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METERING WATER FLOW USING IMAGE PROCESSING*

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ABSTRACT

Metering water flow in pipes is important in a wide range of applications. A special case is where the water pump discharges in a pipe that is open-ended to the atmosphere. Such applications are found, for example, in agricultural irrigation and drilling for fresh water and low-temperature geothermal water. The need for a simple and inexpensive metering method may arise where the installation of accurate metering is not practical and/or too expensive. In this paper, image processing approach is used to draw the trajectory of the water flow from the pipe and deduce its equation for metering its flow rate. Also, the relation between the pump power and the trajectory has been built.

KEY WORDS: image processing, flow Rate, open-ended pipe.

DÉBIT D'EAU DE MESURE PAR TRAITEMENT D'IMAGES

RÉSUMÉ

Débit d'eau dans les tuyaux de dosage est important dans un large éventail d'applications. Un cas particulier est l'endroit où les rejets de pompe à eau dans un tuyau ouvert à l'atmosphère. Ces applications sont trouvés, par exemple dans l'irrigation agricole et de forage pour l'eau douce et à basse température de l'eau géothermique. La nécessité d'une méthode de mesure simple et peu coûteux peuvent survenir lorsque l'installation de dosage précis n'est pas pratique et / ou trop cher. Dans ce papier, l'approche de traitement de l'image est utilisée pour dessiner la trajectoire de l'écoulement de l'eau de la pipe et en déduire son équation pour la mesure de son débit. En outre, la relation entre la puissance de la pompe et la trajectoire a été construit.

MOTS CLÉS: traitement d'image, de débit, ouvertes tuyau.

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1. INTRODUCTION

Design and development system to measure the output parameters like water speed and flow rate of output water, Vision-based and image processing navigation has been investigated and an approach by single camera is presented in this paper. On other hand, camera supported by computer vision can also give some important information about flow output water and its trajectory from output pipe

Flow measuring is to measure the volumetric amount of fluid output in certain time. There are different methods and devices are used for flow measuring in pipe (Ref. (8)) as bucket-and-stopwatch, open flow nozzle, the orifice plate, the Venturi meter and the trajectory method.

Bucket-and-stopwatch is simplest way to measure volumetric flow is to measure how long it takes to fill a known volume container. A Venturi meter constricts the flow in some fashion, and pressure sensors measure the differential pressure before and within the constriction. An orifice plate is a plate with a hole through it, placed in the flow; it constricts the flow, and measuring the pressure differential across the constriction gives the flow rate. The trajectory method is a form of velocity area calculation that can be used for determining the rate of flow discharging from horizontal pipe flowing full. By measuring the horizontal distance (X) and the vertical distance (Y).

This paper proposes automated trajectory flow measuring using image processing. An algorithm used for calculating speed and trajectory of output water from pump using camera and computer vision. We assume a standard computer is used for image processing and data. We have two major tasks in designing this water speed measurement system. First, obtaining an image processing algorithm needed to find water trajectory in image. Second, finding a scaling factor or formula that converts the water position in trajectory (pixels) on the image into real position (meters) to measure the output water speed from pump

2. DESCRIPTION OF THE SYSTEM

The experimental study aims at capturing the fluid motion of output water through visualization then use image processing to measure the output flow of water and also the speed and horizontal displacement. A solid model experimental set up with camera acquisition system is shown in Fig. 1. The experiment consists of pump that gets the water from tank 1 using open-ended pipe to the atmosphere then to tank 2. We put the camera in front of tank 2 to visualize the water trajectory. We use image processing algorithm to detect the water trajectory and get horizontal displacement (X) from image at certain (Y) then get the measurement of the speed and flow rate of output water.

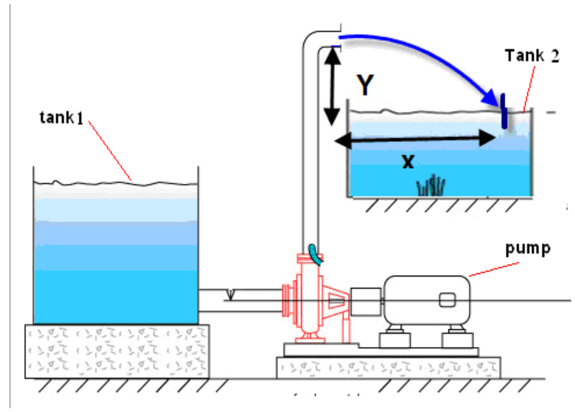


Fig. (1): Solid model of experimental set-up.

