RMT: Retentive Networks Meet Vision Transformers

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Abstract

Transformer first appears in the field of natural language processing and is later migrated to the computer vision domain, where it demonstrates excellent performance in vision tasks. However, recently, Retentive Network (RetNet) has emerged as an architecture with the potential to replace Transformer, attracting widespread attention in the NLP community. Therefore, we raise the question of whether transferring RetNet's idea to vision can also bring outstanding performance to vision tasks. To address this, we combine RetNet and Transformer to propose RMT. Inspired by RetNet, RMT introduces explicit decay into the vision backbone, bringing prior knowledge related to spatial distances to the vision model. This distance-related spatial prior allows for explicit control of the range of tokens that each token can attend to. Additionally, to reduce the computational cost of global modeling, we decompose this modeling process along the two coordinate axes of the image. Abundant experiments have demonstrated that our RMT exhibits exceptional performance across various computer vision tasks. For example, RMT achieves 84.1% Top1-acc on ImageNet-1k using merely 4.5G FLOPs. To the best of our knowledge, among all models, RMT achieves the highest Top1-acc when models are of similar size and trained with the same strategy. Moreover, RMT significantly outperforms existing vision backbones in downstream tasks such as object detection, instance segmentation, and semantic segmentation. Our work is still in progress.

1. Introduction

Since the Transformer was proposed in the field of NLP[52], it has achieved outstanding performance in many downstream tasks. Despite the modality gap between com-

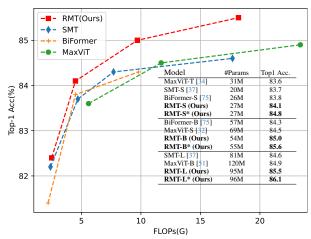


Figure 1. FLOPs vs. Top-1 accuracy on ImageNet-1K with 224×224 resolution. "*" indicates the model trained with token labeling [30].

puter vision and natural language processing, researchers have successfully migrated this architecture to vision tasks, bringing us once again a huge surprise like in previous NLP tasks[3, 12, 13, 28, 34].

Recently, several powerful architectures [43, 48] have emerged in the NLP community, yet no work has attempted to transfer these NLP architectures to visual tasks. Compared to Transformer, Retentive Network (RetNet) [48] has demonstrated stronger performance on a range of NLP tasks. Therefore, we hope to be able to transfer this robust NLP architecture, RetNet, to the domain of vision.

The fundamental operator in RetNet is retention. A significant difference between retention and the basic Self-Attention operator in Transformer is the introduction of decay coefficients, which explicitly control the attention weights of each token with respect to its neighboring tokens, ensuring that the attention weights decay as the distance between tokens increases. This decay effectively introduces prior knowledge about one-dimensional distance

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into the model, resulting in improved performance.

Based on the findings in RetNet, we attempt to further improve retention into a 2D form and introduce it to visual tasks. Specifically, the original version of retention undergoes unidirectional decay, which suits the causal properties of NLP. However, for images without causal properties, this unidirectional decay is not suitable. Therefore, we first expand retention from unidirectional to bidirectional. Additionally, the original version of retention, designed for onedimensional sequential information, is not appropriate for use in two-dimensional space. Hence, considering the spatial characteristics of two dimensions, we design a decay matrix based on 2D distance. Finally, to address the high computational load caused by a large number of tokens during the early stage of the vision backbone, we decompose the 2D computation process separately along the two axes of the image. We name this mechanism adapted to images as the Retentive Self-Attention (ReSA) mechanism. Based on the ReSA mechanism, we construct the RMT family.

We demonstrate the effectiveness of the proposed method through extensive experiments. As shown in Fig. 1, our RMT significantly outperforms the state-of-the-art (SOTA) models on image classification tasks. Additionally, our model exhibits more prominent advantages compared to other models in tasks such as object detection and instance segmentation. Our contributions can be summarized as follows:

- We extend the core mechanism of the Retentive Network, retention, to the two-dimensional scenario, introducing spatial prior knowledge related to distances into vision models. The new mechanism is called Retentive Self-Attention (ReSA).
- We decompose ReSA along two image axes, reducing computational complexity. This decomposition method effectively minimizes the computational burden while having minimal impact on the model's performance.
- Extensive experiments demonstrate the excellent performance of RMT. Particularly in downstream tasks such as object detection and instance segmentation, RMT exhibits significant advantages.

