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RGB-D Salient Object Detection: A Survey

Tao Zhou, Deng-Ping Fan, Ming-Ming Cheng, Jianbing Shen, and Ling Shao

***Abstract*—Salient object detection (SOD), which simulates the human visual perception system to locate the most attractive object(s) in a scene, has been widely applied to various computer vision tasks. Now, with the advent of depth sensors, depth maps with affluent spatial information that can be beneficial in boosting the performance of SOD, can easily be captured. Although various RGB-D based SOD models with promising performance have been proposed over the past several years, an in-depth understanding of these models and challenges in this topic remains lacking. In this paper, we provide a comprehensive survey of RGB-D based SOD models from various perspectives, and review related benchmark datasets in detail. Further, considering that the light field can also provide depth maps, we review SOD models and popular benchmark datasets from this domain as well. Moreover, to investigate the SOD ability of existing models, we carry out a comprehensive evaluation, as well as attribute-based evaluation of several representative RGB-D based SOD models. Finally, we discuss several challenges and open directions of RGB-D based SOD for future research. All collected models, benchmark datasets, source code links, datasets constructed for attribute-based evaluation, and codes for evaluation will be made publicly available at https://github.com/taozh2017/RGBD-SODsurvey.**

***Index Terms*—RGB-D based salient object detection, saliency detection, comprehensive evaluation, light field.**

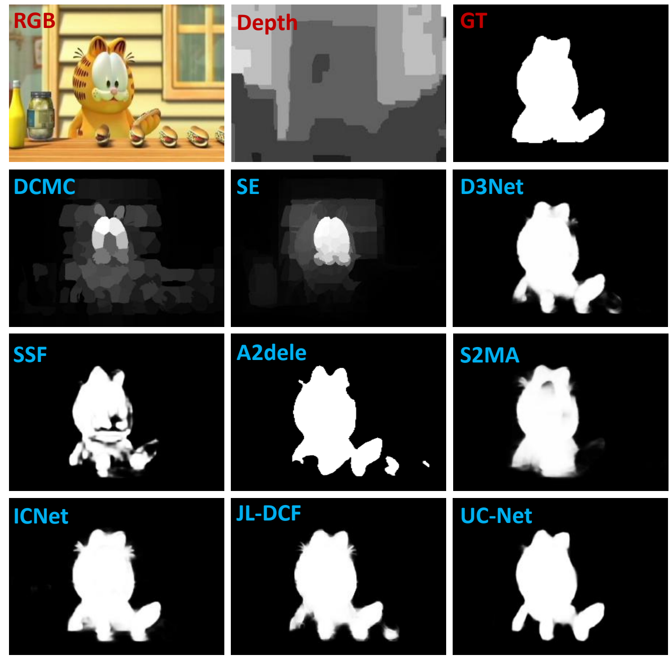

Fig. 1. RGB-D based salient object prediction on a sample image using two classic non-deep models (*i.e.*, DCMC [1] and SE [2]) and seven state-of-the-art deep models (*i.e.*, D3Net [3], SSF [4], A2dele [5], S2MA [6], ICNet [7], JL-DCF [8], and UC-Net [9]).

I. Introduction

Salient object detection (SOD) aims to locate the most visually prominent object(s) in a given scene [10]. SOD plays a key role in a range of real-world applications, such as stereo matching [11], image understanding [12], co-saliency detection [13], action recognition [14], video detection and segmentation [15]–[18], semantic segmentation [19], [20], medical image segmentation [21]–[23], object tracking [24], [25], person re-identification [26], [27], camouflaged object detection [28], *etc*. Although significant progress has made in the SOD field over the past several years [29]–[33], [33]–[41], there is still room for improvement under challenging factors such as complicated background or different lighting conditions in the scenes. One way to overcome these challenges is to employ depth maps, which provide complementary spatial information for RGB images and have become easier to capture due to the large availability of depth sensors (*e.g.*, Microsoft Kinect).

Recently, RGB-D based SOD has gained increasing attention and various methods have been developed [3], [42]. Early RGB-D based SOD models tended to extract handcrafted features and then fuse RGB image and depth maps. For example, Lang *et al.* [43], the first work on RGB-D based SOD, utilized Gaussian mixture models to model the distribution of depth-induced saliency. Ciptadi *et al.* [44] extracted 3D layout and shape features from depth measurements. Besides, several methods [45], [46], [46], [47] measured depth contrast using the depth difference between different regions. In [48], a multi-contextual contrast model including local, global, and background contrast was developed to detect salient objects using depth maps. More importantly, however, this work also provided the first large-scale RGB-D dataset for SOD. Despite the effectiveness achieved by traditional methods using handcrafted features, they tend to suffer from a limited generalization ability for low-level features and lack the high-level reasoning required for complex scenes. To address these limitations, deep learning based RGB-D SOD methods [3] have been developed, showing improved performance. DF [49] was the first model to introduce deep learning technology into the RGB-D based SOD task. More recently, various deep learning-based models [6]–[9], [50]–[52] have focused on exploiting effective multi-modal correlations and multi-scale/level information to boost SOD performance. To clearly describe the progress in the RGB-D based SOD field, we provide a brief chronology in Fig. 2.

This paper provides a comprehensive survey on RGB-D based SOD, which aims to thoroughly cover various aspects of the models for this task and provide insightful discussions on the challenges and open directions for future work. We also

Corresponding author: Ding-Ping Fan (dengpingfan@mail.nankai.edu.cn).
T. Zhou, D.-P. Fan, J. Shen, and L. Shao are with Inception Institute of Artificial Intelligence, Abu Dhabi, UAE.
M.-M. Cheng is with CS, Nankai University, Tianjin 300350, China.

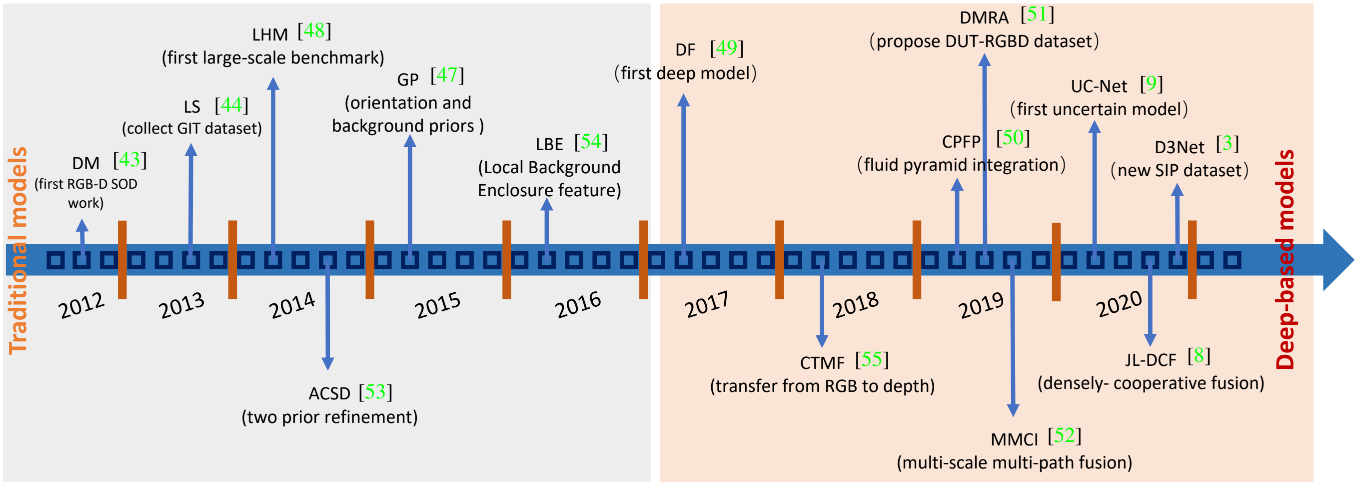

Fig. 2. A brief chronology of RGB-D based SOD. The first early RGB-D based SOD work was the DM [43] model, proposed in 2012. Deep learning techniques have been widely applied to RGB-D based SOD since 2017. More details can be found in § II.

review another related topic, *i.e.*, light field SOD, in which the light field can provide more information (including focal stack, all-focus images and depth maps) to boost the performance of salient object detection. Further, we provide a comprehensive comparison to evaluate existing RGB-D based SOD models and provide their main advantages.

A. Related Reviews and Surveys

There are several surveys that are closely related to salient detection. For example, Borji *et al.* [56] provided a quantitative evaluation of 35 state-of-the-art non-deep saliency detection methods. Cong *et al.* [57] reviewed several different saliency detection models, including RGB-D based SOD, co-saliency detection, and video SOD. Zhang *et al.* [58] provided an overview of co-saliency detection, and review the history of co-saliency detection and summarize several benchmark algorithms in this field. Han *et al.* [59] reviewed the recent progress in SOD including models, benchmark datasets, and evaluation metrics, as well as discussed the underlying connection among object detection, SOD, and category-specific object detection. Nguyen *et al.* [60] reviewed various works related to saliency applications and provided insightful discussions on role of saliency in these. Borji *et al.* [61] provided a comprehensive review of recent progress in SOD and discuss some related works including generic scene segmentation, saliency for fixation prediction, and object proposal generation. Fan *et al.* [10] provided a comprehensive evaluation of several state-of-the-art CNNs-based SOD models, and proposed a high quality SOD dataset, termed **SOC** (Details can be found at: http://dpfan.net/socbenchmark/). Zhao *et al.* [62] reviewed various deep learning-based object detection models and algorithms in detail, and also reviewed various specific tasks including SOD works. Wang *et al.* [63] focused on reviewing deep learning based SOD models. Different from previous SOD surveys, in this paper, we focus on reviewing the existing RGB-D based SOD models and benchmark RGB-D datasets.

B. Contributions

The main contributions are summarized as follows:

- We provide the first systematic review of RGB-D based SOD models from different perspectives. We summarize existing RGB-D SOD models into traditional or deep methods, fusion-wise methods, single-stream/multi-stream methods, and attention-aware methods.
- We review nine RGB-D benchmark datasets that are popularly used in this field, and we provide details for each dataset. Moreover, we provide a comprehensive as well as an attribute-based evaluation of several representative RGB-D based SOD models.
- We supply the first collection and review of the related light field SOD models and benchmark datasets.
- We thoroughly investigate several challenges for RGB-D based SOD field and the relation of SOD with other topics, shedding light on potential directions for future research.

C. Organization

In § II, we review existing RGB-D based models from different aspects. In § III, we summarize and provide details for current benchmark datasets for RGB-D salient object detection. In § IV, we conduct a comprehensive review of light field SOD models and benchmark datasets. In § V, we provide a comprehensive and attribute-based evaluation of several representative RGB-D based models. We then discuss challenges and open directions of this field in § VI. Finally, we conclude this paper in § VII.

II. RGB-D BASED SOD MODELS

Over the past few years, several RGB-D based SOD methods have been developed and obtained promising performance. These models are summarized in Tables I, II, III and IV. The complete benchmark can be found at http://dpfan.net/d3netbenchmark/. To review these RGB-D based SOD models in detail, we introduce them from the following perspectives: (1) Traditional/deep models; (2) fusion-wise models, (3) single-stream/multi-stream models, and (4) attention-aware models.

A. Traditional/Deep Models

Traditional Models. With depth cues, we can often explore several useful attributes, such as boundary cues, shape attributes, surface normals, etc., to boost the identification of salient objects in complex scenes. Over the past several years, many traditional RGB-D models based on handcrafted features have been developed [1], [2], [44]–[48], [53], [54], [66]–[68], [72], [79]–[81], [92]. For example, the early work [44] focused on modeling the interaction between layout and shape features generated from the RGB image and depth map. Besides, the representative work [48] developed a novel multi-stage RGB-D model, and constructed the first large-scale RGB-D benchmark dataset, termed NLPR.

Deep Models. However, the above-mentioned methods suffer from unsatisfactory SOD performance due to the limited expression ability of handcrafted features. To address this, several studies have turned to deep neural networks (DNNs) to fuse RGB-D data [4], [5], [7]–[9], [49]–[52], [80], [90], [91], [93]–[105]. These models can learn high-level representations to explore complex correlations across RGB images and depth cues for improving SOD performance. We review some representative works in details as follows.

- **DF** [49] develops a novel convolutional neural network (CNN) to integrate different low-level saliency cues into hierarchical features, for effectively locating salient regions in RGB-D images. This was the first CNN-based model for the RGB-D SOD task. However, it utilizes a shallow architecture to learn the saliency map.
- **PCF** [89] presents a complementarity-aware fusion module to integrate cross-modal and cross-level feature representations, which can effectively exploit complementary information using cross-modal/level connections and modal/level-wise supervisions explicitly to decrease fusion ambiguity.
- **CTMF** [55] develops a computational model to identify salient objects from RGB-D scene, utilizing CNNs to learn high-level representations for RGB images and depth cues, and exploit the complementary correlations and joint representation simultaneously. Besides, this model transfers the structure of the model from the source domain (*i.e.*, RGB images) to be applicable to the target domain (*i.e.*, depth maps).
- **CPFP** [50] proposes a contrast-enhanced network to produce the enhanced map, and presents a fluid pyramid integration module to effectively fuse cross-modal information via a hierarchical manner. Besides, considering the fact that depth cues easily suffer from noisy, a feature-enhanced module is proposed to learn an enhanced depth cue for boosting the SOD performance. It is worth noting that this is an effective solution.
- **UC-Net** [9] proposes a probabilistic RGB-D based SOD network via conditional variational autoencoders (VAE) to model human annotation uncertainty. It generates multiple saliency maps for each input image by sampling in the learned latent space. This was the first work to investigate uncertainty in RGB-D based SOD, and was inspired by the data labeling process. This method leverages the diverse saliency maps to improve the final SOD performance.

