HYPERPIXELS: FLEXIBLE 4D OVER-SEGMENTATION FOR DENSE AND SPARSE LIGHT FIELDS

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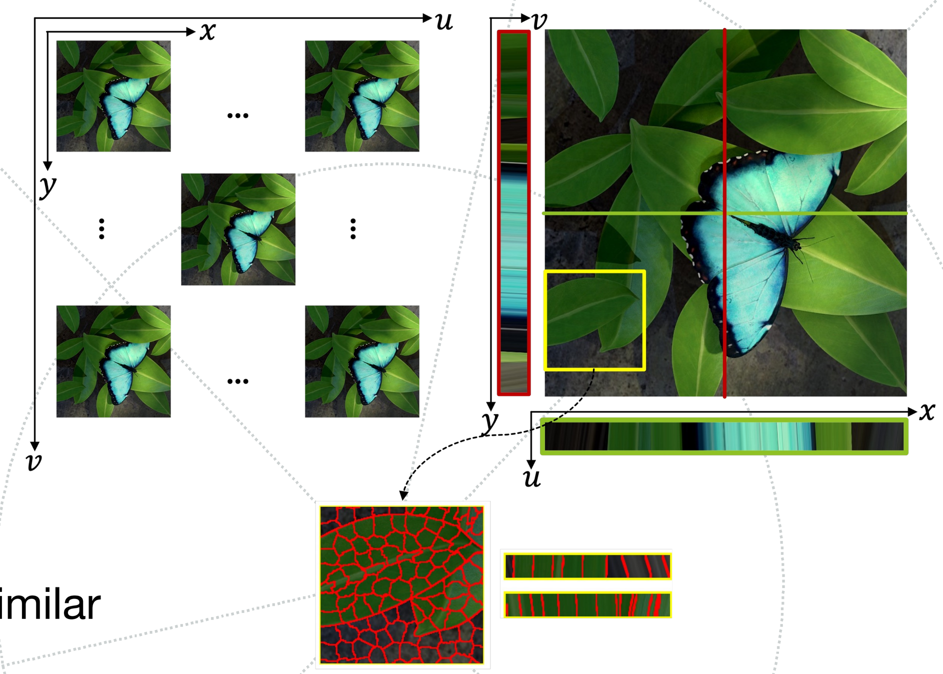
1. Introduction

4D Light Field (LF) imaging conveys both spatial and angular scene information by capturing the same scene from different angles. Depending on the LF capturing approach, dense or sparse 4D LFs can be generated.

Hyperpixels definition – A group of similar pixels in the discrete 4D LF space.



LF over-segmentation

2. Contributions

Existing LF over-segmentation methods assume dense LFs and do not adequately deal with sparse LFs. Additionally, the spatio-angular LF cues are not fully exploited in the existing methods.

To overcome these limitations, the following contributions are considered:

- To propose a flexible and angularly consistent 4D LF over-segmentation method for dense and sparse LFs by considering the 4D space and exploiting the spatio-angular cues.
- To generate a new synthetic dataset for sparse 4D LF.
- To propose a metric that evaluates hyperpixels angular consistency.

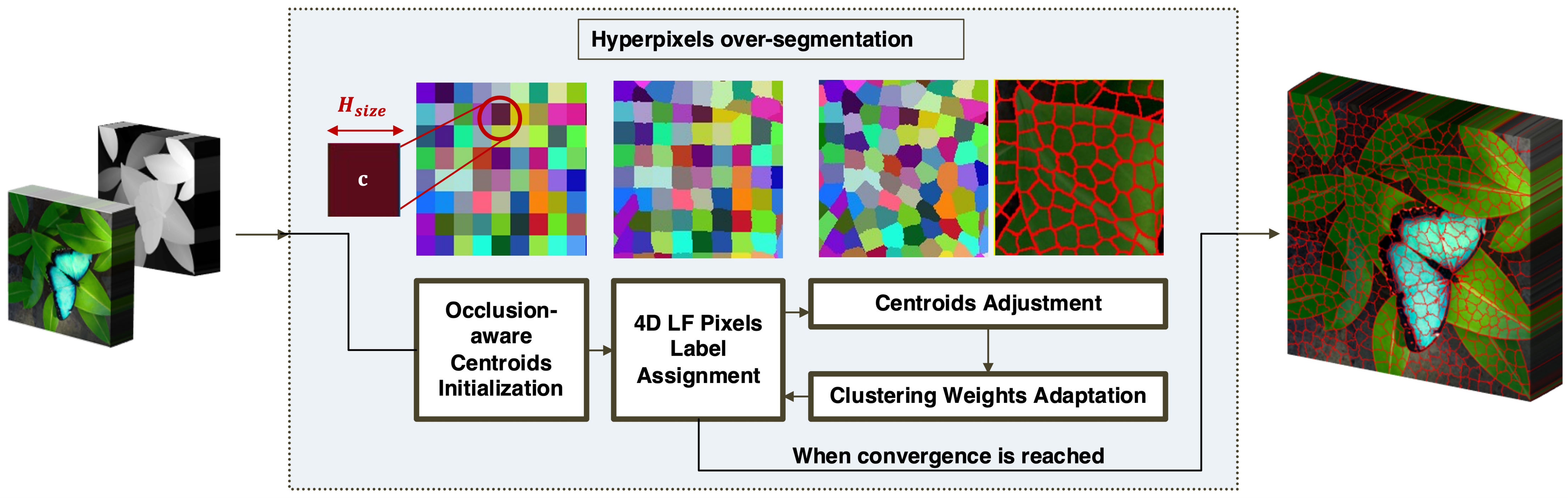
3. Proposed Hyperpixels Over-segmentation

