The Tactile Exploration of a Harsh Environment by a Manipulator with Joint Backlash

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Abstract

This research investigates the robotic tactile exploration when significant backlash affects its joint’s positions. A typical application is the exploration of rough environments such as oil wells, where the harsh conditions dictate the use of tactile exploration. These conditions also result in large, unknown, and variable backlash in the manipulator’s transmissions, strongly affecting the measurement precision. Here, a method is developed to simultaneously map the unknown surface and identify the joint backlash. This method only needs joint encoders, without any delicate force or tactile sensor. The robot probes the surface in several locations and computes the contact points through direct kinematics. These points are used to construct a partial map of the environment, which is described as a combination of geometric primitives. Once a primitive has been identified, additional information on the surface is used to estimate backlash in the joints. This is possible because, when the robot is pressing on the environment, the applied torques force the gears in one side of the backlash play; thus the backlash error can be compensated. Exploration and compensation go hand in hand: mapping allows compensation, which in turns improves the map precision. The effectiveness of the approach is demonstrated in simulation case studies and in several laboratory experiments.
1. Introduction

This research investigates the robotic tactile exploration of unknown environments under very harsh conditions, which are common in environments such as pipes, mines, sewers, nuclear facilities, or oil wells. This paper focuses on an application in the oil-well industry. Oil wells have several junctions where divergent branches leave the main well at an unrecorded depth (Figure 1). Rising oil demand and new extraction technologies make the rehabilitation of abandoned branches economically attractive; however, the location and shape of these branches must be determined to insert tools in them. Time is a key issue in the operation, since keeping an oil well inactive is extremely expensive. The process is made difficult by the harsh down well conditions. Drilling mud, an opaque fluid, prevents the use of range sensors such as cameras, lasers, and sonars. Extremely high pressure (1500 atm) and temperature (300 °C) impose severe mechanical constraints. Under these conditions, force and tactile sensors become unreliable and must be avoided. Tactile exploration using a manipulator, equipped with only joint encoders, has been proposed for this application (Figure 1) [1-3]. The manipulator designed for the purpose is composed of an anthropomorphic arm attached to a long prismatic link. The high pressure requires the use of stiff joint seals that increase joint friction. The wide swing in temperature results in large and time-varying joint backlash. However, backlash is a significant source of measurement error, and needs to be identified and compensated for, while the robot is performing its mapping mission in the well.

Figure 1. Oil well branching structure, with detail showing the four-degree-of-freedom manipulator for tactile exploration.

To deal with this situation, this work proposes a new technique that identifies backlash while simultaneously mapping the unknown surface. The robot probes the surface in several locations, and computes the contact points
using encoder readings and kinematics. The explored surface is completely unknown but assumed regular enough to be described by a combination of geometric primitives. If backlash is not accounted for in the determination of contact, the touch points present significant error. Backlash compensation is possible in this application because, when the robot is pressing on the environment, the applied torques force the gears to be in one side of the backlash play: it is only necessary to estimate the amount of backlash play. But this amount is not a-priori known, given the extreme and variable down-well conditions. Therefore, backlash needs to be identified and compensated while the surface is explored. Here, a least squares minimization is formulated, where both the joint backlash values and the surface parameters are the optimizing variables. The operation is performed while the surface is explored and repeated when new information is available, refining in time both backlash estimate and surface precision. The method has been validated in representative several case studies and hardware experiments. This paper extends a recently published work [4], by improving details in the methodology and adding experimental results.

