Recycling of Circuit Boards by Robot Manipulator Using Stereo Vision and Deep Learning

Intelligent robot for recycling of circuit boards

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Abstract— ***To make possible the recycling of printed circuit boards, automated systems for object classification and degree of overlapping are needed. In this thesis, a recycling system with a robot manipulator was developed by using Deep learning and a stereo vision approach. The system operates in the following order: object detection by deep learning, calculation of 3D point clouds by stereo vision, and grasping by the robot manipulator. Four experiments were conducted to evaluate the developed recycling system. The four experiments were: measurement of object detection accuracy, measurement of stereo vision responsiveness, measurement of vertical judgment accuracy and grasping accuracy, and operation test of the actual machine. Deep learning and stereo vision for the robot manipulator were found to be effective for the printed circuit board recycling system. The results also shed light on the challenges of automating the recycling process.***

Keywords-component; formatting; style; styling; insert (key words)

I. INTRODUCTION

Electronic circuit boards used in computers, smartphones, home appliances, and other devices are made of rare and valuable metals. Therefore, it would be advantage to have an in-depth recycling of the PCBs materials. Several recycling methods for PCBs have already been proposed. Most of the planned works rely on units to separate the components and heating technique to melt the solder ([1], [2]). In addition to manual disassembling, an automatic disassembly was proposed in [3], using the visual data. In [4] a disassembly machine using a robotic arm was proposed. Other works suggested separation methods based on each material's specific density [5], magnetic separation [6,] and integrating gravity and the force of a viscous liquid [7].

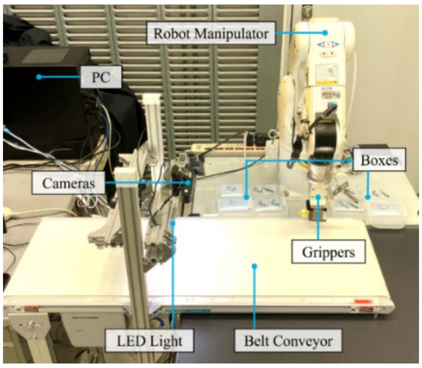
There are still a lot of problems to be resolved even if several ways for recycling PCBs have been suggested. This is as a result of the wide variation in PCBs and their intricate structure. In this paper, we provide a deep learning ([8]) based method for recycling PCB components. Recent Deep Belief Networks (DBN)-based techniques have proven to perform at the cutting edge in a range of tasks, including text databases, natural language processing, picture and speech processing, and many more. Only object classification and recognition are the focus of the majority of DBNs works [9–13]. Previous DBN applications have generally concentrated on niche uses, like robot semantic place recognition [14]. The authors employed a two-step cascade structure with two deep layers and an RGBD depth picture from a kinect sensor in [15].

In this paper, we propose a stereo vision-based object recognition and localization for robotic recycling tasks. In difference from our previous system [16], in our implementation, the robotic manipulator recognizes the PCB components which overlap each-other. The camera image is used as input of the CNN to recognize the recycled objects and separate them in specific boxes.

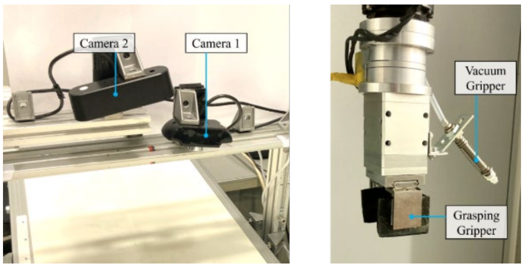
We evaluate the system in in terms of a) object recognition; b) relative vertical location of objects using the stereo vision; c) robotic manipulator grasping accuracy. In our work, the PCBs are cut into tiny objects and placed on a belt conveyor. The robot manipulator motion is developed based on camera data and conveyer speed, and the categorized pieces are then put in different boxes. The performance of two grippers because PCB board components have a variety of sizes, shapes, and are frequently quite flat.

II. SYSTEM CONFIGURATION

A robot manipulator and a belt conveyor are used to separate pieces of printed circuit boards of various types, sizes and shapes, as shown in Fig. 1. Fig. 1(a) shows the system for recycling of circuit boards, using a Denso VS-050 robot manipulator. The robot has a small base, and it can move in a wide range. Two cameras, as shown in (Figure 1(b)), are utilized for object recognition and stereo vision generation. An electric gripper is used to grasp the objects that are not flat (Fig. 1(c)). In addition, for flat objects we use a vacuum gripper (Fig. 1(c)).



