Bathymetric Structure from Motion: Extracting shallow stream bathymetry from multi-view stereo photogrammetry

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Bathymetric Structure from Motion:

Extracting shallow stream bathymetry from multi-view stereo photogrammetry

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Abstract

Stream bathymetry is a critical variable in a number of river science applications. In larger rivers, bathymetry can be measured with instruments such as sonar (single or multi-beam), bathymetric airborne LiDAR, or acoustic doppler current profilers. However, in smaller streams with depths less than 2 meters, bathymetry is one of the more difficult variables to map at high-resolution. Optical remote sensing techniques offer several potential solutions for collecting high-resolution bathymetry. In this research, I focus on direct photogrammetric measurements of bathymetry using multi-view stereo photogrammetry, specifically Structure from Motion (SfM). The main barrier to accurate bathymetric mapping with any photogrammetric technique is correcting for the refraction of light as it passes between the two different media (air and water), which causes water depths to appear shallower than they are. I propose and test an iterative approach that calculates a series of refraction correction equations for every point/camera combination in a SfM point cloud. This new method is meant to address shortcomings of other correction techniques and works within the current preferred method for SfM data collection, oblique and highly convergent photographs. The multi-camera refraction correction presented here produces bathymetric datasets with accuracies of ~0.02% of the flying height and precisions of ~0.1% of the flying height. This methodology, like many fluvial remote sensing methods, will only work under ideal conditions (e.g. clear water),
but it provides an additional tool for collecting high-resolution bathymetric datasets for a
variety of river, coastal, and estuary systems.

Keywords: Structure from Motion (SfM), bathymetry, refraction correction, two-media
photogrammetry, UAV / UAS
Introduction

Stream bathymetry is a critical variable in fluvial geomorphology, alongside variables like width, slope, and velocity, for characterizing the wide range of physical and biological parameters that exist in river systems. This fundamental suite of variables forms the backbone of many hydrologic equations, geomorphic theories, and numeric models used to explain the behaviors and map the complexity and heterogeneity of stream systems (Ward et al., 2002; Marcus and Fonstad, 2008; Lane et al., 2010; Carbonneau et al., 2012).

In many stream systems, we are limited to traditional survey techniques (total station or RTK-GPS) to collect bathymetric data, which are time consuming to complete and, for high-resolution surveys, often limited in spatial scale (Bangen et al., 2014). Remote sensing offers one approach to produce high-resolution bathymetric measurements in streams over broader spatial extents. Woodget et al. (2015) provide an extensive survey of the current literature on remote sensing approaches to bathymetric data collection. An explosion in the use of Structure from Motion (SfM) photogrammetry in geomorphology and the rapid growth of consumer-grade, small unmanned aerial systems (sUAS) provide another approach for collecting high-resolution bathymetric data via optical remote sensing.

Photogrammetry, both traditional stereo and multi-view stereo, offers a way to measure stream bathymetry directly in clear water systems. So called through water, or two-media photogrammetry, has a relatively long history (Tewinkel, 1963; Harris and Umbach, 1972; Fryer and Kniest, 1985b; Westaway et al., 2000, 2001; Butler et al., 2002; Murase et al., 2008; Lane et al., 2010; Woodget et al., 2015). A major limitation is that the
in-water measurements are affected by refraction, the bending of the light as it passes the water/air interface. The effect causes in-water measurements to appear shallower, referred to as the apparent depth, compared to the actual depths. Figure 1 shows a diagram of the refraction trigonometry of a single measurement point/camera combination (variable definitions are given in Table 1). The goal is to solve a system of equations for \( h \) in Figure 1, the actual depth of the underwater point, which can be used on its own or it can be subtracted from the local water surface elevation \( W S_z \) to provide a corrected elevation. Snell’s Law (Eq. 1) governs the refraction of light between two different media:

\[
n_1 \sin i = n_2 \sin r
\]

where \( n_1 \) is the refractive index of fresh water (1.337 (Harvey et al., 1998)), \( n_2 \) is the refractive index of air (1.0), \( i \) is the angle of incidence from the stream bed to the air/water interface, and \( r \) is the angle of refraction from the air/water interface to the camera. We can substitute a variety of trigonometric functions into Eq. 1, depending on which variables in Figure 1/Table 1 are known \textit{a priori} or can be solved for, to ultimately solve for \( h \).

