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BLIND QUALITY OF A 3D RECONSTRUCTED MESH

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ABSTRACT

This paper proposes blind mesh quality measures for a reconstructed 3D model. The assessment of 3D model quality is a fundamental step in the process of 3D reconstruction, to efficiently and iteratively improve the model quality. We first prove that metrics based on a reference model (*extrinsic* metrics) that have been shown to be correlated to subjective interpretation, are able to capture flaws that may occur while reconstructing. However, no reference is available during an iterative reconstruction process, so we study *intrinsic* measures on a 3D model to evaluate the quality of the 3D model being reconstructed. As expected, our results show that these intrinsic metrics give high responses in regions locally corrupted by noises.

Index Terms— 3D mesh, extrinsic and intrinsic quality evaluation, iterative 3D reconstruction.

1. INTRODUCTION

Digital 3D models are present in numerous domains such as Computer Aided Design (CAD), to model technical parts, in cinema to produce animated films, or for cultural heritage conservation. More recently, new technologies like the Metaverse induce high demand for 3D content. Such models can be generated with 3D reconstruction algorithms based on images [1, 2, 3], or from data acquired by a depth sensors such as LiDAR (Light Detection and Ranging) sensor [4, 5, 6]. Although these approaches are now reliable and efficient, and can even generate very large scale models [7], the quality of the generated models is, in general, limited by the data acquisition phase. Indeed, these reconstruction techniques require manual acquisition of data and the choice of shots is the responsibility of the operator who follows general qualitative rules to find a compromise between the capture overlapping and the acquisition of the whole scene [8, 9]. The position and orientation of the sensors w.r.t. the object surfaces are also important and can lead to a non-uniform mesh density or holes in different parts of the scene [10] and, as a consequence, to non-homogeneous level of detail at different locations of the object (see Figure 1).

To overcome these issues, new acquisitions are needed and the problem of finding a new acquisition point is referred to as the Next Best View (NBV) [11]. The NBV allows to

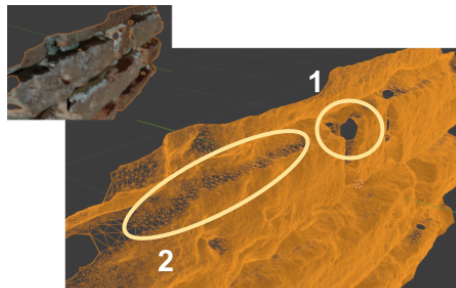


Fig. 1: Common issues of reconstruction 3D algorithms. (1) is a hole in the mesh, (2) shows a non-uniform density.

reconstruct missing parts of the models or to improve the 3D model by estimating the *optimal* point of view of the next acquisition. To this end, we need a metric to identify the regions of the reconstructed object that need to be improved.

In this paper, we propose a state of the art review of the existing metrics to locally evaluate the 3D model quality (extrinsic and intrinsic). We then evaluate the pertinence of the existing metrics for the reconstruction of 3D models. Finally, we introduce a new metric QLR, which is a second order extension of the PLR metric; we show that QLR is able to detect regions of the 3D model that are poorly reconstructed. Intensive experiments confirm the interest of using these intrinsic measures for identifying the parts of the object with a lower quality.

2. EXTRINSIC METRICS

Model comparison metrics, that we denote *extrinsic*, are the most commonly used. Indeed, most of the metrics for assessing the quality of 3D models have been introduced to evaluate compression or watermarking algorithms [12, 13]. We consider state-of-the-art 3D model difference measurements. The Hausdorff distance is the simplest and most used [14]. Then completeness and accuracy measures [15] are an evolution of the Hausdorff distance dedicated to evaluate the quality of a complete 3D reconstruction, so these measures are particularly relevant to our targeted context. The last three measures we consider [16, 17, 18] are derived from 3D modelling and are of great interest since they are able to quantify a perceptual quality. Let us denote (V_r, S_r) , respectively the point set

of the reference model and its surface, and (V, \mathcal{S}) the same elements for the reconstructed model.

