A Fully Object-space Approach for Full-reference Visual Quality Assessment of Static and Animated 3D Meshes

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Abstract: 3D mesh models are exposed to several geometric operations such as simplification and compression. Several metrics for evaluating the perceived quality of 3D meshes have already been developed. However, most of these metrics do not handle animation and they measure the global quality. Therefore, a full-reference perceptual error metric is proposed to estimate the detectability of local artifacts on animated meshes. This is a bottom-up approach in which spatial and temporal sensitivity models of the human visual system are integrated. The proposed method directly operates in 3D model space and generates a 3D probability map that estimates the visibility of distortions on each vertex throughout the animation sequence. We have also tested the success of our metric on public datasets and compared the results to other metrics. These results reveal a promising correlation between our metric and human perception.

1 INTRODUCTION

3D mesh modeling and rendering methods have advanced to the level that they are now common in 3D games, virtual environments, and visualization applications. Conventional way of improving the visual quality of a 3D mesh is to increase the number of vertices and triangles. This provides a more detailed view; nevertheless, it also leads to a performance degradation. As a result, we need a measure for estimating the visual quality of 3D models, to be able to balance the visual quality of 3D models and their computational time.

Most of the operations on 3D meshes cause certain distortions on the mesh surface and requires an estimation of the distortion. For instance, 3D mesh compression and streaming applications require a tradeoff between the visual quality and transmission speed. Watermarking techniques introduce artifacts and one should guarantee the invisibility of these artifacts. Most of the existing 3D quality metrics omit the temporal aspect which is challenging.

Yildiz et al. (Yildiz and Capin, 2017) propose a perceptual visual quality metric devised for dynamic meshes. They measure the 3D spatiotemporal response at each vertex by modeling Human Visual System (HVS) processes such as contrast sensitivity and channel decomposition. Their framework follows a principled bottom-up approach and produces encouraging results. In their method, they first construct an intermediate representation for the dynamic mesh, which is a 4D space-time (3D+time) volume called *spatiotemporal volume*. However, 4D nature of this representation makes the framework computationally inefficient.

In this work, we build on top of the framework in (Yildiz and Capin, 2017) and remove the necessity for the spatiotemporal volume. Thus we make the perceptual pipeline in (Yildiz and Capin, 2017) fully mesh-based. In this method, we benefit from the eigen-decomposition of a mesh since eigenvalues are identified as natural vibrations of a mesh (Botsch et al., 2010, Chapter 4) and hence, they are directly related to the geometric quality of the mesh. We also compare our results to the method in (Yildiz and Capin, 2017), in terms of both accuracy and efficiency.

2 RELATED WORK

We can categorize the methods for mesh quality assessment as perceptual and non-perceptual methods. Non-perceptual methods such as Euclidean distance, Hausdorff distance, root-mean squared error, etc., rely

on purely geometric measurements without considering human visual perception; thus they are not correlated with the human perception. On the other hand, perceptually-based metrics incorporate mechanisms of HVS. Comprehensive surveys on general mesh quality assessment methods can be found in (Bulbul et al., 2011) and (Lavoué and Mantiuk, 2015); whereas surveys on perceptual quality metrics are presented in (Lin and Jay Kuo, 2011) and (Corsini et al., 2013).

Image-based perceptual metrics operate in 2D image space by using rendered images of the 3D mesh while evaluating the visual quality. These metrics generally employ HVS models such as Contrast Sensitivity Function (CSF), which maps spatial frequency to visual sensitivity. Most common image quality metric is Visible Difference Prediction (VDP) method which produces a 2D local visible distortions map, given reference and test images (Daly, 1992). Similarly, Visual Equivalence Detector method outputs a visual equivalence map which demonstrates the equally perceived regions of two images (Ramanarayanan et al., 2007).

