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 the challenges in this field 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 the fact that light fields 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 and conduct an 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 have been made publicly available at https://github.com/taozh2017/RGBD-SODsurvey.

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

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], image retrieval [29], etc. Although significant progress has been made in the SOD field over the past several years [30]–[36], [36]–[44], there is still room for improvement when faced with 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], [45]. Early RGB-D based SOD models tended to extract handcrafted features and then fuse RGB image and depth maps. For example, Lang *et al.* [46], the first work on RGB-D based SOD, utilized Gaussian mixture models to model the distribution

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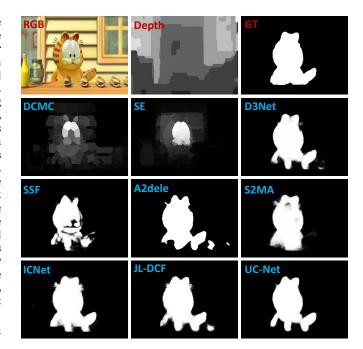


Fig. 1. RGB-D based salient object prediction on a sample image using two classic non-deep models (*i.e.*, DCMC [1] and SE [2]) and seven state-of-the-art deep models (*i.e.*, D³Net [3], SSF [4], A2dele [5], S²MA [6], ICNet [7], JL-DCF [8], and UC-Net [9]).

of depth-induced saliency. Ciptadi et al. [47] extracted 3D layout and shape features from depth measurements. Besides, several methods [48], [49], [49], [50] measure depth contrast using the depth difference between different regions. In [51]. 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 highlevel reasoning required for complex scenes. To address these limitations, several deep learning-based RGB-D SOD methods [3] have been developed, showing improved performance. DF [52] 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], [53]–[55] have focused on exploiting effective multi-modal correlations and multiscale/level information to boost SOD performance. To more clearly describe the progress in the RGB-D based SOD field, we provide a brief chronology in Fig. 2.

In this paper, we provide a comprehensive survey on RGB-D based SOD, aiming 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

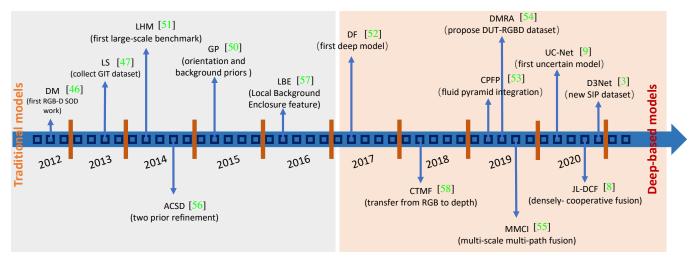


Fig. 2. A brief chronology of RGB-D based SOD. The first early RGB-D based SOD work was the DM [46] model, proposed in 2012. Deep learning techniques have been widely applied to RGB-D based SOD since 2017. More details can be found in § II.

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 discuss their main advantages.

A. Related Reviews and Surveys

There are several surveys that are closely related to salient object detection. For example, Borji et al. [59] provided a quantitative evaluation of 35 state-of-the-art non-deep saliency detection methods. Cong et al. [60] reviewed several different saliency detection models, including RGB-D based SOD, co-saliency detection, and video SOD. Zhang et al. provided an overview of co-saliency detection and reviewed its history, and summarized several benchmark algorithms in this field. Han et al. [62] reviewed the recent progress in SOD, including models, benchmark datasets, and evaluation metrics, as well as discussed the underlying connection among general object detection, SOD, and category-specific object detection. Nguyen et al. [63] reviewed various works related to saliency applications and provided insightful discussions on the role of saliency in each. Borji et al. [64] provided a comprehensive review of recent progress in SOD and discussed 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 stateof-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. [65] reviewed various deep learning-based object detection models and algorithms in detail, as well as various specific tasks, including SOD works. Wang et al. [66] 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 datasets.

B. Contributions

Our 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/multistream methods, and attention-aware methods.
- We review nine RGB-D datasets that are commonly used in this field, and 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, and the relation between SOD and other topics, shedding light on potential directions for future research.

C. Organization

In § II, we review existing RGB-D based models in terms of 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 different perspectives as follows. (1) **Traditional/deep models**: they are viewed from the perspective of feature extraction, that is using the manual features or deep features. It is convenient

for follow-up researchers to grasp the historical development trends of RGB-D SOD models. (2) **Fusion-wise models**: it is critical to effectively fuse RGB and depth images in this task, thus we review different fusion strategies to understand their effectiveness. (3) **Single-stream/multi-stream models**: we consider this problem from the perspective of model parameters. Single stream can save parameters, but the final result may not be optimal, and multiple streams may require more parameters. Thus, it is helpful to understand the balance between the amount of calculation and accuracy of different models. (4) **Attention-aware models**: attention mechanisms have widely been applied in various visual tasks including SOD. We review related works on RGB-D SOD to analyze how do different models use attention. Thus, it is an alternative to design attention modules for future works.

A. Traditional/Deep Models

Traditional Models. With depth cues, several useful attributes, such as boundary cues, shape attributes, surface normals, etc., can be explored 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], [47]–[51], [56], [57], [69]–[71], [75], [82]–[84], [95]. For example, the early work [47] focused on modeling the interaction between layout and shape features generated from the RGB image and depth map. Besides, the representative work [51] 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], [52]–[55], [83], [93], [94], [96]–[108]. 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 detail as follows.

- **DF** [52] 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 [92] presents a complementarity-aware fusion module to integrate cross-modal and cross-level feature representations. It can effectively exploit complementary information by explicitly using cross-modal/level connections and modal/level-wise supervision to decrease fusion ambiguity.
- CTMF [58] employs a computational model to identify salient objects from RGB-D scenes, utilizing CNNs to learn high-level representations for RGB images and depth cues, while simultaneously exploiting the complementary relationships and joint representation. 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** [53] proposes a contrast-enhanced network to produce an enhanced map, and presents a fluid pyramid integration module to effectively fuse cross-modal information in a hierarchical manner. Besides, considering the fact that depth cues tend to suffer from noise, 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 (VAEs) 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 [50], [51], [87], [87], [96]. 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 [52]. 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 [48], [58], [102]. This is denoted as "later feature fusion" (shown in Fig. 3). 2) Two parallel network streams are used to obtain the independent saliency maps for RGB images and depth cues, and then the two saliency maps are concatenated to obtain a final prediction map [115]. 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], [55], [116], [120], [123], [124], [129]. These models can be divided into two categories. The first category learn the cross-modal interactions and then fuse them into a feature learning network. For example, Chen *et al.* [55] developed a multi-scale multi-path fusion network to integrate RGB images and depth maps, with a cross-modal interaction (termed 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 enable complementarity across low-level and high-level representations to be explored. The second category fuse the features from RGB images and depth

