Improving Remotely Sensed River Bathymetry by Image-Averaging

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Abstract Basic data on river bathymetry is critical for numerous applications in river research and management and is increasingly obtained via remote sensing, but the noisy, pixelated appearance of image-derived depth maps can compromise subsequent analyses. We hypothesized that this noise originates from reflectance from an irregular water surface and introduced a framework for mitigating these effects by Inferring Bathymetry from Averaged River Images (IBARI). This workflow produces time-averaged images from video frames stabilized to account for platform motion and/or computes a spatial average from an ensemble simulated by randomly shifting images relative to themselves. We used field observations of water depth and helicopter-based videos from a clear-flowing river to assess the potential of this approach to improve depth retrieval. Our results indicated that depths inferred from averaged images were more accurate and precise than those inferred from single frames; observed versus predicted regression $R^2$ increased from 0.80 to 0.88. In addition, IBARI significantly enhanced the texture of image-derived depth maps, leading to smoother, more coherent representations of channel morphology. Depth retrieval improved with image sequence duration, but the number of images was more important than the length of time encompassed; shorter acquisitions at higher frame rates would economize data collection. We also demonstrated the potential to scale up the IBARI workflow by producing a mosaic of bathymetric maps derived from averaged images acquired at several hovering waypoints distributed along a 2.36 km reach. This approach is well-suited to data collected from helicopters and small unmanned aircraft systems.

1. Introduction

Knowledge of river bathymetry, the spatial pattern of water depths within a stream channel, is essential for a diverse range of studies in fluvial geomorphology and aquatic ecology, as well as numerous practical applications in river management, such as noncontact streamgaging, habitat assessment, and the design and monitoring of river restoration projects. Although detailed, reliable depth information is valuable in all of these contexts, obtaining such data via conventional field methods can be laborious and costly, which limits typical surveys to short, isolated study reaches. Remote sensing techniques provide an alternative means of mapping bathymetry more efficiently over broader areas and image-based approaches could come to play a central role in river-oriented data collection programs such as streamflow monitoring networks. Motivated by this potential, the subdiscipline of fluvial remote sensing has advanced considerably over the past decade as new sensors, platforms, and algorithms have become available; for reviews and further commentary on these developments, the reader is referred to Entwistle et al. (2018), Gleason and Durand (2020), Marcus and Fonstad (2010), and Tomsett and Leyland (2019).

The interaction of light and water provides a sound physical basis for inferring depth from passive optical image data and is described in general terms by Mobley (1994) and in the specific context of rivers by Legleiter et al. (2004, 2009). Legleiter and Harrison (2019) traced the development of spectrally based methods for mapping river bathymetry from pioneering work in coastal environments (e.g., Lyzenga, 1978) through more recent applications based on multispectral satellite images (Legleiter & Overstreet, 2012) and publicly available aerial photography (Legleiter, 2013); alternative approaches, including structure-from-motion photogrammetry (e.g., Dietrich, 2017) and bathymetric lidar (e.g., McKean et al., 2008) also were discussed. Various types of data from the Sacramento River were used to demonstrate the feasibility of accurately estimating water depths from hyperspectral images acquired from both small unmanned aircraft systems (sUASs) and fixed-wing manned aircraft via an Optimal Band Ratio Analysis (OBRA) algorithm. Moreover,
the OBRA framework was generalized to encompass several different functional forms of the relation between an image-derived quantity \( X \) and water depth \( d \), providing greater flexibility in model-fitting and mitigating some of the issues associated with the original linear formulation of OBRA (Legleiter & Harrison, 2019). Although previous studies have established a strong foundation for spectrally based remote sensing of water depth in relatively shallow, clear-flowing rivers, further research is needed to address the remaining limitations of this approach and thus more fully satisfy the application requirements of a growing user community.

In this study, we focused on a specific, key issue that often compromises the utility of bathymetric information derived via existing methods: the grainy, pixelated appearance of depth maps produced from remotely sensed data. This problem is particularly evident when the data are acquired from low-altitude aerial platforms and have a small ground sampling distance (i.e., pixel size). Such high spatial resolution might contribute to noisy bathymetric maps by capturing high-frequency variations in reflectance from an irregular water surface (i.e., sun glint), as well as the passage of waves, foam, or floating debris. Changes in illumination due to cloud cover or shadows also can lead to inconsistencies between images acquired even a few seconds apart; such variability can complicate efforts to apply a relationship between an image-derived quantity and water depth calibrated at one site where field measurements are available to other locations along the same or another river. Regardless of the source of the noise, the use of a grainy depth map might lead to problems with derivative products, such as assessment of habitat suitability for particular species of concern (e.g., Carmichael et al., 2020). Similarly, noisy input bathymetry can interfere with other types of “downstream” analysis, including numerical modeling of flow and sediment transport, an application in which accurate information on channel cross-sectional area is critical (e.g., McKeen et al., 2014).

Reflectance from the water surface, often referred to as sun glint, is perhaps the most common factor contributing to noise in passive optical images, especially if the data are acquired using an imaging system that captures the entire scene instantaneously and at mid-day to optimize sun angle. Remote sensing scientists have long sought to reduce the effects of sun glint, dating back to the seminal work of Cox and Munk (1954), and Kay et al. (2009) provide a useful review. More recently, Overstreet and Legleiter (2017) introduced a river-specific technique that reduces sun glint based on the reflectance observed in a near-infrared band in which the water-leaving radiance is negligible due to strong absorption by the water column. Legleiter et al. (2017) addressed the issue from a more theoretical perspective and gained insight on which combinations of viewing and illumination geometry minimize spurious reflectance from the water surface. Sophisticated image processing approaches to removing sun glint also have been developed and applied with encouraging results (e.g., Duan et al., 2020).

In this study, we attempt to reduce image noise and thus improve remotely sensed river bathymetry by building upon a novel idea proposed by Partama et al. (2018). These authors applied a temporal minimum filter to a series of images (i.e., video frames) to reduce the effects of water surface reflections on sUAS-based shallow-water photogrammetry. The reasoning behind this approach was that any reflectance from the water surface at a given instant in time is added to the total reflectance that would have been observed in the absence of sun glint. If images from multiple points in time, separated by only a fraction of a second, were compiled, the image having the lowest reflectance presumably was the least affected by sun glint. Guided by this logic, we hypothesized that whereas a single image captures an instantaneous view of the river, including reflectance from an irregular water surface, that can lead to noisy, erratic depth estimates, averaging river images in time and/or space could essentially provide an ensemble mean, averaged over multiple realizations of the water surface, that leads to a smoother image texture and enhanced depth retrieval.

This approach to estimating water depth from averaged river images is synergistic with, and inspired by, parallel efforts to use image sequences to infer surface flow velocities via large-scale particle image velocimetry (LSPIV). For example, Legleiter and Kinzel (2020b) showed that continuous velocity fields could be derived from time series of passive optical image data in sediment-laden rivers. An important component of our LSPIV workflow is image stabilization, which serves to align the individual image frames with one another so that any apparent motion can be attributed to the movement of trackable features on the water surface and not the imaging platform. This experience led us to consider the possibility that any smoothing effect produced by time-averaging an image sequence could be the result not only of averaging over multiple realizations of an irregular water surface but also any residual motion that persists through the
image stabilization process. Computing the mean of an image sequence contaminated by any such frame-to-frame displacement thus would introduce a component of spatial as well as temporal averaging. To test the possibility that an image sequence could be smoothed via a purely spatial averaging, we considered an alternative algorithm. This procedure involved randomly shifting an individual frame relative to itself to generate multiple realizations and then computing the ensemble mean of the resulting spatially displaced sequence of images. In essence, this process simulates platform motion and we refer to the technique as jiggle-averaging. Our use of this term is consistent with the definition of the verb jiggle: “To cause to move with quick little jerks or oscillating motions” (Merriam-Webster, 2020). In addition, we tested whether a combination of temporal and spatial averaging, in which each frame in a time series is jigged independently and then the sequence is averaged over time, might yield additional improvement in depth retrieval performance.

In this study, we build upon our LSPIV workflow to develop a more robust approach to mapping channel bathymetry not from a single, instantaneous image but rather images that are averaged over time, by computing the mean of a sequence of video frames acquired from an aerial platform hovering above the channel, and/or over space, by randomly shifting images relative to themselves. In either the temporal, spatial, or hybrid case, we refer to this new methodological framework as Inferring Bathymetry from Averaged River Images (IBARI). More specifically, the following hypotheses motivated this study:

1. Estimating depth from a time-averaged river image derived from a sequence of video frames provides more accurate bathymetric information than inferring depth from an individual frame.
2. In addition, bathymetric maps produced from time-averaged images provide a smoother, more spatially coherent representation of channel morphology.
3. Further improvements in the reliability and texture of image-derived depth maps can be achieved via an analogous spatial-averaging approach that involves simulating multiple image realizations by randomly shifting image frames relative to themselves, a process we refer to as image-jiggling.

