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Analysis of a multi-ring technique for 3D pattern recognition

IMATI REPORT Series

Nr. 17-12 June 2017

Managing Editor Paola Pietra

Editorial Office

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Abstract

Pattern characterization of geometric features is of great interest in the cultural heritage domain, as the style of the some parts such beards, hairs, helms or cuirass decorations would support and enhance the classification and/or cataloguing of the archaeological artefacts and fragments. In this context, a *pattern* is a geometric or colour feature which is repeated over a surface, either on its entirety or on a part (for instance, engravings and chisellings, ornamental decorations, etc.).

In the literature, methods that face this problem either project the surface into an image and then adopt a image pattern recognition techniques or try to extend in 3D an existing image technique to surfaces. In this paper, we analyse the performance of the technique called *mesh Local Binary Pattern* (meshLBP) that works on triangulation meshes, considering implementation defined in [WTBdB15, WBdB15] and freely available¹. Tests are performed on meshes of the repository at STARC – The Cyprus Institute [STA] that correspond to laser scans of earthenware fragments retrieved from the Salamina Island. Fragments are represented with triangulations, not necessarily uniformly sampled. In this paper we analyse two kind of patterns represented by geometric and colorimetric variations on the surface of the fragment. In addition, we discuss a sub–sample strategy to keep the effectiveness of the meshLBP descriptor and the dependence of the operator on parameters such as the surface representation and the number of rings used for its multi–scale evaluation. Finally, the main limitations of the method are discussed and possible improvements and future developments are outlined.

Keywords: 3D pattern analysis, 3D pattern classification, mesh

¹ https://it.mathworks.com/matlabcentral/fileexchange/48875-mesh-lbp

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1 Introduction

Technological advancements caused a remarkable increase of the volume of 3D models available in digital form and shape scans and models often integrate colorimetric and geometric information into a single support defined over a surface. Moreover, for 3D scans, triangular mesh representations are a standard *de-facto*. Besides their representation, describing and recognizing the main features of these 3D models is becoming an acute issue for numerous applications, including CAD, medical imaging, molecular biology, architecture, and cultural heritage.

Despite the abundance and the richness of the mesh representation, the analysis of 3D patterns is still an open issue, either in terms of description and location of the features. 3D pattern recognition, in the sense of the characterization of repeated, geometric and/or colorimetric patterns over the skin of a 3D model, is an interesting topic of research [KCPS15, GBLM16]. Indeed, knowing where and what pattern is located on the surface of an object would give insights to the interpretation of the model and would lead to a more accurate classification.

In this work, we analyse the effectiveness of the meshLBP [WTBdB15, WBdB15] for 3D characterization and pattern classification. The interesting aspect of the meshLBP technique is that it extends to triangular meshes the LBP description [OPH96, OPM02] originally developed for 2D image analysis and that has been shown to be able to successfully deal with 2D pattern recognition.

With respect to the previous work, we firstly test the meshLBP in an operative context, i.e. fragments of 3D scans, possibly with an irregular vertex distribution and holes, eventually equipped with colorimetric information, see Figure 1. We also discuss how to face current limitations, regular vertex valence, uniform vertex distribution, dependence of the pattern recognition to the sample density, proposing a number of solutions.

The rest of this paper is organized as follows. Section 2 briefly introduces the current state of the art of 3D pattern description and analysis, then in Section 3 we describe the meshLBP technique. The experimental set-up and tests are presented in Section 4 while Section 5 concludes the paper discussing how to face the current limitations of the method.

2 State of the art

To the best of our knowledge the direct study of 3D patterns on triangulated meshes is quite limited. While there is a large amount of work for 2D images and 2D patterns, see for instance [GBLM16] and a number of methods for the generation of 3D patterns for visualization and animation purposes [KCPS15], the problem of properly describing and identifying patterns is



Figure 1: Examples of fragments used to tile the 3D patterns used in the experiments, original models come from the STARC repository [STA].

still open.

