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TECHNICAL NOTE

Low-cost stage-camera system for continuous water-level monitoring in ephemeral streams

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ABSTRACT
Monitoring ephemeral and intermittent streams is a major challenge in hydrology. On-site inspections may be impractical in difficult-to-access environments. Motivated by the latest advancements in digital cameras and computer vision techniques, in this work, we describe the development and application of a stage-camera system to monitor the water level in ungauged headwater streams. The system encompasses a consumer-grade wildlife camera with near-infrared (NIR) night vision capabilities and a white pole that serves as reference object in the collected images. The feasibility of the approach is demonstrated through a set of benchmark experiments performed in natural settings. Maximum mean absolute errors between stage-camera and reference data are approximately equal to 2 cm in the worst scenario that corresponds to severe storms with intense rainfall and fog. Our preliminary results are encouraging and support the scalability of the stage-camera in future implementations in a wide range of natural settings.

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1 Introduction

Headwater streams govern runoff formation and debris/sediment mobilization, and thus are important controls for the ecological and geomorphic dynamics of catchments (Bishop *et al.* 2008, Datry *et al.* 2014, Siebers *et al.* 2020). Seasonal and event-based variability of the climatic forcing in these uppermost catchment areas often originates intermittent and ephemeral streams, whereby discontinuous flow or sporadic flow in response to rainfall events poses severe challenges to a thorough characterization of network patterns (Borg Galea *et al.* 2019, van Meerveld *et al.* 2020). Monitoring flow in headwater streams is key to unravelling the complex relationships between climatic and landscape features in temporary rivers.

Conventional observational approaches, including streamgauges and current meters, may often be inadequate to monitor streamflow in these dynamic and highly heterogeneous systems where highly variable cross-sections and water levels often hinder their applicability (Tauro *et al.* 2018). Overland flow detectors were developed by Kirkby *et al.* (1976) and modified versions have been applied in several field studies (Vertessy and Elsenbeer 1999, Elsenbeer and Vertessy 2000, Vertessy *et al.* 2000, Johnson *et al.* 2006, Zimmermann *et al.* 2014, Perez *et al.* 2020). Such passive instrumentation can be deployed onto the soil surface and then manually checked to assess the presence or absence of water. Alternative methodologies have been conceived to automatically monitor the presence of water in ephemeral streams. They include temperature sensors (Constantz 2008) and electrical resistance sensors (Peirce and Lindsay 2015, Jensen *et al.* 2019, Paillex *et al.* 2020). A combination of electrical conductivity (EC) sensors, time-lapse imagery, and conventional gauging afforded monitoring at high spatio-temporal resolution in Assendelft and van Meerveld (2019) and van Meerveld *et al.* (2020).

Data collected from temperature-based or EC systems can be affected by the accuracy of positioning of the sensor at the deepest point in the channel cross-section and are generally difficult to interpret. Notably, ambiguities in detecting zero-flow readings have been shown to have far-reaching implications for hydrological and biogeochemical predictions (Leigh *et al.* 2016, Vander Vorste *et al.* 2020, Zimmer *et al.* 2020). In addition, most of these systems only allow researchers to distinguish between wet and dry conditions, without any additional information on the flow magnitude. To improve identification of the causes of intermittency and to expand monitoring capabilities, visual inspection is often mandatory. Unfortunately, in-person observations are time consuming, and sometimes impossible in impenetrable natural environments. On the other hand, remote sensing has been proposed as an efficient approach to monitor large areas with spatially continuous and frequent coverage (Borg Galea *et al.* 2019).

Cameras have the potential to afford remote and continuous observations of relatively extended areas without affecting the flow field. Therefore, optic systems are increasingly being installed in existing monitoring stations to complement information gathered with and to assess the performance of traditional equipment (Pagano *et al.*

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2020, Vetra-Carvalho *et al.* 2020). Portable and permanent implementations of image-based systems have demonstrated the suitability of photogrammetric approaches to characterize the surface flow velocity field and monitor floods in natural streams (Tauro *et al.* 2014, 2016a, 2016b, Perks *et al.* 2016, Pearce *et al.* 2020). With regards to water level detection, Kaplan *et al.* (2019) adopted time-lapse photography to show the absence or presence of flow in ephemeral and intermittent streams through image processing.

Besides the detection of the flow status, imagery can be effectively used to quantitatively estimate water level. In river systems, imagery has opened novel capabilities towards water level measurement in ephemeral settings (Schoener 2018). Since the pioneering work by Takagi *et al.* (1998), most of these image-processing approaches rely on the detection of the water line – that is, the "boundary" sub-horizontal line at the water–air interface. A similar approach is described by Kim *et al.* (2011), whereby the borderline between the water and a ruler is automatically detected using a histogram of consecutive images. Sakaino (2016) also applied a procedure based on the histogram to detect a flooding event. Staff gauges of uniform colour are proposed by Royem *et al.* (2012) to enhance the visibility of the water line in pictures captured with a low-cost digital camera. Lin *et al.* (2018) integrated computer vision and photogrammetric principles to achieve water level detection in images of a water gauge.

