Precise Forecasting of Sky Images Using Spatial Warping: Supplemental Material

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1. Introduction

In this supplemental material, we expound on topics included in the paper submission in the following sections below:

1. In Section 2, we provide technical details of the U-Net neural network architecture used in our implementation.

2. in Section 3, we discuss a technique to extract solar irradiance from the predicted sky-images in the form of global horizontal irradiance (GHI).

2. Network Architecture

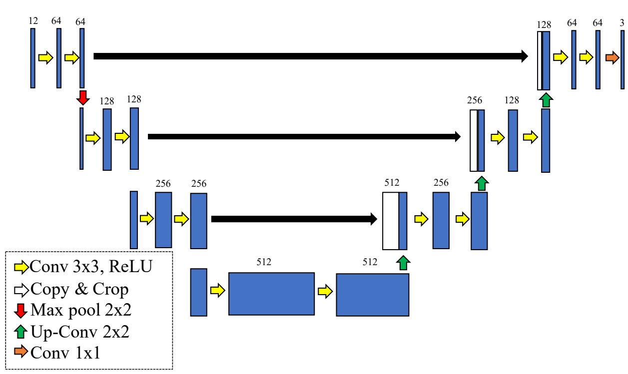

Figure 1: U-Net Architecture

We adapt the future frame prediction model proposed for activity forecasting in [2]. The backbone of this architecture is a U-Net [3] that takes in the input images to predict the image at the next time instant in the time lapse. Figure 1 shows the structure of the U-Net model used. The legend in Figure 1 indicates the operations between each layer. The black arrow between the encoder and decoder structure indicates skip connections that concatenate information from the encoder layer to the subsequent decoder layer.

2.1. Training Details

Our model is implemented in the Python programming language that utilizes the PyTorch machine learning framework. Experimenting with various parameters, the optimal batch size and number of epochs that we utilize are 4 and 40 respectfully. We train our model using 3 NVIDIA GeForce RTX 2080 Ti GPUs which takes about 1.5 hours per epoch to train on a dataset of 42,171 images.

3. GHI

Prediction of cloud movement in a subsequent image is only one step in precise prediction of solar irradiance. Therefore, using the predicted frames, we calculate GHI values similar to [1] in order to validate our results on accurately forecasting solar irradiance. We use a random forest (RF) ensemble model that, when trained with ground truth GHI values and sky-images, predicts a GHI value for that time instance. Figure 2 shows predicted GHI values captured each minute on a day's worth of data. Given 4 previous sky-image frames at time instants $\{t-5, t-3, t-1, t\}$ as input, the predicted image frame at $\widehat{I}_{t+1}$ is used as inference to compute GHI. This is repeated for all time instances throughout the specified day. Table 1 shows comparison SNR metrics for longer term prediction. Time instances after $t+1$ are recursively forecasted using predicted frames. For reference, "SkyNet" in the figures below, denote the SkyNet-UNet model.

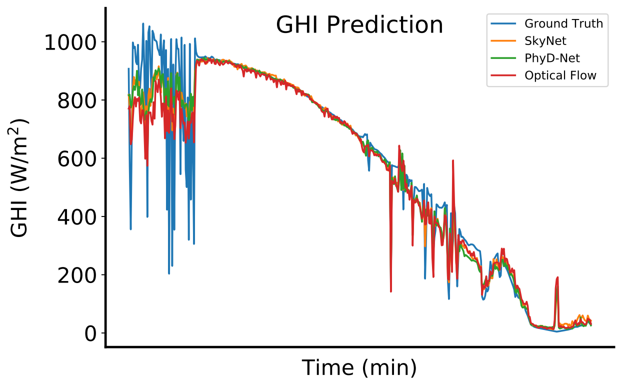

Figure 2: Predicted GHI values captured each minute on August 6, 2003. Each minute interval of GHI is predicted using 4 previous time instances. Table 1 shows comparison metrics.

GHI prediction performance (NMSE in dB)				
	$t+1$	$t+3$	$t+5$	$t+7$
SkyNet	**18.45**	**16.24**	**14.40**	**13.27**
PhyD-Net	17.54	15.27	13.66	12.62
Optical Flow	17.53	15.76	14.34	13.83

Table 1: Comparison of the signal-to-noise-ratio for GHI. Due to the fact that ground truth GHI values are captured each minute, we must predict every other subsequent image frame. For example $t + 5$ represents a 5-min ahead forecasting time using 4 previous time instance frames. These values are averages over 5 days from 08/06/03 to 08/11/03.

References

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[2] W. Liu, D. Lian W. Luo, and S. Gao. Future frame prediction for anomaly detection – a new baseline. In *2018 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018.

[3] O. Ronneberger, P.Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, pages 234–241. Springer, 2015.