AQUABOT: Aquatic Debris Monitoring And Detection Using Raspberry Pi

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Abstract- *Monitoring aquatic debris is of great interest to the ecosystems, marine life, human health, and water transport. This Project presents the design and implementation of AQUABOT – a vision-based surveillance robot system that integrates raspberry pi, robotic fish model along with camera and other sensors for debris monitoring in relatively calm waters and detection of unauthorized activities detection based on Logo recognition and language recognition. AQUABOT features real-time debris detection and coverage-based rotation scheduling algorithms. The image processing algorithms for debris detection are specifically designed to address the unique challenges in aquatic environments. The rotation scheduling algorithm provides effective coverage for sporadic debris arrivals despite camera's limited angular view. In this project, we focus on the design of debris detection and mobility scheduling algorithms running on a single RASP node. The sensing results of multiple nodes can be sent back to a central server via the long-range communication interface for fusion and human inspection.*

I. INTRODUCTION

AQUATIC debris – human-created waste found in water environments – has emerged to be a serious environmental issue. The 2011 Japan tsunami released about one million tons of debris that heads toward North America and U.S. West Coast. Inland waters also face severe threats from debris. Over 15 scenic lakes in New Jersey still suffer debris resulted from Hurricane Sandy after one year of cleaning. This which was the deadliest and most destructive hurricane of the 2012 Atlantic hurricane season, and the second costliest hurricane in United States history. The debris fields pose numerous potential risks to aquatic ecosystems, marine life, human health, and water transport. For example, the debris has led to a loss of up to 4 to 10 million crabs a year in Louisiana, and caused damages like propeller entanglement to 58% fishing boats in an Oregon port. It is thus imperative to monitor the debris arrivals and alert the authorities to take preventive actions for potential risks. Opportunistic spotting by beach-goers or fishermen is often the only viable solution for small-scale debris monitoring. However, this approach is labour-intensive and unreliable. An alternative approach is in situ visual survey by using patrol boats. However, it is costly and can only cover a limited period of time. More advanced method involves remote sensing technologies, e.g., balloon-board camera and satellite imaging. The former is only effective for one-off and short-term monitoring of highly concentrated debris fields that have been already detected, and the latter often has high operational cost and Different from falls short of monitoring resolution.

Recently, autonomous underwater vehicles (AUVs), have been used for various underwater sensing tasks. However, AUV platforms often have high manufacturing costs (over $50,000 per unit). The limitations of these remote sensing and AUV-based approaches make them cost prohibitive for monitoring spatiotemporally scattered debris fields with small-sized objects. For example, the debris from the 2011 Japan tsunami is expected to arrive dispersedly along U.S. West Coast over two years starting from spring of 2012 to late 2014. Existing vision-based systems, we need to deal with unique challenges in aquatic debris monitoring, such as camera shaking and sporadic debris arrivals. Extracting the foreground objects from a sequence of video frames is a fundamental CV task. Background subtraction is a widely adopted approach, which, however, often incurs significant computation overhead to resource constrained devices. A compressive sensing is applied for background subtraction to reduce computation overhead. An adaptive background model is proposed to trade off the object detection performance and computation overhead of background subtraction. These approaches assume a static camera view, and hence cannot be readily applied to the debris detection in water environments where camera is constantly shaking due to waves. This project develops a collection of vision-based detection algorithms that are specifically designed for background subtraction in dynamic water environments and optimized for Smartphone platforms. Water resources and aquatic ecosystems such as oceans, lakes, rivers and drinking water reservoirs are facing severe threats from floating debris. The majority of the debris comes from the human-created waste, which poses numerous risks to public health, ecosystem sustainability and water transport. For instance, debris leads to fish deaths and severe damage to fishing vessels. It is of great importance to monitor aquatic debris and take preventive measures for the potential risks. In the past few decades, debris monitoring has primarily been conducted by manual spotting using patrol boats.

