WALDO: Future Video Synthesis using Object Layer Decomposition and Parametric Flow Prediction

Guillaume Le Moing\(^1,2, *\) \quad Jean Ponce\(^2, 3\) \quad Cordelia Schmid\(^1, 2\)

\(^1\)Inria \quad \(^2\)Département d’informatique de l’ENS (CNRS, ENS-PSL, Inria) \quad \(^3\)Center for Data Science New York University

Abstract

This paper presents WALDO (WAarping Layer- Decomposed Objects), a novel approach to the prediction of future video frames from past ones. Individual images are decomposed into multiple layers combining object masks and a small set of control points. The layer structure is shared across all frames in each video to build dense inter-frame connections. Complex scene motions are modeled by combining parametric geometric transformations associated with individual layers, and video synthesis is broken down into discovering the layers associated with past frames, predicting the corresponding transformations for upcoming ones and warping the associated object regions accordingly, and filling in the remaining image parts. Extensive experiments on multiple benchmarks including urban videos (Cityscapes and KITTI) and videos featuring nonrigid motions (UCF-Sports and H3.6M), show that our method consistently outperforms the state of the art by a significant margin in every case. Code, pretrained models, and video samples synthesized by our approach can be found in the project webpage.\(^1\)

1. Introduction

Predicting the future from a video stream is an important tool to make autonomous agents more robust and safe. In this paper, we are interested in the case where future frames are synthesized from a fixed number of past ones. One possibility is to build on advanced image synthesis models [20, 23, 44, 59] and adapt them to predict new frames conditioned on past ones [79]. Extending these already memory- and compute-intensive methods to our task may, however, lead to prohibitive costs due to the extra temporal dimension. Hence, the resolution of videos predicted by this approach is often limited [36, 95, 96]. Other works resort to compression [64, 82] to reduce computations [63, 97, 103].

\(^*\)corresponding author: guillaume.le-moing@inria.fr
\(^1\)url: https://16lemoing.github.io/waldo
Figure 2. Overview of WALDO. Given an input video sequence and associated semantic segmentation and optical flow maps preprocessed by off-the-shelf models [14, 77], our approach breaks down video synthesis into (a) layered video decomposition: using semantic and motion cues to decompose the sequence into layers represented by both object masks and features, with spatial information in the form of a small set of control points, (b) future layer prediction: predicting the new position of these points in the target output frames, and (c) warping, inpainting and fusion: using the corresponding offset and a thin-plate spline deformation model to warp the input frames and object masks, merge the corresponding regions, and fill in the empty image parts. Our model is trained, without explicit annotations, on a set of videos of $T+K$ frames by using the first $T$ to predict the next $K$. At inference, a (potentially greater) number $K$ of frames is predicted from $T$ input ones by repeating (a), (b) and (c) in an autoregressive fashion if needed.

2. Related work

Video prediction ranges from unconditional synthesis [4, 16, 19, 24, 25, 47, 69, 79, 80, 86] to multi-modal and controlled prediction tasks [32, 33, 38, 61, 97]. Here, we intend to exploit the temporal redundancy of videos by tracking the trajectories of different objects. One may infer future frames by extrapolating the position of keypoints associated to target objects [88, 106], but this requires manual labeling. Some works [12, 21, 34, 37, 60] propose instead to let structured object-related information naturally emerge from the videos themselves. We use a similar strategy but also rely on off-the-shelf models to extract semantic and motion cues in the hope of better capturing the scene dynamics [7, 29, 71, 90, 99, 100]. Without access to ground-truth objects, we discover them via layered video decomposition.

Layered video decompositions, introduced in [89], have been applied to optical flow estimation [75, 101], motion segmentation [66, 104], and video editing [43, 56, 105]. They are connected to object-centric representation learning [5, 10, 22, 31, 46, 54], where the compositional structure of scenes is also essential. Like [104], we use motion in the form of optical flow maps to decompose videos into objects and background. We go beyond the single-object scenarios they tackle, and propose a decomposition scheme which works well on real-world scenarios like urban scenes, with multiple objects and complex motions. In addition, we associate with every layer a geometric transformation allowing the recovery of the flow between past and future frames.

