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A Framework for Extracting Local Binary Patterns from Intermittent Apertures

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Abstract— In this paper, we present a novel and original framework, which we dubbed mesh-local binary pattern (LBP), for computing local binary-like-patterns on a triangular-mesh manifold. This framework can be adapted to all the LBP variants employed in 2D image analysis. As such, it allows extending the related techniques to mesh surfaces. After describing the foundations, the construction and the main features of the mesh- LBP, we derive its possible variants and show how they can extend most of the 2D-LBP variants to the mesh manifold. In the experiments, we give evidence of the presence of the uniformity aspect in the mesh-LBP, similar to the one noticed in the 2D-LBP. We also report repeatability experiments that confirm, in particular, the rotation-invariance of mesh-LBP descriptors. Furthermore, we analyze the potential of mesh-LBP for the task of 3D texture classification of triangular-mesh surfaces collected from public data sets. Comparison with state-of-theart surface descriptors, as well as with 2D-LBP counterparts applied on depth images, also evidences the effectiveness of the proposed framework. Finally, we illustrate the robustness of the mesh-LBP with respect to the class of mesh irregularity typical to 3D surface-digitizer scans.

I. INTRODUCTION

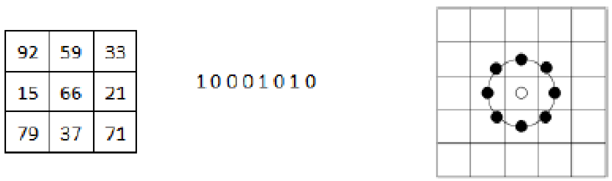
THE Local Binary Pattern (LBP) is a local shape descriptor that has been introduced by Ojala et al. for describing 2D textures in still images. Its computational simplicity and discriminative power attracted the attention of the image processing and pattern recognition community, and rapidly it has found other applications in visual inspection remote sensing face recognition facial expression recognition and motion analysis However, all 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 depth images Manuscript The associate editor coordinating the review of this manuscript and approving it for publication was

The triangular mesh manifold is a simple, compact and flexible format for encoding 3D shape information, which is widely used in many fields, such as animation, medical imaging, computer-aided design and many others. 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. Despite the abundance and the richness of the mesh manifold modality, to the best of our knowledge, there is no a computational support that allows the computation of LBP on this format. One factor that plagued the development of an LBP-based description on the mesh is the lack of an intrinsic order in the triangular mesh manifold, since the LBP requires an ordered support for its computation. On the contrary, computation of

LBP on 2D images benefits from the implicit ordering of the pixels in the 2D image array. Providing such a framework for computing LBP on a mesh could be of great interest for describing 3D texture reflecting the presence of repeatable geometric patterns on the mesh surface (this being a completely separate concept from photometric texture). In fact, there are many applications that require local surface shape analysis and interpretation of 3D textured surfaces. In quality control, texture description can be used for detecting local surface pattern defection. In medicine, most of the imaging data (e.g., ultrasound, microscopic images) are shifting to a 3D mesh format. Many diagnostic rules related to these modalities need description and classification of some organs local surfaces. More generally, texture description on the mesh is useful for any application that needs 3D texture analysis, classification, and retrieval. For example, a typical scenario in the last application is to have a sample of specific 3D texture pattern and detect regions which match that model in a gallery of surfaces.

A. LBP Overview and Related Work

In its original definition, the LBP operator [1] assigns labels to image pixels by first thresholding the 3 × 3 neighborhood



(a) (b)

Fig. 1. (a) Computation of the basic LBP code from the 3×3 neighborhood of a central pixel. Each pixel, starting from the upper-left corner is compared with the central pixel to produce 1 if its value is greater or equal, 0 otherwise.

