Aquatic Robot Design for Water Pollutants Monitoring

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Abstract— this paper focuses on the design and development of an Aquatic Robot for water pollutants monitoring. An aquatic robot is integrated with the smartphone for data acquisition. The implemented design contains CV algorithm for image processing on openCV platform. Regularly monitoring aquatic pollutants is needed for pure aquatic environment and safe aquatic life. The human health and water transport are also main consideration towards this robot design. The proposed Aquatic robot consists of sensors and camera for sensing hazardous pollutants and capturing images of surrounding environment respectively. The aquatic robot can accurately detect pollutants and display results on smartphone in the presence of various conditions.

Keywords- *Aquatic Robot, Raspberry-pi, Arduino, OpenCV, Smartphone.*

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I. INTRODUCTION

Monitoring aquatic debris or pollutants is of great interest to the ecosystems, marine life, human health, and water transport [1].Water resources and aquatic ecosystems are facing various physical, chemical, and biological threats from climate change, industrial pollution, improper waste disposal, disease-causing microbes, and even terrorist attacks. Sensing of aquatic environments is of increasing importance to public health, port and river security, ecosystem sustainability, marine biology, and aquaculture industry. Manual sampling, via boat/ship or with handheld devices, is still a common practice in the monitoring of aquatic environments. This approach is labor-intensive and has difficulty capturing dynamic and spatially distributed phenomena of interest.

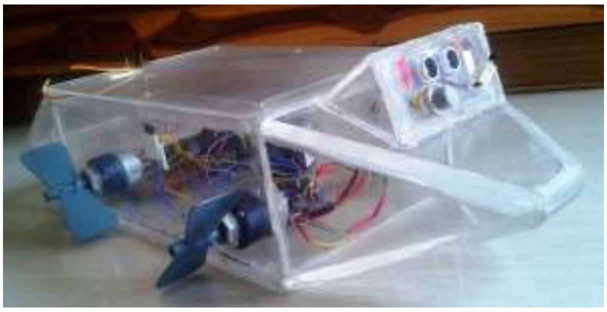

Figure 1. Aquatic Robot

Mobile sensor networks can be greatly used to monitor environmental variables such as temperature, pH, salinity, toxins, and chemical plumes. Significant advances have been made in the area of mobile sensor networks and their applications to environmental sciences. Decentralized environmental modeling by mobile sensor networks was presented in in which control laws were developed for mobile sensors to maximize their sensory information. The Mahdi Jadaliha et.al provides practical solution to the problem of monitoring an environmental process in a large region by a small number of robotic sensors [2]. The aquatic environment presents an almost ideal test-bed for the evaluation and development of robotic technologies. The environment is highly dynamic and three dimensional. Extremely limited off-board communication underwater requires that robots must operate fully autonomously or under operator control through a tether [3].

Recently, there is an increasing interest in the development of autonomous, in situ, real-time sensing platforms for aquatic environments [1-4]. Moreover, sensing platforms equipped with embedded camera sensors provide a promising solution for efficiently and intuitively observing aquatic environments, so we have developed an inexpensive, multipurpose aquatic sensor node enabling long- term aquatic monitoring. Figure 1 shows a completed aquatic robot. The node includes several kinds of aquatic sensors submerged in water and an onboard camera sensor on top. The former periodically collect the water-quality data and the latter captures images for pollutants detection. However, there are some specific problems awaiting solutions for the vision-based aquatic pollutants detection.

First, due to the impact of uncontrollable water surface disturbances such as waves, camera shaking and swaying reflections on the water, it is quite difficult to reliably identify pollutants objects. Second, embedded platforms are not competent for continuous and real-time image processing because of the constraints on computational power and memory [5]. This means the pollutants detection algorithm should have low computation complexity at the same time as achieving desirable detection accuracy. Third, due to the restricted accessibility for replacing batteries of aquatic sensor nodes, the limited energy supply remains a challenge for long-term monitoring. Apart from the acquisition, processing and transmission of water-quality data, both pollutants detection and image transmission incur high energy consumption.

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Due to space constraints, this paper is restricted to discuss the vision-based pollutants detection using our embedded sensing platform. The main contributions of this paper are as follows:

(1) We present the design of aquatic robot and implement the pollutants detection algorithm on the embedded platform.

(2) We propose an accurate and computationally efficient approach to pollutants detection.

