Online Perception of Tactile Directionality Using Hidden Markov Models

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Abstract—Currently, the field of robotics relies on computer vision as the primary sensing modality in unstructured environments. While vision can be used for planning physical interactions, tactile and proprioceptive feedback are often more useful for perceiving forceful interactions with the environment. Local tactile information can be especially useful for the early detection and perception of physical interactions between a grasped object and the environment. Deformable, multimodal tactile sensors that collect pressure and fingerpad deformation data were used to create Hidden Markov Models (HMMs). The HMMs were used to perceive the directionality of perturbations to a grasped object. Log likelihoods for each of 12 HMMs (each representing 30° of a complete 360° circle) were computed continuously in real-time. The HMM that satisfied a user-specified threshold criterion was used to trigger context-appropriate responses in online robot demonstrations of object handover and placement.

Keywords—Haptic Perception; Hidden Markov Models; Tactile Directionality; Tactile Feedback

I. INTRODUCTION

Robots have moved out of structured factory environments into unstructured human environments that are dynamic, unpredictable, and often contain unknown objects [1]. For tasks requiring physical interaction between robots and their environment, tactile feedback enables early detection and perception of forceful interactions between the hand (or handheld objects) and the environment. While computer vision remains a viable option for performing grasping [2], a parallel haptic system would complement the visual system and improve overall performance by providing additional information that cannot be gleaned visually. In this work, we develop capabilities for the haptic perception of tactile directionality, or the “ability to tell the direction of an object's motion across the skin” [3]. With proprioception and knowledge of gravity, a robot that can perceive tactile directionality might be able to more efficiently perform an object handover or more gently place an object on a tabletop, for example.

II. METHODS

A table-mounted BarrettHand (Barrett Technology, Newton, MA) was equipped with two BioTac multimodal tactile sensor fingertips (SynTouch, Los Angeles, CA) (Figure 1b). The BioTac records information about internal fluid pressure, vibration, skin deformation of the fingerpad, and temperature. In this work, we used the internal fluid pressure (DC pressure) and skin deformation data, by way of impedance readings from 19 electrodes embedded in the core of the sensor. DC pressure and impedance are sampled at 100 Hz. Each tactile sensor had a 50° contact angle with the surface of a rigid, parallel-faced object.

The object was attached to the end of a 7DOF Barrett WAM (Barrett Technology, Newton, MA), which was used to perturb the object within the plane perpendicular to the grip axis (axis connecting the two BarrettHand fingertips) (Figure 1a). Each perturbation was comprised of a 15 mm linear displacement of the grasped object in different directions tangential to the fingertip (Figure 1c). The perturbations ranged from 0°-360° in 10° increments and were created through an inverse kinematic solver implemented in MATLAB (MathWorks, Natick, MA). Additionally, perturbation speed (2 cm/s, 4 cm/s) and grip force (low, high estimated from the BioTac fluid pressure) were varied similar to experiments on human perception of movement direction [4].
Data were collected in separate sessions over the course of three days. This was done to add variation to the training and test data and to prevent overfitting. Each experimental session included 3 replicates of each possible perturbation. Five separate experimental sessions, each consisting of 432 randomized trials (3 replicates x 2 forces x 2 speeds x 36 directions), resulted in a total of 2160 trials.

Baseline tactile sensor data from each initial, static grasp of the object were subtracted from all subsequent data in each trial. The changes in tactile sensor data during the initial 500 ms of perturbation movement were used to train Hidden Markov Models (HMMs). HMMs are temporal probabilistic models that have been used for signal processing and classifying continuous data [5]. The size of the input feature matrix was 40 x 50 (1 pressure and 19 electrode changes for each of the two sensors in the 500 ms period with a sampling rate of 100 Hz). Each HMM was associated with a bin created by dividing the 360° into separate sectors. Based on a 30° angular resolution of human tactile direction sensibility [4], we divided the 360° circle into 12 distinct 30° sectors.

