The Whole-Arm Exploration of Harsh Environments

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Abstract This work develops a method for tactilely mapping unknown harsh environments such as oil wells, using a manipulator equipped with only position sensors. Because contact with the environment may occur anywhere on the manipulator, determining the contact location is challenging. Here a method is developed, based on a probabilistic classification of the data according to the contact location on the manipulator, and the reconstruction of the surface using such classified data. The approach effectiveness is demonstrated in several case studies and laboratory experiments.

1 Introduction

Here, the robotic tactile exploration of very harsh environments such as those found in pipes, mines, sewers, nuclear facilities and oil wells is considered, when the environment conditions prevent the use of range, force or tactile sensors. The exploration of oil wells is often required to determine location and shape of junctions between the main well and lateral branches, to permit the insertion of tools into such branches (Figure 1). Oil wells are filled with an opaque fluid preventing the use of any range sensors, and have extremely high pressures (up to 1500 atm) and temperatures (up to 300 ^{o}C) that make force/torque and contact sensors unreliable (Mazzini et al., 2011). This work considers the exploration of such environments by a robot equipped with only position sensors (proprioception), an approach called Whole Arm Exploration .

Methods for robotically mapping environments have largely used range sensors (Thrun, 2005). These methods are very effective, but not applicable in harsh environments. Concepts have been proposed for tactile mapping of surfaces. For example, some works distinguish an object among a library of known objects (Keren et al., 2000; Petrovskaya and Khatib, 2011). Others explore simple surfaces such as concave objects (Moll and Erdmann, 2004; Okamura and Cutkosky, 2001). However, these works cannot explore an

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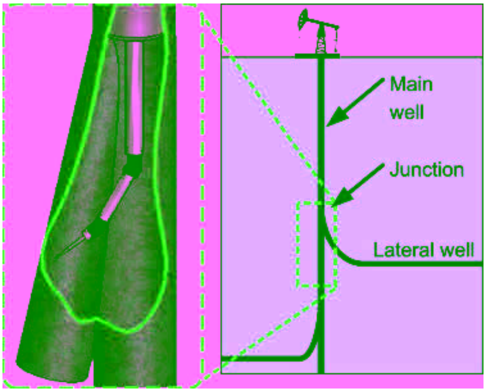

Figure 1. Tactile Mapping of the Junctions in Oil Wells

unknown environment, and they all require a force-torque or tactile sensor, which can be unreliable in harsh environments. Studies have been proposed to estimate the contact location with only position sensors when a manipulator's link is sliding against an object, and they have been used to map a simulated 2D pipeline using a snake robot (Kaneko and Tanie, 1994; Huber and Grupen, 1994; Everist and Shen, 2009). However, these methods can only be applied to a planar environment and sliding motion on the surface is time consuming and usually not feasible in a harsh environment, see (Mazzini et al., 2011). In conclusion, previously developed proprioceptive methods, while valuable contributions, cannot be used for the exploration of harsh, constraining environments.

Our recent studies have addressed the tactile exploration of unknown full 3D surfaces using a manipulator with only position sensors (Mazzini and Dubowsky, 2012; Mazzini, 2011). However, these works assume that contact occurs on the manipulator's tip, so that the contact location is known from the manipulator's kinematics. Here, this work is extended to cases where contact occurs anywhere on the manipulator. This approach is similar in spirit to Whole Arm Manipulation (Gordon and Townsend, 1989).

2 Proprioceptive Tactile Mapping

This work maps an arbitrarily-shaped, unknown environment using a manipulator mounting only position sensors. Contact with the environment is detected by monitoring the constraints on the manipulator's motions. The contact on the manipulator is not known a priori.

The following assumptions are made: the manipulator has a fixed base and its geometry is known (links are cylinders and joints are spheres); the environment is static, rigid and regular enough to be described by a combination of geometric primitives such as planes, spheres, cylinders, cones, and tori. A mesh can be used for the surface parts that cannot be well described by such primitives. The tradeoff between exploration speed and precision is controlled by a parameter, B, denoting the smallest expected surface curvature radius. The manipulator is controlled with an impedance controller so that when the manipulator touches a surface, its motion is obstructed and contact is detected. The impedance controller requires very low forces to detect contact with the environment: this insures that there is little danger to either the robot or the environment during contact.

Surface tactile mapping can be divided into two tasks: efficiently acquiring the environment data and interpreting such data to create a map of the environment. Data acquisition is a motion-planning problem that consists of choosing the manipulator's movements in order to collect the most informative data as quickly as possible. A strategy has been developed for this using an information-theoretic metric (Mazzini, 2011). This paper focuses on the data interpretation, developing a new approach to interpret contact data from a manipulator that is not restricted to end-point contact. It is composed of three steps. First, the link that is in contact is identified. Second, contact data are probabilistically classified into two subsets: contact either on the tip or on the link's body. Third, the two data subsets are used to create a model of the environment.