#	Year	Method	Pub.	Training Set	Backbone	Description											
1	2012	DM [46]	ECCV	Without	Without	Models the correlation between saliency and depth by approximating the joint density											
1	2012	DM [40]	ECCV	Without	Williout	using Gaussian mixture models											
2	2012	RCM [67]	ICCSE	Without	Without	Develops a region contrast based SOD model with depth cues											
3	2013	LS [47]	BMVC	Without	Without	Extends the dissimilarity framework to model the joint interaction between depth cues and RGB images											
4	2013	RC [48]	BMVC	Withoutt	Without	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 [68]	NEURO	Without	Without	Incorporates depth cues for salient object segmentation by suppressing background regions											
6	2014	SRDS [69]	ICDSP	Without	Without	Integrates depth and depth weighted color contrast with spatial compactness of color distribution											
7	2014	LHM [51]	ECCV	Without	Without	Uses a multi-stage RGB-D algorithm to combine both depth and appearance cues to segment salient objects											
8	2014	DESM [49]	ICIMCS	Without	Without	Combines three saliency cues: color contrast, spatial bias, and depth contrast											
9	2014	ACSD [56]	ICIP	Without	Without	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 [50]	CVPRW	Without	Without	Explores orientation and background priors for detecting salient objects, and uses PageR- ank and MRFs to optimize the saliency maps											
11	2015	SFP [70]	ICIMCS	Without	Without	ut Develops a RGB-D based SOD approach using saliency fusion and propagation											
12	2015	DIC [71]	TVC	Without	Without	utilizes random walk algorithm to infer the object boundary											
13	2015	SRD [72]	ICRA	Without	Without	Designs a graph-based segmentation to identify homogeneous regions using color and depth cues											
14	2015	MGMR [73]	ICIP	Without	Without	ut Designs a mutual guided manifold ranking strategy to achieve SOD											
15	2015	SF [74]	CAC	Without	Without	Proposes to automatically select discriminative features using decision trees for better performance											
16	2016	PRC [75]	ACCESS	Without	Without	Saliency fusion and progressive region classification are used to optimize depth-aware saliency models											
17	2016	LBE [57]	CVPR	Without	Without	Uses a local background enclosure to capture the spread of angular directions											
18	2016	SE [2]	ICME	Without	Without	Utilizes cellular automata to propagate the initial saliency map and then generate the final saliency prediction result											
19	2016	DCMC [1]	SPL	Without	Without	Develops a new measure to evaluate the reliability of depth maps for reducing the influence of poor-quality depth maps on saliency detection.											
20	2016	BF [76]	ICPR	Without	Without	Fuses contrasting features from RGB and depth images with a Bayesian framework											
21	2016	DCI [77]	ICASSP	Without	Without	Adopts the original depth map to subtract the fitted surface for generating a contrast increased map											
22	2016	DSF [78]	ICASSP	Without	Without	Develops a multi-stage depth-aware saliency model for SOD											
23	2016	GM [79]	ACCV	Without	Without	Combines color and depth-based contrast features using a generative mixture model											
† † † Concate	nation	Concat	enation	Concatenation		saliency map Convolution lay Skip connection											
	tr.		Hi			Interaction											

TABLE I Summary of RGB-D based SOD methods (published from 2012 to 2016).

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.

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.

(a) Early fusion

Depth

(b) Late fusion

- ICNet [7] proposes an information conversion module to convert high-level features in an interactive manner. In this model, a cross-modal depth-weighted combination (CDC) block is introduced to enhance RGB features with depth features at different levels.
- **DPANet** [116] uses a gated multi-modality attention (GMA) module to exploit long-range dependencies. The GMA module can extract the most discriminative features by uti-

lizing a spatial attention mechanism. Besides, this 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.

(c) Multi-scale fusion

- **BiANet** [120] employs 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.

Method Pub. Backbone Year Training Set Description HOSO [80] 2017 DICTA Without Without Combines surface orientation distribution contrast with color and depth contrast 25 2017 M³Net [81] NLPR(0.65K). VGG-16 Designs a multi-path multi-modal fusion strategy to integrate RGB and depth images in NJUD(1.4K) a task-motivated and adaptive way 26 MFLN [82] Leverages a CNN to learn high-level representations for depth maps, and uses a multi-2017 **ICCVS** NLPR(0.65K). AlexNet NJUD(1.4K) modal fusion network to integrate RGB and depth representations for RGB-D based SOD 27 ICCVW 2017 BED [83] NLPR(0.6K), GoogleNet Uses a CNN to integrate top-down and bottom-up information for RGB-D based SOD, NJUD(1.2K) and uses a mid-level feature representation to capture background enclosure 28 2017 CDCP [84] **ICCVW** Without Without Proposes a novel RGB-D SOD algorithm using a center dark channel prior to boost performance 29 2017 TPF [85] ICCVW Without Without Leverages stereopsis to generate optical flow, which can provide an additional cue (depth cue) for producing the final detection result Without Without 30 2017 MFF [86] SPL Uses a multistage fusion framework to integrate multiple visual priors from the RGB image and depth cue for SOD 31 MDSF [87] 2017 NLPR(0.5K), Without Proposes a RGB-D SOD framework via a multi-scale discriminative saliency fusion NJUD(1.5K) strategy, and utilizes bootstrap learning to achieve the SOD task 32 2017 DF [52] NLPR(0.75K). Without Feeds RGB and depth features into a CNN architecture to derive the saliency confidence NJUD(1.0K) value, and uses Laplacian propagation to produce the final detection result MCLP [88] 33 2017 TCYB Without Without 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 SIVP ISC [89] Without Without Fuses salient features using both bottom-up and top-down saliency cues 35 HSCS [90] 2018 TMM Without Without Utilizes a hierarchical sparsity reconstruction and energy function refinement for RGB-D based co-saliency detection Without Without 36 2018 ICS [91] TIP Exploits the constraint correlation among multiple images and introduces depth maps into the co-saliency model NLPR(0.65K), 37 CTMF [58] TCYB VGG-16 Transfers the structure of the deep color network to be applicable for the depth modality NJUD(1.4K) and fuses both modalities to produce the final saliency map 38 2018 PCF [92] CVPR NLPR(0.65K) VGG-16 Designs the first multi-scale fusion architecture and a novel complementarity-aware fusion NJUD(1.4K) module to fuse both cross-modal and cross-level features 39 2018 SCDL [93] ICDSF NLPR(0.75K), VGG-16 Designs a new loss function to increase the spatial coherence of salient objects NJUD(1.0K) 40 2018 IROS VGGNet Adaptively selects complementary features from different modalities at each level, and ACCF [94] NLPR(0.65K) NJUD(1.4K) then performs more informative cross-modal cross-level combinations 41 2018 CDB [95] NEURO Without Utilizes a contrast prior and depth-guided-background prior to construct a 3D stereoscopic Without saliency model

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

• **BBS-Net** [129] 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 [52], [53], [83], [87], [93], [96], [97] 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 [87] employs 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 [83] 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 [97] 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 [54], [102], [103] 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], [45], [55], [92], [100], [104], [106], [116], [118] 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], [99] and then design different fusion modules to effectively fuse RGB and depth information in order to exploit their correlations.

D. Attention-aware Models

Existing RGB-D based SOD methods often treat all regions equally 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** [106] captures complementary information from RGB images and depth cues using an interweaved fusion, and weights the saliency regions through a deeply supervised attention mechanism.
- AttNet [103] introduces attention maps for differentiating between salient objects and background regions to reduce the negative influence of some low-quality depth cues.

 $TABLE \; III \\ Summary of RGB-D \; based \; SOD \; models \; published in \; 2019 \; and \; 2020 \\$

