Event Camera Data Pre-training

Yan Yang¹ Liyuan Pan^{2 †} Liu Liu³
¹BDSI, ANU ²BITSZ & School of CSAT, BIT ³Cyberverse Dept., Huawei

Yan.Yang@anu.edu.au liyuan.pan@bit.edu.cn liuliu33@huawei.com

Abstract

This paper proposes a pre-trained neural network for handling event camera data. Our model is trained in a selfsupervised learning framework, and uses paired event camera data and natural RGB images for training.

Our method contains three modules connected in a sequence: i) a family of event data augmentations, generating meaningful event images for self-supervised training; ii) a conditional masking strategy to sample informative event patches from event images, encouraging our model to capture the spatial layout of a scene and fast training; iii) a contrastive learning approach, enforcing the similarity of embeddings between matching event images, and between paired event-RGB images. An embedding projection loss is proposed to avoid the model collapse when enforcing event embedding similarities. A probability distribution alignment loss is proposed to encourage the event data to be consistent with its paired RGB image in feature space.

Transfer performance in downstream tasks shows superior performance of our method over state-of-the-art methods. For example, we achieve top-1 accuracy at 64.83% on the N-ImageNet dataset.

1. Introduction

An event camera asynchronously captures the time, location, and polarity of pixel-wise changes in brightness, as a sequence of events. Event cameras are widely used in many applications, *e.g.*, recognition [19], detection [27, 24], segmentation [2], optical flow [39], and SLAM [36]. Compared with conventional RGB cameras which record all pixel intensities at a fixed frame rate, event cameras enjoy high dynamic range and temporal resolution, and are robust to lighting changes and motion blur [19, 33, 22].

This paper studies the problem of event camera data pretraining. Our pre-trained model is trained self-supervisedly, only using paired event data and RGB images for training.

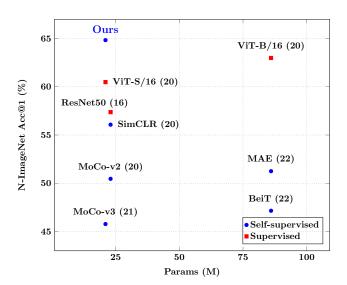


Figure 1: Comparison of our methods and state-of-the art methods on N-ImageNet dataset. The Blue cycle and red square separately denote the self-supervised and supervised pre-training methods. We show top-1 accuracy (%), i. e., acc@1, with respect to number of model parameters (M). We include the publication year of each method in the brackets beside the method names. Best viewed in color on the screen.

One can simply transfer our pre-trained model for diverse downstream tasks.

Significant progresses have been made for RGB images pre-training, in a self-supervised learning (SSL) framework. However, it is non-trivial to replicate the success for event camera data, as there is a domain-gap between RGB images and event data. An RGB image records all pixel intensities of a scene and is spatially dense, while the event data only records scene changes and is spatially sparse.

For network training in the SSL framework, image augmentations (*e.g.*, Gaussian Blur, ColorJitter, RandomResizedCrop) are one of the most important parts. The sparse event camera data can be commonly represented as an event image [19]. One may directly and wrongly perform these

[†] Corresponding author.

augmentations on event images, *e.g.*, blurring a binary event image (0/1 valued pixels) generates a meaningless event image. In contrast, we study how to perform event data augmentations before converting data to an event image.

We formulate our learning problem as a contrastive learning task, taking event images as inputs. One may directly perform a random masking strategy to sample a fixed number of event patches for encouraging the model to capture the spatial layout and fast training. However, an event image is spatially sparse, and random masking would generate non-informative patches, leading to training instability. To mitigate this problem, we propose a conditional masking strategy to sample informative patches.

With event patches, we are able to learn discriminative event embeddings, i. e., pulling together embeddings from similar event images while pushing away embeddings from dissimilar ones. Surprisedly, we find that simply performing metric learning in the event embedding space leads to model collapse, producing over-similar embeddings. The reason comes from the spatial sparsity of event images. To solve this problem, we find that embeddings from paired RGB images can be used as a regularizer, and we propose an embedding projection loss to solve the collapse.

