

Interactive Identification of Writing Instruments and Writable Surfaces by a Robot

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Abstract—This study asks the question: Can a robot learn to identify object-surface pairs that are useful for trace-making and, thus, facilitate writing? Writing is an important skill that humans use everyday and future household robots may have to master in order to be useful. Specifically, our robot performed scribbling behaviors with different objects on different surfaces and monitored which objects leave marks on which surfaces. The frequency with which marks were detected was used by the robot to group the writing instruments and the writable surfaces into meaningful categories, which capture their functional properties from the robot’s point of view.

I. INTRODUCTION

Writing is a unique skill that humans use on a daily basis to convey and capture information. We scribble notes to augment our memory, draw figures to explain concepts, and doodle to kill time. J.J. Gibson pointed out that writing is a special form of tool use, which requires a special tool that has the ability to leave a trace on a surface: “A hand-held tool of enormous importance is one that, when applied to a surface, leaves traces and thus affords *trace-making*. The tool may be a *stylus*, *brush*, *crayon*, *pen*, or *pencil*, but if it marks the surface it can be used to depict and to write, to represent scenes and to specify words” [1, p.134]. Clearly, before humans can master the intricate nature of writing they must learn to identify the object-surface pairs that facilitate this skill.

The ability to choose an object that could leave a mark on a given surface is an important prerequisite for the development of writing skills. For example, a pencil can leave a trace on paper but not on a white board. Additionally, the objects and the surfaces that can be used for writing are not restricted to the things humans commonly use to make marks, e.g., pencil and paper. Even a stick could be used to make marks in a sandbox. Preprogramming a robot with the ability to make these judgments is neither practical nor feasible; there are simply too many object-surface combinations. Furthermore, an object that a human can write with is not necessarily an object that a robot can write with.

Humans acquire many skills through interacting with the environment and perceiving the changes produced by this interaction [2]. Work in developmental psychology also suggests that infants form object categories by processing the relationships between objects which define events [3]. In other words, as infants manipulate objects and observe different outcomes, they also correlate their observations with objects encountered during previous interactions. As they manipulate

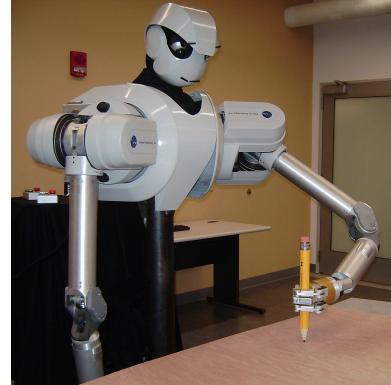


Fig. 1. The upper-torso humanoid robot used in the experiments. The robot is pictured holding an oversized pencil while scribbling on a wooden surface.

more and more objects, they identify relationships among them and start to form categories. This is the approach we took with our robot.

This investigation tests the assumption that a robot can learn to identify a good trace-making object for a given surface. This is done by programming a robot with several trace-making behaviors (scribbles, lines, etc.) and an ability to detect traces. After the robot interacts with different objects and different surfaces, it forms surface categories by using the frequency with which each object left a trace on each surface. The hypothesis is that certain objects are better at leaving traces on some surfaces but not on others and that this property can be detected by the robot using unsupervised clustering.

II. RELATED WORK

There is little related work in robotics that addresses robot writing skills from a developmental point of view. The existing work mostly addresses the control challenges associated with writing (i.e., the positioning and detection of instruments that potentially may be used to write with).

For instance, writing legibly requires precise control of the tip of an object. Kemp and Edsinger [4] proposed a method for autonomous detection and control of the tip of a tool by a robot. In their approach, a robot identified the tip of a tool as the region of an image furthest from the robot’s hand that also moved with it. Once the tip was found, a feature detector was used to track the tip’s position and orientation in the visual



Fig. 2. The twelve objects used in the experiments and their corresponding material types: **(row 1)** 2x2 and 2x4 (wood); plastic toy and PVC pipe (plastic); **(row 2)** noodle and sponge (sponge); hand towel and teddy bear (cloth); **(row 3)** sidewalk chalk and wax candle (soft materials); oversized pencil, whiteboard marker attached to a piece of wood to make it graspable (common writing instruments). Shown not to scale.

field. Using this approach, a robot could potentially learn to detect the tip of writing instruments such as markers. Another work which deals with force control and visual servoing to grasp a writing tool was done by Olsson *et al.* [5] and their study was validated using a connect-the-dots task on a whiteboard using a marker.

