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Vision-based system for the control and measurement of wastewater flow rate in sewer systems

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1. Introduction

Total pollutant mass carried by sewer systems is an important factor affecting the quality of receiving waters [Burton and Pitt 2002]. This is especially the case during sizable rain events, when the total amount of the waste-water/stormwater mixture cannot be treated in the wastewater treatment plant; the overflow water goes directly into the environment (streams, rivers, lakes, coastal seas) through combined sewer overflows (CSOs). This water is untreated and is recognized as an important source of pollution [*e.g.*, Even et al. 2006, Chèvre et al. 2007, Rossi et al. 2009]. Reliable pollutant concentration data are often available via sampling and analysis. However, accurate estimation of the total pollutant mass is infeasible unless the total volumetric flow rate is known with precision and reliability, and so the environmental impact due to CSO's cannot be predicted.

Knowledge of volumetric water flow rate in sewer systems is a key environmental parameter. Robust monitoring of sewers is a challenging task as the environment within them is inherently harsh: constant humidity of 100%, rapid and large water level changes, corrosive atmosphere, presence of gas, difficult access and solid debris inside the flow are some of the usual problems. Accurate monitoring of the volumetric water flow is thus of crucial environmental importance. In this paper, a novel approach to the monitoring of flow in sewers based on video images is presented. Specifically, the method is based on image processing and computer vision techniques for water level and flow velocity estimation.

2. Methodology

The following requirements for a robust vision-based system for monitoring sewers were defined: visual analysis of particular hydraulic behavior, on-line water level and flow measurements, automatic alarm system for particular events (overflows, risk of flooding, etc.), database for data management (images, events, measurements, etc.) and finally the possibility of remote control. These requirements formed the design specifications for hardware and software selection and development for the HydroPix system. The hardware was carefully chosen in order to suit the harsh conditions of sewer systems: cameras are 100% waterproof and corrosion-resistant; infra-red LED illumination systems are water-resistant and have low power consumption; and a waterproof case contains the recording and communication devices. The software was implemented in accordance with modular server/client architecture under National Instrument LabVIEW 8.5.1. Remote access to the data (measurements, images, events, etc.) was achieved using a UMTS modem. The client connects directly to the server's database. The system has the ability to display remotely live images from sewer systems (http://www.hydropix.ch/).

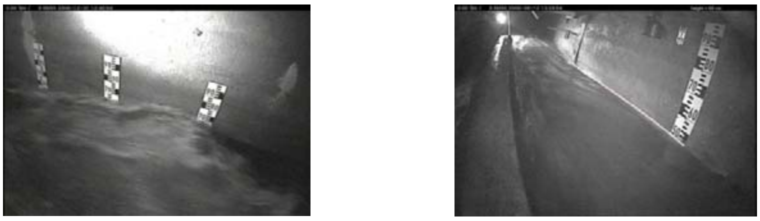
The volumetric water flow Q is defined in Equation 1, where v_N is the normal velocity at each point of cross-section S. Using the mean normal velocity V_m the equation can be simplified to a simple product. Note that the mean flow velocity V_m is directly inferred from the surface water velocity V_S using Equation 2. Parameter λ depends on the nature of the waterbed (material, shape, etc.).

$$Q = \iint_S v_N(S)dS \; = S.V_m \;\; [m^3/s] \tag{1}$$

$$V_m = \lambda . V_S \;\; [m/s] \tag{2}$$

The section S is defined as $S = P(h)\ [m^2]$ where P is the function describing the water channel geometric profile and $h\ [m]$ is the water level. In practice, the channel profile P is known thanks to available construction plans or *in situ* measurements. The two remaining parameters (water level h and mean flow velocity V_m) are measured automatically from the images using computer vision and image processing methods.

A line detection method based on the directional image gradient and the Hough transform [Duda et al. 1972] is used to extract the wall/water interface from images. The detected line is then transferred to the world coordinates system via a calibration step.



(a) (b)

Figure 1 (a) Back-wave effect during a rain event in the Maladière CSO, Lausanne, Switzerland; (b) *In situ* automatic water level measurement in the Denantou CSO, Lausanne, Switzerland (the detected line is shown in white)

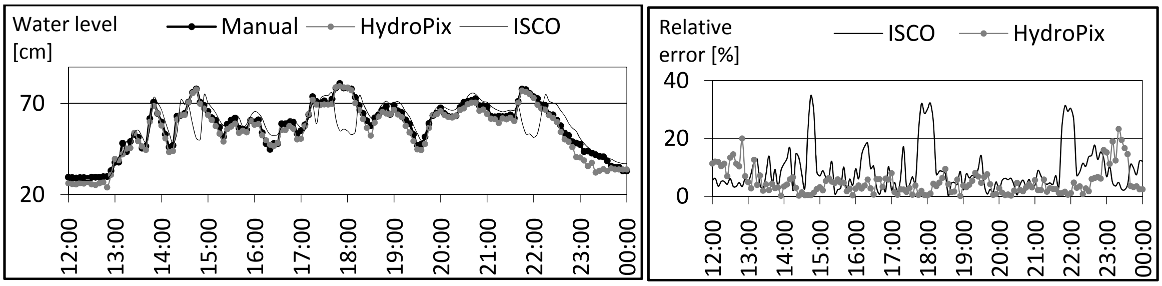
An algorithm processes and analyses the video images in order to provide surface water velocity measurements. After background suppression, a feature tracking method finds correspondences of moving objects in different frames. The program tracks floating objects present in the wastewater surface. Their respective positions are then transferred to the world coordinates using calibration parameters.