Curvature and roughness of a surface are widely employed for describing surface quality. *GL*1 (Karni and Gotsman, 2000) and *GL*2 (Sorkine et al., 2003) are roughness-based metrics that use Geometric Laplacian of the mesh vertices. Lavoue et al. (Lavoué et al., 2006) measure structural similarity between two mesh surfaces by using curvature for extracting structural information. This metric is improved with a multi-scale approach in (Lavoué, 2011). Two definitions of surface roughness are utilized for deriving two error metrics called 3*DWPM*1 and 3*DWPM*2 (Corsini et al., 2007). Another metric called *FMPD* is also based on local roughness derived from Gaussian curvature (Wang et al., 2012). Curvature tensor difference of two meshes is used for measuring the visible errors between two meshes (Torkhani et al., 2014). A novel roughness-based perceptual error metric, which incorporates structural similarity, visual masking, and saturation effect, is proposed by Dong et al. (Dong et al., 2015). There are also recent studies that leverage machine learning methods for mesh quality assessment (Yildiz et al., 2018). A metric specific to the validation of human body models is also proposed in (Singh and Kumar, 2017).

The literature survey shows that most of the existing visual quality metrics do not take the temporal effects into account. Moreover, they are mostly concerned with the global quality of the meshes rather than the local visibility of distortions. These issues were already addressed by (Yildiz and Capin, 2017). The main objective of this study is to remove the ne-

cessity for a spatiotemporal volume in that method; thus making the pipeline fully object-space.

3 APPROACH

In this mesh-based approach, almost the same steps in (Yildiz and Capin, 2017) exist with several adaptations for 3D. The method is applied on the mesh vertices, not on the spatiotemporal volume representation. However, this introduces a restriction for the reference and test meshes to have the same number of vertices, since the computations are done per vertex.

The steps of the method are displayed in Figure 1. Frames for reference and test animations go through the same processing pipeline and the difference between these results gives us the per vertex visible differences prediction map. Details of each step are explained below.

3.1 Preprocessing

In this step, illumination calculation and vertex velocity estimation are performed as in the spatiotemporal volume approach. Instead of the spatiotemporal volume calculation, Manifold Harmonics Basis (MHB) are computed and stored to feed the *Channel Decomposition* step of the proposed approach.

Illumination Calculation. Vertex shades are computed using Phong reflection model with only diffuse and ambient components. Most of the user experiments for measuring the visual quality of 3D meshes in the literature, use such a simple shading scheme.

Calculation of MHBs. Calculation of MHBs is a costly operation since it requires eigen-decomposition of the mesh Laplacian. Fortunately, once they are computed; there is no need to recalculate them.

For a triangle mesh of *n* vertices, a function basis H^k, called MHB is calculated. The kth element of the MHB is a piecewise linear function with values H_i^k defined at i^{th} vertex of the surface, where $k = 1...m$ and $i = 1...n$ (Vallet and Lévy, 2008). MHB is computed as the eigenvectors of discrete Laplacian of $\bar{\Delta}$ whose coefficients are given in Eq. 1.

$$\bar{\Delta}_{ij} = -\frac{cot\beta_{ij} + cot\beta'_{ij}}{\sqrt{|v_i^*||v_j^*|}} \quad (1)$$

