An Experimental Validation of Robotic Tactile Mapping in Harsh Environments such as Deep Sea Oil Well Sites

Francesco Mazzini and Steven Dubowsky

The Field and Space Robotics Laboratory, Massachusetts Institute of Technology, Cambridge, Massachusetts, USA
fmazzini@mit.edu; dubowsky@mit.edu

Abstract This work experimentally validates the feasibility of a tactile exploration approach to map harsh environments such as deep sea oil well sites. The recent collapse of the offshore oil-drilling platform *Deepwater Horizon* in the Gulf of Mexico resulted in the largest marine accidental disaster in history. Initial attempts to control the spill failed because of the very challenging environmental conditions. Knowing the shape and dimensions of the cracks in the leaking structure could have provided critical information to maneuver the Remotely Operated Vehicles. Here, a method developed in our previous work for tactile exploration of oil wells is applied to the problem of mapping underwater disaster sites. This method only requires a manipulator provided with joint encoders, and does not need any range, tactile or force sensor. This makes the approach robust and directly applicable to the mapping of underwater sites. This paper focuses on the experimental validation of the approach. Several experiments are described, showing the effectiveness of the approach in mapping unknown structured environment in short time, and demonstrating its reliability under very harsh conditions, such as irregular environment surfaces, surrounding viscous fluids and high manipulator joint backlash.

1. Introduction

This paper experimentally validates the feasibility of tactile exploration to map harsh environments such as underwater oil well sites. The collapse of the offshore oil-drilling platform Deepwater Horizon in the Gulf of Mexico resulted in the largest marine accidental disaster in history [1, 2]. The final closure of the spill was accomplished by drilling a relief well five months after the accident. Temporary solutions to limit the spill heavily relied on Remotely Operated Vehicles (ROVs), and the only one capable of stopping the spill was the placement of an oil wellhead, three months after the accident. Before that, all the temporary attempts failed, mostly because of the harsh operating environment, and fifty thousand barrels of oil per day escaped into the ocean through three breaks in the pipe that connected the well-head drilling platform and then lay on the seabed.

Knowledge of the shape and dimensions of the cracks would have provided critical information for the repair work. However, vision sensors, normally used for the robot control, were hindered by clouds of escaping oil (Fig. 1). Lasers and sonar were unreliable due to strong turbulence and methane gas mixed with the oil. Deposits of dirt, mud and oil composites accumulated on the surface of the wreckage, and the flow noise from the fast moving hydrates and oil made sonic sensors ineffective.

In our previous work on tactile surface exploration with a robotic manipulator applied to oil wells, we developed algorithms to identify and map complex structures where the harsh environment prevents the use of conventional range, force or tactile sensors and measurement time is critical [4-7]. These methods could have been used in attempts to control the escaping oil in the Deepwater Horizon incident. They only require a manipulator provided with joint encoders, which is available in most of the ROVs operating underwater.

These methods control the robot to autonomously map a man-made surface by representing it as the composition of a set of geometric primitives, an appropriate assumption for the structures in the oil well industry. The provisional map guides the manipulator in the exploration process to increase the accuracy on the surface while minimizing the number of measurement points and hence time.

This paper focuses on the experimental evaluation of the approach when used under harsh environmental conditions such as underwater crash sites. First, the effectiveness of these strategies is shown in laboratory environments reproducing the field conditions in an underwater oil spilling pipe. Then, the robustness of the approach to field conditions is experimentally demonstrated, by separately evaluating the effect of rough and irregular surfaces, surrounding viscous fluids, and the manipulator's joint backlash. Experimental results confirm that the approach developed is well suited for the rapid exploration of these environments.

Fig. 1. Oil spilling from the riser of BP Deepwater Horizon on May 17th, 2010. The oil leaks prevented cameras from determining the shape of the crack [3].

