Visual Saliency Detection with Comprehensive Information

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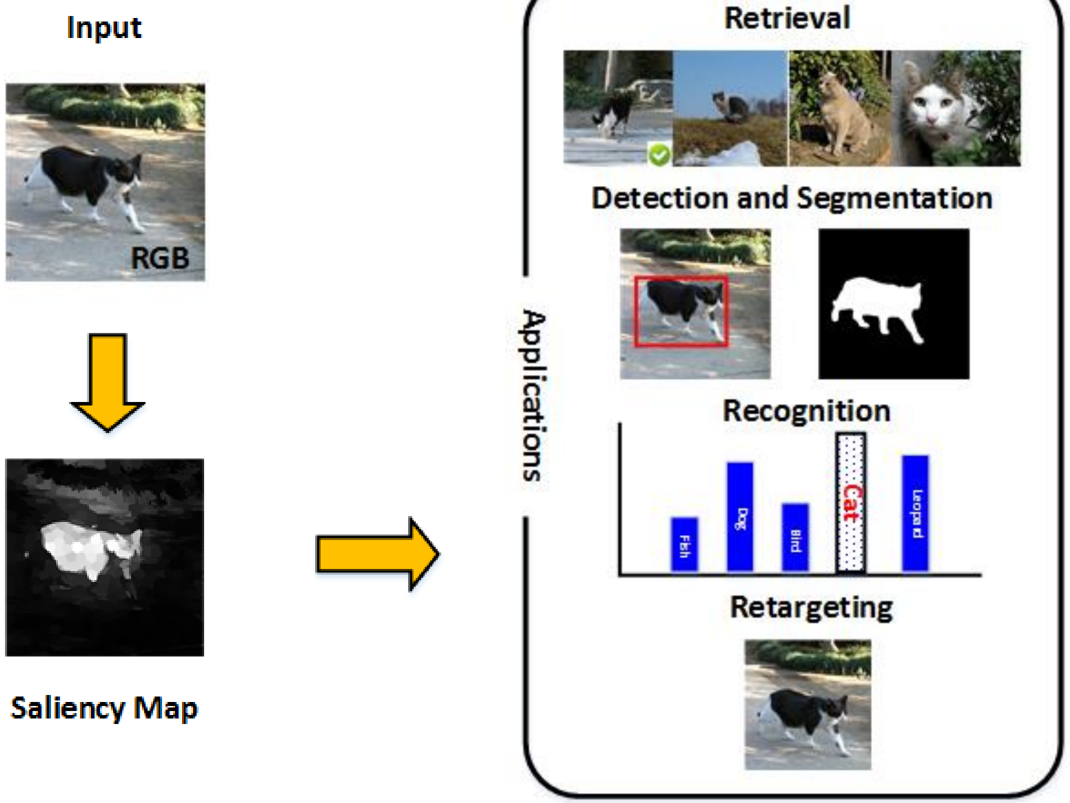
Introduction

- **What is saliency detection?**

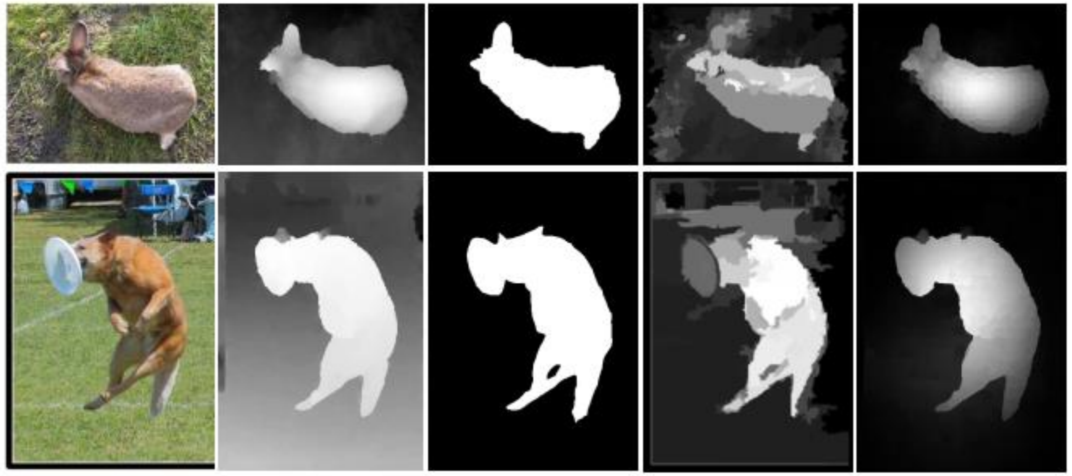


- Saliency detection aims to detecting the salient regions automatically, which has been applied in image/video segmentation, image/video retrieval, image retargeting, video coding, quality assessment, action recognition, and video summarization.
- The last decade has witnessed the remarkable progress of image saliency detection, and a plenty of methods have been proposed based on some priors or techniques, such as uniqueness prior, background prior, compactness prior, sparse coding, random walks, and deep learning.

Introduction

- **What is saliency detection?**

RGBD saliency detection



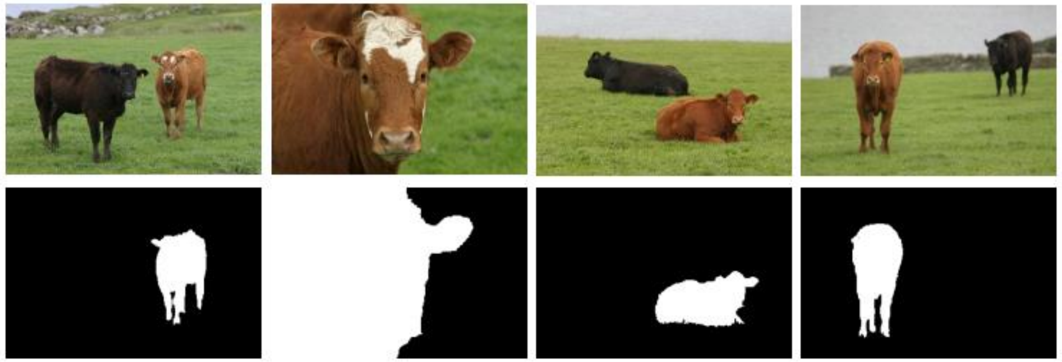
RGB Depth Ground truth RC ACSD

- In fact, the human visual system can not only perceive the appearance of the object, but also be affected by the depth information from the scene. Depth map provides better shape representation and other useful attributes for many vison tasks.
- Generally, depth information can be utilized in two manners: directly incorporating as an additional feature and designing as the depth measure.

Introduction

- **What is saliency detection?**

Co-saliency detection

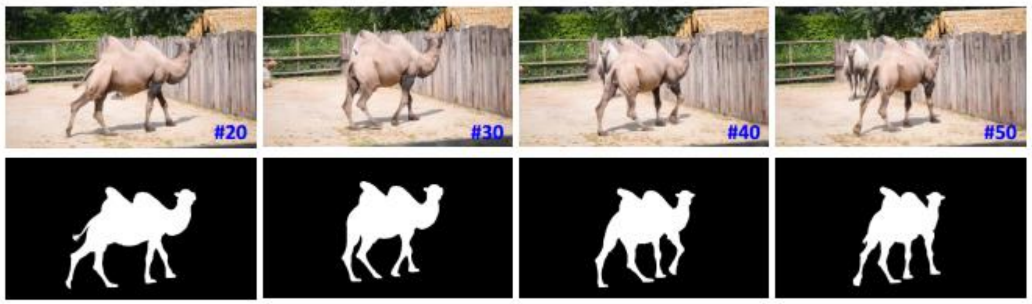


- co-saliency detection aims at detecting the common and salient regions from an image group containing multiple related images, while the categories, intrinsic attributes, and locations are entirely unknown.
- Therefore, the **inter-image correspondence** among multiple images plays a useful role in representing the common attribute.

Introduction

- **What is saliency detection?**

Video saliency detection



Motion cue

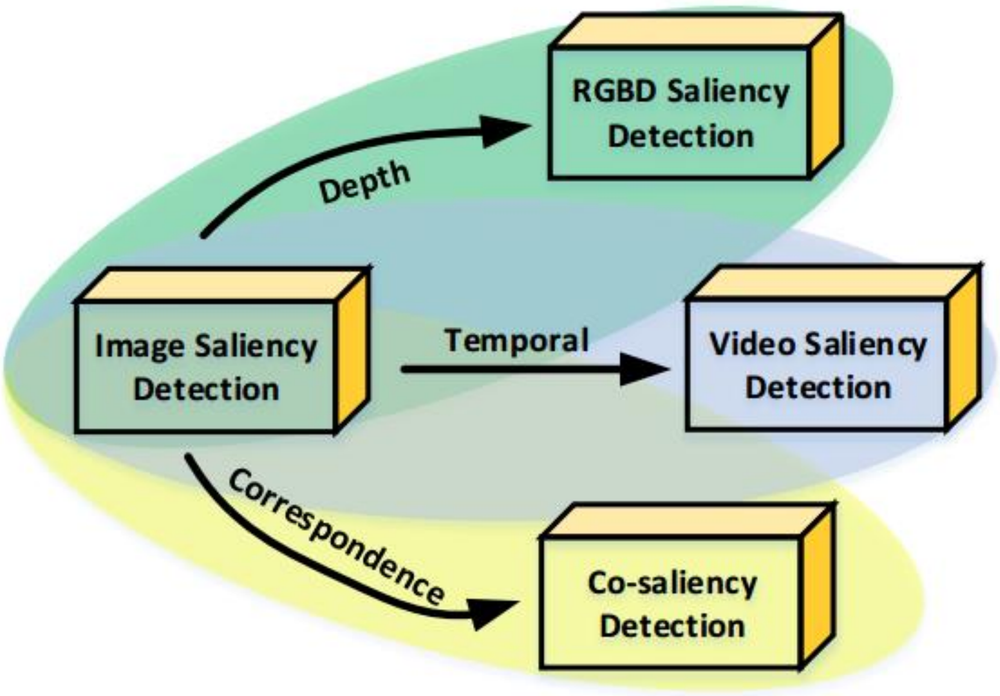
Inter-frame correspondence

Spatiotemporal constraint

- Video saliency detection aims at continuously locating the motion-related salient object from the given video sequences by considering the spatial and temporal information jointly.
- we divide the video saliency detection methods into two categories, i.e., low-level cues based method and learning based method.

Introduction

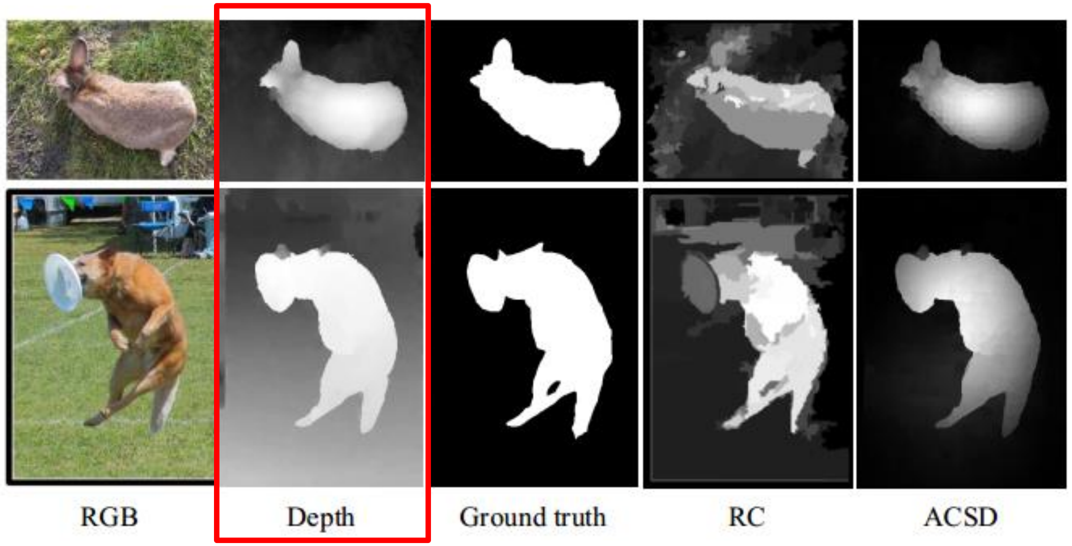
- **Relationship and Comprehensive Information**



The image saliency detection model is the basis for other three models. With the acquisition technology development, more comprehensive information is available, such as the depth cue for RGBD data, the inter-image constraint for image group, and the temporal relationship for video data.

