General Article

Object recognition system by depth camera using k-nearest neighbors and naïve Bayes classification for robot

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Abstract

Today, the robot technology is used for many applications. The robot is expected to dwell in human society with the abilities such as perception, decision, and non-injury. The study aims to determine the efficiency of the robot object recognition using k-nearest neighbor (KNN), and naïve Bayes classification. The red, green, and blue (RGB) camera of Microsoft kinect sensor was use to classify the detail. The experiment showed the accuracy rate of KNN was 77.0%, while the naïve Bayes classification was 60.4%.

Keywords: Robot, object recognition, depth camera, k-nearest neighbor, naïve Bayes classification

Introduction

In the past, robotic technology is only used in the industrial. Today, robots have been developed and improved the abilities that they are able to support many tasks for example, assisting the disabled person, rescuing the people from disaster, and helping in home. The robot must be consisted of the vision, decision, and action. Many interested in object recognition using (red, green, and blue) RBG image processing, which classified into 2 categories that are image processing on the RGB image and on the other types of image. [1]

The consumer depth cameras such as Microsoft kinect sensor, Leap motion, Apple Prime Sense, Intel RealSense, and Google project tango are widespread to use for object classification because of light robustness. The image processing for depth image is simpler than RGB image. So, the depth kernel descriptors for object recognition were utilized, using RGB and Depth image (RGB-D). Two tasks, instance recognition and category recognition, were used by support vector machines (SVM) classifier. [2] A study proposed the information extraction from various features such as texture, illumination, shape, viewpoint, clutter, occlusion, and sensor noises. [3]

In addition, the histogram of oriented normal vector (HONV) was suggested to recognize the local 3D geometric object, with the average accuracy of 55.5% [4], as well as the system for multiple object detection and classification using RGB-D Microsoft Kinect sensor by the linear spatial pyramid matching algorithm, with the average accuracy of 84.3%. [5] Whereas, the objects of daily use finder (ODUfinder) perception system has been utilize to detect and recognize the object's texture, by text retrieval for indexing the vocabulary trees of the scale-invariant feature transform (SIFT) descriptors, with the overall accuracy of more than 80%. The research aims to determine the accuracy of object recognition by Microsoft kinect sensor; RGB-depth (RGB-D) image.

Material and Method

The object recognition was conducted by using the Microsoft kinect sensor; 3D depth sensors, RGB camera, and multi array microphone, concurrence with simple classification using K-nearest neighbor (KNN) or Naïve Bayes Classification. The natural input memory with Bayesian likelihood estimation (NIMBLE) classification was used to categorize the independent component analysis features. The experimental TurtleBot, included Kobuki Base, Asus Xion Pro Live Netbook, and Microsoft Kinect sensor mounting hardware, were applied.

The sensor system of model building and testing identified the unknown object step by step, by capturing the depth of image in many view by rotate the target every 90 degree from normal to 90, 180, and 270 degree. The thinning algorithm, dilation and erosion function in the equation, was applied to remove the selected foreground pixels from the binary images with keeping original region. [7]

After pre-processing step, the feature was extracted from the image by applying the Canny edge detector algorithm (smoothing image, finding gradient, non-maximum suppression, double thresholding, and edge tracking by hysteresis) [8], and Freeman chain code algorithm which was feature extraction that represent the object boundary (4-directional and 8-directional chain code – chain code algorithm of 7777777744444441111111), traversed and started at the top of corner by specific length and direction [9].

The k-nearest neighbors (k-NN) [10] was conducted to supervise the learning method for classification based on majority votes that they were closest neighbors in training set. The Naïve Bayes algorithm [11] was utilized to be based-on the statistical method, to classify the data by the probability calculation. Besides, the RBG camera was used to detect the color, then the color and the brand of the object.

Results

The example RGB-D images of the kinect sensor and output of the Canny edge detection were demonstrated as in Figure 1.

