OPTIMISED MODELS FOR AR/VR BY USING GEOMETRIC COMPLEXITY METRICS TO CONTROL TESSELLATION

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ABSTRACT

AR/VR applications are a valuable tool in product design and lifecycle. But the integration of AR/VR is not seamless, as CAD models need to be prepared for the AR/VR applications. One necessary data transformation is the tessellation of the analytically described geometry. To ensure the usability, visual quality and evaluability of the AR/VR application, time consuming optimisation is needed depending on the product complexity and the performance of the target device.

Widespread approaches to this problem are based on iterative mesh decimation. This approach ignores the varying importance of geometries and the required visual quality in engineering applications. Our predictive approach is an alternative that enables optimisation without iterative process steps on the tessellated geometry.

The contribution presents an approach that uses surface-based prediction and enables predictions of the perceived visual quality of the geometries. This contains the investigation of different geometric complexity metrics gathered from literature as basis for prediction models. The approach is implemented in a geometry preparation tool and the results are compared with other approaches.

Keywords: Virtual reality, Visualisation, Machine learning, Optimisation

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Cite this article: Dammann, M. P., Steger, W., Paetzold-Byhain, K. (2023) 'Optimised Models for AR/VR by Using Geometric Complexity Metrics to Control Tessellation', in *Proceedings of the International Conference on Engineering Design (ICED23),* Bordeaux, France, 24-28 July 2023. DOI:10.1017/pds.2023.286

1 INTRODUCTION

AR/VR applications are a useful tool in product design. Applications reach from the improvement of product models in VR design reviews to the early inclusion of service in virtual maintenance planning. Product geometry plays an essential role in these 3D visualisations. The prevalent geometry representations for these visualisations are polygon meshes that are used with game engines like Unity or Unreal to create AR/VR applications. However, product geometry in engineering is described analytically in CAD systems. The CAD data (analytical geometry and product structure) needs to be transformed to AR/VR data (polygon meshes, product structure, metadata) in a geometry preparation process (Dammann *et al.*, 2022b; Santos *et al.*, 2021; Graf *et al.*, 2002; Salonen *et al.*, 2009).
The main task in this process is the discretisation of the analytical geometry, which is called tessellation (Dammann *et al.*, 2022b). Tessellation algorithms offer parameters to control the accuracy of the discretisation, for example linear deflection and angular deflection from the parametric geometry. The choice of tessellation parameters influences the visual quality of the AR/VR application. Furthermore, perception is determined by e.g.: lighting, reflections, materials, object count, draw calls and physics simulation. In theory the tessellation parameters can be derived from the complexity and importance of the geometry. As product models often contain thousands of components, all geometries are tessellated with the same parameters due to a lack of automated parameter choice (Lorenz *et al.*, 2016; Dammann *et al.*, 2022b). This approach often results in models with too many polygons (e.g.: insignificant components like screws or rivets claim an unreasonable amount of polygons) or with insufficient visual quality and a need for time-consuming manual rework. These problems are particularly evident on mobile devices (tablet, AR-HMD).
The current approach to this problem in geometry preparation is an iterative decimation approach, see Figure 1. This approach relies on the reduction of quality in the polygon mesh by collapsing polygons until an optimisation criterion is satisfied - in most cases the polygon count. The varying importance of different geometries and the human perception of visual quality of the polygon mesh are not taken into account. The approach also requires a high quality of the initial tessellation to ensure good results of the decimation.

