3D Shape Co-segmentation via Sparse and Low Rank Representations

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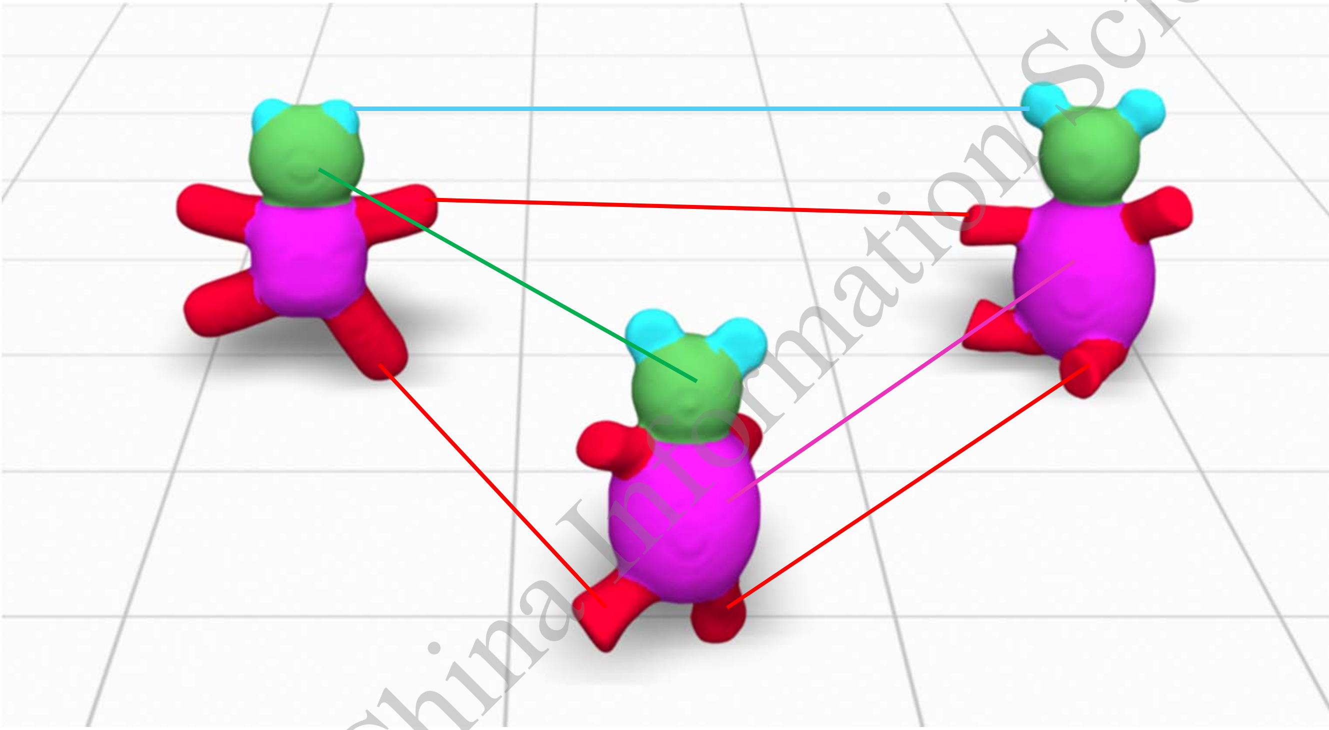
Motivation

As a traditional and fundamental research among computer graphics, 3D shape segmentation has provided large supports to many other 3D processing technologies.

