

INTRODUCTION

As a fundamental and challenging task in computer vision, image segmentation is a process of decomposing an image into independent regions, which plays an important role in many high-level applications. Unsupervised methods receive much attention because they require no prior knowledge. Some representative works of them rely on constructing a reliable affinity graph for the representation of image content, achieving superior performance.

Clearly, for these affinity graph-based methods, the segmentation performance significantly depends on the effectiveness of the constructed affinity graph, with particular emphasis on the neighborhood topology and pairwise affinities between local and global nodes. Due to the advantages of assimilating different graphs, a multi-scale fusion graph (GL-graph) have a better performance than a single graph (adjacency-graph) with single-scale. However, it is not reliable to determine a principle of graph combination. In addition, a global affinity graph built with global nodes is a dense graph, incurring high computation cost.

In this paper, we propose an adaptive affinity graph with subspace pursuit (AASP-graph) for natural image segmentation. This work makes the following **contributions**.

- We construct an AASP-graph to adaptively combine different graphs with the sparsity and a high discriminative power.
- After reducing noise, we apply the affinity propagation clustering (APC) to decide the global nodes, accurately mining the feature distribution of superpixels.
- The results show the effectiveness of our method compared with the state-of-the-art approaches.

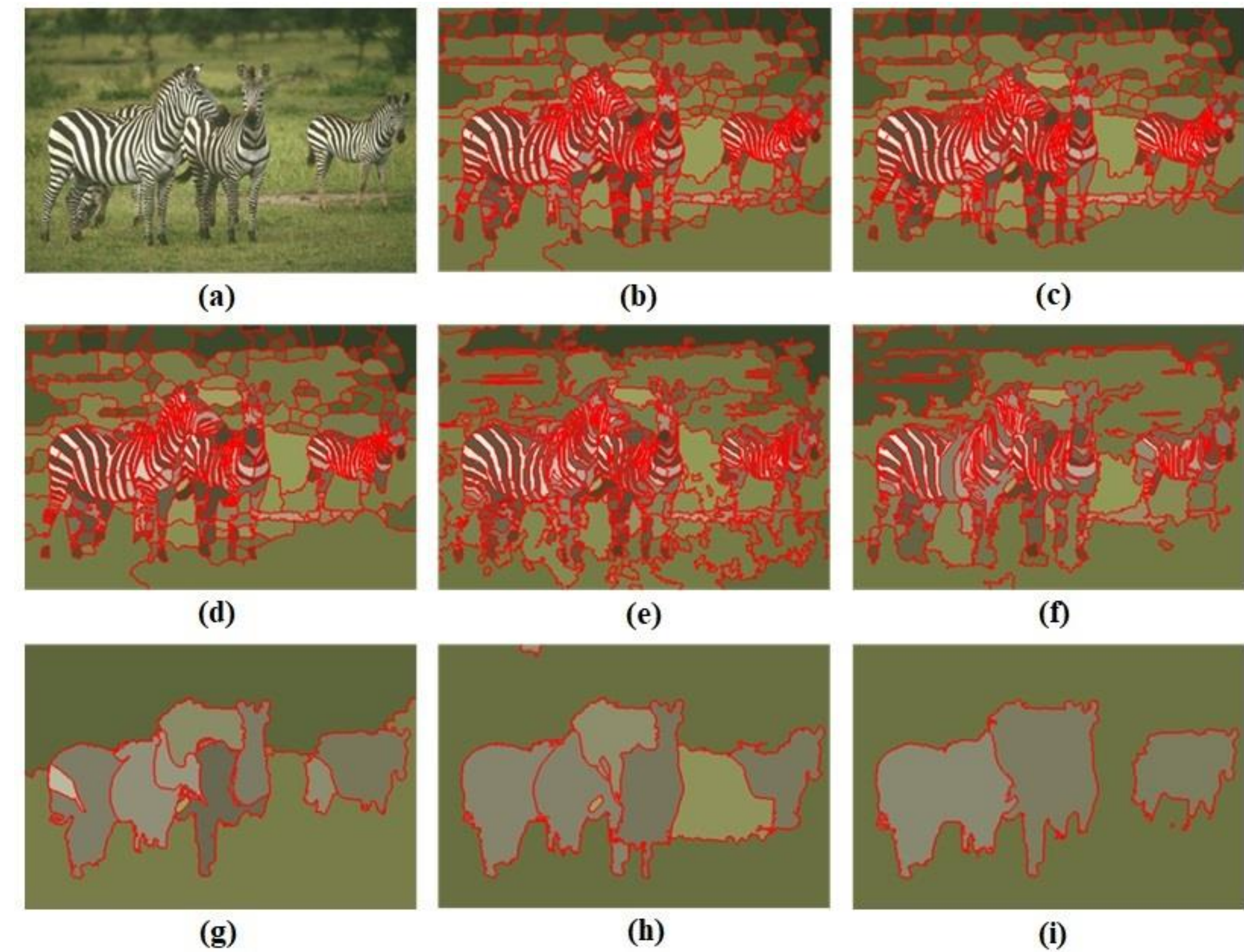
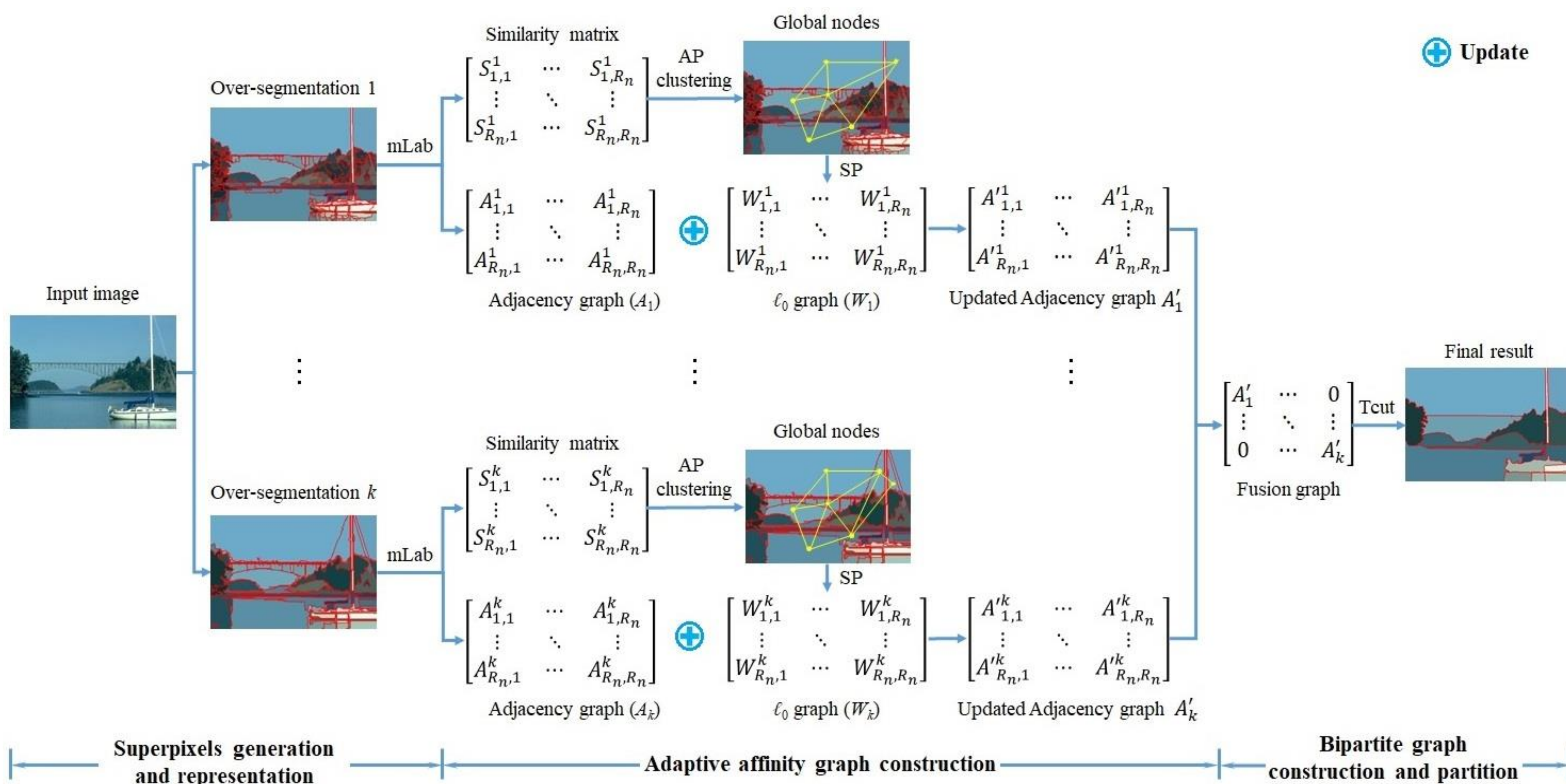


