Research and Design of Marine Trash Classification Robot Based on Color Recognition

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Abstract. The UN (United Nations) identifies sustainable development of the marine ecosystem as a major goal. To achieve the goal, the garbage in the ocean has to be removed, and as people recognize that different types of classification should be disposed differently, classification is critical after garbage is collected. This led to the engineering goal of constructing a robot that can pick up garbage in the water and classify the garbage into its right category. The robot was developed by attaining four critical functions: driving under water condition, a set of gripper, color recognition and garbage classification. Results of data obtained from developing the garbage classification was plotted on multiple graphs including training and validation loss, training time, training and testing accuracy and so on. After the critical functions are fulfilled, it is shown that the accumulative testing accuracy for garbage classification algorithm was around 90.6%, while the programs for the other three critical functions all compiled successfully. It was a regret that datasets weren’t shaped to the same sizes and the critical functions should be synthesized for further research.

Keywords: Arduino; Recycling of Garbage; Robot.

1. Introduction
The United Nation (UN) launched sustainable development goals in 2015 regarding 19 areas including poverty education, climate, economic growth and so on (Assembly, 2015). According to Costanza, one of the areas in which UN Opening Group focuses on is Marine resources, oceans and seas. Marine resources need to be protected especially because biodiversity under the sea is no longer stable. According to Schipper et al., “compared with land species, threat levels are higher among marine mammals” (Schipper et al., 2008), more essentially, threats toward marine species mainly come from accidental mortality and pollution. Derraik further points out that “Marine animals are mostly affected through entanglement in and ingestion of plastic litter.” (Derraik, 2002). On September 17th, 2019, a mysterious feature was spotted on the surface of the Yangtze River in China. The object in the video with a huge linear black body was swimming on the surface of the river with its body swung with the flow of water like a dragon. It was suspected that the object was one of the Yangtze River Monster in Chinese folklore, which caused a huge panic among residents nearby. However, the creature turned out to be an obsolete rubber balloon. Although people were relieved from the idea of river monster, the plastic pollution problem in Yangtze River was brought in front of the public. In January 2017, an enthusiastic whale was found repeatedly beached in Norway. After its suicide, zoologists retrieved
around thirty plastic bags along with other plastic wastes from the stomach of the whale. The non-biodegradable material was a strong potential reason behind the suicide of the whale.

![Plastic mass and particles across the world's surface oceans](image)

**Figure 1.** Plastic mass and particles across the world’s surface oceans.

The pillars represent the amount of plastic (both in mass and particles) in different areas of the world (Adapted from Ritchie & Roser, 2018).

According to Figure 1, in 2010, an estimated 10,000 to 100,000 tonnes of plastics are in the ocean surface waters. And more than 5 trillion plastic pieces weighing over 250,000 tons afloat at sea (Eriksen et al., 2014). In order to save marine animals from marine trash, especially plastics, while it is necessary to warn people from throwing trash into the water, the trash that already existed in the sea should be removed. However, marine trash elimination requires a lot of human swimmer resources. Moreover, “swimmers experienced respiratory ailments most frequently, followed by gastrointestinal, eye, ear, skin, and allergic symptoms, respectively.” (Seyfried et al., 1985). Therefore, automation should be applied to solve the problem of marine trash instead of human resources. With a robot that can function under water, the problem of lack of human resources can be addressed. Moreover, in order to separate trash from the water, a robotic gripper should be applied. Compared to human arms, robotic grippers can better “conform to objects” (Hirose & Umetani, 1978). A gripper can continuously pick up trash from the sea as long as the battery sustains. It can also ensure that the trash is collected “reliably and without distortion, deformation, and/or folding” (Kolluru, Valavanis, Smith & Tsourveloudis et al., 2000), which is especially essential because trash may be dissected and some parts of it may fall back into the ocean.

![Trends: 2000 to 2015](image)

**Figure 2.** The Amount of Waste Sent to Landfill in England.

The pillars represent the amount trash that is processed in different ways (Adapted from the Environment Agency (EA), 2016).
After trash is eliminated from the marine area, disposal is also essential to achieve the goal of sustainable development. Many countries in the world, especially in Asia, are facing a significant decrease of landfill capacity. For example, as shown in Figure 2, the amount of waste sent to landfill in England, the landfill capacity has decreased from 80000 cubic meters to about 45000 cubic meters. The annual waste generation increases in proportion to the rises in population and urbanization (Idris & Hassan, 2004). The most common way of disposing of trash has been landfill, but the process of selecting a suitable space for landfill becomes harder and harder due to the limited amount of land resources. Ways of disposing trash has to be developed other than landfill.