where β_{ij} and β'_{ij} are two angles opposite to edge defined by vertices *i* and *j*, v^* refers to the circumcentric dual of simplex *v*, and $|.|$ denotes the simplex volume.
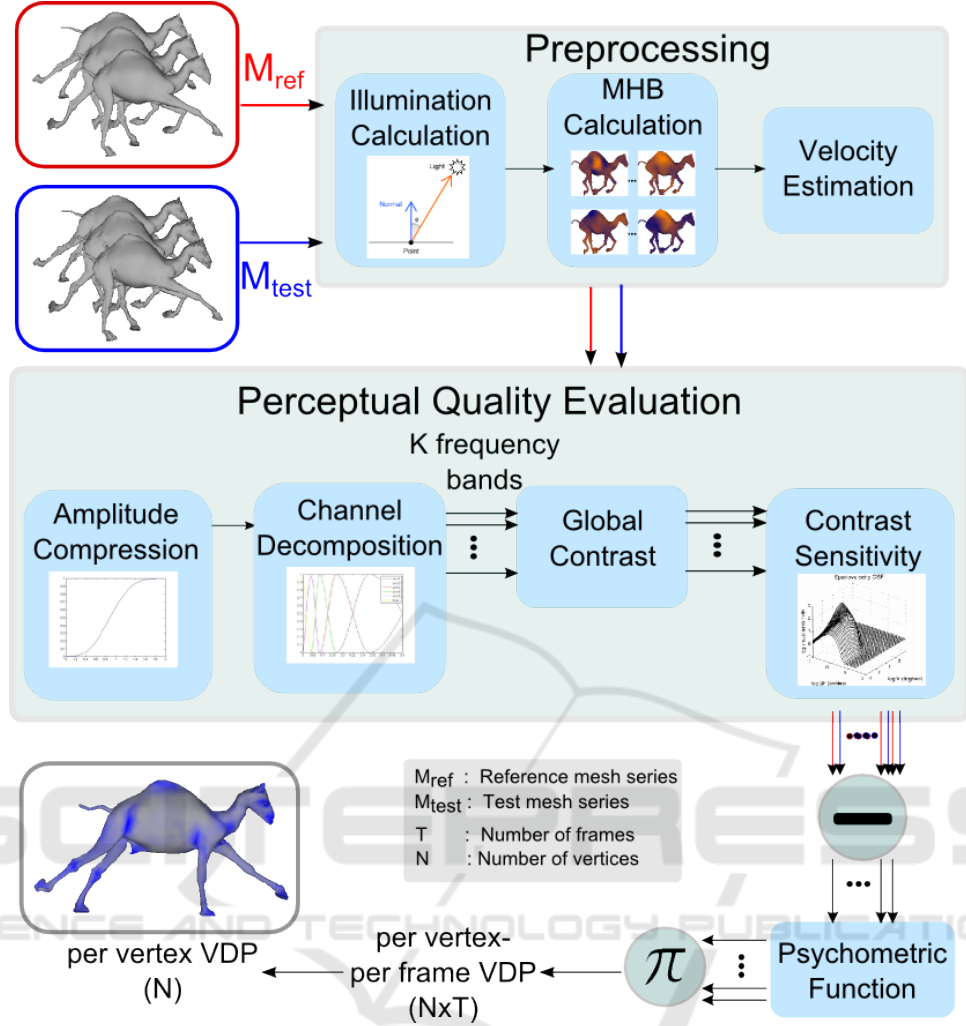
Figure 1: Method overview.

Velocity Estimation. In this step, we calculate the velocity of each vertex at each frame and apply smooth pursuit compensation as described in (Yildiz and Capin, 2017). The aim of smooth pursuit compensation is to handle temporal masking effect which refers to the diminution in the visibility of distortions as the speed of the motion increases.

3.2 Perceptual Quality Evaluation

All the steps of this method are similar to the corresponding steps in the spatiotemporal volume approach, except the Channel Decomposition step which is totally different. To keep the paper self-contained, however, all the steps are explained shortly. Except the Channel Decomposition step, all the steps follow the same procedures described in the previous work, with the exception that equations are

applied per vertex instead of per voxel, since they are not applied on the spatiotemporal volume.

Amplitude Compression. The purpose of this step is to model the photoreceptor response to luminance which "forms a nonlinear S-shaped curve, centered at the current adaptation luminance and exhibits a compressive behavior while moving away from the center" (Aydin et al., 2010).

We apply the local amplitude nonlinearity model by Daly (Daly, 1992) per vertex as in Eq. 2, where i is the vertex index, t is the frame number, $R(i,t)/R_{max}$ is the normalized response, $L(i,t)$ is the luminance value of the vertex, and $b = 0.63$ and $c_1 = 12.6$ are empirical constants.

$$\frac{R(i,t)}{R_{max}} = \frac{L(i,t)}{L(i,t) + c_1 L(i,t)^b} \qquad (2)$$

Channel Decomposition. Our primary visual cortex is known to be selective to certain spatial frequencies and orientations (Aydin et al., 2010). Cortex Transform (Daly, 1992) is commonly used for modeling this visual selectivity mechanism of HVS.