1.1. Previous Work

Robotic exploration has been well studied in the past 20 years, including underwater applications with autonomous systems [8, 9]. Most of these studies deal with large-scale exploration, and rely on vision sensors, which are difficult to use in the cloudy oil/water mixture around a blown-out subsea well. Recently, tactile exploration to map harsh environments was suggested in the literature [4-7, 10]. Our work in this subject was developed to map the junctions inside oil wells, where range, vision, force/torque or tactile sensors are difficult to implement because of the harsh environment conditions, and exploration time is critical [4-7]. This study has some commonalities with methods in robotic touch exploration [11, 12], grasping and haptics [13, 14], proprioceptive sensing [15, 16], and reverse engineering [17]. Nevertheless, these methods do not solve the problem of exploring an unknown, harsh, and constraining environment in a short time. In particular, research has been done where tactile surface mapping does not explore a surface, but simply distinguishes an object among a library of known models [14]. Other approaches intelligently explore a surface, but they either use an inefficient surface representation such as a mesh or a spline [13], or, when using an efficient representation such as the composition of primitives, require a dense evenly spaced grid to collect data points [11, 12]. In addition, these works require a force-torque or tactile sensor, which is not reliable in harsh environments. Proprioceptive robotic sensing has been investigated, but only in regard of local contact detection [15, 16].

This is why our work in the subject can be considered the first exploration method to map harsh environment in limited time [4-7].

2. Technical Approach

The analytical description of our tactile exploration approach has been published [7]. Here, we experimentally explore the ability of this approach to tactilely map an unknown structured surface such as an underwater oil spilling pipe. This approach requires a manipulator mounted on a stationary base and provided with joint encoders. When exploring an underwater crash site, the base is the ROV itself, which can lie on the ocean floor or anchor itself to an existing fixed structure such as a pipeline (Figure 2). Extension of the method to account for base movement is relatively straight-forward [18].

Once the base is fixed, the manipulator autonomously moves to explore the environment. The objective is to tactilely create a map of this environment within a given accuracy, by touching the surface with the manipulator's tip and choosing the movements of the manipulator to minimize the exploration time. The required accuracy is given as a parameter representing the smallest feature to be found by the exploration.

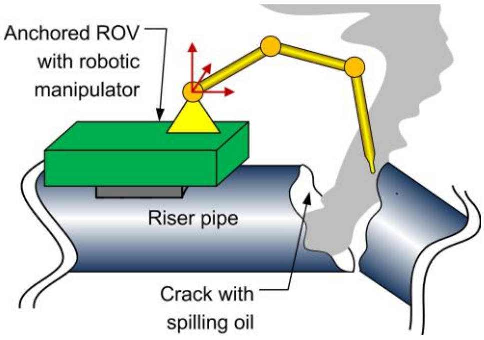

Fig. 2. Schematics of the proposed approach.

2.1. Impedance Control

The manipulator is controlled with an impedance control scheme [19]. The joint torques are controlled to simulate the presence of an impedance between the robotic tip and an arbitrary point in space, called *virtual point*. When the virtual point moves in free space, the robot tip follows it as long as no obstacle prevents its movements. When the virtual point moves beyond the environment surface, the robot cannot follow it and stops, and contact is detected. The position of the probe tip, and therefore the contact point on the surface, can then be determined from the manipulator's joint angles. This controller permits the manipulator to hold its probe against the environment, without any force or tactile sensor. The absence of such sensors makes this approach inexpensive and suitable for harsh environments.

2.2. Mapping Strategy

The overall goal of tactilely mapping the shape of the environment can be divided into two simultaneous problems: *surface model construction*, the interpretation of the existing touch data, and *exploration strategy*, the determination of the robot path to obtain the next set of data.

2.2.1. Surface Model Construction

The objective of surface model construction is to best represent the surface given the points touched on it. Here, the surface is represented with a boundary representation that tries to minimize the number of necessary points to describe the surface. The algorithm first tries to reconstruct the surface as a combination of geometric primitives such as planes, spheres, cylinders, cones or tori. Such shapes are often sufficient to represent structured environments, and require only very few data points [20]. Nevertheless, the approach is easily extended by implementing blends between primitives, and/or by using local triangular meshes when the surface is too complex to be described by primitives.

