# PACKET LOSS RESILIENT TRANSMISSION OF 3D MODELS

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## ABSTRACT

This paper presents an efficient joint source-channel coding scheme based on forward error correction (FEC) for three dimensional (3D) models. The system employs a wavelet based zero-tree 3D mesh coder based on Progressive Geometry Compression (PGC). Reed-Solomon (RS) codes are applied to the embedded output bitstream to add resiliency to packet losses. Two-state Markovian channel model is employed to model packet losses. The proposed method applies approximately optimal and unequal FEC across packets. Therefore the scheme is scalable to varying network bandwidth and packet loss rates (PLR). In addition, Distortion-Rate (D-R) curve is modeled to decrease the computational complexity. Experimental results show that the proposed method achieves considerably better expected quality compared to previous packet-loss resilient schemes.

***Index Terms*—** Visual communications, error correction, computer vision, multidimensional systems, wavelet transform, networks.

## 1. INTRODUCTION

With an increasing demand for visualizing and simulating three dimensional (3D) objects in applications such as video gaming, engineering design, virtual reality and 3DTV, there has been a great amount of research for efficiently representing the 3D data [1] [2]. Among different representations, triangular 3D meshes are very effective and widely used. Typically 3D mesh data consist of geometry and connectivity data. While the geometry data specify 3D coordinates of vertices, connectivity data describes the adjacency information between vertices. In this paper, we use 3D model and 3D mesh interchangeably.

To maintain a convincing level of realism, many applications require highly detailed complex models represented by 3D meshes consisting of huge number of triangles. Due to storage space and transmission bandwidth limitations, there has been a great effort of research on efficient compression of 3D meshes [1] [2]. On the other hand, problem of transmitting 3D meshes through error-prone channels is not tackled very seriously. Only a few works exist in the literature to tackle with error resilient transmission of 3D models [3], [4], [5], [6], [7], [8], [9], [10].

Multiple Description Coding (MDC) is used to achieve error resiliency in [4], [5], [6]. In [4] multiple descriptions are generated by splitting the mesh geometry into submeshes and including the whole connectivity information in each description. In [5], multiple description scalar quantization (MDSQ) is applied to wavelet coefficients of a multiresolution compression scheme. The obtained two sets of coefficients are then independently compressed by the SPIHT coder [11]. In these MDC schemes, descriptions are created with heuristic methods and no optimum solutions are proposed for varying network conditions. In [6], wavelet coefficient trees obtained by Progressive Geometry Compression (PGC) [12] algorithm are partitioned into multiple descriptions. Each set of trees is independently coded with SPIHT. In this scheme, bit-rate for each set is optimized for a given $P_{LR}$. The MDC schemes mentioned here provide resiliency for description losses which is useful for scenarios like multipath transmission or multiple storage. However the schemes are not directly applicable to packet loss transmission cases in which the packet sizes and description sizes considerably differ.

Only works in the literature which employ packet loss resilient 3D model transmission which is scalable with respect to both channel bandwidth and channel packet-loss rate are [7], [8], [9], [10]. In these works, error resilience is achieved by assigning optimal error correcting codes to layers of a progressively coded 3D mesh. The progressive scheme employed in these works is Compressed Progressive Meshes (CPM) [13]. While the ideas are similar in these works, [8] tackles a more general optimization problem which maximizes expected decoded model quality for a given model, total bit budget and packet loss rate $P_{LR}$. Later Ahmad et al. [10] proposed improvements on [9] in terms of complexity and packetization flexibility. Another important property of these methods is that coarse-to-fine representation of the model is achieved with respect to packet losses.

In this work, we propose a method for robust transmission of 3D models in a packet loss network. Our aim is to achieve best reconstruction quality with respect to channel bandwidth and packet loss rate ($P_{LR}$). The proposed algorithm depends heavily on the *Forward Error Correction* (FEC) based packet lost resilient image transmission schemes [14]. We compare our results with [8], [10] in terms of expected distortion and flexibility in packetization and it is shown that better expected distortion with more flexible packetization is achieved.