The most important distinction of our approach lies in the implementation of this step. In the *Channel Decomposition* step of the framework in (Yildiz and Capin, 2017), Cortex Transform is used to filter the spatiotemporal volume with *DoM (Difference Of Mesa)* filters in the frequency domain. While converting the spatiotemporal volume to frequency domain, Fourier Transform (FT) is used. However, FT requires voxelization of the mesh surface. *Manifold Harmonics* can be considered as the generalization of Fourier analysis to surfaces of arbitrary topology (Vallet and Lévy, 2008). Hence, we employ *Manifold Harmonics* for applying DoM filter on the mesh and obtain 6 frequency channels as in the spatiotemporal volume based approach.

In the processing pipeline of *Manifold Harmonics*, firstly, *Manifold Harmonics Basis* is calculated for the given triangle mesh of *N* vertices, which is already performed in the preprocessing step of our implementation. Then the geometry is transformed into frequency space by the help of *Manifold Harmonics Transform (MHT)*, which corresponds to projecting *x* into MHB by solving for the coefficients $\tilde{x}_k$ given in Eq. 3. Frequency space filtering is performed by multiplying the coefficients calculated in MHT step by a frequency space filter $F(w)$ (Eq. 4). Lastly, the mesh is transformed back to the geometric space using *inverse Manifold Harmonics Transform* (MHT^{-1}). In its simplest form, MHT^{-1} is performed using Eq. 5; however if a filtering is performed, we use Eq. 4 to obtain filtered values denoted by x_i^F. For a more detailed explanation of MHT, please refer to (Vallet and Lévy, 2008) and (Botsch et al., 2010, Chapter 4).

$$\tilde{x}_k = \sum_{i=1}^{N} x_i D_{ii} H_i^k \qquad (3)$$

$$x_i^F = \sum_{k=1}^{m} F(w_k) \tilde{x}_k H_i^k \qquad (4)$$

$$x = \sum_{k=1}^{m} \tilde{x}_k H^k \qquad (5)$$

One can discover the similarity between the processing pipeline of *Manifold Harmonics* and frequency domain filtering used in (Yildiz and Capin, 2017). MHT and MHT^{-1} correspond to *Fourier* and *Inverse Fourier Transform*, respectively. We construct DoM filters displayed in Figure 2 to be used as the frequency space filters ($F(w)$). The equations for calculating DoM filters can be found in (Aydin et al., 2010) and (Yildiz and Capin, 2017).
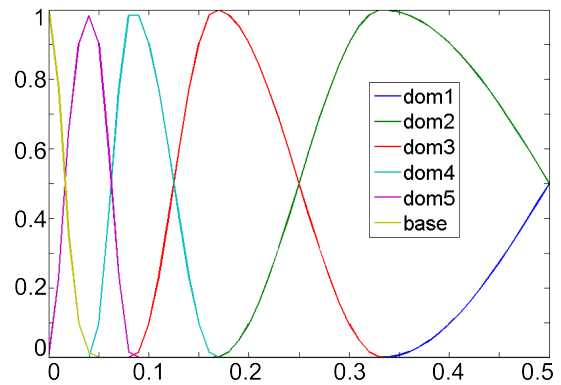

Figure 2: Difference of Mesa (DOM) filters. (x-axis: spatial frequency in *cycles/pixel*, y-axis: response).

Note that the notation in Eq 3-5 was given assuming that the geometry of the mesh will be filtered. It is also possible to filter other attributes of the mesh. For instance, for filtering the color values, we need to replace *x*, *y*, *z* values with *r*, *g*, *b* values. In our case, we need filtering the color values of the mesh with DoM filters.

