

# Modality-Balanced Contrastive Learning for RGB-D Salient Object Detection

Hao Chen<sup>1</sup>, Feihong Shen<sup>1</sup>, Lichuang Zhang<sup>2\*</sup>

<sup>1</sup>School of Computer Science, Southeast University, China

<sup>2</sup>School of Computer Science, Nanjing University, China

{haochen303, feihongshen}@seu.edu.cn, zhanglc@lamda.nju.edu.cn

## Abstract

The scarcity of labelled data is a key obstacle to sufficient multi-modal fusion. The traditional solution that uses ImageNet-pretrained weights as initialization usually results in biased learning due to the cross-domain/modal gaps. In this work, we overcome these limitations by proposing a self-supervised learning framework. Unlike previous multi-modal contrastive learning architectures that are mainly performed by directly optimizing cross-modal agreement and always struggle with the information imbalance between modalities, especially for hard positive instances with noticeable modality-specific noises, we reformulate the multi-modal contrastive learning with imbalanced data to a unimodal contrastive problem to remove the modality gap. To this end, we combine the features from all modalities as a new modality representation via selectively masking the discriminative features in the strong modality to rebalance two modalities. By performing contrastive learning on the synthetic modality, we enable sufficient pre-training for each modality and explicit study of cross-modal correlation for downstream multi-modal fusion. Extensive experiments verify the effectiveness of our framework and designs on the downstream RGB-D salient object detection task.

## Introduction

Salient object detection (SOD) is to highlight the most visual-attractive objects from a scene. With rich geometry cues and additional contrast hints, the paired depth image has largely advanced the accuracy and robustness of SOD, especially for those challenging scenes with low-contrast appearance or weak lighting. Regarding the great success of deep Convolutional Neural Networks (CNNs), various RGB-D SOD methods based on CNNs have been proposed and achieved impressive improvements. These works usually follow a two-stream architecture, which typically includes two parallel encoders with popular networks (e.g., ResNet (He et al. 2016)) as the backbone to extract unimodal features individually. Then, the focus of these CNN-based methods is to design diverse fusion patterns (Chen and Li 2018; Ji et al. 2021) to boost cross-modal cross-level feature interaction, varying feature integration strategies (Chen and Li 2019a; Piao et al. 2020) to fully explore spatial and semantical complements, and some enhancement policies

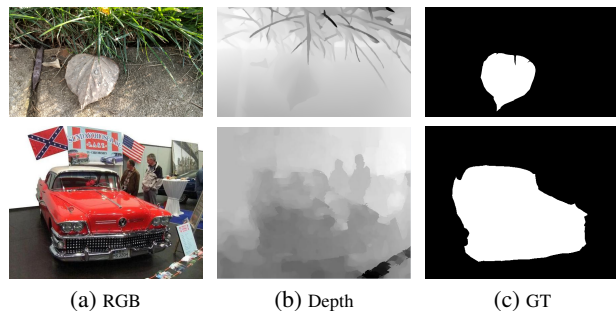


Figure 1: The strong RGB images and the weak depth images.

such as the attention mechanism (Zhou et al. 2018), knowledge distillation (Chen et al. 2021; Piao et al. 2020), mutual information minimization (Zhang et al. 2021a) and feature disentanglement (Chen et al. 2020a), to explicitly reduce the cross-modal redundancy and improve the fusion adaptivity. Given the scarcity of labelled RGB-D SOD data, these works have to use the weights pre-trained on large-scale datasets (e.g., the ImageNet (Deng et al. 2009)) as initialization to partly alleviate the data-hungry nature of CNNs. However, annotating such a million-level dataset for pre-training is time-consuming and costly, especially for dense prediction labels. More importantly, it inevitably introduces biased initialization and insufficient learning due to the domain gap between the pre-training dataset and the downstream one, as well as the modality gap between the source (i.e., RGB) and target (i.e., depth) modalities. Hence, this pre-training paradigm is cost-ineffective and holds limited generalization performance.

Recently, the self-supervised learning scheme (Vincent et al. 2008) directly tackles the deficiency of labelled data by designing various pretext tasks (Pathak et al. 2016; Caron et al. 2018; Misra, Zitnick, and Hebert 2016) and contrastive learning (CL) (He et al. 2020; Chen et al. 2020b) is one of the most popular paradigm. To date, a majority of contrastive learning frameworks are designed for unimodal data. In their domains, positive pairs are generated by different transformations from the same instance and negative pairs are samples from different scenes. By pulling positive pairs together

\*Corresponding Author.

and pushing negative pairs away, contrastive learning can learn feature representations invariant to certain transformations. Multi-modal contrastive learning is a newly rising problem and the basic philosophy is extending the pretext of within-modal instance discrimination to cross-modal agreement, that is regarding the matching multi-modal instance as the positive sample and unpaired ones as negative samples.