The result is an 8-bit binary code; (b) Example of a central pixel with a circular neighborhood of a given radius. of each pixel with the center value (i.e., each pixel in the neighborhood is regarded as 1 if its value is greater or equal to the central value, 0 otherwise), then considering the sequence of 0/1 in the pixel neighborhood as a binary number according to a positional coding convention. This is shown in Fig. 1(a),where the upper left pixel in the neighborhood is regarded as the most significant bit in the final code. This eight bits number encodes the mutual relationship between the gray levels of the central pixel and its neighboring pixels. The histogram of the numbers obtained in such a way can then be used as a texture descriptor. This operator is distinguished by its simplicity and its invariance to monotonic gray-level transformations. An extended LBP version that can operate on circular neighborhood of different radii, also allowing sub-pixel alterations was proposed later in [2] (see Fig. 1(b)). These initial formulations led subsequently to the definition of other neighborhood variants, like the oriented elliptic neighborhood LBP (elongated LBP) proposed by Liao et al. which accounts for anisotropic information, and the multiblock LBP (MB-LBP) that compares the averages of the gray level intensity of neighboring pixels rather than the value of individual pixels, in order to capture macrostructural features in the image.Other versions have been proposed to improve the discriminative power of the descriptor, such as the improved LBP (ILBP) , in which pixel values are compared with the average of the neighborhood, and the extended LBP (ELPB) which encodes, in addition to the binary comparison between pixels values, the amplitude of their difference using additive binary digits. To improve the robustness of LBP, Tan et al. introduced the so-called local ternary pattern (LTP), which substitutes the original binary code by a three-values code (1, 0 and −1) by means of a userdefined threshold. This new operator addressed the sensitivity to noise, though at the cost of the invariance to monotonic gray-level transformations. A fuzzy-logic version of the LTP was proposed later in where a fuzzy membership function substituted the crisp three-states association used in A more complete list and discussion on the many LBP variantsappeared in the literature can be found in .

B. Paper Contribution and Organization

From the analysis above, it emerges that since its introduction the LBP descriptor has attracted great interest for the analysis of 2D images, mainly for its simple and efficient computation and for the effective results that can be achieved relying on the LBP theory. Recently, various attempts have been done for extending the LBP framework to the case of 3D meshes, but none of them succeeded in addressing all the issues posed by the need for a simple and effective processing directly performed on a mesh-manifold. Indeed, existing solutions address the LBP extraction on 3D meshes by resorting to the easier 2D case, through the projection of 3D meshes on 2D depth maps. In this paper, we propose a framework that we call mesh- LBP, for designing and extracting local binary patterns directly from a 2D mesh-manifold. In addition to its originality, the proposed framework is characterized by the following features:

- Effectiveness – The mesh-LBP operates directly on 3D triangular meshes, thus avoiding any expensive pre-processing, such as registration and normalization, required to obtain depth images;
- Generalization – By its ability of handling mesh data, this framework can deal with a larger spectrum of surfaces (e.g., closed, open, self-occluded) as compared to its counterpart defined on depth images;
- Adaptability – This framework can be adapted to hold most if not all the LBP variants proposed in the literature for 2D and depth images;
- Simplicity – The mesh-LBP preserves the simplicity of the original LBP, not requiring any surface parametriza222

II. THE MESH-LBP

The construction of LBP-like patterns on a mesh, first requires a scheme for constructing rings of facets around a central one and for traversing them in an ordered fashion. Let S = _V, F_ be the triangular mesh representation of an open or closed surface, where V and F are, respectively, the sets of vertices and facets of the mesh. Let us start by considering the general case of a convex contour on the mesh, which we assume regular, i.e., each vertex has a valence of six (we will show later that our framework can also cope with meshes that do not comply with this ideal case). Consider the facets that have an edge on that contour . We call these facets Fout facets, as they seem pointing outside the contour. Let us consider also the set of facets that are one-toone adjacent to the Fout facets and which are located inside the convex contour. Each facet in this set, that we call Fin, shares with its corresponding Fout facet an edge located on the convex contour. Let us assume that the Fout facets are initially ordered in a circular fashion across the contour. Given that initial arrangement, we bridge the gap between each pair of consecutive Fout facets, that is we extract the sequence of adjacent facets, located between the two consecutive Fout facets and which share their common vertex (the vertex on the contour). We call these facets Fgap facets (see Fig. 2(b)). The "Bridge" procedure reported in pseudocode in Algorithm 1 is Algorithm 1 Bridge Algorithm 2 GetRing

III. MESH-LBP IMPLEMENTATION

In the following, we provide more insights on the practical implementation of mesh-LBP. In particular, we propose mesh-LBP variants to reduce the descriptor size together with solutions to make the mesh-LBP descriptor invariant with respect to the selection of the initial ORF facet and to make it computable on meshes with non-regular tessellation

