Video Prediction at Multiple Scales with Hierarchical Recurrent Networks

Ani Karapetyan*, Angel Villar-Corrales*, Andreas Boltres1 and Sven Behnke1

Abstract—Autonomous systems not only need to understand their current environment, but should also be able to predict future actions conditioned on past states, for instance based on captured camera frames. For certain tasks, detailed predictions such as future video frames are required in the near future, whereas for others it is beneficial to also predict more abstract representations for longer time horizons. However, existing video prediction models mainly focus on forecasting detailed possible outcomes for short time-horizons, hence being of limited use for robot perception and spatial reasoning. We propose Multi-Scale Hierarchical Prediction (MSPred), a novel video prediction model able to forecast future possible outcomes of different levels of granularity at different time-scales simultaneously. By combining spatial and temporal downsampling, MSPred is able to efficiently predict abstract representations such as human poses or object locations over long time horizons, while still maintaining a competitive performance for video frame prediction. In our experiments, we demonstrate that our proposed model accurately predicts future video frames as well as other representations (e.g., keypoints or positions) on various scenarios, including bin-picking scenes or action recognition datasets, consistently outperforming popular approaches for video frame prediction. Furthermore, we conduct an ablation study to investigate the importance of the different modules and design choices in MSPred. In the spirit of reproducible research, we open-source VP-Suite, a general framework for deep-learning-based video prediction, as well as pretrained models to reproduce our results.

I. INTRODUCTION

For effective human-robot collaboration, autonomous systems, such as domestic robots, need not only to perceive and understand their surroundings, but should also be able to estimate the intentions of nearby agents and make predictions about their actions and behavior. Depending on the desired prediction time-horizon, the level of abstraction of the predicted representations might differ. For instance, when forecasting the immediate future, predictions of high level of detail, such as subsequent video frames, are desirable. For longer time horizons it is no longer possible to foresee these exact details, hence it can be advantageous to predict more abstract representations like human poses or scene semantics. Finally, for planning longer into the future, only representations of a higher level of abstraction, such as actions or locations, might be reliably predicted.

In the last few years, several deep-learning-based approaches [1], [2], [3], [4], [5] have been proposed to predict future video frames. These methods, which often combine variational autoencoders [6] (VAEs) with recurrent neural networks (RNNs), predict one image after another in an autoregressive manner, conditioned on the observed or previously generated frames, often achieving realistic predictions.

Despite these recent successes, existing models are explicitly designed to predict future frames (i.e., RGB images), either in a self-supervised manner, or in a supervised setting using an intermediate representation, such as annotated semantic maps [7] or human poses [8]. However, these models lack the flexibility to simultaneously make predictions of different levels of abstraction. Furthermore, these methods operate in an autoregressive manner, hence requiring a large number of iterations (and therefore computations) to make predictions for longer time-horizons, and are highly prone to error accumulation.

To overcome these issues, we propose Multi-Scale Hierarchical Prediction (MSPred), a convolutional neural network designed to simultaneously predict future possible outcomes of different levels of granularity at different time-scales.
An overview of the MSPreD architecture and its multi-scale prediction concept is illustrated in Figure 1.

To better model the world dynamics and allow for better temporal modeling, MSPreD utilizes a hierarchical predictor module, which applies both spatial and temporal pooling. This allows the model to extract features of different levels of abstraction that change at different temporal resolutions. The hierarchical predictor module is composed of multiple convolutional long short-term memory (LSTM) cells operating at different periods \( T \), i.e., processing every \( T \)-th input. LSTMs operating at a higher frequency specialize on modeling low-level fast-changing features, whereas LSTMs ticking with a higher period capture more abstract features that change more slowly over time. This temporal downsampling allows us to predict slowly changing abstract features far into the future, while requiring only a handful of RNN iterations.

The main contributions of our work are as follows:

- We propose MSPreD, a hierarchical video prediction model able to simultaneously predict future possible outcomes of different levels of granularity at different time-scales, conditioned on past video frames.
- We show how MSPreD outperforms popular deep-learning-based video prediction methods on three diverse datasets.
- We present VP-Suite, an open-source framework for deep-learning-based video prediction. VP-Suite includes implementations of popular models, datasets and evaluation protocols, in order to standardize and make video prediction research more accessible to the community.