Spatial warps, as implemented in [42], have proven useful for various tasks, e.g., automatic image rectification for text recognition [72], semantic segmentation [26], and the contextual synthesis of images [62, 65, 112] or videos [1, 2, 6, 7].
Inspired by D’Arcy Thompson’s pioneering work in biology [78] as well as the shape contexts of Belongie et al. [8], we parameterize the warp with thin-plate splines (TPS) [9], whose parameters are motion vectors sampled at a small set of control points. TPS allow optical flow recovery by finding the transformations of minimal bending energy which complies with points motion. This has several advantages: The flow is differentiable with respect to motion vectors; deformations are more general than affine ones; and the number of control points allow to trade off deformation expressivity for parameter size.

3. Proposed method

Notation. We use a subscript $t$ in $[1, T+K]$ for time, with frames $1$ to $T+K$ available at train time, and the last $K$ predicted from the first $T$ at inference time. We use a superscript $i$ in $[0, N]$ for image layer, where $i=0$ represents the background and $i>0$ represents an object. For example, we denote by $p_i^t$ the control points associated with layer $i$ in frame $t$, by $p_t$ those associated with all layers at time $t$, and by $p_t^l$ those associated with layer $l$ over all time steps.

Overview. We consider a video $X$ consisting of $T+K$ RGB frames $x_t$ to $x_{T+K}$ with spatial resolution $H \times W$. Each frame is decomposed into $N+1$ layers tracking objects and background motions over time. Layers are represented by pairs $(m_i^t, p_i^t)$, where $m_i^t$ is a (soft) mask indicating for every pixel the presence of object $i$ (or background if $i=0$), and $p_i^t$ is the set of control points associated with layer $i$ at time $t$. Our approach (Figure 2) consists of: (a) decomposing frames $1$ to $T$ of video $X$ into layers (Sec. 3.1); (b) predicting the decompositions up to time $T+K$ (Sec. 3.2); and (c) using them to warp each of the first $T$ frames of $X$ into the $K$ future time steps, and finally predicting frames $T+1$ to $T+K$ by fusing the $T$ views for each future time step and filling in empty regions (Sec. 3.3). The three corresponding modules are trained separately, starting with (a), and then using (a) to supervise (b) and (c).

Off-the-shelf preprocessing. Similar to [5, 104], we adopt a motion-driven definition of objectness where an object is defined as a spatially-coherent region which follows a smooth deformation over time, such that discontinuities in scene motion occur at layer boundaries. We compute for the first $T$ frames of the video the corresponding backward flow maps $F = [f_1, \ldots, f_T]$ with an off-the-shelf method [77], where $f_i$ is the translation map associating with every pixel of frame $x_t$ the vector of $\mathbb{R}^2$ pointing to the matching location in $x_{t-i}$. We also suppose that each object has a unique semantic class out of $C$ and compute for the first $T$ frames the corresponding semantic segmentation maps $S = [s_1, \ldots, s_T]$ again with an off-the-shelf method [14], where $s_t$ assigns to every pixel a label (e.g., car, road, buildings, sky) represented by its index in $[1, C]$.

3.1. Layered video decomposition

We associate with each layer $i$ in $[0, N]$ a (soft) object ($i>0$) or background ($i=0$) mask $a_i$ of size $H^i \times W^i$ over which is overlaid a coarse $b^i \times w^i$ regular grid $g_i^t$ of control points. Deformed layer masks $m_i^t$ are obtained by mapping the points in $g_i^t$ onto their positions $p_i^t$ at time step $t$ and applying the corresponding TPS transformation to $a_i$. The decomposition module (Figure 3) maps the segmentation and flow maps $S$ and $F$ onto the positioned control points $p_1$ to $p_T$ and the deformed layer masks $m_1$ to $m_T$.

3.1.1 Architecture

Input encoding. Input flow maps and segmentation maps $F$ and $S$ are fed to a time-independent encoder, implemented by a convolutional neural network (CNN) which outputs temporal feature maps $Y = [y_1, \ldots, y_T]$. Each map $y_t$ lies in $\mathbb{R}^{d \times h \times w}$ with feature dimension $d$ and downscaled spatial resolution $h \times w$ such that $hw \ll HW$. We denote by $l = hw$ the latent feature size, and reshape feature $y_t$ to an $l \times d$ matrix through raster-scan reordering.