We distinguish between methods that are global, i.e., aim at recognizing large features, such as windows, doors and repeated patterns of architectural buildings, and local, i.e. describe the neighbour of a vertex or a face and look for repeated features such as grains, texture, etc.

As a representative of the first group, the Hough transform [Hou62], [DH72] is a well-known technique used to identify lines and circles in images. In 3D, the Hough transform has been used in [OLA14] to identify recurring line elements of buildings; however, the use of 3D Hough transform is limited by the fact that the feature curves to be identified must be locally planar and the Hough transform require a-priori knowledge on the family of curves to be identified (in general an algebraic curve).

Most of methods that are suitable to locally describe a 3D pattern derive from 2D descriptions. For instance, the SIFT (Scale Invariant Feature Transform) descriptor, originally defined for images [Low04], is a positiondependent histogram of the local variation of the gradient in the geometrical directions around a key-point. Scale invariance is obtained through normalization of the size of the local neighbourhood while rotational invariance is achieved through the identification of the dominant orientation of the neighbourhood. An extension of the SIFT description to 3D domain able to code and replicate color patterns on a triangular mesh has been proposed in [LT13]. In this case, the description is mainly used in creation rather than in recognition.

Similarly to SIFT, the Fast Point Feature Histogram (FPFH) by [RBB09] seems to be suitable for the local characterization of repeated patterns. In-



Figure 2: (a): An example of ORF. The central facet is in red, while the facets of the ring are in blue. Is worth notice that there are 12 facets composing the ORF. (b): ORF^2 for the facet f (red). This ring (blue) is compose by 24 facets. In general, if all vertices have 6-valence then ORF^n is composed by 12n facets.

deed, the FPFH description pairs each oriented point (p, n) on the mesh or point cloud with each of its oriented neighbours (p_i, n_i) and builds a vector with three values: (i) the cosine of tangent and the direction vector of the neighbour; (ii) the projection of the neighbour normal in the plane spanned normal and (iii) the tangent normal at p. To make the FPFH description independent of the point cloud density, it is possible to adaptively estimate the size of the neighbourhood of each point [SPS15] and to filter components surrounded by extremely irregular surfaces.

Recently, the Local Binary Pattern (mesh-LPB) [WTBdB15, WBdB15] has been proposed to characterize and recognize 3D patterns, facial expressions and 3D textures [WTBD15b, WTBD15a] and has been shown to outperform over many 3D descriptors, such as spin images [JH99]. For this reason, we have selected this method as the current best state of the art on 3D pattern recognition.

3 The meshLBP descriptor

In this Section we describe how to extract the meshLBP from a triangulation and how to use such a description for 3D pattern characterization. Finally, we discuss the computational complexity of the method.

3.1 Definition

Let $\mathcal{T} = (F, V)$ a triangulation representing a 3D model, with n_f facets and n_v vertexes and let be $h : F \to \mathbb{R}$ a *facet descriptor*, i.e., a scalar function defined over the set of facets.

The key components of the meshLBP are rings of facets, build around a facet $f \in F$. In case the triangulation has vertex 6-valence, its neighbour (first ring) is composed by the 12 facets that share at least a vertex and/or an edge with f (figure 2(a)). The practical construction of these rings is described at [WBdB15]. For each ring, facets are ordered (in clockwise or anti-clockwise manner); with this ordering, the ring is called an *Ordered Ring Facets*, or *ORF*.

Then, the *meshLBP* function over the facet f is defined as follows:

$$meshLBP(f) = \sum_{k=0}^{11} s(h(f) - h(f_k)) \cdot \alpha(k) \quad f_k \in ORF(f);$$
$$s(x) = \begin{cases} 1 & if \quad x \ge 0\\ 0 & if \quad x < 0 \end{cases}$$

The function α is a weight-function that defines the size of the meshLBP, and therefore the range of the values that the meshLBP can assume over the facet f. Two functions are proposed for α : $\alpha_1(k) := 1$ (that, for meshes with 6-valence means the meshLBP(f) can assume 13 different values) and $\alpha_2(k) := 2^k$ (that admits $2^{12} = 4096$ different values).

