

Functional Inspection Using Tactile Perception during Manipulation of Deformable Objects

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Abstract—Assembling deformable objects into manufactured products is a common step in many manufacturing processes which still remains dominated by human expertise. This is due to the need for inspection while manipulating them which arises because of the intrinsic difficulty to manipulate deformable objects. Humans unlike robots are successful at such manipulations as they are constantly ‘inspecting-on-the-fly’ using an array of multimodal sensing methods. This emphasizes the necessity for integrating inspection with manipulation routines for robots in manufacturing. In this paper, we propose a novel tactile-based inspection-on-the-fly method to identify the states of a deformable object, in our case a Ziplock bag. Exploratory manipulations were used to discover all the possible states during training while on-line inspection used Support Vector Machines to classify the discovered states, which are open and close, at every point along the zipper by following its contour using reinforcement learning. Our real-time procedure achieved 92% accuracy on a small sample size in inspecting open and close states while performing exploratory manipulations. The results were replicated on rubber-bands in detecting twists at every point along their surface. Similarly, this can be extended to other complex deformable objects to help robots gain more context and thus achieve a greater range of purposeful and integrated inspection.

Keywords— *inspection-on-the-fly, exploratory manipulation, deformable objects, tactile, support vector machines, reinforcement learning.*

I. INTRODUCTION

Robot manipulators have made strong inroads into many areas of high-volume manufacturing such as automotive final assembly and semiconductor fabrication due to their tireless operation and unwavering repeatability. However, robotic inroads into small batch manufacturing – which could dramatically benefit from their re-taskability -- have been less widespread. This is because of the cost of integration, which is generally 4-to-10 times the cost of the robot itself. Robotic integration relies on highly trained software and hardware experts to simplify the work cell around the robot to eliminate errors – turning the robots, by some accounts, into sophisticated fixed automation.

Humans, on the other hand, are masters at error handling, but error handling depends on knowing when something is wrong and the cause of the error. This makes them easy to integrate into unfamiliar, short-run processes. Humans

employed in fixed automation processes are required to undergo extensive testing and validation on the procedures resulting in their task completion. For a human trainee to be validated or considered reliable to work in the assembly process they are tested on their task repeatability rigorously. During this training period humans adapt themselves very quickly and learn the nuances present in performing the required task using various exploratory procedures or manipulations. These exploratory procedures are in essence trial and error methods performed on the fly by the human while carrying out the task, much similar to how a child would use exploratory manipulation to learn to walk. This in turn helps the human in understanding the various states or context of the task at hand and derives the need for purposeful eventful manipulation. While robots in a tightly controlled work cell are “smart” enough to know if a part is present when a light beam is broken, they are rarely smart enough to know if an errant piece of debris has broken the beam, instead. Furthermore, humans can tell if the part is misshapen or stuck on a conveyor and many other common-sense errors that are easily recovered from. In short, humans are more adaptable partly because they are constantly inspecting-on-the-fly. Hence, we feel it is beneficial to imbue robots with greater ability to inspect-on-the-fly so they can penetrate deeper “down the food chain” of manufacturing logistics, into smaller batch- size applications.

We are exploring the problem of o-ring installation in manufacturing processes and draw inspiration from the work of Hellman on the closure of Ziploc bags [1]. This paper extends this prior work by proposing a novel method to inspect-on-the-fly the two natural states of a Ziploc bag seal (open and closed) in real-time along the contour of its zipper. Identification of these states will not only help us in understanding if our manipulation was successful, but also helps us in adopting corrective manipulation procedures. Studies in [2][3] prove that distinguishing between states is possible from tactile feedback. Using tactile sensing to provide context or object specific features related to the object being manipulated has been a well sought out research work. Many such papers aim at tackling this problem [4][5]. The proposed purposeful inspection method shall help us in ultimately achieving complete inspection-on-the-fly during the manipulation of a Ziploc bag aimed at transitioning between its states as well as purposeful manipulation.