II. RELATED WORK

A. Future Frame Video Prediction

Video prediction is the task of forecasting future video frames conditioned on past video frames. This task gained popularity due to recent advances in neural networks and generative modeling. For a comprehensive review of deep-learning-based video prediction, we refer to [5].

Some approaches perform video prediction by learning geometric transformations between consecutive frames [10], [11], [12]. In [13], [14], the authors perform video prediction by estimating transformations and forecasting future frames in the frequency domain.

The most popular approach to video prediction, which our proposed method also follows, is the use of recurrent networks in combination with convolutional autoencoders in order to extract features from the seed frames, and projecting them into the future [15], [16], [17], [18], [19], [20]. These approaches were later extended by integrating variational inference into the recurrent networks, which allows the video prediction networks to model the underlying uncertainty of the data. Babaiezadeh et al. [21] use an inference network to approximate the true posterior distribution of the data, from which they sample a time-invariant latent vector that models the stochastic properties of the data. Denton et al. [1] use a more flexible inference network that outputs a different posterior distribution for each time step, hence learning more expressive and time-dependent latent variables. Some methods organize the network into a hierarchical structure [22], [4], [23]. This allows the model to use features of different levels of abstraction to predict future video frames, as well as to learn more flexible latent distributions.

The work that is conceptually most similar to ours is CW-VAE [2], in which – similarly to our MSPreD model – a hierarchy of recurrent modules ticking at different clock rates is used to predict higher-level features at coarser time scale. Despite the similarities, the problems addressed by CW-VAE and MSPreD are inherently different: CW-VAE combines features of distinct temporal resolutions to predict video frames far into the future using a fixed temporal granularity. In contrast, we do not aim to forecast realistic frames long into the future, but instead to simultaneously predict frames for shorter time horizons, as well as higher-level representations longer into the future using coarser temporal resolutions.

B. High-Level Feature Prediction

Another line of work performs video prediction using an intermediate high-level representation, instead of directly predicting future frames in the pixel space. These models first extract some high-level representation from the seed frames and project them into the future. Then, the model combines the predicted structured representations and the seed frames in order to forecast the future video frames. This approach simplifies the task of prediction, which can lead to long-term accurate predictions. However, training these models requires human supervision. In practice, different high-level representations have been proven useful, including human poses [8], [24], semantic maps [7], or instance segmentations [25].

Similarly, MSPreD also predicts high-level representations, such as poses or positions. However, these are not used as intermediate features to predict future frames. Instead, MSPreD uses RNNs operating at coarse time-scales in order to predict high-level representations long into the future with a small number of iterations, while still being able to accurately predict future video frames at a fine time-resolution.

C. Multi-Scale Recurrent Networks

Since the introduction of recurrent neural networks [26], [9], several approaches have been proposed to extend recurrent models into temporal hierarchies.

In [27], the authors propose different architectures utilizing several RNNs operating at different time scales in order to learn long-term dependencies on simple sequential tasks. Clockwork RNNs [28] split a recurrent network into parallel recurrent sub-modules that process their inputs at a different temporal granularity, hence allowing the model to learn complex dependencies between temporally distant inputs. Similarly, HM-RNNs [29] propose a multi-scale recurrent model with different networks operating at different clock rates. However, the specific values for these update rates are not fixed, but learned using an adaptive mechanism.
Fig. 2: Illustration of the MSPred architecture. **Left:** The seed video frames are encoded with a shared fully convolutional encoder. Then, Convolutional LSTM modules ticking at different rates are used to forecast the features at future time steps. Slower LSTMs model more abstract representations, whereas the fastest LSTM processes fast-changing low-level details. **Right:** During prediction, feature maps are fed to a convolutional decoder, which decodes and fuses the information from the different predictors. Finally, three distinct decoder heads are used to decode features from different decoder stages into outputs of different levels of abstraction. Higher-level features are decoded into high-level representations, such as human poses or locations; whereas features from the fastest LSTM are used to obtain detailed predictions of future frames. Note that we only display the mid- and high-level decoder heads at the last time-step to unclutter the visualization.