In conventional stereo photogrammetry, the direct application of Snell’s Law is complicated by fact that the point is seen from two overlapping images. The positions of the cameras are different, and therefore the angles \( r \) and \( i \) will be different for each camera, which necessitates that Eq. 1 must be solved for each camera which will result in slightly different actual depths \( (h) \) (Fryer and Kniest, 1985b; Westaway et al., 2001; Butler et al., 2002). SfM datasets further complicate the refraction correction process by adding multiple (3 – 50+) views for a single point. For each point in a SfM point cloud dataset, there is a unique set of photos (a multi-camera set) that can see the point. Each
camera in the multi-camera set is viewing the streambed from a different angle and, by
the laws of refraction, should produce different angles of incidence and refraction ($r$ and
$i$) and therefore different apparent depths ($h_a$) (Figure 2). These different $h_a$ values would
create a wide range of elevations that would be expected to create a very noisy point
cloud. Depending on the SfM software, these points would have high uncertainties and
may be automatically filtered out leaving holes in the final point cloud.

However, in my experiments and those by others (Woodget et al., 2015), the in-
water portions of the SfM point clouds produce a coherent surface with slightly more
surface noise than the above water topography. Woodget et al. (2015) proposed a
method for refraction correction that attempted to circumvent some of the complications
caused by the use of multiple cameras. Their method is specifically for nadir SfM imagery,
and it proposed using a simplified version of Snell’s Law that uses the small angle
approximation substitution. With the small angle approximation, for angles ($\theta = r \parallel i$) that
are less than 10°, the $\sin \theta \cong \tan \theta$ (Eq. 2a/2b) and this simplifies Eq. 1 to Eq. 3:

$$\sin i \cong \tan i = \frac{x}{h}$$
$$\sin r \cong \tan r = \frac{x}{h_a}$$

(2a, 2b)

$$h = 1.337 \times h_a$$

(3)

where $r$ and $i$ are the angle of incidence and refraction, $x$ is the distance from the water/air
interface to the point, $h$ is the actual depth, and $h_a$ is the apparent depth.

This form of refraction correction is appealing in its simplicity. However, current
research on the preferred image collection strategies for SfM suggests that off-nadir
imagery produces SfM datasets with fewer systematic errors and better on-the-job
camera calibrations. Therefore, off-nadir imagery creates higher quality datasets with
better accuracy and precision (James and Robson, 2014; Carbonneau and Dietrich, 2016). Off-nadir camera angles (usually 10° – 30° off vertical) preclude the use of the small angle approximation, because $r$ can range from nadir (0°) to a theoretical limit of 89° and $i$ can range from 0° – ~48° (the limit for total internal reflection). This range of possible angles necessitates an alternate approach for off-nadir multi-view stereo photogrammetry. This means solving the necessary trigonometry for each point/multi-camera combination in the SfM dataset.

The goal of this short communication is to propose and test a multi-camera refraction correction algorithm that is a complete solution for through-water refraction correction for SfM datasets. The equations and their combinations have been published in various forms elsewhere (Tewinkel, 1963; Harris and Umbach, 1972; Fryer and Kniest, 1985b; Westaway et al., 2001; Butler et al., 2002; Murase et al., 2008), however the sources for the variables, their application to SfM datasets, and the development of an open-source software program to process the data are the primary contributions of this research.

**Study Area**

I used two study areas for this research. The first was a controlled experiment used to test the refraction correction algorithm in shallow water (~15cm) within a 1.2m diameter inflatable children’s pool (Figure 3a) filled with coarse gravel (~3cm B-axis) to simulate the bed of a stream and create texture on the pool bottom.

To test the algorithm in a field setting, I used a ~250m reach of the White River near Sharon, Vermont (Figure 3b). This reach of the White River has depths that range
from 0 – ~1.5m with bed sediment ranging from fine sand to cobbles. The split flow around

two mid-channel islands creates a diverse range of flow environments with which to test

this methodology. I collected two sets of imagery at the site, one in October 2015 and

another in June 2016. The dates of the flights were opportunistic when flows were 10 –

12 cms, which provided safe wading conditions for accessing the site and surveying the

bed. However, the two dates did give me an opportunity to test how differing lighting, flow

conditions, aerial platforms, and flying heights might affect the correction.

Methods

Depth Correction

The proposed multi-camera refraction correction is an iterative one. For each point

in the submerged portion of the SfM point cloud, the software calculates the refraction

correction equations that follow for each camera that can see that individual point and

iterates through all the possible point-camera combinations.