Forming written characters also requires following precise movement patterns. Yussof *et al.* [6] argued that programming a robot with a separate trajectory for each character does not scale well as new symbols are added. Instead, they created primitive trajectories (linear and curved) and combined them in different ways to produce distinct characters. For example, the character ‘b’ can be written using one linear and one curved trajectory.

Establishing methods for combining trajectories to produce distinct symbols is another challenging problem. A robot programmed with the framework proposed by Zhang and Weng [7] could learn to combine previously learned trajectories in order to create new ones. The robot used an approach known as *scaffolding* which is a process of using previously learned skills to solve a more complex task. In one demonstration, the robot learned to draw a four-petal flower after a human trained it to draw a single petal.

Franke *et al.* [8] studied a method of providing a strong foundation for signature analysis procedures by means of a writing robot. This robot could take up different writing instruments in order to provide various types of ink deposit. The robot simulated human handwriting movements but the writing instruments and paper were selected by the programmer. Another study used high-level robot planning techniques to reproduce a procedure used by human painters [9].

Pfeifer and Scheier [10] conducted a study in which a robot categorized different-sized objects using its own movements



Fig. 3. The twelve surfaces used in the experiments shown in vertical pairs of two along with their material types: **(column 1)** wrapping paper and cardboard (paper); beans and rice (deformable surfaces formed of small objects); **(column 2)** towel and rug (cloth); terracotta tile and marble (stone); **(column 3)** whiteboard and plexiglass (plastic); wood and bulletin board (wood).

and interactions. Furthermore, Metta and Fitzpatrick [11] found out that the process of categorizing objects could be much easier if the robot is allowed to interact with the objects. This was tested on a task of distinguishing *rollable* objects from *non-rollable* ones. In another study, Katz and Brock [12] used interaction to identify the planar kinematic properties of objects.

A robot can interact with objects to determine not only their functional properties, but also to cluster the objects into meaningful categories. This was illustrated in the following two studies. The robot in Griffith *et al.* [13] formed object categories by observing the movement patterns between two objects. The robot formed ‘container’ and ‘non-container’ object categories and learned a perceptual model that accurately detected the categories of novel objects. Another study done by Sinapov and Stoytchev [14] presented the idea of learning to categorize objects based on their acoustic properties which were obtained by performing a sequence of exploratory behaviors with them (grasp, shake, drop, push, and tap).

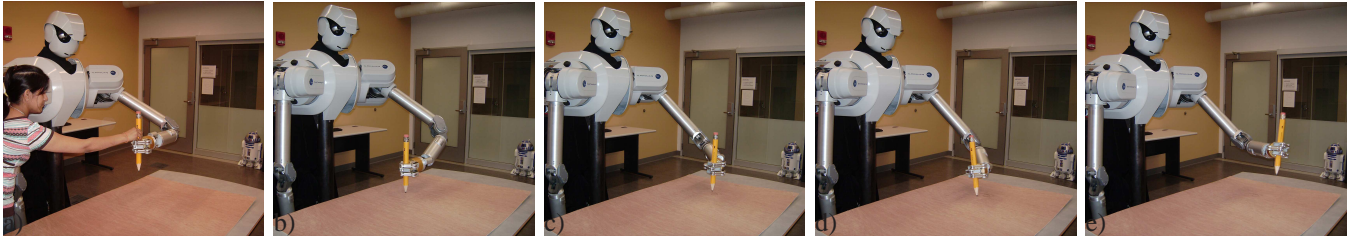


Fig. 4. Snapshots from one experimental trial: a) before each trial, an experimenter placed one of the 12 surfaces (wood in this case) on the table in front of the robot and one of the 12 objects (the oversized pencil in this case) in the robot’s hand; b) The robot moved the object to a randomly chosen position above the surface and then lowered the object until it touched the surface. This event was detected automatically based on the sensed torque values; c) The robot starts to make a trajectory on wood. This trajectory is randomly chosen from one of the five marking behaviors shown in Fig. 5; d) The robot finishes making the trajectory; e) The robot moves the pencil out of its visual field in order to detect any marks that were left on the surface.