With paired event data and RGB images, we also aim to pull together embeddings from matched pairs. This is motivated by the fact that many well pre-trained RGB networks are available, and an event image is less informative than its paired RGB image. An RGB network serves as a teacher for an event network. We propose a probability distribution alignment loss for the learning.

Our network is trained end-to-end. The overall framework is illustrated in Fig. 2. Our contributions are:

- An self-supervised framework for event camera data pre-training. The pre-trained model can be transferred to diverse downstream tasks;
- A family of event data augmentations, generating meaningful event images;
- A conditional masking strategy, sampling informative event patches for network training;
- An embedding projection loss, using paired RGB embeddings to regularize event embeddings to avoid model collapse;
- A probability distribution alignment loss for aligning embeddings from paired event and RGB images.
- We achieve state-of-the-art performance in standard event benchmark datasets (*e.g.*, Fig. 1).

2. Related Work

The SSL frameworks can be generally divided into two categories: contrastive learning and masked modeling. We briefly review their recent achievements, and then introduce event datasets for diverse computer vision tasks.

Contrastive learning. This approach generally assumes augmentation invariance of images [6, 17]. Two or more views of each image are generated for instance discrimination that enforces embedding similarity and dissimilarity among the views [6, 17, 7, 9, 37]. Only enforcing the embedding similarity is also possible and has been studied in [8, 15]. In addition to model design and optimization objectives, contrastive learning approaches usually rely on strong augmentations over images to boost model performance [6, 17, 7, 9, 3, 8]. Under certain tasks, contrastive learning has shown better performance than supervised pre-training [13, 9]. However, one notable drawback of contrastive learning is suffering from model collapse and training instability. Diverse methods including asymmetric network designs (e.g., maintaining a momentum network) [6, 17], partial weight freezing [9], and group-based discrimination [3, 4] are introduced to avoid the model collapse and instability issue.

Masked modeling. Reconstructing masked inputs from the (i. e., unmasked) visible ones is a popular self-supervised learning objective motivated by the idea of autoencoding. The pioneer works can be specified to the natural language processing domain, *e.g.*, Bert [12] and GPT [28]. Recently, masked modeling has been formulated in the image domain, where the objective is defined in a similar vein, and the masking of images is done pixel-wisely or patch-wisely [5, 16, 13, 1, 38]. Some works [1, 38] turn the masked modeling into a classification problem by predicting discrete indices assigned to the masked patches by a tokenizer, *e.g.*, pre-trained discrete VAE [29, 14] or self-distilled network [38, 4]. One could also target to directly regress the pixel intensity of masked patches [5, 16, 13].

Event dataset. The event camera is a novel sensor that asynchronously captures the time, location, and polarity (i. e., direction) of per-pixel brightness change as a sequence of events. With growing interest in event-based computer vision tasks, researchers have collected a wide range of datasets for object recognition [19, 32, 25, 10], semantic segmentation [2], optical flow estimations [39], and so forth [30, 23, 35]. To leverage existing computer vision algorithms, *e.g.*, CNN and ViT, the majority of event-based vision frameworks convert event data into image/video-liked grid representations, where the conversion is done either learnable [31] or by directly using the position and time of each event [19]. This paper leverages the event image representation to study the event-based SSL algorithm that benefits diverse event-based downstream tasks.

3. Method

We start with a brief overview of background knowledge, and then present our self-supervised learning framework in

