SCIENCE CHINA
Information Sciences

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May 2018, Vol. 61 054101:1–054101:3
https://doi.org/10.1007/s11432-017-9331-9

3D shape co-segmentation via sparse and low rank representations

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Received 30 October 2017/Accepted 17 January 2018/Published online 10 April 2018

Citation Yin L Y, Guo K, Zhou B, et al. 3D shape co-segmentation via sparse and low rank representations. Sci China Inf Sci, 2018, 61(5): 054101, https://doi.org/10.1007/s11432-017-9331-9

As a traditional and fundamental research area in computer graphics, 3D shape segmentation has provided large support to many other 3D processing technologies. 3D shape co-segmentation, which together with model sets, co-segments multiple 3D shape parts among the same category, has been attracting significant attention to fully utilize the common features of model sets.

In recent years, many researchers have studied 3D shape co-segmentation [1–3]. Sidi et al. [4] performed a co-analysis method by building a new shape descriptor space, and executed spectral clustering with the aid of diffusion maps. They mapped the whole feature space into a new compact descriptor space, while analyzing one shape set simultaneously. They could achieve global optimal results, which individual shape features were abandoned. Thus, some individual shape parts may not be correctly segmented. Huang et al. [5] considered pairwise relationships as the main criteria. They passed shape similarity and consistency via shape pairs. Consequently, they maintained and propagated the individual shape features. Because the global shape consistency is lost, a large shape variation may lead to wrong results.

To address the above problems, we propose an effective co-segmentation method, combining both individual shape features and global consistence. Given a 3D shape category, we first utilize each single shape as dictionary to sparsely represent the whole shape category. Next, we force every representation of the feature descriptors with low-rank constraints. Eventually, we utilize representation errors to weight the coefficients and obtain the confident ones. Furthermore, through a simple cluster method and smooth process, we achieve the final co-segmentation results. The experimental results show that our approach can outperform other state-of-the-art methods.

Sparse and low-rank representation for co-segmentation. Our co-segmentation method takes one 3D shape category as input. First, similar to Hu et al. [1], 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 [6]. Next, we calculate the feature histograms of each patch. In detail, given the feature histograms of one patch in shape i, we concatenate them into a feature vector denoted as f_i. We further arrange f_i into a matrix, which is denoted as D_i. Because similar patches from corresponding parts often represent similar features, the corresponding similar patch feature vectors may be sparsity-consistent.

Consequently, the task of co-segmenting the primitive patches into homogeneous parts could be cast as segmenting the feature vectors into their respective clusters. Inspired by [1], each patch fea-

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ture matrix in a union of linear clusters can be represented as a linear combination of the others belonging to the same linear cluster. The combination should be sparse and the patch features lying in the same clusters can automatically be obtained. Distinctive from Hu et al. [1], we adopt each single shape as dictionary to represent the whole category. Compared to sparse representation, low-rank constraints have a better performance rate in terms of discovering global structure [7]. The low-rank representation can better uncover data relationships, where the within cluster affinities are dense and the between cluster ones are zeros.

As illustrated above, for each shape dictionary k, we obtain representation coefficients Z_{ki} between shapes k and i. Moreover, to achieve a more compact feature representation, we force the rank of global feature represent coefficient matrix to be low. In detail, if UZ_k denotes the concatenated Z_{ki}, where each column represents one patch coefficient, the affinities among patch features are computed by solving the following sparse and low-rank representation problem:

$$\min_{\substack{Z_{k1},\ldots,Z_{kn}\\E_{k1},\ldots,E_{kn}}} \sum_{i=1}^{n}(\alpha\|Z_{ki}\|_{2,1}+\lambda\|E_{ki}\|_{1,1})+\|\mathrm{UZ}_k\|_*,$$
$$\text{s.t.}\ \ D_i=D_kZ_{ki}+E_{ki},\ Z_{ki}\geqslant 0,$$

where Z_{ki} forms a feature selection and clustering progress. E_{ki} denotes the representation errors, which indicate the precision. $\|\cdot\|_{2,1}$ is the $l_{2,1}$ norm defined by $\|Z_{ki}\|_{2,1}=\sum_{j=1}^{n\cdot\mathrm{np}}\|Z_{ki}(*,j)\|_2$, where np denotes the over-segment patch number and $Z_{ki}(*,j)$ denotes the j-th column vector of Z_{ki}. While $\|\cdot\|_{1,1}$ is the $l_{1,1}$ norm defined by $\|E\|_{1,1}=\sum_{i,j}|E_{ij}|$. Further, we set parameters $\alpha=0.01$, $\lambda=0.9$ to balance the two items. $\|\cdot\|_*$ denotes the nuclear norm, also equaled as the sum of the singular values. Involving both sparse representation and low-rank constraints, we compact the patch features into a consistent and easy-to-cut space.

