VISUAL PATTERN RECOGNITION OF ROBOTICS IN CLEANING PROCESS

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Abstract

The Robotic vision systems has a difficulty in detecting and tracking many objects at the same time but the human eyes can easily detect and track many objects at a time. The Robotic vision has different methods for processing, analyzing and understanding the data and objects. Multiple cues such as color, texture and three-dimensional point-clouds are incorporated adaptively for achieving object recognition. Moreover, near-infrared (NIR) reflection intensities captured by the visual sensor are used for realizing material recognition. The Gaussian mixture model (GMM) is employed for modeling the tabletop surface that is used for detecting ungraspable objects. The proposed system was implemented in a humanoid robot, and tasks such as object and material recognition were performed in various environments. In addition, we evaluated ungraspable object detection using various objects such as dust, grains and paper waste. Finally, we executed the cleaning task to evaluate the proposed system's performance. The results revealed that the proposed system affords high recognition rates and enables humanoid robots to perform domestic service tasks such as cleaning.

Keywords

Visual Recognition , Material Recognition, Object Recognition , Multiple cues and Cleaning tasks

1. Introduction

In a Modern world with the help of technical advancements robots have been used in varying environment for many purposes. In Visual recognition system, the robots that executes various domestic services can perform various tasks. For this kind of tasks the robots should be able to recognize their surroundings. For example, an autonomous robots used for cleaning task can have a trouble of cleaning when there is a objects on a table. For this the Robot should be aware of the objects placed on the table. A visual processing system including object detection, recognition, and material recognition is required for this purpose. If cleaning is performed on a table, then the robot should be aware of graspable and ungraspable objects on it. Graspable objects are like plastic cups, cans, etc. Ungraspable objects such as coffee grains, sugar, etc. A Graspable objects that are first recognized and put into the dustbin, while ungraspable objects should be cleaned immediately. The proposed system is implemented on a humanoid robot that includes various tasks of pattern recognition , object recognition , material recognition and cleaning the house. Robotic manipulation are widely applied to speeding up of the production process. A large number of approaches for visual recognition were developed in past decades. Based on the above approaches , this paper focuses on the visual recognition in the household services.

There are many related works on object recognition, material recognition and cleaning robots. Most existing research on 3D object recognition is based only on 3D point-clouds and does not consider the integration of multiple features [2, 3]. In [4], the authors have proposed color and 3D information-based color cubic higher-order auto-correlation (color CHLAC) features for object detection in cluttered scenarios. However, color CHLAC features are not rotation invariant and change depending on illumination conditions, because color information is directly integrated in the feature. The RGB-D dataset was provided and a 3D object-recognition method based on color, texture and 3D information was proposed in [5]. However, the method yielded different results in different environments, because the features (i.e., color and depth information) were not adaptively incorporated. Appearance-based material recognition has been studied in [6, 7]. In [6], multiple cues such as texture and edges are used for realizing material recognition. However, because these features do not represent material information well, the level of accuracy afforded is insufficient for practical purposes. NIR from environmental light is used in conjunction with color information to realize material recognition tasks in [7]. However, the system is not robust because the amount and the type of NIR in environmental light are unknown, and object shape is not considered. In contrast, the proposed material recognition scheme uses a TOF camera, which offers control over NIR as well as 3D information of target objects.