（a）Recycling system of waste circuit boards.



（b）Cameras （c）Grippers

Fig. 1. Recycling system.

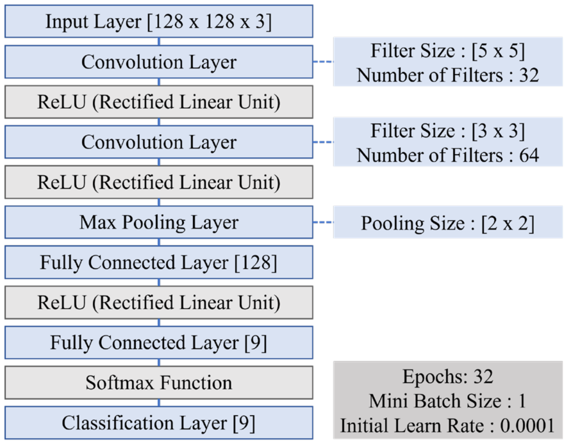


Fig. 2. CNN configuration.

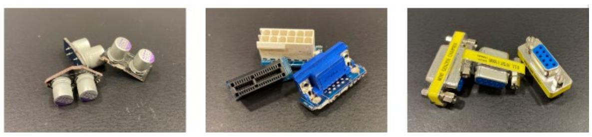
III. Deep Learning

In this work, Faster R-CNN is used to detect the recycled objects in the camera images [17]. Deep learning is a machine learning technique composed of multiple layers like the biological brains. Each layer consists of multiple neurons. During learning, the weights of the neuron connections are trained to generate the features for object recognition. The number of layers and the number of neurons in each layer are adjusted by trial and error. The input of Faster RCNN is the image. Faster R-CNN not only recognizes the object, but also generates the location of the object in the captured image. In addition, it was possible to detect multiple types of objects, simultaneously.

In Faster R-CNNs, the RPN (Region Proposal Network) is first trained, and then the CNN (Convolutional Neural Network) layers are trained. RPN detects if there is an object in the captured image, while CNN recognizes the object. For training, many images containing objects to be classified are prepared as training data. In addition, the position information and type data of the objects in those images are collected.

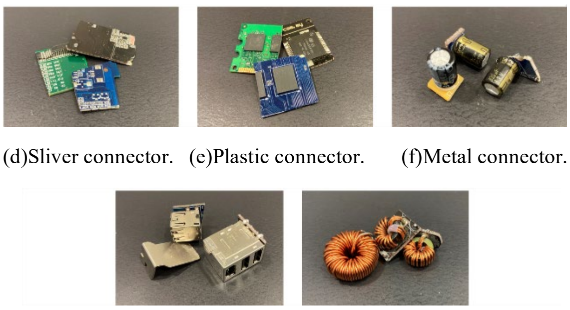
In this work, we investigate the effect of the number of pixels of the training data and the image representation on the detection accuracy. We change the number of pixels from 1920 x 1080 to 960 x 540. RGB and HSV image representations are utilized, and the results are compared. In HSV the image information is stored by three elements "hue, saturation, and brightness". In the RGB images each pixel is composed by red, green, and blue colors. Then, from the prepared training data, 4 patterns are trained with a network composed of 450 convolution layers and maximum pooling layers. The configuration of the network is shown in Figure 2. The learning conditions are 32 epochs, 1 mini-batch size, and 0.0001 learning rate.

In this work, 450 images are used for training and 150 images are used for evaluation. In addition, cross-validation was performed by exchanging the training data and the evaluation data and performing learning four times. The evaluation is done in terms of the recognition rates and the position of the object in the captured images. To judge the types and positions of objects on the belt conveyor, we created a network trained using Faster R-CNN [15]. We first created sample data to train Faster R-CNN. There are eight objects that must be recognized: The eight classes are PCB (the resin part of the board), IC (integrated circuit), Black Condenser, Silver Condenser, Plastic Connector, Metal Connector, Metal Parts (metal plates, USB connectors, etc.), and Coils, as shown in Fig. 3. The reason for choosing these eight classes is that they



are widely used in various electrical circuits.