The first step in the process is testing the visibility of points from all of the cameras

that were used in the SfM reconstruction. I processed all of the photosets using Agisoft

Photoscan Professional (version 1.2.4), although the specific outputs I use from

Photoscan should be available in other SfM software packages. In Photoscan, the camera

positions (x, y, z) with orientations (pitch, roll, and yaw) can be exported to a text file. I

chose to use the “estimated” positons and orientations, as these have been optimized by

the alignment and georeferencing routines in Photoscan. For each camera in the dataset,

the approximate ground coordinates for the corners of the camera’s instantaneous field

of view (IFOV) are calculated based on the exterior orientation parameters (pitch, roll,
and yaw) as well as the camera’s internal parameters (focal length and sensor size). Point cloud points that fall within the calculated IFOV were considered to be visible to the camera. For the visible points, \( r \) from Fig. 2 is calculated by:

\[
r = \tan^{-1} \left( \frac{D}{dH} \right)
\]  

(4)

where \( D \) is the Euclidean distance \( \sqrt{(X_c - X_a)^2 + (Y_c - Y_a)^2} \) between the camera and target point, and \( dH \) is the height difference between the camera and target point \( (Z_c - Z_a) \). It is important to note that \( r \) is the angle from the point through the camera center to the sensor and is not equivalent to the camera’s pitch (from Photoscan).

Water surface elevations are critical to these refraction equations to establish \( h_a \) \( (h_a = W_S Z_a) \). I, like others, assumed a planar water surface for the refraction correction. To establish the water depth in the controlled experiment, I measured the water depth with a ruler as well as by sampling points on the water’s edge visible in the SfM point cloud. For the White River site, the planar water surface was spatially variable, and was defined by GPS points along the water’s edge and supplemented with additional points (~3-7m spacing) digitized from the water’s edge visible in the SfM point cloud. For example, in the June survey there were 85 GPS points on the water’s edge and an additional 213 digitized points.

With \( r \) and \( h_a \) calculated, the refraction correction is based on the other unknown variables in Fig. 2:

\[
i = \sin^{-1} \left( \frac{n_2}{n_1} \sin r \right)
\]  

(5)
\[ x = h_a \times \tan r \]  

(6)

\[ h = \frac{x}{\tan i} = \frac{h_a \times \tan r}{\tan \left[ \sin^{-1} \left( \frac{n_2}{n_1} \times \sin r \right) \right]} \]  

(7)

\[ Z_p = W S_x - \bar{h} \]  

(8)

Because \( Z_a \) is a fixed value from the SfM point cloud, \( h_a \) will also be a fixed value for each point. This leads to differences in \( x \) and \( h \) for each camera that sees any given point. Therefore, \( h \) and \( Z_p \) will have a range of values, and the ultimate corrected value is taken as the mean of all \( h \) values (\( \bar{h} \)) (Butler et al., 2002), which is subtracted from the water surface to give a corrected elevation.

The refractive index of water is not a critical variable in these equations. However, others have reported using a refractive index of 1.34 from Jerlov (1976), which was used by Fryer and Kniest (1985b) and others primarily for through-water photogrammetry in marine environments. For this research, I chose to use a fresh water refractive index that seems more appropriate for shallow water streams. Harvey et al. (1998) report on the refractive index of fresh water at a variety of wavelengths and temperatures. In the visible wavelengths, the index values range from 1.338 at 488nm and 0°C to 1.331 at 632.8nm and 30°C. For this research, I use a value of 1.337 derived from an average of the published values for a range of temperatures (0° to 30°C) and the wavelengths that have the highest transmission through water (488 and 514.5nm). With the system of equations presented here, the resulting difference in \( h \) using a range of values from 1.33 – 1.34 results in differences of ~5mm at 1m depth. It should be noted that the refractive index can be measured in the field with a handheld refractometer and that a constant refractive
index applies only to homogeneous, unaerated water bodies where temperature and salinity are constant with depth (Harvey et al., 1998).

Workflow and correction software

The photosets for this project were processed in Agisoft Photoscan Pro (version 1.2.4). After alignment and georeferencing, the datasets were processed with a “high-quality” dense reconstruction. I exported the resulting dense point clouds to CloudCompare (version 2.7.0, Girardeau-Montaut, 2016), where the cloud is subsampled to a uniform point spacing, using a minimum elevation filter to extract the minimum elevation from each cell, to reduce the data density and decrease the influence of surface noise. The surveyed water surface elevations and the digitized water’s edge points were used to construct a Delaunay mesh that represents the surface of the water. For all of the underwater points two new scalar fields were added to the point cloud, the apparent depth ($h_a$) and the local water surface elevation ($WS_z$). For the apparent depth, a point to mesh distance was calculated (point to water surface mesh), and the sign inverted so $h_a$ is positive. For the water surface elevation at each point ($WS_z$), $h_a$ was added back to the point’s SfM elevation ($Z_a$). The in-water points ($h_a > 0$) were exported as an ASCII comma-delimited file.