The problem of surface model construction is to simultaneously solve two tasks: determine what primitives (type, location, and parameters) are present in the environment according to the existing touch points, and classify which touch points belong to which primitives. This is called *segmentation*, and it has been solved here with an approach called fit and grow [21]. To evaluate how well a set of points fits a specific primitive, a least square approach is used, minimizing the sum of the squared distances between each primitive and the corresponding data points. This minimization is computed reliably, even with few, sparse tactile data points, using an approach based on the projection of the points on specific lines or planes [22].

2.2.2. Exploration Strategy

A manipulator tactilely exploring a harsh surface acquires few, sparse data in a much larger amount of time than using range sensors. Since the total time required is a key performing factor, the robot should accurately plan its movements in order to reduce this time. Nevertheless, the strategy needs to prove to be reliable and effective in very harsh environments.

The robot tip explores the surfaces by probing it discretely in separated points, instead of tracing continuous lines on it. This is because tracing is often not practically feasible in environments with very rough surfaces such as oil well sites. Furthermore, inferring a primitive from a small local line traced by the robot is intrinsically unreliable for a rough and deformed surface, while a set of discrete and sparse points proved to be more robust.

The guidance of the robot to efficiently locate these touched points is essential for a fast tactile mapping. In this study, a technique has been developed to map the environment in short time. It is composed of two main steps: locally touch a surface until a primitive is identified, and then move the robot where the next measurement provides the most information. The first step is used when the surface being probed is unknown. The robot tries to sample the unknown three-dimensional surface with a uniform lattice structure by probing the surface sequentially. The second step is used when the surface has been identified, and it moves the robot to a location that is expected to provide more information. This new location is chosen using an effective geometric approach that brings the robot far from all previously touched points.

2.3. Simulations

The method needs to be robust enough to deal with real conditions such as surface roughness, irregular shapes, high temperature difference and submersion in fluids such as water, oil or a mixture of them. Extensive simulations have been performed to test the feasibility of the approach in such conditions [7].

Simulations in several environments proved the time efficiency of the above methods. The combination of the strategies described above resulted at least twice as fast as a random or partially random approach, as well as any of the two steps of the strategy used separately.

Simulations with rough and irregular surfaces demonstrate the robustness of the mapping algorithm. The primitives are recognized in the presence of high surface noise, even though they require more touch points. Primitive deformations are treated as intuitively expected: low deformations are tolerated, while higher deformations force a primitive to be represented as a composition of similar primitives or a mesh. Figure 3 shows the exploration of an environment composed of both simple primitives and an irregular surface.

Simulations with surrounding viscous fluids showed that, for the speed used in our research, fluids effects do not significantly affect the approach [23, 24].

The main effect of high temperature on the manipulator is the induced thermal expansion of the gears. A considerable joint backlash is required in a down-well manipulator so that the large swings in temperatures do not cause the joints to bind up. One of the main insights provided by the laboratory experiments in this work is the significance of backlash in the overall robot precision. For this reason, the algorithm was extended to identify the amount of backlash simultaneously with the unknown surfaces, and hence eliminate the errors due to the backlash [5]. This method is based on the observation that, while the robot is pressing against a surface, the location of the empty backlash in the gear teeth is always in the direction of the applied torque. The amount of backlash is estimated simultaneously with the unknown surfaces: once a surface is identified, the redundant amount of information inferred from additional points is used to determine the amount of backlash in the joints.

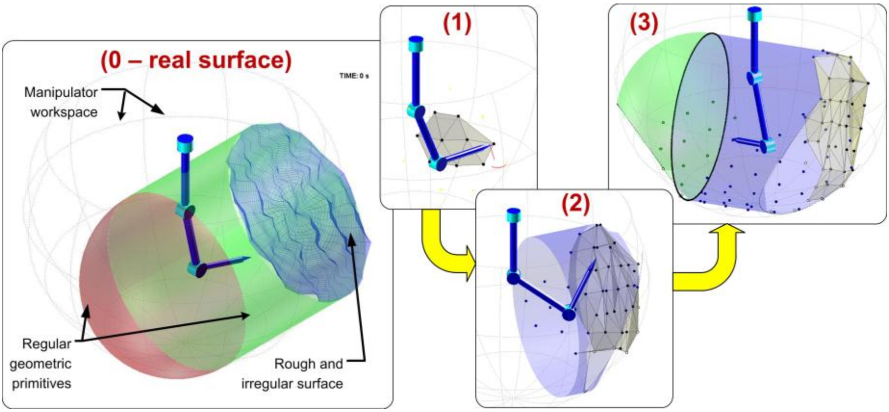

Fig. 3. Exploration of an environment including an irregular shape. (0) Surface to be explored, composed of geometric primitives and a generic, rough surface. (1) Beginning of the exploration: the rough surface is represented as a mesh. (2) A primitive is discovered. (3) End of the exploration. The primitives require much fewer points than the mesh to be correctly described.