II. PROPOSED METHODOLOGY

A. Hardware Design

Robotic unit is consisting of array of sensors and camera which is movable around its axis and also vertically. Raspberry Pi is used for image processing and sending the image to the user through the Wi-Fi is used for communication between Arduino and Raspberry Pi (ARM Processor). Motor driving circuits are used for operating motors. An Aquatic robot is capable of moving in water by a DC motor. The motor is manipulated by a programmable control board, which can communicate with the smartphone through short-range wireless links such as Bluetooth.

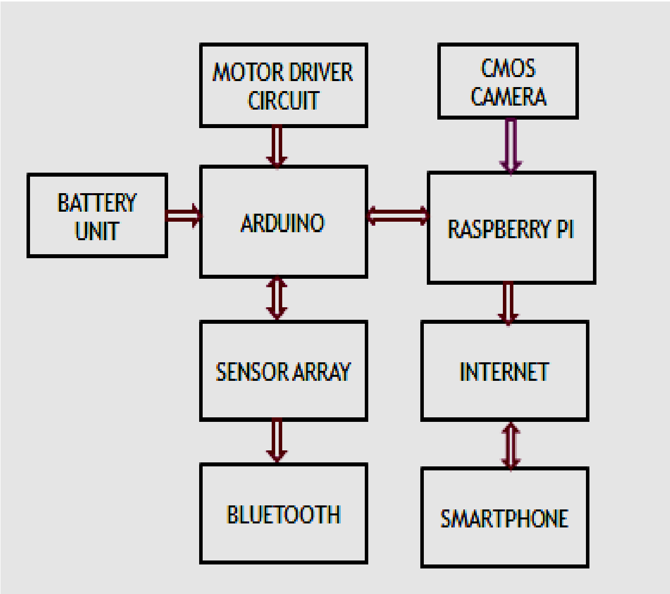

Figure 2. Block diagram for Robotic Unit

The Raspberry Pi here used for image processing on Open CV platform. The Raspberry Pi is a credit-card sized computer that plugs into your TV and a keyboard. It is a capable little computer which can be used in electronics projects, and for many of the things that your desktop PC does, like spreadsheets, word- processing and games. It also plays high-definition image. Raspberry Pi has a strong processing capacity because of using the ARM11 architecture and Linux-based system. In terms of control and interface, it has 8 GPIO, 1 UART, 1 I2C and 1 SPI, which are basically meet the control requirement. There are simple and easy-used open source peripheral driver libraries.

B. Mechanical Design

The robot is approximately 65 cm long, 50 cm wide (at the fins), and 13cm high. It is encased within an acrylic waterproof shell and displaces about 18 kg of water. An Aquatic Robot weighted about 4.3 kg. The robot is powered by two onboard batteries providing over two hours of continuous operation. Camera, sensor and control signals are sent to a floating platform at the surface via fiber-optic tether.

Figure 3. Mechanical Design of Aquatic robot.

As interaction between the robot's body and water occurs, fluid mechanics are also involved, particular the effects of drag on the robot. Drag force can be calculated through applying the equation,

$$F_D = 0.5 * PV^2 * C_d A$$

Besides drag, hydrostatic pressure is also an important aspect to take into account. Looking plainly at a flat plate being submersed underwater, the pressure acting on the plate is directly proportional to its depth underwater, as illustrated in Figure 3. By applying the equation,

$$P_{Hydrostatic} = h \rho g$$

Where

p = pressure (N/m^2, Pa)
h = height of fluid column, or depth in the fluid at which the pressure is measured (m, in)
ρ = density of liquid (kg/m^3)
g = the gravitational constant (9.81 m/s^2, 32.17405 ft/s^2)

Under 2m in seawater maximum pressure around=2*999.97*9.81= 19619.411 Pa

Weight Distribution As the overall weight of the robot is an important aspect for it to overcome the buoyancy force and operate on the seabed, the detailed breakdown of the weight of the various components of the robot.

C. Sensors Data Processing

The developed robotic system has embedded several kinds of sensors for autonomous navigation and quality detection of water. Sensors to be used for autonomous navigation are ultrasonic sensors and accelerometer. The sensors used for quality detection are temperature sensor and gas sensor. In this paper interfacing of all the sensors, DC motors, Bluetooth with Arduino (ATmema328) processor is explained.

An interfacing diagram is shown in fig.4. Ultrasonic sensor is used to calculate distance of obstacle from real position of robot. Accelerometer measures the three axial positions according to the movement or shaking of waves in water environment. Gas sensor MQ2 is used here to measure the amount of gases dissolve in water. If water body is contaminated with large number of harmful gases then gas sensor indicates its presence. The data collected by all the sensors are then sending to the smartphone via Bluetooth. With these features, the aquatic robot can move autonomously on surface of water.