Image-based approaches generally consist of the following steps: extracting greyscale images from digital cameras, applying image binarization through user-defined thresholds, conducting morphological operations to simplify images, and then detecting the water line using edge detectors (Shin *et al.* 2008, Yu and Hahn 2010, Gilmore *et al.* 2013, Lin *et al.* 2013, 2018, Yang *et al.* 2014). Image distances in pixels are related to the real-world reference system using fiducials. Another approach for shore line detection that does not require the presence of measuring boards or staffs in the field of view encompasses a spatio-temporal texture analysis on a sequence rather than a single image (Kröhnert 2016, Kröhnert and Meichsner 2017). This technique has proved particularly suited for implementation on smartphone technology (Elias *et al.* 2019). Further, a combination of this method with high-resolution topography from structure from motion topography obtained with the structure-from-motion technique has enabled accurate water stage estimations in ungauged catchments (Eltner *et al.* 2018). Further computer vision methods for water level detection include semantic segmentation algorithms (Lopez-Fuentes *et al.* 2017), analysis of the water intensity signal relative to fixed features (Leduc *et al.* 2018), principal component analysis (Young *et al.* 2015), and machine learning (Chapman *et al.* 2020).

The pervasive use of digital cameras and the availability of high-performance digital systems at affordable costs make image-based measurements a promising approach to overcome the bottleneck of streamflow data scarcity in headwater streams. On the one hand, large volumes of image data, such as those available through social media posts, can be processed with deep learning algorithms to extract information on the water depth (Chaudhary *et al.* 2020, Feng *et al.* 2020, Lin *et al.* 2020, Jafari *et al.* 2021). On the other hand, crowdsourcing and citizen science initiatives aimed at massively processing large volumes of imagery data may be viable alternative approaches to traditional methods to monitor stream status (Seibert *et al.* 2019, Nardi *et al.* 2021). In fact, public involvement may lead to temporally dense data for multiple locations. Further, citizen-supervision may be highly instrumental in developing benchmark datasets in ungauged sites.

Despite their promise, autonomous photogrammetric methodologies have been sparsely adopted for hydrological measurement. For instance, a proof-of-concept discharge measurement is demonstrated in Stumpf *et al.* (2016), whereby the water level is derived by projecting the digital terrain model on the image plane. Nones *et al.* (2018) used the detection of water line displacement to provide insight on long-term fluvial morphodynamic processes. Ridolfi and Manciola (2018) combined unmanned aerial vehicle technology and water line detection to compute the water level at a dam site. Near-infrared (NIR) imaging from a video surveillance system is proposed by Zhang *et al.* (2019a, 2019b) to measure the water level at large-scale riverine sites in settings with complex illumination.

Motivated by the latest advancements of digital cameras and computer vision techniques, in this work, we design and develop a stage-camera system to monitor the water level in intermittent and ephemeral streams in ungauged headwater areas. Different from approaches that rely on measurement boards, this system seeks to estimate the water depth from the out-of-water length of a simple white-painted steel pole. Images of the pole are captured with a low-cost wildlife camera set in time-lapse mode that enables image acquisition both during the day and at night. Images are processed off-line through a computationally inexpensive algorithm featuring image quantization based on automatically determined intensity thresholds and image binarization. The actual length of the pole is known a priori and care is taken to keep it at the centre of the image to limit image distortion and, thus, circumvent camera calibration through the acquisition of fiducials (Johnson 2017). The feasibility of the stage-camera for hydrological measurements is demonstrated through a set of experiments performed in an actual small-scale catchment. The objectives of this work are: (i) to describe an efficient yet affordable system for water level monitoring in small-scale streams; (ii) to develop a simple procedure to accurately estimate water levels from images in a wide range of illumination and meteorological conditions; and (iii) to demonstrate continuous non-intrusive water level monitoring under a broad range of field conditions. Compared to traditional monitoring methods, the stage-camera offers several advantages: it allows the simultaneous estimation of the water level in headwater streams and supervision of the stream area and banks. Thus, the approach is potentially applicable to monitor an array of variables, including woody debris, sediments, and plastic pollution (van Lieshout *et al.* 2020). Data are derived with negligible flow disturbance through the pole, and, with the exception of major floods, minimal maintenance is required in terms of in-person inspection of the equipment.

Despite these advantages, the potential of stage-cameras for capturing flow patterns in headwater streams still needs to be better explored.