Runmin Cong, Jianjun Lei, Huazhu Fu, Ming-Ming Cheng, Weisi Lin, Qingming Huang, Review of visual saliency detection with comprehensive information, *IEEE Transactions on Circuits and Systems for Video Technology*, 2018. In press.

RGBD Saliency Detection



- shape
- contour
- internal consistency
- surface normal
- ……

Saliency detection for stereoscopic images based on depth confidence analysis and multiple cues fusion

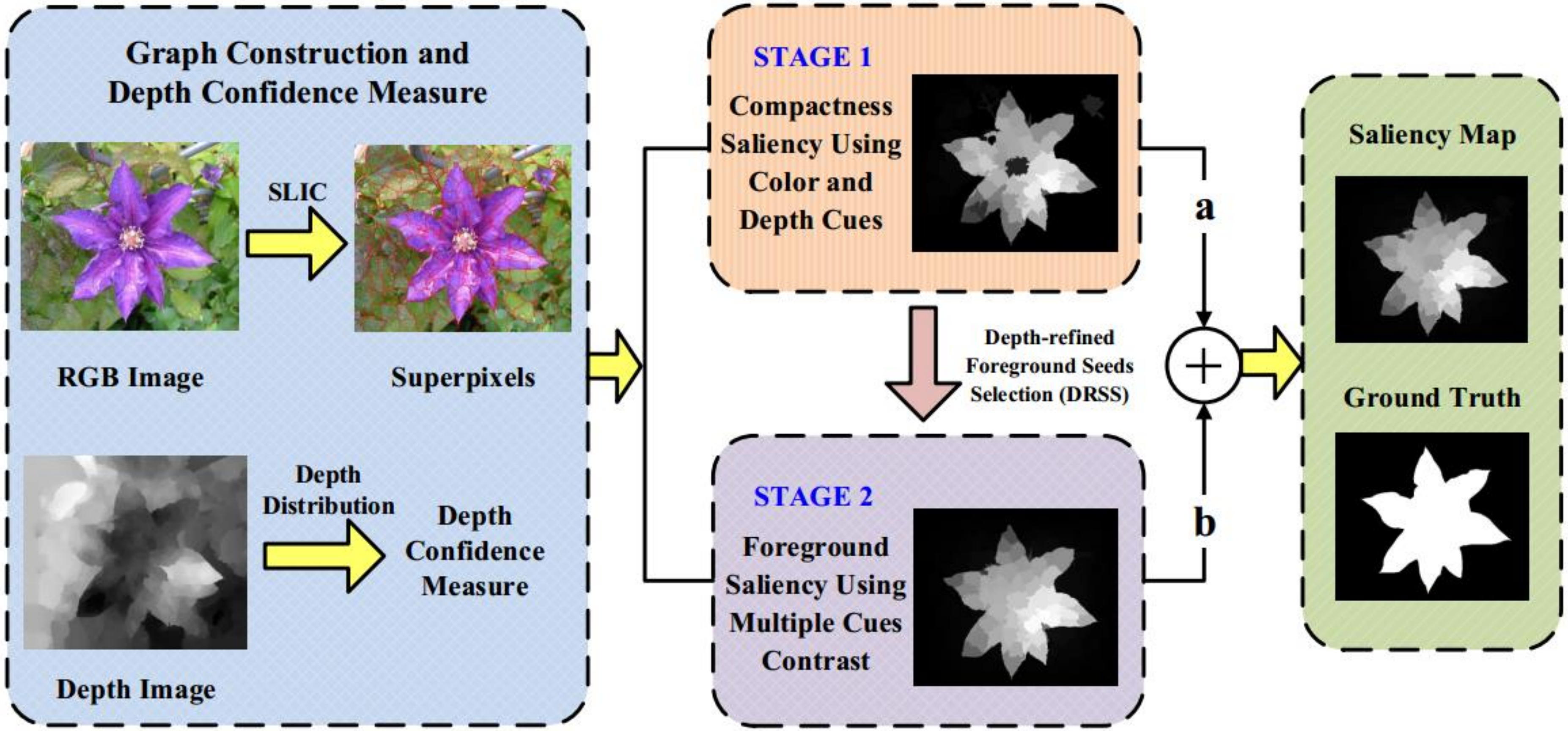
- **Motivations and Contributions.**

1. **Depth map evaluation.** **A good depth map can be benefit for the saliency detection no matter how it produced. According to the observation of depth distribution, a confidence measure for depth map is proposed to reduce the influence of poor depth map on saliency detection;**
2. **Extension of compactness.** **A novel model for compactness integrating color and depth information is put forward to compute the compactness saliency;**
3. **Multiple cues fusion.** **A foreground seeds' selection mechanism based on depth refined is presented. The saliency is measured by contrast between the target regions with seed regions, which integrate color, depth, and texture cues.**

Runmin Cong, et.al, Saliency detection for stereoscopic images based on depth confidence analysis and multiple cues fusion, *IEEE Signal Processing Letters*, vol.23, no.6, pp.819-823, 2016.

Saliency detection for stereoscopic images based on depth confidence analysis and multiple cues fusion

- **Framework**



Saliency detection for stereoscopic images based on depth confidence analysis and multiple cues fusion

- **Depth Confidence Measure**

$$\lambda_d = \exp((1 - m_d) \cdot \mathrm{CV} \cdot H) - 1$$

A larger λ_d corresponds to more reliable of the input depth map.

Fig. 2. Different qualities of depth maps. (a) Good depth map $\lambda_d = 0.8014$. (b) Common depth map $\lambda_d = 0.3890$. (c) Poor depth map $\lambda_d = 0.0422$.

$$S_{\mathrm{CS}}(i) = [1 - \mathrm{norm}(\mathrm{cc}(i) + \mathrm{dc}(i))] \cdot \mathrm{Obj}(i)$$

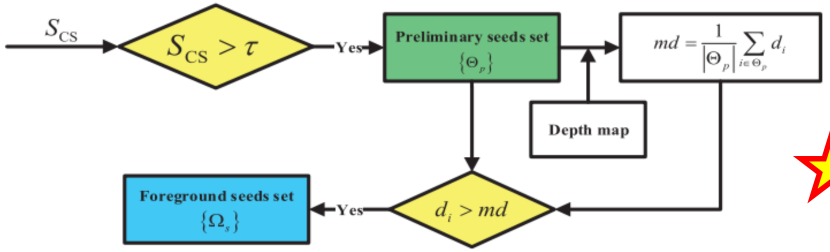
$$\mathrm{cc}(i) = \frac{\sum_{j=1}^{N} a_{ij} \cdot n_j \cdot \|\boldsymbol{b}_j - \boldsymbol{\mu}_i\|}{\sum_{j=1}^{N} a_{ij} \cdot n_j}$$

$$\mathrm{dc}(i) = \frac{\sum_{j=1}^{N} a_{ij} \cdot n_j \cdot \|\boldsymbol{b}_j - \boldsymbol{p}\| \cdot \exp(-\frac{\lambda_d \cdot d_i}{\sigma^2})}{\sum_{j=1}^{N} a_{ij} \cdot n_j}$$

Saliency detection for stereoscopic images based on depth confidence analysis and multiple cues fusion

Foreground Saliency Using Multiple Cues Contrast

- When the salient regions have similar appearances with background, the regions may be wrongly detected. Hence, a **foreground saliency detection method based on multiple cues contrast** is proposed to mitigate this problem. First, a **depth-refined foreground seeds' selection (DRSS)** method is proposed, which considers the depth information. Then, we calculate the contrast of each superpixel with the foreground seeds based on multiple cues, which include color, depth, texture, and position information.



$$S_{\mathrm{fg}}(i) = \sum_{j\in\Omega_s} [a_{ij} \cdot D_t(i,j) \cdot \exp(-\|\boldsymbol{b}_i - \boldsymbol{b}_j\|/\sigma^2) \cdot n_j] \quad (12)$$

where Ω_s is the set of foreground seeds, $\|\boldsymbol{b}_i - \boldsymbol{b}_j\|$ denotes the Euclidean distance between position of superpixels, and $D_t(i,j)$ is the texture similarity between superpixels using LBP feature .

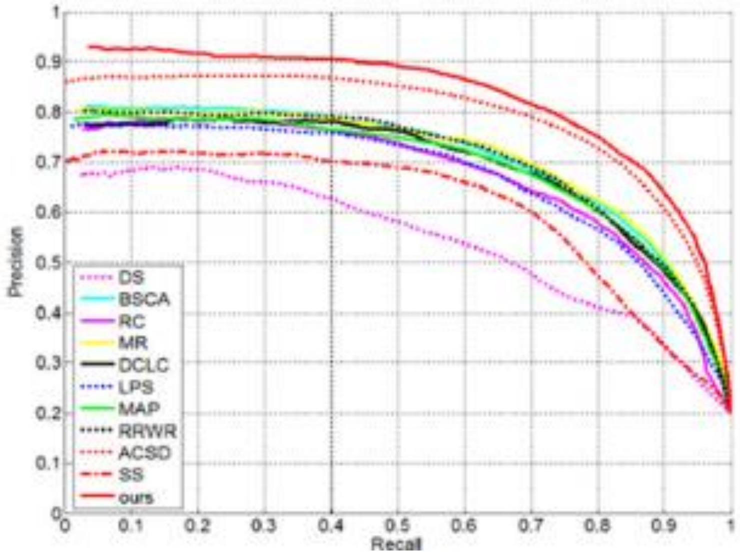
$$S = \gamma \cdot S_{\mathrm{CS}} + (1-\gamma) \cdot S_{\mathrm{FS}} \quad (14)$$

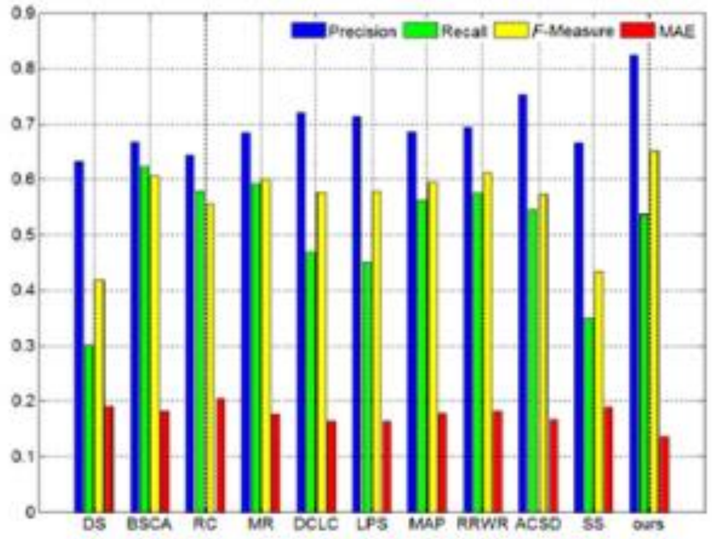
where γ balances the compactness saliency map S_{CS} and foreground saliency map S_{FS}.

