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Computing Local Binary Patterns on Mesh Manifolds for 3D Texture Retrieval

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Abstract

In this paper, we present and experiment a novel approach for retrieving 3D geometric texture patterns on 2D mesh-manifolds (i.e., surfaces in the 3D space) using local binary patterns (LBP) constructed on the mesh. The method is based on the recently proposed mesh-LBP framework [WBD15]. Compared to its depth-image counterpart, the mesh-LBP is distinguished by the following features: a) inherits the intrinsic advantages of mesh surface (e.g., preservation of the full geometry); b) does not require normalization; c) can accommodate partial matching. Experiments conducted with public 3D models with geometric texture showcase the superiority of the mesh-LBP descriptors in comparison with competitive methods.

Categories and Subject Descriptors (according to ACM CCS): I.3.5 [Computer Graphics]: Computational Geometry and Object Modeling—Curve, surface, solid, and object representations

1. Introduction

The geometric information captured by 3D acquisition devices is typically in the form of a cloud of points, which represents the 3D-coordinates of a set of samples of the object surface. The direct processing of these point clouds is not convenient or even possible, so that other representation formats have been established. Depth images are one of the most commonly used imaging modality, since they permit a direct extension to the depth dimension of many computer vision and pattern recognition solutions developed for analyzing the photometric information in 2D images. Though the possibility of a straightforward extension of 2D techniques is attractive, this modality loses the full 3D geometry, by reducing it to a 2.5D projection. The full 3D shape information is instead preserved and encoded in a simple, compact and flexible format by the triangular mesh manifold modality. The recent advances in shape scanning and modeling have also allowed the integration of both photometric and geometric information into a single support defined over a 2D mesh-manifold embedded in 3D. However, despite the abundance and the richness of the mesh manifold modality, the number of solutions for representing the geometry of 3D objects is still limited, and not comparable with the large variety of methods available in 2D. An evidence of this is given by the lack of efficient descriptors to represent the texture component associated to 3D objects. This motivated us to focus on this aspect that can reveal new possibilities in 3D objects retrieval and recognition. In particular, we consider the 3D *geometric texture* as a property of the surface, distinct from the shape, which is characterized by the presence of repeatable geometric patterns (see Figure 1). These patterns can be seen as geometric corrugations of the surface that do not alter the overall 3D shape, but rather change the local smoothness and appearance of the surface. This can result in 3D objects that show similar or equal shape, but very different 3D geometric texture. For capturing this aspect of the 3D object appearance on a mesh support, consolidated approaches do not exist.

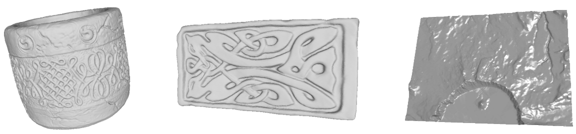

Figure 1: *Example 3D objects characterized by repeatable patterns of the mesh surface (i.e., geometric texture).*

In the literature, the problem of representing the 3D geometric texture has been not addressed directly; rather, it has been managed as a component of the surface shape either recurring to 3D shape descriptors [JH99, OFCD02], that in the large part are not adequate to capture 3D geometric tex-

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ture, or resorting to the 2D case by applying 2D descriptors to planar projections of the 3D surface, in the form of depth images. In this paper, we address the above shortcomings building on the framework of Local Binary Pattern (LBP). Since its first formal definition [OPH96], the LBP has established itself as one of the most effective local shape descriptors for image representations. It has been originally introduced for representing 2D textures in still images, but its computational simplicity and discriminative power attracted the attention of the image processing and pattern recognition community for other tasks. Rapidly, LBP has found applications in visual inspection [CLLH09], remote sensing [LSF05], face recognition [AHP06], facial expression recognition [SGM09], and motion analysis [WM10]. However, the LBP-based methods developed so far operate either on photometric information provided by 2D color images or on geometric information in 2D depth images. The few solutions that extract surface features directly in 3D (typically in the form of surface normals), resort to the 2D case by converting the 3D extracted features to depth values, and then use ordinary LBP processing on 2D images [SZP12]. Recently, LBP construction on triangular mesh manifolds has been introduced in [WBD15]. The mesh-LBP framework keeps the simplicity and the elegance of the original LBP, while relieving the recognition process from the need for normalization, and preserving the full 3D geometry of the shape.

