

Guess What Moves: Unsupervised Video and Image Segmentation by Anticipating Motion

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Abstract

Motion, measured via optical flow, provides a powerful cue to discover and learn objects in images and videos. However, compared to using appearance, it has some blind spots, such as the fact that objects become invisible if they do not move. In this work, we propose an approach that combines the strengths of motion-based and appearance-based segmentation. We propose to supervise an image segmentation network with the pretext task of predicting regions that are likely to contain simple motion patterns, and thus likely to correspond to objects. As the model only uses a single image as input, we can apply it in two settings: unsupervised video segmentation, and unsupervised image segmentation. We achieve state-of-the-art results for videos, and demonstrate the viability of our approach on still images containing novel objects. Additionally we experiment with different motion models and optical flow backbones and find the method to be robust to these change. Project page and code available at <https://www.robots.ox.ac.uk/~vgg/research/gwm>.

1 Introduction

The motion of objects in a video can be detected by methods such as optical flow and used to discover and segment them. A key benefit is that optical flow is object-agnostic: because it relies on low-level visual properties, it can extract a signal even before the objects are discovered, and can thus be used to establish an understanding of objectness.

The potential of motion as a cue is epitomized in *video segmentation* problems, where the input is a generic video sequence and the task is to extract the main object(s) in the

video. In fact, some methods [54, 56] adopt a motion-*only* approach to video object segmentation, arguing that motion patterns are much easier to model and interpret than appearance. However, this approach ignores appearance cues and is ‘blind’ to stationary objects.

Instead, we propose to use motion as *supervision* to discover objects in videos *and* still images without the need for manual annotations. We observe that different objects tend to generate distinctive optical flow patterns which can be well approximated by small parametric models, such as affine or quadratic. We use this fact to train a segmentation network that, given a *single RGB frame* as input, predicts *which image regions* are likely to contain such patterns. The idea is that these regions would then separate the objects from the background.

This approach has several useful properties. First, while motion is used for supervising the network, the latter implicitly learns the appearance of the objects, regularizing the segmentation. Second, because the network works with a single image as input, it does not observe the motion directly. The model must anticipate what *could* move, extracting objects even if they are not in motion. Third, the network avoids predicting the objects’ motion directly, which is a highly-ambiguous task given a single image as input; instead, it predicts only the support regions of the motion patterns, and the training loss measures the compatibility of such regions with the observed motion according to the assumed motion model.

While we are not the first to consider motion as a cue for decomposing an image into objects, our particular way of modeling motion is simple and versatile, and allows two application modes of our approach. First, we consider *internal learning for unsupervised motion segmentation* [47]. Given one or more videos as input (without labels), we optimize a network, as described above, to output a segmentation of the videos, effectively ‘observing’ motion via backpropagation. Our approach achieves state-of-the-art performance on standard benchmarks for unsupervised motion segmentation [86, 88].

The second mode is *transductive learning for unsupervised image segmentation*, which is intended to assess the generalization capabilities of our model as an image segmenter. In this case, the network is first trained on a number of training videos and then evaluated on a disjoint set of images. Since only appearance information is available at test time, the problem solved is not motion segmentation, but image segmentation. In this scenario, our model segments novel objects not observed during training, demonstrating the viability of our approach.

2 Related Work

Our work aims to combine motion and appearance cues for unsupervised object discovery, in that motion can be used as a cue to learn a general object segmenter for both videos and images. As such, there exist several related areas in literature, which we review next.

Unsupervised Video Object Segmentation. The aim of video object segmentation (VOS) is to densely label objects present in a video. Current VOS benchmarks [42, 60, 63] usually define the problem as foreground-background separation, where the foreground comprises the most salient objects. Efforts to reduce the amount of supervision follow two main directions, semi-supervised and unsupervised VOS. Semi-supervised methods require manual annotations for the object(s) of interest in an initial frame during inference; the goal is to re-localize these objects across the video [43]. Unsupervised VOS aims to discover object(s) of interest without the initial targets [25, 29, 45, 60, 62, 75]. However, most unsupervised VOS methods use, in fact, some form of supervised pre-training on external data.