Figure 3. Energy in megajoules (MJ) from treating one ton of paper Incineration vs Recycling in 2018.

The pillars represent the amount of energy generated or saved from different treatments of paper (Adapted from Donahue, 2019).

Trash classification rises as one of the better methods to replace landfill. As presented in Figure 3, the amount of energy saved from recycling paper is significantly greater than the amount of energy generated from incineration. Similar to the marine trash elimination issue, artificial trash classification also has a massive requirement on human resources. Therefore, an autonomous system should also be developed to accomplish the trash classification task. By inputting a set of data that contains characteristics of different kinds of trash and let the computer learn it, once the system encounters a piece of trash in the water, it can complete the classification process by comparing the trash to the characteristics that it previously learned. Furthermore, when the trash is being captured and classified, it is essential that the trash is being put to the right bin. By giving each trash can a distinctive color, once the machine recognizes the color, it can throw the trash into the corresponding trash can. Similar to trash classification, color recognition also involves machine learning. By developing an algorithm from learning a set of data, the machine will be able to apply the algorithm to analyze the type of color that it is faced with, therefore makes the right selection to throw the trash.

To address the problem of effectively disposing of marine trash with technology, this research aims to construct an undersea robot that can dispose different types of marine trash. The functions of the robot include classifying trash to the right category, recognizing the colors correspond to the categories, and removing trash from the sea. With a sophisticated marine trash classification robot, a portion of marine biology can be protected from trash and pollution in the oceans.

2. Methods
The United Nation has identified the protection of Marine resources, oceans and seas as one of the major goals to fulfill sustainable development. One aspect regarding the preservation of marine ecology is dispose of trash that is discarded into the ocean. In order to attain the goals of both eliminating trash from the ocean and disposing of them in a way that doesn’t lead to pollution, a robot that can drive in the marine condition, pick up garbage, classify its category with a camera on the land, and put it into the right bin according to colors. The experiment procedure was divided into three parts: design, critical functions, tests and analysis.
Based on the aims that the robot would achieve, the basic structures of the robot consisted of a chassis, a set of gripper, a sensory system and water-proof materials. The chassis was the most essential part of the robot, it served as the main driving system. The chassis would be made up of a piece of acrylic board with two wheels attached to each side, motivated by two motors at the bottom of the acrylic board. The battery and the electric system would be located on the surface of the chassis. The electric system involved a breadboard that had circuits connected to the Arduino, TCS230 chip and the H Bridge driver, which would be controlling the critical functions of the robot (details accounted in the next paragraphs). The electric system would be protected by water-proof material that covered the chassis. A gripper would be established at the top of the chassis. The structure of the gripper had a major arm and two pieces resembling the function of a clip at the tip of the arm (details accounted in the next paragraphs). The sensory system was located on the gripper. It consisted of a breadboard with an Arduino, a TCS230 chip, and circuits for both the trash type classification system and the color recognition system. The sensory system would also be covered by water-proof materials. The graph of the robot was anticipated through a handmade scratch.

The four critical functions of the robot were driving under the water, trash classification, gripper and color recognition. The task of the driving system was to control the velocity (speed and direction) of the wheels. The driving system would be fulfilled by two motors, two wheels, and a steering gear, controlled by a piece of breadboard. Attached to the breadboard were an Arduino, a TCS230 chip, an H Bridge driver, and the circuits of the driving system. Once the input voltage came into the circuit from the battery, its PWM signal was enlarged through the transistor and passed to the H Bridge (Fig. 4).

![Figure 4. Circuit of Enlarging PWM Signal.](image)

Input PWM signal passes through the transistor and resistor and outputs to the H Bridge.

The chip controlled the PWM signal to alter the status of the four switches on the H bridge shown in Figure 5. When PWM was at its high status, the upper left and lower right switches of the H bridge turned on, and the current drove the motor towards its left. In contrast, setting PWM to its low status turned on the upper right and lower left switches of the H bridge, thus the motor spinned towards its right.

![Figure 5. An H-Bridge Inverter Circuit.](image)
Motor is in the middle which S1-S4 represents the four switches of the circuit. (Adapted from Ali, Daut, Taib, Jamoshid & Razak, 2010)

The speed of the motors was controlled by modifying the Pulse Width Modulation (Duty cycle ratio of DC), which was calculated by $n=(U-IR)/K\varphi$ with $U$ corresponding to the input voltage, $I$ and $R$ corresponding to the current and resistance, and $K$ and $\varphi$ were constant variables. $N$ could only be modified by adjusting the value of $U$ since modifying $I$ and $R$ required a change in the entire circuit diagram and constants couldn’t be modified. The whole circuit of the driving system is shown in Figure 6.