3. IMAGE PROCESSING ALGORITHM

In this system, appearance is needed of water trajectory on the image captured by video camera. Based on the detected water trajectory one can measure the horizontal trajectory distance at certain vertical distance. One used Background subtraction algorithms to detect the water trajectory in image. There are many well-known algorithms for Background Modeling to detect all the foreground objects automatically put this work used static background model before run the system . Our algorithm to detect the water trajectory from image consists of four steps as show in Fig. 2.
Step 1 after reading color image, we apply background subtraction using background image.
Step 2 converts the result image to binary image using threshold level.
Step 3 remove the noise and small white point in image using filter.
Step4 detect the location of white point that represents the water trajectory.

3.1 Background Modeling

The background modeling algorithm defines and updates its background model. In this section, we describe the different background modeling techniques considered in our comparative study. There two different techniques used to get dynamic background modeling: Recursive techniques and Non-recursive techniques.

Recursive techniques: maintain a single background model that is updated with each new video frame. These techniques are generally computationally efficient and have minimal memory requirements. Such as Running Gaussian average (Ref. (10)), Gaussian mixture model (Ref. (11)), approximated median filtering (Ref. (6)). The major strengths of this approach are its computational efficiency, robustness to noise, and simplicity. The notable limitation is that it does not model the variance of a pixel

Non-recursive techniques: maintain a buffer L of n previous video frames and estimate a background model based solely on the statistical properties of these frames.

This causes non-recursive techniques to have higher memory requirements than recursive techniques. However, since they have explicit access to the most recent in video frames they can model aspects of the data not possible with recursive techniques. Such as Median filtering (Ref. (2)), Mediod filtering (Ref. (3)), Eigen back grounds (Ref. (7)).The major limitation of this approach is that computing the basic functions requires a set of video frames without foreground objects. As such, it is not clear how the basic functions can be updated over time if foreground objects are continually present in the scene.

The main problem with those algorithms is the processing time. So we need to develop as simple image processing algorithm as possible to get the background. Before run the pump we can capture some frame then can get the average of this frame as background. The algorithm that used to get background .where pdf is pixels of different frames, n number of frames and k is the index of frames.

```
For each pixel of the frame:
Sum_of_pdf = 0
For k =1 to n
        sum_of_pdf = sum_of_pdf + pdf (k)
End
Background_pixels =sum_of_pdf / n
```

3.2 Background Subtraction Method

A Background subtraction method is used to detect the water trajectory in image. After getting the background of image, one can run the system. Then the water trajectory appears in image as in Fig. 3 (a). In order to detect the pixel in image that represent water trajectory, subtract this image from background image to get image of water trajectory only as in Fig. 3-(b)

3.3 Pre-processing

After getting the image of water trajectory, one apply a simple threshold method to water trajectory image, water trajectory pixel can be separated from other and became white as in Fig. 4 (a). due to camera noise and the threshold level ,one can get small white pixel in image ,So use filter to remove the small object in image and remove the noise as median filter (Ref. (5)) as shown in Fig. 4 (b)

3.4 Detecting Trajectory Location in Image

After pre-processing, one needs to know the trajectory location (row and column) in image. Then a search algorithm as connected-component labeling (Ref. (9)) is applied to obtain the location of white in pixel that represent water trajectory in image as in Fig. 5 (a) then can get the equation of trajectory as in Fig. 5 (b) by using the projectile equations as shown in section 4 .