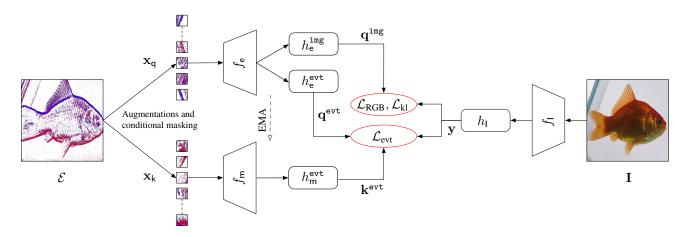


Figure 2: The overall architectures. For pre-training, our method takes event data \mathcal{E} and its paired natural RGB image I as inputs, and outputs a pre-trained network f_e . Given \mathcal{E} (its abstract representation is used for visualization purpose), we first consecutively perform data augmentations, event image generation, and conditional masking to obtain two patch sets $(\mathbf{x_q}, \mathbf{x_k})$. Second, f_e extract features from event patch set $\mathbf{x_q}$, and h_e^{evt} separately project features from f_e to latent embeddings \mathbf{q}^{img} and \mathbf{q}^{evt} . f_m and h_m^{evt} are momentum of f_e and h_e^{evt} , and are updated by the exponential moving average (EMA). The momentum network takes patch set $\mathbf{x_k}$ as input and generates an embedding \mathbf{k}^{evt} . At the same time, the natural RGB image I is embedded into $\mathbf{y} = f_l(h_l(\mathbf{I}))$. Finally, we perform event discrimination, and event and natural RGB image discrimination to train our model. We optimize the network by \mathcal{L}_{evt} (Eq. 4), \mathcal{L}_{RGB} (Eq. 5), \mathcal{L}_{kl} (Eq. 7). \mathcal{L}_{evt} is an event embedding projection loss aiming to pull together paired event embeddings \mathbf{q}^{evt} and \mathbf{k}^{evt} , for event discrimination. \mathcal{L}_{RGB} aims to pull together paired event and RGB embeddings, towards well-structured embedding space of natural RGB images. Best viewed in color on the screen.

this section. The overall architecture is shown in Fig. 2.

Preliminary. Contrastive representation learning aims to learn an embedding space, where similar image pairs stay close to each other while dissimilar ones are far apart. Specifically, images are embedded into vectors to collect a query set $\{q\}$ and a key set $\{k\}$. For each query q, we have a matching key k_+ and non-matching keys $\{k_-\}$. Usually, q and k_+ are generated from views of the same instance, while q and $\{k_-\}$ are generated from views of different instances. Contrastive learning aims to pull together embeddings q and k_+ , and pushes away embeddings q and $\{k_-\}$. In this paper, we use the InfoNCE loss [34],

$$\begin{split} \mathcal{L}_{nce}(\mathbf{q}, \{\mathbf{k}\}) &= -\log \frac{\exp(\mathbf{q} \cdot \mathbf{k}_{+}/\tau)}{\exp(\mathbf{q} \cdot \mathbf{k}_{+}/\tau) + \sum\limits_{\mathbf{k}_{-}} \exp(\mathbf{q} \cdot \mathbf{k}_{-}/\tau)} \;, \end{split}$$

$$\tag{1}$$

where ${\bf q}$ and ${\bf k}$ are first L_2 normalized to a metric space, and the similarity between them are then measured by the cosine similarity using dot-product (\cdot) . τ is a temperature hyper-parameter.

Overall architecture. Given an event data $\mathcal{E} = (u_i, t_i, p_i)_{i=1}^{N}$ and a paired natural RGB image **I**, where u_i ,

 t_i , and p_i separately denotes spatial location, time, and polarity of each event, and N is the length of the event data.

We aim to pre-train a neural network $f_{\rm e}$, such that $f_{\rm e}$ can generate discriminative features for benefiting diverse event-based downstream tasks. Our method is self-supervised and has three components: i) event image patches generation. Given input \mathcal{E} , it generates matching patches $(\mathbf{x}_{\rm q},\mathbf{x}_{\rm k})$ on \mathcal{E} ; ii) event discrimination. It aims to pull together embeddings of $(\mathbf{x}_{\rm q},\mathbf{x}_{\rm k})$; and iii) event and RGB image discrimination. It aims to pull together embeddings of $\mathbf{x}_{\rm q}$ and I. Details of the above three components are given in following paragraphs.

