ABSTRACT

Here the tactile exploration by an autonomous robot when its joints are corrupted by significant backlash is studied. The motivation is the exploration of junctions in 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. Here, a method is developed to simultaneously identify the backlash and map the unknown surface. The method only needs joint encoders, and avoids the use of delicate force or tactile sensors. The mapped surface is described as a combination of geometric primitives. The robot probes the surface in several locations with its tip and computes the contact point through direct kinematics. These contact points are used simultaneously to construct a map of the environment and to identify its joint backlash, improving the precision of the map. The effectiveness of the approach is demonstrated in both simulation case studies and laboratory experiments.

1. INTRODUCTION

This research investigates the robotic tactile exploration of unknown environments under very harsh conditions. Such tasks are found in the robotic exploration and mapping of pipes, mines, sewers, and nuclear facilities. An example of these conditions comes from the oil-well industry. Oil wells have several junctions where divergent branches leave the main well at unrecorded depth (Figure 1). Rising oil demand and new extraction technologies make it attractive to rehabilitate abandoned branches. 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 (cameras, laser, sonars). Extremely high pressure (1400 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, 2]. 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 which increase joint friction. The wide swing in temperature results in large and time-varying joint backlash. However, backlash is a source of large measurement error, and needs to be identified and compensated while the robot is performing its mapping mission in the well.

Tactile exploration and backlash calibration are generally treated separately. Tactile exploration becomes necessary when range sensors, such as cameras or laser, cannot be used. Since most studies in robotic mapping use range sensors [3], 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 [4, 5]. 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 [6-9]. An alternative approach represents the surface as a composition of geometric primitives, which allows a more efficient model construction [10, 11]. 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, the above research requires a force-torque or tactile sensor, which is not feasible in harsh environment. Sensorless exploration has been investigated [12, 13], but only in regard of local contact detection. Recently, methods to efficiently investigate an unknown environment with only encoders have been developed, using a snake-robot for a 2D pipeline [14], or using a manipulator arm for a 3D internal surface [1]. 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 [15-19], but these studies most 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 [18, 19]). 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 it cannot be performed on-site. Another approach excites joints with a band-limited random signal and monitors the coherence function between input and output [20]. This is very sensitive to noise and it does not identify the amount of backlash, only its presence beyond a threshold. Alternatively, backlash can be identified monitoring the change in speed of the input gear due to the impact with the output gear [21]. Unfortunately, this method requires a precise model of the gear geometry and dynamics, including inertias and frictions, which are hard to obtain and change with the environment. The same precise model is also required in another approach which uses a neural network to identify and correct backlash positioning error [22]. In conclusion, the backlash identification techniques proposed in literature are not applicable to a robot exploring harsh, inaccessible environments.

This work proposes a new technique which can be used in this situation. This method solves the backlash identification while mapping an unknown surface. The robot probes the surface in several locations, and computes the contact locations 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 will have significant error. Therefore, backlash and surface need to be identified together. Here, a least squares optimization is formulated, where both the joint backlash values and surface parameters are unknown. The operation is performed while the surface is being explored and repeated when new information is available, refining in time the estimate of the backlash and the precision of the surface. The method has been validated in both representative case studies and hardware experiments.

**SIMULTANEOUS BACKLASH IDENTIFICATION AND EXPLORATION**

This work was developed in the context of oil well exploration, but the approach is applicable to other serial manipulators. 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. Most man-made environments can be easily described with such shapes [23]. If a part of the surface cannot be described by such primitives, a blend or a spline is then used to represent that portion. This is used only if necessary, since the portion represented by the spline will require more touch points, and will not 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

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Figure 1. Oil well branching structure, with cutaway detail showing a tactile inspection 4-degree-of-freedom manipulator with significant joint backlash.
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 nonidealities, link deformations, and encoder resolution, are assumed to be smaller, but not negligible.

The advantage of the use of geometric primitives is that their parameters can be obtained with few touch points. The additional information obtained with further touch points on the same primitive 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.

**Surface Model Construction**

The objective of surface model construction is to best represent the surface given the points touched on it. The surface is represented as a combination of geometric primitives. 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 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 [25]. 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 $P_i$:

$$\beta = \arg \min_{\beta} \sum_{i=1}^{N} (P_i, \beta)^2$$ (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 backlash. Different solutions for this minimization problem have been proposed in literature for large, dense data sets [26-28].

**TACTILE MAPPING**

This section briefly summarizes the autonomous mapping procedure, which is explained in depth in [1]. The manipulator is controlled with an impedance control scheme [24]. This controller permits the manipulator to hold its probe against the environment without any force or tactile sensors. 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 set of data.

