Toward Learning to Write by Identifying Writable Surfaces

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I. INTRODUCTION

Writing is a powerful skill that humans use on a daily basis to convey and capture information. 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 this 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]. Learning to identify objects that could potentially leave traces on novel surfaces is an important skill that humans learn to master. For example, a pencil can leave a trace on paper but not on a white board. The human-assisting robots of the near future would be more useful if they knew how to use writing instruments and tools.

This investigation asks the question: How can a robot learn to identify object-surface pairs that are useful for making traces? This is an initial step toward identifying a developmental sequence that a robot could use in order to learn how to write.

II. RELATED WORK

There is little related work in the field of developmental robotics that addresses robot writing skills from a developmental point of view. The existing work mostly addresses the control challenges associated with writing.

Writing legibly requires precise control of the tip of an object. Kemp and Edsinger [2] proposed a method for autonomous detection and control of the tip of a tool by a robot. Using this approach, a robot could potentially learn to detect the tip of writing instruments such as markers.

Writing well also requires the production of the intricate movement patterns associated with each written character. Yussof *et al.* [3] 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.

A developmental framework proposed by Zhang and Weng [4] was used by a robot to combine previously learned trajectories in order to create new ones. In one demonstration, the robot learned to draw a whole flower after a human trained it to draw petals.

III. METHODOLOGY

This investigation proposes to test the assumption that a robot can learn to identify a good trace-making object for a given novel surface. It does so by programming a robot with several marking behaviors (scribbles, dots, and lines) and an ability to detect traces. After the robot interacts with different objects and different surfaces, it will form 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 than others and that this property can be detected using unsupervised clustering. Next, the robot will acquire a spectral histogram for each surface category such that when given a novel surface, the robot can identify a good trace-making object for that surface.

An upper-torso humanoid robot with two 7-DOF Barrett Whole Arm Manipulators will perform the interactions. The robot will interact with a set of 12 different objects and a set of 12 different surfaces such that each trial consists of one object and one surface. The robot will complete ten interactions with each object-surface pair.

The robot will model the texture of each surface category by first extracting a spectral histogram for each surface of a category and second, by averaging all spectral histograms of a category. Spectral histograms consist of the marginal distributions of filter responses for a bank of filters that work well for texture classification tasks [5] and they will be used for comparing the texture of learned surface categories to that of novel surfaces. Given a novel surface, the robot will extract its spectral histogram, find the best matching surface category, and select the best trace-making object for that category. Finally, it will try to leave a trace on the novel surface with the selected object as a way to validate what it has learned.

REFERENCES

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