III. EXPERIMENTAL SETUP

A. Robot

All experiments described in this paper were performed with an upper-torso humanoid robot. Two 7-DOF Barrett Whole Arm Manipulators (WAMs) are used for the robot’s arms. Each arm has a three-finger Barrett Hand as its end effector (see Fig. 1). The WAMs are mounted in a configuration similar to that of human arms. The arms are controlled in real time from a Linux PC at 500 Hz over a CAN bus interface. The robot is also equipped with two cameras (Quickcams from Logitech). The cameras capture 640x480 color images at 30 fps.

B. Objects and Surfaces

During the experiments, the robot interacted with 12 different objects and 12 different surfaces. The objects and the surfaces include common household items as shown in Fig. 2 and Fig. 3. Before each experimental trial, one of the 12 surfaces was placed on a table in front of the robot.

More specifically, objects and surfaces were selected in pairs based on their material properties as perceived by humans. For example, a towel and a rug are both made of cloth and therefore, the changes on each of these surfaces were expected to be similar. The six pairs of human selected surfaces were: towel and rug (cloth), wrapping paper and cardboard (paper), marble and terracotta tile (stone), wood and bulletin board (wood), plexiglass and whiteboard (plastic), and finally, beans and rice (deformable surfaces formed of small objects).

Humans often try to leave traces in sand since the particles can be easily displaced. The same notion was applied to this study but instead of using fine grains like sand, which could get inside the robot’s drive mechanism, beans and rice were used. Beans and rice have the similar material and functional properties as sand so our results should be applicable to sand as well.

Similar selection criteria were used for the 12 objects. Once again there were six pairs: 2 by 2 and 2 by 4 (wood), plastic toy and PVC pipe (plastic), noodle and sponge (sponge), hand towel and teddy bear (cloth), chalk and candle (soft materials), and pencil and marker (common writing instruments). The objects were selected in such a way that they must be firmly graspable by the robot. The only exception was the whiteboard

marker which was too small and was fixed to a shank of wood to make it graspable by the robot.

The experimental results (described below in section V.) show a different clustering of objects and surfaces by the robot than the intended clusters. In other words, the robot’s perception of these objects and surfaces is different from that of the humans. The clusters that the robot identified are based on the functional properties of the objects and the surfaces as perceived by the robot. Humans cluster these based on their material properties which explains why the clustering produced by the robot is different from what we expected.

C. Behaviors

The robot performed three behaviors during each experimental trial: 1) position the object at a random start location on the surface; 2) execute a trace-making trajectory; and 3) move the hand out of the visual field. The three behaviors are described in more detail below. Figure 4 shows a sequence of snapshots from a sample trial.

1) *Position Behavior*: At the start of each trial, the robot positioned the object directly above the surface. It then lowered its arm until the object touched the surface. The robot automatically detected the touch down based on an empirically determined torque values which was the same for all objects. This was used as a calibration routine since the different objects had different lengths. All the objects were held in the same way.

2) *Mark Behavior*: The robot randomly selected one of five marking behaviors to perform (see Fig. 5). The chosen scribbles, doodles, and check marks were motivated by research in developmental neuroscience, which suggests a progression of mark-making behaviors in infants [15].

The robot added an extra amount of force in the downward direction to leave a trace. The extra amount of force was determined heuristically such that the robot pressed hard enough to make traces with the chalk but light enough that the tip of the marker would not get mashed in. The same amount of force was used for all objects.

3) *Move Behavior*: The robot moved the object out of its visual field at the end of a trace-making behavior. This step allowed the robot to *see* the outcome of the object-surface interaction (detected using the method described below in Section IV.B).



Fig. 5. The five different marking behaviors: (row 1) horizontal scribbles, and vertical scribbles; (row 2) doodles, spiral, and check mark.

IV. METHODOLOGY

A. Data Collection

The robot exhaustively tested whether an object could be used to leave traces on a surface by performing 10 interactions with each object-surface pair. During each interaction, the robot randomly chose one of the five trace-making behaviors shown in Fig. 5 and performed it. Since 12 different objects and 12 different surfaces were used, the robot interacted with 144 different object-surface pairs for a total of 1440 trials.

Experimental data was collected during each trial. A sequence of 640x480 color images were captured from one of the robot’s cameras at 30 fps. The images were processed as described in the next section.