Motivation

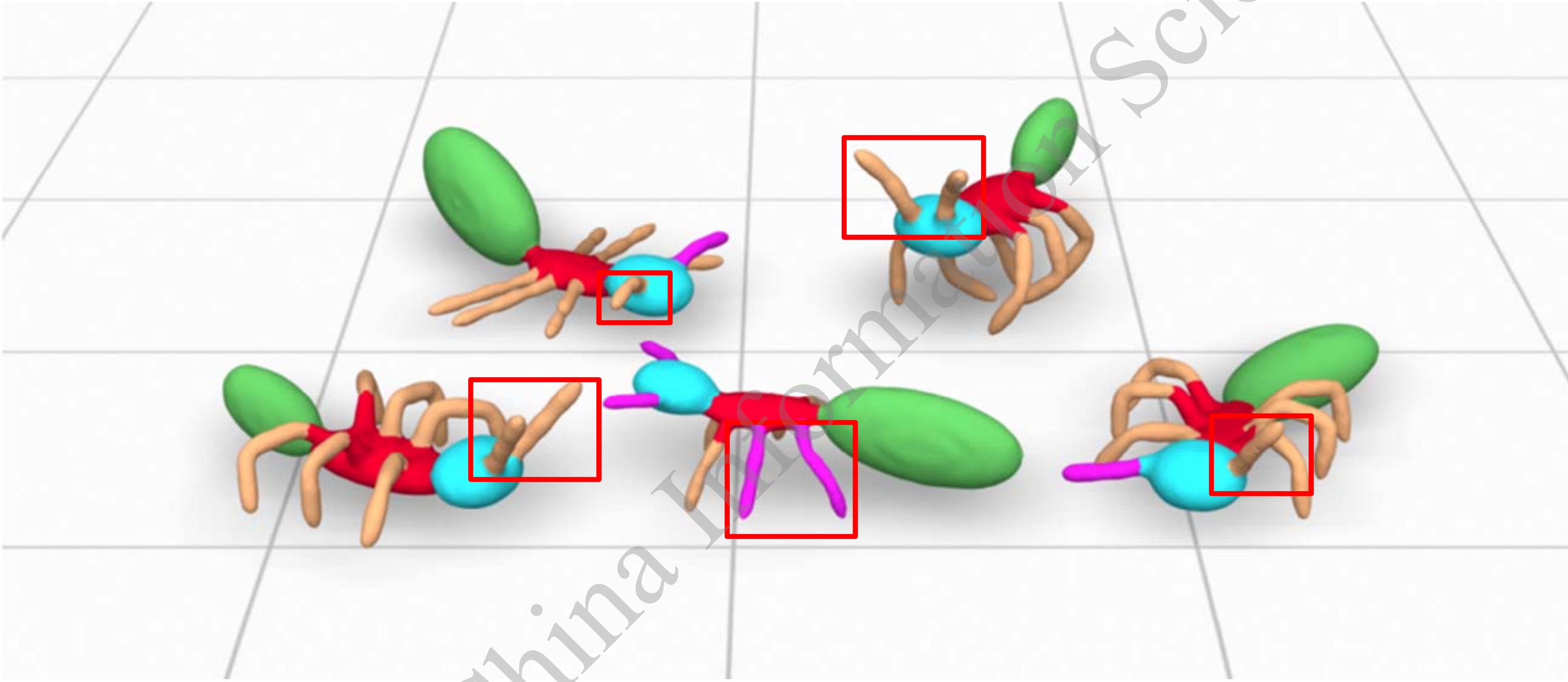
To fully utilize the common characteristics of a model set, 3D shape co-segmentation, which together co-segments multiple 3D shape parts among the same category, attracts more and more attentions.

Problem



Even though there are many similarities and correspondences between various 3D shapes in the same category, effectively co-segment the 3D shape parts still remains many challenges.