The choice of the number of rings r on which compute the meshLBP is flexible and it is called *radial resolution*. As shown in figure 2(b), the second ring of the facet f is the wave-front external expansion of the first ring, i.e., ORF^2 is made of all the facets that share a vertex and/or an edge with the ORF and that are not 'inside' the ORF itself. The same concept iterates over concentric rings (ORF^r is used to call the *r*-th ring) and the meshLBP extends as follows:

$$meshLBP_r^m(f) = \sum_{k=0}^{m-1} s(h(f) - h(f_k^r)) \cdot \alpha(k) \quad f_k^r \in ORF^r(f);$$
$$s(x) = \begin{cases} 1 & if \quad x \ge 0\\ 0 & if \quad x < 0 \end{cases}$$

where m is the number of facets uniformly spaced on the ring (m is called the *spatial resolution*). When the triangulation has 6-valence, usually m = 12. However, 6-valence on vertices is a strong assumption that is not verified by real scans: to make this assumption suitable for real applications, the authors in [WBdB15] suggest to oversample or subsample the ring.

3.2 MeshLBP coding

An histogram can be derived from the definition of $meshLBP_r^m$ on all the facets of a triangulation, once r and m are fixed. As an example, we consider r = 7, m = 12 and α_1 as the weight-function: for each facet f we calculate the $meshLBP_r^m(f)$ and store 7 (one for each ring) histograms made of m + 1 bins. For every value of r, we increase the value of the k-th bin of



Figure 3: (a) A LBP-histogram and (b) a mean LBP-hist.

the r-th histogram by 1 if the value of $meshLBP_r^m(f)$ is k. This can be represented as a single histogram that stores in the *i*-th row the corresponding $meshLBP_i^m(f)$ vector is equivalent to a matrix of dimension 7×13 , as shown in figure 3(a). We call such histogram LBP-histogram.

We also call the average of the LBP-histograms over the triangulation facets (sum of all the LBP-histograms divided by the number of facets) *mean* LBP-hist (see figure 3(b)) and it's used as a description of the 3D model.

3.3 Distance

Given two histograms (LBP or mean LBP) their distance is defined in [WBdB15] as their Bhattacharyya distance. Briefly, the Bhattacharyya distance Bd between two densities p and q in X is defined as follows:

$$Bd(p,q) = \sqrt{1 - BC(p,q)};$$
$$BC(p,q) = \sum_{x \in X} \sqrt{p(x)q(x)}.$$

More details about this distance can be found at [DD09]. Other distances between feature vectors are theoretically possible, such as the Earth Mover's Distance (EMD) [DD09].

As a consequence the distance between two triangulations is defined in terms of their LBP and mean LBP distances. More in detail, given a collection of triangulations, a similarity matrix D is built as follows. The entry D(i, j) represents the values of Battacharyya distance between the the *i*-th and *j*-th mean LBP-hists while D(i, i) is the mean intra variance of the *i*-th mesh, i.e., the average of the Battacharyya distances among the *i*-th mean LBP-hist and every LBP-histogram originated from the facets of the *i*-th mesh. An example of the matrix D is shown in figure 4. By definition, the terms D(i, i) can differ from zero, in particular, if there is a large intra variance of the LBP histograms.



Figure 4: An example of distance matrix between 4 meshes.

3.4 Computational complexity

The computational complexity of meshLBP algorithm depends on two main factors, the number of facets n_f and the radial resolution r: in case the vertex valence is 6 everywhere the computation of the *i*-th ring description requires 12i operations, thus the computation of each multi-ring description is $O(r^2)$ for every facet. Then, the cost of creating the ORFs for the whole model is $O(r^2n_f)$. The oversample and/or subsample operations that guarantee a constant spatial resolution are usually necessary to deal with real data and their cost is $O(rn_f)$. As suggested in [WBdB15], the meshLBP can be approximated using only a limited amount of facets. We are going to discuss this approximation during our experiments, since usually 'real' meshes have a large number of facets.

