Using Digital Image Processing to Estimate the Depth of Urban Streams

Evandro Scudeleti Ortigossa
University of São Paulo
USP
São Carlos, SP, Brazil
Email: evortigosa@usp.br

Fábio Dias
University of São Paulo
USP
São Carlos, SP, Brazil
Email: fabio.dias@icmc.usp.br

Jó Ueyama
University of São Paulo
USP
São Carlos, SP, Brazil
Email: joueyama@icmc.usp.br

Luis Gustavo Nonato
University of São Paulo
USP
São Carlos, SP, Brazil
Email: gnonato@icmc.usp.br

***Abstract*—The urbanization process can present some challenges, such as dealing with the effects of many natural phenomena. In particular, floods can turn into dangerous events. This paper introduces an algorithm to detect and estimate the water level of an urban stream. Using cameras and well defined image processing techniques, we analyze several images of a real stream, aiming at finding the water depth, with encouraging results. Our approach differs from more traditional measurement methods, where specialized equipment are considered, which must be directly inserted on the measurement spot. Through a validation using real images, we demonstrate that our method is a viable alternative to estimate the water level, using cheaper and generic hardware.**

***Keywords*-monitoring; floods; digital image processing; water level;**

I. Introduction

The high population density of modern cities, combined with their effect on the environment, can drastically exacerbate the catastrophic consequences of natural phenomena.

In particular, the urbanization of a region increases the volume and frequency of floods [1]. The damage caused is mainly correlated with two factors: the height of the water during the flood and the warning time between the alert and the occurrence [2]. The problem of modeling and forecasting floods is typically carried out by means of wireless sensor networks (WSN) [3], deployed in locations that are prone to flooding [4]. The gathered information, such as the level and speed of the water, are used as input for complex forecast models in high-performance computers [5].

In this work, we explore the problem of estimating the depth of urban streams through the use of regular cameras, image processing methods, and photogrammetry, as an alternative to specialized sensors. This approach can drastically reduce the cost of a comprehensive monitoring system, as we demonstrate that a smartphone can be used as a monitoring station. Another very significant advantage is that the acquired image can be inspected by a human operator to quickly detect anomalous events, since it conveys more information than only the water level. These images can be stored and reprocessed, improving historical results as the algorithm evolves.

The main contribution of this work is the introduction of a viable method for estimating the water level of streams in urban areas, using generic equipment, which can be a useful alternative in practice, to the more expensive monitoring systems available.

II. Related Work

The problem of monitoring floods in urban streams was already introduced in the literature. Specialized equipment are usually employed, such as depth, water turbidity and speed sensors, inserted directly in the water on locations of interest. Models such as the developed by Basha et al. [6], DeRoure [2] and Humble et al. [7], use a complex wireless-based architecture to broadcast predictive data captured by sensors, covering wide areas with few sensor points. However, the equipment may suffer from interference and accelerated detrition from the submersion in the water stream.

Hughes et al. [8] introduce a Grid-based system that collects information using a collection of sensors. While they use digital cameras to measure the speed of the outflow, the water level is still estimated using depth sensors inside the river. A similar approach is used by Creutin et al. [9], where the particle image velocimetry technique is used to infer the outflow speed, identifying and tracking particles present in the stream. These particles can occur naturally, such as the foam generated by the water turbulence, or be artificially introduced.

Aerial images are used by Puech and Raclot [10] to determine the water level in areas of flood. The images are segmented into sectors, according to a geographical criteria, and the method determines the maximum and minimum depths based on the hydraulic potential of each sector. The method is able to produce an accurate estimate of the water level within centimetres of accuracy. However, the technique requires an aircraft equipped with state-of-the-art high-resolution cameras for image mapping [11].

In a different approach, Giuntoli [12] proposes the elaboration of a participative web-GIS system to map the risk of floods, where the information is not gathered through the use of dedicated sensors but provided by groups of people.