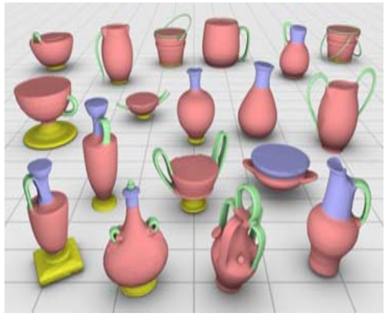
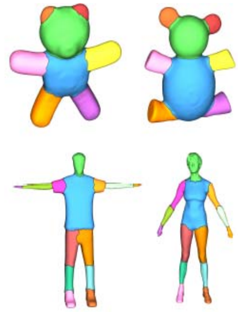
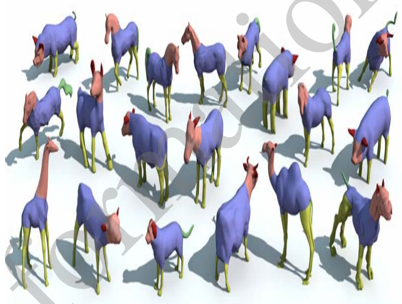
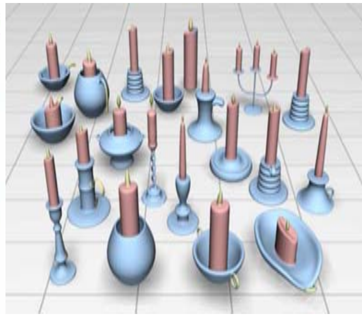
Problem



Each single 3D shape has its individual pose and appearance, and the parts which have similar geometry features may have different semantic labels.

Related works

2011 2011 2012 2012

Sidi et al. [TOG] Introduce unsupervised co-segmentation via descriptor space spectral clustering.