2 Monitoring framework

2.1 Stage-camera system

The system comprises a consumer-grade wildlife camera, the Trap Bushwhacker D3, and a white-painted steel pole (see Fig. 1). The camera captures 16 Mpix images in the time-lapse mode at intervals from 3 s to 24 h. At night, high image visibility is afforded through shooting in the NIR band (850–940 nm). Power loading is enabled through eight rechargeable AA batteries. The pole is 8 mm in diameter and 1.5 m in length and its uppermost end is clearly visible by means of a black stripe. The white paint used is OBI Spray Colour Pure White RAL 9010, Opaque. The pole length is chosen to guarantee that the water level is properly detected even during extreme events. Furthermore, to ensure system stability, the pole is fixed to the ground for 40–50 cm. Once installed in the stream thalweg, the pole's slight thickness yields minimal resistance to the flow. The system costs approximately €185 (the Trap Bushwhacker D3 is available on the market at €110).

In this implementation, the camera is tied to a 1-m-long grounding bar through straps and installed on a river bank at a few decimetres from the river. The grounding bar is fully fixed into the ground to ensure image stability. The camera is set at a distance of 2–4 m from the pole (see the left panel in Fig. 1), with its axis roughly perpendicular to the longitudinal section of the river bed. Care is taken in focusing the pole at the camera's image centre and in positioning the stage-camera system so as to prevent direct sunlight from entering the objective. Images are either 4640 × 3480 pixels or 4032 × 3024 pixels in spatial resolution, which leads to a pixel length of 0.03–0.06 cm. Images are taken every 30 min, thus guaranteeing a system runtime of approximately two weeks, and then stored in a 32 GB SD card.

2.2 Image processing

Image processing consists of two phases. First, the out-of-water pole length is estimated using an image-based algorithm. Then, raw measurements are filtered through a simple statistics-based scheme. These two phases are implemented in Matlab and R environments, respectively, and are detailed below.

2.2.1 Water level detection

The water level estimation procedure relies on the assumption that the pole is the brightest object in the field of view (see the flowchart in Fig. 2). Coloured images are converted to greyscale by eliminating the hue and saturation information while retaining the luminance. Then, a region of interest (ROI) larger than the pole is automatically trimmed around it (see the pre-processing step in Fig. 2). To minimize distortions, the distance of the pole to the camera is kept within the 5 m range with the pole consistently occupying the central region of the image, and, therefore, image geometric correction is not necessary. In fact, in challenging illumination settings, we estimate that the third quantile of the frequency distribution of the absolute difference between water level estimations from raw and undistorted images is equal to 0.001 m.

Images are segmented through the nonparametric unsupervised Otsu method based on grey-level image histogram (Otsu 1979), and then quantized according to the classes assigned in the segmentation (see parameter setting and segmentation in Fig. 2). The number of segmented classes (S in Fig. 2) is set

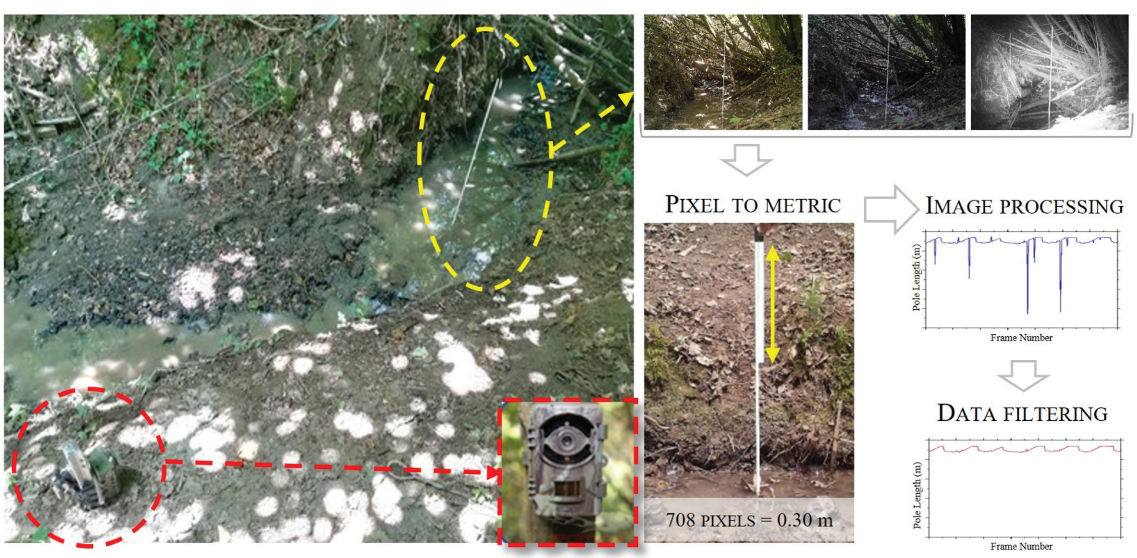

Figure 1. Left, stage-camera system including a wildlife camera installed on a river bank (enclosed in the bottom left dashed circle) and a steel pole fixed in the stream (enclosed in the top right dashed ellipse). In experimental tests, the camera is installed with its axis roughly perpendicular to the longitudinal section of the river bed. Right, images are captured both during the day and at night (see the top sequence of pictures). Pixel to metric conversion is conducted by preliminarily calibrating images in situ (see the ruler placed next to the uppermost part of the pole in the center picture). Greyscale images are processed to detect the pole (see the image processing graph). Then, a filtering procedure removes eventual outliers (see the data filtering graph).

