# Robotic Comprehension of Viscosity

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**Abstract**

At the time of this proposal's composition, there are no published attempts at teaching a robot to distinguish between different liquids or to identify substances by their current material state (e.g. liquid or solid). This proposal represents an intersection between the fields of personal robotics and autonomous intelligence, with potential applications for accessibility, home, and automotive technology. The end goal of our project is to train a robotic arm to allow it to first be able to distinguish between specific liquids and eventually have the ability to distinguish between solids and liquids. To achieve this, we will utilize machine learning algorithms to train the robot to classify substances based on a variety of characteristics, mainly feedback from force receptors in the arm's "fingers," as well as auditory and visual input.

## 1 Introduction and Related Work

Current research efforts include training robots to categorize objects as containers to hold water and utilizing neural networks to detect and track liquids [2]. Work has been done by research collaborators such as Schenk and Fox to use machine learning techniques to get robots to understand the movement of liquids, but these movements are so complex that so far only computer-simulated liquids have been analyzed, and these necessarily differ from real-world liquids [3]. Groups like Griffith and Shane et al. have done experiments with robotic comprehension objects, but most of these objects were either solid or empty and none contained liquids [2]. Identifying and interacting with liquids is important in everything from food production to automotive care, yet this is a virtually unexplored region of robotics. Part of this is due to the fact that robots are generally not waterproof, although more work has been done with robots and water than with other liquids. This is largely because of the work done with submerging robots in water completely and using them to collect data in underwater conditions. Robots have also been made to work with liquids for cooking purposes, but these projects have focused more on food production than machine learning and have not produced any research on robotic comprehension of liquids. Our project aims to explore the cross section of personal robotics and autonomous intelligence that represents an opportunity to create systems which are able to learn about all elements of their environments, enabling them to perform a greater variety of tasks more efficiently and robustly.

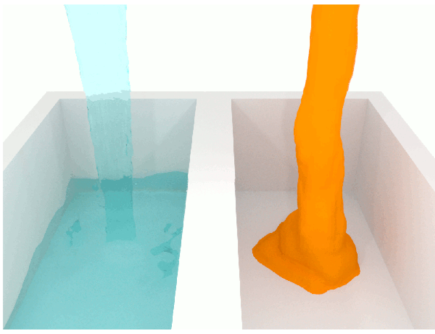

Figure 1: Comparison of liquids exhibiting lower (left) and higher (right) viscosities; courtesy of Wikipedia

## 2 Problem Formulation and Technical Approach

### 2.1 Proposed Hardware

- Kinova Robotic Arm
- Accompanying Joystick

### 2.2 Proposed Software

- ROS
- C++
- Ubuntu
- Terminator

### 2.3 Overview and Considerations

Viscosity is measured in pascal seconds (Pa s) or poise (dyne second per square centimeter [dyne s/cm2]), with ten poise being equal to one pascal second. A higher viscosity corresponds to a thicker (more viscous) fluid, with the viscosities of semisolids and solids being the highest - for example, tar at room temperature [20o C] has a viscosity of 30,000, and water at the same temperature has a viscosity of 1. Viscosity is highly dependent on temperature, with a higher temperature yielding more viscous gases and less viscous liquids [1]. This is an important consideration for this project, as varying temperatures will yield inconsistent results. We plan to only test with liquids generally stored at room temperature, as to prevent skewing the results with liquids exhibiting an unusual viscosity due to ecologically invalid circumstances (e.g. as milk is often refrigerated, it potentially curdles when left in warmer temperatures and this would affect its viscosity).

To help the robot learn about viscosity in a meaningful way, we plan to have it grasp a stirring implement, perform a standard stirring motion, and record the resistance it encounters from liquids in a small test set of liquids using a logging utility.

| Substances | Viscosity at Room Temperature(in Pa s) |
|---|---|
| Blood (Human) | 3-4 |
| Canola Oil | 33 |
| Caulk | 1000 |
| Chocolate Syrup | 10-25 |
| Corn Syrup | 2-3 |
| Honey | 10 |
| Ketchup | 50 |
| Lard | 1000 |
| Machine Oil (Light) | 102 |
| Machine Oil (Heavy) | 233 |
| Maple Syrup | 2-3 |
| Milk | 3 |
| Molasses | 5 |
| Mustard | 70 |
| Olive Oil | 84 |
| Peanut Butter | 150-250 |
| Rubbing alcohol | 2.4 |
| Sour Cream | 100 |
| Soybean Oil | 69 |
| Tar | 20 |
| Vegetable Shortening | 1200 |
| Water | 1 |

Table 1: Courtesy of Physics.info [1]

## 2.4 Grasping

A firm, consistent grasp on the stirring implement is important for both the validity of the data gathered and the safety of the robot when stirring the liquids. To achieve these goals, a number of stirring implements, such as whisks, spoons, paint stirrers, and dowels will be tested to determine which the robot is able to hold most effectively. If necessary, tape will be used, or a gripper will be added to the stirring implement. To prevent losing the grasp on the implement, a stirring motion that will not exert force on the implement parallel to the fingers will be used. The stirring implement used will need to be able to stir liquids of a range of viscosities with consistency (specifically, without getting stuck or reverberating unnecessarily) so as to not become a confounding variable. We will use the grasping technique as a base to develop the stirring process.