2.1. Asymmetric Hausdorff distances

The asymmetric distance [14] is defined as :

$$d(\mathcal{S}_r, \mathcal{S}) := \max_{v_r \in V_r} \underbrace{\min_{v \in V} \delta(v_r, v)}_{d(v_r, \mathcal{S})} \quad (1)$$

where $\delta(x, y)$ represents the Euclidean distance in \mathbb{R}^3 . The distance $d(v_r, \mathcal{S})$ can be used to create a distance map to visualize the closest points from the reference model.

2.2. Completeness and Accuracy

Accuracy [15] measures how close a model \mathcal{S} is to a reference model \mathcal{S}_r : it is defined as the distance d_{T_a} , such as $T_a\%$ of the points from the reconstructed model \mathcal{S} are at a distance, given by $d(v, \mathcal{S}_r)$, less than d_{T_a} of the reference model. *Completeness* [15] measures how much of \mathcal{S}_r is modeled by \mathcal{S} by computing the distance $d(v_r, \mathcal{S})$: it is then defined as the percentage of points that are within a distance d_c of the reconstructed model. The choice of the two thresholds T_a and d_c is clearly fundamental as they introduce a natural filtering of the metric (a noise whose amplitude is less than the distance d_c will not be detected). These metrics only rely on geometrical characteristics while Human Visual System (HVS) is more sensitive to curvature variations and distortions. The following metrics aim at addressing these specificities of the HVS.

2.3. Mesh Structural Distortion Measures

The Mesh Structural Distortion Measure (MSDM) [16] is inspired by the Structural SIMilarity Measure (SSIM), introduced by Wang *et al.* [19]. While SSIM is based on the grey levels, MSDM uses curvature. Thus, the authors use μ et σ , respectively the mean and standard deviation of the curvatures in a given neighborhood. Similar to SSIM, the MSDM measure relies on the computation of three elements: L (resp. C) is the relative difference of μ (resp. σ) between the neighborhoods \tilde{v}_r and \tilde{v} and the structure S is defined as follows:

$$S(\tilde{v}_r, \tilde{v}) = \frac{\|\sigma_{\tilde{v}_r} \sigma_{\tilde{v}} - \sigma_{\tilde{v}_r \tilde{v}}\|}{\sigma_{\tilde{v}_r} \sigma_{\tilde{v}} + K}. \quad (2)$$

The authors recommend using a radius r of \tilde{v} equivalent to 1.5% of the bounding box diagonal. The constant K is introduced to avoid zero-division. These three differences are combined using a Minkowski metric to obtain a local comparison function: Local MSDM (LMSDM).

Subsequently, a multiscale improvement MSDM2 was proposed by the authors [17] in which the same principle as MSDM is applied at different scales. In the framework of 3D models, the scale corresponds to the radius of the local

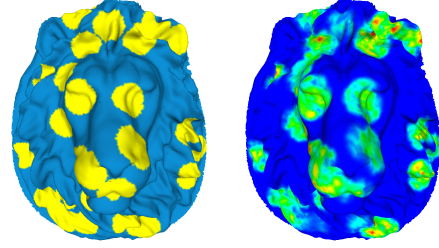


Fig. 2: 3D model with local noise (yellow regions, left image) and the local response of the MSDM2 metric (right model, blue corresponds to low values, red to high ones).

neighborhood used to calculate the curvatures. Their user study has shown the strong correlation of MSDM metrics with subjective quality. Moreover, at the perceptual level, taking into account different scales enhance the similarity to the HVS, so MSDM2 is even more correlated to subjective quality. The distortion maps from the different scales are then summed and normalised to obtain a general distortion map: Multiscale Local Distortion, MLD (see Figure 2).