B. Fusion-wise Models

For RGB-D based SOD models, it is important to effectively fuse RGB images and depth maps. The existing fusion strategies can be grouped into three categories, including 1) early fusion, 2) multi-scale fusion, and 3) late fusion. We provide details for each fusion strategy as follows.

Early Fusion. Early fusion-based methods can follow one of two veins: 1) RGB images and depth maps are directly integrated to form a four-channel input [47], [48], [84], [84], [93]. This is denoted as “input fusion” (shown in Fig. 3); 2) RGB and depth images are first fed into each independent network and their low-level representations are combined as joint representations, which are then fed into a subsequent network for further saliency map prediction [49]. This is denoted as “early feature fusion” (shown in Fig. 3).

Late Fusion. Late fusion-based methods can also be further divided into two families: 1) Two parallel network streams are adopted to learn high-level features for RGB and depth data, respectively, which are concatenated and then used for generating the final saliency prediction [45], [55], [99]. This is denoted as “later feature fusion” (shown in Fig. 3); 2) Two parallel network streams are used to obtain the independent saliency map for RGB images and depth cues, and then the two saliency maps are concatenated to obtain a final prediction map [112]. This is denoted as “late result fusion” (shown in Fig. 3).

Multi-scale Fusion. To effectively explore the correlations between RGB images and depth maps, several methods propose a multi-scale fusion strategy [7], [8], [52], [113], [118], [121], [122], [127] . The first category learn the cross-modal interactions and then fuse them into a feature learning network. For example, Chen *et al.* [52] developed a multi-scale multi-path fusion network to integrate RGB images and depth maps, with a cross-modal interactions (termed as MMCI) module. This method introduces cross-modal interactions into multiple layers, which can empower additional gradients for enhancing the learning of the depth stream as well as explore complementarity across low-level and high-level representations. The second category fuse the features from RGB images and depth maps in different layers and then integrate them into a decoder network (*e.g.*, skip connection) to produce the final saliency detection map (as shown in Fig. 3). Some representative works are briefly discussed as follows.

- **ICNet** [7] proposes an information conversion module to convert high-level features via an interactive manner. In this model, a cross-modal depth-weighted combination (CDC) block is proposed to enhance RGB features with depth features at different levels.
- **DPANet** [113] uses a gated multi-modality attention (GMA) module to exploit long-range dependencies. The GMA module can extract the most discriminative features by utilizing a spatial attention mechanism. Besides, this model

TABLE I
SUMMARY OF RGB-D BASED SOD METHODS (PUBLISHED FROM 2012 TO 2016).

#	Year	Method	Pub.	Dataset	Description
1	2012	DM [43]	ECCV	NUS-3D Saliency dataset	Models the correlation between saliency and depth by approximating the joint density using Gaussian Mixture Models
2	2012	RCM [64]	ICCSE	300 objects	Develops a region contrast based SOD model with depth cues
3	2013	LS [44]	BMVC	GIT	Extends the dissimilarity framework to model the joint interaction between depth cues and RGB images
4	2013	RC [45]	BMVC	UW dataset, Berkeley 3D dataset	Derives RGB-D saliency by formulating a 3D saliency model based on the region contrast of the scene and fuses it using SVM
5	2013	SOS [65]	NEURO	300 RGB-D images	Incorporates depth cues for salient object segmentation by suppressing background regions
6	2014	SRDS [66]	ICDSP	STERE	Integrates depth and depth weighted color contrast with spatial compactness of color distribution
7	2014	LHM [48]	ECCV	NLRP	Uses a multi-stage RGB-D algorithm to combine both depth and appearance cues to segment salient objects
8	2014	DESM [46]	ICIMCS	DES	Combines three saliency cues: color contrast, spatial bias, and depth contrast
9	2014	ACSD [53]	ICIP	1382 images	Measures a point's saliency by how much it stands out from the surroundings, and has two priors (regions nearer to viewers are more salient and salient objects tend to be located at the center)
10	2015	GP [47]	CVPRW	NLPR, NJUD	Explores orientation and background priors for detecting salient objects, and uses PageRank and MRFs to optimize the saliency maps
11	2015	SFP [67]	ICIMCS	NLPR, NJUD	Develops a RGB-D based SOD approach using saliency fusion and propagation
12	2015	DIC [68]	TVC	103 stereo pairs	Fuses the saliency maps from color and depth to generate a noise-free salient patch, and utilizes random walk algorithm to infer the object boundary
13	2015	SRD [69]	ICRA	GIT, MSRA	Designs a graph-based segmentation to identify homogeneous regions using color and depth cues
14	2015	MGMR [70]	ICIP	NLPR	Designs a mutual guided manifold ranking strategy to achieve SOD
15	2015	SF [71]	CAC	NLPR	Proposes to automatically select discriminative features using decision trees for better performance
16	2016	PRC [72]	ACCESS	NLPR, NJUD	Saliency fusion and progressive region classification are used to optimize depth-aware saliency models
17	2016	LBE [54]	CVPR	NLPR, NJUD	Uses a local background enclosure to capture the spread of angular directions
18	2016	SE [2]	ICME	NLPR, NJUD	Utilizes cellular automata to propagate the initial saliency map and then generate the final saliency prediction result
19	2016	DCMC [1]	SPL	NJUD	Develops a new measure to evaluate the reliability of depth maps for reducing the influence of poor-quality of depth maps on saliency detection.
20	2016	BF [73]	ICPR	IRC-cyN/IVC 3D Gaze	Fuses contrasting features from RGB and depth images with a Bayesian framework.
21	2016	DCI [74]	ICASSP	STERE, NJUD	Adopts the original depth map to subtract the fitted surface for generating a contrast increased map
22	2016	DSF [75]	ICASSP	NLPR, NJUD	Develops a multi-stage depth-aware saliency model for SOD
23	2016	GM [76]	ACCV	NLPR	Combines color and depth-based contrast features using a generative mixture model

controls the fusion rate of the cross-modal information using a gate function, which can reduce some effects brought by the unreliable depth cues.

• **BiANet** [118] develops a multi-scale bilateral attention module (MBAM) to capture better global information in multiple layers.

• **JL-DCF** [8] treats a depth image as a special case of a color image and employs a shared CNN for both RGB and depth feature extraction. It also proposes a densely-cooperative fusion strategy to effectively combine the learned features from different modalities.

• **BBS-Net** [127] uses a bifurcated backbone strategy (BBS) to split the multi-level feature representations into teacher and student features, and develops a depth-enhanced module (DEM) to explore informative parts in depth maps from the spatial and channel views.

C. Single-stream/Multi-stream Models

Single-stream Models. Several RGB-D based SOD works [49], [50], [80], [84], [90], [93], [94] focus on a single-stream architecture to achieve saliency prediction. These models often fuse RGB images and depth information in the input channel or feature learning part. For example, MDSF [84] develops a multi-scale discriminative saliency fusion framework as the SOD model, in which four types of features in three levels are computed and then fused to obtain the final saliency map. BED [80] utilizes a CNN architecture to integrate bottom-up and top-down information for SOD, which also incorporates multiple features, including background enclosure distribution (BED) and low level depth maps (*e.g.*, depth histogram distance and depth contrast) to boost the SOD performance. PDNet [94] extracts depth-based features using a subsidiary network, which makes full use of depth information to assist the main-stream network.

Multi-stream Models. Two-stream models [51], [99], [100] consist of two independent branches that process RGB images and depth cues, respectively, and often generate different high-level features or saliency maps and then incorporate them in the middle stage or end of the two streams. It is worth noting that most recent deep learning-based models [5], [7], [42], [52], [89], [97], [101], [103], [113], [116] utilize this two-stream architecture with several models capturing the correlations between RGB images and depth cues across multiple layers. Moreover, some models utilize a multi-stream structure [3], [96] and then design different fusion modules to effectively fuse RGB and depth information to exploite their correlations.

TABLE II
SUMMARY OF RGB-D BASED SOD METHODS (PUBLISHED FROM 2017 TO 2018).

#	Year	Method	Pub.	Dataset	Description
24	2017	HOSO [77]	DICTA	NLPR, NJUD	Combines surface orientation distribution contrast with color and depth contrast
25	2017	M^3Net [78]	IROS	NLPR, NJUD, STERE	Designs a multi-path multi-modal fusion strategy to integrate RGB and depth images in a task-motivated and adaptive way
26	2017	MFLN [79]	ICCVS	NLPR, NJUD	Leverages a CNN to learn high-level representations for depth maps, and uses a multi-modal fusion network to integrate RGB and depth representations for RGB-D based SOD
27	2017	BED [80]	ICCVW	NLPR, NJUD	Uses a CNN to integrate top-down and bottom-up information for RGB-D based SOD, and uses a mid-level feature representation to capture background enclosure
28	2017	CDCP [81]	ICCVW	NLPR, DES	Proposes a novel RGB-D SOD algorithm using a center dark channel prior to boost performance
29	2017	TPF [82]	ICCVW	SSD, NJUD, NLPR, DES	Leverages stereopsis to generate optical flow that can provide an addition cue (depth cue) for producing the final detection result
30	2017	MFF [83]	SPL	NLPR	Uses a multistage fusion framework to integrate multiple visual priors from the RGB image and depth cue for SOD
31	2017	MDSF [84]	TIP	NLPR, NJUD	Proposes a RGB-D SOD framework via a multi-scale discriminative saliency fusion strategy, and utilizes a bootstrap learning to achieve the SOD task
32	2017	DF [49]	TIP	NLPR, NJUD	Feeds RGB and depth features into a CNN architecture to derive the saliency confidence value, and uses a Laplacian propagation to produce the final detection result
33	2017	MCLP [85]	TCYB	Cosal150, Coseg183	Utilizes the additional depth maps and employs the existing RGB saliency map as an initialization using a refinement-cycle model to obtain the final co-saliency map
34	2018	ISC [86]	SIVP	NLPR, ROBOT-TCVA2015	Fuses salient features using both bottom-up and top-down salient cues
35	2018	HSCS [87]	TMM	Cosal150, Coseg183	Utilizes a hierarchical sparsity reconstruction and energy function refinement for RGB-D based co-saliency detection
36	2018	ICS [88]	TIP	Cosal150, Coseg183	Exploits the constraint correlation among multiple images and introduce depth maps into the co-saliency model
37	2018	CTMF [55]	TCYB	NLPR, STERE, NJUD, DES	Transfers the structure of the deep color network to be applicable for depth modality and fuses both modalities to produce the final saliency map
38	2018	PCF [89]	CVPR	NLPR, STERE, NJUD	Designs a novel complementarity-aware fusion module to fuse both cross-modal and cross-level features
39	2018	SCDL [90]	ICDSP	NLPR, NJUD	Designs a new loss function to increase the spatial coherence of salient objects
40	2018	ACCF [91]	IROS	NLPR,NJUD, STERE	Adaptively selects complementary features from different modalities at each level, and then performs more informative cross-modal cross-level combinations
41	2018	CDB [92]	NEURO	STERE	Utilizes contrast prior and depth-guided-background prior to construct a 3D stereoscopic saliency model

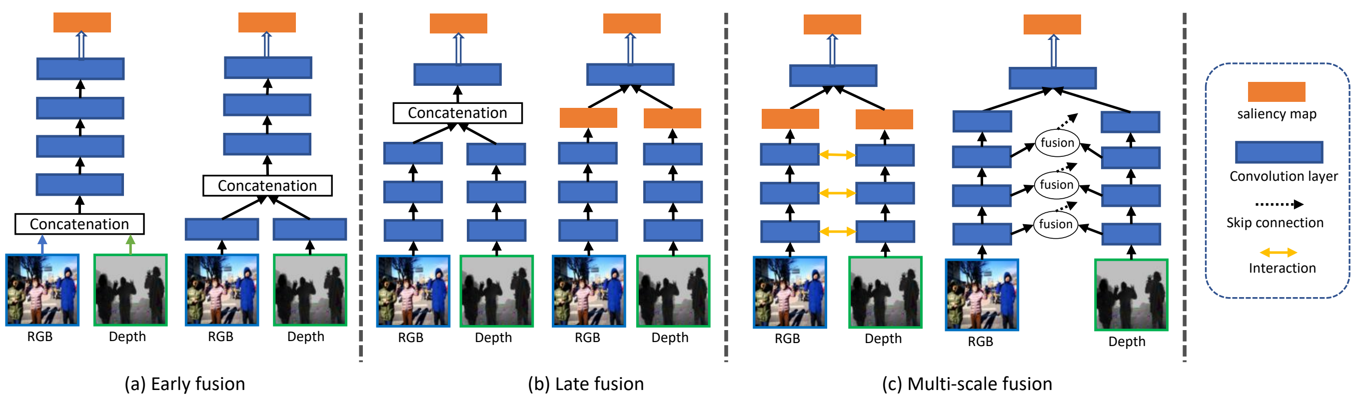

Fig. 3. Comparison of three fusion strategies that explore the correlation between RGB images and depth maps for RGB-D based SOD. These include: 1) Early fusion; 2) Late fusion; 3) Multi-scale fusion.

