Adaptive compression of animated meshes by exploiting orthogonal iterations

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Computer Graphics International 2017, Yokohama, Japan
June 27-30, 2017

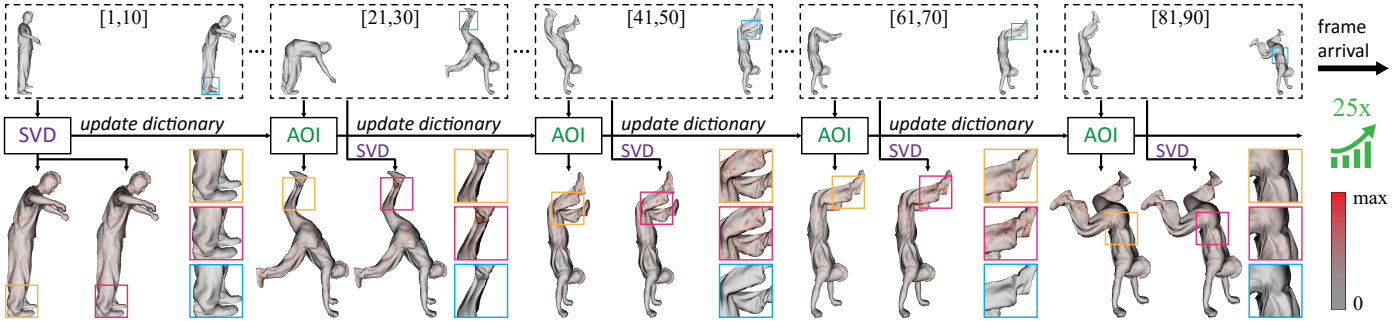
Overview

How to compress arbitrary animated data?

Frames are not known a-priori and they are dynamically generated

- facilitating several applications in fields ranging from :
  1. gaming
  2. engineering (e.g., Microsoft holoportation, autonomous guidance for robots to reconstruct and respond rapidly to their environment; or even to provide immediate feedback to users during 3D scanning) and
  3. medicine (e.g., in radiation therapies, the pre-identified malignant tumors need to be constantly updated using 3D surface capture).

Motivation and Goal



Motivation

- The aforementioned application require fast and lossy compression with low memory requirements.
- SoA approaches assume:
  1. All frames of the animation sequence are already known to the encoder;
  2. the maximum animation length lasts a few seconds;
  3. the geometry size is upperbounded to a fixed number of triangles;

Goal

Design of a general, fast and lossy compression approach suited when the animated data is either dynamically produced or too large to fit into main memory at once.

Assuming sequential arriving of 3D meshes...

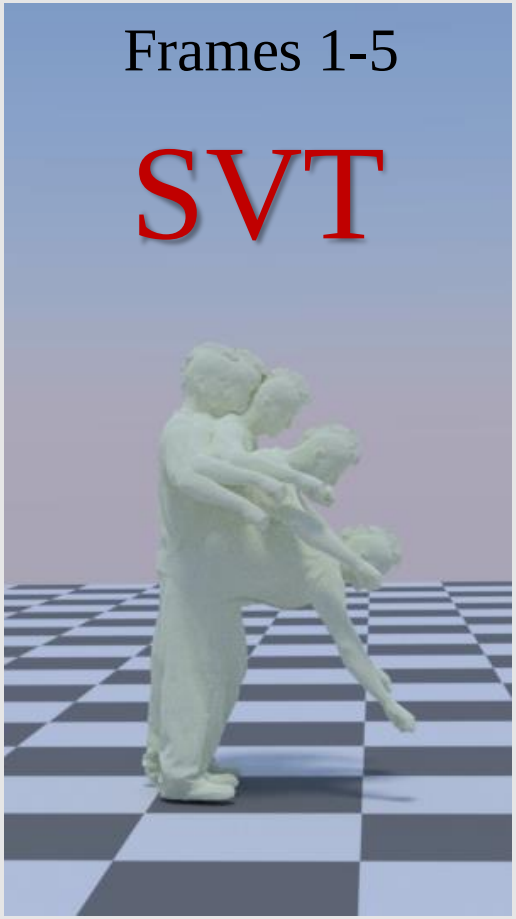
... applying PCA to each one of them individually

