Deep Glacier Image Velocimetry: Mapping glacier velocities from Sentinel-2 imagery with deep learning

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Abstract

Glacier systems are highly sensitive to climate change and play a pivotal role in global mean sea level rise. As such, it is important to monitor how glacier velocities and ice dynamics evolve under a changing climate. The growing wealth of satellite observations has facilitated the inference of glacier velocities from remote sensing imagery through feature tracking algorithms. At present, these rely on sparse cross-correlation estimates as well as computationally expensive optical flow solutions. Here we present a novel use of deep-learning for estimating annual glacier velocities, utilizing the recurrent optical-flow based architecture, RAFT, on consecutive pairs of optical Sentinel-2 imagery. Our results highlight that deep learning can generate dense per-pixel velocity estimates within an automated framework that utilizes Sentinel-2 images over the French Alps.

1 Introduction

The evolution of glaciers is widely regarded as a significant indicator of climate change [1]. These systems play a crucial role in global mean sea level rise, contributing as much as 25–30% over past decades [2, 3]. This, in addition to the increased frequency of natural hazards affecting mountainous communities and evolving local hydrology, motivate the need for improved glacier monitoring [4–6]. Advancements made in spaceborne remote sensing capabilities have led to enhanced data availability with higher spatial resolution and lower revisit times. Glacier surface displacements can be inferred from successive optical or radar remote sensing images through feature tracking algorithms based on cross-correlation and optical flow techniques. A range of toolboxes have been developed with end-to-end workflows for feature tracking, utilizing these classical algorithms [7]. Efforts have been made to produce databases mapping glacier surface velocities at regional and global scales from archives of Sentinel-2 and Landsat imagery [8, 9].

Recently, deep learning computer vision algorithms have been effective at learning velocity fields from series of images, producing state-of-the-art optical flow estimation across synthetic datasets and fluid flow estimation problems [10, 11]. Deep learning for glacier monitoring has been applied to the mapping of glacier extents, glacier debris classification and mapping glacial lakes from remote sensing images [12–16]. However, it remains to be fully investigated the efficacy of deep learning optical flow methods for inferring glacier velocity fields, despite the adoption of these methods across various domains. Therefore, here we present a novel use of deep learning for mapping glacier-scale velocity fields from remote sensing imagery. We adopt a Recurrent All-Pairs Field Transforms

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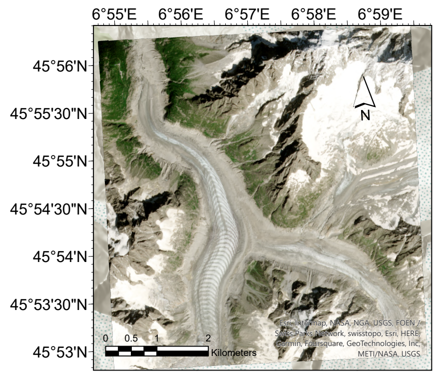

Figure 1: True-colour composite Sentinel-2 image of Mer de Glace, located in the Mont Blanc Massif of the French Alps.

(RAFT) based architecture to estimate dense optical flow velocity fields from Sentinel-2 imagery [17, 18].

2 Methodology

2.1 Workflow

In order to investigate the viability of deep learning based glacier image velocimetry, Sentinel-2 images need to be processed for input to the RAFT model, as well as target velocity fields generated for supervised learning. The employed data processing pipeline used to generate the training and test datasets is similar to the automated framework proposed by Millan et al. for generating glacier velocities from multiple spaceborne imaging platforms [19]. All available Sentinel-2 images over the region of interest are downloaded in Google Earth Engine. Since the images are optical, the search query is filtered by cloud cover, with winter months dominated by snowfall and homogeneous surface texture avoided. The near infrared band, Sentinel-2 band 8, is judged to produce sufficient radiometric response and is therefore the single band utilized here for analysis.

The downloaded images are then Sobel-filtered in both the x and y directions to enhance contrast and mitigate against shadows caused by the complex topography in mountainous regions. Glacier outlines from the Randolf Glacier Inventory are used to generate image masks to remove non-glacierized regions ahead of velocity estimation [20]. The processed images are then combined into image pairs and segmented into overlapping tiles of size 256×256, which is the input size of the RAFT model. Data augmentation is performed on the input images using rotations to modify dataset size and improve robustness. Training labels are generated from a classical multi-level Horn-Schunk solution implemented in Matlab which produces dense per-pixel velocity fields for the image pairs [21]. The resulting velocity fields are filtered for outliers using a 9×9 median filter.

2.2 Study Site

The selected glacier of interest, shown in Figure 1, is the Mer de Glace of the Mont Blanc massif in the French Alps, occupying an area of $\sim$30 km^2. Ogives mark the glacier surface which appear as alternating patterns of bright and dark strips. In-situ GPS measurements monitored as part of the GLACIOCLIM service provide an independent measure of annual velocities for validation. The training and test datasets are constructed from images acquired between the months of June and October in 2021 and 2022 when snow cover is minimal, exposing the surface features. Image pairs are selected by matching each image in 2021 with every available image acquired in 2022. This is to ensure that sufficient displacement has occurred between images as literature reports an annual velocity of $\sim$70 m/yr, requiring larger time intervals to resolve clear displacement between the 10 m resolution Sentinel-2 images [19, 22]. From 2021 and 2022, 10 and 17 images respectively were downloaded and processed according to the aforementioned workflow. This resulted in a training dataset of 14,871 pairs of image tiles, 1,653 for validation and 1,836 for testing.

