Ice lake image analysis

Olle Jernström
Stockholm University
olle.jernstrom@gmail.com

Abstract

This report analyzes different methods in determining lake ice coverage from time-lapse images taken at Lake Tarfala, Kebnekaise Mountains, as part of an ongoing study investigating how lake ice cover at polar lakes changes in response to ongoing global warming. Two main approaches were examined. Static Image Analysis where the method of analysis remains unchanged for each datapoint juxtaposed with Dynamic Analysis where the method of analysis is dependent on the inputs given. Using machine learning is included in Dynamic Analysis. The results showed potential in the Static analysis with the areas of improvement being reducing light reflections by increasing the camera angle and adding a polarizing filter. Machine Learning can also be used, and Unsupervised Learning showed to be best fitted due to difficulties in labeling data. To improve a future investigation the main issue to handle is the reflections from the sun being interpreted by both humans and computers as ice coverage.

Contents

1 INTRODUCTION

1.1 Motivation

Global warming causes changes in Arctic lake ice coverage [1] [2] [3]. Shorter ice-covered seasons imply that lakes may receive higher amounts of solar radiation caused by exposure to warmer air temperatures over a longer timespan, therefore experiencing increased evaporation. Also, lakes are exposed to more wind (driving force for mixing) the longer the ice-free season is, which leads to a shift in seasonal distribution and quantity of physical forcings on lake ecosystems with ramification for primary productivity, biodiversity, carbon cycling and storage, etc. Knowledge of lake ice cover can be obtained using (1) situ measurements, (2) airborne remote sensing, (3) space-borne satellite imagery, (4) modeling, and in the future possibly (5) proxies such as continuous lake water temperatures throughout the water column. A lake water temperature proxy would be unaffected by problems pertinent to (2) and (3) above, including e.g. highly variable illumination conditions (including polar night), cloud coverage, high elevation, etc. All of these are reasons why it is difficult to find a single method that satisfies all needs, and imply that "significant differences have been revealed between remotely sensed and in-situ measurements" [4]. All of (1) to (5) above should be combined to be able to make more precise predictions of ice phenology, that is, the timing of occurrence, duration and vanishing of lake ice during fall, winter and spring.

1.2 Theoretical Background

1.2.1 Image Histograms, Image Thresholding, and Otsu's Binarization

Image histograms show the tonal distribution of gray-scale values by showing the frequency of each occurring gray-scaled value.

The method of image thresholding is to, for every pixel, apply a statically defined threshold. Simple thresholding determines this from individual pixels while adaptive thresholding methods take a small region around the pixel as input. If the value yielded from the inputs is lower than the globally chosen threshold, it is set to zero, otherwise to the maximum value specified, unless otherwise specified. The Simple Thresholding method can be too naive in some cases, thereby yielding ineffective results. In these cases, Adaptive Mean Thresholdning or Adaptive Gaussian Thresholding can yield improved results.

Otsu's Binarization circumvents having to choose an arbitrary thresholding value and determines it automatically. In a bimodal image where the histogram would only consist of two peaks, a good threshold exists somewhere in between these peeks. Otsu's binarization similarly determines an optimal global threshold from the image histogram. [5]

1.3 Purpose

This report summarizes an investigation of methods to determine the amount of ice covering Lake Tarfala across a series of time-lapse taken images. It also includes an outlook on how this investigation could be done in the future and possible improvements to improve the data.

1.4 Objectives

- Ascertaining a reliable method of determining the amount of ice coverage from images of Lake Tarfala.
- Note possible improvements and difficulties to improve the conditions of the investigation.