No.	Year	Method	Pub.	Training Set	Backbone	Description
42	2019	SSRC [96]	NEURO	NLPR(0.65K), NJUD(1.4K)	VGG-16	Uses a single-stream recurrent convolutional neural network with a four-channel input and DRCNN subnetwork
43	2019	MLF [109]	SPL	NJUD(1.588K)	VGG-16	Designs a salient object-aware data augmentation method to expand the training set
44	2019	TSRN [110]	ICIP	NJUD(1.387K)	VGG-16	Designs a fusion refinement module to integrate output features from different modalities and resolutions
45	2019	DIL [111]	MTAP	NLPR(0.5K), NJUD(0.5K)	Without	Designs a consistency integration strategy to generate an image pre-segmentation result that is consistent with the depth distribution
46	2019	CAFM [112]	TSMC	NUS [46], NCTU [113]	VGG-16	Utilizes a content-aware fusion module to integrate global and local information
47	2019	PDNet [97]	ICME	NLPR(0.5K), NJUD(1.5K)	VGG-16	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 [55]	PR	NLPR(0.65K), NJUD(1.4K)	VGG-16	Improves the traditional two-stream architecture by diversifying the multi-modal fusion paths and introducing cross-modal interactions in multiple layers
49	2019	TANet [99]	TIP	NLPR(0.65K), NJUD(1.4K)	VGG-16	Uses a three-stream multi-modal fusion framework to explore cross-modal complementarity in both the bottom-up and top-down processes
50	2019	DCMF [100]	TCYB	NLPR(0.65K), NJUD(1.4K)	VGG-16	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
51	2019	DGT [101]	TCYB	Without	Without	Exploits depth cues and provides a general transformation model from RGB saliency to RGB-D saliency
52	2019	LSF [45]	arXiv	NLPR(0.65K), NJUD(1.4K)	VGG	Designs an RGB-D system with three key components, including modality- specific representation learning, complementary information selection, and cross- modal complements fusion
53	2019	AFNet [102]	ACCESS	NLPR(0.65K), NJUD(1.4K)	VGG-16	Learns a switch map that is used to adaptively fuse the predicted saliency maps from the RGB and depth modality
54	2019	EPM [114]	ACCESS	Without	Without	Develops an effective propagation mechanism for RGB-D co-saliency detection
55	2019	CPFP [53]	CVPR	NLPR(0.65K), NJUD(1.4K)	VGG-16	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
56	2019	DMRA [54]	ICCV	NLPR(0.7K), NJUD(1.485K)	VGG-19	Designs a depth-induced multiscale recurrent attention network for SOD, including a depth refinement block and a recurrent attention module
57	2019	DSD [115]	JVCIR	NLPR(0.5K), NJUD(1.5K)	VGG-16	Uses a saliency fusion network to adaptively fuse both the color and depth saliency maps
58	2020	DPANet [116]	arXiv	NLPR(0.65K), NJUD(1.4K), DUT(0.8K)	ResNet-50	Uses a saliency-orientated depth perception module to evaluate the potentiality of depth maps and reduce effects of contamination
59	2020	SSDP [117]	arXiv	NLPR(0.7K), NJUD(1.485K), DUT(0.8K)	VGG-19	Makes use of existing labeled RGB saliency datasets together with unlabeled RGB-D data to boost SOD performance
60	2020	AttNet [103]	IVC	NLPR(0.65K), NJUD(1.4K)	VGG-16	Deploys attention maps to boost the salient objects' location and pays more attention to the appearance information
61	2020	— [104]	NEURO	NLPR(0.65K), NJUD(1.4K)	VGG-16	Uses an adaptive gated fusion module via a GAN to obtain a better fused saliency map from RGB images and depth cues
62	2020	CoCNN [105]	PR	STERE, NJUD	VGG-16	Fuses color and disparity features from low to high layers in a unified deep model
63	2020	cmSalGAN [118]	TMM	NLPR(0.65K), NJUD(1.4K)	ResNet-50	Aims to learn an optimal view-invariant and consistent pixel-level representation for both RGB and depth images using an adversarial learning framework
64	2020	PGHF [119]	ACCESS	NLPR(0.65K), NJUD(1.4K)	VGG-16	Leverages powerful representations learned from large-scale RGB datasets to boost the model ability

• TANet [99] formulates a multi-modal fusion framework using RGB images and depth maps from the bottom-up and top-down views. It then introduces a channel-wise attention module to effectively fuse the complementary information from different modalities and levels.

E. Open-source Implementations

We summarize the open-source implementations of RGB-D based SOD models reviewed in this survey. The implementations and hyperlinks of the source codes of these models are provided in Tab V. More source codes will be updated at: https://github.com/taozh2017/RGBD-SODsurvey.

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) from these datasets. Moreover, we provide the details for each dataset as follows.

- STERE [138]. The authors first collected 1,250 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 1,000 images were selected to construct the final dataset. This is the first collection of stereoscopic images in this field.
- GIT [47] 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** [49] consists of 135 indoor RGB-D images, which were taken by Kinect with a resolution of 640×640 . When

¹http://www.flickr.com/

²http://photos.3dvisionlive.com/

³http://www.stereophotography.com/

 $\label{thm:table iv} TABLE\ IV \\ SUMMARY\ OF\ RGB-D\ BASED\ SOD\ MODELS\ PUBLISHED\ IN\ 2020.$

No.	Year	Method	Pub.	Training Set	Backbone	Description Description
65	2020	BiANet [120]	TIP	NLPR(0.7K),	VGG-16	Uses a bilateral attention module (BAM) to explore rich foreground and background
				NJUD(1.485K)		information from depth maps
66	2020	ASIF-Net [106]	TCYB	NLPR(0.65K), NJUD(1.4K)	VGG-16	Integrates the attention steered complementarity from RGB-D images and introduces a global semantic constraint using adversarial learning
67	2020	Triple-Net [107]	SPL	Triple-Net	ResNe-18	Uses a triple-complementary network for RGB-D based SOD
68	2020	ICNet [7]	TIP	Triple-Net	VGG-16	Uses a novel information conversion module to fuse high-level RGB and depth features in an interactive and adaptive way
69	2020	SDF [108]	TIP	NLPR,NJUD, DEC,LFSD(1.5K)	VGG-16	Proposes a exemplar-driven method to estimate relatively trustworthy depth maps, and uses a selective deep saliency fusion network to effectively integrate RGB images,
70	2020	GFNet [121]	SPL	NLPR(0.8K), NJUD(1.588K)	Res2Net	original depths, and newly estimated depths Designs a gate fusion block to regularize feature fusion
71	2020	RGBS [122]	MTAP	NLPR(0.65K), NJUD(1.4K)	VGG-16	Utilizes a GAN to generate the saliency map
72	2020	D ³ Net [3]	TNNLS	NLPR(0.7K), NJUD(1.485K)	VGG-16	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
73	2020	JL-DCF [8]	CVPR	NLPR(0.7K), NJUD(1.5K)	VGG-16, ResNet-101	Uses a joint learning strategy and a densely-cooperative fusion module to achieve better SOD performance
74	2020	A2dele [5]	CVPR	NLPR(0.7K), NJUD(1.485K)	VGG-16	Employs a depth distiller to explore ways of using network prediction and attention as two bridges to transfer depth knowledge to RGB images
75	2020	SSF [4]	CVPR	NLPR(0.7K), NJUD(1.485K), DUT(0.8K)	AGG-16	Designs a complimentary interaction module to select useful representations from the RGB and depth images and then integrate cross-modal features
76	2020	S ² MA [6]	CVPR	NLPR(0.65K), NJUD(1.4K)	VGG-16	Fuses multi-modal information via self-attention and each other's attention strategies, and reweights the mutual attention term to filter out unreliable information
77	2020	UC-Net [9]	CVPR	NLPR(0.7K), NJUD(1.5K)	VGG-16	Uses a probabilistic RGB-D saliency detection network via a conditional VAE to generate multiple saliency maps
78	2020	CMWNet [123]	ECCV	NLPR(0.65K), NJUD(1.4K)	VGG-16	Exploits feature interactions using three cross-modal cross-scale weighting modules to improve SOD performance
79	2020	HDFNet [124]	ECCV	NLPR(0.7K), NJUD(1.485K), DUT(0.8K)	VGG-16	Designs a hierarchical dynamic filtering network to effectively make use of cross-modal fusion information
80	2020	CAS-GNN [125]	ECCV	NLPR(0.65K), NJUD(1.4K)	VGG-16	Designs cascaded graph neural networks to exploit useful knowledge from RGB and depth images for building powerful feature embeddings
81	2020	CMMS [126]	ECCV	NLPR(0.7K), NJUD(1.485K)	VGG-16	Proposes a cross-modality feature modulation module to enhance feature represen- tations and an adaptive feature selection module to gradually select saliency-related features
82	2020	DANet [127]	ECCV	NLPR(0.65K), NJUD(1.4K)	VGG-16, VGG-19	Develops a single-stream network combined with a depth-enhanced dual attention to achieve real-time SOD
83	2020	CoNet [128]	ECCV	NLPR(0.7K), NJUD(1.485K), DUT(0.8K)	ResNet	Develops a collaborative learning framework for RGB-D based SOD. Three collaborators (edge detection, coarse salient object detection and depth estimation) are utilized to jointly boost the performance
84	2020	BBS-Net [129]	ECCV	NLPR(0.65K), NJUD(1.4K)	VGG-16, VGG-19, ResNet-50	Uses a bifurcated backbone strategy to learn teacher and student features, and utilizes a depth-enhanced module to excavate informative parts of depth cues
85	2020	ATSA [130]	ECCV	NLPR(0.7K), NJUD(1.485K), DUT(0.8K)	VGG-19	Proposes an asymmetric two-stream architecture taking account of the inherent differences between RGB and depth data for SOD
86	2020	PGAR [131]	ECCV	NLPR(0.7K), NJUD(1.485K)	VGG-16	Propose a progressively guided alternate refinement network to produce a coarse initial prediction using a multi-scale residual block
87	2020	MCINet [132]	arXiv	NLPR(0.65K), NJUD(1.4K)	ResNet-50	Develops a novel multi-level cross-modal interaction network for RGB-D SOD
88	2020	DRLF [133]	TIP	NLPR(0.65K), NJUD(1.4K)	VGG-16	Develops a channel-wise fusion network to conduct multi-net and multi-level selective fusion for RGB-D SOD
89	2020	DQAM [134]	arXiv	NLPR(0.65K), NJUD(1.4K)	Without	Proposes a depth quality assessment solution to conduct "quality-aware" SOD for RGB-D images
90	2020	DQSD [135]	TIP	NLPR(0.65K), NJUD(1.4K)	VGG-19	Integrates a depth quality aware subnet into a bi-stream structure to assess the depth quality before conducting RGB-D fusion
91	2020	DASNet [136]	ACM MM	NLPR(0.7K), NJUD(1.5K)	ResNet-50	Proposes a new perspective of containing the depth constraints in the learning process rather than using depths as inputs
92	2020	DCMF [137]	TIP	NLPR(0.65K), NJUD(1.4K)	VGG-16, ResNet-50	Designs a disentangled cross-modal fusion network to expose structural and content representations from RGB and depth images