III. RESULTS AND DISCUSSION

A. 5-Fold Cross-Validation

A 5-fold cross validation was conducted to assess model performance; each fold was comprised of a separate data collection session. The data were pooled for both training and testing. To simulate a real-time scenario, all 12 HMM log likelihoods were calculated for each time step in the 500 ms perturbation period. For each time step, the preceding 250 ms of data (40 x 25 input feature matrix) was used for the log likelihood calculations.

Log likelihoods of the test trials were plotted over time for each HMM. Figure 2 shows the average log likelihoods of all 12 HMMs for trials that belong to the sector associated with a distal perturbation. In the initial 100 ms, all HMMs calculate relatively the same log likelihood. Afterwards, the log likelihoods of the incorrect HMMs start to decrease quickly compared to that of the correct HMM, for which the value remains consistent. The log likelihood for the correct HMM will be significantly larger than those of the incorrect HMMs.

Figure 2. Log likelihoods for all 12 HMMs for a distal motion of the grasped object. The solid line represents the correct HMM while the dashed lines represent the incorrect ones.

Figure 3. The 5-fold cross validation error rate decreases with time. Each fold is plotted in thin gray, while the average is plotted in thick blue.

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HMMs. This trend is common to all 12 sector-specific HMMs.

The overall 5-fold cross validation error rate decreases as time elapses after the onset of the perturbation (Figure 3). This could be due to the increase in tactile sensor skin stretch as the displacement of the grasped object increases with time. Larger changes in skin stretch from unperturbed baseline values are easier to distinguish from noise. The mechanical deformation of the artificial fingerpad appears to encode directional information about tangential skin displacement, similar in principle to the biological fingerpad [4].

For each of the five folds, each sector had 36 test trials. The number of errors for each sector was averaged across the five folds and the overall error rate is reported in Figure 4 at specific time steps of interest. By 500 ms after the onset of perturbation, the maximum error rate is 23% for Sector 8 (Figure 4b). The error rate at 500 ms is less than or equal to 13% for most sectors.

B. Real-Time Implementation

The trained HMMs were tested in a real-time hardware demonstration for an object handover and placement task (Figure 5). As with the 5-fold cross validation, the preceding 250 ms of data are utilized to calculate the log-likelihoods in real time. The robot was programmed to respond in a context-appropriate manner when a user-specified threshold criterion was met. Inspired by the threshold criterion in [6], the maximum log likelihood of a single HMM had to exceed all other log likelihoods by a minimum threshold $\beta$. There are speed and accuracy trade-offs with the selection of $\beta$. If $\beta$ is too small, the robot may make a short latency, but incorrect response. If $\beta$ is too large, the robot may wait too long to make its context-appropriate response.

To mimic an object handover, an experimenter attempted to pull a box in a distal direction relative to the robot’s reference frame, and the robot perceived the resulting tangential stimulus (green pie chart sector in Figure 5a). The robot then proceeded to an object placement task. Upon contact between the handheld object and a horizontal platform, the robot perceived tangential stimulation in the radial direction relative to its reference frame (Figure 5b). The hand released the box once the $\beta$ threshold was met. In this preliminary demonstration, a $\beta$ threshold of 10,000 was met within 700 ms of the start of an object perturbation.

![Figure 5. Online perception of tactile directionality during a) mock object handover and b) object placement.](image)

IV. CONCLUSION

We have developed capabilities for the online perception of tactile directionality using HMMs that can be used to complement visual feedback during grasp and manipulation. In this work, we discretized movement into 30° sectors based on human tactile direction sensibility [4], but this artificial angular resolution can be refined by using more precise robot movements for model training and collecting more training data to capture variation in the tactile sensor data. If a finer angular resolution is desired, a continuous model of tactile directionality could be developed using Recurrent Neural Networks or other models where regression can be utilized. Ongoing work includes the verification of HMM accuracy in real-time, unstructured scenarios. The generalizability of the model to other conditions (e.g. displacement rates) requires further investigation. Tasks could be performed more efficiently and safely if physical interactions with other agents and the environment could be perceived through handheld objects.

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REFERENCES