1.5 Limitations

This report is solely based on images of Lake Tarfala taken by a Willfine trail camera 4.0 GC., between June 20, 2020, and September 14, 2020, at 1220 m above sea level on a mountain flank along Lake Tarfala's north-eastern shore. The camera's exposure time and aperture stop were set to 1/30 sec, and f/2.8. The Willfine camera sent low-resolution images (640x480) as texts every day in addition to saving full-size images (4032 x 3024) on an SD card. Pictures were taken every other hour and saved in JPEG format (2.5MB or 50kB for full-size and low-resolution images, respectively). The full-sized images were used since they are more precise and the colors blend less into making the differences distinct which helps automated systems. Results will be in a percentage of pixels in the screen containing ice rather than the area due to the angle of photography. Since the incentive of this report is to create a fundamental understanding of the problem the discussed methodologies will not be extensively examined.

2 Dataset

The ongoing study investigating polar lake ice caps collected a total of 955 images from a Willfine trail-camera 4.0 GC-W over three months (20/6 - 14/9). 12,2 megapixels with a resolution of 4032x3024, the JPG files contained within the dataset consists of polar lake trail camera images with a semi-transparent footer displaying the following data: temperature (Cº), temperature(Fº), the current date (format dd/mm/yyyy), current time (format hh:mm:ss), along with the camera name. The lake is viewed from a slightly elevated angle with clear separation from the mountain and surrounding edges. Images were taken with an interval of two hours yielding twelve data points per day, subsequently, the images differ in weather and lighting conditions,

3 Data extraction

Two main ideas of investigating ice coverage were evaluated on the criteria of simplicity and reliability and will include additional notes regarding each method. Below the precise methodology employed for determining ice coverage and evaluation of each technique is described, sorted in the ascending order of viability.

3.1 Static Image analysis and Image Thresholding

Static image analysis is the method of applying a static method to achieve advantageous results. In our case, this includes using Image thresholding (see 1.2.1). The goal of these methods is to transform the image into grayscale and apply thresholding so the pixels in the image containing ice are below the threshold and other pixels above the threshold. If this succeeds we only need to calculate the white pixels in relation to the black pixels inside the bounds of the lake. This method includes Simple-, Adaptive Mean-, and Otsu's Binarization, all of which contain a pre-decided threshold value but differ in how the thresholding function operates (see 1.2.1). These methods were studied with various parameters to gain the most advantageous results. For Otsu's Binarization to yield the best possible results, the image histogram should show two distinct peaks and the image histograms will also be analyzed.

3.2 Dynamic Image Analysis and Machine Learning

The other method of approaching this is to apply Machine Learning (ML) to achieve advantageous results. In this case, the types of ML techniques are task-driven Supervised Learning and data-driven Unsupervised Learning. To understand the advantages and drawbacks separating these methods the types of data ingested has to be understood. There are both labeled and unlabeled data. Unlabeled data consists of samples of data with no explanation behind them such as an image of a lake. Labeled data