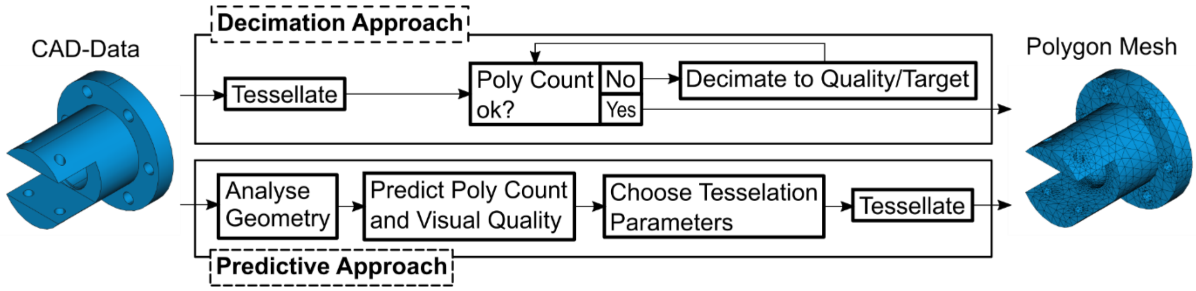

Figure 1: Decimation approach vs. predictive approach for optimisation in geometry preparation (Dammann et al., 2022a)

The predictive approach (Dammann *et al.*, 2022a) is based on geometric complexity metrics (e.g. area, curvature), which are retrieved in an analysis of the CAD geometry. The metrics are used by a regression model to create predictions for the tessellation results of a parameter setting for the tessellation algorithm of choice. In this way the effects of the choice of different tessellation parameters can be quantified in advance. The regression models are created from datasets based on collected geometric complexity metrics and tessellation results (e.g. polygon count). A separate regression model is needed for each parameter setting. The predictive approach uses existing tessellation algorithms and offers a way to automatically adjust their parameters. The approach does not modify tessellation algorithms themselves.
Through the choice of appropriate tessellation parameters for each geometry, iterative process steps in the geometry preparation can be reduced or avoided. In addition, geometric complexity metrics can be used to rate the visual importance of each geometry in the AR/VR application and identify potentially problematic components, which enables further automation of the geometry preparation.
The advantages of the predictive approach as an alternative to the decimation approach has already been demonstrated for part-based predictions. The approach enables targeted polygon count and quality optimisations for large assembly models. This contribution presents an enhancement to the predictive approach by additional predictions of the perceived visual quality of the polygon meshes. Perceptual

https://doi.org/10.1017/pds.2023.286 Published online by Cambridge University Press

visual quality metrics are typically not a part of the geometry preparation, as the calculation generally takes more time than the other steps of the geometry preparation combined.
Furthermore, a transition from part-based to surface-based prediction is explored. In the original approach geometric complexity metrics are collected for each part and predictions for the tessellation results are also generated for each part. In this contribution the metrics are collected for each surface of a part and the predictions are in term calculated per surface, the accumulated surface predictions are then used to calculate e.g. the polygon count of a part.
This contribution explores the following research question:
How do the use of surface-based predictions and predictions of the visual quality affect the prediction accuracy and geometry preparation results of the predictive approach?

We evaluate the following hypotheses (H1-H3):
H1: Surface-based predictions improve the accuracy of the predictive approach.
H2: Surface-based predictions are faster than part-based predictions.
H3: Visual quality predictions enable the creation of polygon meshes with higher visual quality and a similar polygon count as the decimation approach.

The content of this contribution is an important part in a framework for the automated and adaptive geometry preparation for AR/VR applications in engineering. Which, in turn, is essential for the broad and seamless use of AR/VR as a tool in product design. Engineers can focus on product development and design instead of spending time on the preparation and optimisation of content for the AR/VR application.