Motion Segmentation. In videos, the background is usually relatively static whereas objects in the scene have independent motion, thus providing a strong ‘objectness’ signal. Thus, many works approach unsupervised video object segmentation as a motion segmentation problem. Several earlier methods address this problem by grouping point trajectories [10, 69, 40, 58, 69, 74], motion boundaries [62], voting [25] and layered models [13, 65]. More recently, Lamdouar et al. [44], Xie et al. [85] train motion models on generated scenes with synthetic 2D objects and generalize to real videos. CIS [68] proposes an adversarial framework, where an inpainter is tasked with predicting the optical flow of a segment based on context, while the generator aims to create segments with zero mutual information such that the context becomes uninformative. DyStaB [69] extends CIS using the segmentation output of a dynamic model to bootstrap a static one. In contrast to our method, this yields two separate models to choose from based on the application (*i.e.*, video or static image segmentation). Instead, AMD [48] employs a single model with separate appearance and motion ‘pathways’ and performs unsupervised test-time adaptation for video segmentation. Finally, MG [66] abandons the appearance pathway altogether, directly segmenting optical flow inputs with a Slot Attention-like architecture [49].

Closer to our approach, another line of work uses various motion models to group image regions. Early methods [80, 76] consider mixture models of flow to account for the fact that a region may contain multiple motion patterns. Another line of work [6, 0] segments object translation directions from motion angle field obtained by correcting for estimated rotation of the camera. Mahendran et al. [60] employ an affine flow model, using the entropy of flow magnitude histograms for loss to deal with noisy flow in real world. Meunier et al. [52] consider affine and quadratic motion models, however their method uses flows as input which makes it suitable only for videos during inference.

Unsupervised Image Segmentation. While we use motion as a learning signal, our method yields a general-purpose image segmentation network, separating an image into foreground and background, without using ground truth masks for supervision. Early work in unsupervised image segmentation makes use of hand-crafted priors, *e.g.* color contrast [19, 83], while some recent methods also combine handcrafted heuristics to generate pseudo-masks and use them to train using deep networks [57, 92, 93]. Others address this problem via mutual information maximization between different views of the input [31, 60]. A recently emerging line of work [9, 8, 17, 57, 53, 78] explores generative models to obtain segmentation masks. Many of them [9, 8, 17, 57] are based on the idea of generating foreground and background as separate layers and combine them to obtain a real image. Others [63, 78] analyze large-scale unsupervised GANs (*e.g.* BigGAN [9]) and find implicit foreground-background structure in them to generate a synthetic annotated training dataset. Alternative line of work explores feature maps of self-supervised Vision Transformers, such as DINO [14]. For example, STEGO [58] supports segmenting multiple *classes* in an image, performing *semantic* segmentation, by distilling features and class centroids from DINO. In Melas-Kyriazi et al. [56] and TokenCut [82], authors model image patches with an affinity graph based on DINO feature alignment and perform further analysis on this graph to extract masks. Shin et al. [68] cluster features of a variety of self-supervised backbones to produce candidate masks, using them to train a segmenter. Instead, our model is trained on video data using optical flow as a supervisory signal. However, since it only requires a single image as input at test time, we show that our method is applicable to this task, providing an alternative approach to unsupervised object segmentation.