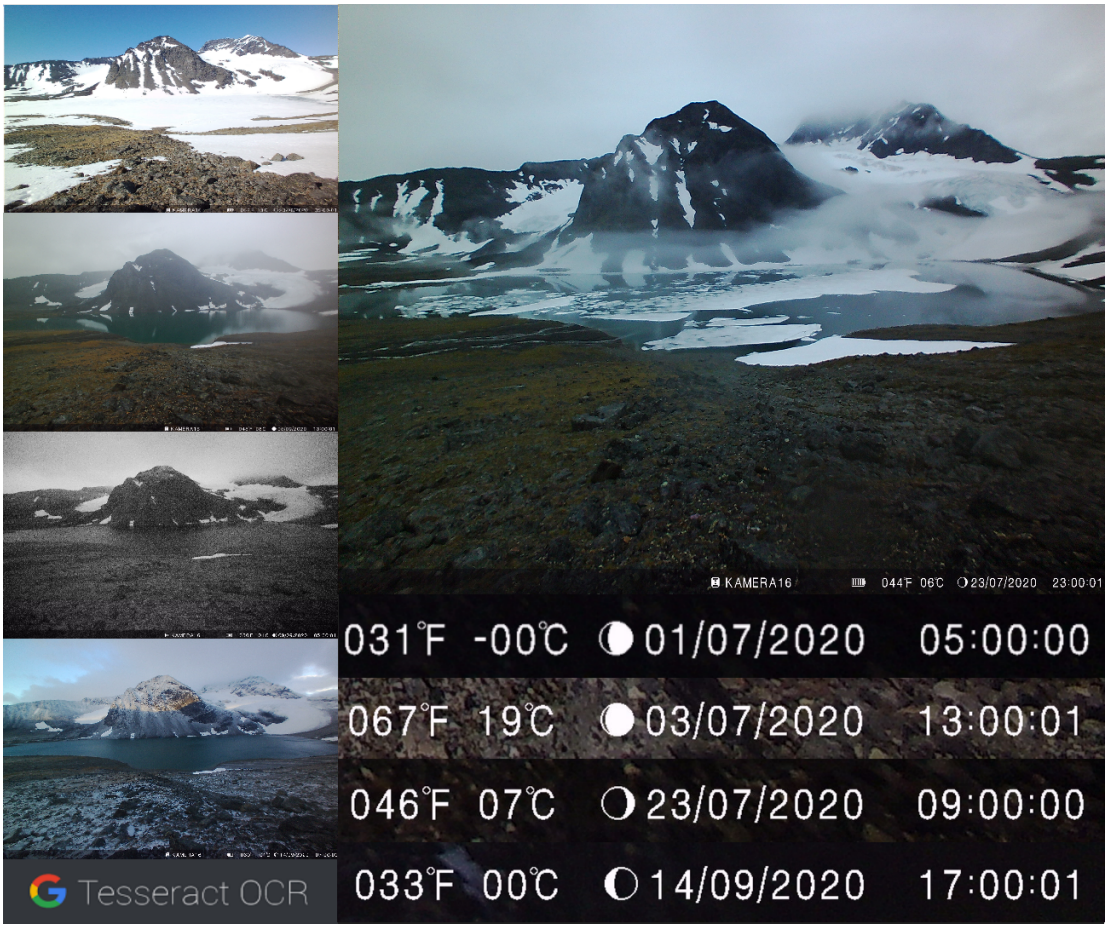

Fig. 1: Figure showing example of contrast in dataset weather conditions, a complete trail camera image, and several example footer datafields.

has a “label”, “tag” or “class” that is somehow descriptive or informative of the data desirable to know such as if the lake contains 60% ice or 0% ice. The labels are obtained by asking humans to judge the given unlabeled data (e.g., “Mark all areas containing ice” and then figure out the percentages from the marked regions) and are greatly more expensive to get compared to the raw unlabeled data.

Supervised Learning includes handing the machine learning algorithm accurately labeled data. This data is called the training dataset, which is a small part of the bigger dataset to give the algorithm understanding of the problem and solution and find characteristics within the labeled parameters. The algorithm establishes relationships between the parameters and yielding a cause and effect relationship between variables given in the dataset. Consequently, giving the algorithm understanding of how the data works and the relationship between input and output. This solution is deployed on the bigger dataset which it also learns from, improving it along the way, generating new relationships from patterns between variables.

Unsupervised Learning has the advantage of working with unlabeled data and no human labor is required to make the dataset machine-readable, allowing larger datasets to be used in the program. Since there are no labels the algorithm creates hidden structures (abstract relationships between data points). Hidden structures make the algorithm versatile since it is not forced to work in the bounds of

the parameters given and instead can adapt to the data by altering these hidden structures dynamically. These changes can also happen post-deployment causing the algorithm to develop itself. These methods were only tested in theory to see drawbacks and advantages since the key points about the images are shown from the Simple Image Analysis

4 Results

The results from the Static Image Analysis are shown in figure 2. The Adaptive Mean Thresholding yields a very noisy image while the Simple Binary Thresholding and Otsu's Binarization yields similar results. Both show that often the reflections are so bright it falls below the threshold interpreting it as ice (clearly seen at the right of image-row 4 and to the left in the last image-row). Figure 3 shows the grayscale color distribution in image histograms where the histograms with two distinct peaks give the best results for Otsu's Binarization. We can see that the first two histograms show an evenly distributed histogram while the middle three have two distinct peaks and the last shows two divided sides with multiple peaks. All images are from the best-tested parameters of each method. The results from reaserching Dynamic Image Analysis are show in Table 1.

