Contact State Estimation using Machine Learning

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Abstract—In this paper we present an approach that uses machine learning to determine the location of a contact between a gripper and a T-bar valve based on force/torque sensor data. The robot performs an exploratory behaviour that produces distinct force/torque data for each contact location of interest: no contact, a contact aligned with the central axis of the valve, and an off-center contact. Probabilistic clustering is utilised to transform the multidimensional data into a one-dimensional sequence of symbols, which is then used to train a hidden Markov model classifier. We present the results of an experiment where the learned classifier can predict a contact location with an accuracy of 97% on an unseen dataset.

I. INTRODUCTION

There is an increased interest in developing robots that can dexterously manipulate objects. Events such as the 2011 Fukushima Daiichi nuclear disaster have sparked an increased interest in the research community to develop disaster response robots that can autonomously inspect and manipulate objects in hazardous environments. In such environments often sensing modalities such as vision are limited or unreliable, hence, direct contact information is important to successfully inspect and/or manipulate an object. Applications of such a system include search and rescue operations and underwater manipulation of objects.

In this paper we propose a method that can be used to inspect an object. As part of the EU FP7 PANDORA project [1], [2] we investigate an object inspection task that consists of determining the location of a contact between a robotic gripper and a T-bar valve. We use an exploratory behavior that at different contact locations induces the force/torque sensor differently. This produces a multidimensional time-series data on the contact location. A contact location, namely, an edge-contact, a center-contact and no-contact can be detected by studying the temporal patterns in the data. Our contribution is a robust autonomous contact determination based on machine learning that relies on non-vision sensing, namely, a force/torque sensor.

To learn a classifier for the gripper-valve contact, we use our previously developed method to analyze temporal patterns in a multidimensional time-series data [3]. In this paper we apply the learning method to a new problem, i.e. gripper-valve contact location classification, we also introduce the use of active exploratory actions to enable the robot to perceive the contact state.

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The learning algorithm is divided into two stages: dimensionality reduction using clustering; and temporal pattern extraction. In the first stage, probabilistic clustering [4] is applied to discover the intrinsic structure of the data. Clustering transforms the multidimensional time-series into a sequence of symbols, each of which is an identifier for a cluster. Thus, an abstract contact condition such as the location of a contact can be represented by a sequence of cluster identifiers. In the second stage, using a supervised hidden Markov model (HMM), the algorithm analyses the sequence and builds a probabilistic model of temporal patterns that correspond to different abstract contact conditions.

Fig. 1 shows the experimental setup, which consists of a gripper attached to a KUKA arm. An ATI Mini45 force/torque sensor is sandwiched between the gripper and the robot’s end-effector. A T-bar valve is placed in the robot’s workspace. The robot performs an exploratory behavior, which, as illustrated by the green arrow in Fig. 1, is a periodic rotary movement around the handle of the valve with a given angle-of-rotation. This action induces the force/torque sensor differently at different contact locations. For example, a contact at the center limits the angle of rotation, resulting in the force/torque sensor registering higher values, which is different to an edge-contact. We show that using this method the robot can successfully predict a contact location.

II. BACKGROUND

Earlier research in valve detection and manipulation assumes a structured environment, where the robot stores detailed information about the environment [5], [6]. Non-vision
that is, the sequence of cluster memberships is analysed to provide an example of a sequence of cluster memberships.

Each cluster is denoted by a letter. A series of data is divided into a sequence of clusters. The data is filtered using a digital filter with a 3 dB point of 5 Hz, and the control signals change at 0.5 Hz. The force torque data are zero-mean normalized from the point of first contact. This process is necessary to make the forces and the torques comparable between different trials.

2) Filtering: The force/torque data are sampled at 500 Hz, the control signals change at 0.5 Hz. Hence, the force torque data is filtered using a digital filter with a 3 dB point of 5 Hz, which is ten times the frequency of the control signals.

B. Principal Component Analysis

Principal component analysis (PCA) is a mathematical transformation that converts a set of variables to a new basis, called the principal components. Each principal component is a linear combination of the original variables. In this space, all variables are orthogonal to each other, i.e., they are uncorrelated. Moreover, in the principal component space, the first component explains the greatest variance in the data, and as many further components capture lower variance as compared to the preceding component. A consequence of this property is that PCA can be also used as a dimensionality reduction tool.

Dimensionality reduction is achieved by only keeping the lower components. A rule of thumb is to drop components once the ratio of cumulative-variance to total-variance has exceeded a predetermined threshold, usually 0.8. In our training data set, the first component exceeded this threshold by reaching a ratio of 0.96. Hence, in the subsequent analysis we only consider the first principal component.