2. Approaches to cleaning

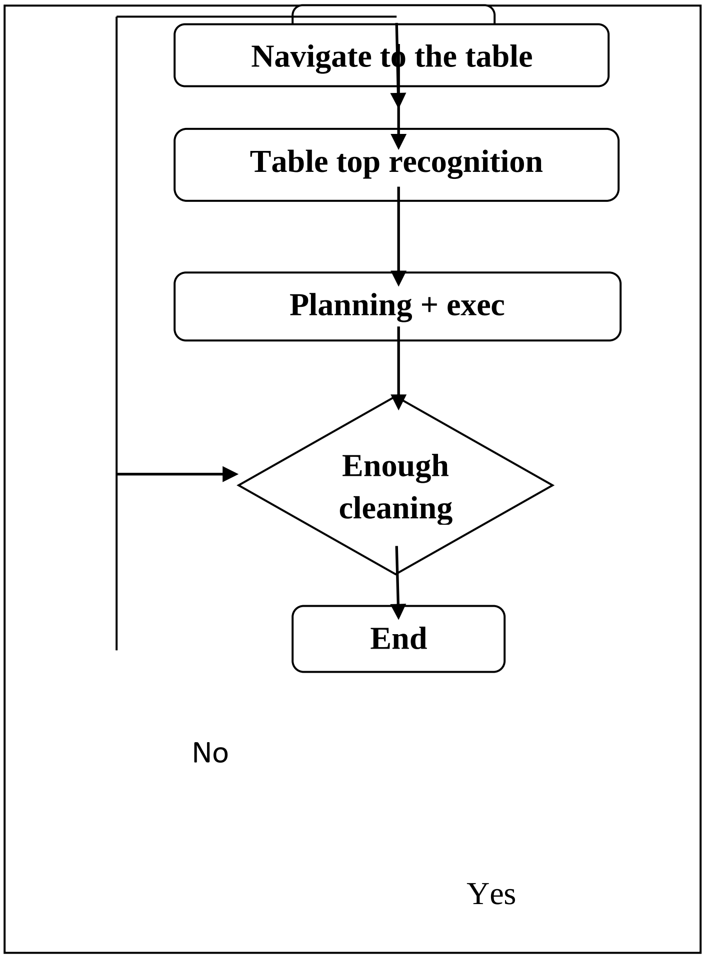
2.1 Learning Phase

In this study, “Cleaning” is defined as a task to the robot. Any objects that was not previously memorized by the robot are known as unknown objects. An ungraspable objects can be categorized as “small” and “big.” Small objects are objects of low height and are difficult to segregate with only plane detection. Normally, small objects are light and fine, such as grills and sugar. Most small objects on the tabletop can be thought of as *rubbish*; given their light weight, these objects can be removed using tools such as a vacuum cleaner. By contrast, big objects have heights such that they can be segregated by only plane detection, but are too heavy to be grasped by the robot, such as an electric kettle or coffee maker. In a normal situation, big objects tend to be categorized as *goods*. However, there are some situations in which small objects fall under the *goods* category, e.g., necklaces and documents, or big objects fall under the *rubbish* category, such as big boxes. This situation is out of the scope of our study. However, in our opinion, this problem can be solved by asking for human assistance.

An Appearance-based material recognition has a multiple ideas such as texture and edges. These are used for realizing material recognition. These features represents the level of accuracy afforded is insufficient for practical purposes. NIR model from environmental light is used in conjunction with color information to realize material recognition tasks .The system is not robust because the amount and the type of NIR in environmental light are unknown, and object shape is not considered. The proposed material recognition scheme uses a TOF camera, which offers control over NIR as well as 3D information of target objects.

The creators of the Figla cleaning robot decided to break out of the box of indoor cleaning and created a robot capable of cleaning surfaces both indoors and out. Figla can navigate the outside world, identifying and accounting for uneven surfaces and detecting trash. One component of the successful use of cleaning robots in the future will involve the design community creating facilities in a way that accommodates robotics cleaning. The building itself was modified to maximum the efficiency of the robot cleaner and to allow interfacing between the building and the robot. It can also pick up and dispose of garbage. Its slender body allows it to clean even in tight spaces and small corridors.

Figure 1.Ungraspable Objects.



Flowchart of Cleaning Robots

2.2 Cleaning Robots

2.2.1 Duct Cleaning Robots

Duct Cleaning can be expensive due to the labor-intensive nature of the job and a certain level of specialty it requires. In addition to improving indoor air quality, regular duct cleaning can also lower cooling and heating costs , making it an especially valuable service for clients seeking environmental certifications. Once in the duct, the robots are remote controlled and require a human operator. They are equipped with cameras to allow their operators to steer them. One of the advantages of robotic duct cleaners is that they can be made quite small, allowing for more effective cleaning of small ducts than humans are often capable of. Many companies have now developed robots designed especially for the task of crawling through air ducts and eliminating dust and debris from them. This technology emerged out of cleaners need to examine the conditions and severity of accumulated debris within the ducts before they entered it for cleaning and evolved with the development of attachments such as brushes and sprayers, eventually allowing the entire cleaning procedures to be completed robotically.