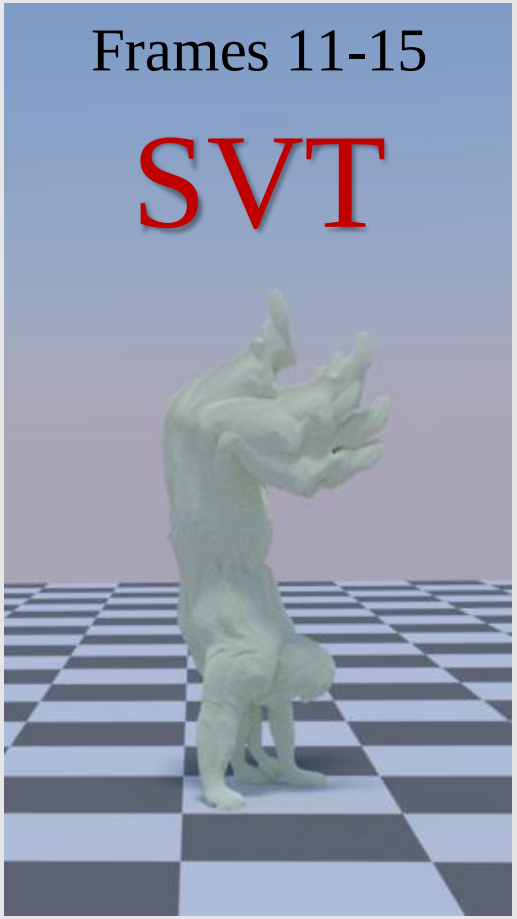
Sequence 1

Sequence 2

Sequence 3

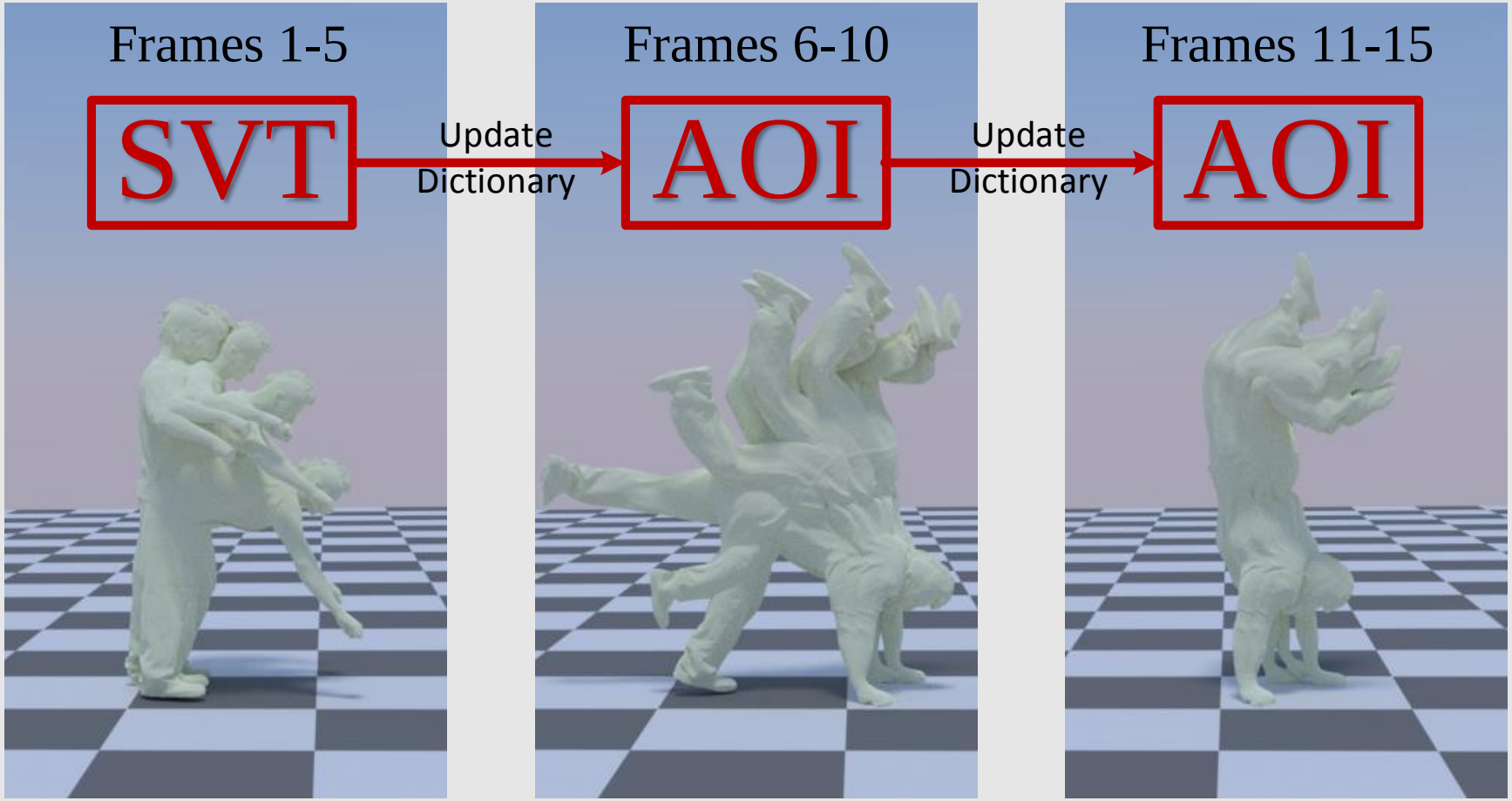
via SVT: Truncated Singular Value Decomposition