1.1. Previous Work

Tactile exploration and backlash calibration are different topic in the robotics literature. Tactile exploration becomes necessary when range sensors, such as cameras or lasers, cannot be used. Since most studies in robotic mapping use range sensors [5], these studies are not applicable when the environment needs to be explored by tactile contact, where data are collected sparsely and in more time. Tactile mapping is investigated in several related fields: robotic touch exploration, grasping and haptics, reverse engineering, and computational geometry. Nevertheless, these studies do not solve the problem of exploring an unknown, harsh, and constraining environment when time is critical. Research has been done where tactile surface mapping does not explore a surface, but simply distinguishes an object among a library of known models [6, 7]. Other approaches intelligently explore a surface, but they use a surface representation such as a mesh or a spline, which is not time efficient because many touch points are needed [8-10]. An alternative approach represents the surface as a composition of geometric primitives, which allows a more efficient model construction [11, 12]. However, these works use either a dense, evenly spaced grid to collect data points or assume that the data have been previously collected. In addition, these works require a force-torque or tactile sensor, which is not reliable in harsh environments. Proprioceptive exploration (with only positional sensors) has been investigated, but only in regard to local contact detection [13, 14]. Recently, methods to efficiently investigate an unknown environment with only encoders have been developed, using a snake-robot for a 2D pipeline [15], or using a manipulator arm for a 3D internal surface
Here, this last work is extended, making it feasible when backlash highly affects the precision of the exploration. To do this, a new backlash identification method is needed.

Robot calibration has been widely studied in the literature [16-20], but these studies mostly deal with kinematic errors, and not with backlash. They also require either some external sensors (open loop methods), or a point or surface as a reference (closed loop methods [16,18]). Only a few studies directly investigate backlash. The standard approach, called static test, manually blocks the output link and monitors the movement of the input: this requires complex manual operations and cannot be performed on-site. A common approach that does not require intervention uses signal processing techniques to detect the presence of backlash [21,22]. One of these studies excites the joints with a band-limited random signal and monitors the coherence function between input and output [21]. Another study exploits the robot’s dynamics during its normal operating movements, and detects backlash using the Wigner-Ville distribution and correlation techniques [22]. These studies are useful to detect the presence of backlash beyond a threshold, but not to identify its amount. Furthermore, they are either very sensitive to noise, or they require the use of several accelerometers. Approaches that try to identify the amount of backlash exist in the literature. One of these identifies it by monitoring the change in speed of the input gear due to the impact with the output gear [22,23]. Another approach uses a neural network to identify and correct backlash positioning error [24]. These methods require a precise model of gear geometry and dynamics, including inertias and frictions, which unfortunately are difficult to obtain and change with the environment. In conclusion, the backlash identification techniques present in the current literature are not applicable to a robot exploring harsh, inaccessible environments.

2. The Approach: Simultaneous Tactile Mapping and Backlash Identification

This work was developed in the context of oil well exploration, but the approach is applicable to any serial manipulator. It is assumed that the robot base is fixed to an arbitrarily-shaped, completely unknown environment. This environment is assumed to be static, rigid and regular enough to be described by a combination of simple geometric primitives, such as planes, spheres, cylinders, cones and tori. This is appropriate because such primitives require few data points, and most man-made environments can be easily described with such shapes [25]. If a part of the surface cannot be described this way, a mesh is used for that portion. This is done only when necessary, since a mesh requires more touch points and cannot be used for backlash identification.

The robot moves in this environment, touching the surface in several locations with its tip (Figure 2). The position of the probe tip, and therefore the contact point on the surface, is computed from the manipulator’s joint
angles. If the joint torque is sufficiently high when the robot is pressing against a surface, the location of the joint in the backlash is in the direction of the applied torque. Thus, the error can be compensated by subtracting the amount of backlash from the encoder measurement. Since the robot is motionless while touching a point, there are no dynamic effects. It is assumed that joint backlash, which can reach a few degrees per joint, is the dominant source of measurement error. Other errors, due to kinematic non idealities, link deformations, and encoder resolution, are assumed to be smaller but not negligible.

![Diagram](image)

Figure 2. The approach: simultaneous primitive estimation and backlash identification.