## 2.5 Stirring

To develop the stirring technique, we will test using small, loose solids such as beans or cereal to minimize the risk of spilling and damaging the robot. If possible, we would like to use several different stirring motions to maximize the amount of data the robot receives. Humans usually stir with the elbow and wrist joints, which could be emulated with the robot and is a useful motion for emulating or copying human motions. However, the robotic arm's wrist can rotate 1000 times a direction before needing to be rotated in the opposite direction, which could be useful for performing tasks not able to be

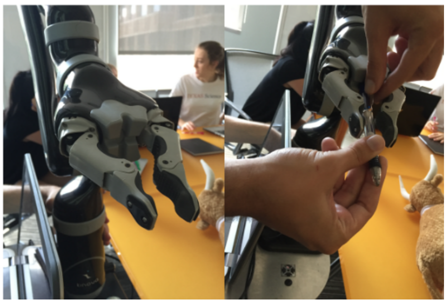

Figure 2: Shots of the robot arm, showing the area where the end of the stirring implement will be placed

performed by humans. Our primary concerns in the stirring motions are not splashing or otherwise damaging the robot while getting the most comprehensive and valuable dataset possible. Once an optimized stirring regimen has been established, we can begin collecting test data to establish our dataset.

### 2.6 The Liquid Set

We plan to compile a list of roughly 20 liquids, semisolids, and test solids (such as rice or gravel), which we will test using our stirring implements and the stirring regimen mentioned previously. Based on the way this set of liquids works with the implements and the regimen, and the sample data collected, the most effective stirring implement will be selected, and a set of about 10 liquids will be chosen to use as our final set. Our goal here is to work with a narrowly defined set of liquids with disparate viscosities to make the initial measurements easier to distinguish for the robot. Once the arm's sensitivity is established, a more complex set could potentially be created and tested. Ideally the liquids tested initially will all be room temperature for ease of testing (as specific temperatures would be very time-sensitive), but for future projects the effect of temperature on stirring could be studied, and perhaps temperature data could even be recorded and analyzed by the robot, as this has been proven to help robotic comprehension of liquid motion [3].

### 2.7 Recording Data

The set of liquids will be necessarily small, as there are a huge number of variations of liquids and temperatures, many of which have negligible differences in viscosity. The robotic arm takes advantage of force sensors as a way of receiving input from the world, which will be helpful in measuring viscosity. We plan to use liquids that the arm will be able to distinguish between with some degree of accuracy, such as peanut butter and water. In addition to the force sensor, we will also use auditory and visual data to help the robot identify the liquids, as some liquids (such as water and milk) have very similar viscosities but have obvious visual differences. We will use ROS and C++ to write a logging utility that listens to the force data gathered by the robot and also listens to some auditory and visual data to create a holistic view of the liquid being observed. We will analyze this data offline and determine how best to classify the liquids so the robot can identify them with reasonable precision.

# 3 Evaluation and Expected Contribution

To test the robot's ability to distinguish between liquids, a randomly generated set of "mystery liquids" (a subset of the liquid set used to create the dataset) will be compiled. The robot will run through the stirring motions on the mystery set using the same stirring implement used to establish the dataset. We hope to have the robot correctly identify the mystery liquid from its understanding of the initial liquid set at least 65 percent of the time. If the robot can meet these requirements, we will consider the project a success, otherwise we will have to re-examine our test set and learning algorithms, and possibly look to adjust the viscosity thresholds for each liquid and the sensitivity of the arm.

If successful, this project could be used as a springboard for research on robotic interaction with and comprehension of liquids, which could in turn be used to create robots that can work with liquids intelligently. This would include such activities as helping with cleaning (distinguishing between cleaning liquids as well as personal care items like shampoo and conditioner), cooking (determining the quality of ingredients and utilizing the viscosity of cake batter to gauge how much longer mixing needs to occur and at what point the batter is ready to be placed into the pan for baking), construction (testing the viscosity of time-sensitive materials like concrete and tar, specifically through stirring the mixture to prevent it from solidifying too early), and even automotive care (to optimize the viscosity of fluids important to car performance, such as freon, motor oil, and windshield washer fluid). The research also poses as an opportunity to advance the field of accessibility robots, specifically in the area of food preparation and aid. Ultimately, the advances made with this research can open doors in several fields, and will hopefully lead to changes that will improve the quality of life for millions.

# 4 Acknowledgments

Thank you Jivko Sinapov for your guidance in defining the scope of this project as well as your willingness to answer questions.

# 5 References

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3. Schenck, Connor, and Dieter Fox. "Detection and Tracking of Liquids with Fully Convolutional Networks." arXiv.org, Cornell University Library, 20 June 2016, arxiv.org/pdf/1606.06266v1.pdf. Accessed 29 Sept. 2016.