A Multi-View Image-Based Volume Visualization Technique

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Abstract

We present an image-based volume visualization approach based on Principal Component Analysis (PCA). Using PCA, a learned model is trained using pre-rendered images from spherically distributed viewing angles. The views are encoded into a compressed and more compact representation and then novel views can be synthesized by interpolating scores in the eigenspace. The main advantage of the PCA model is the low computational complexity in the encoding and decoding phases. Furthermore, the image encoding and reconstruction is independent of the rendering complexity. This is particularly important in the case of computationally demanding rendering techniques such as global illumination. Our technique has potential application in client-server volume visualization or where results of a computationally-complex 3D imaging process need to be interactively visualized on a display device of limited specification.

Index Terms: Image-Based Visualization—Volume Visualization—PCA

1 Method

Assuming pre-rendered images from spherically distributed viewing angles of a static 3D volume using specific rendering technique (such as volume ray-casting) and an input transfer function, each image is considered a high-dimensional vector and is used as input to the PCA model. PCA then computes the eigenspace of the training images which consists of small number of eigenimages. After this, each of the original views can be reconstructed as a linear combination of such eigenimages. The advantage here is that by interpolating the scores of training samples in the eigenspace, we can also synthesize novel views. We apply PCA in three different modes, as illustrated in Figure 1: *Standard PCA*, *Cell-based PCA* [1, 4], and a novel approach we call *Band-based PCA*. The standard approach applies PCA to the whole pixel space, whilst in the latter approaches, we subdivide images into sub-regions before applying PCA individually to each part. In Cell-based PCA, each image is subdivided into uniform blocks of fixed size and then PCA is applied to each block individually, while in the band-based approach, images are divided into non-uniform regions based on a grouping strategy. In this case, each band comprises a subset of attributes (pixel values) with similar features. In this study we used the following mapping

$$B_i = \left\{ \bar{x}_j \mid \bar{x}_j \in \left(\min(\bar{x}) + \frac{i-1}{N_{bands}} \left(\max(\bar{x}) - \min(\bar{x})\right), \min(\bar{x}) + \frac{i}{N_{bands}} \left(\max(\bar{x}) - \min(\bar{x})\right) \right] \right\},$$

where $\bar{x}$ is the sample mean. Here, the range of values of the sample mean is divided into uniform subranges and then attributes of each range are assigned to a band. One additional advantage of the cell-based and band-based approaches is that they allow more flexibility in determining the number of eigenvectors of each part of the image and detecting regions that correspond to background. By adaptively varying the number of eigenvectors per region (cell or band), a more optimal tradeoff between performance and quality is acheived. The number of dimensions (eigenvectors) per region required is determined based on total variability explained by the first p eigenvectors. This can be expressed as $\Theta = \frac{\sum_{i=1}^{p} \lambda_i}{\sum_{j=1}^{n} \lambda_j} > T$, where λ is the eigenvalue, p is the number of first significant eigenvectors that will form the low-dimensional eigenspace, n is the total number of eigenvectors and T is a threshold value, which affects the tradeoff between high variability and low average number of eigenvectors per cell/band. Computational complexity is reduced in all PCA settings, since the final image is effectively obtained by a simple weighted sum of eigenimages, which are much fewer in number than, for instance, the average sampling rate in a volume ray-caster. Furthermore, it should be noted that the cell and band-based techniques have similar computational complexity and memory footprint as the standard PCA in terms of encoding and decoding samples since we essentially perform a larger number of much smaller iterations.

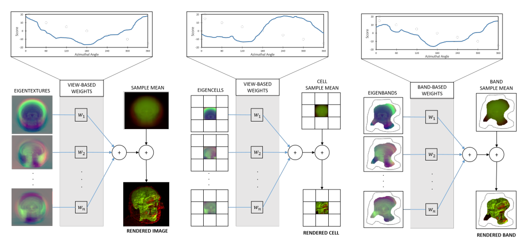

Figure 1: Overview of different PCA modes: *Standard PCA* (left), *Cell-based PCA* (middle) and *Band-based PCA* (right)

2 Results

As a first test, we apply Standard PCA and Cell-based PCA for visualizing the *Head* [1] from the Visible Human dataset, at a resolution of 300×300 pixels. We used 1,500 training images from uniformly-spaced viewing angles (3.6° spacing for azimuthal angle and 12° spacing for elevation angle) to generate the training images. The images were rendered using an implementation of a standard GPU volume ray-caster based on [2] with sampling rate of 1,000 samples per ray. Figure 2 compares the reconstructed novel view images for both Standard PCA (with 100 eigenvectors) and Cell-based PCA (with 100 eigenvectors per cell and 20×20 cell size) with a ray-cast rendering from the corresponding view. Clearly the cell-based approach produces much better quality results compared to the somewhat blurry images resulting from the standard technique, but exhibits some subtle cell-boundary artefacts when zoomed in.