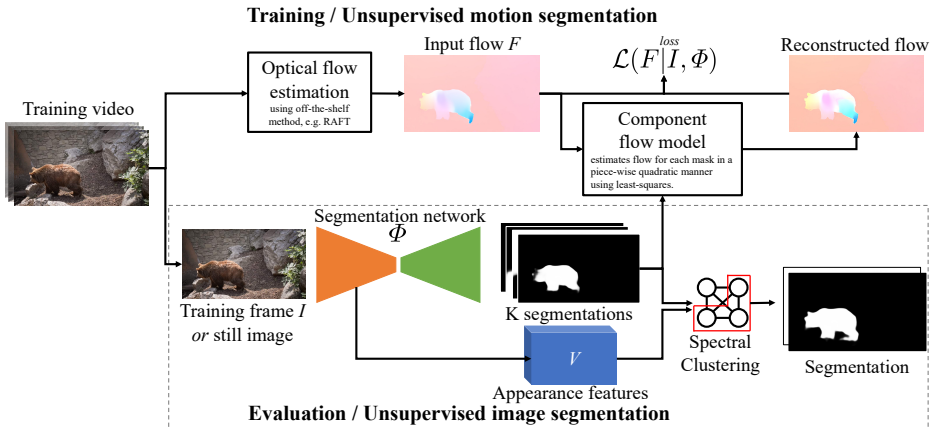


Figure 1: **Model Diagram.** We train a segmentation network to partition an image into K components without manual annotations. Our model is trained using individual frames from video as input and pre-computed optical flow as supervision. The predicted segments are used to approximate the input flow with piecewise quadratic flow models and the training loss is formulated as the error between the reconstructed and the input flow. Appearance features from the backbone are used to merge the predicted K segments into foreground and background components. Motion information is not required at test time and inference can be performed on still images. Optical flow is colored for visualization only.

Unsupervised Object Discovery. While the above methods often aim to segment the most salient object(s) in an image, unsupervised multi-object segmentation explores the problem of decomposing a scene into parts, which typically include each individual foreground object and the background. The usual approach is to learn structured object-centric representations, *i.e.* to model the scene with latent variables (slots) operating on a common representation [10, 20, 22, 23, 24, 27, 32, 46, 49, 59]. While these methods are image-based, extensions to video also exist [6, 8, 21, 33, 36, 41, 42, 53, 56, 70, 91]. These methods often operate in an auto-encoding fashion with inductive bias to separate objects derived from a reconstruction bottleneck [10], that is often dependent on the architecture and the latent variable model. We similarly impose a reconstruction bottleneck on the flow but use a simple model grounded in projective geometry, with a known closed-form solution. It is also important to note that unsupervised *multi-object* segmentation appears to be significantly more challenging, with current methods exploiting the simplicity of synthetic scenes [26, 34], while struggling on more realistic data [53]. Recently, Bao et al. [0] explore an extension of Slot Attention [49], guided by an external supervised motion segmentation algorithm, to real-world data. However, due to the difficulty of the problem, they operate in a constrained domain (autonomous driving) and consider only a limited number of object categories. We instead focus on wide variety of categories and settings encountered in common video segmentation datasets and consider both motion and appearance jointly.

3 Method

In this paper, we present a method that uses motion anticipation to discover and segment objects in images without the need for human annotations (overview in Fig. 1). We use

optical flow from video sequences as supervision for this problem. However, rather than predicting the flow directly, we task a general image segmentation network to predict image regions where motion may be explained by a simple coherent model. Such regions should align with optical flow patterns produced by objects that *could* move (but do not have to).

3.1 Segmentation by Motion Anticipation

Let $I \in \mathbb{R}^{3 \times H \times W} = (\mathbb{R}^3)^\Omega$ be an RGB image defined on a lattice $\Omega = \{1, \dots, H\} \times \{1, \dots, W\}$. Assume that the image is a frame in a video sequence and let $F \in (\mathbb{R}^2)^\Omega$ be the corresponding optical flow (extracted from the video by means of an off-the-shelf optical flow network, such as RAFT [24]). The goal is to decompose the image into K components (or regions), which is a classic segmentation problem. Hence, we learn a segmentation network $\Phi(I) \in ([0, 1]^K)^\Omega$ that, given the image I as input, assigns each pixel u to one of K components in a soft manner, with probabilities:

$$P(m_u = k \mid I, \Phi) = [(\Phi(I))_k]_u, \quad u \in \Omega, k \in \{1, \dots, K\}. \quad (1)$$

$m_u = k$ in Eq. (1) denotes the predicted mask corresponding to component k indexed by u . In particular, we seek to separate the foreground and background, for which one may choose $K = 2$, although as we show later (Section 3.2), this need not be the case.