**Exploration Strategy**

A manipulator tactiley exploring a surface acquires few, sparse data in a much larger amount of time compared with an exploration with range sensors. Since the total time required is a key performing factor, the robot should accurately plan its movement in order to reduce this time. Several advanced strategies have been proposed in robotic literature, usually involving the choice of the best next movement by maximizing the amount information obtained with that movement [1, 3, 29]. Here, a simple and reliable strategy, called *uniform surface density* has been implemented. 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. More advanced methods can also be applied to the identification algorithm proposed in this work, increasing the speed of the exploration.
BACKLASH IDENTIFICATION

The magnitude of joint backlash is identified by comparing the location of the touch points to the primitives, as they become known. Once backlash is identified and compensated, the precision of the touch points increases and the primitive parameters are refined.

The variables used in this analysis are:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Q_E$</td>
<td>Vector of encoder joint angles, corrupted by backlash</td>
</tr>
<tr>
<td>$Q_B$</td>
<td>Vector of joint rotations due to backlash (unknown)</td>
</tr>
<tr>
<td>$Q_R$</td>
<td>Vector of real joint angle locations</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Magnitude of joint backlash (vector)</td>
</tr>
<tr>
<td>$P$</td>
<td>Contact points locations, in Cartesian coordinates</td>
</tr>
<tr>
<td>$\beta$</td>
<td>Surface parameters</td>
</tr>
<tr>
<td>$T$</td>
<td>Joint motor torques (vector)</td>
</tr>
<tr>
<td>$J$</td>
<td>Jacobian of the kinematic equations</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Vector of joint static friction coefficients</td>
</tr>
</tbody>
</table>

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

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

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 values of the backlash, $\alpha$, and to refine the parameters of the primitives, $\beta$, the squared distances between the backlash-compensated points and their belonging primitives is minimized. Using Eq. (2)-(5), and omitting the zero-mean random term, the least squares minimization (1) for the $N$ touch points $P_i$ can be expressed as:

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

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.

**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:

$$
d_j = d_{ui} + \sum_j \frac{\partial d_i}{\partial \alpha_j} \alpha_j + \sum_i \frac{\partial d_i}{\partial \beta_k} \beta_k
$$

The linearized least squares problem becomes:

$$
\begin{bmatrix}
\frac{\partial d_i}{\partial \alpha_j} & \cdots & \frac{\partial d_i}{\partial \beta_k}
\end{bmatrix} \begin{bmatrix}
\alpha_j \\
\beta_k
\end{bmatrix} = -d_{ui}
$$

Figure 3. Backlash model considering the effect of friction. When torque is low, a uniform probability distribution is used.
The derivative terms are easily expressed as a function of the surfaces, the Jacobian and the backlash function. The required computational time for this approach is extremely small. Unfortunately, the estimates obtained this way are not reliable, so the nonlinear formulation need to be used instead.

Nonlinear formulation

As explained in the surface model construction section, effective methods to solve the least square fitting of geometric primitives to constant points have been developed [26-28]. To apply these methods, the minimization (7) is rewritten separating the backlash and surface parts, as:

$$\min_{a} \left[ \min_{\beta} \sum_{i=1}^{N} d_i \left(P_i(\alpha, Q_{E,i}, T_i), \beta\right)^2 \right]$$

(10)

The internal minimization of Eq. (10) is only dependent on the surface parameters, and the surface fitting methods described in the surface model construction section can be used. A few iteration steps 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, with smaller regions of attractions. A local minimizer has the tendency to find only local minima. Therefore a global minimization algorithm is needed [30]. In this research, the Single-Linkage Multi Start algorithm, a simple two-phase stochastic method, provided excellent results. The minimizing function is evaluated in several initial points; these points are clustered according to their function value and their distance, and finally one local search for each of these clusters is computed (again using Levenberg-Marquardt).

Identifiable Parameters

The identification procedure is performed online: the backlash estimation is refined as larger portions of the surface are being explored. Often in the initial stage of the search, not enough data are available to correctly identify all the backlash values. A method is needed to recognize what joints are identifiable, so that the minimization of Eq. (10) will include the identifiable variables while freezing the others until further data are available.

