A Novel Dynamic Slip Prediction and Compensation Approach Based on Haptic Surface Exploration

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Abstract—Slip prediction is important for maintaining the stability of object handling in robust grasping and dexterous manipulation. However, up to date a challenge still remains that how to accurately predict slip occurrence before it actually happens to allow robotic hands to conduct slip compensation in time. The concept of friction cone has been conventionally used to predict slip occurrence, where the static/kinetic friction coefficient is used as a threshold. However, it has been found that this threshold, i.e. the ratio of the friction and normal forces at slip occurrence (also named as break-away friction ratio), is not a constant value but varies with changes in acceleration and disturbing forces applied on the grasped object, raising difficulties when attempting to accurately predict slip. In this paper, we propose a novel approach to accurately predict varying slip thresholds in real time and compensate the predicted slip during a dynamic grasping. To achieve this, first a simple but efficient haptic surface exploration using robotic fingers is carried out to identify the friction properties of an object surface. Once the friction properties are established, the slip threshold at a given grasping condition can be predicted and the grasping forces are adjusted to prevent slip. The presented approach has been evaluated, showing good performance in terms of prediction accuracy and computational efficiency.

I. INTRODUCTION

The study of human grasping reveals that the information of slip is very important for stable and dexterous grasping of objects [1][2]. To enable robotic hands to perform as dexterous as human hands, the determination of the onset of slip between robotic fingers and grasped objects is thus essential [3], especially when grasping and manipulating fragile or slippery objects. Without the slip information, optimal grasping force cannot be appropriately determined to prevent unexpected slippage without crushing the objects. The slip detection has been of the interest in the community of robotic grasping in the past three decades. Various sensing techniques have been developed to detect the onset of slip, such as detecting the change of the strain distribution by using soft fingertips [4-7], analysing magnitudes and/or frequencies of the force/tactile information [8-12], the implementation of accelerometers [13,14] and vision based slip detection [15]. More work on the detection and control of slip for achieving dexterous manipulation can also be found in [16-18].

If the slip is detected at its occurrence, the controller of grasping has to be capable of responding quickly enough to prevent slip. However, if the slip can be predicted before it actually occurs, the grasping controller will work more efficiently and robustly. Conventionally, the concept of friction cone has been used for slip prediction, where the static/kinetic friction coefficient is used as a threshold. When the ratio between the friction and normal force is less than this threshold, contact is considered stable; otherwise, slip occurs. However, there is an issue which has not drawn much attention. The ratio, referred as the break-away friction ratio (BF-ratio), is a property of the dynamic interaction between fingers and objects; and in fact, it varies with the changes in the acceleration and disturbing forces applied on the object [19]. The varying BF-ratio brings difficulties to the grasping controller, since an overestimated BF-ratio could increase the risk of slip while an underestimated BF-ratio would results in an over-applied gripping force.

In this paper, we propose a novel approach to cope with this problem. The proposed approach first applies a simple but efficient haptic surface exploration to identify the friction properties of the surface of an unknown object. The surface exploration only requires the robotic finger to apply two short strokes over the object surface and measures the interaction forces and sliding velocities during the strokes. With the identified friction properties, the slip threshold at a given dynamic grasping condition can be real time predicted. Compared to the conventionally used slip predictor, the developed slip predictor is capable of accurately predicting BF-ratios which vary with different changing rates of the acceleration and disturbing forces applied on the object. Experimental results have shown that the proposed approach achieves good prediction accuracy and computational efficiency. In the paper, a slip compensator has also been created and implemented on the robotic hand using the proposed slip predictor. Since the slip predictor can precisely provide the slip threshold with a safety margin, the compensator can prevent slip in time by adjusting the grasping force. Test results have demonstrated that slip can be effectively prevented using this compensator.