For the correction, I wrote a custom Python script to automate the refraction correction. The point cloud, camera positions/orientations, and camera sensor parameters (focal length, sensor size) are loaded into the Python script which calculates the IFOV for each camera, point visibility, and the refraction correction equations (Eq. 4-8) for all point/camera combinations. The refraction corrected points are exported as a new CSV file. On an average laptop computer, the Python script is optimized to process
at a rate of ~2 seconds per camera and ~200,000 points per minute. The initial release of the software is available as supplemental material with this article and future updates will be available from a GitHub repository (http://github.com/geojames/py_sfm_depth) and the documentation/tutorial is available at https://geojames.github.io/py_sfm_depth/.

Pool experiment

For the controlled experiment, the pool was setup on an approximately level asphalt surface and filled with an even layer of landscaping gravel to simulate a streambed and provide enough texture for the SfM reconstruction. Around the pool, I placed six 30cm square checkerboard targets to act as ground control points (GCPs). Within the pool, an additional four smaller targets were buried in the gravel as depth measurement points. All of the GCPs were surveyed with a total station into an arbitrary metric coordinate system. I collected SfM imagery at two different water depths; zero depth (dry) as the reference for error calculations and ~15cm (wet). All of the imagery was collected with a DJI Phantom 3 Advanced (P3A) quadcopter equipped with a circular polarizing filter to minimize glare of the water surface. The photos were taken in a radial pattern around the pool at two different altitudes, 8m and 12m, and all photos were off-nadir ~20°.

Each of the photosets, dry (51 photos) and wet (41 photos) were processed and the wet dataset was corrected via the workflow above with a point spacing of 0.01m. To check the accuracy of the correction algorithm, I created a Delaunay mesh of the zero depth point cloud (subsampling to the same 0.01m) and calculated the point to mesh distances for a random selection of 1000 of the refraction corrected points.
White River

The flight plan for the White River site was designed to limit both the amount of glare from the sun on the water by maximizing the noon sun at the site and also minimize shadows from the banks and over hanging vegetation. All of the photos were taken at off-nadir angles (~30° off-nadir) in convergent zig-zag patterns over the study area at two different altitudes. The SfM photos for the October flight (190 photos) were taken with a DJI Inspire 1 without any filtering; the images were taken at 40 and 60 meters above ground level (AGL). The June images (220 photos) were taken with the same P3A as the controlled experiment, again with a circular polarizing filter, at 60 and 80 meters AGL. I used an RTK-GPS (Topcon HiperLite) to establish ground control points (30cm square checkerboard targets; 7 for the October flight and 10 for June), survey the water's edge, and survey the streambed topography for validation.

I used the workflow described above with a subsampled point spacing of 0.30m for both data sets. To assess the accuracy of the corrected data, the corrected point attributes from the SfM data were transferred to the nearest neighboring in-water GPS point. I assessed the accuracy of the correction in terms of both depth and absolute elevation. For both datasets the reference depths were calculated by subtracting GPS elevation from the local water surface elevations.

In addition to the standard accuracy statistics for all three datasets, another approach to quantifying the error is with the relative accuracy ratio and the relative precision ratio (James and Robson, 2012). For the relative accuracy ratio, the average flying height is divided by the mean error to give error as a function of the flying height. The relative precision ratio is the average flying height divided by the standard deviation.
of the error. Because these values are ratios, the values allow you to compare the
accuracy and precision of data collected at different spatial scales and can be used to
approximate the accuracy/precision that can be expected depending on the flying height.

Results

Pool Experiment

The raw dense point cloud for the in-water portion of the pool consisted of 9,440
points, and the 0.01m sub-sampled cloud was 4,960 points. The georeferencing
accuracies for both the dry (0 cm) and wet (~15cm) are reported in Table 2. Figure 4a
shows the corrected depths for the pool from the ~15cm experiment. The pool was setup
on a slight incline, so the minimum depth was 12cm and the maximum 17.3cm. In the
depth map there is a slight mottling in the colors that represents the texture of the gravel
on the bottom despite the regular point spacing and filtering. In most of Figure 4b, the
distribution of elevation errors in relation to the dry surface, the error alternates between
positive (an under prediction of depth, corrected elevation > dry elevation) and negative
(over prediction of depth, corrected elevation < dry elevation). The upper left has a
definite positive bias, with the maximum error at +1.3cm, which contributes to the overall
bias in the elevation scatter plot (Figure 4c), the error histogram (Figure 4d), and the error
statistics in Table 3.