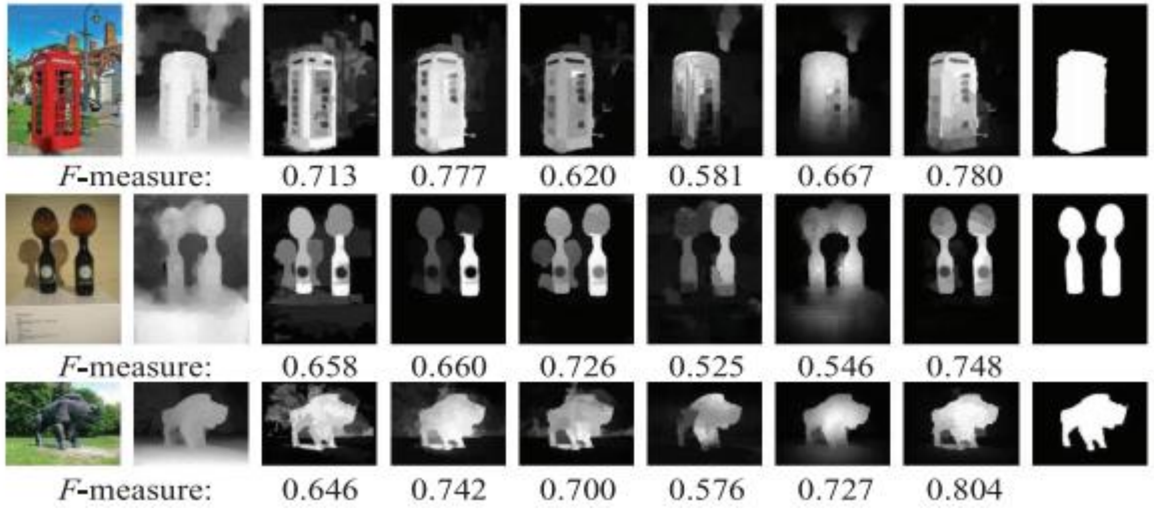
Saliency detection for stereoscopic images based on depth confidence analysis and multiple cues fusion

- **Experiments**

NJU-400 Dataset



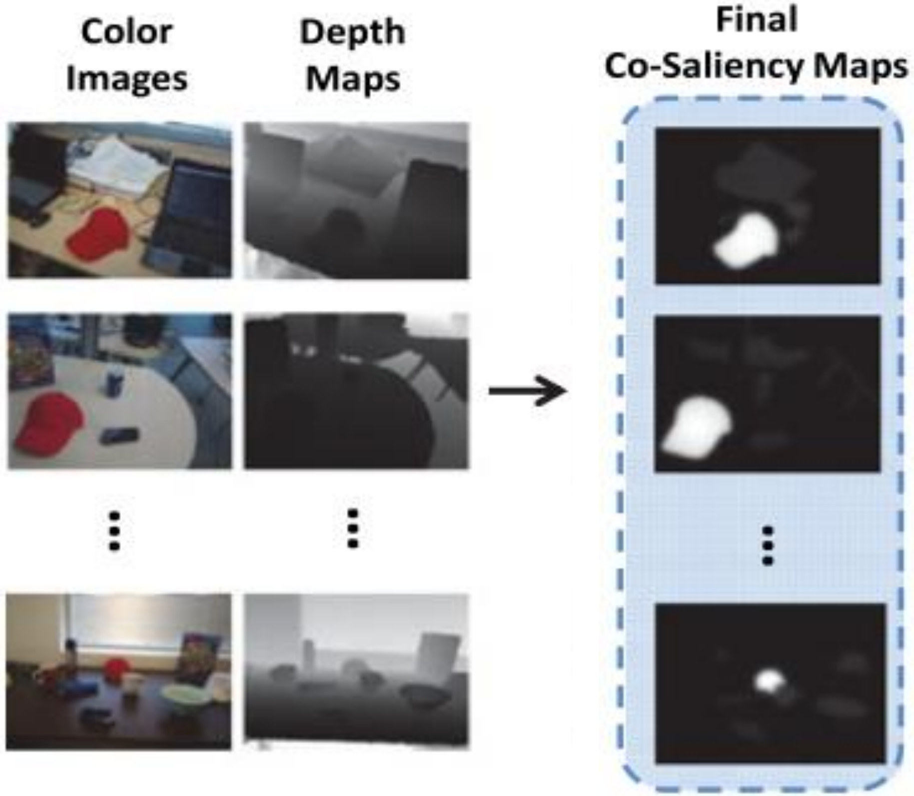




$$F_\beta = \frac{(1+\beta^2)Precision \times Reall}{\beta^2 \times Precision + Recall}$$

$$MAE = \frac{1}{w \times h} \sum_{x=1}^{w} \sum_{y=1}^{h} |S(x,y) - G(x,y)|$$

RGBD Co-saliency Detection



Problems and Important Issues:

how to explore inter-image correspondence among multiple images to constrain the common properties of salient object is a challenge.

how to capture the accurate and effective depth representation to assist in saliency detection is a challenge.

Work 1: Co-saliency detection for RGBD images based on multi-constraint feature matching and cross label propagation

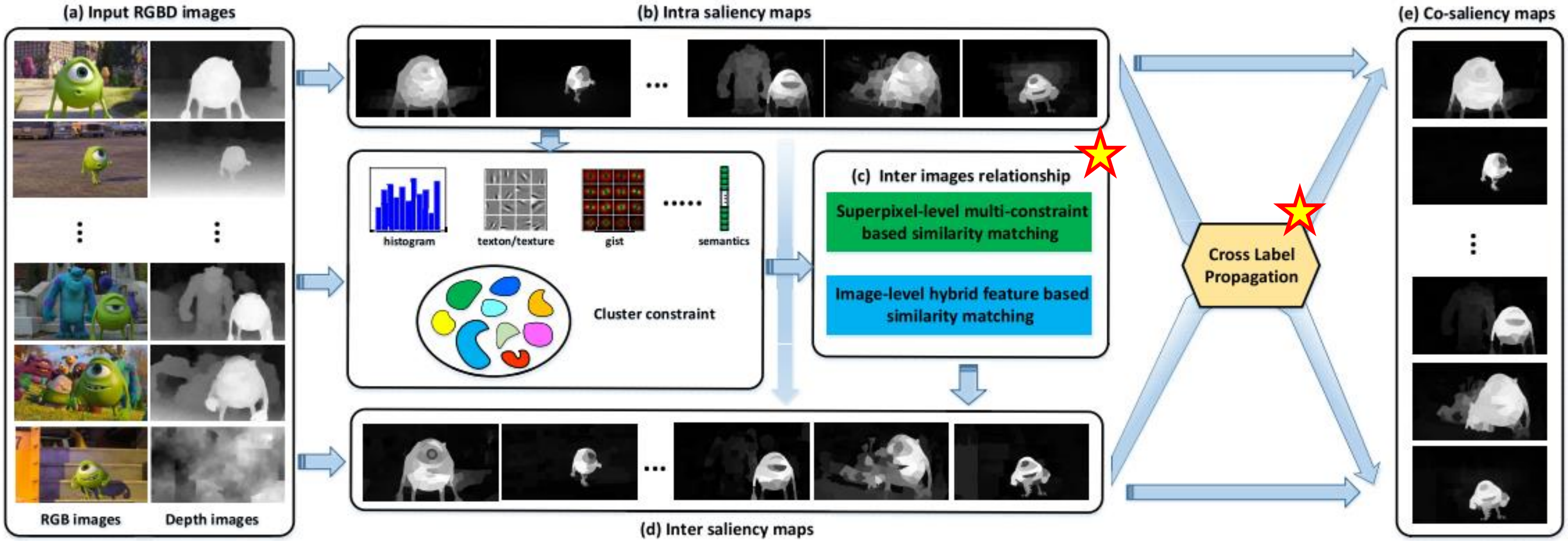
- **Contributions**

1. **This method is the first model that detects the co-salient objects from RGBD images. The depth information is demonstrated to be served as a useful complement for co-saliency detection.**
2. **A multi-constraint feature matching method is introduced to constrain the inter saliency map generation, which is robust to the complex backgrounds.**
3. **The Cross Label Propagation (CLP) method is proposed to optimize the co-saliency model in a cross manner.**
4. **We construct a new RGBD co-saliency dataset, named RGBD Cosal150 dataset, for performance evaluation.**

Runmin Cong, et.al, Co-saliency detection for RGBD images based on multi-constraint feature matching and cross label propagation, *IEEE Transactions on Image Processing*, vol.27, no.2, pp.568-579, 2018.

Work 1: Co-saliency detection for RGBD images based on multi-constraint feature matching and cross label propagation

- **Framework**



Work 1: Co-saliency detection for RGBD images based on multi-constraint feature matching and cross label propagation

- **Inter Saliency Detection**

  - Acquiring the corresponding relationship among multiple images is the key point of co-saliency detection model. In the proposed model, the **matching methods on two levels** are designed to represent the correspondence among multiple images.
  - The first one is the **superpixel-level similarity matching** scheme, which focuses on determining the matching superpixel set for the current superpixel based on three constraints from other images. The second is the **image-level similarity measurement**, which provides a global relationship on the whole image scale.
  - With the corresponding relationship, the inter saliency of a superpixel is defined as the weighted sum of the intra saliency of corresponding superpixels in other images.

Work 1: Co-saliency detection for RGBD images based on multi-constraint feature matching and cross label propagation

- **Inter Saliency Detection: Superpixel-Level Multi-Constraint Based Similarity Matching**

  - At the superpixel level, the correspondence is represented as the **multi-constraint based matching relationship between the superpixels among the multiple images**, which considers the similarity constraint, saliency consistency, and cluster-based constraint.

Similarity constraint:

$$s(r_m^i, r_n^j) = \exp\left(-\frac{\|\mathbf{c}_m^i - \mathbf{c}_n^j\|_2 + \min(\lambda_d^i, \lambda_d^j) \cdot |d_m^i - d_n^j|}{\sigma^2}\right)$$

the Kmax nearest neighbors in each of other images are determined to form $\Phi_1(r_m^i)$

Saliency constraint:

$$\Phi_2(r_m^i) = \{r_n^j \mid |S_{intra}(r_m^i) - S_{intra}(r_n^j)| \leq T_1\}$$

Cluster-based constraint:

$$\Phi_3(r_m^i) = \{r_n^j \mid \arg \min_{C_q^j, q \in [1,K]} Ed(c_p^i, c_q^j)\}$$

Similarity matching:

$$ml(r_m^i, r_n^j) = \begin{cases} 1, & \text{if } r_n^j \in \{\Phi_1(r_m^i) \cap \Phi_2(r_m^i) \cap \Phi_3(r_m^i)\} \\ 0, & \text{otherwise} \end{cases}$$

Work 1: Co-saliency detection for RGBD images based on multi-constraint feature matching and cross label propagation

- **Inter Saliency Detection: Image-Level Hybrid Feature Based Similarity Matching**

  - Enlightened by the observation that the **greater similarity between two images means the greater likelihood of finding the matching regions**, a full-image size similarity descriptor is designed as the weighted coefficient for inter saliency calculation.