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 [51] consists of 1,000 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 [139] includes 100 light fields collected using a Lytro light field camera, and consists of 60 indoor and
- 40 outdoor scenes. To label this dataset, 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 [56] consists of 1,985 stereo image pairs, and these images were collected from the internet, 3D movies, and photographs that are taken by a Fuji W3 stereo camera.
- SSD [85] 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 [98] consists of 800 indoor and 400 outdoor



Fig. 4. Examples of images, depth maps and annotations in nine RGB-D dataset, including (a) STERE [138], (b) NLPR [51], (c) SSD [85], (d) GIT [47], (e) DES [49], (f) LFSD [139], (g) NJUD [56], (h) DUT-RGBD [98], and (i) SIP [3]. In each dataset, the RGB image, depth map and annotation are shown from left to right.

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.

Note that a detailed dataset statistics analysis (including center bias, size of objects, background objects, object boundary conditions, and number of salient objects) can be found in [3].

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 [155]. 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 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 [98]. 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 handcrafted features [98], [139], [141]–[146], [148], [154]. Early work [139], [146] showed that the unique refocusing capability of light fields can provide useful focusness, depth, and objectness cues. Thus, several SOD models using light field data were further proposed. For example, Zhang *et al.* [142] utilized a set of focal slices to compute the background prior, and then combined it with the location prior for SOD. Wang *et al.* [145] proposed a two-stage Bayesian fusion model to integrate

 $\label{thm:table v} TABLE\ V$ A summary of RGB-D based SOD models with open-source implementations.

Year	Model	Implementation	Code link
2014	LHM [51]	Matlab	https://sites.google.com/site/rgbdsaliency/code
	DESM [49]	Matlab	https://github.com/HzFu/DES_code
2015	GP [50]	Matlab	https://github.com/JianqiangRen/Global_Priors_RGBD_Saliency_Detection
2016	DCMC [1]	Matlab	https://github.com/rmcong/Code-for-DCMC-method
	LBE [57]	Matlab & C++	http://users.cecs.anu.edu.au/ u4673113/lbe.html
	BED [83]	Caffe	https://github.com/sshige/rgbd-saliency
2017	CDCP [84]	Matlab	https://github.com/ChunbiaoZhu/ACVR2017
	MDSF [87]	Matlab	https://github.com/ivpshu
	DF [52]	Matlab	https://pan.baidu.com/s/1Y-PqAjuH9xREBjff7H45HA
2018	CTMF [58]	Caffe	https://github.com/haochen593/CTMF
2016	PCF [92]	Caffe	https://github.com/haochen593/PCA-Fuse_RGBD_CVPR18
	PDNet [97]	TensorFlow	https://github.com/cai199626/PDNet
	AFNet [102]	TensorFlow	https://github.com/Lucia-Ningning/Adaptive_Fusion_RGBD_Saliency_Detection
2019	CPFP [53]	Caffe	https://github.com/JXingZhao/ContrastPrior
	DMRA [54]	PyTorch	https://github.com/jiwei0921/DMRA
	DGT [101]	Matlab	https://github.com/rmcong/Code-for-DTM-Method
	ICNet [7]	Caffe	https://github.com/MathLee/ICNet-for-RGBD-SOD
	JL-DCF [8]	Pytorch, 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 [106]	TensorFlow	https://github.com/Li-Chongyi/ASIF-Net
	S ² MA [6]	PyTorch	https://github.com/nnizhang/S2MA
	UC-Net [9]	PyTorch	https://github.com/JingZhang617/UCNet
2020	D ³ Net [3]	PyTorch	https://github.com/DengPingFan/D3NetBenchmark
2020	CMWNet [123]	Caffe	https://github.com/MathLee/CMWNet
	HDFNet [124]	PyTorch	https://github.com/lartpang/HDFNet
	CMMS [126]	TensorFlow	https://github.com/Li-Chongyi/cmMS-ECCV20
	CAS-GNN [125]	PyTorch	https://github.com/LA30/Cas-Gnn
	DANet [127]	PyTorch	https://github.com/Xiaoqi-Zhao-DLUT/DANet-RGBD-Saliency
	CoNet [128]	PyTorch	https://github.com/jiwei0921/CoNet
	DASNet [136]	PyTorch	http://cvteam.net/projects/2020/DASNet/
	BBS-Net [129]	PyTorch	https://github.com/DengPingFan/BBS-Net
	ATSA [130]	PyTorch	https://github.com/sxfduter/ATSA
	PGAR [131]	PyTorch	https://github.com/ShuhanChen/PGAR_ECCV20
	FRDT [140]	PyTorch	https://github.com/jack-admiral/ACM-MM-FRDT

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 [138]	2012	CVPR	1,000	~One	Internet	Stereo camera+sift flow	$ \begin{array}{ccc} [251 \ \sim \ 1200] \times [222 \ \sim \\ 900] \end{array} $
2	GIT [47]	2013	BMVC	80	Multiple	Home environment	Microsoft Kinect	640×480
3	DES [49]	2014	ICIMCS	135	One	Indoor	Microsoft Kinect	640×480
4	NLPR [51]	2014	ECCV	1,000	Multiple	Indoor/outdoor	Microsoft Kinect	$640 \times 480, 480 \times 640$
5	LFSD [139]	2014	CVPR	100	One	Indoor/outdoor	Lytro Illum camera	360×360
6	NJUD [56]	2014	ICIP	1,985	~One	Movie/internet/photo	FujiW3 camera+optical flow	$[231 \sim 1213] \times [274 \sim 828]$
7	SSD [85]	2017	ICCVW	80	Multiple	Movies	Sun's optical flow	960×1080
8	DUT-RGBD [98]	2019	ICCV	1,200	Multiple	Indoor/outdoor	-	400×600
9	SIP [3]	2020	TNNLS	929	Multiple	Person in the wild	Huawei Mate10	992×744

multiple contrasts for boosting SOD performance. Recently, several deep learning-based light field SOD models [150]–[153], [155], [156] have also been developed, obtaining remarkable performance. Besides, in [150], 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. [152] developed a memory-oriented decoder for light field SOD, which fuses multi-level features in a top-down manner using high-level information to guide low-level feature selection. LFNet [155] employs a new integration module to fuse features from light field data according to their contributions and captures the spatial