	Requires Labels	Post-deployment Development	Bounded by inputs
Supervised Learning	Yes	Yes	Yes
Unsupervised Learning	No	Yes	No

Table 1: Table showing the key points of using Machine Learning the difference between the two main method

5 Discussion

Simple Image Analysis showed that the Adaptive Mean Thresholding was not fit for this task with no useful results despite various parameters used. Binary Thresholding with Otsu's Binarization onto a Gaussian filter yielded similar yet better results than Simple Binary Thresholding. The areas where Otsu's Binarization outperformed the most were the noisy areas (along ice edges and reflection edges). Since weather changes between images, there is no clear method of applying a static layer that will work perfectly on all images. For example, the color distribution changes between images (see Figure 3). Dynamic Image Analysis can fit the task if you use it right. The labels are very demanding to create since we need to estimate the ice percentage on the images we want to label. Both methods offer great Post-deployment Development opportunities and the Bounded by inputs just show the differences at which they operate. As seen in the images from the Simple Image Analysis the reflection of the sun can easily be interpreted as ice-coverage both by computer and man, thereby yielding false results. To get the most advantageous results one needs to minimize the amount of the reflected light (see 7).

6 Conclusion

- Simple Image Analysis can be an easy and effective solution if the amount of reflected light can be removed or greatly reduced.
- To get the best results a Machine Learning model could be trained using Unsupervised Learning and unlabeled data, where the goal is not only to see ice but to see the difference between ice and light-reflections. Can also be improved by removing reflected light.

