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Portable, automatic water level estimation using mobile phone cameras

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Abstract

Frequent and more accurate water level measurement will allow for a more efficient distribution of water, resulting in less water loss. Therefore in this paper we propose a novel method for accurate water level detection and measurement applied on images of staff gauges, retrieved from mobile device camera. In the first step, we propose fast segmentation of the staff gauge using a 2-class random forest classifier based on a feature vector of textons. To obtain bars and numbers we apply Gaussian Mixture Model segmentation followed by optical character recognition based on random forest classifier and bar detection using shape moments. Based on the recognized lines and numbers a quadratic function for the water level measurement to obtain metric values is introduced. Finally, we propose a novel step for the water level line detection. The water level function and the detected water line provide the value of the water level based on the units on the staff-gauge. The water level can then be uploaded to a central server to determine if water flow needs to increase or decrease. Testing with a real world images from Dutch canals show very accurate detection with many different staff-gauge locations despite complex challenges of viewpoints variations, low quality images as well as changing illumination conditions.

1 Introduction

Delivering water for agriculture by means of irrigation canals is very important for feeding the growing world population. Unfortunately, on average 40% of water is lost in water transport due to mismanagement by the human operators. Complete automatic control of such canals could reduce water losses to 10% and severely reduce the worlds water problems [7]. Such system requires accurate readouts of water levels to be frequently updated to the water management center.

Several studies propose image-based water level measurement techniques [6], [5]. [6] is based on a measuring water level from a fixed camera using spatial FIR filters while [5] detects the bending of lines on a measuring board with diagonal lines. However these methods have a large disadvantage of being dependent to fixed camera to be installed at the location or extra water measuring gauges to be calibrated. In addition they require constant recalibration of the camera by a human operator due to changing weather conditions.

To reduce these problems several studies propose to use raw images sent to management center for further processing [8], [3]. However they do not deal with uncertainties of field settings such as lighting changes, camera movement or condensation on the lens which have a large impact on image quality and consequently

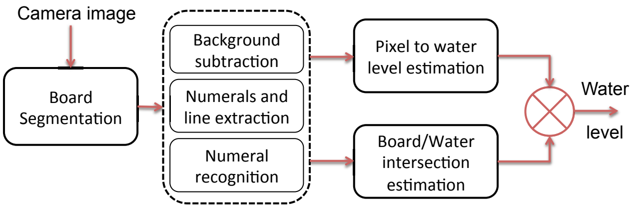

Figure 1: Overview of automatic water level detection algorithm

measurement accuracy. [2] proposes methods for automatic image quality assessment and correction prior to sending. Nevertheless these methods show high sensitivity to dirt and stains on the gauge requiring constant maintenance at many locations.

To solve above mentioned problems in our previous work we have proposed accurate measurements and control of irrigation canals by using smartphones which does not require any additional equipment on field, reduces human error and allows for keeping logs of captured images with water level data. In this paper we propose a novel method for automatic detection of water level invariant to changing environment conditions and state of staff gauge and water. The first step in our method is to locate the staff gauge in the camera image. Once this is obtained, we differentiate various components of the gauge such as the background, the measurement lines and the associated numerals. Then the localized gauge image is warped to obtain vertical alignment of measuring lines, followed by estimating a mapping between the vertical pixel value and the metric units. This is used along with an accurate detection of the gauge - water intersection to obtain the water level in the current image. An overview of the entire algorithm pipeline is presented in Figure 1.

The rest of the paper is organized as follow. The Section 2 explains localization of staff guage. Segmenting different components of the gauge is detailed in Section 3 and dynamic calibration of the gauge and water level estimation are discussed in Section 4 and 5. The experimental results are presented in Section 6 followed by conclusion and future work in Section 7.