The rest of the paper is organized as follows. In Section 2, we briefly review wavelet based scalable mesh coding that our algorithm is based on. In Section 3, problem definition with solution is given. In Section 4, distortion-rate curve modeling to reduce complexity is described. Finally, in Section 5 and 6, we present experimental results and conclusions, respectively.

## 2. WAVELET BASED SCALABLE MESH CODING

3D Mesh compression techniques can be classified into two categories: Single-rate compression and Progressive compression. In single-rate compression, the aim is to compress the mesh as much as possible. The single-rate compressed mesh can only be decompressed if whole compressed bitstream is available, i.e. no intermediate reconstruction is possible with fewer bits. Progressive compression is more suited for transmission purposes in which some parts of the bitstream of the compressed mesh can be missing or erroneous. By progressive compression, the mesh is represented by different levels of detail (LOD) having different rates. Progressive compression techniques can further be classified into two categories: connectivity driven compression and geometry driven compression.

Wavelet based Mesh Coding techniques belong to the geometry driven progressive mesh coding category which changes mesh connectivity in favor of a better compression of geometry data [2]. Recently very efficient wavelet based compression schemes have been reported in literature [1], [2]. In our work, we used Khodakovsky et al.'s Progressive Geometry Compression (PGC) scheme [12] to produce a scalable as well as embedded bitstream. The other wavelet based compression schemes can also be used with minor modifications. PGC is a progressive compression scheme for arbitrary topology, highly detailed and densely sampled meshes arising from geometry scanning. The method is based on smooth semi-regular meshes, i.e., meshes built by successive triangle quadrisection starting from a coarse irregular mesh. Therefore the original model in PGC is remeshed to have a semi-regular structure which allows subdivision based wavelet transform. Resulting semi-regular mesh undergoes a loop-based or butterfly-based wavelet decomposition to produce a coarsest level mesh and wavelet coefficients [12]. Since coarsest level connectivity is irregular, it is coded by Touma and Gotsman's (TG) [15] single-rate coder. Zero-trees consisting of wavelet coefficients are coded with SPIHT algorithm [11]. For improved progressivity, a predetermined number of bit-planes of the coarsest level geometry is transmitted initially with the coarsest level connectivity and refinement bit-planes are transmitted as the SPIHT coder descends a given bit-plane of wavelet coefficients [12].

## 3. PROBLEM DEFINITION AND SOLUTION

In this work we try to obtain best expected distortion of a model transmitted over an erasure channel for given target rate, $P_{LR}$ and channel model. In order to achieve this; 1) The 3D model is compressed with PGC as described in Section 2. The output of the PGC coder, i.e. coarsest level geometry, compressed coarsest level connectivity and SPIHT coded wavelet coefficients are arranged to form the embedded bitstream as shown in Figure 1. 2) Together with optimized FEC assignment, the embedded bitstream is packetized with N packets each of which contains L symbols.

After the embedded bitstream is defined, the problem of optimum loss protection is stated as follows: Our embedded bitstream is to be protected with RS codes and transmitted over an erasure channel as $N$ packets each of which contains $L$ symbols (bytes in this paper). The protection system builds $L$ source segments $S_i$'s, $i = 1, ..., L$, of $m_i \in \{1, ..., N\}$ symbols each and protects each segment with an $(N, m_i)$ RS code. For each $i = 1, ..., L$, let $f_i = N - m_i$ denote the number of RS redundancy symbols that protect segment $S_i$. An example of the above FEC assignment is illustrated in Table 1. If $n$ packets of $N$ are lost, then the RS codes ensure that all segments that contain at most $N - n$ source symbols can be recovered. Thus, by adding the constraint that $f_1 \geq f_2 \geq ... \geq f_L$, if at most $f_i$ packets are lost, then the receiver can decode at least the first $i$ segments. Let $\mathcal{F}$ denote the set of $L$-tuples $(f_1, ..., f_L)$ such that $f_i \in \{0, ..., N-1\}$ for $i = 1, ..., L$ and $f_1 \geq f_2 \geq ... \geq f_L$. Let $p_N(n)$ denote the probability of losing exactly $n$ packets of $N$ and let $c_N(k) = \sum_{n=0}^{k} p_N(n)$, $k = 0, ..., N$. Then $c_N(f_i)$ is the probability that the segment $S_i$ can be decoded successfully. Let $D(R)$ denote the distortion-rate (D-R) function of the source coder. Then in order to achieve an optimum the packet loss protection, we need to find $F = (f_1, ..., f_L) \in \mathcal{F}$ such that the expected distortion