The simultaneous identification approach is represented in Figure 2. Only a few touch points are necessary to identify a primitive. When further touch points are available on the same primitive, this additional information is used by the robot to estimate and compensate for its own backlash. The exploration and the backlash estimation then proceed hand in hand: the backlash estimation improves while a larger portion of the surface is touched; this improvement in turn increases the precision of the robot and therefore helps the correct identification of the primitive parameters. The procedure stops when the interested portion of the surface is discovered and the estimated backlash values converge.
3. Tactile Mapping

This section briefly summarizes the autonomous mapping procedure, explained in depth in [3]. The manipulator is controlled with an *impedance control* scheme [26]. This controller permits the manipulator to hold its probe against the environment without any force or tactile sensor. The overall goal of tactilely mapping the shape of the environment can be divided into two simultaneous problems: surface model construction, the representation of the shape given the existing touch data, and exploration strategy, the determination of the robot path to obtain the next data point.

3.1. Surface Model Construction

The objective of surface model construction is to best represent the surface, represented as a combination of geometric primitives, given the points touched on it. The problem 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 associate each touch point to a primitive. This is called segmentation, and it has been solved here with an approach called fit and grow [27]. The process of determining these primitives requires a method to evaluate how well a set of points fits a specific primitive. This is obtained with a least squares approach, minimizing the sum of the squared distances $d$ between each primitive (with parameters $\beta$) and the corresponding data points $P_i$:

$$\beta = \arg \min_{\beta} \sum_{i=1}^{n} d(P_i, \beta)^2$$  \hspace{1cm} (1)

In this expression, the points $P_i$ are considered constant. In the following section, this same minimization will also be used to identify the backlash values, by making $P_i$ dependent on the backlash. This minimization problem is not trivial for surfaces other than planes and spheres, because the distance function cannot be expressed linearly, and linearized solutions are biased and very sensitive to noise. Several solutions have been proposed in the literature for large, dense data sets, usually derived from laser scans [28-30]. Tactile exploration with limited time produces few, sparse data points, and not all these solutions are applicable. Here, an approach based on the projection of the points on lines or planes has been used [30]. This approach proved to be effective, fast and reliable for few and sparse data.

3.2. Exploration Strategy

Our previous work in tactile exploration showed that, when the environment is rough and irregular, the robot should explore a surface by probing it in discrete, deparated points [3]. Compared to range sensors, obtaining
these few, sparse tactile data is very time consuming, because of the time required for the robot to move. Since the total required time is a key performing factor, the robot should accurately plan its movements in order to reduce this time. Several advanced strategies have been proposed in robotic literature, usually involving the choice of the next movement that maximizes the amount of expected information obtained with such movement [3, 5, 31]. These advanced methods can be applied to the identification algorithm proposed in this work, increasing the speed of the exploration. However, this paper focuses on backlash compensation, and only a simple and reliable strategy has been used. This strategy probes points sequentially, one close to the other, trying to sample the unknown three-dimensional surface with a uniform lattice structure of equilateral triangles. The robot moves its tip along circular paths equidistant to two probed points until it touches the surfaces.

4. Backlash Identification

The magnitude of joint backlash is identified by comparing the location of the touch points to their associated primitives as the surface becomes known. Once backlash is identified and compensated for, the precision of the touch points increases and the primitive parameters are refined. The variables used in this analysis are:

- $Q_E$: Vector of encoder joint angles, corrupted by backlash
- $Q_B$: Vector of joint rotations due to backlash
- $Q_R$: Vector of real joint angle locations
- $\alpha$: Magnitude of joint backlash (vector)
- $P$: Contact points location, in Cartesian coordinates
- $\beta$: Surface parameters
- $T$: Joint motor torques (vector)
- $J$: Jacobian of the kinematic equations
- $\mu$: Vector of joint static friction coefficients