Figure 3 depicts the six frequency channels generated by applying *Cortex Transform* on an image, while Figure 4 includes the outputs of the *Channel Decomposition* step of our mesh-based approach for the hand mesh. One can notice the parallelism between these results as the frequency decreases from channel 1 to 6 and finer details are captured in the high frequency bands.

Global Contrast. Contrast values in each frequency band is calculated using the global contrast definition in Eq. 6 (Myszkowski et al., 2000); as the sensitivity to a pattern is determined by its contrast rather than its intensity. In the equation, C^k contains the contrast values and I^k contains the luminance values in channel *k*, respectively.

$$C^k = \frac{I^k - mean(I^k)}{mean(I^k)} \qquad (6)$$

Contrast Sensitivity. The next step is to filter each frequency channel with the Contrast Sensitivity Function (CSF). Since our model is designed for animated meshes, we use the spatiovelocity CSF which measures the sensitivity of HVS with respect to spatial frequency and velocity.

Each frequency band is weighted with the spatiovelocity CSF in Eq. 7 (Kelly, 1979). Inputs to the CSF are vertex velocities in each frame and the center
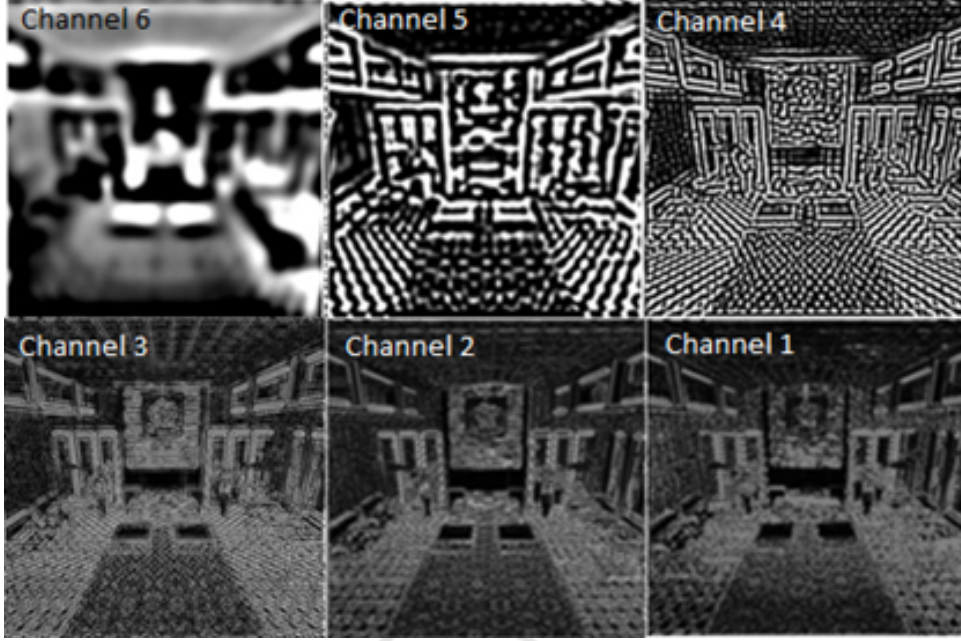
Figure 3: Application of Cortex Transform on an image (Image courtesy of Karol Myszkowski).
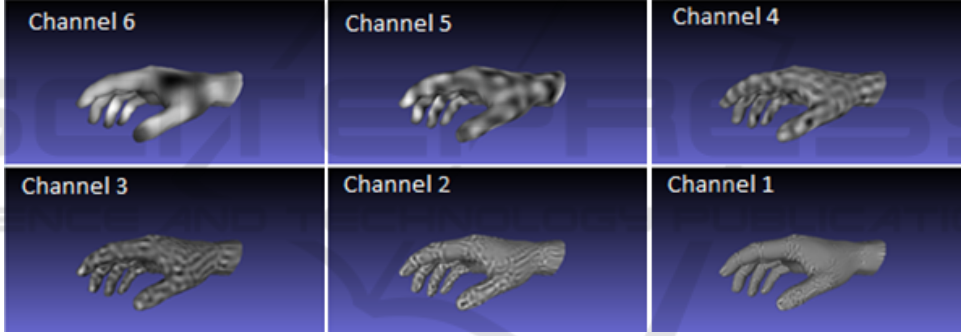