2.4. Field System Design

Working with the Schlumberger Doll Research Laboratory of Cambridge, MA, a representative conceptual manipulator was designed. Kinematic studies indicated that a four degree-of-freedom (DOF) mechanism consisting of a three DOF anthropomorphic arm attached to a long prismatic link is well suited for exploration of long and narrow environments. The manipulator is sealed and pressurized to withstand the harsh environments found in oil exploration (pressures up to 2,000 bar and temperatures up to 300 ºC). As permitted by the algorithms, it does not require range, force and tactile sensors. A description of a field robotic systems is beyond the scope of this paper.

3. Experimental Setup

To confirm that un-modeled effects do not invalidate the algorithms described above, an experimental manipulator was designed and fabricated [4]. The manipulator represents the size and kinematic configuration of a well junction field system, given the constraints of the laboratory. For simplicity, only the 3 DOF arm has been implemented, replacing the first prismatic joint with a mounting ring that can be fixed at different heights. The manipulator links have lengths of 8.0 in and 6.0 in (Figure 4). Each joint assembly consists of a motor, gear train, encoder, and associated support bearings. Brushed DC motors are used. The experimental system is sealed to permit it to operate in viscous fluids such as seawater, oil, or drilling mud.

The control of the manipulator and the mapping and search algorithms are implemented in C, and run on remote computers using tethers. This is the practice in the oil exploration and drilling industry where wireless communications are not considered practical because of field constraints. ROVs are also connected to the

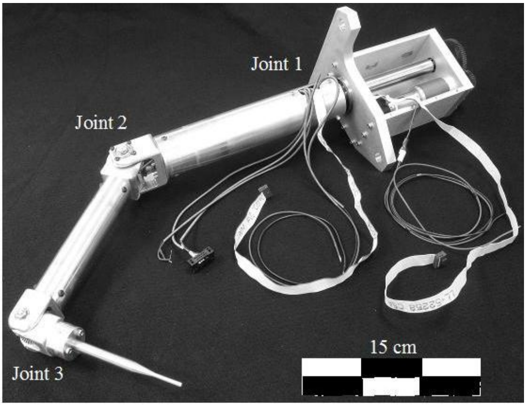

Fig. 4. Experimental robotic manipulator. The seals have been removed to show the joints.

surface by tethers, which provide the robot with power and remote computational capabilities.

The prototype manipulation was tested in two environments reproducing field conditions: a tank representing sea floor conditions such as those near the broken leaking pipes of the Deepwater Horizon (Figure 5 left), and a custom Plexiglas tank built in the shape of an oil well junction (Figure 6 left). These structures are waterproof and allowed testing the manipulator while submerged in water and viscous fluids.

4. Experiments

Extensive experiments have been designed and executed to investigate the robustness of the approach in real field conditions. The following experiments will be presented in this work:

- *Environment mapping*. The search methods have been evaluated when applied to the prototype manipulator exploring environments such as an underwater site with pipelines or an oil well junction.
- *Real time control*. The impedance control scheme has been studied and improved to reliably move the robot and detect contact with the environment, without any force or tactile sensor.
- *Irregular surface*. The behavior of the search methods has been investigated in the presence of rough and irregular surfaces.
- *Viscous fluids*. The environment has been filled with several viscous and dense fluids, and their effect on the robot has been tested.
- *Joint backlash*. The effectiveness of the joint backlash compensation method developed in this research has been validated using various environments.

4.1. Environment Mapping

Simulation results had proven the effectiveness of the algorithms to tactilely map a structured environment in short time.