Huang et al. [TOG] Introduce joint shape segmentation with linear programming.

Wang et al. [TOG] Introduce active co-analysis of a set of shapes.

Hu et al. [CGF] Introduce co-segmentation of 3d shapes via subspace clustering.

How to take both local features and global consistency into consideration?

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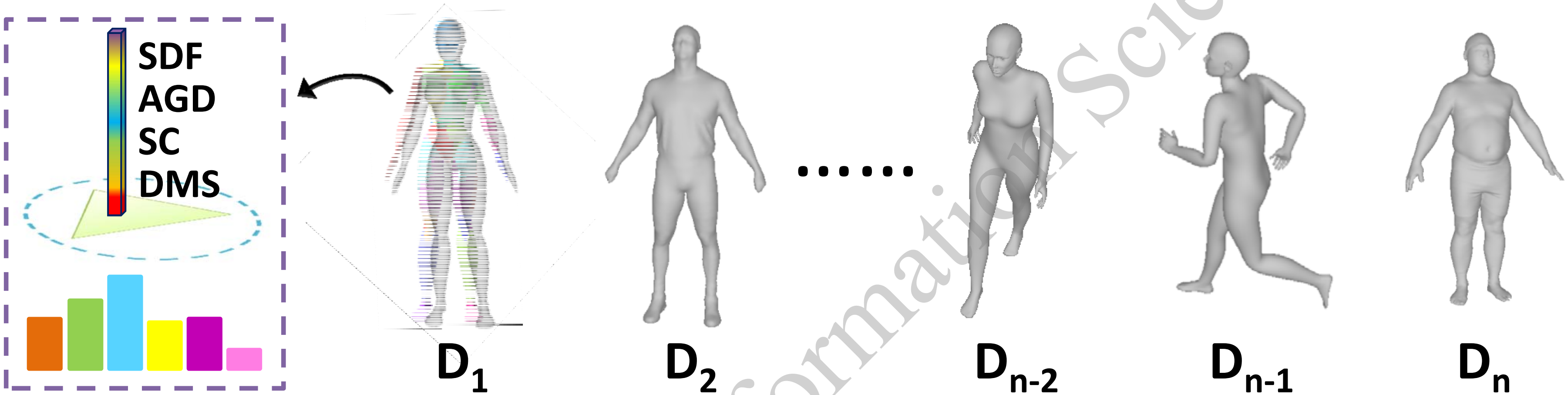
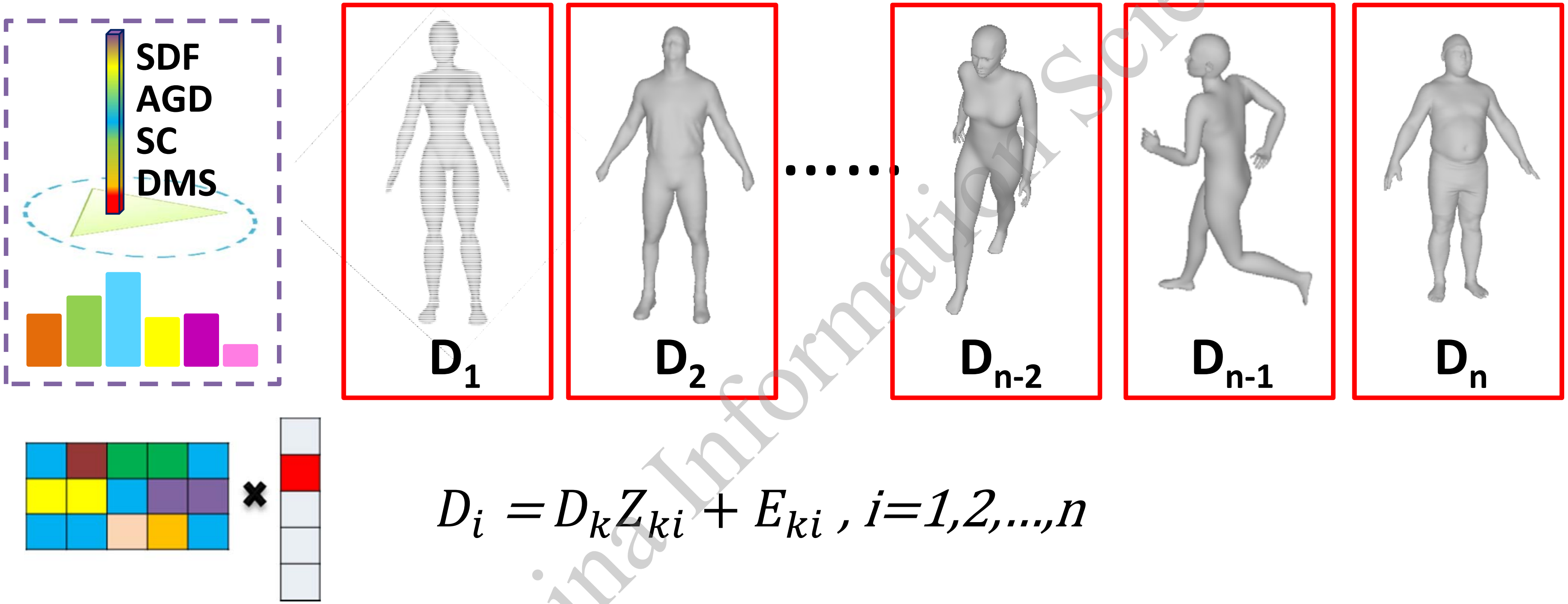
Pre-segment & Patch Features Extraction