II. LITERATURE SURVEY

Current approaches to monitoring aquatic debris fall into three basic categories, including manual spotting, patrol boat-assisted survey, and remote sensing. Manual spotting, although viable for small-scale debris monitoring, is label intensive and lacks robustness. Debris monitoring based on patrol boats and remote sensing is more reliable. However, these approaches are prohibitively expensive for long-term monitoring, especially when debris objects arrive sporadically over vast geographic regions. Several research efforts have explored the integration of cameras with low-power wireless sensing platforms. Cyclops integrates a CMOS imager hosted by a MICA2 mote .It can perform object detection using a naïve background subtraction method. In, a low-end camera module is installed on an AUV for navigation. However, these camera-based platforms can only conduct simple image processing tasks due to the resource constraints of motes. Recently, mobile sensing based on smart phones has received increasing research interest due to their rich computation, communication, and storage resources.

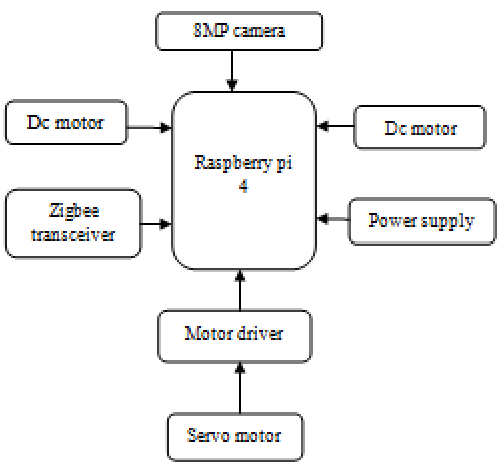
The study in designs a driving safety alert system that can detect dangerous driving behaviours using both front- and rear facing cameras of a Smartphone. This project aims to design an aquatic debris surveillance robot that utilizes the built-in camera, inertial sensors, and other resources on Smartphone. Different from existing vision-based systems, we need to deal with unique challenges in aquatic debris monitoring, such as camera shaking and sporadic debris arrivals. SOAR [1] consists of an off-the-shelf Android Smartphone and a gliding robotic fish. The Smartphone is loaded with an app that implements the CV, movement scheduling, and cloud communication algorithms. The gliding robotic fish is capable of moving in water by beating its tail that is driven by a servo motor. The motor is manipulated by a programmable control board, which can communicate with the Smartphone through either a USB cable or short-range wireless links such as ZigBee. Various closed-loop motion control algorithms based on Smartphone‟s built-in inertial sensor readings can be implemented on either fish control board or Smartphone. The dynamic modelling is implemented towards a multi-joint swimming robotic fish developed in our laboratory. The robotic fish [2] is designed as a streamlined shape inspired by an Esox-lucius, whose mechanical structure and appearance are illustrated in Fig. 1. Mechanically, the robot is composed of a rigid head and a self-propulsive body. Both the head and the body are covered by a compliant waterproof skin made of emulsion, in order to protect the internal mechanism from water. The 2-DOF (degrees of freedom) pectoral mechanism and the novel neck joint can generate excellent 3D (three-dimensional) manoeuvrability.

But we always keep them still, since only planar motion is concerned in this paper. The internal mechanism in the undulating body is essentially a multi-link hinge structure, which is composed of four aluminium skeletons connected in series along the body. The posterior body is ended with a rigid caudal fin fixed to the last link via a slim peduncle. Such a configuration generates totally four rotatable joints within the flexible body, which are actuated by servomotors with strong torque and high speed.

Motion of the robotic fish is controlled by a micro-controller embedded in the head. Red and yellow colour markers made of waterproof material are attached to the head skin out of the rigid shell. It is through tracking the colour markers that we locate the robotic fish and acquire its motion data. Much research on the navigation of mobile robots has been carried out to improve their performance, where localization is one of the crucial technologies. Localization is to identify the pose, i.e., the position and the heading angle of a robot in an environment using information from measured data or initial pose. Localization is certainly needed for robots to efficiently carry out given tasks such as cleaning, serving, guiding, etc. Moving around without localization for robots is the same as walking with closed eyes for people. They do not know where they are and which direction they should move to. It means that localization is very important to mobile robots for intelligent behaviours, and much research on localization has been carried out.