2. Related Work

Transformer. Transformer architecture was firstly proposed in [52] to address the training limitation of recurrent model and then achieve massive success in many NLP tasks. By splitting the image into small, non-overlapped patches sequence, Vision Transformer (ViTs) [12] also have attracted great attention and become widely used on vision tasks [5, 16, 20, 42, 58, 66]. Unlike in the past, where RNNs and CNNs have respectively dominated the NLP and CV fields, the transformer architecture has shined through in various modalities and fields [29, 40, 44, 60].

Prior Knowledge in Transformer. Numerous attempts have been made to incorporate prior knowledge into the Transformer model to enhance its performance. The original Transformers [12, 52] use trigonometric position encoding to provide positional information for each token. [38] proposes the use of relative positional encoding as a replacement for the original absolute positional encoding. [6] points out that zero padding in convolutional layers could also provide positional awareness for the Transformer, and this method of position encoding is highly efficient. In many studies, ConvFFN [14, 15, 18, 54] has been employed to further enrich the positional information in the Transformer. Furthermore, in the recent Retentive Network [48], explicit attenuation has been introduced to provide the model with prior knowledge based on distance changes.

Retentive Network. Retentive Network [48] proposes the retention mechanism for sequence modeling. Compared to traditional Transformer based models [11, 12, 28, 38, 52], retention proposed in RetNet uses the explicit decay to model the prior of 1D distance. It includes three computation paradigms, i.e., parallel, recurrent, and chunkwise recurrent. In retention, it uses a decay matrix multiplied by a weight matrix to control the proportion of each token seeing its surrounding tokens based on distance priors. We attempt to extend this idea to 2D space.

3. Methodology

3.1. Preliminary

Retentive Network. Retentive Network (RetNet) is a powerful architecture for language models. This work proposes the retention mechanism for sequence modeling. Retention brings the explicit decay to the language model, which Transformers do not have. Retention firstly considers a sequence modeling problem in a recurrent manner. It can be written as Eq. 1:

$$o_n = \sum_{m=1}^n \gamma^{n-m} (Q_n e^{in\theta}) (K_m e^{im\theta})^{\dagger} v_m \tag{1}$$

During training, for a parallel training process, Eq. 1 is writed as Eq. 2:

$$Q = (XW_Q) \odot \Theta, \quad K = (XW_K) \odot \overline{\Theta}, \quad V = XW_V$$

$$\Theta_n = e^{in\theta}, \quad D_{nm} = \begin{cases} \gamma^{n-m}, & n \ge m \\ 0, & n < m \end{cases}$$

$$Retention(X) = (QK^{\mathsf{T}} \odot D)V$$
(2)

where $\overline{\Theta}$ is the complex conjugate of Θ , and $D \in \mathbb{R}^{|x| \times |x|}$ contains both causal masking and exponential decay, which

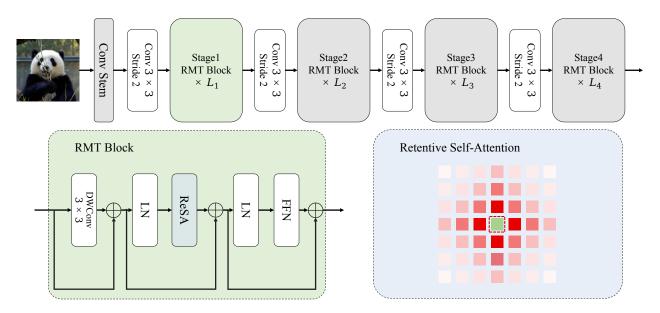


Figure 2. Overall architecture of RMT.

symbolize the relative distance in one-dimensional sequence, which brings the prior knowledge. Based on the 1D explicit decay in the retention, we try to develop it to 2D and bring the spatial prior knowledge to the vision model.

3.2. Retentive Self-Attention

Unidirectional to Bidirectional. Due to the causal nature of language tasks, the retention in RetNet is unidirectional, meaning that each token can only attend to the tokens preceding it and not those following it. This is not suitable for tasks without causal properties, such as image recognition tasks. Therefore, we first extend the retention to two dimensions, where for each token, its output becomes Eq. 3:

$$o_n = \sum_{m=1}^{N} \gamma^{|n-m|} (Q_n e^{in\theta}) (K_m e^{im\theta})^{\dagger} v_m$$
 (3)

where N is the number of tokens. The equation can be rearranged into a parallel form, expressed as Eq. 4:

BiRetention
$$(X) = (QK^{\mathsf{T}} \odot D^{Bi})V$$

$$D_{nm}^{Bi} = \gamma^{|n-m|}$$
(4)

where BiRetention denotes the retention with bidirectional modeling ability.