Input one 3D shape category, similar to Hu et al.[CGF 2012], we use normalized cuts algorithm to divide each shape into primitive patches for reducing computing complexity.

Then we extract the patch features, which include shape diameter function, average geodesic distance, shape context, and distance from medial surface, as the same as Guo et al.[TOG 2015].

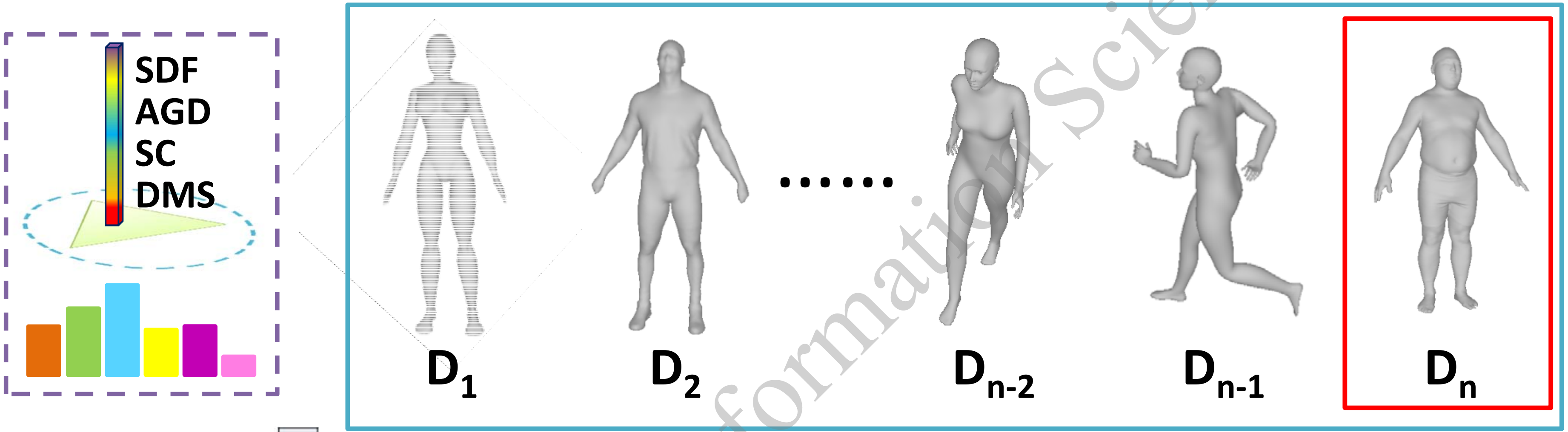
Sparse & low rank representation

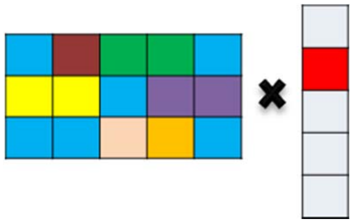


$$D_i = D_k Z_{ki} + E_{ki} \, , \, i=1,2,\ldots,n$$

After pre-segmentation and features extraction processes, we convert the co-segmentation problem into feature clustering issues. Let D_i denotes patch features of model i, we first respectively adopt each single shape as dictionary to represent all the shapes in the same category with sparse constraint.

Sparse & low rank representation

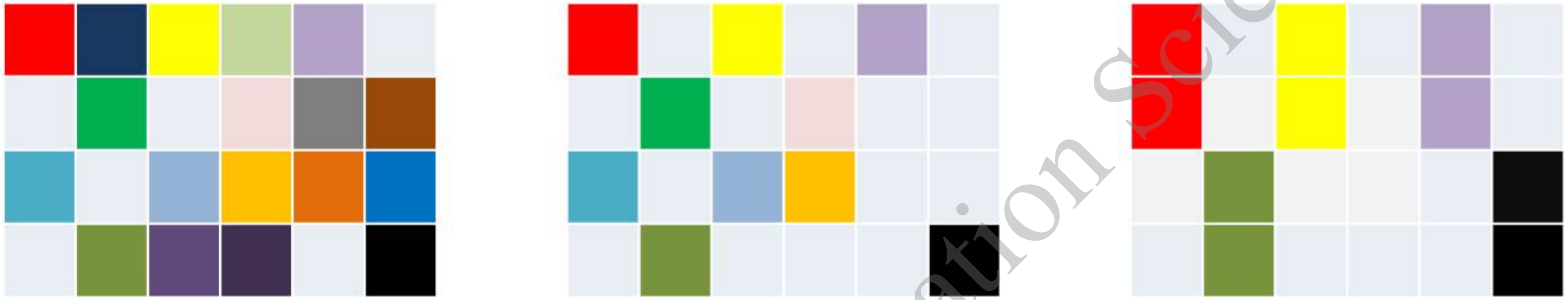




$$\min_{\substack{Z_{k1},Z_{k2},\dots,Z_{kn}\\ E_{k1},E_{k2},\dots,E_{kn}}} \sum_{i=1}^{n} \boxed{\left(\alpha\|Z_{ki}\|_{2,1} + \lambda\|E_{ki}\|_{1,1}\right)} + \boxed{\|UZ_k\|_*}$$

To better find the consistent expression of each class and the global common feature structure, we introduce the low rank constraints. And to achieve more compact feature representation, the rank of the global feature represent coefficients matrix should be low, as shown in the blue box.