![Circuit of the Complete Driving System.](image)

Circuit of enlarging PWM signal at the left hand side and the signal passes through the H Bridge on right hand side to drive the motor.

The gripper system was constructed by five steering gears corresponding to five different degrees of freedom. When the sensory gear sensed the existence of a solid in front of the robot, it would send a signal by changing its indice to the computer. Then the second gear would apply the trash classification process (mentioned later) to determine whether it was identified as a piece of trash, thus decide whether the gripper system should work or not. If the solid was determined to be a piece of trash, the third gear would judge its position with respect to the robot. The fourth gear would be applied to adjust the angle of the gripper which the fifth gear would control the actual performance of picking up and dropping.

The trash classification process was completed on the computer with an algorithm (Lalanne & Lempereur, 1998). The classification process can be further divided into three parts: pre-processing, training and testing. During the pre-processing stage, a combination of two sets of data with images of different types of trash was imported in the code. Then the data was divided into folders labeling as training, validation and testing sets. After reshaping all of the images into the same sizes, the training model of resnet34 was fitted on the training data. A learning rate was founded by plotting loss versus learning rate, and the training accuracy was output. After getting a high training accuracy, the model was fitted on the testing set. Once the testing accuracy achieved a high value, then the algorithm could successfully classify garbage.

The last critical function was color recognition. After the robot picked up a piece of trash and identified its type, the trash should be put to the right trash can. There would be four types of trash: recycle (including paper, plastic bottles etc), harmful wastes (including batteries, electronic devices etc), kitchen wastes (including food, leaves, edible oil etc), and other wastes. The trash cans of the four types of trash would be labeled with colors: blue associating with recycle, red corresponds to harmful wastes, green indicating kitchen wastes, and yellow indicating other wastes. The robot would recognize the trash can corresponding to the trash it picked up by identifying their colors. The color recognition function was accomplished by an Arduino and a TCS320 chip (Fig. 7).
Figures 7. Circuit of the Complete Color Recognition System.

Figure 7 shows the front and back side of the chip; Figures 7 shows the block diagram of the specific functions of the chip. (Figure 6 adapted from Texas Advanced Optoelectronic Solutions, 2003)

Experts like Wang et al. use an algorithm for color recognition, but this project used current to identify colors for convenience. The current released by different light sources with different colors would be read by the chip. Simultaneously, the capacitance was filtered in order to eliminate noises from other currents. Once the Arduino read the current value from the chip, it would determine the corresponding color.

Figure 8. Circuit of the Complete Color Recognition System.

Circuit of detecting frequencies of light emitted by the colors at the left hand side and the chip determines and produces output on the right hand side.

According to the spreadsheet of TCS230, without being filtered, the most responsive wavelength of red is at about 700nm, 550nm and 830nm for green, and 470nm and 830nm for blue (Fig 9). With an eternal filter, the most responsive wavelength of red is at about 610nm, 520nm for green, and 470nm for blue (Fig 9). According to Xiao et al., the wavelength of yellow light is at about 580nm (Xiao et al., 2009). The circuit of the whole color recognition system is shown in Figure 8.
After the critical functions were attained, the robot went through a series of tests to eliminate the potential sources of errors that could cause the robot to behave abnormally. In order to test the driving, gripper, and color recognition system, the codes are exported to the microcontroller of the gripper, and the functions were proved to be successful if the codes would compile. All the codes would be modified after each test until the correct answers occupied a significantly larger frequency than wrong answers. During the trash classification test, the images of garbage in the testing dataset folder were put to the classification model, and the testing accuracy and a confusion matrix of all categories were output by the program.

3. Results
Below are all the graphs generated by the data obtained from the trash classification training and testing data sets.

Figure 9. Typical Characteristics of Responsivity for Different Colors.

Relative responsibility of different colors dependent on the wavelength of the light emitted by different colors. (Adapted from Texas Advanced Optoelectronic Solutions, 2003)

Before putting data in the training set to train the computer to be able to classify garbage, a learning rate was determined by plotting the potential loss over different learning rates. In Figure 10, the curve mostly followed a negative slope, and 1e-03 was chosen as the learning rate because it was in the middle of the downward slope, which yielded a balance between the loss and learning rate. The chosen learning
rate ensured that the loss of the data would be neither very large, nor the data would be learned very slowly.