(a)PCB. (b)IC. (c)Black condenser.



(d)Sliver connector. (e)Plastic connector. (f)Metal connector.

(g)Metal connector. (h)Coil.

Fig. 3. Recycle objects.

IV. Stereo Vision

In our implementation first the objects are recognized in the 2D captured image. When objects overlap each-other, 3D data are required. Stereo vision is a method to calculate 3D information (3D point cloud) of the object using images captured by two cameras. The purpose of the stereo data is to determine the relative position of recognized objects in the case they overlap each-other. This is important to grasp objects correctly and separate them in their respective boxes. The 3D information is obtained from the corresponding points in the two cameras captured images [18]. Referred to parameters shown in Fig. 4, the following equations are written:

$$l = a + b = z\tan\theta_a + z\tan\theta_b \tag{1}$$

$$\therefore z = \frac{l}{\tan\theta_a + \tan\theta_b} \tag{2}$$

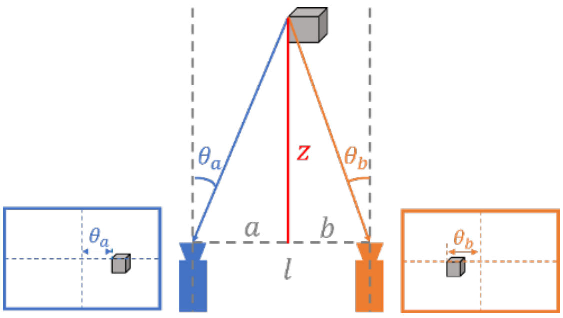


Fig. 4. Depth calculation using stereo vision.

In this work, a checkerboard is used to set the coordinate system for judging the position of the objects and the parameters for the position relationship between the two cameras (Fig. 5). Since the checkerboard is made up of black and white squares, it is easy to detect the corners with edge detection. Since these corners are equally spaced and coplanar, the positional relationship between the camera and the checkerboard is calculated. In other words, you can transform the coordinate system of the camera image and the coordinate system of the surface on which the checkerboard is located. Also, by using this principle, the positional relationship between the two cameras is calculated.

To evaluate the performance of the stereo vision, two pair of overlapping objects are placed on the belt conveyor simultaneously. The 3D information is calculated using the stereo vision. This was repeated 84 times, and the correct average correct results for each class are recorded. As the recycling objects overlap each other, in addition to recognition accuracy, the relative position in the vertical direction generated by the stereo vision is also important. This is strongly related to the grasping accuracy of the robot manipulator. In this work, it is assumed that two overlapping objects can be detected correctly, and 3D information can be calculated by stereo vision.

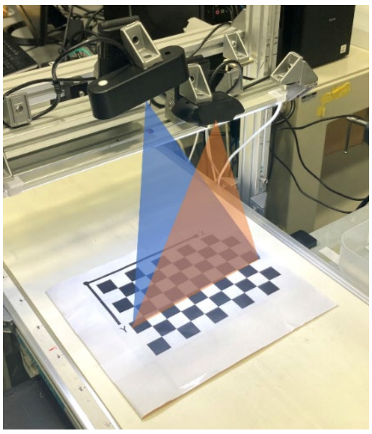


Fig. 5 Using a checkerboard with two cameras.

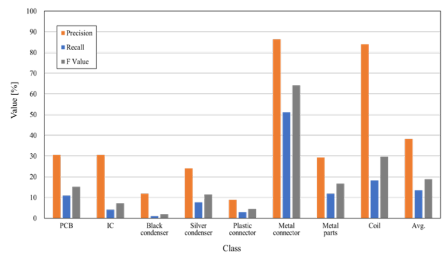
In our implementation, there are 28 combinations of paired recycle objects, making the recognition task difficult. We placed pair of objects on the belt conveyor overlapping each other. The robot grasping accuracy is calculated only in the case when the objects are correctly recognized. The PCBs are collected by the vacuum gripper, and other objects by the electric gripper. To calculate the gripper accuracy, 24 grasping experiments for each pair are conducted.