Figure 4: Output of the Channel Decomposition step for the hand mesh.

spatial frequency of each frequency band.

$$CSF(\rho, v) = c_0(6.1 + 7.3|\,log(\frac{c_2 v}{3})\,|^3) \times$$
$$c_2 v(2\pi c_1 \rho)^2 \times exp(-\frac{4\pi c_1 \rho(c_2 v + 2)}{45.9}) \quad (7)$$

where ρ is the spatial frequency in *cycles/degree*, v is the velocity in *degrees/second*, and $c_0 = 1.14, c_1 = 0.67, c_2 = 1.7$ are empirically set coefficients.

Error Pooling. Both reference and test animations go through the above steps. K frequency bands for each sequence are generated in this pipeline. Then the difference between test and reference pairs for each band is passed to a psychometric function which maps the perceived contrast (C') to probability of detection using Eq. 8 (Aydin et al., 2010). Then each band is combined using the probability summation formula

(Eq. 9) (Aydin et al., 2010).

$$P(C') = 1 - exp(-|\,C'\,|^3) \quad (8)$$

$$\hat{P} = 1 - \prod_{k=1}^{K}(1 - P^k) \quad (9)$$

$\hat{P}$ contains the detection probabilities of each vertex per frame. We merge the probability maps of each frame into a single map, by averaging the values of vertices over the frames. This gives a per vertex visible difference prediction map for the animated mesh.

4 RESULTS

In this section, the performance of the proposed approach is evaluated from accuracy and processing time perspectives, compared to other methods.

173

4.1 Accuracy

In this section, we evaluate the performance of our metric compared to the state-of-the-art metrics. Our metric is applicable on both static and dynamic meshes and generates a 3D local distortion map. However, most of the publicly available datasets measure the global visual quality. Therefore, we first measure the performance of our metric on detecting local distortions using the dataset constructed by Yildiz and Capin (Yildiz and Capin, 2017), which contains local distortion maps for distorted animations with respect to four reference animations. The dataset is composed of four different mesh sequences with number of vertices changing from 8K to 42K.

As the performance measurement, we use Spearman Rank Order Correlation Coefficient (SROCC) between metric results and mean opinion score (MOS) values. Table 1 lists SROCC values for both our metric and the metric proposed in (Yildiz and Capin, 2017).

We also compare our global metric results to the common metric results on LIRIS/EPFL General Purpose dataset (Lavoué et al., 2006), which is used as benchmark in many mesh processing studies. Table 2 includes SROCC values for each model and metric. Both the local and global results show that our mesh-based approach achieves good and almost the same correlation values with the metric in (Yildiz and Capin, 2017).

4.2 Processing Time

We also measured the running time of our metric compared to the previous work (Yildiz and Capin, 2017), for several meshes. Measurements are performed on a 3.3 GHz PC. As depicted from Figure 5, running time of our algorithm is almost proportional to the number of vertices of the mesh; which is reasonable because the algorithm operates per vertex. Note that these meshes are selected to illustrate the dependency of the running time of the algorithm on the number of vertices. Note also these results ignore the preprocessing times.

We know that the running time depends on the number of voxels for the spatiotemporal volume approach (Yildiz and Capin, 2017) and it depends on the number of vertices in our approach. Keeping this observation in mind, we see that the spatiotemporal volume approach runs faster for the *horse* and *camel* animations, although the number of vertices is less than the number of voxels in these cases. This is due to the domination of manifold harmonics calculations for small meshes in our approach. However, the share
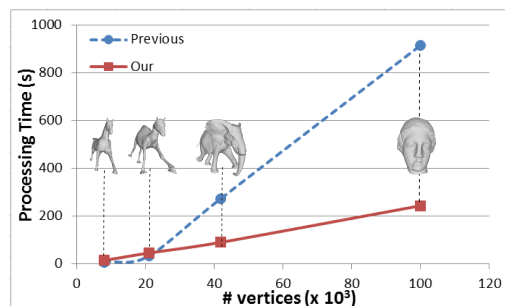

Figure 5: Processing time (in seconds) of one frame for several meshes.

of these calculations diminishes as the number of voxels gets much higher than the number of vertices.