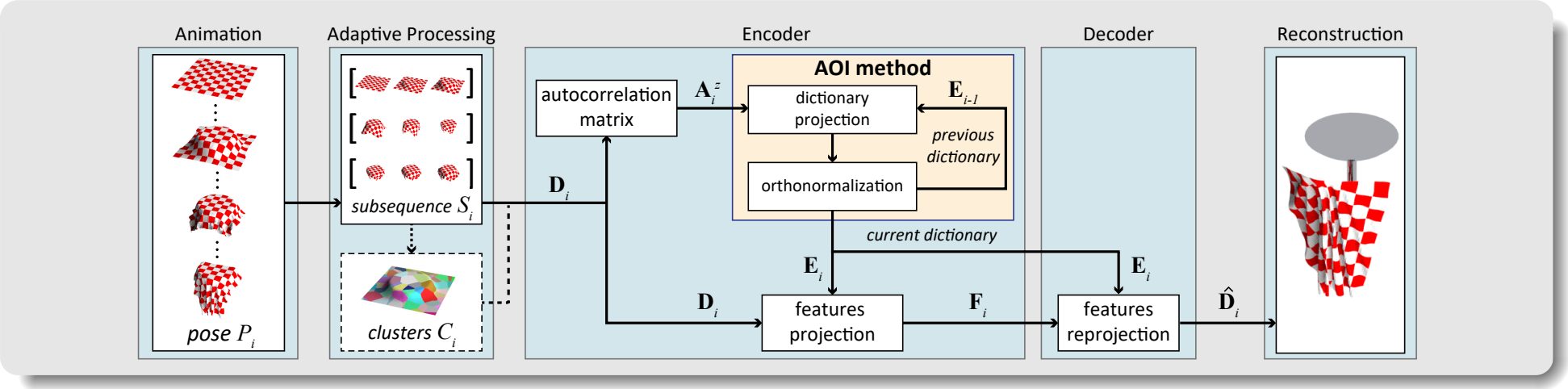
Performance: Slow – Memory: Low – Quality: High

via AOI: Adaptive Orthogonal Iterations



Performance: High – Memory: Low – Quality: High

Adaptive Compression of Animated Meshes



AOI method

The subspace of a positive definite matrix $\mathbf{M} \in \Re^{n \times n}$ can be efficiently estimated by iteratively executing:

$$\mathbf{E}(t) = \mathbf{o\_norm}(\ \mathbf{ME}(t-1)\ ),\ \ t = 1, 2, \ldots$$

where **o_norm** function stands for the ortho-normalization procedure.

- Two novel approaches to support fast and efficient compression of fully dynamic scenarios are proposed: Bandwidth and Quality consistent schemes.