Like the previous methods, MSPred utilizes different recurrent models operating at distinct time-scales in order to capture representations at different temporal resolutions. However, whereas the previous methods used RNNs to process sequential data, we employ convolutional LSTMs [16] in combination with convolutional autoencoders in order to process high-dimensional video sequences.

### III. Method

Video prediction is defined as the task of predicting subsequent video frames $\hat{I} = \hat{I}_1, \hat{I}_2, ..., \hat{I}_N$ conditioned on a certain number $C$ of seed frames $C = C_1, C_2, ..., C_C$. In this work, we extend the task of video prediction to predict not only the future frames, but also to forecast higher-level representations ($\hat{H}_1, \hat{H}_2$), such as human poses or object locations, conditioned on the same seed frames.

In this section we present MSPred, our proposed neural network for simultaneous prediction of representations of different levels of abstraction at multiple temporal scales. We introduce the MSPred architecture, which is depicted in Figure 2. The key component is its hierarchical predictor module (III-B), which forecasts features of different granularity. These features are extracted from the seed frames using a convolutional encoder (III-A), and decoded into future frames or higher-level representations using convolutional decoders (III-C). Furthermore, we discuss the information flow and inference in MSPred (III-D) as well as the training strategy and implementation details (III-E).

#### A. Encoder

MSPred uses a 2D CNN encoder in order to process the seed frames. This network is composed of four convolutional modules, each of them downsampling its input by a factor of two. After encoder blocks two and three, residual connections bridge from the encoder to the decoder through the two lowest-level RNNs respectively, providing features of different levels of abstraction to the decoder. Supplying low-level representations with high-spatial resolution prevents the loss of information in the bottleneck layers, whereas high-level representations of coarser spatial resolution provide the decoder with abstract semantic information. The combination of these features allows our model to achieve accurate predictions for future frames.

#### B. Multi-Scale Prediction

Information in images is often processed in a hierarchical manner using features of different spatial resolution and level of abstraction. Similarly, the flow of information in videos can be represented in a temporal hierarchy. Higher-level features model the slowly changing information that is shared across many frames, whereas lower-level representations model faster-changing information. To account for this temporal hierarchy, MSPred uses a predictor module composed of three recurrent neural networks operating at different temporal resolutions, i.e., processing input frames with a period of one, $T_1$ and $T_2$ respectively ($1 < T_1 < T_2$).

As depicted in Figure 2, the recurrent modules at a particular level receive feature maps from the respective stages of the encoder as input. The lowest-level RNN, which processes all inputs, receives low-level feature maps of high spatial resolution, which correspond to fine-grained information that quickly changes between consecutive frames. The second RNN receives feature maps of coarser spatial resolution, containing more slowly-changing representations. Therefore, this module operates with a slower clock-rate of $T_1$. Finally,
the highest-level RNN obtains as input abstract feature maps of even coarser spatial resolution, which contain high-level features that are shared across many video frames, hence processing just one input every $T_2$ time steps.

The use of this hierarchy of RNNs allows our model to disentangle the temporal information into three different flows, each modeling features varying at distinct time-scales. Furthermore, the temporal abstraction in higher levels allows MSPred to forecast high-level features far into the future using just a small number of iterations, hence mitigating the error accumulation characteristic of autoregressive models.

C. Decoder

The decoder architecture corresponds to a mirrored version of the convolutional encoder but uses transposed convolutions to upsample the feature maps. The features of the residual connections are fused with the decoded feature maps via channel-wise concatenation. As depicted in Figure 2, MSPred uses three separate decoder heads in correspondence to its three levels of processing in order to predict representations of different levels of abstraction. Generating detailed representations, such as future video frames, from the predicted features requires high-level knowledge (i.e. semantics or dynamics) as well as low-level information (i.e. texture or color). Therefore, each decoder uses the most recent predicted feature maps from its own level and all levels above. As higher levels operate at coarser time scales, predicted feature maps from higher levels are re-used until a new feature map is generated. The decoder of the lowest level generates an output every time step. It uses the most recent predicted features of all levels of the RNN hierarchy in order to generate the next predicted video frame. The mid-level decoder produces more abstract representations every $T_1$ time steps by processing the most recent feature maps of its own level and the level above. Finally, the highest-level decoder generates abstract representations such as object locations every $T_2$ time steps, using only the predicted features from the highest level.