Year Method Pub. Dataset Description CVPR LFSD The first light-field saliency detection algorithm employs objectness and focusness cues 2014 LFS [139] based on the refocusing capability of the light field 2015 WSC [141] CVPR LFSD Uses a weighted sparse coding framework to learn a saliency/non-saliency dictionary 3 DILF [142] 2015 IJCAI LFSD Incorporates depth contrast to complement the disadvantage of color and conducts focusness-based background priors to boost the saliency detection performance 2016 RL [143] ICASSP LFSD Utilizes the inherent structure information in light field images to improve saliency detection HFUT, LFSD 2017 MA [144] TOMM Integrates multiple saliency cues extracted from light field images using a random-searchbased weighting strategy 2017 BIF [145] NPL. LFSD Integrates color-based contrast, depth-induced contrast, focusness map of foreground slice, 6 and background weighted depth contrast using a two-stage Bayesian integration framework LESD 2017 LFS [146] TPAMI An extension of [139] 2017 RLM [147] ICIVC LFSD Utilizes the light field relative location measurement for SOD on light field images 2018 SGDC [148] CVPR Designs a saliency-guided depth optimization framework for multi-layer light field displays Proposes a graph model depth-induced cellular automata to optimize saliency maps using 10 2018 DCA [149] FiO LFSD light field data DUTLF-FS, LFSD 11 2019 DLLF [150] ICCV Utilizes a recurrent attention network to fuse each slice from the focal stack to learn the most informative features 12 2019 DLSD [151] 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 2019 NIPS LITLE-ES 13 Molf [152] Uses a memory-oriented decoder for light field SOD 2020 ERNet [153] DUTLF-FS, HFUT, LFSD AAAI Uses an asymmetrical two-stream architecture to overcome computation-intensive and memory-intensive challenges in a high-dimensional light field data 2020 DCA [98] TIP Presents a saliency detection framework on light fields based on the depth-induced cellular automata (DCA) model. It can enforce spatial consistency to optimize the inaccurate saliency map using the DCA model 2020 RDFD [154] MTAP LFSD Defines a region-based depth feature descriptor extracted from the light field focal stack 16 to facilitate low- and high-level cues for saliency detection DUTLF-FS, LFSD, HFUT 2020 TIP Utilizes a light field refinement module and a light field integration module to effectively 17 LFNet [155] integrate multiple cues (i.e., focusness, depths and objectness) from light field images 18 2020 LFDCN [156] TIP Lytro Illum, LFSD, HFUT

TABLE VII
SUMMARY OF POPULAR LIGHT FIELD SOD METHODS.

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 [141], the saliency dictionary was refined using the estimated saliency map. The MA method [144] employs a two-stage saliency refinement strategy to produce the final prediction map, which enables adjacent superpixels to obtain similar saliency values. Besides, LFNet [155] 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 of each dataset as follows

- LFSD [139] 4 consists of 100 light fields of different scenes with a 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%.
- **HFUT** [144] 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** [150] ⁶ consists of 1,465 samples, 1,000 of which are used as the training set, while the remaining 465 images make up the test set. The resolution of each image is 600×400 . This dataset contains several challenges, including lower contrast between salient objects and cluttered background, multiple disconnected salient objects, and dark or strong light conditions.

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

- **DUTLF-MV** [151] ⁷ consists of 1,580 samples, 1,100 of which 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 [156] 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, *i.e.*, precision-recall (PR), F-measure [59], [157], mean absolute error (MAE) [158], structural measure (S-measure) [159], and enhanced-alignment measure (E-measure) [160].

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

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

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

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

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

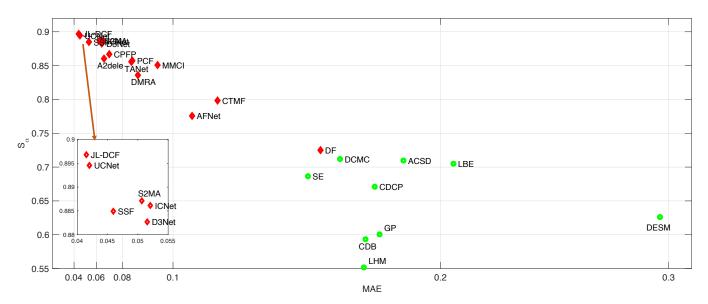


Fig. 5. A comprehensive evaluation for 24 representative RGB-D based SOD models, including LHM [51], ACSD [56], DESM [49], GP [50], LBE [57], DCMC [1], SE [2], CDCP [84], CDB [95], DF [52], PCF [92], CTMF [58], CPFP [53], TANet [99], AFNet [102], MMCI [55], DMRA [54], D 3 Net [3], SSF [4], A2dele [5], S 2 MA [6], ICNet [7], JL-DCF [8], and UC-Net [9]. We report the mean values of S_α and MAE across the five datasets (*i.e.*, STERE [138], NLPR [51], LFSD [139], DES [49], and SIP [3]) in each model. Note that better models are shown in the upper left corner (*i.e.*, with a larger S_α and smaller MAE). Here, red diamonds denote deep models and green circles denote traditional models.

• **PR**. Given a saliency map S, we can convert it to a binary mask M, and then compute the *precision* and *recall* by comparing M with ground-truth G:

$$Precision = \frac{|M \cap G|}{|M|}, \ Recall = \frac{|M \cap G|}{|G|}. \tag{1}$$

A popular strategy is to partition the saliency map S using a set of 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 PR curve that describes the performance of the model at the different thresholds.

• **F-measure** (F_{β}) . To comprehensively consider both precision and recall, the F-measure is proposed by calculating the weighted harmonic mean:

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

where β^2 is set to 0.3 to emphasize the precision [157]. We use different fixed [0, 255] thresholds to compute the F-measure metric. This yields a set of F-measure values for which we report the maximal or average F_{β} .

 \bullet MAE. This measures the average pixel-wise absolute error between a predicted saliency map S and a ground truth G for all pixels, which can be defined by

$$MAE = \frac{1}{W * H} \sum_{i=1}^{W} \sum_{i=1}^{H} |S_{i,j} - G_{i,j}|,$$
 (3)

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 the structural information in an image, S_{α} [159] 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

$$S_{\alpha} = \alpha * S_o + (1 - \alpha) * S_r, \tag{4}$$

where $\alpha \in [0,1]$ is a trade-off parameter. Here, we set $\alpha = 0.5$ as the default setting, as suggested by Fan *et al.* [159].

• E-measure (E_{ϕ}) . E_{ϕ} [160] 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

$$E_{\phi} = \frac{1}{W * H} \sum_{i=1}^{W} \sum_{j=1}^{H} \phi_{FM}(i, j), \qquad (5)$$

where ϕ_{FM} denotes the enhanced-alignment matrix [160].

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) nine traditional methods: LHM [51], ACSD [56], DESM [49], GP [50], LBE [57], DCMC [1], SE [2], CDCP [84], CDB [95]; and 2) fifteen deep learning-based methods: DF [52], PCF [92], CTMF [58], CPFP [53], TANet [99], AFNet [102], MMCI [55], DMRA [54], 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 [138], NLPR [51], LFSD [139], DES [49], 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 methods obtain significantly better performance. This confirms the powerful feature learning ability of deep networks.
 - Comparison of Deep Models. Among the deep learning-based models, D³Net [3], JL-DCF [8], UC-Net [9], SSF [4], ICNet [7], and S²MA [6] obtain the best performance.

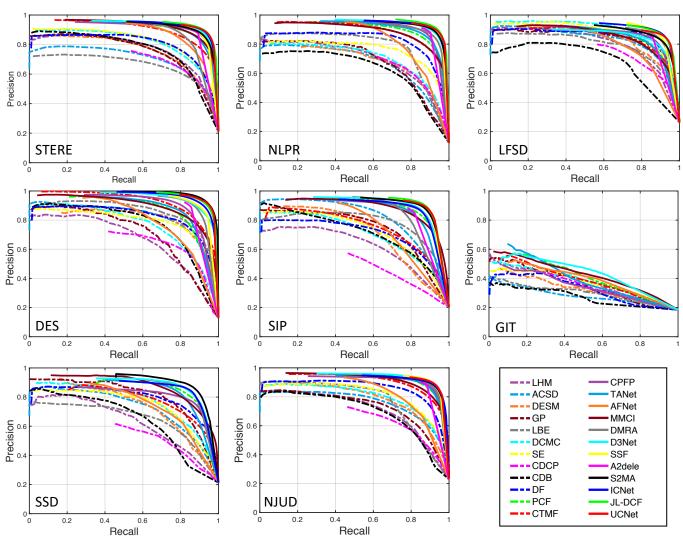


Fig. 6. PR curves for 24 RGB-D based models on the STERE [138], NLPR [51], LFSD [139], DES [49], SIP [3], GIT [47], SSD [85], and NJUD [56] datasets.