In addition, we addressed the following research questions:

1. How sensitive is the time-averaging algorithm to the duration of the image sequence?
2. Moreover, are any improvements in depth retrieval performance gained by time-averaging driven by the length of time encompassed by the image sequence or by the number of images averaged, even if the sequence spans a shorter period of time but is acquired at a higher frame rate?
3. Similarly, how sensitive is the hybrid time- and jiggle-averaging approach to the number of randomly shifted realizations of the original images used to compute an ensemble mean?

2. Materials and Methods

The field measurements and remotely sensed data used in this study are publicly available in Legleiter and Kinzel (2020a). The landing page for this data release includes links to child pages for three individual data sets acquired from the Salcha River in central Alaska, USA: Field measurements of water depth, videos acquired from a helicopter hovering above the channel, and an orthophoto mosaic used to geo-reference images extracted from the videos.

2.1. Study Area

This study is part of an ongoing effort to develop remote sensing techniques for measuring channel hydraulics to facilitate noncontact streamgaging. This objective is especially important in Alaska, which remains only sparsely gaged (Conaway et al., 2019). In this case, we focused on a 2.36 km, gravel-bedded reach of the Salcha River located near the city of Fairbanks in central Alaska (Figure 1). The study area spanned two large meander bends along the highly sinuous channel, which had a water surface slope of 0.00046. The discharge on July 25, 2019, the date of field data collection and image acquisition, was 42.76 m³/s, as recorded at a U.S. Geological Survey (USGS) gaging station (USGS 15484000 Salcha River near Salchaket, AK) at the downstream end of the reach. The stage and discharge remained stable throughout the ∼4-h period during which the image data and field measurements were collected. This flow was only slightly higher than the 25th percentile (41.91 m³/s) of mean daily values recorded on this date over 72 years of record.
and thus represented low, base flow conditions. The mean wetted width at the time of data collection was 48.5 m and the mean ± standard deviation of the depth measurements described below was 1.11 ± 0.55 m. Importantly, the water was much more clear in July 2019 than in August 2018, when we acquired images of the Salcha during a period of exceptionally high runoff and elevated suspended sediment concentration that allowed us to infer surface flow velocities by tracking the movement of sediment boil vortices (Legleiter & Kinzel, 2020b). Sky conditions during image acquisition on July 25, 2019, were partly cloudy with brief, intermittent periods of slightly more direct sunlight.

2.2. Remotely Sensed Data

The remotely sensed data utilized herein were obtained from a Robinson R44 helicopter. This platform is frequently used in Alaska to transport personnel and equipment for discharge measurements and maintenance operations at remote and inaccessible gaging stations throughout the state (Conaway et al., 2019). Helicopters thus represent a viable means of image data acquisition for this important use case. For this study, a Zenmuse X5 video camera in an enclosure was positioned on the nose of the R44 with a Meeker mount; a photograph of the helicopter and a table of sensor characteristics were presented by Legleiter and Kinzel (2020b). Although the camera was mounted on a gimbal to improve stability, direct geo-referencing
was not possible because the sensor was not integrated with the navigation system onboard the helicopter. The pilot was given a set of waypoints distributed evenly along the Salcha River study reach (Figure 1) at a flying height sufficient to ensure that both banks were encompassed within the images, given the focal length of the camera (15 mm) and the dimensions of its detector array (3,840 × 2,160 4.5 μm pixels). Including the banks was critical because distinct, readily identifiable terrestrial features were required to stabilize the image sequences. A mean flying height above ground of 437 m yielded a mean pixel size of 10.7 cm for the 10 hovers (Table 1). The Zenmuse was controlled from inside the helicopter using a mobile phone application that allowed the operator to trigger the camera upon arriving at a waypoint and then view a live video feed while hovering above the channel. The videos were recorded at the camera’s full native frame rate of 30 Hz but also were downsampled to 1 Hz by extracting every 30th frame from the original video files. All videos were at least 1 min in duration but were truncated to 60 s to ensure consistency among the 10 hovers.

In addition to the videos, digital aerial photographs of the Salcha River were acquired from the Robinson R44 on the same day. These images were captured by a Hasselblad A6D-100C 100 megapixel digital mapping camera deployed within a pod mounted on the helicopter’s landing gear (Legleiter & Kinzel, 2020b). The data were collected while transiting a series of flight lines designed to provide complete coverage, with ample overlap, of the entire study area. Also within the pod was an ATLANS GPS/Inertial Motion Unit (IMU) that recorded the position and orientation of the platform during the flight. This information, along with a lidar digital elevation models (DEM) and surveyed ground control points (GCPs), was used to geo-reference the images by performing aerial triangulation and bundle adjustment within the TerraSolid software suite. The resulting orthorectified images had a pixel size of 5 cm and were organized into a set of eight 500 × 500 m tiles. The orthophotos served as a base for geo-referencing raw image frames extracted from the Zenmuse videos described above. This process involved identifying distinct features visible within both the video frame and the orthophoto and using these GCPs to develop an affine transformation that served to establish the scale of the video frame and place it within an established, real-world coordinate system (UTM Zone 6N, NAD83). At least four and as many as nine GCPs were selected for each hover and the root mean squared error (RMSE) of the control points varied from 0.36 to 1.69 m, with a mean geo-referencing error of 0.9 m (Table 1).

### 2.3. Field Data

We collected field measurements of water depth on the Salcha River on the same day as the helicopter flight. These in situ data were obtained along a total of 21 cross-sections distributed evenly throughout the study

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### Table 1

| Hover | Pixel (cm) | GCP | RMSE (m) | XS | Depth validation data |
|-------|------------|-----|----------|----|-----------------------|
|       |            |     |          |    | n | Mean (m) | Median (m) | Std. Dev. (m) | Min (m) | Max (m) |
| 1     | 10.8       | 9   | 0.83     | 1–3* | 130 | 0.90 | 1.01 | 0.43 | 0.47 | 2.04 |
| 2     | 11.0       | 7   | 0.81     | 2*–4 | 154 | 1.45 | 1.23 | 0.44 | 0.47 | 1.82 |
| 3     | 10.1       | 6   | 0.78     | 5–7 | 181 | 1.27 | 1.49 | 0.66 | 0.58 | 3.18 |
| 4     | 10.4       | 5   | 1.13     | 7–9 | 193 | 1.81 | 1.95 | 0.82 | 0.70 | 3.75 |
| 5     | 10.7       | 6   | 1.69     | 9–11 | 239 | 1.01 | 1.12 | 0.47 | 0.46 | 2.18 |
| 6     | 11.1       | 6   | 1.20     | 11–12 | 106 | 0.82 | 0.92 | 0.39 | 0.44 | 1.60 |
| 7     | 10.7       | 6   | 0.53     | 13–15 | 247 | 1.02 | 0.98 | 0.30 | 0.45 | 1.55 |
| 8     | 10.8       | 4   | 0.36     | 15–17* | 200 | 0.81 | 0.92 | 0.35 | 0.44 | 1.64 |
| 9     | 11.1       | 5   | 0.46     | 17–19 | 295 | 0.89 | 0.92 | 0.37 | 0.43 | 2.03 |
| 10    | 10.6       | 4   | 1.02     | 18–21 | 234 | 1.10 | 1.11 | 0.34 | 0.43 | 2.03 |
| Mean  | 10.7       | 5.8 | 0.9      |     | 198 | 1.1  | 1.2  | 0.46 | 0.49 | 2.18 |

*Note.* GCP, ground-control points used for image geo-referencing; RMSE, root mean squared error of GCPs; XS, cross-sections included in each hover (the * symbol denotes partial coverage of a cross-section); n, number of field-based depth measurements used for validation.

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(2020b)
reach, with an along-channel spacing of $\sim 110$ m, roughly twice the mean wetted channel width. Table 1 lists which cross-sections were encompassed within each of the 10 hovers, which is potentially significant because the distribution of depths used for calibration could influence depth retrieval results. Half of the field data were used to calibrate the spectrally based models used to infer river bathymetry and the remainder of the depth measurements were set aside for assessing the accuracy of image-derived depth estimates.

Flow depths were recorded using a Technical Research and Development Institute (TRDI) RiverRay acoustic Doppler current profiler (ADCP; TRDI, 2020) deployed from a catamaran towed behind a boat with an outboard motor. The ADCP was equipped with a Hemisphere A101 differential GPS with a horizontal precision of 0.6 m (Hemisphere GPS, 2020). The ADCP data were collected along 21 channel-spanning cross sections oriented perpendicular to the primary flow direction, as shown in Figure 1, but were not intended for use as discharge measurements and so only a single pass across the channel was performed at each transect. The RiverRay was controlled by an operator in the boat using the TRDI WinRiver II software package while traversing the channel. The ADCP data were postprocessed in WinRiver II and imported into the USGS Velocity Mapping Toolbox (VMT; Parsons et al., 2013). We used VMT to perform spatial averaging with a grid node spacing of 1 m and export files with easting and northing spatial coordinates and depths measured at each location.

