

DETERMINATION OF SURFACE VELOCITY OF A RIVER USING VIDEOS CAPTURED FROM UNMANNED AERIAL SYSTEM (UAS)

Sanjeevan Shrestha^{1,*}, Mahesh Thapa², Leon Gaw Yan Feng⁴, Sarah Abdelkader⁵, Torsten Prinz³, Jan Lehmann³,
Holger Fritze³

¹ Department of Photogrammetry and Remote Sensing, Land Management Training Centre, Government of Nepal-
shr.sanjeevan@gmail.com

² Geodetic Survey Branch, Survey Department, Government of Nepal- mahesh100thapa@gmail.com

³ University of Münster, Münster, Germany – (prinz, jan.lehmann, h.fritze)@uni-muenster.de

⁴ Universidade Nova de Lisboa, Lisbon, Portugal - M2016084@isegi.unl.pt

⁵ University of Jaume I, Castellon, Spain- al361242@uji.es

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ABSTRACT:

Water flow dynamics of a river has significant effect in the ecological functions played by the river. There exists an intricate relationship between discharge in a river and phenomenon such as sedimentation, prevalence of vegetation and river morphology. In order to better understand these phenomena, it is important to determine the velocity of the river. While there exist conventional in-river velocity measurement techniques, UAS based method offers the capability to make large number of measurements at a large number of locations without the need to place measuring instrument at each of these locations. In this paper, we present the results of application of UAS in determining surface velocity of river. In this study, we released floats along the river and captured videos by mounting RGB sensor as well as thermal sensor in the UAS. The videos were processed using OpenCV library as well as Matlab's Image Processing Toolbox. This paper discusses the learnings of our study which indicates that videos captured from UAS can be used to determine surface velocity of a river.

1. INTRODUCTION

Water is essential to life on earth but increasing demands with limited supply is making it a scarce commodity. For water to be useful to humans, it needs to be both adequate in quantity and quality. The quantifiable global change has also altered regional weather patterns that modify river discharge, making water supplies from rivers less predictable (Dobriyal et. al., 2017). Water flow dynamics of a river has significant influence in the ecological functions played by the river. An intricate relationship exists between the discharge in river and important phenomena such as sedimentation, prevalence of vegetation and river morphology (Vargus-Luna, Crosato, & Uijttewaal, 2015). One of the crucial measures for the determination of water flow dynamics is determination of its velocity pattern. Conventionally, the velocity of the river is determined using in-river methods such as float method, dilution method or by use of current meter (Tazioli, 2011). Although accurate result can be achieved through these in-river methods, in order to understand the surface flow dynamics of a river, large number of measurements at a large number of locations is desired. Obtaining these through in-river methods is cumbersome and time consuming. Therefore, alternate methods which provides larger number of measurements with less field effort is desirable. In this regard, we explored use of videos from UAS as an alternative method to determine river velocity. We explored the idea of using both RGB sensors and thermal sensors to capture the videos.

2. STUDY AREA

The section of the River Aa specific to our study lies to the Southwest Münster city (Figure 1). In the past, this section used to be a straight concrete canal. Now, this stretch of the river (all the way to the Lake Aa) has been re-naturalized under the EU WFD (Vision Wasser, 2017). The land use on both sides of the riverbank are for agriculture where wheat and rye are grown. As a result, there are high levels of phosphates from fertilizers running off into the river or leeching into the river via groundwater (ibid.). The combination of high temperatures in summer months and high nutrient loads in the river spurns algal blooms that are detrimental to the aquatic ecology of the river. To mitigate the effects of river pollution, twelve re-naturalization projects along the river Aa were implemented between 2000–2014 (Helmut, 2014). In our study area, the river had been widened and made to meander so that its course resembles what it used to be like in 1830 before it had been canalised (ibid.). In addition, the banks of the river have been re-vegetated to create a buffer of vegetated swales that help to remove coarse and medium sediments and convey storm water in lieu of concrete drainage pipes. These swales not only prevent flooding of the river by slowing the through flow of water into the river, but also control pollution levels in it by absorbing excess nutrients of ground water.



Figure 1. A true color image of the study area captured by UAS in 2018

3. METHODOLOGY

3.1 Experimental Design and Equipment

The experiment was designed to capture videos with both RGB and Thermal sensor while we released three floats in the river. A UAS mounted with a Sony A5100 RGB digital single-lens reflex (SLR) camera and a Forward Looking Infrared (FLIR) Ocean Scout TK thermal sensor (figure 2a) was made to hover above the river while the floats drifted along the river. The resolution of the image taken using RGB sensor was 1080x1920 and that using thermal sensor was 240x320.