	features	description	dim	distance
col	$\boldsymbol{h}_c$	RGB histogram	512	$d_{c1} = \chi^2(\boldsymbol{h}_c^i, \boldsymbol{h}_c^j)$
	$\boldsymbol{t}$	texton histogram	15	$d_{c2} = \chi^2(\boldsymbol{t}^i, \boldsymbol{t}^j)$
	$\boldsymbol{s}$	semantic feature	4096	$d_{c3} = 1 - \cos(\boldsymbol{s}^i, \boldsymbol{s}^j)$
	$\boldsymbol{g}$	GIST feature	512	$d_{c4} = 1 - \cos(\boldsymbol{g}^i, \boldsymbol{g}^j)$
dep	$\boldsymbol{h}_d$	depth histogram	512	$d_d = \chi^2(\boldsymbol{h}_d^i, \boldsymbol{h}_d^j)$
sal	$\boldsymbol{h}_s$	saliency histogram	512	$d_s = \chi^2(\boldsymbol{h}_s^i, \boldsymbol{h}_s^j)$

$$\varphi^{ij} = 1 - (\alpha_c \cdot \Sigma_{i=1}^{4} d_{ci}/4 + \alpha_d \cdot d_d + \alpha_s \cdot d_s)$$

$$\alpha_d = \begin{cases} \lambda_d^{min}, & \text{if } \lambda_d^{min} = \min(\lambda_d^i, \lambda_d^j) \le T_2 \\ 1/3, & \text{otherwise} \end{cases}$$

$$\alpha_c = \alpha_s = \frac{1}{2} \cdot (1 - \alpha_d)$$

Work 1: Co-saliency detection for RGBD images based on multi-constraint feature matching and cross label propagation

- **Inter Saliency Detection**

  - After obtaining the corresponding relationship among multiple images through the superpixel-level feature matching and image-level similarity matching, the inter saliency of a superpixel is computed as the **weighted sum of the intra saliency of corresponding superpixels in other images**.

$$S_{inter}(r_m^i) = \frac{1}{N-1} \sum_{j=1, j \neq i}^{N} \frac{\varphi^{ij}}{N_j} \sum_{n=1}^{N_j} S_{intra}(r_n^j) \cdot ml(r_m^i, r_n^j)$$

where r_m^i denotes the m^{th} superpixel in image I^i, N represents the number of images in the group, N_j is the number of superpixels in the j^{th} image, and φ^{ij} is the similarity measurement between the i^{th} and j^{th} images.

Work 1: Co-saliency detection for RGBD images based on multi-constraint feature matching and cross label propagation

- **Optimization and Propagation**

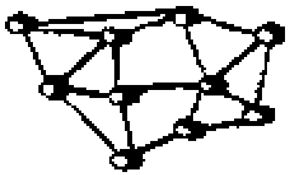
  - In the proposed method, the optimization of saliency map is casted as a "**label propagation**" problem, where the uncertain labels are propagated by using **two types of certain seeds**, i.e. background and salient seeds. **The proposed CLP method is used to optimize the intra and inter saliency maps in a cross way, which means the propagative seeds are crosswise interacted.** The cross seeding strategy optimizes the intra and inter saliency maps jointly, and improves the robustness.

Intra Saliency

Inter Saliency

TF & TB

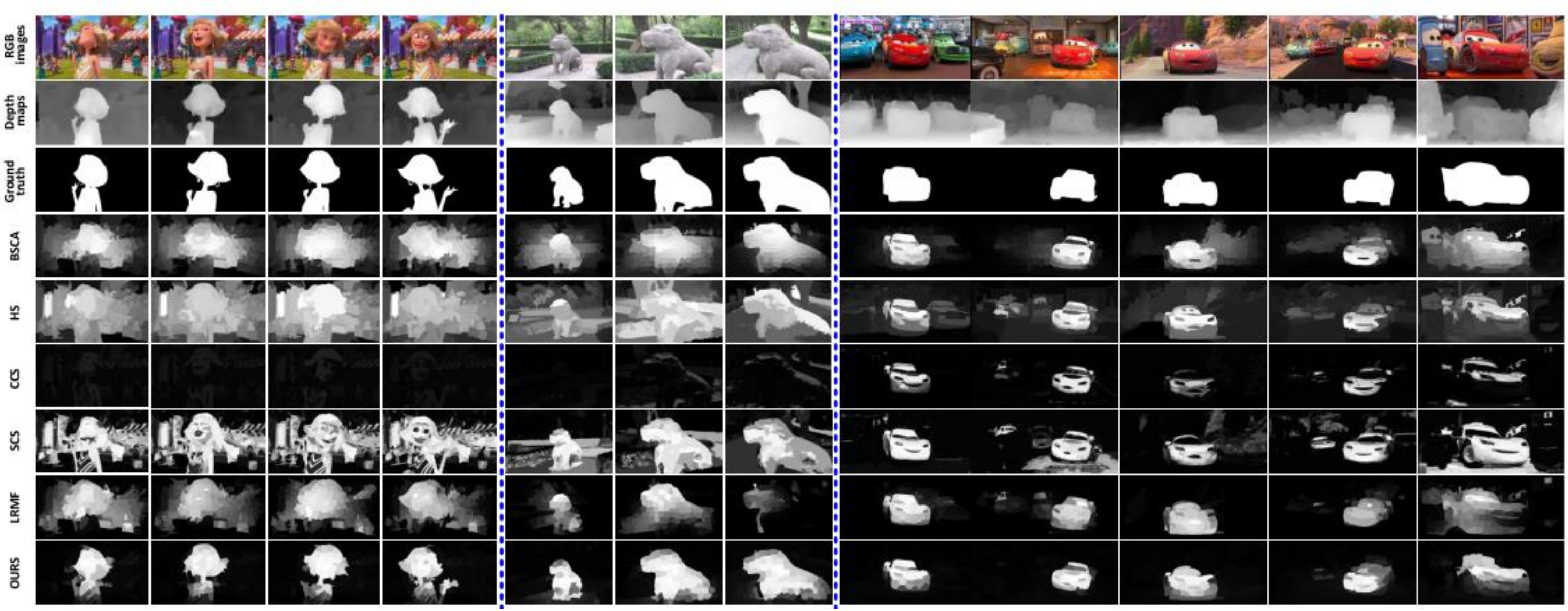
$$V_0^{CLP}(r_m^i) = \begin{cases} 1, & \text{if } S_{inter}(r_m^i) \geq TF(S_{inter}) \\ 0, & \text{if } S_{inter}(r_m^i) \leq TB(S_{inter}) \\ S_{intra}(r_m^i), & \text{otherwise} \end{cases}$$



$$V_{intra}^{CLP}(r_m^i) = \sum_{n=1}^{N_i} w_{mn}^i V_0^{CLP}(r_n^i)$$

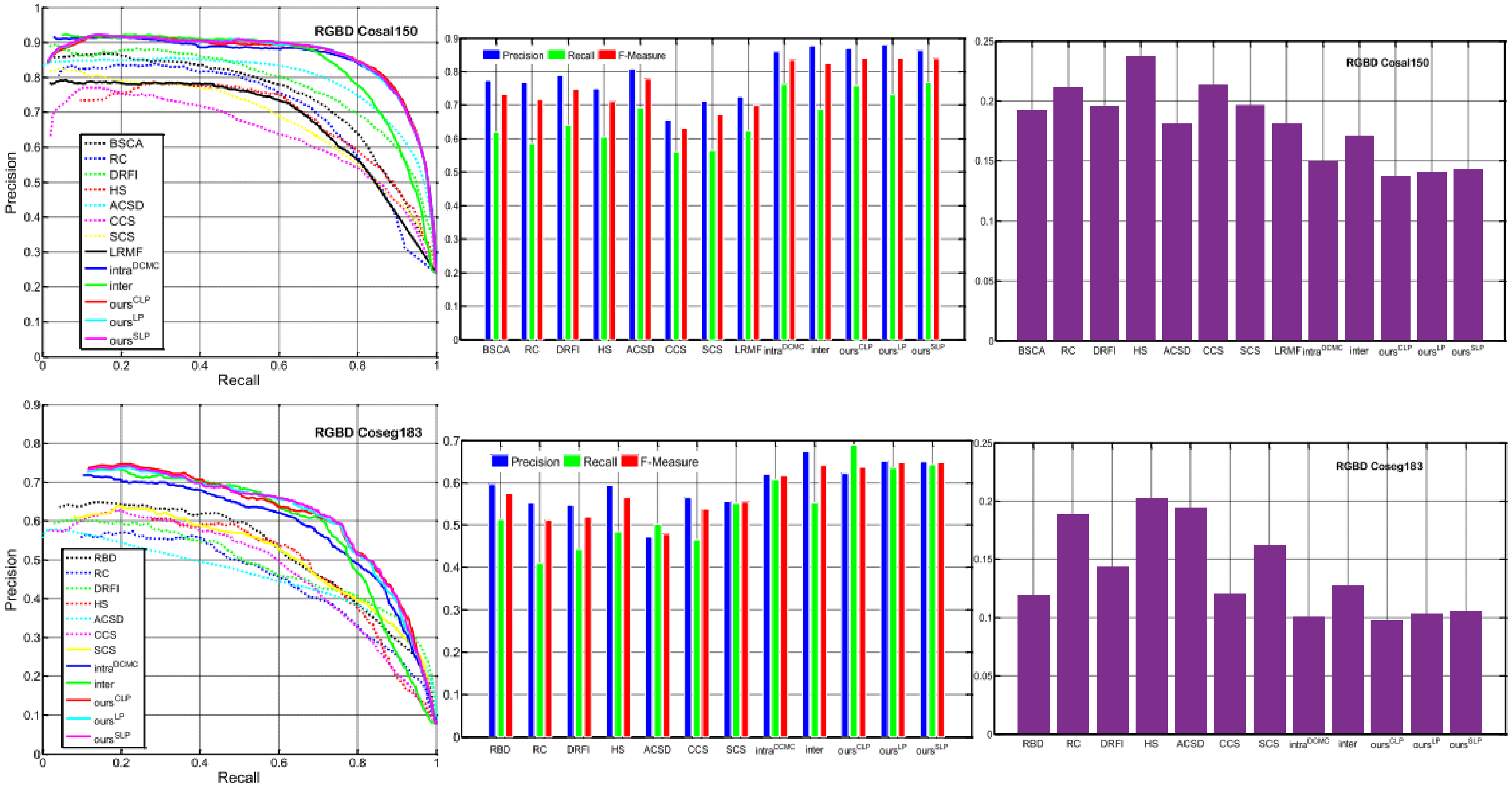
Work 1: Co-saliency detection for RGBD images based on multi-constraint feature matching and cross label propagation

- **Experiments**



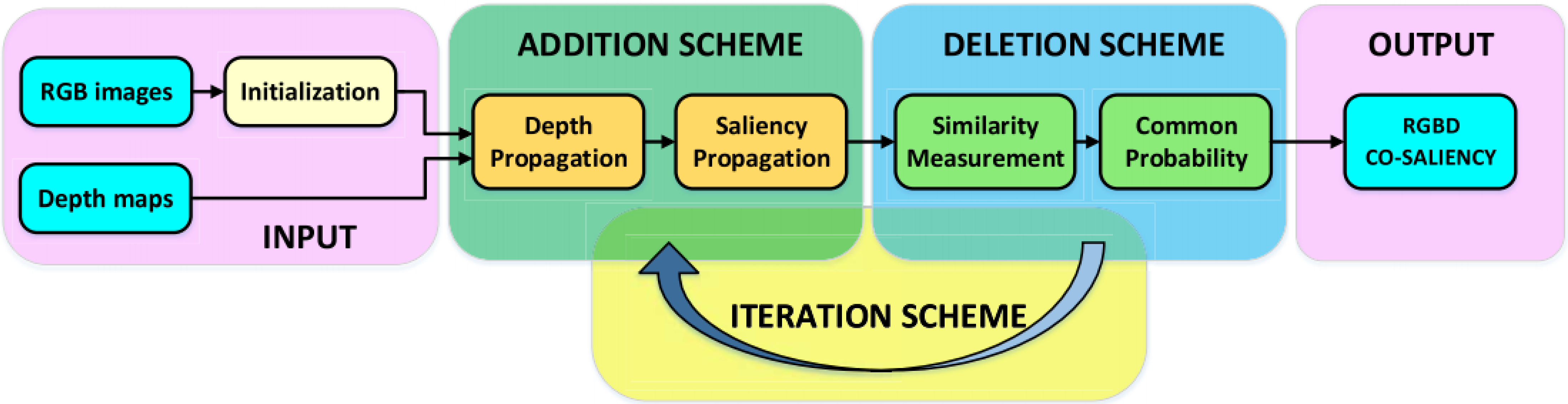
Work 1: Co-saliency detection for RGBD images based on multi-constraint feature matching and cross label propagation

- **Experiments**



Work 2: An iterative co-saliency framework for RGBD images

- **Framework**



In this paper, we propose an iterative RGBD co-saliency framework, which utilizes the existing single saliency maps as the initialization, and generates the final RGBD co-saliency map by using a refinement-cycle model. The proposed method can effectively exploit any existing 2-D saliency model to work well in RGBD co-saliency scenarios.