2.4. Workflow for IBARI

The objective of this study was to evaluate the potential for improving remotely sensed river bathymetry by averaging a sequence of images before estimating depth, rather than inferring depth directly from a single image. We pursued this goal by developing the workflow illustrated in Figure 2 and applying this approach.
to the Salcha River as an initial proof of concept. This case study involved analyzing four types of data: (1) downsampled 1 Hz image sequences extracted from the original Zenmuse videos; (2) the full frame rate (30 Hz) videos; (3) image sequences consisting of 60 spatially shifted image realizations produced by randomly displacing the first frame of the video relative to itself; and (4) image sequences consisting of 60 frames from the 1 Hz video, each one of which was shifted randomly relative to itself. Whereas the first two types of data were subjected to a straightforward time-averaging, the third represents a novel form of spatial averaging and the fourth is a hybrid of both temporal and spatial averaging. For each hover, we examined the depth retrieval performance of these four data types, which we refer to as: (1) FF, for the original first frame of the video; (2) TA, for the time-averaged image derived from the video; (3) JA, for a purely jiggle-averaged version of the first frame; and (4) HA, for a hybrid time- and jiggle-averaged image based on random displacements of each frame in the image sequence. For each of these cases, this new framework provides a means of Inferring Bathymetry from Averaged River Images and we refer to the method as IBARI. The steps involved in the IBARI workflow are shown diagrammatically in Figure 2, where the second, peach-colored column lists general procedures common to both the time- and spatial-averaging approaches as well as the hybrid of the two. Aspects of the workflow that pertain only to time-averaging are shown in the first column in blue, components associated only with spatial-averaging are displayed in the third column in green, and procedures involved in the hybrid approach are represented in the fourth column in yellow. Software used to implement this workflow included the FIJI image processing suite (Schindelin et al., 2012), Global Mapper geographic information system (GIS) package (Blue Marble Geographics, 2020), and, primarily, the MATLAB numerical computing environment, within which we developed custom functions and performed analysis.

2.4.1. Image Acquisition and Preparation

For the time- and spatial-averaging versions of IBARI and the hybrid of the two, the workflow begins with the acquisition of image data. In this study, we used videos of the Salcha River described in Section 2.2, but a sequence of still images captured at a regular, 1-s interval, for example, also would be an appropriate input. For the purely spatial averaging technique, only a single image is required and we used the first video frame for each hover.

Because the helicopter was neither perfectly level nor stationary while hovering above the channel, the next step in the IBARI processing chain involves stabilizing image frames extracted from the video. Image stabilization removes any evidence of platform motion by first identifying distinct, fixed features present throughout the image sequence and then using these tie points to bring all of the images into alignment with one another. We used the TrakEM2 plugin (Cardona et al., 2012) to FIJI to perform stabilization.

To link images to field measurements of water depth for calibration and validation of image-derived depth estimates, the images also had to be geo-referenced to the same coordinate system as the field observations. We used the orthophoto mosaic described in Section 2.2 as a base for geo-referencing the first frame from the stabilized image sequence. GCPs visible on both the orthophoto and the images extracted from the Zenmuse hovers were selected using the Global Mapper interface. The parameters of the affine transformation derived from the GCPs then were applied to each frame of the stabilized image sequence to ensure that that the entire sequence of images was aligned not only internally but also with respect to the field data. The final step in this initial phase of the IBARI workflow involved delineating the area of interest by digitizing a channel mask for the whole study reach.

2.4.2. Image Jiggling

The key step in the purely spatial-averaging version of IBARI involves simulating multiple realizations of an image by spatially shifting, or “jiggling,” a single image. For the hybrid temporal and spatial-averaging version of IBARI, the jiggling procedure is applied independently to each frame of the sequence. In principle, the details of this algorithm could be updated as needed on a case-by-case basis by modifying the jiggling parameters: The number of pixels by which the image is shifted and the probabilities associated with each of those shifts. To provide a specific, concrete example for the Salcha River, we implemented the jiggling procedure as follows:

1. Sample four random numbers $J_1 - J_4$ from a uniform probability distribution between 0 and 1. $J_1$ determines the number of pixels by which the image will be shifted in the horizontal direction and $J_2$ deter-
mines whether this shift will be to the left or to the right. Similarly, the $J_3$ and $J_4$ determine the magnitude and direction of the shift in the vertical direction.

2. The sampled values of $J_1$ and $J_3$ specify the magnitude of the image displacement

\[
\begin{align*}
J_1, J_3 &\in [0, 0.4] \quad \rightarrow \quad 0 \text{ pixel shift} \\
J_1, J_3 &\in (0.4, 0.7] \quad \rightarrow \quad 1 \text{ pixel shift} \\
J_1, J_3 &\in (0.7, 0.9] \quad \rightarrow \quad 2 \text{ pixel shift} \\
J_1, J_3 &\in (0.9, 1] \quad \rightarrow \quad 3 \text{ pixel shift}
\end{align*}
\]

The assignment of a probability to each pixel shift magnitude used in this example is somewhat arbitrary but was based on the reasoning that the displacement associated with each jiggle of the original image is a random process in which a displacement of 0 pixels (i.e., no shift) is most likely and progressively greater shifts are less and less probable.

3. The sampled values of $J_2$ and $J_4$ specify the direction of the image displacement

\[
\begin{align*}
J_2 &\in [0, 0.5] \quad \rightarrow \quad \text{shift left} \\
J_2 &\in (0.5, 1] \quad \rightarrow \quad \text{shift right} \\
J_4 &\in [0, 0.5] \quad \rightarrow \quad \text{shift down} \\
J_4 &\in (0.5, 1] \quad \rightarrow \quad \text{shift up}
\end{align*}
\]

4. To maintain consistent image dimensions, crop the shifted image along the right/left and/or top/bottom margins by the number of pixels dictated by the randomly sampled values of $J_1$, $J_4$ and Equations 1 and 2

5. To generate a jiggled image sequence suitable for spatial averaging, simulate an ensemble by replicating the original image and repeating steps 1–4 $n$ times, where $n$ is the number of times the image is jiggled to produce the ensemble. In this study, we considered $n$ values ranging from 1 to 60.

The resulting probability distribution of pixel shifts is illustrated in a two-dimensional form in Figure 3a. Because the same set of rules was used to specify both the horizontal and vertical shifts, the distribution was symmetric by definition. Pixels are fundamentally discrete and so only integer shifts in each direction were possible, but calculating the magnitude of the resulting displacement vector provided information on the actual spatial distance corresponding to each possible combination of shifts. The resulting probability distribution function (PDF) and cumulative distribution function (CDF) are shown in Figure 3b. Given the parameterization for the Salcha River specified above, the model displacement value is 0 pixels, occurring for 16% of the realizations. The majority of the displacements are small, with nearly half of realizations less than 1.41 pixels and 89% of realizations less than three pixels, equivalent to $\sim 0.33 \text{ m}$ for the Salcha River images. The maximum displacement for this parameterization was 4.24 pixels and occurred for only 1% of the realizations.

2.4.3. Image Cropping, Stacking, and Averaging

For both the time- and spatial-averaging versions of IBARI as well as the hybrid of the two, the next phase of the workflow is to identify the region of interest (ROI) for depth retrieval. For the time-averaging and hybrid approaches, this stage of the process involves extracting the spatial footprint of each frame of the stabilized, geo-referenced image sequence as a vector polygon. Overlaying the footprint polygons in a GIS environment provides a visual representation of the overlap throughout the image sequence, but this area of common coverage can be defined automatically as the intersection of the polygons for all of the frames in the sequence. Intersecting the resulting overlap polygon with the digitized channel mask then serves to define the final ROI. For the purely spatial averaging version of IBARI, the original channel mask can be used as is to specify the ROI. To enhance computational efficiency and reduce memory requirements, the image sequence is cropped to the ROI.

Next, the cropped image sequence is reorganized into a four-dimensional array, which we refer to as a stack. For the time-averaging version of IBARI, this stack consists of stabilized and geo-referenced video frames, each of which represents two spatial dimensions and a third spectral dimension for the red, green, and blue bands of the red, green, blue (RGB) image, layered over time, the fourth dimension of the array. For the purely spatial-averaging case, the jiggled realizations of a single image comprise the fourth dimension. For
the hybrid technique, the fourth dimension of the array consists of an independent jiggle of each image in the time series. Once the data have been compiled in this manner, an averaged RGB river image is obtained by taking the mean over the fourth dimension of the array. The final averaged image then becomes the input to a depth retrieval algorithm.

