Bottle sorting by CNN and physical features extraction via robotic arm

Benjamin Ioller

Bottle sorting by CNN and physical features extraction via robotic arm

Benjamin IOLLER (EAMS LAB, Saitama, Japan)

November 2, 2019

Abstract

Bottles come in all shapes, materials, colors, or sizes but unfortunately tends to end up on our beaches, parks or forests. In this paper, we propose a robotic arm for picking bottle and present an hybrid approach for sorting glass to plastic bottle by combining classic light CNN model and physical features extracted by the robotic arm with no additional sensors. This method allows a fast development and provides good results of classification and take most advantages the robotic arm by transforming the actuators into sensors.

1 Introduction

The expansion of robotics and improvements of A.I allow now-a-day to face and solve global issues (1) (2). Global warning and pollution are a common cause for most of the engineers and researchers, and it without surprises that we see the multiplication of robotics application for monitoring or cleaning the ocean, street or forest(3).

But because trash come in all kind of shape, material, color, sizes and usually partially destroyed, the problem of classifying and sorting the different trashes is not a simple problem. Deep learning improvements solve most of these difficulties but require substantial amount of labelled data and deep network and may require powerful hardware to run and so limit the availability of such practical robots by increasing the price.

In this paper, we present a robot arm able to sort glass and plastic bottle. This arm can be mounted on a rover, and then been used to clean up beaches, or streets. We decided to approach the sorting problem as an human will do: mixing visual and physical information. Our method is an hybrid approach that merge classical deep learning model, and physical features classification extracted by the robotics arm. Our method allows to increase performances on the classification, without the need the need to install other sensors.

This paper firstly expands the principle of mixing images features and physical features for classification. Then, we introduce the robot arm, the feature extraction and the setup. Finally, we will present the experimental data, and summarize the experiment in a brief conclusion.

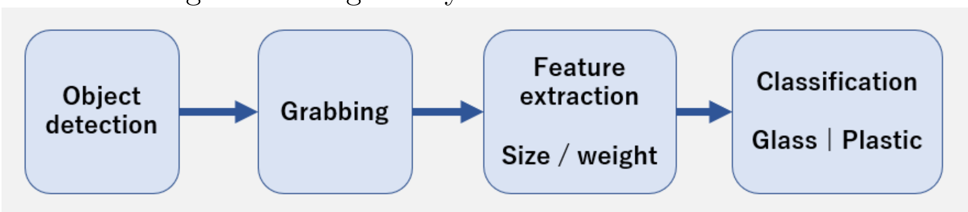
2 Image - Physical features combination

Human does not only use the vision sense to understand the environment. When encountering a new object, we inspect, grab, weight, squeeze it in order to identify the material, composition and object type. We tried to apply the same idea to the robotic arm.

As for the application, the almost infinite variety of shape, color and other parameters of bottles makes naturally the problem of sorting the material of an object just by the image difficult. A glass bottle can be really similar to a plastic bottle in every aspect size, color, shape and so make the classification challenging. Please note that we also applied this method for chestnuts - stone classification for a picking robot.

The idea, described in figure 1, is to detect the bottle on the image, grab it, then extract simple physical features (weight, size, hardness), and finally classify the bottle. The feature extraction is done without the addition of additional sensors.

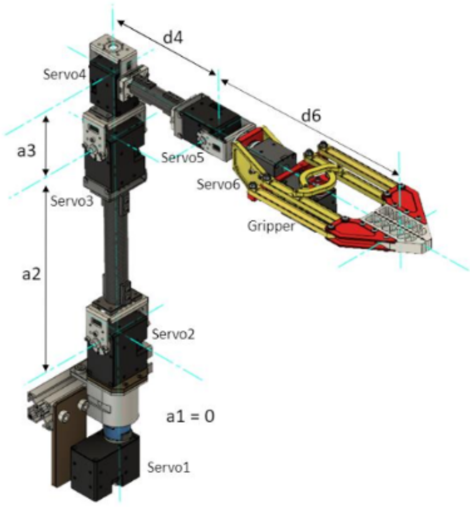
Figure 1: Image - Physical features combination



3 Robot Arm

In this section, we present the robotic arm architecture, camera setup, and experimental setup. The used robotic arm is the LabArm designed by EAMSLab (4). It is a 6 degrees of freedom arm, equipped with Dynamixel robotics servo XM-430-W350-R (5). The use of such motors allows current feedback, and so make the robotics arm smarter, able to sense it's surrounding.

