

Object-Sorting-by-Color in a Variety of Lighting Conditions Using Neural Networks and Lego Mindstorms Robot

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Abstract

Recognizing object color in a variety of lighting conditions is a challenging area of pattern-recognition. Neural networks have been found to be a good solution for that problem, and they are also quick and accurate, and can be used in real-time. We use a LEGO Mindstorms [1] robot to sort objects based on color in a variety of lighting conditions. We will start from simpler objects (LEGO pieces) and move onto more complex objects (apples, oranges, etc). This project is in progress and we hope to achieve classification accuracies of at least 90%.

Introduction

Making machines that successfully recognize object color is challenging for many different reasons. Firstly, human perception of object color is subjective, so different people could train the same machine's color recognition differently. Furthermore, color of an object may be perceived differently by different image-taking devices. Lastly, when lighting conditions change, the perceived color of an object changes.

In this paper we present a LEGO robot that uses a neural network to recognize colors of objects in a variety of lighting conditions. Specifically, the robot will recognize LEGO parts of these colors: red, green, yellow, blue, and white. Further research will focus on classifying fruits.

Compared to human classification which is tedious and error prone [3], our robot will provide consistent and accurate color recognition. The main goal for this research is to perform successful "classification ... under different color saturation, variations of environment lighting and light reflections" [2].

Related Research

Most of the applications of color-recognition using artificial neural networks (ANNs) are found in agriculture: (1) Orange classification based on the overall color into these categories: dark-green, light-green, yellow, light orange, dark orange, and rejected (Simoes et al) [2],

- (2) Apple grading based on the quality of apple surface into the following categories: Superior, excellent, good, poor and injured. For example, the superior grade is defined by having at least 89% surface deep red and orange background, whereas the excellent grade is 70-89% red surface with yellowish orange background. (Nakano) [3]
- (3) Weed identification, given four different types of weeds, using image color-texture (Burks et al) [4]

Some researches, like Shahin and Symmons (in their lentil-grading experiment) found that ANNs are appropriate for the task of color recognition because they have good performance, they are easy to retrain, easy to change classification criteria, simple to setup, and execute [5]. Burks et al found "neural network classifiers ... well suited for real-time control applications" [4]. Simoes et al found out in their orange-sorting experiment that "the use of an artificial neural network as a color classifier allows a robust classification even under orange color saturation variations, brightness, and non-homogeneous ambient illumination conditions" [2]. They achieved 93% average accuracy.

Approach

We chose LEGO Mindstorms robots as our hardware platform because they are easy to setup, easily customizable, and they provide real-time testing environment. The LEGO robot is a prototype of a more sophisticated robot.

Figure 1 shows the design of the robot. The LEGO camera takes pictures of the object on the conveyor belt. The image is sent to the PC which performs image processing using ANN. The color of the object is decided. Command to place the object in an appropriate bin is sent to the LEGO Mindstorms brick. The brick controls the pushers and the conveyor belt. There are 5 bins for objects of 5 different colors: white, yellow, green, red and blue. Pusher Px pushes an object into the corresponding bin. If the object color is blue, no pushers are activated.

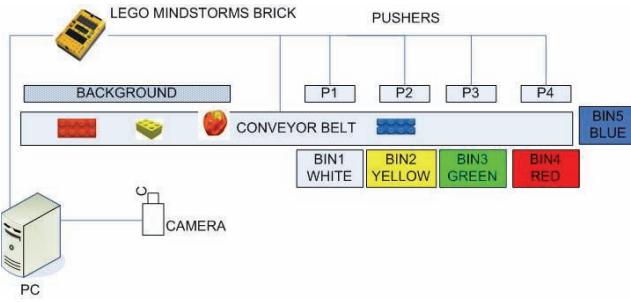


Figure 1 - LEGO robot that sorts objects by color.

We will take multiple pictures of each test object in a variety of lighting: indoors, and outdoors, in sunny and cloudy weather, in the morning and in the afternoon, with and without a direct light source. 75% of pictures for each object will be used for training and the rest for testing.

Technique 1: Reduce the input picture from 352x288 pixels to 15x15 pixels, using pixel averaging algorithm. The reduced image will be the input into the network, and the output will be color categories, such as red, yellow, blue, etc.

Technique 2: First separate the picture of the object-to-be-sorted from the background using one of the region-growing algorithms. Then, every RGB values of every pixel from the object picture will become an input into an ANN. The output of the ANN will be a color designation, e.g. red, green, and yellow. Then each object picture will become a vector, showing how many times each color appears in the original picture. Then vector approximation will be used to decide the color of the object (e.g. if the most occurring color is red, then the object is red). For example, the coordinates will be (red, green, blue, yellow, white) and a sample red object may have these coordinates, where the red coordinate dominates all the others: (200, 4, 6, 0, 45). This approach mimics that of Simoes et al [2].

Technique 3: For more complex sorting tasks, such as sorting apples, we will also use statistical image texture as input into our network. This technique greatly reduces the input size of the neural net, yet it seems to be very promising, as in Burks et al's weed classification [4].

Testing

To test our robotic sorter, objects-to-be sorted will be put on the moving conveyor belt. Camera will take images of the objects in real time and send it to the PC which will perform image processing and classify the objects. Then the robot will place the objects in the appropriate bins, corresponding to their color. Lighting conditions will be varied as to test whether the object color is recognized properly in the variety of conditions.

Figure 2 shows a sampling of red LEGO pieces. Each one of these pieces should be recognized as red by our robot, in any type of lighting, and be sorted into the red bin.

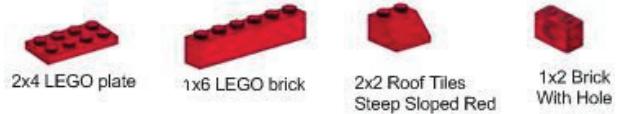


Figure 2 - A sampling of red LEGO pieces

After the robot perfects sorting of LEGO pieces, we will train and test the robot with variety of other objects that can fit on the conveyor belt, such as apples, oranges, candy, etc.

No testing has been done yet but we have high confidence in the system, based on the previous research results. Although Nakano's apple grading did not have favorable results (70% average classification accuracy), many other projects did. For example, Simoes et al's orange classification produced 93% average success rate [2] and Burks et al's weed classification showed very good results (97.6% overall classification accuracy) [4].

Conclusion

We expect to show a successful LEGO robot that can sort objects based on color using artificial neural network in a variety of lighting conditions. We expect that the recognition is fast and accurate, and applicable in the real-world production environment. In the future this robot would be able to replace labor intensive jobs and reduce human error. Future work will include shape recognition.

References

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