III. Proposed Method

A digital image is usually represented as a matrix containing discrete values of luminosity intensity, associated with physical properties of the materials involved in the scene, such as the shape and reflectance [13]. Each element of the array is usually called *pixel* and represents the smallest spatial portion of the considered information. Colour images are commonly represented using three channels for each pixel, representing the contribution of the colours red, green and blue.

The automatic processing of images of an uncontrolled environment can pose difficult problems. To reduce the complexity of our proposed method, we established some requirements that need to be previously satisfied:

- The stream must be enclosed by a floodwall or an equivalent regular surface. Our method searches for the line defined by the interface of the water and its enclosure.
- The floodwall and the water must be visually discernible.
- The scene must be adequately illuminated.
- The camera must be rigidly fixed, capturing the same spatial region at each sample, allowing the use of a single set of scene information.

Our method can be divided into two main steps, the feature detection and the level estimate. The feature detection step uses image processing methods to identify all line segments present in the image that are viable candidates for the water level line. These candidates are then used in the next step to estimate the water level.

A. Feature Detection

The objective of this step is to detect all the potential line segments in the image, including the line corresponding to the water level. The acquired colour image is converted to grayscale, using 256 shades of gray, and preprocessed using a contrast adjustment and a Gaussian filter [14], reducing variations of the original image. While this simple filter was sufficient here, more sophisticated filters can be considered for this step, such as morphological [15] or bilateral filters [16].

The contours of the images are detected using the Sobel filter [17], [14], resulting in a grayscale image where the value of each pixel corresponds to the maximum variation around it, with higher values corresponding to drastic changes in the image. Therefore, this grayscale image represents the spatial variation in the original image, including the interface between the floodwall and the water, that corresponds to the water level we aim to measure. We then threshold [14] this image to generate a binary image. All values smaller than the threshold are transformed into zero, all values greater or equal into one. The appropriate threshold value varies with the conditions of capture and should be determined case by case. Adaptive methods [18] can also be considered.

The result of this step is a set of lines, identified using the Progressive Probabilistic Hough Transform (PPHT) [19]. Based on the Hough Transform [20], it uses a probabilistic approach that takes into account only a subset of random points that are enough to detect lines. It can be interpreted as a Monte Carlo estimate of the standard Hough Transform, reducing its computational cost [21].

B. Level Estimate

The objective of this step is to identify the line that corresponds to the water level among the lines identified previously and generate a metric estimate of the water level.

To simplify this process, we assume that the camera is static and we provide the method with a **reference line**. This line is perpendicular to the water level and is defined by two points located in the floodwall. The distance between these points in the real world is known. These points are related with the real environment in a similar way to the fiducial markers [22]. This simple step is sufficient to provide reasonable measures and avoids the more complex process of camera calibration.

To identify the line segment that corresponds to the water level, we remove all segments that do not cross the reference line in a specific region. This geometric constraint removes lines that cannot physically correspond to the water level, such as lines above the floodwall. However, depending on the resolution of the considered image, several lines can be identified along this interface. In this case, we chose to consider only the line that corresponds to the higher water level. This criteria leads to a method that is biased towards overestimating the water level, which we believe to be a safe option, for false negatives can be far more dangerous than false positives in a flood monitoring context. More complex methods can be used for this selection without significant changes in the rest of the algorithm.

With the selected line segment and the reference line segment, we need to find the intersection point between them. This issue is addressed using the *LU Decomposition* [23], which consists in decomposing the square matrix formed by the coefficients of the general equation of these lines in the product of an inferior triangular matrix L (lower) and an upper triangular matrix U (upper), from which the intersection point can be easily obtained.

To estimate the water level, we compute the distance between the intersection point and the top of the floodwall. To transform this information from pixels into a metric unit, we use the known distance between the reference points provided. To obtain the water level, we subtract this measure of the wall height, known in advance. Alternatively, if the base of the stream is visible, at any point, we can measure the level directly from it. If such real world measurements are not available, this conversion can be ignored and the relative change in the water level can be measured instead.

IV. Experiments and Results

We implemented a prototype using C++ and OpenCV [24]. The source code and the test images are available at **https://github.com/evortigosa/water_level**.