1D to 2D. Although retention now has the ability for bidirectional modeling, this modeling capability remains limited to a one-dimensional level and is still not applicable to two-dimensional images. Therefore, we further extend the one-dimensional retention to two dimensions.

For images, each token has a unique two-dimensional coordinate within the plane. For the nth token, we use

 (x_n, y_n) to represent its two-dimensional coordinate. Based on the 2D coordinates of each token, we modify each element in the matrix D to be the Manhattan distance between the corresponding token pairs at their respective positions, completing the transformation from a 1D to a 2D decay coefficient. The matrix D transfers to Eq. 5:

$$D_{nm}^{2d} = \gamma^{|x_n - x_m| + |y_n - y_m|} \tag{5}$$

In the retention [48], the Softmax is abandoned and replaced with a gating function to increase the nonlinearity of the operator. However, according to our experiments, this approach does not yield better results for vision models. Instead, it introduces additional parameters and computational complexity. Therefore, we still use Softmax to introduce nonlinearity to our model. Based on the steps mentioned above, our Retentive Self-Attention can be expressed as Eq. 6:

$$\operatorname{ReSA}(X) = (\operatorname{Softmax}(QK^{\mathsf{T}}) \odot D^{2d})V$$

$$D_{nm}^{2d} = \gamma^{|x_n - x_m| + |y_n - y_m|}$$
(6)

Decomposed ReSA in Early Stage. The current ReSA is not entirely applicable to image recognition tasks. This is because, in the early stages of the vision backbone, there are a large number of tokens, resulting in excessive computational costs for Attention. This is also the problem that most variants of Vision Transformers strive to solve [46, 57, 58, 61, 66, 72].

Our ReSA also encounters this problem. Therefore, we decompose ReSA into two axes of the image, as described

Cost	Model	Parmas (M)	FLOPs (G)	Top1-acc (%)	Cost	Model	Parmas (M)	FLOPs (G)	Top1-acc (%)
	PVTv2-b1 [54]	13	2.1	78.7		ConvNeXt-S [39]	50	8.7	83.1
	QuadTree-B-b1 [49]	14	2.3	80.0		CrossFormer-B [55]	52	9.2	83.4
	RegionViT-T [3]	14	2.4	80.4		InceptionNeXt-S [68]	49	8.4	83.5
	MPViT-XS [32]	11	2.9	80.9		NAT-S [21]	51	7.8	83.7
<u> </u>	tiny-MOAT-2 [62]	10	2.3	81.0		Quadtree-B-b4 [49]	64	11.5	84.0
tiny model $\sim 2.5 \mathrm{G}$	VAN-B1 [19]	14	2.5	81.1		Ortho-B [27]	50	8.6	84.0
y C 2	BiFormer-T [75]	13	2.2	81.4	j, jel	ScaleViT-B [65]	81	8.6	84.1
tin	Conv2Former-N [25]	15	2.2	81.5	base model $\sim 9.0G$	MOAT-1 [62]	42	9.1	84.2
	CrossFormer-T [55]	28	2.9	81.5	se 1	InternImage-S [56]	50	8.0	84.2
	NAT-M [21]	20	2.7	81.8	bas	DaViT-S [10]	50	8.8	84.2
	QnA-T [1]	16	2.5	82.0		GC-ViT-S [22]	51	8.5	84.3
	GC-ViT-XT [22]	20	2.6	82.0		BiFormer-B [75]	57	9.8	84.3
	SMT-T [37]	12	2.4	82.2		MViTv2-B [34]	52	10.2	84.4
	RMT-T	14	2.5	82.4		CMT-B [18]	46	9.3	84.5
	DeiT-S [50]	22	4.6	79.9		iFormer-B [47]	48	9.4	84.6
	Swin-T [38]	29	4.5	81.3		RMT-B	54	9.7	85.0
	ConvNeXt-T [39]	29	4.5	82.1		DeiT-B [50]	86	17.5	81.8
	Focal-T [63]	29	4.9	82.2		Swin-B [38]	88	15.4	83.3
	InceptionNeXt-T [68]	28	4.2	82.3		LITv2 [42]	87	13.4	83.6
	FocalNet-T [64]	29	4.5	82.3		CrossFormer-L [55]	92	16.1	84.0
	RegionViT-S [3]	31	5.3	82.6		Ortho-L [27]	88	15.4	84.2
	CSWin-T [11]	23	4.3	82.7	_	CSwin-B [11]	78	15.0	84.2
	MPViT-S [32]	23	4.7	83.0	large model $\sim 18.0 \mathrm{G}$	MPViT-B [32]	75	16.4	84.3
lel	ScalableViT-S [65]	32	4.2	83.1	mc 8.0	ScalableViT-L [65]	104	14.7	84.4
small model $\sim 4.5 G$	SG-Former-S [17]	23	4.8	83.2	rge mode ~ 18.0G	SMT-L [37]	81	17.7	84.6
11 r	MOAT-0 [62]	28	5.7	83.3	la ,	DaViT-B [10]	88	15.5	84.6
ma	Ortho-S [27]	24	4.5	83.4		MOAT-2 [62]	73	17.2	84.7
S	InternImage-T [56]	30	5.0	83.5		SG-Former-B [17]	78	15.6	84.7
	GC-ViT-T [22]	28	4.7	83.5		iFormer-L [47]	87	14.0	84.8
	CMT-S [18]	25	4.0	83.5		CMT-L [18]	75	19.5	84.8
	MaxViT-T [51]	31	5.6	83.6		InterImage-B [56]	97	16.0	84.9
	SMT-S [37]	20	4.8	83.7		MaxViT-B [51]	120	23.4	84.9
	BiFormer-S [75]	26	4.5	83.8		GC-ViT-B [22]	90	14.8	85.0
	RMT-S	27	4.5	84.1		RMT-L	95	18.2	85.5