2 RELATED RESEARCH

Tessellation
The tessellation is performed by the use of different tessellation methods. Direct triangulation approaches (Guo *et al.*, 2019; Baker, 2005) like Delaunay triangulations (Cheng *et al.*, 2013; Nguyen *et al.*, 2009), Octree triangulations (Maréchal, 2009; Liang and Zhang, 2014; Ito *et al.*, 2009) and the Advancing Front Technique (Ito *et al.*, 2007) are common. To alleviate weaknesses of the different methods, the algorithms are often combined. The main focus of research of tessellation for AR/VR applications in engineering has been the complete transfer of the geometry without faults (Freeman *et al.*, 2017; Han *et al.*, 2019). Optimisation of the tessellation and parameter choice is mainly discussed for simulation applications such as FEM or CFD (Guo *et al.*, 2019; Laug and Borouchaki, 2011). However, the tessellation results of these approaches are inadequate for high-fidelity real-time visualisations in AR/VR, as they contain unnecessary polygons that do not improve the perceived visual quality.
The subsequent editing of polygon meshes in regards to polygon count and detail is possible (Santos *et al.*, 2021; Han *et al.*, 2019), with the main approaches of decimation (Tang and Gu, 2010) and remeshing (Panozzo *et al.*, 2011). Decimation works by collapsing polygons and thus reducing the polygon count and visual quality of the mesh. For remeshing the outline of the mesh is reconstructed with new but fewer polygons, which leads to better results. Both methods are in principle avoidable in the geometry preparation, by choosing adequate tessellation parameters.
Geometric Complexity
Johnson et al. evaluate different approaches to describe the geometric complexity of CAD-models with regard to the needed modelling time (Johnson *et al.*, 2018). Complexity metrics concerning geometric problems like the tessellation of analytical geometries are called geometric complexity metrics in literature. Examples for geometric complexity metrics are the number of polygons needed to represent a geometry with a polygon mesh (Rossignac, 2005), the ratio of volume to the volume of the bounding box of the geometry (Joshi and Ravi, 2010) or the number of surfaces of the geometry (Denkena *et al.*, 2011). In earlier research we proposed the face weight factor (Dammann *et al.*, 2022a).
Curvature based metrics are frequently discussed. For example the total absolute curvature (Okano *et al.*, 2019) or the approach to combine the curvature with the information theorem by Shannon as a way to measure the human perception of geometric complexity used by Page et al. (Page *et al.*, 2003) and Sukumar et al. (Sreenivas R. Sukumar *et al;* Sukumar *et al.*, 2008).

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Mesh Quality

The visual quality of the polygon mesh is an important factor in the geometry preparation for AR/VR-applications. It can be influenced by the choice of parameters for the tessellation. Purely geometric quality metrics like the Euclidian distance, the Hausdorff distance or root mean squared error (Yildiz *et al.*, 2020) are common in tasks that process polygon meshes. However, the correlation between these geometric criteria and the human perception of the visual quality is weak (Corsini *et al.*, 2013; Lavoue and Corsini, 2010).

Perceptual metrics are more suited to rate the visual quality. These metrics are based on the correlation between mesh properties and a quantification of the human perception. The visual quality is typically captured as Mean Opinion Score (MOS), which is calculated from comparative assessments of meshes by test subjects (Bulbul *et al.*, 2011). This approach is based on established standards in the evaluation of image and video recordings and validated datasets do exist (Corsini *et al.*, 2007).

As the comparative assessment of meshes is not practical in most scenarios, most visual quality metrics use MOS datasets and the correlation between the MOS and geometric characteristics to estimate the visual quality. Common estimators for the visual quality are the roughness (Corsini *et al.*, 2007), the curvature (Dong *et al.*, 2015) or dihedral angles of the mesh (Corsini *et al.*, 2007). Established metrics like e.g. MSDM2 (Lavoué, 2011) use these estimators separately. Machine learning based approaches often combine different estimators to improve the correlation to the MOS (Abouelaziz *et al.*, 2015; Feng *et al.*, 2018; M Muzahid *et al.*, 2018; Yildiz *et al.*, 2020).

3 APPROACH

3.1 Geometric complexity metrics

The evaluation procedure for different geometric complexity metrics in relation to the tessellation results consists of the extraction of existing metrics from literature, the BREP description and the calculation of ratios. The focus lies on metrics which describe the complexity of individual surfaces. The metrics are divided in three types:

Basic Values

Basic values are directly extracted from the BREP model. Examples are the area, the dimension of the bounding box, the memory size or the vertex count of the surface. The elementary surfaces of a BREP geometry are: Plane, Sphere, Cone, Toroid, Cylinder and B-Spline. These surface types are also gathered. Other basic values are the shortest and longest edge of a surface and the number of wires (contiguous edges), as well as the number of unique normal vector directions.