D. Model Inference

Given a sequence of seed images, MSPred encodes these frames and feeds the embedded features to the corresponding recurrent modules (Figure 2 left). During the prediction stage (Figure 2 right), the model forecasts future representations in an autoregressive manner in the feature space, i.e., the outputs of a recurrent module are used as input in the subsequent time step. We do not re-encode predicted frames to mitigate the exponential error accumulation characteristic of autoregressive models. The forecasted features are fed to the corresponding decoder stage in order to decode future frames and high-level representations. Images are predicted at every time-step, whereas higher-level representations are predicted with at the same clock-rate as the higher-level recurrent modules, i.e., once every $T_1$ and $T_2$ time-steps respectively.

E. Implementation Details

For the Moving MNIST dataset, our encoder and decoder follows the DCGAN discriminator [30] architecture. For the other datasets we use VGG16-like [31] encoder and decoder. Each level of our hierarchical predictor uses four ConvLSTM [16] cells using 128 kernels of size $3 \times 3$. The lowest-level ConvLSTM processes all inputs, whereas for the higher levels we use periods of $T_1 = 4$ and $T_2 = 8$ respectively.

Similar to [1], [3], we include skip connections from the last observed frame to the decoder for all frame predictions. The features from the skip connections are added to the outputs of the corresponding RNN. The role of these skip connections is to directly provide the decoder with features of the background and static objects, hence allowing the predictor to focus on modeling pixel-level dynamics that change throughout the sequence.

Our model receives 17 seed frames ($C = 17$), which is the minimum number allowing the highest-level ConvLSTM to process three frames during the seed stage. The models are trained to predict for five iterations using periods of $T_1 = 4$ and $T_2 = 8$, which correspond to time-steps $t = 18, 19, \ldots, 22$ for the lowest level, $t = 21, 25, \ldots, 37$ for the mid-level, and $t = 25, 33, \ldots, 57$ for the highest-level ConvLSTM.

Our model is trained using the ADAM optimizer [32] with an initial learning rate of 0.0003 by minimizing the following loss function:

$$
L = \frac{1}{N} \sum_{i=1}^{N} \left( ||I_i - \hat{I}_i|| + \lambda_1 ||H^1_i - \hat{H}^1_i|| + \lambda_2 ||H^2_i - \hat{H}^2_i|| \right),
$$

where $|| \cdot ||$ is the $\ell_2$ norm, $I_i, H^1_i, H^2_i$ correspond to the ground truth frames and higher-level targets, and $\hat{I}_i, \hat{H}^1_i, \hat{H}^2_i$ correspond to the predicted frames and higher-level representations.

IV. VP-SUITE

While progress in the field of video prediction has been remarkable over the past few years, the complexity of the problem setting results in a tremendous amount of scientific and technical details that differ between publications. These differences include dataset preprocessing, evaluation protocols, or training details, among others. As a consequence, replicating and comparing published results becomes a very tedious task.

In an effort to standardize this task, we introduce VP-Suite\footnote{VP-Suite: https://github.com/AIS-Bonn/vp-suite} a versatile PyTorch-based [33] framework for deep-learning-based video prediction. VP-Suite currently supports a wide variety of popular prediction models (including ConvLSTM [16], SVG [1], PhyDNet [20], among others), and datasets (e.g., Moving MNIST [15] or KTH-Action [34]). VP-Suite serves as an interface for reproducible dataset preprocessing, training, and evaluation of deep-learning-based video prediction models.
TABLE I: Ablation study. We investigate the importance of MSPred modules and design choices by evaluating different versions of the model on Moving MNIST. Namely, we investigate different recurrent cells, and the importance of temporal and spatial hierarchy. The best result is highlighted in boldface, whereas the second best is underlined.