Noticeable works in this line include conducting audio-visual CL to learn unimodal representations (He et al. 2020; Chen et al. 2020b), image-text CL for cross-modal generation (i.e., image caption) (Yuan et al. 2021) and the Point-RGB CL for 3D point understanding (Afham et al. 2022). Differently, our task holds spatial-aligned multi-modal data and the downstream is multi-modal joint inference, which requires each modality to be well learned. Also, it will introduce remarkable benefits for the downstream task if cross-modal correlation can be explicitly explored in the CL process. As shown in Fig. 1, RGB and depth images hold huge differences of data distribution and structure and modal-specific noises. Also, RGB usually carries more and stronger cues than the paired depth. With such a large cross-modal gap, it is difficult to learn sufficient representation from each modality by optimizing the cross-modal agreement. The contrastive loss may be optimized by merely learning the low-level spatial alignment (such as some shared object edges), thus failing to extract high-level semantics from each modality. An alternative solution as done in (Liu et al. 2021, 2020b) is to combine multi-modal data as a joint instance to generate positive/negative samples by controlling the component distribution. In their settings, negative samples are crafted by carefully tuning the distribution of unaligned modalities with hyper-parameters, which is laborious and the resulting negative samples with different distributions actually hold varying similarities to the anchor.

Instead, we propose a new multi-modal contrastive learning paradigm, namely Modality-balanced Contrastive Fusion, to carefully pre-train each modality and cross-modal correlation in RGB-D pairs. First, we combine the aligned RGB-D pairs as a new synthetic modality for instance discrimination. Such a simple scheme fills the modality gap and enables the encoders to learn high-level semantics to differentiate input scenes. More importantly, it is independent of any hyper-parameters to set the modality distribution and largely ease the work of generating negative samples. However, it will still lead to biased sub-optimization by direct concatenating representations from all modalities as the joint instance. Due to the modality imbalance shown in Fig. 1, the network may depend on the stronger modality to discriminate scenes. To avoid the ignorance of the weak depth modality, we manually weaken the strong RGB modality by masking its most discriminative features in the modality synthesis process. In doing so, the depth modality has to learn more supplementary cues for scene discrimination. In summary, the main contributions of this work are as follows:

- We propose a new contrastive framework for self-supervised pre-training on imbalanced multi-modal data.
- We reformulate the cross-modal agreement to instance discrimination scheme to remove the modality gap by in-

roducing an attentive mask modality-synthesis method.

- Comprehensive experiments on wide public datasets of RGB-D salient object detection consistently demonstrate the efficacy of our designs and the large improvement over state-of-the-art supervised learning methods.

## Related Work

### RGB-D Saliency Objection Detection

Initial RGB-D SOD methods utilize handcrafts cues (Lang et al. 2012; Ciptadi, Hermans, and Rehg 2013a; Peng et al. 2014a; Cong et al. 2016) to infer saliency by local/global contrasts. However, these handcrafts features are weak in high-level semantics and hold limited generalization ability. The great success of deep convolutional neural networks (CNNs) motivates the RGB-D SOD community to design CNN-based detectors and generate various noticeable architectures. Single-stream models (Qu et al. 2017) that fuse the modalities directly and adopt an shared encoder to extract joint features. Two-stream architecture is a dominated one, which (Chen and Li 2018) use two encoders to extract features from each modality and designs various multi-scale cross-modal interactions for informative multi-modal fusion. TANet (Chen and Li 2019a) designs a three-stream architecture for RGB-D SOD, which considers the cross-modal complementarity in the encoder additionally to solve the issue that the two-stream architecture only focuses the multi-modal representation fusion in the decoder process.

Generally speaking, these RGB-D SOD methods are equipped with diverse cross-modal cross-level combination paths. To alleviate the deficiency of labelled data in training, they resort to the models well pre-trained on the large-scale labelled dataset ImageNet (Deng et al. 2009) to initialize their encoders. However, these pre-trained encoders are not appropriate to extract depth features due to the large cross-modal gap between RGB and depth. To alleviate the dependence on ImageNet pre-trained weights, (Zhao et al. 2022) proposes to use cross-modal generation and depth contour estimation as pretexts to pre-train encoders for each modality and cross-modal interactions. However, their SSL method is not end-to-end and relies on manually generating pretext labels from the source depth maps. In contrast to designing pretext labels and tasks, we adopt the contrastive learning paradigm and merely use the naturally source data to implement end-to-end SSL. Also, our motivation is to solve the modality imbalance in multi-modal contrastive learning, which significantly differs from (Zhao et al. 2022).

### Multi-modal Contrastive learning

As one of the typical self-supervised methods, contrastive learning has been widely used in tasks with single modality. For example, PIRL (Misra and Maaten 2020) maintains a memory bank to store previously-computed representations, therefore a positive sample can compare with negative samples quantitatively. To address the expensive cost in maintaining a memory bank, MOCO (He et al. 2020) stores the representations with a dynamic queue. SimCLR (Chen et al. 2020b) further simplifies the memory bank and designs an end-to-end framework along with a large batch-size.