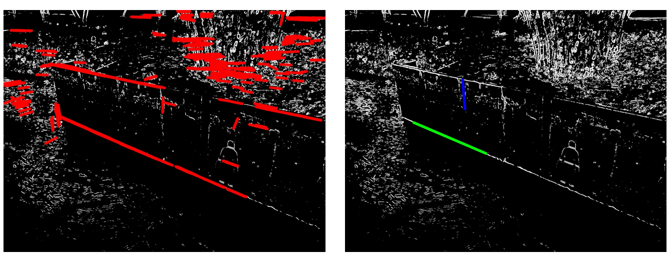
We considered two different experiments, using images from the same stream at different locations. The first experiment is a preliminary evaluation, where we consider images acquired specifically for this purpose. In the second experiment, we consider monitoring images already acquired from the real WSN AGORA deployed in the city of São Carlos, São Paulo, Brazil [25]. In both cases, sensor based measurements are available, allowing a direct validation of our algorithm.

A. Preliminary evaluation

In this experiment we determine if our method is a viable measuring tool in controlled circumstances. We considered eight different images of the Monjolinho stream in the city of São Carlos, São Paulo - Brazil, acquired at approximately the same time on the 4th of May 2015 at 15:28. The images have 2592×1944 pixels, there are no shadows or other illumination issues, and the floodwall is regular and clearly discernible from the water. In this case, each image was captured from a different position, on the bridge above the stream. Since the camera was not fixed, a reference line was provided for each image.

The intermediary results for the image 1 are illustrated in Fig. 1. In this particular case, we used a mask with size 15×15 for the Gaussian filter, and threshold value 25. The minimum length of a line and the maximum gap parameters for the PPHT were 80 and 10 pixels, respectively.

(a) Original image 1. (b) Sobel and Threshold.



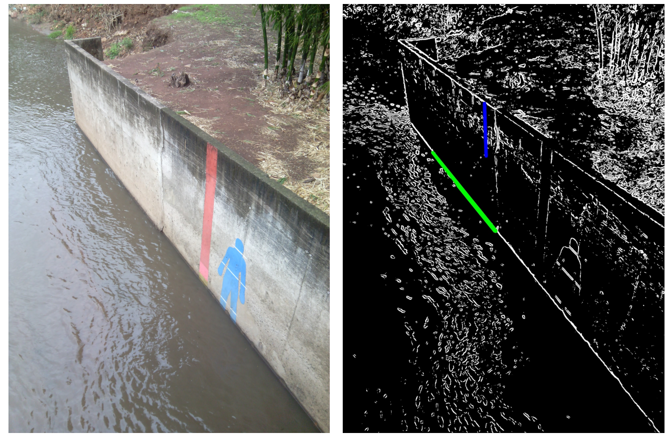
(c) PPHT result. (d) Reference and level lines.

Fig. 1. Illustration of the intermediary results of the proposed method.

To explore the behaviour of the method under different acquisition circumstances, we also varied the angle and orientation of the camera with respect to the floodwall. Image 5 was one of such images and the original image and corresponding result are illustrated on Fig. 2. However, such parameters had little impact on the final result and no clear trend was found.

The results for each image are shown in Table I, including the absolute difference from the average (A.D.) and the error computed considering the water level sensor [25]. The average value obtained by out method was 50.90cm, with a mean absolute difference of 0.37cm. Since the water level was stable, we interpolated the sensor measurement to the moment of the image acquisition, obtaining a value of 51.22cm.

While the conditions of acquisition were ideal, we believe these results to be outstanding. Considering that we are actually measuring the distance between the top of the floodwall and the water level, 0.44cm corresponds to less than 0.2% of relative error, for the height of the floodwall is 2.75m. The maximum error obtained was less than 1cm, which corresponds to less than 0.5% of relative error. Such small margin of error without specialized equipment can be difficult to achieve. Moreover, the camera positioning was reasonably realistic, albeit close.



(a) Original image 5. (b) Resulting image.

Fig. 2. Original and resulting image for image 5.