Figure 2: Robot arm LabArm, designed by Rasheeddo (github)



3.1 Camera

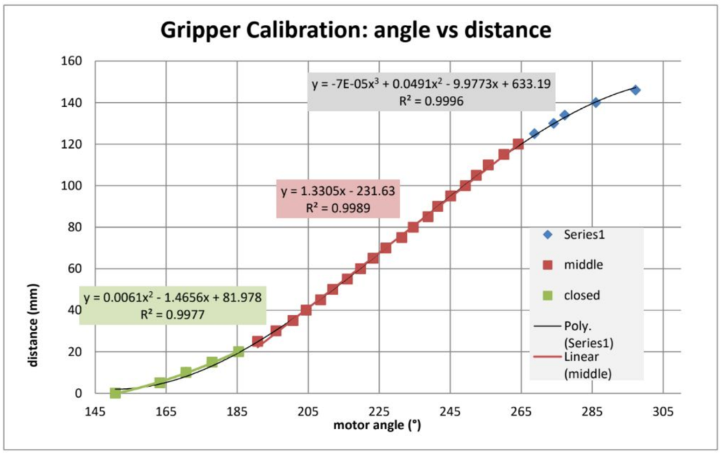
As vision sensor, we used a Real-Sense D415 depth camera. The RBG image is used for the bottle detection, and the depth image provided the position in the arm coordinate that allows precise grabbing (6).

3.2 Feature extraction

As a human will inspect by squeezing, weighting an unknown object, we try to extract the size, deformation and weight of the bottles. This is done without the addition of sensors, using only the smart servo motors.

- **Diameter measurement:**
  After establishing the diameter - angle relationship of the gripper *(servo 7 - gripper)*, we can directly measure the diameter of a sized object from the gripper motor. The relation is illustrated figure 3.

Figure 3: Gripper angle

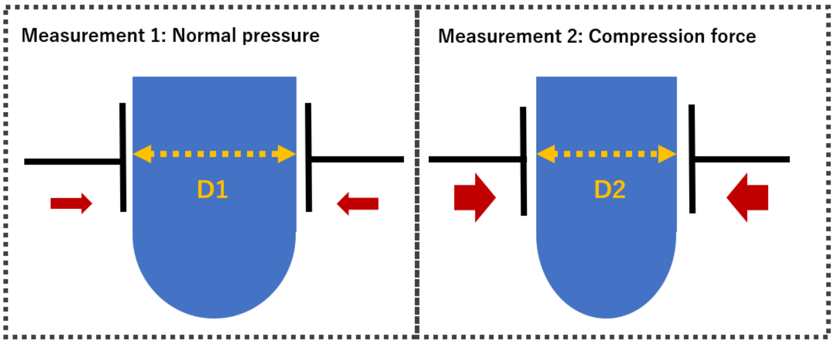


- **Weight estimation:**
  The robotic arm is placed in position so that all the torque in supported by *(servo 6)*. Once in position, the reading of the current provide the weight estimation. The relation is shown figure 4.

Figure 4: Weight measurement after offset

- **Deformation test:**
  By applying a greater current at the gripper motor, we apply a stronger grip and so compress the bottle. By measuring the new deformed diameter, we obtain a deformation feature. The principle is illustrated figure 5.

Figure 5: Deformation measurement in two steps:



4 Implementation

In this section, we detailed the principle implementation: the bottle detection, grabbing techniques and feature extraction process. The complete API was written in C++.

4.1 Image detection

We apply YOLO-v3 CNN for the initial bottle detection, currently a very popular model in robotics thanks to the good performances latency-accuracy (7). In order to save labelling and training time, we firstly choose to use pre-trained weight. Nevertheless, the model was trained with mostly standing bottle, so it was not able to detected lying, and damaged bottle. This is why we retrain the network with a small custom data-set obtained from ImageNet (8), and image augmentation. The figure 6 shows some of the prediction.