2 Staff gauge localization

Locating the staff gauge in the source image is the first and critical step in the overall process. The initial image captured by the user can contain the staff gauge at any arbitrary position. This combined with added variations in scale, skew and rotation and illumination changes make the localization a challenging task. We have tackled this using a texton based approach on a Lab color space. Textons were introduced for the texture recognition and have been later coupled with boosted classifiers for object detection in natural

Figure 2: Source image and ground truth for training

Figure 3: Original image and generated segmentation mask

images [4]. A texton is a higher dimensional representation of a pixel encoding spatial and chromatic properties of the local neighborhood. This is achieved by convolving a filter bank with different channels of the source image. Here, we have used filter bank consisting of a Gaussian, Laplacian of Gaussian and derivative of Gaussian filters of varying σ and *kernel size* applied over individual channels of Lab color space. The filter bank from [4] is used here and it provides with a texton of 17 dimensions for every pixel. Now, each texton is associated with a label of gauge/background using manually obtained ground truths. Sample images and ground truths used here are shown in the Figure 2. The distribution of the gauge/background pixels in this 17 dimensional space is learned using a discriminative classifier. We have used a random forest classifier [1] which learns from small number of samples using bagging. This classifier is used because of its ability to learn a robust non linear model to deal with complex and multi modal feature distribution while having very low computational cost which are suitable for our purposes. After training is compelete, in normal operating conditions a binary mask is obtained by thresholding the probability of every pixel's corresponding texton from the classifier. This results in a reliable localization of the gauge from the source image. A sample test image and its gauge location identification are shown in the Figure 3. Segmenting different components of the localized gauge are discussed in the next Section.

3 Gauge components segregation

Having localized the gauge, we process only this part of the image to segregate the different components such as the background, the measurement lines and the associated numerals. We first remove the background and then split the remaining blobs to lines or numerals based on shape properties.

3.1 Background removal

Almost all staff-gauges in the Netherlands use a dark background with light colored lines and numbers. In order to segment the lines and numbers from the background we have used a Gaussian mixture modeling (GMM) method on a gray-scale image. We approximate the histogram of image intensities as a superposition of two Gaussian components. The parameters of these components (μ, σ) are estimated using an EM algorithm. The regions of the image corresponding to the component with lower mu are considered background and removed to obtain a mask consisting of only lines and numbers. Figure 4 shows an example of the extracted foreground on a staff-gauge.

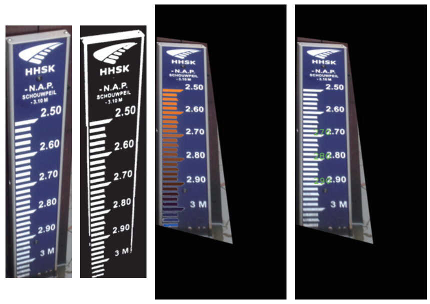

Figure 4: Original image, background extracted mask, warped extracted lines and recognized numbers

3.2 Measurment lines identification

The components of the obtained foreground mask are separated into lines or numbers based on shape characteristics. The shape of each blob on this mask is represented using a 7 dimensional *Hu moments*. The obtained moments are clustered into two groups based on their Euclidean distances. The cluster containing blobs of lines are identified based on the a-priori knowledge of the properties such as uniform shape and orientation. Any blob that deviates from the known properties of lines on a standard staff-gauge is considered as belonging to numerals which are recognized and used in the final estimation of the water level as explained in the next section. The obtained lines are shown in the Figure 4.

4 Dynamic calibration and Water level detection

The determined lines are used to warp the image in order to obtain an accurate water level measurement. The localized gauge image is warped such that all the lines are horizontal and equal in size. A perspective transformation matrix is obtained by using 4 points in the original image and their required positions in the transformed image. This is found using the orientation of lines and change of their horizontal lengths (identified as a rectangle). Figure 4 shows the results of this perspective warping.

After this, a custom trained optical character recognition (OCR) is applied to the remaining blobs after line segmentation. A training character set is created by manual segmentation and labeling of the numerals in the training dataset. Each sample is pre processed by removing excess background and rescaling the image to an $1:1$ aspect ratio with 40 pixels in width and height. A feature describing the character is obtained by vectorizing the processed sample into a binary feature of length 1600. Again, another random forest classifier is trained on this data with labels ranging from $0-9$. Using this trained classifier, at run time each object in the cluster is preprocessed and recognized as a specific numeral. The final step is to connect characters that belong together representing a bigger number. The numbers are combined using their relative location

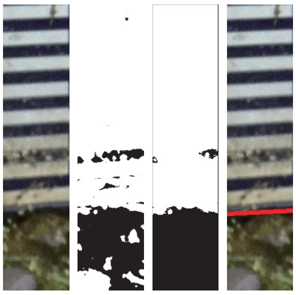

Figure 5: Water sample patch, water probability mask, water mask and estimated water line

in the image, numbers close to each other are assumed to belong together and are read from left to right.