In this paper, we target the problem of representing the 3D texture properties of 2D mesh-manifolds for retrieval applications. In particular, we propose to use the recently proposed mesh-LBP concept [WBD15] to address the above challenges. To the best of our knowledge, this paper is the first one to present and apply a framework, which enables an elegant and effective representation of 3D geometric textures. To show the potential and the suitability of mesh-LBP for such task, and contemporarily show the inadequacy of existing descriptors, two applications have been proposed and investigated: 1) A retrieval approach of 3D objects based on the 3D geometric texture of the surface; 2) A retrieval of terrain models, where the occurrence of small 3D terrain patches is searched for similarity in large terrain mesh models. In both these applications, mesh-LBP shows the capability to construct effective representations, relieving the recognition process from the need for registration and normalization procedures, while preserving the full 3D geometry of the shape. The rest of the paper is organized as follows: In Sect. 2, we give an overview on the mesh-LBP concept; In Sect. 3, the 3D texture retrieval scenario is introduced and the mesh-LBP results are presented in comparison to other solutions; Concluding remarks are discussed in Sect. 4.

2. LBP descriptor on 2D mesh-meanifolds

Werghi et al. [WBD15] elegantly extended the LBP concept to the 2D mesh-manifold by proposing a simple yet efficient technique for constructing sequences of facets ordered in a circular fashion around a central facet (see Figure 2).

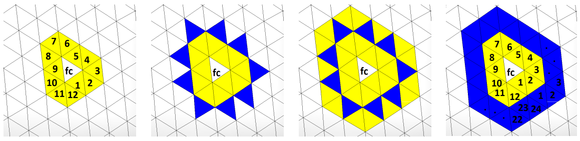

Figure 2: *Generation of a sequence of rings of ordered facets providing the support for computing mesh-LBP.*

The so obtained structure of ordered and concentric rings around a central facet forms an adequate support for computing LBP operators (referred as mesh-LBP in [WBD15]) at different radial and azimuthal resolutions, while preserving the simplicity of the original LBP. Let $h(f)$ be a scalar function defined on the mesh, which can incarnate either a geometric (e.g., curvature) or photometric (e.g., color) information. The mesh-LBP operator is defined as follows:

$$meshLBP_m^r(f_c) = \sum_{k=0}^{m-1} s(h(f_k^r) - h(f_c)) \cdot \alpha(k) \,, \qquad (1)$$

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \,,$$

where r is the ring number, and m is the number of facets uniformly spaced on the ring. The parameters r and m control, respectively, the radial resolution and the azimuthal quantization. The discrete function $\alpha(k)$ permits different LBP variants: with $\alpha(k) = 2^k$ the mesh counterpart of the basic LBP operator firstly suggested in [OPH96] is obtained; with $\alpha(k) = 1$ we obtain the sum of the digits composing the binary pattern (these two functions are referred by α_1 and α_2, respectively). To cope with mesh tessellation irregularities, the scalar function $h(f)$ is interpolated and sub-sampled across each ring, allowing thus to maintain a constant azimuthal quantization. In [WBD15], it has also been found that the majority of patterns have a number of 0-1 transitions below 4 (uniform patterns), which are used in the following.

3. Retrieval based on 3D geometric texture

We consider the 3D geometric texture as a property of the surface, distinct from the shape, characterized by the presence of repeatable geometric patterns. These patterns can be seen as geometric corrugations of the surface that do not alter the overall 3D shape, but rather change the local smoothness and appearance of the surface. This can result in 3D objects that show similar or equal shape, but very different 3D geometric texture. This concept can find applications in distinguishing and retrieving 3D objects where the information of interest lies in the geometric texture of the surface, rather than in the shape (Sect. 3.1), or in the identification of textured query patches in large textured surfaces where the shape feature cannot be effectively used, being it vague or even impossible to represent (Sect. 3.2).