Bandwidth Consistent scheme

Bandwidth-consistent AOI (BAOI(t_{max}))

- A fixed, either insufficient or redundant, number k of components per frame block is used
- A fixed number of AOI iterations (t_{max}) is performed
- Memory: Fixed (Low) $\Longrightarrow$ Performance: Very High, Quality: Medium

BAOI update process

$\mathbf{E}(0) \leftarrow \mathbf{E}_{i-1}$;
For $t \leftarrow 1$ To t_{max}
  $\mathbf{E}(t) \leftarrow \mathbf{o\_norm}(\mathbf{A}_i^z \mathbf{E}(t-1))$;
$\mathbf{E}_i \leftarrow \mathbf{E}(t)$;

Quality Consistent scheme

- In practical scenarios feature vectors resides in subspaces of different sizes
- QAOI identifies the optimal subspace size required for achieving an user-defined acceptable reconstruction quality goal

Quality consistent AOI (QAOI(e_{low}, e_{high}))

- Inspired by the incremental PCA in each iteration we add/remove one normalized column in the estimated subspace and then perform orthonormalization
- To quantify the loss of information at each iteration t, we suggest using the l_2-norm of the *mean residual error*
- A dynamic number of AOI iterations is executed until a goal reconstruction quality (e_{low}, e_{high}) is reached
- Quality: Fixed (High) $\Longrightarrow$ Performance: Medium, Memory: Medium

Simulation Setup

Algorithms

SVD: Jacobi truncated singular value decomposition

BAOI$^z(t_{max})$: bandwidth consistent adaptive orthogonal iterations on the $\mathbf{A}^z$ matrix. Default values for BAOI parameters are $z = 1, t_{max} = 1$ corresponding to BAOI$^1(1)$.

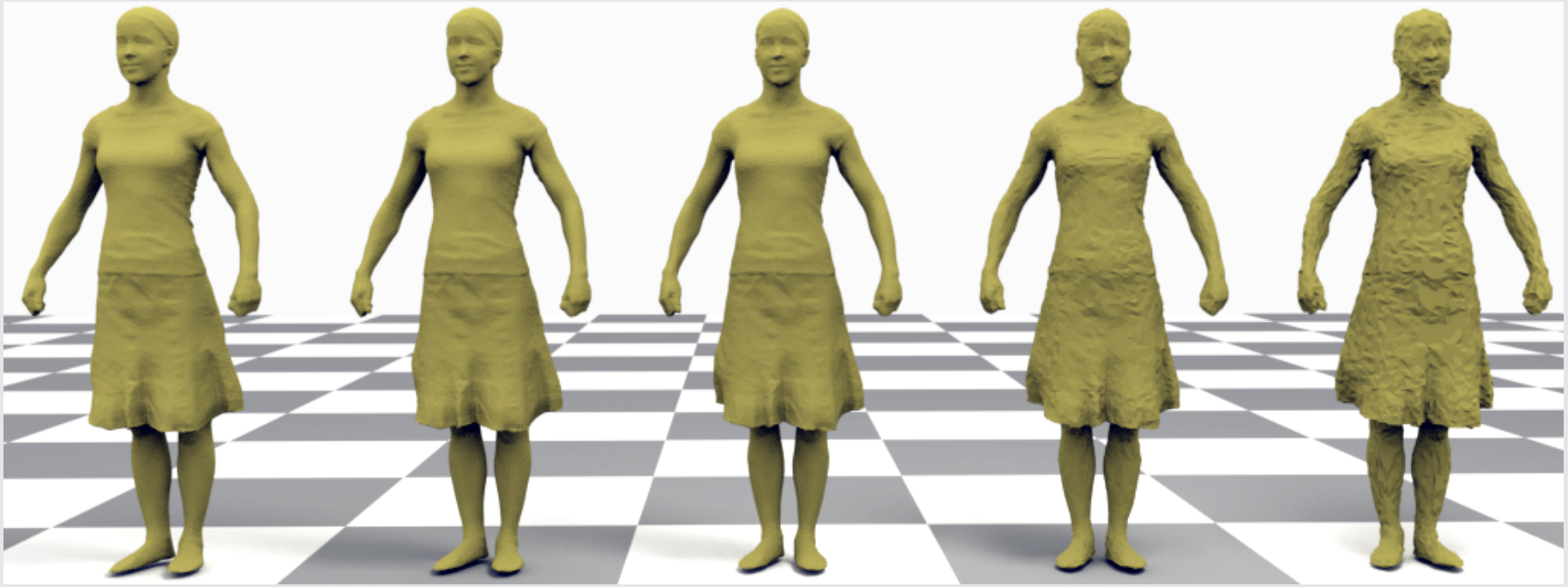
QAOI$(\epsilon_{low}, \epsilon_{high})$: quality consistent adaptive orthogonal iterations.