D. Attention-aware Models

Existing RGB-D based SOD methods often treat all regions using the extracted features equally, while ignoring the fact that different regions can have different contributions to the final prediction map. These methods are easily affected by cluttered backgrounds. In addition, some methods either regard the RGB images and depth maps as having the same status or overly rely on depth information. This prevents them from considering the importance of different domains (RGB images or depth cues). To overcome this, several methods introduce attention mechanisms to weight the importance of different regions or domains.

- **ASIF-Net** [103] captures complementary information from RGB images and depth cues using an interweaved fusion, and weights the saliency regions though a deeply supervised attention mechanism.
- **AttNet** [100] introduces attention maps for differentiating of salient objects and background regions to reduce negative influence of some low-quality depth cues.
- **TANet** [96] formulates a multi-modal fusion framework using RGB images and depth maps from the bottom-up and top-down views, and proposes a channel-wise attention module to effectively fuse the complementary information from different modalities and levels.
- **ACCF** [91] proposes a top-down RGB-D fusion network, in which an attention-induced cross-modal cross-level fusion

TABLE III
SUMMARY OF RGB-D BASED SOD MODELS PUBLISHED IN 2019

No.	Year	Method	Pub.	Dataset	Description
42	2019	SSRC [93]	NEURO	NLPR, NJUD, STERE, LFSD	Uses a single stream recurrent convolution neural network with a four-channel input and DRCNN subnetwork
43	2019	MLF [106]	SPL	NJUD	Designs a salient object-aware data augmentation method to expand the training set
44	2019	TSRN [107]	ICIP	NJUD	Designs a fusion refinement module to integrate output features from different modalities and resolutions
45	2019	DIL [108]	MTAP	NLPR, NJUD	Designs a consistency integration strategy to generate an image pre-segmentation result that is consistent with the depth distribution
46	2019	CAFM [109]	TSMC	NUS [43], NCTU [110]	Utilizes a content-aware fusion module to integrate global and local information
47	2019	PDNet [94]	ICME	NLPR, NJUD	Adopts a prior-model guided master network to process RGB information, which is pre-trained on the conventional RGB dataset to overcome the limited size
48	2019	MMCI [52]	PR	NLPR, NJUD, STERE	Improves the traditional two-stream architecture by diversifying the multi-modal fusion paths and introducing cross- modal interactions in multiple layers
49	2019	DCA [95]	TIP	LFSD	Enforces spatial consistency by constructing an optimization model, and the saliency value of each superpixel is updated by exploiting the intrinsic relevance of similar regions
50	2019	TANet [96]	TIP	NLPR, NJUD, STERE	Uses a three-stream multi-modal fusion framework to explore cross-modal complementarity in both the bottom-up and top-down processes
51	2019	DCMF [97]	TCYB	NLPR, NJUD	Formulates a CNN-based cross-modal transfer learning problem for depth-induced SOD, and uses a dense cross-level feedback strategy to exploit cross-level interactions
52	2019	DGT [98]	TCYB	NLPR, NJUD, STERE	Exploits depth cues and provides a general transformation model from RGB saliency to RGBD saliency
53	2019	LSF [42]	arXiv	NLPR, NJUD, STERE	Designs an RGB-D system with three key components, including modal-specific representations learning, complementary information selection, and cross-modal complements fusion
54	2019	AFNet [99]	ACCESS	NLPR, NJUD, STERE, LFSD, DES	Learns a switch map that is used to adaptively fuse the predicted saliency maps from the RGB and depth modality
55	2019	EPM [111]	ACCESS	NLPR, NJUD, STERE, LFSD, DES	Develops an effective propagation mechanism for RGB-D co-saliency detection
56	2019	CPFP [50]	CVPR	NLPR, NJUD, STERE	Uses a contrast-enhanced network to obtain the one-channel enhanced map, and designs a fluid pyramid integration module to fuse cross-modal cross-level features in a pyramid style
57	2019	DMRA [51]	ICCV	NJUD, NLPR, STERE, LFSD, DUT-RGBD, DES, SSD	Designs a depth-induced multiscale recurrent attention network for SOD, including a depth refinement block and a recurrent attention module
58	2019	DSD [112]	JVCIR	NJUD, NLPR, STERE, DES, SSD	Uses a saliency fusion network to adaptively fuse both the color and depth saliency maps

module is adopted to extract informative features from each modality at different levels.

E. Open-source Implementations

We summarize the open-source implementations of RGB-D based SOD models reviewed in the survey. The implementations and hyperlinks of the source codes of these models are provided in Tab V.

III. RGB-D DATASETS

With the rapid development of RGB-D based SOD, various datasets have been constructed over the past several years. Tab VI summarizes nine popular RGB-D datasets, and Fig. 4 shows examples of images (including RGB images, depth maps, and annotations) for these datasets. Moreover, we provide the details for each dataset as follows.

- **STERE** [128]. The authors first collected 1250 stereoscopic images from Flickr [1], NVIDIA 3D Vision Live [2], and Stereoscopic Image Gallery [3]. The most salient objects in each image were annotated by three users. All annotated images were then sorted based on the overlaping salient regions and the top 1000 images were selected to construct the final dataset. This is the first collection of stereoscopic images in this field.
- **GIT** [44] consists of 80 color and depth images, which were collected using a mobile-manipulator robot in a real-world home environment. Moreover, each image is annotated based on the pixel-level segmentation of the objects.
- **DES** [46] consists of 135 RGB-D indoor images, which were taken by Kinect with a resolution of 640×640. When collecting this dataset, three users were asked to label the salient object in each image, and then the overlapping areas of the labeled object were regarded as the ground truth.
- **NLPR** [48] consists of 1000 RGB images and their corresponding depth maps, which were obtained by a standard Microsoft Kinect. This dataset includes a series of outdoor and indoor locations, *e.g.*, offices, supermarkets, campuses, streets, and so on.
- **LFSD** [129] includes 100 light fields collected using a Lytro light field camera, and consists of 60 indoor and 40 outdoor scenes. To label this datasst, three individuals were asked to manually segment salient regions, and then the segmented results were deemed ground truth when the overlap of the three results was over 90%.
- **NJUD** [53] consists of 1985 stereo image pairs, and these images were collected from the internet, 3D movies,

[1] http://www.flickr.com/
[2] http://photos.3dvisionlive.com/
[3] http://www.stereophotography.com/

TABLE IV
SUMMARY OF RGB-D BASED SOD MODELS PUBLISHED IN 2020.

No.	Year	Method	Pub.	Dataset	Description
59	2020	DPANet [113]	arXiv	NJUD, NLPR, STERE, LFSD, DES, DUT-RGBD, SIP	Uses a saliency-orientated depth perception module to evaluate the potentiality of depth maps and reduce effects of contamination
66	2020	CAF [114]	arXiv	NJUD, NLPR, STERE, SSD, DES	Utilizes depth cues as training priors to facilitate SOD
61	2020	SSDP [115]	arXiv	STERE, LFSD, NJUD, NLPR, SIP, DUT-RGBD, DES	Makes use of existing labeled RGB saliency datasets together with unlabeled RGB-D data to boost SOD performance
62	2020	AttNet [100]	IVC	NJUD, NLPR, STERE, LFSD, DES	Deploys attention maps to boost the salient objects' location and pays more concern to the appearance information
63	2020	GFNet [101]	NEURO	NLPR, NJU, STERE, DES, SIP	Uses an adaptive gated fusion module via a GAN to obtain a better fused saliency map from RGB images and depth cues
64	2020	CoCNN [102]	PR	STERE, NJUD	Fuses color and disparity features from low to high layers in a unified deep model
65	2020	cmSalGAN [116]	TMM	NJUD, NLPR, STERE	Aims to learn an optimal view-invariant and consistent pixel-level representation for both RGB and depth images using an adversarial learning framework
66	2020	PGHF [117]	ACCESS	NJUD, NLPR, LFSD, STERE, DES	Leverages powerful representations learned from large-scale RGB datasets to boost the model ability
67	2020	BiANet [118]	TIP	NJUD, NLPR, STERE, SSD, DES, SIP	Uses a bilateral attention module (BAM) to explore rich foreground and background information from depth maps
68	2020	ASIF-Net [103]	TCYB	NJUD, NLPR, STER, LFSD	Integrates the attention steered complementarity from RGB-D images and introduces a global semantic constraint using adversarial learning
69	2020	Triple-Net [104]	SPL	NJUD, NLPR, STERE, LFSD, DES	Uses a triple-complementary network for RGB-D based SOD
70	2020	ICNet [7]	TIP	NJUD, NLPR, STERE, LFSD, DES	Uses a novel information conversion module to fuse high-level RGB and depth features in an interactive and adaptive way
71	2020	SDF [105]	TIP	NLPR, NJUD, DEC, LFSD	Proposes a exemplar-driven method to estimate relatively trustworthy depth maps, and uses a selective deep saliency fusion network to effectively integrate RGB images, original depths, and newly estimated depths
72	2020	GFNet [119]	SPL	NJUD, NLPR	Designs a gate fusion block to regularize feature fusion
73	2020	RGBS [120]	MTAP	NJUD, NLPR, SIP, STERE	Utilizes a GAN to generate the saliecny map
74	2020	D^3Net [3]	TNNLS	NJUD, NLPR, SSB, LFSD, DES, GIT, STERE, SIP	Uses a depth depurator unit (DDU) and a three-stream feature learning module to employ low-quality depth cue filtering and cross-modal feature learning, respectively
75	2020	JL-DCF [8]	CVPR	NJUD, NLPR, STERE, DES, LFSD, SIP	Uses a joint learning strategy and a densely-cooperative fusion module to achieve better SOD performance
76	2020	A2dele [5]	CVPR	NJUD, NLPR, DUT-RGBD, DES, STERE	Employs a depth distiller to explore ways of using network prediction and attention as two bridges to transfer depth knowledge to RGB images
77	2020	SSF [4]	CVPR	NJUD, NLPR, DUT-RGBD, DES, STERE	Designs a complimentary interaction module to select useful representations from the RGB and depth images and then integrate cross-modal features
78	2020	S^2MA [6]	CVPR	NJUD, NLPR, STERE, LFSD, DUT-RGBD, DES, SSD	Fuses multi-modal information via self-attention and each others attention strategies, and reweights the mutual attention term to filter out unreliable information
79	2020	UC-Net [9]	CVPR	NJUD, NLPR, SSB, LFSD, DES	Uses a probabilistic RGB-D saliency detection network via a conditional VAE to generate multiple saliency maps
80	2020	CMWNet [121]	ECCV	NJUD, NLPR, STERE, DES, LFSD, SSD, SIP	Exploits feature interactions using three cross-modal cross-scale weighting modules to improve SOD performance
81	2020	HDFNet [122]	ECCV	NJUD, NLPR, STERE, DES, LFSD, SSD, SIP, DUT-RGBD	Designs a hierarchical dynamic filtering network to effectively make use of cross-modal fusion information
82	2020	CAS-GNN [123]	ECCV	NJUD, NLPR, STERE, LFSD, DES, SSD	Designs cascaded graph neural networks to exploit useful knowledge from RGB and depth images for building powerful feature embeddings
83	2020	CMMS [124]	ECCV	NJUD, NLPR, STERE, LFSD, SSD, DUT-RGBD	Proposes a cross-modality feature modulation module to enhance feature representations and an adaptive feature selection module to gradually select saliency-related features
84	2020	DANet [125]	ECCV	NJUD, NLPR, DUT-RGBD, DES, SSD, SIP	Develops a single-stream network combined with a depth-enhanced dual attention to achieve real-time SOD
85	2020	CoNet [126]	ECCV	NJUD, NLPR, DUT-RGBD, DES, SSD, LFSD, SIP	Develops a collaborative learning framework for RGB-D based SOD, and three collaborators (edge detection, coarse salient object detection and depth estimation) are utilized to jointly boost the performance
86	2020	BBS-Net [127]	ECCV	NJUD, NLPR, STERE, LFSD, DES, SSD, SIP	Uses a bifurcated backbone strategy to learn teacher and student features, and utilizes a depth-enhanced module to excavate informative parts of depth cues

and photographs that are taken by a Fuji W3 stereo camera.

• **SSD** [82] was constructed using three stereo movies and includes indoor and outdoor scenes. This dataset includes 80 samples, and each image has the size of 960×1080.

• **DUT-RGBD** [95] consists of 800 indoor and 400 outdoor scenes with their corresponding depth images. This dataset includes several challenging factors, *i.e.*, multiple or transparent objects, complex backgrounds, similar foregrounds and backgrounds, and low-intensity environments.

• **SIP** [3] consists of 929 annotated high-resolution images, with multiple salient persons in each image. In this dataset, depth maps were captured using a real smartphone (*i.e.*, Huawei Mate10). Besides, it is worth noting that this dataset covers diverse scenes, and various challenging factors, and is annotated with pixel-level ground truths.

