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Source and magnitude of error in an inexpensive image-based water level measurement system

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SUMMARY

Recent technological advances have opened the possibility to use webcams and images as part of the environmental monitoring arsenal. The potential sources and magnitude of uncertainties inherent to an image-based water level measurement system are evaluated in an experimental design in the laboratory. Sources of error investigated include image resolution, lighting effects, perspective, lens distortion and water meniscus. Image resolution and meniscus were found to weigh the most in the overall uncertainty of this system. Image distortion, although largely taken into account by the software developed, may also significantly add to uncertainty. Results suggest that "flat" images with little distortion are preferable. After correction for the water meniscus, images captured with a camera (12 mm or 16 mm focal lengths) positioned 4–7 m from the water level edge have the potential to yield water level measurements within ±3 mm when using this technique.

1. Introduction

Water level measurement is a critical component for observation and management of water resources. Water supply volumes, storm water discharge, and nutrient transport rates are all commonly calculated based on water level measurements. Heiner et al. (2011) investigated seventy installed flow measurement devices, the vast majority of which depended on water height to calculate discharge, and found that 67% of produced measurements were outside of the design error. In many cases, this was due to improper installation or maintenance of the control structures onsite. In addition to installation and maintenance, the impact of changing hydrologic conditions such as weir submergence or backwater conditions (Rantz et al., 1983) are often unknown unless maintenance or research personnel are onsite. An image-based water level measurement instrument will not correct improper installation or maintenance of control structures. However, the user of an image-based water level measurement system has access to additional information, which can be 'visually' verified and interpreted with the human eye, providing tremendous additional value to the current techniques. Hauet et al. (2008b) added that an image-based water level measurement system would be ideal for measuring river stage as part of a field-based particle image velocimetry (PIV) system.

Because the interpretation of the raw data is performed away from the field (real time or after collection on an SD card), the proposed image-based system does not require on-site calibration and for that reason involves only low skill maintenance such as cleaning the camera lens, and ensuring a clean and plumb target background. This opens the possibility for communities (e.g. flood prone areas) where no hydrological expertise is available to obtain their own verifiable and easily understandable hydrological data. The image-based water level measurement system presented here is to be used in the field and the uncertainties for these conditions are under evaluation from 1 year of data (Birgand et al., in prep.). There are specific challenges inherent to water level measurements in field settings which have consequences on the uncertainties: lighting changes, camera movement, condensation on the lens, etc. (e.g. Bradley et al., 2002; Creutin et al., 2003; Hauet et al., 2008a,b; Muste et al., 2008). To interpret the field performance, however, the sources of uncertainty inherent with this novel technique must be described. Several studies propose image-based water level measurement techniques (Chakravarthy et al., 2002; Iwahashi et al., 2007; Shin et al., 2008; Yu and Hahn, 2010) but none describe in detail the sources of uncertainty associated with

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using images as raw data. This article aims at filling this gap. It describes the sources of uncertainties of this technique using data obtained in controlled laboratory conditions. Laboratory performance of this image-based technique is also compared to two commercially available water level measurement systems for reference.

2. Methods

2.1. Hardware

The camera used in the laboratory study is a rugged wireless surveillance camera (Microseven® Systems M7-RC550WS) equipped with IR lighting for night vision commercially available for less than $300.00 (in 2011). The target background required for the system can be built for less than $100. Access to an FTP server was used to gather data.

2.2. Technique principles

The water level measurement software developed at GaugeCam and available as freeware (http://www.gaugecam.com/product/downloads/) uses machine vision algorithms to measure water levels in two steps. First, water level is detected in the region of interest of an image where water draws a dark line against a white flat background. Second, the equation of the line in pixel coordinates is calibrated to real world coordinates thanks to benchmarks or fiducials, which are printed on the background and thus embedded in each image.

2.3. GRIME software details

GaugeCam Remote Image Manager Educational (GRIME) software was developed by GaugeCam to specifically address the challenges associated with measuring water levels in images. Water level detection is performed with a machine vision tool called an edge detector (ex. Marr and Hildreth, 1980; Torre and Poggio, 1986). On a defined area of an image where the water level draws a line against a flat background, each pixel column is scanned from top to bottom to detect sharp changes in the pixels gray scale using a non-parametric kernel tool. The sharpest gradients are saved as possible indicators of the water surface. The points for all the strong gradients in each column of an image are then evaluated to determine which set of those gradients best fit the expected angle of the water line (based on the rotation of the camera). Considerable amount of work is performed to ignore anomalous points, false lines, glint, etc. The best linear fit for the detected points is considered to be the water line, as shown in Fig. 1. Interestingly, this line's equation is expressed in pixel coordinates and may fall 'between' two pixels, resulting in sub-pixel resolution of the measurements.