Self-localization methods can be classified into relative localization and absolute localization. The relative localization method that uses internal sensors such as odometer and inertial measurement unit is robust against environment changes, but the accumulated error becomes quite large for a long operation time. The absolute localization method [3] that uses external beacons or landmarks can identify a pose of the robot even after abrupt movement from the current location and the accumulated error does not exist. The fusion of these methods is widely used to reduce the localization error by employing Kalman filter or particle filter, which gives more accurate and robust outcome than each single method alone. Traditionally, aquatic monitoring based on sensor networks has focused on low-level sensors that measure 1D data signals, e.g., dissolved oxygen, conductivity, and temperature, which limit the ability to provide richer descriptions of aquatic environments. Recent developments in wireless sensor networks and distributed processing have made the use of camera sensors in environmental monitoring possible. Several low-power wireless sensing platforms integrating camera sensors have been investigated. Cyclops integrates a CMOS camera module hosted by a MICA2 mote. It can perform simple image processing like background subtraction using frame difference. CITRIC consists of a camera daughter board connected to a TelosB mote. The platform has been successfully applied to several typical applications, e.g., object detection and recognition. Besides, multi-tier sensor networks [4] seek to provide a low-latency yet energy-efficient camera sensing solution. SensEye is a notable example which consists of low-power and low-resolution cameras at the bottom tier that trigger higher resolution cameras at the upper tier in an on-demand manner. The study in presents a smart phone-based sensing platform that utilizes the built-in 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.

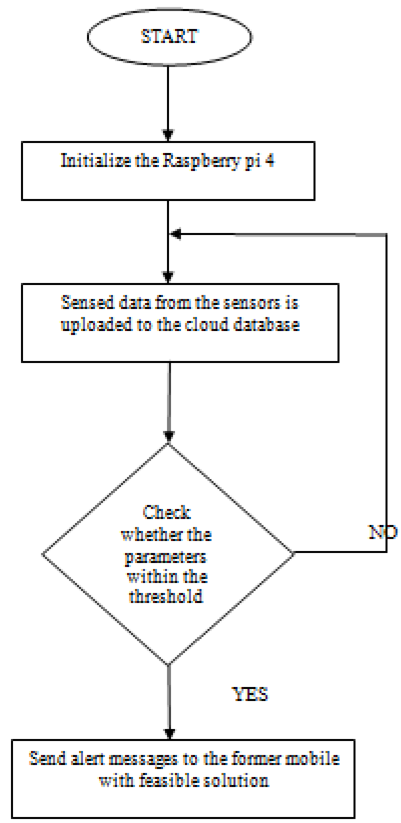
III. BLOCK DIAGRAM



AQUABOT consists of an 8 Mega Pixel camera with raspberry pi3 and a robotic fish. The 8 Mega Pixel camera is loaded with an app that implements the CV, movement scheduling, and cloud communication algorithms. The robotic fish is capable of moving in water by beating its tail that is driven by a 3 servo motor. The motor is manipulated by a programmable control board i.e. is raspberry pi, which can communicate with the all sensors and interfaces through either cable or short-range wireless links such as Wi-fi. Various closed-loop motion control algorithms based on raspberry pi and inertial sensor readings can be implemented on fish control board. AQUABOT is designed to operate on the surface of relatively calm waters, i.e., with mild waves like ripples, and monitor floating debris in near shore aquatic environments.

In this case, the number of needed nodes is the ratio of the length of the monitored shoreline to the coverage range of the Smartphone’s built-in camera. In this paper, we focus on the design of debris detection and mobility scheduling algorithms running on a single AQUABOT node. In particular, the image processing algorithms will incur significantly higher computation overhead due to the distortion in captured images. Mechanical components like servo motors and robot structure can be used to swim the AQUABOT. However, this will complicate the system design and may negatively affect the system reliability.

IV. FLOW CHART



The algorithm for debris detection:

Step 1: Start
Step 2: Run
Step 3: Sense the data from cloud
Step 4: Check the parameter within the range
Step 5: If YES
Step 6: Alert message will send
Step 7: If NO
Step 8:Again it check for the data

V. IMPLEMENTATION

The implementation of the debris detection with the hardware. The hard ware used is Raspberry Pi. So little description of the used hardware with its features and its installation and setup procedure are also described. Mid portion of the chapter described how the entire process of debris detection occurs in water. For conducting this libraries of Open CV is used. Different .xml files of Open Cv are operated on the input and provide the required result.

