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Volume Rendering Using Principal Component Analysis

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Abstract

We investigate the use of Principal Component Analysis (PCA) for image-based volume rendering. We compute an eigenspace using training images, pre-rendered using a standard raycaster, from a spherically distributed range of camera positions. Our system is then able to synthesize novel views of the data set with minimal computation at run time. Results indicate that PCA is able to sufficiently learn the full volumetric model through a finite number of training images and generalize the computed eigenspace to produce high quality novel view images.

1. Background

The use of PCA for analyzing 3D objects has been well reported in the last two decades in Computer Vision and Computer Graphics. Gong et al. [GMC96] were the first to find the relationship between the distribution of samples in the eigenspace and the actual pose in an image of a human face. Nishino et al. [NSI99] suggested a method, called *Eigen-texture*, to render a 3D model by interpolating its training samples scores in the eigenspace. They found that partitioning samples into smaller cell-images before applying PCA reduced blurry effects resulting from the standard PCA approach.

We investigate the use of PCA for volume rendering. We compare results of standard PCA with those obtained from cell-image PCA when applied to RGB images of a volume dataset. Given data samples $X = [x_1\, x_2 \cdots x_n] \in R^{d\times n}$, where each sample is in column vector format, the covariance matrix is defined as

$$C = \frac{1}{n-1} XX^T = \frac{1}{n-1}\sum_{i=1}^{n} x_i x_i^T. \quad (1)$$

We can find the optimal low-dimensional bases that cover most of the data variance by extracting the most significant eigenvectors of the covariance matrix C. Eigenvectors are extracted by solving the following characteristic equation

$$(C-\lambda I)\, v = 0;\; v^T v = 1, \quad (2)$$

where $v \in R^d$ is the eigenvector and λ is its corresponding eigenvalue. Eigenvalues describe the variance maintained by the corresponding eigenvectors. Hence, we are interested in the eigenvectors that have the higher eigenvalues $V = [x_1\, x_2 \cdots x_p]$; $p \ll n$. Having the most significant eigenvectors computed, we can encode a given sample x using its p-dimensional projection values as follows

$$y = V^T x. \quad (3)$$

We can then reconstruct the sample as follows

$$x_{reconstructed} = Vy. \quad (4)$$

One advantage of PCA is the low computational complexity when it comes to encoding and reconstructing samples.

2. PCA for Volume Rendering

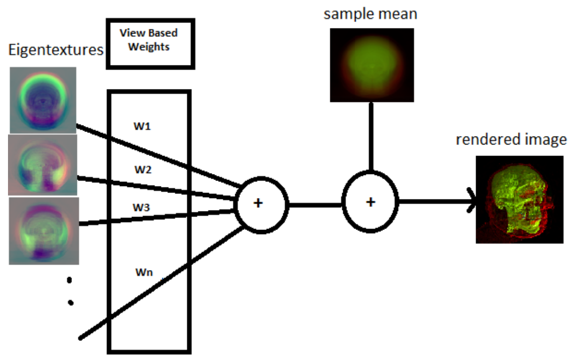

Figure 1: *Final image reconstruction using PCA.*

In the context of raycast volume rendering, where the final image is highly dependent on the viewing angle, we assume a set of rendered images as training samples. We can compute the eigenspace of the volume dataset by applying PCA for a number of training images of uniformly distributed viewing angles. By interpolating the scores of training samples in the eigenspace, we can synthesize test samples from novel viewing angles using the interpolated scores. Fig. 1 shows the steps for reconstructing and rendering a novel view

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image using PCA. In the case of cell-image PCA, the eigenspace is computed for each cell image individually. Thus, we can encapsulate the whole 3D model using a small number of eigenimages. This will reduce the size of the actual image in the eigenspace. Furthermore, the computational complexity is reduced, since the final image is a weighted sum of eigenimages, which are much fewer in number than the average sampling rate in a ray caster.

3. Results and Findings

We applied PCA for rendering the Vismale head volume dataset [†] with an RGB pixel space of resolution 300x300 pixels. We used 1,500 training images from uniformly-spaced viewing angles (3.6° spacing for the azimuthal angle and 12° spacing for the elevation angle) to compute the eigenspace. All training images were acquired using a standard raycaster with sampling rate of 1,000 samples per ray. We then acquired test samples by applying 0.9° spacing for the azimuthal angle and 30° spacing for the elevation angle leading to a total of 2,400 unique views.