II. METHODS

A. Task Procedure

The inspection-on-the-fly procedure has been designed considering all the experimental setup constraints and consists of the following 4 steps – a) Grip Calibration b)

Contour Following c) Exploratory Manipulation and d) Online State Estimation

The workflow during the entire operation is as follows – a) For each Ziploc bag, we start off by statically calibrating the parallel gripper gap at which the third digit is just touching the zipper in the open state. This is determined by closing the gap until some force above the noise floor is detected reliably b) We then use contour following to traverse along the zipper in quantized steps to access all points on its length. At every point, two processes happen; c) We perform a basic exploratory manipulation in which we incrementally try to squeeze the open zipper into closure in a series of progressively firmer steps with the third digit. At each step, we alternate squeezing with a progressively firmer grip and squeezing with the calibrated grip. On the calibrated grip stroke of each incremental step, we d) gather a tactile image to build a training set for a classifier of the state of the zipper. Based on these tactile images, we look for changes in the state represented by different clusters of the images that reliably appear after calibrated taps that follow progressively firmer taps. This exploratory step allows us to discover state changes and states through active manipulation without explicit inspection of known states such as “open” or “closed.” The only assumption is the generic idea that some set of state changes may occur as a result of pressing harder. e) Once the classifier is trained, actual inspection-on-the-fly procedure is carried out where at each step of grip-calibrated-contour- following, exploratory manipulation is repeated for several iterations until we detect a state transition from open to close or until a maximum threshold is reached. Maximum threshold is determined at a point where the zipper is pressed very hard and yet there is no change in state. The same process of exploratory manipulation and on-line state estimation is repeated till we traverse along the whole bag, thus managing to perform inspection on the fly.

B. Super Baxter Collaborative Robot Testbed

The testbed employs a 4 DOF BarrettHand (Barrett Technology, Cambridge, MA) attached to one of the 7-DOF arms of the bimanual *SuperBaxter* [6] (based on the former Rethink Robotics Sawyer arm) – both of which are ROS controlled. Tactile perception is done using force values obtained from a BarrettHand digit which has 24 tactels (8x3 array) with each cell having an area of 0.3cm² in our region of interest (first 3 rows or 9 cells) and a resolution of 0.01N, with the tactile array being rigid. The digit has a joint resolution of 0.005 radians. Also given the rotary joints of the digits of BarrettHand and their limits, there is no configuration possible where we can use 2 digits of the same hand to hold the zipper and have enough contact area for sensing. Hence, we use only the third digit, along with a custom designed fixture placed on the remaining two digits that have been kept in a constant configuration for the entire duration of our task, i.e. until the complete zipper contour has been followed.

III. RESULTS

In the context of state classification and estimation, we were able to achieve a training and validation classification accuracy of 92.8% with SVM and 10-fold cross- validation,

suggesting its ability to generalize. The testing accuracy with the SVM classifier was 94%. Thus, we can estimate the natural states of a Ziplock with 92% accuracy on average, given the current hardware setup on Ziploc bags of different sizes and weights contained within the bag and zippers of different thickness (above a threshold of 2 mm), taking an average time of 4.5 minutes. Videos of task execution were recorded along with actions, contour state and natural states of the bag for each time step which shows successful execution under different conditions.

Using our proposed inspection-on-the-fly method, we can verify if any point in contact with the robot’s tactile sensors along the Ziplock is open or closed thus achieving a means to identify the states during the process of purposeful inspection of the Ziplock. These results can be further extended to objects commonly used in manufacturing assembly processes such as torlon seals and o-rings.

As part of our future work we do plan to use multi sensor modalities with vision integration to help us with the online state estimation and classification. So far, we have implemented an inspection on the fly method based solely on tactile imaging. Humans on the other hand use both vision and tactile feedback to gain context about the object of interest in such dexterous manipulations. Visual perception in humans often easily capture certain obvious scene or object information that might be either lost in haptic-only perception or might be more difficult to acquire. So, not only can we use multi modal sensing techniques like optical touch sensing to improve our tactile imaging, but we can also integrate a vision system to gain this obvious state information. **Visual inspection might prove equally easy to implement if we are not constrained by object properties such as transparency in ziplocks.**

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