A. Reducing Descriptor Size

The LBP operator produces rather long histograms and is therefore difficult to use as a region descriptor. A first solution to this problem was obtained by using just "uniform" patterns (i.e., binary patterns with a number of bitwise 0-1 transitions equal at most to 2) instead of all the possible ones The problem of reducing the dimensionality of the LBP descriptor also inspired the LBP variant called center-symmetric (CSLBP) which modifies the pixels comparison scheme by computing the difference between center-symmetric pairs of pixels rather than comparing each pixel with the central pixel. This halves the number of comparisons for the same number of neighbors. In the context of mesh-LBP, the same result can be obtained using the following equation for the center symmetric mesh-LBP (mesh-CSLBP): meshCSLBPrm

- **Method-1**: Performing a circular bit-wise shift of the binary pattern, as was suggested in the standard LBP , and selecting as initial facet that resulting in the minimum LBP value. However, this method reduces the range of the LBP values and might seriously affect the discriminative power of the operator [30];

- **Method-2:** Adopting intrinsically rotation invariant descriptors only. This set includes the number of transitions, the number of 1-valued bits (i.e., the sum of the binary digits obtained when using α(k) = 1 variant), and the number of 1-valued runs of a given length in the binary patterns. This method preserves the range of the LBP values, yet might still compromise the discrimination power, though to a less extent than the first method;
- **Method-3**: Considering all the binary pattern values that originate by moving the initial facet along the ring, but this solution creates redundancy and further burden the computation;
- **Method-4:** Selecting the first facet with respect to a local reference frame (LRF) determined based on the local morphology of the ring neighborhood. For this purpose, the method proposed by Tombari et al. which ensures a unique and unambiguous LRF can be used. Afterwards, the nearest facet to the x or y axis of the LRF can be selected as the first facet. From the above, the method-4 looks the most reliable and generic, but its implementation requires histograms construction,

which might burden the computational complexity. For this reason, we rather adopted a simpler yet practical solution, tailored to our problem, and which consists of the following steps: (i) First, we generate the sequence of rings starting from any arbitrary adjacent facet to the central facet; (ii) Then, from the obtained sequence of ordered rings

IV CONCLUSION

In this paper, we presented mesh-LBP as a novel framework for computing local binary patterns on triangular mesh manifolds. This framework keeps the simplicity and the elegance characterizing the original LBP and allows the extension of all its variants, developed in 2D image analysis, to the mesh manifold. The mesh-LBP reliefs object surface data from normalization and registration procedure required when using depth images, while it extends the spectrum of LBP analysis to closed surfaces. The experimental tests revealed that mesh-LBP exhibits a “uniformity” aspect for the different types of scalar functions, pretty similar to the one noticed in 2D-LBP. We also provided a simple method for addressing rotation invariance that proved to be effective as was confirmed by repeatability and the other subsequent experiments. The re-sampling scheme of the scalar function over each ORF ring proved to be an effective mechanism for addressing mesh irregularities. In the related experiment, the gaussian curvature

and the shape index exhibited the best robustness score. The comparison of the $\alpha 1$ and $\alpha 2$ operators does not provide conclusive results, apart that they perform best with Gaussian curvature and the angle between facets normal, respectively. However, the compactness of the descriptor obtained with the $\alpha 1$ operator, and the resulting lower computational complexity required to compare descriptors, vote for this solution especially in the cases where time constraints are relevant.

As future work, we plan extending the mesh-LBP to global analysis. One potential approach is extracting ordered blocks from the mesh surfaces and then construct from them, by concatenation, a global histogram. We believe that mesh-LBP will open-up new perspectives for mesh manifold analysis and will be an appropriate complement to other mesh manifold analysis techniques

.REFERENCES

[1] T. Ojala, M. Pietikäinen, and D. Harwood, "A comparative study of texture measures with classification based on featured distributions," Pattern Recognit., vol. 29, no. 1, pp. 51–59, Jan. 1996.

[2] T. Ojala, M. Pietikäinen, and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 971–987, Jul. 2002.

