

Robotic Learning of Haptic Adjectives Through Physical Interaction

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I. INTRODUCTION

Humans use language to describe their perceptual experiences and communicate with others about the world. Current methods of statistical language processing aim to categorize words via occurrence and usage statistics from large bodies of text [1], an approach that elucidates important patterns but cannot alone understand the facets of language that are grounded in the human experience of the physical environment. To deepen our understanding of perceptually grounded language acquisition, this work aims to create a robot that can learn the meaning of touch-based (haptic) adjectives by physically interacting with labeled objects through sensitive fingertips.

Touch is uniquely interactive among the senses, combining both the knowledge of bodily movement and the ability to feel stimuli across the skin. When asked to identify an object's haptic properties, humans perform stereotypical exploratory procedures (EPs) to uncover the object's latent features, e.g., static contact for temperature, a lateral rubbing motion for texture, and normal pressure for hardness [2]. Few robotic systems have attempted to replicate the range and acuity of everyday human touch perception, primarily due to a paucity of tactile sensors. In one early example, Okamura et al. [3] presented robot fingers that roll and slide over the surface of an object to determine texture, ridges, and grooves. More recently, Fishel and Loeb used a SynTouch BioTac sensor and various stroking motions to classify 117 textures with 95.4% accuracy [4]. We aim to bring this line of research into the domain of language by equipping a Willow Garage PR2 humanoid robot with a pair of BioTac sensors and gathering a publicly shared corpus of physical interaction data from real objects that humans methodically labeled with a large number of adjectives. The goal of our research is to deduce the physical meaning of each haptic adjective based only on what the robot felt when touching the labeled objects.

II. HARDWARE INTEGRATION

We added BioTacs to the PR2 to obtain a robotic platform capable of both controlled manipulation and tactile sensing.

This work was supported by the U.S. Defense Advanced Research Projects Agency (DARPA) via Activity E of the Broad Operational Language Translation (BOLT) program.

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Fig. 1: A subset of objects from the Penn Haptic Adjective Corpus alongside the PR2 gripper equipped with BioTac sensors. The item being explored is object #101: car sponge.

SynTouch Biomimetic Tactile Sensor (BioTac): Each human-fingertip-sized BioTac sensor includes a silicone skin filled with conductive fluid over a heated rigid core [4]. Much like a human fingertip, the sensor measures four types of tactile signals: low-frequency fluid pressure (P_{DC}), high-frequency fluid vibrations (P_{AC}), core temperature change (T_{AC}), and a set of nineteen electrode impedances ($E_1 \dots E_{19}$) spatially distributed across the core. P_{AC} is sampled at 2200 Hz, and all other signals are sampled at 100 Hz. As pictured in Fig. 1, we use a pair of BioTacs enable grasping and provide sensory redundancy.

Willow Garage Personal Robot 2 (PR2): The PR2 humanoid robot has two 7-degree-of-freedom (7-DOF) robotic arms, each with a 1-DOF two-fingered gripper, plus a suite of cameras and lidar sensors. To upgrade its touch sensing capabilities, the metal fingers of the left gripper were redesigned to mechanically accommodate the BioTac sensors while maintaining compatibility with the default tactile sensors. Electrically, a 12-Volt USB hub was added to the exterior of the PR2's left shoulder for powering and communicating with the BioTacs. Full details of our mechanical and electrical integration methods are available at <http://bolt-haptics.seas.upenn.edu/>. This modification was successfully implemented on the PR2 robots at both Penn and UC Berkeley. To interface with the Robot Operating System (ROS), a publisher node was built to read in the data from both BioTacs and publish that data at 100 Hz over the ROS network. This package will be available in the near future on <http://www.ros.org/wiki>.

III. PENN HAPTIC ADJECTIVE CORPUS

We recorded data as the BioTac-equipped PR2 repeatedly explored dozens of objects and also had humans label these same objects with dozens of binary haptic adjectives. This full corpus will soon be shared with other researchers.

