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Estimating optimal encoder parameters for a priority-driven connectivity compression algorithm for triangle meshes with known geometry

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1 Introduction

The algorithm proposed in Dvořák et al. (2022) is a state-of-the-art triangle mesh compression algorithm that exploits the knowledge of mesh geometry, i.e., the vertex positions, at both the encoder and decoder to efficiently encode its connectivity, i.e., the triangle faces.

The encoder and decoder process the mesh one triangle at a time. In every iteration, the algorithm extends the processed part with a triangle from the unprocessed part. The processed and unprocessed parts are separated by gates, i.e., the common bordering edges. The selection of the gate to extend the processed part is driven by priority. The priority of a gate is derived from the quality of its individual candidate vertices and represents the certainty of the decoder to identify the actual tip vertex that forms the extension triangle. The quality q_c of the candidate vertex c is a linear combination of geometric properties, illustrated in Fig. 1, and is defined as

$$q_c = \theta_{Cc} - w_1 \cdot d_{cp} + w_2 \cdot \phi_{BC} + w_3 \cdot S_{BC}, \tag{1}$$

weighted by the coefficients w_1, w_2 and w_3. The symbol θ_{Cc} is the inner angle, d_{cp} is the distance to the parallelogram prediction, ϕ_{BC} is the dihedral angle, and S_{BC} is the triangle similarity.

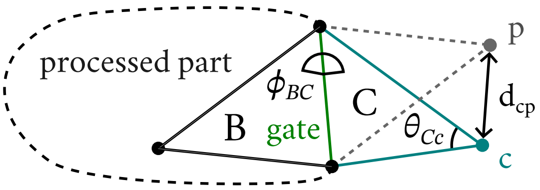

Figure 1: Candidate vertex quality

There is no general means to determine the weights w_1, w_2 and w_3 of the candidate quality function defined by Eq. (1) for an individual mesh. Since these encoder parameters directly influence the performance of the algorithm, it is promising to determine them per mesh based on its general properties and transmit them to the decoder alongside the compressed data.

2 Proposed Method

The proposed method approaches the problem by learning the relation between meshes and the respective optimal encoder parameters. It utilises a set of descriptive statistics to capture the surface of a mesh and its properties and pairs it with the RBF approximant of the data rate for the corresponding mesh. The method involves building a dataset of many sample pairs of global

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surface statistics of meshes and respective data rate approximants. This dataset is then used to train an artificial neural network, which models the relation between the surface statistics and the optimal encoder parameters. The model is trained to predict the encoder parameters that minimise the data rate, utilising the approximate data rate provided by the approximants.

The selected global surface statistics consider the geometric properties of a mesh that directly relate to the candidate vertex quality from Eq. (1) and a few others to provide additional information about the mesh. The considered properties are triangle inner angles, distances of triangle vertices to their parallelogram predictions, dihedral angles between adjacent triangles, the similarity of adjacent triangles, triangle equilaterality, edge lengths, and vertex degrees.

The data rate for a mesh is a function of the weights w_1, w_2 and w_3 from Eq. (1). The function is sampled alongside searching for the optimal parameters over the range of feasible values, as visualised in Fig. 2. The data rate is subject to approximation to enable the estimation of the data rate for parameters for which the function was not sampled, as visualised in Fig. 3.

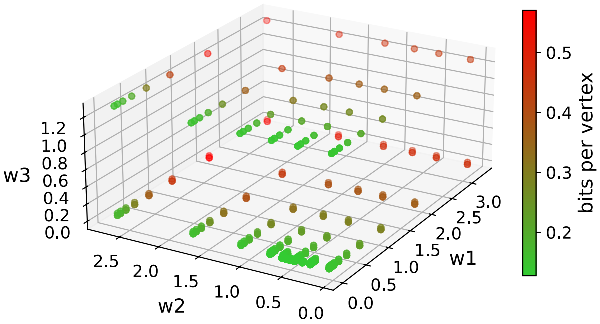

Figure 2: Sampled data rate function

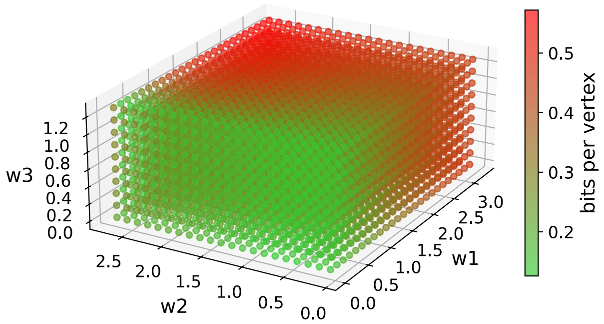

Figure 3: Data rate function approximant

3 Experimental Results

The datasets used in Dvořák et al. (2022) were used to build an experimental dataset comprising 29958 meshes of varying properties. A subset of 26963 meshes was used to train two models, the first model$_{\text{total}}$ minimising the total sum of the data rate for the meshes of the dataset and the other model$_{\text{mesh}}$ minimising the data rate per mesh. The algorithm performance was evaluated on the other subset of 2995 meshes with the estimated mesh-optimal encoder parameters and compared to the default, dataset-optimised, and mesh-optimal encoder parameters. The default and dataset-optimised parameters were determined by Dvořák et al. (2022) to suit all the meshes, respectively, the individual datasets of the experimental dataset well.

The estimator model$_{\text{total}}$ improved the total sum of the data rate by 16.69, respectively, 16.51 per cent over the default and dataset-optimised parameters. The other estimator model$_{\text{mesh}}$ improved the data rate by 17.98, respectively, 12.86 per cent per mesh on average over the default and dataset-optimised parameters. The proposed method improved the data rate to be 22.34 per cent in total, respectively, 18.85 per cent per mesh on average worse than the data rate achieved with the mesh-optimal parameters, compared to 46.85 and 53.56 per cent achieved with the default, respectively, 46.55 and 45.56 per cent with the dataset-optimised parameters.

References

Dvořák, J., Káčereková, Z., Vaněček, P. and Váša, L. (2022) Priority-based encoding of triangle mesh connectivity for a known geometry. *Computer graphics forum*, 42(1), pp. 60–71. Available from: `https://doi.org/10.1111/cgf.14719`.