IV. SALIENCY DETECTION ON LIGHT FIELD

A. Light Field SOD Models

Existing works for SOD can be grouped into three categories according to the input data type, including RGB SOD, RGB-D SOD, and light field SOD [144]. We have already reviewed RGB-D based SOD models, in which depth maps provide layout information to improve SOD performance to some extent. However, inaccurate or low-quality depth maps

Fig. 4. Examples of images, depth maps and annotations in nine RGB-D dataset, including (a) STERE [128], (b) NLPR [48], (c) SSD [82], (d) GIT [44], (e) DES [46] , (f) LFSD [129], (g) NJUD [53], (h) DUT-RGBD [95], and (i) SIP [3]. In each dataset, the RGB image, depth map and annotation are denoted from left to right.

often decrease the performance. To overcome this issue, light field SOD methods have been proposed to make use of rich information captured by the light field. Specifically, light field data contains an all-focus image, a focal stack, and a rough depth map [95]. A summary of related light field SOD works is provided in Tab VII. Further, to provide an in-depth understanding of these models, we also review them in more detail as follows.

Traditional/Deep Models. The classic models for light field SOD often use superpixel-level hand-crafted features [95], [129]–[135], [137], [143]. Early work [129], [135] showed that the unique refocusing capability of light fields can provide useful focusness, depth, and objectness cues, and further proposed several SOD models using light field data. For example, Zhang *et al.* [131] utilized a set of focal slices to compute the background prior, and then incorporate it with the location prior for SOD. Wang *et al.* [134] proposed a two-stage Bayesian fusion model to integrate multiple contrasts for boosting SOD performance. Recently, several deep learning-based light field SOD models [139]–[142], [144], [145] have been developed and obtained remarkable performance. Besides, in [139], an attentive recurrent CNN was developed to fuse all focal slices, while the data diversity was increased using adversarial examples to enhance model robustness. Zhang *et al.* [141] developed a memory-oriented decoder for light field SOD, which fuses multi-level features in a top-down strategy using high-level information to guide low-level feature selection. LFNet [144] employs a new integration module to fuse features from light field data according to their contributions and captures the spatial structure of a scene to improve SOD performance.

Refinement based Models. Several refinement strategies have been used to enforce neighboring constraints or reduce the homogeneity of multiple modalities for SOD. For example, in [130], the saliency dictionary was refined using the estimated saliency map. The MA method [133] employs a two-stage saliency refinement strategy to produce the final prediction map, which enables adjacent superpixels to obtain similar saliency values. Besides, LFNet [144] presents an effective refinement module to reduce the homogeneity among different modalities as well refine their dissimilarities

B. Light Field Data for SOD

There are five representative datasets widely-used in existing light field SOD models. We describe the details for each dataset as follows.

TABLE V
A SUMMARY OF RGB-D BASED SOD MODELS WITH OPEN-SOURCE IMPLEMENTATIONS.

Year	Model	Implementation	Code link
2014	LHM [48]	Matlab	https://sites.google.com/site/rgbdsaliency/code
	DESM [46]	Matlab	https://github.com/HzFu/DES_code
2015	GP [47]	Matlab	https://github.com/JianqiangRen/Global_Priors_RGBD_Saliency_Detection
2016	DCMC [1]	Matlab	https://github.com/rmcong/Code-for-DCMC-method
	LBE [54]	Matlab & C++	http://users.cecs.anu.edu.au/ u4673113/lbe.html
2017	BED [80]	Caffe	https://github.com/sshige/rgbd-saliency
	CDCP [81]	Matlab	https://github.com/ChunbiaoZhu/ACVR2017
	MDSF [84]	Matlab	https://github.com/ivpshu
	DF [49]	Matlab	https://pan.baidu.com/s/1Y-PqAjuH9xREBjfl7H45HA
2018	CTMF [55]	Caffe	https://github.com/haochen593/CTMF
	PCF [89]	Caffe	https://github.com/haochen593/PCA-Fuse_RGBD_CVPR18
	PDNet [94]	TensorFlow	https://github.com/cai199626/PDNet
2019	AFNet [99]	TensorFlow	https://github.com/Lucia-Ningning/Adaptive_Fusion_RGBD_Saliency_Detection
	CPFP [50]	Caffe	https://github.com/JXingZhao/ContrastPrior
	DMRA [51]	PyTorch	https://github.com/jiwei0921/DMRA
	DGT [98]	Matlab	https://github.com/rmcong/Code-for-DTM-Method
2020	ICNet [7]	Caffe	https://github.com/MathLee/ICNet-for-RGBD-SOD
	JL-DCF [8]	Caffe	https://github.com/kerenfu/JLDCF
	A2dele [5]	PyTorch	https://github.com/OIPLab-DUT/CVPR2020-A2dele
	SSF [4]	PyTorch	https://github.com/OIPLab-DUT/CVPR_SSF-RGBD
	ASIF-Net [103]	TensorFlow	https://github.com/Li-Chongyi/ASIF-Net
	S^2MA [6]	PyTorch	https://github.com/nnizhang/S2MA
	UC-Net [9]	PyTorch	https://github.com/JingZhang617/UCNet
	D^3Net [3]	PyTorch	https://github.com/DengPingFan/D3NetBenchmark
	CMWNet [121]	Caffe	https://github.com/MathLee/CMWNet
	HDFNet [122]	PyTorch	https://github.com/lartpang/HDFNet
	CMMS [124]	TensorFlow	https://li-chongyi.github.io/Proj_ECCV20
	DANet [125]	PyTorch	https://github.com/Xiaoqi-Zhao-DLUT/DANet-RGBD-Saliency
	CoNet [126]	PyTorch	https://github.com/jiwei0921/CoNet
	BBS-Net [127]	PyTorch	https://github.com/DengPingFan/BBS-Net

TABLE VI
STATISTICS OF NINE RGB-D BENCHMARK DATASETS IN TERMS OF YEAR (YEAR), PUBLICATION (PUB.), DATASET SIZE (SIZE), NUMBER OF OBJECTS IN THE IMAGES (#OBJ.), TYPE OF SCENE (TYPES), DEPTH SENSOR (SENSOR), AND RESOLUTION (RESOLUTION). SEE § III FOR MORE DETAILS ON EACH DATASET. THESE DATASETS CAN BE DOWNLOADED FROM OUR WEBSITE: HTTP://DPFAN.NET/D3NETBENCHMARK/.

#	Dataset	Year	Pub.	Size	#Obj.	Types	Sensor	Resolution
1	**STERE** [128]	2012	CVPR	1000	∼One	Internet	Stereo camera+sift flow	$[251 \sim 1200] \times [222 \sim 900]$
2	**GIT** [44]	2013	BMVC	80	Multiple	Home environment	Microsoft Kinect	640×480
3	**DES** [46]	2014	ICIMCS	135	One	Indoor	Microsoft Kinect	640×480
4	**NLPR** [48]	2014	ECCV	1000	Multiple	Indoor/outdoor	Microsoft Kinect	640×480, 480×640
5	**LFSD** [129]	2014	CVPR	100	One	Indoor/outdoor	Lytro Illum camera	360×360
6	**NJUD** [53]	2014	ICIP	1985	∼One	Movie/internet/photo	FujiW3 camera+optical flow	$[231 \sim 1213] \times [274 \sim 828]$
7	**SSD** [82]	2017	ICCVW	80	Multiple	Movies	Suns optical flow	960×1080
8	**DUT-RGBD** [95]	2019	ICCV	1200	Multiple	Indoor/outdoor	–	400×600
9	**SIP** [3]	2020	TNNLS	929	Multiple	Person in the wild	Huawei Mate10	992×744

• **LFSD** [129] [4] consists of 100 light fields of different scenes with 360×360 spatial resolution, captured using a Lytro light field camera. This dataset contains 60 indoor and 40 outdoor scenes, and most scenes consist of only one salient object. Besides, three individuals were asked to manually segment salient regions in each image, and then the ground truth was determined when all three segmentation results had an overlap of over 90%.

[4]https://sites.duke.edu/nianyi/publication/saliency-detection-on-light-field/

TABLE VII
SUMMARY OF POPULAR LIGHT FIELD SOD METHODS.

No.	Year	Method	Pub.	Dataset	Description
1	2014	LFS [129]	CVPR	LFSD	Develops the first light-field saliency detection algorithm to employ the objectness and focusness cues based on the refocusing capability of the light field
2	2015	WSC [130]	CVPR	LFSD	Uses a weighted sparse coding framework to learn a saliency/non-saliency dictionary
3	2015	DILF [131]	IJCAI	LFSD	Incorporates depth contrast to complement the disadvantage of color and conducts focusness-based background priors to boost the saliency detection performance
4	2016	RL [132]	ICASSP	LFSD	Utilizes the inherent structure information in light field images to improve saliency detection
5	2017	MA [133]	TOMM	HFUT, LFSD	Integrates multiple saliency cues extracted from light field images using a random-serach-based weighting manner
6	2017	BIF [134]	NPL	LFSD	Integrates color-based contrast, depth-induced contrast, focusness map of foreground slice, and background weighted depth contrast are fused using a two-stage Bayesian integration framework
7	2017	LFS [135]	TPAMI	LFSD	An extension of [129]
8	2017	RLM [136]	ICIVC	LFSD	Utilizes the light field relative location measurement for SOD on light field images
9	2018	SGDC [137]	CVPR	LFSD	Designs a salience-guided depth optimization framework for multi-layer light field displays
10	2018	DCA [138]	FiO	LFSD	Proposes a graph model depth-induced cellular automata to optimize saliency maps using light field data
11	2019	DLLF [139]	ICCV	DUTLF-FS, LFSD	Utilizes a recurrent attention network to fuse each slice from the focal stack to learn the most informative features
12	2019	DLSD [140]	IJCAI	DUTLF-MV	Formulates saliency detection into two subproblems, including 1) light field synthesis from a single view and 2) light-field-driven saliency detection
13	2019	Molf [141]	NIPS	UTLF-FS	Uses a memory-oriented decoder for light field SOD
14	2020	ERNet [142]	AAAI	DUTLF-FS, HFUT, LFSD	Uses an asymmetrical two-stream architecture to overcome computation-intensive and memory-intensive challenges in a high dimension of light field data
15	2020	DCA [95]	TIP	LFSD	uses an asymmetrical two-stream architecture to overcome computation-intensive and memory-intensive challenges in high dimension of light field data
16	2020	RDFD [143]	MTAP	LFSD	Defines a region-based depth feature descriptor extracted from the light field focal stack to facilitate low- and high-level cues for saliency detection
17	2020	LFNet [144]	TIP	DUTLF-FS, LFSD, HFUT	Utilizes a light field refinement module and a light field integration module to effectively integrate multiple cues (*i.e.*, focusness, depths and objectness) from light field images
18	2020	LFDCN [145]	TIP	Lytro Illum, LFSD, HFUT	Uses a deep convolutional network based on the modified DeepLab-v2 model to explore spatial and multi-view properties of light field images for saliency detection

• **HFUT** [133] [5] consists of 255 light fields captured using a Lytro camera. In this dataset, most scenes contain multiple objects that appear within different locations and scales under complex background clutter.

• **DUTLF-FS** [139] [6] consists of 1465 samples, 1000 of which are as training set while the remaining 465 images are as testing set. The resolution of each image is 600×400. This dataset contains several challenges, *e.g.*, lower contrast between salient objects and cluttered background, multiple disconnected salient objects, and dark or strong light conditions.

• **DUTLF-MV** [140] [7] consists of 1580 samples, in which 1100 samples are for training and the remaining is for testing. Images were captured by a Lytro Illum camera, and each light field consists of multi-view images and a corresponding ground truth.

• **Lytro Illum** [145] [8] consists of 640 light fields and the corresponding per-pixel ground-truth saliency maps. It includes several challenging factors, *e.g.*, inconsistent illumination conditions, and small salient objects existing in a similar or cluttered background.

V. MODEL EVALUATION AND ANALYSIS

A. Evaluation Metrics

We briefly review several popular metrics for SOD evaluation as follows.

[5]https://github.com/pencilzhang/HFUT-Lytro-dataset

[6]https://github.com/OIPLab-DUT/ICCV2019_Deeplightfield_Saliency

[7]https://github.com/OIPLab-DUT/IJCAI2019-Deep-Light-Field-Driven-Saliency-Detection-from-A-Single-View

[8]https://github.com/pencilzhang/MAC-light-field-saliency-net

• **MAE**. This is the *mean absolute error* (MAE) [146] between a prediction saliency map S and a ground truth G for all pixels, which can be defined by

$$MAE = \frac{1}{W*H} \sum_{i=1}^{W} \sum_{i=1}^{H} \left| S_{i,j} - G_{i,j} \right|, \tag{1}$$

where W and H denote the width and height of the map, respectively. MAE values are normalized to [0,1].

• **S-measure** (S_α). To capture the importance of image structural information, S_α [147] is used to assess the structural similarity between the regional perception (S_r) and object perception (S_o). Thus, S_α can be defined by

$$S_\alpha = \alpha * S_o + (1-\alpha) * S_r, \tag{2}$$

where $\alpha \in [0,1]$ is a trade-off parameter. Here, we set α = 0.5 as the default setting as suggested by Fan *et al.* [147].

• **E-measure** (E_ϕ). E_ϕ [148] was proposed based on cognitive vision studies to capture image-level statistics and their local pixel matching information. Thus, E_ϕ can be defined by

$$E_\phi = \frac{1}{W*H} \sum_{i=1}^{W} \sum_{i=1}^{H} \phi_{FM}(i,j), \tag{3}$$

where ϕ_{FM} denotes the enhanced-alignment matrix [148].