Derived Values

The derived values are different ratios. An example is the ratio of memory size to area, which expresses the memory density of the surface. Other examples are the ratios of mean curvature to the number of vertexes and the length of the edges to the number of vertexes of the surface.

Calculated Values

Calculated values describe complexity metrics that are defined by equations that require multiple calculation steps. Examples are the bounding box volume, the mean curvature or the curvature variation measure (CVM) according to Sukumar et al. (Sreenivas R. Sukumar *et al.*). The CVM measures the perceived geometric complexity and is defined as:

$$CVM = -\sum p(\kappa) log_n p(\kappa) \quad (1)$$

with p as the probability density of curvature estimated by using kernel density estimators (KDE). The CVM is calculated for the mean curvature. The complete calculation of the CVM is described in Sukumar et al. (Sreenivas R. Sukumar *et al.*).

The face weight factor (FWF) was proposed in (Dammann *et al.*, 2022a). The FWF expresses the average polygonal degree of a surface of a geometry. The FWF of a plane is 1, while the FWF of a cylinder, cone, toroid or sphere is 2 and the FWF of a B-spline surface is the mean of the polygonal degree of the splines in UV-coordinates. In addition, the average edge length of each surface is calculated.

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3.2 Evaluation of geometric complexity metrics

Following our approach, the geometric complexity metrics are investigated in a statistical analysis. Chunk 1 of the ABC dataset (Koch *et al.*, 2019) is analysed in the open source CAD program FreeCAD. This provides a data basis of approximately 150,000 individual parts (duplicates are sorted out) with around 2,500,000 surfaces from 10,000 STEP files. The python modules pandas and scikit-learn are used to collect and analyse the data. All results are created on an AMD Ryzen 7 2700X CPU with 16GB of RAM and a NVIDIA RTX 2080 GPU.

Using the visualisation tessellation algorithm ("Standard Algorithm") of FreeCAD each surface of each individual part is tessellated. The algorithm can be controlled by the main parameters of the surface (linear) deflection and the angular deflection. The maximum linear deviation of a mesh segment from the parametric geometry is controlled by the surface deflection and the angular deflection controls the maximum angle between two mesh segments. Smaller values for both parameters lead to a finer mesh. The following descriptions are based on a surface deflection of 0.1 mm and an angular deflection of 30°. Subsequently to the tessellation the number of polygons and the MOS are calculated for each surface.

The evaluation in (Dammann *et al.*, 2022a) has already shown, that the relations between the complexity metrics and the target variables can be linearised by a logarithmic transformation on both the metrics and the variables. In addition, only the use of multiple metrics is suitable to create predictions with the needed accuracy. In a comparison of different machine learning algorithms (not shown here because of page restriction) for the addressed regression problem, random forest regression is identified as a suitable compromise between prediction accuracy and calculation time. The number of polygons and the MOS are used as target variables for the statistical analysis and regression, because of the use of random forest regression the aforementioned logarithmic transformation is not applied on the data for the following descriptions. For the calculation of the MOS the multi-attribute model after Lavoué et. al. is used. This metric uses a multiple linear regression based on - among others - the curvature, the dihedral angle and the geometric distance, for more information see (Lavoué *et al.*, 2013). The metric is chosen, because it achieves a better correlation to the MOS than established metrics like MSDM2 and similar results to more recent machine learning approaches. In addition, it is easy to reproduce and implement.

3.3 Statistical analysis of geometric complexity metrics

Figure 2 shows a bar chart of the highest Pearson correlations and statistical significances between the geometric complexity metrics and the identified target variables. The first value of each bar is the Pearson correlation coefficient and the second value (in brackets) is the p-value. The p-value indicates a relation with statistical significance (<= 0.05) and is smaller than 0.01 for all metrics in Figure 2.