Event image patches generation. To convert \mathcal{E} into two matching patches $(\mathbf{x}_q, \mathbf{x}_k)$, we consecutively apply our data augmentations, event image generation, and conditional masking strategy. Given augmented \mathcal{E} (refer to our supplementary materials for details), we first generate an event image by applying the event histogram algorithm [20], and then use our conditional masking strategy to obtain patches \mathbf{x}_q and \mathbf{x}_k . Given an event image, considering its sparsity, a random masking strategy to sample patches is prone to generate meaningless/non-informative patches. Therefore, a conditional masking strategy is proposed to sample patches. Let $\{\mathbf{p}_i\}_{i=1}^L$ be a patch set of an event image, \mathbf{p}_i

is the *i*-th patch, and L is the cardinality of the set. After vectorizing \mathbf{p}_i , we calculate the information quantity d_i of each patch,

$$\mathsf{d}_i = |\mathbf{p}_i| \cdot \mathbf{1}, \quad \forall i \in [1, \dots, \mathsf{L}],\tag{2}$$

where 1 denotes a vector of ones. Collecting L information quantities and L_1 normalizing them, we obtain a probability distribution. A patch probability describes how likely it contains meaningful information. We randomly sample a fixed number (\ll L) of patches according to the probability distribution, resulting in \mathbf{x}_q . Then, the same process is performed to generate \mathbf{x}_k .

Event discrimination. With patches \mathbf{x}_q and \mathbf{x}_k , we show how to pull together embeddings of them. \mathbf{x}_q is fed to network f_e to extract features, and features from f_e are fed to a projection head h_e^{evt} to extract an embedding \mathbf{q}^{evt} , $\mathbf{q}^{\text{evt}} = h_e^{\text{evt}}(f_e(\mathbf{x}_q))$. For self-supervised training, \mathbf{x}_k is fed to f_m and h_m^{evt} to extract an embedding \mathbf{k}^{evt} , $\mathbf{k}^{\text{evt}} = h_m^{\text{evt}}(f_m(\mathbf{x}_k))$, where f_m and h_m^{evt} are the momentum [17] of f_e and h_e^{evt} , respectively.

To enforce the similarity between embeddings \mathbf{q}^{evt} and \mathbf{k}^{evt} , one may directly optimize the InfoNCE loss $\mathcal{L}_{\text{nce}}(\mathbf{q}^{\text{evt}},\{\mathbf{k}^{\text{evt}}\})$. However, we find that optimized embeddings collapse, i.e., they are over-similar. The reason would be the sparsity of event images and the sparsity decreases the discriminativeness of event embeddings.

To solve this collapse problem, interestingly, we find that embedding $\mathbf{y} = h_{\mathrm{I}}(f_{\mathrm{I}}(\mathbf{I}))$ of the paired natural RGB image \mathbf{I} is a basis vector and provides good regularization. f_{I} is an image feature extraction network and h_{I} projects features to an embedding. We have the event embedding projection loss,

$$\mathcal{L}_{evt} = \mathcal{L}_{nce}(\zeta(\mathbf{q}^{evt}, \mathbf{y}), \{\zeta(\mathbf{k}^{evt}, \mathbf{y})\}), \quad (3)$$

$$\zeta(\mathbf{v}_1, \mathbf{v}_2) = \mathbf{v}_1 \cdot \mathbf{v}_2 \, \frac{\mathbf{v}_2}{\|\mathbf{v}_2\|},\tag{4}$$

where $\zeta(\mathbf{v}_1, \mathbf{v}_2)$ is the projection function. Here, $\zeta(\mathbf{q}^{\text{evt}}, \mathbf{y})$ and $\zeta(\mathbf{k}^{\text{evt}}, \mathbf{y})$ separately projects event embeddings \mathbf{q}^{evt} and \mathbf{k}^{evt} to embedding \mathbf{y} . We do not perform L_2 normalization on $\zeta(\mathbf{q}^{\text{evt}}, \mathbf{y})$ and $\zeta(\mathbf{k}^{\text{evt}}, \mathbf{y})$ for calculating \mathcal{L}_{evt} .

More analysis and comparisons of our event embedding projection loss and the vanilla InfoNCE loss $\mathcal{L}_{nce}(\mathbf{q^{evt}}, \{\mathbf{k^{evt}}\})$ are given in the supplementary material.