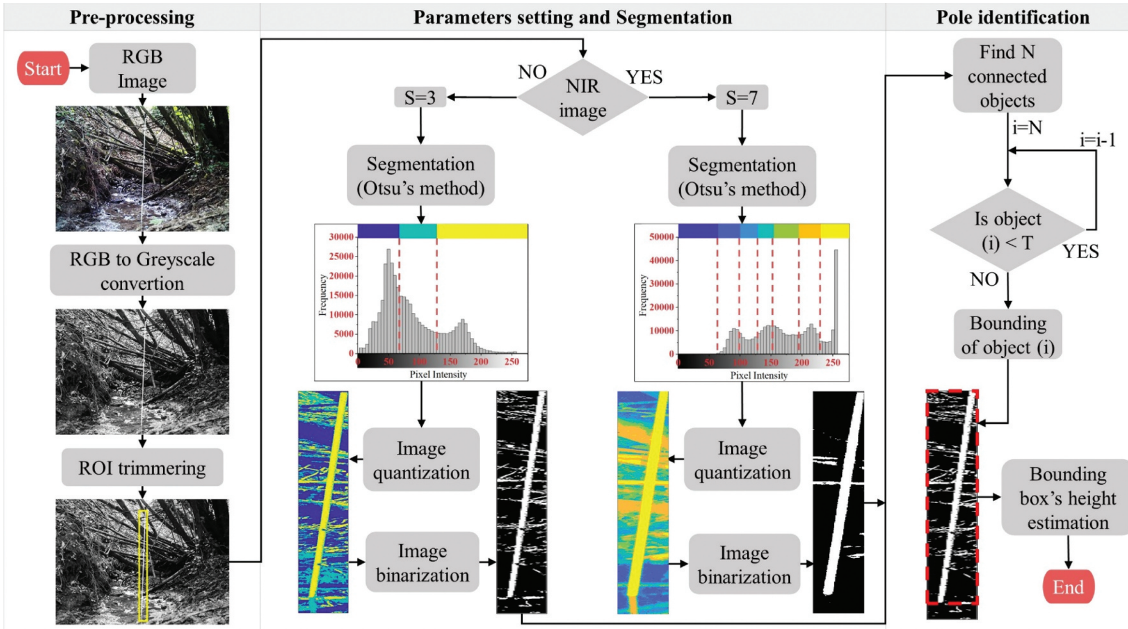

Figure 2. Flowchart of the image processing scheme for a representative experimental test: (i) RGB images are converted to greyscale and a region of interest is established in greyscale pictures; (ii) segmentation through Otsu's method (Otsu 1979) is executed, whereby a different number of segmented classes (S) is adopted if images are taken at night (S = 7) or during the day (S = 3); (iii) images are quantized; (iv) image binarization is performed; and (v) the pole is identified as the largest among 8-connected objects in the image based on a predefined value T, and enclosed in a bounding box to estimate the out-of-water pole length.

according to illumination conditions: in the case of diurnal images, images are segmented in two (three or five) classes if they display homogeneous (heterogeneous) backgrounds; conversely, images captured at night are segmented into four or seven classes. Image binarization is then performed by setting the brightest class to white and the darker classes to black. To prevent eventual ambiguities due to sunlight reflections, the class pertaining to the pole is identified by imposing a constraint on the admissible number of pixels (that is, the amount of pixels pertaining to the pole spans within an a priori defined range; see pole identification in Fig. 2). Specifically, among 8-connected objects (that is, objects whose pixels are connected horizontally, vertically, and diagonally) depicted in the binary images obtained after segmentation, the pole is identified as the object with the largest number of pixels. To this end, a predefined value (T in Fig. 2) is experimentally found by preliminarily analysing a large number of images. Hence, it is automatically bounded in a rectangle and, depending on the image background complexity, either the side or the vertices of the bounding box are used to estimate the out-of-water pole length. Water level is then estimated by subtracting the out-of-water length from the total pole length. Pixel to metric conversion is conducted by calibrating images in situ based on the pole length. Such in situ calibration should be repeated in the case of eventual changes in the setup position due to wind/erosion effects.

2.2.2 Data filtering

Raw water level estimations are further processed through a filtering procedure to remove eventual outliers (Fig. 3). Outlying data may eventually be found due to adverse illumination conditions that yield inaccuracies in detecting the pole in images. First, a moving average with window width set to 3 is computed and subtracted from raw data (ε in Fig. 3c). Outliers are identified by first computing the absolute difference between moving average and raw values. Records whose difference exceeds the 90% quantile are defined outliers. Such data are removed and replaced with inputs obtained through linear interpolation between values acquired at the previous and subsequent time steps. The value of the window width is chosen to maximize the difference between raw and averaged data only on those records that are strongly over- or underestimated. At the same time, this minimizes the difference between raw and average data close to errors, and thus, values immediately before and after outliers fall within the 90% quantile and are not removed.