Figure 2a. A photo of our UAS with an RGB camera and a thermal sensor attached.



Figure 2b. Three floats in different colours with chafing fuel and aluminium foil inner linings.

The floats were cylindrical in shape and constructed from buoyant hardened Styrofoam material with a depression made in the centre to contain chafing fuel that produced heat and a layer of aluminium foil that acted as a heat reflector. Thus, when the top of the float is viewed with a FLIR thermal sensor, the chafing fuel would be detected as a local hot spot. The remaining buffer that circumvents the depression was coloured luminous pink

(with spray paint), metallic (wrapped in aluminium foil), and yellow (colour of the Styrofoam) to distinguish the floats from each other during the subsequent RGB video processing (figure 2b). We placed aluminium sheets across our study area (figure 1) as ground control points (GCPs) to georeference video scenes. Aluminium sheets were used as these can be detected easily in the RGB image as bright spots (because of their high reflectance) and in the thermal image as cold spots (because of their low thermal radiance).

3.2 Video and Data Processing

The video and data processing was divided into three stages: 1) Video pre-processing, 2) Object detection, and 3) Coordinate transformation. In the video pre-processing stage, we clipped the section of the video in which both floats as well as the ground control points were visible. In the object detection stage, we used OpenCV (Laganierre, 2014; OpenCV, 2017) library and Matlab's (2017) Image Processing Toolbox to detect the floats in the videos. Finally, we transformed the image coordinates of the detected floats into real world coordinates. For this, we generated transformation parameter for each image frame based upon image coordinates of the ground control points (aluminium sheets) and their real-world coordinates (2D linear convolution, Jähne, 2005). This transformation parameters were used to compute the real-world coordinates of the floats from their image coordinates. The generalized workflow is illustrated in Figure 3.

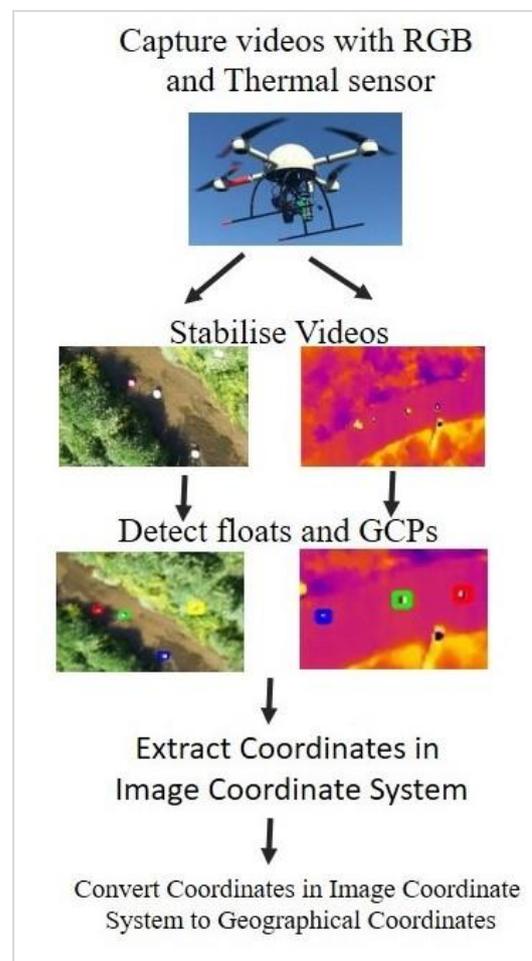


Figure 3. Generalized workflow- thermal and UAS rgb images are being matched by GCP's, facilitating the auto-detection of floats (movement) in a geospatial context

4. RESULTS

In the pre-processing stage, we realized that the field-of-view of the thermal camera was too small that it captured only the floats but not (at least 3) ground control points in a single frame. At least three ground control points are necessary to compute transformation parameters. Although, we were successful in detecting and extracting the image coordinates of the floats in the videos captured from thermal sensor (Figure 4b), their positions could not be converted into real world coordinates. We could only use RGB videos in order to determine the velocity of the floats. A snapshot of the GCPs and floats which are detected in the RGB videos are shown in figure 4a. Some selected data is also available on YouTube:
www.youtube.com/channel/UCnQv0lFlrs0WeDQ7HYbgCsA.