TABLE I
ESTIMATED WATER LEVEL FOR THE PRELIMINARY EXPERIMENT.

Image	Estimated (cm)	A.D. (cm)	Error (cm)
1	50.24	0.67	0.98
2	50.74	0.17	0.48
3	50.71	0.20	0.51
4	50.45	0.45	0.77
5	51.41	0.50	0.19
6	51.55	0.64	0.33
7	50.93	0.02	0.29
8	51.21	0.31	0.01
Mean	50.90	0.37	0.44

B. Monitoring images

In this experiment, we consider monitoring images from the AGORA WSN deployed in Brazil [25]. Their site provides several months of sensor based measurements for locations in the city of São Carlos, São Paulo - Brazil. For one of these locations, they also provide monitoring images. This sensor node is illustrated on Fig. 3

These images have 640×480 pixels and are acquired hourly.

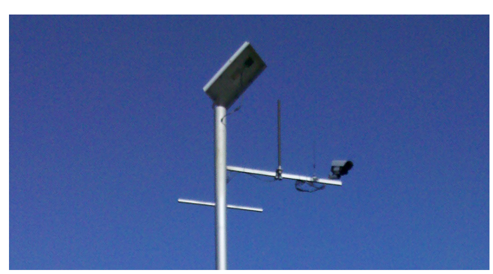
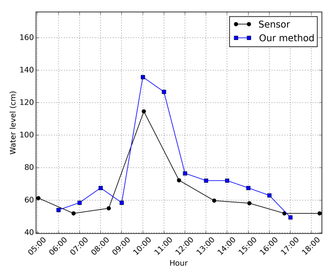


Fig. 3. Sensor node that acquired the images.

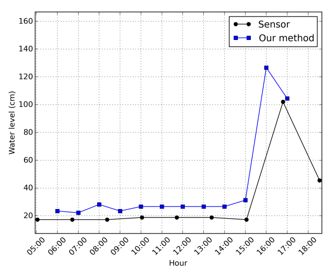
Since this camera is used only for visualization purposes, its positioning changed over time. Indeed, we observed small variations between images captured on the same day. Therefore, we provided each image with a reference line, which is not ideal, but does not invalidate our results, for it is reasonable to assume that a camera positioned for this purpose would not present such variations.

We processed images of four days, with three days containing significant changes in the water level and one day in which the level was stable. The sensor measurements and the water level obtained using our method are illustrated in Fig. 4.

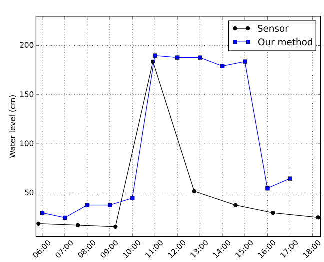
The sensor and the camera acquired information at different times and while the images are referenced by the hour of capture, the exact moment is unknown. Moreover, the interval between measurements is quite large and fast events can occur inside such intervals. Therefore, we are not able to properly calculate error values for all instances. However, we can conclude from Fig. 4 that our method successfully followed the general variations of the water level, albeit a clear bias towards overestimating the water level is noticed, as expected.



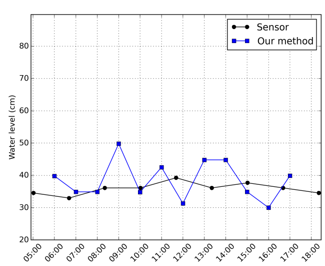
(a) 13th of December 2014.



(b) 5th of January 2015.



(c) 11th of March 2015.



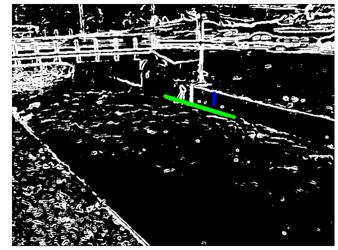
(d) 2nd of April, 2015.

Fig. 4. Comparison between sensor measurements and results of our method.