$$E_D = c_N(N)D(r_0) + \sum_{i=1}^{L} c_N(f_i)(D(r_i) - D(r_{i-1})) \quad (1)$$

is minimized where

$$r_i = \begin{cases} 0, & \text{for } i = 0 \\ \sum_{k=1}^{i} m_k = iN - \sum_{k=1}^{i} f_k, & \text{for } i = 1, ..., L \end{cases} \quad (2)$$

In order to minimize expected distortion in Equation 1, we employed the algorithms of Mohr et al. [16] and Stankovic et al. [17]. In [17], it has been shown that the method in [16] performs very well in terms of expected distortion and the method in [17] has the best complexity with slightly worse expected distortion performance.

In [16], given $p = LN$ points on the operational D-R curve of the source coder, the algorithm first computes the $h$ vertices of their convex hull. Then, a solution is found in $O(hN \log N)$ time. This solution is optimal under the assumption of the convexity of the distortion-rate function and of fractional bit allocation assignment. In [17], a local search algorithm with $O(NL)$ complexity is presented that starts from a solution that maximizes the expected number of received source bits and iteratively improves this solution. The reader is referred to [16], [17] for the details of the algorithms.

| | P1 | P2 | P3 | P4 | P5 |
|---|---|---|---|---|---|
| Segment 1 | 1 | 2 | FEC | FEC | FEC |
| Segment 2 | 3 | 4 | 5 | FEC | FEC |
| Segment 3 | 6 | 7 | 8 | FEC | FEC |
| Segment 4 | 9 | 10 | 11 | 12 | FEC |

**Table 1**. An example of FEC assignment. There are $N = 5$ packets each composed of $L = 4$ symbols. Therefore there are 4 source segments, $S_i$, $i = 1, 2, 3, 4$ each of which contains $m_i$ data symbols and $f_i$ FEC symbols where $m_i + f_i = N$. In this example $m_1 = 2, f_1 = 3, m_2 = 3, f_2 = 2, m_3 = 3, f_3 = 2, m_4 = 4, f_4 = 1$. Earlier parts of the bitstream are assigned more FEC symbols since they contribute more to overall quality.

## 4. MODELING DISTORTION-RATE CURVE

In order to optimize FEC assignments, we need to have $D(R)$ function in Equation 1. In our work, we use $L^2$ distance as distortion metric which has an expensive computation cost. Therefore obtaining all $D(R)$ function requires considerable offline computations. To reduce this complexity, we employed the D-R curve modeling presented in [18] for coding of images. It is found in [6] that output of PGC coder can also be approximated with this model from [18]. In our experiments, we used a Weibull model [18] which is described by

$$D(R) = a - be^{-cR^d}, \quad (3)$$

where real numbers $a$, $b$, $c$, and $d$ are the parameters. To fit this model to D-R curve samples, we used nonlinear least-squares regression. Fig. 2 shows the comparison of true operational D-R curve of PGC coded *Bunny* model and its Weibull model. One can see that the model closely approximates the real data.