II. THE DYNAMIC MODELLING OF FRICTION

A. Dynamic LuGre Model

To predict BF-ratio and use it for slip compensation, it is necessary to model the dynamic friction interactions between the robotic fingers and the grasped objects. In this study, we only address those rigid-rigid and point contacts. Well-known dynamic friction models for this type of contact include the Dahl model [20], the bristles model [21], the LuGre model [19], and the Leuven model [22]. The LuGre model can describe both the pre-sliding and sliding regimes.
with good accuracy and least complexity [19]. Thus it is chosen in this study. While the LuGre model has been widely used for friction compensation in various fields, to the authors’ knowledge, this is the first time that this model is used for slip prediction during the object handling. The LuGre model assumes the asperities of two contacting surfaces as elastic bristles [19]. Taking into account the normal force, the model is given as:

\[
\dot{z} = v - \sigma_0 \frac{\mu_l}{s(v)} z
\]

(1)

\[
s(v) = F_n \left( \mu_c + (\mu_s - \mu_c) e^{-\frac{|v|}{|v_0|}} \right)
\]

(2)

\[
F_t = \sigma_0 z + \sigma_1 \dot{z} + \sigma_2 F_n v
\]

(3)

where \(z\) is the average deflection of the bristles; \(\sigma_0\) and \(\sigma_1\) are constant stiffness and damping coefficients; \(\sigma_2\) is the viscosity coefficient; \(\mu_c\) and \(\mu_s\) are Coulomb friction and static friction coefficients; and \(v_0\) is the Stribeck coefficient. \(F_n\), \(F_t\), and \(v\) are friction force, normal force, and sliding velocity. The coefficients of the model are invariant to the change of \(F_n\), \(F_t\) and \(v\). If the sliding acceleration is low, the LuGre model can be simplified as:

\[
F_t = F_n sgn(v) \left[ \mu_c + (\mu_s - \mu_c) e^{-\frac{|v|}{|v_0|}} \right] + \sigma_2 F_n v
\]

(4)

Equation (4) is the quasi-static form of the LuGre model, containing four coefficients \(\mu_c, \mu_s, v_0\) and \(\sigma_2\).

Our simulation results illustrate that various sliding accelerations result in different sizes of hysteresis loops, Fig. 1. For low accelerations (such as rate=1mm/s and 5mm/s² in Fig. 1), the means of friction forces obtained at velocity increasing and decreasing agree well with the quasi-static LuGre model (red curve in Fig. 1). Thus, the friction-velocity obtained at low sliding accelerations can be approximated as the quasi-static form of the LuGre model [23].

III. TWO-STROKE HAPTIC SURFACE EXPLORATION FOR FRICTION PROPERTY IDENTIFICATION

To use the dynamic LuGre model for slip prediction, the first action is to identify the full set of parameters of this model. In this study, we propose a simple but efficient Two-Stroke haptic surface exploration strategy to achieve this. It is assumed that the friction property is identical across the object surface. We let a robotic finger apply two consecutive strokes over the object surface, one sliding at a low acceleration while the other one at a higher acceleration. Four static coefficients of the model are estimated through the low acceleration stroke; while dynamic coefficients are estimated through the high acceleration stroke. This section presents the algorithms used for identifying these parameters.

In the first stroke, the robotic fingertip needs to create a profile of sliding velocity where velocity increases from zero and then decreases to zero at acceleration lower than 5mm/s² (empirically obtained). During the stroke, sliding velocity and interaction forces are acquired. The curve of velocity against friction ratio (=friction force/normal force) obtained during velocity increasing and the curve obtained during velocity decreasing are averaged to estimate coefficients \(\mu_c, \mu_s, \sigma_1\) of the LuGre model. Define the error function \(S\) as:

\[
S(v, F_t, F_n, P) = \mu_c + (\mu_s - \mu_c) e^{-\frac{|v|}{|v_0|}} + \sigma_2 v - \frac{F_t}{F_n}
\]

(5)

where \(P = [\mu_c, \mu_s, v_0, \sigma_1]^T\) is the parameter vector to be estimated, \(v\) is the sliding velocity vector, and \(F_t\) and \(F_n\) are the friction force vector and normal force vector. Define \(S=[S(1), S(2), \ldots, S(N)]^T\) obtained from a sequence of measurements. The parameter vector \(P\) can be iteratively estimated by applying the generalized Newton-Raphson (GNR) method [23]:

\[
P_{k+1} = P_{k} - J^T S
\]

where \(J^T\) is the pseudo inverse of \(J=[\partial S/\partial P]\) \((i=1,\ldots,4)\).