Figure 4a. Floats detected in RGB imagery

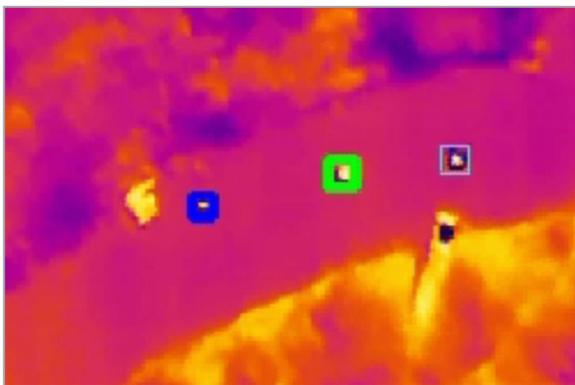


Figure 4b. Floats detected in thermal imagery

We used Template Matching in OpenCV to detect the objects in RGB video. A template of the float was provided as input based on which it would be identified in each subsequent frame. Template Matching would only work for very close (and very few) frames. In case, there were slight changes in reflectance due to the change in orientation of camera as the UAS hovered, the Template Matching in OpenCV failed to detect the correct float. The rate of correct detection of float was slightly improved by dynamically updating the template in each subsequent frame. Even so, Template Matching failed to continuously detect the floats for a longer duration of time. However, we had very good results in detecting the Ground Control Points using Template Matching. In comparison, the rate of float detection was much more successful in Matlab. Hence, we used coordinates obtained from Matlab to determine the velocity as shown in figure 5. In general, the velocities we calculated ranged between $0.45\text{--}1.50\text{ms}^{-1}$.

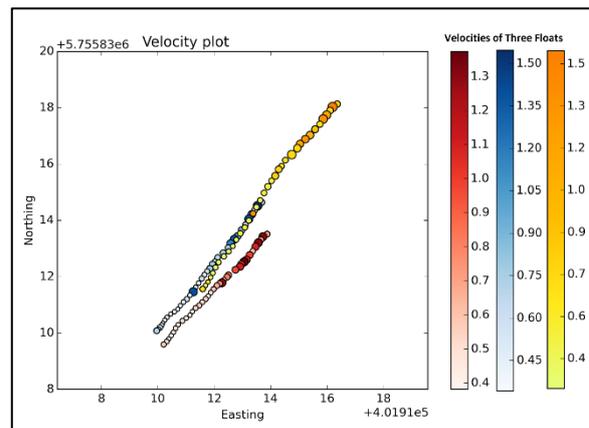


Figure 5. A plot of the velocity of the three floats colour coded into red, blue and yellow. Other than colour, the size of the points are directly proportional to velocity.

5. DISCUSSION

Our plot (figure 5) shows that once the floats have been set in motion along the River Aa, their velocities varies as they drift along the river. Using RGB videos from UAS we were able to detect the floats and compute their velocity at a large number of locations within a very short time. The large number of measurements can be potentially used to model the surface velocity of the river. Due to constraints of our own, we have not calibrated the velocity of the float with the velocity of the river. So, we cannot claim that we have computed the velocity of the river but rather the velocity of the float. However, this can be done by calibrating with in-river measurements.

In terms of the sensors used, our study showed that the narrow field-of-view of thermal sensor as well as its low-resolution poses challenge and hence a more careful flight planning is necessary.

In terms of our methods, the two algorithms we used for object detection have their own strengths and weaknesses. The template matching algorithm in OpenCV had particularly good results in detecting features which did not have large changes in size, orientation and reflectance such as our GCPs. However, this algorithm required many adjustments to detect moving floats when there were sharp changes in reflectance as they passed through shaded regions. Algorithms we applied in Matlab, based on filtering individual bands with thresholds (related to intensity and morphological features) provided good results on detecting the floats. Hence, we combined these two approaches by detecting GCPs using the template matching algorithm in OpenCV and detecting floats using Matlab.

6. CONCLUSION

Our study indicates that it is feasible to use UASs to measure the velocity of rivers by processing videos captured by sensors from a UAS. Our research successfully underlines the feasibility of using UASs for determining surface velocity of river. The use of UASs here provides high spatial and temporal resolution to monitoring the river velocity and its convenience is a boon to researchers as an 'add-on' device. However, we do not suggest that UASs can replace conventional in-river measurements of velocity that are more accurate. Rather, velocity measurements derived from UAS products are complementary to existing techniques so that calculations are more robust. Moreover, UASs

can provide more data collected quickly and conveniently, which, for example, can be applied in to modelling the surface flow of a river.

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