Predicting ice flow dynamics using machine learning

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An Important Problem

Though machine learning has achieved notable success in modeling sequential and spatial data for speech recognition and in computer vision, applications to remote sensing and climate science problems are seldom considered. In this paper, we demonstrate techniques from unsupervised learning of future video frame prediction, to increase the accuracy of ice flow tracking in multi-spectral satellite images. As the volume of cryosphere data increases in coming years, this is an interesting and important opportunity for machine learning to address a global challenge for climate change, risk management from floods, and conserving freshwater resources. Future frame prediction of ice melt and tracking the optical flow of ice dynamics presents modeling difficulties, due to uncertainties in global temperature increase, changing precipitation patterns, occlusion from cloud cover, rapid melting and glacier retreat due to black carbon aerosol deposition, from wildfires or human fossil emissions. We show machine learning methods help improve the accuracy of tracking the optical flow of ice dynamics compared to existing methods in climate science.

Model

We use a stochastic video generation with prior for prediction. The prior network observes frames \( x_{t-1} \) and output \( p_{\phi}(x_{t-1|t}) \) and \( p_{q}(x_{t-1}) \) of a normal distribution and is trained with by maxing:

\[
L_{\theta, \phi, \psi} = \sum_{t | 1:t} \left[\log p_{\phi}(x_{t-1|t}) + \log p_{q}(x_{t-1|t-1}) \right] - \beta D_{KL}(q_{\psi}(z_{t}) || p(z_{t}))
\]

Where \( p_{\phi} \) and \( q_{\psi} \) are generated from convolutional LSTM. \( q_{\psi} \) and \( p_{\phi} \) are generated from encoding the \( x_{t-1} \) together with the prior. The latent space \( z_{t} \) is drawn from \( p_{\phi}(z_{t}|x_{t-1}) \). The details of the model, also referred as stochastic video generation can be found in [1].

Labels

The images are denoted as \( F_i \) where \( i \) is from 1 to 12 and the frames(subscenes) in each image are \( x_{ij} \in \mathbb{R}^{256 \times 256} \), where \( i \in \{1...12\} \) and \( j \in \{1...1525\} \). For finding the next subscene, or clip, that matches the \( x_{ij} \) best, we compare the \( x_{ij} \) to a range of possible regions by calculating the correlation between two clips, the equation writes as:

\[
C(r, s) = \frac{\sum_{m, n} (r_{mn} - \mu_r) (s_{mn} - \mu_s)}{\sqrt{\sum_{m, n} (r_{mn} - \mu_r)^2 \sum_{m, n} (s_{mn} - \mu_s)^2}}
\]

where \( r \) and \( s \) are the two images and \( \mu \) is the mean value.

Experiment Results and Discussion

Previous results also show applying high pass filter on both sides of the pairs can be a feasible solution to increase the correlation at certain areas[1, 2].

Fig. 2: The subscenes in our dataset. Frame 2 and frame 7 are contaminated by the aerosol.

Fig. 3: Results of three models. We train our model with \( z \in \mathbb{R}^{128} \) and 2 LSTM layers, each layer has 128 units. By conditioning on the past eight subscenes, the results of our model on different types of subscenes are shown in Figure 5 and 4.

Fig. 4: The correlation map. a) persistence model (correlation between \( t_2 \) and \( t_3 \)) b) high frequency model (correlation between filters).

Fig. 1: Subscenes generated with different models. The first three columns: the past three subscenes, the fourth column: the latent space \( z_{t} \) from the model, and the last column: the ground truth.

Remarks

Our model can also be improved if more physical and environmental parameters are introduced into the model, for example, the wind speed and the aerosol optical depth components in the atmosphere. The first parameter provides a signal for the ice flow movement and the second parameter gives us a confidence factor about the satellite images quality. Dropout to particular frames can be applied if the aerosol optical depth rises over a threshold. Furthermore, black carbon aerosols were found to accelerate ice loss and glacier retreat in the Himalayas and Arctic from both wildfire soot deposition and fossil fuel emissions.

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References