In practice we use larger values of $H^i$, $W^i$ for the background (same as $H, W$) than for object layers, and we fix the ratio $H^l/h^l$ to 16.
Layer feature extraction. We form layer features \( Z = [z^0, \ldots, z^N] \) from temporal ones \( Y \), where, for each layer, \( z^i \) is an \( l^i \times d \) matrix with \( l^i = h^i w^i \). We implement this with a transformer [83], where self-attention is replaced by a binding mechanism, discovering object-centric features by iteratively grouping intra-object pixels together, as in [54].

Control point positioning. We add a third dimension to the control points \( p^i_t \) positioned in the frame \( x_t \) to record the corresponding layer “depth” ordering \( o^i_t \geq 0 \), with \( o^i_t = 0 \) for the background. In practice, the 3D vectors associated with the points \( p_t \) are once again predicted by a transformer, from the set \( Z \) of layer features and the temporal feature \( y_t \), thus accounting for possible interactions between layers. Control points are typically close to the associated objects, but it is still fine if some end up outside an object mask. Their role is to recover a dense deformation field through TPS interpolation, and what matters is only that the part of this field within the object mask is correct. Figure 1 shows grids of control points extracted by our approach. Note how their structure automatically adapts to fit precise motions.

Layer mask prediction. A CNN maps layer features \( z^i \) onto soft masks \( a^i \) with values in \([0,1]\) corresponding to opaqueness and defined in their own “intrinsic” coordinate systems, in which points associated with \( p^i_t \) lie on a regular grid \( g^i \). The background is fully opaque (\( a^0 = 1 \)). At time \( t \), \( a^i \) is warped onto the corresponding layer mask \( m^i_t \) using the TPS transformation \( w^i_t \) mapping the grid points of \( g^i \) onto their positions \( p^i_t \) in frame \( x_t \). We then improve object contours by semantic refinement using segmentation maps \( S \). Concretely, given a mask \( m^i_t \) corresponding to an object layer (\( i>0 \)), a soft class assignment \( c^i \) in \([0,1]\) is obtained from \( z^i \) with a fully-connected layer, then used to update \( m^i_t \) by comparing \( c^i \) to the actual class in \( s_t \). We finally use the ordering scores \( o_t \) and a classical occlusion model [43,62] to filter non-visible layer parts. More details about this process are in Appendix A-D.

3.1.2 Training procedure

The goal of the decomposition module is to discover layers whose associated masks and control points best reconstruct scene motion. We achieve this by minimizing the objective:

\[
\mathcal{L}_d = \lambda_o \mathcal{L}_o + \lambda_i \mathcal{L}_f + \lambda_r \mathcal{L}_r,
\]

with an object discovery loss \( \mathcal{L}_o \) to encourage objects from different layers to occupy moving foreground regions; a flow reconstruction loss \( \mathcal{L}_f \) to ensure the temporal consistency of the learned decompositions; and a regularization loss \( \mathcal{L}_r \). At train time, we extract layer features from the first \( T \) frames, but also position layers in the \( K \) subsequent ones to have a supervision signal for later stages (Sects. 3.2 and 3.3). At inference, only the first \( T \) frames are used.

Object discovery. Without ground-truth objects for training, we discover reasonable candidates using semantic and motion cues, \( f_t \) and \( s_t \), by positioning objects in \( \mathcal{M}(s_t, f_t) \), a binary mask indicating foreground regions (e.g., cars) with significant motion compared to stuff regions (e.g., road), written \( S(s_t) \). We get the mask \( \mathcal{M}(s_t, f_t) \) by extrapolating the full background flow from \( f_t \) in \( S(s_t) \), and by thresholding with a constant \( \tau_m \), the \( L_1 \) distance between background and foreground flows. The object discovery loss is:

\[
\mathcal{L}_o = \sum_t (k_s S(s_t) - k_m \mathcal{M}(s_t, f_t)) \odot (\max_{i>0} m^i_t),
\]

where \( k_m \) and \( k_s \) are positive scalars, weighting the attraction of discovered objects \( m^i_{t>0} \) towards moving foreground regions (\( \mathcal{M} \)) and the repulsion from stuff regions (\( S \)).