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-based models) are provided in terms of MAE and S_{α} . The three best results are shown in Red, blue and green fonts.

					Traditi	ional r	nodels									Deep	learni	ing-ba	sed m	odels					
	Scale	LHM [51]	ACSD [56]	DESM [49]	GP [50]	LBE [57]	DCMC [1]	SE [2]	CDCP [84]	CDB [95]	DF [52]	PCF [92]	CTMF [58]	CPFP [53]	TANet [99]	AFNet [102]	MMCI [55]	DMRA [54]	D ³ Net [3]	SSF [4]	A2dele [5]	S ² MA [6]	ICNet [7]	JL-DCF [8]	UC-Net [9]
MAE	Small Medium	.065 .178		.319 .287	.098	.177 .210	.108 .158	.056 .150	.128	.073 .179	.087 .152	.042	.065	.044	.041	.046	.051 .079	.030	.033	.031	.032	.035 .052	.036	.032	.034
	Large Overall	.166	.184	.310	.173	.261	.305	.142	.308	.385	.310	.065	.183	.093	.065	.091	.076	.181	.052	.046	.053	.088	.052	.085	.072
S_{α}	Small Medium Large	.624 .543	.668 .732	.517 .658 .686	.650 .598 .450	.645 .723	.700 .727 .604	.775 .676 .479	.661 .683	.666 .585 .424	.745 .730 .597	.847 .863	.789 .805	.840 .877 .855	.846 .862 .827	.792 .779 .682	.832 .859	.860 .838 .734	.879 .888 .846	.876 .893	.859 .865	.877 .893	.882 .892 .845	.881 .906 .859	.883 .901
	Overall	.552	.710	.626	.601	.705	.712	.686	.671	.593	.725	.857	.798	.867	.856	.776		.836	.883	.885	.860	.887	.886	.897	.895

Moreover, Fig. 6 and Fig. 7 show the PR and F-measure curves for the 24 representative RGB-D based SOD models on eight datasets (*i.e.*, STERE [138], NLPR [51], LFSD [139], DES [49], SIP [3], GIT [47], SSD [85], and NJUD [56]). Note that there are 1000, 300, 100, 135, 929, 80, and 80 test samples

for NLPR, LFSD, DES, SIP, GIT, and SSD, respectively. For the NJUD [56] dataset, there are 485 test images for CPFP [53], S²MA [6], ICNet [7], JL-DCF [8], and UC-Net [9], while 498 testing images for all other models.

To understand the top six models in depth, we discuss their

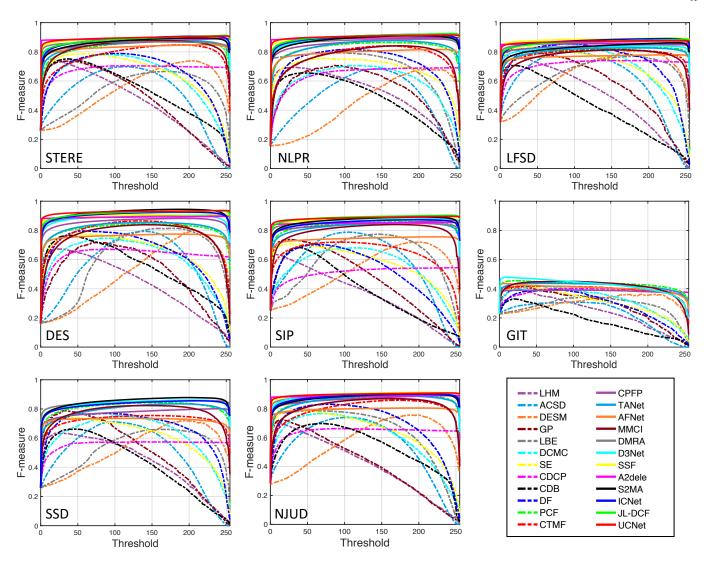


Fig. 7. F-measures under different thresholds for 24 RGB-D based models on the STERE [138], NLPR [51], LFSD [139], DES [49], SIP [3], GIT [47], SSD [85], and NJUD [56] datasets.

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-BASED MODELS) ARE PROVIDED IN TERMS OF MAE AND S_{α} . The three best results are shown in red, blue and green fonts.

				1	Fraditi	onal n	nodels	,								Deep	learn	ing-ba	sed m	odels					
	background	LHM [51]	ACSD [56]	DESM [49]	GP [50]	LBE [57]	DCMC [1]	SE [2]	CDCP [84]	CDB [95]	DF [52]	PCF [92]	CTMF [58]	CPFP [53]	TANet [99]	AFNet [102]	MMCI [55]	DMRA [54]	D ³ Net [3]	SSF [4]	A2dele [5]	S^2MA [6]	ICNet [7]	JL-DCF [8]	UC-Net [9]
MAE	Simple Uncertain Complex	.100 .164 .159	.163 .195 .190	.219 .294 .349	.150 .175 .180	.202 .210 .205	.056 .140 .190	.084 .133 .147	.028 .139 .236	.136 .159 .143	.129 .163	.031 .062 .085	.053 .081 .110	.018 .050 .079	.033 .059 .077	.031 .075 .108	.041 .070 .094	.028 .058 .087	.017 .045 .071	.012 .043 .065	.010 .043 .070	.016 .049 .072	.013 .041 .079	.014 .037 .063	.013 .037 .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 Uncertain Complex	.781 .572 .496	.787 .694 .627	.761 .638 .509	.694 .606 .545	.748 .695 .616	.930 .736 .577	.856 .723 .605	.941 .727 .487	.704 .610 .575	.944 .774 .627	.944 .873 .782	.913 .853 .742	.958 .882 .787	.937 .873 .790	.922 .818 .694	.933 .868 .768	.935 .854 .751	.960 .900 .822	.966 .894 .815	.965 .884 .786	.965 .895 .813	.969 .910 .808	.961 .909 .829	.962 .907 .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

main advantages for the six models below.

• D³Net [3] consists of two key components, *i.e.*, a three-stream feature learning module and a depth depurator unit. In the three-stream feature learning module, there are three subnetworks, *i.e.*, RgbNet, RgbdNet, and DepthNet. The RgbNet and DepthNet are used to learn high-level feature

representations for RGB and depth images, respectively, while the RgbdNet is used to learn their fused representations. It is worth noting that this three-stream feature learning module can capture modality-specific information as well as the correlation between modalities. Thus, balancing the two aspects is very important for multi-modal learning and it has helped to improve the SOD performance. Besides, the depth depurator unit acts as a gate to explicitly filter out low-quality depth maps, which several existing methods do not consider the effects. Because low-quality depth maps can inhibit the fusion between RGB images and depth maps, thus the depth depurator unit can ensure effective multi-modal fusion to achieve robust SOD performance.