V. Results

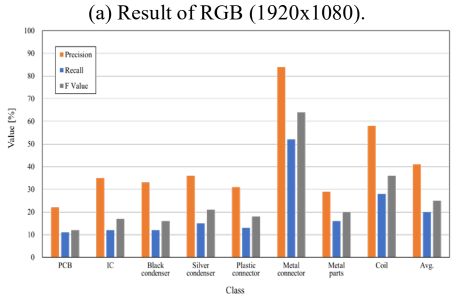
The results of RGB and HSV for different pixel number is shown in Fig. 6 and 7, respectively. During the experiments, the number of pixels of the camera and the training images are the same. The results show that the HSV gave better results compared with RGB. Results show that there is no much difference in computation accuracy of Faster RCNNs trained with pictures of different number of pixels. However, when the number of pixels is reduced by 1/4, the computational load and time is also reduced. Because the computation time is strongly related to the robot response, small number of pixels would be advantage for real time robot implementations. Therefore, the results of pattern 4 are the best among four learning patterns.

We measured the accuracy of 3D information of stereo vision for each class. The average accuracy of 3D information is 63%. Although it is slightly lower than the average recognition accuracy of 67%, it is good for real time implementation. We measured the accuracy of relative vertical position of objects using the visual image. The results for each combination and their average values are shown in Fig. 8. The average accuracy is 72%, and the gripping accuracy is 63%. By class, the values for Metal Connector and Metal Parts are slightly lower. This is because the objects are made of metal reflecting the light, making it difficult for the camera to see the outline of the object.

More than 100 operation experiments are conducted to evaluate the developed system. Fig. 8 shows the screen captured image in which objects are not only recognized but also their relative vertical position is generated. The red color objects are above blue color objects.

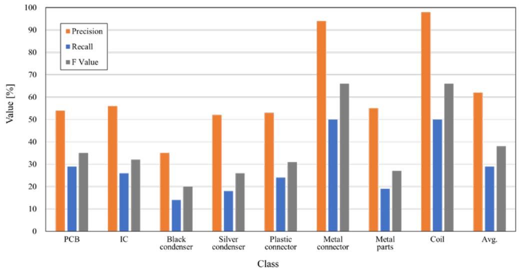


(a) Result of RGB (1920x1080).

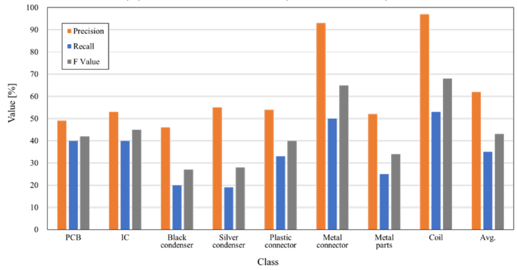


(b) Result of RGB (960x540).

Fig. 6. RGB image results.



(a) Result of HSV (1920x1080).



(b) Result of HSV (960x540).

Fig. 7. HSV image results.

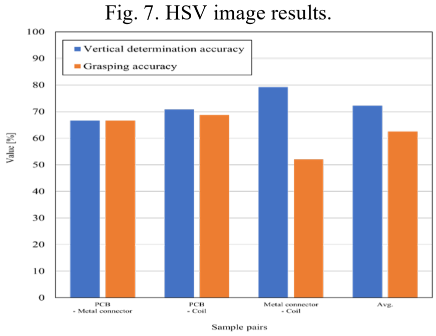


Fig. 8. Overlapping and grasping accuracy.

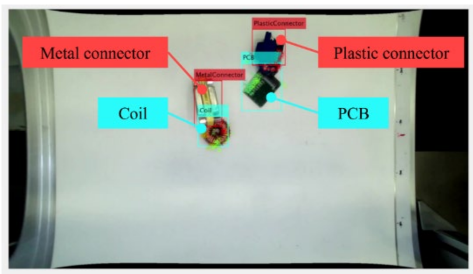


Fig. 9. Object recognition in overlapping situation.

VI. Conclusion

In this work, we proposed a recycling system for printed circuit boards using a robot manipulator, deep learning and stereo vision. RGB and HSV visual representations with different number of pixels are used for recognition and stereo information. The deep learning was trained to generate the object category and the location of the object in the captured image. The results showed that HSV image representation gave a better performance.

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