3D MESH CODING THROUGH REGION BASED SEGMENTATION

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ABSTRACT

In this paper, we are interested in wavelet-based coding of 3D semi-regular meshes in order to ensure the progressiveness of the reconstruction. The contribution of this work relies on the adaptation procedure of the lifting scheme operators carried out at each resolution level. More precisely, we propose to firstly segment the original mesh into nonoverlapping regions. The involved predictors are then optimally computed for each region.

Keywords: data compression, adaptive coding, optimization methods, mesh generation, wavelet transforms.

1. INTRODUCTION

Nowadays, 3D data are widely used in multimedia applications such as video gaming, medical imaging, virtual reality. However, they require huge amounts of memory space and high transmission bandwith. Therefore, the need for data compression is obvious. As the triangular meshing is the most employed method for representing 3D data, much efforts have been focused on the compression of the mesh. A 3D mesh is defined by a sequence of vertices associated with the geometrical information (object shape) and a topological information that describes the connectivity of edges. Generally, the geometry data contribute to the file size much than do the topological data. Consequently, much attention was paid to efficiently compress the vertices sequence. Pioneering works are based on predictive schemes: a vertex position is predicted from those of previously vertices according to a scanning order of the triangle spanning tree which is obtained from the topological data (topological surgery) [1, 2]. With the advent of networked applications, progressive compression methods ensuring the reconstruction of a 3D object at different resolutions, have been developed [3, 4, 5, 6]. Generally, these methods include a remeshing step that replaces the original mesh by a more regular one: a wavelet transform could be further applied on the remeshed geometrical data. To this respect, second generation wavelet transforms based on lifting schemes have been successfully extended to the 3D case [7]. As a result, efficient two-step coders were designed: the first step consists of a wavelet transform and the second one correspond to an optimal quantization of the wavelet coefficients through a bit allocation procedure [8]. A key issue of such compression method is the design of the involved operators of the lifting scheme. To the best of our knowledge, static operators are used such as those corresponding to the unlifted butterfly wavelets. The performance could be improved when the intrinsic spatial properties of the geometrical data are accounted for. The objective of this paper is to propose an *adaptive* wavelet transform. The originality of our contribution relies on a prior segmentation of the input data that simultaneously ensures the progressiveness of the reconstruction and the adaptation to the data content. Furthermore, a region of interest coding is made possible. This paper is organized as follows. Section 2 is devoted to a brief review of semi-regularity and wavelet transform. Then, in Section 3, we describe the adaptive coder we propose. Finally, in Section 4, we present some experimental results and some conclusions are drawn in Section 5.

2. BACKGROUND

2.1. Semi-regular meshes

The mesh regularity is related to the number of incidents edges at each vertex (valence). A semi-regular mesh is mainly composed of vertices with the same valence and a very low number of vertices having variable valences (see figure 1). In order to construct a semi-regular mesh from an irregular one, two main methods were investigated: the multiresolution adaptive parameterization of surfaces [4] and the normal mesh [5]. Both of them start by a decimation of vertices until obtaining a coarse irregular mesh. Then, a remeshing is employed through a quaternary subdivision and a step of refinement until a detailed mesh very similar to the original one is obtained. Consequently, the advantage is the simplicity in passing from a resolution to another since the topological information is implicit. In fact, only the topological information at the coarsest level is required. Hence, we have to compress the connectivity only at the coarsest level and to focus on the coding of the geometry at all the resolution levels. In this work, we are interested in coding semi-regular meshes. In the sequel, we will denote by $v^1, \ldots, v^N$ the N vertices defined on $\mathbb{R}^3$ of the original semi-regular mesh $\mathcal{M}$.

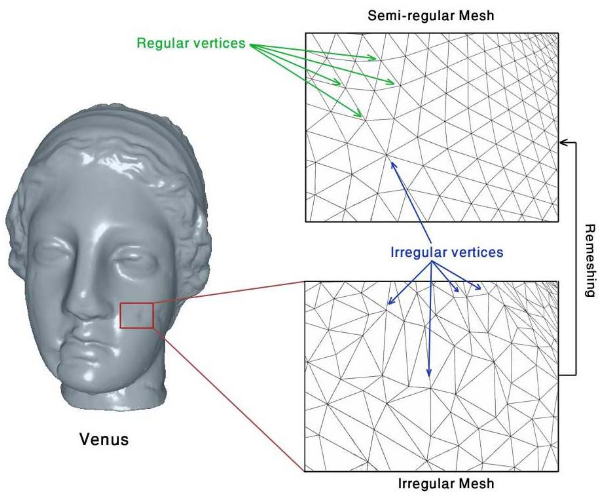

Fig. 1. An example of semi-regular mesh.