B. Mark Detection

The robot processed the image sequences from the camera at the end of a trial to detect whether the object left any marks on the surface. The result was a binary ‘yes’ or ‘no’ to specify the outcome of the trace-making behavior. Specifically, the robot performed image differencing between the first and the last frame in the sequence to find the image regions that changed. Basic morphological operators (one erosion followed by one dilation) were applied to the difference image to filter out any noise. Finally, the connected components of the filtered image were detected and only the ones that had an area of more than 20 pixels were preserved. Figure 6 shows the results of this procedure for three different surfaces. These were 640x480 color images taken from the robot’s left camera. Additional results are described in section V.A.

C. Acquiring Interaction Histories

Let \mathcal{O} denote the set of objects $\{O_1, \dots, O_{12}\}$ and let \mathcal{S} denote the set of surfaces $\{S_1, \dots, S_{12}\}$. Also, let \mathcal{B} denote the set of five marking behaviors $\{B_1, \dots, B_5\}$. During the i -th experimental trial, the robot constructed the tuple (B_i, O_i, S_i, F_i) to indicate that object $O_i \in \mathcal{O}$ and behavior $B_i \in \mathcal{B}$ were used to mark on surface $S_i \in \mathcal{S}$ and the binary mark detection outcome $F_i \in \{0, 1\}$ was observed. The

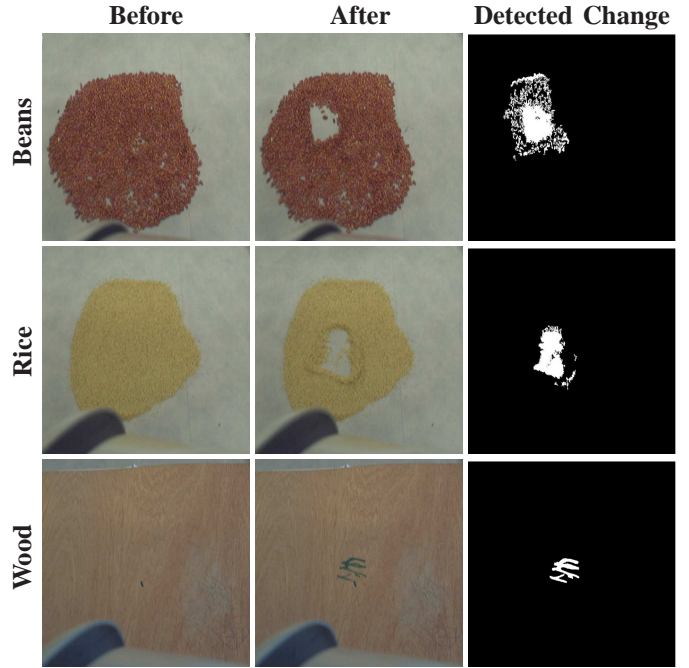


Fig. 6. Before and after snapshots taken from the robot’s camera during several experimental trials: a) spiral scribbles on beans; b) vertical scribbles on rice; c) vertical scribbles on wood.

behavior, B_i , was either a *doodle*, *horizontal scribble*, *vertical scribble*, *spirals*, or a *checkmark* (see Figure 5).

D. Clustering Objects

Certain objects are better at leaving marks on some surfaces than others. For example, a marker can write on almost any surface, while a pencil cannot write on a whiteboard. Presumably, the robot can identify these relationships as it interacts with different object-surface pairs. This section describes how this can be done using unsupervised clustering.

The frequency with which each object left a trace on each surface was used to capture the relationship that some objects are better at leaving traces on some surfaces than others. Let z_j^k be the number of times that a trace-making behavior with object O_j on surface S_k produced a mark. The robot formed the feature vector $X_j = [z_j^1, \dots, z_j^{12}]$ for each object, O_j . The robot used the X-means unsupervised clustering algorithm to categorize the objects, \mathcal{O} , into m categories, $C = \{C^1, \dots, C^m\}$. X-means extends the standard K-means algorithm to estimate the correct number of clusters in the dataset [16]. The results are described in section V.B.

Similarly, the frequency of observing surface traces made by each object was used to capture the writability relationships among the different mediums. The robot formed the feature vector $Y^k = [z_1^k, \dots, z_{12}^k]$ for each surface, S_k . For a second time, the robot used unsupervised clustering with X-means to categorize the surfaces, \mathcal{S} , into n categories, $D = \{D^1, \dots, D^n\}$. Section V.C describes the results.