Event and RGB image discrimination. Considering the sparsity of the event image, a single event image is less informative than an RGB image, possessing difficulty for self-supervised event network training. In contrast, many well-trained RGB networks are available. We aim to teach our event network f_e , using well pre-trained RGB network f_I . We pull together embeddings of paired event and RGB images, \mathbf{x}_q and \mathbf{I} . Features from f_e are fed to a projection

head h_e^{img} to extract an event image embedding \mathbf{q}^{img} . Given embeddings \mathbf{q}^{img} and \mathbf{y} , we enforce their similarity by optimizing the InfoNCE loss,

$$\mathcal{L}_{RGB} = \mathcal{L}_{nce}(\mathbf{q}^{img}, \{\mathbf{y}\}). \tag{5}$$

To better align event and RGB embedding spaces, we first separately fit two probability distributions in the event and RGB embedding spaces, and then use Kullback–Leibler divergence to minimize the mismatch between the two distributions.

Specifically, given a batch of event embeddings $\{\mathbf{q}^{\text{img}}\}$, we first compute the pairwise embedding similarity and then fit an exponential kernel to similarities to compute probability scores. The probability score of the (i,j)-th pair is given by,

$$s_{i,j}^{\mathbf{q}} = \frac{\exp(\mathbf{k}_i \cdot \mathbf{k}_j / \tau)}{\sum_{j} \exp(\mathbf{k}_i \cdot \mathbf{k}_j / \tau)},$$
 (6)

where \mathbf{k}_i and \mathbf{k}_j are the *i*-th and *j*-th embedding of the batch $\{\mathbf{q}^{\text{img}}\}$. τ is the same hyperparameter in Eq. (1). The probability score of \mathbf{y} is obtained in the same way and is denoted as $s_{i,j}^{\mathbf{y}}$.

Our probability distribution alignment loss is given by,

$$\mathcal{L}_{kl} = \sum_{i} \sum_{j} s_{i,j}^{\mathbf{q}} \cdot \log \left(\frac{s_{i,j}^{\mathbf{q}}}{s_{i,j}^{\mathbf{y}}} \right)$$
 (7)

Losses. Our network is trained end-to-end, and the loss is given by,

$$\mathcal{L}_{total} = \mathcal{L}_{evt} + \mathcal{L}_{RGB} + \lambda_1 \mathcal{L}_{kl}, \tag{8}$$

where λ_1 is the hyper-parameter.

4. Experiments

4.1. Experimental Setup

Pre-training dataset. We use the N-ImageNet [19] and ImageNet-1K [11] datasets for pre-training. The N-ImageNet dataset is converted from ImageNet-1K dataset, where a moving event camera observes the monitor displayed natural RGB images. Similar to ImageNet-1K, it contains 1,781,167 samples of event data, covering 1,000 object classes. All event data are recorded in 480×640 resolution. We resize them into 224×224 resolution, and use the officially splitted training partitions for pre-training.

Implementation. We use the ViT-S/16 as default backbone for f_e and f_m , and the same projection head as MoCov3 for h_e^{evt} , h_m^{evt} , and h_e^{img} . We use SSL pre-trained ViT-B/32 as the RGB image backbone f_1 , and set h_1 to a single

Table 1: Comparison of object recognition accuracies on the N-ImageNet dataset [19]. We mainly consider three backbones, i. e., ViT-S/16, ViT-B/16, and ResNet50. We show the top-1 and top-5 accuracies (i. e., acc@1 and acc@5 (%)) for both linear probing and fine-tuning. For linear probing, we simply project features from pre-trained networks using a single linear layer.

Method	Architecture	Parameters	Pre-training Epoch _	Linear Probing		Fine-tuning	
				acc@1	acc@5	acc@1	acc@5
Training from	scratch, i. e., ra	ndom weight i	nitialization.				
ViT [13]	ViT-S/16	21M	-	-	-	46.70	69.89
ViT [13]	ViT-B/16	86M	-	-	-	51.23	74.50
ResNet [18]	ResNet50	23M	-	-	-	48.95	73.24
Transfer learn	ing of supervise	d pre-training	methods, i. e., initial w	eights learn	ed in a supervi	sed manner.	
ViT [13]	ViT-S/16	21M	300	-	-	60.48	83.02
ViT [13]	ViT-B/16	86M	300	-	-	62.98	84.75
ResNet [18]	ResNet50	23M	90	-	-	57.37	80.93
Transfer learn	ing of self-super	rvised pre-trai	ning methods, i. e., initi	ial weights l	earned in a self	supervised ma	ınner.
SimCLR [6]	ResNet50	23M	100	-	-	56.07	80.49
MoCo-v2 [7]	ResNet50	23M	200		-	50.46	75.67
MoCo-v3 [9]	ViT-S/16	21M	300	-	-	45.77	68.89
BeiT [1]	ViT-B/16	86M	800	-	-	47.15	69.27
iBoT [38]	ViT-S/16	21M	800	-	-	19.55	38.72
MAE [16]	ViT-B/16	86M	800	-	-	51.25	72.64
Ours	ViT-S/16	21M	300	59.90	82.26	64.83	86.30

