Measure The Difference between Frames: Reconsidering The Evaluation Method in Dynamic Mesh Simplification

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***Abstract*—Along with the development of 3D multi-media technology, the standardization of 3D volumetric video compression is in progress. Considering there is no objective method to evaluate the dynamic mesh simplification task in 3D video compression, an evaluation system based on mesh registration is established in this study. By converting the tracked mesh from the previous frame into a vertex set, Cloud-to-Cloud and Cloud-to-Mesh Distance can measure the similarity between two meshes from adjacent frames. Mesh surface distance and nearest vertex distance are two metrics designed to assess the performance of dynamic mesh simplification algorithms accurately. The evaluation system is also beneficial to measure the effectiveness of the new dynamic mesh simplification algorithms from similar studies in the future.**

***Index Terms*—Computer Graphics, 3D Video Coding, Mesh Simplification, Mesh Registration, Evaluation Metrics**

I. Introduction

As the demand for 3D multi-media technology continues to grow, the standardization of 3D volumetric video compression is currently underway [1]. One promising approach is dynamic mesh simplification, as the red part shown in Fig.1, which is a prepossessing part in compressing progress. It can reduce the face size of dynamic meshes representing primary 3D volumetric video segments.

One of the challenges faced in this field is the need for an objective method to evaluate the dynamic mesh simplification task in 3D video compression. Most of the existing evaluation methods are designed for static mesh simplification. They are more suitable for comparing the original input and the simplified result from the same frame but cannot be used to evaluate the similarity between two simplified results from different structures.

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To fairly measure the effectiveness of dynamic mesh simplification algorithms, an evaluation system based on mesh registration is established in this study. The new evaluation method contains several innovations, making it more suitable to evaluate the simplified results of dynamic mesh:

- Convert the mesh evaluation to the point cloud similarity estimation. Introduce Cloud-to-Cloud and Cloud-to-Mesh Distance to fetch distance distribution.
- Introduce mesh registration into the evaluation method. Non-rigid registration can align deformed meshes to make the inter-frame evaluation possible.
- Design mesh surface and nearest vertex distance, then use statistical methods to quantify and analyze the distance-based error.

The new evaluation method is used to assess the new dynamic mesh simplification algorithm proposed in another research. The result of the experiment part proves that this proposal can objectively evaluate the effectiveness of the dynamic mesh simplification algorithms in the future.

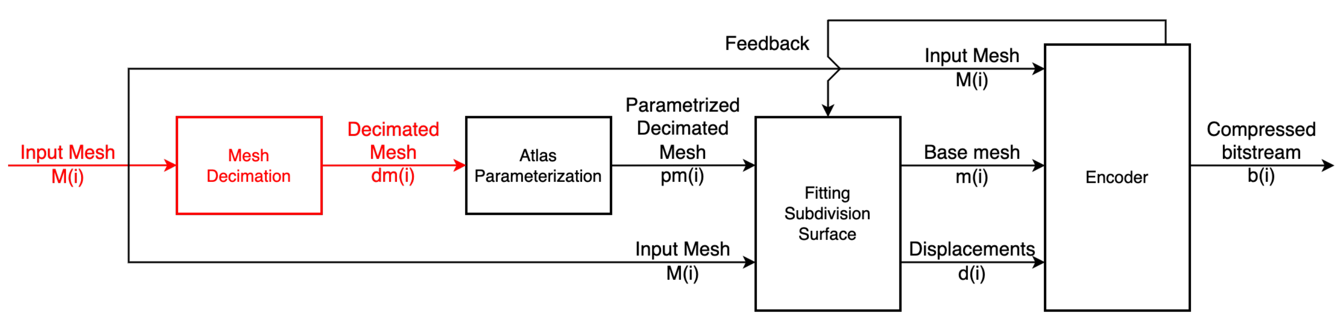


Fig. 1: A typical encoder pipeline for 3D Volumetric video compression.