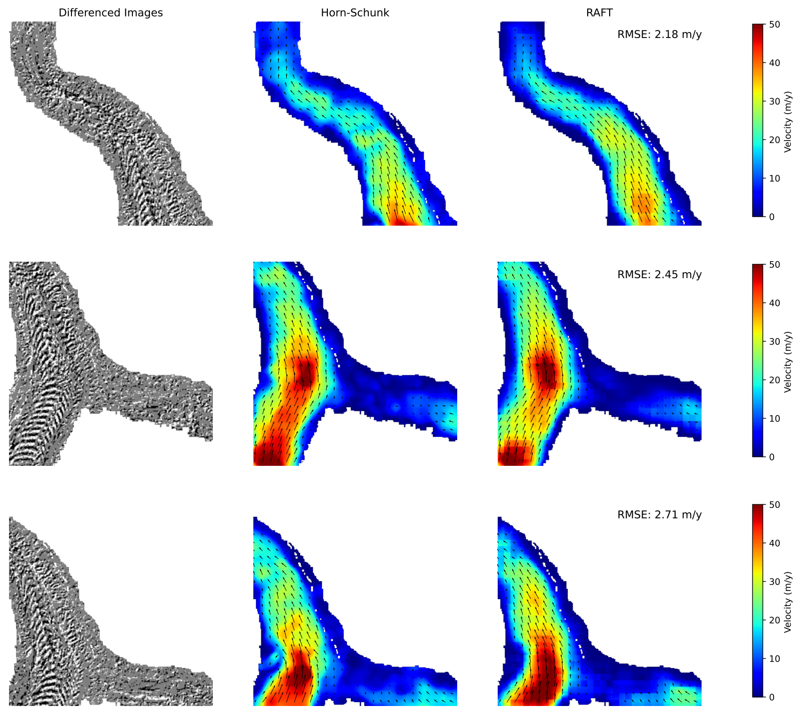

Figure 2: Annual velocity fields inferred from Sentinel-2 satellite image tiles by RAFT (right) and the corresponding target Horn-Schunk solutions (centre).

3 Results

The results shown in Figure 2 indicate that RAFT is able to infer velocities from tiled image pairs within the glacier ablation zones of the test dataset. The displayed RMSE is taken as the L2 norm of the glacierized regions. To further investigate the temporal consistency of the learned velocity field inference, we download and process images from the preceding year, 2020, and similarly create image pairs for the 2020–2021 period. A further 7 images with unoccluded visible texture are downloaded and tiles containing independent GPS locations are created. The resulting velocity fields inferred across all the image pairs are time-averaged to produce a single annual velocity mosaic for comparison with the point GPS measurements. GPS measurements from this period come from 3 stakes in the Langue portion of the glacier measured in September 2020 and September 2021, the distance moved by each stake representing the annual velocity. The starting stake coordinates were converted to pixel locations for comparison with the inferred velocity fields. Figure 3 shows the time-averaged velocity fields from the RAFT inference and the Horn-Schunk solutions for the 2020–2021 period. Although the RMSE value has increased from an average of 2–3 m/yr to 7.69 m/yr, the RAFT model still displays an ability to detect the dominant velocity in the western Langue part of the glacier. From the GPS measurements, stakes 1, 3 and 4 measured 40.43, 31.46 and 31.28 m/yr respectively. The Horn-Schunk solution measured 35.93, 31.94 and 31.14 m/yr respectively while RAFT was consistently lower with estimates of 29.97, 25.09 and 25.05 m/yr respectively across the GPS stakes. Although the inferred velocities were lower, the variation in the RAFT solution was consistent with the observed velocity measurements.

4 Conclusions and Future Work

Archives of satellite imagery have enabled the inference of glacier velocities from successive images through feature tracking which is currently dominated by classical methods. Here we presented a novel use of the deep recurrent optical flow architecture (RAFT) for this purpose, demonstrating its effectiveness at learning per-pixel velocity estimates on Mer de Glace in the French Alps.

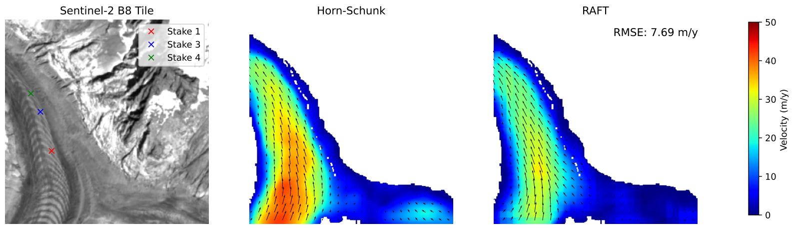

Figure 3: Averaged annual velocity fields for 2020–2021 inferred from Sentinel-2 satellite image tiles by RAFT (right) and the corresponding target Horn-Schunk solutions (centre). Stake locations represent in-situ GPS point measurements from the GLACIOCLIM service (left).

Future work will involve modification of the processing chain to allow the model to learn potential feature maps from multiple bands rather than pre-processed single-channel inputs, which may improve robustness to artefacts such as shadows. Since the training labels were generated by a multi-level Horn-Schunk solution, the exploration of unsupervised learning strategies such as that of Meister et al. to bypass expensive label generation will also be explored [23]. Physics-informed losses could also be investigated to compensate for areas with low contrast. Generalization to glaciers in different climates as well as marine terminating glaciers will also be explored. Additionally, generalization to satellite images from other constellations such as Landsat-8 and Planet cubesats will also be investigated.

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