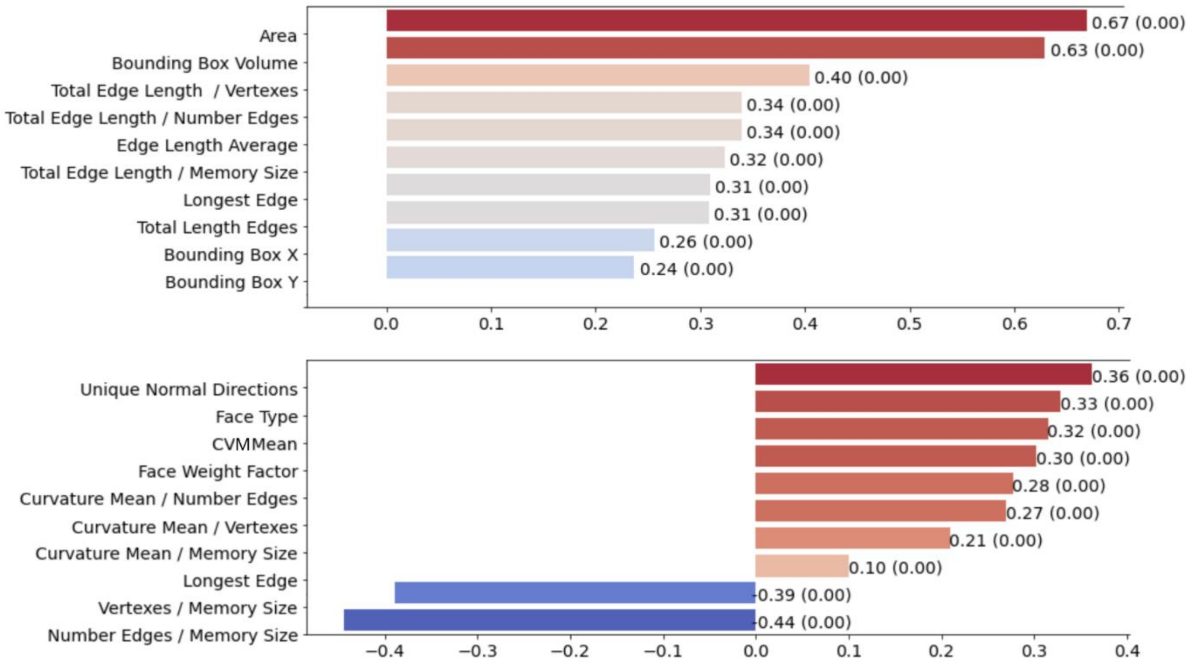

Figure 2: Pearson correlations for polygon count (top) and MOS (bottom), p-value in brackets

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For the polygon count the highest correlations (> |0.6|) are observed for the area and the bounding box volume. The highest correlations with the MOS (>|0.3|) are observed for the number of edges to memory size and vertexes to memory size ratios, as well as the number of unique normal directions, the surface type and the CVM of the mean curvature.
The metrics show multicollinearity between a number of metrics. This is to be expected, as e.g. the complexity metrics of the derived values are calculated based on other metrics. An investigation into the reduction of the used metrics with automated feature selection techniques (e.g. step-wise and boruta feature selection) proves very time consuming and does not yield significant improvements to the prediction accuracy. Therefore, the following results are based on random forest regression models that use all metrics respectively.

4 RESULTS

4.1 Polygon and MOS prediction

The data sets used for training and evaluation of the prediction models contain the geometric complexity metrics and the respective target variable. The polygon count and the MOS both change depending on the selected tessellation parameters, while the complexity metrics are not affected. Therefore, the polygon count and the MOS are collected for different tessellation parameter sets, while the complexity metrics only have to be captured once. Collecting the metrics takes around 2 h for the dataset. For the polygon count and MOS the time depends on the tessellation settings (typically 2 h/ 24 h). The following results use a surface deflection of 0.1 mm and an angular deflection of 30°. Each data set is randomly split into a training and a test data set (80%/20%) with scikit-learn (random seed=0), which is also used for the subsequent training and model creation (around 20 min per model). Figure 3 contains scatter plots of the prediction results for the test data set. Both models show heteroscedasticity, where a higher deviation of the predictions can be observed for higher values of the polygon count or the MOS (light blue range). The prediction accuracy is measured with the mean absolute percentage error (MAPE). The MAPE of the polygon count prediction for the model in Figure 3 is 6.66%, while the MAPE of the MOS is 4.26%. A MAPE <10% is typically considered as a highly accurate forecast (Montaño Moreno *et al.*, 2013). The prediction accuracy is therefore suitable for the intended use (see 4.2).