The identified numbers are associated with the closest lines and this will be used to obtain a pixel position to water level mapping. Since each gauge can have a different measurement range and resolution, a dynamic calibration of pixel distance to metric measure of the gauge is performed every time an image is analyzed. The variation of metric measure with vertical pixel distance is modeled as a second order polynomial function with 3 independent variables as in (1)

$$y_\alpha = x_\alpha^2 a + x_\alpha b + c \tag{1}$$

where, y_α is the metric measure and x_α is the vertical pixel distance. The parameters a, b, c of the model are obtained by using a least square solution of 2. This data matrix is obtained by using 3 pairs of vertical pixel distance from the top of the warped image and the recognized numeric values.

$$\begin{bmatrix} x_1^2 & x_1 & 1 \\ x_2^2 & x_2 & 1 \\ x_3^2 & x_3 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} \tag{2}$$

This function modeling not only allows for robustness against different viewpoints as well as higher precision of the estimation of water level.

5 Water level detection

Now, the water level in pixels is estimated and converted to the level in metric units of the gauge to obtain the actual water level in the current image. The intersection of the gauge and the water is accurately estimated in the following manner.

A similar algorithm to that of staff-gauge detection and segmentation is used to detect the water intersection with the staff-gauge. A small patch of the gauge including some water as seen in Fig. 5 is used to train a random forest classifier on classes of gauge and water. Using the same filter-banks used for staff-gauge detection a 17-dimensional feature vector for each pixel of the image is generated which is used for training.

The patch of the staff-gauge and water is obtained by creating a region of interest around the most bottom line of the staff-gauge. The bottom most line is found using the previously detected lines and numbers from the gauge component segregation method. As water may sometimes reflect the staff-gauge the most bottom detected line might not always be an actual line on the staff-gauge. Extending the region of interest about 3 lines above the last detected line and the same area below the last detected line almost always gives a good sample patch of gauge and water. Once the patch is found it is down sampled and a probability map is generated using the trained random forest classifier.

The obtained map describes the probability of a pixel belonging to water. Any pixel with a probability less than 0.3 is classified as staff-gauge and any pixel with probability greater than 0.7 is classified as water. Pixels with probability in between 0.3 and 0.7 could be falsely classified and must be further analyzed. There arise false classifications due to the presence of dirt on the gauge or reflections of the gauge on clear water. To avoid falsely classified pixels, pixels with probabilities between 0.3 and 0.7 are classified as either water or staff-gauge based on the weighted average of the probabilities of its 16 neighboring pixel probabilities. A pixel with a weighted average of its neighbors greater than 0.5 is classified as water other wise it is considered to be part of the staff-gauge. Fig. 5 shows the initial probability mask obtained from the classifier and the updated mask based on the weighted average of each pixels neighboring pixels.

The outliers caused by dirty gauges and reflection are filtered by performing an Euclidean clustering on the updated mask. The biggest cluster of pixels is considered to be water any other cluster is considered an outlier based on the euclidean distance between the edges of the cluster and the biggest cluster. Once the water segment is completely defined in the patch the upper most point in each column that belongs to the water class is used to fit a water line. As the image was previously transformed such that the lines on the staff-gauge are horizontal the detected water line should also be close to being horizontal. The average of the detected water line points is used as the input into the water level function as in 1 to obtain the final water level. Figure 5 shows the detected water line on a staff-gauges.