Consider the peak value on the 13th of December 2014. At 10:03, the sensor measured a water level of 114.61cm, against 135.8cm from our method. While this difference is greater than the values obtained in the previous experiment, it represents approximately 6% of the height of the wall, which is the reference for our method. The original and resulting images for 10:00 are illustrated on the top row of Fig. 5. Visually, the detected water level seems reasonable.

The tendency for overestimation is also present on the results from the 5th of January 2015, where the water level was mostly constant until 16:00. The original and resulting images for 08:00 are illustrated in the top row of Fig. 6.

(a) Original image 10:00.



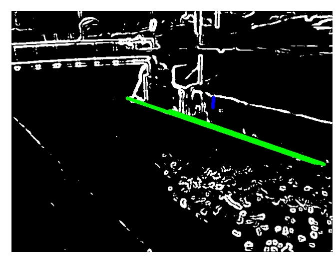
(b) Resulting image 10:00.

Fig. 5. Illustration of results of the 13th of December 2014.

From the original image at 08:00, we can postulate that the result was overestimated due to the low level of the stream, which uncovers a difference in the colour of the floodwall. The resulting image shows that the line corresponding to the actual water level is also detected, but is discarded in favour or the highest line present. While inaccurate, we argue that such behaviour is harmless in a flood monitoring context, for it only occurs when the water level is below the usual level.

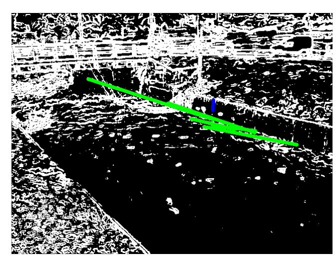
The original and resulting images for 16:00 are illustrated on the bottom row of Fig. 6. The original image was acquired during the rain and shows a high water level. In the resulting image we can see the influence of the rain in the edge detection, notably under the bridge, where the contrast is higher. However, such influence do not change the candidate lines for the water level. The ripples on the surface have more impact on that result, leading to the detection of several different lines. However, the correct water line is detected.

(a) Original image 08:00.



(b) Resulting image 08:00.

(c) Original image 16:00.



(d) Resulting image 16:00.

Fig. 6. Illustration of two results from the 5th of January 2015.

On the 11th of March 2015, we have a high water level around 11:00, which is correctly detected by our method. However, the results in the subsequent hours are greatly overestimated, with an error greater than one metre. The original and resulting images for 13:00 are illustrated on the top row of Fig. 7. In this case, our method detects the portion of the floodwall that is still wet from the previous high level. In contrast to the similar effect on the 5th of January 2015, this one is temporary and ceases at 16:00. Again, we consider this a minor issue, because if the water level would raise above the wet line, the method would correctly detect the water level, avoiding a false negative.

(a) Original image 13:00. (b) Resulting image 13:00.

Fig. 7. Illustration of results from the 11th of March 2015.

We also considered the 2nd of April 2015, a day in which the water level was stable. The results of our method oscillated around the values from the sensors, notably at 12:00, where our method underestimates the water level. The original and resulting images for that time are illustrated on the top row of Fig. 8. From these images, we can infer that our method detected the shadow cast closely to the water level, which obfuscates the line of the water level while providing a candidate line in an acceptable location with a strong contrast. While this will cause the method to always underestimate the water level, the difference will not be large, for it is proportional to the distance between the shadow and the water line. If these lines are well apart, the correct water line would not be so heavily obfuscated and would be detected and chosen as representative. This exact situation is illustrated on the bottom row of Fig. 8, where the shadow moved away of the floodwall and the correct water level line was identified.

(a) Original image 12:00. (b) Resulting image 12:00.

(c) Original image 13:00. (d) Resulting image 13:00.

Fig. 8. Illustration of results from the 2nd of April 2015.

V. Discussion, Limitations and Future Work

Our experiments show that our approach can be a viable alternative to estimate water levels of streams in an urban context. In a controlled environment, our method achieved outstandingly accurate measurements, with a relative error smaller than 0.5%. While the results considering real monitoring images, in an open environment, were not as accurate, we believe they can be accurate enough to complement other types of sensors.