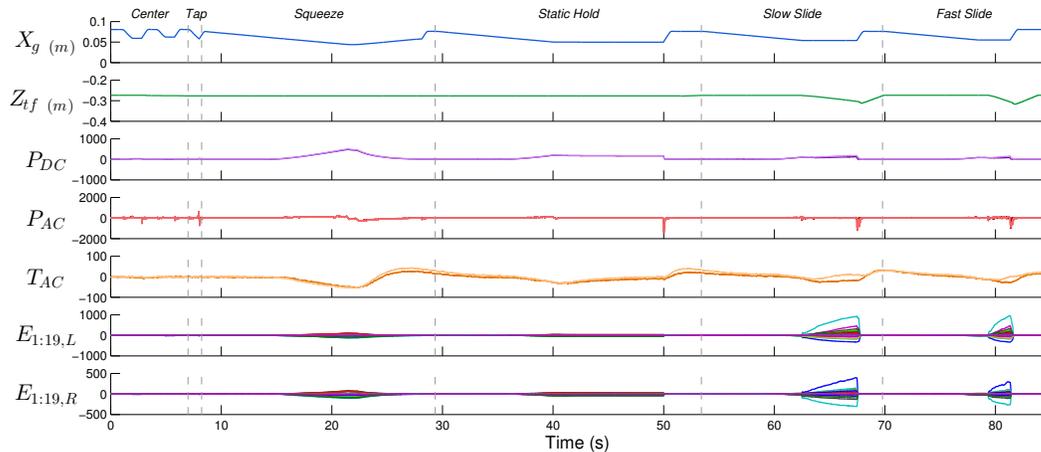


Fig. 2: The haptic data collected as the PR2 touched the car sponge shown in Fig. 1. The BioTac signals are analog-to-digital readings shown in bits. The signals measured from the left and right fingers are shown together, except for the electrode arrays. The majority of the human participants labeled this object as compressible, fuzzy, nice, soft, squishy, and thick.

Objects: 54 distinct everyday objects were selected for inclusion in the corpus; Fig. 1 shows a representative subset. To simplify robotic interaction, all objects can stand upright on a table and have two flat, parallel, vertical sides with identical surface properties. To match the size of the PR2 gripper, each object has a height greater than 10 cm and a thickness between 1.5 cm and 8 cm.

Robotic Exploratory Procedures: The PR2 was programmed to execute a fixed set of movements to tease out interesting haptic signals from each object in the corpus. As shown in Fig. 2, the robot first finds the object during the *Center* phase and then performs five predefined motions that yield streams of data. During the *Tap* phase, the PR2’s gripper quickly closes around the object until contact occurs on both BioTacs, then the aperture opens to release the object. *Squeeze* slowly closes the gripper until a predefined P_{DC} value is achieved, then the gripper opens. During *Static Hold*, the robot gently holds the object for ten seconds to let the fingers reach thermal equilibrium with the object. For both *Slow Slide* and *Fast Slide*, the PR2 lightly contacts the object with both fingers and then moves downward 5 cm, releasing in between and at the end.

Ten runs of this procedure were recorded as ROS bagfiles for each of the 54 objects in the corpus. The bagfiles contain time histories of all PR2 transforms, left arm joint efforts, positions, and velocities, left gripper accelerometer readings, the narrow_stereo_left camera video feed, all readings from both BioTac sensors, and the timing of the controller states and sub-states. As shown in Fig. 2, a subset of these signals was chosen for the current analysis, including all signals from both left and right BioTacs, gripper aperture X_g , and the gripper tool tip’s vertical position, Z_{tf} .

Adjective Labels: Four individuals touched the 54 objects in the corpus without visual or auditory cues. Participants used only two fingers of one hand and limited their motions to those done by the PR2. Each person gave each object a binary rating for each of the following 34 adjectives: absorbent, bumpy, compact, compressible, cool, crinkly, deformable, elastic, fibrous, fuzzy, grainy, gritty, hairy, hard, hollow,

meshy, metallic, nice, plasticky, porous, rough, scratchy, slippery, smooth, soft, solid, springy, squishy, sticky, stiff, textured, thick, thin, unpleasant.

IV. MACHINE LEARNING

We plan to test several approaches to learning the perceptually grounded meanings of the haptic adjectives included in the corpus. Because the signals’ evolution over time provides strong cues about the object’s properties, we have initially explored classification approaches that exploit the time-dependent nature of the data, namely Hidden Markov Models (HMMs) [5]. We segmented the data into the four long motion phases (omitting *Tap*) and discretized the associated tactile data using PCA, subsampling, and k-means. We then created a different HMM for each combination of motion and tactile input, for a total of 16 HMMs. Final adjective labeling is performed by 34 Support Vector Machines (SVMs, one per adjective) with linear kernels operating on the output of the 16 HMMs with labels determined by majority voting. All training sessions used cross-validation with 2/3 splits. We obtained a classification score of 98% on the corpus, averaged over all the adjectives. Moreover, testing these classifiers on 5 previously unseen objects obtained an average score of 88%. These preliminary results show the feasibility of learning haptic adjectives from physical interaction with labeled examples; future work will explore other approaches.

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