The proposed LF over-segmentation method aims at grouping similar pixels in 4D space into hyperpixels. For grouping, several features are considered (i.e., 4D position, color and disparity values).

The hyperpixel over-segmentation can be then considered as an energy minimization problem:

$$E = \arg\min_{H} \sum_{i=1}^{K} \sum_{\mathbf{p}\in H_i} D_w(\mathbf{p}, \mathbf{c}_i),$$

where $\mathbf{p}$ is a pixel in 4D space that belongs to hyperpixel H_i, D_w is the weighted distance, and $\mathbf{c}_i$ is the centroid of H_i in 4D space.

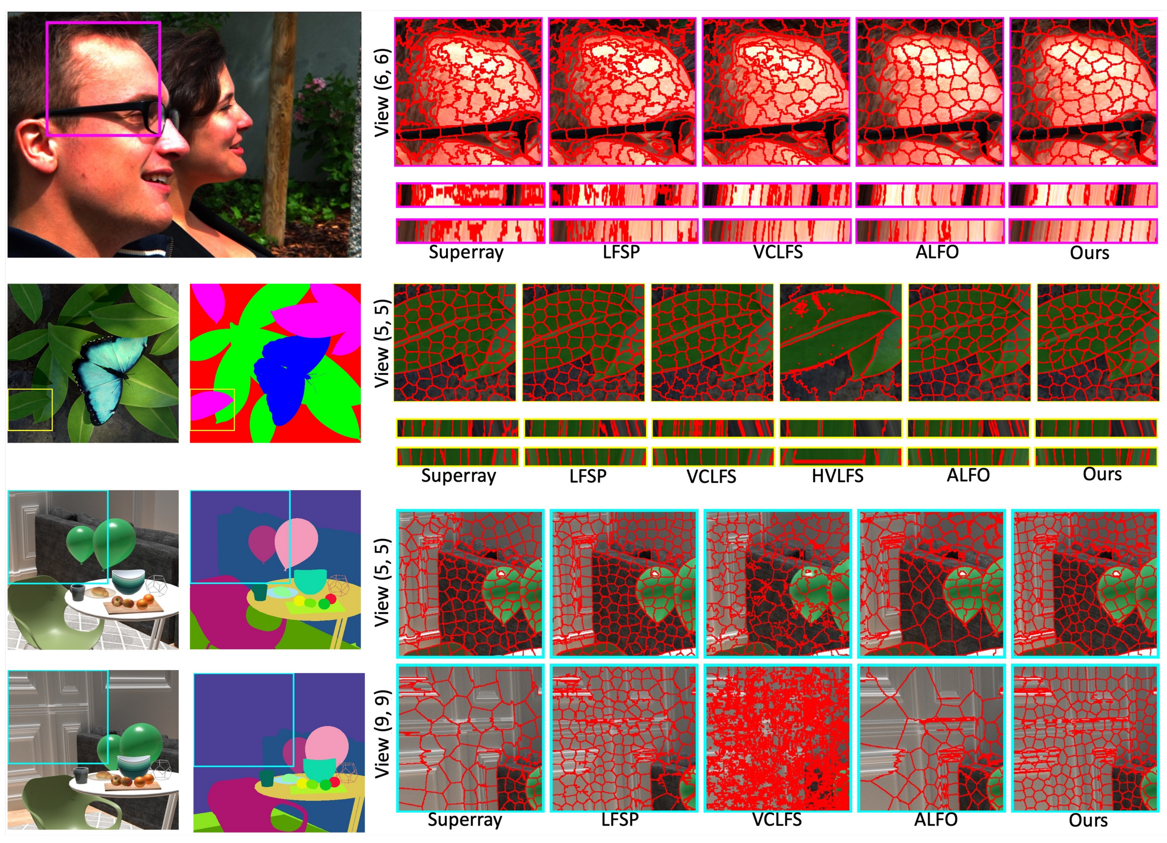


4. Experimental Results

Various dense and sparse LF datasets were used including synthetic and real world LFs.

Different evaluation metrics for over-segmentation spatial accuracy, compactness, and angular consistency were used and reported in the following table and the plots. Additionally, the proposed **Labeling–LF Angular Consistency (LLFAC)** was used to evaluate the proposed method for both dense and sparse LFs.

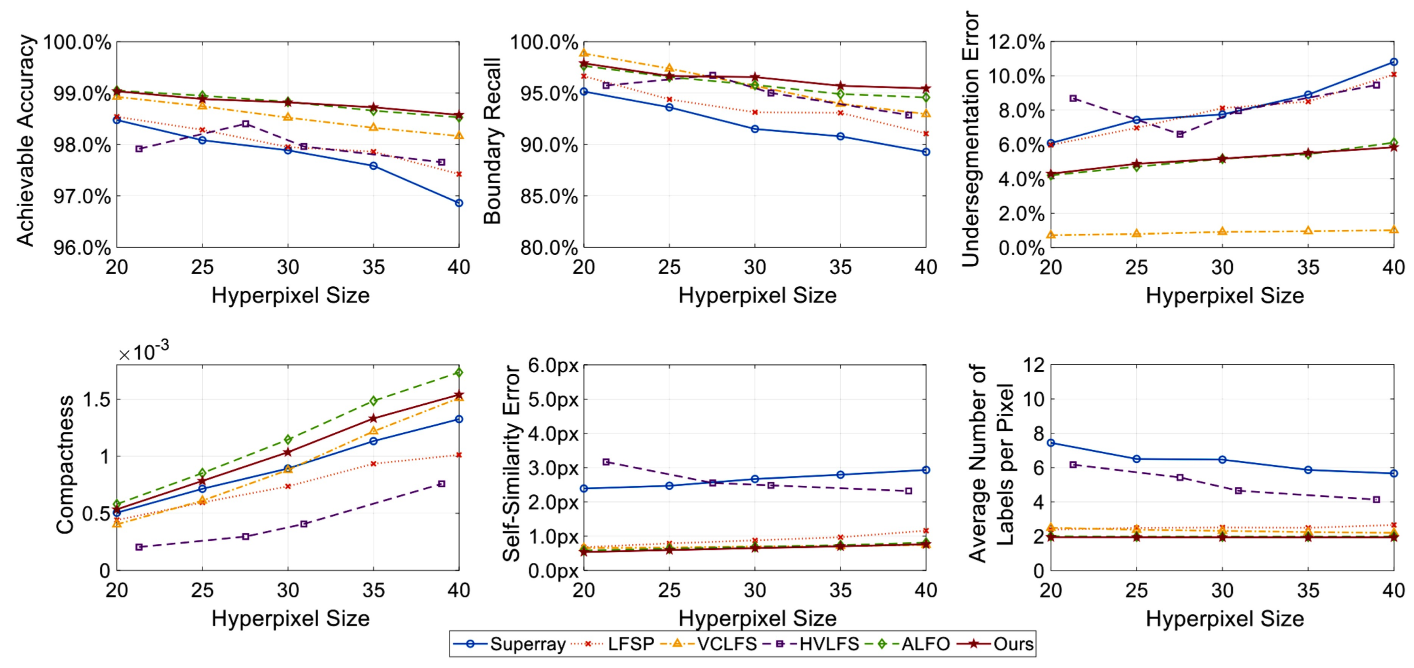
Qualitative results using dense and sparse 4D LF datasets