The effectiveness of the approach has been evaluated in a laboratory experiment reproducing sea floor conditions such as those near the broken leaking pipes of the Deepwater Horizon. The environment represented in the left of Figure 5 presents a rusty, truncated steel pipe, two perpendicular planes covered with gravel and dirt, and a stone of irregular shape. This environment has been mapped autonomously using the strategies described above, without any a-priori knowledge.

The right of Figure 5 represents the result of an exploration trial. The exploration strategy was able to identify the underlying shape of the structured elements in the environment with very few data points: 18 points for the pipe, 12 for the sea floor, and 17 for the lateral graveled surface. Once a shape was identified, the ro-

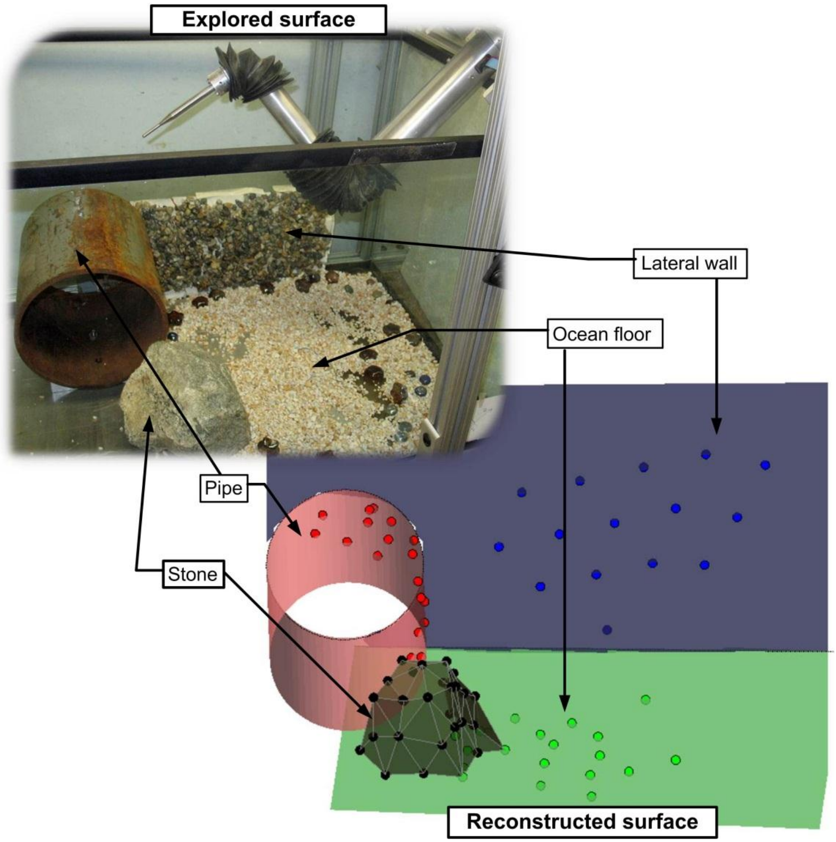

Fig. 5. (Left) Manipulator exploring a reproduced submersed crash site. (Right) the reconstructed surface after the exploration, showing the final surfaces and the touched points.

bot moved to a different, unknown location; this allowed the reduction of the total exploration time. The irregular stone could not be described as any combination of primitives, and more data points were needed to represent it as a triangular mesh.

Several sets of experiments have been performed in the modeled oil well junction shown in Figure 6. These experiments confirm the simulation results, which show that the exploration strategies proposed in this research drastically reduce the amount of time needed to map the surface. The right side of Figure 6 shows the result of the exploration of the junction using two strategies, showing the reduction in the required touch points using the strategy proposed in this research.