4.3 Discussion

Concisely, both approaches produce comparable results from the accuracy perspective. On the other hand, we can deduce from the computational time measurements that our mesh-based VQA method is more efficient than the spatiotemporal volume-based method for large meshes (i.e. # *vertices* > 25K). Nevertheless, it is important to remind that mesh-based approach confines the reference and test meshes to have the same number of vertices. Thus, for large meshes without connectivity changes, our mesh-based approach is preferable because of its efficiency, with the expense of Manifold Harmonics Basis calculations as a preprocessing.

It is also important to note a design issue in the MHB calculations of our method. Calculation of the MHBs for meshes with high number of vertices is a problem due to its space complexity. To overcome this problem, cotangent weight and delta matrices in Eq. 1 are stored as sparse matrices which enables a significant amount of reduction in the memory space. We have also adopted the idea in (Song et al., 2014), where eigen-decomposition is performed on the simplified version of the mesh and the results are mapped to the original mesh using a kd-tree structure, for mesh saliency calculations. Following this process, for large meshes (#*vertices* > 25K, in our implementation), the *Channel Decomposition* step (Section 3.2) is applied on the simplified versions of the meshes and the results are expanded to the original size using a kd-tree representation. For mesh simplification, we employ the *quadric edge collapse decimation* method of MeshLab's implementation (Cignoni et al., 2008), with boundary-preserving option is set. Although the accuracy results are close to the spatiotemporal volume-based approach, performing MHB calculations on reduced meshes may degrade the results and further verification is required for this choice.

Table 1: The performance of our metric on detecting local distortions compared to the metric proposed in (Yildiz and Capin, 2017). SROCC values are given in percentages (%).

	Our metric	The metric in (Yildiz and Capin, 2017)
Camel	84	83
Elephant	63	65
Hand	73	71
Horse	70	70
Overall	73	72

Table 2: Spearman correlation coefficients in percentages (%) for each model and metric (highest values are marked).

	Armadillo	Dinosaur	RockerArm	Venus	Mean
MSDM (Lavoué et al., 2006)	84	70	**88**	86	82
3DWPM2 (Corsini et al., 2007)	71	47	29	26	43
3DWPM1 (Corsini et al., 2007)	64	59	85	68	69
GL1 (Karni and Gotsman, 2000)	68	5	2	**91**	42
GL2 (Sorkine et al., 2003)	76	22	18	89	51
Yildiz et al. (Yildiz and Capin, 2017)	**86**	**79**	**88**	89	**86**
Our metric	**86**	78	**88**	90	**86**

5 CONCLUSION

The aim of this paper is to provide a general-purpose visual quality metric for estimating the local and global distortions in both static and animated meshes. The method extends the costly framework in (Yildiz and Capin, 2017) to fully operate in 3D object space. Our approach incorporates both spatial and temporal sensitivity of the HVS. The algorithm outputs a 3D probability map of visible distortions. The most significant contribution of our method is that we employ *manifold harmonics transformation* to propose a principled way for modeling the visual selectivity mechanism of HVS on 3D surfaces. According to our experimental evaluations, our metric gives promising results compared to its counterparts.

Our method shares the advantages of the metric in (Yildiz and Capin, 2017): It incorporates the effect of temporal variations; which is omitted by most of the studies in the literature. The algorithm can be used for measuring the quality of both static and dynamic meshes. In addition to these, our method is computationally more efficient in certain cases.

The main drawback of our method is the requirement of fixed connectivity mesh pairs. As a future work, we intend to relax this constraint by first applying a vertex correspondence algorithm. Moreover, a more extensive user study, considering the effects of several parameters, is needed.

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