Work 2: An iterative co-saliency framework for RGBD images

- **Initialization**

  - Some existing saliency maps produced by 2-D saliency models are used to initialize the framework. It is well known that different saliency methods own different superiority in detecting salient regions. In our method, the simple average function is used to achieve a more generalized initialization result. In our experiments, five saliency methods including RC [1], DCLC [2], RRWR [3], HS [4], and BSCA [5], are used to produce the 2-D initialized saliency map.

$$S_f^i(r_m^i) = \frac{1}{M_i} \sum_{j=1}^{M_i} S_j^i(r_m^i)$$

[1] M.-M. Cheng, G.-X. Zhang, N. J. Mitra, X. Huang, and S.-M. Hu, "Global contrast based salient region detection," in Proc. CVPR, Colorado Springs, CO, USA, Jun. 2011, pp. 409–416.
[2] L. Zhou, Z. Yang, Q. Yuan, Z. Zhou, and D. Hu, "Salient region detection via integrating diffusion-based compactness and local contrast," IEEE Trans. Image Process., vol. 24, no. 11, pp. 3308–3320, Nov. 2015.
[3] C. Li, Y. Yuan, W. Cai, Y. Xia, and D. D. Feng, "Robust saliency detection via regularized random walks ranking," in Proc. CVPR, Boston, MA, USA, Jun. 2015, pp. 2710–2717.
[4] J. Shi, Q. Yan, L. Xu, and J. Jia, "Hierarchical image saliency detection on extended CSSD," IEEE Trans. Pattern Anal. Mach. Intell., vol. 38, no. 4, pp. 717–729, Apr. 2016.
[5] Y. Qin, H. Lu, Y. Xu, and H. Wang, "Saliency detection via cellular automata," in Proc. CVPR, Boston, MA, USA, Jun. 2015, pp. 110–119.

Work 2: An iterative co-saliency framework for RGBD images

- **Addition Scheme**

  - The addition scheme is designed to extend the saliency region based on the intra-image constraint by using two propagation algorithms.
  - First, a novel depth descriptor, named DSP, is proposed to capture the depth cue and produce an RGBD saliency result in **depth propagation**.
  - Then, **saliency propagation** is utilized to optimize and improve the saliency result furtherly.

Work 2: An iterative co-saliency framework for RGBD images

- **Addition Scheme: Depth Propagation**
  - The depth information is introduced into the framework to enhance the identification of salient objects due to its usefulness in saliency detection. In general, the depth map owns the following properties: <u>i) The salient object appears higher depth value compared to the backgrounds. ii) The high quality depth map can provide sharp and explicit boundary of the object. iii) The interior depth value of the object should be smoothness and consistency.</u>
  - Inspired by these observations, a depth descriptor, namely DSP, is proposed to capture the shape attributes from the depth map and improve the performance of the co-saliency detection by using the depth consistency and shape attributes. **The proposed DSP descriptor is based on depth propagation and region grow**.

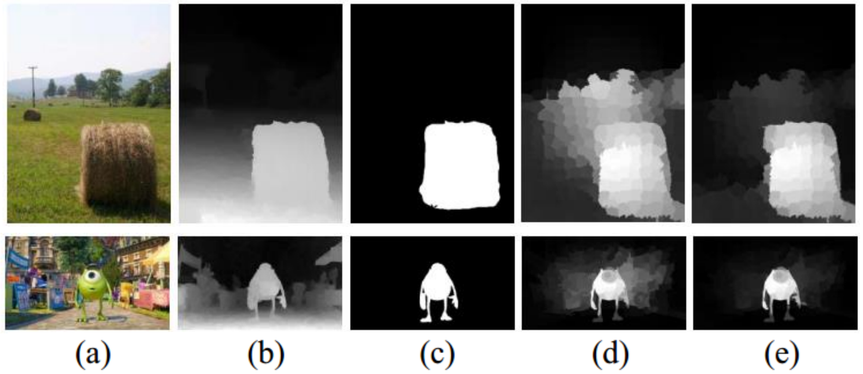
Work 2: An iterative co-saliency framework for RGBD images

- **Addition Scheme: Depth Propagation**
  - **<u>Depth Smoothness</u>**: The depth difference between the neighbor superpixel and former-loop child seeds is less than a certain threshold;
  - **<u>Depth Consistency</u>**: The depth difference between the neighbor superpixel and root seed should be smaller than a specific threshold;

$$\mathrm{DSP}_k^i\left(r_{cp}^i\right) = 1 - \min\left(\left|d_{cp,l}^i - d_{c,l-1}^i\right|, \left|d_{cp,l}^i - d_{rk}^i\right|\right)$$

$$\mathrm{DSP}^i(r_m^i) = \frac{1}{K}\sum_{k=1}^{K}\mathrm{DSP}_k^i(r_m^i)$$

$$S_{dp}^i(r_m^i) = (1-\lambda_d^i)\cdot S_f^i(r_m^i) + \lambda_d^i \cdot S_f^i(r_m^i)\cdot \mathrm{DSP}^i(r_m^i)$$



(a) RGB image. (b) Depth map. (c) Ground truth. (d) RGB saliency result. (e) RGBD saliency result with DSP descriptor.

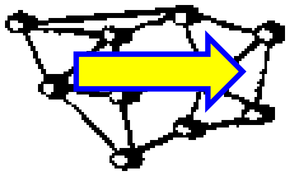
Work 2: An iterative co-saliency framework for RGBD images

- **Addition Scheme: Saliency Propagation**
  - In our method, the superpixels are classified into three groups based on the saliency value first, which is denoted as the saliency seed superpixels, background seed superpixels, and the unknown superpixels. Then, saliency propagation is used to propagate the saliency of unknown superpixels on the graph from the saliency and background seeds.

Initialization:

$$S_0^i(r_n^i) = \begin{cases} 1, & \text{if } r_n^i \in \Psi_F \\ 0, & \text{if } r_n^i \in \Psi_B \\ S_{dp}^i(r_n^i), & \text{otherwise} \end{cases}$$

Propagation:



$$S_{\mathrm{sp}}^i(r_m^i) = \sum_{n=1}^{N_i} w_{mn}^i \cdot S_0^i(r_n^i)$$

$$w_{uv}^i = \begin{cases} \exp\left(-\frac{\|\mathbf{c}_u^i - \mathbf{c}_v^i\|_2 + \lambda_d^i \cdot |d_u^i - d_v^i|}{\sigma^2}\right), & \text{if } r_v^i \in \Omega_u^i \\ 0, & \text{otherwise} \end{cases}$$

Work 2: An iterative co-saliency framework for RGBD images

- **Deletion Scheme**

  - The deletion scheme is designed to capture the corresponding relationship among multiple images, which aims to suppress the common and non-common backgrounds, and enhance the common salient regions from the perspective of multiple images.
  - In our deletion scheme, a superpixel-level similarity measurement is constructed to represent the similarity relationship between two superpixels. Then, **a common probability function using the similarity measurement is used to calculate the likelihood of each superpixel belonging to the common regions**.

common probability function

$$S_{\mathrm{del}}^{i}\left(r_{m}^{i}\right)=S_{\mathrm{sp}}^{i}\left(r_{m}^{i}\right)\cdot\boxed{P_{c}^{i}\left(r_{m}^{i}\right)}$$

Work 2: An iterative co-saliency framework for RGBD images

- **Deletion Scheme: Common Probability Function**
  - For co-saliency detection, it is necessary to discriminate whether the selected salient objects are common or not. Thus, how to determine the common objects is a key point for co-saliency detection. In general, the common object is defined as the object with repeated occurrence in multiple images. Based on this definition, **the common probability function is used to evaluate the likelihood that a superpixel belongs to the common regions, and it is defined as the sum of maximum matching probability among different images**.
  - We selected the most matching superpixel in other images to define the common attribute. Then, these selected superpixels from different images are used to calculate the common probability.

$$P_c^i(r_m^i) = \frac{1}{N-1}\sum_{j=1, j\neq i}^{N} S_M\left(r_m^i, r_k^j\right) \qquad r_k^j = \arg\max_{n\in[1,N_j]} \underbrace{\boxed{S_M\left(r_m^i, r_n^j\right)}}_{\text{similarity between two superpixels}} \qquad S_M(r_m^i, r_n^j) = \frac{\underbrace{S_c\left(r_m^i, r_n^j\right)}_{\text{color}} + \underbrace{S_d\left(r_m^i, r_n^j\right)}_{\text{depth}} + \underbrace{S_s\left(r_m^i, r_n^j\right)}_{\text{saliency}}}{3}$$

Work 2: An iterative co-saliency framework for RGBD images

- **Iteration Scheme**

  - In order to obtain more superior co-saliency map, an iterative scheme is designed in our framework. The iterative scheme works as a refinement model to combine the addition and deletion steps and refine the co-saliency map in loop.
  - In the iteration scheme, a heuristic termination strategy is set by checking the maximum iteration number and the difference between two iterations.

Algorithm 1 Overall Framework

Input: The RGB images and depth maps in an image group.
Output: The co-saliency map for each image.