2.3 Experimental tests

Five experimental tests are carried out to evaluate the efficiency of the stage-camera (see Fig. 4 and Table 1). Tests are executed in a headwater stream in the Montecalvello catchment (20 km from Viterbo). At the cross-section of tests A and C–E, the catchment drainage area is equal to 1.9 km^2. At the cross-section of test B, the stream drains an area of 4.4 km^2. The stream bed is approximately 1 m wide.

Test A is executed in the Montecalvello catchment (Fig. 4). The camera is installed at a stream bank and captures the pole set in the thalweg. Collected images encompass variable light conditions, heterogeneous backgrounds, and water level fluctuations. The site features diverse illumination conditions: diffused light hits the pole early in the morning and late in the afternoon. During the day, scattered sunlight (see, for instance, the bright spots on the left of Fig. 1) occurs and is scattered throughout the field of view due to irregular riparian

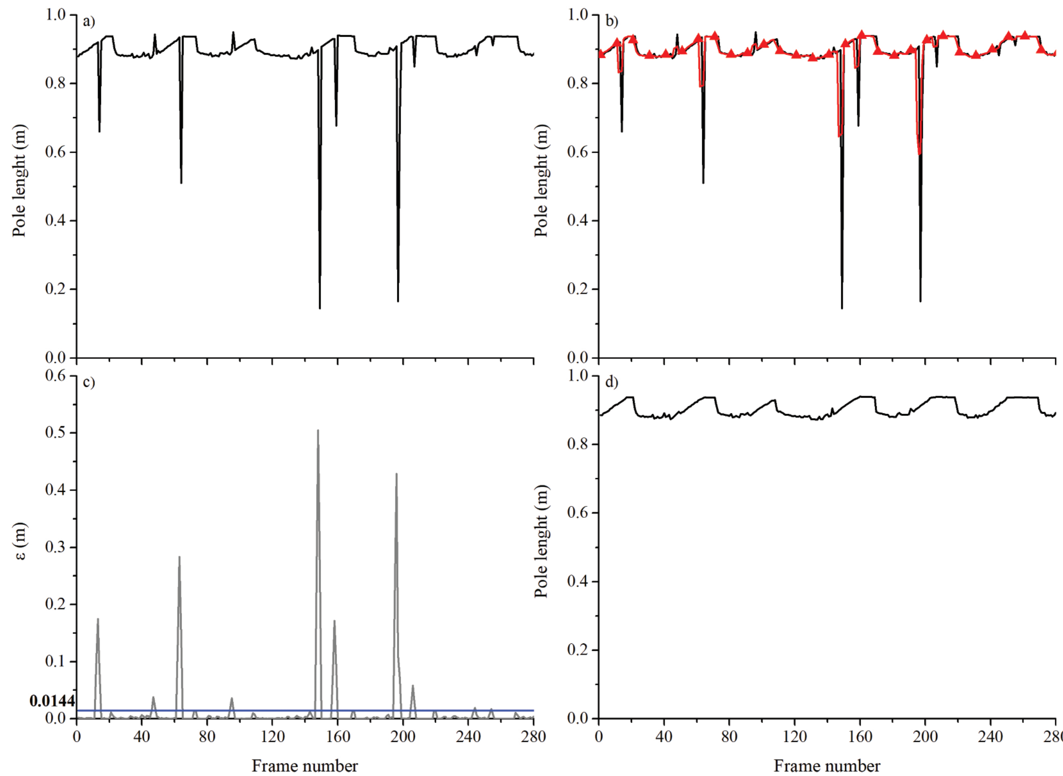

Figure 3. Image filtering scheme: (a) time series of raw out-of-water pole length data; (b) data processed through a moving average (solid line with triangle markers); (c) outliers are identified as data above the 90% quantile (horizontal line); and (d) output filtered water levels.

