Reducing Uncertainty and Acquiring Knowledge Through Interaction

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Abstract

Interaction between robots and humans is a rapidly growing area of research. Of particular interest is the desire to interact with robots or agents using natural language. This gives humans a more natural and effective way of teaching, commanding, and interacting with robotic agents or computers. Our work is designed to process images and provide descriptions of objects that can then be used in interactions with humans. We use images from an RGB-D camera in order to classify properties of objects including size, shape, and color. These descriptions are then fed into a higher-level agent which handles the human interaction. We specifically use a simple I-Spy game to allow users to refer to objects using descriptions in natural language.

1 Introduction

Language is a powerful tool that is just coming into its own as the human interface for various systems. Apple's Siri is an excellent example of this, making interaction with one's phone intuitive, easy, and efficient. Robotic systems in AI can also benefit from greater understanding of language. Such knowledge could allow a human to command or teach a robot agent in a more natural way. Take, for example, a robotic arm system with knowledge of only several nouns and actions: cup, sink, grab/move object, and turning on/off the sink, and the spatial concept of in. Through language, the robot could then be taught the new action of "filling a cup", which means to put the cup in the sink and turn on the sink. Even though the robot has never seen anyone fill a cup before, now it should be able to do so itself. Furthermore, the agent could generalize the concept to new items, like a bowl. This is a powerful way for an agent to learn from a human, without requiring expert instructors.

Our long-term goal is to leverage machine learning techniques in order to train a system to know a small vocabulary of nouns, adjectives, and actions. As a proof of concept, we develop a system that can play the children's game "I spy" using a robotic arm for pointing at and interacting with objects and a Microsoft Kinect which acts as the "eyes" of the system, giving RGB-D data about the scene for classification. To play I Spy, a collection of objects is placed in the view of the camera and a person gives a description of one of the objects. The agent then determines which object is most likely to match the description, and points to it using the robot arm. If the agent is highly uncertain about the objects, it interacts with them using the arm in order to gain further information. If the agent guesses incorrectly, the human then shows them the correct answer, and the agent adjusts its beliefs about object descriptions to reflect its new knowledge.

This work is being incorporated in a larger project which includes teaching the agent new concepts and actions as described above. Such a project relies on having symbolic information provided by our work through object segmentation and classification. The low level features provided by

our system can be analyzed and combined in order to build new concepts such as object categories (like blocks and balls) or object properties (all bananas are yellow). Such reasoning and concept generalization is essential for agents that interact in novel situations. These capabilities could be used on service tasks or with non-robotic systems where a verbal interface offers improvements in efficiency, safety, etc.

The challenges involved in playing I Spy include object detection, feature extraction, classification, robot arm manipulation, and active learning. We discuss these further in Section 3.

2 Related Work

Object classification is a problem that appears throughout a variety of applications, ranging from law enforcement to manufacturing. While historic efforts have focused on the recognition problem, that is, finding a known object in a scene, more recent work has emphasized the more general problem of classifying objects into generic groups by type [5]. For example, we might be interested in identifying vehicles as bikes, motorcycles, trucks, cars, etc. Work by [9] and [3], among others, has shown that powerful classifiers may be constructed through boosting or similar simple feature-specific classifiers such as color, shape, etc.

Recent popularization of sensors that combine both image and depth information like the Microsoft Kinect inexpensively provide richer sensory information. The addition of depth can help disambiguate situations that would be very difficult with a normal camera image alone. Depth can make the determination of an objects underlying geometry much easier, leading to better identification [8]. Previous work has successfully incorporated such cameras (often called RGB-D cameras) with object recognition in indoors domains featuring common household objects [8, 6].

A different approach to this problem is learning words that describe different areas of the feature space, which can then be combined to describe classes of objects. Research in this area focuses on learning to map physically observable qualities to simple words with the intent of using these simple descriptors to learn more complex nouns and relationships. Of particular popularity is an approach focused on learning colors and shapes of small objects using sensory data [13, 10]. Additional approaches focus on learning entities in the environment through interaction with them [4]. These approaches all focus on interaction with physical objects to discover qualities about them.

Although the types of words learned in these works is similar, the approaches and end-goals vary. Semantic clustering [13], decision trees [4], and bag of word models [10] are all used in the learning algorithms. This prior work focuses mostly on visual classification and the corresponding vocabulary.

Though our work does not extend dramatically on this concept, our long term trajectory focuses more on the complex action space, previously less explored. This project lays the groundwork for developing an action-space, both for learning said actions as well as learning objects upon which to act. Additionally, we explore a novel way of extracting additional information from objects. We are unaware of previous work that uses interaction with objects to see them from new angles and thus obtain additional information to make guesses about object descriptions more confident.