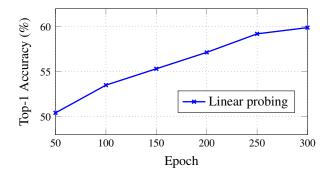


Figure 3: The linear probing accuracy of our method with respect to the number of training epochs.

linear layer. The hyper-parameters λ_1 is set to 2. Please refer to the supplementary material for optimization schemes, ablation of $f_{\rm e}$, $f_{\rm l}$ and $h_{\rm l}$, and more details. All experiments are conducted within the Pytorch framework [26]. Our code and and pre-trained models will be released.

Baselines. We explore three backbones, i.e., ViT-S/16, ViT-B/16, and ResNet50. Our method is compared with three group of methods: 1) Training from scratch. For this group, we train state-of-the-art methods with random weight initialization; 2) Transfer learning of supervised pre-training methods. The initial weights of state-of-the-art methods are obtained in a supervised manner using

the ImageNet-1K dataset; 3) Transfer learning of self-supervised pre-training methods. The initial weights of state-of-the-art methods are obtained in a self-supervised manner using the ImageNet-1K dataset.

Transfer learning tasks. We evaluate our model and state-of-the-art methods on diverse downstream tasks including object recognition, optical flow estimation, semantic segmentation, and so forth. We present the performance of object recognition and flow estimation in the main paper. For experiments on the remaining downstream tasks, please refer to the supplementary material.

4.2. Object Recognition

We first show our object recognition performance on the large-scale N-ImageNet [19] dataset and then report our performance on three small-scale datasets, N-Cars [32], N-Caltech101 [25], and CIFAR-10-DVS [10].

Results on the large-scale N-ImageNet dataset. The comparisons are given in Tab. 1. It shows that fine-tuning our pre-trained model achieves a top-1 accuracy at 64.84%, outperforming all other baselines. Moreover, even linear probing of our pre-trained model achieves good performance, with a top-1 accuracy at 59.90%, outperforming methods in the self-supervised group. The performance of our linear probing accuracy with respect to increasing number of training epochs is given in Fig. 3.

Table 2: Comparison of object recognition accuracies on the N-Cars [32], N-Caltech101 [25], and CIFAR-10-DVS [10] datasets. We show the top-1 accuracies for clarity.

Method	Method Architecture		N-Caltech101	CIFAR-10-DVS	
Training from scratch.					
ViT [13]	ViT-S/16	89.14	55.63	52.45	
ViT [13]	ViT-B/16	93.09	67.11	55.15	
ResNet [18]	ResNet50	91.20	62.69	56.65	
Transfer learning of st	upervised pre-training meth	ods.			
ViT [13]	ViT-S/16	96.76	85.02	76.10	
ViT [13]	ViT-B/16	97.56	86.45	77.45	
ResNet [18]	ResNet50	97.61	86.51	73.40	
Transfer learning of se	elf-supervised pre-training	methods.			
SimCLR [6]	ResNet50	97.10	86.57	75.15	
MoCo-v2 [7]	ResNet50	96.64	84.16	74.65	
MoCo-v3 [9]	ViT-S/16	95.33	76.59	68.40	
BeiT [1]	ViT-B/16	90.61	53.10	53.15	
iBoT [38]	ViT-S/16	92.30	47.36	56.10	
MAE [16]	ViT-B/16	95.34	67.68	68.65	
Ours	ViT-S/16	97.93	87.66	78.00	

Table 3: Comparison of optical flow estimation on the MVSEC dataset [39]. We use average end-point error (AEE) and percentage of outliers (%) for evaluation. Similar to the KITTI benchmark [21], the outlier measures the percentage of pixels that has end-out-error larger than three units and 5% of the ground truth optical flow.