The error statistics suggest that overall, the refraction correction algorithm
performs well given the controlled conditions of the pool. With a small mean error
(0.0017m) and a small standard deviation of the error (0.003m), the majority (99.7%) of
the corrected point elevations are within ~±1cm (±3σ) of the dry elevation values. For this
controlled experiment the relative accuracy ratio was 1:5822 and the relative precision
ratio was calculated at 1:2778. A contributing factor to both the positive and negative errors around the edge of the pool was the weight of the water. As the pool was filled with water, the sides of the pool bulged and stretched the bottom, forcing some of the gravel to shift.

White River

The White River photosets produced dense point clouds with high point densities in the wet portions of the stream (October: 1.3 million points/160 points/m², June: 4.2 million points/390 points/m²). The georeferencing accuracies are reported in Table 2. The 30cm subsampled in-water point cloud reduced the total number of in-water points to 93,600 points for October and 121,300 points for June. Figures 5a and 5b illustrate the corrected depths for the study reach, with both providing a reasonable representation of the bathymetry of the stream. There are some erroneous artifacts in the depth maps, especially in the downstream portion, where noise from the original point cloud can been seen (labeled #1 in Figure 5a/b) as well as some errors related to incorrect water surface elevations (labeled #2). The spatial distributions of error (Figure 5c and 5d) at the GPS validation points for both October and June do not show any large scale systematic errors. However, they do show local pockets of larger errors that are visually correlated with the noisier areas of the depth maps.

There are slight biases in both datasets that can be seen in the scatter plots and error histograms (Figure 6) and the overall error statistics in Table 3. The October data has a small negative bias in the mean elevation error (-0.011m) and the June data has a small positive bias in the mean elevation error (0.014m). The error statistics in Table 3, especially the relative accuracy ratios (1:4545 for October and 1:5000 for June) and the
relative precision ratios (1:649 for October and 1:1186 for June), show that the correction method is providing consistent results under the differing lighting, flow conditions, aerial platforms, and flying heights between the October and June datasets. The standard deviations suggest that there is a fair amount of variation in how the correction algorithm performed across all depths. The scatter plots of depth (Figure 6a/b) and elevation (Figure 6c/d) illustrate this spread, however the slopes of the regression lines for the corrected data do not suggest that there are larger errors with increasing depths. Both elevation error distributions (Figure 6e/f) appear normally distributed, however neither conforms to a normal distribution when tested using a Shapiro-Wilk test (p<0.001). The outliers in both distributions are likely the main contributors to the non-normality.

As a comparison of the method presented here with the method proposed by Woodget et al. (2015), reference lines plotted in Figures 6a and 6b show how Eq. 3 relates to the corrected data for both October and July. I also applied Eq. 3 directly to the June 2016 data and the results (Figure 7) show that their method over predicts elevations (Corrected elevations > GPS elevations) for most of the stream. This is something which Woodget et al. noted as a limitation of the method with their data and it seems to be amplified with its application to off-nadir imagery.

Discussion

Overall the error statistics show the refraction correction algorithm is consistent and produces accurate corrected elevations. The relative accuracy/precision ratios (Table 3) are the key statistic to compare the accuracy of the results between the different experiments (e.g. different conditions and flying heights). These ratios equate to average errors that are 0.017% of the average flying height for the pool experiment, 0.022% for
the October data, and 0.020% for the June data. With precision ratios providing precision
(standard deviation of error) of 0.04% of the average flying height for the pool, 0.015%
for October, and 0.08% for June. The precision ratios are in line with the precision ratios
that James and Robson (2012) reported for early SfM datasets on dry land (~1:1000 or
decimetric precision at 100m altitude) which suggest that the bathymetric correction
presented here is comparable to these early SfM results. As James and Robson (2012)
suggest, these ratios can give other users of this method a planning tool to approximate
the accuracy/precision that can be expected depending on the flying height.