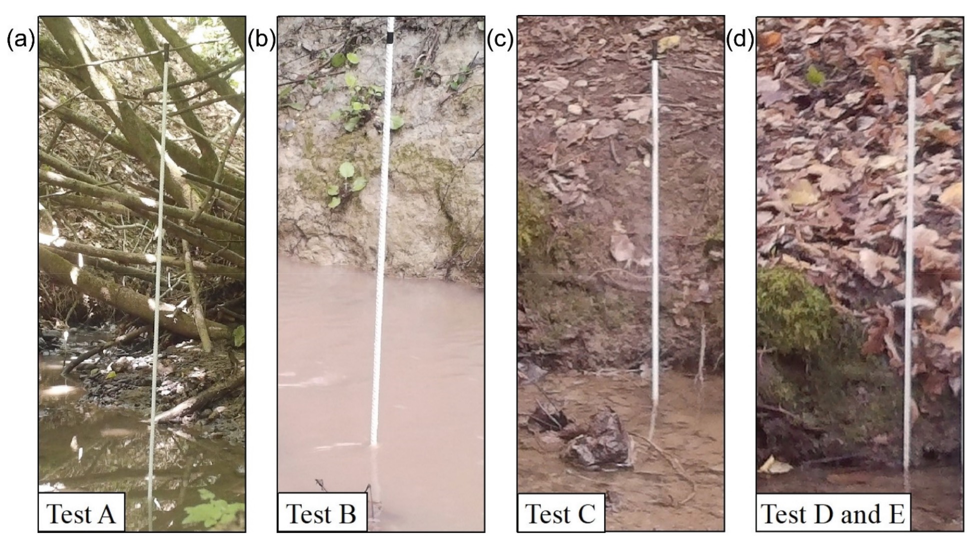

Figure 4. Experimental test conditions: from left to right, variable light conditions, heterogeneous backgrounds, and stream-level fluctuations (test A); intense direct light during most of the day (test B); heterogeneous backgrounds, irregular illumination, and raindrops (test C); and rainfall conditions (tests D and E).

vegetation canopy. Daily fluctuations in the water level lead to a dry riverbed in the afternoon. A total of 286 images collected from 2 to 8 June 2020 are analysed.

Test B is carried out approximately 2 km downstream of site A (Fig. 4). Therein, riparian vegetation canopy is absent and intense light hits the field of view during the day, whereby diffused light occurs early in the morning and late in the afternoon. A total of 28 images collected on 14 and 15 October 2020 are analysed. Towards the end of the test (on 14 October, from 6pm to 10pm), a storm event occurs (average rainfall intensity equal to 5.4 mm/h and 4 h long), which is captured in analysed data.

Table 1. Major characteristics of the experimental tests: catchment area at the test cross-section (Catch. Area), date of the test (Date), number of analysed images (No. of images), light conditions, and presence of rainfall (Rainfall). The number of "+" symbols indicates the severity of the rainfall events during the test.

Test	Catch. area km^2	Date	No. of images	Light conditions	Rainfall
A	1.9	2–8 June	286	Diffused early morn. and late aft.; scattered in the day	–
B	4.4	14–15 October	28	Diffused early morn. and late aft.; intense in the day	++
C	1.9	2–6 March	201	Irregular	+++
D	1.9	1–3 December	100	Irregular	+
E	1.9	5–8 December	180	Irregular	++

Test C is executed in a river segment close to the site of test A in more adverse hydrometeorological conditions (Fig. 4). Specifically, 201 images were collected on 2–6 March 2020, during rainfall events. This case represents critical experimental conditions, where heterogeneous backgrounds combined with irregular illumination and raindrops sensibly affect image quality. In particular, moisture on the camera and mud on the NIR sensor tend to yield noisy images.

Tests D and E also capture a cross-section nearby the location of tests A and C. Test D encompasses 100 images captured 1–3 December 2020, during three consecutive rainfall events. The events lasted for 2.20, 1.20, and 7.20 h and had an average intensity of 1.4 mm/h, 1.8 mm/h, and 3.3 mm/h, respectively. In test E, 180 images were collected 5–8 December 2020, during two rainfall events of 4.10 and 5.30 h, respectively. Average intensities were 4.8 mm/h and 3.3 mm/h, respectively.

2.4 Data validation

Water level data obtained from the automated image processing methodology are benchmarked against values gathered through manual inspection of every picture. Given complex flow and accessibility conditions of the experimental sites, alternative classical measurement equipment, such as pressure transducers and standard water level loggers with stilling wells, are unfeasible. For each experimental test, image sequences are visually analysed, picture by picture, and the pole–water interface (y_{int}) is identified by eye. The uppermost end of the pole (y_{top}) is determined once for each image sequence, and the actual pole length is estimated from $|y_{top} - y_{int}|$. Water levels are finally computed by subtracting this actual length from the pole's a priori known total length. The length in pixels is computed from the pixel-to-metric conversion coefficient introduced in Section 2.2.1. This procedure allows the validation of the accuracy of automatic pole detection in images with computer vision against a manually supervised technique. Further assessment of the occurrence of eventual systematic errors is not investigated.

3 Results and discussion

The mean absolute error (MAE) between image-based water levels and supervisedly estimated benchmark data as in Section 2.4 are between 0.36 cm (0.27 cm) and 2.20 cm (2.02 cm) for the unfiltered (filtered) water levels, Table 2. The relative error (RE) ranges between 3.73% (3.42%) and 26.78% (19.95%) for unfiltered (filtered) values. Interestingly, despite unfavourable rainfall, tests D and E exhibit the closest agreement between image-based and benchmark data (lowest MAE values for both unfiltered and filtered water levels in Table 2). In test A, the reconstruction of water level provided by image processing clearly describes water fluctuations (Fig. 5). Unfiltered data show a few strongly underestimated water levels (leading to large MAE values) in the rising limbs of the time series. Such outliers are effectively removed and corrected with the filtering procedure. Remarkably, this abates the MAE by about 75%.