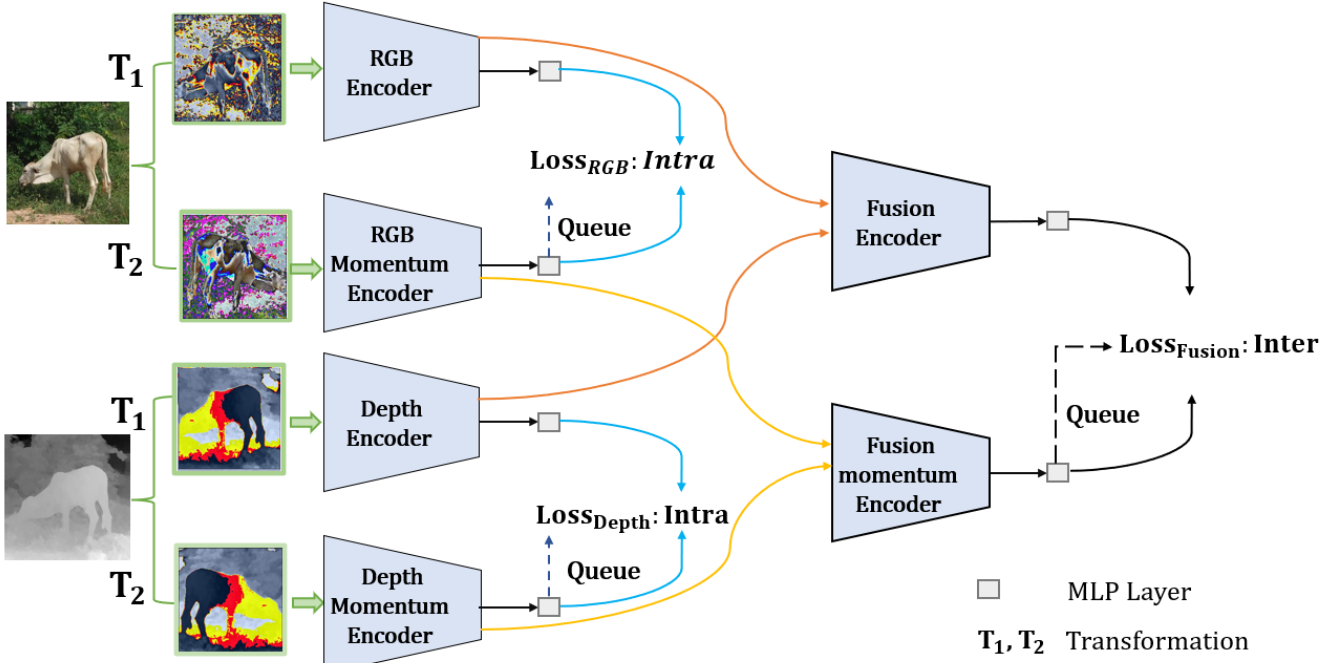


Figure 2: The overall architecture of our proposed method.

For multi-modal data, several contrastive attempts have achieved noticeable results (Tian, Krishnan, and Isola 2019; Morgado, Vasconcelos, and Misra 2021; Alayrac et al. 2020; Afham et al. 2022). Tian et al. propose multiview contrastive learning to maximize the mutual information between different views of the same scene. Morgado (Morgado, Vasconcelos, and Misra 2021) proposes to learn audio and visual representations by optimizing audio-visual cross-modal agreement. Alayrac et al. (Alayrac et al. 2020) leverage visual, audio, and text by a multimodal versatile network and exploit semantic comparisons of them while CrossPoint (Afham et al. 2022) try to capture the compositional correlations between 3D objects and 2D images to benefit 3D point cloud understanding. However, these methods ignore the cross-modal gap and imbalance in contrastive learning, thereby typically resulting in partial or biased pre-training in the weak modality.

To address this problem, Liu et al. (2021) designs a TupleInfoNCE for visual representation learning, which disturb the modality combination to avoid the domination of the strong modality. However, TupleInfoNCE remains two problems to be solved. 1. TupleInfoNCE requires to carefully tune the hyper-parameters for tuple disturbing and augmentation, thus being difficult to well balance modal-shared and modal-specific representations; 2. Their negative samples are heterogeneous and hold varying distances to the anchor, while they fail to take it into account. Instead, we reformulate the unbalanced cross-modal agreement objective to synthetic unimodal instance discrimination by designing a fusion encoder to integrate paired multi-modal data. Be-

sides, we alleviate the domination of the strong modality by proposing an attentive mask to explicitly weaken the contribution of the strong modality when combining multiple modalities in the fusion encoder, forcing the contrastive loss to pay more attention on exploring the representations from the weak modality.