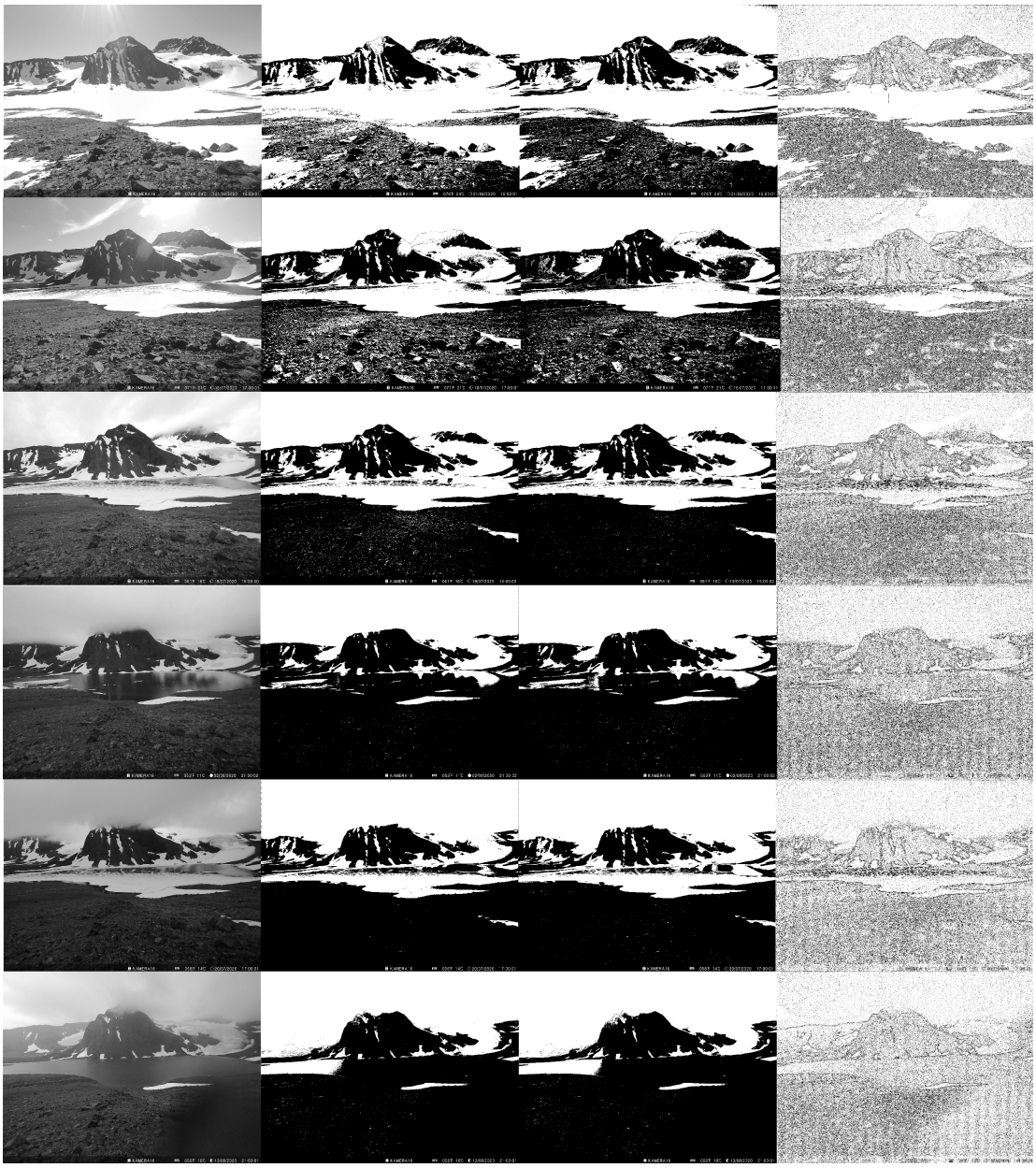

Fig. 2: Figure showing a sample of six different images with thresholding methods applied. From left to right: Original image in grayscale | Simple binary thresholding | Otsu's Binarization on Gaussian filter | Adaptive mean thresholding.

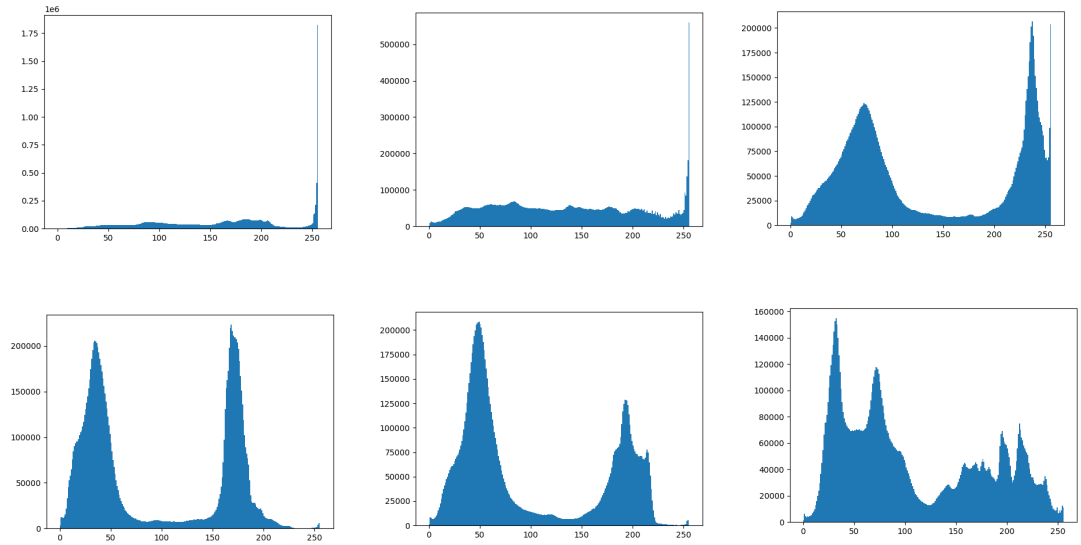

Fig. 3: Figure showing Grayscale Histogram from the six images from figure one as read. The x-axis shows the pixel value and the y-axis shows the quantity of that value.