Fig. 1. Segmentation using superpixels. (a) Input image. (b-f) Superpixels generated by over-segmenting the image. (g-i) Segmentation results by adjacency-graph, GL-graph, and our AASP-graph, respectively.

OVERVIEW



ALGORITHM

Input: Image I , scale k , threshold k_T
Output: Pixel-wise labels.

1. Over-segment the image I by the MS and FH methods and then obtain superpixels of k different scales;
2. Select global nodes of superpixels based on IKDE and APC methods;
3. Build the ℓ_0 -graph by the mLab features extracted from global nodes of superpixels with the SP method.
4. Construct the adjacency-graph by the mLab features extracted from all superpixels;
5. Update the adjacency-graph by the ℓ_0 -graph of global nodes at each scales.
6. Fuse updated graphs at k different scales to obtain the final result (pixel-wise labels) through the Tcut method.

QUANTITATIVE RESULTS

Methods	PRI	VOI	GCE	BDE
Ncut [7]	0.7242	2.9061	0.2232	17.15
MNCut [9]	0.7559	2.4701	0.1925	15.1
JSEG[20]	0.7756	2.3217	0.1989	14.4
HIS-FEM[21]	0.7769	2.3067	0.2215	10.66
FusionTPG[22]	0.7771	3.3089	0.3654	13.2428
NTP[23]	0.7984	2.113	0.2171	13.58
H +R_Better[2]	0.8073	1.826	0.2079	12.16
Co-transduction[24]	0.8083	2.3644	0.2681	14.1972
HO-CC[25]	0.8140	1.743	N/A	10.377
LFPA[26]	0.8146	1.8545	0.1809	12.21
SAS[3]	0.8319	1.6849	0.1779	11.29
ℓ_0 -graph[8]	0.8355	1.9935	0.2297	11.19
GL-graph[4]	0.8384	1.8012	0.1934	10.6633
AASP-graph	0.8446	1.6485	0.1737	14.6416

VISUAL COMPARISON



Fig. 2. Visual comparison obtained with the SAS, ℓ_0 -graph, GL-graph, and AASP-graph. Two columns of the comparison results are shown here. From left to right, input images, the results of the SAS, ℓ_0 -graph, GL-graph, and AASP-graph are presented. The results of AASP-graph are visually better, in particular often more accurate.