After identifying the four coefficients, the fingertip is driven to conduct the second stroke where the velocity also experiences increasing and then decreasing but at acceleration higher than 10mm/s² to identify \(\sigma_0\) and \(\sigma_1\) of the LuGre model. Define \(h(v) = \frac{|v|}{F_n s(v)}\) \((s(v)\) is given by
where $\Omega$ normal force and sliding velocities during a high
model, using data obtained from one high acceleration
simultaneously estimate all six coefficients of the LuG re
uses large
parameters). Defining $\lambda$ becomes a function of the initial displacement
becomes a function of the initial displacement $z_0$. Let $z(k)=\Psi(\sigma_0, z_0, k)$, then Eq. (9) can be rewritten as:
\[
\mu(k) = \frac{1}{F_n(k)} \left[ \sigma_0 - \sigma_0 \sigma_1 h(v(k)) \right] \Psi(\sigma_0, z_0, k)
\] (12)
Using the sequential measurements of the friction force, normal force and sliding velocities during a high acceleration stroke, we can obtain a set of Equs. (12), i.e. $\Omega=[\mu(1), \mu(2), \ldots, \mu(n)]^T$. Define the Chi-squared error function as:
\[
\chi^2 = \frac{1}{2} \sum_{i=1}^{n} [\mu(i) - \hat{\mu}(i)]^2 = \frac{1}{2} (\Omega - \hat{\Omega})^T (\Omega - \hat{\Omega})
\] (13)
where $\hat{\Omega}$ is the estimate of $\Omega$. Estimating vector $x=[\sigma_0, \sigma_1, z_0]^T$ is thus the problem of minimising $\chi^2$. Applying the LM method, vector $x$ can be iteratively estimated using:
\[
x_k = x_{k-1} + J^T(\Omega - \hat{\Omega}) \left[ J^T + \lambda \text{diag}(J^T) \right]^{-1} \] (14)
where $J=\frac{\partial \Psi}{\partial x}$ is the Jacobian matrix, which can be approximated using backwards differences. When the current estimate is far from its real value, the LM updating uses large $\lambda$ (leading to gradient descent update); when the current estimate gets close to its real value, then the value of $\lambda$ is adaptively reduced (leading to Gauss-Newton update) [24].

Theoretically it is also possible to apply the LM method to simultaneously estimate all six coefficients of the LuGre model, using data obtained from one high acceleration stroke. Define the estimated vector as $x=[\sigma_0, \sigma_1, \mu_e, \mu_s, \sigma_2, z_0]^T$ and substitute $h(v(k))$:
\[
h(v(k)) = [v(k)] \left[ F_n(k) \left( \mu_e + (\mu_s - \mu_e) e^{- \left( \left| v(k) \right| / \sigma_2 \right)^2} \right) \right]^{-1}
\]
into Equs. (11) and (12), parameter vector $x$ can be estimated by using Equs. (13)-(14). However, it will be demonstrated in Section V that identifying the full set of LuGre coefficients in one go is not only prone to large errors but also computationally expensive.

IV. ONLINE SLIP PREDICTION AND COMPENSATION

Once the full set of parameters of the LuGre model is established, the BF-ratio can be predicted given the jerk of lifting $\ddot{a}$ (such as Fig. 2) or the changing rate of disturbing force $F$ (such as Fig. 3). In practice, the jerk of lifting $\ddot{a}$ can be readily obtained from accelerometers mounted on the robotic fingers. In our experimental study, we consider the case of applying disturbing force $F$ on the object, Fig. 3. For this case, the changing rate of the drag force $\dot{F}$ can be provided by the fingers where 6-DoF F/T sensors are equipped, since $F=F_1+F_2-G$ before gross slip occurs. $G$ is the object gravity; $F_1$ and $F_2$ are the tangential forces which can be measured by 6-DoF F/T sensors equipped on two fingers.