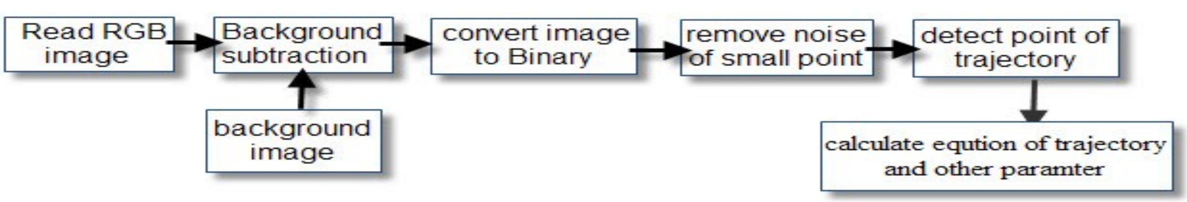


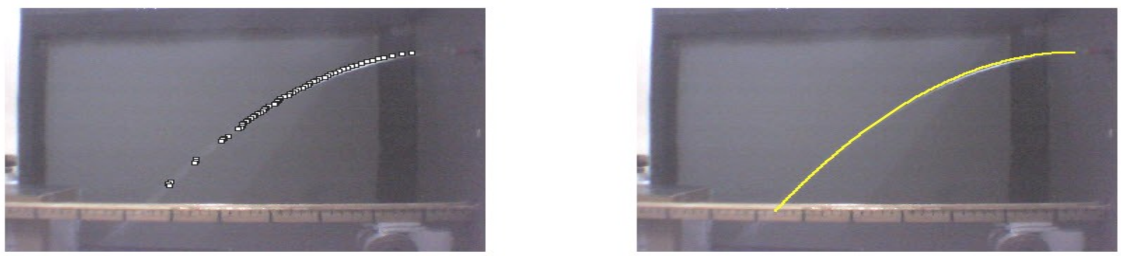
Fig. (2): Flow chart of the algorithm to detect water trajectory.

(a) Captured image. **(b) Subtracted image.**

Fig. 3: Images.

(a) (b)

Fig (4): (a): Images with threshold, and (b): with median filter



(a) (b)

(a) Detection of water trajectory. **(b) Drawing of water trajectory.**

Fig 5: Water trajectory.

4. CAMERA CALIBRATION

To calculate the Parameters after getting the point in the curve of water trajectory in image, use camera intrinsic parameter focal length and Principal point that represent camera model to convert from pixel coordinate to real word coordinate by using pin hole camera model (Ref. (4)) as shown Fig. 6 that the point $(x,y,z)^T$ is mapped to the point$(f\ x/z,\ f\ y/Z,f)^T$ on the image plane, Assuming that the origin of coordinates in the image plane is at the principal point. In practice, it may not be so, in general there is a mapping $(X,Y;Z)^T$ to $(f\ X\ /z + px\ ,\ f\ Y/\ z + py)^T$ in image . Where f is focal length, (X,Y,Z) position of object in x -axis , y-axis, z-axis in real word coordinate system , (px ,py) principal point of camera. We can get the (X,Y) point in real word from pixel point in image using pin hole camera model. Then we can get the output parameter like flow rate and head of water pump using water trajectory equation. According to fluid mechanics, one can metering water flow exiting open-ended Horizontal pipes using trajectory method (Ref. (1)) as show in Fig. 6

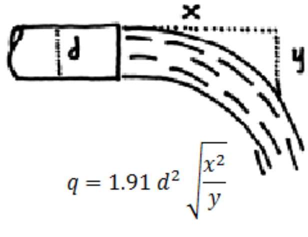


Fig. (6): Equation of flow rate for open-ended horizontal pipes

The water travels a horizontal distance x (m) and falls a vertical distance y (m). The horizontal distance is given by Equation (1) where u_o is the velocity at x=0. In the same time t, the water will fall the vertical distance given by Equation (2), where g×t (m/s) is the vertical downward velocity of the water due to gravity. The water starts at zero and accelerates to subsequent values of g×t (m/s). The time can be eliminated from the two basic equations, such that as in Equation (3).then we can get the relation of speed u_o as in Equation (4). Assuming that the horizontal velocity of the water remains constant for the distances of interest, the subscript can be dropped without any loss of clarity. Using the physical relation between velocity u (m/s) and flow rate q (m^3/s) as in Equation (5) to get the relation between the flow rate and vertical and horizontal distance.

$$x = u_0\, t \tag{1}$$

$$y = \frac{1}{2}\, g * t^2 \tag{2}$$

$$\frac{x^2}{y} = \frac{2\, u_0^{\,2}}{g} \tag{3}$$

$$u_0 = \sqrt{\frac{g\, x^2}{2\, y}} \tag{4}$$

$$q = A u_0 = A\sqrt{\frac{g\,x^2}{2\,y}} = 1.739\,d^2\sqrt{\frac{x^2}{y}} \qquad (5)$$