6 Experimental setup and results

To test our method we have used real data obtained from 9 locations in Dutch water canals. A total of 40 testing images are used taken by a smartphone under varying illumination conditions, from multiple viewing angles and containing challenging water conditions such as reflection and dirt. The tests are preformed on the three steps used for water level measurement; staff-gauge segmentation, water level function formulation and water line detection. Each step of the proposed water level measurement has been tested separately such that each test is controlled and is not depended on the outcome of any of the other tests. The classifiers were trained on forty images taken at several real world locations and various viewing angles.

6.1 Staff-gauge segmentation results

Staff-gauge segmentation has been tested on 40 randomly selected images from 9 different locations. In order to determine the accuracy of segmentation, manually segmented masks have been created for comparison, such as those in Figure. 2. The generated segmentation mask from the classifier is compared on a pixel level to that of the manually segmented mask. Table 1 shows the average pixel level classification accuracy of the 9 separate locations. As can be seen both

Location	False Positive	False Negative	Precision	Recall
1	0.308%	0.776%	98.915%	90.451%
2	0.129%	0.747%	99.124%	95.770%
3	0.0%	1.741%	98.258%	48.429%
4	0.268%	0.124%	99.608%	94.902%
5	0.155%	0.319%	99.526%	94.382%
6	0.442%	0.319%	99.239%	97.53%
7	0.841%	0.098%	99.061%	98.928%
8	0.297%	0.02%	99.682%	99.577%
9	0.435%	0.544%	99.021%	99.009%
Average	0.331%	0.521%	99.159%	90.998%

Table 1: Staff-gauge segmentation results

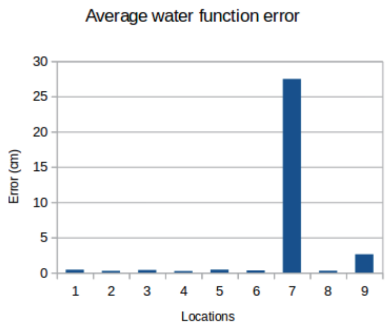

Figure 6: Water function results

precision and recall are very high and present results of above 98% which justifies its application in the real water management system.

6.2 Water level function formulation results

In order to keep the results of water level function formulation independent of the results of staff-gauge segmentation, the tests are performed using manually segmented staff-gauges. Again forty staff-gauges have been randomly selected from 9 different locations. To determine the error of the water level function 5 known measurement points are selected on each of the staff-gauges and compared to the measurement value obtained by the water level function. The graph in Fig. 6 shows the average error of the water level function at each location.

The results show very low errors where the only significant error is at the location 7. The error is due to the fact that the staff-gauge at location 7 is quite dirty making it more difficult to get an accurate read out at this location.

6.3 Water line detection results

For the final test, forty patches from randomly selected images containing both staff-gauge and water are used to test the water line detection method. The error of the water line detection is determined by comparing pixel distance between the detected water line to expert labeled ground truth. Fig. 7 shows the average error at 9 different locations.

Location 4 has the most significant error. At location 4 the water was very clear making it difficult to detect the actual water line as most of the water has similar features to that of the staff-gauge.

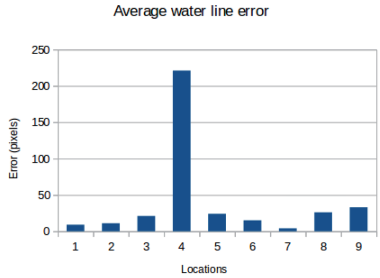

Figure 7: Water line detection results

7 Conclusion

Automatic water management can save millions of liters of water loss and prevent water shortage, however this requires fast and accurate measurement of water level. Therefore, in this paper we have introduced novel method for water level measurement that can be implemented directly on mobile devices, significantly simplifying usability of such solution. To obtain automatic water level detection, we at first performed fast segmentation of the staff gauge followed by fast recognition of bars and numbers to read out relevant information. To obtain readouts in metric values we proposed water line quadratic function and the method for water line detection. To test our solution we obtained real data from different irrigation canals in Netherlands, using a mobile device to capture a picture of a location and staff-gauge. Obtained results show very high precision of detection of above 97% despite changing environmental conditions and dirt on the gauge and water. With minor changes the methods could be applied to measure water levels on staff-gauges around the world.

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