4 Experiments

In this Section we discuss the experimental environment we used, the results we have obtained for 3D pattern recognition and classification and current limitations of the method.

4.1 Dataset and experimental set-up

The method has been tested on a set of 3D models that we derived either from artefacts collected from the STARC repository [STA] or artificially built for testing purposes. To process, crop and sample models, we used Meshlab [Vis] and CloudCompare [Clo].

First, we tailored 4 specific geometric patterns (figure 5) that we call beard, hair, circlets and skin, representing homonym patterns. These tiles have approximately the same size and the same number of faces n_f and we



Figure 5: From left to right, on the first row we depict the class representatives: beard, hair, circlets and skin. On the second row, the respective mean LBP-hists are shown.

will use these patterns as representatives of a *class* of geometric patterns; we call this set of models the geometric *classes*.

In addition, we tile other 8 patterns, with characteristics in common with at least one class and that differ over at least the 20% of the surface. In our experiments, we call this collection of 3D models *samples*, see figure 6. In particular, the samples represents: (i) a beard fragment equipped with two main patterns: the beard one (on around 85% of the mesh) and the skin; (ii) a texture half-beard half-skin; (iii) and (iv) hair; (v): a circlet pattern; (vi) circlets hiding half of an human ear; (vii) the lower part of a human face (mouth and chin); (viii) a skin pattern with a small hair pattern portion.

To experiment with colour patterns we created a synthetic data set, equipped with 2D patterns, and derived data from the STARC Repository, see figures 7 and 8. The synthetic dataset is created over an almost flat tile of skin painted, in sequence, with five different textures, see figure 7. This type of data simulates a 2D pattern on a 3D model. The patterns have been chosen in black and white to build a well distinctive separation between the elements of the pattern and are meant to simulate a chessboard, dots, stripes, a zebra skin and an hive. The others elements are decorations that come from the real artefacts of the STARC repository; some representatives are shown in figure 8.

As a facet descriptor, we analyse two main sets of h functions:

• Curvatures (Mean Curvature, Shape Index, Normal curvature)[KvD92, CSM03]. Since in the experiments we saw that curvatures are qualitatively comparable, results relate to mean curvature when not otherwise specified. Being flat, the 'facet curvature' is not well defined a priori. We define the *facet curvature* as follows: given a triangulation $\mathcal{T} = (F, V)$ and any kind of curvature defined on V, we define *f.c.* of a facet $f \in F$ the average of its vertexes curvatures. To com-



Figure 6: Representation of the samples set. Left to right, top to bottom: Sample 1, 2, 3, 4, 5, 6, 7 and 8.



Figure 7: Chessboard, stripe, ball, hive and zebra patterns are shown respectively in (a), (b), (c), (d) and (e).

pute curvatures and manage the data we used the Matlab's toolbox *ToolboxGraph* [Pey].

• CIELab colorimetric channels. We adopt the CIELab colour embedding [AKK00], which has been proved to approximate human vision in a good way. The L channel is used for the luminosity which closely matches the human perception of light (L = 0 yields black and L = 100yields diffuse white), whereas the a and b channels specify colours, from magenta to green (negative values of a indicate magenta, positive values of a indicate green) and from yellow to blue (negative values of b indicate yellow, positive values of b indicate blue). Since in our color patterns lumunisity seems to be discriminative enough, the experiments are discussed for the L-channel.



Figure 8: Examples of fragments characterized by a colour pattern. These meshes were processed with Meshlab [Vis].

The LBP-histograms and mean LBP-hists of curvatures and L-channel are computed and evaluated separately.

Finally, in the experiments, we adopt the weight-function α_1 because it provides lighter and more compact LBP-histogram and is able to deal with larger meshes.