Table 1. Comparison with the state-of-the-art on ImageNet-1K classification.

in the specific process shown in Eq. 7:

$$Q_{H}, K_{H} = (Q, K)^{B,L,C->B,W,H,C}$$

$$Q_{W}, K_{W} = (Q, K)^{B,L,C->B,H,W,C}$$

$$Attn_{H} = \operatorname{Softmax}(Q_{H}K_{H}^{\mathsf{T}}) \odot D^{H}$$

$$Attn_{W} = \operatorname{Softmax}(Q_{W}K_{W}^{\mathsf{T}}) \odot D^{W}$$

$$D_{nm}^{H} = \gamma^{|y_{n}-y_{m}|}, D_{nm}^{W} = \gamma^{|x_{n}-x_{m}|}$$

$$\operatorname{ReSA}_{\operatorname{dec}}(X) = Attn_{H}(Attn_{W}V)$$

$$(7)$$

Based on this decomposition of ReSA, the shape of the receptive field of each token is shown in Fig. 3, which is identical to the shape of the complete ReSA's receptive field.

In order to further enhance the local expression capability of ReSA, we also introduce a local enhancement module using DWConv:

$$X_{out} = \text{ReSA}(X) + \text{LCE}(X);$$
 (8)

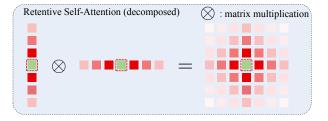


Figure 3. Illustration of decomposed ReSA.

3.3. Overall Architecture

The architecture of our entire model is shown in Fig 2. Similar to traditional backbones, it is divided into four stages. The first three stages utilize the decomposed ReSA, while the last stage uses the original ReSA. Like many previous backbones [18, 33, 75], we incorporate CPE [6] into our model.

Cost	Model	Params (M)	FLOPs (G)	Top1-acc (%)
	LV-ViT-S* [30]	26	6.6	83.3
<u>-</u>	UniFormer-S* [33]	24	4.2	83.4
small model $\sim 4.5 G$	WaveViT-S* [66]	23	4.7	83.9
all moc ~ 4.5G	Dual-ViT-S* [67]	25	5.4	84.1
nal ∠	VOLO-D1* [69]	27	6.8	84.2
S	BiFormer-S* [75]	26	4.5	84.3
	RMT-S*	27	4.5	84.8
	LV-ViT-M* [30]	56	16.0	84.1
75	WaveViT-B* [66]	34	7.2	84.8
og O	UniFormer-B* [33]	50	8.3	85.1
base model $\sim 9.0 \mathrm{G}$	VOLO-D2* [69]	59	14.1	85.2
ase ∼	Dual-ViT-B* [67]	43	9.3	85.2
٩	BiFormer-B*	58	9.8	85.4
	RMT-B*	55	9.7	85.6
	LV-ViT-L* [30]	150	59.0	85.3
gel G	VOLO-D3*	86	20.6	85.4
large model $\sim 18.0 \mathrm{G}$	WaveViT-L* [66]	58	14.8	85.5
	UniFormer-L* [33]	100	12.6	85.6
	Dual-ViT-L* [67]	73	18.0	85.7
	RMT-L*	96	18.2	86.1