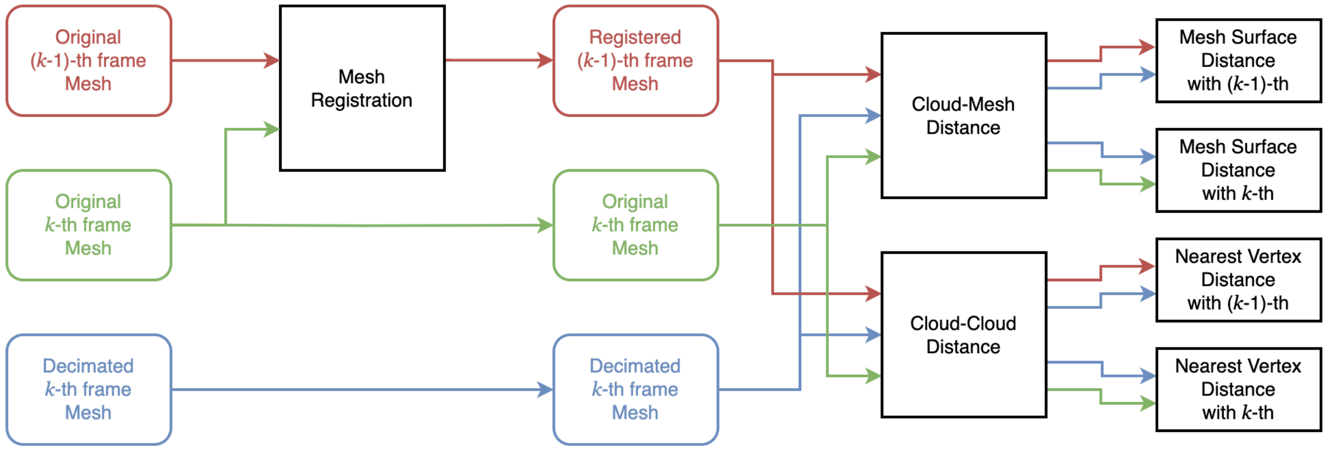


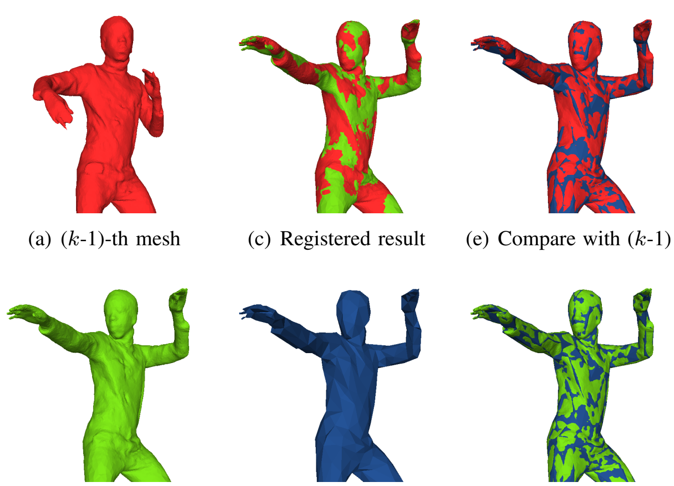
Fig. 2: The flow chart of the entire evaluation system, also including inter-frame conference and mesh registration.

II. Proposed Method

Hence this proposed evaluation system is used to measure the effectiveness of dynamic mesh simplification algorithms, mesh registration is introduced into the system to compare the simplified result with former frame. The whole progress of evaluation is shown in Fig.2.

The proposed cross-framed approach is efficient for evaluating the inter-frame temporal consistency of simplified results. The remaining part of the chapter will introduce the main components of the system in detail to explain this effectiveness.

A. Mesh Registration



(a) (k-1)-th mesh (c) Registered result (e) Compare with (k-1)

(b) k-th mesh (d) Simplified reuslt (f) Compare with k-th

Fig. 3: Mesh registration in dynamic mesh simplification metrics.

Seeing that the dynamic mesh can be regarded as a sequence consisting of static mesh, it is also necessary to compare the simplified result with the previous frame for evaluation. Nevertheless, due to the deformation between successive frames by movement, it is challenging to directly measure the distance between the simplified k-th mesh and the original mesh of the previous (k-1)-th frame.

As shown in Fig.3, mesh registration is introduced into this evaluation system to solve this problem [2].

