISTRATION IPD AND LOCAL SHAPE FEATURES (LSF)

No	Models	Registration	Time	Avg. Error
1	Cheff	IPD (6531)	3m14s	1930
		LSF (201)	55s	1931
2.	Rhino	IPD (5674)	3m04s	1783
		LSF (189)	47s	1701
3.	Angel	IPD (4073)	2m14s	1232
		LSF (105)	50s	1129
4.	Zoe	IPD (4809)	2m46s	1345
		LSF (114)	45s	1318

TABLE III. COMPARISON OF TRANSLATION ERRORS SPIN IMAGE (SI) AND PROPOSED METHOD (PM)

No	Models	Method	x Translation	y Translation	Z Translation
1	Cheff	SI	3.33	35.56	121.38
		PM	2.24	7.69	17.85
2.	Rhino	SI	11.67	34.77	22.89
		PM	1.57	2.45	1.56
3.	Angel	SI	4.44	21.67	22.67
		PM	3.56	16.89	16.85
4.	Zoe	SI	5.85	1.46	1.28
		PM	4.24	1.25	1.04

TABLE IV. COMPARISON OF ROTATION ERRORS SPIN IMAGE (SI) AND PROPOSED METHOD (PM)

No	Models	Method	x Rotation	y Rotation	Z Rotation
1	Cheff	SI	25.83	3.46	3.87
		PM	0.75	0.92	2.81
2.	Rhino	SI	8.12	4.34	8.09
		PM	0.65	0.72	1.01
3.	Angel	SI	4.01	0.78	0.85
		PM	0.67	0.49	0.78
4.	Zoe	SI	0.94	3.12	2.76
		PM	0.41	2.23	0.94

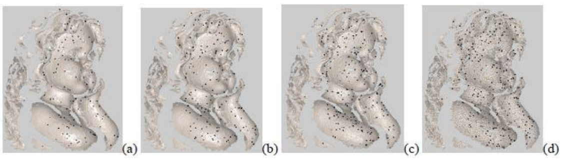

Fig. 8. IPD with different noise levels.

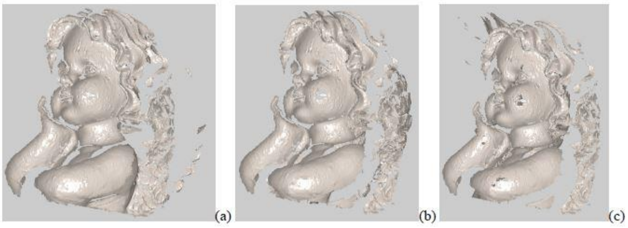

Fig. 9. Registration for four different views of Angel model.

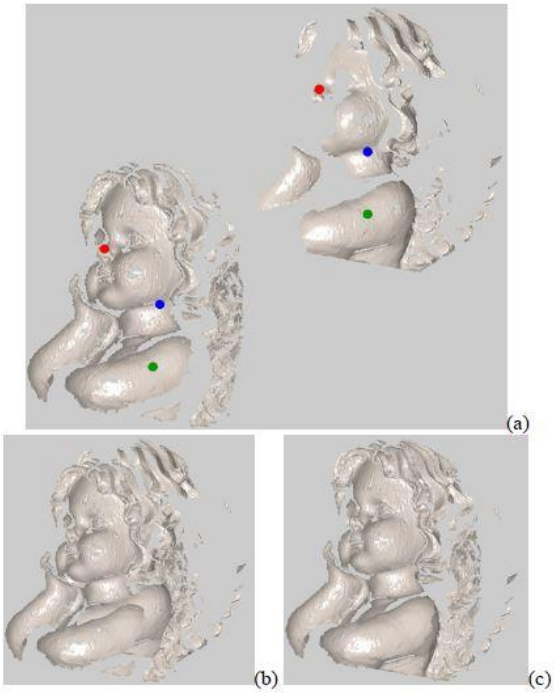

Fig. 10. Pairwise registration for four different views of Angel model

We combined our proposed IPD features method and the SI algorithm as local surface descriptors to register two different views of 3D object models. In Fig. 10 shows the accurate of pairwise registration for global registering 3D object models for three pairs of corresponding IPD features.

VI. CONCLUSION

In this paper, we propose IPD using Harris Operator extension for 3D manifold triangular meshes based Barycentric coordinates is proposed for global registering 3D object models for three pairs of corresponding IPD features. On Initial experiments on a number of different standard triangular meshes described that the method could accurately detect and localize local features from surfaces. The result of experiments showed the effectiveness and accurately of the approach. The High repeatability of the points features and accurate pairwise registration. The our proposed method is used as a preprocessing step in order to improve the accuracy and efficiency of the SI 3D object registration algorithm.

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