2.4. Dihedral Angle based metrics

Dihedral Angle Mesh Error (DAME) [18]. The surface roughness is assumed to be proportional to the dihedral angles between neighbor faces. Since the human eye cannot discern small distortions on a rough surface, the authors propose to keep only dihedral angles of large amplitude. Moreover, they also filter according to a visibility criteria.

Reduced reference metric [20]. Abouelaziz *et al.* proposed a statistical analysis of the dihedral angle distributions between the reference and the reconstructed mesh. More precisely, they compare the local distributions (Gamma and Weibull) of the dihedral angles. This objective metric shows good correlation with the perceptual user study proposed by [16]. However, the objective of this metric is to evaluate the visual perception quality of the object, and not detecting distortions, like the previous metrics.

3. INTRINSIC METRICS

During a 3D reconstruction process a reference model is, in general, not available; it is thus necessary to define intrinsic metrics that only rely on characteristics of the reconstructed model. Methods that blindly assess the quality of a 3D model are usually based on intrinsic properties of the model, such as curvature [21], dihedral angles [22], multiscale saliency maps [23], or local roughness [24]. These methods often use a training dataset whose models are distorted (*e.g.* by adding noise or applying smoothing) and then evaluated by the users, creating a subjective and global measure for each model that correlates [21] or aggregates [25] multiple intrinsic measures

into a Mean Opinion Score. These kind of metrics are interesting but are not adapted for our NBV context since they generally output a global numerical value for the model quality, whereas we are interested in a local score to determine the parts of the mesh that are potentially poorly reconstructed.

In the following, we consider intrinsic measures used to compose the global score of blind methods and we study how suitable they are for detecting distortions introduced by the 3D reconstruction algorithms (non-uniform point density or local noises). All those metrics are defined according to a k -ring neighborhood that will define the different scales of our metrics. As in MSDM2, we combine the different scales using a simple sum, that is, the arithmetic mean of the measure values on the successive k -neighborhoods.

3.1. Plane Local Roughness

Rodriguez *et al.* [26] propose a local roughness measure as the distance between the considered point and the best fitting plane to the point and its neighbors. Similarly, we introduce the Plane Local Roughness (PLR) for each vertex as the distance to the local tangent plane estimated over its k -ring neighborhood, instead of a r -radius sphere neighborhood. We consider the mean, respectively the median, of the PLR over its k -ring neighborhood. The PLR gives us an information on a first order local approximation.

3.2. Mean curvature

Meynet *et al.* [27] introduced a mean curvature measure at vertices of a 3D mesh. For each vertex v of the mesh we consider its k -ring neighborhood \tilde{v} and we compute the least square fitting of a quadric $Q_{\tilde{v}}(v) : z_i = ax_i^2 + by_i^2 + cx_iy_i + dx_i + ey_i + f$, where $v_i = (x_i, y_i, z_i) \in \tilde{v}$. This equation is computed in a local orthonormal frame whose origin is the barycenter of the k -ring neighborhood and such that Z is in the direction of the underlying surface normal computed using a Principal Components Analysis (PCA). The mean curvature is then defined by the derivatives of Q as

$$C(v) = \frac{(1 + d^2)a + (1 + e^2)b - 4abc}{(1 + e^2 + d^2)^{\frac{3}{2}}}. \quad (3)$$

3.3. Quadric Local Roughness

Similarly to the PLR, after the estimation of the best fitting quadric of the neighborhood, we defined the Quadric Local Roughness (QLR) for a vertex of the mesh as the fitting error of the quadrics computed for the mean curvature.

$$\text{QLR}(v) = |Q_{\tilde{v}}(v) - f|, \quad (4)$$

We consider the mean, respectively the median, of the QLR over its k -ring neighborhood \tilde{v} . The QLR gives us an information on a second order local approximation.

4. EXPERIMENTS AND RESULTS

We conduct our experiment on various 3D models (see Figure 3) on which we have applied 37 deformations of different nature (decimation, global noise, local noises), frequency, intensities and support, leading to an experimental dataset of 304 models [28] (see Figure 3).