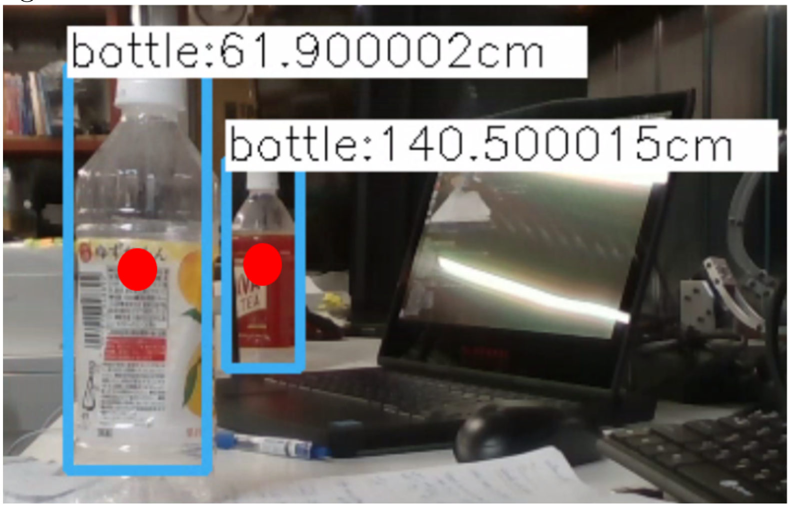
Figure 6: YOLO-V3 retrain for bottle detection

4.2 Bottle grabbing

Once detected the robot arm needs to grab the bottle. It is important to grab the center of the bottle in order to be able to extract the physical features of the bottle. This is done easily as we are using a depth camera. We extract the distance of the center of the bottle, and convert the position into the arm referential.

The arm configuration allows to grab standing and lying bottles at a maximum of 60cm and 45cm respectively (4). The differentiation of the bottle state in simply done by the bounding box shape.

Figure 7: Distance Arm referential - bottle center distances



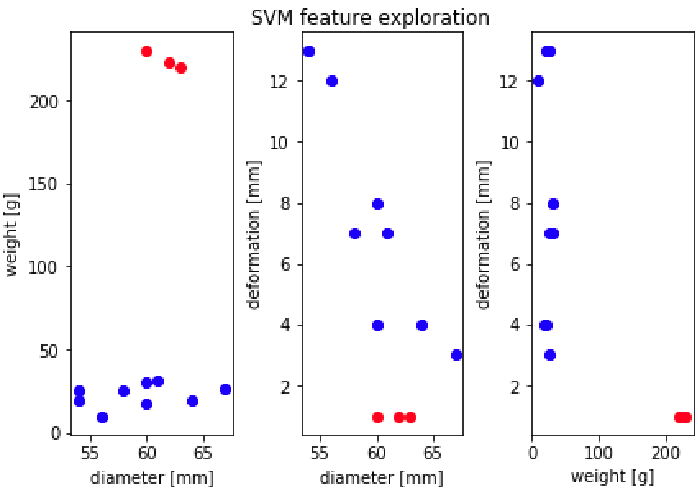
4.3 Final Classification

With the bottle in the gripper of the arm, we can extract the physical features in the following order:

1. Diameters
2. Weight
3. Hardness

The classification glass-plastic is done with a Support Vector Machine (SVM) algorithm. The SVM was trained with 13 bottles (8 plastics / 5 glass). The figure 8 shows features comparaison for between some bottles.

Figure 8: SVM features exploration (blue: plastics, red: glass)



5 Results

The experimentation was done with 5 random bottles taken from the street. The robot successfully sorted all the bottles if the grab was correctly achieved.

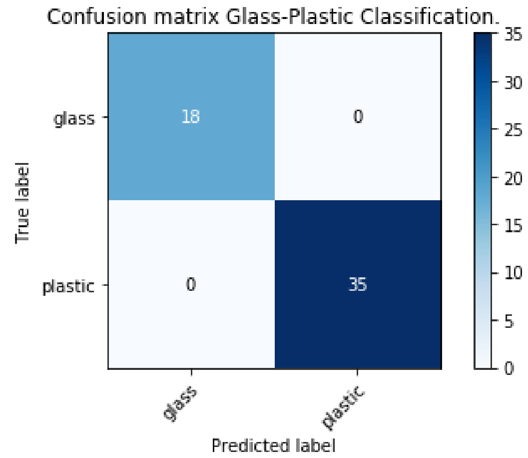
5.1 Grabbing

The main limitation of the application was the grabbing. Sometime the robotic arm failed to grab the bottle correctly. We calibrated the gripper to extract the feature at the middle of the bottles, in some case the bottle was gripped at the very top or rotated at the bottom. With such grabbing, we arm wasn't able to extract the characteristics (weight and deformation), and so not able to do the classification.