[3] T. Mäenpää, J. Viertola, and M. Pietikäinen, "Optimising colour and texture features for real-time visual inspection," Pattern Anal. Appl., vol. 6, no. 3, pp. 169–175, Mar. 2003.

[4] L. Cao, J. Luo, F. Liang, and T. S. Huang, "Heterogeneous feature machines for visual recognition," in Proc. 12th Int. Conf. Comput. Vis., Kyoto, Japan, Sep./Oct. 2009, pp. 1095–1102.

[5] D. Guo, V. Atluri, and N. Adam, "Texture-based remote-sensing image segmentation," in Proc. IEEE Int. Conf. Multimedia Expo, Amsterdam, The Netherlands, Jul. 2005, pp. 1472–1475.

[6] C. Song, F. Yang, and P. Li, "Rotation invariant texture measured by local binary pattern for remote sensing image classification," in Proc. IEEE 2nd Int. Workshop Edu. Technol. Comput. Sci., vol. 3. Wuhan, China, Mar. 2010, pp. 3–6.

[7] A. Lucieer, A. Stein, and P. Fisher, "Multivariate texture-based segmentation of

remotely sensed imagery for extraction of objects and their uncertainty," Int. J. Remote Sens., vol. 26, no. 14, pp. 2917–2936, 2005.

[8] T. Ahonen, A. Hadid, and M. Pietikäinen, "Face recognition with local binary patterns," in Proc. 8th Eur. Conf. Comput. Vis., Prague, Czech Republic, May 2004, pp. 469–481.

[9] T. Ahonen, A. Hadid, and M. Pietikäinen, "Face description with local binary patterns: Application to face recognition," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 12, pp. 2037–2041, Dec. 2006.

[10] L. Wolf, T. Hassner, and Y. Taigman, "Descriptor based methods in the wild," in Proc. ECCV Workshop Faces Real-Life Images, Marseille, France, Oct. 2008, pp. 1–14.

[11] G. Zhang, X. Huang, S. Z. Li, Y. Wang, and X. Wu, "Boosting local binary pattern (LBP)-based face recognition," in Proc. 5th Int. Workshop Adv. Biometric Pers. Authentication, Beijing, China, Oct. 2005, pp. 179–186.

[12] C. Shan, S. Gong, and P. W. McOwan, "Facial expression recognition based on local binary patterns: A comprehensive study," Image Vis. Comput., vol. 27, no. 6, pp. 803–816, May 2009.

[13] L. Cai, C. Ge, Y.-M. Zhao, and X. Yang, "Fast tracking of object contour based on color and texture," Int. J. Pattern Recognit. Artif. Intell., vol. 23, no. 7, pp. 1421–1438, Nov. 2009.

[14] X. Wang and M. Mirmehdi, "Archive film restoration based on spatiotemporal random walks," in Proc. 11th Eur. Conf. Comput. Vis., Crete, Greece, 2010, pp. 478–491.

[15] G. Sandbach, S. Zafeiriou, and M. Pantic, "Local normal binary patterns for 3D facial action unit detection," in Proc. 19th IEEE Int. Conf. Image Process., Orlando, FL, USA, Sep./Oct. 2012, pp. 1813–1816.

[16] H. Li, L. Chen, D. Huang, Y. Wang, and J. Morvan, "3D facial expression recognition via multiple kernel learning of multi-scale local normal patterns," in Proc. 1st Int. Conf. Pattern Recognit., Nov. 2012, pp. 2577–2580.

[17] G. Sandbach, S. Zafeiriou, and M. Pantic, "Binary pattern analysis for 3D facial action unit detection," in Proc. Brit. Mach. Vis. Conf. (BMVC), Guildford, U.K., Sep. 2012, pp. 119.1–119.12. WERGHI et al.: MESH-LBP: FRAMEWORK FOR EXTRACTING LBP 235

[18] S. Liao and A. C. S. Chung, "Face recognition by using elongated local binary patterns with average maximum distance

gradient magnitude," in Proc. 8th Asian Conf. Comput. Vis., Tokyo, Japan, Nov. 2007, pp. 672–679.

[19] L. Zhang, R. Chu, S. Xiang, S. Liao, and S. Li, "Face detection based on multi-block LBP representation," in Proc. Int. Conf. Biometrics, Washington, DC, USA, Sep. 2007, pp. 11–18.

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