- In JL-DCF [8], there are two key components, *i.e.*, a joint learning (JL) and a densely-cooperative fusion (DCF). Specifically, the JL module is used to learn robust saliency features, while the DCF module is used for complementary feature discovery. It is worth noting that this method uses a middle-fusion strategy to extract deep hierarchical features from RGB images and depth maps, in which the crossmodal complementarity can be effectively exploited to achieve accurate prediction.
- In UC-Net [9], instead of producing a single saliency prediction, this model produces multiple predictions by modeling the distribution of the feature output space as a generative model conditioned on RGB-D images. Because each person has some specific preferences in labeling a saliency map, it could fail to capture the stochastic characteristic of saliency while only a single saliency map is produced for an image pair using a deterministic learning pipeline. Thus, the strategy in this model can take into account human uncertainty in saliency annotations. Moreover, considering the fact that depth maps could suffer from noise, directly fusing RGB images and depth maps could cause the network to fit to this noise. Therefore, a depth correction network, designed as an auxiliary component, is proposed to refine depth information with a semantic guided loss. Thus, the above key components are all helpful for improving SOD performance.
- In SSF [4], a complementary interaction module (CIM) is developed to explore discriminative cross-modal complementarities and fuse cross-modal features, where a region-wise attention is introduced to supplement rich boundary information for each modality. Besides, a compensation-aware loss is proposed to improve the network's confidence for hard samples in unreliable depth maps. Thus, these key components enable the proposed model to effectively explore and establish the complementarity of cross-modal feature representations, while at the same time reducing the negative effects introduced by low-quality depth maps, boosting SOD performance.
- In ICNet [7], an information conversion module is proposed to interactively and adaptively explore the correlations between high-level RGB and depth features. Besides, a crossmodal depth-weighted combination block is introduced to enhance the difference between the RGB and depth features in each level, which ensures that the features are treated differently. It is also worth noting that ICNet exploits the complementarity of cross-modal features, as well as explores the continuity of cross-level features, both of which are helpful for achieving accurate predictions.
- In S²MA [6], a self-mutual attention module (SAM) is proposed to fuse RGB and depth images, integrating self-attention and each other's attention to propagate context more accurately. The SAM can provide additional complementary information from multi-modal data to improve SOD per-



Fig. 8. Sample images with different objects scales. The scale ratios are denoted in yellow.

formance, overcoming the limitations of the original selfattention, which only uses a single modality. Besides, to reduce the low-quality (e.g., noise) effects of depth cues, a selection mechanism is proposed to reweight the mutual attention. This mechanism can filter out unreliable information, resulting in more accurate saliency prediction.

- 2) Attribute-based Evaluation: To investigate the influence of different factors, such as object scale, background clutter, number of salient objects, indoor or outdoor scene, background objects, and lighting conditions, we carry out diverse attribute-based evaluations on several 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 and 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 "large"; 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 2,464 images collected from STERE [138], NLPR [51], LFSD [139], DES [49], and SIP [3], where 24%, 69.2% and 6.8% of images have small, medium, and large salient object areas, respectively. The constructed hybrid dataset can be found at https://github.com/taozh2017/RGBD-SODsurvey. Some sample images with different object scales are shown in Fig. 8. The comparison results of the attributebased 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 while they obtain worse performance in detecting large 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 evaluation, we utilize five traditional SOD methods, *i.e.*, BSCA

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-based 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.

				,	Traditi	ional r	nodels	1								Deep	learn	ing-ba	sed m	odels					
	Categories	LHM [51]	ACSD [56]	DESM [49]	GP [50]	LBE [57]	DCMC [1]	SE [2]	CDCP [84]	CDB [95]	DF [52]	PCF [92]	CTMF [58]	CPFP [53]	TANet [99]	AFNet [102]	MMCI [55]	DMRA [54]	D ³ Net [3]	SSF [4]	A2dele [5]	S ² MA [6]	ICNet [7]	JL-DCF [8]	UC-Net [9]
MAE	Car Barrier Flower Grass Road Sign Tree	.158 .197 .105 .164 .189 .107 .192	.163 .177 .122 .161 .167 .126 .193	.301 .308 .306 .279 .281 .268 .310	.159 .180 .099 .155 .176 .110 .190	.201 .201 .186 .184 .187 .184 .241	.185 .196 .158 .167 .181 .126 .194	.154 .176 .063 .138 .164 .079 .183	.202 .251 .141 .182 .225 .134 .230	.171 .203 .101 .176 .189 .118 .219	.171 .202 .132 .167 .169 .096 .205	.085 .073 .091 .041 .070 .058 .083	.134 .149 .075 .110 .140 .101 .157	.094 .060 .133 .035 .054 .063 .083	.084 .078 .100 .048 .072 .060 .091	.101 .128 .090 .088 .125 .077 .132	.093 .089 .081 .059 .078 .083 .109	.069 .093 .046 .056 .093 .051 .106	.061 .068 .095 .037 .059 .055 .083	.063 .054 .107 .030 .049 .051 .067	.078 .074 .051 .046 .072 .054 .074	.055 .057 .104 .033 .050 .048 .092	.067 .075 .025 .043 .065 .054 .097	.058 .052 .054 .023 .045 .050 .063	.057 .053 .075 .029 .044 .057 .071
	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	Car Barrier Flower Grass Road Sign Tree Other	.516 .497 .477 .537 .521 .578 .505 .460	.731 .727 .775 .756 .739 .786 .699	.590 .609 .573 .643 .634 .634 .606	.603 .575 .673 .605 .598 .628 .577 .532	.714 .728 .703 .760 .751 .719 .661 .706	.671 .672 .707 .728 .685 .745 .648	.591 .612 .772 .683 .641 .761 .600	.613 .553 .667 .672 .595 .714 .588	.546 .552 .639 .559 .576 .615 .543	.631 .643 .750 .672 .680 .757 .625	.811 .837 .771 .908 .851 .855 .802	.726 .698 .738 .770 .722 .756 .679	.786 .860 .714 .908 .871 .833 .804 .774	.807 .831 .760 .899 .848 .857 .778 .782	.736 .708 .688 .780 .705 .771 .691	.813 .830 .785 .888 .847 .818 .779 .790	.817 .792 .824 .876 .807 .848 .748	.856 .855 .789 .917 .873 .849 .806	.845 .874 .768 .924 .885 .849 .837	.804 .821 .845 .878 .832 .842 .807 .785	.870 .871 .804 .928 .885 .871 .800	.846 .848 .901 .910 .868 .861 .788	.855 .876 .856 .939 .889 .859 .848	.859 .875 .811 .924 .892 .840 .825 .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	_



Fig. 9. Sample images with three types of background clutter.

[161], CLC [162], MDC [163], MIL [164], and WFD [165], 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 1,400 images collected from three datasets (STERE [138], NLPR [51], and LFSD [139]). Then, we apply the five models to this dataset and obtain the S_{α} values for each, which we use to characterize images as follows: 1) If all S_{α} values are higher than 0.9, the image is denoted as having a "simple" background; 2) If all S_{α} values are lower 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. 9. The constructed hybrid dataset can be found at https://github.com/taozh2017/RGBD-



Fig. 10. Sample images with single or multiple salient objects.

SODsurvey. The comparison results of the attribute-based study *w.r.t.* background clutter are shown in Tab. IX. As can be seen, 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 the top-three best results. Besides, the four most recent models, *i.e.*, D³Net [3], S²MA [6], A2dele [5], and ICNet [7], also obtain better performance than the other models.

• Single vs. Multiple Objects. In this evaluation, we construct a hybrid dataset with 1,229 images collected from the NLPR [51] and SIP [3] datasets. Some example images with single or multiple salient objects are shown in Fig. 10. The comparison results are shown in Fig. 11. From the results,

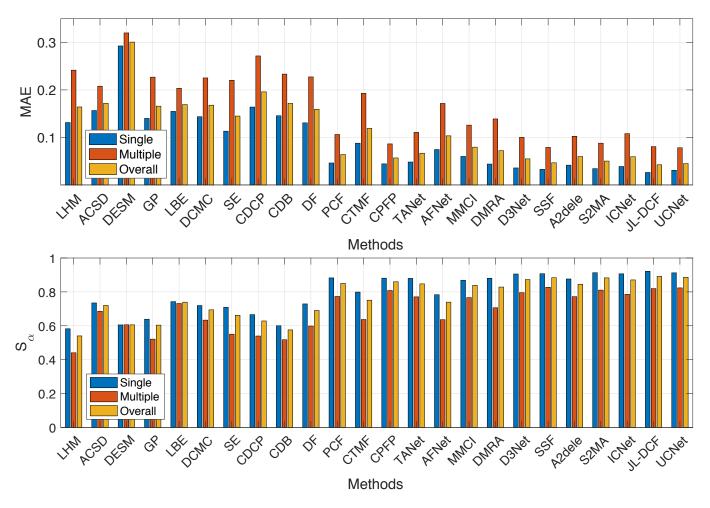


Fig. 11. Attribute-based study *w.r.t.* number of salient objects (*i.e.*, single vs. multiple (multi)). The comparison results on 24 representative RGB-D based SOD models (*i.e.*, LHM [51], ACSD [56], DESM [49], GP [50], LBE [57], DCMC [1], SE [2], CDCP [84], CDB [95], DF [52], PCF [92], CTMF [58], CPFP [53], TANet [99], AFNet [102], MMCI [55], DMRA [54], D³Net [3], SSF [4], A2dele [5], S²MA [6], ICNet [7], JL-DCF [8], and UC-Net [9]) are given in terms of MAE (top) and S_{α} (bottom).