Flow reconstruction. We reconstruct the backward flow \( w_{t_2 \leftarrow t_1} \) between consecutive time steps \( t_1 \) and \( t_2 \), by considering the individual layer warps, denoted \( w^i_{t_2 \leftarrow t_1} \), and computed as \( w^i_{t_2 \leftarrow t_1} = w^i_{t_2} \circ w^i_{t_1} \). The mask \( m^i_t \) and \( p^i_t \) are obtained through the TPS transformation associated with \( p^i_t \) and \( p^i_{t_2} \). We recover \( w_{t_2 \leftarrow t_1} \) by compositing layer warps, i.e.,

\[
w_{t_2 \leftarrow t_1} = \sum_i m^i_t \odot w^i_{t_2 \leftarrow t_1},
\]

where the mask \( m^i_t \) determines layer transparency. The flow reconstruction loss is:

\[
\mathcal{L}_f = \sum_t \|f_t - \hat{f}_t\|_1, \text{ with } \hat{f}_t = w_{t \leftarrow t-1}.
\]

Regularization. The last objective \( \mathcal{L}_r \) is composed of: an entropy term applied to layer mask \( m_t \) to ensure that a single layer prevails for every pixel, and an object initialization term which is the \( L_2 \) distance from regions of interest \( \mathcal{M}(s_t, f_t) \) which are still empty (as per \( m^i_{t>0} \)) to the control points \( p^i_t \) of the nearest object (\( i>0 \)).

3.2 Future layer prediction

Thanks to our layered video decomposition, the prediction of future layers (Figure 4) is reduced to inferring, from past control points \( [p_1, \ldots, p_T] \), the position of future ones.

Architecture. For each time step \( t \leq T \) and each layer \( i \), \( p^i_t \) is mapped onto a vector in \( \mathbb{R}^d \) by a linear layer. Likewise, each \( z^i \) is also mapped onto a vector in \( \mathbb{R}^d \). We concatenate
and feed these vectors to a two-stage transformer to construct representations for the $K$ future time steps by combining self-attention modules applied to intermediate future representations and cross-attention modules between past and future ones. The prediction of the control points $p_i^k$ associated with each layer in the $K$ future time steps is done with a linear layer, which does not output their position directly, but rather their displacement with respect to $p_t$, with $T$ being the last known time step from the past context.

**Training procedure.** We extract training data for past and future time steps by decomposing videos of length $T+K$ as described in Sec. 3.1. We then mask the control points corresponding to the last $K$ time steps and train the future prediction module to reconstruct them by minimizing $L_p$, the $L_1$ distance between extracted and reconstructed control points for time steps $T+1$ to $T+K$. Under uncertainty, $L_p$ makes points converge towards an average future trajectory. When interested in predicting multiple futures, we add noise (as input and in attention modules) and an adversarial term [30] to $L_p$. More details are in Appendix E.

### 3.3. Warping, fusion and inpainting

Last comes the actual synthesis of future frames from past ones (Figure 5), using the layer decompositions extracted from the past, and the ones predicted into the future.

**Architecture.** Given the predicted control points, we compute, for every layer $i$ and pair of time steps $(t_1, t_2)$ in $[1, T] \times [T+1, T+K]$, the layer warp $w_{t_2 \leftarrow t_1}^i$ from $t_1$ to $t_2$ as described in Sec. 3.1. We construct $m_{t_2}^i$ by warping $m_{t_1}^i$ with $w_{t_2 \leftarrow t_1}^i$. We compute $w_{t_2 \leftarrow t_1}^i$ from layer warps and future masks by $w_{t_2 \leftarrow t_1}^i = \sum m_{t_2}^i \odot w_{t_2 \leftarrow t_1}$. Then we warp past frames to produce multiple views of future ones, one for each pair of time steps $(t_1, t_2)$. We obtain $T$ views for each future frame, with different missing regions due to disocclusion. A fusion network, implemented by a U-Net [68], merges these views together according to pixel-level scores predicted for each of them. Regions which remain empty are then filled with an off-the-shelf inpainting network [51], to obtain future frame predictions $\hat{x}_{T+1}$ to $\hat{x}_{T+K}$. We ensure temporal consistency by filling frames one at a time and by using predicted motions to propagate the newly filled content onto the next frames.