Table 2. Models trained with additional supervision. "*" indicates the model trained with token labeling [30].

4. Experiments

We conducted extensive experiments on multiple vision tasks, such as image classification on ImageNet-1K [9], object detection and instance segmentation on COCO 2017 [36], and semantic segmentation on ADE20K [74]. We also make ablation studies to validate the importance of each component in RMT.

4.1. Image Classification

Settings. We train our models on ImageNet-1K [9] from scratch. And we follow the same training strategy in DeiT [50] for a fair comparison. The maximum rates of increasing stochastic depth [26] are set to 0.1/0.15/0.4/0.5 for RMT-T/S/B/L [26], respectively. We use the AdamW optimizer with a cosine decay learning rate scheduler to train the models. We set the initial learning rate, weight decay, and batch size to 0.001, 0.05, and 1024, respectively. We adopt the strong data augmentation and regularization used in [38]. Our settings are RandAugment [8] (randm9-mstd0.5-inc1), Mixup [71] (prob=0.8), CutMix [70] (prob=1.0), Random Erasing [73] (prob=0.25). In addition to the conventional training methods, similar to LV-ViT [30] and VOLO [69], we further train a model that utilizes token labeling to provide supplementary supervision.

Results. We compare RMT against many state-of-the-art models in Tab. 1. Results in the table demonstrate that RMT

consistently outperforms previous models across all settings. Specifically, RMT-S achieves **84.1%** Top1-accuracy with only **4.5** GFLOPs. RMT-B also surpasses iFormer [47] by **0.4%** with similar FLOPs. Furthermore, our RMT-L model surpasses MaxViT-B [51] in top1-accuracy by **0.6%** while using fewer FLOPs. Our RMT-T has also outperformed many lightweight models. As for the model trained using token labeling, our RMT-S outperforms the current state-of-the-art BiFormer-S by 0.5

4.2. Object Detection and Instance Segmentation

Settings. We adopt MMDetection [4] to implement RetinaNet [35] Mask-RCNN [24] and Cascade Mask R-CNN [2]. We use the commonly used " $1\times$ " (12 training epochs) setting for the RetinaNet and Mask R-CNN.Besides, we use " $3\times + \mathrm{MS}$ " for Mask R-CNN and Cascade Mask R-CNN. Following [38], during training, images are resized to the shorter side of 800 pixels while the longer side is within 1333 pixels. We adopt the AdamW optimizer with a learning rate of 0.0001 and batch size of 16 to optimize the model. For " $1\times$ " schedule, the learning rate declines with the decay rate of 0.1 at the epoch 8 and 11. While for " $3\times + \mathrm{MS}$ " schedule, the learning rate declines with the decay rate of 0.1 at the epoch 27 and 33.

Results. Tab. **3**, Tab. **4** and Tab. **5** show the results with different detection frameworks. The results demonstrate that our RMT performs best in all comparisons. For the RetinaNet framework, our RMT-T outperforms FAT-B2 by **+1.1** AP, while S/B/L also perform better than other methods. As for the Mask R-CNN with "1×" schedule, RMT-L outperforms the recent InternImage-B by **+1.8** box AP and **+1.9** mask AP. For "3 × +MS" schedule, RMT-S outperforms InternImage-T for **+1.6** box AP and **+1.2** mask AP. Bisides, when it comes to the Cascade Mask R-CNN, our RMT still performs much better than other backbones. All above results tell that RMT outperforms its counterparts by evident margins.

4.3. Semantic Segmentation

Settings. We adopt the Semantic FPN [31] and Uper-Net [59] based on MMSegmentation [7], apply RMTs which are pretrained on ImageNet-1K as backbone. We use the same setting of PVT [53] to train the Semantic FPN, and we train the model for 80k iterations. All models are trained with the input resolution of 512×512 . When testing the model, we resize the shorter side of the image to 512 pixels. As for UperNet, we follow the default settings in Swin [38]. We take AdamW with a weight decay of 0.01 as the optimizer to train the models for 160K iterations. The learning rate is set to 6×10^{-5} with 1500 iterations warmup.