The link in contact is identified by monitoring joint velocities and commanded torques, as in (Kaneko and Tanie, 1994). When contact occurs at the nth link of the manipulator, all the links from 1 to n will stop, but the outer links still continue to move as long as some torque is applied to their joints. Hence, the link in contact is the last one to stop.

Once the contact link is identified, a soft classification method evaluates the probability that contact occurs on the tip (or joint, if the link is not the last) or on the link's body. This is done considering the manipulator movements at the time of contact and the partially constructed map. Consider a planar robot coming into contact with an unknown environment after a finite displacement. The contact point must be within the area swept by the manipulator during its displacement. If points on the surface are independent and have the same probability of being empty, the probability P_T of touching with the tip is the ratio between the region swept by the tip and the region swept by the whole link, or:

$$P_T = \frac{A_{swept,\,TIP}}{A_{swept,\,TIP+LINK}} \tag{1}$$

However, points are not independent in a real environment because surfaces are continuous. Here, the correlation between surface points is described by the parameter B, the smallest expected curvature radius. Constraining the range of expected surface curvatures is equivalent to dilating the manipulator with a sphere of radius B (Mazzini, 2011), and considering the area swept by the dilated robot, see Figure 2.

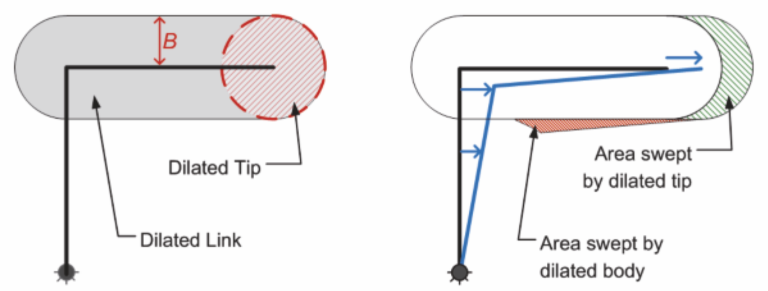

Figure 2. Dilation Area swept by dilated robot and dilated tip.

If the manipulator moves in a partially known environment, the swept area is replaced with the integral of the discrete occupancy probability map over such area (Mazzini, 2011). Here, a simple binary map that only consider the region swept by robot's movements is used. Finally, by making the manipulator displacement infinitesimal, the area swept by a point becomes the dot product between its velocity and the vector normal to the (dilated) manipulator, $\vec{n}_x \cdot \vec{v}_x$:

$$P_{TIP} = \frac{\int_{DIL,\,TIP} (\vec{n}_x \cdot \vec{v}_{TIP})\ P_C\,(g(x))\,dx}{\int_{DIL,\,LINK+TIP} (\vec{n}_x \cdot \vec{v}_x)\ P_C\,(g(x))\,dx} \tag{2}$$

where P_C the probability of a cell being occupied, and $g(x)$ is a function mapping a point x the part of the manipulator that originated it (because the occupancy probability refers to the cells swept by the manipulator). Data are classified using this equation: contact points with high or low P_T are classified as tip contact or link contact respectively.

A surface model of primitives that consists of number, types and parameters of the primitives is generated from the classified contact data. To determine the number and type of primitives, and to classify each data point to the appropriate primitive, a segmentation method called fit and grow is used (Leonardis et al., 1995). It is based on the fitting of primitives to small initial regions and the gradual expanded or regions providing good fits. This required a method to fit both type of data (link and tip contacts) to each primitive.

Surface fitting when contact occurs on the manipulator's tip is well known (Mazzini et al., 2011); here, the same approach is extended to link contact data. If several tip contact points belong to the same primitive, its parameters can be determined with a least squares approach, minimizing the sum of the squared distances between surface and points (Figure 3). If contact is on a circular joint, or if the tip is a circle/sphere of radius w, the same least square minimization can be used by squaring, instead of the distance point-surface d, the difference between d and w. When contact occurs along the link, the contact point is not known but another constraint can be imposed: the surface must be tangent to the side of the link. A least squares minimization can be formulated by requiring the distance from the tangent line to the surface to be zero (Figure 4). Since both tip and link constraints can be expressed as a distance, they can be used together in a common minimization. To account for uncertainty in the tip/link classification process, data points are weighted by the reciprocal of the variance, an estimate of which can be obtained from the tip probability (see (Mazzini, 2011)). The use of weightings reduces the effect of wrong classification, because errors from uncertain points are discounted. Denoting by the number of “tip contacts”, the number of “link contacts”, the link axis, S the primitive, and the width of the link, the minimization to determine the primitive's parameters θ is:

$$\theta = \arg\min_{\theta} \left(\sum_{i=1}^{N_T} \frac{1}{\sigma_i^2} \left[d\left(P_i, S(\theta)\right) - w_i \right]^2 + \sum_{i=1}^{N_L} \frac{1}{\sigma_i^2} \left[d\left(L_i, S(\theta)\right) - w_i \right]^2 \right) \quad (3)$$

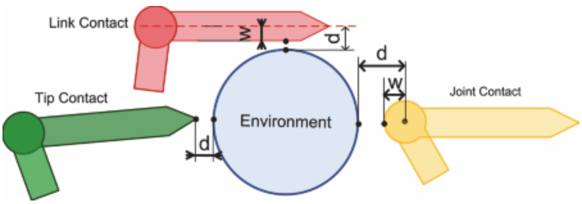

Figure 3. Least squares minimization distance (d).