It is assumed that joint encoder angles are known, and a rough estimate of the joint torques is available. Since the motors are controlled in torque for the impedance controller, the commanded torque can be used for this estimate. The joint angle measurement error is assumed to be only due to backlash:

$$Q_R = Q_e - Q_B$$ (2)
It is assumed that the dominant error in forward kinematics is due to backlash. Further errors, due to imprecise kinematics, deformations, and finite encoder resolution, are modeled with a uniform Gaussian distribution with zero mean and variance $\sigma^2_E$:

$$P = \text{kin}(Q_p) + N(0, \sigma^2_E)$$

(3)

The initial kinematic error due to backlash is assumed to be small enough to allow for the identification of the primitive types using the uncompensated touch points. This assumption is valid in practice, because the backlash error, although significant, is often consistent among close points, and the shape of a small patch is not dramatically altered. The primitive type defines the distance function $d$ between the primitive, with parameters $\beta$, and a touch points $P$:

$$d = d(P, \beta)$$

(4)

For each joint $j$, the backlash model consists of a function $f$ relating the unmeasured joint rotation due to backlash $Q_{ij}$ to the joint torque $T_j$ and to the amount of physical clearance $\alpha_j$. This function depends on the static joint friction, which prevents the joint to reach the end of the clearance when the torque is low. The direction of backlash error depends on the procedure used to set the zero of the joints. Without loss of generality, here we assume backlash to be symmetric and linear in $\alpha$:

$$Q_{ij} = \alpha_j f(T_j)$$

(5)

For negligible joint friction, $f(T_j)$ is simply the sign of $T_j$. With significant friction, the location of backlash is unknown when the torque is smaller than the joint static friction coefficient $\mu$, and it is modeled as a uniform random number. Denoting with $\text{rand}[a,b]$ a uniform distribution between $a$ and $b$, the backlash model (Figure 3) is:

$$Q_{ij} = \alpha_j f(T_j) = \begin{cases} \alpha_j \text{sign}(T_j) & \text{if } |T_j| > \mu_j \\ \text{rand}[-\alpha_j, \alpha_j] & \text{if } |T_j| < \mu_j \end{cases}$$

(6)

An estimate of $\mu$ is obtained by providing an increasing torque to the arm, and monitoring when the link starts to move. Precision on the value of $T$ and $\mu$ is not critical because the backlash function returns one, independently of $T$ and $\mu$, when the torque is sufficiently high.
To estimate the backlash values $\alpha$, and to refine the primitive’s parameters $\beta$, the squared distances between the backlash-compensated points and their associated primitives is minimized. Using Eq.(2)-(5), and omitting the zero-mean random term since it does not affect the result, the least squares minimization (1) for the $N$ touch points $P_i$ can be expressed as:

$$
\min_{\alpha,\beta} \sum_{i=1}^{N} d_i \left( \frac{Q_{E,i} - \alpha f(T_i)}{\beta} \right)^2
$$

This expression is a function of the robot kinematics, the surface ($\beta$ and the function $d_i$), and the backlash ($\alpha$ and the function $f$). The minimization can be solved either by linearizing it or by an iterative nonlinear search.

### 4.1. Linearization

Since backlash is relatively small, and an estimate of the primitive parameters is available, the distance function can be linearized around the known values:

$$
d_i = d_{i,k} + \sum_j \frac{\partial d_i}{\partial \alpha_j} \alpha_j + \sum_k \frac{\partial d_i}{\partial \beta_k} \beta_k
$$

The linearized least squares problem becomes:

$$
\begin{bmatrix}
\frac{\partial d_i}{\partial \alpha_j} & \ldots & \frac{\partial d_i}{\partial \beta_k} & \ldots
\end{bmatrix}
\begin{bmatrix}
\alpha_j \\
\beta_k
\end{bmatrix} = -d_{i,k}
$$

The derivative terms in the above matrix are easily expressed as a function of the surfaces, the Jacobian and the backlash function. The required computational time for this approach is extremely low. Unfortunately, the estimates obtained this way are biased and very sensitive to noise. This is not surprising, because the minimization of Eq. (7) includes the surface parameters, as in Eq.(1), which requires specific nonlinear methods.
to be solved reliably. Thus, Eq. (9) cannot be used to solve the least squares problem. Nevertheless, it has been introduced because it will provide a tool to detect which backlash parameters can be identified.