To measure water levels in real world coordinates, a transfer matrix is calculated to relate the pixel to the world coordinates. Skew, perspective, and lens distortion come into play and are taken into account. Fiducials, or recognizable features (e.g. Fiala, 2010; Russ, 2011), are embedded at known real-world locations in the image, thus providing a reference between pixel and real world positions in each image. 'Bowtie' fiducials placed in two columns and four rows (Fig. 1) are automatically recognized by GRIME using blob analysis. A piecewise linear regression is then used to create the transfer matrix.

2.4. Sources of uncertainty

Detection and calculation of water level both involve uncertainty. Seven potential sources of uncertainty were identified in the lab: uncertainties associated with the image quality (image focus, image resolution, perspective, and lens distortion), uncertainties associated with the local environment (lighting effects, water meniscus) and uncertainties associated with the interpretation of the image by the software.

Obviously, one would want to obtain the clearest pictures possible as raw data. Most digital cameras available in the early 2010s can take at least several megapixel resolution pictures for images several MB in size. While this opens the possibility to have very sharp images, the memory size of such images is currently totally prohibitive, in terms of data volume and transfer time, for a system e.g. that would be placed in the field and remotely send images via cellular networks every 15 min. The camera for this study was purposely chosen so that images would not exceed 100 kb in size, hence limiting the resolution to around 250 kilopixels (details below).

Such images are not, as a result, as 'sharp' to the eye. Therefore, manually achieving optimal focus is not an obvious or a trivial task and is somewhat subjective. Additionally, focus differs within the same picture because the distance between the camera and e.g. the top and the bottom sides of the background differs, for a camera looking from the top. Focus is thus intrinsically linked to resolution and to perspective.

Representing a three dimensional environment onto a plane involves perspective. The software does account for that (e.g. Fig. 1B). The optics of the lenses themselves, however, add distortion. This is evident when straight lines (especially near the edges of an image) are displayed with a definite curvature on a picture. This effect is a more difficult to model and is only partially taken into account by GRIME. Higher focal length lenses provide less distortion and are thus preferable.

Because of surface tension forces, water forms a meniscus at the contact with a background. The size of the meniscus depends on the water and surface properties of the background. While e.g. a Teflon coated background would provide a different meniscus than PVC, it is the combined impact of the lighting and the meniscus size that creates the sharp change in pixel gray scale in an image. The lighting may change as a result of the angle and intensity of the incoming light source (e.g. sun, clouds, and IR illuminator at night).

The sources of uncertainties for image-based water measurement levels are thus intrinsically linked together. An accepted method to calculate uncertainties involves the classical propagation of error approach. A formal mathematical analysis of uncertainty can be performed for image analysis techniques (e.g. Kim et al., 2007), but only at considerable expense. Eq. (1) is the general equation for uncertainty with covariance (Kirkup and Frenkel, 2006).

$$u^2(y) = \sum_{i=1}^{n}\left(\frac{\partial y}{\partial x_i}\right)^2 u^2(x_i) + 2r(x_1,x_2)\frac{\partial y}{\partial x_1}\frac{\partial y}{\partial x_2}u(x_1)u(x_2) + 2r(x_1,x_3)\frac{\partial y}{\partial x_1}\frac{\partial y}{\partial x_3}u(x_1)u(x_3) + \cdots + 2r(x_i,x_j)\frac{\partial y}{\partial x_i} \times \frac{\partial y}{\partial x_j}u(x_i)u(x_j) + \cdots \quad (1)$$

where y is the measurand, $u(y)$ is uncertainty for the measurand, $u(x_i)$ is uncertainty of the input for x_i, $r(x_i,y_j)$ is the correlation coefficient between inputs for x_i and x_j, While rigorous, this approach also requires simplifying assumptions and estimates of individual uncertainties, which in our case are very difficult to separate.

A complete statistical analysis of all potential sources of uncertainty could theoretically be performed, but would require an impractical (and also costly) effort to fully isolate individual uncertainty components, and is beyond the scope of this article. Therefore, we have chosen to design efficient experiments that