![Figure 3: An object is grasped by two fingers while a drag force $F$ is applied to pull it down.](image)

Applying the Newton’s second law can obtain:
\[
\mu_e - \mu = \frac{m}{2F_n} \ddot{v}
\] (15)
where $\mu_e = \frac{F+G}{2F_n}$ is defined as the applied friction ratio and $\mu$ is the friction ratio predicted by the LuGre model (Equ. (9)). $F_n$ is the grasping force, $m$ is the mass of the object which can be obtained when the object is vertically held by the fingers, $v$ is the sliding velocity of the object with respect to the fingers. Define the changing rate of the applied friction ratio $\dot{\mu}$ as $\dot{\rho} = \frac{\mu_e - \mu}{2F_n}$. Since $F=F_1+F_2-G$ before gross slip happens, $\rho$ can be calculated as $\rho = \frac{1}{2F_n} [F_n(F_1 + F_2 - F_n (F_1+F_2))]$. Let $x_1=\mu_e$, $x_2=v$, $x_3=z$, the differential equations representing the dynamic behavior of the object from static stage to slip stage are given below, derived from Equs. (8), (9) and (15):
\[
\dot{x}_1 = \rho
\] (16)
\[
\dot{x}_2 = \frac{2F_n}{m} \left[ x_1 - \frac{1}{F_n} \left( \sigma_0 x_3 + \sigma_1 x_2 - \frac{\sigma_0 \sigma_1 x_3 x_2}{F_n (\mu_e + (\mu_s - \mu_e) e^{- \left( \left| x_2 / \sigma_2 \right| \right)^2})} \right) - \sigma_2 x_2 \right]
\] (17)
\[
\dot{x}_3 = x_2 - \sigma_0 \frac{x_2 x_3}{F_n} \left( \mu_e + (\mu_s - \mu_e) e^{- \left( \left| x_2 / \sigma_2 \right| \right)^2} \right)
\] (18)
This set of first-order differential equations can be solved using the Runge-Kutta forth-fifth order method, using the
identified coefficients of the LuGre model. The BF-ratio is determined when $\dot{\mu}$ changes from positive to negative (which corresponds to a sharp increase in velocity). With each new $\rho$, the differential equations above need to be solved to find the BF-ratio under the given $\rho$. Therefore, duration the period of applying $\hat{F}$, the BF-ratio will be predicted at each time step. The changing of $\rho$ during this period will lead to the variation of the predicted BF-ratio.

In this paper, we define the predicted BF-ratio as the slip threshold $\mu_{\text{slip}}$. If the actual friction ratio reaches the threshold, the object is considered to slip. As shown in Fig. 4, the BF-ratio prediction algorithm (Equs. (16)-(18)) is implemented as a slip predictor to online predict $\mu_{\text{slip}}$ taking fresh inputs of $\rho$ and $\hat{F}$ from the force-sensing fingers. The predicted threshold $\mu_{\text{slip}}$ will vary with the changing of $\rho$ and $\hat{F}$, during a dynamic grasping. To prevent slip in time, a safety margin is set, Fig. 4. The value of the safety margin depends on the frequency of the prediction-and-compensation loop (Fig. 4). A large safety margin is needed for a low frequency system. When the actual friction ratio $\mu_{\text{actual}}$ approaches to the safety margin, the grasping controller will continue applying larger grasping forces by changing the joint angles of the fingers until $\mu_{\text{actual}}$ leaves the safety margin.