Figure 5.1 Interfacing of IR Sensor and Camera

1. To detect the obstacles through IR sensor 2.Provides the images of the obstacles.

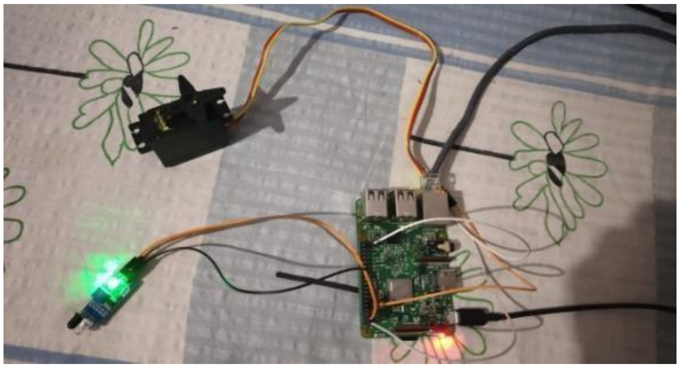


Figure 5.2 Interfacing of IR sensor and Servo motor

1. When the obstacle is detected, the motor stops.
2. If obstacle is not detected, the motor continues to rotate.

Figure 5.3 Interfacing of DC motor

1. DC motor is used for the movements of the fish.
2. The movements can be forward, backward, right and left

VI. RESULTS

To address these challenges, in this project we make the following contributions:

1. Develop several lightweight CV algorithms to address the inherent dynamics in aquatic debris detection, which include an image registration algorithm for extracting the horizon line above water.
2. The offloading decisions are made to minimize the system energy consumption based on in situation measurements of wireless link speed and robot acceleration.
3. Using the analytical debris arriving probability, we design a robot rotation scheduling algorithm that minimizes the movement energy consumption while maintaining a desired level of debris coverage performance.
4. The results show that AQUABOT can accurately detect debris in the presence of various dynamics and maintain a satisfactory level of debris arrival coverage while reducing the energy consumption of robot movement significantly.

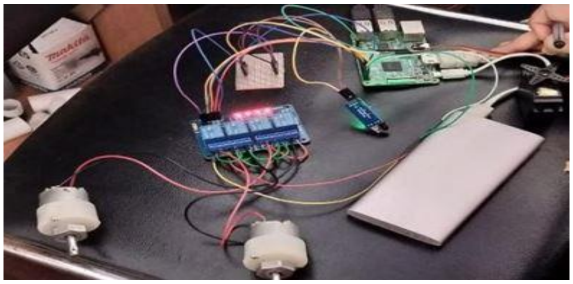


Figure 6.1 Hardware component

Figure 6.2 Aquabot Top View

1. Fins and tail movement of the fish.

2. Eye of the fish.
3. Detection debris.

VII. CONCULSION AND FUTURE WORK

An embedded sensing platform designed for aquatic environment monitoring. Based on this, we propose a lightweight debris detection algorithm, which effectively deals with environmental disturbances. The experiments demonstrate the feasibility and versatility of the proposed method in challenging environments. Moreover, real implementation on embedded sensing platforms shows that our method is more accurate, and consumes less hardware resources than the conventional approaches. Finally, an initial deployment of aquatic sensor nodes shows that the proposed method provides robust debris detection performance, meets the real-time requirement on embedded sensing platforms.

Our future work will focus on the implementation of aquatic mobile platforms and collaboration schemes between multiple nodes for debris detection. Our model is designed for detection of drowsy state of eye and give and alert signal or warning may be in the form of audio or any other means. But the response of driver after being warned may not be sufficient enough to stop causing the accident meaning that if the driver is slow in responding towards the warning signal then accident may occur.

Hence to avoid this we can design and fit a motor drive system and synchronize it with the warning signal so that the vehicle will slow down after getting the warning signal automatically. Also we can avoid the use of Raspberry pi which is not so fast enough for video processing by choosing our own mobile phone as the hardware. This can be done by developing a proper mobile application which will perform the same work as Raspberry Pi and response will be faster and effective.

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