TABLE I

MARK DETECTION RESULTS FOR EACH OF THE 12 OBJECTS AND THE 12 SURFACES. THE TABLE SHOWS THE NORMALIZED FREQUENCY WITH WHICH AN OBJECT LEFT A TRACE ON A GIVEN SURFACE. FOR EXAMPLE, A VALUE OF 0.9 INDICATES THAT AN OBJECT LEFT 9 MARKS IN 10 TRIALS ON A THE CORRESPONDING SURFACE. THE MISSING VALUES ARE ZEROS, WHICH WERE OMITTED FOR CLARITY.

Surface	2x2	2x4	Plastic Toy	PVC Pipe	Noodle	Sponge	Towel	Bear	Chalk	Candle	Pencil	Marker
<i>Wrapping Paper</i>												1
<i>Card Board</i>									0.9			1
<i>Towel</i>	0.7								0.6			1
<i>Rug</i>												1
<i>Whiteboard</i>									0.1			1
<i>Plexiglass</i>		0.2	0.3						0.8		1	1
<i>Beans</i>	1	1	1	1	1	1	1	1	1	1	0.9	1
<i>Rice</i>	1	1	0.8	1	1	1	1	1	1	1	0.9	1
<i>Terra Cotta Tile</i>				0.2								1
<i>Marble</i>									0.1			1
<i>Wood</i>									0.9			1
<i>BulletinBoard</i>									0.6			1

V. RESULTS

A. Mark Detection

Table I shows the results for the frequency with which each object left a trace on each surface. As expected, the table shows that every object consistently left a trace in the beans and rice. Furthermore, the marker left a trace during every trial in which it was used. Surprisingly, the table also shows that neither the pencil nor the candle left easily-perceptible traces. The pencil undoubtedly left traces on some surfaces, but the robot’s camera could not easily detect the small lines. Marks left with the candle were somewhat faint, which made them difficult for the robot to perceive as well.

The challenges associated with performing a large-scale experiment with many different objects and surfaces can explain some of the odd results in the table. For example, in the first round of trials with the towel, the 2x2 object left a mark in 7 out of 10 trials. Shifting creases in the towel caused the robot to detect them as marks. In subsequent trials the experimenter attached the towel steadfastly to the table which prevented this from happening when the other objects were used. Another cause of false positive mark detection errors were changes in background shadows and reflections, since they were not filtered out. This was an issue only for the plexiglass surface, which is highly reflective. Finally, sometimes the robot pushed the surface into a new position while attempting to write on it with the object. This change in surface position was also detected as a mark in the case of the terracotta tile and the PVC pipe.

Most positively, the results of mark detection uncovered several relationships among the different objects and the different surfaces. Namely, many of the objects only left traces in the beans and rice. The marker and the chalk were the only two objects that frequently left marks on other surfaces. Also, five of the surfaces captured marks made by both the marker and the chalk, whereas five other surfaces captured only the traces left by the marker.

These results suggest that the robot might be able to

identify coherent categories of objects and surfaces based on the outcomes of these interactions. The next two subsections describe how this process can be automated.

B. Object Categories

Using unsupervised clustering (X-means) to group objects based on the outcomes shown in Table I resulted in three clusters of objects. The first cluster included the marker and the chalk. The second cluster included the pencil. The last cluster included the rest of the objects.

The robot clearly identified coherent categories of writing instruments. For example, the largest cluster represents the group of objects that provide the least utility in writing tasks - they only leave traces in surfaces that can be displaced. The cluster with the marker and the chalk could be considered to include the best writing instruments, as they leave perceptible traces on most of the surfaces that they are tried on. However, we expected slightly different results. The experiment was formulated to include six groups of objects with different material properties. But the robot instead found three categories, which better reflected the objects’ functional properties (when they are used by a robot and not by a human).

C. Surface Categories

Grouping the surfaces with X-means resulted in three categories: one cluster with the beans and rice; another cluster with the cardboard, towel, plexiglass, wood, and bulletin board; and the last cluster with the wrapping paper, rug, whiteboard, terracotta tile, and marble.

The robot clearly separated the surfaces by their functional properties. The first cluster represented the surfaces on which the robot can write by displacing the individual grains (rice and beans). The second category included the surfaces on which both the marker and the chalk can leave traces. The last group contained the surfaces on which only the marker can leave traces reliably.

The second cluster of surfaces was much more coarse as compared to the glossy surfaces in the third cluster, which ex-

plains why both the marker and the chalk left marks on them. The plexiglass is the exception in cluster two, and it was most certainly unexpected that chalk could leave a trace on that type of surface. This result supports the conclusion that a robot's knowledge should be grounded in its sensorimotor experience [17] [18], i.e., a programmer would have incorrectly classified the relationship between the chalk and the plexiglass.