More specifically, we train Φ to partition pixels according to the Gestalt principle of common fate [21, 29]. This is done by associating each region $k \in \{1, \dots, K\}$ to a model θ_k of the optical flow observed within it. That is, the optical flow corresponding to an input frame can be approximated by piece-wise parametric models, representing the motion or *flow pattern*, of each component independently. According to the common fate principle, pixels within the same region are expected to exhibit *coherent* motion.

A variety of motion models exist for describing the 2D flow of an object ([31, 32]). These are generally of the form $F_u \approx Au + b$, where parameters A, b can be recovered by solving a system of linear equations. One common choice is an affine model (where $u = [x, y]$ are pixel coordinates), which is sufficient if objects are smaller and further away from camera. The affine model, however, struggles if the depth of an object varies significantly resulting in more complex flow patterns. To factor out unknown depth information, each object can be modeled as a plane with a quadratic 8-parameter model [33]. Here, we allow for more complex geometry than planes, by using a simplified 12-parameter quadratic model $\theta_k = (A_k, b_k)$ with $A_k \in \mathbb{R}^{2 \times 5}$ and $b_k \in \mathbb{R}^2$ per region k . In this case, $u = [x, x^2, y, y^2, xy] \in \mathbb{R}^5$ includes quadratic and mixed terms of the pixel coordinates to model quadratic dependencies. The 12-parameter model also allows treating each flow direction independently. We assume that the model predicts the flow up to isotropic i.i.d. Gaussian noise, which results in a simple L^2 fitting loss:

$$-\log p(F_u \mid \theta_k) \propto \|F_u - A_k u - b_k\|^2. \quad (2)$$

Summing over all pixels, learning minimizes the energy function:

$$\mathcal{L}(F \mid \theta, I, \Phi) \propto \sum_{u \in \Omega} \sum_k \|F_u - A_k u - b_k\|^2 \cdot p(m_u = k \mid I, \Phi). \quad (3)$$

In the expression above, we *do not* know the flow parameters θ_k as the network only predicts the regions' extent. Instead, we *min-out* the parameters θ_k in the loss itself and compute

$$\mathcal{L}(F \mid I, \Phi) = \min_{\theta_{k \in \{1, \dots, K\}}} \mathcal{L}(F \mid \theta, I, \Phi). \quad (4)$$

The energy in Eq. (2) is quadratic in θ_k , resulting in a weighted least squares problem that can be efficiently solved in closed form (see supplementary material).

Our model is learned from a large collection \mathcal{T} of video frame-optical flow pairs (I, F) , minimizing the empirical risk:

$$\Phi^* = \underset{\Phi}{\operatorname{argmin}} \frac{1}{|\mathcal{T}|} \sum_{(I, F) \in \mathcal{T}} \mathcal{L}(F | I, \Phi) \quad (5)$$

3.2 Over-segmentation

While the 12-parameter model is more powerful than an affine one, it is still not sufficient to model arbitrary flow patterns. In complex scenes that contain foreground and background clutter, we often observe motion parallax effects. Additionally, non-rigid objects and self-occlusions can result in complex flow patterns within the object that are not captured accurately by the quadratic model.

To account for such complexity, we propose to *over-segment* the input image into $K > 2$ regions. Over-segmentation enables the model to use additional regions to explain several moving objects and to approximate varyingly moving parts of a single non-rigid object as well as motion parallax. To achieve a binary segmentation output, one needs a criterion to merge a number of predicted regions down to foreground and background.