This equation is theoretical and does not take into account whatever losses that arise when water exits horizontally from an open-ended pipe. The distance x (m) is based on a constant water velocity from the pipe-end and into the surrounding air; the trajectory of the issuing water. It seems reasonable to assume that the water velocity decreases with distance away from the pipe-end. This means that the real x (m) value will be smaller than the theoretical x (m) value. Similarly, the real vertical distance y (m) will be larger than the theoretical distance. Taking both of these real distances into account means that the real flow rate q (m^3/s) will be larger than the theoretical value. Adding a discharge coefficient Cd to the theoretical expression makes it possible to adjust the theoretical value to the actual value as shown in Equation (6). The Cd-value for vertical flow above was taken to 10% lower than theoretical (=0.9). It seems reasonable to assume that the C_d-value for horizontal flow be taken to be 10% higher than theoretical (=1.1).). Charts presented by Bos (1976/1989) (Ref. (1)) suggest that such a value may indeed be correct. Then the final relation between flow rate and horizontal and vertical distance is in Equation (7).

$$q = C_d\, A\sqrt{\frac{g\,x^2}{2\,y}} \qquad (6)$$

$$q = 1.91\,d^2\sqrt{\frac{x^2}{y}} \qquad (7)$$

5. EXPERIMENTAL RESULTS

The test purpose was to verify output water speed and flow rate measurement calculated by camera and software with true measurement. First, one had to do distance calibration of the camera. The purpose of the calibration is to find the linear scale of pixel to real distance. The camera has been place 58 cm away from the water trajectory. With this setup, the one pixel horizontal and vertical represented 0.767 mm, 0.7258 mm. the measurement range of this testing was between 0 to 50 cm for the horizontal distance. Second, after the calibration, the background image had been obtained. Then, the input power to the pump had changed from 10% to 55 % with step 2%. After each step, the software captured an image then found the trajectory of output water and measure the real horizontal and vertical distance. After that, the relation between the input power to the pump and the horizontal distance x at vertical distance y= 22.5 cm had been measured. The results are graphed in Fig. 7 and the error between the true distance and the measured distance is given in Fig. 8. After getting the horizontal and vertical distance of the water trajectory, the speed of water can be calculated using the equation 1.4 for each input power step as in Fig. 9 and error in speed in Fig. 10. Finally, the output water flow rate can be calculated using Equation (7). Fig. 11 shows the real and measured water output flow rate versus input power to pump at the diameter of pipe equal 3.4 mm. The real flow obtained by bucket-and-stopwatch by measuring how long it takes to fill volume container. Then the error between real and measured flow is given in Fig. 12 minimum and maximum flow error are -3, 5 %. This experimental result is compared with the other method for measuring flow rate as shown in Table 1. This comparison showed that trajectory method it has medium accuracy but it is not effected by viscosity and also not affect in the flow rate in pipe than other method is connect to the pipe so the other method effect in the fluid motion in pipe.