IPCA: Incremental PCA.

Metrics

1. **Enc. performance** in ms.
2. **Recon. quality (i)**: $\mathbf{KG} = 100 \cdot \frac{||\mathbf{D}-\hat{\mathbf{D}}||_F}{||\mathbf{D}-E(\mathbf{D})||_F}$,
3. **Recon. quality (ii)**: **STED** error metric correlates with perceived distortion by measuring *spatiotemporal edge differences*
4. **Compression efficiency** in *bits per vertex per frame* (**bpvf**)

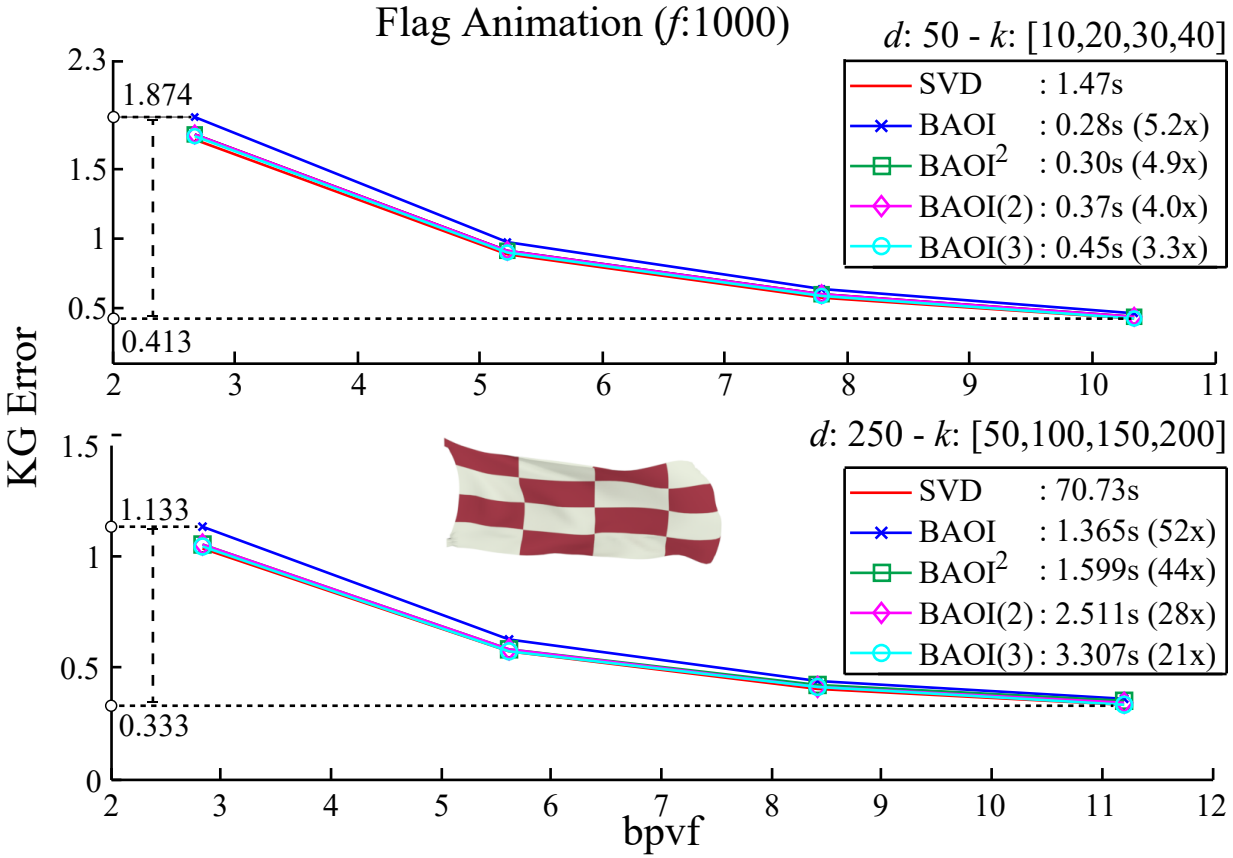
PCA based vs Static Compression Methods



Original	SVD	BAOI	MBL [13]	OD3GC [18]
bpv/KG/time	5.5/1.1/0.002s	5.5/1.2/0.0001s	6.5/12.5/0.02s	6.8/82/0.008s