The calibration models used for the water level and the surface water velocity algorithms are similar. The pin-hole camera model [Tsai 1987] is used for *intrinsic* calibration (calibration of the camera itself); a homography-based method [Sturm 2000] deals with *extrinsic* calibration (calibration of the camera position with respect to the filmed scene).

3. Results

We have conducted long-term conclusive *in situ* tests of the HydroPix system in various sewer configurations (CSOs, storm-water sewerage and wastewater treatment plants). A first system was installed inside a CSO in Lausanne, Switzerland. Inside, two ISCO 4210 (Teledyne ISCO, Lincoln, NE, USA) ultrasonic water level probes were set up in the sewers at a separation distance of 1.5 m. It was observed that they provided different results during rain events. After visual analysis of the images, the cause of these discrepancies between the measurements was identified as a hydraulic back-wave effect (Figure 1a). A second example took place in a storm-water sewer in Zürich, Switzerland [Burkhardt et al. 2007]. During rain events, flow estimations based on water level measurements of an ultrasonic probe provided results that were much greater than what had been expected based on computer simulations. The acquired images revealed that surface particles travelled upstream. Further investigation revealed that the water level in the sewer increased because of back flow of the receiving water (a small river) into the sewage system. This phenomenon was discovered due to the recorded images. Thus, the HydroPix images provide useful information for the understanding of particular hydraulic behaviors.

Offline water level measurements were conducted on images collected during rain events. An illustration of the results of the water level algorithm is displayed in Figure 1b. The algorithm results were compared to an ultrasonic probe and to manual recordings of the water level according to wall-mounted rulers). The manual measurements were used as a reference. A sample result is displayed in Figure 2. The measurements provided by the water level algorithm proved to be very close to the reference values. The mean relative error of the algorithm is 5.6%; the algorithm proved to be more accurate than the ultrasonic probe with a mean relative error of 13.4%.



(a) (b)

Figure 2 Water level algorithm results during a rain event and comparison with an ISCO ultrasonic probe. (a) Manual reference, the HydroPix water level algorithm results and the ISCO measurements; (b) Relative error of the HydroPix water level algorithm and of the ISCO probe

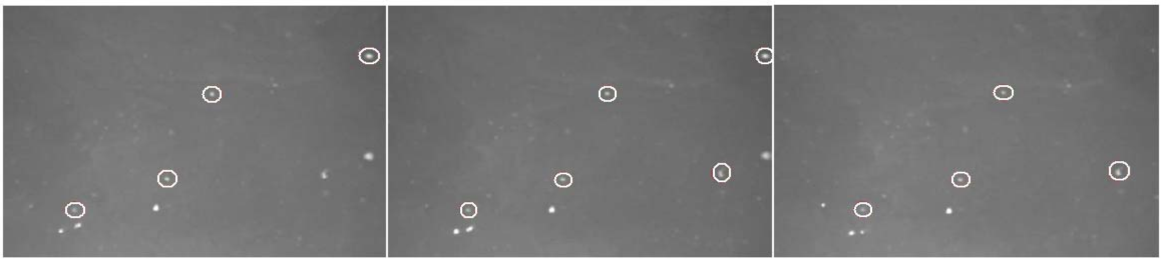


Figure 3 Results of the surface water velocity measurement algorithm. Images were acquired in a wastewater channel. The white circles represent detected and tracked features throughout the three images.

Table 1 Results of the HydroPix feature tracking algorithm. For each test video of wastewater images, the results are compared to the reference (3.28 pixels/frame) found manually. Each video lasts 5 seconds at 200 frames/second.

	Video 1	Video 2	Video 3	Video 4	Video 5
Measured velocity [pixels/frame]	3.6	3.53	3.22	3.41	3.09
Relative error [%]	9.8	7.6	1.8	3.9	5.8

The surface water velocity algorithm was tested on real wastewater images. It was shown to track with reasonable accuracy the features of interest within the flow. Figure 3 illustrates the tracking of floating particles. The tracking algorithm was compared to real values (recorded manually from the images). A comparison of the results can be found in Table 1.

4. Conclusions

Videos and images have been shown to provide valuable information for monitoring harsh environments such as sewer systems. Long term *in situ* tests demonstrated the robustness of the HydroPix system. HydroPix images were found to reliably measure volumetric flows and thereby to provide crucial information leading to better understanding of particular hydraulic behavior. In terms of robustness and accuracy, the water level estimation provided equal or better results compared to traditional ultrasonic probes. Similarly, the video-based surface water velocity algorithm was demonstrated to be accurate for sewer systems. The first results are very encouraging and promising. Further tests must be conducted for a complete validation of the method. Finally, we remark that, in terms of decision making, images can have a strong impact; they have the power to influence choices concerning stormwater management and therefore benefit the ecological status of the receiving water.

5. Acknowledgements

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