We devise a criterion based on *appearance* cues to avoid the ambiguity associated with merging regions based on motion. To this end, we use a pre-trained self-supervised image encoder, such as DINO-ViT [14], to obtain dense features for the input image and merge the segments predicted by Φ based on feature similarity. Formally, let V_u denote the feature vector of pixel u obtained by the self-supervised encoder. Then, $\bar{V}_k = \sum_u V_u p(m_u = k | I, \Phi) / \sum_v p(m_v = k | I, \Phi)$ is the average feature vector for segment k , where pixels are weighed by their probability with which they belong to the segment. We compute the pairwise similarities of different regions via an affinity matrix $\Pi \in \mathbb{R}^{K \times K}$, where entries corresponding to segments i and j are set as

$$(\Pi)_{ij} = \max \left(\varepsilon, \left\langle \frac{\bar{V}_i}{\|\bar{V}_i\|_2}, \frac{\bar{V}_j}{\|\bar{V}_j\|_2} \right\rangle \right), \quad (6)$$

where only feature vectors pointing in the same direction are considered and $\varepsilon = 10^{-12}$ is a small constant that keeps the graph connected. We then perform spectral clustering [16, 52, 56] into two components using the affinity Π .

3.3 Two Scenarios: Motion vs Image Segmentation

We experiment with two modes of application of our model. The first scenario is *internal learning for unsupervised video segmentation*, where the network is evaluated on the same video sequences that have been used for optimization. This is effectively an unsupervised motion segmentation algorithm because the network not only receives as input appearance information, but incorporates motion information via backpropagation, observing indirectly optical flow too. While not explicitly stated in the respective papers, prior motion segmentation works such as [52, 56] also operate in this mode, while directly observing moving objects, often using optical flow as input.

The second scenario is *transductive learning for image segmentation*. In this case, the network is first trained using a number of unlabelled videos, and then used for single-image

	Inf. Input		Input	Flow	Runtime	DAVIS	STv2	FBMS
	RGB	Flow	Resolution	Method	sec ↓	$\mathcal{J} \uparrow$	$\mathcal{J} \uparrow$	$\mathcal{J} \uparrow$
[81] SAGE	✓	✓	–	LDOF [41]	0.9	42.6	57.6	61.2
[25] NLC	✓	✓	–	SIFTFlow [42]	11	55.1	67.2	51.5
[69] CUT	✓	✓	–	LDOF [41]	103	55.2	54.3	57.2
[64] FTS	✓	✓	–	LDOF [41]	0.5	55.8	47.8	47.7
[83] CIS	✓	✓	192 × 384	PWCNet [43]	0.1	59.2	45.6	36.8
[92] AMD	✓	✗	128 × 224	✗	–	57.8	57.0	47.5
[86] MG	✗	✓	128 × 224	RAFT [44]	0.012	68.3	58.6	53.1
[87] EM	✓	✓	128 × 224	RAFT [44]	–	69.3	55.5	57.8
[85] OCLR	✓	✓	480 × 832	RAFT [44]	–	78.9	71.6	68.7
[91] DS [‡]	✓	✓	240 × 426	RAFT [44]	1800 (22.5) [‡]	79.1	72.1	71.8
Ours (UNet)	✓	✗	128 × 224	RAFT [44]	0.027	78.3	76.8	72.0
Ours (MaskFormer)	✓	✗	128 × 224	RAFT [44]	0.059	79.5	78.3	77.4
[88] CIS [†]	✓	✓	192 × 384	PWCNet [43]	11	71.5	62.0	63.5
[89] DyStaB ^{†*}	✓	✓	192 × 384	RAFT [44]	–	80.0	74.2	73.2
Ours[†] (w/ CRF)	✓	✗	128 × 224	RAFT [44]	3.73	80.7	78.9	78.4

Table 1: **Unsupervised video segmentation** on DAVIS2016, SegTrack-v2 (STv2), and FBMS59.