The sources of error in the refraction correction include, but are not limited to,
georeferencing errors, noise in the point cloud (originating from the SfM process), water
surface errors (water surface elevation errors, surface waves, and/or white water), and
the limitations placed on the method by using SfM data. Georeferencing errors are
avoidable with a proper distribution of GCPs and measurement with a suitable high-
accuracy survey instrument (RTK-GPS of Total Station). The influence of random noise
in the point cloud can affect the accuracy of the ultimate refraction correction by creating
artificially higher or lower apparent bed elevations. The primary source of random noise
is a direct result of the SfM reconstruction process, especially in areas with low texture
(Fonstad et al., 2013) or poor image matching (i.e. weak photogrammetric image network)
(James and Robson, 2014; Carbonneau and Dietrich, 2016). Ideally there would be
uncertainties associated with individual points in the SfM point cloud that could be used
to filter points with high uncertainties, but in commercial SfM software packages these
statistics are not currently available. Larger point spacing in some environments may help
reduce the impact of noise, but the point spacing should ultimately be defined by the site
and the research question that the data are being used to answer. Errors in the elevations of the points that define the water surface elevation(s) influence the calculated apparent depths \( h_a \), which are transferred directly to the refraction corrected values. Surface waves come in two main forms: low amplitude, high-frequency, wind driven waves and larger magnitude waves driven by the hydraulic conditions in the stream (e.g. riffles or standing waves). The wind-driven waves will increase noise in the point cloud by affecting the image matching algorithms in the SfM software and if they are extensive, may preclude any measurement of the bathymetry. Larger scale waves have been shown to cause local changes in water surface elevations and waves can also change the \( r \) and \( i \) angles for the correction equation depending on the direction the cameras are viewing them (Fryer and Kniest, 1985a). The multi-camera refraction correction presented here has inherent error from the constraints imposed by using fixed \( Z_a \) and \( h_a \) values for a potentially large range of \( r \) and \( i \) angles for all of the cameras that see a given point. This research, like others (Westaway et al., 2001; Butler et al., 2002) used the mean of the calculated \( h \) values (\( \bar{h} \)) resulting in acceptable accuracy. Future research will look at other statistical measures, like the median or percentile ranks of the distributions of \( h \) values at each point, to see if they provide any improvements in accuracy or precision. Another alternative to these basic statistical measures could be a complex weighted average scheme that accounts for variables like the angles (\( r \) and \( i \)), camera lens parameters, and possibly the altitude.

The error statistics for the two White River datasets show that the refraction correction method presented here produces comparable errors to those reported by Westaway el al. (2001) and Woodget et al. (2015) in similar systems. Westaway el al.,
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who used conventional stereo photogrammetry, reported mean errors from 0.054 – 0.105m with standard deviations of 0.092 – 0.116m. Woodget et al., using nadir SfM, reported mean errors -0.029 – 0.053m and standard deviations from 0.064 – 0.086m. The relative accuracy/precision ratios obtained by Woodget et al. (2015) (flown at altitudes 25 – 28m) ranged from 1:3226 – 1:507 (0.03 – 0.2% of flying height) and the precision ratios ranged from 1:403 – 1:320 (0.25 – 0.31% flying height). The accuracy ratios for October, 1:4545 (0.022% flying height) and June, 1:5000 (0.02%), and the precision ratios for October, 1:649 (0.15%), and June, 1:1186 (0.08%) demonstrate that the method presented here provides a significant improvement in the accuracy and precision for bathymetric SfM datasets.

The GPS validation points with the highest positive errors are associated with areas in the original SfM point cloud with higher roughness that can be seen in Figure 8 (measured by the standard deviation of the elevations in a 0.5m kernel). Examples of this are most visible in the June 2016 data (Figure 5b/d) along the right bank of the riffle that cuts in-between the two islands, in the deepest part of the pool immediately below the riffle, and in the middle of the channel on the downstream end. The source of the noise in the riffle and pool are likely the surface waves and white water throughout this section. The downstream noise matches a section of the bed where the grain size decreases to fine gravel and sand, which has less overall texture for the SfM algorithms to key in on and could contribute to the higher roughness (Fonstad et al., 2013). Potential future research could explore the error associated with these different sediment size classes. In the October data, many of the larger errors occur in areas of high roughness, but the more frequent occurrence of higher error values throughout the reach and the lower
relative precision ratio are likely caused by the presence of small, wind-driven waves on
the water surface, impacting the quality of the surface reconstruction.