**Training procedure.** The inpainting model [51], trained on 8M images from the Places dataset [111], is kept frozen and the objective to train the fusion U-Net is the weighted $L_1$ distance in pixel space and between features $F$ extracted using the VGG [74] classification network trained on [18]:

$$L_u = \sum_{t=T+1}^{T+K} \lambda_p \| x_t - \hat{x}_t \|_1 + \lambda_v \| F(x_t) - F(\hat{x}_t) \|_1,$$

(4)

### 4. Experiments

**Datasets.** We train WALDO on two urban datasets, Cityscapes [17], which contains 2975 30-frame video sequences for training and 500 for testing captured at 17 FPS, and KITTI [28], with a total of 156 longer video sequences (~340 frames each) including 4 for testing. We use suitable resolutions and train / test splits for fair comparisons with prior works (setup from [7] in Table 1 and from [1] in Table 2). We also train on nonrigid scenes from UCF-Sports [67] (resp. H3.6M [41]) using the splits from [13] consisting of 6288 sequences (resp. 73404) for training and 752 (resp. 8582) for testing with roughly 10 frames per sequence. We extract semantic and motion cues using pretrained models, namely, DeepLabV3 [14] and RAFT [77].

**Evaluation metrics.** We evaluate the different methods with the multi-scale structure similarity index measure (SSIM) [94], the learned perceptual image patch similarity (LPIPS) [109], and the peak signal-to-noise ratio (PSNR), all standard image reconstruction metrics for evaluating video predictions. We also use the Fréchet video distance (FVD) [81] to estimate the gap between real and synthetic video distributions. We report in Tables 1-3 the mean and standard deviation for 3 randomly-seeded training sessions.

**Implementation details.** For reproducibility, code and pretrained models are available on our project webpage. WALDO is trained with the ADAM optimizer [45] and a learning rate of $10^{-4}$ on 4 NVIDIA V100 GPUs for about a week. We set $(\lambda_o, \lambda_f, \lambda_r, \lambda_p, \lambda_v) = (1, 100, 1, 1, 1)$, $(k_s, k_m) = (0.25, 1)$ and $\tau_m = 0.005$ by validating the performance on a random held-out subset of the training data. For example, we use spatial resolutions of $128 \times 256$ for training (a) the layered video decomposition, and (b) the future layer prediction module; and $512 \times 1024$ for training (c) the

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3[https://16lemoing.github.io/waldo](https://16lemoing.github.io/waldo)
Table 1. Comparison to state-of-the-art deterministic methods on Cityscapes and KITTI test sets. We compute multi-scale SSIM ($\times 4$) and LPIPS ($\times 10^2$) for the $k^{th}$ future frame and average for $k$ in $[1, K]$. We indicate if methods use semantic or flow ground truths for training.

| Method    | Sem. Flow | $K = 1$ | $K = 5$ | $K = 10$ | $K = 1$ | $K = 3$ | $K = 5$ |
|-----------|-----------|---------|---------|----------|---------|---------|---------|
|           | SSIM ↑PSNR ↑LPIPS ↓SSIM ↑LPIPS ↓SSIM ↑LPIPS ↓FVD ↓ | SSIM ↑LPIPS ↓SSIM ↑LPIPS ↓SSIM ↑LPIPS ↓FVD ↓ | |
| PredNet [55] | 840 260 | 752 360 | 663 522 | - | 563 553 | 514 586 | 475 629 |
| MCNet [85] | 897 189 | 706 373 | 597 451 | - | 753 240 | 635 317 | 554 373 |
| VFlow [53] | 839 174 | 711 288 | 634 366 | - | 539 324 | 469 374 | 426 415 |
| VEST [110] | - - | - - | - - | - | - | - | - |
| VPVFI [100] | ✓ | 945 064 | 804 178 | 700 278 | 159 | 827 123 | 695 203 | 611 264 | 505 |
| VPCL [29] | ✓ | 928 085 | 839 150 | 751 217 | 129 | 820 172 | 730 220 | 667 259 | 075 |
| Vid2vid [90] | ✓ | 882 106 | 751 201 | 669 271 | - | - | - | - | - |
| OMP [99] | ✓ ✓ | 891 085 | 757 165 | 674 233 | 113 | 792 185 | 676 246 | 607 304 | 047 |
| SADM [7] | ✓ ✓ | 959 076 | 835 149 | - | - | - | - | - | - |
| WALDO | ✓ ✓ | 957 ±2 | 049 ±2 | 854 ±1 | 105 ±1 | 771 ±1 | 158 ±1 | 055 ±1 |