## Method

### The Overall Architecture

The overall architecture of our proposed Modality-balanced Contrastive Fusion framework is shown in Fig. 2. Compare with the traditional unimodal contrastive learning methods, we use two encoders to extract features from RGB and depth respectively and the corresponding representations of positive samples are generated by momentum encoders (He et al. 2020). The pre-training model contains two significant contrastive learning parts: intra-modal contrastive learning module (IntraCLM) and inter-modal contrastive learning module (InterCLM) with different objectives. The IntraCLM adopts MoCo (He et al. 2020) as the baseline to learn modal-specific features while the InterCLM, using a synthetic modality combined by paired multi-modal images as the contrastive instance is performed to remove the cross-modal gap and capture cross-modal correlations via a fusion encoder, where a channel attentive masking module is inserted to encourage the learning of the weak modality.

### Intra-modal Contrastive Learning Module

The Intra-modal Contrastive Learning Module (IntraCLM) involves two separate contrastive learning stages: intra-RGB

and intra-depth. We denote the multi-modal RGB-D dataset as  $D = \{(r_1, \dots, r_K, d_1, \dots, d_K)\}$  where  $r$  represents RGB and  $d$  represents depth. Two random data augmentations are adopted for each anchor to generate two augmented views of the same sample. Then, they are input into the encoders  $\theta_q$  and  $\theta_k$  (denoted as momentum encoder) and additional MLPs  $\phi_{r_q}$ ,  $\phi_{r_k}$  are taken to make projections which could benefit the learning progress (Chen et al. 2020b). In the dictionary look-up (He et al. 2020), we describe the former as query and the latter as key. The whole process can be expressed by the following equation:

$$q_j = f_q(I_j; \theta_q, \phi_q), \quad (1)$$

$$k_j = f_k(I_j; \theta_k, \phi_k), \quad (2)$$

where  $I_j$  is the input of the encoder (RGB or depth).

After that, InfoNCE (Van den Oord, Li, and Vinyals 2018) is adopted as our intra-modal loss:

$$\mathcal{L}(q, k_+, k_i) = -\log \frac{\exp(q \cdot k_+ / \tau)}{\sum_{i=0}^K \exp(q \cdot k_i / \tau)}, \quad (3)$$

where  $K$  represents the size of the memory bank which consists of negative samples.

The total intra-modal loss includes the part in both the RGB and depth modalities and can be formulated as:

$$\mathcal{L}_{intra} = \mathcal{L}(q^r, k_+^r, k_i^r) + \mathcal{L}(q^d, k_+^d, k_i^d). \quad (4)$$

### Inter-modal Contrastive Learning Module

After our pre-training model have learned modal-specific features by IntraCLM, we append the Inter-modal Contrastive Learning Module (InterCLM) to learn cross-modal correlations and fuse the features from two modalities through a specifically designed fusion encoder  $f_{F_q}$ . Accordingly, the keys are fused through a fusion momentum encoder  $f_{F_k}$  which have the same structure as the fusion encoder. In doing so, the complementarity and cross-modal high-level semantic features of the two modalities can be well explored. For a paired sample of RGB-D data  $(r_j, d_j)$ , we first pass it through two basic encoders  $f_q$  and  $f_k$  to generate intra-modal specific features  $q$  and  $k$ , then transfer feature maps to generate fused modalities features via a fusion encoder. As same as the IntraCLM, additional MLPs  $\phi_{F_q}$ ,  $\phi_{F_k}$  are taken to make projections in the latent space. The formulation is shown by the following equation:

$$q_j^F = f_{F_q}((q^r, q^d); \theta_{F_q}, \phi_{F_q}), \quad (5)$$

$$k_j^F = f_{F_k}((k^r, k^d); \theta_{F_k}, \phi_{F_k}), \quad (6)$$

For each query  $q^F$ , and key  $k_+^F$  from the same anchor, we can formulate the inter-modal contrastive loss as follows:

$$\mathcal{L}_{inter} = -\log \frac{\exp(q^F \cdot k_+^F / \tau)}{\sum_{i=0}^K \exp(q^F \cdot k_i^F / \tau)}, \quad (7)$$

The total loss combined with InterCLM and IntraCLM can be formulated as:

$$\mathcal{J} = \lambda_1 * \mathcal{L}_{intra} + \lambda_2 * \mathcal{L}_{inter} \quad (8)$$

where  $\lambda_1$  and  $\lambda_2$  are trade-off hyper-parameters and we set them as 0.5 equally without further tuning.