Method	Backbone _	$indoor_flying1$		indoor_flying2		indoor_flying3	
		AEE	Outlier	AEE	Outlier	AEE	Outlier
Training from s	scratch.						
ViT [13]	ViT-S/16	0.68	0.13	1.38	7.58	1.08	3.76
ViT [13]	ViT-B/16	0.64	0.19	1.36	7.21	1.05	3.86
ResNet [18]	ResNet50	0.73	0.66	1.55	9.81	1.23	5.77
Transfer learni	ing of supervised	d pre-trainin	g methods.				
ViT [13]	ViT-S/16	0.88	3.06	1.79	16.63	1.49	8.66
ViT [13]	ViT-B/16	0.65	0.45	1.34	7.65	1.11	4.96
ResNet [18]	ResNet50	0.60	0.23	1.37	8.76	1.15	5.34
Transfer learni	ing of self-super	vised pre-tra	ining methods				
SimCLR [6]	ResNet50	0.65	0.49	1.45	9.33	1.19	5.51
MoCo-v2 [7]	ResNet50	0.61	0.46	1.36	8.68	1.13	5.20
MoCo-v3 [9]	ViT-S/16	0.66	0.35	1.41	8.23	1.17	5.10
BeiT [1]	ViT-B/16	0.64	0.29	1.32	7.34	1.07	4.32
iBoT [38]	ViT-S/16	0.80	0.81	1.47	8.77	1.16	5.43
MAE [16]	ViT-B/16	0.61	0.17	1.29	6.95	1.11	4.64
Ours	ViT-S/16	0.61	0.05	1.26	6.69	1.00	3.11

For methods (except ours) in the self-supervised group, we find that they overfit easily (even achieving 100% top-1 training accuracy) when fine-tuning on the N-ImageNet dataset, though we have tried our best to use diverse regularization techniques. This further demonstrates the value of

this paper – a self-supervised learning framework for event camera data pre-training.

Overall, we significantly outperform the state-of-theart self-supervised methods (SimCLR, MoCo-v2, MoCov3, BeiT, iBoT, and MAE), by 8.76%, 14.37%, 19.06%,

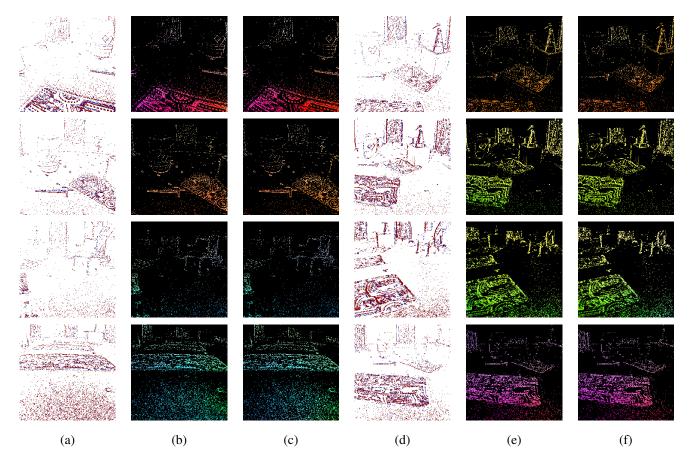


Figure 4: Optical flow predictions examples of our method on the MVSEC dataset [39]. (a)/(d) are event images, where red and blue indicate positive and negative events. (b)/(e) are ground truth optical flows. (c)/(f) are predicted optical flows by using our method.

17.68%, 45.28%, and 13.58% top-1 accuracy in the fine-tuning evaluation. For more analysis of the performance, please refer to the supplementary material.