3 Methodology

3.1 Object Detection and Tracking

In order to play I Spy, the agent must be able to point at objects matching the provided description as well as to nudge objects with low confidence in their descriptions in order to see them from a new angle and gather new information about them. In order for the agent to do this, it is necessary to have localized positions for individual objects in the scene. Additionally, tracking objects between frames allows allows confidence levels to change over time.

The RANSAC algorithm [2] is used to discover the dominant plane in each image, isolating most of the objects in the scene. Further segmentation is performed to try to discover definitive object boundaries. This segmentation considers both the change in color and change in depth of neighboring pixels. From these segmentations we extract a feature vector for each object.

In order to adjust the confidence thresholds to determine which shapes are more certain (discussed below), it is necessary to track an object over time. This can be challenging, as the physical object may change location over time or may be occluded by the robot arm or another object. As each new frame appears, the segmented objects in it are compared to the segmented objects of the most recent frame. They're matched matched if there exists an object with a similar mean color near the same physical location. Any object that does not have a match from the most recent frame is compared to objects from a history of frames. In this case, the objects is matched to a prior object that is nearly the same color which is closest to the current location of the object. This allows previously occluded objects to be matched with their prior selves, and nudged objects to locate where they were nudged from.

3.2 Feature Extraction

Once an object was segmented we extracted relevant features in order to classify color, size, and shape. We considered objects that were of a single color, therefore average red, green, blue, hue, saturation, and value levels across the pixels were used as a six-dimensional feature vector. For size we calculated the diagonal of the 3D axis-aligned bounding box and used that as one of our features. The second feature was the average distance of the points from the centroid. Having the point-cloud data from the Kinect allowed us to compute those features more accurately in three-dimensions and saved us from having to do more complicated depth estimates.

Correctly classifying shapes required much more complicated features. During this work we explored several options for extracting features from objects before settling on the method described in this paper. We experimented with ORB, a rotation invariant feature extractor similar to SIFT and SURF [11]. Additionally we tested several feature detectors from OpenCV, including their square detector [1]. We also explored using RANSAC to discover simple shape types (such as planes, curves, and spheres), in order to determine the number of faces and edges each object has. This work was based off the RANSAC algorithms of Schnabel et al [12]. Although these and other feature detectors are frequently used in object recognition and learning tasks, we ultimately chose to use our own PCA-based method which resulted in more accurate guesses from the agent than the other methods. First we projected the point-cloud back onto the image plane. Next we transformed the image into a canonical representation. To do this we applied Principal Component Analysis to find the axis the points were most spread out along, and rotated the image so that axis was horizontal. An axis-aligned bounding box was found for the image and its height and width were

scaled to unit lengths. To extract features we took evenly-spaced points from the top and bottom edges of the box and calculated the vertical distance from each point to the image. This process is illustrated by [FIGURE]. We used seven sample points along the top and bottom; experimental evaluation showed no significant improvement with additional samples. In addition, we calculated the ratio of the width and height before scaling to get an idea of how elongated the shape was. **Can we include some equations here in addition to the qualitative description of the process?**

3.3 Classification

Initially we used SVM classification to validate our method, but we have since moved to a K-nearest neighbor approach. With the K-nearest neighbor algorithm it is easy to add another example to the training, without recreating the entire training model as was done with SVM classification. Additionally we no longer rely on third party software, namely liblinear [7] to do classification. Using our implementation of a K-nearest neighbor classification we also reported a confidence metric for each label based on the percentage of neighbors with a given label.

3.4 Confidence

One of the difficulties with reasoning about real objects is that the world is partially observable. Objects can have a dramatically different appearance at different orientations. Naturally when given such an object, a human may move their head around to gain more information and confidence as to what the object is. Our system has a fixed vision angle, but it is possible for it to manipulate objects to gain information on objects whose appearance has high orientation dependency. For this purpose a confidence threshold system was developed to learn what objects may have high uncertainty, and therefor would be good candidate for manipulation. When the system is queried for an object that it cannot currently see, it should manipulate an uncertain object with the highest probability of actually being the queried object.

All attributes are given the same default confidence threshold and adjusted using user feedback. To determine the likelihood of a mislabel, the confidence of a label, calculated from the classification system, is compared to the confidence threshold for that shape, color, or size. If the confidence exceeds the threshold then it is reported as unlikely to be a mislabel. For example in our system the rectangle label is commonly misplaced on objects presented head on, so the learned threshold confidence for rectangle is very high.