	Params	FLOPs		ı	Mask R-	CNN 1	×		Params	FLOPs			Retinal	Net 1×		
Backbone	(M)	(G)	AP^b	AP_{50}^b	AP_{75}^b	AP^m	AP_{50}^m	AP_{75}^m	(M)	(G)	AP^b	AP_{50}^b	AP_{75}^b	AP_S^b	AP_M^b	AP_L^b
PVT-T [53]	33	240	39.8	62.2	43.0	37.4	59.3	39.9	23	221	39.4	59.8	42.0	25.5	42.0	52.1
PVTv2-B1 [54]	33	243	41.8	54.3	45.9	38.8	61.2	41.6	23	225	41.2	61.9	43.9	25.4	44.5	54.3
MPViT-XS [32]	30	231	44.2	66.7	48.4	40.4	63.4	43.4	20	211	43.8	65.0	47.1	28.1	47.6	56.5
FAT-B2 [15]	33	215	45.2	67.9	49.0	41.3	64.6	44.0	23	196	44.0	65.2	47.2	27.5	47.7	58.8
RMT-T	33	218	47.1	68.8	51.7	42.6	65.8	45.9	23	199	45.1	66.2	48.1	28.8	48.9	61.1
Swin-T [38]	48	267	43.7	66.6	47.7	39.8	63.3	42.7	38	248	41.7	63.1	44.3	27.0	45.3	54.7
CMT-S [18]	45	249	44.6	66.8	48.9	40.7	63.9	43.4	44	231	44.3	65.5	47.5	27.1	48.3	59.1
CrossFormer-S [55]	50	301	45.4	68.0	49.7	41.4	64.8	44.6	41	272	44.4	65.8	47.4	28.2	48.4	59.4
ScalableViT-S [65]	46	256	45.8	67.6	50.0	41.7	64.7	44.8	36	238	45.2	66.5	48.4	29.2	49.1	60.3
MPViT-S [32]	43	268	46.4	68.6	51.2	42.4	65.6	45.7	32	248	45.7	57.3	48.8	28.7	49.7	59.2
Dual-ViT-S* [67]	-	_	46.5	68.3	51.2	42.2	65.3	46.1	_	_	46.2	67.4	49.9	30.6	49.9	60.9
CSWin-T [11]	42	279	46.7	68.6	51.3	42.2	65.6	45.4	_	_	_	_	_	_	_	_
InternImage-T [56]	49	270	47.2	69.0	52.1	42.5	66.1	45.8	_	_	_	_	_	_	_	_
SMT-S [37]	40	265	47.8	69.5	52.1	43.0	66.6	46.1	_	_	_	_	_	_	_	_
BiFormer-S [75]	_	_	47.8	69.8	52.3	43.2	66.8	46.5	_	_	45.9	66.9	49.4	30.2	49.6	61.7
RMT-S	46	262	49.0	70.8	53.9	43.9	67.8	47.4	36	244	47.8	69.1	51.8	32.1	51.8	63.5
Swin-S [38]	69	359	45.7	67.9	50.4	41.1	64.9	44.2	60	339	44.5	66.1	47.4	29.8	48.5	59.1
ScalableViT-B [65]	95	349	46.8	68.7	51.5	42.5	65.8	45.9	85	330	45.8	67.3	49.2	29.9	49.5	61.0
InternImage-S [56]	69	340	47.8	69.8	52.8	43.3	67.1	46.7	_	_	_	_	_	_	_	_
CSWin-S [11]	54	342	47.9	70.1	52.6	43.2	67.1	46.2	_	_	_	_	_	_	_	_
Dual-ViT-B* [67]	_	_	48.4	69.9	53.3	43.4	66.7	46.8	_	_	47.4	68.1	51.2	29.6	51.9	63.1
BiFormer-B [75]	_	_	48.6	70.5	53.8	43.7	67.6	47.1	_	_	47.1	68.5	50.4	31.3	50.8	62.6
RMT-B	73	373	51.1	72.5	56.1	45.5	69.7	49.3	63	355	49.1	70.3	53.0	32.9	53.2	64.2
Swin-B [38]	107	496	46.9	69.2	51.6	42.3	66.0	45.5	98	477	45.0	66.4	48.3	28.4	49.1	60.6
PVTv2-B5 [54]	102	557	47.4	68.6	51.9	42.5	65.7	46.0	_	_	_	_	_	_	_	_
Focal-B [63]	110	533	47.8	70.2	52.5	43.2	67.3	46.5	101	514	46.3	68.0	49.8	31.7	50.4	60.8
MPViT-B [32]	95	503	48.2	70.0	52.9	43.5	67.1	46.8	85	482	47.0	68.4	50.8	29.4	51.3	61.5
CSwin-B [11]	97	526	48.7	70.4	53.9	43.9	67.8	47.3	_	_	_	_	_	_	_	_
InternImage-B [56]	115	501	48.8	70.9	54.0	44.0	67.8	47.4	_	_	_	-	-	-	-	-
RMT-L	114	557	51.6	73.1	56.5	45.9	70.3	49.8	104	537	49.4	70.6	53.1	34.2	53.9	65.2