Table 2. Comparison to state-of-the-art stochastic methods (“†”) on 20-frame future prediction on Cityscapes and KITTI. We report the best SSIM ($\times 10^2$), PSNR ($\times 10$), and LPIPS ($\times 10^2$) out of 100 trajectories sampled from each test sequence (except for our deterministic variant). We use 4 frames as input but others use 10.

| Method | Cityscapes ($128 \times 256$) | KITTI ($62 \times 310$) |
|--------|----------------------------|----------------------|
| SSIM ↑PSNR ↑LPIPS ↓ | SSIM ↑PSNR ↑LPIPS ↓ |
| SVG† [19] | 606 204 340 | 329 127 | 594 |
| SRVP† [25] | 603 210 447 | 336 134 | 635 |
| HierVRNN† [11] | 618 214 260 | 379 142 | 372 |
| SLAMP† [1] | 649 217 294 | 337 135 | 537 |
| SLAMP-3D† [2] | 643 214 306 | 383 143 | 501 |
| WALDO | 638 ±2 | 220 ±1 | 158 ±1 | 410 ±2 | 145 ±1 | 348 ±1 |
| WALDO† | 653 ±2 | 224 ±1 | 147 ±1 | 418 ±2 | 147 ±1 | 340 ±2 |

Figure 6. Comparison with [29,99,100] on the Cityscapes test set at time step $T+10$. WALDO better extracts objects from the background, better predicts their motion, and is more robust to occlusion. We strongly encourage readers to watch videos in the project webpage.

Figure 7. Comparison to SLAMP [1] on 50-frame prediction on the Cityscapes test set. See project webpage for videos.

4.1. Evaluation with the state of the art

Deterministic prediction. WALDO sets a new state of the art on two urban datasets. On Cityscapes (Table 1(a)), it yields a better than 27% relative gain for LPIPS across all predicted time windows, and a significant margin for $K>1$ with SSIM and FVD. On KITTI (Table 1(b)), WALDO out-
Figure 8. Future prediction comparisons to STRPM [13] from $T=4$ frames on (a) UCF-Sports and (b) H3.6M. In our case, nonrigid motions can be visualized by the associated warps, predicted from the control points between $T$ and $T+10$ (colors represent different directions).

Table 3. Comparison with methods designed for nonrigid motions. We compute PSNR (×10), LPIPS (×10³) for the $k^{th}$ future frames synthesized from 4 past ones on UCF-Sports and H3.6M test sets.

| Method       | UCF-Sports (512 × 512) | H3.6M (1024 × 1024) |
|--------------|------------------------|---------------------|
|              | PSNR ↑ | LPIPS ↓ | PSNR ↑ | LPIPS ↓ |
|              | $k=1$ | $k=6$ | $k=1$ | $k=6$ | $k=1$ | $k=6$ | $k=1$ | $k=6$ |
| BMSE [58]    | 264 | 185 | 290 | 553 | - | - | - | - |
| PRNN [93]    | 272 | 197 | 281 | 553 | 319 | 257 | 126 | 140 |
| PRNN++ [91]  | 273 | 197 | 268 | 568 | 321 | 275 | 138 | 150 |
| SAVP [49]    | 274 | 199 | 255 | 499 | - | - | - | - |
| SV2P [4]     | 274 | 200 | 259 | 513 | 319 | 273 | 139 | 150 |
| HFVP [84]    | - | - | - | - | 321 | 273 | 134 | 145 |
| ELSTM [92]   | 280 | 203 | 251 | 478 | 324 | 277 | 131 | 139 |
| CGAN [48]    | 280 | 200 | 229 | 449 | 328 | 283 | 102 | 110 |
| CrevNet [108] | 282 | 203 | 239 | 481 | 332 | 283 | 115 | 124 |
| MRNN [98]    | 277 | 200 | 242 | 492 | 322 | 280 | 121 | 133 |
| STRPM [13]   | 285 | 206 | 207 | 411 | 333 | 290 | 097 | 104 |
| WALDO        | 292 | 235 | 090 | 183 | 363 | 314 | 058 | 071 |