TABLE XI ATTRIBUTE-BASED STUDY w.r.t. LIGHT CONDITIONS (SUNNY VS. LOW-LIGHT). THE COMPARISON METHODS INCLUDE 24 REPRESENTATIVE RGB-D BASED SOD MODELS (9 TRADITIONAL MODELS AND 15 DEEP LEARNING-BASED 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.

				,	Traditi	ional n	nodels									Deep	learni	ng-bas	sed mo	odels					
	Conditions	LHM [51]	ACSD [56]	DESM [49]	GP [50]	LBE [57]	DCMC [1]	SE [2]	CDCP [84]	CDB [95]	DF [52]	PCF [92]	CTMF [58]	CPFP [53]	TANet [99]	AFNet [102]	MMCI [55]	DMRA [54]	D ³ Net [3]	SSF [4]	A2dele [5]	S^2MA [6]	ICNet [7]	JL-DCF [8]	UC-Net [9]
	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
AE	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
\mathbf{z}	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
	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
٥	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
\overline{s}	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

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 [49], NLPR [51], and LFSD [139] datasets. The comparison results are shown in Fig. 12. From the results, it can be seen that most models struggle more to detect salient objects in indoor scene than outdoor scenes. This is possibly because indoor environments often have varying

light conditions.

• Background Objects. We evaluate the performance of the RGB-D based SOD models when different background objects are present. We use the 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

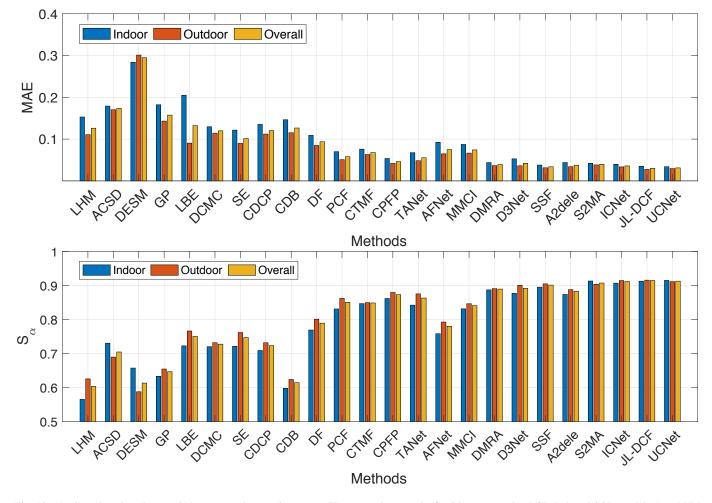


Fig. 12. Attribute-based study *w.r.t.* indoor vs. outdoor environments. The comparison results for 24 representative RGB-D based SOD models (*i.e.*, LHM [51], ACSD [56], DESM [49], GP [50], LBE [57], DCMC [1], SE [2], CDCP [84], CDB [95], DF [52], PCF [92], CTMF [58], CPFP [53], TANet [99], AFNet [102], MMCI [55], DMRA [54], 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).

recent models, *i.e.*, D³Net [3], S²MA [6], A2dele [5], and ICNet [7] obtain 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 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. Among comparison models, UC-Net [9] obtains the best performance under sunny conditions 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. 13 and Fig. 14 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 [54], D³Net [3], SSF [4], A2dele [5], S²MA [6], ICNet [7], JL-DCF [8], and UC-Net [9]). The 1st row shows a small object, while the 2^{nd} row is an example of a large one. The 3^{rd} and 4^{th} rows contain complex backgrounds and boundaries, respectively. The 5^{th} and 6^{th} rows contain multiple salient objects. In the 7^{th} row, there are

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. 13 and Fig. 14, 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, D^3 Net [3], S^2 MA [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 also directly affects the subsequent SOD performance. The quality of depth maps varies tremendously across different scenarios due to the 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,



Fig. 13. Visual comparisons for two classical non-deep methods (DCMC [1] and SE [2]) and three state-of-the-art CNN-based models (DMRA [54], D^3 Net [3], SSF [4]).

in [53], a contrast-enhanced network was proposed to learn enhanced depth maps, which have much higher contrasts compared with the original depths. In [4], a compensationaware loss was designed to pay more attention to hard samples containing unreliable depth information. Moreover, D³Net [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], [53] 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., assign low weights to 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, depth maps that suffer from severe noise or blurred edges, are often discarded. In this case, we have complete RGB images but some samples do not have depth maps, which is similar to the incomplete multi-view/modal learning problem [166]–[170]. 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. Depth estimation provides an effective solution to recover high-quality depths and overcome the effects of low-quality depth maps. Various depth estimation approaches [171]–[174] have been developed, which could

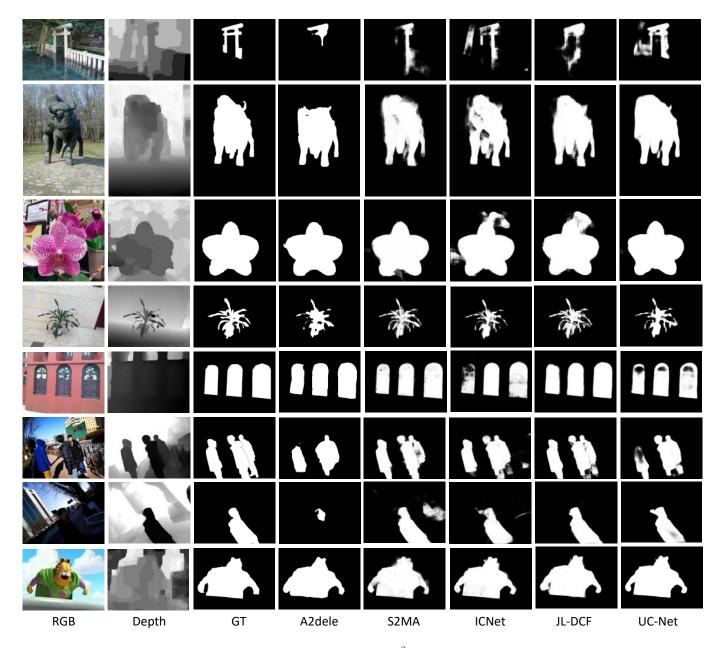


Fig. 14. Visual comparisons for five state-of-the-art CNN-based models (A2dele [5], S²MA [6], ICNet [7], JL-DCF [8], and UC-Net [9]).

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) [175] have gained widespread attention for the saliency detection task [176], [177]. 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 determine whether a given image is synthetic or ground-truth. GAN-based models 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 learn common feature representations for RGB images and depth maps [118], 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 [178]–[181], 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 [182], [183] and video object segmentation [184]. Thus, for the 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 use 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 [185]–[189]. Semi-/weak supervision could also be introduced into RGB-D SOD, by leveraging image-level tags [185] and pseudo pixel-wise annotations [188], [190], for improving the detection performance. Besides, several studies [191], [192] have suggested that models pretrained using self-supervision can effectively be used to achieve 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

Dataset size. Although there are nine public RGB-D datasets for SOD, their size is quite limited, *e.g.*, the maximum size is about 2,000 samples for NJUD [56]. When compared with other RGB-D datasets for generic object detection or action recognition [193], [194], 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 Datasets. 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 systems, 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 from being directly applied on real-work platforms. To overcome this, model compression [195], [196] techniques could be used to learn compact RGB-D based SOD models with promising detection accuracy. Moreover, JL-DCF [8] 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 that fuse 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 zero, making thermal infrared images insensitive to illumination conditions [197]. 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 [197]-[205] and datasets (VT821 [199], VT1000 [203] and VT5000 [205]) 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 we present, to the best of our knowledge, 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 the fact that light fields also provide 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 over the past several decades, there is still significant room for improvement. We hope this survey will generate more interest in this field.

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