This method for recovering depth has, like all optical remote sensing-based
approaches to bathymetry, some limitations to where/when it can be used. The most
obvious being clear water at the site, or in other words the camera has to be able to see
the bottom in order to measure it. Sites where the transmission of light through the water
column is affected (e.g. elevated suspended sediment, tannic conditions) are not suitable
for this technique, as are sites where the majority of the water surface is dominated by
aeration (white water) or surface waves. Small patches of surface waves or white water
can be deleted from the point cloud and replaced using interpolation. Atmospheric
conditions play a critical role in the success of this method as well; hazy or overcast days
can produce unwanted reflections on the water surface, inhibiting accurate
measurements of the bottom, as well as reducing the overall amount of light available to
reflect off the bottom. The effect of some types of reflections can be reduced through the
use of a polarizing filter, which I would highly recommend for most through-water
applications. Shadows from riparian vegetation, large woody debris, and steep banks may
have an effect on the refraction correction. However, at my White River site, the north
south orientation allowed me to optimize the sun angles to eliminate shadows from the
riparian vegetation. Future research is needed to evaluate the effects of shadows on
these refraction corrections. Some optical remote sensing techniques have been shown
to be depth limited to \(\sim 1 – 2\) m (Marcus et al., 2003; Carbonneau et al., 2006; Legleiter et
al., 2009; Walther et al., 2011) and some active (Lidar) techniques can penetrate to \(\sim 20\) m
in ideal conditions (Kinzel et al., 2013). For this technique, unpublished data collected by

http://mc.manuscriptcentral.com/esp
the author at a coastal archeological site in Greece suggests that depths of 5+ meters are visible in the imagery and potentially recoverable. The water quality, water surface conditions, and atmospheric conditions all play a role in the penetration of light to depth, and future research will be necessary to determine if this method is depth limited, either by physics or by the quality of the SfM reconstructions.

This research has focused on aerial (UAS-based) imagery, however ground based imagery, hand-held or pole-based, is another option for collecting the necessary imagery.

The resolution of the imagery will be higher, which will result in higher point densities in the SfM point clouds and potentially greater surface roughness and larger $r$ angles, which could impact the accuracy.

Conclusions

In this paper, I have demonstrated that the multi-camera based refraction correction method for off-nadir SfM datasets presented here produces accurate results with mean errors of ~0.02% of the flying height. Additional research is needed to better understand the boundaries and limitations of this method. After the SfM reconstruction process, the methods presented here take place in free and/or open-source software, which make them flexible enough to accommodate inputs from a variety of SfM software packages. The level of accuracy demonstrated here should be sufficient for many river system applications ranging from geomorphic change detection to habitat and flow modelling as well as bathymetric mapping in other clear water systems beyond rivers and streams, including coastal and estuary systems.
Acknowledgements

I would like to thank Mark Fonstad, Patrice Carbonneau, Jenna Duffin, and Christina Shintani for fruitful discussions about the method and encouragement of this research.

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References


Carbonneau PE, Dietrich JT. 2016. Cost-Effective Non-Metric Photogrammetry from Consumer-Grade sUAS: Implications for Direct Georeferencing of Structure from Motion Photogrammetry. Earth Surface Processes and Landforms : n/a–n/a. DOI: 10.1002/esp.4012

Carbonneau PE, Lane SN, Bergeron N. 2006. Feature based image processing methods applied to bathymetric measurements from airborne remote sensing in fluvial environments. Earth Surface Processes and Landforms 31: 1413–1423. DOI: 10.1002/esp.1341


# Tables and Figures

Table 1: Descriptions of the variables in Fig. 1 and throughout the text

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_a, Y_a, Z_a$</td>
<td>apparent coordinates of the SfM point</td>
</tr>
<tr>
<td>$X_p, Y_p, Z_p$</td>
<td>true coordinates of the point</td>
</tr>
<tr>
<td>$D$</td>
<td>Euclidean distance to the SfM point from the camera</td>
</tr>
<tr>
<td>$dH$</td>
<td>flying height above SfM point</td>
</tr>
<tr>
<td>$r$</td>
<td>angle of refraction (from nadir to the SfM point)</td>
</tr>
<tr>
<td>$i$</td>
<td>angle of incidence</td>
</tr>
<tr>
<td>$x$</td>
<td>distance from the SfM point to the air/water interface point</td>
</tr>
<tr>
<td>$h_a$</td>
<td>apparent depth to the SfM point</td>
</tr>
<tr>
<td>$h$</td>
<td>true depth of point $(X_p, Y_p, Z_p)$</td>
</tr>
<tr>
<td>$n_1$</td>
<td>refractive index of fresh water (1.337)</td>
</tr>
<tr>
<td>$n_2$</td>
<td>refractive index of air (1.0)</td>
</tr>
</tbody>
</table>
Table 2: Georeferencing errors for all sites.