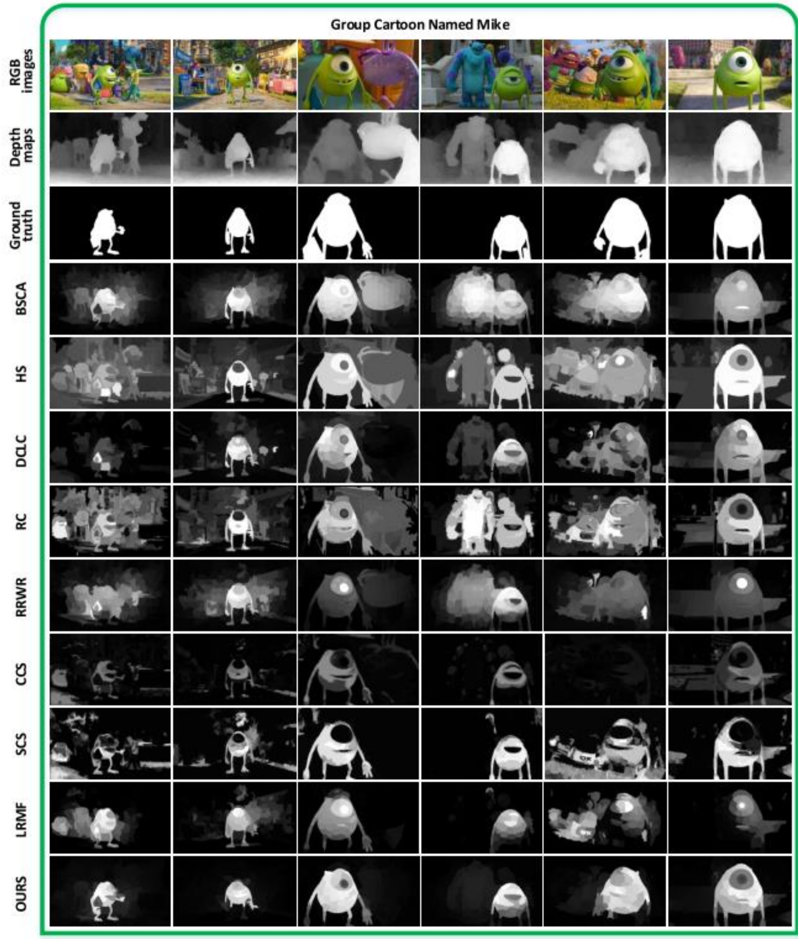
```
for each image in the group do
    Obtain the initialized saliency map using Eq. (1);
    repeat
        Conduct the addition scheme using Eqs. (2-8);
        Conduct the deletion scheme using Eqs. (9-18);
    until D_t^i ≤ ζ or t ≥ I_max
end for
```

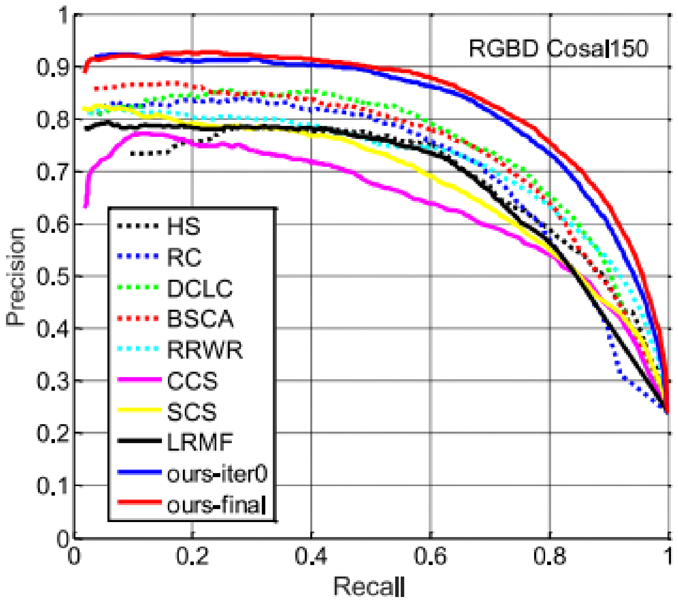
$$D_t^i = \left(\frac{1}{\Pi}\sum\left|S_{\mathrm{del}}^i(t) - S_{\mathrm{del}}^i(t-1)\right|\right) \le \zeta$$

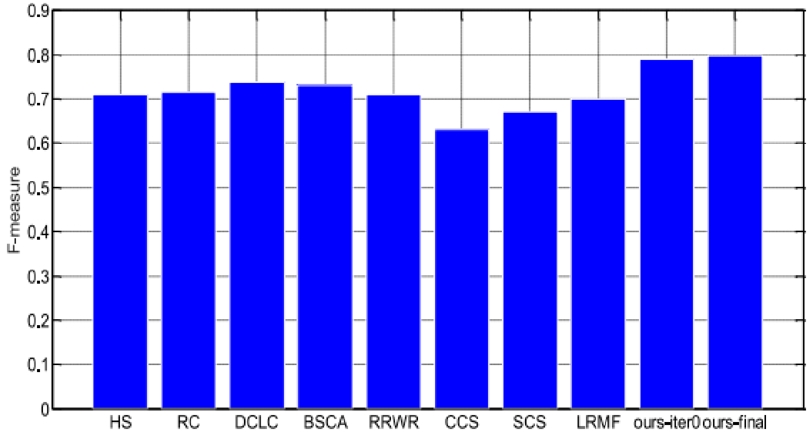
Work 2: An iterative co-saliency framework for RGBD images