† denotes the usage of CRFs and other extra significant post-processing (e.g., multi-step flow, multi-crop, temporal smoothing for CIS [88]). ‡ DS is optimized per sequence; authors report 30 min training time for 80-frame video. * DyStaB utilises supervised pre-training.

foreground object segmentation on an *independent* validation/test set of still images. In this scenario, motion is only used as a supervisory signal: when the network is applied at test time, motion is not considered anymore and the network operates purely as an image-based segmenter. As for any transductive learning setting, the goal is to assess the generalization performance of the network on new images.

4 Experiments

As discussed above, our formulation allows us to evaluate our method in two settings: video object segmentation and general image/object segmentation. We show that learning a network that *guesses what moves* not only results in state-of-the-art performance in video segmentation, but also generalizes to image segmentation without further training.

4.1 Experimental Setup

Architecture. Our formulation enables us to use any standard image segmentation architecture for the model Φ . This has two main benefits: while training the model needs optical flow (and thus video data), inference can be performed on single images alone just like any image segmentation method. Second, using a standard architecture allows us to benefit from (self-)supervised pretraining, ensuring better convergence and broader generalization. We experiment with both convolutional and transformer-based architectures.

Datasets. For the *video segmentation* task, we use three popular datasets: DAVIS2016 (DAVIS) [63], SegTrackV2 (STv2) [44], as well as FBMS [60]. For the *image segmentation* task, we consider the Caltech-UCSD Birds-200 (CUB) dataset [84] and three saliency detection benchmarks: DUTS [80], ECSSD [67], and DUT-OMRON [87].

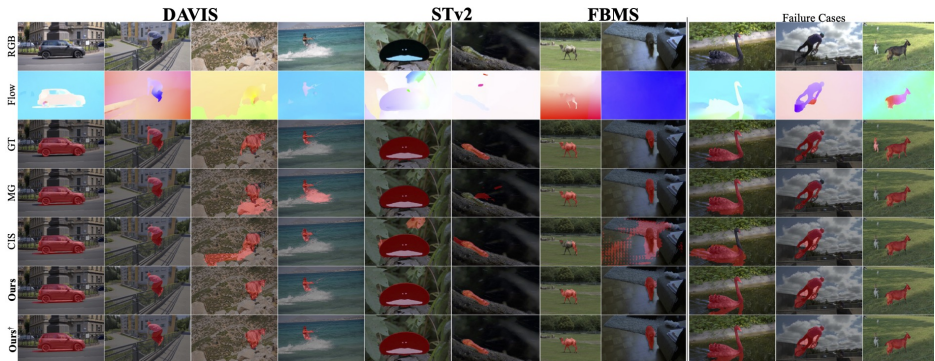


Figure 2: **Qualitative Comparison on DAVIS, STv2, and FBMS.** [†] – indicates use of CRF. Our method correctly segments objects in challenging conditions including strong parallax (2nd, 3rd seq.), small objects (4th), background motion (5th), camouflaged appearance (6th), non-rigid motion (7th) or no motion at all (8th seq.). In the failure cases, our method is confused by ripples and reflection in the water, the front wheel rotating in a different direction and multiple disconnected objects.

Optical Flow. Our method derives its learning signal from optical flow. We estimate optical flow for all frames on DAVIS, STv2, and FBMS following the practice of MotionGrouping [86]. We employ RAFT [44] (supervised) using the original resolution for our main experiments. Please see the supplement for experiments with other flow methods.

Training Details. We use MaskFormer [43] as our segmentation network, and use only the segmentation head. For the backbone and appearance features V , we leverage a ViT-B transformer, pre-trained on ImageNet [53] in a self-supervised manner using DINO [44] to avoid any external sources of supervision. We set the number of components to $K = 4$ unless otherwise noted. Please see the supplement for all details and hyper-parameter settings.