2.2. Butterfly lifting scheme

In the context of wavelet-based image compression, the lifting scheme is recognized to be a powerful tool that is suitable to a progressive transmission and a scalable reconstruction. It consists in decomposing the input signal into two kinds of coefficients: the approximation coefficients that are a coarse version of the original signal and the set of detail coefficients at different resolution levels. Very often, in the case of 3D semi-regular meshes, the four-channel butterfly lifting scheme is used. As it can be seen in Figure 2, at each resolution, the input mesh is decomposed into 3 sets of high frequency coefficients and a set of low frequency ones. More precisely, as the samples of the input mesh present high local correlation, the positions of some vertices are estimated as the average of their 8 neighbouring vertices according to a prediction mask [7]. The prediction separately operates on the three spatial coordinates of the vertices. Furthermore, it is worth to note that the predictor weights do not depend on the input mesh neither on the resolution stage. The resulting prediction errors correspond to the high frequency coefficients. The latter are employed to update the remaining input samples and a set of low frequency vertices is generated which is viewed as an approximation version of the input mesh as shown at the right of Figure 3. Then, the decomposition procedure is recursively repeated $J - 1$ times on the resulting approximation version. The synthesis scheme is very straightforward to design: it is enough to reverse the order and the sign of the prediction and the update operators.

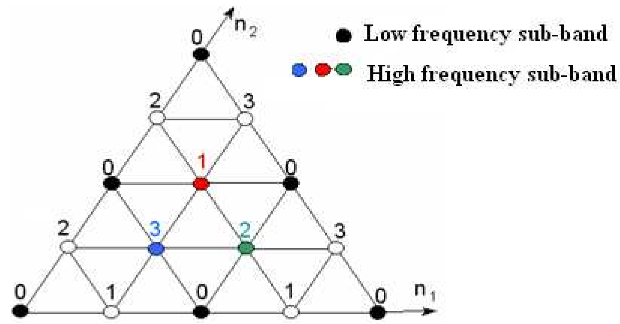

Fig. 2. Subsampling the mesh on high and low frequency.

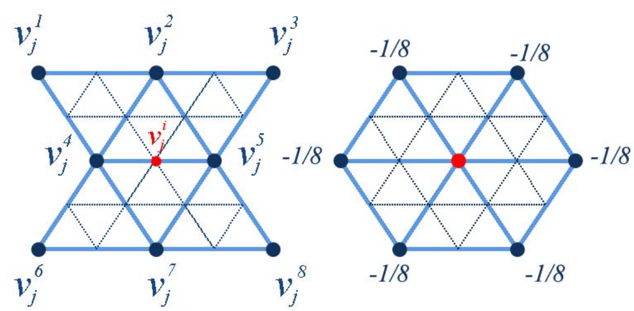

Fig. 3. Predictor and update filters.

3. PROPOSED METHOD

3.1. Global compression scheme

Figure 4 gives an overview of the whole compression chain which is composed by the three following steps.

- **Segmentation**

The segmentation aims at partitioning the initial mesh into C homogeneous regions sharing similar local features characterizing the surface. To this respect, several methods were developed. For instance, in [9], the mesh is decomposed in arbitrary regions whereas in [10, 11], the mesh is segmented into semantic regions.

- **Wavelet transform**

Once the mesh is subdivided into C regions, the goal is to exploit the spatial correlation within every cluster through a multiresolution representation. More precisely, at each resolution level j, we design the optimal operators of a lifting scheme in each cluster (as explained in section 3.2). Then, we apply a wavelet transform adapted to the vertices within each cluster. The procedure is recursively repeated $(J - 1)$ times.

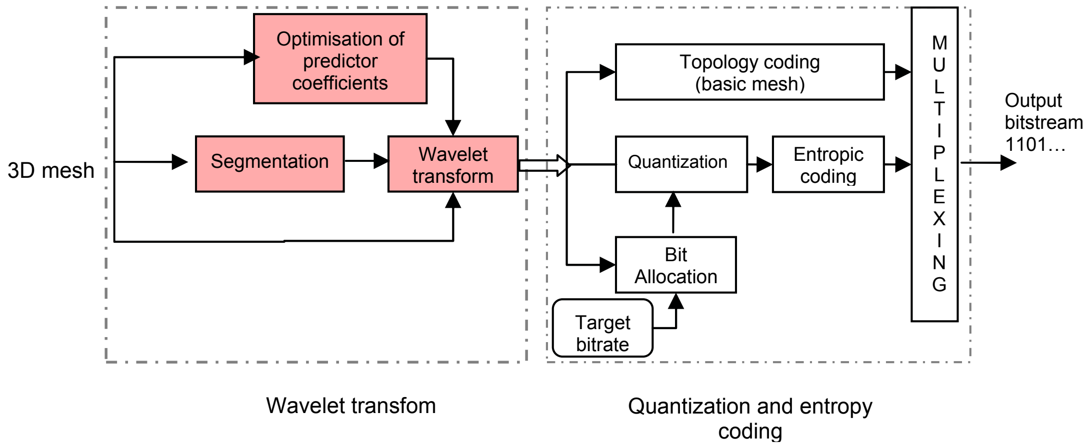

Fig. 4. The proposed compression scheme.

The approximation coefficients at the J-th level and the sequence of wavelet coefficients are then encoded and sent to the decoder. Thereby, the generated coding regions could facilitate the access to a single part of the mesh since it is not necessary to decode the whole object for a partial reconstruction or visualization.