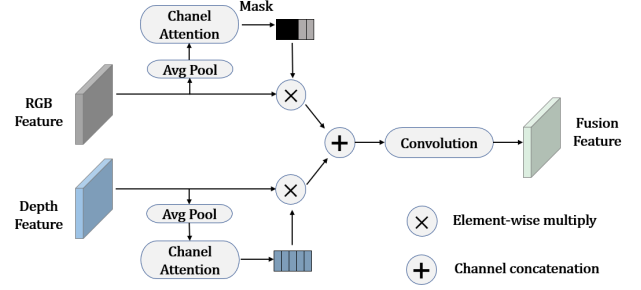


Figure 3: The architecture of fusion encoder in the inter-modal contrastive learning module.

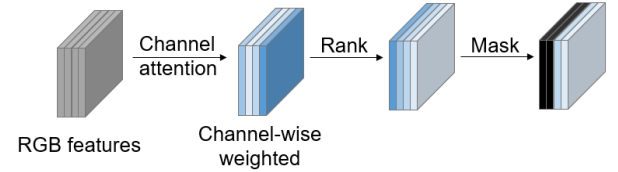


Figure 4: The details of mask for the strong modality.

### Fusion Encoder

To remove the cross-modal gap and encourage sufficient pre-training for both the strong and weak modalities in the contrastive learning process, we propose a fusion encoder in the InterCLM to convert cross-modal agreement to instance discrimination in a synthetic modality. Figure. 3 shows the structure of the fusion encoder. Firstly, the global average pooling layers are taken to remove the redundant noises while reducing the computational costs. After that, we adopt the channel attention operations to enforce our module's focus on meaningful areas of the input feature maps. At last, the features are concatenated in the latent space and passed through the convolution layers to obtain the fused representation.

### Attentive Mask for the Strong Modality

To make full use of the weak modality (depth), we design an attentive mask for the strong modality. The specific details of the mask process is shown in Fig. 4, when computing the RGB channel attention, we have  $c$  channels of RGB features  $f_r^1, f_r^2, \dots, f_r^c$ . We first sort the channels by attention scores and the sorted features are  $f_r^{1'}, f_r^{2'}, \dots, f_r^{c'}$ . Then we mask a certain proportion of the features with the largest weights, i.e., set the important RGB features to 0. The remaining features  $f_r^{m'}, f_r^{m+1'}, \dots, f_r^{c'}$  denotes as  $mask(f_r')$ . The fusion features can be calculated as follow formulas:

$$F_{fused} = Conv(F_r \otimes mask(f_r') \oplus F_d \otimes F_d'), \quad (9)$$

where  $\otimes$  denotes element-wise multiplication,  $\oplus$  means channel concatenation, Conv is the convolution layer. In this way, the depth modality is forced to learn more discriminative features to complement the masked RGB features in the fusion process to guarantee the representation ability learned from the fusion encoder.



## Experiments

### Datasets

For pre-training, we evaluate the proposed model on five public RGB-D SOD datasets which are NJUD (Feng et al. 2016) (1985 image pairs), NLPR (Peng et al. 2014b) (1000 image pairs), DUT (Chen and Li 2019b) (1200 image pairs), ReDWeb-S (Liu et al. 2020a) (3179 image pairs) and COME (Zhang et al. 2021a) (15626 image pairs). We follow the consistent setting in previous works and choose 1485 image pairs in NJUD, 700 image pairs in NLPR, 800 image pairs in DUT, 2179 image pairs in ReDWeb-S and 8025 pairs image in COME15K as the training set and the remaining samples form the testing set. Labels are not used in this stage.

For the downstream task, we adopt the same training set as previous methods (Piao et al. 2020; Zhao et al. 2022), i.e., 800 samples from the DUT, 1485 samples from the NJUD and 700 samples from the NLPR are used for training. The test set involves NJUD, NLPR, DUT, STERE (Niu et al. 2012) (1000 image pairs), SIP (Fan et al. 2020a) (929 image pairs), COME-E and COME-H.

### Evaluation Metrics

We adopt three widely used evaluation metrics to evaluate our model performance. Specifically, Maximum F-measure (Achanta et al. 2009) jointly considers precision and recall under the optimal threshold:

$$F_{\beta} = \frac{(1 + \beta^2) \cdot Precision \cdot Recall}{\beta^2 \cdot Precision + Recall}, \quad (10)$$

where  $\beta$  is set to 0.3 as suggested by Liu (Liu and Han 2016). Maximum enhanced-alignment measure Mean Absolute Error (MAE) computes pixel-wise average absolute error:

$$MAE = \frac{1}{W * H} \sum_{i=1}^W \sum_{j=1}^H |S_{i,j} - G_{i,j}|, \quad (11)$$

where  $y_i$  and  $y'_i$  represent the ground truth pixels and the pixels of the predicted saliency graph respectively.  $E_{\rho}^{max}$  (Fan et al. 2018) simultaneously considers pixel-level errors and image-level errors:

$$E_{max} = \frac{1}{W * H} \sum_{i=1}^W \sum_{j=1}^H \phi_{FM}(i, j). \quad (12)$$

### Implementation Details

The experiment is composed of upstream pre-training and downstream fine-tuning for the RGB-D SOD task. The parameters of RGB encoder and depth encoder are obtained by pre-training learning, and then applied to the downstream tasks. To clearly show the advantages of our pre-training scheme, the model parameters (RGB and depth encoders) obtained by pre-training are frozen, and other parameters of the downstream model are updated by reverse propagation when the downstream task is fine-tuned.