Figure 4. Sensor Interfacing of Aquatic

D. Image Processing

In this paper we present a smartphone-based sensing platform that utilizes CMOS camera, inertial sensor, and other resources. Different from aforementioned sensing platforms, we aim to combine camera sensors with other types of aquatic sensors into a sensor node for multipurpose aquatic monitoring. The key to aquatic pollutants detection is to extract the foreground objects from image sequences captured by camera sensors. A common way to foreground extraction is background subtraction. One such means, Gaussian mixture model (GMM) [1-6] has been widely adopted because of its ability to deal with subtle illumination changes.

Here we employ CV algorithm for image processing on the OpenCV platform. As the camera is an interface with the Raspberry-pi processor the libraries of algorithm are uploaded in processor. The flowchart of CV Algorithm is shown in Figure 6.The images taken by camera processed inside the Processor. For each frame, we first convert it to a gray scale image and detect edges using a Sobel operator. The Sobel operator detects an edge point according to the local intensity of gradient magnitude. Hough transform then finds the horizon line through a voting process based on the number of edge points that each candidate line.

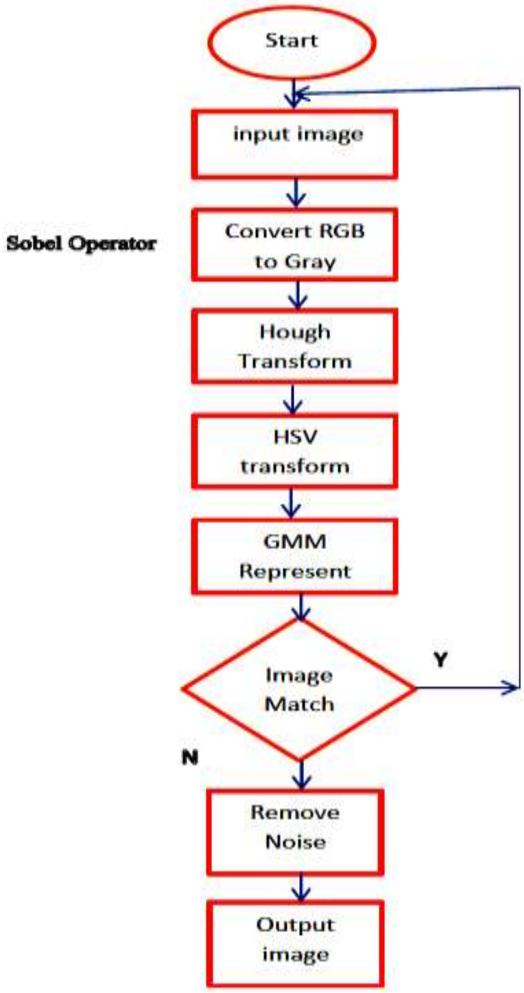

Figure 5. Flowchart of CV Algorithm

We employ Hough transform to extract the horizon line. Hough transform has been widely used to identify the positions of lines in an image [8]. To reduce the energy consumption in image processing, we adopt a lightweight background subtraction approach to detecting the foreground pollutants objects. We first convert the representation of an image to HSV (Hue, Saturation, and Value) model. In HSV, hue represents the color, saturation is the dominance of hue, and value indicates the lightness of the color.

In our approach, the background of a pixel is represented by a Gaussian mixture model (GMM) [7]. The GMM comprises K three-dimensional Gaussians, where each Gaussian characterizes the three channels of HSV color space. When a new frame is available, each pixel is compared with its background model. If the HSV vector of a pixel in the new frame does not fall within a certain range from any mean vector of the K Gaussians, this pixel is considered a foreground pixel candidate; otherwise, it is classified as

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background. Therefore, the color difference between the foreground and background affects the classification accuracy.

The binarized foreground image contains randomly distributed noise pixels. Because the background subtraction is conducted in a pixel-wise manner, the labeling of foreground and background can be affected by camera noise, resulting in false foreground pixels. To deal with these noise pixels, we adopt the opening operation in image morphology. The opening operation, which consists of erosion followed by dilation, eliminates the noise pixels through erosion while preserving the true foreground by dilation.