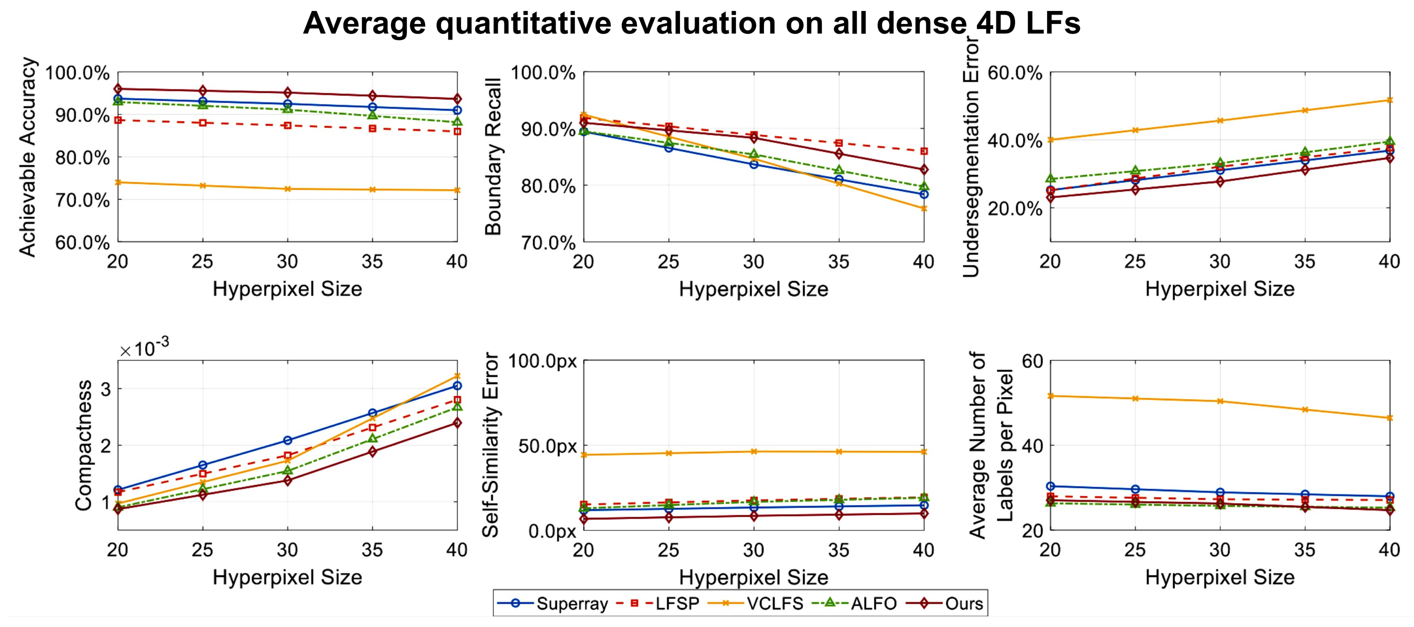
LLFAC for dense and sparse LFs (↑)

	4D LF	Disparity range	Super-ray	LFSP	VCLFS	ALFO	Ours
Dense LF	Buddha	[-8.5, 1.5]	39.00	**39.53**	39.19	39.52	39.42
	Papillon	[-1.2, 0.9]	36.63	36.71	36.38	36.86	**36.94**
	Horses	[-1.4, 0.9]	36.67	37.11	37.86	37.91	**38.12**
	StillLife	[-2.7, 2.6]	35.76	36.47	37.03	**37.20**	37.13
Sparse LF	Kitchen	[3.1, 13.5]	**36.13**	35.57	26.99	35.24	35.27
	Room	[-18.3, 8.9]	30.04	28.86	27.24	29.85	**30.62**
	Balloons	[-35.3, 3.2]	25.06	30.85	27.90	32.22	**32.51**
	Antique	[-5.44, 1.17]	40.94	**41.16**	37.64	39.67	39.15
	Car	[-1.55, 70.31]	29.44	28.58	27.17	29.73	**31.01**
	Chess	[-15.8, 9.8]	**31.73**	29.90	28.12	30.99	31.61
	Leisure	[-34.28, 123.34]	26.12	25.95	23.52	26.31	**26.90**
Average			33.41	33.70	31.73	34.14	**34.43**

Average quantitative evaluation on all sparse 4D LFs



Average quantitative evaluation on all dense 4D LFs



5. Conclusions

The proposed LF over-segmentation method:

- **Considers both dense and sparse LFs by initializing new centroids in unoccluded regions in off-central views.**
- **Applies adaptive K-means clustering in 4D space and exploits the spatio-angular LF information.**
- **Outperforms existing methods in terms of spatial accuracy and angular consistency in most dense and sparse LF datasets.**
- **Can be used as a pre-processing step for sparse and dense LF processing and editing.**

For more details

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