Results on other small-scale datasets. The comparisons on N-cars [32], N-Caltech101 [25], and CIFAR-10-DVS [10] datasets are given in Tab. 2, using same network configurations as Tab. 1. Note that the N-Caltech101 and CIFAR-10-DVS have not provided training and testing splits. We therefore randomly split it for generating training and testing datasets (given in the supplementary material). Our method outperforms all other self-supervised methods, with 97.93%, 87.66%, and 78.00% top-1 accuracy on N-Cars, N-Caltech101 and CIFAR-10-DVS datasets, respectively. More analysis of the performance of state-of-the-art methods are given in the supplementary material.

4.3. Optical Flow Estimation

We show our optical flow estimation performance on the MVSEC dataset [39]. Following [16, 1], we simply append a decoder network to pre-trained networks to estimate the

optical flow. Please refer to the supplementary material for architecture details and train-test spliting. We consider three evaluation scenes: 'indoor_flying1', 'indoor_flying2', and 'indoor_flying3'. The comparisons are given in Tab. 3.

Compared with other methods, our method have lower AEEs and outlier ratios, showing the effectiveness of our pre-trained model for the optical flow estimation task. Interestingly, our self-supervised ViT-based model outperforms supervised ResNet-based model, which is previously considered as a standard backbone for the optical flow task. We show optical flow predictions examples of our method in Fig. 4. More analysis of the performance of state-of-the-art methods are given in the supplementary material.

4.4. Discussion

We visualize attention maps of our pre-trained model in Fig. 5, where features from the last layer of our pre-trained model are used to compute the attention map (please refer to our supplementary materials for details). The results show that our pre-trained model successfully focuses on semantic

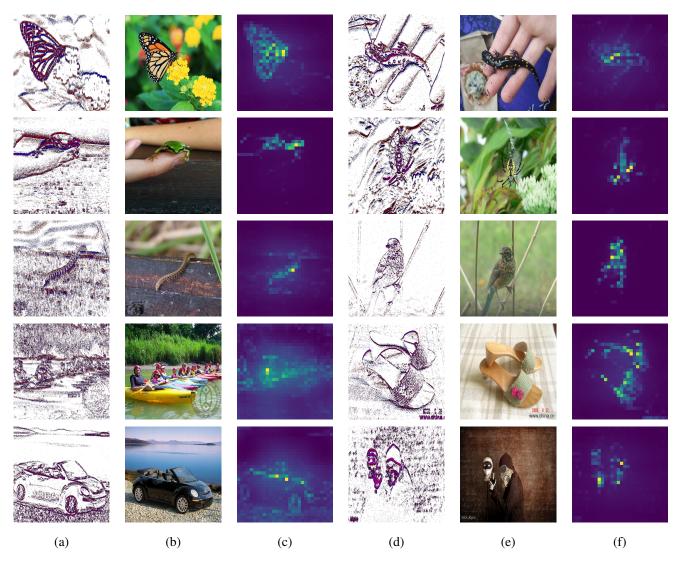


Figure 5: Attention maps of our pre-trained model (without any fine-tuning) on sample data from the N-ImageNet dataset [19]. (a)/(d) are event images. Similarly, we use red and blue indicate positive and negative events. (b)/(e) are corresponding natural RGB images used for visualization assistance. (c)/(f) are our attention maps.

meaningful objects on the noisy event images (*e.g.*, spider on the second row of Fig. 5). This strong pattern discovery ability of our method potentially explains the effectiveness of our pre-trained model when transferring to diverse downstream tasks.

5. Conclusion

In this paper, we have trained a neural network for processing event camera data, in a self-supervised learning framework. The method contains three key components: a family of event data augmentations, a conditional masking strategy, and a contrastive learning approach. Our key insight is enforcing the similarity of embeddings between

matching event images and between paired event-RGB images to pre-train our model. Extensive experiments on downstream tasks (*e.g.*, object recognition, optical flow estimation, *etc.*) demonstrate the superiority of our method over past methods.

Broader impacts. There are diverse potential extensions of our method. For example, our model is promising to achieve zero-shot or few-shot learning by using existing vision-language methods from the RGB image domain, due to event data and RGB images are aligned in our feature space. We hope this paper will inspire future work.

Acknowledgment. Liyuan Pan's work was supported in part by the Beijing Institute of Technology Research Fund Program for Young Scholars.

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