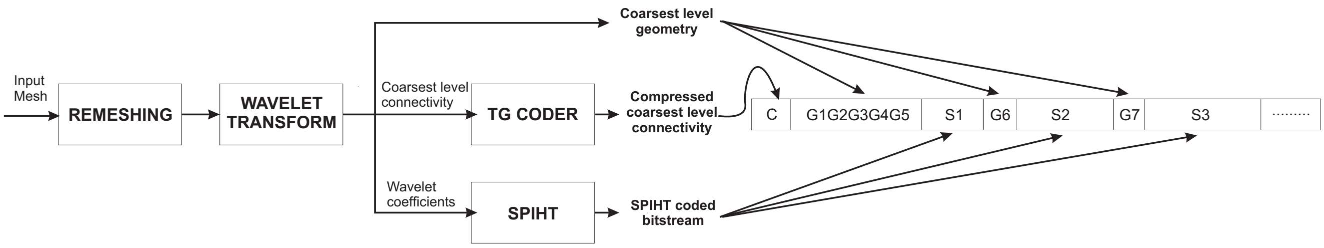


**Fig. 1**. Generation of embedded bitstream from PGC coder. The bitstream starts with compressed coarsest level connectivity (*C*) as it is the most important part on which the whole mesh connectivity depends. The next part of the bitstream is a predetermined number of bit-planes (5 in the figure) of the coarsest level geometry (*G1G2G3G4G5*) since wavelet coefficients would have no use without coarsest level geometry. Remaining part of the bit-stream consists of the output bitstream of SPIHT for different quantization levels (*S1S2S3..*) and after each quantization level, refinement bitplanes of coarsest level geometry (*G6G7..*) are inserted for improved progressivity.

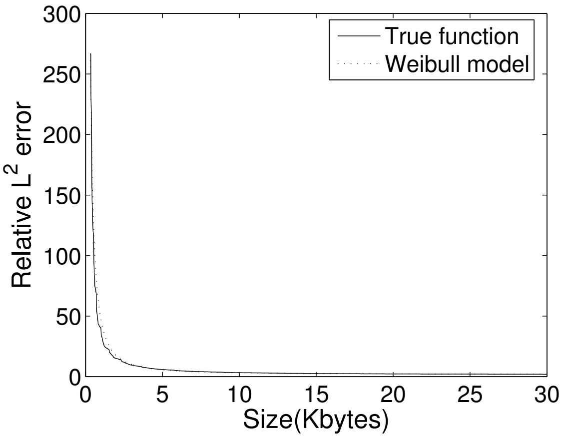


**Fig. 2**. Comparison between the Weibull model (10 points) and operational D-R curve ($L^2$) for *Bunny* model. Distortion metric is relative $L^2$ distance

## 5. EXPERIMENTAL RESULTS

We have performed the experiments with *Bunny* model which is composed of 34835 vertices and 69472 triangles. The model is coded with PGC at 15000 bytes and packetized with $N = 100$ packets each of which is composed of $L = 150$ bytes. The packet erasure channel is modeled as two-state Markov process with average burst length of 5. The $c_N(k)$'s in Equation 1 are calculated according to this channel model. The reconstruction distortion is relative $L^2$ error, which is calculated by Metro tool [19]. Relative error is calculated by dividing $L^2$ distance to the original mesh bounding box diagonal. All the relative $L^2$ errors in this paper are in units of $10^{-4}$. We also provide the same numbers in PSNR scale where $PSNR = 20 \log_{10} peak/d$, $peak$ is the bounding box diagonal, and $d$ is the $L^2$ error.

We optimize FEC assignments with the algorithms of Mohr et al. and Stankovic et al. [16], [17] and label them as *ProposedMohr* and *ProposedStankovic* in the figures. Figure 3 shows expected distortions corresponding to various $P_{LR}$'s for *ProposedMohr* employing the original D-R curve and modeled D-R curve during optimization. It is observed that quite acceptable results can be achieved by D-R curve modeling therefore we present results with modeled D-R curves. Our results are compared with optimized error protected CPM coder obtained by the combination of methods in [8], [10] and it is labeled as *ProtectedCPM*.