performs prior methods in a quite challenging setting, with a frame rate half that of Cityscapes and a quality of precomputed semantic and motion cues poorer on KITTI. Comparisons with latest methods [29, 99, 100] on Cityscapes (Figure 6) show that WALDO successfully models complex object (e.g., cars, bikes) and background (e.g., road markings) motions with realistic and temporally coherent outputs, whereas others produce stationary or blurry videos.

Stochastic prediction. We adapt WALDO to the prediction of multiple futures by injecting noise inputs to the layer prediction module and using (at train time only) a discriminator to capture multiple modes of the distribution of synthetic trajectories. This simple procedure results in significant improvements in the stochastic setting (Table 2). In particular, WALDO outperforms other stochastic methods on the same datasets by a large margin. Interestingly, even our deterministic variant compares favourably to these approaches. Minimizing the $L_1$ reconstruction error (in this variant) make predictions average over all possible futures. Because we predict positions and not pixel values directly, and since averaging still yields valid positions, we obtain sharp images. On the other hand, averaging over pixels inevitably blur them out. This critical distinction is illustrated in Table 4(e). Although the loss function introduced in VPCL [29] aims at sharpening pixel predictions, the examples in Figure 8 show that WALDO is more successful.

Long-term prediction. WALDO produces arbitrary long videos, without additional training, when used in an autoregressive mode. In 20-frame prediction (Table 2), it significantly outperforms prior works, without using its full potential since a lower resolution is used to match those of other methods. Visual comparisons with SLAMP [1] (Figure 7) at full resolution on 50-frame prediction (longer than the 30-frame videos in Cityscapes) are also striking.

Nonrigid prediction. To show that WALDO can handle complex motions, we retrain it on data with significant nonrigid objects, namely UCF-Sports and H3.6M datasets. Since our approach relies on TPS transformations, it can represent arbitrarily nonrigid motions when the number of control points is set accordingly [9]. By increasing the total number of per object points from 16 to 64, WALDO produces realistic videos even for deformable bodies such as human beings (Figure 8). As highlighted by the predicted warps, it successfully handles fine-grained motions covering a variety of human activities such as weight-lifting, doing gymnastics, walking sideways or leaning forward. Moreover, WALDO yields much more realistic outputs than STRPM [13] by producing high quality frames longer into
Table 4. Ablation study on the Cityscapes test set. (a) **Layered video decomposition**: We evaluate decompositions in terms of flow reconstruction and object discovery as captured by $L_f$ and $L_o$. (b) **Future layer prediction**: We measure the accuracy of predicted control points. (c) **Video synthesis**: We evaluate the image reconstruction quality. (d) An example without (left) and with (right) semantic refinement. (e) $L_1$ reconstructions of an image in pixel space (left) and using control points (right) assuming Gaussian uncertainty over the horizontal position of the object. The former is blurry due to the plurality of potential positions. The latter singles out one position and preserves the object appearance.

| N | Input Ref. | $N_c$ | $L_f \downarrow$ | $L_o \downarrow$ |
|---|---|---|---|---|
| 0 | X | 128 | 4.42 | 0.00 |
| 1 | X | 144 | 6.06 | -3.69 |
| 8 | X | 256 | 4.47 | -5.96 |
| 16 | X | 384 | 3.97 | -5.79 |
| 16 | S | 384 | 3.90 | -7.59 |
| 16 | S+F | 384 | 2.69 | -7.56 |
| 16 | S+F ✓ | 24 | 7.44 | 0.00 |
| 16 | S+F ✓ | 72 | 7.01 | -3.26 |
| 16 | S+F ✓ | 176 | 4.17 | -4.78 |
| 16 | S+F ✓ | 288 | 3.16 | -7.93 |
| 16 | S+F ✓ | 384 | 2.59 | -8.16 |
| (b) Future layer prediction. | | | | |
| Arch. | Input | $\Delta p_T$ | $L_p \downarrow$ |
| MLP | P | .514 |
| T | P | .178 |
| T | P ✓ | .150 |
| T | P+Z ✓ | .144 |
| (c) Video synthesis. | | | |
| VGG HR Ctxt. SSIM | | 1 | 812.1 |
| ✓ | 1 | 815.7 |
| ✓ ✓ | 1 | 847.2 |
| (e) Prediction strategy. | | | 4 | 848.0 |