The results of the image-averaging process are illustrated in Figure 4, an example from Salcha River hover #5 zoomed in to an area with distinctive features, including a downed tree and ripples or sun glint on the water surface, that highlight differences in image resolution and texture. The first frame extracted from

Figure 3. (a) Discrete probability distribution of pixel shifts in the horizontal and vertical directions, as specified for the Salcha River case study. (b) Corresponding probability distribution function (PDF) and cumulative distribution function (CDF) of the pixel displacement magnitude.
the original video is shown in Figure 4a and captures fine details of the vegetation along the bank and high-frequency variations in brightness within the channel. The terrestrial features are only slightly blurred in the time-averaged version of the image (Figure 4b), but the water is noticeably smoother. To contrast this time-averaged image with a purely spatial averaging, and thus smoothing, of a single image, we applied the jiggling procedure to the first frame 60 times and then averaged the realizations; the resulting image is shown in Figure 4c and provides some, but less pronounced improvement relative to the original first frame. The hybrid time- and jiggler-averaged image shown in Figure 4d, in contrast, is much less noisy than the original, comparable to the purely time-averaged image. Whereas the first frame was grainy and pixelated in appearance and the purely spatially averaged image only slightly less so, both the time-averaged and hybrid time- and jiggler-averaged images provided a very evident smoothing effect.

2.5. Spectrally Based Depth Retrieval

The IBARI workflow described in Section 2.4 and summarized in the upper portion of Figure 2 is essentially a means of preparing either a sequence of video frames, for the time-averaging or hybrid versions, or a single image, for the purely spatial-averaging version, for input to a depth retrieval algorithm. In this study, we applied the OBRA technique introduced by Legleiter et al. (2009) and more recently generalized by Legleiter and Harrison (2019). The interested reader is referred to these publications for additional detail and only a brief summary is provided herein.

In addition to an RGB, multi, or hyperspectral image, OBRA requires field measurements of water depth for calibrating an empirical relation between an image-derived quantity $X$ and water depth $d$. $X$ is given by

$$X = \ln \left( \frac{R(\lambda_1)}{R(\lambda_2)} \right),$$

where $R(\lambda_1)$ and $R(\lambda_2)$ are reflectances, radiances, or raw digital numbers recorded in the numerator and denominator spectral bands $\lambda_1$ and $\lambda_2$, respectively. In this study, we used the ADCP data described in Section 2.3 for $d$. Legleiter et al. (2009) showed that under certain environmental conditions, primarily shallow, clear water, and for an appropriate combination of wavelengths, defining $X$ as a log-transformed band ratio can lead to a linear relation between $X$ and $d$. OBRA thus involves calculating values of $X$ for all possible band combinations and performing an $X$ versus $d$ regression for each pair of wavelengths. The optimal band ratio is that which yields the highest coefficient of determination, referred to as the OBRA $R^2$.

In addition to identifying the best wavelengths for estimating river bathymetry, OBRA also provides a calibrated relationship between $X$ and $d$ that can be applied throughout an image to produce a continuous depth map. Following Legleiter and Harrison (2019), we used an exponential formulation of the $X$ versus $d$ relation to avoid negative depth estimates or overpredictions of depth along shallow channel margins. In this study, we performed OBRA and generated depth maps for each of the four image types identified above: (1) FF images from 60-image sequences extracted from both the downsampled 1 Hz and full frame rate (30 Hz) videos; (2) TA images produced via the IBARI workflow; (3) JA images derived by randomly shifting the first frame in each sequence 60 times; and (4) HA images generated as described in Section 2.4.

2.6. Evaluation of Image-Derived Bathymetric Maps

Having derived depth maps from each of these four image types, we performed a thorough accuracy assessment to compare the various remotely sensed river bathymetries. This evaluation was based on 50% of the available field measurements of water depth, sampled at random from the full data set, that were excluded from the OBRA calibration process. The same calibration and validation subsets of the available field data were used for all of the different image types we considered to ensure that differences in depth retrieval accuracy and precision were not confounded with random sampling fluctuations. For consistency with previous studies, we used the same metrics of performance as Legleiter and Harrison (2019), including: OBRA calibration $R^2$; visual inspection of depth maps; distributions of depth retrieval errors, defined as the field-measured depth minus the image-derived depth; and observed versus predicted (OP) regressions.
Although these metrics provided information on the reliability of image-derived depth estimates on a point-by-point basis, calculating depth retrieval errors for individual image pixels does not take into consideration their spatial context. The spatial structure, or texture, of the remotely sensed river bathymetry also is important, however, and arguably dominates one’s overall impression of an image-derived depth map. To more rigorously examine the effects of image-averaging on the spatial coherence, or smoothness, of remotely sensed river bathymetry, we also quantified the texture of the depth maps produced from the various image types. This analysis involved computing the standard deviation of image-derived depth estimates within moving windows of various sizes, ranging from 3 × 3 to 15 × 15 pixels, in steps of 2 pixels. For the mean pixel size of the Salcha River hovers, these windows correspond to spatial distances ranging from 0.32 m to 1.61 m. The resulting standard deviation maps provided a visual summary of bathymetric texture, with areas of higher standard deviation indicating noisier or more abruptly varying depth within the moving window at that location. Conversely, lower standard deviations indicate a smoother, more gradually varying local bathymetry. To summarize these results, we computed the mean and standard deviation of the standard deviation maps for each window size. This analysis was performed for each of the 10 hovers for depth maps derived from the first frame of the 1 and 30 Hz videos, a purely jiggle-averaged image derived from the first frame, and the time- and hybrid time/jiggle-averaged images.

2.7. Duration Sensitivity Analysis

To address the research questions posed at the end of Section 1, we performed a sensitivity analysis that quantified the effect of image sequence duration on depth retrieval performance. Moreover, to assess whether this effect was a consequence not of the actual amount of time encompassed by the image sequence but rather the number of images included, we conducted the analysis for both the downsampled 1 Hz sequence and the original 30 Hz sequence. We used the first 60 images from each sequence, representing a full minute in the 1 Hz case but only 2 s for the 30 Hz video. Similarly, we assessed the sensitivity of the hybrid time/jiggle-averaging version of IBARI to the number of randomly shifted image frames used to compute the ensemble mean. For each of these different data types, the sensitivity analysis involved executing the time-averaging and hybrid versions of the IBARI workflow, performing OBRA for the resulting averaged images, and assessing depth retrieval performance for image sequences ranging in length from a single image to 60 images. We summarized our results by plotting the OP $R^2$, mean error, and standard deviation of error against the number of images included in the sequence.

3. Results

3.1. Example From a Single Hover

This subsection emphasizes graphical results and related discussion for one of the 10 hovers along the Salcha River, #5, as a representative example. Parallel analyses were conducted and analogous figures were produced for all 10 of the hovers and the aggregated results are summarized in Section 3.2.

3.1.1. Depth Retrieval Performance

The purpose of the image-averaging workflow illustrated in Figure 2 and described in Section 2.4 was to take as input a video (or, for the purely spatial averaging version of IBARI, a single frame) and produce an output image more conducive to estimating water depth. Overall, our results indicated that inferring depths from averaged river images yielded more reliable bathymetric information than estimating depth from a single frame. For both 1 and 30 Hz 60-image sequences and hybrid time- and jiggle-averaged stacks of 60 images, four key metrics of performance were better for the averaged images than for the mean of the individual frames: (1) higher OBRA calibration $R^2$; (2) lower (in absolute value) depth retrieval mean error; (3) lower standard deviation of depth retrieval errors; and (4) higher OP regression $R^2$. The statistical significance of these results was assessed by pooling each of the four metrics over the 10 hovers and using one-tailed $t$-tests to evaluate the null hypothesis that the mean value of the metric for the purely time- or hybrid time/jiggle-averaged images was not greater than the mean of the metric for the individual frames in the video. This analysis involved 8 $t$-tests (4 metrics × 2 versions of IBARI) and the null hypothesis was rejected in all cases, with $p$-values less than 0.00011. These results imply that the image-averaging process led to depth estimates that were both more accurate and more precise than estimates based on a single frame.
Further detail on one of these metrics, the OBRA calibration $R^2$, is provided in Figure 5, which compares the series of individual video frames and pure jiggles of a single frame to the purely time-, purely jiggle-, and hybrid time/jiggle-averaged images. For the hover #5 example, the OBRA calibration $R^2$ was higher for the purely time- and hybrid time/jiggle-averaged images than for any of the individual video frames or first frame jiggles that comprised the ensemble. Moreover, the OBRA $R^2$ fluctuated from frame to frame over the course of the 60-image sequences, implying that the strength of the $X$ versus $d$ relation varied over time and among the random image displacements. To some extent for hover #5 and to a greater degree for several of the other hovers, irregular frame-to-frame variations in OBRA $R^2$ or trends over time suggested that depth retrieval was sensitive to changing lighting conditions, even on the time scale of 1 min.

In addition to the statistical analysis, visual inspection of depth maps also indicated that image averaging enhanced remote sensing of river bathymetry. Depth maps produced from the FF, TA, JA, and HA image types are shown in Figure 6. This comparison illustrates the smoother, more realistic appearance of the bathymetry inferred from the averaged images. Whereas the map generated from a single frame was grainy and pixelated (Figure 6a) and applying a purely spatial-averaging technique to the image yielded little if any improvement (Figure 6c), both the time-averaged (Figure 6b) and hybrid time/jiggle-averaged (Figure 6d) images yielded more coherent, gradually varying representations of the channel morphology. These differences also were evident in cross-sections extracted from the four depth maps and overlain in Figure 7. Whereas the profiles for the first frame and purely jiggle-averaged images were highly erratic, with several pronounced spikes, the transects for the time- and hybrid time/jiggle-averaged images were smoother and more similar to one another. In all cases, however, the image-derived depths underestimated the depths measured in the field by the ADCP, as is often the case when river bathymetry is inferred from passive optical image data (e.g., Legleiter & Fosness, 2019; Legleiter & Harrison, 2019).