7 Areas of Improvement for Further Investigation

To reduce the amount of reflected light we have two main options. A polarizing filter and the angle of incidence. A polarizing filter will remove scattered light to some extent but may not remove the reflection of the entire lake. To reduce this light we can use Brewster's Angle (the polarization angle) which is an angle of incidence where light with a particular polarization the light is totally transmitted with no reflection. If the light is unpolarized the reflected light is therefore polarized and won't show white the white reflection. The Brewster's Angle for air-water interface (derived from Snell's law) is approximately 53°. Therefore, to eliminate all reflections we could get up high and take the images from a steeper angle.

References

[1] I. Lehnherr and et al., "The world's largest high arctic lake responds rapidly to climate warming," *Nature Communications*, no. 1290, 2018.

[2] T. Šmejkalová1, M. E. Edwards, and J. Dash, "Arctic lakes show strong decadal trend in earlier spring ice-out," Tech. Rep., 2016.

[3] S. Sharma and et al., "Widespread loss of lake ice around the northern hemisphere in a warming world," *Nature Climate Change*, no. 227-231, 2019.

[4] The BACC II Author Team, *Second Assessment of Climate Change for the Baltic Sea Basin*, ser. Regional Climate Studies. New York NY: Springer Cham, 2015.

[5] Intel and Google, "Opencv: Image thresholding," Available at https://docs.opencv.org/image_thresholding.html. (2020/12/16).

Appendix A
Code

```python
import cv2
import numpy as np
import time
from PIL import Image
from matplotlib import pyplot as plt

if __name__ == '__main__':
    for i in ["0029", "0327", "0337", "0349", "0493", "0614"]:
        image_number = 367
        image = cv2.imdecode(np.fromfile(f"sommar/SYFW{i}.jpg", np.uint8), cv2.IMREAD_UNCHANGED)
        # image = cv2.resize(image, (1280, 960))
        image_gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
        blur = cv2.GaussianBlur(image_gray, (3, 3), 0)

        mask = cv2.imdecode(np.fromfile("testimages/mask2.png", np.uint8), cv2.IMREAD_UNCHANGED)
        # mask = cv2.resize(mask, (1280, 960))
        mask = cv2.cvtColor(mask, cv2.COLOR_BGR2GRAY)

        masked_normal = cv2.bitwise_and(image, image, mask=mask)
        masked = cv2.cvtColor(masked_normal, cv2.COLOR_BGR2GRAY)

        ret, th1 = cv2.threshold(image_gray, 127, 255, cv2.THRESH_BINARY)
        ret, th3 = cv2.threshold(blur, 0, 255, cv2.THRESH_BINARY + cv2.THRESH_OTSU)
        thA = cv2.adaptiveThreshold(image_gray, 255, cv2.ADAPTIVE_THRESH_MEAN_C, cv2.THRESH_BINARY, 5, 2)
        #thB = cv2.adaptiveThreshold(image_gray, 255, cv2.ADAPTIVE_THRESH_GAUSSIAN_C, cv2.THRESH_BINARY, 51, 2)

        show = np.concatenate((image_gray, th1, th3, thA), axis=1)

        # Histograms
        plt.hist(image_gray.ravel(), 256, [0, 256])
        plt.savefig(f'hist_{i}.png')
        plt.show()

        # Image comparisons
        pil1 = cv2.cvtColor(show, cv2.COLOR_GRAY2RGB)
        pil = Image.fromarray(pil1)
        pil.show()
        pil.save(i, format="png")
```

Listing 1: Code