![Fig 4. Slip compensation using online predicted slip threshold.](image)

**V. Experimental Results**

**A. Experimental Setup and Procedures**

To evaluate the proposed approach, a test platform consisting of a three-fingered robotic hand (BH8-series BarrettHand\textsuperscript{TM}), 6-DoFs robot arm (RV-6SL Mitsubishi\textsuperscript{TM}) and a DC motor is used, Fig. 5. Each robotic finger has a hemispherical tip (made from ABS plastic) and is instrumented with an ATI Nano17 6-DoF F/T sensor. These specially designed fingertips can robustly measure tangential and normal forces regardless of the fingertip orientation and the object surface curvature [25]. The velocity of the finger sliding over object surface is obtained from encoders of the robot arm. The object used for testing is made from ABS plastic and size of 12cm×2.2cm×1.8cm, with its surface covered by electrical tapes.

**B. Experimental Results**

**B.1 Friction Property Identification Results**

In the experiments, a fingertip first applies two short strokes over the object surface and measures the interaction forces and sliding velocities during strokes, Fig. 5 (a). The data obtained during the stroke at low acceleration are used to identify coefficients $\mu_0$, $\mu_c$, $v_0$ and $\sigma_2$ of the LuGre model, while data obtained during the high acceleration stroke are used to identify coefficients $\sigma_0$ and $\sigma_1$. After the Two-Stroke surface exploration, the object is grasped by the hand with one end attached to a rubber band. The rubber band is then connected to a DC motor, Fig. 5 (b). During the tests, the motor is driven to pull the rubber band to deliberately introduce slip. By applying different voltages on the motor, different changing rate of the applied friction ratio $\rho$ can be generated. As discussed in Section IV, $\rho$ is obtained from the force-sensing fingertips. In the tests, the object is vertically grasped and the force applied to drag the object is along the vertical direction as well. Thus the interaction forces on the two fingers are considered identical. The force sensing and hand control system is run under the Robot Operating System (ROS) framework at a sampling rate of 30Hz.

**Table II. Summarised Estimated Coefficients. Units for Coefficients $\sigma_0$, $\sigma_1$, $v_0$ and $\sigma_2$ are N/mm, Ns/mm, mm/s and s/mm.**

<table>
<thead>
<tr>
<th>GNR</th>
<th>LM-2</th>
<th>LM-6</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_0$</td>
<td>0.36</td>
<td>$\delta_0$</td>
</tr>
<tr>
<td>$\mu_c$</td>
<td>0.13</td>
<td>$\delta_1$</td>
</tr>
<tr>
<td>$\sigma_0$</td>
<td>1.6</td>
<td>$\delta_2$</td>
</tr>
</tbody>
</table>

In the high acceleration stroke, the fingertip slides in an acceleration of 10mm/s\textsuperscript{2} with velocity increasing from 0mm/s to 13mm/s and then decreasing to 0mm/s. During this
stroke, the bristle displacement varies, i.e. \( \dot{\gamma} \neq 0 \), leading to the feasibility of estimating coefficients \( \sigma_0 \) and \( \sigma_1 \). The LM-based method is applied to estimate them using the measurements of the friction-velocity loop (black circles in Fig. 6). The estimation quickly converges within seven iterations. Table II shows the summarised estimation results. For brevity, ‘GNR’ represents the GNR method estimating coefficients \( \mu_1, \mu_2, v_0 \) and \( \sigma_2 \). 'LM-2' represents the LM method estimating two coefficients \( \sigma_0 \) and \( \sigma_1 \).

Using coefficients identified by the GNR and LM-2 algorithm, friction ratios are computed and compared to the measured ones. It can be seen from Fig. 6 that estimates (red circles) have good agreement with the measurements (black circles) with an R-square error of 0.9767.

Estimating the full set of coefficients of the LuGre model in one go using the LM method (LM-6 in Table II) is also implemented (which only requires one high acceleration stroke). Estimated results obtained from the LM-6 algorithm are also given in Table II. It can be observed from Fig. 6 that the friction ratios obtained using LM-6 method (green circles) reach a good agreement with the measurements with an R-square error of 0.9804. Nevertheless, the estimated static coefficient \( \mu_s = 0.98 \) is overly large. This will result in large deviations when estimating the BF-ratio (results are shown in Table III). Thus, the LM-6 method is neither accurate nor robust for the friction property identification.