Figure 5. Optimal Band Ratio Analysis (OBRA) calibration $R^2$ values for individual video frames and first frame jiggles and for the corresponding purely time-, purely jiggle-, and hybrid time/jiggle-averaged images for an example hover, #5, along the Salcha River.
As a complement to this visual assessment, we also performed a quantitative analysis of depth retrieval performance using the subset of the field data that was not used to establish $X$ versus $d$ relations via OBRA but rather set aside to validate image-derived depth estimates. Distributions of depth retrieval errors and OP regression plots based on the validation subset are shown in Figure 8. The mean and standard deviation of depth retrieval errors were smaller for the time-averaged and hybrid time- and jiggle-averaged images than for the original and purely jiggle-averaged versions of the first frame. For all four image types, however, a positive mean error of $3–5 \, \text{cm}$ indicated that depths tended to be underestimated relative to the field measurements. Whereas none of the errors were greater than $50 \, \text{cm}$ in absolute value for the time-averaged and hybrid time/jiggle-averaged images, the error distributions for the raw and jiggle-averaged first frame included a few large overestimates (negative errors) and a sizable tail of errors greater than $50 \, \text{cm}$, indicat-

**Figure 6.** Depth maps derived from (a) first frame, (b) time-averaged, (c) pure jiggle-averaged, and (d) hybrid time/jiggle-averaged images for hover #5. Flow is from lower left to upper right. The black line indicates the location of the profiles shown in Figure 7 and the points represent field-based depth measurements along an ADCP transect.

**Figure 7.** Profiles extracted from depth maps derived from first frame, time-averaged, jiggle-averaged, and hybrid time/jiggle-averaged images for hover #5, along with field measurements of water depth. The location of the ADCP transect and the cross section onto which the data were projected are indicated in Figure 6.
averaged, and hybrid time- and jiggle-averaged images for hover #5. These plots are based on the validation subset of the field data.

Figure 8. Distributions of depth retrieval errors and observed versus predicted regressions for depth maps derived from first frame, time-averaged, pure jiggle-averaged, and hybrid time- and jiggle-averaged images for hover #5. These plots are based on the validation subset of the field data.

Moreover, the OP regression $R^2$ increased from 0.71 and 0.68 for the original and jiggle-averaged versions of the first frame, respectively, to 0.81 and 0.80 for the time-averaged and hybrid time/jiggle-averaged images, respectively. OP regression intercepts closer to 0 and slope coefficients closer to 1 for the time-averaged and hybrid time/jiggle-averaged images also indicated that the IBARI workflow led to depth estimates that tended to be less biased relative to the field data used for validation.

3.1.2. Depth Map Texture

Just as we used quantitative validation of image-derived depth estimates to confirm the visual impression of more reliable river bathymetry derived from averaged images, we also sought to quantify the smoother appearance of the depth maps produced via the IBARI workflow than those generated from single images (Figure 6). To achieve this objective, we quantified depth map texture by computing the standard deviation of depth estimates within moving windows of various sizes. An example of this type of analysis for hover #5 is shown in Figure 9 for the largest window size we considered (15 x 15 pixels, or 1.61 x 1.61 m). The grainy appearance of the depth maps produced from the original and purely jiggle-averaged versions of the first frame translated into higher standard deviation values, in excess of 0.2 m, for much of the channel. The similarity of Figures 9a and 9c implies that a pure jiggle-averaging was not effective in reducing noise or spatially smoothing the image. Conversely, the smoother texture of the bathymetries derived from the time- and hybrid time/jiggle-averaged images led to much lower standard deviations, typically on the order of 0.05 m, within the 15-pixel moving windows except along the margins of the channel where depth varied abruptly from the thalweg toward the banks. When the time- and hybrid time/jiggle-averaged images were used to infer bathymetry, standard deviation maps like those shown in Figures 9b and 9d highlighted more complex areas of the river, rather than noise propagated from the original images.

We generated analogous standard deviation maps for bathymetries derived from each of the four image types for moving windows as small as 3 x 3 pixels (0.33 x 0.33 m). This analysis served to quantify depth map texture across a range of scales and was summarized by computing the median and interquartile range of the standard deviation values pooled over the in-stream area for each window size. Figure 10 indicates...
that for window sizes from 3 × 3 to 15 × 15 pixels (representing areas from 0.103 to 2.58 m²), depth map
texture was roughest for the first frame-based bathymetry, only slightly less irregular for depths derived
from a pure jiggle-averaged image, and much smoother for the bathymetries inferred from time- or hybrid
time/jiggle-averaged images.

Figure 9. Standard deviation of depth estimates within a 15-pixel moving window based on the depth maps derived from the (a) first frame, (b) time-averaged, (c) pure jiggle-averaged, and (d) hybrid time- and jiggle-averaged images shown in Figure 6.

Figure 10. Standard deviation of depth estimates within moving windows of various sizes based on the depth maps derived from first frame, time-averaged, pure jiggle-averaged, and hybrid time- and jiggle-averaged images shown in Figure 6.
3.2. Synthesis Across All Hovers

Similar analyses of depth retrieval performance and depth map texture were performed for the other nine hovers along the Salcha River, in addition to the examples from hover #5 illustrated in Figures 5–10. The results for all 10 hovers are summarized in Table 2 and described in the following subsections.

3.2.1. Depth Retrieval Performance

For all 10 of the hovers along the Salcha River, we executed the time-, jiggle-, and hybrid time/jiggle-averaging versions of the IBARI workflow, produced depth maps, calculated depth retrieval errors and performed OP regressions using the validation subset of the field observations. The results of this analysis are compiled in Table 2, which lists the various performance metrics for each of four image types for each hover: the FF, TA, JA, and HA images defined in Section 2.4. This synthesis indicates that depth retrieval errors were smaller for averaged images, with mean errors of 0.74 and 0.96 cm for time- and hybrid time/jiggle-averaged images, respectively, than when depths were estimated from single frames, which led to mean errors of 1.82 cm and 1.60 cm for the original and purely jiggle-averaged versions of the first frame, respectively. In all cases, these errors were small relative to the 1.1 m mean depth of the Salcha River, ranging from 0.67% to 1.65% of the mean depth. Similarly, the standard deviation of depth retrieval errors was smaller for the time- and hybrid time/jiggle-averaged images, with means of 15.92 and 15.42 cm, respectively, than for the original and jiggle-averaged versions of the first frame, with means of 19.63 and 19.19 cm, respectively. Again, these values represented a small fraction of the reach-averaged mean depth, ranging from 14% to 18%. OP regressions also indicated that the IBARI workflow led to more reliable bathymetric information, with the OP $R^2$ improving from 0.80 to 0.79 for the original and jiggle-averaged versions of the first frame, respectively, to 0.88 for both the time- and hybrid time/jiggle-averaged images. Overall, these results demonstrated that in this clear-flowing river, the image-averaging approach provided depth estimates that were more accurate and precise than bathymetries derived from single frames.

Box plots summarizing the distributions of four key metrics of depth retrieval performance over the 10 hovers further confirmed the improvement associated with image averaging (Figure 11). We also used these box plots to address the research question regarding frame rate we posed at the end of Section 1. For both the downsampled 1 Hz and full frame rate 30 Hz videos and jiggled image sequences derived from the 1 Hz video, the IBARI process led to more reliable bathymetric information. For example, Figures 11a indicates that OBRA calibration $R^2$ values were consistently higher for the time- and hybrid time/jiggle-averaged images than the mean of the OBRA $R^2$ values for individual frames, as shown for the hover #5 example in Figure 5. Differences in OBRA $R^2$ between the mean of the individual frames and the time-averaged images generally were more pronounced for the 1 Hz than for the 30 Hz videos. Overall, both frame rates provided a similar level of accuracy and precision, as indicated by comparable median values of mean error, standard deviation of error, and OP $R^2$. Moreover, validation of depth estimates inferred from the jiggled image sequences, which involved both spatial and temporal averaging, produced similar values of the performance metrics.

3.2.2. Depth Map Texture

As exemplified for hover #5 in Section 3.1.2 and Figures 9 and 10, depth map texture was consistently smoother for bathymetries derived from time- and hybrid time/jiggle-averaged images than from raw and purely jiggle-averaged single frames. Quantitative evidence to support the visual impression of more coherent, gradually varying depth maps for the averaged images was obtained by calculating the standard deviation of image-derived depth estimates within moving windows of various sizes. Averaged over the 10 hovers for each window size, these standard deviation values were reduced by approximately a factor of two for the time- and hybrid time/jiggle-averaged images relative to the original and purely jiggle-averaged single frames, across all window sizes from 3 × 3 to 15 × 15 pixels (Figure 12). These results indicate that image-averaging not only improved depth retrieval performance on a point-by-point, aspatial basis but also led to more realistic, smoothly varying bathymetries when the depth estimates were explicitly considered within their spatial context.