4.2. Nonlinear formulation

As explained in the surface model construction section, effective methods have been developed to compute a least square fit of geometric primitives [28-30]. To apply these methods, the minimization of Eq. (7) is rewritten, separating the backlash and surface parts:

$$
\min_{\alpha} \left[ \min_{\beta} \sum_{i=1}^{N} d_i \left( P_i(\alpha, Q_i, T), \beta \right)^2 \right]
$$

(10)

The internal minimization of Eq. (10) is only dependent on the surface parameters, and the surface fitting method described in the surface model construction section can be used. A few iterations with a local least squares minimizer, such as the Levenberg-Marquardt algorithm, provide a good solution. The external minimization, seeking the best backlash values, is more complex, and presents several small regions of attractions. A local minimizer would have the tendency to find only local minima; thus a global minimization algorithm is needed [32]. In this research, the Single-Linkage Multi-Start algorithm, a simple two-phase stochastic method, provided excellent results. In the first phase, the minimizing function is evaluated in several initial points (chosen either using a grid or stochastically), and these points are clustered according to their function value and their distance from each other. In the second phase, only one local search for each of these clusters is computed, using again Levenberg-Marquardt, and the best result among these searches is chosen.

4.3. Small joint torques

The identification procedure is based on the assumption that the position of a joint in the clearance is known to be in the same direction as the applied torque. When the torque is small this can be not the case, and the real joint position is unknown, as the random term in the backlash model of Eq. (6) describes. This behavior creates two problems. First, the value of the backlash function is required in the minimization, as in Eq. (7), and only a probability distribution is available when torques are low. A good approach in this case is to use the mean of the distribution.

The second problem is more complex: points recorded when some joints have small torques are more imprecise than those with high torques. The approach used in this research consists in weighting the contribution of the points according to their uncertainty. In a general least squares formulation, the best linear unbiased
estimator is obtained by weighting each measurement with the reciprocal of the measurement variance. In this case, the “measurement” is represented by the distance point-surface. Thus, the variance of this distance due to backlash uncertainty is computed, and its reciprocal is used as a weight. The minimization becomes:

$$\min_{u,\beta} \sum_{i=1}^{N} \frac{1}{\sigma_i^2} d_i \left( \sin(Q_{E,i} - \alpha I(T_i), \beta) \right)^2$$

(11)

The variance is computed in three steps (Figure 4):

1) For each joint $j$, the probability distribution of the backlash error $Q_{Ej}$ as a function of the torque $T_j$ is defined by the backlash model, Eq. (6). To make computations feasible, the distribution of $Q_{Ej}$ is approximated as a Gaussian distribution with the same mean $\lambda$ and variance $\sigma^2$ as the original. For a fixed joint friction coefficient $\mu_j$:

$$\sigma_j^2(T_j) = \begin{cases} \alpha_j^2 / 3 & \text{if } T_j < \mu_j \\ 0 & \text{if } T_j \geq \mu_j \end{cases}$$

(12)

If $\mu_j$ is not known with confidence, the uncertainty can be represented by describing it with a mean $\lambda_n$ and variance $\sigma_n^2$. In this case the distribution of $Q_B$ smoothly changes as a function of $T$, and its variance can be expressed, after some algebra, as a function of the Gaussian error function:

$$\begin{align*}
\sigma_j^2(T_j) &= \frac{1}{12} \alpha_j^2 \left( 1 - \gamma \right) \left( 5 + 3 \gamma \right) \\
\gamma &= \operatorname{erf} \left( \frac{T_j - \lambda_n}{\sqrt{2} \sigma_n} \right)
\end{align*}$$

(13)