![Figure 11. Epoch vs Training Loss/Validating Loss/ Error Rate](image1)

Loss values for the training set, validation set and total loss of each epoch.

According to Figure 11, the training loss, validation loss and the total error rate all follow a decreasing trend as the epoch increases. This means that the algorithm is making progress by making fewer errors through each training round.

![Figure 12. Epoch vs Training Time (min).](image2)

Training time of the training dataset output by the computer for each of the ten epochs. Different data points represent different epochs.

According to Figure 12 the training time for each epoch didn’t follow a specific trend. However, the training time was always around 50-75 minutes for each epoch, meaning that the training process is still quite long.

![Figures 13. Confusion Matrix of Training (right). Figures 14. Testing (left) Set.](image3)
Predicted numbers of garbage over actual numbers of garbage of each category in the training and testing sets. Blocks with dark colors represent the amount being correctly classified.

**Figure 15.** Count of Misclassification Over 2 Times (Training)

**Figure 16.** Count of Misclassification Over 2 Times (Training)

Percentages of the proportion among the most misclassified (being misclassified over 2 times) categories (Figure 15). Percentages of the proportion among the most being misclassified as (being misclassified as over 2 times) categories (Figure 16). Different colors represent different categories.

**Figure 17.** Actual vs Predicted (Training)
According to Figures 7, the plastic category was being misclassified the most, while paper and metal are the categories that were most likely to be misclassified as. Moreover, food is the category that the algorithm performed best with, because it was both misclassified and misclassified as for only once.

Actual and predicted numbers of garbage for each category in the training and testing sets. Different colors represent the actual or predicted values; different pairs of polars represent different categories.

Figures 17 and 18 yielded the fact that the algorithm performed best with food because the difference between the actual and predicted values was the least among all categories. However, plastic appeared to be the category that the algorithm performed worst with because it had the most difference between the actual and predicted values.
Statistical values (accuracy, true positive rate, precision, weighted average of precision and recall, and the complementary of false positive rate) for each category the training and testing sets. Different colors represent different features; different sets of points represent different categories.

In all, the algorithm performed well because with a high cumulative testing accuracy of about 91%. According to Figures 19 and 20, the statistical values between the training and testing sets were mostly equivalent. Besides the fact that food category had high statistical values, it was identified that the precision, weighted average of precision and recall, and the complementary of false positive rate of trash category were significantly lower than the other categories, which indicated that the algorithm also performed badly with the trash category.

4. Discussion

According to the results above, in general, the system did well in dealing with different types of trash with a high accuracy of over 90% (Figure 20). In particular, the system was good at recognizing garbage from the food category with only one of the images being misclassified (Figure 14). However, the system didn’t perform as well for trash for garbage from the plastic category with a misclassified rate of about 35.1% (Figure 15). To explain the results, the performance of the system could very likely be attributed to the richness of training data that allowed the algorithm to get familiar with. For the food category, the system had about 250 (Figure 13) data points in the training set, while it could only train with around 100 data points (Figure 13). The least amount of training data was around 35 (Figure 13) for the trash category, which showed the great potential of the algorithm since it correctly identified around 98% (Figure 20) of them in the testing set.

The previous paragraph demonstrated the first weakness of the research which was inconsistency of training data amount. Because as described in the methods session, the training data were combined from two datasets, with all the images of the food category coming from a distinctive dataset. Therefore, there existed a mismatch of data amount. Because the algorithm gained twice the amount of practice for food as the other categories, it was able to attain a testing accuracy of nearly 100% (Figure 11) for the food category. To address the problem, it would be better if the preprocessing of data included shaping datasets to have the same amount, or adding more training data for the other categories. Secondly, it was a regret to be unable to synthesize the four critical functions of the robot while having them completed individually. When determining the method session, only separate critical functions were designed, but there lacked a synthesis session in the research plan which could bring together all individual parts. Because of a shortage in the methods session and a lack of time, the robot didn’t get synthesized with all its functions. If the project were put to further research, the robot should be created with all of the critical functions connecting to each other.

Putting the research into a wider context, the conclusions yielded partly with what Tuia et al. said about active learning algorithms. They concluded that “the high intraclass variance can make an algorithm fail” (Tuia et al., 2011), and in this research, the amount of data points in the training set in each category varied significantly, which caused a difference in classification accuracy between categories.

Acknowledgements

Thanks to Professor Zachery for giving instructions on the driving and color recognition systems, and suggestions on the gripper model.

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