Figure 2. Floor Cleaning Robot

Figure 3. Vessel Cleaning Robot

Figure 4. Robot cleaning Floor using vacuum cleaner

Figure 5. Robot washing clothes

2.2.2 Window Cleaning

The Robot that is designed to handle only flat surfaces, but it does so very quickly and can clean a surfaces fifteen times faster than a human performing the same task. It secures itself to the glass with two belts of suction cups that rotate, tank like , on a guide rail around as it moves. At the same time, it puts spider like suction feet down ahead as it moves, detaching the feet in the back. The Cleanant model can clean curved glass surfaces and uses a different structure: two “feet” that attach to the glass with vacuum power and “walk” along the surface to move .These models can use detergent for cleaning , but they also support more environmentally cleaning methods and the functions just as well using dry ice, demineralized water or a special water –enzyme solution that eats away at the oily buildup that occurs on glass buildings. Human window washers cannot safely perform their jobs if the speed is too high. The cleaning portion of the robot is made up of two parts- a rotating brush and a drying blade. The robot is attached to an “energy trolley”, which is kept in a vehicle used to generate power for the robot and provides it with air compression and water for cleaning. For more modest building requiring window cleaning nearer street level, there are windoro window cleaner.

3. Vision System

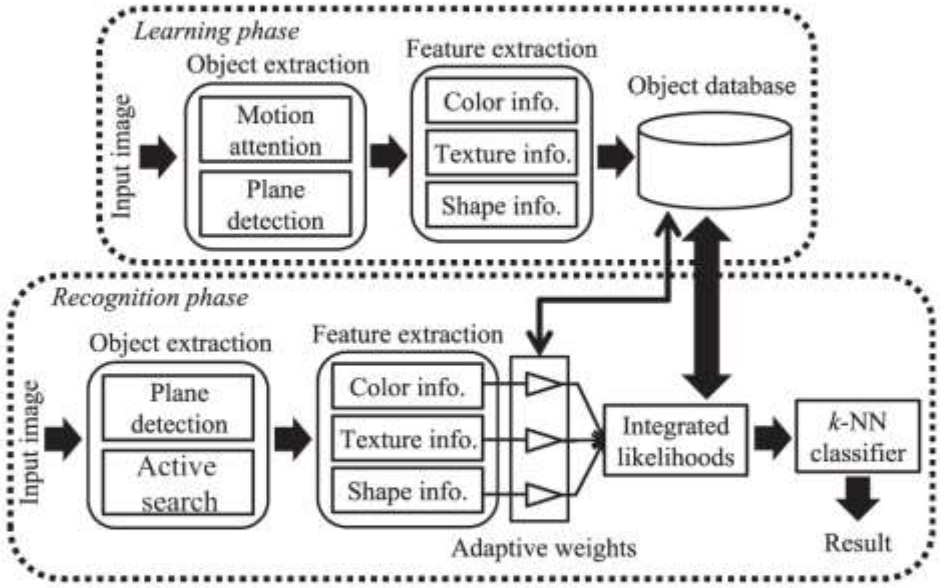
As mentioned in the previous section, robot perception, which is required for executing the cleaning task, consists of object detection, object recognition, and material recognition. In general, in a complex background is not an easy task. In this study, we Employ motion-attention-based object detection, plane-detection-based object detection, active search, and ungraspable object detection can be used for finding novel objects in cluttered scenes during the learning phase are suitable for use in the recognition phase. However, the robotics of complementarily when plane detection fails to achieve the desired level of system robustness. In this study, we focus our discussion for realizing the visual recognition system.

3.1. Visual Sensor

The sensor consists of one TOF and two CCD cameras. Here, colour information and 3D point clouds can be acquired in real time by calibrating the TOF and the two CCD cameras. Moreover, NIR reflection intensities can be acquired from the TOF camera because this sensor uses intensity values for calculating the confidence values of measured depth information. Therefore, color, texture, 3D point clouds and NIR reflection intensities, which are captured by the sensor, are used for realizing object Detection, object recognition and material recognition.