Clearly, we cannot guarantee that our approach is as reliable as specialized sensors, but the equipment can be quite cheaper. Indeed, it can be nearly free, if we consider traffic monitoring cameras operating near urban streams. In this case, it might be possible to use them for both purposes concurrently. The innate unpredictableness of an uncontrolled environment can be mitigated through the use of several cameras, operating in smaller temporal intervals, and a more sophisticated data fusion method, robust to false positives and outliers.

Even considering the use of dedicated equipment, the cost should not rise considerably because we do not consider specialized hardware. One of our experiments considered images from a smartphone camera. Indeed, the acquisition, processing and transmission of the water level can be solved simply by using regular smartphones. Even cheap, low-end devices usually have cameras capable of more than 640×480, micro-SD cards are not expensive and it is already capable of transmitting the data using the mobile network. Moreover, such devices can possibly have enough processing power to perform the computation of the water level on site.

There is another important advantage of using cameras for this problem, the captured images carry more information than just the water level. One can easily verify the measured valued by inspecting the image, which is not possible using only specialized sensors. Again, we cannot guarantee the method to be as accurate as specialized sensors, but, in this context, it can be argued that such accuracy is not necessary, that more sensors with decimetre precision can be more relevant than fewer with millimetre precision.

As we have seen, the reliability of our approach is related to the camera resolution, which means that, the higher camera resolution, the better the accuracy of the estimation. Night images require specific equipment with capacity to work in this conditions. Detritus, channel slope changes, confluence between stretches, steps, bridge beams and other singular characteristics present in the canal section can cause phenomena such as vorticity, backwaters, jumps [26], and many other hydraulic disorders which must be taken into account. Also the installation and positioning of the cameras must be considered, as they also introduce limitations.

The possible future developments can also include the adaptation to slight camera movements, increased robustness to shadows or uneven illumination, different methods to select the correct line among the candidates, and so on. A more comprehensive experiment, considering more than four days should provide interesting new problems.

Since the OpenCV library was already ported to android, the implementation of a prototype running on a smartphone should be straightforward. Moreover, the practical application of the proposed method would probably include several cameras and a robust data fusion method can also be investigated.

VI. Conclusion

This paper introduces a methodology to study the possibility of identifying and measuring a good estimate of the depth of urban streams, using well-established digital image processing techniques. The experimental results were satisfactory and very promising for the detection and estimation of the water position and we conclude that our method is a potentially viable alternative to monitoring. A variation of the water level in a short period of time may mean a flood warning should be issued.

Acknowledgments

Grant $\#2014/12815-1$, São Paulo Research Foundation (FAPESP). The views expressed are those of the authors and do not reflect the official policy or position of the São Paulo Research Foundation.

References

[1] C. P. Konrad, "Effects of urban development on floods," 2003, U.S. Department of the Interior, U.S. Geological Survey, USGS Fact Sheet FS-076-03.

[2] D. DeRoure, "Improving flood warning times using pervasive and grid computing," *submitted to quarterly of Royal Academy of Engineering, UK*, pp. 1: 48–51, May 2005.

[3] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," *Computer Networks*, vol. 38, no. 4, pp. 393–422, 2002.

[4] D. Hughes, P. Greenwood, G. Coulson, and B. Gordon, "GridStix: supporting flood prediction using embedded hardware and next generation grid middleware," in *Proceedings of the 2006 international symposium on world of wireless, mobile and multimedia networks*. ACM, June 2006.

[5] F. Pappenberger, K. J. Beven, N. Hunter, P. Bates, B. Gouweleeuw, J. Thielen, and A. de ROO, "Cascading model uncertainty from medium range weather forecasts (10 days) through a rainfall-runoff model to flood inundation predictions within the European Flood Forecasting System (EFFS)," *Hydrology and Earth System Sciences*, vol. 9, no. 4, pp. 381–393, 2005.

[6] E. A. Basha, S. Ravela, and D. Rus, "Model-based monitoring for early warning flood detection," in *SenSys*, T. F. Abdelzaher, M. Martonosi, and A. Wolisz, Eds. ACM, November, 2008, pp. 295–308.