Table 3. Comparison to other backbones using RetinaNet and Mask R-CNN on COCO val2017 object detection and instance segmentation.

	lp.	EL OD	1		D (2)	ATA LO	3.40	
Backbone	Params		1				<+MS	
	(M)	(G)	$ AP^{o} $	AP_{50}^{o}	AP_{75}^o	AP^{m}	AP_{50}^m	AP_{75}^m
Swin-T [38]	48	267	46.0	68.1	50.3	41.6	65.1	44.9
Focal-T [63]	49	291	47.2	69.4	51.9	42.7	66.5	45.9
NAT-T [21]	48	258	47.8	69.0	52.6	42.6	66.0	45.9
GC-ViT-T [22]	48	291	47.9	70.1	52.8	43.2	67.0	46.7
MPViT-S [32]	43	268	48.4	70.5	52.6	43.9	67.6	47.5
SMT-S [37]	40	265	49.0	70.1	53.4	43.4	67.3	46.7
CSWin-T [11]	42	279	49.0	70.7	53.7	43.6	67.9	46.6
InternImage-T [56]	49	270	49.1	70.4	54.1	43.7	67.3	47.3
RMT-S	46	262	50.7	71.9	55.6	44.9	69.1	48.4
ConvNeXt-S [39]	70	348	47.9	70.0	52.7	42.9	66.9	46.2
NAT-S [21]	70	330	48.4	69.8	53.2	43.2	66.9	46.4
Swin-S [38]	69	359	48.5	70.2	53.5	43.3	67.3	46.6
InternImage-S [56]	69	340	49.7	71.1	54.5	44.5	68.5	47.8
SMT-B [37]	52	328	49.8	71.0	54.4	44.0	68.0	47.3
CSWin-S [11]	54	342	50.0	71.3	54.7	44.5	68.4	47.7
RMT-B	73	373	52.2	72.9	57.0	46.1	70.4	49.9

Table 4. Comparison to other backbones using Mask R-CNN with "3 \times +MS" schedule.

Backbone	Params (M)	FLOPs (G)					N $3 \times AP_{50}^m$	
Swin-T [38]	86	745	50.5	69.3	54.9	43.7	66.6	47.1
NAT-T [21]	85	737	51.4	70.0	55.9	44.5	67.6	47.9
GC-ViT-T [22]	85	770	51.6	70.4	56.1	44.6	67.8	48.3
SMT-S [37]	78	744	51.9	70.5	56.3	44.7	67.8	48.6
Ortho-S [27]	81	755	52.3	71.3	56.8	45.3	68.6	49.2
HorNet-T [45]	80	728	52.4	71.6	56.8	45.6	69.1	49.6
CSWin-T [11]	80	757	52.5	71.5	57.1	45.3	68.8	48.9
RMT-S	83	741	53.2	72.0	57.8	46.1	69.8	49.8
Swin-S [38]	107	838	51.9	70.7	56.3	45.0	68.2	48.8
NAT-S [21]	108	809	51.9	70.4	56.2	44.9	68.2	48.6
GC-ViT-S [22]	108	866	52.4	71.0	57.1	45.4	68.5	49.3
DAT-S [58]	107	857	52.7	71.7	57.2	45.5	69.1	49.3
HorNet-S [45]	108	827	53.3	72.3	57.8	46.3	69.9	50.4
UniFormer-B [33]	107	878	53.8	72.8	58.5	46.4	69.9	50.4
RMT-B	111	852	54.5	72.8	59.0	47.2	70.5	51.4

Table 5. Comparison to other backbones using Cascade Mask R-CNN with "3 $\times + \rm{MS}$ " schedule.