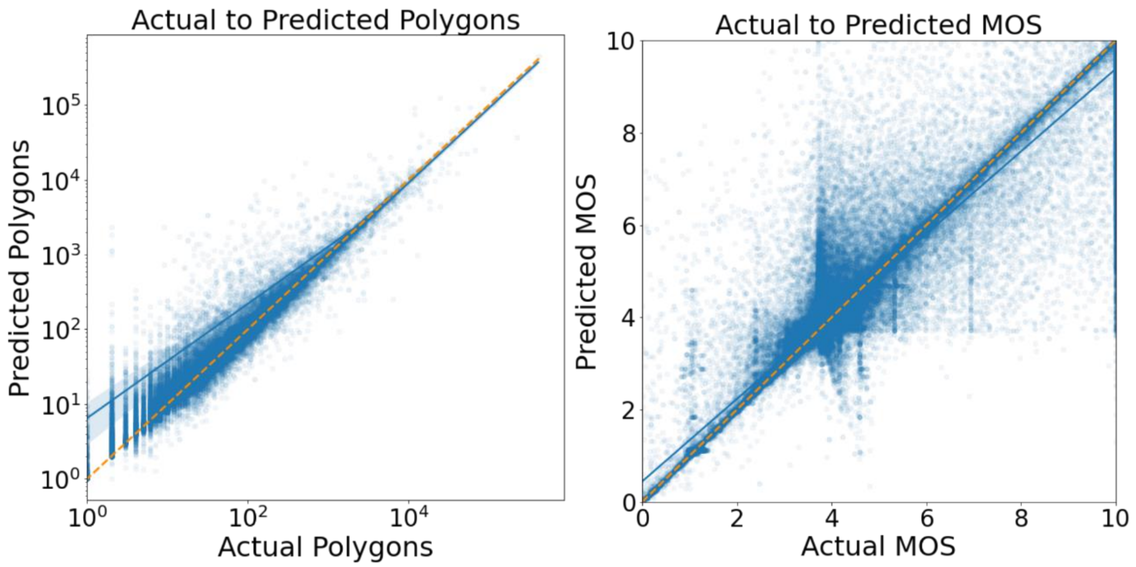

Figure 3: Predicted vs. actual number of polygons (left, logarithmic axes) respectively MOS (right) scatter plots, darker blue indicates a higher concentration of points

4.2 Implementation in the geometry preparation tool GeoPrep

In addition to the prediction models in 4.1, models for the tessellation parameter settings of 1 mm/30° and 1 mm/50° are created. The prediction models are implemented in the developed geometry preparation tool GeoPrep, see (Dammann *et al.*, 2022b). The tool is able to collect the complexity metrics for each CAD geometry from a STEP file. Table 1 contains polygon and MOS prediction

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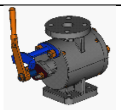
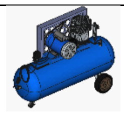
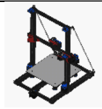
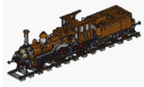
results for a test set of six CAD assemblies. On the assembly level the MAPE of the surface-based polygon predictions is 8.93 %, compared to 13.46 % of the part-based approach (**H1** holds). For the MOS a pseudo MOS is calculated, where all parts are viewed as one connected geometry. This approach is chosen solely to investigate the accuracy of the predictions and should not be used in geometry preparation. The MAPE of the pseudo MOS is 15.44 %. As the MOS is calculated per vertex, the calculation of the pseudo MOS uses the polygon predictions to estimate the vertex count of each surface. This leads to higher deviations due to error propagation.