Through rigid and non-rigid registration, The (k-1)-th frame (Fig.3.(a)) is aligned to have the same appearance and shape as the k-th frame (Fig.3.(b)), but still retains the original geometric and topology structure (Fig.3.(c)).

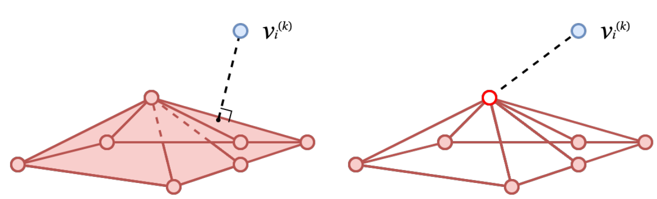
Mesh registration allows the specially designed metrics can work across the frame. The simplified result from k-th frame will be compared with the input mesh from current k-th frame (Fig.3.(e)) and former (k-1)-th frame (Fig.3.(f)). Two different kinds of distance will be measured on each vertex in simplified mesh (Fig.3.(d)) to evaluate the temporal consistency.

B. Distance Measurement

As the equation Eq.(1), the QEM algorithm minimizes the sum of the distances between collapsed vertices and all adjacent planes as an optimization target to obtain the result that has the closest appearance to the original mesh [3].

$$\overline{v} = \arg\min_{v} \sum_{p \in \text{plane}(v_1) \cup \text{ plane } (v_2)} \text{distance}(v, p)^2 \quad (1)$$

Inspired by this fact, the distance between two meshes, i.e., mesh-to-mesh distance [4] [5], can also be used as an indicator to measure the similarity of mesh appearance.



(a) Mesh surface distance (b) Nearest vertex distance

Fig. 4: Two kinds of point-based distance measurement for each vertex.

These methods typically employ point set $S^{(k)}$ sampling on mesh surface to convert the distance from mesh-to-mesh to cloud-mesh [6]:

$$S^{(k)} = \left\{ s_i^{(k)} \middle| \forall s_i^{(k)} \in sample_{surface}(mesh^{(k)}) \right\} \quad (2)$$

Considering the different face numbers between input and simplified mesh, our approach only uses the vertices in simplified mesh:

$$V^{(k)} = \left\{ v_i^{(k)} \middle| \forall v_i^{(k)} \in sample_{vertex}(mesh^{(k)}) \right\} \quad (3)$$

There are two types of point-based methods for distance measurement:

1. Cloud-Mesh Distance: Take the original input mesh as a reference and calculate the distance from simplified vertices set to the surface of the mesh.

2. Cloud-Cloud Distance: The input mesh is also converted into vertices set, then calculate the distance between these two points cloud.

As shown in Fig.4, for each vertex, some methods [7] use traditional algorithm like K-NN [8] to calculate the distance:

1. Mesh surface distance: The shortest distance from each $v_i^{(k)}$ in the vertex set $V_{simp}^{(k)}$ of simplified $mesh_{simp}^{(k)}$ to any position $s_j^{(l)}$ in the point set $S_{ref}^{(l)}$ sampled from surface of registered input mesh $mesh^{(l)}$ for reference:

$$D_{surf(l)}^{(k)} = \left\{ d(i)_{s(l)}^{(k)} = min\|v_i^{(k)}, S_{ref}^{(l)}\| \right\} \quad (4)$$

2. Nearest vertex distance: The shortest distance from each $v_i^{(k)}$ in the vertex set $V_{simp}^{(k)}$ of simplified $mesh_{simp}^{(k)}$ to the corresponding nearest vertex $v_j^{(l)}$ in the reference vertex set $V_{ref}^{(l)}$ of registered input mesh $mesh^{(l)}$:

$$D_{vertex(l)}^{(k)} = \left\{ d(i)_{v(l)}^{(k)} = min\|v_i^{(k)}, V_{ref}^{(l)}\| \right\} \quad (5)$$

C. Statistical Metrics

Mesh is a data-heavy 3D format. Even with compression, the simplified mesh may still have thousands of vertices. Concluding directly from these raw data takes much work.