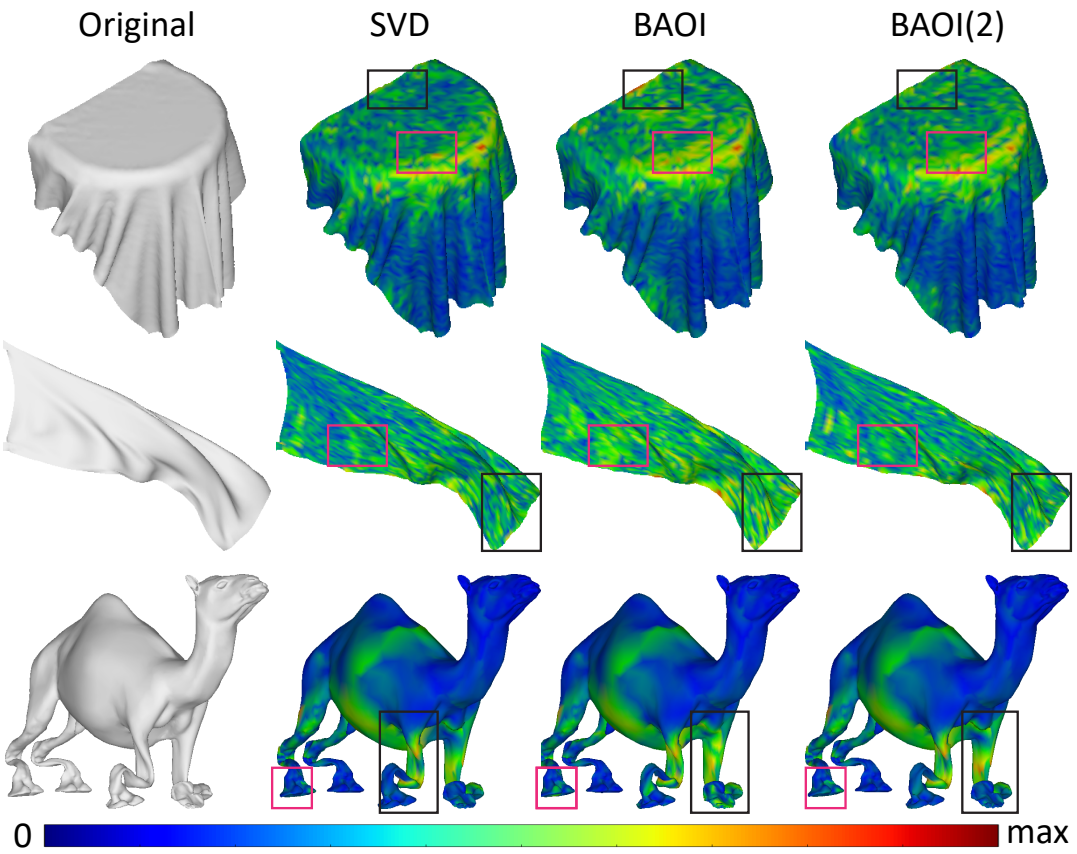
[13] A. Lalos, et al.: Compressed sensing for efficient encoding of dense 3D meshes using model-based bayesian learning. IEEE Transactions on Multimedia 19(1), 41 - 53 (2017)
[18] K. Mamou, et al.: TFAN: A low complexity 3D mesh compression algorithm. Comput. Animat. Virtual Worlds 20(2), 343 - 354 (2009)

Impact of iterations/multiplications (t_{max}, z)