3.1. Textured objects

In this experiment, we assume a sample of specific 3D texture (probe) is available, and we want to automatically detect regions, in a gallery surface, matching that particular probe. To the best of our knowledge, we are the first to attempt retrieving geometric texture on a mesh manifold. The experiments aim to showcase the potential of the mesh-LBP and its performance for such a task in comparison with other standard descriptors. Therefore, we used a naive template-matching-like method, where the gallery mesh surface is browsed, and at each facet a texture descriptor is computed and compared to its probe texture counterpart using a given metric (i.e., the Bhattacharyya distance in this application). Facets exhibiting a distance below a certain threshold are selected as a potential match.

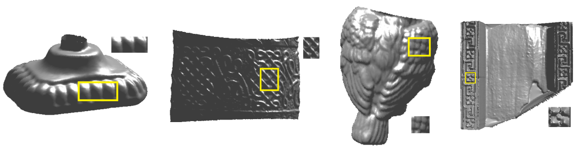

Figure 3: *Surfaces extracted from the bird, pot owl, and mural models, and their corresponding position, highlighted with a rectangle, in the probe models.*

In the experiments, we considered as gallery a representative set of four surfaces (see Figure 3), exhibiting different global and local shape characteristics. These surfaces were extracted from the *bird*, *pot*, *owl*, and the *murail* objects in the MIT CSAIL database [mit08]. The order of the aforementioned objects reflects an ascending level of 3D texture retrieval complexity. The fourth model (*murail*) is a U-shaped surface, composed of harsh flat bottom surface, and two border textured bands. The texture retrieval is deemed the most complex for this object, because what we want to retrieve here, is not the textured areas, but rather a particular 3D shape pattern in the textured surface, shown in the probe sample in Figure 3. The experiment consists in searching each probe within its corresponding surface and then assessing the detection and retrieval capacity of the different descriptors. In so doing, we computed the α_2 mesh-LBP variant, using the *Gaussian curvature* (K), *mean curvature* (H), *angle between facets normal* (D), and *curvedness* (C) as surface functions. In addition, we compared the mesh-LBP with other standard 3D surface descriptors including: the *Shape Distribution* variants [OFCD02], $D1$, $D2$, $D3$, $D4$, and $A3$ (best results are obtained and reported for the $D1$ and $D4$ variants); the *Spin-Images* [JH99]; and the recently proposed *Intrinsic Shape Context* (ISC) descriptor [KBLB12].

Figure 4 shows the maps of the Bhattacharyya distance computed at each facet, and the related retrieval results for the *murail* object (results for the other objects are not reported here due to space limitations). Referring to the distance maps (first row), none of shape distribution descriptors seems capable of detecting the 3D probe pattern. The

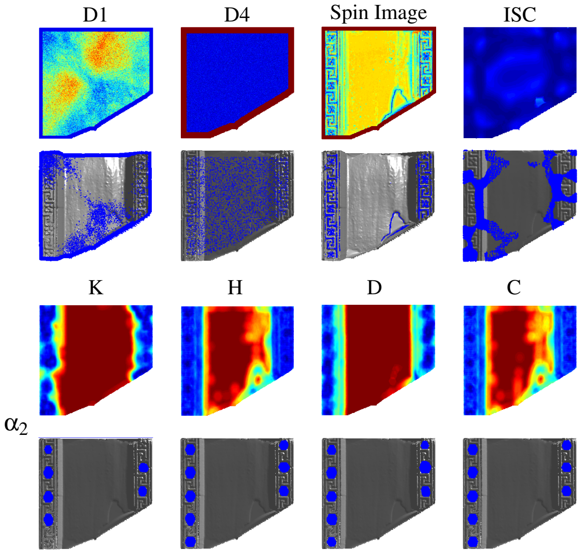

Figure 4: *Results for the owl surface. Two rows are reported in each case: the upper row represents the distance map obtained with the Bhattacharyya distance; in the lower row, the region on the mesh where the probe texture is best identified is highlighted in blue. For competitor methods, results are reported for the Shape Distribution variants $D1$ and $D4$, for Spin Images and Intrinsic Shape Context (ISC). For mesh-LBP, results using the α_2 operator in combination with the surface functions K, H, D and C are reported.*