• **F-measure** (F_β). F_β is popular metric and has been widely applied to evaluate the performance of SOD. Inspired by [56] and [3], we use fixed $[0, 255]$ thresholds to compute this metric. Finally, F_β is calculated by

$$F_\beta = \left(1+\beta^2\right) \frac{P*R}{\beta^2 P + R}. \tag{4}$$

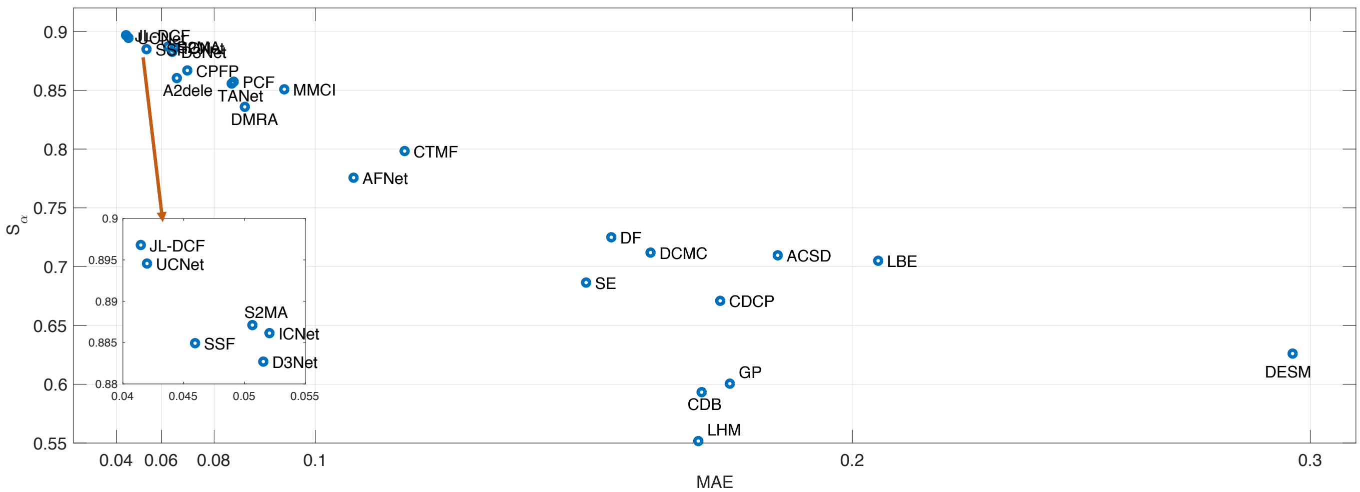

Fig. 5. A comprehensive evaluation for 24 representative RGB-D based SOD models, including LHM [48], ACSD [53], DESM [46], GP [47], LBE [54], DCMC [1], SE [2], CDCP [81], CDB [92], DF [49], PCF [89], CTMF [55], CPFP [50], TANet [96], AFNet [99], MMCI [52], DMRA [51], D3Net [3], SSF [4], A2dele [5], S2MA [6], ICNet [7], JL-DCF [8], and UC-Net [9]. We obtain the terms of S_α and MAE values for the 24 models on five datasets (*i.e.*, STERE [128], NLPR [48], LFSD [129], DES [46], and SIP [3]). We report the mean values of S_α and MAE across the five datasets (*i.e.*, STERE [128], NLPR [48], LFSD [129], DES [46], and SIP [3]) in each model. Note that these better models are shown in the upper left corner (*i.e.*, with a larger S_α and smaller MAE).

where β^2 is set to 0.3 to emphasize the precision.

• **PR Curve**. As proposed in [56], a saliency map S is divided using different thresholds (*i.e.*, it changes from 0 to 255). For each threshold, we first calculate a pair of recall and precision scores, and then combine them to obtain a precision-recall curve that describes the performance of the model at the different thresholds.

B. Performance Comparison and Analysis

1) Overall Evaluation: To quantify the performance of different models, we conduct a comprehensive evaluation of 24 representative RGB-D based SOD models, including 1) 9 traditional methods: LHM [48], ACSD [53], DESM [46], GP [47], LBE [54], DCMC [1], SE [2], CDCP [81], CDB [92]; and 2) 15 deep learning-based methods: DF [49], PCF [89], CTMF [55], CPFP [50], TANet [96], AFNet [99], MMCI [52], DMRA [51], D3Net [3], SSF [4], A2dele [5], S2MA [6], ICNet [7], JL-DCF [8], and UC-Net [9]. We report the mean values of S_α and MAE across the five datasets (STERE [128], NLPR [48] , LFSD [129], DES [46], and SIP [3]) for each model in Fig. 5. It is worth noting that better models are shown in the upper left corner (*i.e.*, with a larger S_α and smaller MAE). From Fig. 5, we have following observations:

- **Traditional vs. Deep Models**. Compared with traditional RGB-D based SOD models, deep learning models obtain significantly better performance. This confirms the powerful feature learning ability of deep networks.
- **Comparison of Deep Models**. Among the deep learning-based models, D^{3}Net [3], JL-DCF [8], UC-Net [9], SSF [4], ICNet [7], and S^{2}MA [6] obtain better performance than other deep models.

Moreover, Fig. 6 and Fig. 7 show the PR and F-measure curves of the 24 representative RGB-D based SOD models on eight datasets (*i.e.*, STERE [128], NLPR [48], LFSD [129], DES [46], SIP [3], GIT [44], SSD [82] , and NJUD [53]). Note that, there are 1000, 300, 100, 135, 929, 80, and 80 samples as testing for the NLPR, LFSD, DES, SIP, GIT, and SSD, respectively. For the NJUD [53] dataset, there are 485 images as testing for CPFP [50], S2MA [6], ICNet [7], JL-DCF [8], and UC-Net [9], while 498 testing images for all other models.

2) Attribute-based Evaluation: To investigate the influence of different factors, such as object scale, background clutter, numbers of salient objects, indoor or outdoor scene, background objects, and lighting conditions, we carry out diverse attribute-based evaluations on the performance of representative RGB-D based SOD models.

• **Object Scale**. To characterize the scale of a salient object area, we compute the ratio between the size of the salient area adn the whole image. We define three types of object scales: 1) when the ratio is less than 0.1, it is denoted as "small"; 2) when the ratio is larger than 0.4, it is denoted as "big"; and 3) when the ratio is in the range of $[0.1, 0.4]$, it is denoted as "medium". In this evaluation, we build a hybrid dataset with 2464 images collected from STERE [128], NLPR [48] , LFSD [129], DES [46], and SIP [3], where 24%, 69.2% and 6.8% of images have small, medium, and big salient object areas, respectively. The constructed hybrid dataset can be found at https://github.com/taozh2017/RGBD-SODsurvey. The comparison results of the attribute-based study *w.r.t.* object scale are shown in Tab. VIII. From the results, it can be observed that all comparison methods obtain better performance in detecting small salient objects (or object areas) while they obtain relatively worse performance in detecting big salient objects. Besides, the three most recent models, *i.e.*, JL-DCF [8], UC-Net [9], and S2MA [6], obtain the best performance. D3Net [3], SSF [4], A2dele [5], and ICNet [7] also obtain promising performance.

• **Background Clutter**. It is difficult to directly characterize background clutter. Since classic SOD methods tend to use prior information or color contrast to locate salient objects, they often fail under complex backgrounds. Thus, in this

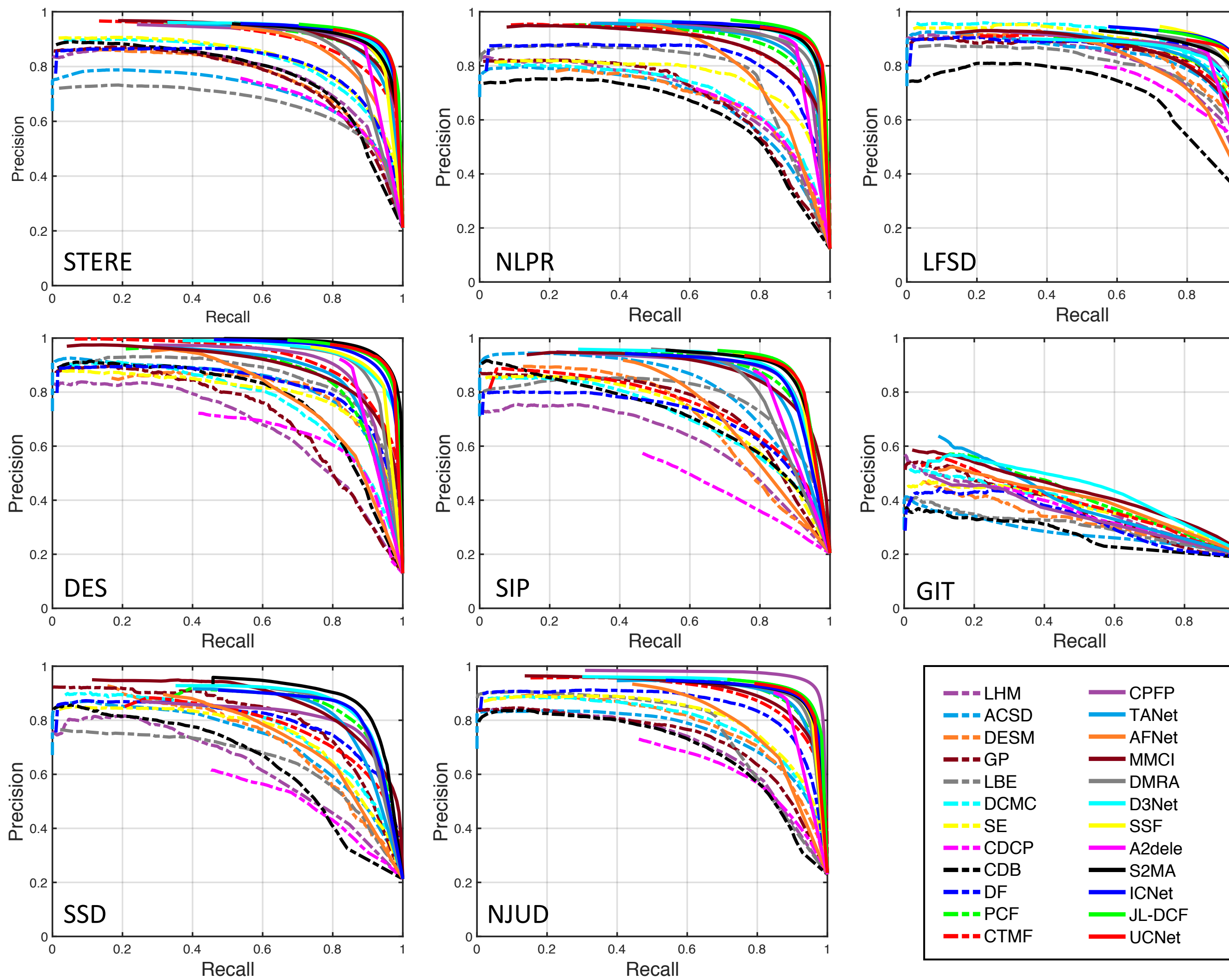

Fig. 6. PR curves for 24 RGB-D based models on STERE [128], NLPR [48], LFSD [129], DES [46], SIP [3], GIT [44], SSD [82] , and NJUD [53] datasets.

TABLE VIII

ATTRIBUTE-BASED STUDY *w.r.t.* SALIENT OBJECT SCALES. COMPARISON RESULTS FOR 24 REPRESENTATIVE RGB-D BASED SOD MODELS (9 TRADITIONAL MODELS AND 15 DEEP LEARNING MODELS) ARE PROVIDED IN TERMS OF MAE AND S_α. THE THREE BEST RESULTS ARE SHOWN IN RED, BLUE AND GREEN FONTS.