Fig. 6. Friction ratios are computed using estimated coefficients of the LuGre model and compared to the measured values.

### B.2 BF-Ratio Prediction Results

Using the identified coefficients of the LuGre model (Table II) and measured \( \rho \) (\( \rho \) is obtained from the fingertip F/T sensors by simply calculating \( \mu_s \), Equ. (15)) and \( F_n \), the BF-ratio can be determined by solving differential equations, Equs. (16)-(18). First, a set of tests with constant \( \rho \) are conducted. In each test, a constant dragging force rate \( \dot{F} \) is applied on the grasped object and the grasping force is maintained at 5N through PID control. This leads to different \( \rho \) for individual tests. The occurrence of slip is determined when the friction force experiences a significant drop. Table III illustrates the test results. The BF-ratios predicted using coefficients obtained from the GNR+LM-2 method coincide with the measurements reasonably well, with an overall percent error of 5.80%. However, the LM-6 method results in significant errors (averaged percent error of 117.98%), indicating the poor performance of identifying all coefficients in one go. From Table III, it is also shown that over the tested range, the measured BF-ratio decreases from 0.339 to 0.219. This further implies the need of accurately predicting the BF-ratio.

#### Table III. Predicted BF-Ratio Using Different Methods.

<table>
<thead>
<tr>
<th>Changing rate ( \rho ) ((s^{-1}))</th>
<th>Measurement</th>
<th>GNR+LM-2 Estimates</th>
<th>Percent error (%)</th>
<th>LM-6 Estimates</th>
<th>Percent error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.019</td>
<td>0.339</td>
<td>0.328</td>
<td>3.245</td>
<td>0.861</td>
<td>153.982</td>
</tr>
<tr>
<td>0.033</td>
<td>0.331</td>
<td>0.317</td>
<td>4.230</td>
<td>0.819</td>
<td>147.432</td>
</tr>
<tr>
<td>0.077</td>
<td>0.290</td>
<td>0.288</td>
<td>0.690</td>
<td>0.704</td>
<td>142.759</td>
</tr>
<tr>
<td>0.112</td>
<td>0.289</td>
<td>0.266</td>
<td>7.958</td>
<td>0.620</td>
<td>114.533</td>
</tr>
<tr>
<td>0.136</td>
<td>0.283</td>
<td>0.262</td>
<td>7.420</td>
<td>0.602</td>
<td>112.721</td>
</tr>
<tr>
<td>0.160</td>
<td>0.279</td>
<td>0.246</td>
<td>11.828</td>
<td>0.543</td>
<td>94.624</td>
</tr>
<tr>
<td>0.242</td>
<td>0.242</td>
<td>0.233</td>
<td>3.719</td>
<td>0.490</td>
<td>102.479</td>
</tr>
<tr>
<td>0.334</td>
<td>0.219</td>
<td>0.203</td>
<td>7.306</td>
<td>0.384</td>
<td>75.342</td>
</tr>
</tbody>
</table>

Averaged error: 5.80% - 117.984

In addition, it can also be observed from Table III that the increasing of \( \rho \) causes the predicted BF-ratio to change in an opposite way. This indicates that if a large \( \rho \) is applied, the object is more prone to slip due to a low BF-ratio. This also coincides with simulation results illustrated in Section II. B.