Model	Params(M)	FLOPs(G)	Top1-acc(%)	AP^b	AP^m	mIoU(%)
RMT-T	14.3	2.5	82.4	47.1	42.6	46.4
ReSA->Attention	14.3	2.5	81.6	44.6	40.7	43.9
Softmax ->Gate	15.6	2.7	Nan	_	_	_
w/o LCE	14.2	2.4	82.1	46.7	42.3	46.0
w/o CPE	14.3	2.5	82.2	47.0	42.4	46.4
w/o Stem	14.3	2.2	82.2	46.8	42.3	46.2

Table 6. Ablation study

Backbone	Semantic FPN 80k						
Backbolle	Params(M)	FLOPs(G)	mIoU(%)				
ResNet18 [23]	15.5	32.2	32.9				
PVTv2-B1 [54]	17.8	34.2	42.5				
VAN-B1 [19]	18.1	34.9	42.9				
EdgeViT-S [41]	16.9	32.1	45.9				
RMT-T	17.0	33.7	46.4				
DAT-T [58]	32	198	42.6				
CrossFormer-S [55]	34	221	46.0				
UniFormer-S [33]	25	247	46.6				
CSWin-T [11]	26	202	48.2				
Shuted-S [46]	26	183	48.2				
RMT-S	30	180	49.4				
DAT-S	53	320	46.1				
UniFormer-B [33]	54	350	47.7				
CrossFormer-B [55]	56	331	47.7				
CSWin-S [11]	39	271	49.2				
RMT-B	57	294	50.4				
DAT-B	92	481	47.0				
CrossFormer-L	95	497	48.7				
CSWin-B [11]	81	464	49.9				
RMT-L	98	482	51.4				

Table 7. Comparison with the state-of-the-art on ADE20K. The framework is SemanticFPN.

Results. The results of semantic segmentation can be found in Tab. 7 and Tab. 8. All the FLOPs are measured with the resolution of 512×2048 . All our models achieve the best performance in all comparisons. Specifically, our RMT-S exceeds Shunted-S for **+1.2** mIoU with Semantic FPN. Moreover, our RMT-B outperforms the recent InternImage-S for **+1.3** mIoU. All the above results demonstrate our model's superiority in dense prediction.

4.4. Ablation Study

ReSA. We verify the impact of Retentive Self-Attention on the model, as shown in the Tab. 6. ReSA improve the model's performance in image classification and downstream tasks.

Softmax. In RetNet, Softmax is abandoned in favor of a non-linear gating function. We attempt to replace Soft-

Backbone	UperNet 160k						
Dackbolle	Params(M)	FLOPs(G)	mIoU(%)				
DAT-T [58]	60	957	45.5				
NAT-T [21]	58	934	47.1				
InternImage-T [56]	59	944	47.9				
MPViT-S [32]	52	943	48.3				
HorNet-T [45]	55	924	49.2				
SMT-S [37]	50	935	49.2				
RMT-S	56	937	49.8				
DAT-S [58]	81	1079	48.3				
SMT-B [37]	62	1004	49.6				
HorNet-S [45]	85	1027	50.0				
InterImage-S [56]	80	1017	50.2				
MPViT-B [32]	105	1186	50.3				
CSWin-S [11]	65	1027	50.4				
RMT-B	83	1051	51.5				

Table 8. Comparison with the state-of-the-art on ADE20K. The framework is UperNet.

max with this gating function in ReSA, but we find that the model utilizing the gating function is unable to undergo stable training in our architecture.

LCE&CPE&Stem. We have conducted ablation experiments on the LCE, CPE, and Stem components. The experimental results indicate that all three components contribute to the improvement of model performance to a certain extent.

5. Conclusion

We propose RMT, a vision backbone that integrates retentive network and Vision Transformer. RMT introduces explicit decay related to distance, which brings spatial prior knowledge to visual models. The new mechanism is called Retentive Self-Attention (ReSA). To reduce the complexity of the model, RMT also employs a method that decomposes the ReSA into two axes. Extensive experiments validate the effectiveness of RMT, especially in downstream tasks such as object detection, where RMT demonstrates significant advantages. Our work is still in progress.

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