3.2. Multiple-Cue-based 3D Object Recognition

Multiple cues acquired from the visual sensor are used to construct the object recognition system. The proposed system is divided into the learning and recognition phases. Object extraction, which is the first step in both phases, is built based on motion-attention and plane detection. The motion-attention-based method uses a motion detector for extracting an initial object region; the object region is then refined using the color and depth information of the initial region. For more details on this method, please refer to [13]. For detecting objects on a table, the plane detection [14] technique is beneficial. The 3D randomized Hough transform (3DRHT)
is used for fast and accurate plane detection. In the learning phase, an object database consisting of multiple feature vectors in various views is generated. Here, scale-, translation- and rotation-invariant properties are desirable. A histogram-based feature is employed in the proposed method because it can realize the rotation and translation-invariant properties. Moreover, we can
use 3D information to normalize scale and achieve the scale-invariant property. Because it is difficult to achieve the view-invariant property, we realized the same by matching all features obtained from various viewpoints. Next, we explain the features employed in this study.



Object Recognition System

4. Realization of Cleaning Task

Robot perception, robot navigation, and object manipulation are integrated to realize the cleaning task . In the learning phase, the robot memorizes information regarding the target table and the *goods* placed on the table. Color and material information of the table surface is learned by estimating the GMM parameter mentioned in section 3.4. Once this parameter is learned, the robot learns information regarding the clean state. Here, graspable *goods* are detected using plane detection, and 3D object recognition is performed to recognize *goods* for memorizing their positions. After the robot memorizes the table with the *goods* on it, it can perform the actual task at any time. Task execution can be divided into tabletop recognition using robot perception (see section 3), planning and execution, which involves robot navigation and manipulation of graspable and ungraspable objects. At task commencement, the robot navigates to the target table. Because the robot is LRF-equipped, iterative-closest-point (ICP)-based [26] SLAM is used for localization and mapping. For robot navigation path planning, we use an RRT-based [12] algorithm. After reaching the target table, the robot performs graspable object detection (i.e., plane-detection-based object detection or active-search-based object detection) to detect graspable objects on the table.

Thereafter, specific object recognition using 3D object recognition is performed to recognize graspable objects. If the object is known (i.e., *goods*), it is grasped by the left hand, because the right hand holds the vacuum cleaner, and placed on another table. If the object is unknown (i.e., *rubbish*), the robot performs material recognition to classify the *rubbish* as burnable or unburnable. When there is some graspable *rubbish*, the robot can grasp the same and place it in the dustbin. Graspable object manipulation is performed until all graspable *rubbish* is thrown into the dustbin and all *goods* are placed on another table. In this study, path planning of the object-manipulation arm is performed using the RRT [12] algorithm. After cleaning graspable *rubbish*, ungraspable object detection is performed using the GMM-based object detection scheme. Once ungraspable *rubbish* is detected, the vacuum cleaner is switched on automatically through an XBee wireless radio module. Then, the vacuum cleaner's hose is moved over each piece of detected ungraspable *rubbish*, as mentioned in section 3.4, for cleaning. To ensure that the ungraspable *rubbish* is cleared efficiently, the vacuum cleaner is moved around the centre of a detected location.

Feature	Recognition Rate [%]
Color information	60.2
SIFT	47.1
Texture Information	66.8
Shape Information	67.0
Color SIFT	62.7
Color and Texture Information	76.0
Integration of color, texture and shape information without weighting	89.1
Integration of color, texture and shape information without weighting	91.5

Table 1. 3D Object Recognition Results

5. Recognition by Color and Texture Information

The object can be recognized relatively easily using texture information as opposed to color information, as can be inferred from Table 1. The standard SIFT [19] approach shows a similar tendency in this case, especially for categories 2 and 5, the objects of which have only a few reliable key points. It can be seen from Fig. 11, which have well-defined colors or rich textures, can be recognized almost perfectly using color and texture information. As a matter of course, it is difficult to recognize category 2 objects, which are of a single color and have fewer textures. Recognition of the white objects in category 5 under varying illumination conditions is even more difficult. It is natural that the best recognition result was obtained at Location 1, where the learning phase had been conducted, as shown in Fig. 12. However, the results deteriorate with changes in illumination. Recognition results obtained using Color-SIFT [27] are superior to those obtained using only color information, but inferior to those obtained using texture information or a combination of color and texture information. The Color-SIFT used in this experiment employs the Harris-Laplace detector, with which it is difficult to detect objects having fewer textures. This leads to false recognition and an inability to match owing to insufficient key points. We can see from Table 1 that the integration of color and BoK-based texture (76.0 %) can improve the recognition result of the Color-SIFT scheme (62.7 %) by 13%. *5.1.2. Recognition by Shape Information* As can be seen from Fig. 11, recognition by shape information yielded almost the same result as texture-based recognition, except in the case of category 4. This category comprises objects of similar size and shape, thus making recognition difficult using the shape-based