4.1.1 Validity of the meshLBP definition on real meshes

Before discussing the capability of the method to correctly describe patterns we analyse on which facets the meshLBP is defined. As an example, we consider the beard class and LBP histogram (using mean curvature as the function h); blue dots in figure 9 represent facets with an invalid meshLBP description.



Figure 9: The results of a 'validation' test of the meshLBP description. Roughly 65% of the facets has a valid meshLBP.

The boundary of every meshes has invalid meshLBP description, whose size depends on the radial resolution r: indeed, if one of the rings cannot be created, the meshLBP is considered invalid on all the rings. Despite this, on real models having degenerate triangles, irregular tessellation, etc., roughly 70% of facets has a valid meshLBP description. In our experiments, we see

that the invalid facets far from the border are quite 'randomly' distributed.

4.1.2 Facet sampling

One major issue of the meshLBP method is its computational complexity. As suggested in [WTBdB15], the meshLBP could be computed on a subset of facets on every triangulation. In this experiment we tested how the selection of the facets is crucial and influences the results. We are therefore looking at the consistency of the results when the number and the facets used to approximate the meshLBP varies. In practice, we check if the entries of the distance matrices among the models are stable (their values slightly differ in percentage with respect to the distance matrix made with all the facets) when different samples of the models are chosen.

In this analysis we compared the distance matrix obtained with all the facets with the ones obtained by randomly selecting a limited number M of facets with valid meshLBP. In this experiment we set M = 1000 and repeat 1000 time the creation of the distance matrix, each time randomly selecting 1000 facets on each mesh. The mean LBP-hists obtained using



Figure 10: Image (a) shows the distance matrix created using all the facets, while figure (b) represent the one created picking only 1000 instances on the meshes.

all the facets and M = 1000 samples on the model that are representatives of the geometric patterns are reported in figure 10(a) while figure 10(a) represents an example of the matrix obtained with 1000 facets. From a statistical analysis of the outcome of this experiment, we noticed that the meshLBP description is meaningful, in the sense that the approximated matrix is close to the complete one, when we select approximately the 6/7%of the facets.

4.1.3 Towards a weighted multi ring description

Looking at the mean LBP-hist representation and the multi-ring nature of the facet description, each ring carries a specific information and, depending on the type of patterns, some rings could become more significant than others. For this reason, a weight was applied to the rings, providing a kind



Figure 11: Distance matrices obtained using the filter shown in the corrective title.

of multiplicative factor to each ring. In practice, a weight is a set of 7 positive numbers that act on the mean LBP-hist as follows: the first row of the mean LBP-hist is multiplied by the first number of the filter, the second row by the second number and so on. The test was repeated 1000 times for each weight. Distance matrices and weights used are shown in figure 11. The information captured by the smaller rings seems to be less significant, while the bigger rings seems to be more significant. In practice, we notice that discarding small rings acts as a smoothing effect applied to the description.

4.2 3D pattern recognition

Firstly, we analyse the set of geometric patterns (the classes) with same sizes and elements. The meshLBP is computed and a distance matrix is created as described in section 3.3 (figure 5).

Second, we classify the 8 samples with respect the four classes using their mean-lbp hists and the nearest neighbour classifier.

The data obtained in this test are summarized in figure 12 and figure 13.



Figure 12: Mean LBP-hist of the eight samples (with the same order described in figure 6).

| 2 | 2 | | | | | F | 2 | B | Contraction of the second seco | TIG | 0 | |
|---|------|------|------|------|------|------|------|------|--|------|------|------|
| | 0.00 | 0.11 | 0.13 | 0.10 | 0.11 | 0.08 | 0.12 | 0.14 | 0.14 | 0.09 | 0.09 | 0.09 |
| | 0.11 | 0.00 | 0.07 | 0.07 | 0.12 | 0.12 | 0.07 | 0.08 | 0.07 | 0.11 | 0.16 | 0.12 |
| | 0.13 | 0.07 | 0.00 | 0.09 | 0.13 | 0.12 | 0.08 | 0.10 | 0.07 | 0.11 | 0.17 | 0.12 |
| | 0.10 | 0.07 | 0.09 | 0.00 | 0.14 | 0.10 | 0.08 | 0.10 | 0.10 | 0.09 | 0.12 | 0.08 |
| | | | | | 1 | - | | | 1 | | | |

Figure 13: Distance matrix between classes and samples.