4.2 Unsupervised Video Segmentation

In Table 1 we report our performance on the DAVIS, STv2, and FBMS datasets and compare to other unsupervised video segmentation approaches. Our method achieves state-of-the-art performance, even without CRF post-processing. Fig. 2 provides a qualitative comparison of the results. Our model provides better segmentation with sharper boundaries despite complex non-rigid motion, parallax effects or lack-of-motion. However, on challenging scenarios our method still struggles to segment small details or non-connected instances.

Our method is not restricted to a specific segmentation architecture. To investigate, MaskFormer is replaced with a simple convolutional U-Net architecture [64], as in EM [34], and trained from scratch for a fair comparison. The U-Net based model achieves comparable results on DAVIS and FBMS and 76.8 on STv2 (Table 1), outperforming earlier methods even without transformers.

4.3 Flow Model and Number of Components

Using DAVIS, we now study the effectiveness of the individual components of the method. In Table 2 we evaluate the performance of the model under different flow models: constant,

Flow Model	K	DAVIS ($\mathcal{J}\uparrow$)	DAVIS ($\mathcal{J}_{\text{oracle}}\uparrow$)
Constant ($A = 0$)	4	76.8	77.7
Affine ($u = [x, y]$)	4	77.1	78.8
Quadratic (Eq. (2))	4	79.5	81.5
Quadratic (Eq. (2))	2	74.5	74.5
Quadratic (Eq. (2))	3	77.8	79.5
Quadratic (Eq. (2))	4	79.5	81.5
Quadratic (Eq. (2))	5	76.0	79.9

Table 2: **Flow Model and Number of Components.** We ablate the choice of flow model and the number of components K . More complex flow models improve performance, and over-segmentation helps until the assignment problem between components and the final binary segmentation becomes too difficult at $K = 5$. To evaluate the quality of the clustering of components we also report the oracle clustering performance as an upper bound.

affine, and quadratic. We find that more complex models lead to improved performance, likely due to the fact that many scenes in the DAVIS benchmark are highly dynamic with complex objects and backgrounds. Additionally, in the same table we evaluate how the number of components, K , influences the final performance after clustering. With $K = 2$ the model directly performs foreground-background separation but needs to model each with a single component which is often difficult, *e.g.* due to complex motions of deformable objects and/or parallax effects. Increasing the number of components is beneficial up to $K = 4$, after which the assignment problem from over-segmentation to foreground and background becomes too difficult for simple spectral clustering. This can be seen by evaluating the segmentation performance under an optimal oracle assignment of the components to foreground and background (oracle column in Table 2). In all cases $K \leq 4$, spectral clustering nearly reaches oracle performance.








	CUB			DUTS			ECSSD			OMRON		
	Acc	$\mathcal{J}\uparrow$	$\max F_\beta\uparrow$	Acc	$\mathcal{J}\uparrow$	$F_\beta\uparrow$	Acc	$\mathcal{J}\uparrow$	$F_\beta\uparrow$	Acc	$\mathcal{J}\uparrow$	$F_\beta\uparrow$
 Voynov <i>et al.</i>	94.0	71.0	80.7	88.1	51.1	60.0	90.6	68.4	79.0	86.0	46.4	53.3
 AMD	—	—	—	—	—	60.2	—	—	—	—	—	—
 Kyriazi <i>et al.</i>	92.1	66.4	78.3	89.3	52.8	61.4	91.5	71.3	80.6	88.3	50.9	58.3
 Kyriazi <i>et al.</i>	—	76.9	—	—	51.4	—	—	73.3	—	—	56.7	—
 DyStaB [†]	—	—	—	—	—	—	—	—	88.1	—	—	73.9
 TokenCut	—	—	—	90.3	57.6	—	91.8	71.2	—	88.0	53.3	—
 SelfMask	—	—	—	92.3	62.6	—	94.4	78.1	—	90.1	58.2	—
Ours	93.5	64.6	80.9	91.5	49.2	65.6	88.5	56.1	74.3	89.3	41.31	56.3

Table 3: **Unsupervised object segmentation** benchmark CUB and three saliency detection benchmarks: DUTS, ECSSD, and DUT-OMRON (*OMRON*). [†] DyStaB uses CRF post-processing, supervised pre-training, and self-training on each dataset. (SoTA only table - please see the supplement for a complete version of this table including many older methods.)