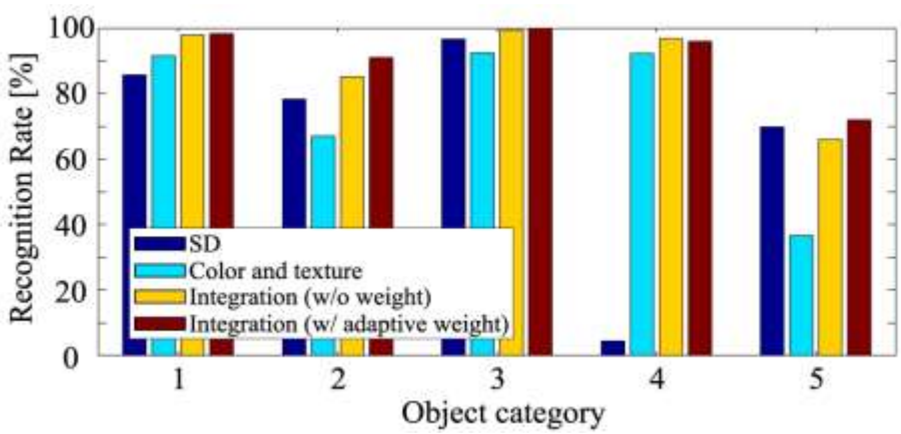


Figure 6 . Recognition results by category.

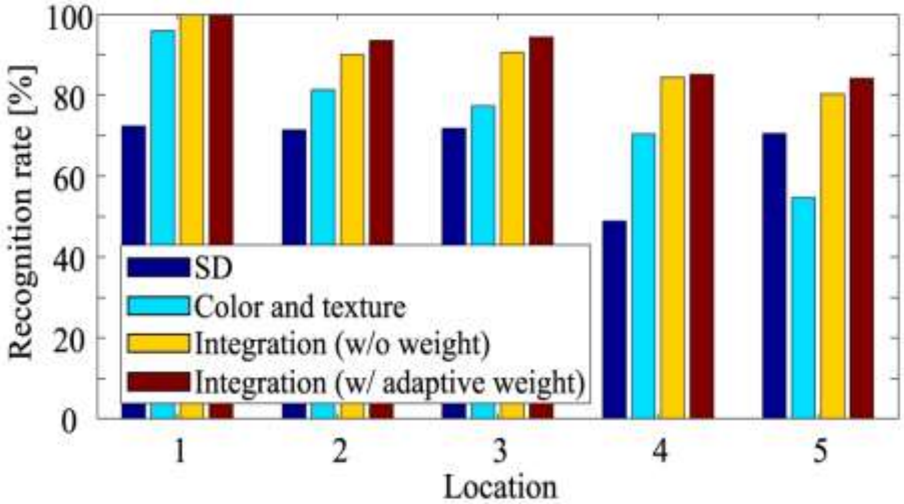


Figure 7 . Recognition results by location.