Upstream contrastive learning experiment: for the intra-modal contrastive learning module, we adopt ResNet50

as the encoder for two modalities. The data augmentation methods for input samples include random clipping, grayscale transformation and random flip. The intra-modal temperature coefficient  $\tau_{intra}$  is set to 0.1. We use the stochastic gradient descent (SGD) with a momentum of 0.9 and a weight decay of 0.0002 for optimization. The batch size is set to 64, epoch is 50, queue size is 16384. We train the model on 2 Tesla V100.

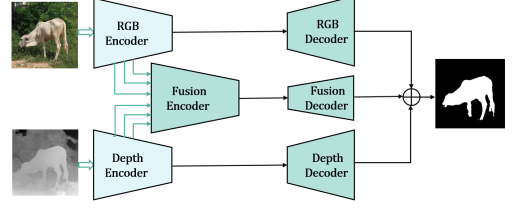


Figure 5: The architecture of downstream RGB-D SOD model.

Downstream RGB-D SOD task: the architecture of downstream RGB-D SOD model is shown in Fig. 5. We follow (Ji et al. 2021) to set the batch size to 16, learning rate to 0.0001, and train it on Tesla V100 with 100 epochs.

### Comparison with State-of-the-art

In order to verify the effectiveness of the proposed multi-modal contrastive learning framework, we compare it with three supervised SOTA models and two other popular training strategies random initialization (denoted by "Random") and Imagenet-pretraining (denoted by "Supervised") on five RGB-D SOD datasets. Our downstream is similar to DCF but without the pre-process depth calibration block. Tab. 1 shows that the performance of our proposed method with an simple downstream network is close to the current supervised SOTA models, especially on the NJUD datasets. Fig. 7 shows the superiority of our detection results in localizing the salient object and highlight its details.

Compare with the random initialization, our self-supervised learning brings significant improvement to the downstream RGB-D SOD task, which illustrates that our self-supervised learning framework can effectively learn the intra-modal and inter-modal features.

### Ablation Study

In this section, we verify the effectiveness of each proposed structure by ablation experiments, including intra-modal and inter-modal contrastive learning paths, the attentive mask module for the strong modality and the two-stage pre-training strategy.

#### Effectiveness of our contrastive learning framework.

In order to verify the effectiveness of the proposed contrastive learning framework, we compare the traditional contrastive method with ours. Specifically, traditional contrastive learning only focuses on intra-modal and extracts unimodal features respectively, which is denoted as "Intra-modal" in Tab. 2. Our method consider the complementarity in multi-modal encoders and extracts their joint fea-

Table 1: Comparisons with state-of-art methods on 5 datasets

Dataset	Metrics	CoNet (Ji et al. 2020)	BBS-Net (Fan et al. 2020b)	DCF (Ji et al. 2021)	ours Supervised	ours Random	ours Self-supervised
NJUD	$maxF \uparrow$	0.893	0.874	0.913	0.908	0.862	0.904
	$E^{max} \uparrow$	0.937	0.949	0.949	0.945	0.914	0.945
	$MAE \downarrow$	0.046	0.035	0.038	0.039	0.057	0.040
NLPR	$maxF \uparrow$	0.893	0.918	0.923	0.896	0.841	0.880
	$E^{max} \uparrow$	0.948	0.961	0.961	0.953	0.943	0.896
	$MAE \downarrow$	0.027	0.023	0.023	0.027	0.039	0.030
DUT	$maxF \uparrow$	0.932	0.870	0.920	0.916	0.828	0.914
	$E^{max} \uparrow$	0.959	0.912	0.947	0.946	0.896	0.945
	$MAE \downarrow$	0.029	0.058	0.032	0.037	0.067	0.036
STERE	$maxF \uparrow$	0.901	0.903	0.907	0.918	0.872	0.876
	$E^{max} \uparrow$	0.947	0.942	0.931	0.955	0.916	0.919
	$MAE \downarrow$	0.037	0.041	0.037	0.034	0.048	0.046
SIP	$maxF \uparrow$	0.873	0.884	0.887	0.890	0.842	0.867
	$E^{max} \uparrow$	0.917	0.922	0.920	0.927	0.895	0.917
	$MAE \downarrow$	0.048	0.055	0.051	0.049	0.074	0.058

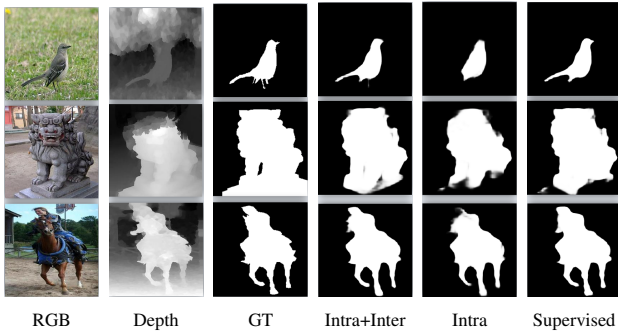


Figure 6: The comparison of saliency maps generated by our proposed model, intra-modal encoder and supervised model.