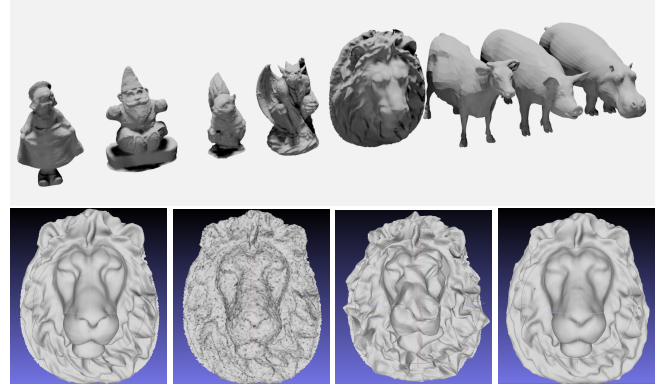


Fig. 3: At the top, 3D models used for the study and, at the bottom, from left to right, a reference model, a noisy model, a local noisy model, and a reconstructed model.

In order to compare metrics results on a modified model, we use the global definition of MSDM and MSDM2 [17] obtained by using a Minkowski pooling; this choice is relevant for perceptual data. We thus also apply Minkowski pooling for having a global score for the proposed intrinsic metrics (PLR, QLR and mean curvature). We have validated (not shown here) our implementation of the extrinsic metrics by assessing their value monotonously decreases on a gradually decimated model.

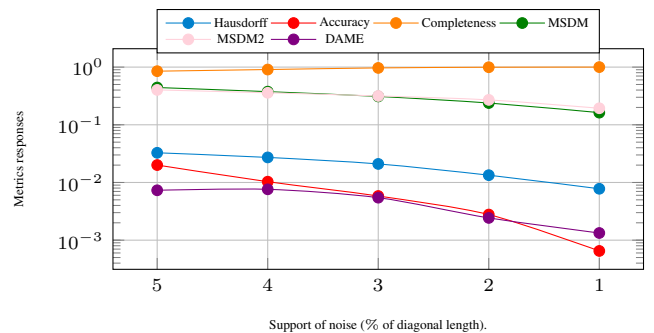


Fig. 4: Extrinsic metrics evolution, for a fixed number of noise germs: 0.5% of the number of vertices of the mesh.

The extrinsic measures have the expected behavior, *i.e.* the responses are correlated to the level of noise on the model (see Figure 4 and 5). Moreover, MSDM2 is not only able to highlight reconstruction defaults as the scores given by this metric increases monotonously both, with the augmentation

of the noise level, and with the augmentation of the number of corrupted regions (see Figure 6); moreover, MSDM2 has been shown to be correlated to perception [17]. On the other hand, DAME (see Figure 5) does not respond as expected as it is not strictly monotonic.

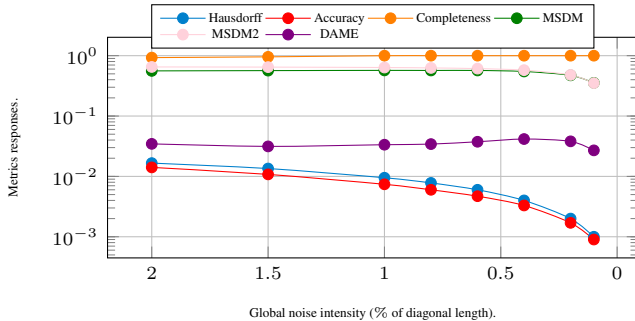


Fig. 5: Extrinsic metrics evolution. All of them are strictly monotonic, except for DAME and completeness.