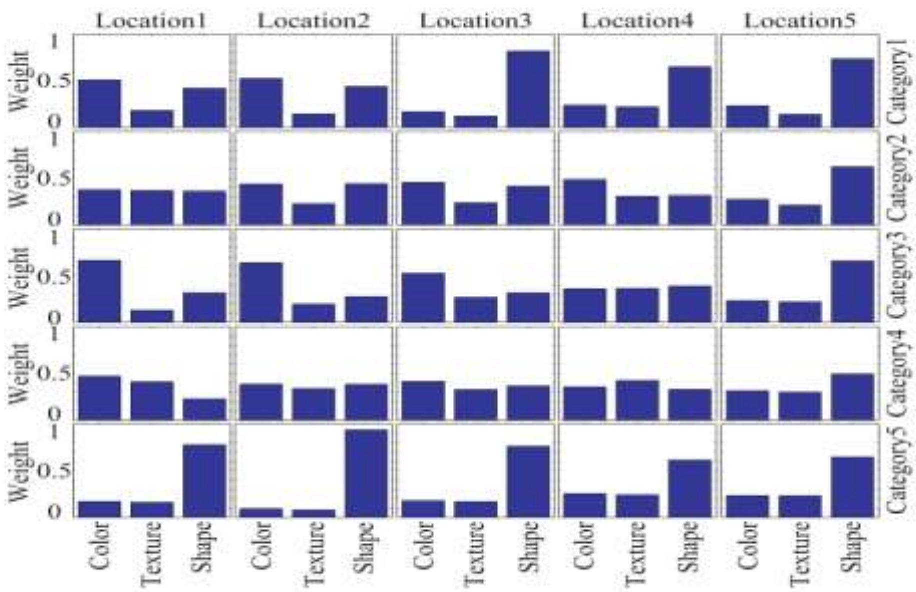


Figure 8 . Examples of adaptive weights.

Each histogram depicts the weight of each feature. Variation of weights across the five locations is illustrated from left to right in a category, while variation across the five categories is illustrated from top to bottom in a location. method. However, the recognition result for category 5, the objects in which are difficult to recognize by color or texture, can be improved using shape information

Figure 9. Objects used for Material Recognition

6. Evaluation of Cleaning Task*s*

The proposed cleaning task was then implemented on a real robot platform. Visual recognition, which was conducted on the tabletops. Recognition results of graspable objects that were to be disposed (*rubbish*, indicated by green frames), put on another table for tidying the target table (*goods*, indicated by blue frames), and the objects required to be cleaned away using the vacuum cleaner (ungraspable *rubbish*, indicated by red frames), are shown. A quantitative evaluation of the cleaning task is difficult to do because the definition of "similar" as the initial state is difficult to measure. However, the proposed method can be evaluated on qualitative criteria such as "How close are the results to the initial state?". An action plan is generated based on the visual recognition results for performing the cleaning task. Figure 19 shows how the robot actually performed the cleaning task based on the flowchart. It can be seen from Fig. 19 that the robot, which memorized the initial tabletop state, navigates to the table and recognizes it.

Thereafter, the robot searched for graspable *rubbish* and disposed of the same into the dustbin. After all graspable *rubbish* was eliminated, the robot grasped the *goods* and put them on another table except the last *goods* item. The last *goods* item was grasped in the left hand, and ungraspable rubbish was cleaned by the vacuum cleaner in the robot's right hand. After vacuuming the ungraspable *rubbish*, the robot navigated to the other table where it had placed the *goods* to bring them back to their original locations. To evaluate the proposed method, the cleaning task was conducted over 10 trials; seven trials succeeded, while three failed. In the failed trials, the robot either missed when throwing *rubbish* into the dustbin or placing the *goods* on another table. In these cases, the target table was cleaned, but, as the whole, the task was not performed as desired. Among the successful trials, five trials were considered qualitatively clean, while in the other two trials, ungraspable *rubbish* was left on the table. Examples of several conditions after the completion of cleaning.Overall, the robot's navigation errors during the task were responsible for the lack of accuracy in placing the *goods* in their initial positions and failure to position the vacuum cleaner at the desired location for cleaning the ungraspable *rubbish*.

7. Conclusion

In this paper, we proposed a visual recognition system based on multiple cues acquired using a 3D visual sensor. The proposed system consists of 3D object recognition that adaptively incorporates multiple features and NIR-reflection-intensity-based material recognition. Moreover, ungraspable object detection using the GMM model was proposed. We showed that the visual recognition system yields good results for each performance aspect, i.e., object identification under various illumination conditions, material recognition of unknown objects, and ungraspable object detection. Furthermore, the visual recognition system was implemented on a humanoid robot and examined through a cleaning task. The results showed that a relatively clean state could be achieved over several trials.

REFERENCES:

1. **A Survey on Visual Place Recognition for Mobile Robots Localization,** Yutian Chen Wenyan Gan, Lei Zhang, IEEE, 2017

2. A survey on object recognition and segmentation techniques, Anshika Sharma**,IEEE, 2016**

3. Survey paper on Text Recognition Using Image Processing Mr.Rahul R. Patil Mr.Audumbar R. Misal Mr.Ketan R. Nalawade, IJARECE, 2015.