| MSPred Modules | RNN Cell | Spatial Temp. | MSE↓ | PSNR↑ | SSIM↑ | LPIPS↓ |
|----------------|----------|---------------|------|-------|-------|-------|
| 1 ConvLSTM ✓ ✓  | 34.44    | 26.82         | 0.975| 0.024 |
| 2 LSTM ✓       | 208.71   | 17.95         | 0.827| 0.202 |
| 3 ConvLSTM - ✓ | 73.47    | 22.81         | 0.950| 0.057 |
| 4 ConvLSTM ✓ -  | 92.45    | 20.81         | 0.921| 0.093 |
| 5 ConvLSTM ✓ ✓  | 112.18   | 20.97         | 0.912| 0.097 |
| 6 LSTM - -      | 134.22   | 20.31         | 0.900| 0.114 |

V. EXPERIMENTS

We perform an ablation study, investigating the importance of several modules and design choices of MSPred in Subsection V-B. In Subsection V-C, we present results of multi-scale predictions of MSPred. Finally, we compare MSPred with existing video prediction methods on three diverse datasets in Subsection V-D. Further results are available on the project website.

A. Evaluation Metrics and Datasets

We evaluate our MSPred model on three different video datasets of different levels of complexity, namely Moving MNIST [15], KTH-Action [34], and SynpickVP.

**Moving MNIST** is a standard video prediction dataset containing sequences of two random digits from the MNIST dataset [35] moving with constant speed in a $64 \times 64$ grid, and bouncing off the image boundaries. In this work, we consider Moving MNIST frames as RGB images. We train our models on random sequences generated on the fly, and evaluate on a fix test set containing 10,000 sequences.

**KTH Actions** is a dataset consisting of real videos of humans performing one out of six possible actions, e.g. jogging or waving. The dataset includes 600 videos (over 290k frames) of 25 different humans performing the actions in various indoor and outdoor environments.

**SynpickVP**: we introduce SynpickVP, a novel video prediction dataset containing sequences of challenging bin-picking scenarios, in which a suction-cap gripper robot moves objects in a cluttered box. We generate the dataset by selecting sequences from the recently proposed SynPick [36] dataset. More precisely, we select 300 videos (240 for training and 60 for evaluation), which are split into sequences with 60 frames. This is a challenging video prediction benchmark, in which the model needs to predict the motion of the robotic gripper, as well as the displaced objects, while still representing a cluttered complex background.

**Evaluation Metrics**: We evaluate our models for video prediction using four popular metrics. Mean squared error (MSE), peak signal-to-noise ratio (PSNR), and structural similarity [37] (SSIM) measure pixel or statistical differences between predicted and target images. Despite being widely used, they tend to correlate poorly with human perception, favoring blurred predictions over more detailed, though imperfect, generations [38]. Therefore, we also evaluate using LPIPS [38], which measures the distance between CNN feature maps, and has been shown to better correlate with human judgment. For all metrics, we average the results across all five predicted frames.

B. Ablation Study

We first investigate the importance of different components and design choices in our MSPred model. Namely, we investigate the relevance of the temporal and spatial hierarchy, and the type of recurrent cell used in our predictor. For our ablation study, we focus on the Moving MNIST dataset. The results of our ablation study are listed in Table I.

First, we note that the base MSPred model (row 1) outperforms all other variants, which demonstrates that combining spatial with temporal hierarchy leads to a superior performance. Second, removing either the spatial (row 3), temporal (row 4), or all (row 5) hierarchical structure from the predictor leads to a decrease of performance, hence demonstrating that providing features of different levels of (temporal and spatial) granularity improves the prediction performance of the model.

Finally, when replacing the ConvLSTM predictor cell with a standard LSTM (row 2), the prediction performance significantly decreases, leading to the worst overall results among all compared models. However, replacing the ConvLSTM predictor cell with a linear LSTM cell in a simpler non-hierarchical baseline (row 6) leads to a more moderate performance loss. Therefore, we conclude that reshaping the spatially fine feature maps from the low-levels prior to feeding them to the linear LSTMs destroys necessary positional information inherently encoded in the convolution feature maps, hence leading to a large drop in performance.

C. Multi-Scale Prediction

Unlike most existing video prediction models, MSPred has been specifically designed to predict higher-level representations at coarse time scales in addition to subsequent video frames. For KTH-Action, MSPred predicts human keypoints on its intermediate level, and a person center-point on its highest level. Keypoint annotations are obtained using OpenPose [39], and we select the mid-point between the shoulders as person center-point.