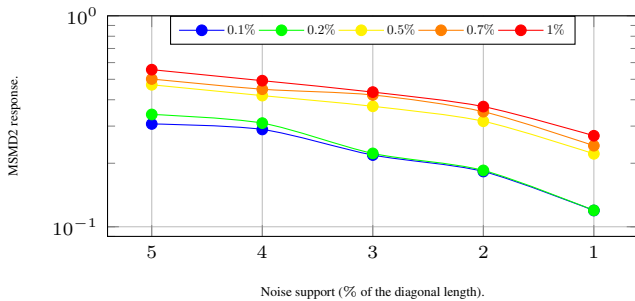


Fig. 6: MSDM2 evolution according to the percentage of noises (colored curves).

In order to assess if the intrinsic measures give a good response in corrupted areas, we compute the difference between the measure response on the deformed and the reference models. These difference maps (see Figure 7) show that high responses are located in the regions corrupted by noise. The intrinsic global difference measures associated with PLR and QLR also vary monotonously with the variation of both number of corrupted regions and their amplitude (see Figure 8).

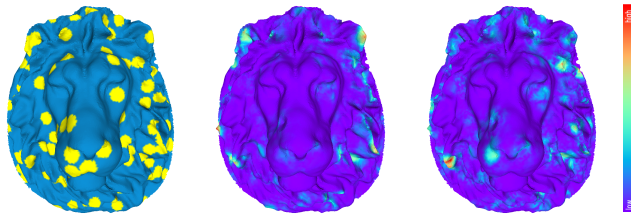


Fig. 7: From left to right: deformation zones of the model and the difference maps for the median QLR and mean PLR response.

Mean curvature gives an information of the local geometry and enables to detect high curved zones that are known to be difficult to reconstruct. Moreover, using the curvature as a global score is challenging because its range of values is not bounded and highly dependant of the particular geometry of each model. In future work, we could rather use the curvature as a indicator for the required point density.

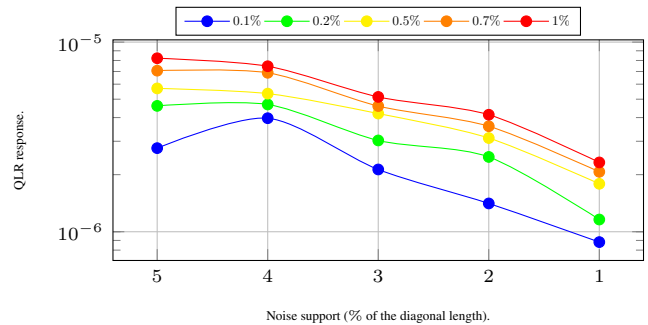


Fig. 8: QLR evolution on the dataset models according to the percentage of local noise (colored curves).

The experiments show that the PLR and QLR metrics have a greater response on the deformed models than on the reference one, thus indicating they can detect the presence of 3D reconstruction defaults. The mean and median responses are quite similar in our experiments because of the nature the noise we applied, we do not have points that can be considered as *outliers*. Besides, the median might hide high values, that is, a high curvature zones, that represent *interesting* parts of the object that the reconstruction should focus on. Note that, the intrinsic metrics do not respond only on the defaults but also on sharp and salient zones of the object (*e.g.* for the lion's mane on Figure 9).

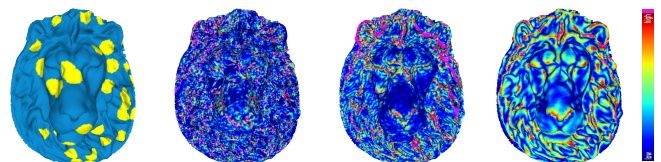


Fig. 9: Local responses to the deformations (yellow regions, leftmost image) of the mean curvature, QLR and PLR on a 3-ring neighborhood, respectively.

5. CONCLUSION AND PERSPECTIVES

Our experiments show that the considered intrinsic metrics have in general a higher response on the deformed zones of the objects but their response also focus on the salient and sharp zones of the object. The next step is to combine these intrinsic metrics in a NBV pipeline, to guide users in the choice of the viewpoint that could improve the poorly reconstructed regions.

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