We applied PCA in two different contexts. In the first context, the eigenspace was computed for the full-size training images (300x300 RGB pixel space). In the second context, we partitioned each image into a number of equally-sized cell images (20x20 pixels). Then, we computed the eigenspace of each cell image individually. For each unique view, we synthesize the corresponding scores (projection values onto the first significant eigenvectors) by interpolating the scores of the training samples using spline interpolation. We used 100 eigenvectors to represent the eigenspace. Fig. 2 compares the reconstructed novel view images for both standard PCA (full-image PCA) and cell-image PCA. Clearly, the cell-image PCA approach leads to much better quality results compared to the full-image PCA, which results in somewhat blurry images with the same distribution of training samples. This is consistent with what was reported in the previous literature [NSI99]. One problem with the cell-based PCA is that it results in subtle discontinuity artefacts at the cell boundaries in the reconstructed images. In terms of computational complexity, the PCA based methods require only 100 scalar-vector multiplications in the case of the test scenario we presented. This is computationally much cheaper compared to the operation required in the equivalent raycast rendering. Furthermore, it should be noted that the cell-image technique has the same computational complexity and memory footprint as the direct-PCA technique as we essentially perform a larger number of much smaller iterations.

4. Conclusion

In this poster, we presented a preliminary investigation of the use of PCA for volume rendering. The cell-image PCA method was able to reconstruct the volumetric model through a finite number of training images and generalize the eigenspace to produce high quality novel view images. One limitation when using PCA for rendering is that a change in transfer function (material colors and opacities) requires a change in the whole eigenspace. One solution to this could be be to combine eigenspaces of different materials (eigenflesh, eigenbone, etc). Despite the limitations, PCA appears to be an interesting and viable alternative technique for image-based volume rendering. The benefits in terms of computational complexity and compression of information may lead to potential advantages in applications such as client-server visualization systems.

In future work, we plan to conduct perceptual studies to measure the conspicuity of artefacts in both PCA approaches under different viewing and training configurations and across different scales and types of data sets. Based on these results, we plan to investigate strategies to ameliorate the artefacts appearing in the cell boundary regions.

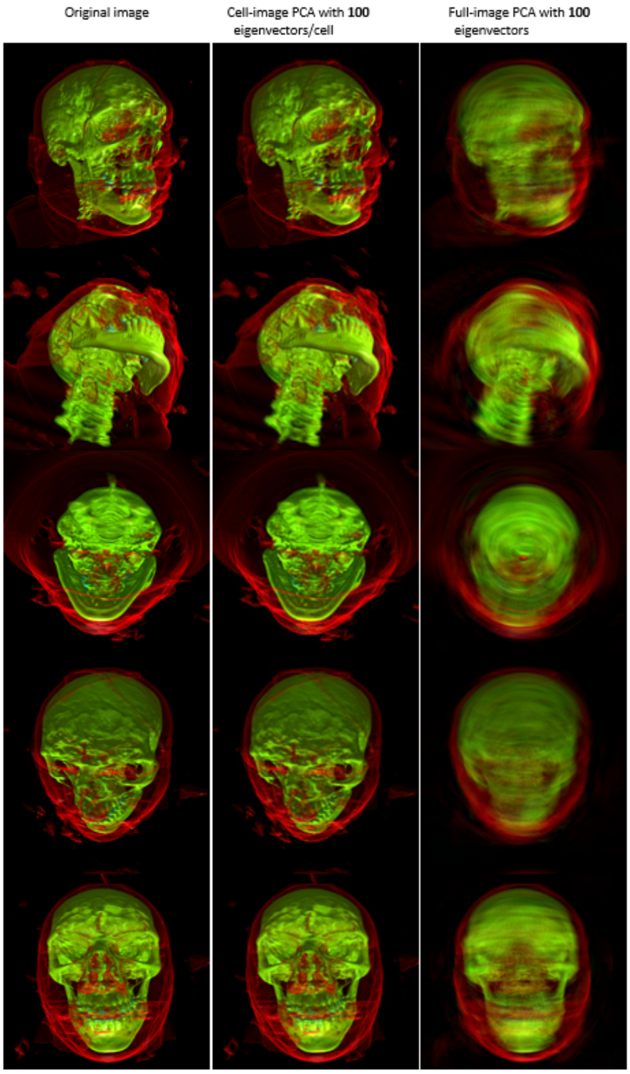

Figure 2: *Five novel views rendered using PCA.*

Acknowledgement

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† https://www.nlm.nih.gov/

References

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