• **Coding**

At this stage, we have a sequence of wavelet coefficients and a coarse level with its topological information. We use the same coder such as described in [8] in which the wavelet coefficients are quantized after a bit allocation according to a target bitrate. Finally, an entropy coding is performed to generate the bitstream.

3.2. Optimization of the prediction step

The key issue of the proposed method relies on the adaptation of the update and the predictor to the content of the underlying region. In our experiments, it has been observed that the decrease of the bitrate is mainly due to the optimization of the predictor operators. Hence, for the sake of simplicity, we propose to employ the same update operator at all resolution levels for all the C clusters. Consequently, the problem reduces to the adaptation of the predictor. Therefore, we have two freedom degrees for designing the predictor: the choice of its mask and the computation of its weights. In our experiments, we have selected the same neighborhood mask as the one used in the Butterfly lifting scheme. More precisely, as indicated in Figure 3, in order to predict any vertex v_j^i in a cluster c at level j of resolution, the vector of reference vertices is $\tilde{v}_j^i = (v_j^1, v_j^2, v_j^3, v_j^4, v_j^5, v_j^6, v_j^7, v_j^8)^\top$. The detail coefficients d_j^i can be written as:

$$d_j^i = v_j^i - (p_j^c)^\top \tilde{v}_j^i \tag{1}$$

where p_j^c is the vector of prediction weights associated to cluster c ($c = 1, \ldots, C$). We propose to set p_j^c so as the variance of the details coefficients will be minimized. It could be easily shown that it is equivalent to solve the following set of normal equations:

$$\mathsf{E}\{\tilde{v}_j^i (\tilde{v}_j^i)^\top\} p_j^c = \mathsf{E}\{v_j^i \tilde{v}_j^i\}. \tag{2}$$

Thus, the optimal predictor could be easily computed through a basic resolution of a linear system.

4. EXPERIMENTAL RESULTS

Simulation tests were conducted on several images of 3D objects. For the sake of clarity, experimental results are only given for the "Venus" object. In order to measure the quality of our compression scheme, the surface to surface distance d_S between the irregular original object and the reconstructed semi-regular one is computed with the MESH software [12]. This distance d_S enables to evaluate the following peak signal to noise ratio:

$$PSNR = 20 \log_{10} \left(\frac{bb}{d_S} \right) \tag{3}$$

where bb is the diagonal bounding box of the object [8]. Since the main objective of this work is adaptive coding, we have performed a supervised segmentation of the original mesh. We have carried out the segmentation on the irregular mesh at the coarsest resolution resulting from the remeshing procedure. So, the propagation of the segmentation map could be easily performed to the finer resolution stages. Figure 5 shows the resulting segmentation with $C = 5$ clusters. Figure 6 illustrates the output PSNRs obtained by the standard wavelet transform, the optimized wavelet transform without clustering and the proposed method. It indicates that our approach is the most efficient. Besides, it is clear that the gain comes essentially from segmentation. Then, the proposed method compared to the standard wavelet transform yields to a gain around 1.62 dB when the bitrate is 0.03 bit / irregular vertex. Consequently, the proposed method produces a significant gain in terms of accuracy at very low bitrates.

5. CONCLUSION

In this paper, we have introduced a novel adaptive wavelet transform based on a prior segmentation. This method allows a flexible and a progressive reconstruction. Indeed, a user can encode or decode a region of interest at different levels of resolution. Furthermore, our method achieves a considerable gain in terms of PSNR especially at low bitrates. There are many related works that are worth further investigating. For instance, additional gains could be obtained thanks to an improvement of the segmentation procedure and the optimization of the quantization procedure.

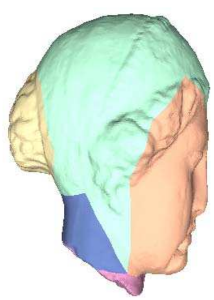

Fig. 5. The "Venus" mesh segmented into 5 regions.

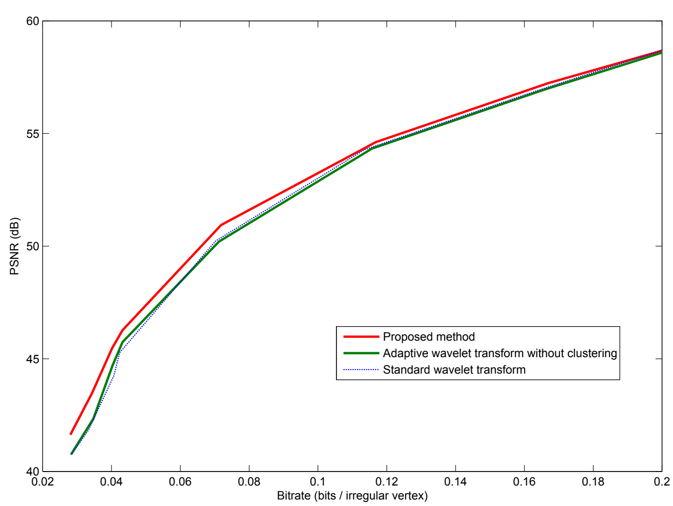

Fig. 6. Evolution of the $PSNR$ (in dB) with the bitrate in terms of bits/irregular vertex.

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