Table 2. Mean absolute error (MAE) and relative error (RE) values between image-based water levels and supervisedly estimated benchmark data for each experimental test. Values are computed both on unfiltered (unfilt.) and filtered (filt.) water levels.

Test	MAE (unfilt.) cm	MAE (filt.) cm	RE (unfilt.) %	RE (filt.) %
A	1.34	0.33	26.78	5.70
B	1.39	1.54	18.08	19.95
C	2.20	2.02	17.41	16.43
D	0.46	0.27	7.34	4.24
E	0.36	0.32	3.73	3.42

The storm event that occurred on 14 October is accurately captured in both unfiltered and filtered water levels in test B (Fig. 5). However, severe illumination from 2.10pm to 3.30pm leads to level overestimations during this period. Unfortunately, application of the filtering procedure did not remove such inaccuracies, thus leading to a higher MAE value than for unfiltered data. Test C shows the highest MAE values due to challenging rainfall conditions (Fig. 5). Poor image quality leads to some underestimations in the water level towards the end of the event, with maximum discrepancies on the order of more than 10 cm. Notably, application of the filtering procedure reduced the MAE by 8%. Measured water levels in tests D and E accurately reflect the actual fluctuations of the stream. While the technique is generally successful at identifying the pole length, a few localized discrepancies occur. For instance, the sharply underestimated value in image 47 of test E is attributable to low image quality due to moisture on the lens combined with adverse illumination conditions. Experimental findings emphasize the influence of image quality on the performance of the stage-camera approach to accurately capture streamflow dynamics. This may have adverse implications for long-term monitoring in severe rain and illumination conditions, and mandates further research to improve automated image processing. We emphasize that the proposed system is inherently designed for small and ephemeral streams with cross-sections ranging within 0.1–5 m. In the case of larger sections, channel geometry and streamflow are likely more stable and, in turn, traditional instrumentation may be more appropriate. Importantly, vegetation on the stream banks was dense enough to minimize wind effects that led to negligible motion of the pole-camera system during tests. In parallel, volatile material did not obstruct the view even during storms, and camera acquisitions were never hindered.

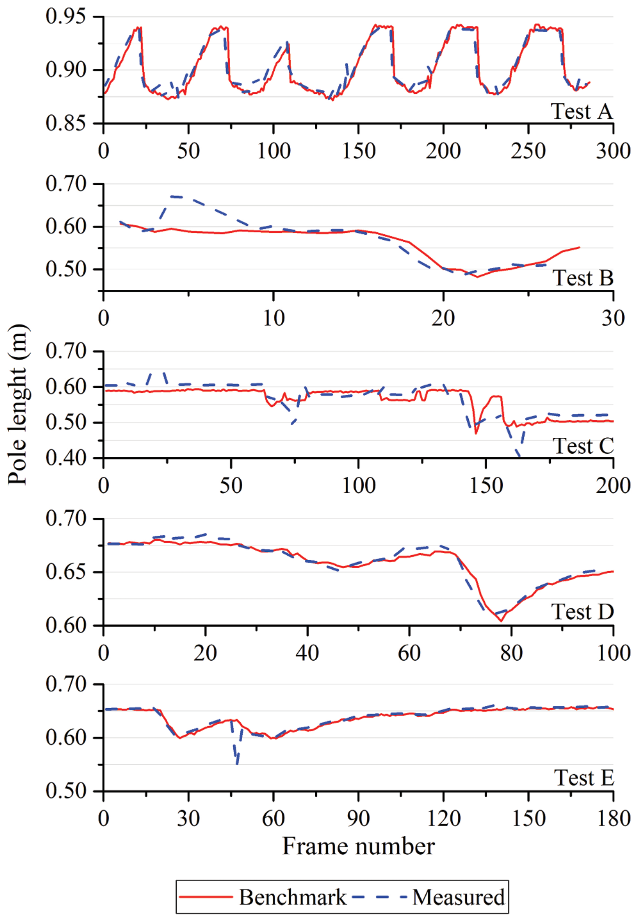

Figure 5. Experimental results: from top to bottom, the time series of filtered water levels (dashed lines) are compared against benchmark values for all experimental tests (solid lines).