		Traditional models									Deep learning models														
	Scale	LHM [48]	ACSD [53]	DESM [46]	GP [47]	LBE [54]	DCMC [1]	SE [2]	CDCP [81]	CDB [92]	DF [49]	PCF [89]	CTMF [55]	CPFP [50]	TANet [96]	AFNet [99]	MMCI [52]	DMRA [51]	D3Net [3]	SSF [4]	A2dele [5]	S2MA [6]	ICNet [7]	JL-DCF [8]	UC-Net [9]
MAE	Small	.065	.149	.319	.098	.177	.108	.056	.128	.073	.087	.042	.065	.044	.041	.046	.051	.030	.033	.031	.032	.035	.036	.032	.034
	Medium	.178	.183	.287	.180	.210	.158	.150	.173	.179	.152	.068	.107	.055	.067	.095	.079	.069	.053	.045	.054	.052	.052	.041	.042
	Big	.403	.311	.310	.377	.261	.305	.364	.308	.385	.310	.112	.183	.093	.118	.213	.130	.181	.102	.105	.114	.088	.104	.085	.072
	Overall	.166	.184	.296	.173	.206	.156	.142	.171	.167	.147	.065	.102	.055	.065	.091	.076	.067	.052	.046	.053	.051	.052	.041	.042
S_α	Small	.624	.668	.517	.650	.645	.700	.775	.661	.666	.745	.847	.789	.840	.846	.792	.832	.860	.879	.876	.859	.877	.882	.881	.883
	Medium	.543	.732	.658	.598	.723	.727	.676	.683	.585	.730	.863	.805	.877	.862	.779	.859	.838	.888	.893	.865	.893	.892	.906	.901
	Big	.386	.630	.686	.450	.731	.604	.479	.586	.424	.597	.838	.761	.855	.827	.682	.830	.734	.846	.837	.815	.863	.845	.859	.876
	Overall	.552	.710	.626	.601	.705	.712	.686	.671	.593	.725	.857	.798	.867	.856	.776	.851	.836	.883	.885	.860	.887	.886	.897	.895

evaluation, we utilize five traditional SOD methods, *i.e.*, BSCA [149], CLC [150], MDC [151], MIL [152], and WFD [153], to first detect salient objects in various images and then group these images into different categories (*e.g.*, simple or complex background) according to the results. Specifically, we first construct a hybrid dataset with 1400 images collected from three datasets (STERE [128], NLPR [48], and LFSD [129]). Then, we conduct the five models on this dataset and

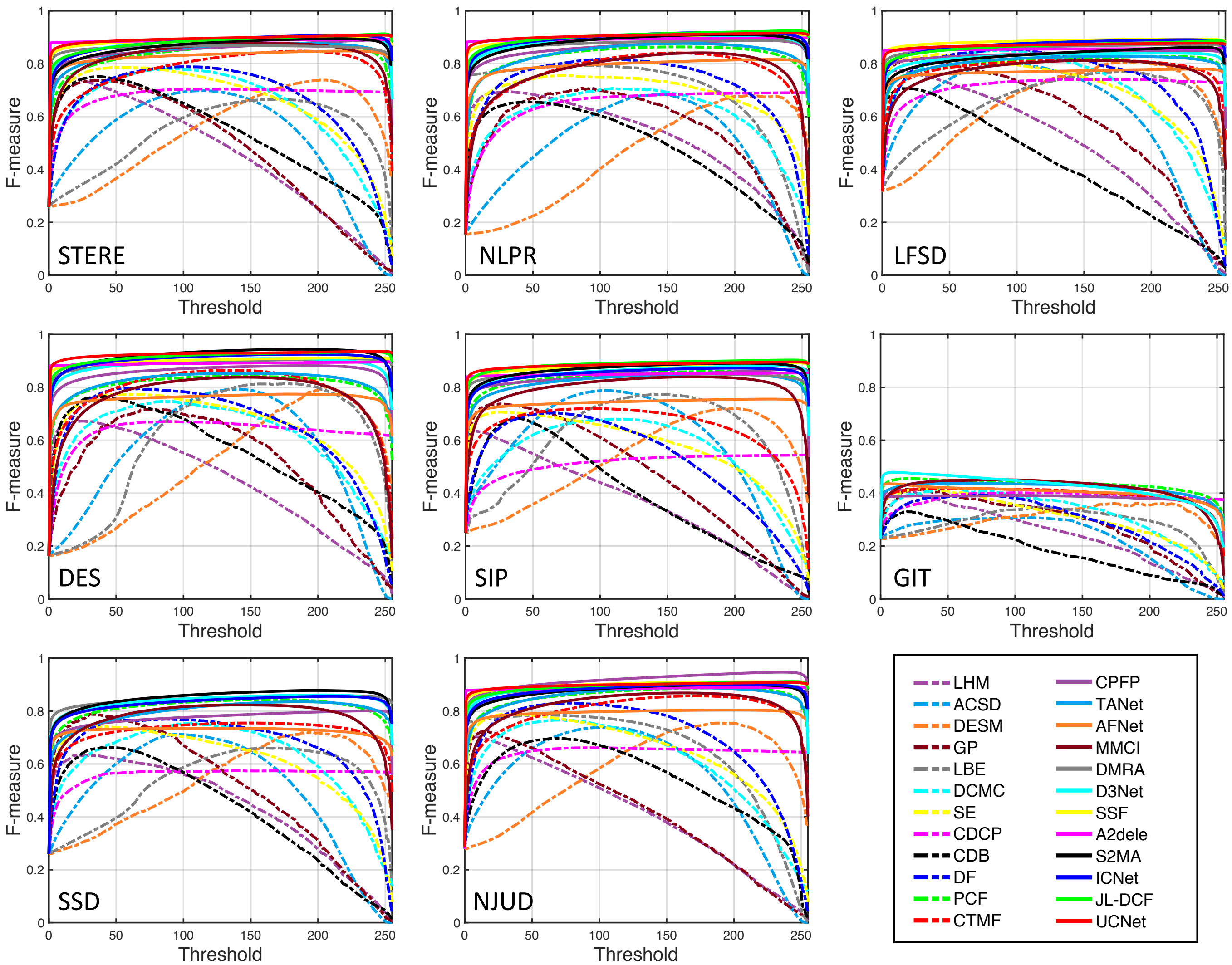

Fig. 7. F-measures under different thresholds for 24 RGB-D based models on STERE [128], NLPR [48], LFSD [129], DES [46], SIP [3], GIT [44], SSD [82] , and NJUD [53] datasets.

TABLE IX

ATTRIBUTE-BASED STUDY *w.r.t.* BACKGROUND CLUTTER. COMPARISON RESULTS FOR 24 REPRESENTATIVE RGB-D BASED SOD MODELS (9 TRADITIONAL MODELS AND 15 DEEP LEARNING MODELS) ARE PROVIDED IN TERMS OF MAE AND S_α. THE THREE BEST RESULTS ARE SHOWN IN RED, BLUE AND GREEN FONTS.

		Traditional models									**Deep learning models**														
	background	LHM [48]	ACSD [53]	DESM [46]	GP [47]	LBE [54]	DCMC [1]	SE [2]	CDCP [81]	CDB [92]	DF [49]	PCF [89]	CTMF [55]	CPFP [50]	TANet [96]	AFNet [99]	MMCI [52]	DMRA [51]	D3Net [3]	SSF [4]	A2dele [5]	S2MA [6]	ICNet [7]	JL-DCF [8]	UC-Net [9]
MAE	Simple	.100	.163	.219	.150	.202	.056	.084	.028	.136	.045	.031	.053	.018	.033	.031	.041	.028	.017	.012	.010	.016	.013	.014	.013
	Uncertain	.164	.195	.294	.175	.210	.140	.133	.139	.159	.129	.062	.081	.050	.059	.075	.070	.058	.045	.043	.043	.049	.041	.037	.037
	Complex	.159	.190	.349	.180	.205	.190	.147	.236	.143	.163	.085	.110	.079	.077	.108	.094	.087	.071	.065	.070	.072	.079	.063	.065
	Overall	.160	.193	.295	.174	.209	.140	.132	.141	.157	.127	.063	.082	.051	.059	.076	.070	.059	.046	.043	.043	.049	.043	.038	.038
S_α	Simple	.781	.787	.761	.694	.748	.930	.856	.941	.704	.944	.944	.913	.958	.937	.922	.933	.935	.960	.966	.965	.965	.969	.961	.962
	Uncertain	.572	.694	.638	.606	.695	.736	.723	.727	.610	.774	.873	.853	.882	.873	.818	.868	.854	.900	.894	.884	.895	.910	.909	.907
	Complex	.496	.627	.509	.545	.616	.577	.605	.487	.575	.627	.782	.742	.787	.790	.694	.768	.751	.822	.815	.786	.813	.808	.829	.833
	Overall	.576	.693	.633	.606	.691	.732	.720	.718	.612	.770	.869	.847	.878	.869	.813	.863	.850	.896	.891	.879	.892	.904	.904	.904

obtain the S_α values for each, which we use to characterize images as follows: 1) If all S_α values are more than 0.9, the image is denoted as having a "simple" background; 2) If all S_α values are less than 0.6, the image is said to have a "complex" background; 3) The remaining images are denoted as "uncertain". Some example images with the three types of background clutter are shown in Fig. 8. The constructed hybrid dataset can be found at https://github.com/taozh2017/RGBD-

TABLE X

ATTRIBUTE-BASED STUDY *w.r.t.* BACKGROUND OBJECTS (*i.e.*, CAR, BARRIER, FLOWER, GRASS, ROAD, SIGN, TREE, AND OTHER). THE COMPARISON METHODS INCLUDING 24 REPRESENTATIVE RGB-D BASED SOD MODELS (9 TRADITIONAL MODELS AND 15 DEEP LEARNING MODELS) EVALUATED ON THE SIP DATASET [3] IN TERMS OF MAE AND S_α. THE THREE BEST RESULTS ARE SHOWN IN RED, BLUE AND GREEN FONTS.

		Traditional models									**Deep learning models**														
	Categories	LHM [48]	ACSD [53]	DESM [46]	GP [47]	LBE [54]	DCMC [1]	SE [2]	CDCP [81]	CDB [92]	DF [49]	PCF [89]	CTMF [55]	CPFP [50]	TANet [96]	AFNet [99]	MMCI [52]	DMRA [51]	D3Net [3]	SSF [4]	A2dele [5]	S2MA [6]	ICNet [7]	JL-DCF [8]	UC-Net [9]
MAE	Car	.158	.163	.301	.159	.201	.185	.154	.202	.171	.171	.085	.134	.094	.084	.101	.093	.069	.061	.063	.078	.055	.067	.058	.057
	Barrier	.197	.177	.308	.180	.201	.196	.176	.251	.203	.202	.073	.149	.060	.078	.128	.089	.093	.068	.054	.074	.057	.075	.052	.053
	Flower	.105	.122	.306	.099	.186	.158	.063	.141	.101	.132	.091	.075	.133	.100	.090	.081	.046	.095	.107	.051	.104	.025	.054	.075
	Grass	.164	.161	.279	.155	.184	.167	.138	.182	.176	.167	.041	.110	.035	.048	.088	.059	.056	.037	.030	.046	.033	.043	.023	.029
	Road	.189	.167	.281	.176	.187	.181	.164	.225	.189	.169	.070	.140	.054	.072	.125	.078	.093	.059	.049	.072	.050	.065	.045	.044
	Sign	.107	.126	.268	.110	.184	.126	.079	.134	.118	.096	.058	.101	.063	.060	.077	.083	.051	.055	.051	.054	.048	.054	.050	.057
	Tree	.192	.193	.310	.190	.241	.194	.183	.230	.219	.205	.083	.157	.083	.091	.132	.109	.106	.083	.067	.074	.092	.097	.063	.071
	Other	.246	.217	.329	.224	.229	.216	.229	.274	.233	.233	.106	.177	.111	.111	.170	.124	.140	.095	.083	.099	.100	.100	.084	.086
	Overall	.184	.172	.298	.173	.200	.186	.164	.224	.192	.185	.071	.139	.064	.075	.118	.086	.085	.063	.053	.070	.057	.069	.049	.051
S_α	Car	.516	.731	.590	.603	.714	.671	.591	.613	.546	.631	.811	.726	.786	.807	.736	.813	.817	.856	.845	.804	.870	.846	.855	.859
	Barrier	.497	.727	.609	.575	.728	.672	.612	.553	.552	.643	.837	.698	.860	.831	.708	.830	.792	.855	.874	.821	.871	.848	.876	.875
	Flower	.477	.775	.573	.673	.703	.707	.772	.667	.639	.750	.771	.738	.714	.760	.688	.785	.824	.789	.768	.845	.804	.901	.856	.811
	Grass	.537	.756	.643	.605	.760	.728	.683	.672	.559	.672	.908	.770	.908	.899	.780	.888	.876	.917	.924	.878	.928	.910	.939	.924
	Road	.521	.739	.634	.598	.751	.685	.641	.595	.576	.680	.851	.722	.871	.848	.705	.847	.807	.873	.885	.832	.885	.868	.889	.892
	Sign	.578	.786	.634	.628	.719	.745	.761	.714	.615	.757	.855	.756	.833	.857	.771	.818	.848	.849	.849	.842	.871	.861	.859	.840
	Tree	.505	.699	.606	.577	.661	.648	.600	.588	.543	.625	.802	.679	.804	.778	.691	.779	.748	.806	.837	.807	.800	.788	.848	.825
	Other	.460	.687	.594	.532	.706	.669	.563	.554	.542	.600	.786	.677	.774	.782	.647	.790	.722	.800	.828	.785	.809	.799	.821	.823
	Overall	.511	.732	.616	.588	.727	.683	.628	.595	.557	.653	.842	.716	.850	.835	.720	.833	.806	.860	.874	.828	.872	.854	.880	.875

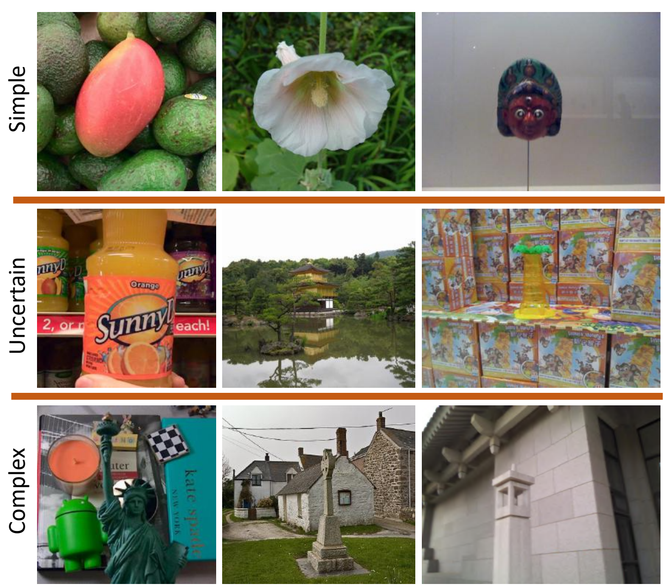

Fig. 8. Sampling images from three types of background cluster.