Figure 3 depicts an example of multi-scale prediction in MSPred. We display three seed frames as well as the first four predictions for each decoder head. The lowest-level decoder achieves detailed subsequent video frame predictions for a short time horizon, i.e. five frames into the future. The higher level decoders predict human poses and person locations up longer into the future using a coarser temporal abstraction.

From Figure 3 we observe how the higher level features enable accurate pose and location predictions on different scenarios. We argue that MSPred encodes the overall person motion and local movements into its higher levels.
Fig. 3: Predictions of different levels of abstraction on the KTH dataset. We display three seed frames as well as the first four predictions for each decoder. MSPred forecasts detailed frames on short time horizons, while also predicting representations of higher levels of abstraction, i.e. human poses and locations, longer into the future using a coarse temporal resolution.

**TABLE II: Quantitative comparison between video prediction models.** MSPred outperforms all other methods on the Moving MNIST dataset, and achieves the best perceptual results (LPIPS) on KTH-Action and SynpickVP. All baseline results have been computed and can be readily reproduced with our VP-Suite. The best result is highlighted in boldface, whereas the second best is underlined.

|                | Moving MNIST     |                        | KTH-Action                  |                        | SynpickVP        |
|----------------|------------------|------------------------|-----------------------------|------------------------|------------------|
|                | MSE↓  | PSNR↑ | SSIM↑ | LPIPS↓ | MSE↓  | PSNR↑ | SSIM↑ | LPIPS↓ | MSE↓  | PSNR↑ | SSIM↑ | LPIPS↓ |
| CopyLast       | 857.69 | 11.73 | 0.638 | 0.233 | 50.72 | 23.84 | 0.909 | 0.049 | 87.24 | 25.97 | 0.889 | 0.028 |
| ConvLSTM [16]  | 271.95 | 17.22 | 0.833 | 0.144 | 12.49 | 31.54 | 0.957 | 0.048 | 49.90 | 27.98 | 0.907 | 0.059 |
| TrajGRU [19]   | 164.75 | 20.02 | 0.895 | 0.075 | 12.24 | 31.71 | 0.958 | 0.039 | 51.12 | 28.10 | 0.908 | 0.041 |
| SVG-Det [1]    | 134.22 | 20.31 | 0.900 | 0.114 | 35.74 | 26.64 | 0.927 | 0.068 | 60.60 | 26.92 | 0.879 | 0.068 |
| SVG-LP [1]     | 133.68 | 20.36 | 0.907 | 0.115 | 26.60 | 27.60 | 0.932 | 0.063 | 51.12 | 27.38 | 0.886 | 0.066 |
| PredRNN++ [18] | 154.52 | 20.20 | 0.911 | 0.055 | 13.74 | 30.68 | 0.941 | 0.068 | 51.73 | 27.50 | 0.894 | 0.053 |
| PhyDNet [20]   | 153.54 | 20.43 | 0.915 | 0.054 | 26.35 | 28.01 | 0.913 | 0.125 | 57.31 | 26.84 | 0.877 | 0.053 |
| MSPred (ours)  | 34.44  | 26.82 | 0.975 | 0.024 | 23.18 | 27.81 | 0.951 | 0.029 | 53.09 | 27.89 | 0.881 | 0.033 |

**D. Comparison to Existing Methods**

We compare our MSPred model with several existing video prediction methods based on recurrent neural networks, including ConvLSTM [16], TrajectoryGRU [19], deterministic (SVG-Det) and learned prior (SVG-LP) variants of SVG [1], PredRNN++ [18], and PhyDNet [20]. Furthermore, we include a simple baseline (CopyLast) that naively copies the last seed frame.

The results are listed in Table II. The best result is highlighted in boldface, whereas the second best is underlined. All baseline results have been computed and can be reproduced with our VP-Suite. MSPred consistently performs among the best of all compared models across all scenarios.