2) The probability distribution in joint space is transformed into Cartesian coordinates through the kinematic Jacobian. This is easy to compute, because the convolution of Gaussian distributions is a Gaussian distribution with as mean and variance the sum of the means and variances. The variance of the distribution in Cartesian space is the sum of the contribution of all the joints, plus the contribution of the random measurement error $\sigma_e$ that was defined in Eq. (3). For the $x$ component:

$$\sigma_x^2 = \sum_{j=1}^{M} \sigma_j^2 + \sigma_e^2$$

(14)

where $j = 1 \ldots M$ represent the degrees of freedom of the robot. The same applies for the $y$ and $z$ components.
3) Since the least squares minimizes the distance points-surface, the only component of the error affecting the minimization is the one normal to the surface (Figure 5). Thus, only the component of the variance in the normal direction $\sigma_n$ is used in Eq. (11). Denoting by $\eta$ the surface normal vector, this variance is:

$$\sigma_n^2 = \eta_x^2 \sigma_x^2 + \eta_y^2 \sigma_y^2 + \eta_z^2 \sigma_z^2$$

(15)

This weighting system is computationally very fast as it involves only a few multiplications. Note that since the expression in Eq. (12) depends on $\alpha$ and the normal depends on $\beta$, the weights are a function of both backlash and surface: they are updated after every iteration of the minimization. The weighting system works as intuitively expected: if some points have small torques in joints that create some normal uncertainty, their variance will be higher and their weight smaller. The variance never goes to zero because of the presence of random measurement noise $\sigma_e$ in Eq. (14). If this random term is high compared to the backlash, all the weights will have comparable values.

![Figure 4. Weighted least squares according to the uncertainty due to small torques and joint friction.](image)

![Figure 5. Backlash generates error (and therefore uncertainty) in the distance function only when its effect on the tip position is normal to the surface.](image)

4.4. Identifiable Parameters

Since the identification procedure is performed simultaneously with the exploration, the backlash values are refined as larger portions of the surface are explored. In the initial stage of the search, or when the explored environment is small, not enough data are available to correctly estimate all the backlash values. Given the complexity of the minimizing function in Eq. (10), the estimation of a parameter without enough data could potentially lead to a drastically wrong number, and compromise the success of the whole procedure. Therefore, a procedure is needed to recognize which joints can be estimated, so that the minimization of Eq. (10) will include only those variables, while temporarily freezing the others.

To determine if a parameter should be estimated, the linear model of Eq. (9) is used. This model is too simple to provide a precise estimate of the parameters, but it is sufficient to evaluate if this estimate is reliable. Let $A$ denote the normalized version of the matrix with the derivative terms in Eq. (9). The normalization is needed
because the parameters in $A$ have different units (length and angle). Let $B = A^T A$, and compute its condition number (the ratio between the largest and the smallest eigenvalues). When this number is close to unity, all the variables can be found reliably. When the condition number is high, instead, some variables do not have enough data point to be estimated. To determine which variables, let us consider the eigenvectors of $B$ whose corresponding eigenvalues are zero (or very small, in the presence of noise). These eigenvectors represent the relationship between the variables that cannot be estimated, given the current data. Therefore, the nonzero elements of those eigenvectors (or large enough compared to the noise) indicate which variables must be frozen in the minimization.

This linear formulation determines whether a parameter can be reliably estimated given the points touched during the exploration. However, identifiability is different: it is the theoretical possibility to obtain the value after an infinite number of measurements. This is not a function of the process or the touched points, but only of environment shape and robot kinematics. Identifiability is useful to determine if a surface is appropriate to estimate all the backlash parameter, or as a check to decide whether to stop the exploration process if no more parameters can be identified. Here, we propose one way to compute it, by evaluating the size of the part of the surface where each joint backlash has an influence. Only if this portion is large, compared to the size of random errors, there is enough information to evaluate the backlash. The influence of a joint’s backlash is evaluated with the function $f(T_j)$ of the backlash model in Eq. (6), where $T_j$ are the joint torques creating a force $F_0$ normal to the surface and with magnitude defined by the impedance controller:

$$T = J^T \cdot F_0 \hat{n}$$

(16)