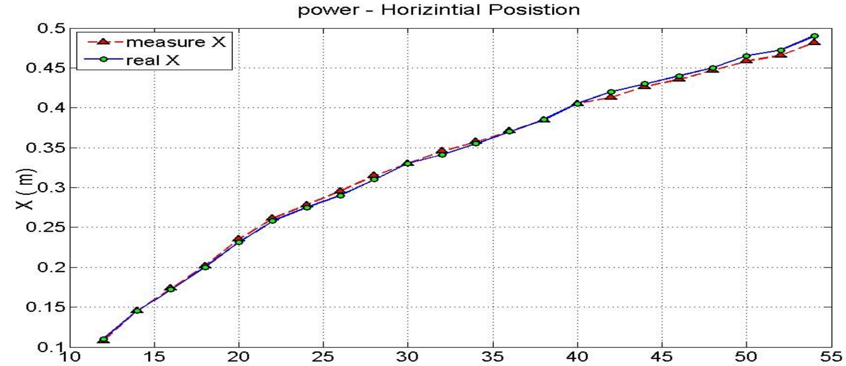


Fig (7): Input power to pump versus measured and true distance at y=22.5 cm

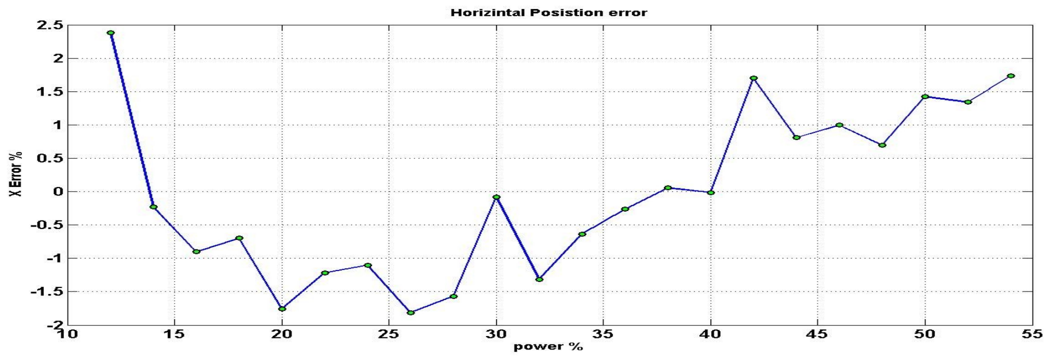


Fig. (8): Error distance in measured horizontal relative to real distance at y=22.5 cm