**Moving MNIST:** MSPred achieves exceptionally sharp and accurate reconstructions for all five predicted frames, outperforming all other models by a large margin. Figure 4 depicts a qualitative comparison of different methods on three sequences from the Moving MNIST dataset. The top row corresponds to the original sequences, from which we display four seed frames as well as ground truth for five predictions. In general, due to the simplicity of the dataset, all models achieve overall accurate frame predictions. An interesting case is depicted in Figure 4c, which shows a challenging sequence in which digits overlap. Baseline methods learn the dynamics of the sequence, but obtain blurred predictions and are unable to recover the original digit shape, whereas MSPred successfully achieves accurate frame predictions. We argue that the information about digit identity and shape is encoded in the higher levels of the hierarchy, which are updated with a coarser temporal resolution, hence being more robust to overlap between digits.

**KTH-Action:** MSPred produces low MSE and PSNR scores, indicating higher pixel differences with respect to the target frames. However, MSPred achieves the best LPIPS result, demonstrating a high perceptual similarity to the target frames. Figure 5 contains a qualitative comparison on three KTH-Action sequences, showing the actions **waving**, **walking**, and **boxing**, respectively. On the one hand, baseline methods with the highest PSNR results, i.e. ConvLSTM and TrajGRU, obtain blurred predictions, such as the arms in Figures 5a and 5c. On the other hand, our MSPred model achieves sharper predictions, especially with respect to the human figure and performed action.

**SynpickVP:** Similarly to the experiments on KTH-Action, ConvLSTM and TrajGRU achieve the best MSE, PSNR and SSIM results, outperforming our proposed method. However, MSPred once again outperforms existing video prediction models on the perceptual metric. Interestingly, due to the
Fig. 4: Qualitative results on Moving MNIST. Top row corresponds to ground truth frames. We display four seed frames as well as the five predicted frames for three test-set sequences. In general, all compared methods achieve good frame predictions. However, only MSPred accurately resolves challenging cases in which digits overlap.

Fig. 5: Qualitative results on the KTH-Action dataset. Top row corresponds to ground truth frames. We display four seed frames as well as the five predicted frames for three test-set sequences. MSPred achieves the sharpest and more accurate reconstructions among the compared methods.

Fig. 6: Qualitative results on the SynpickVP dataset. Top row corresponds to ground truth frames. We display four seed frames as well as the five predicted frames for three test-set sequences. MSPred qualitatively outperforms the compared methods, achieving sharp reconstructions, whereas the baseline methods tend to blur the predictions.

high complexity of the SynpickVP dataset, all models tend to blur the predicted frames, thus the CopyLast simple baseline achieves the best LPIPS results. Figure 6 depicts a qualitative comparison of different video prediction models on the SynpickVP dataset. Baseline video prediction methods tend to blur the suction cap gripper as well as the objects moved by it, whereas MSPred achieves more accurate predictions.

VI. CONCLUSION

We proposed MSPred, a novel video prediction model that extends the effective prediction horizon of related approaches by leveraging hierarchies of recurrent neural networks operating at different temporal resolutions in order to predict outcomes of varying levels of granularity at different time scales. In its lowest prediction level, MSPred forecasts subsequent
video frames, whereas higher levels predict more abstract representations longer into the future using coarser temporal resolutions. In our experiments, we show how MSPred outperforms several existing video prediction methods for the task of future frame prediction. Furthermore, we show how the higher level decoders can be used to forecast more abstract representations, such as human poses or object locations, over longer time horizons. We hope that the contributions of our work, such as the hierarchical recurrent predictor or our open-source video prediction framework, enable further research on hierarchical video prediction. We firmly believe that the hierarchical features from MSPred could be used as representations to improve autonomous agents’ perception and reasoning capabilities.

REFERENCES

[1] E. Denton and R. Fergus, “Stochastic video generation with a learned prior,” in International Conference on Machine Learning (ICML), 2018, pp. 1174–1183.

[2] V. Saxena, J. Ba, and D. Hafner, “Clockwork variational autoencoders,” International Conference on Machine Learning (ICML), 2021.

[3] R. Villegas, A. Pathak, H. Kannan, D. Erhan, Q. V. Le, and H. Lee, “High fidelity video prediction with large stochastic recurrent neural networks,” Advances in Neural Information Processing Systems (NeurIPS), vol. 32, 2019.

[4] L. Castrejon, N. Ballas, and A. Courville, “Improved conditional vrams for video prediction,” in IEEE/CVF International Conference on Computer Vision (ICCV), 2019, pp. 7608–7617.