Sparse & low rank representation

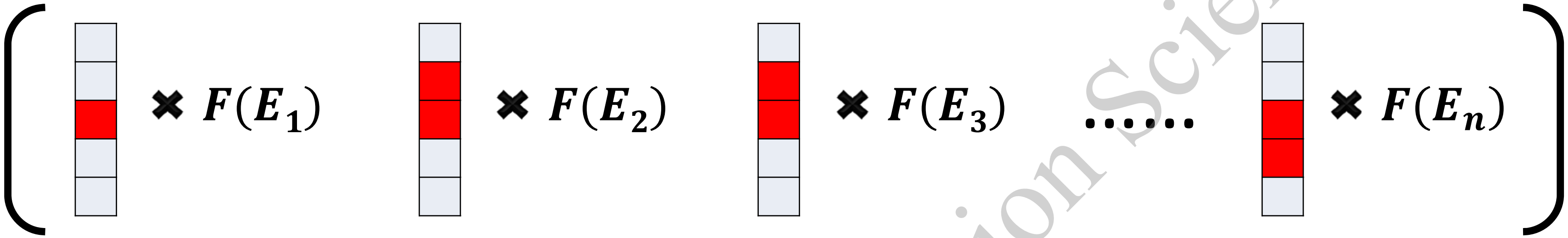


(a) (b) (c)

While involving both sparse representation and low rank constraints, we compact the patch features into a consistent and easy-to-cut space. To intuitively exhibit the easy-cutting space, we show a sketch map in the figure.

Figure (a) shows coefficients of a normal feature representation, where grey grids denote zero value and other grids denote non-zero values. Figure (b) shows coefficients with sparse constraints, and figure (c) shows the ones with both sparse and low-rank constraints.

Co-segmentation via confidence weighting



$$SE_i = \sum_{j=1}^{n*np} |UE_i(*,j)|, i = 1,2, \dots, n \qquad (1)$$

$$UZ_{conf} = UZ \bullet \big(2/(NSE + \beta)\big) \qquad (2)$$

Then we gather the coefficients and weight them by a confidence weighting procedure. In detail, we first normalize the coefficients as shown in Equ.1. Then through a non-linear map, we achieve the weighted coefficients as shown in Equ.2. Finally, we apply simple k-means and fuzzy cuts methods as optimization and achieve the final shape co-segmentation results.

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Results

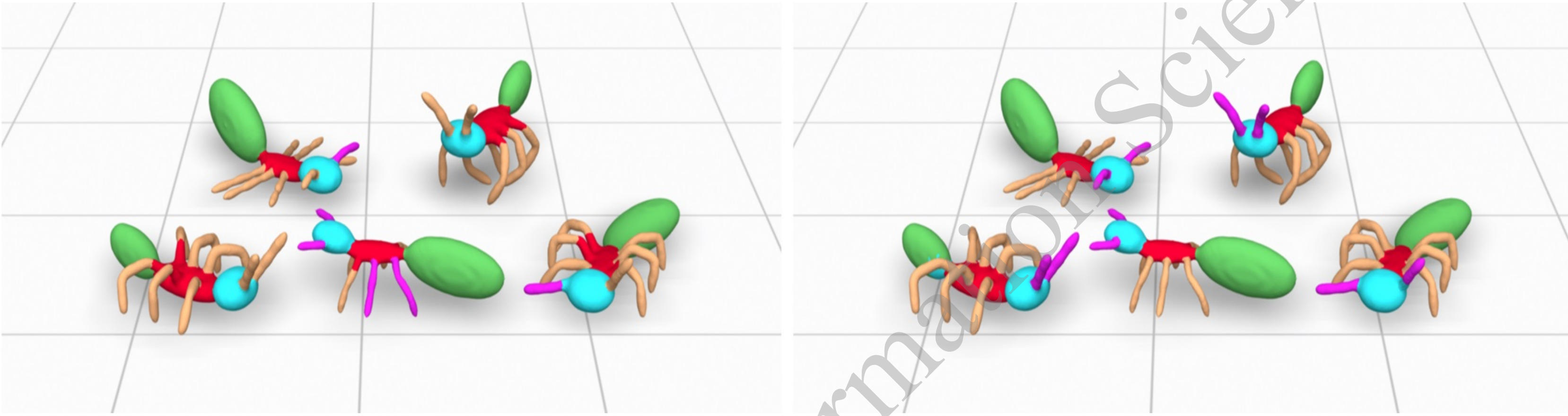
We exhibit various experiments and comparisons on Princeton Segmentation Benchmark and Shape COSEG Dataset. Here we show two typical results, and more results are shown in the demo video.