4.2. Real Time Control

The robustness of the impedance controller and its ability to reliably detect contact is a fundamental prerequisite for the success of the exploration. Extensive experi-

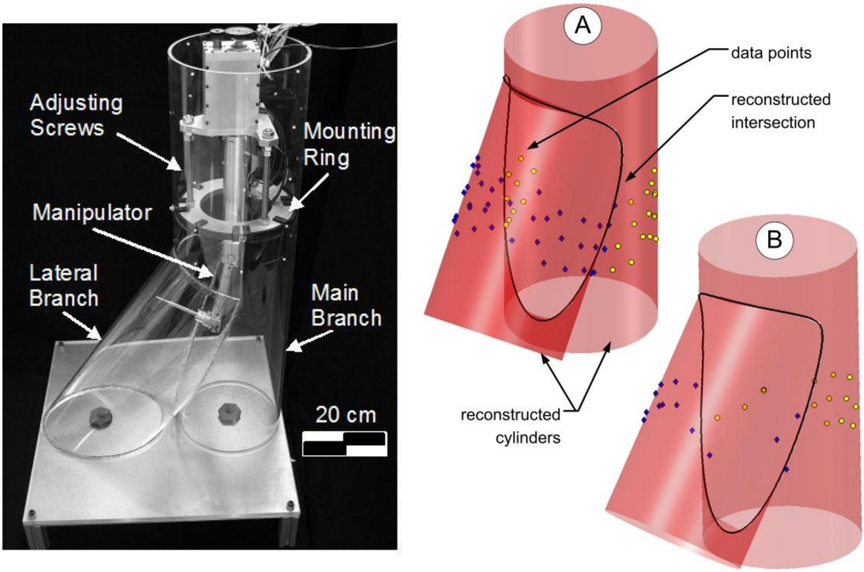

Fig. 6. (Left) Plexiglas tank reproducing an oil well junction, with tactile manipulator. (Right) Result of the exploration using (A) a uniform sampling and (B) the algorithm developed in this work: the number of required points decreases.

mentations provided the insights to ensure the robustness of the scheme in very harsh conditions. A simple compliant controller did not prove to be reliable, because joint friction and different robot configurations caused several false contact detections. Joint friction in a real field robot is extremely high because of the harsh environment conditions and the need of pressurized seals surrounding the joints. Friction compensation algorithms [25] reduced the problem, but did not solve it. The solution to this problem has been found in the introduction of an integral term to the standard real time impedance controller. By resetting every time the tip speed exceeds a small threshold, it is effectively active only when the robot stops. It also saturates to a limit value, to limit the force applied to the environment. The introduction of such term drastically decreased the number of false contact detection to a negligible number even in very harsh conditions.

4.3. Irregular Surfaces

Experiments have been performed to test the ability of the algorithm to map a rough surface and to recognize its approximate shape in spite of local imperfections. Figure 7 shows the exploration of a cylindrical shape covered with a layer of gravel of size 3 to 10 mm. The robot behavior depends on the parameter f describing the required exploration accuracy. When f is lower than the average gravel size, the underlying cylinder is not recognized. With higher f the cylinder is cor-

Fig. 7. The surface of a cylinder is covered with gravel, and the ability of the robot to determine the approximating cylinder is evaluated.

rectly identified, but more touch points are required compared to the smooth surface underneath, because the effect of local imperfections needs to be filtered. When f = 4mm, 14 points were required in average, against the 8 points required by the smooth surface. These experiments prove that the presence of rough surfaces increases the exploration time, but does not affect the feasibility of the algorithm.

4.4. Viscous Fluids

To investigate the behavior of the robot when surrounded by viscous and dense fluids, the robot has been submersed in several liquids (Figure 8). The fluids used are water, simulating properties of some lower-density oil well fluids, and two sucrose solutions (with 45% and 60% sugar concentration) simulating more viscous and dense well fluids. The addition of sugar increases viscosity and density: water at environment temperature has viscosity $\nu = 1$ mPa·s and density $\rho = 1$ kg/l; the 45% sucrose solution has $\nu = 10$ mPa·s, $\rho = 1.2$ kg/l; the 60% solution has $\nu = 60$ mPa·s, $\rho = 1.3$ kg/l.

Manipulator torques and speed has been carefully monitored when the robot was performing exactly the same exploration task, but surrounded by different fluids. Experimental results did not show any significant difference between any of the fluids. These results are in line with simulations: water or viscous fluids do not significantly affect the behavior of the robot at these speeds, and the approach can be reliably used underwater or submerged in highly viscous fluids.

4.5. Backlash Compensation

A new backlash identification and compensation strategy to deal with thermal expansion in the gears due to the high temperature swings has been developed [5].