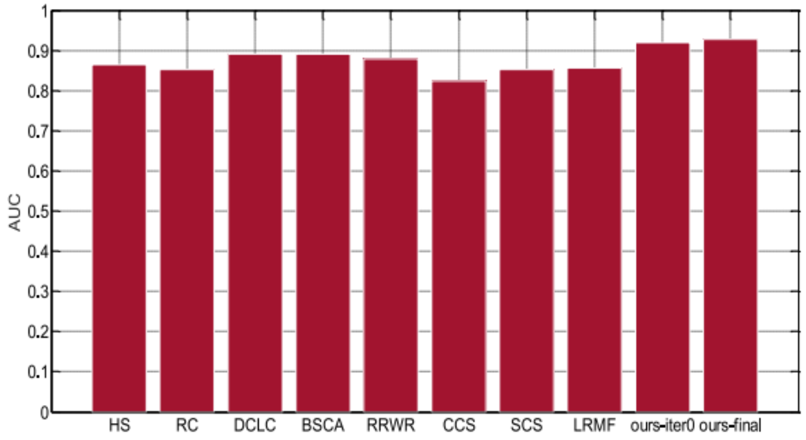
- **Experiments**

RGBD Cosal150 dataset



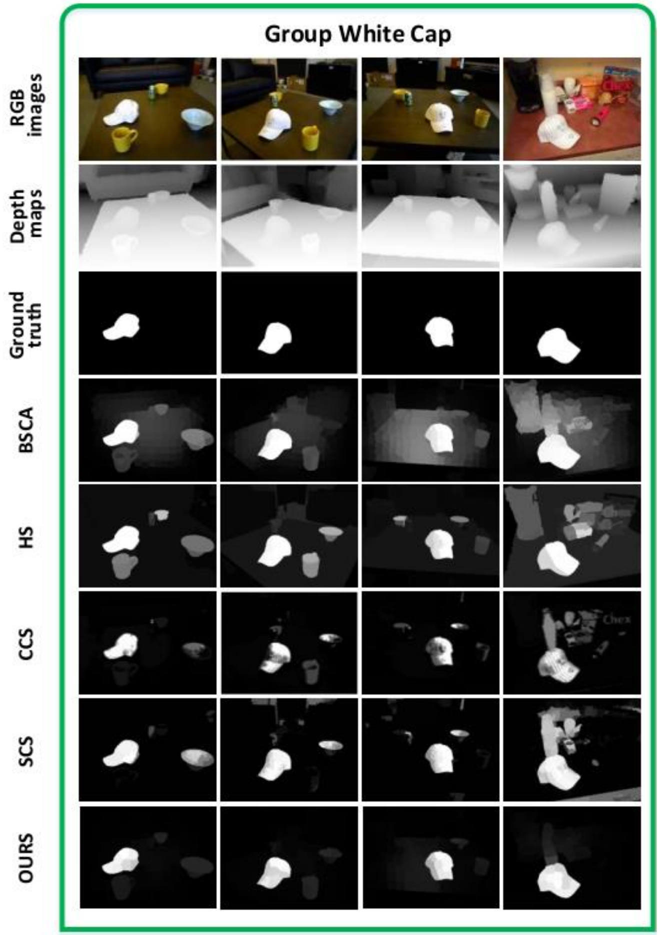


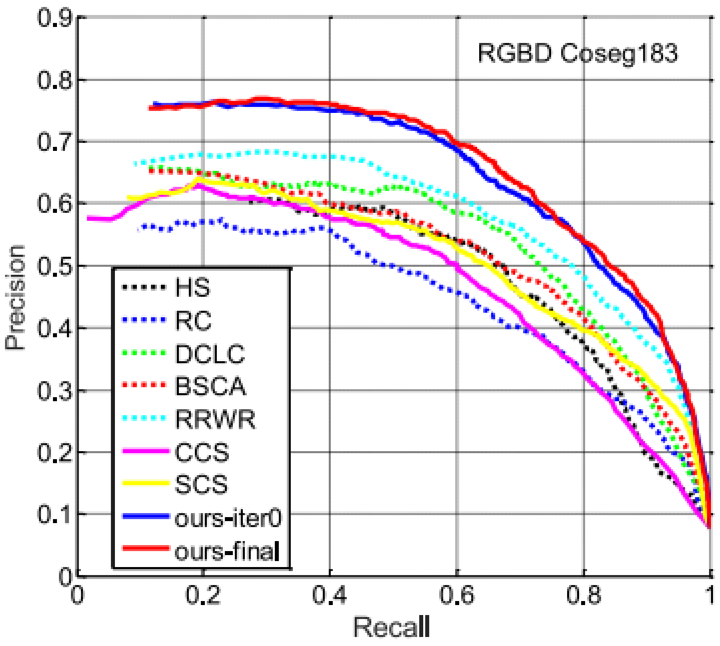


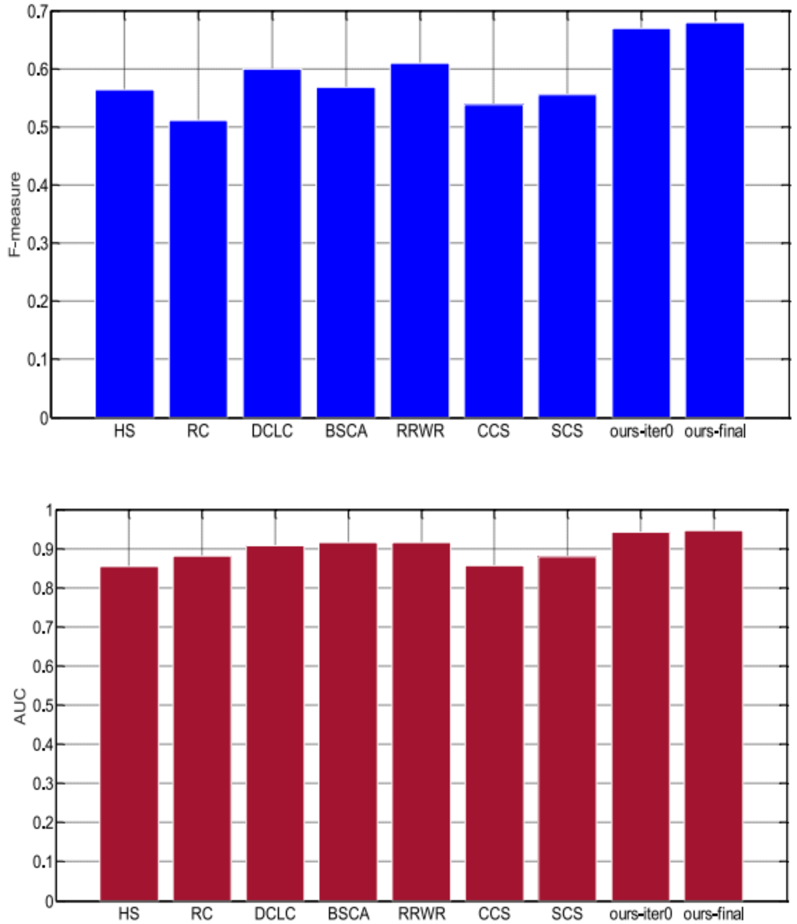


Work 2: An iterative co-saliency framework for RGBD images

- **Experiments** RGBD Coseg183 dataset

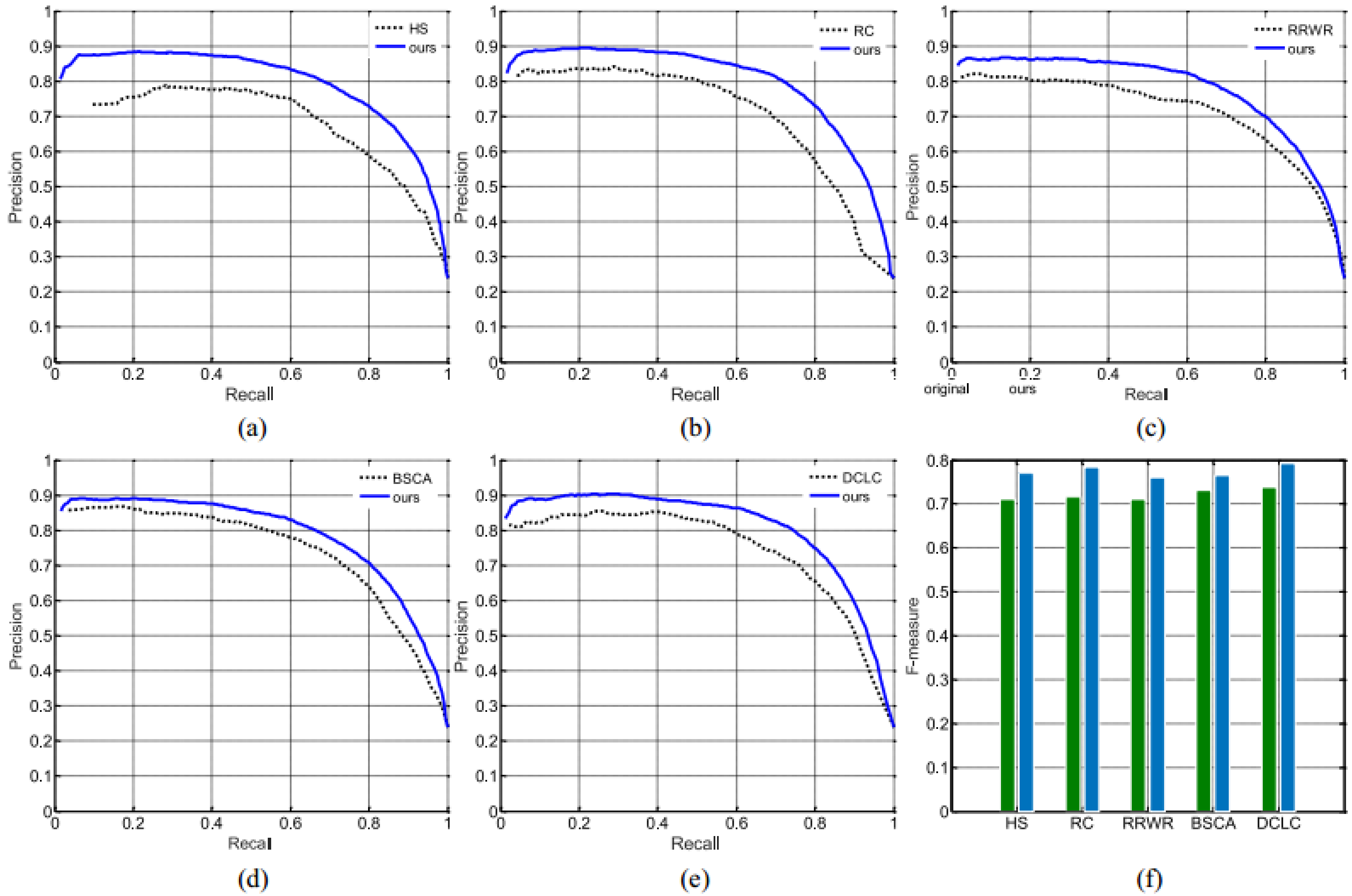




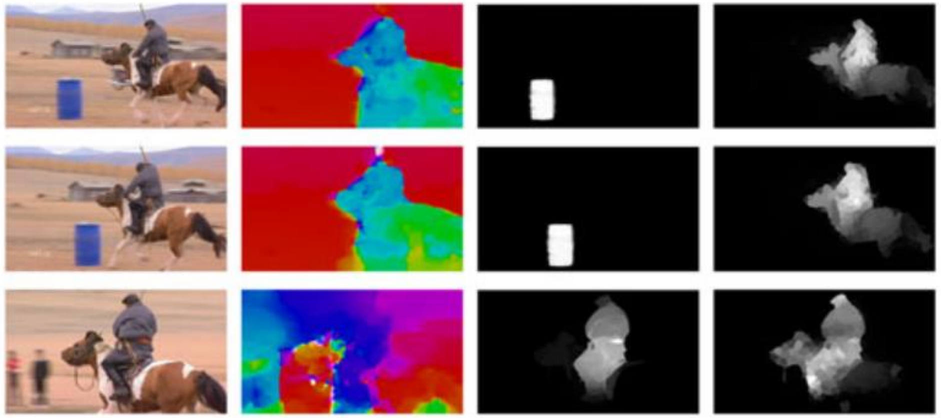


Work 2: An iterative co-saliency framework for RGBD images

- **Experiments**



Video Saliency Detection



Problems and Important Issues:

Motion cue plays more important role in discovering the salient object from the clustered and complex scene.

The inter-frame correspondence represents the relationship among different frames, which is used to capture the common attribute of salient objects from the whole video.

The spatiotemporal consistency constrains the smoothness and homogeneity of salient objects from the spatiotemporal domain.

Video saliency detection via sparsity-based reconstruction and propagation

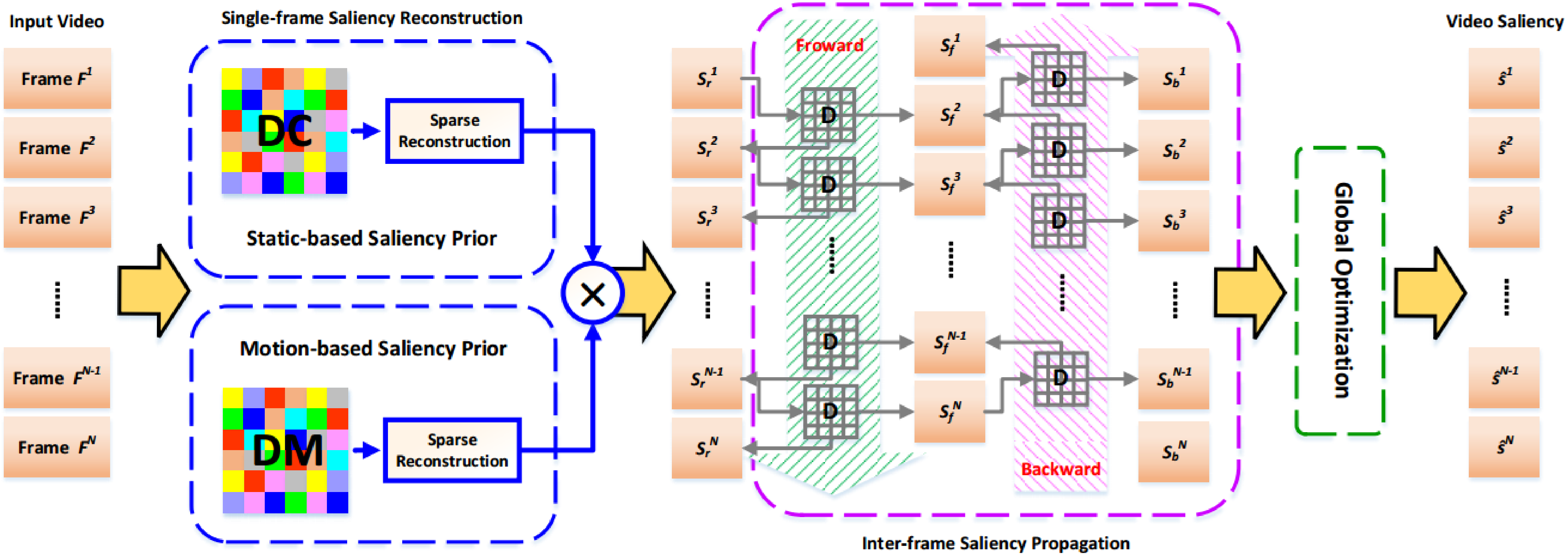
- **Contributions**

1. A novel sparsity-based saliency reconstruction is introduced to generate single-frame saliency map, making the best use of the static and motion priors. The motion priors are defined as motion compactness cue and motion uniqueness cue.
2. A new and efficient sparsity-based saliency propagation is presented to capture the correspondence in the temporal space and produce inter-frame saliency map. The salient object is sequentially reconstructed by the forward and backward dictionaries.
3. To attain the global consistency of the salient object in the whole video, a global optimization model, which integrates unary data term, spatiotemporal smooth term, spatial incompatibility term, and global consistency term, is formulated.

Runmin Cong, Jianjun Lei, Huazhu Fu, Fatih Porikli, Qingming Huang, Chunping Hou, Video saliency detection via sparsity-based reconstruction and propagation, *IEEE Transactions on Image Processing*, 2018. Major Revisions.

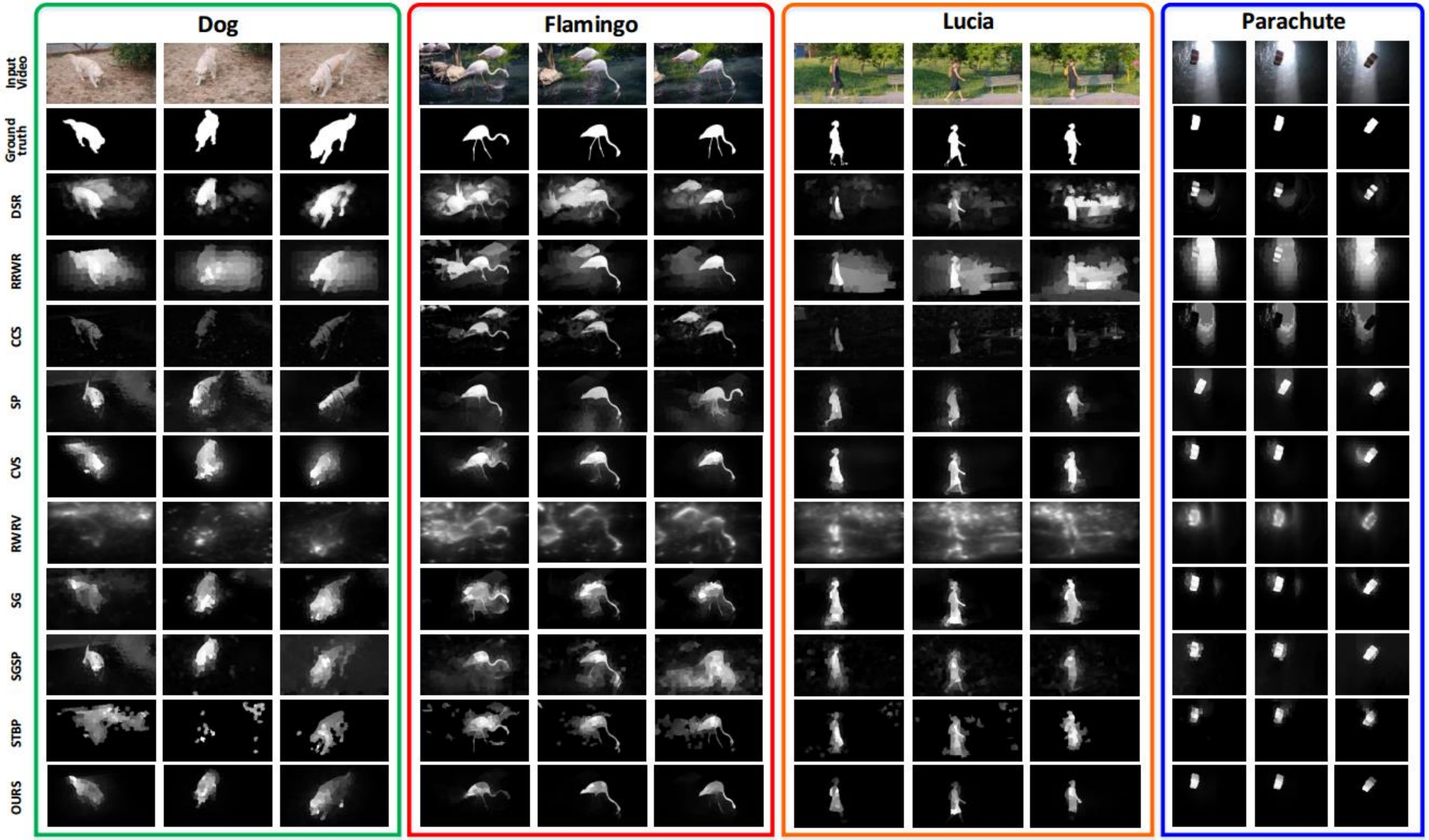
Video saliency detection via sparsity-based reconstruction and propagation