Comparisons

Sidi et al. [TOG2011] VS Ours

For more intuitive comparison, we show the visual comparison with Sidi et al. [TOG2011] in the figure. From the figure obviously, e.g. the neck of the guitars, our method can achieve more accurate and meaningful co-segment results.

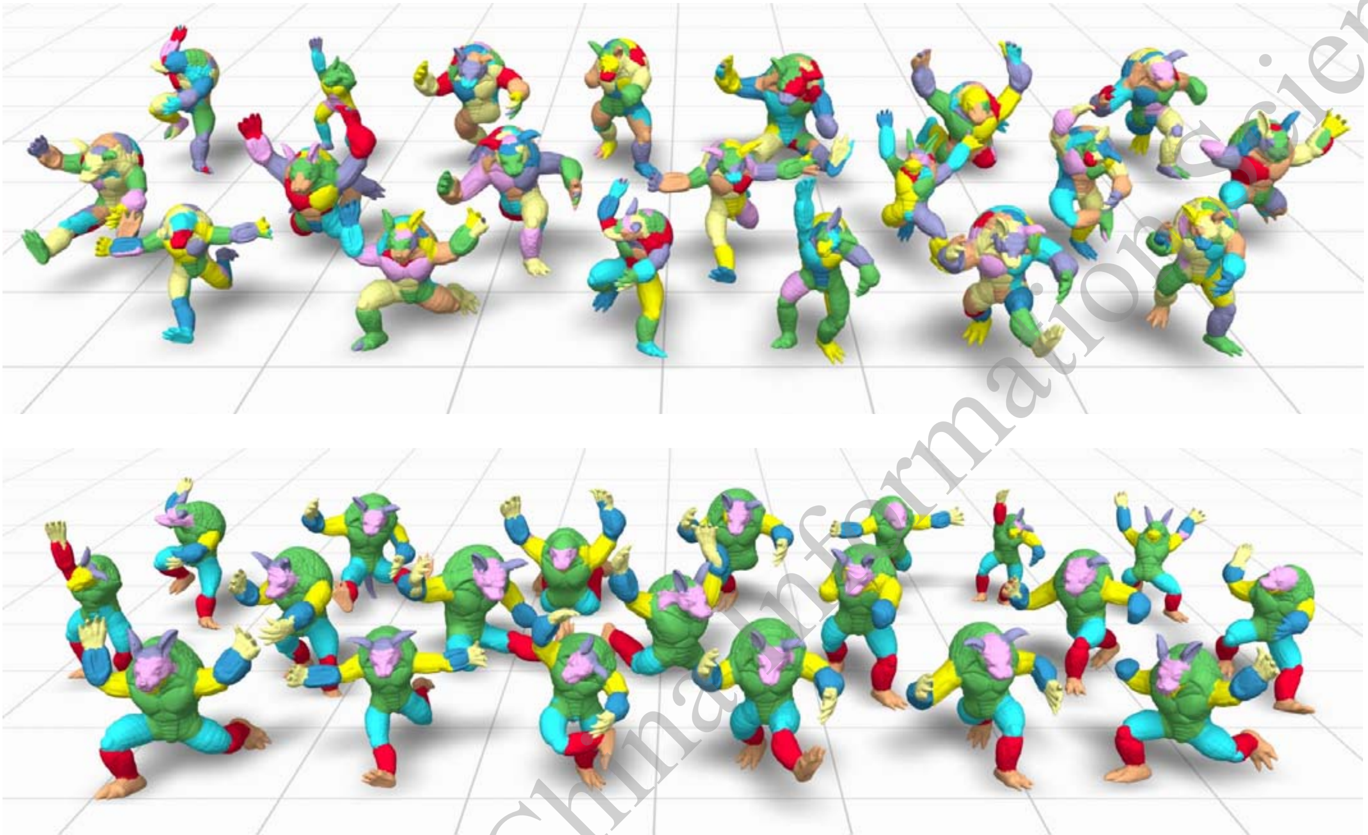
Comparisons



Hu et al. [CGF2012] VS Ours

Moreover, to show our method outstanding performance, we also make a visual comparison with Hu et al. [CGF2012]. As exhibited in the figure, through our sparse and low rank representation, we could get better co-segment results, e.g. the antennas and legs of the ants.

Comparisons

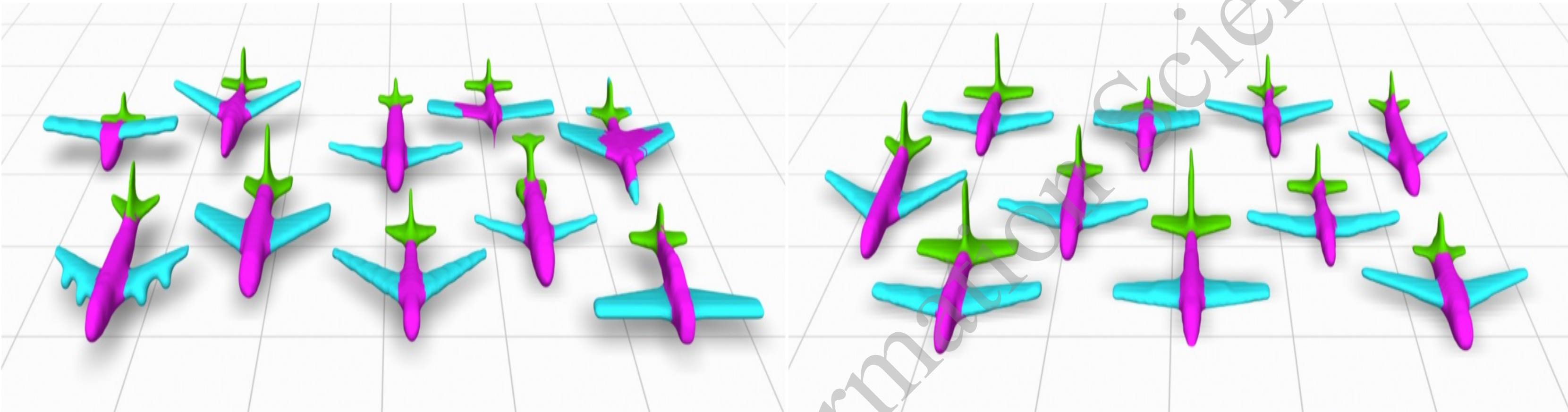


Results without weighting

VS

Results with weighting

To exhibit the effect of the representation coefficients confidence weighting process, we show visual comparisons in the figure. From the figure we could obviously find the results without weighting are confusing and meaningless.



Co-segmentation results with half-number models

Specifically, our method could also achieve comparable co-segmentation results using fewer shapes. As shown in the figure, the left ones are front ten models of airplane and the right ones are behind ten. The left and right ones are separately processed, while both of their co-segmentation results are state-of-the-art.

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Conclusion

Our method

- **CTRB 1** — ***proposing a new 3D shape co-segmentation framework via spare and low rank representation***
- **CTRB 2** — ***utilizing the representation errors as confident metrics to weight representation coefficients***
- **CTRB 3** — ***achieving state-of-the-art co-segmentation results on several general benchmarks***

Our method aims at finding compact and consistent feature representation, and we truly do not find any new features. Thus, our method in a way depends on the initial geometry features. Lacking the semantic label information and topological guides, there is still much room for improvement.

Thanks!