After the noise removal, we employ region growing to identify the pollutants objects from the foreground image. It uses the foreground pixels as the initial seed points and forms connected regions that represent the candidate pollutants objects by merging nearby foreground pixels.

III. EXPERIMENTAL RESULTS

Here Aquatic robot evaluated through experiment done in swimming tank. The experimental results are obtained on smartphone validate the feasibility of Aquatic robot by evaluating the computation overhead, effectiveness of each module, and the overall performance of a fully integrated Aquatic robot. The simulations extensively evaluate the performance of Aquatic robot working under wide ranges for parameter settings.Fig.6 shows the simulation results of all the sensors implemented in hardware of aquatic robot.

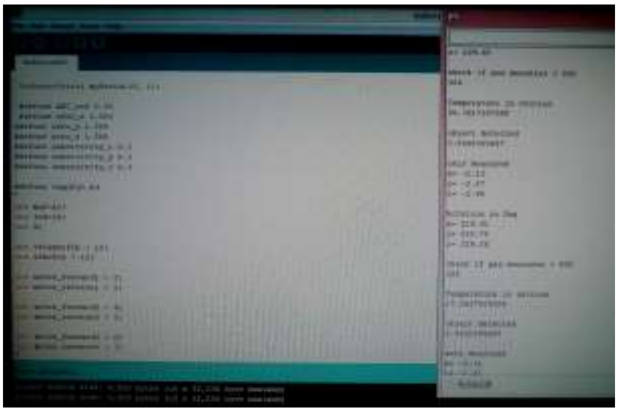

Figure 6. Simulation Result of Sensors of Aquatic Robot

Fig.7 shows the results of image processing done in openCV which is directly obtained on smartphone.The base of image processing is the CV algorithm. The following figure shows a sample of background subtraction. Specifically, Figure 7(a) is the original frame where the red dashed lines represent the extracted horizon lines for this frame and the registered predecessor frame, respectively. Figure 7(b) shows the background model, where each pixel is the mean vector of the Gaussian with the largest weight in the GMM. Figure 7(c) is the result of background subtraction with image registration.

a. b. c.

Figure 7. Image processing output a. foreground image, b. background image, c. output image.

The output of image processing and all sensors are obtained on smartphone via Wi-Fi network and bluetooth respectively.The main advantage of this is that if Aquatic robot is placed at remote location we are able to access data of surroundig aquatic environment accurately.

Since the aquatic robot is designed at a low cost, it can be used in various applications like sampling lakes, monitoring aqua farms and safeguarding water reservoirs. Aquatic robot could give researchers far more precise data on aquatic conditions, deepening the knowledge of critical water supplies and habitats. Aquatic robot will carry sensors recording things such as temperature, dissolved oxygen, pollutants and toxic algal blooms. Image processing algorithm improves the accuracy for detecting pollutants.

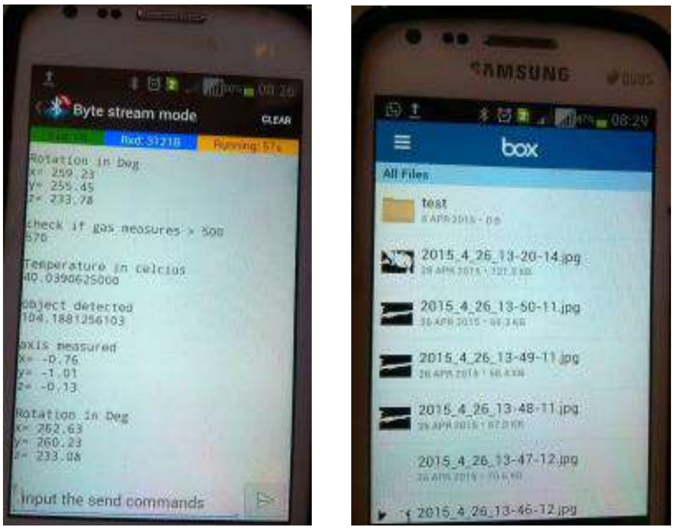

Figure 8. Results obtained on Smartphone a) output of sensors on Bluetooth b) output of camera on Bluetooth

CONCLUSION

This paper presents design of aquatic robot for aquatic pollutants monitoring. The android smartphone is integrated with aquatic robot to capture images and to acquire data of different sensors. The real time pollutants detection is done with the CV algorithm efficiently. In our future work, this can

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be extended to, use aquatic robot in an inland lake and evaluate it under various conditions such as debris flow speed and brightness/lightening.

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