4.4 Unsupervised Image Segmentation

While the main aim of our work is object segmentation in videos, we also assess the image segmentation performance on common image segmentation and saliency benchmarks: CUB,

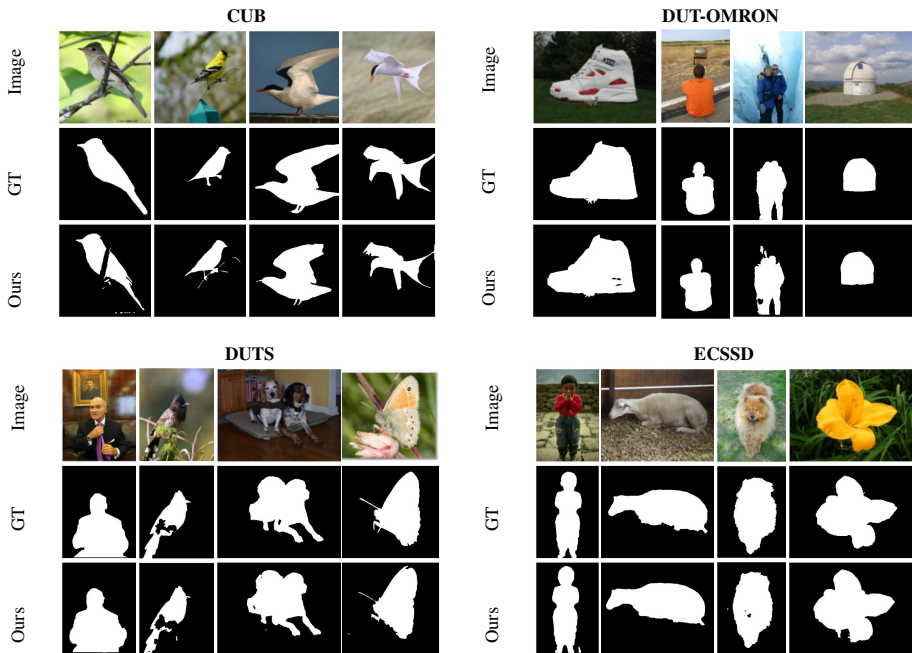


Figure 3: **Qualitative Comparison.** Our method can extract salient object in various environments and works even for novel object that were not included in the training data.

DUTS, DUT-OMRON, and ECSSD. For this experiment, we train our model on all three motion segmentation datasets (DAVIS, FBMS and STv2) jointly and apply the resulting network to the image segmentation benchmarks without any further fine-tuning. In Table 3, we report the performance of our method and compare to the current state of the art. It is worth noting that most prior work (except [26, 27, 28]) relies on dataset-specific training, self-training, post-processing or supervised pre-training to achieve image segmentation.

Finally, we evaluate the model qualitatively in Fig. 3 on all four benchmarks. We observe our model works well on a diverse set of classes, such as buildings, certain animals and plants, even though they were not part of the foreground (moving) objects in the training data.

5 Conclusions

We have proposed a simple approach to exploit the synergies between motion in videos and objectness for segmenting visual objects without supervision. The key idea is using motion anticipation as a learning signal: we train an image segmentation network to predict regions that likely contain simple optical flow patterns, as these have a high chance to correspond to objects. We find that the complexity of the motion model is important to model complicated flow patterns that can arise even for rigid objects. Our results show that this approach achieves state-of-the-art performance in video segmentation benchmarks. Future work could thus consider extensions to more sophisticated motion models, accounting for the 3D shape of objects, and to separate multiple objects.

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