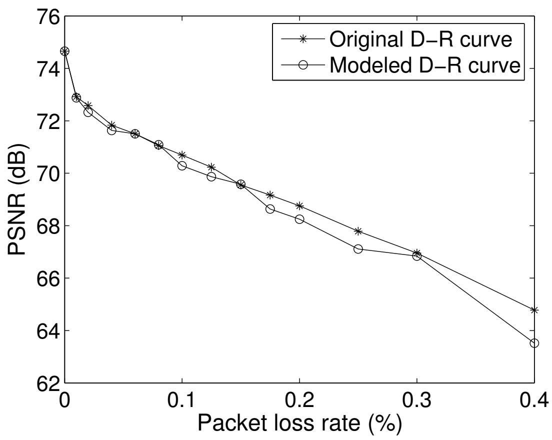


**Fig. 3**. Comparison of using original D-R curve and using modeled D-R curve during optimization in terms of expected distortion for various $P_{LR}$'s.

Table 2 and Figure 4 show the distortions corresponding to various $P_{LR}$'s in terms of relative $L^2$ error and in PSNR scale respectively. It is observed that, our method significantly outperforms the method in [8] and [10] in terms of expected distortion. Actually this is due to the fact that PGC has a significantly better D-R characteristics than CPM coder. Another observation is that *ProposedStankovic* shows comparable performance with *ProposedMohr* while it showed the best optimization time performance in experiments.

## 6. CONCLUSION

In this work we proposed a system for robust transmission of 3D models over packet loss prone channels. The method is scalable with respect to both channel bandwidth and packet loss rate. Employing an embedded bitstream, the packetization is flexible and optimization is efficient. The complexity is decreased considerably by using D-R curve modeling at the cost of a small performance loss. Experimental results show that graceful degradation of 3D model quality is achieved with respect to packet losses and the method outperforms the previous works in literature.

| | Expected distortion for different $P_{LR}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Packet loss rate | PLR=0% | PLR=1% | PLR=4% | PLR=6% | PLR=10% | PLR=15% | PLR=20% | PLR=40% |
| *ProposedStankovic* | 1.8900 | 2.4100 | 2.6100 | 2.7800 | 3.0900 | 3.4800 | 3.7800 | 5.8900 |
| *ProposedMohr* | 1.8500 | 2.2700 | 2.6200 | 2.6600 | 3.0600 | 3.3200 | 3.8700 | 6.6700 |
| *ProtectedCPM* | 6.0000 | 7.5810 | 8.5411 | 8.8165 | 10.0053 | 11.1130 | 12.3531 | 17.2771 |

**Table 2**. Expected distortion results of three algorithms for different $P_{LR}$. The distortion metric is relative $L^2$ error in units of $10^{-4}$.

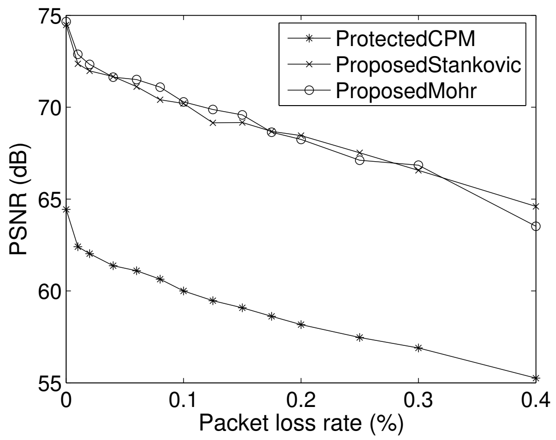


**Fig. 4**. $P_{LR}$ vs Expected Distortion in PSNR scale.

## 7. ACKNOWLEDGEMENTS

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## 8. REFERENCES

[1] P. Alliez and C. Gotsman, "Recent advances in compression of 3D meshes," in *Proc. Symposium on Multiresolution in Geometric Modeling*, 2003.