If an object exists that the agent believes fits the description provided by the user, the agent points to it regardless of the confidence in the accuracy of the description or the corresponding confidence thresholds. As a result, when the agent correctly identifies an object and the confidence is lower than the threshold for the given descriptions, the thresholds can be lowered to reflect the correctness of the lower confidence. Conversely, the thresholds are increased when the agent selects an incorrect object or when it cannot find the correct object. In the first case, the thresholds associated with the incorrectly guessed object are increased so they are less likely to be chosen incorrectly in the future. In the second case, Similar effects result from nudging an object and determining the correct label.

The thresholds are increased or decreased using the following formula:

$$\text{Thresh}_\text{t} = \text{Thresh}_{\text{t}-1}\lambda^t direction(t)$$

$$direction(t) = \begin{cases} 1 & \text{if threshold should increase;} \\ -1 & \text{if threshold should decrease.} \end{cases}$$

where t =mathrmnumber of times the threshold has changed. **My additions are okay, James should read over this and adjust to reflect the actual code.**

3.5 Robot Arm Manipulation

3.6 Active Learning

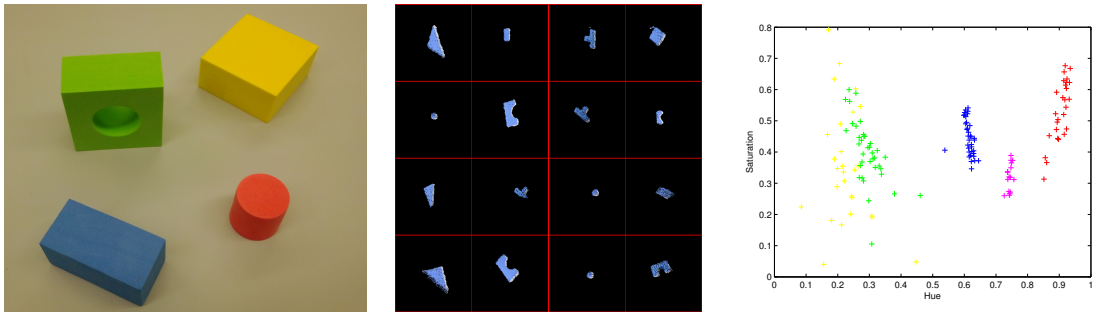
equations

4 Experimental Results

4.1 Data Collection and Training

We acquired a large variety of children's foam blocks in many shapes, sizes, and colors to act as our objects for classification. A small subset of the blocks can be seen in Figure 1a. The foam of the blocks is an ideal material to work with as it. Some of these objects can be seen in Figure **figure**. (1) has a smooth, matte finish, (2) comes in a variety of distinct colors, and (3) is deformable enough to be grabbed by the arm but still retain its shape. Additionally we collected more familiar objects to test our classifier on, demonstrating the ability of the system to abstract general shapes to real world objects.

Our system, seen in figure **screenshot**, segments objects found in the predefined play area and labels them with the most confident shape, size, and color. Additionally a user can train new shapes, colors, and sizes by simply clicking on that image and supplying the relevant label. This is sufficient for creating a large number of training samples, preferably at different positions and orientations. This method is not efficient for generating a large number of training samples of many different objects, so we collected a training dataset of footage of the foam blocks at numerous positions and angles throughout the play area which were then segmented and labeled with relevant descriptors.



(a) Foam Blocks (b) Segmented Images (c) Real-world test data

Figure 1: Real world data is extracted from toy foam blocks. The blocks themselves can be seen in (a). Using a segmentation algorithm, we extract the blocks from the Kinect data (b) and generate feature vectors for each object. Finally, we hand label the data for features such as color and shape for classification training. In (c), we see the actual distribution of our training samples in the hue and saturation dimensions.

red	yellow	green	blue	purple
96.43%	92.00%	97.37 %	100.00%	88.57%

Table 1: This shows the result of OVA classification for five color types across 160 objects. Each test involved training on 80% of the points, with 20% left out for testing.

Testing our system requires direct interaction and presentation of new objects or objects at new angles. Additional testing can be done by training the system with new shapes and colors and observing how quickly and effectively it can learn and apply the new information. Qualitatively it is easy to see whether the system is performing well. However to do a less subjective, quantitative evaluation of our methodology, we used the leave-one-out-cross-validation(LOOCV) method on our collected training data. This testing method mirrors the scenario where a novel object is presented to this system.

The results in Table 1 **todo** show LOOCV percentages for the shape, color and size. Unsurprisingly it has more difficulty with shape , which varies greatly by angle and position, and size, which is a more subjective attribute. It has particular problems with shapes that are presented head on, which tend to resemble rectangles. This is the primary motivation for developing a confidence threshold learning mechanism, which allows the system to determine which labels are inherently uninformative.

5 Conclusion

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