Figure 12 represents the mean LBP-hists of all the samples and Figure 13 depicts the distance matrix created comparing classes and samples mean LBP-hists. The classification using the nearest neighbour classifier is summarized in the table 1.

- Sample 1. This sample is correctly classified as a 'beard'. In particular, the fact that the portion of skin is close to the boundary slightly influences the meshLBP description.
- Sample 2 is challenging because the 'beard' and 'skin' patterns are equally balanced. We think that the classification of this pattern as a 'beard' mainly depends on the properties of the Bhattacharyya's distance that seems to be more sensitive to the 'geometrical' structure of the histogram than the absolute value of its entries. Indeed, this dis-

tance was originally created as a distance between probability density and when applied to histograms, they are transformed in probability density thus loosing their value-information.

- Sample 3, 4 and 5: these meshes were pretty simple and correctly classified.
- Sample 6 is another challenging pattern. Although we could say that this is half circlets and half skin, it is classified as a 'skin'. We think that this classification is due to the fact that the circlets are really close to be a flat pattern and the circlet mean LBP-hist has a unique peak in the south-west part, that is almost 'deleted' by the amount of not-circlets facets LBP-histogram.
- Sample 7 is labelled as a 'beard' even if it represents a mouth (that is outside of our classes). In our opinion, this classification is due to the fact that the mouth is at the 'center' of the sample. Also, a mouth can be seen as a depression in the triangulation along a straight line, as our beard pattern is.
- Sample 8 is mainly composed by a skin pattern and the hair portion it is not considered due to its position on the border, therefore it is classified as a 'skin'.

Considering our experiments, the meshLBP description seems well suited for 3D models with a single pattern. Also, it is tailored to deal with patterns that have high variation of the descriptor, while seems weaker with patterns that have a small and smooth variation of the facet descriptor h.

We repeated the consistency test also for 3D pattern classification purposes, picking only a limited number M of facet's instances on every triangulations. We started by fixing M = 500 (around 3 - 4% of the original facets) and we make this test 1000 times; at the end we sum up all the results and we look for the 'mean classification': the classification obtained with this facet subsampling is identical to the one in table 1. This result is really encouraging: despite the high amount of time required to compute the meshLBP for the whole model, meaningful (or at least consistent) results are obtained only computing the meshLBP on a limited amount of facets.

The following test suggests that also the pattern classification with respect to the CIElab channels, an in particular the L-channel, is promising. The classification with the L-channel function is performed on a set of 9 fragments tailored from real scans of artefacts, some of these models are shown in figure 8. The results are shown in figure 14: some fragments are 'well' separated from the others while for other the distance obtained is of more difficult interpretation. To validate our feeling, we compared the performance of meshLBP with a simple color histogram with 128 bins. The

| | Beard | Hair | Circlets | Skin |
|----------|--------------|--------------|--------------|-----------------------|
| Sample 1 | \checkmark | | | |
| Sample 2 | \checkmark | | | |
| Sample 3 | | \checkmark | | |
| Sample 4 | | \checkmark | | |
| Sample 5 | | | \checkmark | |
| Sample 6 | | | | \checkmark |
| Sample 7 | \checkmark | | | |
| Sample 8 | | | | \checkmark |

 Table 1: Classification results considering all facets.

distance between histograms computed in this way is measured with L^2 norm, and the final result is shown in figure 14(b).