Fig. 8. Experimental robot submersed in water (left) and in a viscous sucrose solution (right).

The strategy has been tested and validated in experiments, using both a two DOF manipulator and the robot prototype for oil well exploration. Here, the results of the exploration of an environment composed of three perpendicular planes will be presented (Figure 9). Backlash in the three links has been measured to be in average 1.4°, 1.1° and 2.6° respectively. This reported value is an average, because the robot manufacturing tolerances and the use of bevel gears made the backlash play slightly dependent on the robot configuration.

The environment was explored using a strategy that probes the unknown surface uniformly. Results for the final, mapped surface and the behavior of the backlash estimates are shown in the right of Figure 9. The backlash estimates reached a final value very close to the average measured number: respectively 1.38°, 1.15°, and 3.09°, which represent a percentage error of 1.2%, 8.3%, and 18%. Precision on the final surface is highly improved. This can be shown comparing the root mean square distance of the points to the planes that they fit. This RMS value decreases from 3.2 mm without backlash compensation, to 1.1 mm when compensation is used.

5. Conclusions

This paper experimentally validates the feasibility of a tactile exploration approach to map harsh environments such as the site of the Deepwater Horizon in

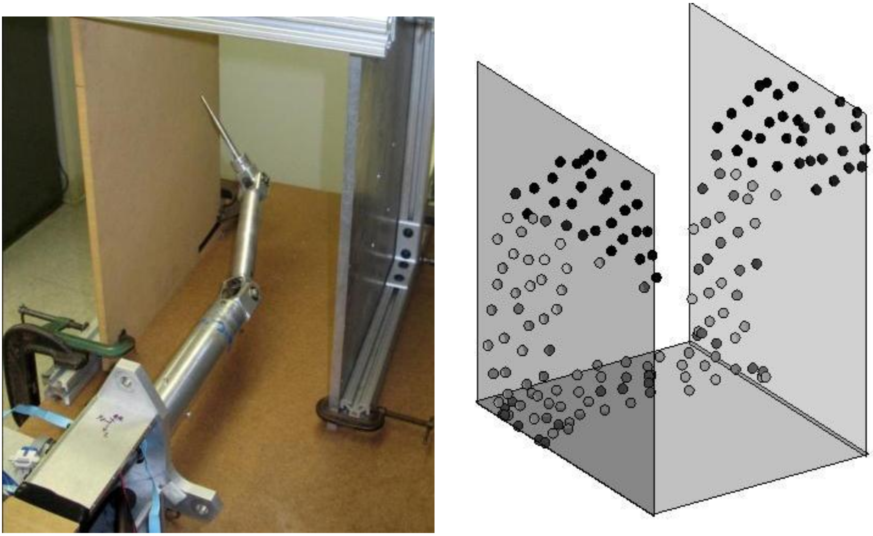

Fig. 9. (Left) Three-planes environment for the evaluation of joint backlash. (Right) Touched points and reconstructed surface. The intensity of the points represents the magnitude of the backlash correction for the first link.

the Gulf of Mexico incident. The approach requires only a manipulator provided with joint encoders: no range, tactile or force sensor is needed. Therefore it can be readily implemented on the underwater Robotic Operated Vehicles that have been extensively used to limit the damage of the oil spill disaster.

Several experiments prove the effectiveness of the approach in mapping such environments in short time. Extensive experiments study the method under harsh environmental conditions: rough surfaces, surrounding viscous fluids, and high temperature swings generating significant gear backlash. The results of these experiments prove the robustness under such conditions, and suggest that the approach developed in this work can successfully be applied to a field robot.

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References

[1] Robertson, C. and C. Krauss: Gulf Spill Is the largest of Its Kind, Scientists Say. In: The New York Times, August 2010.
[2] BP Leak the world's worst accidental oil spill. In: The Daily Telegraph, 03 August 2010.
[3] BP website: www.bp.com.
[4] Kettler, D.: Robotic Tactile Oil Mapping: Feasibility, Experimental System and Digital Mechatronic Concepts. MIT Master's Thesis, 2009.