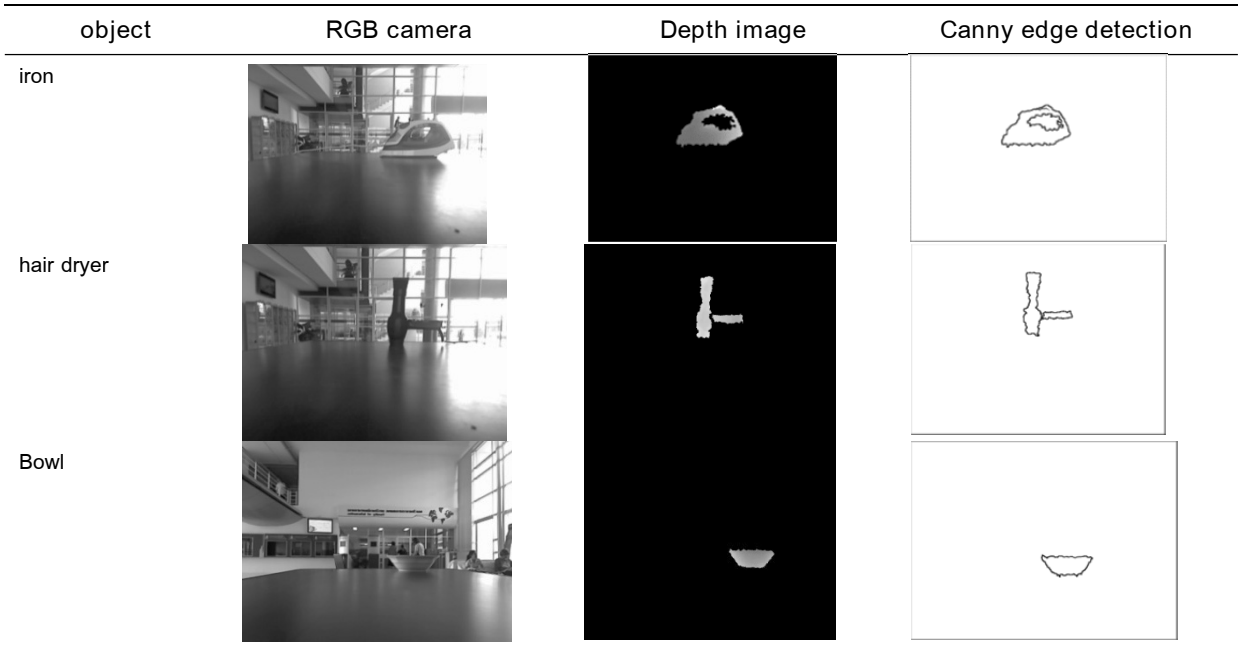

Figure 1 Examples of RGB-D image from Kinect sensor and output of the Canny edge detection

The experiment was investigated among 480 images of 12 objects to build the training set and 48 tested images (4 images for each class) to test the accuracy rate. The K-value was tested among 48 images, and the accuracy rates (correct) were 37 (77.0%), 34 (70.8%), 31 (64.5%), 33 (68.7%), and 32 (66.6%) at K equaled to 3, 5, 7, 9, and 11, respectively. The naïve Bayes classification accuracy rate (correct) was 29 in 48 images (60.4%). The most incorrect detection was founded in TV remote.

Discussion

The RBG image is unstable in term of brightness. Moreover, the complex pre-processing of image is unable to process in low central processing unit. However, the image processing for RGB image is very complicated for solving some problem such as unstable light and various color shade. The image process is very complex. Moreover, it is unsuitable for using in low central processing unit of robot. [1]

The selected consumer RDB-D image for robot in this research is Microsoft Kinect Sensor, because of wide range, fast, light weight, and low cost. [5]

Normally, the central processing unit of robot is very low central processing unit, because of light weight and non-power consumption, thus the complex algorithm usually used high computational time is unable to use in low central processing unit. The study proposed the simple algorithm for object classification using the K-Nearest Neighbor (KNN) algorithm compared with the Naïve Bayes classification.

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