From an engineering perspective the geometric complexity metrics and predictions enable the automated identification of problematic components or surfaces in the geometry preparation. Examples are geometries with a high complexity in a small space like screws or springs, which very often have no central importance in e.g., design reviews. The prediction of the MOS allows to identify components that would suffer a great loss in visual quality through the reduction of the tessellation quality. This can be used to identify possible required manual rework.

Table 1: Prediction results on assembly level for polygon count (part-based approach in italic) and MOS

Assembly	**1**	**2**	**3**	**4**	**5**	**6**
Image						
Polygon Prediction Surface	38,799	153,604	196,692	983,696	1,327,602	2,534,811
Polygon Prediction Part	*52,550*	*181,306*	*185,049*	*856,517*	*969,838*	*1,874,084*
Polygon Actual	44,170	159,036	181,927	996,259	1,188,989	2,166,863
Pseudo MOS Prediction	5.21	6.09	5.68	5.91	5.03	5.58
Pseudo MOS Actual	4.24	6.98	5.09	6.14	5.37	8.63

The performance of the predictive approach is evaluated in comparison to the decimation approach. To test a geometry preparation the assembly 6 from Table 1 has to be reduced to a polygon target of one million. Table 2 shows the results for the prediction approaches in GeoPrep which uses the OCCT kernel of FreeCAD and the decimation approach in different software tools. The tessellation parameters for the initial tessellation are chosen in each software to produce a polygon count similar to Table 1. In FreeCAD the decimation approach takes 16 s for the initial tessellation and 10 s for the decimation, producing 1,091,442 polygons. Pixyz Studio performs the fastest decimation with 19 s overall and a polygon count of 961,588. The decimation approaches are implemented in C/C++, while a large portion of the implementation of the predictive approach is currently written in python.

The runtime of the surface-based predictive approach is 13 s and produces a polygon count of 1,051,842. The collection of the geometric complexity metrics and the prediction take 8 s, while the tessellation takes only 5 s. This is an improvement over the part-based prediction which takes 22 s (**H2** holds). If the geometry preparation requires an even lower polygon count or a preparation for different target platforms (e.g. tablet, AR HMD or CAVE) the advantages of the predictive approach increase.

Table 2: Time for geometry preparation and time for decimation/prediction in a selection of software tools (prediction approach bold)

Software	Total Time (s)	Thereof Prediction Time (s)	Thereof Decimation Time (s)	Polygons
FreeCAD 0.20 (surface-based)	**13**	**8**	**-**	**1,051,842**
Pixyz Studio 2022	19	-	11	961,588
FreeCAD 0.20 (part-based)	**22**	**17**	**-**	**1,051,842**
FreeCAD 0.20	26	-	10	1,091,442
FreeCAD 0.20 + Blender 3.1.2	28	-	12	1,012,299
Autodesk 3ds Max 2023	38	-	28	1,011,590
SolidWorks 2022-2023	240	-	212	1,017,978
FreeCad 0.20 + Simplygon 10	448	-	432	990,293

Through the use of the predictive approach, produced polygon models with similar polygon count have a higher visual quality than the decimation approaches in comparison. In figure 4 this is visualised through a colour grading of the visual distortions of the models. Warmer colours indicate high distortion values, which will be noticeable to the observer. The decimation approaches show a higher global distortion and also areas with very high distortion values. In practical application, the predictive approach can either achieve a higher visual quality with a similar number of polygons, or a similar visual quality with a lower number of polygons (**H3** holds). The addition of predictions for the visual quality allows to use this advantage of the approach in an automated way. This is particularly beneficial when visualising very complex assemblies or when using low-performance hardware (AR-HMD, tablet). In addition, the prediction of the MOS is faster than the calculation of the MOS. Thus, the MOS prediction (for Figure 4) takes only 0.2 s, while the MOS calculation takes 3 s (for comparison: the tessellation takes 0.8 s).