[5] Mazzini, F. and S. Dubowsky: The tactile exploration of a harsh environment by a manipulator with joint backlash. In: ASME 2010 International Design Engineering Technical Conference. Aug. 2010: Montreal, Canada.

[6] Mazzini, F., et al.: Tactile Robotic Mapping of Unknown Surfaces: an Application to Oil Well Exploration. In: IEEE International Workshop on Robotic and Sensors Environments. 2009 p. 80-85.

[7] Mazzini, F., et al.: Tactile Robotic Mapping of Unknown Surfaces, with Application to Oil Wells. In: IEEE Transactions on Instrumentation and Measurement, in print.

[8] Eustice, R., et al.: Visually mapping the RMS Titanic: Conservative covariance estimates for SLAM information filters. In: The international journal of robotics research, 2006. 25(12): p. 1223.

[9] Thrun, S., W. Burgard, and D. Fox: Probabilistic robotics. The MIT Press, 2005.

[10] Everist, J. and Wei-Min S.: Mapping opaque and confined environments using proprioception. In: IEEE Int. Conf. on Robotics and Automation. 2009.

[11] Allen, P.K. and Michelman P.: Acquisition and interpretation of 3-D sensor data from touch. In: IEEE Trans. Robotics and Automation, 1990. 6(4): p. 397-404.

[12] Keren, D., et al.: Recognizing 3D Objects Using Tactile Sensing and Curve Invariants. In: Journal of Mathematical Imaging and Vision, 2000. 12(1): p. 5-23.

[13] Moll, M. and Erdmann M.: Reconstructing the shape and motion of unknown objects with active tactile sensors. In: Algorithmic Foundations of Robotics V, Springer-Verlag, 2004: p. 293–309.

[14] Okamura, A.M. and Cutkosky M.R.: Feature Detection for Haptic Exploration with Robotic Fingers. In: The Int. J. of Robotics Research, 2001. 20(12): p. 925.

[15] Huber, M. and Grupen R.: 2-D contact detection and localization using proprioceptiveinformation. In: IEEE Transactions on Robotics and Automation, 1994. 10(1): p. 23-33.

[16] Kaneko, M. and Tanie K.: Contact point detection for grasping an unknown object usingself-posture changeability. In: IEEE Trans. on Robotics and Automation, 1994. 10(3): p. 355-367.

[17] Vosniakos, G.C. and Giannakakis T.: Reverse engineering of simple surfaces of unknown shape with touch probes: scanning and compensation issues. In: Proc. of the Institution of Mechanical Engineers, Part B: J. of Eng. Manufacture, 2003. 217(4): p. 563-568.

[18] Dubowsky, S. and Tanner A.: A study of the dynamics and control of mobile manipulators subjected to vehicle disturbances. MIT Press, 1988.

[19] Hogan, N.: Impedance control-An approach to manipulation. I-Theory. II-Implementation. III-Applications. In: ASME, Trans., Journal of Dynamic Systems, Measurement, and Control (ISSN 0022-0434), 1985. 107.

[20] Requicha, A. and Voelcker H.: Solid Modeling: A Historical Summary and Contemporary Assessment. In: Computer Graphics and Applications, IEEE, 1982. 2(2): p. 9-24.

[21] Besl, P. and Jain R.: Segmentation through variable-order surface fitting. In: IEEE Transactions on Pattern Analysis and Machine Intelligence, 1988. 10(2): p. 167-192.

[22] Jiang, X. and Cheng D.: A Novel Parameter Decomposition Approach to Faithful Fitting of Quadric Surfaces. In: Lecture Notes in Computer Science, 2005. 3663: p. 168-175.

[23] Antonelli, G.: Underwater Robots: Motion and Force Control of Vehicle-Manipulator Systems. In: Springer Tracts in Advanced Robotics. 2006: Springer-Verlag New York, Inc. Secaucus, NJ, USA.

[24] Yuh, J.: Modeling and control of underwater robotic vehicles. In: IEEE Trans. on Systems, Man and Cybernetics, 1990. 20(6): p. 1475-1483.

[25] Olsson, H., et al.: Friction models and friction compensation. In: European Journal of Control, 1998. 4: p. 176-195.