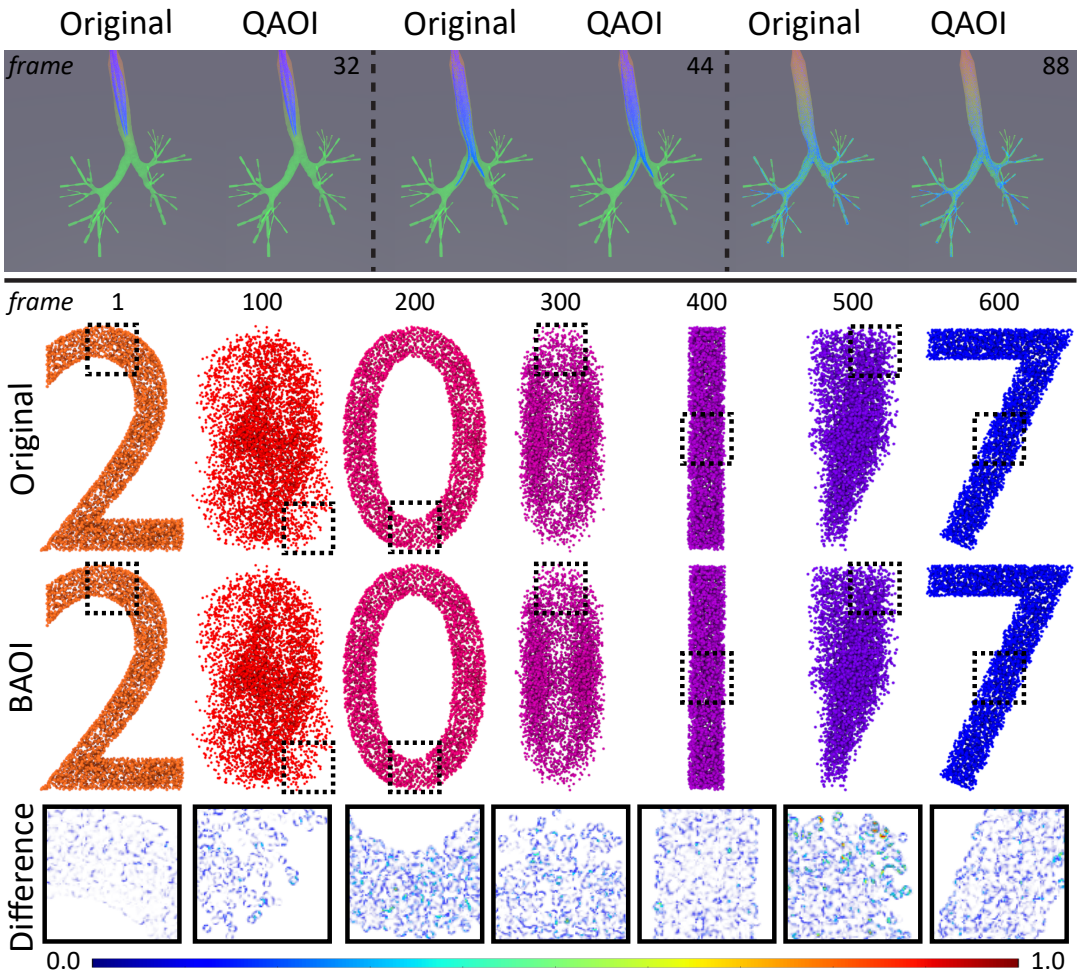
- BAOI closes the gap and finally reaches, in high precision, the levels of reconstruction quality (in both KG and STED metrics) derived by the SVD
- The speedup of BAOI is exponentially decreased when moving to higher OI

Impact of iterations/multiplications (t_{max}, z)