The Chamfer and Hausdorff distance is the primarily used method to measure this kind of distance collection between the two non-empty compact subsets. They use the max value of min distance to describe the degree of matching between two point sets, which is difficult to reflect the data distribution.

As shown in Fig.2, the distance will be calculated on vertices set $V_{simp}^{(k)}$ of simplified mesh from specific k-th frame, with the k-th and registered (k-1)-th frame mesh, four sets consist of distance are created:

1. Mesh surface distance with (k-1)-th mesh: $D_{surf(k-1)}^{(k)}$

2. Mesh surface distance with k-th mesh: $D_{surf(k)}^{(k)}$

3. Nearest vertex distance with (k-1)-th mesh: $D_{vertex(k-1)}^{(k)}$

4. Nearest vertex distance with k-th mesh: $D_{vertex(k)}^{(k)}$

For these four distance sets, each collection may have thousands of values. Some statistical numerical analysis methods need to be introduced to evaluate the degree of convergence, stability, and processing ability of abnormal values.

Therefore, the typical metrics like Chamfer and Hausdorff distance are replaced by statistical methods in proposed evaluation systems to quantize the performance between algorithms better:

1. Average: An alternative to summation, used to indicate the general level to describe the distribution of the distance set.

2. Variance: The degree of dispersion of the evaluation error used to evaluate the algorithm's convergence.

3. Standard Deviation: The root of the variance reflects the degree of error dispersion between vertices.

4. Mean Square Error: Used to measure how well the simplified vertices match the input mesh model.

5. Root Mean Square Error: The root of the MSE, which is more sensitive about abnormal values far from Group Truth.

III. Experiments & Results

A. Experimental conditions

In the experiment part, two different mesh simplification methods are compared to prove the effectiveness of this evaluation system. One is the original QEM Algorithm commonly used in traditional Computer Graphics, which is usually used for static mesh simplification.

As shown in Fig.5, the other is a Registered QEM Algorithm proposed in another recent research. This algorithm considers the time consistency between frames. It uses the mesh of the previous frame as a reference input for simplification, which is more suitable for dynamic mesh.

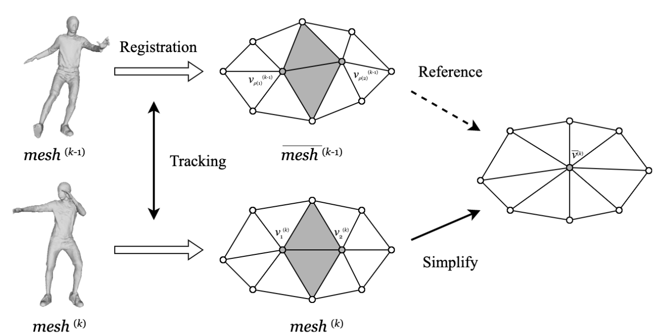


Fig. 5: Dynamic mesh simplification with mesh registration.

Several successive frames were captured from a small 3D volume video used as test data. This video recorded an action performance, only containing one mesh model scanned by the martial artist, without other 3D models of the scene and objects. The mesh model in each frame has about 20,000 valid vertices, 40,000 triangles, and 60,000 edges.

B. Optimal Performance

In this experiment, A representative frame pair was selected to ensure a rigorous assessment. This careful selection aimed to showcase the optimal performance of the two simplification algorithms, especially under conditions that approach the ideal scenario. Specifically, both algorithms were utilized to simplify the meshes while reducing their triangle count by 3%. All other parameters are controlled under the same condition.

The data shown in TABLE I and TABLE II can be obtained based on this data. The later k-th frame is the object to be simplified, and the earlier (k-1)-th frame is the reference input in the Registered QEM algorithm.

TABLE I: Best result of Mesh Surface Distance.

Algorithm	Mesh	Evaluation Metric (Indicator)				
		Ave	*Var*	*STD*	*MSE*	*RMSE*
Orig QEM	(k-1)-th	93.96	7833	88.50	58.09	7.622
	k-th	55.56	2729	52.24	20.85	4.566
Reg QEM	(k-1)-th	**58.13**	**2793**	**52.85**	**56.52**	**7.574**
	k-th	**36.30**	**1095**	**33.09**	**20.41**	**4.518**

Retain 4 valid digits except variance.