<table>
<thead>
<tr>
<th>Site</th>
<th>Statistics</th>
<th>Error Components (meters)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Pool</td>
<td>Dry</td>
<td>Mean Error</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mean Abs. Error</td>
</tr>
<tr>
<td></td>
<td></td>
<td>σ Error</td>
</tr>
<tr>
<td></td>
<td></td>
<td>RMSE</td>
</tr>
<tr>
<td>Wet</td>
<td>Mean Error</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Mean Abs. Error</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>σ Error</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>0.003</td>
</tr>
<tr>
<td>White River</td>
<td>Oct. 2015</td>
<td>Mean Error</td>
</tr>
<tr>
<td></td>
<td>Mean Abs. Error</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>σ Error</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>June 2016</td>
<td>Mean Error</td>
</tr>
<tr>
<td></td>
<td>Mean Abs. Error</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>σ Error</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>0.017</td>
</tr>
</tbody>
</table>
Table 3: Overall error statistics versus reference data for both the pool experiment and the White River.

<table>
<thead>
<tr>
<th>Site</th>
<th>Source</th>
<th>Mean Error</th>
<th>σ Error</th>
<th>Mean Sq. Error</th>
<th>Mean Abs. Error</th>
<th>RMSE</th>
<th>Min Error</th>
<th>Max Error</th>
<th>Relative Accuracy Ratio</th>
<th>Relative Precision Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pool</td>
<td>Elevation</td>
<td>0.0017</td>
<td>0.0036</td>
<td>0.0000</td>
<td>0.0032</td>
<td>0.0040</td>
<td>-0.0114</td>
<td>0.0131</td>
<td>1:5882</td>
<td>1:2778</td>
</tr>
<tr>
<td>White River</td>
<td>Oct. 2015</td>
<td>-0.011</td>
<td>0.077</td>
<td>0.006</td>
<td>0.056</td>
<td>0.077</td>
<td>-0.262</td>
<td>0.291</td>
<td>1:4545</td>
<td>1:649</td>
</tr>
<tr>
<td></td>
<td>June 2016</td>
<td>0.014</td>
<td>0.059</td>
<td>0.003</td>
<td>0.039</td>
<td>0.061</td>
<td>-0.112</td>
<td>0.381</td>
<td>1:5000</td>
<td>1:1186</td>
</tr>
</tbody>
</table>
Figure 1: Trigonometry of the refraction angles for a single camera/point combination
Figure 2: Refraction angles and apparent depth locations from four different camera angles/locations. The differences in the apparent depths illustrate one of the challenges of using multiple camera locations (as in SfM) to resolve depth.
Figure 3: A) Layout of the pool experiment and B) Orthophotograph of the White River site from June 2016 with the October 2015 and June 2016 study extents.
Figure 4: Pool experiment results. A) Corrected Depths, B) Spatial distribution of error between the dry and corrected wet datasets, C) Scatter plot of corrected elevations (only 1000 randomly selected points are shown for clarity), the regression line is a reduced major axis regression, and D) Histogram of the elevation errors for the 1000 points shown in (C), the distribution is representative of the full point cloud.
Figure 5: White River Depths; A) October 2015 and B) June 2016. #1 in A) and B) highlights noisy areas of the corrected point cloud and #2 highlights errors in the water surface elevations. White River elevation error; C) October 2015 and D) June 2015. Positive errors indicate that the corrected SfM elevation is above the GPS elevation (an under prediction of depth). Negative errors indicate that the corrected SfM elevation is below the GPS elevation (an over prediction of depth).
Figure 6: Scatter plots of corrected depth vs. actual depth (A, B), corrected elevation vs. GPS elevation (C, D), and elevation error histograms (E, F) for both White River datasets. The elevation range differences between (C) and (D) are a result of a difference in the GPS control used for the survey, (C) was surveyed on the WGS84 vertical datum and (D) was surveyed from a new control point established with NAVD88 (GEOID12A) elevations.
Figure 7: Comparison of the refraction correction method proposed by Woodget et al. (2015) and the method presented in this paper for the June 2016 White River dataset.
Figure 8: Error as a function of roughness. A) Maps of point cloud roughness with GPS points with large errors (>±1.5σ) overlayed. B) Graphs of error as a function of point cloud roughness.