3.2.3. Duration Sensitivity Analysis

Although our results showed that averaging images can improve depth retrieval, we also sought to address the question of how many images must be averaged to obtain more reliable bathymetric information. To
| Hover # | Image type | n  | Mean (cm) | S.D. (cm) | Min (cm) | Q1 (cm) | Median (cm) | Q3 (cm) | Max (cm) | OP | R² | Int. (cm) | Slope |
|--------|------------|----|-----------|-----------|----------|---------|-------------|---------|---------|----|-----|----------|-------|
| 1 | FF | 129 | −0.58 | 27.00 | −95.98 | −17.25 | 1.29 | 20.71 | 43.18 | 0.72 | 28.11 | 0.72 |
| TA | 129 | −1.55 | 11.67 | −42.00 | −8.68 | 0.51 | 6.14 | 20.12 | 0.94 | 9.56 | 0.89 |
| JA | 130 | 1.88 | 21.89 | −41.81 | −15.35 | −0.21 | 19.87 | 47.21 | 0.72 | 12.35 | 0.89 |
| HA | 130 | −0.06 | 10.60 | −34.26 | −8.69 | 0.25 | 8.05 | 21.52 | 0.93 | 1.78 | 0.98 |
| 2 | FF | 154 | −1.29 | 22.11 | −85.27 | −11.19 | −0.81 | 11.62 | 56.88 | 0.79 | 22.23 | 0.81 |
| TA | 154 | 1.73 | 15.67 | −35.99 | −14.28 | −2.08 | 10.08 | 86.01 | 0.89 | 6.57 | 0.97 |
| JA | 154 | −1.49 | 22.39 | −86.48 | −10.76 | 0.44 | 12.31 | 51.32 | 0.93 | 12.17 | 0.95 |
| HA | 154 | 0.45 | 15.78 | −39.58 | −6.12 | 1.36 | 7.16 | 33.75 | 0.88 | 15.19 | 0.88 |
| 3 | FF | 181 | −0.03 | 18.74 | −57.23 | −12.03 | −1.16 | 12.81 | 55.22 | 0.92 | 7.92 | 0.95 |
| TA | 181 | 0.70 | 23.13 | −58.29 | −12.57 | −0.19 | 17.08 | 70.78 | 0.87 | −1.66 | 1.02 |
| JA | 181 | 2.53 | 17.48 | −52.76 | −8.76 | 3.04 | 12.99 | 58.89 | 0.93 | 10.40 | 0.95 |
| HA | 181 | 2.07 | 21.81 | −35.99 | −14.28 | −2.08 | 10.08 | 86.01 | 0.89 | 6.57 | 0.97 |
| 4 | FF | 193 | 4.51 | 23.82 | −45.91 | −12.62 | 5.21 | 21.12 | 63.61 | 0.92 | 6.05 | 0.99 |
| TA | 193 | 0.44 | 29.80 | −54.86 | −22.80 | 1.52 | 10.32 | 86.75 | 0.87 | 15.16 | 0.92 |
| JA | 193 | 2.07 | 25.58 | −63.64 | −11.68 | 1.33 | 18.24 | 64.69 | 0.68 | 24.67 | 0.79 |
| HA | 193 | 2.74 | 21.81 | −35.99 | −14.28 | −2.08 | 10.08 | 86.01 | 0.89 | 6.57 | 0.97 |
| 5 | FF | 239 | 4.57 | 25.10 | −69.60 | −11.39 | 3.28 | 18.66 | 71.05 | 0.71 | −3.67 | 1.08 |
| TA | 239 | 2.73 | 20.79 | −42.25 | −13.87 | 1.25 | 19.52 | 43.75 | 0.81 | −5.81 | 1.08 |
| JA | 239 | 2.47 | 25.58 | −63.64 | −11.68 | 1.33 | 18.24 | 64.69 | 0.68 | 2.31 | 1.00 |
| HA | 239 | 3.27 | 20.56 | −40.63 | −14.28 | 2.61 | 19.59 | 42.91 | 0.80 | −2.72 | 1.05 |
| 6 | FF | 106 | 2.37 | 21.79 | −71.35 | −13.29 | −0.88 | 21.49 | 43.53 | 0.69 | −4.28 | 1.07 |
| TA | 106 | 0.98 | 17.00 | −27.06 | −9.47 | −2.42 | 8.59 | 37.39 | 0.81 | 2.28 | 0.99 |
| JA | 106 | 3.59 | 21.19 | −67.73 | −12.79 | 0.03 | 21.87 | 42.65 | 0.66 | 3.92 | 1.00 |
| HA | 106 | 2.80 | 16.00 | −23.10 | −8.50 | −1.09 | 11.51 | 36.40 | 0.83 | 3.51 | 0.99 |
| 7 | FF | 247 | 3.95 | 15.66 | −41.86 | −7.94 | 5.24 | 14.69 | 39.10 | 0.74 | −4.85 | 1.09 |
| TA | 247 | 1.06 | 11.20 | −22.86 | −8.28 | 2.72 | 8.98 | 27.20 | 0.87 | 3.63 | 0.97 |
| JA | 247 | 2.12 | 15.46 | −47.43 | −9.57 | 3.03 | 13.72 | 34.33 | 0.73 | −3.60 | 1.06 |
| HA | 247 | 0.89 | 11.25 | −21.92 | −8.70 | 2.38 | 9.04 | 27.05 | 0.86 | 1.89 | 0.99 |
| 8 | FF | 295 | 1.46 | 13.10 | −34.09 | −6.26 | 0.47 | 8.90 | 37.48 | 0.87 | −1.00 | 1.03 |
| TA | 295 | 0.83 | 8.42 | −21.01 | −5.01 | 0.17 | 5.27 | 22.64 | 0.95 | 1.77 | 0.99 |
| JA | 295 | −1.18 | 15.76 | −55.47 | −7.91 | −1.17 | 8.58 | 35.62 | 0.82 | 9.80 | 0.89 |
| HA | 295 | −0.12 | 8.78 | −22.28 | −6.73 | −0.61 | 5.32 | 21.08 | 0.95 | 5.18 | 0.94 |
| 9 | FF | 234 | 2.95 | 19.36 | −55.71 | −7.34 | 3.75 | 15.75 | 66.93 | 0.69 | 13.49 | 0.90 |
| TA | 234 | 0.56 | 13.70 | −33.55 | −11.41 | 3.74 | 11.44 | 28.42 | 0.86 | 15.23 | 0.87 |
| JA | 234 | 2.86 | 18.81 | −75.82 | −5.57 | 3.10 | 15.20 | 47.98 | 0.70 | 16.84 | 0.87 |
| HA | 234 | −0.68 | 13.47 | −31.62 | −13.15 | 1.67 | 10.23 | 26.87 | 0.85 | 14.07 | 0.87 |
do so, we analyzed the sensitivity of depth retrieval accuracy and precision to the duration of the image sequence being averaged for both the time-averaged approach and the hybrid time/jiggle-averaging technique that also introduced a component of spatial averaging. In addition, for the purely time-averaging version of IBARI, we considered both downsampled 1 Hz and the original, full frame rate 30 Hz videos to assess whether improvements in depth retrieval were driven by the time duration of the image sequence or simply by the number of images averaged, even if those images span a much shorter period of time (i.e., 60 s to obtain 60 images at 1 Hz vs. 2 s to capture the same number of images at 30 Hz).

The results of this analysis are summarized in Figure 13, which indicates that, averaged over the 10 hovers, the OP $R^2$ increased while both the absolute value of the mean depth retrieval error and the standard deviation of the errors decreased as more images were averaged, for both the time- and hybrid time/jiggle-averaging approaches. Comparison of the 1 and 30 Hz sequences in Figure 13 also suggests that, for a given number of images, the downsampled 1 Hz image sequence yielded more reliable depth estimates than the full frame rate 30 Hz video. The trends were similar for both frame rates, however, implying that the number of images averaged, rather than the amount of time captured by the image sequence, was the more important factor influencing depth retrieval performance. Moreover, the three metrics tended to stabilize by about 30 images for both frame rates as well as the hybrid time/jiggle-averaging approach based on the 1 Hz sequence.

In addition, visual inspection of depth maps produced from videos acquired at the two frame rates suggested the 30 Hz video led to a rougher bathymetry than the 1 Hz version. This impression was substantiated by the quantitative results shown in Figure 12, where the spatial standard deviations within moving windows of various sizes were slightly higher for the 30 Hz than for the 1 Hz videos, with the latter yielding nearly the same standard deviation values for a given window size as the hybrid time/jiggle-averaging approach based on the 1 Hz sequence.