Despite challenging image quality, the use of the stage-camera system is promising for monitoring intermittent and ephemeral streams in cases where other technologies for discharge monitoring are not viable options. Notably, pressure transducer observations at consistent cross-sections of the tests herein reported led to poor-quality water level estimations. In particular, in the aftermath of a low flood, the instrumentation was easily bypassed and silted. With regards to the vulnerability of the stage-camera system to eventual changes in the imaging geometry caused, for instance, by wind or water, we note that, since the system installation, we did not note any significant modifications in the position and orientation of the camera or the pole. This was well demonstrated by close to null image intensities obtained by subtracting images collected at different times and consistent cross-sections. Conversely, while we recognize that major floods may inevitably bend or even rip away the pole, we remark that such inexpensive instrumentation may be easily replaced for future measurements. Also, even the possibility of capturing images during such major events is a significant asset in hydrological monitoring: visual consideration of the channel geometry may in fact offer valuable insights on the flood dynamics.

Future ameliorations of the image processing technique may help in further enhancing the performance of the approach. First, illumination conditions and the presence of scattered sunlight are important controls on image quality and severely affect the estimation of the out-of-water pole length. Currently, no image is discarded before image processing irrespective of eventual image intensity saturation regions. In future implementations, preliminary controls on the global brightness of single images may be conducted to inform the application of specific enhancement procedures or a more advanced selection of the number of segmentation classes. Alternatively, the setup may be integrated with luminance sensors to guide image processing.

Our analysis indicates that rainfall has a high impact on image quality. The presence of raindrops leads to images with unsharpened edges, making the identification of the pole challenging. During test C, raindrops directly fell on the lens and affected the image field of view, while during tests D and E, raindrops had no tangible effects, thus leading to improved image quality and MAEs. The issue of raindrops may be mitigated by covering the camera and eventually tilting it to prevent raindrops to spill onto the camera objective. In this latter case, introducing an orthorectification phase before image processing may be required. Regardless of the specific hydrometeorological conditions, pole visibility can be further enhanced by replacing the pole with a wider board and/or a board of an alternative uniform colour. These modifications may help in unambiguously emphasizing the board as the brightest object in the field of view. On the other hand, increasing pole dimensions may also lead to large quantities of suspended material stacking around it on the stream surface. This will affect the image intensity of the region in proximity of the pole–water interface. In our experiments, stacking of suspended material is observed only for test C; however, this leads to minimal overestimations of water levels during the recession of the rainfall event, which are partially compensated by the filtering procedure. In future experiments, installing a pole (or board) upstream of the measurement site is expected to help in intercepting the suspended material before its transit across the camera field of view.

In some cases (e.g. test B), the filtering procedure is not fully successful in removing water level overestimations. This is due to the fact that the moving average window width is minimized to efficiently identify the outliers. When image-based water levels are not greatly overestimated, though, it may be difficult to detect eventual outliers. For instance, in test B, the presence of a sequence of slightly overestimated records causes higher discrepancies between averaged and accurate raw data than between averaged and overestimated records. Thus, accurate records are replaced with higher values, and the MAE on filtered data increases. Increasing image acquisition frequency, thus better delimiting erroneous records, may be a strategy to compensate for such an issue. In turn, increasing the time-lapse interval has implications for on site image storage and the overall system energy consumption. To this end, future efforts will be devoted to optimizing the stage-camera setup and software components towards the development of an autonomous sensing platform. Hardware ameliorations will in fact enable to capture streamflow dynamics at the seasonal or even multi-year temporal scales. Specifically, solar panels may be installed to enable longer runtimes and on-site image processing through an embedded computing unit. Low-power embedded systems present several advantages for environmental monitoring in remote environments (Tosi *et al.* 2020). Also, they open novel avenues in terms of the scalability of such remote measurement approaches. By interfacing an agile stage-camera platform with a wireless infrastructure, it may be possible to directly transmit water level data in real time to a master system, thus circumventing the need for onsite inspections and greatly simplifying data acquisition and processing. This is expected to facilitate the installation of numerous stage-camera platforms to fully capture expansion and contraction cycles of the headwater drainage network.

4 Conclusions

In this paper, a cost-effective remote approach was developed to estimate the water level of ephemeral and intermittent streams. The system comprises a wildlife camera and a reference pole of known length. A simple image-based processing algorithm was developed and combined with a filtering procedure to compute water level data in complex natural settings. In the presented implementations, the stage-camera captured images every 30 min and featured an autonomy (of both battery and data storage) of two weeks. Stage-camera data were in general agreement with benchmark values (maximum mean absolute errors around 2 cm in severe hydrometeorological conditions) and the filtering procedure was effective at identifying outlying data. Mean errors observed in different tests ranged within 0.27–2.20 cm, suggesting a good potential of this approach for stage monitoring.

The illustrated approach is particularly promising for monitoring the dynamics of headwater drainage networks. In fact, in upland areas, small fluctuations in the water level correspond to significant flow discharge variations, and, therefore, the accurate and continuous observations enabled by stage-cameras may be highly beneficial to map flow intermittency. Finally, the system is inherently designed for enabling accurate and continuous observations at multiple locations in ungauged areas of natural catchments. Therefore, we believe that stage-cameras may be valuable additions to the toolkit available to experimental hydrologists and environmental practitioners.

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Disclosure statement

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