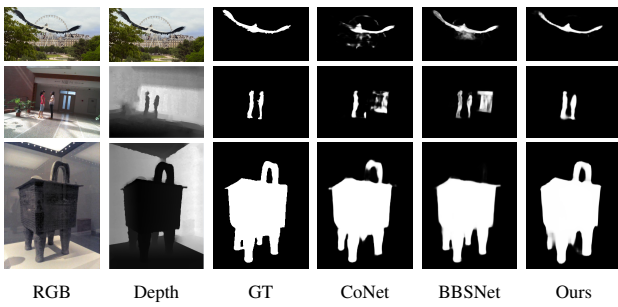


Figure 7: Comparison with other SOTA methods. "Our" denotes the model adopt two-stage strategy, fusion encoder and mask for strong modality. From the figure we can easily draw the conclusion that with our proposed methods, the downstream network has stronger comprehension ability to catch the saliency objects, no matter in locating or in details.

tures, which is denoted as "Intra-modal+Inter-modal" in Tab. 2. We can easily find that training the intra-modal and inter-modal modules together brings significant improvement over using the intra-modal module only. Fig. 6 well shows the benefits of our (Intra+Inter) pre-training scheme, which achieves better details than Intra-model only and comparable to the supervised learning model. Hence, for multi-modal representation learning, it is highly recommended to additionally learn the complementary cross-modal features rather than learning the representation of each single modal respectively. The proposed model combining the intra-modal and inter-modal contrastive learning modules, can successfully learn modal-specific representations and the cross-modal complementary representations and their combinations at the same time.

**Effectiveness of two-stage training strategy.** To effectively explore the complementarity between two modalities, we propose a two-stage training strategy, i.e., we first train the intraCML to keep the independence of each modality and then train the intraCML and interCML together to catch the correlation between two modalities. Specifically, line "one-stage" in Tab. 3 means the variant that we train the whole model together with 150 epochs at a learning rate of 0.07, line "two-stage" denotes the variant that we train the intraCML first with 200 epoch at a learning rate of 0.03 and train both the intraCML and interCML with 100 epoch at a learning rate of 0.05. These parameters perform best in their corresponding training processes. Experiment results in Table 3 show that two-stage training strategy is largely better than one-stage, which illustrates that learning well the uni-modal features plays a decisive role in multi-modal representation learning. The cross-modal representations can be effectively learned only if the single model representation is strong enough.

**Effectiveness of mask for strong modality.** To prevent the strong modality from dominating the Inter-modal CL process and sufficiently explore the weak modality as well

Table 2: Ablation study of training intra-modal only and training intra-modal and inter-modal together.

Settings	NLPR		DUT		COME-E		COME-H	
	$maxF \uparrow$	$MAE \downarrow$	$maxF \uparrow$	$MAE \downarrow$	$maxF \uparrow$	$MAE \downarrow$	$maxF \uparrow$	$MAE \downarrow$
Intra-modal	0.845	0.039	0.828	0.069	0.531	0.200	0.523	0.231
Intra-modal+Inter-modal	<b>0.867</b>	<b>0.033</b>	<b>0.845</b>	<b>0.061</b>	<b>0.579</b>	<b>0.180</b>	<b>0.567</b>	<b>0.213</b>

Table 3: Ablation experiments of two-stage training strategy and mask for strong modality.

Dataset	Metrics	One-stage			Two-stage		
		No mask	25%mask	50%mask	No mask	25%mask	50%mask
NLPR(Peng et al. 2014b)	$maxF \uparrow$	0.867	0.868	0.871	0.884	0.887	<b>0.892</b>
	$E^{max} \uparrow$	0.939	0.936	0.941	0.944	0.948	<b>0.950</b>
	$MAE \downarrow$	0.033	0.032	0.031	0.030	0.028	<b>0.027</b>
DUT(Chen and Li 2019b)	$maxF \uparrow$	0.845	0.853	0.864	0.900	0.899	<b>0.902</b>
	$E^{max} \uparrow$	0.905	0.910	0.919	0.935	<b>0.937</b>	0.935
	$MAE \downarrow$	0.061	0.058	0.054	0.045	<b>0.043</b>	<b>0.043</b>
COME-E(Zhang et al. 2021a)	$maxF \uparrow$	0.579	0.581	0.594	0.699	0.705	<b>0.710</b>
	$E^{max} \uparrow$	0.717	0.720	0.727	0.790	0.795	<b>0.803</b>
	$MAE \downarrow$	0.180	0.180	0.169	0.136	0.13	<b>0.128</b>
COME-H(Zhang et al. 2021a)	$maxF \uparrow$	0.567	0.571	0.582	0.656	0.676	<b>0.684</b>
	$E^{max} \uparrow$	0.692	0.695	0.701	0.760	0.762	<b>0.771</b>
	$MAE \downarrow$	0.213	0.210	0.201	0.170	0.167	<b>0.162</b>