### 4. Discussion

#### 4.1. Limitations, Applicability, and Alternatives

This study introduced a workflow for averaging river images to enhance passive optical remote sensing of river bathymetry. Although this approach led to quantitative improvements in depth retrieval accuracy and precision and image-derived depth maps with noticeably smoother texture, the IBARI framework also was subject to a number of limitations. The most important of these constraints is the most general and pertains to any method of estimating depth from passive optical images: Depth retrieval from such data is only feasible under certain environmental conditions. The water must be clear, with the attenuation of sunlight dominated by pure water absorption rather than scattering by suspended sediment (Legleiter et al., 2004, 2009), and the flow relatively shallow, typically less than 2–3 m, depending on the radiometric sensitivity of the imaging system (Legleiter & Fosness, 2019; Legleiter & Overstreet, 2012). Favorable atmospheric conditions (i.e., sunny skies) and an unobstructed view of the channel also are desirable, if not essential. Although these criteria were largely satisfied for our study area along the Salcha River in July 2019, a previous
campaign on the same river a year earlier yielded images that could not be used for bathymetric mapping due to elevated concentrations of suspended sediment. This example serves to illustrate the inherently contingent nature of spectrally based remote sensing of river bathymetry; neither IBARI nor any other image processing workflow can circumvent the fundamental limitations dictated by the physics governing the interaction of light and water.

This requirement for clear water also implies that remote sensing of water depths and surface flow velocities might be an either/or proposition for a particular river at any one time. For example, although previous research on the Salcha demonstrated the potential to estimate velocities via LSPIV without seeding the flow with artificial tracer particles, such inference was only possible due to high runoff at the time of image acquisition in August 2018, which conveyed a quantity of suspended sediment sufficient to produce boil vortices visible at the water surface (Legleiter & Kinzel, 2020b). These conditions were not conducive to depth retrieval, however. Conversely, lower flows and clearer water in 2019 enabled bathymetric mapping but prohibited LSPIV due to a lack of trackable features. For this reason, most prior studies have relied upon artificial seeding, but such manipulation is logistically challenging and can lead to inconsistent results if particles are not distributed evenly (e.g., Strelnikova et al., 2020). If seeding is feasible, requiring a major effort on even a medium-sized river such as the Salcha, one strategy for characterizing channel hydraulics might be to collect one video to infer velocities and then another, after the tracers have passed, for mapping depth. Given these challenges, alternative approaches to inferring depth given velocity (e.g., Jin & Liao, 2019; Nelson et al., 2012), or vice versa, merit further research attention.

Another limitation of the OBRA algorithm we incorporated into the IBARI workflow in this study, or any other empirical depth retrieval method, is the need for field-based depth measurements to establish a calibrated relation between an image-derived quantity $X$ and water depth $d$. Ideally, field data collection and image acquisition would occur simultaneously, and our results suggest that, for helicopter-based video a separate calibration might be required for each hover to account for variable illumination and/or camera exposure settings. For example, the erratic fluctuations in the OBRA calibration $R^2$ shown in Figure 5 might...
reflect changes in lighting conditions from frame to frame during the one-minute video acquisition. This illumination issue also was illustrated in Figure 11, which indicates that differences in the OBRA calibration $R^2$ between individual frames and time-averaged images were more pronounced for 1 Hz than for 30 Hz videos. We attribute this distinction to the fact that at the lower frame rate acquiring 60 images required 60 s, during which lighting conditions might have varied to a greater degree than during the 2 s required to obtain 60 images at 30 Hz.

In addition, the distribution of depths used for calibration also might influence the accuracy of the resulting bathymetric maps. Previous studies have shown the importance of including a broad range of depths in the calibration data set (Legleiter & Fosness, 2019; Legleiter et al., 2018). If field data are not available, or at least not for all of the hovers included in a reach-scale mapping effort, alternative depth retrieval algorithms that do not require field measurements for calibration could be employed. Examples of such techniques include Hydraulically Assisted Bathymetry (HAB; Fonstad & Marcus, 2005), Flow Resistance Equation-Based Imaging of River Depths (FREEBIRD; Legleiter, 2015), and Image-to-Depth Quantile Transformation (IDQT; Legleiter, 2016). The latter method, which involves linking the frequency distribution of pixel values to that of depths, might be particularly useful in this context. Field observations from even a single hover location could be used to establish the distribution of depths and identify an image-derived quantity that is monotonically related to depth. This variable, $X$, could then be calculated from the averaged images for the other hovers and the IDQT process used to assign a depth to each pixel based on the sampled distribution of depths, assumed to be representative of the distribution throughout the reach. An even simpler approach would involve normalizing $X$ by its mean to obtain a standardized image that is

Figure 12. Standard deviation of depth estimates within moving windows of various sizes, averaged over the 10 hovering image sequences for first frame (FF), time-averages (TA) of 1 and 30 Hz image sequences, and hybrid time- and jiggle-averaged (HA) images derived from the 1 Hz video. Note that the lines for TA 1 Hz and HA overlap one another.
essentially a relative depth map; multiplying the result by the mean depth would then yield absolute values of the bathymetry on a per-pixel basis.

Spatial resolution is another important consideration in assessing the applicability our image-averaging framework to a particular use case. The IBARI workflow was developed in the context of, and is most well-suited to, high resolution image data for which the pixel size is a small fraction of the mean channel width, especially for the pure jiggling and hybrid versions of IBARI that involve spatial averaging. For the 10.7 cm, helicopter-based images of the Salcha River, this ratio was 0.0022. For coarser resolution data, we hypothesize that the improvements realized by image-averaging would be less pronounced or disappear altogether. For images with larger pixel sizes, such as those acquired from fixed wing aircraft deployed at higher altitudes or from satellite platforms, much of the averaging can be considered to have already occurred within a pixel. Further aggregation in postprocessing might obscure important variations in channel morphology for small-to moderate-sized rivers. In addition, the larger the pixel size relative to the channel width, the more the random image displacements simulated via jiggling would contaminate in-stream pixels near the banks with adjacent terrestrial features.

Another factor directly affected by image spatial resolution is the computational requirements of the IBARI workflow. For the ~10 cm-pixel images used in this study, the IBARI techniques were efficient to implement on a standard desktop computer and the overall personnel time needed to implement the proposed methodology for the data set described herein was on the order of half an hour per hovering image sequence. For images consisting of pixels up to an order of magnitude smaller (i.e., 1 cm, as could be achieved by acquiring data from a sUAS), the computational demands would be much greater and run time could increase significantly, though the amount of direct user interaction would not be expected to change. Future refinements

![Figure 13](image-url)
that automate some components of the workflow, such as selecting GCPs for geo-referencing and digitizing a channel mask, could reduce the personnel time required to perform an IBARI-based analysis.

The significance of spatial resolution effects also raises the question of which types of platform might be the most appropriate means of obtaining image data suitable for IBARI. In this study, we used a camera deployed from a helicopter to acquire videos from a series of waypoints distributed throughout the reach, but a similar data set also could have been acquired via sUAS. Each kind of aircraft has advantages and drawbacks. Helicopters typically allow for greater flying heights and thus more extensive spatial coverage and also are more readily deployed to remote, inaccessible locations, such as many of the streamgages in Alaska. However, helicopters also are more expensive to obtain and operate, requiring specialized, licensed pilots that often are employed by private firms. In contrast, sUAS are better-suited to smaller-scale missions focused on relatively short reaches with convenient ground access and unrestricted airspace. These platforms also offer greater flexibility because sUAS can be acquired and utilized at a lower cost more likely to be within the budget of academic institutions and management agencies. In addition, mobilization of sUAS can be more opportunistic, capitalizing on favorable weather and/or the availability of field personnel for making depth measurements, than working with a flight contractor. The lower flying height of sUAS implies a smaller image footprint for a given hover and thus more takeoffs, landings, and battery swaps to obtain the same total area of coverage. Flying lower also yields smaller pixels, however, and thus provides images conducive to structure-from-motion photogrammetry, a widely used approach for deriving high-resolution topographic data for terrestrial areas adjacent to the channel (e.g., Anderson et al., 2019). Another intriguing possibility is video acquired from satellite platforms. At present, these sensors provide panchromatic images, not multispectral, but having only grayscale data does not necessarily preclude depth retrieval. Although OBRA requires multiple bands, other algorithms do not rely on spectral information and can be applied to panchromatic images (e.g., Winterbottom & Gilvear, 1997).

4.2. Advantages and Extensions of IBARI

The IBARI framework introduced herein could offer some significant advantages over existing methods for mapping water depth from remotely sensed data. For example, although our results indicated that depth retrieval can be highly sensitive to variable illumination on a frame-by-frame basis, image-averaging could make depth estimates more robust to these effects. Another plausible physical explanation for the improved bathymetric accuracy and precision observed in this study is that time-averaging mitigates the confounding influence of sun glint. Spatial-averaging via image jiggling could produce a similar effect by simulating multiple realizations of an irregular water surface and then computing an ensemble mean. This approach could enable depth retrieval from high spatial resolution, glint-contaminated image sequences that would be of no use if analyzed as individual frames. If the glint is extreme, using a temporal minimum filter, as suggested by Partama et al. (2018), might be more effective than an averaged image. Other approaches to mitigating sun glint so as to achieve illumination invariance could be explored in future research and include contrast limited adaptive histogram equalization (Dal Sasso et al., 2020) and homomorphic filtering (Nnolim & Lee, 2008).