[5] S. Oprea, P. Martinez-Gonzalez, A. Garcia-Garcia, J. A. Castro-Vargas, S. Orts-Escolano, J. Garcia-Rodriguez, and A. Argyros, “A review on deep learning techniques for video prediction,” IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 2020.

[6] D. P. Kingma and M. Welling, “Auto-encoding variational Bayes,” in International Conference on Learning Representations (ICLR), 2014.

[7] J. Pan, C. Wang, X. Jia, J. Shao, L. Sheng, J. Yan, and X. Wang, “Video generation from single semantic label map,” in IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 3733–3742.

[8] R. Villegas, J. Yang, Y. Zou, S. Sohn, X. Lin, and H. Lee, “Learning to generate long-term future via hierarchical prediction,” in International Conference on Machine Learning (ICML), 2017, pp. 3560–3569.

[9] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[10] Y. Wang, H. Wu, J. Zhang, Z. Gao, J. Wang, P. S. Yu, and M. Long, “PredRNN: A recurrent neural network for spatiotemporal predictive learning,” 2021.

[11] X. Shi, Z. Gao, L. Lausen, H. Wang, D.-Y. Yeung, W.-k. Wong, and W.-c. Woo, “Deep learning for precipitation nowcasting: A benchmark and a new model,” Advances in Neural Information Processing Systems (NeurIPS), vol. 30, 2017.

[12] V. L. Guen and N. Thome, “Disentangling physical dynamics from unknown factors for unsupervised video prediction,” in IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 11 474–11 484.

[13] M. Babaeizadeh, C. Finn, D. Erhan, R. H. Campbell, and S. Levine, “Stochastic variational video prediction,” in International Conference on Learning Representations (ICLR), 2018.

[14] I. Prémont-Schwarz, A. Illin, T. Hao, A. Rasmus, R. Boney, and H. Valpola, “Recurrent ladder networks,” Advances in Neural Information Processing Systems (NeurIPS), vol. 30, 2017.

[15] B. Wu, S. Nair, R. Martin-Martin, L. Fei-Fei, and C. Finn, “Greedy hierarchical variational autoencoders for large-scale video prediction,” in IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2021, pp. 2318–2328.

[16] N. Fushishita, A. Tejero-de Pablos, Y. Mukuta, and T. Harada, “Long-term human video generation of multiple futures using poses,” in European Conference on Computer Vision (ECCV), 2020, pp. 596–612.

[17] P. Luc, C. Couprie, Y. Lecun, and J. Verbeek, “Predicting future instance segmentation by forecasting features,” in european conference on computer vision (ECCV), 2018, pp. 584–599.

[18] J. L. Elman, “Finding structure in time,” Cognitive science, vol. 14, no. 2, pp. 179–211, 1990.

[19] S. Hihi and Y. Bengio, “Hierarchical recurrent neural networks for long-term dependencies,” Advances in Neural Information Processing Systems (NeurIPS), vol. 8, 1995.

[20] J. Koutník, K. Greff, F. Gomez, and J. Schmidhuber, “A clockwork rnn,” in International Conference on Machine Learning (ICML), 2014, pp. 1863–1871.

[21] J. Chang, S. Ahn, and Y. Bengio, “Hierarchical multiscale recurrent neural networks,” International Conference on Learning Representations (ICLR), 2017.

[22] A. Radford, L. Metz, and S. Chintala, “Unsupervised representation learning with deep convolutional generative adversarial networks,” International Conference on Learning Representations, ICLR, 2016.

[23] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” International Conference on Learning Representations, ICLR, 2015.

[24] D. P. Kingma and J. Ba, “A method for stochastic optimization,” in International Conference on Learning Representations (ICLR), 2015.

[25] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, “Image quality assessment: from error visibility to structural similarity,” IEEE Transactions on Image Processing, vol. 13, no. 4, pp. 600–612, 2004.

[26] R. Zhang, P. Isola, A. A. Efros, E. Shechtman, and O. Wang, “The unreasonable effectiveness of deep features as a perceptual metric,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018, pp. 586–595.

[27] Z. Cao, T. Simon, S.-E. Wei, and Y. Sheikh, “Realtime multi-person 2d pose estimation using part affinity fields,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 7291–7299.