4.2. Ablation studies

We conduct a detailed analysis on the Cityscapes test set to compare and highlight the key novelties of WALDO. The set of hyperparameters validated through this study have proven to work well on other datasets without any tuning.

**Layered video decomposition** is illustrated in Figure 9 and evaluated in Table 4(a) through the lens of our object discovery criterion ($L_o$) and flow reconstruction ($L_f$). We observe that the more object layers ($N$) the better, except for $N=1$ where fitting multiple objects with a single layer is suboptimal. Comparing inputs, we find using segmentation maps ($S$) better than RGB frames ($X$) alone for object discovery, and that using flow maps ($F$) helps motion reconstruction. Semantic refinement (Ref.) yields further gains, especially to segment thin objects like traffic lights, see Table 4(d). Finally, increasing the number of control points ($N_c$) allows us to capture finer motions, so we use as much as fits into memory (384 per time step). Our motion representation is scalable, with parameter size reduced from a quadratic ($TK$) to a linear ($T+K$) dependency on time compared to methods relying on optical flow directly.

**Future layer prediction** is illustrated in Figure 10 and evaluated in Table 4(b) in terms of trajectory reconstruction. Our baseline is a multi-layer perceptron (MLP), which maps past control points $P=\{p_t\}_{t=1}^T$ to future ones. Our actual architecture relies on a transformer (T) [83], which performs much better. Further gains are obtained by not predicting control points directly but rather their relative position ($\Delta p_T$) with respect to time step $T$, and by using layer features $Z=\{z^i\}_{i=0}^N$ as input.

**Warping, fusion and inpainting** is illustrated in Figure 11 and evaluated in Table 4(c) in terms of SSIM. Control points, obtained by the layer decomposition module, are

Figure 9. Visualization of control points and layer masks with different colors for each layer. See project webpage for videos.
Figure 10. Visualization of future layer prediction. We use control points from the layered video decomposition as supervision. We compare motion vectors reconstructed from these points to the ones predicted for up to time step $T + 10$ from a context of $T = 4$ past frames. The motion vectors are computed between time step $T$ and time step $t$ in $\{T + 1, T + 10\}$. Different colors correspond to different layers.

Figure 11. Visualization of the synthesis process: warped visible regions and inpainted disoccluded ones between $T$ and $T+10$.

used to warp, fuse and inpaint different views of the past frames to reconstruct future ones. We find using the feature distance (VGG) to be slightly better than the pixel one alone. The flexibility of WALDO, which trains at low resolution ($128 \times 256$) but produces dense motions well suited for high resolution (HR) inputs ($512 \times 1024$), results in higher SSIM than keeping the same resolution than for training during inference. We further improve SSIM by warping not only one but all of the four past context frames (Ctx.).

**Off-the-shelf models.** We compare standard approaches in Appendix H, and find that WALDO is robust to the choice of the pretrained segmentation [14, 15, 70] and optical flow models [76, 77]. We also show in Appendix I that although we use an inpainting method [51] pretrained on external data [111] to produce realistic outputs in filled-in regions, it does not provide quantitative advantage to WALDO with at best marginal improvements in SSIM, LPIPS and FVD.

5. Conclusion

We have introduced WALDO, an approach to video synthesis which automatically decomposes frames into layers and relies on a compact representation of motion to predict their future deformations. Our method outperforms the state of the art for video prediction on various datasets. Future work includes exploring extensions of WALDO for applications from motion segmentation to video compression.

**Limitations.** Our performance depends on the accuracy of the layer decomposition. Failure cases include objects moving in different directions but merged into the same layer, or segmentation failures, where parts of an object are missed.

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