4.3 Discussions

A drawback highlighted in our experiments is that a large difference between the number n_f of facets of two models influences the meshLBP performance. While, it works well when applied to patterns of comparable size and number of facets (also the tests on consistency were conducted with the same number of subsamples), differences become evident when comparing irregular triangulations with different number of vertices and vertex valence different from 6. This bring an over-sample/down-sample of the rings and requires a regular re-sampling of the pattern. Also, the uniformity of the mesh sampling is crucial because it indirectly defines the size of the rings and therefore influences the quality and the size of the facet neighbour and the sensitiveness of the meshLPB to the pattern characteristics.

Another critical aspect of the method is robustness to noise. Our experiments confirm that the quality of the pattern classification depends on the smoothness of the surface and a good quality (sharpness) of the pattern borders. To confirm our thinking, we analyse the close-to-flat dataset with user-defined black and white patterns shown in figure 7. The results obtained (figure 14(b)) are comparable but, while the color histograms only depends on the colour distribution the meshLBP seems to be sensitive to the local topology of the L-channel (i.e., luminosity). The distribution of black and white facets on the chessboard and the striped pattern should be quite balanced (not exactly the same because of the irregularity of the mesh). The irregular distribution of the facets in this mesh and the irregular pattern borders (figure 15) limit the meshLBP discriminative power.

In figure 16 we analyse the meshLBP distance among these models when different weights are assigner to the rings of the ORF. From left to right, from top to bottom, we show the distance using the original meshLBP description, the distance using only the first three rings of the meshLBP and



Figure 14: Distance matrices with respect to the mean LBP (a) and color histograms (b). Fragments 2 and 4 are identical.



Figure 15: In the elliptic selection we highlight that the facet distribution is irregular. In the rectangular selection, the pattern is aligned with the triangulation edges.

the one with the last four rings. Using only large rings acts as a filter of the local color perturbation and better discriminates the color patterns. This fact is noticeable in the distance between the chessboard and the striped pattern (element (2,5) of the distance matrices).

5 Conclusions and future work

From our analysis, the meshLBP description performs well when the 3D texture has only one pattern but it is sensitive to an irregular distribution of



Figure 16: Distance matrices with variable ring weights, shown at the top of each picture.



Figure 17: The red lines indicate the depressions of this meshes: computing the meshLBP descriptor on those lines could give us better results.

vertices on the triangulation. Requiring the valence of the vertices to be 6 is a strong hypothesis for scanned models. Since these limitations are apparently due to the ORF construction that is based on wave-front expansion, we conjecture that an improvement would be given by considering "geometrical rings", or rather rings of elements with an equal distance from the central facet. This, even if computationally heavier, would not suffer the irregular distribution of the vertices. Computing the meshLBP on a limited number of facets (as the selection is random) seems trustworthy, but it's likely to get worse with triangulations that have a huge amount of facets (instances could be taken all on one area of the mesh, in the worst cases). We also foresee that the combination of several meshLBP histograms, for instance computing the sum of the curvatures and CIElab channel, could improve the performance of the method and yield the joint analysis of colorimetric and geometric properties.

Finally, we plan to localize regions of the surface that are significant and to compute the meshLBP description only on that areas, such as in the example in figure 17. The distinctive characteristic of this pattern is the set of stripes that are well characterized with zero-Gaussian curvature.

For this reason we foresee that the combination of the meshLBP description with feature characterization techniques or the Hough transform is promising. In this case, the meshLBP descriptor could be computed only on the feature points (facets) and, depending on the feature itself, the size of the ring could become feature-adaptive.

Acknowledgements The authors thank all the colleagues from IMATI-CNR for their fruitful comments and, in particular, B. Falcidieno and M. Spagnuolo who provided insight and expertise that greatly assisted their research. Work developed in the CNR research activity DIT.AD004.028.001, and partially supported by the GRAVITATE European project, "H2020 REFLECTIVE", contract n. 665155, (2015-2018).

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