The most important advantage of IBARI might be more qualitative: A marked improvement in the appearance of bathymetric maps derived from averaged river images. In comparing the depth maps generated from the original and purely jiggled-averaged versions of a single frame to those produced from time- and hybrid time/jiggle–averaged images (Figure 6), the most salient difference is the smoother, more coherent texture of the bathymetries inferred from the time- and hybrid time/jiggle-averaged images. This type of improvement is not captured by standard metrics of performance, which evaluate depth estimates by comparing individual pixels to single field measurements in isolation, with no consideration of their spatial context. Although the IBARI workflow led to improved depth retrieval in terms of conventional indices such as the mean error and OP R², we also quantified enhanced depth map texture by calculating the spatial standard deviation of depth estimates within moving windows of various sizes. Such smoothing could provide bathymetric data more suitable for input to subsequent analyses, such as flow modeling, and thus translate into more reliable predictions of bed material transport (McKean et al., 2014), for example. A peripheral but not insignificant consideration in this context is that the smoothness of a depth map strongly influences one’s subjective assessment of its quality and, ultimately, its utility. Another advantage of the IBARI framework
is thus the potential to simply make depth maps “look” better, which could help to build confidence in remote sensing methods among a broader user community and therefore lead to more widespread adoption of these techniques in river research and management.

Another benefit of IBARI is that improved bathymetric mapping performance can be achieved without highly specialized image data or substantial modifications to typical image acquisition procedures. For example, the duration sensitivity analysis summarized in Section 3.2.3 implied that relatively brief time periods of hovering above the channel might be sufficient, particularly if image data can be acquired at a higher frame rate with a video camera such as the Zenmuse X5 used in this study. Sensors of this kind are widely available and inexpensive, even included with many sUAS kits. Shorter duration hovers at a high frame rate would be most efficient, but our results suggest that even a standard, nonvideo camera with a 1 s capture interval could provide reliable depth information for durations on the order of 30 s. Another important factor to consider in selecting an imaging system is the field of view, which depends on the flying height and thus tends to be smaller for sUAS- than for helicopter-based data collection. The footprint must be extensive enough to include at least one bank, and preferably both, to ensure that distinct, stationary terrestrial features are available for the critical image stabilization step in the time- and hybrid time/jiggle-averaging versions of IBARI.

Although our initial conceptualization of this approach focused on a more intuitive time-averaging technique, considering the residual effects of platform motion that persists through the stabilization process also led us to develop and test a spatial-averaging analog. The results of this study indicated that randomly displacing a single image multiple times, which we referred to as pure jiggling, and then averaging the resulting ensemble of realizations led to depth maps that were not as accurate, precise, or smooth as those derived from time-averaged images. This finding implies that the enhanced depth retrieval performance achieved by time-averaging over an image sequence could be safely attributed to the time-averaging process itself, not an inadvertent component of spatial averaging due to shifts in spatial location from frame to frame associated with platform motion that was not accounted for by the image stabilization algorithm. However, applying the jiggling procedure to each frame of an image time series yielded some additional improvement beyond a simple time-averaging. These results suggest that improving depth retrieval via image-averaging will require acquiring a time series or video rather than a single still image. Because a purely spatial-averaging approach (i.e., jiggling) is inadequate, potential users of the IBARI framework must allow time to acquire image time series or videos, ensure sufficient data storage is available, and plan flights to capture at least one bank so that images include stationary terrestrial features that can be used to stabilize the sequence. From a theoretical point of view, our results suggest that observing multiple realizations of the irregular water surface should occur directly in the temporal domain rather than via simulation in a jiggled, pseudo-spatial domain. The hybrid time/space approach to averaging over a complex hydraulic phenomenon, complex water surface topography in our case, is analogous to techniques for characterizing form-induced stresses by double-averaging turbulent flow fields in both time and space (Nikora et al., 2007a, 2007b).

In Section 3.1, we focused on results from a single hover and presented bathymetric maps, cross-sections, validation summaries, and analyses of depth map texture in Figures 6–10 as representative examples, but similar outputs also were generated for nine other hovers along the Salcha River. This study thus demonstrated the potential to produce bathymetric maps spanning longer reach-to-segment-scales by collecting images at multiple waypoints spaced along the channel and then assembling the hovers into a mosaic. The end result of such a workflow is illustrated in Figure 14, which shows continuous depth maps for a 2.36 km reach of the Salcha River derived from the first frame acquired at each hovering location and from a hybrid time/jiggle-averaged image for each hover. Even at this scale, the smoother texture of the bathymetry inferred from the averaged image is evident, indicating that the enhanced depth retrieval achieved via IBARI scales up from the 200–300 m encompassed by a single hover to a reach of more than 2 km spanned by multiple hovers. For the Salcha River example, conservative flight planning in terms of image overlap allowed us to obtain continuous coverage by retaining only every other hover (Figure 1). In this study, each hover included field measurements from at least one ADCP transect, but providing local calibration data for each tile of a reach-scale mosaic increased the field data requirements. The ability to reduce if not eliminate the need for such field observations is one reason to pursue alternative techniques like IDQT that do not rely upon simultaneous, co-located field data. Another strategy would be to develop approaches to standardize
(i.e., color balance) the images comprising a mosaic. In any case, minimizing the number of tiles needed to provide full coverage of a particular study area is desirable and represents a distinct benefit of helicopters, which can fly higher and thus provide a larger field of view, over sUAS. This advantage would be even more pronounced for satellite platforms, provided that the images acquired from space are of sufficient spatial resolution. Future work also could explore the potential of image pyramid procedures, which use Gaussian smoothing to create multiscale representations of salient features of the imaged region (Stanfill, 1991), to improve the performance of the IBARI approach and provide multiresolution bathymetric data sets suitable for various purposes. Similarly, the simple image-jiggling technique employed in this study could be improved via image augmentation methods that can be combined with convolutional neural networks to create feature-invariant detection and tracking algorithms (Bloice et al., 2017).

5. Conclusions

Although the potential for spectrally based remote sensing of river bathymetry has been demonstrated through several previous studies, further research is needed to address the limitations of this approach and allow image-based techniques to become a more efficient and widely used means of characterizing fluvial systems. In this study, we focused on one such issue: the grainy, pixelated appearance of depth maps derived from passive optical image data. This kind of noise-riddled bathymetry is often perceived as being of lower quality and can have a negative impact on subsequent applications, such as habitat assessment and flow modeling. One source of noise is reflectance from an irregular water surface, or sun glint, and we hypothesized that whereas an instantaneous snapshot of a river captures this variability and can lead to erratic depth estimates, averaging images could yield a smoother image texture and enhance depth retrieval performance. Our objectives in this study thus were to develop a workflow for IBARI and to evaluate whether and to what extent this approach could yield more reliable, useful bathymetric information. We pursued this goal using field observations of water depth and a series of videos acquired from a helicopter hovering above several locations along the Salcha River, a clear-flowing, gravel-bed stream in central Alaska, USA. Revisiting the hypotheses and research questions posed in the Introduction, our results indicated that:

1. Depth estimates derived from time-averaged images produced from videos were more accurate and precise than depths inferred from individual frames.
2. Bathymetric maps generated from time-averaged images also had a smoother texture, quantified in terms of the spatial standard deviation of depth estimates within moving windows of various sizes, and thus provided a more spatially coherent, realistic representation of channel form conducive to subsequent analyses.

3. An analogous spatial-averaging approach that involved simulating multiple image realizations by randomly shifting a single frame relative to itself (i.e., image-jiggling) did not enhance the reliability and texture of image-derived depth maps, however.

4. Although depth retrieval from time-averaged images improved with the duration of the image sequence, performance metrics including the mean and standard deviation of depth retrieval errors and the observed versus predicted $R^2$ tended to stabilize after about 30 s of data collection at a frame rate of 1 Hz.

5. The number of images averaged was more important than the length of time encompassed by an image sequence, implying that capturing video at 30 Hz could reduce acquisition times without compromising depth retrieval.

6. Similarly, using a larger number of randomly shifted image realizations to compute an ensemble mean via the hybrid time- and jiggling-averaging version of IBARI led to more reliable depth estimates but with diminishing returns beyond about 30 images.

In addition, we demonstrated the ability to scale up the IBARI workflow by compiling depth maps derived from averaged images acquired at 10 hover waypoints along a 2.36 km reach of the Salcha River. This approach could thus facilitate reach-scale bathymetric mapping based on remotely sensed data acquired from helicopters, sUAS, and possibly satellite platforms.

Data Availability Statement

All of the remotely sensed data and field measurements used in this study are publicly available through a data release (Legleiter & Kinzel, 2020a) and accessible via a DOI link: https://doi.org/10.5066/P9S4T8YM.

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