It is interesting to note that the surfaces that provide the most utility in writing tasks (e.g., the beans and the rice) are the surfaces that do not require a specific writing instrument. Almost every object could consistently displace them to make marks. Furthermore, the traces made in these surfaces are only temporary, whereas the marks left on the other surfaces were more permanent.

VI. DISCUSSION

The robot clearly formed coherent object categories and coherent surface categories, which shows that the robot acquired meaningful relationships from its sensorimotor experience. The results also show that it is not necessary to preprogram a robot to make judgments about specific object-surface pairs, i.e., 144 pairs in our case. Instead the robots should be in charge of making these judgments on its own. Also, the programmer would have undoubtedly made incorrect judgments, e.g., assuming that chalk only leaves traces on coarse surfaces, while, in fact, it works well on plexiglass. A programmer would probably also have made some simplifying assumptions, e.g., that a robot could adequately grasp a marker, when in fact, we had to construct an artificial object with properties similar to those of a marker that the robot could grasp.

The mere fact that we had to construct a graspable marker is evidence that an object a human can write with is not necessarily an object a robot can write with. The robot has its own perceptual world, or *umwelt*, which is clearly different from our own [19]. Consequently, the amount of force that a human would have to apply with a writing instrument would probably also vary greatly from the amount of force that a robot would have to apply. This discrimination between the two is closely tied to the fact that the robot did not always perceive that a mark was made even when the experimenters did. The experimenters could clearly see the pencil marks that the robot made on the majority of the surfaces, but the marks were too faint and too slim for the robot to perceive. Therefore, it should not have been surprising that the robot would find different relationships among the objects and the surfaces compared to those that we expected.

We expected that the robot would form six different categories of writing instruments and six different categories of writable surfaces because of the different material properties among the categories. This was certainly what Brooks meant when he stated that the perceptual world "we humans provide our programs is based on our own introspection" [19]. Because the robot has a different sensorimotor apparatus from us, however, the robot was predisposed to form categories that are different from those that we expected. Subsequently, we should have initially expected the robot to form *different* categories

(which is what the robot did). In the case that we had gotten categories *exactly* similar to those that we selected for the experiments, it would have been likely that we made too many simplifying assumptions.

Thus, our results represent more experimental evidence in support of the idea of letting robots learn their own representations from their own interactions with the environment [17] [18]. Human programmers should resist hardcoding representations that the robot cannot be independently test, verify, and correct by itself.

VII. CONCLUSIONS AND FUTURE WORK

This study addressed three important questions inherent to the problem of creating robots that can learn how to form categories of writing instruments and writable surfaces. First, this paper studied whether a robot could learn from its interactive behaviors to identify the objects and the surfaces that facilitate writing. Second, it tested whether a robot could categorize objects in a coherent way based on their mark-making properties. Finally, it tested whether a robot can group different surfaces based on the ease with which it can leave traces on them.

This paper showed that a robot can interactively form categories of writing instruments and writable surfaces by detecting marks after it manipulates objects and surfaces in its environment. It also showed that the robot can use its interaction history to identify the functional similarities among the objects and the surfaces. The robot used 5 different trace-making behaviors to interact with 12 different objects and 12 different surfaces. The robot exhaustively tested the 144 different object-surface pairs to identify which combinations provide the most utility in writing tasks. Also, the robot used the frequency with which each object left a trace on each surface to learn categories of writing instruments and writable surfaces.

One aim of this research was to determine if the robot would categorize the objects and the surfaces in the same way that categories were perceived by humans. We found that the robot did not, which is an indication that robots are not like humans, instead, they have their own perception of objects and surfaces. The robot learns these relationships from its own sensorimotor experience and, therefore, new categorizations of objects and surfaces were found.

This paper is one of the first studies that explored the idea of creating robots that can learn how to write on their own. During the process, it revealed several non-trivial problems that are left for future investigation. For instance, robots that write must be capable of modifying the force that they apply with different writing instruments. A robot that presses too firmly would squish the tip of a marker, whereas a robot that presses too gently could not use chalk to make traces. Another extension is to explore how a robot could learn that *trace-making* is tightly coupled with the robot's own movement. A further extension could be to learn perceptual models of writing instruments and writable surfaces based on

some interactive trials in order to avoid extensive trial and error for many other novel objects.

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