The assumption of normal force is not severe because, as seen before, only normal displacements create positioning errors. Thus, $f(T_j)$ behaves as expected: only where backlash has influence the torque is high, and $f(T_j)$ returns one. The final expression for $S_j$ the portion of the surface that can be used to identify backlash in joint $j$, is a simple integration of this influence function over the surface reachable by the robot tip, $S_{reach}$:

$$S_j = \int_{S_{reach}} f(T_j) ds$$

(17)

1 A computationally faster approach involves the QR factorization of matrix $A$. But for few, sparse data the difference is negligible, on the order of the microsecond, and this approach is much simpler to implement.
5. Representative Case Studies

The simultaneous mapping and backlash identification has been tested in two environments modeled in Matlab™. The robot chosen for these studies has the shape of the laboratory prototype built for oil-well exploration (Figure 11), with all link lengths set to 1 m for simplicity. The environment is completely unknown and is composed of geometric primitives. Each point measurement is corrupted by both backlash and an independently distributed Gaussian noise, as in Eq. (3).

![Diagram of environments](image)

*Figure 6. The two environments chosen in the case studies: two barrels (left) and L-shaped junction (right).*

The two environments are shown in Figure 6, together with the touch points at the end of an exploration trial. The first shape represents two barrels on a flat floor; the second an L-shaped junction with a spherical cup.

In the first environment, the three joints have respectively ±1°, ±1°, and ±2° of backlash. Joint friction is such that in 46% of the sample points at least one of the joint torques is smaller than the friction coefficient, generating a uniform random location of the joint within the backlash play. The value of the friction coefficient is not known, but an estimate is available within 30% precision. Measurement noise is \( \sigma = 1 \text{ mm} \).

The autonomous robot probes the environment sequentially, until no more points in the workspace can be reached. Backlash is estimated and compensated during the computation, thus increasing the surface precision. Figure 7 shows the estimation of backlash and primitives as a function of the number of points touched on the surface. The upper part describes the error in the estimation of the three joint backlash values. The bottom graph shows the improvement on the parameter estimates of the four primitives (four because the tops of the two barrels are geometrically the same plane). The goodness of the estimated primitives is evaluated with a normalized similarity measure that includes primitive position, orientation and dimensions, divided by a representative
dimension. The amount of backlash at the end of the study is estimated with an average error on the three joints of 0.015°, which is 1.3% of the real backlash value. The backlash compensation greatly increases the precision of the reconstructed surface: as an example, at the end of the simulation the radius of the barrels is retrieved with accuracy of 99.8%, against an accuracy of 94.4% without backlash compensation. The evolution in time shown in Figure 7 is also interesting: backlash in the first joint could not be estimated before 50 points, and its value was not computed. The precision of backlash and surfaces go hand in hand, and it greatly increases when new surfaces are discovered.

The second case study, in the L-shaped environment on the right of Figure 6, has been performed with the same robot, but in different conditions: double noise (σ equal to 2 mm) and smaller backlash (α equal to ±0.5°, ±1°, ±1°). Backlash is therefore harder to identify. As expected, this implies a slower backlash and parameter estimation, as shown in Figure 8. Nevertheless, the final estimates are good: the final average backlash error is 0.03° (3.3% of the real backlash value), and the radius of the spherical cup has a precision of 99.7% relative to the real value.

![Figure 7. Progress of the backlash (top) and surface (bottom) estimates for the two barrels environment, when more touch points become available.](image1)

![Figure 8. Progress of the backlash estimate for the L-shape while more points are touched. The detection of a primitive is shown by its name on the graph.](image2)

6. Experiments

The method proposed here has been tested in two sets of laboratory experiments, using first a two-dimensional manipulator, and then the oil-well prototype robot.