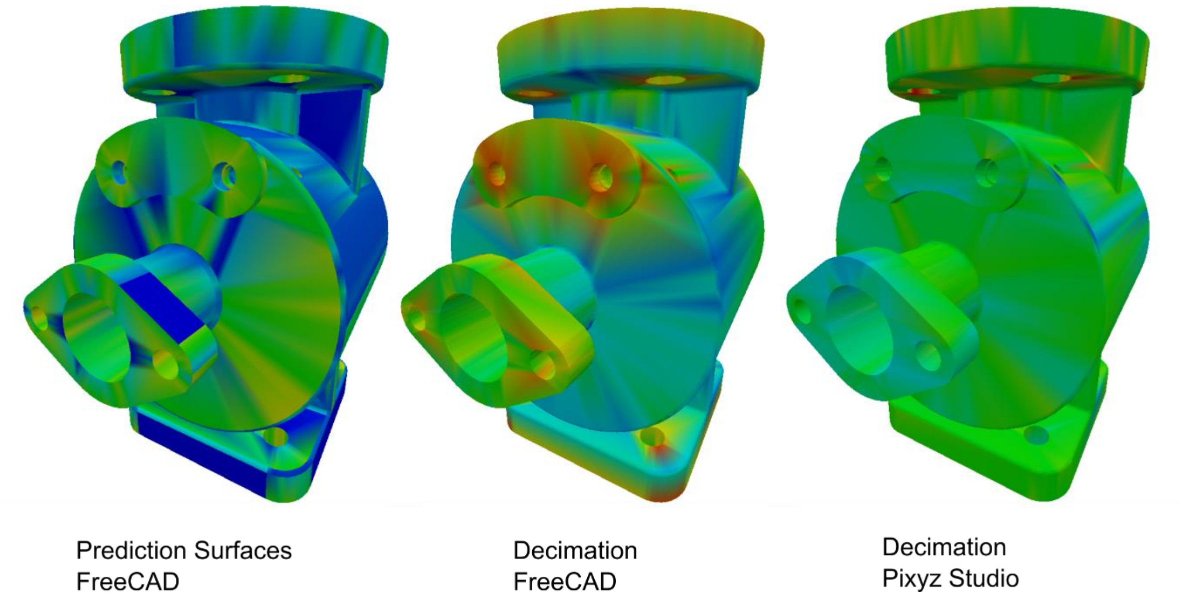


Figure 4: Visualisation of the visual perception of mesh distortions for models with similar polygon count (~12.000), warmer colours represent higher distortion values.

As the predictive approach relies on statistics, predictions might show high deviations for outliers. Therefore, the decimation approach may be used as a fallback method for these cases.

5 SUMMARY

The use of geometric complexity metrics for the control of the geometry preparation enables the prediction of the polygon count and the MOS as measures for the visual quality before the tessellation. With the surface-based approach and the use of the ABC dataset, the prediction accuracy has been improved in comparison to the part-based approach. Iterative mesh operations in the geometry preparation can be reduced or avoided in this way.

The surface-based prediction enables new possibilities in the automated geometry preparation in design. This includes the targeted and well-founded simplification of geometries by the removal of features like holes, fillets or interior geometry (e.g., interior of cast components). The use of the MOS allows a stronger alignment of the geometry preparation with human perception. Here, the predictive approach is particularly valuable, as the prediction is significantly faster than the calculation of the MOS. Again, the surface-based prediction allows a targeted and grounded choice of tessellation parameters based on the visual importance of the individual surfaces. The improvements to the predictive approach enable the creation of models with higher visual quality than the compared decimation approaches, while also being faster.

In future research the aim lies on enabling predictions for arbitrary tessellation parameters and the application of the predictive approach in a framework for the automated and adaptive geometry preparation for AR/VR applications on different target platforms in design. The results can also be used to make the preparation of CAD data for other visualisation purposes more efficient.

https://doi.org/10.1017/pds.2023.286 Published online by Cambridge University Press

ACKNOWLEDGEMENTS

Some of the results presented were developed as part of the ZIM cooperation projects ZF4123410SS9 and ZF4004704SS9, which were funded by the AiF.

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