5.2 Sorting Plastic-Glass bottle

If correctly grabbed the arm was able to sort the glass to plastic bottle with an accuracy of **100%**. The confusion matrix figure 9 was obtained experimentally when the bottle was correctly grabbed.

Figure 9: Confusion Matrix, when correctly grabbed



5.3 Can bottle

A specificity in Japan is the presence of aluminium bottle. We try to classify the *Can-bottle*, for that we retrained the SVM, and redo a classification test (Figure 10).

These results show that the classifier mainly focus on the deformation feature and therefor miss classify the *can-bottle* with plastic bottle. These can be solved by extracting more clever feature as the deformation type (elastic - plastic deformation), more training sample.

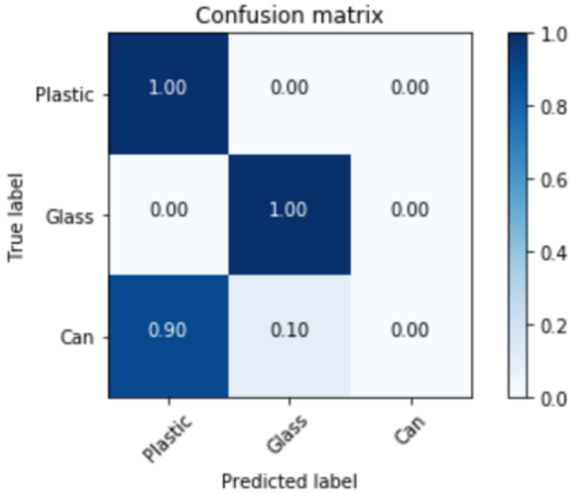
6 Conclusion and Future work

This paper demonstrate the combination of image and physical data for sorting bottle, as a human will do. The robot arm was able to separate the bottles with a very high accuracy assuming that the grabbing was correct. However, the robot was not able to separate the can bottle to the plastic bottle. This lead to several possible improvements and research topics (9).

One current limitation of the robot is the weight measurement accuracy and response time. A solution can be to measure the weight by momentum (10).

A way to improve the classification is to increase the feature space by adding new features like deformation type, object density, ... We can also think of a deep model conjuring some image feature (shape, mask) and the physical feature at the classification level.

Figure 10: Glass - Plastic - Can Classification



References

[1] Laura Parker. Plastic pollution fact info-graphics, National Geographic, 2018

[2] 21,200 output on Google Scholar for 2019 papers, $https://scholar.google.com/scholar?as_ylo = 2019q = robotic + armhl = enas_sdt = 0,5$

[3] Oscar Alvear, Nicola Roberto Zema
Using UAV-Based Systems to Monitor Air Pollution in Areas with Poor Accessibility, 2017, Journal of advanced transportation

[4] Robot arm documentation, EAMSLAB.Co, 2018 Japan, https://github.com/rasheeddo/LabRobotArmOfficial/blob/master

[5] Robotics Dynamixel motors documentation, http://www.robotis.us/dynamixel/

[6] Realsense datasheet, https://www.mouser.com/pdfdocs/Intel$_D400_Series_Datasheet.pdf$

[7] Redmon, Joseph and Farhadi, Ali,
YOLOv3: An Incremental Improvement, 2018, arXiv

[8] Jia Deng; Wei Dong; and associates
ImageNet: A large-scale hierarchical image database, IEEE, 2009

[9] Difference between Elastic and Plastic Deformation, 2018, https://pediaa.com/difference-between-elastic-and-plastic-deformation/

[10] Momentum How it works, Science Clarified, http://www.scienceclarified.com/everyday/Real-Life-Chemistry-Vol-3-Physics-Vol-1/Momentum-How-it-works.html