6.1. Two-Dimensional Robot
In this experiment, a two-dimensional robotic arm explores an unknown environment made of a single straight line, see Figure 9. Both joints have the same motor-encoder-gearbox unit. Measurements in the joints have very high resolution (250,000 counters per rev), but they present large backlash. This backlash has been measured statically to be 0.97°. This agrees with the manufacturer information. Joints also present significant elasticity, but its effect can be avoided by reducing the applied torques at the moment of recording a contact point location. The static joint friction coefficient is approximately 0.2 Nm.

As the manipulator autonomously explores the environment, the line parameters and the joint backlash are iteratively estimated online. At the end of the exploration, the line is probed in 19 points. The final estimated backlash values are 0.96° and 0.94°, very close to the values measured statically. Figure 10 shows the touched points with and without backlash compensation, together with their best fit line. Compensation greatly improves the precision: the average error of the points from the real line decreases from 2 mm to 0.25 mm.

Figure 9. Two degree-of-freedom arm used in the line probing, and detail of one of the motor-gearbox units.

Figure 10. Probed points and best fit lines with and without backlash compensation, relative to the real line.

6.2. Oil-Well Exploration Prototype

The second set of experiments studies backlash compensation with the prototype robot for oil-well exploration (Figure 11). The prototype and the exploration performances are described in details in [1,2]. The properties of this robot are more complex than in the previous case, mainly due to the manually-assembled bevel gears in the joints. Both backlash play and joint friction are not constant, but slightly dependent on the robot configuration. Therefore, only an average value for backlash (1.4°, 1.1° and 2.6° respectively) and friction (1 Nm, 0.7 Nm and 0.1 Nm) could be measured.
The algorithm has been first tested in the modeled oil well junction (Figure 11). In such environment, the robot’s first joint axis is aligned with the main cylinder’s axis, making most of the environment radial symmetric with respect to the robot. With such geometry, backlash in the first joint is tangent to the surface, and it does not create any error, but it also cannot be identified. This can be shown evaluating the size of the surface where the joint has influence. The total surface that can be touched is 760 cm$^2$, while the surfaces $S_j$ where backlash has influence, computed using Eq. (17), are respectively 80, 750 and 700 cm$^2$ for the three joints. The value for the first joint is very small, and cannot be identified; the other two joints, instead, can be correctly estimated.

To show a situation where backlash in all joints can be estimated, an experiment with a different environment was performed. This environment is composed of three straight planes, as in Figure 12. The same exploration strategy as in the simulations has been used. Results for the final, mapped surface and the behavior of the backlash estimates are shown in Figure 12. The final estimated backlash values are respectively 1.38°, 1.15°, and 3.09°, which represent a percentage error of 1.2%, 8.3%, and 18% compared to the statically-measured values. There reason why these values are not as close as in the previous experiment lies on the complexity of backlash in this prototype robot. The precision on the final surface is highly increased. This is evaluated comparing the root mean square distance from the touched points to the planes that they fit: without backlash compensation the RMS distance is approximately 3.2 mm, while with compensation this is reduced to 1.1 mm.
This work proposes a technique to tactilely explore an unknown environment using a manipulator with significant and unknown joint backlash. The approach consists of touching the surface in several points, and using these points to simultaneously identify both the backlash and the surface parameters. The robot is only equipped with joint encoders. The approach is autonomous, can be applied during the actual exploration and does not require the knowledge of the explored surface or a model of the robot dynamics. Both case studies and hardware experiments demonstrate the feasibility of the approach, reaching a good estimate of the robot backlash and dramatically increasing the precision of the exploration.

Acknowledgments

The authors would like to thank the Schlumberger Doll Research for its financial support and Julio Guerrero for his consultancy. The authors would also like to thank Daniel Kettler for his fundamental contribution in this research, and Paulo Jorge Sequeira Gonçalves for his Matlab-ServoToGo library.

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