- **Framework**



Video saliency detection via sparsity-based reconstruction and propagation

- **Experiments**



Video saliency detection via sparsity-based reconstruction and propagation

- **Experiments**

	SegTrackV1 Dataset		DAVIS Dataset		ViSal Dataset	
	F-measure	MAE	F-measure	MAE	F-measure	MAE
DCLC [8]	0.2755	0.1496	0.4783	0.1350	0.6700	0.1265
DSR [10]	0.4445	0.1305	0.4972	0.1303	0.6923	0.1061
RRWR [11]	0.3267	0.1963	0.5089	0.1693	0.6707	0.1690
HS [28]	0.3821	0.3142	0.4523	0.2505	0.6442	0.2019
BSCA [29]	0.3579	0.2366	0.4680	0.1957	0.6949	0.1703
HDCT [30]	0.4681	0.1268	0.5664	0.1346	0.7047	0.1282
CCS [40]	0.1486	0.1437	0.3476	0.1510	0.5317	0.1427
SCS [41]	0.1137	0.2664	0.2307	0.2567	0.4384	0.2523
SP [19]	0.2159	0.1195	0.4616	0.1430	0.5723	0.1510
CVS [20]	0.5370	0.1085	0.6212	0.1004	0.6676	0.1139
RWRV [50]	0.4458	0.1511	0.3776	0.2001	0.4662	0.1903
SG [51]	0.6218	0.0810	0.5553	0.1034	0.6640	0.1129
SGSP [53]	0.6275	0.1258	0.6911	0.1374	0.6226	0.1772
STBP [54]	0.6583	0.0342	0.5848	0.1015	0.6815	0.0987
VFCN* [56]	–	–	0.7488	0.0588	–	–
SPR	0.6830	0.0949	0.7652	0.0688	0.7517	0.0924

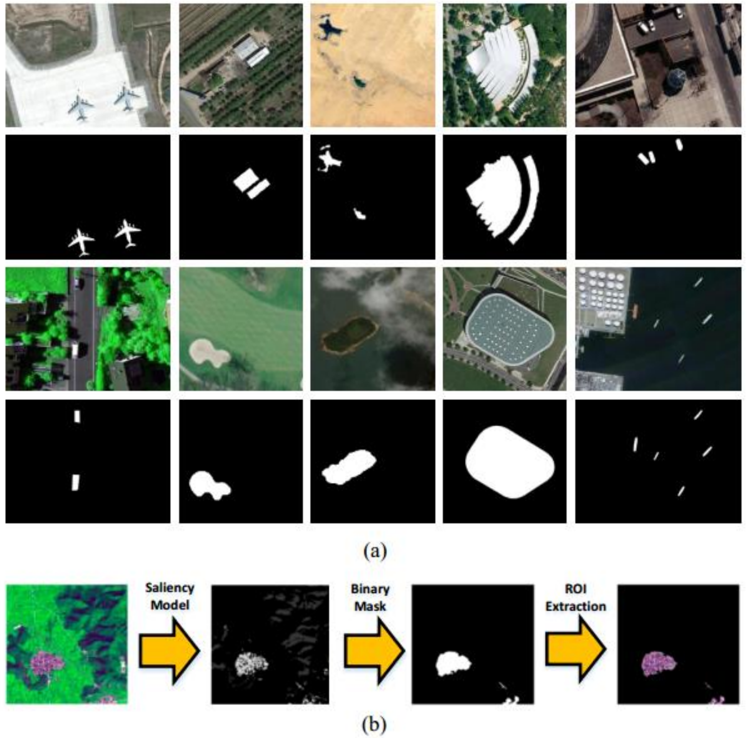
Conclusion and Future Work

1. **New attempts in learning based saliency detection methods, such as small samples training, weakly supervised learning, and cross-domain learning. Limited by the labelled training data, more work, such as designing a special network, can be explored in the future to achieve high-precision detection with small training samples. In addition, weakly supervised salient object detection method is a good choice to address the insufficient pixel-level saliency annotations. Furthermore, the cross-domain learning is another direction that needs to be addressed for learning based RGBD saliency detection method.**

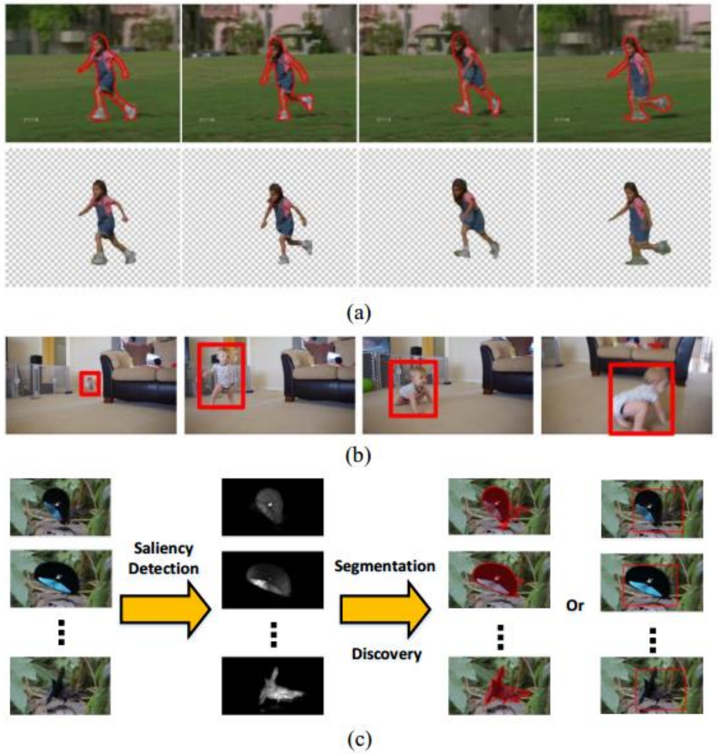
Conclusion and Future Work

2. **Extending the saliency detection task in different data sources, such as light filed image, RGBD video, and remote sensing image.** In the light filed image, the focusness prior, multi-view information, and depth cue should be considered jointly. For the RGBD video data, the depth constraint should be introduced to assist in the spatiotemporal saliency. In the remote sensing image, due to the high angle shot photographed, some small targets and shadows are included. Thus, how to suppress the interference effectively and highlight the salient object accurately should be further investigated in the future.

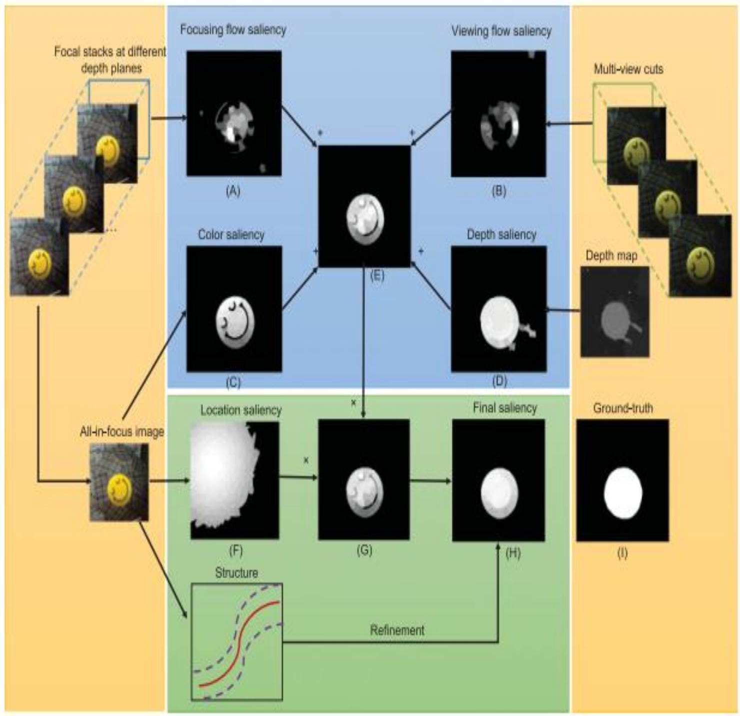
Conclusion and Future Work



Saliency Detection in Optical Remote Sensing Image



Primary Object Detection in Video



Saliency Detection in Light Filed[1]

[1] Jun Zhang, Meng Wang, Liang Lin, Xun Yang, Jun Gao, and Yong Rui. 2017. Saliency detection on light field: A multi-cue approach. ACM Trans. Multimedia Comput. Commun. Appl. 13, 3, Article 32 (July 2017), 22 pages.

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- **Runmin Cong**, Jianjun Lei, Huazhu Fu, Qingming Huang, Xiaochun Cao, and Chunping Hou, ***Co-saliency detection for RGBD images based on multi-constraint feature matching and cross label propagation***, IEEE Transactions on Image Processing, vol.27, no.2, pp. 568-579, 2018. (SCI, IF=5.071)
- **Runmin Cong**, Jianjun Lei, Huazhu Fu, Weisi Lin, Qingming Huang, Xiaochun Cao, and Chunping Hou, ***An iterative co-saliency framework for RGBD images***, IEEE Transactions on Cybernetics, 2018. In Press. (SCI, IF=8.803)
- **Runmin Cong**, Jianjun Lei, Huazhu Fu, Qingming Huang, Xiaochun Cao, and Nam Ling, ***HSCS: Hierarchical sparsity based co-saliency detection for RGBD images***, IEEE Transactions on Multimedia, 2018. In Press. (SCI, IF=3.977)
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- **Runmin Cong**, Ping Han, Chongyi Li, Jiaji He, and Zaiji Zhang, ***Manmade target extraction based on multi-stage decision and its application for change detection in polarimetric synthetic aperture radar image***, Journal of Electronic Imaging, vol.25, no.5, 2016. (SCI, IF=0.780)
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- Yonghua Zhang, Liang Li, **Runmin Cong**, Xiaojie Guo, Hui Xu, and Jiawan Zhang, ***Co-saliency detection via hierarchical consistency measure***, IEEE ICME, pp. 1-6, 2018. (**Best Student Paper Runner-Up Award**)
- Chongyi Li, Jichang Guo, Chunle Guo, **Rrunmin Cong**, Jiachang Gong, ***A hybrid method for underwater image correction***, Pattern Recognition Letters, vol.94, pp. 62-67, 2017. (SCI, IF=1.952)
- Chongyi Li, Jichang Guo, **Runmin Cong**, Yanwei Pang, and Bo Wang, ***Underwater image enhancement by dehazing with minimum information loss and histogram distribution prior***, IEEE Transactions on Image Processing, vol.25, no.12, pp.5664-5677, 2016. (SCI, IF=5.071)
- Chongyi Li, Jichang Guo, Bo Wang, **Runmin Cong**, Yan Zhang, and Jian Wang, ***Single underwater image enhancement based on color cast removal and visibility restoration***, Journal of Electronic Imaging, vol.25, no.3, 2016. (SCI, IF=0.780)

More information including the datasets, codes, and results can be found on my Homepage

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Q&A


THANK YOU FOR
YOUR ATTENTION