To solve the equation illustrated above, we employ the augmented lagrange multiplier method [8]. We repeat the above representation process for each shape among the whole shape category. Consequently, we achieve n represent coefficient sets, which represent each individual shape feature and entirely maintain global shape category consistency.

Co-segmentation via representation coefficient confidence weighting. A traditional way for the final co-segmentation is to concatenate the representation coefficients and directly apply a cut algorithm. However, equally measuring the coefficients may not reflect the character of each representation and may lead to incorrect classification. Considering the above issues, we propose a representation coefficient confidence weighting procedure. Through the sparse and low-rank representation progress, we obtain n represent coefficient matrix sets $\mathrm{UZ}=[\mathrm{UZ}_1,\mathrm{UZ}_2,\ldots,\mathrm{UZ}_n]$, and n represent error matrix sets $\mathrm{UE}=[\mathrm{UE}_1,\mathrm{UE}_2,\ldots,\mathrm{UE}_n]$, where $\mathrm{UE}_i=[E_1,E_2,\ldots,E_n]$. We first calculate $\mathrm{SE}_i=\sum_{j=1}^{n\cdot\mathrm{np}}|\mathrm{UE}_i(*,j)|$, where np denotes the patch count in one shape. Then, we normalize SE, denoted as NSE. Next, we repeat and expand NSE according to the dimension of UZ. Eventually, we use NSE to achieve $\mathrm{UZ}_{\mathrm{conf}}=\mathrm{UZ}\cdot(2/(\mathrm{NSE}+\beta))$, where '$\cdot$' operator indicates the dot product. Additionally, we set $\beta=2$ as a parameter to balance the weight of NSE.

After the confidence weighting process, we achieve the reliable representation coefficients, which respect the patch feature relationships with each other. For simplicity, we apply simple k-means method to cut $\mathrm{UZ}_{\mathrm{conf}}$ into various classes. Specifically, to relax the feature coefficient distances, we apply a larger class center number for initial k-means. Then, according to the smoothness between two adjacent patches, we merge the initial k-means results into correct classes. Finally, to achieve smooth segment boundaries, we apply the fuzzy cuts method [9].

Experiments and comparisons. We conducted various experiments and comparisons on different benchmarks to demonstrate the effectiveness of our approach. The benchmarks we used are two generic 3D shape datasets, one of which is Princeton segmentation benchmark (PSB) established by Chen et al. [10] and the other is the shape COSEG dataset from [4, 11]. The PSB has 19 shape categories, including various man-made shapes, such as cup, glasses, airplane, chair, and non-rigid shapes, such as human, ant, fish, and fourleg. We excluded three categories (bearing, mech, and bust) as the same as other methods, because the shapes in these categories do not have meaningful correspondences between segmentations. Note that the PSB benchmark contains various manual segmentation results and we chose the appropriate ones, same as [1]. From the shape COSEG dataset, we chose 4 shape categories (candelabra, goblet, guitar, and lamp) for our experiments and comparisons.

Intuitively, we calculated the co-segmentation accuracy illustrated in [6], and compared it with Hu et al. [1] as shown in Table 1. We can see the superiority of our method from the table. We achieved outstanding results for not only man-made shapes, such as airplane and chair, but also

Table 1 Co-segmentation accuracy comparison with Hu et al. [1] on PSB and shape COSEG dataset

Category	Hu et al.	Ours	Category	Hu et al.	Ours
Human	70.40	71.86	Plier	86.00	87.90
Cup	97.40	97.96	Fish	85.60	87.34
Glasses	98.30	98.60	Bird	71.50	78.77
Airplane	83.30	86.58	Armadillo	87.30	88.52
Ant	92.90	93.94	Vase	80.20	80.00
Chair	89.60	90.83	Fourleg	88.70	88.98
Octopus	97.50	97.65	Candelabra	93.90	94.07
Table	99.00	99.37	Goblet	99.20	99.24
Teddy	97.10	93.56	Guitar	98.00	98.40
Hand	91.90	92.28	Lamp	90.70	92.07

for non-rigid shapes, such as ant, fish, and bird. Further, we obtained comparable results in teddy and vase. We also performed many other comparisons in the supplement video.

Conclusion and discussion. In this article, we presented an unsupervised approach for 3D shape co-segmentation. Under the sparse representation and low-rank constraints, we proposed a confidence weighting process and achieved shape co-segmentation results. Experiments on several general benchmarks and comparisons with other state-of-the-art methods show that our method is robust and superior compared to the other methods.

Our method aims at finding compact and consistent feature representations, and we do not produce any new features. Thus, our method depends on the initial geometry features. There is still room for improvement in the current approach because it lacks semantic label information and topological guides. It is feasible to incorporate other constraints for optimization, such as shape correspondence and shape structure analysis. Furthermore, it is interesting to process non-manifold shapes or 3D point clouds in the future.

Acknowledgements This work was supported by National Natural Science Foundation of China (Grant Nos. 61532003, 61421003).

Supporting information Videos and other supplemental documents. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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