[2] J. Peng, C.-S. Kim, and C.-C. J. Kuo, "Technologies for 3D mesh compression: A survey," *Journal of Visual Communication and Image Representation*, vol. 16, pp. 688–733, Dec. 2005.

[3] Z. Yan, S. Kumar, and C.-C. J. Kuo, "Error resilient coding of 3-D graphic models via adaptive mesh segmentation," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 11, pp. 860–873, Jul. 2001.

[4] P. Jaromersky, X. Wu, Y. Chiang, and N. Memon, "Multiple-description geometry compression for networked interactive 3D graphics," in *Proc. ICIG'2004*, Dec. 2004, pp. 468–471.

[5] M. O. Bici and G. Bozdagi Akar, "Multiple description scalar quantization based 3D mesh coding," in *Proc. IEEE Int. Conf. Image Processing*, Atlanta, US, Oct. 2006.

[6] A. Norkin, M. O. Bici, G. Bozdagi Akar, A. Gotchev, and J. Astola, "Wavelet-based multiple description coding of 3-d geometry," in *to be presented in VCIP 2007*, San-Jose, US, Jan. 2007.

[7] G. AlRegib, Y. Altunbasak, and J. Rossignac, "An unequal error protection method for progressively transmitted 3-D models," *IEEE Trans. Multimedia*, vol. 7, pp. 766–776, Aug. 2005.

[8] G. AlRegib, Y. Altunbasak, and R. M. Mersereau, "Bit allocation for joint source and channel coding of progressively compressed 3-D models," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 15, no. 2, pp. 256–268, Feb. 2005.

[9] G. AlRegib, Y. Altunbasak, and Jarek Rossignac, "Error-resilient transmission of 3-d models," *ACM Trans. on Graphics*, vol. 24(2), pp. 182–208, Apr. 2005.

[10] S. Ahmad and R. Hamzaoui, "Optimal error protection of progressively compressed 3d meshes," in *Proceedings IEEE International Conference on Multimedia and Expo (ICME'06)*, Jul 2006.

[11] A. Said and W. Pearlman, "A new, fast, and efficient image codec based on set partitioning in hierarchical trees," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 6, no. 3, pp. 243–250, June 1996.

[12] A. Khodakovsky, P. Schröder, and W. Sweldens, "Progressive geometry compression," in *Siggraph 2000, Computer Graphics Proceedings*, 2000, pp. 271–278.

[13] R. Pajarola and J. Rossignac, "Compressed progressive meshes," *IEEE Transactions on Visualization and Computer Graphics*, vol. 6, no. 1, pp. 79–93, Jan.-Mar. 2000.

[14] Alexander E. Mohr, Eve A. Riskin, and Richard E. Ladner, "Graceful degradation over packet erasure channels through forward error correction," *Proceedings of the 1999 Data Compression Conference (DCC)*, 1999.

[15] C. Touma and C. Gotsman, "Triangle mesh compression," in *Proc. Graphics Interface*, Vancouver, BC, Canada, Jun. 1998.

[16] A. Mohr, E. Riskin, and R. Ladner, "Approximately optimal assignment for unequal loss protection," in *Proc. ICIP'00*, 2000, pp. 367–370.

[17] V. Stankovic, R. Hamzaoui, and Z. Xiong, "Packet loss protection of embedded data with fast local search," *Image Processing. 2002. Proceedings. 2002 International Conference on*, vol. 2, 2002.

[18] Y. Charfi, R. Hamzaoui, and D. Saupe, "Model-based real-time progressive transmission of images over noisy channel," in *Proc. WCNC'03*, New Orleans, LA, Mar. 2003, pp. 347–354.

[19] P. Cignoni, C. Rocchini, and R. Scopigno, "Metro: Measuring error on simplified surfaces," *Computer Graphics Forum*, vol. 17, pp. 167–174, 1998.