Figure 3 shows the VisMale Head rendered at 1080x1080 resolution using volume ray-casting, compared to reconstructions using the cell-based (with 30×30 pixels per cell) and band-based (with 100 bands) techniques. At normal viewing resolution the reconstructed images are quite similar to a ray-cast image of the original data. However, when zoomed in closely, we see the aforementioned boundary artefacts in the cell-based PCA. The band-based approach,

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[1] *VisMale Head* is obtained from the Volume Library of Stefan Roetger

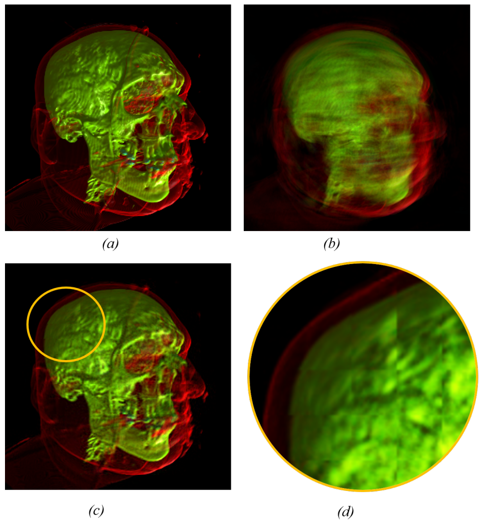

Figure 2: Novel view of the *Vismale Head* reconstructed at 300 x 300 pixel resolution. (a) Reference image rendered using the volume ray-casting technique (b) Standard-PCA reconstruction (c) Cell-PCA reconstruction (d) subtle cell-boundary discontinuity artefacts are visible in the cell-based reconstruction when zoomed in.

on the other hand, results in a more subtle dithering-like effect. Increasing the number of bands generally leads to increased image quality as can be seen in Table 1 and demonstrated in Figure 4.

Table 1: SSIM scores for increasing no of bands for the *VisMale Head* dataset rendered at 1080p resolution with Band-based PCA

No. Bands	50	100	150	200
SSIM	0.866	0.8779	0.8905	0.8911

Fig. 5 shows a proof-of-concept reconstruction of a chest dataset[2] rendered at 1080p resolution using the Exposure Renderer [3], which achieves highly detailed progressive rendering by exploiting high-end GPUs. In this case, we allowed the progressive rendering to converge for 5 seconds for each frame rendered on an Intel PC equipped with a 3.4GhZ i5-4670 CPU, NVIDIA GeForce GTX 775M GPU and 16GB RAM. Once the eigenspace is computed, our approach can be used to efficiently recreate such complex images in high detail at real-time, even on a display device without a powerful GPU.

It should be noted that both subdivision modes are applicable to any image resolution. Because the overall approach is image dependent, any increase in computational cost scales better than applying 3D rendering techniques such as ray-casting at higher resolutions. The overall results are analogous to lossy compression and may be unsuitable for some applications such as in medical diagnoses but the quality-performance tradeoff can be tuned to suit the requirements of many visualization applications.

Acknowledgments

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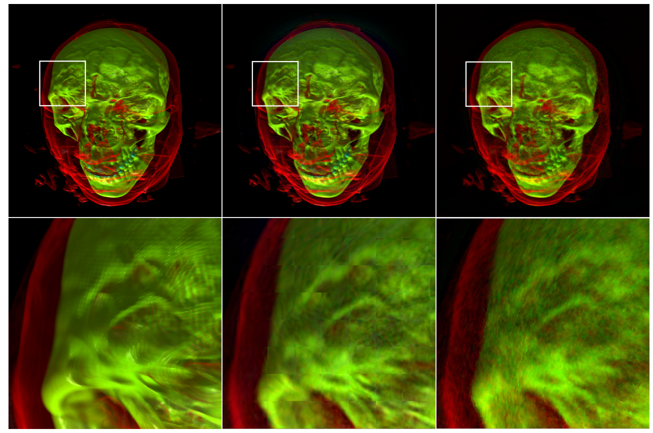

Figure 3: Comparison of the *Vismale Head* dataset ray-cast at 1080p (left) and reconstructed using cell-based PCA (middle) and the band-based PCA (right). Bottom row shows zoomed-in views.

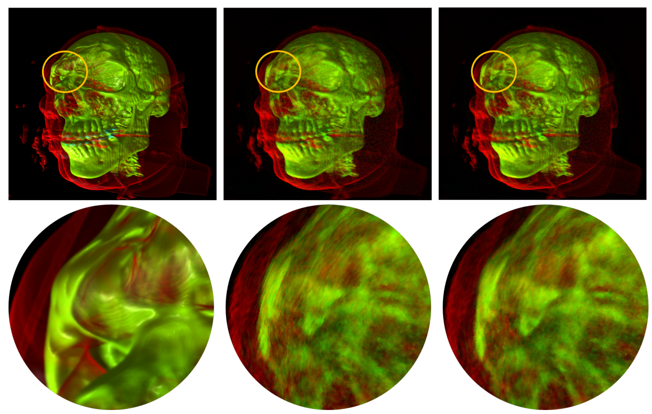

Figure 4: Sample views of band-based PCA reconstruction of Vismale dataset. Left: reference image by ray-casting. Middle: result of using 50 bands (SSIM: 0.8666). Right: 100 bands (SSIM: 0.8779).

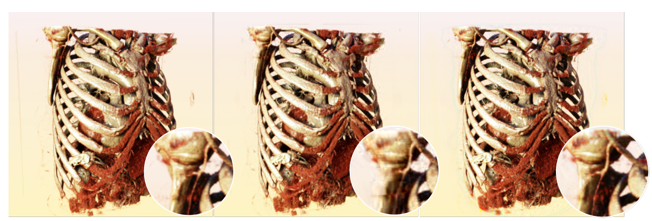

Figure 5: Sample views of PCA reconstruction of photo-realistic volume renderings. Left: reference image; Middle: Cell-based PCA reconstruction with 30x30 cell size (SSIM: 0.9819); Right: Band-based PCA Reconstruction with 50 bands (SSIM: 0.9991).

References

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[2]The chest dataset, ARTIFIX, is obtained from the DICOM Sample Image Library: http://www.osirix-viewer.com/resources/dicom-image-library/