TABLE II: Best result of Nearest Vertex Distance.

Algorithm	Mesh	Evaluation Metric (Indicator)				
		Ave	*Var*	*STD*	*MSE*	*RMSE*
Orig QEM	(k-1)-th	188.2	31460	177.3	**154.9**	**12.44**
	k-th	167.0	25082	158.3	**107.2**	**10.35**
Reg QEM	(k-1)-th	**147.8**	**18742**	**136.9**	157.6	12.55
	k-th	**120.0**	**12366**	**111.2**	112.8	10.62

Retain 4 valid digits except variance.

In the best situation, the result indicates that regardless of measurement, the Registered QEM Algorithm has a smaller distance. The result may be because the difference between the two successive frames is tiny, and there is almost no deformation. The richer surface information from superimposed two meshes provides more reference than a single frame.

C. Average performance

The best results can show the algorithm's performance in the ideal state. However, the data of the 3D video is very complicated, and the content of each frame may be very different. Some fierce and complex scenes may have a significant impact on the performance of the algorithm.

Therefore, other segments in the same video must also be evaluated for a more fair conclusion. Five experiments were performed to obtain the distance collection of the simplified Mesh to simulate the natural work conditions of 3D video compression in a complex scene.

TABLE III: Average Data of Surface Distance in Experiments.

Algorithm	Mesh	Evaluation Metric (Indicator)				
		Ave	*Var*	*STD*	*MSE*	*RMSE*
Orig QEM	(k-1)-th	124.1	13834	117.6	85.98	9.272
	k-th	**60.17**	**3022**	**54.98**	58.40	7.642
Reg QEM	(k-1)-th	**81.26**	**5846**	**76.46**	**73.32**	**8.563**
	k-th	62.96	3342	57.81	**55.52**	**7.451**

Retain 4 valid digits except variance.

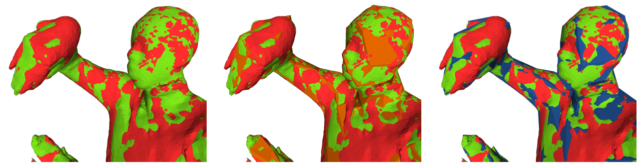
TABLE IV: Average Data of Vertex Distance in Experiments.

Algorithm	Mesh	Evaluation Metric (Indicator)				
		Ave	*Var*	*STD*	*MSE*	*RMSE*
Orig QEM	(k-1)-th	238.8	51239	226.3	227.9	15.09
	k-th	**175.5**	**26886**	**136.9**	184.4	13.58
Reg QEM	(k-1)-th	**197.5**	**35501**	**188.4**	**176.4**	**13.28**
	k-th	192.0	34194	184.9	**155.9**	**12.45**

Retain 4 valid digits except variance.

By the statistical information of four groups of distance that comes from the average result in all five mesh pairs from the five groups of experiments, the data shown in TABLE III and TABLE IV can be obtained.

From these data, it is easy to see that in more complex scenarios, the original QEM algorithm only uses single-frame information can get better performance on the current k-th frame. Compared with the previous (k-1)-th data frame, the Registered QEM algorithm gets a minor error, which means better temporal consistency.



(a) Registered result (b) Original QEM (c) Registered QEM

Fig. 6: Visualization results of two different QEM algorithms in experiment.

In addition, it is worth noting that although the current k-th frame performance is not such brilliant, the Registered QEM algorithm still has better MSE and RMSE. It means that the results are smoother than the traditional QEM algorithm in visual. It is consistent with the visualization results in Fig.6. The output of the registered QEM (the blue model in Fig.6.(c)) is better attached to the registered surface than the Original QEM (the orange model in Fig.6.(b)).

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IV. Conclusion

A new evaluation system for assessing dynamic mesh simplification algorithms is proposed in this research. An evaluation system with objective metrics to estimate the effect of the dynamic mesh simplification algorithm has been established through two different distance measurement methods. Then this approach is used to evaluate the new method proposed in another research. The experimental result proves that the proposed evaluation system can objectively quantify the effectiveness of the dynamic mesh simplification algorithm and continue to be used in other subsequent similar studies.

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