SODsurvey. The comparison results of attribute-based study *w.r.t.* background clutter are shown in Tab. IX. As can be seen from the results, all models obtain worse SOD performance on images containing complex backgrounds than simple ones. Among the representative models, JL-DCF [8], UC-Net [9] and SSF [4] achieve top-three best results. Besides, the four most recent models, *i.e.*, D3Net [3], S2MA [6], A2dele [5], and ICNet [7] also obtain relatively better performance than the other models.

- **Single vs. Multiple Objects**. In this evaluation, we construct a hybrid dataset with 1229 images collected from the NLPR [48] and SIP [3] datasets. The comparison results are shown in Fig. 9. From the results, we can see that it is easier to detect single salient object than multiple ones.
- **Indoor vs. Outdoor**. We evaluate the performance of different RGB-D based SOD models on indoor and outdoor scenes. In this evaluation, we construct a hybrid dataset collected from the DES [46], NLPR [48], and LFSD [129] datasets. The comparison results of attribute-based study *w.r.t.* indoor vs. outdoor are shown in Fig. 10. From the results, it can be seen that most models difficultly detect salient objects on indoor scene than outdoor ones. This is possibly because indoor environments often suffer from uncertain light conditions.
- **Background Objects**. We evaluate the performance of the RGB-D based SOD models when different background objects are present. We use SIP dataset [3], and split it into nine categories, *i.e.*, car, barrier, flower, grass, road, sign, tree, and other. The comparison results are shown in Tab. X. As can be seen, all methods obtain diverse performances under different background objects. Among the 24 representative RGB-D based models, JL-DCF [8], UC-Net [9] and SSF [4] achieve the top-three best results. In addition, the four most recent models, *i.e.*, D3Net [3], S2MA [6], A2dele [5], and ICNet [7] obtain relatively better performance than the others.
- **Lighting Conditions**. The performance of SOD can be affected by different lighting conditions. To determine the performance of different RGB-D based SOD models under different lighting conditions, we conduct an evaluation on

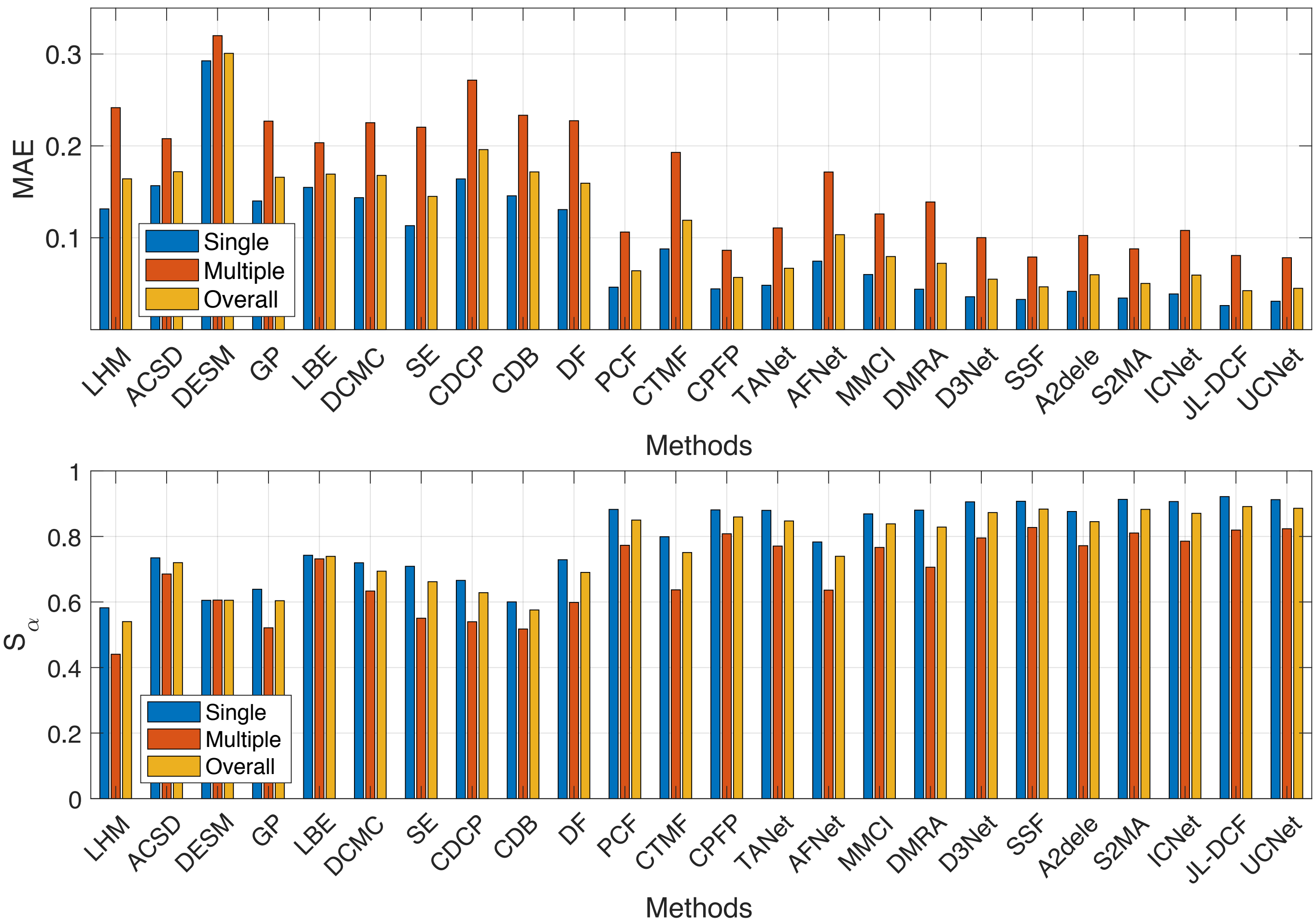

Fig. 9. Attribute-based study *w.r.t.* number of salient object(s) (*i.e.*, single vs. multiple (multi)). The comparison results on 24 representative RGB-D based SOD models (*i.e.*, LHM [48], ACSD [53], DESM [46], GP [47], LBE [54], DCMC [1], SE [2], CDCP [81], CDB [92], DF [49], PCF [89], CTMF [55], CPFP [50], TANet [96], AFNet [99], MMCI [52], DMRA [51], D3Net [3], SSF [4], A2dele [5], S2MA [6], ICNet [7], JL-DCF [8], and UC-Net [9]) in terms of MAE (top) and S_α (bottom) metrics.

TABLE XI
ATTRIBUTE-BASED STUDY *w.r.t.* LIGHT CONDITIONS (SUNNY VS. LOW-LIGHT). THE COMPARISON METHODS INCLUDING 24 REPRESENTATIVE RGB-D BASED SOD MODELS (9 TRADITIONAL MODELS AND 15 DEEP LEARNING MODELS) EVALUATED ON THE SIP DATASET [3] IN TERMS OF MAE AND S_α. THE THREE BEST RESULTS ARE SHOWN IN RED, BLUE AND GREEN FONTS.

		Traditional models									**Deep learning models**														
	Conditions	LHM [48]	ACSD [53]	DESM [46]	GP [47]	LBE [54]	DCMC [1]	SE [2]	CDCP [81]	CDB [92]	DF [49]	PCF [89]	CTMF [55]	CPFP [50]	TANet [96]	AFNet [99]	MMCI [52]	DMRA [51]	D3Net [3]	SSF [4]	A2dele [5]	S2MA [6]	ICNet [7]	JL-DCF [8]	UC-Net [9]
MAE	Sunny	.182	.171	.294	.171	.200	.183	.160	.218	.190	.181	.069	.137	.062	.075	.116	.085	.083	.062	.052	.068	.057	.068	.048	.051
	Low-light	.198	.178	.323	.187	.201	.207	.193	.268	.208	.211	.078	.154	.073	.076	.130	.091	.103	.067	.059	.080	.058	.081	.059	.055
	Overall	.184	.172	.298	.173	.200	.186	.164	.224	.192	.185	.071	.139	.064	.075	.118	.086	.085	.063	.053	.070	.057	.069	.049	.051
S_α	Sunny	.516	.733	.622	.593	.728	.690	.639	.607	.560	.660	.843	.718	.852	.834	.723	.833	.811	.861	.875	.831	.872	.856	.882	.876
	low-light	.481	.721	.573	.554	.722	.635	.556	.515	.543	.610	.838	.701	.838	.837	.700	.832	.775	.855	.867	.810	.871	.839	.867	.871
	Overall	.511	.732	.616	.588	.727	.683	.628	.595	.557	.653	.842	.716	.850	.835	.720	.833	.806	.860	.874	.828	.872	.854	.880	.875

the SIP dataset [3], which we split it into two categories, *i.e.*, sunny and low-light. The comparison results are shown in Tab. XI. As can be seen, low-light negatively impacts SOD performance. Specifically, UC-Net [9] obtains the best performance under sunny condition while JL-DCF [8] achieves the best result under low-light condition.

In addition, we report the saliency maps generated for various challenging scenes to visualize the performance of different RGB-D based SOD models. Fig. 11 and Fig. 12 show some representative examples using two classic non-deep methods (DCMC [1] and SE [2]) and eight state-of-the-art CNN-based models (DMRA [51], D3Net [3], SSF [4], A2dele [5], S2MA [6], ICNet [7], JL-DCF [8], and UC-Net [9]). The 1^{st} row shows a small object, while 2^{st} row is an example of a big one. The 3^{rd} row and 4^{th} rows contain complex background and boundaries, respectively. The 5^{th} and

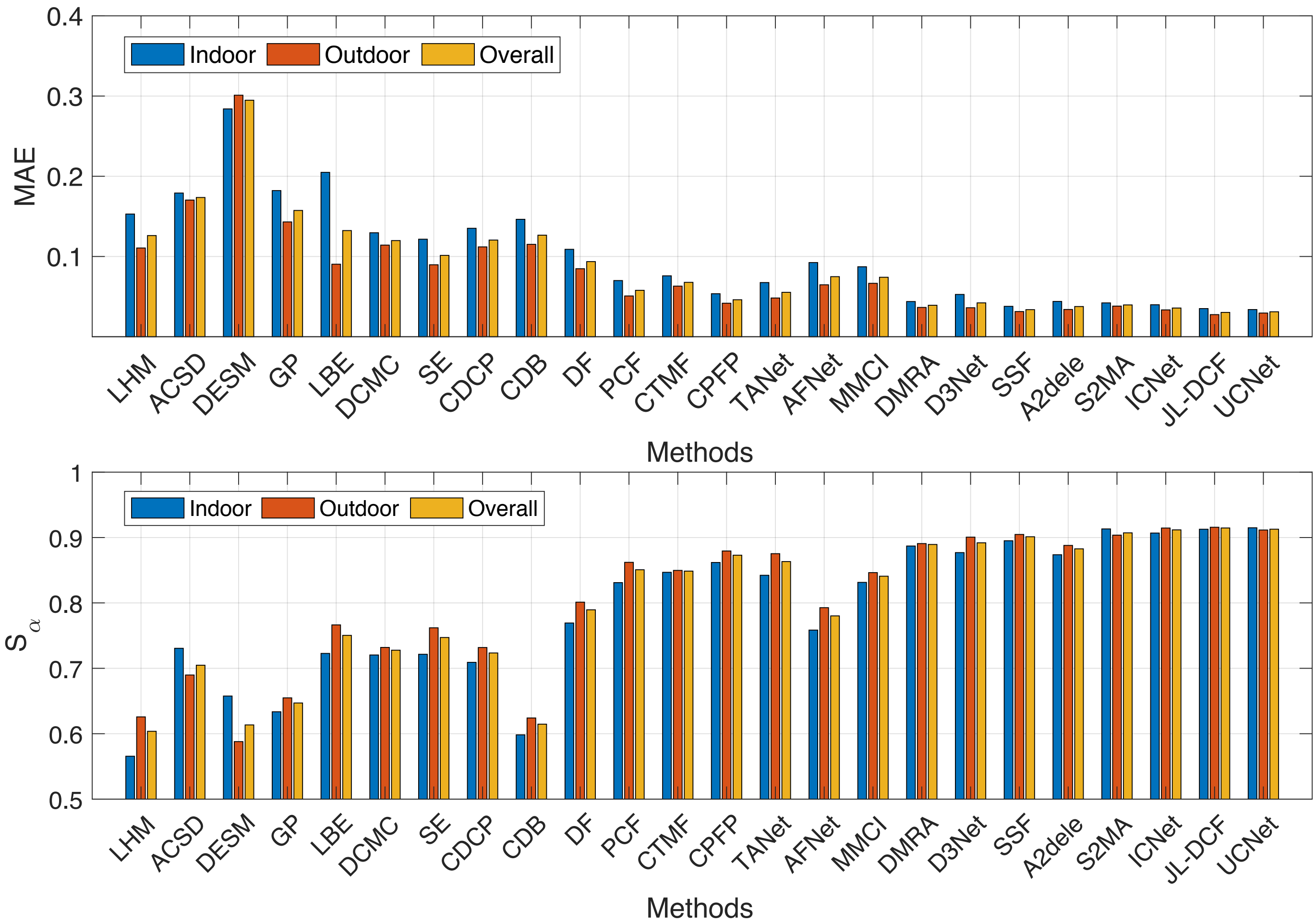

Fig. 10. Attribute-based study *w.r.t.* indoor vs. outdoor environments. The comparison results for 24 representative RGB-D based SOD models (*i.e.*, LHM [48], ACSD [53], DESM [46], GP [47], LBE [54], DCMC [1], SE [2], CDCP [81], CDB [92], DF [49], PCF [89], CTMF [55], CPFP [50], TANet [96], AFNet [99], MMCI [52], DMRA [51], D3Net [3], SSF [4], A2dele [5], S2MA [6], ICNet [7], JL-DCF [8], and UC-Net [9]) are provided in terms of MAE (top) and S_α (bottom).