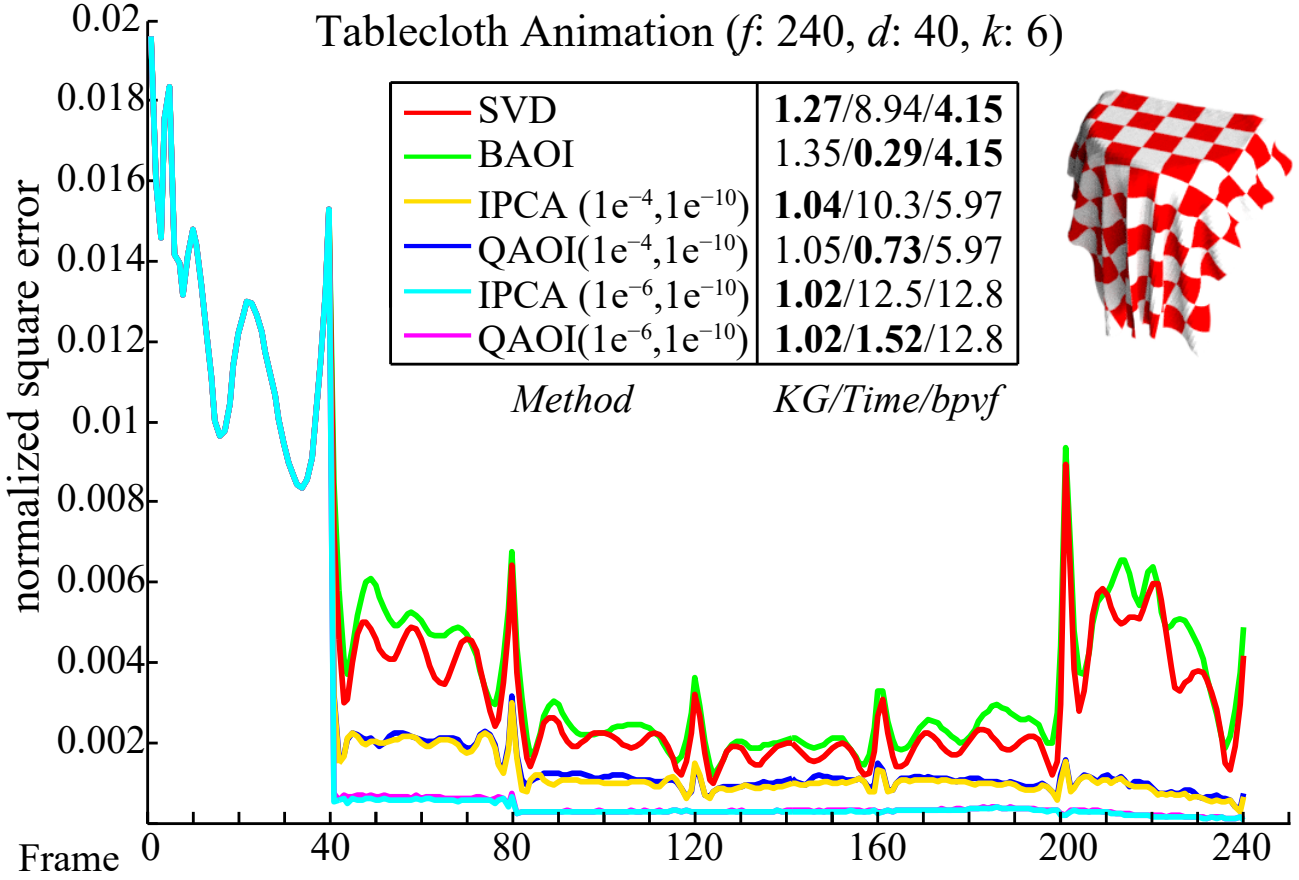
- Heatmap visualization differences of KG between SVD and BAOI for Tablecloth (top), Flag (middle) and Camel Collapse poses (bottom).
- Insets highlight how the severe approximation artifacts are mitigated using one extra OI.

Impact of frame incoherence



QAOI (top) and BAOI (bottom) produces high quality visual reproduction despite the extreme temporal incoherence between frame blocks in two particle simulations.

Impact of error thresholds ($\epsilon_{low}, \epsilon_{high}$)



Observe how fast QAOI reaches the levels of reconstruction quality of IPCA for the entire Tablecloth animation.

Adaptive Compression Results

Conclusions

1. The subspace tracking approaches allow the robust estimation of dictionaries at significantly lower execution times compared to the direct SVT implementations
2. BAOI scheme focuses on fast-streaming scenarios, while QAOI approach aims at providing progressively high reconstruction accuracy
3. The approximation artifacts that occur in a single frame block may slightly increased and propagated when moving to the subsequent ones
4. Solution: Re-initialize the subspace of interest using the SVT or QAOI, when the decoded meshes are drifted too far from the original ones
5. High potential for novel improvements such as dynamic clustering is feasible in the near future

Thank you for your Attention! Questions?