3 Simulation Case Studies

The first simulation study uses a planar manipulator in a planar environment of four lines and two circles. Figure 4 shows the progress after the first contact point (left), and at the end of the exploration (right). The tip probability (shown as percentage) improves when the region around a point is explored, converging to a value close to 100% or 0%. Link contacts are correctly identified (shown as short line segments) and used for surface fitting.

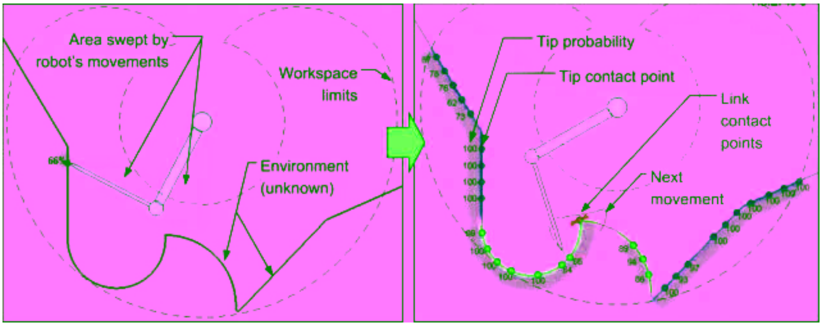

Figure 4. Exploration of a planar environment

Figure 5 shows the results of a simulation of a spatial manipulator exploring an environment composed of two cylinders, a plane and a sphere. Figure 5 shows the environment with the manipulator in its starting position (1), during the exploration (2) and the surface at the end of the exploration (3). The decrease of tip probability for one of the link contact points is shown.

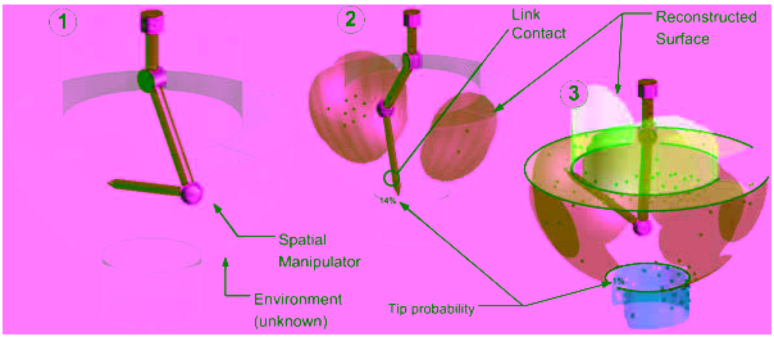

Figure 5. Spatial Exploration

4 Experimental Validation

The whole-arm exploration method has been evaluated experimentally using a two jointed planar manipulator mounting only joint encoders for sensors. Figure 6 (left) shows the manipulator with a circular tip in an environment composed of a circle and two straight lines. The manipulator first comes into contact with the circle on its link. The environment is then explored with 12 tip-contact points, and 10 link-contact points. Figure 6 shows the final reconstructed surface, superimposed with several snapshots of contact between robot and environment. The use of both types of data determines the circle radius with an error of 3%. Figure 6 (right) shows the same manipulator mounting a sharp tip while exploring an environment composed of two circles and three lines. Again the algorithm successfully explores this environment correctly recognizing both types of data.

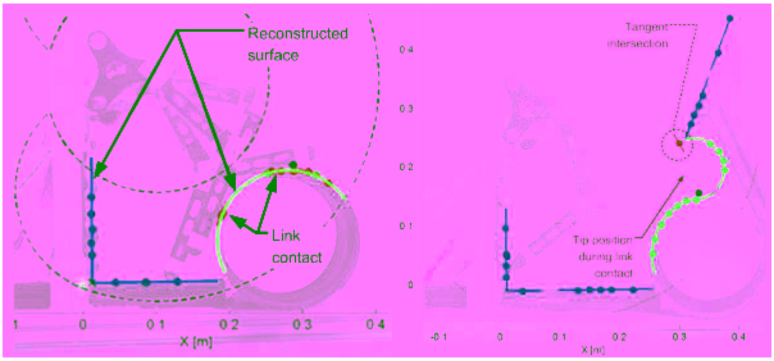

Figure 6. Experimental Validation With a Planar Manipulator.

5 Summary and Conclusions

A method to tactilely explore an unknown environment using a manipulator with only position sensors, when contact can occur anywhere on the manipulator, is presented. It consists of three steps. The first estimates what link is in contact using information from torques and velocities. The second probabilistically classifies the contact data in two subsets: tip contact and link contact. The third uses both subsets to create a model of the environment's surface. Simulations and experiments demonstrate the effectiveness of the approach.

5.1 Acknowledgements

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