C. Clustering

We use probabilistic clustering [4], which uses the minimum message length (MML) principle as the optimization criterion, to build a Gaussian mixture model of the data. In this section we explain the theory behind MML clustering and show how we use it to extract features.

Cumulative-variance is calculated by summing the variance of all components up to the component of interest.
Hence, maximizing the posterior probability can be achieved by a message of length in information theory, we know that an event of probability \( p \) can be coded by a message of length \( -\log_2 p \). This allows the algorithm to perform an action. In this case the action is to perform an exploratory behavior at a contact point. The training examples are generated by allowing the robot to learn a mapping from the temporal sequence of clusters to a classification of the contact state. The accuracy of the classifier is tested by applying it to a novel sequence, where the contact state is unknown to the robot.

Fig. 2(a) shows an example of a sequence generated after the application of the clustering algorithm. The corresponding feature vector is also shown and consists of temporal sequence of couples of the form \( \text{cluster-membership, contact-state} \). Fig. 2(b) is an HMM used to learn a representation for the the emerging temporal patterns. The HMM has three states, one for each contact condition. It is trained using the sequence of clusters as the observation. When the robot is presented with a novel pattern, the robot uses the model to make a prediction.

IV. EXPERIMENTAL SETUP

The method was tested using the setup (Fig. 1) described in Section I. In this section we will define the contact locations, which is followed by a description of the exploratory behavior and a detailed description of the experiment.

A. Contact-location categorization

A contact between the gripper and the valve is categorized as follows:

1) Edge-contact: In an edge-contact, the area of contact between the valve and the gripper is at least \( \frac{1}{3} \) of the width of the gripper, and the central axis of the valve is not covered.

2) Centre-contact: In center-contact, the central axis of the valve is covered the gripper.

B. The exploratory behavior

The exploratory behavior is chosen to produce distinctive signals depending on the location of a contact. A roll that is pivoting on the valve will produce a different signal when it is on either one of the edges compared to a contact that is at the center of the valve, where the movement of the gripper is restrained by the valve’s axis. Thereby, inducing the force/torque sensor. The angle-of-rotation can take an arbitrary value, but it should be sufficiently large to guarantee the tip of the valve makes a contact with the central-axis of the valve when the gripper is at the center. In our experiments the angle of rotation was varied by 0.5 radians on either side of the starting position.

C. The learning task

The experimental setup shown in Fig. 1 is used collect data to train and test the learning algorithm. In this setup, the a gripper is attached to a KUKA arm. An ATa Mini-45 force/torque sensor is attached between the gripper and the robot’s end-effector. A T-bar valve is placed in the robot’s workspace. The robot performs the exploratory behavior in the workspace, which we will refer to as a trial henceforth.

Fig. 3 shows the configuration of the valve in the beginning of each trial. Three positions are sampled for an edge-contact, where the contact area, \( l \), between the valve and the gripper is varied. In the first position \( l = \frac{1}{3} \) of the length of the gripper, in the second position \( l = \frac{2}{3} \) of the length of
the gripper, and in the third position there is a full contact. Similarly, for the center-contact three positions are sampled. The first position is selected such that the central-axis of the valve is aligned with the first $\frac{1}{12}$ of the length of the gripper, in the second position the central-axis of the gripper and the central-axis of the valve are aligned. The third position is a mirror image of the first position. These positions are chosen to expose the learning algorithm to positions that are valid contact positions, within the tolerance of the control of the robot for safe manipulation.

Two separate datasets were collected: a training set and a testing set. Each set consists of nine samples for no-contact, nine samples for center-contact, and nine samples for edge-contact. The samples for the edge-contact were collected on either side of the central axis of the valve, which resulted in eighteen samples for the edge-contact. Fig. 4 shows the force/torque data where the colored regions represent a specific contact location.

V. RESULTS

The feature vector for the learning algorithm is a seven-dimensional vector that consists of the six-dimensional force/torque sensor data, and the control data, that is, the commanded angle-of-rotation. An HMM model was learned using the training set. We also varied the number of clusters to study the effect of this parameter on the performance. Table I shows the confusion matrix for three clusters and four clusters. We get an accuracy of 92% with three clusters, which is increased to 97% with four clusters. This is expected as an increase in the number of clusters increases the expressive power of the models.

VI. CONCLUSION & FUTURE WORK

We have presented a method that can successfully predict the location of a contact between a gripper and a valve using only force/torque sensor data. The presented approach is suitable for autonomous inspection of objects. In the future we will consider a larger set of behaviors that can result in a more detailed information such as the orientation of the valve or whether the valve is stuck. We will also study the performance of the proposed method in underwater scenarios.

REFERENCES

[2] “Persistent Autonomy through learnNg, aDaptation, Observation, and Re-plAnning (PANDORA). Online: http://persistentautonomy.com/.”