To determine a parameter’s identifiability, the linear model of Eq. (9) is used. In fact, the linear model is too simple to provide a precise estimate of the parameters, but it is sufficient to estimate their identifiability. Let $A$ denote the matrix with the derivative terms in Eq. (9), and let $B \equiv A^T A$. When the condition number (the ratio between its largest and smallest eigenvalues) of $B$ is high, some parameters are not identifiable, because some columns of $A$ are linearly dependent. The unidentified parameters are found using the eigenvectors of $B$ whose corresponding eigenvalues are zero (or very small, in the presence of noise). The nonzero elements of those eigenvectors indicate that the ratio between these values cannot be found, and their variables are frozen in the minimization. It is worth noting that, since the matrix $A$ includes terms having different units (meters and radians), a normalization is needed before computing the eigenvalues.

Small joint torques

The identification procedure is based on the assumption that the position of the 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 model is required in the minimization, as in (9)-(10), and only a probability distribution is available. A good approach in this case is to use the mean of the distribution.

The second problem is more complex: points where 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 touch 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. The “measurement” in eq. (7) is represented by the distance point-surface: thus the variance of this distance due to backlash uncertainty is computed for each point, and its reciprocal is used as a weight. The minimization becomes:

$$\min_{a, \beta} \sum_{i=1}^{N} \frac{1}{\sigma^2_j} d_i \left(\text{kin}(Q_{E,i}, -\alpha f(T_j), \beta)\right)^2$$

(11)

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

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

$$\sigma^2_j (T_j) = \begin{cases} \frac{\sigma^2}{3} & \text{if } T_j < \mu_j \\ 0 & \text{if } T_j \geq \mu_j \end{cases}$$

(12)

If $\mu$ is not known with confidence, the uncertainty can be represented by describing $\mu$ with a mean $\lambda_\mu$ and variance $\sigma^2_\mu$. In this case the distribution of $Q_{E,j}$ smoothly changes as a function of $T$, and its variance can be expressed, after

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

1 A computationally faster approach involves the QR factorization of matrix $A$. But for few, sparse, data the difference is negligible.
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 another Gaussian distribution with mean and variance the sum of the means and variances. The variance of the distribution in 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 (3). For the \( x \) component:

\[
\sigma_j^2 = \sum_{j=1}^{M} J_{jx}^2 \sigma_{jx}^2 + \sigma_e^2
\]  
(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, only the component of the error normal to the surface affects the precision (Figure 5). Thus, the variance in normal direction \( \sigma_n \) is the one be to used in Eq. (11). Denoting by \( n \) the surface normal vector, the variance is:

\[
\sigma_n^2 = n_x^2 \sigma_{nx}^2 + n_y^2 \sigma_{ny}^2 + n_z^2 \sigma_{nz}^2
\]  
(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 in each iteration of the minimization. The weighting system works as intuitively expected. If some points have small torques in directions that give some normal uncertainty, their variance will be higher and the weight smaller. The variance never goes to zero because of the random measurement noise in (15). If this random term is high compared to the backlash, the weights will all have comparable values.

**REPRESENTATIVE CASE STUDIES**

The simultaneous mapping and backlash identification has been tested in two environments modeled in Matlab\textsuperscript{TM}. The robot chosen for these studies has the shape of the manipulator used in the oil-well exploration (Figure 1), without the first translational joint. The link lengths have been set to 1 m. The environment is completely unknown and is composed of geometric primitives. Each point measurement is corrupted both by backlash and by an independently distributed Gaussian noise, as in Eq. (3).

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

In the first environment, the three joints have respectively \( \pm 1^\circ \), \( \pm 1^\circ \), and \( \pm 2^\circ \) of backlash. Joint friction is such that in 46\% of the sample points, the joint torque is smaller than the friction coefficient, generating a uniform random location of the joint within the backlash values. The value of the friction coefficient is not known, but an estimate is available within 30\% precision. Measurement noise is \( \sigma = 1 \) 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 refinement of the four primitive parameters (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 correct value. The backlash compensation greatly increases the precision of the reconstructed surface: as an example, at the end of the

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

![Figure 6. The two environments chosen in the case studies: two barrels (left) and L-shaped junction (right).](image)
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 correct value), and the radius of the spherical cup has a precision of 99.7% relative to the real value.

**EXPERIMENTS**

The method proposed here has been tested in a laboratory experiment. A 2-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 using Eq. (7). 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.

A second set of experiments has been performed using a prototype robot for oil-well exploration, acting in a modeled oil-well junction. The prototype and the exploration performances are described in [1, 2]. A comprehensive description of the backlash estimation in this environment and its results goes beyond the scope of this paper.

**CONCLUSIONS**

This work proposes a technique to tactiley 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 thanks the Schlumberger Doll Research and for its financial support. The authors would also like to thank Daniel Kettler for his fundamental contribution in this research.

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