Figure 7 illustrates an example of BF-ratio prediction with varying \( \rho \) (Fig. 7 (b)). To create varying \( \rho \) in a test, the voltage applied on the motor is changed with time. The LuGre coefficients estimated by the GNR+LM-2 method are used in the test. It is observed from Fig. 7 that the changing of \( \rho \) results in the variation of the predicted BF-ratios (red x-marks in Fig. 7 (a)). The BF-ratio is predicted at each time step and each predicted value represents the threshold beyond which slip will occur if the current \( \rho \) continues to be applied on the object. Before the actual friction ratio (green crosses in Fig. 7 (a)) reaches the predicted BF-ratio, the object grasping is static; however, when the actual friction ratio gets very close to the predicted BF-ratio, the object is about to slip, Fig. 7 (a). It is also found from Fig. 7 that at the occurrence of slip, the actual BF-ratio is smaller than the static friction coefficient \( \mu_s \) and larger than the Coulomb friction coefficient \( \mu_C \). Therefore, compared to the static and kinetic friction model conventionally used, the proposed prediction approach can provide more accurate BF-ratios.

#### B.3 Online Slip Prediction and Compensation
Figure 8 illustrates test results of online slip prediction and compensation. In the test, the predicted BF-ratio at each time step is used as the slip threshold $\mu_{\text{slip}}$. The safety margin is set to 5% in the test, which means once the relative gap between the actual friction ratio $\mu_{\text{actual}}$ and the slip threshold is less than 5%, the grasping controller will start to compensate the predicted slip. As shown in Fig. 8, slip compensation has been successfully conducted twice in this test when $\mu_{\text{actual}}$ enters the safety margin. After each compensation, $\mu_{\text{actual}}$ is decreased below the safety margin area, since the fingers applies larger grasping forces on the object. In the experiment, to reduce the computational cost of slip prediction, instead of predicting $\mu_{\text{slip}}$ at every step, once $\mu_{\text{actual}}$ is found decreasing and leaving from the safety margin area, the slip predictor will suspend and use the most recent value as its output until $\mu_{\text{actual}}$ increases again.

B.4 Analysis of Computational Cost

On a PC with a 2.66GHz Intel® Core™ 2 Duo processor and 3GB RAM, the proposed approach is implemented in C++ under ROS. For identifying coefficients $\mu_s$, $\mu_c$, $v_0$ and $\sigma_2$, the GNR method usually can converge within 20 iterations with 450μs needed for each iteration. To identify $\sigma_0$ and $\sigma_1$ using the data of a friction-velocity loop such as Fig. 6 which contains 205 measurements, the LM-2 method takes seven iterations to converge, with an averaged computational time of 289ms per iteration. The computational speed can be increased by using fewer measurement data. After two strokes over the object surface and coefficient estimation, the BF-ratio can be predicted online in a frequency of 300Hz (3ms) once a dynamic grasp starts.

VI. CONCLUSION AND FUTURE WORK

This paper proposes a novel dynamic slip prediction and compensation approach based on haptic surface exploration, which can enhance the stability of object handling during robust grasping and dextrous manipulation. To summarise, the paper has two main contributions. 1. A Two-Stroke surface exploration strategy is proposed to identify the friction properties of an unknown object. This strategy is simple to implement and can efficiently provide very rich friction information. Moreover, it paves the way to the second contribution. 2. A novel online slip predictor and compensator are developed in this study. The slip predictor has demonstrated two advantages. First, the slip predictor can accurately predict slip thresholds before the actual occurrence of slip, instead of detecting the onset of slip, thus allowing a grasping controller to conduct slip prevention in time. Second, the proposed slip predictor overcomes the drawback of conventional predictors which assume a constant BF-ratio for any dynamic grasping condition. The developed slip predictor can predict accurate BF-ratios which are varied with different jerk $\ddot{F}$ and different rate of disturbing force $\dot{F}$. Experimental results have proved the varying BF-ratio phenomenon and also the good performance of our proposed approach.

In future work, the approach will be tested on more surface materials. Although experiments have validated the accuracy and computational efficiency of the algorithm for friction property identification, the robustness and numerical stability of the algorithm needs to be further investigated. In addition, the proposed approach will have difficulties if grasping soft objects, which will introduce area contact and rotational slip [18]. To solve this, the friction modelling of the rigid finger-soft object contact needs to be explored.

REFERENCES