[7] J. Humble, C. Greenhalgh, A. Hampshire, H. L. Muller, and S. R. Egglestone, "A generic architecture for sensor data integration with the grid." in *SAG*, ser. Lecture Notes in Computer Science, P. Herrero, M. S. Pérez, and V. Robles, Eds., vol. 3458. Springer, 2004, pp. 99–107.

[8] D. Hughes, P. Greenwood, G. Blair, F. Pappenberger, G. Coulson, P. Smith, and K. Beven, *An intelligent and adaptable grid-based flood monitoring and warning system.* National E-Science Centre, 2006, pp. 53–60.

[9] J. D. Creutin, M. Muste, A. A. Bradley, and S. C. Kim, "River gauging using PIV techniques: A proof of concept on the Iowa river," *A. Kruger, Journal of Hydrology*, no. 277, pp. 182–194, 2003.

[10] C. Puech and D. Raclot, "Using geographical information systems and aerial photographs to determine water levels during floods." *Hydrological Processes*, no. 16, pp. 1593–1602, 2002.

[11] V. Klemas, "Remote sensing of floods and flood-prone areas: An overview." *Journal of Coastal Research, In-Press, Coconut Creek (Florida)*, 2014.

[12] I. Giuntoli, "Sistema web-GIS participativo associado a indicadores de gestão descentralizada de risco de inundações." *Dissertação de Mestrado - Escola de Engenharia de São Carlos, Universidade de São Paulo, São Carlos.*, 2008.

[13] Y. Ma, J. Košecká, S. Soatto, and S. S. Sastry, *An Invitation to 3-D Vision*, 1st ed. Springer, 2010.

[14] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 2nd ed. Prentice Hall, 2002.

[15] L. Najman and H. Talbot, *Mathematical Morphology*, 1st ed. John Wiley & Sons, 2013.

[16] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in *Computer Vision, 1998. Sixth International Conference on*, Jan 1998, pp. 839–846.

[17] I. Sobel, "A 3x3 isotropic gradient operator for image processing," *Machine Vision for Three-Dimensional Scenes, H. Freeman (eds), Academic Press, Boston*, pp. 376–379, 1990.

[18] N. Otsu, "A threshold selection method from gray-level histograms," *Automatica*, vol. 11, no. 285-296, pp. 23–27, 1975.

[19] J. Matas, C. Galambos, and J. V. Kittler, "Robust detection of lines using the progressive probabilistic Hough transform," *Computer Vision and Image Understanding*, vol. 78, no. 1, pp. 119–137, 2000.

[20] R. O. Duda and P. E. Hart, "Use of the Hough transformation to detect lines and curves in pictures." *Commun. ACM*, vol. 15, no. 1, pp. 11–15, 1972.

[21] J. R. Bergen and H. Shvaytser, "A probabilistic algorithm for computing Hough transforms," *Journal of Algorithms*, vol. 12, no. 4, pp. 639–656, 1991.

[22] C. B. Bose and I. Amir, "Design of fiducials for accurate registration using machine vision," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 5, no. 12, pp. 1196–1200, 1990.

[23] D. Poole, *Linear Algebra: A Modern Introduction*, 2nd ed. Canada: Thomson Brooks/Cole, 2006.

[24] OpenCV. (2015) OpenCV, the open source computer vision library. [Online]. Available: http://opencv.org/

[25] F. E. A. Horita, J. P. de Albuquerque, L. C. Degrossi, E. M. Mendiondo, and J. Ueyama, "Development of a spatial decision support system for flood risk management in brazil that combines volunteered geographic information with wireless sensor networks," *Computers and Geosciences*, vol. 80, pp. 84 – 94, 2015. [Online]. Available: http://www.agora.icmc.usp.br

[26] W. H. Hager, R. Bremen, and N. Kawagoshi, "Classical hydraulic jump: length of roller," *Journal of Hydraulic Research*, vol. 28, no. 5, pp. 591–608, 1990.