as the complements between two modalities, we propose an attentive mask operation for the strong modality. Specifically, we mask 0%, 25% and 50% most discriminative channels in RGB features and compare their performance on the downstream RGB-D SOD task. Tab 3 shows that the attentive mask operation improves the performance consistently in one-stage or two-stage training settings, which verifies its efficacy in encouraging the weak modality to learn more complementary information and promoting the downstream performance. Also, we find that masking with 50% performs better than 25%.

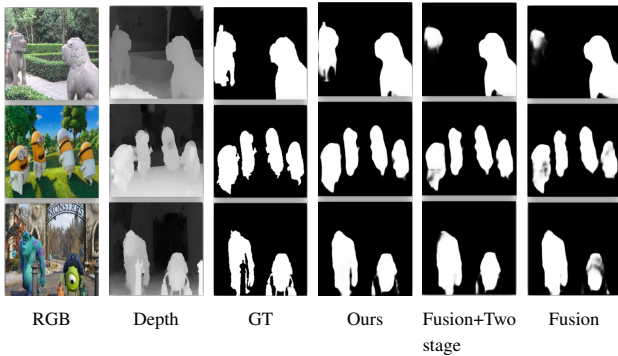


Figure 8: The visualization of ablation experiments about fusion encoder, two stage strategy and mask for strong modality.

### Compare with Traditional Alignment Methods

Traditional multi-modal contrastive learning methods extract the features respectively and adopt cross-modal align-

ment(Yuan et al. 2021; Liu et al. 2021; Liang et al. 2022) as contrastive objective by shortening the distance of multi-modal features from the same anchor scene. Line "Alignment" in Tab. 4 denotes that the alignment method and "Fusion+50%mask" denotes our proposed modality-balanced CL with a attentive fusion encoder. They have the same settings in intraCLM with 0.1 temperature coefficient. For interCLM, the best temperature coefficient is 0.1 for alignment, and 0.04 for ours. Tab. 4 shows that our proposed modality-balanced contrastive fusion scheme outperforms the alignment largely on all datasets.

Although the alignment reduces the distance of similar representations from different modalities, it also closes the distance between two nearest but unpaired samples, especially for hard negative samples, which further lowers the discriminative ability of model. Therefore, we adopt fusion operation to combine two modal representations, and drive the fused representation close to positive samples and away from negative samples, which prevents hard negative samples from resistance to reduce inter-modal differences. Fig. 8 also shows the advantages of our CL framework, which generates more uniform and correct salient object detection.

## Conclusion

In this work, we propose a new CL for multi-modal dense prediction. We propose to combine multi-modal pairs as a synthetic modality to remove the modality gap, and an attentive masking module to rebalance modalities for sufficient training of each modality and exploration of cross-modal correlations and informative cross-modal fusion.

Table 4: Comparison between the traditional alignment and our fusion contrastive schemes.

Datasets	Metrics	One-stage		Two-stage	
		Alignment	Fusion+50%mask	Alignment	Fusion+50%mask
NLPR	$maxF \uparrow$	0.860	0.871	0.889	<b>0.892</b>
	$E^{max} \uparrow$	0.936	0.941	0.948	<b>0.950</b>
	$MAE \downarrow$	0.033	0.031	0.027	<b>0.027</b>
DUT	$maxF \uparrow$	0.859	0.864	0.895	<b>0.902</b>
	$E^{max} \uparrow$	0.916	0.919	0.931	<b>0.935</b>
	$MAE \downarrow$	0.056	0.054	0.045	<b>0.043</b>
COME-E	$maxF \uparrow$	0.589	0.594	0.698	<b>0.710</b>
	$E^{max} \uparrow$	0.724	0.727	0.799	<b>0.803</b>
	$MAE \downarrow$	0.178	0.169	0.130	<b>0.128</b>
COME-H	$maxF \uparrow$	0.578	0.582	0.680	<b>0.684</b>
	$E^{max} \uparrow$	0.699	0.701	0.769	<b>0.771</b>
	$MAE \downarrow$	0.210	0.201	0.166	<b>0.162</b>

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