spin-image could only achieve a partial retrieval of the textured areas, with some false positives detected at flat surface though. The ISC does not indicate a particular ability for spotting the probe texture. These observations are confirmed in the texture retrieval results (second row), which indicate a nearly total failure in recovering the searched texture. The mesh-LBP distance maps (third row), on the opposite, indicate a neat superior performance with an overall improvement. We can observe that the regions in related maps look compact and well localised when compared with the other descriptors. The appearances of these maps suggest an even more ability in texture retrieval, which has been confirmed in the detection results depicted in the last row. Results indicate clearly the ability of the mesh-LBP descriptors for detecting and retrieving the 3D pattern of the *murail* object. The H and C variants exhibit the best performance whereby the eight 3D pattern instances have been successfully detected. We can appreciate this performance by observing their distance-maps showing saliently the 3D texture pattern locations.

3.2. Terrain models

In this experiment, we considered a remote sensing application. Here the retrieval task is described as follows: given a 3D terrain query representing a specific area, find its corresponding match in a gallery of 3D terrain models. We used terrain models from the public "The Visualization Virtual

Services databases"[†]. These terrain models are originally digital elevation models (DEM) converted into mesh models. A set of 21 terrain mesh models have been set as gallery models. From these models, we generated three rotated sets at angles of 45^o, 90^o and 135^o, thus obtaining 63 query models simulating different sensor poses. Also, to simulate the effect of distortion in the mesh construction from the DEM model, which might result from the sensor pose change, we applied the rotation on the cloud of points derived from the terrain model after perturbing their positions by small amount, then we construct a new mesh out of them. Figure 5 depicts samples of gallery and query terrain models.

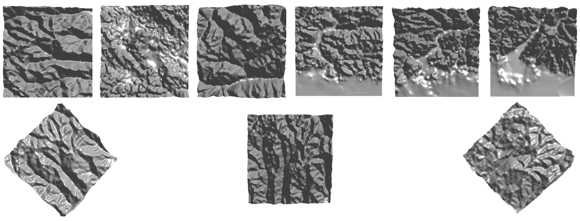

Figure 5: *Samples of gallery terrain models (top), and of probe models with 45^o, 90^o and 135^o rotations (bottom).*

In each query model, we selected a sample area to be used as probe. The area is a geodesic disc around a given point, which is approximated, in the terrain mesh, by the facets confined within a given sphere. The histogram of mesh-LBP descriptors computed at this area is compared with its counterpart computed at each facet of the gallery models, looking for the instance that produces the minimum distance. Table 1 shows the rate of correctly retrieved models with the different mesh-LBP descriptors (in this case we also reported results when the *Shape Index* (SI) descriptor is used as surface scalar function in Eq. 1). We restricted the comparison to the *Spin Image* descriptor in view of the previous experiment results, in which the *Spin Image* performed quite above the others. We notice the neat superiority of the mesh-LBP over the *Spin Image*, with the *K* and *D* performed best.

	mesh-LBP α_2				
Spin Image	K	H	SI	D	C
84.1%	100%	98.4%	95.2%	100%	96.8%

Table 1: *Retrieval accuracy for terrain models.*

4. Discussion and conclusions

In this paper, we propose a new 3D retrieval paradigm based on the 3D geometric texture of a mesh surface. This is regarded as a 3D property of a surface different from the shape, which is evidenced by the presence of repeatable geometric patterns, so that 3D objects can have similar shapes, but very different geometric texture of the surface. To capture such property, we propose to use the mesh-LBP descriptor. This framework keeps the simplicity and the elegance characterizing the original LBP, relieving object surface data from normalization and registration procedures required when using depth images, while it extends the spectrum of LBP analysis to closed surfaces. The potentials of this new 3D retrieval paradigm are reported in: 1) An original 3D retrieval paradigm based on the 3D texture of mesh surfaces; 2) A terrain model retrieval application. Results revealed the great potential of the mesh-LBP descriptors and the incapacity of the standard descriptors for such tasks.

[†] http://shapes.aimatshape.net/ontologies/shapes/

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