6^{th} rows contain multiple salient objects. In the 7^{th} row, there is low-light condition. In the 8^{th} row, the depth map is coarse with very inaccurate object boundaries, which could inhibit the SOD performance. From the results in Fig. 11 and Fig. 12, it can be observed that deep models perform better than non-deep models on these challenging scenes, confirming the powerful expression ability of deep features over handcrafted ones. In addition, D3Net [3], S2MA [6], JL-DCF [8], and UC-Net [9] perform better than other deep models.

VI. Challenges and Open Directions

A. *Effects of Imperfect Depth*

Effects of Low-quality Depth Maps. Depth maps with affluent spatial information have been proven beneficial in detecting salient objects from cluttered backgrounds, while the depth quality directly affects the subsequent SOD performance. The quality of depth maps varies tremendously across different scenarios due to limitations of depth Sensors, posing a challenge when trying to reduce the effects of low-quality depth maps. However, most existing methods directly fuse RGB images and original raw data from depth maps, without considering the effects of low-quality depth maps. There are a few notable exceptions. For example, in [50], a contrast enhanced network was proposed to learn enhanced depth maps, which have much higher contrasts compared with the original depths. In [4], a compensation-aware loss was designed to pay more attention to some hard samples containing unreliable depth information. Moreover, D^{3}Net [3] uses a depth depurator unit (DDU) to classify depth maps into two classes (*i.e.*, reasonable and low-quality). The DDU also acts as a gate that can filter out the low-quality depth maps. However, the above methods often employ a two-step strategy to achieve depth enhancement and multi-modal fusion [4], [50] or an independent gate operation for filtering out poor depths, which could bring a suboptimal problem. There is thus a need to develop an end-to-end framework that can achieve depth enhancement or adaptively weight the depth maps (*e.g.*, assigns low weights for poor depth maps) during multi-modal fusion, which would be more helpful for reducing the effects of low-quality depth maps and boosting SOD performance.

Incomplete Depth Maps. In RGB-D datasets, it is inevitable for there to be some low-quality depth maps due to the limitations of the acquisition devices. As previously discussed, several depth enhancement algorithms have been used to improve the quality of depth maps. However, when

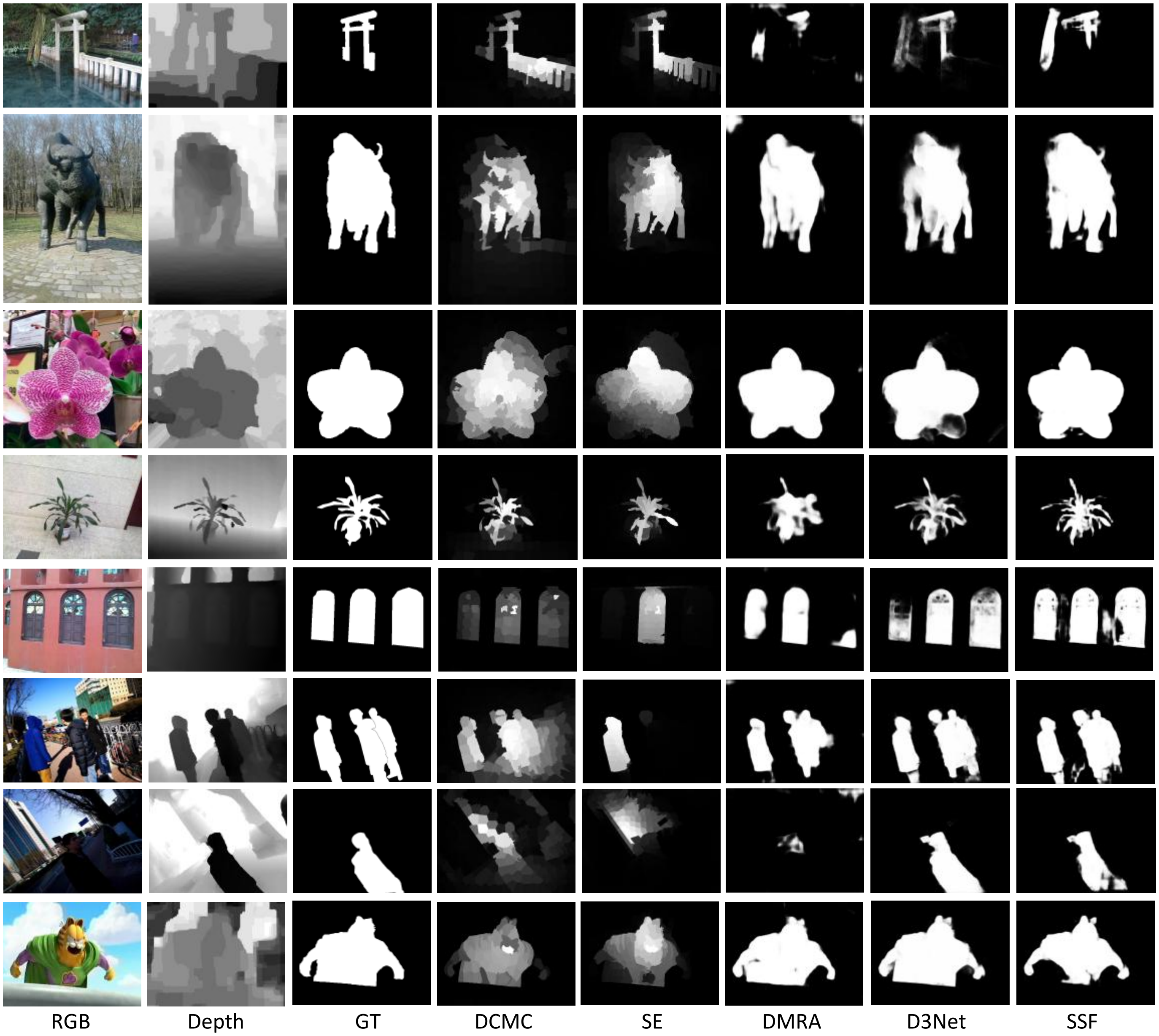

Fig. 11. Visual comparisons for two classical non-deep methods (DCMC [1] and SE [2]) and three state-of-the-art CNN-based models (DMRA [51], D3Net [3], SSF [4]).

some depth maps suffer from severe noise or blurred edges, these depth maps could be discarded. In this case, we have complete RGB images but some samples without having depth maps, which is similar to the incomplete multi-view/modal learning problem [154]–[158]. Thus, we call it "incomplete RGB-D based SOD". As current models only focus on the SOD task using complete RGB images and depth maps, we believe this could be a new direction for RGB-D SOD.

Depth Estimation. Furthermore, depth estimation provides an effective solution to recovery high-quality depths and overcome the effects of low-quality depth maps. Various depth estimation approaches [159]–[162] have been developed, which could be introduced into the RGB-D based SOD task to improve performance.

B. Effective Fusion Strategies

Adversarial Learning-based Fusion. It is important to effectively fuse RGB images and depth maps for RGB-D based SOD. Existing models often employ different fusion strategies (*e.g.*, early fusion, middle fusion, or late fusion) to exploit the correlations between RGB images and depth maps. Recently, generative adversarial networks (GANs) [163] have gained widespread attention for the salient detection task [164], [165]. In common GAN-based SOD models, a generator takes RGB images as inputs and generates the corresponding saliency maps, while a discriminator is adopted to distinguish whether a given image is synthetic or ground-truth. GAN-based model could easily be extended to RGB-D SOD, which could be helpful for boosting performance due to their superior feature learning ability. Moreover, GANs could also be used to

Fig. 12. Visual comparisons for five state-of-the-art CNN-based models (A2dele [5], S2MA [6], ICNet [7], JL-DCF [8], and UC-Net [9]).

learn the common feature representations for RGB images and depth maps [116], which could help with feature or saliency map fusion and further boost the SOD performance.

Attention-induced Fusion. Attention mechanisms have been widely applied to various deep learning-based tasks [166]–[169], allowing networks to selectively pay attention to a subset of regions for extracting discriminative and powerful features. Besides, co-attention mechanisms have been developed to explore the underlying correlations across multiple modalities, and are widely studied in visual question answering [170], [171] and video object segmentation [172]. Thus, for RGB-D based SOD task, we could also develop attention-based fusion algorithms to exploit correlations between RGB images and depth cues to improve the performance.

C. Different Supervision Strategies

Existing RGB-D models often used a fully supervised strategy to learn saliency prediction models. However, annotating pixel-level saliency maps is a tedious and time-consuming procedure. To alleviate this issue, there has been increased interest in weakly and semi-supervised learning, which have been applied to salient object detection [173]–[177]. Semi-/weak supervision could also be introduced into RGB-D SOD, by leveraging image-level tags [173] and pseudo pixel-wise annotations [176], [178], for improving the detection performance. Besides, several studies [179], [180] have suggested that models pretrained using self-supervision can effectively be used for achieving better performance. Therefore, we could train saliency prediction models on large amounts of annotated RGB images in a self-supervised manner and then transfer the pretrained models to the RGB-D SOD task.

D. Dataset Collection

Large-scale. Although there are nine public RGB-D datasets for SOD, there size is quite limited, *e.g.*, the maximum size is about 2000 samples for NJUD [53]. When compared with other RGB-D datasets for generic object detection or action recognition [181], [182], the size of RGB-D datasets for SOD is also very small. Thus, it is essential to develop new large-scale RGB-D datasets that can serve as baselines for future research.

Complex Background & Task-driven. Most existing RGB-D datasets collect images that contain one salient object or multiple objects but with a relatively clean background. However, real-world applications often suffer from much more complicated situations (*e.g.*, occlusion, appearance change, low illumination, etc), which could decrease the SOD performance. Thus, collecting images with complex background is critical to improve the generalization ability of RGB-D SOD models. Moreover, for some tasks, images with specific salient object(s) must be collected. For example, one important technology is road sign recognition in driver assistance system, which requires images with road signs to be collected. Thus, it is essential to construct task-driven RGB-D datasets like SIP [3].

E. Model Design for Real-world Scenarios

Some smartphones can capture depth maps (*e.g.*, images in the SIP dataset were captured using Huawei Mate 10). Thus it would be feasible to conduct the SOD task in real-world applications, *e.g.*, on smart devices. However, most existing methods include complicated and deep DNNs to increase the model capacity and achieve better performance, preventing them for being directly applied to real-work platforms. To overcome this, model compression [183], [184] techniques could be used to learn compact RGB-D based SOD models with promising detection accuracy. Moreover, JL-DFC utilizes a shared network to locate salient objects using RGB and depth views, which largely reduces the model parameters and makes real-world applications feasible.

F. Extension to RGB-T SOD

In addition to RGB-D SOD, there are several other methods fusing different modalities for better detection, such as RGB-T SOD, which integrates RGB and thermal infrared data. Thermal infrared cameras can capture the radiation emitted from any object with a temperature above absolute zeros, making thermal infrared images insensitive to illumination conditions [185]. Therefore, thermal images can provide supplementary information to improve SOD performance when salient objects suffer from varying light, reflective light, or shadows. Some RGB-T models [185]–[193] and datasets (VT821 [187], VT1000 [191] and VT5000 [193]) have already been proposed over the past few years. Similar to RGB-D SOD, the key aim of RGB-T SOD is to fuse RGB and thermal infrared images and exploit the correlations between the two modalities. Thus, several advanced multi-modal fusion technologies in RGB-D SOD could be extended to the RGB-T SOD task.

VII. Conclusion

In this paper, to the best of our knowledge, we present the first comprehensive review of RGB-D based SOD models. We first review the models from different perspectives, and then summarize popular RGB-D SOD datasets as well as provide details for each. Considering that the light field also provides depth information, we also review popular light field SOD models and the related benchmark datasets. Next, we provide a comprehensive evaluation of 24 representative RGB-D based SOD models as well as an attribute-based evaluation. Specifically, we perform attribute-based performance analysis by constructing new datasets for the 24 representative RGB-D based SOD models. Moreover, we discuss several challenges and highlight open directions for future research. In addition, we briefly discuss the extension work to RGB-T SOD to improve performance when salient objects suffer from varying light, reflective light, or shadows. Although RGB-D based SOD has made notable progress in the past several decades, there is still significant room for improvement. We hope this survey will generate more interest works in RGB-D based SOD.

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