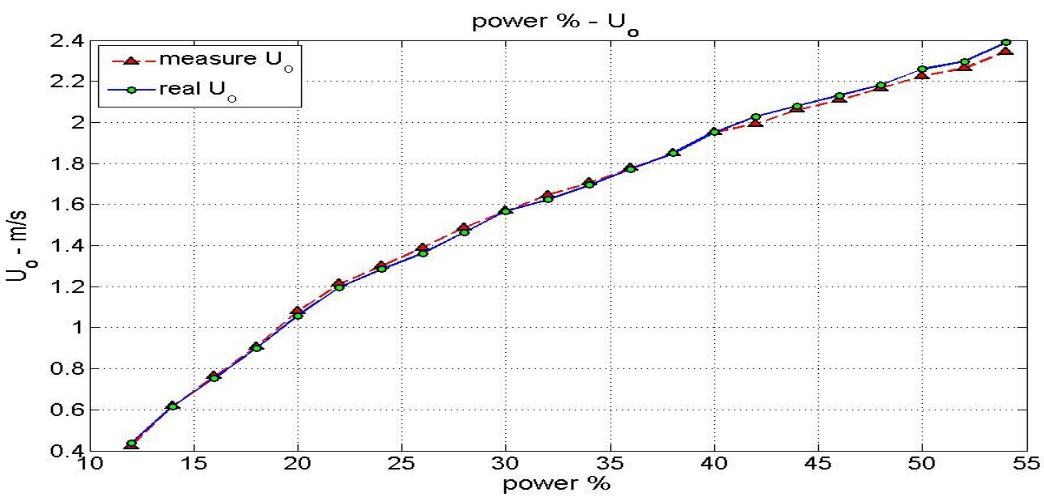


Fig. (9): Real and measured water output speed versus input power

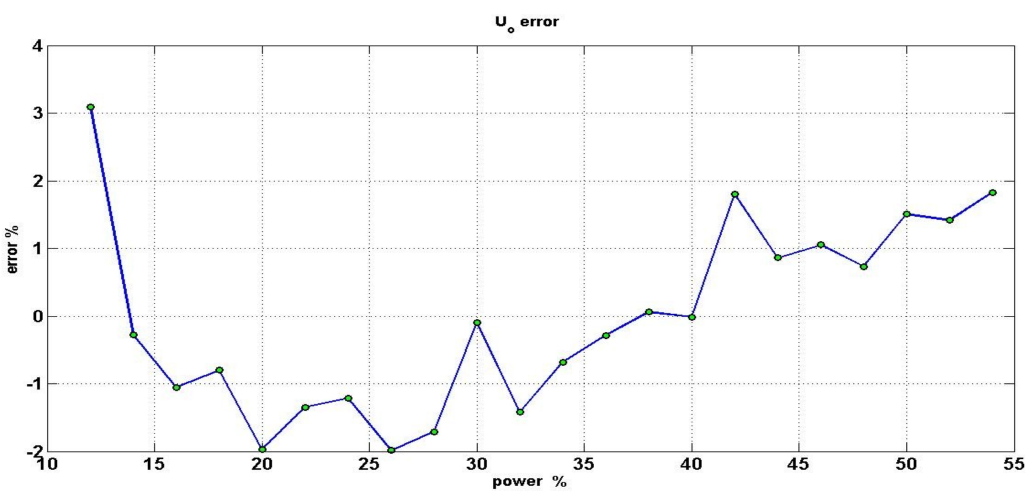


Fig. (10): Error in measured velocity relative to true velocity

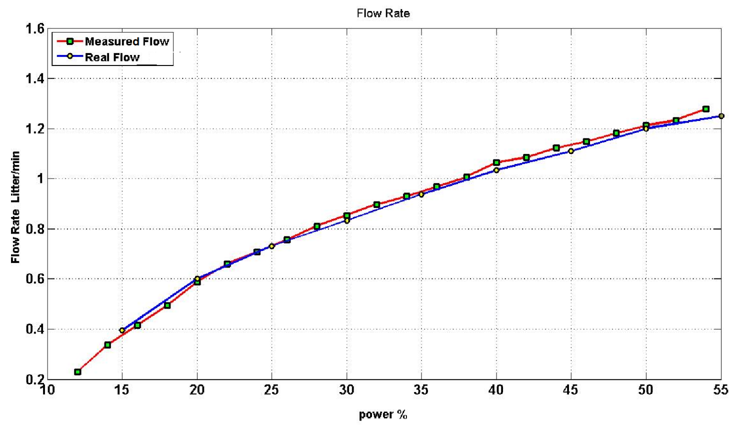


Fig. 11: Real and measured water flow rate versus input power

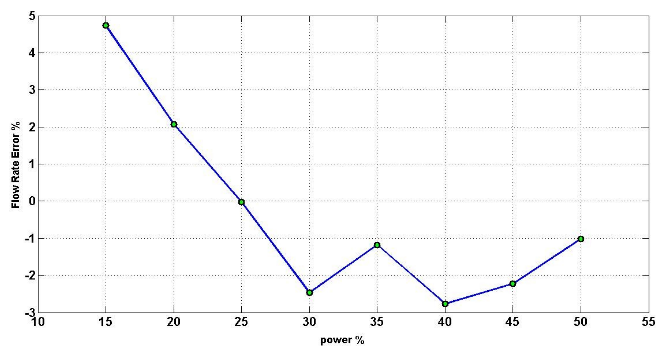


Fig. 12: Error in measured water flow rate versus input power

Table (1): Comparison between different methods of measuring flow rate

Open flow nozzle	Orifice Plate	Venturi meter	Trajectory method
Typical accuracy 5 %	Typical accuracy is 2 to 4%	Typical accuracy is 1 to 2%	Typical accuracy is 5 - 10 %
Required upstream pipe length is 10 to 30 diameters	Required upstream pipe diameter is 10 to 30 diameter length	Required upstream pipe length 5 to 20 diameters	Open horizontal pipe length > 6 diameters
Viscosity effect is high	Viscosity effect is high	Viscosity effect is high	Viscosity effect is low
Relative cost is medium	Relative cost is low	Relative cost is medium	Relative cost is very low
Coefficient of discharge ranges from 0.94 to 0.98	Discharge coefficient is 0.60 Usable range is limited head loss is about 70 to 75%	coefficient of discharge ranges from 0.93 to 0.97	coefficient of discharge typically is 1.1 Depends on pipe being straight and truly horizontal over at least a length of 6 diameters

6. CONCLUSION

This paper proposes a low cost but powerful flow rate measurement system, by automated trajectory method using image processing. It is concluded that the maximum error in water velocity +3% and the minimum is -2%. Also the experiment shows that the maximum flow rate error is 5 % and the minimum is -3%. However, the trajectory method is very low in cost. Other methods (Table (1))are affected by fluid motion in pipe and also have high viscosity effects. The benefit of using the camera lies in the remote measuring sensor. Since, there is no physical connection between the camera and water flow and therefore no interference.

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